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COVID-19’s lockdown effect on air quality in Indian cities using air quality zonal modeling

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\textbf{ABSTRACT}

The complete lockdown due to COVID-19 pandemic has contributed to the improvement of air quality across the countries particularly in developing countries including India. This study aims to assess the air quality by monitoring major atmospheric pollutants such as AOD, CO, PM\textsubscript{2.5}, NO\textsubscript{2}, O\textsubscript{3} and SO\textsubscript{2} in 15 major cities of India using Air Quality Zonal Modeling. The study is based on two different data sources; (a) grid data (MODIS- Terra, MERRA-2, OMI and AIRS, Global Modeling and Assimilation Office, NASA) and (b) ground monitoring station data provided by Central Pollution Control Board (CPCB) / State Pollution Control Board (SPCB). The remotely sensed data demonstrated that the concentration of PM\textsubscript{2.5} has declined by 14%, about 30% of NO\textsubscript{2} in million-plus cities, 2.06% CO, SO\textsubscript{2} within the range of 5 to 60%, whereas the concentration of O\textsubscript{3} has increased by 1 to 3% in majority of cities compared with pre lockdown. On the other hand, CPCB/SPCB data showed more than 40% decrease in PM\textsubscript{2.5} and 47% decrease in PM\textsubscript{10} in north Indian cities, more than 35% decrease in NO\textsubscript{2} in metropolitan cities, more than 85% decrease in SO\textsubscript{2} in Chennai and Nagpur and more than 17% increase in O\textsubscript{3} in five cities amid 43 days pandemic lockdown. The restrictions of anthropogenic activities have substantial effect on the emission of primary atmospheric pollutants.

\textbf{Abbreviations:} AIRS, Atmospheric Infrared Sounder; AOD, Aerosol Optical Depth; AQI, Air Quality Index; AQZM, Air Quality Zonal Modeling; BSPCB, Bihar State Pollution Control Board; CAAQM, Continuous Ambient Air Quality Monitoring; CEPI, Comprehensive Environmental Pollution Index; CO, Carbon Monoxide; COVID, Coronavirus Disease; CPCB, Central Pollution Control Board; GES DISC, Goddard Earth Sciences Data and Information Services Center; GPCB, Gujarat Pollution Control Board; GSPC, Goddard Space Flight Center; LPG, Liberalisation, Privatisation and Globalisation; MAAQM, Manual Ambient Air Quality Monitoring; MERMA-2, Modern Era Retrospective Research and Application; MODIS-terra, Moderate Resolution Imaging Spectroradiometer; MPCA, Maharashtra Pollution Control Board; NASA, National Aeronautics and Space Administration; NCR, National Capital Region; NH\textsubscript{3}, Ammonia; NO\textsubscript{2}, Nitrogen Dioxide; NOx, Nitrogen Oxide; O\textsubscript{3}, Ozone; OMI, Ozone Monitoring Instrument; PCR, Principal Components Regression; PM\textsubscript{10}, Particulate Matter $\leq$ 10 $\mu$m; PM\textsubscript{2.5}, Particulate Matter $\leq$ 2.5 $\mu$m; RSPCB, Rajasthan State Pollution Control Board; RSPM, Respirable Suspended Particulate Matter; SO\textsubscript{2}, Sulphur Dioxide; SPCB, State Pollution Control Board; SPM, Suspended Particulate Matter; TSP, Total Suspended Particles; TSPCB, Telangana State Pollution Control Board; UPPCB, Uttar Pradesh Pollution Control Board; VOCs, Volatile Organic Compounds; WBPCB, West Bengal Pollution Control Board; WHO, World Health Organization.

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1. Introduction

Globally air pollution and ensuing degraded air quality has become a serious concern due to its damaging effect on human health and environment particularly in developing countries like India (Guttikunda et al., 2019; Kumar et al., 2015; Pant et al., 2018; Rahaman et al., 2020a) and China (Fan et al., 2020; Kuerban et al., 2020; Li et al., 2020; Wang et al., 2020; Xu et al., 2019; Zhang et al., 2017). According to the latest estimation of WHO (2019) around 91% of the world population is living in places where air quality exceeds WHO guidelines level and the ambient air pollution causes about 4.2 million deaths every year due to stroke, heart disease, lung cancer and chronic respiratory diseases (Amal et al., 2018). However, it is noteworthy that air quality in urban areas is the prime concern as population in urban areas will increase to 66% by 2050 (United Nations, 2014). Vehicular and industrial emissions are the major sources of atmospheric pollutants in urban areas due to fossil fuel combustion and biomass burning (Gong et al., 2017; Perera, 2017; Wang et al., 2010; Wu et al., 2016). These two sources emit major harmful pollutants in the form of particulate matter PM$_{2.5}$ (Particulate Matter $\leq 2.5 \mu m$), PM$_{10}$ ($\leq 10 \mu m$), gaseous pollutants such as the Nitrogen Oxides (NOx), Carbon Monoxide (CO), Ozone (O$_3$), Sulphur Dioxide (SO$_2$) and other Volatile Organic Compounds (VOCs) such as Benzene, Ethylene Glycol, Formaldehyde, Methylene Chloride, Tetrachloroethylene, Toluene, Xylene etc. But the stringent regulation of vehicular movements and industrial emission has suddenly reduced air pollution and subsequently improved the overall air quality. Recently the complete lockdown effect due to the Coronavirus disease 2019 (COVID-19) pandemic has reduced air pollution to a greater extent worldwide and particularly in developing countries like India (Devara et al., 2020; Mahato et al., 2020; Mitra et al., 2020; Peshave and Peshave, 2020; Ramasamy et al., 2020; Sharma et al., 2020) and China (Wang et al., 2020; Bao and Zhang, 2020; Chen et al., 2020; Chen et al., 2020c; Han et al., 2020; He et al., 2020; Liu et al., 2020; Qi et al., 2020; Wang and Su, 2020; Xu et al., 2020).

Strict regulations of human activities considerably affect the air quality as it restrained the emission of atmospheric pollutants. A number of studies have documented that ‘weekend effect’ or ‘holiday effect’ has surprisingly affected the level of concentration of atmospheric pollutants in European cities (Drewnick et al., 2006; Mlakar et al., 2012; Moreno et al., 2010; Riga-Karandinos and Saitanis, 2005; Riga-Karandinos et al., 2006), USA (Jimenez et al., 2005; Qin et al., 2004; Seidel and Birnbaum, 2015) and China (Gong et al., 2014; Lai and Brimblecombe, 2020; Lei et al., 2015; Li et al., 2006; Tan et al., 2009; Zhao et al., 2015). Recently the COVID-19

![Study area: Major cities of India.](source:Survey of India, 2011)
pandemic has brought the world into halt as all kinds of anthropogenic activities including vehicular movements and industrial activities have been strictly constrained. It was first exposed in Wuhan city, China (Chen et al., 2020a; Lu et al., 2020a) and then gradually spread globally. In India the first positive case was detected on 30th January and then gradually spread over other parts of the country. Due to uncontrollable transmission of COVID-19 infection a countrywide lockdown was imposed on 24th March till 14th April and extended up to 3rd May and then again extended for second time up to 17th May and in third time up to 31st May. Here lockdown refers to complete restriction from stepping out of house except emergency. The government of India suspended all modes of transport across the country; only transportation of essentials goods, fire, police and emergency services were allowed. Besides, educational institutions, industrial activities, construction works and hospitality services were strictly restrained. However, services such as banks/ATMs, petrol pumps, medical shops, grocery shops and other essentials were permitted during the lockdown. Consequently, emission of atmospheric pollutants has also been reduced to a larger extent and improved the overall quality of air. Sharma et al. (2020) demonstrated that due to lockdown the air pollution has dramatically reduced across the cities of the country. In recent years, many studies have analysed spatial and temporal nature of pollutants focusing metropolitan cities (Lu et al., 2020b; Arulprakashajothi et al., 2020). In addition, studies have also demonstrated that due to lockdown the air pollution has dramatically reduced across the cities in India (Srivastava et al., 2020; Kumar et al., 2020; Kumari and Toshniwa, 2020; Vadrevu et al., 2020). In this context the present study aims to assess the impact of the lockdown effect due to COVID-19 pandemic on air quality of 15 major cities in India based on both the ground and space data whereas the previous studies mainly based either on ground monitoring dataset or space born dataset. The novelty of the study lies in the fact that it attempted to monitor overall pollution load of major pollutants such as CO, PM\textsubscript{2.5}, PM\textsubscript{10}, NO\textsubscript{2}, O\textsubscript{3} and SO\textsubscript{2} during before and after lockdown period across the 15 major cities in India.

![Spatial distribution of AOD, CO, Dust (PM\textsubscript{2.5} only), NO\textsubscript{2}, O\textsubscript{3} and SO\textsubscript{2} in India. Left: before 43 days of lockdown (9th Feb. 2020 to 23rd Mar. 2020) and, Right: after lockdown (24th Mar. 2020 to 4th May 2020), daily and time average concentration. Source: MODIS- Terra, MERRA-2, OMI, AIRS, 2020.](image-url)
2. Data and methods

2.1. Study region

According to recent report published by World Economic Forum (2020) and CBSnews (2020), among the top 10 world’s most air polluted cities 6 cities belong to India which are situated in Delhi and NCR (National Capital Region); about 1.25 million people die because of very poor air quality in India every year. A macro level study on India with focus on 15 major cities namely, Ahmedabad, Asansol, Bengaluru, Chennai, Delhi, Ghaziabad, Hyderabad, Jaipur, Kanpur, Kolkata, Lucknow, Mumbai, Nagpur, Patna and Siliguri (Fig. 1) has been selected for an assessment of the effect of lockdown on air quality. These cities represent areas of high population concentration and economic activities, whereas 150 random grid samples were taken for Air Quality Zonal Modeling for MODIS- Terra, MERRA-2, OMI, AIRS remotely sensed data (Fig. 6). Approximately 3,530,000-pixel samples have been taken to assess the pixel to pixel relation and extract each pollutants load and overall pollution load from individual pixel for two different time periods; 43 days before (9th Feb. 2020 to 23rd Mar. 2020) and after lockdown (24th Mar. 2020 to 4th May 2020) (Figs. 2, 6).

2.2. Data sources

We have collected data from two different sources (a) remote sensing data and (b) ground-based monitoring data. The remote sensing data were collected from different sensors such as MODIS- Terra, MERRA-2, OMI and AIRS, Global Modeling and Assimilation Office, NASA. The ground-based monitoring data were obtained from Central Pollution Control Board (CPCB)/State Pollution Control Board (SPCB) with different monitoring instruments i.e. Continuous Ambient Air Quality Monitoring (CAAQM)/ Ambient Air Quality Monitoring (AAQM). And. The air pollutants in remotely sensed data were monitored at 550 m above the surface whereas the data provided by CPCB/SPCB are ground-based data from different monitoring stations. Daily average concentration of CO, O₃, NH₃, NO₂, PM_{10}, PM_{2.5} and SO₂ from 1st Feb 2019 to 4th May 2019 and 1st Feb. 2020 to 4th May 2020 have been collected from 15 different monitoring stations; Ahmedabad (Maninagar) Gujarat Pollution Control Board (GPCB), Asansol (Asansol court area) Kolkata (Victoria) Patna (IGSC Planetarium Complex) Bihar State Pollution Control Board (BSPCB), Hyderabad (Sanathnagar) Telangana State Pollution Control Board (TS PCB), Jaipur (Adarsh Nagar) Rajasthan State Pollution Control Board (RSPCB), Mumbai (Bandra) Nagpur (GPO Civil Lines) Maharashtra Pollution Control Board (MPCB), Patna (IGSC Planetarium Complex) Bihar State Pollution Control Board (BSPCB). The area averaged time series (30% cloud screened) and time average tropospheric column (1/cm²) with spatial resolution 0.25° × 0.25°, 0.5° × 0.625° and 1° from 9th February 2020 to 23rd March 2020 (43 days before lockdown) and 24th March 2020 to 4th May 2020 (after lockdown) of Aerosol Optical Depth 550 nm, Carbon Monoxide Total Column, Dust Surface Mass Concentration (PM_{2.5} only), Sulphur Dioxide Column Mass Density, Nitrogen Dioxide Total Column and Ozone Total Column provided by MODIS- Terra, MERRA-2, OMI, AIRS, Global Modeling and Assimilation Office, NASA.

2.3. Data analysis method

The time averaged map (1/cm²) shows extract data value for individual grid cell within user’s specified region. Area Averaged Time Series (30% cloud screened) data provides spatial averages over the user’s specified area of selected variables for each time. Fill values do not contribute to the time average and also do not contribute to the spatial averages for both datasets. In this study, we extracted and compiled 86 days average of MODIS-Terra, MERRA-2, OMI and AIRS remotely sensed data for AOD, CO, O₃, PM_{2.5}, NO₂ and SO₂. Previous studies have also documented the general behavior of MERRA-2, MODIS-Terra and AIRS model retrieving AOD, CO, O₃, PM_{2.5}, and SO₂ (Zhang and Reid, 2006); Remer et al., 2002, 2005). In addition, OMI remotely sensed data have also been used for detecting the concentration of NO₂ levels in the atmosphere (Zhang et al., 2017; Krotkov et al., 2015). This kind of OMI total column map and time area-averaged datasets have been used in the various research for assessing the air quality in any region especially for macro scale (Krotkov et al., 2015; Mallik and Lal, 2014; Zhang et al., 2017; Duncan et al., 2013).

We have selected 15 major cities of India for assessing the average concentration of AOD, CO, O₃, PM_{2.5}, NO₂ and SO₂ before and after the epidemic event of COVID-19 and divided India with 350 grids (97 × 97sq. km) as whole for micro-level study based on remotely sensed data. After that we have calculated the area of total air pollution load from each grid and also extracted individual pollutant’s concentration from 15 cities from grid data using Air Quality Zonal Modeling. A comparative analysis of different air pollutants for 43 days before and after lockdown has been done based on area averaged map and time series analysis using Air Quality Zonal Modeling accomplished in different phases. Air Quality Zonal Model refers to a total pollution load based on several pollutant particles in any specific region computed by grid space data. In the first phase we have extracted each pollutant’s average concentration from individual grid. The concentration of air pollutants has been categorized based on Air Quality Zonal Modeling (AQZM) rank. Composite indexing made on the basis of AQZM rank for each category of air pollutants in the third phase. Zonal indexing has been formulated for extracting the exact value and also checked the rank of AQZM in the fourth phase. Area-wise/grid-wise total air pollution load has been calculated in the fifth phase in this model. The last and final phase assigned for the total pollution load based on individual pollutant’s AQZM rank, composite indexing and zonal indexing using spatial analysis tools in GIS.

On the other hand, we have compiled daily average concentration of CO, O₃, NH₃, NO₂, PM_{10}, PM_{2.5} and SO₂ to 43 days daily average concentration before (9th Feb. 2020 to 23rd Mar. 2020) and after lockdown (24th Mar. 2020 to 4th May 2020) data provided by CPCB/SPCB for 15 major cities of India. Compound bar diagram has been made to show 43 days average concentration before and
after epidemic in total absolute number and also in percentage. Time series analysis of 86 days daily average data from 1st Feb. to 4th May for the same period for 2019 and 2020 has been made for monitoring each air pollutants concentration for comparative study.

As we mentioned earlier daily average concentration of air pollutants obtained from two different datasets; remotely sensed datasets (MODIS- Terra, MERRA-2, OMI and AIRS, Global Modeling and Assimilation Office, NASA) and point datasets (Continuous Ambient Air Quality Monitoring / Manual Ambient Air Quality Monitoring stations, provided by CPCB and SPCB). In order to ensure spatial and temporal similarity test has been made on the basis of increasing/ decreasing trend of each air pollutants from two different datasets.

Fig. 3. Time average concentration of AOD, CO, Dust (PM$_{2.5}$ only), NO$_2$, O$_3$ and SO$_2$ of 15 cities in India during 43 days before and after lockdown. Percentage of change in air pollutants is shown in barplots.

Source: Compiled and calculated by authors, remotely sensed data: MODIS- Terra, MERRA-2, OMI, AIRS, 2020.
2.4. Remotely sensed data retrieval and statistical analysis

We have used following sets of equations for extracting and interpreting remotely sensed data based on GES-DISC time averaged map and area averaged time series data provided by MODIS- Terra, MERRA-2, OMI and AIRS. The moving average has been computed using Eq. (1) and total air pollution load calculated from each pollutants grid has been extracted using Eq. (2), whereas Eq. (3) has been used to show the change in air quality in comparison to 43 days before and after pandemic in percentage and daily AQI weighted index by using Eq. (4). We have further refined the datasets using Eq. (5) and calculated the total area of each category using Eq. (6). Similarity test has been made with the help of Eq. (7) on the basis of increasing and decreasing trend rate of each pollutant from both datasets where we have found 85.33% similarity. The remaining proportion of dissimilarity is due to difference in the distance of detecting air pollutants; remotely sensed data capture pollutants from 550 m above the ground whereas the point data is monitored at ground level.

\[ m = \frac{\sum x_1, x_2, x_3, x_4, x_5, x_6 \times (n)}{\sum i_c} \]  

(1)

where, \( m \) = moving avg., \( x_1, x_2, x_3, x_4, x_5, \) and \( x_6 \) represents AOD, CO, NO₂, O₃, PM₂.₅ and SO₂ respectively; \( n \) = number, \( i_c \) = individual count.

\[ \sum_{taop} = \frac{\sum x_1, x_2, x_3, x_4, x_5, x_6 \times (n)}{\sum i_c} \]  

(2)

where, \( taop \) = total air pollution load, \( tc \) = total column count.

\[ p = \frac{(43a-43b)}{43a} \times 100 \]  

(3)

where, \( p \) = percentage, \( 43 \) = daily average concentration, \( a \) = after, \( b \) = before.

\[ a = \sqrt{\frac{\sum w_i (x_i - \bar{x})^2}{\sum w_i}} \]  

(4)

where, \( a \) = area of individual cells, \( w = \) weights, \( i = \) an index over all the data points being averaged and \( x = \) individual pollutants variables

\[ t = \sum taop - ex \]  

(5)

where, \( t \) = total pollution counts in individual grids, \( ex = \) excluding ‘no data available’ grids

\[ a = N - S \]  

(6)

where, \( a \) = overall area, \( N \) = number of countable grids in each category, \( S = \) size of grid (97 × 97 sq. km.)

\[ s = \frac{m \times 100}{c - ex} = 85.33 \]  

(7)

where, \( s = \) similarity test, \( c = \) total number of counts, \( ex = \) excluding number of no data available, \( m = \) total number of match and \( u \) represents ‘un-match’ based on increasing/ decreasing trends observed from both data sets. Where we find total number of columns = 75, total number of un-matches = 8, total number of matches = 64, no data = 3 (Tables 2a, 2b).

3. Results

3.1. Spatial distribution of air pollutants before and after lockdown

The evaluation of 43 days period lockdown in 15 cities have witnessed substantial diminution of the primary pollutants AOD, PM₂.₅, NO₂ SO₂, O₃ and CO (Fig. 2). However, when probe deeper into city level data analysis (Fig. 3) the concentration has decreased on an average up to 15% in most of the northern Indian cities, the highest value of (−14.2%) for Patna followed by Siliguri (−12.1%) and Ahmedabad (−10.1%). The lowering of total mass concentration of PM₂.₅ in Delhi (−2.5%), Ghaziabad (−2.6%), Kanpur (4.64%) and Lucknow (4.48%) could be attributed to effect of the reduced vehicular traffic and closer of industries. A notable decrease existed in southern Indian cities viz. Chennai (−39.1%), Bengaluru (−25%) and Hyderabad (−22.2%).

The mean mass concentration of carbon monoxide (CO km/m²) across the cities decreased by 2.06% compared with pre lockdown. The emission from large road traffic particularly diesel, gasoline and presence of manufacturing and power industries in cities like Delhi (−2.52%), Ahmadabad (2.06%), Ghaziabad (−2.67%), Kanpur (−2.48%), Lucknow (−2.20%) and Patna (−2.78%) have decreased within the range of (−3%). The peak decrease was witnessed in Mumbai (−3.61%) the highest of any other cities in the country. A minimum change was observed in Chennai (−1.09%) and Bengaluru (−1.19%).
3.2. Change in air quality: an assessment from remotely sensed data

During the observed span the concentration of NO$_2$ has decreased sharply in all the cities with an exception to Siliguri. The absence of dominant anthropogenic pollutants in major cities through vehicular pollution is effectively contributing to its decreased value in Delhi (−37.40%), Ghaziabad (−35.32%) and Mumbai (−32.96%). The cities within the decrease value range 25% to 30% were the
million plus cities of Chennai (−30.21%), Nagpur (−23%), Kolkata (−26.29%), Bengaluru (−22.3%) and Asansol (−25.06%). Cities with lesser traffic flow accounted for lesser range of decrease in NO\textsubscript{2} as evident from Jaipur (−10%), Patna (−9.99%), Lucknow (10.09%) and Hyderabad (−8.99%).

The column mass density of SO\textsubscript{2} has been observed to decline within the range of −5% to −60%. The north Indian cities such as Delhi (−40%), Jaipur (−37.50%), Lucknow (−20.00%) and Patna (−28.57%) have showed substantial decline. The concentration of thermal power industries, petroleum processing units being still activated in lieu of emergency services has kept its high rise in Mumbai (58.33%). The closure of heavy industry clusters has lowered the SO\textsubscript{2} level at Asansol (−22.22%), Ahmadabad (−41.67%) and Nagpur (−33.33%). The changes in natural parameters like precipitation, humidity condition and onset of summer season have contributed in lower level of SO\textsubscript{2} in most of the southern Indian cities.

Finally, the concentration levels of O\textsubscript{3} noticeably increase during the lockdown period in few of the cities in India. The higher reduction of NO\textsubscript{2} and SO\textsubscript{2} has largely contributed in augmentation of O\textsubscript{3} in cities like Chennai (0.39%) and Nagpur (0.39%). The overall highest rise in the O\textsubscript{3} concentration level is seen in Siliguri (3.91%). The higher deceasing percentage of SO\textsubscript{2} and AOD concentration can be one of the potential reasons to it. The peak decrease is visible in Mumbai (−8.55%) followed by Jaipur (−6.49%), Delhi (−6.05%) and Ghaziabad (−6.01%). Most of the central and southern cities have negligible decrease in O\textsubscript{3} concentration which accentuates for a positive effect improving air quality with decrease in SO\textsubscript{2}, NO\textsubscript{2} and PM\textsubscript{2.5} level.

The changes in AOD show a steady decreasing pattern moving south to north Indian cities. An increase in the value is observed in Bengaluru (+13.58%), Chennai (+7.02%) and Hyderabad (+3.45%) post lockdown within 43 days. Moving towards central India there is a decrease observed lowest in Nagpur (−11.56%) and Mumbai (−9.96%). The percentage decreases are less than 15% in Delhi and Ahmadabad. The decrease of AOD concentration of higher than 15% was observed in 60% of the total observed cities. The highest decrease percent is observed in Lucknow (−22.5%) followed by Patna (−21.05%) and Siliguri (−19.05%).

### 3.3. Change in air quality: an assessment from CPCB/SPCB data

The assessment of the air pollutants and its concentration as point data from varied governmental sources further enable the ground validation. The daily average of major pollutants in 15 cities as evident from Fig. 4 shows a similar decrease in its absolute

### Table 1

Daily average concentration of air pollutants before and after lockdown and its change in percentage of 15 cities in India.

| City         | CO  | NH\textsubscript{3} | NO\textsubscript{2} | O\textsubscript{3} | PM\textsubscript{2.5} | PM\textsubscript{10} | SO\textsubscript{2} |
|--------------|-----|---------------------|---------------------|-------------------|----------------------|-----------------------|-------------------|
| Before       | After | Change in % | Before   | After  | Change in % | Before      | After    | Change in % | Before       | After    | Change in % | Before    | After    | Change in % |
| Ahmedabad    | 0.75 | 0.45               | −40.76            | none    | none     | 59.99       | 23.26    | −54.39      | 47.83        | 44.50    | −6.97        |
| Asansol      | 0.74 | 0.50               | −32.55            | 14.02    | 14.84    | 27.00       | 16.13    | −40.27      | 24.13        | 23.96    | −0.73        |
| Bengaluru    | 0.92 | 0.89               | −3.37             | none    | none     | 31.45       | 19.23    | −38.87      | 39.15        | 37.57    | −4.05        |
| Chennai      | 1.32 | 0.82               | −37.76            | 44.47    | 46.54    | 20.02       | 12.95    | −35.30      | none         | none     | none         |
| Delhi        | 1.48 | 2.02               | 36.19             | 44.17    | 14.32    | 32.09       | 21.40    | −33.31      | 25.53        | 46.25    | 80.46        |
| Ghaziabad    | 1.17 | 0.75               | −35.91            | 37.30    | 28.34    | 58.07       | 27.86    | −52.03      | 34.17        | 40.14    | 17.49        |
| Hyderabad    | 0.68 | 0.44               | −34.95            | none    | none     | 25.08       | 5.98     | −76.14      | 34.36        | 44.72    | 30.16        |
| Jaipur       | 0.85 | 0.64               | −24.53            | 32.53    | 18.87    | 39.54       | 11.47    | −70.99      | 59.92        | 55.68    | −7.07        |
| Kanpur       | 1.20 | 1.06               | −11.44            | none    | none     | 37.13       | 16.71    | −54.98      | 35.11        | 27.57    | −21.48       |
| Kolkata      | 1.11 | 0.83               | −24.63            | 22.50    | 22.31    | 67.84       | 13.86    | −79.58      | 58.50        | 54.87    | −6.21        |
| Lucknow      | 1.20 | 1.06               | −11.44            | none    | none     | 37.13       | 16.71    | −54.98      | 35.11        | 27.57    | −21.48       |
| Mumbai       | 2.22 | 0.97               | −56.49            | none    | none     | 71.95       | 9.92     | −86.21      | 47.29        | 10.45    | −77.91       |
| Nagpur       | 0.89 | 0.50               | −43.86            | 25.11    | 30.22    | 54.49       | 22.16    | −59.33      | 46.23        | 54.83    | 18.60        |
| Patna        | 1.40 | 1.70               | 28.87             | none    | none     | none        | none     | none        | none         | none     | none         |
| Siliguri     | 0.75 | 0.56               | −25.47            | 32.15    | 30.68    | 51.36       | 28.61    | −44.30      | 23.94        | 29.36    | 22.62        |
concentration values. The particulate matter load both PM$_{2.5}$ and PM$_{10}$ shows variations across cities. Most of the north Indian cities witnessed more than 40% decrease in its absolute value. Ghaziabad city showed a decrease of 55.7% (PM$_{2.5}$) and 47% for PM$_{10}$ with values reducing from 104 µg/m$^3$ to 46 µg/m$^3$ and 200 µg/m$^3$ to 106 µg/m$^3$ respectively. Similar high decrease percentage for PM$_{2.5}$ were observed in cities like Kanpur (48.12%), Lucknow (48.12%), Chennai (43.47%), Ahmadabad (50%) and Asansol (52.85%) whereas, most of the cities in southern India viz. Hyderabad (32.25%), Bengaluru (19.37%) and coastal cities like Mumbai (35.1%) and Kolkata (32.1%) witnessed comparatively lesser change (within range of 20–40%). The values of PM$_{10}$ was prompt in Kolkata (47%), Asansol (44.20%) and Ahmadabad (54%) with high decrease percentage along with PM$_{2.5}$. The other western and central Indian cities including Jaipur (76%), Nagpur (58.4%) and Ahmadabad (54.9%) also showed higher values. The southern cities have considerably lesser decrease percentage viz. Bengaluru (38.7%), Chennai (35%) compared to eastern city like Siliguri (43.1%). As observed, the pan Indian status of the absolute value of SO$_2$ has relatively changed less. The decrease is notably high at Nagpur (–85%) and Chennai (–87%). In contrast to the deceasing pattern Mumbai witnessed increase in concentration of SO$_2$ (14 µg/m$^3$ to 33 µg/m$^3$) along with trivial increase in cities like Bengaluru (17%) and Patna (30%) (Fig. 4, Table 1).

Another primary pollutant CO shows reverse change in terms of raised value in two cities of northern India namely Delhi (36%) and Patna (21%) followed by decrease in its percentage value ranking Ghaziabad (–30%) > Jaipur (–25%) > Kanpur and Lucknow at –11% each. The central Indian cities rank higher in its decrease percentage thereby –56% in Mumbai (2.22 mg/m$^3$ to 0.97 mg/m$^3$) > Nagpur (–44.5%) > Ahmadabad (–41.12%). The least decrease was observed in southern Indian city Bengaluru (–3.1%) followed by < Hyderabad (–35.1%) and < Chennai (–38%). A sharp decrease is observed in the pollutant NH$_3$ in Chennai (44 mg/m$^3$ to 14 mg/m$^3$) and Hyderabad (33 mg/m$^3$ to 19 mg/m$^3$). An increase of 20% at Nagpur (20 mg/m$^3$ to 30 mg/m$^3$) followed by miniscule increase at Ahmadabad (6%) and Bengaluru (5%) is noted (Fig. 4, Table 1).

The spatial characteristics of O$_3$ are opposite to the other major pollutants. In the northern part with two centers Delhi (–80%) and Ghaziabad (+17%) rises in its concentration. The average high value decrease of NO$_2$ (–52%) and PM$_{2.5}$ (–49.34%) could have been the probable factors though SO$_2$ has increased its total value in Ghaziabad. Hyderabad (+30%) in southern India and Nagpur (+19%) in central India establishes the fact of dwindling NO$_2$ along with PM$_{2.5}$ and rise of O$_3$. The rise of 23% O$_3$ in eastern Indian city of Siliguri is accentuated with an average decline of 45% in both NO$_2$ and PM$_{2.5}$ concentrations. A noted decrease in Mumbai (–78%) followed by Lucknow and Kanpur (–21%) is a jolt. Despite sharp decrease in NO$_2$ values (upto 50%) and relatively lower decrease in PM$_{2.5}$ value (upto 33%) the role of rising SO$_2$ (141%) can be marked in Mumbai. A similar trend is also identified for Siliguri. Among the other components of air quality indices ozone has shown minuscule decrease in most of the stations and reflect the effect of NO$_2$, PM$_{2.5}$ and SO$_2$ on it.

3.4. Validation/similarity/accuracy assessment for both data sets

Similarity test has been made on the basis of increasing and decreasing trends of five major air pollutants (CO, O$_3$, PM$_{2.5}$, NO$_2$ and SO$_2$) from both the datasets, where we found a total number of 75 columns. Out of them 8 columns were un-matched and total number of matched columns was 64 and 3 columns had no data. The remotely sensed data demonstrated that the concentration of CO over Delhi and Patna has decreased whereas CPCB data is showing that it has been increased over the same locations. Similarly, the concentration of NO$_2$ in Siliguri has increased as observed from remotely sensed data whereas SPCB data is displaying reverse results. Total O$_3$ concentration in Delhi and Ghaziabad has observed an increasing trend in CPCB/SPCB data; on the other hand, it has been decreased as observed in remotely sensed data. In addition, CPCB data also showed that the total concentration of SO$_2$ in Bengaluru, Ghaziabad and Patna have increased whereas it has been reversed observed from remotely sensed data. However, it is noteworthy that

Table 2a

| Cities    | CO   | Dust$^a$ | NO$_2$ | O$_3$ | SO$_2$ |
|-----------|------|----------|--------|-------|--------|
|           | MERRA-2 | CPCB$^b$ | MERRA-2 | CPCB | OMI | CPCB | AIRS | CPCB | MERRA-2 | CPCB |
| Ahmadabad | –2.06 | –40.76   | –10.13 | –50.51 | –25.94 | –54.39 | –4.12 | –6.97 | –41.67 | –49.55 |
| Asansol   | –1.53 | –32.55   | –2.04  | –53.35 | –26.41 | –40.27 | –1.04 | –0.73 | –22.22 | –36.34 |
| Bengaluru | –1.19 | –3.37    | –25.00 | –7.80  | –22.60 | –38.87 | –0.28 | –4.05 | –25.00 | 16.59  |
| Chennai   | –1.09 | –37.76   | –39.13 | –44.06 | –30.21 | –35.30 | 0.15  | none  | –60.00 | –87.17 |
| Delhi     | –2.52 | 36.19    | –2.60  | –19.36 | –37.40 | –33.31 | –6.05 | 80.46 | –40.00 | –25.09 |
| Ghaziabad | –2.67 | –35.91   | –2.63  | –55.98 | –35.32 | –52.03 | –6.01 | 17.49 | –33.33 | 23.45  |
| Hyderabad | –2.52 | –34.95   | –22.22 | –29.80 | –8.19  | –76.14 | 1.05  | 30.16 | –14.29 | –28.87 |
| Jaipur    | –2.68 | –24.53   | –10.53 | –37.61 | –10.00 | –70.99 | –6.49 | –7.07 | –37.50 | –15.25 |
| Kanpur    | –2.48 | –11.44   | –4.69  | –41.77 | –16.27 | –54.98 | –4.05 | –21.48 | –8.33  | –9.53  |
| Kolkata   | –1.22 | –24.63   | –4.55  | –63.24 | –26.29 | –79.58 | –0.06 | –6.21 | –4.17  | –26.18 |
| Lucknow   | –2.78 | –11.44   | –4.48  | –41.77 | –10.99 | –54.98 | –3.91 | –21.48 | –20.00 | –9.53  |
| Mumbai    | –3.61 | –56.49   | –8.33  | –33.52 | –32.96 | –86.21 | –8.55 | –77.91 | 58.33  | 141.38 |
| Nagpur    | –1.69 | –43.86   | –6.82  | –32.96 | –23.00 | –59.33 | 0.39  | 18.60 | –33.33 | –84.66 |
| Patna     | –2.20 | 20.87    | –14.29 | –31.24 | –9.30  | none   | –2.34 | none  | –28.57 | 38.53  |
| Siliguri  | –1.20 | –25.47   | –12.96 | –48.58 | 8.77   | –44.30 | 3.91  | 22.62 | –20.00 | –12.64 |

$^a$ Dust including PM$_{2.5}$ only.

$^b$ CPCB or SPCB.
we found 85.33% similarity from observed and remotely sensed datasets during the study period (Tables 2a, 2b).

Comparative analysis of daily time series data from 9th Feb 2019- 4th May 2019 and 9th Feb. 2020- 4th May 2020

In order to supplement the discussion on air pollutants (six variables) and its pattern of concentration across 15 cities in India, a comparative analysis of the same 86 day period is done with the preceding year. As evident from Fig. 5 the decreasing pattern in variables of air pollution is clearly visible in this window period. The major air pollutant variables including CO, NH3, NO2, PM2.5 and PM10 along SO2 shows a decrease in values for Delhi in 2020 compared to 2019. The lag is prominent for the variable SO2 and concentrated mass of particulate matter. The tail end of the graph display more gap in the variables of the observed period than the former (43 days) as the differences is more prominent in later halves (43 days) of observation. The sharp rise in O3 is well documented in Delhi. Notably, the status of O3 do not follow the similar trend. The graphs are much lower for Ghaziabad, Kanpur and Lucknow. With an exception to Delhi all the other North Indian cities have sharply decreased value of total mass concentration of CO. The values for NH3 shows positive variations both in Delhi and Ghaziabad. A complete dip in the values of NO2,SO2, PM2.5 and PM10 was observed in the latter phase of the graph as witness to positive effect of the lockdown with a highest lag seen in Patna for SO2 concentration followed by Kanpur.

Cities in eastern and central India exhibit a similar trend when compared with 2019. Ahmadabad along with Mumbai have rising graph for CO during early phases of February but the sharp decline is evident for late March to May. A similar trend is evident for NO2 and particulate matter but the level of SO2 have shown an increase when compared to 2019 data for Mumbai. The steep fall in NO2 value is similar to all other variables of pollutants for Nagpur. It also shows decrease in mass concentration of O3.

The trend of decrease in values of the air pollutants has a simillar picture in eastern Indian cities (Kolkata, Asansol and Siliguri). The values for CO exhibit increasing trend in early phases of February 2020 in comparision to 2019 and consequetively decline post March in Kolkata. The graphical depiction of O3 also shows increasing trend in the early weeks of Feruary 2020 whereas the increase is steep towards the later phase of the window period. The graph for SO2 in Siliguri has a unique stature depicting stagnant line of decreased value compared to 2019. A similar trend for NH3 data is visible for Asansol. Noted fluctuations depict change in variables NO2, PM2.5 and CO values towards decreasing trend whereas SO2 depicts rise in its values when compared to 2019.

3.5. Total pollution load over the space using air quality zonal Modeling

Air Quality Zonal Modeling of 43 days average concentration of air pollutants before and after lockdown (Fig. 6a) demonstrated that the level of AOD has immensely reduced amid pandemic and came under 0.50–0.66 range which clearly shows its depletion in the atmosphere. On the other hand, the areas having AOD <0.13 and ranging between 0.14 and 0.34 have increased to a large extent. Similarly, the areas under high concentration of carbon monoxide (CO) exceeding 1.75 (mg/m3) have substantially reduced particularly in eastern part of the country. It is noteworthy that the areas under 1.26–1.75 (mg/m3) category have transformed into 0.76–1.25 (mg/m3) areas revealing the decreasing level of CO. In addition, the dust surface mass concentration (PM2.5 only) displays its striking reduction from very high (>100 µg/m3) and high concentration (ranging between 81 and 100 µg/m3) to low (ranging between 41 and 60 µg/m3) and very low (<40 µg/m3) concentration that reflect the improving air quality. Similarly, the concentration of NO2 has also tremendously reduced as the areas under low (31–40 µg/m3) and very low (<30 µg/m3) categories have noticeably increased during the pandemic. Besides, the Ozone (O3) concentration has also evidently reduced as the areas under very high (> 50 µg/m3) and high (41-50 µg/m3) concentration that have conspicuously decreased after lockdown. Furthermore, level of SO2 has also noticeably declined to a large extent as it can be seen from the Fig. 6a. The areas under very high (> 20 µg/m3) and high (12-19 µg/m3) concentration SO2 have come down whereas the areas under low (3-7 µg/m3) and very low (<3 µg/m3) concentration have remarkably increased; indicating improved air quality after pandemic lockdown.

Fig. 6b displays that there were 49 grids under very high concentration category and has declined to 25 grids after the lockdown due to pandemic. Conversely, the numbers of grids under low and very low concentration of pollutants have remarkably increased.

| Cities      | CO | Dust | NO2 | O3 | SO2 |
|-------------|----|------|-----|----|-----|
| Ahmedabad   | m  | m    | m   | m  | m   |
| Asansol     | m  | m    | m   | m  | m   |
| Bengaluru   | m  | m    | m   | m  | u   |
| Chennai     | m  | m    | m   | n  | m   |
| Delhi       | u  | m    | m   | u  | m   |
| Ghaziabad   | m  | m    | m   | u  | u   |
| Hyderabad   | m  | m    | m   | m  | m   |
| Jaipur      | m  | m    | m   | m  | m   |
| Kanpur      | m  | m    | m   | m  | m   |
| Kolkata     | m  | m    | m   | m  | m   |
| Lucknow     | m  | m    | m   | m  | m   |
| Mumbai      | m  | m    | m   | m  | m   |
| Nagpur      | m  | m    | m   | m  | m   |
| Patna       | u  | m    | n   | n  | u   |
| Siliguri    | m  | m    | u   | m  | m   |
Ahmedabad
Asansol
Bengalam
Chennai
Delhi
Ghaziabad
Hyderabad
Jaipur
Kanpur
Kolkata
Lucknow
Mumbai
Nagpur
Patna
Siliguri

|  | CO | NH₃ | NO₂ | O₃ | PM₂.₅ | PM₁₀ | SO₂ |
|---|---|---|---|---|---|---|---|
| Ahmedabad |  |  |  |  |  |  |  |
| Asansol |  |  |  |  |  |  |  |
| Bengaluru |  |  |  |  |  |  |  |
| Chennai |  |  |  |  |  |  |  |
| Delhi |  |  |  |  |  |  |  |
| Ghaziabad |  |  |  |  |  |  |  |
| Hyderabad |  |  |  |  |  |  |  |
| Jaipur |  |  |  |  |  |  |  |
| Kanpur |  |  |  |  |  |  |  |
| Kolkata |  |  |  |  |  |  |  |
| Lucknow |  |  |  |  |  |  |  |
| Mumbai |  |  |  |  |  |  |  |
| Nagpur |  |  |  |  |  |  |  |
| Patna |  |  |  |  |  |  |  |
| Siliguri |  |  |  |  |  |  |  |

(caption on next page)
denoting improved quality of air. When we considered the grids with areas (1 grid represents 97 × 97 km² area) it reveals that there were 460,000 km² areas under high concentration of pollutants 43 days before pandemic and it declined to 230,000 km² after the lockdown. Contrast to it, the areas under low pollutants concentration has increased from 740,000 km² before pandemic to 990,000 km² after the lockdown.

The total pollution load (Fig. 6c), shown through pixel to pixel relation (meaning thereby how much pollution was there in each individual pixel before and after lockdown), reveals that the total pollutants have substantially decreased from the areas where there was high concentration of pollutants. For instance, the pixels which are having high concentration of pollutants (in red colour) display a significant decrease in pollution load.
higher rate of decrease in pollutants after lockdown (in green). The study also found (Fig. 6d) that the overall air pollution has drastically decreased after 43 days of lockdown across the cities. The study also demonstrates that the north and western parts of the country has experienced remarkable change in air pollution. It is visibly implicit that the large green circles (Fig. 6e), representing high rate of reduction ranging between 22%- 5%, have substantially increased, thus, showing improved air quality. Here only 9 large red circles (representing increased air pollutants) can be seen where the overall air pollution has increased during the study period. But it is noteworthy that many green circles have come up after the lockdown reflecting reduction of air pollution between 5 and 22% particularly in north and western India.

4. Discussion

The results demonstrate that the primary atmospheric pollutants AOD, PM₂.₅, NO₂, SO₂, O₃ and CO have declined across the cities after 43 days nationwide lockdown. The finding is in consistency with several previous studies that focused on the reduction of air pollution in the world’s leading cities noticeably experienced after lockdown (Saadat et al., 2020; Muhammad et al., 2020; Anjum, 2020; Shrestha et al., 2020). There is a decrease in concentration of major pollutants up to 15% in Indian cities. The study exhibits that the total mass concentration of PM₂.₅ has tremendously declined in major north Indian cities such as Delhi Ghaziabad (−2.6%), Kanpur (4.64%) and Lucknow as well as in major southern Indian cities viz. Chennai, Bengaluru and Hyderabad. These are cities with high traffic concentration and industrial activities. In order to minimize the movement of people and social contact the strict measures implemented has substantially reduced the movement of vehicles and closing of industries leading to improve in air quality particularly dominated ones like PM₂.₅, PM₁₀. Several studies are in congruence of the fall of major atmospheric pollutants in metropolitan cities such as in Delhi (Mahato et al., 2020), Kolkata (Mitra et al., 2020) and also across the major cities due to combustion practice by and large from road traffic, particularly the use of diesel and small degree of gasoline (Devara et al., 2020; Peshave and Peshave, 2020; Ramasamy et al., 2020; Sharma et al., 2020).

As pertinent amount of pollutants have regional background in its origin the results also reveal that most of the north Indian cities such as Delhi, Ghaziabad, Kanpur and Lucknow have observed more than 40% decrease in PM₂.₅, whereas Ahmadabad and Asansol have experienced more than 50% reduction. The decrease in concentration of particulate matters have remarkably drop off due to stringent restriction on automobile emissions, incomplete combustion, construction dust, and biomass burning (Streets et al., 2003; Latha and Highwood, 2006; Moreno et al., 2006).

The traffic dominated locations also exhibit change in concentration of two major pollutants namely NO₂ and CO₂. The firm restriction on emission from huge road traffic particularly diesel, gasoline and closure of manufacturing and power industries have contributed to reduce its concentration in cities like Mumbai, Delhi, Ahmadabad, Nagpur, Ghaziabad, Kanpur, Lucknow and Patna. A number of recent studies have also evidenced the emission of CO has immensely reduced after lockdown due to COVID-19 pandemic and subsequently improved the air quality index (Cadotte, 2020; Watts and Kommenda, 2020; Rahaman et al., 2020b). The study has found decrease of another primary pollutant CO across the cities; its mean mass concentration has decreased by 2.06% compared to pre lockdown as average in the observed 15 cities.

Our study apprehend the increase in O₃ concentration during the observed period in most of the industry dominated cities. The higher decrease of NO₂ and SO₂ might have largely contributed to increase O₃ in these cities. This is in consistent with previous studies that argued that decrease in other major pollutants of NO₂, PM₂.₅, PM₁₀ and SO₂ have contributed to increase faster ozone production and hence the high concentration of O₃ is experienced particularly in nitric oxide (NOx) concentrated areas (Seidel and Birnbaum, 2015; Ma et al., 2012; Murphy et al., 2007). Hence it is mention worthy that NO₂ is the most important precursor and quencher of O₃ through NOx titration particularly during wintertime (Jhun et al., 2015). The effect of environmental factors such as distance from the sea, increased insolation during the months of March to May have contributed to its increased concentration in most of the inland cities like, Siliguri, Kanpur, Lucknow and Nagpur. Among the anthropogenic factors decrease percentage of SO₂ and AOD concentration can be one of the potential reasons to it. The partial restriction on necessary transportation and controlled industrial activities in order to procure energy and essential commodity during lockdown have contributed to the results displaying reduction in the concentration of O₃ in two important northern cities viz. Delhi and Ghaziabad in the COVID-19 pandemic lockdown.

The column mass density of SO₂ has also been declined in most of the cities as the results revealed areas under high concentration of SO₂ have reduced and areas under low level of SO₂ have increased according to remotely sensed data. On the other hand, the CPCB surface data showed that the north Indian cities Delhi, Jaipur, Lucknow, and Patna have experienced substantial decline in SO₂. A study by Saadat et al. (2020) has also confirmed that most of the northern, southern and eastern cities have experienced low concentration of SO₂ after lockdown. Moreover, the closure of heavy industry clusters in central and eastern Indian cities have lowered the SO₂ level at Asansol, Ahmadabad and Nagpur; whereas no restrictions, in lieu of emergency, on power plants and petroleum processing units have contributed to rise of concentration of SO₂ in Mumbai. Consistent with previous research our study has also found that the slight decrease in the concentration of SO₂ as compared to last year winter in most of the north Indian cities (Sharma et al., 2020). On the other hand, changes in natural parameters like precipitation, humidity condition and onset of summer season have contributed in lower level of SO₂ in most of the southern Indian cities.

One of the most stringent outcomes of the study is the positive effect on standards of air quality and improvement of overall air quality index due to strict restriction of vehicular movement, industrials units and production activities. As pertinent amount of NO₂, CO, PM₂.₅, PM₁₀, and SO₂ have regional background origin, it evidently indicated the intensity of improvement in air quality across the traffic and industry dominated city locations across the Indian subcontinent. Within the context of inter seasonal disparity in meteorological conditions like humidity, wind direction and temperature conditions this is a clear indication that a substantial improvement of air quality can be expected with strict implementation of restrictions on vehicular movement and industrial activities. Prior to
this many international studies have revealed the holiday effect or weekend effect on declining particulate matters and subsequent improved air quality (Li et al., 2006; Chen et al., 2020a; Chen et al., 2014; Huang et al., 2012; Zhang et al., 2010). The study also indicates that PM$_{2.5}$ and PM$_{10}$ were the main factors influencing air quality, while SO$_2$ and NO$_2$ played an important role in the formation of PM$_{2.5}$ and O$_3$. The regions where energy related activities were high and strict lockdown measures have been opted air quality improvement has been observed. This study is yet another attempt advocating short term halt (phases of 2–3 days) and execution of lockdown practices as a regulatory plan to improve air quality. It is suggested to augment periodical regional lockdown in transport activity (like cluster zone of Delhi-Ghaziabad-Kanpur) in and around mega cities. Though any policy related decision would require cost benefit analysis of such closures and research on seasonal contrasts of meteorological conditions and effectiveness of such measures.

5. Conclusions

The study has analysed six major air pollutants to monitor the changes in air quality after restricted human activities due to COVID-19 pandemic in 15 major cities of India during 43 days before (9th Feb. 2020 to 23rd Mar. 2020) and after lockdown (24th Mar. 2020 to 4th May 2020). The study has found reduction of almost all the pollutants except NO$_2$ and SO$_2$ in Mumbai during the lockdown window period. The spatial changes in air quality during study period reveals that overall air quality has considerably improved after the pandemic. While looking at the geographical extent it is observed that there were 460,000 km$^2$ areas under high concentration of pollutants before lockdown whereas after lockdown it has declined to 230,000 km$^2$. Air Quality Zonal Modeling has also demonstrated reduction of all primary air pollutants except O$_3$ which displayed substantial increase across the cities with exception of decrease in Mumbai, Lucknow and Kanpur. The dissimilarity result between remotely sensed data and CPCB/SPCB surface data, for instance, the concentration of CO over Delhi and Patna has decreased in remotely sensed data whereas CPCB data is showing its rise is because of the fact that remotely sensed data measured the pollutants at 550 m above the surface whereas the CPCB/SPCB stations monitored ground level data. The reduction of pollutants has been experienced because of closing of power plants in industrial cities whereas cities like Delhi experienced decline due to both closer of industrial activities and restriction of vehicular mobility after lockdown. However, the study indicates that stringent implementation of regulation on emission of air pollution may be an alternative measure for pollution reduction in industrial and transport dominated locations.

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Urban Climate Journal.

Authorship contributions

Please indicate the specific contributions made by each author (list the authors’ initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

Category 1.
Conception and design of study: S. Rahaman, S. Jahangir, R. Chen, S. Thakur; acquisition of data: S. Rahaman; Software: S. Rahaman; Validation: R. Chen, P. Kumar, S. Thakur; analysis and/or interpretation of data: S. Jahangir, R. Chen, P. Kumar, S. Thakur.

Category 2.
Drafting the manuscript: S. Rahaman, S. Jahangir, P. Kumar, S. Thakur; revising the manuscript critically for important intellectual content: S. Rahaman, S. Jahangir, P. Kumar, S. Thakur, R. Chen.

Category 3.
Approval of the version of the manuscript to be published (the names of all authors must be listed): S. Rahaman, S. Jahangir, R. Chen, P. Kumar, S. Thakur.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships t.

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