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Spatiotemporal Change of Air-Quality Patterns in Hubei Province—A Pre- to Post-COVID-19 Analysis Using Path Analysis and Regression

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Abstract: Mitigation measures and control strategies relating to the novel coronavirus disease 2019 (COVID-19) have been widely applied in many countries to reduce the transmission of this pandemic disease. China was the first country to implement a strong lockdown policy to control COVID-19 when countries worldwide were struggling to manage COVID-19 cases. However, lockdown causes numerous changes to air-quality patterns due to the low amount of traffic and the decreased human mobility it results in. To study the impact of the strict control measures of the new COVID-19 epidemic on the air quality of Hubei in early 2020, the air-quality monitoring data of Hubei's four cities, namely Huangshi, Yichang, Jingzhou, and Wuhan, from 2019 to 2021, specifically 1 January to 30 August, was examined to analyze the characteristics of the temporal and spatial distribution. All air-quality pollutants decreased during the active-COVID-19 period, with a maximum decrease of 26% observed in PM₁₀, followed by 23% of PM_{2.5}, and a minimum decrease of 5% observed in O₃. Changes in air pollutants from 2017 to 2021 were also compared, and a decrease in all pollutants through to 2020 was found. The air-quality index (AQI) recorded an increase of 2% post-COVID-19, which shows that air quality will worsen in future, but it decreased by 22% during the active-COVID-19 period. A path analysis model was developed to further understand the relationship between the AQI and air-quality patterns. This path analysis shows a strong correlation between the AQI and PM₁₀ and PM_{2.5}, however its correlation with other air pollutants is weak. Regression analysis shows a similar pattern of there being a strong relationship between AQI and PM₁₀ ($r^2 = 0.97$) and PM_{2.5} ($r^2 = 0.93$). Although the COVID-19 pandemic had numerous negative effects on human health and the global economy, it is likely that the reduction in air pollution and the significant improvement in ambient air quality due to lockdowns provided substantial short-term health benefits. The government must implement policies to control the environmental issues which are causing poor air quality in post-COVID-19.

Keywords: air pollution; COVID-19; particulate matter; China

1. Introduction

In January 2020, the novel coronavirus (COVID-19) pneumonia epidemic was first identified in Wuhan [1]. The Chinese Government and various government departments placed great importance on addressing it and quickly initiated prevention and control

measures to prevent the spread of the virus. Epidemic control measures restricted human activities [2] and improved air quality overall, but the air quality in some cities or regions did not improve [3], and after the epidemic control measures were lifted and air quality returned to previous levels [4]. Thus, epidemic prevention and control provided contemporary society with a good opportunity to observe the relationship between human activities and air quality, to review past atmospheric environmental protection measures, and to better plan future atmospheric environmental protections.

Lockdown during COVID-19 brought different changes in air quality worldwide and different researchers highlighted those changes in their studies. Altuwayjiri et al. highlights the changes in chemical properties and oxidative potential $PM_{2.5}$ during the lockdown period in Italy. Both $PM_{2.5}$ and NO_2 showed a reduction during lockdown period due to a decrease in primary emission from road traffic [5]. Elshorbany et al. used remote-sensing data to find reductions in the air pollutants during COVID-19 in USA and identified potential factors in the change of tropospheric ozone (O_3) [6]. Menut et al. studied the change of the air-quality pattern in Western Europe and used the WRF-CHIMERE modelling strategy to highlight the major change in NO_2 concentration while there were minor changes in $PM_{2.5}$ concentrations during COVID-19 [7]. Clemente et al. shared the change in PM_1 and PM_{10} , and observed temporal variations in PM_1 and PM_{10} concentrations were strongly affected by the frequency of Saharan dust events with a 35% decrease [8].

Zangari et al. have observed decreases in $PM_{2.5}$ (36%) and NO_2 (51%) concentrations shortly after the shutdown took place due to COVID-19 [9]. On 24 March 2020, India enforced stringent lockdown measures to manage COVID-19, and this resulted in a 17% decrease in ambient AQI and an increase in the ozone (O_3) concentration [10]. This also reflects a positive correlation with an increase in COVID-19 cases due to poor air quality and indicates a correlation between COVID-19-vulnerable regions and air pollution selected spots, which suggests that air pollution may exacerbate the clinical manifestations of the disease. Bar et al. detected a reduced $PM_{2.5}$ across 50 countries post-COVID-19, with the highest decreases recorded in America and Europe [11]. Stratoulis et al. studied the air-quality impact post-COVID-19 in a medium-sized urban area in Thailand and found a 33.7% decrease in NO_2 concentration just three weeks after lockdown. Similar results were observed for other pollutants, namely $PM_{2.5}$, particulate matter with aerodynamic diameters $\leq 10 \mu m$ (PM_{10}), and O_3 , which decreased by 21.8%, 22.9%, and 12.5%, respectively [12].

The COVID-19 pandemic has had a positive environmental impact due to improved air quality. Therefore, the period of epidemic prevention and control is a good point in time for the further exploration of the main factors affecting urban air quality changes. [13]. In this study, we examine the AQI and the levels of six ambient air pollutants, namely NO_2 , O_3 , sulphur dioxide (SO_2), carbon monoxide (CO), PM_{10} , and $PM_{2.5}$, before, during and after the 2020 COVID-19 lockdown in the four cities of Hubei province in China, namely Huangshi, Yichang, Jingzhou, and Wuhan. The period between January 2020 and August 2020 was selected because a strict lockdown was in place in all four of the cities. Additionally, the AQI and pollutant concentrations during the same period in the prior two years, namely 2017 to 2018, are assessed. The relationship between the AQI and each air pollutant ($PM_{2.5}$, PM_{10} , SO_2 , NO_2 , CO, and O_3) in each city is investigated using a spatiotemporal change analysis. This exercise sought to improve understanding of changing air-quality patterns in each city pre-COVID-19, during active COVID-19, and post-COVID-19. Furthermore, correlation analyses between the six air pollutants and the AQI during the three periods are performed to ascertain the sources of air pollutants during and after lockdown. Regression models are developed to analyze the trends of air-quality patterns and their changes over time. This study is the first to assess the relationships between the concentrations of the six named pollutants and the AQI before, during and after Hubei's COVID-19 lockdown.

2. Materials and Methods

2.1. Study Area Monitoring Stations

Hubei Province is located in the south of Central China, the middle reaches of the Yangtze River, and the north of Dongting Lake, hence the name Hubei, or “E” for short, and the provincial capital is Wuhan. Hubei lies between $29^{\circ}05'$ and $33^{\circ}20'$ north latitude and $108^{\circ}21'$ and $116^{\circ}07'$ east longitude. It is connected to Anhui to the east, Jiangxi and Hunan to the south, Chongqing to the west, Shaanxi to the northwest, and Henan to the north. Hubei is surrounded by mountains in the east, west, and north, and it has the Jiangshan Plain, which is known as the “land of fish and rice”, in the middle [14]. The geographical location of Hubei is excellent. Any other province in the country can be reached by crossing two provinces at the most. It is the only province in China where this can be done. For this study, the four cities of Huangshi, Yichang, Jingzhou, and Wuhan within the Hubei Province were selected because of the availability of more monitoring stations and the high number of COVID-19 cases recorded in these cities. Together, these four cities contain 29 air-quality monitoring stations. Huangshi has six, Jingzhou has five, Wuhan has eleven, and Yichang has seven. Figure 1 shows Hubei Province with the selected cities and dots marking the locations of these stations. Most of the monitoring stations are in urban areas because the main pollution exists in these developed areas with more traffic.

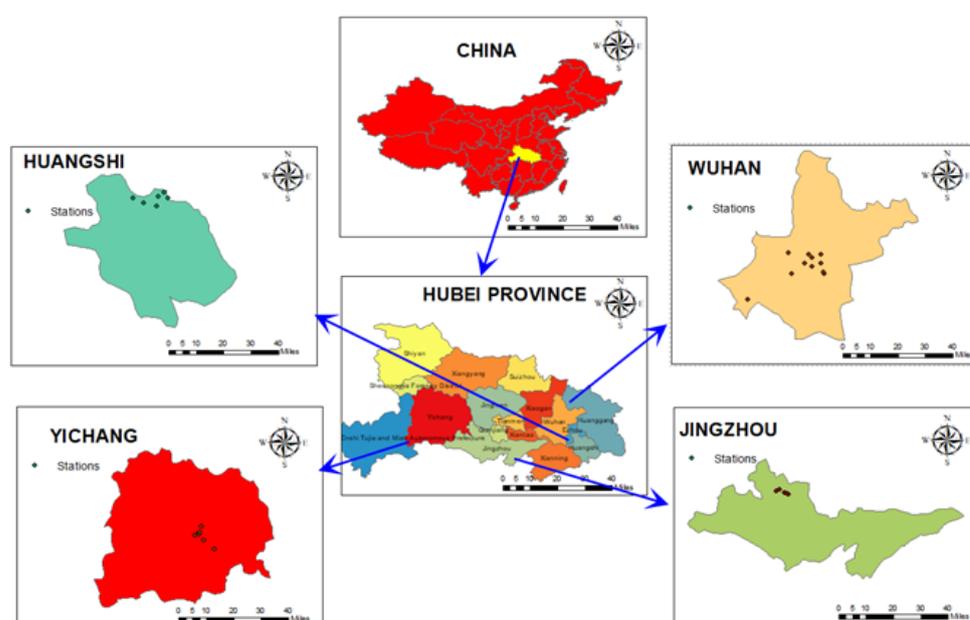


Figure 1. The study area of Hubei with the locations of the monitoring stations in the four cities.

2.2. Air Pollutant Data

This paper primarily employs the daily average datasets of the air pollutants from the various stations. The mass concentration data used for the AQI and the ambient atmospheric pollutants ($PM_{2.5}$, PM_{10} , SO_2 , NO_2 , CO , and O_3) were obtained from the weather post report on tianqihoubao.com. Each monitoring station’s ambient $PM_{2.5}$, PM_{10} , NO_2 , CO , SO_2 , and O_3 concentrations were recorded hourly and then, from these values, the provincial daily average and each city’s stations’ average were computed.

In order to meet the requirements of air quality under the new circumstances, in 2021 (Table 1 shows the standard values of AQI), China issued the new national ambient air-quality standard (GB 3095-2012) [15], which clarified the calculation method of AQI:

Table 1. Air Quality Index range and corresponding impact.

Air Quality Index Range	Air Quality Level	Air Quality Category	Representative Color	Impacts on Human Health and Recommended Actions
0–50	Level I	Superior	Green	The air quality is satisfactory. There is basically no air pollution, and no impact on human activities
51–100	Level II	Good	Yellow	The air quality is acceptable. There are certain air pollutants that may cause health issues to a small number of people who should reduce outdoor activities.
101–150	Level III	Mild Pollution	Orange	Symptoms in susceptible people would intensify, and healthy people would show irritation symptoms. Elderly people and children should avoid long duration of high-intensity outdoor exercises.
151–200	Level IV	Moderate Pollution	Red	Symptoms in susceptible people would further intensify, and the breathing of healthy people would be affected. Elderly people and children should avoid outdoor sports.
201–300	Level V	Heavy Pollution	Purple	Ordinary people would show symptoms. Elderly people and children should avoid outdoor sports. The general population should reduce outdoor activities.
>300	Level VI	Severe Pollution	Maroon	Obvious and strong symptoms would appear, and all groups of people should avoid outdoor activities.

First calculate the individual Air quality index of certain pollutant ($IAQI_p$):

$$IAQI_p = \frac{IAQI_{HI} - IAQI_{Lo}}{BP_{HI} - BP_{Lo}} (C_p - BP_{Lo}) + IAQI_{Lo} \tag{1}$$

In the equation above, C_p represent the mass concentration of pollutant p ; BP_{HI} is the higher threshold of pollutant concentration near C_p corresponding to the specific IAQI (Individual Air Quality Index) regulated by government policy; BP_{Lo} is the lower threshold of pollutant concentration near C_p regulated by the government; $IAQI_{HI}$ is the corresponding IAQI to BP_{HI} ; while $IAQI_{Lo}$ is the corresponding IAQI to BP_{Lo} .

Then take the largest number from all $IAQI_p$ to calculate the AQI:

$$AQI = \max\{IAQI_1, IAQI_2, IAQI_3, \dots, IAQI_n\} \tag{2}$$

2.3. Regression and Path Analysis Model

Multiple linear regression reflects the direct effect between the independent variable and the dependent variable, but the relationship between the variables is often intricate. Some are unidirectional influence relationships, and some are mutual influence relationships. It is often difficult for analysts to use only one regression model. In this study, a regression analysis is conducted and the multiple regression advanced model, i.e., the path analysis model, is used to elaborate on the relationship between the pollutants. The path analysis model was pioneered by the geneticist Wright [16] for use in color genetic research on two pigs in theme parks and environments in 1983, and it was later widely used in sociology, biology, and geography, as well as other fields. The path analysis model is a multiple regression model. Typically, path models consist of independent and dependent variables that are depicted graphically as boxes or rectangles. The roles of the different parts of the simulation model boxes show direct and indirect effects to describe the relationship between variables more comprehensively. In the regression model, all variables in the path model are random variables, and all variables can be correlated, which is more in line with the reality of social economics. If it comprises a one-way arrow, it is only a regression

model. However, if a dynamic arrow materializes on the box and a circular path appears, it is an acyclic model. The path analysis model is a relationship model that discloses complex relationships, such as non-existent realistic relationships, gradual loops, and self-feedback. The arrow to the other component represents a direct path.

2.4. Statistical Analysis

This study mainly focuses on analyzing the impact of COVID-19 on air pollution. Therefore, the levels of the six air pollutants were examined during the following three consecutive periods: pre-COVID-19 (from 1 January to 30 August 2019), during active COVID-19 (from 1 January to 30 August 2020) and post-COVID-19 (from 1 January to 30 August 2021). The year 2019 was selected as the pre-COVID-19 period to compare all four seasons rather than only winter, since air pollutant patterns change with the seasons [17]. For further assessment, the results from 2017 (AQ-2017) and 2018 (AQ-2018) were compared to better evaluate the impact of the changes on air pollutant patterns. Statistical analysis of the data was performed using SPSS software (version 25; IBM Company). For comparison of means we used the least significant difference (LSD) statistical method. If the value at a particular level of statistical probability (e.g., $p \leq 0.05$ means with 95% accuracy) when exceeded by the difference between two means for a particular characteristic, then the two means are said to be distinct for that characteristic at that or lesser levels of probability. LSD calculates the minimum significant value between two means as if tested on these two means (instead of grouping them all). This allows you to directly compare two means in two separate groups. Any difference greater than LSD is considered a significant result. When the F ratio recommends rejecting the null hypothesis H_0 , that is, when the difference between population means is large, use the least significant difference (LSD) test in the context of analysis of variance.

Least significant difference (LSD) (5%) = S.E. xt value by using error degrees of freedom, where $S.E. = \sqrt{\frac{2MSE}{r}}$.

3. Results and Discussion

This study is being conducted to highlight the changes in the patterns of the AQI and air pollutants post-COVID-19.

3.1. City-Wide Change in Air-Quality Patterns from 2017 to 2021

The change in air-quality patterns in the four cities within Hubei Province over the last five years is shown in Figure 2. The AQI level of all four cities is reduced yearly due to continuous air quality monitoring by the government with policy implications for the environment friendly transport system, and it can be observed that until 2020 (before active COVID-19) the AQI was decreasing; however, in the post-COVID-19 period, it began to increase due to an increase in economic development and traffic. A similar pattern was observed for some of the air-quality pollutants, namely NO_2 and PM_{10} . The concentration of O_3 was increasing in the pre-COVID-19 period, but it reduced after the active-COVID-19 period and continued to decrease in the post-COVID-19 period. The concentration of $PM_{2.5}$ decreased yearly from 2017 until 2021, but its decrease in 2021 is less notable compared to the active-COVID-19 period.

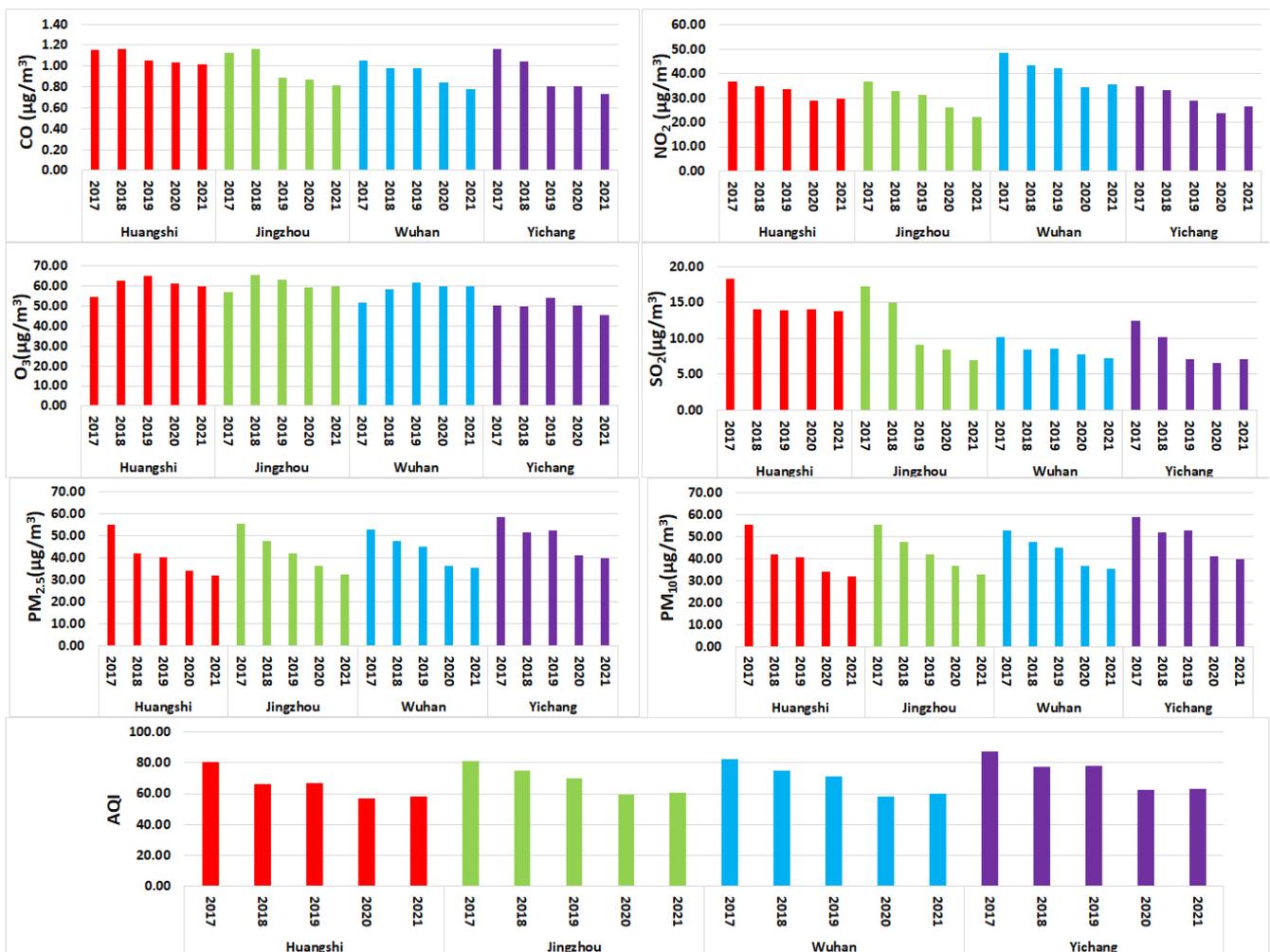


Figure 2. City-wide daily changes in air-quality patterns.

Table 2 shows the statistical results of analysis performed on data of all cities.

The LSD test helps to identify the population whose means are significantly different. After applying LSD on Table 2, values of AQI by year shows that there are three groups (A, B, C) among group means that are significantly different from one another. For CO, there are five groups (A, B, C, D, E) and all five groups' means are significantly different from one another. The LSD test of NO₂ by year shows that there are 3 groups (A, B, C) among group means that are significantly different from one another while for O₃ LSD comparisons show two groups (A and B) which are significantly different from one another. The PM_{2.5} and PM₁₀ LSD test shows three groups (A, B, C) whose group means are significantly different from one another. The LSD test of SO₂ by year shows there are there are 4 groups (A, B, C, D) among group means that are significantly different from one another.

Table 2. Statistical explanation of data.

Year	Method	Statistical Analysis of Air Pollutants						
		AQI	CO	NO ₂	O ₃	PM ₁₀	PM _{2.5}	SO ₂
2021	Max	259.63	2.70	99.29	153.04	368.88	208.42	80.96
	Min	15.96	0.20	2.96	1.50	4.17	2.00	1.21
	Mean	60.37 C	0.82 E	30.92 C	56.83 AB	63.75 C	35.42 C	8.61 D
	Std.	29.71	0.28	15.76	26.53	37.45	23.76	4.87
	Median	55.41	0.79	27.75	54.92	55.04	30.33	7.46
2020	Max	238.75	7.66	143.38	155.79	255.21	189.13	160.86
	Min	12.38	0.13	1.92	1.88	5.29	2.17	1.00
	Mean	59.23 C	0.87 D	29.84 C	57.87 A	58.90 C	37.25 C	8.76 D
	Std.	30.46	0.30	17.53	25.97	33.86	25.40	6.47
	Median	53.54	0.84	25.54	57.57	51.90	30.71	7.17
2019	Max	346.33	2.78	121.73	181.00	340.08	296.33	59.21
	Min	15.54	0.13	3.74	3.22	8.95	3.00	1.04
	Mean	72.02 B	0.94 C	36.04 B	60.67 A	74.33 B	45.79 B	9.37 C
	Std.	35.97	0.33	18.55	33.90	38.00	32.09	5.71
	Median	63.46	0.90	31.96	57.54	66.22	36.96	8.00
2018	Max	353.83	4.43	135.61	212.96	465.08	248.04	68.54
	Min	11.25	0.15	3.79	1.57	6.00	3.42	1.06
	Mean	73.74 B	1.06 B	37.85 B	58.28 A	78.02 B	47.69 B	10.82 B
	Std.	38.92	0.36	18.52	30.50	46.45	31.57	6.62
	Median	63.42	1.00	33.42	55.04	65.64	39.08	9.42
2017	Max	478.17	5.29	137.42	217.17	743.25	351.04	132.00
	Min	12.33	0.16	2.00	2.08	6.31	2.88	1.04
	Mean	83.06 A	1.11 A	41.47 A	52.81 B	91.16 A	55.11 A	13.40 A
	Std.	44.87	0.35	20.48	28.39	53.16	37.19	9.53
	Median	74.58	1.06	36.71	48.67	82.70	46.45	11.08

Letters indicate which means are significantly different at the 95% level of confidence.

Change in concentration of pollutants in Wuhan and other cities has involved different local environmental policies and control measures due to COVID-19. In late January 2020, due to the COVID-19 epidemic, the Wuhan region implemented strict regulations. Traffic restrictions reduced vehicle emissions in urban areas to the utmost extent. Existing observations have shown that the atmospheric composition in eastern China changed significantly in February 2020 compared to January 2020.

Yichang city experienced several rare continuous serious pollution processes before COVID-19, which caused widespread concern for government. The control of air pollution has always been an important part of protecting people's lives and health in Yichang City. During the pre-COVID period, the Yichang City Government and the Environmental Protection Bureau implemented compulsory measures to reduce air pollution. These measures included artificial rain enhancement and haze reduction; strengthening the management of motor vehicles and rectifying yellow-label vehicles; stopping part of construction site operations; stopping and limiting production of key polluting enterprises; reducing pollution from coal-burning facilities; and reducing organic waste. However, significant change in air pollutant can be observed during active-COVID when the strict lockdown was implemented.

In recent years, air pollution has been caused by the rapid increase in the number of motor vehicles in Jingzhou city. Jingzhou's transportation has been continuously developed in last few years, but road construction has been relatively lagging. Many different causes are the reason for the pre-COVID and post-COVID increase of pollutants such as insufficient infrastructure in all counties in Jingzhou, narrow roads in the old towns, low green coverage, bare ground and ground dust caused by citizens' production and life, plus temperature inversion, dense fog, and severe weather such as haze will directly and indirectly affect the air quality of relevant areas.

Huangshi City is in the south of the Yangtze River area, with four distinct seasons. Spring and winter are dry and less rainy. There is more floating dust in the air due to its weather conditions. Therefore, dust in the city and construction site soil and sand dust seriously affect the air quality of this city. The large fog formed is not conducive to the diffusion of air pollutants, causing PM_{2.5} and PM₁₀ to exceed the standard. O₃ is a secondary pollutant and is closely related to NO_x. Its generation is mainly controlled by meteorological conditions. The summer weather is hot, and it is affected by meteorological effects such as solar radiation and high temperature that are beneficial to photochemical reactions. Nitrogen oxides and hydrocarbons in the air are exposed to strong sunlight. Under irradiation, after a series of complex atmospheric photochemical reactions, more O₃ is produced and enriched, which causes O₃ to become the main pollutant in summer. This is the reason that from 2017 to 2019 pollutants were high in Huangshi city which decreased during active-COVID period.

3.2. Daily Change in Air Pollutants during Active-COVID-19

Figure 3 shows the daily change in air-quality patterns for two months i.e., from January to February (to show variations due to lockdown) since the emergence of the COVID-19 virus.

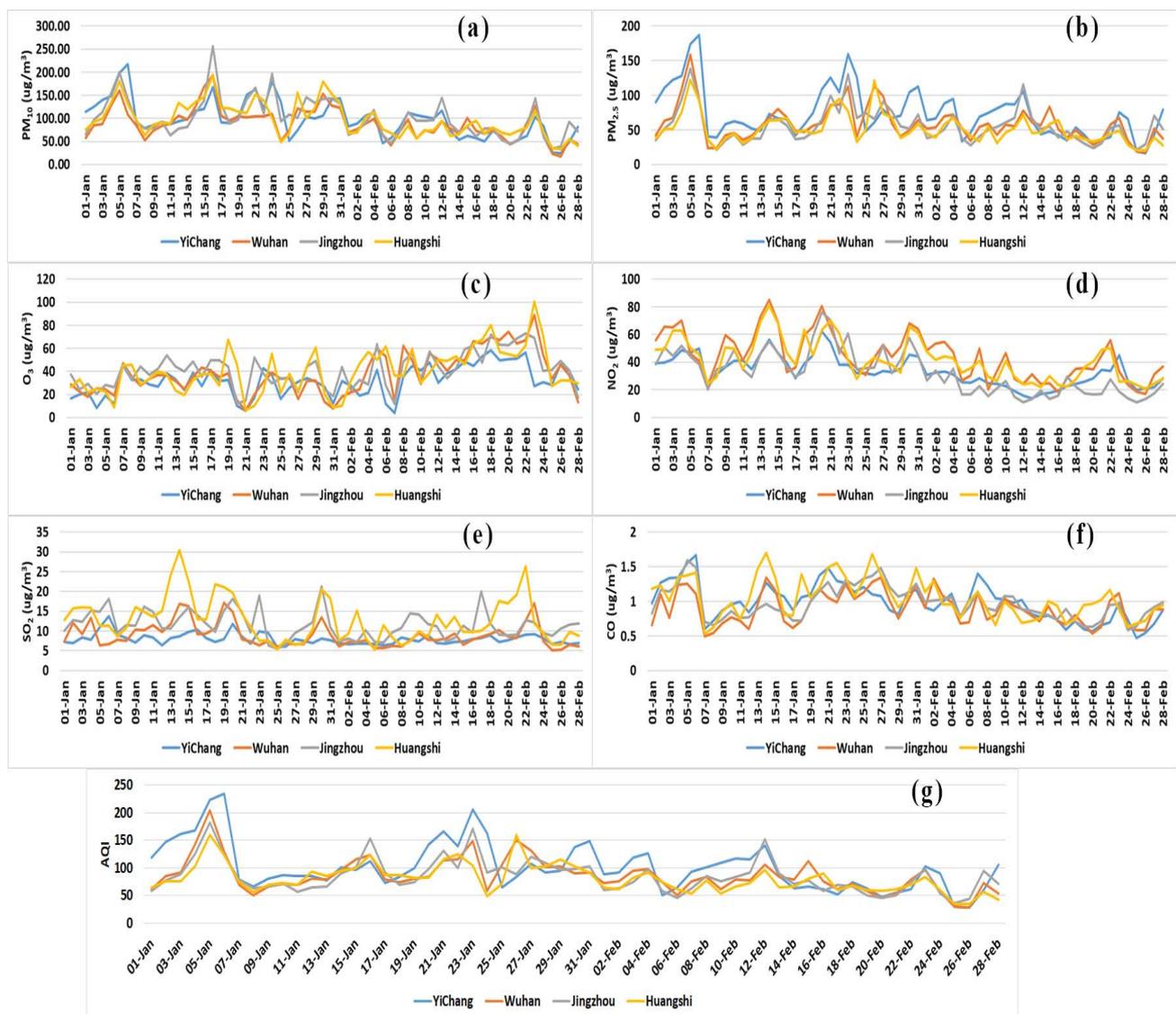


Figure 3. Daily change in air-quality patterns (a) PM₁₀ (b) PM_{2.5} (c) O₃ (d) NO₂ (e) SO₂ (f) CO (g) AQI.

It can be observed that the AQI gradually decreases after the implementation of a lockdown in Wuhan and nearby cities on 23 January 2020 [18]. Soon after the lockdown begins, the pollutants and the AQI had a sudden decrease, and after a few days of lockdown continuously decrease due to low human activity and less economic development [19]. The only pollutant which was increasing during lockdown was only O_3 . After the lockdown was lifted on 8 April 2020, the AQI level started increasing once again, while the level of O_3 , which was decreasing, shifted towards increasing after the lockdown ended. However, with the rapid increase in the number of motor vehicles, the NO_2 concentration in Wuhan increased. Traffic control was implemented in Wuhan on 23 January 2020. There was little change in the concentration of NO_2 in Wuhan after 23 January 2020 compared to the same period pre-COVID-19, however the NO_2 concentration dropped from $47 \mu\text{g}/\text{m}^3$ to $29 \mu\text{g}/\text{m}^3$ between 20 January and 24 January. Although motor vehicle travel was banned in Wuhan's central urban area on 26 January 2020, the level of NO_2 in Wuhan was the lowest at the end of January at an average concentration of $8 \mu\text{g}/\text{m}^3$. This is mainly since the motor vehicle ban was during a period of sustained humidity. Contrary to O_3 , due to a weaker convection and diffusion effect when the temperature is low, $PM_{2.5}$ concentrations are highest in winter, and they gradually decrease as the temperature rises. The change in the trend of $PM_{2.5}$ concentration is consistent with that of NO_2 . In Wuhan, the concentration of $PM_{2.5}$ decreased by 23.6% overall in 2020, in Jingzhou it decreased by 15.3%, in Huangshi it decreased by 18.2%, and in Yichang it decreased by 28.6%. Similarly, PM_{10} levels also decreased on a daily basis after the execution of the lockdown. The actual contribution of the prohibition to the reduction of particulate matter in Wuhan is limited, especially as the daytime maximum temperature rises above 20°C in mid-March, which leads to the degree of conversion of NO_2 into particulate matter weakening, and the $PM_{2.5}$ concentration is similar to that of the same period the previous year. This shows that although the strict traffic control during the epidemic minimized motor vehicle emissions, sources of major pollution emissions, such as industrial production, still existed.

Man-made SO_2 emissions mainly come from industrial coal, which is an important source of particulate matter [20]. After China began implementing a desulfurization policy in 2006, the concentration of SO_2 in Wuhan has continued to decline and is currently at a relatively low level [21]. From 22 January to 28 January 2020 (Spring Festival), the level of SO_2 in the Wuhan area remained at $5 \mu\text{g}/\text{m}^3$, but it rose to $11 \mu\text{g}/\text{m}^3$ on 31 January 2020, unlike the sharp drop in NO_2 concentration in 2020. During the lockdown period, the concentration of SO_2 dropped from $9 \mu\text{g}/\text{m}^3$ in the same pre-COVID-19 period the previous year to $8 \mu\text{g}/\text{m}^3$, indicating that the SO_2 concentration during the pandemic has reduced compared to SO_2 levels before the pandemic. Emissions related to industrial activities did not significantly reduce.

3.3. Path Analysis Implementation

Path analyses were used to find relationship of primary and major pollutants therefore we calculated the relationship of PM_{10} and $PM_{2.5}$ (dependent variables) with other pollutants (independent variables). The path analysis model was used to predict the direct and indirect relationship between the air pollutants and the AQI (Figure 4 and Table 3). β is the correlation coefficient range from 0 to 1. The higher the value of beta, the stronger the association between the variables.

It can be observed that $PM_{2.5}$'s β coefficient with the AQI is 0.94, whereas it is low with SO_2 and NO_2 and lowest with O_3 in the post-COVID-19 period. Similar patterns were observed for the active-COVID-19 period, where the β coefficient with the AQI is 0.866 for $PM_{2.5}$ but is lower for the other variables. The pre-COVID-19 $PM_{2.5}$ β coefficient is still higher compared to the other pollutants. The post-COVID-19 PM_{10} is strongly correlated with the AQI, with a β coefficient of 0.801, but negatively correlated with the other pollutants. Pre-COVID-19 and during active COVID-19, the same pattern of it having a strong relationship with the AQI but negative relationships with the other pollutants can be observed. The air-quality index is calculated based on averages of all pollutant

post-COVID-19 ($r^2 = 0.23$). The regression of $PM_{2.5}$ and SO_2 during the active-COVID-19 period ($r^2 = 0.30$) is higher than pre-COVID-19 ($r^2 = 0.15$) and post-COVID-19 ($r^2 = 0.15$). $PM_{2.5}$ and CO have an average medium regression ($r^2 > 0.51$ to $r^2 < 0.69$) value throughout every year, but the lowest value recorded is during the active-COVID-19 period ($r^2 = 0.53$). The regression between $PM_{2.5}$ and AQI is strong every year ($r^2 > 0.89$ to $r^2 < 0.96$), however the lowest value recorded is in the post-COVID-19 period ($r^2 = 0.89$) (Figure 5).

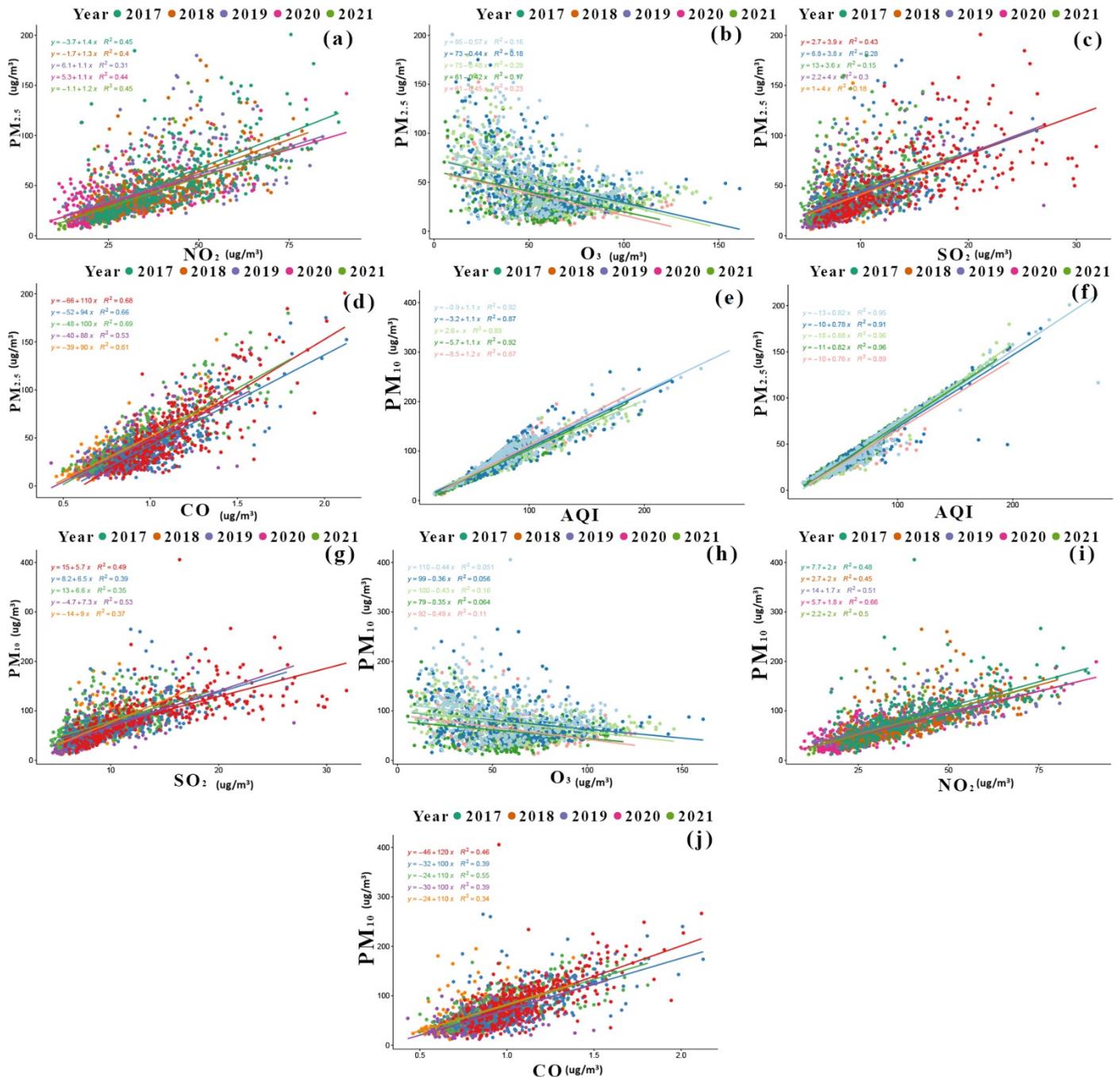


Figure 5. Yearly regression changes in air-quality patterns in Hubei (all four cities) (a) $PM_{2.5}$ with NO₂ (b) $PM_{2.5}$ with O₃ (c) $PM_{2.5}$ with SO₂ (d) $PM_{2.5}$ with CO (e) PM_{10} with AQI (f) $PM_{2.5}$ with AQI (g) PM_{10} with SO₂ (h) PM_{10} with O₃ (i) PM_{10} with NO₂ (j) PM_{10} with CO.

Similarly, the regression between PM_{10} and AQI is strong every year ($r^2 > 0.87$ to $r^2 < 0.92$), however the lowest value recorded is post-COVID-19 ($r^2 = 0.87$). PM_{10} and SO₂ have an average medium regression over all five years ($r^2 > 0.35$ to $r^2 < 0.53$), with the

highest value being recorded in the active-COVID-19 period ($r^2 = 0.53$) and lowest value being recorded pre-COVID-19 ($r^2 = 0.35$). PM_{10} and O_3 also have a weak regression over all five years ($r^2 > 0.051$ to $r^2 < 0.11$), with the highest value being recorded post-COVID-19 ($r^2 = 0.11$) and the lowest value being recorded in the year 2017 ($r^2 = 0.051$). It can also be observed that the regression value during the active-COVID-19 period ($r^2 = 0.064$) is lower compared to pre-COVID-19 ($r^2 = 0.16$) and post-COVID-19 ($r^2 = 0.11$). The regression between PM_{10} and NO_2 is medium every year ($r^2 > 0.44$ to $r^2 < 0.66$), however the highest value recorded is during the active-COVID-19 period ($r^2 = 0.66$). PM_{10} and CO also have a medium regression every year ($r^2 > 0.55$ to $r^2 < 0.34$), but post-COVID-19 ($r^2 = 0.34$) saw the lowest value of regression and pre-COVID-19 ($r^2 = 0.55$) saw the highest value of regression. This regression model helps predict the relationship of PM_{10} and $PM_{2.5}$ with other pollutants in order to gain an understanding of the changing behavior of air quality.

Since the COVID-19 pandemic, many scholars at home and abroad have discussed the characteristics of the changes in air quality under epidemic prevention and control, but relatively few studies have used statistical methods for their analysis [22,23]. In this study, a path analysis and a regression analysis were the main methods used to measure the relationships between the AQI value, the number of days of primary pollutant pollution, the pollutant concentration, and NO_2/SO_2 , among other values, from January 2019 to August 2021 and the same period in 2017 and 2018. The aim was to compare and analyze the changes in air quality in Wuhan and nearby cities during the period of epidemic prevention and control, to discuss the impact of epidemic prevention measures on air quality, to provide a reference and idea of how air pollutant patterns are changing yearly, and to suggest ways to improve air quality and adjust prevention and control measures.

From the analysis of the results, it can be said that the air quality in Hubei improved significantly during the epidemic prevention and control period compared to the previous three years. This is clearly in line with the epidemic prevention and control measures implemented in Hubei during the pandemic, namely traffic restrictions, closed community management, and enterprise production and operation control [24]. These greatly restricted peoples' production and living activities, and this is closely related to the reduction in pollutants. The successive implementation of the above measures has reduced urban pollution sources and the emission of pollutants that affect ambient air quality [25,26]. However, due to closed management and the fact that the population is relatively dense, the demand for heating increased exponentially. Therefore, after traffic restrictions were adopted in Hubei, the concentration of particulate matter increased slightly. Due to the needs of social life, the order and scope of the implementation of the above measures have gradually slowed down in Hubei, production and living activities have gradually resumed. Compared to the same period in previous years, the difference in daily average AQI has gradually decreased. This research also provides clarification regarding the management of ambient air quality. The results show that a temporary social blockade cannot improve the pollution of all pollutants. Due to the increase in fireworks emissions and coal combustion, the number of pollution days of O_3 and $PM_{2.5}$ increased during certain periods. Therefore, the focus of Hubei Province's future environmental protections should still be on the reduction of emissions through technological innovations in industry, transportation, and living activities. The removal of pollution sources may not be a good strategy for energy conservation and emissions reduction.

Through a year-on-year comparison of the concentration of basic pollutants during and before the pandemic, this study also explored the sources and influencing factors of air pollution during the COVID-19 pandemic. During the epidemic prevention and control period in Hubei, the concentrations of pollutants such as $PM_{2.5}$, PM_{10} , NO_2 , SO_2 , and CO all declined, which is consistent with changes in the ambient air quality in other countries and regions [27–30]. In particular, the concentration of SO_2 pollution improved significantly during the epidemic prevention and control period. This is because in recent years, Hubei Province had actively adopted environmental protection measures such as

improving stoves in cities and towns, eliminating small and medium-sized boilers, and switching to anthracite.

Declining industrial control is, therefore, an important measure for the reduction of SO₂ emissions. After the gradual relaxation of the epidemic preventions and controls, the concentrations of PM_{2.5} and CO in Hubei showed a downward trend. This is because a rise in temperature, which was occurring at the time, is conducive to the complete combustion of fuel, which results in a decrease in PM_{2.5} and CO emissions, so fuel is improved, and heating is increased. This method may be a better measure than restricting traffic and reducing exhaust emissions in terms of reducing PM_{2.5} and CO emissions. In addition, heating tools, such as heaters and boilers, are also important sources of PM_{2.5} and CO. Their utilization rate decreases with climate warming. When the temperature rises, the concentration of these pollutants will drop further.

4. Conclusions

This study shows that the daily average AQI value and the concentration of various pollutants in Hubei during the epidemic prevention and control period improved to varying degrees compared to the same period in 2018 and 2019. For all the air quality pollutants studied, a decrease in concentration was recorded during the active-COVID-19 period, with a maximum decrease observed in PM₁₀ at 26% followed by PM_{2.5} at 23% and the lowest decrease observed in O₃ at 5%. The changes in air pollutant levels from 2017 to 2021 were further compared and a decrease in all pollutants through to 2020 was found. However, in 2021, air pollution began to increase. The analysis of the primary pollutants during the epidemic prevention and control period showed that only the number of days of PM₁₀ pollution decreased, with PM_{2.5} and O₃ pollution increasing after the traffic blockade was established because of increased emissions from coal and fireworks. The above results indicate that the lockdown during the COVID-19 pandemic may have had both positive and negative effects on ambient air quality.

This study has some shortcomings, which are as follows:

- This study verifies that the lockdown during the COVID-19 pandemic may have had both positive and negative effects on ambient air quality. However, due to limitations in the availability of data from all the air-monitoring stations, some stations' data has been excluded, and thus, this outcome cannot be applied to all the stations.
- Further monitoring of stations can be improved if their locations are far from each other so that the overall air pollutants' real concentration can be calculated across all parts of the city.

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