

Article

Spatial Characteristics of PM_{2.5} Pollution among Cities and Policy Implication in the Northern Part of the North China Plain

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Abstract: In the recent decade, the North China Plain (NCP) has been among the region's most heavily polluted by PM_{2.5} in China. For the nonattainment cities in the NCP, joint pollution control with related cities is highly needed in addition to the emission controls in their own cities. However, as the basis of decision-making, the spatial characteristics of PM_{2.5} among these cities are still insufficiently revealed. In this work, the spatial characteristics among all nonattainment cities in the northern part of the North China Plain (NNCP) region were revealed based on data mining technologies including clustering, coefficient of divergence (COD), network correlation model, and terrain and meteorology analysis. The results indicate that PM_{2.5} pollution of cities with a distance of less than 180 km exhibits homogeneity in the NCP region. Especially, the sub-region, composed of Xinxiang, Hebi, Kaifeng, Zhengzhou, and Jiaozuo, was strongly homogeneous and a strong correlation exists among them. Compared with spring and summer, much stronger correlations of PM_{2.5} between cities were found in autumn and winter, indicating a strong need for joint prevention and control during these periods. All nonattainment cities in this region were divided into city-clusters, depending on the seasons and pollution levels to further helping to reduce their PM_{2.5} concentrations effectively. Air stagnation index (ASI) analysis indicates that the strong correlations between cities in autumn were more attributed to the transport impacts than those in winter, even though there were higher PM_{2.5} concentrations in winter. These results provided an insight into joint prevention and control of pollution in the NCP region.

Keywords: PM_{2.5}; clustering; coefficient of divergence; spatial characteristics; air stagnation index

1. Introduction

Fine particulate matter (PM_{2.5}; particulate matter with an aerodynamic diameter less than 2.5 μm) has been linked to negative impacts on human health [1–3]. As one of the rapidly developing countries, China has experienced rapid economic growth in the past two decades, but it has also triggered serious air pollution problems, especially in the northern and central regions [4]. Since a record-breaking severe haze episode occurred in January 2013, PM_{2.5} pollution in China has attracted wide attention [5,6]. With the

launch of the three-year action plan in 2018 (i.e., to win the battle to protect the blue sky), clear targets have been set to improve air quality. For instance, an 18% reduction in $PM_{2.5}$ concentration is required for all nonattainment cities at the prefecture-level and above. Moreover, compared with 2015, it is required to reduce the number of heavy pollution days by more than 25% by the end of 2020. Although air quality has improved significantly, haze pollution episode characterized by high concentrations of $PM_{2.5}$ is still the most concerning issue in China [7–9], especially in the North China Plain (NCP) [10,11]. Reducing $PM_{2.5}$ concentration for cities that do not meet the standards will still be an important task for air quality management in the next few years.

As revealed in many studies [12–17], the variations of $PM_{2.5}$ concentrations are related to many processes, such as emission, transport, wet deposition, dry deposition, chemical reaction, and physical changes, but essentially these processes are controlled by emission and meteorological conditions. Many meteorological factors have significant impacts on $PM_{2.5}$ concentrations. For instance, a shorter planetary boundary layer (PBL) usually leads to a higher $PM_{2.5}$ concentration for constant emissions [18,19]. Accordingly, $PM_{2.5}$ concentrations of two cities with the same change pattern of PBL height are usually strongly correlated. In addition, the transport of $PM_{2.5}$ aided by winds can affect the $PM_{2.5}$ concentration of neighboring cities, as a result, the correlations of $PM_{2.5}$ concentrations among these cities can be enhanced. Hence, air pollution is usually not confined to certain cities but tends to show regional transport characteristics.

Many studies have shown that the concentration of $PM_{2.5}$ in one city is caused not only by local emissions but also by transport contribution from nearby cities [20–22]. For instance, it was found that $PM_{2.5}$ in Baoding, a city in Hebei Province near Beijing, was transported to Beijing, while bidirectional $PM_{2.5}$ transport was evident between Beijing and Tianjin [23]. Furthermore, $PM_{2.5}$ concentration in China's top three urban agglomerations was found to increase by 0.34% for every 1% increase in the average urbanization level of its neighboring cities [24], especially in Beijing–Tianjin–Hebei (BTH) where $PM_{2.5}$ spillover effects were notably strong [25,26]. Therefore, the “territorial” environmental management system can not cope with the $PM_{2.5}$ pollution problem of regional transport, and the establishment of a regional mechanism for joint prevention and control of air pollution is urgently needed.

As the initial effort of regional prevention, the Ministry of Ecology and Environment of the People's Republic of China (MEEP) launched an air pollution prevention and control project called “One City One Policy” in the BTH region and its surrounding areas. The project involved Beijing, Tianjin, and other 26 cities (i.e., “2 + 26” cities) [27]. However, the understanding of joint prevention and control of $PM_{2.5}$ was far from sufficient, which was attributed to the fact that the policy for joint prevention and control highly depends on the spatial correlation features of $PM_{2.5}$ pollution among cities. Thus, a number of studies that had analyzed the spatial patterns of $PM_{2.5}$ pollution in the “2 + 26” cities [27,28]. The results showed that the pollution centers of the “2 + 26” cities were located in Xingtai and Handan, and gradually moved southwestwards. It also stated that the reduction of $PM_{2.5}$ pollution in this region is important for the mitigation of pollution in the whole NCP region.

Admittedly, $PM_{2.5}$ pollution varies greatly with changes in meteorology conditions and emissions, and similarly, the correlation between the $PM_{2.5}$ concentrations of the two cities also varies greatly. Some studies [26,29] provided analyses of the spatio-temporal pattern of $PM_{2.5}$ pollution but they focus on a large scale, the whole China mainland, or only 13 cities in the BTH region. Moreover, they did not pay attention to non-attainment cities and did not give city-scale suggestions for joint prevention and control that vary with pollution seasons and pollution levels. There are other some studies [30–32] that proposed an approach for joint control between cities in the region (i.e., BTH and surrounding cities and the Yangtze River Delta), but they also did not pay attention to non-attainment cities in their research domain. Moreover, they did not discuss more the impact of meteorological conditions such as air stagnation index (ASI) which can greatly affect the spatial pattern of $PM_{2.5}$. In addition, these studies did not take the pollution levels into account for joint

control. Therefore, to bridge this gap, a more specific spatial relationship of $PM_{2.5}$ pollution needs to be studied for the different seasons among these nonattainment cities to enhance the benefits from joint prevention and control and enable timely achievement of air quality targets in the nonattainment cities of this region.

This study applied multiple data mining techniques to reveal the spatial relationship of $PM_{2.5}$ pollution over 42 prefecture-level cities in the northern part of the North China Plain (NNCP), expanding the coverage of the “2 + 26” cities. Section 2 describes the methods that were used in this study, including the clustering analysis, network correlation analysis, coefficient of divergence analysis (COD), and ASI. Section 3 presents the results on spatial clustering, heterogeneity, and correlation, particularly for the nonattainment cities. Different levels of joint prevention and control city groups are given for different seasons. Besides, analyses of the terrain and meteorology conditions using ASI are conducted to reinforce the understanding of spatial correlations of $PM_{2.5}$ among these cities. Finally, conclusions and policy implications were given in Section 4.

2. Data Source and Methods

2.1. Research Region and Data Source

The research domain covers 42 cities, composed of Beijing, Tianjin, other 11 cities in Hebei Province, 17 cities in Shandong province, 7 cities in Henan Province, and 5 cities in Shanxi Province, as shown in Figure 1. Most of these cities are located in the NNCP region. Few cities in Shanxi province are outside but close to the NNCP region. The study domain also includes the “2 + 26” cities as the important air pollution transport corridors in the Beijing-Tianjin-Hebei region. The data of $PM_{2.5}$ concentration from 1 January 2015 to 31 December 2018, were obtained from China Urban Air Quality Real-Time Publishing Platform (<http://106.37.208.233:20035>), which is supported by the MEEP. Hourly meteorological data were obtained from the National Centers for Environmental Information in the National Oceanic and Atmospheric Administration (NOAA) (<https://www.ncei.noaa.gov/access/search/data-search/global-hourly>). Data are accessible from FTP (<ftp://ftp.ncdc.noaa.gov/pub/data/noaa>, last access: 30 November 2020).

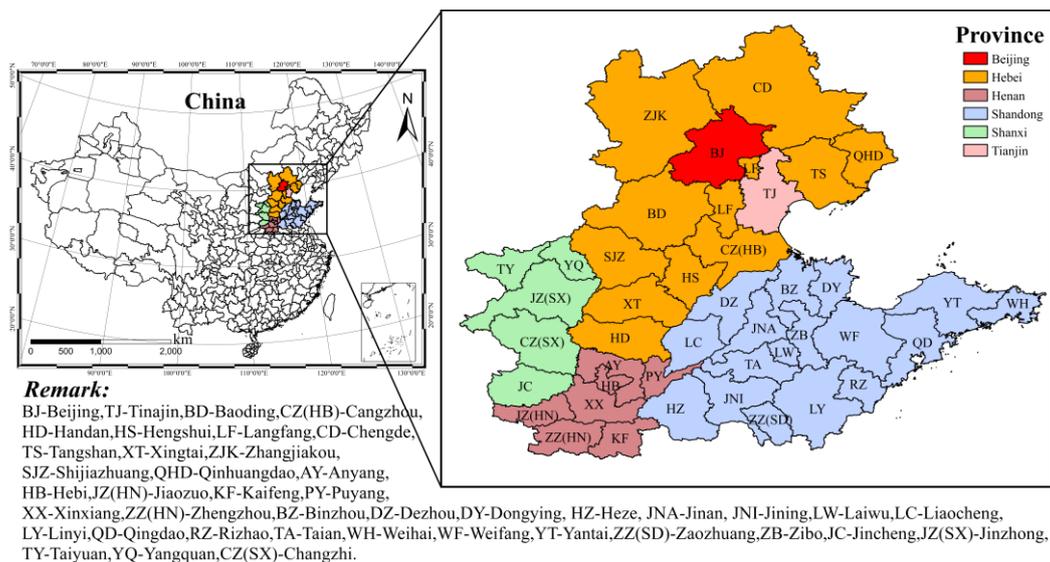


Figure 1. The study domain and cities in the northern part of the North China Plain (NNCP) region.

2.2. Methods

2.2.1. Agglomerative Hierarchical Clustering Model

Agglomerative Hierarchical clustering (AHC) is a bottom-up statistical method that initially treats each object as a single cluster, merges it according to certain distance algo-

rithm and similarity algorithm criteria, and iterates until the requirements are met [33,34]. This method can be used to study spatial characteristics of air quality at the regional scale [35–37]. In this work, the daily average concentrations of PM_{2.5} for each prefecture-level city in the NNCP region were considered as one initial object. Therefore, there were 42 initial objects which were input into the clustering model.

The distance between every two clusters was computed with the Euclidean distance [38], which can be used to calculate the degree of similarity between PM_{2.5} concentrations in two cities, as shown in Equation (1).

$$Eu_{ij} = \sqrt{\sum_{k=1}^m (x_{i,k} - x_{j,k})^2} \quad (1)$$

where Eu_{ij} is the Euclidean distance between the i_{th} city and the j_{th} city, m is the number of daily mean concentrations of PM_{2.5} in city i over the study period.

2.2.2. Coefficient of Divergence

The coefficient of divergence (COD) was used to measure the relative consistency in concentrations between cities, ranging from 0 to 1.0 in some studies [39–41]. Usually, 0.2 is considered the boundary value of COD [42,43]. Such that, COD value larger than 0.2 indicates the heterogeneous spatial distribution of PM_{2.5}, while a COD value less than 0.2 represents a uniform spatial distribution of PM_{2.5}. Therefore, COD points out the degree of spatial differences in PM_{2.5} concentration within each city-cluster region. The COD was defined according to Equation (2). Representative cities within the city-cluster are selected as the benchmark by Equations (3) and (4). The city with the highest $Index_i$ value is regarded as the representative city of the city-cluster.

$$COD_{ij} = \sqrt{\frac{1}{n} \sum_{k=1}^n \left(\frac{x_{ki} - x_{kj}}{x_{ki} + x_{kj}} \right)^2} \quad (2)$$

where x_{ki} and x_{kj} represent the average daily PM_{2.5} concentration for day k at cities i and j of the city cluster, and n is the studied days.

$$Eu_i^* = \frac{Eu_i}{\max(Eu_i)} \quad (3)$$

$$Index_i = \frac{R_i}{Eu_i^*} \quad (4)$$

where Eu_i is a normalized Euclidean distance and $Eu_i \in (0, 1)$, R_i refers to Pearson's correlation coefficient between the PM_{2.5} concentration of any city i in the city-cluster and the average PM_{2.5} concentration of the city-cluster.

2.2.3. Complex Network Correlation Model

The network correlation model can be used to calculate the correlation between the research objects. It has been used in the analysis of the PM_{2.5} correlation on a regional scale [44–46]. The network correlation model based on Pearson's correlation coefficient was applied to measure the correlation strength between every two cities in the NNCP region, describing the direct and indirect interaction of daily mean PM_{2.5} concentrations. For any two cities, their daily average PM_{2.5} concentration were taken as the matrixes $X = \{x_1, x_2, \dots, x_n\}$ and $Y = \{y_1, y_2, \dots, y_n\}$, respectively, and then their Pearson's correlation coefficient $\rho(X, Y)$ [47] was calculated based on Equation (5). The ρ value of any two cities is less than 1.0. The closer to 1.0, the greater the correlation. Pearson's correlation distance

is another distance based on the correlation coefficient [48], which was calculated by Equation (6).

$$\rho(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (5)$$

$$D_{cor}(X, Y) = 1 - \rho(X, Y) \quad (6)$$

where $\rho(X, Y)$ is the Pearson's correlation coefficient between X and Y . x_i and y_i were daily $PM_{2.5}$ concentration of i_{th} city and j_{th} city. \bar{x} and \bar{y} were the average concentration of $PM_{2.5}$ in the city i and city j .

2.2.4. Air Stagnation Index

The air stagnation index (ASI) is an important meteorological indicator of the ability of the atmosphere to dilute air pollutants. The ASI was originally developed by the National Oceanic and Atmospheric Administration (NOAA). Using geopotential height, Planetary boundary layer height (PBLH), and precipitation variables from the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) dataset, Feng et al. have developed the ASI for the NCP in China [49,50]. ASI data used in this study for autumn and winter in 2018 is from the previous study by Feng et al.

3. Results and Discussion

3.1. Basic Temporal-Spatial Distribution

The annual mean concentrations of $PM_{2.5}$ from 2015 to 2018 were $75.7 \mu\text{g}\cdot\text{m}^{-3}$, $69.3 \mu\text{g}\cdot\text{m}^{-3}$, $62.8 \mu\text{g}\cdot\text{m}^{-3}$, and $54.8 \mu\text{g}\cdot\text{m}^{-3}$, respectively, as shown in Figure 2. This is synonymous with annual decrease ratios of 8%, 10%, and 13% in 2016, 2017, and 2018, respectively. It is evident that the highest average concentration of $PM_{2.5}$ were witnessed in the seven cities of Henan Province. This is a clear indication that Henan province suffers from severe $PM_{2.5}$ pollution and therefore more attention is required. It was also worth noting that, the concentration trend of $PM_{2.5}$ in the five cities of Shanxi province inconsistent with the whole NNCP region. Clearly, while $PM_{2.5}$ concentrations declined year after year since 2015–2018 in the rest of the NNCP region, $PM_{2.5}$ pollution in the five cities of Shanxi Province worsened in 2016 and 2017 with slight fluctuations in 2018. Generally, Beijing, Tianjin, Henan, Shandong, and “2 + 26” urban agglomerations all gained significant reduction of $PM_{2.5}$ concentrations between 2015–2018. Nevertheless, their $PM_{2.5}$ concentrations were still higher than the National Ambient Air Quality Standards (NAAQS) of $35 \mu\text{g}\cdot\text{m}^{-3}$.

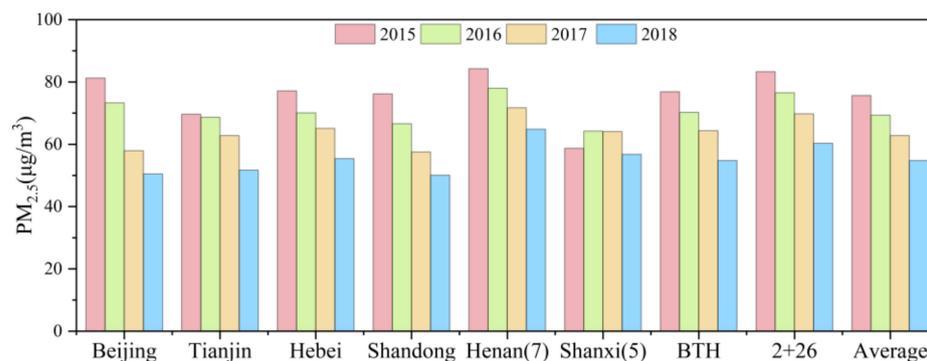


Figure 2. Average $PM_{2.5}$ concentrations in the different sub-regions of NNCP (2015–2018).

The details about classification standards of air quality pollution levels and some discussion on the variations of the number of pollution days in the whole NNCP region during 2015–2018 (Figures S1 and S2) can be referred to the supporting information file. As shown in Figure 3a, the number of non-excellent days shows a declining trend with years. An average of 53% decrease is noticeable in the number of days heavily polluted days and above in 2018 relative to 2015, indicating a great improvement in air quality.

However, there is a notable rebound (in 2017) in Hebei, Henan, and Shanxi. The cities with the greatest improvement in the number of non-excellent days from 2015 to 2018 were Qingdao (−45%), Yantai (−41%), Dongying (−34%), Weihai (−32%), Rizhao (−31%), and Linyi (−31%). Compared with the high $PM_{2.5}$ concentration in 2015, non-excellent days in 2018 increased by 18% in Yangquan. In general, Shanxi Province has benefited less from the national implementation of air quality control plans and thus require more attention.

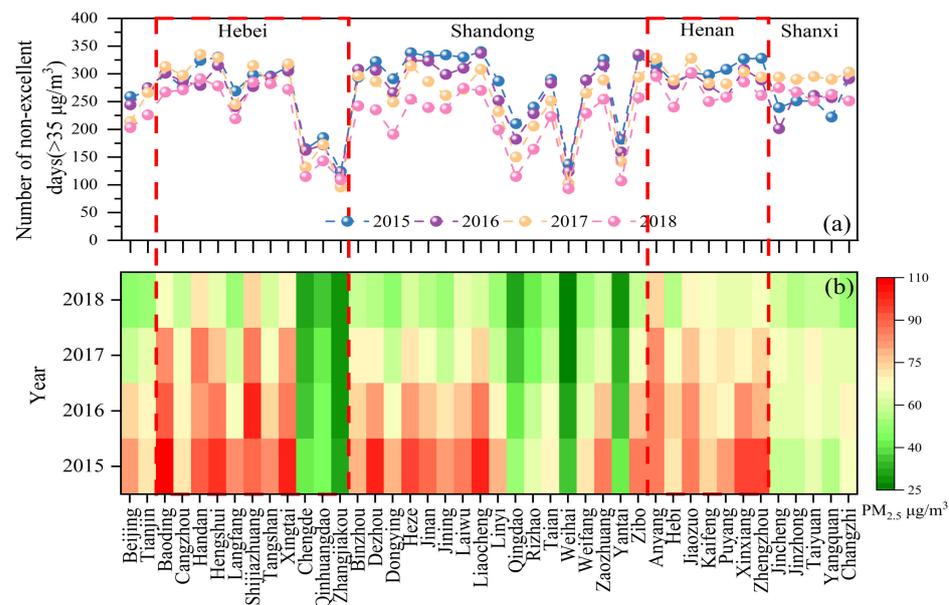


Figure 3. The number of non-excellent days (a) and variations of annual $PM_{2.5}$ concentrations (b) by city from 2015 to 2018 in the NNCP region.

As shown in Figure S3, high $PM_{2.5}$ pollution was mainly concentrated in the central and southern parts of Hebei as well as the northern part of Henan. In 2015, only one city (Zhangjiakou), met the target of $PM_{2.5}$, and by 2018, four more cities (Chengde, Qingdao, Yantai, and Weihai) achieved attainment. These cities with low $PM_{2.5}$ concentrations are distributed over the northernmost and easternmost parts of the entire NNCP region. It is noted that Langfang was the city with the biggest drop rate (39%) of $PM_{2.5}$ in the whole NNCP region. In 2015, the highest annual concentration of $PM_{2.5}$ in the NNCP region was found in Baoding ($106.7 \mu\text{g}\cdot\text{m}^{-3}$), more than three times the $PM_{2.5}$ limit value in NAAQS ($35 \mu\text{g}\cdot\text{m}^{-3}$). Anyang, located in the north of Henan Province and near Hebei Province, had a higher annual $PM_{2.5}$ concentration ($74.4 \mu\text{g}\cdot\text{m}^{-3}$) than any other city in the NNCP region in 2018. Overall, there were 37 nonattainment cities in the NNCP region in 2018.

3.2. Spatial Clustering Analysis

According to hierarchical clustering based on the clustering of Euclidean distance and Pearson's correlation distance, the NNCP region was divided into 6 sub-regions as shown in Figure 4a,b, respectively. Determination of the number of clusters was based on the elbow method, see Figure S4. Euclidean distance clustering grouped cities with comparable daily average $PM_{2.5}$ concentrations into one category or similar cluster. Evidently, the first cluster comprises the eastern coastal cities and the northern cities, including Yantai, Weihai, Qingdao, Rizhao, Chengde, and Qinhuangdao, with an annual average $PM_{2.5}$ concentration ranged from 26.6 to $42.1 \mu\text{g}\cdot\text{m}^{-3}$. The second cluster includes Beijing, Tianjin, Tangshan, and Langfang, with an annual average concentration of $PM_{2.5}$ ranged from 50.5 to $60.2 \mu\text{g}\cdot\text{m}^{-3}$. One of the most polluted clusters covered the cities in central and southern Hebei, and the northern city of Anyang in Henan with annual average $PM_{2.5}$ concentration ranged from 55.2 to $74.4 \mu\text{g}\cdot\text{m}^{-3}$.

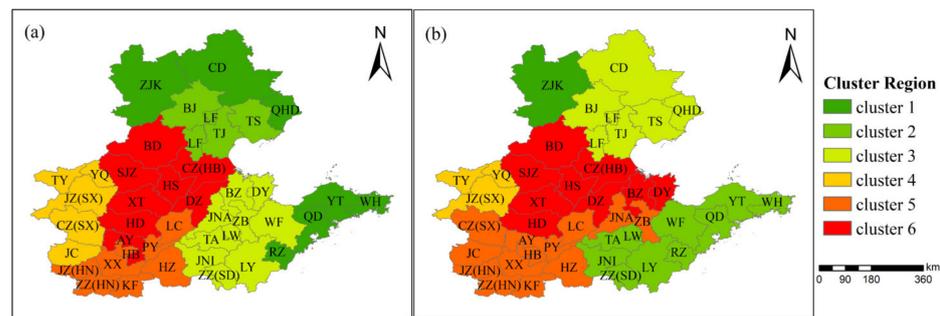


Figure 4. Clustering results based on daily $PM_{2.5}$ concentrations of Euclidean distance (a) and Pearson's correlation distance (b) in 2018.

Pearson's correlation distance clustering reveals contrasting results (Figure 4b). Basically, the Pearson's correlation distance measures the similarity of the correlation between cities based on $PM_{2.5}$ concentrations. For instance, the stronger the correlation between $PM_{2.5}$ concentrations of two cities, the smaller the Pearson's correlation distance. By comparison, it is clear from Figure 4a,b that clustering results for cities close to Taishan Mountain were different. In addition, Chengde, Zhangjiakou, Qingdao, Weihai, and Yantai, which were attainment cities in 2018, were not in the same sub-region in Pearson's distance clustering results. In particular, Zhangjiakou, located in the northwest of the Taihang Mountains, was in its own category. Moreover, Jincheng and Changzhi were no longer in the same cluster as Jinzhong in Shanxi Province. Essentially, topographical features and meteorological conditions were two important factors that affect the clustering results in Pearson's correlation distance [51]. As mentioned earlier, $PM_{2.5}$ concentration is impacted by the combined effect of emission and meteorological conditions. However, some meteorological conditions, especially wind speed and direction are also greatly impacted by topographical features. Meteorological conditions (particularly PBL and wind, that control the transport of pollutants) are the main factors that influence the correlation of $PM_{2.5}$ concentration between cities.

3.3. Spatial Heterogeneity Analysis

The city with the highest representative index S_i among the cities in the same region is regarded as the representative city for that region. The representative cities of the six clusters based on Euclidean clustering were Yantai, Langfang, Taian, Jinzhong, Xinxiang, and Handan, respectively. However, Zhangjiakou, Rizhao, Langfang, Jinzhong, Xinxiang, and Hengshui were the representative cities based on Pearson's correlation distance clustering. The COD was used to measure the relative consistency of $PM_{2.5}$ concentrations between cities. The COD values between these representative cities based on the two kinds of clustering distances are shown in Tables S1 and S2. Except for Handan and Xinxiang, the COD value of every two representative cities was greater than 0.2 (Table S1), indicating the obvious heterogeneity of $PM_{2.5}$ pollution between the representative cities. COD values of Yantai and any other representative city were greater than 0.38, suggesting that the $PM_{2.5}$ pollution in Yantai was significantly different from that of other representative cities. On the contrary, the COD values of Handan and Xinxiang were 0.14, less than 0.2, indicating that the pollution homogeneity of both cities was strong.

Furthermore, the COD results for Pearson's correlation distances shows that Zhangjiakou and any other representative city had COD value greater than 0.37 (Table S2). This signifies strongly heterogeneous $PM_{2.5}$ pollution in Zhangjiakou in relation to other representative cities in the NNCP region. Besides, Langfang, Jinzhong, and Xinxiang belong to the same representative cities for the two kinds of clustering results but have different $PM_{2.5}$ pollution features.

Additionally, a detailed analysis of the regional homogeneity of $PM_{2.5}$ concentrations is shown in Figure 5. This was achieved by computing the COD between the representative city and any other city in a given cluster. The values in horizontal axis are the geographical

distances between the representative city and any other city in the same cluster. The COD value in the cluster 1, 3, 4, and 6 (based on Euclidean distances clustering), was less than 0.2 when the geographical distance between the corresponding city and the representative city was less than 180 km. This means that PM_{2.5} pollution was homogeneous. However, when the distance exceeded 180 km, COD was greater than 0.2. Thus, the spatial scale of PM_{2.5} pollution in the clusters was about 180 km. Notably, in clusters 1 and 4, COD values increased monotonically with distance. Whereas, in cluster 2, the COD value was directly proportional to the increase in the distance except for Beijing. Remarkably, Beijing is closest to the representative city (Langfang, 47.2 km), but the COD value is 0.21, indicating a lack of homogeneity in the PM_{2.5} pollution of Beijing and Langfang. This is mainly attributed to the different industrial structures between these two cities, more so because Beijing is the capital city and the cultural center of China. While, the results of clusters 3, 4, and 6 were slightly more complicated, the results of cluster 5 present vital information. It is important to note that, COD between Xinxiang and any other city of Hebi, Kaifeng, Zhengzhou, and Jiaozuo were all less than 0.14, far less than the judgment standard of 0.2. This means that there is a very strong homogeneity of PM_{2.5} pollution among them. In addition, the geographical locations of Hebi, Kaifeng, Zhengzhou, and Jiaozuo are a short distance from Xinxiang (≤ 70 km). Within such short distances coupled with relatively flat terrain, PM_{2.5} can be easily transported among these cities. Therefore, joint prevention and control among these cities can be very important to alleviate PM_{2.5} pollution.

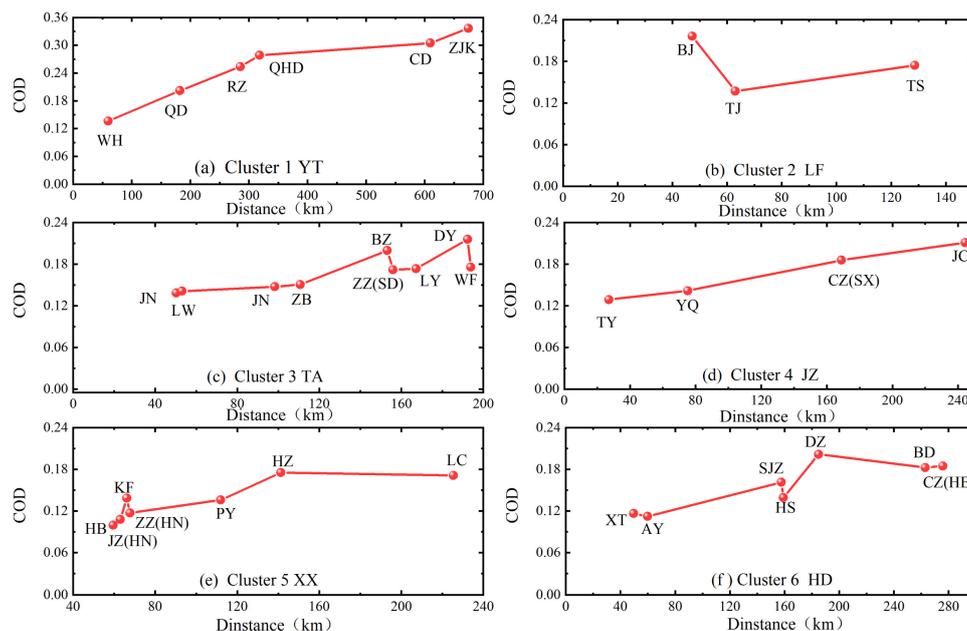


Figure 5. The variations of coefficient of divergence (COD) values with the geographical distance of any other city away from the representative city for the six clustered regions (a–f) based on Euclidean distances clustering.

In the same way, as mentioned above, the corresponding analysis was conducted for the clusters based on Pearson’s correlation distances clustering as shown in Figure 6. In cluster 3, 4, and 6, the COD values (<0.2) further demonstrate a uniform distribution of PM_{2.5} pollution in these clusters when the distance of one city to the representative city is less than 180 km. In cluster 2, COD values of both Qingdao and Linyi were less than 0.2 and their distances are both about 100 km away from Rizhao. It was noteworthy that all cities had COD values less than 0.20 in sub-region 5 except for the cities of Jincheng and Changzhi. Similar to Figure 5e, strong homogeneity of PM_{2.5} pollution is also observed in Figure 6d among Hebi, Jiaozuo, Kaifeng, Zhengzhou, and Xinxiang. In addition, there exists a slight pollution homogeneity between Xinxiang and some northern cities of Mount Tai, namely Liaocheng, Jinan, and Zibo, which are more than 200–450 km away from

Xinxiang. This phenomenon is mainly due to the prevalence of northeast winds during winter in Xinxiang. Therefore, in addition to local pollution sources, the results indicate that the impact of transport of seriously polluted urban pollutants in this (northeast) direction is significant [52]. Notably, all these four cities belong to the “2 + 26” city agglomeration as the transport corridor of PM_{2.5}. Here, the special terrain of Mount Tai plays an important role in the transport impact of PM_{2.5} pollution between these cities. Ultimately, the impact of inter-city transport of PM_{2.5} cannot be ignored to effectively reduce the pollution level for these cities.

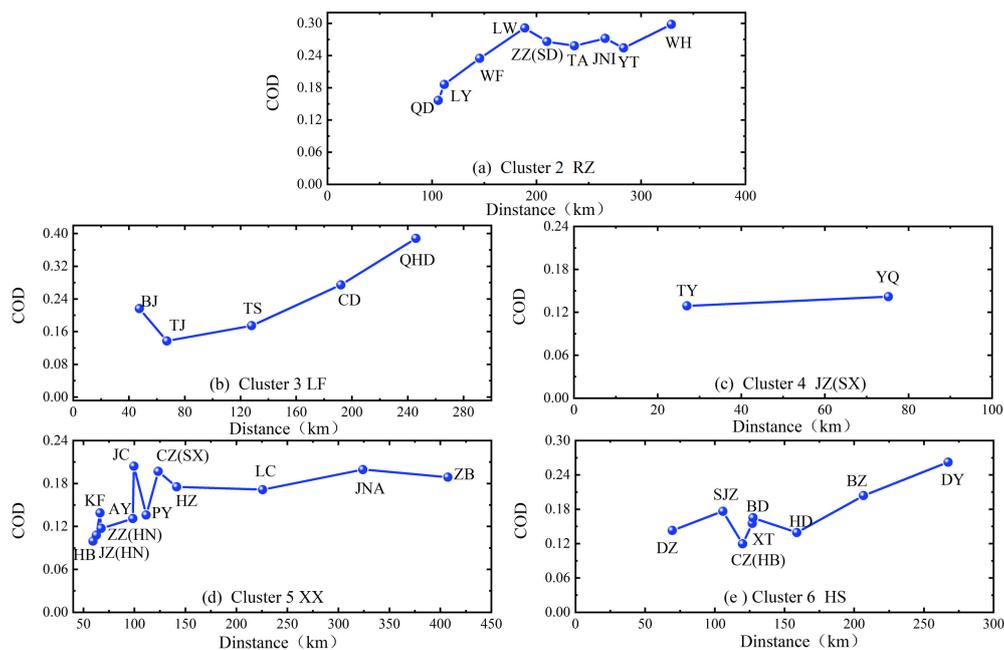


Figure 6. The variations of COD values with the geographical distance of any city relative to the representative city for the five clustered regions (a–e) are based on Pearson’s correlation distances clustering.

3.4. Network Correlation Analysis

Essentially, the network correlation model focuses on the correlation coefficient (ρ value) between every two cities. In principle, the larger the ρ value, the stronger the correlation of PM_{2.5} concentrations in the two cities (i.e., the impact of PM_{2.5} transport between the two cities is substantial). To clearly present the connection between cities, a provisional threshold value of ρ was set at 0.88. The results of the PM_{2.5} network correlation model in different seasons of the NNCP region in 2018 are presented in Figure 7. Note that, the connection between two cities with ρ values less than 0.88 are not displayed. It is evident that the network correlation between cities in the NNCP region is strong in autumn and winter, as opposed to spring and summer. This shows that autumn and winter seasons have potentially greater impacts of PM_{2.5} transport on surrounding cities or rather in cities with stronger common meteorological conditions.

For two nonattainment cities, the greater the impact of PM_{2.5}, the greater the need for joint prevention and control. On the contrary, when more cities unite, the more difficult it is to implement a joint control strategy. According to the necessity and difficulty of the joint prevention and joint control between cities, different threshold values of ρ s can be used to further categorize city-clusters into three levels. The threshold for the first level of joint control with the least difficulty is 0.92, the second level is 0.90 and the third level is 0.88. Results of the complex network correlation model also suggest that, for nonattainment cities to realize the timely achievement of PM_{2.5} targets in NAAQS, then joint prevention and control need to be implemented in city-clusters. Therefore, cities with daily average concentrations of PM_{2.5} between 35–75 $\mu\text{g}\cdot\text{m}^{-3}$ need to implement the first level joint

prevention and control, while those with $\text{PM}_{2.5}$ concentrations between $75 \mu\text{g}\cdot\text{m}^{-3}$ and $115 \mu\text{g}\cdot\text{m}^{-3}$ are recommended to execute the second level, along with the first level of joint prevention and control. However, cities with $\text{PM}_{2.5}$ concentrations above $115 \mu\text{g}\cdot\text{m}^{-3}$ are recommended to perform the third level, besides the first and second levels.

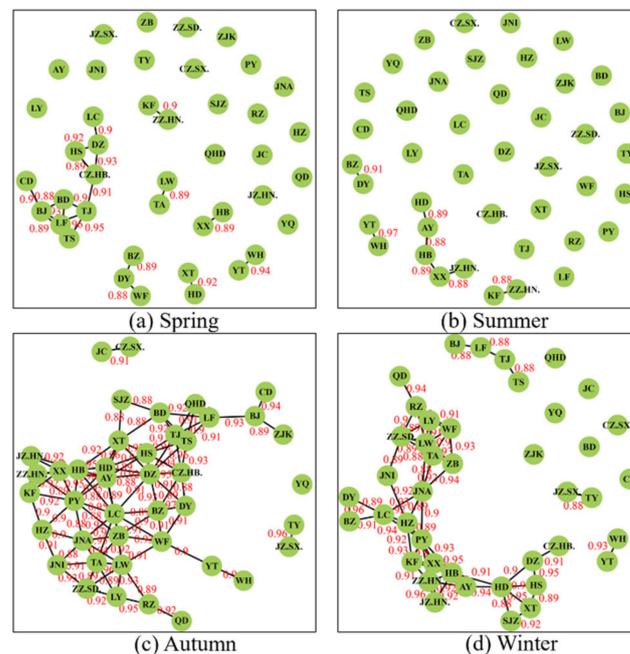


Figure 7. Network correlations between cities in different seasons (a): Spring, (b): Summer, (c): Autumn, (d): Winter, in the NNCP region ($\rho \geq 0.88$).

The city-clusters of the first, second, and third levels of joint prevention and control are presented in Figures 8 and 9, and Figure S5 for all the seasons in 2018. Comparatively, the number of city-clusters in the first level is highest but lowest in the third level. It worth mentioning that, when the city-cluster of a certain level is not presented, it means that there was no proposed city-cluster of joint control for that level. What is more, there were no city-clusters for all levels during summer. In general, the average $\text{PM}_{2.5}$ concentrations of city-clusters in winter were much higher than those in autumn. Besides, there were most city-clusters in autumn, followed by winter.

The results of the first-level joint prevention and control are presented in Figure 8. Clearly, in spring, Tianjin-Tangshan, Tangshan-Langfang, and Tianjin-Langfang city-clusters all have higher ρ values (>0.94), indicating a strong correlation between them. However, there were only two city-clusters in the second level and one city-cluster in the third level, due to the relatively low $\text{PM}_{2.5}$ concentration. During autumn, the ρ values for many city-clusters in the first-level, including Handan-Anyang, Xingtai-Handan, Hebi-Anyang, Taian-Laiwu, Hengshui-Dezhou, Tianjin-Tangshan, Tianjin-Cangzhou, Dezhou-Binzhou, Zibo-Jining, Dongying-Binzhou, Taiyuan-Jinzhong, Rizhao-Linyi, were obviously higher than 0.94, with even more than five city-clusters whose ρ values were higher than 0.96. For the first-level city-clusters in autumn and winter, the most polluted city-clusters are located in adjacent areas of Henan and Hebei provinces.

For the second-level in autumn, the $\text{PM}_{2.5}$ concentrations in the city-cluster of Xingtai-Anyang-Handan were the highest, followed by the city-cluster of Xinxiang-Anyang-Puyang (Figure 9). For the third-level, the city-cluster of Heze-Puyang-Liaocheng-Jinan-Handan-Hebi-Xinxiang-Zhengzhou suffered from severe $\text{PM}_{2.5}$ pollution in autumn (Figure S5). The cities in this city-cluster belong to different provinces (i.e., Henan, Hebei, and Shandong Provinces, respectively). This is an indication that joint control between cities across provincial boundaries is feasible and essential in autumn.

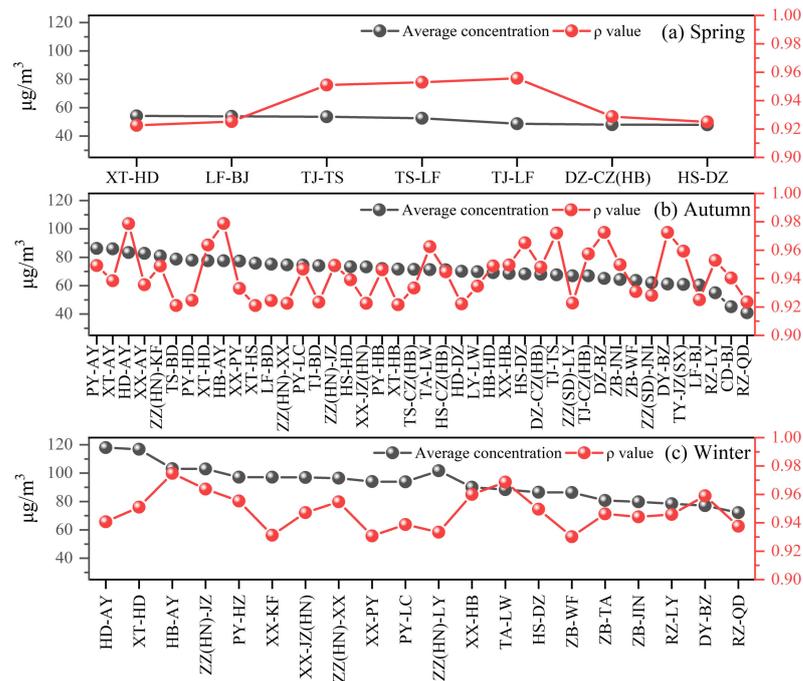


Figure 8. The city-clusters with their average PM_{2.5} concentrations and ρ values for the first level in seasons (a): Spring, (b): Autumn, (c): Winter.

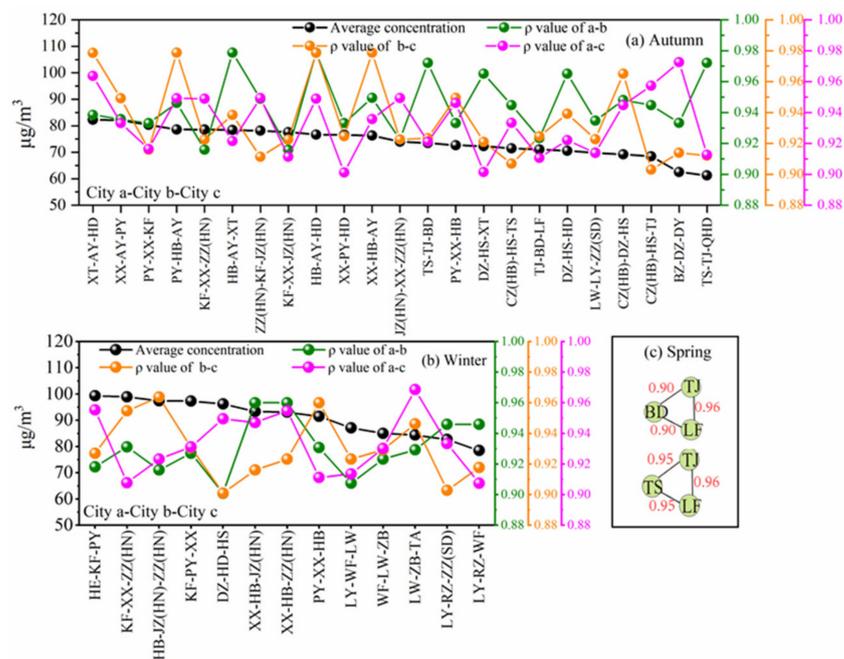


Figure 9. The city-clusters with their average PM_{2.5} concentrations and ρ values for the second-level in seasons (a): Autumn, (b): Winter, (c): Spring.

During the winter, the two city-clusters exhibiting severe PM_{2.5} pollution include Heze-Kaifeng-Puyang and Kaifeng-Xinxiang-Zhengzhou for the second-level (Figure 9). For the third-level, there were only two city-clusters. Handan-Shijiazhuang-Xingtai-Hengshui-Dezhou ranked first and Hebi-Jiaozuo-Kaifeng-Puyang-Zhengzhou-Xinxiang city cluster ranked second in terms of average PM_{2.5} concentrations, as shown in Figure S5. Except for Dezhou, all four cities in the first city-cluster belong to Hebei Province, and all six cities in the second city-cluster belong to Henan Province, indicating that pollution control in

Hebei and Henan Provinces should be paid more attention. As mentioned above, Xinxiang was the representative city of the fifth cluster according to both the Euclidean distance and Pearson’s correlation distance. The COD values between Xinxiang and any other city in the same city-cluster, such as Hebi, Jiaozuo, Kaifeng, Puyang, and Zhengzhou, were all less than 0.14. This is proof that cities in the city-cluster of Hebi-Jiaozuo-Kaifeng-Puyang-Zhengzhou-Xinxiang were strongly related to each other. Based on the clustering of Pearson’s correlation distances, Hengshui was the representative city in the city-cluster, and the COD value was less than 0.15 for Dezhou, which is about 50 km away from Hengshui. The COD values of Shijiazhuang, Xingtai, and Handan, which are 100–180 km away from Hengshui, were also less than 0.18. This indicates a strong homogeneity and strong correlation between these five cities. In addition to the emission reduction of their own cities, strengthening joint prevention and control is highly needed to mitigate PM_{2.5} pollution, not only for themselves but also for other cities.

3.5. Topographic, Meteorological, and Air Stagnation Index Analysis

Mountain terrain significantly changes the wind speed and direction, and thus affects the transport strength and pathway of PM_{2.5}. As shown in Figure 10 and Figure S6 for autumn and winter, respectively, Taihang Mountains and Yan Mountain are located in the west and northwest of Hebei. The two cities of Jinan and Taian are separated by Mount Tai, and the transport impact between them is relatively small. The dominant wind of Zhangjiakou in autumn and winter was the northwest wind, and 16% of the frequency wind in Beijing came from the direction of Zhangjiakou, mostly on days when the air quality was excellent. The transport between Zhangjiakou and Beijing was weak due to the low PM_{2.5} concentration in Zhangjiakou and the interference from Yan Mountain. As a result, Zhangjiakou alone became one cluster according to Pearson’s correlation clustering. Correspondingly, the ρ value between Zhangjiakou and Beijing was not large, which was not high enough to be combined with other cities in the first-level.

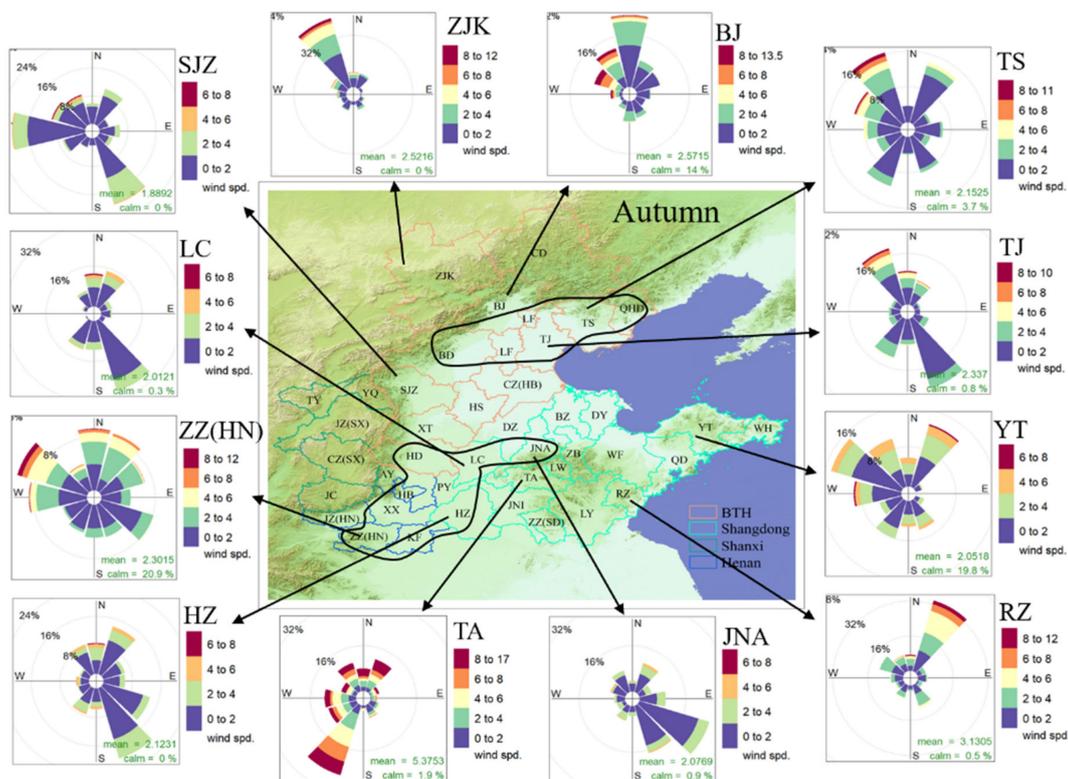


Figure 10. Topographic map and winds rose diagrams of some cities for the autumn of 2018 in the NNCP region.

In autumn, the wind frequency from the northwest direction in Tangshan was relatively high, and the fastest wind speed about 10 m s^{-1} , (Figure 10). Such, high wind speed is very beneficial to diffuse $\text{PM}_{2.5}$ and to prevent the formation of heavy haze pollution. In addition, there also exists northwest winds around 2 m s^{-1} in the path of Langfang, (northwest of Tangshan) with the potential of a large impact on $\text{PM}_{2.5}$ transport. This is consistent with the result of the network correlation model, indicating a strong correlation between $\text{PM}_{2.5}$ concentrations in Tangshan and Langfang. The significant frequency of the winds from northeast and southwest of Tangshan with moderate speeds influences Tianjin, an adjacent city to Tangshan. This is also evidenced by the fact that wind frequencies in the southwest direction of Tangshan predominantly occur on non-excellent days. This was consistent with the results of the autumn in third-level based on the network correlation model. The terrain of Zhengzhou, Xinxiang, Hebi, Kaifeng, and Puyang is very flat, and the distances between cities are very close. The high frequency of northeast winds in Zhengzhou facilitates obvious transport impact on Xinxiang and Kaifeng cities, which is consistent with the results of the network correlation model. Similarly, Zhengzhou was also strongly related to cities like Xinxiang and Kaifeng in winter.

In addition, the Air Stagnation Index (ASI) is also a very important factor of meteorology to describe the ability of the atmosphere to dilute air pollutants. Neighboring cities with high ASI usually show a similar change pattern of $\text{PM}_{2.5}$ concentrations. Hebi and Anyang were grouped into one city-cluster with the strongest correlation in autumn (0.98) (Figure 8), while their mean $\text{PM}_{2.5}$ concentration and ASI were $77.5 \mu\text{g}\cdot\text{m}^{-3}$ and 1.31, respectively. In winter, the ASI of 1.69 was much higher than that in autumn, suggesting that weather conditions in winter were closer to stagnation, as a result, their mean $\text{PM}_{2.5}$ concentration ($103.1 \mu\text{g}\cdot\text{m}^{-3}$) was much higher than that in autumn. However, the correlation of $\text{PM}_{2.5}$ concentrations between the two cities in winter was 0.97, which was slightly lower than that in autumn. Zhengzhou and Kaifeng are also a noteworthy city-cluster, with a mean ASI of 1.39 in autumn and 2.10 in winter, and corresponding average $\text{PM}_{2.5}$ concentrations of $80.9 \mu\text{g}\cdot\text{m}^{-3}$ and $103.1 \mu\text{g}\cdot\text{m}^{-3}$ in autumn and winter, respectively. However, the correlation (0.95) in autumn was significantly higher than that in winter (0.91). Therefore, it can be concluded that higher ASI does not always contribute to a higher correlation of $\text{PM}_{2.5}$ concentrations. In other words, the transport of $\text{PM}_{2.5}$ concentrations can be attributed to the higher correlation of $\text{PM}_{2.5}$ concentrations between cities.

Clustering analyses based on $\text{PM}_{2.5}$ concentrations and ASI for autumn and winter are shown in Figure 11, respectively. In autumn, only Baoding and Shijiazhuang had both the highest concentrations and ASI. Cities in northeastern Shandong have the lowest ASI and also the lowest concentrations. However, cities in Henan belong to cluster 5 in the concentration clustering, and cluster 3 in the ASI clustering. The main reason for the big difference between the two clustering results is that pollutant transport was strong in these cities in Henan, which is consistent with the above analysis. In winter, the difference between the two clustering results in these cities in Henan is minimal, indicating a static stability index in winter with a significant effect on the correlation of $\text{PM}_{2.5}$ concentrations.

Table 1 shows the mean distribution of $\text{PM}_{2.5}$ concentration, ρ value, and air stagnation index for the different sub-regions with the Euclidian distance in autumn and winter respectively. It can be seen that the ASI is significantly higher in winter than autumn, indicating that the NNCP region is more prone to stagnant weather, correspondingly with higher $\text{PM}_{2.5}$ concentrations, during winter. However, from Figures 7 and 8, we can see that the correlations between cities are usually stronger in autumn than those in winter, suggesting that the strong correlations between cities in autumn are more attributed to the transport impacts than those in winter. Nevertheless, the transport contribution to high correlations in winter cannot be ignored due to the existing winds. Overall, the spatial correlation of $\text{PM}_{2.5}$ concentrations between neighboring cities is not only influenced by the common stationary meteorological conditions but also impacted by the transport between cities.

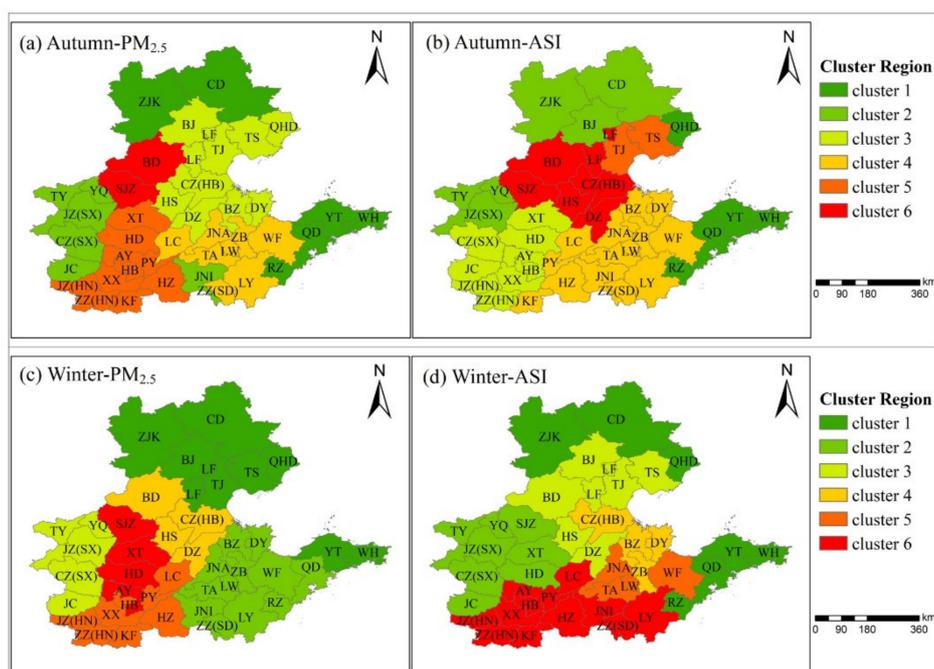


Figure 11. Clustering results based on Euclidean distance for average daily $PM_{2.5}$ concentrations (a,c) and daily air stagnation index (ASI) (b,d) in autumn 2018.

Table 1. Mean of $PM_{2.5}$ concentrations, ρ value, and ASI for cluster sub-regions based Euclidian distance in autumn and winter 2018, respectively.

Sub-Region	Autumn			Winter		
	$PM_{2.5}$ Concentration ($\mu g \cdot m^{-3}$)	ρ Value	ASI	$PM_{2.5}$ Concentration ($\mu g \cdot m^{-3}$)	ρ Value	ASI
1	33.4	0.62	0.98	44.0	0.55	1.43
2	57.5	0.64	1.26	78.5	0.82	1.74
3	63.5	0.85	1.39	81.4	0.72	1.51
4	66.5	0.89	1.37	86.9	0.81	1.79
5	77.1	0.88	1.36	96.3	0.89	1.90
6	84.5	0.88	1.49	114.6	0.90	1.61

4. Conclusions

This work focused on the spatial characteristics of $PM_{2.5}$ pollution in the NNCP region, one of the key $PM_{2.5}$ pollution regions in China. Through data mining technologies, insight was provided for better joint prevention and control in nonattainment cities. The main conclusions include:

(1) The distance between cities with $PM_{2.5}$ pollution homogeneity in the NNCP region is less than 180 km based on the clustering analysis and coefficient of divergence analysis. It is necessary to strengthen joint prevention and control for cities with strong $PM_{2.5}$ pollution homogeneity in the same clustering region.

(2) The COD values between Xinxiang and any one of Hebi, Kaifeng, Zhengzhou, and Jiaozuo were all less than 0.14, far lower than the judgment standard, indicating that there was a strong $PM_{2.5}$ pollution homogeneity among them. Geographically, $PM_{2.5}$ in these four cities was easily transported to neighboring cities due to such a short distance and flat terrain. It is very important to carry out joint prevention and control between these cities.

(3) According to the correlation of $PM_{2.5}$ concentration between cities, three levels of city-clusters were proposed. City-clusters for the nonattainment cities were recommended to perform joint prevention and control depending on seasons and $PM_{2.5}$ pollution levels.

(4) Overall, the spatial correlation of PM_{2.5} concentrations between neighboring cities is not only influenced by the common meteorological conditions but also impacted by the transport between cities. However, the correlations of PM_{2.5} between cities were generally stronger in autumn than those in winter but there were higher ASI values in winter, suggesting that the strong correlations between cities in autumn are more attributed to the transport impacts than those in winter. Therefore, these above policy implications are reasonable based on the spatial characteristics of PM_{2.5} concentrations in the NNCP region.

Supplementary Materials: The following are available online at <https://www.mdpi.com/2073-4433/12/1/77/s1>. Figure S1: The occurrence frequency of different PM_{2.5} pollution levels in NNCP region year by year during 2015–2018 (left) and month by month in 2018 (right), Figure S2: The variations of the monthly average concentration of PM_{2.5} in the NNCP region in different years, Figure S3: The spatial distribution of PM_{2.5} average annual concentrations in the NNCP region from 2015 to 2018, Figure S4: Elbow method for determining the number of clusters based on Euclidean distance (a) and Pearson's correlation distance (b), Figure S5: The city-clusters with their average PM_{2.5} concentrations and ρ values for the s third-level in seasons (a): Autumn, (b): Winter, (c): Spring, Figure S6: Topographic map and winds rose diagrams of some cities for the winter of in 2018 in the NNCP region, Table S1: The COD values for six sub-regions based on Euclidean distance clustering, Table S2: The COD values for six sub-regions based on Pearson's correlation distance clustering.

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