



Interpreting the COVID effect on atmospheric constituents over the Indian region during the lockdown: chemistry, meteorology, and seasonality

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Received: 10 June 2021 / Accepted: 5 March 2022 / Published online: 14 March 2022
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Abstract Most of the published articles which document changes in atmospheric compositions during the various lockdown and unlock phases of COVID-19 pandemic have made a direct comparison to a reference point (which may be 1 year apart) for attribution of the COVID-mediated lockdown impact on atmospheric composition. In the present study, we offer a better attribution of the lockdown impacts by also considering the effect of meteorology and seasonality. We decrease the temporal distance between the impacted and reference points by considering the difference of adjacent periods first and then comparing the impacted point to the mean of several

reference points in the previous years. Additionally, we conduct a multi-station analysis to get a holistic effect of the different climatic and emission regimes. In several places in eastern and coastal India, the seasonally induced changes already pointed to a decrease in PM concentrations based on the previous year data; hence, the actual decrease due to lockdown would be much less than that observed just on the basis of difference of concentrations between subsequent periods. In contrast, northern Indian stations would normally show an increase in PM concentration at the time of the year when lockdown was effected; hence, actual lockdown-induced change would be in surplus of the observed change. The impact of wind-borne transport of pollutants to the study sites dominates over the dilution effects. Box model simulations point to a VOC-sensitive composition.

Highlights

- Observed lockdown effects in India in previous studies are spurious.
- Actual lockdown effect in pollutant concentration computed considering meteorology.
- Pan-India study of lockdown impact in wide environmental and emission regimes.
- Decrease in PM levels is already observed in lead up to lockdown.
- O₃ simulations point to a VOC-sensitive regime.
- Impact of atmospheric dilution negligible is compared to atmospheric transport.

Keywords Meteorology · Seasonal change · Emissions · Lockdown effect · PM · Trace gases

Introduction

The year 2020 will forever be etched in the annals of time in memory of our (human beings) fight against coronavirus, and it came with one of the most impactful changes in all our lives — the lockdown. As the novel coronavirus began settling itself in India and the number of positive cases reached nearly 500, a nationwide lockdown was announced by the honorable

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prime minister of India on 24 March 2020. In his order for the phase I of the Lockdown of 21 days, the prime minister mandated a restriction on all non-essential travel and services. The phase 2 of the lockdown was initiated from 14 April 2020, extending the ongoing nationwide lockdown until 3 May. In this second phase, all commercial and non-commercial activities were paused. After nearly 5 weeks of total nationwide lockdown, some relief came in phase 3 of the lockdown during 4–17 May 2020, characterized by partial reopening. Phase 4 of the nationwide lockdown was announced on 17 May 2020 and extended until 31 May. The country was split into 3 zones: red (high coronavirus cases and a high doubling rate), orange (comparatively fewer cases than red zone), and green (without any cases during the past 21 days). Normal movement was permitted in green zones with buses limited to 50% capacity. Orange zones would allow only private and hired vehicles but no public transportation. Complete lockdown was maintained in red zones which were further divided into containment and buffer zones. The fourth phase instituted a slow reopening with several relaxations. The curb on anthropogenic activities during the lockdown including restrictions on movement of people and vehicles had its repercussions on the concentrations of air pollutants. In addition, several industries were shut down, vehicles on the road disappeared, and power plants were operating with reduced load, which resulted in a significant decrease in the concentration of atmospheric pollutants as seen in many parts of India. As rising levels of air pollutants have been a major problem in India with repercussions on human health (Lelieveld et al., 2015) and economy (Lal et al., 2017), understanding the lockdown-mediated change in atmospheric pollutant concentrations would be helpful to frame policy decisions.

Emission sources

Emissions of pollutants comprising particulate matter (aerosols) and gases (NO_2 and CO) play a vital role in the environment and human health (Xu et al., 2020). The most commonly identified sources of primary air pollutants comprising particulate matter (aerosols) and gases (NO_2 and CO) are vehicular emissions, manufacturing, power generation, manufacturing industries, construction

activities, road dust, waste burning and combustion of oil, coal, and cooking activities in the households. Figure 1 shows the source apportionment for $\text{PM}_{2.5}$ for 11 cities of India based on data from UrbanEmissions.info. UrbanEmissions.info was a program to build an emission inventory for the following pollutants (i) PM, (ii) SO_2 , (iii) NO_x , (iv) CO, (v) CO_2 , and (vi) NMVOCs (Guttikunda et al., 2019). The emission inventory was built at a spatial resolution of $1 \times 1 \text{ km}^2$ which included anthropogenic sources, large and small scale power generations, industries, domestic, open waste burning, and open fires and non-anthropogenic sources, such as sea salt, dust storms, biogenic, and lightning. While emissions from vehicles contribute the maximum to $\text{PM}_{2.5}$ in Guwahati (35%), Thiruvananthapuram (60%), Jaipur (38%), and Pune (35%), industrial emissions dominate the $\text{PM}_{2.5}$ sources in Nagpur (83%), Ahmedabad (63%), Kolkata (54%), Amritsar (32%), and Hyderabad (28%), while road dust is the major $\text{PM}_{2.5}$ contributor in Jodhpur (42%).

Guttikunda et al. (2014) observed that one of the major sources of PM_{10} is road dust, and it can account for up to 30–40% of the PM_{10} pollution in most cities. Figure 1 also shows the sources of PM_{10} in 11 cities of India based on data from UrbanEmissions.info. It can be seen that the major contribution to PM_{10} is road dust and construction activities. In Guwahati, Hyderabad, Thiruvananthapuram, Pune, and Jodhpur, road dust constitutes more than 60% in PM_{10} . In Kolkata, 37% of PM_{10} comes from road dust and 38% from industrial emissions. The two major sources of PM_{10} in Nagpur are industrial emissions and road dust. They contribute 72% and 16%, respectively. In Ahmedabad, the major sources of PM_{10} are road dust (45%) and industrial emissions (39%). In Delhi, the road dust and construction activities contribute 45% of the PM_{10} , followed by 17% from burning of waste (agricultural and domestic waste) and 14% from vehicular emissions (Guttikunda et al., 2014).

The restriction on transport sector during the lockdown in India, in addition to shutdown of factories and industries, induced a remarkable decrease in PM concentrations (Devara et al., 2020; Mahato et al., 2020; Mitra et al., 2020; Peshave & Peshave, 2020; Rahaman et al., 2021; Ramasamy et al., 2020; Sharma et al., 2020). In Delhi, 14% of PM_{10} is contributed

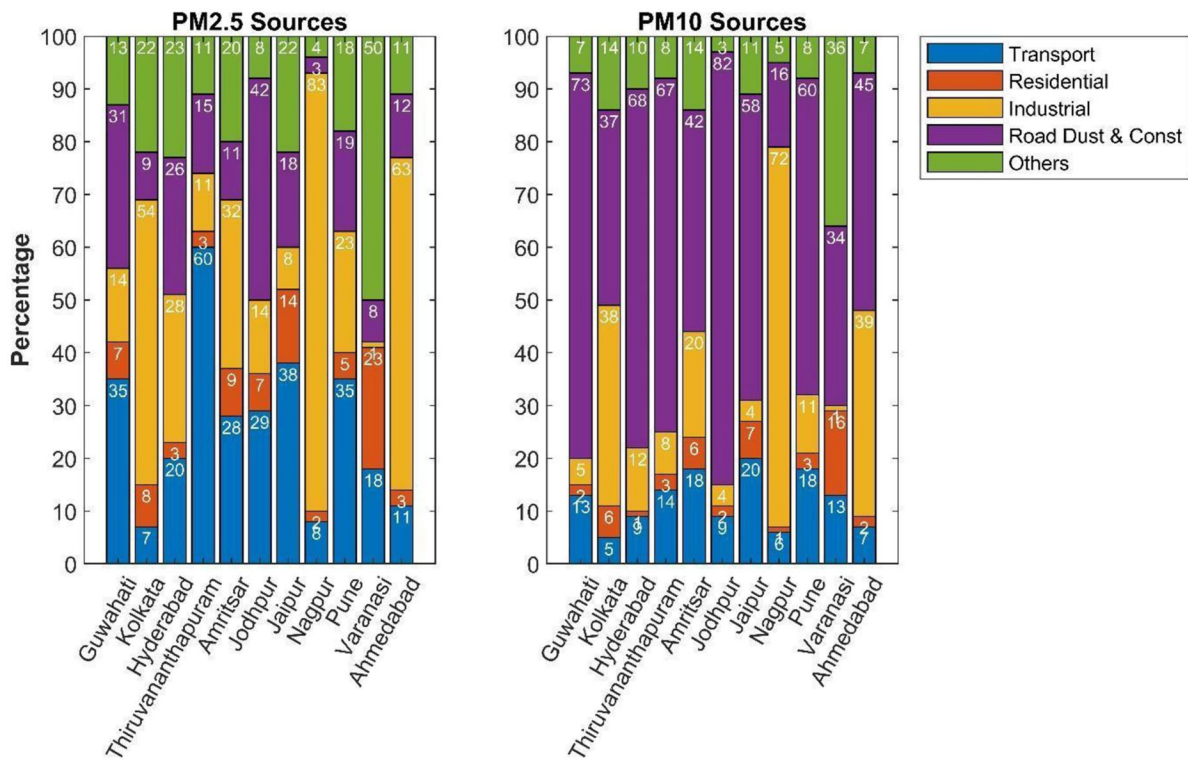


Fig. 1 Average percent contributions of major sources to PM_{2.5} pollution (UrbanEmissions.info)

by vehicles (Guttikunda et al., 2014), so then we can expect some decrease in the concentration of PM₁₀ during the lockdown just due to reduction in vehicular emissions neglecting effects of dilution, oxidation, and other seasonal/meteorological impacts. Further, the restriction on vehicular transport has an additional impact on road dust resuspension in addition to reduced tail-pipe emissions.

Similarly, 45% of total NO_x emissions in India is contributed by coal burning in thermal power plants (Garg et al., 2001). Road transport contributes another 32% of NO_x emissions (Garg et al., 2001). As thermal power plants were running at reduced capacities and road transport came to a total halt, a reduction in NO_x is envisaged. However, O₃ being a secondary pollutant, changes in O₃ would be much more difficult to unravel from direct observations, and the dependency on hydrocarbons, NO_x, and meteorological factors needs to be investigated. Coincidentally, xylenes were found the largest contributor to the O₃ formation followed by toluene in Delhi (Hoque et al., 2008).

Some observations pertaining to COVID-induced changes in atmospheric constituents

Pathakoti et al. (2020) studied the impact of nationwide lockdown on air pollution and observed that the aerosols/particulate matter over the country decreased by ~24% from the 5-year mean level with a marked reduction over the Indo-Gangetic plains (IGP) region. During the lockdown period, the world’s most polluted city, Ghaziabad, showed a reduction of 57% in PM₁₀ and 48% in PM_{2.5} compared to the average levels of 2019 (Kumari et al., 2020). Kumari et al. (2020) also observed reductions of 57% in PM_{2.5} and 58% in PM₁₀ in Patiala city.

Using the ratio of NO₂ and HCHO vertical column densities measured from MAX-DOAS in Mohali, it was found that the peak daytime O₃ production regime is sensitive to both NO_x and VOCs in winter but strongly sensitive to NO_x during summer (Kumar, Beirle, et al., 2020; Kumar, Pratap, et al., 2020). Chen et al. (2020) pointed out that O₃ production is less

sensitive to solar radiation in summer compared to winter. Reducing NO_x alone increases O_3 , such that a 50% reduction in NO_x emissions leads to a 10–50% increase in surface O_3 . In contrast, reducing VOC emissions can reduce O_3 efficiently, such that a 50% reduction in VOC emissions leads to a 60% reduction in ozone for Delhi (Chen et al., 2020). The sensitivity of atmospheric oxidants on NO_x levels was also elaborately studied during the Cyprus Photochemical Experiment (Mallik et al., 2018). Kumar (2020) found 37% reduction for NO_2 over India in comparison to the average value of 2017–2019. Jain et al. (2021) having studied the phase-wise variations in atmospheric constituents during the COVID-19 lockdown over a tropical rural site (Gadanki in southern India) point out that trace gases, viz., NO , NO_2 , CO , SO_2 , CO_2 , and CH_4 , whose emission sources are dominated by predominantly anthropogenic origin have shown a reduction of over 50% due to COVID lockdown-induced emission reductions.

While a plethora of publications point to the reductions in primary pollutants as a result of lockdown-mediated reduced emissions, we feel that comparison of direct year-to-year concentration change to estimate the lockdown impact is inappropriate. Therefore, we took up the following study analyzing data over twenty-four stations covering different parts of India (Fig. 2) with the following objectives:

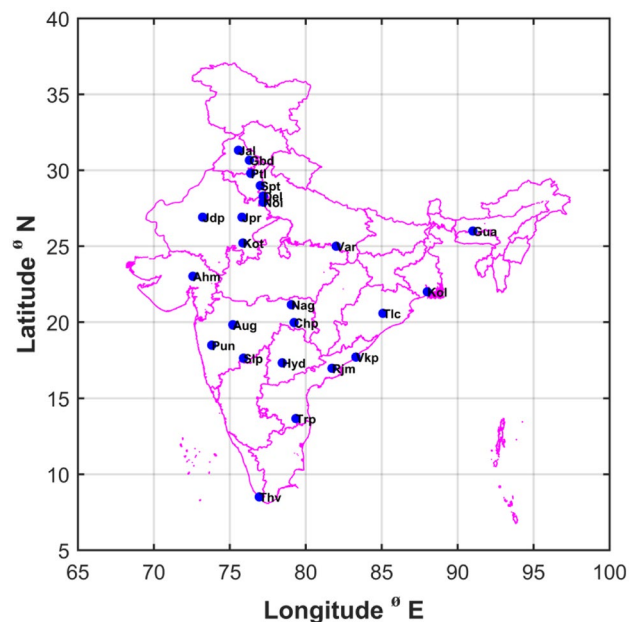
- Take up a more holistic approach to estimate the impact of lockdown over the Indian region by analyzing data from different environmental regions of India.
- Use a multi-species approach to estimate the lockdown impact as different species have different source contributions.
- Estimate the expected change over each station for each species and compare it with the observed change to get the actual/effective change in pollutant concentrations due to lockdown effect.

Methodology

The air quality data for the selected cities have been taken from the Central Pollution Control Board (CPCB) of India. The CPCB monitors the ambient air quality across 233 stations spanning the entire Indian region with the help of the State Pollution Control Boards and other agencies under the National Air Quality Monitoring Programme (NAMP) (<http://cpcb.nic.in/air.php>). The measurements are done for six criteria for air pollutants (CPCB, 2020):

- Particular matter (PM) of aerodynamic diameter less than $2.5 \mu\text{m}$ ($\text{PM}_{2.5}$)

Fig. 2 Map of study locations selected for the present analysis. The details of the stations are provided in Table 1



- (ii) Particular matter of aerodynamic diameter less than 10 μm (PM_{10})
- (iii) Sulfur dioxide (SO_2)
- (iv) Nitrogen dioxide (NO_2)
- (v) Ozone (O_3)
- (vi) Carbon monoxide (CO)

The measurement techniques for O_3 , CO , NO_x , SO_2 , $\text{PM}_{2.5}$, and PM_{10} are available from the technical specifications for continuous ambient air quality monitoring (CAAQM) (CPCB, 2019, <https://cpcb.nic.in/>). The ultraviolet photometric O_3 gas analyzers work on the Beer Lambert's principle on absorption of radiation at 254.7 nm by atmospheric O_3 . The detection limit of the instrument is 1 ppb with a response time of 30 s or less. The CO instruments are based on gas filter correlation technology and operate on the principle of infrared absorption at 4.67 μm vibration-rotation band of CO (Nedelec et al., 2003). It has a detection limit of 100 ppbv at a 60 s response time. The zero noise of the instrument is 20 ppbv root-mean-square (RMS) at 30 s averaging time. The NO_x instruments are based on the detection of chemiluminescence produced by the oxidation of nitric oxide (NO) by O_3 molecules, which peak at 630 nm radiation (Navas et al., 1997). The method is specific to NO only. NO_2 is measured by converting it into NO using a molybdenum convertor and then measuring total NO_x as NO . Unfortunately, the reduction of NO_2 to NO is not specific for NO_2 , and other nitrogen species are also reduced to NO and act as interferences in the NO_2 measurements. The detection limits of these instruments are around 1 ppb at a response time of 120 s or less. The PM_{10} measurements are based on the principle of β -ray attenuation. The particulate matter in ambient air is sampled through the instrument at a flow rate of 16 l/min and collected on fiberglass filter tape. Comparison of measurements of β -ray radiation by scintillation/G.M. counter before and after sampling gives a measure of the amount of PM_{10} . The $\text{PM}_{2.5}$ measurements are similar to PM_{10} , but the particle size cutoff is in the range of 0–2.5 μm .

For this analysis, twenty-four stations are selected representing the different emission and climatic regimes across India. Initially, thirty-two stations were selected to derive a pan-Indian representativeness. However, based on data availability, the final number of stations is reduced to twenty-four such that at least five criteria pollutant data are available for the lockdown period and the corresponding time in previous year. The study locations

span north, east, west, and south India including the IGP and north-east. Together, the stations represent most of the major emission sources of PM and NO_2 across India. The stations also represent various climatic regimes ranging from the arid regions (e.g., Jodhpur) to tropical wet (Kolkata), from hilly (Aurangabad) to coastal (Visakhapatnam). The details of these stations are provided in Table 1, and henceforth, the stations are represented by their 3-letter station codes only.

In order to remove the outliers, the raw data were filtered station-wise and species-wise to remove values above 95 percentile and below 5 percentiles at every 4-month interval. Since we are concerned with the average variation of the pollutants, the kind of filtering helps to remove the bias due to extreme events (meteorological or chemical) and errors related to instruments, sampling, and human effects. Additionally, data was also checked manually for inconsistencies. The weekly/fortnightly means before and after lockdown of 2020 were compared to the corresponding difference of the average of the data for the year 2015 to 2019 for this analysis. The data availability is shown in Fig. 3. A robust regression analysis was performed to identify the dependence of $\text{PM}_{2.5}$ and PM_{10} on the planetary boundary layer (PBL) height for each of the stations. Hourly resolution PBL data at each measurement stations were taken from linear interpolation of 0.25° ERA5 reanalysis dataset (Hersbach et al., 2020). The PBL in ERA5 is estimated using the bulk Richardson number following the methods proposed by Siedel et al. (2012). The dependence was tested for different levels of significance using a two-tailed Student's t test.

O₃ simulations using Framework for 0-D Atmospheric Modeling (FOAM) box model

A zero-dimensional atmospheric box model FOAM version 4.1 (Wolfe et al., 2016) was set up for calculating the O_3 concentrations as a result of atmospheric photochemical processes for an example site over Ahmedabad. Ahmedabad was selected because of availability of VOC data. The model employs Master Chemical Mechanism (MCM) 3.3.1 chemistry (Jenkin et al., 2015). The MCM setup included a total of 1363 species and 4205 chemical reactions (Kumar et al., 2018). The rate constants used in the model are taken from the reviewed rate constants published by Atkinson et al. (2006). The model was constrained with hourly averaged concentrations of NO , NO_2 , and

Table 1 List of stations selected for this study and site characteristics. CEPI represents the comprehensive environmental pollution index (<https://cpcb.nic.in/comprehensive-environmental-pollution-index-cepi/>)

Sl No	Station name	State	Latitude (°N) longitude (°E) elevation	Climate type	Data availability from (in table) to October 2020	Geographical characteristics/major industries in the region
1	Visakhapatnam (VKP)	Andhra Pradesh	17.72, 83.30/45 m	Tropical wet & dry	Jan 2017	East Coast of India Steel, fertilizers, petrochemicals. Navy weapon, (CEPI 70.82)
2	Rajamahendravaram (Rjm)	Andhra Pradesh	16.98, 81.73/14 m	Tropical hot & humid	Sep 2017	River Godavari Textile, paper, gas
3	Tirupati (Trp)	Andhra Pradesh	13.67, 79.35/154 m	Tropical wet & dry	Jun 2017	Biosphere reserve, Sri Vivekananda National Park, Low anthropogenic pollution
4	Guwahati (Gua)	Assam	26.18, 91.74/56 m	Tropical Monsoon climate	Feb 2019	Near River Brahmaputra
5	Sector 125 Noida (Noi)	Delhi	28, 77/200 m	Humid subtropical with semi-arid	Jul 2017	PM10 average 3 times than normal, PM 2.5 Avg 10 times than normal (CEPI 78.9)
6	IGI Airport Delhi (Del)	Delhi	28.6, 77.2/217 m	Cwa & BSh	Apr 2015	Capital of India, Fossil fuel combustion
7	Ahmedabad (Ahm)	Gujarat	23.02, 72.57/53 m	Semi-arid, extreme dry	Jan 2015	Textile, steel, marble slabs (CEPI 75.28)
8	Sonipat (Spt)	Haryana	28.99, 77.01/224 m	Arid to semi-arid average rainfall- 355 mm	Dec 2018	Stubble burning, Khaddar sandy region
9	Thiruvananthapuram (Thv)	Kerala	8.51, 76.94/10 m	Tropical savanna & monsoon climate	Jun 2017	Rubber, leather, polymer, pharma
10	Aurangabad (Aug)	Maharashtra	19.838, 75.24/568 m	Hilly upland terrain in Deccan traps, semi-arid	Sep 2017	Pharmaceutical factory (CEPI 77.44)
11	Chandrapur (Chp)	Maharashtra	19.97, 79.23/188 m	Hot & dry	Aug 2016	Tadoba tiger reserve(national park), roofing tiles, Coal (CEPI 83.88)
12	Nagpur (Nag)	Maharashtra	21.15, 79.05/310 m	Tropical savannah climate with dry prevailing	Mar 2016	Western coalfield limited, mines
13	Pune (Pun)	Maharashtra	18.50, 73.81/560 m	Hot semi-arid	Jun 2015	Leeward side of sahyadri mountain(WG) range, Fiberglass Metropolitan area
14	Solapur (Slp)	Maharashtra	17.65, 75.90/457 m	Arid & semi-arid	Mar 2015	Most polluted city in Maharashtra
15	Talcher (Tlc)	Odisha	20.58, 85.08/150 m	Tropical wet & dry	Dec 2017	Coal fields Most polluted city of Odisha (CEPI 82.09)
16	Gobindgarh (Gbd)	Punjab	30.66, 76.29/300 m	Semi-arid	Mar 2017	Steel city (CO,SOx,NOx,PM2.5) (CEPI 75.08)
17	Jalandhar (Jal)	Punjab	31.32, 75.57/228 m	Humid subtropical climate	Feb 2018	Soil dust, wooden furniture, rubber goods

Table 1 (continued)

<i>Sl No</i>	<i>Station name</i>	<i>State</i>	<i>Latitude (°N) longitude (°E) elevation</i>	<i>Climate type</i>	<i>Data availability from (in table) to October 2020</i>	<i>Geographical characteristics/major industries in the region</i>
18	Patiala (Ptl)	Punjab	30.33, 76.38/351 m	Steppe climate	Feb 2018	Biomass burning, agricultural implements
19	Jaipur (Jpr)	Rajasthan	26.91, 75.80/431 m	Mist	Jun 2017	Increase vehicles, urbanization
20	Jodhpur (Jdp)	Rajasthan	26.91, 75.88/231 m	Dry hot semi-arid	Jan 2016	Thar desert
21	Kota (Kot)	Rajasthan	25.21, 75.86/271 m	Semi-arid	Oct 2017	Volcanic upland
22	Hyderabad (Hyd)	Telangana	17.34, 78.45/542 m	Tropical wet and dry	Sep 2015	Zoological park
23	Varanasi (Var)	Uttar Pradesh	25.35, 82.90/81 m	Humid subtropical	Jan 2015	Dust from construction work
24	Kolkata(Kol)	West Bengal	22.54, 88.34/9.14 m	Tropical wet and dry	Jul 2016	High SPM, vehicular emission

CO from CPCB database and temperature, pressure, and relative humidity from wunderground.com for Ahmedabad site for 24 March 2020 as prelockdown and 31 March 2020 as lockdown period. Individual days were taken for comparing the simulation instead of the weekly mean because the average precursor ratios may not represent the true precursor composition for observed O₃. Therefore, days with relatively high O₃ were selected for the simulation. It should be noted that our purpose with these simulations is not to predict the observed O₃ concentrations but to get an idea of the VOC-NO_x regimes operating during the period. The VOCs values used in the simulation are taken from published literature over Ahmedabad listed in Table 4. Hydrogen (H₂) mixing ratios are held constant at 550 ppb, respectively. The model calculated concentrations of secondary species at the end of each hour were used as the initial concentration of the model run for the second hour. The simulations are performed in steady-state conditions with a spin-up period of 3 days.

Results

Meteorology during lockdown/unlock periods

A major objective of this paper is to decouple the emission changes during lockdown from meteorological

impacts on atmospheric pollutant concentrations. Crilley et al. (2021) found that though the lockdown has brought down the local emission sources, the chemical processes in the atmosphere and weather events independently contribute to the observed changes in the pollutant levels.

During winter in northern India, the winds are north-easterly and westerly with thick fog, low wind speeds, and low boundary layer height which can degrade air quality further (Tiwari et al., 2018). The year 2020 was the eighth warmest year in India since 1901. The annual mean land surface air temperature averaged over the country was +0.29 °C above normal of the average of 1981–2010. However, this value was very much lower than the highest warning year over India during 2016 (+0.71 °C anomaly from normal).The monsoon and post-monsoon seasons of 2020 showed mean temperature anomalies +0.43 °C and +0.53 °C.

One significant meteorological feature of 2020 was the higher numbers of western disturbances that continued even in the summer season. Due to the consecutive arrival of western disturbances in northern India, the ventilation and dispersion of pollutants can result in a better air quality. The wind system showed a major change in northern India and IGP during the first half of March bringing in the transition from winter to pre-monsoon. Also, Bhawar et al. (2021) observed that the transport of dust from West Asia was lower compared to the previous years during the

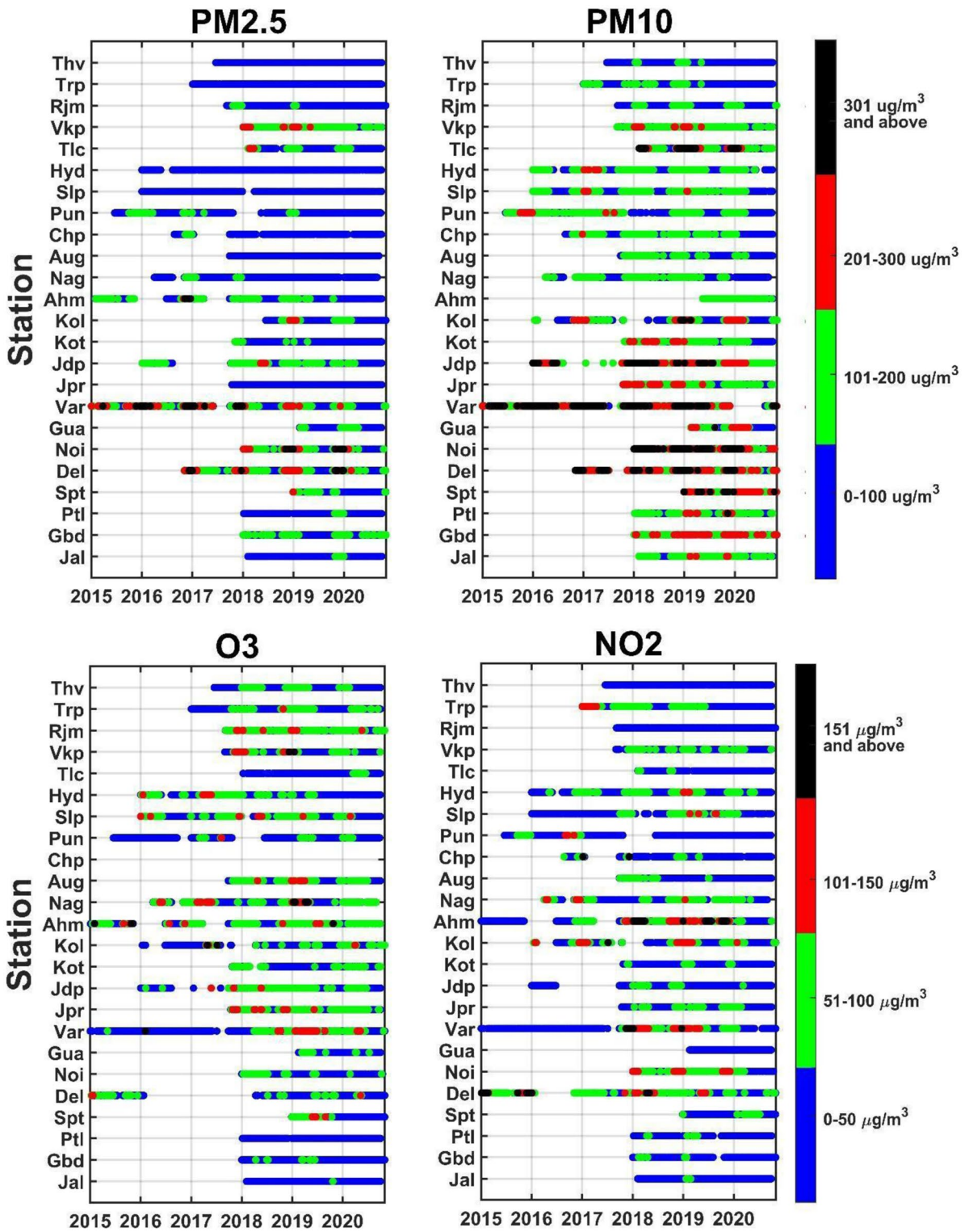


Fig. 3 Daily data availability for the study locations from 2015 to 2020

lockdown period, in spring of 2020. This led to the reduction of dust aerosols over the Indian region.

The cyclone Amphan was the first pre-monsoon (20 May) super cyclone of the century (Kumar et al., 2021). The year 2020 was also the third to record the highest precipitation during the last 30 years. The country received 109% rainfall of long period average (LPA) with June (118%), August (127%), and September (104%) witnessing above normal rainfall. Weather conditions and pollutant levels have a strong linkage that may obscure the variation in emission levels over different cities (Radaideh, 2017). Meteorological variability was found to account for 40–70% of ozone variability and 20–50% of particulate matter variability in Southwestern USA (Wise & Comrie, 2005).

Ventilation coefficient is another parameter used as an indicator of atmospheric dispersive capacity. It is the product of mixing layer height multiplied by average wind speed. It is an important factor for the determination of pollution potential over a region (Chan et al., 2012). If $VC < 6000 \text{ m}^2 \text{ s}^{-1}$, the air pollution potential is considered to be high. In winter, the VC values are lower due to stable atmospheric conditions and lower wind speeds ranging 2–3 m/s. Similarly, VC is higher in summer due to unstable atmospheric conditions and increasing the wind speed. The coinciding phases of lockdown implementation and transition from winter to summer, i.e., lower to higher VC, can also have effects on the concentration of atmospheric constituents and are analyzed here.

Estimating the role of emissions from weekly changes in atmospheric constituents

Weekly changes in surface concentrations of particulate matter (PM_{2.5} and PM₁₀ average 2015–2019 vs. average 2020)

Figure 4a, b show the weekly change (average 2015–2019 vs average 2020) in the concentration of PM_{2.5} and PM₁₀, respectively, over the study locations. The plots with red show the average of the data from the year 2015 to 2019, and the plots with blue represent the data of the year 2020. The vertical line in black color represents the start of the lockdown period, i.e., the 25 March 2020, and the vertical line with blue color represents the beginning of unlock phase, i.e., 1 June 2020. The horizontal lines represent the permissible levels of pollutants based on the National

Ambient Air Quality Standards given by CPCB (24 h averages of $60 \mu\text{g}^{-3}$ and $100 \mu\text{g}^{-3}$ for PM_{2.5} and PM₁₀, respectively, while these are $80 \mu\text{g}^{-3}$ (24 h) and $100 \mu\text{g}^{-3}$ (8 h) for NO₂ and O₃, respectively).

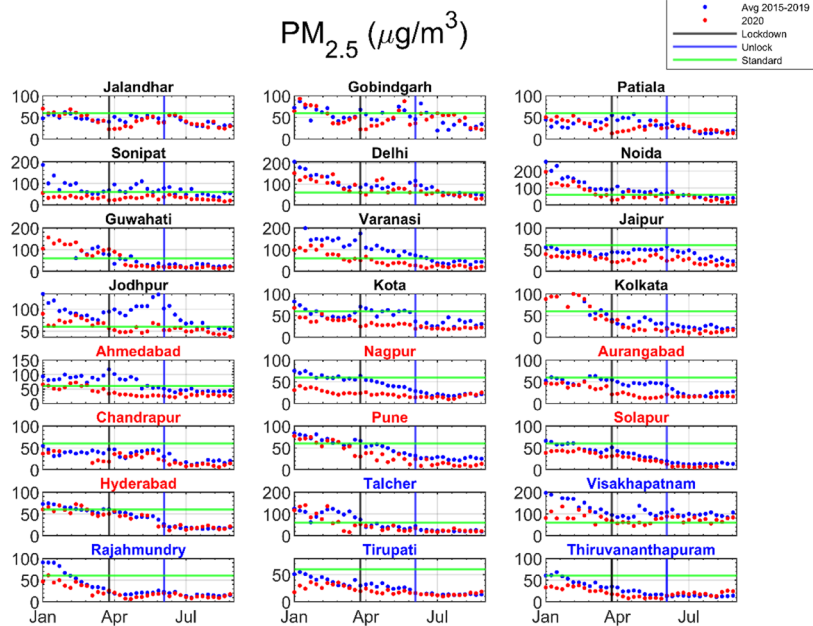
A significant decrease in PM_{2.5} concentrations during lockdown compared to the previous period is observed over in northern India, i.e., Jalandhar (47%), Gobindgarh (53%), Noida (59%), Patiala and Sonapat (67%), and Delhi (33%). Mahato et al. (2020) have also estimated a similar reduction of PM_{2.5}, viz., 39%, in Delhi during the said time period. Chikara and Kumar (2020) also observed an appreciable decrease in the concentration of various pollutants (PM_{2.5}, PM₁₀) in Delhi, Mumbai, and Kolkata due to lockdown (Table 2).

PM_{2.5} concentrations have also decreased in western India; the decrease recorded just in comparison to similar period in previous year is as follows: Jaipur (49%), Jodhpur (44%), Kota (56%), Ahmedabad (65%), Pune (37%), Aurangabad (52%), and Solapur (29%). Navinya et al. (2020) also mention a decline in PM_{2.5} of about 68% over Ahmedabad. Similarly, a large decrease in PM_{2.5} of about 58% is observed over Nagpur in Central India. However, other stations in this region do not exhibit such a large decline, viz., Chandrapur (17%) and Hyderabad (9%).

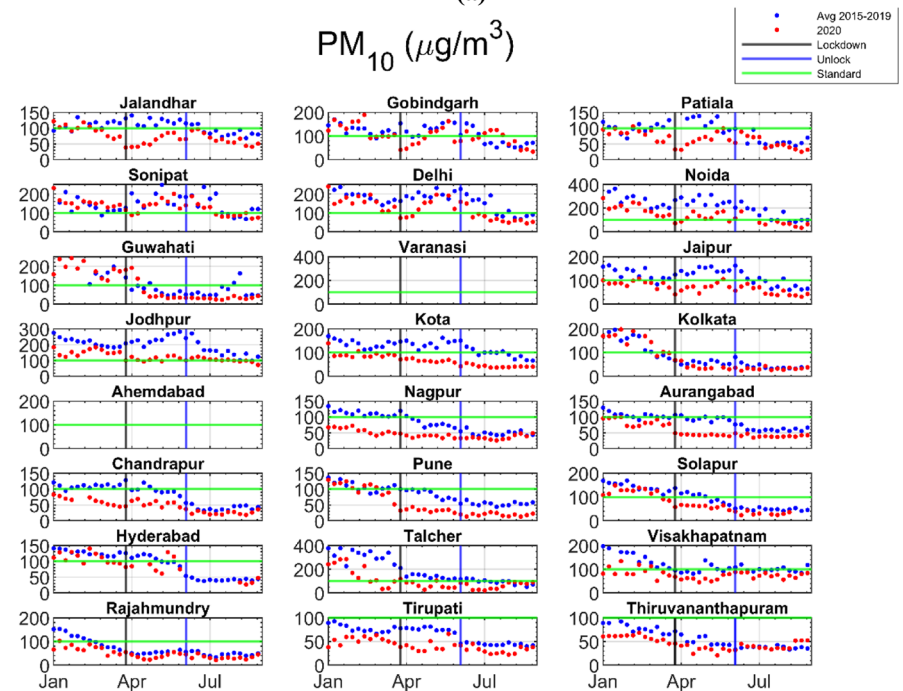
Mixed signals are observed in IGP with a 52% decrease in Varanasi and negligible decrease in Kolkata (1.5%) and, surprisingly, a large increase in Guwahati (75%). Singh and Chauhan (2020) observed that due to the dominance of westerly winds from arid and semi-arid regions, a lower boundary layer (due to lower temperatures) prevails over Delhi and central IGP cities compared to other major cities like Mumbai, Hyderabad, and Kolkata. In March, the average concentration of PM_{2.5} in Delhi and central IGP remains higher in comparison to other regions.

Stations in coastal India also show variable features, decrease in Visakapatnam (30%), Tirupati (33%), and Thiruvananthapuram (49%), while an increase is observed in Rajamundry (7%). About 60% of India's mean population-weighted PM_{2.5} concentrations come from anthropogenic source sectors, while the remainder are from other sources, wind-blown dust and extra-regional sources (Venkataraman et al., 2018). As mentioned in Fig. 1 as well as studied by Venkataraman et al. (2018), leading contributors to PM_{2.5} are residential biomass combustion, emissions from power plant and industrial coal combustion, and anthropogenic dust.

Fig. 4 Weekly changes in **a** $PM_{2.5}$, **b** PM_{10} , **c** NO_2 , and **d** O_3 . The first vertical line in black color represents the start of the lockdown period, i.e., the 25 March 2020, while the second vertical line with blue color represents the beginning of unlock phase, i.e., 1 June 2020. The horizontal green line represents the standard air quality value given by CPCB

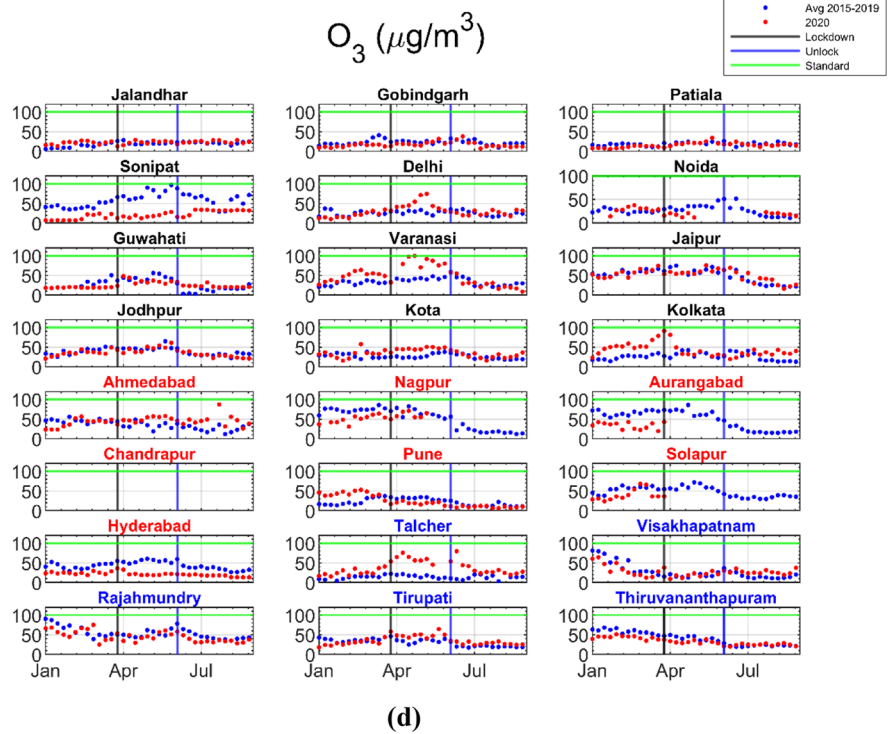
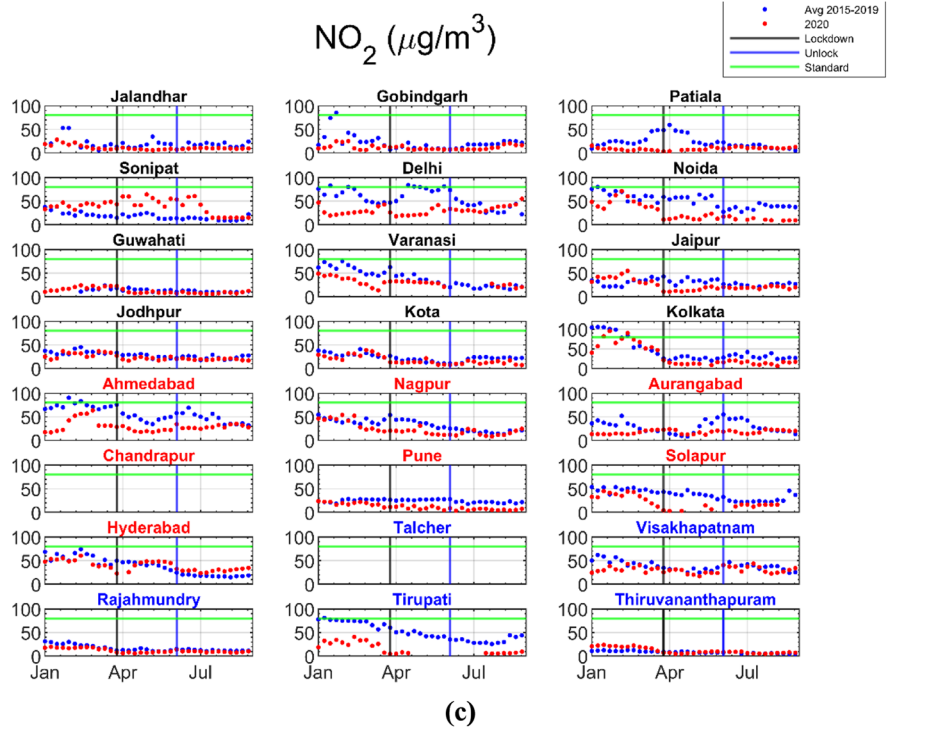


(a)



(b)

Fig. 4 (continued)



Like PM_{2.5}, a rapid decrease in PM₁₀ concentrations is observed in northern India in comparison to

previous period, viz., Jalandhar (68%), Gobindgarh (55%), Noida (64%), Patiala (74%), Sonipat (35%), and

Table 2 Comparison of lockdown effects from different studies across India. Results are for Delhi where not otherwise mentioned

Reference	Data source/location	Methodology	Parameter/location results
(Bedi et al., 2020)	CPCB 4 cities: Delhi, Mumbai, Kolkata & Chennai	Difference in the concentration in 2020 for 15 days before lockdown and 15 days during lockdown	PM _{2.5} : - 63.9% PM ₁₀ : - 56.7% NO ₂ : - 63.9% O ₃ : + 50.9%
(Biswal et al., 2020)	NASA Aura satellite OMI sensor over India	Comparison of data from 1 March to 18 April 2020 vs. 2019	NO ₂ : - 65.9%
(Chikara & Kumar, 2020)	CPCB 3 cities: Delhi, Mumbai, Kolkata	Difference of prelockdown (1–24 March) and lockdown (25 March to 30 April) concentrations	PM _{2.5} : + 5.76% PM ₁₀ : - 16.2% NO ₂ : - 42.27% SO ₂ : - 9.12% NH ₃ : - 66.29%
(Jain et al., 2020)	NO ₂ - OMI Gadanki	1 Feb to 31 May 2020 compared to 2019 for the same period. Phase-wise analysis has been done here	Gadanki in Southern India In 1st phase NO ₂ : - 58.3% O ₃ : - 9.4% NO ₂ OMI: - 33.6%
(Kumari & Toshniwal, 2020)	CPCB data For NO ₂ European Space Agency (ESA) Delhi, Mumbai and Singrauli	Difference in mean concentration before lockdown (1 March to 24 March) and during lockdown (25 March to 15 April) for just 2020	PM ₁₀ : - 55% NO ₂ : - 60% PM _{2.5} : - 49% SO ₂ : - 19%
Kumari et al., 2020)	CPCB OMI for NO ₂ Patiala	24 March to 31 May in 2020 and compared with the same time period in 2019	PM ₁₀ : - 58% (Patiala) PM _{2.5} : - 57% (Patiala) NO ₂ : - 79% (Patiala)
Mahato et al., 2020)	CPCB, DPCC, SAFAR: IITM Pune over Delhi	24 March to 14 April 2020 compared to average of 2017–2019 for the same period	PM _{2.5} : - 32.62% PM ₁₀ : - 56.55%
(Pathakoti et al., 2020)	Satellite data Aura/OMI for NO ₂ Terra/MOPITT for CO Aqua-Terra/MODIS for AOD over India	Lockdown Period: 25 March to 3 May 2020 compared with 2015–2019 with same period	NO ₂ : - 14.5% CO: increase of 8% and 9% in 1st and 2nd phase of lockdown in India
(Rahaman et al., 2021)	CPCB Ahmedabad and Delhi	9 February 2020 to 23 March 2020 (43 days before lockdown) and 24 March 2020 to 4 May 2020 (after lockdown)	Ahmedabad PM _{2.5} : - 50% PM ₁₀ : - 54% Delhi PM _{2.5} : - 19% PM ₁₀ : - 28%
(Ramasamy et al., 2020)	CPCB 4 cities: Delhi, Kolkata, Mumbai, Chennai	1 Feb 2020 to 20 March 2020 before lockdown compared to 23 March 2020 to 30 April 2020	AQI Delhi: - 58% Kolkata: - 65.5% Chennai: - 52% Mumbai: - 66%
(Sharma et al., 2020)	CPCB East India	Average of 16 March to 14 April 2017–2019 compared to 2020 for the same period	East India O ₃ : + 89%
(Singh et al., 2020)	CPCB data over 134 sites in India	2017 to 2019 compared to 2020 during lockdown period (25 March to 3 May)	PM ₁₀ : - 59% NO ₂ : - 56% PM _{2.5} : - 47% CO: - 33% SO ₂ : - 23% O ₃ : + 23%

Table 2 (continued)

Reference	Data source/location	Methodology	Parameter/location results
(Singh & Chauhan, 2020)	US Environmental Protection Agency (EPA) for PM _{2.5} Delhi, Kolkata, Hyderabad, Mumbai, and Chennai	2020 compared to 2019 during lockdown period (22 March to 31 March)	PM _{2.5} : -27.57%
(Vadrevu et al., 2020)	TROPOMI Data over 41 cities of India	Lockdown (25 March to 3 May 2020) compared to the prelockdown (1 January to 24 March 2020)	NO ₂ : -61.74%

Delhi (56%). The total emission of PM₁₀ from different sources was estimated using ISCS3 model as follows: industrial point sources (26%), vehicles (21%), domestic fuel burning (19%), paved and unpaved road dust (15%), and the rest as other sources (Behera & Sharma, 2010). Mahato et al. (2020) observed a 60% reduction in PM₁₀ during lockdown compared to the last year (i.e., 2019). In western India, PM₁₀ also shows a decrease like PM_{2.5}, viz., Jaipur (56%), Jodhpur (50%), Kota (49%), Pune (62%), Aurangabad (54%), and Solapur (48%). In Central India, Nagpur (61%) shows a large decrease. However, Chandrapur which had shown only 17% decrease in PM_{2.5} now shows a 43% decrease w.r.t. PM₁₀. The coastal stations also show decrease in PM₁₀ during the lockdown, viz., Visakhapatnam (30%), Tirupati (50%), Thiruvananthapuram (28%), and Rajamundry (11%). Navinya et al. (2020) have also observed a decline of 71% in PM₁₀ over Delhi.

From Fig. 2, it is observed that the PM_{2.5} and PM₁₀ concentrations in the stations of northern India have started to increase in the later part of the lockdown. The regulation for movement of residents relaxed after the end of the first phase of the lockdown which might be the primary reason for the increase in emissions, which could be attributed to automobiles, and a consequent increase in the concentrations of atmospheric pollutants. During the second phase, the PM_{2.5} and PM₁₀ concentrations in Chandigarh increased by 7.7% and 22.3% respectively, as compared to the first phase (Mor et al., 2021). Mor et al. (2021) also observed that the air temperature in Chandigarh during the first, second, and third phase of lockdown increased by 4.5 °C, 3.3 °C, and 1.6 °C, respectively, compared to the prelockdown period due to the onset of the summer season. Therefore, a slight decrease in pollutant levels during the lockdown period can be attributed to higher temperature. The increase in

temperature increases the vertical mixing of pollutants in the troposphere (Ravindra et al., 2019).

From Fig. 2, an increase in PM_{2.5} is observed over Jaipur and Jodhpur in between the lockdown and unlock periods in the months of late March and April. This could be attributed to the prevailing upper air cyclonic circulation and western disturbances that caused several dust storms with gust winds and thunderstorms over different parts of Rajasthan reducing the temperature to markedly below normal values (<https://m.dailyhunt.in/news/uae/english/gplus+english-epaper-gpls/3+fire+incidents+reported+across+guwahati-newsid-n263310294>).

Studying the simultaneous changes in PM_{2.5} and PM₁₀ over the different study locations, it is observed that in general, PM₁₀ and PM_{2.5} changes over most of the locations in the pandemic year compared to the previous year(s) average are almost going hand in hand for the weekly time series. However, there are some exceptions like Delhi, where the PM_{2.5} percentage change shows a stronger increase in the initial phase of lockdown compared to PM₁₀. This feature is also visible in Chandrapur and to some extent in Pune. This indicates that the lockdown measures were able to subdue the sustained natural tendency for PM increase during this period, both from emission sources and atmospheric chemical means. Here, we would like to point out that a source apportionment study of PM_{2.5} and PM₁₀ for Delhi NCR indicates that biomass burning (BB) contributes 12% and 15% to PM₁₀ and PM_{2.5}, respectively, during summer. The contribution of BB is slightly higher during winter with 14% and 22% influence on PM₁₀ and PM_{2.5}, respectively (ARAI and TERI (2018)).

Guo et al. (2017) observed that during 2015, SOA contributed a miniscule of 7% and 3% to PM_{2.5} over Jaipur and Delhi, respectively. Behera and Sharma (2010) have estimated that SOA contributes about

18% mass in winter and 12% mass in summer to $PM_{2.5}$ in Kanpur city in IGP. In Delhi and nearby regions, SOA was found to contribute $16 \pm 6 \mu g^{-3}$ ($5.8 \pm 2.6\%$ of $PM_{2.5}$ mass) in summer (Nagar et al., 2017). The oxygenated organic aerosols (OOA) over Delhi are roughly 1.7 times lower during spring compared to winter, with a distinct diurnal variation exhibiting around $15 \mu g^{-3}$ during peak photochemical periods, while values increase to over $30 \mu g^{-3}$ during night (Bhandari et al., 2020). Organic aerosol, which contributes 55–75% of PM_1 over Ahmedabad, was measured to be about $7.5 \pm 8.2 \mu g^{-3}$ during early October, out of which OOA was found to constitute about 58% (Singh et al., 2019). During lockdown, the light volatile (LV) and semivolatile (SV) components together constituted about 74% of the organic aerosol over Ahmedabad (Dave et al., 2021). From this paper, it is important to note that the decrease of hydrocarbon like organic aerosols during lockdown over prelockdown was much larger compared to the decrease in volatiles and semi-volatiles. The daytime peak in LV-OOA was about $4.5 \mu g^{-3}$ before lockdown, while it decreased to around $3.5 \mu g^{-3}$ during lockdown, but the night-time values were identical.

Figure 5 shows the dependence of $PM_{2.5}$ and PM_{10} on PBL height. The association has been tested for significance using Student's *t* test. The dependence of $PM_{2.5}$ on PBL is significant at 95% confidence level over Jalandhar, Guwahati, and Kota; at 90% in Gobindgarh, Delhi, and Solapur; and at 99% confidence level in Jaipur. The relationship between PM_{10} and PBL is significant at 95% confidence level over Jalandhar, Guwahati, Thiruvananthapuram, and Tirupati; at 90% over Patiala and Kota; and at 99% in Jaipur and Solapur. It is further observed that PM changes are positively correlated with the PBL changes except for Visakhapatnam (Fig. 5). Positive association of PBL with PM indicates that dilution effects are negligible compared to the import of pollutants by air masses. Of course for a site with strong marine influence, viz., Visakhapatnam, the role of PBL dilution comes into picture as increasing PBL height results in lower concentrations. Moreover, Visakhapatnam is bounded by the Eastern Ghats on three sides along with warm and humid climate, thus restricting the dispersion of particulate matter. But

for all other sites, ventilation coefficient needs to be considered as transport effects dominate over dilution impacts.

Figure 6 shows the weekly change of $PM_{2.5}$ and PM_{10} for the selected locations. In the 1st phase of lockdown, the capital city of India experienced a decrease of around 30% in the concentrations of $PM_{2.5}$. Noida, Jaipur, Jodhpur, and Kota experienced a decrease of around 50% in $PM_{2.5}$ concentration. Some stations in central India (e.g., Nagpur and Aurangabad) also saw a decrease of more than 50% in the initial phase of the lockdown. Some of the stations in Coastal India, Visakhapatnam and Tirupati, also recorded a decrease of 30% and more. A decrease of 50–60% is observed in the cities of Punjab and Haryana. Varanasi recorded a decrease of 50% in $PM_{2.5}$ concentration. The lowest change in the concentration of $PM_{2.5}$ during 1st phase of lockdown was seen in Kolkata, and it was estimated to be around 1.5%. Stations in northern India, i.e., Delhi, Gobindgarh, Patiala, and Noida, all experienced a decrease of more than 50% in the concentration of PM_{10} during the 1st phase of lockdown. A similar reduction in PM_{10} concentration was seen in all the stations in Western and Central India. All the stations in coastal India experienced a reduction of around 30–40%. An increase of only 2% in PM_{10} concentration was seen in Kolkata.

Guwahati was the only among the selected stations which showed an increase of around 70% in both $PM_{2.5}$ and PM_{10} concentrations. An increase in fire counts around Guwahati was observed during March 2020 from MODIS (Fig. 7). The fire events were observed both around the city and within the city. Among the many fire events within the city was a major fire during 30 March 2020 near Lalmati near Games Village, Guwahati, and fires during March 19 at Guwahati's Fancy Bazaar area (Web Ref 1, Web Ref 2). Further, according to Guttikunda et al. (2014), 80% of the households here have non-gas cookstove. Increased residential emissions in Guwahati might also add to an increase in the concentration of PM from fires. Therefore, the impact of lockdown, viz., closure of vehicular traffic in the 1st phase, is not seen in Guwahati, instead a spike is observed because of possible enhancement in fires and residential activities. Hari et al. (2021) observed a shift in the peak fire counts over Patiala to the end of May of 2020 instead

PM_{2.5} & PBL

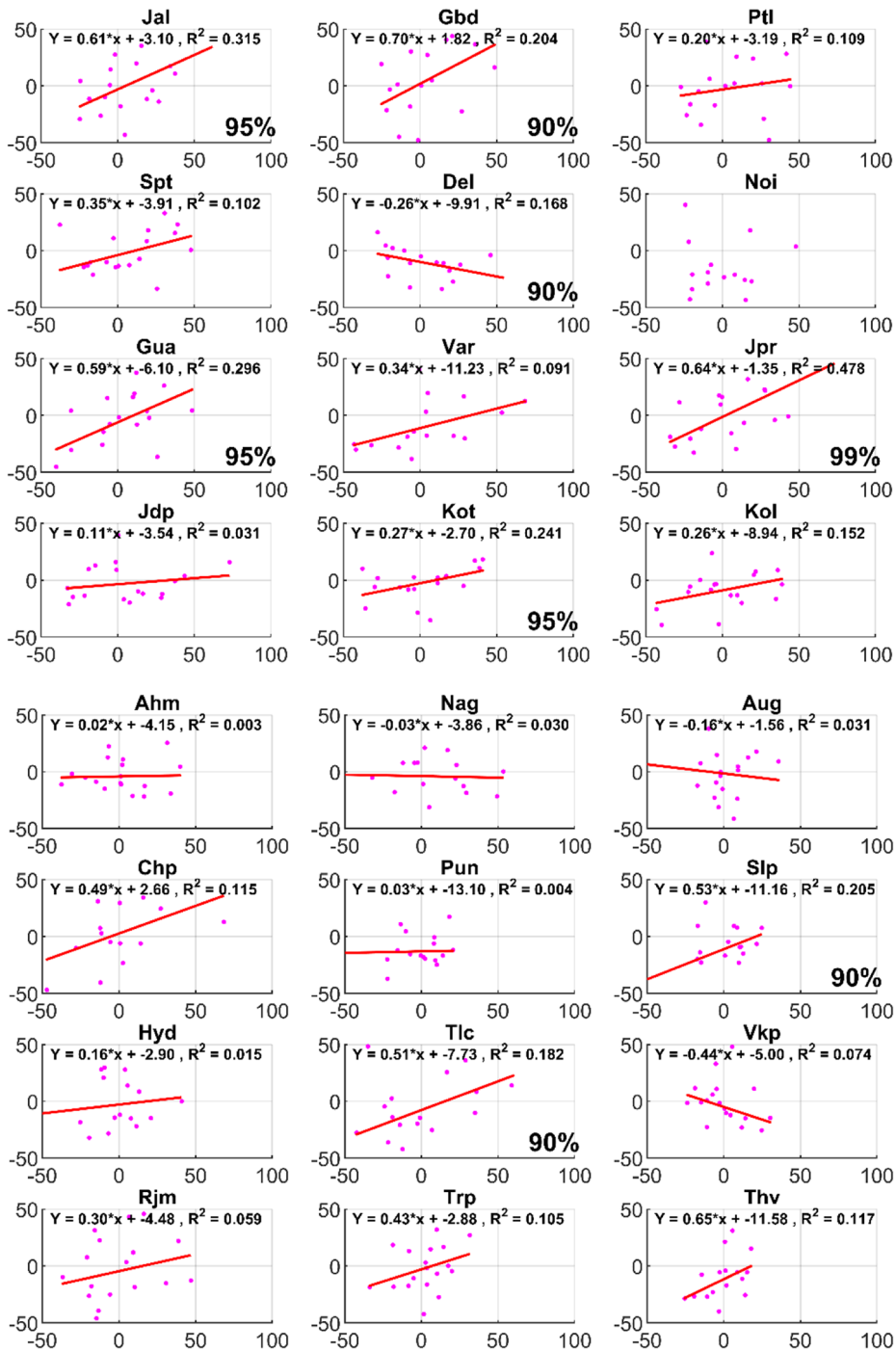


Fig. 5 Dependence of PM concentrations **a** PM_{2.5} and **b** PM₁₀ on PBL height

PM₁₀ & PBL

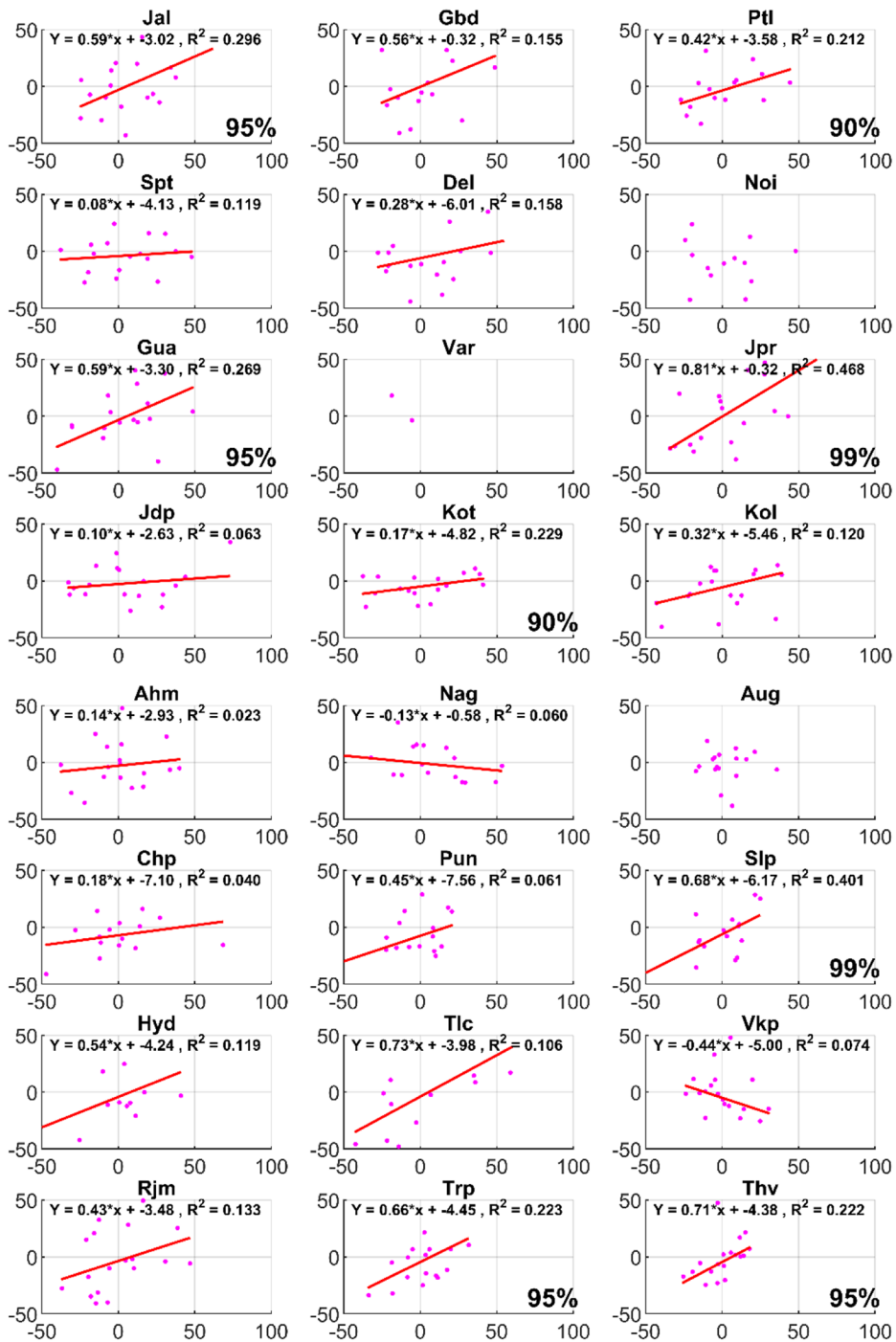
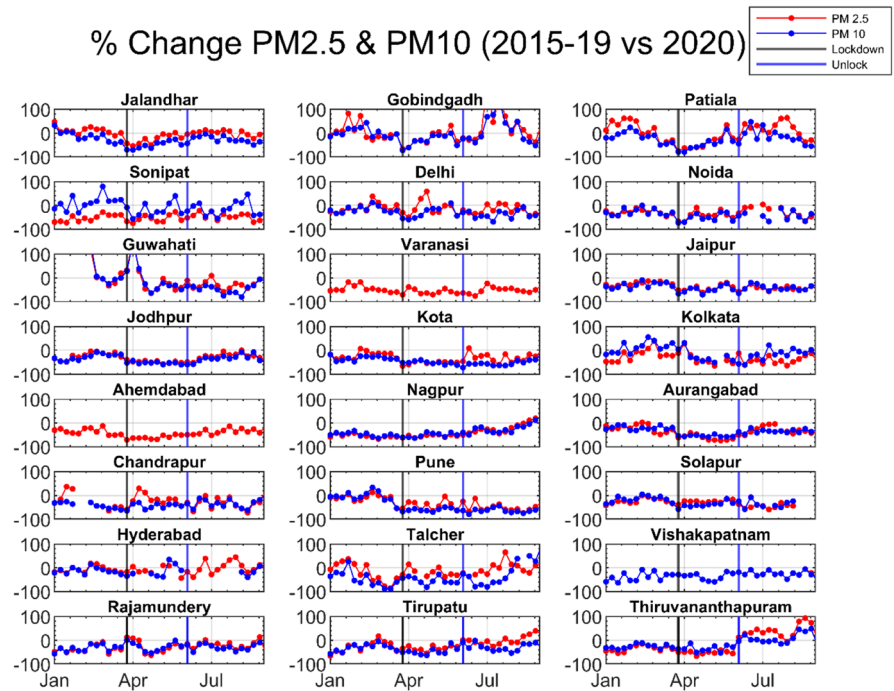


Fig. 5 (continued)

Fig. 6 Percentage change of PM_{2.5} and PM₁₀



of the beginning of May which occur during the normal periods due to the imposition of lockdown.

Hence, Patiala experiences a positive change after a delay when compared to the normal years.

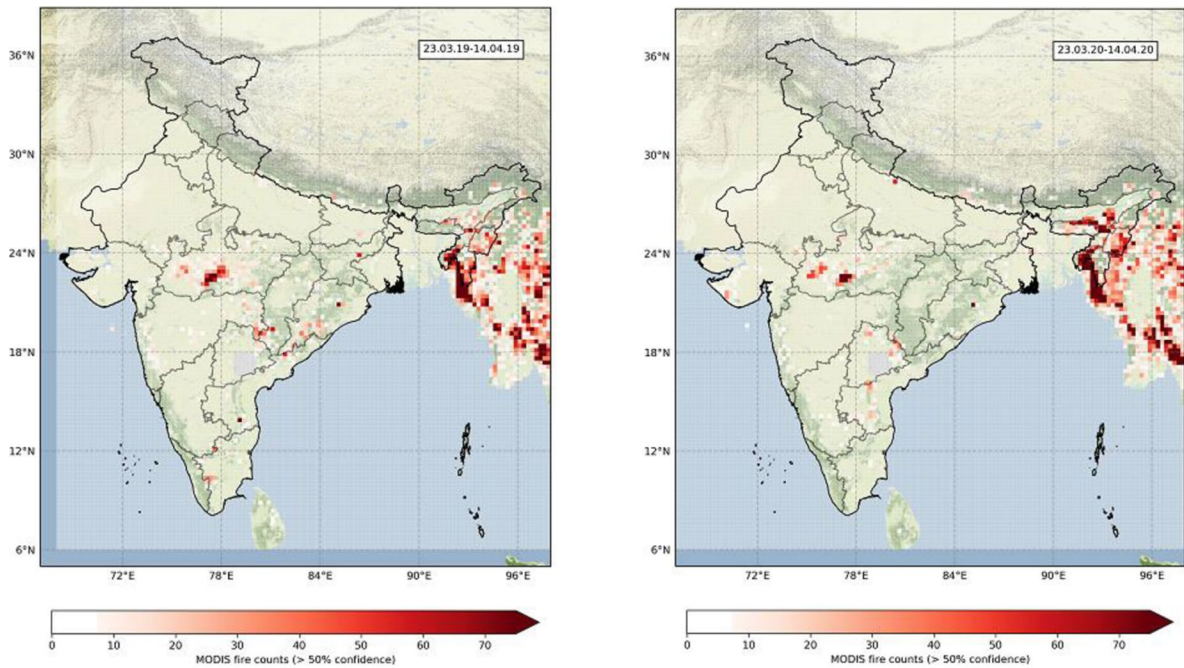


Fig. 7 Comparison of fire counts in and around Guwahati during March between 2019 (left panel) and 2020 (right panel)

Weekly changes in surface concentrations of NO_2 and O_3 (average 2015–2019 vs. average 2020)

One of the largest impacts of the lockdown was the restriction in movement of vehicles leading to large decrease in NO_2 concentrations. In northern India, 30% decrease in NO_2 was observed over Delhi, while Jalandhar (20%), Patiala (80%), Gobindgarh and Noida (20%), and Sonipat (60%) all show a decline in the initial phase of lockdown compared to same period in previous years. Chikara and Kumar (2020) pointed to a reduction of 42.27%, 69.28%, and 74.80% in concentration of NO_2 in Delhi, Mumbai, and Kolkata, respectively, based on the difference of prelockdown (1–24 March) and lockdown (25 March to 30 April) concentrations. Bedi et al. (2020) also observed significant fall (63.9%) for NO_2 over Delhi using a slightly different comparison period of 15 days before and after lockdown (Table 2). Even satellite observations showed a reduction in NO_2 columns, while the average tropospheric NO_2 column was 214.4×10^{13} molecules cm^{-2} over India during March; it subsequently decreased by 12.1% due to lockdown (Biswal et al., 2020). Satellite-based seasonal variations of tropospheric NO_2 concentrations show a maximum during winter–summer month and a minimum during the monsoon seasons, with the change between maxima and minima being 2–4 times in various regions of India (Ghude et al., 2008). Mallik and Lal (2014) estimated a 20–40% enhancement in NO_2 in winter compared to pre-monsoon months. Thus, the lockdown-induced decrease in NO_2 is comparable to the seasonal change in NO_2 over Delhi. Chimurkar et al. (2020) show that the northern Indian region showed nearly 100% decrease for NO_2 during lockdown compared to prelockdown, while this value was 38% in 2019. During the lockdown period starting from 22 March 2020, a sudden drop in tropospheric NO_2 concentrations over IGP was observed (Singh & Chauhan, 2020). NO_2 reductions were also observed in our study locations of IGP: Varanasi (5%) and Kolkata (10%). Strangely enough, Guwahati showed an increase of 40% in NO_2 during the lockdown period.

NO_2 reductions were also observed in Western India: Jaipur (60%), Jodhpur (20%), Kota (30%), Ahmedabad (50%), Solapur (80%), and Pune (40%) show a decrease, while a 50% increase was observed in Aurangabad. NO_2 decreases were also observed in coastal India: Visakhapatnam (20%), Tirupati (80%), Rajahmundry

(20%), and Thiruvananthapuram (20%). Chimurkar et al. (2020) have also observed a decline of 63% in NO_2 over Nagpur in Central India.

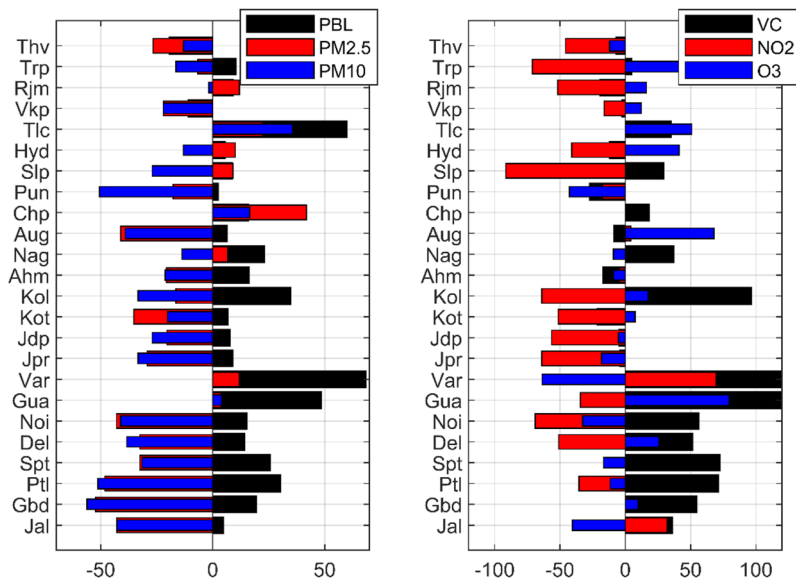
In contrast to other pollutants, O_3 concentrations showed varied features not only in India but across the world. The mixed signal was observed in O_3 concentrations in northern India: Delhi (50%) and Jalandhar (40%) showed an increase, while Gobindgarh (20%), Noida (20%), and Sonipat (60%) show a decrease in O_3 . Most of the stations in western India show an increase in O_3 : Jaipur (20%), Jodhpur (20%), Kota (60%), Ahmedabad (40%), Aurangabad (20%), and Solapur (15%). However, Pune shows a 20% decline in O_3 . For most places during the lockdown, an increase in concentration of O_3 can be related to a corresponding decrease in NO_x under VOC-limited conditions (Sharma et al., 2020). For stations in coastal India, decrease in O_3 was observed: Visakhapatnam (20%), Tirupati (20%), Thiruvananthapuram (10%), and Rajahmundry (20%).

Singh et al. (2020) point out that O_3 also showed a mixed variation with a mild increase in IGP and a decrease in the south. Das et al. (2021) point out that average concentration of O_3 increased by 28% during lockdown in comparison to 30 days average prior to lockdown.

Figure 8 shows the difference between the mean of the data from 11 to 24 March 2020 and 25 March to 7 April 2020. In Fig. 8 (left panel), the black bar shows the change in PBL. The red and blue bar represents $\text{PM}_{2.5}$ and PM_{10} , respectively. In all the stations in northern India, the decrease in PM concentration is seen coinciding with the increase in PBL. Similar behavior is seen in Western India except for Solapur. However, regression analysis (Fig. 5) clearly indicates that PBL dilution may not be the major cause of decrease in PM levels as import of pollutants could have a much stronger effect. In Solapur, $\text{PM}_{2.5}$ increases along with an increase in PBL indicating import of $\text{PM}_{2.5}$ to the site. The increase in PM concentration is observed in Varanasi and Guwahati with an increase in PBL. A similar change can be observed in Chandrapur and Talcher. This could be because of the transport of particles (VC is very high here). The decrease in PM concentration is seen with decreasing PBL in Visakhapatnam and Thiruvananthapuram. These regions may have an overwhelming influence of the sea which led to the dilution of the PM concentration.

Fig. 8 Observed percentage changes in PM, NO₂, O₃, PBL, and VC between the lockdown fortnight with the prior fortnight

Lockdown(mean 25 Mar-7 Apr)-Pre-Lockdown(mean 11-24 Mar)



In Fig. 8 (right panel), the black bar shows the change in VC. The red and blue bar represents NO₂ and O₃, respectively. In coastal India with a decrease of VC, NO₂ concentration also decreases, and O₃ concentration increases. In the IGP region of Varanasi with an increase of VC, NO₂ also increases, whereas O₃ decreases. This means that the increase in NO₂ is brought about by atmospheric transport, while this same NO_x-rich air influx leads to decreased O₃ due to titration effects. But for Guwahati, variation is the opposite, and with an increase of VC, NO₂ concentration decreases and O₃ increases. In western India, Jaipur, Jodhpur, Pune, and Ahmedabad show the same variation of decrease of NO₂ and O₃ with a decrease in VC, but in Kota and Aurangabad, O₃ concentration increases with decreasing VC.

Computing actual lockdown-induced changes

Although published literature deals with a comparison of the lockdown phase with similar phases during previous years to estimate the impact of lockdown, it is observed that the concentration of aerosols in some stations of northern India and northwestern India started to decrease even before the imposition of lockdown. The reasons for this decrease can be specific to different pollutants, but an overarching

effect of reduction/closure of emission sources must be normalized to the impact of change in air mass trajectories (*Meteorology during lockdown/unlock periods* section, Fig. 10) to make a real estimate of the lockdown-induced changes. Further, the change in prevailing wind direction is not a sharp point in space and must be estimated judiciously station-wise. Also, fairly widespread rainfall/thunderstorm activity was observed over Western Himalayan region and Northwest India in the month of March 2020 IMD reports (a, b). The precipitation occurring due to the western disturbances removes some of the aerosols over the region by wet deposition, and the wet conditions reduce the introduction of fresh aerosols into the atmosphere. One way to resolve this cocktail of effects is to derive an expected change in concentration of pollutants and compare it with the observed change in the lockdown year; the difference would indicate the actual lockdown-induced change. For this analysis, the expected change is calculated based on the difference of subsequent fortnights before and after the imposition of lockdown. Fortnight is taken instead of week to subdue effects of sudden changes on a particular day, and a longer averaging period would make the mean more robust. The difference of subsequent fortnights is calculated for 2015–2019 (depending on data availability) for each station and

then averaged to produce the final expected change station-wise which is then compared to the observed change in the lockdown year:

Actual Change = Observed Change – Expected Change

Table 2 shows a comparison of lockdown effects on air pollutants from different studies in India. As can be observed from Table 2, there have been two popular approaches to nail the impact of lockdown. One approach is to compare data from the start of lockdown (week, fortnight, month) to the period before lockdown from the same year. The second approach is to compare the data from the lockdown period to the data from the same period of previous year/years. The problem with the first approach is that the effect of meteorology will not be accounted for in the difference between subsequent weeks as it is highly likely that the impact of temperature, pbl, and moisture have continued to change during the subsequent periods which are being compared. Similarly, the second approach is also problematic as the comparing periods are too distant in time to eliminate the impact of other factors apart from lockdown-induced emission changes. Our approach of estimating the actual lockdown impact aims to improve upon the previous approaches while still maintaining the simplicity in approach and attribution. First, we compare the percentage changes between subsequent weeks/fortnights. This takes care of the fact that we are not comparing too distant times. Next, we make an average of percentage changes during 2015–2019 to ensure we are not taking 1 year but accounting for the effect of different meteorological changes over years. Ideally, a much longer average would be preferable here, but availability of data from different stations limits us to this period only. Next, we compare the average difference of subsequent weeks/fortnights to the similar difference during lockdown year, hoping that the effect of meteorology will be taken care by the average percentage change and the difference between average and the lockdown year will be mainly the lockdown impact.

In Fig. 9, the blue bar shows the difference between the mean of the data for 11–24 March 2015–2019 and 25 March to 7 April 2015–2019, and the red bar shows us the difference between the mean of the data for 11–24 March 2020 and 25 March to 7 April 2020. Here, the blue bar gives us an understanding about the expected change, and the red bar shows the

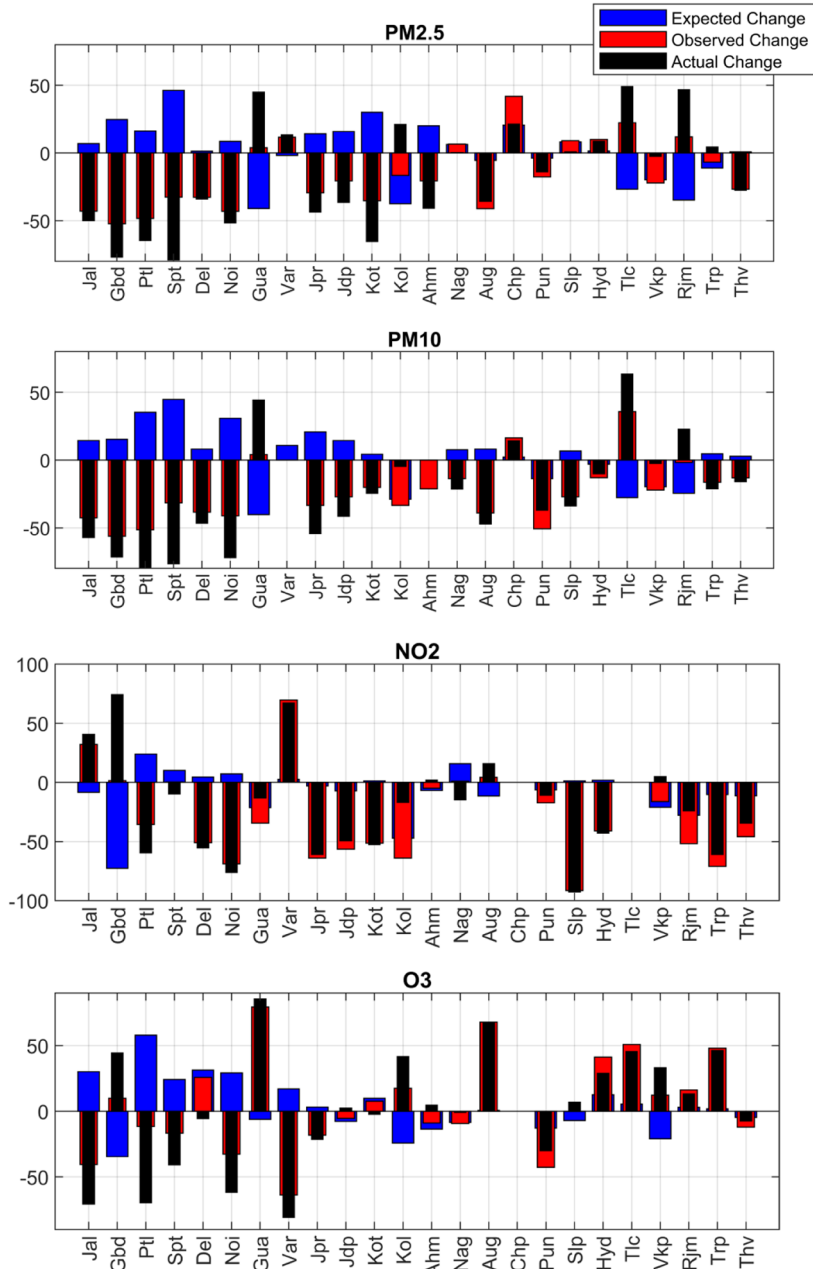
observed change. The actual change can be calculated by taking the difference of the observed change and the expected change. Table 3 also shows the change in values between fortnight prelockdown and the fortnight of the lockdown.

In case of $PM_{2.5}$, for all the stations in northern India, a negative change is observed during the lockdown fortnight. This is also evinced in Figs. 2 and 3, as well as several earlier studies for different stations in India. Here, we would like to point out that for stations like Delhi, Noida, and Patiala, a decrease during this time is visible even before the lockdown for 2020 as well as the mean of previous years (Fig. 6). Surprisingly, for these stations, our calculations point to an expected positive change. This is corroborated by the fact that this is the season of widespread biomass burning in this region, but the observed change in all these stations is negative. This means the actual lockdown-induced change is much larger than what a simple difference of corresponding periods shows, a method that has been used in many earlier studies. Similarly, in a dust-dominated western India, viz., Jaipur, Jodhpur, Kota, and Ahmedabad, a positive change was expected, but observed change was negative. The expected change in $PM_{2.5}$ over Talcher, Eastern India (east of Chotta Nagpur Plateau), was -27% , but we observed a positive change of 22% . Thus, the actual lockdown-induced change in Talcher gives us an increase of 49% , much higher than the observed value. Similar behavior is seen in Rajamundry. In coastal India, in most cases, expected changes are negative (due to increasing marine influence) and aligned with the observed change. In Thiruvananthapuram, no change was expected, but the actual change was seen to be a decrease of 27% . In Guwahati, the expected change was negative (-41%), but the observed change was a mere 3% . Thus, the actual lockdown-induced change in $PM_{2.5}$ over Guwahati cumulates to $+44\%$.

In the case of PM_{10} , for all the stations in northern India, a positive change was expected, but the observed changes in all the stations were negative. Thus, the accentuated COVID-induced lockdown effect was actually much more significant in this region. In the dust-dominated western India, Jaipur, Jodhpur, Kota, and Ahmedabad, as well as Solapur, a positive change was expected, but observed change was negative. Dust is a major contributor to both $PM_{2.5}$ and PM_{10} (*Emission sources* section, Fig. 2). Increasing wind speeds in March compared

Fig. 9 Observed, expected, and actual changes for PM_{2.5}, PM₁₀, NO₂, and O₃

Lockdown(mean 25 Mar-7 Apr)-Pre-Lockdown(mean 11-24 Mar)



to February also increase the amount of wind-blown dust, accumulating to the total PM loading. In biomass burning-dominated Guwahati valley in the east of IGP, the expected change in PM₁₀ was -40%, but the observed change was 4%; hence, the actual change in Guwahati is +44%. The negative expected change would be an effect of boundary layer dilution, while

observed increase in PM (both 2.5 and 10) could be due to an increase in residential activities including residential cooking along with increased fire events (Fig. 7). The expected change in Talcher in Eastern India (east of Chotta Nagpur Plateau) was -28%, but we observed a positive change of 35%; thus, the actual change in Talcher gives us an enhanced

Table 3 Comparison of the observed and actual lockdown-induced changes

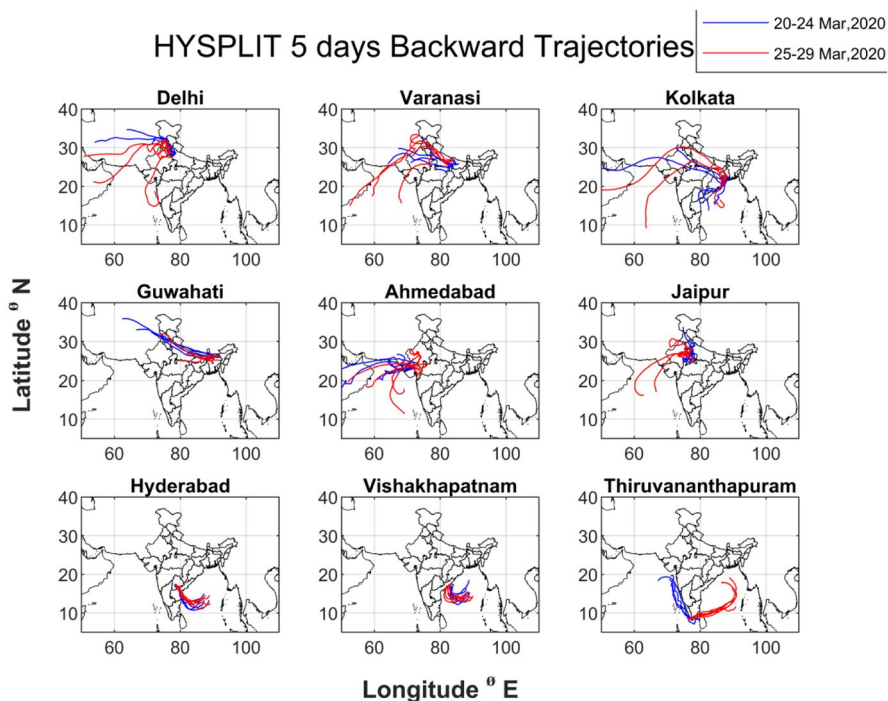
Station		PM _{2.5}		PM ₁₀		NO ₂		O ₃	
		Observed change (%)	Actual change (%)	Observed change (%)	Actual change (%)	Observed change (%)	Actual change (%)	Observed change (%)	Actual change (%)
North India	Jalandhar	-42.91	-49.94	-42.69	-57.13	32.14	40.58	-40.59	-70.67
	Gobindgarh	-52.24	-76.88	-56.16	-71.48	1.45	74.21	9.88	44.40
	Patiala	-48.26	-64.52	-51.39	-86.67	-35.52	-59.57	-11.60	-69.60
	Sonipat	-32.6	-78.88	-31.57	-76.39	0.28	-9.79	-16.66	-40.81
	Delhi	-32.62	-33.96	-38.44	-46.54	-50.92	-55.98	25.68	-5.55
	Noida	-42.99	-51.59	-41.17	-72.02	-69.00	-76.12	-32.64	-61.71
IGP	Guwahati	3.87	44.9	4.05	44.28	-34.45	-13.16	79.30	85.43
	Varanasi	11.7	13.47	NaN	NaN	69.63	67.03	-63.71	-80.75
	Kolkata	-16.45	21.08	-33.40	-4.52	-64.03	-16.94	17.48	41.61
Western India	Jaipur	-29.36	-43.59	-33.36	-54.09	-63.96	-60.93	-18.23	-21.31
	Jodhpur	-20.57	-36.41	-27.05	-41.51	-56.53	-49.32	-5.39	2.80
	Kota	-35.23	-65.32	-20.17	-24.54	-51.34	-52.59	7.54	-2.30
	Ahmedabad	-20.63	-40.76	NaN	NaN	-4.89	1.88	-8.90	4.60
	Pune	-17.69	-13.85	-50.59	-36.89	-17.31	-10.86	-42.76	-29.98
	Aurangabad	-41.1	-35.63	-39.03	-47.13	4.17	15.72	NaN	NaN
	Solapur	9.07	0.87	-27.03	-33.70	-91.51	-92.68	NaN	NaN
Central India	Nagpur	6.61	0.25	-13.73	-21.38	0.96	-14.33	-9.24	-0.80
	Chandrapur	41.82	21.29	16.45	14.19	NaN	NaN	NaN	NaN
	Hyderabad	10.07	8.57	-13.06	-10.04	-41.05	-42.74	41.25	28.67
	Talcher	22.37	49.04	35.71	63.39	NaN	NaN	50.86	45.38
Coastal India	Visakapatnam	-22.15	-2.43	-22.14	-2.43	-16.28	4.79	12.21	33.11
	Rajamundry	11.96	46.72	-1.79	22.75	-51.80	-24.03	16.15	13.17
	Tirupati	-6.69	4.44	-16.40	-21.04	-71.11	-60.84	47.99	46.18
	Thiruvananthapuram	-26.64	-27.48	-13.08	-15.95	-45.81	-34.40	-12.01	-7.34

lockdown impact of 63%. However, in coastal India, change in air masses with higher marine influence would decrease the relative amount of wind-blown dust. In Thiruvananthapuram, only 3% of positive change was expected, but the observed change was a decrease of 13%, and the total change was -16%. This can be associated with complete change in air mass trajectories after the start of lockdown such that the northwesterly trajectories coming from along west coast of India were replaced by completely marine trajectories from the east (Fig. 5).

The expected NO₂ change is positive for the northern part of India, but the observed change is negative (Fig. 9). The expected increase in NO₂ during this period is contributed to some extent due to change in air masses connecting the study locations to pollution plumes (Fig. 10). The observed decrease in NO₂ is very much on the

expected lines as local traffic emission is the major contributor to NO₂ in cities across India. For the IGP region, expected change for Kolkata and Guwahati was negative due to lower influence from IGP and increasing marine influence (Mallik et al., 2014). The observed change for Kolkata and Guwahati was -64.03 and -34.45, respectively, but it must be noted that the whole -64.03 and -34.45% decrease cannot be attributed to lockdown, only the difference, i.e., $64.03 - 47.09 = -16.94\%$ is the actual lockdown influence for Kolkata and $34.45 - 21.29 = 13.16\%$ for Guwahati. For Varanasi, the expected change was positive (2.59%), and observed change was positive (69.63%), indicating impact of lockdown. In western India for Jaipur and Kota, expected change and observed change are both negative. However, for Ahmedabad, Jodhpur expected change was positive, while the observed changes were negative. Similar

Fig. 10 Comparison for 5-day backward trajectories before and after lockdown over a few selected study locations in India



to PM for coastal India, expected and observed changes in NO₂ are negative and aligned. This can be attributed to increasing marine influence as well as dilution. But it would be important to note that the actual change in this case would be much lower than the observed change.

For stations like Nagpur, Chandrapur, Solapur, and Hyderabad, the observed and the actual changes for PM_{2.5} were positive. For PM₁₀, Chandrapur in the Central India experienced a positive actual change. Pandey and Vinoj (2021) observed that reduction in wind speed, because of converging northwesterly and southeasterly over Central India during the lockdown period, provided a conducive environment for the stagnation of pollutants over the region which led to the increase in AOD (+10%, +20%, and +18% from Terra, Aqua, and MERRA2, respectively). Madineni et al. (2021) also found that long-range transport and stagnant conditions over Central India led to the increase in AOD during lockdown. Also, local biomass burning and fires associated with agricultural activities led to the enhancement of aerosol concentration over Central India (Bhawar et al., 2021).

An aerosol source apportionment study in Varanasi by Kumar et al. (2020a), Kumar et al. (2020b) showed that during the months of post-monsoon and winter periods from October to February, the particles are mainly from

biofuel and vehicular emissions. With the imposition of lockdown, the main emission source was cut down leading to the observed reduction in ambient concentration of particulate matters. In Varanasi, during March to May, coarse-mode particles dominate, whereas during the months of August and September, transported particles mix along with local emissions.

For coastal regions like Visakhapatnam and Trivandrum, the influence of synoptic features and mesoscale circulations, especially the land and sea breeze circulations, is vital to the advection and dispersion of the pollutants (Remiszewska et al., 2007). Rajeevan et al. (2019) showed the relationship between wind direction and the aerosol concentration over Trivandrum in the presence of an active sea breeze circulation.

The largest intricacies regarding the impact of lockdown on atmospheric pollutants were observed for O₃. Because O₃ is a secondary pollutant and its concentrations depend on non-linear chemical interactions, the changes in O₃ were not unidirectional due to lockdown-induced reductions in NO₂ and VOCs. Out of 21 stations analyzed for O₃, the observed change was positive for only 10 stations, and in the remaining stations, the observed changes were negative. Among these 10 stations, 6 stations are from

central and coastal India, including Kolkata close to the Bay of Bengal. Among these 10 stations, 5 stations showed an observed positive change of greater than 25%, these being Delhi, Guwahati, Hyderabad, Talcher, and Tirupati. When we compare the observed change to the actual change, in 8 out of 10 stations, the observed positive changes translate into actual positive changes.

Expected O₃ percentage change is positive in the northern part of India due to production from precursors; a significant amount of which can be sourced to biomass burning (Kumar et al., 2011), but observed changes are negative for most part of northern India except Gobindgarh. But for Delhi expected and observed change, both were positive. For IGP region, expected change for Kolkata was -24.12, but observed change showed 17.48% enhancement, and for Varanasi, expected change was positive (17.03%), while actual change aligned with observed negative change (-63.71%). In western India for Ahmedabad, Jodhpur, and Pune, expected changes and observed changes, both were negative, and for Kota, expected and observed change, both were positive. For coastal India, Rajamundry and Tirupati expected and observed changes, both were positive, and for Thiruvananthapuram, both were negative. For Visakhapatnam, expected change was negative, but the observed is positive.

The largest actual positive change in O₃ is over Guwahati where 85% enhancement in O₃ occurred. This can be a result of higher O₃ production due to increase in precursors from increased fire counts (Fig. 10). The actual change is also above +40% in Gobindgarh, Kolkata, Talcher, and Tirupati. For Gobindgarh, a positive change in O₃ is associated with a positive change in NO_x. However, over Kolkata and Tirupati, positive changes in O₃ are associated with negative changes in NO_x. This would be possible if the decrease in NO_x over had been sufficient to reach the NO_x-sensitive (limited) region where O₃ is not much sensitive to VOCs but increases with increasing NO and increasing HO_x. On the other hand, if NO_x did not decrease sufficiently and we are in the VOC-sensitive regime, O₃ would increase with decreasing NO_x and/or increasing VOCs. It is highly likely that most of the O₃ increases occurred in VOC-sensitive regimes. Soni et al. (2021) studied the changes in O₃ in Ahmedabad due to lockdown using a photochemical box model and found that O₃ production was

enhanced during the lockdown period due to lower NO_x conditions and higher solar irradiance.

The model simulations are described in Table 4. The average O₃ concentration during peak photochemical period (1300–1500 IST) is also shown in this table. *Simulation 1* is a base simulation with only observed concentrations of NO, NO₂, and CO for 24 March 2020 with CH₄ fixed at 1.85 ppmv. Meteorological parameters for simulation 1 are based on the observed meteorology for the same day over Ahmedabad. *Simulation 2* takes all input values of simulation 1 but adds in the effect of C2–C5 anthropogenic VOCs. In this case, we observed an increased O₃ concentration by 20.7%.

Simulation 3 adds in more traffic-related aromatic hydrocarbons (benzene, xylene, toluene); however, these increase O₃ concentration by a further 30.9%, cumulating to 57.9% enhancement over simulation 1. The addition of 1 ppbv isoprene in simulation 4 increases the average peak O₃ by only 8.7% further. However, the addition of pinenes in *simulation 5*, based on Tripathi and Sahu (2020) PTR-MS measurements over Ahmedabad, increases O₃ by 1.9%. The addition of PAN, H₂O₂, and HCHO in *simulation 6* increases O₃ further by 192.4% and takes O₃ closest to the observed prelockdown average peak O₃ of 120 μg⁻³, the simulation values being only 15.3% lower compared to observed values. The greater O₃ production from biogenic VOCs is due to their higher OH reactivity potentially leading to greater OH recycling (HO₂ → OH) and hence NO → NO₂ → O₃.

To understand the effect of NO_x in this air mass composition over our example city Ahmedabad, we changed the NO_x values (maintaining the NO to NO₂ ratio) in our best obtained *simulation 6*. Decreasing NO_x by a factor of 2 in *simulation 7* causes a (14.9%) increase in O₃. Surprisingly, increasing NO_x by a factor of 2 decreased O₃ by 13.8% pointing to a VOC-sensitive composition. *Simulations 9* is the same as simulation 6 but with anthropogenic hydrocarbons (C2-C5, BXT) reduced by 0.5; this led to a decrease of O₃ by 9.2%. *Simulations 10 and 11* are the same as simulation 9, but additionally, biogenic hydrocarbons (isoprene, apinene, bpinene) reduced by 50% and 25%, respectively, leading to 0.15 and 5% increases, respectively, in O₃. If anthropogenic hydrocarbons are not decreased, but only biogenics are decreased, decrease of O₃ is insignificant. This

Table 4 Simulations for Ahmedabad using date for prelockdown (24 March 0.2020) and lockdown (31 March 2020). The concentration values shown are the average of 13:00–15:00 IST. For simulations of 31 March 2020 (1a–6a during lockdown), all CxHy, benzene, toluene, PAN, and HCHO were

multiplied by the factor 0.42. This constant 0.42 is the ratio of the average value of HCHO during lockdown (25 to 31 March 2020) to the average value of HCHO before lockdown (18 to 24 March 2020)

Simulation	Concentrations (ppbv)	Avg O ₃ (µg ⁻³) 24 March 2020 Simulations 1–11	Avg O ₃ (µg ⁻³) 31 March 2020 Simulations 1a–11a	Reference
Observed O ₃		120.16	93.7	
Simulation 1	NO, NO ₂ , CO	20.14	19.84	Observed CPCB
Simulation 1a	T, RH, PBL CH ₄ : 1850 ppbv			Observed wunderground Fixed
Simulation 2	Simulation 1 +	24.3	22.66	(Tripathi & Sahu, 2019)
Simulation 2a	C ₂ H ₆ :10; C ₂ H ₄ : 5 C ₃ H ₈ : 15; C ₃ H ₆ :2 i-C ₄ H ₁₀ :5 i-C ₅ H ₁₂ ,n-C ₅ H ₁₂ :10			
Simulation 3	Simulation 2 +	31.8	28.04	(Tripathi & Sahu,2020)
Simulation 3a	Benzene: 5 Toluene: 2			
Simulation 4	Simulation 3 +	34.56	31.26	(Tripathi & Sahu, 2019)
Simulation 4a	C ₅ H ₈ : 1			
Simulation 5	Simulation 4 +	35.22	31.98	(Chutia et al., 2019)
Simulation 5a	Apinene: 0.5 Bpinene: 0.50			
Simulation 6	Simulation 5 +	103	96.86	(Zhang et al., 2014)
Simulation 6a	PAN: 1 HCHO: 1 H ₂ O ₂ : 0.5			
Simulation 7	Same as simulation 6/6a but	118.34	106.34	Anthropogenic & biogenic not reduced
Simulation 7a	NO=NO/2 NO ₂ =NO ₂ /2			
Simulation 8	Same as simulation 6/6a but	88.74	89.92	Anthropogenic & biogenic not reduced
Simulation 8a	NO=NO×2 NO ₂ =NO ₂ ×2			
Simulation 9	Same as simulation 6/6a but	93.5	92.68	Anthropogenic reduced
Simulation 9a	Anthropogenic VOCs reduced by 0.5			
Simulation 10	Same as simulation 9/9a but	93.36	92.6	Anthropogenic & biogenic reduced
Simulation 10a	Apinene = apinene×0.5 Bpinene: bpinene×0.5			
Simulation 11	Same as simulation 9/9a but	98.16	92.64	Anthropogenic & biogenic reduced
Simulation 11a	Apinene = apinene×0.75 Bpinene: bpinene×0.75			
Simulation 12	Same as simulation 6/6a but	102.88	96.78	Anthropogenic not reduced Only biogenic reduced
Simulation 12a	Apinene = apinene×0.5 Bpinene: bpinene×0.5			
Simulation 13	Same as simulation 6/6a but	102.94	96.82	Anthropogenic not reduced Only biogenic reduced
Simulation 13a	Apinene = apinene×0.75 Bpinene: bpinene×0.75			
Simulation 14	Same as simulation 11/11a	105.64	99.78	Anthropogenic & biogenic reduced
Simulation 14a	but NO=NO/2 NO ₂ =NO ₂ /2			

Table 4 (continued)

Simulation	Concentrations (ppbv)	Avg O ₃ (μg ⁻³)		Reference
		24 March 2020 Simulations 1–11	31 March 2020 Simulations 1a–11a	
Simulation 15	Same as simulation 11/11a but	83.72	87.86	Anthropogenic & biogenic reduced
Simulation 15a	NO=NO×2 NO ₂ =NO ₂ ×2			

is evinced in *simulations 12 and 13* which are the same as simulation 6 but with biogenic hydrocarbons (isoprene, alpha-pinene, beta-pinene) reduced by 50% and 25%, respectively, leading to 0.1 and 0.05% decreases, respectively, in O₃ compared to simulation 6. To understand how changes in NO_x impact O₃ in this reduced VOC scenario, we multiplied NO_x by 0.5 and 2 in simulations 14 and 15, maintaining other conditions of simulation 11, i.e., anthropogenic×0.5 and biogenics×0.75 (scaled as per CO ratio between prelockdown and lockdown). Now we see that decreasing NO_x by 0.5 increases O₃ by 7.6% in this reduced VOC scenario. In the reduced VOC scenario, increasing NO_x by twice decreased O₃ by a negligible 14.7% pointing to a VOC-sensitive regime.

Simulations 1a–15a are similar to simulations 1–15 but using the observed NO, NO₂, and CO values for 31 March instead of 24 March, thus representing the lockdown period. In both simulation 1 and simulation 1a, the values were 80.24% and 78.8% lower compared to the observations. The NO, NO₂, and CO values are 39.6, 10.3, and 34.45% lower on 31 March 2020 compared to 24 March 2020. Adding C2–C5 hydrocarbons has a similar effect in *simulation 2a* over simulation 2 by increasing O₃ by 14.2%; however, adding BTX increases O₃ by 23.7% more in *simulation 3a*. Adding isoprene in *simulation 4a* increases O₃ by 11.5% more, which is much higher than 8.7% increase in prelockdown simulation 4. Adding apinene and bpinene in *simulation 5a* increases O₃ by 2.3%. Adding PAN, H₂O₂, and HCHO actually now increases O₃ by a whopping 202.9%. Nevertheless, *simulation 6a* is closer to the observed O₃ compared to previous simulations of this series for 31 March 2020. Decreasing NO_x by 0.5 increases O₃ by 9.8% (simulation 7a), while increasing NO_x by 0.5 in *simulation 8a* decreases O₃ by 7.2% again pointing to a VOC-sensitive region.

Reducing anthropogenic VOCs by 0.5 reduces O₃ by 4.4% in *simulation 9a*. Reducing biogenic VOCs by 50% and 25% in simulations 10 and 11, respectively, with anthropogenics still kept reduced by 50% reduces O₃ by insignificantly. Similarly, reducing only biogenics by 0.5 and 0.25 without reducing anthropogenic changes O₃ negligibly in simulations 12a and 13a. Between 1 and 11a, simulation 9a is the closest to observations on 31 March 2020 with only a difference of 1% on the lower side, while simulation 6a was 3.4% more than observed O₃. However, simulation 13a with reduced biogenic VOCs is also quite closer to observed O₃, the difference being 3.3% only. Reducing NO_x in a reduced VOC scenario (anthropogenic×0.5, biogenic×0.75) reduces O₃ by 7.7% in simulation 14a, while increasing NO_x by 2 has a decrease of 5.2% in simulation 15a. It is highly plausible that the reduced biogenic composition represents more appropriate lockdown conditions due to reduced emissions and dilution in an increased PBL. This could be the reason that the reduced VOC composition resulted in a much closer representation to the observed lockdown O₃.

Conclusion

Lockdowns were a hallmark of the year 2020 having several ramifications including changes in concentrations of atmospheric pollutants. The lockdown-induced changes in atmospheric constituents have been documented at local and regional scales based on surface and satellite measurements. However, the lockdown period in India also coincided with a seasonal change from winter to pre-monsoon. A major shortcoming in several published literature for the Indian region was the overlooking of this seasonal change leading to a spurious attribution of the lockdown effect on

atmospheric constituents. A major objective of this paper is to decouple the emission changes during lockdown from meteorological impacts on atmospheric pollutant concentrations. PM, NO₂, and O₃ from 24 urban regions spanning different emission and climatic regimes in India are studied to estimate the actual impact of lockdown. The actual lockdown-induced change is calculated from the difference of expected and observed changes.

For PM, the expected change in North India is positive; meaning in absence of any external forcing like lockdown, the PM concentrations would be enhanced during this period of the year (first fortnight starting with lockdown) compared to the previous period (last fortnight ending before lockdown) as a result of increased biomass burning emissions. However, the lockdown brought down the pollutant levels as outdoor emissions were curbed. The observed decrease is though not the actual impact of lockdown. If the natural increase of concentrations during this period is taken into account, the actual lockdown effect would be much stronger than the observed effect. Similarly, in the dust-dominated western India, a positive change was expected due to enhanced dust loading during this period, but observed change was negative, indicating an accentuated COVID-induced lockdown effect than was observed. In coastal India, in most cases, expected changes are negative (due to increasing marine influence) and aligned with the observed change, so actual lockdown-induced change would be much milder than observed.

For species like NO_x which have strong local sources and short residence times, the reduction is much more dramatic. The observed decrease in NO₂ is very much on the expected lines as local traffic emissions are the major contributor to NO₂ in cities across India. For eastern endpoint of IGP, e.g., for Kolkata, the expected change was a decrease (−47.09%) due to lower influence from IGP as well as reduction in local emissions and increasing marine influence. The observed change for Kolkata is also a negative (−64.03%), but it must be noted that the whole 64% decrease cannot be attributed to lockdown, only the difference, i.e., −16.94%, is the actual lockdown influence. An enhancement in O₃ was observed at many stations immediately after lockdown, viz., Patiala, Delhi, and Guwahati. This can happen in a VOC-sensitive regime, where a decrease in NO_x would lead to enhancement in O₃ for the same VOC level.

VOC-sensitive regimes generally occur in urban areas where the rate of NO_x production is much larger compared to the OH production rate. In other places like Kolkata, Talcher, Jalandhar, Hyderabad, and Tirupati, O₃ was already increasing before the lockdown. This is aligned with the expected positive percentage changes in O₃. In the Northern part of India, the positive expected change is a result of production from biomass burning, but observed changes are negative for most part of northern India due to lower levels of NO₂ except Delhi and Patiala, where NO₂ levels are higher compared to other north Indian stations selected for this study.

Box model simulations for an example station (Ahmedabad) using available NO_x and CO data and approximating hydrocarbon data from different years showed that anthropogenic VOCs (C2–C5, BZT) increase O₃ by 57.9% during prelockdown and 41.3% during lockdown. However, C2–C5 VOCs have a lower contribution in lockdown O₃ enhancement compared to BZT. Biogenic hydrocarbons like isoprene and pinenes do not have much impact on increasing O₃ during either prelockdown or lockdown. The addition of PAN, HCHO, and H₂O₂ also increases O₃ significantly both during prelockdown and during lockdown.

Using simulation 6 and 6a as base for prelockdown and lockdown, i.e., keeping the original level of VOCs, increasing NO_x by a factor of 2 causes significant O₃ decrease during both prelockdown (13.8%) and lockdown (7.1%), while decreasing NO_x by a factor of 2 increases prelockdown O₃ by 14.9% and lockdown O₃ by 9.8%, indicating slightly higher response to NO_x during prelockdown period. Similarly, decreasing anthropogenic VOCs by a factor of 2 reduces prelockdown O₃ by 9.2% and lockdown O₃ by 4.3%. Reducing biogenic VOCs by half reduces O₃ negligibly both during prelockdown and lockdown. Increasing NO_x by 2 and decreasing NO_x by 0.5 at a reduced VOC composition caused prelockdown O₃ to change by −14.7% and 7.6%, respectively, while lockdown O₃ changed by −7.2% and 9.8%, respectively. The fact that increasing NO_x promotes O₃ reduction (opposing effect) both for the prelockdown (24 March) and lockdown (31 March) for Ahmedabad example while changing VOCs had an accompanying impact on O₃ points to a VOC-sensitive composition. In the absence of actual hydrocarbon measurements, detailed simulation of chemistry to understand the O₃ changes during the lockdown

period would be a challenging task, and any attribution of causes to the O₃ results remain speculative at best at this point.

In the end, it can be concluded that the actual lockdown-induced changes in atmospheric pollutants are different from what is represented by simple trend in a time series. For pollutants like PM and O₃ in North India, the natural enhancement due to biomass burning which camouflaged the severity of lockdown-induced decreases. For coastal stations like Visakhapatnam, the lockdown effect is much milder due to prior dilution and ventilation effects.

Acknowledgements We thank the reviewers for their constructive comments which have greatly improved the quality of the MS. We thank the editor for getting the MS reviewed in difficult times of the pandemic.

Funding The first author acknowledges the support from Harithasree Sreedevan in identification of events.

Data availability The air quality data was downloaded from the CPCB website: <https://app.cpcbccc.com/ccr/#/caaqm-dashboard/caaqm-landing/caaqm-comparison-data>. The PM sources are based on analysis presented in UrbanEmissions.info. PBL height is taken from ERA5 reanalysis. While the raw data is freely available on the above mentioned sites, the datasets generated during and/or analyzed during the current study are available from the corresponding author on request. O₃ simulations are carried out using FOAM box model: <https://sites.google.com/site/wolfegm/models>.

Declarations

Competing interests The authors declare no competing interests.

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