Spatial Disparity of Meteorological Impacts on Carbon Monoxide Pollution in China during the COVID-19 Lockdown Period

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ABSTRACT: Lockdown due to the novel coronavirus disease 2019 (COVID-19) pandemic offers a unique opportunity to study the factors governing the variation in air pollution. A number of studies have investigated the cause underlying the occurrence of heavy haze pollution around the world during the lockdown period. However, information about spatiotemporal variations in gaseous pollutants and detailed quantifications of potential meteorological (METRO) impacts are limited. Ground measurements show that carbon monoxide (CO) pollution deteriorated in northern China despite strict control of human and industrial activities during the lockdown period in early 2020. In this study, a four-dimensional decomposition model was used to quantitatively extract the METRO impacts on the CO pollution over China. The results show that weakened winds elevated CO concentrations near Beijing and in northeastern China. Increased temperatures slightly elevated CO concentrations in northern and eastern China but reduced CO concentrations in northwestern China. Remarkable amounts of CO increases in northern China (e.g., by 0.21 mg/m³ within Beijing) were explained by anomalously high humidity, which could be associated with an enhanced interaction between aerosol and the boundary layer. After excluding the METRO impacts, the CO concentrations drastically declined across China (e.g., by 0.22 mg/m³ within Beijing), indicating that the lockdown indeed greatly lessened CO concentrations. However, the adverse METRO conditions counteracted the beneficial outcomes of emission reductions, leading to a deterioration of the CO pollution in northern China. These results indicate that the METRO factors can play a critical role in worsening air pollution despite a strict control of anthropogenic emissions.

KEYWORDS: carbon monoxide, air pollution, meteorology, lockdown, COVID-19

INTRODUCTION

Carbon monoxide (CO) is recognized to be a significant threat to human health,1,2 and plays an essential role in various photochemical oxidation processes in the atmosphere, such as the formation of tropospheric ozone.3,4 CO is mainly produced from biomass burning and an incomplete combustion of fossil fuels from industrial sectors.5 In urban areas, industry, transportation, and boiler heating can be major emission sources of CO.5 Variation in CO concentration is determined by not only emission reductions but also meteorological (METRO) conditions.7 For instance, wind conditions greatly affect horizontal transport and dispersion of air pollutants.6,9 The wind impacts are particularly important for the dispersion of air pollutants produced by industrial emission sources in urban areas and the transport of smoke released by natural sources (e.g., wildfire).10,11 Significant wind impacts on the pollutant transport were even found in the Arctic region.12 Because the CO is less affected by wet scavenging, it has been frequently used as a tracer of other air pollutants to identify the transport efficiency.12 Boundary layer height determines the extent of vertical mixing and diffusion of air pollutants.13,14 Numerous studies have documented clear connections between pollutant concentration and wind or boundary layer height.15 Severe air pollution episodes frequently occurred under adverse METRO conditions that hindered the dispersion of air pollutants in the boundary layer.16,17

Because of the novel coronavirus disease 2019 (COVID-19) pandemic, intensive lockdowns have been enforced around the world.18,19 The lockdown offers a unique opportunity to study the factors governing the variation in air pollution. A number of studies have revealed significant impacts of METRO factors on the evolution of heavy air pollution in China during the COVID-19 lockdown (CVL) period in early 2020.20,21 An

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anomalously shallow boundary layer was believed to be a key cause of the severe air pollution that occurred in northern China.\textsuperscript{22} Intense wildfires in Southeast Asia greatly contributed to the occurrence of heavy air pollution in southwestern China.\textsuperscript{11} Some diurnal variation analyses showed that the pollution–meteorology interaction may impede the reduction of air pollutant concentration in the afternoon.\textsuperscript{25} However, most of them were performed to explore the cause underlying the severe haze pollution, which is mainly determined by particulate matter.\textsuperscript{24,25}

To understand the impact of lockdown on the CO pollution in Wuhan, Lian et al. (2020)\textsuperscript{26} analyzed the ground measurements of CO concentrations in the city and found a reduction rate of 23%. Another assessment performed by Shi and Brasseur (2020)\textsuperscript{27} found a similar rate of CO reduction in Wuhan and an insignificant change in CO pollution in Beijing. Su et al. (2020)\textsuperscript{22} compared ground measurements of CO concentrations during the CVL period with climatological averages and noticed that the CO concentrations remained steady or even remarkably increased in northern China. Some other studies relied on satellite-based measurements to evaluate the variation in CO pollution under the lockdown circumstances.\textsuperscript{31,32} A number of studies have investigated the causes underlying the occurrence of heavy CO pollution and found that the low boundary layer and a significant amount of transboundary transport worsened the CO pollution in certain regions.\textsuperscript{11,22} Although some features of the CO variations have been revealed in aforementioned studies, quantitatively extracting the impacts of METRO factors is limited.

Quantification of the METRO impacts on air pollution remains a big challenge.\textsuperscript{30} The methods mainly include simulation- and observation-based models. Simulation-based models compare the predictions of air pollutant concentrations among different scenarios with a fixed METRO condition or a fixed pollutant emission.\textsuperscript{31,32} These simulation-based models require a heavy load of computations and may embody considerable prediction uncertainties.\textsuperscript{33} Meanwhile, a requirement of emission inventory can considerably delay the investigations.\textsuperscript{34} Observation-based models apply various statistical techniques, such as multiple linear regression, to identify the METRO impacts on air pollution.\textsuperscript{35–37} By analyzing the change in frequency distribution of METRO factors, Song et al. (2021)\textsuperscript{38} used a four-dimensional (4D) model to extract the METRO impacts on the occurrence of heavy haze pollution across China during the CVL period in early 2020.

In this study, we shall focus on investigating the spatial disparity of the CO variation and quantitatively extracting the potential impacts of METRO factors on the CO pollution across China during the CVL period in early 2020. First, we will comparatively evaluate the CO concentrations across China between 2019 and 2020. Second, associations between the CO concentrations and the METRO variables will be discussed. Then, the 4D decomposition model from Song et al. (2021)\textsuperscript{38} will be applied to quantify the impacts of various METRO factors on the CO pollution. Third, the CO variations after excluding the METRO impacts will be described in detail to help understand the effectiveness of strict controls of human and industrial activities.

## DATA AND METHODOLOGY

**METRO Monitoring.** This study was performed to understand the METRO impacts on the CO pollution from 23 January to 10 March 2020 when a strict lockdown was implemented across China.\textsuperscript{38} We comparatively evaluated the METRO and air quality data during the same period between 2020 and 2019. Ground-level hourly METRO data, including wind speed, wind direction, temperature, and relative humidity, were acquired from the World Meteorological Organization (WMO) global telecommunication system. As shown in Figure S1, the METRO values were regularly monitored at 216 stations across China. According to the WMO, the required precisions of minute measurements of wind, temperature, and relative humidity are ±0.5 m/s, ±0.1 °C, and ±3%, respectively.

**CO Concentration.** A database of the Institute for the Environment (IENV) regularly collates air quality monitoring data across China (http://envf.ust.hk/dataview). Hourly data on ground-level CO concentration over China were obtained from government agencies of mainland China, Taiwan, Hong Kong, and Macau. To align CO concentration with the METRO data, we averaged the CO concentrations at all monitoring stations within a distance of 50 km from each METRO station. Thus, hourly CO concentration data at 216 METRO stations during 23 January–10 March of 2019 and 2020 were obtained for the analyses in this study. According to the Chinese ambient air quality monitoring standards (HJ 965-2018), precision of the CO measurement using the nondispersive infrared spectrometry method ranges from 1.4 to 8.6%.

**Daily Maximal Mixing Layer Height.** Vertical sounding of METRO values can be used to calculate the mixing layer height (MLH). In China, upper-level METRO values are regularly measured using radiosondes that are hung from balloons at 8:00 am and 8:00 pm local time (i.e., Beijing time) every day. In this study, the radiosonde measurements across China were acquired from the WMO and were then applied to estimate the daily maximal MLH at 2:00 pm using the parcel method, which assumes a uniform profile of potential temperature within a layer that is well mixed.\textsuperscript{39} More details on the calculation of daily maximal MLH can be found in previous studies.\textsuperscript{40,41} We notice that the upper-level sounding data over China in 2020 may not be available in the WMO system due to the data uploading issue. In this study, our analyses mainly applied the sounding data during 23 January–10 March in 2019. Good agreement was found between the nocturnal MLH derived from the radiosonde and the lidar observations in Hong Kong with a correlation coefficient of 0.63 (N = 2075) and a percentage deviation of around 20%.\textsuperscript{40}

**Meteorology–Pollution Decomposition Model.** A 4D meteorology–pollution decomposition model\textsuperscript{38} was applied to quantify major METRO impacts on the variation in CO concentration. The decomposition model is summarized in brief in the section. More details can be found in Supporting Information and in previous studies.\textsuperscript{38,42}

We define a 4D “METRO matrix” ($F_{M}$) to depict the normalized frequency distribution of the METRO values and define a 4D “pollution matrix” ($C_{M}$) to depict the variation in CO concentration as a function of the METRO values. The change in CO concentration between two periods can be expressed as

$$\Delta C = C_{M1} - C_{M2}$$

$$\Delta C = C_{M1} - C_{M2}$$

$$\Delta C_{M1} = C_{M1} - C_{M2}$$

(1)
\( F_{M_2}(C_{M_2} - C_{M_1}) \) indicates the change in CO concentration resulting from the non-METRO impact. The last term \( \varepsilon_M \) indicates the unresolved change in CO concentration resulting from a nonlinear interaction between the METRO and non-METRO values. The confidence level of the linear decomposition is identified by a linear index

\[
L = 1 - \frac{|\varepsilon_M|}{|C_{M_1}(F_{M_2} - F_{M_1})| + |F_{M_1}(C_{M_2} - C_{M_1})| + |\varepsilon_M|} 
\]

(2)

The linear index of >0.98, >0.93, and >0.87 indicates confidence levels of 99, 95, and 90% respectively.

### RESULTS

#### Change in CO Concentration

We compared the CO concentration levels during 23 January–10 March between 2020 and 2019. Figure S2 shows the average CO concentrations at all stations across China in (a) 2019 and (b) 2020. The highest CO concentration levels were found in the North China Plain (NCP). The national average CO concentration reduced from 0.92 ± 0.30 mg/m³ in 2019 to 0.78 ± 0.26 mg/m³ in 2020. The change in CO concentration at all stations across China from 2019 and 2020 is illustrated in Figure 1. The lockdown remarkably lessened CO concentration levels in most regions of China. In Shanghai, Guangzhou, Wuhan, and Chengdu, the CO concentration reduced by 0.09, 0.25, 0.05, and 0.21 mg/m³, respectively. Unexpectedly, the CO concentration level remained steady or even increased around Beijing, the capital of China. The CO concentration level remained steady or even increased around Beijing, the capital of China. The unexpected change in CO concentration level was 90%.

#### Wind Impact in Beijing

Association between the CO concentration and relative humidity (\( C_{H_1} \) for 2019 and \( C_{H_2} \) for 2020) in Beijing is shown in Figure 3a. The CO concentration significantly elevated with relative humidity. Ground-level monitoring of relative humidity in Beijing shows that average relative humidity remarkably increased from 35.5 ± 21.0% in 2019 to 59.6 ± 25.0% in 2020. The frequency distribution pattern of relative humidity in Beijing (\( F_{T_1} \) for 2019 and \( F_{T_2} \) for 2020) is shown in Figure S3. Panel (b) of Figure S4 identifies the change in the temperature matrix. The average temperature in Beijing slightly increased from 1.1 ± 6.5 °C in 2019 to 1.2 ± 5.2 °C in 2020. In addition, the frequencies of moderate temperature values greatly increased (e.g., frequency of temperature within 0–10 °C increased by 15%). The temperature variation can result from the impacts of the weather system and the variation in aerosol loading. Under such circumstances, the temperature impact (i.e., a dot product between \( C_{T_1} \) and \( F_{T_2} - F_{T_1} \)) slightly elevated the CO concentration by 0.01 mg/m³ with a linear index of 0.99 (corresponding confidence level was 99%).

#### Humidity Impact in Beijing

The association between the CO concentration and relative humidity (\( C_{H_1} \) for 2019 and \( C_{H_2} \) for 2020) in Beijing is shown in Figure 3b. The CO concentration significantly elevated with relative humidity. Ground-level monitoring of relative humidity in Beijing shows that average relative humidity remarkably increased from 35.5 ± 21.0% in 2019 to 59.6 ± 25.0% in 2020. The frequency distribution pattern of relative humidity in Beijing (\( F_{T_1} \) for 2019 and \( F_{T_2} \) for 2020) is shown in Figure S3. Panel (b) identifies the change in the humidity matrix. The occurrence frequencies of humid weather conditions drastically increased during the CVL period in 2020. Under such circumstances, the humidity impact (i.e., a dot product between \( C_{H_1} \) and \( F_{H_2} - F_{H_1} \)) remarkably elevated the CO concentration by 0.21 mg/m³ with a linear index of 0.87 (the corresponding confidence level was 90%).

#### Integrated METRO Impact in Beijing

The integrated METRO impact on the CO pollution in Beijing is identified based on the 4D decomposition model. The results show that the integrated METRO impact (i.e., a dot product between \( C_{M_1} \) and \( F_{M_2} - F_{M_1} \)) greatly increased the CO concentration by 0.26 mg/m³ in 2020. The change in CO concentration during 23 January–10 March between 2019 and 2020 is illustrated in Figure 1. The lockdown remarkably lessened CO concentration by 0.01 mg/m³ with a linear index of 0.99 (corresponding confidence level was 99%).

**Figure 1.** Change in CO concentration between 2019 and 2020 at all stations across China.

**Figure 2.** Association between CO concentration and wind (\( C_{W_1} \) for 2019 and \( C_{W_2} \) for 2020) within Beijing.
by 0.22 mg/m³ from 2019 to 2020 in Beijing. After excluding the integrated METRO impact, the non-METRO impact (i.e., a dot product between $F_{M1}$ and $C_{M2} - C_{M1}$) substantially reduced CO concentration by 0.22 mg/m³. The unresolved variation in CO concentration was estimated to be 0.03 mg/m³, with a linear index of 0.93 (corresponding confidence level was 95%). These results suggest that the strict controls of human and industrial activities resulting from the lockdown indeed remarkably reduced the CO concentration level in Beijing (by 28%). The unfavorable METRO conditions (e.g., indicated by lower wind speed and enhanced humidity), however, drastically elevated the CO concentration, which even counteracted the lockdown impacts.

**Spatial Disparity of the METRO Impacts in China.** The association between CO concentration and each METRO value across China is assessed. Figure 4a–c shows correlation coefficients between the daily average CO concentration and three METRO factors at all stations across China in 2019. Overall, the CO concentrations were inversely correlated with the wind speed, particularly in northern China, indicating the significant impact of horizontal dispersion on CO pollution. The national average correlation coefficient is identified as $-0.25 \pm 0.24$.

The relationship between CO concentration and temperature was diverse across China. Positive correlation coefficients were found in northern and eastern China, whereas negative correlation coefficients were identified in northwestern and southern China. Similar results were found in previous studies, showing that CO concentrations were positively correlated with relative humidity in northern and northeastern China.44 The cause underlying these positive correlations can be related to the interaction between aerosol and the boundary layer. It is well recognized that high humidity can promote the gas-to-particle transformations, thereby enhancing the formation of secondary aerosols via multiphase reactions.17,47 High loading of scattering aerosols cools the air near the ground and results in a more stable boundary layer, which further worsens air quality.48 Significant connection between the downwelling solar radiation and surface air pollution has been frequently documented.15 In particular, the interaction between aerosol and the boundary layer greatly enhances when the aerosol loading is high.49 Therefore, the humid weather can greatly enhance the interaction between aerosol and the boundary layer, leading to shallow boundary layers and high CO concentrations.

Figure S6 shows the change in (a) wind speed, (b) temperature, and (c) relative humidity at all stations across China between 2019 and 2020. It is found that the wind...
speeds increased in the NCP but decreased around Beijing and in northeastern China. The temperature extensively increased in most regions of China but dropped in northeastern China. More importantly, relative humidity remarkably increased in northern China, including Beijing. The change in daily maximal MLH at some stations surrounding China between 2019 and 2020 is presented in Figure S7. Although the MLH data over China in 2020 were not available from the database, the spatial pattern of the MLH change is consistent with that reported by Su et al. (2020), showing that the MLH drastically reduced in northern China.

Figure 5 summarizes the change in CO concentration from 2019 to 2020 resulting from the impact of three METRO factors for each province in China (the station-based results are shown in Figure S8). The weakened winds elevated CO concentrations near Beijing and in northeastern China (by 0.06 and 0.05 mg/m³ within Beijing and Heilongjiang, respectively). The enhanced temperature increased CO concentrations in northern and eastern China (by 0.02 mg/m³ in Hebei) but decreased CO concentrations in northwestern China (by 0.04 mg/m³ in Shaanxi). Remarkable amounts of CO increases in northern China (by 0.21 and 0.24 mg/m³ in Beijing and Liaoning, respectively) were explained by anomalously high humidity, which can greatly enhance the interaction between aerosol and the boundary layer. Spatial distribution of the confidence level of the decomposition of the impact of wind, temperature, and humidity is plotted in Figure S9. The averaged linear index at all stations across China for the wind, temperature, and humidity decomposition was estimated to be 0.91 ± 0.10, 0.91 ± 0.10, and 0.90 ± 0.12, respectively. These results indicate an average confidence level of 90% for the decompositions.

The integrated METRO impact on CO pollution over China is further assessed. Figure 6 shows the change in CO concentration resulting from the (a) METRO and (b) non-METRO impacts for each province of China (the station-based results are shown in Figure S10). The integrated METRO impact increased the national average of CO concentration by 0.01 ± 0.07 mg/m³, while the non-METRO impact reduced CO concentration by 0.14 ± 0.14 mg/m³. Spatial distribution of the confidence level of the humidity decomposition is plotted in Figure S11. High confidence levels of 99, 95, and 90% occurred at 26, 73, and 134 stations, respectively. The national average of the linear index at all stations across China was estimated to be 0.87 ± 0.11, suggesting an average confidence level of 90%.

In particular, the integrated METRO impact remarkably elevated CO concentrations in northern China (e.g., by 0.22 and 0.14 mg/m³ within Beijing and Tianjin, respectively). After excluding the integrated METRO impacts, the CO concentrations drastically dropped in northern China (e.g., by 0.22, 0.29, and 0.37 mg/m³ in Beijing, Tianjin, and Shanxi, respectively). These results reveal the significant impacts of the strict controls of human and industrial activities on the CO pollution in northern China during the CVL period. However, the unfavorable METRO conditions counteracted the beneficial outcomes of lockdown and thus deteriorated the CO pollution in northern China.

The METRO and non-METRO impacts on the CO variations in five key cities of China are illustrated in Figure 7. In Beijing, the METRO impact (mainly indicated by

![Figure 5](https://example.com/figure5.png) Change in CO concentration from 2019 and 2020 resulting from (a) wind, (b) temperature, and (c) relative humidity impacts for each province of China.

![Figure 6](https://example.com/figure6.png) Change in the CO concentration resulting from the (a) METRO and (b) non-METRO impacts for each province across China.
humidity) remarkably elevated the CO concentration. In Chengdu, the METRO impact reduced the CO concentration by approximately 0.04 mg/m³. The METRO impacts were within ±0.02 mg/m³ in Shanghai, Guangzhou, and Wuhan. Overall, the non-METRO impact played a dominant role in governing the variation in CO concentration in most regions of China, except in northern China. These results suggest that the restriction of human and industrial activities extensively declined the CO concentration in most regions of China during the CVL period. However, ascribing CO variation to the aforementioned restrictions may be misleading in certain areas, such as northern China, if the effects of METRO factors are not appropriately considered.

## DISCUSSION

Extreme haze pollution events (mainly associated with fine particulate matter) that occurred in northern China during the CVL period in early 2020 have been extensively investigated. Compared to the studies on haze pollution, investigation of the occurrence of gaseous pollution is limited. Although some features of the CO variation across China have been revealed, information about the cause underlying the deterioration of CO pollution and quantification of the METRO impacts is limited. This motivated us to have this study to investigate the spatial disparity of the CO variation and quantitatively extract the potential METRO impacts on the CO pollution across China during the CVL period.

An observation-based decomposition model was applied to extract the METRO and non-METRO impacts on the CO pollution. Several strengths exist with this decomposition model. First, the model is operated based only on the measurements from the ground monitoring network and does not embody complicated numerical simulations. Second, the model introduces a linear index to assign the uncertainty and validity of the results. Nationally, the average linear index was identified as 0.91 ± 0.10, 0.91 ± 0.10, 0.90 ± 0.12, and 0.87 ± 0.11 for extracting the impacts of wind, temperature, relative humidity, and integrated meteorology, respectively. The levels of these linear indices indicate a 90% confidence level for the decomposition in this study.

Analyses revealed a large spatial disparity of the METRO impacts on CO pollution across China. For instance, strengthened winds were observed in the NCP, whereas weakened winds appeared around Beijing and in northeastern China. As a result, the CO concentrations reduced in the NCP but increased near Beijing due to the impact of wind variation. Meanwhile, the CO concentrations showed different types of dependence on temperature across China. The CO concentrations increased with temperature in eastern and northeastern China but decreased with temperature in northwestern China. Finally, anomalously high levels of relative humidity were found in northern China, which could trigger the interaction between aerosol and the boundary layer. As a result, the shallow boundary layer (with high relative humidity) would hinder the dispersion and diffusion of air pollutants, thereby increasing CO concentrations.

Analyses in this study also showed that the significant METRO impact was responsible to the deterioration of CO pollution in certain regions of China during the CVL period in early 2020. The METRO impact remarkably increased CO concentrations in northern China, which even counteracted the beneficial outcomes of strict controls of human and industrial activities. After excluding the integrated METRO impact, CO concentrations greatly dropped across China, evidencing the beneficial outcomes of the emission reductions. In other words, ascribing the variation in CO pollution to emission controls without considering the METRO impacts could be misleading in certain regions.

This study aims to quantify the METRO impacts on air pollution. Reliable measurements of METRO values with a sufficient resolution are required. By design, the decomposition model in this study considered the impacts of three major METRO factors, which are regularly reported by the governments. The lack of reliable information of boundary layer height with a sufficient temporal resolution (e.g., hourly) within a large area is a limitation of this study. Reliable

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**Figure 7.** METRO and non-METRO impacts on the CO variations in five major cities across China.

**Figure 8.** Correlation coefficients between the MLH at 14:00 pm and each METRO value [wind speed in (a), temperature in (b), and relative humidity in (c)] at all stations across China in 2019. The points with a black edge indicate that the correlations have a 95% confidence level.
measurement of the boundary layer height remains a big challenge around the world. The upper-air measurements of METRO values using radiosondes are only available twice every day at a small number of stations. Although recent developments of lidar techniques allow remote sensing of the boundary layer height with a dense temporal resolution, the lidar network has not been available in China. Guo et al. (2016) analyzed the sounding data across China and concluded that the boundary layer height is negatively associated with surface pressure and lower tropospheric stability but positively associated with near-surface wind speed and temperature. In addition, good agreement was found between the boundary layer height derived from the radiosonde observations and reanalysis data. The MLH data set used in this study was evaluated by lidar measurements in Hong Kong. It is important to systematically compare the boundary layer height values derived from different measurements, such as the radiosondes and lidar systems, to improve our understanding of the data uncertainties.

To better understand the interaction between the boundary layer height and ground METRO variables, Figure 8 presents the correlation coefficients between daily maximal MLH at 14:00 pm and each METRO value across China in 2019. Overall, positive relationships between the MLH and temperature were identified across China, with a national average correlation coefficient of 0.51. Meanwhile, significant negative relationships were identified between the MLH and relative humidity across China, with a national average correlation coefficient of −0.54. Relative weak associations were found between the MLH and wind speed. Su et al. (2020) assessed the change in several METRO values across China during the CVL period and found that the boundary layer heights were anomalously low but relative humidity values were anomalously high in northern China. These results indicate that there is a considerable interaction between the boundary layer height and the ground METRO variables.

In northern China, there could be a considerable interaction between relative humidity and boundary layer height. Figure S12a shows the time series of relative humidity and daily maximal MLH in Beijing at 14:00 pm on each day during 23 January−10 March of 2019. High humidity values frequently occurred when the MLHs were low. A negative correlation coefficient of −0.42 (N = 47) was identified between the two variables. The box plot, as shown in Figure S12b, further confirms the negative correlation between the MLH and relative humidity. High humidity can enhance the formation of secondary aerosols, which cools the air near the ground and results in a more stable boundary layer. The lower mixing layer (with higher relative humidity) would inhibit the dispersion of air pollutants, thereby increasing CO concentration. Therefore, a considerable overlap effect on the CO pollution could exist between the boundary layer height and relative humidity. In summary, this study relied on regular METRO measurements to quantitatively extract the METRO impacts. Future studies can be performed to incorporate more METRO variables (e.g., boundary layer height) into the analyses when sufficient measurements are available.

The results imply that the interaction between aerosol and the boundary layer can play a critical role in the occurrence of both aerosol and gaseous pollution. It appears that a strong interaction between aerosol and the boundary layer was triggered during the lockdown period. A high loading of aerosols greatly increased the stability of the boundary layer, which further worsened air quality and increased ground-level concentrations of various air pollutants. These results indicate that a comprehensive investigation of air pollution mixtures is essential for understanding the mechanism of the occurrence of a severe air pollution event.

In this study, the MLH data were mainly applied to assist the decomposition analyses. Correlation coefficients between the MLH and each METRO value were estimated. Here, we further assess the impacts of the uncertainty of the MLH. Taking relative humidity as an example, we applied the Monte Carlo simulations to explore how the uncertainty of MLH affected the correlation between the MLH and relative humidity. In 1000 tests, we added random fluctuations on the MLH with a deviation of 20%. The national average of the correlation coefficient between relative humidity and MLH is estimated to be −0.46 ± 0.01, with a 99% confidence level. These results indicate that the interaction between relative humidity and boundary layer height is significant and stable.

Uncertainties of the METRO values and CO concentration can be transferred to the decomposition results. We applied the Monte Carlo simulations to explore how the uncertainties of METRO and CO data were transferred to the decomposition results. We used Beijing as the study region. In 1000 tests, we added random fluctuations on the hourly wind, temperature, relative humidity, and CO concentration with a standard deviation of ±0.5 m/s, ±0.1 °C, ±3%, and ±0.05 mg/m³ (i.e., 5% from 1 mg/m³), respectively. The 4D decomposition results show that the integrated METRO effect increased CO concentration by 0.21 ± 0.01 mg/m³, with a percentage deviation of 4.8%. Meanwhile, the anthropogenic effect reduced CO concentration by −0.23 ± 0.01 mg/m³ with a percentage deviation of 4.3%. These results indicate that the decomposition uncertainty resulting from the METRO values and CO concentration was well within 10%.

Due to the internal interaction between the METRO values, direct summation of the wind, temperature, and humidity effects may lead to a significant bias in the computation of the integrated METRO effect. Figure S13a shows the direct summation of the wind, temperature, and humidity effects for each province. The spatial pattern is similar to that obtained using the 4D decomposition model. Panel (b) shows the difference between the direct summation of the individual METRO effects and the integrated METRO effect estimated using the 4D decomposition method. In most provinces, the direction summation was larger than the effect estimated using the 4D decomposition method, resulting from the internal interactions between the METRO effects. Large METRO interactions were observed in northern China. For instance, the METRO interactions contributed 0.11 mg/m³ and 0.14 to the CO variation in Liaoning and Tianjin, respectively.

Su et al. (2020) discussed the major cause of the anomalously low boundary layer height that occurred in northern China during the CVL period and concluded that it was attributed to atmospheric dynamics. In specific, Beijing was located on the southeastern flank of a low-pressure system during the CVL period. The southwesterly winds then transported warm air masses over the cold surface, which stabilized the boundary layer. This dynamic process heated the upper boundary layer and had a cooling effect near the surface, resulting in a temperature inversion within the boundary layer. After the dynamical processes initiated the temperature inversion, areas near Beijing experienced a period with continuously shallow boundary layer height. As shown in this
The results in this study reveal that the lockdown indeed greatly lessened CO concentrations in China. After excluding the METRO impacts, the CO concentrations were negatively correlated with the anomalously high humidity. The integrated METRO factors on the CO pollution in northwestern China. More importantly, remarkable amounts of CO increases in northern China were attributable to the METRO impact induced by the anomalously high humidity. The integrated METRO influence remarkably increased CO concentrations in northern China. After excluding the METRO impacts, the CO concentrations drastically decreased across China, evidencing that the lockdown indeed greatly lessened CO concentrations. The results in this study reveal a significant interaction between the METRO factors and air pollution.

**CONCLUSIONS**

In this study, we aim to quantify the METRO impacts on the CO pollution and gain a better understanding of the cause underlying the deterioration of the CO pollution in northern China during the CVL period. A 4D meteorology–pollution decomposition model was used to extract the impacts of METRO factors on the CO pollution. A large spatial disparity in the CO pollution and gain a better understanding of the cause underlying the deterioration of the CO pollution in northern China during the CVL period. A 4D meteorology–pollution decomposition method and other plots (PDF)

**ASSOCIATED CONTENT**

**Supporting Information**

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsearthspacechem.1c00251.

Meteorology pollution decomposition method and additional figures showing meteorological and air quality monitoring stations in China, Spatial distribution of the average CO concentration at all stations in China during January 23–March 10 in 2019 and 2020, frequency distribution of wind, confidence level, spatial pattern, and other plots (PDF)

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**Notes**

The authors declare no competing financial interest.

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