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PM sensors as an indicator of overall air quality: Pre-COVID and COVID periods

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ABSTRACT

Nowadays, there has been a substantial proliferation in the use of low-cost particulate matter (PM) sensors and facilitating as an indicator of overall air quality. However, during COVID-19 epidemics, air pollution sources have been deteriorated significantly, and given offer to evaluate the impact of COVID-19 on air quality in the world’s most polluted city: Delhi, India. To address low-cost PM sensors, this study aimed to a) conduct a long-term field inter-comparison of twenty-two (22) low-cost PM sensors with reference instruments over 10-month period (evaluation period) spanning months from May 2019 to February 2020; b) trend of PM mass and number count; and c) probable local and regional sources in Delhi during Pre-COVID (P-COVID) periods. The comparison of low-cost PM sensors with reference instruments results found with $R^2$ ranging between 0.74 and 0.95 for all sites and confirm that PM sensors can be a useful tool for PM monitoring network in Delhi. Relative reductions in PM$_{2.5}$ and particle number count (PNC) due to COVID-outbreaks showed in the range between (2–5%) and (4–13%), respectively, as compared to the P-COVID periods. The cluster analysis reveals air masses originated ~52% from local, while ~48% from regional sources in P-COVID and PM levels are encountered 47% and 66–70% from local and regional sources, respectively. Overall results suggest that low-cost PM sensors can be used as an unprecedented aid in air quality applications, and improving non-attainment cities in India, and that policy makers can attempt to revise guidelines for clean air.

1. Introduction

Air pollution is a major concern, particularly in Asian countries such as India and China. According to studies conducted as part of the Global Burden of Disease (GBD), air pollution is a major contributor to the rising rates of mortality caused by cardiovascular and pulmonary diseases (Balakrishnan et al., 2019; Brauer et al., 2016; Burnett et al., 2018; Chowdhury et al., 2020). Out of other gaseous pollutants, particulate matter (PM) characteristics are desired and needed massive number of continuous ambient air quality monitoring stations (CAAQMS) in non-attainment cities in India (NCAP, 2015), while these are high capital and operating cost, lack or portability. Therefore, such instruments are unable to provide spatio-temporal variation and evaluate hot-spot the health risk (Wang et al., 2015).

Recently, proliferation and adoption of low-cost PM sensors offers high-resolution data collection, adequate accuracy with compact size and high portability (Kumar et al., 2015; Wang et al., 2015; Sousan et al., 2016; Kelly et al., 2017; Rai et al., 2017). However, numerous low-cost PM sensors have evaluated in the laboratory (Kelly et al., 2017; Li and Biswas, 2017; Liu et al., 2017, 2019; Malings et al., 2019; Sousan et al., 2016; Zikova et al., 2017), and field (Bulot et al., 2019; Dubey et al., 2022; Feenstra et al., 2019; Sayahi et al., 2019). They found substantial agreement in comparison with reference instruments. However, these studies also reveal that PM sensors can be affected by
varying temperature and humidity, and urgent need for correction factors. Few studies have discussed that low-cost PM sensor network system enables the collections of robust air quality data professionally and it is beneficial for identifying hot-spot region, spatial-temporal variation, and health exposure (Gulia et al., 2020; Li et al., 2020; Prakash et al., 2021; Zheng et al., 2019). However, the long-term field performance governs strength, stability of low-cost PM sensors to perform robust environmental conditions of air quality and meteorology (Cui et al., 2021; Zheng et al., 2019). During COVID-19 outbreaks, PM emission sources were switched-off which provides the opportunity to understanding potential sources in urban atmosphere, mitigate the emission source, and policy to improve urban air quality in near future. The novel coronavirus (COVID-19) is declared as pandemic in March 2020 by word health organization (WHO) (WHO, 2020). In India, Government of India (GOI) announced “complete lockdown” on March 24, 2020, to prevent social distancing as per WHO guidelines (WHO 2020). In India, various studies have been published on COVID-19 associated air quality during early lockdown phases, especially in criteria pollutants (CO, NO₂, O₃, SO₂, PM₁₀, and PM₂.₅), and these studies reported ~50% average reduction in PM₂.₅ and PM₁₀ concentration, while other pollutants were found to marginal decrement except NO₂ (Chauhan and Singh, 2020; Dhaka et al., 2020; Jain and Sharma, 2020; Kumar et al., 2020; Kumari and Tosniwal, 2020; Mahato et al., 2020; Mitra et al., 2020; Selvam et al., 2020; Sharma et al., 2020). These studies focused on the early COVID period, publicly available CAAQMS data from CPCB, and other modeling predictions. However, these studies were unable to provide information of PM sources and their effects in various lockdown phases in Delhi. Also, these studies have not been discussed about unfavorable meteorology and variation of PM sources during initial COVID periods.

To add insights of long-term field evaluation of low-cost PM sensor networking and impacts of COVID-outbreaks in air quality of Delhi city, we deployed twenty-two (22) low-cost PM sensors networked system for the first time in Delhi and assessed the long-term performance. Further, we also aim to: trends of PM mass and number level during Pre-COVID (P-COVID), during-COVID, and following-COVID periods; and lessening contribution of local and regional sources in Delhi during and following COVID periods as compared to P-COVID periods.

2. Material and methods

We developed cloud-based sensor network system (now named as “Real-time source apportionment study in Delhi city”) in Delhi has been discussed in earlier our companion work by Prakash et al. (2021). The specific purposes for network system are more reliable and durable for of data transmit and analysis using Internet of Things (IoT) setting. In present study, we planned in three different aspects a) long-term field comparison of twenty-two (n = 22) APT low-cost PM sensors with co-located reference FEM instruments (BAM); b) trend of PM mass and number concentration during P-COVID and COVID Periods; c) probable local and regional sources in Delhi during COVID periods for better understanding of low-cost PM sensor performance and reliability for mapping of air quality trend. Detailed methods for this study are as follows.

2.1. Monitoring sites

Table 1 summarizes the twenty-two (22) monitoring sites of NCT of Delhi their characteristics. Delhi has very complex land use pattern and diverse sources of aerosol such as on-road transport, industrial (small scale industries, power plants), residential, and commercial (diesel generators sets, tandoor making in restaurants) sector. Fig. 1 displays the spatial distribution of 22 low-cost sensors with co-located reference FEM instruments such as Beta Attenuation Monitor (BAM). The monitoring site less than 100 m from main road is considered as sources from “fresh vehicle emission”, and away 100 m from road, as sources from “aged vehicle emission”. The sources from upwind direction are considered as background emission. Few monitoring sites are close to near paved and unpaved road, so that pollutants also receive resuspension dust/or road dust. Delhi also has variety of micro-small and medium scale industries and processing units, as well as residential (local burning), and commercial area (diesel generators sets, tandoor making in restaurants), all of which contribute city’s poor air quality.

### Table 1

| Sr No | Sensor Nodes | Monitoring sites¹ | Sensor height (m) | Distance from road (m) | Site characteristics |
|-------|--------------|-------------------|-------------------|-----------------------|---------------------|
| 1     | 19           | Major Dhyan Chand National Stadium | 3.5 | 200 | Commercial & Residential |
| 2     | 20           | Anand Vihar | 3.4 | 100 | Hot spot |
| 3     | 33           | Suri Aurbindo Marg | 3.5 | 200 | Residential |
| 4     | 34           | Dr. Karmi Singh Shooting Range | 3.5 | 500 | Background |
| 5     | 35           | R.K. Puram | 3.5 | 100 | Residential |
| 6     | 36           | Okhla Phase-2 | 3.5 | 100 | Residential |
| 7     | 37           | PGDAV Nehru Nagar | 3.5 | 200 | Commercial |
| 8     | 38           | Jawahar Lal Nehra Stadium | 3.5 | 200 | Commercial & Residential |
| 9     | 39           | Dwarka, Sector 8 | 3.5 | 50 | Commercial & Residential |
| 10    | 40           | Najafgarh | 3.5 | 500 | Residential |
| 11    | 42           | Punjabi Bagh | 3.5 | 50 | Commercial & Residential |
| 12    | 43           | Mundka | 3.5 | 200 | Industrial |
| 13    | 44           | Patparganj | 3.5 | 200 | Commercial & Residential |
| 14    | 45           | Pusa | 3.5 | 100 | Industrial |
| 15    | 46           | Vivek Vihar | 3.5 | 200 | Industrial |
| 16    | 47           | Jahangirpur | 3.5 | 100 | Commercial & Residential |
| 17    | 48           | Wazirpur | 3.4 | 200 | Industrial |
| 18    | 49           | Alipur | 3.4 | 300 | Commercial |
| 19    | 50           | Ashok Vihar | 3.5 | 200 | Industrial |
| 20    | 51           | Bawana | 3.5 | 200 | Industrial |
| 21    | 52           | Rohini | 3.5 | 200 | Residential |
| 22    | 53           | Narela | 3.5 | 200 | Industrial |

¹ Monitoring sites abbreviation: Major Dhyan Chand National Stadium (NS); Anand Vihar (AV); Suri Aurbindo Marg (SAM); Dr. Karmi Singh Shooting Range (DKSSR); R.K. Puram (RKPURAM); Okhla (OKHLA); PGDAV Nehru Nagar (PGDAV); JLN Stadium (JLN); Dwarka sector-8 (DWARKA); Najafgarh (NAJAFGARH); Punjabi Bagh (PB); Mundka (MUNDKA); Patparganj (PATPARGANJ); Pusa (PUSA); Vivek Vihar (VV); Jahangirpur (JPURU); Wazirpur (WAZIPUR); Alipur (ALIPUR); Ashok Vihar (AVIHAR); Bawana (BAWANA); Rohini (ROHINI); Narela (NARELA).

2.2. APT low-cost PM sensors and reference instruments

Low-cost sensor (APT_Maxima) is developed by Applied Particle Technology (APT), and evaluated in Aerosol Air Quality Research Laboratory (AAQRL), Washington University in St. Louis and now its commercialized. A key components of low-cost PM sensors is discussed in Fig. S1 in the supplementary information (SI). Sensors were mounted at roof top of CAAQMS (~3.5–4 m from the ground) sites with suitable weather shelter. In Delhi, a total of twenty-six (26) Continuous Ambient Air Quality Monitoring Stations (CAAQMS) have been set up and governed by Delhi Pollution control committee (DPCC) to help improve air quality datasets and characterize the variabilities and their sources (http://www.dtpcadata.com). To advance a robust comparison, a Federal Equivalent Method (FEM) instrument [Beta-attenuation monitor-BAM-1020, Ecotech, AECOM group, Australia] was compared with an APT low-cost sensor. The co-located stations also provided...
meteorological parameters (temperature, relative humidity, wind speed, wind direction, and solar radiation) from the weather station, which was installed at each site by the government of NCT of Delhi.

2.3. Sampling periods

For long-term field evaluation, twenty-two low-cost sensors and BAM PM$_{2.5}$ datasets were taken sampling periods of 10-months from May 2019–February 2020; spanning the summer, monsoon, autumn, and winter seasons in Delhi. The sampling period is referred as “Evaluation periods” onwards in discussion (See Table 2). The duration amongst lockdown restriction (1 May to May 31, 2020) is referred as COVID periods and previous year (1 May to May 31, 2019) data was considered as P-COVID periods. Due to vehicle restrictions and a lack of field operator resources, only two hot-spot monitoring sites in Delhi (PB and DWARKA) were operational during the lockdown phases II to IV (COVID periods). Therefore, we have limited discussion regarding air quality trends and the variation of source contributions during P-COVID and COVID periods for the PB and DWARKA sites.

2.4. Data analysis

Following basic statistics, data points were refined by removing NAs, outliers, zero value, and negative value, and invalid data-points (text or symbols). Further, data-points were averaged in hourly datasets and combined to the hourly-resolved reference BAM data with meteorological parameters. Missing values in all rows either from sensor, or BAM data were excluded for further analysis. Statistical analysis was applied on hourly PM$_{2.5}$ data of low-cost sensor and BAM-PM$_{2.5}$ data to scrutinize data completeness, least-square linear regression, accuracy.

The least square linear regression, where PM$_{2.5}$ data of BAM monitor and APT low-cost sensor is considered as the independent and dependent variable, respectively. The equation can be expressed as Eq.-1.

\[ Y = mX + c \]

where, \( Y \) is the hourly PM$_{2.5}$ data of low-cost PM sensor, \( X \) is the hourly PM$_{2.5}$ data of BAM data, \( m \) is the slope of the best fit line, and \( c \) is the intercept of the best fit line. Ideally, Linear regression offers a best fit of sensor and BAM PM$_{2.5}$ data, and slope \( m \) should be 1, intercept \( c \) 0, and the coefficient of determination \( R^2 \) should be close to 1.

Mean bias error (MBE) and mean absolute error (MAE), Root Mean Square Error (RMSE), and Accuracy are considered for long-term field performance. The equations for MBE, MAE, RMSE, and accuracy are found in eqs. (2)–(5).

![Fig. 1. Monitoring sites of low-cost PM sensors deployed at co-coated CAAQMS stations of NCT-Delhi (as indicated by solid dots). Site’s abbreviation refereed as similar as described in Table 1.](image-url)
Mean Bias Error (MBE) = \frac{1}{N} \sum_{i=1}^{N} (X_{LCS} - X_{ref})

(2)

Mean Absolute Error (MAE) = \frac{1}{N} \sum_{i=1}^{N} |X_{LCS} - X_{ref}|

(3)

Root Mean Square Error (RMSE) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_{LCS} - X_{ref})^2}

(4)

Accuracy = 100 - \left( \frac{\left( \frac{X_{LCS}}{X_{ref}} \right) - 1}{X_{ref}} \right) \times 100

(5)

where $X_{LCS}$ is the mean concentration examined by the APT low-cost sensor, and $X_{ref}$ is the mean concentration monitored by the reference BAM monitors. $N$ is the number of data points.

MBE and MAE indicate the tendency of sensor to either under or over-estimate the reference instrument data and identifies the reason of error during regression analysis. RMSE is also key statistic parameters for observing outsized measurement error. Accuracy describes the degree of confidence between the sensor and reference data points (Polidori et al., 2016). To determine the reduction in PM mass and number concentration and trace gases (CO, NOx, NO, SOx, and O3), non-parametric statistical method (Kruskal-Wallis One Way Analysis of Variance (ANOVA) on Ranks) among COVID and P-COVID periods were performed with pairwise comparison using Dunn’s method (Dunn, 1964; Kruskal and Wallis, 1952). All statistical tests were conducted using R-3.5.1, with the packages ‘openair’, ‘ggplot2’, ‘dplyr’, and “tidyverse”.

2.5. Function of location (dependence of sources)

To examine the sensor performance in different sources (as function of location) were carried out. The data-points of all 22 monitoring sites are categorized in different sources of groups such as vehicle, construction, local burning, and industries during 10-months covering summer, monsoon, autumn, and winter with pre-dominant wind direction, and the linear regression was conducted for the PM$_{2.5}$ mass between low-cost sensor and reference instruments.

2.6. Contribution of local and regional sources

The cluster analysis and PSCF analysis is determined to contribution of local and regional air masses during the P-COVID and COVID periods. Air mass trajectories were retrieved for 120-h backward during for the sampling period 2019–2020, and each day at intervals of 3 h using Atmospheric Administration (NOAA) Air Resources Laboratory (ARL) Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) (Rolph et al., 2017) with global data integration system meteorological data as input with a spatial resolution of 1° x 1° at arrival height of 500 m above the ground level. For downloading monthly meteorological files from the HYSPLIT PC model, merging every 3-h back-trajectories end-point files of receptor site, the functions and codes were discussed in openair R-package manual (D. Carslaw and Ropkins, 2012).

3. Results and discussion

3.1. Normality-test, data completeness and field conditions

Prior to long-term performance, normal distributions, Skewness, Kurtosis, and data completeness of PM$_{2.5}$ were evaluated for PM sensors and reference instruments during evaluation period (see Table S1 in the SI). The hourly data of PM$_{2.5}$ for low-cost sensor and reference instrument were not normally distributed ($p < 0.05$). It was also noted that the PM$_{2.5}$ from the low-cost PM sensors and reference instruments were positively skewed and ranges between 1.3 and 6.4. High kurtosis is an indicator that data has heavy tails or outliers. Five locations namely AV, PGDAV, PB, VV, JPURI, WAZIPUR, AVIHAR were found high kurtosis in the range between 27.4 and 427.6, rest 17 monitoring sites were found in the range between 5.7 and 15.8 during evaluation period. Regarding data completeness, low-cost PM sensors showed good data completeness (>72–97%) for hourly average datasets, except monitoring sites, namely NAIJAFGRAH and ALIPUR. The possible reason was a limitations of field operator resources for troubleshooting of PM sensors or BAM instruments. To assess the environmental conditions between 22 monitoring sites in Delhi, the summary statistics for meteorological parameters [temperature, relative humidity (RH), and solar radiation (SR)] were summarized in Table S2 in the SI. The mean temperature varies between the 22 monitoring sites and ranges between 1.4 and 48.9 °C indicating that seasonal difference in temperature. The RH of 22 monitoring sites was ranged from 1% to 99% with mean 64 ± 22%. The covariance (CV) of RH in all locations were 34%, which indicating the seasonality variance in RH. The mean SR for the 22 sites ranged from 0 to 998 Wm$^{-2}$ with mean 124 ± 183 Wm$^{-2}$. The wind patterns at 22 monitoring sites in Delhi are summarized in Table S3 and Fig. S2 of the SI. Among the meteorological parameters, the wind and temperature were higher during the day than at night, as expected.

3.2. Long-term field performance of PM sensors

3.2.1. Linearity of PM sensors

The inter-comparison between low-cost PM sensors and reference BAM monitors at 22 monitoring sites was performed using regression analysis during evaluation period (01 May 2019–15 February 2020). Linear regression was assessed between hourly PM$_{2.5}$ data points, and the results presented in Fig. 2. As shown in Fig. 2, the R$^2$ values from linear regression between the PM sensors and the reference instruments were high association with ranged between 0.78 and 0.95, among 22 monitoring sites.

Slope, MBE, MAE, and RMSE are used for accuracy and measurement error during inter-comparison between low-cost PM sensors and reference instruments (see Fig. 2). Two background sites, namely NAGAFGHAR and ALIPUR, were found to have slope values close to ideal with measurement error (MBE: 1–10 μg m$^{-3}$; MAE: 26–29 μg m$^{-3}$; RMSE: 36–44 μg m$^{-3}$). The slope for residential sites, namely NS, RKPURAM, PB, SAM, JLN, have MAE less than 35 μg m$^{-3}$, while RMSE was ranged from 43 to 82 μg m$^{-3}$ with slope 0.91–1.2. Interestingly, industrial sites, namely, OKHLA, MUNDKA, PATPARGANJ, PUSA, JPURI, WAZIPUR, ROHINI, AVIHAR, BAWANA, NARELA, VV have MAE less than 50 μg m$^{-3}$, and RMSE were ranged from 35 to 82 μg m$^{-3}$ with slope 0.75–0.97. Sites near road, namely AV, PGDAV, DWARKA, DKSSR, showed MAE value range between (22–39 μg m$^{-3}$) with RMSE (35–82 μg m$^{-3}$). It was noted that the ratio MBE to MAE for the sites namely, NS, AV, OKHLA, PGDAV, and DWARKA, was found >0.5, which indicate sensor was suffering with bias error rather than random error. Rest monitoring sites, the MBE/MAE ratio was ranged from 0.10 to 0.40, indicating the error is dominating by random error, possibly due to variation of sources and their emission at receptor sites (Feenstra et al., 2019). Seasonal comparisons of low-cost sensors and BAM monitors are discussed in Fig. S3-S6 in the SI. The results showed a high degree of association (0.73 > R$^2$ > 0.96 and 0.72 slope 1.05) in autumn and winter, except for PUSA and WAZIPUR. Summer and monsoon seasons showed low to moderate association (0.24 > R$^2$ < 0.75) and slope (0.46 a and 0.79).

Overall, low-cost PM sensors highlights high fidelity to urban city like Delhi especially, autumn and winter, when several PM$_{2.5}$ episodic events occurred due to Diwali, high smog (Prakash et al., 2021). However, summer and monsoon season is highly impacted by varying RH and temperature, and drift in temperature, zero-offset, and etc. during transmitting output data (Feenstra et al., 2019).
3.2.2. Accuracy of low-cost PM sensors

Data accuracy between low-cost sensors and reference monitoring sites at the twenty monitoring sites during the various seasons are presented in Fig. 3. Among sites, box plot proves moderate to satisfactory data accuracy (70%–92%) in the autumn and winter seasons, except PGDAV sites. In contrast, PM$_{2.5}$ data-points were harmonized (55%–80%) between sensors and reference instruments during summer and monsoon seasons, except NAJAFGARH site. The moderate accuracy in summer and monsoon could be possible due to dust deposition on the sensor’s photodetector, which can affect light scattering and fan speed, thus decline PM$_{2.5}$ level. However, few studies reported that cleaning dust by blowing zero air inside, and results showed no improvement in accuracy (Bulot et al., 2019; Sayahi et al., 2019). This indicates that the long-term field evaluation of PM sensors requires sensor drift and dust deposition.
removal. Other variables such as temperature, relative humidity, and PM$_{2.5}$ sources may also contribute to the reliable data discussed in the following section.

3.2.3. Effects of RH and temperature

To evaluate the effect of RH and temperature on sensor response, scatter plots of hourly bias error against the hourly RH and temperature for all 22 low-cost PM sensors (see Fig. 4). In an ideal situation, the slope of the line of best fit would be zero and it would be on the y = 0 axis. The bias error by RH plot for the sites namely, AV, OKHLA, PGDAV, JLN, VV, and WAZIRPUR, shows that increasing RH had little effect on bias error of PM$_{2.5}$ between sensors and BAM monitors. The remaining 16 sensors showed gradually increasing positive bias error as RH increased. Several studies have investigated into RH variations and sensor performance (Feenstra et al., 2019; Jayaratne et al., 2018; Prakash et al., 2021; Sayahi et al., 2019), and they suggested the high RH results overestimate PM$_{2.5}$ during conversion from particle count to particle mass concentration. However, a large body of literature has been devoted to adjusting $R^2$ from linear regression between PM$_{2.5}$ and RH, and it has been suggested that PM sensors should be improved/calibrated for RH, temperature, and other field conditions (Bulot et al., 2019; Liu et al., 2020). It was also noted that the reference instrument has a heated tube for setting temperature and RH prior to PM sampling, and that low-cost sensor data may be biased. The effect of temperature on the PM sensors was also investigated in terms of bias error (Fig. 5). The predominant positive bias error was noticed between 10 and 30 °C, while at high temperatures, the sensors show scatter nearly distributed to negative bias error. Overall, the error between positive and negative bias can tell us how low-cost sensors respond to reference instruments, implying the need for different correction methods for better low-cost PM sensor performance. The bias error of low-cost sensors would likely decrease if the effects of RH on these sensors were addressed and fixed, either by improving OPC hardware or by developing RH correction algorithms. When developing correction algorithms, make sure that the model or algorithm is based on scientifically relevant inputs (i.e. ambient temperature and RH collected in real-time). Field evaluation is also needed to capture seasonal variations in temperature and relative humidity, which will aid in understanding the effects of local weather conditions on PM sensors.

3.2.4. Low-cost PM sensors response in different aerosol sources

Delhi has been variety of PM$_{2.5}$ sources originated from fresh vehicle emission, aged vehicle emission, industries, commercial, dust, residential, and background emission. The possible sources were identified based on the dominant wind direction and physical characteristics of monitoring sites during the evaluation period and further they were merged by wind direction of all sites (see Table S4).

The linear regression results between low-cost PM sensors and reference instrument are shown in Fig. 5. For NS site, the linear regression coefficients were good associated with fresh and aged vehicle emission, dust, and commercial emissions ($R^2 = 0.83–0.85$). The urban background sites, namely SAM, NAJAFGARH, DKSSR, and ALIPUR were found to be good association with background, residential, fresh, and aged vehicle emissions. The hotspot region, namely AV is highly associated with fresh and aged vehicle emission near periphery of the site. Commercial monitoring sites, namely as RKPURAM, PGDAV, JLN, DWARKA, PB, JPURI, ROHINI were highly associated with dust, fresh vehicle emissions, commercial emission (restaurants, tandoor making), and aged vehicle emissions. For Industrial sites such as OKHLA, MUNDKA, PUSA, AVIHAR, and NARELA were more sensitive to emission from industries, dust, commercial, fresh, and aged vehicle emissions with high $R^2$ values (0.82–0.95) between low-cost sensors and reference PM$_{2.5}$. Others industrial sites, namely PATPARGANI, VV, WAZIRPUR, and BAWANA are highly associated with industries, fresh and aged vehicle emission, commercial emission, and dust, respectively.

3.3. PM trends in P-COVID and COVID periods

To assess the changes in air quality trends and percentage of reduction during COVID periods, the low-cost PM sensors data from two hot-spot sites, namely PB and DWARKA were discussed and compared to P-COVID periods. In this section, we also discussed probable local and transboundary sources contribution in P-COVID periods (25th March to May 31, 2019) as compared to COVID periods using conditional bi-variate probability function (CBPF), trajectory cluster, and PSCF analysis.

The hourly-resolved variation of low-cost PM sensors data [PM mass (PM$_{10}$, PM$_{2.5}$, and PM$_{1.0}$) number concentration (0.3 μm–10 μm)] are shown in Fig. S7 in the SI for P-COVID and COVID periods for both sites (PB and DWARKA) of Delhi. In P-COVID periods, the average PM$_{1.0}$ mass concentration at PB site varied 39.9 ± 31.4 μg m$^{-3}$, ranged from 8.9 to 247.7 μg m$^{-3}$. The average mass concentration of PM$_{1.0}$ at DWARKA site varied 31.6 ± 15.9 μg m$^{-3}$, ranged from 9.8 to 120.1 μg m$^{-3}$ in P-COVID periods.

For COVID periods, the hourly PM$_{1.0}$ concentration at PB site varied 5.9 to 87.1, with average of 32.5 ± 12.2 μg m$^{-3}$ during phase-III of COVID outbreak (4th May – 17 May, 2020), while interestingly high elevated peaks of PM$_{1.0}$ mass ranged between 2.3 and 234.3 μg m$^{-3}$ with average of 46.4 ± 50.6 μg m$^{-3}$ during Phase-IV (18th – May 31, 2020) of COVID outbreak. PM$_{2.5}$ and PM$_{1.0}$ mass concentration behaved similarly to PM$_{1.0}$ at PB and DWARKA site. For DWARKA, the mean PM$_{2.5}$ showed slight difference between P-COVID and COVID periods.

Interestingly, the mean value of PM$_{2.5}$ increased (~37%) in Phase-IV of COVID periods (86.3 μg m$^{-3}$) as compared between P-COVID periods (63.2 μg m$^{-3}$), and slight difference (~25%) between Phase-III of COVID and P-COVID periods. The slight difference of PM$_{10}$ between the median values of COVID vs P-COVID was noted at DWARKA site, while again substantial increase (~46%) at PB site was observed between P-COVID vs Phase-IV of COVID periods. Remarkably, the level of particle number count (PNC range: (1.9–81.8) × 10$^3$ # cm$^{-3}$) found in P-COVID periods at PB-site, while PNC ranged between (0.8–85.5) × 10$^3$ # cm$^{-3}$ with average of (14.3 ± 18.7) × 10$^3$ # cm$^{-3}$ during Phase-IV of COVID periods and it was ~40% higher than P-COVID periods at PB. However, the frequency distribution of PM$_{1.0}$, PM$_{2.5}$, PM$_{10}$ and PNC levels and their peaks in P-COVID and COVID periods are also shown in Fig. S7 in the SI, which shows that distribution of PM$_{2.5}$ and PNC were less positive skewed in COVID periods as compared to P-COVID periods. This indicates that substantial decline in PM mass and number concentration due to lockdown constraint. For better interpretation, the high peaks of CO (trace gases CO, NO$_2$, and NO collected from DPCC CAQM) and high PM$_{2.5}$/PM$_{10}$ ratio are strengthened to elevated peaks of PM$_{2.5}$ during Phase-IV of COVID periods (Fig. S8 in the SI). The increase of CO could be attributed to substantial emission of local burning during the COVID periods at PB site. Other gases (NO$_2$ and NO) were consistent and low concentration which illustrated that vehicular emission is a major source at PB site which was reduced in COVID periods as compared to P-COVID periods. To determine the reduction due to COVID outbreaks, the observed concentration of PM$_{2.5}$ and trace gases were compared using non-parametric test and discussed in further section.

The diurnal variation of PM$_{2.5}$ are illustrated in Fig. 6 (a) for both monitoring sites. In P-COVID periods, the PM$_{2.5}$ concentration of PB site appears to start rising from morning traffic peak hour (7–10 a.m.), and then start decreasing and almost constant in afternoon (12–18 p.m.), and then rising in evening hours. In COVID period, diurnal pattern of PM$_{2.5}$ significantly (p < 0.05) shifted to earlier time (7 a.m.) and dark and morning hours (see Fig. 6a) for PB site, possibly due to local burning activities during lockdown phases. Interestingly, these diurnal swungs were constant for P-COVID periods compared to COVID periods at DWARKA site. The maximum reduction (~40%) in PM$_{2.5}$ in COVID periods were observed in morning traffic hours (7–10 a.m.) as compared to P-COVID periods for PB site and not significant reduction of PM$_{2.5}$ at DWARKA site. In P-COVID periods, mean PM$_{2.5}$ ranged between 47.5 and 125 μg m$^{-3}$ for PB sites, while during COVID periods were substantially high PM$_{2.5}$, with
Fig. 4. Effects of RH and temperature on the bias error between low-cost PM sensors and reference instruments at 22 monitoring sites of Delhi. Ideally, the slope of the best fit line would be zero (solid orange line) would be $y = 0$ axis.
hourly PM$_{2.5}$ ranging diurnally from 25.0 μg m$^{-3}$ to 170 μg m$^{-3}$. The mean PM$_{2.5}$ concentration varied much less and almost constant during P-COVID and COVID periods (range of PM$_{2.5}$ in diurnal cycle: 40–70 μg m$^{-3}$) at DWARKA site. The box plots of P-COVID and COVID periods for PM$_{2.5}$ and PNC are shown in Fig. 6b,c. In COVID periods, the median concentration of PM$_{2.5}$ and PNC were slightly declined compared to P-COVID periods for PB site, while there was no significant difference in PM$_{2.5}$ and PNC in between P-COVID and COVID periods for DWARKA site. This indicates that COVID periods at DWARKA site was led by summer seasons and played important role in the reduction in PM$_{2.5}$ due to high dispersion and high mixing height. The wind direction variable PM$_{2.5}$ values were also compared for P-COVID and COVID periods (Fig. S9 in the SI). The southern and northeastern direction of PB site were found with significant changes in values of PM$_{2.5}$ between P-COVID and COVID periods, while no significant variations were found in different wind direction for DWARKA site.

3.4. Reduction in PM$_{2.5}$, particle number, and trace gases

To determine the reduction in PM mass and number concentration and trace gases (CO, NO$_2$, NO, SO$_2$, and O$_3$) were compared using non-parametric test and discussed. The statistical analysis for the PM and other trace gases during P-COVID and COVID periods are summarized in Table 3.

For PB site, the median value of PM$_{2.5}$ decreased marginally (2%) with insignificant differences between P-COVID and COVID periods (41.3–40.5 μg m$^{-3}$) (Fig. 6b and Table 3). A smaller difference of ranks (59.4) was observed between P-COVID and COVID periods. PNC behaved similarly to PM$_{2.5}$. The differences in the median values of PNC among two periods were found to be statistically significant. The median values of PNC slightly declined (4%) between P-COVID vs COVID (6707.2–6461.8 # cm$^{-3}$) (Fig. 6c and Table 3). The Dunn’s test showed that all the pairwise difference was significant. The difference (51.67) of ranks was noted small between P-COVID and COVID periods (Table S6). The differences in the median values NO$_2$ among P-COVID and COVID periods were found to be statistically significant and declined between P-COVID vs COVID (39.0–16.6 μg m$^{-3}$). Dunn’s test, the difference of ranks was observed 470.5 between P-COVID vs COVID periods and NO$_2$ levels decreased by 57% during the COVID period, indicating that vehicular emission is one of the sources in Delhi (Table 3). CO performed similarly to NO$_2$. The median value reduced monotonically with significant differences between P-COVID vs COVID (1.0–0.54 μg m$^{-3}$, and difference of rank-506.9) and significant reduction (~46%) in CO was observed during the COVID period compared to P-COVID periods. Statistically, significant difference in the median values of SO$_2$ (Table 3) and the median values of SO$_2$ declined with significant differences between P-COVID vs COVID periods. According to the Dunn’s test the pairwise differences were found to be statistically significant, and difference of ranks was observed 449.9 between P-COVID vs COVID periods (Table 3). The decline in SO$_2$ during the COVID period may be relaxed to local coal burning used in restaurants/streets foods. O$_3$ level slightly increased across the periods and with significant differences in median values between P-COVID vs COVID periods (51.6.0–59.8 μg m$^{-3}$, +14% increase) (Table 3). From the Dunn’s test, the pairwise difference was statistically significant. The difference of ranks was smaller 49.8 compared to P-COVID vs COVID periods. The increase in O$_3$ level during the COVID period may be attributed to the reduction of NOx emissions due to large reduction of vehicular emission and switched off other commercial activities.

For DWARKA site, the median value of PM$_{2.5}$ decreased marginally

![Fig. 5. Scatterplots of hourly mean PM$_{2.5}$ concentrations between low-cost PM sensors and reference instruments under different aerosol sources at 22 monitoring sites over Delhi. (reader can refer to web version of this figure for better interpretation of the aerosol sources).](image-url)
(5%) with insignificant differences in among periods (43.9–41.9 µg m⁻³) (Fig. 6b and Table 3). A smaller difference of ranks (51.90) was observed between P-COVID and COVID periods. However, PNC the differences in the median values of PNC among two periods were found to be statistically significant (Table 3). The median values of PNC declined (13%) in COVID (7694.8–6714.2 # cm⁻³) as compared to P-COVID periods (Fig. 6c and Table 3). The difference of ranks was noted low (60.1) between P-COVID and COVID periods. Further, the differences in the median values of NO₂ among P-COVID and COVID periods were found to be statistically significant and declined between P-COVID vs COVID (62.4–29.5 µg m⁻³, 53%). The median value reduced monotonically with significant differences between P-COVID vs COVID (2.2–0.77 µg m⁻³), and difference of rank-427.5) and significant reduction (~64%) in CO were observed during the COVID period as compared to P-COVID periods. The substantial difference in the median values of SO₂ and declined with 30% between P-COVID vs COVID periods (26.0–14.9 µg m⁻³). The Dunn’s test indicates that differences were found to be statistically significant, and difference of ranks was observed 449.9 between P-COVID vs COVID periods. The Dunn’s test indicates that differences were found to be statistically significant, and difference of ranks was observed 104.5 between P-COVID vs COVID periods. Interestingly, O₃ showed decreased in COVID periods significant differences in median values (29.8–9.2 µg m⁻³, 69% decrease). Interestingly, O₃ showed decreased in COVID periods significant differences in median values (29.8–9.2 µg m⁻³, 69% decrease). From the Dunn’s test, the pairwise difference was statistically significant with difference of ranks 216.7. The decrease in O₃ level during the COVID period may be attributed to the increase of NO₂ emissions due to low concentration of volatile organic carbons (VOCs).

3.5. Variation in meteorology in P-COVID and COVID periods

Meteorological can affect the PM level and their sources, therefore in order to examine the influence of local sources near the sites, the conditional bivariate probability function (CBPF) and differential probability plots were shown in Fig. 7, using the R package in R-studio (version 3.1.1; R Core Team, 2014) statistical software (D. C. Carslaw and Rolinski, 2012). For PB site, the highest PM₂.₅ values are associated with moderate wind speeds (2–3 m s⁻¹) from north-east (NE) and at low-wind speed (<1 m s⁻¹) from west (W) and south (S) directions for P-COVID periods. In COVID periods, highest PM₂.₅ values are associated with low wind speeds from west (W) direction. The result of the differential CBPF (ΔCBPFs) between the P-COVID and COVID periods was also shown in Fig. 7. Generally, negative CBPF value indicates where the probability of being a local source decreased. The PM₂.₅ prevailingly linked to fresh and aged vehicle emission in NE and residential/commercial emission are from west and south direction which shows moderate (|0.3|) differential probability and increases local sources from NE and south direction, while decreases from western sector. The box plot of PM₂.₅ in different wind directions (Fig. S9 in the SI) suggest the effects of fresh and aged vehicle emissions in PB, showing the slightly inclined in COVID periods from Southern sector, and substantial changes of PM₂.₅ during COVID periods from northeastern direction. For DWARKA site, the highest PM₂.₅ Value is linked with low wind speed (<1 m s⁻¹) from NE and NW site during COVID periods, while North direction at low-wind speed in COVID periods. These direction, fresh vehicle emission and dust sources are pre-dominated. The result of the differential CBPF (ΔCBPFs) between the P-COVID and COVID periods was also shown in Fig. 7. The ΔCBPF exhibited moderate decreases PM₂.₅ value in the northeastern, northwestern, and north direction, indicating an overall decline in concentrations for the major local sources (fresh vehicle emission and dust). The box plot of PM₂.₅ with wind directions (Fig. S9 in the SI) suggest the effects of fresh and aged vehicle emissions in DWARKA, showing the slightly declined in COVID periods from northeastern sector.

For better interpretation, we normalized the PM₂.₅ concentrations as per function of location using dominant wind direction and associated sources near the sites (detailed discussion in material and method). The box plots of P-COVID and COVID periods for PM₂.₅ sources are shown in Fig. S10. For PB site, the fresh PM₂.₅ emissions were declined ~30–50% compared to P-COVID periods, while ~5–10% reduction was observed in aged PM₂.₅ emissions during the COVID periods. For DWARKA site, the highest reduction was found in residential source (~30%), followed
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by aged PM$_{2.5}$ (~19%), and fresh vehicle PM$_{2.5}$ (~12%), respectively in COVID periods, while dust PM$_{2.5}$ was increased (~10%) in COVID periods compared to P-COVID periods. Overall, wind speed or wind direction can favor in dispersion of PM$_{2.5}$ during COVID, while such reduction in COVID periods are expected, therefore detailed source apportionment study or local/regional source identification are needed to confirm accurate reduction in PM$_{2.5}$ and their sources.

3.6. Contribution of transboundary sources in P-COVID and COVID periods

To understand the contribution of regional contribution on low-cost sensor PM$_{2.5}$ data, we analyzed the cluster analysis a group of air mass back trajectories which comes from similar origins. The distance approach method was followed by Carslaw and Ropkins (2012). Generally, the back trajectory cluster analysis revealed that four main clusters were identified, and they originated from regional [North-West (NW): Pakistan, Afghanistan, Iran], Thar Desert, and two local (-air mass within India originating from Delhi, Punjab, Haryana, and Uttar Pradesh). In present study, we have identified four major contributing clusters (C1, C2, C3 and C4) based on total spatial variance (TSV), and variance should be greater than 20%, which recommended by Sateesh et al. (2018). The trajectory cluster plots were shown in Fig. S11 in the SI for P-COVID and COVID periods. For both sites, group of trajectories are similar direction, and their contributions were consistent in these periods. During P-COVID, the shortest and slow-moving air mass by clusters (C2+ C1) originating from local North (N) and East (E) and they contributed 52.8% of group of trajectories (Fig. S11). The C3 and C4 cluster are originating from NW direction (South-Asian countries: Afghanistan and Pakistan) and SW direction (Thar desert), and local states of India, and they contributed 24.7% and 22.5% of total trajectories. The COVID period is highly dominated by air mass trajectories travelled from local near receptor site from North (N) and contributed ~47% (C4). About 31.8% of trajectories (C2+C3) are clustered within NW direction (Pakistan, Afghanistan, Iran, Iraq), and 21% (C1) of ensemble of trajectories, which governs from south-west (SW) indicating influence of Thar desert and dust air mass (Fig. S11 in the SI).

The results of PSCF plots for PB and DWARKA site during P-COVID and COVID periods are presented in Fig. 8. For PB site, PM$_{2.5}$ exhibited higher probabilities for air mass pathways over the North-western (NW) direction in P-COVID and moderate probabilities northwesterly (local part of receptor site) in COVID periods (Fig. 8a). The PSCF plots show PM$_{2.5}$ of DWARKA site is highly originated from NW direction which appears mostly sources of local states (Punjab and Haryana) sources in P-COVID periods, while PM$_{2.5}$ marginally dominated by local sources in COVID periods (Fig. 8b). Overall, PM$_{2.5}$ showed moderate decreases in PSCF in COVID periods compared to P-COVID periods for PB site, whereas PSCF for PM$_{2.5}$ reflect the substantial reductions in COVID periods for DWARKA site. Decreases in PSCF values were observed due to shut down of vehicle and commercial activities in COVID outbreaks.

4. Conclusions

This study illustrates the importance of evaluating the long-term field performance of twenty-two (22) low-cost PM sensors (APT Maxima) under real-time low-cost sensors network system in Delhi. PM$_{2.5}$ concentrations at 22 different sites were compared to the BAM measurements over a 10-month period from May 2019 to February 2020. The low-cost sensor PM$_{2.5}$ measurements were well correlated to the BAM measurements, with $R^2$ values ranging between 0.74 and 0.95 for all sites. The high accuracy was observed in autumn and winter season and lowest accuracy found during the monsoon season. The other confounding factors such as temperature, relative humidity, and PM sources were discussed relative to the linearity of the sensor and BAM data, and the results indicate the importance of the use of long-term field calibration algorithms. Overall, consideration of long-term sensor
performance in the field is crucial to understanding the measurements produced from networks of low-cost PM sensors. This work performed low-cost sensors and suggested that low-cost sensor can be a useful tool for monitoring PM$_{2.5}$ and different function of location to improve air quality management. Furthermore, the impact of COVID-outbreaks on air quality in Delhi was evaluated by comparing the PM sensor data and other gases pollutants (CO, NO$_2$, SO$_2$, and O$_3$) of two sites (PB and DWARKA) during P-COVID and COVID periods. During COVID periods, PM$_{2.5}$, PNC declined by 2–13%, while other gases were substantially declined by (~43–65%) compared to P-COVID periods for both sites. Interestingly, the slight increase (~14%) and significant decrease (~69%) in O$_3$ for PB and DWARKA receptor site, which indicates that ozone in Delhi due to rise of photochemical activity due to increased solar radiation and temperature. The application of the differential probability functions suggested that major changes in local emission and that can affect the air quality. Changes in regional emission mostly drove the decreases in secondary aerosol in Delhi. These findings point to the necessity of a thorough investigation of emissions and the potential value of strong policy implications for enhancing Delhi’s local air quality.

**Author contribution**

JP: Methodology, software, validation, writing original draft, writing review & editing SC: monitoring, data curation, and analysis, RR: Writing - review & editing, supervision, project administration, funding acquisition, TSC: Resources, dashboard updating, and maintenance, and review & editing, JF: Resources, dashboard updating and maintenance, and review & editing, P. Biswas: Supervision, conceptualization, project administration, and funding acquisition methodology, writing - review & editing.

**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.apr.2022.101594.

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