Zhang *et al. City and Built Environment (2023) 1:13*
https://doi.org/10.1007/s44213-023-00013-0

City and Built Environment

ORIGINAL ARTICLE

Open Access

Air pollution reduction during COVID-19 lockdown in China: a sustainable impact assessment for future cities development

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Abstract

COVID-19 has significantly impacted people's daily lives worldwide in the past three years. During the COVID-19 lockdown in China, people's activities were restricted, private cars were banned, and some factories were shut down. It is expected that air pollution would be mitigated due to the reduction of automobile exhaust and factory pollution gas emissions during the COVID-19 lockdown. In this study, a city-level comparative study was investigated to quantify the impact of lockdown on air pollution in China. The concentration changes of air pollutants (NO_2, SO_2, CO, $PM_{2.5}$, PM_{10}) caused by the lockdown are studied covering 345 cities in China. The sensitivity analysis method was adopted to explore the variation scale of pollutant concentration in typical cities. Furthermore, the spatial distribution of pollutant changes between 2019 and 2020 and typical months are discussed using a composite index. The results showed that NO_2, SO_2 and PM_{10} concentrations had a significant reduction due to the lockdown, ranging from 15 to 30%. Pollutant emissions of 321 cities in February and March 2020 fell noticeably, and 272 cities showed a rebound of pollutant emissions after April 2020 when work and production resumed. The lessons learned from COVID-19 lockdowns offer valuable insights into how cities can better prepare for future crises and improve their resilience and adaptability.

Keywords: COVID-19 Lockdown, Pollutant emissions, Composite index, Human activities, Resumption

Introduction

In early 2020, the COVID-19 pandemic swept across the world. Almost all countries have taken some measures to prevent the spread of COVID-19 (Ranjbari et al. 2021; Zhang et al. 2021). Wearing masks and reducing aggregation are effective ways to reduce the risk of virus transmission, which has been widely adopted worldwide (Sun et al. 2020; Andrejko et al. 2023). In China, not only people responded quickly to fight COVID-19 by wearing masks and reducing aggregation, but also the government published a strict policy that all people were encouraged to stay at home to prevent the spread of coronavirus (Sun et al. 2020; Dai et al. 2022). From January 23 to April 8, 2020, China began a two-month strict lockdown when all people stayed at home without any outdoor activities (Yan et al. 2021). During the strict lockdown, factories shut down and many industries stagnated, which had a significant influence on the sustainable development of cities (Jena et al. 2021).

Some researchers have studied the influence of the COVID-19 lockdown on agriculture (Feng et al. 2022), industry production (Ananda et al. 2023), energy application and transportation (Persis and Ben Amar 2023; Azad et al. 2020). Iman Haqiqi et al. assessed COVID-19 impacts on American counties using the immediate impact model of local agricultural production and found that there was a decline in agricultural output in all the American counties ranging from 1.18% to 7.14% of total production due to the COVID-19 pandemic (Haqiqi and Bahalou Horeh 2021). Qadeer et al. (2022) provided a critical view of the impacts of COVID-19 on sustainable development goals and concluded the positive and short-term effects on the environment. Wen et al. analyzed the impacts of COVID-19 on China's electric vehicle industry from both the demand side and the supply side. It was found that the COVID-19 outbreak had reduced electric vehicle sales in the short-term, but may also stimulate future electric vehicle demand, especially for large electric cars with better performance (Wen et al. 2021). Szczygielski et al. investigated the impact and the timing of the impact of COVID-19-related uncertainty on returns and volatility for 20 national energy indices and a global energy index, and pointed out that the net energy exporters on average incurred greater losses (−35.63%) since the onset of the pandemic than net energy importers (−27.71%) (Szczygielski et al. 2021). In reference (Cui et al. 2021), the impacts of the COVID-19 pandemic on China's transport sectors were studied based on the CGE model coupled with a decomposition analysis approach. It was expected that the outputs of the freight transport sectors and passenger transport sectors would decline by 1.03–2.85% and by 3.08–11.44%, respectively.

In addition, some literature focused on the impact of COVID-19 on air pollution (Mandal et al. 2022; Sathe et al. 2021). Mohammad et al. reported that NO_2 levels in major Indian cities, such as Ahmedabad, Mumbai and Pune, decreased between 40 and 50% during the time of lockdown (Shakil et al. 2020). In reference (Wang and Su 2020), an evaluation of the dynamic impact of COVID-19 on the environment was conducted, and the results indicated that the outbreak of COVID-19 improved China's air quality in the short term and significantly contributed to global carbon emission reduction. Liu et al. investigated the tropospheric nitrogen dioxide in China after the outbreak of COVID-19. They reported that there was a 48% drop in tropospheric nitrogen dioxide vertical column densities from the 20 days averaged before the 2020 Lunar New Year to the 20 days averaged after (Liu et al. 2020). Corinne et al. revealed that daily global CO_2 emissions decreased by 17% (11 to 25% for $\pm 1\sigma$) in early April 2020, compared with the mean 2019 levels, just under half from changes in surface transport (Quéré et al. 2020) (Table 1).

The impact of COVID-19 on the environment has been studied in existing literature (Liu et al. 2022; Wang and Li 2021). However, the impact of the strict lockdown on air pollution and the sustainable development of cities in China was rarely investigated. Therefore, the objective of this paper is to study the quantitative impact of the lockdown on air pollution, especially for typical pollutants. During the strict lockdown, some factories stopped production or shut down and the traffic volume also dropped sharply. The

Table 1 Existing studies and their contributions, and the originality of this study

Literature	Scope of Geography	Assess the impact on which aspects
Haqiqi and Bahalou Horeh (2021)	America	Agricultural production
Qadeer et al. (2022)	Globe	Sustainable development of the environment
Wen et al. (2021)	China	Electric vehicle industry
Szczygielski et al. (2021)	Globe	Returns for energy indices
Cui et al. (2021)	China	Transport sectors
Mohammad et al. (2020)	India	Pollutant NO_2
Wang and Su (2020)	China	Environment and air quality
Liu et al. (2020)	China	Tropospheric pollutant NO_2
Corinne et al. (2020)	Globe	Global CO_2 emissions
This study	China	Air pollutants NO2, SO2, CO, PM2.5 and PM10, and the sustainable development of cities

concentration of pollutant gases in cities during the lockdown is expected to be reduced since automobile exhaust and factory pollution gas emissions are the main contributors to pollutants, such as NO_2, SO_2 and $PM_{2.5}$.

The COVID-19 pandemic has immensely impacted the economic, social, and environmental pillars of sustainability in human lives. This paper aims to provide an inclusive insight into the sustainability perspectives, dynamics, and practices in the wake of the COVID-19 pandemic crisis. This study investigated a city-level comparative analysis to quantify the impact of lockdown on air pollution in China during the lockdown. The concentration changes of air pollutants (NO_2, SO_2, CO, $PM_{2.5}$, PM_{10}) caused by the lockdown are studied covering 345 cities in China. The sensitivity analysis method was adopted to explore the variation scale of pollutant concentration in typical cities. Furthermore, the spatial distribution of pollutant changes between 2019 and 2020 and typical months are discussed using a composite index. The results offer valuable insights into how cities can better prepare for future crises and improve their resilience and adaptability, and alleviate the pandemic's negative impacts on the sustainable development of cities.

Methodology

In this section, the outline of this study is presented. The correction coefficient method aims to attenuate the influence of other factors (e.g., policy intervention, seasonal variation) when making a comparison. In following section, the correction coefficient method was proposed to quantify the concentration change of pollutant gases in different years. Last section introduces the sensitivity analysis to quantify the change degree of pollutants related to a strict lockdown in a certain city. In final section, the composite index related to pollutants is defined to quantify the concentration change of five types of pollutant gases.

Outline of the framework

Before COVID 19 pandemic, the factory was running and there were a large number of vehicles on the road every day, which are the main contributors to air pollution, particularly, NO_2, SO_2, CO, $PM_{2.5}$, and PM_{10}. In early 2020, the COVID-19 pandemic swept across the world. The Chinese government has taken strict lockdowns to prevent the spread of viruses and fight the COVID-19 pandemic. The sudden drop in traffic volume and the shutdown of factories due to the strict lockdown are considered to have an impact on the concentration of pollutants. In this paper, a city-level study covering 345 cities was investigated to explore air pollution reduction during the COVID-19 lockdown in China. Five kinds of pollutants were studied by adopting the composite index (***CI***) method to quantify the impact of the COVID-19 lockdown on air pollutants in cities (Fig. 1).

Correction coefficient method

The correction coefficient method is used to improve the accuracy, balance and integrity of measurement data. In general, the correction coefficient method can be expressed as multiplying a value by a correction coefficient to get a corrected value that is closer to the real value. The correction coefficient method is widely used in many professional fields because of its simplicity and reliability.

Yearly correction factors

To compare the concentration of pollutants in different years, the yearly correction factor was proposed to attenuate the influence of different years on pollutant concentration. The influence of different years mainly includes policy intervention and climatic change. For instance, in China, multiple policies targeting reducing the concentration of pollutants were published and strictly executed. It means that the government strictly

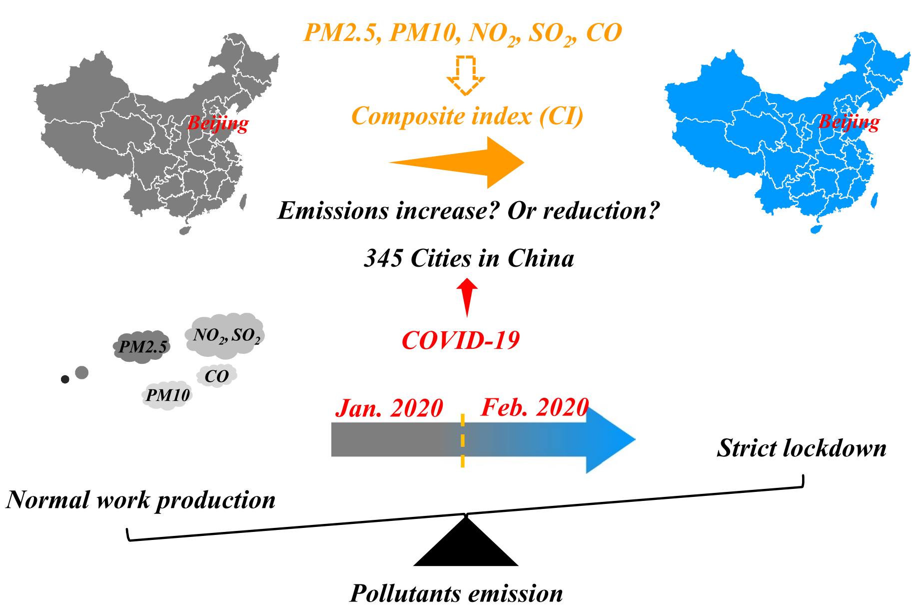

Fig. 1 Graphical abstract of the assessment of air pollution reduction during the COVID-19 lockdown

controlled the concentration of pollutants emitted by factories and vehicles. It was followed that the emission concentration of pollutants decreased year by year. Hence, it is necessary to correct the yearly concentration of pollutants when making a comparison in different years. In this study, the yearly correction factor can be given as Eq. (1).

$$\alpha_x = \left(\frac{AVG_{y1}}{AVG_{y2}}\right)x \tag{1}$$

Where α is the yearly correction factor, x are different pollutants, such as NO_2, SO_2, $PM_{2.5}$; AVG_{y1} is the average concentration of the pollutant x in year 1; AVG_{y2} is the average concentration of the pollutant x in year 2. Therefore, the yearly correction between the year 2019 and the year 2020 can be expressed as Eq. (2).

$$\alpha_x = \left(\frac{AVG_{2020}}{AVG_{2019}}\right)x \tag{2}$$

Where x can be NO_2, SO_2, CO, $PM_{2.5}$, or $PM_{10.}$

Monthly correction factors

As explained above, the yearly concentration of pollutants needs to be corrected due to the influence of policies. Similarly, the monthly concentration of pollutants should be corrected as well because of the changes in different seasons. For example, there would be more pollutant emissions in the heating season while relatively fewer pollutant emissions in non-heating seasons, because more fossil energy (e.g., coal, oil and natural gas) was used and burned in the heating season and more pollutants were produced due to high-temperature combustion process. Additionally, at the end of a year, it is common that factories will increase production to maximize the annual profit so that more pollutants are emitted, which might cause an increase in pollutant concentration at the end of a year. Thus, the monthly correction factor was proposed to correct the monthly value when making a comparison between different months. The monthly correction formula can be expressed as Eq. (3).

$$\beta_x = \left(\frac{AVG_{m1}}{AVG_{m2}}\right)x \tag{3}$$

Where β is the yearly correction factor, x are different pollutants, such as NO_2, SO_2, $PM_{2.5}$; AVG_{m1} is the average concentration of the pollutant x in month 1; AVG_{m1} is the average concentration of the pollutant x in month 2. For example, the yearly correction between February and October can be expressed as Eq. (4).

$$\beta_x = \left(\frac{AVG_{Feb}}{AVG_{Oct}}\right)x \tag{4}$$

Where x can be NO_2, SO_2, CO, $PM_{2.5}$, and $PM_{10.}$

Quantitative comparative analysis during COVID-19 lockdown

Quantitative analysis is to express some non-specific and fuzzy factors with specific data, to achieve the purpose of analysis and comparison. It is necessary to quantify the comparison of pollutant concentrations in different years or months because quantitative data could make the results clearer and more convenient for comparison. In this paper, a quantitative comparison between the same months in different years was conducted by adopting the yearly correction factor. The specific calculation equation is shown as Eq. (5).

$$D_x = AVG_{2020\mathrm{m}} - \alpha_x \times AVG_{2019\mathrm{m}} \tag{5}$$

Where D_x is the concentration difference of pollutant x between 2020 and 2019;$AVG_{2020\mathrm{m}}$ and $AVG_{2019\mathrm{m}}$ are the average concentration of a certain month in 2020 and 2019; α_x is a yearly correction method.

Sensitivity analysis on pollutants change due to lockdown

In this study, a sensitivity analysis method was adopted to further assess the change degree of pollutants related to a strict lockdown in a certain city. Sensitivity analysis is a kind of uncertain analysis technology to study the influence of some changes of relevant factors on a certain or a group of key indicators from the perspective of quantitative analysis. In this study, the sensitivity analysis method was adopted to explore the variation scale of pollutant concentration during the period of strict lockdown in comparison with the period of work resumption. The sensitivity index of different pollutants in a certain city is calculated as Eq. (6).

$$SI_x = \left| \frac{(\alpha_x \times AVG_{2019(2-3)} - AVG_{2020(2-3)})}{\alpha_x \times AVG_{2019(2-3)}} \right|_x \tag{6}$$

Where x can be NO_2, SO_2, CO, $PM_{2.5}$, and $PM_{10.}$

Definition of the composite index related to pollutants

In this section, a ratio was used to quantify the comparison of pollutant concentration in different years or months. The ratio of different pollutants was defined as Eq. (7).

$$R_x = \left(\frac{AVG_1}{\alpha_x(\beta_x) \times AVG_2} \right)_x \tag{7}$$

Where, R_x is the concentration ratio of pollutant x in different years or months; AVG_1 is the average concentration of year 1 or month 1; AVG_1 is the average concentration of year 2 or month 2; $\alpha_x(\beta_x)$ is the yearly correction factor (monthly correction factor).

A composite index (***CI***) was proposed to comprehensively and objectively evaluate the change in pollutant concentration. The composite index consists of the weighted sum of several kinds of pollutant concentration. As previously mentioned, this paper mainly discussed five kinds of pollutants. Therefore, to measure the change in pollutant concentration comprehensively, the composite index was composed of the sum of the product of uniform weight and the concentration of the five pollutants (NO_2, SO_2, CO, $PM_{2.5}$, and PM_{10}), the reason of which was that uniform weight can avoid the prominent influence of a certain pollutant. As a result, ***CI*** can be defined as Eq. (8).

$$CI = 0.2 \times (R_{NO_2} + R_{SO_2} + R_{PM_{2.5}} + R_{PM_{10}} + R_{CO}) \tag{8}$$

Where R_{NO_2}, R_{SO_2}, $R_{PM_{2.5}}$, $R_{PM_{10}}$ and R_{CO} are the concentration ratio of NO_2, SO_2, $PM_{2.5}$, PM_{10} and CO in different years or months, respectively.

Data processing and the temporal and spatial range of the assessment

Source and temporal range of pollutant data

The data used in the paper was selected from a public air data website issued by the Ministry of Ecology and Environment of the People's Republic of China (M.o.E.a.E.o.t.P.s.R.o. China 2021). For a comparison between the strict lockdown and resumption period, the pollutant data in 2019 and 2020 were collected. As known, 2020 is the COVID-19 pandemic year, and 2019 is a year without the pandemic that is continuous with 2020. The selection of the data in these continuous two years has better comparability and could avoid the impact of long-time span.

Representative pollutants and cities

Concerning the types of pollutants, NO_2, SO_2, CO, $PM_{2.5}$ and PM_{10} were selected as case studies in this study. The effects of NO_2 and SO_2 are various, involving the generation of acid rain, ecological environment destruction, human health damage and climate deterioration, one of which is extremely harmful to the earth. Man-made NO_2 mainly comes from the release of high-temperature combustion processes, such as vehicle exhaust, boiler exhaust emissions, etc. SO_2 is mainly produced in many industrial processes and exhaust of motor vehicles.

The pollution of CO is mainly reflected in the harm to people. CO is a kind of pollutant with strong toxicity to the blood and nervous system. Man-made CO comes from a wide range of sources. The incomplete combustion of carbonaceous compounds will produce carbon monoxide. The main sources of CO in the atmosphere are industrial and mining enterprises, transportation, household stoves, heating boilers, fireworks, charcoal combustion, etc.

$PM_{2.5}$ has always been a topic of concern. The main sources of $PM_{2.5}$ are the residues from combustion in the process of daily power generation, industrial production and automobile exhaust emission, most of which contain toxic substances such as heavy metals. $PM_{2.5}$ will enter the alveoli through the respiratory tract and deposit in the lungs, causing a series of lesions, especially for children and the elderly. PM_{10} comes from direct emissions from pollution sources, such as chimneys and vehicles, which are also a main contributor to lung-related diseases.

Two typical cities, Beijing and Wuhan, were selected. Beijing is the capital of China. Wuhan, as the first city to find the COVID-19 pandemic, is also extremely representative of the COVID-19 lockdown.

Results and discussion

The first section mainly discusses and analyzes the change in pollutant concentration in these two cities during the strict lockdown. The sensitivity analysis method was adopted to investigate the response degree of different pollutants in a certain city. In last section, the spatial distribution of pollutant changes was studied and discussed covering 345 prefecture-level cities.

Quantitative analysis of different polluted gases in four cities

The variation of NO_2 during COVID-19

Figure 2 shows a comparison of NO_2 concentration with time between 2019 and 2020 in Beijing (a) and Wuhan (b). The blue area represented the sum of NO_2 concentration in 2020, while the grey area represented the sum of NO_2 concentration in 2019. In both Beijing and Wuhan, there was an obvious area difference between the blue area and the grey area during the strict lockdown. It means a significant concentration difference of NO_2 between 2019 and 2020 during the strict lockdown. This is because motor vehicles were banned and factories stopped production during the strict lockdown, which was the main contributor to the production of NO_2. Therefore, the concentration of NO_2 in 2020 was reduced during the strict lockdown compared with that in 2019 when all vehicles and factories ran normally.

To further quantify the concentration difference between 2019 and 2020, the yearly correction factor was used to eliminate the influence of policies (there are strict policies to control the emission of pollutants every year in China). According to Eq. (5), when the corrected concentration difference between 2020 and 2019 was greater than 0 ($(AVG_{2020\mathrm{m}} - \alpha_x \times AVG_{2019\mathrm{m}}) > 0$), the concentration of pollutants in 2020 increased in comparison to 2019. The corrected concentration difference between 2020 and 2019 was less than 0 ($(AVG_{2020\mathrm{m}} - \alpha_x \times AVG_{2019\mathrm{m}}) < 0$). It indicates that the concentration of pollutants in 2020 was reduced in comparison to 2019. In general, if there was no COVID-19 pandemic, the corrected difference would fluctuate around zero throughout the year.

The quantitative comparison results of the same month in different years were shown in Fig. 3. As seen, in both Beijing and Wuhan, the NO_2 concentration difference between 2020 and 2019 was less than 0 ug/m^3 during the strict lockdown. It means that the NO_2 concentration in 2020 decreased compared with 2019. Additionally, it can be observed that the NO_2 concentration difference between 2020 and 2019 fell at different levels from January to May, whereas the concentration difference of NO_2 fluctuated between greater

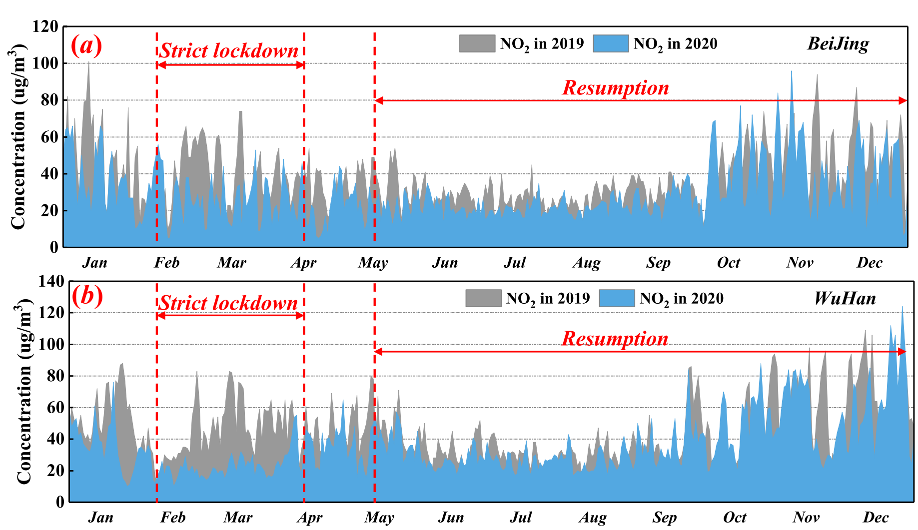

Fig. 2 Comparison of NO_2 concentration with time between 2019 and 2020

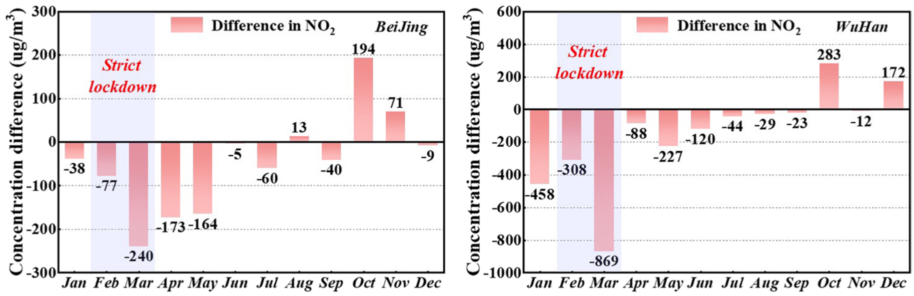

Fig. 3 Quantitative comparison of NO_2 concentration in different months between 2019 and 2020

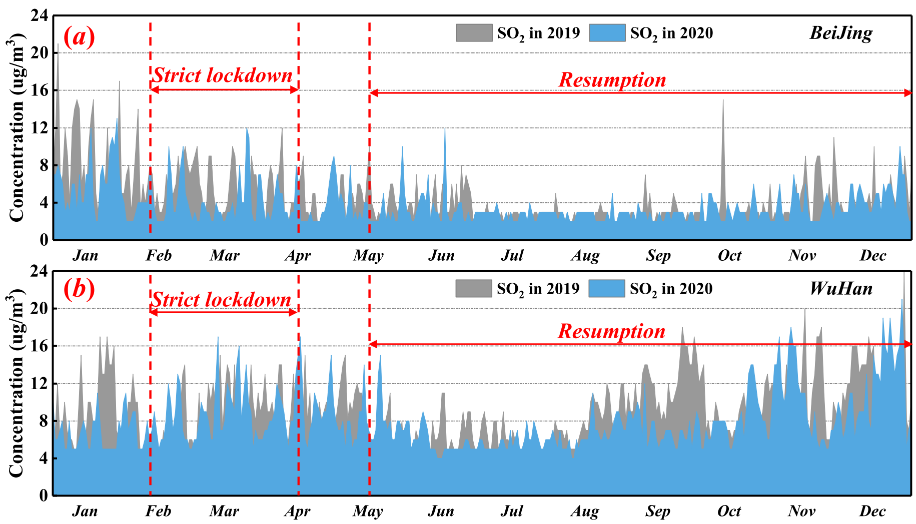

Fig. 4 General comparison of SO_2 concentration with time between 2019 and 2020

than 0 ug/m^3 and less than 0 ug/m^3 after May. The reason was that February and March were strict lockdowns when private cars were banned and factories stopped production. Therefore, there is a maximum reduction of NO_2 concentration. April and May were the transition period that was a gradual recovery process but also affected by the lockdown, so the concentration of NO_2 also decreased to a certain extent. After May, work and production resumed so that NO_2 concentration fluctuated around 0 ug/m^3.

The variation of SO_2 during COVID-19

Figure 4 shows a comparison of SO_2 concentration with time between 2019 and 2020 in Beijing (a) and Wuhan (b). The blue area represented the sum of SO_2 concentration in 2020, while the grey area represented the sum of SO_2 concentration in 2019. It seems like there was not a significant difference in SO_2 concentration from the area map. In Beijing, the grey area was a bit more than the blue area during the strict lockdown., whereas Wuhan saw almost the same blue and grey areas in Fig. 4(b).

Figure 5 shows the quantitative comparison results of the same month in different years. The change of SO_2 concentration difference between 2020 and 2019 in Beijing had the same changing trend with NO_2, that is, a clear concentration reduction during the strict lockdown, a gradual decreasing concentration reduction during the

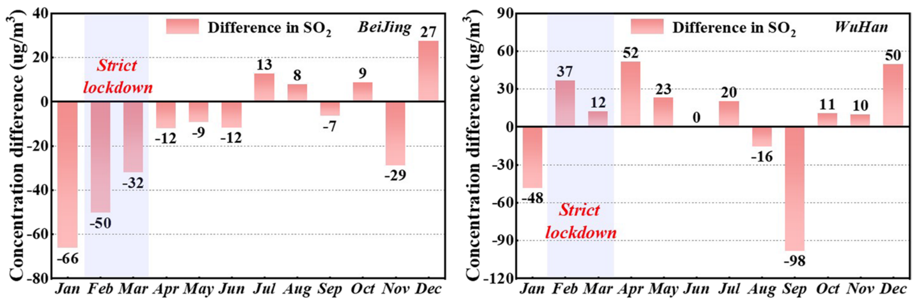

Fig. 5 Quantitative comparison of SO_2 concentration in different months between 2019 and 2020

transition period and a fluctuation around 0 ug/m^3 during resumption period. However, it was worth noting that the reduction of concentration was small compared with NO_2 although the SO_2 concentration difference between 2020 and 2019 was less than 0 ug/m^3. In Wuhan, the concentration difference of SO_2 between 2020 and 2019 had a fluctuation of around 0 ug/m^3 throughout the year. It means that there was no obvious change in the SO_2 concentration difference between 2020 and 2019. The small concentration difference in Beijing and Wuhan can be could be attributed to the following reason. Due to years of national treatment of SO_2 in China, such as the implementation of the policy of limiting SO_2 emission, the concentration of SO_2 remained at a low level in recent years. It can be observed from Fig. 4, the emission of SO_2 was small during the non-pandemic period (2019), fluctuating around 10 ug/m^3. Desulfurization devices were installed on vehicles and factories as required in recent years, resulting in the contribution from factories and vehicles to SO_2 emission decreasing largely. Therefore, although during the COVID-19 pandemic period, vehicle and factory emissions were limited, there was no significant impact on SO_2 concentration. The results could also reflect that the result of SO_2 treatment was better than that of NO_2 treatment in recent years.

The variation of CO during COVID-19

Figure 6 shows a comparison of SO_2 concentration with time between 2019 and 2020 in Beijing (a) and Wuhan (b). The blue area represented the sum of CO concentration in 2020, whereas the grey area represented the sum of CO concentration in 2019. It was difficult to find an apparent change in CO concentration during the strict period.

Figure 7 shows the quantitative comparison results of the same month in different years. Clearly, throughout the year, the concentration difference of CO between 2020 and 2019 fluctuated around 0 mg/m^3 without an obvious change during the strict lockdown or resumption period. The results illustrate that strict lockdown had little effect on the change in CO concentration.

The main reason for such results was the sources of CO production, and the essence of CO production was from the incomplete combustion of carbonaceous compounds. The combustion of carbonaceous compounds can be seen everywhere in life, like boiler plants, heating plants, and automobile internal combustion engines, all accompanied by inadequate combustion. It should be noted that the unit of pollutant CO is mg/m^3 rather than ug/m^3, also indicating that CO has a wider source than SO_2 and NO_2. Therefore, it was difficult to detect the change in CO concentration caused by the COVID-19

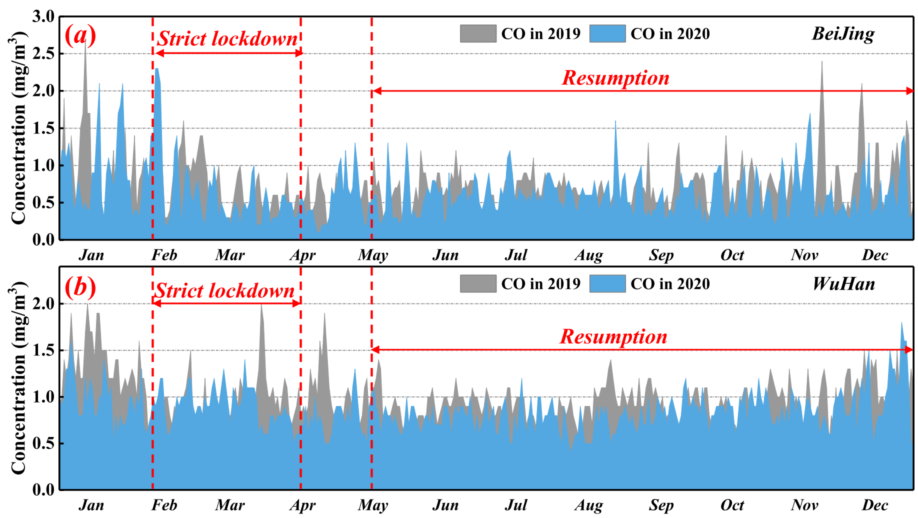

Fig. 6 General comparison of CO concentration with time between 2019 and 2020

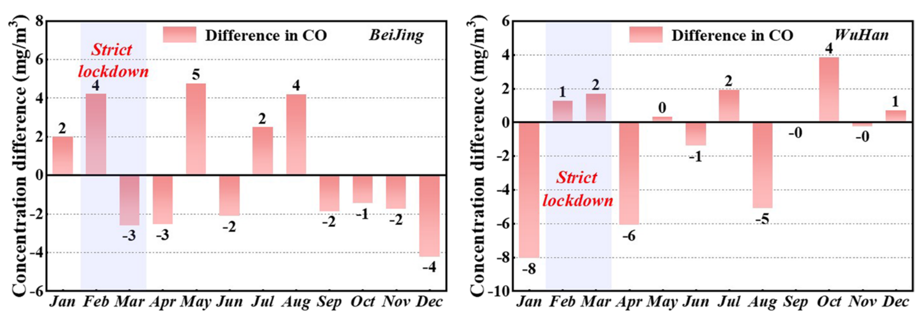

Fig. 7 Quantitative comparison of CO concentration in different months between 2019 and 2020

pandemic under a larger order of magnitude (mg/m^3). Taking Beijing as an example, during the strict lockdown (February), it was also the heating season when many carbonaceous compounds were combusted to heat the whole city. When such a plant dominated the emission of CO and made a great contribution to the unit level (mg/m^3), the change of CO concentration (might be ug/m^3) caused by the lockdown would be negligible. It was followed that the concentration difference of CO between 2020 and 2019 in Beijing fluctuated around 0 mg/m^3 throughout the year.

The variation of PM2.5 during COVID-19

Figure 8 shows a comparison of $PM_{2.5}$ concentration with time between 2019 and 2020 in Beijing (a) and Wuhan (b). There was a certain area difference between 2020 and 2019 (the blue area represented the sum of $PM_{2.5}$ concentration in 2020, while the grey area represented the sum of $PM_{2.5}$ concentration in 2019). Figure 9 shows the quantitative results of the $PM_{2.5}$ concentration difference between 2020 and 2019.

In Wuhan, there was a reduction in $PM_{2.5}$ concentration difference between 2020 and 2019 during the strict lockdown, similar to the change of NO_2. However, in Beijing, although there was a significant decline in the $PM_{2.5}$ concentration difference between

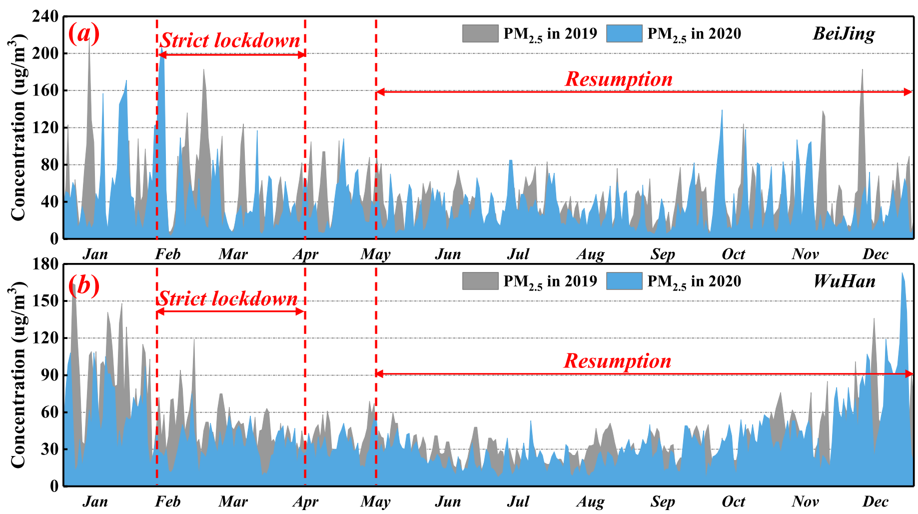

Fig. 8 General comparison of $PM_{2.5}$ concentration with time between 2019 and 2020

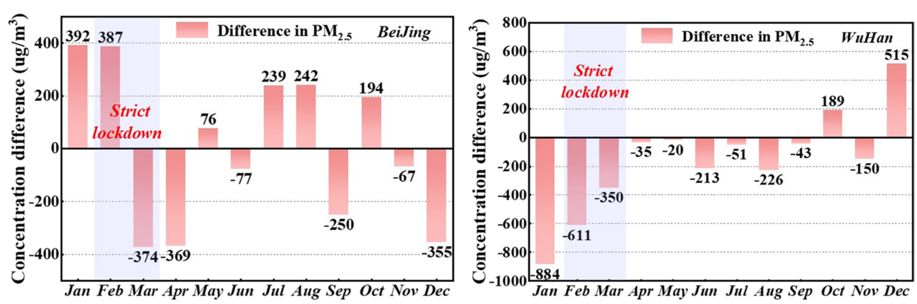

Fig. 9 Quantitative comparison of $PM_{2.5}$ concentration in different months between 2019 and 2020

2020 and 2019 in March, February saw an increase in the $PM_{2.5}$ concentration difference between 2020 and 2019. The main sources of $PM_{2.5}$ are the residues from combustion in the process of power generation, industrial production and automobile exhaust emission. Therefore, it was inferred that the decline in February could attribute to the fact that Beijing was still in the heating season in February. In March and April without heating, there was a significant decrease in the $PM_{2.5}$ concentration difference between 2020 and 2019.

The variation of PM10 during COVID-19

Figure 10 shows a comparison of PM_{10} concentration with between 2019 and 2020 in Beijing and Wuhan. The blue area represented the sum of PM_{10} concentration in 2020, while the grey area represented the sum of PM_{10} concentration in 2019. The area difference was the representative of concentration difference. Throughout the year, the blue area was less than the grey area. It means the gradual decrease of PM_{10} concentration due to the lockdown.

Figure 11 shows the quantitative comparison results of the same month in different years. When the concentration difference was less than 0, the concentration of PM10 in 2020 dropped in comparison to 2019, and vice versa. The reduction of PM_{10} reached

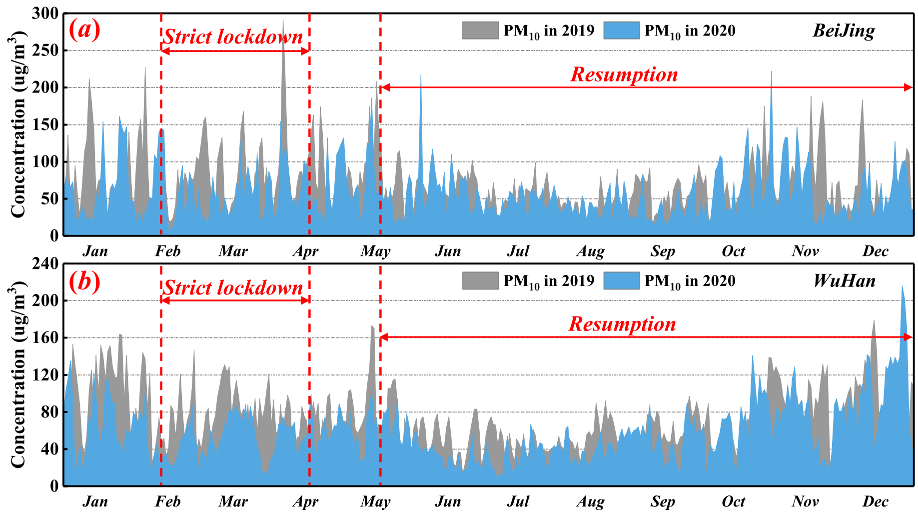

Fig. 10 General comparison of PM_{10} concentration with time between 2019 and 2020

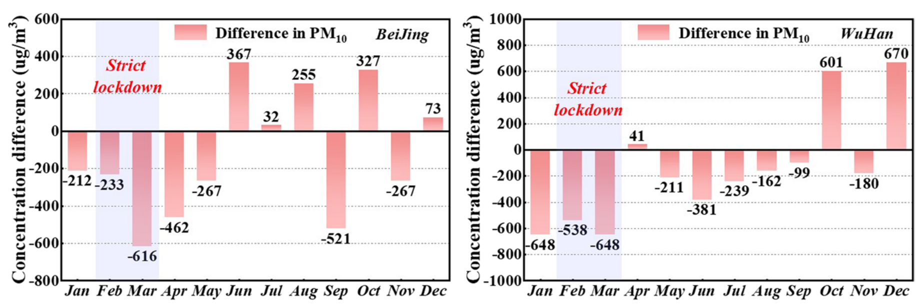

Fig. 11 Quantitative comparison of PM_{10} concentration in different months between 2019 and 2020

the maximum during the period of strict lockdown in both cities. Beijing saw a maximum reduction of 616 mg/m^3 and Wuhan saw a maximum reduction of 648 mg/m^3 both in March. In the following months, the reduction gradually decreased and fluctuated around 0 mg/m^3 in the second half of the year. By and large, the strict lockdown had a certain contribution to the reduction of PM_{10} concentration.

Sensitivity analysis

Figure 12 shows the response degree of five types of pollutants to Beijing and Wuhan. Sensitivity indexes were calculated according to Eq. (6) and the results were shown in the following radar map. In general, the two cities had different sensitivity indexes regarding various pollutants. CO was the least sensitive pollutant, with a CO sensitivity index of 0.042 in Beijing and 0.056 in Wuhan. This was mainly caused by a wide range of sources of CO emissions and the value unit of CO (mg/m^3). During the strict lockdown, the change in CO concentration caused by the decrease in traffic flow and the shutdown of some factories was negligible under the value unit of mg/m^3.

SO_2 was relatively sensitive to the strict lockdown with the same SO_2 sensitivity index in both cities (0.258). In Beijing, SO_2 ranked first in the sensitivity index of pollutants, while SO_2 in Wuhan took third place. NO_2 had a great response to the strict lockdown

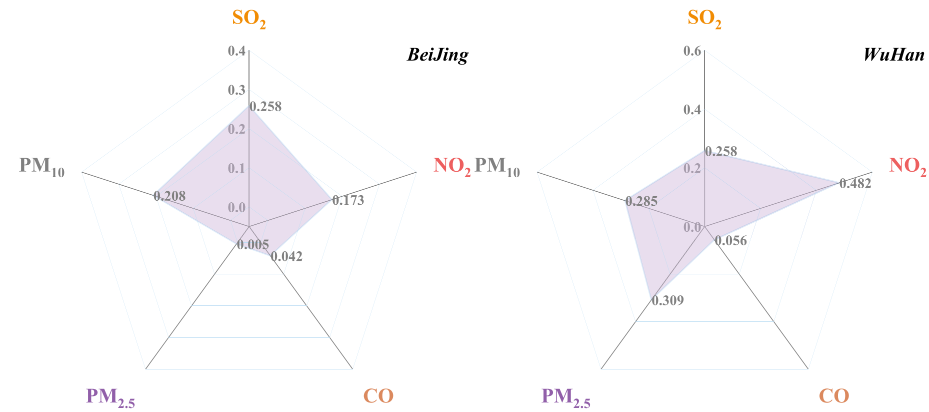

Fig. 12 Sensitivity index of different pollutants to lockdown in Beijing and Wuhan

during the COVID-19 pandemic with the NO_2 sensitivity index of 0.173 in Beijing and 0.487 ranking first in Wuhan. A large part of NO_2 and SO_2 emissions came from factories and vehicles so SO_2 and NO_2 both were relatively sensitive to the pollutants for the strict lockdown.

According to common sense, $PM_{2.5}$ and PM_{10} should have similar response degrees to strict lockdown, or both more sensitive or less sensitive. However, such results only occurred in Wuhan, with $PM_{2.5}$ and PM_{10} sensitivity indexes of 0.309 and 0.285, respectively, showing extremely similar sensitivity. In Beijing, PM_{10} had a good sensitivity index to a strict lockdown with a value of 0.208, whereas the sensitivity index of $PM_{2.5}$ to Beijing was only 0.005. This large contrast can be attributed to two factors. First, the Beijing government has been very strict in the governance of $PM_{2.5}$ in recent years so the emission of $PM_{2.5}$ has dropped below the specified level. As a result, the strict lockdown had little effect on the concentration of $PM_{2.5}$. Second, the composition of $PM_{2.5}$ was complex and the sources of $PM_{2.5}$ were extensive. Moreover, the composition of $PM_{2.5}$ in each city was also different. According to relevant literature (Chen et al. 2020; Xue et al. 2000), the composition of $PM_{2.5}$ in Beijing is various, including dust, inorganic salts, coal burning, exhaust emissions from diesel and gasoline, crops and even smoking. Perhaps in Beijing, emissions from factories and vehicles accounted for only a small share.

Discussion of city-level pollutant changes due to the pandemic lockdown

Spatial distribution of pollutant changes between 2019 and 2020

Figure 13 shows a spatial distribution map of composite indices of pollutant concentration change between 2019 and 2020, covering 341 cities prefecture-level cities and 4 municipalities directly under the central government. When the ***CI*** of a city is less than 1, the map of this city is marked with a blue series color. It means the pollutant emission in 2020 decreased compared with that 2019. When the ***CI*** is greater than 1, the map is marked with a red series color, indicating that the pollutant emissions in 2020 rose compared with that in 2019. As seen, the whole picture is full of blue fill. It indicates that the pollutant emissions of almost all cities in China substantially decreased during the strict lockdown. The results show that pollutant emissions of over 90% of cities (321 cities) were reduced during the strict lockdown (as shown in Fig. 14). During the strict lockdown, only a few cities were marked with red series colour. Even so, the CI of these cities

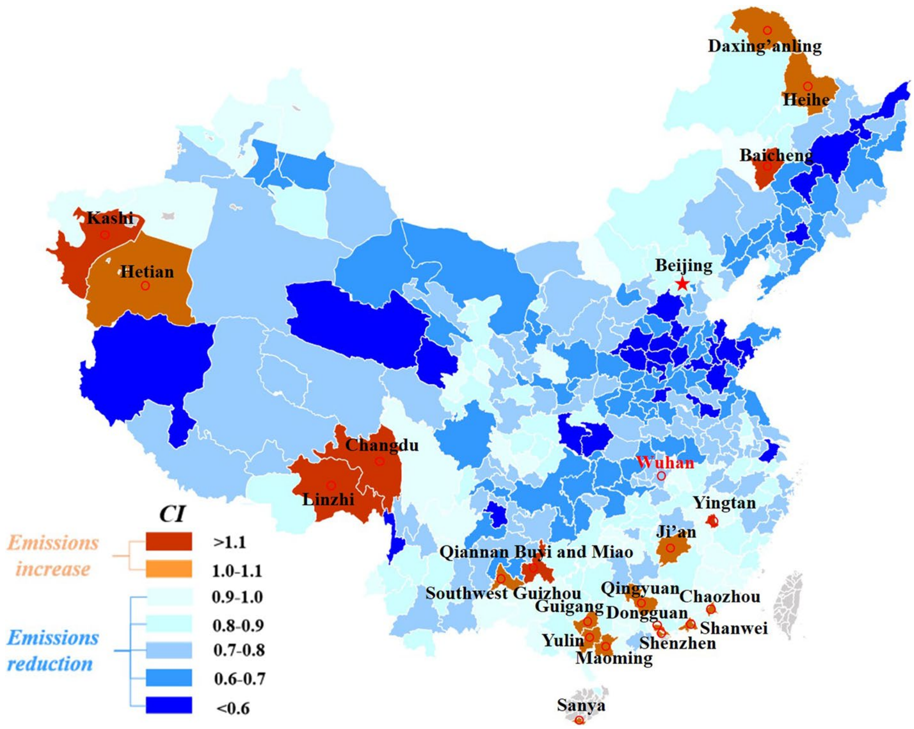

Fig. 13 Spatial distribution map of composite indices of pollutant concentration change between 2019 and 2020

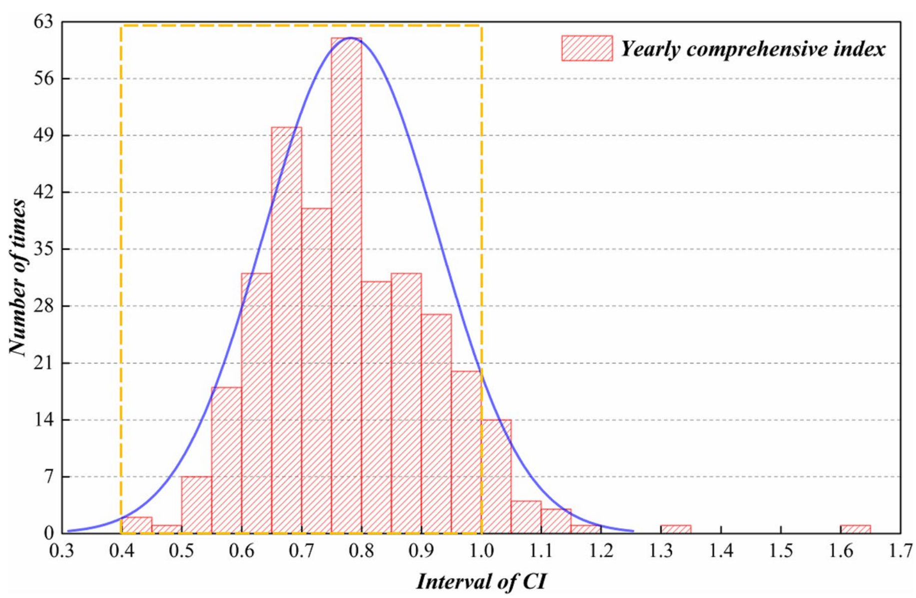

Fig. 14 City-level composite index interval distribution during the strict lockdown

rarely exceeds 1.2. In general, the strict lockdown have resulted in pollutant emissions reduction largely and air quality improvement.

The regions with CI less than 0.7 are mainly distributed in North China Plain (including Hebei Province, Shandong Province, Henan Province and Shanxi Province), three provinces in the northeast of China (including Heilongjiang Province, Jilin Province and Liaoning Province) and central China (including Chongqing and Hubei province). According to the "*Report on remote sensing monitoring of China sustainable development*" published by the Chinese Academy of Sciences in 2016 (C.A.o. Sciences 2017), air-polluted areas in China were concentrated in North China Plain and central China (as shown in Fig. 15). In other words, before the strict lockdown, these regions marked with red color in Fig. 15 have high concentrations of pollutants (Li et al. 2020). In addition, due to the floating population during the Spring Festival, Hubei Province, Henan Province, Shandong Province and Hebei Province (Jiang et al. 2017), as vital export provinces to Wuhan, published more strict home isolation policies. Human activities, including working in factories and travelling using private cars, were further limited due to government controls, and pollutant emissions were reduced. It was observed that the ***CI*** of these regions significantly decreased when compared with that before the strict lockdown. Meanwhile, slight pollutant emissions increase or emissions reduction occurred in other regions, due to insensitive or low pollutants concentration before COVID-19 in these regions.

Spatial distribution of pollutant changes in typical months

In Figs. 16 and 17, cities with CI greater than 1 are marked with red colors. Pollutant emissions in these cities increased compared with that before the strict lockdown. While cities with CI greater than 1 are marked with green colors. Pollutant emissions fall

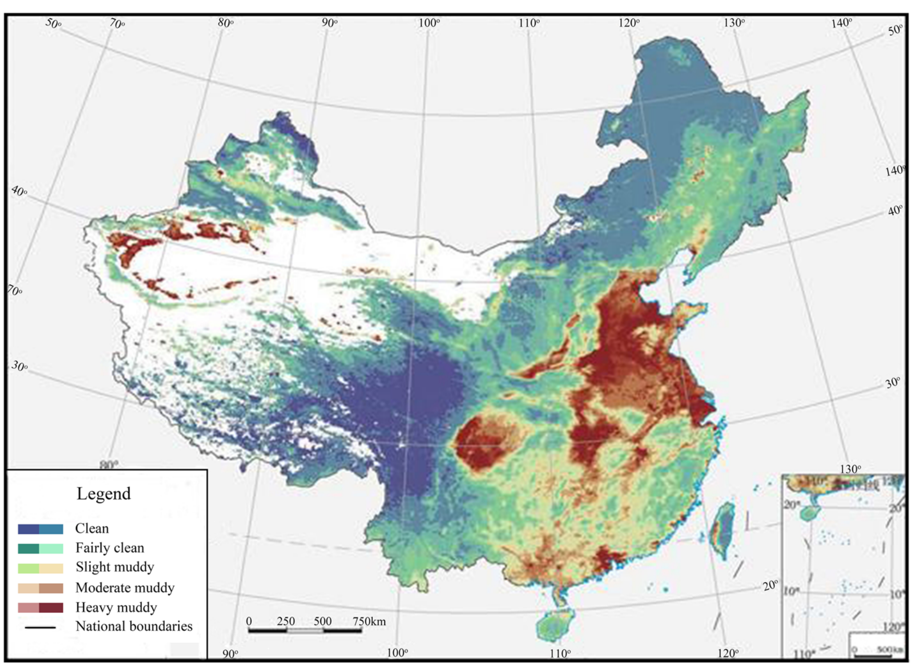

Fig. 15 2010–2015 air quality map in China

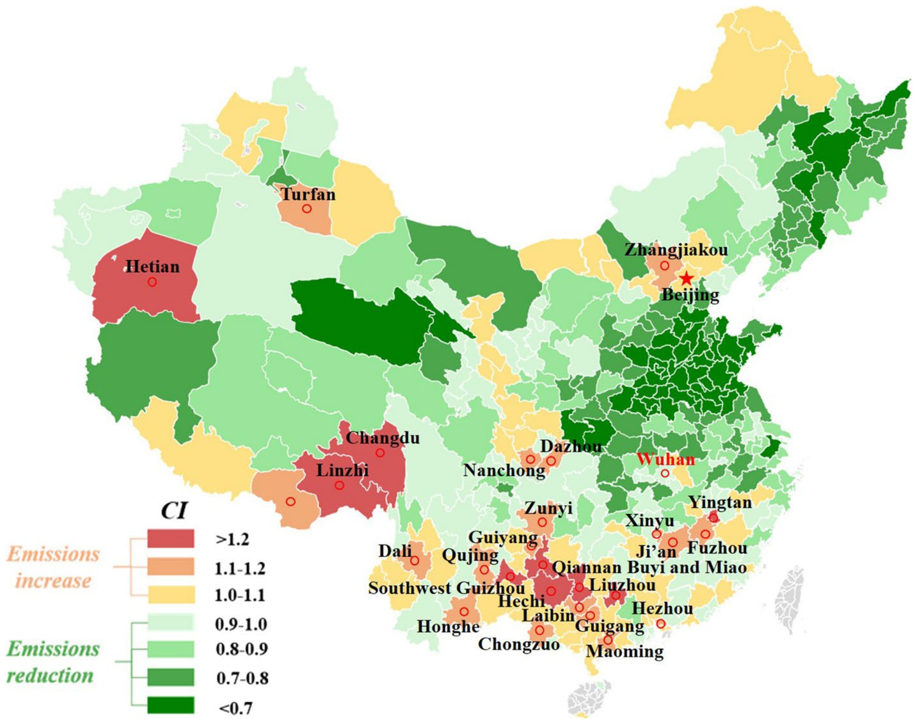

Fig. 16 Spatial distribution map of composite indices of pollutant concentration in February 2020

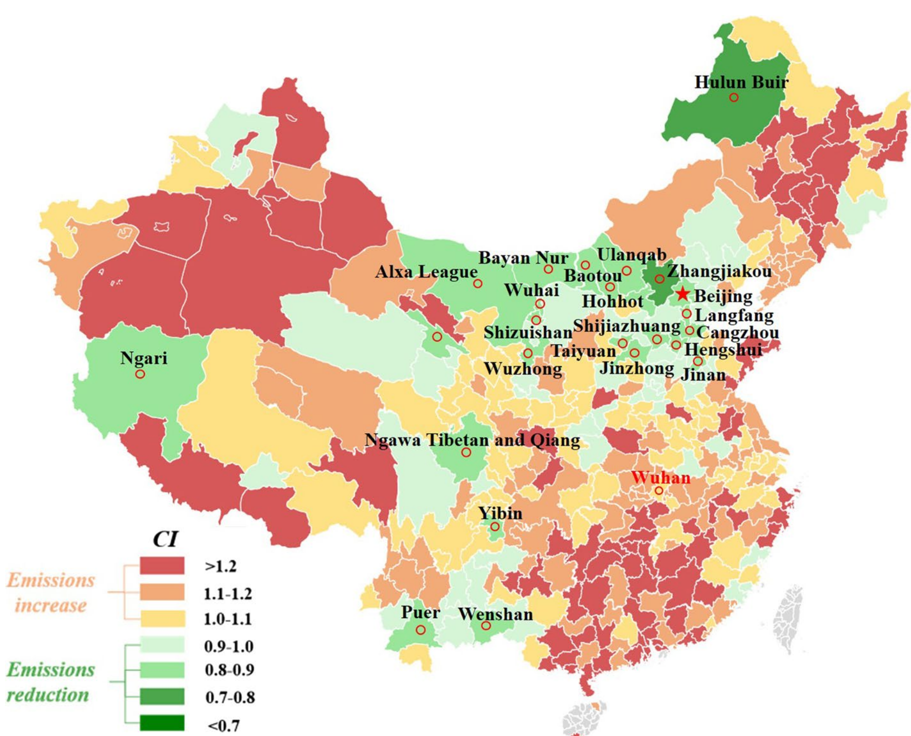

Fig. 17 Spatial distribution map of composite indices of pollutant concentration in April 2020

compared with that before the strict lockdown. In January and February 2020, all cities executed strict control measures to cut off the spread of COVID-19. Thus, most cities were drawn with green colors, and these cities are mainly distributed in Northeast China Region, North China Plain, central China and the Northwest region. Owing to higher pollutants concentration in these cities before 2020, the concentration reduction caused by the strict lockdown was obvious. On the contrary, the regions with an increase in emissions were located in the southwest region of China. This may be contributed to surrounding countries without strict control policy, and part of the pollutants in these countries was carried by wind to the southwest region of China. In addition, the effect of a traditional festival, the spring festival, on pollutant emissions could not be ignored. Some necessary activities during the spring festival, such as visiting relatives and friends, firecrackers and gun salutes for celebrations, may also contribute to pollutant emissions. Far away from Wuhan, these cities did not issue strict restrictive measures, and pollutants emissions in these cities slightly increased.

After a strict control policy for preventing the spread of COVID-19, the number of new cases in the whole of China decreased from 15,152 on February 12 to around 20 in March. Owing to depressed national economic development during the strict lockdown, some provinces that were slightly affected started gradual restoration of economic development in April, including shop opening, factory running, the flight/car increasing and school opening. Economic behavior was bound to increase human activities, leading to rising pollutant emissions. Data from the National Bureau of Statistics indicates that year-on-year growth of gross industrial production in April increased by around 3%, while that in February and March decreased by about 1% (N.B.o. Statistics, Monthly national economic statistics 2021). Industrial production gave rise to an increase in pollutant emissions, and 272 cities in April have been proven as cities with increasing emissions (shown in Fig. 17).

Among all cities, cities in south China were almost filled with red colors due to improved COVID-19 conditions with open industrial production and transportation. While Beijing-Tianjin-Hebei Region, as a key national political-economic zone, realized a reduction of pollutant emissions because of strong government control of human activities.

Figure 18 shows the composite indices of 345 cities in different months. The ***CI*** of 345 cities fell from 0.98 (January) to 0.89 (February), and then increase from 0.92 (March) to 1.1 (April). The strict lockdown minimized human activities and lowered energy production-utilization to reduce pollutant emissions. With the economic recovery of most cities in China, emissions from industry and transportation gradually increased and then remained stable. This change rule of mean ***CI*** agreed with the law of industrial production and gross domestic product (GDP). From another view, the mean CI of 345 cities also indicated the improvement of COVID-19 in China.

Conclusions and policy implications

The COVID-19 pandemic has immensely impacted the economic, social, and environmental pillars of sustainability in human lives. This paper aims to provide an inclusive insight into the sustainability perspectives, dynamics, and practices in the wake of the COVID-19 pandemic crisis. This study investigated a city-level quantitative and

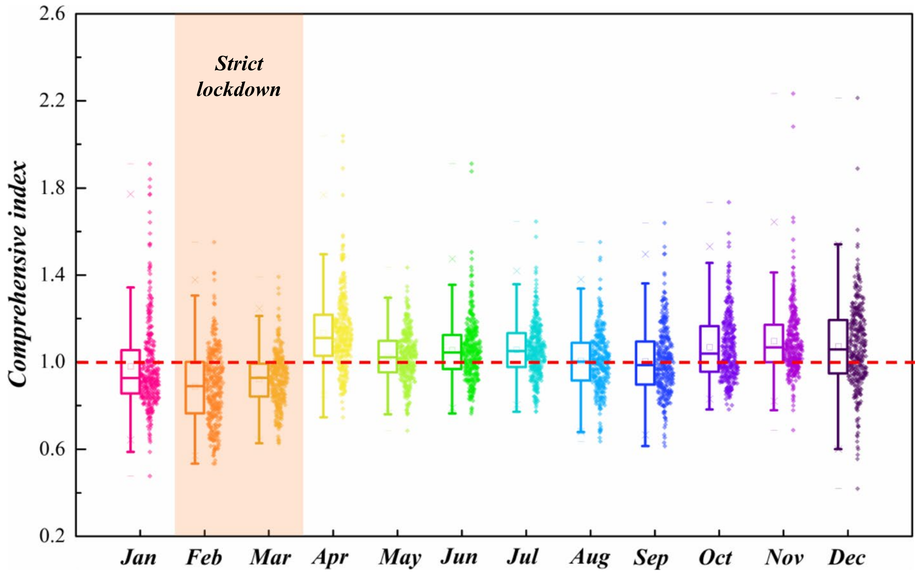

Fig. 18 Composite index of 345 cities in different months in 2020

comparative analysis to quantify the impact of lockdown on air pollution in China during the lockdown. In this study, a city-level comparative study was investigated to quantify the impact of lockdown on air pollution in China. The concentration changes of air pollutants (NO2, SO2, CO, PM2.5, PM10) caused by the lockdown are studied covering 345 cities in China. The spatial distribution of pollutant changes between 2019 and 2020 and typical months are discussed using a composite index.

NO_2 and SO_2 had obvious reductions during the strict lockdown, ranging from 15–30% in Beijing and Wuhan. CO did not show an apparent change due to the contributors to CO were various and traffic volume and some factories might account for a small share. PM_{10} also has a significant reduction in both cities, approximately 20–30%. In addition, pollutant emissions of 321 cities in February and March 2020 fell markedly and composite indices showed that 272 cities had a rebound of pollutant emissions after April 2020 when work and production resumed. The limitation of this study is the lack of a detailed analysis of the changes in air pollutants in the post-pandemic era. The COVID-19 pandemic has immensely impacted the economic, social, and environmental pillars of sustainability in human lives. After resumption, it is necessary to realize the significance of an accelerated transition in favour of renewables for alleviating the pandemic's negative impacts on the sustainable development of cities. Furthermore, this study shows the importance of having resilient and adaptable urban systems in city production and environmental protection. Especially for the cities that were better prepared to deal with the pandemic were those that had invested in infrastructure and services that were flexible and could quickly adapt to changing circumstances.

Abbreviations

COVID-19	Coronavirus disease 2019
NO_2	Nitrogen Dioxide
SO_2	Sulfur dioxide
CO	Carbon monoxide
$PM_{2.5}$	Particulate Matter 2.5

PM_{10}	Particulate Matter 10
CI	Composite index
SI	Sensitivity index
α	Yearly correction factor
β	Monthly correction factor
D	The concentration difference of pollutant
R	The concentration ratio of pollutant
AVG	The average concentration of the pollutant
x	Pollutants (NO_2, SO_2, CO, $PM_{2.5}$, and PM_{10})

Acknowledgements
The authors acknowledge the support from Ministry of Ecology and Environment of the People's Republic of China for their help in the collection of environmental data processing.

Compliance with ethical standards
The authors have no relevant financial or non-financial interests to disclose.
The authors have no competing interests to declare that are relevant to the content of this article.
All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.
The authors have no financial or proprietary interests in any material discussed in this article.

Authors' contributions
Yingbo Zhang: Writing - original draft, Investigation, Revision. Chunxiao Zhang: Data reduction and Supervision. Zhengguang Liu: Date collection and Supervision. Xiaohu Yang: Investigation.

Availability data and materials
The data that support the findings of this study are available from Ministry of Ecology and Environment of the People's Republic of China, but restrictions apply to the availability of these data, which were used under license for the current study and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of Ministry of Ecology and Environment of the People's Republic of China. The data in the study can be obtained by contacting the corresponding author.

Declarations

Competing interests
The authors declared that they have no conflicts of interest in this work.

Received: 12 April 2023 Accepted: 4 July 2023
Published online: 28 August 2023

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