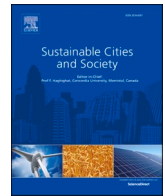




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# Surface and satellite observations of air pollution in India during COVID-19 lockdown: Implication to air quality

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## ABSTRACT

The strict nationwide lockdown imposed in India starting from 25<sup>th</sup> March 2020 to prevent the spread of COVID-19 disease reduced the mobility and interrupted several important anthropogenic emission sources thereby creating a temporary air quality improvement. This study conducts a multi-scale (national-regional-city), multi-species, and multi-platform analysis of air pollutants and meteorological data by synergizing surface and satellite observations. Our analysis suggests a significant reduction in surface measurements of nitrogen dioxide (NO<sub>2</sub>) (46–61 %) and fine particulate matter (PM<sub>2.5</sub>) (42–60 %) during the lockdown period that are also corroborated by the reduction in satellite observed aerosol optical depth (AOD) (3–56 %) and tropospheric NO<sub>2</sub> column density (25–50 %) data over multiple cities. Other species, namely coarse particulate matter (PM<sub>10</sub>) (24–62 %), ozone (22–56 %) also showed a substantial reduction whereas carbon monoxide (16–46 %), exhibited a moderate decline. In contrast, sulfur dioxide (SO<sub>2</sub>) levels did not show any defined reduction trend but rather increased in Mumbai, Bengaluru, and Kolkata. The temporary air quality improvement achieved by the painful natural experiment of this pandemic has helped demonstrate the importance of reducing emissions from other sectors along with transportation and industry to achieve the national air quality targets in the future.

## 1. Introduction

The Novel Corona Virus Disease (COVID-19) initially identified in Wuhan of China in 2019 have caused significant disruption with more than 16.56 million infections worldwide (until July 29<sup>th</sup>, 2020; WHO, 2020a). To control the exponential spread of COVID-19, Government of India announced a nation-wide lockdown starting midnight of 25<sup>th</sup> March 2020 and it was extended till 17<sup>th</sup> May 2020 in a phase-wise manner, putting its 1.3 billion citizens inside their homes. There was a strict ban on the movement of people during this lockdown and activities such as transportation (including road, rail and air), construction, and industries were completely restricted, except essential services such as medical facilities, electricity, supply of vegetables and fruits. Power plants were also functional during the lockdown period but at a reduced scale due to the decline in the electricity demand in industrial and commercial units (CRISIL, 2020). The effect of lockdown measures was

soon reflected in the mobility with notable changes in mobility index statistics (Table S1, Google, 2020). The mobility to outside places such as parks and workplaces significantly reduced while the residential category showed an upsurge in all the Indian states as a result of nation-wide lockdown.

Although these restrictions were primarily meant to flatten the COVID-19 infection curve, they created a unique experiment to assess the effect of anthropogenic activities on air pollution. Similar to India, many other countries have imposed certain limitations and observed lockdown with a varying magnitude of restrictions and implementation. The reduction in anthropogenic activities worldwide has fortified several researchers around the globe to investigate the environmental effects of the lockdown. A study by Tobias et al. (2020) observed a significant reduction in NO<sub>2</sub> (47.0 %–51.0 %), BC (~45.0 %) and PM<sub>10</sub> (27.8 %–31.0 %) concentrations in Barcelona, Spain during the lockdown period (March 14<sup>th</sup> to March 30<sup>th</sup>, 2020) compared to the

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pre-lockdown period (February 16<sup>th</sup> to March 13<sup>th</sup>, 2020); however, ozone (O<sub>3</sub>) concentrations exhibited an opposite trend and reported an increase ranging from 28.5%–57.7%. A significant reduction of traffic-related pollutants such as PM<sub>10</sub>, PM<sub>2.5</sub>, BC, benzene, CO, and NO<sub>x</sub>, is reported in the city of Milan in Italy during the lockdown period (Collivignarelli et al., 2020). United States (U.S.) counties also observed an overall decrease in NO<sub>2</sub> (25.5 %) and PM<sub>2.5</sub> (11.3 %) concentrations (Berman & Ebisu, 2020). Whereas, Bekbulat et al. (2020) showed that the PM<sub>2.5</sub> and ozone pollution levels during the lockdown did not drop consistently across U.S. Li et al. (2020) attempted to simulate the impact of lowered human activities on air quality changes using chemical transport model such as WRF-CAMx in Yangtze River Delta Region in China and reported a considerable decrease in pollutant concentrations of PM<sub>2.5</sub>, NO<sub>2</sub> and SO<sub>2</sub> compared to the year 2019. Liu et al. (2020) analysed NO<sub>2</sub> tropospheric vertical column density (TVCD) from the Ozone Monitoring Instrument (OMI) over China and reported an abrupt decline in NO<sub>2</sub> TVCD up to 48 % during the lockdown period.

Space agencies such as European Space Agency (ESA) and National Aeronautics and Space Administration (NASA) have initially reported a significant reduction in NO<sub>2</sub> and aerosol levels over India (ESA, 2020b; NASA, 2020) in their respective early satellite observations releases. A number of peer-reviewed studies have recently reported change in pollutants over India using multiple surface, satellite and model analysis. The extent of the analysis published in these studies varies and there still is a need to provide a comprehensive analysis supported by high-quality data sets. Sharma et al. (2020) estimated the effect of restricted human activities in India and reported an improvement in Air quality index (15%–44%) in different parts of India. The study only reported the first twenty days (until April 14<sup>th</sup>, 2020) of changes and focused on 22 major cities using ground data alone. Similarly, Jain and Sharma (2020) reported similar changes in five major cities for the first twelve days of the lockdown and only considered 2019 data as baseline concentrations. Navinya, Patidar, & Phuleria, 2020 extended this period until May 3, and covering 17 cities and using 2019 only data for baseline calculations. Singh and Chauhan (2020) used data primarily from U.S. embassy locations in five cities on PM<sub>2.5</sub>, and analyzed OMI NO<sub>2</sub> data at coarser resolution (0.25 degree) and consider period until April 14, 2020. The study also compared 2020 values with 2019 to estimate changes. Similarly, Kumar et al. (2020) used data from U.S. embassy locations in India from 25<sup>th</sup> March to 11<sup>th</sup> May for 2015–2020 to investigate PM<sub>2.5</sub> reduction during the lockdown period. A more recent study by Pandey and Vinoj (2020) utilized satellite and AERONET measurements of aerosols along with MERRA-model reanalysis data and concluded that the populated Indian regions showed a decline up to ~40 % while central India showed an unexpected increase up to 20 % during 24<sup>th</sup> March to 22<sup>nd</sup> April 2020. The study used 1 × 1 degree coarse resolution MODIS AOD data and concluded that an increase in AODs in central India is partially associated with high relative humidity. All these early studies reported changes in pollutant concentration for partial lockdown period and primarily used data from selected cities only. Studies which used satellite data are limited in using coarser resolution data. Also, most studies compared only 2019 and 2020 measurements to estimate changes.

The emissions sources seem common in major cities, but their magnitude is highly variable in space and time. In addition to emissions, meteorology, physical and chemical processes in the atmosphere significantly influence the air quality in a given region. Hence, any changes in air quality require analysis at different scales vis-à-vis changes in emissions, meteorology and atmospheric chemistry. The ground measurements of air pollutants have been traditionally used to investigate the changes in air pollution levels. Although the ground measurements have an advantage of high temporal resolution, they lack the spatial coverage and typically represent near-surface area surrounding the monitoring site. Conversely, the satellite measurements (polar-orbiting satellites) have an advantage of greater spatial coverage but provides an instantaneous measurement at a particular location.

When used together, both these measurement techniques can complement each other in terms of spatial and temporal limitations.

Therefore, in this study, we attempt to fill some of the gaps in earlier published studies as outlined above. We specifically address these gaps by a) extending the analysis to the three phases of complete lockdown period (i.e. March 25 to May 17) in India; b) using three years of data (i.e. 2017–2019) to form a baseline; c) using a large network of stations in six major cities and for all the criteria pollutants, d) using high-resolution pixel-level satellite observations; e) extending the analysis from national to regional to local scales, and f) finally by discussing the impact of lockdown on air quality changes and its implication for the long-term air quality management policies in India.

## 2. Data and methods

### 2.1. Study area

In this study, we analysed the impact of lockdown measures at different spatial scales i.e. national, regional and local (city, and within the city). The national and regional scale analysis was aimed at determining the changes in atmospheric loading of aerosols and columnar NO<sub>2</sub> observations using satellite data products during the lockdown period. The national scale analysis considered entire India as study domain while the regional analysis was performed over three selected areas (see boundaries in Fig. 1(C)) i.e. Indo-Gangetic plain (IGP), Central Southern India (CSI) and South India (SI), which observed a significant change as shown in satellite retrieved aerosols and NO<sub>2</sub> measurements. However, a synergistic approach utilizing satellite and surface measurements was used to assess the impact of lockdown measures at local scale. Six metropolitan cities in India (Fig. 1(B)) including Bengaluru (BEN), Chennai (CHN), Delhi (DEL), Kolkata (KOL), Mumbai (MUM) and Pune (PNE) were identified to represent different topography, climatic conditions, economic activities, and air pollution sources.

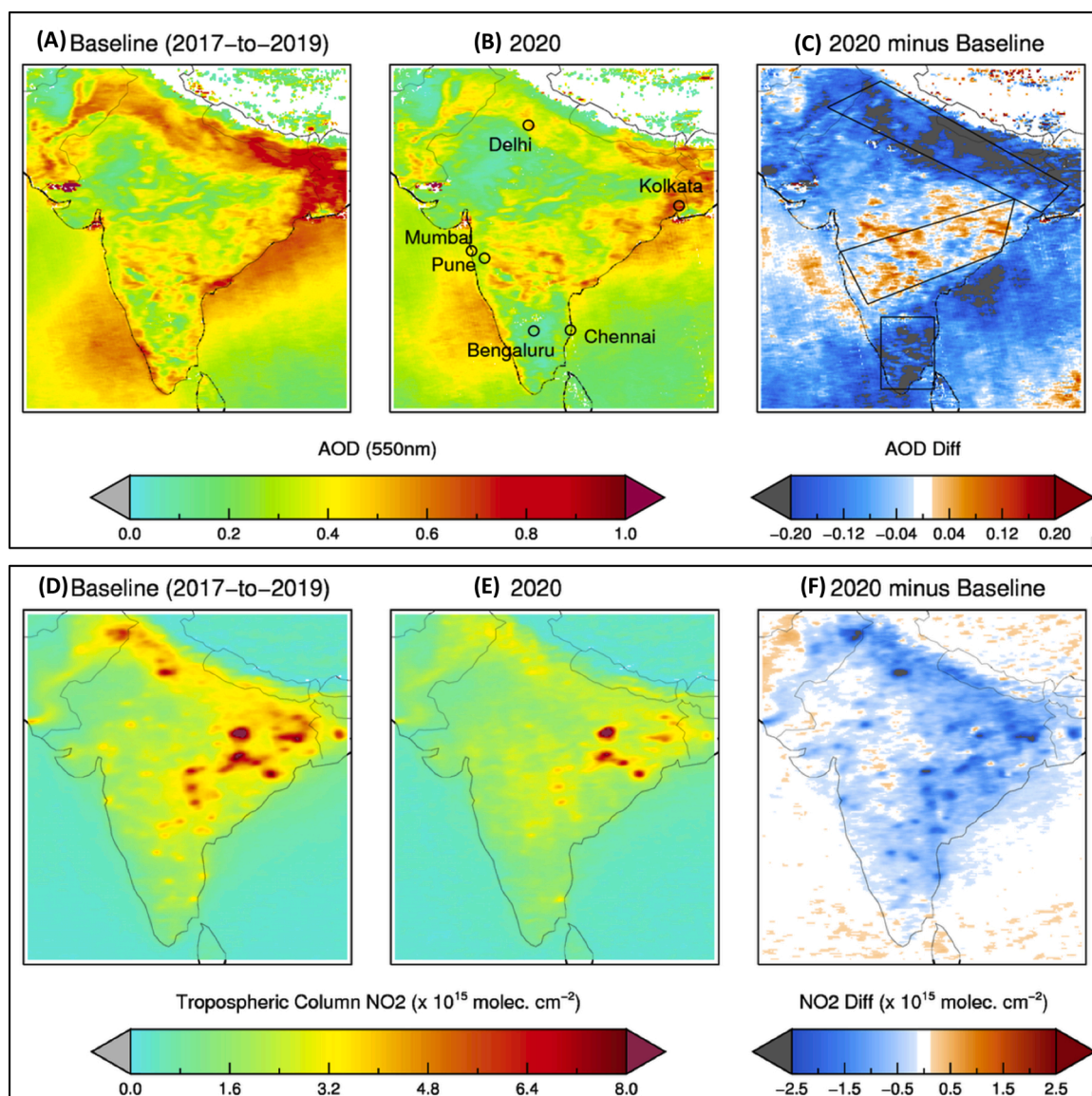
### 2.2. Surface measurements

#### 2.2.1. Air pollutants

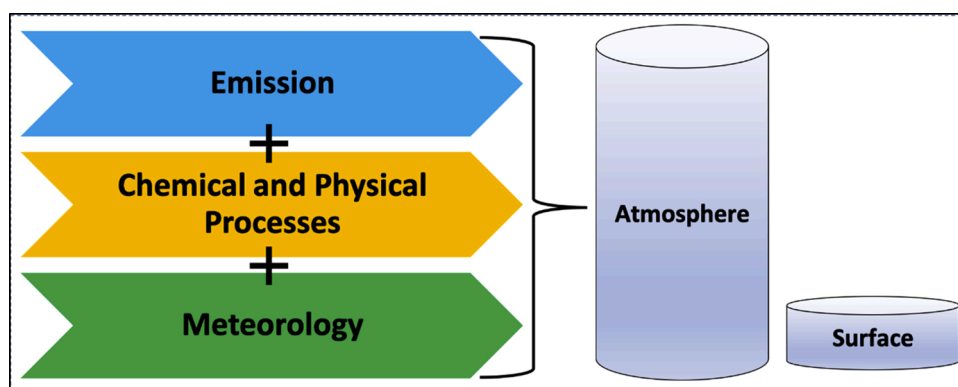
Air pollutants including PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub> and CO, are routinely monitored in 6 selected cities using continuous ambient air quality monitors. We obtained the hourly concentrations data from the Central Pollution Control Board (CPCB) database (CPCB, 2020a). A total of 51 monitoring stations with at least one year of valid measurements from 1<sup>st</sup> January to 17<sup>th</sup> May from 2017 to 2019 were selected to define the baseline conditions. The data availability for the same time period during the present year i.e. 2020 was also ensured before finalizing these stations. The number of monitoring stations with valid data varied significantly in each city (Table S2, and S3). The measurement errors in data obtained from the CPCB monitoring stations were typically reported to be less than 5% (CPCB, 2011; Hama et al., 2020). We obtained the hourly concentrations data from CPCB screened it to eliminate invalid and outliers (abrupt changes) points to quality control the data. The quality-assured hourly data are used to calculate 24-hly and/or 8-hly mean concentrations for further analysis.

#### 2.2.2. Meteorology

The surface meteorological parameters are routinely monitored at the international airports in selected cities and are reported to the Integrated Surface Database (Smith, Lott, & Vose, 2011; NOAA, 2020). This database consists of quality-assured global hourly and synoptic observations compiled from numerous sources (NOAA, 2020). In this analysis, we used four parameters namely dry bulb temperature (TEMP), relative humidity (RHUM), wind speed (WSPD) and wind direction (WDIR), considering their role in regulating air pollution at the surface.



**Fig. 1.** The spatial distribution of mean AOD (550 nm) (A–C) and tropospheric NO<sub>2</sub> column density (D–F) for the period of March 25 to May 17 (A & D) baseline period of 2017 to 2019, (B & E) lockdown period of 2020, and (C & F) the difference between baseline and lockdown period. The blue shades in the difference map represents area where AOD / tropospheric NO<sub>2</sub> column density is lower in 2020 during the lockdown period compared to baseline years for the same temporal window. And the red shades represents area where respective values are higher in 2020 compared the baseline years. The three regions marked by dotted lines are for the time-series analysis presented in the later part of the paper (i.e. Fig. 1(C)).



**Fig. 2.** Schematic showing processes affecting air pollution.



### 2.3. Satellite measurements

#### 2.3.1. Aerosol Optical Depth (AOD)

MODIS aboard two NASA's Earth Observing Satellites (EOS) Terra and Aqua have been providing aerosol observations since 2000 and 2003, respectively. Aerosol optical depth (AOD) at 550 nm retrieved using MODIS observations has been used to address various climate and air quality research questions. The operational AOD data from MODIS is currently retrieved using multiple algorithms (Gupta, Levy, Mattoo, Remer, & Munchak, 2016; Hsu et al., 2013; Levy et al., 2013; Lyapustin, Wang, Korokin, & Huang, 2018); in this analysis, we used a high resolution ( $0.1 \times 0.1$  degree) level 3 AODs, which combined Dark Target (DT), Deep Blue (DB) retrievals (Gupta, Remer, Patadia, Levy, & Christopher, 2020) from MODIS-Aqua satellite. The validation study over India shows the correlation between MODIS and AERONET larger than 0.9 with a mean bias of 0.05 and 70 % retrieval within predefined uncertainty envelope (Gupta et al., 2020). We have also analysed the MODIS-Terra data for consistency check and arrived at very similar results; MODIS-Terra analysis is not presented in this paper. The daily gridded high-resolution AOD data were then used to understand the impacts of lockdown on the atmospheric loading of aerosols in the study region.

#### 2.3.2. OMI tropospheric column NO<sub>2</sub>

The Dutch and Finnish-built Ozone Monitoring Instrument (OMI) onboard NASA's Aura satellite is a nadir-viewing ultraviolet-visible spectrometer, measuring the solar-backscattered radiation in the 270–500 nm range (Levelt et al., 2006, 2018). Launched in July 2004, the OMI/Aura has been providing data from October 2004 to present from a sun-synchronous polar orbit with an equator crossing time of about 13:45 local time. With a 2600 km swath, it provides daily global coverage. For this study, we have used the latest version (V4.0) of the NASA standard tropospheric NO<sub>2</sub> column density Level-2 (L2) product available from the Goddard Earth Sciences Data and Information Services Center (GES DISC) and Level-3 (L3) gridded product available from the Aura Validation Data Center (AVDC) website (Lamsal et al., 2020). The ground resolution of the L2 product varies across swath ranging from 13 km x 24 km (along-track x across-track) at swath center to 24 km x 160 km at the outermost edges of the swath. We used data with cloud fraction less than 30 % that are not affected by the OMI row anomaly (Dobber, Voors, Dirksen, Kleipool, & Levelt, 2008). To create L3 product, a day's worth of clear-sky (effective cloud fraction < 0.3) good quality L2 data are mapped into a regular  $0.1^\circ$  latitude by  $0.1^\circ$  longitude grid. NO<sub>2</sub> column data in any grid cell is an area-weighted average of all L2 data that have any overlap with that grid cell.

### 2.4. Method

To quantify the impact of lockdown on atmospheric loading of pollutants, we performed following analysis: a) day-to-day variability using time-series, b) mean percentage changes in pollutants during the lockdown, c) spatial distribution of anomalies at national, regional, and local scales, d) change in air quality indices and its implications. We chose to use the past three years of data (2017–2019) for the same period to derive baseline conditions assuming it to represent atmospheric loading of pollutants in the year 2020 in absence of lockdown. Although longer time-series of data are available, to avoid the effect of the temporal trend in pollution, we generated baseline using data from these three years only. Thus, the baseline period is defined as March 25-May 17, 2017 to 2019 (referred as "baseline") and March 25-May 17, 2020 is considered as lockdown period (referred as "lockdown"). Air Quality Indices (AQI) in each city were also analysed during the baseline and lockdown periods. AQI is a measure that relates air quality to human health exposure and is derived by translating the weighted concentrations of individual pollutants (CPCB, 2015, Ott, 1978).

### 3. Results and discussion

#### 3.1. Air pollution as viewed from space during the lockdown

We first analyzed satellite data of AOD and columnar NO<sub>2</sub> to understand large scale changes over the region. Fig. 1(A–C) each shows the AOD for baseline, the lockdown and their differences. AOD is a measure of light extinction by scattering and absorption from aerosol particles as the light passes through the earth's atmosphere. The AOD is always measured at a specific wavelength and represents columnar loading of atmospheric aerosols from the surface to top-of-the-atmosphere. There have been many studies (Christopher & Gupta, 2020; Gupta et al., 2006; Liu, Paciorek, & Koutrakis, 2009; Sathe et al., 2019; van Donkelaar, Martin, Li, & Burnett, 2019; Yang et al., 2019) over the years to demonstrate the relationship between AOD and surface mass concentration of PM<sub>2.5</sub>. In this study, we have not used AOD to derive PM<sub>2.5</sub> but used it as a surrogate to assess the relative change in particle pollution in the atmosphere due to lockdown. The white areas in the Fig. 1(A–C) are areas with missing data from the satellite due to various retrieval limitations such as clouds, snow/ice on the surface or complex topography. The baseline map (Fig. 1(A)) represents the typical aerosol distribution over India for the season. The mean AOD ranges from 0.05 to  $\geq 1$  with elevated AODs ( $>0.5$ ) in the IGP, CSI, and over the seas adjoining India. Contrary to the previous 3 years, in the year 2020, the maximum AOD is  $\leq 0.75$  (Fig. 1(B)). The IGP region and the SI have strikingly low AOD values of  $\leq 0.25$ . However, CSI maintained high seasonal mean AOD ranging from 0.3 – 0.75 in 2020 as well. These high values are partially related to crop residual burning. After the harvesting of the wheat crop, crop residue burning is typically observed during March to May (pre-monsoon) in some of Indian states when fields are prepared for monsoon crops (Hays, Fine, Geron, Kleeman, & Gullett, 2005; Liu et al., 2018; Vadrevu, Badarinath, & Vermote, 2011).

Fig. 1(C) shows the AOD anomaly (2020 minus the baseline). Compared to the baseline, the AOD in the year 2020 dropped across the country except over CSI. A drastic decrease in AOD is seen over the IGP and SI regions with AOD anomaly exceeding -0.20 with a 25 % drop in regional mean AOD. The mean percentage decrease in AOD over SI is 30 % while the mean change in CSI is insignificant (~1%). Satellite data shows fires (not shown here) in CSI throughout the months of March and April ([www.firesandaq2020.info](http://www.firesandaq2020.info)). The elevated AODs in this region can be attributed to these burning activities in the region. A more recent study explained these elevated AODs partially associated with an effect of relative humidity on hygroscopic aerosols (Pandey & Vinoj, 2020). In addition, the north-western part of India and neighbouring countries demonstrated an overall decline in AOD values with some positive random anomalies. The overall changes observed in the atmospheric aerosols loading were mainly caused by a) reduced emissions due to lockdown, b) change in meteorological conditions, c) emissions and transport of dust and smoke.

Fig. 1(D–F) shows average OMI tropospheric NO<sub>2</sub> column density during the lockdown period compared with average NO<sub>2</sub> columns over the same period of the baseline. Tropospheric NO<sub>2</sub> data exhibit a strong spatial variation with higher values over cities, industrial areas, and power plants. While the spatial patterns remain consistent, NO<sub>2</sub> data during lockdown are significantly lower than the baseline values. Fig. 1(F) shows changes in tropospheric NO<sub>2</sub> columns between these two periods. The nation-wide decline in NO<sub>2</sub> of about 19 % is consistent with the strict lockdown that affect various activities linked to NO<sub>x</sub> emissions. The observed differences could arise from i) reduced NO<sub>x</sub> emissions during lockdown; ii) inter-annual variation in NO<sub>x</sub> emissions during 2017–2020; and iii) changes in NO<sub>2</sub> columns driven by changes in weather that affect NO<sub>2</sub> lifetime, transport, and concentrations. We further discuss these in subsequent sections.

### 3.2. Meteorology and air pollution

The prevailing meteorological conditions have a substantial influence on air quality and it is considered as one of the key drivers of air quality after emissions in a given region (Fig. 2). For example, change in winds can either disperse the pollutant to the larger area (i.e., high winds) or it can stagnant pollutant in the smaller area (i.e., calm winds). Similarly, depending on wind direction, pollution can transport towards cities (or human settlements or monitors) or away from cities. Boundary layer height is another important parameter, which impacts the concentration of a pollutant at the surface, usually, well-mixed boundary layers (deeper layer) dilute the pollution in larger volume thus reducing the mass concentration at the surface and vice-versa. Chemical and physical processes in the atmosphere help in the production of secondary pollutants such as sulphate and nitrate aerosols and it can be affected by temperature and relative humidity. Certain pollutant's lifetime in the atmosphere also gets affected by meteorological conditions. For instance, NO<sub>2</sub> has a much longer lifetime in colder temperatures because of lower concentrations of OH and RO radicals. The longer wintertime

NO<sub>x</sub> lifetime and shallow planetary boundary layer (PBL) causes the build-up of NO<sub>2</sub> concentrations. Therefore, it is important to account for meteorology while change in mass concentrations are studied to evaluate reduction in emissions due to limited human activities during the lockdown period. The meteorological parameters observed during the lockdown period were compared against the baseline period. Fig. 3 shows the frequency distribution while Table S5 summarizes the descriptive statistics of meteorological parameters. The meteorological parameters during this period of year typically represent spring-to-summer time conditions with moderate to high temperatures and wind speeds, increased mixing depth and lower frequency of temperature inversions, which are in turn favourable for pollutant dispersion in the atmosphere. The change in meteorological conditions from winter to spring, usually favour lower pollution levels in spring as compared to winter months. This impact of change in weather conditions reflects decreased pollutant concentration during spring from winter (Fig. 4). In general, no significant change is observed in meteorological parameters during the lockdown compared to the baseline period. The mean Relative humidity (RHUM) was observed to increase from 34.2%–45.4% in

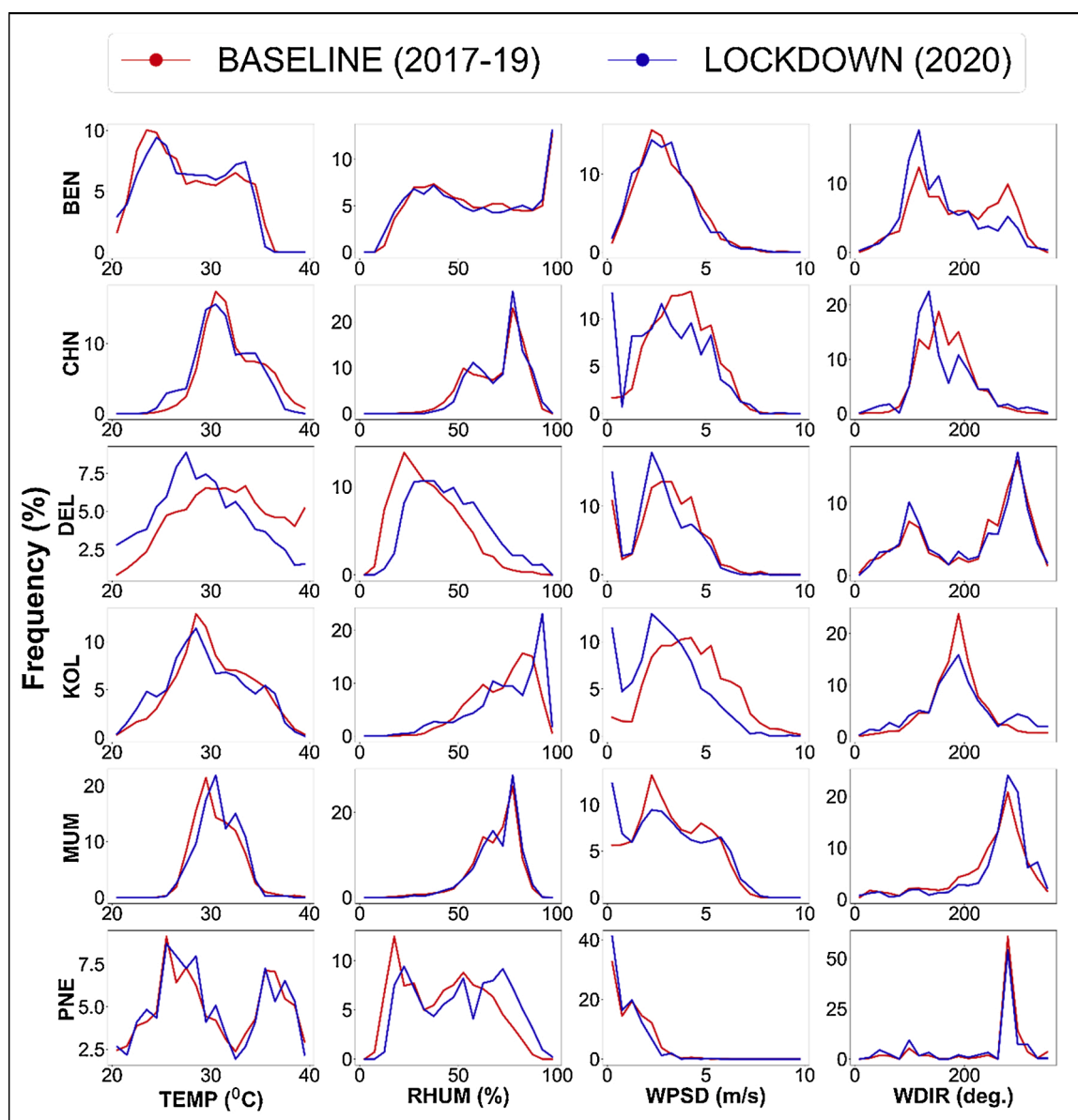
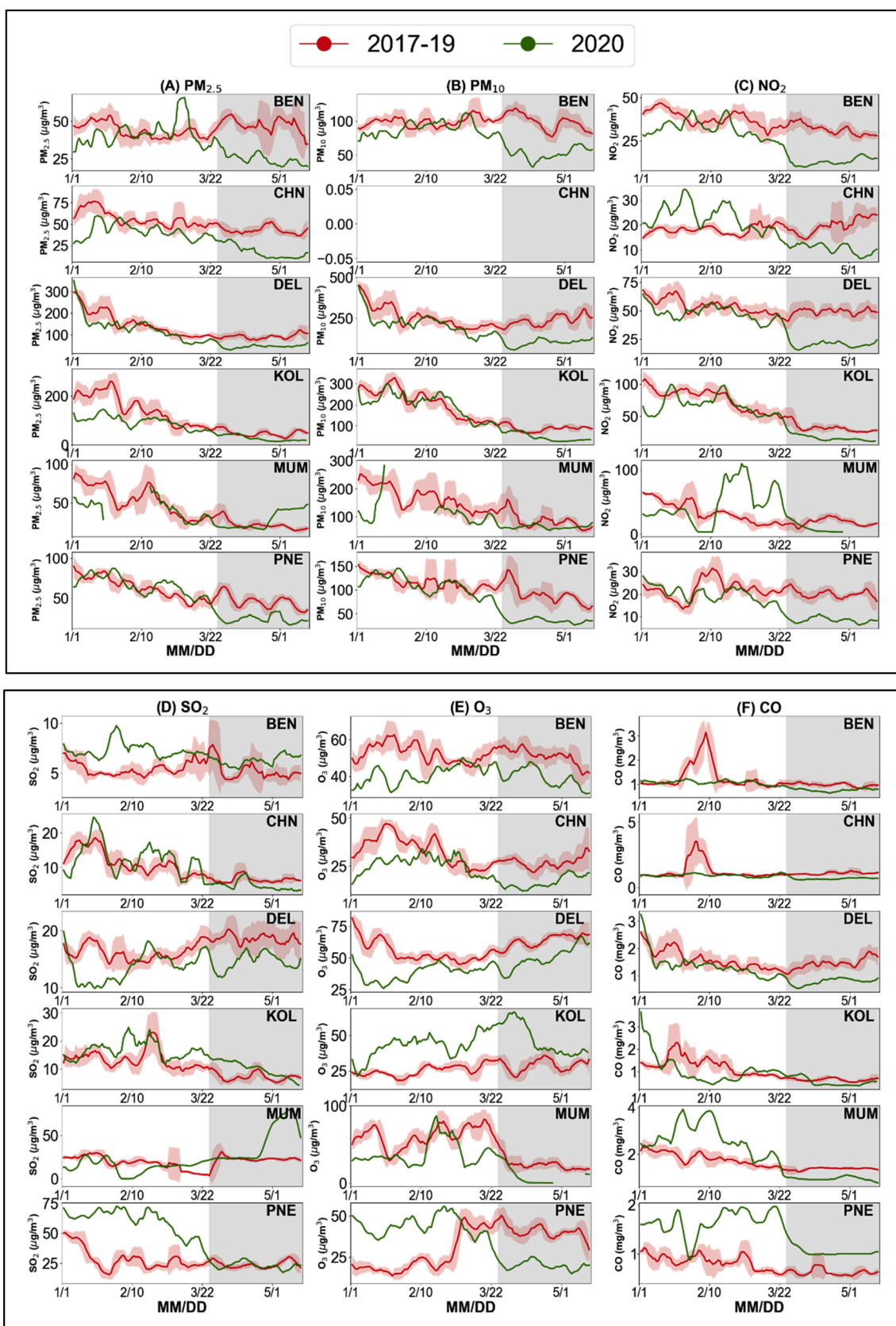


Fig. 3. Histograms showing the changes in meteorological parameters (TEMP, RHUM, WSPD, and WDIR) observed in six Indian cities during the baseline (2017-19) and the lockdown period (2020).



**Fig. 4.** 7-day moving average time-series of surface measured pollutants  $PM_{2.5}$ (A),  $PM_{10}$  (B),  $NO_2$ (C),  $SO_2$ (D),  $O_3$ (E) and CO (F) in Bengaluru (BEN), Chennai (CHN), Delhi (DEL), Kolkata (KOL), Mumbai (MUM) and Pune (PNE). The red line (shaded region) shows 7-day moving average for previous years i.e. 2017-19 (Std. deviation) and the green line indicates 7-day moving average for present year i.e. 2020.



Delhi and from 42.1%–50.7% in Pune during the lockdown period compared to baseline. In addition to RHUM, the dry bulb temperatures (TEMP) in Delhi were also lower by  $\sim 2.3$  °C in the lockdown compared to the baseline period, but changes in other cities were not significant. The wind-rose diagrams (Fig. S8) show a very little or no variation in Pune, Mumbai and Kolkata with westerly winds being predominant in Pune and Mumbai and southern winds in Kolkata. Chennai and Delhi exhibited slight variations in the wind distribution. Bengaluru exhibited the largest difference in wind distribution with westerly winds dominating during previous years 2017–19 while ESE winds dominated during the year 2020. The meteorological conditions during the lockdown were similar to those observed during the baseline period with some variability. This suggests that meteorology may not be a dominating factor in the reduced pollution levels seen during the lockdown. We have also noted certain specific observed changes in pollutant concentrations throughout the paper where weather (i.e. rain) had a significant impact. It is noteworthy that similarity of histograms suggests

that the overall impact of meteorology for the entire study period could be similar during the baseline and lockdown years, but the day-to-day and diurnal variation may be different in the two periods; this can create different effects. This study does not aim to separate the impact of meteorology and lockdown on pollutant concentrations, but rather uses the meteorological parameters for the qualitative interpretation of changes in pollutants. A more advanced analysis with model simulations may be needed to isolate individual effects.

### 3.3. Surface and satellite observed pollution over selected cities

Figs. 4 and 5 shows the day-to-day evolution of surface and satellite measurements starting from 1<sup>st</sup> January to 17<sup>th</sup> May for the previous (2017–19) and present (2020) years, respectively. Over Mumbai and Pune, the surface data were available only for one station each. Also, baseline surface data for Mumbai (Pune) were not available for years 2017 and 2018 (2018). Fig. 6 on the other hand presents the result of the

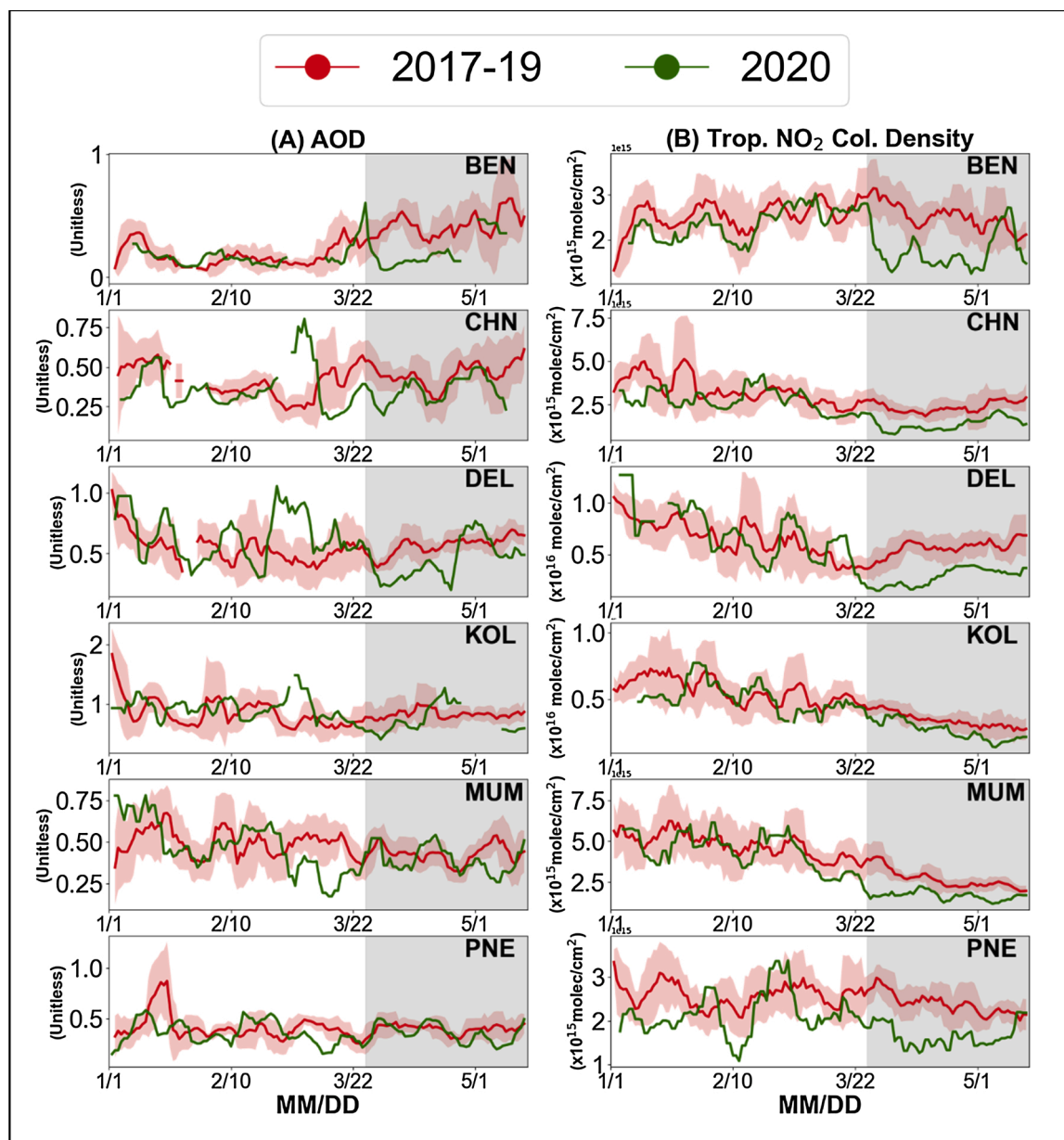


Fig. 5. 7-day moving average time-series of satellite measurements AOD (A) and Tropospheric NO<sub>2</sub> column density (B) in Bengaluru (BEN), Chennai (CHN), Delhi (DEL), Kolkata (KOL), Mumbai (MUM) and Pune (PNE). The red line (shaded region) shows 7-day moving average for previous years i.e. 2017–19 (Std. deviation) and the green line indicates 7-day moving average for the present year i.e. 2020.



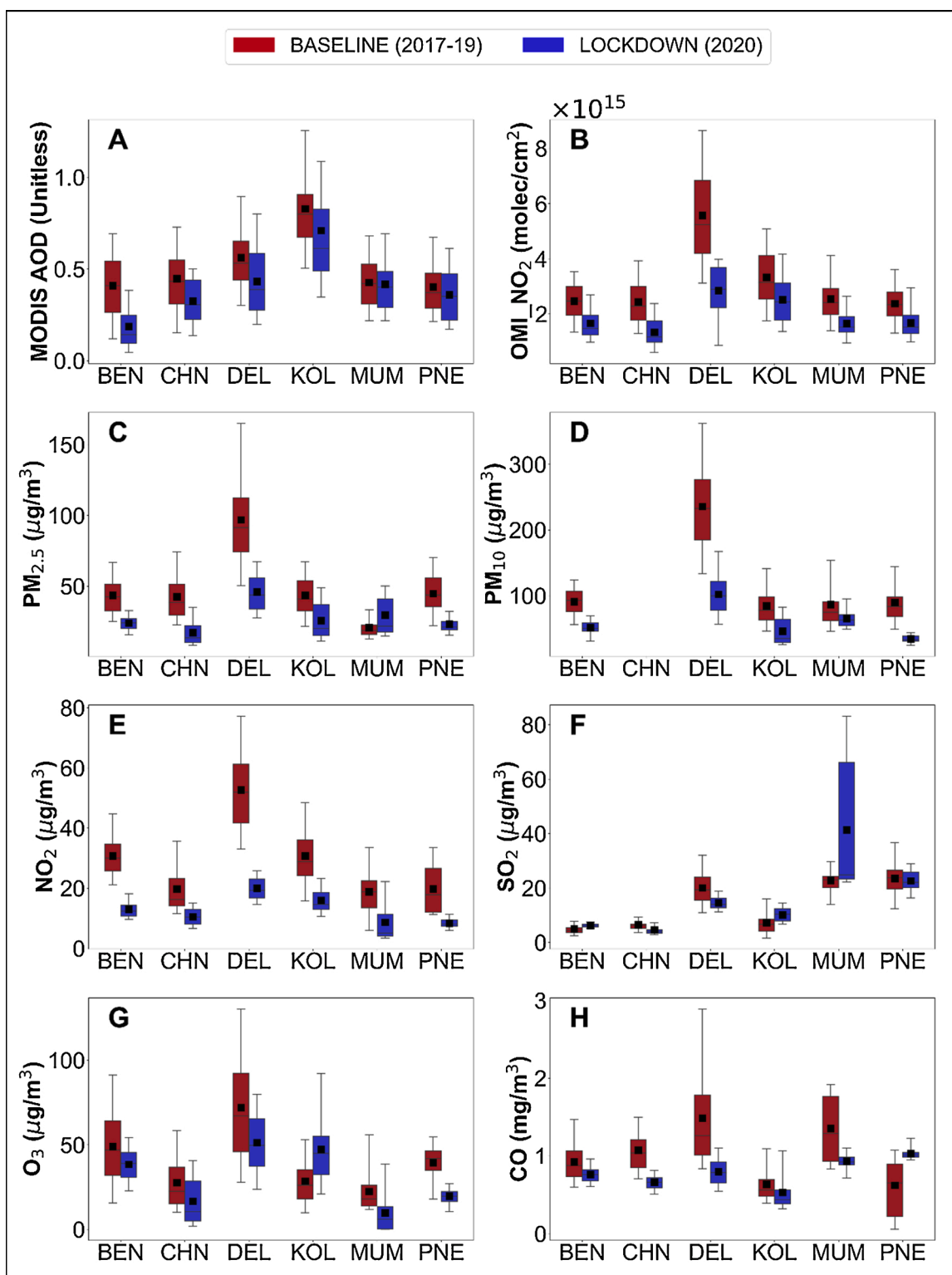


Fig. 6. Boxplot distributions of MODIS AOD (A), OMI NO<sub>2</sub>(B), PM<sub>2.5</sub>(C), PM<sub>10</sub>(D), NO<sub>2</sub>(E), SO<sub>2</sub>(F), O<sub>3</sub>(G) and CO (H) during baseline (2017 to 2019) and lockdown (2020) periods in six cities.

overall impact of lockdown on eight different pollutants/parameters measured from surface and satellite over six selected cities. The time-series shows changes in pollution levels as cities in India moves from winter to spring time weather conditions; and a comparison of pre-vs-post lockdown period in 2020. Changes in sources of certain pollutants and transport pattern also occur from one season to another. Time-series analysis over six cities (Fig. 4) shows that most of the primary

pollutants exhibit strong seasonality and an overall decreasing trend from January to May. One of the causes for the pollution build-up during January – February is meteorological conditions i.e. low temperature, high relative humidity, and low mixing height; these favour the formation and accumulation of secondary particles (Pan et al., 2015; Schnell et al., 2018). These conditions then gradually change to typical summer-time unstable conditions associated with higher wind speeds

that are conducive for dispersion of pollutants.

### 3.3.1. $PM_{2.5}$ and AOD

$PM_{2.5}$  (Fig. 4(A–B)) show an overall declining trend from January to May in all the cities (except Bengaluru). Satellite-based AOD showed similar trends as surface  $PM_{2.5}$  observations (Fig. 5(A)), except that AOD exhibited more day-to-day variability and trends are less steep. The trends are stronger in surface measurements. These differences can arise from the fact that AOD is column value and averaged over a larger area as compared  $PM_{2.5}$ , which are at the surface and represent a point measurement. In Bengaluru,  $PM_{2.5}$  concentrations changed substantially during the lockdown period, in comparison to the baseline conditions, with daily  $PM_{2.5}$  concentrations plummeting up to  $13.5 \mu\text{g m}^{-3}$ . These were the lowest values observed in the city over the last 4 years during this specific period. The AOD also decreased to about half of its previous year's value. Although, Delhi recorded the high particulate concentrations in the month of January, the  $PM_{2.5}$  concentrations during year 2020 were found to be lower (by  $\sim 14\%$ ) than baseline before the imposition of lockdown (Table S7). The lockdown imposed on 25<sup>th</sup> March 2020 induced a remarkable reduction in Delhi's particulate concentrations, with daily  $PM_{2.5}$  and AOD dipping up to  $22.7 \mu\text{g m}^{-3}$  and  $\sim 0.1$ , respectively on 28<sup>th</sup> March 2020. This was a huge reduction especially considering the prevailing levels of aerosols in Delhi over the last decade. This drop in  $PM_{2.5}$  concentrations resulted from the combined effect of lockdown and heavy rainfall (as reported by GPM satellite, not presented here) in northern India during the first week of lockdown. Though, Delhi's PM levels remained lower than the baseline mean concentrations during the entire lockdown period, a slightly increasing trend was observed starting in the second week of April 2020. AOD also increased back to previous year values, with a small drop in May.  $PM_{2.5}$  levels in cities such as Chennai, Kolkata and Pune showed an obvious decreasing trend with a considerable reduction during the lockdown period. The AOD over these cities are generally lower than in January but with no significant trend. Baring Mumbai and Pune, there is a reduction in AOD, especially during the first phase of lockdown. From mid-January till May, there is an overall decrease in AOD during the baseline years. However, over both Mumbai and Pune, the AOD in 2020 is lower than previous years in both March and May with an increase in AOD after 1<sup>st</sup> week of May. This increasing trend (in  $PM_{2.5}$  and AOD) towards the end of the lockdown period could be due to the relaxations permitted during second (15<sup>th</sup> April to 3<sup>rd</sup> May 2020) and third (4<sup>th</sup> May to 17<sup>th</sup> May 2020) phases of the lockdown in certain parts of the country.

As shown in (Fig. 6(C)), with the exception of Mumbai all the cities showed an obvious reduction in  $PM_{2.5}$  concentrations during the lockdown period. The transport sector is the major contributor to  $PM_{2.5}$  in cities such as Bengaluru, Delhi, and Pune, and accounts for 35–40 % of  $PM_{2.5}$  emissions while industries contribute 49–70 % in remaining cities (i.e., Chennai, Kolkata and Mumbai) (Table S6). Besides, a ban on the operation of industries except essential goods manufacturing and construction/demolition activities led to further reductions in  $PM_{2.5}$  concentrations during the lockdown period. The decline in  $PM_{2.5}$  during the lockdown was in range of 41 % (Kolkata) to 60 % (Chennai). The satellite-based aerosol measurements (i.e. AOD, (Fig. 6(A)) showed similar results with the highest change (56 %) for Bengaluru and lowest (3%) for Mumbai. It is important to note that AODs are spatially averaged over larger regions and represent an entire column of the atmosphere under ambient conditions as compared to PMs representing the surface mass concentration of certain size particles, under controlled conditions. Mumbai showed a moderate increase in  $PM_{2.5}$  concentrations (42 %) compared to the baseline period. Furthermore, the satellite retrieved mean AOD values (a proxy for surface  $PM_{2.5}$ ) over Mumbai also remained substantially unchanged during the lockdown period (AOD reduction:  $\sim 3\%$ , Fig. 6(A)). This phenomenon can be explained by three possible causes: i) the lack of data in years 2017 and 2018 to form the “baseline” conditions, thereby missing the inter-annual variations, ii) an increase in household coal combustion as people spent more time

indoors and there was a likely increase in the cooking and heating activities during the lockdown period and iii) the photochemical oxidation of  $SO_2$  to sulphate particles by hydroxide free radical due to the presence of high OH concentration during summer (Khoder, 2002; Megaritis, Fountoukis, Charalampidis, Pilinis, & Pandis, 2013). The results from Mumbai are unexpected and require further analysis with more station data and meteorological variables. Kumar et al. (2020) also observed the least  $PM_{2.5}$  reduction ( $\sim 12\%$ ) at U.S. Embassy monitoring station in Mumbai during the lockdown period compared to other Indian cities such as Delhi, Chennai, Kolkata and Hyderabad and cited coal/biomass combustion as the primary reason.

### 3.3.2. $PM_{10}$

The coarse particulates i.e.  $PM_{10}$ , exhibited an overall decreasing trend from January to May owing to seasonal changes during both present and previous years, except for Bengaluru that showed a slightly increasing trend (Fig. 4(B)). The  $PM_{10}$  time-series showed several oscillations where  $PM_{10}$  concentrations in the present year exceeded the corresponding previous year values. Further,  $PM_{10}$  concentrations in Delhi experienced maximum year-to-year variability during the previous years whereas Bengaluru exhibited minimum. It is also important to note that, Delhi witnessed a substantial increase in  $PM_{10}$  ( $133.1\text{--}181.6 \mu\text{g m}^{-3}$ ) during 13<sup>th</sup> to 16<sup>th</sup> April 2020 when a mild dust storm carrying dust particles from Thar desert in Rajasthan and Gulf countries hit the Delhi region (CPCB, 2020b). During the lockdown period,  $PM_{10}$  concentrations in all cities experienced a significant reduction (Fig. 6(D)) ranging from 24 % (Mumbai) and 62 % (Pune). The re-suspended and construction dust are the major contributors to  $PM_{10}$  emissions in these cities with a share ranging from 28 to 61 % (Table S6). Hence, the main reason for decline could be the reduction in Vehicular Kilometres Travelled (VKT) which not only prevents the exhaust emissions but also reduces non-exhaust emissions (tyre, brake and clutch wear) and re-suspended road dust. Further, the absence of construction activities during the lockdown period also resulted in lowered  $PM_{10}$  concentrations.

### 3.3.3. Nitrogen dioxide ( $NO_2$ )

Both surface and columnar (OMI)  $NO_2$  concentrations in cities such as Bengaluru, Delhi, Kolkata and Pune exhibited strong seasonality with an overall downward trend from January to May during previous and present years (Figs. 4(C) and 5 (B)). The seasonality in  $NO_2$  is primarily driven by changes in lifetime and mixing layer depth. For example, in winter  $NO_x$  lifetime is long and mixing layer depth is shallow causing the build-up of  $NO_2$  concentrations while in summer the situation reverses. The strict lockdown measures (starting 25<sup>th</sup> March, 2020) led to a substantial reduction in  $NO_2$  concentrations (Fig. 6(E)) in all six cities (46–61 %), with Delhi showing the maximum reduction. The transport sector is a major contributor to  $NO_x$  emissions in cities such as Delhi (85 %), Bengaluru (42 %), Kolkata (25 %), Mumbai (29 %) and Pune (29 %) while the industries accounted for 28–58 % of total  $NO_x$  emissions in cities such as Bengaluru, Kolkata, Mumbai and Pune (Refer Table S6). Hence, the  $NO_2$  reductions in these cities can be explained by the restrictions on the movement of people and ban on industrial operations imposed during the lockdown period. Furthermore, the  $NO_2$  reductions in Indian cities are comparable to the reductions observed in European cities (52 %) and Wuhan (57 %) in China (Sicard et al., 2020). These results are consistent with the reductions in tropospheric  $NO_2$  columns (25%–50%) observed by OMI (Fig. 6(B)).

### 3.3.4. Ozone ( $O_3$ )

The ozone ( $O_3$ ) concentrations showed different day-to-day behaviour and did not follow a consistent trend across different cities throughout the analysis period (Fig. 4(E)), but concentrations throughout 2020 were comparatively lower than the previous year's mean (2017–19) except for Kolkata and Pune. Kolkata reported higher than baseline ozone concentrations throughout the year 2020 while

Pune had higher ozone concentrations till 3<sup>rd</sup> week of March 2020. During the lockdown a significant reduction in mean O<sub>3</sub> concentrations (22–56%) was observed (Fig. 6(G)) as compared to the baseline years in different cities except for Kolkata, which showed an enormous increase (66%). It is important to note that ozone is secondary pollutant formed as a result of complex and non-linear interplay between NO<sub>x</sub>, Volatile Organic Compounds (VOCs) and solar radiation (Kroll et al., 2020; Menut et al., 2020). In polluted environments, carbon monoxide (CO) can also produce ozone through similar reactions with OH<sup>-</sup> radicals as the VOCs. The reduction in emissions of NO<sub>x</sub> and VOCs in cities during the lockdown could be assumed as the primary reason for the overall reduction in ozone concentrations, but the meteorology and chemical interactions need further investigation. Further, a slight increase in VOC emissions can be expected especially in COVID-19 like situation when the community disinfection practices such as spraying of sodium hypochlorite solution (Chatterjee, 2020), frequent use of sanitizers, etc. were followed rigorously within the cities to control the spread of the disease. This situation typically represents a NO<sub>x</sub>-limited chemical regime and an overall decrease in O<sub>3</sub> concentrations can be expected. In Kolkata, however, a contradictory scenario was observed, where NO<sub>x</sub> emissions were reduced, consistent with NO<sub>2</sub> reduction of 47%, during the lockdown period. However, there is a possibility of the existence of a VOC-limited chemical regime, thereby enhancing the in O<sub>3</sub> formation.

### 3.3.5. Sulfur dioxide (SO<sub>2</sub>)

Similar to O<sub>3</sub>, SO<sub>2</sub> (Fig. 4(D)) in the cities also showed a mixed behaviour, and SO<sub>2</sub> levels remained relatively constant from January through May, with an exception of Mumbai and Pune. Mumbai observed a normal behaviour until the 4<sup>th</sup> week of April 2020 (SO<sub>2</sub> < 50 μg m<sup>-3</sup>), but then increased rapidly reaching up to 90.1 μg m<sup>-3</sup> whereas in Pune the SO<sub>2</sub> levels remained unchanged when compared to the 2017–2019 average. During the lockdown period (Fig. 6(F)), only Chennai (32%) and Delhi (29%) observed a moderate decrease in mean SO<sub>2</sub> concentrations. Both Chennai and Delhi have more than 85% of SO<sub>2</sub> emissions originating from the industrial sector, which includes thermal power-plants (Table S6). The ban on the operation of industries and partial reduction in power-plant operations can explain the SO<sub>2</sub> reduction in these cities. As discussed earlier, the mean SO<sub>2</sub> concentrations in Pune remained more or less constant (Percentage change: ~+4%) during the two periods while Bengaluru and Kolkata experienced a moderate increase of 31% and 42%, respectively. These three cities had seen higher SO<sub>2</sub> concentrations throughout the year 2020 as compared to previous years mean. In Bengaluru and Kolkata, the inclined SO<sub>2</sub> concentrations could be attributed to primary emissions from thermal power-plants and background SO<sub>2</sub> contributions from surrounding regions (ESA, 2020a). Surprisingly, Mumbai showed the highest increase in mean SO<sub>2</sub> concentrations (81%) during the lockdown period in comparison to the baseline period, and the concentrations during the lockdown period ranged from a minimum of 20.69 μg m<sup>-3</sup> to a peak value of 90.07 μg m<sup>-3</sup>. The examination of time-series revealed a substantial increase in daytime SO<sub>2</sub> concentrations during 26<sup>th</sup> April to 14<sup>th</sup> May 2020 at Bandra, Mumbai. A slight increase was observed in PM<sub>2.5</sub> and CO concentrations during this period. There can be multiple reasons for this increase: i) more than 90% of SO<sub>2</sub> emissions in Mumbai region are thought to be originated from the industrial sector and some heavy industries such as power and refineries were allowed to operate at reduced capacity during the second and third phases of the lockdown (Hindustan Times, 2020); ii) idling ships were spotted in the ports near Mumbai (Hindustan Times, 2020); iii) baseline concentrations could be lower due to non-inclusion of 2017–18 SO<sub>2</sub> data (Section 3.3.2); and iv) people spent more time indoors during the lockdown period, thereby increasing the residential sector emissions due to more cooking and heating activities (Kumar et al., 2020).

### 3.3.6. Carbon monoxide (CO)

With the exception of Pune, all the cities showed a moderate

reduction of 16–46% in CO concentrations during the lockdown period in comparison to the baseline period (Fig. 6(H)). The reduction in CO can be attributed to the limitation of combustion activities in sectors such as transport, industries, and residential (Refer Table S6), wherein CO is a primary pollutant resulting from an incomplete combustion process. However, Pune showed a large increase of 66% in CO concentrations as compared to the baseline years. In the view of the reduction in anthropogenic activities during the lockdown, such an increase in CO concentrations seems rather unexpected and suggests suspicious CO measurements, maybe due to a faulty calibration of the sensor and needs further investigation.

### 3.4. Citywide spatial distribution

Air quality varies from location to location in and around the city and depends on sources, topography, land use type, and meteorological conditions. To evaluate changes in different parts of the city, we choose Delhi, where there are 34 ground monitors located, to map the spatial distribution of three selected pollutants namely PM<sub>2.5</sub>, NO<sub>2</sub>, and O<sub>3</sub>. Fig. 7 provides maps of mean concentrations for baseline (A, C, E) and lockdown (B, D, F) periods. The PM<sub>2.5</sub> values for the baseline period (Fig. 7(A)) varied from 60 to 121 μg m<sup>-3</sup> whereas it dropped to 24–74 μg m<sup>-3</sup> during the lockdown. The average PM<sub>2.5</sub> reduction during the lockdown period ranged from 18% (at ITO station) to 80% (at Shadipur station) in different parts of the city. Shadipur station is surrounded by numerous small and medium scale industries. Industries are mostly associated with heavy-duty diesel vehicle (HDDV) traffic for transportation of raw and processed materials to and fro this location. Hence, shut down of industrial operations along with associated HDDV traffic could explain the reason for maximum PM<sub>2.5</sub> reduction during the lockdown period. ITO square, on the other hand, is dominated by huge daily traffic flow and is surrounded by Government offices which were allowed to operate partially during the second and third phases of the lockdown. Typically, PM<sub>2.5</sub> values were higher in the northern part of the city and lower in the southern part of the city.

NO<sub>2</sub> concentrations showed high values in the centre of the city and decreased as one moves away from the centre to the outside of the city. This may be primarily due to the presence of dominating sources of NO<sub>2</sub> such as vehicles and thermal power plants in the inner part of the city. The transportation sector alone contributes to more than 85% of NO<sub>x</sub> emissions in Delhi city (ARAI & TERI, 2018). Traffic restrictions imposed during lockdown had reduced NO<sub>x</sub> emissions in Delhi city and it is reflected in lowering the NO<sub>2</sub> concentrations. NO<sub>2</sub> reduction over stations ranged from 20% to 80% across the city.

Ozone concentrations exhibited high spatial variability and showed an overall mixed change in concentrations. For example, 17 stations showed an increase while remaining 17 stations showed reduction in ozone concentrations during the lockdown period in comparison to the baseline years. Maximum increase of 244% in O<sub>3</sub> concentrations was observed at ITO square (Percentage reduction in NO<sub>2</sub> > 73%) while maximum reduction of 85% was observed at Jahangirpuri (percentage increase in NO<sub>2</sub> ~4%). The major source of NO and NO<sub>2</sub> (i.e., NO<sub>x</sub>) in cities is vehicular emissions, and their ratio is about 20:1. NO plays a critical role in ozone chemistry including its destruction in the atmosphere. In the absence of NO, O<sub>3</sub> concentration can go up; a probable effect was seen over Delhi with a net increase in O<sub>3</sub> during the lockdown.

### 3.5. Regional changes using satellite observations

To examine the footprints of lockdown induced emission reduction at regional scales, we analyzed the satellite-derived AOD and NO<sub>2</sub> data. The area-averaged daily AOD and NO<sub>2</sub> values during January–May of 2020 were compared to the baseline period. From the spatial analysis in Section 3.1, we choose to perform regional analysis over three regions (box enclosed with solid black lines in Fig. 1(C)) that show large AOD and NO<sub>2</sub> anomalies. Fig. 8 shows 7-day moving average time-series

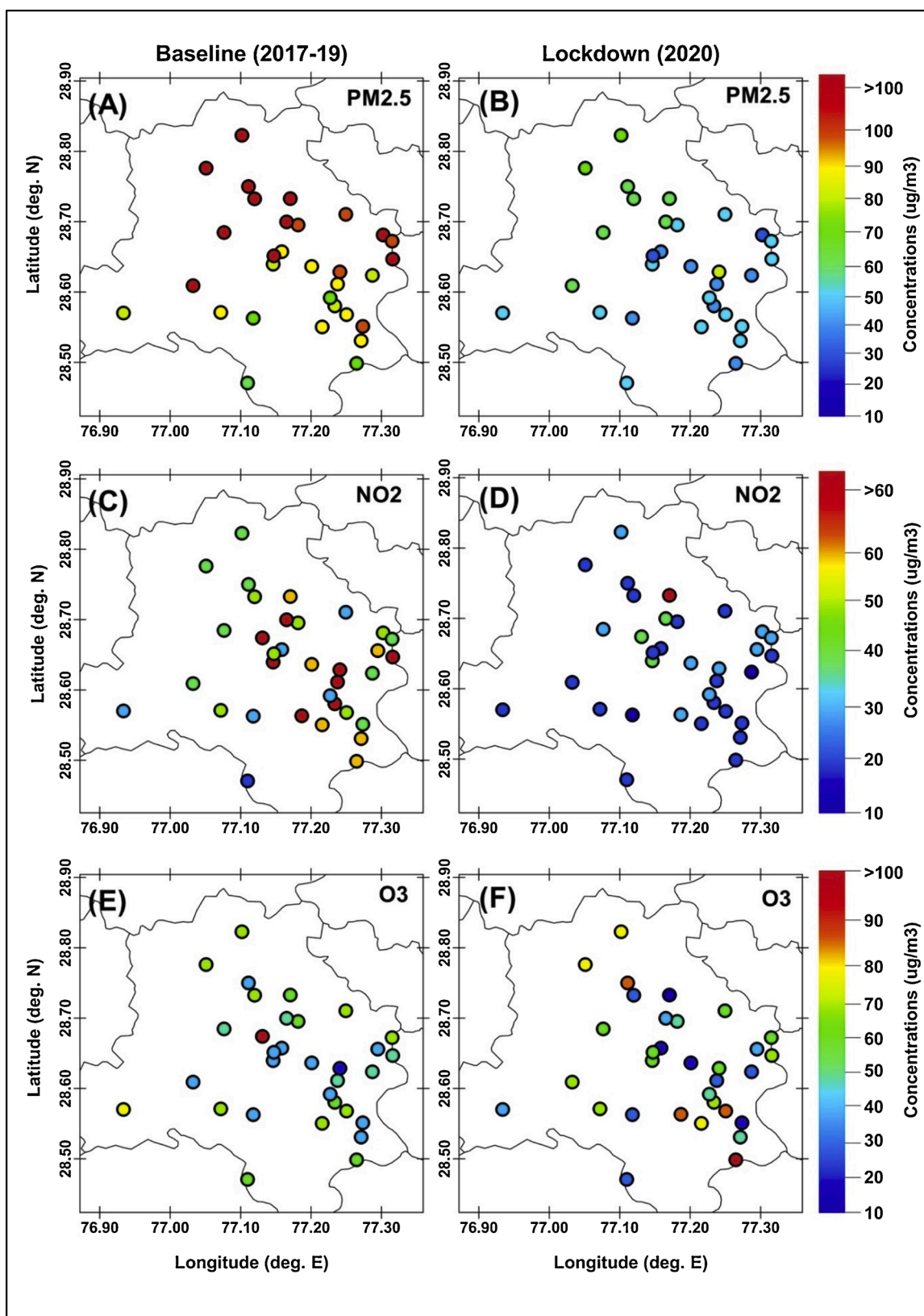
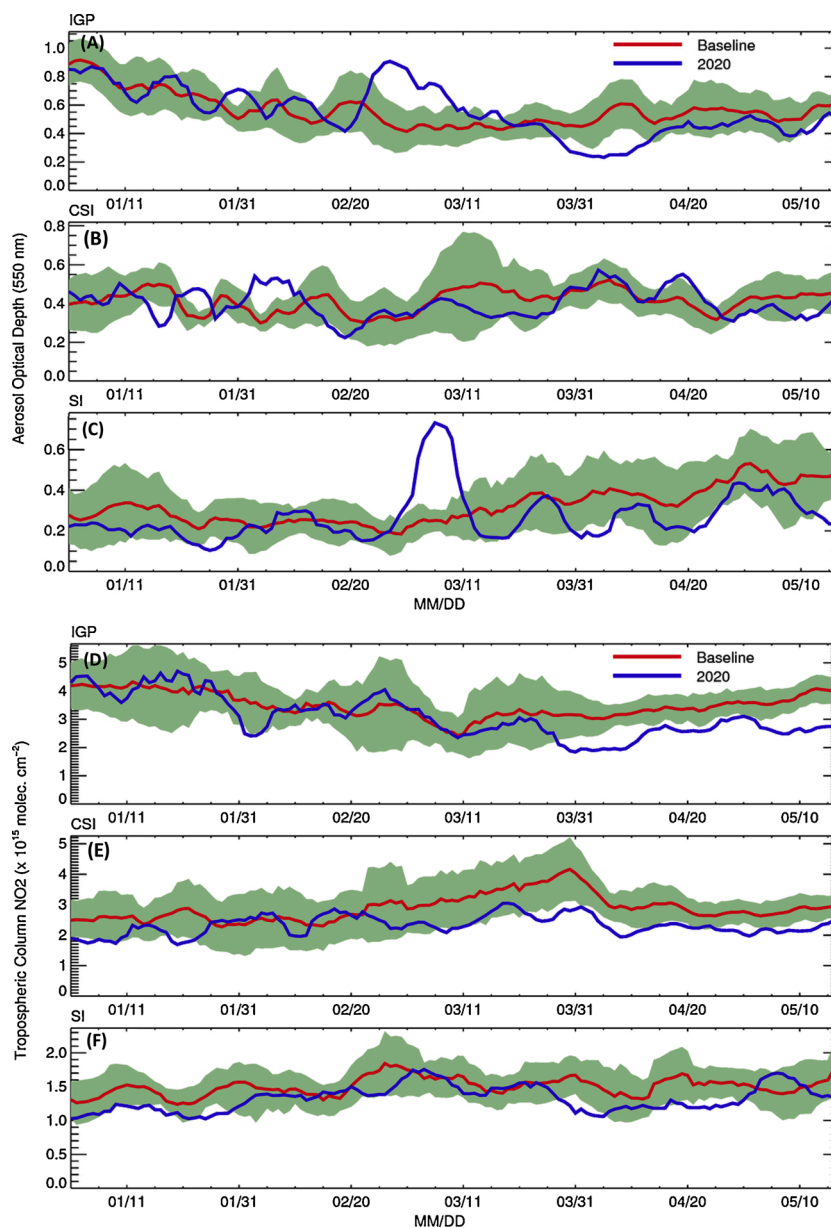


Fig. 7. Spatial distribution of daily mean surface measurements of PM<sub>2.5</sub> (A and B), NO<sub>2</sub> (C and D) and O<sub>3</sub> (E and F) during the baseline (25<sup>th</sup> March to 17<sup>th</sup> May, 2017-19) and the lockdown (25<sup>th</sup> March to 17<sup>th</sup> May, 2020) periods in Delhi city.





**Fig. 8.** Regional time-series of satellite measurements AOD (A, B, and C) and Tropospheric NO<sub>2</sub> column density (D, E, and F) averaged over three regions i.e. Indo-Gangetic plain (IGP), Central South India (CSI) and South India (SI), respectively. The red line (green shaded region) shows 7-day moving average for previous years i.e. 2017–19 (Std. deviation) and the blue line indicates 7-day moving average for the present year i.e. 2020.

starting January 1 through May 17 for previous years and 2020.

Home to millions, the IGP has the highest population density in the country, as well as house to several industries, power plants, and major agricultural areas. Emissions from all of these sources contribute to regional air pollution. IGP is also unique for its geography and topography with the Himalayas on the north side, Chota Nagpur Plateau in the south, and Iranian Plateau in the west. Fig. 8(A) shows that in the IGP region, during baseline years, the AOD decreases from January until the beginning of March (red line) and then remains nearly flat through mid-May with one small oscillation (increase & drop) in early to mid-April. The AOD starts increasing slightly as April progresses. The change in meteorological conditions and pollution sources from January to April provide favourable conditions for improved air quality in the IGP and greater northern India region. Warmer temperatures with increased wind speed help pollution to disperse in larger atmospheric volume. As the region progresses out of crop growing season (January–March) and subsequent harvesting in April–May, crop residues are burnt to prepare

the land for the next crop. Around the same time (starting April), dust storm originated from the various arid parts of India, Pakistan, and Arabian Peninsula affects the air quality in the region. Consistent with previous years, AOD in 2020 (blue line) is seen to decrease from January to mid-February. Elevated AOD observed over the next two weeks (Mid-February to March first week) is due to biomass burning and dust storms in the region (based on visual satellite imagery analysis not presented here) after which the AOD values dropped back to the average values during that time of the month. The IGP region houses thermal power plants, industries, and high density of vehicles. With most of these major sources of pollution turned off simultaneously (except power plants), the daily mean AOD values decreased from 0.5 on March 23<sup>rd</sup> to 0.2 on March 26<sup>th</sup> and a lowest value 0.14 on March 29<sup>th</sup>. The AOD values during the same period in the baseline years remained between 0.4 and 0.5. In addition to reduced emissions, heavy rain fall helped cleaning the air during March 25–31. However, unlike the air quality conditions normally obtained after rain showers in the region, AOD continued to

decrease in the following week and remained below the minima of the standard deviation [blue shaded area] in daily mean values. During the second and third phase of the lockdown (15<sup>th</sup> April – 3<sup>rd</sup> May 2020), conditional relaxation allowed certain businesses including agricultural businesses, cargo transportation, trucks, trains, and planes to operate. For IGP, the return of some of the sources of pollution (and a dust storm) coincides with an increase in AOD from 15<sup>th</sup> April – 3<sup>rd</sup> May 2020. The mean AOD values for the second phase of lockdown were 0.57 in the baseline years and reduced by about 16 % to 0.47 in the lockdown year. North India also witnessed high cloud cover and some heavy rainfall events in March and April (by visual inspection of GPM rainfall data on NASA worldview, analysis is not presented here). The AOD values in the IGP region were about 25 % lower during the lockdown period compared to the baseline years with minimum daily values of up to 0.14.

The daily mean AOD values in Central India (Fig. 8(B)) varied between 0.17 and 0.66 throughout January – May of the previous years. The year to year AOD variability (shaded area) was high in the months of February and March. At the beginning of the year 2020, the daily mean values matched the baseline value. However, AOD was seen to be oscillating below and above the baseline mean AOD throughout mid-Jan to Mid-May of 2020. The response of ambient aerosol particles to the lockdown was different from the IGP region. AOD in this region was lower than the baseline year before the lockdown period, increased to match baseline values during the first phase of lockdown, was higher during the second phase of lockdown, and finally became lower than the baseline AODs in May. The AOD varies between 0.58 and 0.30 for the baseline and 0.73 to 0.20 for the lockdown period with an overall mean value remained the same (0.43). The high variability in the 2020 AOD time-series seems to have resulted from data gaps from several days of cloud cover over the region. During the lockdown period, there was also

a persistent presence of fires in the region (visual analysis using worldview, not shown here). Southern India (Fig. 8(C)) consistently showed lower AOD values in 2020 as compared to the same period of the previous years. The mean decline in AOD in SI was about 30 % during the lockdown as compared to the baseline years. The lowest observed AODs for the region were 0.19 and 0.09 for the baseline and lockdown periods with a maximum value of 0.7 for both periods.

The lower panels of Fig. 8(D–F) show the time series of tropospheric NO<sub>2</sub> columns for the three selected regions. Among the three regions, the IGP region exhibits the highest level of NO<sub>2</sub> pollution prior to the lockdown period. The seasonality is not obvious in the mean values during January through May, although more polluted locations ought to exhibit higher values in winter and lower values in spring and summer as discussed earlier. The baseline tropospheric NO<sub>2</sub> column values tend to be higher than 2020 even prior to the lockdown period, suggesting that there were some declines in NO<sub>2</sub> during the period of our study (2017–2020) although prior studies (e.g. Duncan et al., 2016; Krotkov et al., 2017) suggested a considerable positive trend in NO<sub>x</sub> emissions in India. During the lockdown, there was an additional decline in NO<sub>2</sub> of 15 % in SI, 23 % in CSI, and 28 % in IGP, which are consistent with the trends observed at the ground sites discussed in the previous section.

### 3.6. Implication to city air quality

This section discusses the air quality indices (AQI) calculated in six cities during the baseline and lockdown periods and its implication to short and long-term national air quality goals and future directions. The AQI is multi-pollutant AQI and details on the method and the formulation are provided in the supplementary material (Refer SM19). Fig. 9 (A–F) shows the distribution of six AQI categories calculated using the



Fig. 9. Distribution of six Air Quality Index (AQI) categories in Bengaluru (A), Chennai (B), Delhi (C), Kolkata (D), Mumbai (E) and Pune (F) during the baseline (25<sup>th</sup> March to 17<sup>th</sup> May, 2017-19; Left panel) and the lockdown (25<sup>th</sup> March to 17<sup>th</sup> May, 2020; Right panel) periods.

monitoring data during the baseline and the lockdown periods. The AQIs in these cities were mainly driven by PM<sub>10</sub> followed by PM<sub>2.5</sub> and occasionally by CO and O<sub>3</sub>. This was also evident from the exceedance of National Ambient Air Quality Standards (NAAQS) in these cities (not presented here).

An examination of AQI during the baseline period revealed that air qualities in these cities were mainly distributed in Satisfactory (60–84 %) and Moderate (15–38 %) AQI classes, except for Delhi. Delhi's air quality during the same period was mainly distributed between Moderate (39 %), Poor (38 %), and Very Poor (21 %), and seldom attained the Satisfactory (1%) level. The air quality situation improved significantly during the lockdown period when the combined proportion of Good and Satisfactory AQI classes in Bengaluru (100 %), Chennai (100 %), Pune (96 %), Kolkata (92 %) and Mumbai (87 %) were substantially higher as compared to the baseline period. Although Delhi's air quality very rarely made to the Good (4%) category, it attained Satisfactory (48 %) and Moderate (46 %) levels for majority of cases during the lockdown period.

These findings are very important from the perspectives of the National Clean Air Program (NCAP) launched recently by Govt. of India (MoEFCC, 2020). The NCAP is primarily aimed at reducing the national level PM<sub>2.5</sub> and PM<sub>10</sub> concentrations by 20–30 % by the year 2024, as compared to 2017. PM<sub>2.5</sub> has been a matter of serious concern in India due to its complex sources and health effects. It is important to note that, when emissions from vehicles, industry and construction activities were switched off during the lockdown, the PM<sub>2.5</sub> levels improved by 40–60 % in different cities. Hence, to reduce PM<sub>2.5</sub> below the targeted levels, the remaining sources such as thermal power plants, diesel generators, residential biomass burning, open burning of waste, and trans-boundary contribution should also be given a due consideration. The positive impact on air quality due to the reduction of air pollutants in cities is likely temporary and will last till the lockdown restrictions are in place. Substantial improvements in the air quality are evident by this unique experiment, wherein some of the sources were turned-off in real-time, provided a guiding example for governments and policymakers to take long term preventive measures in the future.

#### 4. Summary and conclusion

The ongoing pandemic created a unique natural experiment for the first time in the modern industrial era. The natural experiment provided an opportunity to environmental and Earth science community to assess the impact of reduced human activities on many different aspects of the Earth-atmosphere system including air, water, and land pollutions.

In response to COVID-19 pandemic, India implemented a nationwide complete lockdown that lasted for 53 days (March 25 to May 17, 2020) in three different phases. The lockdown created a unique environmental condition where emissions of air pollutants from human activities were either completely shut down or limited. Air pollution measurements from surface and satellite monitors showed a sharp decline in many parts of the country. In this study, we provided a comprehensive analysis of surface and satellite measurements of air pollutants for the lockdown period comparing them with observations during the recent years of 2017–2019. We also quantified the decline in air pollutants at varying spatial (community, city, regional, and national) and temporal (hourly, daily, and seasonal) scales. We used data from two space sensors MODIS and OMI, and 52 ground stations located in 6 major cities in India.

The followings are important findings of our analysis:

- Surface concentrations of PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, CO, and O<sub>3</sub> from ground monitors, and AOD and NO<sub>2</sub> columns from satellite sensors consistently showed lower values during the lockdown as compared to the baseline period.
- Satellite AOD data recorded the highest decline in the IGP region, where population density and level of pollution are highest in the

region. The observed AODs were among the lowest in the region in the two decade long data record.

- Periodic dust storms and biomass burning in northern India and neighbouring countries offset some of the declines in atmospheric aerosols concentrations in the IGP and larger northern India.
- Central Southern India reported an increase in AOD during the lockdown period as compared to the baseline period. These increases were mostly associated with increases in biomass burning and favourable meteorological conditions in the region.
- Surface measurements show similar meteorological conditions in both lockdown and baseline years. Overall decline in pollution was driven by reduction in emissions.
- PM<sub>2.5</sub>, PM<sub>10</sub> and AOD exhibited the lowest decline (41 %, 24 %, and 3%) in Kolkata and Mumbai (PM<sub>10</sub> and AOD) whereas the highest declines of 60 %, 57 %, and 56 % were reported in Chennai, Delhi, and Bengaluru cities, respectively.
- NO<sub>2</sub> from the ground stations showed the lowest decline of 46 % in Chennai city and highest (61 %) in Delhi city whereas OMI reported 28 % decline over the IGP region.
- O<sub>3</sub> concentrations in the cities observed an overall decline during the lockdown period (22–56%), except in Kolkata, which recorded a significant increase (66 %). These changes were mainly due to complex photochemical reactions with limiting substances such as NO<sub>x</sub> and VOCs. Several individual stations have also reported an increase in O<sub>3</sub> during the lockdown.
- Diurnal profile of pollutants during lockdown exhibited similar patterns as the baseline period but with a substantially reduced magnitudes.
- The station-level data measured in various communities in Delhi showed spatial variability in pollutant concentration and varying scale of reduction during the lockdown period PM<sub>2.5</sub> (18–80%) and NO<sub>2</sub> (23–82%). The complex O<sub>3</sub> chemistry resulted in a mixed effect with 18 stations recording an increase (7–244%) while remaining showing a decline (11–85%).

#### 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 material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.scs.2020.102688>.



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