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Process-based diagnostics of extreme pollution trail using numerical modelling during fatal second COVID-19 wave in the Indian capital

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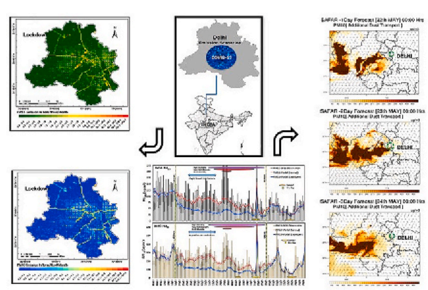
HIGHLIGHTS

- Unusual surge in PM_{10} and $PM_{2.5}$ levels under lockdown during 2nd COVID-19 wave.
- Lockdown Emission inventory developed and used in SAFAR-framework model.
- Model explained high pollution events and revealed a hidden source of emission.
- Prolonged high PM2.5 pollution event coincided with high mortality counts.
- A surge in PM_{10} (690 μg/m^3) was associated with large scale dust transport.

GRAPHICAL ABSTRACT



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ABSTRACT

The world's worst outbreak, the second COVID-19 wave, not only unleashed unprecedented devastation of human life, but also made an impact of lockdown in the Indian capital, New Delhi, in particulate matter (PM: $PM_{2.5}$ and PM_{10}) virtually ineffective during April to May 2021. The air quality remained not only unabated but also was marred by some unusual extreme pollution events. SAFAR-framework model simulations with different sensitivity experiments were conducted using the newly developed lockdown emission inventory to understand various processes responsible for these anomalies in PM. Model results well captured the magnitude and variations of the observed PM before and after the lockdown but significantly underestimated their levels in the initial period of lockdown followed by the first high pollution event when the mortality counts were at their peak (~400 deaths/day). It is believed that an unaccounted emission source was playing a leading role after balancing off the impact of curtailed lockdown emissions. The model suggests that the unprecedented surge in PM_{10} (690 μg/m^3) on May 23, 2021, though Delhi was still under lockdown, was associated with large-scale dust transport originating from the north west part of India combined with the thunderstorm. The rainfall and local dust lifting played decisive roles in other unusual events. Obtained results and the proposed interpretation are

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likely to enhance our understanding and envisaged to help policymakers to frame suitable strategies in such kinds of emergencies in the future.

1. Introduction

Ambient air pollution is closely linked to multiple adverse health problems and may leads to adverse economic impacts, thus dampening the Global Domestic Product (Pandey et al., 2020). Air pollution in mega cities poses a major challenge for the global environment (Molina et al., 2020). Beig et al. (2018) reported that multiple emission sources led by transportation, domestic, and industrial categories, besides road dust and waste burning, contributes to pollution in the Indian megacity of Delhi. Chen et al. (2020a, 2020b) have recently highlighted the mitigation pathways of $PM_{2.5}$ and ozone in Delhi. While already struggling with air quality issues, Delhi was hit hard by the COVID-19 pandemic, the clinical disease caused by infection with the novel coronavirus SARS-CoV-2, which swept through countries around the world, making it a pandemic disease (Yadav et al., 2020) in early 2020.

As the cases significantly reduced by January 2021, there was a sense of complacency in India with a public narrative that India had conquered COVID-19 as daily cases fell nearly 90% from the first wave peak. However, infection cases in India started rising again by March 2021, and this time, Delhi was struck hard. The second wave was far deadlier than the first wave and cases and deaths continued to increase at an unprecedented pace until the end of May 2021. In April 2021, Delhi got overwhelmed by the rising number of COVID-19 cases and fatal-ities. On the ground, these numbers translate to heart-wrenching tragedy. The speed and scale of the outbreak suggested that India probably had an emerging variant of the virus. Genomic surveillance data show that the Delta variant was first identified in India. The Delta variant contributed to an overwhelming surge in Delhi (Singh et al., 2021). To control the surge in cases, Delhi imposed a lockdown from 19th March to 31st May 2021. There are many studies addressing air quality concerns with COVID-19 during the first wave of 2020 (Beig et al., 2020a, and references therein) but work assessing the 2nd wave of 2021 in India in terms of air quality is sparse. Therefore, this study is an important contribution to the global knowledge of the impact of local lockdowns on air quality.

As the second wave of the COVID-19 raged across the National Capital, Delhi, experts have warned that the COVID-19 is airborne and the low-temperature incomplete combustion of biofuel will have lethal effect as virus piggyback on aged carbon particles (Rathod and Beig, 2021) and may further aggravate casualties. As both COVID-19 and air pollution predominantly affect the upper respiratory tract and lungs, it has become a matter of great concern for the Indian capital city of Delhi. Chen et al. (2020a) have recently highlighted the local characteristics of $PM_{2.5}$ and its exposure in Delhi. However, unlike the 1st pandemic wave (Beig et al., 2020a), the levels of PM could not show any significant decline and on the contrary, several unusual high pollution episodes were witnessed. In the present work, the System of Air Quality and Weather Forecasting and Research (SAFAR)-Framework model combined with observations and trajectory analysis has been used to understand the processes controlling the unusual features in the variability of most toxic air pollutants PM_{10} and $PM_{2.5}$, under different regimes starting from the pre-lockdown to post-lockdown (unlock) period of March to June 2021. The unusual or high pollution events have been defined as the sudden surge or dip in particulate matter when PM mass concentration coupled with an unusually low or high ratio of $PM_{2.5}/PM_{10}$ is observed as compared to the prevailing trend before and after the episode. The most prominent emergency episodes have been examined and discussed further in detail.

We examined the dominant processes among large-scale circulation, local meteorology and local emissions while COVID-19 lockdown was in force.

2. Materials and methodology

2.1. Study area and observations

This study was carried out in one of the largest mega cities of the world, Delhi which is the capital of India and located at 28.61°N, 77.23°E towards the Northern part of India as shown in Fig. 1, having a population of around 19 millions. Both summer and winter in Delhi experience extreme weather from an Indian climatological perspective when the temperature may rise to about 47 °C in summers and go down to about 2 °C in winter. Delhi is located at an elevation of 216 m above mean sea level. Delhi receives a moderate rainfall of about 553 mm

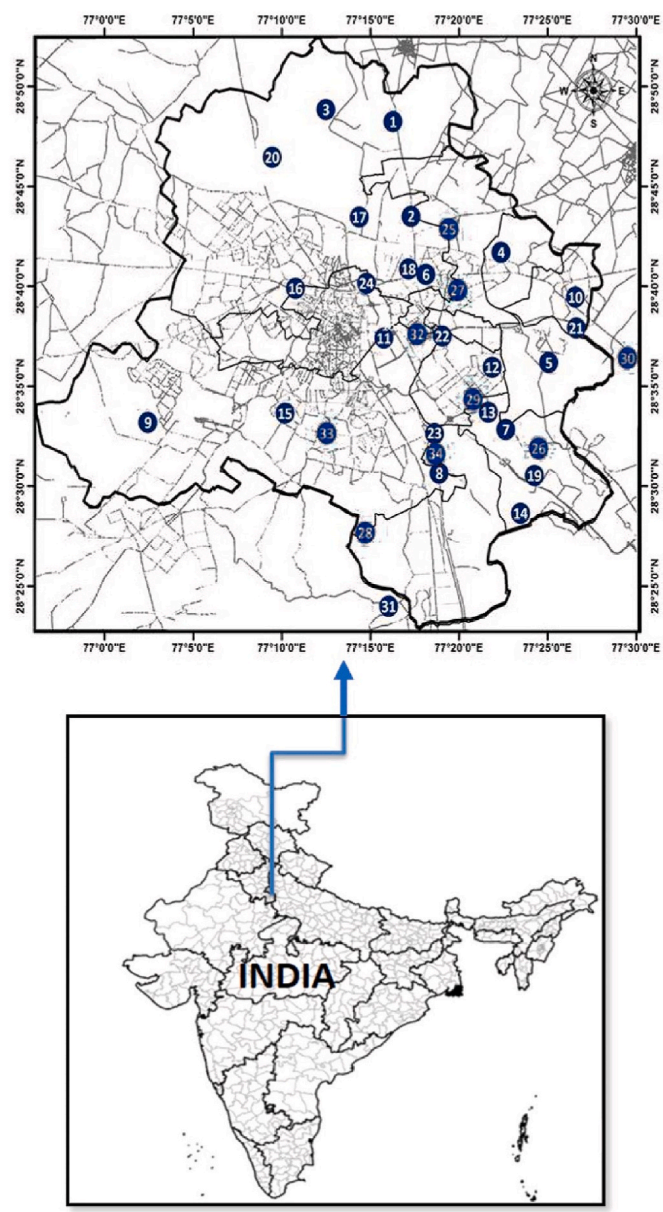

Fig. 1. (The geographical map of India where the location of study area, Delhi national capital region (NCT) is marked, which is further zoomed to represent locations of 34 air quality monitoring stations in different micro-environments.

during the monsoon season which starts in late June and lasts until the end of September.

This study used the data obtained from the largest monitoring network of Delhi comprising 34 online automatic air quality and weather monitoring station maintained by the Delhi Pollution Control Committee (https://www.dpcc.delhigovt.nic.in/indexdup.php, last visited 10th Dec 2021) of the Delhi Government and SAFAR, India's first air quality forecasting framework of the Govt. of India and a pilot project of the World Meteorological Organization (WMO) (Beig et al., 2015). Locations of various stations in and around Delhi are shown in Fig. 1. The data obtained from the monitoring network are time-resolved and bin ned for 1-h intervals for further analysis to get the 24 h mean daily mass concentrations (in μg/m^3). The observed daily levels of these pollutants in Delhi during the study period (1st March to June 30, 2021) are averaged across all stations spread in different micro-environments of Delhi. Averaging removes the inhomogeneity in the data sets and can best be considered as representative of the city air quality as per the WMO guidelines (Grimmond et al., 2014). The mass concentration of $PM_{2.5}$ and PM_{10} was monitored continuously using online analyzers approved by the United States Environmental Protection Agency.

These analyzers are based on the industry-proven principle of Beta-ray attenuation methodology (BAM-1020; Met One Instruments, Inc, USA), whose details are provided elsewhere (Beig et al., 2020a; Yadav et al., 2017) and hence not discussed here in detail. The instrument's span calibration is verified hourly (Anand et al., 2019; Yadav et al., 2019). In this work data was collected for the period from 1st March to 30th June for the study years (2017–2019 and 2021). The rainfall (mm) has been measured using the Automatic Weather Stations (Anand et al., 2019) which were co-located with each air pollution monitoring station. The data of mortality and infectious cases related to COVID-19 are taken from the Union Ministry of Health and Family Welfare (https://www.mygov.in/covid-19/, last visited July 15, 2021) portal of the Government of India.

2.2. SAFAR-framework model

The SAFAR-framework model is based on the Weather Research and Forecasting - Chemistry (WRF-Chem version 3.9; (Grell et al., 2005; Powers et al., 2017). The detailed set-up and methodology of this interactive high-resolution chemistry-transport model have been discussed in several publications elsewhere (Beig et al., 2020b, 2021a, 2021b). This model uses four nested domains with 45, 15, 5, and 1.67 km resolution. Two outermost domains cover part of Europe and Asia with 195 (W-E) x 173 (*N*–S) grid cells, and India stretching from 55.4°E to 95°E (258 grid cells), and 2.7°N to 55.4°N (270 grid cells). The third domain covers North India (273 × 258 grid cells), and the fourth and innermost domain covers Delhi and surrounding areas and contains 69 × 75 grid cells. The dust emissions are simulated using the GOCART (Goddard Global Ozone Chemistry Aerosol Radiation and Transport) dust scheme (LeGrand et al., 2019). Dust emission from the erodible surface is calculated by the emission scheme (Ginoux et al., 2001). The MOSAIC scheme includes the chemistry of sea salt, soil (lumped inorganics), secondary inorganic aerosols (nitrate, sulfate and ammonium ions), carbonaceous aerosols (organic carbon and black carbon), and equilibrium between water vapor, four inorganic trace gases (NH_3, H_2SO_4, HNO_3, and HCl) with inorganic ions (nitrate, sulfate, NH_3 and Cl). The dust mass was included in the other inorganics concentration. To simulate chemical parameters properly, we provided the latest anthropogenic emissions of gaseous pollutants for 3 outer domains from Emissions Database for Global Atmospheric Research-Hemispheric Transport of Air Pollution (EDGAR-HTAP) version 4.3 (Crippa et al., 2018). The emission inventory of the inner most domain for PM ($PM_{2.5}$, PM_{10}) at a horizontal resolution of 1.67 km is taken from our earlier studies (Beig et al., 2018; Sahu et al., 2011) for the normal case. For the sensitivity simulations, provisions to use different scenarios are kept. The SAFAR-interactive model uses the newly developed lockdown emission inventory scenario as per the methodology described in detail by us earlier (Beig et al., 2021a) and is discussed briefly in the next section. The SAFAR-Framework model is routinely validated being an operation service (http://safar.tropmet.res.in, last accessed 10th December 2021) and also validated independently for normal as well as extreme pollution cases on numerous occasions by us earlier (Beig et al., 2019, 2020b, 2021b). The back trajectory analysis is done using the Hybrid Single-Particle Lagrangian Integrated Trajectory, Version 4 model of NOAA-ARL (Draxler and Rolph, 2003) whose detailed methodology is discussed previously in the literature (http://www.arl.noaa.gov/ready/hysplit4.html, last accessed December 10, 2021). The analysis was performed with the Global Data Assimilation (GDAS) dataset and the starting time of 23:00 h UTC, the altitude of 500 m AGL, a level where transport is likely to take place.

2.3. Lockdown emission inventory

The normal baseline gridded emission inventory along with detailed methodology as adopted in this work is discussed in many of our recent publications along with associated uncertainties elsewhere (Beig et al., 2018, 2020a, 2021b; Sahu et al., 2011) and hence discussed here only briefly. To construct the emission scenario of the lockdown period of April to May 2021, the above-mentioned normal emissions are used as a base level. The activity data for 16 major/minor sectors are targeted which was rearranged into six major categories, namely, Transport, Power, Industry, Residential, Windblown dust (re-suspended dust) and rest others which includes many unattended sources like a brick kiln, crematorium, etc as shown in Figure S1 along with special distribution of normal and lockdown emissions (tons/month) for $PM_{2.5}$ and PM_{10} where the hot spot regions are visible. The percentage contribution of these major six sectors in Delhi is also included in the pie chart in Figure S1. The summary of the source-specific details of emissions of PM is tabulated in Table 1.

In a normal case scenario (Beig et al., 2018, 2021b), the major contribution in $PM_{2.5}$ is from the transport sector (41%) followed by windblown resuspended dust (21%) whereas for PM_{10}, major source is windblown dust (46%) followed by the transport sector (18%). The total emissions from all sources under normal scenarios during the period from March to May were 6420 tons/month and 14,849 tons/month for $PM_{2.5}$ and PM_{10} respectively (Table 1). This lockdown in India during 2021 was not as strictly implemented as that of the first wave in 2020 due to several practical constraints and medical emergency situations. India has a unique distinction where the majority of the urban slums still use household biofuel sources (wood, cow dung, etc.) for cooking. The household emission was unchanged even during the lockdown in India as it was related to livelihood. Given the lack of $PM_{2.5}$ and PM_{10} emissions inventory data during the lockdown period, we devised an alternative approach to estimate city-level emissions based on a confinement index (CI) (Le Qúéŕ et al., 2020) conceived to capture the extent to which different policies and strict directive affected emissions during the lockdown. This was done based on available socio-economic/industrial activity data like electric production/consumption pattern, industrial production, and various types of fossil fuel consumed directly from the disseminating source of fuel by various sectors collected from government authorities. At the same time, the data related to unorganized sectors like slums, street vendors, cooking activities, and small scale industrial activities were collected from local municipal authorities. Based on available information from authentic sources like government agencies, municipal corporations and other associated organizations (https://www.delhi.gov.in/; https:https://www.mohfw.gov.in/; https://www.mohfw.gov.in/, last accessed in July 2021) and personal judgment, we have estimated the reduction in activities and corresponding % reduction in emissions during lockdown as compared to the normal case which are shown in the 3rd and 6th columns in Table 1. The overall estimated net emission present during the lockdown period for $PM_{2.5}$ was 3238 tons/month (51% of normal) and that of PM_{10} was 8599

Table 1
Source emissions (Tons/month) of PM_{10} and $PM_{2.5}$ for Normal Scenario and that of lockdown scenario of 2021 along with % reduction wrt normal case for the period 19th March to May 31, 2021.

Sources	PM_{10} Emissions (Delhi)-2021			$PM_{2.5}$ Emissions (Delhi)-2021		
	Normal emissions (Tons/month)	% Reduction in lockdown wrt normal	Net emissions (lockdown) (Tons/month)	Normal emissions (Tons/month)	% Reduction in lockdown wrt normal	Net emissions (lockdown) (Tons/month)
Transport	2710	50	1356.49	2630	50	1315.74
Industry	2100	80	432.89	1190	80	238.83
Power	1230.5	0	1230.48	315.7	0	315.70
Biofuel	296.5	0	296.50	190	0	189.93
WB-Dust	6880	30	4815.16	1380	30	966.61
Others	1560	70	466.99	700	70	211.17
Total	14,840	42%	8598.50	6420	49%	3237.98

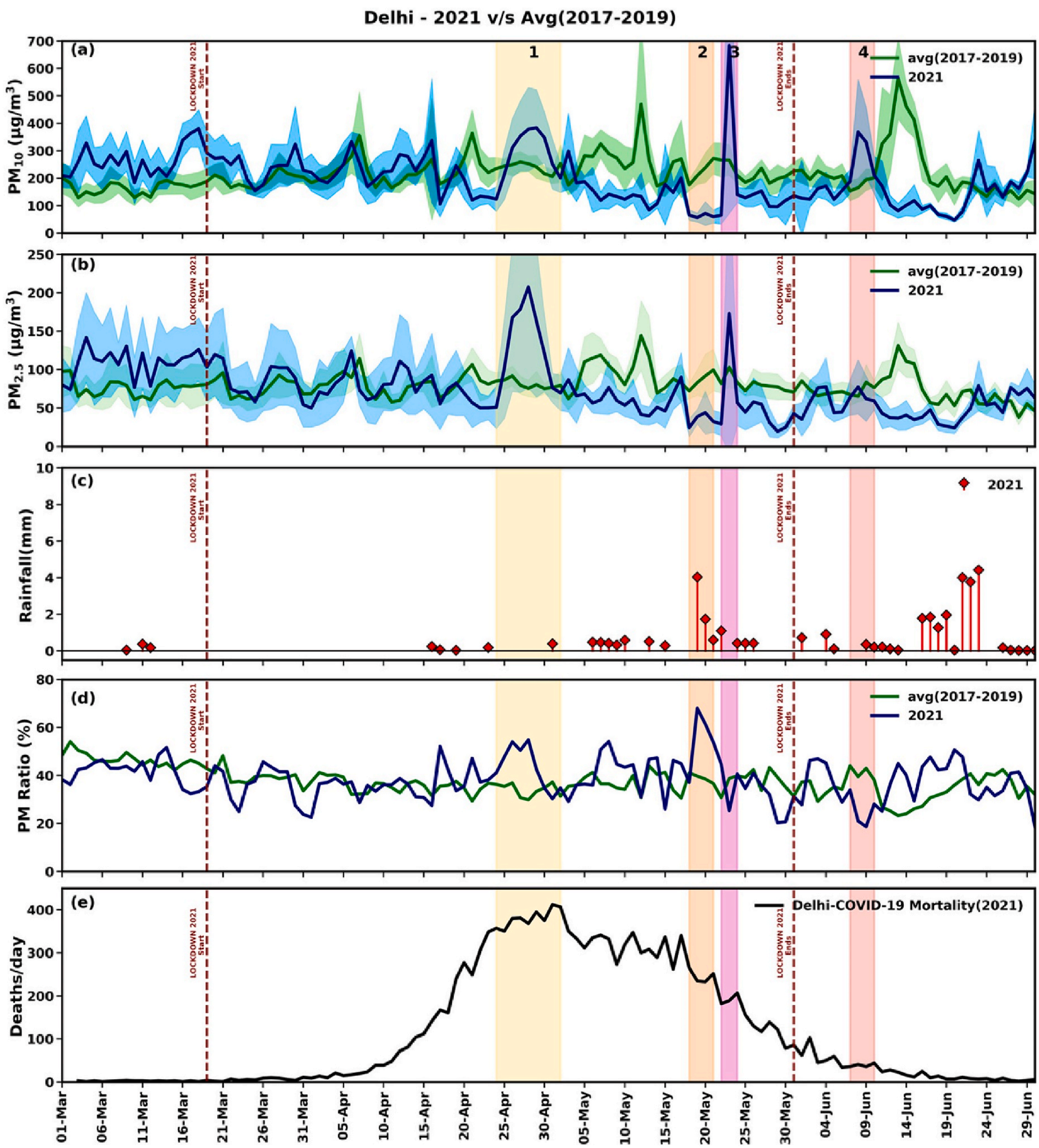

Fig. 2. The time series of the mass concentration of PM_{10} and $PM_{2.5}$ and the ratio (%) of $PM_{2.5}$ to PM_{10} (PM ratio) during the period 1st March to June 30, 2021 are compared with the averaged levels of 2017–19 during the identical period. The daily cumulative rainfall and number of mortality counts due to COVID-19 in 2021 are also shown. The specific extreme events (marked as 1 to 4) are shown as shaded area in the respective plots.

tons/month (58% of normal case). The change in PM emissions associated with the confinement is informative in multiple ways. First, the changes in emissions are entirely due to a forced reduction in activity. The developed lockdown emission inventory is a quantitative indication of the potential limits that lockdown measures could deliver where consumption of fossil fuel and unchanged household emissions are the major factor influencing the outcome. However, due to the medical emergency situation, a number of vehicles and ambulances were pressed into service for commuting to hospitals and other medical services. Accounting all these confounding factors, we estimated that the fuel consumption reduced only about 50% of normal days during lockdown.

The power grid was working on normal capacity. However, industries were largely shut down due to absence of working staff but ~20% of the total industries required for essential products and services were still functional based on the available information. Biofuel emissions remained almost unchanged in the lockdown scenario. The uncertainty in emission inventory mainly arises from the activity data and emission factors. Hence, the data collection source and uncertainty evaluation are strongly linked. In the present work, calculation of error propagation is done by critically following various step and by accommodating different past studies as described in our recent publication in detail (Beig et al., 2021b) and also documented by other authors (Arora et al., 2013; Gurjar et al., 2004) for a better comparison and accuracy in analysis. The uncertainty quantifying is not an easy task as it requires continuous monitoring of emissions at the source point which is not practical in real conditions. Till date, no systematic approach for the identification of uncertainty is available (Beig et al., 2021b) and hence inventory could not be validated. Major factors of uncertainty are around 10 Beig et al. (2021b), The uncertainty in emission inventory mainly arises from the uncertainty in input data, mainly related to activity data and emission factors (Beig et al., 2021b). Monte Carlo analysis is used for detailed category-by-category assessment of uncertainty, particularly where uncertainties are not distributed normally as per Beig et al. (2021b). We made an attempt to collect city specific micro-level activity data to reduce uncertainties associated with the data. Monte Carlo analysis is performed at the category level, for aggregations of categories or for the inventory as a whole. Calculation of error propagation is done by critically following the step and by accommodating different previous studies for a better comparison and accuracy in analysis; the past studies (Gurjar et al., 2004, Arora et al., 2013) are taken into account. Combined uncertainty is calculated by considering the emission factor and activity data uncertainty in original and lockdown periods. We have adopted region-specific emission factors variability in processes producing emissions, variation in meteorological factors, methods and assumptions used to fill in knowledge gaps about emissions processes and estimated the uncertainty around 25–35%. Although the reduction estimate are based on various departments of Government which are quite accurate, there is a scope of marginal additional uncertainty. The past literature (Saikawa et al., 2017) reveals that the magnitude of the uncertainty is in emission inventory is in general high due to several factors as discussed above. Considering above aspects, we feel that we have estimated emissions reasonable well with lower level of uncertainty mainly due to usage of authentic government sources as stated earlier in the section (which includes government agencies and municipal corporations) for activity data accompanied by available country specific emission factors.

3. Results and discussion

3.1. Observations

Fig. 2 shows the time series of the daily averaged concentrations of PM_{10} and $PM_{2.5}$ (μg/m^3), and the (%) of $PM_{2.5}$ to PM_{10} ratio (hereafter will be called as 'PM ratio') for the period 1st March to June 30, 2021 which are compared for the past 3 years averaged value (2017–2019) for the identical period (hereafter called as 'reference level'). The year 2020, the pandemic year, is deliberately omitted as it could have influenced the average. Also plotted are the daily cumulative rainfall (mm) and daily mortality counts for the same period in 2021. The lockdown period of 19th March to 31st May is marked by vertical lines in Fig. 2. It is pertinent to mention here that during this time of the year, under normal conditions, the PM ratio generally remains between 45 and 50%.

As the objective of the current study is to understand the variability during 2021, we will focus our attention on discussing 2021, in particular the four unusual events represented as the shaded area and marked 1 to 4 in Fig. 2. The event-1 was a high pollution event that occurred from 24th April to 2nd May when an unprecedented peak is observed; the event-2 was a low pollution event centered around 19th May; event-3 was an extreme pollution event that occurred with a sharp 1-day peak on 23rd May and the last event-4 (fourth) was again a high pollution episode on 8th June when a prominent peak in PM_{10} is noticed but not in $PM_{2.5}$ making the PM ratio significantly low. During the normal period, prior to the imposition of lockdown on March 19, 2021, when anthropogenic emissions were as per the normal business-*as*-usual scenario (Beig et al., 2018). PM levels were consistently higher than the reference level. Immediately after the lockdown, a significant declining trend in PM was expected. However, despite of lockdown emission reduction in PM emissions (as discussed in an earlier section), no appreciable decline in PM was noticed as compared to reference years for about a month followed by the event-1, when a prolonged peak in PM mass concentrations during the period 24th April to May 2, 2021 (depicted with shaded region) is observed. This period coincided with the time when a rapid surge in COVID-19 related mortality and morbidity was recorded as evident from Fig. 2(e). During the event-2, values of PM_{10} and $PM_{2.5}$ touched minimum levels (57 17 μg/m^3 and 38 10 μg/m^3 respectively) and the PM ratio was as high as 68% due to faster washout of coarser particles related to consistent rain as evident from rainfall data during this period. During the monsoon season when precipitation reaches to a certain level when the washout effect becomes active, even the impact of any other source of emissions also get minimized and that might be the reason for a declining trend during lockdown for the first time in the initial 2 weeks of May 2021 in the last week of lockdown. However, immediately after the end of the prolonged rain spell on 22nd May, there was sunshine for a day on 23rd May with thunderstorm leading to event-3 when the level of PM_{10} (684 ± 524 μg/m3) touched the emergency levels on 23rd May. There was a moderate increase in $PM_{2.5}$ (173 ± 150 μg/m3); hence, the PM ratio has gone down significantly to 24%. This episode is further investigated using the model and discussed in detail in the next section of this paper.

3.2. Model simulations and discussion

We have performed 2 model sensitivity scenario runs using the SAFAR-Framework model for the period 1st March to June 30, 2021. Fig. 3 shows the time series of daily averaged PM_{10} and $PM_{2.5}$ where the maroon line indicates time series obtained when the model accounted for normal case scenario (Table 1) even during lockdown period and the blue line indicates the result when the model is forced with reduced emissions during the lockdown period and normal emissions during unlock period. The model results shown in Fig. 3 are averaged over those grids where observed data were available. The vertical lines in the model plot are standard deviations from the mean. Model results are compared with observed data which are represented as a vertical bar along with standard deviation from the mean. The marking near the x-axis filled with dark yellow color represents the intense rainfall period whereas the yellow dot on 23rd May represents a dry day with sunshine as can also be confirmed from the rainfall plot of Fig. 2. Model results were well in agreement with observations before and after the lockdown periods (before 19th March and after 31st May) validating it well. However, the model simulated a significant reduction in both PM_{10} and $PM_{2.5}$ when the lockdown scenario was used (blue) and results highly

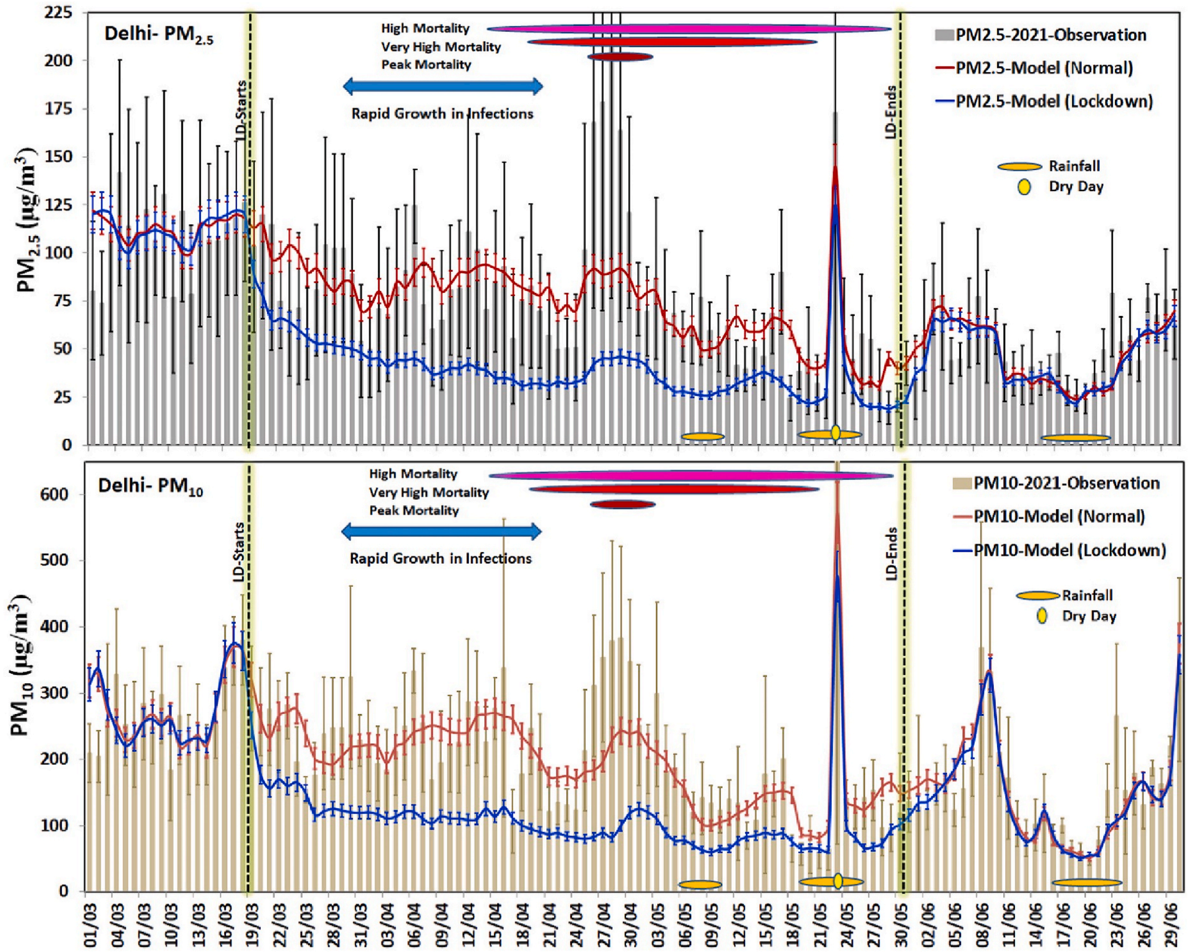

Fig. 3. SAFAR-Framework model simulated time series of $PM_{2.5}$ and PM_{10} as per the normal and lockdown emission scenario which are compared with observed data for the period 1st March to June 30, 2021. The intense rain period, dry day in between rains, different intensity of mortality periods and rapid growth of infection period are also represented in this figure and marked with different symbols and cited in the figure. LD-Start and LD-End represent dates of 'lockdown start' and 'lockdown end' respectively.

underestimated observations. Observed levels of PM during lockdown period were found to be as high as model results with normal emission scenario in the initial period followed by the first prolonged peak during 26th April to 1st May (event-1) when surprisingly observed values were found to be higher than the model simulated values even with normal emission scenario, particularly of $PM_{2.5}$. Although model results show an increasing tendency at around 28th April during event-1, but the magnitude of the prolonged peak could not be captured by the model. The back trajectory ending on 28th April (Figure S2) indicates that winds were coming from the desert region of the North-West part of India towards Delhi but the wind speed was quite high which could have prevented particles to get accumulating.

Hence, the dust flow could be one of the reasons for the peak observed around 28th April but it is not sufficient enough to fully explain the prolonged peak observed in particulate matter during event-1 as evident from model results in Fig. 3. This tends to suggest that a strong unaccounted source was not only offsetting the declined emissions of lockdown in the initial phase but also adding additional emissions during the entire period of event-1 as the model accounted for dust storm-related transport. This led us to believe that an unaccounted additional emissions source, rich in producing finer particles like biofuel or fossil fuel rather than the dust was active because the growth rate in $PM_{2.5}$ levels was much higher with respect to PM_{10} as also confirmed from the PM ratio (~40–55%) in Fig. 2(d) which is relatively higher than the normal. During the lockdown, as traffic flow reduced, the transport-related fossil fuel emissions may not have played a significant role. Hence, this additional significantly high emission may be related to low-temperature combustion associated with biomass burning in crematories which were at peak during this period. Many unconfirmed news articles reported that the situation was so dire during the almost same period that Delhi crematories are overwhelmed which have never seen such a never-ending assembly line of deaths. The high mortality, very high mortality and peak mortality period are marked in Fig. 3a and b. As evident, the peak mortality period was directly coinciding with peak levels of $PM_{2.5}$. The high levels of observed PM matching with normal emission simulated magnitude instead of lockdown simulated values, coincide with steep surge in infection counts. There are more than 50 Crematorium's of conventional open pyre type and very few of electrical and CNG type in Delhi. Hence, as per the Indian cremation rituals, dead bodies are mainly burned using bio-fuel. One of the largest and biggest cremation grounds of Delhi is Nigam Bodh Ghat. One study reported that the total amount of wood required for cremation is around 300–400 kg/pyre for open pyre (Kumar et al., 2019). The crematoria flue gases contains a higher percentage of organic, inorganic matter and particulate dust material. This additional biomass emission was so high and multiple pyres were used 24×7 for several days during peak that it superseded the impact of lockdown. This statement can be verified by looking at the direct correlation of mortality with the period of surge in PM when other extreme events (like a dust storm, etc) were not active. Also, due to a high number of patients needing hospitalization, many ambulances and private vehicles must be on road. Additionally, surplus vehicles due to heavy demand for oxygen cylinders were deployed for service as an emergency measure. Hence this surge in PM levels might be related to a combination of biomass burning and fossil fuel emissions besides other possible emission sources. However, in absence of any reliable additional biomass burning emission data, we are unable to further investigate. The event-2 was due to consistent rainfall-related washout which is quite obvious and the trend is well simulated by the model in both the scenarios. It is noteworthy to mention that during the lockdown period, the impact of dominant natural events in PM was relatively well captured by the model during both event-2 and event-3 albeit varying magnitudes. The peak in event-3 was unprecedented during this time of the year wherein PM_{10} peaked much faster than $PM_{2.5}$ unlike event-1. We have investigated this event using the model in detail to understand the underlined processes.

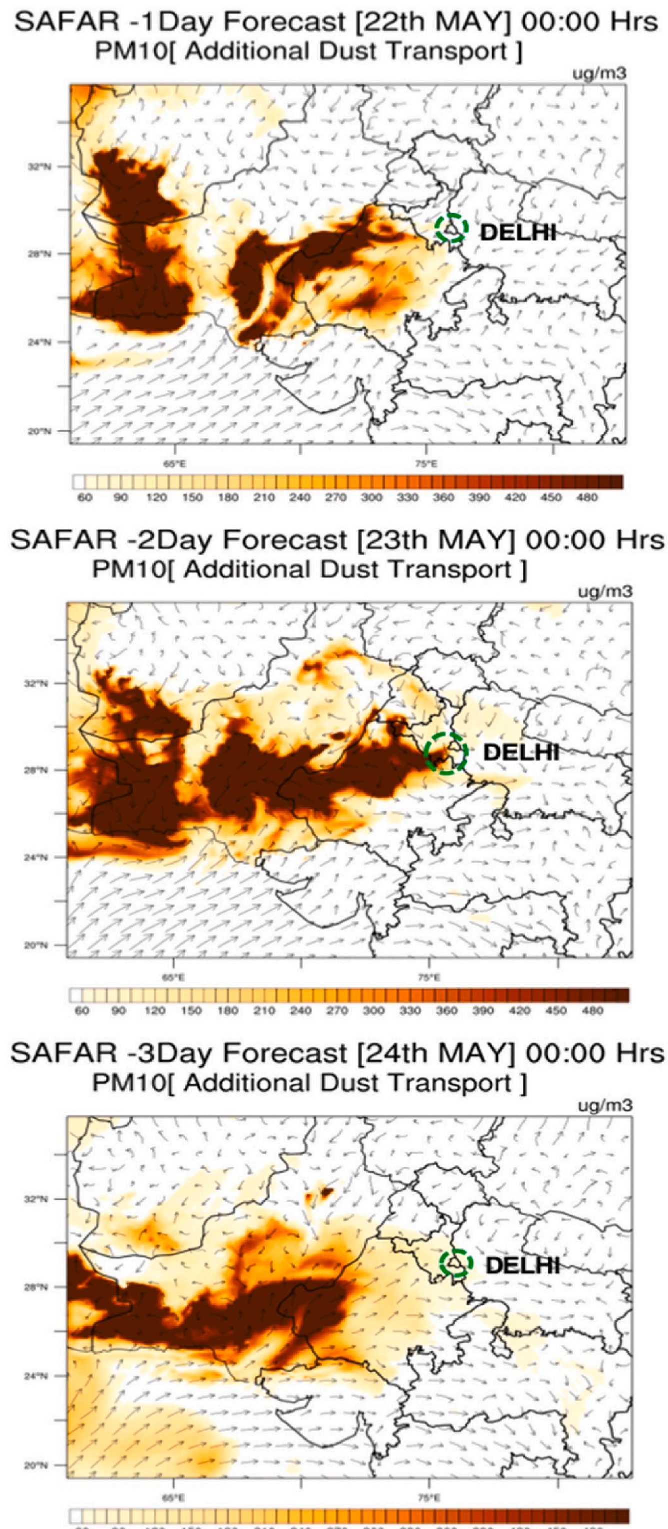

Fig. 4. The SAFAR-Framework model simulated circulation pattern and the processes governing the dust particle movement during the event-3 (22nd −25th May) when the lockdown was in force. The location of Delhi in the map is marked with circle.

Fig. 4 shows the model simulated circulation pattern and the processes governing the dust particle movement during the event-3 (22nd −25th May 2021) when the lockdown was in force. The period before and after 23rd May was marked by significant rainfall but there was sunshine for a day on 23rd May with heavy thunderstorms and winds started to blow from the North-North-West part of India with a rapid and heavy influx of dust leading to event-3. The synoptic analysis revealed that under the influence of a westerly disturbances (WD) and formation of the east-west trough in lower levels strong surface winds prevailed over Rajasthan and adjoining Pakistan region along with West Afghanistan region from 22nd May onwards and heavily accumulated the uplifted dust on 23rd May leading to an unprecedented increase in PM levels as evident from Fig. 4. The strong favorable upper-level winds are also evident from the analysis of the back trajectory ending on 23rd May (Figure S2). To understand the rapid buildup of additional PM_{10} particles overnight, the model simulated spatial distribution and pathways of dust clouds are shown at 00 h on 23rd May 2021 in Fig. 4. The daily average PM10 level has increased rapidly from less than 65 ± 32 μg/m3 on 22nd May to 684 ± 524 $\mu g/m^3$ overnight (Fig. 2). There was an increase in $PM_{2.5}$ levels but the magnitude of increase was not as high as PM_{10}.

During this period, the PM ratio declined significantly (25%), indicating the highly dominant role of coarser particles. Thereafter, the impact of dust inflow has reduced significantly in the Delhi region and under the influence of Westerly disturbances, widespread rainfall started again from 24th May onwards washing away the accumulated mass and levels of PM rapidly declined within 24hr. Thereafter as the rain continued, substantial improvement in PM levels was observed which continued even after the lockdown was lifted on 31st May. The last event-4 (depicted with light Indian red shaded region) in Fig. 3 has shown a different character than those in events-1 and 2. In this case, PM_{10} level has increased significantly but level of $PM_{2.5}$ remained almost unchanged. This peak is reasonably well captured by the model when the dominance of coarser particles played a major role. The long-range transport of dust is ruled out as the back trajectory ending on 8th June (2, last panel) indicates that flow was from the southeast and not from the desert region as was the case in the previous event. This peak is attributed mainly due to the lifting of local dust due to very high local wind during a broken spell of rainfall under bright sunshine and warmer temperature. It dried out the surface dust quickly. Also the moisture supply from the southeast, triggered thunderstorms in Delhi locally to lift the dust on a local scale. With an increase in on-road traffic after the lockdown was lifted, high winds and dry atmosphere also started to lift the local dust leading to a peak in PM_{10} on 8th-9th June 2021 but this local scale event could not affect the abundance of finer particles ($PM_{2.5}$).

4. Conclusions

This work investigated the variability in the particulate matter to understand the processes responsible for the same using the SAFAR-Framework model which accounted for lockdown emissions observed during the deadly 2nd wave of pandemic during April and May 2021 in Delhi. We developed the emission inventory of lockdown emissions. The overall estimated net emission present during the lockdown period for $PM_{2.5}$ was 3238 tons/month (51% of normal) and that of PM_{10} was 8599 tons/month (58% of normal). However, these estimated emissions are informative in multiple ways and not free from uncertainty which may range between 20 and 35%. The model reproduced well the impact of extreme pollution events in the trend of PM caused due to natural processes (events 2–4) but failed to reproduce some observed unusual features mainly related to an unaccounted hidden source of emission which was related to biomass burning at the crematorium in all likelihood. All four afore mentioned events had different characteristics and processes which havebeen explained in the current work. The model underestimated the continued elevated levels of PM in the initial week after the lockdown followed by the prolonged peak of event-1, a period that coincided well with the peak mortality period. The hidden source of emission is believed to be associated with additional biofuel burning related to crematories whose emissions could not be accounted in the model in absence of reliable source specific data. The model also established that the North-westerly winds often brought dust particles from the desert region to Delhi leading to peaks in PM even during the lockdown. Both COVID-19 and the dust storms can cause overlapping respiratory symptoms; hence, a suitable strategy needs to be worked out during such emergencies. That can include the science-based coordinated effort to prioritize source-based mitigation planning. The modelling effort to understand the correlation between the COVID-19, additional biomass emissions and natural episodes can enhance the current state of knowledge that could provide directions to future research benefitting both environmentalists and epidemiologists.

Authors contributions

Gufran Beig designed the research problem and written the first draft of the paper. **K.S. Jayachandaran** and **M.P. George** provided the data, supervised and edited the manuscript. **S.B. Sobhana** made model simulations and model data analysis. **Aditi Rathore** made observations, data analysis and partial writing of the paper. **S. K. Sahu developed** the emission inventory for model runs. **Rajnikant Shinde** and **V. Jindal** helped in data management and collation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chemosphere.2022.134271.

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