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Research article

Advanced statistical analysis of air quality and its health impacts in India: Quantifying significance by detangling weather-driven effects

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ABSTRACT

Air quality has emerged as a significant concern due to its direct impact on human health. Over recent decades, India has witnessed a marked deterioration in air quality due to rising anthropogenic emissions and climate change. The COVID-19 lockdown offered a unique opportunity to examine air pollutant reductions under restricted human activities. This study conducted a long-term analysis of air quality in five major Indian cities—Delhi, Kolkata, Bengaluru, Hyderabad, and Visakhapatnam—by analysing variations in $PM_{2.5}$, PM_{10}, NOx, NH_3, SO_2, CO, and O_3, incorporating a de-weathering strategy to isolate meteorological influences. In Delhi, we observed significant reductions in PM_{10} (92.50–136.70 μg/m³), NOx (62.13–151.91 ppb), and CO (0.53–0.88 mg/m³), which shifted health risks from the 'extreme' to 'low' category. Visakhapatnam also experienced notable declines in NOx levels (7.50–17.13 ppb). Conversely, Hyderabad exhibited no significant reductions, and AQHI increased (+0.97) due to rising NOx concentrations. Ozone concentrations showed a significant increase across cities, attributed to VOC-limited effects. The analysis revealed that meteorological variability and long-range transport of airmass played critical roles in shaping pollutant concentrations. These findings highlight the complexity of urban air quality dynamics and underscore the benefits of emission reductions for public health.

1. Introduction

India is one of the most populous countries in the world, with a population of approximately 1.4 billion people [1]. Over the past two decades, this population has experienced substantial growth, resulting in a density of 481 individuals per km^2, positioning India among the most densely populated countries worldwide. In addition to its vast population, India has emerged as the fifth largest economy in the world [2]. However, this rapid growth and development come at a high environmental cost, as escalating air pollution has become a pressing concern, affecting the health and quality of life of millions across the country. Major contributors to air quality

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degradation in India include biomass burning, construction activities, emissions from thermal power plants and industries, vehicle exhaust, mining operations, dust storms, and a variety of other natural and human-induced sources [3–9]. Air quality in India's urban setups is consistently worse than in rural areas, with many metros enduring poor air quality year-round ([10]; Khaiwal et al., 2023; [11–13]) and long-term studies conducted in various Indian cities have highlighted elevated concentrations of aerosols, particulate matter, and other gaseous pollutants ([14–16]; Moorthy et al., 2013; [17]). In recent years, elevated pollution concentrations in major urban areas of India have posed significant risks to public health, with numerous studies highlighting adverse impacts on respiratory and cardiovascular health [4,18].

Globally, concerns over the detrimental effects of poor air quality on human health have intensified, emphasizing the worsening air quality predominantly driven by increased anthropogenic activities and dependence on conventional energy resources [19–23]. The COVID-19 pandemic further exacerbated this crisis, creating both a direct health emergency and compounding respiratory vulnerabilities [24–29]. According to the United Nations, millions of lives have been lost due to COVID-19, with the pandemic having profound and lasting effects on respiratory health [30]. India has also experienced a major health crisis due to the COVID-19 pandemic since the beginning of 2020. The first case of COVID-19 was reported in India on January 30, 2020, prompting the implementation of a nationwide lockdown on March 25, 2020, which was extended in three phases until May 31, 2020 [31,32]. As the pandemic unfolded, the Government of India faced the challenge of balancing public health concerns with economic requirements. Consequently, from June 1, 2020, a gradual relaxation of restrictions was introduced, leading to multiple unlocked phases and a gradual return to pre-COVID-19 life [26,27,33]. In response to a major surge in COVID-19 cases in 2021, several cities in India remained in lockdowns during May and June 2021 [24]. However, unlike in 2020, anthropogenic activities were not entirely halted in 2021. Similar to India, numerous other nations also implemented lockdown measures, leading to an abrupt halt in emissions from various anthropogenic sources. This created a unique opportunity to assess the impact of reduced human activities on air pollution and offered valuable insights into the potential benefits of such interventions for human health.

Several studies have discussed the change in the concentration of air pollutants during the lockdown periods ([13,26–28,34–39], 204). Sharma et al. [37] and Singh and Chauhan [13] have shown the changes in air quality in major cities of India using ground and satellite data. Both studies compared the previous years' concentration of air pollutants (before 2020) to assess the change during 2020. Singh et al. [38] have shown the diurnal variation in the air quality parameters during the 2020 lockdown period. These studies calculated the statistical mean values and did not discuss the weather impacts. Further, without using statistical analyses and considering the same period in different years, Garg et al. [40] simply compared mean air pollutant concentrations in pre-lockdown, during-lockdown, and post-lockdown periods in the same year for multiple cities across India. Their findings revealed that during the COVID-19 lockdown, several cities experienced significant reductions in pollutants such as PM_{10}, $PM_{2.5}$, and NO_2.

Similar studies were also done for major cities across the globe. Chauhan and Singh [35] have shown the change in air quality due to the COVID-19 lockdown across the major cities of the world. They discussed only particulate matter concentration variations and

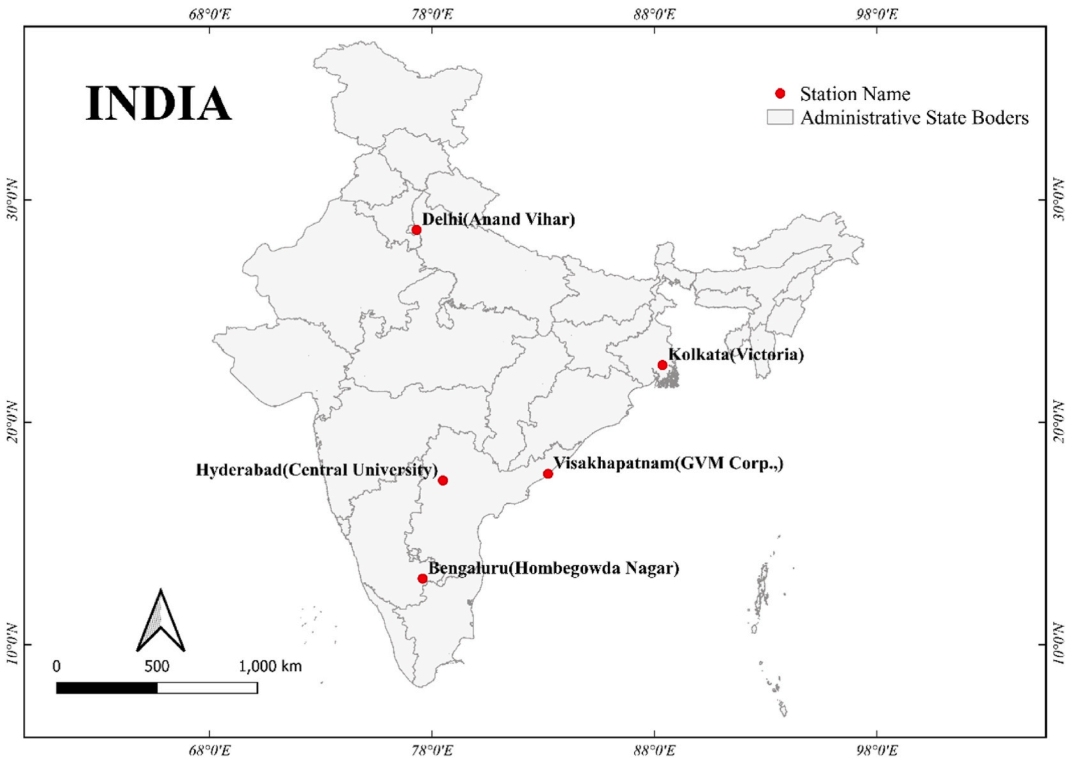

Fig. 1. Map emphasizing the geographic focus of the research.

compared the monthly mean values from 2017 to 2020. Sulaymon et al. [41], while using statistical methods (ANOVA and Shapiro-Wilk) to examine the differences in air pollutant concentration between the pre-lockdown, during-lockdown, and post-lockdown periods in China, did not consider the same period in different years and the impact by weather. The results indicated that $PM_{2.5}$ and NO_2 experienced significant reductions during the lockdown period, while PM_{10}, SO_2, and CO did not exhibit significant reductions in both parametric and non-parametric tests. Krecl et al. [25] have discussed the impact of reduction of human activities on NOx emissions in São Paulo during COVID induced lockdown. Singh et al. [27] carried out the discussed the impact of COVID-19 lockdown on the particulate matter concentration in Delhi and Riyad. Singh et al. [29] have discussed the impact of the COVID-19 lockdown in major cities of south Asia. Likewise, without using statistical analyses and considering the different periods in the same year, Adams [42] simply compared the mean air pollutant concentration in Ontario. Their findings revealed that during COVID-19, several areas experienced a significant reduction in pollutants such as $PM_{2.5}$, NO_2, NO_x, and O_3. However, the downtown Toronto region witnessed a notable increase in O_3 concentration. Another study by Jephcote et al. [43] simply examined the daily median values of key pollutants during the lockdown period in the UK and compared them with data from the equivalent time frames in the preceding three years. However, these studies are limited in accounting for the impact of weather conditions before, during, and after the lockdown over the pollutants (Table S1). Weather variations significantly affected pollutant concentrations, potentially altering the associated health benefits of their reduction. To address this gap, we performed a de-weathering analysis using meteorological variations to evaluate the impact lockdown on pollutant concentrations. The results of this analysis were then used for an Air Quality Health Analysis which provided the health benefits of reduction of pollutant concentrations on human health. Also, previously no such study has been conducted in India. The significance of this investigation lies in the comprehension of the efficacy of lockdown measures in alleviating air pollution. The findings obtained from this study will serve as a foundation for developing strategies aimed at improving air quality and safeguarding public health in all urban cities with very dense populations. By addressing the crucial issue of air pollution, this research contributes to the broader scientific understanding of the unintended environmental implications by the COVID-19 lockdown and lays the groundwork for future initiatives focused on improving air quality in these megacities.

1.1. Study area

As illustrated in Fig. 1, the study area comprises five major cities in India: Delhi, Kolkata, Bengaluru, Hyderabad, and Visakhapatnam. All these cities, except Visakhapatnam (with a population of 2 million), have populations exceeding 10 million [44]. These cities serve as significant economic hubs, attracting a large migrant workforce from across India. Consequently, during the COVID-19 lockdown, a substantial migration was observed in these cities as major industries and workplaces temporarily shut down [38]. Due to their geographic locations, the weather conditions of these cities very significantly in comparison to each other.

India generally experiences four distinct seasons. Summer (March to June) is the hottest period, with temperatures often exceeding 35 °C across much of the country and sometimes surpassing 45 °C [45]. Monsoon (July to September) brings significant rainfall with the onset of the Indian monsoon. Post-monsoon (October and November) features transitional weather [46]. Winter (December to February) ushers in cooler temperatures, especially in northern regions where they can drop below 10 °C, while southern areas remain milder.

Specific climate conditions vary by city. Delhi experiences extreme seasonal temperatures (up to 45 °C in summer, below 10 °C in winter). Kolkata has hot, humid summers, mild winters, and abundant monsoon rainfall. Bengaluru, situated at a higher elevation, enjoys a moderate climate with rainfall from both southwest and northeast monsoons [46]. Hyderabad experiences hot, dry summers, mild winters, and moderate monsoon rains. Coastal Visakhapatnam has a tropical climate with hot summers, mild winters, heavy monsoon rains, and occasional cyclones [46].

2. Material and methods

2.1. Data Selection

In this study, seven pollutants were taken into consideration, $PM_{2.5}$, PM_{10}, NO_x, NH_3, SO_2, CO, and O_3. The ground-monitored data of these pollutants were obtained from the official website of the Central Pollution Control Board (CPCB) at (https://app.cpcbccr.com/AQI_India/). The data for Delhi, Kolkata, Bengaluru, Hyderabad, and Vishakhapatnam was respectively collected from Anand Vihar station, Victoria station, Hombegowda Nagar station, Central University station, and GVM Corporation station. In this study, we collected five years' worth of data spanning from 2018 to 2022. Furthermore, we conducted a comparison between the data captured before the lockdown period (March 11, 2020 to March 24, 2020) and during the lockdown period (March 25, 2020 to April 07, 2020) in the same year and in the different years (03/25 to 04/07 in 2020 versus 03/25 to 04/07 in 2018, 2020, 2021 and 2022). The concentration data is obtained at a temporal resolution of 24 h with maximum values for each location provided in the data file for each individual station. There are few limitations associated with the current study. First, there we have only included one observation stations for each city. In the current study, we are using only one station data for each mega city. Also, due to data limitation, we have done de-weathering analysis only for three cities.

2.2. Trajectory analysis

To investigate the impact of the transport of the air pollutants from long range and near-by regions, we used HYSPLIT backward airmass trajectory analysis. We used GDAS meteorology which is avaiable at $1^\circ \times 1^\circ$. The details regarding the HYSPLIT airmass trajectory model are discssed by Stein et al. [47]. The model accesses meteorological files based on user input and generates the airmass trajectory. For each trajectory, the model was run in the backward direction for 72 h, with daily analyses providing a new trajectory every 24 h, starting at 1:00 a.m. Analyzing back-trajectories over a duration of 48–72 h is considered a suitable time frame for assessing the impact of transboundary transport [48]. The trajectory path reveals the starting location of the airmass, providing insight into its source region. Additionally, the trajectory's path offers information about the regions influenced along its course.

2.3. Statistical analysis

A rigorous statistical analysis was conducted to evaluate temporal trends and inter-city variations in pollutant concentrations, focusing on $PM_{2.5}$, PM_{10}, NO_x, NH_3, CO, and O_3. Prior to analysis, missing data were imputed using the K-Nearest Neighbors (KNN) algorithm, which estimates missing values based on the proximity of similar observations, ensuring a complete dataset for accurate evaluation [49]. Outliers, defined as extreme values deviating significantly from the main data distribution, were treated using Tukey's method, identifying data points outside 1.5 times the interquartile range for careful examination and adjustment where necessary [50]. Temporal trends were quantified using the coefficient of determination (R^2) derived from linear regression models to assess the proportion of variance explained by time, while paired sample p-tests were applied to determine the statistical significance of changes in pollutant concentrations between two time periods, with a significance level set at $p < 0.05$ [51]. To complement the numerical results, heatmaps were generated to visualize pollutant variations across cities and time, providing intuitive insights into spatial and temporal dynamics. All statistical analyses were performed using SPSS software (version 16, SPSS Inc., Chicago, IL, USA), and visualizations were created in Python using the seaborn library. This integrated approach, incorporating robust outlier treatment, advanced statistical tests, and high-quality visual analytics, ensured the reliability, accuracy, and scientific rigor of the findings [52]. All the necessary details regardin the analysis are given in supplementry text S1 and Table S2.

2.4. De-weathering analysis

We used Indian Meteorological Department [53] meteological data for our de-weathering process. The de-weathering process, as described by Ropkins and Tate [54] and Solberg et al. [55], involves applying a generalized additive model (GAM) to air pollutant data to normalize concentrations and remove the effects of meteorological variables. This approach smooths the data, reducing the impact of weather variability and daily fluctuations. GAM is a widely used statistical technique that allows for the examination of complex relationships between multiple independent variables and the dependent variable. By incorporating non-linear relationships and smoothing functions, GAM provides a flexible modelling framework that can capture intricate data patterns. In this study, we used the mgcv package [56] in R to implement the de-weathering process. Six key parameters—air temperature, relative humidity, wind velocity, wind direction, air pressure, and day of the year—were included in the model, while solar radiation and rainfall were excluded due to data limitations. The choice of Generalized Additive Model (GAM) in this study is motivated by its flexibility in capturing nonlinear relationships, its interpretability, and its computational efficiency. GAM's ability to represent relationships as smooth functions makes it particularly suitable for modelling the complex interactions between climatic factors and pollutant concentrations. While alternative methods such as Random Forest or Support Vector Machines are available, they often lack the transparency provided by GAM, which is critical for understanding and communicating the influence of climatic variables. Future research could expand on this work by comparing GAM's performance with other modelling approaches to further evaluate its robustness and accuracy.

2.5. Health impacts

The discernible effects of atmospheric pollutants on human health are manifest. Variability in the concentration of particulate matter and trace gases within the atmosphere may precipitate modifications in human health. The computation of both air quality and health advisories can be facilitated through the utilization of the Air Quality Health Index (AQHI). Given the absence of a specifically developed AQHI for India, we adopted the AQHI for total mortality derived from the 24 h average concentration of $PM_{2.5}$ and NO_2, along with the 8 h maximum concentrations of O_3 in China, as per the following equation [57]:

$$AQHI = \left(\frac{10}{13.2}\right) \times 100 \times [exp(0.000187 \times PM_{2.5}) - 1 + exp(0.000675 \times NO_2) - 1 + exp(0.000119 \times O_3) - 1]$$

This index serves as the basis for formulating health advisories directed toward both vulnerable individuals and the general public. For example, AQHI values falling below 3 signify 'low health risk' while those within the 4–6 range indicate a 'moderate health risk'. Values between 7 and 10 denote a 'high health risk,' and values exceeding 10 points to an 'extremely high health risk'.

3. Results

3.1. Variability of air quality at major cities in past five years

In Fig. 2, we have shown the daily mean concentration of $PM_{2.5}$ at all five cities. In Delhi, $PM_{2.5}$ and PM_{10} concentrations ware higher consistently in January, November, and December, exceeding 500 μg/m^3 on most days (Fig. 2, S1). However, from February to June and October, the concentration was lower, ranging between 300 and 500 μg/m^3. In Kolkata, the variations in both $PM_{2.5}$ and

PM_{10} are like Delhi however here the concentration was lower in comparison to Delhi. In Bengaluru, particulate matter concentration was more than 140 μg/m^3 from January to March and November to December and during other months the daily mean values were lower and a similar patten was also observed in Hyderabad. At Vishakhapatnam, the concentration was higher (more than 240 μg/m^3) during January to March and October to December. However, in other months the concentration varied between 160 and 240 μg/m^3. This was significantly different than other cities as during monsoon months, the concentration of particulate matters were distinctly lower in all other cities. The daily mean variations of all other parameters are shown in Figs. S1–S6. Also, the missing data is shown with white colour in the figures.

The nationwide lockdown implemented in March 2020 and various anthropogenic activities were affected. In Fig. 3, we have shown the temporal variation of daily mean concentrations of pollutants. The particulate matter ($PM_{2.5}$ and PM_{10}) decreased just after the implementation of lockdown in Delhi however much variations were observed at other cities (Fig. 3a and b). While comparing these changes with other years (2018-19, 2021–2022; Fig. 4a and b), we observed lower mean and median values in lockdown period of 14 days in 2020 in all cities except Kolkata. However, the variations were lower especially in higher concentrations.

Due to its limited atmospheric residence time, NO_x variation is directly influenced by anthropogenic emissions. The NO_x concentration was very highest in Delhi, followed by Kolkata, Vishakhapatnam, Bengaluru and Hyderabad. On comparing the month-wise variation, higher concentration was observed during November, December and January and moderate concentrations were recorded during February, March and October. The remaining months had relatively low concentrations. This patten was observed in all cities expect the Vishakhapatnam. Here lower values were observed during the May and November. These variations indicated that the source of emission in Vishakhapatnam were different and hence the seasonal variation was lower however in other cities the emission sources had seasonal variation which were often due to the natural sources like higher dust and crop burning activities followed by the significant variation in the meteorology. Due to the lockdown, we observed significant fall in NO_x in all cities expect Hyderabad (Fig. 3c) and hence the mean and median values in lockdown periods were smaller in Delhi, Kolkata, Bengaluru and Vishakhapatnam (Fig. 4c) however the mean and median values were higher in Hyderabad which could be due to more natural emissions rather than the anthropogenic.

Furthermore, distinct patterns are observed across different years and cities in the temporal variations of SO_2 concentrations. In Delhi, during April, May, June, and August exhibited lower SO_2 concentrations were observed during 2018 below 40 μg/m^3, while concentrations in the remaining months surpassed this limit. A similar variation was also observed in 2019, 2021, and 2022, where peak concentrations predominated from February to May, and moderate concentrations were recorded in October, November, and December, with the intervening months showcasing lower daily SO_2 concentrations. The variations in Kolkata were similar to Delhi except during 2021 and 2022 when higher shifts were observed during monsoon months. In Bengaluru, during 2019, from August to December, higher concentration was observed and in 2020, not much variation were observed in daily mean values. In Hyderabad, the seasonal and year by year variations were prominent and similar variations were observed in Vishakhapatnam. Due to the lockdown, no major variation was observed in daily values while comparing pre and lockdown period (Fig. 3d) in SO_2 concentration however, the mean and median values were declined except Bengaluru where higher mean and median values were higher during lockdown. Similar variations were also observed in the concentration of the NH_3 and CO at all major cities. During the lockdown, pollutant concentration varied across cities. So, Bengaluru experienced an increase in CO concentrations. However, NH_3 concentrations remained consistent with pre-lockdown concentrations. In Hyderabad, O_3 concentrations decreased compared to previous years. Visakhapatnam saw no

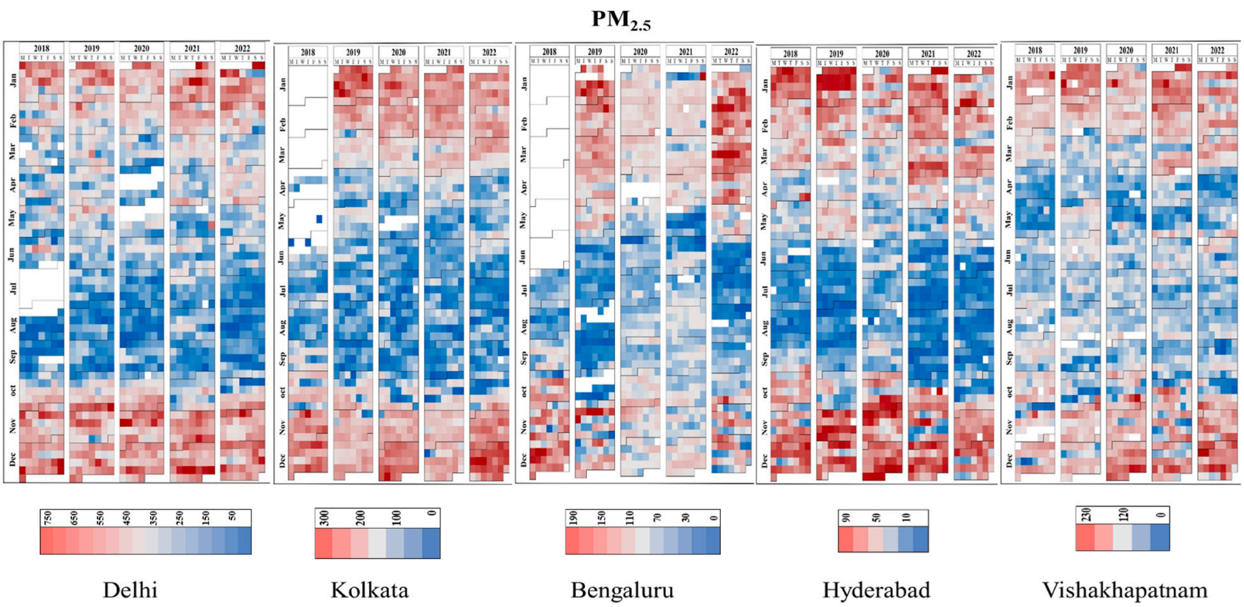

Fig. 2. Daily mean values of $PM_{2.5}$ in Delhi, Kolkata, Bengaluru, Hyderabad and Vishakhapatnam for 2018, 2019, 2020, 2021, and 2022.

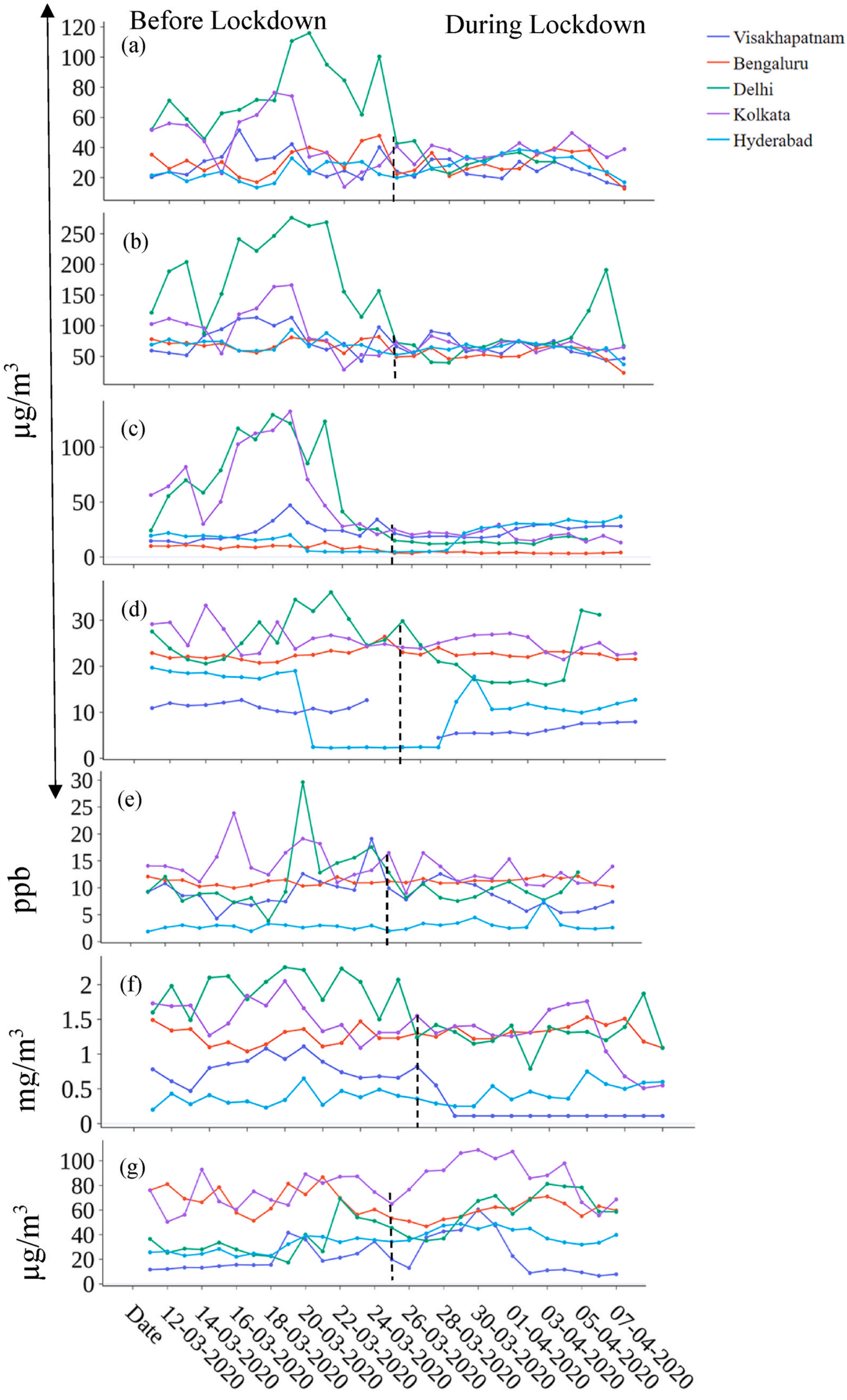

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Fig. 3. The fluctuation of (a) $PM_{2.5}$, (b) PM_{10}, (c) SO_2, (d) NH_3, (e) NO_x, (f) CO and (g) O_3 in 14 days before to lockdown and 14 days following lockdown.

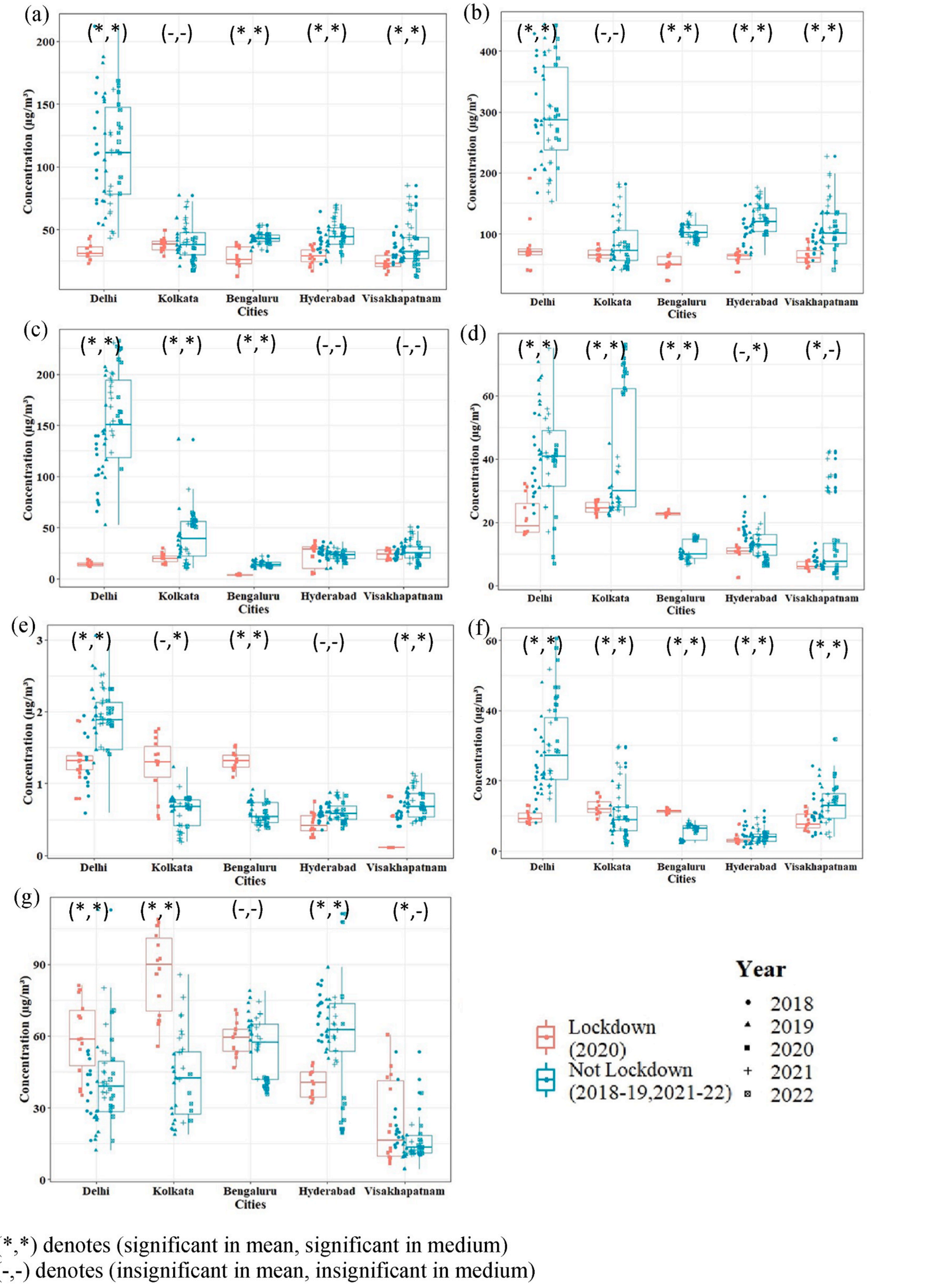


Fig. 4. (a) $PM_{2.5}$, (b) PM_{10}, (c) NO_x, (d) NH_3, (e) SO_2, (f) CO and (g) O3 concentrations throughout a variety of year.

initial change in CO during the first lockdown month, but observed a decrease afterward, with O_3 concentrations staying moderate.

In Delhi and Kolkata, lower ozone concentrations were observed in January, February, March, October, November, and December, with occasional spikes in other months. In Bengaluru and Hyderabad, higher ozone concentrations were observed during January to May with moderate concentrations during November and December and lower during other months. In Vishakhapatnam, higher concentrations were observed during January, February, November and December followed by October with moderate and lower in other months. The ozone concentration decreased for one or two days just after the implementation of the lockdown (Fig. 3g) and later peaks were observed and while comparing with other years, the mean and median values were higher in all major cities expect where it was lower during the lockdown period of 2020. The analysis of pollutants indicated a clear distinction between the air pollution concentrations during the nationwide lockdown in 2020 and other years. So, it is required to further carry out statistical analysis before the de-weather of the pollutant to higher the impact of lockdown and role of the natural sources.

3.2. *Statistical analysis of variation in pollutant concentrations*

Following a comprehensive analysis, it was observed that there was a notable decrease in both the mean and median concentrations of specific pollutants during the lockdown period compared to other periods in the same year or the same period in different years, as illustrated in Table 1, Table 2, and Figs. 3 and 4.

3.2.1. *Impact of lockdown on particle pollution*

In Delhi, the mean concentrations of $PM_{2.5}$ and PM_{10} plummeted significantly during the lockdown period comparing to other periods (before lockdown) in 2020 (or the same period in different years (2018, 2019, 2021, 2022)), with a 56 % reduction for both pollutants (Table 1, Figs. 3 and 4). Similarly, the median values also showed a dramatic decrease of 54 % and 55 % for $PM_{2.5}$ and PM_{10}, respectively, in 2020 (Table 2). These findings indicate a substantial improvement in air quality due to fall in particle pollution during the lockdown, affirming the detrimental influence of regular human activities in Delhi.

Nevertheless, the situation in Kolkata presented a contrasting scenario. Despite various analyses, both the mean and median concentrations of $PM_{2.5}$ and PM_{10} exhibited negligible reductions. This implies that the sources responsible for PM pollution in Kolkata may not have been effectively curtailed during the lockdown period and these are not local sources [13].

In Bengaluru, the mean concentrations of $PM_{2.5}$ and PM_{10} showed significant reductions, ranging from 13 % to 25 %, but the significant reduction for median (31 %) only for PM_{10}. During the 2020 lockdown, both the mean and median concentrations of $PM_{2.5}$ and PM_{10} showed a decrease compared to the same period in other years (Fig. 4).This indicates a positive influence of the lockdown on particle pollution in Bengaluru, despite the city's typically lower pollutant concentrations compared to others.

Hyderabad showed a mixed picture, with significant reductions in mean concentrations of PM_{10}. However, the mean and median concentration of $PM_{2.5}$ interestingly increased by 21 % and 23 % in the same-year analysis suggested that there is no major impact of lockdown on fine particle pollution. During the same period in different years, the pollutants concentration showed a significant decrease in both mean and median values of PM_s (Fig. 4). In Visakhapatnam, there were significant reductions of PM_s concentrations in both period analyses (except for those medium values with insignificance in the same-year analysis). These reductions range from 26 % to 27 %.

Fig. 3a and b clearly illustrate a remarkable decrease in $PM_{2.5}$ and PM_{10} concentrations throughout the lockdown period as compared to preceding times. Furthermore, it is evident that Delhi initially experienced notably higher $PM_{2.5}$ and PM_{10} concentrations compared to other cities. In summary, the lockdown period resulted in significant reductions in particulate matter concentration across these cities, albeit with a few exceptions. These findings underscore the profound influence of human activities on particle pollution.

Table 1
Comparative analysis of mean pollutant concentrations before and during COVID-19 lockdown in 2020.

City	Period	PM2.5	PM10	NOx	NH3	SO2	CO	O_3
Delhi	Before	75.49	178.16	68.57	27.29	13.27	1.93	39.08
	During	32.88	78.77	14.15	21.59	9.65	1.29	59.27
	Variation (%)	**-56***	**-56***	**-79***	**-21***	**-27***	**-33***	**52***
Kolkata	Before	42.78	91.84	70.88	25.47	15.62	1.52	75.51
	During	37.86	66.83	19.99	24.65	12.55	1.24	86.59
	Variation (%)	**-11**	**-27**	**-72***	**-3***	**-20**	**-18***	**15***
Bengaluru	Before	32.34	69.77	9.09	22.73	10.84	1.22	67.62
	During	28.28	52.47	3.82	22.62	11.30	1.32	58.86
	Variation (%)	**-13***	**-25***	**-58***	**-1***	**4***	**8***	**-13**
Hyderabad	Before	23.94	69.50	11.25	10.19	2.79	0.39	31.47
	During	29.05	61.66	22.90	9.81	3.21	0.45	40.37
	Variation (%)	**21***	**-11***	**104***	**-4**	**15**	**16**	**28***
Visakhapatnam	Before	32.22	87.31	27.17	11.14	9.60	0.85	23.78
	During	23.97	63.31	23.29	6.29	8.32	0.19	24.52
	Variation (%)	**-26***	**-27***	**-14**	**-44***	**-13**	**-77***	**3***

*Denotes significant difference (p-value <0.05).

Table 2
Comparative analysis of median pollutant concentrations before and during COVID-19 lockdown in 2020.

City	Period	PM2.5	PM10	NOx	NH3	SO2	CO	O3
Delhi	Before	68.34	156.05	68.65	26.65	11.05	2.04	35.04
	During	31.19	70.29	13.52	18.78	9.18	1.32	58.69
	Variation (%)	**-54***	**-55***	**-80***	**-30***	**-17**	**-36***	**67***
Kolkata	Before	35.23	77.71	60.37	25.42	14.73	1.43	74.90
	During	38.42	65.18	19.90	24.57	11.92	1.31	89.86
	Variation (%)	**9**	**-16**	**-67***	**-3**	**-19***	**-9***	**20***
Bengaluru	Before	33.48	72.61	8.89	22.43	10.72	1.20	65.49
	During	25.87	50.11	3.62	22.68	11.30	1.32	59.48
	Variation (%)	**-23**	**-31***	**-59***	**1**	**5**	**10**	**-9**
Hyderabad	Before	23.45	67.095	10.445	9.88	2.915	0.36	33.08
	During	28.96	63.78	28.72	10.775	2.845	0.42	40.455
	Variation (%)	**23***	**-5**	**175***	**9**	**-2**	**17**	**22***
Visakhapatnam	Before	32.54	95.88	24.19	10.89	8.61	0.88	20.05
	During	23.24	60.02	23.68	5.85	7.59	0.11	16.40
	Variation (%)	**-29**	**-37**	**-2**	**-46***	**-12**	**-87***	**-18**

*Denotes significant difference (*p*-value <0.05).

3.2.2. Changes in the concentrations of trace gas

In Delhi, the mean and median concentrations of NO_x plummeted significantly in the same year by 79 % and 80 %, respectively (Tables 1 and 2). This substantial drop can be attributed to the reduced vehicular and industrial emissions during the lockdown. However, the lockdown's impact was less prominent on NH_3, SO_2, and CO, with reductions ranging from 21 % to 36 % (SO_2 was not significant at the medium concentration). Interestingly, O_3 concentrations exhibited a notable increase of 52 % and 67 % in mean and median values, respectively. In the different year analysis, NO_x, NH_3, SO_2, and CO concentrations (both mean and median) exhibited a significant decrease. Conversely, O_3 concentrations significantly increased (Fig. 4).

In Kolkata, the mean and median NO_x and CO concentration significantly decreased in the same year by 72 % and 67 % as well as 18 % and 9 %, respectively. For other gaseous pollutants, the city saw a variation of significant reduction. Meanwhile, the city witnessed a rise in both mean and median O_3 concentrations, which could be attributed to reduced NO_x concentrations. In the same-year analysis, NO_x and NH_3 concentrations displayed a notable reduction in both mean and median values during the lockdown. In the case of SO_2, while only the median showed a significant increase. Both CO and O_3 saw a marked rise in their concentrations (mean and median) (Fig. 4).

In Bengaluru, the lockdown resulted in significant reductions in mean NO_x concentration (58 %) and median NO_x concentration (59 %) in the same year. However, changes in NH_3, SO_2, and CO was less pronounced. Interestingly, O_3 did not show a significant decrease in the mean and median concentrations. Compared to different years, Bengaluru experienced a pronounced drop in the concentration of NO_x (both mean and median) during the lockdown. In contrast, NH_3, SO_2, and CO concentrations surged significantly. Although there was an observed rise in O_3 concentrations, it did not reach statistical significance for the medium values (Fig. 4).

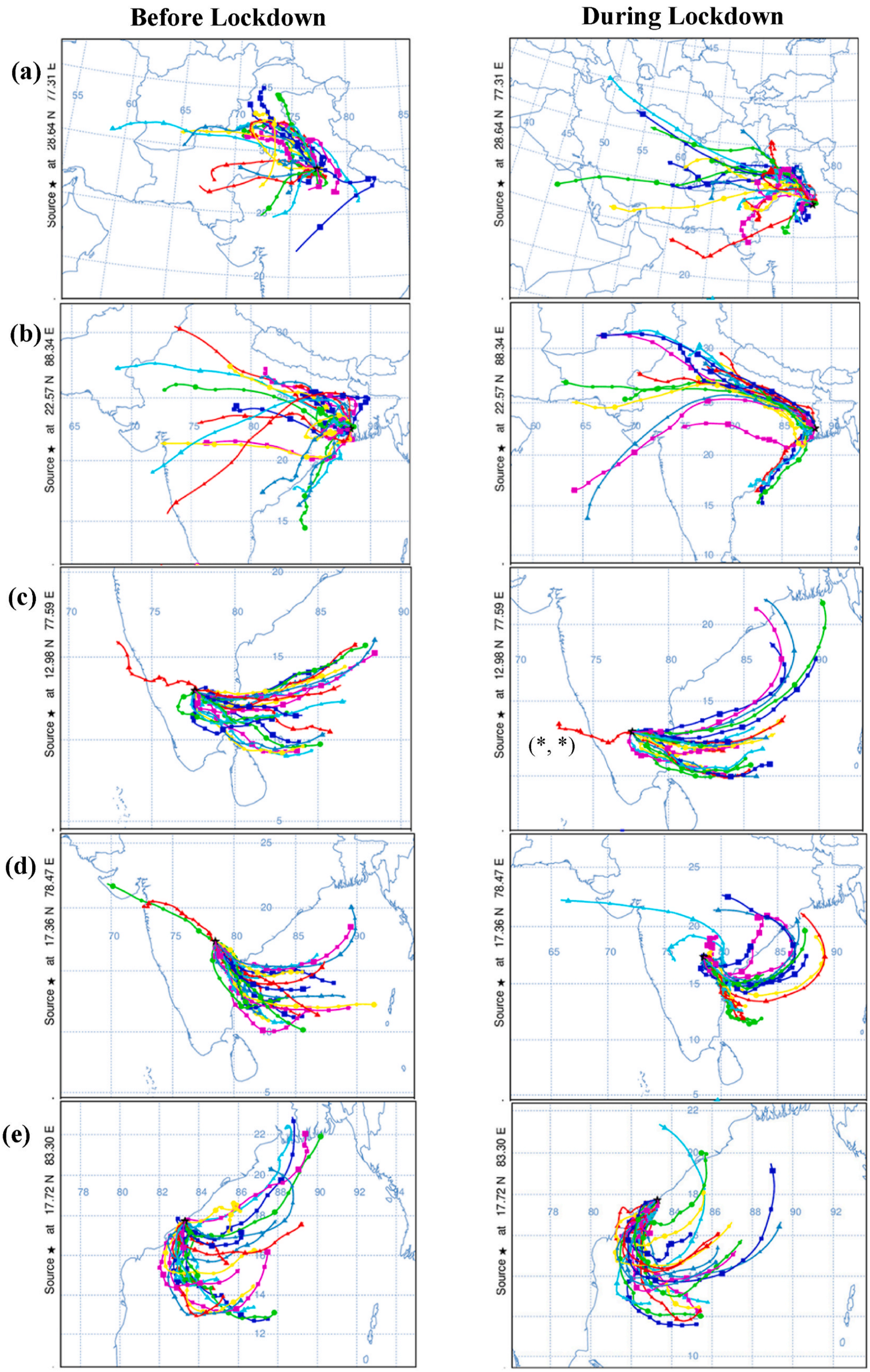
In Hyderabad, significant enhancement (ranging from 104 % to 175 %) were observed in NO_x during the same-year analysis along with significant increases of O_3 (28 % and 22 %) for both mean and median values. In the different-year analysis, CO displayed significant reductions, and O_3 showed significant increases for both mean and median values. Meanwhile, in Visakhapatnam, the same-year analysis revealed significant reductions in NH_3 and CO (approximately 40 % and 80 %), while in the different-year analysis, both SO_2 and CO showed significant reductions for both mean and median values.

In summary, the lockdown period has demonstrated the profound impact of human activities on various gaseous pollutants. NO_x and CO concentrations, in particular, decreased dramatically in most cities, likely due to reduced vehicular and industrial emissions, while changes in other gas phase pollutants varied across cities, indicating different local sources and dynamics. The ozone concentration have shown a increase during the lockdown period as the clear sky conditions with lower aerosols and fall in NOx concentration [58].

3.3. Influence of transport of airmass

To better understand the variability of pollutants due transport of pollutants before and during the lockdown spanning from March 11, 2020 to April 24, 2020, we have investigated the airmass trajectory. In Delhi, before the lockdown, the westerly and north-westerly airmass form Pubjab, Haryana and Pakistan were reaching Delhi along with few easterly sources (Fig. 5a). During lockdown, Iran and Iraq could be additional contributors of the airmass. These regions are major sources of dust and biomass burning pollutants. Also, Pakistan did not undergo a complete nationwide lockdown, thereby emphasizing the intricate nuances of transboundary pollution dynamic that affect the CO, and Ozone concentration in Delhi [24].

Kolkata's atmospheric conditions suggest a distinctive scenario (Fig. 5b). Prior to the lockdown, a significant portion of the airmass was coming from regions such as West Bengal and central India and minor airmass was influenced by areas like western Indo-Gangetic Plains and southern India. However, during the lockdown, the primary parcels might predominantly be significant amount of airmass was reaching from the Thar Desert, Iran and also from Arabian sea. These regions are the major source of desert dust and the long-range transport of the desert airmass affected the particulate matter and trace gas concentration [24].



(caption on next page)

Fig. 5. The Backward trajectory of the study area before and during the lockdown in (a) Delhi, (b) Kolkata, (c) Bengaluru, (d) Hyderabad and (e) Vishakhapatnam.

We observed distinct patterns in potential sources of airmass at Bengaluru's (Fig. 5c). Prior to the lockdown, the airmass was mostly originated from Bay of Bengal and the coastal stretches of Tamil Nadu. However, during the lockdown, airmass was coming from costal parts of Bangladesh and Odisha and travelled a significant distance over the ocean which affected the physical and chemical properties of the airmass and hence affected the gases pollutant concentration. The alterations in air mass trajectory elucidate the escalation observed in SO_2 and CO, consequently influencing the concentrations of ozone as well.

Hyderabad, an interesting pattern in the potential sources of air primary parcels emerges (Fig. 5d). Prior to the lockdown, a significant portion of the city's primary airmass might have been associated with regions like as the Bay of Bengal, with Gujarat potentially playing a minor role. As the lockdown took effect, change in the airmass trajectory observed and possible predominant sources such as Odisha, Madhya Pradesh, Chhattisgarh, and Maharashtra. These regions are the hotspot of most gaseous pollutants and hence significant rise in NO_x and O_3 was observed at Hyderabad. For Visakhapatnam, a major portion of the pre-lockdown air primary parcels might have been influenced by regions such as Bangladesh and West Bengal (Fig. 5e). Yet, as the lockdown progressed, there emerged a possibility of enhanced influences from Odisha and the Bay of Bengal, hinting at a potential shift in regional atmospheric circulation patterns. So, the change in airmass trajectory helped in understanding of the change especially rise in the concentration of the pollutants even the lockdown were enforced in India.

3.4. De-weathering of air-pollutant data

Due to the unavailability of a complete meteorological dataset, our analysis was limited to only three stations for de-weathering analysis of the pollutants. Table 3 presents the de-weathered data with different time periods within the same year (2020) and with the same time period but different years (2020 compared to 2018, 2019, 2021, and 2022). Nonetheless, the de-weathered data revealed distinct trends compared to the unprocessed dataset for the same stations. In Delhi, for both the same-year and different-years analysis, only the de-weathered PM_{10} (92.50 and 136.70 μg/m^3), NO_x (62.13 and 151.91 ppb), and CO (0.53 and 0.88 mg/m^3) showed a significant decrease during the lockdown period, indicating the impact of COVID-19 restrictions. It is also noteworthy that the O_3 concentration is higher which is also discussed in previous studies by Chauhan et al. [24] in India and Liu et al. [58] in China. However, in Hyderabad, there were no noticeable changes in pollutant concentrations affected by COVID-19 lockdown. As for Visakhapatnam, only NO_x shown a significant decrease during the lockdown period for same year and different-year analysis. The de-weathered $PM_{2.5}$, NH_3 and CO also have significant decrease only for different-year analysis.

When considering the impact of weather factors in Delhi, it's important to note that wind direction, pressure, and temperature significantly contribute to the variation in $PM_{2.5}$ and PM_{10} concentrations. During pre-monsoon months, due to influence of westerly winds, the dust density remains higher due to long-range transport of airmass. Moreover, pressure has a noteworthy influence on gas phase pollutants, excluding O_3 when associated with relative humidity and wind direction. Shifting focus to Hyderabad, it's essential to emphasize that wind velocity and pressure play a substantial role in shaping PM and gas phase pollutants, except for O_3 when linked to temperature. In the case of Visakhapatnam, it's worth highlighting that wind velocity and pressure hold a significant influence over PM and gas phase pollutants.

3.5. Health impacts analysis

we calculated the AQHI level for the same and different years through de-weathering analysis results (with notable significance indicated by a p-value$<$0.05). We only obtained significant decrease of NO_x in both same year and different years in Delhi and Vishakhapatnam. So, first we have calculated the AQHI based on NO_x only. For Delhi, the derived diminished AQHI value, measuring -5.75 and -13.29 for same year and different years, suggests a possible shift from the 'extreme high health risk' classification to the category of 'moderate health risk' or even 'low health risk' (Table 4). Similarly, for Vishakhapatnam, the diminishing AQHI are -1.65 and -0.72 for same year and different years. These results indicate the benefits of the reduction in the anthropogenic closures. Also, Vishakhapatnam has quite less concentration of the air pollutants in comparison to Delhi. So, even small improvement signifies be merits of the COVID-19 lockdown associated with the human health. Further, we have also calculated the AQHI values using all possible combinations of significant de-weathering analysis results for $PM_{2.5}$, NO_x and O_3 (Table 5). We obtained further diminishing

Table 3
Result of de-weathering analysis.

City	Period	PM2.5	PM10	NOx	NH3	SO2	CO	O3
Delhi	Same year	**-55.96***	**-92.50***	**-62.13***	-7.70	-1.70	**-0.88***	-2.22
	Different year	-14.22	**-136.70***	**-151.91***	-12.80	**-15.71***	**-0.53***	**26.12***
Hyderabad	Same year	1.10	-1.89	1.89	2.70	-0.77	-0.11	3.64
	Different year	-9.68	**-59.32***	**9.93***	3.97	0.47	-0.10	19.84
Visakhapatnam	Same year	-6.15	-17.39	**-17.13***	-3.28	-5.69	-0.09	-3.92
	Different year	**-20.50***	-70.08	**-7.50***	**-17.95***	-0.35	**-0.61***	-0.93

*Denotes significant difference (*p*-value <0.05).

values for Delhi and Vishakhapatnam. Even there is a significant rise in Ozone in Delhi while comparing results for different years, AQHI values still do not change much (−13.29 to −13.06). In Hyderabad, we observed an increase in AQHI (+0.97), primarily due to rising NOx concentrations, likely driven by sustained industrial activities, even during lockdown periods. These findings suggest that emission sources were not entirely halted, underscoring the critical need to adopt environmentally sustainable and renewable energy sources.

4. Discussion

This study examined the impact of lockdown measures on air quality, employing statistical analyses to compare pollutant levels during the lockdown with both other periods in 2020 and corresponding timeframes in preceding and subsequent years (2018, 2019, 2021, and 2022). These comparisons provided insights into the extent of air quality changes and their potential implications. De-weathering analysis was included to isolate the impact of lockdown-related emission reductions from meteorological effects. Based on the analysis, the reduction in human activity resulted in decreases in PM10, NOx, and CO levels in Delhi and in NOx levels in Visakhapatnam. These observations diverged from those of Garg et al. [40] and Pant et al. [59] in Delhi, where improvements in all air pollutants (PM10, PM2.5, NO2, NOx, NO, O3, NH3, SO2, CO, benzene, and AQI) were reported. Furthermore, Pant et al. [59] documented reductions in PM2.5, PM10, NO2, NH3, SO2, and CO levels during the COVID-19 pandemic in Kolkata. Nonetheless, the comprehensive statistical analysis indicated that only NH3 and CO experienced notable reductions. Significant reductions in NOx levels during the lockdown period were found across most cities. This decrease in NOx levels aligned with the drastic reduction in traffic volume during the lockdown. The de-weathering analysis (as shown in Table 3) revealed a significant difference in NOx levels in Delhi and Visakhapatnam during the lockdown compared to the same period in a different year. NOx levels in Delhi showed a significant decrease of 62.13 ppb in the same year and an even larger decrease of 151.91 ppb when compared to a different year. Similarly, in Visakhapatnam, a significant decrease in NOx levels was observed in both same-year and different-year comparisons (17.13 ppb and 7.50 ppb). Interestingly, Hyderabad exhibited a significant increase in NOx levels in the different-year comparison. Back trajectory analysis indicated that the majority of airmasses during the lockdown originated from neighbouring states, where coal power plants and coal mines were located, and also travelled over the ocean, which contributed to enhanced NOx levels [36].

Our study also observed an unexpected increase in O_3 levels in some cities during the lockdown period. This phenomenon can be explained by the complex chemistry of O_3 formation. As a secondary pollutant, O_3 is formed through photochemical reactions between NO_x and volatile organic compounds (VOC_s) in the presence of sunlight. Interestingly, the reduction in NO_x levels during the lockdown can sometimes lead to increased O_3 concentrations due to the "NO_x titration effect", as highlighted in previous studies [35,60]. Previous studies have categorized the relationship between O_3 concentration and its precursors as either VOCs-limited or NO_x-limited, with non-linear effects [61–63]. In a VOCs-limited regime, higher VOCs concentrations result in increased O_3 levels, while increasing NO_x-sensitive compounds lead to lower O_3 levels [64,65]. Thus, based on these findings, the observed average decrease in NO_x and increase in O_3 in this study area may indicate a dominance of VOCs-limited effects. In this study, the analysis of de-weathered data indicates that the changes in O_3 during the COVID-19 lockdown period were predominantly influenced by meteorological factors.

Our study reveals that while the COVID-19 lockdown led to notable reductions in pollutant concentrations due to decreased human activity, however external factors, particularly meteorological conditions, significantly influenced these levels. This is evident in Hyderabad, where the observed increase in AQHI (+0.97) suggests that ongoing industrial operations and the transport of air masses can diminish the effects of reduced local emissions, even during lockdowns. This distinctive observation underscores the critical role of weather and external pollution sources, which our de-weathering analysis seeks to address.

These findings highlight that, while temporary reductions in human activity can lead to immediate air quality improvements, the role of meteorological factors can potentially be even more pronounced. This insight is valuable for policymakers aiming to develop effective mitigation and adaptation measures that account for both anthropogenic emissions and weather patterns to achieve long-term benefits in air quality and public health (Ching and Kajino, 2020).

5. Conclusion

This study presents a comprehensive suite of analyses, encompassing both qualitative and statistical evaluations, which distinguishes it from previous research in the field that often lacked such multifaceted examination. In our comprehensive assessment, we delved into the nuanced interplay between the COVID-19 lockdown, its repercussions on air quality in several Indian cities and its health impacts. The data elucidates the significant role of transboundary pollution in dictating urban atmospheric dynamics. Leveraging de-weathered data, our findings highlighted varied trends in cities, with Delhi witnessing marked reductions in certain pollutants during the lockdown. Yet, the narrative was heterogenous across regions, underscoring the imperative for tailored strategies

Table 4
AQHI variation using de-weathering analysis (only NO_x). NOx concentration is in μg/m^3.

City	Period	NO_x	AQHI Variations (Only NO_x)
Delhi	Same Year	−116.95	−5.75
	Different Year	−285.8	−13.29
Vishakhapatnam	Same Year	−32.6	−1.65
	Different Year	−14.22	−0.72

Table 5
AQHI variation using de-weathering analysis. All pollutants concentration is in μg/m^3.

City	Period	$PM_{2.5}$	NO_x	O_3	AQHI Variations
Delhi	Same Year	55.96	−116.95	0	−6.54
	Different Year	–	−285.8	26.12	−13.06
Hyderabad	Same Year	–	–	–	–
	Different Year	–	18.88	–	0.97
Vishakhapatnam	Same Year	–	−32.6	–	−1.65
	Different Year	−20.5	−14.22	–	−1.01

in addressing air pollution. Utilizing the AQHI enhanced our understanding of health-related consequences linked to air quality variations. Intriguingly, post-lockdown AQHI values for Delhi and Vishakhapatnam suggest potential reductions in health risks, attributed to transient pollutant declines. It's crucial to note the temporal scope of our study. In essence, this study emphasizes the delicate balance of urban air quality, modulated by a spectrum of factors, both local and beyond. The lockdown period provided invaluable insights, revealing the potential of targeted interventions in significantly ameliorating air quality and associated health outcomes.

CRediT authorship contribution statement

Akshansha Chauhan: Writing – review & editing, Software, Investigation. **Guggilla Pavan Sai:** Writing – original draft, Software, Investigation, Data curation. **Chin-Yu Hsu:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Consent to participate

All authors have significantly contributed to this work.

Consent to publish

All authors agreed to publish.

Data availability statements

All the data used in the current study is obtained form the open access resources and the weblinks for the data sources is provided in the manuscript.

Ethical approval

The ethical approval requirement is not applicable.

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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

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