Hindawi
Advances in Meteorology
Volume 2022, Article ID 4051221, 11 pages
https://doi.org/10.1155/2022/4051221

Research Article

Reduced Air Pollution during the Prevailing of COVID-19 Pandemic: Five Years Observation and Path Analysis in the Fenwei Plain, Northwest China

Yuanyuan Meng[1] **and Wanlong Sun**[2]

[1]*State Key Laboratory of Continental Dynamics, Department of Geology, Northwest University, Xi'an 710069, China*
[2]*Shaanxi Minernal Resources and Geological Survey, Xi'an 710068, China*

Correspondence should be addressed to Yuanyuan Meng; myychd@163.com

Received 30 January 2022; Revised 21 March 2022; Accepted 1 April 2022; Published 27 April 2022

Academic Editor: Giulia Pavese

Heavy pollution in North China has attracted extensive attention in recent decades, and numerous studies have been conducted in developed regions, while studies on the heavily polluted Fenwei Plain in Northwest China are still scarce. In this study, we analyzed the continuous air pollution records of Weinan city on the Fenwei Plain from 2016 to 2020 to provide specific prevention and control strategies for the region. From 2016 to 2020, pollutant concentrations showed an overall decreasing trend, with a slight increase in O_3 concentration. The study found that during the COVID-19 lockdown period, O_3 was also significantly affected by the lockdown policy. During the prevailing COVID-19 pandemic in 2020, anthropogenic emissions were reduced due to restraints on commercial and social activities. NO_2 responds sensitively during COVID-19, and $PM_{2.5}$ has a delayed response. We applied pathway analysis to investigate the contribution of different pollutants and meteorology to $PM_{2.5}$. The results show that CO and NO_2 have the largest positive comprehensive effect, while wind speed and temperature have the largest negative comprehensive effect. Spearman's correlation analysis shows that NO_2 contributes significantly to O_3 production in different AQI ranges. We advocate that the NO_x should be given more attention and become the new focus of air control.

1. Introduction

Both accelerated economic growth and rapid urbanization occurred in China during the past 40 years. China's urbanization rate has increased, twice as much as Economic Reform and open up. While the economy is growing at a high rate, it is also generating serious environmental problems. Air pollution has always been a critical topic for research in China, and it has attracted increasing public attention, although the causes and influencing factors of air pollution have never been fully explored and identified. The long period and high-resolution air pollution observation are needed to clarify the atmospheric pollution status in China [1]. The increased number of private cars and consumption of fossil fuels, as well as other anthropogenic factors, have led to the high level of CO_2, $PM_{2.5}$, PM_{10}, O_3, SO_2, and NO_2 in atmosphere [2]. Globally, about 87 percent of people live in environments with high PM2.5 concentrations (above standard limits set by the World Health Organization), and in low- and middle-income countries, 90 percent of the population lives with unsafe air pollution, according to previous studies [3]. Many surveys have studied the link between aerosol pollution and adverse health consequences [4–6]. For example, when $PM_{2.5}$ binds with PAHs, they can cause cancer and mutations linked to pollution of the atmosphere by human activities [7]. Further observations have shown that the type of city and its local emissions (e.g., residents heating-derived coal combustion emissions) have a great influence on the measured concentrations of air pollutants [8–10].

Air pollution (concentration, degree of pollution) varies significantly in different areas, depending on the city, energy mix, and local population. The Chinese government has taken note of the problem and adopted different solutions for different cities, proposing a “one city, one policy” policy for targeted governance. Therefore, we focus on Weinan city in the Fenhe and Weihe River plain to provide reference for the local government to control local pollution reasonably. The data from various air quality monitoring stations can be used to analyze the local aerosol pollution, and the establishment of air pollution forecast plays an important role [11].

In the past, many researches concentrated on the characteristics, sources, and mechanisms of PM contamination and their negative health effects in most of Chinese megacities (e.g., Beijing and Shanghai) were published [12–16]. Moreover, the reduction of social activities and business during the COVID-19 pandemic has decreased the total emissions of air pollutants to a certain extent, but the O_3 pollutant levels have not been reduced. Therefore, research on changes during the COVID-19 period is beneficial to the control of air pollution [17]. There were also some scholars which have conducted recent studies on the Fenwei Plain, which have examined the impact of rural solid fuel burning on biomarkers in women and have fully explained the air pollution-associated health hazards [18]. The characteristics and potential sources of atmospheric pollutants in Linfen area near the Weihe Plain were also reported [8]. These works concluded that the local pollution was aggravated by unfavorable meteorological conditions, such as weak wind speed, high humidity, low air temperature, and low boundary layer height. Therefore, meteorologies have been considered as the main factors of atmospheric pollution [19]. A city scale study (68 major cities in seven geographic regions) in China has shown that the $PM_{2.5}$ pollution was significantly influenced by different meteorological factors and other human factors, which also presented the spatial and seasonal variation [20]. However, the factors causing air pollution are relatively complex, different cities have unique industrial and agricultural development models, cultural characteristics, and geographical characteristics; therefore, it is not enough to only study the air pollution situation of big cities.

As the area surrounded by mountains, the adverse meteorological conditions occurred frequently in Fenwei Plain (Weinan city), which further influenced the air pollution. Air pollution in the region is serious, and the government has issued a comprehensive air pollution control document. The Fenwei Plain is located southwest of the Beijing-Tianjin-Hebei “2 + 26” urban circle. It is the general term for the Fenhe Plain, the Weihe Plain, and its terraces. The main cities include Xi’an, Xianyang, Weinan in Shaanxi Province, and other cities in Shanxi Province. In these cities, including Yuncheng, Linfen, and Lvliang, government documents encourage a focus on the air pollution situation in the Fenwei Plain, but there are few reports on air pollution in this region. Given that previous work is mainly interested in large cities and neglected in small- and medium-sized cities, we take the Weinan city (Fenwei Plain) as a case to study the five-year air pollution. The purposes are to explore the variations in the atmospheric pollution levels and air quality index (AQI) and to reveal the controlling factors of atmospheric contaminants by using the correlation coefficient and path analysis, in particular the COVID-19 influenced period during 2020.

2. Methodology

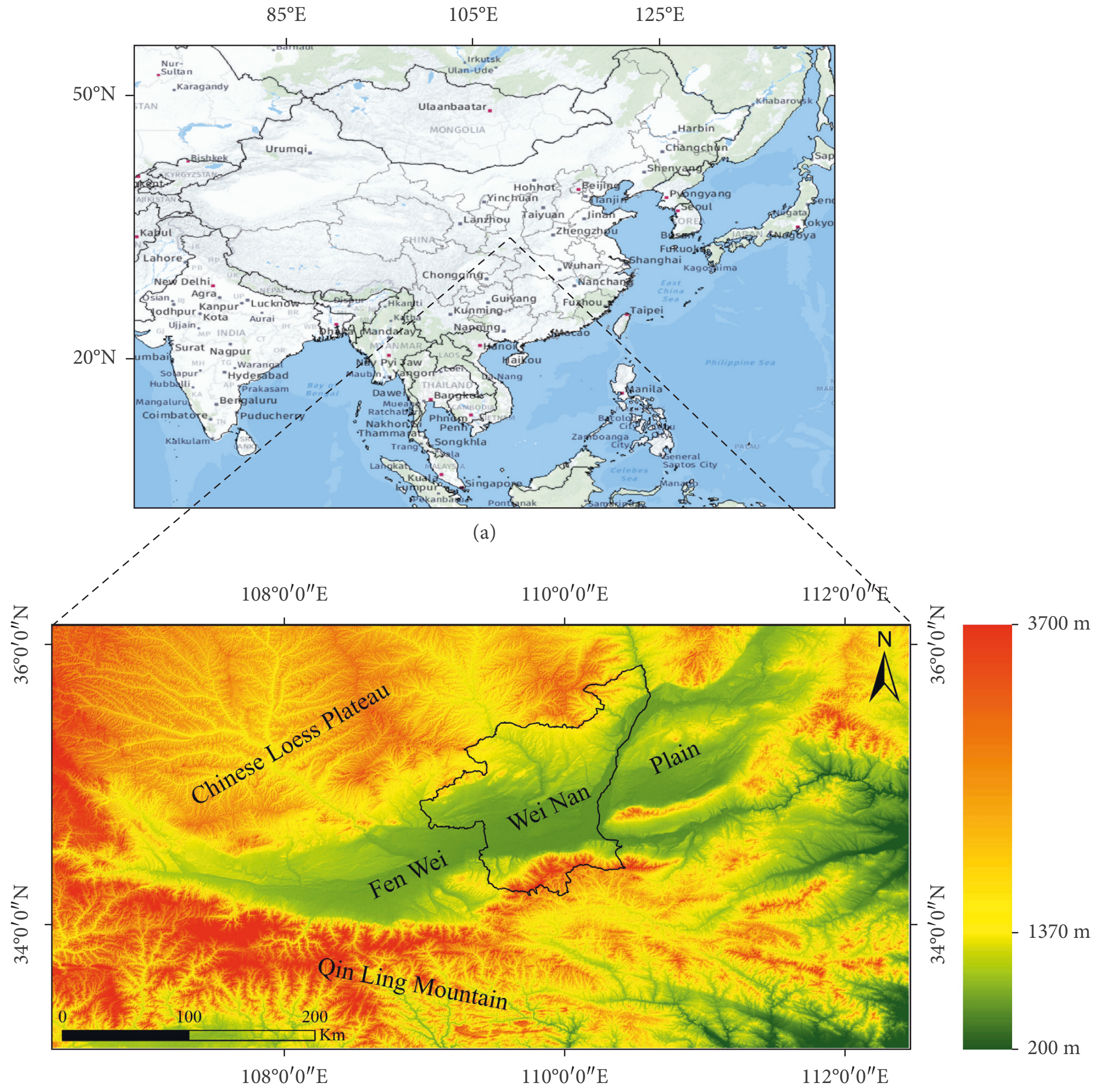
2.1. Study Region. Weinan city is located in the eastern part of the Fenwei Plain (108°58′~110°35′E and 34°13′~35°52′N) with a total area of 13030 km^2. The terrain is centered on the Weihe River, comprising five major mountains in the north and south, two plateaus, and central Pingchuan. As shown in Figure 1, the geographical location of Weinan city is surrounded by the Beishan Mountains in the north and Qinling Mountains in the south. Such natural topographical factors make it difficult for air pollutants to spread/diffuse.

The annual average value of meteorological factors in Weinan city from 2016 to 2020 is shown in Table 1. The warm temperate zone with a semihumid and semiarid monsoon climate is the characteristic of this area. Groundwater resources are abundant in the Weinan city, which are mainly distributed in the quaternary bedrock in the southern and northern mountainous areas and distributed in loose rock formations in the rest of areas.

2.2. Data Sources and Processing. The monitoring data of AQI, $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and O_3 concentration in Weinan city were taken from the China Environmental Monitoring Centre (CEMC). According to previous studies, the data from the CEMC are statistically reliable [21]. All data were collected from 2016 to 2020, including daily average values of the AQI and the six air pollutants mentioned above. The corresponding data of meteorology, including air temperature, relative humidity, wind speed, and visibility were taken from the China Meteorological Administration.

The AQI is an indicator to represent air quality, which is calculated by the concentrations of the following atmospheric pollutants: $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and O_3 [22]. The AQI value can vary between 0 and 500, the higher AQI value indicates worse air quality. The AQI can be divided into six degrees, that is, excellent (AQI = 0~50), good (AQI = 51~100), light pollution (AQI = 101~150), moderate pollution (AQI = 151~200), heavy pollution (AQI = 201~250), and severe pollution (AQI>300) [20]. The descriptive statistics and trend graphs of the particle mass concentration were performed by Origin 2018. Spearman’s correlation analysis was applied to analyze the relationship between particulate matter, meteorology data, and other atmospheric contaminants by IBM SPSS Statistics 26.

To date, there are still many uncertainties about the quantified source contribution of $PM_{2.5}$. To obtain effective air pollution prevention, it is necessary to carry out targeted control by combining the different characteristics of urban development and to adapt the measures to local conditions. Previous research data mainly investigated the relationship between many pollutant-related factors, but few studies considered the indirect impact of pollutants [23]. In this work, the path analysis (see details in [23]) was performed to



(a)

(b)

Figure 1: Geography of the study area: (a) the overall location of the study area; (b) the specific location of the study area.

Table 1: Annual average of meteorological factors in the study area for 2016–2020.

	2016	2017	2018	2019	2020
Temperature (°C)	14.8	15.2	14.9	14.7	14.1
Relative humidity (%)	68.2	67.1	68.0	68.7	68.0
Wind speed (m/s)	1.6	1.6	1.6	1.1	1.8

explain the direct or indirect effects between different variables and to better analyze the potential variations in the concentration of particulate matter and more comprehensively describes the complex relationship between particulate matter [24].

Path analysis was used to explain the factors of interest either directly or indirectly in combination with path coefficient evaluation, mainly to clarify the influence of meteorological factors and O_3, SO_2, NO_2, and CO on atmospheric particulate matter. The software used for the path analysis was IBM SPSS Amos 26.0.

The general methodology and procedures of the path analysis [23].

(i) The canonical equation of standardized linear regression:

$$R_{xx}b^* = R_{xy}, \tag{1}$$

where R_{xx} is the correlation matrix for $x_1, x_2, \ldots x_P, b_j^* = (b_1^*, b_2^*, \ldots, b_P^*)^T$, b_j^* is the direct effect of x_j on y, $r_{jk}b_k{}^*$ is the indirect influence of x_j on y through x_k, and R_{xy} is the correlation matrix of x to y.

(ii) According to equation $R_{xx}b^{*} = R_{xy,}$, the path coefficient $b_j^{*} = R_{xx}^{-1}R_{xx}$ is the inverse matrix of R_{xx}.

(iii) The decision coefficient can be obtained from the path coefficient:

$$\begin{aligned} R_j^2 &= b_j^{*\,2}, \\ R_{jk} &= R_{k_j} = 2b_j r_{jk} b_k, \end{aligned} \tag{2}$$

where R_j^2 is the direct determination coefficient of x_j to y, and R_{jk} is the indirect determination coefficient of x_j about y through χ_k.

(iv) The total decision coefficient of x_j about y is $R(j) = R_j^2 + \sum_{j \neq k} R_{jk} = 2\ b_r^2 r_{jk}\text{-}(b_j^{*})^2,\ j = 1, 2, \ldots, P.$

3. Results and Discussion

3.1. Annual Average Trend of Air Pollution and $PM_{2.5}/PM_{10}$ Trend Analysis. As shown in Figure 2, the overall pollutant concentration is in a decreasing trend from 2016 to 2019. It indicates that the effect of managing air pollutants in recent years is relatively significant. The trend of pollutant changes as well as the standard deviation value in the figure can be visualized. Compared with 2016, the reduction in concentration values of AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO in 2019 is 13%, 25%, 23%, 55%, 8%, 4%, and 30%. The greatest degree of reduction was seen in SO_2 and CO, with sulfur-containing coal and incomplete combustion being among the larger sources of these two pollutants. The concentration of pollutants has gradually decreased by eliminating obsolete equipment as well as improving the energy mix. China has made significant achievements in combating air pollution in recent years. Compared to 2019, the concentration values of each pollutant AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO are in a decreasing trend in 2020, 12%, 7%, 13%, 13%, 9%, 2%, and 11%, respectively. Due to the impact of the COVID-19 pandemic, some factory enterprises and others may be in a semireturned state with overall lower pollutant concentrations.

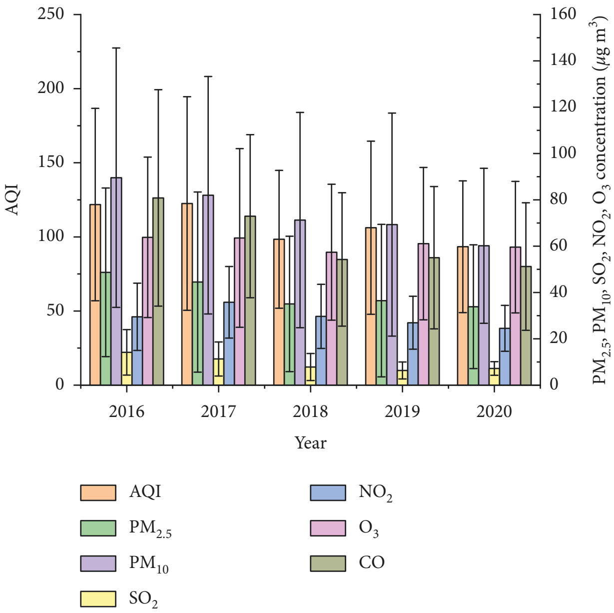
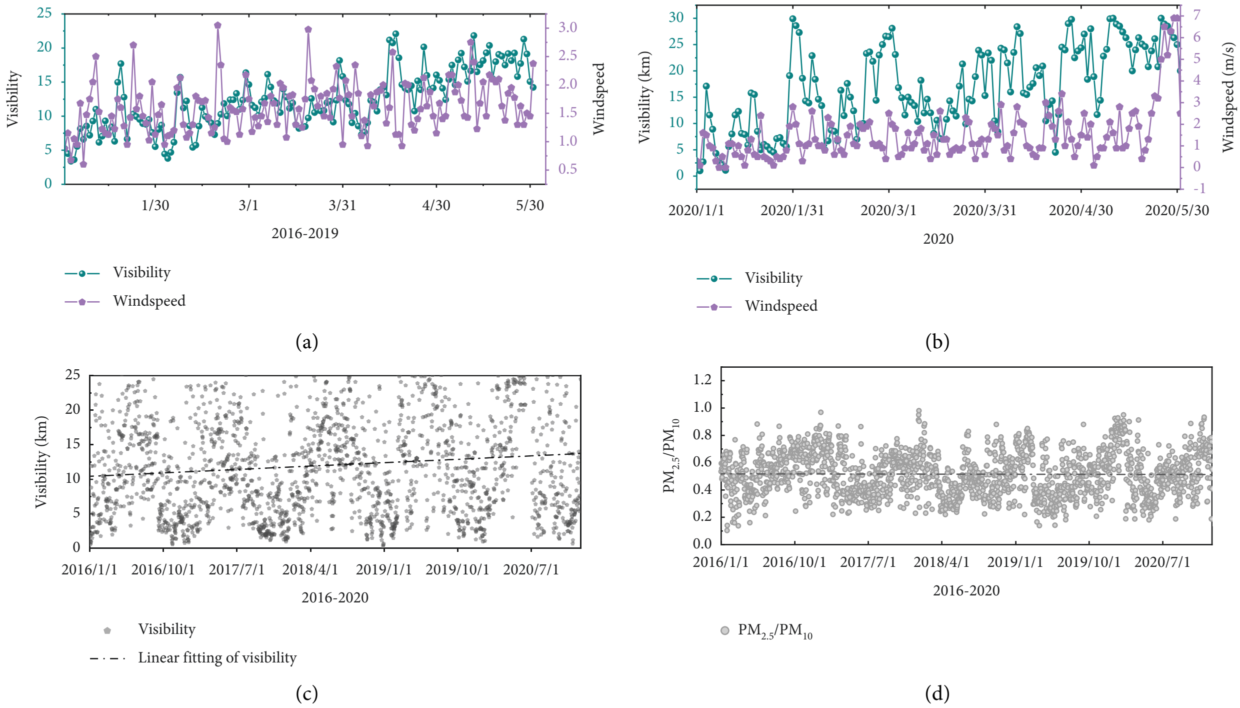


FIGURE 2: Variations of AQI and air pollutants annual mean values in Weinan city (for the convenience of calculation, the CO concentration in the figure is expanded by 100 times).

As can be seen in Figures 3(a) and 3(b), the overall visibility is higher from January to February 2020 than from January to February 2016–2019. Overall, this reflects lower pollutant concentrations during the COVID-19 lockdown. Visibility from March to May 2020 is also higher than the same period in 2016–2019, indicating that although some work resumed and production resumed during COVID-19, the overall concentration of pollutants is lower and visibility is higher. The average visibility from 2016 to 2020 was 12.1 km (Figure 3(c)). The number of days with visibility greater than 12 km from January to May 2020 is 68% and the number of days with visibility greater than 12 Km in the same period of 2016–2019 accounts for 50%. Over the past five years, the average visibility has shown an overall upward trend, but the trend has been slow (Figure 3(c)). The concentration of atmospheric pollutants has gradually decreased, visibility has increased, and solar radiation reaching the ground increased. As the photochemical reaction increases, the O_3 concentration increases to a certain extent [25]. There is a positive correlation between visibility and wind speed, while there is a negative correlation between visibility and particulate matter concentration. Weak wind speeds are conducive to the accumulation of contaminants, resulting in reduced visibility. The particulate matter concentration in China exhibits a downward trend, but in the eastern part of the country, 64% of the cities still have annual $PM_{2.5}$ mass concentrations that exceed the "China New Standard for Ambient Air Quality Level II" (GB3095-2012) [26]. The concentrations of $PM_{2.5}$ in the Taihang Mountains, Fenhe River, Weihe Plain, and Wuchang in Xinjiang are still high, and heavy haze pollution occurs frequently in autumn and winter [7].

In recent years, there are many studies on $PM_{2.5}/PM_{10}$ ratio, trying to reflect the proportion of fine particles in air pollution [27]. The $PM_{2.5}/PM_{10}$ ratios in major economic regions of China revealed that more severe air pollution was observed when the ratio $PM_{2.5}/PM_{10}$ ratio was higher [28]. Previous studies have examined the characteristics of pollutants at a deeper level by interpreting the meaning of $PM_{2.5}/PM_{10}$. The study of the $PM_{2.5}/PM_{10}$ ratio in 23 cities in China clarified the type of contamination and potential sources of pollution to a considerable extent [29]. It is possible that the larger the ratio is, the more severe the secondary pollutants in the city [30]. Therefore, $PM_{2.5}/PM_{10}$ ratio = 0.5 is used to reflect the severity of secondary pollution in Weinan. The overall $PM_{2.5}/PM_{10}$ ratio in Weinan city from 2016 to 2020 was 0.52, and the winter $PM_{2.5}/PM_{10}$ ratios from 2016 to 2020 were 0.63, 0.56, 0.53, 0.67, and 0.56 (Figure 3(d)). Research in other cities, such as Lhasa, shows that the $PM_{2.5}/PM_{10}$ ratio in winter is 0.48 [31], while the $PM_{2.5}/PM_{10}$ ratio observed in Beijing is 0.67 [32]. $PM_{2.5}$ in winter accounts for a relatively high proportion of PM_{10}, which indicates that $PM_{2.5}$ is the main pollutant in Weinan winter and reduces visibility.

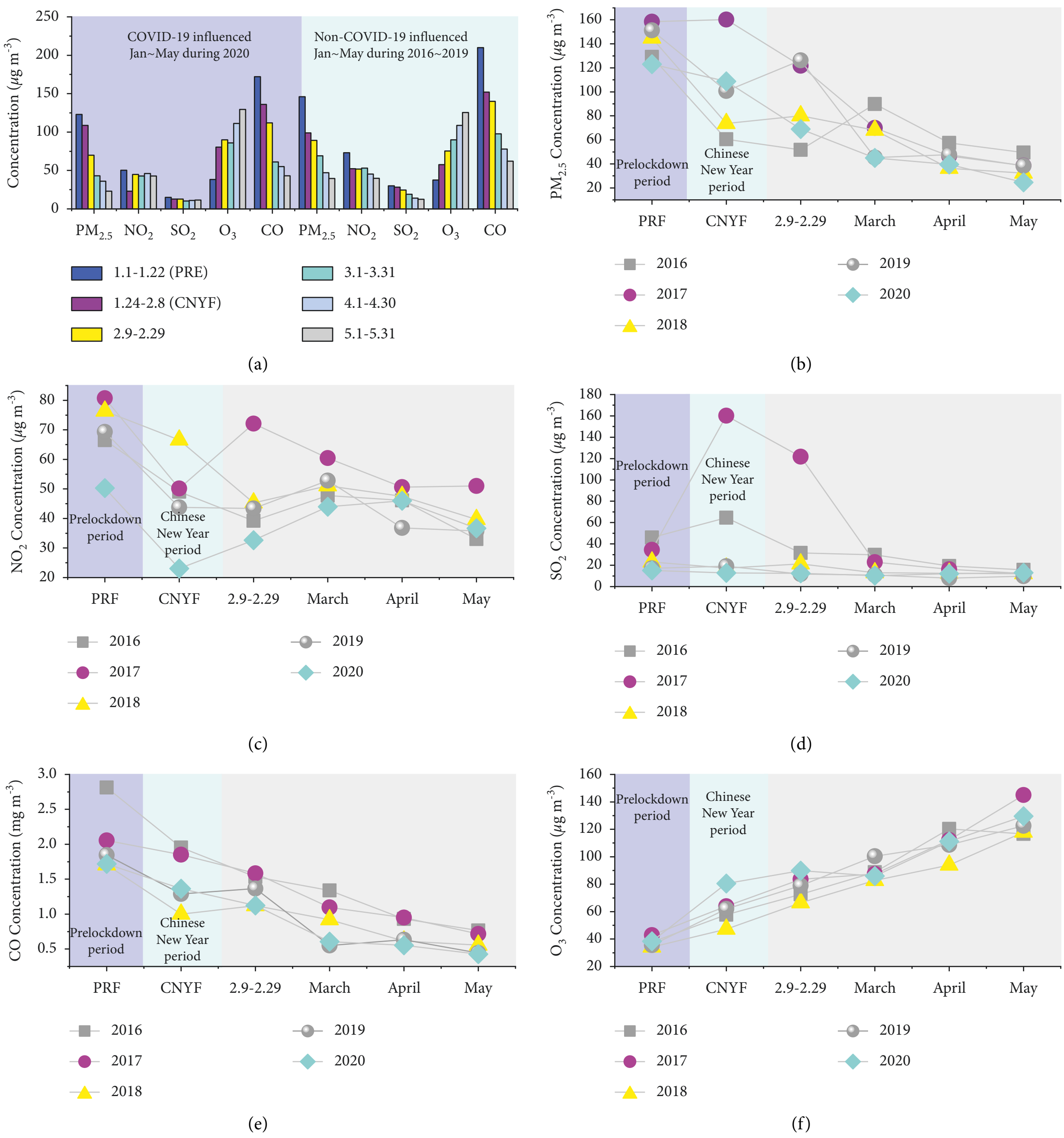


(a) (b) (c) (d)

FIGURE 3: Visibility and wind speed trends from 2016 to 2019 and from January to May 2020 (a, b); visibility trend with time and $PM_{2.5}/PM_{10}$ ratio trend (c, d).

3.2. Impact of the COVID-19 Pandemic on Air Pollution. The period from January 1, 2020, to May 31, 2020, was selected as the study phase to compare the concentrations of $PM_{2.5}$, NO_2, SO_2, CO, and O_3 before the COVID-19 lockdown with those during the lockdown and the resumption of work and production (Figure 4). The first phase (January 1–22) is the prelockdown phase (PRF); the second phase is China's Spring Festival (CNYF, January 24 to February 8); and the third phase is February 9 to 29. March, April, and May are considered the fourth, fifth, and sixth phases, respectively. The air quality has improved during the COVID-19, which was mainly caused by the reduction in emissions of transportation sector and the industry. In 2020, the $PM_{2.5}$ concentration of the second phase (CNYF) was 12% lower than that of the PRF phase (January 1 to January 22) (Figure 4(b)). Compared with the first stage, the $PM_{2.5}$ concentrations in the third, fourth, fifth, and sixth phases were reduced by 43%, 65%, 70%, and 81%, respectively. The Chinese New Year is from January 24 to February 8, so the use of firecrackers led to an increased concentration of pollutants on February 9. As of February 29, the $PM_{2.5}$ concentration was 38.8% smaller than that of the previous period CNYF (Chinese New Year). $PM_{2.5}$ has a slow response and lag during the control period of COVID-19. The average concentrations of $PM_{2.5}$ in the winter of 2016–2020 were $146.91\,\mu g\,m^{-3}$, $106.08\,\mu g\,m^{-3}$, $114.83\,\mu g\,m^{-3}$, $98.86\,\mu g\,m^{-3}$, and $79.31\,\mu g\,m^{-3}$, which are much higher than the concentration of $35\,\mu g\,m^{-3}$ in Lhasa [31], which in turn is lower than the concentration of $144.6\,\mu g\,m^{-3}$ in Urumqi [33]. The number of days with daily $PM_{2.5}$ concentrations greater than $75\,\mu g\,m^{-3}$ in the winter of 2016–2020 accounted for 74%, 66%, 72%, 76%, and 61% of the total monitoring days; the number of days with a daily concentration higher than $150\,\mu g\,m^{-3}$ accounted for 38%, 21%, 27%, 18%, and 10% of the total monitoring days. From 2016 to 2019, a large proportion of annual pollutant days can reflect severe air pollution in this area. The main reason for the decline in particulate concentration in 2020 is related to the lockdown during the epidemic, so pollutant emissions during this period were relatively low.

Generally, the transportation sector is the main factor in reducing NO_2 levels. As shown in Figure 3(c), the most significant decrease in NO_2 concentrations (from $50.27\,\mu g\,m^{-3}$ in prelockdown phase to $23.06\,\mu g\,m^{-3}$ in CNYF phase) was observed in 2020. The CNYF phase was a period during lockdown when the Chinese New Year also stopped traffic and reduced travel, and these results indicated that NO_2 was the pollutant that was most sensitive to the lockdown policy. These results indicated that the control measures during COVID-19 have significantly reduced pollutant emissions caused by population movements. After the first PRF stage, NO_2 was sharply decreased showing to be more sensitive to COVID-19 lockdown compared to $PM_{2.5}$. After the resumption of work on February 9th, the transportation industry began to operate and a few factories began to resume work. The NO_2 concentration increased again (Figure 4(c)). As the main pollutant emitted from coal-burning heating in winter [21], the SO_2 concentration decreased insignificantly (Figure 4(d)), indicating that coal-fired emissions were less influenced by COVID-19 control measures. The main reason is that coal-fired heating in winter has not been affected by COVID-19. Therefore,



(a)

(b)

(c)

(d)

(e)

(f)

Figure 4: Comparison of the concentration trends of $PM_{2.5}$, NO_2, SO_2, CO, and O_3 in 2020 and the historical concentration trends (2016–2019). PRF represents the prelockdown period; CNYF represents the Chinese New Year.

COVID-19 control measures have a small impact on SO_2, with a relatively small range of change before and during the lockdown in 2020, with the average value of ~11 $\mu g\,m^{-3}$ (Figure 4(d)). In comparison with the corresponding period in 2016–2019, the mean concentrations of $PM_{2.5}$, NO_2, and SO_2 generally declined, indicating that the emissions of pollutants during the lockdown period generally decreased. Emissions from motor vehicles and factory closures have been reduced due to lockdown and were significantly lower in 2020 than those in the same period in 2016–2019. In general, among these three air pollutants, NO_2 was the most sensitive to variations in anthropogenic activities during the COVID-19 lockdown in Weinan city.

Figure 4(e) shows a gradual decrease in CO concentrations, with an overall decrease in traffic emissions due to factory shutdowns during the lockdown period. The cessation of heating between March and May may also have contributed to the continued decline in CO. As can be seen in Figure 4(f), the O_3 concentration increased rapidly during the Chinese Spring Festival, which was also the lockdown period, when the overall decrease in pollutant concentrations leads to a decrease in the precursors that form O_3 and therefore O_3 concentrations increase during this period. After that (February–May), with the resumption of work and production begins, the overall concentration of pollutants increased again, and the concentration of O_3 gradually decreased.

Overall, it can be seen that O_3 responds more significantly to the lockdown policy during the COVID-19 period also because the lower $PM_{2.5}$ represents a less effective sink for hydroperoxy radicals (HO_2), which would increase peroxy radical-mediated O_3 production (Li et al., 2019). The above results also showed that the residential sector emissions need to control [17].

3.3. Wind Pollution Rose Diagram for $PM_{2.5}$. Atmospheric contamination is influenced by various factors such as special terrain conditions, socioeconomic development level, and energy structure, and it is also closely related to meteorological conditions during the polluted weather process [34]. It can be seen in Figure 5 that the dominant wind direction in Weinan is the northeast direction. In spring, high concentrations of $PM_{2.5}$ occur in the north and northeast. When the wind direction is northeast and the wind speed is 4.5 m/s, high concentration values of $PM_{2.5}$ appear, indicating that there may be potential pollution sources in the northeast of the monitoring site. In summer, when the wind direction is south and the wind speed is 1 m/s, high concentration values of $PM_{2.5}$ may appear, indicating that there are pollution sources near the southern part of the monitoring point.

In autumn, when the wind direction is southwest and the wind speed is 3.5 m/s, high values of $PM_{2.5}$ may easily appear, indicating that there may be obvious pollution sources in the southwest of the monitoring point in autumn. In winter, when the wind direction is south and the wind speed is 0.5 m/s, the pollutant concentration reaches 344~409 $\mu m/m^3$, indicating that the pollutants are mainly produced close to the sampling point, the static wind weather in winter is not conducive to the diffusion of pollutants, and the accumulation of pollutants is serious.

During January to February 2020, the high concentration of pollutants was concentrated in the static wind range with a wind speed of 0.5 m/s, produced close to the sampling point was the main factor, and pollutants were easy to accumulate, the $PM_{2.5}$ response lags after the plant shutdown during the COVID-19 blockade, and higher values exist for a period of time. From March to May 2020, when the wind direction is southeast and the wind speed is 2.0 m/s, the $PM_{2.5}$ concentration is in the range of 65.5–76.0, and the overall $PM_{2.5}$ concentration is lower than the same period, which may be related to the resumption of work and production. At the same time, affected by the hysteresis of $PM_{2.5}$, the overall pollutant concentrations were lower in this stage. From a comparison of Figures 5(a) and 5(f), it can be concluded that, despite the similarity of the sources, the $PM_{2.5}$ concentrations are significantly lower in the spring of 2020. When the pollutants concentration is high in the northeast wind direction, it may be influenced by the transport of pollutants from neighboring cities. The frequent industrial activities in the windward cities have a great impact on the air quality of Weinan. Therefore, the joint prevention and control policy is very essential. Meanwhile, weak wind speed can cause air pollutants to accumulate and not easily spread.

3.4. Path Analysis Results. The seasonal atmospheric pollutants are generally varied due to the variations in meteorology [35,36]. As shown in Figure 6, PM_{10} in the four seasons has the greatest direct effect on $PM_{2.5}$. In spring (Figure 6(a)), RH presented the greatest positive direct effect on $PM_{2.5}$, followed by O_3 and CO. RH has the most positive and indirect effects are on SO_2 and NO_2, and it has the most negative direct effect on T. In summer (Figure 6(b)), RH presented the highest positive direct effect on $PM_{2.5}$, followed by CO; NO_2 has the largest negative direct effect; SO_2 and NO_2, O_3, and T have the largest positive and indirect effects; RH, SO_2, and O_3 have the largest negative indirect effects. CO has the greatest direct and indirect effect on $PM_{2.5}$ in autumn (Figure 6(c)), followed by RH. O_3 and T had the greatest positive and indirect effects, followed by SO_2, NO_2, and CO; the pollutants with combined direct and positive as well as indirect effects are CO, SO_2, and NO_2. In winter (Figure 6(d)), CO has the greatest positive and direct effect on $PM_{2.5}$, followed by RH. SO_2 and NO_2 are the most indirectly affected, and the most significant pollutants are CO, SO_2, and NO_2. The positive indirect effect is greatest for CO and SO_2, and the negative indirect effect is greatest for O_3 and WS. Thus, the positive combined effect of NO_2 and CO is the largest, while the negative combined effect due to wind speed and temperature is the largest. NO_2 and CO are considered the main pollutants affecting Weinan $PM_{2.5}$. This indicates that the incomplete combustion process of coal in Weinan city in autumn and winter provides more CO in the air, which affects the $PM_{2.5}$ concentration values. The main factor considered is incomplete combustion during the heating process. Second, NO_2 is another important factor that affects $PM_{2.5}$ in multiple seasons. It can be concluded that automobile and industrial emissions contribute to the growth of $PM_{2.5}$.

3.5. Correlation Analysis of Pollutants under Different Air Quality Indexes. The correlations between AQI values and the air pollutants from 2016 to 2020 are shown in Table 2. According to the six degrees of AQI values, the correlation analysis was also calculated in different degrees, including excellent (AQI = 0~50), good (AQI = 51~100), light (AQI = 101~150), moderate (AQI = 151~200), heavy (AQI = 201~250), and severe pollution (AQI>300). When the AQI is categorized as good or as heavy pollution, the correlation between the AQI and PM10 is best (0.49($p < 0.01$) and 0.35($p < 0.01$), respectively), followed by that with PM2.5. The correlation coefficients between AQI and PM2.5 were significant when AQI was in 51–100, 101–150, 151-120, and 201–250 $R = 0.442$ ($p < 0.01$), 0.419 ($p < 0.01$), 0.341 ($p < 0.01$), and 0.502 ($p < 0.01$). It shows that PM2.5 and PM10 are the major causes affecting atmospheric quality. The correlation between PM2.5 and PM10 was better

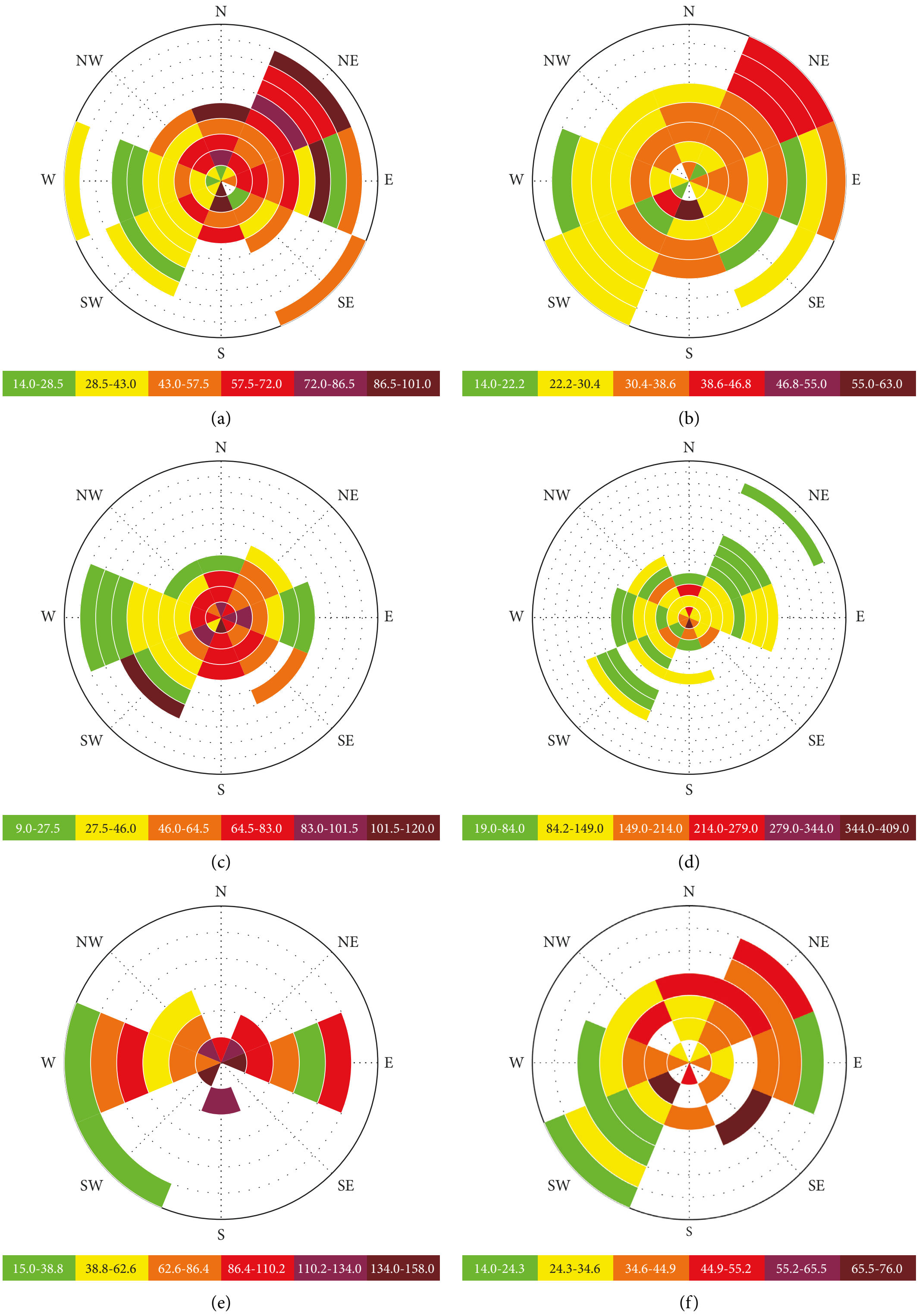
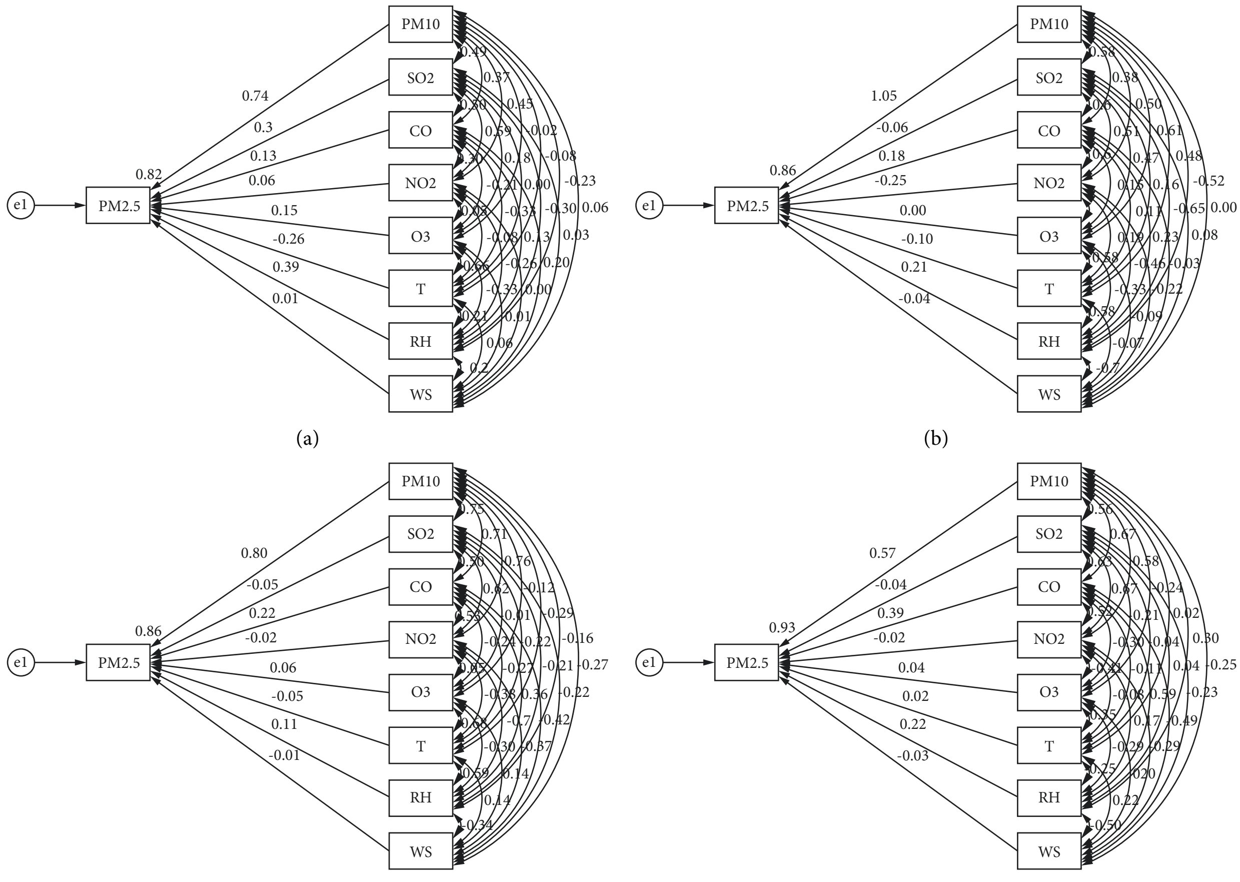


FIGURE 5: $PM_{2.5}$ pollution roses for spring, summer, autumn, and winter 2016–2019 and $PM_{2.5}$ pollution roses for January-February and March–May 2020.



(a) (b) (c) (d)

Figure 6: Path analysis of different pollutants and main meteorological factors (*T* = temperature, RH = relative humidity, and WS = wind speed).

Table 2: Correlation among six air pollutants under different AQI value ranges; **represents a significance level of 0.01 (P<0.01); *represents a significance level of 0.05 (P<0.05).

	0–50						51–100					
	PM$_{2.5}$	PM$_{10}$	SO$_2$	CO	NO$_2$	O$_3$	PM$_{2.5}$	PM$_{10}$	SO$_2$	CO	NO$_2$	O$_3$
AQI	0.366**	0.490**	0.183*	−0.041	0.286**	0.423**	0.442**	0.566**	0.214*	0.124**	0.273*	0.280**
PM$_{2.5}$	1	0.732**	0.092	0.233**	0.189*	−1.37	1	0.635**	0.279**	0.388**	0.330**	−0.352**
PM$_{10}$		1	0.388**	0.127	0.308**	0.057		1	0.369**	0.112**	0.589**	−0.245**
SO$_2$			1	0.357**	0.190*	0.142			1	0.636**	0.330**	−1.59**
CO				1	−0.054	−0.58				1	0.29	−2.22**
NO$_2$					1	−0.247**					1	−0.329**
O$_3$						1						1
	101–150						151–200					
AQI	0.419**	0.369**	0.217**	0.300**	0.121**	−0.120**	0.341**	0.347**	0.91	0.171*	0.120	-0.61
PM$_{2.5}$	1	0.702**	0.450**	0.754**	0.456**	−0.757**	1	0.49**	0.203*	0.611**	0.234**	−0.689**
PM$_{10}$		1	0.509**	0.485**	0.478**	−0.619**		1	0.346**	0.256**	0.272**	−0.466**
SO$_2$			1	0.672**	0.520**	−0.406**			1	0.665**	0.358**	−0.243**
CO				1	0.455*	−0.617**				1	0.335**	−0.537**
NO$_2$					1	−0.517**					1	−0.286**
O$_3$						1						1
	201–250						>300					
AQI	0.502**	0.368**	−0.010	0.073	0.140	−0.044	0.075	0.350**	−0.27	−0.158	−0.215	−0.153
PM$_{2.5}$	1	−0.083	0.061	0.247*	0.302*	−0.145	1	0.476**	0.450*	0.678**	0.480**	−0.474
PM$_{10}$		1	0.287	0.178	0.346**	−0.98		1	0.342**	0.312**	0.142	−0.292*
SO$_2$			1	0.552**	0.500**	−0.58			1	0.697*	0.444**	−0.175
CO				1	0.381**	−0.281*				1	0.616**	−0.542**
NO$_2$					1	−0.238					1	−0.557**
O$_3$						1						1

when AQI values were at best, good, and severe with $R = 0.732$ ($p < 0.01$), 0.635 ($p < 0.01$), and 0.476 ($p < 0.01$), which indicates that PM2.5 concentrations account for a large part of PM10 variation and in agreement with the previous studies [37,38]. When AQI indicates light, moderate, heavy, and severe pollution, the correlation coefficients between CO and PM2.5 are $R = 0.754$ ($p < 0.01$), 0.611 ($p < 0.01$), 0.247 ($p < 0.05$), and 0.678 ($p < 0.01$), respectively. The next most important parameter is nitrogen dioxide, with correlations $R = 0.456$ ($p < 0.01$), 0.234 ($p < 0.01$), 0.302 ($p < 0.05$), and 0.480 ($p < 0.01$) for PM2.5 and NO_2. Under conditions of heavy and severe pollution, motor vehicle emissions are the main factor affecting CO. The strong correlation between CO and PM2.5 is due to factory and motor vehicle emissions, while the diffuse sources of NO2 are mainly associated with automobile traffic [39]. CO and NO2 are important factors in the formation of PM2.5. Moreover, the main relationship between O3 and PM10, PM2.5, SO2, CO, and NO2 was negative across each AQI degree. The strongest correlation between NO2 and O3 ($-0.56 < R < -0.25$, $p < 0.01$) indicates that NO2 is a significant cause of the O3 formation among the five pollutants. NO2 is an important factor in PM2.5 and O3.

4. Conclusions

This study comprehensively and systematically analyzes the current situation of air pollution in Weinan city. The improvement in air quality is due to strict controls (industrial closures, traffic restrictions, and strict household segregation) during the COVID-19 lockdown period. NO_2 was the most sensitive to the lockdown, O_3 was also significantly affected by the lockdown policy, and the $PM_{2.5}$ response was smaller and delayed. The path analysis method analyzes $PM_{2.5}$ and potential and direct influencing factors. NO_2 is an important factor affecting $PM_{2.5}$ in different seasons, and CO and NO_2 are the main reasons that affect $PM_{2.5}$. O_3 and NO_2 correlated significantly, indicating that among the five pollutants, NO_2 is the most significant factor in the O_3 formation. Therefore, NO_2 is an important factor for $PM_{2.5}$ and O_3. $PM_{2.5}$ is still the most challenging problem in China's urban pollution control. Combining local climate and topographic features to optimize the geographic distribution of industries, implement strict emission policies to reduce NO_2 emissions, especially traffic emissions. In short, the problem of air pollution is still serious, and there are differences in air pollution in different regions. The most important thing is to take targeted measures according to the local pollution situation. Therefore, adjust measures according to local conditions to control air pollution has great significance. With the continuous improvement of $PM_{2.5}$ control and governance levels, it becomes important to control the precursors of $PM_{2.5}$.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Yuanyuan Meng developed the methodology, investigated the study, and wrote the original draft. Wan long Sun developed the methodology, investigated the study, did formal analysis, and reviewed and edited the manuscript. All authors contributed to the interpretation of the results and the improvement of this paper.

Acknowledgments

The authors are very grateful to Dr. Jie Zeng of the China University of Geosciences (Beijing) for his advice and help with the mapping and other aspects of this paper. The authors are also very grateful to Professor Fu Chaofeng for his comments and suggestions on this paper. Yi wang helped in the language revisions in the manuscript revision process.

References

[1] H. Guo, X. Gu, G. Ma et al., "Spatial and temporal variations of air quality and six air pollutants in China during 2015-2017," *Scientific Reports*, vol. 9, no. 1, Article ID 15201, 2019.

[2] B. L. Boys, R. V. Martin, A. van Donkelaar et al., "Fifteen-year global time series of satellite-derived fine particulate matter," *Environmental Science & Technology*, vol. 48, no. 19, pp. 11109–11118, 2014.

[3] M. Brauer, G. Freedman, J. Frostad et al., "Ambient air pollution exposure estimation for the global burden of disease 2013," *Environmental Science & Technology*, vol. 50, no. 1, pp. 79–88, 2016.

[4] B. Brunekreef and B. Forsberg, "Epidemiological evidence of effects of coarse airborne particles on health," *European Respiratory Journal*, vol. 26, no. 2, pp. 309–318, 2005.

[5] M. Delikhoon, M. Fazlzadeh, A. Sorooshian et al., "Characteristics and health effects of formaldehyde and acetaldehyde in an urban area in Iran," *Environmental Pollution*, vol. 242, pp. 938–951, 2018.

[6] S. Motesaddi Zarandi, M. Alimohammadi, V. Kazemi Moghaddam et al., "Long-term trends of Nitrogen oxides and surface ozone concentrations in Tehran city, 2002-2011," *Journal of Environmental Health Science and Engineering*, vol. 13, no. 1, p. 63, 2015.

[7] Y. Wang, W. Li, W. Gao et al., "Trends in particulate matter and its chemical compositions in China from 2013-2017," *Science China Earth Sciences*, vol. 62, no. 12, pp. 1857–1871, 2019.

[8] L. Liu, X. Ma, W. Wen, C. Sun, and J. Jiao, "Characteristics and potential sources of wintertime air pollution in Linfen, China," *Environmental Monitoring and Assessment*, vol. 193, no. 5, p. 252, 2021.

[9] J. Zeng, G. Han, Q. Wu, and Y. Tang, "Effects of agricultural alkaline substances on reducing the rainwater acidification: insight from chemical compositions and calcium isotopes in a karst forests area," *Agriculture, Ecosystems & Environment*, vol. 290, Article ID 106782, 2020.

[10] J. Zeng, F.-J. Yue, S.-L. Li et al., "Determining rainwater chemistry to reveal alkaline rain trend in Southwest China: evidence from a frequent-rainy karst area with extensive

agricultural production," *Environmental Pollution*, vol. 266, Article ID 115166, 2020.

[11] J. Hu, Y. Wang, Q. Ying, and H. Zhang, "Spatial and temporal variability of PM2.5 and PM10 over the north China plain and the yangtze river delta, China," *Atmospheric Environment*, vol. 95, pp. 598–609, 2014.

[12] L. Li, C. H. Chen, J. S. Fu et al., "Air quality and emissions in the yangtze river delta, China," *Atmospheric Chemistry and Physics*, vol. 11, no. 4, pp. 1621–1639, 2011.

[13] S. Liu, M. Hu, S. Slanina et al., "Size distribution and source analysis of ionic compositions of aerosols in polluted periods at Xinken in Pearl River Delta (PRD) of China," *Atmospheric Environment*, vol. 42, no. 25, pp. 6284–6295, 2008a.

[14] S. Liu, M. Hu, Z. Wu, B. Wehner, A. Wiedensohler, and Y. Cheng, "Aerosol number size distribution and new particle formation at a rural/coastal site in Pearl River Delta (PRD) of China," *Atmospheric Environment*, vol. 42, no. 25, pp. 6275–6283, 2008.

[15] D. Wang, J. Hu, Y. Xu et al., "Source contributions to primary and secondary inorganic particulate matter during a severe wintertime PM2.5 pollution episode in Xi'an, China," *Atmospheric Environment*, vol. 97, pp. 182–194, 2014.

[16] J. Zheng, M. Shao, W. Che et al., "Speciated VOC emission inventory and spatial patterns of ozone formation potential in the pearl river delta, China," *Environmental Science & Technology*, vol. 43, no. 22, pp. 8580–8586, 2009.

[17] Y. Wang, Y. Yuan, Q. Wang, C. Liu, Q. Zhi, and J. Cao, "Changes in air quality related to the control of coronavirus in China: implications for traffic and industrial emissions," *The Science of the Total Environment*, vol. 731, Article ID 139133, 2020.

[18] R. Feng, H. Xu, K. He et al., "Effects of domestic solid fuel combustion emissions on the biomarkers of homemakers in rural areas of the Fenwei Plain, China," *Ecotoxicology and Environmental Safety*, vol. 214, Article ID 112104, 2021.

[19] B. Mamtimin and F. X. Meixner, "Air pollution and meteorological processes in the growing dryland city of Urumqi (Xinjiang, China)," *The Science of the Total Environment*, vol. 409, no. 7, pp. 1277–1290, 2011.

[20] S. Yan, H. Cao, Y. Chen, C. Wu, T. Hong, and H. Fan, "Spatial and temporal characteristics of air quality and air pollutants in 2013 in Beijing," *Environmental Science and Pollution Research*, vol. 23, no. 14, 14007 pages, Article ID 13996, 2016.

[21] M. Kuerban, Y. Waili, F. Fan et al., "Spatio-temporal patterns of air pollution in China from 2015 to 2018 and implications for health risks," *Environmental Pollution*, vol. 258, Article ID 113659, 2020.

[22] J. Hu, Q. Ying, Y. Wang, and H. Zhang, "Characterizing multi-pollutant air pollution in China: comparison of three air quality indices," *Environment International*, vol. 84, pp. 17–25, 2015.

[23] H. Yang, Q. Peng, J. Zhou, G. Song, and X. Gong, "The unidirectional causality influence of factors on PM2.5 in Shenyang city of China," *Scientific Reports*, vol. 10, no. 1, p. 8403, 2020.

[24] D. F. Alwin and R. M. Hauser, "The decomposition of effects in path analysis," *American Sociological Review*, vol. 40, no. 1, pp. 37–47, 1975.

[25] D. Li, J. Liu, J. Zhang et al., "Identification of long-range transport pathways and potential sources of PM2.5 and PM10 in Beijing from 2014 to 2015," *Journal of Environmental Sciences*, vol. 56, pp. 214–229, 2017a.

[26] M. Cheng, G. Tang, B. Lv et al., "Source apportionment of PM2.5 and visibility in Jinan, China," *Journal of Environmental Sciences*, vol. 102, pp. 207–215, 2021.

[27] R.-J. Huang, Y. Zhang, C. Bozzetti et al., "High secondary aerosol contribution to particulate pollution during haze events in China," *Nature*, vol. 514, no. 7521, pp. 218–222, 2014.

[28] D. Zhao, H. Chen, E. Yu, and T. Luo, "$PM_{2.5}/PM_{10}$ ratios in eight economic regions and their relationship with meteorology in China," *Advances in Meteorology*, vol. 2019, Article ID 5295726, 2019.

[29] L. Xu, S. Batterman, F. Chen et al., "Spatiotemporal characteristics of PM2.5 and PM10 at urban and corresponding background sites in 23 cities in China," *The Science of the Total Environment*, vol. 599-600, pp. 2074–2084, 2017.

[30] S. Wang, T. Liao, L. Wang, and Y. Sun, "Process analysis of characteristics of the boundary layer during a heavy haze pollution episode in an inland megacity, China," *Journal of Environmental Sciences*, vol. 40, pp. 138–144, 2016.

[31] X. Yin, B. de Foy, K. Wu, C. Feng, S. Kang, and Q. Zhang, "Gaseous and particulate pollutants in Lhasa, Tibet during 2013-2017: spatial variability, temporal variations and implications," *Environmental Pollution*, vol. 253, pp. 68–77, 2019.

[32] R. Li, L. Cui, J. Li et al., "Spatial and temporal variation of particulate matter and gaseous pollutants in China during 2014-2016," *Atmospheric Environment*, vol. 161, pp. 235–246, 2017.

[33] D. Rupakheti, X. Yin, M. Rupakheti et al., "Spatio-temporal characteristics of air pollutants over Xinjiang, northwestern China," *Environmental Pollution*, vol. 268, Article ID 115907, 2021.

[34] P. D. Hien, V. T. Bac, H. C. Tham, D. D. Nhan, and L. D. Vinh, "Influence of meteorological conditions on PM2.5 and PM2.5–10 concentrations during the monsoon season in Hanoi, Vietnam," *Atmospheric Environment*, vol. 36, no. 21, pp. 3473–3484, 2002.

[35] Y. Wang, G. Zhuang, A. Tang et al., "The ion chemistry and the source of PM2.5 aerosol in Beijing," *Atmospheric Environment*, vol. 39, no. 21, pp. 3771–3784, 2005.

[36] Y. Xiang, T. Zhang, J. Liu, L. Lv, Y. Dong, and Z. Chen, "Atmosphere boundary layer height and its effect on air pollutants in Beijing during winter heavy pollution," *Atmospheric Research*, vol. 215, pp. 305–316, 2019.

[37] Y. Wang, Q. Ying, J. Hu, and H. Zhang, "Spatial and temporal variations of six criteria air pollutants in 31 provincial capital cities in China during 2013-2014," *Environment International*, vol. 73, pp. 413–422, 2014b.

[38] Y.-L. Zhang and F. Cao, "Fine particulate matter (PM2.5) in China at a city level," *Scientific Reports*, vol. 5, no. 1, Article ID 14884, 2015.

[39] P. Ielpo, C. Mangia, G. P. Marra et al., "Outdoor spatial distribution and indoor levels of NO2 and SO2 in a high environmental risk site of the South Italy," *The Science of the Total Environment*, vol. 648, pp. 787–797, 2019.