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Development and evaluation of a scheme system of joint prevention and control of $PM_{2.5}$ pollution in the Yangtze River Delta region, China

Yangjun Wang [a, b], Ziyi Liu [a], Ling Huang [a, b], Guibin Lu [c], Youguo Gong [d], Elly Yaluk [a], Hongli Li [a], Xin Yi [a], Liumei Yang [a], Jialiang Feng [a, b], Cesunica Ivey [e], Li Li [a, b, *]

[a] School of Environmental and Chemical Engineering, Shanghai University, Shanghai, 200444, China
[b] Key Laboratory of Organic Compound Pollution Control Engineering, Ministry of Education, Shanghai, 200444, China
[c] School of Economics, Shanghai University, Shanghai, 200444, China
[d] Research Institute of Chemical Defense, Beijing, 102205, China
[e] Department of Chemical and Environmental Engineering, University of California, Riverside, CA, 92521, USA

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A B S T R A C T

Although many efforts have been done to reduce $PM_{2.5}$ pollution in recent years, there are still many nonattainment cities in East China for national standards. How to collaborate with surrounding cities to reduce $PM_{2.5}$ has been a critical issue for all nonattainment cities. In this work, a framework of developing a practical scheme system of joint prevention and control of $PM_{2.5}$ pollution based on data mining technologies was presented. Moreover, one specific scheme system for Yangtze River Delta region was developed and evaluated by five indicators. The results indicate that the scheme system was divided into three grades depending on pollution levels except for summer with two grades. The heavier the $PM_{2.5}$ pollution was, the higher the grade was recommended to be implemented along with low grades. Moreover, more city-clusters were involved in each grade in winter than any other season. For Grade one in winter, the city-cluster with Xuzhou and Suqian was the most urgent to control emission jointly; the city-cluster with Suzhou and Shanghai was linked to the biggest impact on health, but for integrated indicator, the city-cluster with Nanjing and Changzhou ranked first. These results not only enable an enriched understanding of the significance of $PM_{2.5}$ control in city-clusters, but also accelerate $PM_{2.5}$ reduction for all nonattainment cities by collaboration with their most correlated cities in this region.

1. Introduction

With the rapid urbanization and increase of energy consumption in recent decades, China has frequently suffered from severe haze events in several regions (Han et al., 2016; Wang et al., 2019; Zeng et al., 2019). Haze events are usually caused by high concentrations of fine particulate matter with aerodynamic diameters less than 2.5 mm (i.e. $PM_{2.5}$). As a complex mixture, $PM_{2.5}$ is linked to negative health impacts (Wang et al., 2015a; Song et al., 2017a).

In order to protect human health, many efforts have been made by government to prevent further air quality deterioration caused by $PM_{2.5}$ pollution. $PM_{2.5}$ was included for the first time as a routine inspection indicator in Chinese National Ambient Air Quality Standards (NAAQS) issued in 2012. Later, the Air Pollution Prevention and Control Action Plan (APPCAP) was released in September 2013 and was implemented from 2013 to 2017 (Zhang et al., 2016a; Wang et al., 2017). The APPCAP may have been one of China's most influential environmental policies in the past five years. It helped China to attain significant improvement in air quality by setting targets in three key regions including the Yangtze river delta (YRD) region, one of the most populous and largest economic regions in China. During the time period from 2013 to 2017, Anhui province was not yet included nominally in the YRD region in terms of $PM_{2.5}$ monitoring and appraising. Accordingly, all cities in Anhui province had not been subject to the $PM_{2.5}$ target of this action plan for YRD region during that time period.

When the Three-year Action Plan for Winning the Blue-Sky Defense War was issued in 2018 by the Chinese government, the $PM_{2.5}$ target was set for the whole region by adding the whole Anhui province, which is relatively far from Shanghai. In this Three-year Action Plan, it was stated that the annual concentrations of

* Corresponding author. School of Environmental and Chemical Engineering, Shanghai University, Shanghai, 200444, China.
E-mail address: lily@shu.edu.cn (L. Li).

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$PM_{2.5}$ in prefecture-level cities and above prefecture-level that failed to meet the national standards should be reduced by at least 18% and the days with severe pollution should be reduced by at least 25% by the end of 2020 compared to 2015. In addition, an amended law named Law of the People's Republic of China on the Prevention and Control of Atmospheric Pollution, came into effect since January 2016. It has been regarded as an important milestone in Chinese air pollution prevention because $PM_{2.5}$ and O_3 were listed as the target pollutants for the first time, and joint prevention and control were mentioned for the first time too. Admittedly, the Chinese government has attached a great importance to reduce $PM_{2.5}$ pollution in recent years. In the end of 2019, an outline of the integrated regional development of the Yangtze River Delta was issued, in which environmental standards were laid out to be met by 2025 in terms of $PM_{2.5}$ (http://www.gov.cn/zhengce/2019-12/01/content_5457442.htm). Therefore, the reduction of $PM_{2.5}$ in the YRD region is highly needed and YRD region was chosen as the research domain in this work.

Many studies have explored temporal and spatial distributions of $PM_{2.5}$ concentrations to assess the effectiveness of emission reduction measures or to provide basic information for policy making to gain better air quality (Cheng et al., 2017; Chen et al., 2019). Zhang et al. (2018) have assessed the improvements due to implementation of the APPCAP and their results showed that the annual mean concentration of $PM_{2.5}$ decreased by more than 30% throughout the country. Three years' time series of $PM_{2.5}$, as well as other pollutants were studied to understand the severity of China's air pollution (Song et al., 2017b). Temporal variations of $PM_{2.5}$ concentrations and the attainment rate in 2016 for 338 cities in China, indicated that regional transport impact of $PM_{2.5}$ in the BTH region and the neighboring areas (Ye et al., 2018). More literatures reported the spatiotemporal patterns of air pollution at different spatial scales. The analysis of hourly air quality data from 2014 to 2015 for 35 monitoring stations in Beijing suggested that neighboring area's air quality plays an important role in the air quality of Beijing (Chen et al., 2015). Study on the spatial and temporal variability of $PM_{2.5}$ suggested strong temporal correlation between cities within 250 km in the YRD region (Hu et al., 2014). Spatial distribution of $PM_{2.5}$ in the YRD region was negatively correlated with forest land and grassland, but positively correlated with urban construction land (Lu et al., 2018). There were several methods to analyze the relationship between the spatial distribution of $PM_{2.5}$ with other factors, such as the Multivariate Moran model (Yao et al., 2019). Wang and Fang (2016) showed that the spatial and temporal distribution characteristics of $PM_{2.5}$ in the Bohai Rim Urban were closely related to the GDP per capita, urbanization rate and construction of the cities. Usually, understanding of the spatial and temporal characteristics is prerequisite of environmental policy.

Furthermore, both of emission changes and meteorological conditions have been shown to affect the variation of ambient $PM_{2.5}$ concentrations in certain regions (He et al., 2003; Wang et al., 2015b; Khuzestani et al., 2017). Consequently, the strong transport contribution of $PM_{2.5}$ can increase the difficulty to improve urban air quality without collaboration among cities or regions. The importance of regional joint prevention and control has been proposed in some studies. An empirical study of the BTH region suggested that the expense on pollution control can be saved if regional air pollution control can be effectively implemented (Wu et al., 2015). Zhang et al. (2018) suggested that joint control among seven major province-level regions was important based on the analysis of spatiotemporal trends in $PM_{2.5}$ levels. However, their studies usually refer to the joint control among relatively large regions such as provinces. They are often not practical in implementation because there are usually quite obvious differences for $PM_{2.5}$ concentration and economic structure among these cities within the same province. As a result, the same control measures usually cannot be implemented in all these cities even though they are within the same province. Therefore, a precision scheme of joint prevention and control between or among cities is highly needed.

Wang and Zhao (2018) proposed a joint prevention and control method for sub-area division in winter season in the BTH region, and this was the first attempt to define a sub-region within provinces for the joint prevention and control. Similarly, based on the data analysis of $PM_{2.5}$ concentrations, Xie et al. (2018) studied only fifteen cities in the YRD region and did not focus on nonattainment cities but on the whole region. Therefore, there is still a big gap between these studies and the practical needs, and the gap mainly includes four parts: 1) Previous studies involved only a small part of the new expanded YRD region. 2) Their researches identified only a few combinations of cities for the whole region. 3) Variations with seasons and pollution levels were not taken into account to present city combinations for joint prevention and control of $PM_{2.5}$ pollution. 4) Many nonattainment cities were not taken into account in their studies. Currently, all nonattainment cities in the YRD region are still facing great pressures to meet the NAAQS. To fill the gap, our goal is to develop a more practical and precision scheme system of joint prevention and control of $PM_{2.5}$ pollution (JPCPP) depending on seasons and pollution levels, in order to help all nonattainment cities in the new expanded YRD region to reduce $PM_{2.5}$ effectively to attain for the national standards.

In this work, one framework of developing a practical scheme system of JPCPP was presented. Firstly, $PM_{2.5}$ pollution and exposure patterns for the 41 prefecture-level cities in the YRD region from 2015 to 2018 were explored based on statistical analysis. Secondly, a precision scheme system for 41 prefecture-level cities was developed by applying data mining technologies. In this scheme system, many city-cluster- regions were designed and grouped into several grades depending on seasons and pollution levels. According to each grade, corresponding JPCPP city-clusters were recommended to be implemented from the view of prefecture-level cities, in order to drive these nonattainment cities effectively to meet the Chinese NAAQS. Finally, all city-clusters were evaluated based on five indicators including urgency, health impact, elasticity of pollution control, pollution impacts on the whole region and an integrated indicator, suggesting the top city-clusters of JPCPP from different perspectives.

2. Data source and methods

One framework for developing a practical scheme system of Joint Prevention and Control of $PM_{2.5}$ Pollution was presented, as shown in Fig. 1. The input data included daily $PM_{2.5}$ concentrations, population and the area of each city in the YRD region. Data-mining methods including statistical analysis, clustering analysis and network correlation model have been used to explore the correlations between all cities in this region. Correlation thresholds were set to generate a JPCPP city-clusters of depending on seasons, pollution levels and grades. Finally, evaluation was conducted for each city-cluster by five indicators involving urgency indicator, indicator of health impact, elasticity of pollution control, degree of influence on the whole YRD region, and integrated indicator.

2.1. Research domain and data source

The YRD region led by Shanghai is one of the most important economic zones in China and is close to the East China Sea. There are 41 prefecture-level cities in the expanded YRD region covering Shanghai Municipality, Jiangsu, Zhejiang and Anhui provinces, as shown in Fig. 2. The capital cities for Jiangsu, Zhejiang and Anhui are Nanjing, Hangzhou and Hefei, respectively. There are 16

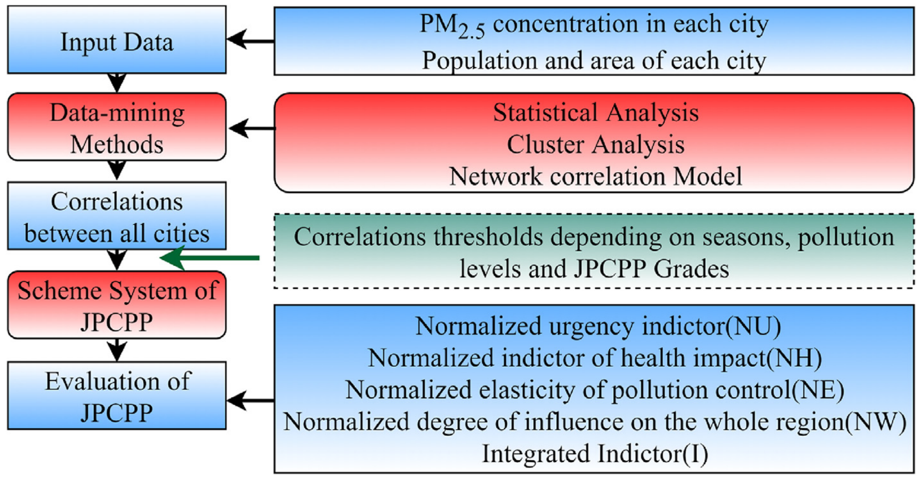

Fig. 1. Framework for developing a practical scheme system of Joint Prevention and Control of $PM_{2.5}$ Pollution (JPCPP)

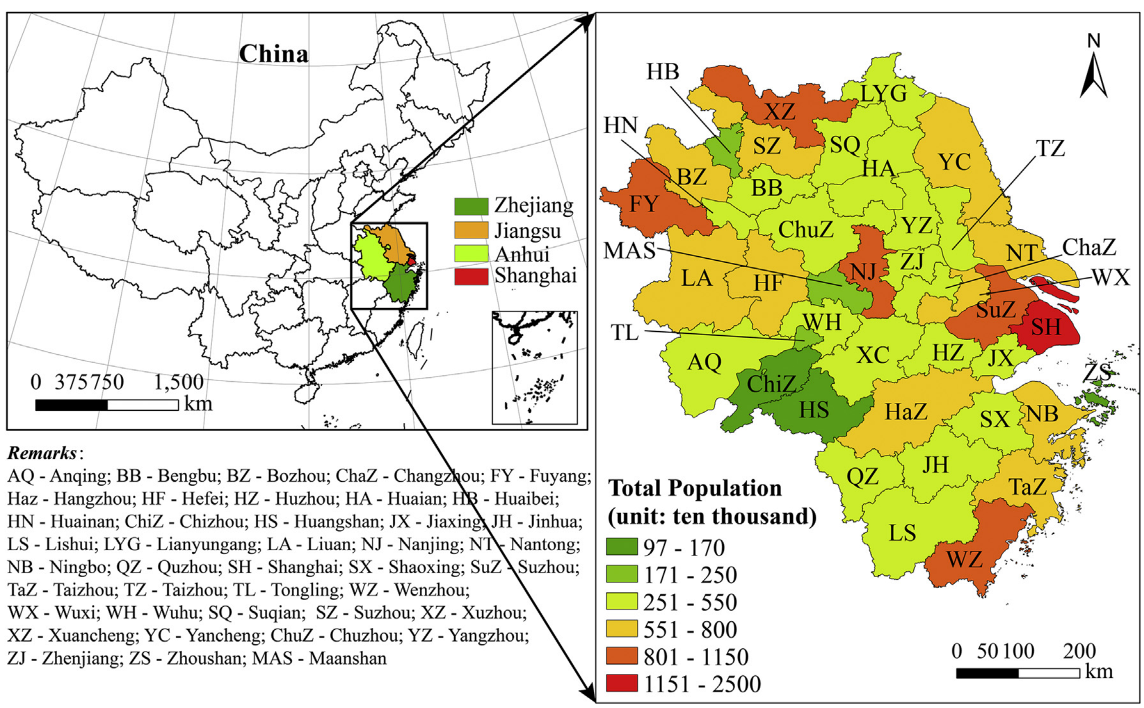

Fig. 2. Locations and populations of cities in the YRD region.

prefecture-level cities in Anhui, while 14 and 11 prefecture-level cities are located in Jiangsu and Zhejiang provinces, respectively. Shanghai, with a population of over 24 million, is the most populous city in the YRD region. Besides Shanghai, there are four cities with populations more than 8 million, which are Suzhou, Xuzhou, Nanjing, Wenzhou. Suzhou is the second most populous city, just following Shanghai. The population for each prefecture-level city in YRD region is acquired from the census database of the National Bureau of Statistics of China (Ning et al., 2017).

The pollution data used in this work are abstracted from the air monitoring data center of Ministry of Ecology and Environment of the People's Republic of China (MEEP). In China, routine monitoring of $PM_{2.5}$ was rolled out by the government in 2013 with strict adherence to NAAQS guidelines (GB 3095–2012) in terms of instrument operation and management, data assurance, and quality control. The first phase covered 74 cities that included municipalities directly under the Central Government (Beijing, Shanghai, Tianjin and Chongqing), provincial capital cities, and the cities specifically designated in the national socioeconomic plan. The second and third phases were rolled out to include 161 cities in 2014 and all prefecture-level cities in China were among the 338 cities included in the routine monitoring of $PM_{2.5}$ in 2015. With each prefecture-level city having several national air quality monitoring stations, the hourly $PM_{2.5}$ concentrations for all 41 prefecture-level cities in the YRD region started to be observed from 2015 and consequently informing the time period of this study. The hourly $PM_{2.5}$ concentrations of all prefecture-level cities in the YRD region during the period from 2015 to 2018 were used in this study. $PM_{2.5}$ pollution and exposure patterns from 2015 to 2018 were explored. Besides, data in 2018 were used to develop a scheme system of JPCPP in order to better support the city governments' joint prevention and control of $PM_{2.5}$ pollution in the future. The data of $PM_{2.5}$ concentrations were obtained from MEEP and hourly concentration values were obtained from the China Urban Air Quality Real-Time Publishing Platform (http://106.37.208.233:20035). Each prefecture-level city in the YRD region has several national air quality monitoring stations.

2.2. Methods

Data mining technologies, including clustering analysis and complex network correlation model, were introduced, and definitions of five indicators were shown as follows. Five indicators are composed of Normalized pollution control urgency (NU), Normalized health impact (NH), Normalized elasticity of pollution control (NE), Normalized pollution impact on the whole region and integrated indicator (NW).

2.2.1. Population exposure intensity to $PM_{2.5}$

Population exposure intensity can reflect the health risk associated with the number of people in a certain area exposed to $PM_{2.5}$. This is expressed by population density and $PM_{2.5}$ concentration in Equation (1) (Kousa et al., 2002), and its units is $\mu g \cdot 10^4$ persons/(m^3 km ^{2}).

$$E_i = \frac{P_i C_i}{A} \tag{1}$$

where, E_i is the population exposure intensity in city i in the YRD region; C_i is the $PM_{2.5}$ mass concentration of the same city, P_i is the population in the same city, and A is the area of this city. $PM_{2.5}$ is the only pollutant considered in this study.

2.2.2. Hierarchical clustering analysis

Hierarchical clustering, also referred to as hierarchical cluster analysis, agglomerative hierarchical clustering or "bottom-up" hierarchical clustering (Norušis, 2011), is an algorithm that groups similar objects into categories called clusters. Hierarchical clustering typically works by sequentially merging similar clusters and begins by treating each object as a separate cluster (Madhulatha, 2012; Granato et al., 2018). It repeatedly executes the following steps: (1) identify two clusters that are the most similar, and (2) merge the two closest clusters into one cluster. This continues repeatedly until all the clusters are merged together producing a set of distinct clusters apparently with similar objects within each cluster (Jiang et al., 2015). The main output of hierarchical clustering is a dendrogram, which shows the hierarchical relationship between the clusters. In this study, 41 prefecture-level cities in the YRD region were treated as the initial objects for hierarchical clustering. The characteristic variables for each city are daily average concentrations of $PM_{2.5}$ for a whole year or different seasons and the input data of the cluster analysis can be shown as follows:

$$\mathrm{X} = (x_{ik})_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{n1} \\ x_{21} & x_{22} & \cdots & x_{n2} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{nm} \end{bmatrix} \tag{2}$$

where n is the number of cities, and m is the number of characteristic variables which are the daily average concentrations of $PM_{2.5}$ in a whole year for city i. The observed characteristic variables of the city i are a vector: $(x_{i1}, x_{i2}, \cdots x_{im})^T$, $i = 1, 2, \cdots n$.

The distance, as a similarity measure, between two clusters was computed from one cluster to another during clustering. The choice of distance metric should be made based on theoretical concerns from the specific study. In this study, the Euclidean distance (Zhang et al., 2016b), shown as Equation (3), is the appropriate measure of distance between every two cities.

$$d_{ij} = \sqrt{\sum_{k=1}^{m} \left(x_{i,k} - x_{j,k}\right)^2} \tag{3}$$

where, d_{ij} is the distance between i^{th} city and j^{th} city. Simultaneously, $d_{ij} = d_{ji}$.

In Equation (2) the number of cities is n, and the distance between every two cities can be calculated using Equation (3) to obtain the first symmetric matrix as follows:

$$D_0 = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \dots & \vdots \\ d_{n1} & d_{n2} & \dots & d_{nn} \end{bmatrix} \tag{4}$$

Finding the minimum distance from the non-main diagonal of matrix D_{ij}, the class G_i, G_j can be merged into a new class ($G_r = (G_i, G_j)$) by removing the row and column of the class G_i, G_j in the matrix D, and the distance between the new class G_r and the rest of the class. The new matrix D_{n-1} of the n-1 order is obtained, and the above calculation step was repeated for the new matrix D_{n-1} to obtain a new matrix D_{n-2}, which is sequentially calculated, until all the samples were gathered into one large class in the end. In the process of merging classes, it is necessary to record the level of the merged sample and the two types of merging, and finally draw the cluster pedigree diagram.

2.2.3. Complex network correlation model

Pearson's correlation coefficient is one of the methods used to analyze relationship between variables (Rodriguez-Lujan et al., 2010; Zhang et al., 2018). Network correlation model based on Pearson's correlation coefficient, as shown in Fig. 3, was used in this study. A greater absolute value of P indicates a stronger correlation between two cities or regions. The absolute values P for every two

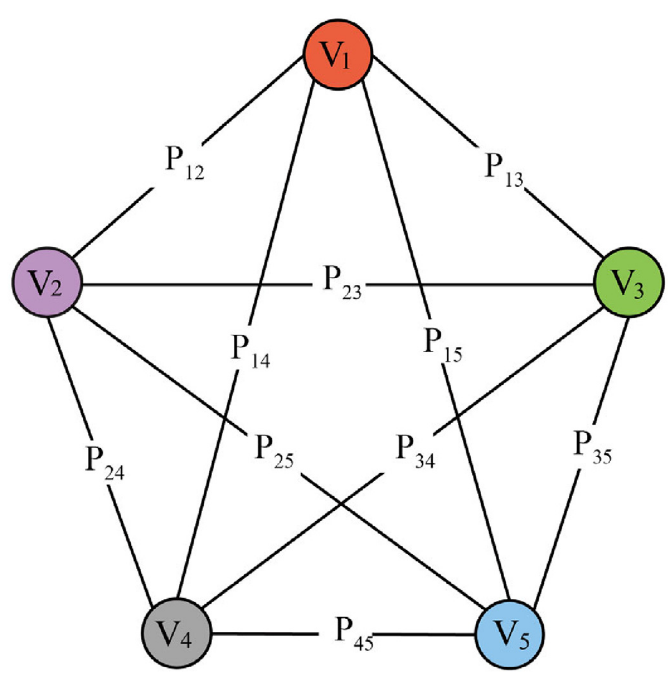

Fig. 3. Schematic of the $PM_{2.5}$ network correlation model.

cities are less than 1.0, and two cities are linearly independent when their value P is zero. For any two vector variables $X = \{x_1, x_2, \cdots x_m\}$ and $Y = \{y_1, y_2, \cdots y_m\}$, P(X, Y) between these two cities based on $PM_{2.5}$ concentrations with time series is defined as Equation (5). The correlation-based distance, also known as Pearson correlation distance, was used to measure the correlation of $PM_{2.5}$ pollution between every two cities. Correlation-based distance was defined by subtracting the correlation coefficient from 1.0. The Pearson correlation distance was defined in Equation (6).

$$P(X,\ Y) = \frac{\sum_{i=1}^{m}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{m}(x_i - \overline{x})^2 \sum_{i=1}^{m}(y_i - \overline{y})^2}} \tag{5}$$

$$d_{cor}(X,\ Y) = 1.0 - \frac{\sum_{i=1}^{m}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{m}(x_i - \overline{x})^2 \sum_{i=1}^{m}(y_i - \overline{y})^2}} \tag{6}$$

where, x_i and y_i were daily $PM_{2.5}$ concentration of i^{th} city and j^{th} city, $\overline{x}$ and $\overline{y}$ were the average concentration of $PM_{2.5}$ in city i and city j.

2.2.4. Definition of evaluation indicators

Firstly, the important goal of $PM_{2.5}$ pollution prevention for every city in YRD region is to attain for the Chinese NAAQS. Hence, it is necessary to define a Normalized urgency indicator of pollution control (NU) for each city-cluster from the perspective of $PM_{2.5}$ concentration reduction. Average concentration of $PM_{2.5}$ for each city-cluster was used and normalized into 'NU' value by the Min-max normalization method. Equation (7) shows the Min-max normalization method and y refers to the normalized indicator 'NU'. Other indicators were also normalized in the same way.

$$y = \frac{x_i - \min\limits_{1 \le i \le m}\{x_i\}}{\max\limits_{1 \le i \le m}\{x_i\} - \min\limits_{1 \le i \le m}\{x_i\}} \tag{7}$$

Secondly, the ultimate purpose of JPCPP strategy is to protect human health, therefore it is necessary to define Normalized health impact indicator (NH). For each city-cluster, the intensity of population exposure to $PM_{2.5}$, calculated by Equation (1), was normalized into 'NH' value by the Min-max normalization method as shown in Equation (7).

Thirdly, each city-cluster has a different elasticity of pollution control due to the diverse geographical locations, climate and pollution purification conditions. In this study, evaluation of Normalized elasticity of pollution control indicator (NE) was chosen as one indicator, reflecting seasonal concentration range of a certain city. This indicator can be calculated firstly by Equation (8) and then normalized by Equation (7). The greater the value of NE is, the greater the potential elasticity of $PM_{2.5}$ reduction is.

$$e = \frac{\delta}{\overline{\overline{X}}} \tag{8}$$

where, δ is the standard deviation of the daily average concentration of each city-cluster, $\overline{X}$ is the average daily concentration of each city-cluster, e is the coefficient of variation.

Fourthly, the concentration of $PM_{2.5}$ of each city-cluster can impact the average concentration of $PM_{2.5}$ on the whole YRD region, but the impact varies with different city-cluster. Thus, it is necessary to use the indicator of normalized pollution impact on the whole YRD region (NW) as one evaluation indicator. Linear regression was performed with daily average concentration of $PM_{2.5}$ in the whole of YRD region as the dependent variable Y; and daily average concentration of $PM_{2.5}$ in each city-cluster as the independent variable X. The slope was normalized into 'NW' value by the Min-max normalization method as shown in Equation (7). The greater the value of 'NW' is, the greater the influence of this city-cluster on $PM_{2.5}$ pollution in the whole of YRD region is.

Based on the Min-max normalization method of standardization, the above four indicators were made comparable. Finally, an integrated indicator (I) is defined as the sum of the four indicators (NU, NH, NE and NW), as shown in Equation (9). Accordingly, this indicator represents the comprehensive evaluation for each city-cluster of JPCPP. The larger the integrated indicator is, the greater the significance of priority prevention and control is, and the greater the gains obtained.

$$I = NU + NH + NE + NW \tag{9}$$

3. Results and discussions

3.1. p.m.$_{2.5}$ pollution pattens

Annual concentrations of $PM_{2.5}$ varied widely with cities in 2018 in the YRD region as shown in Fig. 4. According to $PM_{2.5}$ limit of Class II in the Chinese NAAQS, annual concentration exceeding 35 $\mu g/m^3$ was regarded as nonattainment. Only Huangshan in Anhui province, which is famed for its natural scenery of Mount Huang, attained for the standard. Similarly, in Zhejiang province seven cities (Zhoushan, Ningbo, Taizhou, Wenzhou, Lishui, Jinhua, Quzhou) attained the annual standard. However, most cities, which are located in the central and northern parts of YRD region, including Xuzhou, Suzhou in Anhui province, Huaibei, Bozhou and Huainan, did not fulfill the NAAQS requirement in 2018. In the entire Jiangsu province, there was not a single city that attained the annual $PM_{2.5}$ requirement. Moreover, Xuzhou recorded the highest concentration of $PM_{2.5}$ in the northern Jiangsu, while Changzhou and Zhenjiang in the southern Jiangsu were the most polluted cities in 2018.

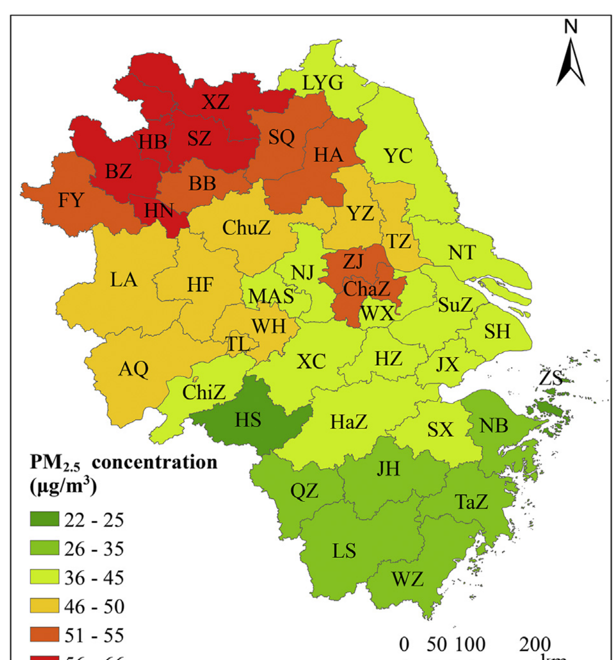

Fig. 4. Spatial distribution of annual $PM_{2.5}$ concentrations in 2018 in the YRD region.

The monthly average concentrations of $PM_{2.5}$ in 2018 were presented in U-shaped pattern for all cities in YRD region, varying significantly with high concentrations in the both ends of the year, as shown in Fig. 5. The monthly $PM_{2.5}$ concentration began to decrease from a high value in January during winter to a low value in July during summer after a transition in spring, and finally increased to a high value in December. Seasonal variations of meteorological conditions were mainly responsible for this U-shaped pattern. Xuzhou city reached the highest monthly concentration of $PM_{2.5}$ in January (138.5 μg/m^3), while Huangshan had the lowest concentration in July with only 10.1 μg/m^3. According to the seasonal variations of $PM_{2.5}$ concentrations in the YRD region, the median values were higher than 35 μg/m^3 except in July and August, showing that most cities in the YRD region still experienced $PM_{2.5}$ pollution and did not attain the NAAQS requirement.

According to the Chinese NAAQS and the Technical Regulation on Ambient Air Quality Index of China, 24-h average concentration of $PM_{2.5}$ can be assigned to one of these six levels: 'excellent' (≤35 μg/m^3), 'good' (35–75 μg/m^3), 'lightly polluted' (75–115 μg/m^3), 'moderately polluted' (115–150 μg/m^3), 'heavily polluted' (150–250 μg/m^3) and 'severely polluted' (≥250 μg/m^3). Using this classification method, 'attainment' means that the daily concentration of $PM_{2.5}$ for a city does not exceed 75 μg/m^3 and 'non-attainment' means that $PM_{2.5}$ concentration exceeds 75 μg/m^3. Consequently, based on this classification method, the days of each level can be counted, and the percentage of each level can be calculated for all the cities in YRD region as shown in Fig. 6. In 2018, the percentage of the 'excellent' days was the highest in July and August, followed by September, June and October in the YRD region. The smallest percentage of 'excellent' days occurred in February, while the percentages of days with 'heavily polluted' and 'severely polluted' in January were higher than any other month. There was more than 40% of daily $PM_{2.5}$ concentrations exceeding the $PM_{2.5}$ standard, indicating that $PM_{2.5}$ pollution tends to occur more frequently during winter.

The monthly concentrations of $PM_{2.5}$ averaged in the whole YRD region during summer in 2018 showed much lower than those in previous years, as shown in Fig. 7. The monthly concentration of $PM_{2.5}$ in March averaged in the whole YRD region was significantly lower than those in the other years presented except in 2016. In recent years, targets of $PM_{2.5}$ concentration for all prefecture-level cities in key regions of China including YRD region, have been set, by MEEP for the autumn-winter period from 1st October of the present year to 31st March the following year. If one government of prefecture-level city failed to meet its target of $PM_{2.5}$, it will face great pressure coming from the central government. Therefore, all the city governments have to pay great attention to achievement of $PM_{2.5}$ targets for the autumn-winter period, as well as the whole year because of annal targets. The governments of cities with heavy $PM_{2.5}$ pollution could take some unconventional measures in the end of autumn-winter period, in order to achieve the $PM_{2.5}$ targets, which can partly explain the obviously low value of monthly $PM_{2.5}$ concentration in March 2018, besides the influence of meteorological conditions. Similarly, an annual target of $PM_{2.5}$ concentration has been set by MEEP for each prefecture-level city in the YRD region. For those prefecture-level cities with heavy $PM_{2.5}$ pollution, their governments could also take some unconventional measures of controlling emission at the end of year, usually in December, in order to meet their annual $PM_{2.5}$ targets. This can partly explain the significantly low monthly $PM_{2.5}$ concentration in December 2018.

Annual average concentrations of $PM_{2.5}$ in Shanghai and Zhejiang decreased rapidly from 2015 to 2018, respectively, as displayed in Fig. 8. Similarly, the values of Shanghai and Zhejiang in 2018 were close to 35 μg/m^3, the annual limit of $PM_{2.5}$ in Chinese NAAQS. The annual $PM_{2.5}$ concentration of 58 μg/m^3 averaged in Jiangsu was the highest in the YRD region in 2015, while Jiangsu showed relatively low decline rates from 2016 to 2018. The annual concentration of $PM_{2.5}$ averaged in Anhui province suddenly rose to 56.4 μg/m^3 in 2017 and became the highest record from 2015 to 2018 in the province, and it also was the highest $PM_{2.5}$ concentration in the whole YRD region in 2017. This is partly because Anhui province was not subject to APPCAP and had not been formally enjoined into the YRD region as it is presently. It is therefore evident that the implementation of APPCAP from 2013 to 2017 has played a significant role in reducing $PM_{2.5}$ pollution in the YRD region before the inclusion of Anhui province. Even though there

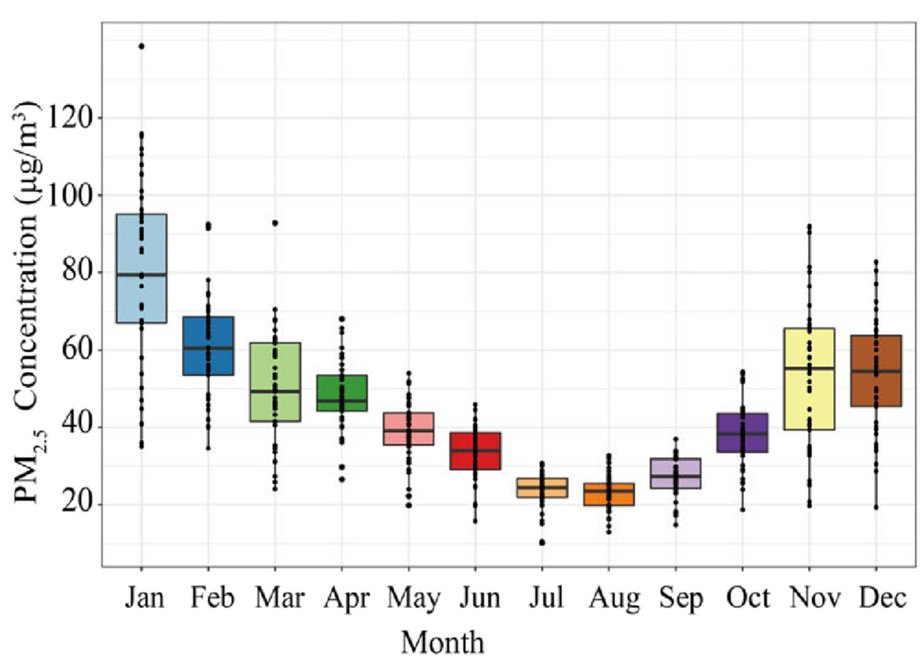

Fig. 5. Variation of Monthly $PM_{2.5}$ concentrations for cities in the YRD region in 2018.

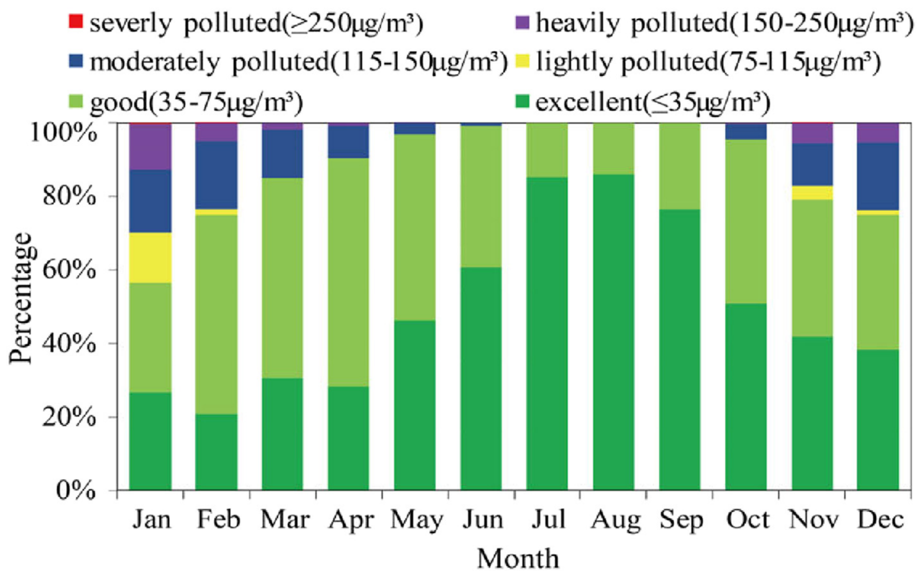

Fig. 6. Percentages of daily $PM_{2.5}$ for different levels in the YRD region in different months in 2018.

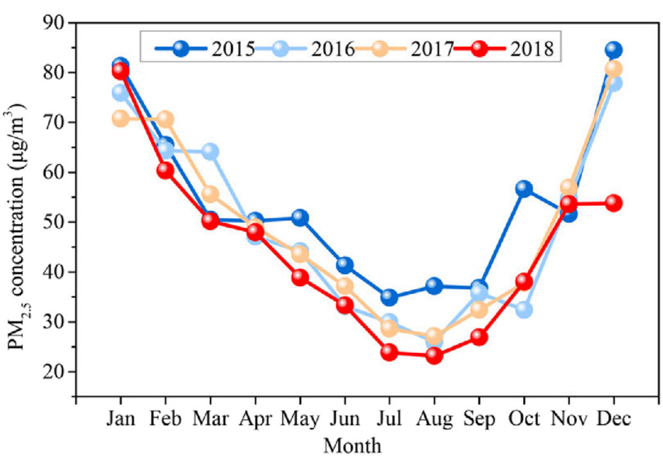

Fig. 7. Variations of monthly $PM_{2.5}$ concentrations averaged in the whole YRD region from 2015 to 2018.

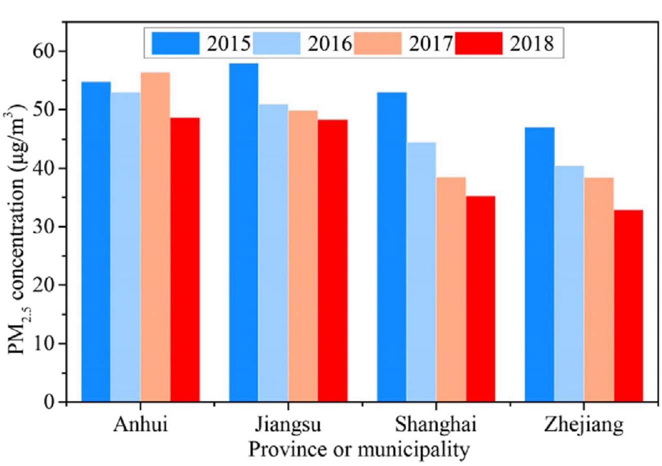

Fig. 8. Variations of annual $PM_{2.5}$ concentrations over the YRD region from 2015 to 2018.

was an obvious decrease of $PM_{2.5}$ in Anhui from 2017 to 2018, average concentration in 2018 was still higher than those in Shanghai and those in Shanghai and Zhejiang. Generally, Anhui and Jiangsu had a long way to go for attaining the $PM_{2.5}$ standard in NAAQS.

As shown in Fig. 9, the heat-map of annual $PM_{2.5}$ concentrations for 41 prefecture-level cities in the YRD region from 2015 to 2018, displays that Huangshan and Zhoushan had the lowest $PM_{2.5}$ concentrations, as a result of their small population and weak industrial economy. It is known that Huangshan is famous for Huang Mount, and Zhoushan is an island city and famous for ocean scenery. Admittedly, several cities in Zhejiang had already attained the $PM_{2.5,}$ standard in the NAAQS. However, there were still many cities suffered heavy $PM_{2.5}$ pollution, as shown in Fig. 9. Most of them are prefecture-level cities with high coal consumption and located in Anhui and Jiangsu province. All cities in Zhejiang province and most cities in Jiangsu province, as well as Shanghai, had make great progress in reduction of $PM_{2.5}$ concentrations from 2015 to 2017, as a result of the implementation of APPCAP from 2013 to 2017. However, $PM_{2.5}$ concentrations in most cities in Anhui province increased from 2016 to 2017. This is mainly because all cities in Anhui province were not enjoined into the YRD region before 2018, thereby these cities were not subjected to a very important policy, i.e. APPCAP. This is also one of the most important reasons for particularly high $PM_{2.5}$ concentrations in 2017 in many cities, such as Fuyang, Huaibei, Suzhou in Anhui province. Another important reason for that is the transport contribution from other cities, even from long-range distance transport. This is also the main motivation of this study to focus on developing joint prevention and control of $PM_{2.5}$ concentrations for all nonattainment cities in the YRD region.

In Fig. 9, it is also worth noting that annual $PM_{2.5}$ concentration in Xuzhou, one of cities in the north of Jiangsu province, was very high, even higher than many cities' in Anhui province in 2017, although there was a decrease of 6.1% compared with 2017, the average annual $PM_{2.5}$ concentration in Xuzhou City was as high as 62 $\mu g/m^3$ in 2018. In addition to high coal consumption in industrial sector, there are also two other main reasons for Xuzhou's heavy $PM_{2.5}$ pollution. One reason is that Xuzhou is located in the border among Jiangsu, Shandong and Anhui, and hence Xuzhou is susceptible to the contribution of $PM_{2.5}$ transport from Shandong and

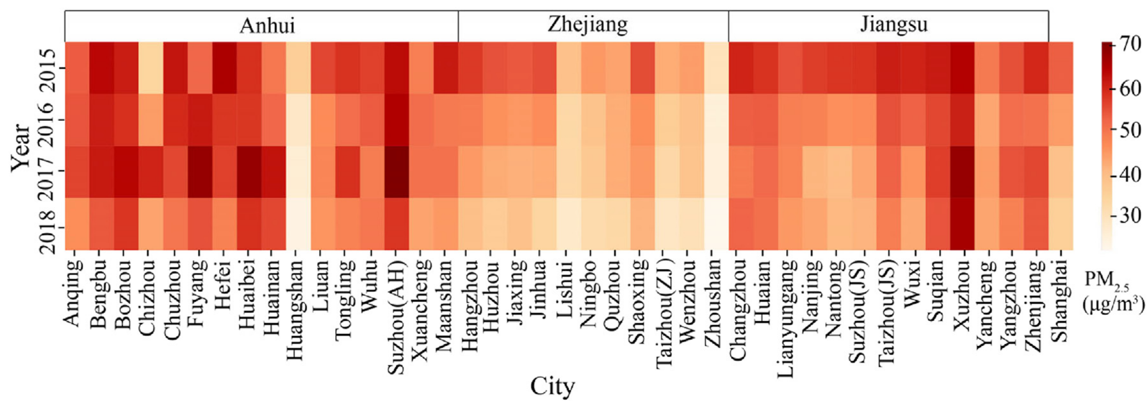

Fig. 9. Heatmap of annual $PM_{2.5}$ concentrations for cities in the YRD region.

the north part of Anhui, which are frequently heavily polluted areas. Therefore, joint prevention and control of $PM_{2.5}$ has been a crucial issue for many nonattainment cities. Another reason for high $PM_{2.5}$ concentration in Xuzhou is that Xuzhou was only one city in the YRD region that provides heating for residents in winter, leading to a large amount of emissions in Xuzhou.

Overall, annual $PM_{2.5}$ concentrations in most cities were obvious lower in 2018 than those in 2017 in the YRD region. This change was most likely attributed to stringent enforcement of environmental protection laws, and inspections in these cities, as well as the stage-by-stage strict targets set by MEEP.

3.2. Population exposure intensity

The ultimate goal of air pollution research and governments' air quality management is to protect people's health. To some extent, population exposure intensity to $PM_{2.5}$ pollution can be used to measure health risks resulted from $PM_{2.5}$ pollution. As shown in Fig. 10 (a), the population exposure risk in Shanghai was the highest in the YRD region, although the annual $PM_{2.5}$ concentration in Shanghai was low. Huaibei, as a small city in Anhui province, its population exposure intensity to $PM_{2.5}$ was the second highest in annual scale in the YRD region. Most cities with low population exposure intensity are located in southern Zhejiang, western Zhejiang, southern Anhui and western Anhui. In recent years, the implementation of increasingly stringent environmental protection policies in eastern China has promoted to reduce the annual concentration of $PM_{2.5}$ year by year in the YRD region. The population exposure intensity in Suzhou, Nanjing, Fuyang, Xuzhou and Wenzhou were all higher than 2.0 $\mu g \times 10^4$persons/($m^3 \times km^2$). There was a positive correlation between population and exposure risk. Therefore, intensified pollution control in cities with higher population density should be given more attention in order to help reduce the negative impact of $PM_{2.5}$ on human health.

As shown in Fig. 10 (b), the population exposure intensity increased from summer to autumn and reached maximum in winter. The summer season presented the lowest population exposure intensity to $PM_{2.5}$ for all cities in the YRD region. The variations of population exposure intensities in the YRD region were closely linked to the seasonal variations of $PM_{2.5}$

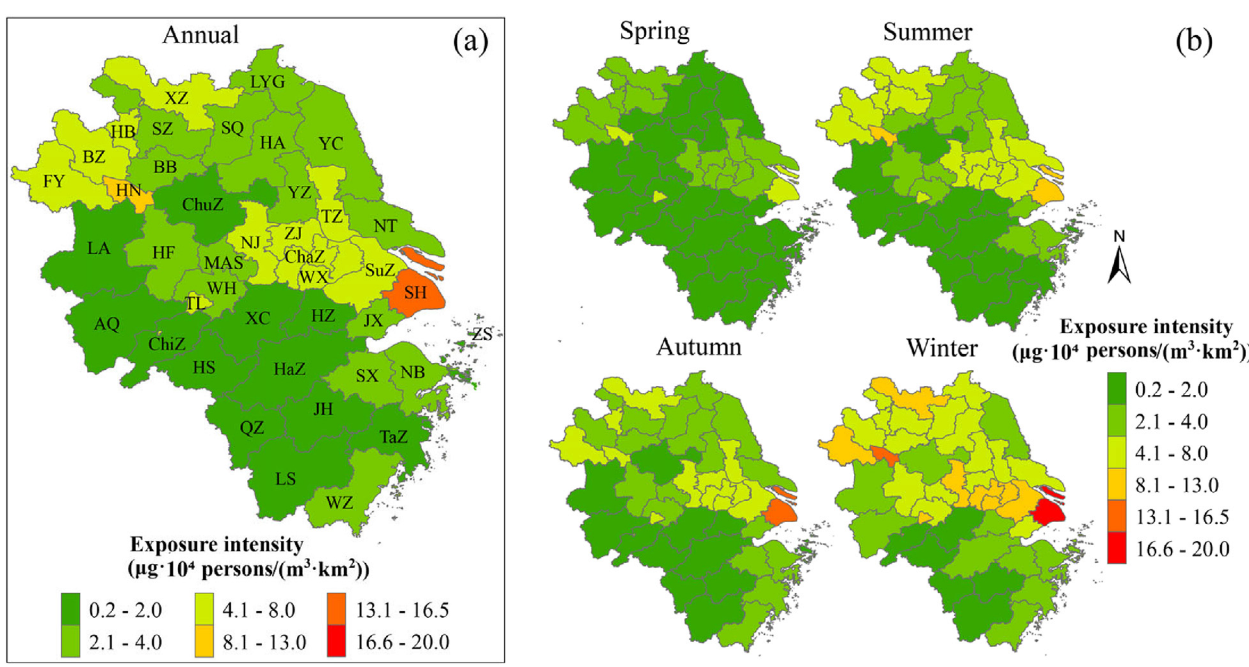

Fig. 10. Distributions of population exposure intensities to $PM_{2.5}$ for annual (a) and seasons (b) in 2018 in the YRD region.

concentrations in the region. Shanghai, followed by Huainan, had the highest population exposure intensity to $PM_{2.5}$ for all seasons in YRD region. However, Tongling, as the smallest city in Anhui province, its population exposure intensity was higher than any city around it, but lower than Huainan in northern Anhui province. The northern Anhui and the southern Jiangsu both suffered a relatively high exposure risk.

3.3. Clustering analysis

Based on the daily concentration of $PM_{2.5}$, the YRD region was clearly divided into five clusters or sub-regions as shown in Fig. 11 (a). The cities in the same cluster showed the relative uniformity of $PM_{2.5}$ concentration to some extent. The northern Anhui and Xuzhou were in the same cluster, which representing the highest concentration of $PM_{2.5}$ in the YRD region. The impact of $PM_{2.5}$ transport from around areas on one city usually promoted a more uniform distribution of the $PM_{2.5}$ concentrations in this city and around areas. Fig. 11 (b) shows that Shanghai formed a cluster by itself because its population exposure intensity was much higher than other cities in the YRD region. The high population density in southern Jiangsu is also one of the reasons for the relatively high exposure intensity. Xuzhou in Jiangsu, Huaibei, Bozhou, Fuyang, Huainan in the northern Anhui, Tongling in the middle of Anhui, and some cities in the southern Jiangsu were all in the same cluster whose population exposure intensity was lower than Shanghai but higher than other cities. More attention was required for all the cities in cluster 2, 3, 4, due to the relatively high health impact of $PM_{2.5}$ in these areas. Compared with Zhejiang, Anhui and Jiangsu showed more diversity in both $PM_{2.5}$ concentration and population exposure intensity.

3.4. Variations of population exposure intensity with years

Based on population exposure intensity to $PM_{2.5}$, Shanghai ranked first among all cities in the YRD region with 20.8 $\mu g \times 10^4$ persons/($m^3 \times km^2$) and 13.8 $\mu g \times 10^4$ persons/($m^3 \times km^2$) for 2015 and 2018, respectively, as shown in Fig. 12 (a) and (b). However, the population exposure intensity of Shanghai in 2018 had significantly reduction compared with 2015, due to the decrease of annual $PM_{2.5}$ concentration. The annual population exposure intensity of Huangshan ranked the last in both 2015 and 2018, with 0.5 $\mu g \times 10^4$ persons/($m^3 \times km^2$) and 0.4 $\mu g \times 10^4$ persons/($m^3 \times km^2$), respectively. Some cities had big changes in their rankings. In 2018, Huainan ranked first among the cities in Anhui province and ranked second among the 41 cities in the YRD region. Tongling ranked third, whereas Fuyang, Huaibei, Bozhou, Suzhou, Bengbu and Hefei ranking 5th, 10th, 12th, 14th, 16th and 19th respectively in 2018. The ranking of Fuyang rose from 8th place in 2015 to 5th place in 2018. Huainan moved up from the 5th in 2015 to the second in 2018. Similarly, the rank of Huaibei city rose from the 14th in 2015 to the 10th in 2018. Bozhou and Bengbu ranked higher in 2018 than that in 2015. In 2018, Ningbo ranked the highest among cities in Zhejiang province in terms of population exposure intensity to $PM_{2.5}$.

Compared with 2015, the population exposure intensities for Chizhou and Fuyang increased significantly in 2016, with growth rates from 20% to 30%, while most cities had negative growth rates, suggesting that most cities had lower $PM_{2.5}$ concentrations in 2016, as shown in Fig. 12. Compared with 2016, population exposure intensities increased in 18 cities in 2017, including 11 cities in Anhui province, 2 cities in Zhejiang province and 5 cities in Jiangsu province. The biggest increase in population exposure intensity in 2017 was in Chizhou by about 35%, followed by Huainan, Huaibei and Tongling. The results suggest that $PM_{2.5}$ pollution in 2017 obviously deteriorated in these cities compared with 2016. Compared with 2017, there were only four cities including Changzhou, Nanjing, Nantong and Wuhu with a small increase of population exposure intensity to $PM_{2.5}$ in 2018. Overall, compared with 2015, the exposure population intensities in most cities were reduced by a large percentage in 2018, although the exposure intensity of the population in four cities increased in the YRD region.

3.5. Specific scheme system

The correlation of $PM_{2.5}$ concentrations between any two cities in the YRD region can be calculated based on network correlation model. The results of $PM_{2.5}$ network correlations for 41 cities in the winter of 2018 are shown in Fig. 13. A large correlation coefficient (i.e. P) between two cities indicates that their $PM_{2.5}$ concentrations

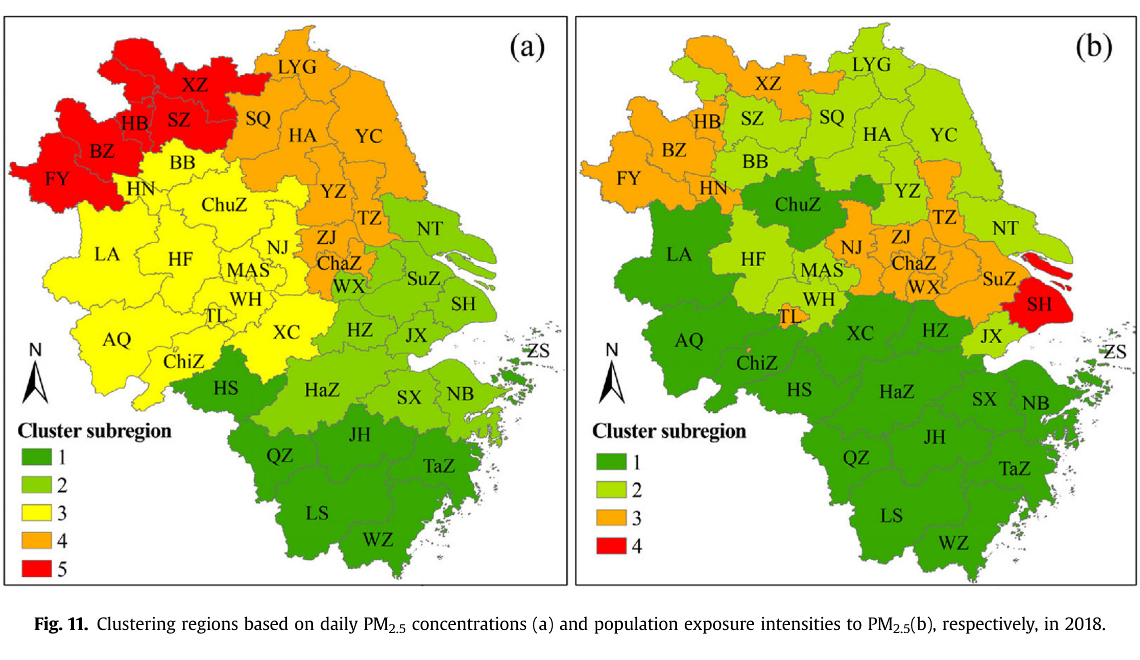

Fig. 11. Clustering regions based on daily $PM_{2.5}$ concentrations (a) and population exposure intensities to $PM_{2.5}$(b), respectively, in 2018.

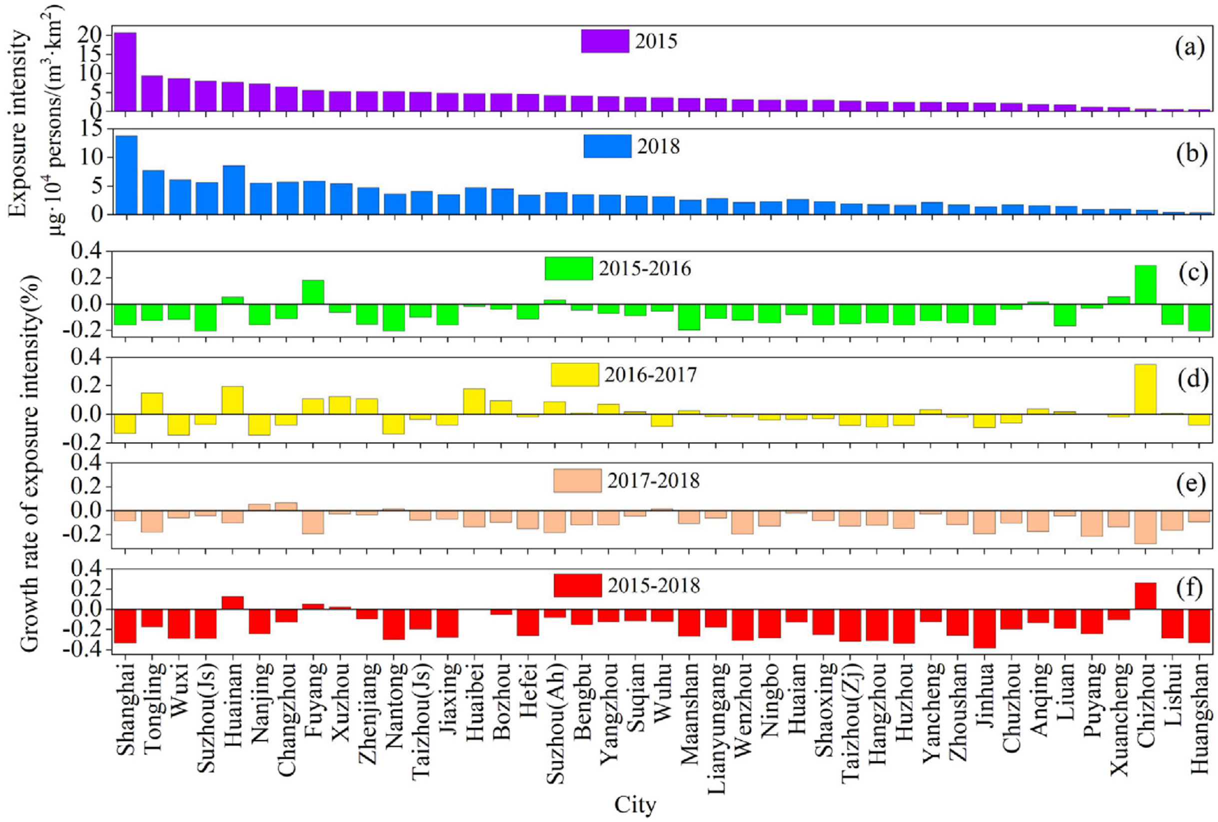

Fig. 12. Ranking (a and b) and growth rates (c ~ f) of population exposure intensity for all cities in the YRD region.

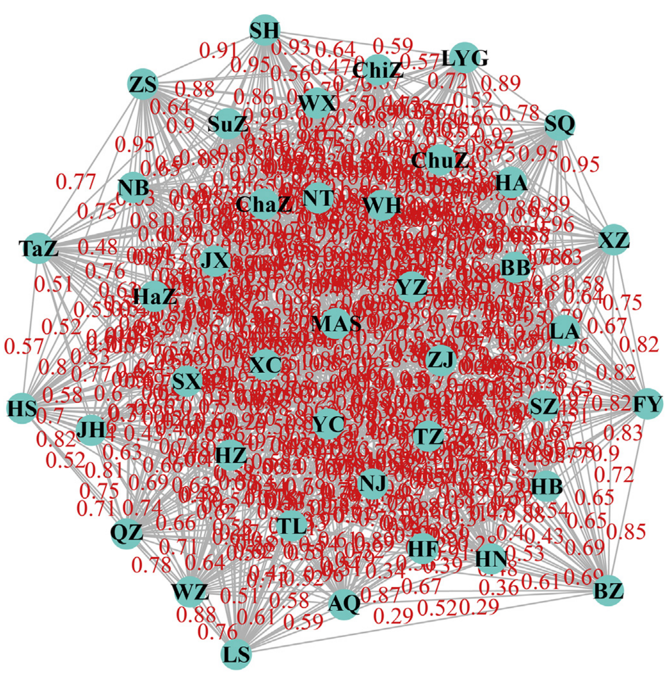

Fig. 13. Network diagram of correlation coefficient ($P \geq 0$) for 41 cities based on $PM_{2.5}$ concentrations in winter of 2018 in the YRD region.

had strong correlation, further suggesting that regional transport had potential great influence on each other, so it is necessary to carry out joint prevention and control between these cities. In order to display the cities connection clearly, we set the threshold value of network correlation coefficient in Fig. 14. When the network correlation coefficient between two cities was less than the threshold value, the connecting line between every two cities would not be shown in Fig. 14. The threshold values set are relatively high, which was to show more clearly the internal relationship between high-network-related cities. Fig. 14 shows the network correlation of $PM_{2.5}$ between cities in the YRD region for spring, summer, autumn and winter, respectively, in 2018. The threshold value of network correlation coefficient in spring and summer were set at 0.88, while the threshold values in winter and autumn were set at 0.91. The threshold value was set higher in winter and autumn because there were more cities with strong network correlation of $PM_{2.5}$ in autumn and winter, so as to show the relationship between these cities with strong network correlation more clearly. Generally, the network correlation between cities in the YRD region was the strongest in winter, and basically all the cities in the YRD region showed strong correlations except Huangshan and several cities with excellent air quality in the southern Zhejiang. The network correlation between cities in autumn was weaker than that in winter, but stronger than that in spring and summer. However, in spring and summer there were many city-clusters whose correlation coefficients were greater than 0.88, suggesting that there were still relatively strong network correlations in spring and summer in 2018. In short, the $PM_{2.5}$ concentration between cities in the YRD region was highly correlated, indicating that the regional transport between cities was

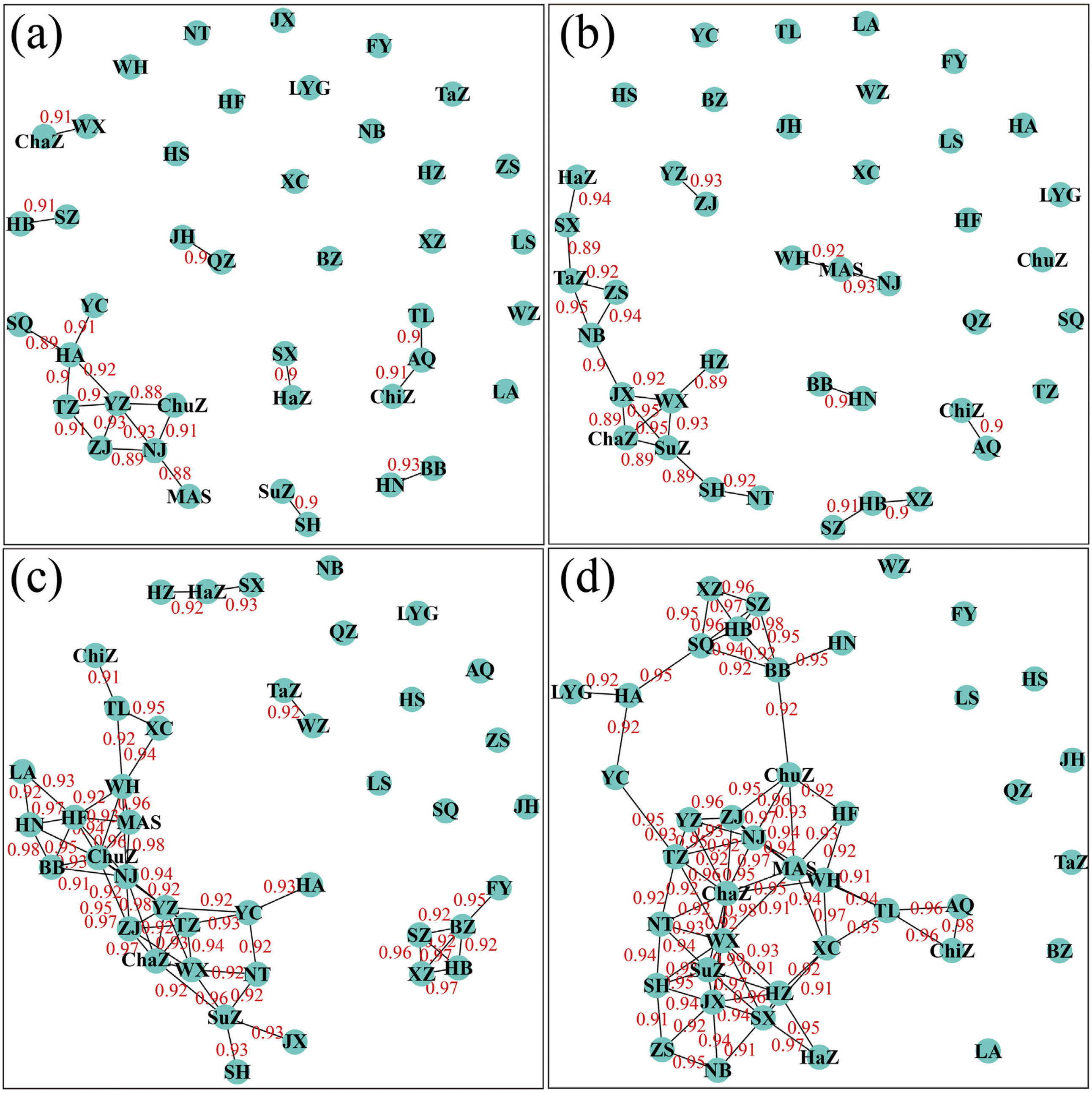

Fig. 14. Diagram of $PM_{2.5}$ network correlation for 41 cities in the YRD region based on correlation coefficient $P \geq 0.91$ for spring(a) and summer (b) and $P \geq 0.88$ for autumn (c) and winter (d)).

significant, and the JPCPP between cities needed to be strengthened, especially in winter.

The transport effect of $PM_{2.5}$ makes the pollution between cities correlated, so cluster analysis based on the distance of $PM_{2.5}$ correlation can help identify the city clusters with strong demand for joint prevention and joint control. The city-clusters with clustering characteristics of the correlation distance between the 41 prefecture-level cities in the YRD region based on the annual scale were shown in Fig. 15 (a). The cities marked in white were clustered alone because they had a relatively small distance of $PM_{2.5}$ correlation from other cities. Moreover, Huangshan in Anhui province and Lishui, Wenzhou and Taizhou in Zhejiang province were all the cities which had already met the $PM_{2.5}$ standard in NAAQS. Shanghai was in a city-cluster with several cities in southern Jiangsu province together, even though the annual average concentrations of $PM_{2.5}$ in Changzhou, Wuxi and Suzhou in southern Jiangsu province were relatively high.

Jinhua and Quzhou are both located in Jinqu basin in central Zhejiang, thus $PM_{2.5}$ is much easy to transport between each other, leading to a small distance of correlation between these two cities. Consequently, Jinhua and Quzhou were within one cluster as shown in Fig. 15 (a). Several cities in central Jiangsu and Yancheng form a city-cluster. The correlations between cities in northwest Jiangsu and northeast Anhui were strong. Similarly, the cities in central Anhui constitute a cluster. Fuyang in northwest Anhui had an obvious correlation with Bozhou. In this way, the results of cluster analysis based on correlation distance in annual scale provided a simple and intuitive basic information of air pollution joint

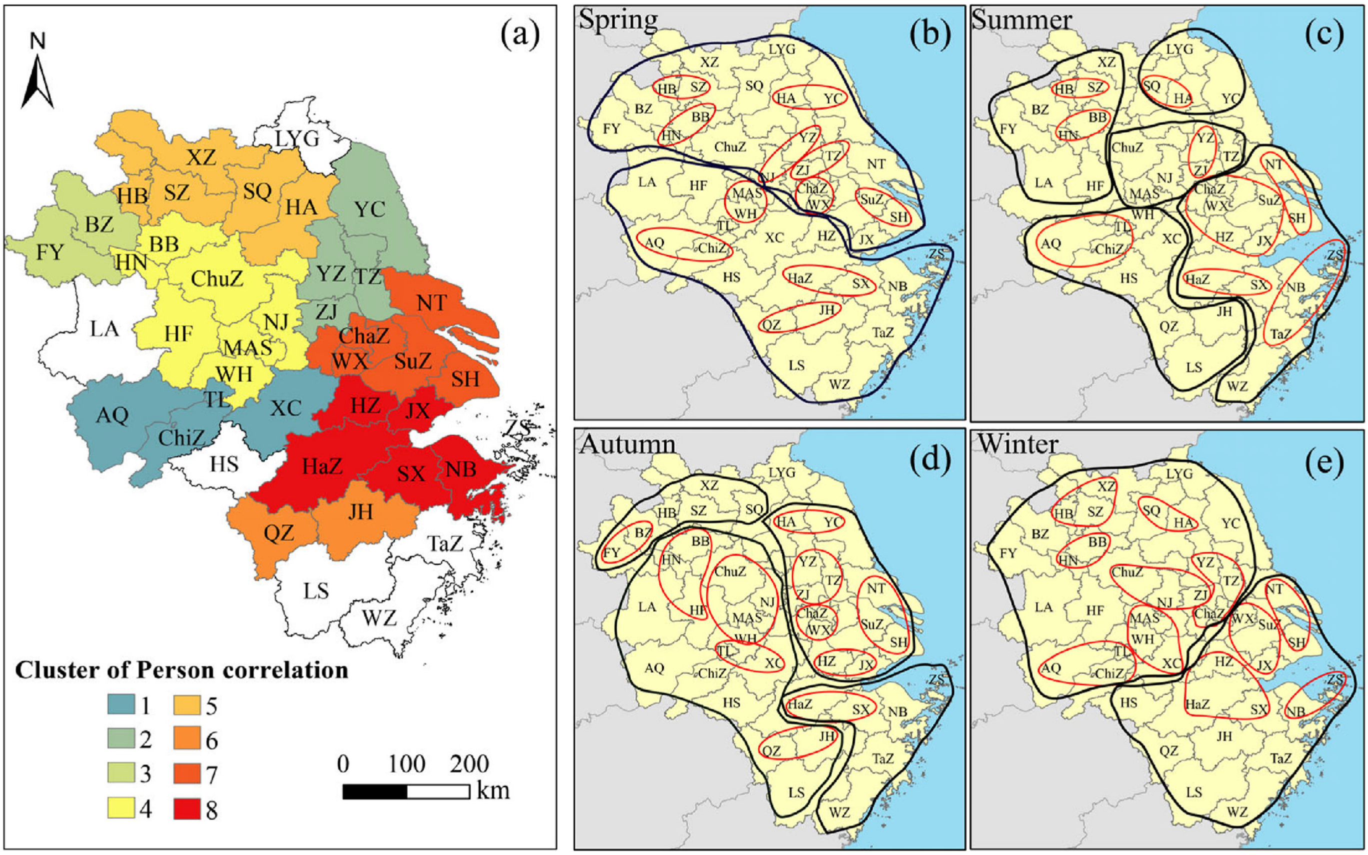

Fig. 15. The city-clusters based on correlation distance of $PM_{2.5}$ concentrations for annual (a) and seasons (b) ~ (e) in 2018.

prevention and control over 41 prefecture-level cities in YRD region. However, the meteorological conditions in the YRD region were susceptible to seasonal changes. For this reason, it was worth analyzing the clustering based on the correlation distance of $PM_{2.5}$ concentration in different seasons.

As shown in Fig. 15 (b) ~ (e), the city-clusters based on correlation distance varied widely with seasons. For both winter and spring, two main city-clusters were presented in the YRD region. The larger number of main clusters in summer can be explained by the relatively low concentration of $PM_{2.5}$ in summer, leading to a relatively low contribution of $PM_{2.5}$ transport between cities. Some sub-regions with closed red line represent internal strong correlation. Control measures of $PM_{2.5}$ in these cities not only can help these cities themselves reduce $PM_{2.5}$ concentrations, but also can help other cities reduce the $PM_{2.5}$ concentrations, especially cities in the same cluster. Fig. 15 shows the correlation among cities from a view of the whole YRD region while more specific correlation between cities can be found in Fig. 14, which was from a view of prefecture-level cities.

One scheme system of JPCPP with three grades in the YRD region was proposed based on the strength of network correlation between cities and the difficulty of implementation. The more cities that are jointly controlled, the more difficult it is to implement the joint control, so the design of this scheme system considered that the implementation difficulty should be reduced as much as possible. When the pollution level was low, as few cities as possible carry out joint control. In the case of heavy pollution, in order to increase the control efforts to achieve a large reduction in $PM_{2.5}$ concentration, it was necessary to adopt a wider joint prevention and joint control within the city-cluster that combines more cities. Therefore, according to the pollution level and the difficulty of implementation, we divided the scheme system into three grades. The first grade was for the situation with the lowest pollution level and the need for joint prevention and control. Accordingly, one city-cluster in grade 1 usually includes two cities. The second grade was for the situation when the pollution level was medium and the cities in the city-cluster wasslightly more. The third grade was for the situation when the pollution was much heavier and needed more powerful and broader joint prevention and control.

The details of all the grades of JPCPP scheme for spring, summer, autumn and winter were shown in Fig. 16 There were three grades involved in spring, autumn and winter, but only two grades were involved in summer due to the low $PM_{2.5}$ concentration in summer. Grade 1, also referred to the low-intensity JPCPP scheme, is the lowest and the easiest JPCPP scheme to implement. In this grade, each city-cluster typically comprised two cities except for one city-cluster which was composed of three cities (Jiaxing in Zhejiang, Suzhou and Wuxi in Jiangsu) in winter due to the very strong correlation between every two cities by P values greater than 0.97, as shown in Fig. 16 (d). Grade 2 was the medium-intensity JPCPP scheme where a city-cluster consisted of three cities. Grade 3 was the high-intensity JPCPP scheme where a city-cluster was composed of more than three cities. There were 19 clusters for Grade 1, 5 clusters for Grade 2 and one cluster for Grade 3 for spring. There were 15 clusters for Grade 1 and 4 clusters for Grade 2 for summer. For autumn, 20 clusters for Grade 1, 7 clusters for Grade 2 and 3 clusters for Grade 3, as shown in Fig. 16. In the YRD region, a much stronger JPCPP in winter was required for implementation that involved more cities. This scheme presented 43 clusters for Grade 1, 17 clusters for Grade 2 and 4 clusters for Grade

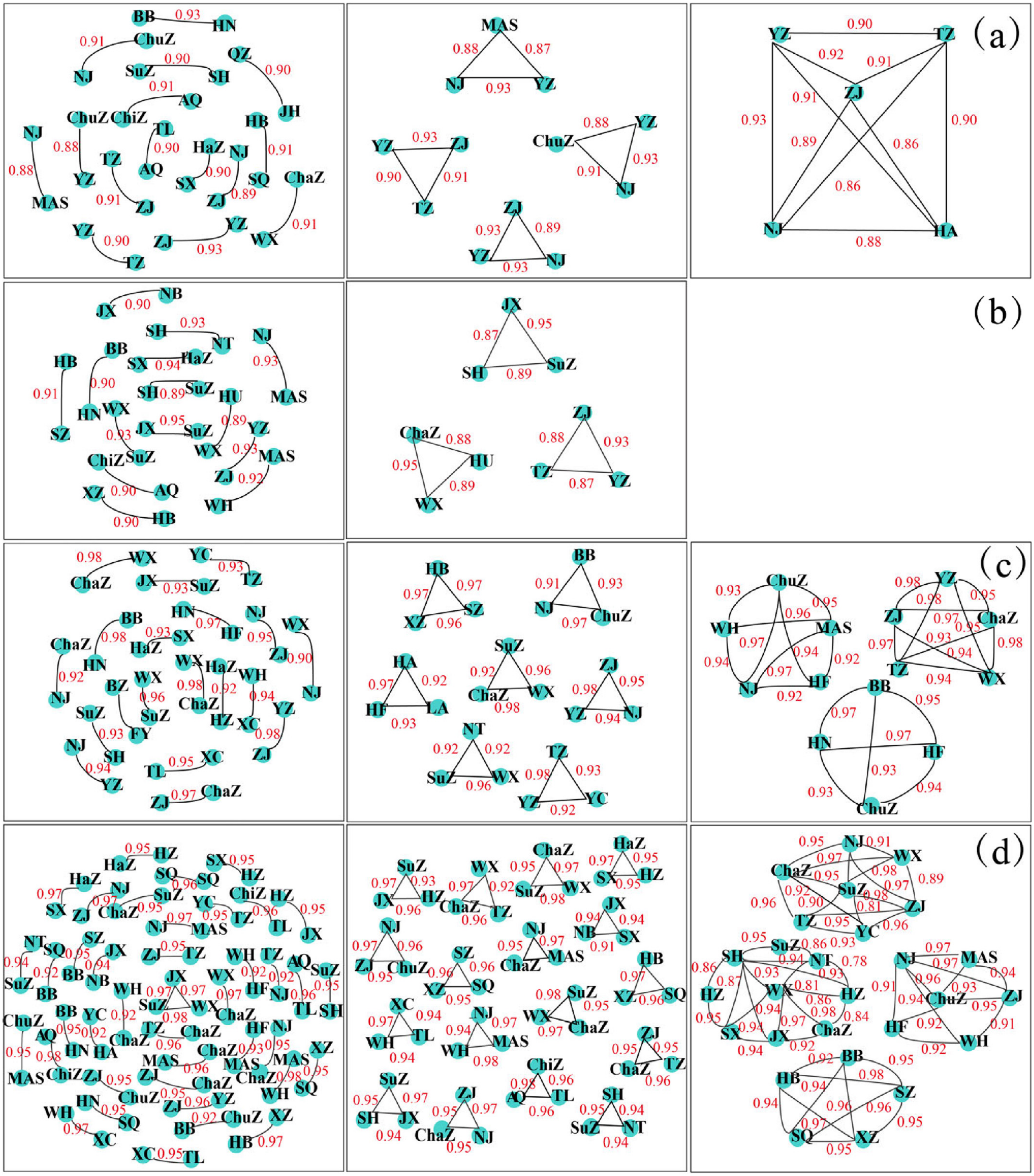

Fig. 16. The joint prevention and control of $PM_{2.5}$ pollution scheme for spring (a), summer (b), autumn (c) and winter (d).

3 in winter. Furthermore, more cities were included in the clusters of Grade 3 in winter than any other season. The task of joint prevention and control was the heaviest in winter because of the most serious pollution season.

Regarding the JPCPP scheme in the YRD region for all seasons, implementation of Grade 1 of the JPCPP scheme is recommended whenever hourly concentrations of $PM_{2.5}$ are in the range of 35–75 $\mu g/m^3$. Accordingly, both Grade 1 and Grade 2 should be implemented together whenever hourly $PM_{2.5}$ concentrations are in the range of 75–115 $\mu g/m^3$. In addition, once hourly concentrations of $PM_{2.5}$ exceed 115 $\mu g/m^3$, simultaneous implementation of Grade 3, alongside Grade 1 and 2, is recommended. In general, Fig. 16 shows a specific scheme system of JPCPP for 41 prefecture-level cities in YRD region for spring, summer, autumn, winter, respectively. This specific scheme is vital for all nonattainment cities to effectively reduce $PM_{2.5}$ concentrations and enable timely achievement of the Chinese NAAQS.

3.6. Evaluation of city-clusters

Evaluation results for each city-cluster based on: Normalized urgency indicator (NU), Normalized health impact (NH), Normalized elasticity of pollution control (NE), Normalized pollution impact on the whole YRD region (NW) and integrated indicator (I) are displayed in Fig. 17 for Grade 1 and Stable 01–04 for Grade 2 and Grade 3. For Grade 1 in winter, Xuzhou-Suqiani, Suzhou-Shanghai, Suzhou-Shanghai, Maanshan-Nanjing (along with Nanjing-Changzhou), Nanjing-Changzhou were ranked top for NU, NH, NE, NW and I indicators respectively. The urgency indicator measures the $PM_{2.5}$ pollution level of a city-cluster, so the larger NU values indicate the heavier $PM_{2.5}$ pollution in the city-cluster. The city-cluster composed of Xuzhou-Suqian was ranked first by NU indicator, closely followed by Maanshan-Wuhu, Xuzhou-Huaibei for Grade 1 in winter. Obviously, city-clusters in the northern of YRD are in great need of JPCPP. In terms of health impact for Grade 1 in winter, Suzhou-Shanghai cluster had the highest NH value than Huainan-Bengbu which was ranked second, while Wuxi-Suzhou, Wuxi-Changzhou, Nanjing-Changzhou, Xuzhou-Huaibei, Zhengjiang-Nanjing clusters followed. The larger the NH value, the greater the health risk of the city-cluster compared to other city-clusters in the YRD region. NE is an indicator which indicate the potential of $PM_{2.5}$ reduction. The smaller the NE value, the more difficult it is to control the $PM_{2.5}$ of this city-cluster compared to other city-clusters in the YRD region. Similarly, the top seven city-clusters ranked by NE value for Grade 1 in winter were Suzhou-Shanghai, Wuxi-Suzhou, Suzhou-Jiaxing, Wuxi-Changzhou, Wuxi-Jiaxing and Nanjing-Changzhou. In addition, Maanshan-Nanjing, Maanshan-Changzhou, Maanshan-Wuhu, Nanjing-Changzhou, Zhenjiang-Changzhou, Zhenjiang-Nanjing showed the top six city-clusters with high NW values for Grade 1 in winter. Evaluation of I indicator showed that, Nanjing-Changzhou is ranked first, followed by Zhenjiang-Nanjing and Suzhou-Shanghai as shown in Fig. 17. For Grade 1 in spring, Zhenjiang-Yangzhou, Suzhou-Shanghai, Yangzhou-Taizhou, Yangzhou-Nanjing, Zhenjiang-Taizhou are ranked as the first city-cluster in terms of NU, NH, NE, NW and I indicators, respectively. For Grade 1 in summer, Huainan-Bengbu, Shanghai-Nantong, Zhoushan-Ningbo, Maanshan-Nanjing were the top city-clusters based on NU, NH, NE, NW and I indicators respectively. For Grade 1 in autumn, Xuzhou-Huaibei, Huainan-Bengbu, Zhenjiang-Yangzhou, Nanjing-Chuzhou and Fuyang-Bozhou were ranked top for NU, NH, NE, NW and I indicators respectively. The completed details of the city-clusters for the JPCPP are presented in Stable 01–04. The evaluation of each city-cluster of the JPCPP based on five indicators for different Grades and seasons was conducted from different points of view. Multi-angle evaluation can deepen our understanding the significance of each city-cluster of the JPCPP scheme system in the YRD region. Nevertheless, for nonattainment cities, NU should be the most important indicator and attaining for the NAAQ should be their first goal for then in the next years.

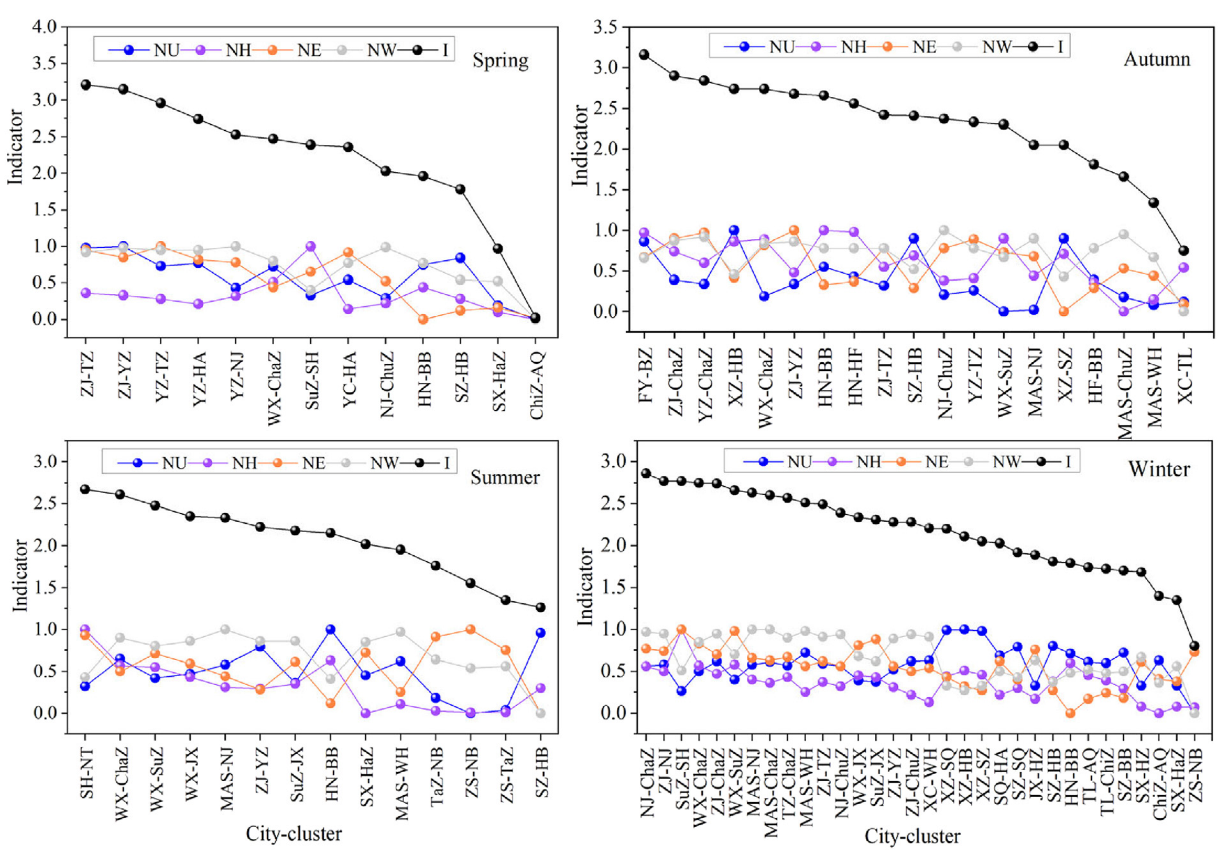

Fig. 17. Evaluation city-clusters of JPCPP by five indicators for Grade 1 in spring, summer, autumn and winter.

4. Conclusions

Although $PM_{2.5}$ concentrations in the YRD region of China have decreased significantly in recent years, many cities still fail to meet the $PM_{2.5}$ requirements in the NAAQS and are facing great pressure. The cities in northern Anhui and northwestern Jiangsu were the most polluted region with high levels of $PM_{2.5}$. However, Shanghai had the largest population exposure intensity in 2018 in the YRD region.

This study proposed a framework of developing a practical scheme system of joint prevention and control of $PM_{2.5}$ pollution based on data mining technologies. Moreover, one specific scheme system for 41 prefecture-level cities in the YRD region was developed. This scheme system was divided into three grades depending on pollution levels and seasons except for summer (two grades). The heavier the $PM_{2.5}$ pollution was, the higher the grade was recommended to be implemented along with low grades. Winter was the season with the worst $PM_{2.5}$ pollution due to unfavorable meteorological conditions. This scheme presented 43 city-clusters for Grade 1, 17 city-clusters for Grade 2 and 4 city-clusters for Grade 3 in winter. Each grade in winter contains more city-clusters than other seasons, indicating that winter was the most important period for joint defense and joint control.

Fiver indicators, including Normalized urgency indicator, Normalized health impact, Normalized elasticity of pollution control, Normalized pollution impact on the whole region and integrated indicator, were used to evaluated all city-clusters of the JPCPP in the YRD region for each grade and each season, respectively. For Grade 1 in winter, the city-cluster with Xuzhou and Suqian was the most urgent to control emission jointly; the city-cluster with Suzhou and Shanghai was linked to the biggest impact on health, but for integrated indicator, the city-cluster with Nanjing and Changzhou ranked first. For nonattainment cities, NU should be the most important indicator and attaining for the NAAQ should be their first goal for then in the next years. Based on the evaluation of city-clusters of scheme system by applying five indicators, readers or governments can choose their own city-cluster priority of PM2.5 control from their own evaluation angles.

This JPCPP scheme system is pegged on prefecture-level cities to hasten timely realization of the Chinese NAAQS. Combining this JPCPP scheme with current or future environmental protection policies can effectively accelerate $PM_{2.5}$ reduction for all nonattainment cities by collaboration with their most correlative cities in the YRD region, China. The framework proposed in this study can also be customized for joint prevention and control of $PM_{2.5}$ pollution for other regions.

CRediT authorship contribution statement

Yangjun Wang: Conceptualization, Writing - original draft. **Ziyi Liu:** Methodology, Writing - original draft. **Ling Huang:** Software. **Guibin Lu:** Conceptualization, Software. **Youguo Gong:** Visualization. **Elly Yaluk:** Formal analysis, Data curation. **Hongli Li:** Visualization. **Xin Yi:** Writing - review & editing. **Liumei Yang:** Validation. **Jialiang Feng:** Writing - review & editing. **Cesunica Ivey:** Writing - review & editing. **Li Li:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acronyms of city names were shown below.

Code	City	Code	City	Code	City
HF	Hefei	NJ	Nanjing	SH	Shanghai
LA	Liuan	SuZ	Suzhou	HZ	Hangzhou
WH	Wuhu	WX	Wuxi	JX	Jiaxing
ChiZ	Chizhou	ChaZ	Changzhou	HZ	Huzhou
TL	Tongling	NT	Nantong	QZ	Quzhou
HS	Huangshan	ZJ	Zhenjiang	SX	Shaoxing
XC	Xuancheng	YZ	Yangzhou	JH	Jinhua
AQ	Anqing	TZ	Taizhou	NB	Ningbo
MAS	Maanshan	YC	Yancheng	ZS	Zhoushan
ChuZ	Chuzhou	HA	Huaian	LS	Lishui
FY	Fuyang	SQ	Suqian	TaZ	Taizhou
HN	Huainan	XZ	Xuzhou	WZ	Wenzhou
BB	Bengbu	LYG	Lianyungang		
BZ	Bozhou				
SZ	Suzhou				
HB	Huaibei				

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Acronyms

YRD	Yangtze River Delta
JPCPP	Joint prevention and control of $PM_{2.5}$ pollution
APPCAP	The Air Pollution Prevention and Control Action Plan
NAAQS	The National Ambient Air Quality Standards
NU	Normalized urgency indicator
NH	Normalized indicator of health impact
NE	Normalized elasticity of pollution control
NW	Normalized degree of influence on whole region
I	Integrated indicator

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.122756.

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