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COVID-19 strict lockdown impact on urban air quality and atmospheric temperature in four megacities of India

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ABSTRACT

COVID-19 pandemic has forced to lockdown entire India starting from 24th March 2020 to 14th April 2020 (first phase), extended up to 3rd May 2020 (second phase), and further extended up to 17th May 2020 (third phase) with limited relaxation in non-hotspot areas. This strict lockdown has severely curtailed human activity across India. Here, aerosol concentrations of particulate matters (PM) i.e., PM10, PM2.5, carbon monoxide (CO), nitrogen dioxide (NO2), sulphur dioxide (SO2), ammonia (NH3) and ozone (O3), and associated temperature fluctuation in four megacities (Delhi, Mumbai, Kolkata, and Chennai) from different regions of India were investigated. In this pandemic period, air temperature of Delhi, Kolkata, Mumbai and Chennai has decreased about 3°C, 2.5°C, 2°C and 2°C respectively. Compared to previous years and pre-lockdown period, air pollutants level and aerosol concentration (~41.91%, –37.13%, –54.94% and –46.79% respectively for Delhi, Mumbai, Kolkata and Chennai) in these four megacities has improved drastically during this lockdown period. Emission of PM2.5 has experienced the highest decrease in these megacities, which directly shows the positive impact of restricted vehicular movement. Restricted emissions produce encouraging results in terms of urban air quality and temperature, which may encourage policymakers to consider it in terms of environmental sustainability.

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1. Introduction

On December 31, 2019, several unusual pneumonia cases were reported in Wuhan, central China, and on January 7, 2020, the World Health Organization (WHO) announced the discovery of a new virus, severe acute respiratory syndrome coronavirus (SARS-CoV-2). The new disease known as COVID-19 and its global spread has greatly affected normal human activities with serious threats and economic consequences (Muhammad et al., 2020; Wang et al., 2020a). With the passage of time, the rapid spread of COVID-19 has become a global health crisis, and a public health emergency has been declared by WHO on January 30th, 2020, in response to the global concern (Bashir et al., 2020b). Thereafter, due to the unusual spread of COVID-19 and its effect on human health, on 11th March 2020 WHO declared coronavirus disease 19 (“a global epidemic”. Initially, the COVID-19 virus spread throughout every province of China, and within a few weeks, this virus had spread to several countries in Asia and surrounding continents. Beyond the China, on January 20th, the first COVID-19 case was reported in Wuhan, central China, and on January 7, 2020, the World Health Organization (WHO) announced the discovery of a new virus, severe acute respiratory syndrome coronavirus (SARS-CoV-2). The new disease known as COVID-19 and its global spread has greatly affected normal human activities with serious threats and economic consequences (Muhammad et al., 2020; Wang et al., 2020a). With the passage of time, the rapid spread of COVID-19 has become a global health crisis, and a public health emergency has been declared by WHO on January 30th, 2020, in response to the global concern (Bashir et al., 2020b). Thereafter, due to the unusual spread of COVID-19 and its effect on human health, on 11th March 2020 WHO declared coronavirus disease “a global epidemic”. Initially, the COVID-19 virus spread throughout every province of China, and within a few weeks, this virus had spread to several countries in Asia and surrounding continents. Beyond the China, on January 20th, the first COVID-19 case was reported in Washington State, the United States of America, and on January 24th, the first COVID-19 case was reported in Europe (Dantas et al., 2020). In Latin America, first case was reported on 25th February and on 5th March Argentina faced first corona cases (Rodriguez-Morales et al., 2020). The Kingdom of Saudi Arabia was discovery the first case on 2nd March 2020. In February 2020, the outbreaks of COVID-19 have started in India and Iran. Regarding the current information of 1st may 2020, death reached to 234,393 (7.06%), active cases were 2,036,960 and 1,049,260 (31.60%) is recovered over global population. To combat this situation, a global lockdown was imposed. The most significant ramifications are an unprecedented lockdown and several restrictions on measures in various countries around the world (Menut et al., 2020). As a result, in response to the pandemic, government of various countries across the world implemented lockdown measures such as prohibiting cross-city travel, closing schools and
workplaces, restricting public transportation and people movement, suspending national and international flights, and reducing industrial and commercial activities (Bherwani et al., 2020; Wang et al., 2020b). The COVID-19 pandemic was first challenge by China and declared lockdown from 23th January 2020 in Wuhan, which was the very first epicentre of coronavirus. Following China, various countries of the world were also declared unprecedented lockdown period to control this epidemic. After China, Italian government implemented lockdown and other restrictions in various phases and was nationwide complete lockdown by 23th March 2020 (Ceylan, 2020). Many cities in the United States implemented partial lockdown in early March, and as the virus spread rapidly, partial lockdown turned into complete lockdown (Muhammad et al., 2020). In India, south eastern part of the country like Maharashtra, Kerala, and in northern portion Delhi was the first state to be affected. The government then made the decision to restrict public gathering in different places such as shopping malls, institutions, and industrial workplaces. The first fourteen-hour lockdown took place on March 22nd (6 AM to 9 PM). Another 21-day lockdown began on March 24th and ended on April 14th, with the deterioration of increasing cases and extending until May 3rd, furthermore it was again extended to May 17th. This global lockdown ensures self-containment with social gatherings restricted. Almost every country across the world has applied strict lockdown and other measurements to stop the spread of COVID-19 disease and minimize the number of positive cases. As a result, strict lockdown has leading to a noteworthy reduction of the concentration of several atmospheric pollutants and gradually decreases air pollution accordingly. Extensive literature studies on the effect of lockdown impact on air pollution and associated climatic condition has been shown that there is significant reduction of atmospheric pollutants and improvement of air quality. In Germany and Netherlands, the concentration level of NO2 was significantly reduced of –15% to –30%, whereas other countries has shown the ranges of concentration reduction of –35% to –45% (Menut et al., 2020). In California, significant reduction of NO2 (23.1%), PM10 (19.6%) and PM2.5 (17.7%) was observed during the lockdown period (Shakoor et al., 2020). Moreover, the global air pollution has been drastically reduced due to unprecedented lockdown affect and several associated measure (Bao and Zhang, 2020). Therefore, significant reduction on air pollution has also reduced the atmospheric temperature and others weather related phenomenon. Studies has been shown that during the COVID-19 lockdown period the temperature and relative humidity ranges from –21 °C to 20 °C and 49% to 100% respectively in China, and in USA it ranges from –10 °C to 29 °C and 16% to 99% respectively (Wang et al., 2020c). In Italy, during the COVID-19 lockdown period the average temperature and relative humidity ranges from –5.28 °C to 34.30 °C and 11.39% to 88.42% respectively (Wu et al., 2020). In Kolkata metropolitan city, research study has is shown that reduction of lightning flashes about 49.16% during the COVID-19 lockdown period because of lower atmospheric pollution from the previous year record (Chowdhuri et al., 2020). The considerable reduction of pollution has been noticed a large number of cities except some cities like Rome, Las Vegas and others due to the implementation of late lockdown period (Kumari and Toshniwal, 2020). The main reason for reduction of atmospheric pollutants is due to the arrest of various anthropogenic activities like traveling, transportation, industry and more, which are the basic source of pollutants (Sharma et al., 2020).

The previous various literature studies have suggested that during the COVID-19 lockdown period the restriction in various measures have greatly impacted on air quality improvement. Although, the complete lockdown throughout the world have greatly impacted on global economy and gradually outbreak of corona virus severely affected the world economic growth (Rajput et al., 2021), particularly global economic and social distress. In addition to this, mobility particularly among migrant workers in the developing countries also created chaos among the people in various way (Pal et al., 2020). To save human life from COVID-19 pandemic several kinds of economic activities have been shut down for a long time period and which causes severe demographic changes and unemployment (Bashir et al., 2020a). In a nutshell, COVID-19 pandemic has remarkably effect on environmental issues and related various socio-economic changes across the world (Fattorini and Regoli, 2020). International Monetary Fund (IMF) reported that due to COVID-19 pandemic global economy pushed into a recession state and growth rate of economy may reduce by 4% in 2020 (Bank, 2020). Hence, several studies indicate that lockdown period has improved the regional air quality across the world (Adams, 2020; Gautam, 2020; Liu et al., 2020). Several countries in the world have put a number of effective policies and restrictions to stop spreading of COVID-19 disease. And as a result of the strict lockdown and restricted economic activities, the air quality has improved. However, this clean air quality will not last forever, and air pollution levels may rise significantly in the future.

The different studies reveal that the quality of the air was drastically improved and the level of pollutants has decreased at large scale during the lockdown period but the changing trend, impact on regional climate and its pattern are not still well explored. Therefore, the main objective of this study is to estimate the changing rate and associated pattern of air pollutants and temperature of four major megacities in India such as New Delhi, Mumbai, Kolkata, and Chennai during lockdown period; in addition, the relationship between trend of the aerosol concentration and fluctuation of temperature in the mentioned four major megacities of India has also been explored to understand the impact on regional climate. Finally, this study will help to the policymakers and environmentalist research community for sustainable management plan for environment to control and reduced air pollution in various polluted areas.

2. Study area

The present research work has been carried out in four megacities of India i.e., Delhi, Mumbai, Kolkata and Chennai (Fig. 1). The scenario of urban population has been increasing rapidly in the megacities of India during last few decades. Thus, due to huge number of population, megacities face different types of problems i.e. on infrastructures as well as on environment and human health (Wenzel et al., 2007). Delhi is the capital of India and one of the largest megacities of South Asia with the total population of 16.31 million (2011 census of India). The major cause of air pollution in Delhi is due to large number of industries, huge vehicles on road and power plants. Mumbai is popularly known as financial capital of India and the capital of state of Maharashtra. According to census of India (2011) population density of Mumbai is 19,652 km². The major causes of pollution in Mumbai are to expansion of industries and increases in vehicles. Kolkata is one of the most polluted megacities and it is known as ‘City of Joy’ and the capital of state of West Bengal. According to census of India (2011) total number of population in Kolkata is 14.11 million with a density of 7480 km². The major causes of air pollution in Kolkata are due to unplanned urbanization, uncontrolled vehicular numbers and badly maintained roads (Gurjar et al., 2016). Among the four megacities mentioned above in India, Chennai is not as bad in terms of air pollution as the other three. Essentially, vehicles are the primary source of poor air quality in Chennai.
3. Data sources and methodology

In this study, to fulfill the aforementioned objectives Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data was used to measure aerosol concentration. Alongside, several atmospheric pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$, NH$_3$, SO$_2$, CO and O$_3$) data was also collected and used accordingly. Two most popular statistical indices namely Man-Kendal and Sen’s slope estimation were used to understand the trend of air pollution and associated regional temperature. Furthermore, we have also suggested various policies regarding this issue for both local and international level.

3.1. Data used

MODIS satellite data was used to retrieve aerosols concentration over land surface and collected from https://modis.gsfc.nasa.gov/data/dataprod/. Alongside, most popular atmospheric pollutants data such as particular matters (PM$_{10}$ and PM$_{2.5}$), carbon monoxide (CO), nitrogen dioxide (NO$_2$), sulphur dioxide (SO$_2$), ozone (O$_3$) and ammonia (NH$_3$) were collected from the Central Pollution Control Board (CPCB), India (https://app.cpcbcr.com/AQI_India/). The average temperature data for the four megacities i.e. Delhi, Mumbai, Kolkata and Chennai are available and collected from https://www.iari.res.in/, during the period of 2016 to 2020.

3.2. Methods

The methodology is an integral and most important part for proper development and analysis of a research study. Therefore, the framework of research methods i.e., research design allows researchers to perfect study on research methods that are suitable for the subject matter and analysis them accordingly. An impactful research design generally creates a minimum bias in data and amplifies trust in the accuracy of collected data. A research design that developed the least margin of inaccuracy in experimental research is usually considered the desired outcome (Kothari, 2004). The present research design is presented in Fig. 2. In a nutshell, satellite MODIS Terra and several atmospheric pollutants data were used to identify atmospheric pollutants level and following average temperature data was also collected to find the correlation between atmospheric pollutants level and associated temperature. The trend analysis of various atmospheric pollutants was calculated through statistical analysis of Man-Kendal and Sen’s slope estimation in IBM SPSS 22 statistic package. The following section described in details of analysis process and result presentation accordingly.

3.2.1. Aerosol concentration

The aerosol concentration is measured by different techniques, but Remote sensing (RS) data with geographical information system (GIS) technique is best and time saving. In this study, aerosol concentration measured from the Moderate Resolution Imaging Spectroradiometer (MODIS) data (Shaw and Gorai, 2018). This MODIS data provide first passive satellite radiometers designed to gain aerosols data from land and ocean (Xia et al., 2008). The basic strategy for retrieving aerosol data from MODIS satellite data was introduced by Kaufman et al. (1997). Thereafter, the algorithm has been gradually modified through time depending on various collections since the initiate of MODIS (Remer et al., 2005). MODIS
Terra and Aqua satellites data are provided by National Aeronautics and Space Administration (NASA) which acquire two measurements of aerosol optical depth (AOD) per day (at 10:30 and 13:30 local time) (Chang et al., 2014). MODIS Terra daily level 2 and 3 data have 10 km spatial resolution with 550 nm wavelength (Alam et al., 2011) which have been used for this study. After extraction of AOD level for the selected metropolitan areas (Shaw and Gorai, 2018), we link the PM2.5 data by linear regression and Pearson’s correlation methods (Chang et al., 2014; Mhawish et al., 2018). The Eqs.(1)–(3) of statistical downscaling technique for extraction aerosol concentration is from AOD given below, which is followed by Chang et al. (2014).

\[ AC_s(t) = a_0(t) + a_1(s, t)AOD_s(t) + \varepsilon(s, t) \tag{1} \]

\[ x_0(t) = \beta_0 + \beta_0(t) + \gamma_0z_0 \tag{2} \]

\[ x_1(s, t) = \beta_1(s) + \beta_1(t) + \gamma_1z_1 \tag{3} \]

Where, \( AC_s(t) \) is the aerosol concentration rate, \( x_0(t) \) and \( x_1(s, t) \) are intercept and slope in a specific location and day, and \( \varepsilon(s, t) \) is the residual error. From the above equation we have got the aerosol concentration rate for each day of four metropolitan areas. The validation is done by the correlation between PM2.5 concentration and aerosol concentration and all the result have a positive relation.

3.2.2. Mann-Kendall (MK) trend test

For estimating the trend of the pollutant, the Mann-Kendall trend test and Sen’s slope estimator has been considered in this study. The Mann–Kendall (MK) analysis is a non-parametric study of the trend to define the growing and declining trend in time series. This measure the relative sample data sizes instead of the data attributes itself (Gilbert, 1987). The MK experiment is first applied using the null hypothesis H0 of no pattern testing, i.e. the findings \( x_i \) are spontaneously ordered in time, against the alternative hypothesis, H1, where a logarithmic pattern is rising or reducing. The main advantage of MK test is no outer data properties or non-normal data sequence influence the result of this test (Kendall, 1975). In general, MK test has been widely used to analysis in hydrological and weather-related studies. In this study, the direction of air quality index (AQI) was studied based on MK test. The MK test was measure through rank based non-parametric technique with skewed variables (Pal et al., 2021). All following data variables are contrasted with the data values assessed as organized time series.

The Mann-Kendall test base described as follows on the test statistics \( S \) in Eq.(4)

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \tag{4} \]

Here \( x_j \) is the continuous data value, \( n \) is the data sets length, and

\[ \text{sgn}(\theta) = \begin{cases} 1 & \text{if } \theta > 0 \\ 0 & \text{if } \theta = 0 \\ -1 & \text{if } \theta < 0 \end{cases} \tag{5} \]

Mann (1945) and Kendall (1975) have reported that statistics \( S \), with the mean and variance as followed, are distributed essentially normally when \( n \geq 8 \)

\[ E(S) = 0 \tag{6} \]

\[ V(S) = \frac{n(n-1)(2n+5)}{18} - \sum_{i=1}^{n} t_i(i-1)(2i+5) \tag{7} \]

Where \( t_i \) is the degree number of relations \( i \). Standardized statistics of tests \( Z \) are determined by Eq.(8)
\[ Z_{MK} = \begin{cases} \frac{S - 1}{\sqrt{Var(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{1 - S}{\sqrt{Var(S)}}, & S < 0 \end{cases} \] (8)

3.2.3. Sen’s slope estimator

The estimation of Sen’s slope is analysis the pattern of intensity of a dataset and is also a non-parametric approach to median exploitation (Gilbert, 1987). In Sen’s slope analysis, the dataset has been arranged in an ascending order. In the X axis, first sub-series data will be positioned and in the Y axis, the Cartesian coordinate system will cover about half of the sub-series (Pal et al., 2020). The magnitude of the trend is estimated with the help of the Sen’s estimator. The slope \( T_i \) for all datasets are estimated with considering the following Eq. (9) (Sen, 1968).

\[ T_i = \frac{x_j - x_k}{j - k} \text{ for } i = 1, 2, \ldots, N \] (9)

Here \( x_j \) and \( x_k \) are accordingly regarded as data values at time \( j \) and \( k \) \((j > k)\). The median of such \( T_i \) N values is defined as Sen’s slope estimator provided by Eqs. (10) and (11)

\[ Q_i = T_{\text{med}} \text{ for } N \text{ odd} \] (10)

\[ Q_i = \frac{1}{2} \left( T_{\text{med}}^{(\text{odd})} + T_{\text{med}}^{(\text{even})} \right) \text{ for } N \text{ even} \] (11)

If \( N \) appears odd, Sen’s estimator is determined as \( Q_{\text{med}} = T_{\text{med}} \) while it is known as \( Q_{\text{med}} = \frac{1}{2} \left( T_{\text{med}}^{(\text{odd})} + T_{\text{med}}^{(\text{even})} \right) \) if \( N \) appears even. Ultimately, \( Q_{\text{med}} \) is determined by a two-sided experiment at a confidence interval of 100%×(1-\( \alpha \)) and a real slope could be acquired by the non-parametric method.

\( Q_i \)’s positive value shows a forward or upward direction, and \( Q_i \)’s negative value provides a decreasing or outwards direction in time series.

4. Results

As has already been mentioned, the COVID-19 pandemic imposed a national lockdown, restricted human activities from 24th March to 17th May 2020 resulting in drastic improvements in air pollution and decreased aerosol concentration could have a positive impact on the regional climate and its surrounding environment. The most significant and far-reaching positive impact of megacities could be a change in atmospheric climate. This study will focus on the effects of forced lockdowns on the atmosphere and climate in megacities. In the first two segments, a summary of the current work will be discussed. The effects of the COVID-19 pandemic on climate and aerosol concentrations will be discussed in detail in the sections that follow.

4.1. Temporal variation of major air pollutants

The improvement in the concentration of major air pollutants is very clear from the estimated findings that the megacities witnessed major air pollutants during the pre-lockdowns period of COVID-19 (before 24th March 2020), as in previous months or years, but after the complete lockdowns (24th March 2020) a significant reduction of atmospheric pollutants was observed in the megacities as a result of COVID-19 pandemic. Particularly reductions in the quantity of pollutants such as PM\(_{10}\), PM\(_{2.5}\), CO, NO\(_x\), SO\(_2\) and NH\(_3\) have been recorded during the lockdown phase. PM\(_{10}\) and PM\(_{2.5}\) declined by \(-39.25\%\) and \(-50.20\%\) respectively in Delhi, whereas PM\(_{10}\) and PM\(_{2.5}\) decreased by \(-56.30\%\) and \(-70.08\%\) respectively in Mumbai. The concentrations of PM\(_{10}\) and PM\(_{2.5}\) in Kolkata decreased by \(-68.92\%\) and \(-81.02\%\) respectively, while the concentrations of PM\(_{10}\) and PM\(_{2.5}\) in Chennai decreased by \(-43.51\%\) and \(-53.01\%\) respectively due to COVID-19 pandemic.

Decreases in particulate matter are directly related to emissions from automobiles, dust, burning smoke or dynamic chemical processes such as SO\(_2\) and NO. Other pollutants that displayed a substantial change during pre-lockdown and lockdown are CO \((-14.34\%)\) and NO\(_2\) \((-25.59\%)\), whereas SO\(_2\) \((-8.29\%)\) displayed a very small decrease relative to other contaminants in Delhi. Similarly, in Mumbai, the pollutants that showed significant changes during pre-lockdown and lockdown are CO \((-24.24\%\)\) and NO\(_2\) \((-76.88\%)\), while SO\(_2\) \((-5.47\%)\) showed a very small decrease compared to other contaminants. Moreover, CO \((-57.57\%)\) and NO\(_2\) \((-56.95\%)\) are pollutants in Kolkata, which saw a substantial decline during pre-lockdown and lockdown time (Table 1). Similarly, CO \((-46.77\%)\) and NO\(_2\) \((-26.27\%)\) are pollutants in Chennai, which has seen a significant fall during pre-lockdown and lockdown period. The O\(_3\) level has been increased in all four megacities areas, especially in industrial and transport-dominated areas, a decrease in NO which contributes to a decrease in O\(_3\) consumption (NO + O\(_3\) = NO\(_2\) + O\(_2\)) and to an increase in O\(_3\) levels (Fig. 3). The Mann-Kendal and Sen's slope trends test estimation shows the same significant fall of various pollutants level in these selected four megacities in India (Table 2). The trend of different pollutant and gases in the cities of Kolkata show that the significant decreasing trend of PM\(_{2.5}\) was 1.586 mg/m\(^3\) per day, whereas, the PM\(_{10}\) decreasing trend rate was 1.00 mg/per day. Moreover, all the pollutant gases also showing decreasing trend; among the gases pollutant, highest rate of decreasing trend found in SO\(_2\) and NO\(_2\). The trend of different pollutant and gases in the cities of New Delhi show the significant decreasing trend. Here, per day decreasing trend of PM\(_{2.5}\) was \(-1.308\) mg/m\(^3\), whereas, the PM\(_{10}\) decreasing trend rate was 0.643 mg/m\(^3\) per day. Moreover, all the pollutant gases also showing decreasing trend; among the gases pollutant, highest rate of decreasing trend found in SO\(_2\) and NO\(_2\). In the city of Mumbai, the trend of different pollutants and gases shows significant decreasing trend. The PM\(_{2.5}\) and PM\(_{10}\) had been decreasing at the rate of 0.182 and 1.154 mg/m\(^3\) per day, whereas, the pollutants gas like NO\(_2\) decreasing at \(-0.81\) mg/m\(^3\). In the city of Chennai, the trend of different pollutants and gases showed that the significant decreasing trend of PM\(_{2.5}\) (1.333 mg/m\(^3\)) per day).

Moreover, the PM\(_{10}\) decreasing trend rate was 0.056 mg/m\(^3\) per day. Moreover, all the pollutant gases also showing decreasing trend; among the gases pollutant, highest rate of decreasing trend found in NO\(_2\) and ozone.

4.2. Atmospheric aerosol concentration of four megacities

As megacities are not an industrial region, therefore, manmade pollutants are generated by vehicle traffic and household activities. Observation of this result reveals that the concentration of aerosols declined \(-41.91\%, -37.13\%, -54.94\%\) and \(-46.79\%\) (Table 2) respectively for Delhi, Mumbai, Kolkata and Chennai significantly during the lockdown process, while the average concentration of aerosol in pre-lockdown (8th March to 23 March 2020) period are 140.88, 60.99, 96.66, 53.19 mg/m\(^3\) for Delhi, Mumbai, Kolkata and Chennai megacities was observed during the pre-lockdown period. In Delhi and Kolkata, the declining and rising trend in aerosol concentration is very prominent due to the minimal relaxation (14th April 2020) of COVID-19 lockdown operation by the central government, which has enabled citizens to carry out the necessary vehicles and human activities outside the red zone, with a marginal effect on aerosol concentration. It is a clear indicator that a significant decrease in the concentration of air pollutants side by side could be expected if the strict enforcement of pollution control measures, such as lock-down, were applied.
### Table 1
Overall variation of different pollutants in four megacities of India.

| Types of Pollutants | Overall Variation | Delhi | Mumbai | Kolkata | Chennai |
|---------------------|-------------------|-------|--------|---------|---------|
|                     | Net %             | %     | %      | %       | %       |
| PM$_{2.5}$          | 84.4416           | -50.2036 | -86.3449 | -70.0843 | -134.783 | -40.5524 | -50.8166 |
| PM$_{10}$           | 58.618            | -39.251 | -76.572 | -56.302 | -109.487 | -68.9278 | -19.3854 | -41.1058 |
| NO$_2$              | -12.8937          | -25.5935 | -42.0553 | -76.8868 | -35.3198 | -56.9511 | -4.1312 | -23.6706 |
| NH$_3$              | 0.004136          | 0.057427 | -7.2635 | -70.5249 | -3.58073 | -45.9586 | -18.0886 | -61.3537 |
| SO$_2$              | -1.77647          | -8.29857 | -1.46234 | -5.47748 | -15.8103 | -61.7749 | -21.3471 | -67.6495 |
| CO                  | -8.89225          | -14.3467 | -13.6025 | -24.2477 | -30.7311 | -57.5708 | -32.1665 | -45.7892 |
| O$_3$               | 18.16384          | 59.58699 | 0.904696 | 2.86376 | 29.9493 | 40.6701 | 48.86725 | 191.7078 |

**Fig. 3.** Comparison of various pollutants (average) in four megacities (a) Delhi, (b) Mumbai, (c) Kolkata and (d) Chennai.

### Table 2
Average aerosol concentrations before and after lockdown in four megacities of India.

| Average Aerosol concentration (µg/m$^3$) | Delhi | Mumbai | Kolkata | Chennai |
|----------------------------------------|-------|--------|---------|---------|
| Before lockdown                         | 140.88 | 61.00  | 96.66   | 53.19   |
| After lockdown                          | 81.84  | 38.35  | 43.56   | 28.30   |
| Net variation                           | -59.04 | -22.65 | -53.10  | -24.89  |
| % of Variation                          | -41.91 | -37.13 | -54.94  | -46.79  |
Table 3
Mann–Kendal and Sen’s slope trends test estimation.

|       | Kolkata Mann–Kendal Z | Sen’s slope | Chennai Mann–Kendal Z | Sen’s slope | Mumbai Mann–Kendal Z | Sen’s slope | New Delhi Mann–Kendal Z | Sen’s slope |
|-------|-----------------------|-------------|-----------------------|-------------|----------------------|-------------|------------------------|-------------|
| PM$_{2.5}$ Average | -2.95*** | -1.586*** | -2.98*** | -1.333*** | -2.50*** | -0.500*** | -2.93*** | -1.308*** |
| Minimum | -2.01*** | -1.214*** | -2.92*** | -0.778*** | -1.55*** | -0.182*** | -3.76*** | -0.643*** |
| Maximum | -2.01*** | -1.463*** | -2.64*** | -2.510*** | -2.97*** | -1.136*** | -3.10*** | -1.818*** |
| PM$_{10}$ Average | -2.82** | -1.000** | -2.05** | 0.056*** | -3.19*** | -1.154*** | -1.47*** | -0.575** |
| Minimum | -2.86 | -1.414** | -1.74*** | -0.238** | -2.11*** | -0.889** | -2.58*** | -0.667*** |
| Maximum | -2.56** | -1.370** | -1.66** | -0.221** | -1.50** | -0.300*** | -0.96*** | -0.682*** |
| NO$_2$ Average | -2.64*** | -0.500** | -1.02** | -0.041*** | -0.85** | -0.080** | -0.94** | -0.100** |
| Minimum | -2.51** | -0.167** | -1.01*** | -0.060*** | -0.87** | -0.112** | -0.39** | -0.010*** |
| Maximum | -0.04*** | -0.973** | -0.64** | -0.120** | -0.69** | -1.126** | -1.64** | -0.300** |
| NH$_3$ Average | -0.52*** | -0.051** | -5.51*** | -0.237** | -0.81** | -0.587** | -0.81** | -0.059** |
| Minimum | -0.81 | -0.040** | -1.74** | -0.208** | -0.62** | -0.524** | -0.90** | -0.210** |
| Maximum | -0.74*** | -0.512** | -0.52** | -0.121*** | -0.65** | -0.252** | 0.49** | 0.310** |
| SO$_2$ Average | -0.91*** | -0.183** | -0.91** | -0.160** | -0.77** | -0.346** | -0.84** | -0.320** |
| Minimum | -0.64** | -0.303** | -0.34** | -0.400** | -0.39** | -0.084** | -0.76** | -0.600** |
| Maximum | -0.52** | -0.023** | -0.61** | -0.287** | -2.53** | -0.659** | -0.54** | -0.350** |
| CO Average | -0.61*** | -0.140** | -0.24** | -0.138** | -0.56** | -0.510** | 0.43** | 0.063** |
| Minimum | -0.61 | -0.301** | -0.62** | -0.081** | -0.45** | -0.292** | -0.94** | -0.300** |
| Maximum | -5.51*** | -0.249** | -0.61** | -0.050** | -0.37** | -0.333** | -0.56** | -0.280** |
| Ozone Average | -0.34** | -0.514*** | -0.54** | -0.410*** | -0.19** | -0.224** | -0.45** | -0.820** |
| Minimum | -0.02** | -0.472** | -0.40** | -0.127** | -0.21** | -0.181** | -0.39** | -0.240** |
| Maximum | -0.01** | -0.359** | -0.31** | -0.128** | -0.13** | -0.139** | -0.85** | -0.400** |

***, **, and * are the significant at the 1%, 5%, and 10% level of significance, respectively.
that the concentration of atmospheric aerosol in these four megacities decreased dramatically due to forced shutdowns (Fig. 4). Table 3 shows that net and percentage variation of average aerosol concentration in aforementioned four megacities.

4.3. Lockdown impact on regional climate

During the COVID-19 epidemic period (8th March 2020 to 6th May 2020) the regional temperature of four megacities was measured on a daily basis to infer spatial–temporal variations. A substantial decrease in temperature was observed in Delhi and Kolkata, while a slight drop in temperature was observed in Mumbai and Chennai owing to their geographical location (Fig. 5). As the COVID-19 lockdown restricted human activities and the movement of vehicles, it also restricted the emissions of pollutants and the concentration of aerosols in the atmosphere, which eventually contributed to a significant decrease in temperature. This decline in temperature in India’s four megacities has contributed to regional climate change. The results of this research reveal that near about 3 °C temperature falls in Delhi due to a drastic decline in atmospheric pollutants and aerosols, whereas 2.5 °C temperature falls in Kolkata. The temperatures in Mumbai and Chennai have decreased by 2 °C.

4.4. Relation between concentrations of major pollutants

The correlation between various atmospheric pollutants in four megacities of India during the study period (i.e., from 8th March 2020 to 6th May 2020) is shown in Fig. 6. In Delhi, the mean daily aggregation of PM10 is closely related to the average daily accumulations of PM2.5 (r = 0.81). Similarly, Fig. 5 shows average daily accumulations of NO2 is directly correlated with the maximum daily concentration of PM2.5 (r = 0.79) and PM10 (r = 0.54). The mean daily concentration of SO2 is directly linked to the average daily accumulations of PM2.5 (r = 0.30) PM10 (r = 0.40) and NH3 (r = 0.44). The mean daily concentration of CO is directly linked to the average daily accumulations of PM2.5 (r = 0.79) PM10 (r = 0.84), NO2 (r = 0.57), NH3 (r = 0.31) and SO2 (r = 0.32). In Mumbai, the mean daily aggregation of PM2.5 is closely related to the average daily accumulations of CO (r = 0.73). Similarly, the average daily accumulation of PM10 is directly correlated with the maximum daily concentration of PM2.5 (r = 0.94) and CO (r = 0.25). The mean daily concentration of NO2 is directly linked to the average daily accumulations of PM2.5 (r = 0.82) and PM10 (r = 0.83). The mean daily concentration of NH3 is directly linked to the average daily accumulations of PM2.5 (r = 0.35), PM10 (r = 0.30) and NO2 (r = 0.46). Similarly, the average daily accumulation of SO2 is linked with NH3 (r = 0.47). The daily accumulation of CO has a positive

Fig. 5. Comparison of average temperature in four megacities between the years of 2016 to 2020 (a) Delhi, (b) Mumbai, (c) Kolkata and (d) Chennai.
relation with PM$_{2.5}$ ($r = 0.61$), PM$_{10}$ ($r = 0.69$), NO$_2$ ($r = 0.71$) and NH$_3$ ($r = 0.32$). In Kolkata, the mean daily aggregation of PM$_{2.5}$ is closely related to the average daily accumulations of SO$_2$ ($r = 0.85$). Similarly, the average daily accumulation of PM$_{10}$ is directly correlated with the maximum daily concentration of PM$_{2.5}$ ($r = 0.99$) and SO$_2$ ($r = 0.74$). The mean daily concentration of NO$_2$ is directly linked to the average daily accumulations of PM$_{2.5}$ ($r = 0.55$), PM$_{10}$ ($r = 0.54$) and NO$_2$ ($r = 0.40$). Similarly, the mean daily accumulation of SO$_2$ is linked with PM$_{2.5}$ ($r = 0.59$), PM$_{10}$ ($r = 0.60$) and NO$_2$ ($r = 0.39$). The daily accumulations of CO have a positive relation with PM$_{2.5}$ ($r = 0.75$) and PM$_{10}$ ($r = 0.78$), NO$_2$ ($r = 0.66$) and SO$_2$ ($r = 0.54$). In Chennai, the mean daily aggregation of PM$_{2.5}$ is closely related to the average daily accumulation of CO ($r = 0.30$). Similarly, the average daily accumulations of PM$_{10}$ are directly correlated with the maximum daily concentration of PM$_{2.5}$ ($r = 0.79$). The mean daily concentration of NO$_2$ is directly linked to the average daily accumulation of PM$_{2.5}$ ($r = 0.73$), PM$_{10}$ ($r = 0.54$) and SO$_2$ ($r = 0.66$). The mean daily concentration of NH$_3$ is directly linked to the average daily accumulations of PM$_{2.5}$ ($r = 0.55$), PM$_{10}$ ($r = 0.54$) and NO$_2$ ($r = 0.39$). Similarly, the average daily accumulations of SO$_2$ is linked with PM$_{2.5}$ ($r = 0.68$), PM$_{10}$ ($r = 0.79$), NO$_2$ ($r = 0.48$), SO$_2$ ($r = 0.85$) and NH$_3$ ($r = 0.37$). However, there is on such correlation between PM$_{2.5}$ and PM$_{10}$, NH$_3$, NO$_2$, SO$_2$ and O$_3$ PM$_{10}$ and SO$_2$ and O$_3$, NO$_2$ and NH$_3$, SO$_2$, CO and O$_3$, NH$_3$ and NO$_2$, SO$_2$, CO and O$_3$, as well as SO$_2$ and O$_3$, CO, NH$_3$ and NO$_2$ have been found in these selected four megacities.

5. Discussion

Excess amount of pollutants exposure into the atmosphere causes poor air quality and associated damages the human health and ecosystem beyond the expectation level. Air pollution and several associated harmful results is a serious challenge and one of the major global issues. COVID-19 pandemic throughout the world has presented an opportunity to reduce various atmospheric pollutants concentration level through the strict measure of lockdown effect. The evaluation and measurement of COVID-19 lockdown impact on climate and atmospheric pollutants in megacities remains a fairly recent topic in the field of atmospheric science. While research on pollutants level and impact on regional climate are fairly common, comparable attempts to measure megacity emissions are even less available. The first report on the impact of urban pollutants on regional pollution levels was reported by Mayer et al. (2000). Though not directly focusing on the effect of megacity on regional climate patterns, it studied the correlation among rapid urbanisation and main ambient contaminant components such as NO$_2$, ozone and hydroxyl radicals. A relatively limited number of researches directly examined the geographic effects of air pollutants in several megacities across the world. The effect of megacity on the regional scale was first investigated in a set of simulation studies based on regional atmospheric dispersion of contaminants (Beirle et al., 2011; Gurjar et al., 2016; Guttikunda et al., 2005). Economic impacts of megacity have usually been found to be very small and relatively less than the proportion of megacity pollutants. The regional impacts can, however, be quite significant (Baklanov et al., 2010). Fortunately, lockdown policies in various regions of the world have given an incentive to explain away human effects on the climate. The findings of this study may also help to reconsider the degree to which we are liable for our suffering. It could also help to understand that lockdown will be an innovative step to preserve the climate and provide local residents with a better environment. Since in urban environments, in order to achieve the goal of economic development, the sources of environmental resources are sometimes neglected, as a consequence of which residents are at risk for safety. The horrible disease, on the other hand, is threatening our existence, but the natural regeneration cycle is still in progress.

As a result, the lockdown placed a strong emphasis on restricting transportation and travel, as well as preventing people from leaving their homes, in order to limit the spread of the Corona virus while reducing anthropogenic emissions of air pollutants. The

![Fig. 6. Correlation of various atmospheric pollutants in four megacities (a) Delhi, (b) Mumbai, (c) Kolkata and (d) Chennai.](image-url)
reduction of atmospheric pollutant emissions alters the concentration level of surface pollutants in various countries. The extensive literature studies from an international perspective have revealed that numerous works were done on the effects of lockdown impact on air quality due to fluctuations of environmental pollutants. In China, January 2020, after the pandemic has been started, surface pollutants data analysed has shown that lockdown reduced the concentration of PM$_{2.5}$ and NO$_2$ by 35% and 60% respectively (Shi and Brasseur, 2020). In central China, NO$_2$ emission cut down near about 30% (Dutheil et al., 2020) and reduction in CO$_2$ by 25% and 6% in China and worldwide respectively (Broomandi et al., 2020). In Barcelona region of Spain, surface measurement has shown that Black Carbon and NO$_2$ decreased by $-45\%$ to $-51\%$ and for PM$_{10}$ it is $-28\%$ to $-31\%$ with significant increasing of ozone i.e. $+33\%$ to $+57\%$ (Tobías et al., 2020). In Europe, the measurement of air quality from satellite data is shown that there have significant reduction improvements in air quality. A significant reduction of NO$_2$ by $-20\%$ to $-38\%$ has been observed in Western Europe (Bauwens et al., 2020). In São Paulo, Brazil, a significant decline is found in CO, NO$_2$ and NO by 64.8%, 54.3% and 77.3% respectively with remarkable increasing of O$_3$ by 30% (Nakada and Urban, 2020). In India, a similar decline has been found among the PM$_{2.5}$, PM$_{10}$, CO and NO by 43%, 31%, 10% and 8% respectively during the lockdown period compared to the previous year (Sharma et al., 2020). In the city of Milan, a significant reduction of SO$_2$ has been noticed during the lockdown period with appreciable drop of others atmospheric pollutants (Collivignarelli et al., 2020). Another study in India has shown that improvement of air quality significantly reduced the atmospheric daily temperature by 0.3 $^\circ$C (Pal et al., 2021). Sharma et al. (2020) has shown that only for first four days lock down over nation, 88 cities reduced pollution level drastically based on official data from Central Pollution Control Board (CPCB). This lockdown period regulates measurement for combating air pollution and current existing work carried out in the lockdown period due to changing air quality and the spread of COVID-19 due to climatic events.

In India, studies have been shown that significant reduction of atmospheric pollutants (PM$_{2.5}$, PM$_{10}$ and NO$_2$) concentration level was noticed during the lockdown period and it is clearly indicates the positive effect of lockdown measurements on air quality (Sharma et al., 2020). During the lockdown period all industrial and commercial activities were fully stopped and this is the key reasons for significant reduction of atmospheric pollutants (Wang et al., 2020). In this study, the effect of the lockdown (24th March 2020) on the accelerated spread of the COVID-19 pandemic in the atmosphere of four megacities of India was assessed owing to the concentration of major pollutants and aerosols throughout the climate. The study mainly focused on reduction of atmospheric pollutants due to COVID-19 lockdown and associated effect on regional temperature. Here, Mann-Kendal and Sen’s slope statistical estimation were used to do so. Alongside, we have also discussed the air pollution related policy recommendation for future environmental sustainability. All four megacities are globally recognised polluted cities in India. Throughout all the time the above mentioned four megacities are always covered by high atmospheric pollutants and poor air quality. But, the lockdown period effect on aerosol concentration and atmospheric pollutants such as PM$_{2.5}$, and PM$_{10}$ have undergone highest decline accompanied by NH$_3$, SO$_2$, NO$_2$, and CO. The Mann-Kendal and Sen’s slope trends test estimation reveals this significant fall of pollutant levels in four selected megacities in India. This drastic fall of aerosols and atmospheric pollutants has provided huge impact of the selected megacities regional climate. The result reveals that the temperature of these selected four megacities decreased at significant level i.e. $3\, ^\circ$C and $2.5\, ^\circ$C temperature falls in Delhi and Kolkata respectively. In the case of Mumbai and Chennai megacity, the temperature has decreased by $2\, ^\circ$C because of drastic decline in atmospheric pollutants and aerosols. The results show that implementing the lockdown would result in a significant improvement in the concentration of aerosols and atmospheric pollutants, and that it should be implemented as an alternative method of reducing pollution in order to maintain a healthy regional climate.

The pandemic of COVID-19 has emerged several challenges to societies and humanity across the world. More or less, all countries in various part of the globe are faced this risk challenges but developing countries with low-income level have faced severe challenges due to the lack of proper health infrastructure, human resources and financial condition (Rasul, 2020). The COVID-19 pandemic has recognized the connection among the human health, environment, agricultural system and economy (Gillespie et al., 2021). Furthermore, the pandemic has recognised the reorganisation of the agricultural system and the reduction of the climate change phenomenon. As a result, identifying the most appropriate policies to address COVID-19 pandemic-related challenges with appropriate social goals is critical for combating this pandemic. Policymakers in developing countries such as India have faced a number of challenges, including prioritising policies to achieve environmental sustainability, managing health crises and food during pandemics, and ultimately recovering the economy. Among the several policies, travel restriction and shutdown of industries are the most important to prevent this type of global pandemic. Alongside, various policies related to vehicle emissions such as stricter emission limit before 2023 (Leirião et al., 2020), renewal of public as well as self-transport vehicles, and inspection and maintenance of vehicles in a certain time period properly are the most important (Krecl et al., 2020). This type of policies has been under taken not only local or region level but also in global level (Saha et al., 2021). Basically, implementation of policies has been taken based on the three criteria i.e., coherence, compatibility, and congruence. In which, coherence emphasize on achieving multiple goals in an optimal way, compatibility indicates consistency in various policy goals and congruence indicates ability of various policy option and strategies (Rasul, 2020). Therefore, policy makers are enabling to prioritize socio-economic and environmental policy choices and initiate better connectivity from local to global.

Several policy makers and association aim to refresh the higher level of atmospheric pollution relative to the policy-implemented pre-COVID-19 lockdown period to postpone Green New Deal projects and reduce vehicle emissions, and to obstruct the implementation of renewable energy and supply side work. The world leaders try to maintain the net zero emission through reduction targets of pollutants in various field and the impact of climate change in the world’s economic responses to COVID-19 are expected to have an impact on pollutants emissions in the coming years. Therefore, this research study has various importance considering the relation of several atmospheric particulate matter and associated weather phenomenon like temperature, and in near future further detail study should be perform in this topic.

6. Conclusion

Impact of COVID-19 lockdown particularly on atmospheric quality and air temperature has been studied over four Indian megacities i.e., Delhi, Mumbai, Kolkata and Chennai. The finding of this study is shown that during the lockdown period air pollution level in all these megacities have fallen to an unimaginable limit. From the previous year, this year during the lockdown time aerosol concentration has decreased by $-41.91\%$, $-37.13\%$, $-54.94\%$ and $-46.79\%$ in Delhi, Mumbai, Kolkata and Chennai respectively. From the output, it is clearly understood that lockdown effect has positive impact on atmospheric quality in India.
Due to low level of air pollution, heat island effect in these megacities has diminished during this period. The air temperature of Delhi, Kolkata, Mumbai and Chennai decreased by 3°C, 2.5°C, 2°C and 2°C, respectively, which eventually had a significant impact on the regional climate. This lockdown may be seen as a “Blessing in Disguise,” as the nature is rejuvenating itself in these highly polluted megacities. The environmental impact of this temporary lockdown clearly shows that the air pollution can be reduced by implementing strict plans. Thus, policy implementation and recognition of the best policies for COVID-19 challenges is an important criterion for long-term recovery from this situation. As a result, the government implements a variety of policies and programmes that ultimately influence the outcome. In future, this type of periodic lockdown may be required to improve the overall environment in the long run, and policymakers at the federal level should consider it as a possible solution. Furthermore, in this study only secondary data of aerosol concentrations and statistical method of Mann-Kendall is used to understand the COVID-19 induced lockdown and atmospheric quality and it is the limitation of this study. Hereafter, in future more advanced satellite data and machine learning algorithm will be very much useful for this type of research work and proper sustainable planning implementation.

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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