Assessment of air quality during lockdowns in Delhi

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EXECUTIVE SUMMARY

This study has been carried out to understand the changes in Delhi's air pollution levels and prevailing sources during the COVID related lockdowns enforced in the city in the months of April-May 2020. Scope of this study includes a statistical analysis to assess the significance of change in $PM_{2.5}$, NOx concentrations and meteorological datasets in 2020 w.r.t. 2019. It also contains a comprehensive chemical analysis of spatially monitored $PM_{2.5}$ particles during the lockdown period, which were used for an in-depth assessment of source contributions using positive matrix factorization (PMF) technique.

The statistical analysis of air quality data from 32 monitoring stations in Delhi unearthed many exciting results for the two pollutants ($PM_{2.5}$ and NOx) due to the unprecedented restrictions in the year 2020. Pollutant concentrations were studied for three timeline categories- Pre-Lockdown (1st January – 24th March), Lockdown (25th March – 31st May), and Unlock-1/ Post-Lockdown (1st June – 30th June), for the years 2019 and 2020. Statistical analysis was also carried out to assess change in ventilation coefficients (VC= wind speeds x mixing heights) in Delhi during both the years. The reduction in $PM_{2.5}$ and NOx was found to be statistically significant during the Lockdown and Unlock period. Average reductions of 43% and 61% were observed in $PM_{2.5}$ and NOx concentrations at 32 stations in Delhi during the period of lockdowns in 2020 with respect to 2019. $PM_{2.5}$ also had a smaller but statistically significant decrease in the Pre-Lockdown period as well, whereas NOx was not significantly reduced during the same period. This decrease can be partially attributed to meteorological conditions (high mixing heights and precipitation) during pre-lockdown period in 2020 w.r.t. 2019. In summary, the concentration of two pollutants decreased in 2020 wrt 2019 despite reduced wind speeds, indicating towards reduced emissions from sources, especially during the lockdowns.

Special air quality monitoring has been carried out in this study at three locations in Delhi - Central (IHC-Lodhi Road), West (PN-Patel Nagar), and East (LN-Laxmi Nagar). Monitoring was carried out for the period between 22nd April '20 – 5th June '20) for $PM_{2.5}$ and the samples were analysed for different chemical components of $PM_{2.5}$. Monitored $PM_{2.5}$ concentrations at the three locations were found to be close to the observations at nearby CPCB monitoring stations. Analysis of $PM_{2.5}$ data shows that despite lockdowns in place during the monitoring period, 31-60% of days violated the daily $PM_{2.5}$ standards at these three locations. Chemical characterization of $PM_{2.5}$ shows that total carbon was the most dominating at all three sites, followed by ions and metals, respectively.

PMF based source apportionment shows that while in absolute terms pollution contributions have reduced from many sources during the lockdowns, in terms of relative contribution, industrial sector and biomass burning have the higher shares. Most industries and households in Delhi have shifted to gas, hence, the industrial and biomass based contributions are mainly attributable to upwind areas of National Capital Region. The relative decrease in vehicular movements and industrial activities in Delhi resulted in inflated contributions from other sectors like biomass, agricultural residue burning, waste burning, and dust, which previously had a relatively lower share in Delhi's PM2.5 concentrations.

The unfortunate COVID-19 and associated lockdowns led to reduced pollutant concentrations in Delhi. This study, carried out during the natural experiment opportunity created by lockdowns, has helped us identify some of the key points related to local and regional sources of pollution in Delhi.

Key findings

1. Reductions (43% and 61% in $PM_{2.5}$ and NO_x concentrations, respectively) observed in $PM_{2.5}$ and NO_x concentrations during lockdowns in 2020 w.r.t 2019 were statistically significant.

2. Despite lockdowns, $PM_{2.5}$ levels violated the daily standard 31-60% times at the three locations in Delhi.

3. Contributions were found to be lower from transport, and higher from biomass and industrial combustion activities, indicating regional

contributions from outside of Delhi.

4. Air pollutant reductions during lockdowns shows that vehicles and industries are important sectors contributing to PM2.5 concentrations in Delhi, and controls over them (as in lockdowns) can lead to significant reductions in PM2.5 concentrations.

5. Significantly high pollutant levels observed in Delhi despite restrictions point towards substantial contributions of several non-local sources and the need for delineation of airshed for Delhi and also for other non-attainment cities for development of effective air quality management plans.

1. Introduction

Air quality has become a primary concern in India, with more than 70% of Indian cities violating the prescribed standards of PM_{10} (particulate matter less than 10 mm). The several sources of pollution – transport, industries, construction, biomass burning, etc., contribute to the overall levels of pollutants in varying proportions. Delhi, the capital city, is severely polluted in terms of PM_{10} and $PM_{2.5}$ concentrations. Figure 1 shows the average of the 24-h average concentrations of $PM_{2.5}$ at 29 monitoring stations in 2018, 2019, and 2020. The 24 hourly average $PM_{2.5}$ concentration remains above standards in most parts of the year except during monsoons, when the rain downwash effect reduces particulate concentrations. Winters show higher concentrations due to adverse meteorological conditions caused by low wind speeds and shallower mixing heights. Consistently for the last so many years, Delhi has witnessed highest $PM_{2.5}$ concentrations during early November. This episode is mainly attributable to post-harvest agricultural residue burning in the upwind regions of Delhi, coupled with adverse meteorology.

Primary sources that contribute to $PM_{2.5}$ levels in Delhi in winters and summers (as estimated by TERI & ARAI, (2018) are transport (17-28%), industries including power plants (20-30%), and biomass burning (14-15%). Dusty fugitive sources (both natural and anthropogenic) contribute to about 17-38% in the two seasons.

COVID-19 pandemic has touched all spheres of human lives. While it has been disastrous, the lockdowns enforced for control of the COVID-19 spread have resulted in significant air quality improvement. India went under a lockdown on 24th March 2020 initially for 21 days. Later, on 14th April 2020, the nationwide lockdown was extended till 3rd May, with some conditional relaxations in some areas after 20th April 2020. The lockdowns were further extended on 1st May by two weeks until 17th May. Various districts in the country were divided into three categories based on the corona virus's spread—green, red, and orange. Lastly, lockdowns got extended from 17th May till 31st May. The restrictions were gradually lifted thereafter, with continued restrictions in the containment zones.

Figure 1 shows a lower $PM_{2.5}$ concentrations during the period of lockdown (March to June, 2020) compared to the previous two years. . This was the period during which the restrictions were imposed on the vehicular movements, industrial operations (except for essential industries such as power plants, refineries, pharmaceutical, milk

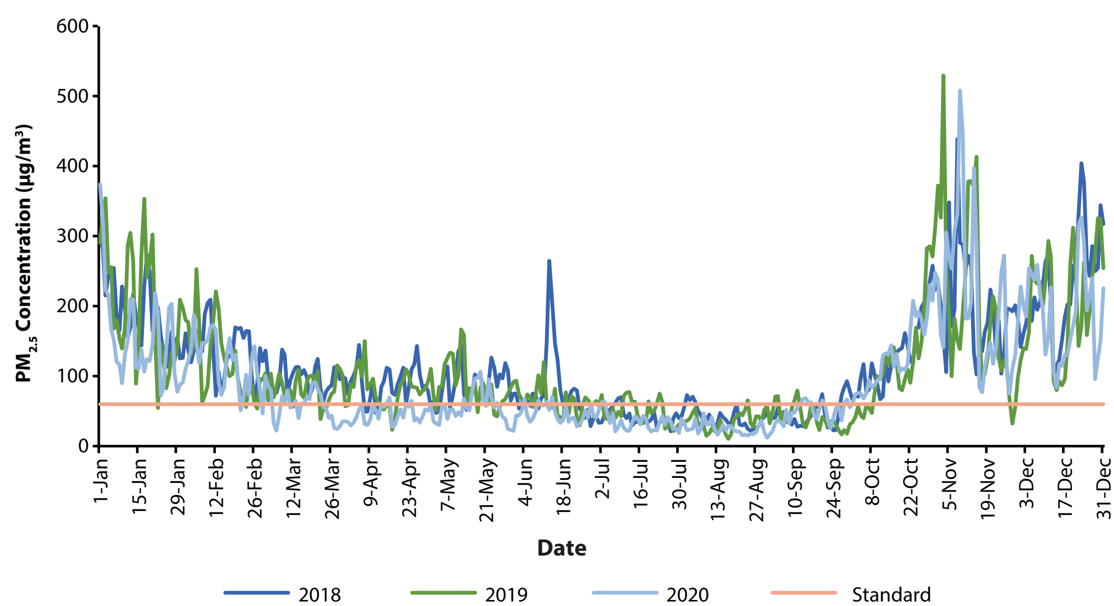


Figure 1: Daily $PM_{2.5}$ concentrations in Delhi (average of 29 stations) in 2018, 2019, and 2020
* Jan 2018 had 15 stations

plants etc.), construction activities, etc. These sources being the critical contributor of pollution in Delhi city, a restricted activity of these sources is expected to lower the $PM_{2.5}$ concentrations during that period. It becomes an interesting proposition to study the effects of these restrictions imposed on the source activity on the ambient air quality. Besides, it is crucial to understand the chemical composition and sources contributing to the $PM_{2.5}$ concentrations in the city during that period in order to identify the potential sources in the absence of local contributing sources. With support from Bloomberg Philanthropies, TERI has conducted primary ambient air quality monitoring at three different receptor locations in Delhi during the lockdown period in order to carry out chemical characterization and source profiling. The study provide useful insights into the contributing sources during restricted conditions in the city and help in identifying appropriate policy interventions to target specific sources in order to meet the air quality related goals in the context of particulate matter concentrations.

2. Scope and Objectives

The study aimed at studying the impacts of restricted source activity during the lockdown period (March to June, 2020) on the ambient air quality (particulate matter concentrations) of Delhi and carry out chemical speciation and source profiling of the sources contributing to the $PM_{2.5}$ concentrations during this period of restricted activities.

The specific objectives of the study are

a. To analyze the effect of source activity restrictions imposed during lockdown on ambient air quality.
b. To assess the chemical characteristics of $PM_{2.5}$ concentrations (chemical speciation)
c. To identify contributing sources to the $PM_{2.5}$ concentrations

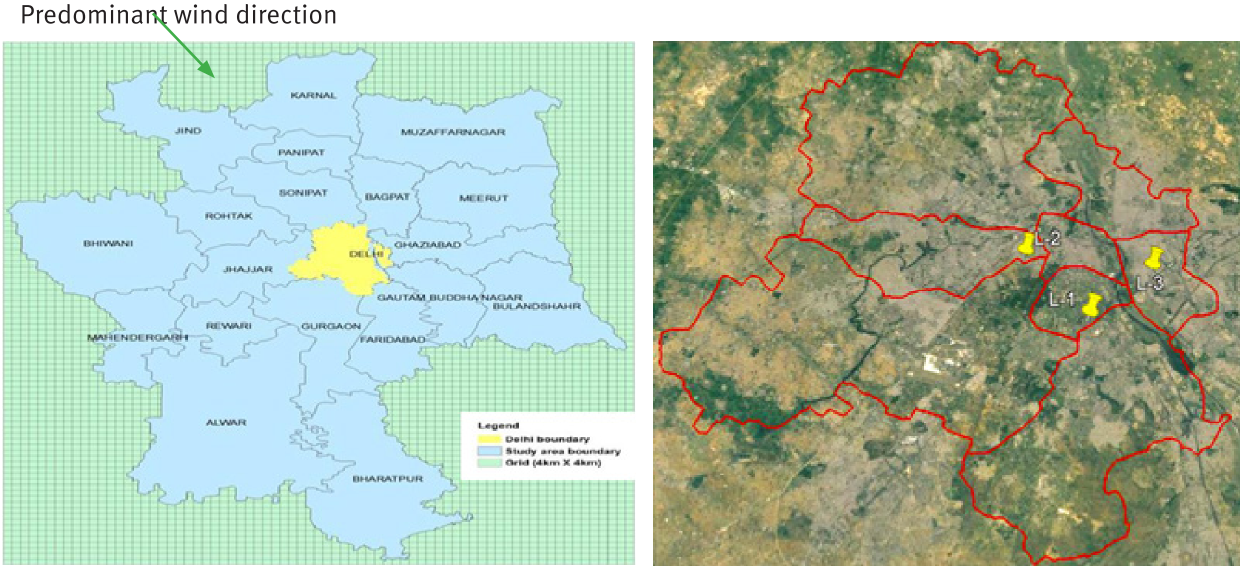
3. Methodology

3.1 Assessment of effect of restricted source activity due to lockdown on air quality

The assessment of effect of lockdown on ambient air quality has been carried by exploratory analysis, box-whisker plots and comparative statistical analysis of the ambient air quality for the years 2019 and 2020. The statistical analysis is carried out on $PM_{2.5}$ and NOx data for the year 2019 and 2020 for three timelines, namely, pre-lockdown, lockdown and post-lockdown period. In order to study the influence of meteorology, a separate statistical analysis has been undertaken for the wind speed (WS), mixing heights (MH) and ventilation coefficients (VC= WS x MH), for the same three durations. In order to assess the statistical significance of the change observed in Delhi, the test of normality (Anderson-Darling test) was conducted on the 2020 and 2019 dataset of $PM_{2.5}$ and NOx. Thereafter, after confirming the normality of the data, parametric paired t-tests – 2 sample t-tests were conducted on the dataset of 2019 and 2020 to identify p values and see if the change is significant or not. The details and the results have been presented and discussed in section 4. In addition, a two-sample F-test was also conducted to assess the statistical significance of ratio of variances corresponding to years 2019 and 2020, for $PM_{2.5}$ and NO_x concentrations data. A comparison of variance of the pollutant concentrations during the three time periods (pre-lockdown, lockdown, and Unlock-1) for the years 2019 and 2020 has been made in order to assess any change in the variability of the data w.r.t two years.

3.2 Special monitoring and chemical characterization during lockdowns

Figure 2 shows the location of national capital region and three monitoring stations on Delhi's map. National capital region is comprised of 28 districts falling in three states of Haryana, Uttar Pradesh and Rajasthan, with Delhi being in the center. While Delhi city is known for its vehicular density, road dust, construction activities for its emission sources, the rest of NCR has several additional sources such as industries using coal and other fuels, coal based power plants, biomass burning in rural kitchens, agricultural residue burning, etc. The predominant wind direction in Delhi is from N-W as shown in the Figure 2, and hence atmospheric transport from upwind districts like Jind, Panipat, Rohtak, Jhajjar, Sonipat etc influence the air quality of Delhi considerably. In this study, air quality monitoring



National capital region

Delhi

Figure 2: National capital region and location of 3 monitoring stations in Delhi.

is carried out only in Delhi which is influenced by sources in both Delhi and rest of NCR. Three zones in Delhi- Central (L1, IHC- Lodhi Road), West (L2, PN-Patel Nagar), and East (L3, LN- Laxmi Nagar), were selected for carrying out ambient air quality monitoring.

Out of the three selected locations, two (L3 (LN.), and L2 (PN.)) were typically residential, while L1 (IHC) is mainly an institutional area, with low-density residences around. Also, the site at L1 (IHC) is close to a busy road, while L3 (LN) and L2 (PN) were confined to pure residential setups. We installed the instrument at the height of 5-10m from ground level at L2 and L3 and 25-30m from ground level at L1 (IHC building's roof top, Lodhi road).

$PM_{2.5}$ monitoring was conducted with special permissions following the guidelines concerning the COVID-19 outbreak. All the instruments were calibrated, sanitized, and installed at each of the selected monitoring locations. The $PM_{2.5}$ sampler (APM 550M, Envirotech make, India) set at a flow rate of 16.7 LPM was used to monitor $PM_{2.5}$ in each of the selected locations. At all the chosen locations, 24-hourly monitoring of $PM_{2.5}$ was carried out for 45 days starting from 22nd April 2020 till 5th June 2020. The methodology followed was strictly according to the guidelines laid down by the Central Pollution Control Board (CPCB) and the Bureau of Indian Standards (BIS). Quartz and Teflon filters of 47 mm diameter were used for the collection of $PM_{2.5}$ samples. $PM_{2.5}$ samples collected in different filter media such as Teflon and quartz were used for the chemical characterization of various metals, ions, and carbonaceous particle, as shown in Table 1 below.

3.2.1 Chemical Analysis of $PM_{2.5}$ samples

The quantitative analysis of elements in $PM_{2.5}$ samples' elements collected on Teflon filters was carried out using Energy Dispersive X-ray Fluorescence Spectrometer (ED-XRF) at ARAI. As XRF analysis is a non-destructive technique, same filter was used for subsequent analysis of water-soluble inorganic ions using Ion Chromatography. PM samples collected on quartz filters were subjected to O.C. (organic carbon) and E.C (elemental carbon) analysis using the Thermal/Optical Carbon Analyzer. Details of the sample analysis are given below.

The ED-XRF spectrometry (EDX 7000, Shimadzu, Japan) was used to determine the concentrations of elements including Al, Si, K, Ca, Ti, V, Fe, Co, Ni, Cu, Zn, As, Se, Zr,

Table 1: Filters and analytical methods used for analysis

Component	Required filter matrix	Analytical method
$PM_{2.5}$	Teflon & quartz filter	Gravimetric
Elements (Na, Mg, Al, Si, P, S, Cl, Ca, Br, V, Mn, Fe, Co, Ni, Cu, Zn, As, Ti, Ga, Rb, Y, Zr, Pd, Ag, In, Sn, La Se, Sr, Mo, Cr, Cd, Sb, Ba, Hg, and Pb)	Teflon filter	Energy Dispersive X-Ray Fluorescence (ED-XRF) spectrometry (EDX 7000, Shimadzu, Japan)
Ions (F^-, Cl^-, Br^-, NO_2^-, NO_3^-, SO_4^{-2}, K^+, NH_4^+, Na^+, Ca^{++}, Mg^{++})	Teflon filter	Ion chromatography (IC) system (ICS Aquion, ThermoFishr Scientific)
Carbon Analysis (O.C., E.C. & Total Carbon)	Quartz filter	Thermal/Optical Carbon Analyzer (DRI Model 2001A; Desert Research Institute, USA)

Mo, Pd, Cd, Ce, and Pb, on the Teflon filters. Calibration standards, in the form of filter paper, of Micromatter Inc. for various elements were used for calibration of equipment. Measurements were also made on the blank filter, and correction in the intensities was made for the loaded filters. Data acquisition and quantitative analysis were carried out by using the equipment software.

The water-soluble inorganic ionic components in PM collected on Teflon filters were determined using the ion chromatography method. Each sample was ultrasonically extracted using 50 mL of deionized water for 90 minutes. The extract was filtered through a 0.22 µm nylon membrane syringe filter to remove insoluble matter and then analyzed using an ion chromatography (I.C.) system (ICS Aquion, ThermoFisher Scientific). The cations' concentration (Na^+, K^+, Mg^+, NH_4^+, Ca^{2+}) was determined using an IonPac CS16, 5mm analytical column. It's CDRS600, 4mm guard column, 3.8 mM Methanesulfonic Acid was used as eluent while the concentrations of anions (Cl^-, F^-, Br^-, NO_3^-, SO_4^{2-}) were determined using a separation analytical column IonPac AS23; 4mm and guard column ADRS600, 4mm), and 4.3 mM carbonate and 0.8mM bicarbonate as eluent. The blank filters were also analyzed for the cations and anions.

A 0.495 cm^2 punch from a quarter of each quartz filter sample was used for the analysis of organic carbon (O.C.) and elemental carbon (E.C.) using a Thermal/ Optical Carbon Analyzer (DRI Model 2001A; Desert Research Institute, USA) following IMROVE_A protocol. The four O.C. fractions, i.e., OC1, OC2, O.C., and OC4, are produced in a step-wise manner at 140, 280, 480, and 580 °C temperatures, respectively, in a pure Helium (100% He) atmosphere. This analysis was further continued for three more temperatures, i.e., 580, 740, and 840 °C, to determine three E.C. fractions, i.e., EC1, EC2, and EC3, respectively, in 98% helium and 2% oxygen-containing atmosphere. The pyrolyzed carbon fraction (O.P.) is also determined when the reflected laser signal returns to its initial value after oxygen is added to the Helium atmosphere. The IMPROVE protocol defined O.C. as OC1+OC2+OC3+OC4+OP and E.C. as EC1+EC2 +EC3-OP. Each filter and blank filters were analyzed to get the representative estimation of O.C. and E.C. concentrations.

4. Statistical Analysis of pollutant concentrations during lockdowns

Air pollutants concentrations are inherently random variables because of their dependence on various source emissions, meteorological, and other spatiotemporal variables. When sets of random samples of historical ambient air quality data are available, different statistical characteristics can be determined and assigned to the pollutant concentrations. The raw air quality and meterological data for 32 stations in Delhi was obtained from the CPCB website and was subjected to statistical analysis to assess the impact of lockdown on the ambient air pollutant concentration over Delhi. Exploratory data analysis was first carried out, which included computation of summary statistics, Box and Whisker, and time series plot for three periods

- pre-lockdown (1st January – 24th March);
- lockdown (25th Mar-31st May); and
- post-lockdown/Unlock 1(1st Jun-30th Jun).

The purpose of the Box and Whisker plot was to preliminarily assess the skewness, variation, and outlying observations in the data. The time-series plot gave an idea of temporal variation in air quality data and observe any bending in the curve from the day the lockdown was introduced. An exploratory analysis was also carried out for wind speed (WS), mixing height (MH) and ventilation coefficient (VC=WS X MH), which are critical meteorological parameters responsible for the horizontal and vertical spread of the pollutants and also contributing to the mechanical turbulence and hence dispersion. VC, which is the product of mixing depth and the average wind speed, is an atmospheric condition which gives an indication of pollution dispersion potential, i.e., the ability of the atmosphere to dilute and disperse the pollutants over a region. Exploratory analysis was carried out to assess the effect of meteorology on concentration levels during the lockdown.

The data were first assessed for normality by conducting a goodness-of-fit test. This test is required to decide the appropriate test of significance – parametric tests are used for the raw or the transformed data that follows a normal distribution, and non-parametric tests are applied on data not following a normal distribution. This normality check was done by testing the null hypothesis (Ho) that pollution data comes from a normal distribution against the alternative hypothesis (H1), that the data comes from some other distribution form. In the present study, the goodness–of–fit was evaluated using Anderson and Darling (A-D) test and visually examining the probability plots (Kottegoda and Rosso, 2008). Also, to ascertain the normality of the data, coefficient of skewness and kurtosis were determine for each dataset. Analyzing the A-D test, coefficient of skewness and kurtosis, datasets were subjected to different statistical test. The examination revealed that the processed air quality data followed normal and log-normal distribution. The meteorological parameters followed a log-normal while some of them did not follow any statistical distribution. Thus, to assess the impact of lockdown due to the COVID-19 pandemic, a pairwise comparison between the 2019 and 2020 dataset were conducted for all three scenarios (Pre-Lockdown, Lockdown, Unlock-1) using the paired t test for datasets which followed normal distribution. Dataset which followed lognormal distribution were first transformed and then paired t test were performed on them. Datasets following no distribution pattern, were subjected to Wilcoxon nonparametric test to assess if the change in datasets is significant or not. In addition, a two-sample F-test was also conducted to assess the ratio of variances of both pollutants corresponding to 2019 and 2020, respectively. The Two-Sample f-Test tests was conducted to assess the change in variance for the data corresponding to two years for both the pollutants. A comparison of variances of the pollutant concentrations in three time periods (pre-lockdown, lockdown, and Unlock-1) during 2019 and 2020 is made. During lockdown period, emission source activity of the local sources was reduced and therefore, a reduction in variance of ambient pollutant concentrations is expected w.r.t the same duration during 2019.

4.1 Exploratory Analysis:

Percentage change in 2020 with respect to 2019 for $PM_{2.5}$ and NOx concentration in Delhi is presented in Table 2a. The highest % reduction is observed during the Lockdown period and then in post-lockdown (Unlock 1). Reduction in pollutants concentration was also observed in the Pre-Lockdown period. A 43% reduction in $PM_{2.5}$ during lockdowns shows the impacts of restrictions on vehicular and industrial activity in the region. Also, a 61% reduction in NOx, which is a primary pollutant contributed by the vehicular sources, shows the impact of restricted vehicular movement in the city. An analysis of meteorological parameters such as wind speed, mixing height, and VC indicate a lower average value in 2020 compared to 2019 during the lockdowns and Unlock 1 periods. This shows that concentrations are found to be less despite adverse meteorological conditions in 2020. Hence, reductions in $PM_{2.5}$ and

NO_x concentration levels are attributed primarily to reduced emissions during the lockdown and Unlock-1 periods. During the pre-lockdown period, VC was found to be higher in 2020 implying more dispersion and hence reduced ambient concentrations. Moreover, the precipitation data shows higher rainfall in 2020 than in 2019 during the pre-lockdown period, resulting in more wet deposition and reduced particulate matter concentrations. Meteorological conditions were more conducive for dispersion in pre-lockdown period of 2020 w.r.t. 2019, as indicated by higher VC for 2020. Therefore, reduction in this period may be attributed to better meteorology for pollutant dispersion However, during the lockdown and Unlock-1 periods, where meteorology has been found to be adverse during 2020 and lower concentrations have been observed, the reduction essentially is attributed to reduction in source emissions. This gives adequate evidence of positive impact of lockdown resulting in reduced source activity causing reduced pollution levels.

In addition to this, variance has also been calculated to assess the variability in the data of $PM_{2.5}$ and NO_x concentration in the three time periods for 2019 and 2020 (Table 2b). It is evident that variance was found to be much less in 2020. The reduction in variance was more pronounced during lockdown and Unlock-1 phases. Low variability in data indicates towards reduced contributions from local sources in 2020, which otherwise add to variability in the pollutant concentrations. The variance was ~10-times lower for NOx concentrations during lockdown period in 2020 w.r.t. 2019, which can be attributed to significant reduction in vehicular activity.

4.2 Box and Whisker Plots

The Box and Whiskers plots were made for each of the three categories for 2019 and 2020. These plots show the whole range of pollutant concentrations in three different lockdown categories in the two years. The averages and the range of pollution concentrations went down during the lockdown period for both pollutants. It can be seen that the interquartile range (IQR) and the range are very close to each other in the lockdown and post-lockdown period for both the pollutants, indicating significantly less variability in the pollutant concentration. This may be attributed to a stricter observation of the lockdown resulting in restricted source activity and consequent limited source emission variability. The reduced spread of these ranges suggests that major source activities contributing to pollution in the cities were cut down, and the pollution concentrations went down to similar background levels. The coefficient of skewness and Kurtosis were also calculated for different datasets and were not found close to zero, indicating the skewness in the datasets; which was also indicating with datasets not following normal distributions. The time series plot clearly shows that after the lockdown was announced (25^{th} March 2020), a dip in concentration is observed for both $PM_{2.5}$ and NO_x.

4.3 Tests of significance

To assess the statistical significance of the reductions observed in Delhi, the following tests have been performed.

Table 2a: % Change in 2020 with respect to 2019 concentrations and meteorological parameters

%reduction w.r.t. 2019	$PM_{2.5}$	NO_x	WS	MH	VC
Pre-Lockdown	-17	-12	-16	+61	+34
Lockdown	-43	-61	-15	-12	-26
Unlock 1	-27	-43	-34	-27	-52

Table 2b: Variances observed in $PM_{2.5}$ and NOx concentrations in 2019 and 2020

	$PM_{2.5}$		NOx	
	2019	2020	2019	2020
Pre-Lockdown	6345	3719	1173	647
Lockdown	851	352	349	36
Unlock 1	467	139.	277	27

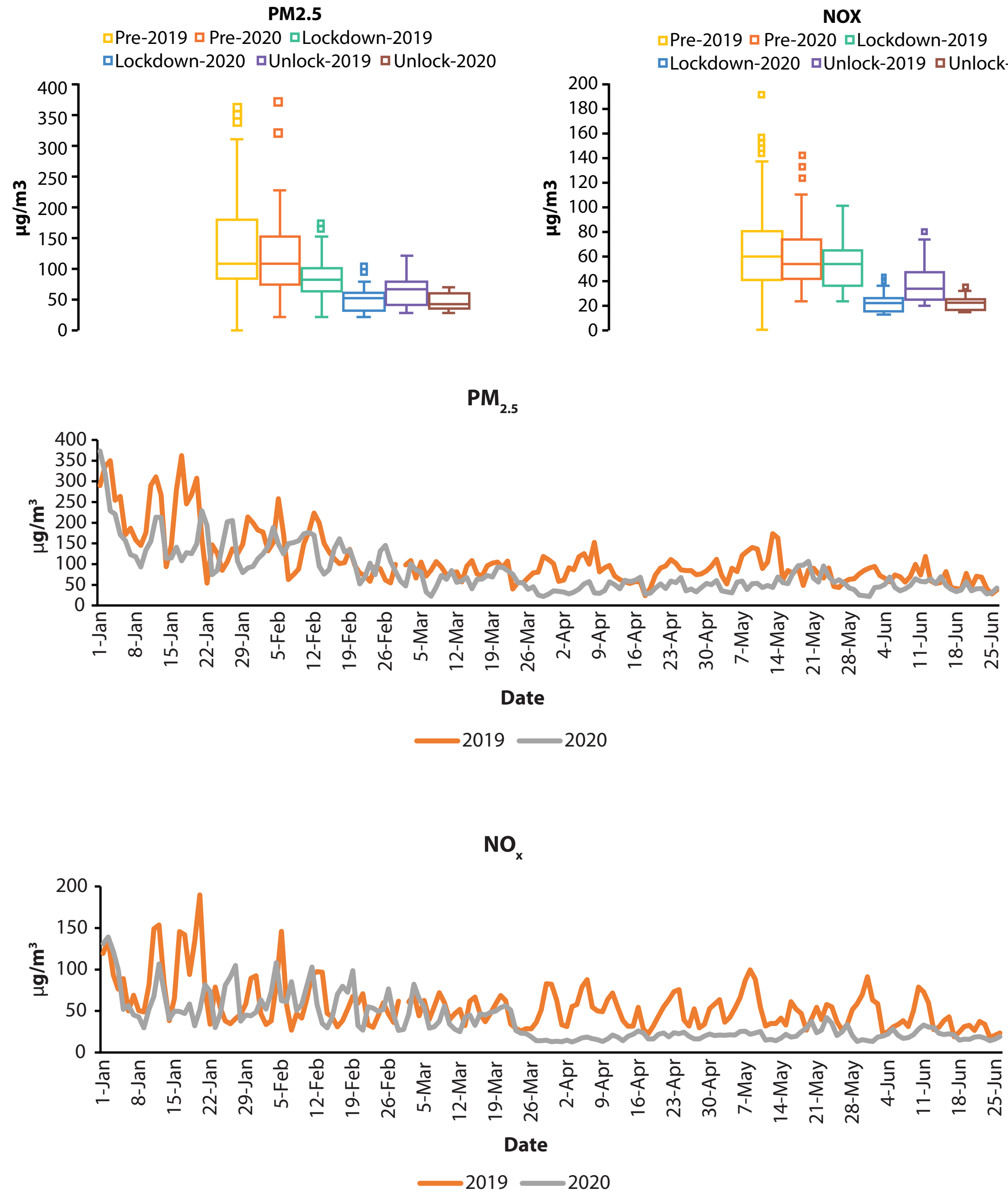


Figure 3: Box and Whisker plots and daily average $PM_{2.5}$ and NO_x concentrations at 32 stations in Delhi during Jan-Jun 2020

- Test of normality – Anderson-Darling test was conducted on the 2020 and 2019 dataset of $PM_{2.5}$ and NOx.
- Parametric paired t-tests – 2 sample t-tests were conducted on the dataset of 2019 and 2020 to calculate p values and assess if the

change is significant or not. Also, on dataset which followed log-normal distribution, data was transformed to natural logarithm value, and then paired t test was applied to find the p values.

- Non-Parametric Wilcoxon test – This was conducted on datasets which did not follow any distribution., for calculation of p values.
- Two sample F-test was conducted to assess whether the variances for pollution data for the two years were same or different

To check the normality, a goodness-of-fit test (test of normality) was conducted on the 2019 and 2020 dataset both for ambient air quality and wind speed data. It was found that all the datasets had a normal distribution, which suggested a parametric paired t-test to be conducted on the dataset. The test was done at 0.05 significance level. Thus, a p-value smaller than 0.05 indicate statistically significant change and vice versa.

For the pre-lockdown period $PM_{2.5}$, the p-value is less than 0.05, which is indicative of the fact that $PM_{2.5}$ was reduced in 2020 (before COVID-19 restrictions) significantly, mainly due to meteorological changes. However, NO_x levels showed insignificant change during the pre-Lockdown period. During the lockdown period, statistically significant reduction was found in the concentration levels of both the pollutants. In addition, low p-value of winds speeds, mixing heights, and VC datasets also suggests statistically significant change during 2020 with respect to 2019 for the three different periods. The fact that VC is reduced significantly confirms that emission reduction played a significant role in reducing pollution during lockdowns, even though meteorology was unfavourable.

Two sample F-test for variance was also conducted to assess the variance of $PM_{2.5}$ and NO_x during three time periods. The one tail p- value of the F-test conducted on all the above-mentioned dataset was less than 0.05 (confidence level of 95%), indicating that variance for 2019 was higher than 2020 data. All the statistical tests conducted above indicate that in lockdown and unlock-1 scenarios, emission sources have decreased and resulted in reduced ambient air pollution when compared to 2019 data. However in pre-lockdown period during 2020, it cannot be confirmed that pollution has reduced due to emission reduction only, as meteorological conditions in the form of higher VC and precipitation have contributed towards better dispersion and wet deposition resulting to reducing pollutant concentrations.

Using the results of these tests, inferences were drawn for $PM_{2.5}$ and NO_x for Delhi. The city has shown a general reduction in pollutant concentration, which is statistically significant. A finding comes out that even during the pre-lockdown phase, the $PM_{2.5}$ in 2020 was significantly reduced compared to 2019 data. However, the reduction may be attributed more to meteorological conditions resulting in dilution of pollution levels (higher VC and precipitation)). However, reduction in NO_x is not significant during the pre-lockdown period, which shows that even though $PM_{2.5}$ has reduced, NOx has not shown a similar reduction. During the lockdown period, a statistically significant reduction in the pollutant concentration was observed despite of adverse meteorological conditions during this period in 2020, clearly indicating the favourable impact of restricted source emission activity in Delhi and neighbouring areas.

Table 3: p values of paired 2 t-test

p-value	$PM_{2.5}$	NOx	WS	MH	VC
Pre-Lockdown	0.0004	0.068	0.00	0.000	0.000
Lockdown	0.000	0.000	0.00	0.000	0.000
Unlock 1	0.000	0.000	0.00	0.000	0.000

5. Special monitoring and chemical characterization of $PM_{2.5}$ in Delhi

Ambient $PM_{2.5}$ monitoring was carried out at 3 locations in Delhi- IHC, L.N., and P.N. The comparative results of $PM_{2.5}$ concentrations in the 3 sites are presented in subsequent sections.

5.1 Ambient $PM_{2.5}$ status of the three selected locations

The results of the ambient $PM_{2.5}$ monitoring carried out at the three locations are summarized below. The $PM_{2.5}$ levels at three sites were compared with the observations at nearest stations monitored by CPCB under the National Air Monitoring Program (NAMP). All the results were compared with the National Ambient Air Quality Standards (NAAQS) set by CPCB.

The $PM_{2.5}$ levels at Lodhi Road (L1) during the monitored period from April to June indicate that for 60% of the monitored period levels were above the 24-hr average NAAQS of 60 µg/m³ prescribed by CPCB. A similar finding was observed in the data collected from the nearest CPCB monitoring station. The $PM_{2.5}$ levels at this location during the monitoring period ranged between 27-137 µg/m³ with an average level of 67 µg/m³, whereas the corresponding levels at Lodhi Road monitored by CPCB went between 21-121 µg/m³, averaging about 60 µg/m³.

The $PM_{2.5}$ levels measured at the Laxmi Nagar location were found to violate the prescribed standard 47% of the times during this period. The $PM_{2.5}$ levels at this location during the monitoring period varied between 35-122 µg/m³ with an average of 65 µg/m³. There were no close CPCB stations to this site. Hence an average of 4 sites in east Delhi, closest to the station, were taken. The average $PM_{2.5}$ values of the four locations in the eastern part of Delhi monitored by CPCB in the same period indicated a 31% times violation of the standard, and the levels ranged between 23-100 µg/m³ with an average value of 53 µg/m³. This reduction in the percentage violation, range and average values in the CPCB data may be attributed to the averaging effect (the values are average of four monitoring stations).

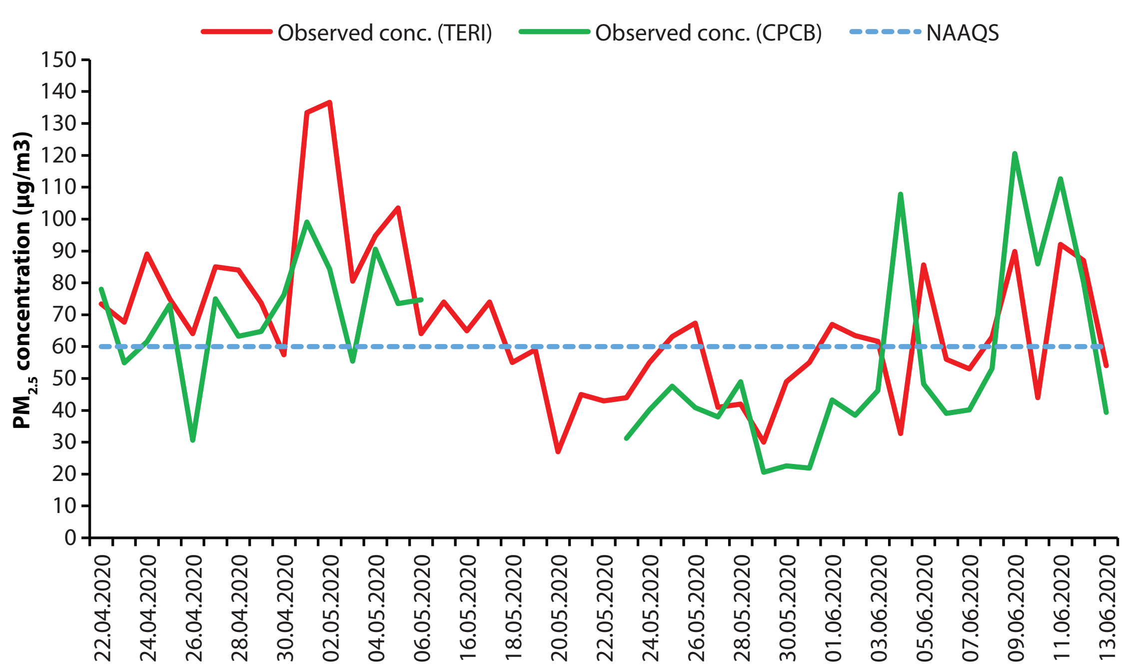


Figure 4: $PM_{2.5}$ levels at Lodhi Road

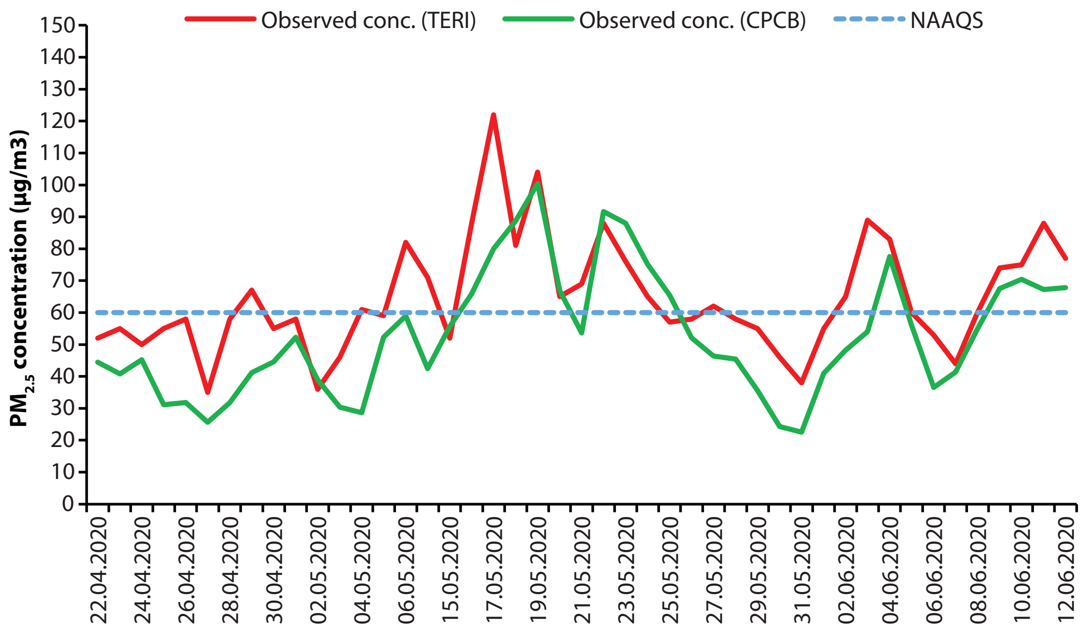
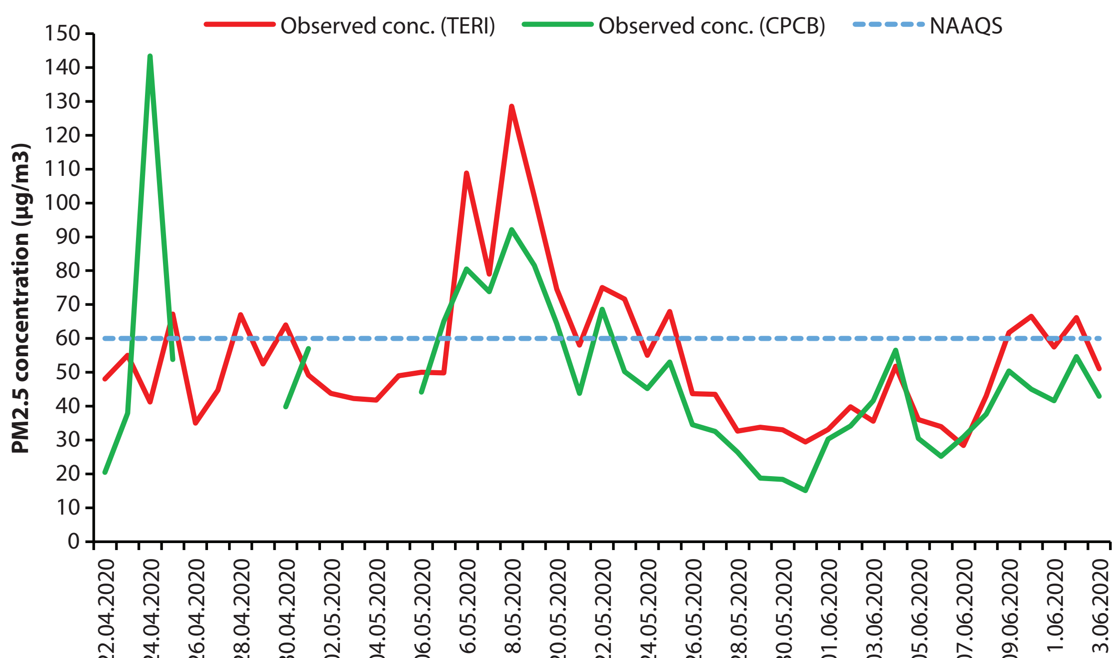


Figure 5: $PM_{2.5}$ levels at Laxmi Nagar.

*Observed concentration of CPCB is the average of $PM_{2.5}$ levels at four locations in the east of Delhi such as Vivek Vihar, IHBAS, Anand Vihar, and Vivek Vihar.

The $PM_{2.5}$ concentrations measured at the Patel Nagar location indicated that most of the time, the levels were well within the prescribed limit except for a few observations (~29% violation). The $PM_{2.5}$ levels at this location during the entire monitoring period ranged between 28-129 µg/m³, averaging to 54 µg/m³. The data collected from the nearest site (Pusa Road) of Patel Nagar operated by CPCB also indicated that the



Figures 6: $PM_{2.5}$ levels at Patel Nagar

levels at this location for most of the monitored period were well within the standard (~31% violation); the levels at this location ranged between 15-143 µg/m^3 with an average of 48 µg/m^3 over the entire monitoring period,

5.2 Chemical speciation of $PM_{2.5}$ at Delhi during the lockdown

5.2.1 Carbon

During the monitoring period, mass distribution of chemical species (elements, carbon, and ions) showed that total carbon was the most dominating chemical constituent in $PM_{2.5}$ samples at all the three monitoring locations. A significantly higher proportion of total carbon was observed across different areas, 51% at IHC, followed by 41% at Laxmi Nagar and 31% at Patel Nagar. This shows the presence of significant combustion sources in the $PM_{2.5}$ levels. Ions were identified as the second most abundant species, followed by elements. Among different monitoring locations, the highest ion relative contribution of 29% was observed at Patel Nagar, followed by 18% at Laxmi Nagar and 14% at IHC. Similarly, the highest elemental contribution of 21% was observed at Patel Nagar, followed by 16% at Laxmi Nagar and 11% at IHC. About 25%, 23%, and 19% of chemically characterized $PM_{2.5}$ species remained unidentified at Laxmi Nagar, IHC, and Patel Nagar, respectively, which can be attributed to the rest of the organic matter attached to the organic carbon and oxides attached with the metals.

5.2.2 Elements

Mass distribution of elemental species showed that Si, S, Cl, K and Fe was identified as the most dominating elemental constituents in $PM_{2.5}$ samples across the respective monitoring locations. Highest proportion of Si with relative share of 29% was observed at Laxmi Nagar, followed by 23% at IHC and 14% at Patel Nagar. High concentrations of silica at Laxmi Nagar indicates towards a specific source of dust in the vicinity of station. Across respective monitoring locations, the highest of S with relative abundance of 22% was observed at IHC, followed by 19% at Laxmi Nagar and 16% at Patel Nagar. A specific source of coal (which has significant quantities of sulphur) is indicated near IHC locations, above the general influence of regional scale industrial source at all the sites. Similarly, significantly highest proportion of Cl, having relative share of 29% was observed at Patel Nagar, followed by 15% and 14% at IHC and Laxmi Nagar respectively. Highest share of Fe and Na having relative abundance of 8% and 9% respectively was identified at Patel Nagar monitoring site.

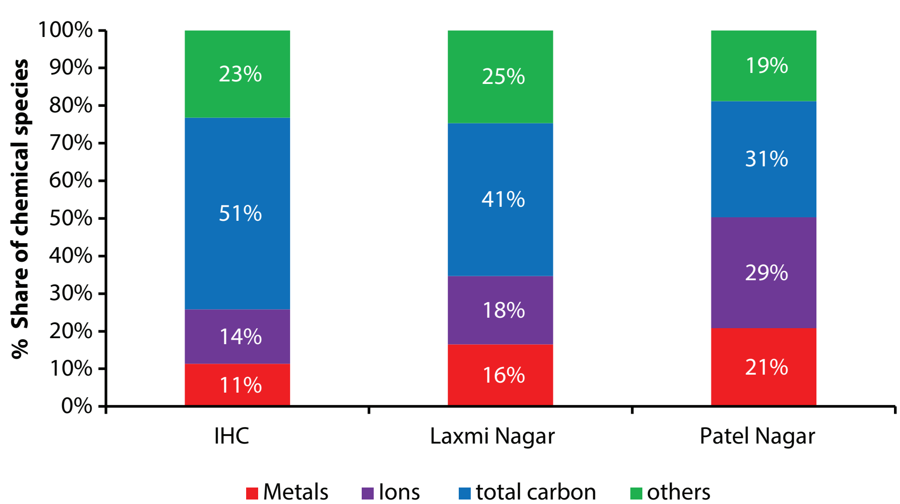


Figure 7: Percentage share of elements, ions, carbon, and other species in $PM_{2.5}$ samples at IHC, Laxmi Nagar, and Patel Nagar monitoring locations in Delhi during April- June, 2020

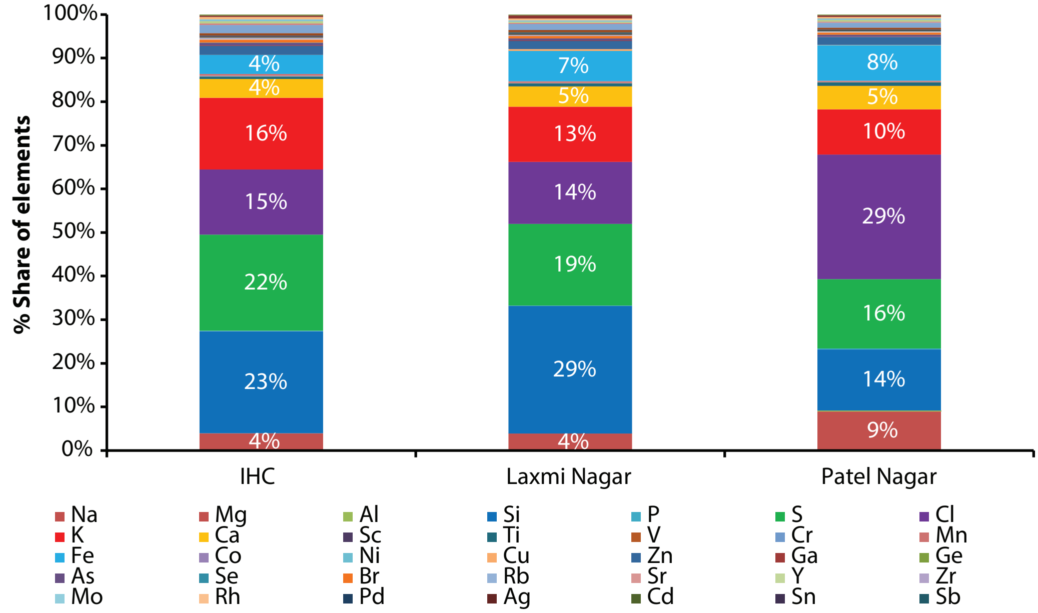


Figure 8: Percent share of different elements in overall elements concentrations in $PM_{2.5}$ at 3 sites

5.2.3 Ions

Mass distribution of ionic species showed $SO4^{2-}$, NH_4, Cl^-, $NO3^-$, K^+, Ca^{+2}, and Na+ were observed as the most dominating species in PM2.5 samples at all the three monitoring locations. $NH4^+$ was identified as the most abundant species among the chemically characterized cationic species, followed by K^+, Ca^{+2}, and Na+. The highest proportion of NH4+ having a relative share of 42% was observed at Patel Nagar, followed by 18% at IHC and 15% at Laxmi Nagar. This depicts a more substantial influence of regional, scale secondary inorganics at Patel Nagar, which is upwind to the city centre and expected to be influenced by regional pollution. The highest proportion of K+ with a relative

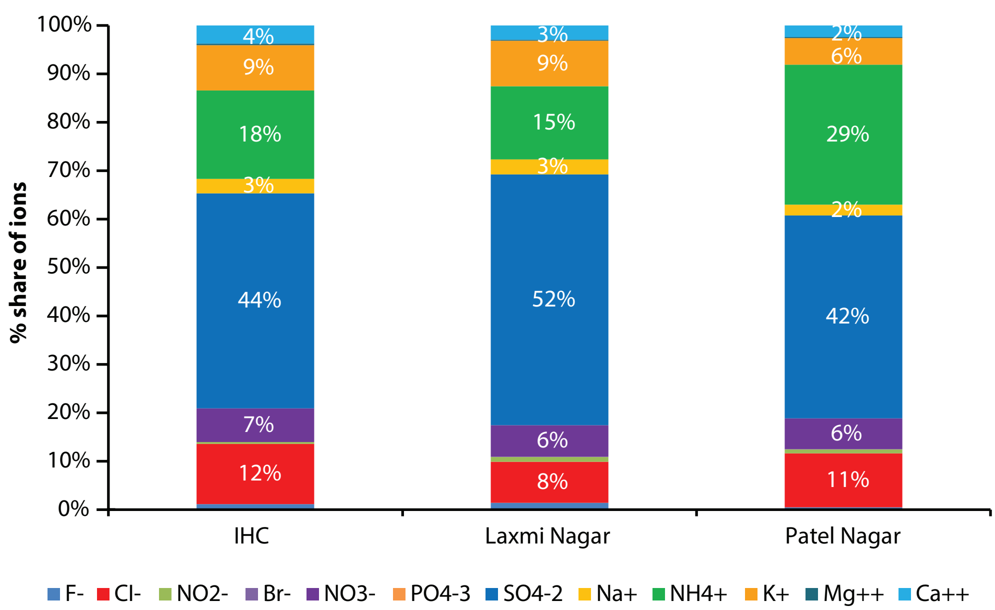


Figure 9: Percent share of different ions in overall ion concentrations in $PM_{2.5}$ at 3 sites

contribution of 9% was observed at IHC and Laxmi Nagar monitoring locations.

Moreover, among different chemically characterized anionic species, $SO4^{-2}$ was identified as the most abundant species, followed by Cl^- and NO_3^-. This indicates industrial sources emit SO2, which eventually converts to sulphates after going through a series of chemical reactions. A significantly higher proportion of SO_4^{-2} having a relative contribution of 52% was observed at Laxmi Nagar, followed by 44% at IHC and 42% at Patel Nagar. Moreover, the higher proportion of Cl^- and NO_3^- having a relative share of 12% and 7%, was witnessed at the IHC monitoring location.

6. Assessment of source contributions using positive matrix factorization

In this study, positive matrix factorization has been used to derive sources' contributions towards prevailing $PM_{2.5}$ concentrations. EPA-PMF software has been used for this purpose, which has been successfully used in several studies before. The basic methodology used in the PMF analysis is based on finding a solution to the mass balance equations as in various other multivariate receptor models. The chemical mass balance equation used in the model

$$X_{ij}=\Sigma_{k=1}^{p} G_{ik} \cdot F_{kj} + e_{ij}$$

Where X_{ij} is the concentration of species *j* measured on sample *i*, *p* is the number of factors contributing to the samples, F_{kj} is the concentration of species *j* in factor profile *k*, G_{ik} is the relative contribution of factor *k* to sample *i*, and e_{ij} is the residual of the PMF model for the *j* species measured on sample i.

The model attempts to adjust the values of *Gik* and *Fkj* until a minimum value of *Q* for a given *p* is found, where *Q* is

$$Q=\sum_{i=1}^{n}\sum_{j=1}^{m}\left[\frac{X_{ij}-\Sigma_{k=1}^{p} G_{ik} \cdot F_{kj}}{u_{ij}]}\right]^2$$

where u_{ij} is the uncertainty of the *jth* species concentration in sample *i*, *n* is the number of samples, and *m* is the number of species.

EPA PMF carries out multiple iterations to identify the best possible factor contributions and profiles. The model searches for the factor profiles, starting with a randomly generated factor profile, which then gradually modified in different iterations using the gradient approach to find the best-fit solution. Lowest Q value determines the best solution.

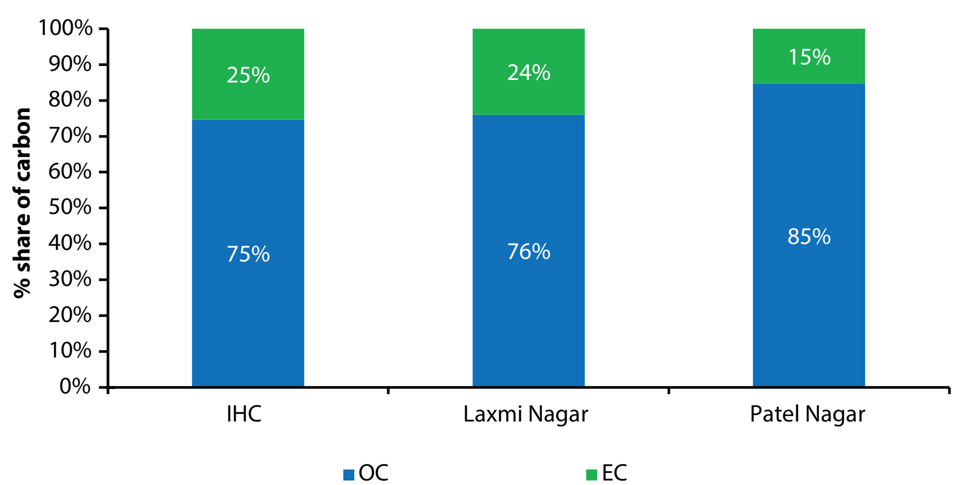


Figure 10: Percent share of E.C. and O.C. in overall carbon concentrations in $PM_{2.5}$ at 3 sites

Q (robust) and its variability across different runs act as a critical parameter for choosing the optimal run from the multiple runs. Limited variation in the Q(full) values ensures more stability of the solution. Variability of the PMF solution is estimated using the following two methods.

a) **Bootstrap (B.S.) analysis:** This is employed to assess and detect whether a small set of observations influence the PMF solution disproportionately. B.S. error intervals can determine the effects caused by random errors and to some extent effects of rotational ambiguity (which could be caused due to existence of an infinite number of similar solutions).

b) **Displacement (DISP) analysis**: This is used to understand the sensitivity of the selected solution to small changes. DISP error intervals include effects of rotational ambiguity but do not include consequences of random errors in the data.

The data from the three sites (IHC, L.N., and P.N.) were compiled and was run using the EPA-PMF software. In the PMF-EPA model, $PM_{2.5}$ was designated as Total species. The data were first analyzed by assessing the Signal/Noise (S/N) ratios for different species and then categorized into 'strong,' 'weak, and 'bad' categories (Annexure 1). After that, we evaluated the time series of $PM_{2.5}$ and other species and derived useful inferences. It was found that concentrations of $PM_{2.5}$ and EC1, and O.C. rise considerably in between the monitoring period, which coincides with the period of agricultural residue burning in the upwind regions of Punjab and Haryana.

After that, correlations between species were assessed. It was found that EC1 and EC2 don't correlate well, depicting that they come from different sources. EC1 being at low temperature can come from biomass burning, or industrial burnings, while EC2 can come from high-temperature vehicular combustions. The PMF model runs have been performed with 12 sources initially but reduced down to 8 sources finally by looking at bootstrap tests' results. Several iterations were done to bring Q(True) closer to Q(Robust), which eventually came out to be the same. Simultaneously, attempts were also made to reduce Q/Qexp for the overall run and individual species, and finally, it was found to be less than 2 for all species. Additional modelling uncertainty was assumed to be 12% to account for errors in uncertainty estimations. For different iterations, the species which were not predicted well by the model were removed from the analysis (categorized as Bad). Once the base runs were completed, bootstraps (100) were performed, and the mapping of bootstrap factors to base factors was found to be more than 80%. Finally, eight factors could be identified, which could be attributed to different sources contributing to the prevailing $PM_{2.5}$ concentrations. Figure 11 shows the consistency observed in Q (R) values across the 20 runs performed by the model, which shows the appropriateness and consitentcy of the model results.

Figure 12 shows the observed and predicted values of $PM_{2.5}$ concentrations by the model. Figure 13 shows time series reduction of PM2.5 concentration by the model.

6.1 Factor identification

In all, the model could distinguish and identify eight factors. The fingerprints of the eight identified factors are shown in Figure 14.

The first factor is identified as an aged profile resulting from long distance transport of emissions due to agricultural residue burning and industries. The profile shows high abundance of potassium, and sulphate, along with organic & elemental carbon, and a significant proportion of chlorides. The factor also shows increase in contributions in some days of monitoring which coincides with the period of increased number of fires detected in the upwind regions of Delhi. Post-harvesting of the wheat crop, residues are burnt in upwind states of Delhi, and due to atmospheric transport, aerosols travel towards Delhi and contribute to $PM_{2.5}$ concentration. Moreover, there are several industries in the upwind districts and states of Delhi (Figure 2) and presence of sulphates in the profile points towards their contribution through long range transport.

The second factor is identified as secondary inorganic particulates, like ammonium, sulphate, and nitrate,

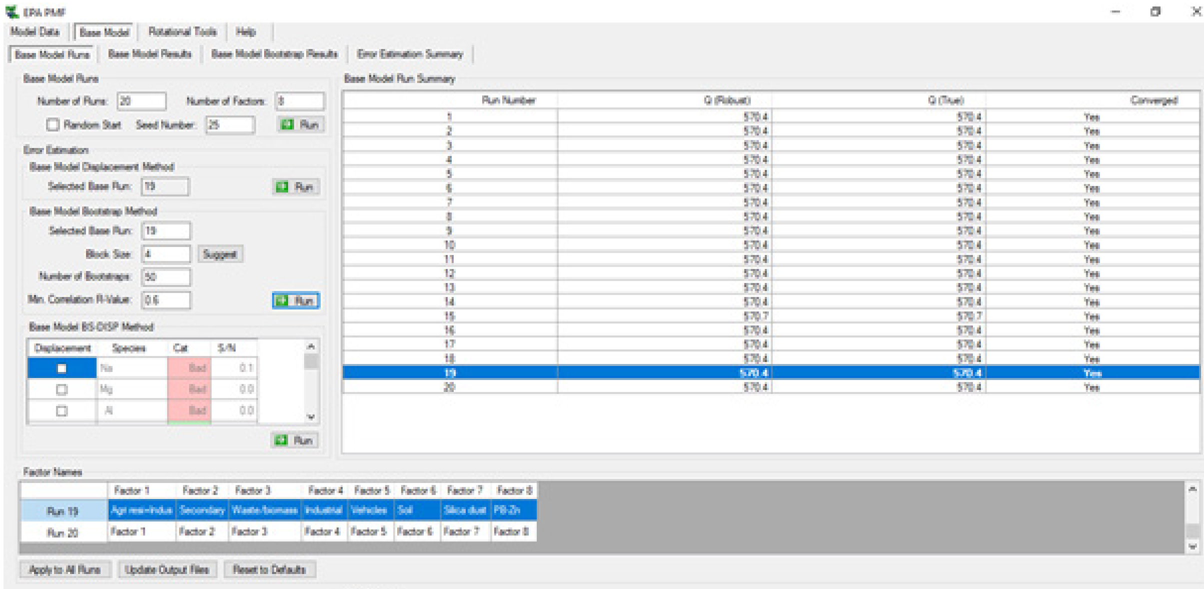


Figure 11: Consistency of Q(r) and Q(True) values during several PMF runs for the three sites

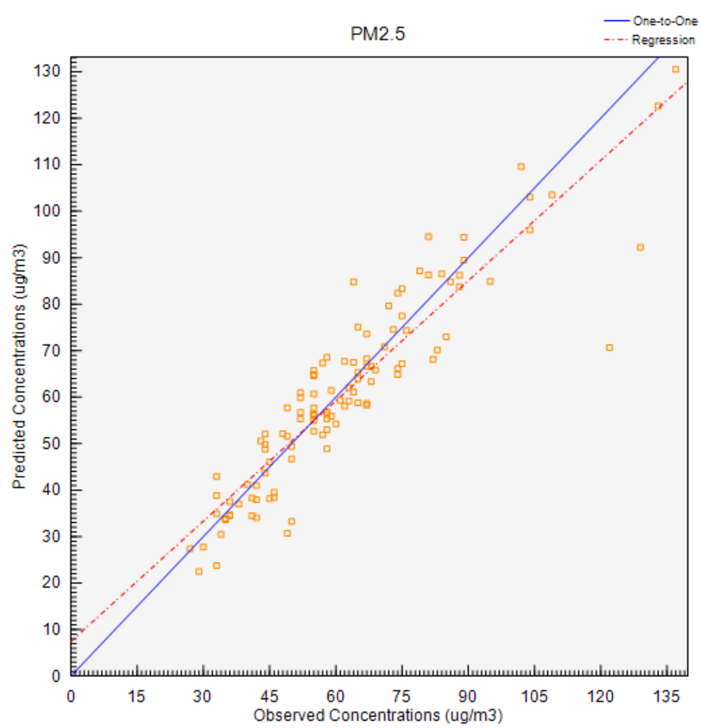


Figure 12: Predicted and observed concentrations of $PM_{2.5}$ at three sites by the EPA-PMF Model

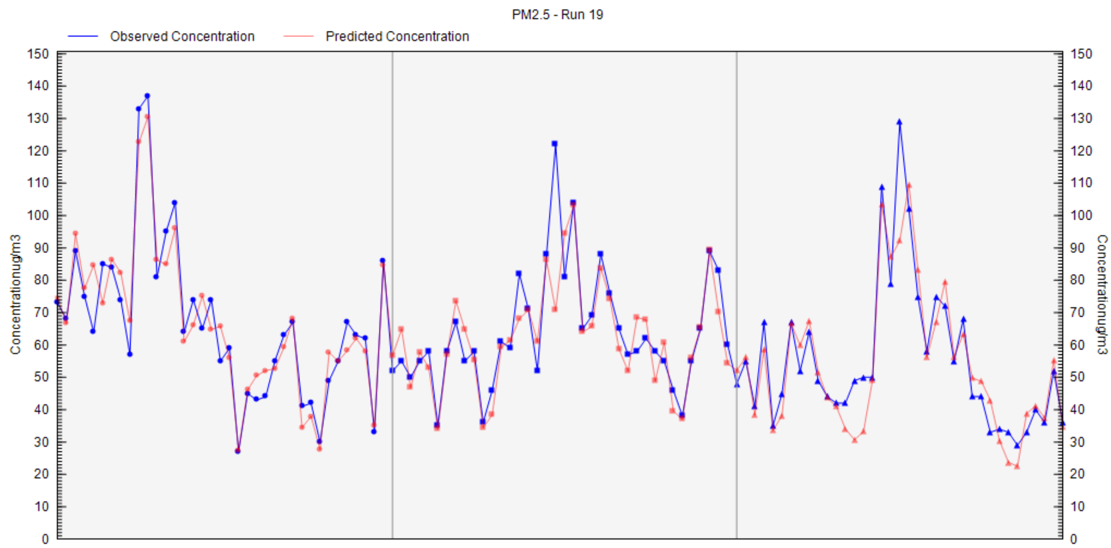


Figure 13: Time-series of predicted and observed values of PM2.5 concentrations at 3 sites in Delhi

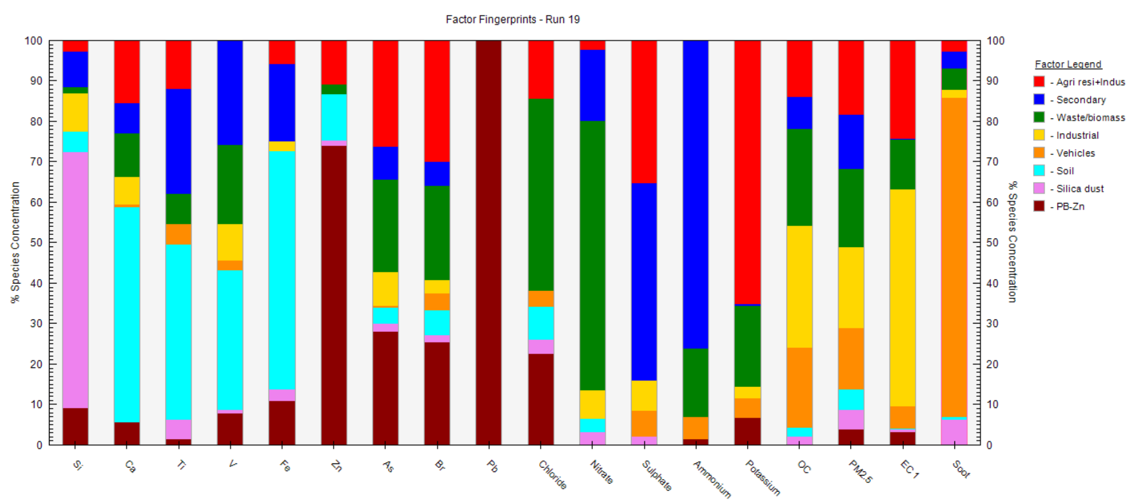


Figure 14: Fingerprints of eight identified factor profiles for Delhi

which show higher abundances. Reactions of gases such as SO_2, NOx, and NH_3 form secondary inorganic aerosols. The reaction of H_2SO_4(g) (formed by SO_2) and HNO_3(g) (formed by NOx) with NH_3 form ammonium sulfates $(NH_4)_2SO_4$ and ammonium nitrates NH_4NO_3 (Stockwell et al., 2003; Squizzato et al., 2013). Secondary particles are, in most cases, attributable to long-range atmospheric transport. Sulfates are formed by slow oxidation of SO_2 to SO_4^{-2} (Querol et al., 1998) and are part of aged masses transported from long distances (Manousakas et al., 2017). As the monitoring time is in summer seasons, sulfates are found to be more in quantities than nitrates. Lower temperatures provide favourable conditions for ammonium nitrate formations (Stelson and Seinfeld et al., 1982). Presence of sources of ammonium (through use of fertilizers and livestocks), sulphates and nitrates (through combustive sources) in the upwind regions (Figure 2) ensures significant contributions to the mass of $PM_{2.5}$ observed in Delhi.

Waste burning and biomass burning is identified as the crucial third factor contributing to $PM_{2.5}$ concentrations in Delhi. In the nearby regions outside of Delhi, a significant number of households were estimated to be dependent on biomass for daily cooking purposes (TERI&ARAI, 2016). Diapouli et al. (2014) resolved profile of biomass burning mainly by the presence of high K and to a lesser extent by presence of Cl in the factor. However, significant presence of chlorides also points towards possibility of municipal solid waste burning.

The presence of high EC1, significant contributions of sulphates and OC characterizes the fourth factor, which is identified as coal-based burning (power plants or industries). Smaller quantities of Si, As and Fe are also found to be present. There are low-efficiency industrial processes (e.g., brick manufacturing), which emit significant quantities of EC. Also, due to the presence of sulfur in coal, sulfates can be attributed to these industries. Matwale et al. (2014) show the source profile of brick manufacturing sectors, which shows an abundance of high EC fractions. The presence of vanadium and silica (as coal ash) in small quantities also points towards industrial fuel burning. There is a limited number of industries in Delhi, and most of them have been reported to be shifted to cleaner gaseous fuels. However, outside of Delhi, there are about 5000 brick kilns and and almost equivalent number of industries and coal based power plants. While during the initial phase of the lockdown most industries were closed, but in the latter part of April, many of these industries started to function again (I.E., 2020). Delhi does not have a coal-based power plant now and most industries have moved to gas, but still, several sources (coal based industries and power plants) in the upwind of Delhi city (Figure 2) continue to emit PM and SO_2 and contribute to the elements and ions mentioned above in Delhi's $PM_{2.5}$ concentrations.

The fifth factor identified is the motor vehicle, which shows dominance of E.C. emissions (in the form of soot) and organic particles. Diesel vehicles are known to emit soot along with organic carbon particles. While during the initial phase of lockdown, the vehicle movement was very much restricted, a greater number of vehicles started plying towards the end of April, when $PM_{2.5}$ monitoring was going on.. Also, the movement of diesel driven heavy-duty trucks continued for the supply of essential goods during the lockdown period.

The sixth factor can be identified as soil dust, which shows the dominating presence of crustal minerals like Ca, Ti, Fe, etc. Summer season is known for high wind speeds, and once it goes beyond a threshold, the soil particles get air-borne and add to the pollutant loads.

The seventh factor has been identified as silica dust, which clearly shows the high abundance of silica. Silica is found in soil, construction material, sand, concrete, masonry, rock, granite, and landscaping materials. Silica particles are abundant in the dust generated by cutting, grinding, drilling, or handling these materials. In context of this study, it is specifically found abundant at one of the sites and hence can be treated as a specific dust generation activity near the site.

The eighth factor is characterized by Pb's dominance, followed by Zn and Br, which can be attributed to industrial lead smelting sources. Rai et al. (2020) also reported a Pb-rich profile contributing significantly to Delhi's PM concentrations. There are several possibilities of a Pb-rich source, e.g., open waste/ plastic burning (Kumar et al., 2015; Kumar et al., 2018), lead smelting (Jaiprakash et al., 2017; Patil et al., 2013), lead recovery from used car batteries, brake wear (Bukowiecki et al., 2009) and waste incineration, etc. Rai et al. (2020) also suggested that the northeast part of Pakistan, Punjab, and Haryana could be the potential source region of this factor profile.

Daily contributions of eight-factor profiles towards $PM_{2.5}$ concentrations are shown in Figure 15. Factor 1 (Agri residue burning and industries) contributions are present at all sites and in a consistent manner show an increase during the same days indicating towards enhanced agricultural burning contributions during those days. This period of enhanced contributions of

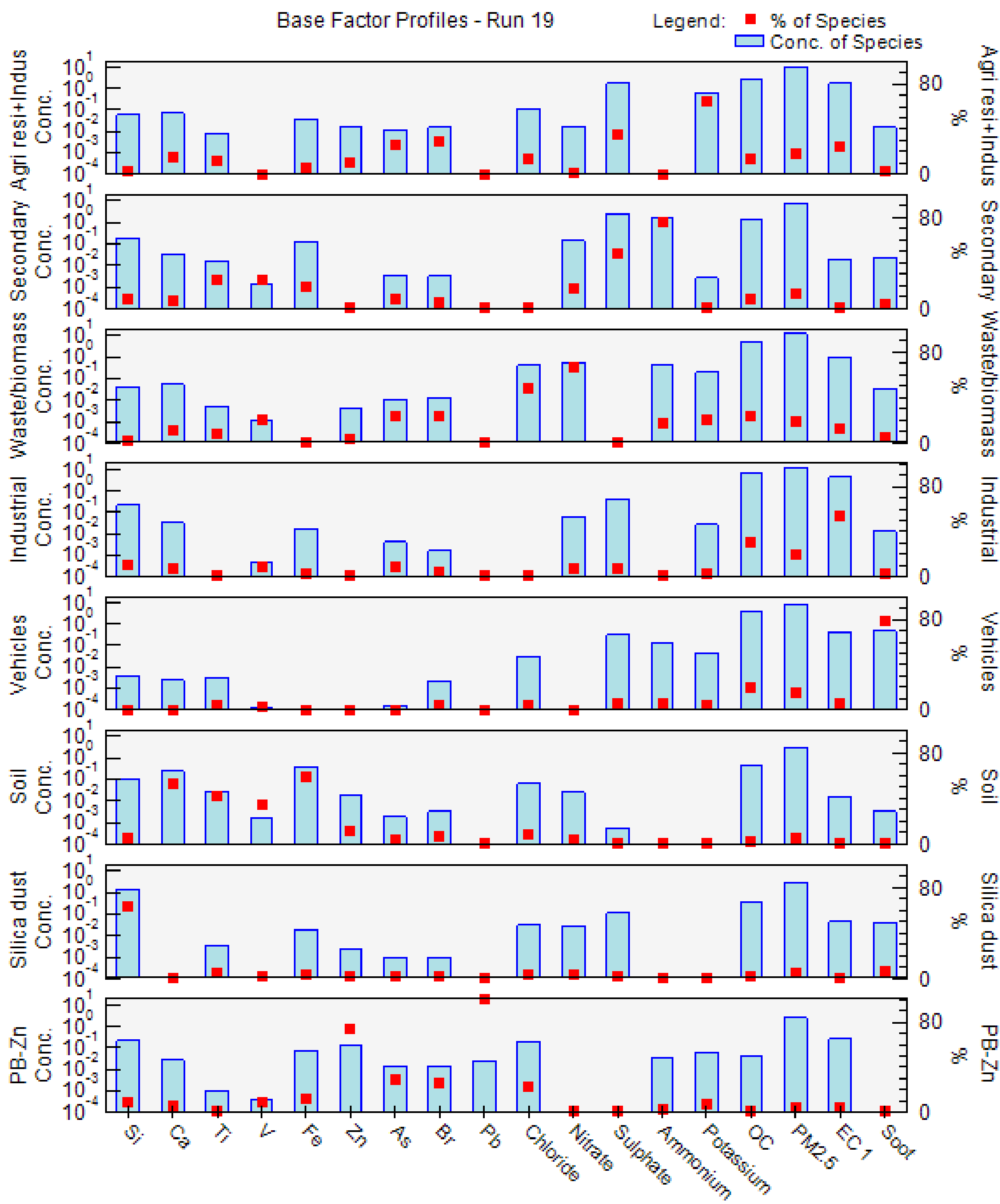


Figure 15: Factor profiles of the identified eight sources by the PMF model

biomass coincides with agricultural fires detected in the upwind regions. Post-harvest burning of wheat residues is a significant source contributing to $PM_{2.5}$ concentrations in the area.

The contributions of factor 2 (Secondary particulates) are the highest at Patel Nagar site, which is in the north-west of the city center and expected to be influenced by outside background flow of pollutants. Sites near the centre generally have contributions more local sources, while sites in the upwind (north-west in case of Delhi as shown in Figure2) bring in background contributions (including secondary particles) to the city's pollution levels. Third factor profile, (waste and biomass burning) also show consistent contributions across the three sites, with peaks in between.

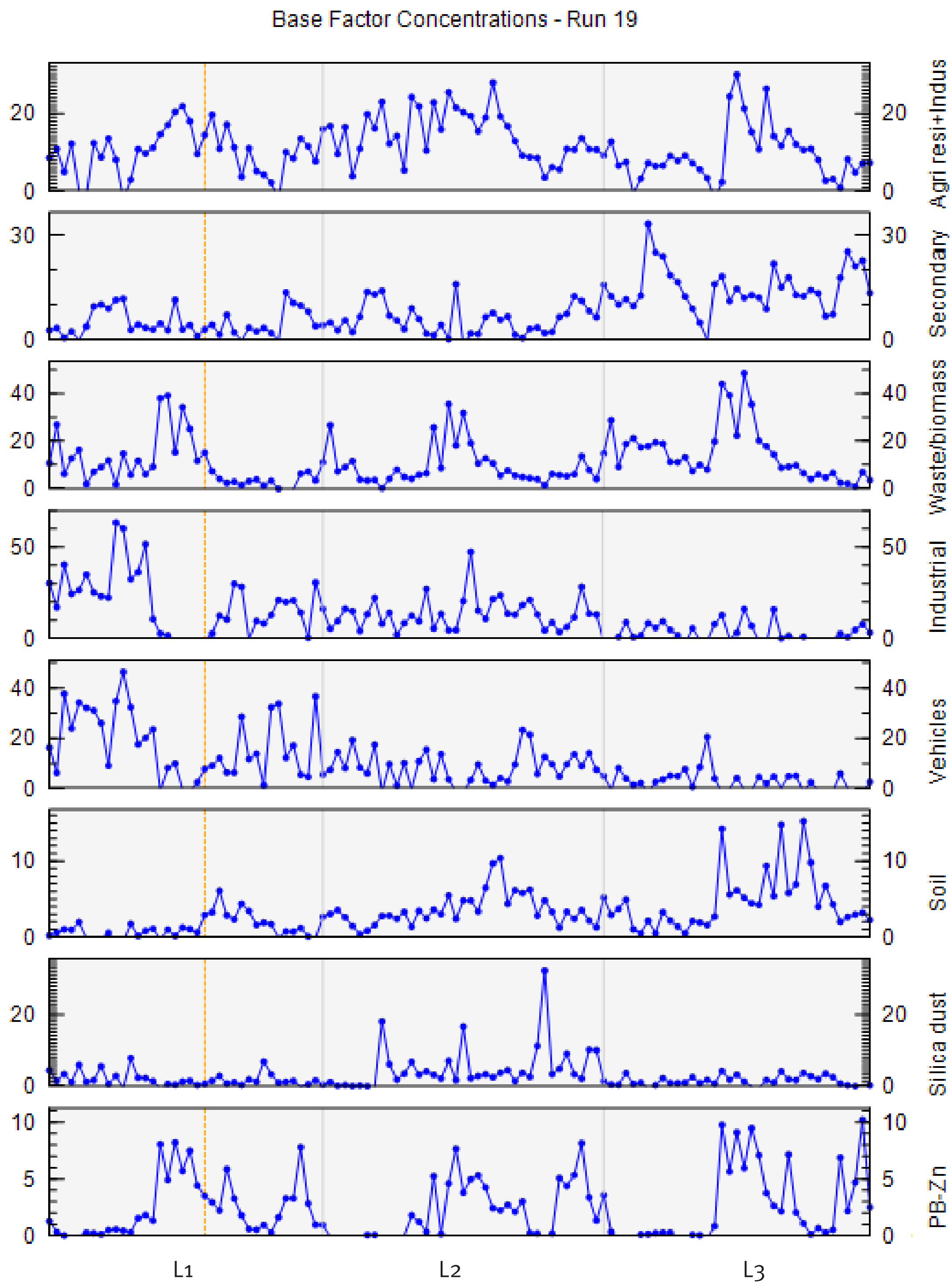


Figure 16: Daily factor contributions (μg/m³) estimated by the PMF model for different locations

Factor 4 (coal combustion industries and power plants) contributions are high and detected at all the sites. However, additional contributions are seen at the IHC (Lodhi road site) on some days, possibly due to impact of local sources- the IHC complex is surrounded by several street eateries where clay oven (tandoors) is being used for baking purposes in which coal is used as fuel. Combustion process in these tandoors is inefficient resulting in intermittent emissions detected during this period. Factor 5 (Vehicles) is again highest at IHC- Lodhi road (as the monitoring station was installed on a building next to road), while lower vehicular contributions are visible at the other two dominantly residential sites.

Factor 6 (Soil dust) is more dominant at Patel Nagar and Laxmi Nagar but less at IHC (Lodi road). The monitor at Lodhi road site is placed at about 25-30m height and is expected to catch lesser dust. Factor 7 (Silica dust) is mostly more visible at the Laxmi Nagar site due to ongoing construction activity. The Factor 8 (Pb-Zn) profile is consistently visible at all three sites depicting the long-range effect.

6.2 Source contributions estimation

The identified factor profiles have been apportioned for their contributions to the prevailing $PM_{2.5}$ concentrations at the three sites'. Figure 17 shows the contributions of the identified sources at the three locations. IHC (Lodi road) site shows the dominance of coal-based combustion sources mainly from industrial activities (29%). While there are no industries nearby, the contributions are expected to be from outside of Delhi city as the monitor is placed at the height of 25-30m which can significantly capture regional source contributions to the city. Intermittent coal use near the monitoring site has been also observed as a cause of increased contribution on some days. The site is next to a road, and hence transport contributions are also high (26%). Government offices near the IHC site were partially functional in may 2020 and the corresponding traffic flows have contributed to transport emissions.

On the other hand, LN and PN are residential sites, although in different city locations. Because of lower contributions from local sources, Patel Nagar shows

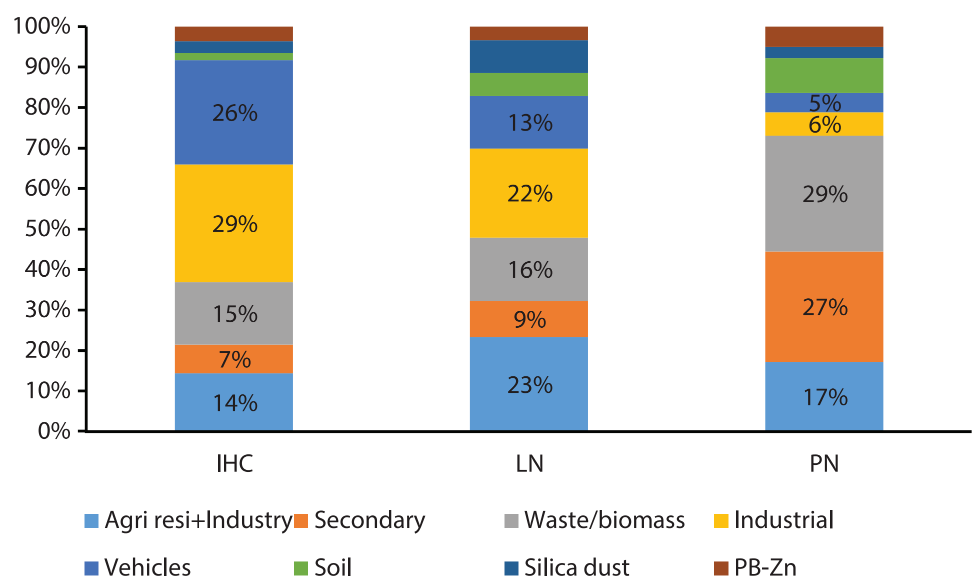


Figure 17: Source contributions estimated at the three sites in Delhi

* Industrial factor will have an overlap with local coal combustion happening near the monitoring site (e.g., local street eateries)

more influence of long-range secondary particulates (29%) and waste and biomass-based sources (27%). The site is more upwind from the city center and is expected to capture contributions from outside of city. Also, vehicular movement was well-restricted in the area and showed meager contributions of 5%. On the other hand, Laxmi Nagar offers significant contributions of regional coal-based industrial activities (22%) and also local effects due to vehicles (13%).

The average results of three locations in Delhi are shown below (Figure 18). Coal combustion (Industries and local sources) contributed most significantly (20%) to the $PM_{2.5}$ concentrations. The contribution of waste and biomass burning was estimated to be 19%. Dust in all contributed to about 10%. Vehicles still contributed to about 15%. However, leaving the IHC location (which was next to the road) aside, the vehicular contributions were about 9.5%. Mixed aged profile of agri. residue burning and industries was found to contribute to about 18%, while lead-based industrial/non-industrial sources accounted for 4%. Secondary inorganic particulates (NH_4, SO_4^{2-}, and NO_3^-) have accounted for about 14% to $PM_{2.5}$ concentrations in line with the total mass of these particles observed in chemical speciation analysis.

7. Conclusions

This analysis has been carried out to understand the air quality variation observed in Delhi during the lockdowns. The major conclusions which can be drawn out of the overall study are:-

- The reductions observed in $PM_{2.5}$ and NOx concentrations during the period of lockdowns in 2020 with respect to the same period in 2019 were statistically significant.
- Average reductions of 43% and 61% were observed in $PM_{2.5}$ and NOx concentrations observed at an average of 32 stations in Delhi during the period of lockdowns with respect to 2019.
- Reductions in pollutant concentrations were observed during the lockdowns despite reduced VC in 2020, with respect to 2019. This ascertains the reduced source emission levels from various sources contributing to $PM_{2.5}$ and NOx levels during lockdowns.
- Low variability observed in pollutant concentration data during lockdowns in 2020 w.r.t. 2019 also suggests reduction of emissions from local sources.
- Special monitoring was carried out at IHC, Laxmi Nagar, and Patel Nagar locations from 22nd April to 5th June. Despite lockdowns, the $PM_{2.5}$ levels violated the daily standard by 60%, 47%, and 31% times at IHC, L.N., and P.N., locations, respectively.
- IHC site being close to the road and some local activities shows the highest carbon share in $PM_{2.5}$ concentrations. P.N. upwind forming the city center, shows the highest percentages of secondary particulates.

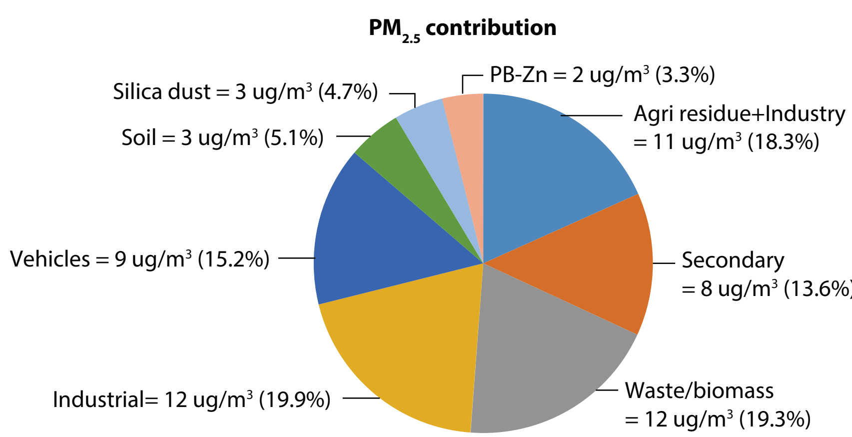


Figure 18: Average source contribution analysis for the three sites in Delhi

- Source contributions also vary based on the locations of monitoring stations. IHC, being close to the road, shows the highest vehicle contributions, while the same is found to be relatively smaller at L.N., and very small at P.N. location. The vehicular activity is somewhat restricted in this second period of lockdowns, although it is not entirely restricted like in the first phase of lockdowns.
- Industrial activities were also affected during the lockdowns, and hence in absolute terms, the emissions and contributions must have decreased from the source (as depicted in the reduced $PM_{2.5}$ concentrations). However, in relative terms, this still accounted for a significant share in Delhi's $PM_{2.5}$ concentrations. While most Delhi industries have shifted to gas, contributions from outside of NCR seem to be high.
- Share of biomass, agricultural residue and waste burning were enhanced than typically observed in Delhi, mainly due to restrictions and associated reductions in other sectors like industries and vehicles.
- Contributions of dust have also been found to be significant because of reduced contributions of other sectors
- Analysis during lockdowns shows that vehicles and industries are important sectors contributing to $PM_{2.5}$ concentrations in Delhi, and controls over them (as in lockdowns) can lead to significant reductions in $PM_{2.5}$ concentrations.
- Biomass burning and industries are the significant sources contributing to the deterioration of air quality at the regional scale and, despite lockdowns, continue to pollute in substantial quantities.

The study concludes that an airshed based approach needs to be adopted in order to address the problem of air pollution in Delhi. Despite severe restriction on the local source emission activities, contributions from upwind locations kept the pollution levels above the prescribed standards in Delhi. This study provides a strong basis for adoption of an airshed approach in tackling air pollution problems of the capital city. A natural experimentation opportunity got created due to the COVID pandemic, which resulted in extreme restrictions on source emission activities. Despite of such restrictions, significantly high pollutant levels were observed during the lockdown period indicating contribution of several non-local sources. The study highlights the importance of long range transport of pollutants and need for delineation of airshed for each non-attainment city to develop effective air quality management plans.

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Annexure 1

The species which were categorised in three categories based on S/N ratios and coefficient of correlation between observed and predicted values.

Species	Category
Na	Bad
Mg	Bad
Al	Bad
Si	Strong
P	Bad
S	Bad
Cl	Bad
K	Bad
Ca	Strong
Sc	Bad
Ti	Strong
V	Weak
Cr	Bad
Mn	Bad
Fe	Strong
Co	Bad
Ni	Bad
Cu	Bad
Zn	Strong
Ga	Bad
Ge	Bad
As	Strong
Se	Bad
Br	Strong
Rb	Bad
Sr	Bad
Y	Bad
Zr	Bad
Mo	Bad
Rh	Bad
Pd	Bad
Ag	Bad
Cd	Bad
Sn	Bad
Sb	Bad
Te	Bad
I	Bad
Cs	Bad

Species	Category
Ba	Bad
La	Bad
W	Bad
Au	Bad
Hg	Bad
Pb	Weak
In	Bad
Fluoride	Bad
Chloride	Weak
Nitrite	Bad
Bromide	Bad
Nitrate	Strong
Phosphate	Bad
Sulphate	Strong
Sodium	Bad
Ammonium	Strong
Potassium	Strong
Magnesium	Bad
Calcium	Bad
OC	Strong
EC	Bad
UI	Bad
PM2.5	Weak
OC 1	Bad
OC 2	Bad
OC 3	Bad
OC 4	Bad
PC	Bad
EC 1	Strong
EC 2	Bad
EC 3	Bad
Char	Bad
Soot	Strong