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Environmental impact of COVID-19 led lockdown: A satellite data-based assessment of air quality in Indian megacities

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ABSTRACT

The strategies to contain the spread of COVID-19 pandemic, including restricted human movement and economic activities, have shown positive impacts on the environment. Present research analysed the effects of COVID-19 led lockdown on air quality with special reference to major pollutants, namely nitrogen dioxide (NO_2), carbon monoxide (CO), sulphur dioxide (SO_2) and aerosol optical depth (AOD). The assessment has been conducted for megacities of India (Delhi, Mumbai, Bengaluru, Chennai and Kolkata) for four months, that is, March and April in 2019 and 2020 using Sentinel 5P and MCD19A2 data. A decrease in concentrations of air pollutants, specifically NO_2 and SO_2, has been observed during the lockdown period in all the cities; whereas CO and AOD have exhibited discrete pattern of spatio-temporal variation. Four megacities except Kolkata have revealed a positive correlation between NO_2 concentration and population density. The results conclude overall improvement in air quality during COVID-19 led lockdown. The current situation provides a unique opportunity to implement a structural economic change that could help us move towards a city with low emission economy. Realizing the achievable improvement of air quality, the study suggests further in-depth research on source attribution of individual pollutants to assess the prospect of emission reduction actions.

1. Introduction

1.1. The pandemic and environmental quality

The novel coronavirus, namely COVID-19, was first detected in December 2019 and gradually spread across the globe (Li et al., 2020; Lu et al., 2020; Xu et al., 2020; Zhu et al., 2020). Due to the massive impact of coronavirus, the World Health Organization (WHO) declared that COVID-19 is a public health emergency on 30th January 2020. Because of the various measures taken by countries to control the virus as a consequence of this pandemic, the world economy has also been adversely affected. However, this economic disruption has given rise to betterment of environment by reduction in vehicular and industrial emissions because of limited industrial activities and restricted human mobility. With almost standstill economic activities in India because of the nation-wide lockdown declared on 24thMarch 2020, reports and news of tangible improvement in environmental quality have overwhelmed the

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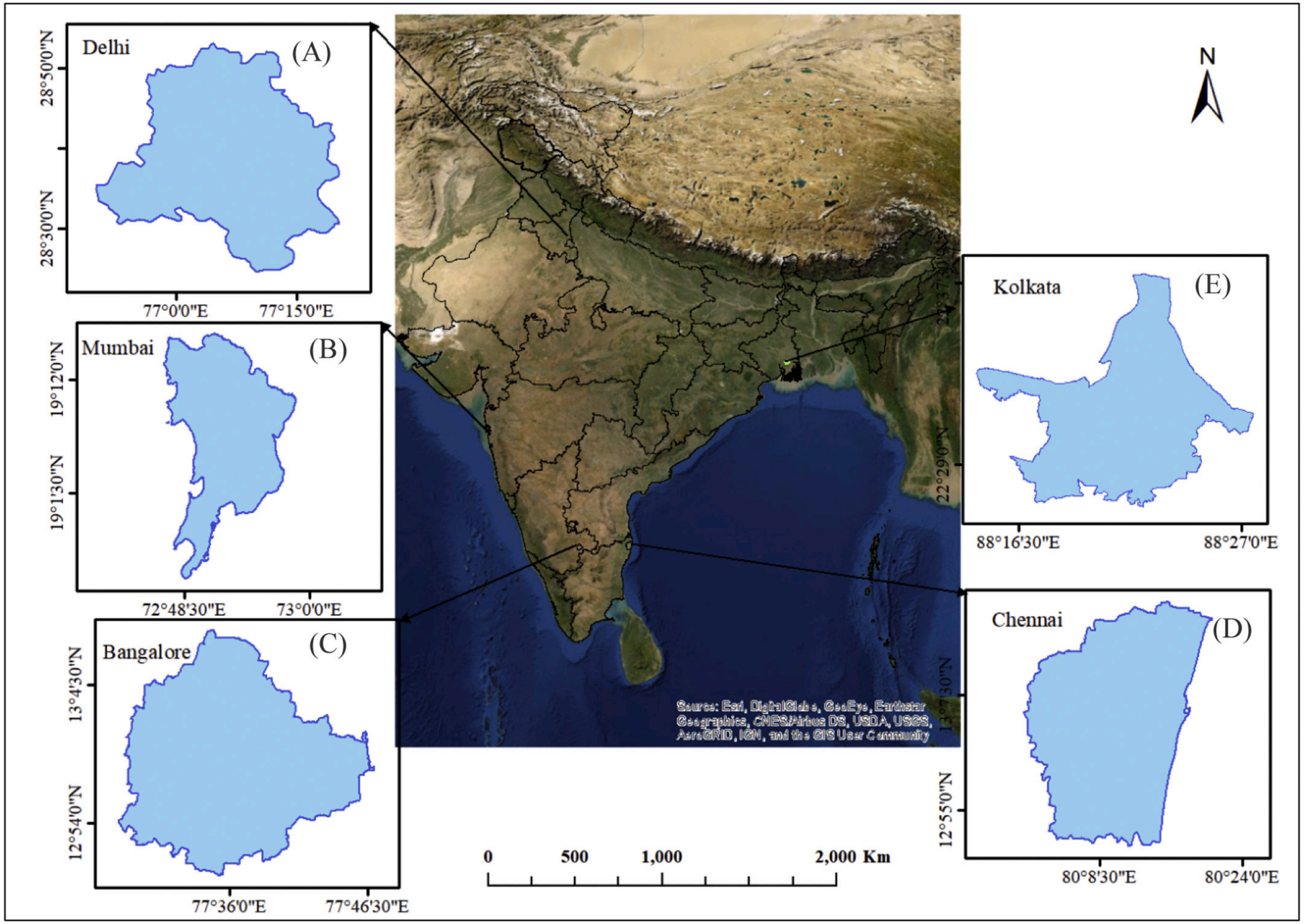

Fig. 1. Study area of present research in five megacities in India (A) Delhi, (B) Mumbai, (C) Bengaluru, (D) Chennai and (E) Kolkata.

mass media.

Air pollutants increase the risks of health hazards. Several studies have reported that air pollution has direct effects on human health, specifically the induction of respiratory diseases (Dominici et al., 2006; Hansel et al., 2016; Zhu et al., 2020). The impact of COVID-19 has resulted in a decrease of atmospheric pollutants due to the shutdown or minimized operation of all anthropogenic sources of emissions. Severe acute respiratory syndrome (SARS) and atmospheric pollutants have a proven positive relationship where higher levels of pollutants increase the risk of fatality (Cui et al., 2003; Chakraborty et al., 2020). According to WHO, air pollution is a major environmental risk that kills an estimated seven million people per year worldwide (WHO, 2020). Particulate matter 2.5 ($PM_{2.5}$) causes adverse effects on health conditions, which has a significant impact on the respiratory system (Stanaway et al., 2018). Atmospheric pollutants such as NO_2, SO_2, CO and O_3 adversely affect the human respiratory system, and people with heart ailments and asthma are more vulnerable. According to data from air quality monitoring stations, overall air quality indices of the megacities of India have improved during the lockdown (Goswami et al., 2020). As a result, various similar studies have identified the impact of lockdown on air quality, which show a 50% decline rate in particulate matter over Indian cities, whereas Delhi has the highest decline in pollutant concentration (Mahato et al., 2020; Navinya et al., 2020; Sharma et al., 2020). Decreasing concentrations of NO_2 over various locations of India during the lockdown period was widely reported based on CPCB (Central Pollution Control Board) data (Mahato et al., 2020; Sharma et al., 2020; Singh et al., 2020) and also satellite based data has been widely reported (Biswal et al., 2020; Pathakoti et al., 2020; Siddiqui et al., 2020).Therefore, analysing changes in concentration of individual atmospheric pollutants is useful for evaluating the impacts of the lockdown due to the COVID-19 outbreak while also assessing the role of pollution as a controlling factor in the spread of the virus COVID-19 in regions with high pollution levels during the pre-COVID-19 situation.

1.2. Urbanization and air quality

According to the UN report 2012, the world population was 7.2 billion in 2013 and is expected to cross 9.6 billion in 2050 (UN, 2013). The rise in the urban population is more rapid in middle- and low-income countries. At present, out of 33 megacities in the world, India hosts five namely, Delhi, Mumbai, Chennai, Bengaluru and Kolkata, and by 2030, Hyderabad and Ahmedabad will be included in the list (UN, 2016). Megacities can face a serious problem due to rapid urbanization with serious consequences for human health and environment (Wenzel et al., 2007; Gurjar et al., 2016). A study by Gupta et al. (2008) revealed that among 18 megacities worldwide, only 5 megacities are in the “fair” air quality range, whereas all the remaining 13 have “poor” air quality. These cities contribute to an increase in pollution concentration due to a variety of factors (Butler et al., 2008; Ravindra et al., 2016), which include emissions by factories, commercial setups, vehicles and residential areas along with other sources such as construction, road dust, waste burning, household consumption, and so on (Guttikunda et al., 2014).

1.3. Significance and objectives of the study

Satellite observations play a crucial role in monitoring the Earth’s atmosphere and provide various information on air quality. MODIS and Sentinel 5P imagery can be used to extract climatic information such as temperature, humidity, pollution, cloud cover, ice, snow, land and sea surface temperature, fire counts, and so on. Researchers in the past have conducted studies using these satellite imageries for the assessment of air quality. The TROPOspheric Monitoring Instrument (*TROPOMI*) on board the Sentinel-5 Precursor satellite and Ozone Monitoring Instrument have been used to successfully assess column concentrations of atmospheric constituents (Bauwens et al., 2020; Fioletov et al., 2020). Safarianzengir et al. (2020) studied the spatial and temporal monitoring and analysis of air pollution using sentinel-5P data and MODIS satellite data with LST index for monitoring daily and nocturnal temperatures. They observed that the highest increase in air pollution occurs during the cold months in Iran. Engel-Cox et al. (2004) studied the qualitative and quantitative analyses of air quality using MODIS sensing data in urban areas. Omrani et al. (2020) have studied the spatio-temporal data on air pollutant nitrogen dioxide in France using Sentinel satellite data. Climate change and air pollution are always a significant area of research for analysing the impact of air pollution on health (Gurjar et al., 2016; Ravindra et al., 2016). Further, impact of COVID-19 on air pollution using TROPOMI NO_2 and MODIS Aerosol Optical Depth (AOD) datasets for 41 cities in India highlighted that the NO_2 reduced by 13% from March 25, 2020 to May 03, 2020 as compared to the pre-lockdown period during January to March 2020 (Vadrevu et al., 2020). Similar findings on fluctuations of pollution pattern were obtained by Biswal et al. (2021) and Tyagi et al. (2021) for same points of time. Since, the coronavirus infection is mostly manifested as a respiratory disease, the assessment of air quality parameters may provide an insight into the relationship between pollutants and health. Therefore, the present study aims to analyse the changes in atmospheric pollutants in megacities of India during the lockdown enforced to control COVID-19. It also intends to compare the concentrations of air pollutants during the lockdown with past air quality under normal circumstances. It has also attempted to investigate the relationship between ambient air quality and parameters (e.g. population density) representing the level of urbanization.

1.4. Study area

The present study has been conducted in five megacities or Tier 1 cities of India (Fig. 1). Delhi is the eighth largest metropolitan city and highly populated city with 16.75 million residents (Bharath et al., 2018). Delhi is located on the bank of the Yamuna River and has extreme climatic conditions with 3 °C in winter and 45 °C in summer with an average rainfall of 400–600 mm (Singh et al., 2014). The projected population data of the megacities (Mumbai, Chennai, Bengaluru and Kolkata) were obtained from World Population Review (online). Mumbai is the capital of Maharashtra, a coastal city that is bound by the Arabian Sea. Mumbai is the financial capital of India with a high level of economic activity and shelters a population of 20.66 million. Chennai is the capital of Tamil Nadu and has a population of 11.2 million. (Chennai is well developed with industries such as automobile, software, textiles and many such activities. Bengaluru, the Silicon Valley of India, is the capital of Karnataka, which has a population of 12.76 million. Bengaluru receives a good average annual rainfall of 896 mm (Aithal et al., 2013). Kolkata is the capital of West Bengal state in India, located on the banks of River Hooghly. Kolkata's climate is hotter in summer, with temperature ranging between 24°Cand 42 °C, while in winter it ranges from 8 °C to 26 °C (Mandal et al., 2019). According to recent estimation, the population of Kolkata is 14.97 million.

The status of COVID-19 outbreak in the five megacities till 16thJuly 2020, and population data from Census of India are summarized in Table 1. All the five cities were assigned poor air quality status from time to time (e.g., World Air Quality Report-2018 by AirVisual (2019), CPCB-AQI etc.). Being the largest city in terms of population, Delhi has also witnessed the highest number of COVD-19 positive cases. A wide-ranging impact on the economy has been observed during this pandemic, which includes the decrease in employment in both urban and rural areas of the country. Due to this lockdown, both organized and unorganized sectors have stopped functioning, thus resulting in an increase in unemployment rates from around 10% pre-lockdown to more than 25% during the lockdown in India [Centre for Monitoring Indian Economy (CMIE)]. This data definitely indicates a slow down in economic activities during the COVID-19 led lockdown in the country.

2. Materials and methods

Table 1 shows data on COVID-19 reported cases obtained from https://www.covid19india.org/ for India. TROPOMI instruments are used to produce the Sentinel 5P data, and can measure various pollutants such as NO_2, SO_2, CH_4, CH_2O, CO column concentrations and Aerosol Index (Zheng et al., 2019; Omrani et al., 2020). TROPOMI instruments consist of hyperspectral spectrometer that observes eight bands including ultraviolet, visible, near-infrared and shortwave infrared portions of electromagnetic spectrum (Veefkind et al., 2012). In this study total vertical columns are evaluated with airborne and ground-based column density measurements. Spatio-temporal characteristics of atmospheric data were analysed for the megacities of India using satellite data (Table 2) to assess the concentrations of pollutants in air.

Sentinel 5P was launched on 13thOctober 2017 to monitor the atmosphere. Sentinel 5P is a new remote sensing data source whose measurements are made by the state of the art instrument called TROPOMI (Potts et al., 2021). This instrument is a multispectral imaging spectrometer that detects reflected solar radiation or scattered back to space from Earth's atmosphere and surface. As spectral signature of each atmospheric gases is known, its concentration can be estimated as identification of spectral signature in different parts of the electromagnetic spectrum. The sentinel 5P imageries have been used to assess the total columns of NO_2, SO_2 and CO concentrations and MODIS for Aerosol Optical Depth (AOD). Total column of NO_2 is expressed as the ratio of slant column density of NO_2 and total air mass factor, which are retrieved using the TROPOMI's spectrometer back scattered solar radiation measurements in the wavelength of 405–465 nm (Platt and Stutz, 2008a). Total NO_2 column density was retrieved from Level-1b radiance and irradiance spectra, measured by TROPOMI, which is based on Differential Optical Absorption Spectroscopy (DOAS) approach (Platt and Stutz, 2008b). A data assimilation system information based on TM5-MP chemical transport model suggested that NO_2 column density is separated into stratospheric and tropospheric part. Further, the stratospheric and tropospheric slant column densities are converted into vertical column densities by applying an appropriate air mass factor which is based on look-up table of altitude-dependent air mass factors (AMFs) and information on the vertical distribution of NO2 from TM5-MP chemistry transport model. All measurements of atmospheric gases (TROPOMI) are column data that represent the full depth of the atmosphere. The column concentrations of NO_2 have been established as a representation of surface concentration of NO_2 with good correlation (R = 0.7–0.9) between the two variables (Lorente et al., 2019; Zheng et al., 2019). TROPOMI instruments are used to produce the Sentinel 5P data, and they can measure various pollutants such as NO_2, SO_2, CH_4, CH_2O and Aerosol Index (AI). NO_2, SO_2 and CO column number densities, as well as AOD, have been assessed for the months of March and April in the years 2019 and 2020. We collected average data for the months of March and April for both years using Google Earth Engine, n.d (https://earthengine.google.com/) and analysed it on a GIS platform. MODIS (MCD19A2) AOD were downloaded and processed using Google Earth Engine. Further, all layouts are prepared in GIS environment and flow chart of the adopted methodology is given in Fig. 2.

Table 1
Indicators for economy, demography and impact of COVID-19 in five megacities of India.

Cities	Greater Mumbai	Delhi (NCT)	Chennai (CMA)	Bengaluru City	Kolkata (KMC)
Total reported case of COVID19	96,474	116,993	80,961	22,942	10,975
Death rate (% of infected persons)	5.67	2.98	1.62	1.90	4.78
Population density (Person/sq. km)	20,038	11,297	26903* Chennai Municipal Corporation	4378* Bengaluru District	24,252
Population density (GHS)	28,907	11,746	8026 (Chennai Metropolitan Area)	13,961	26,592
GDP in billion $ (2018) *	310	293.6	110	86	150.1
No. of vehicle (In Thousands)**	2820	8851	4938	6113	741
Geographical Area (km^2)	446	1484	1189	709	206.1

Sources: Population data: Census of India, 2011; COVID-19 related data from https://www.covid19india.org/ as on 16th July 2020;*GDP: AEGONLife** MOTOR VEHICLES - Statistical Year Book India 2018, Total Registered Motor Vehicle Million Plus Cities GoI; Ministry of Statistics and Programme Implementation. NCT (National Capital Territory); CMA (Chennai Metropolitan area); KMC (Kolkata Municipal Corporation).

Table 2
Data used in present study.

Parameters	Year	Spatial Resolution	Source
Aerosol optical Depth	2019 & 2020	1Km	MCD19A2
Nitrogen Dioxide	2019 & 2020	0.01°	Sentinel 5P
Sulphur Dioxide	2019 & 2020	0.01°	Sentinel 5P
Carbon Monoxide	2019 & 2020	0.01°	Sentinel 5P
GHS-POP	2015	1 Km	European commission Global Human Settlement

Moreover, these parameters were statistically and graphically analysed for all the megacities for minimum, maximum, mean and standard deviations of concentrations. Population density data have been acquired from the web portal of European Commission Global Human Settlement to analyse the population density in megacities, which is available for 2015 at 1 km spatial resolution. The Global Human Settlement layer provides global spatial information that describes the distribution and density of humans on the Earth. Furthermore, the population density data were correlated with NO_2 measurement data for April 2019 and April 2020 (Kaplan and Avdan, 2020).All megacities are highly populated regions, and NO_2 in these cities is emitted from anthropogenic activities; therefore, NO_2 values were considered to analyse its variation with respect to population density.

3. Results

3.1. Major pollutants in megacities of India

Spatio-temporal variations of atmospheric parameters are presented and mapped in Fig. 3a-d and Figs. 4–13 respectively. We examined the status of five megacities of India during the lockdown, namely, Delhi, Mumbai, Bengaluru, Chennai and Kolkata, all of which are known to be highly polluted. Due to the occurrence of the COVID-19 pandemic, unprecedented improvement in air quality parameters was observed in these cities as a result of shutdown of industrial activities along with meagre vehicular movements. In this case, four major indicators of atmospheric parameters were considered for the study, that is, nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO) and AOD at two points of time for two months (March and April) in 2019 and 2020. The maximum and minimum column number densities of these three parameters (NO_2, SO_2 and CO) and AOD for the four months assessed are presented in Fig. 3a–d.

NO_2 column concentrations based on remote sensing interpretation depicted a significant decrease in the year 2020 for Bengaluru. NO_2 mean measurement was 0.0001292 mol/m^2 in March and 0.0001201 mol/m^2 in April 2019, which are close values; however, a significant reduction was observed in March 2020 (0.0000884 mol/m^2) and a further reduction in measurement to 0.0000703 mol/m^2 in April (Table 3). The maximum measurement in Delhi was very high in both of the studied months of 2019, ranging from 0.0002243 mol/m^2 to 0.0002341 mol/m^2,but it was reduced to less than half in April (0.0001059 mol/m^2). Similarly, higher levels of NO_2 were observed in March 2019 and a decrease in April 2019 in Mumbai. Apart from this, an unusual fall in NO_2 measurement in April 2020 was observed. In Kolkata, the maximum measurement observed was high in March 2019 at 0.0001782 mol/m^2 and 0.0001384 mol/m^2 in April 2019. A slight decrease in maximum measurement was noticed in 2020, which showed 0.0001285 mol/m^2 in March and 0.000119 mol/m^2 in April.

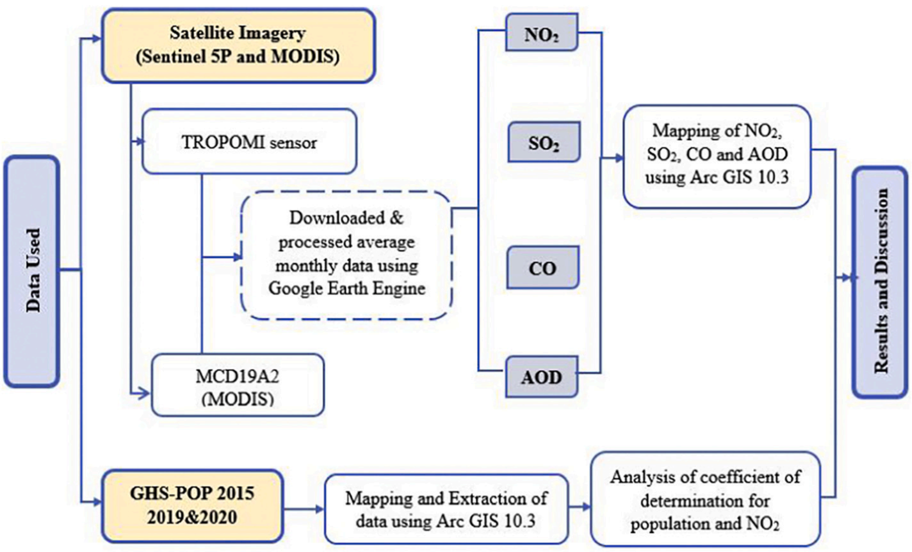

Fig. 2. Flow chart of the adopted methodology.

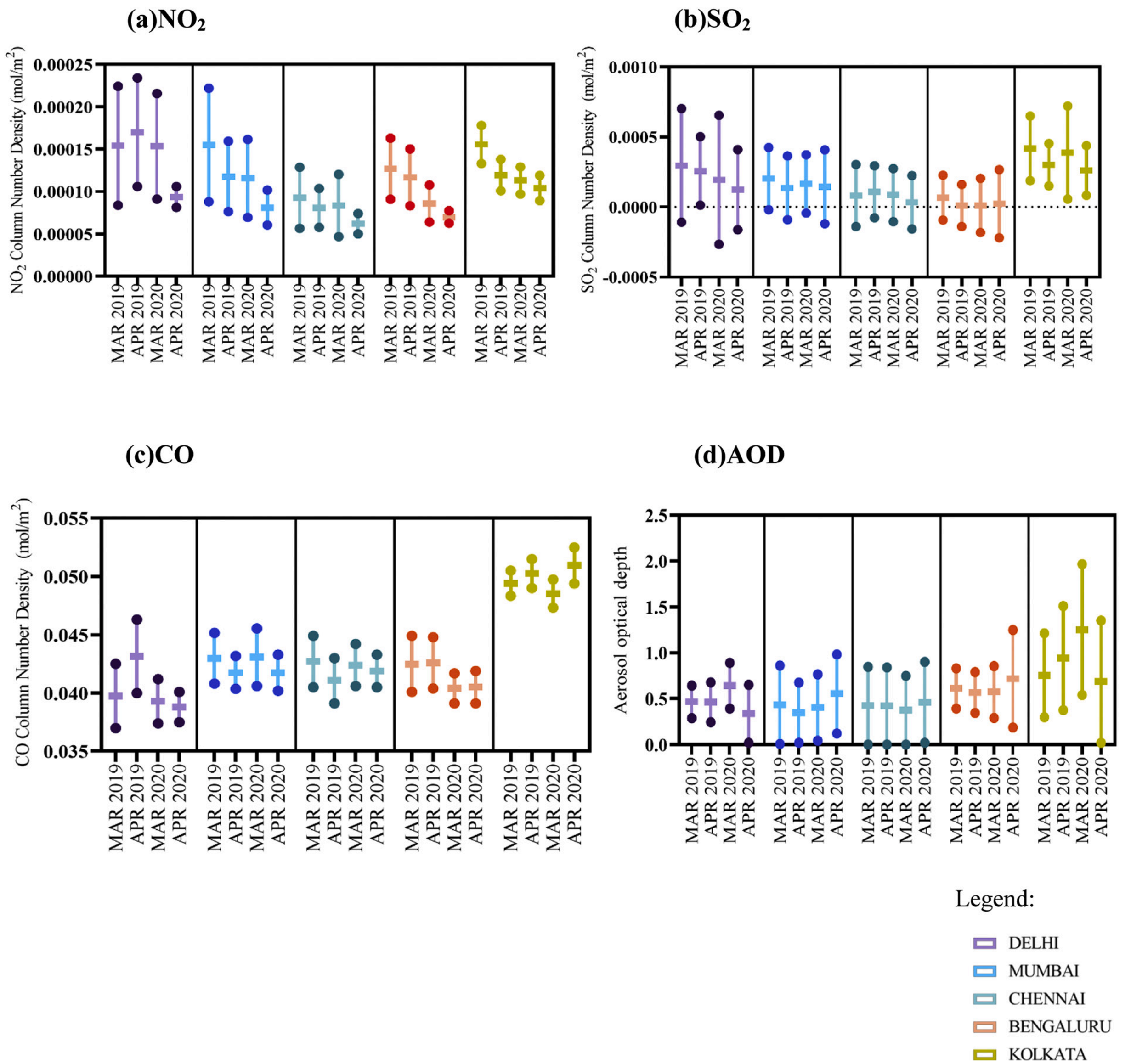

Fig. 3. (a-d): Maximum and minimum measurements of air quality parameters for the studied months in all five megacities of India.

The results show a decrease in SO_2 column number density in Bengaluru from 0.0000144 mol/m^2 in March 2020 to 0.0000036 mol/m^2 in April 2020 where a decline in measurements has been seen as compared to 2019 in both the respective months. The difference in SO_2 measurements has been observed the highest in Chennai from March 2020 to April 2020 where the mean observation has decreased abruptly from 0.0000853 mol/m^2 to 0.0000191 mol/m^2. A similar change was observed in Delhi for levels of maximum concentration of SO_2. In Delhi, 0.0007016 mol/m^2 maximum measurement was observed in March 2019, which went down to 0.000654 mol/m^2 in March 2020. Following this, a sudden fall was observed in April 2020 with a level of 0.0004094 mol/m^2 in Delhi. However, in Kolkata, high levels of SO_2 were observed, that is, 0.0007203 mol/m^2 in March 2020 which was reduced during lockdown in April 2020 to 0.0004377 mol/m^2. In Mumbai, 0.0003727 mol/m^{2}was observed in March 2020 and 0.0004084 mol/m^2 in April 2020. A slight increase in maximum SO_2 levels over the year was found in Mumbai, whereas the mean measurement has shown a decline.

Analysis shows that Kolkata has the highest levels of CO among the five megacities during all four studied months. In March 2020, the maximum value of CO was 0.050 mol/m^2, and in April 2019, the value was 0.049 mol/m^{2}shows a slight increase during the lockdown. Carbon monoxide levels, in general, have been found to not show much variation pre- and post-lockdown. For example, the difference between minimum and maximum levels in Delhi was 0.0038 mol/m^2.

According to an analysis of AOD maximum values in Indian megacities, AOD levels were high (1.5) in Kolkata in March 2020 and low (1.4) in April 2019. It is the highest difference in maximum values of AOD pre and post lockdown for the studied city. This

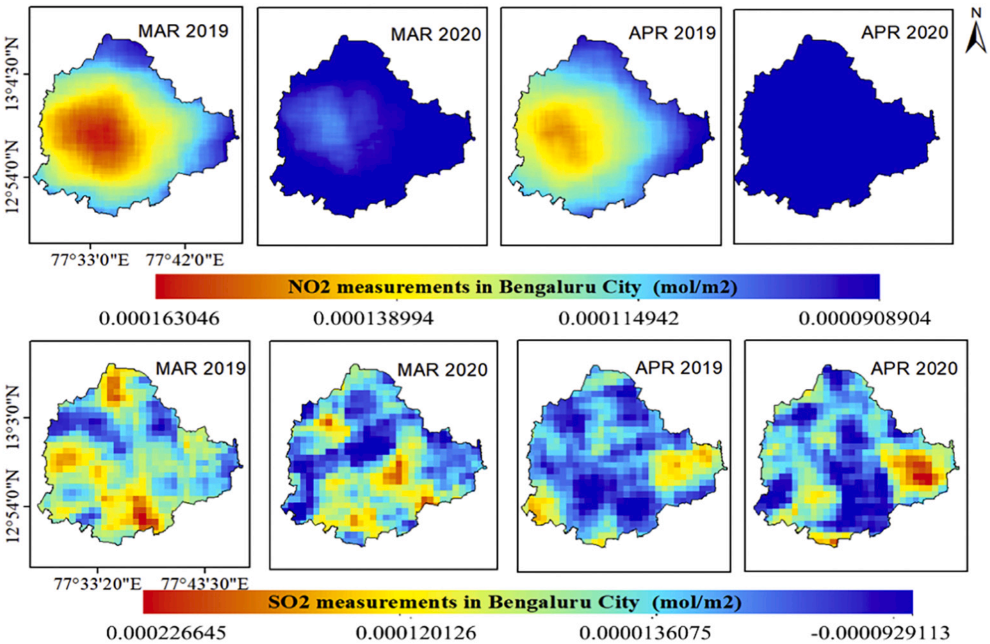

Fig. 4. NO_2 and SO_2 measurements in Bengaluru city.

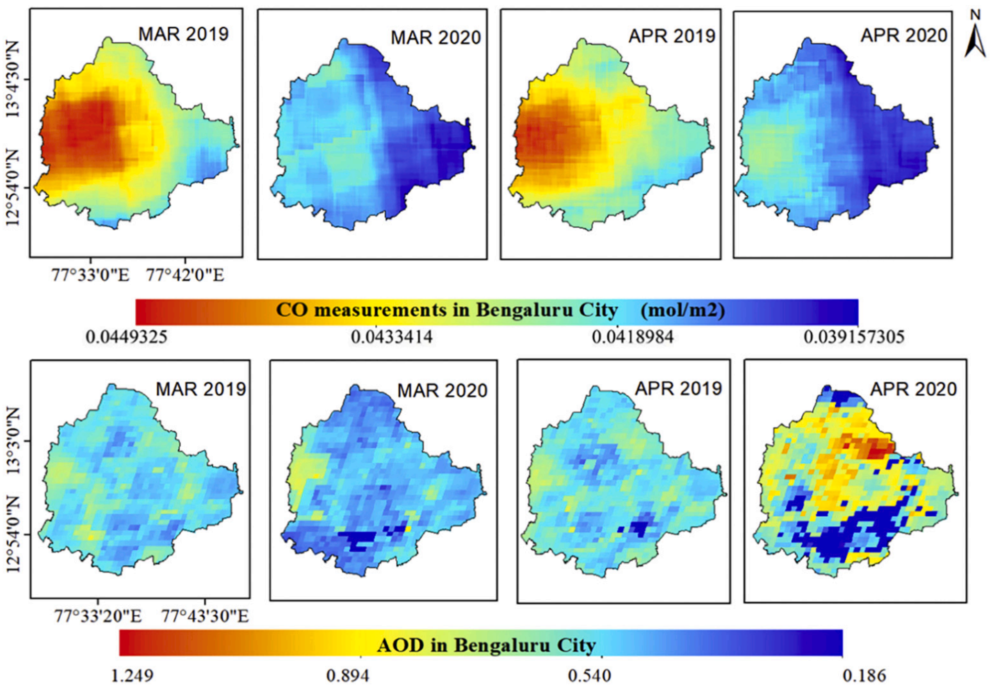

Fig. 5. CO and AOD measurements in Bengaluru city.

observation is most likely due to the distribution of local emission sources such as industries in the city that alleviate air pollution. Contrary to other findings, Bengaluru's AOD is high, with a value of 1.25 in April 2020, which elevated from 0.79 during the same month of 2019. Delhi is famous for its particulate pollution, but during the lockdown, a significant reduction of AOD was observed in April 2020 where the observed level was 0.65, whereas in March 2020, aerosol level (0.89) was comparatively higher. A fluctuation of maximum level was observed in Chennai from 0.85 in March 2019 and 0.84 in April 2019 to 0.75 in March 2020 and 0.9 in April 2020. However, the decrease in mean values was observed in Chennai. Analysis reveals that average monthly AOD was highest in Kolkata in

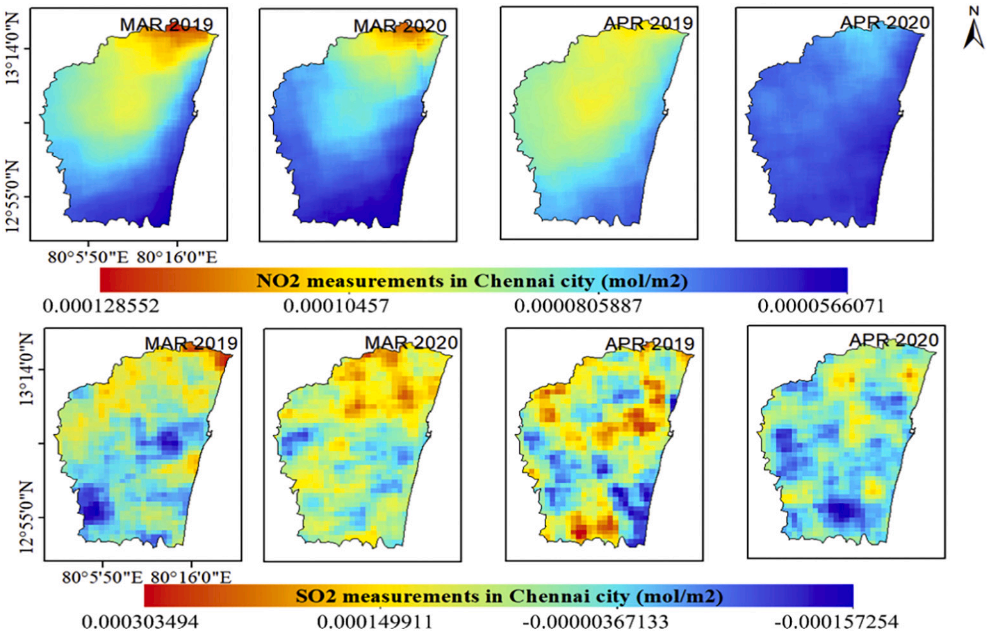

Fig. 6. NO_2 and SO_2 measurements in Chennai.

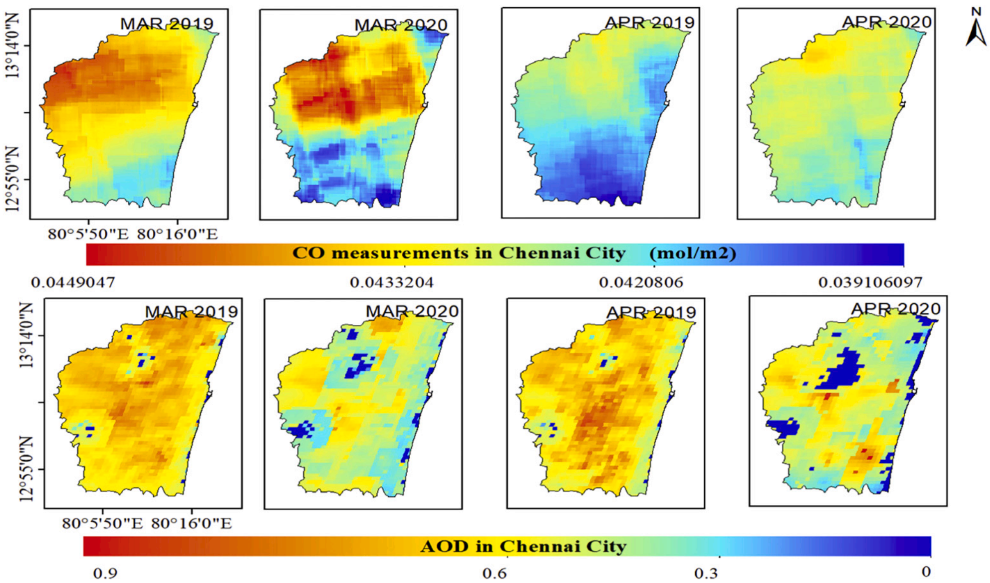

Fig. 7. CO and AOD measurements in Chennai.

both years, whereas Mumbai had the least mean aerosol values among the five studied megacities during the lockdown. Mumbai has low particulate pollution during the no-lockdown situation (April 2019) as compared to Kolkata, Bengaluru and Chennai.

The change in mean measurements of all the four studied air pollutants from April 2019 (Business-as-Usual 'BAU') to April 2020 (Lockdown) is presented in Table 3. The pattern of changes in mean levels of all the studied air quality parameters in five megacities shows that the highest decrease was observed in the case of SO_2 in Chennai (81.2%). In other four megacities, the decrease ranges from 9% to 56.6%. A decrease in mean column measurements from April 2019 to April 2020 is seen for NO_2 and SO_2 for all the cities, whereas very negligible change has been noticed in three cities (Mumbai, Chennai and Kolkata) for CO levels. AOD levels have dropped (2%–18.6%) in four cities during the lockdown month of 2020 as compared to previous year except in Bengaluru, where a 32.49% increase in AOD has been observed. Kolkata has experienced the lowest decrease in overall pollutant levels as compared to all the other megacities studied.

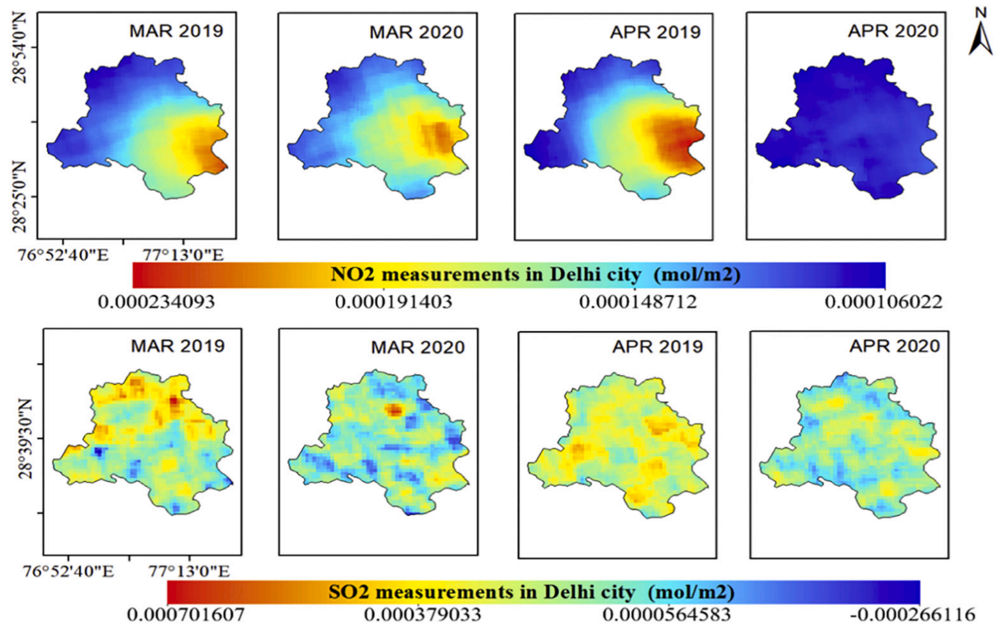

Fig. 8. NO_2 and SO_2 measurements in Delhi.

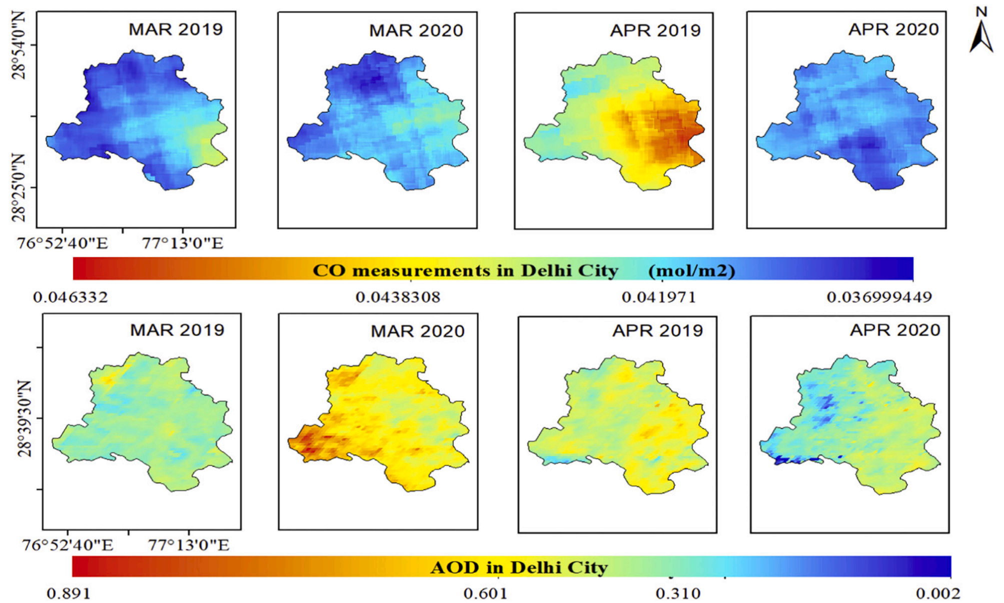

Fig. 9. CO and AOD measurements in Delhi.

3.2. Urbanization and pollution

Population density is the most important measurement for level urbanization among others like percentage of built-up area, percentage of non-agricultural households, and so on. Population density map (Fig. 14) was derived using Global Human Settlement Layer (GHSL) population dataset available at 1 km spatial resolution. The unit of population density used in this study is person per sq. km. India is one of the most populated countries in this world, and in the case of the megacities, Delhi is the most populated as compared to other four megacities. The results presented in the previous section pertaining to Delhi also coordinate with the historical repute of poor air quality of the city among five megacities. Population density of Bengaluru is low (4378 per sq. km) as compared to other megacities (Delhi, Mumbai, Chennai and Kolkata with 20,038, 11,297, 26,903 and 24,252 per sq. km., respectively). If we compare visual interpretations of column concentrations of pollutants with the maps of population density (Fig. 14), it is apparent that

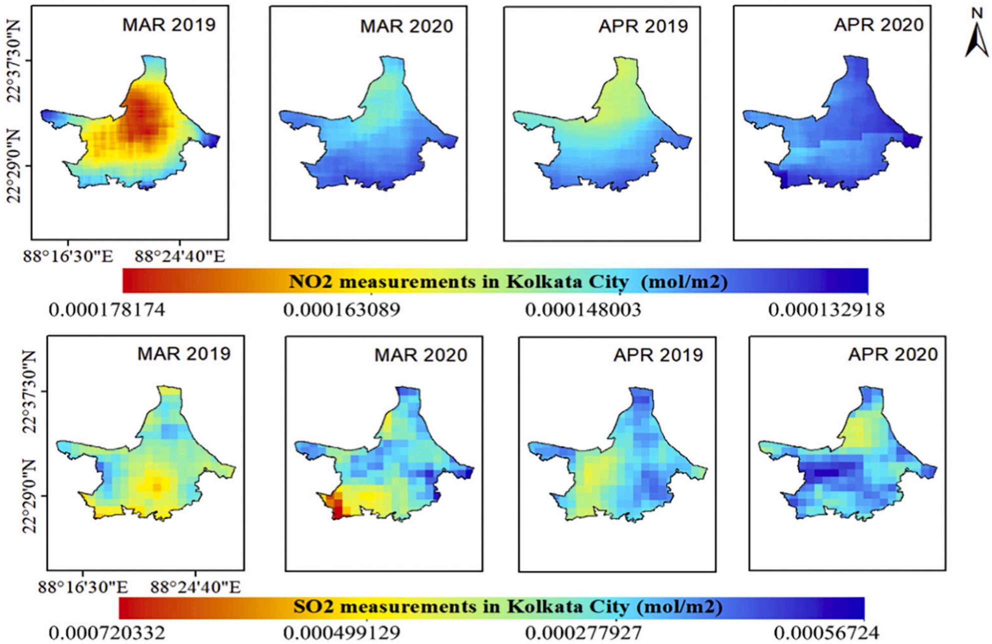

Fig. 10. NO_2 and SO_2measurements in Kolkata.

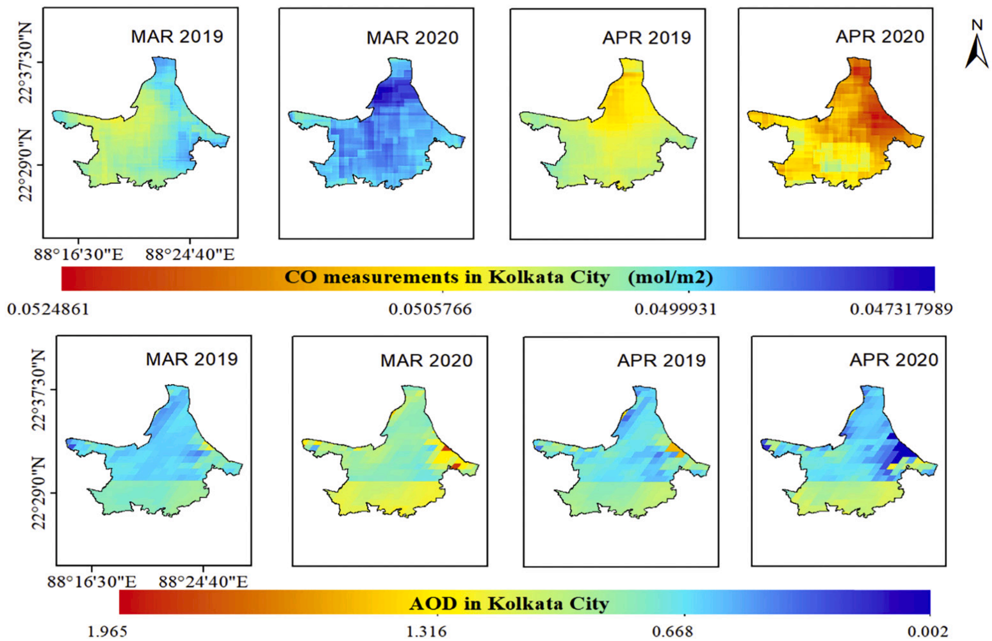

Fig. 11. CO and AOD measurements in Kolkata.

NO_2 and CO have a positive correlation with population density. The pattern is relatively clear in Delhi and Bengaluru.

To assess the impact of population density on NO_2 levels, the coefficient of determination was analysed between NO_2 concentration of data during the lockdown and the same month last year (April 2019 and April 2020) and population density in 2015. Table 4 shows that for all megacities, NO_2 concentration and population density have a positive correlation with moderate strength during business-as-usual situations (April 2019). The uniform values of R^2(0.55, 0.50, 0.53, 0.50 and 0.51, respectively, in Bengaluru, Mumbai, Delhi, Chennai and Kolkata) across all five cities also indicate the positive association between the two variables. During the lockdown period, the correlations between population density and NO_2 concentration slightly deteriorated in four of the five megacities; whereas, in Kolkata, the R value shows almost no association between population density and NO_2. The decreasing strength of the

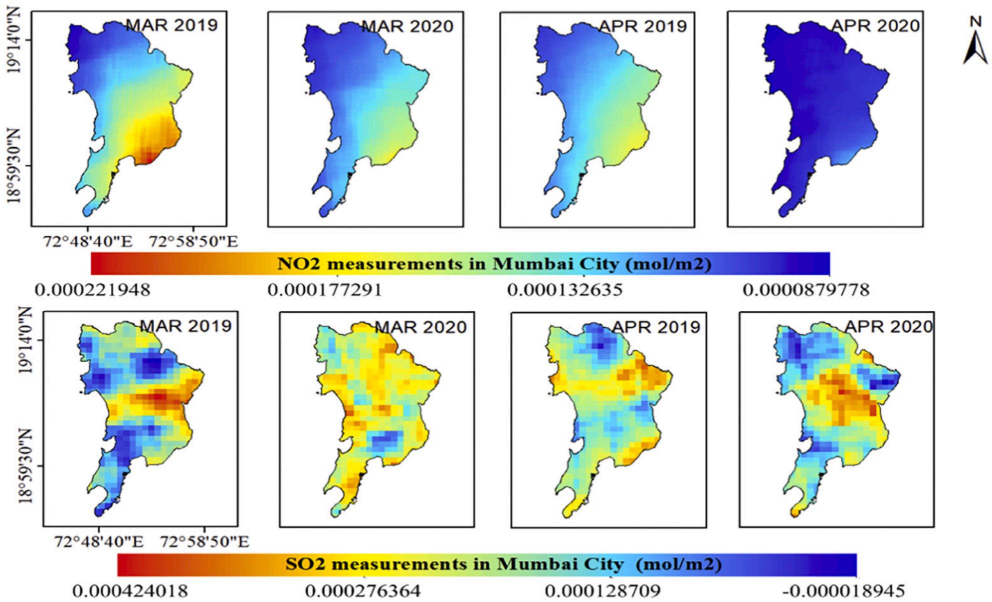

Fig. 12. NO_2 and SO_2measurements in Mumbai.

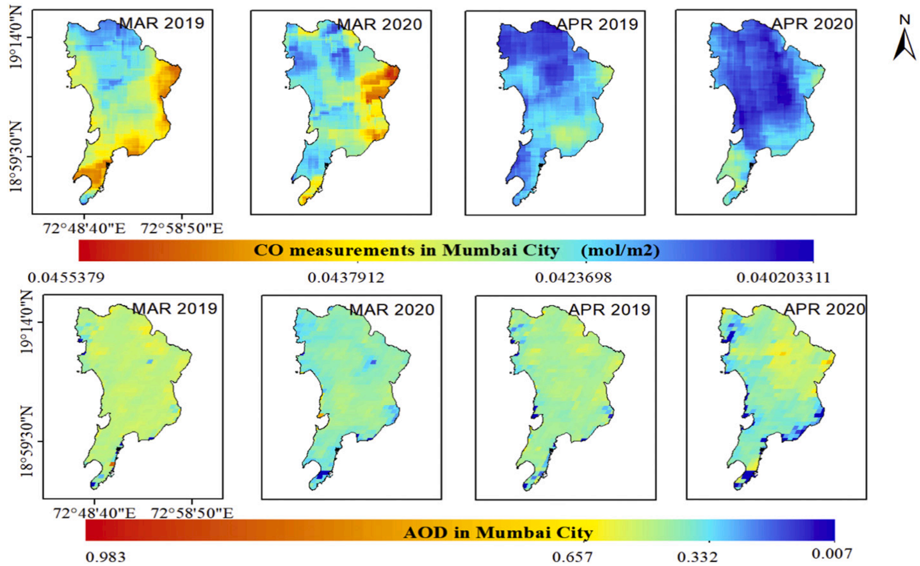

Fig. 13. CO and AOD measurements in Mumbai.

correlation between NO_2 levels and population density in all the cities clearly indicates the decreased impact of anthropogenic emissions on air quality. The correlation between fugitive source emission (e.g., traffic point) and NO_2 observations has a better correlation than the correlation between other pollutants and sources like industry (Hennig et al., 2016). High traffic emissions are spatially associated with high population density areas. The weak correlation, especially in Kolkata during the lockdown may be induced by high emissions from industries (which were not shut down) in low population density areas or significant decrease in contribution from traffic emissions. Levels of NO_2 irrespective of population density during the lockdown period mostly represent the background levels of NO_2 over the studied cities. Further, source attribution assessment, meteorological conditions, transportation and dispersion patterns of pollutants can explain those relations better.

4. Discussion

The present approach to analysing the impact of the COVID-19 led lockdown on air pollutants in megacities of India (Delhi,

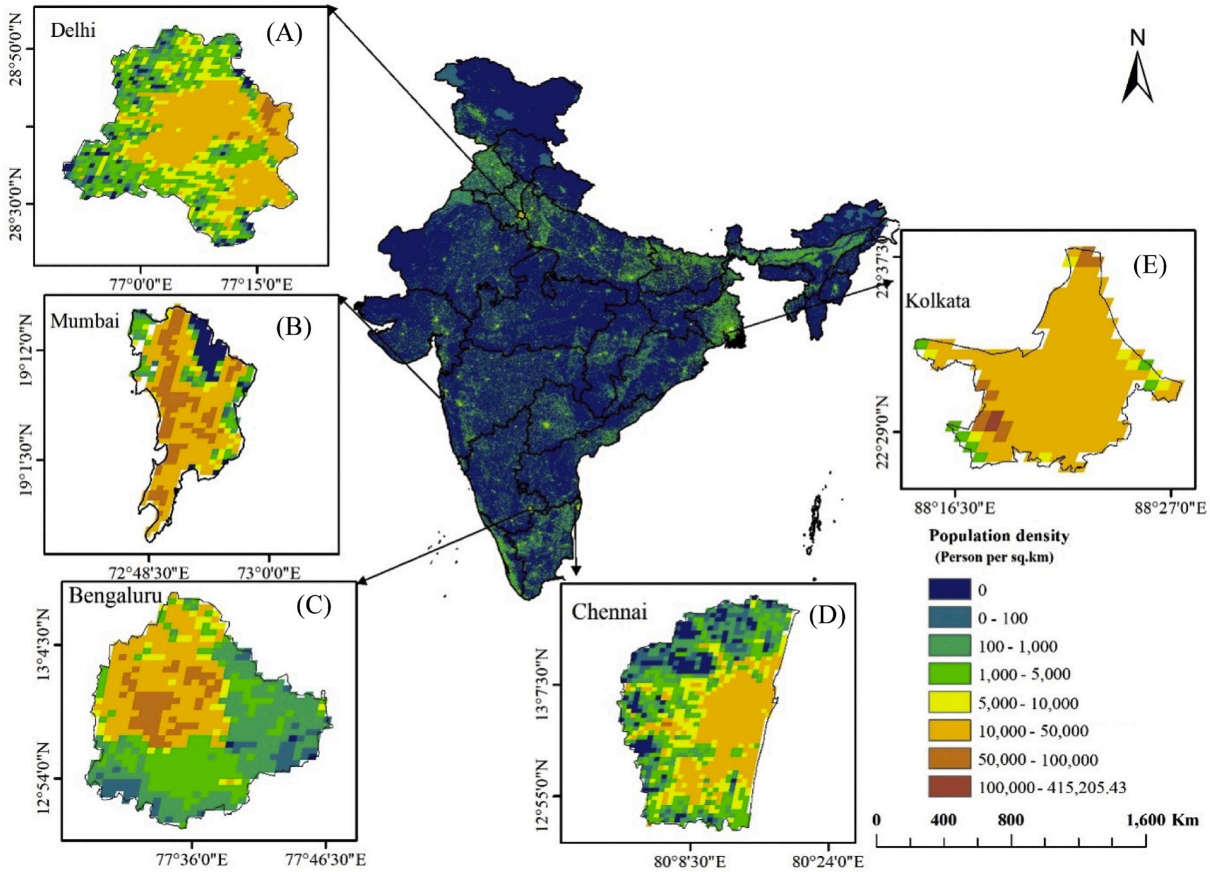

Fig. 14. Population density map of the megacities (A, B, C, D, E as given in Fig. 1) as in 2015.

Mumbai, Bengaluru, Chennai and Kolkata) shows that there has been a reduction in pollution levels in terms of major constituents of pollution (NO_2 and SO_2) in all the megacities and AOD in four megacities. The TROPOMI total column of NO_2 observations showed high correlation with ground-based observations and revealed TROPOMI's capability to produce the temporal variations in NO_2 concentrations. As a result, in addition to standard air quality measurements, satellite-based monitoring provides a temporal and spatial variation of NO_2 in the vicinity of major cities (Ialongo et al., 2020). In the global validation of TROPOMI total column density of CO with Copernicus *Atmosphere* Monitoring Service (CAMS), CO shows a good results of Pearson correlation coefficient of 0.97 (Borsdorff et al., 2018). NO_2 is a trace gas that present in both layers – the troposphere and the stratosphere. Tropospheric NO_2 is a pollutant that can affect the air quality and cause various impact on human health. The presence of tropospheric NO_2 mainly observed in polluted region that accounts for 50%-90% of the total column amount (Hains et al., 2010). The catalytic reactions of stratospheric NO_2 destroys the ozone layer and also converts hydrogen compounds into dormant pool type such as nitric acid (HNO_3) hence constitutes one of the significant aerosol sources (Seinfeld and Pandis, 2016; Cersosimo et al., 2020). In present study we used the total column of NO_2 to analys the results in both, the troposheric and stratospheric layers. Sentinel data were used by Siddiqui et al. (2020) to examine the NO_2 levels during the lockdown in different cities of India. They observed a considerable decrease in NO_2 levels (70% in Bengaluru, 57% in Mumbai, 34% in Kolkata and 33% in Chennai). The variations in NO_2 concentrations during the lockdown support the sensitivity of column to changes in local emissions. Another study by Biswal et al. (2020) examined tropospheric NO_2 concentrations during the lockdown period and their findings show 12.1% reduction over India. Improvement of air quality, more specifically reduction of AOD, can be linked to a positive impact on controlling the spread of the virus because of less binding particles available. Another benefit to mention is the improvement of respiratory health, which can boost the capacity to fight against the virus. Extreme high levels of mortality due to COVID-19 have been linked to atmospheric pollution as a co-factor (Conticini et al., 2020). Isaifan (2020) also attributed COVID-19 death cases to air pollutants (NO_2, O_3 and particulates) and pointed out that the COVID-19 led lockdown might have saved more lives by improving air quality that limiting the spread of the virus. Mumbai was known to indolently follow the lockdown in the initial phase; this has been reflected in less improvement of ambient air pollution as well as higher number of COVID-19 positive reported cases. Station-level data that are used to calculate air quality index for the five cities show that improvement of ambient air was observed in all the megacities, but only Kolkata and Bengaluru have been able to achieve "Good" air quality standard by fifth week of the lockdown (Goswami et al., 2020). Mumbai has also witnessed a higher rate of mortality due to COVID-19 (>5% of infected population) as compared to other four megacities. Particulate matter and NO_2 are known to have many

Table 3
Percentage change in mean measurementsof the pollutants from April 2019 to April 2020 in five megacities.

CITY	Delhi		Mumbai		Bengaluru		Chennai		Kolkata	
YEAR	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
NO_2										
MEAN measurements (mol/m2)	0.0001596	0.0000919	0.0001116	0.0000726	0.0001201	0.0000703	0.0000817	0.0000604	0.0001196	0.0001057
% change		42.42		34.95		41.47		26.07		11.62
SO_2										
MEAN measurements(mol/m2)	0.000277	0.0001605	0.0001441	0.000131	0.0000083	0.0000036	0.0001016	0.0000191	0.0002844	0.0002547
% change		42.06		9.09		56.63		81.20		10.44
CO										
MEAN measurements(mol/m2)	0.0427	0.0392	0.04159	0.0413	0.0426	0.0405	0.0412	0.042	0.0503	0.05117
% change		8.20		0.70		4.93		−1.94		−1.73
AOD										
MEAN	0.502	0.409	0.453.56	0.444	0.558	0.739	0.626	0.51	0.778	0.759
% change		18.60		2.00		−32.49		18.48		2.90

Table 4
Correlation between NO_2 and population density of Indian megacities.

Megacities	Coefficient of determination (R^2)		Coefficient of Correlation(R)	
	2019 (BAU)	2020(Lockdown)	2019 (BAU)	2020(Lockdown)
Delhi	0.58	0.54	0.76	0.73
Mumbai	0.50	0.47	0.70	0.68
Bengaluru	0.62	0.37	0.79	0.61
Chennai	0.51	0.39	0.71	0.62
Kolkata	0.52	0.03	0.72	0.19

hazardous health effects for example 16–23 times more as compared to SO_2 (Pandey et al., 2005). SO_2 is responsible for adverse health effects related to lung function and respiratory symptoms (Iwasawa et al., 2009). Improvement in SO_2 levels has been noticed as significant where levels have attained negative values in four of the megacities, except Kolkata. The negative value in vertical column concentrations of SO_2 is considered as clean or low SO_2 emission regions. This is being explained in the description of Sentinel-5 Precursor. Such low concentrations and fluctuations observed in this study cannot be attributed completely to the lockdown; concentrations are also largely influenced by atmospheric pressure, wind and other meteorological parameters (Unal et al., 2000).

NO_2 is the most significant constituent of urban air pollution, and the major portion of NO_2 is released from combustion of fossil fuels such as coal, oil and gas. Higher NO_2 concentration is directly associated with greater level of vehicular activity and higher level of urbanization (Rodriguez et al., 2016; Zhan et al., 2018; Forster et al., 2020). NO_2 concentration is positively correlated to the level of urbanization (Zhan et al., 2018). Road density per unit population, road network, population density and NDVI (Vegetation Index) are considered as major determinants of urban NO_2 pollution (Novotny et al., 2011; Zhan et al., 2018; Ryu et al., 2019) where the first is the major source and the second is an absorbent of the pollutant. In the case of Kolkata, the almost negligible correlation between population density and NO_2 concentration may be contributed by other factors such as biomass burning or soil emissions. Population density is positively correlated with road density (Ji et al., 2014). It is indicative in Kolkata that pollution sources other than vehicular emission of NO_2 might act as a determinant of concentrations that are not linked to the level of urbanization. The decreasing value of correlation coefficients in all the cities during the lockdown period as compared to the same month of the previous year indicates the reduction of pollution in higher population density areas. NO_2 has a strong correlation with industrial land use followed by residential land use (Lamsal et al., 2015). The cities with higher GDP (Mumbai followed by Delhi) have experienced the highest fall in maximum concentration values for NO_2 during the month of lockdown. The correlation between population density and pollution concentration was observed low during lockdown period as compared to business-as-usual scenario (Biswal et al., 2020). It is a consequent of larger reduction in NO_2 levels in densely populated areas. Population density is closely related minor road traffics and residential road traffics (Singh et al., 2018) which results in a better correlation between NO_2 and population density during traffic movement in normal days. A near zero vehicular movement during lockdown brought the NO_2 levels down leaving ambient NO_2 mostly emitted from non-vehicular sources. Other major sources of NO_2 (such as thermal power plants, scattered industrial establishments) are not associated with population density; hence a weaker correlation with NO_2 during the lockdown was observed.

Outdoor CO doesn't have a direct health hazard as it hardly goes beyond permissible limits to be inhaled by humans which can enter the bloodstream and cause severe damage. However, CO has a significant role in aggravating air pollution by reacting with other pollutants in various ways such as formation of smog, methane, ozone, and so on. The results of this study show a decline in the maximum concentration of column CO in three of the five cities, leaving Kolkata and Bengaluru with increasing areas of maximum concentration. A previous study found that lateral in-flow and anthropogenic sources contribute to both boundary layer and free tropospheric CO concentration. CO has a mean tropospheric lifetime of 2 months (Yashiro et al., 2009), which makes the results non-relatable to the impacts of lockdown. The distribution and concentration of CO in ambience are controlled by a wide range of physical and chemical factors such as emission sources, photochemistry, transport, deposition, and so on (Kumar et al., 2013a). Detailed source attribution study along with other determinants can help to understand the spatial and temporal fluctuations in CO concentrations. Pathakoti et al. (2020) have also studied the change in air quality due to lockdown and observed mixed variations in CO emissions over Indian region.

The improvements in air quality vary from city to city. According to the Central Pollution Control Board (CPCB), semi-urban and rural regions did not see improvements on a similar scale. Cities like Delhi show reduction in air quality in the early and middle phase of lockdown, whereas Mumbai seems to be improving its air quality in the middle phase of lockdown during April–May. According to a study (Kumar et al., 2020), aerosol loading decreased by 29% in Chennai, 11% in Delhi, 4% in Hyderabad and 1% in Mumbai. AOD has been taken as an indicator for fine particulate matter ($PM_{2.5}$) in air. Except for Delhi and Kolkata, the other three cities have shown a decrease in maximum values of AOD during April 2020 as compared to all the other three studied months; however, the mean AOD showed an increase in AOD pollution except Bengaluru during the lockdown. Interpretation of AOD values suggests that a value of 0.01 implies an extremely clean environment, whereas a value of 0.4 indicates a hazy condition (NOAA, https://www.noaa.gov). Our study results reveal that aerosol levels in all cities, irrespective of lockdown, have higher values than 0.4 (ranges from 0.4 to 0.9), potentially resulting in extremely hazy conditions. Ground-based monitoring has shown a significant decrease in $PM_{2.5}$ across the monitoring stations of Bengaluru both in the first week of lockdown and the fifth week of lockdown as compared to pre-lockdown period (Goswami et al., 2020). A few covariate factors, which mostly include relative humidity and height of boundary layer, may invert the relation between fine particulate matter and AOD. Along with emission sources, topographic conditions and atmospheric processes and their interactions vary across regions, and these factors can have a substantial effect on the relationship between $PM_{2.5}$ and AOD (Chu et al., 2016). Lower rate of decrease in pollutants in Kolkata as compared to other cities may be influenced by any of those factors. Contribution of pollution sources such as residential clusters and thermal power plants (Ghose et al., 2004; Gupta et al., 2008), which are not much affected by the lockdown, may have a significant share. The dissimilarity in terms of pollution reduction in Kolkata may be attributed to some relaxations in lockdown instructed by State Government (Outlook, 9th April, 2020).

The major sources of pollutants in Delhi are emissions from transportation, building construction, dust, industries, roadside biomass burning and thermal power plants (Kumar et al., 2013b; Nagpure et al., 2015). In Bengaluru, major sources of the pollutants are transport and construction, unplanned growth of city, construction of flyover and traffic. In Chennai, the major sources are industry, chemical and petrochemical industry, manufacturing, thermal power plants (Guttikunda et al., 2019). Similarly in Mumbai, the major sources are traffic and industries. It was apparent that most of those sources of pollution were affected during the lockdown, resulting in rapid decrease in levels of pollutants in air. Historically, Delhi, Mumbai and Kolkata are more polluted than the other two megacities. Among the megacities of the world, Delhi, Kolkata and Mumbai were ranked 7th, 9th and 11th, respectively, according to the ambient air quality measurements and Multi-Pollutant Index (MPI) (Gurjar et al., 2008). With some more degradation, Delhi went down to 5th position in the world as the most polluted city (World Air Quality Report, 2019). These three cities have exhibited a higher mortality rate (2.98%–5.67%) than the other two megacities. Several studies have shown a positive correlation between concentrations of air pollutants and coronavirus-related fatality (BBC, 20th April, 2020; Isaifan, 2020; Ogen, 2020; Toppi et al., 2020; Wu et al., 2020; Yao et al., 2020). An extensive study in the USA states that long-term exposure to $PM_{2.5}$ is likely to lead to a higher rate of mortality, where pollution also contributes to a compromised immune system (Wu et al., 2020). Particulate pollution has a potential role in spreading the virus as COVID-19 as particulates can act as a binding medium by adsorbing or absorbing the virus (Toppi et al., 2020). However, previous studies on respiratory diseases and temperature established a negative correlation between the stated variables (Ye et al., 2016). Martelletti and Martelletti (2020) have mentioned that there is a connection of air pollutants (PM, $NO_2$and CO) with longevity and severity of the virus, and they demand detailed epidemiological studies to validate such claims.

5. Conclusion

The research analysed atmospheric pollutants over the Indian megacities during the COVID-19 led lockdown. The intensity of reduction in concentrations of pollutants of COVID-19 is not consistent across cities. The variations in change in each pollutant (NO_2, SO_2 and AOD) studied can certainly be associated with the lockdown. One constraint observed in SO_2 data is that due to noise in the data, negative vertical column values are observed over clean region or for low SO_2 emissions. The analysis based on remote sensing data gives a fair status of surface air pollution as a good correlation between column number density of pollutants and ground observations has been reported by several previous research studies. Nevertheless, more research on coherence of both the data is required to establish the conversion of remotely estimated measurements to surface concentrations. However, detailed source attribution for each parameter can further aid in strategizing pollution control measures in respective cities. Station-based data coupled with satellite data should be modelled considering local emission sources, meteorological, boundary layer and topographic parameters. A robust and authentic emission inventory can help in environmental planning for achieving source control and related regulations. Further epidemiological studies with respect to long-term exposure to particular pollutants, and severity of the symptoms and lethality should be conducted. Such studies will help in understanding the health burden of air pollution and consequent economic impacts. The experience of better air quality during the lockdown can definitely open up the scope of further research to identify pathways for emission reduction, formulate actions at institutional level and to mould individual behaviour for environment-friendly practices.

Author statement

SN, MG conceptualized the idea and developed detailed framework for the study. MG, SN designed and implemented the data collection, analysis with SP, YDIK. All authors contributed in writing and contributed during the revision process of the manuscript.

Declaration of Competing Interest

None.

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