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Analysis of the meteorological factors affecting the short-term increase in O₃ concentrations in nine global cities during COVID-19

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A B S T R A C T
Surface ozone (O₃) is a major air pollutant around the world. This study investigated O₃ concentrations in nine cities during the Coronavirus disease 2019 (COVID-19) lockdown phases. A statistical model, named Generalized Additive Model (GAM), was also developed to assess different meteorological factors, estimate daily O₃ release during COVID-19 lockdown and determine the relationship between the two. We found that: (1) Daily O₃ significantly increased in all selected cities during the COVID-19 lockdown, presenting relative increases from −5.7% (in São Paulo) to 58.9% (in Guangzhou), with respect to the average value for the same period in the previous five years. (2) In the GAM model, the adjusted coefficient of determination (R²) ranged from 0.48 (Sao Paulo) to 0.84 (Rome), and it captured 51–85% of daily O₃ variations. (3) Analyzing the expected O₃ concentrations during the lockdown, using GAM fed by meteorological data, showed that O₃ anomalies were dominantly controlled by meteorology. (4) The relevance of different meteorological variables depended on the cities. The positive O₃ anomalies in Beijing, Wuhan, Guangzhou, and Delhi were mostly associated with low relative humidity and elevated maximum temperature. Low wind speed, elevated maximum temperature, and low relative humidity were the leading meteorological factors for O₃ anomalies in London, Paris, and Rome. The two other cities had different leading factor combinations.

1. Introduction
The abrupt outbreak of the COVID-19 pandemic had significant societal and environmental impacts globally (Guzman, 2021). COVID-19 emerged and spread rapidly through the air to all parts of the world (Delhikhoon et al., 2021), with the World Health Organization (WHO) labelling the outbreak a global pandemic on March 11, 2020 (https://www.who.int/). To curb the spread of virus among humans and to avoid the collapse of medical systems, most national governments implemented lockdown measures aimed at containment (Shi and Brasseur, 2020). As a consequence of the lockdown, economic activity associated with transport and mobility were nearly eliminated in many countries, and emissions from the transport and industrial sectors decreased markedly because of the significant reduction in human activities (Bauwens et al., 2020; Forster et al., 2020).

Recently, many studies have analyzed the impact of COVID-19 based on the changes in pollutants, such as particulate matter (PM) with an aerodynamic diameter <2.5 μm and 10 μm (PM₂.₅ and PM₁₀), nitrogen dioxide (NO₂), sulfate dioxide (SO₂), carbon monoxide (CO), and ozone (O₃). For example, Bauwens et al. (2020) and Forster et al. (2020) recorded the decline in PM concentrations over some major cities globally. Venter et al. (2020) found declines in the population-weighted concentration of ground-level NO₂ (~60%), and PM₂.₅ (~31%) in 34 countries during the lockdown period from March 15, 2020. Sharma et al. (2020) reported that air quality improved because of the decreased levels of PM₂.₅, PM₁₀, CO, and NO₂ emissions in 22 Indian cities during the lockdown period. Y. Wang et al. (2020) linked NO₂ reductions to the transportation sector in northern China, whereas the decrease in PM, CO, and SO₂ emissions was linked to the industrial sector during the COVID-19 control period. Conversely, increases in near-surface O₃ have
been reported. Sicard et al. (2020) found an average increase of 17% in O₃ in four southern European cities compared with that in the same spring period in the three previous years. Zhao et al. (2020) and Kumari and Toshniwal (2022) also reported that O₃ levels increased significantly during the COVID-19 lockdown.

Here, we focus on near surface O₃ changes in nine global cities during the COVID-19 lockdown. This pollutant is produced by the photochemical reaction of volatile organic compounds (VOCs) and nitrogen oxides (NOₓ = NO + NO₂), and is enhanced by hydrogen oxide radicals (HOx = OH + peroxy radicals), which act as oxidants (Li et al., 2020). Increased near surface O₃ concentrations pose a serious threat to human health (X. Wang et al., 2020). For instance, Chen et al. (2020) reported an increasing trend in O₃-related mortality with an increase in O₃ concentrations from 2014 to 2018. Zhang et al. (2020a,b) presented a relationship between higher concentrations of air pollutants (increased O₃ in particular) and increased risk of COVID-19 infection. Apart from human health, high O₃ concentrations also induce plant cell death and yield reductions (Li et al., 2019; Xue et al., 2020). The studies mentioned above suggest that increased O₃ pollution during the lockdown has become an increasing concern that underlies the reported air quality improvement (Fu et al., 2021; Ran et al., 2020).

In addition to the major influence of the anthropogenic emissions of O₃ concentrations, meteorological factors play an important role in the formation, dispersion, transport, and dilution of O₃. For example, Lu et al. (2019) estimated the influence of meteorology on O₃ concentrations by using the GEOS-Chem chemical transport model in China. Gong et al. (2018) used the generalized additive model (GAM) to investigate the impact of changes in meteorological factors on O₃ variations in 16 important Chinese cities. Specifically, COVID-19 restrictions directly led to reduced anthropogenic activities, thereby providing a unique opportunity to investigate the relationship between atmospheric pollutants, especially O₃, and meteorological factors. However, to our knowledge, no controlled studies have compared the differences in the relationship between O₃ concentrations and meteorological elements in various cities across the planet during the COVID-19 pandemic.

In this study, we attempt to quantify the effect of lockdowns in various cities on O₃ levels in nine global cities and used GAM to examine the leading meteorological factors that affected O₃ concentrations during lockdown. GAM is an effective regression model, which can flexibly handle the complex nonlinear relationships between air pollutants (e.g., PM₂.₅, O₃, SO₂, and CO) and meteorological factors. (Habeebullah, 2020; Hünövá et al., 2019; Ma et al., 2020). This study aims to describe the monthly and daily variations in O₃ concentrations in nine global cities during pre- and post-lockdown periods. We also used the GAM approach to quantitatively identify the leading factors that controlled daily O₃ variations in each city during the COVID-19 lockdown.

2. Materials and methods

2.1. Study area

In this study, we selected nine major metropolitan cities worldwide, namely, Beijing (China), Guangzhou (China), Wuhan (China), Seoul (South Korea), Delhi (India), Sao Paulo (Brazil), London (UK), Paris (France), and Rome (Italy), to investigate the impact of their lockdown on surface O₃ and its relationship with meteorological factors. The primary reasons for selecting the nine cities are following. First, the selected cities have high population density, anthropogenic emissions, energy consumption, and air pollution levels. Second, the selected cities implemented strict lockdown measures during the COVID-19 pandemic. As strict lockdown significantly reduces personnel movement and outdoor activities, these cities provide an ideal experimental environment to study the impact of meteorological factors on O₃. Finally, these cities also have entirely different geographical settings and climatic conditions. For example, Beijing experiences a temperate monsoon climate, whereas Delhi is semi-arid. To analyze the global impact of restriction measures on O₃ and the relationship between O₃ and meteorological factors, the locations were selected from different continents across the globe, as shown in Fig. 1 and Table S1. Based on the above facts, the selected cities provide suitably diverse areas for this study.

2.2. O₃ concentration data

The daily records of surface O₃ concentration spread across the nine selected cities were downloaded from the World Air Quality Index (WAQI) portal (https://waqi.info/). The O₃ concentration of each selected city is the average value of all monitoring values in that city. The data were collected from January 1 to June 30 (from 2015 to 2020) for each selected city. In addition, for each city, the daily average O₃ concentrations (5-year average O₃ concentrations) from January to June were also calculated based on data from 2015 to 2019, to present a baseline. We assume that the 5-year average O₃ concentrations is normal, whereas O₃ concentration varies in March, April, and May 2020 because of the country-specific measures undertaken during the COVID-19 lockdown. Therefore, the 5-year average O₃ concentrations in March, April, and May were compared with those in 2020. Moreover, the information regarding lockdown start and end dates was collected from government reports of the selected cities, as shown in Table S1.

2.3. Meteorological data

The multi-scale interactions of meteorological conditions have a complex effect on air quality (He et al., 2017; Liu et al., 2017). The daily average meteorological data in the nine global cities from January to June (from 2015 to 2020) were obtained from the National Centers for Environmental Information reanalysis dataset (https://www.ncdc.noaa.gov/data/) and used to analyze their relationship with O₃ concentration. The daily average meteorological data included maximum temperature (Tmax, °F), mean dew point (DEWP, °F), mean visibility (VISIB, miles), mean wind speed (WDSP, knots), relative humidity (Rel.hum, %), and precipitation (PRCP, inches). A detailed description of each meteorological parameter can be found in Table S2.

2.4. Monthly relative rate of change

The monthly relative rate of change was used to compare the differences in O₃ concentrations in different periods (He et al., 2021). The monthly relative rate of change was given by:

\[
Y_m = \left( \frac{X_{m2020} - X_{m2015}}{X_{m2015}} \right) \times 100%
\]

where \(Y_m\) is the monthly relative change rate of O₃ concentration in month \(m\), \(X_{m2015}\) is the 5-year average O₃ concentrations in month \(m\), and \(X_{m2020}\) is the O₃ concentration in month \(m\) in 2020.

2.5. Statistical model

GAM is a flexible and free regression model that considers the additive effects of predictors on predicted values and their non-linear relationships. This model is usually used to quantify the influence of meteorology on O₃ concentration time series. In this study, we applied this statistical model, which was provided in the “mgcv package” of R software, to each city separately to characterize the relationship between the O₃ concentrations and meteorological factors. The equation is as follows:

\[
Y = \beta_0 + f_1(x_1) + f_2(x_2) + f_3(x_3) + \ldots + f_n(x_n) + \epsilon
\]

where \(Y\) indicates the dependent variable; \(x_1, x_2, \ldots, x_n\) are explanatory variables of \(Y\); \(\beta_0\) is the intercept; \(f_1, f_2, \ldots, f_n\) are smooth functions of the explanatory variable; and \(\epsilon\) is the residual.

In this study, to explore the main drivers influencing O₃ changes, without considering the degree of pollution caused by O₃, we considered...
the daily average O\textsubscript{3} concentration of each city as dependent variables, and the daily mean or daily maximum of meteorological factors as independent variables. Meanwhile, we used the Gamma distribution for mathematical rationality, as the frequency distribution of O\textsubscript{3} concentration in most cities is not a normal distribution (Fig. S1). In addition, we used F-statistics in GAM to identify important predictors. Previous studies have shown that F-statistic is an effective indicator to identify the independent variable that is the most important. It comprehensively considers the degree of freedom (e.d.f.) and the \( p \) value of each variable. In general, the larger the F statistic, the greater the importance of the variable. The modeling process and verification process of the GAM model can be found in the supplementary information (SI).

3. Results

3.1. Overview variations of O\textsubscript{3}

O\textsubscript{3} concentrations increased in January and February of 2020 in all cities, except Delhi, Rome and Sao Paulo, compared to the 5-year average O\textsubscript{3} concentrations from 2015 to 2019. Guangzhou (62.1%) had the largest increase in average O\textsubscript{3} concentrations in January. Whereas in February, Paris (16.6%) and London (18.6%) exhibited the largest increases in O\textsubscript{3} concentrations. The largest decreases in O\textsubscript{3} levels were observed in Sao Paulo (-15.2%). Compared to the 5-year average O\textsubscript{3} concentrations from 2015 to 2019, March 2020 saw significant increases in O\textsubscript{3} concentrations in Beijing (21.5%), Wuhan (31.4%), and Sao Paulo (28.1%). All cities except Beijing (-10.0%) and Seoul (-2.9%) in May 2020, exhibited significant increases in O\textsubscript{3} concentrations in April and May 2020, compared with the average concentrations from the previous 5 years. In June, Beijing, Delhi, London, Paris, Seoul, and Sao Paulo exhibited significant increases in O\textsubscript{3} concentrations in 2020 compared with those in the previous 5-year average. In contrast, Guangzhou, Wuhan, and Rome exhibited decreases in O\textsubscript{3} levels in June 2020 compared with the previous 5-year average (Table 1).

Fig. 2 shows the time series of daily O\textsubscript{3} concentrations for the nine selected cities. Prior to the COVID-19 lockdown, daily O\textsubscript{3} concentrations were close to the average for the same period in the previous five years in Sao Paulo (-5.7%) and Rome (-7.6%), while they were much lower in Delhi (-22.6%) and much higher in Guangzhou (58.9%), London (36.2%) and Paris (38.0%). All selected cities exhibited a significant increase in O\textsubscript{3} concentrations during the lockdown period. The most significant increase compared with the previous 5-year average concentrations was observed in Wuhan (49.3%), followed by London (47.5%), Paris (31.8%), Sao Paulo (28.9%), Guangzhou (20.1%), Delhi (20.0%), Beijing (18.4%), Seoul (17.9%), and Rome (4.8%). It is worth noting that Wuhan, London, Sao Paulo, and Paris are highly polluted cities where anthropocentric activities are the main source of emissions.

3.2. Impact of meteorology on O\textsubscript{3} during the COVID-19 lockdown

The GAM model was used to fit the O\textsubscript{3} concentrations for each city using the meteorological data listed in Table S2. The fitting effect of GAM was measured based on the adjusted \( R^2 \) value. Fig. 3 shows predicted and observed O\textsubscript{3} concentrations in the nine cities based on GAM fitting data. The results showed that the GAM model explained most of the changes in O\textsubscript{3}, the adjusted \( R^2 \) ranging from 0.51 (Sao Paulo) to 0.85 (Rome). The residuals of daily O\textsubscript{3} concentration were normally distributed, and the average residuals of all cities were close to 0 (Fig. S4). The

| Region | January | February | March | April | May | June |
|--------|---------|----------|-------|-------|-----|------|
| Beijing | 17.4%   | 3.2%     | 21.5% | 20.4% | -10.0% | 9.5% |
| Delhi   | -37.5%  | -18.9%   | -12.9%| 13.5% | 35.2%| 3.0% |
| Guangzhou| 62.1%   | 21.7%    | 39.1% | 50.7% | 16.1%| -22.7% |
| London  | 18.6%   | 60.5%    | 38.8% | 45.0% | 44.5%| 34.4% |
| Paris   | 16.6%   | 76.6%    | 24.3% | 37.1% | 23.6%| 12.4% |
| Rome    | -27.3%  | -6.3%    | 5.3%  | 7.5% | 12.8%| -4.0% |
| Sao Paulo| -14.1%  | -15.2%   | 31.4% | 27.3% | 29.8%| 28.8% |
| Seoul   | 11.2%   | 8.4%     | 14.1% | 31.5% | -2.9%| 22.0% |
| Wuhan   | 31.0%   | 38.8%    | 49.7% | 33.0% | 4.7% | -20.6% |
standard deviations of the residuals were between 2.72 (Delhi) and 6.89 (Wuhan) (Table S3). In all cities, except Sao Paulo (51%), the total deviance for meteorological factors reported by GAM were over 65% (Fig. S5). These results indicated that the GAM model can explain the variation in \( O_3 \) concentration well.

To identify the leading meteorological factors influencing \( O_3 \) variations in each city during the COVID-19 lockdown, we statistically analyzed the \( F \) statistic value of each parameter in the GAM model. Table 2 displays the \( F \) value for the three most important variables of each city during the lockdown. For example, relative humidity was the most important meteorological factor in Guangzhou and Rome as their \( F \) statistics were as high as 107.62 and 39.12, respectively; these values were also much higher than those for the second factors in these cities. Specifically, mean dew point, daily average relative humidity, and maximum temperature were the top three leading factors affecting the changes in \( O_3 \) concentrations in Beijing, Wuhan, and Delhi. Mean wind speed, maximum temperature, and relative humidity were the top three leading factors affecting \( O_3 \) changes during the COVID-19 lockdown in London, Paris, and Rome. The other three cities had different leading factor combinations. Daily average relative humidity, mean dew point, and maximum temperature were the top three leading factors of \( O_3 \) changes in Guangzhou during the COVID-19 lockdown. Mean wind speed, mean visibility, and mean dew point were the top three leading factors of \( O_3 \) changes in Seoul during the COVID-19 lockdown. Mean wind speed, mean visibility, and relative humidity were the top three leading factors of \( O_3 \) changes in Sao Paulo during the COVID-19 lockdown.

To further explore the impacts of meteorological factors on \( O_3 \) in each selected city during the COVID-19 period, we developed a GAM model to assess multiple meteorological variables and \( O_3 \) concentration response variables. This was done to identify the smooth regression function of the meteorological variables and the influence of meteorological factors on \( O_3 \) concentrations, to analyze the specific influences of meteorological factors on \( O_3 \) concentrations. Fig. 4 illustrates how relative humidity, maximum temperature, mean dew point, mean visibility, mean wind speed, and precipitation impacted the \( O_3 \) concentration in Wuhan during COVID-19. The effect responses for other cities are not shown for brevity. The GAM model successfully visualized the nonlinear relationship between \( O_3 \) and different explanatory variables. For example, in Fig. 4, all selected meteorological factors (except mean visibility) have a nonlinear relationship with \( O_3 \) concentration. Specifically, mean dew point fluctuated and decreased as \( O_3 \) concentration increased. \( O_3 \) concentration had a nonlinear positive correlation with the maximum temperature. When the temperature was below 55 °F (approximately 13 °C), \( O_3 \) concentration decreased with increases in maximum temperature. However, when the air temperature is more than 70 °F (approximately 21 °C), \( O_3 \) concentration significantly increased with increase in maximum temperature. \( O_3 \) concentration was negatively correlated with relative humidity and precipitation, and decreased as relative humidity increased. In contrast, \( O_3 \) concentration was positively correlated with average wind speed. When the wind speed was less than six knots (approximately 3 m/s), \( O_3 \) concentration significantly increased with increase in wind speed, whereas when the wind speed was greater than six knots, the magnitude of increases in \( O_3 \) concentration decreased. These results indicate that high temperature,
mean dew point, low humidity and wind speed increased O$_3$ concentration in Wuhan during the COVID-19 lockdown. The effects of meteorological factors in other cities on O$_3$ concentrations can be found in the SI. In addition, we used the GAM results to evaluate whether the observed O$_3$ concentration anomalies during COVID-19 lockdown were within the expected range or if the concentrations were close to those for the typical O$_3$ changes during the same period. Fig. 5 shows the time series of O$_3$ concentration predicted by the GAM model with all meteorological factors. By comparing the adjusted R$^2$, we found that the GAM model displayed the variations in O$_3$ concentration well, with relatively low standard deviation for the daily observations (Fig. 5). The dotted black lines indicate the daily concentrations of O$_3$ in 2019 as the reference, whereas the gray rectangle indicates the COVID-19 lockdown period. We also plotted the observed concentrations (red dotted lines) and the concentrations predicted by GAMs (blue line) from January 1st, 2020 to June 30th, 2020. Through the analysis of Fig. 5 and Section 3.1, the selected cities exhibited a significant short-term increase in O$_3$ levels during the COVID-19 lockdown period. When we predicted O$_3$ concentration with all the meteorological data (blue) and leading meteorological data (green) in 2020, the O$_3$ concentrations predicted by the GAM model in Delhi and Sao Paulo were lower than the values observed in 2020. The O$_3$ concentrations predicted by the GAM model in the other cities were close to the observed value in 2020. In contrast, when the

**Table 2**

Leading meteorological factors influencing O$_3$ for all cities during the COVID-19 lockdown.

| City     | Rel.hum  | Tmax  | DEWP  | VISIB | WDSM | PRCP | DOY |
|----------|----------|-------|-------|-------|------|------|-----|
| Beijing  | 13.86*** | 15.51*** | 23.73*** | 1.8  | 5.77** | 0.93 | 17.66*** |
| Guangzhou | 107.62*** | 2.1*  | 6.62*** | 7.25*** | 1.46 | 4.14* | 14.93*** |
| Wuhan    | 6.27*** | 3.27*  | 4.61*** | 2.63 | 2.91* | 0.44 | 13.43*** |
| Seoul    | 4.15**  | 2.7*   | 3.93*** | 13.22*** | 17.18*** | 0.98 | 36.88*** |
| Delhi    | 3.66**  | 1.67   | 5***   | 2.97* | 1.42  | 0.32 | 8.13*** |
| London   | 4.25*   | 4.32*** | 1.82   | 1.71 | 22.27*** | -   | 9.66*** |
| Paris    | 46.98*** | 9.88*** | 6.14*** | 9.81*** | 87.93*** | 4.73*** | 21.94*** |
| Rome     | 39.12*** | 8.42*** | 3.51**  | 0.79  | 17.41*** | 1.28 | 35.55*** |
| Sao Paulo | 2.53*   | 9.83*** | 1.96   | 0.12  | 7.08*** | 3.26* | 8.46*** |

Note: * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001.
lockdown was lifted in these cities, the O\(_3\) meteorological forecast values of all cities (except Guangzhou and Wuhan) quickly became close to the reference values and remained so. The observation O\(_3\) value and meteorological forecast value in 2020 were lower than the reference values due to the continuous precipitation from June to July in Guangzhou and Wuhan.

Figs. 2 and 5 also show that the observed O\(_3\) concentrations in Wuhan, London, and Paris were considerably higher than those in the six other cities during the COVID-19 period. Specifically, during the intermediate stage of the lockdown, the O\(_3\) concentrations in these cities were much higher than those in the summer of the reference period. By predicting the O\(_3\) concentrations in Wuhan, London, and Paris using all the meteorological data and leading meteorological data and comparing them to the O\(_3\) concentrations in the same period in 2019, we found that the predicted O\(_3\) concentrations under the two conditions remained higher than the reference values. This indicated that the meteorological conditions during the COVID-19 lockdown favored the O\(_3\) production.

During the COVID-19 lockdown, Delhi and Sao Paulo also observed significant increases in O\(_3\) concentrations. When we predicted the O\(_3\) concentrations of Delhi and Sao Paulo for the COVID-19 lockdown period using meteorological data from 2020, we found that the predicted values for the two cities were lower than the observed values. However, when the lockdown was lifted in both cities, the predicted and observed values of O\(_3\) concentrations gradually approached the reference values, indicating that meteorological factors had a certain impact on the O\(_3\) concentrations in Delhi and Sao Paulo during the COVID-19 lockdown. Human emissions and other factors also played important roles.

4. Discussion

In this study, the temporal variation of O\(_3\) concentration and influence of meteorological factors in nine cities around the world were analyzed for the period encompassing the COVID-19 lockdown. We determined that the concentration of O\(_3\) significantly increased during the COVID-19 lockdown period in 2020 compared with the O\(_3\) levels measured during the same period in 2019, as confirmed in previous studies (Kumari and Toshniwal, 2022; Shi and Brasseur, 2020; Venter et al., 2020a). The increase in O\(_3\) concentration can be attributed to the following reasons.

4.1. Reduction of O\(_3\) precursors

Previous studies revealed that O\(_3\) is a secondary pollutant, and its concentration depends on the local availability of its precursors (Xue et al., 2020). In urban areas, O\(_3\) formation depends on the VOC: NO\(_x\) ratio (Pusede and Cohen, 2012). In general, urban areas are characterized by low ratios because of high NO\(_x\) concentrations. For example, Zeng et al. (2018) and Anav et al. (2019) reported that high concentrations of VOCs were observed on days when high O\(_3\) levels were reported in Wuhan and in Southern Europe. Thus, a reduction in VOC emission would reduce O\(_3\) formation, but a reduction in NO\(_x\) emission would increase O\(_3\) formation (Eqs. 1–7).

\[
\begin{align*}
\text{RCHO} + \text{HO}_2 &\rightarrow \text{RC}\text{(O)O}_2 + \text{H}_2\text{O} \quad (1) \\
\text{RCHO} + \text{h} &\rightarrow \text{RO}_2 + \text{HO}_2 + \text{CO} \quad (2) \\
\text{RC(O)O}_2 + \text{NO}_2 &\rightarrow \text{NO}_3 + \text{RO}_2 + \text{CO}_2 \quad (3) \\
\text{HO}_2 + \text{NO} &\rightarrow \text{NO}_2 + \text{HO} \quad (4) \\
\text{RO}_2 + \text{NO}_2 &\rightarrow \text{R'CHO} + \text{HO}_2 \quad (5) \\
\text{NO}_2 + \text{h} &\rightarrow \text{NO} + \text{O} \quad (6)
\end{align*}
\]
During the COVID-19 lockdown, global NO$_2$ concentrations dropped significantly (Venter et al., 2020a). Sicard et al. (2020) found that the daily average NO$_2$ concentrations in Nice, Rome, Turin, Valencia, and Wuhan decreased by 62.8%, 45.6%, 30.4%, 69.0%, and 57.2%, respectively, compared with the baseline conditions (2017–2019). Similarly, Ordóñez et al. (2020) revealed that the daily maximum NO$_2$ decreased consistently across Europe, with reductions ranging from 5% to 55% for the same period in 2015–2019 for 80% of the sites considered. In addition, Delhi (60.0%) (Kumari and Toshniwal, 2022), Sao Paulo (54.3%) (Nakada and Urban, 2020), Beijing (33.3%) (He et al., 2020), Seoul (43.0%), and Guangzhou (30.0%) (Bauwens et al., 2020) also exhibited significant decreases in NO$_2$ concentrations. These phenomena suggest that, in the investigated cities, strict lockdown measures led to a reduction in NOx emissions, leading to higher O$_3$ concentrations. These leading meteorological factors are the main driving factors for daily changes in air quality (He et al., 2017; Wang et al., 2017; Zhao et al., 2016). Our study shows that the maximum temperature had a significantly nonlinear relationship with O$_3$ concentration and a significantly positive effect on O$_3$ concentration. During the COVID-19 lockdown, O$_3$ concentration increased as the air temperature increased in selected cities. This finding is consistent with the results from previous studies (Li et al., 2020; Lia et al., 2020; Y. Wang et al., 2020). An increase in the air temperature is a major reason for an increase in the O$_3$ concentration. For example, rising air temperatures lead to increases in O$_3$ concentrations in Europe (Hunová et al., 2019) and in China (Sun et al., 2019).

Relative humidity was found to have a significantly negative effect on O$_3$ concentration in the selected cities during the COVID-19 lockdown. We found that O$_3$ concentration decreased linearly (Wuhan,
Beijing, Seoul, Delhi, and Sao Paulo) or nonlinearly (Guangzhou, London, Paris and Rome) with increase in relative humidity. These results are consistent with studies in Europe (Mertens et al., 2019; Ordóñez et al., 2020), Brazil (Siciliano et al., 2020), and the South China (Fu et al., 2021). Previous studies have shown that water vapor can not only absorb and release energy through the change of water phase but also react with O$_3$ (Ma et al., 2020; Wang et al., 2019), resulting in a decrease in O$_3$ concentration. In addition, air humidity is usually positively correlated with the amount of cloud cover. Increase in humidity indicates an increase in cloud cover area. Simultaneously, the accompanying water vapor can decrease solar ultraviolet radiation, thus affecting photochemical reactions and the O$_3$ concentration (Huang et al., 2019; Yin et al., 2019). Interestingly, however, the average relative humidity was less than 50% in cities where O$_3$ concentrations changed significantly during the COVID-19 lockdown, such as Wuhan, London, and Paris. Li et al. (2018) and Wang et al. (2019) pointed out that when relative humidity was lower than 50%, O$_3$ concentration increased with relative humidity; O$_3$ concentration could also reach a peak in the range of 50%–60% relative humidity. This may be one of the reasons why O$_3$ concentrations in these cities rose rapidly during the COVID-19 lockdown period.

Generally, wind speed tends to have a significantly negative effect on O$_3$ concentration (He et al., 2017; Liu et al., 2017). When the wind speed is high, O$_3$ and its precursors can be easily removed, thereby reducing O$_3$ accumulation (Li et al., 2020). However, O$_3$ concentrations increased as wind speed increased in all the selected cities during the COVID-19 lockdown. Specifically, in Asian cities, such as Wuhan, Beijing, Guangzhou, Delhi, and Seoul, O$_3$ concentration had a significant nonlinear relationship with average wind speed, and the influence of wind speed on O$_3$ concentration was less than that of other meteorological factors (e.g., temperature and relative humidity). This may be caused by the typical seasonal weather conditions in these cities involved a mean wind speed that was mostly lower than five knots (about 2.5 m/s). Liu et al. (2020) pointed out that the possibility of removing environmental pollutants is extremely small at low wind speed. Meanwhile, low wind speeds are not conducive to the horizontal dispersion and vertical transport of O$_3$ and reduce the downward transport of O$_3$ pollutants at high altitudes (Zhang et al., 2018). In addition, previous studies have pointed out that lower wind speeds reduce the amount of ozone mixed with urban air (Ma et al., 2020; Yi et al., 2015). As a result, the increase in wind speed was beneficial for the increase in O$_3$ concentration. Similar results have also been reported in other global cities, such as Shanghai (Gu et al., 2020), central eastern China (Sun et al., 2019), and Barcelona (Tobías et al., 2020). In contrast, in London, Paris, and Rome, O$_3$ concentration increased linearly as mean wind speed increased. Furthermore, the mean wind speed was an important meteorological factor for the increase of O$_3$ concentration in London, Paris, and Rome during the period of COVID-19. This may be because of the reduced zonal airflow at low levels in many European cities (Ordóñez et al., 2020).

5. Conclusion

This study investigates the impact of the COVID-19 lockdown on O$_3$ concentration in nine cities across the globe. The GAM approach was used to identify the leading factors that influenced daily O$_3$ variations in the investigated cities during the COVID-19 lockdown. We found that the O$_3$ concentration exhibited a remarkable increase during the post-lockdown period compared with that during the pre-lockdown period for all selected locations. Furthermore, meteorological effects contributed to increasing O$_3$ concentrations in all selected cities, accounting for a large proportion of all observed changes. However, the main meteorological variables driving O$_3$ anomalies varied with geographical location. They were dominated by relative humidity and maximum temperature in Beijing, Wuhan, Guangzhou, and Delhi; maximum temperature and mean wind speed in Sao Paulo; mean wind speed, maximum temperature, and relative humidity in London, Paris, and Rome.

Thus, our study only discusses the changes in O$_3$ concentrations and the meteorological factors driving these changes before and after the COVID-19 lockdown in nine cities around the world. Furthermore, this analysis is equally applicable to other countries and regions around the globe. Our findings can be used to predict O$_3$ concentrations and variation patterns based on meteorological factors and human activity levels, leading to policies to reduce O$_3$ pollution and improve public health.

Credit author statement

Yun Zhang Li, Zhongsong Bi, and Chao He conceptualized the idea, designed the research, and wrote the paper; Zhongsong Bi and Chao He analyzed the data and interpreted the results; all authors discussed the results and revised 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.2022.101523.

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