



Influence of meteorology, mobility, air mass transport and biomass burning on PM_{2.5} of three north Indian cities: phase-wise analysis of the COVID-19 lockdown

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Abstract Recent studies concluded that air quality has improved due to the enforcement of lockdown in the wake of COVID-19. However, they mostly concentrated on the changes during the lockdown period, and the studies considering the consequences of de-escalation of lockdown are inadequate. Therefore, we investigated the changes in fine particulate matter (PM_{2.5}) during the pre-lockdown, strict lockdown, unlocking, and post-lockdown scenarios. In addition,

we assessed the influence of meteorology, mobility, air mass transport, and biomass burning on PM_{2.5} using Google's mobility data, back trajectory model, and satellite-based fire incident data. Average PM_{2.5} concentrations in Ghaziabad, Noida, and Faridabad decreased by 60.70%, 63.27%, and 60.40%, respectively, during the lockdown. When compared with the preceding year (2019), the reductions during the shutdown period (25 March–31 May) were within the range of 36.34–44.55%. However, considering the entire year, this reduction in PM_{2.5} is momentary, and a steady increase in traffic density and industrial operations within cities during post-lockdown reflects a potent recovery of aerosol level, during which the average mass of PM_{2.5} three- to four-folds higher than the lockdown period. Back trajectories and fire activity results showed that biomass burning in the nearby states (Haryana and Punjab) influence aerosol load. We conclude that a partial lockdown in the event of a sudden surge in pollution would be a beneficial approach. However, reducing fossil fuel consumption and switching to more environmentally friendly energy sources, developing green transport networks, and circumventing biomass burning are efficient ways to improve air quality in the long term.

Highlights

- Reduction in PM_{2.5} due to the COVID-19 lockdown is momentary.
- PM_{2.5} level was three- to four-folds higher in post-lockdown than in the lockdown and relaxing periods.
- Community mobility is directly related to the PM_{2.5} mass.
- PM_{2.5} concentration is 16.19 µg/m³ higher on days with higher fire events and FRP.

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Introduction

Severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), a new coronavirus that has emerged in Wuhan, China, has created an emergency due to its global infection. On 30 January 2020, the World Health Organization's emergency committee declared coronavirus disease 2019 (COVID-19) as a global health emergency due to the unrelenting growth rate of worldwide cases (WHO, 2020). Depending upon the extent of COVID-19 impact in each country and country-specific situations and capacities, governments around the world are taking different levels of interventions, including travel restrictions and lockdowns, to contain the spread of the highly contagious virus (MoHFW, 2020). In India, a nationwide lockdown was implemented from 24 March 2020 to contain the spread of the pandemic virus and preserve the health and safety of citizens (<https://www.mohfw.gov.in>). Vehicle transport, including flights, was suspended; factories and industrial activities ceased; people were allowed to leave their homes only in emergencies following social distancing (Dasgupta & Srikanth, 2020; Ghosh & Ghosh, 2020). Following the first lockdown, different lockdown stages were put in place, with subsequent relaxations based on the country's number of COVID-19-positive cases (Gouda et al., 2021). Even though enforcement of nationwide lockdown measures adversely influenced India's economy (Jain & Sharma, 2020; Nigam et al., 2021), it played a vital role in controlling the spread of the pandemic virus, thereby avoiding life loss (Gulia et al., 2021).

In addition to controlling virus spread, limiting anthropogenic activities during the lockdown period also significantly improves the environmental compartments. A decline in air pollution due to curfews and restricted mobility in the wake of the COVID-19 pandemic has been observed and reported worldwide (Todorović, 2020; Torkmahalleh et al., 2021). Several studies have shown significant changes in the concentration of the air pollutants during these blackout periods and have contributed to cleaner air quality and a better air quality index (AQI) across India. In general, a decrease in fine particulate matter (PM_{2.5}), respirable particulate matter (PM₁₀), nitrogen oxides (NO₂), carbon monoxide (CO), and sulfur dioxide (SO₂) was observed during the closure period (Bera et al., 2021; Kolluru et al., 2021; Masum & Pal, 2020; Rahaman et al., 2021). Data from satellite and monitoring stations

showed a considerable decrease in PM_{2.5} in Mumbai, followed by Delhi, Kolkata, Chennai, and Bengaluru during the lockdown (Lal et al., 2020).

Although massive reductions in PM_{2.5} have been reported across the country, 13 of the world's 15 most polluted cities are still in India (IQAir, 2020). Best of our knowledge, most of the published studies have only looked at the implications of lockdown, and no past research has investigated the consequences of relaxing measures that may have the opposite effect on the existing environment. Relaxing lockdown would lead to a sudden surge in pollution levels, possibly increasing morbidity and mortality attributable to air pollution. In addition, virus particles can stick to dust particles and travel further, which in turn potentially infecting more people (Comunian et al., 2020). In this context, a separate investigation is essential to determine whether pollution levels after lifting lockdown are coherent with the strict lockdown conditions. The comparison of pollutant concentrations before, during, and after lockdown is vital to determine whether lockdown is solely responsible for enhancing air quality. This paper aimed to present the changes in the PM_{2.5} of three north Indian cities during four different circumstances (pre-lockdown, lockdown, unlock, and post-lockdown) and compared the observations with the identical period in the previous year (under no lockdown restrictions). In addition, statistical (ANOVA, Tukey's post-hoc test, correlation, and bivariate polar plots) and model-based approaches were applied for this study to assess the influence of meteorology, mobility, long-range air mass transport, and biomass burning on the PM_{2.5} levels.

Materials and methods

Study cities

This study focused on three major north Indian cities: Ghaziabad, Noida, and Faridabad. These three cities were closely situated to National Capital Delhi and are areas of high population and economic activities and were among the most polluted cities globally in terms of PM_{2.5}. As per IQAir's (2020) World Air Quality study, in the list of regional cities with the worst air quality, Ghaziabad (annual mean PM_{2.5}, 106.6 µg/m³), Noida (94.3 µg/m³), and Faridabad (83.3 µg/m³) ranked 2nd, 6th, and 11th positions, respectively. Ghaziabad, located on the western edge of Uttar Pradesh,

is the second largest industrial city in the state with 3.4 million inhabitants (<https://ghaziabad.nic.in>). New Okhla Industrial Development Authority (Noida) is a planned city in the Gautam Buddha Nagar district of Uttar Pradesh with a populace of 6.4 lakhs (Census of India, 2011). Noida is classified as the special economic zone and one of the fast-growing industrial hubs in the state. Faridabad, located in the Southeastern part of Haryana, covers a geographical area of 741 km² (Faridabad township, 18.1 km²) and has a population of 1.8 million (<https://faridabad.nic.in>). The location of monitoring cities and the distribution of monitoring stations for the air quality are shown graphically in Supplementary Fig. S1.

PM_{2.5} data collection and statistical analysis

Daily average (24-h) concentrations of PM_{2.5} data from ground-based Continuous Ambient Air Quality Monitoring Stations (CAAQMS) were obtained from the Central Pollution Control Board (CPCB) web portal (<https://app.cpcbcr.com/ccr/#/caaqm-dashboard-all/caaqm-landing>). Data from four CAAQMS (Indirapuram, Loni, Sanjay Nagar, and Vasundhara) of Ghaziabad, four CAAQMS (Sector-125, Sector-62, Sector-1, and Sector-116) of Noida, and four CAAQMS (new industrial town, Sector-11, Sector-30, and Sector-16A) of Faridabad, which is maintained by the respective State Pollution Control Boards and CPCB were collected. CAAQMS of the study cities, nature of the location, and geographical coordinates are provided in Supplementary Table S1. PM_{2.5} data for 2019 and 2020 were retrieved and categorized based on the lockdown guidelines given by the Ministry of Health and Family Welfare (MoHFW, 2020), Government of India, as (i) pre-lockdown (Pre-LD): 01/01/2020 to 24/03/2020; (ii) lockdown (LD): 25/03/2020 to 31/05/2020; (iii) unlock (UL): 01/06/2020 to 31/10/2020; and (iv) post-lockdown (Post-LD): 01/11/2020 to 31/12/2020. The different phases of lockdown and unlock and their time periods are listed in Supplementary Table S2. For the periods mentioned above, descriptive statistical analyses (central tendency and dispersion measures) were carried out to assess the pollutant events over time and compare their relative changes. Pairwise comparisons were made by ANOVA and Tukey's post-hoc test using Statistical Package for the Social Sciences (SPSS) software version 21. PM_{2.5} level in lockdown phases (of 2020) compared with the concentrations observed during the same periods of the previous

year (2019). Data before 2019 were not included in the present investigation due to large inconsistencies.

Community mobility data

Mobility data utilized in this study was collected from Google COVID-19 Community Mobility Reports (Google, 2020), consisting of district-wise time series data from 15/02/2020 to 31/12/2020. These data contain six categories of mobility: retail and recreation, grocery and pharmacy, parks, public transport, workplaces, and residential. Variations in mobility were presented as percentage change compared to the baseline value (i.e., the median value, for the corresponding day of the week, during the period: 3 January 2020–6 February 2020) (Google, 2020). For a better understanding, PM_{2.5} changes for each day are also calculated using a similar method defined in the COVID-19 Community Mobility Reports. Therefore, the daily changes of the fine aerosols compared with the equivalent baseline weekday, for example, data on a Monday compared to corresponding data from the baseline series for a Monday. In addition, Pearson's correlation analysis was performed between mobility changes and PM_{2.5} variations to assess the influence of people's mobility on PM_{2.5} levels.

Meteorology analysis

Daily meteorological data, namely ambient air temperature, relative humidity (RH), wind velocity (WS), and wind direction (WD) for 2020, were retrieved from the CPCB web portal (<https://app.cpcbcr.com/ccr/#/caaqm-dashboard-all/caaqm-landing>). The relationship between the pollutant concentrations and the corresponding wind speed and wind direction was examined through bivariate polar plots. Changes in the concentration of a species regarding WS and WD were graphically illustrated in polar coordinates. It can provide directional information about sources and the WS dependence of concentrations by means of which emissions sources can be effectively distinguished (Grange et al., 2016; Hama et al., 2020; Uria-tellaetxe & Carslaw, 2014). Statistical software R programming language (R Core Team, 2018) and its package "openair" (Carslaw & Ropkins, 2012) were applied to perform data analysis and develop bivariate polar plots. The openair website at <http://www.openair-project.org> provides more information concerning the project

and a comprehensive manual supporting the package. The details of the statistical procedure have been demonstrated previously by Carslaw and Ropkins (2012), hence not repeated here. In order to investigate the relationship between $PM_{2.5}$ and four meteorological variables (temperature, WS, WD, and RH), correlation analysis was performed with IBM SPSS (version 21).

Backward trajectory model and fire incident analysis

Backward trajectories have often been utilized to understand the potential medium- and long-range transport of air masses that are being delivered at the recipient location at any given time. The Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPPLIT) model developed by the National Oceanic and Atmospheric Administration's Air Resources Laboratory (Rolph et al., 2017; Stein et al., 2015) was used to locate the distant sources and to track the vertical movement of the air mass reaching the study region during the pre-lockdown, strict lockdown, unlock and post-lockdown phases. The trajectories of three cities were confined within close proximity, so these cities were considered as a single unit. More details on the HYSPPLIT model can be found at <http://ready.arl.noaa.gov/HYSPPLIT.php>. Three-day (72-h) backward trajectories at 500 m above ground level (AGL) were run using data from the Global Data Assimilation System (GDAS) of the National Centers for Environmental Prediction (<https://www.ready.noaa.gov/archives.php>), which has $1^\circ \times 1^\circ$ latitude-longitude grid spatial resolution and 3-h time resolution. MODIS (Moderate Resolution Imaging Spectroradiometer) fire data were retrieved from Fire Information for Resource Management System (<https://firms.modaps.eosdis.nasa.gov/>). Only fires with a confidence level equal to or greater than 75% were selected for further analysis. ArcGIS Pro software (version 2.5) has been used to integrate and analyze the trajectory and fire data, both spatially and temporally. In addition, the concentrations were compared between days with high and low fire activity to estimate the contribution of biomass burning to $PM_{2.5}$ pollution. High fire activity days were defined as the days with a daily cumulative fire radiative power (FRP) above the 75th percentile for the whole of 2020, while all other remaining days are defined as low fire activity periods. FRP is the measure of radiant heat output, which is related to the rate of fuel consumption. A high FRP rate is directly linked to higher

particulate matter emissions (Wooster et al., 2005; Kaiser et al., 2011).

Results and discussion

Changes in the concentration of $PM_{2.5}$

The panels of Fig. 1a-c present the daily trend of $PM_{2.5}$ concentrations during 2020 in Ghaziabad, Noida, and Faridabad, respectively. The concentration flow of $PM_{2.5}$ in all three cities follows a parallel trend that begins to deteriorate immediately after the lockdown was enforced on 25 March 2020. The mean concentration of $PM_{2.5}$ in Ghaziabad declined to $43.83 \pm 19.60 \mu\text{g}/\text{m}^3$ (LD1) from $135 \pm 66.77 \mu\text{g}/\text{m}^3$ (Pre-LD) just within 21 days of strict closure. Likewise, about 71.14 and 69.41% reduction in $PM_{2.5}$ was observed in Noida and Faridabad during the first phase of lockdown (LD1). Fine PM remained at the lower level throughout the lockdown period in all three cities, with mean \pm standard deviation (SD) of $53.05 \pm 25.16 \mu\text{g}/\text{m}^3$ (Ghaziabad), $44.99 \pm 18.76 \mu\text{g}/\text{m}^3$ (Noida), and $42.82 \pm 24.09 \mu\text{g}/\text{m}^3$ (Faridabad) (Supplementary Table S3). Industrial sectors, thermal power plants, burning waste, vehicular emissions, and road dust from vehicle movement were the primary sources of fine PM in the study area (Kumari et al., 2020). Since all kinds of industrial operations and commercial activities were ceased during the lockdown, this could be the main reason behind the $PM_{2.5}$ reduction. Several authors have already reported similar observations in Indian urban cities (Bera et al., 2021; Das et al., 2021a; Dasgupta & Srikanth, 2020; Kolluru et al., 2021; Kumar et al., 2021; Kumari et al., 2020; Nigam et al., 2021; Saxena & Raj, 2021; Srivastava et al., 2020). Most interestingly, a slight incline in PM level at the UL4 period (September 2020) was observed, which increases drastically in UL5 and reached maximum level during post-LD. The maxima $PM_{2.5}$ concentrations of $531 \mu\text{g}/\text{m}^3$ for Ghaziabad, $474 \mu\text{g}/\text{m}^3$ for Noida, and $389 \mu\text{g}/\text{m}^3$ for Faridabad were recorded on 09/11/2020 (post-LD period).

The summary of the percent variation and Tukey's post-hoc test between Pre-LD, LD, UL, and Post-LD is shown in Table 1. Tukey's test results clearly indicate that there is a significant variation between the study phases. However, there are no substantial variations in

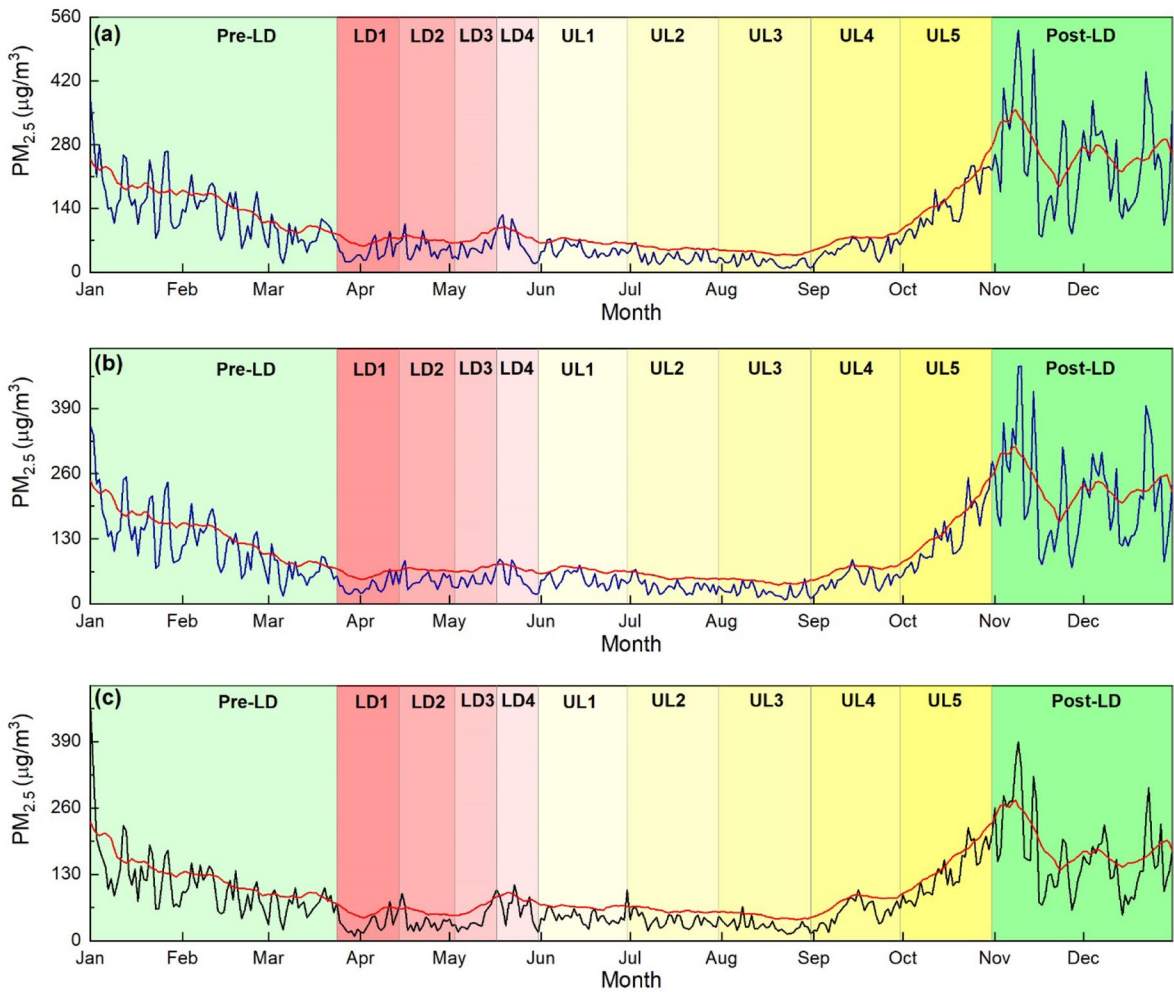


Fig. 1 Time series of daily mean $PM_{2.5}$ concentrations between January and December 2020 in (a) Ghaziabad, (b) Noida, and (c) Faridabad. The solid red line represents a 15-day moving average of $PM_{2.5}$

PM values between LD and UL states, depicted by a p -value > 0.05 . It is quite surprising to find that the $PM_{2.5}$ concentration during post-LD was three to four times higher than the LD and UL phases. Notably, it was even higher than the Pre-LD scenario. When compared with the Pre-LD phase, about 84%, 76%, and 56% of the increase in $PM_{2.5}$ levels were observed in Ghaziabad, Noida, and Faridabad, exclusively. This unforeseen rise in aerosol concentrations is attributed mainly to the progressive refurbishment of normal day-to-day activities, i.e., vehicle transport, industrial operations, and economic activities. This argument is consistent with the conclusions of Kumar et al. (2021) in India and Viteri et al. (2021) in Madrid, Spain, who

found a marginal increase in the pollution level during the de-escalation period.

Comparison with the previous year (2019)

Meteorological patterns and emission sources directly influence air quality, hence showing solid temporal patterns. To inspect the influence of changes that happened during 2020, a comparison was made with mean and percentage variations during the similar period of 2019. It was one of the easiest ways to control the effects of meteorological factors (Gama et al., 2018). As shown in Fig. 2, reductions in $PM_{2.5}$ are observed throughout 2020 compared to forgoing

Table 1 Variation of PM_{2.5} and Tukey's post-hoc test results between before lockdown (Pre-LD), during lockdown (LD), unlock (UL), and post-lockdown (post-LD) periods across study cities

Phases	Variation (in %)	Variation ($\mu\text{g}/\text{m}^3$)	SEM ^a	q value	p-value	LCL ^b	UCL ^b
Ghaziabad							
LD vs Pre-LD	-60.70	-81.945	10.717	10.814	0.000	-109.605	-54.284
UL vs Pre-LD	-54.63	-73.751	8.921	11.691	0.000	-96.777	-50.725
UL vs LD	15.44	8.193	9.575	1.210	0.828	-16.519	32.906
Post-LD vs Pre-LD	83.97	113.362	11.051	14.506	0.000	84.838	141.885
Post-LD vs LD	368.14	195.306	11.586	23.841	0.000	165.404	225.209
Post-LD vs UL	305.51	187.113	9.948	26.600	0.000	161.437	212.789
Noida							
LD vs Pre-LD	-63.27	-77.507	9.961	11.004	0.000	-103.216	-51.797
UL vs Pre-LD	-51.66	-63.287	8.292	10.793	0.000	-84.689	-41.885
UL vs LD	30.60	14.220	8.900	2.260	0.381	-8.750	37.190
Post-LD vs Pre-LD	76.37	93.560	10.272	12.881	0.000	67.048	120.072
Post-LD vs LD	380.20	171.066	10.768	22.466	0.000	143.273	198.860
Post-LD vs UL	348.60	156.847	9.246	23.989	0.000	132.982	180.712
Faridabad							
LD vs Pre-LD	-60.40	-65.308	8.730	10.579	0.000	-87.840	-42.776
UL vs Pre-LD	-43.29	-46.802	7.267	9.108	0.000	-65.560	-28.045
UL vs LD	43.21	18.505	7.800	3.355	0.084	-1.626	38.637
Post-LD vs Pre-LD	55.77	60.304	9.003	9.473	0.000	37.068	83.540
Post-LD vs LD	293.36	125.612	9.438	18.823	0.000	101.253	149.971
Post-LD vs UL	174.66	107.106	8.104	18.691	0.000	86.190	128.022

^aSEM standard error of the mean

^bLCL 95% lower confidence limit of the mean; UCL 95% upper confidence limit of the mean

phases to equivalent periods of 2019. Overall, PM_{2.5} concentrations in the study regions are on average 21.84 $\mu\text{g}/\text{m}^3$ (Ghaziabad), 18.67 $\mu\text{g}/\text{m}^3$ (Noida), and 14.97 $\mu\text{g}/\text{m}^3$ (Faridabad) lower in 2020. Interestingly, slight decline even before the lockdown lifted (Pre-LD), reflecting the probable reductions due to changes in emission sources and meteorology. The most significant decline was noted in Faridabad (30.35 $\mu\text{g}/\text{m}^3$), followed by Ghaziabad (20.95 $\mu\text{g}/\text{m}^3$) and Noida (11.31 $\mu\text{g}/\text{m}^3$).

PM_{2.5} levels remarkably dropped by 44.55%, 41.04%, and 36.34%, respectively, between 2019 and 2020 during LD (25 March–31 May) in Noida, Faridabad, and Ghaziabad. This is attributed to the blockage of all likely emissions, such as transport and industrial operations, as often observed in the literature. Despite the general decline, there have been some periods when concentrations of PM_{2.5} were higher in 2020 than they were in 2019, particularly during UL4 (in September), shortly after most

lockdown measures were relaxed. Faridabad saw a maxima surge in PM_{2.5} of 98.36% and 21.69%, respectively, during UL4 and UL5. Though in Noida and Ghaziabad, PM_{2.5} changes are +30.69 and +32.94% in UL4 during 2020, which was 36.86 and 38.96 $\mu\text{g}/\text{m}^3$ in 2019. Post-LD concentrations remained lower in 2020 in the study area except in Ghaziabad, which displays a minor rise of about 2.87%. This study results exhibited a range of values comparable with the range of changes reported in India (CPCB, 2021; Bera et al., 2021; Das et al., 2021a, b; Gautam et al., 2021; Mandal et al., 2021; Ravindra et al., 2021; Saxena & Raj, 2021).

Effects of meteorological parameters

Figure 3 shows the bivariate polar plots of phase-wise mean PM_{2.5} concentrations in relation to wind speed and wind direction in their respective study cities. The color scale of the polar graphs shows the fine

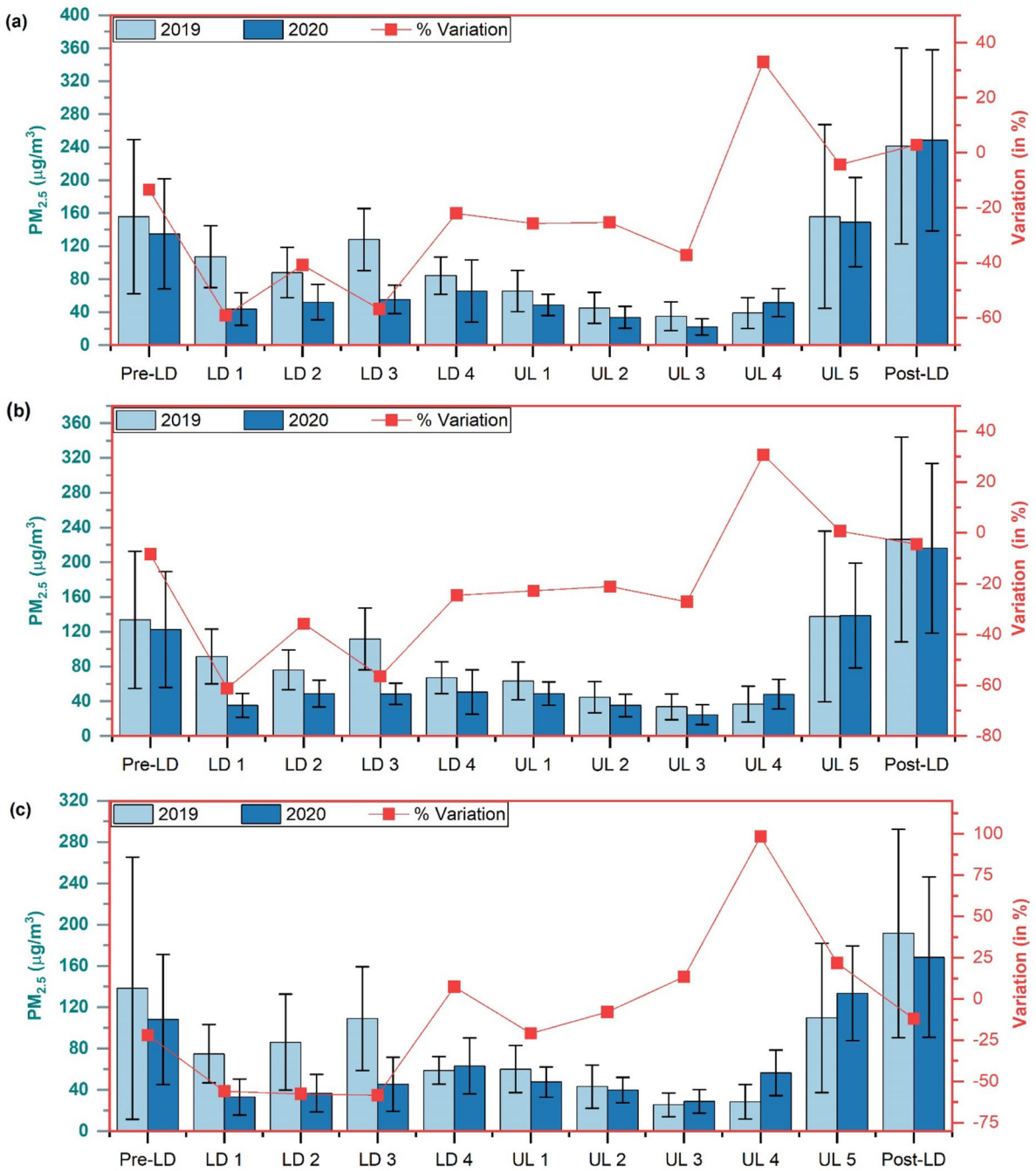


Fig. 2 Mean concentrations of PM_{2.5} for the phases of pre-lockdown (01 January to 24 March), lockdown (25 March to 31 May), unlock (01 June to 31 October), and post-lockdown (01 November to 31 December) in 2019 and 2020: (a) Gha-

ziabad, (b) Noida, and (c) Faridabad. Differences represent the variations between the corresponding periods of 2019 and 2020

aerosol concentration, and the radial scale shows the wind speed. Depending on the local wind conditions at the sampling locations, a variation in concentrations can be evidently seen. The concentration decreases radially outwards from the core of the diagram. Bivariate graphs signify that $PM_{2.5}$ sources were predominantly localized, as depicted by high concentrations in the center at low wind speeds ($WS < 2$ m/s). Lower WS during Pre-LD (< 5 m/s) and post-LD (< 2 m/s) facilitates the accumulation of pollutants, while higher WS (> 10 m/s) during UL eases the dispersion. Visualization in Fig. 3a suggests that Ghaziabad receives local-sourced particulate matter mainly from the south and southwest direction, where industrial sectors of Noida are located (within a 20-km radius). Along with its own sources, emissions from nearby industrial cities add up to the degree of pollution. While in Faridabad, $PM_{2.5}$ mass was dominated by local sources with low WS (< 5 m/s) and elevated concentrations in the center bin owing to the dearth of dispersion. Plots observed for Noida also revealed a pattern that is comparable to Faridabad (Fig. 3c). These results were reliable with the findings of Kumar et al. (2021) and Hama et al. (2020).

Meteorological parameters influence the transport, spread, and deposition of particulate matter in the atmosphere over any region on different time scales, i.e., from diurnal to seasonal, annual, and decadal (Chowdhury et al., 2019; Coskuner et al., 2018). Monthly descriptive statistics of temperature, WS , and RH for the study cities in 2020 are shown in Supplementary Tables S4, S5, and S6, respectively. Regression analysis was used to analyze the correlation between $PM_{2.5}$ and meteorological parameters. The correlation plot presented in Fig. 4 shows the strong negative association of $PM_{2.5}$ with wind speed in all three cities. At the same time, the relationship between $PM_{2.5}$ and temperature was weak positive (0.28) in Faridabad and weak negative (-0.19) in Noida. Surprisingly, no relationship was found in Ghaziabad. This demonstrates why mean $PM_{2.5}$ concentrations were higher in the center of the polar plots and vice versa. These bivariate plots and correlation analysis results strongly suggest that wind speed is the significant factor that influences $PM_{2.5}$ levels in 2020.

Effects of community mobility

Figure 5 illustrates the fact that the transport sector has been severely affected by the enforced

COVID-19 restrictions. All means of mobility sharply decreased in the initial periods of restriction and then inclined again after the officials restrained the control measures. On average, people's activity reduced by 82.86% (retail and recreation), 49.43% (grocery and pharmacy), 85.71% (parks), 80.20% (public transport), and 68.92% (workplaces) during the period 24 March–31 May. Traveling to places like national parks, beaches, marinas, and public gardens was complete under control until November (Post-LD). The same was observed in all three cities, but the rates were higher in Noida, followed by Ghaziabad and Faridabad (Fig. 5). It is unsurprising to find that there is a considerable increase in residential activity, which indicates the migration of the population towards places of residence. Resumption of activities just after strict lockdown (i.e., after 31 May) traduced in positive mobility trend, especially for groceries (hypermarkets, food granaries, marketplaces, and specialty food shops) and pharmacies.

For the current study, the data from the Google COVID-19 Community Mobility database (Google, 2020) was utilized as a proxy for transport activity. Correlation analysis was applied to identify the link between the variations in atmospheric $PM_{2.5}$ concentrations and community activity. The relationship observed between the mobility categories and $PM_{2.5}$ changes is summarized in Table 2 and is found to be highly significant (at the level 99%; $p < 0.01$). The $PM_{2.5}$ variations were positively substantially related to grocery and pharmacy, retail and recreation, and public transport. A positive correlation shows that with a deterioration in mobility, the $PM_{2.5}$ value decreases and vice versa. In Fig. 5, a drastic reduction in these three mobility activities in the study cities could be clearly seen, which possibly directly influenced the aerosol level. Parks and workplace mobility had a weakly positive association with $PM_{2.5}$. Surprisingly, residential mobility showed a weak negative association with $PM_{2.5}$ variations. There are two possible explanations for these observations. Firstly, residential activities may not reflect the aid of motor vehicle transport. Another possible explanation is that the sharp decline in other kinds of activity could outweigh the effects of residential mobility. Overall, it becomes clear that the constraint in people's mobility is one of the main reasons for the massive reduction in fine dust pollution.

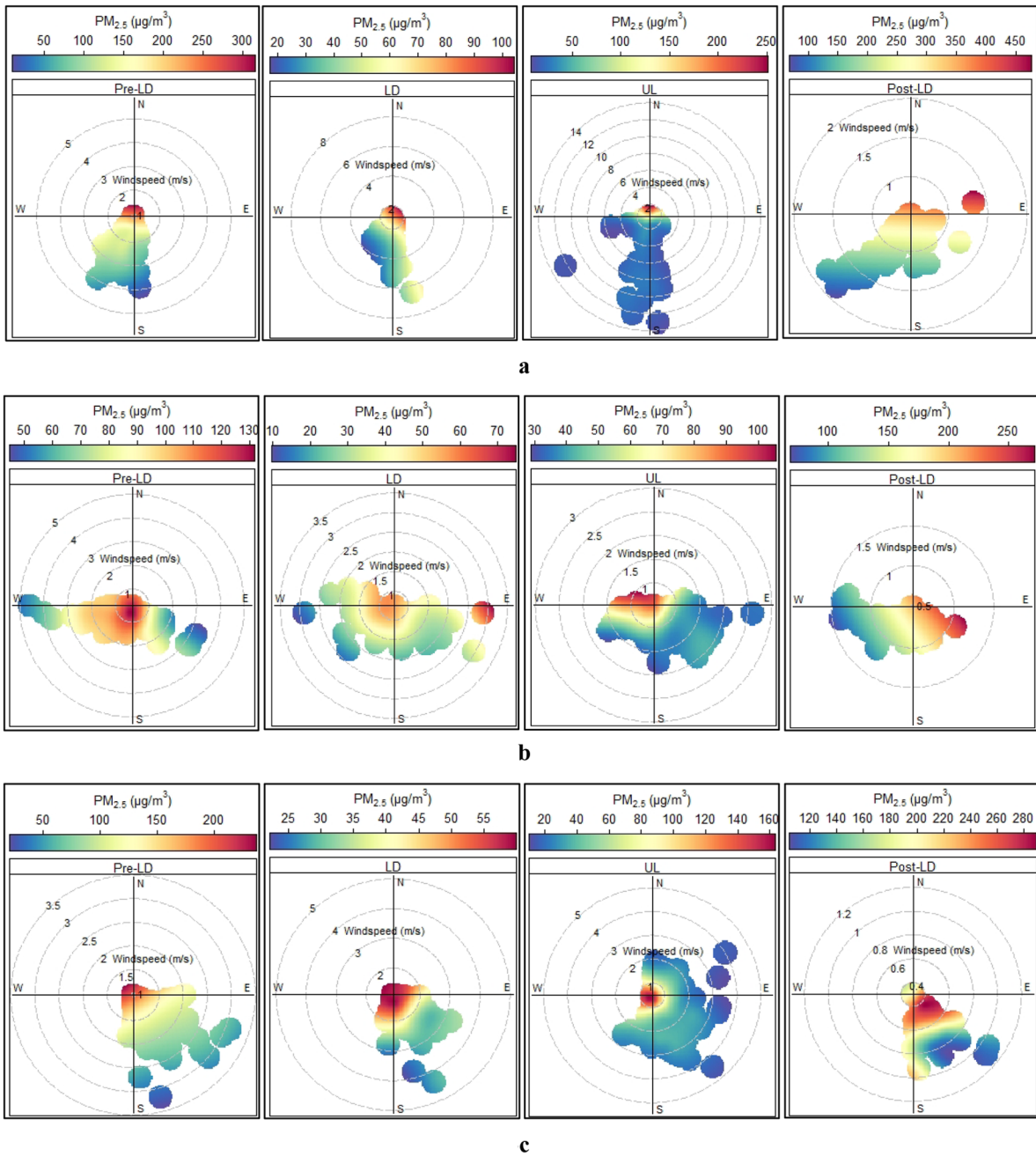


Fig. 3 a Bivariate polar plots of $PM_{2.5}$ during different phases in Ghaziabad. b Bivariate polar plots of $PM_{2.5}$ during different phases in Faridabad. c Bivariate polar plots of $PM_{2.5}$ during different phases in Noida

Impact of long-range transport and biomass burning

Air mass backward trajectories and the spatial distributions of fires over the study area before, during, and after lockdown are illustrated in Fig. 6. During

the Pre-LD, the trajectories showed the unidirectional movement of polluted air masses mainly from a north-westerly direction. The main areas in these regions are Haryana, Punjab, and the regions of Pakistan. In addition, patterns of slowly moving air

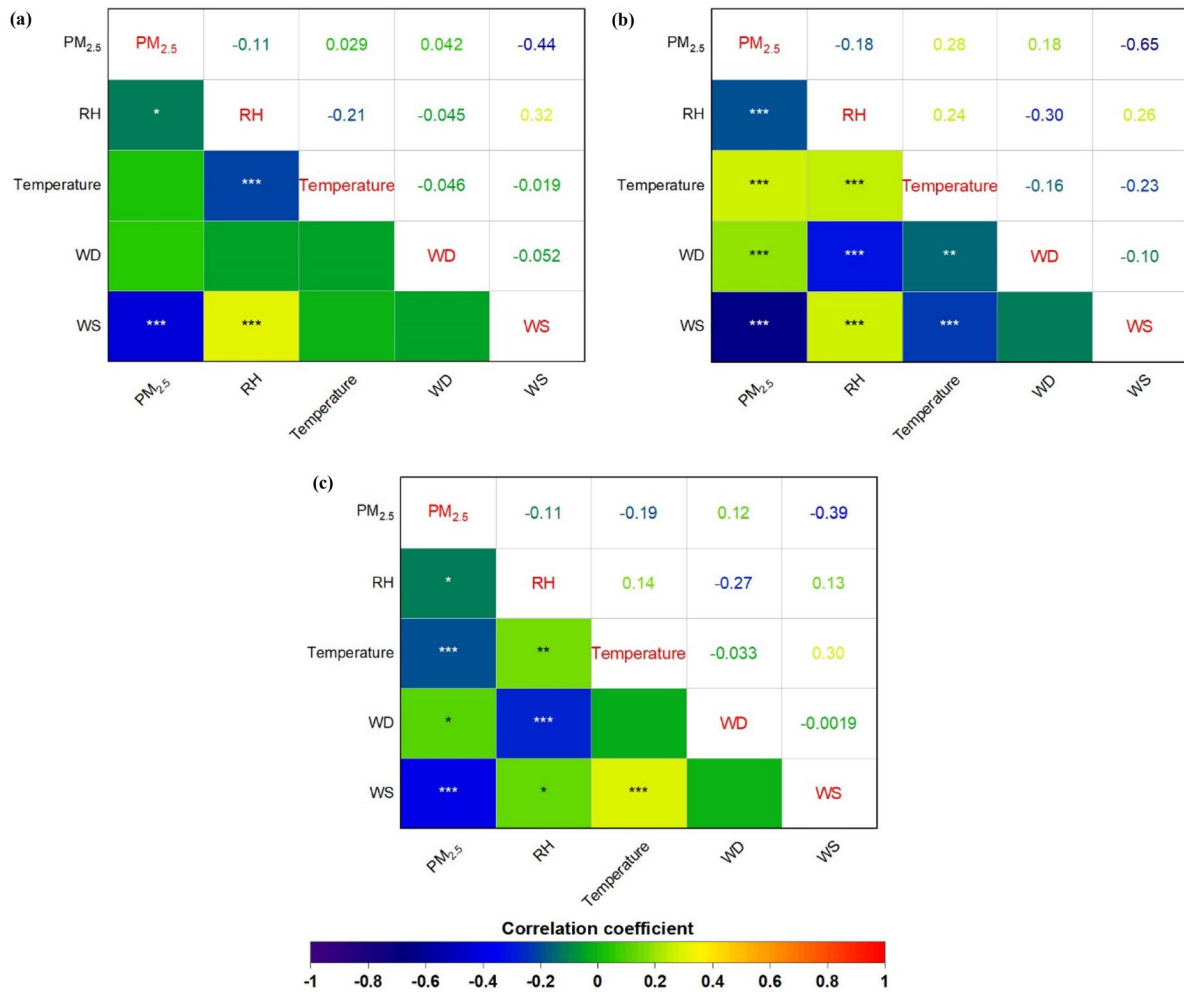


Fig. 4 Correlation analysis plot between fine aerosol concentrations and meteorological parameters: (a) Ghaziabad, (b) Noida, and (c) Faridabad

masses from the directions southwest (Gujarat), south (region of Central India), and east (Uttar Pradesh) were observed. During LD, the area was influenced by the dust from the Thar Desert. These clusters transported from Iran, Afghanistan, and Pakistan, which typically followed a more extensive flow pattern across Haryana and Punjab before reaching the receptor site. Another cluster of air masses from the Arabian Sea followed a curve pattern from the southwest direction. Far-reaching air masses have also been instigated from adjacent eastern regions of Bihar and Uttar Pradesh and the southern areas of Nepal, with the main dense springs being in urban areas of the Indo-Gangetic Plain. During UL, clusters from

different wind directions were identified, although long-range regional transport from the southwest (from the Arabian sea) and southeast (from Bangladesh) dominated the carriage directions. Trajectory density plot of the Post-LD period showed that polluted air masses to receptor location came to emanate from northwest, south, and east (Fig. 6: post-lockdown), while air mass cluster from the south path is a long-range conveyance.

The fire numbers were highest during the LD, followed by UL, Post-LD, and Pre-LD. Sparse and isolated fire events in Pre-LD are attributed to the fact that it falls in the winter season (i.e., January and February). The density of the fire sources was highest in the

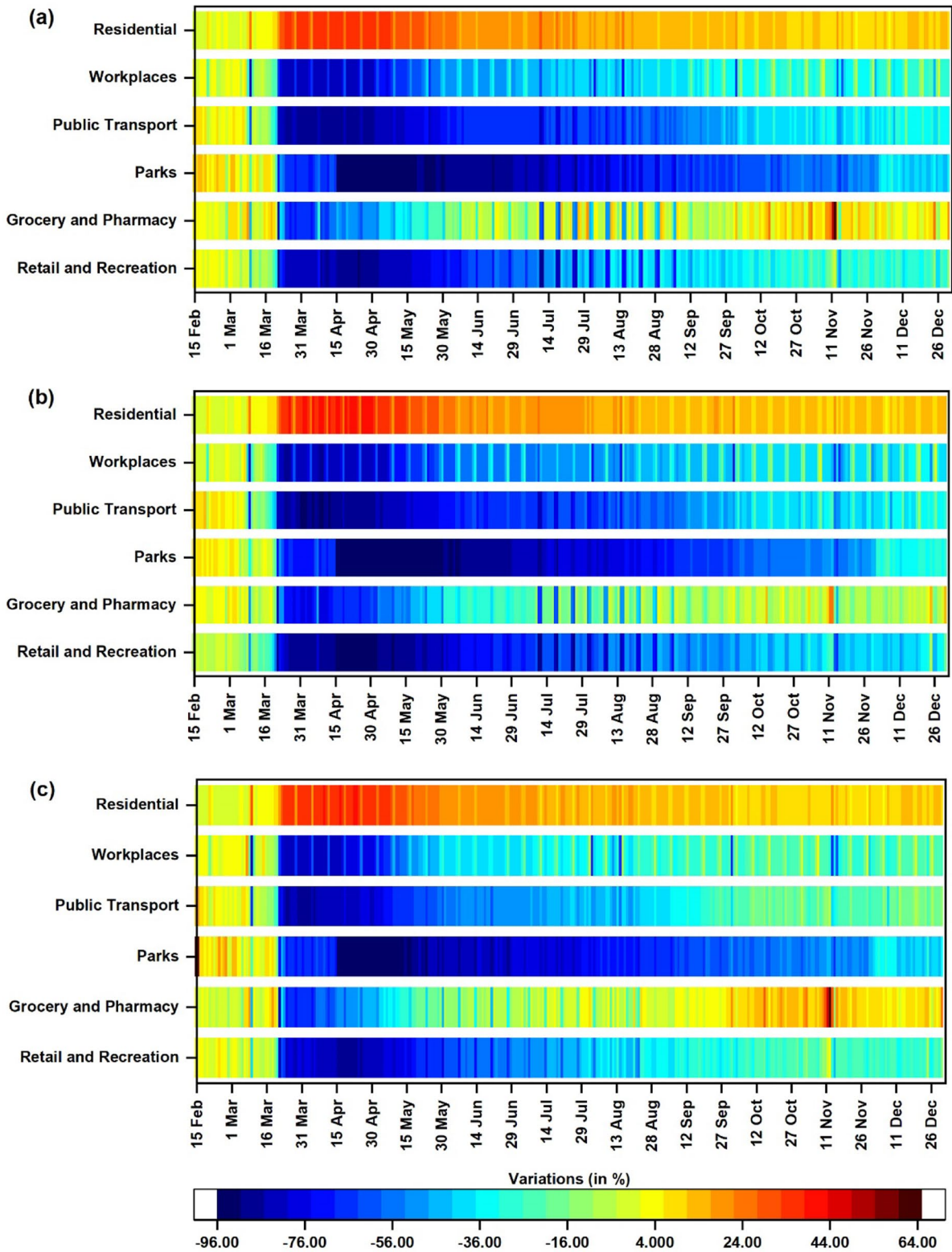


Fig. 5 Daily variations in the community mobility at (a) Ghaziabad, (b) Noida, and (c) Faridabad obtained from Google COVID-19 Community Mobility Reports 2020. Variations represent the daily percentage change in mobility compared to the baseline period

Table 2 Results of Pearson's correlation coefficient analysis of PM_{2.5} and mobility

	Retail and recreation	Grocery and pharmacy	Parks	Public transport	Workplace	Residential
Ghaziabad						
Grocery and pharmacy	0.85**					
Parks	0.83**	0.47**				
Public transport	0.94**	0.70**	0.89**			
Workplaces	0.84**	0.68**	0.69**	0.91**		
Residential	-0.89**	-0.74**	-0.72**	-0.91**	-0.96**	
PM _{2.5}	0.45**	0.46**	0.34**	0.42**	0.31**	-0.31**
Noida						
Grocery and pharmacy	0.89**					
Parks	0.89**	0.61**				
Public transport	0.95**	0.81**	0.88**			
Workplaces	0.79**	0.70**	0.73**	0.92**		
Residential	-0.85**	-0.81**	-0.71**	-0.90**	-0.95**	
PM _{2.5}	0.43**	0.43**	0.38**	0.41**	0.28**	-0.30**
Faridabad						
Grocery and pharmacy	0.84**					
Parks	0.82**	0.43**				
Public transport	0.96**	0.83**	0.77**			
Workplaces	0.83**	0.74**	0.62**	0.91**		
Residential	-0.90**	-0.77**	-0.69**	-0.93**	-0.96**	
PM _{2.5}	0.45**	0.50**	0.30**	0.45**	0.28**	-0.31**

**Denotes significant correlations at $p < 0.01$

northwestern regions of the study area. Most interestingly, between 25 March and 31 May 2020, intensive fire events were observed in the states of Haryana, Punjab (northwest side), and Uttar Pradesh (east direction), which bring vast PM mass of biomass burning emissions into the study cities (Fig. 6: lockdown). Next to LD, intensive fire activities, especially in Haryana and Punjab, were also observed during UL and Post-LD. The daily number of fire incidents and cumulative fire radiative power (MW) in 2020 is shown in the supplementary Fig. S2. Observations of Fig. S2 agree with the evidence from previous studies, which indicated that in Haryana and Punjab, higher fire incidents occur during the spring season (i.e., March–May) (Kumar et al., 2011), and paddy residue burning typically occurs in October and November (Chowdhury et al., 2019). In these months, a typical north-westerly wind transports the dust particles towards Delhi National Capital Region (NCR) and thus causes severe pollution episodes in this region (Chowdhury et al., 2019). A long-term (15 years from 2001–2002 to 2015–2016)

study by Chowdhury et al. (2019) highlighted that the ambient PM_{2.5} concentrations are 1.25 times higher in the downwind (study area) than the upwind areas of Delhi NCR (i.e., Haryana and Punjab).

The mean values of fine dust in times of low and high fire activity are shown in Table 3. The annual average concentration of PM_{2.5} during high fire incident days was 16.19 $\mu\text{g}/\text{m}^3$ (14.81%), higher than its level in the time of low activity days. PM_{2.5} level in Pre-LD was slightly lower (-4.44%) during low fire activity days than its rival. Interestingly, the fluctuations in PM_{2.5} between fire-impacted and low fire activity periods for LD, UL, and Post-LD were higher than the annual fluctuations. The rise in PM_{2.5} during LD, UL, and Post-LD due to high fire events was estimated to be 24.58%, 64.74%, and 26.27%, respectively. This increase in ambient dust levels is attributed to the transport of pollutants from open biomass combustion in upwind rural areas, dust transport in the summer, and transport of pollution emitted from brick kilns throughout the year

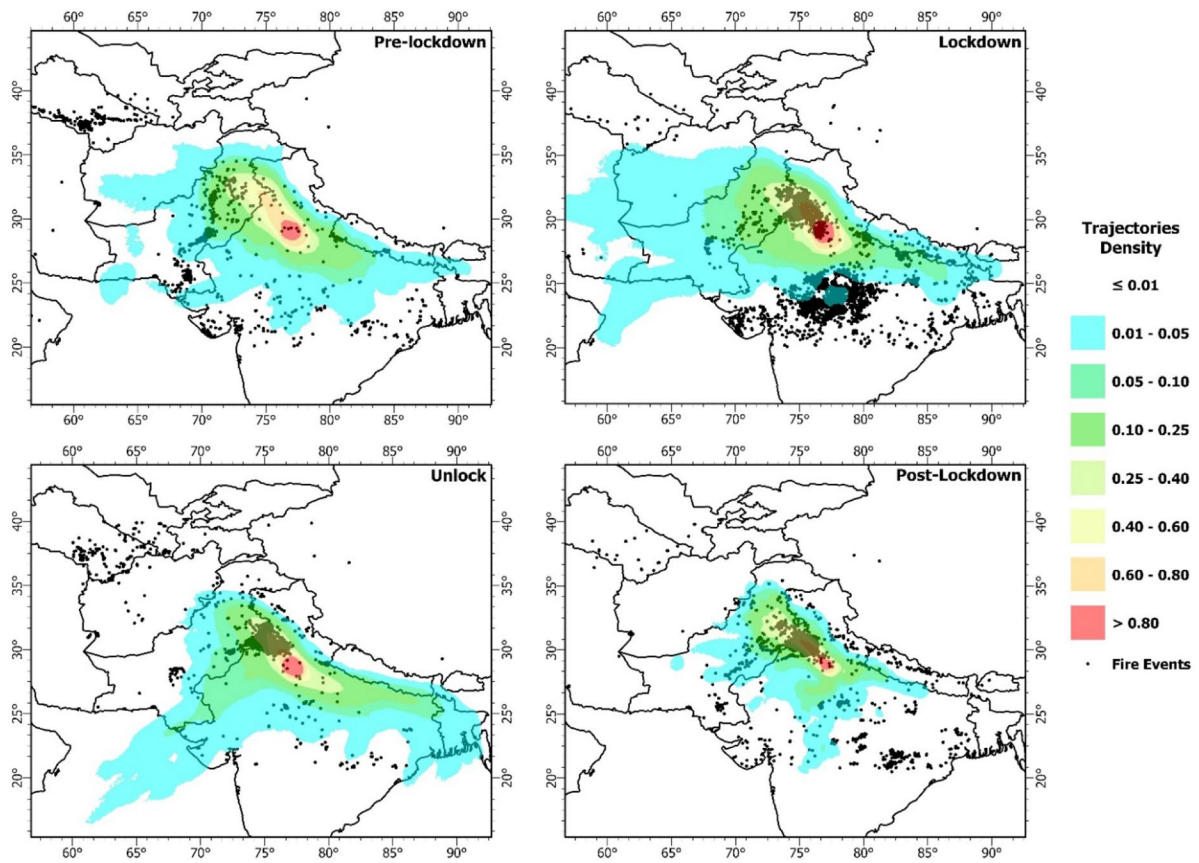


Fig. 6 Fire activity (MODIS) and density plots of back trajectories (HYSPPLIT) over study region during pre-lockdown (01 January–24 march), lockdown (25 March–31 May), unlock (01 June–31 October), and post-lockdown (01 November–31 December)

(Cusworth et al., 2018) add up to local sources. As discussed earlier, transport and industrial activities were entirely suspended during the LD and partially halted during the UL period, which leads to control of local sources. While comparing the results, the PM level during LD and UL might be much lower if not affected by long-range transport of dust and biomass burning emissions. A recent investigation by

Mendez-Espinosa et al. (2020) found that the PM_{2.5} in Northern South America was increased by almost 20 µg/m³ due to biomass burning events in March and April. A recent study in Reno, Nevada, USA, has highlighted an increase of 17.7% in COVID-19 cases during the period hit by forest fires (Kiser et al., 2021). This research is the first step towards a more profound understanding of the relationship between

Table 3 Average PM_{2.5} mass and percentage changes at receptor site during high and low fire activity periods for 2020

Period	Mean PM _{2.5} concentration (µg/m ³)			Variations ^a	
	High FRP days	Low FRP days	Overall	(µg/m ³)	in %
Pre-LD	117.22 ± 28.23	122.43 ± 67.30	121.87 ± 64.13	-5.21	-4.44
LD	49.46 ± 21.07	37.30 ± 15.18	46.95 ± 20.51	12.16	24.58
UL	151.82 ± 71.40	53.53 ± 38.94	60.59 ± 48.90	98.29	64.74
Post-LD	258.89 ± 101.86	190.88 ± 81.82	210.95 ± 92.76	68.01	26.27
2020	109.30 ± 97.97	93.11 ± 75.95	97.18 ± 82.20	16.19	14.81

^aVariations in PM_{2.5} concentrations between high FRP and low FRP days

dust pollution, wildfire smoke events, and COVID-19 incidents and mortality.

Summary and conclusion

Restrictions imposed to stop the spread of COVID-19 over India have given a unique opportunity to study the potential factors that influence $PM_{2.5}$ mass. In this study, statistics and a model-based approach were applied to assess the influence of mobility, meteorology, biomass burning, and long-range dust transport over three highly polluted north Indian cities. The salient conclusions from the study can be drawn as:

- (1) A significant reduction has been observed during the COVID-19 lockdown in all the cities, mainly due to the absence of local anthropogenic emissions. $PM_{2.5}$ has shown a variation of -60.70% , -63.27% , and -60.40% for Ghaziabad, Noida, and Faridabad during the lockdown period than before lockdown. However, reductions in $PM_{2.5}$ concentration are not consistent throughout the year, and it reversed back to the pre-LD range at the end of 2020, that is, during post-lockdown. The $PM_{2.5}$ level was three- to four-folds higher after lockdown when compared to lockdown and relaxing periods.
- (2) $PM_{2.5}$ has also shown significant variations between 2019 and 2020. Once again, the reductions were maximum during the lockdown. Data has shown a reduction of 44.55% , 41.04% , and 36.34% in Noida, Faridabad, and Ghaziabad, respectively. Despite the general trend of lower concentrations in 2020, during UL4, the $PM_{2.5}$ level was higher in 2020 than in 2019.
- (3) A significant negative correlation of WS with $PM_{2.5}$ and higher concentration of aerosols during low wind speed (as observed in Bivariate polar plots) has shown the impact of wind speed on the pollution dispersal.
- (4) A decrease in people's mobility during the lockdown and unlocking periods is the resultant of reductions in pollution load due to control of local emission sources. Daily changes in $PM_{2.5}$ have shown a significant positive association with all type of mobility, except residential. Parallel changes in both mobility and fine dust concentrations evidently revealed the contribution of vehicular emissions on PM load.
- (5) Trajectories are shown that the study area receives air mass mainly from the northwest direction, from Haryana, Punjab, and parts of eastern Pakistan. Long transport of air mass from Thar Desert was observed in lockdown, whereas during unlocking period, the same was from Arabian Sea and Bangladesh.
- (6) The maximum number of fire events was recorded in LD, followed by UL and Post-LD. These observations are in good agreement with previous studies. There have been striking differences in the $PM_{2.5}$ concentrations of fire impacted and non-fire impacted days. Such an increase in fine dust showing the influence of biomass burning on the pollution load of nearby regions, especially those is located in downwind direction.

Overall, COVID-19 lockdown retrieved the air quality in the urban cities where anthropogenic activities degraded the green environment. However, at the same time, this improvement in air quality is impermanent. Therefore, it must be concluded that partial lockdown would be a beneficial approach in case of a sudden rise in pollution load. However, reducing ongoing fossil fuel consumption, switching from fossil fuel to less-polluting natural gas or renewable biomass energy sources, developing green transport networks, and circumventing biomass burning are efficient directions to achieve long-term improvements in air quality.

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Author contribution Mr. M. Arunkumar: Conceptualization, data curation, software, investigation, writing—original draft. Dr. S. Dhanakumar: Conceptualization, supervision, writing—review and editing.

Data availability The data used in the manuscript are publicly available. Data on fine particulate matter and meteorological parameters are available under the open data platform of Central Pollution Control Board, Government of India: <https://app.cpcbcr.com/ccr/#/caaqm-dashboard-all/caaqm-landing>. Active fire data presented in this study are openly available in <https://firms.modaps.eosdis.nasa.gov>. Google Community Mobility Reports publicly available in <https://www.google.com/covid19/mobility/>.

Declarations

Competing interest The authors declare no competing interests.

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