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COVID-19 and environmental -weather markers: Unfolding baseline levels and veracity of linkages in tropical India

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ABSTRACT

The COVID-19 pandemic, caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is rapidly spreading across the globe due to its contagion nature. We hereby report the baseline permanent levels of two most toxic air pollutants in top ranked mega cities of India. This could be made possible for the first time due to the unprecedented COVID-19 lockdown emission scenario. The study also unfolds the association of COVID-19 with different environmental and weather markers. Although there are numerous confounding factors for the pandemic, we find a strong association of COVID-19 mortality with baseline PM2.5 levels (80% correlation) to which the population is chronically exposed and may be considered as one of the critical factors. The COVID-19 morbidity is found to be moderately anti-correlated with maximum temperature during the pandemic period (~56%). Findings although preliminary but provide a first line of information for epidemiologists and may be useful for the development of effective health risk management policies.

1. Introduction

The 90% of people worldwide are exposed to high levels of air pollution as per the World Health Organisation which estimated that around 7 million mortality every year from exposure to fine particles in polluted air. The foul air penetrates deep into the lungs and cardiovascular system, causing diseases including stroke, heart disease, lung cancer, chronic obstructive pulmonary diseases and respiratory infections, including pneumonia (WHO, 2018). On every continent, people suffer the negative health impacts of air pollution. However, in recent times, the outbreak of novel coronavirus (COVID-19) has become a global public health challenge and it’s ever-increasing in India. The first case of COVID-19 was found in the Wuhan city of China during the month of December and has been spread from Wuhan to the many countries of the world (i.e. Italy, Europe, Asia) within a few months (Bontempi, 2020; Bontempi et al., 2020) and turned to be a worldwide epidemic. To control the epidemic conditions, the world wide countries went to the lockdown (Muhammad et al., 2020). First COVID-19 case in India was confirmed on 30 January 2020, which rose to three cases by 3rd February. Later, no significant transmissions were observed in India Meteorological Department, New Delhi, India

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Air Quality Report, 2019) suggests that India has the most cities with high air pollution levels. Although, there are many factors which regulate the lethality of COVID-19 like underlying health conditions, age, their sex, variation in prevention policies across regions, reporting system of infects/deaths and strategy to deal with crisis. Nevertheless, the majority of European cities and western world have much lower levels of ambient air pollution but still the death rates reported are found to be relatively much lower in India. What is more shocking is if we go by the reported logic then the population who have spent decades living in a polluted city such as Delhi should be more susceptible to virus mortality. However, data so far indicates that it is not true as many less polluted Indian cities have much higher rates of COVID-19 related deaths as compared to Delhi. As for example, Mumbai where pollution level is significantly lower as compared to Delhi (Anand et al., 2019) the COVID-19 related Deaths are higher. Hence, more work is needed to explore the actual cause and understand the role of other environmental markers in Indian environment. To better understand the adverse health effects associated with air pollution, accurate exposure assessment is essential. Some cities may be highly polluted but the health outcome will depend on the exposure. In general, pollution exposure greatly varies from person to person based on his/her movement and activity levels. Hence, the population is not necessarily exposed to uniform ambient high or low levels all the time. The term used in this work as baseline pollution represents the lowest levels of ambient air pollution that is not produced locally from anthropogenic sources or a level that would have been naturally present and remain under photochemical equilibrium. However, up until now research has not significantly addressed this lowest fraction of pollution as a representative marker of a permanent concentration or baseline levels of ambient air pollution to which the population is chronically exposed and must have developed chronic health deficiencies associated with long term exposure and also reported to weaken the immune system. Major reason was the lack of observational data on baseline that was practically impossible to get due to uninterrupted emissions of some or other sources of pollution in any urban complex. Most of the work reported so far on baseline estimates are based on modeling or theoretical calculations using long term data sets which have their own inherent uncertainty and rely on several assumptions and without observational validation. There is a number of evidence that confirms that a moderate increase in long term exposure to background or baseline ambient air pollution will increase prevalence of respiratory and atopic indicators in children. Scientists need to carry out further research to determine the significance of air pollution and to understand better the other factors that may affect the lethality of the virus. On the other hand, the changes in the prevailing weather conditions may be a considerable factor to have a contribution in COVID-19 related mortality and morbidity. Several studies have been done to understand the impact of weather parameters such as temperature, winds, humidity, and solar radiation on the COVID-19 related cases in recent time (Sarmadi et al., 2020; Saadat et al., 2020; Coccia, 2020a, 2020b; Muhammad et al., 2020; Zhao et al., 2020; Jon Brassey et al., 2020). However, no detailed investigation is done in Indian tropical environment. This work focuses on the specific fraction of pollution known as baseline pollution levels and then addresses the question of factors that may affect the lethality of the virus. Two of the hazardous and major air pollutants relevant to Indian mega cities, PM$_{2.5}$ and NO$_2$ are considered in this work. The work reported here focuses on understanding the association of COVID-19 related mortality and morbidity with various other environmental and weather parameters like temperature and long-term ambient levels of pollution in search of an environmental marker which can be considered closely associated with COVID-19. Present work considers 6 major mega cities reported to be pollution hot spots of India, namely, Delhi, Mumbai, Ahmedabad, Pune, Kolkata and Chennai.

2. Material and method

2.1. Study area

This study focuses on six Indian mega cities as shown in Fig. 1. Delhi is a highly urbanized landlocked city situated at an elevation of 216 m above sea level and covers an area of 1483 sq. km. with a population of about 17 million and it is rapidly growing. Due to the proximity to the Arabian sea Mumbai has a humid weather, Mumbai is at an elevation of about 14 m above sea level and has a population of 12 million and surrounded on 3 sides by ocean. Pune is located in the Western Ghats of Sahyadri mountain range and at 559m above mean sea level with a population of approximately 9 million. Ahmedabad has a tropical semi-arid climate located at an elevation of about 53 m above mean sea level having a population of over 5 million. Kolkata is located in the eastern part of India. It has spread linearly along the banks of the Hooghly River. The city is near sea level, with the average elevation being 17 feet. The whole area in the Ganges Delta starts within 100 km south of the city. Most of the city was originally marshy wetlands, remnants of which can still be found especially towards the eastern parts of the city. Kolkata has a subtropical climate with a seasonal regime of monsoons. It is warm year-round, with average high temperatures ranging from about 27°C in December and January to nearly 38°C in April and May. The atmospheric pollution has greatly increased since the early 1950s. Factories, motor vehicles, and thermal-generating stations, which burn coal, are primary causes of this pollution, but monsoon winds act as cleansing agents by bringing in fresh air masses. Another mega city of India, Chennai is located at 13.04°N 80.17°E on the southeast coast of India. It is located on a flat coastal plain known as the Eastern Coastal Plains. The city has an average elevation of 6 m. Chennai features a tropical wet and dry climate. Chennai lies on the thermal equator and near the coast, which prevents extreme variation in seasonal temperature. For most of the year, the weather is hot and humid. The hottest part of the year is late May and early June, with maximum temperatures around 38–42°C. The coolest part of the year is January, with minimum temperatures around 18–20°C. The city gets most of its seasonal rainfall from the north-east monsoon winds, from mid-September to mid-December. Cyclones in the Bay of Bengal sometimes hit the city. The most prevailing wind in Chennai is the South westerly between the end of May to end of September and the North easterly during the rest of the year.

2.2. Data and sources

The air pollution data in the present work is obtained by online automatic analysers mainly from the project- “System of Air Quality and Weather Forecasting and Research (SAFAR)” of Ministry of Earth Sciences, Government of India that is also adopted as a pilot project of World Meteorological Organization (WMO) (Beig et al., 2015). The SAFAR data is used for 4 Indian cities, namely, Delhi, Mumbai, Ahmedabad and Pune. Each city network consists of 8–10 Air Quality Monitoring Stations (AQMS), distributed in different microenvironments viz. downtown area, background, industrialized area, residential area, traffic areas etc. in such a way that they cover the whole city and the average can be representative of the city as per WMO guidelines (Grimmond et al., 2014). Data of Chennai and Kolkata are collected as part of SAFAR national wide network project MAPAN (Modelling Atmospheric Pollution and Networking) and that of Central Pollution Control Board (https://data.gov.in/ministrydepartment/central-pollution-control-board). The meteorological parameters such as wind speed (km hr$^{-1}$), relative humidity (%) and temperature (°C) have been measured using the automatic Weather Stations (Anand et al., 2019) for six Indian megacities during the study period have been given in Table 1. The number of patients tested positive for COVID-19 and fatality counts in different Indian cities, considered in this work, are given in Table 1 (as on 22nd May’ 2020) along with other parameters discussed later in
this paper. The data of mortality and infectious cases related with COVID-19 in India are taken from India’s Ministry of Health and Family Welfare (https://www.mygov.in/covid-19/). The numbers of COVID-19 related confirmed death count in all 6 cities are also provided in Table 1. These numbers are representative of the actual death and not related to the number of deaths relative to the number of confirmed cases of infection. We preferred to take actual death counts because asymptomatic cases or patients with very mild symptoms might not be tested and will not be identified but in case of death, identification with a cause of death is officially done as per the prevailing standard protocol and accounted if cause of death is found to be COVID-19.

### 2.3. Measurements

The measurements of fine particulate matter (PM2.5) in micrograms per cubic meter (μg/m³) were carried out with the help of Beta Attenuation Monitor (BAM-1020) during the study period. In BAM-1020, carbon-14 (¹⁴C) elements which give a constant source of high energy electrons are well known as beta rays and these particles are detected and counted by a scintillation detector. The external pump pulls a measured amount of air sample (dust laden). Afterwards, the filter tape weighed down with dust is automatically placed between the source and the detector. The attenuation of the beta particle signal is used to determine the mass concentration of aerosols collected on the filter tape. The extensive details of the BAM 1020 are reported in our previous studies (Beig et al., 2020; Yadav et al., 2017). BAM-1020 measures the mass concentration of particulate matters with a lower detection limit of ~1 μg/m³. The span calibration of the instrument is automatically verified on hourly basis (Anand et al., 2019; Yadav et al., 2019). The chemiluminescence based detection is used for the measurements of nitrous oxide (NO), nitric dioxide (NO₂) and oxides of nitrogen (NOx) that is also a US-EPA approved (http://www.environment-sa.com/caps-chemiluminescence-no2-measurement/) instrument. The instrument consists of NO₂-to-NO converter (molybdenum), reaction tube, and detector (PMT). The zero and span calibration of the instrument were performed using the standard calibration mixture.

![Fig. 1.](image)

Table 1

| MARKERS | MUMBAI | AHM BAD | PUNE | DELHI | KOLKATA | CHENNAI |
|---------|--------|---------|------|-------|---------|---------|
| Latitude, Longitude | 19.07° N, 72.87° E | 23.02° N, 72.57° E | 18.52° N, 73.85° E | 28.70° N, 77.10° E | 22.57° N, 80.27° E | 28.70° N, 77.10° E |
| PM2.5 (μg/m³) Baseline Level | 33 ± 7 | 32 ± 7 | 29 ± 6 | 22 ± 5 | 17 ± 4 | 6 ± 2 |
| NO₂ (ppb) Baseline Level | 5 ± 2 | 6 ± 2 | 4 ± 1 | 8 ± 3 | 1.7 ± 0.5 | 1.7 ± 0.5 |
| Mortality Counts | 909 | 645 | 243 | 231 | 176 | 70 |
| Infection Counts | 2725 | 9724 | 4993 | 12910 | 1570 | 9370 |
| Population Density (per km²) | 20482 | 4217 | 5609 | 11297 | 24252 | 26903 |
| Mortality/0.1 million population | 7.3 | 8.3 | 3.7 | 1.4 | 1.3 | 0.8 |
| Infections/0.1 million population | 219 | 125 | 75 | 79 | 11 | 108 |
| Temperature-Max (March-May 2020) (°C) | 32.5 | 40 | 37 | 37 | 35.5 | 36 |
| Wind speed (Average) (23 Mar - 22 May 2020) (km hr⁻¹) | 11.4 | 8.3 | 2.6 | 6.4 | 10.5 | 11.9 |
| Relative Humidity (Average) (23 Mar - 22 May) (%) | 69 | 35 | 51 | 56 | 70 | 75 |
lower detection limit of the species is about 0.4–0.5 ppbv. Additional details of working methods are reported elsewhere (Beig et al., 2013; Anand et al., 2020; Yadav et al., 2014). The meteorological parameters were at the same time measured using Automatic Weather Station co-located alongside air quality monitoring stations whose details are provided elsewhere (Anand et al., 2019) and hence not discussed here in detail. The thermometer technique measures temperature with an accuracy of ±1 °F. The anemometer device measures wind speed with an accuracy of ±0.45 m/s. The temperature sensor used has a resolution of 1 °F with accuracy ±1 °F. The relative humidity (RH) sensor measures RH in percentage with an accuracy of ±3% (Yadav et al., 2016).

2.4. Data analysis procedure

The basic dataset of PM$_{2.5}$ in the present study was recorded for 1 h interval and averaging has been done to derive daily data while NO$_2$ were recorded for 5 min interval and averaging has been done to derive 24 h data. The saturation point methodology under fair weather conditions is used in this work to determine the baseline levels of PM$_{2.5}$ and NO$_2$ using the above-mentioned data. The emission inventory of major pollutants in Indian mega cities have been developed earlier by SAFAR (Sahu et al., 2011; Beig et al., 2018) which classify six major categories of emissions, namely, fossil fuel, biofuel, industrial, power, and wind-blown dust and rest other like brick kiln, open trash burning etc. Major source of anthropogenic emissions of PM$_{2.5}$ and NO$_2$ is fossil fuel combustion followed by other sources as stated above (Beig et al., 2018). The COVID-19 lockdown in India resulted in a dramatic decline of almost all major Human-made sources of emissions. Lockdown created an unprecedented emission scenario with near negligible magnitude, which was virtually impossible under normal scenario and paved the way to determine the baseline levels. Immediately after the lockdown while weather was very calm, steady, and consistent, the levels of all pollutants sharply dropped and attained a minimum within a 4–6 day time period, and remained steady for more than 2–3 days. As per the saturation point methodology, this minimum level is known as saturation level and the value is defined as the baseline value of concern pollutant. However, once the weather becomes variable, slight fluctuations are noticed in the levels of these pollutants around the saturation level. It is noteworthy to mention here that amid lockdown, biofuel emissions from residential cooking remain unchanged. However, the contribution of biofuel emissions in these mega cities for pollutants PM$_{2.5}$ and NO$_2$, considered in this work, is likely to be minimal under fair weather condition and assumed to be negligible (Sahu et al., 2011, 2015bib, Sahu et al, 2011bib, Sahu et al, 2015; Beig et al., 2018) in the first week after the lockdown. Nevertheless, results presented here are subjected to some uncertainty due to the above factor which is unlikely to be more than 5%. The correlation coefficient has been calculated by statistical method (Schober et al., 2018) between different environmental markers and that of mortality and morbidity counts. In addition to this, to rationalize the mortality and morbidity based on the population, we have determined the mortality and morbidity rate per 0.1 million population in each city. The correlation of all major environmental factors have also been derived with this rationalized counts per 0.1 million population. To determine the significant level of the derived correlation coefficient, results were subjected to a p-value test. The p-value ≤ 0.1 signifies that results are significant with 90% confidence level and p-value ≤ 0.05 indicates that results are significant with 95% confidence level.

3. Results and discussion

The data thus obtained from the above study design as per the saturation point methodology is shown in Fig. S1. This figure shows a time series of two major criteria pollutants for all 6 megacities considered in this work during the period 20$^{th}$ February 2020 to 14$^{th}$ April 2020 that include two regimes, namely before lockdown (Normal) and after lockdown and marked with a vertical line in these figures starting from 24$^{th}$ March 2020. The data is compared with pollution levels of 2019 during the identical period for reference to provide a feel of COVID-19 related lockdown decline in different pollutants in different cities. The time series for Kolkata and Chennai are plotted together for PM$_{2.5}$ and NO$_2$ respectively only for 2020. As evident from Fig. S1 that different pollutants behaved differently in different cities immediately after the lockdown but their levels started to fall sharply and reached a saturation level after about 4–6 days beyond which their concentrations became stagnant with minor fluctuations due to day to day slight variability in weather parameters. During the time from lockdown to saturation period, the weather was fairly consistent and also the probability of long-range transport of pollution from neighboring regions was negligible because the lockdown was observed countrywide and the biofuel influence is minimal on these pollutants. Hence, the significant fall in the level of pollutant concentrations after lockdown can be directly attributed to reduction in COVID-19 lockdown emission scenario. Based on the saturation level, the baseline concentrations of various pollutants are determined and the blue dotted line is marked to calculate the value. The levels thus determined are also shown in Table 1. These numbers show the baseline levels of PM$_{2.5}$ and NO$_2$ in different cities as determined in this work. The number with ± sign indicates the standard deviation from the mean. These are baseline natural levels of the atmosphere for PM$_{2.5}$ and NO$_2$, which are supposed to be permanently present near the surface and remain in equilibrium until a significant external forcing disrupts the equilibrium towards increase or decrease of these levels. As shown in Table 1, the level of permanent concentration of PM$_{2.5}$ is found to be highest for Mumbai (33 ± 7 µg/m$^3$) and lowest for Chennai (6 ± 2 µg/m$^3$). The baseline values of NO$_2$ are highest for Delhi (8 ± 3 ppb) and lowest for Kolkata and Chennai (1.7 ± 0.5 ppb). The high magnitude of NO$_2$ (8 ppb) in Delhi implies the dominant role of fossil fuel emissions from transport sources in influencing the base level of NO$_2$. Table 1 also provides the maximum temperature (T-max) of the day averaged over the pandemic period of March-May’ 2020 in different cities. The lowest T-max of 32.5 °C is found in Mumbai whereas the warmest city is found to be Ahmedabad followed by Delhi. Fig. 1a shows the base map of spatial distribution of hotspots of COVID-19 infectious counts in different states of India (https://www.mohfw.gov.in/) as on 22nd May 2020. The locations of 6 megacities are marked and the number in the bracket after the city name represents the number of Deaths due to COVID-19. Filled circles represent the number of infectious cases in each city and counts are given in the bottom right side of Fig. 1a wherein bracket values indicate death counts. These numbers are also stated in Table 1. The white area in this figure indicates no cases of COVID-19. The baseline levels of PM$_{2.5}$ (histogram) and standardized mortality count per 0.1 million population (red line) in different cities of India are shown in Fig. 1b. Error bars in the histograms are standard deviation from the mean. The correlation between these two parameters are found to be 0.84 (84%) which is found to be significant at 95% confidence level (p-value<0.05) as shown in Table 2. Results indicate that, in general, city having a high level of PM$_{2.5}$ baseline level is associated with a higher number of deaths and those cities which have a smaller magnitude of PM$_{2.5}$ baseline level have relatively lesser numbers of mortality. The baseline levels of PM$_{2.5}$ and direct total mortality count without rationalizing in different cities of India are also shown in the bottom panel as Fig. 1c. The highest mortality counts are found in Mumbai where the baseline level of PM$_{2.5}$ is highest. The PM$_{2.5}$ baseline level and mortality count also indicates significant correlation (r = 0.80 with p-value<0.1) at 90% confidence level (Table 2). These are two most significant correlations found among all the environmental parameters accounted for in the present study and both are associated with PM$_{2.5}$ baseline levels.

The correlation of mortality and morbidity with other weather and pollution markers are also determined in this work. In a recent work, Jon Brassey et al. (2020) reported that the environmental conditions may...
possibly affect the COVID-19 outbreak with the help of epidemiological data. Figs. S2 and S3 show the correlation of other variances of PM$_{2.5}$, NO$_2$, respectively with mortality, morbidity, and standardized mortality rate in various cities accounted for in this work. The calculated correlation coefficient is provided in Table 2. Although insignificant but relatively higher correlation is noticed between annual mean PM$_{2.5}$ level and mortality rate (49%), PM$_{2.5}$ base level and infection counts (43%), and NO$_2$ baseline levels with mortality and infections counts (42%). Hence, the current study confirms that the COVID-19 in India at present do not have any significant association with prevailing pollution levels, annual pollution levels as shown in Table 2 but have strong relationship with baseline levels of PM$_{2.5}$. Environmental pollutants are foreign products that change the normal composition and properties of the environment and are directly or indirectly harmful to humans and other organisms (Nakat et al., 2015). The severity of air pollutants is highly dependent on its nature, chemical, physical and biological contaminants (Lacal et al., 2010). The harm of environmental pollutants to the human body is mainly reflected in respiratory mucosa damage and obstructive pulmonary disease because the respiratory tract is the first thing affected by environmental exposure (Gorska et al., 2017). Respiratory tract is highly vulnerable to Coronavirus.

The current study reveals that Delhi recorded relatively fewer deaths as compared to many cities in India until the time of writing this manuscript where ambient pollution levels were much lower as compared to Delhi (Fig. 1a). The explanation of such anomaly is explained in our finding of baseline concentration as shown in Fig. 1a. Although normal ambient pollution level is highest in Delhi (Annual mean PM$_{2.5}$ = 100 µg/m$^3$) but the baseline levels of PM$_{2.5}$ is much lower in Delhi as compared to Mumbai, Pune, and Ahmedabad. The death count is maximum (909 as on 22nd May) in Mumbai as PM$_{2.5}$ baseline level is highest (~33 µg/m$^3$) where as it is comparatively very low (22 µg/m$^3$) in Delhi where Death counts is relatively low at 231 around the same period. This mortality count of Delhi is even lower than that of relatively less polluted cities like Pune or Ahmedabad because the baseline levels of later 2 cities are higher than that of Delhi (Table 1). Present work tends to suggest a significant rise in the fatality in people with underlying conditions because of chronic exposure to baseline air pollution levels rather than averaged ambient air pollution levels for PM$_{2.5}$ and shown in Fig. 1b and (c). Baseline air pollution level seriously weakens the immune system, compromising people’s ability to fight off infection as they are chronically exposed to it (Glencross et al., 2020). Further, such chronic exposure represents one of the most well-known causes of prolonged inflammation, eventually leading to an innate immune system hyper-activation. It’s also making people more vulnerable to infection, illness, and premature death (Cao et al., 2020).

Several studies have shown that in air pollution, the cilia in the human respiratory tract become shorter or are missing, which affects their ability to clear the respiratory tract. In addition, mucosal cilia clearance may be inhibited due to factors such as quantity of contaminant concentration and duration of exposure which is highest in case of baseline level.

Table 2

| Parameters               | Markers       | Mortality count (total) | Infection count (total) | Mortality/0.1 million population | Infection/0.1 million population | Mortality rate w.r.t infections |
|--------------------------|---------------|-------------------------|-------------------------|----------------------------------|----------------------------------|--------------------------------|
| PM$_{2.5}$ (µg/m$^3$)    | Baseline Level| 0.80*                   | 0.43                    | 0.84*                            | 0.47                             | 0.18                           |
|                          | Annual Mean   | -0.06                   | -0.17                   | -0.18                            | -0.46                            | 0.49                           |
|                          | Avg (Lockdown: 23 March-22 May) | 0.40                  | 0.23                    | 0.40                             | 0.09                             | 0.06                           |
| NO$_2$ (ppb)             | Baseline Level| 0.41                    | 0.42                    | 0.39                             | 0.31                             | 0.32                           |
|                          | Annual Mean   | 0.16                    | 0.19                    | 0.02                             | -0.09                            | 0.04                           |
|                          | Avg (Lockdown: 23 March-22 May) | 0.16                  | 0.24                    | 0.11                             | 0.03                             | 0.24                           |
| Temperature (°C)         | Temperature -Avg (MAM) | -0.12                 | -0.27                   | 0.05                             | -0.11                            | 0.14                           |
|                          | Temperature -Max (MAM) | -0.25                 | -0.56                   | 0.11                             | -0.39                            | 0.14                           |

*significant at p < 0.1; **significant at p < 0.05.

People living in areas with prolonged chronic exposure of dirtier air had a higher level of inflammatory cytokine cells, leaving them more vulnerable to the virus (Conticini et al., 2020). The effects of permanent levels of air pollution permeate every organ in the human body at every stage of life as we are always exposed to that level irrespective of our movement. In addition to this, chronic exposure to air pollution damages the cilia in a person’s lungs. Cilia, which are microscopic, hair-like organelles, are one of the first lines of defence against infection (Cao et al., 2020). Whereas, ambient pollution exposure is not uniform due to an individual person’s mobility as we keep moving from one place to another. Baseline level of air pollution by means of chronic exposure has already damaged the airways and lung tissue from the beginning and hence there is already a reduced reserve to cope with the onslaught of coronavirus. This implies that people with the greatest long-term chronic pollutant exposure are the most vulnerable to COVID-19 related mortality.

To understand the association of COVID-19 with weather and climatological parameters, the correlation study has been done in the present work. Fig. S4 shows the correlation plots of COVID-19 related mortality, morbidity, and mortality rate with mean temperature (March–May), minimum temperature. The correlation coefficients of all these parameters are shown in Table 2. In addition to the above, correlation with many other parameters like wind speed and humidity has also been calculated but not shown in Figure. The morbidity and maximum temperature of the day during the pandemic period so far (March to May) in different cities of India are found to be anti-correlated with the correlation coefficient of ~0.56 (~56%) as indicated in Table 2. This result indicates that higher the maximum temperature, probability of infection due to COVID-19 reduces and the population is less susceptible to be infected. However this correlation is not significant even at 90% confidence level. It can be noticed from Table 1 that Mumbai is the hot spot region for infections with a maximum count of 27,251 where $T_{max}$ is lowest among these 6 cities during the analysis period. The inverse relationship between temperature and humidity along with COVID-19 has also been reported recently (Islam et al., 2020; Ma et al., 2020; Chen et al., 2020; Notari, 2020). These authors have suggested that colder and drier atmospheres are more favorable conditions for virus survival. Wu et al. (2020) have reported that temperature and relative humidity are negatively associated with the daily new infection cases and daily new mortality due to COVID-19. To some extent, these studies are in line with our findings. However, Yao et al. (2020) reported no relationship of COVID-19 transmission with temperature, while Xie and Zhu (2020) suggested positive correlation between mean temperature and the number of confirmed case. As evident from Table 2 and Fig. S4 that association of COVID-19 with rest of the weather markers are insignificant. In the present work, no correlation is noticed with
4. Conclusion

The present study provides the COVID-19 impact and their consequences in a context of environmental policy science. Results presented here provide two unique findings. Firstly, the baseline levels of major criteria pollutants have been experimentally achieved. Secondly, our research concludes that people having exposure to higher baseline levels of particulate pollution are at greater risk of dying from COVID-19. Findings tend to suggest that the baseline levels of PM$_{2.5}$ play a leading role in mortality whereas warmer temperatures show some sign in minimizing the infections. Results presented here are subjected to uncertainty that may be due to sampling size, age and presence of pre-existing and background diseases, health infrastructure, testing capability, environmental and climatological conditions and hence should be viewed with caution. Current findings are expected to serve as an incremental advancement in epidemiological research in India and in framing the response strategies and ambient air quality standards for these urban cities to be useful for control measures vise vies the economic development.

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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

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2020.110121.

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Author contributions

GB conceived the problem and designed the study and drafted the paper, SB did the detailed analysis, and rest of all other authors critically edited and made value addition to the paper and gave final approval for the version to be published. All authors agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work.

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