Aggravation of CoVID-19 infections due to air pollutant concentrations in Indian cities

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Received: 24 March 2022 / Accepted: 3 November 2022 / Published online: 5 April 2023
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Abstract
The CoVID-19 infections began rising worldwide during the initial weeks of March 2020, reacting to which the Government of India called for nationwide lockdown for ~ 3 weeks. The concentration of pollutants during the lockdown were compared with pollution levels recorded during the preceding year for the same time frame. A direct relationship was established between the high level of air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$) and CoVID-19 infections being reported in the Indian cities. The correlation indicates that the air pollutants like PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$ are aggravating the number of casualties due to the CoVID-19 infections. The transmission of the virus in the air is in the form of aerosols; and hence places which are highly polluted may see a proportionate rise in CoVID-19 cases. The high-level exposure of PM$_{2.5}$ over a long period is found to be significantly correlated with the mortality per unit confirmed CoVID-19 cases as compared to other air pollutant parameters like PM$_{10}$, NO$_2$ and SO$_2$.

Keywords Air quality · CoVID-19 infections · Environmental health · Linear regression · SARS-CoV-2

1 Introduction
CoVID-19 had emerged as a severe health problem affecting people of all age groups throughout the globe [1] due to which the World Health Organization (WHO) had attributed it as a pandemic. India announced a country-wide lockdown to safeguard the citizens on 25th March 2020 and continued it for ~ 3 months in multiple phases. Due to the restrictions during the lockdown phases, a significant drop in the pollution levels were observed in different parts of the country [2–6].

The tier-1 cities of India (Ahmedabad, Bengaluru, Chennai, Delhi, Hyderabad, Kolkata, Mumbai, Pune) have been considered for the study as they are the single largest contributor to the urban population and pollution. Urban air quality due to high levels of air pollution are being reported in Indian megacities and are one of the highest in the world due to industrial expansions, high population density and use of motor vehicles [7–9]. The high annual population growth in these cities causes serious damage on the environmental conditions due to exponential growth of industrialization and transportation leading to the worsening air quality [10–12].

The air pollution is a risk factor for respiratory infection by carrying microorganisms and affecting body’s immunity [13–19]. Studies have shown that the CoVID-19 is a respiratory related disease and SARS-CoV-2 can remain active when they are bound in aerosols for a considerable amount of time [20]. Hence it is important to inspect the consequences of the pollutants like particulate matters and pollutant gases on the spread of the CoVID-19 infections. Air Quality Index (AQI), which illustrates the probable effect of the air quality on the human health is primarily dependent on the concentration of key five pollutants like particulate matters and pollutant gases on the spread of the CoVID-19 infections. Air Quality Index (AQI), which illustrates the probable effect of the air quality on the human health is primarily dependent on the concentration of key five pollutants like particulate matters (PM$_{2.5}$ and PM$_{10}$) along with pollutant gases like ground-level ozone (O$_3$), NO$_x$ and SO$_2$. In this present work, a direct relationship has been established between the high level of air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$) and CoVID-19 and aggravating the number of casualties.
2 Methodology

This study attempts to find the differences between the pollution levels from different phases of lockdown in the selected tier-1 cities of India. The data of ambient air quality levels of each sampling site of tier-1 Indian cities are taken from the website of Central Pollution Control Board which reports continuous ambient air quality data throughout the country, which are being recorded using multiple monitoring stations operated by the CPCB [21], respective state pollution control boards (SPCB) and India meteorological department (IMD). The data which are being reported in this study are taken from a total number of 78 monitoring stations. Ambient air quality parameters like PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$ listed in NAAQS are taken into account for the current study. Data of ambient air pollutants were taken (24 h average) from the period of 1st January to 17th May for the current and preceding years.

2.1 Site selection

The cities in India are categorized in different groups based on the population density. Based on this criterion of classification, the cities are being divided in category tier-1, tier-2 and tier-3 cities [22]. In India, there are 8 tier-1 cities, 26 tier-2 cities, 33 tier-3 cities and over 5000 tier-4 cities, generally known as towns [23]. The 8 tier-1 cities that were taken into account for the current study are Bengaluru (Karnataka), Chennai (Tamil Nadu), Delhi, Mumbai (Maharashtra), Kolkata (West Bengal), Ahmedabad (Gujarat), Hyderabad (Telangana) and Pune (Maharashtra).

The CoVID-19 pandemic outbreak worldwide made the Governments shutdown their respective countries completely to minimize the spread of the deadly virus to the citizens. Likewise, India too announced lockdown in the entire country on 25th March 2020, which restricted factories to operate in lieu of the increasing number of CoVID-19 cases. Government of India also implied complete movement restrictions for the civilians. Police were deployed to check and monitor the movement of the citizens in different cities. Only few individuals were exempted from the travel restrictions like the medical practitioners, health-care workers and govt appointed vehicles to provide essential commodities to different parts of India. The tier-1 cities of India were selected for the present study as they are the population and pollution hubs due to which these cities observe fastest growth rates in India [24].

2.2 Descriptive statistics

The statistical analysis was executed using the MS-EXCEL and MINITAB software. Experimental results for PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$ as well as CoVID-19 counts were stated as the mean ± SD (standard deviation). In this study the particulate matter concentration and the CoVID-19 data for the confirmed cases, active, recovered and deceased has been considered for the 8 tier-1 cities like Bengaluru, Chennai, Delhi, Mumbai, Pune, Ahmedabad, Hyderabad and Kolkata.

The study period for the CoVID-19 spread analysis was divided into 2 segments to demarcate the relaxation norms in the Indian sub-continent. The first segment (henceforth labelled as Phase-1) illustrated the duration from 26th April 2020 to 3rd May 2020 during which strict lockdown norms were being implemented with minimum public interaction and restricted movement. The second segment (henceforth labelled as Phase-2) illustrated the time period from 4th May 2020 to 17th May 2020 during which strict lockdown norms were lifted and marketplaces were opened for public.

2.3 Linear regression

In order to demonstrate the association between the response variable (mortality % per unit confirmed
CoVID-19 cases) and the air pollution parameters (PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$), a linear regression analysis was used. The analysis was achieved with a single air pollution parameter at a time because these parameters were neither mutually exclusive nor independent. The linear regression probabilistic model is characterized by a straight line as depicted by the Eq. 1 [25]:

$$Y = mX + C + \varepsilon$$

(1)

where the response variable is termed as ‘Y’, which is the percentage mortality per total confirmed cases. The variable ‘m’ is the slope while the variable ‘X’ signifies the predictor variable, i.e., the air pollution parameter which is assumed to be normally distributed with equality of variance for every observation while C is the model constant. In our study the model X was calculated using the logarithmic alteration which reduces the skewness of the data set. ‘ε’ is the error which is uncorrelated and have zero mean. ANOVA (analysis of variance) on the regression model is executed to enumerate the strength of the relation of particle matter on the response variable which is depicted by the $R^2$ value. In order to analyze the influence of the predictor variable more closely on the response variable, multiple linear regression model has been done for the particle matter PM$_{2.5}$ on the percentage mortality per confirmed CoVID-19 cases. The multiple linear regression model as a curve is depicted by the Eq. 2:

$$Y = a_0 + a_1x + a_2x^2$$

(2)

where $a_0$, $a_1$, $a_2$ are parameters. In this model when the predictor variable changes from x to (x + 1), expected change in the response variable is $a_1 + a_2(2x + 1)$. For the small change in the predictor variable, the effect on the response is given by the total derivative with respect to x, i.e., $a_1 + 2a_2x$. The change in the response variable is what makes the
relationship between the predictor and response variables non-linear even though the model is linear in parameters.

3 Results and discussion

The data reported in the current study are particulate matters (PM10 and PM2.5) and pollutant gases like SO2 and NO2. The data from multiple monitoring stations are averaged for a single representative data for whole city. The data for the said air pollutants are reported for the 8 tier-1 cities of India for the year 2020 which were then compared with the data from the preceding year for the same time frame.

3.1 Particulate matters

Rapid urbanization and industrialization in India are one of the key factors for the increase of air pollution levels of India. The pollution levels being reported in India are one of the highest reported levels in the world. As per the findings of WHO, 14 out of 15 most polluted cities of the world are from India [26]. Balakrishnan et al. [27] reported that the number of deaths due to the ambient particulate matter (PM10 and PM2.5) was 0.67 million in India with population weighted mean for PM2.5 was found to be 89.9 μgm⁻³. The PM2.5 and PM10 were observed to drop during the lockdown implemented in 2020 as compared to the preceding year in all the tier-1 cities of India. The highest drop in the PM10 levels during the lockdown period were observed at Pune (63.2%) while the lowest was reported at Mumbai (20.9%). The national capital territory of Delhi too witnessed a drop of 58.3% in PM10 levels during the lockdown period as compared to preceding year during the similar time frame. On the other hand, Ahmedabad witnessed the highest drop in PM2.5 levels (64.7%) in 2020 as compared to the year 2019 during the period of lockdown. On the contrary, Mumbai witnessed a rise of 3.7% in PM2.5 levels.

3.2 Pollutant gases

Ambient NO2 pollutants in ambient air have significant health impacts and also deter plant growth. Photochemical smog and acid rain are also associated with increased concentration of tropospheric NO2. An inventory given by Garg et al. [28] reported that the emission of NO2 is related to industrial processes (50%), vehicular emissions (32%) and biomass burning (10–20%). Ramachandran et al. [29] marked Delhi, Mumbai & Kolkata region as hotspots of NO2 emissions during the span of 8 years, i.e., 2003–2011 with annual average emissions greater than ~30 μgm⁻³. In the year 2019, India overtook Russia and China to be the world’s highest emitter of ambient SO2, and accounts for over 15% to total global anthropogenic SO2 emissions [30]. Almost all the SO2 emissions from India is due to coal burning which is mainly used for power generation. Suneja et al. [31] reported that the average concentration of SO2 for 8 years (2011–2018) in Indian megacity of Delhi was 5.92 ± 1.26 μgm⁻³ with highest and lowest values of 6.44 ± 1.78 μgm⁻³ and 4.89 ± 0.94 μgm⁻³ for the years 2018 and 2013 respectively.

The NO2 and SO2 levels too were observed to drop during the lockdown implemented in 2020 as compared to the preceding year in all the tier-1 cities of India. The highest drop in ambient NO2 and SO2 levels were observed at Ahmedabad with 69.2% and 49.8% respectively. On the contrary, Pune and Bengaluru witnessed an increase of 24.3% and 20.4% in NO2 and SO2 levels during the lockdown period. The increase in NO2 levels in Pune might be due to elevated transportation activities in the vicinity of the sensor being installed. This is quite evident with sudden point spikes in NO2 concentration. The data however might not be much reliable as Pune has single monitoring site collecting air pollution data. The SO2 concentration levels recorded in Kolkata too showed a minor increase by 0.75%. Increase in SO2 levels in Bengaluru during the lockdown period might be due to the elevated biomass burning incidents in industrial as well as domestic sectors. Kolkata has 2 thermal power plants in the 50 km radius which are the primary SO2 pollution source for Kolkata and since they were operated throughout the lockdown period as the preceding year, the emissions were found to be quite similar for both the years. The SO2 levels during the lockdown being reported in the rest of the tier-1 cities of India are found to be below the levels recorded in the previous year.

3.3 Impact of air pollutant parameters on CoVID-19 cases

The tier-1 cities of Bengaluru, Chennai, Delhi, Mumbai, Pune and Ahmedabad are well-known hotspots of the atmospheric pollution. The pollution parameters of PM2.5, PM10, NO2, and SO2 concentration are often seen to exceed the safe levels prescribed by the WHO guidelines and Indian NAAQS permissible limits [32–35]. The study found that during the investigated period 26th April–3rd May 2020 (Phase-1) for each six tier-1 cities, the pollution levels (PM2.5, PM10, NO2, and SO2) had reduced drastically and the air quality had significantly improved than the preceding year for the same time frame. During the Phase-2 (4th May–17th May 2020), the lockdown was eased allowing certain relaxations in public movement and re-opening of market, the air pollution began to increase (Table 2). The relaxations and re-opening of marketplaces after ~40 days witnessed huge gathering especially in popular market areas where the people were generally seen flouting the social-distancing which resulted in huge upsurge in the CoVID-19
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The values of the air pollutants exceeded the Indian NAAQS limits. For the regression analysis, data for the PM$_{2.5}$, PM$_{10}$, NO$_2$, and SO$_2$ has been considered from 25th March 2020–17th May 2020 which covers both the phases i.e., period of complete lockdown followed by lockdown with relaxation. The data of the positive coronavirus infection cases has been considered from 26th April–17th May 2020.

The mean of PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$ for the year 2020 (during the lockdown period) in the tier-1 cities along with the percentage mortality per unit confirmed for CoVID-19 cases is calculated and given in the Table 3. Using the linear regression model, a relationship is established between the air pollution parameters and percentage mortality per unit confirmed cases of CoVID-19 (Table 4). The linear regression model on the response variable is fitted with respect to the particulate matters (PM$_{2.5}$ and PM$_{10}$) and pollutant gases (NO$_2$ and SO$_2$). It also portrays the regression model coefficients and associated standard error (SE) for the regression coefficients. It has been observed that PM$_{2.5}$ has substantial impact on the 'Y' (response variable), i.e., the percentage mortality per confirmed CoVID-19 cases ($p < 0.05$ at confidence interval 95%). However, the air pollutants PM$_{10}$, NO$_2$ and SO$_2$ (with $p > 0.05$) does not show any substantial impact on the response (Table 5).

The analysis of variance on the regression model is presented in Table 6 from which it can be inferred that the percentage mortality per confirmed CoVID-19 cases is correlated significantly with PM$_{2.5}$ ($R^2 = 86.98\%$) than with PM$_{10}$ ($R^2 = 19.59\%$), NO$_2$ ($R^2 = 14.99\%$), but significantly with SO$_2$ ($R^2 = 57.16\%$). The linear regression plot for the percentage mortality per confirmed CoVID-19 cases with PM$_{10}$ during the complete lock down ($R^2 = 0.61\%$) (Fig. 1a) and during the relaxed lock down ($R^2 = 0.35\%$) (Fig. 1b). Quadratic linear regression model for the percentage mortality per confirmed CoVID-19 cases with NO$_2$ for the complete lockdown and relaxed lock down period has been shown in Fig. 2a and b.

For predicting the mortality rate based on the developed regression model needs much bigger data set which is not possible in this case due to the non-availability of data. In Table 6, the analysis of variance on the multiple regression model for the PM$_{2.5}$ and can be inferred that percentage mortality per confirmed CoVID-19 cases is correlated significantly with PM$_{2.5}$.

Table 7 recapitulates the Pearson Coefficient descriptive statistics of CoVID-19 cases in the six tier-1 cities (total confirmed, active, recovered and deceased) and the 24 h average air pollutant levels of PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$ (as per the availability of data). Figure 3 represents the best fit line plot (for PM$_{10}$, NO$_2$ and SO$_2$) and the best fit curve plot (only for PM$_{2.5}$) for the parameters with 95% at confidence interval. The residuals are shown in Fig. 4 through normal probability plot. The residuals

| City          | PM$_{2.5}$ (µgm$^{-3}$) | PM$_{10}$ (µgm$^{-3}$) | NO$_2$ (µgm$^{-3}$) | SO$_2$ (µgm$^{-3}$) | Total reported cases | Total reported deaths | CoVID-19 cases (Till 17th May 2020) | Percentage mortality per unit reported case |
|---------------|--------------------------|--------------------------|---------------------|--------------------|----------------------|-----------------------|----------------------------------|---------------------------------------------|
| Ahmedabad     | 29.3                     | 79.6                     | 22.1                | 26.2               | 8683                 | 555                   | 6.39                             | 4.69                                         |
| Bengaluru     | 24.6                     | 52.1                     | 13                  | 6.3                | 240                  | 7                     | 2.91                             | 1.59                                         |
| Chennai       | 16.2                     | 79.3                     | 7.4                 | 5.3                | 7125                 | 57                    | 0.8                              | 0.44                                         |
| Delhi         | 46.2                     | 103.6                    | 20.4                | 14.3               | 10,054               | 160                   | 1.59                             | 0.74                                         |
| Hyderabad     | 30.2                     | 61.6                     | 22                  | 5.8                | 981                  | 23                    | 2.34                             | 1.24                                         |
| Kolkata       | 24.9                     | 47.8                     | 10.2                | 5.3                | 1372                 | 165                   | 12.02                            | 6.28                                         |
| Mumbai        | 21.4                     | 63.8                     | 7.4                 | 12.9               | 20,150               | 734                   | 3.64                             | 1.84                                         |
| Pune          | 43.9                     | 35.3                     | 16.6                | 22.7               | 3821                 | 197                   | 5.15                             | 2.54                                         |
The contour plot for the percentage mortality per unit confirmed CoVID-19 cases is depicted in Fig. 5a–e. It can be observed that the highest values of the response variable are in the upper right corner of the plot which corresponds with the high values of both PM2.5 and PM10 indicates the higher impact of these pollution parameters on the mortality rate and as it is skewed more to the Y-axis indicates that the impact of PM2.5 is more compared to PM10. The impact of other air pollutants on the percentage mortality rate per unit confirmed CoVID-19 cases is also calculated. Fig. 5e shows that the impact of NO2 is more compared to PM10 on the percentage mortality rate per unit confirmed cases. But the impact of SO2 is also not less on the percentage mortality rate per unit confirmed cases. The correlation also supports that along with PM2.5, SO2 and NO2 are also accelerating the number of CoVID-19 confirmed cases.

### 3.4 Correlation among the particle matters

The correlation among the concentrations of PM2.5, PM10, NO2, SO2 during the study period shows between PM10 and PM2.5, a strong positive correlation in all the 5 cities Ahmedabad (R = 0.63), Bengaluru (0.75), Chennai (R = 0.60), Delhi (R = 0.87), Mumbai (R = 0.90) (with p < 0.05) which is considered to be highly relevant and verifying the interactive effect among these particular matters except in Pune (R = 0.27), it shows positive correlation (with p > 0.05).

If we consider, PM10 and NO2, there is a positive correlation in four cities Ahmedabad (R = 0.62), Bengaluru (R = 0.49), Delhi (R = 0.65), Mumbai (R = 0.51) (with p < 0.05). In Pune (R = 0.27) there is a positive correlation (with p > 0.05). But in Chennai (R = −0.09) between PM10 and NO2, there is a negative correlation (with p > 0.05).

And among PM2.5 and SO2 in Pune (R = 0.99) and in Delhi (R = 0.50) shows strong positive correlation which is highly relevant (with p < 0.05), Ahmedabad (R = 0.39),
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Bengaluru ($R = 0.20$) shows positive correlation with ($p > 0.05$) and Chennai shows a negative correlation ($R = -0.11$) between PM$_{10}$ and SO$_2$.

Among PM$_{2.5}$ and NO$_2$, in all the 6 cities shows positive relationship as Ahmedabad ($R = 0.49$), Bengaluru ($R = 0.52$), Pune ($R = 0.99$), Delhi ($R = 0.83$), Mumbai ($R = 0.48$) (with $p < 0.05$) and Chennai ($R = 0.01$) ($p > 0.05$) which is highly relevant.

Among PM$_{2.5}$ and SO$_2$, there is a positive correlation in cities Ahmedabad ($R = 0.53$), and Delhi ($R = 0.59$) (with $p < 0.5$). In other cities there exists a week relation between these two particle matters. In Mumbai there is a negative correlation of ($R = -0.36$), Chennai ($R = -0.16$).

And among NO$_2$ and SO$_2$, there is a strong positive relation in Ahmedabad ($R=0.71$, $p<0.05$) and a strong negative relationship in Pune ($R=-0.99$) (with $p<0.05$) which verifies the interacting effect of these pollutants. In Delhi ($R=0.30$, $p>0.05$), Chennai ($R=0.37$, $p>0.05$), Bengaluru ($R=0.30$, $p>0.05$). In Mumbai, negative correlation ($R=-0.17$, $p>0.05$).

4 Conclusion

CoVID-19 is likely to spread rapidly in humans with people coming in contact or in nearby vicinity to an infected person. Also, the transmission of the virus in the air is in the form of aerosols; and hence places which are highly polluted may see a proportionate rise in CoVID-19 cases due to the compromised immune system of the person living in that area. In this present work, a direct relationship has been established between the high level of air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$) and CoVID-19. This correlation indicates that the air pollutants like PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$ are aggravating the number of casualties due to the CoVID-19 infections. Further, it has been observed that high level exposure of PM$_{2.5}$ over a long period is found to be significantly correlated with the mortality per unit confirmed CoVID-19 cases as compared to other air pollutant parameters like PM$_{10}$, NO$_2$ and SO$_2$. Concluding with the results, it is evident that the air pollution is in turn acting as a catalyst in the mortality rates due to the CoVID-19 infections. As the virus carrying aerosols are in the range of 1 – 5 µm, hence outside wearing of mask in tier-1 cities should be compulsory. In the light of increasing CoVID-19 infections worldwide, it is vital to
identify the hotspots with very high concentrations of air pollution and implement strict rules on the movement of residents freely without following safety protocols. Usage of masks should be made compulsory and high amount of monetary fines to be implemented to those found without following safety norms.

Tier-1 cities, are by default, in high-risk zone and hence government authorities need to have pro-active steps to curb and control it, in terms of health care, patient tracking, restricted movement etc. Being a developing country (India), its challenging but it needs to be addressed by controlling the high amount of pollution and promoting healthier lifestyle. Viruses, one form or the other will be encountered in future also, but human immune system should be strong enough to deal with it, at its capacity.
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Fig. 3 Quadratic Regression fitted line plot for a PM$_{2.5}$; Linear Regression fitted line plot for b PM$_{10}$; c NO$_2$; d SO$_2$

Fig. 4 Normal probability plot depicting the residual for a PM$_{2.5}$; b PM$_{10}$; c NO$_2$; d SO$_2$
Author contributions AM had collected the data, analyzed them and drafted the manuscript. AS carried out the statistical analysis part, contributed in manuscript drafting and shaping the manuscript into the final format. SKS collected the data and helped in manuscript writing. SM and AKM conceptualized the idea, provided overall guidance in planning and had contributed in shaping manuscript into the final format.

Funding Authors declare that they have not received any funding for the present work.

Data availability All data generated or analyzed during this study are included in this published article and its supplementary information files. The data were gathered from the websites of Central Pollution Control Board, Ministry of Environment, Forest and Climate Change (MoEFCC) for the ground-based observations of PM$_{2.5}$, PM$_{10}$, NO$_2$ and SO$_2$ and SO$_2$ obtained from website (https://app.cpcbccr.com/ccr) and the Ministry of Health and Family Welfare (MoHFW) for the total counts of CoVID-19 cases being reported officially from the website (https://www.mohfw.gov.in/).

Fig. 5 Contour plot for the percentage of mortality per unit confirmed cases with respect to a PM$_{2.5}$ and PM$_{10}$; b PM$_{2.5}$ and NO$_2$; c PM$_{2.5}$ and SO$_2$; d SO$_2$ and NO$_2$; e PM$_{10}$ and NO$_2$. 

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Declarations
Conflict of interest The authors declare that they have no conflict of interest.

Consent for publication Not applicable.

Ethical approval Not applicable.

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