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

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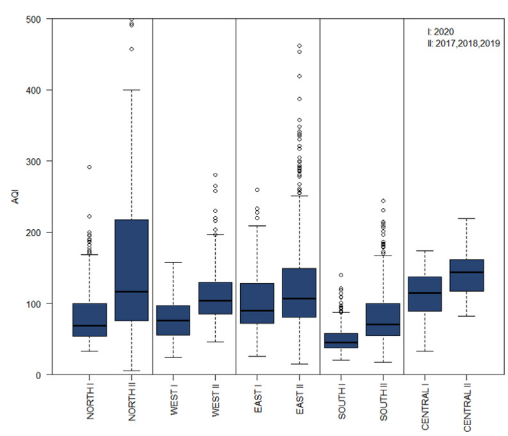
HIGHLIGHTS

- 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.

GRAPHICAL ABSTRACT



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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 un-favourable 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

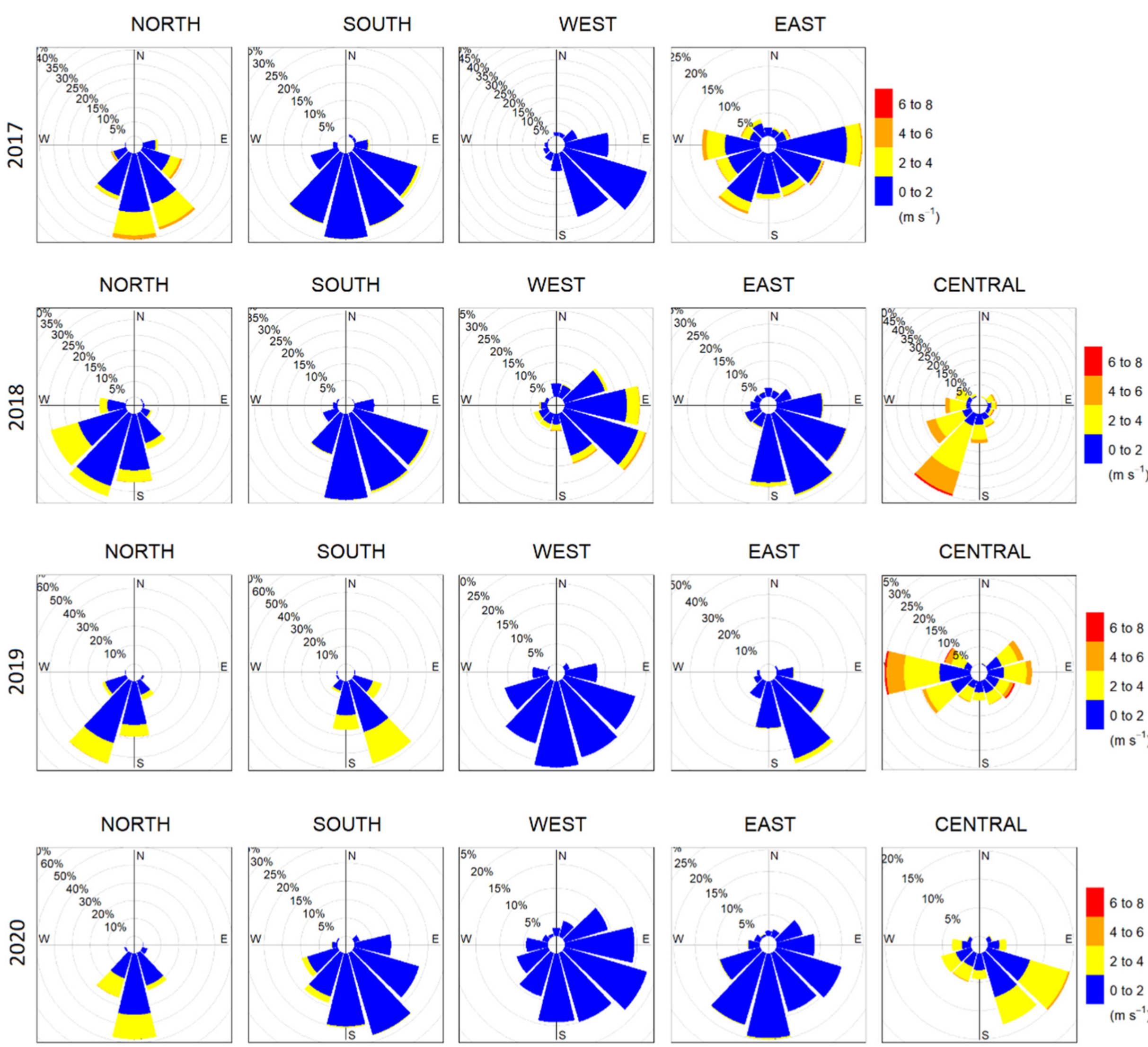

Fig. 1. Wind rose plots showing the distribution of wind speed and direction in five different regions of the country during the analysis period.

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)

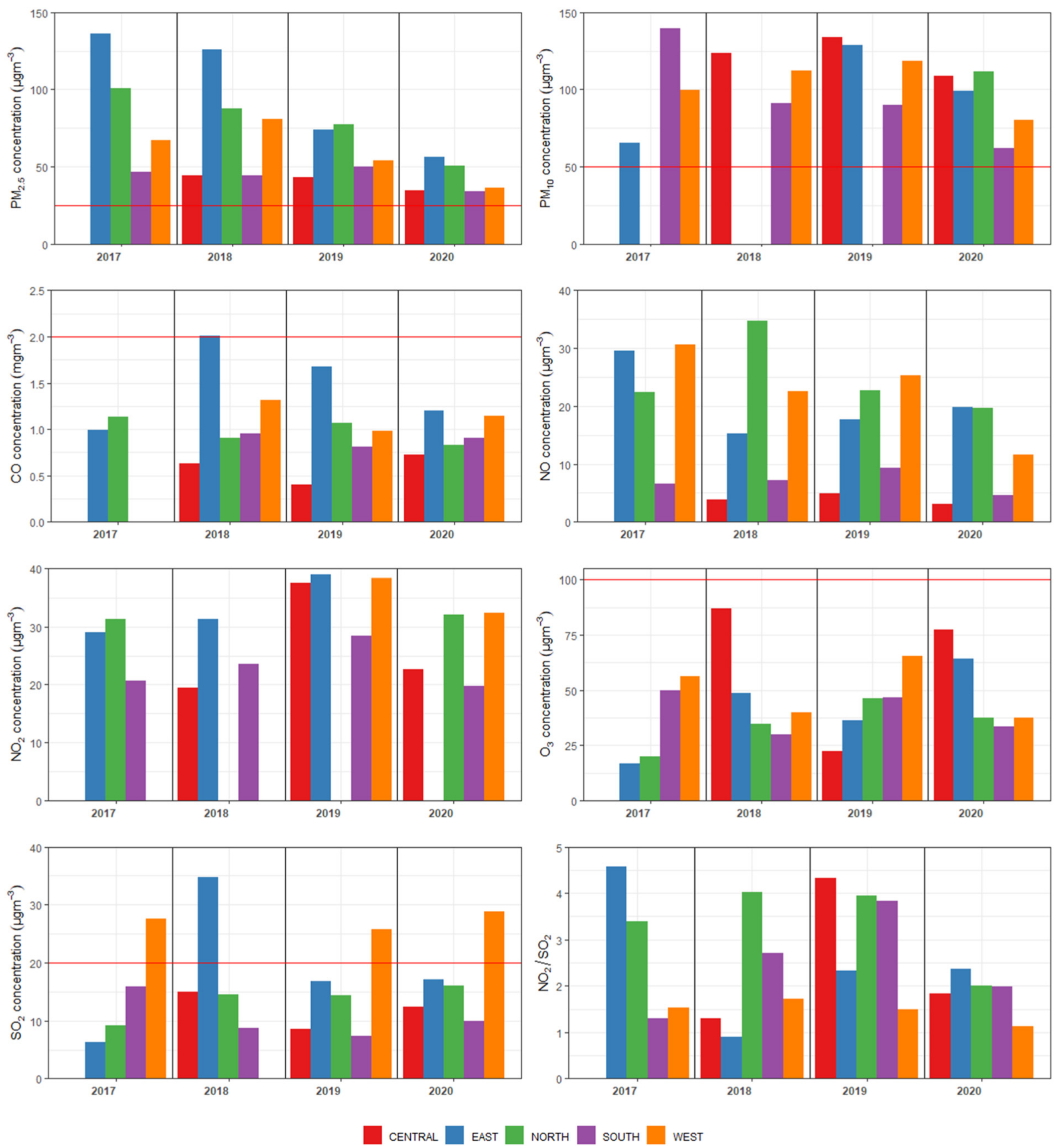

Fig. 2. Mean $PM_{2.5}$, PM_{10}, CO, NO, NO_2, NOx and O_3 concentrations during March 16th to April 14th of years 2017 to 2020. Mean concentrations of all the observation stations in different regions are shown. The line in each plot indicates the corresponding WHO limit for all pollutants but CO.

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 PM_{10}, $PM_{2.5}$, NO_2, O_3, CO, SO_2, NH_3 and Pb, of which minimum concentrations three pollutants should be available, with at least one being either $PM_{2.5}$ or PM_{10}. The concentrations are converted to a number on a scale of 0–500. The sub index AQI (AQI_i) for each pollutant(i) is calculated using Eq. (1)

$$AQI_i = \frac{IN_{HI} - IN_{LO}}{B_{HI} - B_{LO}} \times (C_i - B_{LO}) + IN_{LO} \quad (1)$$

where, C_i is the concentration of pollutant 'i'; B_{HI} and B_{LO} are breakpoint concentrations greater and smaller to C_i and IN_{HI} and IN_{LO} are corresponding AQI values. The overall AQI is the maximum AQI_i, 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).

$$RR_i = \exp\left[\beta_i (C_i - C_{i,0})\right], C_i > C_{i,0} \quad (2)$$

where RR_i is the relative risk of pollutant i, β_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 β values are 0.038%, 0.032%, 0.081%, 0.13% and 0.048% for m^3, PM_{10}, SO_2, NO_2 and O_3 per μg/m^3 respectively, and for CO, it is

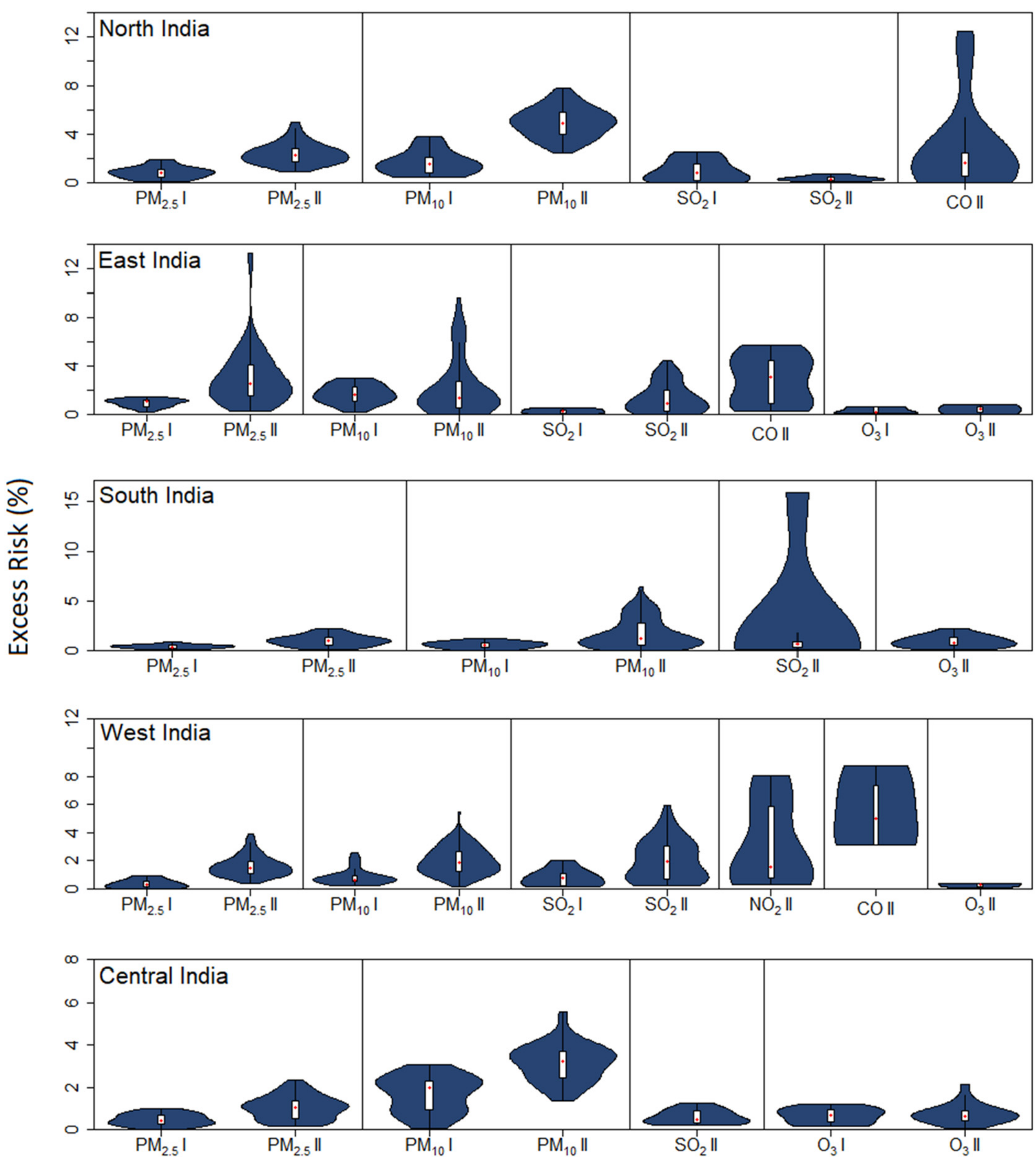

Fig. 3. Excessive risk (ER) associated with criteria pollutants, $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2 and CO in different regions of India. ER during 2020 and other three years (2017, 2018 and 2019) during the analysis period is shown separately.

3.7% per mg/m^3 (Hu et al., 2015; Shen et al., 2020). $C_{i,0}$ 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).

$$ER_i = RR_i - 1 \tag{3}$$

$$ER_{total} = \sum_{i=1}^{n} ER_i = \sum_{i=1}^{n} (RR_i - 1) \tag{4}$$

2.3. WRF-AERMOD modelling system

The effect on meteorology on the $PM_{2.5}$ 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 ms^{-1}. In southern, eastern and western India, while predominant wind direction was south and southeast, the average wind speeds were ~1 ms^{-1}, ~0.7 ms^{-1} and ~0.8 ms^{-1}, respectively. However, in central India, even though wind speeds in all the years were similar (~2.1 ms^{-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

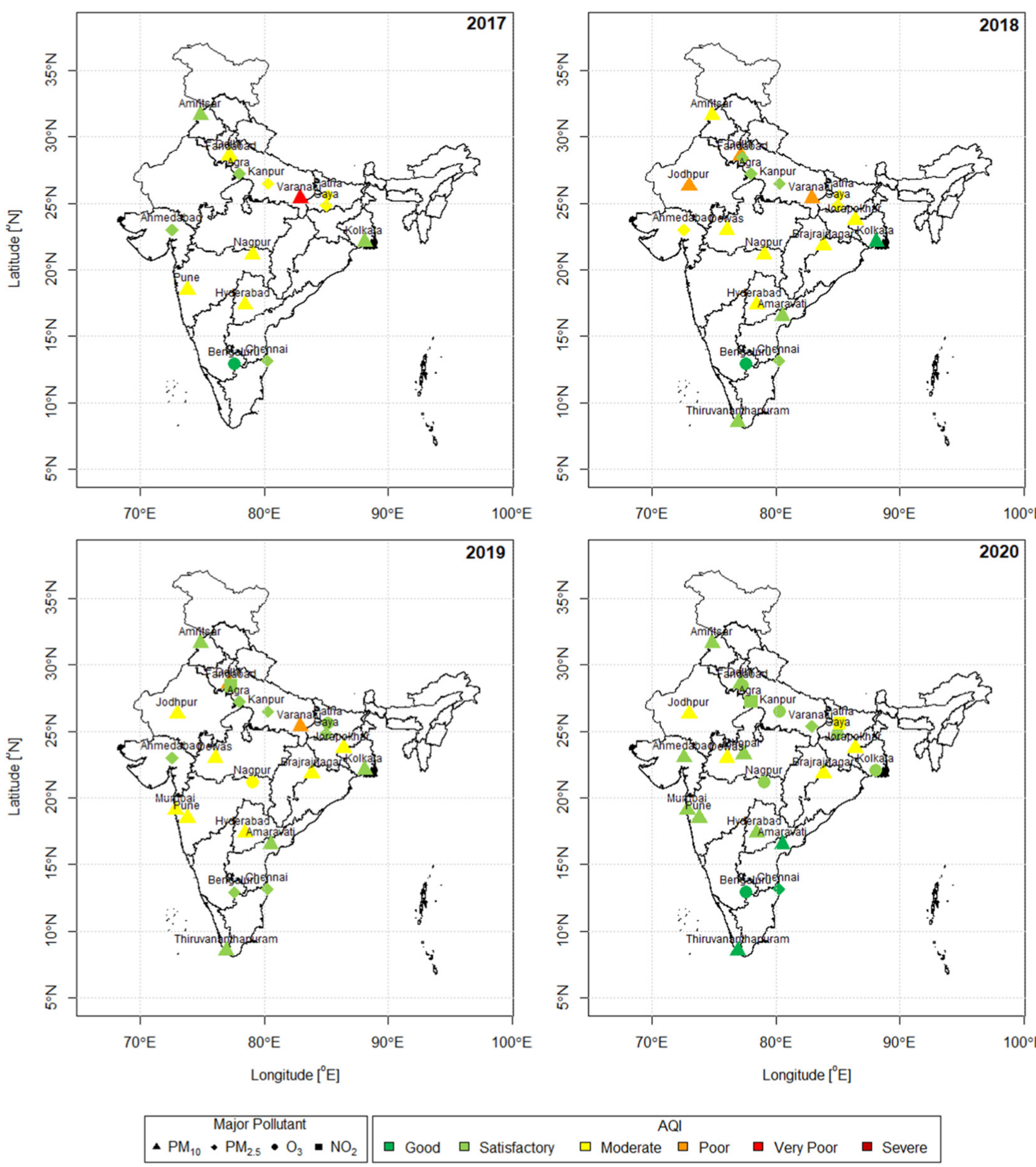

Fig. 4. Change in AQI in 22 Indian cities during March 15th to April 14th of the years 2017 to 2020. Different symbols are used to denote the dominant pollutant in a city.

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).

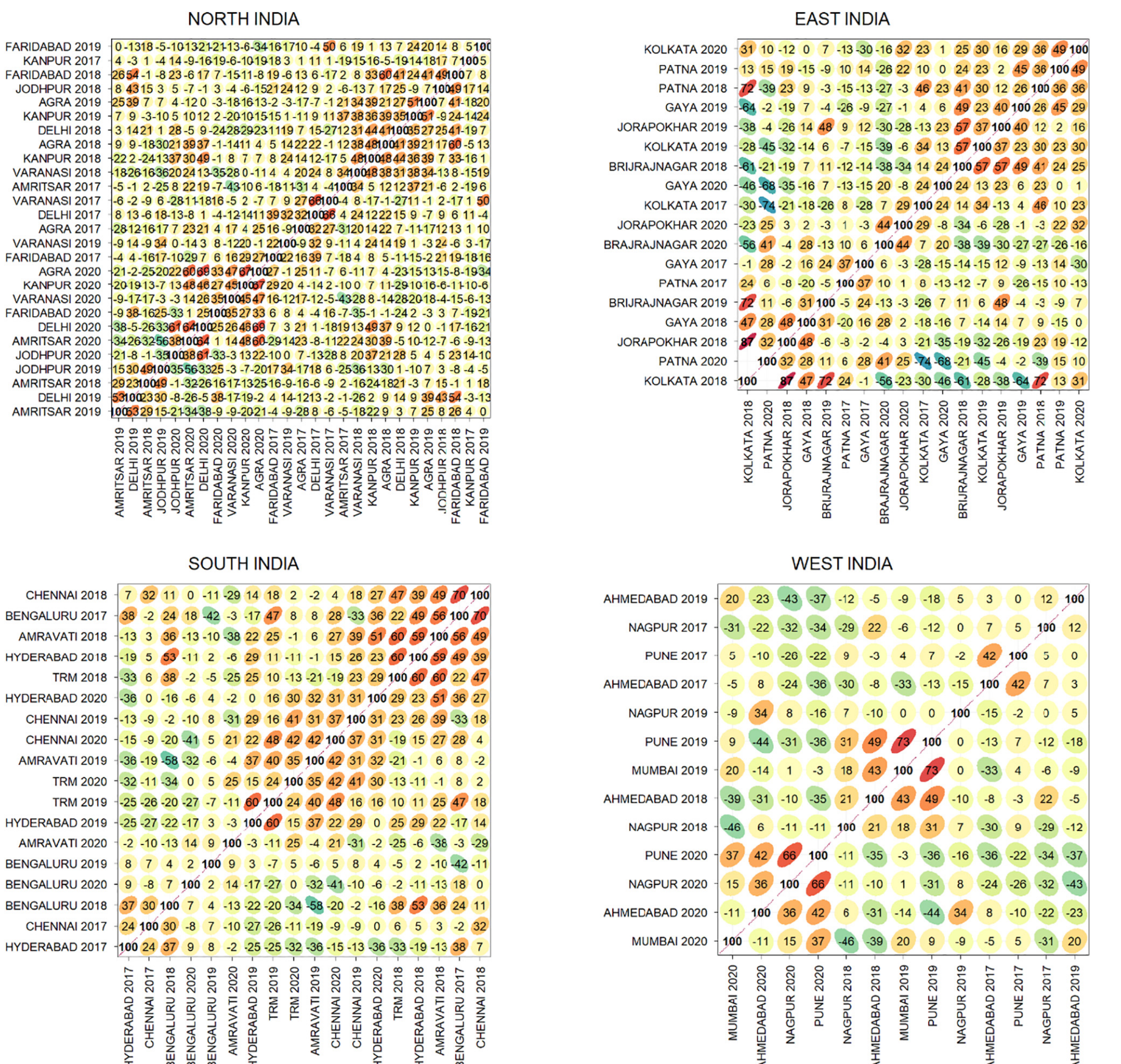

Fig. 5. Correlation between AQI in cities of different regions during the analysis period.

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/m^3 (24 hour mean), 50 μg/m^3 (24 hour mean), 100 μg/m^3 (8 hour mean), 200 μg/m^3 (1 hour mean) and 20 μg/m^3 (24 hour mean) for $PM_{2.5}$, PM_{10}, O_3, NO_2 and SO_2 were considered for t calculation. For CO, the recommended air quality guidelines of CPCB, 4 mg/m^3 (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 SO_2 in north India and O_3 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 lock down 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, 29, 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 O_3, it changed to NO_2 for Agra and Patna. This is expected as the maximum reduction was observed for $PM_{2.5}$ among all pollutants.

Table 1
Model performance using Mean Fractional Bias (MFB) and predicted change in concentrations in the worst meteorology case compared to the base case in the observation sites in Delhi-NCR.

Station	MFB	Change (%)
Anand Vihar	−0.3	64.30
Ashok Vihar	−0.1	71.32
Burari Crossing	−0.6	105.27
CRRI Mathura Road	−0.9	17.62
DTU	0.8	*−75.08*
Dwarka-Sector 8	−0.4	*−38.30*
IGI Airport (T3)	−0.4	*−52.73*
IHBAS, Dilshad Garden	−0.2	104.51
ITO	0.4	154.64
Jahangirpuri	−0.7	120.21
JLN Stadium	−0.9	4.04
Lodhi Road	0.0	28.19
Mandir Marg	−0.1	21.75
MDC National Stadium	0.1	33.29
Najafgarh	−0.1	*−54.33*
Narela	−0.7	*−40.40*
Nehru Nagar	−1.1	28.15
North Campus, DU	0.8	*−23.03*
NSIT Dwarka	0.3	*−43.13*
Okhla Phase-2	−0.4	12.97
Patparganj	0.3	57.09
Punjabi Bagh	0.1	*−21.10*
Pusa	0.4	29.37
R K Puram	0.1	*−47.06*
Rohini	0.1	*−48.35*
Shadipur	−0.4	12.31
Sirifort	0.8	0.45
Sonia Vihar	−0.3	31.20
Vivek Vihar	−0.4	36.65
Wazirpur	0.6	268.75

Note: MFB not following the US EPA criteria limit was underlined and the values where the concentrations in worst meteorology is lower than base case is shown using italics.

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 μgm^{-3}, which is less than the CPCB standard (60 μgm^{-3}) 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 O_3 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 O_3 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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