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Effect of restricted emissions during COVID-19 on air quality in India

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HIGHLIGHTS
• The effect of restricted human activities due to the COVID-19 pandemic in India on air quality in 22 cities was estimated.
• PM$_{2.5}$ had maximum reduction in most regions.
• Correlation between cities especially in northern and eastern regions improved in 2020 compared to previous years.
• The substantial reduction in concentrations resulted in a 4 times reduction in total ER.
• PM$_{2.5}$ could increase due to unfavourable meteorology but the average concentration would still be under CPCB limits.

ABSTRACT
The effectiveness and cost are always top factors for policy-makers to decide control measures and most measures had no pre-test before implementation. Due to the COVID-19 pandemic, human activities are largely restricted in many regions in India since mid-March of 2020, and it is a progressing experiment to testify effectiveness of restricted emissions. In this study, concentrations of six criteria pollutants, PM$_{10}$, PM$_{2.5}$, CO, NO$_2$, ozone and SO$_2$ during March 16th to April 14th from 2017 to 2020 in 22 cities covering different regions of India were analysed. Overall, around 43, 31, 10, and 18% decreases in PM$_{2.5}$, PM$_{10}$, CO, and NO$_2$ in India were observed during lockdown period compared to previous years. While, there were 17% increase in O$_3$ and negligible changes in SO$_2$. The air quality index (AQI) reduced by 44, 33, 29, 15 and 32% in north, south, east, central and western India, respectively. Correlation between cities especially in northern and eastern regions improved in 2020 compared to previous years, indicating more significant regional transport than previous years. The mean excessive risks of PM reduced by ~52% nationwide due to restricted activities in lockdown period. To eliminate the effects of possible favourable meteorology, the WRF-AERMOD model system was also applied in Delhi-NCR with actual meteorology during the lockdown period and an unfavourable event in early November of 2019 and results show that predicted PM$_{2.5}$ could increase by only 33% in unfavourable meteorology. This study gives confidence to the regulatory bodies that even during unfavourable meteorology, a significant improvement in air quality could be expected if strict execution of air quality control plans is implemented.

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1. Introduction

Air pollution has come up as a growing concern all over the world, especially in developing nations like India. India witnessed economic growth, rapid expansion of cities, industrialization, and fast-paced development of infrastructure since liberalization during the 1990s. Simultaneously, the level of air pollution in India has increased to a major health risk and cause of large premature mortality. Approximately one million people died in 2015 due to ambient particulate matter (PM) pollution alone in India (Guo et al., 2017). Indian cities have been always making into the top 20 most polluted cities of the world for the past few years and exceeding the ambient air quality standards recommended by the World Health Organization and Central Pollution Control Board (CPCB) (Garaga et al., 2018; Kota et al., 2018; Mukherjee and Agrawal, 2018).

PM, the most dominant pollutant, in major parts of India has major contributions from vehicles, residential, energy, industrial and dust (Guo et al., 2017; Guo et al., 2019). To control the severe air pollution in the country, the National Clean Air Programme (NCAP) launched a five-year action plan was launched in 2019 with a goal of reducing PM by 30% nationwide (MoEFC, 2019). Are effective strategies followed up by efficient implementation can reduce the air pollution as expected? It is an open question as atmospheric processes that determine concentrations of air pollutants are nonlinear and changing meteorology plays significant roles in pollution formation. For example, the Chinese five year clean air action plan resulted in improved air quality in China (J. Li et al., 2019). However, the peak PM$_{2.5}$ concentrations during episodes in winter did not reduce due to unfavourable meteorology (Wang et al., 2019). Similarly, Zhang et al. (2014) estimated ~33% reduction in nitrate in eastern US by emission control was offset by meteorology. A simulation done in China showed that metrology played very important role in air pollution formation and severe air pollution was not avoided during the lockdown in January and February 2020 (Wang et al., 2020).

The spread of Coronavirus disease 2019 (COVID 19), which was initially identified in Wuhan of China, resulted in more than one million cases worldwide within the first four months. This has resulted in lockdown in many nations worldwide. While, the first confirmed case in India was on January 30th, 2020, the first international travel advisory posing restrictions on travel to China, Republic of Korea, Iran, Italy and Japan was issued on March 11th of after the country saw sudden jump in COVID-19 cases on March 4th (https://www.mohfw.gov.in/). Southern state of India, Kerala, which was initially the most effected state imposed curtails on mass gatherings on March 10th. Starting from March 16th all places of mass gatherings such as institutions, shopping malls and theatres were closed across the country. The first nationwide lockdown for fourteen hours was on March 22nd, which was followed by 21 days lockdown starting from March 24th. This lockdown enforces restrictions and self-quarantine measures, which reduce emissions from

![Wind rose plots showing the distribution of wind speed and direction in five different regions of the country during the analysis period.](image-url)
transportation and industries. The changes in air pollution in this lockdown period can provide an insight into the achievability of air quality improvement when there are significant restrictions in emissions from many sources and gives regulators better plans to control air pollution.

In this paper we analysed the variations in ground-based air quality and meteorological data obtained from a network of air quality monitoring stations across 22 different cities in India for the past four years (2017–2020) for the time period of March 16th to April 14th. Comparison of data in the last four years helps in understanding the potential effect of change in emissions during days with similar meteorology. This paper also explores the possible scenario which could result in national capital region if similar control on anthropogenic emissions occurs in worst meteorology conditions using Weather Research Forecasting (WRF)- Air Quality Dispersion Modelling System (AERMOD).

2. Methodology

2.1. Data sources

To study the changes in air quality during the lockdown period, the data from 22 cities covering different regions of India were analysed, i.e. Bhopal and Dewas in centre, Jorapokhar, Patna, Gaya, Brajrajnagar and Kolkata in the east, Faridabad, Amritsar, Jodhpur, Delhi, Agra, Kanpur and Varanasi in the north, Amravati, Bengaluru, Thiruvananthapuram and Chennai in the south, as well as Ahmedabad, Mumbai, Nagpur and Pune in the west. Concentrations of the different pollutants for the time period of March 16th to April 14th from 2017 to 2020 were analysed. The hourly concentrations of seven air pollutants including particulate matter (PM$_{2.5}$ and PM$_{10}$), nitrogen oxides (NO$_x$, NO and NO$_2$), sulfur dioxide (SO$_2$), ozone (O$_3$) and carbon monoxide (CO)
along with meteorological parameters including wind speed, wind direction, temperature and relative humidity were obtained from the CPCB online portal for air quality data dissemination (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing).

2.2. AQI and health risk calculations

To understand the overall improvement in air quality, air quality index (AQI) was computed. The details of AQI are available elsewhere (CPCB, 2014; Sahu and Kota, 2017), and only briefly summarized here. AQI uses PM10, PM2.5, NO2, O3, CO, SO2, NH3 and Pb, of which minimum concentrations three pollutants should be available, with at least one being either PM2.5 or PM10. The concentrations are converted to a number on a scale of 0–500. The sub index AQI (AQIi) for each pollutant(i) is calculated using Eq.(1)

\[
\text{AQI}_i = \frac{\text{IN}_{\text{HI}} - \text{IN}_{\text{LO}}}{\text{B}_{\text{HI}} - \text{B}_{\text{LO}}} \times (\frac{\text{C}_i - \text{B}_{\text{LO}}}{\text{B}_{\text{HI}} - \text{B}_{\text{LO}}}) + \text{IN}_{\text{LO}}
\]

where, \(C_i\) is the concentration of pollutant ‘i’; \(B_{\text{HI}}\) and \(B_{\text{LO}}\) are breakpoint concentrations greater and smaller to \(C_i\) and \(\text{IN}_{\text{HI}}\) and \(\text{IN}_{\text{LO}}\) are corresponding AQI values. The overall AQI is the maximum AQIi, and the corresponding pollutant is the dominating pollutant. The AQI is divided into five categories: good, satisfactory, moderate, poor, very poor and severe depending on whether the AQI falls between 0–50, 51–100, 101–200, 201–300, 301–400 and 401–500, respectively.

The potential health benefits in different cities due to change in concentrations were estimated using the excess risks associated with the pollutant loads during similar periods with and without lockdown. The relative risks of a pollutant are calculated using Eq. (2).

\[
\text{RR}_i = \exp[\beta_i \left( \frac{C_i - C_{i,0}}{C_{0}} \right)] \quad C_i > C_{i,0}
\]

where RRi is the relative risk of pollutant i, \(\beta_i\) is the exposure-response coefficient indicating the additional health risk (such as mortality) caused by per unit of air pollutant i, when it exceeds a threshold concentration. The \(\beta\) values are 0.038%, 0.032%, 0.081%, 0.13% and 0.048% for \(\text{m}^3\), PM10, SO2, NO2 and O3 per \(\mu\text{g}/\text{m}^3\) respectively, and for CO, it is

![Fig. 3. Excessive risk (ER) associated with criteria pollutants, PM2.5, PM10, O3, SO2, NO2 and CO in different regions of India. ER during 2020 and other three years (2017, 2018 and 2019) during the analysis period is shown separately.](image-url)
3.7% per mg/m³ (Hu et al., 2015; Shen et al., 2020). CI₀ is the threshold concentration, meaning that when the concentration of pollutant i is below or equal it has no excess health risk. The excess risk (ER) from pollutant i and the total ER of all pollutants are estimated using Eqs. (3) and (4).

\[
ER_i = RR_i - 1
\]  

(3) \[\text{ER}_{\text{total}} = \sum_{i=1}^{n} ER_i = \sum_{i=1}^{n} (RR_i - 1)\]  

(4)

2.3. WRF-AERMOD modelling system

The effect on meteorology on the PM₂.₅ concentrations in National Capital Region (NCR) of Delhi was studied using the Air Quality Dispersion Modelling System (AERMOD). Required meteorology data was simulated by the Weather Research Forecasting (WRF) model version 3.7.1 with initial and boundary conditions from FNL (Final) Operational Global Analysis data on 1.0 × 1.0 degree grids from NCAR for every 6 h (http://dss.ucar.edu/datasets/ds083.2/). The 400 × 400 m gridded emissions for Delhi-NCR by the SAFAR-Indian Ministry of Earth Sciences for 2018 (Beig and Sahu, 2018) (http://safar.tropmet.res.in/) was used to drive the model.

3. Results and discussions

3.1. Variation in meteorology during the analysis period

Fig. 1 shows the wind rose plot for March 15th to April 14th of 2017, 2018, 2019 and 2020 for five different regions in India. Except central India, the wind pattern in most of the years during the analysis period was similar. In north India, south and southwest are the predominant wind direction with average wind speed of ≈1.5 m s⁻¹. In southern, eastern and western India, while predominant wind direction was south and southeast, the average wind speeds were ≈1 m s⁻¹, ≈0.7 m s⁻¹ and ≈0.8 m s⁻¹, respectively. However, in central India, even though wind speeds in all the years were similar (≈2.1 m s⁻¹), wind direction in 2020 (southeast), 2019 (west) and 2018 (southwest) were different. Furthermore, there were negligible variations in temperature in different regions during this period. For example, the average temperature in north India was 29.2 °C (coefficient of variation ≈3%). Overall, it can be
concluded that the meteorology in the analysis period during 2017 to 2020 was similar.

3.2. Change in concentrations of pollutants

Fig. 2 shows the temporal change in the average concentrations of the six criteria pollutants in the five regions. Overall, around 43, 31, 10, and 18% decreases in PM$_{2.5}$, PM$_{10}$, CO, and NO$_2$ were observed during lockdown period compared to the previous years. While there were 17% increase in O$_3$ and negligible change in SO$_2$. The higher decrease in PM$_{10}$ compared to PM$_{2.5}$ could be due to its greater contribution from anthropogenic sources (Klimont et al., 2017).

Significant decreases in concentrations of PM$_{2.5}$, PM$_{10}$, NO and NO$_2$ were observed in north India. For example, compared to an average decrease of 12% in the previous years, PM$_{2.5}$ concentration in 2020 decreased by 34%, clearly indicating the effect of lockdown. Similar conclusions can be derived for PM$_{2.5}$ and PM$_{10}$ in other regions. A slight increase in SO$_2$ concentrations was observed in 2020 compared to previous year. This could be due to no restrictions on power plants in northern India and using coal powered energy an essential commodity during lockdown period. A decrease in O$_3$ was observed in 2020 compared to 2019, while compared to last three years averagely, the concentrations in 2020 were 10% higher.

In east India, while there was a decrease in CO concentration, an increase in other gaseous pollutants was observed in 2020 compared to 2019. O$_3$ had 77% increase compared to 2019 and 89% increase compared to the average concentration in 2017 to 2019. In southern India, clear decrease in NO, NO$_2$ and O$_3$ was observed during the lockdown period, while increase in CO was observed. Increases in O$_3$ and CO and decreases in NO and NO$_2$ were observed in central India. Most cities in northern, western and southern regions are VOC limited (Sharma et al., 2016), thus this increase in O$_3$ could be due to more decrease in NOx compared to VOC. Furthermore, this could also be attributed to decrease in PM concentrations, which can result in more sunlight passing through atmosphere encouraging more photochemical activities and thus higher O$_3$ production (Dang and Liao, 2019; K. Li et al., 2019).
3.3. Excessive risk associated with pollutants

Excessive risks (ER) associated with the criteria pollutants during the lockdown compared to the same period in the previous three years are included in Fig. 3. As per WHO air quality guidelines (WHO, 2005), the threshold values of 25 μg/m³ (24 hour mean), 50 μg/m³ (24 hour mean), 100 μg/m³ (8 hour mean), 200 μg/m³ (1 hour mean) and 20 μg/m³ (24 hour mean) for PM_{2.5}, PM_{10}, O₃, NO₂ and SO₂ were considered for t calculation. For CO, the recommended air quality guidelines of CPCB, 4 mg/m³ (1 hour mean), were used.

Overall, significant health risks due to PM_{2.5} and PM_{10} were obtained in all the regions even during lockdown period. However, the mean ER due to PM reduced by ~52% on an average in the country. Except SO₂ in north India and O₃ in east India, ER for all pollutants in every region reduced during lockdown period. This overall reduction in ER in India during the lockdown period (~4 times) could save ~0.65 million deaths in India in a year.

3.4. AQI in different regions

Fig 4 shows the change in AQI and the corresponding dominant pollutant during the analysis period in 22 Indian cities. Overall, a significant improvement is observed in 2020 during the lockdown period in the entire country compared to the previous years. 30% reduction in AQI was observed in the analysis period of 2020 compared to the previous years. About 44, 33, 19, 15 and 32% reductions in AQI were observed in north, south, east, central and western regions. Delhi observed the maximum reduction of 49% in AQI. This reduction in AQI was also associated with a change in dominant pollutant in many cities. While in Gaya, Kolkata, Kanpur and Nagpur, the dominant pollutant during the lockdown period changed to O₃, it changed to NO₂ for Agra and Patna. This is expected as the maximum reduction was observed for PM_{2.5} among all pollutants.

Correlation between AQI of cities in four different regions, north, east, west and south, during the analysis period is shown in Fig. 5. Correlation between cities especially in northern and eastern parts of the country improved in 2020 compared to previous years. For example, the correlation between the largest city in north India, Delhi with other cities increased by a factor of 1.9 to 2.8. The best correlation (0.82) between the two central Indian cities Bhopal and Dewas was observed in 2020. This clearly indicates that the increased dominance of regional transport compared to local contributions in the cities during lockdown period.

3.5. Predicting effect of meteorology on concentrations

Furthermore, this betterment of overall air quality could be due to more dispersion during the pre-monsoon period when this lockdown happened. Similar lockdown in China did not result in significant improvement in air quality due to unfavourable meteorology (Wang et al., 2020). To understand this effect, two simulations were carried out. While in Simulation 1 the actual meteorology during the analysis period in 2020 was used, in Simulation 2 the meteorology pertaining to worst case during early November of 2019 was used (Beig et al., 2020). In both cases the emissions from all sources but energy, residential and windblown dust in Delhi NCR was zeroed out to predict PM_{2.5}. The model performance in 30 observations stations in the city are shown in Table 1. Results indicate that except in eight sites, the mean fractional bias (MFB) falls under the USEPA criteria of ±0.6 (EPA, 2007). The relative change in concentration in Simulation 2 compared to Simulation 1 is also included in Table 1. In 24 sites an increase in concentration was observed due to unfavourable meteorology. On an average the concentration in Simulation 2 in sites with good model performance increased by 33% compared to Simulation 1. This indicates that even the meteorology was not favourable, the average daily PM_{2.5} concentration in Delhi-NCR would increase to 54 μg/m³, which is less than the CPCB standard (60 μg/m³) and 1.13 times more than the corresponding WHO standard. However, this increase might not be accurate in the air pollution episode during November, even though similar restrictions on human activities are implemented, as the residential emissions increase in north India mainly due to space heating (Guo et al., 2017).

4. Conclusions

The effect of restricted human activities due to the COVID-19 pandemic in India since mid-March of 2020 was studied by analysing concentrations of six criteria pollutants during March 16th to April 14th from 2017 to 2020 in 22 cities covering different regions. Among all pollutants, PM_{2.5} had maximum reduction in most regions. In contrary, in most regions an increase in O₃ was observed, which could be due to the decrease in PM in addition to decrease in NOX. This substantial reduction in concentrations resulted in a 4 times reduction in ER. As expected, a significant reduction in AQI was observed in 2020 compared to previous years. However, four cities had O₃ as their dominant pollutant instead of PM_{2.5}, suggesting that attention should also be given to decreasing emissions of precursors to secondary pollutants in addition to controlling primary PM. Correlation between cities especially in northern and eastern regions improved in 2020 compared to previous years, indicating more significant regional transport than previous years. Further analysis on actual and unfavourable meteorology using WRF-AERMOD modelling system concluded that even the predicted PM_{2.5} could increase due to unfavourable meteorology, the average concentration would still be under CPCB limits. This study gives confidence to the regulatory bodies that a significant improvement in air quality in India could be expected if strict execution of air quality control plans is implemented.
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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