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Characteristics of air quality in different climatic zones of China during the COVID-19 lockdown

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ABSTRACT

The diverse climate types and the complex anthropogenic source emissions in China lead to the great regional differences of air pollution mechanisms. The COVID-19 lockdown has given us a precious opportunity to understand the effect of weather conditions and anthropogenic sources on the distribution of air pollutants in different climate zones. In this study, we divided 358 Chinese cities into eight climate regions. Temporal, spatial and diurnal variations of six major air pollutants from January 1 to April 18, 2020 were analyzed. The differences in the characteristics of air pollutants in different climate zones were obvious. PM$_{2.5}$ reduced by 59.0%–64.2% in cold regions (North-East China (NEC) and North-Western (NW)), while O$_3$ surged by 99.0%–99.9% in warm regions (Central South (CS) and Southern Coast (SC)). Diurnal variations of atmospheric pollutants were also more prominent in cold regions. Moreover, PM$_{2.5}$, PM$_{10}$, CO and SO$_2$ showed more prominent reductions (20.5%–64.2%) in heating regions (NEC, NW, NCP and MG) than no-heating regions (0.8%–48%). Climate has less influence on NO$_2$, which dropped by 41.2%–57.1% countrywide during the lockdown. The influences of weather conditions on the atmospheric pollutants in different climate zones were different. The wind speed was not the primary reason for the differences in air pollutants in different climate zones. Temperature, precipitation, and air pollution emissions led to prominent regional differences in air pollutants throughout the eight climates. The effect of temperature on PM, SO$_2$, CO, and NO$_2$ varied obviously with the latitude, at which condition temperature was negatively correlated to PM, SO$_2$, CO and NO$_2$. The rainfall has a strong removal effect on atmospheric pollutants in different climate zones with more precipitation, but it increases the pollutant concentrations in the climate regions with less precipitation. In regions with more emission sources, air pollutants experienced more significant variations and returned to pre-lockdown levels earlier.

1. Introduction

With the strengthening of the convergence effect of resources, population, and education in big cities, the problem of atmospheric pollution in urban areas has become increasingly prominent in recent years (Awasthi et al., 2017; Li et al., 2017; Nielsen et al., 1996; Roorda-Knape et al., 1998; Shi et al., 2020; Xie et al., 2021). Having experienced decades of rapid development, China has seen rapid urbanization, followed by the increasing problem of air pollution (Guo et al., 2014; Han et al., 2016; Xu et al., 2013). A regional severe haze pollution incident broke out in central and eastern China in January 2013. Then China issued the “Air Pollution Prevention and Control Action Plan”, which formulated a

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series of detailed air pollutant emission reduction targets, and since then China has embarked on an arduous task of air pollution prevention and control (Andersson et al., 2015; Feng et al., 2019; Tao et al., 2014; Yang et al., 2015; Zheng et al., 2017). By 2017, China had completed the first phase of the air pollution prevention and control task for PM$_{2.5}$ pollution, and the annual PM$_{2.5}$ concentration in China had decreased significantly from 72.3 ± 37.4 to 47.4 ± 20.6 µg m$^{-3}$ (Wang et al., 2020b). Although PM$_{2.5}$ concentration in China has been continuously declining, O$_3$ concentration has shown a significant increase, and O$_3$ pollution has become increasingly serious (Li et al., 2020a; Lu et al., H. Wang et al., 2015; Zheng et al., 2017). By 2017, China had completed the first phase of the air pollution prevention and control task for PM$_{2.5}$ pollution, and the annual PM$_{2.5}$ concentration in China had decreased significantly from 72.3 ± 37.4 to 47.4 ± 20.6 µg m$^{-3}$ (Wang et al., 2020b). Although PM$_{2.5}$ concentration in China has been continuously declining, O$_3$ concentration has shown a significant increase, and O$_3$ pollution has become increasingly serious (Li et al., 2020a; Lu et al., H. Wang et al., 2015; Zheng et al., 2017).

The concentrations of air pollutants are mainly affected by unfavorable meteorological conditions (external factors) and emissions (internal factors). For a specific region, the emission of pollutants is relatively stable in the short term, so the impact of meteorological conditions on the concentration of air pollutants is relatively important (He et al., 2017; Li et al., 2019b; Shen et al., 2021a; Zhang et al., 2020b). During COVID-19, strict home quarantine measures were implemented nationwide, and anthropogenic emission sources were drastically reduced. However, air pollution still occurred in central and eastern China (Filonchyk and Peterson, 2020a; 2020b; Le et al., 2020; Zhu et al., 2020), indicating the significant impact of meteorological conditions on the formation and dissipation processes of air pollution. Filonchyk and Peterson (2020) found that daily concentrations of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$ and CO in the Yangtze River Delta region during the lockdown period were reduced by 9%, 77%, 31.3%, 60.4%, and 3%, respectively, compared to the same period in 2019. Zhao et al. (2020) found that meteorological variables helped decrease PM$_{2.5}$ and O$_3$ in some cities but helped increase PM$_{2.5}$ and O$_3$ in others, closely related to terrain.

Although there have been studies of improving Chinese air quality that resulted from short-term intervention (Chen et al., 2013; Liu et al., 2017), air quality’s reaction with a long-term and large-scale lockdown could be different. The past short-term air quality control mainly was concentrated in a specific area, and the control of the anthropogenic pollution sources primarily was focused on a few areas, so inter-regional transmission and the influence of local anthropogenic emission sources cannot be ignored (Gao et al., 2017; Ji et al., 2018; Shen et al., 2017). On a global scale, daily confirmed Covid-19 cases increased from discovering the virus until August 2020. Awasthi et al. (2020) found out the trend of COVID-19 cases with temperature, and it is estimated that with an increase in temperature by 1 °C, 30 new COVID-19 cases on daily basis will be expected to observe. In January 2020, the Chinese government adopted the emergency health response plan to inhibit the spread of COVID-19, including closing factories and restricting transportation (Tian et al., 2020; Wang et al., 2020a, 2021a). In addition, during COVID-19, the management and control of anthropogenic emission sources, such as traffic sources, were comprehensive, so it is beneficial for us to explore the impact mechanism of different pollution sources on air pollutants (Chapin and Roy, 2021; Le et al., 2020; Li et al., 2020b; Shen et al., 2021a, 2021b). Due to the sharp reduction of emission sources, major air pollutants like PM$_{2.5}$ and SO$_2$ decreased significantly during the lockdown (Chu et al., 2020b; Li et al., 2020b). However, ozone concentration kept increasing, while the variations of SO$_2$ concentration were not noticeable in warm climate regions (Almond et al., 2020; Li et al., 2020b; Wang et al., 2020c).

China has a vast territory and complex and diverse climate types. There are arid and rainy subtropical monsoon climates. The meteorological conditions in different climate zones are quite different, and their impacts on air pollutants are also different (Kan et al., 2012; Peng et al., 2020; Wang et al., 2021b). It is worth noting that China’s population distribution and economic structure also show apparent differences in different climatic zones (http://www.stats.gov.cn/). For example, the Yangtze River Delta, located in central and eastern China, covers an area of about 3.7% of China, and its total permanent population and total gross domestic product (GDP) account for 16% and 23.5% of the country. By contrast, the Xinjiang Uygur Autonomous Region, located in northwestern China, covers an area of approximately 16.7% of China, but the total permanent population and total GDP only account for 1.8% and 1.38% of the country. The considerable differences in climate, economic structure, and population have determined the significant differences in the characteristics of air pollution in different regions of our country. The lockdown measures implemented during COVID-19 provided us with a previous opportunity to understand the influence mechanism of meteorological conditions and anthropogenic emission sources on the distribution of atmospheric pollutants in different climate zones. There have been a large number of studies discussing changes in air pollutants during COVID-19 (Bao and Zhang, 2020; Chu et al., 2020b; Le et al., 2020b; Le et al., 2020b; Shen et al., 2021a, 2021b), Shen et al. (2021b) found out that the primary pollutants reductions in large cities were larger than those in small-medium cities during lockdown. Wang et al. (2021a) found that PM$_{2.5}$, aerosol chemical compositions, NO$_2$ and CO decreased by 9.9%–64.0% during the Chinese New Year (CNY). Griffith et al. (2020) used the Community Multiscale Air Quality model (CMAQ) simulation with 50% reduced emission in China to simulate PM$_{2.5}$ in Taiwan. Wang et al. (2021c), utilizing the dynamic-chemistry simulations, estimated that emission reduction during the lockdown weakened the aerosol-PBL interaction and thus caused a decrease of 25 µg m$^{-3}$ (~50%) in PM$_{2.5}$ enhancement. However, most of these studies are conducted in a specific area, and there has never been a systematic study of the impact of meteorological conditions and anthropogenic sources on air pollutants in different climatic zones during COVID-19. Since China possesses a large land area with complex changes in topography and geomorphology, regional climate and socio-economic characteristics significantly impact air pollutants concentrations. Although the lockdown brought about considerable emission reduction, meteorological conditions such as static wind and temperature inversion could significantly increase PM$_{2.5}$ (Sharma et al., 2020; Wang et al., 2020c).

Local economic conditions and industrial presence also influence regional air pollutant concentration (Zhang et al., 2007). Furthermore, severe air pollution can increase the risk of COVID-19 infection (Chauhan and Johnston, 2003; Hendryx and Luo, 2020). Hence, there is a need to investigate the role of the climatic and socio-economic factors that affected air quality change during the lockdown. In this study, we utilized the daily observation data of 609 stations from 1971 to 2000 to divide China into 8 climatic zones and combined them with the nationwide air pollution data (PM$_{2.5}$, PM$_{10}$, SO$_2$, CO, NO$_2$, and O$_3$), data of meteorology (temperature, wind speed, and precipitation), GDP and car ownership to analyze the temporal and spatial distribution characteristics of air pollutants in different climate zones and their influencing factors. Moreover, the influence of meteorological elements and anthropogenic sources on air pollutants in different climate zones was analyzed in detail. This study could deepen our understanding of the formation mechanism of atmospheric compound pollution in different climate zones and provide a theoretical basis for formulating precise air pollution control measures in different climate zones.

2. Materials and methods

2.1. Study period and area

China’s newest official climate classification scheme was based on daily observation data of 609 stations from 1971 to 2000 (Zheng et al., 2010). Based on this scheme, we divided China into eight regions (Fig. 1, Table 1): North-East China (NEC) consists of the cold temperate climates and the humid/semi-humid mid-temperate climates, including 31 cities; Inner Mongolia (MG) consists of the semi-arid mid-temperate climate,
including 8 cities; North China Plain (NCP) consists of the semi-humid warm temperate climate, including 91 cities; North-Western (NW) consists of the arid and semi-arid mid-temperate climate, including 30 cities; Yangtze River basin (YR) consists of the humid north subtropical climate, including 60 cities; Central South (CS) mainly consists of the humid mid-subtropical climate, including 73 cities; Southern Coast (SC) consists of the south subtropical climate, including 46 cities; Tibet Plateau (TP) consists of the plateau climate, including 19 cities. The climate classification was then validated by the NOAA meteorological data from January 1 to April 18 (Table 1).

The period from January 1 to April 18, 2020 was divided into four phases: pre-lockdown (Pre-lock), Alert Level 1, Alert Level 2, and Alert Level 3, corresponding to a different level of restriction in the public health emergency plan (Fig. 2). According to the China State Council, industrial activities and transportation were forcibly suspended during Alert Level 1 (Jan 24-Feb 25) because of the dramatic growth of confirmed cases. Some industrial production parts resumed in Alert Level 2 (Feb 26-Mar 31), and traffic began increasing. During Alert Level 3 (Apr 1–18), the spread of COVID-19 in China was well controlled. Most production and living activities were restored to their pre-lockdown status.

Table 1
The average of meteorological and socioeconomic variables in the eight regions.

| Region  | Number of cities | Temperature (°C) | Wind Speed (m s⁻¹) | Precipitation (mm) | GDP (10⁹ CNY) | Private vehicle population (10⁶) |
|---------|------------------|------------------|--------------------|-------------------|----------------|---------------------------------|
| NEC     | 31               | -15.3            | 2.8                | 42.8              | 151.3          | 0.57                            |
| NW      | 30               | -12.9            | 2.4                | 26.4              | 119.1          | 0.46                            |
| NCP     | 91               | -11.6            | 3.0                | 66.1              | 318.8          | 1.19                            |
| MG      | 8                | -14.1            | 2.8                | 22.9              | 185.0          | Missing                         |
| TP      | 19               | -17.4            | 2.5                | 39.8              | 28.4           | Missing                         |
| YR      | 60               | 3.4              | 2.2                | 379.4             | 515.3          | 0.98                            |
| CS      | 73               | 6.1              | 2.1                | 654.5             | 347.2          | 0.69                            |
| SC      | 46               | 14.0             | 2.7                | 385.6             | 314.4          | 0.97                            |

Fig. 1. Map of air pollution monitoring stations distribution and climate classification.

Fig. 2. Lockdown timeline from January 1 to April 18.
status, which resulted in increased air pollutant emissions (Li et al., 2020b).

2.2. Data source

Air pollution data from 358 cities (Table 1) including 1663 stations were collected from the National Urban Air Quality Real-time Release Platform of the Ministry of Environmental Protection of China (https://air.cnemc.cn:18007/), with a time resolution of 1 h. We averaged the station data in each prefecture city to obtain the mean concentration of a city. Data from cities in each climate zone were then averaged to obtain the regional mean concentration. The micro oscillating balance method and the β absorption method are both used to measure PM$_{2.5}$ and PM$_{10}$, NO$_2$, SO$_2$, and O$_3$ are measured using the chemiluminescence method, ultraviolet fluorescence, and UV-spectrophotometry, respectively. CO is measured using the non-dispersive infrared absorption method and the gas filter correlation infrared absorption method. The continuous monitoring systems for atmospheric pollutants consist of the sampling unit, the calibration device, the analytical instrument, and the data collection and transport unit. The meteorological data of 406 Chinese surface stations were collected from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Data (ISD) (ftp://ftp.ncdc.noaa.gov/pub/data/noaa/isd-lite/).

The quality assurance and data controls were implemented based on HJ 630–2011 and GB/T 37301-2019 specifications before releasing air pollutants data and meteorological data, respectively. The quality assurance/quality control procedure was also provided to all the operators in all cities, and all the gas analyzers were calibrated with standard gases once a week. The valid air pollutants and meteorological data for all climate zones exceed 99.5%. A detailed description of the instruments and data quality could be seen elsewhere (Zhao et al., 2016, 2020).

Regional air pollution conditions are tightly correlated with socio-economic factors (Han et al., 2014; Wang et al., 2017; Zhao et al., 2019). Hence, obtaining regional socio-economic data is essential for studying the regional differences in air pollution variations during the lockdown. Studies have shown that PM$_{2.5}$ is significantly correlated with the gross domestic product (GDP) and vehicle population (Han et al., 2014; Wang et al., 2017; Zhao et al., 2019). Therefore, we chose the GDP and vehicle population to evaluate the regional emission potential. Since the official 2019 statistical yearbook has not yet been published and vehicle population data was absent in some cities, we did a web scraping of the annual GDP and private vehicle population from the 2019 Statistical bulletin of 367 cities in China Statistical Information Network (http://www.tjcn.org/tjgbsy/nd/36163.html).

3. Results

3.1. Temporal variations of air pollutants

As shown in Fig. 3, temporal air pollutant fluctuations varied markedly between regions, highlighting the differences between the eight climate zones. Since the lockdown started, the concentrations of PM$_{2.5}$, PM$_{10}$, SO$_2$, CO$_2$, and NO$_2$ dropped more significantly in NEC, NW, NCP, MG than in TP, CS, and SC. For example, in NCP, PM$_{2.5}$ dropped by 88.9% from 137.3 μg m$^{-3}$ on Jan 22 to 15.2 μg m$^{-3}$ on Feb 15, while in SC PM$_{2.5}$ merely dropped by 43.0% from 28.4 μg m$^{-3}$ on Jan 22 to 16.2 μg m$^{-3}$ on Feb 15. As shown in Table 1, NEC, NW, MG, and NCP had lower temperatures (from −11.6 to −15.3 °C) and less precipitation (from 22.9 to 66.1 mm) than southern China. More frequent temperature inversions and fewer removal processes in cold climates led to increased accumulation of air pollutants. Therefore, once the lockdown started and the number of emission sources sharply reduced, the concentration of air pollutants in NEC, NW, MG, and NCP dropped significantly to the same levels as other regions.

Despite the emission reductions, severe pollution events still occurred in northern China due to an abnormally shallow boundary layer (Su et al., 2020). More frequent high concentration pollutant peaks were observed in several regions, namely NEC, NW, MG, and NCP in Fig. 3. Moreover, the heating demands of NEC, NW, MG, NCP, and TP gradually decreased as the temperature increased, resulting in significant air pollutant reductions in cold regions. For example, from Jan 15 to Apr 15 in MG, CO dropped by 73.7% from 1.9 mg m$^{-3}$ to 0.5 mg m$^{-3}$. On Apr. 15, the CO concentration of MG was even lower than that of SC.

As the lockdown measurements mainly reduced anthropogenic sources of air pollution, the lockdown effect on reducing air pollution was most effective in more developed regions (He et al., 2020). As shown in Table 1, YR has a much higher GDP and vehicle population than other regions. Similar to what happened in cold regions, air pollution in YR was also more significantly reduced than in underdeveloped regions like TP. For example, from Jan 19 to Feb 15, the concentration of NO$_2$ in YR dropped by 77.7% from 44.6 μg m$^{-3}$ to 10.4 μg m$^{-3}$.
m$^{-3}$, while the concentration of NO$_2$ in TP dropped by a mere 43.6% from 15.6 μg m$^{-3}$ to 8.8 μg m$^{-3}$. In arid regions like NW, PM$_{10}$ concentrations could still have peaks over 300 μg/m$^3$. O$_3$ continued to increase and fluctuate as the temperature increased (Fig. S1), with no remarkable difference between the eight climates in Fig. 3. Air pollutants in TP, CS, and SC remained stable with low-level concentrations. Compared to other regions, TP has the lowest GDP and vehicle population, indicating fewer anthropogenic sources, and that TP is the region least influenced by lockdown measures. As for CS and SC, high temperature and ample rainfall provided favorable dispersion and removal conditions for air pollutants.

3.2. Spatial distributions of air pollutants

To quantify regional differences in air pollutant variations, average concentrations at pre-lockdown, Alert Level 1, Alert Level 2, and Alert Level 3, the percentage changes of the concentrations of air pollutants of each Alert Level in relative to that of pre-lockdown were calculated, and the maximum percentage changes of different climates were compared.

Fig. 4 and Table 2 show that PM$_{2.5}$ dropped significantly by 59.0%–64.2% in NEC, NW, NCP, and MG. But in CS and SC, which possess favorable dispersion and removal conditions for air pollutants, PM$_{2.5}$ merely dropped by 17.0%–26.0%, not to mention that the average concentrations of PM$_{2.5}$ at pre-lockdown in CS and SC were less than half of that in NCP. Similarly, the reduction of PM$_{10}$ reached 40.3% and 47.3% in NEC and MG, respectively, while it only reached 21.3% and 27.5% in CS and SC, respectively. In arid climates like NW and TP, PM$_{10}$ increased by 48.9% and 21.7%, respectively. In the underdeveloped TP, the primary source of SO$_2$ and CO was residential heating.

As shown in Fig. 3, concentrations of SO$_2$ and CO in TP kept decreasing until Level 3, reflecting the decreasing heating demand during the lockdown. Similarly, SO$_2$ and CO dropped significantly by 41.1%–46.9% and 47.4%–63.6%, respectively, in cold regions like NEC, NW, MG, and NCP. In comparison, in warm regions like YR, CS, and SC (with no heating demands in winter), SO$_2$ and CO moderately dropped by 7.5%–23.2% and 20.6%–31.6%, respectively. At Level 3, when lockdown measures were relaxed, SO$_2$ even increased by 5.2%–20.9% in YR, CS, and SC due to increasing traffic and industrial activities.

Variations of NO$_2$ and O$_3$ exhibit no evident regional difference over the eight regions. NO$_2$ dropped by 41.2%–57.1% in all regions. Similarly, large declines of NO$_2$ were consistent in different regions of India during the lockdown (Singh et al., 2020). Therefore, NO$_2$ reductions were less noticeably influenced by changing climatic conditions. But in developed regions like NCP and YR, reductions of NO$_2$ were more significant at Level 1. NO$_2$ reductions in developed regions rebounded to pre-lockdown levels earlier than in developing regions, like NEC and MG. As light intensity and temperature increased through lockdown, O$_3$ surged by 79.2%–115.5% in almost all regions. However, in SC and TP, O$_3$ merely increased by 23.2% and 25.5%, respectively. We calculated the Kendall correlation coefficients of 5% significance between O$_3$ and other air pollutants. We observed that generally, O$_3$ was negatively correlated with other air pollutants. For example, O$_3$ was negatively correlated with PM$_{2.5}$ (r = 0.19) and NO$_2$ (r = 0.39) in TP. Hence, massive reductions in other air pollutants may have resulted in a drastic increase in tropospheric O$_3$ concentration, attesting to the finding that a decrease in PM$_{2.5}$ would speed up O$_3$ production (Li et al., 2019a). Le et al. (2020) concluded that the NOx titration effect was the main cause of the O$_3$ increase during the lockdown. However, we revealed that the spatial difference of NO$_2$ variations was not as prominent as other pollutants. Therefore, this study opines that reducing other air pollutants like PM$_{2.5}$ may have more significantly influenced surface O$_3$ increase during the COVID-19 lockdown period.

The Kendall correlation tests were conducted to assess the correlations between meteorological factors and air pollutants in the eight regions. Overall precipitation intensity, temperature, and wind speed were negatively correlated with the concentrations of air pollutants. Temperate climates like NEC and NW had the lower average temperature and greater temperature increase through the lockdown than in other climates (Fig. S1). As shown in Table 3, air pollutants in temperate climates generally show higher coefficients than those in subtropical climates and plateau climates. In arid regions like NW, MG, and TP, the correlations between precipitation and air pollutants generally failed to satisfy a 5% level of significance, suggesting a weak precipitation impact on air pollutants’ concentrations in arid climates. SO$_2$ and NO$_2$ were negatively correlated with temperature in cold regions like NEC, NW, NCP, and TP with heating demands. Still, they were positively correlated with warm areas like YR, CS, and SC. CO was negatively correlated with meteorological variables in all regions, showing an especially significant correlation with wind speed. Different from other pollutants, O$_3$ was significantly positively correlated with temperature and wind speed. In the cold areas with more incredible temperature growth from January to April, O$_3$ was more significantly associated with temperature than in warm regions.

![Fig. 4. The average concentrations of pre-lockdown, Level 1, Level 2, and Level 3.](image-url)
Table 2
Percentage changes of the average concentrations of air pollutants at Alert Level 1, 2 and 3 in relative to the pre-lockdown concentrations during COVID-19 lockdown in China.

| Period    | Area | PM$_{2.5}$ | PM$_{10}$ | SO$_2$ | CO  | NO$_2$ | O$_3$ |
|-----------|------|------------|-----------|--------|-----|--------|-------|
| Alert Level 1 | NEC  | -33.0%     | -31.4%    | -23.0% | -27.6% | -49.1% | 47.8%  |
|            | NW   | -28.7%     | -1.8%     | -5.7%  | -20.5% | -44.0% | 55.2%  |
|            | NCP  | -34.5%     | -32.0%    | -28.2% | -31.7% | -53.2% | 77.7%  |
|            | MG   | -28.9%     | -19.2%    | -20.3% | -34.3% | -48.7% | 52.8%  |
|            | TP   | -23.8%     | -8.7%     | -9.4%  | -15.6% | -41.2% | 12.7%  |
|            | NR   | -34.4%     | -33.7%    | -7.5%  | -21.5% | -53.1% | 62.0%  |
|            | SC   | -17.7%     | -21.3%    | -17.4% | -23.3% | -53.2% | 48.4%  |
| Alert Level 2 | NEC  | -59.0%     | -47.3%    | -46.9% | -47.4% | -54.6% | 68.3%  |
|            | NW   | -43.2%     | 21.5%     | -31.9% | -52.3% | -50.0% | 62.4%  |
|            | NCP  | -58.3%     | -37.2%    | -42.2% | -51.1% | -38.6% | 87.4%  |
|            | MG   | -64.2%     | -40.3%    | -40.9% | -59.8% | -57.1% | 69.0%  |
|            | TP   | -32.2%     | -3.3%     | -19.5% | -29.1% | -36.9% | 24.7%  |
|            | NR   | -48.0%     | -28.7%    | 3.1%   | -24.8% | -25.5% | 69.0%  |
|            | SC   | -26.1%     | -12.8%    | -0.8%  | -25.7% | -19.7% | 63.1%  |
| Alert Level 3 | NEC  | -19.3%     | -6.7%     | -43.6% | -37.9% | -34.9% | 86.2%  |
|            | NW   | -36.3%     | 48.9%     | -41.1% | -61.5% | -46.1% | 79.2%  |
|            | NCP  | -59.8%     | -34.6%    | -39.7% | -52.6% | -30.5% | 115.5% |
|            | MG   | -63.3%     | -29.6%    | -48.1% | -63.6% | -50.3% | 91.6%  |
|            | TP   | -20.7%     | 21.7%     | -24.1% | -33.8% | -26.2% | 25.5%  |
|            | NR   | -43.4%     | -16.0%    | 20.9%  | -31.6% | -3.4%  | 99.0%  |
|            | SC   | -24.6%     | -6.1%     | 13.4%  | -29.1% | -6.1%  | 99.9%  |
|            | SC   | -5.4%      | -2.5%     | 5.2%   | -13.0% | -3.1%  | 23.2%  |

Table 3
Correlation coefficients between air pollutants and meteorological factors.

| Region | Variable | PM$_{2.5}$ | PM$_{10}$ | SO$_2$ | CO | NO$_2$ | O$_3$ |
|--------|----------|------------|-----------|--------|-----|--------|-------|
| NEC    | Precipitation | -0.208*   | -0.192*   | -0.226* | -0.179* | -0.196* | 0.625* |
|        | Temp     | -0.177*   | -0.193*   | -0.229* | -0.476* | -0.445* | 0.378* |
| NW     | Precipitation | 0.163***  | 0.242***  | 0.326*  | 0.494*  | 0.541*  | 0.425* |
|        | Temp     | -0.417*   | -0.23*    | -0.518* | -0.673* | -0.345* | 0.149* |
| NCP    | Precipitation | -0.306*   | 0.201*    | -0.469* | -0.582* | -0.419* | 0.425* |
|        | Temp     | -0.209*   | -0.185*   | -0.405* | -0.454* | -0.172* | 0.279* |
| MG     | Precipitation | 0.156**   | 0.166**   | -0.353* | -0.405* | -0.219* | 0.537* |
|        | Temp     | -0.31*    | -0.151**  | -0.373* | -0.385* | -0.348* | 0.382* |
| TP     | Precipitation | -0.139**  | 0.286*    | -0.215* | -0.209* | 0.289*  | 0.207* |
|        | Temp     | -0.176*   | -0.222*   | -0.283* | -0.219* | 0.191*  | 0.242* |
| SC     | Precipitation | -0.074*   | -0.304*   | -0.211* | -0.138* | -0.138* | 0.154** |
|        | Temp     | -0.332*   | 0.366*    | 0.438*  | 0.317*  | 0.429*  | 0.207* |

*p < 0.01.
**p < 0.05.

3.3. Diurnal variations of air pollutants

The bimodal distributions of PM$_{2.5}$ and PM$_{10}$ were especially evident in NEC and TP (Fig. 5, Fig. 34). Once the lockdown started, the diurnal variation flattened out. The decrease of the diurnal range was most pronounced in NEC, where the diurnal range for PM$_{2.5}$ dropped by 58.3% from 30.7 μg m$^{-3}$ (Pre-lock) to 12.8 μg m$^{-3}$ (Level 2), and for PM$_{10}$ by 59.3% from 35.9 μg m$^{-3}$ (Pre-lock) to 14.6 μg m$^{-3}$ (Level 2). Then in Level 3, when traffic and manufacturing activity restarted, the diurnal range of NEC for PM$_{2.5}$ surged by 308.6% to 52.3 μg m$^{-3}$ and the daily range for PM$_{10}$ surged by 288.4% to 56.7 μg m$^{-3}$. As shown in Fig. S5 and Fig. S6, diurnal variations of SO$_2$ and CO were prominent in cold regions with heating demands (NEC, NW, MG, TP). But the diurnal ranges remained stable among different Alert levels. Nevertheless, in NEC, the coldest region, SO$_2$ and CO still show significant variations of diurnal ranges among different levels. From Alert Level 2 to Alert Level 3 in NEC, SO$_2$ increased by 47.8% from 6.7 μg m$^{-3}$ to 9.9 μg m$^{-3}$, and CO increased by 85.7% from 0.21 mg m$^{-3}$ to 0.39 mg m$^{-3}$. While in other regions, there are no remarkable variations of diurnal ranges during Alert Level 2 to Alert Level 3.

NO$_2$ showed a double peak distribution. Since NO$_2$ is easily photolyzed, the troughs became more noticeable with time. The growth of diurnal ranges of NO$_2$ was evident in NEC, NW, and TP (Fig. S7). For instance, in NW, the diurnal range grew by 78% from 17.0 μg m$^{-3}$ (Pre-
lock) to 30.2 μg m⁻³ (Level 3). Along with the increase in the average concentration of O₃, the diurnal ranges of O₃ also grew significantly. In NEC, NCP, YR, SC, and CS, the diurnal ranges of O₃ rose from 20 to 30 μg m⁻³ (Level 2) to 40–60 μg m⁻³ (Level 3) as shown in Fig. S8. In SC, different from the stable trend of O₃ in sections 3.1 and 3.2, the diurnal ranges of O₃ changed significantly. The diurnal range of O₃ was 46.0 μg m⁻³ in Pre-lock and then be significantly suppressed to about 28.0 μg m⁻³ in Level 2.

4. Discussion

Air pollutants have different impact ranges due to the difference in their residence time in the atmosphere (An et al., 2019; Seinfeld and Pandis, 2016). Take the secondary pollutants, PM₂.₅ and O₃, for example, PM₂.₅ stays in the boundary layer for a long time, so it has the characteristics of regional pollution; O₃ has a shorter stay in the boundary layer, so the pollution range is relatively small (Seinfeld and Pandis, 2016). Therefore, there are significant differences in the response of different pollutants to meteorological conditions. And even with the same meteorological conditions, different regions have different effects on air pollutants. For example, the cold air in winter in the North China Plain tends to rapidly reduce the concentration of pollutants, while the cold air in the Yangtze River Delta region may bring a large quantity of pollutants and enhance the local pollution (Huang et al., 2020; Kang et al., 2019; Zheng et al., 2015). Therefore, at the current stage in China, where the control of PM₂.₅ has been below the standard, but O₃ pollution is prominent, and the characteristics of air pollution have gradually evolved into the composite pollution situation in which O₃ and aerosols coexist. It became essential to sort out the relationship between meteorological conditions and air pollutants and their differences in different climate zones.

In China, the distribution characteristics of topography, climate, population, and economy have consistency in space. China is divided into two distinct regions based on the “Heihe-Tengchong Line” (Chen et al., 2016; Zhang et al., 2020a). The terrain in the northwest of the “Heihe-Tengchong Line” is dominated by plateaus, mountains, grasslands, and deserts, accounting for 56.2% of the whole land area, but only 4% of the population is inhabited here, where the precipitation is sparse, the land is large, the population is sparse, and arid and semi-arid climates dominate the climate. However, the southeast of the “Heihe-Tengchong Line” terrain is dominated by the plain, accounting for 43.8% of the land area, but up to 96% of the population is inhabited there. Even in the southeast, there is a vast difference in climate between north and south. Heilongjiang province in northern China belongs to the cold temperate climate and temperate continental monsoon climate, while Hainan province in southern China belongs to the marine tropical monsoon climate. In addition, the urbanization process of different regions varies greatly. The North China Plain, the Yangtze River Delta, the Sichuan Basin, and the Pearl River Delta have formed dense large urban agglomerations with severe anthropogenous pollution (An et al., 2019; Guo et al., 2014; Han et al., 2016; Shen et al., 2021a,b; Shi et al., 2020; Xu et al., 2013). So, due to the differences in climate, topography, and emission sources in different regions, the evolution characteristics of air pollutants are different. A comprehensive review of the distribution characteristics of air pollutants, meteorological conditions, and the mechanism of the impact of emission sources on air pollutants in different climatic regions is important for the coordinated regional control of complex air pollution.

To prevent the spread of COVID-19, strict lockdown measures are implemented nationwide. Implementing these measures provides us with a precious opportunity to understand the mechanism of the influence of meteorological conditions and anthropogenic sources on the
distribution of atmospheric pollutants in different climate zones. For example, the strict nationwide home quarantine measures during lockdown made the traffic emission sources drastically reduced. And except for the necessary transportation, all other means of transportation have been interrupted (Li et al., 2020b; Le et al., 2020). That has made the difference in traffic sources due to different city scales and urban-rural differences disappear, and it provides us a valuable opportunity to assess the degree and mechanism of the impact of traffic sources on air pollutants in different regions. In this study, we utilized the daily observation data of 609 stations from 1971 to 2000 to divide China into 8 climate zones and combined them with the nationwide air pollution data (PM$_{2.5}$, PM$_{10}$, SO$_2$, CO, NO$_2$, and O$_3$) data of meteorology (temperature, wind speed, and precipitation), GDP and car ownership to analyze the temporal and spatial distribution characteristics of air pollutants in different climate zones and their influencing factors. Moreover, the influence of meteorological elements and anthropogenic sources on air pollutants in different climate zones was analyzed in detail. PM$_{2.5}$ reduced by 59.0%-64.2% in cold regions (NEC and NW), while O$_3$ surged by 99.0%-99.9% in warm regions (CS and SC). Diurnal variations of atmospheric pollutants were also more prominent in cold regions. The influences of weather conditions on the atmospheric pollutants in different climate zones were different. As the region with the least emissions, TP experienced a moderate decrease of air pollutants as heating demands decreased and dispersion conditions improved. Meanwhile, the reducing demands for house heating in cold regions (NEC, NW, NCP, and MG) resulted in more significant reductions in PM$_{2.5}$, SO$_2$, and CO than in warm regions (YS, CS, and SC). There were less prominent spatial variations of NO$_2$ and O$_3$ during the lockdown. NO$_2$ dropped by 41.2%-57.1% countrywide, showing no distinct regional difference among the eight climates. Although O$_3$ increased by around 24% in SC and TP, O$_3$ surged by 79.2%-115.5% in all other regions.

5. Conclusions

Lockdown measurements in response to COVID-19 have indirectly improved air quality. Since different regions in China is different in climate and economics, the air pollution variation in the lockdown also has regional characteristics. Additionally, air pollution may increase the possibility of respiratory infections. Hence, studying the regional differences in air pollution changes is necessary for better control of air pollution and the epidemic. In this study, regional characteristics of spatial and temporal variation were analyzed based on the data of major air pollutants (PM$_{2.5}$, PM$_{10}$, SO$_2$, CO, NO$_2$, O$_3$) from January 1st to April 18th, 2020. Together with meteorological and socio-economic data, the impacts of climate and socio-economic factors were discussed.

The differences in the characteristics of air pollutants in different climate zones were noticeable. PM$_{2.5}$ reduced significantly by 59.0% and 64.2% in cold NEC and NW, respectively, but dropped by only 17.0% and 26.0%, respectively, in warm CS and SC. O$_3$ increased by 99.0% and 99.9%, respectively, in warm YR and CS, around 20% larger than NW (79.2%). Diurnal variations of atmospheric pollutants were also more prominent in cold regions. The influences of weather conditions on the atmospheric pollutants in different climate zones were different. The wind speed was not the primary reason for the differences in air pollutants in different climate zones. The wind speed was directly proportional to ozone but was negatively correlated to most other pollutants for a specific climate region. Temperature, precipitation, and air pollution emissions led to prominent regional differences in air pollutants throughout the eight climates. The temperature was positively correlated to ozone in different climate zones, and the correlation was the highest in NEC and the lowest in SC. The rainfall has a strong removal effect on atmospheric pollutants in climate regions with more precipitation, but it increases the pollutant concentrations in climate regions with less precipitation. The composition of pollution sources of a region resulted from the regional characteristics of climate and economy. The reducing demands for house heating in cold regions (NEC, NW, NCP, and MG) resulted in more significant PM$_{2.5}$, SO$_2$ and CO reductions than warm regions (YS, CS, and SC). In regions with more emission sources like NCP and YR, air pollutants exhibited greater variations and rebounded to pre-lockdown levels earlier than their surrounding regions. There were less prominent spatial variations of NO$_2$ and O$_3$ during the lockdown. NO$_2$ dropped by 41.2%-57.1% countrywide, showing no distinct regional difference among the eight climates. Although O$_3$ increased by around 24% in SC and TP, O$_3$ surged by 79.2%-115.5% in all other regions. The sharp reductions of air pollutants like PM$_{2.5}$ may have caused the drastic increase in O$_3$ production rather than the titration effect of NO$_x$.

Author contributions

Honglei Wang: Conceptualization, Methodology, Visualization, Investigation, Writing - Original Draft, Writing - Review & Editing, Funding acquisition; Tan Yue: Writing - Original Draft, Investigation, Software, Writing - Review & Editing; Lianxia Zhang: Writing - Original Draft, Investigation, Software; Lijuan Shen: Conceptualization, Methodology, Visualization, Investigation, Writing - Original Draft; Tianliang Zhao and Xia Li: Writing - Review & Editing; Qihang Dai and Tianyi Guan: Conceptualization, Methodology, Visualization, Writing - Original Draft; Yue Ke: Conceptualization, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://doi.org/10.1016/j.apr.2021.101247.

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