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# Silver linings in the dark clouds of COVID-19: Improvement of air quality over India and Delhi metropolitan area from measurements and WRF-CHIMERE model simulations

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ABSTRACT

The current study examines the impact of the COVID-19 lockdown (25th March until May 17, 2020) period in particulate matter (PM) concentrations and air pollutants ($NO_x$, $SO_2$, CO, $NH_3$, and $O_3$) at 63 stations located at Delhi, Uttar Pradesh and Haryana states within the Delhi-NCR, India. Large average reductions are recorded between the stations in each state such as $PM_{10}$ (−46 to −58%), $PM_{2.5}$ (−49 to −55%), $NO_2$ (−27 to −58%), NO (−54% to −59%), CO (−4 to −44%), $NH_3$ (−2 to −38%), while a slight increase is observed for $O_3$ (+4 to +6%) during the lockdown period compared to same periods in previous years. Furthermore, PM and air pollutants are significantly reduced during lockdown compared to the respective period in previous years, while a significant increase in pollution levels is observed after the re-opening of economy. The meteorological changes were rather marginal between the examined periods in order to justify such large reductions in pollution levels, which are mostly attributed to traffic-related pollutants ($NO_x$, CO and road-dust PM). The WRF-CHIMERE model simulations reveal a remarkable reduction in $PM_{2.5}$, $NO_2$ and $SO_2$ levels over whole Indian subcontinent and mostly over urban areas, due to limitation in emissions from the traffic and industrial sectors. A $PM_{2.5}$ reduction of −48% was simulated in Delhi in great consistency with measurements, rendering the model as a powerful tool for simulations of lower pollution levels during lockdown period.

## 1. Introduction

Air pollution and human health are issues of growing concern all over the globe, especially in the highly-populated countries in Asia such as India and China (e.g. Lu et al., 2011; Cao et al., 2014; Das et al., 2018; Wang et al., 2019a). In India, due to the rapid economic growth, vast expansion of metropolitan areas, urbanization and fast-paced development of infrastructure, air pollution has been significantly increased to levels causing important premature mortality and cancer risk (Khanna et al., 2015; Izhar et al., 2016; Kumar and Mishra 2018; Pant et al., 2018; Balakrishnan et al., 2019; Guo et al., 2019). Particulate matter ($PM_{2.5}$ & $PM_{10}$; aerodynamic diameters less than 2.5 and 10 μm, respectively) is the most dominant air pollutant, mainly emitted from vehicular exhausts, industries and power plants, residential wood burning, agricultural biomass burning and dust outbreaks (e.g. Hopke et al., 2008; Mukherjee and Agrawal, 2018; Dumka et al., 2019a; Guo et al., 2019).

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Recently, the Ministry of Environment, Forest and Climate Change (MOEFCC), Govt. of India, initiated a five-year action plan, named "*National Clean Air Programme (*NCAP, MOEFCC, 2019*)*", to tackle the severe air pollution problem over the Indian subcontinent. The main aims and challenges of NCAP is to reduce the $PM_{2.5}$ and $PM_{10}$ levels by ~20–30% till 2024. Similarly, the Chinese government started the *Air Pollution Prevention and Control Action Plan* in September 2013 that significantly improved the air quality in Chinese megacities, except during the winter period when the $PM_{2.5}$ levels have not been drastically reduced due to unfavourable meteorological conditions (e.g. Li et al., 2019; Wang et al., 2019b). Further, the high pollution levels in Delhi and around the National Capital Region (NCR), caused by anthropogenic and natural sources, constitute a major issue for environment and public health (e.g., Cusworth et al., 2018; Dumka et al., 2019a; Jethva et al., 2019; Jain et al., 2020) and, therefore, it is necessary to understand and quantify the changes in air pollution due to limitation strategies like the odd/even traffic system (Chowdhury et al., 2017; Kumar et al., 2017, 2018; Tiwari et al., 2018), and the nationwide lockdown during the COVID-19 pandemic period (March–May 2020).

The novel coronavirus, also known as severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2 or COVID-19; Chen et al., 2020; Huang et al., 2020; Lu et al., 2020) is a new highly contagious disease firstly appeared in Wuhan city, Hubei Province, China in late December 2019 (Shi et al., 2020). Due to the rapidly rising global death tolls from the high infective virus, on January 30, 2020, it was declared by the World Health Organization as global health emergency or "Public Health Emergency of International Concern (PHEIC)" (WHO: World Health Organization, 2020). Later on, COVID-19 was gradually spread over 215 countries around the world and on March 11, 2020, it was declared as global pandemic by WHO (WHO, 2020). Till October 22, 2020 more than 41 million people (total confirmed cases) and more than 1.1 million deaths have been reported around the world, with the highly populated nations like USA, Brazil, India facing a tremendous increasing trend in the infection rates and reported deaths **(**https://www.worldometers.info/coronavirus/; https://www.covid19india.org/**)**. As a consequence, the global scientific community has been alarmed and thousands of papers have been published during the last 5–6 months regarding the way of spreading of the corona virus, its fatality rates and other medical issues, as well as studies concerning socio-economic and atmospheric-pollution research due to governmental measures of social distancing and/or general lockdowns in national economies in a way to limit the spread of the virus. The nationwide lockdowns have led to dramatic effects on the national GDPs and global economy along with large improvement in air quality, especially in urban areas (e.g. Lal et al., 2020; Shrestha et al., 2020). During the lockdown periods, emissions of particulate matter ($PM_{2.5}$ and $PM_{10}$) and air pollutants from sectors like traffic and industry were significantly reduced all around the world (Bauwens et al., 2020; Broomandi et al., 2020; Liu et al., 2020; Shi and Brasseur, 2020; Wang and Su, 2020; Xu et al., 2020a, b; Zhang et al., 2020, among many others). Ground-based and space-borne measurements have revealed significant reductions of PM, $NO_2$, $SO_2$, CO over China, USA, south Europe, south America and southeast Asia with positive effects on environment and human health (Dutheil et al., 2020; Grivas et al., 2020; Karkour and Itsubo, 2020; Li and Tartarini, 2020; Muhammad et al., 2020; Stratoulias and Nuthammachot, 2020; Tobías et al., 2020; Venter et al., 2020; Wang et al., 2020).

In India, the first confirm cases of COVID-19 were detected in late January 2020 (PIB, 2020) and later on, in the beginning of July, India become the 3rd most affected country in the world (https://www.worldometers.info/coronavirus/). Nowadays, India is facing a significant rise in the number of new cases and deaths (https://www.worldometers.info/coronavirus/; https://www.covid19india.org). Due to the rapid spread of COVID-19 infection, the central government of India imposed one day Janata Curfew on March 22, 2020. During this Janata Curfew all the flights (domestic and international), trains and buses were closed, and later on, March 25, 2020, the government imposed a nationwide complete lockdown, when India had 600 confirmed cases of COVID-19. Till then, the lockdown was extended four times, via re-considering the epidemiologic situation over the nation. After May 17, 2020, several norms were relaxed at different phases and government of India decided to extend the lockdown till June 30, 2020 in the containment zone. During the lockdown period, several restrictions were imposed, with completely disruption in the business and industrial activities, all kind of transport and vehicular traffic, which improved air quality across the country. The improve in air quality became apparent to people living in Delhi-NCR, since the large increase in visibility allowed views of the snow-capped Himalayas for the first time after several decades. In India, several studies have been carried out examining the changes in air pollution associated with COVID-19 lockdown period, reporting large reductions in aerosols and pollutants (Chauhan and Singh, 2020; Jain and Sharma, 2020; Kumar et al., 2020; Lokhandwala and Gautam, 2020; Mitra et al., 2020; Sharma et al., 2020; Singh et al., 2020a). Further, Singh et al. (2020b) reported a significant linkage between short-term $PM_{2.5}$ exposure and daily COVID-19 confirmed cases.

The present work aims to evaluate the plausible reductions in air pollutants and aerosols over the Indian subcontinent, with emphasis on Delhi-NCR, during the COVID-19 lockdown period. More specifically, we analyse the changes in ground-based pollutants ($PM_{2.5}$, $PM_{10}$, NO, $NO_2$, CO, $SO_2$, $O_3$ and $NH_3$) at 63 stations (urban, traffic, suburban, rural) around Delhi-NCR during lockdown (25th March to May 17, 2020) with pre- (1st to March 24, 2020) and post-lockdown (18th May to June 4, 2020) periods, as well as the satellite AODs and $NO_2$ levels over the Indian subcontinent during the same periods. In addition, the same analysis was expanded to the previous years and for the same period (1st March to 4th June), in order to assess the influence of limitation in anthropogenic emissions and the recovery of them after the re-opening of the economy, which has not been fully quantified. In parallel, the WRF-CHIMERE model simulations over the whole Indian subcontinent have been also analysed to assess the reduction in emissions and pollutant concentrations in April 2020 b y considering a lockdown scenario with complete shutdown of the traffic and industrial sectors against the usual scenario. Comparison of the model estimates under the two scenarios with measurements around Delhi-NCR will allow assessment of the fraction of the reduced human activities in the pollution levels during the lockdown period. The results will be especially important for general public as well as local governments and policy-makers for formulating the stringent policies in the post COVID-19 period for maintaining the improved air quality over the region, also in view of the NCAP strategy.

## 2. Study site, observations and methodology

The study area, Delhi-NCR (national capital of India), is the second largest megacity in India and one of the most polluted cities worldwide (e.g. Bisht et al., 2015; Tickell and Ranasinha, 2018; Dumka et al., 2018). Delhi has the largest urban agglomeration in India with ~16.8 million residents and a decadal growth rate of 21% (census, 2011; http://census2011.co.in). It has a population density of 11297 people per $km^2$ increasing at an average annual rate of 37.6% (Mahato et al., 2020). According to several studies, the very high $PM_{2.5}$ levels in Delhi have deleterious effects on public health such as breathing problems, chronic respiratory disorders, pneumonia, acute asthma etc. (Dholakia et al., 2013; Rizwan et al., 2013; Kumar et al., 2018; Chowdhury et al., 2019).

The air pollution data, on hourly basis, were obtained from the Central Pollution Control Board (https://www.cpcb.nic.in/), referring to concentrations of $PM_{2.5}$, $PM_{10}$, near-surface ozone ($O_3$), nitrogen oxides ($NO_x$; namely nitrogen dioxide [$NO_2$] and nitric oxide [NO]), carbon monoxide (CO), sulfur dioxide ($SO_2$) and ammonia ($NH_3$). CPCB provides quality assurance or quality control data, while the measurement methods for the various pollutants are under the WHO guidelines. $PM_{10}$ and $PM_{2.5}$ are measured using BAM monitors on the principle of beta attenuation, $NO_x$ are measured via Thermo 42i NO–$NO_2$-$NO_x$

monitors (Thermo Fischer Scientific Inc., USA), while UV photometric 49i (Thermo Fischer Scientific Inc., USA) was used for $O_3$. CO was monitored via Non-Dispersive Infrared (NDIR) spectroscopy, while $SO_2$ from Ultraviolet fluorescence (Kumar et al., 2017; Hama et al., 2020). More details of methodology and measuring protocols are available at http://cpcbenvis.nic.in/air_pollution_main.html. $NO_2$ and surface $O_3$ are secondary pollutants formed by the precursor gases in the presence of sunlight, while primary emission sources include combustion of fossil fuels in automobiles and industries, biofuel and waste material burning, agricultural fires etc. (Tiwari et al., 2015; Jain et al., 2020). Analysis of temporal evolution and trends in the pollutant gases was performed at 63 air quality monitoring stations within the Delhi metropolitan agglomeration (36 stations in Delhi, 13 in Uttar Pradesh and 14 in Haryana states; see Suppl. Table 1), aiming to quantify the impact of lockdown on air pollution. The 63 stations exhibit different characteristics and pollution levels as they are located in traffic, urban, suburban, residential and rural areas around Delhi-NCR. Meteorology plays an important role in determining the pollutant concentrations, and we also used surface meteorological parameters (temperature, wind speed, relative humidity) from certain CPCB stations to compare modelling results and to assess the impact of meteorology on the pollution changes. The study period is divided and analysed in three sub-periods, (i) pre-lockdown (01$^{st}$ −24th March 2020), (ii) lockdown (25th March to May 17, 2020) and (iii) post-lockdown (18th May – June 4, 2020). Same sub-periods were considered in the previous year's 2017–2019 for comparison with 2020 observations.

Furthermore, columnar AOD and tropospheric $NO_2$ concentrations were obtained over the Indian subcontinent from MODIS (Moderate Resolution Imaging Spectroradiometer) on-board Terra and Aura-OMI (Ozone Monitoring Instruments) satellites, respectively. The $NO_2$ data at 25 km spatial resolution was obtained from the daily level_3 $NO_2$ product from Aura OMI. Details about Aura-OMI and Terra-MODIS retrievals are described in a series of papers (e.g. Li et al., 2020a) and are not repeated here. Furthermore, daily temperature and RH data are taken from Atmospheric Infrared Sounder (AIRS) satellites (Aqua and Terra) with spatial resolution of 13.5 km at nadir from 705.3 km orbit, while the Vis/NIR spatial resolution is 2.3 km (https://airs.jpl.nasa.gov/). Hourly wind speed data were obtained from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), which is the latest atmospheric reanalysis of the modern satellite era produced by NASAs Global Modelling and Assimilation Office (GMAO) with spatial resolution of 0.5 ° × 0.625 ° (Gelaro et al., 2017). In addition, total precipitation (mm) data are obtained from Global Precipitation Measurement (GPM, version GPM_3IMERGDF_v06; Skofronick-Jackson et al., 2018) with a spatial resolution of 10 km 10 km. All meteorological parameters were considered at the domain 20°-30° N, 75°-85° E covering the northern part of India. Satellite and re-analysis data from previous years were also used to understand the changes in emissions and concentrations during the 2020 lockdown compared to same periods in previous years, while analysis was also performed for the post-lockdown period in order to assess the increase in pollution due to re-opening of the economy.

## 3. WRF-CHIMERE model setup

To further aid the evaluation of the reduction in air pollution due to the lockdown effect, a chemical transport model, CHIMERE (version: 2014b) (Menut et al., 2013), externally forced by Weather Research and Forecasting (WRF-V3.7) model as a meteorological driver in offline mode, was applied. Model simulations are performed for April 2020, keeping a spin-up time of 15-days in March 2020 i.e., from 16 to 31 March, as suggested in previous studies for CHIMERE simulations (Menut et al., 2013, 2020; Bessagnet et al., 2017). The initial and boundary meteorological conditions for WRF simulations are obtained from the Global Forecast System (GFS) National Center for Environmental Prediction - FINAL operational global analysis data. The WRF is

**Table 1**
Reduction in pollution levels due to COVID-19 lockdown effect in India and Asia.

| Study Site | Main Findings | References |
|---|---|---|
| Delhi (India) | Reduction of $PM_{10}$ (−26%), $PM_{2.5}$ (−29%), $NO_2$ (−47%), CO (−19%) | Present Study |
| NCR-UP (India) | Reduction of $PM_{10}$ (−14%), $PM_{2.5}$ (−28%), $NO_2$ (−38%), $SO_2$ (−11%), CO (−9%) | Present Study |
| NCR-Haryana (India) | Reduction of $PM_{10}$ (−7%), $PM_{2.5}$ (−24%), $NO_2$ (−27%), $SO_2$ (−10%), CO (−28%) | Present Study |
| Delhi (India) | Reduction of $PM_{10}$ (−60%), $PM_{2.5}$ (−39%), $NO_2$ (−53%), CO (−30%) | Mahato et al. (2020) |
| Kolkata (India) | 30–40% reduction of $CO_2$ | Mitra et al. (2020) |
| 22 cities in India | Reduction of $PM_{2.5}$ (−43%), $PM_{10}$ (−31%), mean excessive PM risk (−52%), CO (−10%), $NO_2$ (−18%) Enhancement of $O_3$ (+17%), negligible changes in $SO_2$ Reduction of AQI by −44% (north India), −33% (south), −29% (east), −15% (central), −32% (west) | Sharma et al. (2020) |
| 134 sites in India | Reduction of ~ −40 to −60% in $PM_{2.5}$ and $PM_{10}$; ~- 30 to −70% in $NO_2$; ~-20 to −40% in CO | Singh et al. (2020a) |
| India (different cities) | Reduction of $PM_{2.5}$ (Kolkata: −22%; Hyderabad: −26%, Chennai: −28%) | Kumar et al. (2020) |
| Delhi, Mumbai, Kolkata, Bangalore (India) | Declines in $PM_{2.5}$ (−41%), $PM_{10}$ (−52%), $NO_2$ (−51%), CO (−28%) | Jain and Sharma (2020) |
| India | Reduction of $PM_{2.5}$ (Mumbai: −14 to −43%; Delhi: −35 to −39%) | Chauhan and Singh (2020) |
| China | Reduction of $NO_2$ (−30%) near Wuhan, $CO_2$ (−25%) in China and −6% globally | Dutheil et al. (2020) |
| China | Decline in $PM_{2.5}$ (−14.8%), $PM_{10}$ (−20.5%), $NO_2$ (−25%), CO (−6.2%), $SO_2$ (−21.4%) | Wang and Su (2020) |
| Anqing, China | $PM_{2.5}$ (−29.7%), $PM_{10}$ (−47.2%), $NO_2$ (−36.5%), CO (−19.7%), $SO_2$ (−48.5%), $O_3$ (+8.2%) | Xu et al. (2020a) |
| Hefei, China | $PM_{2.5}$ (−35.8%), $PM_{10}$ (−35.7%), $NO_2$ (−21.7%), CO (−24.5%), $SO_2$ (−47.6%), $O_3$ (+3.3%) | Xu et al. (2020a) |
| Suzhou, China | $PM_{2.5}$ (−33.5%), $PM_{10}$ (−19.0%), $NO_2$ (−36.5%), CO (−5.8%), $SO_2$ (−67.1%), $O_3$ (−0.06%) | Xu et al. (2020a) |
| Wuhan, China | $PM_{2.5}$ (−44.0%), $PM_{10}$ (−47.9%), $NO_2$ (−54.7%), CO (−16.2%), $SO_2$ (−29.9%), $O_3$ (+27.1%) | Xu et al. (2020b) |
| Jingmen, China | $PM_{2.5}$ (−30.5%), $PM_{10}$ (−48.4%), $NO_2$ (−64.3%), CO (−31.9%), $SO_2$ (−34.9%), $O_3$ (+8.9%) | Xu et al. (2020b) |
| Enshi, China | $PM_{2.5}$ (−15.7%), $PM_{10}$ (−25.1%), $NO_2$ (−65.2%), CO (−35.8%), $SO_2$ (−35.4%), $O_3$ (+6.9%) | Xu et al. (2020b) |
| Yangtze River Delta Region (China) | Reduction of $SO_2$ (−16 to −26%), $NO_X$ (−29 to −47%), $PM_{2.5}$ (−27 to −46%) and VOCs (−37 to −57%) | Li et al. (2020b) |
| Northern China | Decrease in $PM_{2.5}$ (−29 ± 22%), $NO_2$ (−53 ± 10%) and increase in $O_3$ (+2.0 ± 0.7%) | Shi and Brasseur (2020) |
| Malaysia and southeast Asia | Decline in AOD (urban areas: −40 to −70%), $PM_{2.5}$ (industrial: −20 to −42%, urban: −23 to −32%), decline in $PM_{10}$ (industrial: −28 to −39%, urban: −26 to −31%), in $NO_2$ (industrial: −33 to −46%, urban: −63 to −64%), in $SO_2$ (urban: −9 to −20%) and CO (urban: −25 to −31%) | Kanniah et al. (2020) |
| Tehran, Iran | $PM_{2.5}$ (+10.50%), $PM_{10}$ (−11.33%), $NO_2$ (−13%), CO (−13%), $SO_2$ (−12.5%) and $O_3$ (+3%) | Broomandi et al. (2020) |
| Almaty, Kazakhstan | $PM_{2.5}$ (−29%), $NO_2$ (−35%), CO (−49%), $SO_2$ (7%) and $O_3$ (+15%) | Kerimray et al. (2020) |
| Globe | Reduction of $PM_{2.5}$ (Paris: −53%; Amsterdam: −47%; London: −45%) | Shrestha et al. (2020) |

nudged by NCEP fields every 6 h and meteorological fields are simulated in WRF at the same temporal and horizontal resolution as that for CHIMERE. More details about the WRF-CHIMERE modelling setup for the Indian region and the recent model evaluations are provided in recent studies (e.g., Verma et al., 2017; Ghosh et al., 2020). The WRF simulated meteorology compared reasonably well with meteorological observations in India. Monthly means of simulated temperature and relative humidity values for April month were found to be consistent within a bias of ±15% compared with available observations at selected stations in India (Ramachandran and Kedia, 2010; Dumka et al., 2013; Pani, 2013; Aruna et al., 2014) (Suppl. Fig. 1).

Simulations of air quality in CHIMERE, including nitrogen oxides ($NO_2$), Sulfur oxides ($SO_2$) and $PM_{2.5}$, are carried out over the Indian subcontinent (6–38° N and 68°–99.25° E) at a temporal resolution of 1 h, horizontal grid resolution of 25 km × 25 km and twenty vertical levels in sigma-pressure coordinates ranging from the surface (997 hPa) to 300 hPa. Aerosol constituents contributing to $PM_{2.5}$ mass include black carbon (BC), sulfate, nitrate, ammonium, primary organic matter (POM), secondary organic aerosols (SOA), sea salt, and mineral dust. Details about the chemical mechanisms for gaseous species and aerosols in CHIMERE are described elsewhere (Bessagnet et al., 2010; Menut et al., 2013).

Aerosol emissions from anthropogenic activities implemented in CHIMERE include fuel consumption for energy in industrial, transportation and residential household sectors. Besides, these also include emissions due to open biomass burning in the agricultural sector and forest fires. The anthropogenic emissions implemented in the WRF-CHIMERE modelling setup are observation-constrained emissions recently estimated over the Indian region for BC, POM, $SO_2$ at a grid resolution of 25 km × 25 km, using integrated modelling approaches (Verma et al., 2017; Kumar et al., 2018; Ghosh and Verma, 2020). The $NO_2$ emissions are from global bottom-up emission inventory of Emission Database for Global Atmospheric Research-V4 (EDGAR-V4) (Janssens-Maenhout et al., 2012; http://edgar.jrc.ec.europa.eu/htap_V2/index.php) extracted over India and re-gridded to the same resolution as the Indian emission database. The simulated concentrations of atmospheric species have been found to represent well the present-day ambient values in India (Verma et al., 2017; Ghosh et al., 2020). In this study, the CHIMERE simulations are performed for two scenarios (i) a usual scenario "US", when all activities are going on as usual, (ii) a pandemic lockdown scenario "PLS", on which the decrease in anthropogenic emissions is evinced due to closedown of activities in industrial and transportation sectors. For the PLS scenario, emissions due to domestic activities, open agricultural burning and forest fires have been only considered from the emission database mentioned above. The monthly-mean (April) simulated $SO_2$, $NO_2$ and $PM_{2.5}$ concentrations for these two scenarios are analysed over the Indian subcontinent.

## 4. Results and discussion

### 4.1. Meteorological conditions

Changes in local and regional meteorology are especially important for evaluation of the anthropogenic impact during the lockdown period (Grivas et al., 2020; Su et al., 2020), since, especially over northern India, strong winds may transfer dust plumes from the Thar desert in pre-monsoon (Dumka et al., 2019b), while low temperatures and increased RH levels may escalate the haze and pollution smog conditions

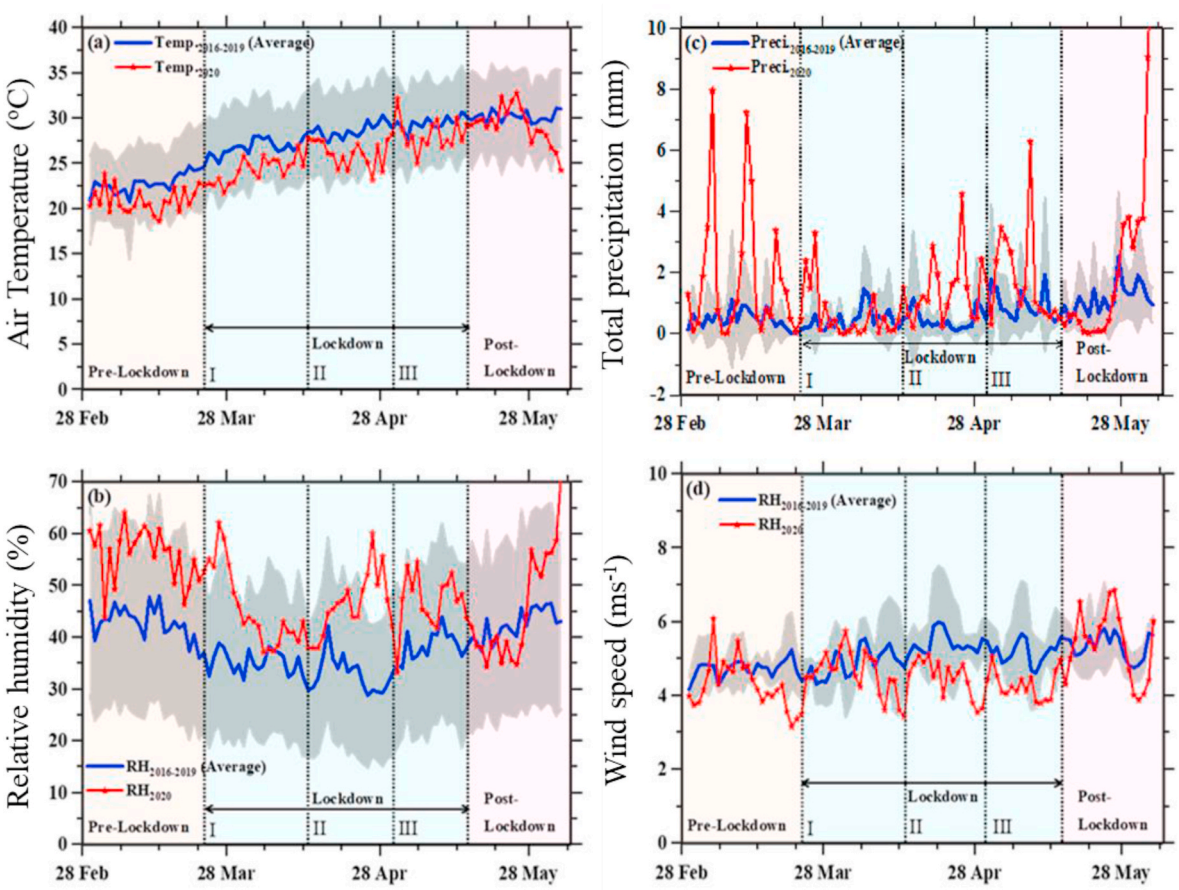


**Fig. 1.** Mean daily variation of meteorological parameters over north India [20°-30° N, 75°-85°E] during the examined period in 2016–2019 (blue) and in 2020 (red). The grey area corresponds to the standard deviation of the daily mean during 2016–2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(Bisht et al., 2015; Tiwari et al., 2015). Fig. 1 shows the daily evolution of the air temperature at 2 m, RH, precipitation and wind speed during 1 March – 6 June for the years 2020 (red lines) and the means (blue lines) during the period 2016–2019, as obtained from MERRA-2 reanalysis database over north India (20°-30° N, 75°-85° E). Air temperature in 2020 is slightly lower (~−5%) from the 2016–2019 mean, but well within the standard deviation area, while RH follows an opposite tendency with increased values during the lockdown period in 2020. These conditions, along with the slightly weaker than normal winds and normal rainfall levels (except for few days), would facilitate the accumulation of pollution over the Delhi urban environment in the examined period of 2020 under normal emission conditions and weak effects from long-range transported aerosols. However, the nationwide lockdown had drastically altered this situation, and the changes in aerosol and pollutant concentrations are attributed to limitation in anthropogenic emissions and only marginally can be ascribed to changes in meteorology.

### 4.2. Changes in AOD and $NO_2$ from satellite observations

In order to quantify the impact of COVID-19 lockdown on columnar AOD over the Indian subcontinent, we estimated the (%) changes of AOD in year 2020 against the previous years. The composite maps of Terra-MODIS AOD changes during the lockdown period with respect to previous years (selected for minimising the impact of meteorological conditions) are shown in Fig. 2. The spatial variation of AOD changes demonstrates contradict tendencies (increase and decrease) over different parts of the Indian subcontinent. The comparisons of the years 2020 vs. 2019 (Figs. 2a), 2020 vs. 2018 (Figs. 2b) and 2020 vs. 2017 (Fig. 2c) indicate an about −30% to −50% decrease of AOD over north India, and particularly over the Indo-Gangetic Plains (IGP), as well as over parts of the Bay of Bengal and the Arabian Sea, which, however, are mostly attributed to natural causes, i.e. inter-annual variability of dust and sea salt emissions (Dey and di Girolamo, 2010; Kaskaoutis et al., 2011; 2014). IGP is the most densely populated and the major aerosol hot spot area in south Asia with dominance of anthropogenic emissions, mixed with dust from the Thar desert and wheat-residue burning during the pre-monsoon season (Dey and di Girolamo, 2010; Srivastava et al., 2012; Singh et al., 2018a). Therefore, the notable decrease in columnar AOD during pre-monsoon of 2020 is ascribed to a remarkable reduction in anthropogenic sources, mainly consisted of emissions from traffic, industries, power plants and biofuel burning in the megacities of Delhi, Kanpur, Varanasi, etc (e.g. Chakraborty and Gupta, 2010; Jaiprakash et al., 2016; Jain et al., 2017; Gadi et al., 2019; Singh et al., 2019). This indicates that the lockdown impact on air quality can be detected even from columnar aerosol measurements, which are generally less affected by short-term changes in human activities compared to near-surface pollution concentrations (Kanniah et al., 2020). On the contrary, Fig. 2 shows rather unchanged AODs over central India, while in some areas increasing AODs during the 2020 period are detected, which were attributed to changes in meteorological conditions (Selvam et al., 2020). Furthermore, these areas are not so densely populated with weaker anthropogenic emissions compared to IGP, justifying the less effect on columnar AOD. A significant decrease in AOD during the COVID-19 lockdown was also observed at several parts in southeast Asia, mainly over the urban centers like Kuala Lumpur, Singapore, Manila, which recorded a reduction of −40% to −70% compared to the same period in previous years (Kanniah et al., 2020).

Furthermore, the (%) AOD changes between lockdown and pre- and post-lockdown periods were analysed for the year 2020 and compared with the respective changes in 2019, 2018 and 2017 (Fig. 3). Since AOD over India is generally escalating from March to May, especially in the northern part due to influence of dust, the analysis of the lockdown vs. pre- or post-lockdown periods may be masked from sources other than human emissions and, therefore, these four years are examined. In the year 2020, a considerable reduction in AOD, which may reach to 20–30%, is observed over the northern part of India during the lockdown compared to pre-lockdown period (Fig. 3a). This decrease was not observed in the previous years (2017–2019) (Fig. 3c, e, 3g), thus highlighting the impact on anthropogenic-AOD reduction due to lockdown compared to the period before. The increase in AOD during the post-lockdown period in 2020 over northern India (Fig. 3b) cannot be totally ascribed to the re-opening of the economy and to increase in anthropogenic emissions as a result of relaxation of the restriction measures in transportation, since such an increasing tendency is also detected over the Thar desert, implying enhancement in dust emissions as well. A general increase in AOD from March to May, but with large variability between the years, is mostly observed over continental India in the rest of the years (Figs. 3d, 2f and 2h). Therefore, the net impact of the re-opening in the economy on AOD is really difficult to be quantified, since dust activity plays a major role and its increasing tendency by the end of the pre-monsoon season masks the increasing AOD trend after the lockdown period. The temporal evolution of daily Terra and Aqua MODIS AODs over north India (20°-30° N, 75°-85° E) showed a notable AOD decrease during the lockdown period compared to the mean of 2016–2019, while similar AOD levels in 2020 with the 2016–2019 mean was observed for the pre-lockdown period (Suppl. Fig. 2a). On the contrary, AODs in May 2020 remained slightly below the mean levels.

In a similar study, Pathakoti et al. (2020) showed higher AODs over the IGP and central India during the pre-lockdown period due to the seasonal dust transport that enhances the AOD (David et al., 2018). The nationwide lockdown had strong impact on aerosol loading over the Indian subcontinent highlighting the significance of the anthropogenic emissions. In a recent study, Kumar et al. (2020) found AOD reductions over Chennai (−29 to −57%), Delhi (−11 to −29%), Kolkata (−2 to −14%) and Mumbai (−1 to −48%) during March-April 2020 compared

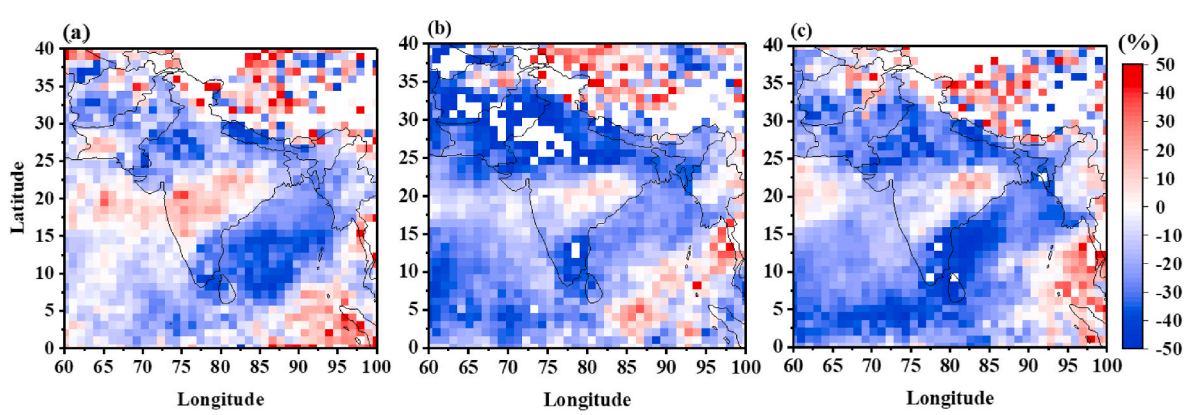


**Fig. 2.** Spatial distribution of (%) changes in AOD during the lockdown period (25th March to May 17, 2020) compared to the same period in 2019 (a), 2018 (b) and 2017 (c). Changes [$((AOD_{2020} - AOD_{201X})/AOD_{201X})*100$].

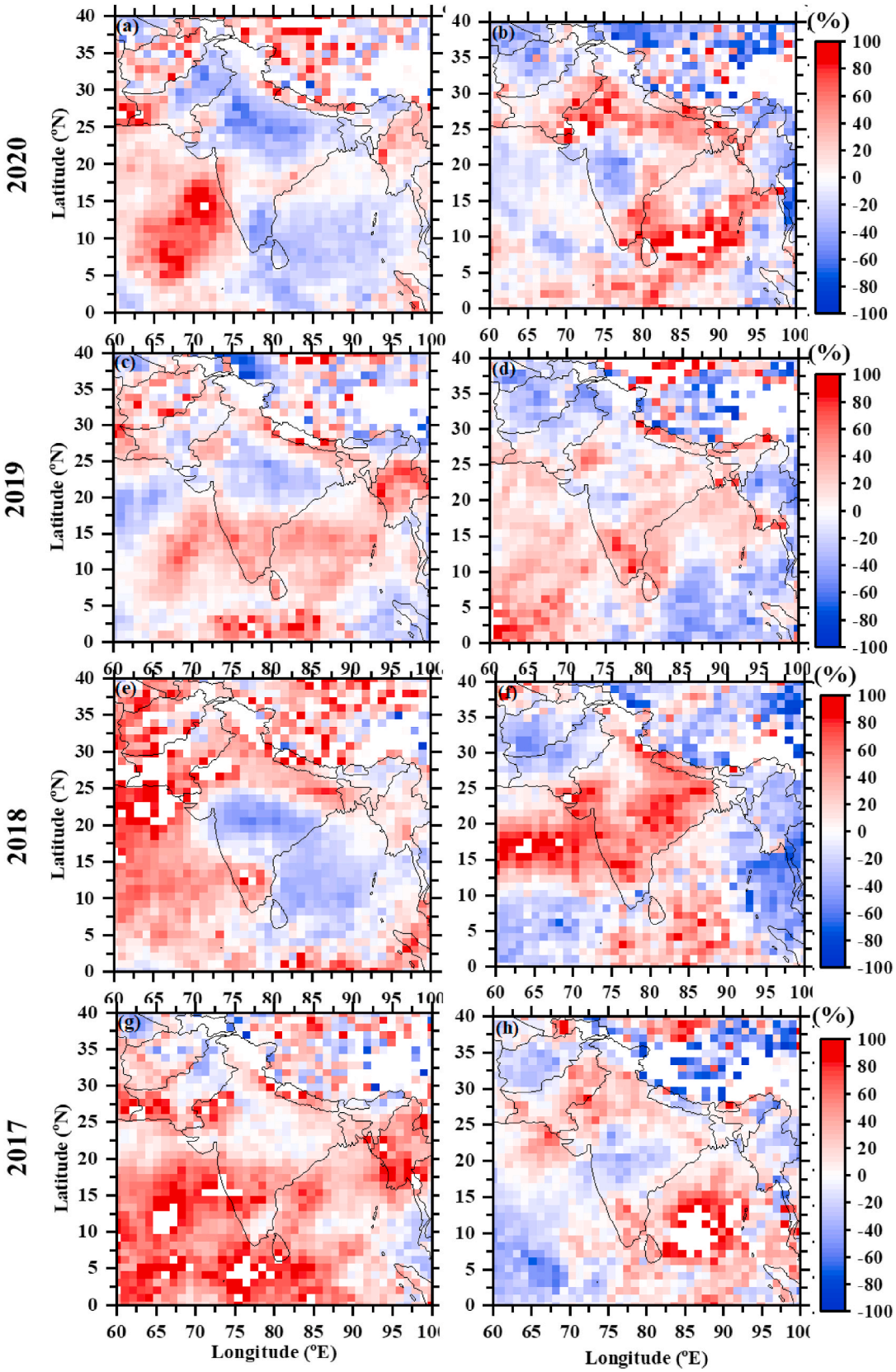


**Fig. 3.** Percentage (%) changes in Terra-MODIS AODs over the Indian subcontinent between lockdown and pre-lockdown (left panels), lockdown and post-lockdown (right panels) for 2020 and same for the years 2019, 2018 and 2017. [((lockdown – pre-lockdown)/pre-lockdown)*100 and ((post-lockdown – lockdown)/lockdown)*100].

to the previous year. Using the MODIS–based Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm, Ranjan et al. (2020) studied the changes in AOD over the Indian subcontinent during the lockdown period (25th March to May 15, 2020) and compared them with long-term (2000–2019) aerosol climatology for the same period, reporting an average AOD reduction of −45% (−36.5% over Delhi-NCR). Based on ground measurements at six sites in India and Pakistan, Pandey and Vinoj (2020) computed a significant AOD decrease during the lockdown period, with highest reductions over Lahore (−60% compared to pre-lockdown period) and Kanpur (−40%), whereas lower decreases were reported over the coastal sites (i.e. Bhola). A summary of AOD decreases during the COVID-19 lockdown period at several sites is included in Table 1.

Fig. 4 shows the spatial distribution of the (%) changes of tropospheric $NO_2$ over the Indian subcontinent during the lockdown period, by comparing same periods between 2020, 2019, 2018 and 2017. The results show a remarkable reduction of tropospheric $NO_2$ during the 2020 lockdown period compared to the previous years, which maximizes over the IGP and parts of the eastern India, approaching −30% to −50% (Biswal et al., 2020). $NO_2$ is emitted from traffic exhausts and fossil-fuel combustion in Indian megacities, while coal-fired power plants mostly located in north and east India are also significant sources of $NO_2$ (Prasad et al., 2012; Singh et al., 2018b). As $NO_2$ has a limited atmospheric lifetime of 1–2 days, its concentrations maximize over the major emission sources (urban agglomerations and power plants), which are mostly associated with the highest decreasing fractions of $NO_2$ during the COVID-19 lockdown. Over the oceanic areas and the Tibetan Plateau, the tropospheric $NO_2$ concentrations are very low and the percentage changes are highly uncertain. Similar reductions of tropospheric $NO_2$ have been also reported at several sites over the globe during the COVID-19 lockdown (e.g. Bauwens et al., 2020; Li et al., 2020b; Mahato et al., 2020; Tobías et al., 2020, Table 1). Over Southeast Asia, Kanniah et al. (2020) noticed a significant decreasing trend of tropospheric $NO_2$ (−27% to −30%) during the COVID-19 lockdown period in areas not affected by agricultural biomass burning.

Furthermore, Fig. 5a–h shows the (%) $NO_2$ changes between pre-lockdown and lockdown (left columns) and lockdown to post-lockdown (right columns) for the year 2020 (a, b), as well as in previous years (2019, 2018, 2017) for the same periods. The comparisons of the lockdown with pre-lockdown and post-lockdown periods did not reveal a significant change over the Indian subcontinent (Fig. 5a and b), while notable reductions are observed over Myanmar, which, however, may be attributed to changes in agricultural burning in this area during the pre-monsoon season (Kalita et al., 2020). Similar results of no detectable changes in tropospheric $NO_2$ levels between the examined periods are seen in the other years. The spatial-averaged $NO_2$ concentration over the Indian subcontinent during the lockdown period in 2020 was $8.07 \times 10^{14}$ molecules $cm^{-2}$ against 9.20, 9.21 and $9.51 \times 10^{14}$ molecules $cm^{-2}$ in 2019, 2018 and 2017, respectively, corresponding to an average reduction of −14% to −18%. The high $NO_2$ concentrations at point locations over India (Singh et al., 2018b; Biswal et al., 2020) and its short atmospheric lifetime are likely reasons for the relative small $NO_2$ changes using satellite measurements at large spatial domains. This necessitates analysis of data on specified locations in order to quantify the influence of the lockdown in air pollutant concentrations. Therefore, over north India tropospheric $NO_2$ was lower during the lockdown period by −23.7% compared to the mean of 2016–2019 (Suppl. Fig. 2b), while the same was evident during the whole spring season of 2020.

### 4.3. Changes in near surface air pollution during COVID-19 lockdown

Fig. 6 shows the (%) changes of $PM_{2.5}$, $PM_{10}$, NO, $NO_2$, $O_3$, and CO between lockdown (25th March to May 17, 2020) and pre-lockdown (01st −24th March 2020) and post lockdown (18th May – June 4, 2020) to lockdown periods (Fig. 6a and b, respectively) at stations in the Delhi-NCR, as well as the respective changes between the same periods in 2019 and 2018. Considering the changes during the lockdown period in 2020 (Fig. 6a), significant reductions mostly in the range of −30% to −50% compared to the pre-lockdown period are observed at all stations, especially for NO (−64%), but also for $NO_2$ (−47%). The reductions for the other pollutants are found to be significantly lower, ranging between −49.7% and +3.0% (mean of −26.5%) for $PM_{10}$, -62.9% to −100.8% (mean of −29%) for $PM_{2.5}$ and −61.4 to +88.3% (mean of −19%) for CO. In contrast, $O_3$ concentrations increased during the lockdown period at nearly all the examined stations (mean increase of +37%). Increase in tropospheric $O_3$ during the lockdown period with minimum fossil-fuel combustion emissions were reported at several urban areas in India (Navinya et al., 2020) and around the world like Kuala Lumpur, Malaysia (Kanniah et al., 2020), Yangtze River Delta, China (Li et al., 2020b), Barcelona, Spain (Tobías et al., 2020), Rio de Janeiro, Brazil (Dantas et al., 2020), Sao Paolo, Brazil (Nakada and Urban, 2020), Almaty, Kazakhstan (Kerimray et al., 2020). This increase in $O_3$ levels is attributed to the large decrease in primary NO concentrations that lower down the $O_3$ consumption via titration process, as $O_3$ is a secondary pollutant formed by NO titration in the presence of UV light or via volatile organic compounds (VOCs) (e.g. Reche et al., 2018). On the contrary, the change in atmospheric pollutants between the same periods in the previous years 2019 and 2018 (Fig. 6c, e), did not reveal a systematic trend and exhibited a considerable variability between the stations. The higher $PM_{10}$ levels in the period 25 March - May 17, 2019 (Fig. 6c) indicated an increase in coarse-mode particles due to very low changes in $PM_{2.5}$, while the increase in $O_3$ is likely attributed to higher formation rates in this period due to increase in solar UV radiation compared to 1–24 March. This weakens the effect of the lower NO

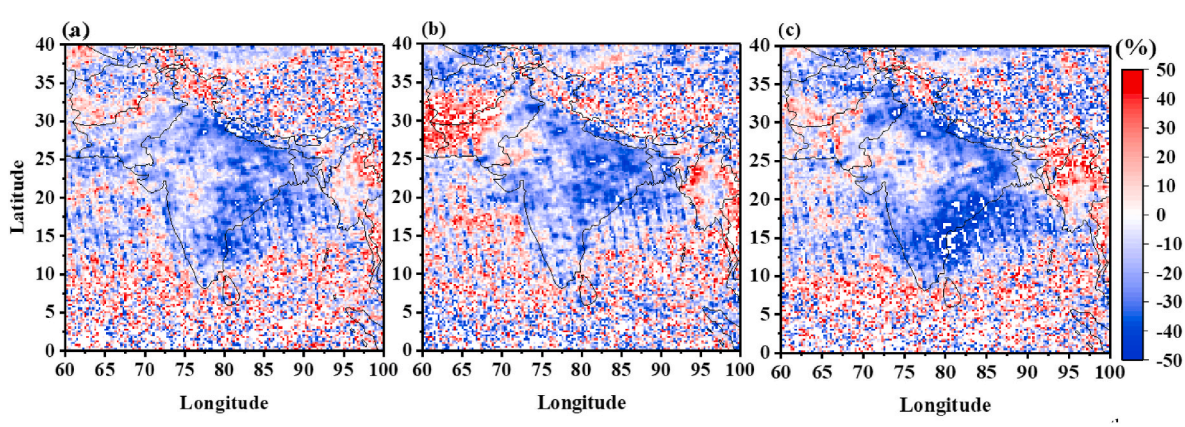


**Fig. 4.** Spatial distribution of (%) changes in tropospheric $NO_2$ during the lockdown period (25th March to May 17, 2020) compared to the same period in 2019 (a), 2018 (b) and 2017 (c). Changes $[((NO_{2\ 2020}\ NO_{2\ 201X})/NO_{2\ 201X})*100]$.

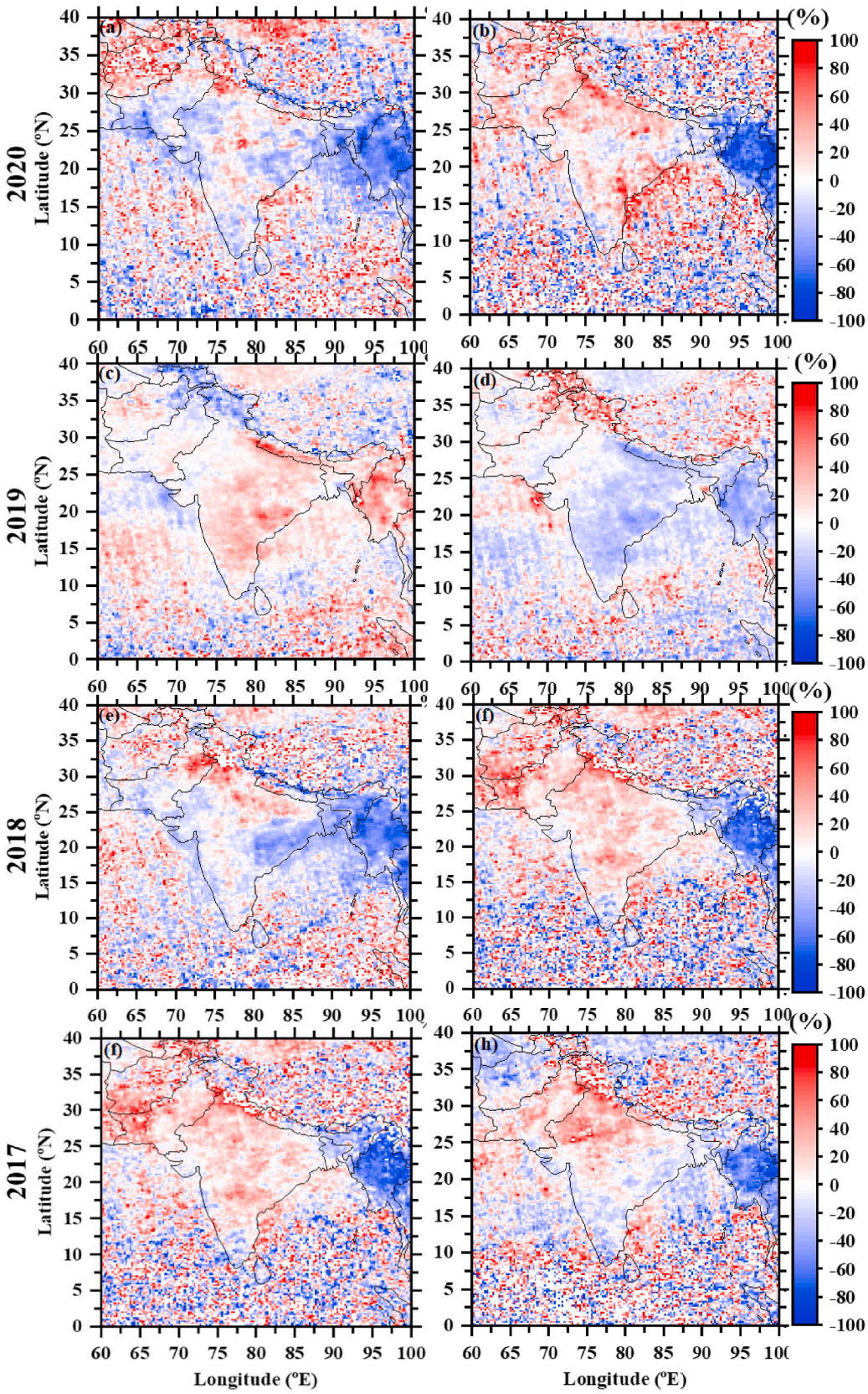


**Fig. 5.** Percentage (%) changes in tropospheric $NO_2$ over the Indian subcontinent between lockdown and pre-lockdown (left panels), lockdown and post-lockdown (right panels) for 2020 and same for the years 2019, 2018 and 2017. [((lockdown – pre-lockdown)/pre-lockdown)*100 and ((post-lockdown – lockdown)/lockdown)*100].

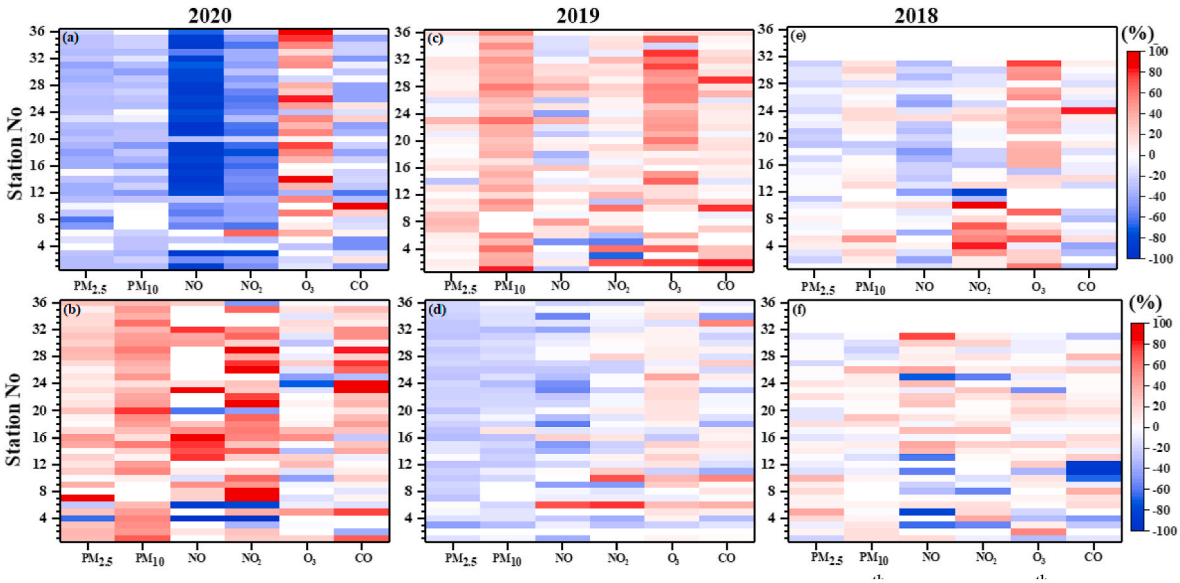


**Fig. 6.** Percentage (%) changes of air pollutants between the lockdown (25th March to May 17, 2020) and pre-lockdown (01st –24th March 2020) (upper panels) and post-lockdown (18th May – June 4, 2020) to lockdown (lower panels) periods at stations in Delhi state and respective changes between the same periods in 2019 and 2018.

titration for the increasing $O_3$ levels during the lockdown period in 2020, since $O_3$ variations also depend on the UV radiation amounts and on biogenic VOCs concentrations (Reche et al., 2018). On the other hand, a pronounced increase (except for few stations) is observed in atmospheric pollutants (except $O_3$) during the post-lockdown period – compared to lockdown – in 2020 (Fig. 6b). $NO_2$ concentrations exhibit the highest percentage increase between the stations (mean of +46%), while lower increases are seen for $PM_{10}$ (+42%), which may be also attributed to natural causes, and $PM_{2.5}$ (+25%). These results indicate that the re-opening of the economy and the termination of the restrictions in transportation around Delhi-NCR led to an increase in $NO_2$ levels, which are highly related to traffic emissions. Lower increases, which are mostly detected at specific stations (traffic), are seen for CO (+24%), since combustion activities are rather limited during May and June in Delhi compared to winter (Bisht et al., 2015). On the contrary, slight changes in $PM_{10}$, $PM_{2.5}$, $NO_x$ levels and in other pollutants were

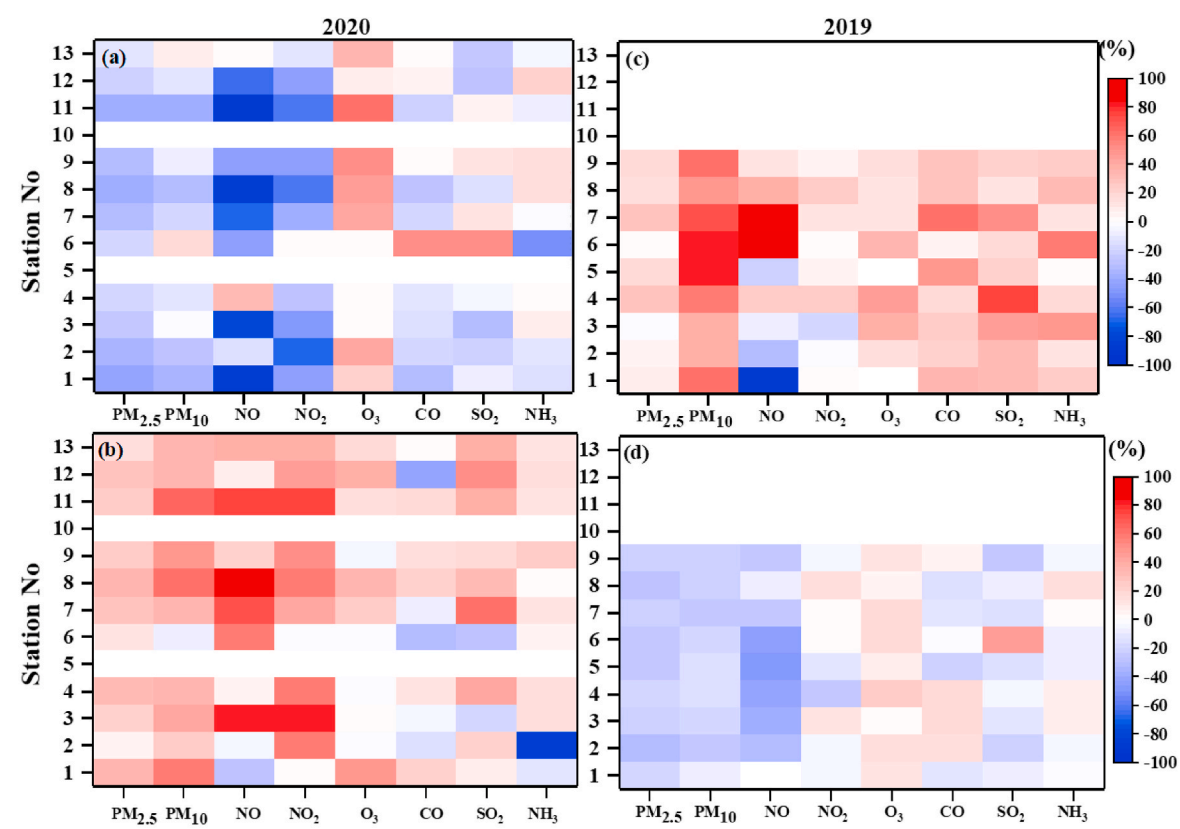


**Fig. 7.** Same as in Fig. 6, but for stations in Uttar Pradesh state.

observed from the comparison between the examined periods in previous years, 2019 (Figs. 6d) and 2018 (Fig. 6f). This indicates that the escalation of these pollutants during the post-lockdown period in 2020 is attributed to the low levels during the lockdown.

Earlier study in Delhi showed a statistically significant reduction in $PM_{10}$, $PM_{2.5}$, CO and $NO_2$ by −52%, −41%, −28% and −51%, respectively during the lockdown period (Jain and Sharma, 2020). Selvam et al. (2020) analysed $PM_{10}$, $PM_{2.5}$, $NO_2$, $SO_2$, CO and $O_3$ concentrations across four different zones in the industrialized Gujarat state in west India and reported significant improvement in air quality during the lockdown period (24 March to April 20, 2020) compared to pre-lockdown (1 January to March 23, 2020). An overall improvement of 58% in Air Quality Index (ACI) over the state was estimated during the first four months of 2020 compared to the same period of the previous year, while reductions of −38% to −78%, −32% to −80%, −30% to −84% and −3% to −55% were observed for $PM_{2.5}$, $PM_{10}$, $NO_2$ and CO levels, respectively (Selvam et al., 2020).

Figs. 7 and 8 show the (%) changes of the same pollutants, also including $SO_2$ and $NH_3$, between the three examined periods in the years 2020 and 2019, at Delhi-NCR stations located in Uttar Pradesh [U.P] and Haryana states, respectively. Focusing on the U.P. stations (Fig. 7), a significant reduction is noticed for NO concentrations during the lockdown period (~−45% to −65%), supporting the declining tendencies observed in Fig. 6. Furthermore, $PM_{2.5}$ and $PM_{10}$ are reduced by −28% and −14%, on average, respectively, while mean reductions of −11%, −9%, and −2% were found for $SO_2$, CO and $NH_3$, respectively. $NH_3$, as a basic end product of biogenic activity, being emitted mostly by animal excreta, farming and fertilization (Kouvarakis et al., 2001; Tsimpidi et al., 2007), is strongly related with meteorological conditions and agriculture activities and, therefore, its concentrations are not so much affected by the restrictions during the lockdown period in the urban stations. However, some anthropogenic sources of $NH_3$ such as industries (mainly manufacture of $NH_3$ and N containing fertilizers), coal burning, power generation, sewage systems, waste incineration and vehicle emissions (Zhao et al., 2012; Tutsak and Koçak 2019) could have been affected during the lockdown period. As also shown above, $O_3$ levels increased during the lockdown period (+27%) due to lower NO concentrations and higher UV-radiation during April–May compared to 1–24 March (pre-lockdown period). Similar to previous results (Fig. 6), the pollutant concentrations present an increasing tendency during the post-lockdown period from its lowest levels during the lockdown (Fig. 7b). More specifically, an average increase between the stations of +36% was observed for $PM_{10}$, followed by NO (+33%), $NO_2$ (+31%) and $PM_{2.5}$ (+25%). Analysis in the respective periods of 2019 showed totally different results, since there was no decrease in the pollutant levels during 25 March – 17 May (Fig. 7c), whereas an important increase of +14 to +60% was observed for $PM_{10}$. Also, the analysis between the "lockdown" and "post-lockdown" periods in 2019 reveals only slight changes for all pollutants (Fig. 7d).

The analysis at the Haryana stations (Fig. 8) also shows a decrease in pollutant concentrations during the lockdown period compared to pre-lockdown (Fig. 8a), which, however, is slightly lower compared to those found at stations in Delhi and U.P., since the pollution levels are generally lower and several stations have rural characteristics. An average reduction of −27% was found for $NO_2$ and -24% for $PM_{2.5}$, while an increase was also observed during the post-lockdown period, which was maximum (+31%) for $PM_{10}$ and $NO_2$. An interesting finding is the large $NH_3$ reduction (−31%) in the lockdown period compared to the period before and −38% compared to the same period in 2019, indicating that the high $NH_3$ levels in these rural stations have been also notably decreased due to lockdown. In addition, very different results were observed at these stations when analysing the same periods in 2019, without the lockdown effect (Fig. 8c and d).

Fig. 9 shows the temporal evolution of the daily-mean concentrations of $PM_{2.5}$, $PM_{10}$ and air pollutants at stations in Delhi state covering the pre-lockdown, lockdown and post-lockdown periods in 2020 and the

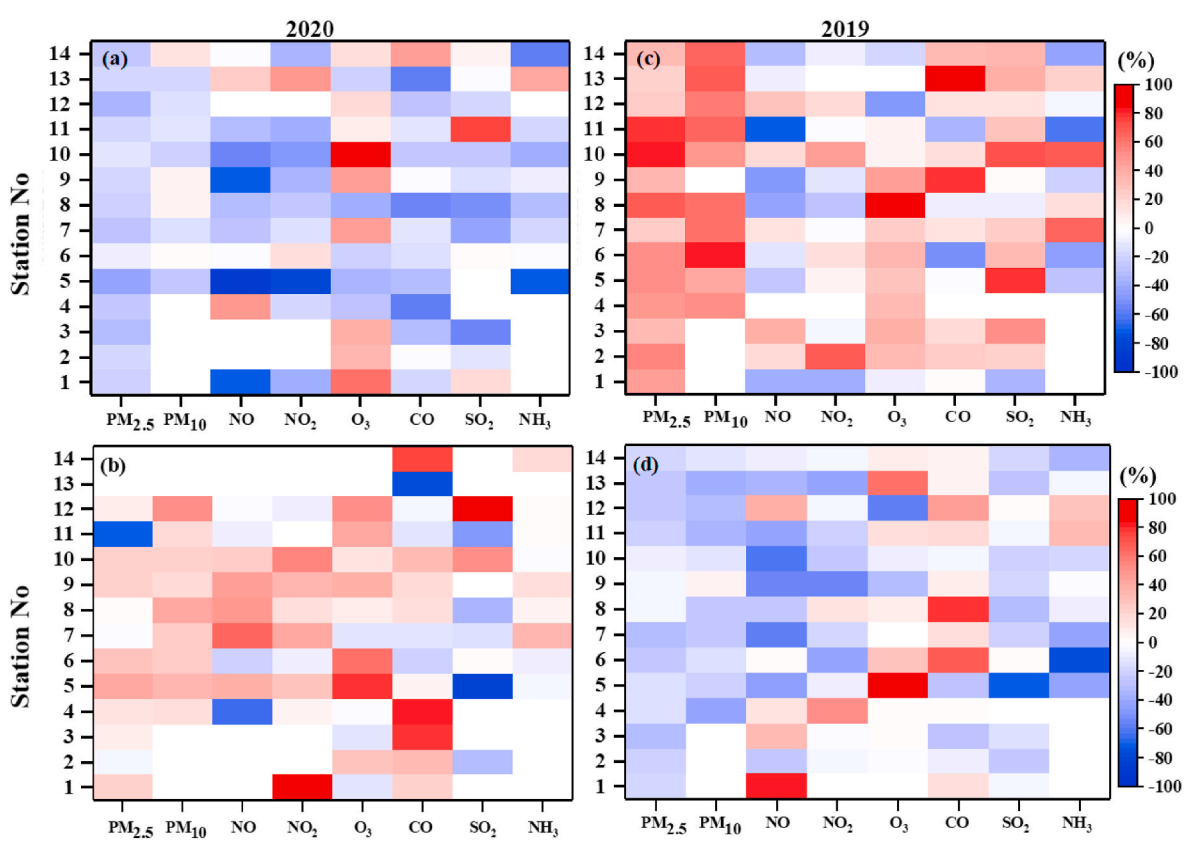


**Fig. 8.** Same as in Fig. 6, but for stations in Haryana state.

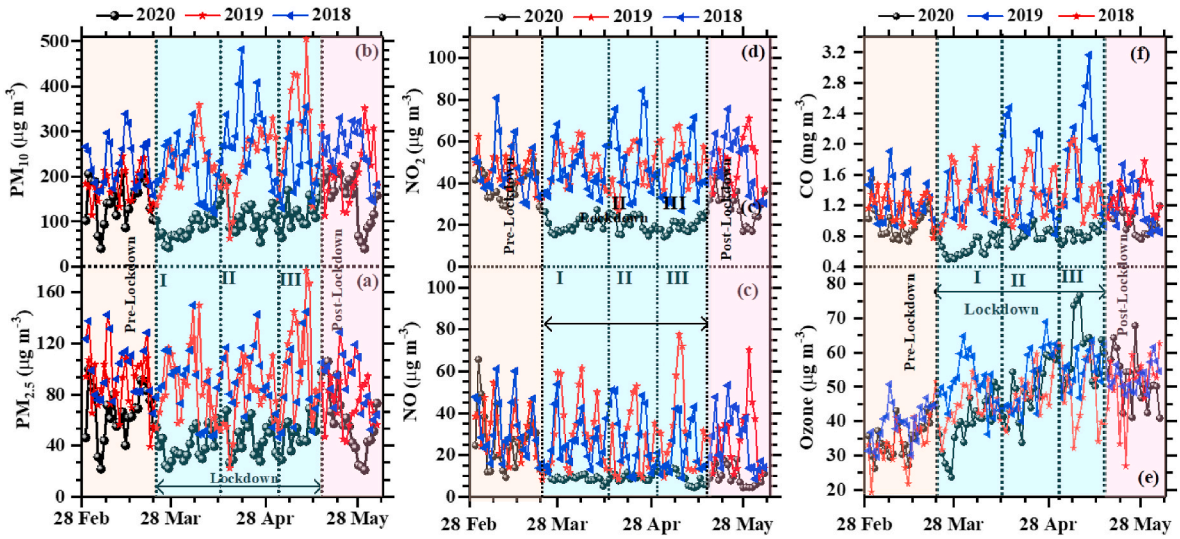


**Fig. 9.** Temporal evolution of daily mean concentrations of $PM_{2.5}$, $PM_{10}$ and air pollutants at stations in Delhi state covering the pre-lockdown, lockdown and post-lockdown periods in year 2020 and the same periods in 2019 and 2018.

same time frames in the previous years 2019 and 2018. The time series indicate a notable decrease in all pollutants (except $O_3$) during the lockdown period of 2020 compared to the years 2019 and 2018, while during the pre- and post-lockdown periods, the pollution levels exhibited slight variations between the years, highlighting the high pollution levels in Delhi. For example, the ratios of the mean concentrations between lockdown and pre-lockdown periods ranged from 0.36 (NO) to 0.81 (CO), while in 2019 all these ratios were above 1, indicating higher pollution levels during 25 March – 17 May compared to 1–24 March. In addition, the reductions of $PM_{2.5}$ and $PM_{10}$ at Delhi stations were found to be around −43% to −58% during the lockdown period in 2020 compared to the same periods in previous years 2019 and 2018. The respective reductions of NO were found in the range of −54% to −69%, while $NO_2$ levels were lower by −54% to −58%. Lower decreases were observed for CO (−42% to −44%), whereas $O_3$ displayed an average increase of +4 to +7%.

Figs. 10 and 11 show the daily mean variations of the pollutant concentrations at stations in U.P. and Haryana states, respectively during the same periods in 2020 and 2019. In general similarity with the Delhi stations, the $PM_{2.5}$ and $PM_{10}$ concentrations at the U.P. stations decreased during the lockdown period by −50% and 57%, respectively compared to 2019. Furthermore, the mean respective reductions in NO and $NO_2$ reached to −66% and −54%, respectively, while $O_3$ exhibited lower concentrations throughout the study period in 2020 compared to 2019 (Fig. 10). Furthermore, no significant difference was observed in CO concentrations during the lockdown and post-lockdown periods, while in pre-lockdown the CO levels were higher in 2020 than 2019. The stations in Haryana (Fig. 11) also display a notable reduction in pollution levels during the lockdown period with respect to the same period in 2019 such as −46% for $PM_{10}$, -55% for $PM_{2.5}$, −26% for $NO_2$, -30% for CO and −21% for $SO_2$. In general, even during the lockdown period, $PM_{2.5}$, $PM_{10}$ concentrations and the other pollutants present significant daily variability (Figs. 9–11) that could be attributed to changes in emissions from domestic household activities and emergency services that remained open. Emissions from the coal-fired power plants, wood burning, industrial or domestic LP gas combustion were the main sources of aerosols and pollutants during the lockdown period (Singh et al., 2020a). The concentrations of PM and air pollutants for the examined periods, the differences between lockdown and periods before and after it, as well as compared to previous years are summarized in Suppl. Tables 1 and 2

The diurnal patterns of PM and air pollutants, averaged for all the

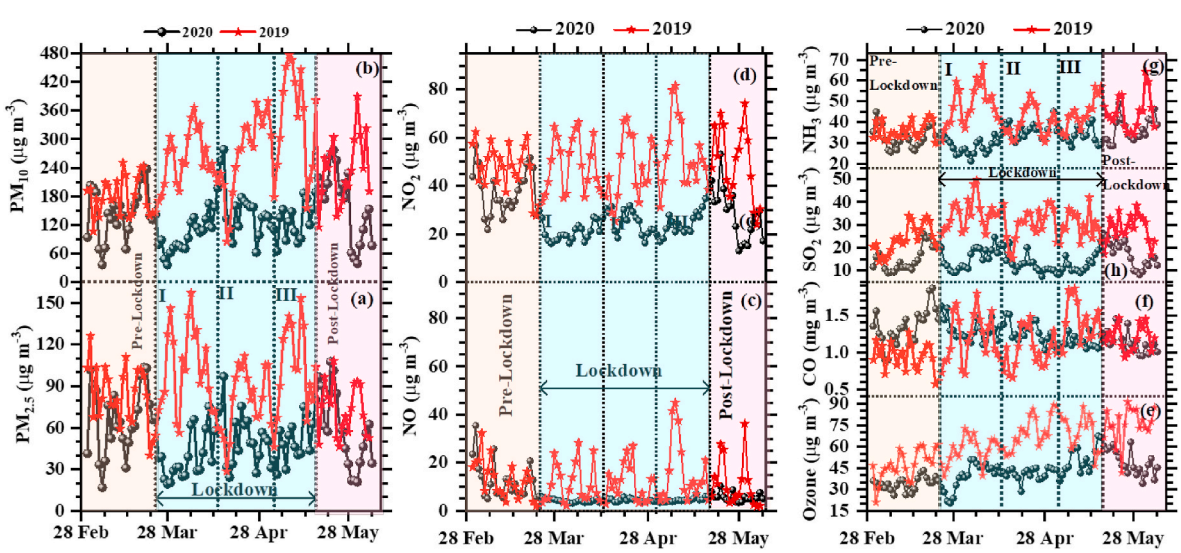


**Fig. 10.** Same as in Fig. 9, but for stations in Uttar Pradesh state.

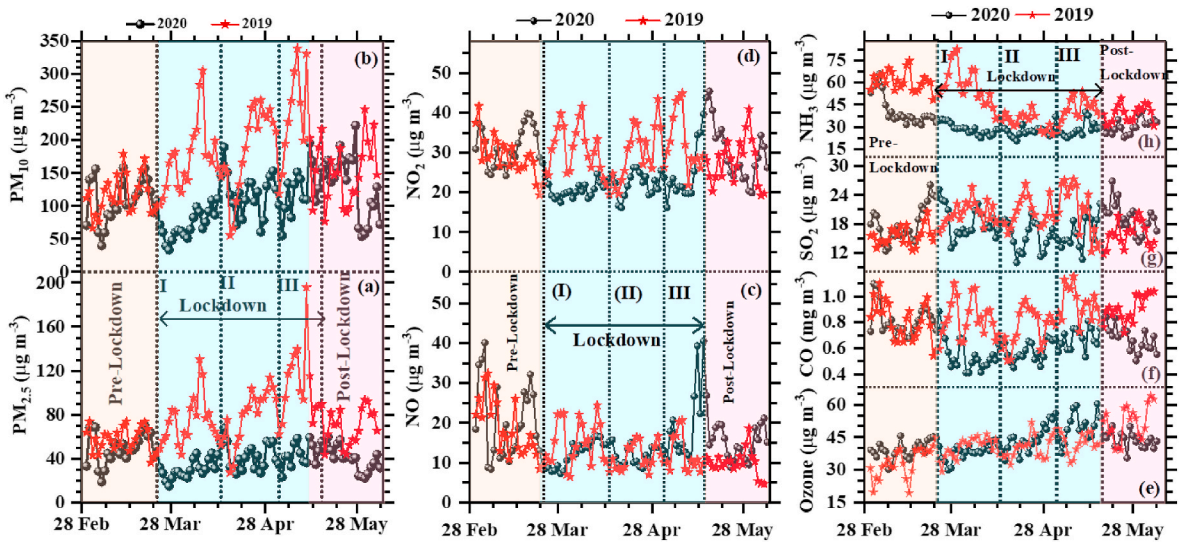


**Fig. 11.** Same as in Fig. 9, but for stations in Haryana state.

examined stations in the three periods (Suppl. Figs. 3–5), revealed a large decrease in the traffic-related pollutants (NO, $NO_2$, CO) during lockdown, and in $PM_{10}$ and $PM_{2.5}$ concentrations as well, mainly during the morning traffic (around 8:00 LST) and in the evening rush hours. These decreases are especially high for NO and $NO_2$, while during noon, when the dilution and dispersion of pollutants are favoured due to deeper boundary layer (Dumka et al., 2018), the reductions were much lower. The diurnal patterns highlight a clear evidence that the reduction in pollution levels in Delhi-NCR due to lockdown is mainly attributed to the limitation in emissions from the traffic sector, while the notable differences between stations in the three states are attributed to different station characteristics (traffic, industrial, urban, suburban, rural sites), with those in Haryana to exhibit more suburban and rural characteristics.

Navinya et al. (2020) reported that the highest pollutant reductions during the lockdown period compared to the previous year (2019) were detected over northern India and in the major urban centers like Ahmedabad (−68% for $PM_{2.5}$), Delhi (−71% for $PM_{10}$), Bangalore (−87% for $NO_2$) and Nagpur (−63% for CO). Notable reductions in air pollutants and −17.5% in $PM_{2.5}$ and $PM_{10}$ levels were also found in Kolkata during the lockdown period, compared to years before (Dutheil et al., 2020), while Bera et al. (2020) recommended solutions for a post-lockdown sustainable management plan, concerning plant species in open urban areas and roof tops for maintaining air quality at acceptable levels in this highly-polluted city. Chauhan and Singh (2020) reported a decline in $PM_{2.5}$ levels of −11%, −35%, −14%, −50%, −50%, −32% and −4% over Dubai, Delhi, Mumbai, Beijing, Shanghai, New York and Los Angeles, respectively, during March 2020 compared to March 2019. Similarly, $NO_2$, $SO_2$ and CO concentrations have been decreased by −64%, −9% to −20% and −25% to −31%, respectively at urban areas in Malaysia during the lockdown period (Kanniah et al., 2020), while results from several studies in India and abroad are summarized in Table 1.

### 4.4. WRF-CHIMERE model simulation during lockdown

This section examines the changes in pollutant emissions over the Indian subcontinent in the month of April 2020, based on WRF-CHIMERE simulations with a usual and lockdown scenario. The ambient weather conditions over Delhi-NCR were not significantly changing during the simulation period, while no intense dust storms were noticed able to significantly affect the $PM_{2.5}$ concentrations. The two scenarios used the same meteorological conditions and a comparison between them allows to assess the changes in air pollution without the biases of meteorological conditions. The (%) changes in $PM_{2.5}$, $NO_2$ and $SO_2$ concentrations due to lockdown effect are estimated as:

$$(\%)change = \frac{Concentration_PLS - Concentration_US}{Concentration_US} \text{X } 100 \quad (1)$$

where PLS and US are the pandemic lockdown and usual scenarios, respectively. The estimated reductions correspond to limitation in anthropogenic emissions due to shutdown of traffic and industrial sectors.

According to usual scenario, large monthly-averaged $PM_{2.5}$ concentrations reaching up to 80–100 μg $m^{-3}$, or even more, are estimated at parts of the eastern IGP, central India and around mega-cities like Delhi, Mumbai and Kolkata (Fig. 12). Model simulates satisfactorily the pollution outflow over the south Arabian Sea, as well as the enhanced $PM_{2.5}$ levels over the Taklimakan desert due to dust. Significant reductions in $PM_{2.5}$ concentrations are simulated due to PLS, with levels to be within the NAAQS (National Ambient Air Quality Standards) over the Indian landmass, while in Thar Desert the lockdown effect is rather negligible (Fig. 12). Interestingly, the $PM_{2.5}$ concentrations in PLS scenario are still significant over parts of central India, eastern Indo-Gangetic plains and north-eastern India due to prominent agricultural residue burning, including the prevalence of forest fires.

According to WRF-CHIMERE simulations the reductions in $NO_2$ concentrations due to lockdown effect (no emissions from the traffic and industrial sectors) are much larger than those in $PM_{2.5}$, reaching and/or overcoming 100% in urban, industrial areas and along the coastal regions, in general agreement with the highest $NO_2$ reductions observed from the current measurements (Figs. 4, 6–11) and numerous other studies (see Table 1). Even for the lockdown scenario, the highest $NO_2$ concentrations were observed over the central IGP and in the major urban centers of Delhi, Mumbai and Kolkata, as well as in Kerala state in the south. In agreement with measurements, simulated $SO_2$ levels have also been significantly reduced across the Indian landmass in the PLS scenario, while $SO_2$ peaks are detected at point measurements, like urban centers and locations of power plants (Ramachandran and Shwetmala, 2009; Singh et al., 2019; Selvam et al., 2020). Even in these areas, the $SO_2$ levels are simulated to be significantly lower in the PLS scenario, while the reductions over the Indian subcontinent range from about −30% to −90%. It is characteristic that the shipping emissions in the southern part of the Arabian Sea and in the strait of Sri Lanka do not present notable reductions in the PLS scenario (Fig. 12). A previous work

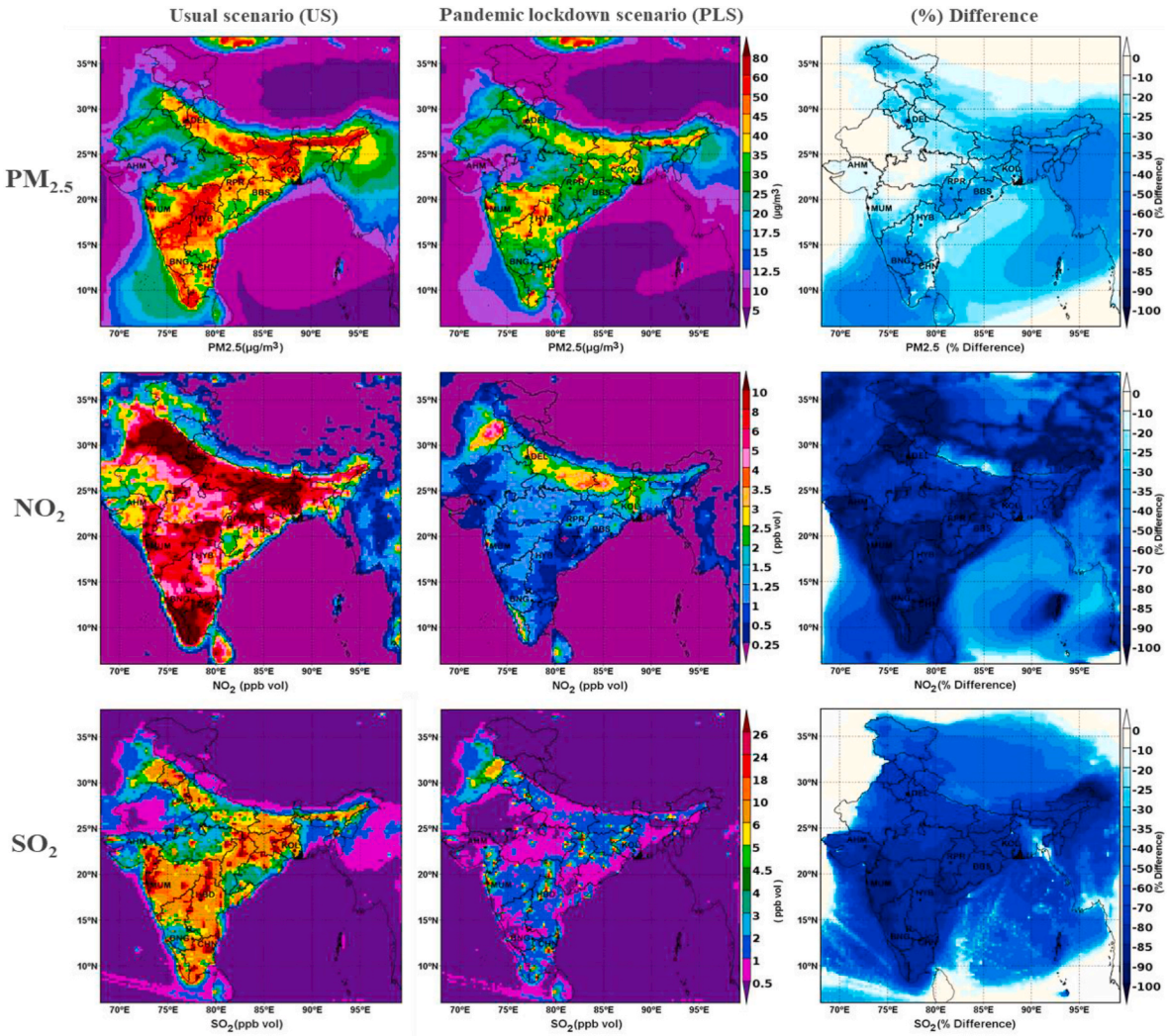


**Fig. 12.** WRF-CHIMERE model simulations of $PM_{2.5}$, $NO_2$, and $SO_2$ over the Indian subcontinent in April for usual scenario, lockdown scenario and their (%) differences.

(Ramachandran and Shwetmala, 2009), indicated that the transport sector in India, including aviation and train, emits PMx, CO and $SO_2$ up to 153.1, 5692.1 and 709.1 Gg year$^{-1}$. Therefore, the 54 days of the lockdown period might have reduced the total annual emissions from the transport sector by ~14.8% in India.

The simulated and measured reductions in $PM_{2.5}$, $NO_2$ and $SO_2$ were also analysed over major urban agglomerations in India (Fig. 13), revealing that the traffic and industrial sectors contribute large fractions of the total $PM_{2.5}$, $NO_2$ and $SO_2$ emissions. The model results reveal $PM_{2.5}$ reductions ranging from −20% in Mumbai (MUM) to −48% in Delhi (DEL) and −53% in Chennai (CHN), where the influence from marine aerosols may be also important (Verma et al., 2006, 2016). Measurements taken from CPCB stations at the examined cities also reveal considerable variations in $PM_{2.5}$ concentrations and associated reductions between the cities, either overestimating or underestimating the model simulations. The measured values for April 2020 correspond to the PLS scenario and those for April of 2018 and 2019 to the US scenario. The $PM_{2.5}$ simulations in Delhi are in satisfactory agreement with the measured $PM_{2.5}$ reductions, which ranged between −43% and −58% for the Delhi-NCR stations (Figs. 6 and 9), while the daily $PM_{2.5}$ variability over Delhi-NCR revealed slightly larger concentrations even using the PLS scenario, but mostly within the standard deviation of the measurements (Suppl. Fig. 6).

On the other hand, gaseous species, such as $NO_2$ and $SO_2$, show more than 70% decrease in most of the cities, indicating much larger effect from the traffic and industrial sectors. The simulated reductions for $NO_2$ (in the range of −55% to −92%) are overestimated than the measured ones, which mostly ranged between −50% and −70% for Delhi and other Indian cities (Fig. 13; Table 1). However, even a limited industrial activity (e.g. power plants, brick kilns, manufactures) and transportation (private cars, buses, rickshaws, etc) took place during the lockdown period, while the model PLS scenario totally ignored the traffic and industrial sectors, so the higher reductions (by ~20%) are logic compared to measurements. At several cities, model $NO_2$ simulations using the US scenario are similar to measurements during April 2018–2019 (red circles in Fig. 13), while the measured $NO_2$ concentrations in April 2020 (lockdown period) are significantly higher compared to model estimates due to limited but existed emissions from traffic and industries. Similar results are observed for the $SO_2$ reductions (−56% to −85% according to model), which are higher compared to the measured ones in most of the cities, as the basic industries and thermal power plants that are the main sources of $SO_2$ in India were on operation during the lockdown period, while the model simulates reasonably well the reduced $SO_2$ levels (Fig. 13). It should be noted that the changes in measured pollutants are biased by meteorological conditions between 2020 and previous years. Therefore, the model simulated reductions, which are unbiased by meteorology and reflect to the decrease in anthropogenic activity only, are reasonably consistent with the

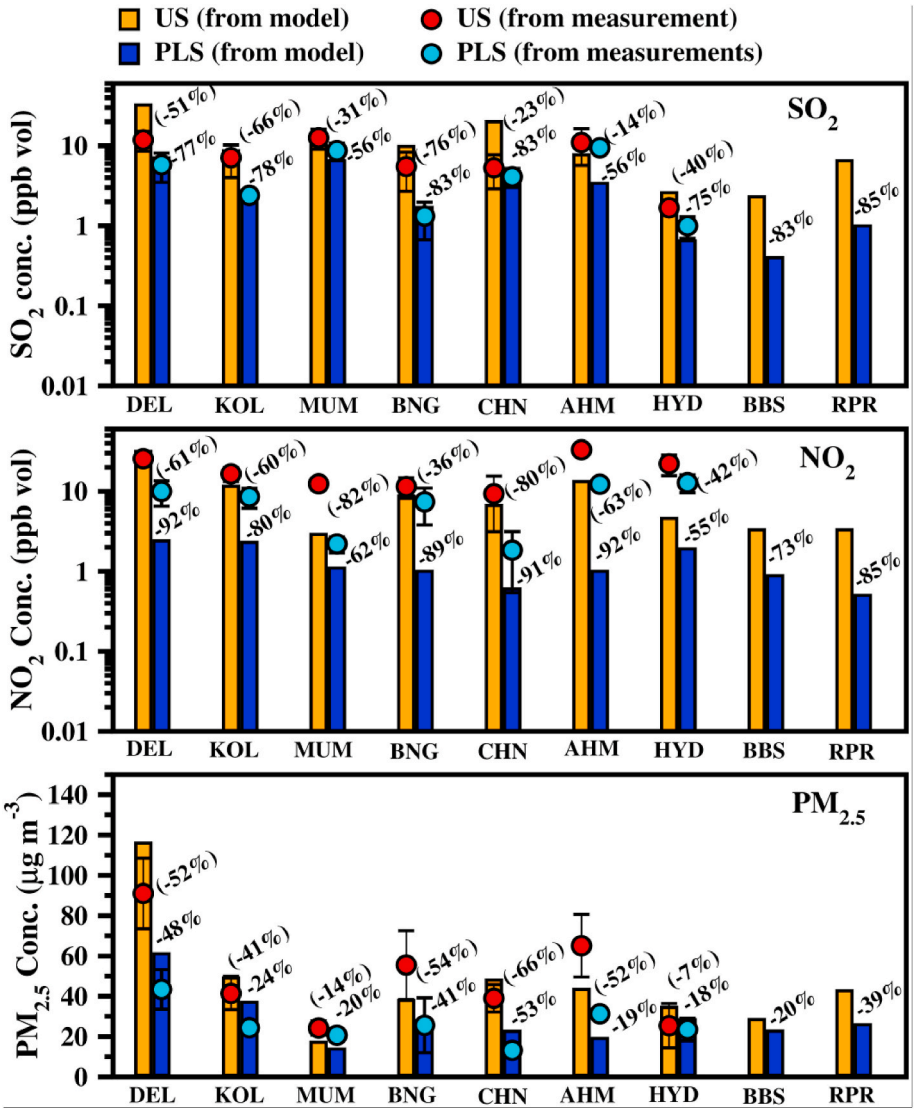


**Fig. 13.** WRF-CHIMERE model simulations of $PM_{2.5}$, $NO_2$, and $SO_2$ concentrations for the usual and pandemic lockdown scenarios in major cities in India. The percentage changes refer to the model results, while those in parenthesis correspond to the observations. [DEL: Delhi, KOL: Kolkata, MUM: Mumbai, BNG: Bangalore, CHN: Chennai, AHM: Ahmedabad, HYD: Hyderabad, BBS: Bhubaneswar, RPR: Raipur].

measurement results.

In a similar study based on WRF-AERMOD model simulations, Sharma et al. (2020) reported an about −43% reduction of $PM_{2.5}$ levels during March 2020, in comparison with previous years. Based on TROPOMI Sentinel-5P data, an average reduction of −46% in $NO_2$ along with 27% improvement in Air Quality Index (AQI) was estimated over the Indian cities (Siddiqui et al., 2020), with the highest $NO_2$ reductions to be detected over Delhi (∼−70%), Bangalore (−63%), Mumbai (−57%) and Ahmedabad (−56%), about 20%–30% lower than the current model simulations. In addition, WRF-CAMx model simulations over the Yangtze River Delta in eastern China revealed significant reductions of $SO_2$ (−16% to −26%), NOx (−29% to −47%) and $PM_{2.5}$ (−27% to −46%) concentrations, in satisfactory agreement with pollution measurements (Li et al., 2020b). In a similar modelling approach in Athens, Grivas et al. (2020) used reduced emissions scenarios for the lockdown period of −46% for road transport, −35% for industry, −85% for air transport and −2% in energy, resulting in great consistency between the reduced simulations and measurements for $NO_2$ and $PM_{2.5}$. Therefore, the highest modelling reductions of $NO_2$ (mainly) and $SO_2$ (secondarily) compared to measurements in the Indian cities (Fig. 13) are due to complete shutdown of traffic and industrial sectors that is considered in the model.

The spatial distribution and trends of aerosols over the Indian subcontinent are also affected by natural sources like dust storms and/or anthropogenic activities (e.g. biomass burning) not related to the restrictions in transportation and shutdown of the economy. Therefore, the spatial distributions of the aerosol and pollutant changes are highly heterogeneous across the country, as shown by both satellite observations and model simulations. Large reductions in atmospheric aerosols over the Indian subcontinent during the lockdown period, apart from the benefits in improving air quality, may also have a significant effect (increase) on downward solar radiation, which has high linkage with the solar dimming/brightening phenomenon and monsoon circulation patterns (e.g. Kambezidis et al., 2012; Shrestha et al., 2018; Pathak et al., 2020; Srivastava et al., 2019). Recently, Bashir et al. (2020) reported a linkage between limited human exposure to atmospheric pollution and lesser infected COVID-19 cases as well as lesser mortality rates in California, which may also be applicable in India. As the country now faces a continuous dramatic increasing rate in daily infections and deaths, social distancing and efforts for a cleaner environment seem to be highly important.

## 5. Conclusions

This study analysed key air pollutants ($PM_{2.5}$, $PM_{10}$, NOx, $SO_2$, CO, $O_3$, $NH_3$) and the changes in their concentrations during the lockdown period due to COVID-19 pandemic at 63 stations located in and around the Delhi, National Capital Region (Delhi-NCR). Apart from the ground-based air pollution measurements at the Central Pollution Control Board (CPCB) stations, satellite observations of AOD and tropospheric $NO_2$ were obtained from MODIS and OMI sensors, respectively over the whole Indian subcontinent. The pollution concentrations were compared during the lockdown period (25 March to May 17, 2020) with levels during similar periods in the previous years (2017–2019), while analysis was also performed between lockdown and pre- (01–24 March 2020) and post-lockdown (18 May – June 4, 2020) periods. Furthermore, WRF-CHIMERE model simulations were used to assess the reductions in $PM_{2.5}$, $NO_2$ and $SO_2$ levels over India in April 2020 using two scenarios, a usual and a lockdown, considering shutdown of the traffic and industrial sectors in the lockdown scenario.

The impact of the strict lockdown measures in transportation, constructions, industrial manufacturing and generally in anthropogenic activities, caused reductions in air pollutant concentrations in nearly all stations, compared to the pre-lockdown and the same period in previous years, but with large variability in the magnitude of changes between the stations and pollutants. The highest reduction was observed for NO (−27% to −64%), $NO_2$ (−27% to −47%), $PM_{2.5}$ (−24% to −29%) and $PM_{10}$ (−7% to −26%) compared to pre-lockdown, while $SO_2$ (−10% to −11%) and CO (−9% to −28%) displayed generally lower reductions. The highest reductions for $NO_x$ concentrations reflect the drastic limitation in transportation and construction activities, which have also a significant impact on PM concentrations due to lower re-suspended dust from the road traffic and the termination of construction activities. On the contrary, $SO_2$ reductions were much lower, as they are strongly related with the industrial sector, which continued operation at least for the basic services of power generation, food industries, etc. On the contrary, $O_3$ levels in Delhi-NCR generally increased by +4 to +7%, on average, due to lower NO titration and the increased photolysis rates as a result of the reduction in aerosols and pollutants. Further analysis showed an increase in pollution levels, especially for the $NO_x$ and $PM_{10}$, during the post-lockdown period due to re-opening on the economy and the relaxation of the strict measures. In addition, the highest reductions for aerosol and pollutants were detected during the morning traffic and evening hours. Satellite observations also revealed a notable decrease in columnar AOD during the lockdown period, reaching at 30–50% over the most polluted northern India, while lower changes were observed over central India. WRF-CHIMERE model simulations revealed a significant reduction in $PM_{2.5}$, $NO_2$ and $SO_2$ concentrations all over the country, with reductions of $PM_{2.5}$ over major Indian cities ranging from −20 to −48% (for Delhi), in close agreement with the measured results. Complete shutdown of the traffic and industrial sectors in the model lockdown scenario resulted in simulated $NO_2$ reductions in the order of −55% to −92% over major Indian cities and respective reductions for $SO_2$ ranging between −56% and −85%, which are much higher (in absolute values) than those obtained from the measurements, since even limited transportation and industrial activity took place during the strict lockdown period.

The current results showed a notable decrease in atmospheric pollutants at several stations within and around the Delhi metropolitan area during the lockdown period, resulting in a significant improvement of air quality with several benefits for human health, ecosystems and climate, as Delhi is one of the most polluted cities worldwide. These results revealed rather the maximum reductions that can be attained in air pollutants over India under strict scenarios of shutdown of the economic activity, which are not so feasible in the future.

## Credit author statement

U. C. Dumka: Conceptualization, Formal analysis, Investigation, writing original draft, review and editing, D. G. Kaskaoutis: Writing original draft, Investigation, writing, reviewing and editing, Shubha Verma: WRF- CHIMERE model simulation, Discussion, reviewing and editing, Shantikumar S. Ningombam: Discussion, Satellite data analysis and editing, Sarvan Kumar: Formal data analysis, Investigation and editing, Sanhita Ghosh: WRF- CHIMERE Simulation, Discussion and Investigation

## Declaration of competing interest

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

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## Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.apr.2020.11.005.

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