Impact of reduced anthropogenic emissions during COVID-19 on air quality in India

Mengyuan Zhang\textsuperscript{1}, Arpit Katiyar\textsuperscript{2}, Shengqiang Zhu\textsuperscript{1}, Juanyong Shen\textsuperscript{3}, Men Xia\textsuperscript{4}, Jinlong Ma\textsuperscript{1}, Sri Harsha Kota\textsuperscript{2}, Peng Wang\textsuperscript{4}, Hongliang Zhang\textsuperscript{1,5}

\textsuperscript{1}Department of Environmental Science and Engineering, Fudan University, Shanghai 200438, China
\textsuperscript{2}Department of Civil Engineering, Indian Institute of Technology Delhi, 110016, India
\textsuperscript{3}School of Environmental Science and Engineering, Shanghai Jiao Tong University, Shanghai 200240, China
\textsuperscript{4}Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, 99907, China
\textsuperscript{5}Institute of Eco-Chongming (IEC), Shanghai 200062, China

Correspondence to: Peng Wang (peng.ce.wang@polyu.edu.hk); Hongliang Zhang (zanghl@fudan.edu.cn)

Abstract. To mitigate the impacts of the pandemic of coronavirus disease 2019 (COVID-19), the Indian government implemented lockdown measures on March 24, 2020, which prohibit unnecessary anthropogenic activities and thus leading to a significant reduction in emissions. To investigate the impacts of this lockdown measure on air quality in India, we used the Community Multi-Scale Air Quality (CMAQ) model to estimate the changes of key air pollutants. From pre-lockdown to lockdown periods, improved air quality is observed in India, indicated by the lower key pollutant levels such as PM\textsubscript{2.5} (-26%), maximum daily 8-h average ozone (MDA8 O\textsubscript{3}) (-11%), NO\textsubscript{2} (-50%), and SO\textsubscript{2} (-14%). In addition, changes in these pollutants show distinct spatial variations with the more important decrease in northern and western India. During the lockdown, our results illustrate that such emission reductions play a positive role in the improvement of air quality. Significant reductions of PM\textsubscript{2.5} and its major components are observed especially for secondary inorganic aerosols with decreasing rates up to 92%, 57%, and 79% for nitrate (NO\textsubscript{3}\textsuperscript{-}), sulfate (SO\textsubscript{4}\textsuperscript{2-}), ammonium (NH\textsubscript{4}\textsuperscript{+}), respectively. On average, the MDA8 O\textsubscript{3} also decreases 15% during the lockdown period although it increases sparsely in some urban locations, which is mainly due to the lower NO\textsubscript{x} and VOCs emissions. More aggressive and localized emissions control strategies should be implemented in India to mitigate air pollutions in the future.

1 Introduction

India, the second-most populous country in the world, has been suffered from severe air pollution along with rapid urbanization and industrialization in recent decades (Karambelas et al., 2018), and 13 Indian cities were among the world's top 20 most polluted cities according to the World Health Organization (WHO) (WHO, 2018). High-level pollution leads to health risks and ecosystem damages, which caused 1.24 million deaths in India in 2017 (Balakrishnan et al., 2019) and a great loss of crops (Oksanen et al., 2013; Lal et al., 2017). To mitigate air pollution, the Indian government has been promoting effective emission control strategies such as the conversion of fossil fuels to clean fuels in the nationwide campaign Clean India Mission (CIM).
However, such long-term or short-term reduction strategies seem to show insufficiency in the restoration of ambient air quality (Beig et al., 2013; Purohit et al., 2019; Banerjee et al., 2017).

Due to the pandemic of coronavirus disease 2019 (COVID-19), nationwide or partial lockdown measures have been implemented in many countries (Chintalapudi et al., 2020; Dantas et al., 2020; Ehrlich et al., 2020). Indian government declared corresponding bans since the detection of the first confirmed case on January 30, 2020. Then, to counter the fast contagion of COVID-19, a 3-week nationwide lockdown was imposed in India on March 24, which was expended till June 30. The lockdown measures mitigate the impact of COVID-19 on Indian health infrastructure and it also helped in curbing the rate of the spread of this infectious disease among people (Pai et al., 2020; Anderson et al., 2020). Because of the prohibition of industrial activities and mass transportation, anthropogenic emissions showed a tremendous reduction. Besides, several studies showed that dramatic emission reductions had an enormous impact on the formation of air pollution and positively influence air quality (Isaifan, 2020; Bao and Zhang, 2020; Gautam, 2020). Thus, the lockdown also provides a valuable opportunity to assess the changes in air pollutants with significantly reduced anthropogenic emissions in a short time.

Conspicuous reductions in concentrations of pollutants were also claimed in different regions (Otmani et al., 2020; Dantas et al., 2020; Nakada and Urban, 2020). Most Indian studies claimed the greatest reduction of particulate matter with an aerodynamic diameter of less than 2.5 μm (PM$_{2.5}$), up to 50% (Kumar et al., 2020; Mahato et al., 2020; Sharma et al., 2020). However, an increase in ozone (O$_3$) concentrations was observed (Collivignarelli et al., 2020; Sicard et al., 2020) and severe air pollution events still occurred after large emissions reduction due to unfavorable meteorological conditions (Wang et al., 2020). Moreover, another analysis showed that the effects of lockdown during the COVID-19 pandemic on PM$_{2.5}$ and O$_3$ pollution levels were less than the expected response to the enacted stay-at-home order (Bujin et al., 2020). Hence, the significance and impacts of lockdown measures are still not well understood.

Therefore, it is significant to understand the mechanisms involving in air pollution formation before and after dramatic emission changes comprehensively, in addition to the comparison of air pollution levels. Mahato et al. (2020) concluded that air quality in India from March 24 to April 14 was improved sharply according to the change of the National Air Quality Index, especially for Delhi. Srivastava et al. (2020) reported the concentrations of primary air pollutants are drastically lowed as a result of emission reduction. Kumari and Toshniwal (2020) also stated that the concentration of key pollutants such as PM$_{2.5}$ in both Delhi and Mumbai shows a decreasing trend. These studies pointed out that the air quality was improved during the lockdown period compared with the period before lockdown and depends on the duration of the lockdown (Kumar et al., 2020; Mor et al., 2021). Besides, compared with the same period in previous years, Gautam (2020) claimed that aerosol concentration levels are at their lowest in the last 20 years during lockdown based on satellite data. Selvam et al. (2020) stated that Air Quality Index (AQI) was improved by 58% in Gujarat state of western India during lockdown (March 24, 2020 – April 20, 2020) compared to 2019. Kabiraj and Gavli (2020) concluded that the mean concentration of PM$_{2.5}$ decreased by 42.25% from January to May in 2020 compared with 2019. Similarly, Das et al. (2020) also showed that great reductions of PM$_{2.5}$ were found across cities in the Indo-Gangetic Plain (IGP) compared with 2018 and 2019. However, the role of meteorological conditions and chemical reactions involving changes in air quality is not clear from these observation-based studies, which
only showed the phenomenon of concentration reduction and switch of major primary pollutants mainly in urban cities. Further, the number of monitoring stations in the country is way below the guidelines by the governing bodies and not uniformly distributed, which results in observation data limitations in India (Sahu et al., 2020).

In this study, the Community Multi-Scale Air Quality (CMAQ) model was used to investigate changes in air pollutants during the pre-lockdown (from February 21, 2020 to March 23, 2020) and lockdown (from March 24, 2020 to April 24, 2020) periods throughout Indian region. We explored the synergetic impacts from the meteorological conditions and anthropogenic emissions during the pre-lockdown and lockdown periods. Besides, we directly quantified the change in air quality during the lockdown due to the reduced anthropogenic emissions by comparing the differences between Case 1 (without emission reductions) and Case 2 (with emission reductions). The model performance was evaluated by comparing the simulation results with the observation data, which is collected by the Central Pollution Control Board (CPCB). This study has important implications for developing control strategies to improve air quality in India.

2 Methodology

2.1 Data collection

We used observed hourly PM$_{2.5}$, O$_3$, carbon monoxide (CO), and nitrogen dioxide (NO$_2$) data from February 21, 2020 to April 24, 2020 from the CPCB online database (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing, last access: July 07, 2020), which is widely applied in previous studies (Kumar, 2020; Sharma et al., 2020; Srivastava et al., 2020; Shehzad et al., 2020). The CPCB database provides data quality assurance (QA) or quality control (QC) programs by establishing strict procedures for sampling, analysis, and calibration (Gurjar et al., 2016). Besides, the observed daily averages of PM$_{2.5}$ and maximum daily 8-h average ozone (MDA$_8$ O$_3$) have been further calculated to analyze the change in air quality during the pre-lockdown (from February 21, 2020 to March 23, 2020) and lockdown (from March 24, 2020 to April 24, 2020). The satellite-observed NO$_2$ and formaldehyde (HCHO) column number density datasets are from the Sentinel-5 Precursor TROPospheric Monitoring Instrument (S-5P TROPOMI) (https://scihub.copernicus.eu). Besides, we filter the satellite data under the recommended criteria of QA values greater than 75% for tropospheric NO$_2$ column number density datasets and 50% for HCHO (Apituley, 2018).

2.2 Model description

This study applied CMAQ (Byun and Schere, 2006) version 5.0.2 with updated SAPRC-11 photochemical mechanism (Carter, 2011; Hu et al., 2016) and aerosol module (AERO6) (Binkowski and Roselle, 2003) to simulate air pollution across India with a horizontal resolution of 36 km × 36 km (117 × 117 grid cells). Figure 1 shows the simulation domain with positions of main Indian cities. The simulation was conducted from February 21 to March 23 as a pre-lockdown and March 24 to April 24 as a lockdown period.
The Weather Research & Forecasting model (WRF) version 3.6.1 was utilized to generate meteorology fields driven by the latest FNL (Final) Operational Global Analysis data. Anthropogenic emissions were from the monthly data from the Emissions Database for Global Atmospheric Research (EDGAR) version 4.3 (http://edgar.jrc.ec.europa.eu/overview.php?v=431). The monthly emissions from different source sectors were divided into six major groups of residential, industrial, agriculture, on-road, off-road, and energy before being adjusted from the base year of 2010 to 2019 based on population and economic growths similar to Guo et al. (2017) and the adjustment factors are shown in Table S1-S3. Weekly and diurnal profiles were used to convert monthly emissions to hourly inputs and the US EPA's SPECIATE 4.3 source profiles were used to speciate total particulate matters (PM) and volatile organic compounds (VOCs) to model species (Wang et al., 2014).

The biogenic emissions were derived from The Model of Emissions of Gases and Aerosols from Nature (MEGAN) version 2.1 (Guenther et al., 2012), and the emissions from biomass burning for 2018 were based on the Fire Inventory from the National Center for Atmospheric Research (FINN) (Wiedinmyer et al., 2011).

2.3 Emission reduction during COVID-19

Due to the COVID-19 lockdown, human activities were limited and related anthropogenic emissions were reduced. Different sources were used to obtain changes in anthropogenic emissions from different sectors in comparison to 2019.

For the sector of on-road and off-road, the vehicle emissions changes were based on the number of registered vehicles verified from the article (Bureau, 2020). The changes in energy demand were obtained from official data released by Power System Operation Corporation (POSOCO) (Abdi, 2020). Residential and agricultural emissions remain unchanged due to a lack of sufficient information.

For the industrial sector, we classify the Indian industries into 3 different classes based on the degree of air pollution caused (https://www.indianmirror.com/indian-industries/environment.html) (Table S4): 1) the red being the most polluting, 2) the orange, and 3) the green. The Pollution Index (PI) of any industry is a number ranging from 0 to 100 and the increasing value of PI denotes the increasing degree of pollution load from the industry. CPCB, State Pollution Control Boards (SPCBs), and the Ministry of Environment, Forest and Climate Change (MoEFCC) have finalized the following criteria on “Range of Pollution Index” for the purpose of categorization of the industrial sector (https://pib.gov.in/newsite/printrelease.aspx?relid=137373) which is shown in Table 1.

Based on the above definition of the red, orange, and green industry, the scores of 1, 0.6, and 0.4 have been assigned to each category. The emissions before lockdown can be expressed as:

\[ E_1 = 25x + 7y + 31z , \]  

where the ratio of x, y, and z is 1: 0.6: 0.4 as the scores and the numbers of red, orange, and green industries identified are 25, 7, and 31 before lockdown. Similarly, the emissions during the lockdown are as follows:

\[ E_2 = 5x + y + 5z , \]
Therefore, the percent reduction of industrial emissions can be calculated as:

\[\% \text{reduction} = \frac{E_1 - E_2}{E_1} \times 100,\]  

In this study, two sensitivity simulations were conducted during the lockdown periods. Case 1 assumes business as usual with the same emissions as in 2019, while Case 2 adjusts anthropogenic emissions using factors obtained above for different sectors (Table 2). The differences between Case 2 and Case 1 can be assumed as the effects of COVID-19 lockdowns.

3 Results and discussion

3.1 WRF-CMAQ model validation

Meteorology plays an important role in emissions, transport, deposition, and formation of air pollutants (Zhang et al., 2015). Hence, the performance of WRF is validated to assure accurate air pollution simulation against available observation from the National Climate Data Center (NCDC). There are more than 1300 stations within the simulation domain with hourly observations. The considered variables contain temperature at 2 m above the surface (T2), wind speed (WS), wind direction (WD), and relative humidity (RH). Table S5 shows the statistics of mean observation and mean prediction of meteorological parameters, along with mean bias (MB), gross error (GE), and root mean squared error (RMSE), which are compared to benchmarks suggested by Emery et al. (2001b). All the statistical indexes are listed in Table S6.

In general, the WRF model performance is acceptable and similar to previous studies in India (Kota et al., 2018). For the pre-lockdown and lockdown period, predicted T2 was under-estimated with MB values of -1.5 K and -1.2 K, respectively. The GE values for WS were 1.7% (pre-lockdown) and 1.8% (lockdown), satisfying the suggested criteria of 2.0%, and RMSE was slightly over the criteria. The MB values for WD were 3.2° and 2.6° during the two periods, which are within the criteria of ±10°. The GE and RMSE for WD were slightly out of the benchmarks. The under-predicted RH was also observed in this study, which was reported in other Asian studies (Hu et al., 2015). Those statistic values that did fall in the benchmark were mainly due to the resolution (36 km) applied in this study compared to the finer resolution (4–12 km) suggested in Emery et al. (2001a) (Sahu et al., 2020).

Table S7 shows the model performance of MDA8 O₃, PM₂.₅, CO, and NO₂ in five major cities in India including Delhi, Mumbai, Chennai, Hyderabad, and Bengaluru. For PM₂.₅, the averaged mean fractional bias (MFB) (-0.48) and mean fractional error (MFE) (0.61) values met the criteria limits of ±0.6 and 0.75 claimed by the EPA (2007) in all the five urban cites after excluding some abnormally high values of greater than 300 µg m⁻³. For O₃, a cut-off value of 40 ppb is applied, which is based on EPA's recommendations (EPA, 2005). Besides, the model was able to reproduce the variation trends of observed hourly O₃ in all these major cities, although slightly over-estimations have occurred. And averaged MFB (-0.05) and MFE (0.25) values of O₃ also satisfy the benchmarks of ±0.15 and 0.30 set by the EPA (2005) in most of these cities with Chennai and Hyderabad exceeding the limits slightly. The performance of PM₂.₅, NO₂, O₃, and CO in these urban areas was also similar to Kota et al. (2018), which could provide robust results for the following air quality study.
To further validate modeled HCHO and NO₂, we compared our simulated results with satellite-observed data during pre-lockdown and lockdown periods (Fig. S1). The tropospheric column densities of NO₂ and HCHO were calculated by summing their concentrations of 17 vertical layers in the CMAQ model (H. J. Eskes, 2020). The predicted regional distribution of tropospheric column NO₂ and HCHO is similar to satellite-observations. Overall, HCHO and NO₂ are higher in eastern and northern India than in other regions. And their variation trends from CMAQ and TROPOMI are consistent that NO₂ decreases while HCHO increases during the lockdown. We also acknowledge that the uncertainty of emission inventory and chemical mechanism in the modelling may affect the simulated results (Dominutti et al., 2020; Kitayama et al., 2019).

### 3.2 Changes in air quality from pre-lockdown to lockdown periods

Figure 2 shows predicted and observed PM₂.₅ from February 21 to April 24 in Delhi, Mumbai, Chennai, Hyderabad, and Bengaluru. The model succeeds in estimating the observed peak and valley values with slight under-estimation in all these cities. Overall, sharp decreases are found in the observed PM₂.₅ in all these cities, and the averaged PM₂.₅ level drops from 43.18 µg m⁻³ to 27.62 µg m⁻³. The mean observed PM₂.₅ concentrations during lockdown are 42.47 µg m⁻³ (Delhi), 24.53 µg m⁻³ (Mumbai), 15.73 µg m⁻³ (Chennai), 31.29 µg m⁻³ (Hyderabad), 24.08 µg m⁻³ (Bengaluru), which are reduced by 41%, 40%, 42%, 10%, and 43% respectively compared with that of the pre-lockdown period. Besides, the observed peak values of PM₂.₅ in each city also decrease appreciably (up to 57%) during the lockdown period. On March 24 that the first day of lockdown, a significant drop in PM₂.₅ concentration due to the emission reduction of primary pollutants is observed (Fig. S2). However, most of the PM₂.₅ concentrations are still above the WHO annual guideline values of 10 µg m⁻³ (WHO, 2016) during the lockdown period, with peak values over 60 µg m⁻³ occasionally.

Figure 3 shows the temporal variation of MDA₈ O₃ in these five cities. The predicted MDA₈ O₃ is consistent in trend with observation values in most days, while simulated concentrations are overall higher, particularly in Hyderabad. The observed average MDA₈ O₃ during lockdown is higher than that of pre-lockdown in Delhi (2%), Hyderabad (12%), and Bengaluru (2%). This is likely due to the fact that O₃ formation in these cities is under VOC control (Sharma et al., 2020), and nitrogen oxide (NOₓ) reduction leads to O₃ increase by enhanced hydrogen oxide radicals (HOₓ) concentrations (Zhao et al., 2017). The increase of monthly average T2 from pre-lockdown (281.0 K) to lockdown (285.1 K) could also lead to an increase of O₃ (Chen et al., 2019). In contrast, the observed average MDA₈ O₃ during lockdown is reduced compared with the pre-lockdown period in both Mumbai (-35%) and Chennai (-13%). This could be caused by a much larger reduction in emissions as Mumbai and Chennai are the most affected areas. In specific, Mumbai accounted for more than a fifth of infections in India (Mukherjee, 2020).

Figure 4 shows the comparison of predicted air pollutants before and during the lockdown throughout India. Generally, decreasing trends of key pollutants including particulate matter with an aerodynamic diameter of less than 10 µm (PM₁₀) (-16%), PM₂.₅ (-26%), MDA₈ O₃ (-11%), NO₂ (-50%), and sulfur dioxide (SO₂) (-14%) are observed across India. Changes in these pollutants present distinct regional variations. In northern and western India, the lower levels of these pollutants are observed during the lockdown, with the reductions of PM₂.₅ and PM₁₀ up to 79%. In particular, the most significant decreases
are found in the populated, industrialized, and polluted IGP region during the lockdown. The average PM$_{2.5}$ even drops from approximately 35–70 µg m$^{-3}$ (pre-lockdown) to 15–40 µg m$^{-3}$ (lockdown) in these regions because local emissions are generally the largest contributor (38–78%) to PM$_{2.5}$ in India (David et al., 2019). However, rising trends of these key pollutants are found mainly in the northeastern, eastern, and parts of southern India.

Besides, changes in PM$_{2.5}$ also show prominent differences in the rural and urban areas. In India, rural areas have different emission sources from urban areas and are less influenced by lockdown measures (Garaga et al., 2020). In megacities such as Delhi, the predicted concentrations of PM$_{2.5}$ decline during the lockdown, which is consistent with previous results (Kumari and Toshniwal, 2020; Chauhan and Singh, 2020). For instance, over a 60% reduction of PM$_{2.5}$ is estimated in Delhi and Ahmedabad. However, rising trends of PM$_{2.5}$ (~20%) are observed in the far-flung northeastern part of India. Variations in near-surface meteorological factors during lockdown also play an important role in PM$_{2.5}$ changes. As is shown in Fig. S3, lower PM$_{2.5}$ in urban areas during lockdown (Fig. 4) may attribute to the decrease of RH and increase of planetary boundary layer (PBL) height, while the decrease of precipitation and WS allows PM$_{2.5}$ to accumulate in some rural areas (Schnell et al., 2018; Le et al., 2020).

As gaseous precursors of major components to PM$_{2.5}$ (Jain et al., 2020), concentrations of NO$_2$ and SO$_2$ also decrease significantly in most regions by up to 90% and 87%, respectively. However, their levels increase in parts of the east and south India and thus leading to higher levels of PM$_{2.5}$ and PM$_{10}$ in the same regions. MDA8 O$_3$ is also rising in eastern India by the highest increasing rate of 29%, while a 30% reduction is observed in northern and western India. Although significant reductions are found in O$_3$ precursor emissions throughout India during the lockdown, the MDA8 O$_3$ has not shown comparable decreasing trends, which is affected by meteorological conditions such as an increase of temperature and decrease of RH (Fig. S3). Higher temperature speeds up photochemical processes that produce O$_3$, while higher RH reduces them (Chen et al., 2019; Zhao et al., 2017; Ali et al., 2012).

In summary, the decrease of PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, and the increase of MDA8 O$_3$ during lockdown is consistent with previous results (Srivastava et al., 2020; Mahato et al., 2020). In the case of Delhi, compared with the previous studies, the PM$_{2.5}$ reduction (34%) is comparable with 35% reported by Chauhan and Singh (2020), while less than 53% stated by Mahato et al. (2020) and 49% calculated by Kumari and Toshniwal (2020) during the first phase of lockdown (from March 24, 2020 to April 15, 2020). These differences highly depend on the duration of lockdown because there is an increase in traffic flow and some relaxation in the later lockdown period (after April 15, 2020) (Kumar, 2020). Moreover, the different characteristics of these air pollutants in rural and urban areas have not been investigated comprehensively in previous studies. Kumari and Toshniwal (2020) also concluded that concentrations of PM$_{10}$, PM$_{2.5}$, and SO$_2$ tended to rise in Singrauli (rural area, located in central India) during the lockdown, contrary to the results of Delhi and Mumbai. Therefore, our results have important implications for the study of air quality changes and their regional distribution across India and indicate more strident emission reduction policies should be implemented across India, especially in the later phases of lockdown and in rural areas.
3.3 Effects of emission reductions on PM$_{2.5}$ during the lockdown

There are significant changes of PM$_{2.5}$ between the lockdown and pre-lockdown periods, but it remains unclear regards the direct impacts of emission reductions during the lockdown. Figure 5 shows the differences in major PM$_{2.5}$ components during the lockdown period with (Case 2) and without (Case 1) control measures. Major components of PM$_{2.5}$ including nitrate (NO$_3^-$), sulfate (SO$_4^{2-}$), ammonium (NH$_4^+$), elemental carbon (EC), primary organic aerosol (POA), and secondary organic aerosol (SOA), decreased significantly in Case 2 compared to Case 1, indicating the positive effects of emission reduction. Primary components of PM$_{2.5}$ (EC and POA) are dropped by an average of 37% and 14%, respectively. EC is usually emitted from combustion sources and a drastic decrease of up to 74% directly reflected the impact of emission reductions from industry and transportation. Secondary inorganic aerosol (SIA) including NO$_3^-$, SO$_4^{2-}$, and NH$_4^+$ and SOA accounted for most of the PM$_{2.5}$ bulk mass (39%) and showed greater decreases than primary components. Moreover, the spatial distribution of SIA is similar to PM$_{2.5}$ in that the reduction is more significant in the north of India where the decrease of NO$_3^-$, SO$_4^{2-}$, and NH$_4^+$ are up to 92%, 57%, and 79% respectively. The largest reduction of NO$_3^-$ by averaged 62% resulted from transportation reduction and SO$_4^{2-}$ reduction (averaged 31%) is likely due to the falling release of industry (Gawhane et al., 2017; Wang et al., 2020). On average, NH$_4^+$ and SOA are decreased by 41% and 14%, respectively. The significant decrease in NH$_4^+$ cannot be attributed to the absence of reduced agricultural emissions in the simulation but may be due to the relatively reduced (NH$_4$)$_2$SO$_4$ and NH$_4$NO$_3$ in the CMAQ chemistry-transport model (Fountoukis and Nenes, 2007). By contrast, compared with VOCs, an important precursor of SOA, the smaller reduction of SOA may be related to the weakening of the atmospheric oxidizing capacity (AOC), which plays an important role in the formation of SOA (Feng et al., 2019). Besides, the reduction of NO$_x$ may lead to an increase in SOA offsetting some of the influence by the reduction in VOC emissions (Kroll et al., 2020).

Figure 6 shows the predicted response of changes in concentration of primary PM$_{2.5}$ (PPM) and secondary components to the reduced emissions of related precursors in Delhi, Mumbai, Kolkata, Bengaluru, Hyderabad, Chennai, Ahmedabad, and Lucknow. Generally, all species decreased with the reduced emissions and the great sensitivity of PM$_{2.5}$ component concentrations to emissions showed the important role of meteorology and the effectiveness of stringent measures to reduce emissions.

On average, NO$_3^-$ shares the largest reduction of 77% mainly driven by the decrease of its gaseous precursor NO$_x$ (71%). At least a 27% decrease of SO$_4^{2-}$ is found in each city caused by the largest reduction of SO$_2$ (averaged 59%). Over 70% average reduction of NO$_x$ and NO$_3^-$ may still relate to the reduction of vehicles. And SOA is dropped by an average of 18% because of the lack of precursors due to the emission reduction of VOCs (29%). Due to the reduction of emitting precursors, the concentration reduction of PM$_{2.5}$ secondary components is less than that of primary components. The ratios of PPM reduction in emission (averaged 39%) are larger than the reduction in concentration (averaged 43%) in five selected cities. Especially, a 7% reduction in emission of PPM caused a 43% decline in its concentration in Hyderabad. Emissions of EC and organic carbon (OC) have also been reduced by a certain proportion resulting in a similar or greater reduction in concentrations.
The response of concentration to emissions in all cities presented a nonlinear change that has been confirmed previously by Zhao et al. (2017), which is related to various meteorological conditions (Wang et al., 2020). For example, in Lucknow, PPM, EC, OC, SO2, NOx, and VOCs decreased by 14%, 25%, 8%, 39%, 55%, and 11% respectively, while the concentration of PPM, EC, OC, SO4^2-, NO3-, and SOA dropped by 21%, 32%, 12%, 43%, 78%, and 18%. Besides, the concentration response to emission reduction is likely to be more prominent in highly polluted and industrialized areas. The highest reductions in PPM and these secondary components of PM2.5 happened in Ahmedabad (an industrial city located in western India) with high vehicular populations. While Bengaluru, a major southern Indian city, is considered as one of the cleaner Indian major cities because of its low PM2.5 concentrations with no heavy industries (Guttikunda et al., 2019). Consequently, the reduction in PM2.5 and its major components (especially for secondary components) in Bengaluru is not as significant as in Ahmedabad although a similar reduction in emissions is observed.

### 3.4 Effects of emission reductions on O3 during the lockdown

We investigated the changes of MDA8 O3 and its major precursors NOx and HCHO which is one of the major contributors to total VOCs reactivity (Zhang et al., 2012; Steiner et al., 2008) during the lockdown period. Figure S4 shows that HCHO has a strong correlation with total VOCs ($R^2$ up to 0.93). Figure 7 shows that MDA8 O3, NOx, and HCHO decreased all over India. The average reduction rates of MDA8 O3, NOx, and HCHO are approximately 15%, 50%, and 15%, respectively. For both Case 1 and Case 2, the higher levels of MDA8 O3 are in eastern India (over 60 ppb, Case 1) in which the higher NOx is also observed (over 12 ppb, Case 1) during the lockdown. Compared to PM2.5, no significant north-south differences are found in the change of O3. NOx concentration has the greatest reduction that is mostly driven by the large cutting of energy emission by 26%, which is consistent with the decline of India's electricity consumption (9.2%) (Reuters, 2020).

Figure S5 shows the O3 production sensitivity ($O_3/NO_y$) in India during the lockdown, which is considered as an indicator of O3 sensitivity to NOx and VOCs (Sillman, 1995; Sillman and He, 2002). In India, NOx-limited regimes ($O_3/NO_y > 8$) are found in vast areas from both Case 1 and Case 2, which was also reported in previous studies (Mahajan et al., 2015). Compared to Case 1, the VOC-limited area ($O_3/NO_y < 6$) expands mainly in the northwest and south of India from Case 2 during the lockdown. The transition regimes ($6 < O_3/NO_y < 8$) that O3 formation is controlled by both NOx and VOC emissions in the vicinity of the VOC-limited regions. Simultaneously, the rise of MDA8 O3 (averaged 5% and up to 21%) is found sporadically in these VOC-limited areas in which more significant decreases of NOx (compared with VOCs) reduce the O3 consumption ($NO + O_3 = NO_2 + O_2$) and enhance HOx concentrations result in an increase in O3 levels.

Figure 8 compares the concentrations of MDA8 O3, HCHO, and NOx with emissions of VOCs, HCHO, and NOx in eight major cities of India, Delhi, Mumbai, Kolkata, Bengaluru, Hyderabad, Chennai, Ahmedabad, and Lucknow. Generally, the decline in O3 concentration in Delhi (14%), Mumbai (23%), Kolkata (24%), Bengaluru (20%), Hyderabad (17%), Chennai (20%), Ahmedabad (21%), and Lucknow (15%) showed that effectiveness of emission reductions that play an important role in the control of O3 pollution, even in these VOC-limited areas.
The changes in emissions and concentrations of MDA8 O₃, HCHO, and NOₓ showed a non-linear response. In Delhi, a 76% reduction in NOₓ emissions resulted in a 77% reduction in its concentration, while a 29% reduction in HCHO resulted in only an 11% reduction. In a megacity like Delhi, about 7 million vehicles and many fossil fuel-based plants lead to high NOₓ emissions, and local restricted transportation and industrial activities during lockdown could lead to a significant reduction of primary NOₓ emissions (Sharma et al., 2016). The concentration of NOₓ is appreciably highly sensitive to a primary NOₓ emission reduction. However, the VOCs emission reduction resulting from the lockdown is relatively less than NOₓ in each city. And most of the reduction of HCHO concentration is less than that of emission reduction, which is different from NOₓ, which indicated that the change of HCHO concentrations is not dominated by primary HCHO emission reduction.

4 Conclusion

Compared with pre-lockdown, observed PM₂.₅ during the lockdown in Delhi, Mumbai, Chennai, Hyderabad, and Bengaluru shows an overall decreasing trend. In contrast, MDA8 O₃ increases in three of these cities. The comparison of predicted air pollutants across India before and during the lockdown shows distinct regional characteristics. The most significant reductions of PM₂.₅ and PM₁₀ (up to 79%) are observed in most of northern and western India including all these megacities. However, increases of MDA8 O₃ (up to 29%) and other key pollutants are reported in northeastern, eastern, and parts of southern India covering most of the rural areas. It can be concluded that meteorological conditions play an important role in those increases according to the comparison between pre-lockdown (Case 1), and lockdown (Case 2).

The drastic decline in PM₂.₅ and its major components during the lockdown period in Case 2 compared with Case 1 shows the positive impacts of emission control measures, especially for SIA. During the lockdown, the decrease of MDA8 O₃ (averaged 15%) occurs in most regions in India, which is attributed to the lower emissions of NOₓ (48%) and VOCs (6%) that are precursors of O₃. Our results demonstrate that the strident emissions controls due to the lockdown have mitigated air pollution in India. However, more stringent mitigation measures are needed to achieve effective control of air pollution from secondary air pollutants and their components, particularly in rural areas. We also find the scattered increases in MDA8 O₃ (up to 21%) in some urban locations in the VOC-limited areas due to the emissions reduction. This indicates that a more localized control policy with the consideration of the O₃ sensitivity regime should be implemented in India to improve the air quality especially for secondary pollutants such as O₃.

Data availability. The datasets used in the study can be accessed from websites listed in the references or by contacting the corresponding authors (peng.ce.wang@polyu.edu.hk; zhanghl@fudan.edu.cn).

Author contribution. MZ conducted the modelling and led the writing of the manuscript. AK carried out the data collection and initial analysis. SZ, JS, and JM assisted with the data analysis. MX, SK assisted with the interpretation of the results and the writing of the paper. HZ and PW designed the study, discussed the results, and edited the paper.

Competing interests. The authors declare that they have no conflict of interest.
Acknowledgments. We acknowledge the publicly available WRF and CMAQ models that make this study possible. This project was funded by the Institute of Eco-Chongming (ECNU-IEC-202001).

References

Ali, K., Inamdar, S. R., Beig, G., Ghude, S., and Peshin, S.: Surface ozone scenario at Pune and Delhi during the decade of 1990s, Journal of Earth System Science, 121, 373-383, https://doi.org/10.1007/s12040-012-0170-1, 2012.

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., and Hollingsworth, T. D.: How will country-based mitigation measures influence the course of the COVID-19 epidemic?, The Lancet, 395, 931-934, https://doi.org/10.1016/s0140-6736(20)30567-5, 2020.

Apituley, A., Pedergnana, M., Sneep, M., Pepijn Veefkind, J., Loyola, D., Landgraf, J., Borsdorff, T.: Sentinel-5 Precursor/TROPOMI Level 2 Product User Manual Carbon Monoxide, . Royal Netherlands Meteorological Institute., 2018.

Balakrishnan, K., Dey, S., Gupta, T., Dhaliwal, R. S., Brauer, M., Cohen, A. J., Stanaway, J. D., Beig, G., Joshi, T. K., Aggarwal, A. N., Sabde, Y., Sadhu, H., Frostad, J., Causey, K., Godwin, W., Shukla, D. K., Kumar, G. A., Varghese, C. M., Muraleedharan, P., Agrawal, A., Anjana, R. M., Bhansali, A., Bhardwaj, D., Burkart, K., Cercy, K., Chakma, J. K., Chowdhury, S., Christopher, D. J., Dutta, E., Furtado, M., Ghosh, S., Ghoshal, A. G., Glenn, S. D., Guleria, R., Gupta, R., Jeemon, P., Kant, R., Kant, S., Kaur, T., Koul, P. A., Krish, V., Krishna, B., Larson, S. L., Madhipatla, K., Mahesh, P. A., Mohan, V., Mukhopadhyay, S., Mutreja, P., Naik, N., Nair, S., Nguyen, G., Odell, C. M., Pandian, J. D., Prabhakaran, D., Prabhakaran, P., Roy, A., Salvi, S., Sambandam, S., Saraf, D., Sharma, M., Shrivastava, A., Singh, V., Tandon, N., Thomas, N. J., Torre, A., Xavier, D., Yadav, G., Singh, S., Shekhar, C., Vos, T., Dandona, R., Reddy, K. S., Lim, S. S., Murray, C. J. L., Venkatesh, S., and Dandona, L.: The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: the Global Burden of Disease Study 2017, The Lancet Planetary Health, 3, e26-e39, https://doi.org/10.1016/S2542-5196(18)30261-4, 2019.

Banerjee, T., Kumar, M., Mall, R. K., and Singh, R. S.: Airing 'clean air' in Clean India Mission, Environmental Science and Pollution Research, 24, 6399-6413, https://doi.org/10.1007/s11356-016-8264-y, 2017.

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

Beig, G., Chate, D. M., Ghude, S. D., Mahajan, A. S., Srinivas, R., Ali, K., Sahu, S. K., Parkhi, N., Surendran, D., and Trimbake, H. R.: Quantifying the effect of air quality control measures during the 2010 Commonwealth Games at Delhi, India, Atmospheric Environment, 80, 455-463, https://doi.org/10.1016/j.atmosenv.2013.08.012, 2013.

Binkowski, F. S., and Roselle, S. J.: Models-3 Community Multiscale Air Quality (CMAQ) model aerosol component 1. Model description, Journal of Geophysical Research: Atmospheres, 108, https://doi.org/10.1007/s12040-012-0170-110.1029/2001jd001409, 2003.

Bujin, B., Joshua S., A., Dylan B, M., Allen, R., Kelley C., W., and Julian D., M.: PM$_{2.5}$ and Ozone Air Pollution Levels Have Not Dropped Consistently Across the US Following Societal Covid Response, 2020.
Byun, D., and Schere, K. L.: Review of the governing equations, computational algorithms, and other components of the models-3 Community Multiscale Air Quality (CMAQ) modeling system, Applied Mechanics Reviews, 59, 51-77, https://doi.org/10.1115/1.2128636, 2006.

Carter, W. P. L.: SAPRC Atmospheric Chemical Mechanisms and VOC Reactivity Scales, http://www.cert.ucr.edu/~carter/SAPRC/, 2011.

Chauhan, A., and Singh, R. P.: Decline in PM$_{2.5}$ concentrations over major cities around the world associated with COVID-19, Environmental Research, 187, 109634, https://doi.org/10.1016/j.envres.2020.109634, 2020.

Chen, Z., Zhuang, Y., Xie, X., Chen, D., Cheng, N., Yang, L., and Li, R.: Understanding long-term variations of meteorological influences on ground ozone concentrations in Beijing During 2006–2016, Environmental Pollution, 245, 29-37, https://doi.org/10.1016/j.envpol.2018.10.117, 2019.

Chintalapudi, N., Battineni, G., and Amenta, F.: COVID-19 virus outbreak forecasting of registered and recovered cases after sixty day lockdown in Italy: A data driven model approach, Journal of Microbiology, Immunology and Infection, 53, 396-403, https://doi.org/10.1016/j.jmii.2020.04.004, 2020.

Collivignarelli, M. C., Abba, A., Bertanza, G., Pedrazzani, R., Ricciardi, P., and Carnevale Miino, M.: Lockdown for CoViD-2019 in Milan: What are the effects on air quality?, Science of The Total Environment, 732, 139280, https://doi.org/10.1016/j.scitotenv.2020.139280, 2020.

Dantas, G., Siciliano, B., Franca, B. B., da Silva, C. M., and Arbilla, G.: The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil, Science of The Total Environment, 729, 139085, https://doi.org/10.1016/j.scitotenv.2020.139085, 2020.

Das, M., Das, A., Sarkar, R., Saha, S., and Mandal, A.: Examining the impact of lockdown (due to COVID-19) on ambient aerosols (PM$_{2.5}$): A study on Indo-Gangetic Plain (IGP) Cities, India, Stochastic Environmental Research and Risk Assessment, https://doi.org/10.1007/s00477-020-01905-x, 2020.

David, L. M., Ravishankara, A. R., Kodros, J. K., Pierce, J. R., Venkataraman, C., and Sadavarte, P.: Premature Mortality Due to PM$_{2.5}$ Over India: Effect of Atmospheric Transport and Anthropogenic Emissions, Geohealth, 3, 2-10, https://doi.org/10.1029/2018GH000169, 2019.

Dominutti, P., Nogueira, T., Fornaro, A., and Borbon, A.: One decade of VOCs measurements in São Paulo megacity: Composition, variability, and emission evaluation in a biofuel usage context, Science of The Total Environment, 738, 139790, https://doi.org/10.1016/j.scitotenv.2020.139790, 2020.

Ehrlich, H., McKenney, M., and Elkbuli, A.: Protecting our healthcare workers during the COVID-19 pandemic, The American Journal of Emergency Medicine, 38, 1527-1528, https://doi.org/10.1016/j.ajem.2020.04.024, 2020.

Emery, C., Tai, E., and Yarwood, G.: Enhanced meteorological modeling and performance evaluation for two Texas ozone episodes, Prepared for the Texas natural resource conservation commission, by ENVIRON International Corporation, 2001a.
Emery, C., Tai, E., and Yarwood, G.: Enhanced meteorological modeling and performance evaluation for two Texas ozone episodes, 2001b.

EPA: Guidance on the Use of Models and Other Analyses in Attainment Demonstrations for the 8-hour Ozone NAAQS, 2005.

EPA, U. E. P. A., Office of Air Quality Planning Standards: Guidance on the use of models and other analyses for demonstrating attainment of air quality goals for ozone, PM$_{2.5}$, and regional haze, 2007.

Feng, T., Zhao, S., Bei, N., Wu, J., Liu, S., Li, X., Liu, L., Qian, Y., Yang, Q., Wang, Y., Zhou, W., Cao, J., and Li, G.: Secondary organic aerosol enhanced by increasing atmospheric oxidizing capacity in Beijing–Tianjin–Hebei (BTH), China, Atmospheric Chemistry and Physics 19, 7429-7443, https://doi.org/10.5194/acp-19-7429-2019, 2019.

Fountoukis, C., and Nenes, A.: ISORROPIA II: a computationally efficient thermodynamic equilibrium model for K$^+$–Ca$^{2+}$–Mg$^{2+}$–NH$_4^+$–Na$^+$–SO$_4^{2-}$–NO$_3^-$–Cl$^-$–H$_2$O aerosols, Atmospheric Chemistry and Physics, 7, 4639-4659, https://doi.org/10.5194/acp-7-4639-2007, 2007.

Garaga, R., Gokhale, S., and Kota, S. H.: Source apportionment of size-segregated atmospheric particles and the influence of particles deposition in the human respiratory tract in rural and urban locations of north-east India, Chemosphere, 255, 126980, https://doi.org/10.1016/j.chemosphere.2020.126980, 2020.

Gautam, S.: The Influence of COVID-19 on Air Quality in India: A Boon or Inutile, Bulletin of Environmental Contamination and Toxicology, 104, 724-726, https://doi.org/10.1007/s00128-020-02877-y, 2020.

Gawhane, R. D., Rao, P. S. P., Budhavant, K. B., Waghmare, V., Meshram, D. C., and Safai, P. D.: Seasonal variation of chemical composition and source apportionment of PM$_{2.5}$ in Pune, India, Environmental Science and Pollution Research, 24, 21065-21072, https://doi.org/10.1007/s11356-017-9761-3, 2017.

Guenther, A. B., Jiang, X., Heald, C. L., Sakulyanontvittaya, T., Duhl, T., Emmons, L. K., and Wang, X.: The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling biogenic emissions, Geoscientific Model Development, 5, 1471-1492, https://doi.org/10.5194/gmd-5-1471-2012, 2012.

Guo, H., Kota, S. H., Sahu, S. K., Hu, J., Ying, Q., Gao, A., and Zhang, H.: Source apportionment of PM$_{2.5}$ in North India using source-oriented air quality models, Environmental Pollution, 231, 426-436, https://doi.org/10.1016/j.envpol.2017.08.016, 2017.

Gurjar, B. R., Ravindra, K., and Nagpure, A. S.: Air pollution trends over Indian megacities and their local-to-global implications, Atmospheric Environment, 142, 475-495, https://doi.org/10.1016/j.atmosenv.2016.06.030, 2016.

Guttikunda, S. K., Nishadh, K. A., Gota, S., Singh, P., Chanda, A., Jawahar, P., and Asundi, J.: Air quality, emissions, and source contributions analysis for the Greater Bengaluru region of India, Atmospheric Pollution Research, 10, 941-953, https://doi.org/10.1016/j.apr.2019.01.002, 2019.

S5P Mission Performance Centre Nitrogen Dioxide [L2__NO2___] Readme: https://sentinel.esa.int/documents/247904/3541451/Sentinel-5P-Nitrogen-Dioxide-Level-2-Product-Readme-File, 2020.
Hu, J., Wu, L., Zheng, B., Zhang, Q., He, K., Chang, Q., Li, X., Yang, F., Ying, Q., and Zhang, H.: Source contributions and regional transport of primary particulate matter in China, Environmental Pollution, 207, 31-42, https://doi.org/10.1016/j.envpol.2015.08.037, 2015.

Hu, J., Chen, J., Ying, Q., and Zhang, H.: One-year simulation of ozone and particulate matter in China using WRF/CMAQ modeling system, Atmospheric Chemistry and Physics, 16, 10333-10350, https://doi.org/10.5194/acp-16-10333-2016, 2016.

Isaifan, R. J.: The dramatic impact of Coronavirus outbreak on air quality: Has it saved as much as it has killed so far?, Global Journal of Environmental Science and Management, 6, 275-288, https://doi.org/10.22034/gjesm.2020.03.01, 2020.

Jain, S., Sharma, S. K., Vijayan, N., and Mandal, T. K.: Seasonal characteristics of aerosols (PM$_{2.5}$ and PM$_{10}$) and their source apportionment using PMF: A four year study over Delhi, India, Environmental Pollution, 262, 114337, https://doi.org/10.1016/j.envpol.2020.114337, 2020.

Kabiraj, S., and Gavli, N. V.: Impact of SARS-CoV-2 Pandemic Lockdown on Air Quality Using Satellite Imagery with Ground Station Monitoring Data in Most Polluted City Kolkata, India, Aerosol Science and Engineering, 4, 320-330, 10.1007/s41810-020-00077-z, 2020.

Karambelas, A., Holloway, T., Kiesewetter, G., and Heyes, C.: Constraining the uncertainty in emissions over India with a regional air quality model evaluation, Atmospheric Environment, 174, 194-203, https://doi.org/10.1016/j.atmosenv.2017.11.052, 2018.

Kitayama, K., Morino, Y., Yamaji, K., and Chatani, S.: Uncertainties in O$_3$ concentrations simulated by CMAQ over Japan using four chemical mechanisms, Atmospheric Environment, 198, 448-462, https://doi.org/10.1016/j.atmosenv.2018.11.003, 2019.

Kota, S. H., Guo, H., Myllyvirta, L., Hu, J., Sahu, S. K., Garaga, R., Ying, Q., Gao, A., Dahiya, S., Wang, Y., and Zhang, H.: Year-long simulation of gaseous and particulate air pollutants in India, Atmospheric Environment, 180, 244-255, https://doi.org/10.1016/j.atmosenv.2018.03.003, 2018.

Kroll, J. H., Heald, C. L., Cappa, C. D., Farmer, D. K., Fry, J. L., Murphy, J. G., and Steiner, A. L.: The complex chemical effects of COVID-19 shutdowns on air quality, Nature Chemistry, 12, 777-779, https://doi.org/10.1038/s41557-020-0535-z, 2020.

Kumar, P., Hama, S., Omidvarborna, H., Sharma, A., Sahani, J., Abhijith, K. V., Debele, S. E., Zavala-Reyes, J. C., Barwise, Y., and Tiwari, A.: Temporary reduction in fine particulate matter due to ‘anthropogenic emissions switch-off’ during COVID-19 lockdown in Indian cities, Sustainable Cities and Society, 62, 102382, https://doi.org/10.1016/j.scs.2020.102382, 2020.

Kumar, S.: Effect of meteorological parameters on spread of COVID-19 in India and air quality during lockdown, Science of The Total Environment, 745, 141021, https://doi.org/10.1016/j.scitotenv.2020.141021, 2020.

Kumari, P., and Toshniwal, D.: Impact of lockdown measures during COVID-19 on air quality- A case study of India, International Journal of Environmental Health Research, 1-8, https://doi.org/10.1080/09603123.2020.1778646, 2020.

Lal, S., Venkataramani, S., Naja, M., Kuniyal, J. C., Mandal, T. K., Bhuyan, P. K., Kumari, K. M., Tripathi, S. N., Sarkar, U., Das, T., Swamy, Y. V., Gopal, K. R., Gadhavi, H., and Kumar, M. K. S.: Loss of crop yields in India due to surface ozone: an
15

estimation based on a network of observations, Environmental Science and Pollution Research, 24, 20972-20981, https://doi.org/10.1007/s11356-017-9729-3, 2017.

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., and Seinfeld, J. H.: Unexpected air pollution with marked emission reductions during the COVID-19 outbreak in China, Science, 369, 702, https://doi.org/10.1126/science.abb7431, 2020.

Mahajan, A. S., De Smedt, I., Biswas, M. S., Ghude, S., Fadnavis, S., Roy, C., and van Roozendael, M.: Inter-annual variations in satellite observations of nitrogen dioxide and formaldehyde over India, Atmospheric Environment, 116, 194-201, https://doi.org/10.1016/j.atmosenv.2015.06.004, 2015.

Mahato, S., Pal, S., and Ghosh, K. G.: Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India, Science of The Total Environment, 730, 139086, https://doi.org/10.1016/j.scitotenv.2020.139086, 2020.

Mor, S., Kumar, S., Singh, T., Dogra, S., Pandey, V., and Ravindra, K.: Impact of COVID-19 lockdown on air quality in Chandigarh, India: Understanding the emission sources during controlled anthropogenic activities, Chemosphere, 263, 127978, https://doi.org/10.1016/j.chemosphere.2020.127978, 2021.

Mukherjee, K.: COVID-19 and lockdown: Insights from Mumbai, Indian Journal of Public Health, 64, 168-171, https://doi.org/10.4103/ijph.IJPH_508_20, 2020.

Nakada, L. Y. K., and Urban, R. C.: COVID-19 pandemic: Impacts on the air quality during the partial lockdown in Sao Paulo state, Brazil, Science of The Total Environment, 730, 139087, https://doi.org/10.1016/j.scitotenv.2020.139087, 2020.

Oksanen, E., Pandey, V., Pandey, A. K., Keski-Saari, S., Kontunen-Soppela, S., and Sharma, C.: Impacts of increasing ozone on Indian plants, Environmental Pollution, 177, 189-200, https://doi.org/10.1016/j.envpol.2013.02.010, 2013.

Otmani, A., Benchrif, A., Tahri, M., Bounakhla, M., Chakir, E. M., El Bouch, M., and Krombi, M.: Impact of Covid-19 lockdown on PM$_{10}$, SO$_2$ and NO$_2$ concentrations in Sale City (Morocco), Science of The Total Environment, 735, 139541, https://doi.org/10.1016/j.scitotenv.2020.139541, 2020.

Pai, C., Bhaskar, A., and Rawoot, V.: Investigating the dynamics of COVID-19 pandemic in India under lockdown, Chaos, Solitons & Fractals, 138, 109988, https://doi.org/10.1016/j.chaos.2020.109988, 2020.

Purohit, P., Amann, M., Kiesewetter, G., Rafaj, P., Chaturvedi, V., Dholakia, H. H., Koti, P. N., Klimont, Z., Borken-Kleefeld, J., Gomez-Sanabria, A., Schopp, W., and Sander, R.: Mitigation pathways towards national ambient air quality standards in India, Environment International, 133, 105147, https://doi.org/10.1016/j.envint.2019.105147, 2019.

Sahu, S. K., Sharma, S., Zhang, H., Chejarla, V., Guo, H., Hu, J., Ying, Q., Xing, J., and Kota, S. H.: Estimating ground level PM$_{2.5}$ concentrations and associated health risk in India using satellite based AOD and WRF predicted meteorological parameters, Chemosphere, 255, 126969,https://doi.org/10.1016/j.chemosphere.2020.126969, 2020.

Schnell, J. L., Naik, V., Horowitz, L. W., Paulot, F., Mao, J., Ginoux, P., Zhao, M., and Ram, K.: Exploring the relationship between surface PM$_{2.5}$ and meteorology in Northern India, Atmospheric Chemistry and Physics, 18, 10157-10175, https://doi.org/10.5194/acp-18-10157-2018, 2018.
Selvam, S., Muthukumar, P., Venkatramanan, S., Roy, P. D., Manikanda Bharath, K., and Jesuraja, K.: SARS-CoV-2 pandemic lockdown: Effects on air quality in the industrialized Gujarat state of India, Science of The Total Environment, 737, 140391, https://doi.org/10.1016/j.scitotenv.2020.140391, 2020.

Sharma, S., Chatani, S., Mahtta, R., Goel, A., and Kumar, A.: Sensitivity analysis of ground level ozone in India using WRF-CMAQ models, Atmospheric Environment, 131, 29-40, https://doi.org/10.1016/j.atmosenv.2016.01.036, 2016.

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

Shehzad, K., Sarfraz, M., and Shah, S. G. M.: The impact of COVID-19 as a necessary evil on air pollution in India during the lockdown, Environmental Pollution, 266, 115080, https://doi.org/10.1016/j.envpol.2020.115080, 2020.

Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paoletti, E., Rodriguez, J. J. D., and Calatayud, V.: Amplified ozone pollution in cities during the COVID-19 lockdown, Science of The Total Environment, 735, 139542, https://doi.org/10.1016/j.scitotenv.2020.139542, 2020.

Sillman, S.: The use of NOy, H2O2, and HNO3 as indicators for ozone-NOx-hydrocarbon sensitivity in urban locations, Journal of Geophysical Research: Atmospheres, 100, 14175-14188, https://doi.org/10.1029/94JD02953, 1995.

Sillman, S., and He, D.: Some theoretical results concerning O3-NOx-VOC chemistry and NOx-VOC indicators, Journal of Geophysical Research: Atmospheres, 107, ACH 26-21-ACH 26-15, https://doi.org/10.1029/2001JD001123, 2002.

Srivastava, S., Kumar, A., Baudh, K., Gautam, A. S., and Kumar, S.: 21-Day Lockdown in India Dramatically Reduced Air Pollution Indices in Lucknow and New Delhi, India, Bulletin of Environmental Contamination and Toxicology, 105, 9-17, https://doi.org/10.1007/s00128-020-02895-w, 2020.

Steiner, A. L., Cohen, R. C., Harley, R. A., Tonse, S., Millet, D. B., Schade, G. W., and Goldstein, A. H.: VOC reactivity in central California: comparing an air quality model to ground-based measurements, Atmospheric Chemistry and Physics, 8, 351-368, https://doi.org/10.5194/acp-8-351-2008, 2008.

Wang, D., Hu, J., Xu, Y., Lv, D., Xie, X., Kleeman, M., Xing, J., Zhang, H., and Ying, Q.: Source contributions to primary and secondary inorganic particulate matter during a severe wintertime PM_{2.5} pollution episode in Xi'an, China, Atmospheric Environment, 97, 182-194, https://doi.org/10.1016/j.atmosenv.2014.08.020, 2014.

Wang, P., Chen, K., Zhu, S., Wang, P., and Zhang, H.: Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak, Resources, Conservation and Recycling, 158, 104814, https://doi.org/10.1016/j.resconrec.2020.104814, 2020.

WHO: Global urban ambient air pollution database (Update 2016), 2016.

WHO: WHO Global Ambient Air Quality Database (Update 2018), 2018.

Wiedinmyer, C., Akagi, S. K., Yokelson, R. J., Emmons, L. K., Al-Saadi, J. A., Orlando, J. J., and Soja, A. J.: The Fire INventory from NCAR (FINN): a high resolution global model to estimate the emissions from open burning, Geoscientific Model Development, 4, 625-641, https://doi.org/10.5194/gmd-4-625-2011, 2011.
Zhang, H., Wang, Y., Hu, J., Ying, Q., and Hu, X. M.: Relationships between meteorological parameters and criteria air pollutants in three megacities in China, Environmental Research, 140, 242-254, https://doi.org/10.1016/j.envres.2015.04.004, 2015.

Zhang, Q., Shao, M., Li, Y., Lu, S. H., Yuan, B., and Chen, W. T.: Increase of ambient formaldehyde in Beijing and its implication for VOC reactivity, Chinese Chemical Letters, 23, 1059-1062, https://doi.org/10.1016/j.cclet.2012.06.015, 2012.

Zhao, B., Wu, W., Wang, S., Xing, J., Chang, X., Liou, K.-N., Jiang, J. H., Gu, Y., Jang, C., Fu, J. S., Zhu, Y., Wang, J., Lin, Y., and Hao, J.: A modeling study of the nonlinear response of fine particles to air pollutant emissions in the Beijing–Tianjin–Hebei region, Atmospheric Chemistry and Physics, 17, 12031-12050, https://doi.org/10.5194/acp-17-12031-2017, 2017.

### Table 1: The criteria on the “Range of Pollution Index” for the purpose of categorization of industrial sectors.

| Categories      | Pollution Index score |
|-----------------|-----------------------|
| Red category    | ≥60                   |
| Orange category | 41–59                 |
| Green category  | 21–40                 |

### Table 2: Percent reduction in anthropogenic emissions in India during COVID-19 lockdown.

| Sector   | %Reduction |
|----------|------------|
| Residential | 0          |
| Industrial  | 82         |
| Agriculture | 0          |
| On-road    | 85         |
| Off-road   | 85         |
| Energy     | 26         |
Figure 1: The simulation domain with the location of major Indian cities selected for analysis.
Figure 2: Comparison of predicted and observed PM$_{2.5}$ from February 21 to April 24, 2020 in Delhi, Mumbai, Chennai, Hyderabad, and Bengaluru. The unit is µg m$^{-3}$.
Figure 3: Comparison of predicted and observed MDA8 O₃ from February 21 to April 24, 2020 in Delhi, Mumbai, Chennai, Hyderabad, and Bengaluru. The unit is ppb.
Figure 4: Predicted PM$_{10}$ (µg m$^{-3}$), PM$_{2.5}$ (µg m$^{-3}$), MDA8 O$_3$ (ppb), NO$_2$ (ppb), and SO$_2$ (ppb) before lockdown, during the lockdown and the changes between them in India. “Case2 - Case1” indicates (Case 2 – Case 1)/Case 1, reported as %. 
Figure 5: Predicted PM$_{2.5}$ components and the changes caused by lockdown measures from March 24 to April 24, 2020 in India. The unit is µg m$^{-3}$. “Case2 - Case1” indicates (Case 2 – Case 1)/Case 1, reported as %.
Figure 6: Predicted relative changes in concentrations of primary and secondary components, and emissions of their precursors in eight cities of India in Case 2 to Case 1.
Figure 7: Predicted O₃, NOₓ, HCHO, and the changes caused by nationwide lockdown measures from March 24 to April 24, 2020 in India. The unit is ppb. “Case2 - Case1” indicates (Case 2 – Case 1)/Case 1, reported as %.
Figure 8: Predicted relative changes in concentrations of O$_3$, HCHO, and NO$_x$ and emissions of VOCs, HCHO, and NO$_x$ in eight major cities of India in Case 2 to Case 1.