SPATIAL OVERFLOW EFFECT OF INTERCITY PARTICULATE POLLUTION: A CASE STUDY IN HUBEI, CHINA

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ABSTRACT:

Complex interaction between emissions, meteorology and atmospheric chemistry makes accurate predictions of particulate pollution difficult. Advanced data mining techniques can dig out potential laws from massive data, providing new possibilities for understanding the evolution and causes of particulate pollution. Based on the Granger method and block modeling analysis, this study explored the spillover effects of hourly $PM_{2.5}$ to determine the specific role (i.e., overflow, bilateral, inflow and limited inflow) of each city in Hubei, China. The results suggest that the northern and central cities with high level PM concentration in Hubei have a significant spillover effect, while the eastern and southern cities generally play a role as the sink of pollutant.

1. INTRODUCTION

With dramatic urbanization and industrialization over the past decades, large amounts of particulate matter (PM) have been discharged into the atmosphere, causing outbreaks of choking smog and haze. PM, especially $PM_{2.5}$ (particles with aerodynamic diameters $\leqslant$ 2.5 μm), has been proved to have a significant impact on climate systems and human health (Croft et al., 2020; Manisalidis et al., 2020), and draws public concern. Despite a series of emission reduction measures taken by the Chinese government and some success achieved, the average PM concentration level is still higher than the health standards of the World Health Organization, especially in the plains and basins of central and eastern China. In addition to anthropogenic emissions, particulate pollution is influenced by many factors, such as meteorology and atmospheric chemistry. The disturbance and interaction of these factors make it difficult to figure out the spatial distribution changes and evolutionary mechanisms of pollution outbreaks (Li et al., 2020).

Statistical algorithms and atmospheric numerical models are commonly used to analysing PM pollution. For example, G. Xu et al. (2020) investigated the relationship between $PM_{2.5}$ and factors such as weather, underlying surface and socioeconomic conditions based on multivariate analysis of variance in the Yangtze River Delta (YRD), and they found that underlying surface had a significant effect on the distribution of $PM_{2.5}$. Mao et al. (2020) explored the influence of regional transmission on $PM_{2.5}$ pollution in Wuhan by quantifying the correlation of $PM_{2.5}$ in the city and its surrounding four directions (within 10 degrees). While simple statistical analysis can provide an indication of the underlying spread mechanisms of particulate pollution, the causality in the process still remains undetermined. The traditional numerical model can be used to figure the spatiotemporal distribution and evolution of pollutants, but due to the initial field and emission inventory errors, the model results are uncertain (Hong et al., 2022).

Advanced data mining techniques can dig out potential laws from massive data, thus providing new possibilities for understanding the causes and evolution of particulate pollution. Ma et al. (2019) analysed spatial patterns of haze pollution in the YRD region based on the improved output density model, and suggested a significant PM spillover effect from the urban agglomeration to surrounding areas. Zhang et al. (2020) further examined the PM spillover effects in Cheng-Yu urban agglomeration based on the Granger causality test, and suggested that the spatial spillover effects were more instructive in explaining the formation and transmission of aerosol pollution than the simple geographic proximity.

This study aims to explore the PM spatiotemporal associations among cities in Hubei, a key province in Central China. Compared with other urban agglomerations (e.g., BTH and YRD) which are often focused on in China, few studies have been pursued to understand spatiotemporal associations of particulate pollution in Central China, one of the most important economic and industrial regions in the country. More importantly, this region is the north-south (east-west) passage of the East Asian monsoon across mainland China, and the terrain here is very complex. The interaction between anthropogenic emissions, large-scale pollution transport and local climate change makes the pollution pattern shows significant compound characteristics (Xu et al., 2017). By introducing data mining theory, we hope to develop a new method to further explore the intercity spatiotemporal associations of pollutants in Hubei and understand the causes of regional pollution, so as to cross-verify and complement the results of atmospheric models and jointly serve the prevention and control of regional air pollution.

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2. DATA AND METHOD

2.1 Study Area

Hubei Province is located in the central part of China, with a developed economy, convenient transportation, and uneven population distribution. The terrain in this region is an incomplete basin that rises on three sides, is low and flat in the middle, and is notched in the north and open to the south (Figure 1). Specifically, Hubei Province is surrounded by the mountains such as Wudang, Wushan, Tongbai, Dabie and Mufu in the west, north and east, respectively. There are the Dahong Mountains in the north-central part and Jianghan Plain in the south-central part. Most of Hubei has a subtropical monsoon climate except for the high mountain areas, with four distinct seasons and an annual average temperature of 15~17°C. Due to the developed water system (e.g., the Yangtze River and the Han River) and dense lakes in this region, the humidity is relatively high throughout the year, with annual precipitation of 860~2100 mm (Zang et al., 2021). These unique terrain and climate conditions make cause analysis and spread estimate of particulate pollution in Hubei very difficult (Feng et al., 2019).

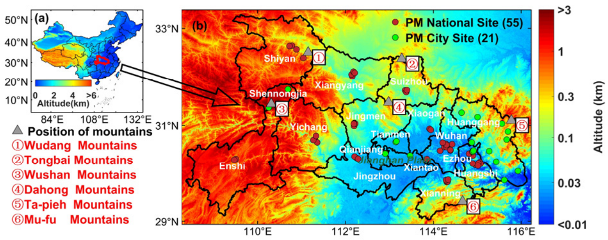

Figure 1. (a) Location of Hubei in China; (b) distribution of PM monitoring sites. The red circles denote national observation sites, while the green ones denote provincial observation sites. The mountains are marked by gray triangles.

2.2 Data and processing

Hourly $PM_{2.5}$ and PM_{10} data used in this study are ground-based observations derived from 55 national sites (http://www.cnemc.cn/zzjj/jcwl/dqjcwl/) and 21 provincial sites, covering all 17 cities in Hubei Province (Figure 1). Wind-field and topographic data were used as auxiliary in this study to analyze the transport potential of pollutants. Among them, hourly wind speed at 2 m height (WS, including meridional and zonal winds, unit: m/s) was obtained from ERA-5 reanalysis dataset, released by the European Centre for Medium-Range Weather Forecasts (https://cds.climate.copernicus.eu/). The digital elevation model produced by the United States Geological Survey (https://www.usgs.gov/) was used describe the relief of the terrain. All data cover the period from March 1, 2018 to February 28, 2019.

All data containing negative values due to instrument faults or other reasons were removed. Cubic spline interpolation was performed on null values (including missing or removed records) to obtain the continuous hourly observations at each site. Due to the small amount of null data (accounting for 4% of the total data), the interpolation algorithm will not have a significant impact on the time series of $PM_{2.5}$, as shown in Table 1. The standard deviation of data before and after interpolation is basically unchanged. Finally, the hourly $PM_{2.5}$ concentration of each city was obtained by calculating the simple average of all observations in the corresponding city.

Table 1. Statistical characteristics of $PM_{2.5}$ in each city before and after interpolation.

City	Mean (μg/m³)	Standard deviation	Extreme	Deletion rate
Enshi	33.84 (33.86)	4.69 (4.71)	109 (104)	5.14%
Ezhou	44.93 (45.78)	5.46 (5.49)	258 (258)	5.42%
Huanggang	38.34 (38.78)	5.07 (6.84)	153 (155)	0.02%
Huangshi	42.02 (42.7)	5.13 (5.16)	176 (175)	5.65%
Jingmen	61.12 (60.05)	7.19 (7.10)	1173 (1025)	5.87%
Jingzhou	48.16 (48.02)	5.64 (5.64)	341 (329)	5.50%
Qianjiang	45.48 (45.49)	6.11 (6.11)	503 (503)	0.02%
Shennongjia	18.12 (18.12)	3.96 (3.96)	5 (5)	0.00%
Shiyan	42.2 (41.84)	5.51 (5.52)	230 (229)	5.01%
Suizhou	45.9 (45.77)	5.7 (5.71)	373 (346)	5.45%
Tianmen	44.34 (44.36)	6.22 (6.22)	477 (477)	0.05%
Wuhan	47.62 (48.39)	5.73 (5.76)	405 (401)	6.00%
Xiangyang	65.45 (62.97)	7.66 (7.35)	1276 (1119)	5.09%
Xianning	36.8 (37.15)	4.9 (4.94)	165 (164)	5.30%
Xiantao	49.57 (49.7)	6.1 (6.1)	495 (495)	0.45%
Xiaogan	43.64 (44.1)	5.34 (5.38)	213 (213)	5.48%
Yichang	55.14 (55.51)	6.81 (6.86)	930 (921)	5.33%

Note： The term of “Mean” represents the average of $PM_{2.5}$ concentration; “Standard deviation” represent the standard deviation of $PM_{2.5}$ concentration; “Extreme” means sample size with $PM_{2.5}$ greater than 115 μg/m³; “Deletion rate” means the rate of missing data. The values in brackets are pre-treated data characteristics, and the data outside the brackets are post-treated data.

2.3 Algorithm

The Granger method and block modeling analysis were used to explore the spillover effects of hourly PM to determine the specific role of each city. The methodology is shown in Figure 2.

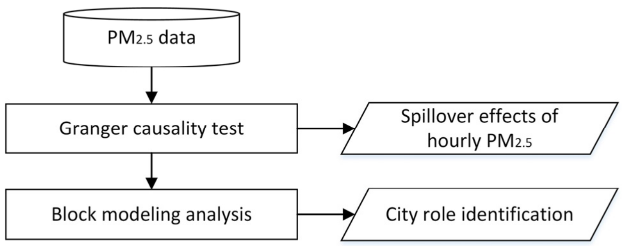

Figure 2. Analysis framework of intercity OVERFLOW effect of $PM_{2.5}$.

2.3.1 Spillover effect analysis based on the Granger causality test

Granger causality is one popular method that infers causal influences between events based on temporal precedence (Granger, 1969, 1980). This analytical tool is bases on the vector auto regressions (VAR) theory, and has been widely used in economic (Ike et al., 2020; Salahuddin et al., 2018), environmental pollution (Runge et al., 2019), climate change (Papagiannopoulou et al., 2016) and other fields (Risser & Wehner, 2017). Different from correlation analysis, the construction of Granger network is directional and can provide causality relation between factors, which is named as spillover effect (L. Xu et al., 2020). The spillover effect is actually a manifestation of spatial dependence, referring to the impact of a spatial unit on its surroundings. Here we constructed a $PM_{2.5}$ Granger network with each city described as a network node. If there is a PM spillover effect from X to Y (denoted by X → Y), the PM concentration fluctuation in City X can be used to predict subsequent fluctuations of PM concentration in City Y, i.e., pollution in X is the (part) cause of that in Y. The VAR model can be expressed as follows:

$$X_t = \beta_{1,0} + \sum_{i=1}^{n} \beta_{1,i} X_{t-i} + \sum_{j=1}^{n} \gamma_j Y_{t-j} + \mu_{1,t} \tag{1}$$

$$Y_t = \beta_{2,0} + \sum_{i=1}^{m} \beta_{2,i} Y_{t-i} + \sum_{j=1}^{m} \theta_j X_{t-j} + \mu_{2,t} \tag{2}$$

Where X_t and Y_t are the PM concentrations of City X and City Y at t time; β, γ, θ are the fitted coefficients. The parameters m, n are the forward time window, determined by the AIC (Akaike information criterion) principle, and here we set them as 1, consistent with Zhang et al. (2020); $\mu_{1,t}$, $\mu_{2,t}$ are random disturbance terms. By checking whether the fitted parameters (i.e., γ, θ) of Y_{t-j} and X_{t-j} are zero or not, the $PM_{2.5}$ spatial relationship between City X and City Y can be determined (Table 2).

Table 2. Criteria used for Granger causality test when the forward time window = 1 (Zhang et al., 2020).

Null hypothesis	Result	Null hypothesis	Result	Relationship	Type (X perspective)
$\gamma = 0$	Rejected	$\theta = 0$	Accepted	X ← Y	Receiving
$\gamma = 0$	Accepted	$\theta = 0$	Rejected	X → Y	Sending
$\gamma = 0$	Rejected	$\theta = 0$	Rejected	X ↔ Y	Two-way
$\gamma = 0$	Accepted	$\theta = 0$	Accepted	No	/

Specifically, we define the null hypothesis as that X and Y are independent, so the corresponding coefficients (i.e., γ, θ) are assumed to be zero. If the null hypothesis is rejected at a preset significance level (in this study, we adopted the significance level of 0.01), then a Granger causality between the variables would be determined. From the perspective of City X, the relationship between City X and City Y can be divided into sending relationship, receiving relationship or two-way relationships depending on the different results of the Granger causality test. For example, when the null hypothesis of X is accepted (i.e., all γ values are 0) but the null hypothesis of Y is rejected (i.e., not all θ values are 0), we can say there is a sending relationship from City X to City Y.

2.3.2 City role determination based on Block modelling

Block modelling was adopted to identify the role of each city in regional PM pollution, based on the Granger causality results. This method interprets network characteristics by clustering (White et al., 1976; Wolfe, 1995), and it can be conducted by the CONCOR (CONvergence of iterated CORrelations) algorithm. The core idea of CONCOR algorithm is block segmentation based on convergence of iterative correlation among related data (Breiger et al., 1975). More details can be referred to Su and Yu (2019) and Zhang et al. (2020). The network nodes would automatically be divided into several blocks, and then block types could be identified according to the connections inside and outside the blocks (Lv et al., 2019; Su & Yu, 2019; Wang et al., 2018).

In this study, we predefined four types of connections (i.e., overflow, bilateral, inflow and limited inflow) to depict regional PM pollution evolution. The overflow blocks have more sending relationships to other blocks than receiving relationships from others. When sending relationships is 2.5 times or more than receiving relationships in a city, it will be classified as the overflow block. Bilateral block sends comparable number of relationships to other blocks as they receive from others. The inflow and limited inflow blocks receive more relationships from other blocks than they send, and the former has more receiving relationships.

3. RESULTS AND DICUSSIONS

3.1 Intercity spillover relationship pattern in PM pollution

The annual and seasonal average PM concentration of each city in Hubei Province is presented in Figure 3. Xiangyang, a city on the northern border of the province, is the most polluted area with an annual average $PM_{2.5}$ (PM_{10}) concentration of 65.45 (98.56) μg/m^3. The three central cities of Jingmen, Yichang, and Xiantao are the second most polluted areas in the province, with annual average $PM_{2.5}$ (PM_{10}) of 61.12 (85.21), 55.14 (82.96), 49.57 (89.26) μg/m^3, respectively. Shennongjia has the lowest pollution levels (average $PM_{2.5}$ = 18.12 μg/m^3; PM_{10} = 34.84 μg/m^3) due to low anthropogenic emissions and high forest coverage. Figure 3(c) and Figure 3(d) indictes that Xiangyang is also the city with the most frequent extreme pollution incidents, followed by Jingmen and Yichang. The particulate pollution in Hubei Province is dominated by fine particles, and the ratio of $PM_{2.5}/PM_{10}$ in each city is more than 0.55, except for Shennongjia. There are significant seasonal differences in PM pollution, with the most serious pollution in winter, followed by spring, autumn and summer. Therefore, the study focuses on the spatiotemporal association rules of $PM_{2.5}$ pollution during wintertime.

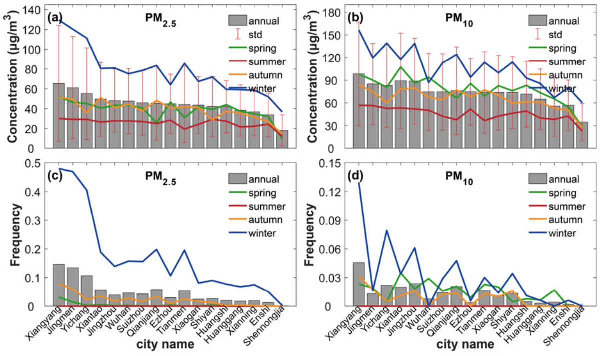

Figure 3. Variation characteristics of PM concentration in Hubei from 2018/3/1 to 2019/2/28: (a) average $PM_{2.5}$ concentration; (b) average PM_{10} concentration; (c) frequency of extreme $PM_{2.5}$ pollution (defined as $PM_{2.5} \geqslant 115$ μg/m^3); (d) frequency of extreme PM_{10} pollution (defined as $PM_{10} \geq 250$ μg/m^3).

Table 3. The results of $PM_{2.5}$ in winter Granger causual network centrality degree.

City	Outdegree	Indegree
Enshi	0	5
Ezhou	5	13
Huanggang	5	9
Huangshi	4	12
Jingmen	14	2
Jingzhou	8	9
Qianjiang	8	13
Shennongjia	1	7
Shiyan	5	5
Suizhou	12	3
Tianmen	9	8
Wuhan	10	6
Xiangyang	13	1
Xianning	6	13
Xiantao	9	7
Xiaogan	14	4
Yichang	5	11

Figure 4(a) shows the topology diagram of $PM_{2.5}$ spatial spillover network in Hubei during winter. The colour represents the number of relationships (including sending and receiving relationships) related to the target city, which has also been counted in Table 3. There are 128 relationships in the whole network. Qianjiang has the largest number of relationships, including 8 sending relations and 13 receiving ones, while $PM_{2.5}$ in Enshi has the weakest correlation with other cities, and only five links were extracted. The spillover network implies that the intercity association of $PM_{2.5}$ mainly occurs among the central and eastern cities.

Clustering characteristics of the spillover network were further explored, as shown in Figure 4(b) and Table 4. All 17 cities in Hubei Province were divided into four types of blocks (i.e., overflow, bilateral, inflow and limited inflow), according to the difference of number of sending and receiving relationships in each city. To be specific, Xiangyang, Jingmen, Suizhou, Xiaogan and Wuhan are divided into the overflow block, where there are 63 sending relationships and only 16 receiving ones. The five cities are distributed in northern and central Hubei Province. There also are five cities in the inflow block, including Qianjiang, Huanggang, Ezhou, Xianning and Huangshi. Except for Qianjiang in the central part, the cities are located in the eastern part of Hubei province. For the bilateral block, the number of sending relationships is almost equal to the number of receiving relationships (23 vs. 20), and except for Shiyan, Tianmen and Xiantao are surrounded by other cities, having a lot of PM two-way interaction with other cities. The remaining four cities (Enshi, Shennongjia, Yichang and Jingzhou) are classified as the limited inflow block.

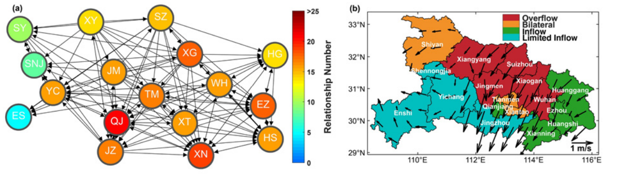

Figure 4. City role determination in regional $PM_{2.5}$ pollution: (a) topology of spillover effects in each city; (b) block type classification. In subplot (a), the abbreviation of ES, EZ, HG, HS, JM, JZ, QJ, SNJ, SY, SZ, TM, WH, XY, XN, XT, XG, YC represents Enshi, Ezhou, Huanggang, Huangshi, Jingmen, Jingzhou, Qianjiang, Shennongjia, Shiyan, Suizhou, Tianmen, Wuhan, Xiangyang, Xianning, Xiantao, Xiaogan, Yichang, respectively; the color represents the number of relationships established in the corresponding city and the arrow represents relationship among cities. In subplot (b), the arrow represents wind vector.

Table 4. Statistics of spatial relationships in $PM_{2.5}$ spillover network.

Block type	Num. of cities	Receiving relationship		Sending relationship	
		inter.	exter.	inter.	exter.
Overflow	5	9	7	9	54
Bilateral	3	2	18	2	21
Inflow	5	18	42	18	10
Limited Inflow	4	4	28	4	10

Note: The term of "Num." means Number; The "inter." means "internal", i.e., relationships between cities inside of one block; The "exter." means "external", i.e., relationships between cities outside of one block.

Figure 5 shows the receiving and sending relationships of $PM_{2.5}$ in four typical cities under different block types. As a member of the overflow block, Xiangyang is characterized significantly by the outward output of $PM_{2.5}$. It has established 13 relationships with other cities in Hubei Province, 12 of which are sending relationships and 1 is a two-way relationship. Tianmen is located in the center of Hubei Province, and the number of sending and receiving relationships in the city is almost the same (6 v.s. 5). Notably, the receiving relationships are established between Tianmen and its northern cities, and the sending relationships are established between the city and its downwind southern cities. In all 10 relationships in Huanggang, the number of receiving and sending relationships are 5 and 1, respectively, reflecting the typical characteristics of the inflow block. Although the number of receiving relationships is also much larger than that of sending relationships in Yichang, considering the spillover effect of the city on other cities, Yichang is still assigned to the limited inflow block finally.

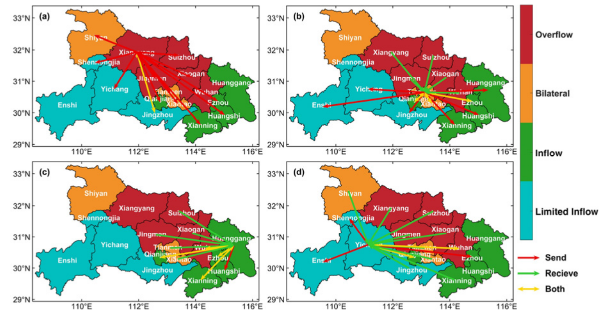

Figure 5. $PM_{2.5}$ overflow effects in four typical cities: (a) Xiangyang (Overflow type); (b) Tianmen (Bilateral type); (c) Huanggang (Inflow type); (d) Yichang (Limited inflow type).

4. CONCLUSIONS

This study aims to investigate the spatiotemporal associations of urban $PM_{2.5}$ pollution based on data mining method. The major findings in this study is that PM pollution in Hubei shows significant spatio-temporal heterogeneity. Xiangyang, a city in northern part, is the most PM polluted area, especially during wintertime. The three central cities Jingmen, Yichang, and Xiantao are the second most polluted areas in the province. Shennongjia, due to the low emissions and large forest cover, has the lowest pollution level. In terms of the role of cities, Xiangyang, Jingmen, Wuhan and other central and northern cities are the overflow block cities, which shows that $PM_{2.5}$ concentration has a great influence on other cities, while Ezhou, Enshi, Qianjiang are considered as the inflow block cities because $PM_{2.5}$ concentration is affected by other cities.

Notably, the algorithms used in this study are mainly based on linear assumptions, but it does not mean that the impact of upstream pollutants on the downwind area is linear. On the contrary, due to the interaction of local meteorology and anthropogenic emissions, the final result should be nonlinear. We will further develop nonlinear Granger networks for multivariate co-analysis and, in conjunction with plume models, further analyse meteorological, chemical and emission contributions in pollution formation.

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