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Meteorology-normalized variations of air quality during the COVID-19 lockdown in three Chinese megacities

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1. Introduction

Air pollution is a global public health concern, particularly in developing countries such as China (Lelieveld et al., 2015) and India (Guo et al., 2017). In 2015, PM$_{2.5}$ pollution was responsible for 4.2 million deaths a year globally, including 1.1 million in China (Cohen et al., 2017). Studies have shown that poor air quality increases the prevalence and mortality of novel coronavirus pneumonia (Coccia, 2020; Liang et al., 2020).

To prevent the spread of COVID-19, governments throughout the world have imposed strict lockdown measures (Tian et al., 2020), which have led to a visible decline in economic activity and thus reduce air pollutant emissions (Le et al., 2020). The unprecedented decline in human activities caused by the COVID-19 lockdown provides a unique natural-triggered experimental chance to research the possible impacts of anthropogenic emissions on air quality and a basic reference for promulgating air pollution management regulations in the coming years.

Many studies have analyzed air quality variations due to COVID-19. Most of them compared observed air pollutants during the lockdown with before the lockdown or historical periods through satellite remote sensing (Liu et al., 2020a) or ground observations (Mahato et al., 2020). Several studies even compared changes in pollutants under similar weather conditions (Covignarelli et al., 2020). However, the concentration variations in various air pollutants are determined jointly by meteorological factors and emissions (Cameletti, 2020). Additionally, numerous actions have been implemented to alleviate atmospheric pollution over the years (Zhang et al., 2019). Furthermore, changes in...
the heating season are also one influencing factor. Therefore, it is inaccurate to simply compare the observed values of pollutant concentrations before and after the lockdown. Comparisons between 2019 and other years (e.g., the average value from 2015 to 2017) are also likely to be skewed. These results may not be sufficient to reveal the impact of emissions control measures and changes in meteorological conditions. A series of studies used chemical transport models to assume reductions in emissions (Wang et al., 2020) and estimate the impact on pollutant concentrations (Liu et al., 2020b). However, it is difficult to estimate emission changes attributed to the lockdown.

Several studies have applied mathematical models to evaluate the impact on air quality. Venter et al. (2020) used the multiple linear regression model to make predictions in 34 various countries in the world. Bao and Zhang (2020) used the least square dummy variable model (LSDV model) to investigate variations in northern China. Wang et al. (2021) established one difference-in-difference model to evaluate the impact in the Beijing-Tianjin-Hebei region. In addition, the impact of travel bans and the strength of regulatory behavior on air quality heterogeneity were also discussed. However, the accuracy of the adopted model is relatively low, e.g., the model accuracy of Venter et al. (2020) is usually less than 0.6, and some assumptions applied in the model are also uncertain.

As a reliable method, machine learning can be used to quantify changes in air quality caused by meteorology and emissions. In fact, several studies have applied the RF (random forest) model to remove the impact of meteorology. Vu et al. (2019) used the RF model to normalize the meteorology of six criteria pollutants in Beijing from 2013 to 2017, to evaluate the effectiveness of the clean action plan in reducing the level of air pollution in Beijing. Petetin et al. (2020) used the ML model to investigate the reduction in NO2 concentration in Spain due to the COVID-19 lockdown and found that NO2 mixing ratios at urban background and traffic stations were found to decrease by approximately –50% due to the lockdown. Cole et al. (2020) used the RF method to eliminate the mixed influence of meteorological conditions. They found that NO2 concentrations fell by as much as 24 μg/m³ during the lockdown while there was no obvious change trend of SO2 and CO.

Previous studies have been performed to analyze air quality variations related to COVID-19. However, few of them take into account the detailed studies of all 6 criteria air pollutants at different types of monitoring stations. Additionally, there is a lack of investigation on the impact of meteorology on the variations. In addition, the analysis of the high spatial resolution of cities in western China is also lacking. Therefore, in this study, we combined a weather normalization technique optimized by Shi et al. (2021) to provide a comprehensive assessment of the air quality variations induced by COVID-19 at a multiscale (multicity, multistation, multipollutant) and high spatial-temporal resolution, which included Wuhan (located in Central China and breakout epicenter of COVID-19), Beijing (located in North China and the Capital of China) and Urumqi (located in Western China and Capital city of Xinjiang Autonomous Region). Additionally, ground air quality monitoring stations in these cities were divided into four types to examine the influence of emission source changes on ambient air pollution. This study examined the potential causes of changes in pollutant concentrations and provides a reference for the change in pollutant concentrations at the urban scale during the lockdown period. To the best of our knowledge, this is the first study to explore the impact of the COVID-19 pandemic on six different criteria pollutants in eastern, central, and western China with high temporal and spatial resolutions, especially considering meteorological variability.

2. Materials and methods

2.1. Study areas and data sources

2.1.1. Description of study areas

Three cities were selected with different longitudes with strong spatial representation in our study, which were named Beijing, Wuhan, and Urumqi. These three cities were geographically located in eastern, central, and western China, respectively (see Fig. 1). New coronavirus disease first broke out in Wuhan (Li et al., 2020). Beijing and Urumqi have also been affected along with the evolution and diffusion of the COVID-19 pandemic. Additionally, their climatic conditions and air quality are quite different. These cities permitted the study of the heterogeneity of air quality variations related to COVID-19 lockdown in different regions.

2.1.2. Data sources

The hourly data of criteria air pollutants (CAPs, which include NO2, PM2.5, O3, PM10, SO2, and CO) were acquired from China National Environmental Monitoring Center (CNEMC). It included data from January 1 to May 31 each year for six years from 2015 to 2020. In Wuhan, data from 9 stations were used. In Beijing, 16 stations were analyzed. In Urumqi, 6 stations were selected (see Fig. 1). Among these stations, they were distinguished into four categories according to the characteristics of the station’s surroundings: urban, traffic, industry, and rural stations. For example, the traffic station is determined as a station closer to the heavy traffic hub. Industry stations are defined as many industrial parks nearby, which are more affected by industrial emissions. The detailed classification information was shown in Table S1. The hourly wind speed, wind direction, temperature, relative humidity, and atmospheric pressure for selected cities are obtained using the “worldmet” R software package from the nearest weather station (https://CRAN.R-project.org/package=worldmet). Fig. 1 shows the map of the study areas. Detailed information is summarized in Table S1.

2.2. De-weather model

Changes in the concentrations of atmospheric pollutants are jointly affected by emissions and meteorology. To highlight the role of emissions, the “normalweather” R package (Vu et al., 2019) was utilized to eliminate the impact of meteorological factors (Grange and Carslaw, 2019). Here, a machine learning-based RF algorithm optimized by Shi et al. (2021) was applied to eliminate the influence of meteorology.

Random forest (RF) is a statistical learning theory. It uses the bootstrap resampling method to extract multiple samples from the original sample, conducts decision tree modeling for each bootstrap sample, and then combines the prediction of multiple decision trees to obtain the final prediction result through voting. In general, a random forest randomly generates hundreds to thousands of classification trees and then selects the tree with the highest degree of repetition as the final result (Breiman, 2001).

The overall idea of the RF algorithm includes first predicting the concentration of pollutants based on a set of characteristic values (including meteorological data and other time variables) and training a reliable RF model. Then, the RF model can be used to predict the concentration of pollutants under a series of meteorological conditions, and the relevant average value is called the normalized time series of meteorology. In the algorithm, the concentration of a certain pollutant at a specific time point can be predicted by resampling meteorological data. This process was repeated 1000 times, and 1000 predicted concentrations were averaged to calculate the final weather standardized concentration for that particular hour, day, and year. In the process, only the weather data, not the time variable, was normalized and resampled from the entire study period. The flowchart of the machine learning-based RF algorithm can be observed in Fig. ST1.

In this study, RF models were developed for each pollutant at each monitoring station for the corresponding period each year (January to May of each year from 2015 to 2020). The air pollutant concentration predicted by the RF model was the meteorological normalized concentration (called the “deweathered” concentration). The weather normalization was carried out by the “rmweather” R package. Details of the models can be observed in the separate Supporting Information (SI).
2.3. Data analysis

For better analysis, the study time span spilled two periods: pre-
lockdown period (before the lockdown: January 1 – 20, “PD”) and lock-
down period (during the lockdown: February 1 - March 15, “LD”). First,
the percentage change in observed pollutant concentrations (P_{obs}) was
calculated by comparing the observed concentration between PD and LD
in 2020. To exclude the effect of meteorological conditions and reveal
the variations in emissions. The changes in deweathered concentrations
(P_{dew}) were calculated by the relative changes in deweathered pollutant
concentrations in PD and LD. The difference between P_{obs} and P_{dew}
indicated the contribution of meteorology to the changes in the
pollutant concentration observations. Furthermore, the historical data
for 2015–2019 during the same time span were a criterion for
detrending. The average percentage change in pollutant concentration
between PD and LD from 2015 to 2019 was taken as the “trend” item to
represent the change in emissions when “business as usual”. Addition-
ally, the moving average of deweathered concentrations was calculated
from 2015 to 2019 as the baseline to eliminate meteorological effects as
much as possible. Finally, the detrended variation rate (P*) was calcu-
late d by Eq. (1):

\[ P^* = P_{2020} - P_{2015-2019} \]  

where P_{2020} and P_{2015-2019} represent the deweathered concentra-
tion variation rates (LD versus PD) in 2020 and 2015–2019, respectively. P*
reflected the extent to which air quality was truly affected by the
lockdown.

3. Results and discussion

3.1. Evaluation of model performance

Ten statistical indices were used to evaluate our model in different
ways. The model evaluation metrics are shown in Table 1. The high R
values range 0.81–0.94 indicate that the relation between the predicted
values and the observed values was significant. The RF model perfor-
mance is shown in Fig. 2. The R^2 values were generally higher than 0.6,
and some were even higher than 0.9. This indicates that the features of
the established model were excellent and far better than those of the
regression model (Venter et al., 2020). FAC2 values of 0.92, 0.91, 0.94,
0.93, 0.98, and 0.90 for PM_{2.5}, PM_{10}, NO_2, SO_2, CO, and O_3,
which suggest that our model satisfies the condition for the fraction of pre-
dictions. MB value ranged –0.15-0.12 show that the bias produced by
our model was very small. Similarly, the lower values of NMB and NMGE
indicate that our model performed well. It was considered that our
model had satisfactory prediction capability, as verified by all the
indices.

3.2. Diurnal variations in air pollutants

The diurnal variation in pollutant concentration is closely related to
the trajectory of human activities. A change in anthropogenic emissions
has an important impact on the variations in air pollutant concentrations
at different times in a day. Therefore, in this section, the diurnal vari-
ations in CAPs during the lockdown are examined, which provides
insight into the interrelationship between air pollutants and different
emission sources.

The diurnal variations in pollutants at four types of stations in three
cities can be observed in Fig. 3 and S1. NO_2 and CO are air pollutants
related to traffic activities with a bimodal distribution at each traffic
Fig. 3a shows that double peaks occurred at 8:00–9:00 and 20:00–21:00 in Beijing and Wuhan but approximately 2 h later in Urumqi, which can be explained by the time difference of a 2-h lag between Urumqi and Beijing (Beijing Time is adopted in all of China). Similar to other studies, the peak distribution of the diurnal variations of ambient NO₂ and CO was closely related to the commuting peak time at local (Singh et al., 2020; Sheng et al., 2019). At urban and traffic stations, traffic is the leading source of CO. With the decrease in traffic

| Pollutants | RMSE | R   | R²   | FAC2 | MB  | MGE | NMB | NMGE | COE | IOA |
|------------|------|-----|------|------|-----|-----|-----|------|-----|-----|
| PM₂₅       | 19.8 | 0.94| 0.86 | 0.92 | 0.12| 12.45| 0.00| 0.20 | 0.68| 0.84|
| PM₁₀       | 42.2 | 0.87| 0.79 | 0.91 | 0.11| 23.60| 0.00| 0.24 | 0.58| 0.79|
| NO₂        | 13.6 | 0.88| 0.75 | 0.94 | 0.06| 9.64 | 0.00| 0.22 | 0.57| 0.79|
| SO₂        | 6.7  | 0.81| 0.70 | 0.93 | −0.05| 3.01 | −0.00| 0.25 | 0.56| 0.78|
| CO         | 0.3  | 0.87| 0.71 | 0.98 | 0.004| 0.19 | 0.01| 0.17 | 0.62| 0.81|
| O₃         | 13.4 | 0.94| 0.88 | 0.90 | 0.07| 9.40 | 0.00| 0.17 | 0.71| 0.85|

Note: FAC2 (fraction of predictions with a factor of two), MB (mean bias), MGE (mean gross error), NMB (normalized mean bias), NMGE (normalized mean gross error), COE (Coefficient of Efficiency), IOA (Index of Agreement).

Fig. 2. Model validation for testing data set of each air pollutant (in hourly time resolution) in 2015–2020.
flow, CO peak weakened significantly at urban stations and traffic stations, especially at traffic stations (see Fig. 3a), which suggested that the COVID-19 lockdown had a greater impact on CO concentrations at traffic stations. However, the source of CO at the industry station was mainly from industrial activities, and the industrial activities were less interrupted during the lockdown. Therefore, the decline of CO peak at industry stations (7.7% in Wuhan and 13.3% in Urumqi, see Fig. 3b) is much smaller than that at urban and traffic stations.

On lockdown days, the daily cycle variation pattern of NO\(_2\) at all types of monitoring stations was similar (Fig. 3a and S1). In summary, although the peak value of NO\(_2\) was weak in lockdown, the daily cycle variation trend of its production and depletion was the same as that before the lockdown, suggesting the inherent diurnal photochemical reaction cycle of NO\(_2\). Compared with CO, a larger decline in the peak value of NO\(_2\) was observed (see Fig. 3b), showing a closer relationship between traffic activities, which is consistent with previous studies (Venter et al., 2020; Wang et al., 2020). The peak concentration of NO\(_2\) related to morning and evening traffic activities decreased markedly, which coincides with the noticeable reduction in traffic volumes.

As an important precursor for O\(_3\) production, NO\(_2\) has an important influence on the daily variations in O\(_3\). The O\(_3\) concentration peaked in the late afternoon hours in Wuhan and Beijing and much later in Urumqi because of the long daylight hours. In Beijing, different daily circulation patterns between traffic and non-traffic stations were observed (Fig. 3a). The O\(_3\) peak of traffic stations was about 3 h earlier than at non-traffic stations, revealing the important contribution from the exhaust of vehicles. During the lockdown, the O\(_3\) concentration unexpectedly increased, especially at traffic stations, where there was a sharper increase at the peak, which may be caused by a decrease in the titration reaction. Additionally, O\(_3\) peaked slightly later in the lockdown period. A higher increase in O\(_3\) concentrations at night than during the day was observed (Fig. 3a).

PM\(_{2.5}\) comes from complex sources and the generation of secondary aerosols is affected by a variety of factors. The general diurnal variation showed a bimodal distribution at most stations but was not evident (Fig. 3a and S1). The peak in the morning was due to traffic emissions, while the increase in the evening was closely related to household emissions (Srivastava et al., 2021). Before the lockdown, the diurnal variation pattern of PM at each station was inconsistent, but after the lockdown, the daily variation trend in PM at all stations in each city was similar and the average daily variation range was small, perhaps related to the reduction in human activities.

Fig. 3. (a) Diurnal concentration variations of CO, NO\(_2\), O\(_3\), and PM\(_{2.5}\) pollutants at three types of stations in three cities during lockdown period (1 February to 15 March) versus pre-lockdown period (1 January to 20 January). (b) Percentage reduction in morning peak of CO and NO\(_2\) during the lockdown.
Overall, although air pollutant concentrations responded to changes in emission sources, peak times did not change significantly, which indicates that meteorology acted a major characteristic in CAP variations compared with reductions in anthropogenic emissions.

3.3. Concentration variations due to activity changes after excluding the meteorological impact

The observed NO\textsubscript{2} levels were highly variable, with daily concentrations changing notably during the study period (Fig. 4 and S2). The mean levels of NO\textsubscript{2} declined by 49.7%, 42.9%, and 48.1% during the lockdown in Wuhan, Beijing, and Urumqi at urban stations, respectively (Table S2). At traffic stations, the reduction percentage of observed NO\textsubscript{2} ranged from 33.5% to 57.7%. At the same time, observed NO\textsubscript{2} at industry stations and rural stations also decreased significantly after the lockdown (Fig. S2).

Deweathered NO\textsubscript{2} exhibits a similar pattern to that of the observed value, but the magnitude of the change is different. A sudden decrease in deweathered NO\textsubscript{2} during the lockdown period was observed in Wuhan and Urumqi, but not pronounced in Beijing (Fig. 4), which is consistent with previous studies (Wu et al., 2021). This may be related to the fact that Beijing still has a high level of necessary traffic activity during the epidemic (Fig. S7). Fig. S7 shows that the Travel Intensity of Wuhan and Urumqi has dropped to the extreme, while Beijing has an obvious weekend effect. Meanwhile, the timing of the rapid decline for deweathered NO\textsubscript{2} was remarkably coincident with the start of the lockdown in Wuhan. However, a few days after the lockdowns, there was a sudden drop in Urumqi. This may be because of undemanding control measurements at the beginning in Urumqi. The change percentages of deweathered NO\textsubscript{2} at urban stations in Beijing, Urumqi, and Wuhan were −32.2%, −34.8%, and −43.7%, respectively (Table 2). Deweathered NO\textsubscript{2} decreased the most in Wuhan because of the stringent lockdown measures. A sudden drop, distinct from the data in 2019, is clearly observed in 2020 after the lockdowns began, especially in Urumqi (Fig. 4 and S2). This confirms that the sudden decline in 2020 was caused by the lockdown measures.

In contrast to changes in NO\textsubscript{2}, observed O\textsubscript{3} follows an increasing trend during the lockdown at all stations (Fig. 4 and S2). Because of the weakening of unbalanced economic activity, the decline in NOx emissions of the study cities is greater than that of VOC emissions, resulting in a decrease in the titration effect to O\textsubscript{3}. In addition, the decrease in PM concentration will also result in increased O\textsubscript{3} concentrations (Liu et al., 2013). Due to the low PM emissions in the lockdown period, higher insolation also promotes the formation of O\textsubscript{3} (Murphy et al., 2007). Observed O\textsubscript{3} in Urumqi increased the most, with the percentage changes ranging from +54.5% in Beijing to +243.0% in Urumqi (Table S2). In contrast to observations, deweathered O\textsubscript{3} increased the most in Wuhan because automobile exhaust contributes the most to O\textsubscript{3} production, contributing 30% on days when O\textsubscript{3} is not high (Zeng et al., 2018). The minimum increment of deweathered O\textsubscript{3} during the lockdown period is

Fig. 4. Daily average concentration of observed and deweathered NO\textsubscript{2} and O\textsubscript{3} at urban and traffic stations in three cities from 1 January to 31 May in 2020 versus 2019.
observed in Beijing. The percent change for deweathered $O_3$ ranged from $+49.7\%$ in Beijing to $+114.3\%$ in Wuhan at traffic stations, from $+39.6\%$ in Beijing to $+115.3\%$ in Wuhan at urban stations, and from $+32.4\%$ in Beijing to $+68.4\%$ in Wuhan at rural stations, respectively (Table S3). The smallest increase at rural stations was observed among the four types of stations in all three cities. Increased $O_3$ concentrations are also found in other cities across the world, including Delhi (Sharma et al., 2020; Rathod et al., 2021), the Yangtze River Delta (Yuan et al., 2021), and Nice (Sicard et al., 2020). These studies reveal that coordinated NO$_2$ and VOC control is required to restrain urban and regional ground-level $O_3$ pollution.

As shown in Fig. 5, during the lockdown, observed PM$_{2.5}$ dropped most significantly in Urumqi, where air pollution was more severe in winter, and no distinct change was observed in Wuhan and Beijing. To one’s surprise, in Beijing and Urumqi, pollution incidents still occurred during the lockdown (Fig. 5). During the study period, average observed PM$_{2.5}$ concentrations at urban stations in Wuhan, Urumqi, and Beijing were $36.4 \pm 17.6 \mu g/m^3$, $67.9 \pm 53.0 \mu g/m^3$, $53.5 \pm 53.2 \mu g/m^3$, respectively, which decreased $36.7\%$, $45.6\%$ and increased $21.7\%$ (see Table S2), respectively.

Compared with the large variation range of observed values, deweathered PM$_{2.5}$ had a clearer trend and pattern than observed PM$_{2.5}$, especially in Beijing (Fig. 5). The PM$_{2.5}$ concentrations in the lockdown period were lower and less variable. Unlike deweathered NO$_2$, no abrupt drop in deweathered PM$_{2.5}$ was observed after lockdown started in Beijing, Wuhan, and Urumqi. However, it can be seen from Fig. 5 that

| Table 2 |
| Change rates (%) in deweathered and detrended mass concentrations of CAP at urban stations and traffic stations during the study period (2020.2.1–3.15 vs 2020.1.1–1.20) in the three studied cities. |
| Deweathered | NO$_2$ | O$_3$ | PM$_{2.5}$ | PM$_{10}$ | CO | SO$_2$ |
| Wuhan urban | $-43.7\%$ | $+115.3\%$ | $-36.9\%$ | $-30.6\%$ | $-11.5\%$ | $+1.0\%$ |
| traffic | $-55.2\%$ | $+114.3\%$ | $-43.6\%$ | $-30.2\%$ | $-15.6\%$ | $-5.3\%$ |
| Beijing urban | $-32.2\%$ | $+39.6\%$ | $-11.8\%$ | $-3.1\%$ | $-31.2\%$ | $-29.4\%$ |
| traffic | $-24.8\%$ | $+49.7\%$ | $-14.0\%$ | $-5.1\%$ | $-34.3\%$ | $-25.5\%$ |
| Urumqi urban | $-34.8\%$ | $+93.0\%$ | $-45.3\%$ | $-14.5\%$ | $-32.3\%$ | $-2.3\%$ |
| traffic | $-39.1\%$ | $+93.3\%$ | $-50.3\%$ | $-27.0\%$ | $-33.0\%$ | $-7.8\%$ |
| Detrended | NO$_2$ | O$_3$ | PM$_{2.5}$ | PM$_{10}$ | CO | SO$_2$ |
| Wuhan urban | $-33.2\%$ | $+69.3\%$ | $-14.6\%$ | $-17.3\%$ | $-3.6\%$ | $+18.6\%$ |
| traffic | $-46.2\%$ | $+57.3\%$ | $-21.7\%$ | $-19.9\%$ | $-2.8\%$ | $+8.3\%$ |
| Beijing urban | $-19.8\%$ | $+2.1\%$ | $-17.0\%$ | $+6.0\%$ | $-12.2\%$ | $-9.1\%$ |
| traffic | $-16.4\%$ | $+7.0\%$ | $-16.6\%$ | $+2.9\%$ | $-16.0\%$ | $-7.2\%$ |
| Urumqi urban | $-31.8\%$ | $+40.1\%$ | $-34.0\%$ | $-8.7\%$ | $-16.7\%$ | $+13.7\%$ |
| traffic | $-25.3\%$ | $+35.4\%$ | $-34.7\%$ | $-20.0\%$ | $-15.2\%$ | $+3.6\%$ |

Fig. 5. Observed and deweathered daily PM$_{2.5}$ concentrations at four types of stations in three cities from 1 January to 31 May in 2020 versus 2019.
sudden decreases were observed in Wuhan and Urumqi a few days after the lockdown began but less so in Beijing. After the first week of the lockdown, people were able to use private cars despite the disruption to public transport in Wuhan and traffic with other cities (Pei et al., 2020). In Beijing, there was an increase in deweathered PM$_{2.5}$ after the lockdown began initially, but there was a decrease afterward.

During our study period, the $P_{dew}$ values (Table 2 and S3) for deweathered PM$_{2.5}$ range from −14.0% in Beijing to −50.3% in Urumqi at traffic stations, from −11.8% in Beijing to −45.3% in Urumqi at urban stations, and from −33.6% in Wuhan to −54.2% in Urumqi at industry stations. Among Beijing and Wuhan, the largest decrease was found at traffic stations. Generally, the local road traffic source has been suggested to be the dominate contributor to PM$_{2.5}$ on the road of heavy traffic (Hu et al., 2014). Meanwhile, a significant decrease in volume of petrol and diesel vehicles was reported during the COVID-19 pandemic (Wang et al., 2020), the average speeds in Beijing increased overall by 43% from January 24 to February 9, and traffic volumes decreased by 58% (Wang et al., 2020). Additionally, the deweathered PM$_{2.5}$ dropped more markedly in Urumqi, especially at the industry station. It reflects the different industrial structures of each city and the different pollution source apportionments. In addition, the lockdown measures have different effects on the production and economic activities in different cities. Both traffic and industrial activity in Urumqi have dropped significantly. Consistent with previous studies, lockdown may have a greater impact on colder and more industrially polluted cities (He et al., 2020). The fact that substantial decreases in PM$_{2.5}$/CO (Fig. S5) and PM$_{2.5}$/PM$_{10}$ (Fig. S6) ratios in Urumqi accompanied the decrease in deweathered PM$_{2.5}$. Ultrastrict short-term control measures are more effective in alleviating PM$_{2.5}$ pollution in Urumqi.

The overall changes in PM$_{10}$ are larger than those in PM$_{2.5}$, and there is more variability at different stations (Fig. S3). In general, the sudden decline can be observed after the lockdown, but less impact on industry stations. In Beijing, the trend of PM$_{10}$ was similar to that of 2019. In addition, an increase in deweathered PM$_{10}$ at rural stations was observed in Beijing. Compared with Wuhan and Beijing, a clear downward trend was observed in Urumqi (Fig. S3). Deweathered PM$_{10}$ decreased most at the industry station in Urumqi (−38.2%), reflecting the source of industrial dust.

Deweathered CO levels were lower after lockdown started than before in 2020. A sudden change is observed in Urumqi only (Fig. S4). In Beijing, deweathered CO increased slightly after the lockdown began, before falling for about 2 weeks, after which there was a substantial increase at all three types of stations. In Wuhan, the decreasing trend in deweathered CO is not distinguishable from that in 2019. In Urumqi, a decline in deweathered CO is observed a week after the lockdown began, with −32.3% at urban stations and −33.0% at traffic stations. With the economic development, the number of motor vehicles in Urumqi has increased rapidly. The restriction of traffic in Urumqi during the COVID-19 lockdowns significantly reduced the concentration of major pollutants in car exhaust in the ambient air. Changes in traffic flow have a great impact on CO concentration in the air.

Deweathered SO$_2$ decreased from west to east, with higher concentration values (6.9–13.5 μg/m$^3$) in Urumqi and Wuhan and lower values (4.4–5.6 μg/m$^3$) in Beijing during lockdown (see Table S3). The variation in deweathered SO$_2$ relied on specific stations and cities. No sudden change is observed in any of the cities immediately after the lockdowns. In Beijing, deweathered urban and traffic SO$_2$ increased at first and then decreased by −30%. In opposite, the increase in deweathered rural SO$_2$ might be relevant to rising resident combustion. Meanwhile, deweathered SO$_2$ in 2020 was significantly lower than in 2015–2019, indicating that from 2013 to 2017, a number of SO$_2$ governance solutions have had a positive effect on reducing SO$_2$ (Zhang et al., 2019; Xue et al., 2019). Therefore, the reduction in SO$_2$ is relatively limited. A huge decrease in deweathered SO$_2$ at industry stations reflects the heavy industry structure of Urumqi.

### 3.4. Driving forces of variations in air pollutants

#### 3.4.1. The influence of meteorology

In our study, a great difference between observed and deweathered pollutants concentrations can be observed among three cities (Fig. 4 and S2 to S4), reflecting the importance of the meteorological effect. Fig. 6 illustrates the contribution of meteorology and anthropogenic emissions to percentage changes of six pollutants concentrations (2020.2.1–3.15 vs. 2020.1.1–1.20) at urban stations in Beijing, Wuhan, and Urumqi.

Different temporal variations and distinct meteorological and emission impacts could be found among the three cities. Except for O$_3$, anthropogenic emissions of most pollutants were reduced. In Beijing, observed PM$_{2.5}$ increased by 21.7% (Table S2). However, the increase in PM$_{2.5}$ is mainly due to adverse meteorological conditions, which contributed to +33.5%. The deweathered concentrations of air pollutants were significantly lower than their observed values, indicating unfavorable meteorological conditions for pollutant dispersion (Zhang et al., 2020). In fact, the emission reduction contributed to an 11.8% decrease in PM$_{2.5}$ (Table 2). A credible interpretation for this unexpected outcome was that an increase in secondary aerosol formation counteracts the benefit of the reduction in primary PM$_{2.5}$ emissions (Huang et al., 2021). The fact that great increases in PM$_{2.5}$/CO ratios along with the increase in deweathered PM$_{2.5}$ in Beijing was observed in Fig. S5. Our study demonstrates that meteorology contributes the most to variations in pollutant concentrations in Beijing. The results are similar to those of previous studies (Wang et al., 2020; Li et al., 2020; Sun et al., 2020; Sun et al., 2020; Zhao et al., 2021). Therefore, except for strict local emission control from industry, transportation as well as residential use, air pollution control in Beijing should strengthen regional joint prevention and control as well as heavy pollution weather emergency measures.

The effects of O$_3$ are more complex. In Beijing, observed O$_3$ increased by 76.4%, with emissions accounting for +39.6% and meteorology accounting for +36.8%. In Urumqi, unfavorable meteorological conditions predominated. In contrast, the level of O$_3$ in Wuhan significantly increased by 115.3%, primarily due to large changes in precursor

![Fig. 6. Proportion of contribution of meteorological and emission factors to the change rate of six pollutants concentrations (2020.2.1–3.15 vs. 2020.1.1–1.20) at urban stations in three cities.](image-url)
emissions, especially for NO$_2$. In short, emission variations and meteorological conditions contribute to the increase in ground-level O$_3$. From this natural experiment, O$_3$ pollution does not only occur during the hot summer months; reducing NO$_x$ emissions such as this simply is not the right approach (Huang et al., 2021). It is necessary to strengthen VOC control and promote coordinated emission reduction of PM$_{2.5}$ and O$_3$. In Urumqi, a megacity located in western China, the levels of PM$_{10}$ significantly decrease by 35.6%, and meteorological impacts dominated the declines. Some studies in other countries and regions also reveal the importance of meteorological conditions in air quality changes. A study of Israel showed that the total percentage change of pollution emissions explained by the lockdown was up to 26%, which increased to 47% by taking meteorological conditions as a factor in addition to the lockdown effect (Agami and Dayan, 2021). In India, Mandal et al. (2022) noted that adverse meteorological conditions exacerbated Delhi’s air pollution situation.

3.4.2. True effects on air quality

Through a simple comparison before and after the lockdown, the concentration of pollutants is affected by meteorological conditions as well as seasonal changes in emissions (Hernandez-Paniagua et al., 2021). As shown in Fig. 7 (a), whether there is a lockdown or not, obvious changes in deweathered pollutants during the same periods were also observed in 2015–2019. For example, during the same period from 2015 to 2019, despite the absence of lockdown, deweathered O$_3$ increased 46.0%, 41.7%, and 52.9% (trend) in Wuhan, Beijing, and Urumqi, respectively (Table 3). In addition to the elimination of meteorological effects, the elimination of trends in “activity as usual” change is also crucial for estimating the actual change resulting from the intervention (i.e., the lockdown). In this section, our study quantified the true influence of regulatory behavior on air quality during the COVID-19 epidemics.

Considering urban stations in Beijing as an example, observed NO$_2$, PM$_{2.5}$, and O$_3$ changed by $\pm$42.9%, $\pm$21.7% and $\pm$76.4%, respectively (obtained from unadjusted concentration data before/during lockdown, Table 3). However, the observed values are considerably higher (sometimes by a factor of 10) than our detrended results, which are $\pm$19.8% for NO$_2$, -17.0% for PM$_{2.5}$ and $\pm$2.1% for O$_3$. This may demonstrate the necessity of disentangling the changes due to meteorological variation and seasonality and from the lockdown-driven changes in emissions to understand the resulting differences in air pollutant concentrations.

From Table 3 and S4, in Wuhan, the net effect due to lockdown was $\pm$17.3% (PM$_{10}$), $\pm$14.6% (PM$_{2.5}$), $\pm$3.6% (CO), $\pm$33.2% (NO$_2$) and $\pm$69.3% (O$_3$), respectively. In Beijing, the pollutant concentrations decreased by 17% (PM$_{2.5}$), 12.2% (CO), and 19.8% (NO$_2$). In Urumqi, the concentrations declined by 8.7% (PM$_{10}$), 34.0% (PM$_{2.5}$), 16.7% (CO) and 31.8% (NO$_2$). Our detrended results demonstrate that the decline in CAPs concentrations attributable to the lockdowns was not as large as that observed.

The true NO$_2$ decreased by 33.2%, 19.8%, and 31.8% in Wuhan, Beijing, and Urumqi, respectively. We investigated the change in the traffic intensity in the three cities during the study period (Fig. S7). Before the lockdown, the travel intensity in 2019 and 2020 was similar, while when the lockdown went into effect in 2020, the travel intensity decreased significantly compared with the same period last year. The travel intensity was reduced by 60.2%, 76.9%, and 86.3% in Beijing, Urumqi, and Wuhan (Fig. S7) during the lockdown period (2020.2.1–3.15) compared with pre-lockdown (2020.1.1–1.20). The travel intensity data refers to the exponential results of the ratio of the number of people who travel out of the city to the resident population in the city and can be used to measure the degree of urban vitality recovery (Wang et al., 2021). The change in the travel intensity index of the three cities is consistent with the decrease in NO$_2$. There is a strong correlation between NO$_2$ pollution and traffic activity intensity (Wang et al., 2021). Results in Table S2 show that the NO$_2$ level in three cities almost reached the National level standard (40 μg/m$^3$) due to the lockdown measures. According to our research, we found that traffic activity management is

![Fig. 7](http://example.com/fig7.png)

Fig. 7. (a) Concentration change rate of deweathered pollutants during lockdown period versus pre-lockdown period in 2020 and 2015–2019 and (b) the true percentage change (due to lockdown) of air pollutants at urban stations in three cities.
of great significance for NO\textsubscript{2} pollution control in densely populated urban areas.

4. Conclusions

In this study, we utilize a deweathering machine learning algorithm to explore the air quality variations caused by COVID-19 in three Chinese megacities (Wuhan, Beijing, and Urumqi) improved due to the COVID-19 pandemic. However, the CAPs were found to have markedly different responses to containment measures at different stations in different cities. Our results emphasize the need for high spatial resolution ground-based research to capture the variation of different pollutants. From our results, NO\textsubscript{2} was the most sensitive to the lockdown in all three cities, deweathered NO\textsubscript{2} decreased by 43.7% in Wuhan, 34.8% in Urumqi and 32.2% in Beijing, a consequence of the decline in traffic activities. In Wuhan and Urumqi, deweathered CO and NO\textsubscript{2} decreased the most at traffic stations and the least at industry stations. However, unlike observations in Wuhan and Urumqi, deweathered NO\textsubscript{2} in Beijing showed the smallest decline at traffic stations (−24.8%). Although an increase in deweathered O\textsubscript{3} was generally observed, the increase was minimal at rural stations among three cities. In addition, the SO\textsubscript{2} variation reveals a mixed pattern, determined by city and station type. Removing the effects of meteorology, deweathered PM\textsubscript{2.5} declined by 36.9%, 11.8%, and 45.3% in Wuhan, Beijing, and Urumqi, respectively, which showed that reducing primary emissions from mobile sources is the most effective way to alleviate PM\textsubscript{2.5} pollution in Urumqi compared with Beijing and Wuhan. At the same time, we can see that the adverse meteorological conditions have a great effect on the occurrence of haze in Beijing. Consequently, it is essential to assess variations in air pollutant concentrations without meteorological influence.

After detrended analysis, we found that the lockdown did have a significant impact on air quality. The results show that the true percent change in CO, NO\textsubscript{2}, and PM\textsubscript{2.5} ranged from −0.7% to −16.7%, −15.2% to −46.2%, and −2.3% to −40.2%, respectively. Reducing traffic activity is the most effective way to reduce NO\textsubscript{2} pollution. Although the largest percentage decrease in PM\textsubscript{2.5} was observed in Urumqi, its absolute concentration was still the highest among the three cities. This indicates that the situation of air pollution control in Urumqi is still very serious in the future. The optimization of the industrial structure and increase in clean energy use should be valued in Urumqi. In addition, the frequent pollution events that occurred during the lockdown suggest that actions on a similar scale are far from sufficient to prevent sporadic pollution events.

Our results show that there is obvious heterogeneity among different cities. Our study provides a reference for the change of pollutant concentration at the city scale during plugging. Future regulatory actions must adopt city-specific methods for NO\textsubscript{2}, O\textsubscript{3}, and PM\textsubscript{2.5}, as well as several other non-criteria pollutants, such as VOCs and NH\textsubscript{3} which have not been under contiguously monitored at the current Chinese air quality monitoring stations, considering both primary discharge and secondary generation processes of pollutants to maximize the total benefits for air quality and human health.

CRediT author statement

Yunqian Lv: Conceptualization, Methodology, Modelling, Software, Investigation, Writing – original draft, preparation. Hezhong Tian: Conceptualization, Data curation, Formal analysis, Writing – review & editing, and, Supervision. Lining Luo: Validation, Formal analysis, Visualization. Shuhan Liu: Validation, Formal analysis, Visualization. Xiaoxuan Bai: Validation, Formal analysis, Visualization. Hongyan Zhao: Formal analysis, Writing – review & editing. Shumin Lin: Formal analysis, Visualization. Shuang Zhao: Formal analysis, Visualization. Zhihui Guo: Validation, Formal analysis. Yifei Xiao: Validation, Formal analysis. Junqi Yang: Validation, Formal analysis, All authors contributed to interpretation of the data and provided comments on the manuscript.

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 to this article can be found online at https://doi.org/10.1016/j.apr.2022.101452.

References

Agami, S., Dayan, U., 2021. Impact of the first induced COVID-19 lockdown on air quality in Israel. Atmos. Environ. 262 https://doi.org/10.1016/j.atmosenv.2021.118627.

Bao, R., Zhang, A., 2020. Does lockdown reduce air pollution? Evidence from 44 cities in northern China. Sci. Total Environ. 731, 139052. https://doi.org/10.1016/j.scitotenv.2020.139052.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Camelliti, M., 2020. The effect of corona virus lockdown on air pollution: evidence from the city of Brescia in Lombardia region (Italy). Atmos. Environ. 239 https://doi.org/10.1016/j.atmosenv.2020.117794.

Coccia, M., 2020. Factors determining the diffusion of COVID-19 and suggested strategy to prevent future accelerated viral infectivity similar to COVID. Sci. Total Environ. 729, 138474. https://doi.org/10.1016/j.scitotenv.2020.138474.
Pei, Z., Han, G., Ma, X., Su, H., Gong, W., 2020. Response of major air pollutants to COVID-19 lockdowns in China. Sci. Total Environ. 743, 140877. https://doi.org/10.1016/j.scitotenv.2020.140877.

Petetin, H., Bowdalo, D., Soret, A., Guevara, M., Jorba, O., Serradell, K., Perez Garcia-Pando, C., 2020. Meteorology-normalized impact of the COVID-19 lockdown upon NO2 pollution in Spain. Atmos. Chem. Phys. 20 (18), 11119–11141. https://doi.org/10.5194/acp-20-11119-2020.

Rathod, A., Sahu, S.K., Singh, S., Beig, G., 2021. Anomalous behaviour of ozone under COVID-19 and explicit diagnosis of O3-NOx-VOCS mechanism. Heliyon 7 (2). https://doi.org/10.1016/j.heliyon.2021.e05642.

Sharma, S., Zhang, M., Anshika Gao, J., Zhang, H., Kothi, S., 2020. Effect of restricted emissions during COVID-19 on air quality in India. Sci. Total Environ. 728, 138878. https://doi.org/10.1016/j.scitotenv.2020.138878.

Sheng, T., Pan, J., Duan, Y., Liu, Q., Fu, Q., 2019. Study on characteristics of typical traffic environment air pollution in Shanghai, China. Sci. Total Environ. 39 (8), 3139–3140. https://doi.org/10.1016/j.scitotenv.2019.01.044.

Shi, Z., Song, C., Liu, B., Lu, G., Xu, J., Yuan, V., Elliott, R.J.R., Li, W., Bliss, W.J., Harrison, R.M., 2021. Abrupt but smaller than expected changes in surface air quality attributable to COVID-19 lockdowns. Sci. Adv. 7 (3), eabd6696. https://doi.org/10.1126/sciadv.abd6696.

Sidorchuk, P., D’Alessio, G., Sato, M., 2020. Amplified ozone pollution in cities during the COVID-19 lockdown. Sci. Total Environ. 735, 139542. https://doi.org/10.1016/j.scitotenv.2020.139542.

Singh, V., Singh, S., Biswal, A., Kesarkar, A.P., Mor, S., Ravindra, K., 2020. Diurnal and temporal changes in air pollution during COVID-19 stratlock down over different regions of India. Environ. Pollut. 266, 115368. https://doi.org/10.1016/j.envpol.2020.115368.

Srivastava, A.K., Bhoyar, P.D., Kanawade, V.P., Devaraj, P.C.S., Thomas, A., Soni, V.K., 2021. Improved air quality during COVID-19 at an urban agglomeration over the Indo-Gangetic Basin: from stringent to relaxed lockdown phases. Urban Clim. 36, 100791. https://doi.org/10.1016/j.uclim.2021.100791.

Sun, Y., Lei, Z., Zhou, Y., Chen, C.H., He, Y., Sun, J., Li, Z., Xu, W., Wang, Q., Ji, D., Fu, P., Wang, Z., Worsnop, D.R., 2020. A chemical cocktail during the COVID-19 outbreak in Beijing, China: insights from six-year aerosol particle composition measurements during the Chinese New Year holiday. Sci. Total Environ. 742, 140739. https://doi.org/10.1016/j.scitotenv.2021.140739.

Tian, H., Liu, Y., Li, Y., Wu, C.H., Chen, B., Kramer, M.U.G., Li, B., Cai, J., Xu, B., Yang, Q., Wang, B., Yang, Y., Song, Y., Zheng, Y., Wang, Q., Bjomstad, O.N., Yang, R., Grenfell, B.T., Pybus, O.G., Dye, C., 2020. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 368 (6491), 638. https://doi.org/10.1126/science.abb1055.

Venter, Z.S., Aunan, K., Chowdhury, S., Lievens, J.V., 2020. COVID-19 lockdown causes global air pollution declines. Proc. Natl. Acad. Sci. U.S.A. 117 (32), 18984–18990. https://doi.org/10.1073/pnas.2006531117.

Yu, T.V., Shi, Z., Cheng, J., Zhang, Q., He, K., Wang, S., Harrison, R.M., 2019. Assessing the impact of clean air action on air quality trends in Beijing using a machine learning technique. Atmos. Chem. Phys. 19 (17), 11303–11314. https://doi.org/10.5194/acp-19-11303-2019.

Wang, J., Xu, X., Wang, S., He, S., He, P., 2021. Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China. Appl. Energy 282, 116179. https://doi.org/10.1016/j.apenergy.2020.116179.

Wang, P., Chen, K., Zhuo, S., Zhang, P., Wang, H., 2020. Severe air pollution events not mediated by reduced anthropogenic activities during COVID-19 outbreak. Resour. Conserv. Recycl. 158, 108414. https://doi.org/10.1016/j.resconscr.2020.108414.

Yang, R., Grenfell, B.T., Pybus, O.G., Dye, C., 2020. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 368 (6491), 638. https://doi.org/10.1126/science.abb1055.

Wu, C., Wang, L., Cai, W., He, H., Ni, A., Peng, Z., 2021. Impact of the COVID-19 Lockdown on Roadside Traffic-Related Air Pollution in Shanghai, China. Building and Environment, p. 194. https://doi.org/10.1016/j.buildenv.2021.107718.

Xue, Y., Zhang, S., Zhou, Z., Kang, L., Liu, K., Wang, X., Shi, A., Xu, K., Tian, H., 2019. Spatio-temporal variations of multiple primary air pollutants emissions in Beijing, China. Atmosphere 10 (9), 494. https://doi.org/10.3390/atmos10090494.

Zheng, Q., Zhang, Y., Tong, D., Shao, M., Wang, S., Zhang, Y., Xu, X., Wang, J., He, H., Liu, W., Ding, Y., Lei, Y., Li, J., Wang, Z., Zhang, X., Wang, J., Cheng, J., Liu, Y., Shi, Q., Yan, L., Geng, G., Hong, C., Li, M., Liu, F., Zheng, B., Cao, J., Ding, A., Gao, F., Fu, Q., Hao, J., Li, J., Liu, Y., Yang, F., He, K., Hao, J., 2019. Drivers of improved PM2.5 air quality in China from 2013 to 2017. Proc. Natl. Acad. Sci. U.S.A. 116 (49), 24463–24469. https://doi.org/10.1073/pnas.1907956116.

Zhao, X., Wang, G., Wang, S., Zhao, N., Zhang, M., Yue, W., 2021. Impacts of COVID-19 on air quality in mid-eastern China: an insight into meteorology and emissions. Atmos. Environ. 266. https://doi.org/10.1016/j.atmosenv.2021.118750.