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Time series analysis of COVID-19 stringency measures on the spatio-temporal dynamics of air pollution

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ABSTRACT

Introduction: Execution of COVID-19 lockdown measures caused variations in air pollution worldwide. This paper investigates the impact of COVID-19 stringency measures on the spatio-temporal dynamics of air pollution in Mumbai, India, using a comprehensive two-and-a-half-year pandemic period dataset.

Materials and methods: We classified the pandemic period into 7 phases and 21 sub-phases based on the severity of the Oxford COVID-19 Government Response Tracker (OxCGRT) Stringency Index (SI). Optimized Hotspot analysis (OHS) and Ordinary Least Square Regression models explored the spatio-temporal fluctuations and the effect of stringency measures on air quality.

Results: The R^2 value varied; with the best model R^2 of 0.61 for Particulate Matters (PM_{10}) and Nitrogen dioxide (NO_2) and lowest of 0.23 for Sulfur dioxide (SO_2). A 10-point increase in SI caused a 3-7% reduction in air pollutants. Substantial reduction in average PM_{10}, $PM_{2.5}$, NO_2, and Carbon monoxide (CO) was observed throughout the COVID-19 phases. Meteorology and SI collectively caused maximum reduction of 82.6%, 72.7%, 53.8%, 52.2%, 49.1%, 28.4% for NO_2, $PM_{2.5}$, PM_{10}, NH_3, CO, and SO_2 respectively, during complete or extreme lockdown phases. Except SO_2, seasonality significantly influenced the pollutant concentrations. Winter was the worst period while monsoon was the best. OHS identified central Mumbai wards as hotspots and areas close to the national park as coldspots.

Conclusion: PM_{10}, NO_2 and CO were more affected by SI measures than NH_3 and SO_2. For a rapid emergency response to high PM_{10}, implementation of SI, very high (≥ 80 score) and above is advised. Findings of this study have significant public health policy implications, especially among global south nations.

Introduction

Air pollution is the world's largest environmental health threat [1]. In economies around the world, urban air pollution is a major problem. Ambient particulate matter pollution was attributed to both an estimated 6.45 million deaths and the largest increase in exposure risk for Disability Adjusted Life Years (DALYs) in 2019 [2]. December 2019,

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the first case of COVID-19 caused by a novel coronavirus in Wuhan, China was reported. The pandemic allowed the largest scale experiment ever to examine the relative changes in air quality compared to that during normal times due to COVID-19 responses [3].

World Health Organisation (WHO) on 11th March 2020, declared COVID-19 a global pandemic, due to the rapid spread and high mortality rate. Following this, globally, unprecedented government action was prompted to curtail the rapid spread of COVID-19 virus [4]. The stringent lockdown measures imposed across the world caused reduction in air pollution levels due to reduced industrial, commercial, and human activities [5]. Due to the lockdown, we could comprehend the impact of anthropogenic activities on overall air quality. A study covering 76 countries worldwide, reported differences in response of various air pollutants to lockdown measures. It estimated a reduction of 23-37% of NO_2, 14-20% of PM_{10}, 2-20% of SO_2, 7-16% of $PM_{2.5}$ and 7-11% of CO [3]. An estimated 20-40% reduction in NO_2, Particulate Matters (PM_{10} and $PM_{2.5}$) during the lockdown period was reported by a study involving five European nations [5]. Reductions in hospitalizations for respiratory ailments including asthma, were the most impacted short-term outcomes of air pollution during lockdowns [6]. Additionally, a decline in number of premature deaths of around 99,270 to 146,649 were reported due to improved air quality in a study across 76 countries [3].

India executed one of the most stringent nationwide COVID-19 lockdowns around the world. Further, during a two-and-a-half-year period, stringency measures of different strengths (varying levels of activities) were imposed to tackle the spread of virus across the country. Though people and businesses had to bear a lot of hardships, one of the favourable outcomes of the stringency measures was the improvement in environmental conditions. The stringency measures are the containment and closure policies imposed to reduce the transmission of COVID-19. These measures resulted in improved air quality in Indian cities, however it was not uniform across cities and pollutants [7, 8]. Indian studies also reported significant reductions in the range of 18-70 % of NO_2, 31 – 60 % of PM_{10} and $PM_{2.5}$, and 10-40 % of CO during lockdown-1. Significant drops were likewise observed in SO_2, NH_3 concentrations [9-11]. A 51% reduction in National Ambient Air Quality Index (NAQI) was noted in Delhi during the lockdown period [12]. Likewise, the average Air Quality Index (AQI) values in Mumbai reduced from 132 (moderate) of pre-lockdown to 71–53 (satisfactory) and 34 (good) during the lockdown and unlock phases [9]. The air quality improved, because the lockdown process decreased industrial and commercial activity, including human movement [13]. The combined effect of changes in the emissions, meteorology, and atmospheric chemistry were responsible for the changes reported during the lockdown and hence requires detailed investigations [10].

Air pollution is highly spatial and temporal in nature. India has 12 of the 15 most polluted cities in Central and South Asia [1]. Reduction in PM_{10}, $PM_{2.5}$ and NO_2 and enhancement in O_3 during the COVID-19 lockdown period was observed to be proportional to the population density of the region [10]. Mumbai, the financial capital of India has a very high population density and consistently high pollution levels. A boom in commercial activity, construction and vehicular traffic has led to acute air pollution conditions in the megacity, Mumbai [14]. The implementation and formulation of policies are usually at the city scale while most of the studies focus on a national or regional scale [15]. To initiate the policies for reducing air pollution, an amalgamation of Geographical Information System (GIS) and statistical analysis can help to identify relative critical areas that need more consideration from decision makers [16]. Hence, using geospatial tools, an attempt has been made in this study to understand the spatial and temporal distribution of air pollutants due to stringency measures at the smallest administrative level (ward) in an urban city of India. Also note that there is lack of studies focussing on the ward level seasonal air pollution hotspot mapping for

Mumbai. Identification of hotspots and coldspots enhances development policies and strategies for air pollution reduction.

The major gap in the literature is the focus of studies confined to specific phases, especially the first COVID-19 lockdown phase. This paper contributes to the existing literature gap by attempting a long-term time-series analysis of the impact of stringency measures on air quality. The long-term time series analysis provides an extensive view of the impact of meteorology and stringency measures on air quality throughout the different phases of COVID-19. This will assist to determine the best stringency measures and facilitate both emergency and long-term pollution reduction strategies. To our knowledge, this is the first of its kind study on COVID-19 stringency measures and various air pollutants using comprehensive daily data for a two- and half-year pandemic period. To understand the spatio-temporal dynamics, this study aims to analyse the seasonal trends in air pollutants. It then identifies the seasonal effects on air quality index hotspots using Optimized Hotspot analysis (OHS), investigates the relationship between stringency measures and air quality for a two- and half-year time-line using Ordinary Least Square (OLS) regression. Finally, it estimates the percent change in air pollutants compared to pre-lockdown (No-Lockdown) and complete lockdown scenarios and suggests appropriate mitigation measures. To summarize the methodology, the data was processed for two separate timelines. First, a seasonal average was used to estimate the seasonal fluctuations in hotspots, and then a phase-wise average based on the COVID-19 Stringency Index (SI) was determined to comprehend the impact of SI on air quality.

Materials and methods

Study area

Mumbai, the financial capital of India, is located (18º 58' and 19º 17' N latitudes and 72º 46' and 72º 60' E longitudes) on the western coast of the country in the state of Maharashtra. It is an island city separated from the mainland by a narrow Thane creek and a wider Harbour Bay. To the north of the city lies a reserved forest, the Sanjay Gandhi National Park (SGNP) also called the green lung of Mumbai covering 103 Km^2 area, with great biodiversity and archaeological significance. Mumbai experiences a monsoon climate with four major seasons summer (March-May), monsoon (June-August), post-monsoon (September-November) and winter (December-February). Being a megacity, Mumbai was one of the worst COVID-19 impacted cities in India and hence, compared to other cities, stringent measures of varying strengths were enforced for a longer period in Mumbai.

The study area comprises of Mumbai district and Mumbai suburban district together called Greater Mumbai (henceforth referred to as Mumbai). The total area of Mumbai is 476.24 Km^2 [17] divided into 24 wards. Out of 12.44 million [18] people living in Mumbai, 52.5 % people live in slums which creates a huge difference in their socio-economic conditions.

To evaluate the spatio-temporal dynamics of COVID-19 stringency measures on air pollution, a three-stage analysis was carried out. First, a seasonal trend analysis, then a seasonal hotspot analysis, followed by a regression analysis of different phases of COVID-19.

Air quality and meteorological data

Daily air quality data for a three-year period from 1st June 2019 to 21st Aug 2022 for PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3 and CO were acquired from Central Pollution Control Board (CPCB) [19] managed Continuous Ambient Air Quality Monitoring Stations (CAAQMS) online data portal. Mumbai has twenty CAAQMS, however, only eight stations provided continuous data for all the variables throughout the study period, hence these eight-station data were used. The CAAQMS also monitor meteorological variables. Daily Temperature (Temp), Relative Humidity (RH) and Wind Speed (WS) data from 1st June 2019 to 21st

August 2022 were acquired from the same portal. Locations of CAAQMS used in the study are shown on a ward-level map of Mumbai in Fig. 1.

Stringency index data

COVID-19 emerged as a global pandemic impacting almost all the countries worldwide. To track the government responses globally (stringency measures), the Oxford COVID-19 Government Response Tracker (OxCGRT) [4] was introduced which also estimates a composite index of stringency (stringency index-SI). The stringency index score ranges from 0-100, where 0 indicates no restrictions, and 100 indicates complete lockdown. The stringency index is calculated based on eight indicators of containment and closure policies (school closing, workplace closing, cancel public events, restrictions of gathering size, closed public transport, stay-at-home requirements, restrictions on internal movements and restrictions on international travel) and one health systems policy (public information campaigns). All the indices were ordinal where school closing, workplace closing and stay at home requirements have three values (0, 1, 2, 3), restrictions on public gathering and restrictions on international travel have four values (0, 1, 2, 3, 4) and the remaining indices have two values (0, 1 ,2). Eash sub-index score for any indicator on a given day is calculated, which normalizes the different ordinal scores to produce sub-index score between 0-100. These are then used to calculate the index score. The detailed calculations of the SI index is beyond the scope of this paper and can be referred to in Hale's research [4].

We considered daily stringency data from 1st Jan 2020 to 21st Aug 2022, downloaded from Oxford COVID-19 Government Response Tracker, (OxCGRT) [20] portal for Mumbai, India. The data was classified into seven main phases consisting of twenty-one sub-phases based on the stringency measures applied in Mumbai. The five main phases are No Lockdown (NLD) with SI- 0, Low (L) with SI-1 to 29.9, Medium (M) with SI-30 to 49.9, High (H) with SI-50 to 69.9, Very High (VH) with SI- 70 to 89.9, Extreme (EX) with SI-90 to 99.9, and Complete Lockdown (CLD) with SI-100. Low has L1 and L2, Medium has M1, M2 and M3, High has H1, H2, H3, H4 and H5, Very high has VH, VH2, VH3, VH4, VH5 and VH6 and Extreme has EX1, EX2 and EX3 sub-phases respectively. No Lockdown (NLD) phase refers to the days prior to the implementation of any stringency measures (pre-lockdown). The details of the various COVID-19 lockdown phases from 1st Jan 2020 to 21st Aug 2022 are given in Table 1.

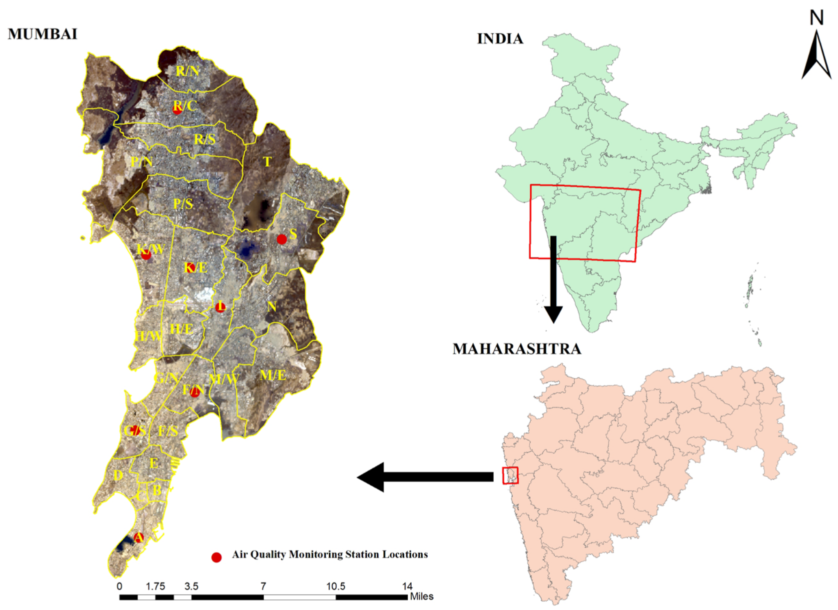


Fig. 1. Air quality monitoring station locations on a ward-level map of Mumbai

Table 1. Details of the various COVID-19 lockdown phases from 1st Jan, 2020 to 21st Aug, 2022

Lockdown Phase Name	Period	Stringency Index	COVID-19 Total Confirmed Cases	COVID-19 Total Confirmed Deaths	Meteorology Avg RH (%)	Meteorology Avg Temp (ºC)	Meteorology Avg WS (m/s)
NLD	1/1/20-29/1/20	0.00	0	0	69.07	23.62	1.24
L1	30/1/20-12/3/20	8.85	32	0	62.95	25.35	1.16
M1	13/3/20-24/3/20	41.20	634	0	62.34	26.78	1.19
CLD	25/3/20-19/4/20	100.00	35935	2194	73.87	28.36	1.24
EX1	20/4/20-31/5/20	97.22	1154069	41380	74.68	30.22	1.31
VH1	1/6/20-6/9/20	83.50	36213635	1271085	89.93	27.20	1.33
H1	7/9/20-4/11/20	63.21	83229902	2219130	83.69	27.72	1.10
M2	5/11/20-31/3/21	40.20	298398930	7352920	66.12	26.36	1.16
H2	1/4/21-4/4/21	54.63	11724359	221811	76.16	27.89	1.13
VH2	5/4/21-13/4/21	84.26	29591987	515768	74.02	28.98	1.12
EX2	14/4/21-10/5/21	97.22	118663863	1802529	76.40	29.72	1.17
VH3	11/5/21-24/5/21	87.96	75773453	1163344	77.49	29.81	1.24
EX3	25/5/21-31/5/21	91.67	39834084	651331	78.53	29.98	1.30
VH4	1/6/21-6/6/21	80.56	34785182	588756	78.95	29.40	1.24
H3	7/6/21-28/6/21	66.03	130838287	2503664	89.23	27.34	1.38
VH5	29/6/21-30/6/21	70.83	12113037	243749	86.06	28.09	1.13
H4	1/7/21-9/1/22	62.54	1255618623	26498416	81.25	26.66	1.38
VH6	10/1/22-23/1/22	72.22	101180054	1985928	72.48	22.48	1.09
H5	24/1/22-31/1/22	66.67	61106880	1139228	58.93	22.13	1.20
M3	1/2/22-1/4/22	45.08	471186576	8646453	66.08	26.19	1.10
L2	2/4/22-21/8/22	13.89	1128367410	21006517	84.00	28.51	2.76

Estimation of temporal dynamics

Seasonal spatial analysis was carried out for four seasons Summer, Monsoon, Post-Monsoon and Winter based upon the variations of local meteorological characteristics. For the period of 2019 to 2022 the variations in air pollutant concentrations viz., PM_{10}, $PM_{2.5}$, NOx, SO_2, NH_3 and CO for Mumbai city were analysed.

Since the air quality and meteorological data were available for only eight stations in Mumbai we interpolated the data to get a complete wardwise statistics. We performed interpolation of air pollutants and meteorology in a fishnet created for the study region consisting of 153 points using the eight monitoring station data in ArcGIS. Among the different interpolation techniques Inverse Distance Weighted (IDW), Kriging and Spline are most used in air pollution studies, among these Kriging and IDW give better results than Spline [21]. Compared to kriging, IDW showed better similarity between measured and interpolated values for SPM, SO_2 and NO_2 [22]. Between IDW and Kriging, it is difficult to conclude which method is better than the other, however, for the gaps, IDW fills in well where due to the absence of data stationarity, Kriging fails to interpolate [23]. Hence, IDW was used in this study. IDW assumes that things closer to each other are more alike than those which are farther apart and higher weights are assigned to the points closest to the target location, which change as an inverse function of distance [23].

Air quality index estimation

Indian national ambient air quality index (referred henceforth as AQI), 2014 demonstrates the nature and breathability of the ambient air as a single index value obtained from the cumulative calculation of the major criteria pollutants [9]. For AQI estimation, sub-indexes were calculated for each pollutant, which is a linear function of concentration. The worst sub-index is the AQI for that location. The AQI is classified as good (0–50), satisfactory (51–100), moderate (101–200), poor (201–300), very poor (301–400), and severe (>401). We used seasonal AQI averages to interpolate AQI for all wards of Mumbai using IDW interpolation technique from 1st June 2009 to 21st Aug 2022 based on PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3 and CO.

Optimized hotspot analysis

For a systematic investigation of hotspots, statistical tools like Global Moron's I and Getis-Ord Gi* are used to explain the spatial pattern. Global Moron's I indicates if the space is clustered or an outlier while and Getis-Ord Gi* provides information if the clusters are of high or low value. Hence, Getis-Ord Gi* was used to measure the strength of the clusters. ArcGIS has an inbuilt Optimized Hotspot analysis (OHS) tool, which is a local clustering tool based on Getis-Ord Gi* statistic. It identifies statically significant spatial clusters of high (hotspots) and low (coldspots) values. The only difference is OHS tool has an automatic incremental spatial autocorrelation to find the distance band compared to Getis-Ord Gi* thus reducing the manual error. The OHS tool creates a new Output Feature Class with a z-score, p-value and confidence level bin (Gi_Bin). Features in the +/-3 bins are statistically significant at the 99 % confidence level; features in the +/-2 bins reflect a 95 % confidence level; features in the +/-1 bins reflect a 90 % confidence level; and the clustering for features with 0 for the Gi_Bin field is not statistically significant. We used the interpolated seasonal AQI from 1st June 2019 to 21st Aug 2022 for optimized hotspot analysis in ArcGIS 10.2.

Ordinary least square (OLS) regression

We estimated the impact of stringency measures on air quality using OLS regression analysis in SPSS software. For the time series model, applying OLS is the most straightforward strategy [3]. Meteorological factors (wind speed, temperature, relative humidity) play a vital role in the concentration and distribution of air pollutants. Interpolated data from eight monitoring stations of daily air pollutants (PM_{10}, NO_2, SO_2, NH_3 and CO) and meteorology (relative humidity, temperature and wind speed) along with SI averaged over the twenty-one sub-phases of COVID-19 was used for OLS regression. Furthermore, lagging the pollution variable helped overcome the autocorrelation issue in the data. Log of the dependent variables helps in normalizing the data and in reducing the influence of outliers [3]. Hence, we used a log of the dependent variables.

To estimate the effect of the stringency index on air quality, we specify the following regression equation:

$$\ln(Y_t) = \theta_1 \ln(Y_{t-1}) + \theta_2 OxCGRT_t + \theta_3 Met_t + €_t \quad (1)$$

Where, Y_t represents the air pollutant on day t, Y_{t-1} indicates the lagged air pollutant concentration, $OxCGRT_t$ is the SI on day t and Met are the meteorological variables (relative humidity, temperature, and wind speed) on day t for Mumbai. θ_1, θ_2, and θ_3 are the coefficients of pollutant, stringency index and meteorological variables respectively. € denotes the random error term in Eq. 1.

Results and discussion

The main objectives of this study were to identify the spatio-temporal dynamics of air pollutants seasonally and to assess the magnitude of changes in air pollutants in Mumbai city during different phases of COVID-19 policies.

Temporal analysis

We performed temporal analysis to understand the seasonal impacts of air pollutants (PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3 and CO) based on data from June 2019 to Sept 2022. Data from eight monitoring stations were used for the five criteria pollutants except for CO (seven station data). Temporal analysis in Fig. 2. demonstrated seasonal fluctuations; with highest concentrations in winter followed by post-monsoon or summer and the lowest in monsoon season for all pollutants except SO_2. The low concentrations during monsoon can be attributed to high wind speed and washout due to precipitation.

Particulate Matters (PM_{10} and $PM_{2.5}$) exhibited high seasonal fluctuations. A clear annual seasonal trend starting from post-monsoon and peaking in winter and reducing during summer to reach the lowest during monsoon months was observed for particulate matter (both PM_{10} and $PM_{2.5}$). This is in accordance to the results of a study [16] that showed temporal distributions of SPM and PM_{10}; where summer and winter had the highest concentrations while monsoon had the lowest. May, 2022 recorded the highest mean concentration in ward K/W for PM_{10} (298.4 µg/m^3) and Jan, 2021 for $PM_{2.5}$ (119 µg/m^3) in ward L. Meanwhile July, 2020 in ward R/C recorded the lowest mean concentrations for both PM_{10} (16.9 µg/m^3) and $PM_{2.5}$ (4.8 µg/m^3) respectively. May 2022, recorded abnormally high concentrations of PM_{10} at all stations. This could be attributed to the broad relaxation of stringency measures and opening-up of commercial and industrial activities.

Seasonal effects of NO_2 were observed in all wards except wards R/C and S. NO_2, concentrations exceeded the CPCB standard of 80 µg/m^3, just four times throughout the study period, in the months of January and February. August, 2020 recorded the lowest mean concentration of NO_2, 0.7 µg/m^3 (ward R/C) and highest mean of 104.1 µg/m^3 (ward F/N) was recorded during January 2021.

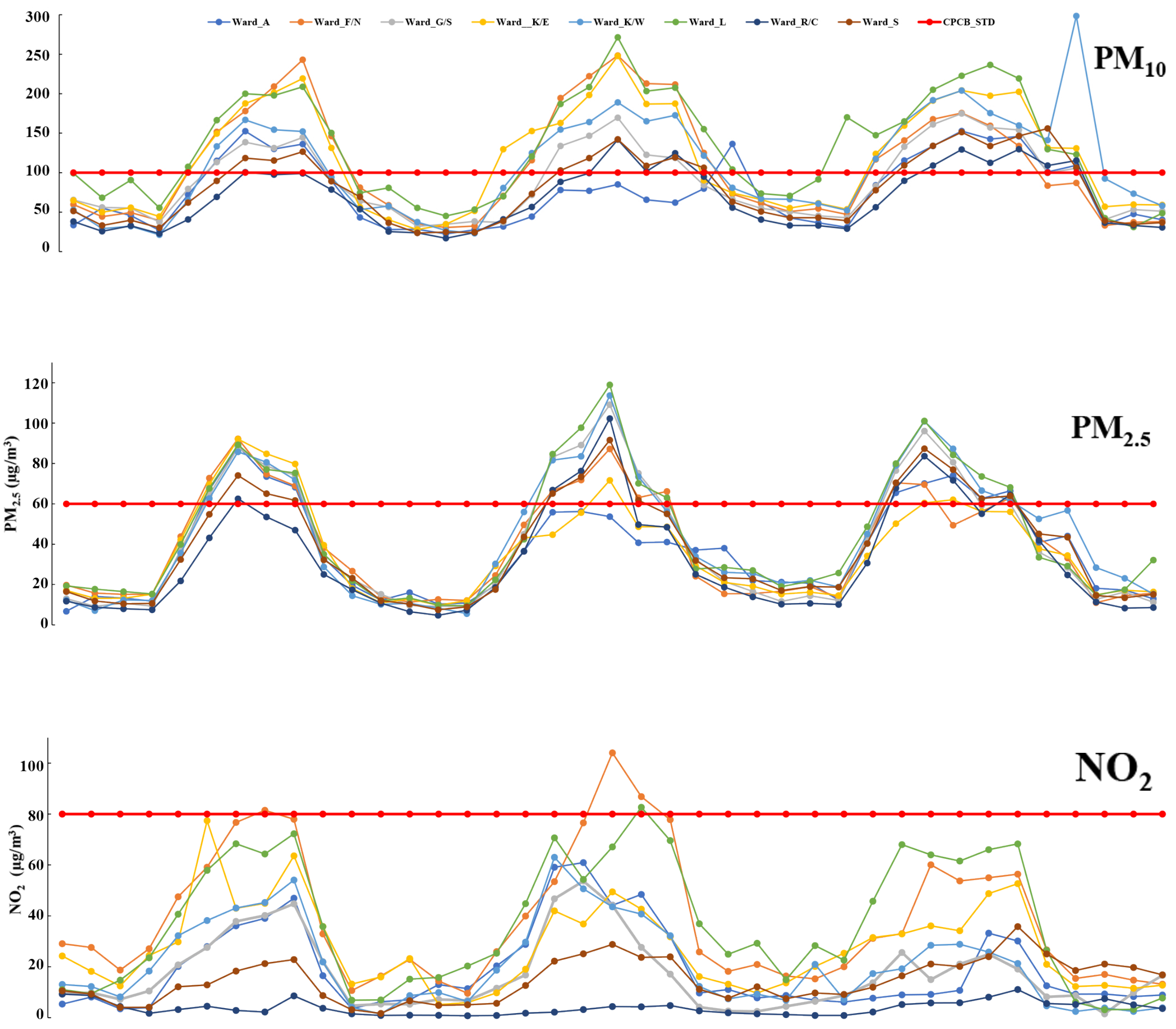
Absence of a seasonal SO_2 trend indicates that sources impacted SO_2 levels more than meteorology. SO_2 conformed to the CPCB standard of 80 µg/m^3 throughout the study period. August, 2022 recorded the highest mean SO_2 of 77 µg/m^3 (ward F/N) while August, 2019 recorded the lowest mean SO_2 of 1.5 µg/m^3 (ward G/S).

Ammonia mostly showed the seasonal trend except a few times when it recorded anomalous peaks however, throughout the study period it conformed to the CPCB limit of 400 µg/m^3. June, 2021 recorded the lowest mean concentration of NH_3, 0.2 µg/m^3 (ward G/S) and highest mean of 163.5 µg/m^3 (ward F/N) was recorded during November, 2020.

CO also depicted a seasonal trend except a few times when it measured anomalous peaks. CO concentrations exceeded the CPCB standard of 2 mg/m^3, just thrice throughout the study period. August, 2020 recorded the lowest mean concentration of CO, 0.06 mg/m^3 (ward G/S) while highest mean of 2.61 mg/m^3 (ward K/W) was recorded during October, 2020.

During the inter-year comparison of the gases, we noted that the concentrations were below the CPCB standard during most of the study period. However, the particulate matter concentrations exceeded the standards during winter, post-monsoon, and summer seasons. We identified November to April and November to February as crucial months for PM_{10} and $PM_{2.5}$ concentrations respectively. May, 2022 for PM_{10} and March, 2022 for $PM_{2.5}$ showed abnormally high concentrations compared to the previous years. This could be due to greater relaxations in COVID-19 lockdown measures and a boom in economic activities.

The percentage of pollutants responsible for AQI is given in Fig. 3. Particulate matter (PM_{10} followed by $PM_{2.5}$) was primarily responsible for poor air quality throughout all the seasons in Mumbai. CO contributed to AQI once in post-monsoon, SO_2 contributed twice in monsoon while $PM_{2.5}$ contributed numerous times in winter to AQI throughout 2019-2022 period. Summer AQI was completely dominated by PM_{10} throughout the study period. Hence, we infer that among all the pollutants particulate matter is responsible for poor AQI, the most. This calls for the immediate implementation of mitigation policies focusing on particulate matter reduction for improvement of Mumbai's air quality index.



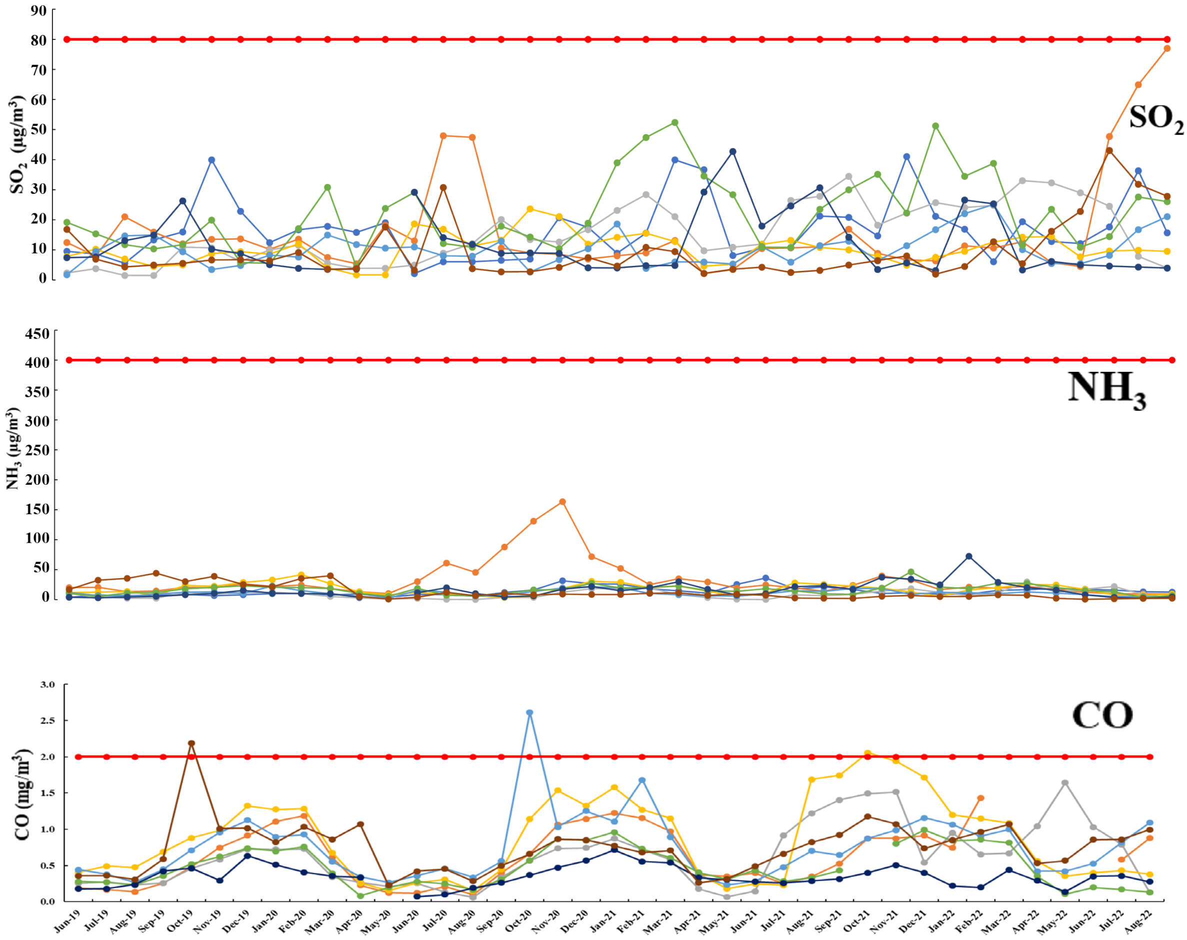


Fig. 2. Average monthly trend of criteria air pollutants from eight monitoring stations of Mumbai from June 2019 to August 2022

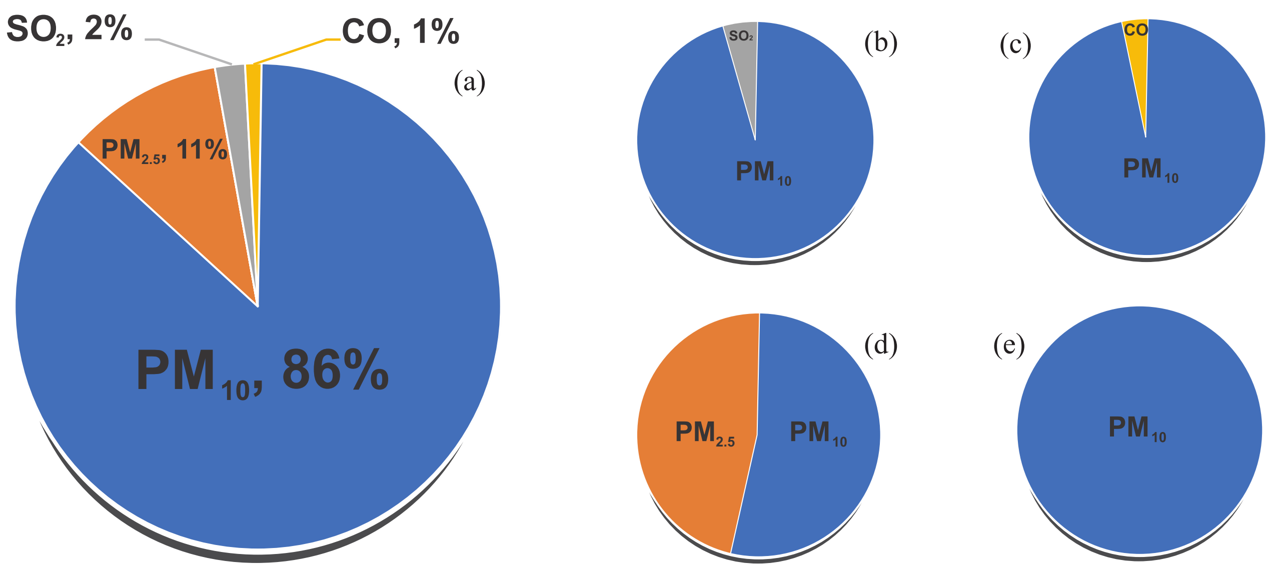


Fig. 3. Percentage contribution of criteria pollutants to (a) Annual AQI (b) Monsoon AQI (c) Post-Monsoon AQI (d) Winter AQI (e) Summer AQI

Seasonal impact on AQI hotspots

Comparing the spatial distribution of AQI hotspots and coldspots (Figs. 4. and 5) seasonally across 2019-2022 helped establish the hotspot wards in Mumbai city. Temporal profiles ward-wise show if the hotspot identified is consistently high during the study period or if the patterns suggest the high values are more transient.

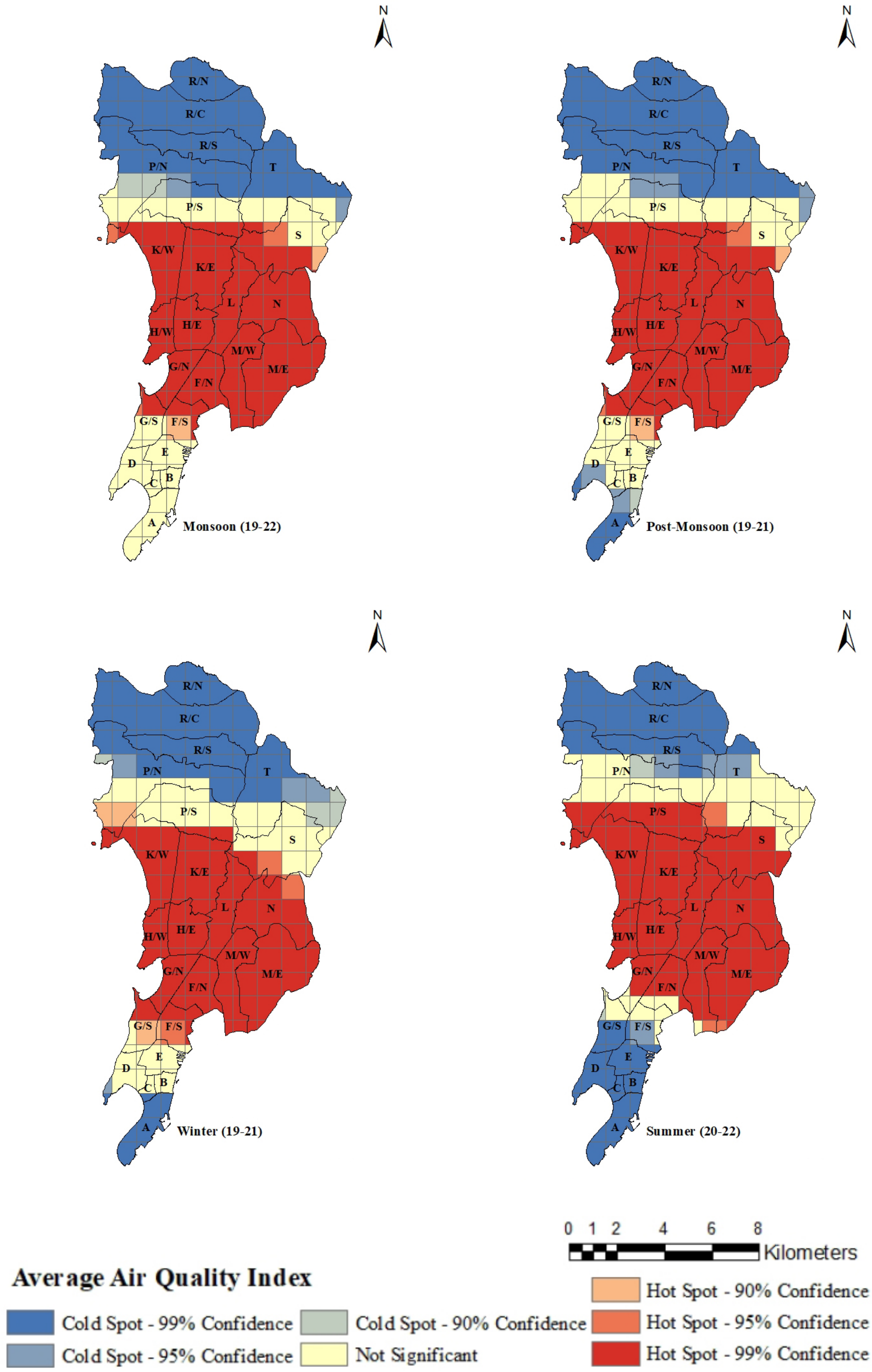
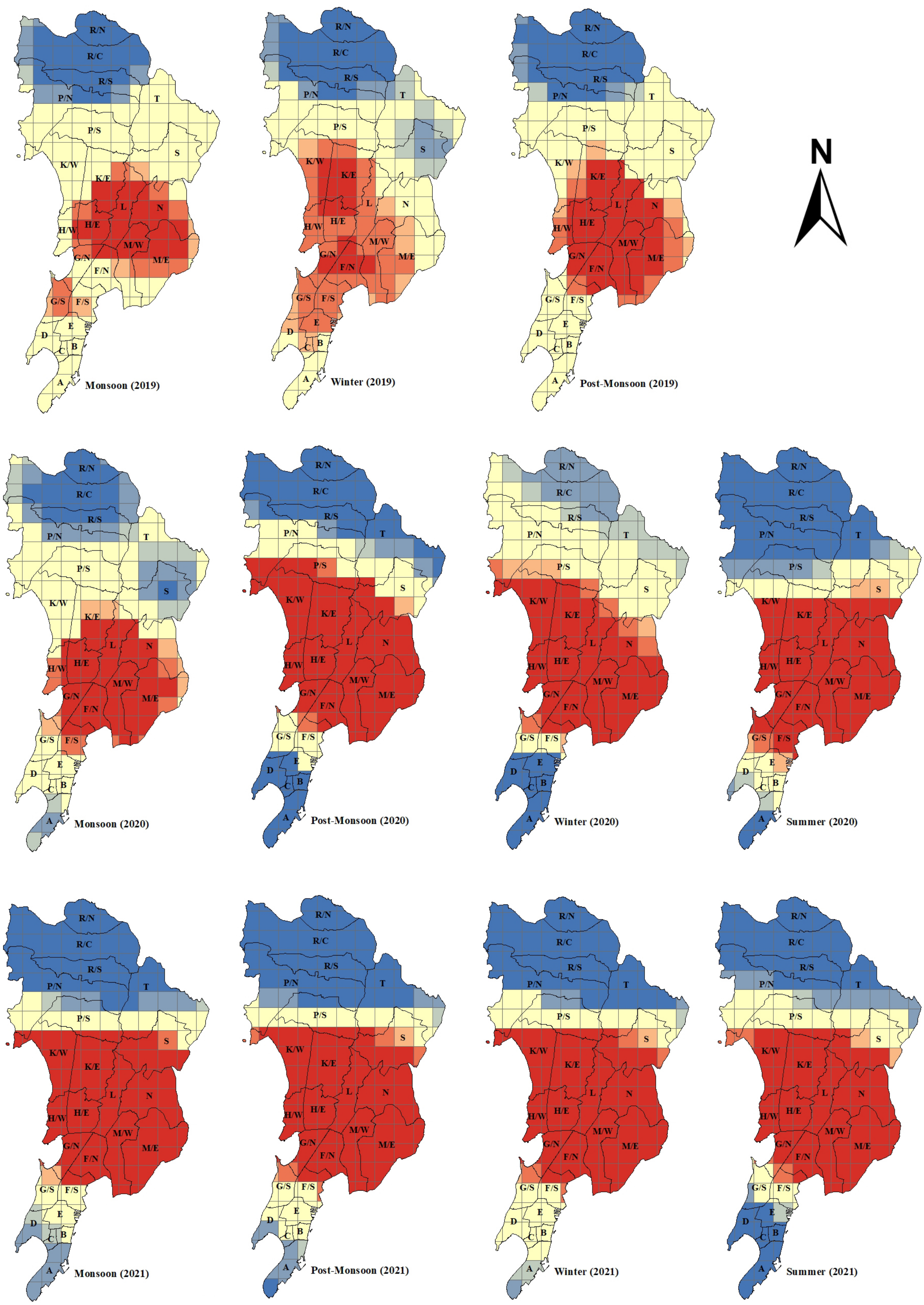


Fig. 4. Overall seasonal average air quality index hotspot map


Monsoon (2019)
Winter (2019)
Post-Monsoon (2019)
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Monsoon (2020)
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Winter (2021)
Summer (2021)

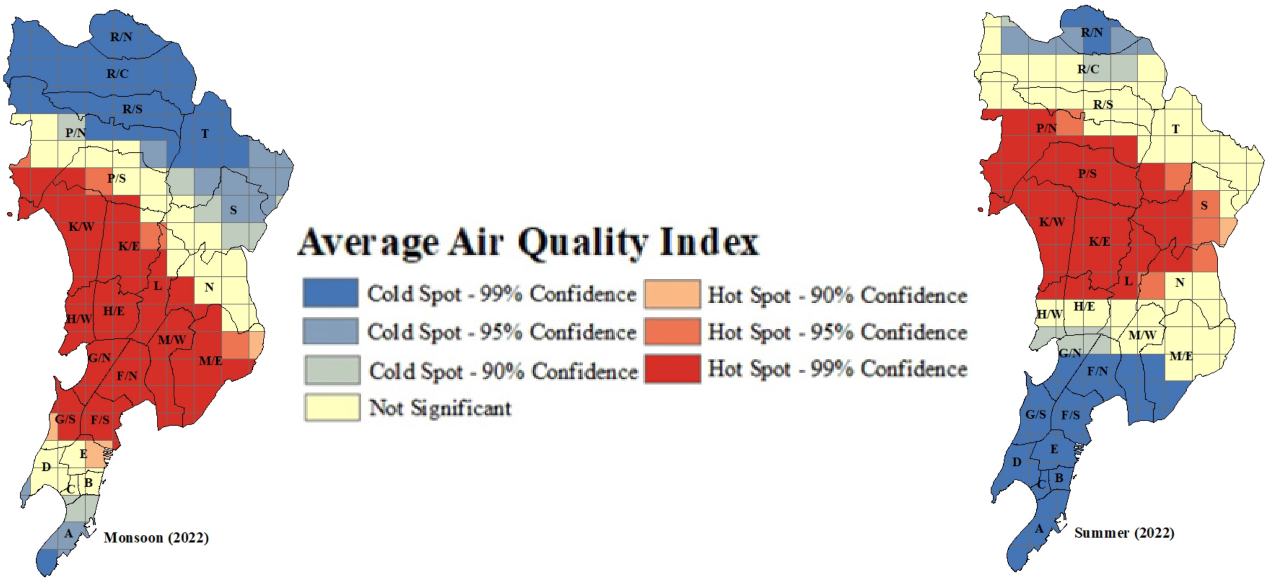


Fig. 5. Season-wise variation in air quality index hotspot map for the period 2019-2022

Hotspot analysis indicated wards K/W, K/E, L, N, H/E, H/W, M/E, and M/W were hotspots with 99% significance in all the seasonal averages for the 2019-22 period; contrastingly, wards R/N, R/C, R/S and A were coldspots with 99% significance. The hotspots identified can be regarded as steady because they have remained consistent across most of the seasons for over three years. The hotspot analysis delineates central Mumbai wards as the high pollution hotspots throughout the study period, while wards north near the national park are coldspots throughout the year. This highlights the importance of green cover in pollution control in Mumbai. The Sanjay Gandhi national park is the last green space left in Mumbai and it needs to be protected at all cost. Apart from the northern wards as coldspots only ward A from south Mumbai is a coldspot across the seasons. Ward A could be a coldspot because of its geographic location (situated at the tip of the Mumbai peninsula) surrounded by sea, which transports away the pollution quickly. We also observe a dramatic shift in hotspot wards in summer, it moves more towards the north, compared to other seasons indicating a shift in wind direction. Our results are consistent with theories that city centres are typically air pollution hotspots. The reason for central Mumbai wards being persistent hotspot areas could be less green cover, high road density, ongoing largescale construction activities and presence of small- and large-scale industries in these wards.

Time series dynamics in air quality due to stringency measures

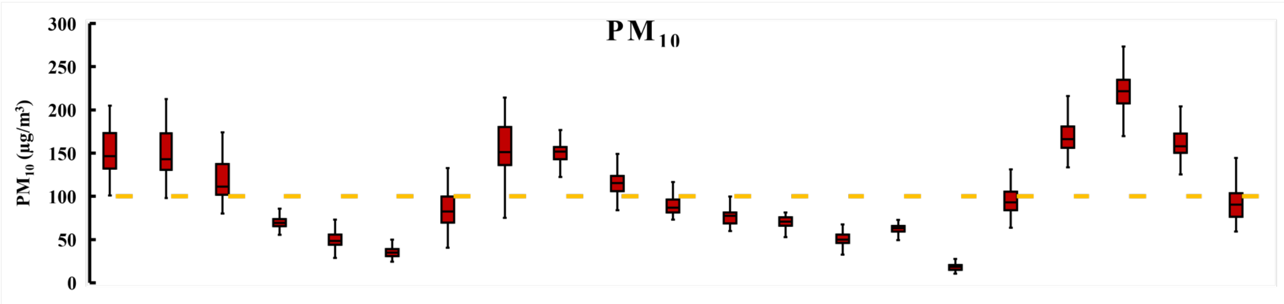
The box and whisker plot (Fig. 6.) evidently captures the temporal dynamics of COVID-19 stringency measures on various pollutants. The imposition of the harshest policy measures during the most stringent initial phases of the COVID-19 lockdown drastically reduced the concentration of all the pollutants. Except for SO_2, the other five pollutants conform to the trend; reduction during the high stringency period and increase in concentration during low stringency period.

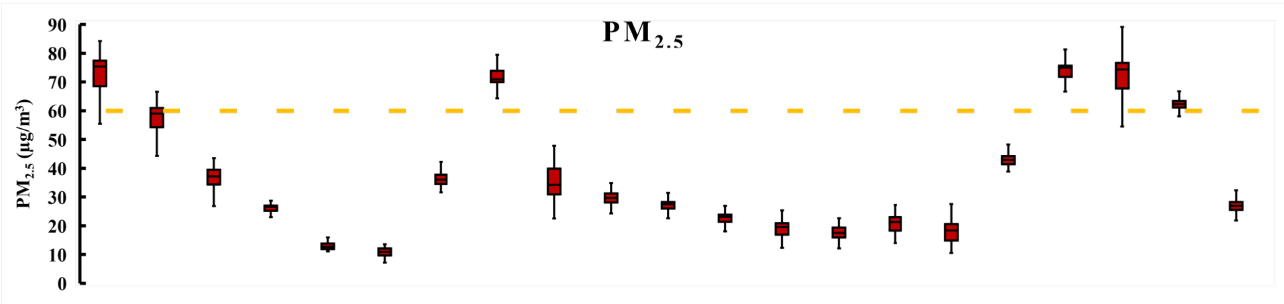
The most prominent reductions during the COVID-19 stringency phases were observed during VH5 for (10.59 µg/m^3) PM_{10}, VH1 for (7.24 µg/m^3) $PM_{2.5}$, VH5 for (1.14 µg/m^3) NO_2, EX2 and EX3 for (1.06 µg/m^3) SO_2, EX3 for (1.56 µg/m^3) NH_3, EX3 for (0.13 mg/m^3) CO. Though the most stringent phase was CLD (complete lockdown phase) the particulate matter concentrations recorded lowest during VH5 and VH1 both of which coincided with the monsoon season. PM_{10} recorded lowest of 10.59 µg/m^3 during VH5 while $PM_{2.5}$ recorded lowest of 7.24 µg/m^3 during VH1. This highlights the role of meteorology in particulate matter reduction through wet deposition. Similarly, we observe a decline in the concentrations of gaseous pollutants more during the phases following the complete lockdown period. In the second phase of the lockdown measures even though relaxations were provided for selected non-essential activities the emissions declined further than the complete lockdown period. It indicated that either the enforcement of the lockdown was more stringent or people were not ready to take advantage of the relaxations due to the fear of COVID-19 virus [7].

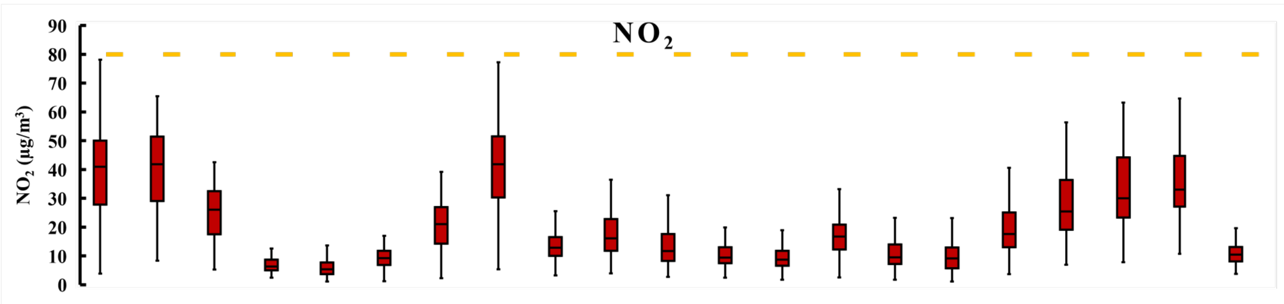
Sub-phases VH1, VH4, H3, VH5 and a part of H4 coincided with monsoon season. Sub-phases NLD, part of L1, part of M2, H4, VH6, H5 and part of M3 coincided with winter season. A very distinct seasonal impact can be seen on particulate matter (PM_{10} and $PM_{2.5}$) during the different sub-phases of the stringency index. Despite the imposed stringency measures, seasonal trend starting from post-monsoon and peaking in winter and reducing during summer to reach the lowest during monsoon months could be observed. The highest mean concentrations throughout the COVID-19 pandemic period were recorded during the sub-phases H5 for (273.29 µg/m^3) PM_{10}, H5 for (89.09 µg/m^3) $PM_{2.5}$, NLD for (78.14 µg/m^3) NO_2, H5 for (55.44 µg/m^3) SO_2, VH6 for (56.60 µg/m^3) NH_3 and M3 for (1.32 mg/m^3) CO. All of which were during the winter season. Hence, this analysis reconfirms the impact of the winter season on pollutant concentrations.

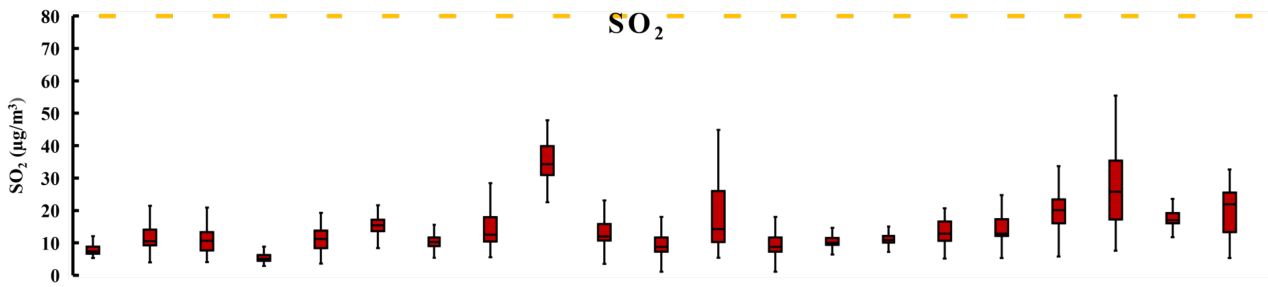
Throughout the COVID-19 stringency assessment period all gases were below the CPCB standards while the mean values of particulate matter (PM_{10} and $PM_{2.5}$) exceeded the CPCB standard a few times. Mean PM_{10} concentrations exceeded during NLD, L1, M1, M2, H2, VH2, VH6, H5 and M3 while $PM_{2.5}$ exceeded during NLD, M2, VH6, H5 and M3 sub-phases. All these sub-phases coincided with winter except M1, H2 and VH2 which coincided with summer. Apart from the meteorology, another important reason for high pollution during winter could be due to more relaxations in stringency measures during the winter period. The most stringent COVID-19 measures mostly coincided with summer and monsoon and eased during the other periods as the number of COVID-19 cases reduced. This could be another cause of high pollutants during the phases of winter compared to other period.

The average, minimum, maximum of air pollutants and stringency index for different phases of COVID-19 are given in Table.2. Stepping-up to the phase level, we still observe that the average PM_{10} exceeded the CPCB standards in phases NLD, L, M and H while average $PM_{2.5}$ exceeded in phase NLD. Ammonia and SO_2 concentrations were way below the CPCB standards even during no lockdown period. NO_2 and CO averages were also below CPCB standard but the maximum values were close to the limits indicating a need to exercise control in these emissions. Except for CLD period, PM_{10} maximum values exceeded the CPCB standard greatly. Also, the average PM_{10} concentrations exceeded the CPCB standard till High (H) period. Indicating very high and above stringency measures need to be applied to bring the values under CPCB standard while for achieving the WHO standard long term aggressive action plan was required.


PM10
PM10 (µg/m³)
300
250
200
150
100
50
0


PM2.5
PM2.5 (µg/m³)
90
80
70
60
50
40
30
20
10
0


NO2
NO2 (µg/m³)
90
80
70
60
50
40
30
20
10
0


SO2
SO2 (µg/m³)
80
70
60
50
40
30
20
10
0

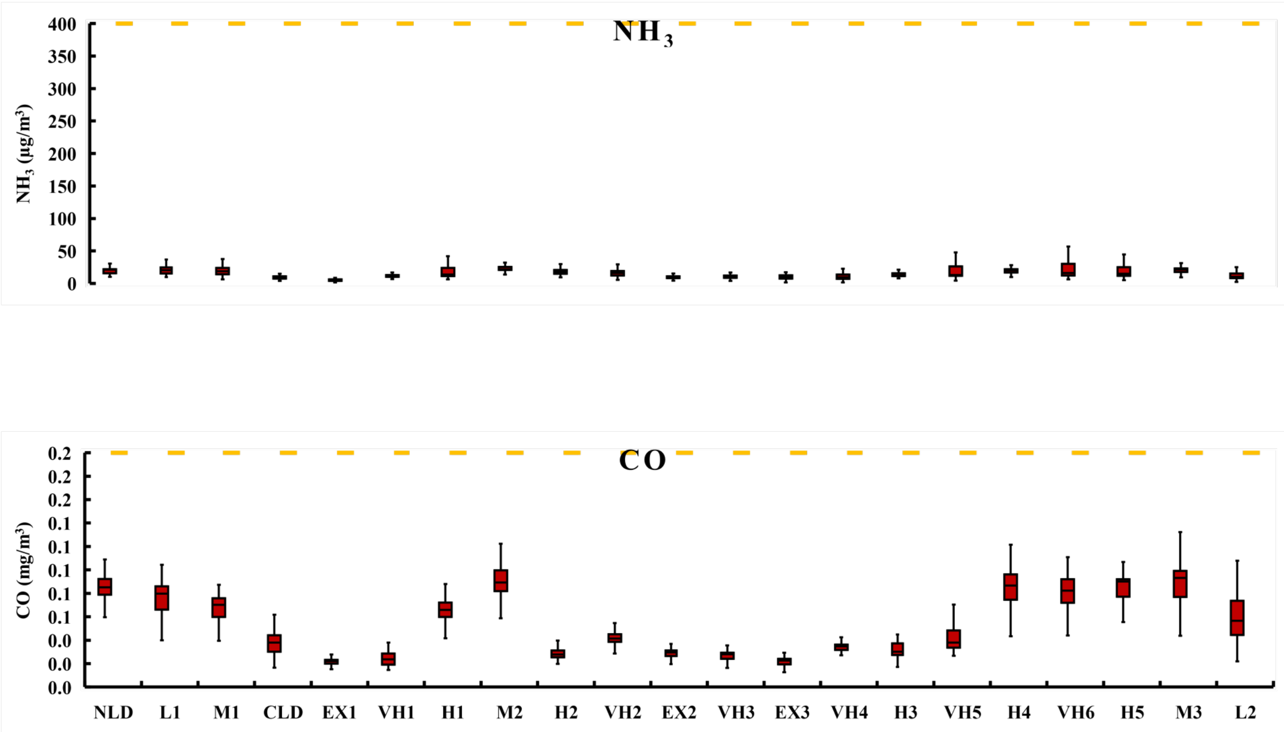


Fig. 6. Box plot of air pollutant variations during different stages of COVID-19 stringency measures

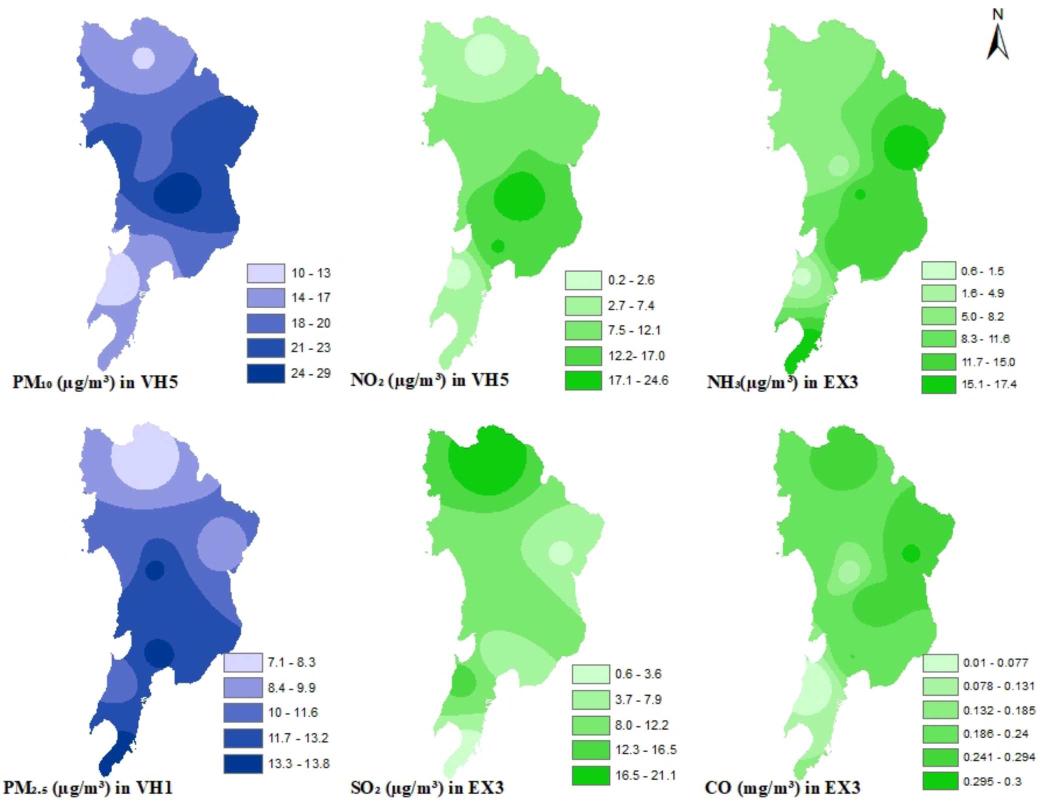


Fig. 7. Baseline map of air pollutants in Mumbai COVID-19

Table 2. Average, minimum, maximum of air pollutants and stringency index for different phases of COVID-19

Lockdown Phase		PM_{10} (μg/m^3)	PM_{25} (μg/m^3)	NO_2 (μg/m^3)	SO_2 (μg/m^3)	NH_3 (μg/m^3)	CO (mg/m^3)	Sch_Cls	Wrkcls	Cncl_Pblc_Evnts	Rstrc_Gathrngs	Cls_Pblc_T	StayHome_Req	Rstrc_Int_Mvmnt	Intrnational_Trvl_C ntrl	SI
	AVG	150.9	72.7	38.9	7.8	19.2	0.8	0	0	0	0	0	0	0	0	0
NLD	MIN	100.9	55.2	3.9	5.3	10.1	0.5	0	0	0	0	0	0	0	0	0
	MAX	204.9	84.2	78.1	12.0	30.4	1.2	0	0	0	0	0	0	0	0	0
	AVG	122.0	42.8	25.3	15.6	17.2	0.7	0	0	0	0	0	0	0	2	11
L	MIN	59.2	21.9	3.8	4.0	2.5	0.2	0	0	0	0	0	0	0	1	9
	MAX	212.4	66.6	65.4	32.6	53.9	1.1	0	0	0	0	0	0	0	2	14
	AVG	145.1	56.6	33.3	14.3	21.8	0.8	2	2	1	1	1	0	0	2	42
M	MIN	80.1	22.5	3.3	4.1	6.4	0.2	1	1	1	0	0	0	0	1	41
	MAX	222.1	85.4	77.2	33.2	61.5	1.4	3	2	1	2	2	1	1	3	45
	AVG	122.1	41.6	19.1	19.5	19.0	0.6	2	2	2	3	1	1	1	3	63
H	MIN	40.8	14.0	1.8	3.5	1.8	0.2	1	1	1	2	0	0	0	2	40
	MAX	273.3	99.7	63.3	55.4	115.0	1.6	3	3	2	4	2	2	2	3	67
	AVG	76.9	28.9	14.9	15.5	16.5	0.4	3	2	2	4	1	2	2	3	80
VH	MIN	10.6	10.6	1.1	0.7	1.6	0.0	2	2	1	3	1	0	0	2	63
	MAX	215.9	86.4	56.4	52.8	94.3	1.1	3	3	2	4	2	3	2	3	88
	AVG	70.7	19.8	9.2	10.3	8.4	0.2	3	3	2	4	2	3	2	3	95
EX	MIN	24.5	7.2	1.2	3.6	1.6	0.1	3	2	2	3	1	1	2	3	84
	MAX	138.7	35.1	31.0	20.6	22.7	0.4	3	3	2	4	2	3	2	4	97
	AVG	69.8	26.2	6.8	5.6	9.2	0.4	3	3	2	4	2	3	2	4	100
CLD	MIN	55.6	23.0	2.5	2.9	3.8	0.2	3	3	2	4	2	3	2	4	100
	MAX	85.6	28.7	12.6	12.4	14.8	1.1	3	3	2	4	2	3	2	4	100

The COVID-19 harsh stringency measures helped estimate the lowest average possible concentrations during 2020 to 2022 period among the twenty-one sub-phases. It can be termed as the baseline values of each pollutant for Mumbai city. The baseline values observed for Mumbai were 10.59 μg/m^3, 7.24 μg/m^3, 1.14 μg/m^3, 1.06 μg/m^3, 1.56 μg/m^3 and 0.13 mg/m^3 for PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3 and CO respectively. This directly indicates the impact of stringency measures, that caused decrease in anthropogenic activities, affecting the pollution concentration levels in Mumbai. Fig.7. indicates the spatial distribution of baseline period of the six criteria pollutants due to COVID-19 stringency measures during the two-and-half year study period. Though all the values were below the CPCB standards and without much variation we plotted the maps to understand the spatial distribution (using standard deviation) during baseline conditions. Even during the lowest concentrations, we observe variations in spatial distribution with relatively high concentrations in the central Mumbai wards for PM_{10}, $PM_{2.5}$, NO_2, SO_2 and NH_3. This is in concordance with the hotspot analysis results. The baseline conditions developed due to complex interactions between source emissions, meteorology, and mainly due to slowdown of anthropogenic activities.

Relation between stringency measures and air pollution

Regression models (Table 3) were used to explore the association between local meteorological factors, stringency index and air quality using ArcGIS. The best fit model was for PM_{10} and NO_2 with adjusted R^2 of 0.61 implying a good interrelation within estimated and predicted PM_{10} concentrations. This was followed by CO with an adjusted R^2 value of 0.57, 0.49 for NH_3 and 0.23 for SO_2. This indicates that factors other than those considered in the model play a vital role in SO_2 and NH_3 concentrations. Electricity generation during lockdown period was allowed to function under the essential service category which contributes to SO_2. Hence the imposition of stringency measures did not have much impact on SO_2 concentrations. We used a stepwise OLS regression model which eliminated wind speed from NO_2, implying that wind speed does not have a strong impact on NO_2 concentration.

Coefficients of most of the variables were significant and in the expected direction. As expected, the results indicate a negative relationship between air pollutants and stringency index. The coefficient of stringency index is statistically significant and in the range of -0.003 to -0.007 indicating that a 10-point increase in the stringency index results in 3-7 % reduction in levels of the five air pollutants.

Table 3. Regression models to explain effect of stringency index on air pollutants

	Ln (PM_{10})	Ln (NO_2)	Ln(SO_2)	Ln (NH_3)	Ln (CO)
Constant	8.509	5.725	2.960	2.885	2.607
Lag_pollutant	.124	.392	.338	.534	.230
Temperature	-.067	-.091	-.048	-.085	-.075
Relative Humidity	-.035	-.019	.006	.015	-.008
Wind Speed	.041	-	-.061	-.112	-.048
Stringency Index	-.003	-.003	-.004	-.004	-.007
Adjusted R^2	0.606	0.608	0.230	0.491	0.570
Durbin-Watson	1.991	1.353	2.070	1.795	1.734

Effect of stringency measures (OXCGRT) on pollutants

We analysed the effect of stringency measures on pollutants (Fig. 8.) using two scenarios. The first scenario was the percent change in the six criteria pollutants with respect to No-lockdown (before stringency measures were implemented) and the second scenario was comparison in change with complete lockdown (100% stringency measures were implemented). The scenario one results show a decline among all the pollutants except SO_2 during most of the sub-phases as compared to the no lockdown scenario. This indicates that stringency measures of different strength helped in decline of air pollutants and improve air quality. However, the opposite effect was seen in SO_2 which shows an increase despite lockdown measures. This indicates that the stringency measures had very little or no impact in reducing the SO_2 concentrations.

In scenario two, compared to the complete lockdown scenario all the pollutants have shown an increase during most of the sub-phases of the stringency measures. We found reduction of some pollutants during EX1, VH1, H2, EX2, VH3, EX3, VH4, H3 and VH5 sub-phases compared to the complete lockdown period.

Results of both the scenarios clearly indicate that though there is a varying degree, the five pollutants PM_{10}, $PM_{2.5}$, NO_2, NH_3 and CO are impacted by the imposition of lockdown measures. Nature of economic activities in a city determines the range of air quality improvement due to lockdown measures [7]. Hence, implementation of correct stringent policy measures can help reduce the pollutants.

We analysed the overall impact of stringency phases on air pollutants compared to No lockdown phase (Fig. 9.). A substantial reduction was observed in average PM_{10}, $PM_{2.5}$, NO_2, and CO during all the phases of stringency measures. Ammonia also showed reduction in concentration except during M phase where it recorded an increase in concentration. Except for the complete lockdown phase SO_2 increased in all the phases, indicating very little impact of stringency measures on SO_2 concentration. This indicates that the pollutants are highly dependent on anthropogenic activities and the air quality can be improved by imposing appropriate policy measures.

We estimated the maximum and minimum impacts during the two and a half year COVID-19 stringency measures on air pollutant concentrations in Mumbai city. Compared to no lockdown phase (1st January 2020 to 29th January 2020) a maximum reduction throughout the COVID-19 stringency phases (30th January 2020 to 21st August 2022) were 53.8%, 72.7%, 82.6%, 28.4%, 52.2% and 49.1% for PM_{10}, $PM_{2.5}$, NO_2, NH_3 and CO during Complete Lockdown (CLD) or Extreme (EX) phases. While the maximum increment observed was during the medium phase for all pollutants except SO_2 (phase high). This asserts that SO_2 is not affected much by meteorology or stringency measures and that NO_2 followed by PM_{10} and $PM_{2.5}$ were highly meteorology and stringency index dependent. Thus, it can be concluded that the COVID-19 indirectly helped in improving air quality for Mumbai city, a boon in disguise and that appropriate mitigation measures can help in reducing air pollution drastically.

There is always a level of uncertainty in modelling studies which can be addressed only through more research [24]. The study has some limitations, we could not include some important determinants of air pollution such as land-use pattern, source apportionment studies, role of individual SI indicators on air quality, due to data and time confines. This could have enhanced our understanding on the impact of stringency measures on air quality and improved the SO_2 and NH_3 regression models. We recommend more studies in this context to fill the gaps and provide a comprehensive understanding on the impact of SI on air quality.

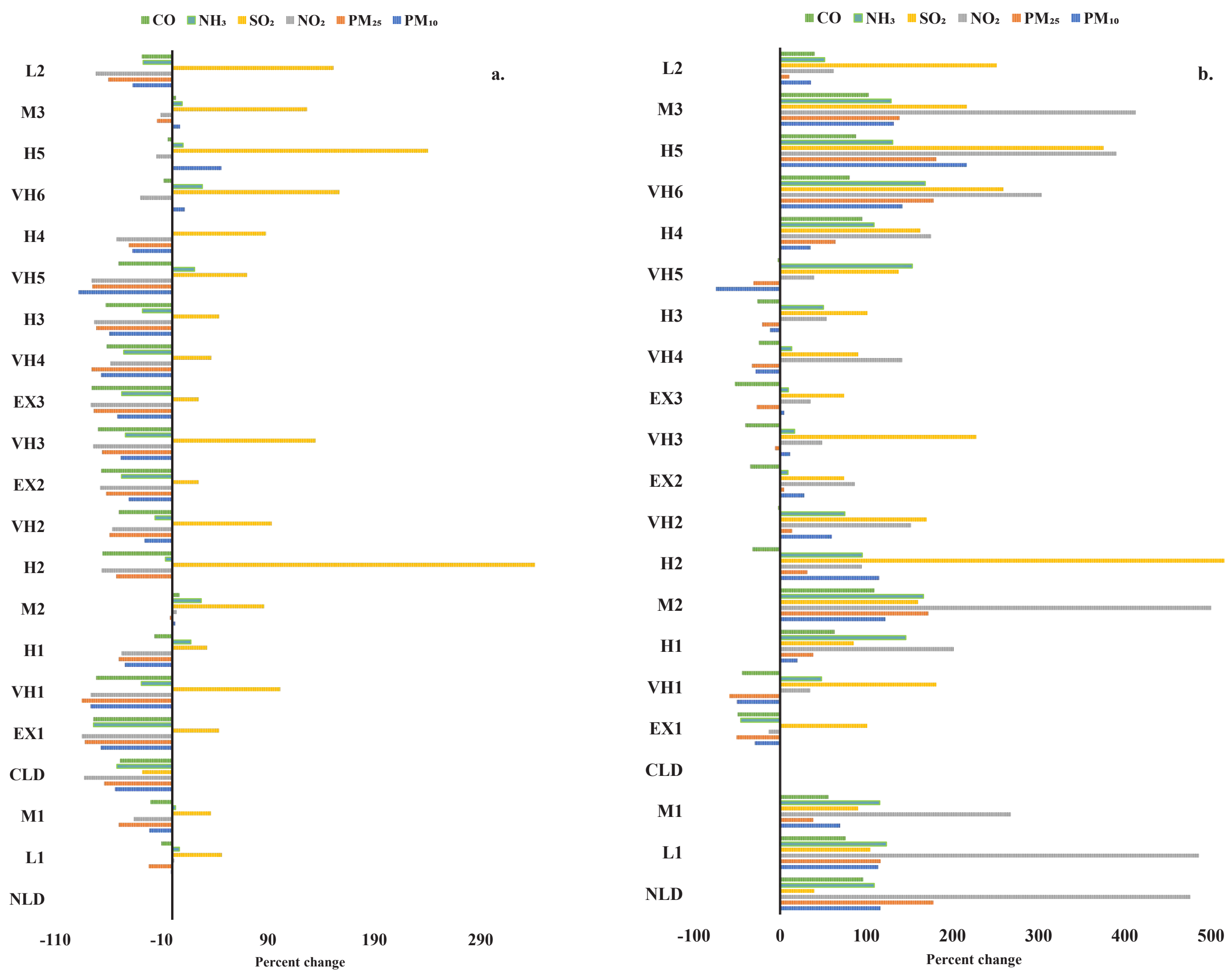


Fig. 8. Percent change in criteria pollutants during different phases of SI (a) percent change compared to no-lockdown period (SI-0) (b) percent change compared to complete lockdown period (SI-100)

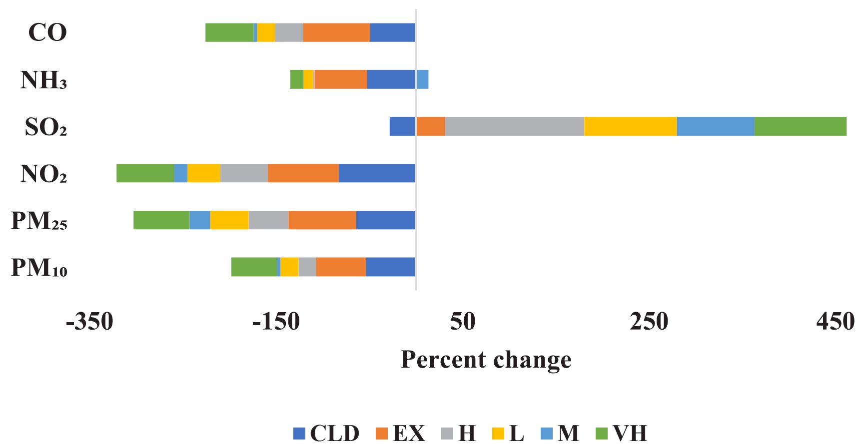


Fig. 9. Overall effect of stringency phases on air pollutants compared to no lockdown phase

Conclusion

This study estimated the spatio-temporal variations of criteria air pollutants and the impact of stringency measures on air pollution using a comprehensive two-and-a-half-year COVID-19 period dataset for megacity, Mumbai. We identified particulate matter to be the highest contributor to poor AQI. In India, one of the foremost risk factors for the mortality and morbidity burden is exposure to Particulate Matter ($PM_{2.5}$) [25]. Hence to reduce the health impacts on people of Mumbai, we recommend to focus specific mitigation measures targeting particulate matter to be implemented urgently. Our temporal analysis indicated that seasonality significantly influenced the pollution concentrations except SO_2. Winter was the worst period while monsoon was the best.

We conducted a hotspot analysis of seasonal AQI to identify the regions of high and low pollution areas in Mumbai. Central Mumbai wards K/W, K/E, L, N, H/E, H/W, M/E and M/W showed a significant hotspot clustering of 99% in all the seasons while northern wards R/N, R/C and R/S and Colaba- A ward in the south showed coldspot clustering with 99% significance. The existance of coldspots in the northern wards could be related to the Sanjay Gandhi National Park. It highlights the importance of green cover in air pollution reduction. Green infrastructure can play a crucial role in mitigating urban air pollution [24]. Low-level hedges improve air quality in street canyons while for streets/open roads green walls and roofs are more effective. Hence, in the central Mumbai wards we recommend to develop a strong green infrastructure to mitigate pollution.

Since the industrial revolution for the first time the suspension activities during COVID-19 lockdown gave the atmospheric environment time to recover due to the absence of industrial air pollution [13]. Due to the lockdown, we could comprehend the impact of anthropogenic activities on overall air quality. In concordance with previous studies, a drastic reduction was observed for all pollutants during complete lockdown period. The most prominent reductions during the COVID-19 stringency sub-phases were observed during VH5 for (10.59 $\mu g/m^3$) PM_{10}, VH1 for (7.24 $\mu g/m^3$) $PM_{2.5}$, VH5 for (1.14 $\mu g/m^3$) NO_2, EX2 and EX3 for (1.06 $\mu g/m^3$) SO_2, EX3 for (1.56 $\mu g/m^3$) NH_3, EX3 for (0.13 mg/m^3) CO. Sub-phases VH1, VH4, H3, VH5 and a part of H4 coincided with monsoon season. Sub- phases NLD, part of L1, part of M2, H4, VH6, H5 and part of M3 coincided with winter season. Though the most stringent phase was CLD (complete lockdown phase) the lowest particulate matter concentrations were recorded during VH5 and VH1 which coincided with the monsoon season. The highest mean concentrations throughout the COVID-19 pandemic period were recorded during the sub-phases H5 for (273.29 $\mu g/m^3$) PM_{10}, H5 for (89.09 $\mu g/m^3$) $PM_{2.5}$, NLD for (78.14 $\mu g/m^3$) NO_2, H5 for (55.44 $\mu g/m^3$) SO_2, VH6 for (56.60 $\mu g/m^3$) NH_3 and M3 for (1.32 mg/m^3) CO. All of which were during the winter season. Hence, this analysis reconfirms the impact of meteorology on pollutant concentrations.

The relationship between air quality, meteorology and stringency index was explored using the OLS regression. PM_{10}, NO_2 and CO were more affected by SI variations than NH_3 and SO_2. The regression models varied in R^2, 0.23 for SO_2, 0.49 for NH_3, 0.57 for CO, and 0.61for PM_{10} and NO_2. They indicated an inverse relationship with stringency index for the five pollutants. A similar inverse relation was found between temperature and windspeed. The coefficient of stringency index was in the range of -0.003 to -0.007 indicating that a 10-point increase in the stringency index results in 3-7 % reduction in levels of air pollutants. The study has some limitations, we could not include some important determinants of air pollution such as land-use pattern, source apportionment studies due to data confines. This could have enhanced our understanding on the impact of stringency measures on air quality and improved the SO_2 and NH_3 models. Future studies could examine the impact of individual policies on air quality and help in identifying the most effective ones.

We estimated a substantial reduction in average

PM_{10}, $PM_{2.5}$, NO_2, NH_3 (except medium phase) and CO during all the phases of stringency measures meanwhile SO_2 showed an increase during the same period. The maximum percent reduction observed was 53.8%, 72.7%, 82.6%, 28.4%, 56.5%, and 72.0% for mean PM_{10}, $PM_{2.5}$, NO_2, NH_3, and CO during complete lockdown (CLD) or extreme (EX) phases. With the exception to SO_2 (high phase), all pollutants exhibited maximum increment during the medium phase. Major sources contributing to PM_{10} concentrations in Mumbai are dust (35%), Transport (17%), Waste burning (16%), SIA (15%), Industries (13%) and Marine (4%). Dust comprises of particles from unpaved roads, pavements, wear and tear of tyres, brakes and materials from the roads and street furniture [26]. While industries and automobiles were the main sources of NO_2. Depending upon the SI, the strict controls influenced all these anthropogenic activities hence the concentrations of PM and NO_2 reduced drastically. On the other hand, Vehicles, power plants and fertilizer factories were the sources of SO_2 and NH_3 respectively. They were operational during lockdown period and hence there was little impact of SI on SO_2 and NH_3. Though SO_2 was not largely affected by the stringency measures, the decrease observed during the COVID-19 phases compared to NLD could be attributed to drop in emissions from Power Plants (PP). The lockdown caused shutdown of all industrial activities and thus reducing the power demand from PP.

In conclusion, several air pollution mitigation measures exist in India which includes policies to control vehicular emissions, industrial emissions, dust from roads and construction-demolition activities. The NCAP (National Clean Air Programme) established by the government of India has outlined source and sector specific mitigation measures. Despite this, there remains a serious public health concern in cities like Mumbai due to poor AQI. The mean concentrations of PM_{10} and $PM_{2.5}$ surpassed the WHO standards by 36% and 43% even during CLD phase. This indicates that even the most stringent regulations, in conjugation with favourable meteorology (summer and monsoon) were unable to assist in meeting the WHO's PM_{10} and $PM_{2.5}$ standard of 45 $\mu g/m^3$ and 15 $\mu g/m^3$ respectively. Hence, long-term mitigation measures should be implemented to tackle this. We advise to include green designing and sustainable development strategies like green infrastructure of green walls around building surfaces and structures such as bridges, fly-overs, retaining walls, and noise barriers. They can help reduce air pollution 95% more compared to the absence of green walls [24].

Meanwhile, to rapidly reduce mean PM_{10} levels below the CPCB standards of 100 $\mu g/m^3$, SI (≥ 80) of very high and above should be implemented. The specific policy responses must be atleast in the scale of three for closing schools, two for closing workplaces, two for cancelling public events, four for restricting the size of gatherings, one for closing public transport, two for requiring people to stay at home and two restricting internal movements and three for travelling abroad. This indicates that the maximum value of stringency for school closing, cancelling public events, restrictions on gathering size and restrictions on internal movement must be imposed to rapidly confine the PM_{10} concentrations below the 100 $\mu g/m^3$ CPCB threshold and reduce impact on health. The authors are aware that implementing the stringency measures ($\geq$ 80) of very high and above would not be economically feasible. However, for a rapid emergency response to high PM pollution we suggest implementing the recommended stringent actions for a short period. Simultaneously, continuous implementation of long-term mitigation measures for reduction will help keep the background concentrations low. The findings of this study have important policy implications and provides significant pointers for public health management.

Limitations of the study

Air pollution is a very complex issue with multiple factors affecting the air quality. The study has a few limitations, we could not include some important determinants of air pollution such as land-use pattern, source apportionment studies, role of individual SI indicators on air quality, due to data and time confines. This could have enhanced our understanding on the impact of stringency measures on air quality and improved the SO_2 and NH_3 regression models. For advanced future work, a broader approach including these variables may be explored.

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Competing interests

The authors declare that there are no competing interests.

Authors' contributions

Gouri Nair: Conceptualization, methodology, analysis, validation, writing-drafting manuscript; Dr. Ramesh Veerappan: Analysis, reviewing and editing and Dr. Mohammed Irshad: Supervisor, reviewing and editing.

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Ethical considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc) have been completely observed by the authors).

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