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Evaluating the Performance of Low-cost PM Sensors over Multiple COALESCE Network Sites

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ABSTRACT

Air quality is a global concern, with particulate matter receiving considerable attention due to its impact on human health and climate change. Recent advances in low-cost sensors allow their deployment in large number to measure spatio-temporal and real-time air quality data. Low-cost sensors need careful evaluation with both regulatory approved methods and other data sets to understand their efficacy. In this work, PM concentrations measured by deploying low-cost sensors at four regional sites are evaluated through comparison with satellite-based model MERRA-2 and the SASS reference instrument. Daily $PM_{2.5}$ mass concentration variation was analyzed at four regional sites of India from January 2020 to July 2020, including pre-lockdown and six different lockdown periods. Higher $PM_{2.5}$ concentration was observed at Rohtak (119 $\mu g\ m^{-3}$) compared to Mahabaleshwar (33 $\mu g\ m^{-3}$), Bhopal (45 $\mu g\ m^{-3}$) and Kashmir sites during the pre-lock down period. During the lockdown period, the $PM_{2.5}$ mass concentration was reduced significantly compared to the pre-lockdown period at every location, although the $PM_{2.5}$ concentration was different at each location. The air quality trend was quite similar in both the measurements, however, MERRA-2 reconstructed $PM_{2.5}$ was significantly lower in the pre-lockdown period compared to the lockdown periods. Significant differences were observed between low-cost sensor measurements and MERRA-2 reanalysis data. These are attributed to the MERRA-2 modelling analysis that measures less $PM_{2.5}$ concentration as compared to ground-based measurements, whereas low-cost sensor are ground-based measurements but needs corrections as it is subject to the calibration dependencies and biases.

Keywords: $PM_{2.5}$, Air quality, Low-cost sensor, SASS, MERRA-2, COVID-19 lockdown

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1 INTRODUCTION

Air pollution is a major environmental challenge for many nations due to its harmful impact on health, economy, and society in general, leading to poor quality of life (Jain and Sharma, 2020; Kumar *et al.*, 2015). Recent studies have indicated nearly 9 million premature deaths in 2015 were associated with exposure to air pollution (Fuller *et al.*, 2022). The major sources of air pollutants include vehicular emissions, industrial emissions, and other anthropogenic actions (Bedi *et al.*, 2020; Fierz *et al.*, 2008; Reizer and Juda-Rezler, 2016; Rohde and Muller, 2015), and their relative contribution varies over time and location. In the last few years, many cities have experienced a higher PM concentration, and recently 132 non-attainment cities across India were declared according to the India National Clean Air Programme (NCAP) in 2019. Among the major air pollutants, particulate matter ($PM_{2.5}$ and PM_{10}) are considered to be the most harmful pollutant as they are easily respirable and have a tendency to deposit in the pulmonary region depending on their size (Gupta *et al.*, 2020; Jayaratne *et al.*, 2020; Reizer and Juda-Rezler, 2016).

The air quality had changed significantly due to the COVID-19 pandemic (Bedi *et al.*, 2020; Wang *et al.*, 2020). Some studies reported that the spread of COVID-19 had increased due to air pollution, and and the government imposed many restrictions after March 25, 2020 to prevent the spread of COVID-19 (Kolluru *et al.*, 2021; Kumar *et al.*, 2020; Li *et al.*, 2020b; Zhang *et al.*, 2021). Business and activities were halted as a result of the lockdown, with the exception of a few necessary services. Emissions from anthropogenic sources was limited, and air pollution was expected to reduce as a result of the interruption of anthropogenic activities. Due to the lockdown, many countries around the world like Brazil, China, Barcelona, India, reported a decline in air pollution (Xu *et al.*, 2020), and a similar improvement in air quality was reported by other researchers (Dantas *et al.*, 2020; Mahato *et al.*, 2020; Tobías *et al.*, 2020). The improvement in air quality and spatio-temporal variation in PM due to lockdown may vary depending on restriction on location-specific emission sources and meteorological parameters (Jain and Sharma, 2020). The monitoring stations installed by Central Pollution Control Board (CPCB), India at selected locations for air quality are limited in number and provides average data for a whole region (Navinya *et al.*, 2020). It is challenging to capture regional air quality in some of the newly emerging regional polluted locations (Bali *et al.*, 2019). This limitation can be addressed by deploying low-cost sensors to improve the spatio-temporal resolution of air quality measurements (Jiao *et al.*, 2016; Li *et al.*, 2020b; Zheng *et al.*, 2018). Although deploying a large number of low-cost sensors will be helpful for continuous spatial and temporal variation monitoring, accuracy in measurements and other disadvantages associated with low-cost sensor requires more research and development (Amaral *et al.*, 2015; Jayaratne *et al.*, 2020; Li *et al.*, 2020a; Li and Biswas, 2017; Wang *et al.*, 2015). However, there are a number of inherent challenges associated with the optical instruments used to measure mass concentration such as the estimation of mass and number concentrations from light scattering data, hygroscopic growth of particles in high RH conditions, the detection limit of the laser light used in the device, various aerosol properties including shape, particle size distribution, and complex refractive indices, which tend to cause inaccuracies in the measurements (Badura *et al.*, 2018; Kelly *et al.*, 2017; Malyan *et al.*, 2023; Tryner *et al.*, 2020). Spatio-temporal variation in $PM_{2.5}$ may differ due to lockdown as the pollutant emission sources are different at different regional sites. The change in pollution level due to these restricted activities can provide useful insight to regulators about the air quality improvement plan (Chauhan and Singh, 2020; Mahato *et al.*, 2020; Sahoo *et al.*, 2021).

In this study, APT Maxima low-cost sensors were deployed under the NCAP-COALESCE (**N**ational **C**arbonaceous **A**erosols **P**rogramme-**C**arb**O**naceous **A**eroso**L** **E**mission, **S**ource apportionment, and **C**limat**E** Impacts) project at four regional sites of India. The sampling sites have been strategically selected such that it does not give only the regional information of $PM_{2.5}$ mass concentration, but by combined all the places, it explains the spatio-temporal variability across the country (Lekinwala *et al.*, 2020a, 2020b). In this study, the low-cost sensor's $PM_{2.5}$ mass concentration data is compared with Speciation Air Sampling System (SASS) sampler periods & MERRA-2 reanalysis data for the pre-lockdown and lockdown periods. This study aimed to understand the impact of lockdown periods on spatio-temporal variation of $PM_{2.5}$ at four regional sites based on ground-based low-cost sensor data and also compared with the ground level SASS sampler $PM_{2.5}$ data for low-cost sensor

ORIGINAL RESEARCH
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performance evlautaion. Additionally, MERRA-2 derived $PM_{2.5}$ data is compared to enhance understanding of air quality improvement strategies.

2 MATERIALS AND METHODS

2.1 Site Description and Data Collection by Low-cost Sensor

Local information provides essential insights in figuring out key drivers of $PM_{2.5}$ concentration at a site. As Lekinwala *et al.* (2020b) mentioned, the sampling site should satisfy some criteria, which are as follows: (1) Site should be far away from local sources such as agricultural burning or residential biomass burning, and traffic busy roads, (2) Site should not be on downwind side of any local emission source to avoid the dominance of $PM_{2.5}$ concentration at the site, (3) Topography of site should be such that it does not affect the wind pattern or wind speed of that specific region, (4) Site should be such that it can represent the long-range regional transport characteristics. Under the National Carbonaceous Aerosol Programme (NCAP) project, 11 regional sampling sites were selected to deploy the APT maxima low-cost sensor. The sampling sites were selected across India for the study as shown in Fig. 1.

The SASS samplers were installed, and air quality measurements were started at the respective sites from January 2020. The 11 regional sites selected as per Fig. 1 are the University of Kashmir (University of Kashmir (UoK)), Mysuru (Indian Institute of Technology (IIT) Madras), Hyderabad (Indian Institute of Technology (IIT) Hyderabad), Mahabaleshwar (Indian Institute of Tropical

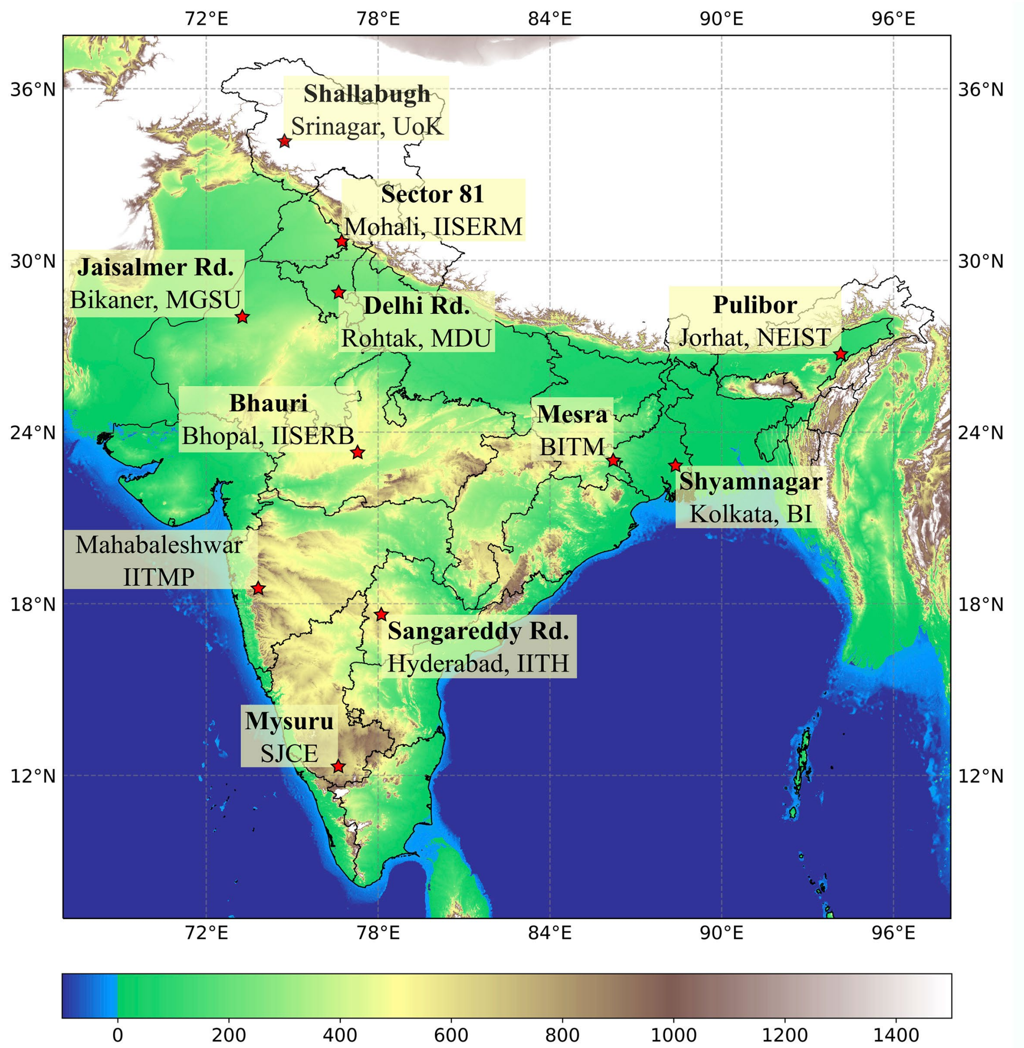

Fig. 1. Site locations identified for the COALESCE project (adapted from Lekinwala *et al.*, 2020b).

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Meteorology (IITM) Pune), Bhopal (Indian Institutes of Science Education and Research (IISER) Bhopal), Delhi (Indian Institute of Technology (IIT) Delhi), Ranchi (Birla Institute of Technology (BIT) Mesra), Kolkata (Bose Institute), Jorhat (Council of Scientific & Industrial Research-North East Institute Of Science And Technology (CSIR-NEIST) Jorhat), Rohtak (Maharshi Dayanand University (MDU) Rohtak), and Mumbai (Indian Institute of Technology (IIT) Bombay). At four of the regional sites namely UoK – Kashmir, IITM – Mahabaleshwar, IISER – Bhopal, and MDU – Rohtak, low-cost sensors were collocated with the SASS sampler for assessment of LCS accuracy compared to the reference instrument. The data from these four regional sites are considered in this paper. These sites were chosen due to their distinct local meteorological conditions such as temperature and relative humidity, and the range of PM concentration based on the sources of emisssions. The aim is to evaluate the sensor performance in the variable weather conditions (low to high range of relative humidity, and low to high degree of temperature), throughout the pre-lockdown and subsequent lockdown and unlock periods at the selected regional sites.

The field measurements were carried out at all four monitoring sites by low-cost sensors as discussed earlier. APT Maxima sensor was kept under the protective shed to protect it from high temperatures and heavy rain. A built-in fan at the bottom of the sensor was used to draw the atmosphere's ambient air through an aperture in the box. The installed sensors recorded the data at an interval of 30 seconds starting January 2020. The data collected from January to July 2020 (which covers the pre-lockdown, lockdown, unlock phases) are used for this study. A more detailed survey across various NCAP sites and their detailed analysis is part of future research papers.

2.2 Low-cost Sensor Instrumentation

The APT maxima low-cost sensor developed by Applied Particle Technology, USA, is equipped with a Plantower PMS5003 sensor module. These sensors were deployed to monitor the deployed area's real-time air quality. This sensor works based on the light scattering principle, i.e., laser light is passed through the air sample and lit the particles. Due to this phenomena, the light is scattered at different angles with different intensities and based on that mass concentration and particle counts can be determined with time (Li *et al.*, 2020a; Zheng *et al.*, 2018). This sensor gives the output in the digital interface which includes a timestamp (date and time), meteorological parameters such as relative humidity (%), temperature (°C), and pressure (pa), and also the particle counts in six size bins (0.3 µm, 0.5 µm, 1 µm, 2.5 µm, 5 µm, and 10 µm) and PM concentrations (PM_1, $PM_{2.5}$, PM_{10} in µg m^{-3}). The device components of the APT maxima low-cost sensors are shown in Fig. 2.

2.3 Speciation Air Sampling System (SASS)

In this study, a highly efficient aerosol collecting device, speciation air sampling system (SASS) instrument is used. The SASS sampler is 24-hr filter-based sampling instrument equipped with a multi (5) channel single event speciation sampler with pump, 5 sampler canisters wlth filter holder, 5 $PM_{2.5}$ SCC (6.7 LPM) and 1MgO denuder (SASS Speciation Sampler, Met One Instruments). For particle separation, SASS uses a sharp cut cyclone (SCC). To provide a circular motion to the incoming air inlet, the cyclonic flow inlet uses the impellers. In SASS, the sampler's flow rate is maintained around 6.7 litres per minute so that impellers impart the centripetal force on the particles in the incoming air stream, which moves them towards the walls of a cylindrical tube. The cylindrical tube wall is coated with oil or grease so that particle adhered once it will come into contact with walls or it dropout the air streamlines and collected in a hopper at the bottom of the tube. The cyclone grit (hopper) cap must be cleaned before running the instrument so that efficiency can be maintained and particle re-entrainment can be prevented (Solomon *et al.*, 2000).

The SASS collects the $PM_{2.5}$ samples by using various filter media, and each media is analyzed differently for different components. One is the Teflon filter used for total mass and trace metals. The second one is the Nylon filter, which is used to measure the concentration of nitrates, sulfates, potassium, ammonium, and sodium by using chromatography techniques. The third one is the quartz filter which is used to measure total organic and elemental carbon. To calculate the total sample volume in cubic meters (m^3), SASS has electronic systems designed to monitor and record the sampling time and maintain the volumetric flow rate. After collecting the filter, the

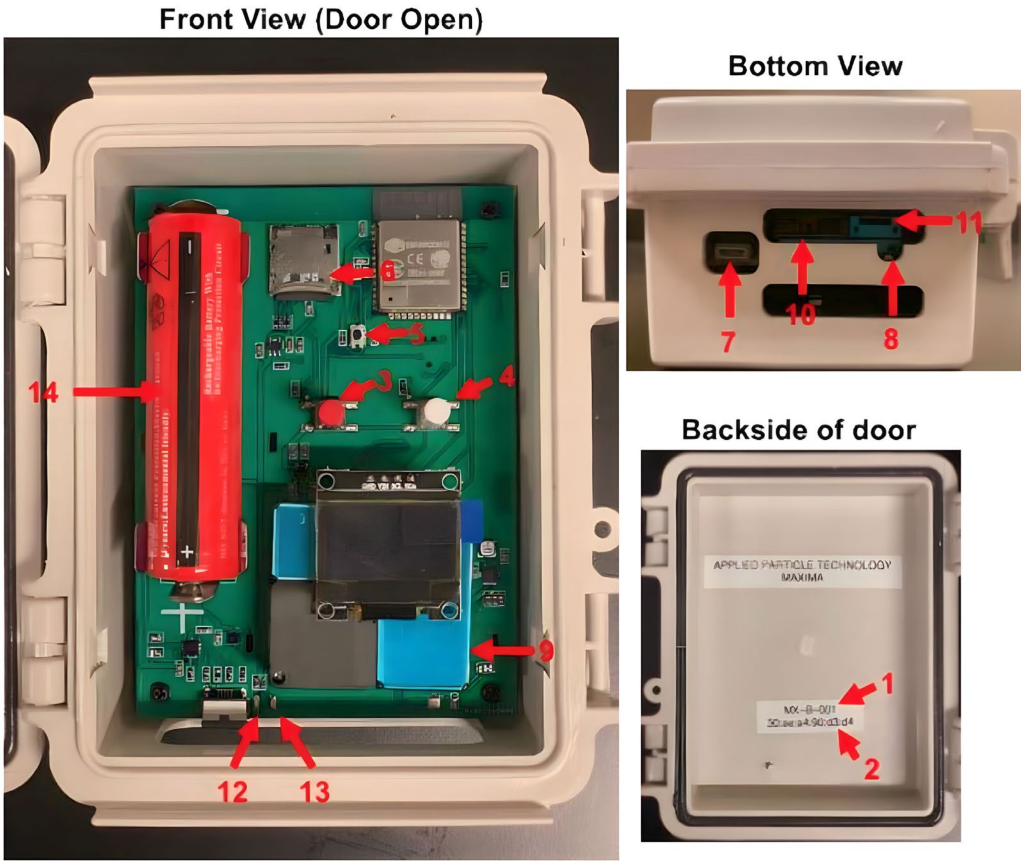

Fig. 2. Device components of APT maxima low-cost sensor (APT Maxima Manual). (1) Product ID, (2) MAC address, (3) POWER Button, (4) MISC Button, (5) Hard Reset Button, (6) MicroSD card slot, (7) Micro-USB charging port, (8) Temperature, Pressure, and Humidity Sensor, (9) Optical Particle Counter (OPC), (10) OPC exhaust, (11) OPC Intake, (12) External power indicator, (13) Battery Charging indicator, (14) Lithium-ion battery.

supporting laboratory gives the sample data in micrograms per cubic meter (µg m^{-3}). The channel flow by utilizing various components like software, mass flow controller, microprocessor, filter temperature, and ambient barometric pressure sensor (Solomon *et al.*, 2014). In this study, the SASS instrument is colocated with a Low-cost sensor at every regional site in India. The entire setup for sampling using SASS is shown in Fig. 3.

2.4 Reconstruction of MERRA-2 Data

The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), is the modern satellite era that uses the Goddard Earth Observing System Model and produced by NASA's global modelling and assimilation office (GMAO) (Gelaro *et al.*, 2017). The MERRA-2 is developed with two prime objectives: to provide real-time climate analysis and progress towards developing a future integrated Earth system analysis (IESA) capability (Randles *et al.*, 2017). MERRA-2 considers the Goddard chemistry, aerosol, radiation, and transport (GOCART) model and simulates natural and anthropogenic aerosols (Rizza *et al.*, 2019). The reanalysis process in MERRA-2 relies on the underlying forecast model to properly integrate the different observations with a dataset for a wide range of variables that cannot be observed directly (Ma *et al.*, 2020). This GOCART model simulates the sources, sinks, and chemistry of mixed aerosol tracers: Dust, sea salt (S.S.), hydrophobic and hydrophilic B.C. and O.C., and Sulfate, and doing reanalysis of these components, $PM_{2.5}$ mass concentration data can be obtained (Bali *et al.*, 2019; Gelaro *et al.*, 2017; He *et al.*, 2019; Song *et al.*, 2018). The MERRA-2 products can publicly provide daily $PM_{2.5}$ mass concentration data after 1980 to observe the long-term effect of meteorological conditions on $PM_{2.5}$ (Rizza *et al.*, 2019). From the MERRA-2 products, various parameters can be

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Fig. 3. General arrangements of APT maxima low-cost sensor and SASS sampler.

used to determine $PM_{2.5}$ concentration. Major aerosol species considered in MERRA-2 reanalysis are $Dust_{2.5}$, $Sea\text{-}salt_{2.5}$, BC, SO_4, and O.C. and from the obtained data sets, $PM_{2.5}$ can be calculated by the following equation (He *et al.*, 2019):

$$PM_{2.5} = DUST_{2.5} + SS_{2.5} + BC + (1.375 \times SO_4) + (1.6 \times OC) \quad (1)$$

Dust, SS, BC, SO_4, and OC represent the dust and sea-salt particulate matter of diameter less than 2.5 µm, black-carbon, sulfate, and organic carbon from the GOCART aerosol module (Randles *et al.*, 2017). The sulfate concentration is assumed in the form of neutralized ammonium sulfate, calculated from the mass of sulfate ion (provided by the MERRA-2) multiplied by a factor of 1.375 (Song *et al.*, 2018). To estimate organic matter (O.M.), MERRA-2 simulates OC aerosol, in which OC aerosol is multiplied by a factor (molecular weight per carbon weight ratio) which accounts for contributions from other elements that are directly associated with organic matter which can be varied spatially and temporally with values between 1.2 and 1.6 (Song *et al.*, 2018). A constant value of 1.6 is taken here because surface measurements have indicated an averaged ratio of 1.59 ± 0.18 in $PM_{2.5}$ over China (Zhang *et al.*, 2013). Low-cost sensor evaluation can be done by comparing daily average data with MERRA-2 $PM_{2.5}$ mass concentration data. In this study, the scope is limited to compare the $PM_{2.5}$ concentration with the MERRA-2 reconstructed $PM_{2.5}$ data at the four regional sites used for the analysis.

2.5 Lockdown Periods and Restricted Activities

As per the Ministry of Home Affairs (MHA) order no. 40-3/2020-D dated March 24, 2020, some guidelines and preventive measures were taken amid the COVID-19 pandemic in the country. Lockdown-1 was imposed from March 25, 2020, to April 14, 2020, and after that, it was extended as lockdown-2 up to May 3, 2020. During these lockdown times, almost all major activities were restricted which includes all offices of the Government of India, it's autonomous/subordinate offices, public corporations offices except defence, central armed police forces, public utilities (including petroleum, Compressed Natural Gas (CNG), Liquefied Petroleum Gas (LPG), Piped Natural Gas (PNG)), power generation plants, transportation facilities for necessary items, and early warning agencies. All commercial and private established were ordered to remain closed except hospitals and all manufacturing and distribution units, both in the public and private sector, such as chemist and medical shops, laboratories, ambulances. All the industrial establishments were closed excepts production units for essential commodities. All transport services were suspended such as air, road, and railway services, except for emergency cases and other transportation facilities for essential goods only. In the lockdown-3 which started from May 4, 2020, the guidelines changed slightly and zone identification was made in the entire country, including three-zone as Red zone, Orange zone, and Green zone. The red zone was a hotspot zone with strict rules and activities were prohibited while in the Orange Zone, the necessary preventive actions were taken to improve the condition. In the Green zone, some activities were restarted like buses were restarted with 50% seating capacity. Interstate goods/cargo movements were allowed. In the lockdown-4 from May 17, 2020, to May 31, 2020, new guidelines were passed, interstate train facilities were started, daytime activities were also allowed, and night curfew was applied from 7 pm to 7 am. All major activities were allowed to restart except air travel facilities, metro rail services, school and college opening, hotels and restaurants, cinemas and shopping malls, and public gatherings for any public event/function. In the lockdown-5 which was from June 1, 2020, to June 30, 2020, the only change was the night curfew duration was reduced to 9 pm to 5 am and some activities that were allowed to start further were hotels, restaurants, religious places, and shopping malls. In the lockdown-6, from July 1, 2020, to July 31, 2020, the night curfew was relaxed and time changed to 10 pm to 5 am. Outside the containment zones, all the major activities were allowed to run with the Government of India's precautionary measures.

2.6 Comparative Statistical Data Analysis

To check the performance of the low-cost sensor, statistical analysis and regression parameters include slope, y-intercept, Normalized Root mean square error (NRMSE), Mean absolute error (MAE), and Normalized mean bias (NMB) was determined by the following equation (He *et al.*, 2019):

$$\mathrm{NRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{PM}_{2.5(\mathrm{LCS\ data})i} - \mathrm{PM}_{2.5(\mathrm{SASS/MERRA-2})i}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}\mathrm{PM}_{2.5(\mathrm{SASS/MERRA-2})i}} \tag{2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\mathrm{PM}_{2.5(\mathrm{LCS\ data})i} - \mathrm{PM}_{2.5(\mathrm{SASS/MERRA-2})i}\right| \tag{3}$$

$$\mathrm{NMB} = \frac{\sum_{i=1}^{n}\left(\mathrm{PM}_{2.5(\mathrm{LCS\ data})i} - \mathrm{PM}_{2.5(\mathrm{SASS/MERRA-2})i}\right)}{\sum_{i=1}^{n}\left(\mathrm{PM}_{2.5(\mathrm{SASS/MERRA-2})i}\right)} \tag{4}$$

where, NRMSE = normalized root mean square error; $\mathrm{PM}_{2.5(\mathrm{LCSdata})i}$ = LCS measurement; $\mathrm{PM}_{2.5(\mathrm{SASS/MERRA\text{-}2})i}$ = SASS or MERRA-2 measurement; MAE = mean absolute error; NMB = normalized mean bias.

The Mean absolute error (MAE) measures the average magnitude or errors from a given dataset. MAE is the linear score, giving the equally-weighted average value from different individual error values (Feenstra *et al.*, 2019; Malings *et al.*, 2020). Whereas in NRMSE, the individual errors are squared, and after then it is averaged over the whole dataset, and finally the square root of the average is taken (Li *et al.*, 2020a). As the NRMSE squared the individual errors, which indicates that this formula gives high weightage to the large errors, so it's easy to characterize the sensor performance at different sites (Munir *et al.*, 2019). So, NRMSE is widely useful in such a type of case where large errors are highly undesirable. Usually, MAE and NRMSE are used together to observe

ORIGINAL RESEARCH
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the variation in a given dataset's errors. The larger difference between these two values indicates a larger variance in individual errors. For a perfect match or higher accuracy, MAE and NRMSE values should be lower. A correlation coefficient (R) is used to determine the type of relationships and relationship strength (Kim, 2019; Lekinwala *et al.*, 2020b; Wang *et al.*, 2010). R-value may be negative and positive and zero also, where a negative value indicates that for every positive increase in one variable, there is a negative decrease in another variable, and a positive value indicates that for every positive increase in one variable, there is also a positive increase in another variable and if values are nearly +1 or –1 it suggests that there is a strong relationship between this two-variable (Munir *et al.*, 2019; Wang *et al.*, 2014). The zero value of R indicates that no relationship exists between these two variables. In conclusion, the higher the R values, the stronger the relationship. The Normalized mean bias (NMB) is the ratio of difference of LCS $PM_{2.5}$ mass concentration data and MERRA-2 $PM_{2.5}$ mass concentration data to the MERRA-2 $PM_{2.5}$ mass concentration data. The negative NMB values indicate that MERRA-2 $PM_{2.5}$ observed higher $PM_{2.5}$ mass concentration then LCS $PM_{2.5}$ mass concentration and positive NMB values indicates that LCS $PM_{2.5}$ mass concentration is higher than the MERRA-2 observation. NMB value of nearly zero indicates no significant difference between these two measurements (Ruiz and Bandera, 2017).

3 RESULTS AND DISCUSSION

3.1 Comparison of Ground-based Low-cost Sensor Data against SASS $PM_{2.5}$ Data

Daily mean $PM_{2.5}$ mass concentration from low-cost sensor and SASS is compared for the selected regional sites to understand the variation in the measurements. Low-cost sensor data for pre-lockdown and lockdown period was unavailable for Kashmir and Rohtak sites respectively. In Fig. 4, daily mean $PM_{2.5}$ mass concentration data is represented with dot plots (with one standard deviation) and bar chart for LCS and SASS measurements respectively. The total height of stacked bar chart represents the $PM_{2.5}$ mass concentration measured using SASS. For the pre-lockdown phase, LCS recorded $PM_{2.5}$ mass concentration is lower as compared to SASS for Kashmir, Bhopal, and Mahabaleshwar site, however, LCS has recorded higher $PM_{2.5}$ mass concentration for Rohtak site. As indicated by Lekinwala *et al.* (2020b), the Rohtak site is heavily polluted with traffic emissions, domestic burning, agricultural field burning, construction work, and diesel pump emissions, which explains the high $PM_{2.5}$ concentrations in the pre-lockdown period. In the lockdown periods, LCS $PM_{2.5}$ measurements are lower for all regional sites in comparison to SASS recorded data with variation under one standard deviation.

In this study, various statistical analysis were performed to observe the relationship between $PM_{2.5}$ mass concentration data measured using LCS and SASS. The comparion of $PM_{2.5}$ concentartion between SASS and LCS $PM_{2.5}$ at the sites for all pre lockdown and six lock down periods are shown in Fig. 5. Standard metrics were used to check the accuracy between the LCS and SASS $PM_{2.5}$ mass concentrations recorded at the regional sites. For the Kashmir site, the observed errors were low as NRMSE and MAE were 34% and 5 $\mu g\ m^{-3}$ respectively, which shows that the accuracy of LCS measurements is high at low concentrations. These figures were cross-validated by calculating the NMB value (–0.07) which is nearly zero, suggesting that the LCS measurements are close to the $PM_{2.5}$ mass concentration measured by the SASS sampler. In the Bhopal site, NRMSE and MAE values were 47% and 14 $\mu g\ m^{-3}$ respectively, which is higher than the Kashmir site. From the graph, it can be directly observed that the SASS has measured almost 1.5 times higher concentration than the low-cost sensor in the lockdown as well as the pre-lockdown periods. It can also be observed from the NMB value (–0.3) that the low-cost sensor has recorded lower concentration than the SASS sampler. For Mahabaleshwar site, the Pearson correlation coefficient (R = 0.73) is high, however, the error values are significant as NRMSE and MAE are 42% and 10 $\mu g\ m^{-3}$ respectively. This shows that there is deviation between the LCS and SASS recorded data. LCS measurements are lower which is also seen from the NMB value (–0.13). In the Rohtak site, NRMSE and MAE are exceptionally high with values of 46% and 72 $\mu g\ m^{-3}$ respectively which may be due to limited data collected and high $PM_{2.5}$ mass concentration observed at the site. These statistical metrics show that the accuracy of LCS is quite satisfactory when the $PM_{2.5}$ mass

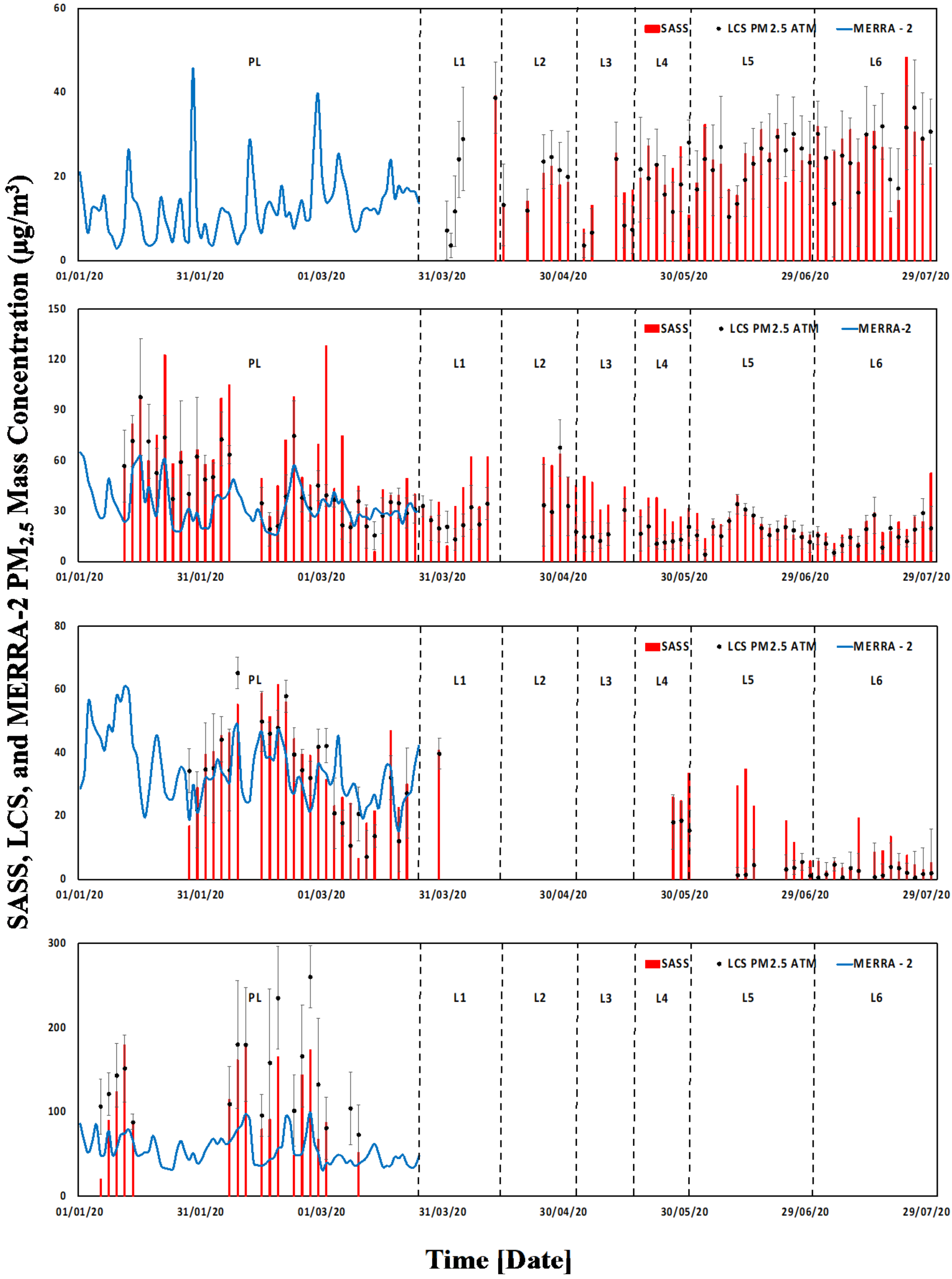

Fig. 4. Daily Mean LCS $PM_{2.5}$ & SASS $PM_{2.5}$ concentration variation during pre-lockdown periods and six different lockdown periods at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

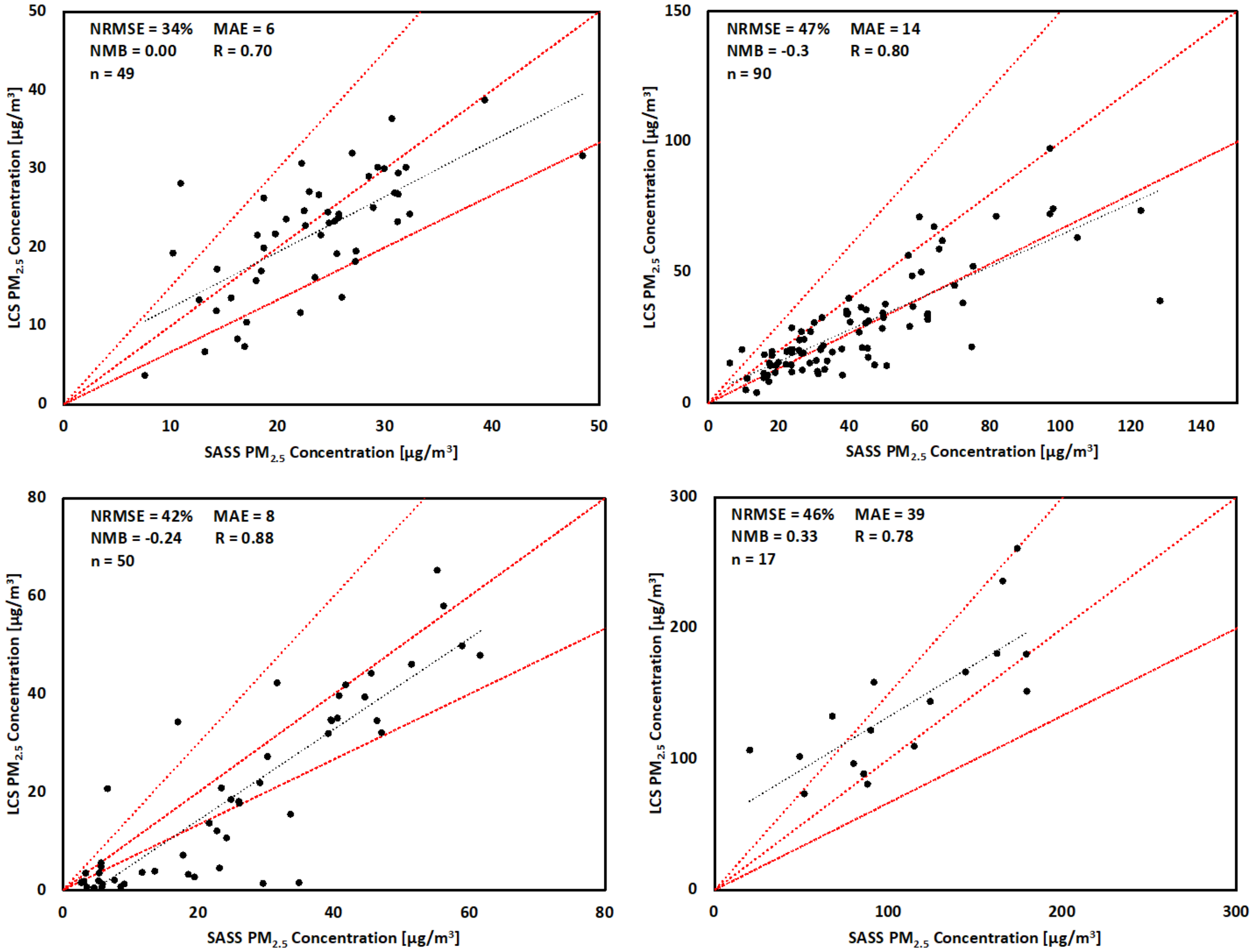

Fig. 5. LCS $PM_{2.5}$ concentration vs. SASS $PM_{2.5}$ during pre-lockdown and six different lockdown periods at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

concentration is in the low-concentration regime, however, the accuracy of LCS decreases when the concentration is high. This could be attributed to the fact that the PMS5003 sensor exhibits a non-linear response when $PM_{2.5}$ concentration are higher, typically more than 40 µg m^{-3} (Kelly *et al.*, 2017). Similar trend in LCS performance with respect to the aerosol concentration was reported by Jayaratne *et al.* (2020).This study also indicates that meteorological parameters such as relative humidity (RH) and temperature (T) may have impact on the LCS measurements and may be considered for calibration of LCS to reduce the error in the measuremnts.

The average values of LCS and SASS $PM_{2.5}$ mass concentations were calculated to observe the impact during the different phases of lockdown and pre-lockdown period at the regional sites. Fig. 4 and Fig. 5 indicate that LCS can be used to observe the impact of lockdown periods on the ambient $PM_{2.5}$ mass concentration as it provides fairly accurate results. The average values were calculated and mentioned in Table 1, and the variation in $PM_{2.5}$ mass concentration across the pre-lockdown and lockdown periods is shown in Fig. 6 using box plots. A good correlation is observed at all regional sites between LCS and SASS measurement data. The correlation coefficient (R) values for Kashmir, Bhopal, Mahabaleshwar, and Rohtak site are 0.70, 0.81, 0.73, and 0.67 respectively. The error values are low for the selected sites with Rohtak site being an exception due to less data collected and high variability in the $PM_{2.5}$ mass concentrations observed at the site.

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Table 1. Average LCS $PM_{2.5}$ & SASS $PM_{2.5}$ values during pre-lockdown and six different lockdown periods in (a) Kashmir (b) Bhopal site (c) Mahableshwar and (d) Rohtak site.

Location	Time	Duration	Average $PM_{2.5}$ ($\mu g\ m^{-3}$)	
			LCS	SASS
Kashmir	PL	01-01-20 to 25-03-20	NA	66
	L1	25-03-20 to 14-04-20	NA	29
	L2	15-04-20 to 03-05-20	19	18
	L3	04-05-20 to 17-05-20	10	16
	L4	18-05-20 to 31-05-20	20	21
	L5	01-06-20 to 30-06-20	23	24
	L6	01-07-20 to 31-07-20	26	27
Bhopal	PL	01-01-20 to 25-03-20	44	61
	L1	25-03-20 to 14-04-20	25	40
	L2	15-04-20 to 03-05-20	36	56
	L3	04-05-20 to 17-05-20	18	41
	L4	18-05-20 to 31-05-20	15	31
	L5	01-06-20 to 30-06-20	19	23
	L6	01-07-20 to 31-07-20	16	22
Mahabaleshwar	PL	01-01-20 to 25-03-20	37	33
	L1	25-03-20 to 14-04-20	NA	NA
	L2	15-04-20 to 03-05-20	NA	NA
	L3	04-05-20 to 17-05-20	NA	NA
	L4	18-05-20 to 31-05-20	28	17
	L5	01-06-20 to 30-06-20	18	3
	L6	01-07-20 to 31-07-20	7	2
Rohtak	PL	01-01-20 to 25-03-20	136	104
	L1	25-03-20 to 14-04-20	NA	NA
	L2	15-04-20 to 03-05-20	NA	NA
	L3	04-05-20 to 17-05-20	NA	NA
	L4	18-05-20 to 31-05-20	NA	NA
	L5	01-06-20 to 30-06-20	NA	NA
	L6	01-07-20 to 31-07-20	NA	NA

3.2 Comparison of Ground-based LCS and MERRA-2 $PM_{2.5}$ Mass Concentration Data

Ground-based LCS recorded data was compared with MERRA-2 estimated $PM_{2.5}$ mass concentration data to observe the correlation between them. MERRA-2 reconstruction data may prove to be crucial for data scarce regions as a proxy for reference grade or LCS measurement data. Fig. 7 shows the daily mean $PM_{2.5}$ mass concentration data recorded using LCS represented with dot plots (one standard deviation), and MERRA-2 $PM_{2.5}$ mass concentration data as a stacked bar chart which is calculated using Dust, SS, OC, BC, and Sulfate mass concentration data. It is observed that the LCS recorded data are higher than the calculated $PM_{2.5}$ mass concentration values using MERRA-2 reanalysis data across the selected regional sites. Fig. 7 shows the variation in $PM_{2.5}$ mass concentration measured using LCS and estimated using MERRA-2 for the pre-lockdown period across the Bhopal, Mahabaleshwar, and Rohtak sites. The LCS was not operated during the pre-lockdown period at the Kashmir site. In the current study, the MERRA-2 reanalysis data was considered only for the pre-lockdown period as MERRA-2 reconstructs $PM_{2.5}$ mass concentration from the mass concentration of five aerosol components supplied by the GOCART module instead of providing direct $PM_{2.5}$ ground concentration. These components are black carbon (BC), organic carbon (OC), DUST (dust particulate matter with a diameter < 2.5 µm), sea salt (SS; sea salt particulate matter with a diameter < 2.5 µm), and sulfate (SO_4). During the lockdown and unlock periods, several restrictions were imposed due to which the ground-based measurements of these components is not available for that period. Therefore, the MERRA-2 reconstructed $PM_{2.5}$ measurements for the lockdown and unlock period is unreliable and have not been used in this study.

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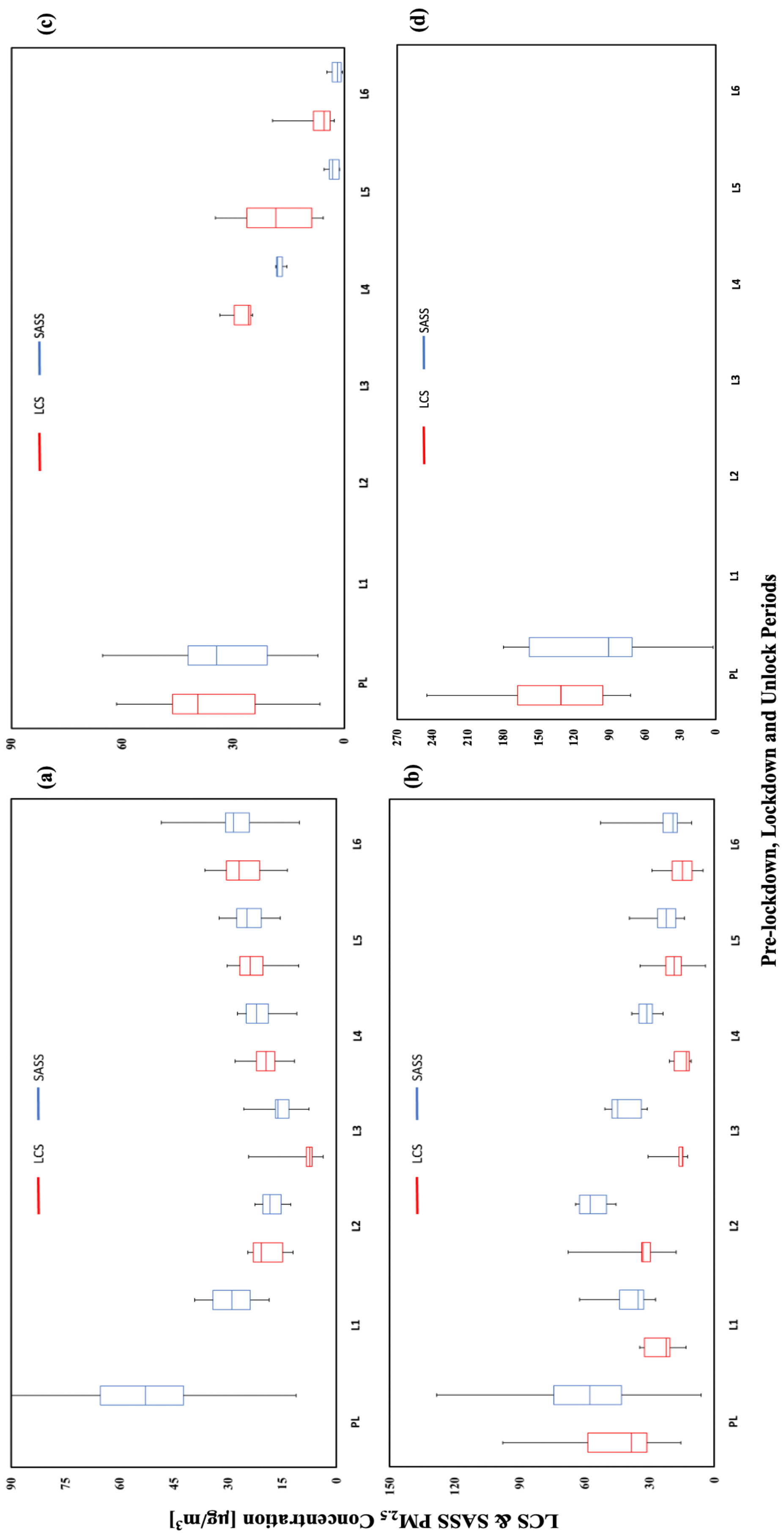

Fig. 6. Difference in variation of $PM_{2.5}$ concentration across unlock and six lockdown periods for LCS & SASS measurements at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

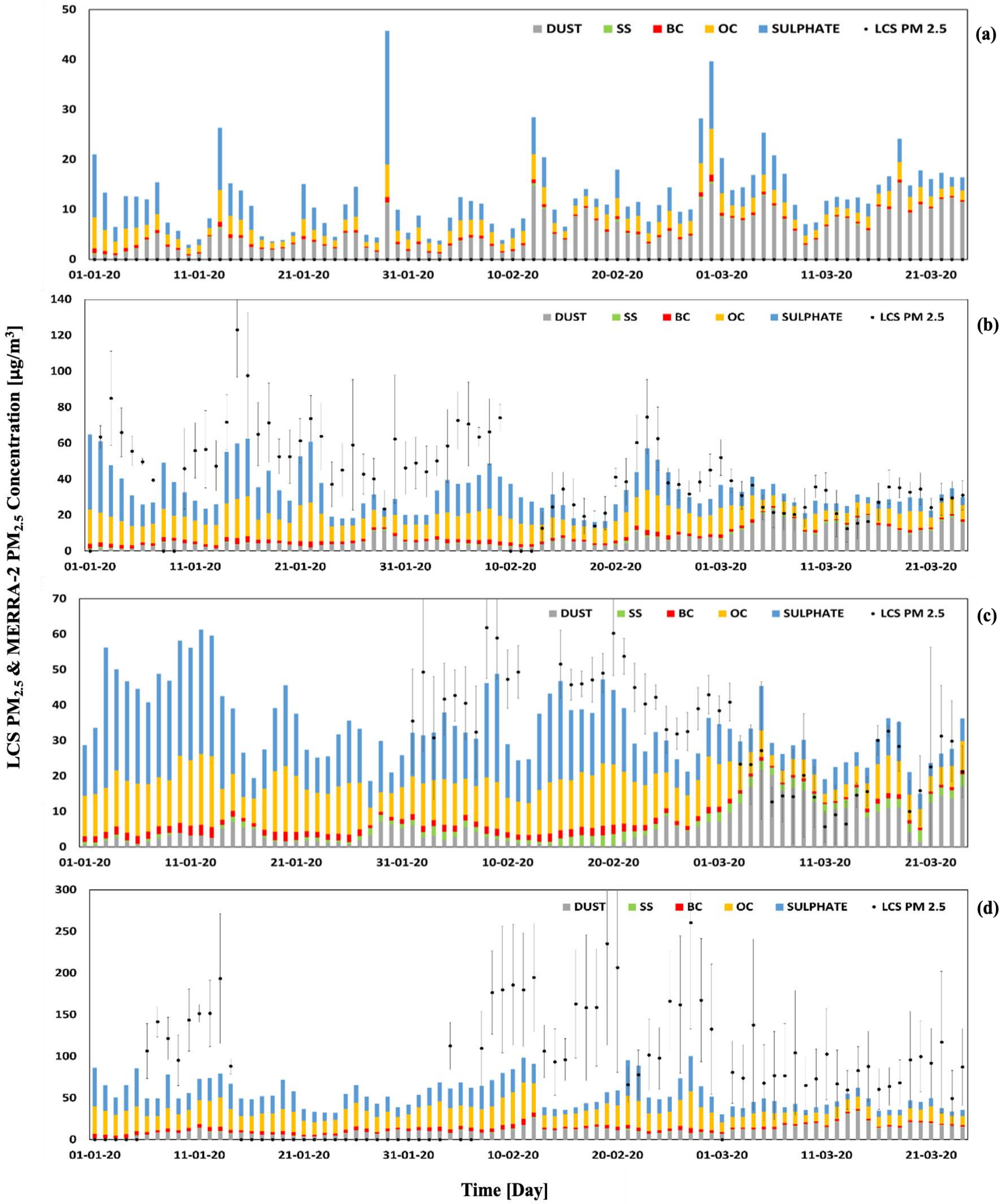

Fig. 7. Daily Mean LCS $PM_{2.5}$ & MERRA-2 $PM_{2.5}$ concentration variation during pre-lockdown periods at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

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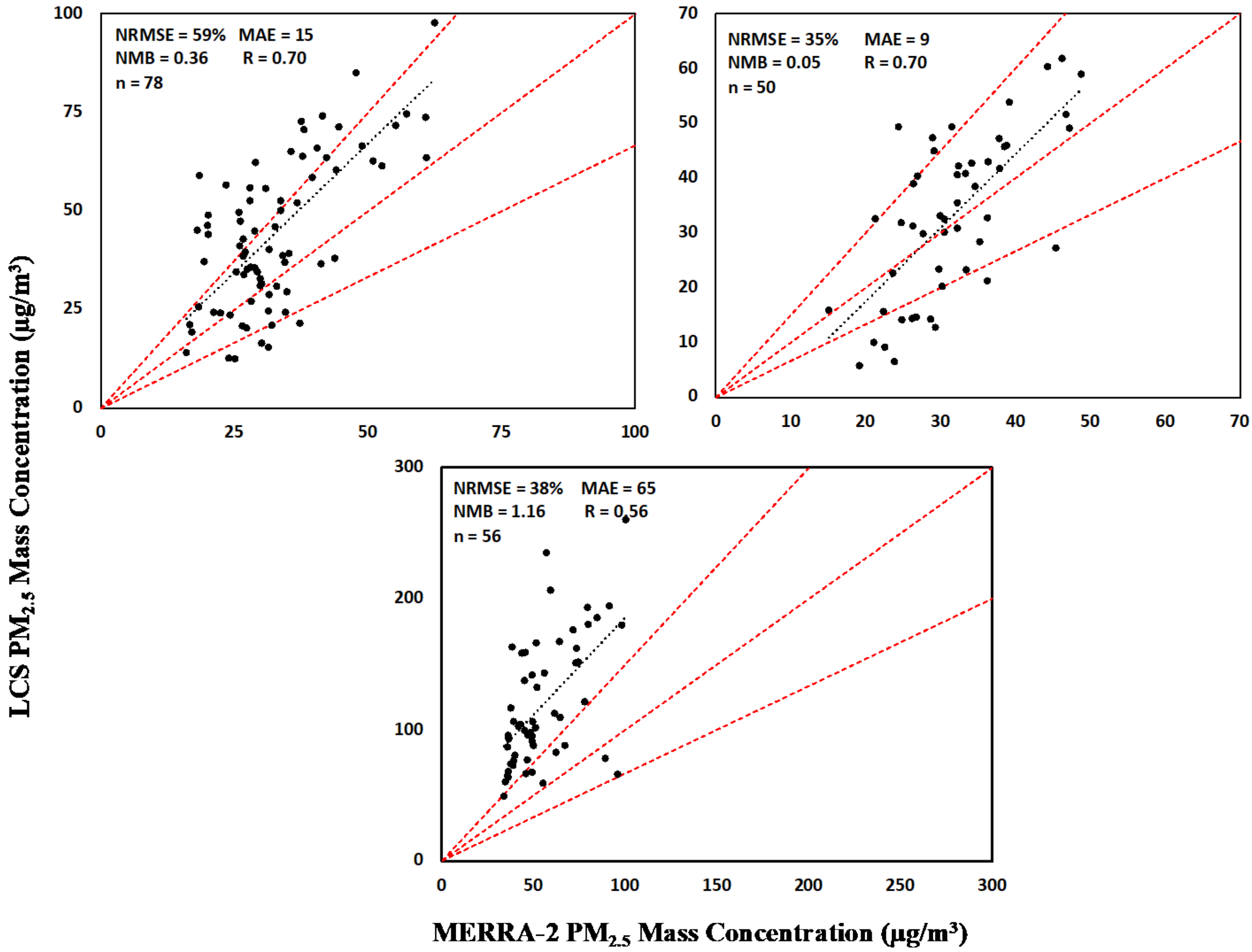

Fig. 8. LCS $PM_{2.5}$ concentration vs. MERRA-2 $PM_{2.5}$ during pre-lockdown periods at (a) Bhopal (b) Mahabaleshwar (c) Rohtak sites.

The scatter plots for LCS vs. MERRA-2 $PM_{2.5}$ mass concentration during pre-lockdown period for all four regional sites are shown in Fig. 8. It is observed that the NRMSE and MAE values are 38% and 65 µg m^{-3} respectively for Rohtak site. Additionally, the NMB value is 1.16, which indicates that LCS recorded measurements is higher as compared to the MERRA-2 calculated values in the pre-lockdown period. For other regional sites, the NRMSE and MAE values are less with good correlation coefficient values of 0.70 for both Bhopal and Mahabaleshwar sites. These are the limitations of the low-cost sensor as raw data is not entirely reliable and indicates that the evaluation of the LCS is necessary as large errors were observed. In contrast, as per Navinya *et al.* (2020), these MERRA-2 data also need some corrections as MERRA-2 estimated mass concentrations are model derived data which is a proxy of the ground-based $PM_{2.5}$ mass concentration measurements.

3.3 Impact of COVID-19 Lockdown Periods on Air Quality on the Regional Sites Periods

LCS measured data can be useful and the air quality trend can be observed in the pre-lockdown and different lockdown periods for the regional sites. LCS exhibits a significant correlation with the ground based data for the regional sites as discussd in the pevious section. So, LCS measured data can be used to assess the air quality of a region. A time series plot of the daily averaged $PM_{2.5}$ mass concentration at four regional sites was plotted for pre-lockdown and six lockdown periods as shown in Fig. 9. 24 hours averaged $PM_{2.5}$ mass concentration and ± one standard deviation for

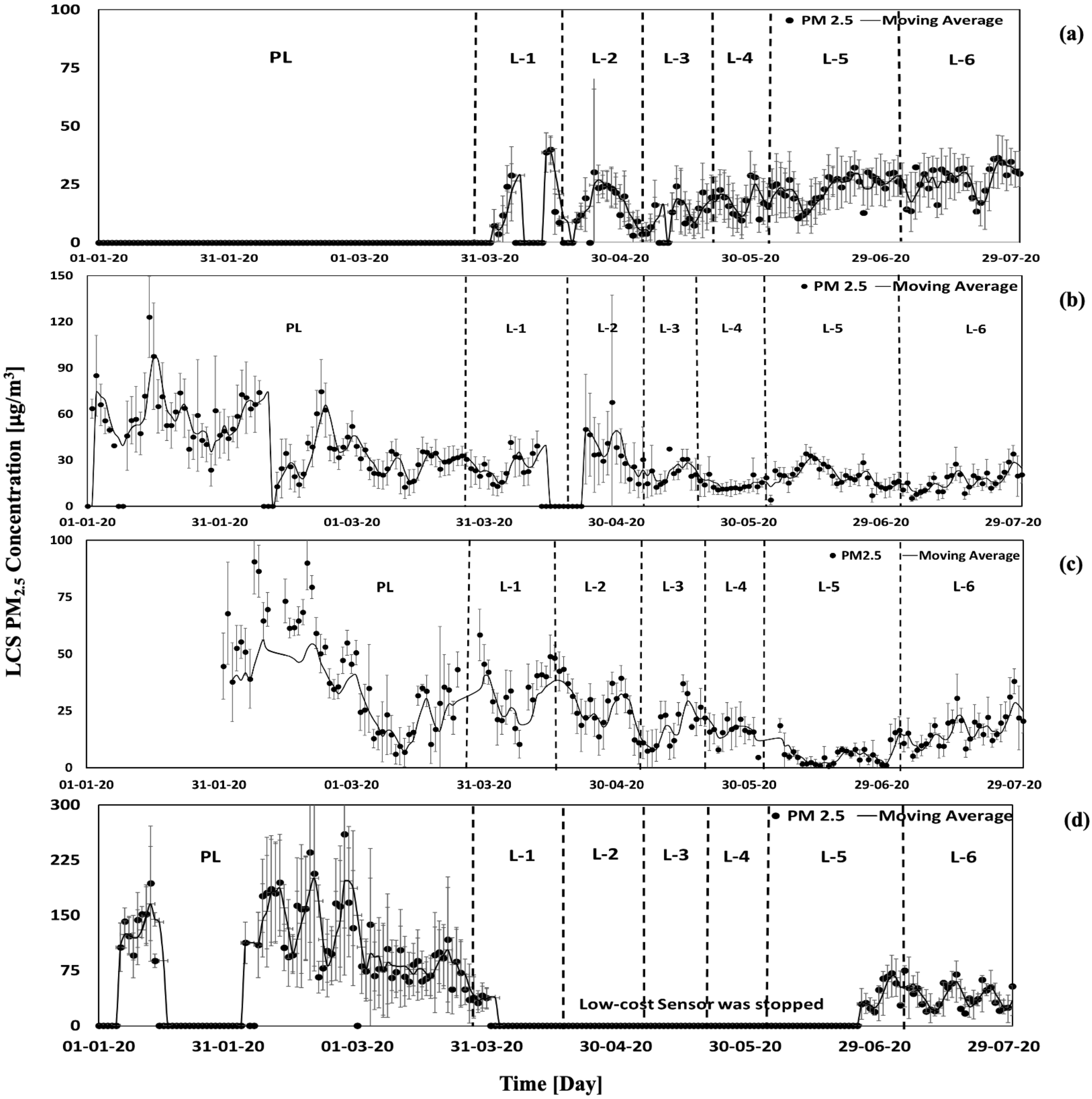

Fig. 9. Daily average (24-hr) (dots) and 3-day moving average trend (solid line) of $PM_{2.5}$ concentration variation during pre-lockdown and six different lockdown periods at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

the day were considered to analyze the time-series graph. Air quality was expected to be improved in lockdown periods than pre-lockdown periods and unlock (lockdown-5 and lockdown-6) periods. As seen in the graphs from four regional sites, a decreasing trend was observed at every site. In the Mahabaleshwar site, $PM_{2.5}$ mass concentration was 33 µg m^{-3} in the pre-lockdown period whereas, in the lockdown-1 period, $PM_{2.5}$ concentration was 30 µg $m^{-3,}$ which was reduced by 9% only. It indicates that there was no significant effect of lockdown-1 as the primary emission sources were not affected due to lockdown-1. In the Bhopal site, $PM_{2.5}$ mass concentration was 45 µg m^{-3} in the pre-lockdown period whereas, in the lockdown-1 period, $PM_{2.5}$ concentration was 26 µg $m^{-3,}$ which was reduced by 42% it indicates that there was a significant effect of lockdown-1. Sharma *et al.* (2020) reported that a 43% reduction was observed in $PM_{2.5}$ mass concentration in India's central region. In contrast, in this study, similar results were observed in the Bhopal site during this period. In the Jorhat site, $PM_{2.5}$ mass concentration was 92 µg m^{-3} in the pre-lockdown period, whereas, in the lockdown-1 period, $PM_{2.5}$ concentration was 64 µg m^{-3} was reduced by 31% and in lockdown-2 it reduced to 30 µg m^{-3}. Thus it can be concluded that there was a significant effect of lockdown periods the results, which were observed in other urban sites in the same region (Sharma *et al.*, 2020; Singh *et al.*, 2020). In the Rohtak site, $PM_{2.5}$ mass concentration was 119 µg m^{-3} in the pre-lockdown period, whereas in the lockdown-1 period, $PM_{2.5}$ concentration was 44 µg m^{-3} which was reduced by 63% which indicates that the primary source of emission was traffic and nearby local industries which were restricted in the lockdown-1 period.

In the Kashmir site, the $PM_{2.5}$ mass concentration was reduced to 29 µg m^{-3} (≈ 56% reduced from 66 µg m^{-3}) in the first phase of lockdown (lockdown-1) based on SASS measurements. In the subsequent lockdown phases, the average $PM_{2.5}$ mass concentration recorded by LCS shows good agreement with the SASS measurements. It is observed that the $PM_{2.5}$ concentrations in the lockdown periods were below 30 µg m^{-3} for both LCS and SASS measurements, showing a reduction of more than 60% compared to the pre-lockdown period. The LCS measured data and SASS derived data were similar, and percentage changes were also similar throughout the lockdown periods. In the Bhopal site, the impact of lockdown is observed as in the lockdown-1, the $PM_{2.5}$ concentration was reduced to 25 µg m^{-3} (≈ 45% reduced from 44 µg m^{-3}). Similarly, except lockdown-2, the $PM_{2.5}$ concentrations were below 20 µg m^{-3}, showing a reduction of ≈ 60% compared to the pre-lockdown period. It can also be observed from Fig. 10 that the SASS measurements were also reduced significantly during these periods showing the impact of different lockdowns on the air quality at the Bhopal site. These results indicate that this site is affected by the vehicular emission, industry emission, or any local sources that were stopped during the lockdown periods due to which there is a significant change observed in the $PM_{2.5}$ concentration. The Mahabaleshwar site had a low $PM_{2.5}$ mass concentration in the pre-lockdown as well as the lockdown periods in comparison to the other regional sites. The concentration reduced by 48.5% by lockdown-4 and continued to reduce in lockdown-5 and lockdown-6 periods. The $PM_{2.5}$ concentration reduced by ~94% from the pre-lockdown to the lockdown-6 period which shows a clear impact of lockdown on the air quality in Mahabaleshwar. For the Rohtak site, mass concentration data is not recorded in the lockdown periods, however, in the pre-lockdown phase, the $PM_{2.5}$ mass concentration is 136 µg m^{-3} and 104 µg m^{-3} as recorded by LCS and SASS respectively.

It is observed that the results obtained from regional sites are similar to the urban sites except for the Mahabaleshwar site. Sharma *et al.* (2020) and Singh *et al.* (2020) have observed a reduction in $PM_{2.5}$ concentration by ~40% in various urban sites of India. Lower $PM_{2.5}$ concentrations observed due to the imposition of COVID-19 lockdown primarily due to the restricted activities as mentioned earlier. A similar analysis was done in four metropolitan cities of India by Bedi *et al.* (2020) and the obtained results were the same as observed in this study. Another study was done in Delhi to assess the air quality in the pre-lockdown and lockdown period which indicates a similar pattern (Mahato *et al.*, 2020). Sahoo *et al.* (2021) has also discussed the effect of lockdown on air quality in Maharashtra from January 2020 to July 2020. It was reported that the $PM_{2.5}$ mass concentration was reduced significantly after lockdown as compared to the pre-lockdown period. The 3-day moving average was used to clarify and observe an accurate trend by smoothening the daily fluctuations. It is also useful in working out the average variations across a longer period, and the 3-day moving average was selected because it gives an average of consecutive 3-days which falls in the middle of the given series and hence it can be easily compared with the actual trend (Kowalska *et al.*, 2019). 3-day moving average showed the normalized trend of the $PM_{2.5}$ mass concentrations over all the periods. From the graphs, it is clear that the trend fluctuates, however, overall $PM_{2.5}$ concentration had decreased in the lockdown periods.

The quantitative comparison was made to get more insight into the variation in different pre-lockdown and lockdown periods across four sites. A significant impact of lockdown was observed at the selected sites as shown in Fig. 10. The normality of the data was tested using the standard Shapiro–Wilk test and the data was found to be normal, following which a students' t-test was performed to compare the $PM_{2.5}$ average concentration in the pre-lockdown and lockdown period. In Mahabaleshwar site, the pre-lockdown period mean was 33 µg m^{-3}, whereas except

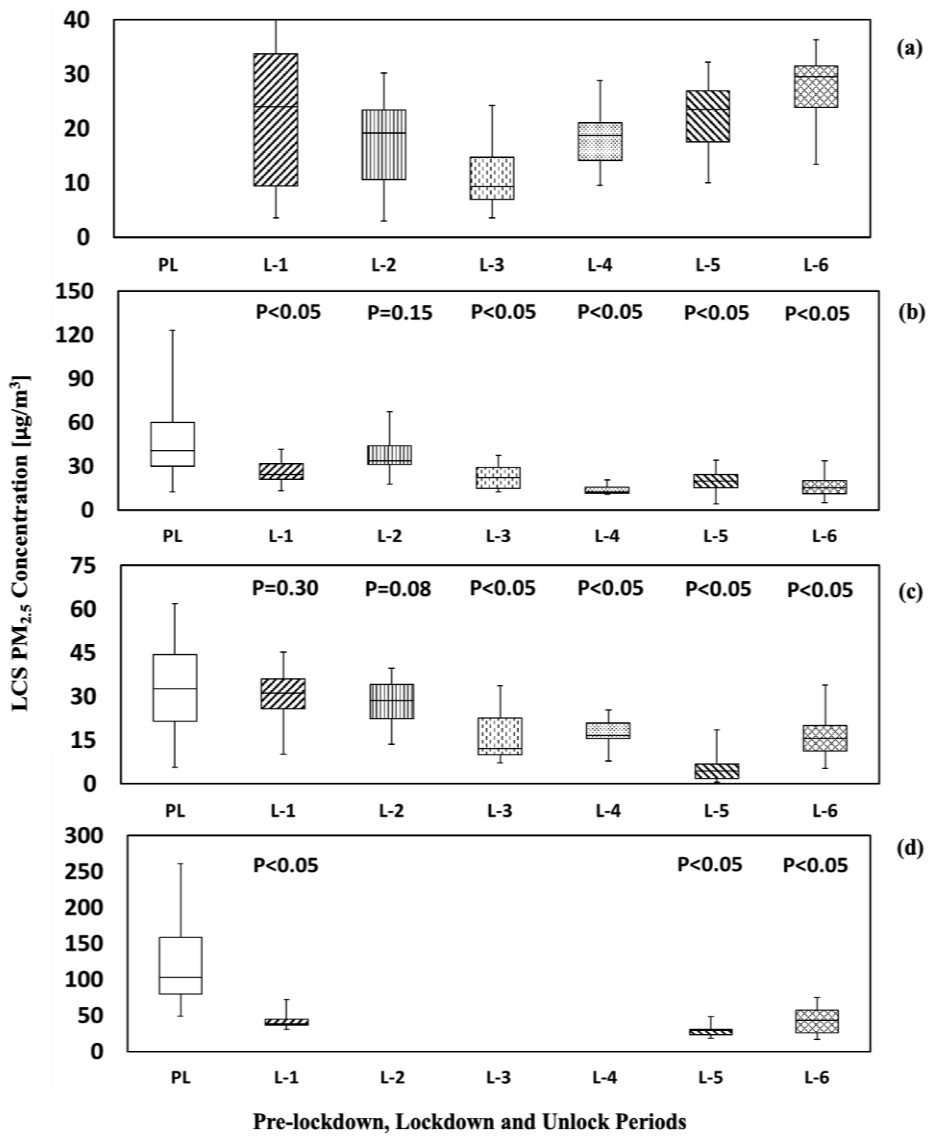

Fig. 10. Difference in variation of $PM_{2.5}$ concentration across unlock and six lockdown periods at (a) Kashmir (b) Bhopal (c) Mahabaleshwar (d) Rohtak sites.

lockdown-1 (30 µg m^{-3}, *p*-value = 0.30) and lockdown-2 (28 µg m^{-3}, *p*-value = 0.08) the p-values were less than 0.05 which indicates that lockdown-1 and 2 had no significanty effect on $PM_{2.5}$ concentration. In the Bhopal site, the pre-lockdown period mean was 45 µg m^{-3}, whereas, except lockdown-2 (38 µg m^{-3}, *p*-value = 0.15) the p-values were below 0.05 which means that there is a significant difference in mean concentration with respect to pre-lockdown mean $PM_{2.5}$ concentration. In the Rohtak site, the sensor was not operated in lockdown-2 to lockdown-4 period. The rest of the data were compared with the pre-lockdown period, and a significant effect of lockdown was observed as in the pre-lockdown period the mean $PM_{2.5}$ mass concentration was 119 µg m^{-3} whereas in rest of the lockdown mass concentration value was decreased significantly ($p < 0.05$). One of the major reasons for the significant difference in observed mass concentration in all sites is the different activities were restricted during the lockdown period and later restarted phase-wise. This situation already impacted fuel consumption as Jain and Sharma (2020) mentioned that India's fuel consumption declined by nearly 60–70%.

A time series plot of the 1-hour averaged Particulate matter ($PM_{2.5}$) mass concentration of four regional sites was plotted for pre-lockdown and six lockdown periods (Supporting Information Fig. S1). 1-hour averaged $PM_{2.5}$ mass concentration and ± one standard deviation for the day were considered to analyze the time-series graph. The diurnal variation of $PM_{2.5}$ mass concentration was observed at all four sites. Generally analyzing data on a particular day, two peaks were observed during the morning and evening hours. This trend was observed due to traffic rush in these durations; however, more accurate information about source emissions can be achieved by source apportionment of sensor location. During lockdown due to the restriction of major activities, the $PM_{2.5}$ mass concentration variation was not varying significantly during the daytime and in that duration, the mass concentration was almost constant.

3.4 Mass Mean Diameter (MMD)

After discussing and comparing $PM_{2.5}$ mass concentration, mass mean diameter was analysed for pre-lockdown and for six different lockdown duration. As discussed earlier, in the pre-lockdown period, all the anthropogenic activities were operating normally, whereas, in lockdown-1 and 2, everything was restricted apart from the necessary items. $PM_{2.5}$ was calculated based on the number of particles of various sizes (0.3, 0.5, 1.0 and 2.5 µm) observed by the low-cost sensor at all sites. In the calculation of mass mean diameter (MMD), the quantity averaged is the diameter, but it is weighted according to its mass contribution to the total mass of particles. Therefore this particular value of mass mean diameter can explain the mass contribution variation in the pre-lockdown and lockdown period. From the graphs (Supportive Fig. S2), the difference between pre-lockdown and six lockdown periods can be observed. In almost every site, MMD value was reduced in lockdown periods compared to the Pre-lockdown period; this actively demonstrates a significant lockdown effect. In the Rohtak site, the MMD value in the pre-lockdown period was 1.08 µm which reduced to 1.06 µm in the lockdown periods, indicating an overall reduction in the number of particle in every size bins. The particular reason for this circumstance is the observed reduction in $PM_{2.5}$ mass concentration. In the Bhopal site, a drastic change observed in the MMD value as it reduced to 0.86 µm from 1.00 µm. The larger particle size, between 1.0 µm and 2.5 µm, was reduced significantly in the lockdown period and MMD value drops down to 0.86 µm. In the Mahabaleshwar site, the $PM_{2.5}$ mass concentration was less compared to other sites. On this site, MMD values reduced slightly, which indicates overall reduction in the number of particles in every size bins. To sum up, everything that has been stated so far shows that the number of larger particle size reduced in all site in the lockdown period, and the MMD value was reduced in every site.

4 CONCLUSION

Four NCAP regional sites in India were selected and the sensors were installed to observe the impact of lockdown during the COVID-19 pandemic. The $PM_{2.5}$ mass concentration data from pre-lockdown periods to lockdown-6 was collected from using SASS sampler and APT Maxima sensor installed at four different sites across India. A good correlation coefficient is observed between the LCS and SASS measurement data with values of 0.70, 0.81, 0.73, and 0.67 for Kashmir, Bhopal, Mahableshwar, and Rohtak site respectively. It implies that the LCS recorded data can be used to study the impact of lockdown on the air quality of the regional sites. A significant impact of COVID-19 lockdown on air quality was observed as $PM_{2.5}$ mass concentration was reduced significantly at each site. The $PM_{2.5}$ mass concentration data recorded using LCS was compared with MERRA-2 reanalysis $PM_{2.5}$ estimated mass concentrations and the same trend was observed in the lockdown period. No significant difference between the two measurements was observed for the Kashmir, Bhopal, and Mahableshwar site. However, the LCS recorded measurments were higher compared to the estimated mass concentrations using MERRA-2 data (NMB = 1.16). It indicates that the MERRA-2 data is not entirely reliable and need some corrections for future applications. During the unlocking phase, the activities were restarted again the $PM_{2.5}$ mass concentration was increased which directly indicates that the lockdown has a significant impact on $PM_{2.5}$ mass concentration at these four regional sites in India. The study indicates that different levels of restriction on activities can impact PM pollutant concentration and indicate the activities that need to be regulated for improving the overall air quality in the regional site. The low-cost sensor had shown nearly accurate measurements when compared with the reference SASS instrument. By calibrating it with the reference SASS instrument, data accuracy can be increased, and it may prove suitable for deployment to assist the existing air quality stations in the country.

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SUPPLEMENTARY MATERIAL

Supplementary material for this article can be found in the online version at https://doi.org/10.4209/aaqr.220390

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