Analysis of Spatio-Temporal Heterogeneity and Socioeconomic driving Factors of PM$_{2.5}$ in Beijing–Tianjin–Hebei and Its Surrounding Areas

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Abstract: Due to rapid urbanization and socio-economic development, fine particulate matter (PM$_{2.5}$) pollution has drawn very wide concern, especially in the Beijing–Tianjin–Hebei region, as well as in its surrounding areas. Different socio-economic developments shape the unique characteristics of each city, which may contribute to the spatial heterogeneity of pollution levels. Based on ground fine particulate matter (PM$_{2.5}$) monitoring data and socioeconomic panel data from 2015 to 2019, the Beijing–Tianjin–Hebei region, and its surrounding provinces, were selected as a case study area to explore the spatio-temporal heterogeneity of PM$_{2.5}$ pollution, and the driving effect of socioeconomic factors on local air pollution. The spatio-temporal heterogeneity analysis showed that PM$_{2.5}$ concentration in the study area expressed a downward trend from 2015 to 2019. Specifically, the concentration in Beijing–Tianjin–Hebei and Henan Province had decreased, but in Shanxi Province and Shandong Province, the concentration showed an inverted U-shaped and U-shaped variation trend, respectively. From the perspective of spatial distribution, PM$_{2.5}$ concentrations in the study area had an obvious spatial positive correlation, with agglomeration characteristics of “high–high” and “low–low”. The high-value area was mainly distributed in the junction area of Henan, Shandong, and Hebei Provinces, which had been gradually moving to the southwest. The low values were mainly concentrated in the northern parts of Shanxi and Hebei Provinces, and the eastern part of Shandong Province. The results of the spatial lag model showed that Total Population (POP), Proportion of Urban Population (UP), Output of Second Industry (SI), and Roads Density (RD) had positive driving effects on PM$_{2.5}$ concentration, which were opposite of the Gross Domestic Product (GDP). In addition, the spatial spillover effect of the PM$_{2.5}$ concentrations in surrounding areas has a positive driving effect on local pollution levels. Although the PM$_{2.5}$ levels in the study area have been decreasing, air pollution is still a serious problem. In the future, studies on the spatial and temporal heterogeneity of PM$_{2.5}$ caused by unbalanced social development will help to better understand the interaction between urban development and environmental stress. These findings can contribute to the development of effective policies to mitigate and reduce PM$_{2.5}$ pollutants from a socio-economic perspective.

Keywords: PM$_{2.5}$; spatio-temporal heterogeneity; socio-economic driving factors

1. Introduction

With the advancement of industrialization and urbanization, many cities around the world are experiencing severe air pollution, especially particulate matter pollution. On a global scale, China, India, and South Asia have the most severe particulate matter pollution in the world [1]. In China, since 2011, Beijing–Tianjin–Hebei [2], the Yangtze River Delta [3], and other regions have experienced frequent smog, and air pollution has caused widespread concern. High concentrations of PM$_{2.5}$ can, not only accelerate the formation of haze but also significantly affect people’s health [4]. It has been proved that long-term exposure to high PM levels can easily cause a variety of diseases [5] and increase
the risk of death [6]. In 2017, the State Ministry of Environmental Protection issued the “Beijing–Tianjin–Hebei and Surrounding Area Air Pollution Prevention and Control Work Plan in 2017”, which first proposed the concept of “2 + 26 cities” and implemented a large number of pollution control measures in these cities to alleviate air pollution in North China. Therefore, strengthening scientific understanding of the regulations of regional air particulate pollution will help to formulate urbanization policies and ensure that targeted air pollution control measures are properly implemented.

At present, research on PM$_{2.5}$ pollution mainly focuses on temporal and spatial distribution rules [7], influencing factor analyses [8], source analyses [9], and health risk assessments [10] along with other aspects. Among them, influencing factors mainly include meteorological factors and socio-economic factors. Meteorological factors affect PM$_{2.5}$ concentration by changing its diffusion and chemical reaction conditions. Chen et al. [11] summarized the methods to quantify the impact of meteorological factors on PM$_{2.5}$ and comprehensively reviewed their impact mechanisms. Xu et al. [12] conducted a study on the temporal and spatial distributions of the influence of meteorological conditions on PM$_{2.5}$ concentration in China from 2000 to 2017, which showed an overall downward trend in PM$_{2.5}$ concentration, and the influence of meteorology varied greatly between different provinces. The socio-economic factors that directly or indirectly affect PM$_{2.5}$ concentration in the process of urbanization and economic development, include the national economy, industrial structure, population density, transportation, and other factors [13]. These factors mainly represent the impact of human activities on PM$_{2.5}$. The average urban PM$_{2.5}$ level is mainly affected by anthropogenic emissions of local air pollutants and the surrounding ecological level. Cheng et al. [14] used a dynamic spatial panel model to analyze the impact of foreign direct investment (FDI) on China’s PM$_{2.5}$ pollution, and the results showed that FDI significantly aggravated China’s urban PM$_{2.5}$ pollution. The study of Yan et al. [15] expressed that there was a heterogeneous relationship between PM$_{2.5}$ concentration and economic growth, urbanization, industrialization, and FDI and that population density had the greatest positive impact on PM$_{2.5}$ pollution. Zhang et al. [16] noted that PM$_{2.5}$ pollution was positively correlated with urbanization and road density, and negatively correlated with the proportion of tertiary industries.

Although many studies have been conducted on the temporal and spatial distributions of PM$_{2.5}$ and its influencing factors, the study areas of most studies mainly concentrate on the level of countries, urban agglomerations, and cities, while comparisons between regions are relatively rare. In addition, with rapid economic development, the North China region has been experiencing severe PM$_{2.5}$ pollution. Shanxi Province is located in the central region and has a decreasing economic development. Therefore, this study selects Beijing City, Tianjin City, Hebei Province, Henan Province, and Shanxi Province as the study areas. There are significant distinctions of PM$_{2.5}$ and economic development levels between the different cities, which provides advantages for studying the impact of socio-economic factors and spatial spillover effects on the PM$_{2.5}$ level. The aims of this study are: (1) explore the temporal and spatial distribution characteristics of PM$_{2.5}$ levels; (2) compare the spatial heterogeneity of PM$_{2.5}$ distribution characteristics in different regions, and (3) determine the influence of socio-economic factors and spatial spillover effects on PM$_{2.5}$ levels.

2. Materials and Methods

2.1. Study Area

This study selects Beijing City, Tianjin City, Hebei Province, Henan Province, and Shanxi Province as the study areas, which contains 56 cities in four provinces and two municipalities, as shown in Figure 1. Among them, Hebei Province, Shandong Province, Shanxi Province, and Henan Province have 11, 16, 11, and 18 prefecture-level cities, respectively. The names and abbreviations of all cities are shown in Table S1. The study area is located between 31°23′ N–42°40′ N and 110°14′ E–122°42.3′ E in China, with the Loess Plateau in the west and the North China Plain in the east. With its rapid economic...
development and rapid consumption of energy, the air quality in North China is not better and haze pollution incidents occur frequently; this area is considered one of the most polluted areas of China. In addition, the study area includes, not only the eastern regions with their rapid economic development, such as the Beijing–Tianjin–Hebei urban agglomeration and Shandong Province but also the central regions with slower economic development speeds, such as Shanxi Province. The socio-economic development of the study area is very unbalanced, which provides favorable conditions for analyzing the influence of socioeconomic factors on PM$_{2.5}$ concentration. Therefore, this paper selects four provinces and two municipalities as the study areas to explore the temporal and spatial heterogeneity of PM$_{2.5}$ and the influence of socioeconomic factors on PM$_{2.5}$ concentrations in 2015–2019.

Figure 1. Study area.

2.2. Data Sources and Validity

This study collected hourly PM$_{2.5}$ concentration data from 347 automatic air quality monitoring stations in the study area, from 1 January 2015, to 31 December 2019. This set of data was obtained from the Urban Air Quality Distribution platform of the National Environmental Monitoring Center (http://www.moc.cma.gov.cn, accessed on 9 October 2021). Based on the hourly PM$_{2.5}$ data, the arithmetic mean method was used to calculate the annual PM$_{2.5}$ concentration in each city, from 2015 to 2019. To improve the validity of the data, we processed the missing values according to the provisions of the Ambient Air Quality Standard (GB3095−2012). When calculating the daily average concentrations, we required that the number of hourly average concentrations or the sampling time should be more than 20, otherwise the daily average concentration was considered invalid. In calculating the average monthly concentrations, we required at least 27 (February: 25) daily average concentration values, otherwise, the monthly mean concentration was considered invalid. At least 324 daily average concentrations were required to calculate the annual average concentration, otherwise, the annual average concentration was considered invalid.

The potential impact of socioeconomic indicators on PM$_{2.5}$ pollution has been widely discussed. Based on previous studies and the availability of socioeconomic data, we selected seven indicators (Table 1): Population (POP), Gross Domestic Product (GDP), Green Ratio of Built-up Area (GR), Output of Second Industry (SI), Proportion of Urban Population (UP), Roads Density (RD), and Proportion of Built-up Area (BA). Among them, POP, GDP, and GR, respectively, represent population size, economic development level,
and urban greening; SI and RD express industrial structure and traffic factors, respectively; UP and BA represent population urbanization and spatial urbanization. The annual statistical data of POP, GDP, SI, and RD were acquired from the Social and Economic Development Bulletin and Statistical Yearbook of each city in the study area, while those of GR and BA were obtained from the China Urban Statistical Yearbook. The time span of all socioeconomic indicators was consistent with that of PM$_{2.5}$ data in this study. Figure S4 provides detailed statistical information on these socioeconomic factors, for each city.

Table 1. Socioeconomic indicators and the abbreviations and units.

| Category                          | Variable                        | Abbreviation | Units       |
|-----------------------------------|---------------------------------|--------------|-------------|
| Independent variable              | PM$_{2.5}$ concentration        | PM$_{2.5}$   | $\mu g/m^3$ |
| Dependent variable                | Total Population                 | POP          | $10^4$ persons |
|                                   | Gross Domestic Product          | GDP          | $10^4$ CNY  |
|                                   | Green Ratio of Built-up Area    | GR           | %           |
|                                   | Output of Second Industry       | SI           | $10^4$ CNY  |
|                                   | Proportion of Urban Population  | UP           | %           |
|                                   | Roads Density                   | RD           | km/km$^2$   |
|                                   | Proportion of Built-up Area     | BA           | %           |

2.3. Statistical Methods

2.3.1. Moran’s I Test

Air pollution usually has obvious spatial distribution characteristics with regional aggregation. Many researchers usually use Moran’s I to test the spatial correlation of variables. In this study, we used the Global Moran’s I to test the overall spatial effect of PM$_{2.5}$ concentrations in 58 cities, from 2015 to 2019. The Global Moran’s I model can be explained as follows [17]:

$$Global\,\,Moran's\,\,I_i = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S_0 \sum_{i=1}^{n} (y_i - \bar{y})^2}$$ (1)

$$Z = \frac{1 - E(I)}{\sqrt{Var(I)}}$$ (2)

$$E[I] = -1/(n - 1)$$ (3)

$$V[I] = E[I^2] - E[I]^2$$ (4)

where $y_i$ is the PM$_{2.5}$ concentration of city $i$, $y_j$ is the PM$_{2.5}$ concentration of city $j$, and $\bar{y}$ is the average PM$_{2.5}$ concentration of the study area. $w_{ij}$ is the spatial weight matrix; if two cities share a common boundary, the weight is 1, otherwise, it is 0; $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ is the aggregation of all spatial weights; $n = 56$ is the number of cities. $Z$ score and $p$ values used to judge the Moran’s I significance level; when the $|Z| > 1.96$ or $p < 0.05$, the result is considered significant at the 95% confidence level; when the $|Z| > 2.58$ or $p < 0.01$, the result is considered significant at the 99% confidence level. In this paper, the Global Moran’s I was calculated using ArcGIS software.

2.3.2. Hot Spot Analysis

Hot Spot Analysis is often used to identify potential spatial agglomeration characteristics of PM$_{2.5}$ pollution, and PM$_{2.5}$ levels are divided into cold spots, insignificant points, and hot spots. The Getis-Ord Gi* of ArcGIS was used to calculate the Gi* of each city in the study area. The principle formulae are as follows [18]:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{x} \sum_{i=1}^{n} w_{ij}}{\sqrt{\left[\frac{\sum_{j=1}^{n} w_{ij} - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}\right]}}$$ (5)
This heterogeneity may be related to differences in economic development, environment, and policy measures. The regions with the highest PM2.5 concentration in 2015 were Beijing and Hebei province. The PM2.5 concentrations in most cities in the two provinces were consistent with their corresponding provinces. However, the patterns of cities in Shanxi Province and Shandong Province were quite different from the others. To be more specific, PM2.5 concentrations in Shanxi province had an inverted U-shaped trend. In Shandong Province, it first went down, and then increased and reached another peak in 2014 before decreasing since then [19]. It had been increasing since 2000 until reaching a peak in 2008, and then it fluctuated after 2008 as the harm of PM2.5 pollution was widely known after the Beijing Olympic Games and China gradually entered the stage of economic restructuring [20].

Some studies on the long-term variation trends of PM2.5 concentrations have shown that the influence of different socio-economic factors on PM2.5 concentration could be explained by Formula (7):

$$Y = \rho WY + X\beta + \epsilon, \epsilon \sim N[0, \sigma^2 I]$$

where Y indicates the PM2.5 concentration; X expresses the independent variables, including all introduced socioeconomic factors; \(\rho\) is the spatial effect coefficient, and its value ranges from 0 to 1. The spatial matrix is represented by W, which indicates whether two spatial elements have a common boundary; \(\beta\) represents the regression coefficient of explanatory variables; and \(\epsilon\) is the error term.

3. Results and Discussion
3.1. Temporal Variation Characteristics of PM2.5
3.1.1. Temporal Variation Trend of PM2.5 Concentration

The variation trend of PM2.5 concentration in the study area was determined by calculating the Probability Density Functions (PDFs) and annual average concentrations of PM2.5 in the study area, from 2015 to 2019. As shown in Figure 2, the PM2.5 concentration in the study area expressed a downward trend from 2015 to 2019. As a large number of emission reduction measures have already been implemented, the reduction in PM2.5 will gradually reduce in the future. Therefore, the speed of pollution mitigation may be slowed down, and the spatial difference between different cities would become narrower. From this aspect, Jiang et al. [22] reported that there was a significant decrease in PM2.5 concentration in Beijing and Tielin, Tianjin, and most cities in Hebei and Henan Provinces decreased from 2015 to 2019, indicating that PM2.5 pollution in the study area was still severe. The frequency distribution of PM2.5 can be found in the PDF graph. From 2015 to 2019, the probability density curve moved to the left as a whole, indicating that PM2.5 concentration had decreased in all concentration intervals. The curves of 2015 and 2016 are similar, while those of 2017, 2018, and 2019 are similar. Compared with 2016, the occurrence probability of high concentration decreased significantly in 2017, resulting in a significant increase in probability in the low concentration intervals, and then remained stable. This sudden change may be related to the stricter air pollution control measures that were implemented in 2017.

![Probability density function (PDFs) and annual concentration of PM2.5 from 2015 to 2019.](image-url)
The mitigation trend was more significant in the context of concentration levels. In 2015, the average annual concentration of PM$_{2.5}$ in all cities ranged from 34.6 to 106.42 µg/m$^3$, but was 26.52–72.39 µg/m$^3$ in 2019. We can find that there was a large difference between different cities, with the maximum concentration being about three times that of the minimum. During the period of 2015–2019, the maximum concentration occurred in BD in 2015 and the minimum concentration occurred in WH in 2018. In addition, we also determined the statistics on the percentage of exceeding standard days in each city, from 2015 to 2019, as shown in Figure S1. In 2015, the average percentage of exceeding standard days in the study area was 37.45%, but it dropped to 15.66% in 2019. This apparent mitigation of PM$_{2.5}$ pollution did not just start in 2015, it had been going on for a long time. Some studies on the long-term variation trends of PM$_{2.5}$ concentrations have shown that it had been increasing since 2000 until reaching a peak in 2008, and then it fluctuated continuously and reached another peak in 2014 before decreasing since then [19]. It fluctuated after 2008 as the harm of PM$_{2.5}$ pollution was widely known after the Beijing Olympic Games and China gradually entered the stage of economic restructuring [20]. China’s government began to implement strict pollution control measures and regarded PM$_{2.5}$ as a routine monitoring pollutant after issuing the Action Plan for Air Pollution Prevention and Control in 2013, which may be why PM$_{2.5}$ concentration continued to decrease after 2014 [21]. As a large number of emission reduction measures have already been implemented, the reduction in PM$_{2.5}$ will gradually reduce in the future. Therefore, the speed of pollution mitigation may be slowed down, and the spatial difference between cities would become narrower. From this aspect, Jiang et al. [22] reported that there was a spatial convergence trend for PM$_{2.5}$ concentrations in the Beijing–Tianjin–Hebei region.

3.1.2. The Spatial Heterogeneity of Temporal Variations

Although PM$_{2.5}$ concentrations in the study area have been decreasing on the whole, they express different temporal regulations in various areas. As shown in Figure S2, Beijing, Tianjin, and most cities in Hebei and Henan Provinces decreased from 2015 to 2019, while a few cities showed different patterns. The average concentrations in Hebei Province and Henan Province also had the same patterns as most of the cities under their jurisdictions. However, the patterns of cities in Shanxi Province and Shandong Province were quite different from the others. To be more specific, PM$_{2.5}$ concentrations in Shanxi Province first went up but then decreased, and reached their highest level in 2017, presenting an inverted U-shaped trend. In Shandong Province, it first went down, and then it went up, reaching the lowest level in 2018 and showing a U-shaped trend. The patterns of most cities in the two provinces were consistent with their corresponding provinces. This heterogeneity may be related to differences in economic development, environmental protection policies, geographical differences, and other factors between the different provinces. The regions with the highest PM$_{2.5}$ concentration in 2015 were Beijing and Henan Provinces, and Henan Province exhibited the highest PM$_{2.5}$ concentration for the period of 2016–2019. After five years of decline, Beijing ranked last among the four provinces and two municipalities in 2019.

Specific to the urban level, the discrepancies in the reduction rates among different regions were more obvious, as shown in Figure S3. Specifically, BJ, BD, LF, DZ, and LC exhibited the highest reduction rate if more than 40%. Those of TY, YQ, JC, YC, and LFF were slightly less than 10%. The former was mainly concentrated in the Beijing–Tianjin–Hebei region, while the latter was under the jurisdiction of Shanxi Province. To further explore the differences in temporal variations, we plotted the PDFs of PM$_{2.5}$ in each province or municipality from 2015 to 2019, as shown in Figure 3. To facilitate comparison, we divided the study area into the Beijing–Tianjin–Hebei region and its surrounding regions (Shandong, Hebei, Shanxi Province). In 2015, the PDFs of each province varied greatly. Shanxi Province had the highest peak value, while Beijing had the lowest. Although the concentration ranges of the two peak areas were similar, the occurrence probability of high PM$_{2.5}$ concentration in Beijing was high, indicating that Beijing was prone to PM$_{2.5}$ pollution events. On the whole, the peaks in the Beijing–Tianjin–Hebei region were lower, while those
in the surrounding region were higher, indicating that PM$_{2.5}$ pollution in the Beijing–Tianjin–Hebei region was more serious than in its surrounding areas. From the temporal point of view, the curve variation of the Beijing–Tianjin–Hebei region is very significant, especially in terms of BJ. The Shandong, Henan, and Shanxi regions also showed a trend of pollution alleviation. It is worth noting that the PDFs curve of Henan Province was always at the bottom, indicating that it had higher PM$_{2.5}$ pollution. After five years of improvement, the PDFs curves of the six regions showed a tendency to gradually coincide. Until 2019, the curves were quite similar, showing that the spatial differences of PM$_{2.5}$ concentration were narrowing, which is similar to the research results of Jiang, He, and Zhou [22].

3.2. Spatial Variation Trend of PM$_{2.5}$

To determine the spatial distribution characteristics of PM$_{2.5}$ concentrations in the study areas, we calculated the Global Moran’s I during 2015–2019. As shown in Table 2, with $p$-values < 0.01 and Z-score > 2.58, the Global Moran’s I was acceptable. From 2015 to 2019, the PM$_{2.5}$ concentrations in the study areas showed a significant positive spatial correlation, which indicated that the diffusion of PM$_{2.5}$ concentrations between cities was not random, and rather showed similar spatial connections and tended to aggregate. This spatial correlation has been gradually increasing since 2016. To better exhibit the agglomeration characteristics of the study area, we drew a Moran scatter diagram, as shown in Figure 4. Most cities are concentrated in the first and third quadrants, and only a few cities appear in the second and fourth quadrants which indicate that PM$_{2.5}$ pollution in the study areas presented obvious “high–high” and “low–low” agglomeration. This spatial characteristic is caused by the unbalanced economic development in the earlier period. With the sustainable development of the economy and the transformation of urban planning and layout, it would change.

Table 2. Global Moran’s I from 2015 to 2019.

| Year | I     | p-Value  | Z-Score |
|------|-------|----------|---------|
| 2015 | 0.372501 | 0.000001 | 4.855292 |
| 2016 | 0.344208 | 0.000006 | 4.532812 |
| 2017 | 0.363731 | 0.000002 | 4.796205 |
| 2018 | 0.389324 | 0.000000 | 5.123085 |
| 2019 | 0.414598 | 0.000000 | 5.429379 |

To clearly determine the high and low concentration areas of PM$_{2.5}$ pollution, we drew a Getis-Ord Gi* statistical graph for the study area during 2015–2019, as shown in Figure 5. On the whole, the cold spots in the study area were mainly distributed in the north of Shanxi and Hebei Provinces, and the eastern coastal areas of Shandong Province and the hot spots were mainly concentrated in the junction area of Hebei, Shandong, and Henan Provinces. In terms of temporal change, the cold spots gradually shifted from the northwest to the north of the study area, while those in the eastern coastal region of Shandong Province were composed of YT, QD, and WH with no change. Additionally, the hot spot moved to the southwest gradually from 2015 to 2019. This moving of the PM$_{2.5}$ pollution center does not mean that the air quality in hot spots city were getting worse. In fact, almost all cities had been experiencing PM$_{2.5}$ pollution alleviation at different levels. The PM$_{2.5}$ concentration in some cities, such as SJZ, JN, and DZ, decreased sharply from hot spots to insignificant spots; some cities, such as JY, LYY, and PDS, declined slowly from insignificant spots to hot spots. This conversion of hot and cold spots is essentially determined by the transformation of the local industrial structure and the implementation of environmental protection policies. In fact, the upgrading and relocation of heavily polluting enterprises in the Beijing–Hebei–Tianjin region may also be one of the reasons for the moving of the pollution centroid. XT, HD, LC, AY, KF, PY, HB, XX, and other cities had always been hot spot cities during 2015–2019, indicating that the pollution in these cities was relatively serious and that control measures still needed to be taken for reducing the PM$_{2.5}$ pollution risk level.
Figure 3. Probability density functions of each province during 2015–2019.
3.3. Analysis of Socioeconomic Influence Factors

To clearly determine the high and low concentration areas of PM2.5 pollution, we drew a Getis-Ord Gi* statistical graph for the study area during 2015–2019, as shown in Figure 5. On the whole, the cold spots in the study area were mainly distributed in the northwest to the north of the study area, while those in the eastern coastal region of Shandong Province were composed of YT, QD, and WH with no change. Additionally, the hot spots were mainly concentrated in the junction area of Hebei, Shandong, and Henan Provinces. In terms of temporal change, the cold spots gradually shifted from the northwest to the north of Shanxi and Hebei Provinces, and the eastern coastal areas of Shandong Province to the southwest gradually from 2015 to 2019. This moving of the PM2.5 pollution center does not mean that the air quality in hot spots city were getting worse. In fact, almost all cities had been experiencing PM2.5 pollution alleviation at different levels. Hot spots to insignificant spots; some cities, such as JY, LYY, and PDS, declined slowly for the moving of the pollution centroid. XT, HD, LC, AY, KF, PY, HB, XX, and other cities had always been hot spot cities during 2015–2019, indicating that the pollution in these cities was relatively serious and that control measures still needed to be taken for reducing the PM2.5 pollution risk level.

In 2017, local emission sources remain important contributors to the Beijing–Tianjin–Hebei region but the interactions between cities are also strong. Different socioeconomic indicators reflect different human activities, which could affect the PM2.5 concentration. To ensure the data conformed to the normal distribution, a logarithmic transformation was performed on the socioeconomic data and economic factors on PM2.5 concentrations. To determine the impact of various socioeconomic factors, we used a spatial lag model (SLM) to determine the influence of PM2.5 levels from the surrounding areas on the local area. From 2015 to 2019, the spatial lag model introduced the spatial effect coefficient ρ to characterize the influence of PM2.5 concentrations in the surrounding areas on the local area. This spatial correlation coefficient ranged from 0.436 to 0.533, indicating a significant positive correlation between PM2.5 concentrations in the surrounding areas and the local area. This finding is consistent with other studies. Therefore, it is essential to consider the correlation of PM2.5 concentrations in surrounding areas when analyzing the PM2.5 concentration in our area. This correlation can also improve the prediction and control of PM2.5 pollution.

To determine the key socioeconomic factors affecting PM2.5 concentration, we used spatial econometric models to quantify the impact of socioeconomic development and industrial upgrading on PM2.5 concentration. This is consistent with our previous findings, almost all cities had been experiencing PM2.5 pollution alleviation at different levels. Yet, the study area is still in the haze pollution center, and the high concentration area is the Beijing–Tianjin–Hebei region but the interactions between cities are also strong. Economic development and industrial upgrading were the main driving forces for haze pollution. The Beijing–Tianjin–Hebei region is a developed economy, which is conducive to effective integration and utilization of resources, affecting the local industrial structure and urban layout. Dong et al. [23] studied the pollution transmission contribution in the Beijing–Tianjin–Hebei region and the results showed 32.5% to 68.4% contribution of PM2.5 transmission from the surrounding areas.

3.3.2. Sources of PM2.5 Pollution

Figure 4. Moran scatter diagram from 2015 to 2019. (a) 2015; (b) 2016; (c) 2017; (d) 2018; (e) 2019.


different results. Yan, Kong, Jiang, Huang, and Ye [13] observed that the impacts of economic development on PM 2.5 pollution varied with the development level of local economy. For highly developed regions, the impact of economic development on PM 2.5 pollution is relatively large, whereas the impact is minimal for low-developed regions. This is consistent with our findings, but other studies have shown different results. Yan, Kong, Jiang, Huang, and Ye [13] observed that the impacts of economic development on PM 2.5 pollution varied with the development level of local economy. For highly developed regions, the impact of economic development on PM 2.5 pollution is relatively large, whereas the impact is minimal for low-developed regions. This is consistent with our findings, but other studies have shown different results. Yan, Kong, Jiang, Huang, and Ye [13] observed that the impacts of economic development on PM 2.5 pollution varied with the development level of local economy. For highly developed regions, the impact of economic development on PM 2.5 pollution is relatively large, whereas the impact is minimal for low-developed regions. This is consistent with our findings, but other studies have shown different results.
3.3. Analysis of Socioeconomic Influence Factors

Different socioeconomic indicators reflect different human activities, which could affect the spatial and temporal heterogeneity of PM$_{2.5}$ concentrations to various degrees. In this study, we used a spatial lag model (SLM) to determine the impact of various socioeconomic factors on PM$_{2.5}$ concentrations. To ensure the data conformed to the normal distribution, a logarithmic transformation was performed on the socioeconomic data and PM$_{2.5}$ concentrations before using SLM. Table 3 shows the quantified results of the SLM model from 2015 to 2019.

| Variable | Coefficient | Probability | Coefficient | Probability | Coefficient | Probability | Coefficient | Probability | Coefficient | Probability |
|----------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| ρ        | 0.560       | 0.000**     | 0.583       | 0.000**     | 0.739       | 0.000**     | 0.724       | 0.000**     | 0.574       | 0.000**     |
| GDP      | −0.405      | 0.005**     | −0.328      | 0.088       | −0.489      | 0.001**     | −0.364      | 0.012*      | −0.415      | 0.002**     |
| POP      | 0.222       | 0.001**     | 0.195       | 0.047*      | 0.289       | 0.000**     | 0.244       | 0.003**     | 0.243       | 0.002**     |
| UP       | 0.085       | 0.010*      | 0.225       | 0.317       | 0.422       | 0.039*      | 0.351       | 0.091       | 0.339       | 0.080       |
| SI       | 0.375       | 0.007**     | 0.238       | 0.110       | 0.323       | 0.005**     | 0.202       | 0.062       | 0.248       | 0.018*      |
| RD       | 0.337       | 0.000**     | 0.271       | 0.000**     | 0.163       | 0.011*      | 0.146       | 0.020*      | 0.218       | 0.001**     |
| BA       | −0.036      | 0.199       | −0.020      | 0.480       | −0.029      | 0.193       | −0.005      | 0.031       | 0.015       | 0.533       |
| GR       | 0.217       | 0.332       | −0.112      | 0.560       | −0.132      | 0.631       | −0.166      | 0.582       | −0.163      | 0.595       |

**: Significant at 0.01 levels; *: significant at 0.05 levels.

The spatial lag model introduced the spatial effect coefficient $\rho$ to characterize the influence of PM$_{2.5}$ levels from the surrounding areas on the local area. From 2015 to 2019, there was a positive relationship between PM$_{2.5}$ concentration in local and surrounding regions, indicating that local PM$_{2.5}$ levels were significantly influenced by surrounding areas. This is consistent with the “high–high” and “low–low” agglomeration characteristics of PM$_{2.5}$ concentrations in the study area. Local PM$_{2.5}$ pollution was not only related to local pollutant emissions but was also affected by pollution transport from other regions. Dong et al. [23] studied the pollution transmission contribution in the Beijing–Tianjin–Hebei region and the results showed 32.5% to 68.4% contribution of PM$_{2.5}$ transmission in 2017. Local emission sources remain important contributors to the Beijing–Tianjin–Hebei region but the interactions between cities are also strong.

GDP represents the local economic development level. Except for 2016, GDP showed a significant negative correlation with the PM$_{2.5}$ level, indicating that economic development had a certain inhibitory effect on PM$_{2.5}$ pollution in the study area. As an economy grows, local investment in air pollution control will also increase. In addition, a relatively developed economy is conducive to effective integration and utilization of resources, affecting the local industrial structure and urban layout. Dong et al. [24] found that economic development and industrial upgrading were the main driving forces for haze pollution improvement in China’s regions, while the transportation industry and construction industry were the two major sources of PM$_{2.5}$ pollution. This is consistent with our findings, but other studies have shown different results. Yan, Kong, Jiang, Huang, and Ye [13] observed that the impacts of economic development on PM$_{2.5}$ pollution varied with the degree of development. Economic development can alleviate PM$_{2.5}$ pollution in developed areas, while it can promote PM$_{2.5}$ pollution in underdeveloped areas. As noted by the theory of the Environmental Kuznets Curve (EKC), a later stage of urbanization is ultimately conducive to alleviating the pollution caused by the early stage of urbanization, and there is a threshold of an inflection point in the middle. Wang et al. [25] explained this in detail and obtained similar results to us.

Over 2015–2019, POP and PM$_{2.5}$ levels showed a positive correlation, passing the significance test, indicating that population growth contributed to the formation of urban PM$_{2.5}$ pollution. The increase in the population size resulted in growing demands for employment, housing, transportation, and energy consumption, thus, promoting the emission of pollutants. Han et al. [26] analyzed the relationship between population variations and PM$_{2.5}$ levels, and the results showed that there was a positive trend between population and PM$_{2.5}$ in most cities in China and that the contribution rate of megacities
was 5.40 ± 4.80 μg/m³ per million people. However, there was also a negative trend between population size and PM$_{2.5}$ in some regions [13], because megacities with dense populations help to integrate resources and improve the utilization efficiency of urban infrastructure and natural resources, thus reducing PM$_{2.5}$ pollution.

UP refers to the proportion of the urban population in the total population, which is usually used to represent the level of urbanization. The results of Table 3 indicate that UP had a positive impact on PM$_{2.5}$ pollution in 2015 and 2017, but did not pass the significance test in other years. The growth or aggregation of an urban population usually leads to an increase in automobiles, housing and energy consumption, industrial production, and construction activities, which would have an impact on the increase in PM$_{2.5}$ concentrations. Relevant studies [27] showed that the relationship between the proportion of the urban population and ecological environment pressures in the Beijing–Tianjin–Hebei region also conformed to the EKC theory, and it could effectively alleviate ecological environment pressure until it reached 80%, which was the turning point in EKC for most cities. By 2019, the proportion of the urban population in BJ and TJ exceeded 80%, while others were within the scope of 40–60%, below the threshold, indicating that we still have a long way to go in the urbanization process.

SI is the value-added of Secondary Industry and is used to represent the industrial structure. There was a significant positive correlation between SI and PM$_{2.5}$ concentrations in 2015, 2017, and 2019. According to the statistical results of the output of the secondary industry, as shown in Figure S4, it had been decreasing or first increasing and then decreasing in AY, BJ, BD, LC, JNN, LF, PY, SJZ, TJ, and TA during 2015–2019, while it increased in other cities. These cities were often accompanied by severe PM$_{2.5}$ pollution, which indicated that these cities may have already carried out the elimination of backward production capacity or the transfer of secondary industry to alleviate local PM$_{2.5}$ pollution. The national development strategy has significantly increased the proportion of tertiary industries in the Beijing–Tianjin–Hebei region through the relocation and replacement of traditional secondary industries, which is consistent with our results. The results of Hao and Liu [28] are similar to ours, and they believe that PM$_{2.5}$ concentrations in Chinese cities are also strongly influenced by secondary industry. In 2019, the average ratio of secondary industry to GDP in the study area was 41.97 percent. In addition, energy-intensive industries characterized by high emissions have a large-scale base, and the effect of industrial transformation and upgrading is not obvious in the short term. Therefore, to effectively reduce the level of urban PM$_{2.5}$, it is necessary to accelerate the transformation of economic structures and reduce the dependence on secondary industries, especially heavy industries.

RD, road length per unit area, is often used to represent the impact of traffic factors on PM$_{2.5}$. During the study period, there was a significant positive relationship between PM$_{2.5}$ concentration and RD. According to the statistical results, as shown in Figure S4, the road length of most cities in the study area kept increasing in 2015–2019, except for BJ and TJ. A dense urban road traffic network promotes the increase in vehicle ownership, and pollutants from vehicle exhaust, such as NOx, are important sources of PM$_{2.5}$ [29,30]. In addition, the increase in roads also enhances road dust, which is also a source of PM$_{2.5}$ [31]. In this regard, traffic will continue to have an impact on continuing PM$_{2.5}$ levels. There are also related studies [24] that use other indicators to characterize the influence of traffic factors and obtain similar results. Ding et al. [32] used per capita vehicle ownership to characterize traffic impacts, which determined that this factor had a driving effect on PM$_{2.5}$ pollution and that it fluctuated during the study period.

In this study, BA and GR did not pass the significance test and were not statistically significant, so the results were not credible. BA is the ratio of the built-up area to the area of the municipal district. Due to the jurisdiction of the county, BA cannot completely represent the overall situation of cities in the research region. The GR of all cities was about 40% with slight distinctions. This may be why the results were not statistically significant. In addition, some studies used related indicators to explore the influence on PM$_{2.5}$. For example, Wang, Yao, Xu, Sun, and Li [25] found an inverted U-shaped relationship between

built-up area and PM$_{2.5}$ levels but lacked in-depth discussions. Qin et al. [33] simulated the impact of urban greening on atmospheric particulate matter, and the results showed that reasonable tree cover could reduce PM by 30%. In addition, there are still many deficiencies in this study. First, in addition to socio-economic factors, PM$_{2.5}$ is also affected by topography, meteorology, pollution emissions, and other factors, which are not involved in this study. Secondly, the social and economic data used in this study are from various statistical yearbooks and bulletins, which may have certain deviations and bring certain uncertainties. In future studies, more factors should be considered to ensure the accuracy of the results.

4. Conclusions

This study used PDFs to analyze the temporal variation trends and spatial distribution differences of PM$_{2.5}$ concentrations in the Beijing–Tianjin–Hebei region and its surrounding provinces from 2015 to 2019. Then, the spatial distribution characteristics of PM$_{2.5}$ concentrations were analyzed using Moran’s I and Getis-Ord-Gi*. Finally, SLM was adopted to quantify the driving effect of socioeconomic factors on PM$_{2.5}$ levels. The main results were as follows:

(1) From 2015 to 2019, PM$_{2.5}$ in the study area showed an overall downward trend. The Beijing–Tianjin–Hebei region and Henan Province decreased for the period of 2015 to 2019; Shanxi and Shandong Provinces expressed a variation trend of an inverted U-shape and U-shape, respectively. In a word, air quality in the study area had been improving from 2015 to 2019.

(2) From the perspective of spatial distributions, PM$_{2.5}$ concentrations in the study area indicated an obvious positive spatial correlation with “high–high” and “low–low” agglomeration characteristics. The high-value area of PM$_{2.5}$ was mainly concentrated in the junction of Henan, Shandong, and Hebei Provinces, which had a characteristic of moving to the southwest. The low values were mainly distributed in the northern part of Shanxi and Hebei Provinces, and the eastern part of Shandong Province.

(3) Socio-economic factor analysis showed that POP, UP, SI, and RD had a positive effect on PM$_{2.5}$ concentration, while GDP had a negative driving effect. In addition, PM$_{2.5}$ was also affected by PM$_{2.5}$ pollution levels in surrounding areas. Although PM$_{2.5}$ levels in the study area decreased, PM$_{2.5}$ pollution was still a serious problem until 2019. The significance of this study is to highlight the spatio-temporal heterogeneity of PM$_{2.5}$ concentration distributions and the driving role of socioeconomic factors on PM$_{2.5}$ pollution in the Beijing–Tianjin–Hebei region and its surrounding areas. Identifying the differences in PM$_{2.5}$ concentration caused by socioeconomic development is helpful to better understand the interaction between urbanization and ecological environmental problems.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/atmos12101324/s1, Table S1: Names and abbreviations of cities in the study region, Figure S1: the percentage of exceeding standard days in each city from 2015 to 2019, Figure S2: PM$_{2.5}$ concentration in each city and province from 2015 to 2019, Figure S3: Decreasing rate of PM$_{2.5}$ concentration in 2019 compared with 2015, Figure S4: Statistics of social and economic factors in each city from 2015 to 2019.

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