Pol. J. Environ. Stud. Vol. 32, No. 6 (2023), 5245-5260
DOI: *10.15244/pjoes/169367* ONLINE PUBLICATION DATE: 2023-09-04

Original Research

Study on the Spatiotemporal Heterogeneity and Driving Factors of $PM_{2.5}$ Pollution in Shandong Province during 2014-2020

Xiao Ma[1], Wei Jiang[1, 2]*, Weidong Gao[1], Peng Song[1], Ke Du[1]

[1]School of Water Conservancy and Environment, University of Jinan, Jinan, China
[2]College of Geography and Environment, Shandong Normal University, Jinan, China

Received: 13 April 2023
Accepted: 7 July 2023

Abstract

Shandong suffered from severe $PM_{2.5}$ pollution in recent years as a result of its energy-intensive heavy industry. The initial step in implementing targeted control measures was to identify the main factors affecting $PM_{2.5}$ concentrations. This paper explored the spatiotemporal characteristics of $PM_{2.5}$ pollution in Shandong province during 2014-2020 based on observation data of 103 monitoring stations, thereafter, screened out the key natural and social-economical driving factors with the spatial Durbin model (SDM). The findings indicated that between 2014 and 2020, the annual average concentration of $PM_{2.5}$ in Shandong decreased from 75.32 μg/m^3 to 46.46 μg/m^3. The monthly variation followed a clear U-shaped pattern and the daily variation followed an N-shaped distribution with peak concentrations at 09:00 and 23:00 respectively. Spatially, cities with high $PM_{2.5}$ concentration tended to cluster and present high-west and low-east agglomeration characteristic at provincial scale. $PM_{2.5}$ pollution showed considerable positive spatial autocorrelation and it took an apparent spatial agglomeration pattern in central and western cities. According to the estimates of the spatial Durbin model (SDM), $PM_{2.5}$ pollution had significant spatial spillover effects in Shandong, and the indirect effects of the same factor were generally greater than the direct effects, indicating that the influence of neighboring cities could not be ignored. Of the multiple factors, socioeconomic factors had a considerably lesser influence on $PM_{2.5}$ pollution than did natural ones like temperature, relative humidity and wind speed.

Keywords: $PM_{2.5}$ pollution, spatial-temporal characteristic, spatial Durbin model

Introduction

Surging urbanization and industrialization of China has caused the constantly increasing energy consumption and deteriorating air pollution during past decades. As the most serious atmospheric pollutant, $PM_{2.5}$ has drawn widespread attention for its increased morbidity and mortality from cardiovascular disease and respiratory disease [1]. It was estimated that PM-related death tolls in China reached 650 thousand in 2015, accounting for 6.92% of China's total [2]. Facing such a severe situation, the Chinese government

*e-mail: stu_Jiangw@ujn.edu.cn

not only enacted new National Ambient Air Quality Standards in 2012 but also promulgated the Air Pollution Prevention and Control Action Plan (2013-2017) (APPCAP) and Battle for Blue Sky (BBS) (2018-2020) which was considered the most stringent air pollution plan in China's environment protection history. At the same time, a series of enforcement measures such as clean energy transition, industry structure adjustment and technological innovation were formulated [3]. Improving air quality has been the top priority of local government, however, it still unclear what changes have taken place to $PM_{2.5}$ concentration and spatial distribution after the implication of the action plan, and how socioeconomic and meteorological factors impact the variation, as well as what's the underlying associated relationship between them. Answering such question was crucial for local government to making targeted mitigation measure.

Many studies have been devoted to answering these questions presented above at national scales and regional scale. There were two categories of these studies, one is empirical analysis focusing on the relationship between economy growth and $PM_{2.5}$ pollution, such as the verification of environmental Kuznets Curve in different regions which focus on the relationship between economic development and $PM_{2.5}$ pollution. Using an extended green Solow model, Chang et al. [4] found that GDP and $PM_{2.5}$ concentration were related in an inverted U-shape, and the turning point will occur earlier given the spillover effect of abatement technology. The other focused on meteorological or social-economic condition of $PM_{2.5}$ pollution. As key factors, meteorological conditions, such as temperature, wind speed, relative humidity and precipitation, would affect the accumulation, transfer and diffusion of $PM_{2.5}$ pollution and have been widely investigated [5]. Results showed that there were great regional variations in the effects of metrological factors on $PM_{2.5}$ concentration, with a greater impact on $PM_{2.5}$ pollution in the south and along China's southeast coast than in the country's center [6, 7]. It seems on the surface that unfavorable meteorological condition was the proximate cause of $PM_{2.5}$ pollution, while the underlying drivers were heedless activity of pollutant emission from economic production, energy consumption, urban expansion, dramatic increase of vehicles, and so on [8]. However, research results about the strength and direction of these factors were inconsistent, or even opposite conclusion. For instance, using the Spatial Lag model, Zhang et al. [9] examined the power of utilization on urbanization and found that urbanization was a positive correlation with $PM_{2.5}$ pollution. Utilizing fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) methods. Luo et al. [10] took "2+26" as an example to analyze the relationship with urbanization and found it varied with the cities' development level. $PM_{2.5}$ pollution was compounded by many factors through multiple-factor interaction and it was necessary to integrated meteorological or social-economic condition together into a proper model for reflecting their effects on $PM_{2.5}$ pollution.

Driving Factors of $PM_{2.5}$ pollution have been studied by scholars from many aspects at different spatial scales. Employing the generalized additive models (GAMs), Weeberb et al. found that meteorological factors, such as wind speed, temperature, and relative humidity, had significant impact on the $PM_{2.5}$ composition in the United States [11]. Based on the ground-level $PM_{2.5}$ concentration of 287 Chinese cities, Liu et al. [12] adopted geographically and temporally weighted regression (GTWR) to reflect the influence of the natural and social-economic factors on $PM_{2.5}$ pollution of and found that direction and strength of these factors varied by regions. Despite various data sources and time spans, case studies on the Yangzi River Economic Belt [13] and Yellow River Economic Belt [14] reached similar conclusions. These inconsistent or controversial findings meant that, to effectively control $PM_{2.5}$ pollution, we need a more prudent analysis of the driving factors for different regions according to area-based features. As the middle-tier between central and grass-roots government and the main environment pollution control unit of China, provincial governments had great discretion in environment policy formulation and implementation, and it was necessary to pinpoint the spatial-temporal features and motivating elements at provincial scale.

As far as research method, a series of methods have been conducted to pinpoint the parameters that affect $PM_{2.5}$ pollution, consisting of quantile regression, the Bayesian Model Averaging method [15], the EKC [16], the spatial econometric method [17] and so on. Because air pollutants such as $PM_{2.5}$ were rapidly dispersed and transported, the air quality in one place was unavoidably influenced by neighboring regions [18]. Provided that spatial effect exists, the assumptions conditions of independent and identically distributed (IID) in traditional econometrics would be breached, hence, such estimate approach might be skewed. Instead, spatial econometric method could illustrate the spatial dependence and investigate spatial spillover effects. Ding et al. [19] confirmed the association between economic growth and $PM_{2.5}$ pollution in the Beijing-Tianjin-Hebei (BTH) area, using the spatial Durbin model (SDM) and verifying the existence of a spatial effect of $PM_{2.5}$ pollution.

As the important gateway of Yellow River Basin and the land-sea transportation hub of the One Belt and One Road, Shandong Province not only have established integrated industrial system composed of all industrial sectors but also produced high output value, whose provincial GDP reached to ¥ 7312.9 billion and rank 3rd among all the provinces of China. However, economic prosperity and industry agglomeration of Shandong has also come at the cost of the resources and environment. Its heavy industry-oriented industry structure led to large amount of fuel energy consumption and gigantic atmospheric pollutants emission, and five cities among the total seventeen prefecture cities of Shandong were listed in the top 20 most polluted cities of China in 2020 [20]. Even though great efforts have recently seen significant improvement in Shandong province, issues with $PM_{2.5}$ pollution still remain unresolved. Only tailored control measure according to the specific local characteristic and causes was the road to really working on air pollution. In this study, spatial-temporal characteristics of $PM_{2.5}$ were investigated and spatial econometric model was employed to evaluate the effects of key meteorological and social-economic factors on Shandong province $PM_{2.5}$ pollution. The conclusion of this study was expected to rich and expand the existing research results of $PM_{2.5}$ pollution control and provide theory and policy suggestions for local government.

Materials and Methods

Study Region

Shandong Province locates in the eastern coast of China and the lower reaches of the Yellow River. It includes 17 prefecture-level cities with a total land area of approximately 157,901 km^2 and a combined population of 101.65 million at the end of 2020. Under the influence of East Asian monsoon, Shandong exhibits a typical temperate semi-humid continental monsoon climate with four clearly distinct season characterized by significant winds direction and temperature variation, and has three months' heat and rain corresponding period (June, July and August) as well as three months' cold and dry winter (December, January and February). According to the characteristic of natural environment and economic links of cities, we divide Shandong province into three major regions: eastern, central and western Shandong (Fig. 1).

Data Description

Three categories of data are comprised in this study:

(1) $PM_{2.5}$ concentration data. Compared with aerosol optical depth (AOD) data which was significantly influenced by weather conditions, monitoring station data had high spatiotemporal resolution and were better suit for provincial analysis. The Chinese National Ministry of Environmental Protection started to release hourly $PM_{2.5}$ data in 2012 and established monitoring network since 2015, which have provided data base for air pollution control. The hourly $PM_{2.5}$ concentration data (unit: μg/m^3) of 103 monitoring stations from January 1st 2014 to December 31st 2020 in Shandong Province was collected from China National Environmental Monitoring Center (https://air.cnemc.cn/), and each the city had 5-10 distributed stations which depended on their size. Following the definition of China Ambient Air Quality Standards GB3095-2012 strictly, the annual, quarterly, monthly and daily concentration data were calculated through arithmetic average according to hourly $PM_{2.5}$ concentration data of each station at the aid of SPSS 24. In order to guarantee the correctness and continuity of data, a straightforward linear interpolation approach was used to rescue the missing data when the percentage of missing data was less than 1%.

(2) Meteorological data. According to existing researches, meteorological factors considered in this paper include the annual average wind velocity (AW, unit: m/s), annual average humidity (AH, unit: %) and annual average temperature (AT, unit: ºC) and relevant data came from the Meteorological Data Center of China Meteorological Bureau (http://data.cma.cn/).

(3) Socioeconomic data. Socioeconomic factors effecting $PM_{2.5}$ pollution was complicated. In reference to previous achievements and considering the availability of data, per capita gross domestic product

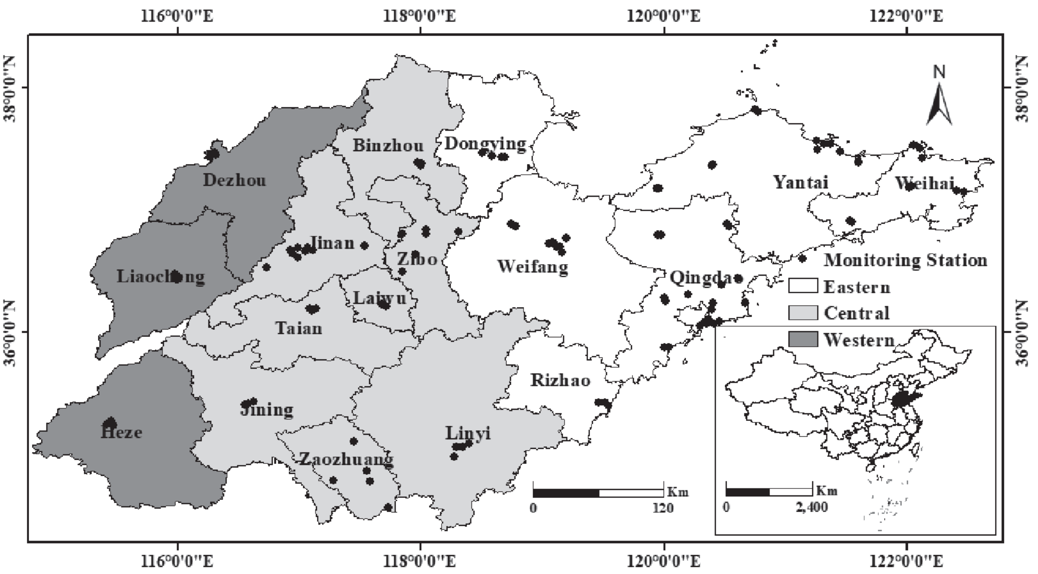

Fig. 1. Study domain and the distribution of ground $PM_{2.5}$ observation stations.

(GDPP, unit: 10^4 yuan), the electricity consumption (EC, unit: 100 million kWh), urbanization rate (UR, unit: %), expenditure of environment (EE, unit: 10^4 yuan), population density (PD, unit: people/km^2) were selected as the indicators for economic development, industrial structure, urbanization level, environmental protection support and population. Relevant data was retrieved from the Chinese City Statistic Yearbook and Shandong Province Statistic Yearbook (2015-2021). All statistical data was processed and performed in Stata 16 and the original data were treated logarithmically in order to remove heteroscedasticity and lower variable volatility. Descriptive statistics information on the socioeconomic data was showed in Table S1.

Methodology

Spatial Interpolation Method

In order to convert sparse data of ground-level station to surface data and depict the spatial distribution feature of $PM_{2.5}$ pollution in Shandong province accurately, yearly and seasonal mean $PM_{2.5}$ concentration data of ground-level observation station were used to derive regional $PM_{2.5}$ maps through spatial interpolation method. Through analysis and comparison of the Normalized Mean Bias, the Mean Bias, the Root Mean Square error and Correlation coefficient of various interpolation methods such as inverse distance weighting (IDW), Spline methods and Nearest Neighbor, Ordinary Kriging (OKM) was employed to obtain the spatial distribution of $PM_{2.5}$ pollution within the study area in this paper for its better accuracy and reliability.

Spatial Agglomeration Analysis

In order to quantify the spatial autocorrelation of regional $PM_{2.5}$ pollution from a quantitative point of view, the Global Moran's Indicator is used to assess the overall spatial pattern of sample according to their value and relative position. Local Moran's Indicator (LISA) is used to identify the specific type of relationship of units and to find where positive or negative clustering exist. The formulas are expressed as follows:

$$Global\ Moran\quad s\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij})\sum_{i=1}^{n}(x_i-\bar{x})^2}, i \neq j \tag{1}$$

$$Local\ Moran\quad s\ I = \frac{n(x_i-\bar{x})\sum_{j=1}^{m}\omega_{ij}\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}(x_i-\bar{x})^2}, i \neq j \tag{2}$$

$$Z = \frac{I-E(I)}{\sqrt{VAR(I)}} \tag{3}$$

Where, x_i and x_j is the observed value of $PM_{2.5}$ concentration in city i and j, $\bar{x}$ is the mean value of the studied variable, ω_{ij} is the spatial weight (inverse geographic distance) matrix in this paper, n is the number of cities. Standardized statistic Z-value is the statistic value for significance. The Global Moran's I lie between [-1, 1], values less than 0 (or greater than 0) suggest a spatial clustering (or discretion). The greater the geographical association, the higher the value. The results of Local Moran index are divided into four categories: high-high clustering (LL type), low-high clustering (LH type), high-low clustering (HL type) and high-high clustering (HH type).

Spatial Econometric Model

Under the influence of multiple factors such as atmospheric circulation, wind direction, products trade and technology diffusion, the $PM_{2.5}$ concentration of an area will be affected not only by local emissions but also by that of neighboring areas. Therefore, an ordinary regression model without considering spatial correlation will yield cause biased estimation results. Comparatively, spatial panel models can well capture the spatial-temporal variability of statistical correlations between variables, and take into account the samples' spatial-temporal characteristics [21]. Spatial regression models include Spatial Error Model (SEM), Spatial Lag Model (SLM) and Spatial Durbin Model (SDM) according to different spatial effects. SDM considers both independent and dependent variables' spatial dependence effects, it is more general and practical than SLM and SEM and easy to get a more accurate estimate result [22]. Because SDM can degenerate into SLM or SEM, statistical tests are required in the selection of model. The specific form of SDM can be expressed as follows:

$$Y = \rho WY + X\beta + WX\alpha + \varepsilon, \varepsilon \sim N(0, \delta^2) \tag{4}$$

where, Y is the observation value of $PM_{2.5}$ for the period of 2014 to 2020, X are explanatory variables, ρ is the spatial autoregressive coefficient of the dependent variable which measures the effect of spatial spillover; W is an inverse geographic distance weight matrix in this paper; β is a parameter vector of order $K\times1$, which is used to evaluate the marginal effect of the independent factors of neighboring units on dependent variables; α is the spatial regression coefficient of the independent variables, which represents the spatial interaction of independent variables; ε is a random error term.

Results and Discussion

Temporal Variation Characteristics

Data analysis showed that the annual average $PM_{2.5}$ concentration in Shandong took a downward trend

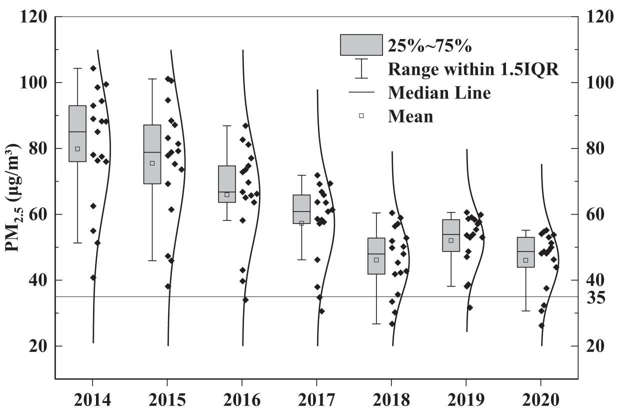

Fig. 2. The average annual $PM_{2.5}$ concentrations of 17 cities in Shandong during 2014-2020.

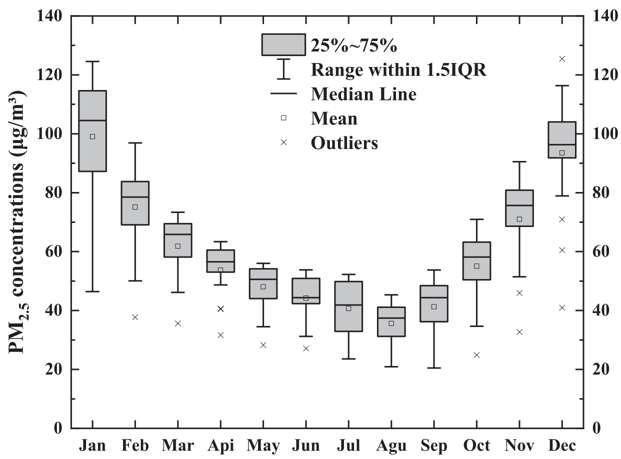

Fig. 3. Variations of monthly average $PM_{2.5}$ concentrations (μg/m³).

and decreased from 79.8 to 46.1μg/m³ (a decrease of 42.2%) during 2014-2020 (Fig. 2). The steepest dropping took place in 2015 and 2018 with an average decline rate 15.1%, which indicated that mandatory emission reduction really played a crucial role in the air pollution government after the implication of APPCAP and BBS. Although affected by the shutdown of COVID-19, $PM_{2.5}$ concentrations remained stable since 2019, and this meant that campaign-style enforcement would give a reprieve but could not be resolved $PM_{2.5}$ pollution fundamentally. As for 2020, the annual average $PM_{2.5}$ concentration of 64.7% of cities over around 45-55 μg/m³ which was still much higher than the Chinese Ambient Air Quality Standard Level 2 (CAAQSL2, 35 μg/m³) and World Health Organization guideline value (10 μg/m³), the potential for emission reduction which relied on an end-treatment model was becoming less and less.

Fig. 3 showed the statistical variations in monthly average $PM_{2.5}$ concentrations in 17 cities from 2014 to 2020. The monthly variations followed a "U-shaped" pattern with a rapid decline from January to March and a relatively gentle decline from March to August, which followed by a rapid rebound until December when it returned to relatively large values. Maximum and minimum concentrations took place in January and August respectively. The $PM_{2.5}$ concentration difference between cities was more significant in winter (112.6-41.7 μg/m³) than in summer (49.7-23.9 μg/m³). The high $PM_{2.5}$ pollution in winter was largely influenced by coal-fired heating [23]. Due to the dry and cold weather in winter, the heating period in Shandong Province ran from November 15 to March 15. Large emissions of pollutants coupled with the weak convective movement in winter resulted in the frequently occurrence of haze weather. Comparatively, the $PM_{2.5}$ pollution was low in June, July and August benefiting from the monsoon rain that the wind brought with it. Then, prioritizing accelerating the adjustment of energy structure should be one of the key tasks for Shandong province at present.

Fig. 4 reflected the daily variation of $PM_{2.5}$ pollution in Shandong from January 2014 to December 2020. According to National Ambient Air Quality Standards (2012), the daily average $PM_{2.5}$ concentrations were divided into six grades: excellent (0-35 μg/m³), good (35-75 μg/m³), lightly polluted (75-115 μg/m³), moderately polluted (115-150 μg/m³), heavily polluted (150-250 μg/m³) and severe polluted (above 250 μg/m³). Same as the monthly variation, the daily average concentrations had a clear cyclical variation with a U-shaped trend within a calendar year, too. Although it fluctuated all the year, both the duration of heavy $PM_{2.5}$ pollution episodes and the maximal value of $PM_{2.5}$ concentration (more than 250 μg/m³) decreased and faded away gradually during the study period, which indicated the air pollution policy had obtained initial achievement. Meanwhile, the proportion of days attaining excellent and good grades increased from 5.63% to 46.3% and 54.65% to 86.03% between 2014 and 2020. In contrast, the percentage of lightly, moderately and heavily polluted days decreased from 32.11%, 9.01% and 4.23% to 10.68%, 1.37% and 1.92% between 2014 and 2020, respectively (Table. S2). Nevertheless, winter still was the high-incidence stage of $PM_{2.5}$ pollution, a great deal of attention should be paid to $PM_{2.5}$ pollution control in winter if a great deal of improvement was to be achieved for air quality.

Statistical analysis of hourly $PM_{2.5}$ concentration data from observation stations was conducted and the diurnal variation curve took an apparent N-shaped distribution across the whole. Although the $PM_{2.5}$ concentration was different for seasons, the peak value of $PM_{2.5}$ concentrations of Shandong province occurred at 9:00 and 23:00 local time respectively and the daily minimum appeared at 16:00 (Fig. 5). In comparison with summer, the gap between peak and valley value was greater in winter and wave form of winter took W-shaped transform. Studies showed that meteorological variables were the primary factors determining daily variation in pollutant concentration, contributing more than 70%

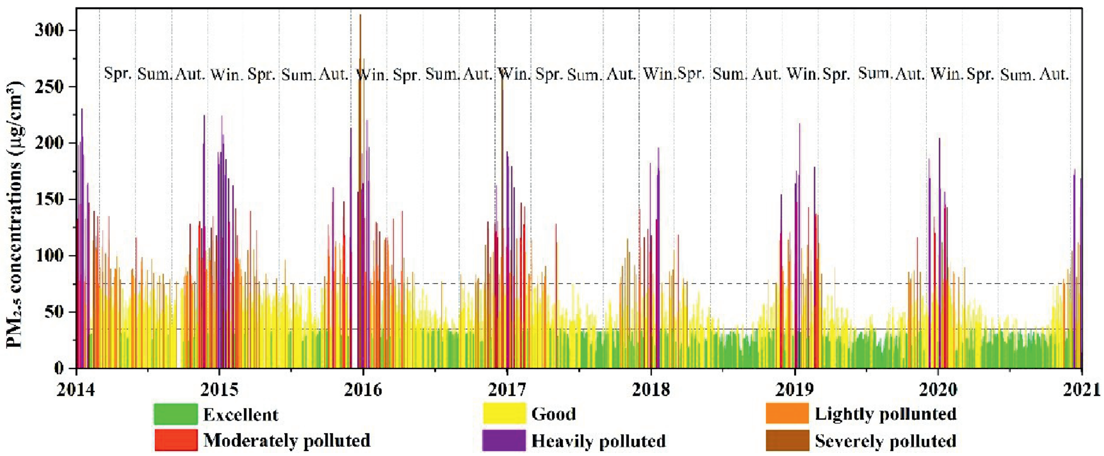

Fig. 4 Daily variations in daily average $PM_{2.5}$ concentrations for Shandong province from January 2014 to December 2020.

of variation [5]. It was easy to form inversion layer in the morning and evening during the winter, which restrained the convection and favored the accumulation of ambient pollutant. The other reason led to the double-peak distribution of $PM_{2.5}$ concentrations might be partly due to the anthropogenic activities such as traffic jam during the morning and evening rush hours and heavy diesel vehicles driving at night [24, 25].

Spatial Distribution Characteristics

Fig. 6 was the spatial distribution of annual $PM_{2.5}$ concentration based on the Ordinary Kriging interpolation method during 2014-2020. According to the figure legend, the $PM_{2.5}$ concentration ranged from 15 to 105 μg/m³ in the portrayed four years and color getting redder and redder indicated a serious $PM_{2.5}$ pollution. Overall, the distribution of $PM_{2.5}$ concentration in Shandong exhibited a distinct regional difference that was high in west and low in the east, forming two unbroken area. Benefit from more rain and sea-land breeze, $PM_{2.5}$ concentration of eastern coastal areas such as Weihai, Yantai and Qingdao were relatively low (about 30 μg/m³) in these years.

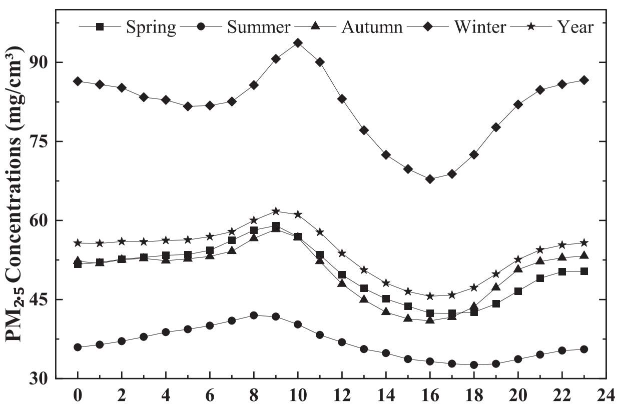

Fig. 5. Diurnal variation of $PM_{2.5}$ concentrations in Shandong from 2014 to 2020.

Because of the agglomeration of coal-fired power plants and heavy industry, western cities, namely Dezhou, Liaocheng, Heze, Zibo, Linyi and Laiwu, and western parts of Jinan, and Jining, had been the most polluted area of Shandong, and the highest annual average $PM_{2.5}$ concentration reached 110 μg/m³ in 2014, which was three times of the national secondary standard limit for annual $PM_{2.5}$ (35 μg/m³). After that, the area heavily polluted diminished gradually from east to west of Shandong following the implementation of air pollution control policies. Although the annual $PM_{2.5}$ levels in most areas of Shandong province decreased to <60 μg/m³ by 2020, $PM_{2.5}$ pollution in many western cities of Shandong such as Zaozhuang, Zibo, Liaocheng was still very serious (≥54 μg/m³). In terms of decline rate of $PM_{2.5}$ concentration, the relative change between cities was obvious too (Fig. S1). Comparably, the downward trend of mid-western cities was more significant, with a decrease of 56.2, 45.7, 44.5, 44.3 and 40.8 μg/m³ in Dezhou, Laiwu, Liaocheng, Jinan and Linyi respectively compared to the 2014 data, indicating that rigorous emission control act had remarkable effect in reducing $PM_{2.5}$ pollution.

Fig. 7 illustrated the spatial distribution of seasonal $PM_{2.5}$ average concentrations during 2014-2020. The seasonal differences in the spatial distribution of $PM_{2.5}$ pollution were apparent. Winter was the most polluted season in all year in Shandong and almost all the cities suffered from heavy $PM_{2.5}$ pollution (above 57.0 μg/m³) except for Weihai (41.7 μg/m³). $PM_{2.5}$ pollution was particularly severe in the western and southern cities of Shandong. The reasons for these phenomena were the increased local emission for heating system, least rainfall, adverse meteorological condition for vertical diffusion and regional transportation in winter. In contrast winter, the $PM_{2.5}$ value in summer of most cities was only 1/3 that of winter. Although the $PM_{2.5}$ pollution in spring and autumn was better than in winter, its general situation was tough enough because of its large amounts of energy-intensive industries. Serious winter pollution in Shandong warned us the $PM_{2.5}$ pollution

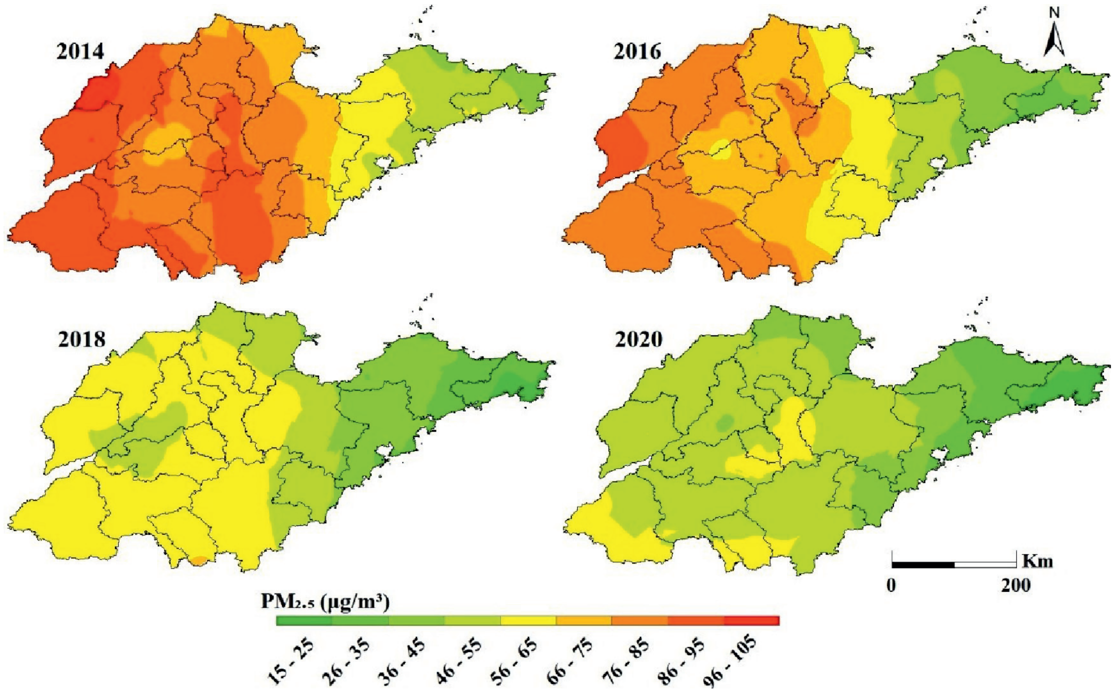

Fig. 6. Spatial distribution of $PM_{2.5}$ pollution in Shandong Province in 2014-2020.

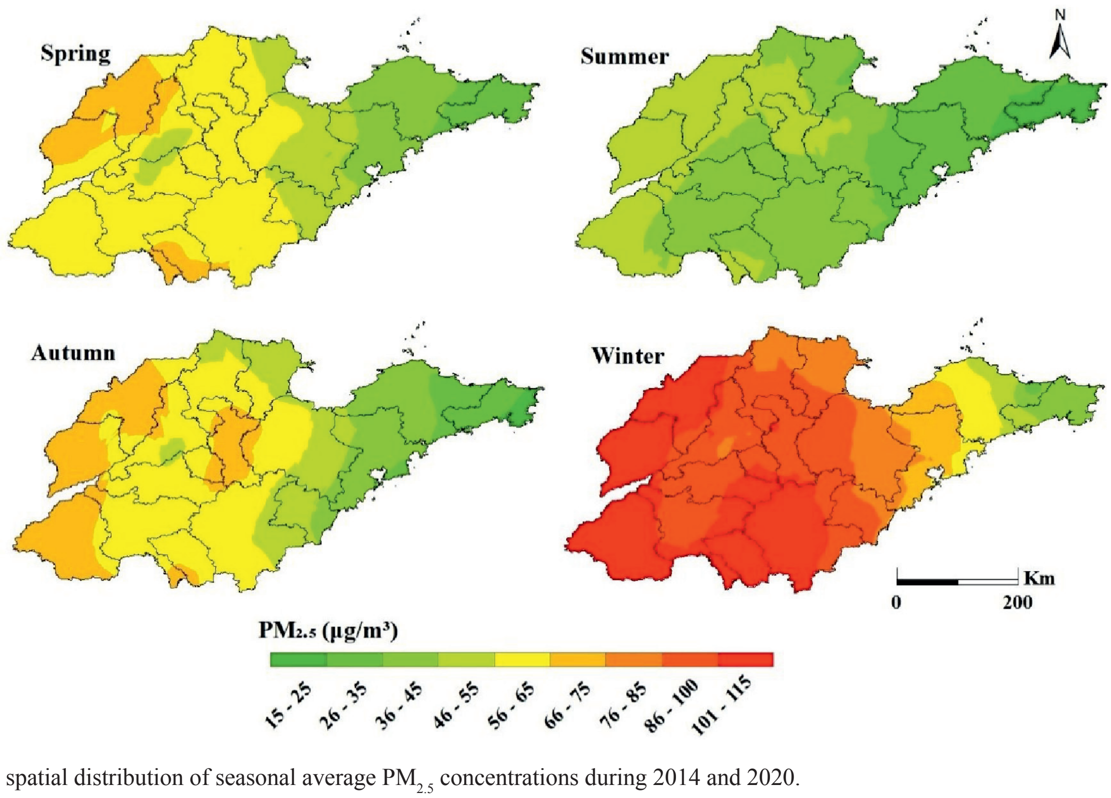

Fig. 7. The spatial distribution of seasonal average $PM_{2.5}$ concentrations during 2014 and 2020.

situation still grim and local government should prepare for long-term campaign with air pollution.

Spatial Aggregation Variations

The values of Global Moran's I of the $PM_{2.5}$ in Shandong from 2014 to 2020 were listed in Table. 1. The index was positive and increased from 0.649 in 2014 to 0.720 in 2016 then dipped to 0.573 in 2020, also, all results were significant at 1% level. The results indicated that $PM_{2.5}$ pollution was influenced not only by local emissions but also by nearby cities. Therefore, when exploring the influencing elements of $PM_{2.5}$ pollution, the spatial effect of variables could not be ignored.

Table. 1 Values of Global Moran' I of Shandong PM2.5 pollution and its statistical test.

Year	2014	2015	2016	2017	2018	2019	2020
I	0.649	0.703	0.720	0.655	0.617	0.607	0.573
P	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Z	27.35	29.64	29.88	29.96	26.68	27.76	25.94

To further study the agglomeration effect of $PM_{2.5}$ in Shandong Province, LISA cluster diagram was drawn (Fig. S2). From the perspective of the spatial clustering of $PM_{2.5}$ level, the scope of low-low clustering and high-high clustering was relatively stable, that was, cities in middle and western Shandong showed high-high clustering, while cities in the eastern coastal cities, such as Yantai, Weihai, Qingdao and Rizhao, formed a low-low clustering distribution. That was to say, middle and western cities took an apparent spatial agglomeration pattern of $PM_{2.5}$ pollution and strengthening of the coordination mechanism in the surrounding areas contributed to the reduction of $PM_{2.5}$ pollution.

Drivers of Spatial Variations in $PM_{2.5}$ Pollution

Estimation Result of SDM

With panel data of Shandong's 17 prefectural level cities during 2014-2020, SDM was used to investigate the spatial effect of social and natural factors on $PM_{2.5}$ pollution and to explore the spatial heterogeneity of effects across cities. To avoid multi-collinearity, data was processed with logarithm and variance inflation factors of all the models were less than 7.5 (Table S3), signifying that there were no serious collinear problems. Both LM test and robust LM test rejected the hypothesis that there was no spatial lag term and no spatial error term at the significance of 1%, that was to say, SDM was more preferable model specification (Table 2). In order to select a more robust model from model with fixed effect or random effect, a Hausman test was conducted and result indicated that model with fixed effect was more suitable. LR test and Wald test results rejected the null hypothesis that SDM would degenerate into SLM or SEM at 1% level. Moreover, the LR test rejected the original hypothesis that individual fixation or time fixation was better than dual fixation, with the significance of 10% or 1% respectively, indicating that time and individual dual fixation was the optimal model.

Estimation results of SDM indicates that three natural factors were significantly negative, which indicated that an increase in temperature, humidity and precipitation reduced $PM_{2.5}$ concentrations in Shandong Province (Table 3). Comparatively, the increase in urbanization rate, electricity consumption and population density led to an increase in regional $PM_{2.5}$ concentrations, indicating that the increase in urbanization level, electricity consumption and population density were key factors contributing to $PM_{2.5}$ pollution in Shandong Province. In terms of the spatial lags (Wx) of variables, the social development of surrounding cities, the increase in environmental awareness and the increase in wind speed effectively reduced the local $PM_{2.5}$ concentration, while the increase in economic growth, energy consumption and population density in the surrounding areas significantly increased the local $PM_{2.5}$ concentration.

Since the spatial lag term was included in the model, the estimation coefficient of regression could not accurately reflect the relationship with $PM_{2.5}$ pollution, and therefore the impact was split into direct and indirect effects (Table 3). In a city, the direct effect on $PM_{2.5}$ pollution was determined by the city's changes in the explanatory variables, while the indirect effect was determined by other cities' changes in the explanatory variables. As can be seen, the indirect effects of all the explanatory variables were greater than the direct effects, implying that surrounding influence

Table 2. Diagnostic test for model specification.

Variable	Statistics	P-value	Variable	Statistics	P-value
LM-spatial lag	53.415	0.000***	Wald-spatial lag	28.02	0.0005***
LM-spatial error	176.992	0.000***	Wald-spatial error	26.40	0.0009***
Robust LM-spatial lag	31.781	0.000***	Hausman	250.38	0.0000***
Robust LM-spatial error	155.358	0.000***	LR-both ind	17.04	0.0736*
LR-spatial lag	32.28	0.0001***	LR-both time	94.08	0.0000***
LR-spatial error	29.73	0.0002***			

Note: * p<0.1, ** p<0.05, *** p<0.01.

Table 3. Estimation results of SDM.

	SDM (fe)	Wx	Direct	Indirect	Total
lnGDPP	-0.022	0.149	-0.016	0.189	0.173
	(-0.30)	(0.67)	(-0.22)	(0.64)	(0.55)
lnEC	0.022	0.532***	0.032	0.670**	0.702**
	(0.66)	(2.62)	(0.87)	(2.46)	(2.30)
lnUR	0.282	-2.878***	0.248	-3.579***	-3.331***
	(0.99)	(-4.11)	(0.89)	(-5.00)	(-4.88)
lnEE	-0.074***	-0.169	-0.077***	-0.211	-0.288**
	(-3.76)	(-1.57)	(-4.29)	(-1.56)	(-2.17)
lnPD	0.014	1.472**	0.044	1.866**	1.910**
	(0.17)	(2.35)	(0.55)	(2.16)	(2.11)
lnAW	-0.067	-0.534	-0.075	-0.684	-0.759
	(-1.43)	(-0.93)	(-1.40)	(-0.97)	(-1.04)
lnAT	-0.604	4.727***	-0.507	5.581***	5.074***
	(-1.05)	(3.97)	(-0.87)	(4.33)	(4.49)
lnAH	-0.521*	3.705***	-0.459	4.421***	3.962***
	(-1.71)	(4.29)	(-1.40)	(7.12)	(7.02)
ρ/λ	0.202				
Σ^2	0.002***				
R^2	0.739				
Log	195.18				

Note: * p<0.1, ** p<0.05, *** p<0.01.

was significant and that improving overall air quality required a focus on integrated regional development.

In terms of the effects of the individual independent variables, an increase of average annual temperature led to an increase in $PM_{2.5}$ pollution in Shandong Province, with a 5.074% increase in $PM_{2.5}$ for every 1% increase in temperature. Temperature could affect atmospheric turbulence and chemical reactions, resulting in no significant linear relationship with pollutants. On the one hand, as temperatures rose, aerosol particles diffused and diluted due to increased Brownian motion, leading to a lower local $PM_{2.5}$ concentration. On the other hand, higher temperatures promoted the transformation of different pollutants and the formation of secondary pollution, which led to an increase in $PM_{2.5}$ pollution [26]. The decomposition of the spatial effects revealed that the direct effect of temperature (-0.507) on $PM_{2.5}$ was less than the indirect effect (5.581), an increase of temperature in neighboring cities led to a significant increase in local $PM_{2.5}$ pollution.

The average humidity showed a negative direct effect (-0.459), a positively significant spillover effect (4.421), and a positive effect (3.962) on the whole in Shandong. The influence of relative humidity on $PM_{2.5}$ pollution was complex, the humidity can reduce pollutants in the local air through the washing process, as the same time, fine particles usually expanded when they absorbed moisture and gradually shifted into an accumulation mode [27, 28] which lead to an increase in $PM_{2.5}$ at low air velocities and exacerbating $PM_{2.5}$ pollution in neighboring cities through pollution transport. The circulation and meteorological conditions in North and Northeast China were unfavorable for pollutant dispersion and removal when weak high pressure covered eastern China and the relative humidity was relatively high [29].

The direct effect of urbanization rate on $PM_{2.5}$ concentration was positive (0.248), as the higher rate of urbanization of the population, the higher rigid demand for housing, infrastructure development and transportation, all of which were strongly related to energy-intensive sectors such as steel and cement [30]. However, taking full advantage of population clustering could increase the efficiency of transport and energy use, thus offsetting the pollution generated by additional construction. Alternatively, a significant negative spillover effect (-3.579) might be due to the fact that neighboring cities attracted populations migrating from surrounding areas, thus reducing the environmental burden on local cities. Both the direct effect (0.044) and the indirect effect (1.866) of population density showed positive effects, indicating that an increase in population density exacerbated local $PM_{2.5}$ pollution and also put pressure on neighboring cities. Areas with high population densities were accompanied by more diverse needs, and the energy consumption and direct and indirect emissions of pollutants resulting from the concentration of production and living aggravate atmospheric pollution [31]. As urban population density increase, traffic intensity, land use and energy consumption, indirectly leading to a rise in $PM_{2.5}$ pollution [32].

Both the direct (-0.075) and indirect effects (-0.684) of wind show negative values, which indicated an increase in wind speed in both local and neighboring cities reduced local $PM_{2.5}$ pollution. Wind affected the dispersion and dilution of pollutants in the atmosphere, causing the concentration of local pollutants to decrease as wind speed increased [33]. Yang et al. [34] identified the drivers of $PM_{2.5}$ pollution in the Yellow River Basin and found that wind speed had a negative effect, particularly on concentrated contiguous areas of high pollution in the lower reaches of the basin.

Emissions from the combustion of energy substances for energy supply were an major anthropogenic source of $PM_{2.5}$ pollution [35], and this paper used electricity consumption to characterize energy consumption. All coefficients were positive (0.032 and 0.670), indicating that increased consumption not only exacerbated local $PM_{2.5}$ pollution, but also showed significant positive spillover effects. Relevant research showed that energy consumption still put greater pressure on the environment due to a large industrial base resulting in high total pollutant emissions, as well as due to inefficient energy conversion and use, and cross-regional transfer of pollution [36, 37].

Local government played a crucial role in environmental governance, and environmental investment was a particularly effective means [38]. Government expenditure showed a significant negative direct effect (-0.077) and also a negative spillover effect (-0.211), indicating that the large amount of money invested in energy conservation and environmental protection in Shandong province has been effective in improving $PM_{2.5}$ pollution both in local and neighboring cities.

Different stages of economic development had different relationships between GDP and $PM_{2.5}$ pollution. In line with the above results, the direct effect (-0.016) results of this paper indicated that the increase in GDP per capita in Shandong Province had a mitigating effect on local $PM_{2.5}$ pollution (-0.016). Economic development led the government to invest more money in environmental management, strengthening environmental infrastructure, and thus reducing local pollution [39]. In contrast, there was a positive spillover effect of GDP per capita (0.189) but not significant, probably due to the fact that urban environmental governance focused on the local region and did not have enough power to drive environmental governance behaviours in the surrounding cities.

Robustness Check

In this paper, dynamic SDM was utilized to check the results' robustness; in other words, we separately put in the inclusion of lagged terms of the explanatory variables, spatial lags with the inclusion of lagged terms of the explanatory variables and double-lagged in the model and regressed again (Table. S4). We could see that most conclusions of the explanatory variables and lagged terms were the same as both signs and significance levels, with different coefficient values. The coefficients of $L.PM_{2.5}$ and $L.WPM_{2.5}$ passed the significance test when only considering the lagged term of the explanatory variable or double lag, suggesting that pollution in the city was largely influenced by past pollution concentrations and the spatial effects of past pollution. The reason for this was not difficult to understand: environmental pollution had been an "irreversible" process for a considerable period of time under ineffective management in the past, and the so-called "accumulation of heavy pollution" was a tautological expression.

In comparison with SDM, we found that when the lag effects of time and space were considered, the influence of natural factors decreased while the influence of socio-economic factors became larger, the urbanization rate showed a positive spillover effect, and temperature and humidity showed an ameliorating effect on local pollution. Other results remained largely consistent with the aforementioned discussions, and the previous conclusions still hold, which confirms our model's robustness.

Heterogeneity Analysis

In order to identify the effects of multiple factors on $PM_{2.5}$ pollution produce spatially heterogeneous effects, Shandong province was separated into three regions: eastern, central and western, and analyzed by the spatial Durbin model (Table S5). From the spatial autoregressive coefficient ρ, there was a negative spatial spillover effect in eastern and central areas, which to a certain extent exerts a "demonstration effect" on neighboring provinces, while there was a positive spillover effect in the west. Government expenditure and population density were not significant in the eastern region, and GDP per capita was not significant in the central region. The coefficient signs of the explanatory variables and lag terms were all consistent in the eastern region, with some variables differing in the central and western regions. There were regional differences in the effects of the other explanatory variables, except for population density, which had a positive effect in all three regions.

In terms of natural factors, the effects of temperature and humidity in the central and western regions were consistent with the overall results in that they both mitigated local pollution and exacerbated pollution in surrounding areas, while in the eastern region they showed an exacerbating effect on both local and neighboring areas; the effects of increasing wind speed in the central region were consistent with the overall findings in that they both mitigated local pollution and had a negative spillover effect, while in both the eastern and western regions they exacerbated pollution.

In terms of socio-economic factors, the development of urbanization had a positive spillover effect in the western region, probably due to the fact that the problems of industrial development and infrastructure construction accompanying the urbanization process in the western region had not yet been properly resolved, thus brought pressure on the surrounding areas. GDP per capita growth had significant mitigation and aggravation effects on the eastern and western regions, but an insignificant mitigating effect in central area. This was probably due to the level of economic development in the east being the highest, where the benefits and efficiency improvement gained from economic development could offset the pollution generated; while more attention was paid to improving economic strength than to environmental protection in the west. As a result of increased electricity consumption in central and western areas, pollution was exacerbated, whereas in eastern region, energy efficiency and green technologies mitigate pollution. Government expenditure had effectively improved pollution in central and western areas, but there was an insignificant positive effect in the eastern area, which might be due to the relatively insufficient investment in environmental protection compared with the large economic output and energy consumption.

Conclusions

In this study, the spatial-temporal heterogeneity of $PM_{2.5}$ pollution of Shandong province and its effecting factors were investigated based on the $PM_{2.5}$ concentrations data of 17 cities during 2014-2020. The findings can be summarized as follows:

Overall, the concentrations of the $PM_{2.5}$ pollutant showed a clear temporal pattern in Shandong province during the study period. Firstly, the annual average concentration of $PM_{2.5}$ of Shandong province decreased greatly, however, there were still many cities that do not meet the national secondary standard for $PM_{2.5}$ concentrations, and the downward trend had slowed significantly in recent years. Secondly, the monthly variations in $PM_{2.5}$ concentrations followed a "U-shaped" pattern, $PM_{2.5}$ concentration from May to September is lower than other months. Conversely, $PM_{2.5}$ concentrations from December to February is higher than 75 μg/m^3. Thirdly, there was a "U" shaped cycle for daily average concentrations of $PM_{2.5}$ throughout the year, heavily polluted days occurred in winter and spring, and overall pollution conditions were significantly worse than in other seasons. Fourth, the diurnal variation of $PM_{2.5}$ concentrations showed a bimodal distribution with broadly similar hourly trends in seasonal and annual.

Spatially, the $PM_{2.5}$ concentrations showed a clear spatial pattern. Eastern coastal cities had relatively low $PM_{2.5}$ concentrations compared with central and western cities and the annual average concentrations between varied greatly between cities during the study period. The pollution situation in the central and western cities had improved considerably while the eastern cities had improved less, but only three cities on the peninsula had achieved the national secondary standard for annual average concentrations. Therefore, most cities in the central and western regions were now facing greater pressure to control $PM_{2.5}$ pollution. Seasonal differences in pollution spatial distribution were evident, with pollution levels much higher but with relatively little regional variation in winter than in other seasons, and large regional differences in spring and autumn.

The results of SDM indicated that $PM_{2.5}$ pollution was influenced by both local and neighborhood multiple factors, and the influence of natural factors was larger than human factors, and the indirect effect of them was generally stronger than the direct effect. Urbanization rates put pressure on local pollution, GDP per capita, temperature and wind speed put pressure on pollution in surrounding areas, and other factors act in the same direction for local and neighboring areas, with increased electricity consumption and population density adding to pollution. A regional variation perspective examined the heterogeneity of the effects of multiple factors on pollution in three regions - Eastern, Central and Western - and finds that there were regional differences in the effects of factors other than population density.

Facing serious $PM_{2.5}$ pollution, the outcomes of this paper clarified the spatial-temporal variation of $PM_{2.5}$ concentration of Shandong province and therefore could help local government formulate the effective policy to deal with the air pollution. Results of key influencing factors analysis on $PM_{2.5}$ although natural factors were difficult to vary significantly, effective adaptation measures need to be found, such as the rational design of urban breezeways and road green belts and the strengthening of ecological corridors. In fact, unhealthy human production methods were the root cause of pollution, and strict control of pollutant emissions caused by human activities was the key to cracking the $PM_{2.5}$ problem. The focus should be on economic development patterns, energy consumption restructuring and population distribution issues, giving full play to the advantages of urban development stages, population clustering and government financial support, strengthening technology introduction and technological innovation. Moreover, given the spatially clustered distribution and different pollution conditions, targeted strategy and regional cooperation should be considered in pollution control. A zoning scheme for joint regional prevention and control should be established to precisely implement the responsibilities and tasks of each geographical location.

Acknowledgments

This work was funded by the key Research and Development Program of the Shandong Province (2019GSF109077), the National Natural Science Foundation of China (21607054). The authors would like to thank the editors and anonymous referees for their valuable comments on an earlier version of this manuscript.

Conflict of Interest

No conflict of interest exits in the submission of this manuscript, which has been approved by all authors for publication.

References

1. FIGUERES C., LANDRIGAN P.J., FULLER R. Tackling air pollution, climate change, and NCDs: time to pull together. The Lancet **392** (10157), 1502, **2018**.
2. MAJI K.J., DIKSHIT A.K., ARORA M., DESHPANDE A. Estimating premature mortality attributable to $PM_{2.5}$ exposure and benefit of air pollution control policies in China for 2020. Science of The Total Environment **612**, 683, **2018**.
3. ZHAN D.S., KWAN M.P., ZHANG W.Z., YU X.F., MENG B., LIU Q.Q. The driving factors of air quality index in China. Journal of Cleaner Production **197**, 1342, **2018**.
4. CHANG H.-Y., WANG W., YU J. Revisiting the environmental Kuznets curve in China: A spatial dynamic panel data approach. Energy Economics **104**, 105600, **2021**.
5. HE J., GONG S., YU Y., YU L., WU L., MAO H., SONG C., ZHAO S., LIU H., LI X., LI R. Air pollution characteristics and their relation to meteorological conditions during 2014-2015 in major Chinese cities. Environmental Pollution **223**, 484, **2017**.
6. XU Y., XUE W., LEI Y., HUANG Q., ZHAO Y., CHENG S., REN Z., WANG J. Spatiotemporal variation in the impact of meteorological conditions on $PM_{2.5}$ pollution in China from 2000 to 2017. Atmospheric Environment **223**, 117215, **2020**.
7. CHEN Z., XIE X., CAI J., CHEN D., GAO B., HE B., CHENG N., XU B. Understanding meteorological influences on $PM_{2.5}$ concentrations across China: a temporal and spatial perspective. Atmospheric Chemistry and Physics **18** (8), 5343, **2018**.
8. LIU L., CHEN Y., WU T., LI H. The drivers of air pollution in the development of western China: The case of Sichuan province. Journal of Cleaner Production **197**, 1169, **2018**.
9. ZHANG X., GU X., CHENG C., YANG D. Spatiotemporal heterogeneity of $PM_{2.5}$ and its relationship with urbanization in North China from 2000 to 2017. Science of The Total Environment **744**, 140925, **2020**.
10. LUO X., SUN K., LI L., WU S., YAN D., FU X., LUO H. Impacts of urbanization process on $PM_{2.5}$ pollution in "2+26" cities. Journal of Cleaner Production **284**, 124761, **2021**.
11. REQUIA W.J., JHUN I., COULL B.A., KOUTRAKIS P. Climate impact on ambient $PM_{2.5}$ elemental concentration in the United States: A trend analysis over the last 30 years. Environment International **131**, 104888, **2019**.
12. LIU Q., WU R., ZHANG W., LI W., WANG S. The varying driving forces of $PM_{2.5}$ concentrations in Chinese cities: Insights from a geographically and temporally weighted regression model. Environment International **145**, 106168, **2020**.
13. LIU X.J., XIA S.Y., YU Y., WU S.Y., ZHOU Y.N., REN Y.W. Spatiotemporal dynamics and impacts of socioeconomic and natural conditions on $PM_{2.5}$ in the Yangtze River Economic Belt. Environmental Pollution **263** (Pt A), 114569, **2020**.
14. JIANG W., GAO W., GAO X., MA M., ZHOU M., DU K., MA X. Spatio-temporal heterogeneity of air pollution and its key influencing factors in the Yellow River Economic Belt of China from 2014 to 2019. Journal of Environmental Management **296**, 113172, **2021**.
15. LIN B., ZHU J. Changes in urban air quality during urbanization in China. Journal of Cleaner Production **188**, 312, **2018**.
16. WU J., ZHENG H., ZHE F., XIE W., SONG J. Study on the relationship between urbanization and fine particulate matter ($PM_{2.5}$) concentration and its implication in China. Journal of Cleaner Production **182**, 872, **2018**.
17. YU H., LIU Y. The influential factors of urban $PM_{2.5}$ concentrations in China: a spatial econometric analysis. Journal of Cleaner Production **112**, 1443, **2016**.
18. MADDISON D. Environmental Kuznets curves: A spatial econometric approach. Journal of Environmental Economics and Management **51** (2), 218, **2006**.
19. DING Y., ZHANG M., CHEN S., WANG W., NIE R. The environmental Kuznets curve for $PM_{2.5}$ pollution in Beijing-Tianjin-Hebei region of China: A spatial panel data approach. Journal of Cleaner Production **220**, 984, **2019**.
20. MINISTRY OF ECOLOGY AND ENVIRONMENT THE PEOPLE'S REPUBLIC OF CHINA. Available online: https://www.mee.gov.cn/hjzl/sthjzk/, **2021** (accessed on 2023-03-13)
21. ZHONG C., HU R., WANG M., XUE W., HE L. The impact of urbanization on urban agriculture: Evidence from China. Journal of Cleaner Production **276** (2), 122686, **2020**.
22. LEE L.F., YU J. Estimation of spatial autoregressive panel data models with fixed effects. Journal of Econometrics **154** (2), 165, **2010**.
23. WANG W., TANG X., YANG X., ZHANG B., ZHANG Y., HÖÖK M. Energy savings in China's energy sectors and contributions to air pollution reduction in the 12th Five Year Plan. Journal of Cleaner Production **200**, 305, **2018**.
24. SANCHEZ K.A., FOSTER M., NIEUWENHUIJSEN M.J., MAY A.D., RAMANI T., ZIETSMAN J., KHREIS H. Urban policy interventions to reduce traffic emissions and traffic-related air pollution: Protocol for a systematic evidence map. Environment International **142**, 105826, **2020**.
25. XIAO C., CHANG M., GUO P., CHEN Q., TIAN X. Comparison of the cost-effectiveness of eliminating high-

polluting old vehicles and imposing driving restrictions to reduce vehicle emissions in Beijing. Transportation Research Part D: Transport and Environment **67** (1), 291, **2019**.
26. KHOSHSIMA M., AHMADI-GIVI F., BIDOKHTI A.A., SABETGHADAM S. Impact of meteorological parameters on relation between aerosol optical indices and air pollution in a sub-urban area. Journal of Aerosol Science **68**, 46, **2014**.
27. ZIEMBA L.D., LEE THORNHILL K., FERRARE R., BARRICK J., BEYERSDORF A.J., CHEN G., CRUMEYROLLE S.N., HAIR J., HOSTETLER C., HUDGINS C., OBLAND M., ROGERS R., SCARINO A.J., WINSTEAD E.L., ANDERSON B.E. Airborne observations of aerosol extinction by in situ and remote-sensing techniques: Evaluation of particle hygroscopicity. Geophysical Research Letters **40** (2), 417, **2013**.
28. ECK T.F., HOLBEN B.N., KIM J., BEYERSDORF A.J., CHOI M., LEE S., KOO J., GILES D.M., SCHAFER J.S., SINYUK A.F., PETERSON D.A., REID J.S., AROLA A., SLUTSKER I., SMIRNOV A.V., SOROKIN M.G., KRAFT J., CRAWFORD J.H., ANDERSON B.E., THORNHILL K.L., DISKIN G., KIM S.W., PARK S. Influence of cloud, fog, and high relative humidity during pollution transport events in South Korea: Aerosol properties and $PM_{2.5}$ variability. Atmospheric Environment **232** (1), 117530, **2020**.
29. HE J., GONG S., YU Y., YU L., WU L., MAO H., SONG C., ZHAO S., LIU H., LI X., LI R. Air pollution characteristics and their relation to meteorological conditions during 2014-2015 in major Chinese cities. Environmental Pollution **223**, 484, **2017**.
30. ZHU W., WANG M., ZHANG B. The effects of urbanization on $PM_{2.5}$ concentrations in China's Yangtze River Economic Belt: New evidence from spatial econometric analysis. Journal of Cleaner Production **239**, 118065, **2019**.
31. VANDEWEGHE J.R., KENNEDY C. A spatial analysis of residential greenhouse gas emissions in the Toronto census metropolitan area. Journal of Industrial Ecology **11** (2), 133, **2007**.
32. ZHONG Y., LIN A., HE L., ZHOU Z., YUAN M. Spatiotemporal dynamics and driving forces of urban land-use expansion: A case study of the Yangtze River Economic Belt, China. Remote Sensing **12** (2), 287, **2020**.
33. CHEN D., XIA L., GUO X., LANG J., ZHOU Y., WEI L., FU X. Impact of inter-annual meteorological variation from 2001 to 2015 on the contribution of regional transport to $PM_{2.5}$ in Beijing, China. Atmospheric Environment **260** (D22), 118545, **2021**.
34. XIAOLIN Y., YIYAN C., YILING L., HAO C. Study on the spatiotemporal heterogeneity and spatial spillover effect of urban $PM_{2.5}$ in the Yellow River basin. Resource development and market **38** (10), 1208, **2022**.
35. XUE W.B., FU F., WANG J., TWANG G., LEI Y., YANG J., WANG Y. Numerical study on the characteristics of regional transport of $PM_{2.5}$ in China. China Environmental Science **34** (6), 1361, **2014**.
36. DOU J., HAN X. How does the industry mobility affect pollution industry transfer in China: Empirical test on Pollution Haven Hypothesis and Porter Hypothesis. Journal of Cleaner Production **217**, 105, **2019**.
37. ZHANG G., LIU W., DUAN H. Environmental regulation policies, local government enforcement and pollution-intensive industry transfer in China. Computers & Industrial Engineering **148** (1), 106748, **2020**.
38. WU L., MA T., BIAN Y., LI S., YI Z. Improvement of regional environmental quality: Government environmental governance and public participation. Science of The Total Environment **717** (5), 137265, **2020**.
39. REN L., MATSUMOTO K. Effects of socioeconomic and natural factors on air pollution in China: A spatial panel data analysis. Science of The Total Environment **740**, 140155, **2020**.

Supplementary Material

Table S1. The details of the variables.

Variable	Abbreviation	Unit	Definition
Meteorological factors	AW	m/s	Wind speed
	AT	ºC	Temperature
	AH		Relative humidity
Socioeconomic factors	GDPP	10^4 Yuan per capita	GDP per capita
	EC	100 million kWh	Electricity consumption
	UR		Urbanization rate
	EE	10^4 Yuan	The government expenditure on energy conservation and environmental protection
	PD	people/km^2	Population Density in Municipal District

Table S2. The proportion of $PM_{2.5}$ with different grade in Shandong from 2014 to 2020.

	2014	2015	2016	2017	2018	2019	2020	Concentrations (μg/m³)
Excellent	5.63%	8.88%	16.67%	25.75%	41.92%	37.36%	46.30%	<35
Good	49.01%	56.45%	52.73%	53.70%	43.01%	43.96%	39.73%	35-75
Lightly polluted	32.11%	22.06%	19.67%	14.25%	10.96%	11.54%	10.68%	75-115
Moderately polluted	9.01%	6.30%	7.38%	4.11%	2.47%	4.95%	1.37%	115-150
Heavily polluted	4.23%	5.44%	3.01%	2.19%	1.64%	2.20%	1.92%	150-250
Severely polluted	0.00%	0.86%	0.55%	0.00%	0.00%	0.00%	0.00%	>250

Table S3. Descriptive statistics of variables.

Variables	Max	Min	Mean	p50	SD	VIF
$lnPM_{2.5}$	4.644	3.267	4.06	4.069	0.32	
lnGDPP	12.29	10.48	11.27	11.22	0.451	4.30
lnEC	7.119	4.602	5.623	5.622	0.567	1.77
lnPD	9.816	8.637	9.179	9.256	0.291	3.01
lnUR	4.335	3.762	4.089	4.088	0.128	3.00
lnEE	12.92	9.829	11.65	11.62	0.656	1.78
lnAW	1.66	0.336	0.785	0.672	0.341	2.34
lnAT	2.774	2.472	2.662	2.666	0.0572	4.57
lnAH	4.322	3.958	4.157	4.156	0.0726	2.45

Table S4. Estimation of dynamic spatial Durbin model

	Time lag		Spatial lag		Both	
	SDM	Wx	SDM	Wx	SDM	Wx
$L.PM_{2.5}$	0.340***				0.392***	
	(3.47)				(3.84)	
lnGDPP	-0.011	0.153	-0.021	0.303	0.010	0.459
	(-0.15)	(0.34)	(-0.29)	(0.63)	(0.14)	(0.97)

Table S4. Continued.

lnEC	0.117	1.463***	0.072	1.473***	0.132*	1.610***
	(1.62)	(2.88)	(1.00)	(2.83)	(1.81)	(3.14)
lnUR	0.576*	0.823	0.645*	0.327	0.683**	1.840
	(1.71)	(0.29)	(1.87)	(0.11)	(2.02)	(0.64)
lnEE	-0.063**	-0.173	-0.089***	-0.172	-0.055**	-0.035
	(-2.53)	(-1.20)	(-3.70)	(-1.08)	(-2.21)	(-0.22)
lnPD	0.099	2.236***	0.127	2.650***	0.077	2.096***
	(0.95)	(3.20)	(1.21)	(3.82)	(0.74)	(3.01)
lnAW	-0.026	-0.364	-0.013	-0.622	-0.018	-0.383
	(-0.25)	(-0.54)	(-0.13)	(-0.91)	(-0.18)	(-0.57)
lnAT	-1.826***	-0.616	-1.569***	-2.149	-1.789***	-2.142
	(-3.21)	(-0.21)	(-2.75)	(-0.69)	(-3.17)	(-0.70)
lnAH	-1.118***	-1.668	-1.178***	-2.446	-1.063***	-2.669
	(-3.02)	(-0.87)	(-3.16)	(-1.22)	(-2.89)	(-1.35)
L.$WPM_{2.5}$			0.331		1.265*	
			(0.51)		(1.89)	
ρ	0.892**		0.681*		0.797**	
$Σ^2$	0.002***		0.002***		0.002***	
R^2	0.226		0.100		0.216	
Log	-4045.44		-3002.25		-1682.47	

Note: * p<0.1, ** p<0.05, *** p<0.01. *t* statistics were listed in parentheses.

Table S5. Heterogeneity analysis of different regions.

	Eastern		Central		Western	
	SDM	Wx	SDM	Wx	SDM	Wx
lnGDPP	-0.407***	-0.970***	-0.083	-0.072	1.120***	0.514*
	(-2.63)	(-2.91)	(-0.78)	(-0.35)	(7.99)	(1.68)
lnEC	-0.612**	-0.414	-0.017	0.204*	1.056***	1.655***
	(-2.46)	(-0.52)	(-0.65)	(1.68)	(36.25)	(17.53)
lnUR	-0.091	-3.335***	-0.086	-3.815***	-0.694**	0.695***
	(-0.16)	(-3.15)	(-0.58)	(-5.62)	(-2.41)	(6.70)
lnEE	0.106	0.335	-0.096***	-0.145	-0.266***	-0.276***
	(1.19)	(1.20)	(-3.50)	(-1.44)	(-8.04)	(-18.61)
lnPD	0.171	0.590	0.006	1.160***	1.577***	4.144***
	(0.44)	(0.62)	(0.07)	(2.81)	(7.05)	(5.87)
lnAW	0.321**	1.207***	-0.188	-1.248***	0.127*	0.003
	(2.17)	(2.78)	(-1.46)	(-3.34)	(1.73)	(0.02)
lnAT	1.729	8.891***	-1.842**	5.114***	-2.003***	7.246***
	(1.40)	(4.02)	(-2.42)	(3.36)	(-8.42)	(12.42)
lnAH	2.203	5.206***	-0.388	1.974***	-2.253***	3.913***
	(1.47)	(2.81)	(-0.63)	(3.42)	(-7.37)	(10.49)

Table S5. Continued.

ρ	-0.682***		-0.154		0.065	
Σ^2	0.002***		0.001***		0.000**	
R^2	0.236		0.738		0.305	
Log	73.66		74.46		107.11	

Note: * p<0.1, ** p<0.05, *** p<0.01. *t* statistics were listed in parentheses.

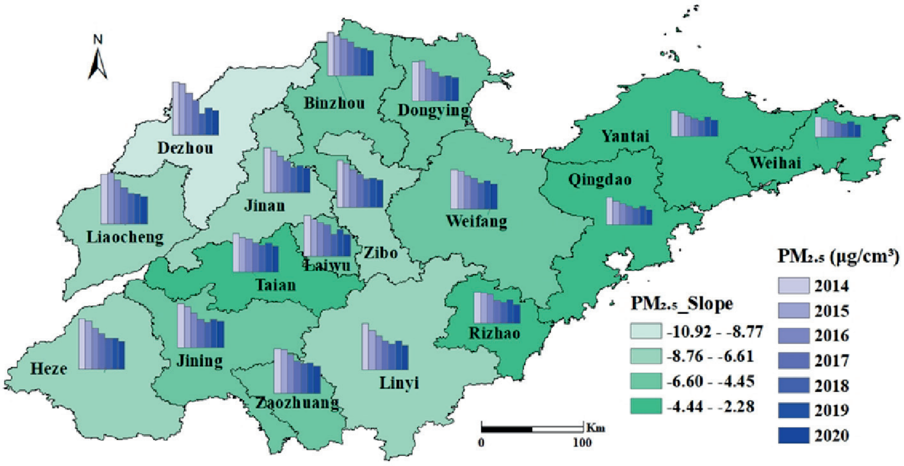

Fig. S1. Spatial and temporal distribution of $PM_{2.5}$ pollution of Shandong in 2014–2020.

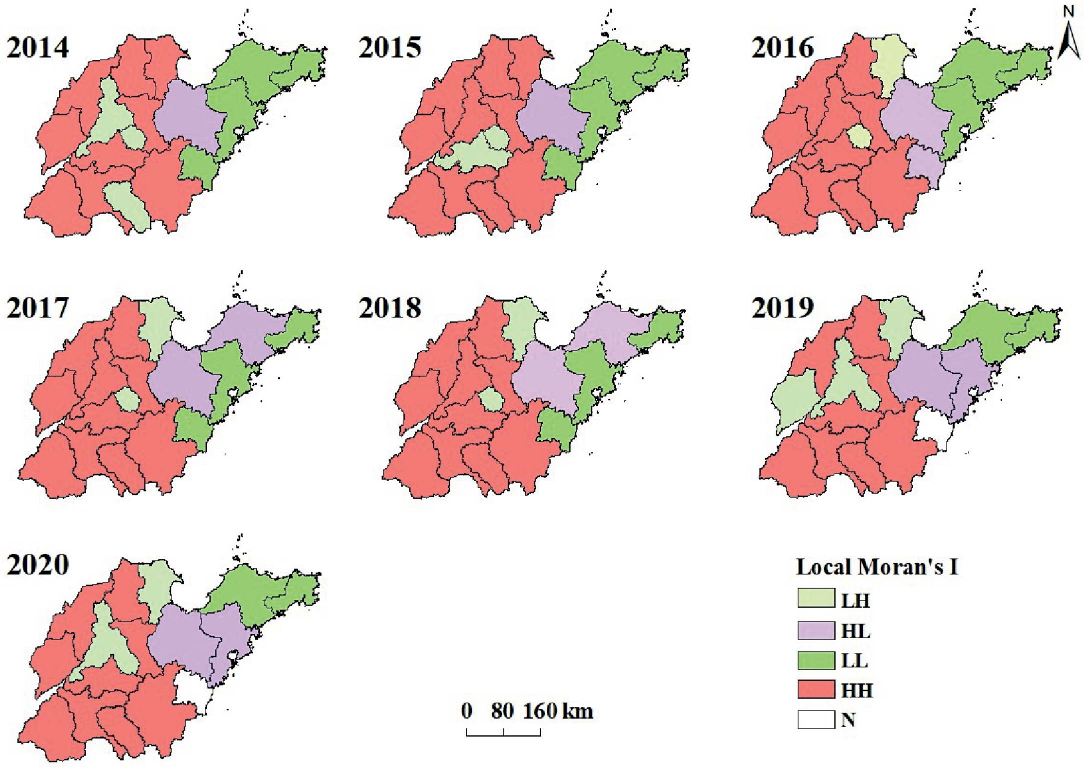

Fig. S2. The spatial cluster of $PM_{2.5}$ level in Shandong from 2014 to 2020.