SPATIAL AND TEMPORAL DISTRIBUTION CHARACTERISTICS OF $PM_{2.5}$ AND VARIATION FACTORS OF THE AQI IN THE BEIJING-TIANJIN-HEBEI REGION FROM 2015 TO 2018

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Abstract. The current air pollution situation in northern China, especially in the Beijing-Tianjin-Hebei region, is particularly critical. How to prevent and control air quality in the Beijing-Tianjin-Hebei region has become the focus of China's environmental protection departments. Based on the hourly monitoring data from available monitoring stations in the Beijing-Tianjin-Hebei region from 2015 to 2018, The annual pollution frequency of the city was calculated, and the temporal and spatial distribution characteristics of the $PM_{2.5}$ concentration are analyzed in the study area from 2015 to 2018 by using the spatial interpolation method. The impact of various air pollutants and ground meteorological factors on air quality are studied using the Pearson correlation analysis method. The results are as follows: (1) With the increase of time, the pollution situation of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region has steadily improved. (2) $PM_{2.5}$ and PM_{10} were the decisive pollutants that had the greatest impact on the AQI. (3) The influence of ground pressure and temperature on the $PM_{2.5}$ concentration and the AQI were more closely related than other meteorological factors. These research results help to deepen the understanding and prediction of air quality changes in the Beijing-Tianjin-Hebei region and provide theoretical support for policy-makers to improve air quality in the region.
Keywords: *variation trend, multiple factors, spatial interpolation, correlation analysis*

Introduction

With increasing awareness of environmental protection, people are paying more attention to air pollution because these problems will not only have an adverse impact on the environment but also damage human health (Kuo et al., 2021). The concentration of fine particles has always been a key indicator of China's environmental quality and a core factor that restricts sustainable development (Qian et al., 2021). Therefore, particulate matter ($PM_{2.5}$) pollution has become a major and urgent challenge facing China and the focus of the central government (Liu et al., 2021). $PM_{2.5}$ pollution in the environment has been associated with a variety of adverse health effects (Ru et al., 2021). Many studies have reported that long term exposure to fine particulate matter ($PM_{2.5}$) will increase the risk of chronic obstructive pulmonary disease (COPD) (Bo et al., 2021). Globally, the number of COPD deaths and the daily deaths caused by environmental $PM_{2.5}$ increased by more than 90% from 1990 to 2019 (Xiaorong et al., 2021). Exposure to long term air pollution, especially fine particulate matter, is a contributor to incidence rate and mortality worldwide and is also known as risk factor for coronary heart disease (CAD) and myocardial infarction (MI) (Slawsky et al., 2021).

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Moreover, long term $PM_{2.5}$ exposure is closely related to incidence rate and mortality rate of cancer (Pei et al., 2021). Therefore, understanding and analyzing the temporal and spatial distribution characteristics of $PM_{2.5}$ and the relevant influencing factors of the $PM_{2.5}$ concentration will help to deepen people's understanding of $PM_{2.5}$ and provide a reference for formulating air pollution control policies based on health effects. This is of great significance for controlling air pollution and protecting people's health (Yu et al., 2019).

The air quality index (AQI) can undoubtedly reflect the air quality of a region more directly, and its level directly affects the survival of human beings in a region, although the definition and scope of the AQI vary from country to country (Meng et al., 2021). Scholars all over the world have never stopped studying the regional trend changes and influencing factors of the AQI and its pollutants. Dutta et al. (2021) analyzed the air pollution trends and patterns of the three major cities in India under a temporal and spatial framework and pointed out that the seasonal distribution of the AQI showed that the pollution concentration was high in winter. Bhutiani et al. (2021), based on the temporal and spatial changes of air quality in integrated industrial estate, Haridwar, and its surrounding areas, demonstrated the important role of highway transportation in environmental air quality. Farhadi et al. (2018) analyzed the sensitivity of meteorological parameters and the instability index to the carbon monoxide concentration, particulate matter, and the AQI and discovered that particulate matter was the most important influence on the AQI. Mangayarkarasi et al. (2021) utilized $PM_{2.5}$ as the core factor, then, using the seasonal autoregressive comprehensive moving average and Facebook's Prophet database, proposed an AQI prediction model that provides strong support for the AQI prediction. In particular, during the worldwide novel coronavirus pandemic, regulators need to consider $PM_{2.5}$ and PM_{10} in monitoring ambient air quality so as to prevent potential hazards associated with human exposure (Richard et al., 2021). As the economic and political center of China, the Beijing-Tianjin-Hebei region has a large population density. An analysis of the change trend factors of the AQI in the Beijing-Tianjin-Hebei region not only is conducive for the formulation of environmental protection policies but also plays a reference role in the prevention and control of COVID-19 in the region.

This study set out to: (1) determine the decisive pollutants that affect the AQI and analyze the internal correlations of air pollutants; (2) analyze the temporal and spatial variation law of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region from 2015 to 2018; and (3) explore the important influencing factors of meteorological factors on the AQI and $PM_{2.5}$ concentration changes.

Data and Methods

Study area

The Beijing-Tianjin-Hebei region is located in the north of the North China Plain at a west longitude of 113°7′ 20″–119°50′47″ and a north latitude of 36°3′–42°36′58″ (*Fig. 1*). It is adjacent to the Yanshan Mountains in the north, the North China Plain in the south, the Taihang Mountains in the west, and Bohai Bay in the east. The terrain in the northwest and north is high, and the terrain in the south and east is relatively flat. The area includes a variety of geomorphic features, but it is still dominated by a plain landform with an altitude of -52 to 2836 m (Nuan et al., 2021). The Beijing-Tianjin-Hebei region is one of the four major industrial zones in China that includes two

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municipalities directly under the central government (Beijing and Tianjin) and 13 cities in Hebei Province such as Zhangjiakou, Chengde, Qinhuangdao, Tangshan, Langfang, Baoding, Cangzhou, Shijiazhuang, Hengshui, Xingtai, and Handan. It has an extremely important economic and political status (Meng et al., 2021).

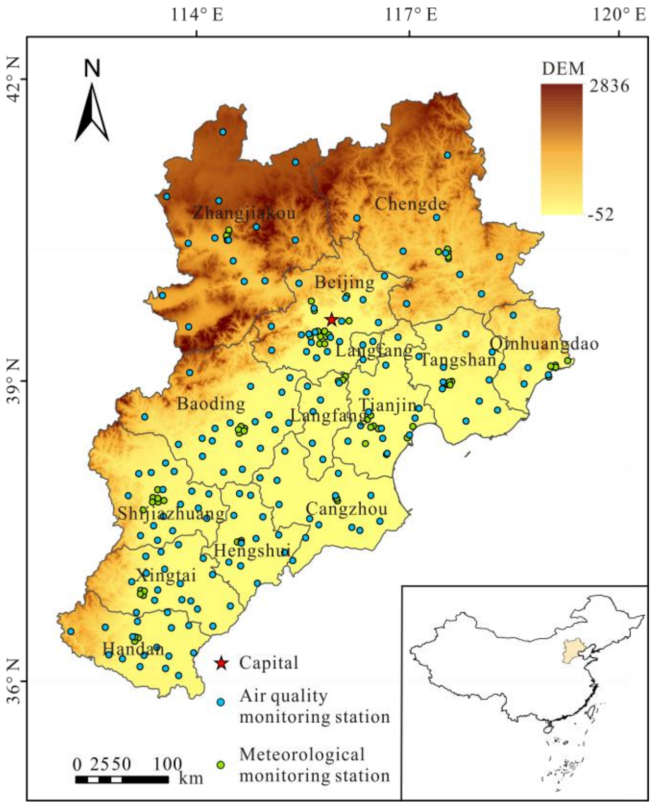

Figure 1. *Study area and monitoring station locations*

Data sources

The hourly air quality data of the Beijing-Tianjin-Hebei region from 2015 to 2018 included the AQI, $PM_{2.5}$, O_3, PM_{10}, NO_2, SO_2, and CO. There exist 72 available air quality monitoring points in the study area (*Fig. 1*), and they publish their data on the national urban air quality real-time release platform of the China Environmental Monitoring Station (http://www.cnemc.cn). The pollutant concentration data used in the calculation in this paper is the hourly data. The IAQI of single category pollutants is calculated by using the concentration limit of single category pollutants and the concentration of pollutants respectively, and the maximum value in the calculation result is the air quality index of this hour or that day.

The hourly meteorological data observed in the Beijing-Tianjin-Hebei region from 2015 to 2018 included the temperature, ground pressure, relative humidity, two-minute average wind speed, two-minute average wind direction, precipitation, and other parameters. There are 171 meteorological monitoring stations in the study area (*Fig. 1*). The China Meteorological Data Network (http://data.cma.cn) Release contains data that are quality controlled. Therefore, actual rate of each data parameter exceeds 99.9%, and the accuracy of the data is near 100%.

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Study methods

Correlation analysis

A Pearson correlation analysis is suitable for measuring the degree of correlation between two variables, and this is defined as the quotient of the covariance and standard deviation between two variables. The correlation coefficient is between -1 and 1. When the absolute value is closer to 0, the correlation is weaker. When the absolute value is closer to 1, the correlation is stronger (Yao, 2021). The correlation grades are shown in *Table 1*.

Table 1. *Correlation strength comparison*

Correlation coefficient (r)	Degree of correlation between variables
1.0≧|r|≧0.8	Extremely strong correlation
0.8>|r|≧0.6	Strong correlation
0.6>|r|≧0.4	Moderate correlation
0.4>|r|≧0.2	Weak correlation
0.2>|r|	Weak correlation, Basically irrelevant

Spatial interpolation method

The spatial interpolation algorithm is based on the data of known sample points and is used to deduce unknown data in the same area. An inverse distance weighted interpolation (IDW) combines the advantages of the multiple regression gradient method and the natural proximity method. It is a global interpolation method. Experiments have demonstrated that the predicted sample values on a continuous surface generated by the inverse distance weighted interpolation method are completely equal to the actual measured sample values. Hence, the IDW is an accurate interpolation method (Rahman and Lateh, 2016).

Results

Subsection

The correlations between the concentrations of various kinds of atmospheric pollutants and air quality are shown in *Figure 2*.

The AQI had a very significant and very strong positive correlation with $PM_{2.5}$ and PM_{10}, with correlation coefficients of 0.877 and 0.947, respectively. Among the six types of pollutants, $PM_{2.5}$ and PM_{10} had the greatest impact on the AQI and were determined to be decisive pollutants. With increases in the $PM_{2.5}$ and PM_{10} concentrations, the air quality became significantly worse.

The correlation coefficient of $PM_{2.5}$ with PM_{10} with CO passed the significance level test of $P < 0.05$. $PM_{2.5}$ showed a strong positive correlation with PM_{10} and the CO and NO_2 concentrations, and the correlation coefficients were 0.775, 0.814, and 0.642, respectively.

There was a significant and strong positive correlation between the SO_2 concentration and the NO_2 concentration, and the correlation coefficient was 0.743. There was a significant and strong negative correlation with the O_3 concentration, and the correlation coefficient was -0.777.

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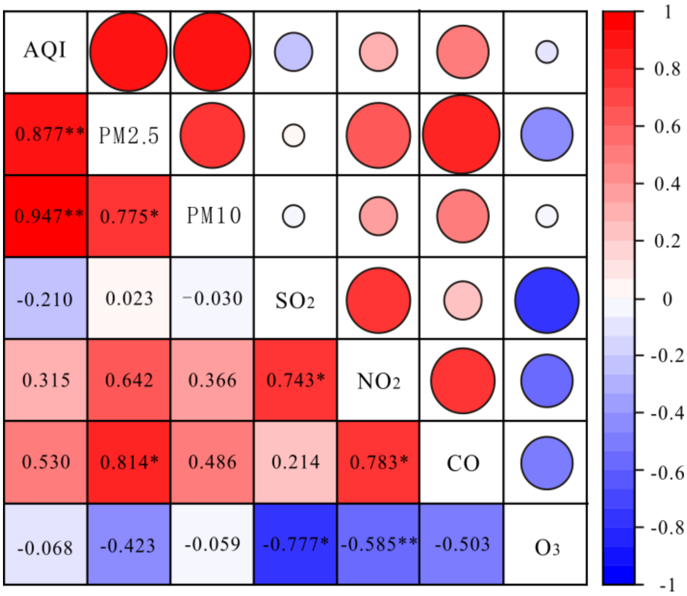

***Figure 2.** Correlations between the atmospheric pollutant concentration and the AQI*

There was a significant and strong positive correlation between the NO_2 concentration and the CO concentration, with a correlation coefficient of 0.783, and a very significant and moderate negative correlation with the O_3 concentration, with a correlation coefficient of -0.585. The concentrations of CO and O_3 showed insignificant and moderate negative correlations, respectively. The concentration of O_3 was negatively correlated with the concentration of the other five pollutants, among which the correlation coefficient was the strongest with the concentration of SO_2 and the smallest with the concentration of PM_{10}. The correlation degree between SO_2 and PM_{10} was the weakest.

The annual temporal and spatial distribution characteristics of $PM_{2.5}$

The inverse distance weighted spatial interpolation method was used to interpolate the annual average concentration of $PM_{2.5}$ of 72 air quality monitoring stations in the Beijing-Tianjin-Hebei region from 2015 to 2018, and the continuous surface generated by interpolation is shown in *Figure 3*. From 2015 to 2018, the annual average concentration range of $PM_{2.5}$ in Beijing Tianjin Hebei region was 28–114 ug/m³ (2015, *Fig. 3a*), 26–101 ug/m³ (2166, *Fig. 3b*), 25–90 ug/m³ (2017, *Fig. 3c*), 7–75 ug/m³ (2018, *Fig. 3d*).

From 2015 to 2018, the southern regions of the Beijing-Tianjin-Hebei region, primarily Baoding, Xingtai, Shijiazhuang, Hengshui, and Handan, had the highest annual average concentration of $PM_{2.5}$ compared with other regions that were seriously affected by fine particles. The central region primarily includes Cangzhou, Tianjin, Langfang, Tangshan, and Beijing. The annual average concentration of $PM_{2.5}$ was low and was less affected by fine particles. Zhangjiakou, Chengde, and Qinhuangdao in the northern region had the lowest annual average concentrations of $PM_{2.5}$ and were less affected by fine particles (*Fig. 3*).

Generally speaking, the distribution of $PM_{2.5}$ high concentration areas in the Beijing-Tianjin-Hebei region from 2015 to 2018 was basically unchanged, but the highest value of $PM_{2.5}$ concentration showed a decreasing trend with time. In terms of the spatial

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distribution, the annual average concentration of $PM_{2.5}$ from high to low showed distribution characteristics of the highest in the south, the second in the middle, and the lowest in the north.

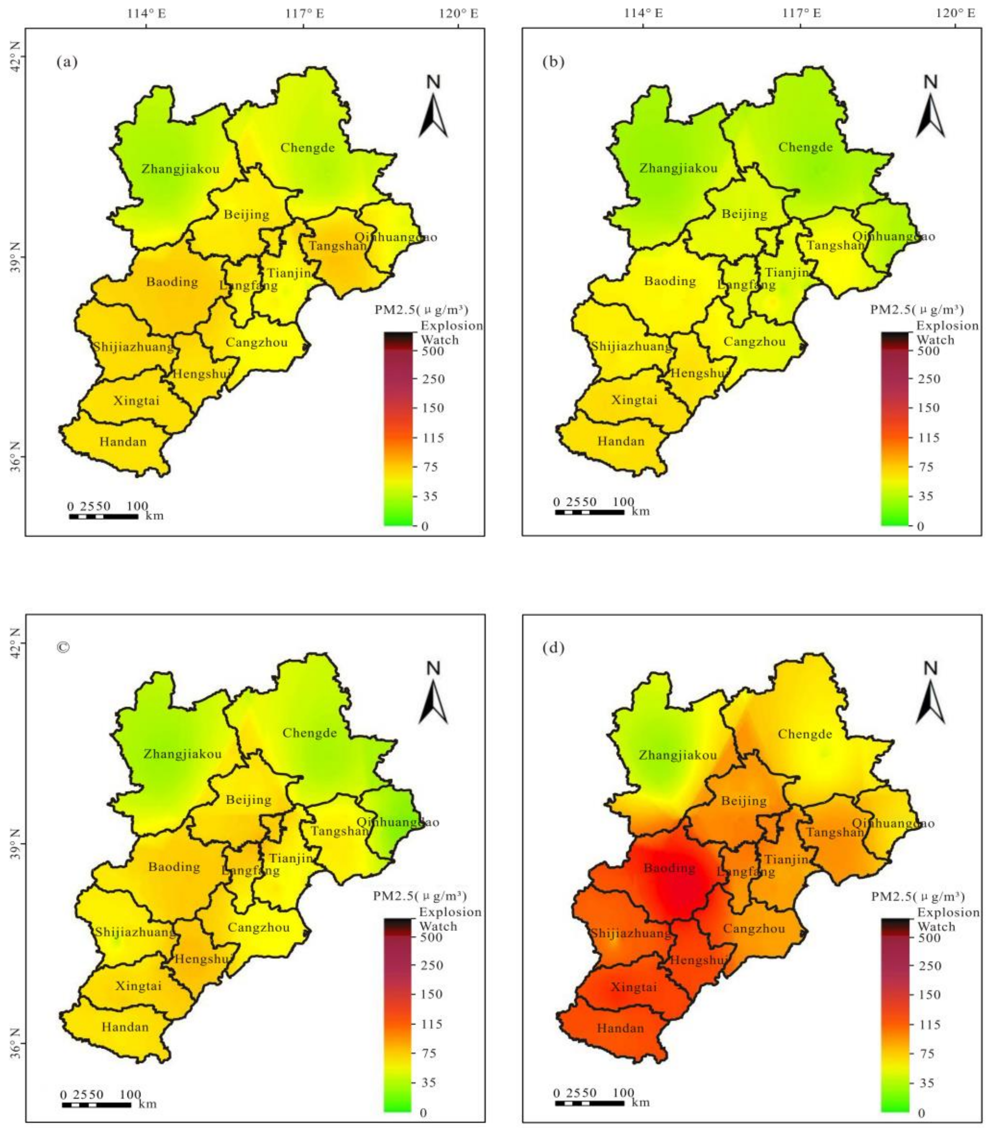

Figure 3. *The annual average concentration distribution of $PM_{2.5}$ from 2015 to 2018*

Seasonal temporal and spatial distribution characteristics of $PM_{2.5}$

According to the climate status of the Beijing-Tianjin-Hebei region in China, the $PM_{2.5}$ concentration data of all the air quality monitoring stations in the Beijing-Tianjin-Hebei region from 2015 to 2018 were divided into four seasons according to the time attribute as shown in *Table 2*.

Table 2. *Season determination*

Seasons	Spring	Summer	Autumn	Winter
Month	3, 4, 5	6, 7, 8	9, 10, 11	12, 1, 2

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The seasonal spatial and temporal distribution of the $PM_{2.5}$ concentration in the Beijing-Tianjin-Hebei region during 2015–2018 is shown in *Figure 4*.

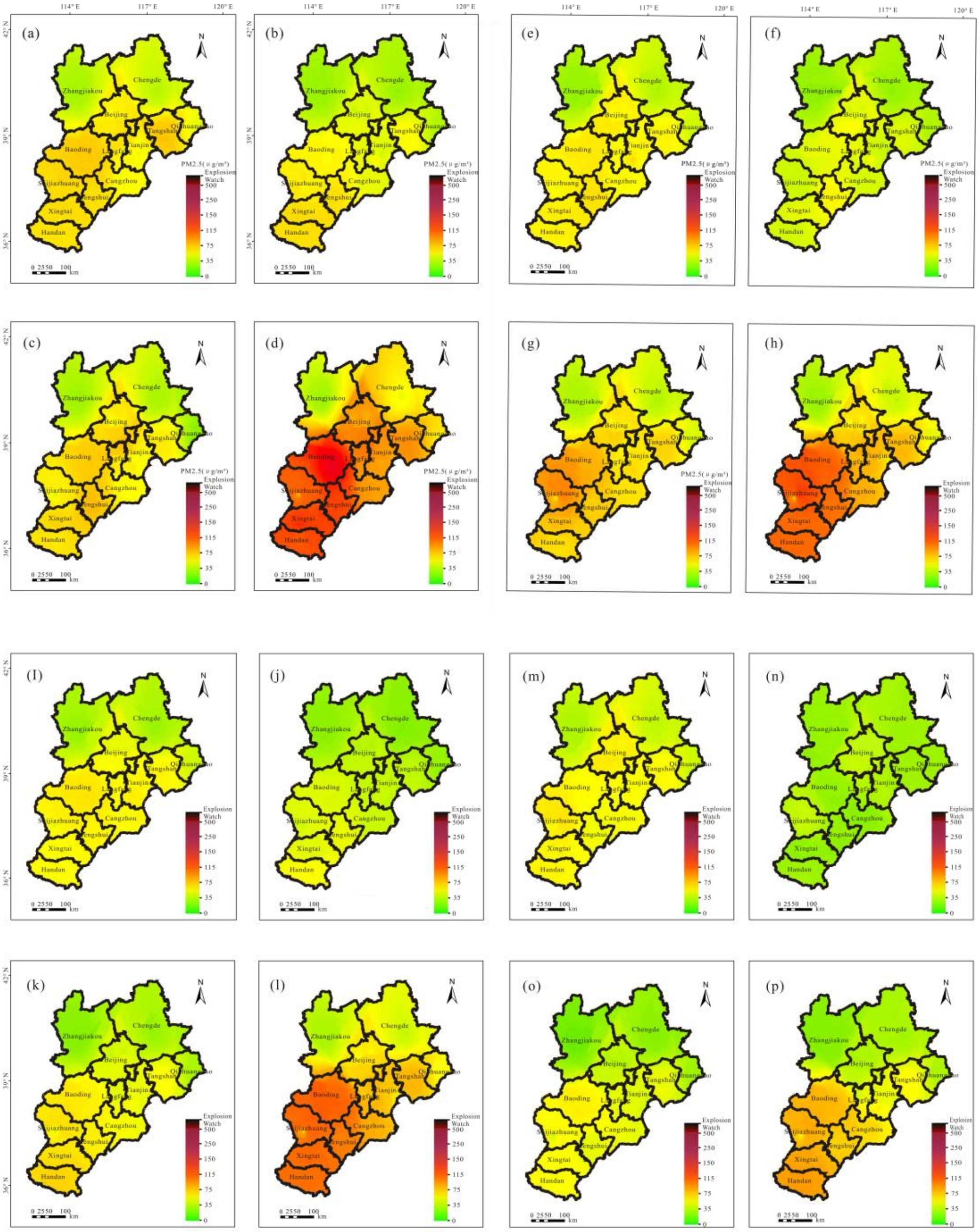

Figure 4. *Seasonal spatial distribution of the $PM_{2.5}$ average concentration from 2015 to 2018*

In the spring of 2015, the minimum concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 28 ug/m³, and the maximum value was 97 ug/m³. The average concentration of $PM_{2.5}$ was the highest in the south, followed by the middle, and the lowest in the north (*Fig. 4a*). The minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region in summer was 24 ug/m³, and the maximum value was 91 ug/m³. The atmospheric environment in the southern part of the Beijing-Tianjin-

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Hebei region was most seriously affected by the concentration of $PM_{2.5}$, and the atmospheric environment in the northern portion was least affected by the concentration of $PM_{2.5}$. The concentration of $PM_{2.5}$ was low in most areas, and the overall air quality of the region was the best (*Fig. 4b*). The minimum average concentration of $PM_{2.5}$ in autumn was 23 ug/m³, and the maximum value was 102 ug/m³. The maximum average concentration of $PM_{2.5}$ had an obvious upward trend compared with summer. The high value area of the $PM_{2.5}$ concentration was primarily distributed in the south, and the $PM_{2.5}$ concentration in the north was the lowest (*Fig. 4c*). In winter, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 27 ug/m³, and the maximum value was 211 ug/m³. The highest $PM_{2.5}$ concentration was primarily distributed in the south, the lowest $PM_{2.5}$ concentration in the north, and the Beijing-Tianjin-Hebei region has the worst air quality in winter (*Fig. 4d*).

In the spring of 2016, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 25 ug/m³, and the maximum value was 80 ug/m³. The atmospheric environment in the south was most affected by the concentration of $PM_{2.5}$, and the concentration of $PM_{2.5}$ in the north was the lowest (*Fig. 4e*). In summer, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 22 ug/m³, and the maximum value was 70 ug/m³. The high value areas were primarily distributed in Hengshui and Beijing, and the concentrations of $PM_{2.5}$ in the other areas were low (*Fig. 4f*). The minimum average concentration of $PM_{2.5}$ in autumn was 30 ug/m³, and the maximum value was 126 ug/m³. Compared with summer, the maximum value increased by 56 ug/m³, and the minimum value increased by 8 ug/m³. The high P value area was primarily distributed in the south, and the $PM_{2.5}$ concentrations in other areas were low (*Fig. 4g*). The average concentration in winter was 27 ug/m³, and the maximum value was 170 ug/m³. In addition, the highest concentration displayed a rapid upward trend. The high value area was primarily distributed in the south of the Beijing-Tianjin-Hebei region, followed by the central region (*Fig. 4h*).

In the spring of 2017, the minimum concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 27 ug/m³, and the maximum value was 77 ug/m³. The high value area was primarily distributed in Baoding, and the concentrations of $PM_{2.5}$ in Zhangjiakou and Chengde in the north were the lowest (*Fig. 4i*). In summer, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 19 ug/m³, and the maximum value was 73 ug/m³. The high value areas were primarily concentrated in the south, of which the atmospheric environmental pollution in Handan was most seriously affected by the concentration of $PM_{2.5}$, and the concentration of $PM_{2.5}$ in the north was low (*Fig. 4j*). The minimum average concentration of $PM_{2.5}$ in autumn was 12 ug/m³, and the maximum value was 85 ug/m³. The high value areas were primarily distributed in Handan and Xingtai in the south. The impact of the $PM_{2.5}$ concentration on the atmospheric environment during autumn was significantly more serious than during spring and summer (*Fig. 4k*). In winter, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 25 ug/m³, and the maximum value was 157 ug/m³. Compared with other seasons, the average concentration of $PM_{2.5}$ was the largest in winter, and the pollution degree of the atmospheric environment was also the most seriously affected by the $PM_{2.5}$ concentration. The high value area was primarily distributed in the south, and the $PM_{2.5}$ concentrations in Zhangjiakou and Chengde in the north were the lowest (*Fig. 4l*).

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In the spring of 2018, the minimum average concentration range of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 9 ug/m³, and the maximum value was 79 ug/m³. The high value areas were primarily distributed in Baoding. The atmospheric environment of Zhangjiakou and Chengde in the north was the least affected by the $PM_{2.5}$ concentration, and the $PM_{2.5}$ concentration was the lowest (*Fig. 4m*). In summer, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 17 ug/m³, and the maximum value was 50 ug/m³. In summer, the concentration of $PM_{2.5}$ in the study area was low, and the maximum value pm significantly (*Fig. 4n*). The minimum average concentration of $PM_{2.5}$ in autumn was 19 ug/m³, and the maximum value was 73 ug/m³. The high value areas were primarily distributed in Handan, Baoding, and Shijiazhuang in the south, and the atmospheric environment in the north was least affected by the $PM_{2.5}$ concentration (*Fig. 4o*). In winter, the minimum average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region was 26 ug/m³, and the maximum value was 113 ug/m³. In winter, the concentration of $PM_{2.5}$ reached the maximum value in a year, and the high value areas were primarily distributed in the south. Zhangjiakou and Chengde in the north were the least affected by the concentration of $PM_{2.5}$, and the concentration of $PM_{2.5}$ was the lowest (*Fig. 4p*).

Overall, from 2015 to 2018, the regional distribution of high $PM_{2.5}$ concentrations in each corresponding season in the Beijing-Tianjin-Hebei region was roughly the same, with high concentrations in the south, followed by the middle and low concentrations in the north. With increased time, the pollution during the four seasons eased from 2015 to 2018, and the overall $PM_{2.5}$ concentration decreased. According to the chronological order of different years, the $PM_{2.5}$ concentration was the highest in winter, with the widest impact on the distribution range, and the pollution was the most serious. The concentration of $PM_{2.5}$ was the lowest in summer. The ranking of the $PM_{2.5}$ concentration from low to high was the following: summer < spring < autumn < winter.

The frequency of exceedance of PM2.5 concentration in cities

The 24-hour mean value data of $PM_{2.5}$ in each city in the study area from 2015 to 2018 are statistically analyzed and compared with the air quality standard of $PM_{2.5}$ (0-35 $\mu g/m^3$ is good, 35-75 $\mu g/m^3$ is moderate, and more than 75 $\mu g/m^3$ is polluted) specified in 《Ambient Air Quality Standard》(GB 3095—1996). *Figure 5a,b* is obtained.

Taking Beijing as an example, from 2015 to 2018, the annual frequency of air quality ($PM_{2.5}$) above moderate level has increased year by year. The annual frequency of good level increases year by year, from 29.32% in 2015 to 34.43% in 2018.The frequency of pollution level days decreases year by year, from 39.18% in 2015 to 20.60% in 2018, with a decrease of 18.58%. The air quality is significantly improved (*Fig. 5*).

Among the cities in Beijing Tianjin Hebei region, the air quality of $PM_{2.5}$ in Hengshui City improved most significantly. The frequency of polluted level days in the whole year decreased by 35.24% from 55.77% in 2015 to 19.76% in 2018, and the good level frequency also increased from 36.26% to 55.35%, an increase of 19.09%. Zhangjiakou is relatively unique, from 2015 to 2018, although the air quality has improved slightly, the change range is the smallest. In 2016, the polluted level frequency even increased in Zhangjiakou, but in 2015, most of the pollution frequencies of other cities in Beijing Tianjin Hebei region were more than 30%. The polluted frequency of Zhangjiakou was 4.93%, and the frequency of good air quality was as high

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as 63.84% (*Fig. 5*). The high quality of air quality and the stability of change, it may benefit from the excellent geographical location of Zhangjiakou in Shankou.

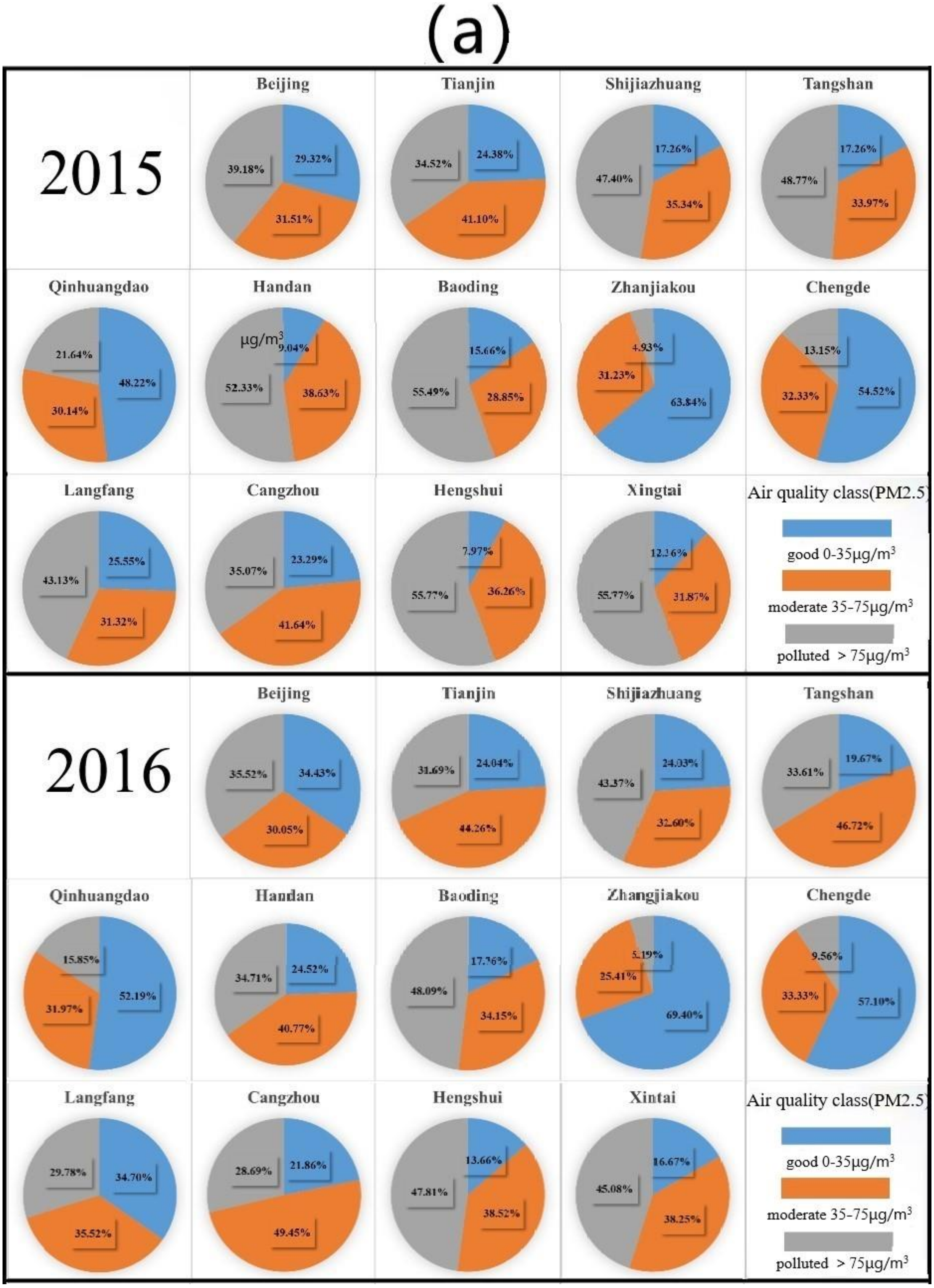

Figure 5(a). *Annual frequency of air quality($PM_{2.5}$) from 2015 to 2016*

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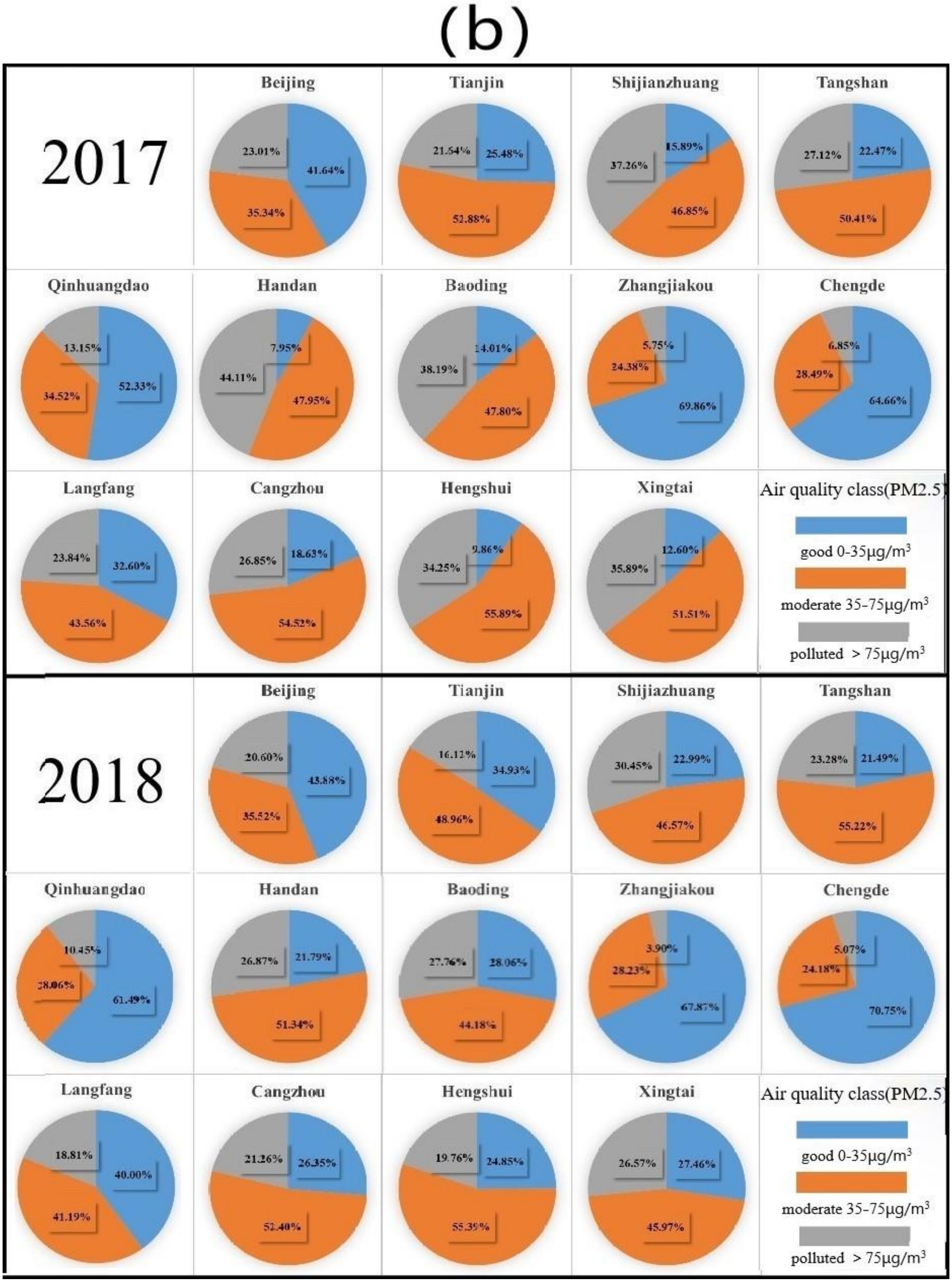

Figure 5(b). *Annual frequency of air quality($PM_{2.5}$) from 2017 to 2018*

Influence of meteorological factors on air quality

A correlation analysis between the meteorological factors, air quality, and air pollutants was conducted, and the results are shown in *Figure 6*.

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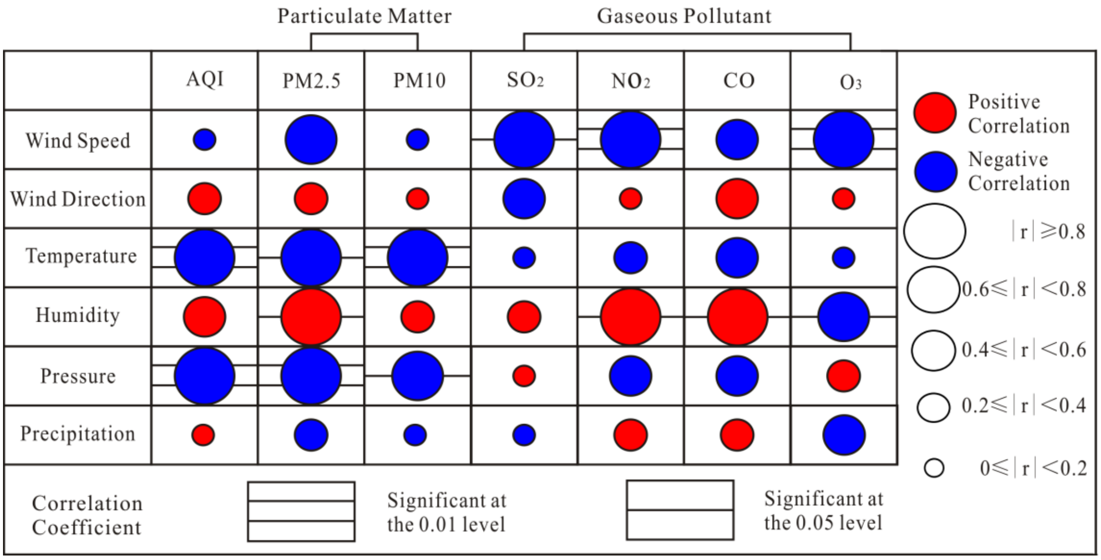

Figure 6. *Correlation of the meteorological factors with the AQI and air pollutants*

Wind speed had a very significant and very strong negative correlation with SO_2 and NO_2, with correlation coefficients of -0.815 and -0.859, respectively. Wind speed had a significant and strong negative correlation with O_3, with correlation coefficient of -0.918, and had no significant negative correlation with the AQI and other pollutants (*Fig. 6*). On the whole, the average wind speed in the study area had a negative correlation with the AQI and the concentrations of six pollutants. This means that when the average wind speed was greater, the smaller the concentration of various pollutants, and the better the air quality.

Wind direction had no significant correlation with the AQI and the six types of pollutants. Wind direction had a medium positive correlation with CO, a medium negative correlation with SO_2, and a weak positive correlation with the AQI and other pollutants (*Fig. 6*). On the whole, the wind direction value is negatively correlated with SO_2 and positively correlated with other air pollutants. The smaller the wind direction (the larger the value means that the wind direction was more east and south) value, the greater the SO_2 content, the smaller the content of other air pollutants, and the smaller the AQI, and the better the air quality. Compared with other pollutant concentrations, the influence of wind direction on SO_2 and CO was more significant.

Temperature had a very significant and very strong negative correlation with the AQI and PM_{10}, and the correlation coefficients were -0.929 and -0.924, respectively. Temperature had a significant and very strong negative correlation with $PM_{2.5}$, and the correlation coefficient was -0.806, but it had no significant negative correlation with other pollutants (*Fig. 6*). The research demonstrated that temperature had a negative correlation with the AQI and the concentration of six pollutants. When the temperature increased, this was conducive to the diffusion of pollutants. In addition, the concentrations of various pollutants were reduced, improving air quality.

Humidity had a significant and very strong positive correlation with $PM_{2.5}$, NO_2, and CO, and the correlation coefficients were 0.812, 0.823, and 0.833, respectively. Humidity had a significant and strong negative correlation with O_3, and the correlation coefficient was -0.790. Humidity had insignificant and medium positive correlations with the AQI, which was related to PM_{10} (*Fig. 6*). The results showed that the relative

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humidity was positively correlated with the AQI and the concentrations of five pollutants except O_3. This means that the greater the relative humidity, the smaller the O_3 concentration, but the concentration of other pollutants increased, especially the concentrations of $PM_{2.5}$, NO_2, and CO, which accelerate the accumulation of pollutants and easily cause heavy pollution.

There was a very significant and very strong negative correlation between pressure and the AQI and $PM_{2.5}$, and the correlation coefficients were -0.894 and -0.868, respectively. There was a significant and strong negative correlation between pressure and PM_{10}, and the correlation coefficient was -0.790. The pressure had a moderate positive correlation with NO_2 and CO, a weak positive correlation with O_3, and a very weak positive correlation with SO_2 (*Fig. 6*). The results showed that the greater the near surface pressure, the more favorable the diffusion of the pollutant concentration, the lower the concentrations of various pollutants, and the better the air quality.

Precipitation had a very weak positive correlation with the AQI, a weak positive correlation with NO_2 and CO, a moderate negative correlation with O_3, a weak negative correlation with $PM_{2.5}$, and a very weak negative correlation with PM_{10} and SO_2. The correlations between precipitation and the AQI and the six types of pollutants were not significant (*Fig. 6*). The research showed that when the precipitation increased, the increasing and decreasing trends of various pollutants were different. However, generally speaking, the air quality was developing a favorable trend. In general, changes in temperature, humidity, and pressure had the greatest impact on the changes in the $PM_{2.5}$ concentration in the study area, and temperature and air pressure had the greatest contributions to changes in air quality in the study area.

Discussion

Currently, with the rapid industrial development in the world, the concentration of particulate matter and various air pollutants in the air continues to increase. The impact of various pollutants on air quality has always been a focus of world atmospheric environmental researchers. Mavrakis et al. (2021) studied the effects of early heat wave events on human thermal discomfort and urban air quality in an industrialized plain in the Mediterranean region, and they determined that particulate matter (diameter < 10 μm) had a significant impact on poor air quality. Vehicle emissions, dust events, and the combustion of fossil fuels and other organic compounds can increase the urban PM concentration (He et al., 2021; Grmasha et al., 2021). However, there have been different conclusions regarding the types of primary pollutants in the ambient air due to different regions and seasons. In the autumn of 2014–2018, the ozone concentration in the Pearl River Delta increased sharply and became the primary pollutant in the ambient air (Huang et al., 2021). Liu et al. (2020) determined that in Nanchong City, the $PM_{2.5}$ value showed a downward trend with each year, and $PM_{2.5}$ was the primary atmospheric pollutant. Bogomolova et al. (2021) concluded that $PM_{2.5}$ has the potential to predict novel corona pneumonia. From 2015 to 2018, the impact of PM_{10} and $PM_{2.5}$ on the AQI in the Beijing-Tianjin-Hebei region was far greater than that of other air pollutants (*Fig. 2*). Because $PM_{2.5}$ causes more direct harm to the human body, the primary pollutant affecting air quality in the Beijing-Tianjin-Hebei region was identified as $PM_{2.5}$, which is understandable because the Beijing-Tianjin-Hebei region is one of China’s four major industrial zones.

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The large-scale temporal and spatial distribution characteristics of $PM_{2.5}$ not only represent the temporal and spatial distribution characteristics of the AQI to a certain extent but also more intuitively reflect the harm caused by regional atmospheric environmental changes to the human body. Wang et al. (2019) and others used the $PM_{2.5}$ data of 338 cities in China from 2014 to 2017 for real-time monitoring, and they found that the annual average value of the $PM_{2.5}$ concentration decreased annually. However, more than two thirds of cities still exceeded the standard value specified by the Chinese government (35 μg/m3). The high concentration of $PM_{2.5}$ was primarily distributed in the Henan Province in the middle of east China (including Shandong, Jiangsu, Anhui, and other provinces) and the Beijing-Tianjin-Hebei region (Li et al., 2019; Zhao et al., 2021). The concentrations of $PM_{2.5}$ in northern and eastern China were higher than that in southern and western China (Zhou et al., 2019), and the primary air pollutant in northern China was also $PM_{2.5}$ (Huimin et al., 2021). There were obvious regional differences in the urban air quality. The average annual concentration of the AQI and $PM_{2.5}$ showed a ranking of the following: northern cities > southern cities, inland cities > coastal cities (Jia and Ye, 2019). The primary reason for the formation of haze is that the concentration of $PM_{2.5}$ is too high. Determining the spatial heterogeneity of the $PM_{2.5}$ concentration and its influencing factors is of great significance for regional air quality control and management. Zhou et al. (2019) showed that the decreasing trend of the $PM_{2.5}$ concentration in the Beijing-Tianjin-Hebei region from 2015 to 2018 agreed with the change trend of China’s air quality this year that showed the distribution characteristics of the highest in the south, the second in the middle, and the lowest in the north (*Fig. 3*). This was also caused by the industrial distribution in the Beijing-Tianjin-Hebei region and the decrease in altitude when the terrain in the region decreased from the north to the south (*Fig. 1*). From 2015 to 2018, most cities in Beijing Tianjin Hebei region showed that the frequency of annual pollution days decreased year by year, and the frequency of annual excellent air quality days increased year by year. The frequency of $PM_{2.5}$ in the whole region was roughly the same. The emission of $PM_{2.5}$ was significantly controlled and improved year by year, and the air quality was getting better and better (*Fig. 5*). Different from other cities, Zhangjiakou has a unique and stable change law, which also confirms that the change trend of $PM_{2.5}$ concentration has spatial differences and regional characteristics. Seasonal variation was very evident in the temporal and spatial variation of the $PM_{2.5}$ concentration. Zhang et al. (2019) showed that the air quality in summer and autumn was better than that in spring and winter by using data from national monitoring stations in 2015. In Tibet, the pollutant concentration in winter was even 38% higher than that in summer (Deqing et al., 2021). There were obvious seasonal differences in the air quality and pollutant concentrations in the Beijing-Tianjin-Hebei region (Cheng et al., 2019). The variation in the $PM_{2.5}$ concentration in Shijiazhuang City in the Beijing Tianjin Hebei region was ranked as the following: winter > autumn > spring > summer (Yue et al., 2021). From 2015 to 2018, the spatial distribution of high $PM_{2.5}$ concentration areas in each season in the Beijing-Tianjin-Hebei region was basically the same. The seasonal change was basically consistent with the national $PM_{2.5}$ change trend and was ranked as the following: winter > autumn > spring > summer (*Fig. 4*).

A study that examines the driving factors of air quality change and $PM_{2.5}$ concentration change is conducive for formulating targeted environmental improvement policies. Secondary aerosols contribute greatly to the $PM_{2.5}$ concentration. Low temperature, low wind speed, and high relative humidity will aggravate the

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accumulation of regional pollutants in winter (He et al., 2021). In Chengdu, the air quality had a significant positive correlation with the air temperature, air pressure, visibility, and sunshine hours (Cheng et al., 2018). Sindosi et al. (2021) used the city of Ivanina in northern Greece as an example, and they showed that, in addition to meteorological factors, socioeconomic factors also determined the level of atmospheric particulate matter. Bowen et al. (2021) confirmed that changes in the $PM_{2.5}$ concentration were affected by many factors by using the daily air pollutant concentration and meteorological element data of Lanzhou from 2013 to 2020. By utilizing the air pollution index and surface meteorological elements of the Beijing-Tianjin-Hebei region from 2001 to 2010, Shi et al. (2018) confirmed that meteorological factors had an important impact on air pollution. The novel coronavirus pneumonia outbreak occurred at the end of 2019, and the air quality and $PM_{2.5}$ concentration have been shown to be significantly associated with the spread of novel coronavirus pneumonia. Changes in human activity have had a significant impact on air quality during the novel coronavirus pneumonia period (Bogomolova et al., 2021; Gao et al., 2021). The AQI of most cities decreased significantly in NO_2, SO_2, Co, $PM_{2.5}$, and PM_{10}, but the change in O_3 was not significant (Fu et al., 2020). The mortality of the novel coronavirus pneumonia was found to be positively correlated with the mean temperature and the AQI. However, mortality was found to be independent of wind speed, relative humidity, and precipitation (Huang et al., 2020). This suggests that the novel coronavirus pneumonia case fatality rate (CFR) may be predicted by $PM_{2.5}$ and other air pollutants (Hou et al., 2020). The increases in temperature and air pressure in the Beijing-Tianjin-Hebei region from 2015 to 2018 led to a significant decrease in the air quality index in the study area. Wind speed, wind direction, humidity, and precipitation had no significant impact on the air quality index in the study area. The change in the $PM_{2.5}$ concentration in the study area had strong correlations with the temperature, humidity, and air pressure (*Fig. 6*), and the variation in the regional temperature and atmospheric pressure played an important role in the regional air quality trend.

Conclusions

(1) $PM_{2.5}$ and PM_{10} had the greatest impact on the air quality index and were decisive pollutants. PM_{10} and CO had the greatest impact on $PM_{2.5}$, and CO had the greatest impact on PM_{10}.

(2) From 2015 to 2018, the overall air quality of the Beijing-Tianjin-Hebei region obviously recovered and developed in a good direction. From the perspective of the spatial distribution, the $PM_{2.5}$ high value area was primarily concentrated in the south, and the areas least affected were primarily concentrated in Chengde and Zhangjiakou. Overall, the annual average concentrations of $PM_{2.5}$ areas from low to high in the study area were ranked in the following order: north < central < south.

(3) From 2015 to 2018, the concentration of $PM_{2.5}$ decreased during each season, but the spatial distribution of the high value area of the $PM_{2.5}$ concentration during each season remained basically the same. The pollution degree and pollution range were similar in different seasons, ranking as the following: winter > autumn > spring > summer. There was no significant difference in the regional distribution characteristics of the high $PM_{2.5}$ value during the same season.

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(4) From 2015 to 2018, the $PM_{2.5}$ air quality of cities in Beijing Tianjin Hebei region improved year by year, the frequency of annual pollution days decreased year by year, and the frequency of annual high-quality air quality days increased year by year.

(5) An increase in temperature and air pressure significantly reduced the air quality index in the study area, and the air quality improved. The influences of wind speed, wind direction, humidity, and precipitation on the air quality index in the study area were not significant. However, a change in the $PM_{2.5}$ concentration in the study area had a strong correlation with temperature, humidity, and air pressure. An increase in temperature and air pressure and a decrease in humidity led to a significant decrease in the air quality index in the study area, and the air quality developed a good trend. Changes in wind speed, wind direction, and precipitation had no significant correlations with changes in the $PM_{2.5}$ concentration in the study area.

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