



Assessing the spatio-temporal impact of the COVID-19 pandemic lockdown on air quality in Jiangsu province, China

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Abstract

The Chinese government has implemented severe restrictions and lockdown (LD) measures in response to the COVID-19 pandemic. This kind of environment offers a terrific opportunity to work in this area. The current study sought to evaluate the COVID-19 lockdown's spatiotemporal impact on Jiangsu Province, China's air quality. We examined the data gathered from 72 monitoring stations for each of the six air pollutant factors: PM₁₀, SO₂, PM_{2.5}, CO, NO₂, and O₃ from 2017 to 2021. Our findings indicate that air pollution concentrations abruptly decreased as a result of the COVID-19 lockdown. During the active-LD period, SO₂, NO₂, PM₁₀, PM_{2.5} and CO concentrations declined by – 17.85%, – 38.07%, – 29.52%, – 30.33%, and – 19.05%, respectively, while O₃ concentrations significantly increased by 58.62%, because of a combination of decreased emissions of NO_x and VOCs, and variations in the weather. In contrast to the historical data (2017–19), O₃ levels increased by 3.53%, while SO₂, NO₂, PM₁₀, PM_{2.5}, and CO reductions were – 50.11%, – 34.95%, – 36.51%, – 33.16%, and – 23.60%, respectively. Among the selected pollutants, PM₁₀, PM_{2.5}, NO₂, and CO all exhibited increasing tendencies, while SO₂ and O₃ concentration levels reduced in 2021. According to the correlation analysis, Jiangsu's active-LD phase observed a considerable relationship between SO₂, PM_{2.5}, NO₂, PM₁₀, and CO. The findings suggest that the COVID-19 lockdown measures had a significant influence on both raising and declining air pollution levels. These findings illuminate a new light and are helpful for the scientific community and local authorities to create strategies to protect the environment.

Keywords COVID-19 · Lockdown · Air quality · Air pollution · Jiangsu province · China

1 Introduction

The World Health Organization (WHO) has classified the new coronavirus disease 2019 (COVID-19) as a “global pandemic”, indicating a significant risk to public health (WHO, 2020a). As of August 6, 2020, 18,354,342 persons were afflicted, and the COVID-19 was responsible for 696,147 deaths worldwide (WHO, 2020b). The impacted nations enforced lockdowns, limitations on human movement, and bans on commercial, educational,

sporting, religious, and cultural activities to contain and reduce the large-scale spread of the COVID-19 (Hu et al., 2021; Wang et al., 2021). The lockdowns and other forced restrictions not only stopped the COVID-19 pandemic from spreading, but they also greatly improved the air quality in these areas and regions, which helped to partially offset the costs associated with implementing these measures during the pandemic (Abdullah et al., 2020; Li et al., 2020).

By the end of January 2020, the Chinese government enforced several stringent restrictions and forced limitations in the national public health response to stop the COVID-19 pandemic from spreading quickly (Tian et al., 2020; Zhang et al., 2021a). The COVID-19 hub in Wuhan and the surrounding areas were placed under lockdown, with limited human movement and the cessation of all non-essential activity. In a matter of days, the lockdown's boundaries were expanded nationwide on January 23, 2020. Because of this kind of environment, transportation was suspended, human mobility was reduced, and industrial production was lowered, all of which contributed to a sharp decline in air quality (Zhang et al., 2021b). According to recent studies, all pollutant concentrations observed a significant reduction and decline during the lockdown period, both regionally and globally (Hua et al., 2020; Orak et al., 2021; Ghasempour et al., 2021). Hasnain et al. (2023) reported an abrupt drop in air pollution during the COVID-19 active-LD phase in the Yangtze River Delta, China. The authors of this study observed a remarkable increase in O₃ levels during the corresponding period. Another study documented by Bhatti et al. (2022) also indicated similar findings in Anhui Province of China. A sizeable decline in air pollution was reported by the authors of this study.

One of the main problems in developing nations that seriously endangers public health is air pollution (He et al., 2017). According to Xu and Lin (2017), the main sources of air pollution are the growing economy, the use of fossil fuels in various industries, and the rate of urbanization. The two biggest issues facing the world and local communities in recent years have been environmental degradation and air pollution. The most important pollutants in global urban regions are nitrogen dioxide (NO₂), sulfur dioxide (SO₂), ozone (O₃), carbon monoxide (CO), and particulate matter (PM₁₀ and PM_{2.5}). These pollutants can be impacted heavily by mobile sources (Ghasempour et al., 2021).

Many scholars found that the COVID-19 lockdown and stringent regulations caused a notable drop in industrial and transportation emissions, which in turn caused an improvement in air quality (Tian et al., 2020; Hua et al., 2020; Orak et al., 2021). According to TROPOMI instrument data, during China's lockdown period, there was a significant decrease (40%) in NO₂ concentration as compared to the previous year (Bauwens et al., 2020). The primary reasons for this drop in NO₂ levels are fewer industrial emissions and less traffic on the roads. Comparable findings were also reported in the analysis of CO, NO₂, SO₂, and particulate matter (PM₁₀ and PM_{2.5}), which shows that during China's COVID-19 control period, the concentration levels of SO₂, NO₂, CO, PM₁₀, and PM_{2.5} dramatically decreased (Chang et al., 2020). According to Chen et al. (2020), the concentrations of NO₂, PM_{2.5}, CO, SO₂, and PM₁₀, showed declining trends, while O₃ levels increased during the China's COVID-19 period. Studies by Zhu et al. (2021) and Zhang et al. (2022) have given detailed insights into the rise in ozone (O₃) levels in Chinese cities during the COVID-19 epidemic. The observed ozone increase can be attributed to reduced nitrogen oxide (NOx) emissions from decreased traffic and industrial activities during the lockdown, leading to a lower O₃ titration. Additionally, favorable meteorological conditions, such as increased solar radiation and higher temperatures, have enhanced ozone production through photochemical reactions (Kang et al., 2021; Zhang et al., 2022; Zhu et al., 2021).

The present study used daily average data from 72 monitoring stations in Jiangsu Province to investigate six air pollutant parameters: NO₂, SO₂, PM_{2.5}, PM₁₀, CO, and O₃. We investigated the levels of these air pollutants in the seven periods: pre, active and post periods of COVID-19, and 2021 (same dates of lockdown). The outcomes were also compared with those of the prior three years, 2017–19 (same lockdown's dates), for a deeper analysis and to find new findings. Numerous studies on the effects of the COVID-19 pandemic lockdown have been documented in the past. Other studies have mostly focused on either the comparison with previous years or the assessment of air quality from pre-to-active lockdown periods, while most studies have demonstrated that the lockdown measures and strict restrictions led to a decline in air pollutant levels for limited time periods. In contrast to earlier studies, our study spans pre-, active-, and post-lockdown times and provides a deeper analysis with new findings and a new paradigm. It also compares the selected air pollutants with the last three years (2017–19) and the following year 2021. The present study aimed to: (1) evaluate the spatiotemporal effects of the lockdown era of COVID-19 on air quality in the pre, active, post periods of COVID-19, and 2021; (2) identify variations in different air pollutants in various time periods; and (3) investigate the levels of air pollutants in Jiangsu Province during the corresponding dates in the preceding three years, 2017–19. In order to help the scientific community and local authorities develop strategies to enhance and manage air pollution in the coming years, the study offers helpful information and a new paradigm.

2 Materials and methods

2.1 Study area

One of the most significant regions of the Yangtze River Delta (YRD) is Jiangsu Province, which has highly developed industrial sectors with a GDP of 12.82 trillion yuan (about 1.8 trillion US dollars) in 2023. With an area of 107,200 km², Jiangsu is situated between 30°45' and 35°20' N and 116°18' and 121°57' E. There are thirteen (13) cities in the province, and Jiangsu plays an important role in urbanization and modernization because of its strong economy and favorable location. Based on the data from 2019, Jiangsu is home to a sizable population of about 80.5 million people. Administrative districts at the county level number 78 in the province. Jiangsu has abundant energy resources, traditional industries, and steel smelting.

Figure 1 depicts the locations of 72 monitoring stations in Jiangsu Province that are currently in operation and collecting air pollutants data. Each of these observation stations belonged to a distinct area (S1). Among these areas, Maigaoqiao is connected with an industrial area, Meadow gate represents a populated area, Xuanwu Lake covers a park area, Shangshan stations belongs to a suburban and mountainous site, Wuzhong district represents a manufacturing zone, Star Lake Gardan is connected with a park and green area, Hongmen station belongs to a central city area, municipal monitoring station represents a municipal area, Huang Chao represents a populated area, New district office belongs to a business zone, Park road covers a green area, Palji Mountain represents a mountainous area, Yangcheng in connected with an industrial and manufacturing zone, Suqian covers an institutional area. The complete detail of all these monitoring stations is given in Table S1.

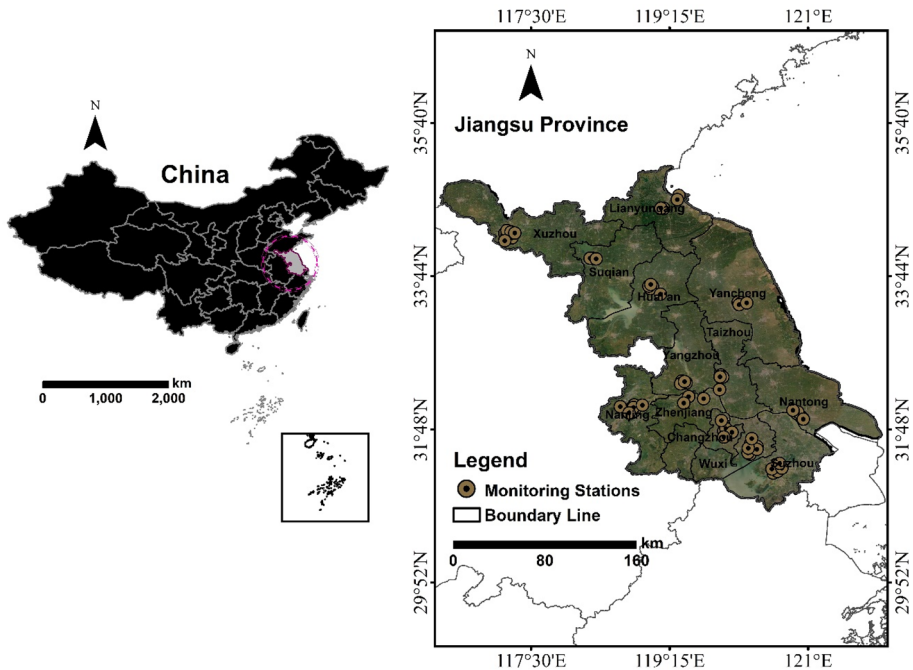


Fig. 1 Location of the study area and the air pollution monitoring stations in Jiangsu Province

2.2 Air quality data and study period

Daily average data for the six air pollutant factors—SO₂ (sulphur dioxide), CO (carbon monoxide), PM₁₀ (particulate matter with diameters of $\leq 10 \mu\text{m}$), NO₂ (nitrogen dioxide), PM_{2.5} (particulate matter with diameters of $\leq 2.5 \mu\text{m}$), and O₃ (ozone)—were analyzed in order to determine the spatiotemporal impact of the lockdown era of COVID-19 on air quality. The China Environmental Monitoring Station (CNEMC, 2019) provided the data from 72 monitoring locations (Fig. 1). These monitoring stations are scattered among 13 cities in Jiangsu province: Suzhou (8), Nantong (5), Lianyungang (4), Xuzhou (11), Changzhou (6), Zhenjiang (4), Taizhou (4), Huaian (5), Yancheng (4), Suqian (4), and Nanjing, the province's capital (9). The COVID-19 lockdown's effects on air quality were examined by dividing the data into seven time periods between 2017 and 21: Pre-LD (November 11, 2019–January 24, 2020), active-LD (January 25, 2020–April 8, 2020), post-LD (April 9, 2020–June 22, 2020), post-LD (January 25, 2020–April 8, 2020), (iv) similar dates of active-LD in the subsequent year 2021, and (v–vii) same dates of active-LD in the last three years of 2017–19.

2.3 Meteorological data

For the three study periods (pre-LD, active-LD, and post-LD) in Jiangsu Province, daily meteorological data, including wind speed, relative humidity, precipitation and

air temperature, were obtained from the meteorological data service of NASA (<https://power.larc.nasa.gov>).

2.4 Data analysis

The six air pollutant parameters (NO_2 , SO_2 , O_3 , PM_{10} , CO and $\text{PM}_{2.5}$) were examined in different periods: pre, active and post periods of lockdown, the lockdown dates in the following year 2021, and the last three years 2017–19. This allowed researchers to better understand the spatiotemporal impact of the lockdown (LD) phase of COVID-19 on Jiangsu's air quality. We investigate the variations in air pollution concentrations to observe how the pollutants have changed; the percentage change and net difference were also given for the study period. To determine if the climatic conditions during the pre-, active-, and post-LD periods were typical, a number of meteorological factors were evaluated, including air temperature, relative humidity, wind speed, and precipitation. We used the library of Geopandas in Python to create a spatial distribution map of all the air pollution components. To depict the regional distribution of the six air pollution parameters over the study period, the data were mapped. Meanwhile, line plots were made to demonstrate how the climatic parameters were normal. During Jiangsu's lockdown, linear regression analysis was done to look at the relationships between the selected air pollutants and meteorological factors. In this work, Python was used to construct regression plots and ArcGIS 10.2.2 was used to create a study area map.

3 Results and discussion

3.1 Pre to post lockdown changes in pollutant concentrations

The Yangtze River Delta (YRD), the Pearl River Delta (PRD) and Beijing-Tianjin-Hebei region (BTH) have garnered significant attention from scholars and researchers studying air pollution due to their highly populated and economically developed locations. One of the most significant regions of the YRD is Jiangsu Province, which has recently had the worst air quality due to rapid growth in a variety of sectors (Zhang et al., 2020). Table 1 summarizes the statistical analysis for the six criteria air pollutants from before to after lockdown (LD). The findings show that during the pre-active-LD changes in Jiangsu, O_3 increased by 58.62% while the levels of SO_2 , NO_2 , PM_{10} , $\text{PM}_{2.5}$, and CO fell by an average of -17.85% , -38.07% , -29.52% , -30.33% , and -19.05% , respectively. With very minor exceptions, the patterns of particulate matter concentrations ($\text{PM}_{2.5}$ and PM_{10}) in the decrease scenario were similar. NO_2 was shown to have a significantly declining value among other pollutants, while SO_2 and CO showed mixed reductions during the active-LD period. Jiangsu saw a growing tendency for O_3 throughout the same period, in contrast to other pollutants. Supporting our findings, numerous studies (Han et al., 2021; Sulaymon et al., 2021; Zhang et al., 2021b; Zheng et al., 2020) reported that during pre-active-LD changes in China, there was an abrupt fall in the levels of these air pollutants, while O_3 levels increased. According to Mor et al. (2021), the active-LD period's reduction in industrial operations, traffic restrictions, and community constraints is responsible for the notable drop in air pollution concentrations.

In Jiangsu Province, the concentrations of CO , NO_2 , PM_{10} , and $\text{PM}_{2.5}$, decreased by -9.21% , -18.80% , -14.82% , and -26.44% , respectively, from pre- to post-LD

Table 1 24 h average concentration and pre to post lockdown (LD) variation of pollutants in Jiangsu Province

Pollutants	Pre-LD	Active-LD	Avg. pre and active-LD	Post-LD	Variation (active and pre-LD)		Variation (post-LD and avg. of pre and active-LD)	
					Net	%	Net	%
<i>PM₁₀</i>								
Max	288.67	189	238.835	239.05	-99.67	-34.53	0.215	0.09
Avg	81.24	57.26	69.25	58.99	-23.98	-29.52	-10.26	-14.82
Min	7.02	6.59	6.805	5.13	-0.43	-6.13	-1.675	-24.61
<i>PM_{2.5}</i>								
Max	318.27	182	250.135	194.5	-136.27	-42.82	-55.635	-22.24
Avg	55.03	38.34	46.685	34.34	-16.69	-30.33	-12.345	-26.44
Min	3.85	5.42	4.635	1.33	1.57	40.78	-3.305	-71.31
<i>SO₂</i>								
Max	74	34.56	54.28	37.32	-39.44	-53.30	-16.96	-31.25
Avg	8.18	6.72	7.45	7.51	-1.46	-17.85	0.06	0.81
Min	1.05	1	1.025	1	-0.05	-4.76	-0.025	-2.44
<i>NO₂</i>								
Max	182.2	101.05	141.625	140.07	-81.15	-44.54	-1.555	-1.10
Avg	43.76	27.1	35.43	28.77	-16.66	-38.07	-6.66	-18.80
Min	4.33	1.79	3.06	3.21	-2.54	-58.66	0.15	4.90
<i>CO</i>								
Max	5.33	1.71	3.52	2.29	-3.62	-67.92	-1.23	-34.94
Avg	0.84	0.68	0.76	0.69	-0.16	-19.05	-0.07	-9.21
Min	0.14	0.12	0.13	0.1	-0.02	-14.29	-0.03	-23.08
<i>O₃</i>								
Max	95.25	125.43	110.34	211.25	30.18	31.69	100.91	91.45
Avg	42.29	67.08	54.685	87.07	24.79	58.62	32.385	59.22
Min	1	5.94	3.47	21.92	4.94	494.00	18.45	531.70

changes, while the concentrations of SO₂ and O₃ increased by an average of 0.81% and 59.22% (Table 1). PM_{2.5} exhibited a strong downward trend from pre- to post-LD, while PM₁₀, NO₂, and CO behaved differently in the reduction scenario. SO₂ concentrations among other pollutants showed a small increase throughout this period, while O₃ concentrations increased significantly. According to a study by Hu et al. (2020), Wuhan, China's O₃ concentration levels increased following the shutdown. It can be noted that compared to the pre-active-LD changes, the increment ratio in the O₃ levels was comparatively larger during the post-LD period. The drop in PM₁₀ concentration was greater during the active-LD period compared to the post-LD decrease, while PM_{2.5} showed similar decreasing tendencies in both times. Distinct patterns were observed in the SO₂ concentration, while a notable decrease in NO₂ was observed in the corresponding times. Of the pollutants that were chosen, CO and O₃ exhibited comparable patterns in both timeframes. The spatial distribution of these air contaminants is shown in Figs. 2, 3, 4, 5, 6, 7, where we can observe the clear changes over time in Jiangsu.

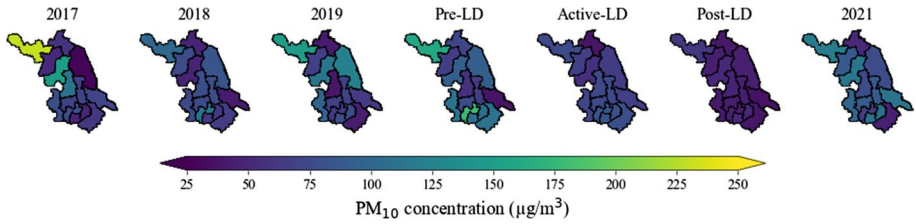


Fig. 2 Daily average concentration of PM₁₀ during the all-study periods in Jiangsu Province

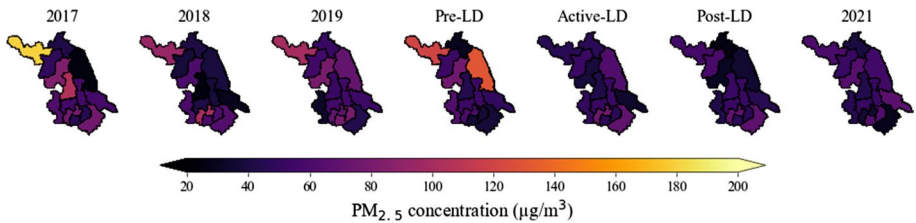


Fig. 3 Daily average concentration of PM_{2.5} during the all-study periods in Jiangsu Province

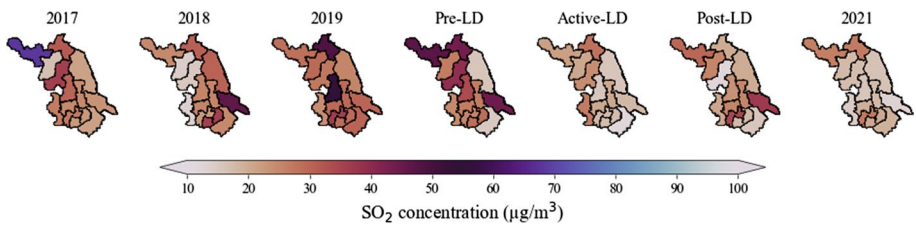


Fig. 4 Daily average concentration of SO₂ during the all-study periods in Jiangsu Province

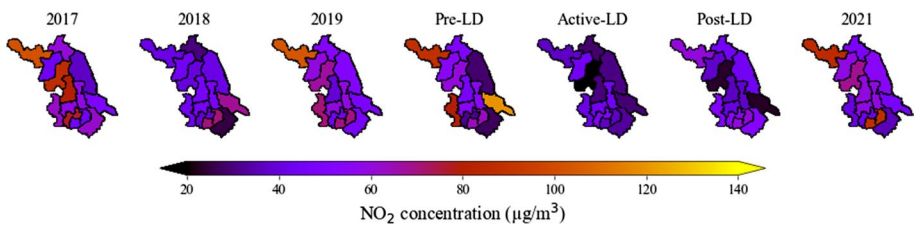


Fig. 5 Daily average concentration of NO₂ during the all-study periods in Jiangsu Province

There are a number of reasons for the variances in the drops in various air pollutants that occurred during the active-LD period of COVID-19. The sources of pollution's emissions differ. For instance, particulate matter (PM) can come from a variety of sources, including industrial operations, construction activities, dust, and wildfires, whereas nitrogen dioxide (NO₂) is mostly released by automobile exhaust and industrial activity. As a

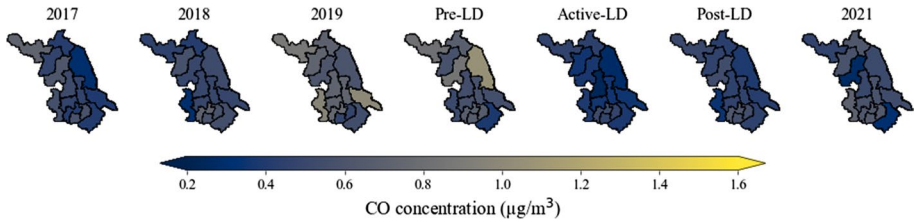


Fig. 6 Daily average concentration of CO during the all-study periods in Jiangsu Province

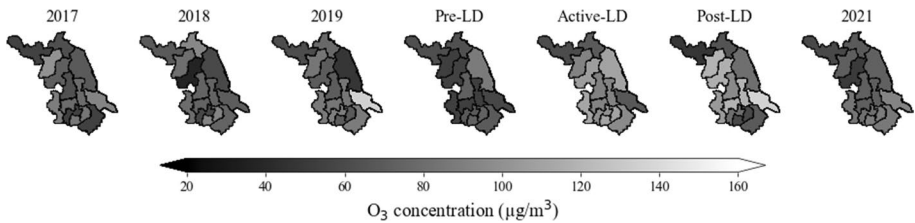


Fig. 7 Daily average concentration of O₃ during the all-study periods in Jiangsu Province

result, lockdown procedures may or may not be successful in lowering emissions from various sources. The chemical reactivity and atmospheric lifespan of pollutants vary as well. Certain pollutants may experience swift chemical reactions in the environment and have brief lifespans, whilst others could last for extended periods of time. Pollutant interactions can also affect the concentrations of individual pollutants. For instance, through chemical reactions and physical processes, the presence of certain pollutants can affect the chemistry of the atmosphere and the behavior of others.

3.2 Changes in pollutant concentrations during the equivalent lockdown period over the previous three years (2017–19)

Table 2 summarizes and presents the spatiotemporal variations and changes of the six criteria air pollutants from the previous three years to active-LD. The findings indicate that during Jiangsu's active-LD time, NO₂, SO₂, PM₁₀, CO and PM_{2.5} levels reduced by an average of – 28.55%, – 27.66%, – 33.23%, – 13.92% and – 29.83%, respectively, while the levels of O₃ increased by up to 6.59%, in comparison to the previous year 2019. According to the findings, stringent regulations and control measures limit traffic, industries, and construction projects, which lowers the concentration of different air pollutants during the lockdown period in 2020 compared to 2019. The highest and lowest declining trends for CO and PM₁₀, respectively, were noted throughout this time. Among other pollutants, such as NO₂, SO₂, and PM_{2.5} showed mixed tendencies, while O₃ presented an upward trend. According to a study (Wang et al., 2020), during China's active-LD season, the levels of PM_{2.5}, PM₁₀, NO₂, CO and SO₂, decreased while levels of O₃ increased in comparison to the previous year 2019. According to another study published by Mahato et al. (2020), during Delhi, India's active-LD era, the concentration levels of SO₂, NO₂, PM_{2.5}, PM₁₀ and CO were lower than they were in 2019, while O₃ was higher.

Table 2 24 h average concentration and variation of pollutants during 2017–20 (same dates of active-LD) in Jiangsu Province

Pollutants	2017	2018	2019	Avg. of 2017–2019	2020	Variation (2020 and 2019)		Variation (2020 and avg. of 2017–19)	
						Net	%	Net	%
<i>PM₁₀</i>									
Max	342.46	302.88	322.91	322.75	189	-133.91	-41.47	-133.75	-41.44
Avg	92.85	91.96	85.76	90.19	57.26	-28.5	-33.23	-32.93	-36.51
Min	20.45	14.07	14.33	16.28	6.59	-7.74	-54.01	-9.69	-59.53
<i>PM_{2.5}</i>									
Max	195.23	253.75	209.48	219.49	182	-27.48	-13.12	-37.49	-17.08
Avg	59.16	58.29	54.64	57.36	38.34	-16.3	-29.83	-19.02	-33.16
Min	10.24	2.22	4.15	5.54	5.42	1.27	30.60	-0.12	-2.11
<i>SO₂</i>									
Max	86.58	59.46	65.78	70.61	34.56	-31.22	-47.46	-36.05	-51.05
Avg	17.85	13.27	9.29	13.47	6.72	-2.57	-27.66	-6.75	-50.11
Min	2.05	1.42	1	1.49	1	0	0.00	-0.49	-32.89
<i>NO₂</i>									
Max	124.83	158.21	105.79	129.61	101.05	-4.74	-4.48	-28.56	-22.04
Avg	43.94	43.11	37.93	41.66	27.1	-10.83	-28.55	-14.56	-34.95
Min	1.88	3.35	1.96	2.40	1.79	-0.17	-8.67	-0.61	-25.31
<i>CO</i>									
Max	4.1	3.42	2.45	3.32	1.71	-0.74	-30.20	-1.61	-48.55
Avg	0.98	0.9	0.79	0.89	0.68	-0.11	-13.92	-0.21	-23.60
Min	0.15	0.1	0.1	0.12	0.12	0.02	20.00	0.00	2.86
<i>O₃</i>									
Max	160.75	162.67	142.08	155.17	125.43	-16.65	-11.72	-29.74	-19.16
Avg	69.12	62.33	62.93	64.79	67.08	4.15	6.59	2.29	3.53
Min	4.83	8.05	3.17	5.35	5.94	2.77	87.38	0.59	11.03

Our findings indicate that the concentrations of $PM_{2.5}$, PM_{10} , NO_2 , SO_2 , and CO reduced by an average of -33.16%, -36.51%, -34.95%, -50.11%, and -23.60%, respectively, O_3 levels increased by up to 3.53% during the previous three years to active-LD changes, in Jiangsu (Table 2, Figs. 2, 3, 4, 5, 6, 7). In Anhui Province, which is likewise located within the YRD zone, Bhatti et al. (2022) also discovered a noteworthy decrease in air pollutant concentrations during the active-LD period compared with the preceding three years (2017–19). This abrupt drop in air pollutant concentrations during the COVID-19 lockdown period compared with the previous three years was caused by a reduction in industrial, vehicular, construction, and heating activities. It is noteworthy that during both times, every air pollutant shown similar trends. SO_2 was observed to have significantly decreased from the previous three years to active-LD, while particulate matter, NO_2 , and CO indicated almost comparable declining trends with minor variations. The declining spell in PM_{10} and $PM_{2.5}$ concentrations was similar, indicating that urban areas were likely the source of both pollutants. We found that during both times, O_3 levels increased. Jiangsu experienced notable drops in air pollution levels during the previous three years to

active-LD changes, according to comparison analysis between 2019 to active-LD and the prior three years to active-LD changes. In contrast, O_3 showed the reverse pattern in this analysis. Moreover, the concentration of SO_2 exhibited the greatest decrease, while NO_2 presented mixed performance during the corresponding periods.

3.3 Active to post lockdown changes and the previous three years (2017–19)

From active to post-LD, an increasing trend was found for PM_{10} concentration (3.02%), while the levels of $PM_{2.5}$ decreased (− 10.43%) in Jiangsu (Table 3, and Figs. 2, 3). The findings reveal that the concentration levels of NO_2 , O_3 , SO_2 and CO increased by an average of 6.16%, 29.80%, 11.76%, and 1.47%, respectively, during active to post-LD changes in Jiangsu (Table 3, and Figs. 4, 5, 6, 7). During this period, all air pollutants revealed increasing trends except for $PM_{2.5}$. According to Sulaymon et al. (2021), the PM_{10} , SO_2 , and CO concentrations increased, while $PM_{2.5}$ and NO_2 decreased during the period of post-LD in Wuhan, China. The increase in the levels of different air pollutants can be attributed to the emissions from vehicles and industries following the shutdown. $PM_{2.5}$ levels decreased from active to post-LD changes, but the decrease in $PM_{2.5}$ concentration was greater during the active-LD phase in Jiangsu. Among other pollutants, PM_{10} and CO showed a slight increase, while SO_2 and NO_2 showed mixed rise during this window of time. Moreover, O_3 revealed continuously increasing trend.

Our results reveal that except for O_3 , all the other pollutants were decreased at a significant level, PM_{10} (− 34.59%), $PM_{2.5}$ (− 40.14%), SO_2 (− 44.25%), NO_2 (− 30.94%) and CO (− 22.47%) during the previous three years (2017–19) to post-LD changes in Jiangsu Province (Table 3 and Figs. 2, 3, 4, 5, 6, 7). The maximum reduction was found for SO_2 , while $PM_{2.5}$, PM_{10} , NO_2 , and CO presented the second, third, fourth and fifth decreasing values respectively, during this period. NO_2 , SO_2 , PM_{10} , and CO showed different patterns during the changes of active to post-LD and the previous three years to post-LD changes, while $PM_{2.5}$ and O_3 exhibited similar trends in both periods. The concentration of O_3 was found to have significantly increased during the period of post-LD, measuring 34.38%, when compared to the historical data (2017–19), in Jiangsu. According to Fu et al. (2020), compared with the previous four years (2016–19), the levels of O_3 increased during and after the lockdown periods in South China. It should be noted that the post-LD phase had a higher increase ratio in O_3 levels than the active-LD phase.

3.4 Active to post lockdown in 2021 changes and the previous three years (2017–19)

Between active-LD and 2021 (the same dates of active-LD), Jiangsu had a change in the pattern of air pollution levels. The findings show that during the following year 2021, the concentrations of PM_{10} , NO_2 , $PM_{2.5}$, and CO increased by 26.51%, 15.13%, 2.63%, and 2.94%, respectively, compared with the phase of active-LD, while a decline in SO_2 and O_3 levels was observed by − 6.10% and − 8.29%, respectively, in Jiangsu (Table 4 and Figs. 2, 3, 4, 5, 6, 7). PM_{10} and $PM_{2.5}$, two of the selected pollutants, showed different rising tendencies during this window of time. PM_{10} revealed a significant growing trend, while $PM_{2.5}$ presented a small increase. There was a significant increase in NO_2 , while compared to the other pollutants SO_2 and O_3 presented different tendencies, to be reduced in Jiangsu. The findings suggest that the 2020 active-LD period's declining SO_2 , NO_2 , CO and PM concentrations can be associated to the COVID-19 pandemic's stringent limitations and

Table 3 24 h average concentration and variation of pollutants (2017–20 to post-LD) in Jiangsu Province

Pollutants	2017	2018	2019	Avg. of 2017–2019	Active-LD (2020)	Post-D	Variation (active and post-LD)		Variation (post-LD and avg. of 2017–19)	
							Net	%	Net	%
<i>PM₁₀</i>										
Max	342.46	302.88	322.91	322.75	189	239.05	50.05	26.48	-83.70	-25.93
Avg	92.85	91.96	85.76	90.19	57.26	58.99	1.73	3.02	-31.20	-34.59
Min	20.45	14.07	14.33	16.28	6.59	5.13	-1.46	-22.15	-11.15	-68.50
<i>PM_{2.5}</i>										
Max	195.23	253.75	209.48	219.49	182	194.5	12.5	6.87	-24.99	-11.38
Avg	59.16	58.29	54.64	57.36	38.34	34.34	-4.00	-10.43	-23.02	-40.14
Min	10.24	2.22	4.15	5.54	5.42	1.33	-4.09	-75.46	-4.21	-75.98
<i>SO₂</i>										
Max	86.58	59.46	65.78	70.61	34.56	37.32	2.76	7.99	-33.29	-47.14
Avg	17.85	13.27	9.29	13.47	6.72	7.51	0.79	11.76	-5.96	-44.25
Min	2.05	1.42	1	1.49	1	1	0.00	0.00	-0.49	-32.89
<i>NO₂</i>										
Max	124.83	158.21	105.79	129.61	101.05	140.07	39.02	38.61	10.46	8.07
Avg	43.94	43.11	37.93	41.66	27.1	28.77	1.67	6.16	-12.89	-30.94
Min	1.88	3.35	1.96	2.40	1.79	3.21	1.42	79.33	0.81	33.94
<i>CO</i>										
Max	4.1	3.42	2.45	3.32	1.71	2.29	0.58	33.92	-1.03	-31.09
Avg	0.98	0.9	0.79	0.89	0.68	0.69	0.01	1.47	-0.20	-22.47
Min	0.15	0.1	0.1	0.12	0.12	0.1	-0.02	-16.67	-0.02	-14.29
<i>O₃</i>										
Max	160.75	162.67	142.08	155.17	125.43	211.25	85.82	68.42	56.08	36.14
Avg	69.12	62.33	62.93	64.79	67.08	87.07	19.99	29.80	22.28	34.38

Table 3 (continued)

Pollutants	2017	2018	2019	Avg. of 2017–2019	Active-LD (2020)	Post-D	Variation (active and post-LD)		Variation (post-LD and avg. of 2017–19)	
							Net	%	Net	%
Min	4.83	8.05	3.17	5.35	5.94	21.92	15.98	269.02	16.57	309.72

Table 4 24 h average concentration and variation of pollutants (2017–21) in Jiangsu Province

Pollutants	2017	2018	2019	Avg. of 2017–2019	Active-LD (2020)	2021	Variation (active-LD-2021)		Variation (2021 and avg. of 2017–19)	
							Net	%	Net	%
<i>PM₁₀</i>										
Max	342.46	302.88	322.91	322.75	189	637.57	448.57	237.34	314.82	97.54
Avg	92.85	91.96	85.76	90.19	57.26	72.44	15.18	26.51	-17.75	-19.68
Min	20.45	14.07	14.33	16.28	6.59	9.17	2.58	39.15	-7.11	-43.68
<i>PM_{2.5}</i>										
Max	195.23	253.75	209.48	219.49	182	140.46	-41.54	-22.82	-79.03	-36.01
Avg	59.16	58.29	54.64	57.36	38.34	39.35	1.01	2.63	-18.01	-31.40
Min	10.24	2.22	4.15	5.54	5.42	6.24	0.82	15.13	0.70	12.70
<i>SO₂</i>										
Max	86.58	59.46	65.78	70.61	34.56	27.42	-7.14	-20.66	-43.19	-61.17
Avg	17.85	13.27	9.29	13.47	6.72	6.31	-0.41	-6.10	-7.16	-53.16
Min	2.05	1.42	1	1.49	1	1	0.00	0.00	-0.49	-32.89
<i>NO₂</i>										
Max	124.83	158.21	105.79	129.61	101.05	91.21	-9.84	-9.74	-38.40	-29.63
Avg	43.94	43.11	37.93	41.66	27.1	31.2	4.10	15.13	-10.46	-25.11
Min	1.88	3.35	1.96	2.40	1.79	1.92	0.13	7.26	-0.48	-19.89
<i>CO</i>										
Max	4.1	3.42	2.45	3.32	1.71	3.02	1.31	76.61	-0.30	-9.13
Avg	0.98	0.9	0.79	0.89	0.68	0.7	0.02	2.94	-0.19	-21.35
Min	0.15	0.1	0.1	0.12	0.12	0.13	0.01	8.33	0.01	11.43
<i>O₃</i>										
Max	160.75	162.67	142.08	155.17	125.43	174.2	48.77	38.88	19.03	12.27
Avg	69.12	62.33	62.93	64.79	67.08	61.52	-5.56	-8.29	-3.27	-5.05

Table 4 (continued)

Pollutants	2017	2018	2019	Avg. of 2017–2019	Active-LD (2020)	2021	Variation (active-LD-2021)		Variation (2021 and avg. of 2017–19)	
							Net	%	Net	%
Min	4.83	8.05	3.17	5.35	5.94	2.26	- 3.68	- 61.95	- 3.09	- 57.76

lockdown policies as opposed to the 2021 increase in different air pollutant levels. Among the six pollutants, only SO₂ demonstrated a consistently declining trend from active-LD to 2021, while O₃ exhibited different trends during both phases.

All pollutant concentrations in Jiangsu showed a significant decline from the last three years to 2021 (the same dates of LD). During the corresponding period, there was an approximate drop of - 31.40%, - 53.16%, - 19.68%, - 21.35%, - 25.11%, and - 5.05% in the concentration levels of PM_{2.5}, SO₂, PM₁₀, CO, NO₂, and O₃, (Table 4 and Figs. 2, 3, 4, 5, 6, 7). The results demonstrate that an abrupt decline in SO₂ was found, while CO, PM_{2.5}, PM₁₀, and NO₂ showed mixed reductions. There was a small rise in the concentration of O₃. It should be noted that excluded SO₂ and O₃, the other pollutant levels increased during the changes of active-LD to 2021, while the levels of the six pollutant parameters were considerably reduced during the last three years to 2021 changes. Except for O₃, Jiangsu observed a notable drop in air pollution during the period of active-LD in 2020 compared to the three years prior to the decline in 2021. Overall, our findings reveal that during the COVID-19 pandemic, the lockdown policies and stringent regulations had a major impact on changing and declining the levels of air pollution.

3.5 Co-relationships between air pollutants

Figure 8 shows the relationships between the six criteria air pollutants during Jiangsu's active-LD era. The daily (24-h) average concentrations of PM_{2.5} and PM₁₀ showed a strong correlation ($R^2=0.55$). PM₁₀ and SO₂ had a high correlation ($R^2=0.52$) with NO₂ had a high correlation ($R^2=0.34$). Due to the mutual pollution sources of PM₁₀ and PM_{2.5}, including industrial, vehicle, and construction emissions, there is a strong link between the two. The results of the correlation analysis demonstrated that during the active-LD phase, there was a strong correlation between PM₁₀ concentration and NO₂ concentration ($R^2=0.39$), but a weak correlation between PM₁₀ and O₃ ($R^2=0.16$). The daily average concentrations of PM_{2.5} showed a weak correlation with SO₂ ($R^2=0.10$) and NO₂ ($R^2=0.04$), while PM_{2.5} and CO had a strong significant correlation ($R^2=0.74$). Moreover, there was a poor correlation

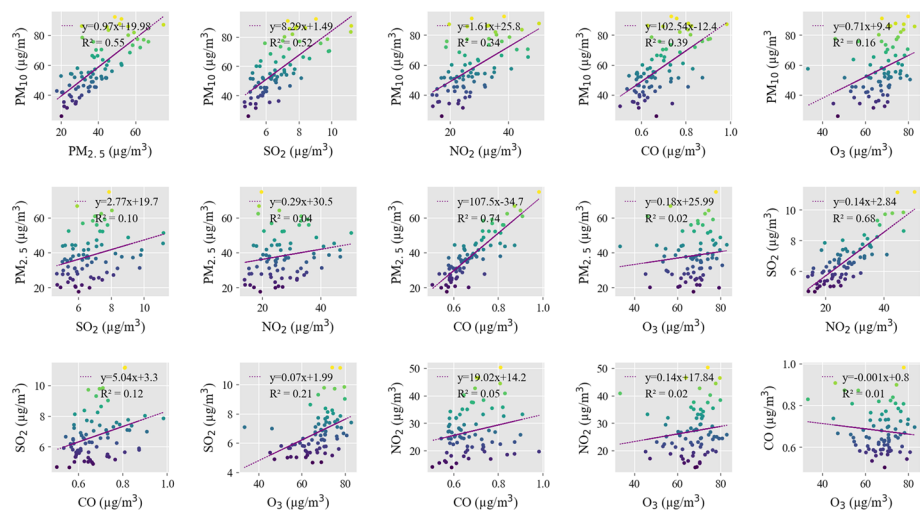


Fig. 8 Co-relationships between air pollutants

between SO_2 and CO ($R^2=0.12$) and O_3 ($R^2=0.21$), but a strong correlation between the daily (24-h) average concentration of SO_2 and the NO_2 concentration ($R^2=0.68$). The strong correlation between SO_2 and NO_2 can be attributed to their mutual pollution sources in urban areas. NO_2 , CO , and O_3 had the following relationships: $R^2=0.05$, $R^2=0.02$, and $R^2=0.01$). These findings imply that when the levels of other pollutants decreased, the concentration of O_3 increased.

3.6 Role of meteorological parameters during the three periods

Jiangsu Province's daily mean for air temperature, relative humidity, wind speed, and total rainfall during the periods of pre-, active-, and post-LD are presented in Fig. 9. Because they have an impact on air pollution emissions, transportation, formation, and deposition both directly and indirectly, meteorological parameters are important in determining ambient air quality (Zhang et al., 2015). Overall, with only minor variations, air temperature showed an increasing tendency from the periods of pre- to post-LD. The air temperature constantly increased during the active-LD and post-LD periods, but initially showed a falling trend during the phase of pre-LD. An increased upward mixing of air pollution characteristics is made possible by the atmosphere being subverted by the higher air temperature (Mandal et al., 2021). Hence, higher air temperatures promote the reduction of air pollution concentrations (Ravindra et al., 2019). The pattern for relative humidity was different. Figure 9 makes it clear that relative humidity had an increasing tendency throughout the pre-LD era and, with some changes, it demonstrated a nearly similar pattern during the period of active-LD. According to Yoo et al. (2014), relative humidity aids in lowering the concentrations of air pollutants. The findings show that relative humidity showed an increasing trend during the post-LD period, after initially declining. Zhang et al. (2015) discovered that in the North China Plain (NCP) region, the O_3 mixing ratio clearly depended on both temperature and relative humidity.

Moreover, Jiangsu observed a comparable wind speed pattern during the same dates, with slight fluctuations. When compared to the pre- and post-LD periods, the difference was discernible only during the active-LD period (Fig. 9). It implies that throughout the active-LD period, wind speed had negligible effect on lowering air pollution levels. The

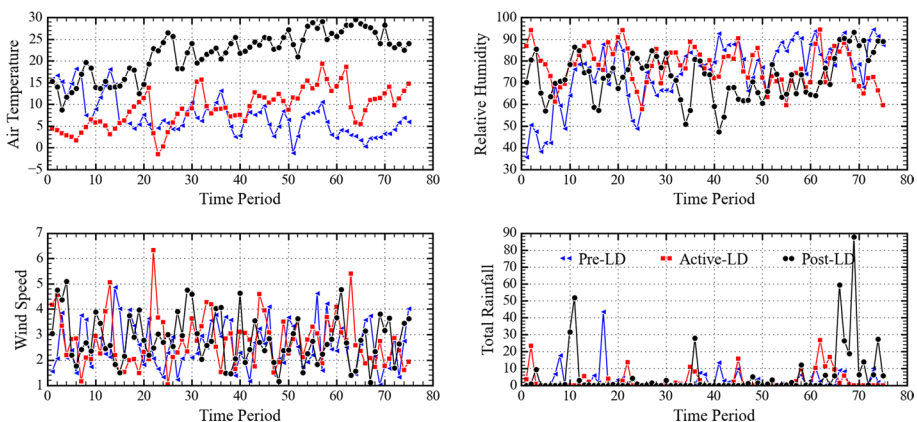


Fig. 9 Daily mean of the meteorological parameters (air temperature, relative humidity, wind speed, and total rainfall) during the three study periods in Jiangsu Province

findings indicate that, with very minor exceptions, rainfall patterns throughout the pre- and active-LD periods were similar. During the pre-LD phase, there was initially a minor increase in rainfall, but during the active-LD period, there was mixed performance. Rainfall during the post-LD period exhibited an increasing trend when compared to the periods of pre- and post-LD. It may be concluded that, like other meteorological factors, rainfall had negligible effect on declining air pollution concentration levels during the active-LD phase.

3.7 Relationship between air pollutants and meteorological factors

The generation, dispersion, and transportation of air pollutants are greatly influenced by meteorological factors (Chen et al., 2019; Hasnain et al., 2023). A linear regression analysis was carried out to assess the correlation between meteorological variables and ambient air pollutants (Fig. 10). During Jiangsu's active-LD period, most of the pollutants had a negative correlation with the meteorological factors. PM_{10} and air temperature had a positive association ($R^2=0.14$), as did SO_2 and temperature ($R^2=0.30$). NO_2 , on the other hand, had a strong positive correlation ($R^2=0.64$) with air temperature. Moreover, during the active-LD period, there was a negative correlation between all air pollutants and other meteorological factors such as relative humidity, wind speed, and rain (Fig. 10). The results of this study closely resemble those of Zhou et al. (2020), who observed a negative relationship between air pollution and meteorological conditions in Nanjing and Beijing.

4 Conclusions

While the COVID-19 pandemic has undoubtedly been designated a deadly disease and has killed countless people worldwide, it has also had a good effect on the environment. To determine the spatiotemporal impact of the COVID-19 lockdown (LD) on Jiangsu Province's air quality, the six air pollutant parameters, SO_2 , NO_2 , CO , O_3 , PM_{10} , and $PM_{2.5}$ were evaluated in the current study. The results revealed that during the period of active-LD, except for O_3 , all pollutant concentrations had significantly decreased. Except for SO_2 and O_3 , all the remaining four pollutant concentrations dropped from pre-active to post-LD changes. However, the reductions during the active-LD period were significantly larger than the post-LD reduction. Jiangsu had a maximum decrease in the concentrations of SO_2 , NO_2 , PM_{10} , $PM_{2.5}$, and CO from 2019 to active-LD and from the previous three years (2017–19) to active-LD. During the phase of active-LD, O_3 levels slightly increased. PM_{10} , SO_2 , CO , NO_2 , and O_3 levels increased from the active to the post-LD phase, while $PM_{2.5}$ levels decreased. During active-LD to 2021 changes, the concentration levels of NO_2 , $PM_{2.5}$, PM_{10} , and CO increased while those of SO_2 and O_3 declined. In 2021, there was a notable decrease in all pollutant concentrations as compared to the three years prior, 2017–19. The results of this study demonstrate that, except for O_3 , the active-LD period observed the greatest fall in pollutant concentrations. This suggests that the COVID-19 pandemic lockdown had a significant impact on the environment and declining the levels of air quality. As discussed in Sect. 1, most of the studies have mainly focused on either the comparison with previous years or the assessment of air pollution from pre-lockdown to active lockdown periods, while other studies have demonstrated that the lockdown measures and strict limitations led to a decline in air quality levels for limited time periods. However, a variety of comparisons were made in the current study, and it is possible to

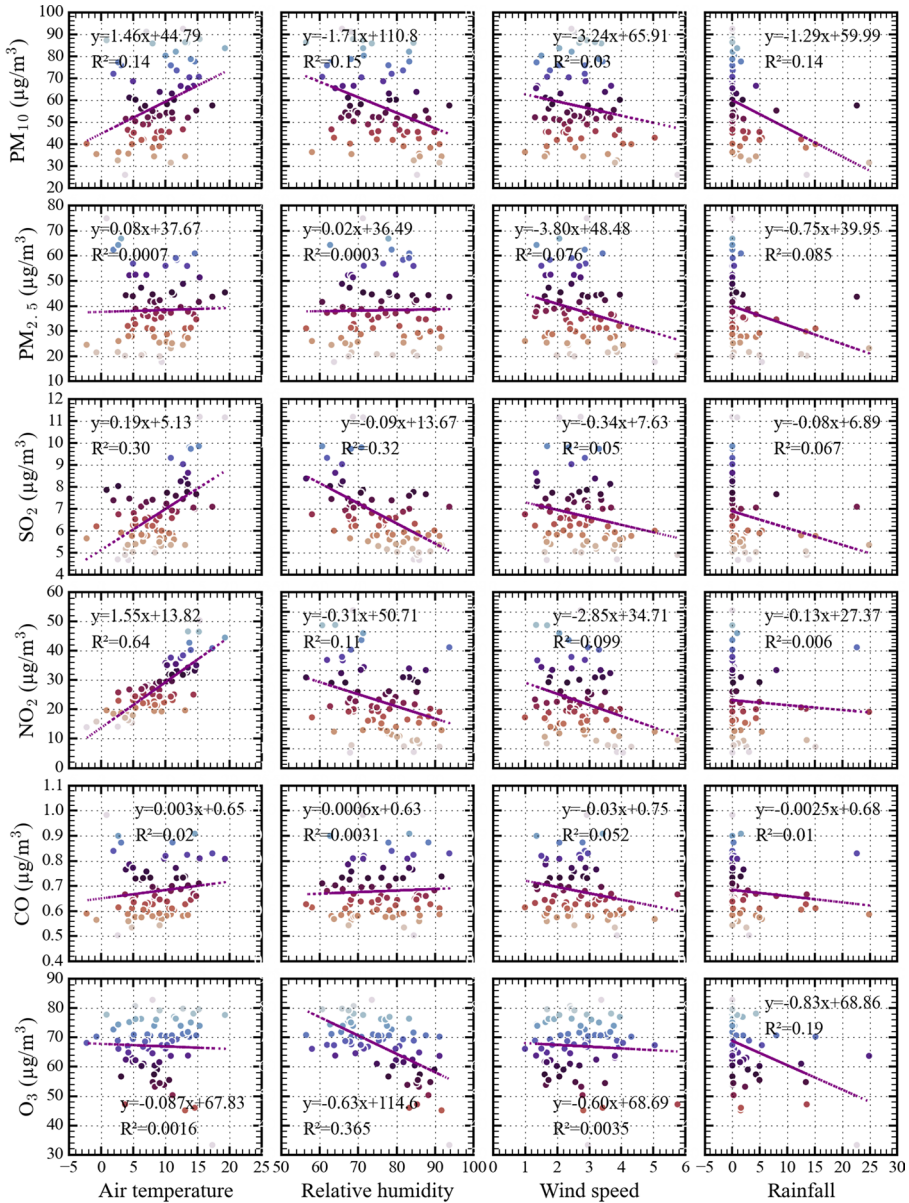


Fig. 10 Relationship between air pollutant parameters and meteorological factors

expand its scope to other regions and areas to obtain new results in upcoming years. The scientific community, policy makers, and local authorities may use all these new insights to help develop new laws and guidelines that will protect the environment and enhance air quality in the years to come.

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Data availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References


- Abdullah, S., Mansor, A. A., Napi, N. N. L. M., Mansor, W. N. W., Ahmed, A. N., Ismail, M., & Ramly, Z. T. A. (2020). Air quality status during 2020 Malaysia Movement Control Order (MCO) due to 2019 novel coronavirus (2019-nCoV) pandemic. *Science of the Total Environment*, 729, 139022.
- Bauwens, M., Compennolle, S., Stavrakou, T., Müller, J. F., Gent, J., Eskes, H., Levelt, P. F., Van Der, A. R., Veeffkind, J. P., Vlietinck, J., Yu, H., & Zehner, C. (2020). Impact of coronavirus outbreak on NO₂ pollution assessed using TROPOMI and OMI observations. *Geographical Research Letters*. <https://doi.org/10.1029/2020gl087978>
- Bhatti, U. A., Wu, G., Bazai, S. U., Nawaz, S. A., et al. (2022). A pre- to post-covid-19 change of air quality patterns in Anhui province using path analysis and regression. *Polish Journal of Environmental Studies*, 31(5), 1–14. <https://doi.org/10.15244/pjoes/148065>
- Chang, Y., Huang, R. J., Ge, X., Huang, X., Hu, J., Duan, Y., Zou, Z., Liu, X., & Lehmann, M. F. (2020). Puzzling haze events in China during the coronavirus (COVID-19) shutdown. *Geographical Research Letters*, 47(12), e2020GL088533. <https://doi.org/10.1029/2020gl088533>
- Chen, Y., Zheng, M., Lv, J., Shi, T., et al. (2019). Interactions between ambient air pollutants and temperature on emergency department visits: analysis of varying coefficient model in Guangzhou China. *Science of the Total Environment*, 668, 825–834. <https://doi.org/10.1016/j.scitotenv.2019.03.049>
- Chen, Q. X., Huang, C. L., Yuan, Y., & Tan, H. P. (2020). Influence of COVID-19 event on air quality and their association in Mainland China. *Aerosol & Air Quality Research*, 20, 1541–1551.
- CNEMC. (2019). China national environmental monitoring centre. <http://www.cnemc.cn/>. Retrieved 08 Aug 2019.
- Ghasempour, F., Sekertekin, A., & Kutoglu, S. H. (2021). Google Earth Engine based spatio-temporal analysis of air pollutants before and during the first wave COVID-19 outbreak over Turkey via remote sensing. *Journal of Cleaner Production*, 319, 128599.
- Han, Li., Zhao, J., & Gu, Z. (2021). Assessing air quality changes in heavily polluted cities during the COVID-19 pandemic: A case study in Xi'an China. *Sustainable Cities and Society*, 70, 102934.
- Hasnain, A., Sheng, Y., Hashmi, M. Z., Ahmed, Z., & Zha, Y. (2023). Assessing the ambient air quality patterns associated to the COVID-19 outbreak in the Yangtze River Delta: A random forest approach. *Chemosphere*, 314, 137638. <https://doi.org/10.1016/j.chemosphere.2022.137638>
- He, W., Wang, Y., Zuo, J., & Luo, Y. (2017). Sectoral linkage analysis of three main air pollutants in China's industry: Comparing 2010 with 2002. *Journal of Environmental Management*, 202, 232–241.
- Hu, M., Chen, Z., Cui, H., Wang, T., Zhang, C., & Yun, K. (2021). Air pollution and critical air pollutant assessment during and after COVID-19 lockdowns: Evidence from pandemic hotspots in China, the Republic of Korea, Japan, and India. *Atmospheric Pollution and Research*, 12, 316–329. <https://doi.org/10.1016/j.apr.2020.11.013>
- Hua, J., Zhang, Y., Foy, B. D., Shang, J., et al. (2020). Quantitative estimation of meteorological impacts and the COVID-19 lockdown reductions on NO₂ and PM_{2.5} over the Beijing area using Generalized Additive Models (GAM). *Journal of Environmental Management*, 291, 112676.
- Kang, M., Zhang, J., Zhang, H., & Ying, Q. (2021). On the relevancy of observed ozone increase during COVID-19 lockdown to summertime ozone and PM_{2.5} control policies in China. *Environmental Science & Technological Letters*, 8(4), 289–294. <https://doi.org/10.1021/acs.estlett.1c00036>
- Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., et al. (2020). Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: An insight into the impact of human activity pattern changes on air pollution variation. *Science of the Total Environment*, 732, 139282.
- Mahato, S., Pal, S., & Ghosh, K. G. (2020). Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi India. *Science of the Total Environment*, 730, 139086. <https://doi.org/10.1016/j.scitotenv.2020.139086>
- Mandal, J., Samanta, S., Chanda, A., & Halder, S. (2021). Effects of COVID-19 pandemic on the air quality of three megacities in India. *Atmospheric Research*, 259, 105659.

- Mor, S., Kumar, S., Singh, T., Dogra, S., Pandey, V., & Ravindra, K. (2021). Impact of COVID-19 lockdown on air quality in Chandigarh, India: Understanding the emission sources during controlled anthropogenic activities. *Chemosphere*, 263(127978), 2020. <https://doi.org/10.1016/j.chemosphere.2020.1279780045-6535/0>
- Orak, N. H., & Ozdemir, O. (2021). The impacts of COVID-19 lockdown on PM10 and SO2 concentrations and association with human mobility across Turkey. *Environmental Research*, 197, 111018.
- Ravindra, K., Singh, T., Mor, S., Singh, V., Mandal, T. K., Bhatti, M. S., Gahlawat, S. K., Dhankhar, R., Mor, S., & Beig, G. (2019). Real-time monitoring of air pollutants in seven cities of North India during crop residue burning and their relationship with meteorology and transboundary movement of air. *Science of the Total Environment*, 690, 717–729.
- Sulaymon, I. D., Zhang, Y., Hopke, P. K., Zhang, Y., Hua, J., & Mei, X. (2021). COVID-19 pandemic in Wuhan: Ambient air quality and the relationships between criteria air pollutants and meteorological variables before, during, and after lockdown. *Atmosphere Research*, 250, 105362.
- Tian, H., Liu, Y., Li, Y., Wu, C. H., Chen, B., Kraemer, M. U. G., Li, B., Cai, J., et al. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*, 368(6491), 638–642.
- Wang, Y., Yuan, Y., Wang, Q., Liu, C. G., Zhi, Q., & Cao, J. (2020). Changes in air quality related to the control of coronavirus in China: Implications for traffic and industrial emissions. *Science of the Total Environment*, 731, 139133.
- Wang, J., Xu, X., Wang, S., He, S., & He, P. (2021). Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China. *Applied Energy*, 282, 116179. <https://doi.org/10.1016/j.apenergy.2020.116179>
- WHO (2020a), Coronavirus Disease (2019).
- World Health Organization (WHO). (2020b). Corona virus disease (COVID19). *Situation Report*, 198, 19 p. https://www.who.int/docs/defaultsource/coronaviruse/situation-reports/20200805-covid-19-sitrep-198.pdf?sfvrsn=f99d1754_2. Retrieved 25 Oct 2020.
- Xu, R., & Lin, B. (2017). Why are there large regional differences in CO2 emissions? Evidence from China's manufacturing industry. *Journal of Cleaner Production*, 140, 1330–1343.
- Yoo, J. M., Lee, Y. R., Kim, D., Jeong, M. J., Stockwell, W. R., Kundu, P. K., Oh, S. M., Shin, D. B., & Lee, S. J. (2014). New indices for wet scavenging of air pollutants (O3, CO, NO2, SO2, and PM10) by summertime rain. *Atmospheric Environment*, 82, 226–237. <https://doi.org/10.1016/j.atmosenv.2013.10.022>
- Zhang, H., Wang, Y., Hu, J., Ying, Q., & Hu, X. M. (2015). Relationships between meteorological parameters and criteria air pollutants in three megacities in China. *Environmental Research*, 140, 242–254.
- Zhang, T., Liu, P., Sun, X., Zhang, C., Wang, M., Xu, J., et al. (2020). Application of an advanced spatiotemporal model for PM2.5 prediction in Jiangsu Province China. *Chemosphere*, 246, 125563. <https://doi.org/10.1016/j.chemosphere.2019.125563>
- Zhang, H., Ma, X., Han, G., Xu, H., Shi, T., Zhong, W., & Gong, W. (2021a). Study on collaborative emission reduction in green-house and pollutant gas due to COVID-19 lockdown in China. *Remote Sensing*, 13, 3492. <https://doi.org/10.3390/rs13173492>
- Zhang, X., Tang, M., Guo, F., Wei, F., Yu, Z., et al. (2021b). Associations between air pollution and COVID-19 epidemic during quarantine period in China. *Environmental Pollution*, 268, 115897.
- Zhang, K., Liu, Z., Zhang, X., Li, Q., Jensen, A., et al. (2022). Insights into the significant increase in ozone during COVID-19 in a typical urban city of China. *Atmospheric Chemistry and Physics*, 22(7), 4853–4866.
- Zheng, B., Geng, G., Ciais, P., Davis, S. J., et al. (2020). Satellite-based estimates of decline and rebound in China's CO2 emissions during COVID-19 pandemic. *Science Advances*, 6, 4998.
- Zhou, H., Yu, Y., Gu, X., Wu, Y., et al. (2020). Characteristics of air pollution and their relationship with meteorological parameters: Northern versus southern cities of China. *Atmosphere*, 11, 253. <https://doi.org/10.3390/atmos11030253>
- Zhu, S., Poetzscher, J., Shen, J., Wang, S., Wang, P., & Zhang, H. (2021). Comprehensive insights into O3 changes during the COVID-19 from O3 formation regime and atmospheric oxidation capacity. *Geophysical Research Letters*, 48(10), e2021GL093668.

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