Spatial–temporal variations and influencing factors of air quality in China’s major cities during COVID-19 lockdown

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Abstract
To control the spread of COVID-19, the Chinese government announced a “lockdown” policy, and the citizens’ activities were restricted. This study selected three standard air quality indexes, AQI, PM2.5, and PM10, of 2017–2021 in 40 major cities in six regions in China to analyze their changes, spatial–temporal distributions, and socioeconomic influencing factors. Compared with 2019, the values of AQI, PM2.5, and PM10 decreased, and the days with AQI levels “AQI ≤ 100” increased during the “lockdown” in 2020. Due to different degrees of industrialization, the concentration of air pollutants shows significant regional characteristics. The AQI values before and after the “lockdown” in 2020 show significant spatial autocorrelation, and the cities’ AQI values in the north present high autocorrelation, and the cities in the south are in low autocorrelation. From the data at the national level, carbon emission intensity (CEI), per capita energy consumption (PEC), per capita GDP (PCG), industrialization rate (IR), and proportion of construction value added (PCVA) have the greatest impact on AQI. This study gives regulators confidence that if the government implements regionalized air quality improvement policies according to the characteristics of each region in China and reasonably plans socioeconomic activities, it is expected to improve China’s air quality sustainably.

Keywords COVID-19 · Lockdown · Air quality · Spatial autocorrelation · Influencing factors · Environmental governance policy

Introduction
In December 2019, the first case of unknown pneumonia appeared in Wuhan, China, and then the virus causing pneumonia spread rapidly in China and even around the world and was named COVID-19 by WHO (WHO 2020). Due to the spread of COVID-19 from Wuhan to other provinces in China, the Chinese government announced the “lockdown” of Wuhan on January 23, 2020. Subsequently, all provinces’ governments announced the launch of the first-class response to major national public health events and began implementing epidemic restriction measures nationwide. These government restrictions include residents being restricted from going out; large gatherings being banned; schools, shopping centers, construction sites, and factories being temporarily suspended; and traffic and transportation being controlled. Since the “lockdown” started during the Chinese lunar new year, traffic control restricted a large number of population movements, which affected the economic activities of the whole country, but also provided an opportunity for China’s air pollution research.

Studies have shown that air quality will change during significant events. During the 2008 Olympic Games and the 2014 APEC summit, Beijing issued policies to restrict factory production and transportation in order to improve air quality (Chen et al. 2013). During the annual plenary session of the National People’s Congress and the National Committee of the Chinese People’s Political Consultative Conference from 2013 to 2016, due to the temporary implementation of strict air quality governance measures at the annual meeting, the air quality index AQI decreased by 5.7%. During the APEC meeting in 2014, the AQI index decreased by 35.9% due to the most stringent air governance measures issued by the China central government, and the values of
PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and CO decreased by 41.3%, 48.2%, 56.5%, 38.9%, and 35.5% respectively (Li et al. 2017). The G20 Summit in Hangzhou in 2016 proved that the holding of large-scale events is related to the changes of air quality (Li et al. 2019). However, the impact of the COVID-19 “lockdown” is unmatched by the previous major events in China.

Recent studies in many countries have shown that the “lockdown” caused by the spread of COVID-19 and the reduction of traffic and industrial activities have a positive impact on the environment (Li et al. 2020). The study found that the AQI, PM$_{2.5}$, and PM$_{10}$ of major cities in India decreased significantly during the one month of “lockdown” (Naqvi et al. 2021; Das et al. 2021; Yadav et al. 2020). Anthropogenic emissions reduce processes that promote secondary aerosol formation through measurements of aerosol composition during COVID-19 (Sun et al. 2020). The study found that PM$_{2.5}$ emission levels are strongly linked to the deaths of people infected with COVID-19, with regions dominated by fossil fuel emissions significantly affecting the number of COVID-19 cases (Sahu et al. 2021; Ali et al. 2021).

Based on the conventional pollutant monitoring data for 4 years and 3 months in the same period from 2018 to 2021, this paper analyzes air quality indexes in 40 major cities in China before, during, and after the “lockdown” in 2020. On this basis, the spatial effect test model of air quality and test model of air quality influencing factors are established to study the differences of socioeconomic factors on air quality both national and regional wide. The research results are helpful in understanding the evidence of the impact of human social activities on air quality during the period of strict policy restrictions, as well as the regional characteristics of air pollution, and provide a reference for formulating related air pollution governance policies and measures.

**Materials and methods**

**Data sources and processing**

This paper selects the data of monitoring points of 40 major cities in China, which spatially covers the developed cities in all provinces and regions in China. We collected daily air pollution data from China’s national environmental monitoring center from December to March 2017–2021 and selected air quality indexes AQI, PM$_{2.5}$, and PM$_{10}$.

Due to the characteristics of regional transmission of air pollutants, the air pollutants concentration of each city will be affected by the surrounding cities (Li et al. 2017). In this study, 40 major cities are divided into six regions according to their economic development level, industrial and energy structure, urban agglomeration development characteristics, regional climate characteristics, and geographical location (Miao et al. 2019; Xu et al. 2021; Hao et al. 2018; Luo et al. 2021; Zhu et al. 2018; Wei et al. 2020; Li et al. 2021); details are shown in Table 1.

January 23, 2020, the 29th of the lunar calendar, is the day before the Chinese lunar New Year’s Eve, which is during the Chinese Spring Festival holiday; people all over the country are reuniting with their families. Even if there is no “lockdown,” the economic activities in all regions of China will be significantly reduced. In order to make the data analysis more accurate, this paper selected the years 2018, 2019, and 2021 as the lunar calendar date range of the same period of the “lockdown” in 2020 for analysis, that is, 18 days before the 29th of the lunar calendar (before the “lockdown”), 18 days after the 29th of the lunar calendar (during the “lockdown”), and 18 days after the end of the “lockdown.”

**Spatial effect test model of air quality**

The global Moran’s I can indicate whether there is a spatial clustering phenomenon of unit urban air quality, judge the similarity between units in adjacent cities, and describe the overall distribution of air quality per unit city (Moran 1950). The calculation formula is as follows:

$$ \text{Global Moran I} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} $$

The global Moran’s I was proposed by Anselin in 1995 and can be used to explain the correlation between the air

| Regions                        | Cities                                      |
|-------------------------------|---------------------------------------------|
| Northeast                     | Harbin, Hohhot, Jilin, Changchun, Shenyang, Dalian |
| Beijing-Tianjin-Hebei (BTH)   | Beijing, Tianjin, Shijiazhuang, Tangshan, Jinan, Yantai, Qingdao |
| Yangtze River Delta           | Shanghai, Nanjing, Suzhou, Wuxi, Hefei, Hangzhou, Ningbo |
| Pearl River Delta             | Guangzhou, Shenzhen, Fuzhou, Quanzhou, Nanchang |
| West                          | Chongqing, Chengdu, Guiyang, Kunming, Nanning, Lanzhou, Yinchuan |
| Central                       | Zhengzhou, Luoyang, Nanyang, Wuhan, Xiangyang, Changsha, Taiyuan, Xian |
The corresponding calculation formula is as follows: 

$$w = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix}, \quad w_{ij} = \begin{cases} 1, & \text{the } i_{th} \text{ city is adjacent to the } j_{th} \text{ city} \\
0, & \text{the } i_{th} \text{ city is not adjacent to the } j_{th} \text{ city} \end{cases}$$

(2)

The economic weight is the reciprocal of per capita GDP, represented by \(W_E\); then, the economic weight can be expressed as \(W_E = (\overline{PCG_i} - \overline{PCG_j})^{-1}, (i \neq j)\); if \(\xi\) is used to represent the proportion of different weights, the economic geographic weight is represented by \(W_{EG}\), and then the calculation formula of economic geographic weight can be expressed as 

$$W_{EG} = \xi W_E + (1 - \xi) W_A$$

(3)

In order to improve the effect of spatial test, the standard statistic \(Z\) was used to test the significance level of the index. According to the principle of statistical test, the standard statistic calculation formula of Moran’s index \((I)\) can be expressed as follows:

$$I^* = [I - E(I)] \cdot [\text{Var}(I)]^{-1/2}$$

(4)

Since the global spatial autocorrelation test cannot test the heterogeneity in the spatial, the local spatial autocorrelation test is introduced, and the Moran index method is still used. The corresponding calculation formula is as follows:

$$I = \frac{n(\bar{z} - \bar{z}) \sum_{j=1}^{n} w_{ij}(z_i - \bar{z})}{\sum_{i=1}^{n} (z_i - \bar{z})}$$

$$I^* = [I - E(I)] \cdot [\text{Var}(I)]^{1/2}$$

(5)

The \(I\) value can judge the autocorrelation degree of urban air quality level. \(I > 0\) indicates that there is a positive spatial correlation, and the urban air quality index shows high-high or low-low autocorrelation; \(I < 0\) indicates a negative spatial correlation, and the urban air quality index presents a uniform or dispersed distribution of high-low or low-high; \(I = 0\) indicates that the urban air quality index is randomly distributed and there is no autocorrelation. In this paper, the spatial autocorrelation of air quality observations AQI among 40 major cities in China will be presented through the scatter diagram, in which the first and third quadrants of the scatter diagram represent the positive spatial correlation of observations and the second and fourth quadrants represent the negative spatial correlation.

### Test models of air quality influencing factors

Due to the “lockdown” policy, traffic is controlled, factories and construction sites are shut down, shopping malls and residential communities are closed, and non-essential economic activities are suspended. This paper selects nine explanatory variables: per capita GDP, urbanization rate, industrialization rate, per capita energy consumption, carbon emission intensity, the proportion of construction value-added, unqualified rate of vehicle emission, the proportion of environmental treatment investment, and the proportion of R & D investment. The socioeconomic data are from the China Urban Statistical Yearbook, the National Bureau of Statistics, and the Traffic Administration Bureau of the Ministry of Public Security of China.

Per capita GDP significantly affects environmental pollution; there is a U-shaped curve relationship between per capita GDP and air pollution in China (Zheng and Chen 2020). The development of urbanization rate and industrialization rate has a considerable impact on China’s air quality (Wu et al. 2018; Fu and Li 2020; Liu et al. 2022). Energy consumption uses coal and petroleum as fuel, and a large amount of particulate matter and harmful gases are released during the combustion process to increase carbon emissions, and thermal power generation in China accounts for more than 70% of the total power generation (Shon et al. 2020). The industrialization rate represents the level of pollution emissions impacted from factories (Hao and Liu, 2016). The proportion of construction value added is used to reflect the level of construction dust (Li et al. 2021; Hong et al. 2017); unqualified rate of vehicle emission reflects the situation of vehicle emission and pollution to the environment. It is a conventional energy consumption method (Walsh 2014). Both proportion of environmental treatment investment and proportion of R & D investment are important means to reduce air pollution and improve air quality. To analyze the influencing factors of urban air quality, AQI is used to represent urban air quality, the influencing factor is \(X_i\), and the driving force model of urban air quality is

$$AQI_i = \prod_{i=1}^{n} aX_i^\beta$$

(6)

\(AQI\) is the dependent variable, which is the abbreviation for air quality index. The Chinese central government has released national air quality index data since 2012, and
Provinces have also begun to release local air quality index data. The independent variable is the influencing factor of AQI, which affects the air quality of Chinese cities. On the basis of comprehensive analysis, this paper selects per capita GDP, urbanization rate, industrialization rate, per capita energy consumption, carbon emission intensity, the proportion of construction value-added, unqualified rate of vehicle emission, the proportion of environmental treatment investment, and the proportion of R & D investment, a total of nine independent variables. Among them, $X_i$ is PCG, which is the abbreviation of per capita GDP, calculated according to the historical statistics of the National Bureau of Statistics; that is, the annual GDP divided by the total population at the end of the year; $X_2$ is UR, which is the abbreviation of urbanization rate, using the calculation results of the National Bureau of Statistics; $X_3$ is IR, which is the abbreviation of industrialization rate and the ratio of annual industrial added value to GDP in the same period, using the calculation results of the National Bureau of Statistics; $X_4$ is PEC, which is the abbreviation of per capita energy consumption, using the calculation results of National Bureau of Statistics; $X_5$ is CEI, which is the abbreviation of carbon emission intensity, expressed as the ratio of the total energy consumption and carbon emissions in a certain period to the GDP of the same period, using the calculation results of the National Bureau of Statistics; $X_6$ is PCVA, which is the abbreviation of the proportion of construction value-added, using the official statistical results of each city’s government; $X_7$ is URVE, which is the abbreviation of unqualified rate of vehicle emission, using the statistics of China’s traffic management department; $X_8$ is PETI, which is the abbreviation of the proportion of environmental treatment investment, using the statistics of the National Bureau of Statistics; and $X_9$ is PRD, which is the proportion of R & D investment. This paper uses the data of the total R&D investment amount from the National Bureau of Statistics. $\beta_i$ is the coefficient corresponding to the independent variable in the test sum equation ($i = 1, 2, \ldots, 9$), and $\epsilon$ is the error random term. To eliminate the influence of heteroscedasticity on the model estimation, take the natural logarithm on both sides of Eq. (6). The test equation for the influencing factors of China’s urban air quality index can be expressed as

\[
\ln \text{AQI}_t = \beta_0 + \beta_1 \ln \text{PCG}_t + \beta_2 \ln \text{UR}_t + \beta_3 \ln \text{IR}_t + \beta_4 \ln \text{PEC}_t + \beta_5 \ln \text{CEI}_t + \beta_6 \ln \text{PCVA}_t + \beta_7 \ln \text{URVE}_t + \beta_8 \ln \text{PETI}_t + \beta_9 \ln \text{PRD}_t + \mu
\]

This is the basic test model of urban air quality. To analyze the spatial effect of urban air quality, two econometric regression models, the spatial lag model (SLM) and the spatial error model (SEM), are introduced. In the selection of spatial models, it is necessary to use the least-squares method to estimate the constraint model of spatial correlation and select the model by comparing the significance of Lagrangian multipliers. Based on a comprehensive analysis, the spatial lag test model of urban air quality is constructed on the basic model as follows:

\[
\ln \text{AQI}_t = \rho W_{SE} \ln \text{AQI}_t + \beta_0 + \beta_1 \ln \text{PCG}_t + \beta_2 \ln \text{UR}_t + \beta_3 \ln \text{IR}_t + \beta_4 \ln \text{PEC}_t + \beta_5 \ln \text{CEI}_t + \beta_6 \ln \text{PCVA}_t + \beta_7 \ln \text{URVE}_t + \beta_8 \ln \text{PETI}_t + \beta_9 \ln \text{PRD}_t + \mu
\]

In the formula, $\rho$ is the spatial coefficient, $W_{SE}$ is the $n \times 1$ order spatial weight matrix, and $\mu$ is the error variable. If LM (error) is statistically significant than LM (lag) and R-LM (error) is more significant than R-LM (lag), a spatial error model is used, which is expressed as

\[
\ln \text{AQI}_t = \beta_0 + \beta_1 \ln \text{PCG}_t + \beta_2 \ln \text{UR}_t + \beta_3 \ln \text{IR}_t + \beta_4 \ln \text{PEC}_t + \beta_5 \ln \text{CEI}_t + \beta_6 \ln \text{PCVA}_t + \mu
\]

In the formula, $\mu$ is the spatial error coefficient, $W_{SE}$ is the spatial weight matrix of order $n \times 1$, $\beta_i$ is the model parameter to be estimated, $\mu$ is the error random term, and $\epsilon$ is the normal distribution random error vector. Model parameters can be estimated using the maximum likelihood estimation method, and the weight matrix can be calculated and the model can be tested using GeoDa spatial analysis software.

**Results and discussion**

**Results**

Figure 1 shows the daily value changes of AQI, PM$_{2.5}$, and PM$_{10}$ in China during the 54 days from December 29 to February 4 in the same period of the lunar calendar from 2018 to 2021. Phases I, II, and III are 18 days before the “lockdown,” 18 days in the “lockdown,” and 18 days after the “lockdown” in 2020. In phase II, compared with phase I, AQI, PM$_{2.5}$, and PM$_{10}$ decreased by 15.83%, 16.08%, and 22.12% respectively. It can be seen that the impact of Wuhan City’s “lockdown” policies and measures is national wide and other provinces have certain responses to the policies. In phase III, the three indexes showed an upward trend, which may be affected by the resumption of factories and the traffic resumed (Li et al. 2020). Compared with the same period in 2019, the three indexes in phases II and III in 2020 decreased; AQI, PM$_{2.5}$, and PM$_{10}$ decreased by 22.54%, 13.94%, and 22.30% respectively; and the three indexes decreased by 4.22%, 16.26%, and 4.72% respectively compared with the same period in...
It can be seen that the implementation of the city “lockdown” policy in 2020 has a positive impact on the values of three indexes, both month on month and year on year.

In Fig. 2, AQI, PM$_{2.5}$, and PM$_{10}$ values in Northeast, Yangtze River Delta, and Pearl River Delta showed a downward trend in phases II to III compared with phase I in 2020, reaching more than 30%. It can be seen that the “lockdown” has an obvious effect on human activities. Due to the intensive heavy industry in Northeast China, the “lockdown” closed most production and processing factories, resulting in reduced air pollutant emissions. The Yangtze River Delta and the Pearl River Delta are located in China’s coastal regions and belong to the two regions with the most developed economy in China. The secondary industry is developed, and the trade import and export business are busy. Under the “lockdown” and trade control policies, the large-scale shutdown of factories leads to the reduction of air pollutant emissions, which may lead to the decline of air quality indexes’ values (Fujii et al., 2013).

As shown in Fig. 3, the AQI, PM$_{2.5}$, and PM$_{10}$ values of the West, BTH, and Central regions showed a more stable change trend in 2020 compared with the Northeast, Yangtze River Delta, and Pearl River Delta. Compared with the Northeast, Yangtze River Delta, and Pearl River Delta, the development of secondary industry in the West and Central regions lags behind, and the “lockdown” measures have relatively little impact on the air pollutant emissions of factories. The secondary industry in the BTH region is developed, and the air quality indexes’ values do not fluctuate significantly after the “lockdown” began. It might be that the BTH region is located in Bohai Bay, with a strong sea breeze. The change in air pollutant concentration level is affected by natural factors such as wind speed and wind direction or the diffusion of air pollution in other cities and counties (Shi et al. 2019).

### Days to reach various levels of air quality

Figure 4 shows the proportion of days in 54 days total that reach six different AQI air quality levels in China and its six regions during the “lockdown” in 2020 and the same period in 2019. The outer ring of the ring chart is the data for 2020, and the inner ring is the data for 2019. According to the Chinese Environmental Quality Index (AQI) Technical Regulation “HJ633-2012,” AQI air quality index is divided into six levels: excellent (0 < AQI ≤ 50), good (50 < AQI ≤ 100), light pollution (100 < AQI ≤ 150), moderate pollution (150 < AQI ≤ 200), heavy pollution (200 < AQI ≤ 300), and serious pollution (300 > AQI).

From nationwide, the number of days with good air quality or above accounted for 100% during the “lockdown” in 2020. In the same “lockdown” period of 2019, the average number of days with good air quality or above accounted for 89%, and the number of days with light pollution accounted for 11%. As the result, the proportion of the average number of days reaching good or above level in 40 major cities in 2020 increased compared with 2019 nationwide.

During the “lockdown” of six regions in 2020, the proportion of days with light pollution and below decreased compared with the same period in 2019, which can be observed from Fig. 4 that the proportion of pollution days in 2019 is ranked from high to low as Central (92%), BTH (50%), Yangtze River Delta (46%), Northeast (20%), West (6%), and Pearl River Delta (0%), from high to low in 2020, followed by BTH (44%), Central (33%), Northeast (31%), Yangtze River Delta (3%), West (0%), and Pearl River Delta (0%). In 2019 and 2020, the Central region and BTH region are the two most polluted regions, and the number of pollution days is much higher than the national average. West and Pearl River Delta are the two least polluted regions in both years, while the Northeast region is the only region with an increase in pollution days in 2020.
AQI spatial distribution

Figure 5 shows the comparison chart of the global spatial autocorrelation analysis results of AQI concentrations in 40 major cities in China 18 days before and after the “lockdown” in 2020. The Moran index results before and after the “lockdown” are 0.669 and 0.656 respectively, which are both greater than 0, and significant at the level of 1%, indicating that the air quality in major cities in China shows significant spatial autocorrelation, and the air pollution has regional autocorrelation. In the comparison chart, most cities before and after the “lockdown” are located in the first and third quadrants. Before the “lockdown,” only two cities are located in the second quadrant. After the “lockdown,” three cities are in the second quadrant, and there is no significant autocorrelation in other cities. The AQI index of major cities in China shows a trend of autocorrelation of high-high areas and low-low areas.

The AQI local autocorrelation of major cities 18 days before and after the “lockdown” is analyzed, and the AQI Local Indicators of Spatial Association cluster map is drawn using ArcGIS software. It can be seen from Fig. 6 that 18 days before the “lockdown,” the high-high autocorrelation areas are mainly concentrated in northeastern China, including the Northeast region, BTH region, Inner Mongolia Autonomous Region, and Shanxi Province. Low-low autocorrelation areas are concentrated in the southern coastal regions, including Guangxi Province, Guangdong Province, and Hainan Province. After the “lockdown” of the city, Jilin Province in Northeast China and Hebei Province in BTH region separated from high-high autocorrelation areas and Guangdong Province in
Fig. 3 Fluctuations of AQI, PM$_{2.5}$, and PM$_{10}$ values in West, BTH, and Central regions during the “lockdown” from 2018 to 2021.

Fig. 4 The proportions of days that reach six different levels of AQI during “lockdown” in 2019–2020.
the Pearl River Delta and Hainan Province separated from low-low autocorrelation areas. China’s urban air quality index AQI presents high autocorrelation in the north and low autocorrelation in the south, and there are more autocorrelation areas in the north. Such autocorrelation characteristics show that the implementation efficiency of measures in response to the “lockdown” policy of the central government is different in each region, which might lead to a change in the regional air pollution AQI index values, thus affecting the change of autocorrelation.

Analysis on the influencing factors of air quality evolution after the “lockdown”

Descriptive analysis of variables in estimating models

Table 2 shows the descriptive statistical analysis of the variables in the test models of air quality influencing factors.

During the observation period, the average value of AQI is 79.8919, and the average of PCG, UR, IR, PEC, CEI, PCVA, URVE, PETI, and PRD are 6.8724 yuan/person, 72.27%,
50.2724%, 15.28 tons/person, 2.2534 tons/10,000 yuan, 9.85%, 2.24%, 2.0125%, and 1.2326%, respectively.

**Analysis of influencing factors of urban air quality evolution**

This paper uses the relevant data of the selected 40 cities of the air quality index influencing factor indicators, and the result of the global autocorrelation test using the Moran index is 0.6694, showing a significant spatial correlation. The correlations between variables tested by SPSS software were all less than 0.80, and the results of the VIF test were all less than 5, indicating that the variables in the test model did not have multicollinearity. The constraint model of spatial correlation estimated by the OLS method found that the results of the test using the Lagrangian multiplier (SLM) method were more statistically significant and the robustness was also better. Therefore, this paper chooses the test results of the spatial lag model. The model estimation results are shown in Table 3.

It can be seen from Table 3 that the result of the variable correlation test using the OLS method is $R^2 = 0.4126$ and the result of the variable correlation test using the SLM method is $R^2 = 0.7216$; the spatial lag model has a better fit. According to the test results, the per capita GDP and the proportion of environmental treatment investment are negatively correlated with the air quality index. The increase in the proportion of environmental treatment investment is a key factor in reducing air pollution and improving air quality. The increase in per capita GDP will increase the scale of investment in environmental pollution treatment and will also play a role in reducing air pollution and improving air quality. Other variables are positively correlated with the air quality index, and the degree of influence from strong to weak is carbon emission intensity, per capita energy consumption, industrialization rate, the proportion of construction value-added, unqualified rate of vehicle emission, urbanization rate, and the proportion of R&D investment.

**Air quality evolution and influencing factors in major cities**

In order to reduce or avoid the instability of the test results caused by too many variables and samples, this paper selects five indicators that have a greater impact on AQI: per capita energy consumption, industrialization rate, per capita GDP, carbon emission intensity, and the proportion of environmental treatment investment. The selected influence indicators are used to process the influencing factors test for the AQI of the whole country and six regions of China. The specific test results are shown in Table 4.

According to the test results in Table 4, among the influencing factors of urban environmental quality in China, PCG and PETI are inversely correlated with AQI, and other variables are positively correlated with AQI. In the Northeast region, the impact of variables negatively correlated with AQI is that for every 1% increase in those variables, AQI decreases by 0.702% and 1.236%, respectively. Conversely, every 1% increase in variables positively correlated with AQI increases it by 1.185%, 1.157%, and 1.367%, respectively. In the BTH region, every 1% increase in per capita GDP can reduce AQI by 0.421%, and every 1% increase in the proportion of environmental treatment investment can reduce AQI by 1.506%; every 1% increase in other variables that have positive correlations with AQI can increase AQI 1.352%, 0.984%, and 1.463% respectively. In the Yangtze River Delta region, the impact of variables negatively correlated with AQI is that for each 1% increase in them, AQI decreases by 0.681% and 1.177%, respectively; the impact of variables positively correlated with AQI is that for every 1% increase in them, the AQI will increase by 1.115%, 1.018%, and 1.311%, respectively. In the Pearl River Delta region, for every 1% increase in variables negatively correlated with AQI, it decreases by 0.601% and 1.051%, respectively; the impact of variables positively correlated with AQI is that for every 1% increase in them, the AQI increased by 1.018%, 1.025%, and 1.215% respectively. In the West region, for every 1% increase in variables negatively correlated with AQI, AQI decreases by 0.643% and 1.156%, respectively; the impact of variables positively correlated with AQI is that for every 1% increase in them, the AQI increased by 1.108%, 1.089%, and 1.295% respectively. In the central region, the impact of variables that have negative correlations with AQI is as follows: every 1% increase in the variables makes AQI decrease by 0.623% and 1.325%, respectively; the impact

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**Table 3** Analysis of overall air quality evolution and influencing factors in Chinese cities in 2020

| Coefficient of independent variable | Least squares (OLS) | Spatial lag model (SLM) |
|-------------------------------------|---------------------|------------------------|
|                                     | Coefficient value   | $T$ value              | Coefficient value | $Z$ value |
| $b_0$                               | 0.021               | 0.034                  | $-0.065^{***}$    | $-1.964$  |
| $b_1$(PCG)                          | $-0.316^{***}$      | $-4.24$                | $-0.293^{***}$    | $-4.053$  |
| $b_2$(UR)                           | 0.121               | 1.68                   | 0.108             | 1.972     |
| $b_3$(IR)                           | 0.386               | 3.667                  | 0.352             | 3.465     |
| $b_4$(PEC)                          | 0.435**             | 3.281                  | 0.427**           | 2.984     |
| $b_5$(CEI)                          | 0.527***            | 5.324                  | 0.486             | 4.267     |
| $b_6$(PCVA)                         | 0.3026              | 3.363                  | 0.293             | 3.021     |
| $b_7$(URVE)                         | 0.2831              | 3.871                  | 0.226             | 3.254     |
| $b_8$(PETI)                         | $-0.4927$           | $-2.833$               | $-0.467$          | $-2.164$  |
| $b_9$(PRD)                          | 0.0894              | 0.892                  | 0.068             | 0.785     |
| $\mu$                               | –                   | –                      | 0.7021***         | 18.52     |
| $R^2$                               | 0.4126              | –                      | 0.7216            | –         |
| Log likelihood                      | –                   | –                      | 162.31            | –         |

$^{***}p<0.01, ^{**}p<0.05, ^{*}p<0.1$
of variables that have positive correlations with AQI is as follows: every 1% increase of them will increase the AQI by 1.435%, 1.054%, and 1.383%, respectively.

### Policy proposals

By analyzing the spatial distribution of air quality indexes, even in regions with similar economic development levels, there are significant differences in air quality indexes due to the comprehensive influence of climate, resources, environment, and other factors. Specifically, the air quality level in the southeast coastal and west region is high; Northeast region, BTH region, and Central region have poor air quality, which are the high incidence areas of haze. There are significant differences in the air quality of cities with similar economic development levels in these regions. Shenzhen and Guangzhou have high economic and urbanization development levels with good air quality. However, Beijing and Hangzhou’s economic development and urbanization levels are similar to Shenzhen and Guangzhou, but the air pollution is serious. Furthermore, Nanyang and Hohhot have low economic development levels, insufficient urbanization, and poor air quality. However, Kunming and Guiyang are both backward cities in economic development, and their air quality is much better than that of Nanyang and Hohhot. It can be seen that socioeconomic factors such as industrial and energy structure are important factors affecting the change of urban air quality. Urbanization driven by high pollution industries will only lead to the continuous aggravation of air pollution, but cities that rely on high-tech industries to promote economic development and urbanization have fewer pollutant emissions (Peng et al. 2021; Guo et al. 2021). At the same time, urban air quality can be affected by natural factors such as resources, climate, and environment (Melamed et al., 2016; Zhang et al. 2019; MAC Kinnon et al. 2018). Therefore, although humans can control most socioeconomic factors when studying the methods to inhibit the deterioration of air quality, however, we should not only rely on curbing the level of economy and urbanization to achieve the purpose of air purification but also confirm the direction and focus of environmental governance in combination with various factors mentioned above.

The “lockdown” policy of the epidemic is short-lived and temporary. However, some of its policy measures are consistent with the government’s conventional environmental governance plan in China, such as traffic control and the “Odd–even License Plate” policy; construction site shutdown is similar to the government’s mandatory watering and dust reduction on the construction site, and factory shutdown and scale factories emission reduction policies can be corresponding. Although the “lockdown” policy efforts are stronger than the conventional environmental governance policy, it has improved air quality. Once the COVID-19 epidemic is over, the production and life of residents will be fully restored, the air pollutants will increase, and the air quality will still be negatively affected. Therefore, appropriate environmental protection policies based on regional characteristics can better achieve the purpose of long-term improvement of environmental quality. Because of the high population density of China’s big cities, the limited traffic governance policy will bring the problems of low resource utilization and rising costs. Encouraging green travel, developing public transport, promoting clean energy vehicles, green investment in new energy vehicle manufacturers, and subsidies for new energy vehicle buyers are environmental policies for sustainable development. The government should formulate environmental protection policies for factories in various regions of China in line with local economic development. Economically backward regions mainly carry out end-of-pipe treatment for factories.
to ensure their rapid economic growth. Industrially developed regions can appropriately improve environmental protection requirements, urge them to develop emission reduction technologies, replace energy, and improve production efficiency. Northeast region, BTH region, and other regions with high industrial pollution and high energy consumption should establish a new development concept, phase out backward production capacity, promote joint atmospheric prevention and treatment, strengthen regulatory means, optimize the industrial structure, innovate in key regions of the industrial chain, and achieve high-quality development. In regions where high-tech enterprises such as the Yangtze River Delta should promote the ecological development of industrial parks, develop low-carbon technologies such as alternative energy, light energy, wind energy, and ultra-high voltage, comprehensively layout green energy to connect to the power grid, and help the region realize a green and low-carbon way of production and life.

**Conclusion**

This paper analyzed the change trends of AQI, PM$_{2.5}$, and PM$_{10}$ on the “lockdown” restrictions and the socioeconomic factors of AQI change in 40 major cities and six regions in China during the “lockdown” from December 29 to February 4 in the same period of the lunar calendar from 2018 to 2021. Compared with the 36 days after the “lockdown,” the three air quality indexes’ average values showed a downward trend in the 18 days before the “lockdown” in 2020, of which PM$_{10}$ decreased the most. Compared with the same period in 2018 and 2019, the three air quality indexes showed a downward trend, of which PM$_{2.5}$ decreased the most in 2018 and AQI decreased the most in 2019. Among the six regions, the three air quality indexes in the regions with developed manufacturing factories and enterprises decreased significantly after the “lockdown,” while the decrease in other regions was smaller. In 2020, compared with the same period in 2019, the number of days when AQI reaches good or above levels in six regions in China increased except for the Northeast. Using global and local Moran I for further analysis, it was found that the regional autocorrelation of air pollution in major cities is obvious. The northern region of China is a high pollution autocorrelation region, and the low pollution autocorrelation region is distributed on the southern coast. Using the spatial lag model to analyze the socioeconomic factors influencing air quality changes in major cities in China has more advantages than the OLS model. The per capita GDP and the proportion of environmental treatment investment play a key role in reducing air pollution and improving air quality. If the government strictly implements air pollution governance policies, China’s air quality will significantly improve.

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**Declarations**

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