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Spatial self-aggregation effects and national division of city-level $PM_{2.5}$ concentrations in China based on spatio-temporal clustering

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ABSTRACT

With growing haze episodes in China, comprehensive air quality management has been frequently proposed and implemented during major events or heavy pollution episodes. However, except for such heavily polluted regions as the Beijing-Tianjin-Hebei region, regional integration of air quality management in other parts of China has rarely been discussed, due to limited research on the spatio-temporal aggregation of $PM_{2.5}$ concentrations. To fill this gap, we employed a repeated-bisection method, which supports high dimensional datasets and bootstrap clustering, for spatio-temporal clustering of city-level $PM_{2.5}$ concentrations in China using time-series $PM_{2.5}$ data and the test of geographical detector proved the reliability of the clustering. Since no weighted geographical information was employed during the clustering process, this research suggested that $PM_{2.5}$ concentrations in China were of strong spatial self-aggregation effects, which proved the necessity for regional integration of air quality management. Based on the spatio-temporal clustering of $PM_{2.5}$ concentrations, we further proposed six divisions of $PM_{2.5}$ concentrations across China, within which $PM_{2.5}$ concentrations display similar variation patterns and specific emission-reduction measures can be implemented accordingly. The division output of $PM_{2.5}$ concentrations was highly consistent with the recent "2017 air pollution prevention and management plan for the Beijing-Tianjin-Hebei region and its surrounding areas" plan, indicating the reliability and practical significance of the national division of $PM_{2.5}$ concentrations based on spatio-temporal clustering. The findings and methodology from this research provide useful reference for improving regional air quality management by better understanding spatio-temporal aggregation of $PM_{2.5}$ concentrations.

1. Introduction

With rapid social and economic growth in China, growing emphasis has been placed on the sustainability of people's living environment. Amongst a variety of environmental elements, ambient air quality is one of the most concerning issues due to severe air pollution episodes that have frequently occurred in recent years. The haze, which is caused by high $PM_{2.5}$ (fine particulate matter) concentrations, has attracted worldwide attention since the outbreak of one serious haze episode in Beijing, in December 2012. During this haze episode, the city suffered from the worst $PM_{2.5}$ pollution in history (the highest hourly $PM_{2.5}$ concentrations once reached 886 $\mu g/m^3$) (Zhang et al., 2013). The haze episodes been witnessed across China at a much higher frequency since then. For 2014, more than 90% of monitored cities in China failed to satisfy the guideline of annual mean $PM_{2.5}$ concentrations, 35 $\mu g/m^3$, indicating that serious air pollution has become a national environmental issue.

Recent studies revealed that airborne pollutants, especially $PM_{2.5}$, were closely related to all-cause and specific-cause mortality. Garrett and Casimiro (2011) revealed that the relative risk for cardiovascular disease-related mortality for alder groups (>65

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years) was 2.39% (95%C.I. 1.29%, 3.50%) for each 10 $\mu g/m^3$ $PM_{2.5}$ increase. Qiao et al. (2014) found an interquartile range increment in $PM_{2.5}$ concentration (36.47 $\mu g/m^3$) led to a 0.57% [95% confidence interval (CI): 0.13%, 1.01%] increase in emergency room visits. Through experiments in nine French cities, Pasca et al. (2014) observed a notable effect of $PM_{2.5}$ (+0.7%, [−0.1; 1.6]) on all year non-accidental mortality for all age groups. In five European cities, estimation results suggested that a 12.4 $\mu g/m^3$ increase in the $PM_{2.5}$ concentration can lead to 3.0% [− 2.7%; 9.1%] increase in cardiovascular mortality (Lanzinger et al., 2015). In this case, more and more cities have been added to a national network of air quality monitoring. Furthermore, general public and local governments in China are placing increasing emphasis on a better understanding of airborne pollutants from different perspectives. Since the outbreak of serious haze events in China, a large body of studies has been conducted recently to analyze characteristics of $PM_{2.5}$ in Beijing (Liu et al., 2014; Chen et al., 2015; etc.), Wuhan (Zhang et al., 2015; etc.) and a large number of major cities across China (Cao et al., 2012; Zhang et al., 2016; etc.). At a large scale, Ma et al. (2014) employed aerosol optical depth (AOD) retrieved by MODIS and a national-scale geographically weighted regression (GWR) method to map spatial variations of $PM_{2.5}$ concentrations across China.

Recent studies have proved that air pollution in China had strong regional characteristics in the Beijing-Tianjin-Hebei region (Wang et al., 2015) and Shandong Province (Yang and Christakos, 2015). Chen et al. (2016a,b) further proved the strong bidirectional interactions between the air quality in neighboring cities. Given the key role of regional transport of airborne pollutants in affecting local air quality, understanding the spatio-temporal variation patterns of airborne pollutants at a regional scale is more likely to provide comprehensive and reliable reference for improving both local and regional air quality. Take the Beijing-Tianjin-Hebei region for example. The Beijing-Tianjin-Hebei region is one of the most influential and polluted regions in China. Therefore, a strategy of regional air pollution management has been proposed for the Beijing-Tianjin-Hebei area. Within the framework of the proposed Beijing-Tianjin-Hebei integration, a high priority is given to the regional, instead of isolated local, environmental protection. Recently, based on the analysis of spatio-temporal variation of $PM_{2.5}$ concentrations in Beijing and its neighboring cities, Ministry of Ecology and Environment of the People's Republic of China (MEP) recognized that a regional $PM_{2.5}$ transport network, which included Beijing, Tianjin, Hebei Province, Shandong Province, Shanxi Province and Henan Province. To further promote regional integration of air quality management, Ministry of Environmental Protection of the People's Republic of China released “2017 air pollution prevention and management plan for the Beijing-Tianjin-Hebei region and its surrounding areas” (MEP, 2017). According to this plan, unified emission-reduction measures will be implemented simultaneously in Beijing, Tianjin and another 26 cities (well-known as “2 + 26”) within the four neighboring provinces during local and regional heavy pollution episodes. This“2 + 26” regional integration strategy for air quality improvement has been conducted twice in Beijing during two heavy pollution episodes in November 2017 and March 2018, and achieved satisfactory results in reducing local and regional $PM_{2.5}$ concentrations. With the implementation of long-term and contingent regional emission-reduction measures, the peak $PM_{2.5}$ concentrations in Beijing during heavy pollution episodes can be reduced by 20% (Cheng et al., 2017) and the annually mean $PM_{2.5}$ concentrations in Beijing dropped to 58.0 $\mu g/m^3$ in 2017 from 89.5 $\mu g/m^3$ in 2013.

Although regional-integration air quality protection in the Beijing-Tianjin-Hebei region was effective, it remains challenging to transfer this strategy to other regions in China. The main difficulty lies in properly dividing China into several regions, within which airborne pollutants follow similar variation patterns, and implementing comprehensive policies, regulations and laws to improve regional air quality accordingly. Due to the notable variation across China (Chen et al., 2018), a better understanding of spatio-temporal patterns of $PM_{2.5}$ concentrations across China is required for proper division of $PM_{2.5}$ concentrations and conducting regional-integration air quality protection. Traditional spatial clustering methods based on socio-ecological attributes (e.g. GDP and population) are not suitable for clustering based on time-series data (Zhang and Cao, 2015). This is because traditional spatial clustering methods can usually include only one value for a specific feature, ignoring the temporal variations of the feature. Therefore, traditional spatial clustering using the average of time series data (Austin et al., 2013) can cluster those areas, which have close average $PM_{2.5}$ concentrations, yet a completely different time series of $PM_{2.5}$ concentrations, into one group and leads to impractical clustering effects. For instance, Beijing and Chengdu, which located in different regions, have a similar annual mean $PM_{2.5}$ concentrations and distinct $PM_{2.5}$ variation patterns, may be wrongly clustered into the same group based on pure spatial clustering methods.

To fill these gaps, this research aims to investigate spatio-temporal pattern of $PM_{2.5}$ concentrations across China by clustering time series $PM_{2.5}$ data and appropriately divide the entire country into several regions, within which $PM_{2.5}$ concentrations have similar temporal variation patterns. Based on the clustering outputs and characteristics of $PM_{2.5}$ concentrations within each division, environmentalists and decision makers can propose specific measures accordingly. Furthermore, some potential suggestions are discussed for improving local and regional air quality based on proper division of $PM_{2.5}$ concentrations.

2. Materials and methods

2.1. Data sources

$PM_{2.5}$ data was obtained from the website (PM25.in). This website collects official $PM_{2.5}$ data provided by China National Environmental Monitoring Center (CNEMC) and publishes hourly air quality information for cities which have been monitored. Before Jan 1st, 2015, there were 190 cities whose $PM_{2.5}$ concentrations were monitored. Since Jan 1st, 2015, the number has increased to 367 (Fig. 1). By calling a specific API (Application Programming Interface) provided by PM25.in, we collected hourly $PM_{2.5}$ data, and daily $PM_{2.5}$ concentrations for each city were calculated by averaging over hourly $PM_{2.5}$ concentrations measured at all available local observation stations. Since the complete national $PM_{2.5}$ monitoring network was established in January 2015, for a consecutive division of different seasons (the beginning of spring in China is generally considered as March) and multi-year analysis, we collected $PM_{2.5}$ data from March 1st, 2015 to February 28th, 2018 for following analysis.

2.2. Study area

For a comprehensive understanding of spatio-temporal patterns of $PM_{2.5}$ concentrations across China，363 of 367 cities (due to the lack of continuous data, 4 cities，Ali, Changdu, Shannan and Chuji, were excluded) within the national air quality monitoring network were selected for this research. These cities included most major cities (Beijing, Shanghai, Guangzhou, etc.) in China. For regions (e.g. Beijing-Tianjin-Hebei region) with heavy air pollution, the density of monitored cities was much higher than that for regions with good air quality. As demonstrated in Fig. 1, the $PM_{2.5}$ concentrations

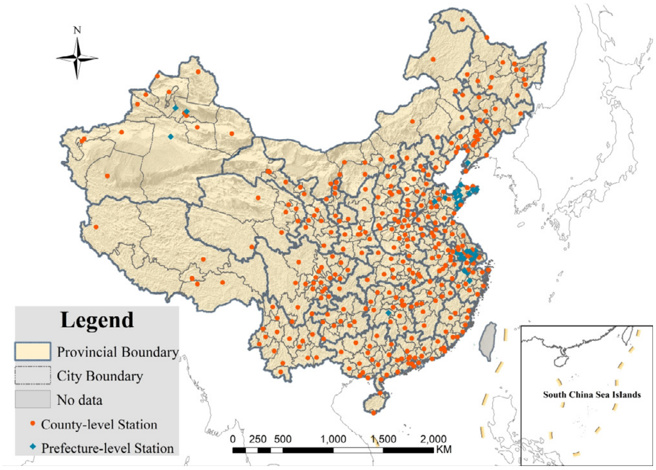

Fig. 1. The spatial distribution of ground $PM_{2.5}$ observation stations across China since January 1st, 2015

for these monitored cities can well present the spatial distribution of air pollution across China.

2.3. Spatio-temporal clustering method

Due to the seasonal characteristic, we divided the time series data into four groups according to seasons, namely Spring (from March 1st to May 31st), Summer (from June 1st to August 31st), Autumn (from September 1st to November 31st) and Winter (from December 1st to February 28st). For each group, each city was treated as an object and the $PM_{2.5}$ concentrations of each day in this season in three years were attached to them as high-dimensional attributes. The Spring and Summer group have 276 attributes respectively, Autumn group has 273 attributes and Winter group has 271 attributes. The large number of high-dimension attributes more likely leads to clustering outputs that fully considers the temporal variation of $PM_{2.5}$ concentrations. After the original data sources have been pre-processed to meet format requirements of the software, only few parameters are required to run this gcluto model: Similarity Function (a function to explain the similarity between two objects), Criterion Function (a function to evaluate the output clusters during the clustering process for adjusting clustering algorithms), Number of Iterations (Number of iterations during the clustering process), Number of Trials (Number of Trials before the clustering to find the optimal clustering parameters) , Number of Clusters (The number of output clusters). As introduced, the appropriate Similarity Function and Criterion Function for repeated-bisection clustering are Cosine and I2. Through preliminary tests, we found the increase of Iterations and Trials from 10 to 100 led to no difference in the clustering result. Therefore, considering the clustering accuracy and computational efficiency, the Number of Iterations and Trials was set 10 for this research. The key parameter for most clustering methods is the Number of Clusters.

The gCLUTO (Graphical Clustering Toolkit), which has excellent capability in processing high-dimensional data was used to carry out the clustering. Meanwhile, gcluto supports bootstrap clustering for managing the uncertainty in monitoring data and thus producing reliable results (Zhao and Karypis, 2003).

The repeated-bisection clustering method in gCLUTO, which conducts clustering by recursively dividing the selected group into two groups until the stopping criteria are met (Desikan and Grace, 2013), is employed for this research. Kou et al. (2014) evaluated six frequently used clustering algorithms (k-means, expectation–maximization (EM), COBWEB, repeated-bisection method, graph-partitioning algorithm and density-based method) using a multiple criteria decision making (MCDM) based approach and suggested that the repeated-bisection method outperformed other methods in all data sets. Zhao and Karypis (2004) also pointed out that the repeated-bisection method led to clustering results with high quality and low computational resources.

When running the repeated-bisection method, we did not include geographical coordinates of cities in their attributes to force spatial continuity although the location information is usually given the largest weight in most spatial clustering methods. Through this clustering strategy, it is highly possible that two remotely distributed cities are clustered into the same group. Therefore, if there exists clear regional patterns of $PM_{2.5}$ concentrations, spatial aggregation effects of $PM_{2.5}$ concentrations can be revealed effectively.

The Cosine function in formula (1) is used as the similarity measure (Zhao and Karypis, 2004) whilst the clustering criterion function in equation (2) is optimized using a greedy strategy (Zhao and Karypis, 2004).

$$\cos(d_i, d_j) = \frac{d_i^t \ d_j}{d_i d_j} \tag{1}$$

where d_i and d_j are vectors containing attributes of two objects to be clustered, d_i^t is the transpose of d_i, d_i is the modulus of d_i.

$$I_2 = \sum_{i=1}^{k} \sqrt{\sum_{d_i, d_j \in S_i} cos(d_i, d_j)} \tag{2}$$

where k is the numbers of clusters, S_i is the ith cluster, d_i and d_j are two objects belonging to S_i.

2.4. Assessment for spatio-temporal clustering

To evaluate the clustering result, the traditional "ISim" (average of similarity between the objects within one cluster) and "ESim" (average of similarity between the objects of one cluster and objects in other clusters) are not suitable, as the two metrics mix $PM_{2.5}$ concentrations of all days in one specific season (all high-dimension attributes) together. By clustering cities with daily $PM_{2.5}$ concentration as high-dimensional attributes, clusters of cites with similar temporal variations $PM_{2.5}$ concentrations can be extracted. Therefore, the aim for evaluating spatio-temporal clustering was to examine whether the temporal variation of $PM_{2.5}$ concentrations in cities categorized in the same cluster was similar and notably different from that of cities categorized in other groups.

Geodetector is a widely used method to analyze spatial pattern (Wang et al., 2016). It's has been employed and proved its efficiency in the spatial pattern analysis based on $PM_{2.5}$ concentrations and socioeconomic development (Zhou et al., 2018), multiple determinants (Zhan et al., 2018), anthropogenic and ecological factors (Yun et al., 2018) and natural and socioeconomic factors (Yang et al., 2018). The q index of Geodetector which measures the difference among clusters versus the similarities within clusters, is a reliable indicator for evaluating spatio-temporal clustering of $PM_{2.5}$ concentrations. Since the spatio-temporal clustering for this research is to group together cities that have similar temporal variations of time series $PM_{2.5}$ data, the q index for each day is calculated as formula (3) and the average q index used to assess the clustering results is calculated as formula (4)

$$q_t = 1 - \frac{1}{N\delta_t^2}\sum_{h=1}^{L} N_h \delta_{ht}^2 \tag{3}$$

Where q_t is the q value of the day t, N denotes the number of all cities joining the clustering, L is the number of clusters, h is the ID of each cluster, N_h is the number of cities in cluster h, δ_t^2 is the total variance of $PM_{2.5}$ concentrations of all cities on day t, δ_{ht}^2 is the variance of $PM_{2.5}$ concentrations of cities in stratum h on day t.

$$q_{avg} = \sum_{t=1}^{T} q_t \tag{4}$$

where q_{avg} is the average of time series q_t, T is the number of days in the season covered by the clustering.

q_t falls into [0, 1], 0 if $PM_{2.5}$ concentrations of cities in different clusters on day t have no difference, 1 if the $PM_{2.5}$ concentrations of cities on day t are the same within each cluster and are completely distinct from other clusters. Large q_t indicated a satisfactory clustering result. Similarly, a large q_{avg} and spatially continuous clusters indicates an efficient regional differentiation of $PM_{2.5}$ concentrations across China.

3. Results and discussion

3.1. Spatio-temporal clustering of $PM_{2.5}$ concentrations using different data sources

Since previous studies (Chen et al., 2016a,b, 2017.) have shown significant seasonal variations for $PM_{2.5}$ concentrations, we divided the study period into four seasons according to traditional category: Spring, from March 1st, 2015 (2016, 2017) to May 31st, 2015 (2016, 2017); Summer, from June 1st, 2015 (2016, 2017) to August 31st, 2015 (2016, 2017); Autumn, from September 1st, 2015 (2016, 2017) to November 30th, 2015 (2016, 2017); Winter, from December 1st, 2015 (2016, 2017) to February 29th, 2016 (2017, 2018). The spatio-temporal clustering of national $PM_{2.5}$ concentrations at city level was conducted for each season respectively. The gcluto executes clustering automatically (Rasmussen and Karypis, 2004). A 3D mountain map can be produced to evaluate the quality of clustering. As displayed in Fig. 2, each 3D peak represents a cluster. Distances between neighboring peaks are inverse to the similarities between to clusters, distant peaks indicate acceptable inter-cluster differences whilst half-merged double peaks indicate insufficient inter-cluster differences. The height of each peak is proportional to average similarities of object within the same cluster, and its volume is proportional to the number of objects. The color of each peak indicates standard deviation of objects belonging to the corresponding cluster. Red represents low deviation, whereas blue represents high deviation.

In this research, we adjusted this parameter gradually and selected the appropriate cluster number accordingly for each season. Based on a visual check of 3D view, the optimal cluster number is the one that leads to the most peaks and retains no half-merged peaks. We experimented clustering repeatedly and compared the visual effects of 3D mountain maps to find a proper number of clusters for each season. For each season, the 3D peaks for each season are demonstrated as Fig. 2. The distinct mountain peaks indicated a satisfactory discrimination among clusters. For each mountain, the warm color indicates a small inner-cluster standard deviation whilst the cold color indicates a large inner-cluster standard deviation. The q value is controlled by the hierarchical differentiation of the research sample and how clustering methods explain the differences among clusters. Therefore, the range of q

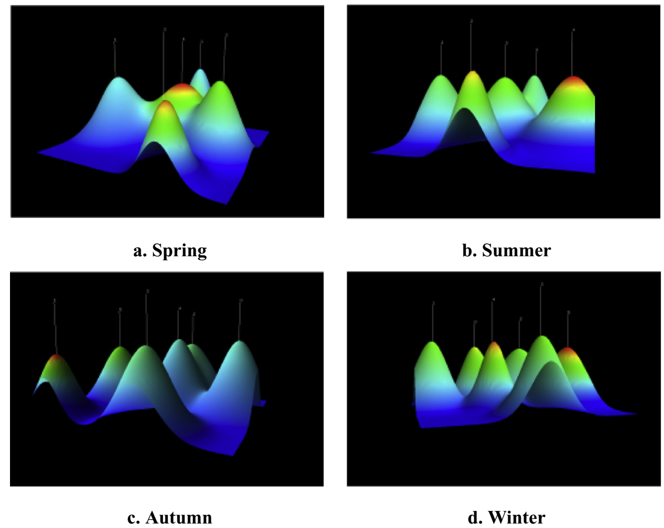

Fig. 2. 3D mountain view for output clusters based on spatio-temporal clustering of $PM_{2.5}$ concentrations across China from 2015 to 2018.

value varies significantly for different data sets and there is no strict threshold for an acceptable q value. The relative comparison of q value between similar studies demonstrated the reliability of the clustering-methods and parameter setting. Therefore, we collected the calculated q value (directly citied from references) for national $PM_{2.5}$ clustering based on different influencing factors by recent studies (Zhou et al., 2018; Zhan et al., 2018; Yun et al., 2018; Yang et al., 2018), which ranged from 0.02 to 0.12, 0.16–0.34, 0.01–0.32, 0.01–0.12, 0.10–0.56 and 0.16–0.29 respectively. Compared with clustering outputs from these studies, the average q value of the spatio-temporal clustering outputs for each season was 0.23 (Significance 0), 0.29 (Significance 0) , 0.26 (significance 0) and 0.31 (significance 0) respectively. The relatively large q value indicated a distinct spatio-temporal clustering result for this research. The spatio-temporal clustering outputs of $PM_{2.5}$ concentrations for each season in China are demonstrated respectively as Fig. 3.

As shown in Fig. 3, although weighted geographical information was not included in the repeated-bisection clustering, notable spatial continuity and aggregation effects were detected in the

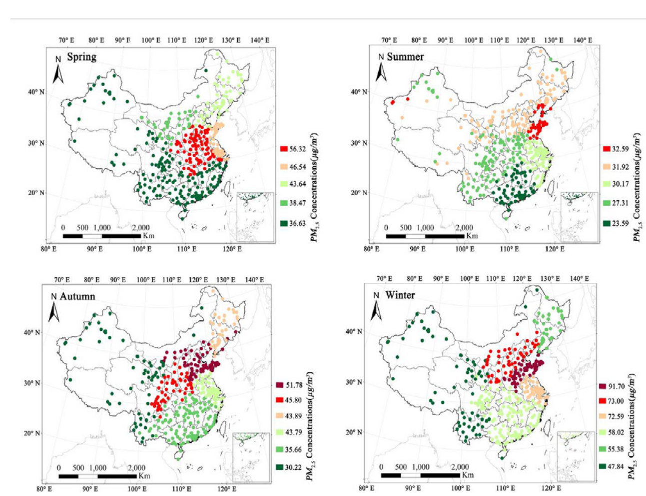

Fig. 3. Spatio-temporal clustering of $PM_{2.5}$ concentrations across China for different seasons.

clustering outputs. For autumn and winter, the optimal number of clusters was six whilst the optimal number of clusters for spring and summer was five. A potential explanation is that during spring and summer months there is weaker static stability, more vertical mixing, and fewer cases of stagnant cold pools trapped by the local/regional topography than in autumn and winter. For the most polluted winter, the clustering results demonstrated the most spatial homogeneity and presented the most notable regional similarity (the largest q value), indicating temporal $PM_{2.5}$ variations within the same cluster are highly similar.

Liu et al. (2018) attempted to delineate the boundary of $PM_{2.5}$ concentrations in China using a wave comparison and an unweighted pair group arithmetic averages (UPGMA) method based on 157 cities. During the clustering process, Liu et al. (2018) measured the similarities using the maximum correlation coefficient between $PM_{2.5}$ concentrations of two cities at all time lags. This strategy led to some clusters that included regions far distant from each other, causing extra difficulties in implementing unified regional integrative emission-reduction measures. On the other hand, our spatio-temporal clustering without weighted geographical information achieved strong aggregation effects. In other words, geographically adjacent cities possess similar patterns in temporal variation of $PM_{2.5}$ concentrations. Chen et al. (2016a,b) proved that air quality in one city significantly influence that in its neighboring cities and thus the improvement of local $PM_{2.5}$ concentrations highly depends on the simultaneous variation of regional $PM_{2.5}$ concentrations. Similarly, spatial self-aggregation effects of $PM_{2.5}$ concentrations revealed in this research also suggested the necessity of managing air quality at a regional scale, which was consistent from previous studies (Chen et al., 2016a,b). Compared with previous studies, the homogenous and continuous spatio-temporal clustering outputs, as well as the Geodetector-based accuracy assessment, proved that the repeated-bisection method was a useful tool for extracting the spatio-temporal patterns of $PM_{2.5}$ concentrations across China and guiding regional management of air pollution.

3.2. Division of $PM_{2.5}$ concentrations across China and its implementations

Recently, the Beijing-Tianjin-Hebei integrated air pollution management and strategy has been proposed to improve the regional economy, traffic and environment from a comprehensive perspective. Specifically, a "2 + 26" plan has been proposed in 2016 for instantly reducing $PM_{2.5}$ concentrations in Beijing and its surrounding areas by conducting simultaneous and contingent emission-reduction measures during heavy local or regional pollution episodes. This comprehensive regional-integration strategy led to notably decreased $PM_{2.5}$ concentrations in Beijing during two air pollution episodes in November 2017 and March 2018. Similarly, regional control and management of air pollution for other regions within China should also be investigated in-depth before implementation. Previous studies (Chen et al., 2016a,b, 2017; etc.) demonstrated that local air quality, especially $PM_{2.5}$ concentrations, was influenced significantly by the transportation of airborne pollutants from neighboring areas. Hence, proper division of regions, within which $PM_{2.5}$ concentrations have similar variation patterns, is crucial, yet highly challenging for regional integration of air quality management. Based on the spatio-temporal clustering using $PM_{2.5}$ data, we propose a national division of $PM_{2.5}$ concentrations in China. Considering seasonal variations of clustering results and the fact that $PM_{2.5}$ concentrations are generally the highest in winter, the clustering output for winter were given the most emphasis during the division. The final division result is demonstrated as Fig. 4.

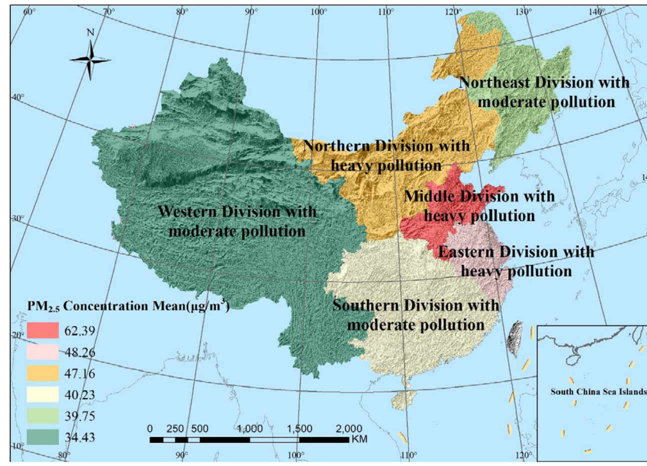

Fig. 4. National division of $PM_{2.5}$ concentrations in China.

As shown in Fig. 4, we categorized six divisions: Western Division with moderate pollution (annually mean $PM_{2.5}$ concentration was 34.43 $\mu g/m^3$), Northern Division with heavy pollution (annually mean $PM_{2.5}$ concentration was 47.16 $\mu g/m^3$), Middle Division with heavy pollution (annually mean $PM_{2.5}$ concentration was 62.39 $\mu g/m^3$), Northeast Division with moderate pollution (annually mean $PM_{2.5}$ concentration was 39.75 $\mu g/m^3$), Eastern Division with heavy pollution (annually mean $PM_{2.5}$ concentration was 48.26 $\mu g/m^3$) and Southern Division with moderate pollution (annually mean $PM_{2.5}$ concentration was 40.23 $\mu g/m^3$). It is worth mentioning that during the spatio-temporal clustering, temporal variations of $PM_{2.5}$ concentrations, instead of the annually mean $PM_{2.5}$ concentrations, were regarded as the key factor for generating output clusters. Furthermore, similar temporal variations of $PM_{2.5}$ concentrations provide direct and highly important references for regional air quality management. Therefore, although annually mean $PM_{2.5}$ concentrations for the Middle, Northeast and Eastern Division were very close, these Divisions cannot be merged due to different temporal variations of $PM_{2.5}$ concentrations within specific Divisions.

The national division of $PM_{2.5}$ concentrations based on spatio-temporal clustering was consistent with relevant research. Based on field survey and model simulation, Ministry of Environmental Protection revealed that a large region, including Beijing, Tianjin and another 26 cities in Hebei, Shandong, Shanxi and Henan province, formed the transport network for $PM_{2.5}$ pollution in the Beijing-Hebei-region. For this research, the Middle Division included Beijing, Tianjin and another 23 out of these 26 cities that have been officially designated in the "2 + 26" plan, indicating this division output well fit the actual regional transportation of $PM_{2.5}$ and provides reliable reference for regional integrative management of $PM_{2.5}$ in other parts of China. As mentioned above, the implementation of "2 + 26" regional emission-reduction measures effectively mitigates long-term and short-term $PM_{2.5}$ concentrations within this region. However, due to the lack of appropriate divisions of $PM_{2.5}$ concentrations across China, research and relevant policies for regional air quality management in other regions are very limited. Therefore, in addition to the Middle Division, the other five divisions proposed in this research provide important reference for regional integrative air quality management in China. With a similar variation pattern of $PM_{2.5}$ concentrations within each division, specific long-term and contingent emission-reduction measures can be designed and implemented accordingly. For instance, for the Western Division with moderate pollution level, relatively loose emission-reduction strategies can be implemented when a local or regional pollution episodes occurs. For the Middle Division with heavy pollution level, relatively strict emission-reduction strategies can be implemented one or two days before a predicted local and regional pollution episode (Cheng et al., 2017).

Previous studies (Chen et al., 2017, 2018) suggested that meteorological factors exerted a strong influence on $PM_{2.5}$ concentrations. Therefore, we compared the map of climatic division of China (Zheng et al., 2010) with the division of $PM_{2.5}$ concentrations in China from this research to examine the meteorological influences on the spatio-temporal distribution of $PM_{2.5}$ concentrations. According to Fig. 5, we can see that except for the Western division, which was grouped as a large area due to limited monitoring cities in the Northwestern China, the boundary of other divisions of $PM_{2.5}$ concentrations demonstrated some similarities with that of climatic divisions, proving that the distribution of meteorological factors was an important driver for the spatio-temporal variations of $PM_{2.5}$ concentrations. Meanwhile, the differences between boundaries of climatic divisions and $PM_{2.5}$ divisions suggested that anthropogenic emissions were also crucial for the distribution of $PM_{2.5}$ concentrations in China.

The division of $PM_{2.5}$ concentrations in China based on spatio-temporal clustering can be further improved. As demonstrated in Fig. 4, due to limited monitoring cities (363 cities for this research), the spatio-temporal clustering resulted in only six clusters, each of which covered a very large area. In this case, regional integrative emission-reduction measures can only be designed and implemented at a relatively coarse scale. Given the large spatio-temporal variations of $PM_{2.5}$ concentrations across China, a much finer scale of spatio-temporal clustering and divisions of $PM_{2.5}$ concentrations is highly necessary. Currently, environmental institutions and private companies are installing a large number of $PM_{2.5}$ monitoring stations. For instance, there are hundreds of nonpublic $PM_{2.5}$ monitoring stations in Beijing, compared with 35 public $PM_{2.5}$ stations from the national monitoring station. In future studies, with growing data availability from many more $PM_{2.5}$ monitoring stations, the repeated-bisection spatio-temporal clustering method can better understand fine-scale spatio-temporal patterns of $PM_{2.5}$ concentrations and extract fine-scale divisions of $PM_{2.5}$ concentrations across China, based on which specific emission-reduction measures for each province (even city) can be designed and implemented accordingly.

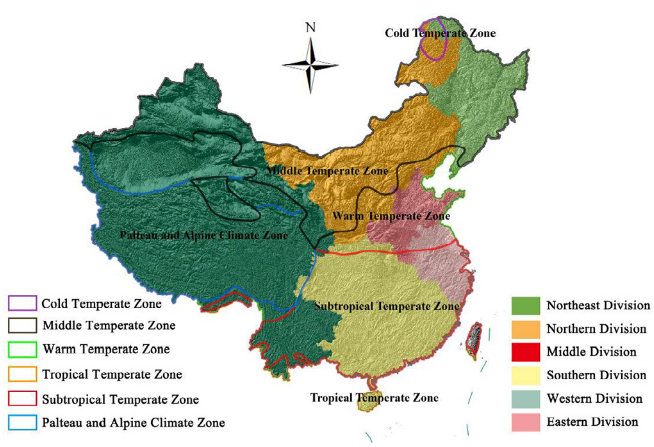

Fig. 5. The comparison of climatic divisions and $PM_{2.5}$ divisions in China.

4. Conclusions

We employed a repeated-bisection method for spatio-temporal clustering of city-level $PM_{2.5}$ concentrations in China using time series $PM_{2.5}$ data and the q value of the geographical detector proved the validity of the clustering outputs.

Based on the clustering results, some major conclusions are as follows:

(1) During the clustering process, the spatially homogenous clusters were generated without the use of geographical locations of each city, indicating that $PM_{2.5}$ concentrations in China demonstrated notable spatial self-aggregation effects. The revealed aggregation effects of $PM_{2.5}$ concentrations suggested the necessity of regional integration of air pollution management and proved that such regional integrative strategies as the recent "2 + 26" plan, which implement unified emission-reduction measures within multiple provinces simultaneously, are a valid approach to maintain satisfactory air quality for a major city (e.g. Beijing) during heavy pollution episodes.
(2) Based on the clustering results, we proposed six divisions of $PM_{2.5}$ concentrations across China: Western Division with moderate pollution, Northern Division with heavy pollution, Middle Division with heavy pollution, Northeast Division with moderate pollution, Eastern Division with heavy pollution and Southern Division with moderate pollution. Specifically, the cities grouped in the Middle Division were highly similar to the cities officially designated in the "2 + 26" plan, indicating this division strategy based on the spatio-temporal clustering well fit the actual regional transportation of $PM_{2.5}$ and presents of reliability and practical significance.
(3) With growing data availability from many more $PM_{2.5}$ monitoring stations, the repeated-bisection spatio-temporal clustering method can better understand fine-scale spatio-temporal patterns of $PM_{2.5}$ concentrations and extract fine-scale divisions of $PM_{2.5}$ concentrations across China, leading to a better regional integrative management of $PM_{2.5}$ pollution at the provincial (even city) level.

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The $PM_{2.5}$ data are available at website PM25.in. Daily average $PM_{2.5}$ data for each city can be calculated by averaging the $PM_{2.5}$ concentrations from all observation stations within the target city. The meteorological data are available at the "China Meteorological Data Sharing Service System" (http://www.cma.gov.cn/2011qxfw/2011qsjgx/). We would like to acknowledge Dr. Richard Russell for his proof reading. This research is supported by National Natural Science Foundation of China (Grant Nos 210100066), State Key Laboratory of Earth Surface Processes and Resource Ecology (2017-KF-22) and Beijing Training Support Project for excellent scholars 2015000020124G059.

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