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Air Quality and Air Pollutant Correlation in Xi'an, China: A Case Study of Differences Before, During, and After Lockdown Due to the COVID-19 Pandemic

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Abstract

In order to effectively control the spread of the 2019 novel coronavirus (COVID-19), China has undertaken relatively strict blockade measures, which can effectively reduce population mobility and eliminate transmission pathways at the source. Therefore, it is of great significance to understand the impact of urban blockades on the air quality before, during, and after COVID-19. This study uses data collected from monitoring stations in Xi'an, a typical city in northwestern China, from 2018 to 2023 to conduct an in-depth analysis of the changes in concentration of various pollutants in the atmosphere from a spatiotemporal perspective. The results showed that the average concentrations of particulate matter with aerodynamic diameters less than 2.5 μm ($PM_{2.5}$), particulate matter with aerodynamic diameters less than 10 μm (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO) decreased during the epidemic lockdown (2020–2022) by 18.7%, 15.4%, 29.4%, 20.9%, 0.03%, and 28.1%, respectively. After the implementation of urban lockdown (2023), the annual average concentrations of the five major pollutants other than O_3 decreased, while the concentration of O_3 increased. The monthly changes in concentration of $PM_{2.5}$, PM_{10}, CO, SO_2, and NO_2 were similar during 2018–2023, being "higher in winter and lower in summer". The monthly average concentration of O_3 changed in a "unimodal" manner. The concentrations of SO_2, NO_2, and PM_{10} decreased the most in January, by 46.4%, 33.5%, and 26.4%, respectively. The concentration of CO decreased the most in April, by 37.3%. $PM_{2.5}$ decreased the most in May, with a decrease of 26.7%. O_3 showed the largest increase in November, by 28.6%. After taking relevant measures, the concentrations of various pollutants and their correlations decreased. However, after resuming work, the concentrations of pollutants were still relatively high, and long-term management of air quality in Xi'an is still needed. These results provide a scientific basis for formulating more precise and effective air pollution control strategies.

Keywords: urban air pollutants; air levels; lockdown; Xi'an; China; time trends

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1. Introduction

Air quality is one of the key parameters for directly evaluating the urban living environment [1]. However, in recent years, with the acceleration of urbanization and industrialization, air pollution has become increasingly severe, attracting widespread attention from all sectors of society, especially regarding the impact of air pollution on

residents' quality of life and physical health [2,3]. Numerous studies have shown [4–6] that different types of pollutants in the air can have varying degrees of impact on the physical and mental health of individuals, such as respiratory diseases [4], cardiovascular diseases [5], lung cancer [6], and even death [7–9]. Other studies suggest that there may be correlations between different pollutants [10,11]. Therefore, it is of great significance to effectively control air pollution, ensure residents' health, and promote sustainable urban development.

At present, scholars and research institutions from various countries have conducted a large amount of research on air pollution [12–16], focusing on the composition of pollutants [12], regional control of particulate matters [13], dispersion patterns of pollutants [14], and the correlation between pollutants and meteorological factors [15,16]. Although some achievements have been made, research on inland cities in northwestern China remains scarce. In addition, various functional zones are formed by different landforms and climate characteristics [17]; therefore, air pollution characteristics will also differ between regions. The existing conclusions cannot be generalized or directly applied, and need to be dynamically adjusted according to local economic development and urban pattern changes [18].

A new type of coronavirus pneumonia (COVID-19) spread rapidly in China and the rest of the world in December 2019 [19], and had an unprecedented impact on human health and the economies of all countries. In response to the epidemic, strict prevention and control measures were implemented in various regions of China, such as lockdowns, restrictions on personal movement, and suspension of industrial production [20]. These measures have had a significant impact on the air quality of cities while also controlling the spread of the epidemic. At the same time, the emissions of major pollution sources such as industrial and transportation sources were significantly reduced [21]. Compared with normal periods, the human activity patterns in cities underwent fundamental changes during the epidemic period [21]. Therefore, domestic and foreign institutions and individual experts have conducted extensive research on the changes in air quality under different pollution source emission intensities and the interrelationships between pollutants [22–24]. Statistical analysis methods have been used to investigate the impact of meteorological and human factors on environmental air quality during epidemic control, and detailed analysis has been conducted using air quality models [25], machine learning models [26], and other methods. These studies have discovered the distribution characteristics of pollutants during the epidemic shutdown period.

During the prevention and control of COVID-19, human activities were significantly reduced, leading to a significant reduction in industrial production, construction, and other activities, which further led to a reduction in emissions. For example, research abroad mainly focuses on the short-term impact of lockdown measures on air quality during the pandemic [27,28]. The population-weighted exposure and total-time comprehensive exposure levels have been studied in Hamburg, Germany; Liege, Belgium; and Marseille, France. The results showed that the lockdown measures significantly reduced the concentrations of NO_2 and $PM_{2.5}$, while increasing the concentration of O_3 [29]. The air quality in Portugal improved after the restrictions were implemented during the COVID-19 pandemic in all study periods and regions except industrial sites. This verified that the measures taken during the epidemic had a practical impact on air quality [30]. Other studies have investigated the impact of the lockdown on $PM_{2.5}$ concentrations and aerosol optical depth values in Colombia [31]; the relationship between air pollution and mortality of COVID-19 in the United States and Europe [32–35]; the effects of COVID-19 lockdown on urban air quality in Monterrey, Mexico [36]; and risk factors for Middle East respiratory syndrome coronavirus [37]. Correlation between NO_2 and COVID-19 mortality was assessed by satellite

data and machine learning [38], and remote sensing was used to investigate the COVID-19 pandemic [39,40]. National researchers in China have conducted more comprehensive and in-depth research on the changes in air quality during the epidemic [41,42]. By analyzing the distribution of air pollution during the lockdown in Xi'an, it was found that the concentration of O_3 increased by 100.6%, while the concentrations of $PM_{2.5}$ and PM_{10} decreased by 22.4% and 20.7%, respectively. During the recovery period, the concentration of PM_{10} increased by 12.8% [43]. By studying six types of air pollutants in Nanjing, China, during the epidemic lockdown period compared with the pre- and during-lockdown phases, PM_{10}, $PM_{2.5}$, and NO_2 showed decreasing trends while SO_2, CO, and O_3 concentrations increased [44]. Therefore, it can be seen that the epidemic lockdown period has relatively good air quality, effectively reducing the production of greenhouse gasses such as CO_2 [41]. However, with the lifting of lockdowns in some areas of China and the resumption of work and production by enterprises, there has been a large-scale flow of people and goods, and the emission of air pollutants has gradually increased [45].

However, existing research has only focused on typical cities; there is a lack of research on Xi'an. Xi'an is also located in the Guanzhong Plain, with relatively enclosed terrain and complex climate conditions. The diffusion and transformation patterns of pollutants may differ from other cities [46], but there is currently limited targeted research in this area. In addition, the changes in air quality and correlations between various pollutants during the resumption of work and production after the epidemic with the recovery of human activities and changes in pollution source emissions has not been fully studied and explored.

Based on the above practical problems, the air quality and correlation between various pollutants before, during, and after the lockdown in Xi'an have been compared and analyzed. This provides a scientific basis for formulating more accurate and effective air pollution control strategies and is of practical value.

2. Methods

2.1. Data Sources

Xi'an is located in the Guanzhong Basin in the middle of the Yellow River Basin in the hinterland of the Chinese Mainland, between 107° 40′–109° 49′ E and 33° 39′–34° 45′ N, as shown in Figure 1. In 2020, the permanent population of Xi'an was 12.95 million. Xi'an is the starting point of the ancient Silk Road and an important node city of the "the Belt and Road" initiative. The data in this paper were used from a monitoring platform, located at http://www.tianqi.com/air/xian.html, accessed on 13 June 2024 and http://www.tianqihoubao.com/aqi/xian.html, accessed on 13 June 2024. The concentrations of various pollutants in Xi'an from 31 January 2018 to 31 December 2023 are provided. By calculating the annual, monthly, and daily average values of SO_2, NO_2, CO, PM_{10}, $PM_{2.5}$, and O_3 in Xi'an, differences can be compared in different times and spaces. IBM SPSS Statistics (SPSS V26.0) is supplied by International Business Machines Corporation, Armonk, NY, USA. It is used to organize the data, and relevant standards (GB3095-2012, HJ663-2013) are used to process the data effectively and ensure the validity of the statistics [47,48].

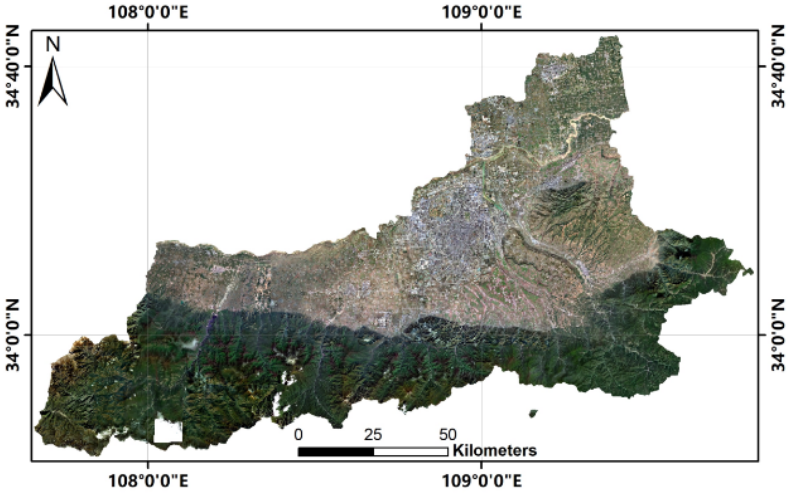


Figure 1. An area map of Xi'an.

2.2. Classification of Epidemic Prevention and Control Stages

COVID-19 broke out at the beginning of the 2020 Spring Festival, and the epidemic was fully concluded on 7 December 2022 [49]. Therefore, the period from 2018 to 2023 was divided into pre-pandemic lockdown (2018–2019), pandemic lockdown (2020–2022), and post-pandemic lockdown (2023). For the purposes of this work, we decided that the period between March and May was spring, summer was from June to August, autumn was from September to November, and winter was from December to February of the following year.

3. Results and Discussion

3.1. Annual Variation in Air Pollutants

The annual trends in various air pollutants from 2018 to 2023 are shown in Figure 2.

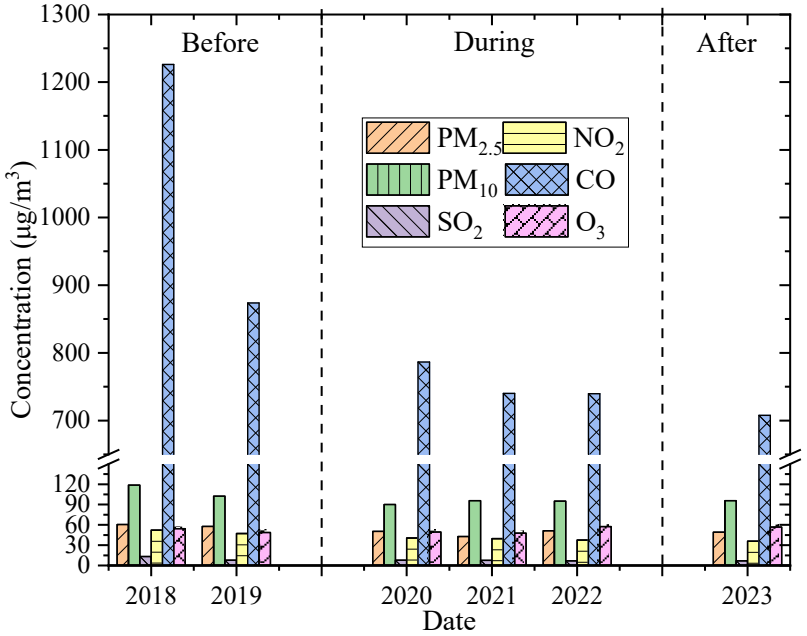


Figure 2. Annual variation in pollutant concentration in Xi'an City from 2018 to 2023.

From Figure 2, it can be seen that the annual concentrations of various pollutants show a decrease from 2018 to 2023, with a concentration distribution of CO > PM_{10} > $PM_{2.5}$ > O_3 > NO_2 > SO_2. The whole period's average concentration values of $PM_{2.5}$ and PM_{10} are both higher than the national first level concentration limits (15 μg/m^3 and

40 μg/m^3, respectively) and second level concentration limits (35 μg/m^3 and 70 μg/m^3, respectively) [47]. The annual average concentrations of $PM_{2.5}$ from 2018 to 2023 are as follows: 60.7 μg/m^3, 57.7 μg/m^3, 50.3 μg/m^3, 42.7 μg/m^3, 51.3 μg/m^3, and 49.4 μg/m^3, respectively. The annual average concentrations of PM_{10} from 2018 to 2023 are as follows: 118.9 μg/m^3, 102.5 μg/m^3, 90.0 μg/m^3, 95.7 μg/m^3, 95.1 μg/m^3, and 95.8 μg/m^3, respectively, indicating that PM pollution is still an important factor affecting the air quality in Xi'an and that efforts to prevent and control it need to be strengthened. The value of average concentration of SO_2 from 2018 to 2023 (8.5 μg/m^3) is lower than the national first level concentration limit (20 μg/m^3) [47], while the value of average concentration of NO_2 from 2018 to 2023 (42.3 μg/m^3) is slightly higher than the national first and second level standard limits (40 μg/m^3) [47].

Before the lockdown due to the epidemic, the annual average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO were 59.2 μg/m^3, 110.7 μg/m^3, 10.6 μg/m^3, 49.7 μg/m^3, 51.6 μg/m^3, and 1.0 mg/m^3, respectively. The average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO in the city during the lockdown were 48.1 μg/m^3, 93.6 μg/m^3, 7.5 μg/m^3, 39.3 μg/m^3, 51.6 μg/m^3, and 0.8 mg/m^3, respectively. They decreased by 18.7%, 15.4%, 29.4%, 20.9%, 0.0% (0.03%), and 28.1%, respectively. This is because many factories shut down due to the needs of epidemic prevention and control, students suspended classes, and strict traffic control was implemented [50], indicating that human activities made a certain contribution to pollutant concentrations. The epidemic lockdown reduced human activities, the number of car journeys decreased, and the anthropogenic sources of pollutants were significantly reduced, significantly affecting the environmental air quality [27].

After the lockdown due to the epidemic, the average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO were 49.4 μg/m^3, 95.8 μg/m^3, 7.0 μg/m^3, 36.0 μg/m^3, 56.8 μg/m^3, and 0.7 mg/m^3, respectively. Except for O_3, which increased by 9.3%, the average concentrations of the other five air pollutants decreased compared to before the lockdown. Compared to during the lockdown, $PM_{2.5}$, PM_{10}, and O_3 increased by 2.5%, 2.3%, and 9.3%, respectively, while the average concentrations of the other three air pollutants decreased. The increase in O_3 concentration indicates that the problem of ozone pollution in Xi'an has become increasingly prominent in recent years. O_3 is mostly generated under conditions of light, high temperature, and low humidity [51,52], and is a product of volatile organic compounds (VOCs) emitted from various pollution sources and NO_x [53]. This also indicates that human activities rapidly recovered during the post-lockdown period of the epidemic, and various emissions from production and daily life intensified the formation of ozone precursors such as NO_2 and VOCs. In addition, the implementation of coal to gas and coal to electricity projects in Xi'an in recent years has reduced the contribution of CO, SO_2, and other emissions from coal-fired sources to air pollution [54]. In addition, the measures taken to suspend work during the epidemic have reduced emissions from industrial sources, indicating that the reduction in anthropogenic sources has a certain impact on O_3 concentration. However, further research is needed on the formation mechanism of ozone pollution in Xi'an. However, it is also evident that China's air pollution prevention and control measures have been continuously promoted in recent years [55], and the concentrations of various pollutants have shown a downward trend year on year. This indicates that the reduction in human activity intensity and the shutdown of industrial activities have had an impact on pollutant emissions [56].

3.2. Number of Days with Particulate Matter Exceeding the National Standard

The changes in the number of days with excessive particulate matter from 2018 to 2023 are shown in Table 1.

Table 1. Parameter statistics of PM_{10} and $PM_{2.5}$ from 2018 to 2023.

Content	Lockdown	Year	Days	Max ($\mu g/m^3$)	Avg ($\mu g/m^3$)	Min ($\mu g/m^3$)	Exceeding the Primary Standard Days	Percentage Exceeding the Standard (%)	Exceeding the Secondary Standard Days	Percentage Exceeding the Standard (%)
PM_{10} ($\mu g/m^3$)	Before	2018	363	568	118.9	20	316	87.1	92	25.3
		2019	363	576	102.5	10	288	79.3	72	19.8
	During	2020	366	297	90.0	16	289	79.0	41	11.2
		2021	365	658	95.7	8	263	72.1	60	16.4
		2022	365	570	95.2	9	294	80.6	56	15.3
	After	2023	365	1116	95.8	11	242	66.3	60	16.4
$PM_{2.5}$ ($\mu g/m^3$)	Before	2018	363	292	60.7	9	228	62.8	94	25.9
		2019	363	292	57.7	5	200	55.1	79	21.8
	During	2020	366	225	50.3	6	193	52.7	73	20.0
		2021	365	278	42.7	4	166	45.5	45	12.3
		2022	365	202	51.3	5	195	53.4	88	24.1
	After	2023	365	294	49.4	6	161	44.1	70	19.2

From Table 1, it can be seen that the annual average values fluctuate; they generally show a downward trend. Overall, from 2018 to 2023, the proportion of days with PM_{10} exceeding the first level standard in Xi'an decreased 20.8%, corresponding to 74 days [47]. The proportion of days exceeding the second level standard decreased 8.9%, corresponding to 32 days [47]. At the same time, the proportion of $PM_{2.5}$ days exceeding the first level standard in Xi'an decreased 18.7%, corresponding to 67 days. The proportion of days exceeding the second level standard decreased 6.7%, corresponding to 24 days. It can be clearly seen that the proportion of days with low concentration has increased, while the proportion of days with excessive concentration has decreased. As shown in Table 1, if the number of days with PM_{10} and $PM_{2.5}$ exceeding the first level concentration decreases (50 $\mu g/m^3$, 35 $\mu g/m^3$), it indicates an increase in the number of days that meet the first level concentration. The first level concentration refers to a relatively low concentration, indicating an increase in the number of days with low concentration and an increase in its proportion, while the second level concentration (150 $\mu g/m^3$, 75 $\mu g/m^3$) refers to a relatively high concentration, and the decrease in the number of days exceeding the standard is relatively small compared to the first level concentration. This indicates that the air quality in Xi'an is gradually improving, and the concentration of particulate matter in the air is showing a decreasing trend.

Before the lockdown due to the epidemic, the proportion of PM_{10} exceeding the first and second level standards was 83.2% and 22.6% [47], respectively. The proportion exceeding the first and second level standards for PM_{10} during the lockdown due to the epidemic was 77.2% and 14.3%, respectively. Compared to before the lockdown, the proportion of PM_{10} exceeding the first and second level standards decreased by 6.0% and 8.3%, respectively. This indicates that after implementing epidemic control measures, there has been an improvement in air quality, and the amount of excessive particulate matter has decreased. The proportion exceeding the first and second level standards for PM_{10} after the lockdown due to the epidemic was 66.3% and 16.4%, respectively. Compared to before the lockdown, the proportion of PM_{10} exceeding the first and second level standards decreased by 16.9% and 6.2%. Compared to during the lockdown, the proportion of PM_{10} exceeding the first level standard decreased by 10.9%, while that exceeding the second level standard rebounded, increasing by 2.1%.

Before the lockdown due to the epidemic, the proportion of $PM_{2.5}$ exceeding the first and second level standards was 59.0% and 23.8% [47], respectively. The proportion of $PM_{2.5}$ exceeding the first and second level standards during the lockdown was 50.5% and 18.8%, respectively. Compared to before the lockdown, the proportion of $PM_{2.5}$ exceeding the first and second level standards decreased by 8.4% and 5.0%, respectively.

This also indicates that after implementing epidemic control measures, the phenomenon of excessive particulate matter decreased. The proportion of $PM_{2.5}$ exceeding the first and second level standards after the lockdown due to the epidemic was 44.1% and 19.2%, respectively. Compared to before the lockdown, the proportion of $PM_{2.5}$ exceeding the first and second level standards decreased by 14.8% and 4.7%. Compared to during the lockdown, the proportion of $PM_{2.5}$ exceeding the first level standard decreased by 6.4%, while that exceeding the second level standard rebounded, increasing by 0.4%.

This indicates that some activities were reduced, such as the shutting down of some factories, schools, restaurants, and other entertainment facilities, and the reduction of unnecessary outings for residents. The significant reduction in anthropogenic sources led to a decrease in pollutant emissions, resulting in an improvement in air quality. In the late stage of the epidemic lockdown, work and production gradually resumed, and industrial enterprises began to discharge pollutants. The gap in air quality gradually narrowed, and even rebounded. For example, the average concentration of PM_{10} in 2023 (95.8 $\mu g/m^3$) increased compared to the concentrations in 2020–2022 (90.0 $\mu g/m^3$, 95.7 $\mu g/m^3$, 95.2 $\mu g/m^3$). Therefore, the control of pollutants in the air still needs to be further strengthened.

3.3. Monthly Variation in Pollutant Concentration

The monthly changes in different air pollutants before, during, and after the epidemic lockdown are shown in Figure 3.

From Figure 3, it can be seen that from 2018 to 2023, the monthly changes in concentration of $PM_{2.5}$, PM_{10}, CO, SO_2, and NO_2 are similarly "higher in winter and lower in summer". This is consistent with the conclusion given in the literature [57]. This can indicate that the concentration of these five pollutants increased due to the use of coal for heating in winter, coupled with the relatively low temperature and weak light intensity in Xi'an, making it difficult for pollutants to diffuse and dilute [53]. The relatively low concentration of pollutants in summer was mainly due to the reduction in coal-fired sources and the strong sunlight and precipitation in summer, which reduce their concentration. However, PM_{10} remains at a relatively high concentration, mainly due to the influence of sandstorms in the north, resulting in a higher concentration of airborne particulate matter.

The monthly average concentration of O_3 changes in a "unimodal" manner, with the highest concentration in summer and the lowest concentration in winter. This is mainly related to the temperature and the strength of solar radiation [53]. In summer, the temperature is higher and the solar ultraviolet radiation is enhanced, which easily forms O_3. In winter, the temperature is lower and the ultraviolet intensity is also lower, which is more stable and not conducive to the occurrence of photochemical reactions. Therefore, the concentration of O_3 is the lowest in winter.

Compared to before the lockdown, the concentration of SO_2 during and after the epidemic lockdown decreased by 29.8% and 34.6%, respectively. The concentration during the epidemic lockdown decreased the most in January compared to before the lockdown, by 46.4%. After the epidemic lockdown, the concentration decreased the most in December compared to before the lockdown, by 67.3%, while it also decreased the most in December compared to during the epidemic lockdown, by 45.9%. The concentration of NO_2 decreased by 21.1% and 27.6%, respectively. During the epidemic lockdown, the concentration decreased the most in January compared to before the lockdown, by 33.5%. After the epidemic lockdown, the concentration decreased the most in May compared to before the lockdown, by 45.7%. Similarly, the concentration decreased the most in May compared to during the epidemic lockdown, by 34.2%. The concentration of CO decreased by 28.2% and 32.6%, respectively. During the epidemic lockdown, the concentration decreased the most

in April compared to before the lockdown, by 37.3%. After the epidemic lockdown, the concentration decreased the most in March compared to before the lockdown, by 44.8%. Similarly, the concentration decreased the most in November compared to during the epidemic lockdown, by 20.1%.

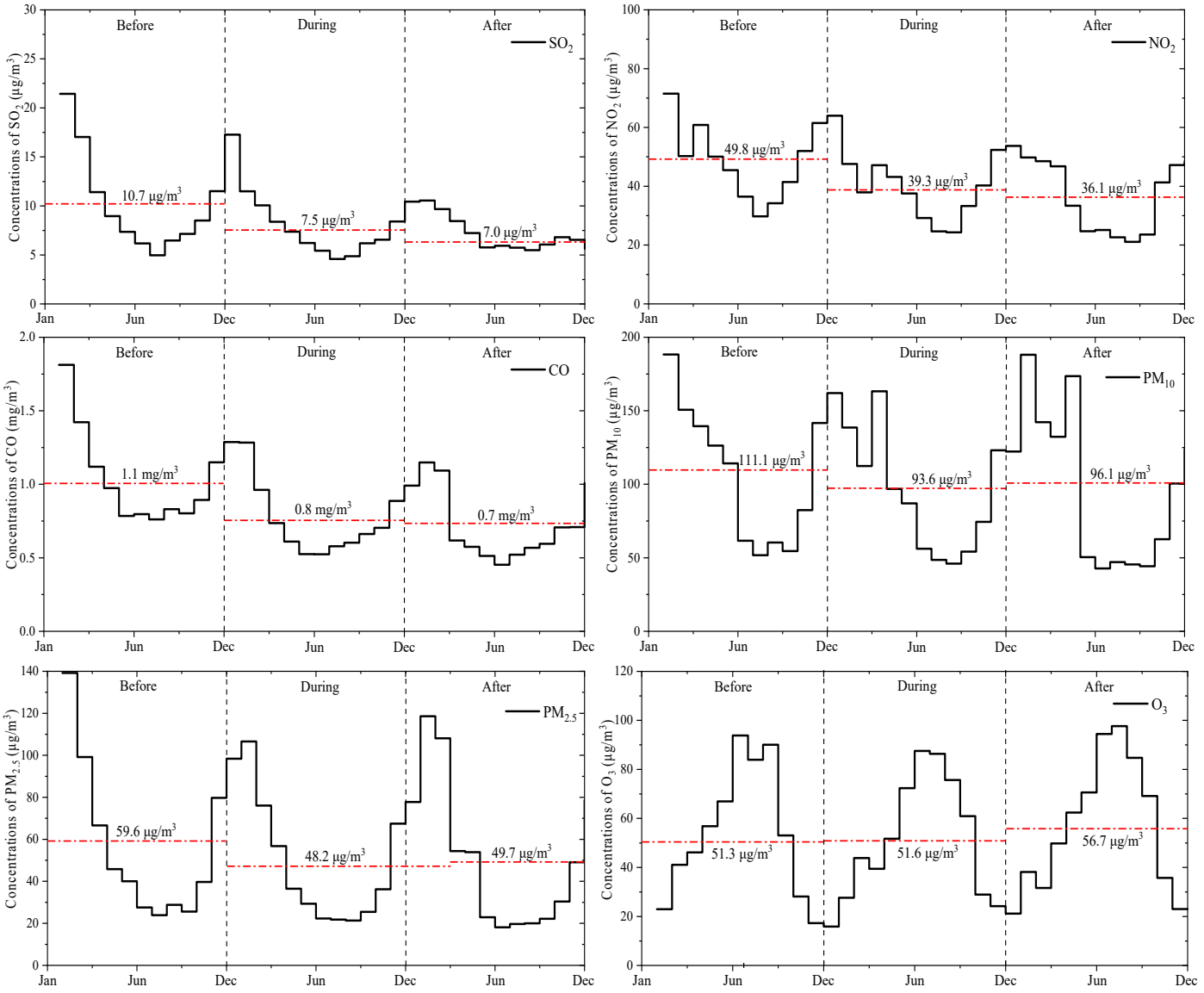


Figure 3. Monthly variation in pollutant concentration in Xi'an at different times.

PM_{10} and $PM_{2.5}$ showed a decrease before and during the lockdown period, but showed an upward trend after the lockdown. The concentration of PM_{10} during the epidemic lockdown decreased the most in January compared to before the lockdown, by 26.4%. After the epidemic lockdown, the concentration decreased the most in May compared to before the lockdown, by 55.8%. Similarly, the concentration decreased the most in April compared to during the epidemic lockdown, by 44.2%. The concentration of $PM_{2.5}$ decreased the most in May during the epidemic lockdown compared to before the lockdown, by 26.7%. After the epidemic lockdown, the concentration also decreased the most in May compared to before the lockdown, by 42.8%. Similarly, the concentration of $PM_{2.5}$ decreased the most in April compared to during the epidemic lockdown, by 32.3%.

O_3 showed an upward trend before, during, and after the epidemic lockdown. Compared to before the lockdown, the concentration of O_3 has increased by 0.6% and 9.4%, respectively. During the mid-term of the epidemic lockdown, the concentration increased

the most in November compared to before the lockdown, reaching 28.6%. After the lockdown due to the epidemic, the concentration increased the most in January compared to before the lockdown, reaching 39.8%. Similarly, during the later stage of the epidemic lockdown, the concentration also increased the most in January compared to the mid-term of the epidemic lockdown, reaching 27.7%.

3.4. Comparative Analysis of Pollutant Concentrations

The daily changes in various pollutants before, during, and after the epidemic lockdown are shown in Figure 4.

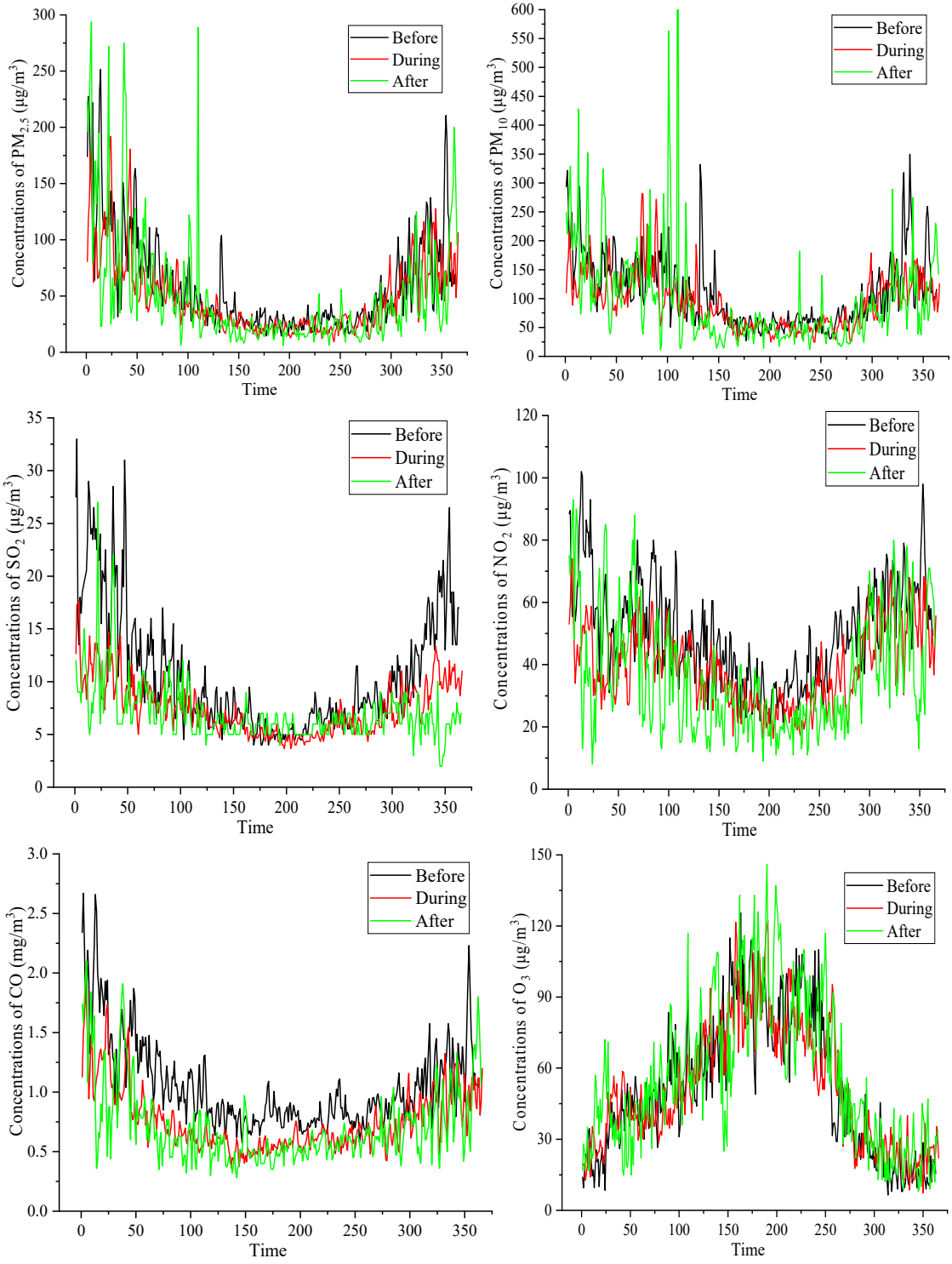


Figure 4. Daily variation in different pollutant concentrations.

From Figure 4, SO_2, NO_2, and CO had the highest daily average before the epidemic lockdown; PM_{10}, $PM_{2.5}$ and O_3 had the highest daily average after the epidemic lockdown. The daily average concentration ranges of PM_{10}, SO_2, NO_2, CO, O_3, and $PM_{2.5}$ before the lockdown were 10.0~576.0 μg/m^3, 2.0~50.0 μg/m^3, 12.0~114.0 μg/m^3, 0.3~3.2 mg/m^3, 4.0~149.0 μg/m^3, and 5.0~292.0 μg/m^3, respectively. The daily average concentration ranges of PM_{10}, SO_2, NO_2, CO, O_3, and $PM_{2.5}$ during the epidemic lockdown were 8.0~658.0 μg/m^3, 3.0~22.0 μg/m^3, 6.0~93.0 μg/m^3, 0.3~2.1 mg/m^3, 4.0~138.0 μg/m^3, and 4.0~278.0 μg/m^3, respectively. The concentrations of six pollutants decreased; this indicates that after taking relevant measures, such as decreasing residents' outings, in the result was a decrease in pollutant emissions and an improvement in air quality.

After the epidemic lockdown, the daily average concentration ranges of PM_{10}, SO_2, NO_2, CO, O_3, and $PM_{2.5}$ were 11.0~1116.0 μg/m^3, 2.0~27.0 μg/m^3, 8.0~93.0 μg/m^3, 0.3~2.1 mg/m^3, 8.0~146.0 μg/m^3, and 6.0~294.0 μg/m^3, respectively. Compared to before the epidemic lockdown, except for an increase in O_3 concentration, the concentrations of other pollutants decreased. However, PM_{10} and $PM_{2.5}$ reached their extreme values at around 100 days, due to the intensified emissions of pollutants caused by the resumption of production and work, as well as the impact of sand and dust transport [58], resulting in extreme concentrations of particulate matter. This aligns with the results of previous studies [59], so precise prevention and control of typical weather still need to be carried out.

Similarly, compared to during the epidemic lockdown, the concentrations of pollutants are shown to increase in Figure 4. It can be seen that with the gradual resumption of work and production, the amount of personal travel and the emissions of automobile exhausts and factories also gradually increased; the daily average concentration also increased accordingly, and a rebound phenomenon even occurred. Further differences in the concentrations of various pollutants are shown in Table 2.

Table 2. Differences in daily average concentration of pollutants.

Pollutant	Before	During	After	Variation (During and Before Lockdown)		Variation (During and Before Lockdown)		Variation (During and Before Lockdown)	
	$PM_{2.5}$ (μg/m^3)			Net	%	Net	%	Net	%
Max	292	278	294	−14.0	−4.8	16.0	5.8	2.0	0.7
Avg	59.2	48.1	49.4	−11.0	−18.7	1.2	2.6	−9.8	−16.6
Min	5	4	6	−1.0	−20.0	2.0	50.0	1.0	20.0
	PM_{10} (μg/m^3)			Net	%	Net	%	Net	%
Max	576	658	1116	82.0	14.2	458.0	69.6	540.0	93.8
Avg	110.7	93.6	95.8	−17.1	−15.4	2.2	2.3	−14.9	−13.4
Min	10	8	11	−2.0	−20.0	3.0	37.5	1.0	10.0
	SO_2 (μg/m^3)			Net	%	Net	%	Net	%
Max	50	22	27	−28.0	−56.0	5.0	22.7	−23.0	−46.0
Avg	10.6	7.5	7.0	−3.1	−29.5	−0.5	−6.8	−3.6	−34.3
Min	2	3	2	1.0	50.0	−1.0	−33.3	0.0	0.0
	NO_2 (μg/m^3)			Net	%	Net	%	Net	%
Max	114	93	93	−21.0	−18.4	0.0	0.0	−21.0	−18.4
Avg	49.7	39.3	36.0	−10.4	−20.9	−3.3	−8.4	−13.7	−27.6
Min	12	6	8	−6.0	−50.0	2.0	33.3	−4.0	−33.3
	CO (mg/m^3)			Net	%	Net	%	Net	%
Max	3.23	2.12	2.1	−1.1	−34.4	0.0	−0.9	−1.1	−35.0
Avg	1.1	0.8	0.7	−0.3	−27.6	−0.1	−6.6	−0.3	−32.4
Min	0.34	0.25	0.28	−0.1	−26.5	0.0	12.0	−0.1	−17.6
	O_3 (μg/m^3)			Net	%	Net	%	Net	%
Max	149	138	146	−11.0	−7.4	8.0	5.8	−3.0	−2.0
Avg	51.6	51.6	56.8	0.0	0.0	5.3	10.2	5.3	10.2
Min	4	4	8	0.0	0.0	4.0	100.0	4.0	100.0

3.5. Correlation Analysis Between Various Pollutants

By analyzing the correlation between these six pollutants, it is possible to effectively understand their interaction, and within that, the type and distribution of the same or different sources of air pollutants, especially comparing these values through the three periods. The changes in correlations between various pollutants before, during, and after the epidemic lockdown are shown in Figure 5.

It can be seen from Figure 5 that before the epidemic lockdown, the average correlation values between $PM_{2.5}$ and PM_{10}, SO_2, and CO are 0.718, 0.723, and 0.881, respectively. The average correlation value between SO_2 and CO is 0.739, showing they are highly correlated. The average correlation values of $PM_{2.5}$ with NO_2 and O_3 are 0.530 and 0.358; the average correlation values of PM_{10} with SO_2, NO_2, and CO are 0.538, 0.504, and 0.527; the average correlation value of CO with O_3 is 0.350; the average correlation values of NO_2 with SO_2, CO, and O_3 are 0.585, 0.538, and 0.480; and the average correlation value of SO_2 and O_3 is 0.373, all of which are moderate correlations. The average correlation value between PM_{10} and O_3 is 0.283, indicating a weak correlation.

During the epidemic lockdown, the average correlation values between $PM_{2.5}$ and SO_2 and CO are 0.734 and 0.879, respectively, and the average correlation value between SO_2 and CO is 0.671. All are highly correlated. The average correlation values between $PM_{2.5}$ and PM_{10}, NO_2, and O_3 are 0.620, 0.468, and 0.365, respectively. The average correlation values of PM_{10} with SO_2, NO_2, and CO are 0.524, 0.529, and 0.389, respectively. The average correlation value between CO and O_3 is 0.395; the average correlation values between NO_2 and SO_2, CO, and O_3 are 0.602, 0.395, and 0.476, respectively; and the average correlation value between SO_2 and O_3 is 0.399. All are moderately correlated. The average correlation value between PM_{10} and O_3 is 0.294, indicating a weak correlation.

After the epidemic lockdown, the average correlation value between $PM_{2.5}$ and CO is 0.686, indicating a high degree of correlation. The average correlation values between $PM_{2.5}$ and PM_{10}, SO_2, and NO_2 are 0.602, 0.377, and 0.450, respectively. The average correlation values between NO_2 and SO_2, CO, and O_3 are 0.358, 0.524, and 0.330, respectively, all of which are moderate correlations. The average correlation value between $PM_{2.5}$ and O_3 is 0.190, and the average correlation values between PM_{10} and SO_2, NO_2, CO, and O_3 are 0.199, 0.197, 0.175, and 0.083, respectively. The average correlation value between CO and O_3 is 0.315, and the average correlation values between SO_2 and CO and O_3 are 0.297 and 0.042, respectively, indicating weak correlation. These results indicate the following: Firstly, pollution homogeneity can be revealed: a significant correlation between pollutants (such as $PM_{2.5}$ and SO_2) can directly prove that they may come from the same emission source (such as coal combustion), providing core data support for tracing pollution sources. Secondly, if the correlation between two pollutants is extremely strong, it indicates that there is information redundancy in the monitoring data. Based on this, the layout of monitoring stations or indicator settings can be adjusted to reduce monitoring costs while ensuring data validity. In addition, easily monitored pollutants (such as PM_{10}) can be used as alternative indicators for difficult to monitor pollutants (such as VOCs), simplifying the input parameters of air quality prediction models and improving prediction efficiency.

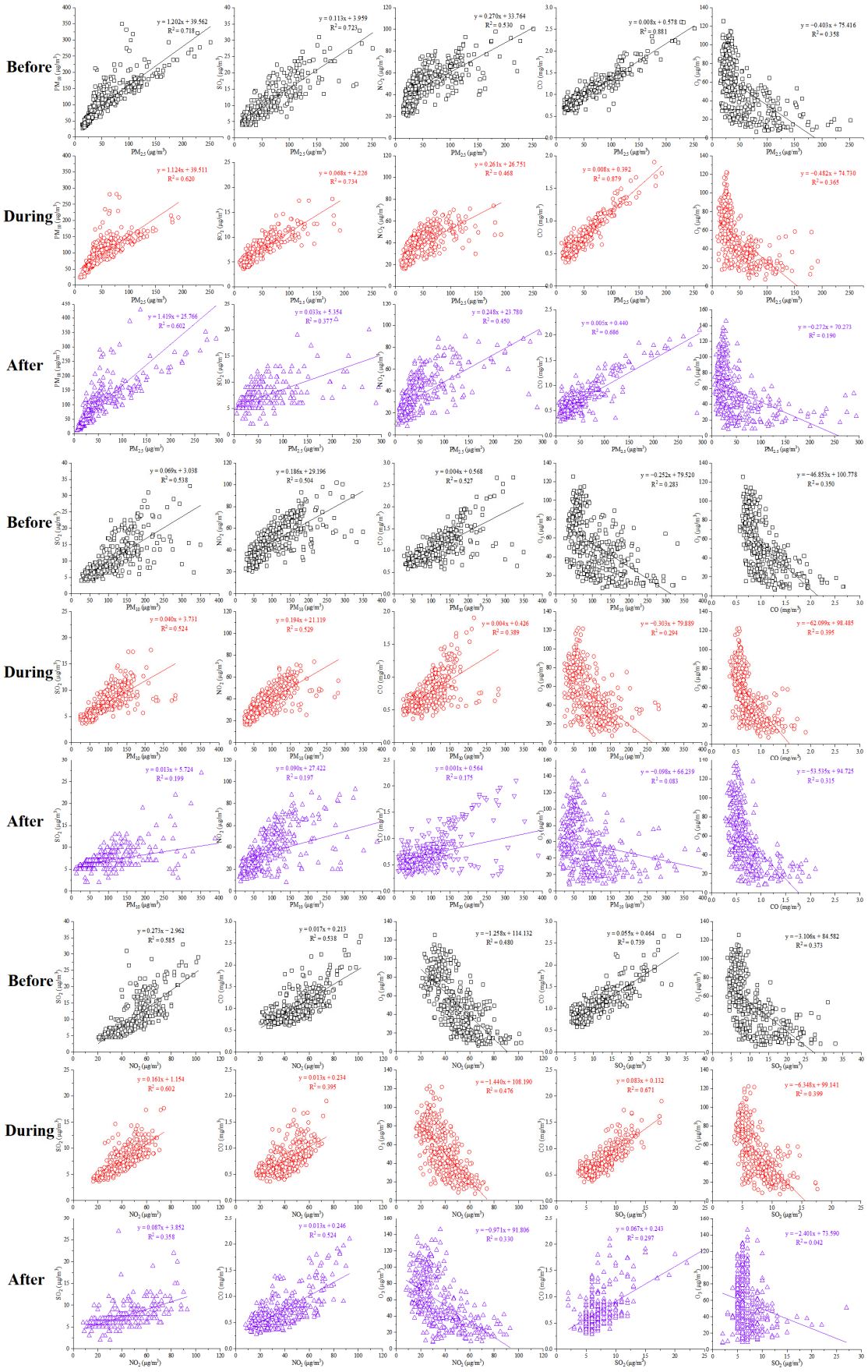


Figure 5. Correlation curves of various pollutants at different time points. Weak correlation: 0–0.33, moderate correlation: 0.33–0.66, high correlation: 0.66–1 [60].

However, with the resumption of work and production, multi-source pollution is still one of the primary problems to be solved in Xi'an. The control of pollutants in the air still requires long-term management. For special environments such as underground [61–64], more focused research is needed to provide a reference for effective treatment of pollutants in multi-dimensional environments.

This study focuses on the comparison of the concentrations of six pollutants in the atmosphere before, during, and after the lockdown, but there are two limitations: Firstly, it does not fully integrate meteorological data with atmospheric diffusion parameters, and fails to quantify the delayed effects mediated by pollutant accumulation cycles and diffusion rates, resulting in a lack of comprehensive interpretation of the concentration wave mechanism. Secondly, it mainly relies on concentration data from monitoring stations and lacks a combination of dynamic changes in pollution source emission inventories, making it difficult to accurately distinguish the cumulative effects of delayed effects and changes in emission intensity. Future research can quantify the actual contribution of delay effects by coupling meteorological observation data with atmospheric diffusion models and special in-depth research on the mechanism of ozone formation, while expanding to regional scales and extending time series to compare differences in delay effects under different geographical backgrounds and long-term evolution patterns in the post-pandemic era.

4. Conclusions

This paper is based on a statistical analysis of monitoring data from Xi'an from 2018 to 2023, and conducts in-depth analysis of the concentration changes in various pollutants in the atmosphere from a temporal perspective. The conclusions are as follows:

1. After the epidemic lockdown (2023), the annual average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO decreased, while the concentration of O_3 increased. Compared to before the epidemic lockdown, the average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO during the epidemic lockdown (2020–2022) decreased by 18.7%, 15.4%, 29.4%, 20.9%, 0.03%, and 28.1%, respectively.
2. Compared to before the epidemic lockdown, the proportion of PM_{10} exceeding the first and second level standards in the city decreased by 6.0% and 8.3%, respectively. The proportion of $PM_{2.5}$ exceeding the first and second level standards in urban areas under the epidemic lockdown decreased by 8.4% and 5.0%, respectively.
3. The monthly changes in concentration of $PM_{2.5}$, PM_{10}, CO, SO_2, and NO_2 were "higher in winter and lower in summer". The monthly average concentration of O_3 changed in a "unimodal" structure. The concentrations of SO_2, NO_2, and PM_{10} decreased the most in January, by 46.4%, 33.5%, and 26.4%, respectively. The concentration of CO decreased the most in April, by 37.3%. $PM_{2.5}$ decreased the most in May, with a decrease of 26.7%. O_3 showed the largest increase in November, reaching 28.6%.
4. After taking relevant measures, such as shutting down some factories, schools, restaurants, and other entertainment facilities, and reducing unnecessary outings for residents, the significant reduction in anthropogenic sources led to a decrease in pollutant emissions, resulting in an improvement in air quality. Therefore, long-term management of air quality in Xi'an is still needed. This paper explores more detailed information so that the decision-makers can choose adequate strategies.

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