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RESEARCH ARTICLE

Geospatial View of Air Pollution and Health Risk Over North Indian Region in COVID-19 Scenario

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Abstract

Air pollutant concentration, air quality index (AQI), and Excess risk (ER%) is assessed during January 2020 to June 2021 and in three scenarios including pre-lockdown, lockdown and post-lockdown based on 47 ground station data (during January 2020 to June 2020) distributed over northern part of India (including Delhi, Haryana, Punjab, part of Uttar Pradesh, and part of Rajasthan) using statistics and geographic information system (GIS) techniques. Daily and monthly variations of air pollutants (During January 2020 to June 2021) over the region showed a systematic pattern with high pollutant level during October and November while low during March, April (in dry period) and July–September (in wet period). In three scenarios viz. pre, during and post-lockdown the average concentration for $PM_{2.5}$ was 71.1 ± 45 μg/m^3, 39 ± 20 μg/m^3 and 40 + 17 μg/m^3, for PM_{10} was 139 ± 72 μg/m^3, 96 ± 55 μg/m^3 and 105 ± 57 μg/m^3, for NO_2 was 28 ± 21 μg/m^3, 17 ± 13 μg/m^3 and 18 ± 12 μg/m^3, for NH_3 was 33 ± 24 μg/m^3, 25 ± 18 μg/m^3 and 29 ± 22 μg/m^3, for CO was 1 ± 0.65 mg/m^3, 0.7 ± 0.5 mg/m^3, and 0.7 ± 0.5 mg/m^3, for O_3 was 29 ± 20 μg/m^3, 39 ± 23 μg/m^3 and 39 ± 22 μg/m^3 and for SO_2 was 14 ± 11 μg/m^3, 14 ± 12 μg/m^3 and 12.5 ± 8.9 μg/m^3. Significant decrease in mean pollutants concentration, AQI and ER % was observed in lockdown period amid COVID-19. $PM_{2.5}$, PM_{10}, NO_2, NH_3 and CO decreased by 46%, 31%, 39%, 24% and 34%, respectively, in lockdown scenario as compared to the pre-lockdown scenario while the O_3 get increased. A decrease of 39% in AQI was observed as compared to pre-lockdown scenario; however, the difference was less when compared with post-lockdown scenario. The decrease in total ER% was 60.36% over the study area due to improvement in air quality over the region amid COVID-19 lockdown. The meteorological conditions in 2020 were found consistent with respect to 2019 and very less influence was observed on the concentration of air pollutants (less r^2 among the pollutants and meteorological parameters).

Keywords COVID-19 · Air quality · Excess health risk · North India · Criteria pollutants

Introduction

In these days world population is facing threat from the corona virus which is also known as COVID-19. Corona Virus causes respiratory illness such as severe acute respiratory syndrome (WHO, 2020). This has modified the anthropogenic activities across the world in terms of reduced human movement, reduced vehicle emissions and reduction in industrial activities which showed reduced level (ranging from 10 to 50%) of air pollution/pollutants across the Globe (Lal et al., 2020; Mahato et al., 2020; Muhammad et al., 2020; Sharma et al., 2020; Siddiqui et al., 2020; Singh & Nanda et al., 2021c; Srivastava et al., 2020; Tobías et al., 2020). In China human activity reduced by 69.85% in 44 cities and which mediated Air Quality Index (AQI), Particulate Matter 2.5 ($PM_{2.5}$), Carbon Monoxide (CO) partially and Particulate Matter 10 (PM_{10}), Sulphur dioxide (SO_2) and Nitrogen dioxide (NO_2) completely (Bao & Zhang, 2020). Transport, social activities, and consumption of oil has been attenuated distinctly (Filonchyk et al., 2020; Muhammad et al., 2020).

COVID-19 has caused millions of death worldwide (5,542,359 till 18 January 2022), since its first reported

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instance from the Wuhan city of the China (WHO, 2021). India is the 2nd largest populated country after China with high population density, along with limited health care facilities, faced high risk from pandemic COVID-19 in terms of deaths, economy, and health hazard. When affected patients were increased, Indian government took action to control the spread of COVID-19 in India and declared first countrywide lockdown for 21 days on 24 March 2020 after a complete curfew on 22 March, 2020 followed by further lockdown stages till 31st May 2020. Non-essential services like school, colleges, markets, shopping mall, offices and tourist place were banned completely while essential services (water, electricity department, bank, hospitals, pharmaceutical store, milk dairy, etc.) were allowed during lockdown (Sharma, 2020). The lockdown has significantly reduced the transportation, mobility, and industrial operations which resulted in to the reduced level of air pollutants and improvement in the air quality (Sharma et al., 2020; Siddiqui et al., 2020; Singh & Nanda et al., 2021c; Srivastava et al., 2020; Sur et al., 2021).

The changes in the pattern and magnitude of anthropogenic activities amid COVID-19 lockdown have clear impact on air quality and recent pandemic, i.e. COVID-19 has shown the glimpses for the same (Bao & Zhang, 2020; Bhawre, 2020; Dantas et al., 2020; Filonchyk et al., 2020; Kant et al., 2020; Lal et al., 2020; Nakada & Urban, 2020; Otmani et al., 2020; Pathakoti et al., 2020; Ranjan et al., 2020; Sharma et al., 2020; Siddiqui et al., 2020; Singh & Nanda et al., 2021c; Srivastava et al., 2020; Sur et al., 2021).

Lots of research has been done on the assessment of effect of lockdown on air quality in India based on ground data and satellite data (Dhaka et al., 2020; Kant et al., 2020; Lal et al., 2020; Mahato et al., 2020; Navinya et al., 2020; Pathakoti et al., 2020; Ranjan et al., 2020; Sharma et al., 2020; Siddiqui et al., 2020; Singh & Nanda et al., 2021c; Srivastava et al., 2020). In Lucknow and New Delhi major impacts of lockdown were observed on the concentration of $PM_{2.5}$, NO_2, and CO and less on the SO_2 (Srivastava et al., 2020). In Delhi and Mumbai NO_2 concentration get declined by 40–50% due to Lockdown (Shehzad et al., 2020). When the data of air pollutant of the year 2018, 2019 and 2020 were compared for various cities of India, researchers found decrease in the concentration of $PM_{2.5}$, PM_{10}, and O_3 as compared to the first two years but there were no change in the temperature and humidity (Bhawre, 2020; Navinya et al., 2020). Sur et al., (2021) reported 20–40% reduction in the concentration of NO_2 over Indo-Gangetic region constitute the part of the current study. Kant et al., (2020) and Singh and Nanda (2020) reported reduction (35–46%) in AOD over Northern India and Haryana state, respectively. Singh and Nanda et al. 2021c reported reduction in air pollutants over Haryana amid COVID-19 lockdown which resulted in the improvement of air quality index (44%) and excess health risk (71%) over the study area.

Efforts have also been put to understand the influences of meteorology on the concentration of air pollutants in the atmosphere (Banarjee et al., 2011; He et al., 2017; Ilten & Selici, 2008; Jayamurugan et al., 2013; Navinya et al., 2020). Researchers found the influence of temperature on the concentration of SO_2 and NO_2. High influence is found in summer and rainy season, and low in other seasons in case of northern India. Relative humidity had no significant relation with SO_2 and NO_2 and negatively correlated with PM (Jayamurugan et al., 2013). Concentration of pollutants were positively correlated with temperature and negatively with wind speed and relative humidity (He et al., 2017). Pollutant concentration is low when the temperature or wind speed is high due to high rate of dispersion (Banerjee et al., 2011). However, little influence of meteorology was observed on air quality during lockdown period (Navinya et al., 2020).

Very few studies have focused a complete scenario starting from individual pollutant level to AQI to further health risk or Excess Risk (ER %) due to COVID-19 driven lockdown (Sharma et al., 2020; Singh & Nanda et al., 2021c). Further spatial studies related to ER % over the currently taken region (part of Indo-Gangetic plain) is lacking except Singh and Nanda et al. 2021c in spite its urgent need. Sharma et al. (2020) reported 4 times reduction in total ER % due to COVID-19 lockdown over various parts of India however, the spatial distribution of AQI, and ER% were not attempted. Again the assessment during the lockdown in May 2021 is not reported yet in any of the earlier studies.

Thus, the current study is being done to analyse the variability in air pollutants, AQI and ER% during January 2020 to June 2021 and in three scenarios viz. pre-lockdown (1 January 2020 to 21 March 2020), during lockdown (22 March 2020 to 31 May 2020) and post-lockdown (1 June 2020 to 30 June 2020) using ground based data, statistics, and GIS technologies. Efforts are also been put to understand the effect of meteorology on the concentration of pollutants especially due to the lockdown. The key objectives of the study are to (a) understand the variations of the pollutants concentration from January 2020 to June 2021 over the study area (b) Assess the impact of COVID-19 driven lockdown on air pollutants (c) Assess the variations in AQI and ER% in response to COVID-19 driven lockdown.

Study Area

Study area lies in Northern part of the India between Latitude 29°43′ 42.091 and 32°34′ 27.131″N and Longitude 75°51′ 45.409–78°29′ 26.983″N and constitute part of Indo-Gangetic Plain (IGP) which is among the highly polluted regions in the world (Singh & Dahiya et al., 2021a). It includes Districts of Haryana, Punjab, Rajasthan, Uttar Pradesh (PU), Delhi and Union territory of Chandigarh (Fig. 1). The study area was selected based on the continuous data availability from ground-based stations. It was also considered that the stations are well distributed over the study area. A total of 47 ground stations for air pollutants measurement were taken in the study area, working under the maintenance of central pollution control board (CPCB). The total geographical area is 191032 ha and largely covered by agriculture and built-up/habitation. The elevation ranges from 140 to 673 m. The annual average rainfall is ~740 mm with arid to semi-arid type of climate.

It is affected by both type of air pollution sources, i.e. natural (dusty wind from Thar desert of arid Rajasthan) and anthropogenic (like biomass and crop stubble burning, Industrial activities, dense population and high transport/vehicular movements) depending on the season and time (Huang et al., 2018). Further the topography and weather conditions also influences the pollution level of the study area especially during monsoon (June–September) and winter (November–February). Taking the geographical location, population density, ground data availability, and persistent air pollution problem throughout the year (increased pollution in May and October-December every year as reported by Singh and Kundu et al. (2021b) and c among others) into the consideration, the current study area need to be examined exhaustively for a better air quality management.

The current COVID-19 condition has largely affected the anthropogenic activities in the region and thus the changes in the level of air pollutants, AQI, and ER% is considered to be influenced by this (Navinya et al., 2020; Sharma et al., 2020). The consistencies in natural pollution favouring conditions have also been reported by Bhawre (2020) for these regions. Study area includes 196 blocks distributed in 37 districts of six states and Union Territory

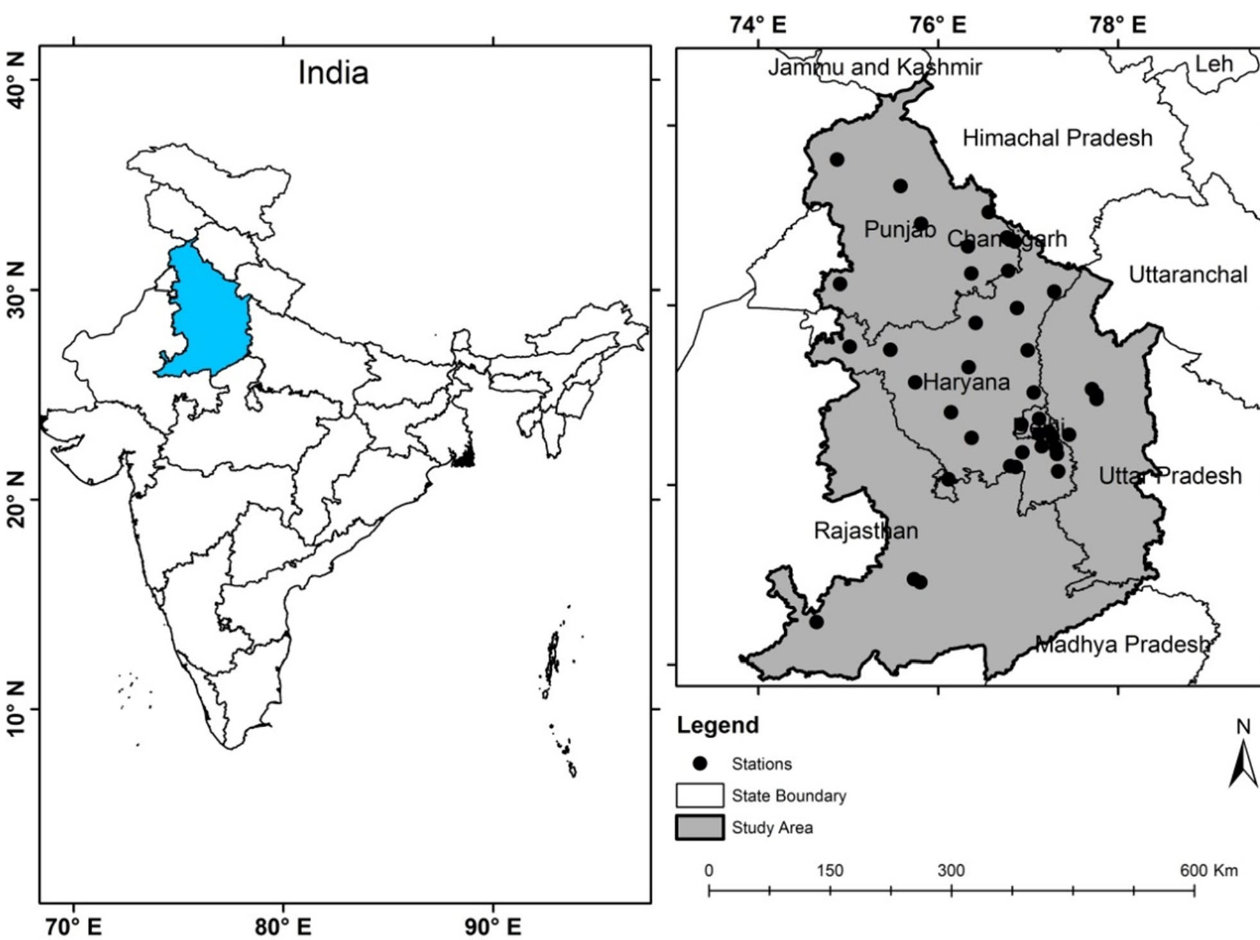

Fig. 1 Study Area Map

having 47 ground stations. A map showing these administrative units is given in Fig. S1 (in supplementary material) and list of the administrative units (name of the 196 blocks) are given in Table A1 (supplementary material).

Methodology

Daily and monthly variation of the air pollutants over the whole study area was presented in the form of time series graph and as mean ± standard deviation (SD), respectively. Influence of COVID-19 driven lockdown on air pollution, AQI, and related ER % was assessed taking three scenarios into account viz. pre-lockdown, during lockdown, and post-lockdown. Pollutant concentrations from ground stations were processed for AQI and ER % in GIS environment through Invers Distance Weighted (IWD) interpolation for assessing spatial variability in pre-defined scenarios. Flowchart of methodology is presented in Fig. 2.

Data Source

To assess the AQI and related ER% of selected study area on a monthly basis and in predefined scenarios namely pre-lockdown, during lockdown and post-lockdown, the ground data from CPCB stations (n = 47) were downloaded for a period of 1.5 years starting from 01 January 2020 to 30 June 2021 on daily temporal resolution from https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing/caaqm-comparison-data. Since the meteorological data for 2021 were limited data for 2019 (January to June) were also downloaded and used in the correlation analysis between pollutants and meteorological parameters. The correlation analysis was done to understand the influence of meteorology on the pollutants concentration with assumption that the correlation would be high for influential meteorological parameters.

Ground stations are distributed at the various parts of the different states and territory in northern India (Delhi, Chandigarh, Haryana, Punjab, Uttar Pradesh, and Rajasthan). Daily concentration of seven criteria pollutants ($PM_{2.5}$, PM_{10}, NO_2, NH_3, CO, O_3, and SO_2.) has been processed at individual station level. The CPCB facility provides 24-h average concentration of the $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, and 8-h average CO, O_3, respectively. Stations along with their geographical coordinates are listed in Table 1.

Statistics of Criteria Pollutants

The criteria pollutants were assessed including $PM_{2.5}$, PM_{10}, NO_2, NH_3, CO, O_3, and SO_2 on a daily basis from January 2020 to June 2021. Statistical analysis was done for the description of the concentration of all pollutants (for whole time period on a monthly basis as well as for three scenarios) which includes the mean, and SD. Mobility related data from apple navigation facility were also used to link pollutants variation amid COVID-19 (Fig. 3). Variation in pollutant concentration over Delhi (Fig. 4a–d), Haryana (Fig. 4e–h), and Punjab (Fig. 4i–l) during January 2020 to June 2021 and related controls are presented in Fig. 4a–l. These data were further analysed for the effect of COVID-19 driven lockdown on air pollutants.

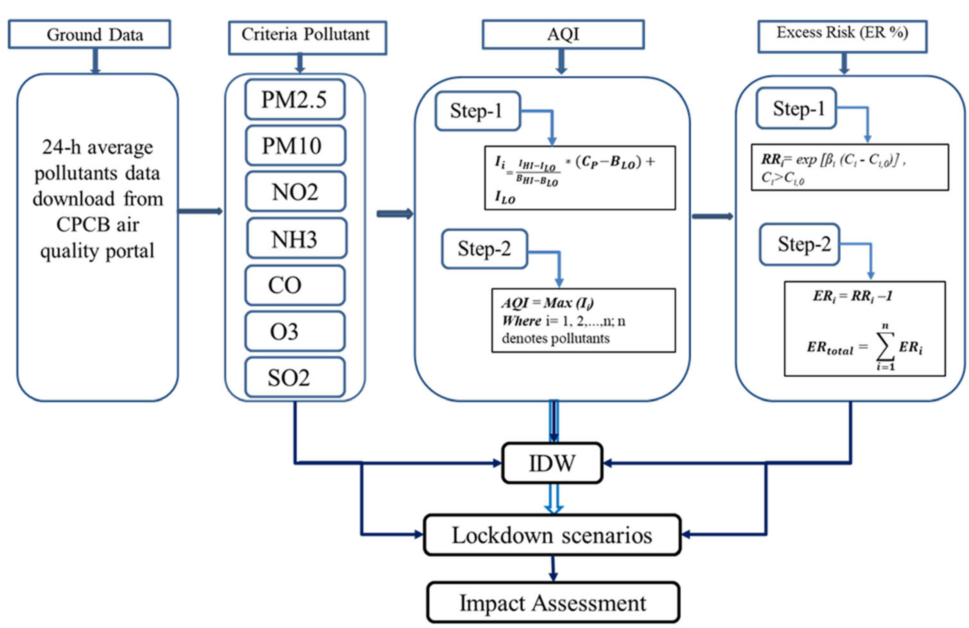

Fig. 2 Flowchart of method applied for the current study

Table 1 Ground monitoring stations of study area. Source Central Control Room for Air Quality Management

Sl.no	Station name	Latitude	Longitude
1	Patti Mehar, Ambala	76.77833	30.37959
2	Arya Nagar, Bahadurgarh,jhajjar	76.92540	28.67010
3	Nathu Colony, Ballabgarh,Faridabad	77.31970	28.34192
4	H.B. Colony, Bhiwani	76.14111	28.80622
5	Municipal Corporation Office, Dharuhera,Rewari	76.79970	28.20680
6	Sector- 16A, Faridabad	77.30991	28.40884
7	Huda Sector, Fatehabad	75.46793	29.50366
8	NISE Gwal Pahari, Gurugram—IMD	77.15000	28.42600
9	Urban Estate-II, Hisar	75.74494	29.14056
10	Police Lines, Jind	76.33762	29.30781
11	Rishi Nagar, Kaithal	76.41550	29.80060
12	Sector-12, Karnal	77.00270	29.69530
13	Sector-7, Kurukshetra	76.87588	29.96694
14	General Hospital, Mandikhera,Mewat	76.99380	27.90020
15	Sector-2 IMT, Manesar, Gurugram	76.93609	28.36070
16	Shastri Nagar, Narnaul,Mahendergarh	76.11312	28.06025
17	Shyam Nagar, Palwal	77.33207	28.14856
18	Sector-6, Panchkula	76.85318	30.70578
19	Sector-18, Panipat	76.99333	29.49797
20	MD University, Rohtak	76.37138	28.52123
21	F-Block, Sirsa	75.01580	29.53640
22	Murthal, Sonipat	77.06210	29.02720
23	Gobind Pura, Yamuna Nagar	77.28935	30.14806
24	RIICO Ind. Area III, Bhiwadi,Alwar	76.86230	28.19491
25	Hardev Nagar, Bathinda	74.90776	30.23301
26	Model Town, Patiala	76.36664	30.34939
27	RIMT University, Mandi Gobindgarh, Fatehgarh	76.33144	30.64996
28	Kalal Majra, Khanna,Ludhiana	76.20969	30.73606
29	Sector-25, Chandigarh	76.76288	30.75146
30	Punjab Agricultural University, Ludhiana	75.80860	30.90280
31	Civil Line, Jalandhar	75.57891	31.32191
32	Ratanpura, Rupnagar	76.56230	31.03255
33	Golden Temple, Amritsar	74.87651	31.62000
34	New Mandi, Muzaffarnagar	77.71940	29.47235
35	Pallavpuram Phase 2, Meerut	77.70972	29.06351
36	Ganga Nagar, Meerut	77.75904	28.99926
37	Jai Bhim Nagar, Meerut	77.76229	28.95359
38	Knowledge Park—V, Greater Noida,	77.45366	28.55705
39	Rohini, Delhi	77.11992	28.73253
40	Lodhi Road, Delhi	77.22731	28.59182
41	Sri Aurobindo Marg	77.19016	28.53135
42	Okhla Phase-2, Delhi	77.27126	28.53079
43	IGI Airport (T3), Delhi	77.11801	28.56278
44	Shastri Nagar, Jaipur	75.73094	26.95029
45	Police Commissionerate, Jaipur	75.79949	26.91641
46	Adarsh Nagar, Jaipur	75.83685	26.90291
47	Civil Lines, Ajmer	74.64659	26.47086

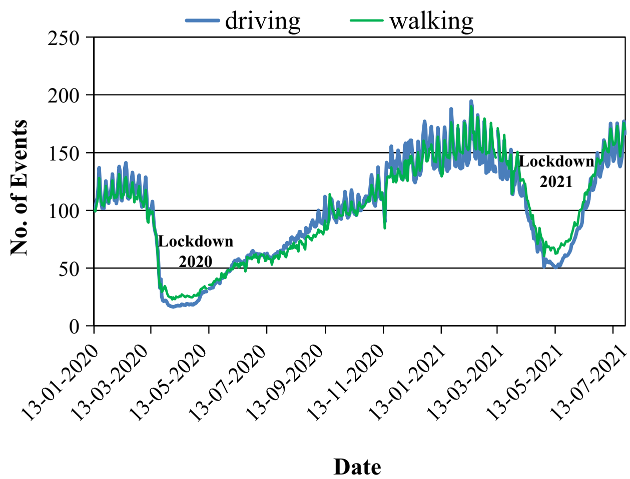

Fig. 3 Driving and walking trend in India during last 1.5 years (Jan 2020 to July 2021) of the study period (source: https://covid19.apple.com/mobility)

Air Quality Index (AQI)

AQI defines the transformation of the weighted value of the parameters of air pollutants into the single, unit less number (Singh & Nanda et al., 2021c). Out of all the criteria pollutants viz. $PM_{2.5}$, PM_{10}, NO_2, NH_3, CO, O_3, and SO_2 a minimum of three pollutants should be available and one should be PM_{10} or $PM_{2.5}$ as suggested by CPCB. AQI scale varies from 0 to 500 and divided into six categories viz. Good (0–50), Satisfactory (51–100), Moderate (101–200), Poor (201–300), Very poor (301–400) and Severe (401–500). Two steps are involved into the AQI calculation. In first step, Sub-Index is calculated for each air pollutant by using the following formula (Kanchan et al., 2016; Singh & Nanda et al., 2021c).

$$I_i = \frac{I_{HI} - I_{LO}}{B_{HI} - B_{LO}} * (C_P - B_{LO}) + I_{LO} \quad (1)$$

where I_i = Sub index I_{HI} = AQI value corresponding of the B_{HI} B_{HI} = Greater breakdown concentration I_{LO} = AQI value corresponding of the B_{LO} B_{LO} = Smaller breakdown concentration C_p = Concentration of pollutant.

In the second step, AQI is calculated from the maximum concentration of the sub-index of the all air pollutant, as shown in equation two.

$$AQI = \text{Max}\ (I_i) \quad (2)$$

where i = 1, 2,…,n; n denotes pollutants.

Concentration ranges for individual pollutants those limits the categories of AQI are listed in Table 2. These limits are called break points and identified by CPCB for AQI estimation. Further, the average values of AQI in three scenarios were analysed both statistically as well as in spatial domain for understanding the effect of COVID-19 driven lockdown. Inverse distance weighting (IDW) method of spatial interpolation is used for understanding variations of air pollutants in spatial domain following Kumar et al. (2016) and Singh and Nanda et al. 2021c. IDW works on the assumption that the things those are close to one another are similar than those are farther apart. It estimates the values of unknown locations from the average values of the available neighbour locations taking inverse of their distances into consideration. IDW is a deterministic spatial interpolation approach to estimate a missing value from given values as presented in Eq. 3 (http://www.gitta.info/ContiSpatVar/en/html/Interpolatio_learning Object2.xhtml).

$$v = \frac{\sum_{i=1}^{n} \frac{v_i}{d_i}}{\sum_{i=1}^{n} \frac{1}{d_i}} \quad (3)$$

where v = value to be estimated.v_i = known value.d_i……d_n = distances from the n data points to the point estimated n.

This technique has been found to be applicable for the interpolation of air pollutants (Kumar et al., 2016; Singh and Nanda et al., 2021c); however, there are some drawbacks like (a) It is not able to estimate above of the maximum and less than the minimum value (b) not good for peaks and mountains area. Since our study area is flat terrain this method may provide acceptable results. Maps of the concentration of the air pollutants are also prepared and presented in Fig. 5a–d and in Figs. S2–S4 (supplementary materials).

Health Risk Calculations

Health risk from the air pollutant is measured in term of exposure of the human being from the concentration of the each pollutant (Sharma et al., 2020). Pollutants concentration is changed with time and location so health risk of the area is also variable. For the health risk assessment, ER% was considered. The ER% was estimated based on Relative Risk (RR) of each pollutant. RR of the each pollutant are estimated by following Eq. 4 (Sharma et al., 2020; Singh & Nanda et al., 2021c).

$$RR_i = \exp\left[\beta_i\left(C_i - C_{i,0}\right)\right],\ C_i > C_{i,0} \quad (4)$$

where RR_i is the Relative risk of pollutant i, β_i is exposure response coefficient of additional health risk (Such as mortality) caused by per unit of pollutant i, when it exceeds a thresholds concentration. C_i is the concentration of the pollutant i and $C_{i,0}$ is the threshold concentration of pollutant (when threshold concentration of pollutant is less than the pollutant concentration then relative risk is greater than 0). β_i and threshold value taken for the present study are presented in Table 3. ERi% and total ER% of the

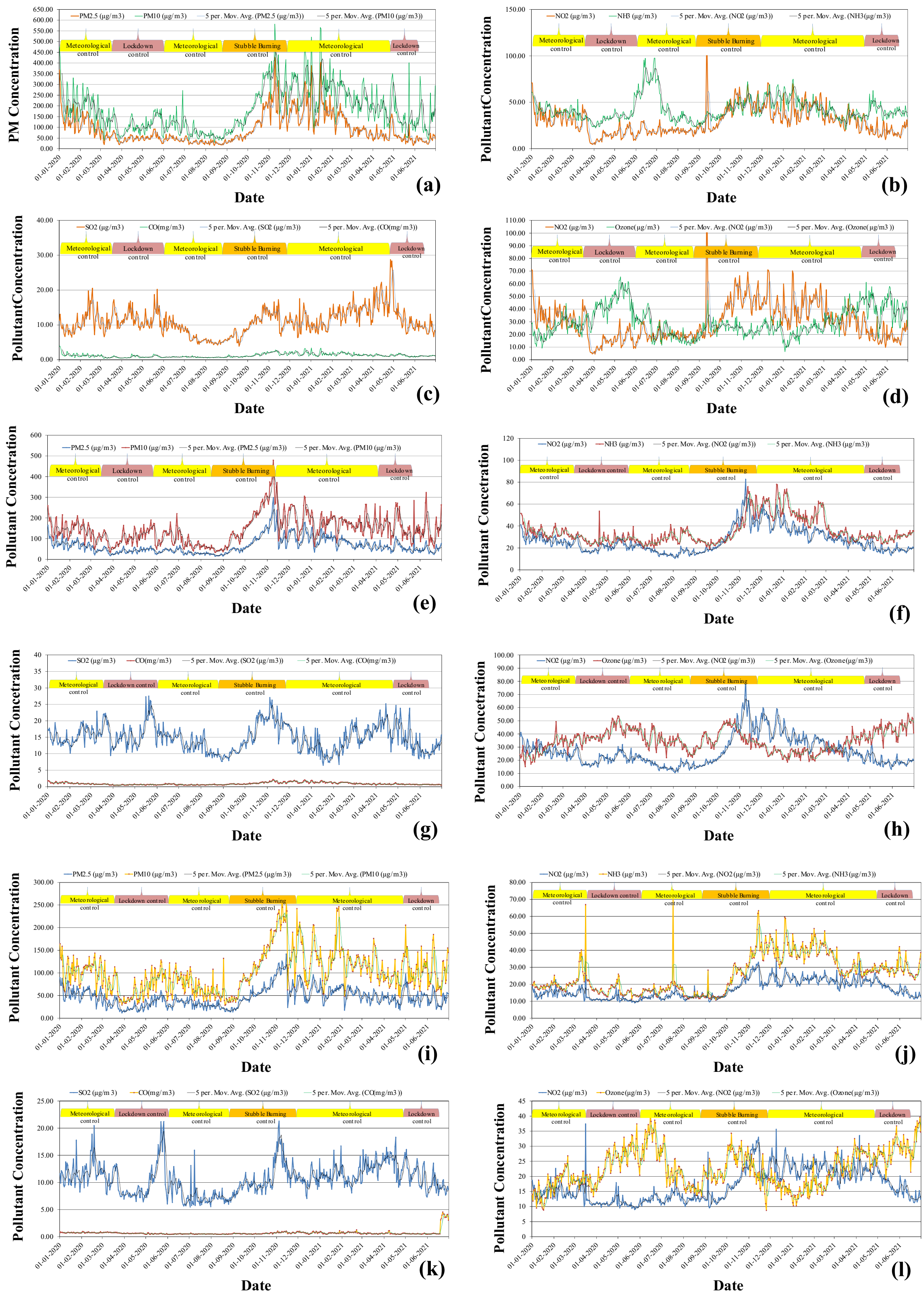

Fig. 4 Variation in pollutant concentration over Delhi (**a**–**d**), Haryana (**e**–**h**), and Punjab (**i**–**l**) during last 1.5 years (Jan 2020 to June 2021) and related controls

Table 2 Breakdown for AQI scale of all Air Pollutant. Source (CPCB, 2014)

AQI category	Concentration range							
	$PM_{2.5}$	PM_{10}	NO_2	NH_3	CO	O_3	SO_2	Pb
Good	0–30	0–50	0–40	0–200	0–1.0	0–50	0–40	0–0.5
Satisfactory	31–60	51–100	41–80	201–400	1.1–2.0	51–100	41–80	0.5–1.0
Moderate	61–90	101–250	81–180	401–800	2.1–10	101–168	81–380	1.1–1.2
Poor	91–120	251–350	181–280	801–1200	10–17	169–208	381–800	2.1–3.0
Very poor	121–250	351–430	281–400	1200–1800	17–34	209–748	801–1600	3.1–3.5
Severe	250 +	430 +	400 +	1800 +	34 +	748 +	1600 +	3.5 +

CO and O_3 are 8-h average concentration and other pollutants are 24-h average concentration and CO is measured in mg/m_3 and other pollutant measured in $\mu g/m^3$

pollutant is estimated by using Eqs. 5, 6 (Sharma et al., 2020; Singh & Nanda et al., 2021c).

$$ER_i = RR_i - 1 \tag{5}$$

$$ER_{total} = \sum_{i=1}^{n} ER_i \tag{6}$$

Results

Variations in Criteria Pollutants Over the Study Area

Pattern and statistical analysis was done by using the ground data from January 2020 to June 2021. Daily and monthly variations in the concentration of all pollutants are shown in Fig. 4a–l and in Table 4, respectively. Daily variation in the pollutant concentration over Delhi (Fig. 4a–d), Haryana (Fig. 4e–h) and Punjab (Fig. 4i–l) show specific pattern with high values during winter (December–February) and low values during summer (March–April) and rainy season (June–September). The peaks were observed during the Month of October and November (Fig. 4a–l) which is attributed to the stubble burning in both 2020 and 2021; however, the influence of Lockdown could be seen during April 2020 and May 2021 (Table 4). The reduction in pollutant level amid lockdown was less in 2021 as compared to 2020 (Table 4).

4.2. Impact of COVID-19 Driven Lockdown on the Concentration of Criteria Pollutants

Descriptive statistical analysis was done for three scenarios and results are presented in Table 5. Mean and SD of criteria pollutants viz. $PM_{2.5}$, PM_{10}, NO_2, NH_3, CO, O_3, and SO_2 were 71 ± 45 $\mu g/m^3$, 139 ± 72 $\mu g/m^3$, 28 ± 21 $\mu g/m^3$, 33 ± 24 $\mu g/m^3$, 1.00 ± 0.65 mg/m^3, 29 ± 20 $\mu g/m^3$ and 13.8 ± 11 $\mu g/m^3$ in pre-lockdown, 39 ± 20 $\mu g/m^3$, 96 ± 55 $\mu g/m^3$, 17 ± 13 $\mu g/m^3$, 25 ± 18 $\mu g/m^3$, 0.7 ± 0.5 mg/m^3, 39 ± 23 $\mu g/m^3$ and 13.7 ± 11.6 $\mu g/m^3$ were during lockdown and 40 ± 17 $\mu g/m^3$, 105 ± 57 $\mu g/m^3$, 18 ± 12 $\mu g/m^3$, 29 ± 22 $\mu g/m^3$, 0.7 ± 0.6 mg/m^3, 39 ± 22 $\mu g/m^3$ and 12.7 ± 8.9 $\mu g/m^3$ were in post-lockdown. The concentration of $PM_{2.5}$, PM_{10}, NO_2, NH_3, and CO decreased by 46%, 31%, 39%, 24% and 34% in lockdown scenario as compared to the pre-lockdown scenario. The concentration of PM_{10}, $PM_{2.5}$, NO_2, NH_3, and CO shows clear cut reduction due to lockdown as movements of both the vehicle and human was restricted during the lockdown condition (Fig. 3) and most of the anthropogenic activities were delimited.

SO_2 concentration was similar in pre-lockdown and during lockdown may be due to no restriction on the power plant operations during lockdown period. O_3 concentration was increased during lockdown may be due to presence of clear sky condition, sun light and ozone forming nuclei's, i.e. NO_x and VOC_s. Inter-correlation between pollutants showed that the $PM_{2.5}$ and PM_{10} are highly correlated with each other (r^2 = > 0.6) and in agreement with earlier study done by Wai et al. (2013). However, other pollutants were found to be less correlated. Individual pollutant concentrations showed high values during pre-lockdown, lowest values during lockdown and medium values during post-lockdown (Fig. 5a–d); however, the differences were less during and post-lockdown. The minor differences in the values may be due to lockdown in April and Meteorology during June (Table 4). Nevertheless, the concentration of pollutants remained high during January and February which get decreased during March and April. Reduction in pollutant level after lockdown on 24 march 2020 may also be seen in Fig. 4(a–l) except for O_3 following the earlier findings of Siddiqui et al. (2020), Sur et al. (2021), and Singh and Nanda et al. 2021c among others. In the last week of April and during May, the process of stubble burning get started which have compensated the reduced level of pollutants due to lockdown amid COVID-19 (Fig. S5 supplementary material). The decreasing pattern of the pollutants (especially $PM_{2.5}$ and

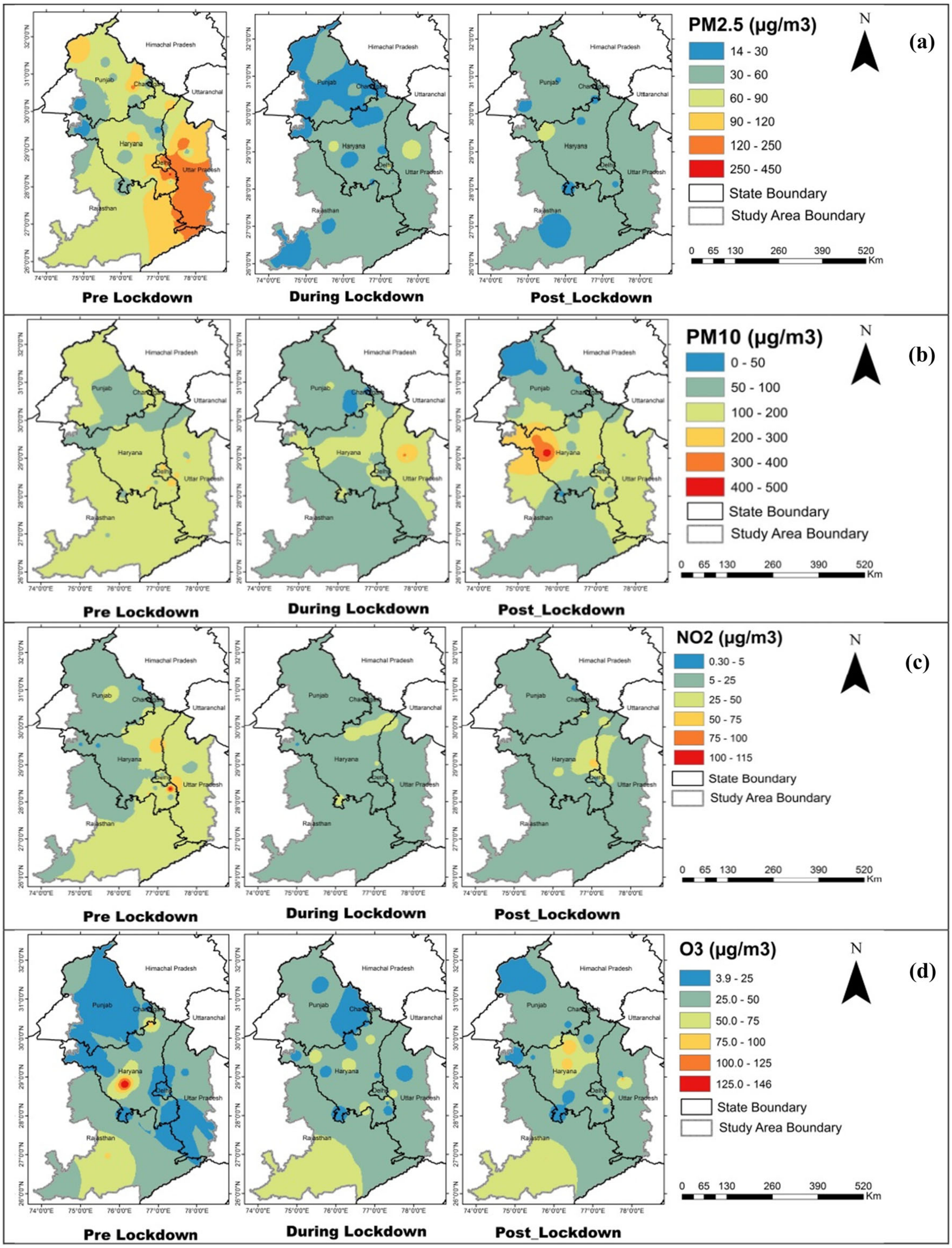

Fig. 5 Variations in Pollutant concentration in three scenarios viz. Pre, During and Post-Lockdown over the study area

PM_{10}) is also observed during June due to meteorological conditions (Fig. 4a–l). It was observed that the pollutants concentration was high during lockdown (May 2020) as compared to the post-lockdown (June 2020) probably due to (a) compensation of reduced air pollutants from stubble burning emission and (b) less pollutants concentration during June supported by meteorological conditions (Table 4). Further, there was less reduction in pollutant concentration during the lockdown in 2021 (Table 4).

Table 3 β_i and threshold value for each criteria pollutant required for Relative Risk (RR) estimation

S.no	$PM_{2.5}$ μg/m^3 (24-h)	PM_{10} μg/m^3 (24-h)	NO_2 μg/m^3 (24-h)	CO mg/m^3 (24-h)	SO_2 μg/m^3 (24-h)
β-Value	0.038%	0.032%	0.13%	3.7%	0.081%
Threshold value	35	50	40	2	50

Table 4 Statistics for concentration of Air Pollutants (in μg/m^3 for all parameters except CO which in mg/m^3) during Jan 2020 to June 2021

	$PM_{2.5}$ Mean ± SD	PM_{10} Mean ± SD	NO_2 Mean ± SD	NH_3 Mean ± SD	SO_2 Mean ± SD	CO Mean ± SD	O_3 Mean ± SD	AQI Mean ± SD	ER% Mean
2020									
Jan	85 ± 55.7	149.61 ± 84	30.3 ± 22.6	35.9 ± 25	12.7 ± 11.12	1.1 ± 0.8	23 ± 16.3	183 ± 62	3.36
Feb	72.5 ± 35.4	148 ± 65	28 ± 20	32 ± 22	14 ± 10	1 ± 0.5	31 ± 20	171 ± 65	3.10
March	40.8 ± 22	92.8 ± 51.5	21.8 ± 17.4	29.6 ± 23	14 ± 11	0.8 ± 0.5	33 ± 22	105 ± 52	1.89
April	34.8 ± 17.8	85 ± 48.5	16 ± 12.5	24.3 ± 18.2	12.3 ± 8.7	0.64 ± 0.50	36.8 ± 20.5	96 ± 49	2.24
May	44.7 ± 20.6	116.8 ± 57	19 ± 14.7	26.2 ± 17.3	15.1 ± 14.1	0.7 ± 0.4	43 ± 24.5	118 ± 57	2.48
June	39.7 ± 16.8	102.7 ± 56.6	18.2 ± 12	29.1 ± 22.3	12.41 ± 12.44	0.7 ± 0.5	38.6 ± 22	112 ± 57	1.94
July	31.7 ± 18.7	74 ± 46.8	16 ± 10	29 ± 22	10.7 ± 12.3	0.60 ± 0.35	31.3 ± 21.1	85 ± 47	1.32
August	23.1 ± 11.4	52.1 ± 34.4	15.2 ± 11.8	26.4 ± 23.2	9.1 ± 8	0.60 ± 0.45	24.4 ± 17.8	64 ± 34	0.80
Sept	41.5 ± 20.5	95.2 ± 47	18.8 ± 20.2	23.8 ± 17.7	10 ± 8	0.7 ± 0.5	29.8 ± 17.1	109 ± 48	1.82
Oct	96 ± 50.5	207.5 ± 90.4	34.3 ± 27.8	33.7 ± 24.3	15.4 ± 11.2	1.0 ± 0.6	40.5 ± 24.6	224 ± 91	5.23
Nov	137.8 ± 94.5	251 ± 137.3	47.3 ± 36.7	52 ± 41	18 ± 15.2	1.3 ± 0.8	32.5 ± 23	279 ± 138	6.58
Dec	116 ± 71	212 ± 108	44.7 ± 37	54.6 ± 41.3	13 ± 10	1.3 ± 0.8	26.4 ± 19	240 ± 110	5.37
2021									
Jan	105 ± 69	185 ± 111	42 ± 41	51 ± 38	11.16 ± 11.22	1.2 ± 0.8	23.5 ± 21.2	211 ± 94	5.82
Feb	87.2 ± 47.5	181 ± 90	37.3 ± 28	48.4 ± 44.5	13.5 ± 12	1.14 ± 0.6	24.4 ± 17.6	194 ± 90	6.02
March	66.1 ± 32.7	172.7 ± 86.4	33.6 ± 38.4	36.4 ± 27.7	17 ± 12.5	0.8 ± 0.5	31.7 ± 22.7	141 ± 85	2.67
April	62.5 ± 38	164 ± 87	30.5 ± 38	32 ± 26.4	19.3 ± 14.5	0.8 ± 0.5	38 ± 26.5	155 ± 87	4.31
May	50.3 ± 27.7	132.4 ± 69.2	19.34 ± 19	30 ± 21.7	14.25 ± 14.4	0.7 ± 0.5	40 ± 27	125 ± 70	3.58
June	46.7 ± 24.5	132.3 ± 82	19 ± 14	31 ± 23	11.5 ± 9	0.96 ± 2.8	41.2 ± 26	129 ± 77	3.77

4.3. Impact of COVID-19 Driven Lockdown on Air Quality Index (AQI)

Figure 6a–b clearly show less AQI during lockdown scenario and very high in the period of pre-lockdown. First time lockdown was declared on 24th march 2020 and extended up to the end of the May in different phases; however, we had also taken Janta curfew in our analysis which was on 22 March 2020. No activity was allowed during first lockdown while limited activities were allowed in the consecutive lockdown periods. Industrial operations, bus services, personal vehicles, and offices were closed and thus air was observed cleanest during lockdown period with decreased level of air pollutants. High mean and SD of AQI (154 ± 87.58) in pre-lock down scenario was observed. As compared to pre-lockdown, the AQI values (94 ± 46.5) were significantly less during lockdown; however, in post-lockdown scenario, a little difference was observed in average AQI with respect to lockdown period (Table 6) probably due to the meteorological controls. A decrease of 39% in AQI was observed during lockdown from pre-lockdown scenario. However, the difference was less when compared with post-lockdown scenario.

4.4. Excess Risk (ER%) from Air Pollutants

Total ER% is estimated as sum of the ER% of the five criteria pollutants including $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO. During the analysis the minimum, maximum and mean of total ER% was 10.2, 32.8, and 16.9 in pre-lockdown, 0.69, 16.2, and 6.7 during lockdown, and 0.67, 9.7, and 3.3 in post-lockdown, respectively, for whole study area (Figs. S6 and S7, supplementary material). During lockdown total ER% was less as compared to pre-lockdown but higher from post-lockdown. Again it is to be mentioned that the post-lockdown period is mainly controlled by meteorological conditions and the concentration of pollutants remain low throughout the rainy season

Table 5 Statistical values of parameters (in µg/m^3 except for CO which is measured in mg/m^3) in three scenario (Pre, during and Post-Lockdown)

Lockdown scenario	Parameters	Total observations	Mean	Standard deviation	Minimum	Median	Maximum
Pre	$PM_{2.5}$	3688	71.12	44.95	3.42	59.53	475.22
	PM_{10}	3474	139.29	72.77	16.19	121.72	591.96
	NO_2	3571	28.17	20.88	1.16	23.64	247.49
	NH_3	3042	33.31	23.97	0.57	28.20	310.40
	CO	3633	1.00	0.65	0.01	0.82	5.23
	O_3	3548	28.73	20.08	1.18	22.72	148.86
	SO_2	3404	13.75	10.85	0.72	10.87	173.76
During	$PM_{2.5}$	3242	38.67	20.14	3.93	34.64	156.26
	PM_{10}	2979	96.06	54.86	10.68	82.58	348.35
	NO_2	3027	17.29	13.49	0.28	14.46	151.16
	NH_3	2545	25.45	17.88	2.49	22.38	288.12
	CO	3167	0.66	0.46	0.01	0.53	5.38
	O_3	3071	38.89	22.69	1.96	33.73	134.81
	SO_2	2944	13.69	11.56	1.24	10.72	161.16
Post	$PM_{2.5}$	1364	40.44	16.78	5.32	38.35	124.80
	PM_{10}	1242	104.94	56.58	20.74	90.66	456.20
	NO_2	1316	18.47	12.15	0.05	16.42	99.79
	NH_3	1107	29.05	22.31	0.22	25.29	171.48
	CO	1319	0.69	0.50	0.01	0.60	5.25
	O_3	1310	38.55	22.09	1.20	33.69	125.83
	SO_2	1243	12.7	8.9	0.52	8.93	85.36

(Fig. 4a–c) and thus low ER% was obtained (Fig. 7a, b). This study shows a very low ER% during and post-lockdown (Fig. 7a) periods.

Statistical analysis of ER% shows the significant decrease ($p = 0.00$) during lockdown and post-lockdown when compared with pre-lockdown. ER% was high during lockdown as compared to post-lockdown because of the higher concentration of $PM_{2.5}$, SO_2, and NO_2 in the month of May where the reduced pollution level were compensated by stubble burning incidences (Figure S5 supplementary material). It was observed that the ER% is highly affected by NO_2 and thus the change in the centration of NO_2 (Figure S8, and Table A2, supplementary material) leads to the high ER% in the last week of May. At the initial stage of lockdown, all activities including industrial, services, and vehicular movement were prohibited (Fig. 3 for vehicle movement obtained from TomTom GO Navigation Maps services of Apple) which leads to the reduction in air pollutants concentration and thus ER%. But at the end of April and till May, 2020, the lockdown was relaxed, so the industrial and vehicular emissions were started increasing which was further supported by stubble burning in May 2020 (Fig. S5, supplementary material). However, the overall ER% (mean) was high in pre-lockdown when compared with both during and post-lockdown scenario (Fig. 7a, b).

Severe ER% during pre-lockdown period was observed. The risk was high in some blocks of Haryana (Faridabad, Hathin, Palwal, Panipat, Ganaur, Sonipat, Hisar), and Delhi. Here, it is to be noted that the ER% obtained through interpolation for the marginal blocks (i.e. blocks at the edge of study area boundary) may be erroneous due to statistical assumptions taken in interpolation and this is one of the limitation for the current study. However, the blocks identified inside the study area especially for Haryana, Punjab, and Delhi may be taken as the priority pollution management sites. Consistently high ER% was observed in nearby regions of Delhi, NCR due to high vehicular pollution, industrial operations and poor wind circulation pattern (Fig. 7a, b). Main reason of high ER% in the districts of Haryana including Panipat, Gurugram, Faridabad, and Hisar during pre-lockdown is industrial emissions (Singh & Nanda et al., 2021c). Faridabad is one of the largest industrial cities in Haryana and thus showed high AQI values and high ER%. Panipat also have many large and small industries such as thermal power plant, national fertilizer limited, oil refinery and other textile industries. Jindal Steel and power limited may be the main reason of

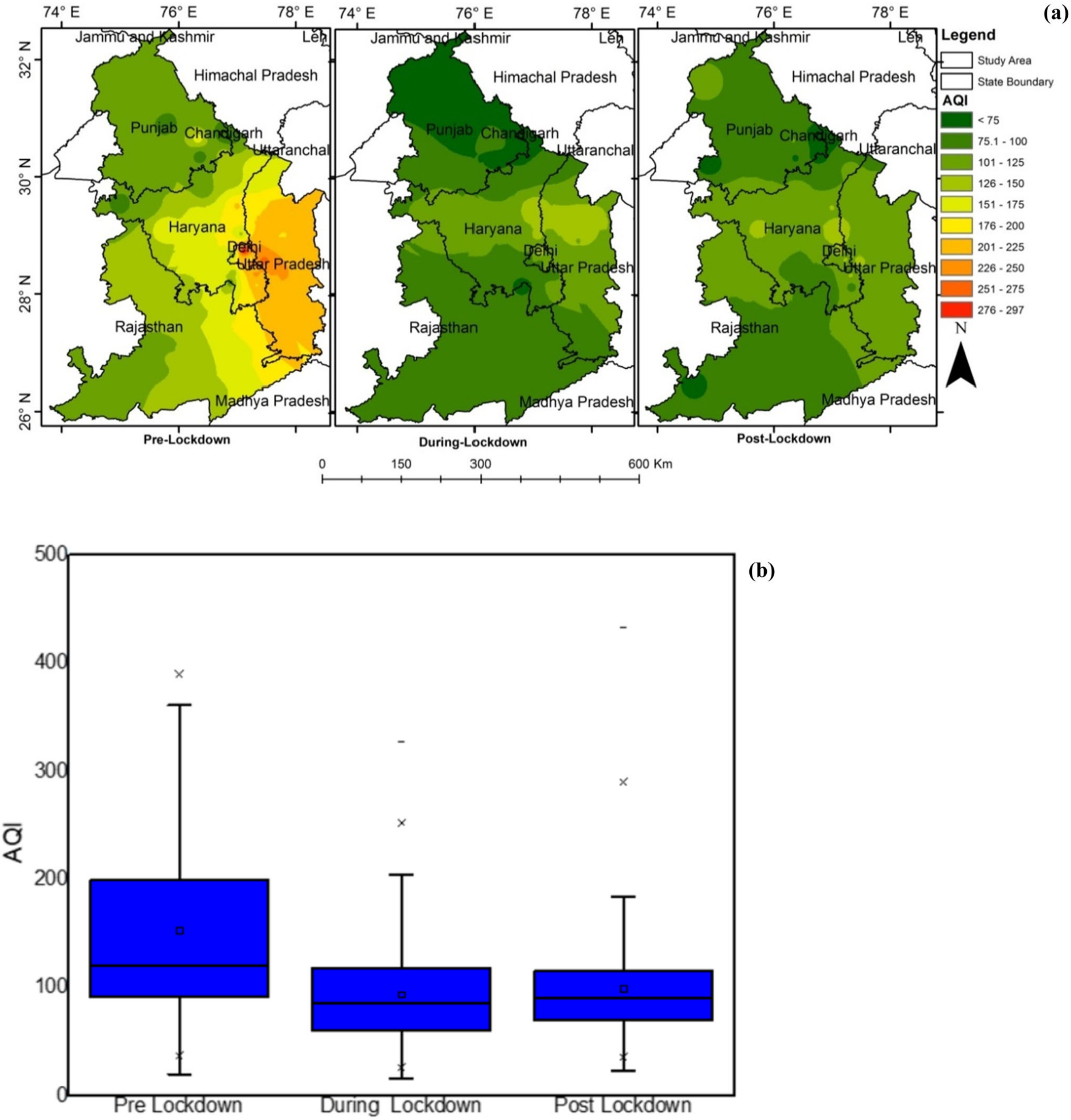

Fig. 6 Variation in Air quality index (AQI) in three scenarios- spatial **a** and statistical **b**

Table 6 Statistical analysis of air quality index (AQI) in different scenarios of lockdown

AQI	N total	Mean	SD	Minimum	Median	Maximum
Pre-lockdown	3731	154	87.58	20.4	121.03	602.45
During lockdown	3254	94	46.49	16.98	86.085	327.89
Post-lockdown	1415	100	47.07	24	91.13	432.75

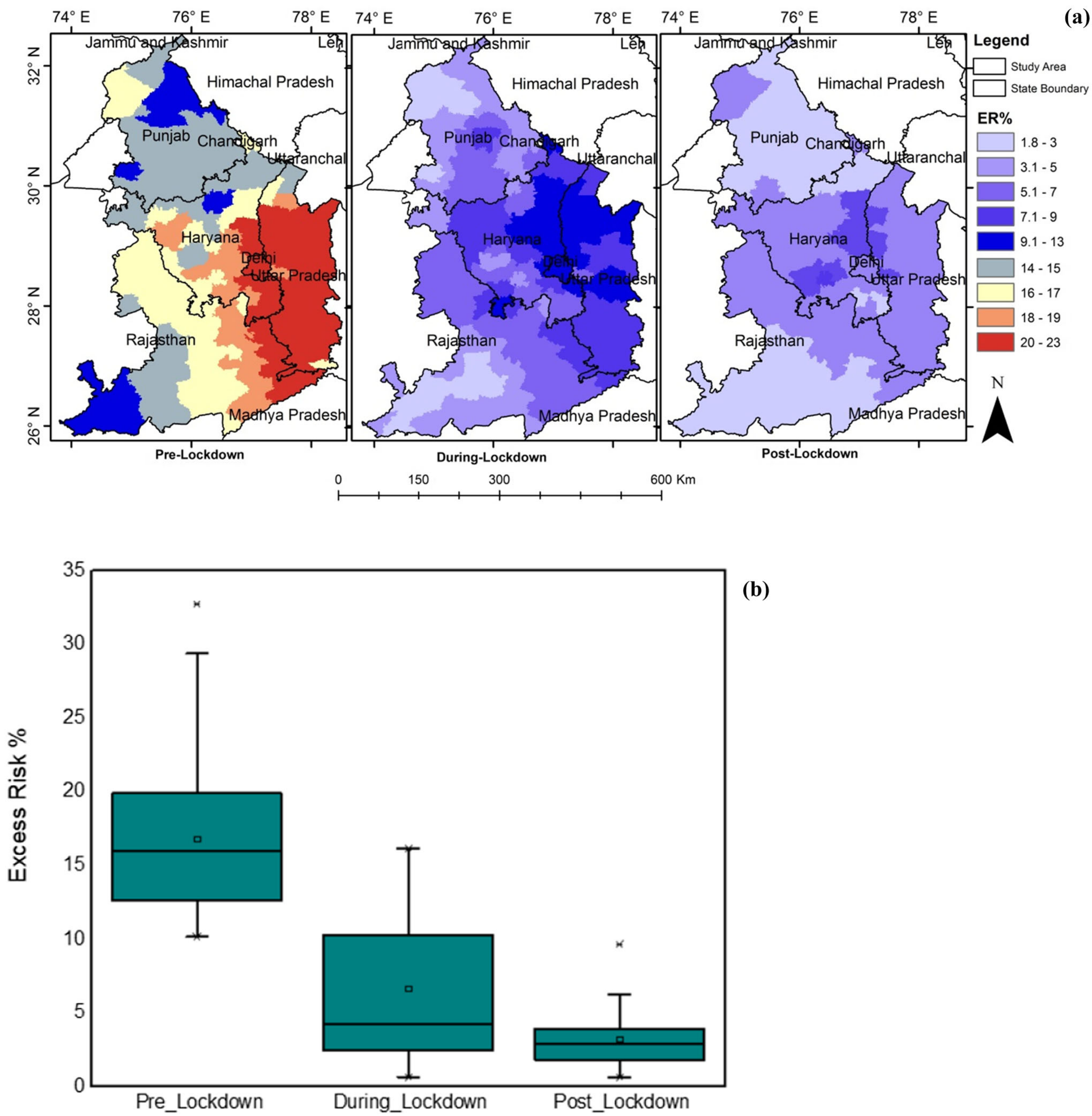

Fig. 7 ER% variation in three scenarios-spatial (**a**), statistical (**b**)

the air pollution in Hisar district during winter (Singh & Nanda et al., 2021c).

Effect of Metrological Parameters on Air Pollutants

In general the meteorological control on the pollutants concentration is seen during January–March 2020, November–December 2020, and January–April 2021 (Fig. 4a–l). It was also found that the metrological parameters have small change in the year 2020 when compared with 2019 and 2021 (Table A3, and Fig. S9–S12, supplementary material) but a huge change was observed in the concentration of pollutants especially during April–May 2020 (Singh & Nanda et al., 2021c). Data for 2019 were used for the comparison due to its continuous availability. The changes in meteorological parameters for 2019 and 2020 were also found to be minimum (Figure S9 for temperature, S10 for RH, S11 for WS, and S12 for WD). Inter-correlation among various pollutants and metrological parameters was analysed for the year 2019 and 2020 and found significant correlation among them, but correlation (r^2) were weak and lies below 0.36 in all the combinations (Tables 7, 8, respectively, for 2019 and 2020). With this weak correlation, our assumption that, the highly influential meteorological parameters will show high r^2 values and vice-versa, get accepted. This also showed that the meteorological parameters have less influence (i.e. weak r^2) on the change in the pollutants concentration during lockdown following Navinya et al. (2020) however, have potential to worsen the situation especially during winters. $PM_{2.5}$ is significantly correlated with relative humidity in the year 2020 with $r = 0.21$ whereas for the year 2019 the correlation was very less. However, from the analysis it was observed that the RH for the year 2020 (during lockdown period) is little higher as compared to the RH of the year 2019 (average difference 9.51%, Table A3, supplementary material) but the $PM_{2.5}$ get reduced significantly (average difference −15.79). This analysis clearly shows that there is less effect of meteorological parameters on the concentration of air pollutants (Tables 7 and 8) and thus the reduced anthropogenic activities may be responsible for the decrease in AQI in the year 2020 (Navinya et al., 2020). However, the influence of stubble burning during the last week of April and in the month of May cannot be denied seeing the pattern obtained in pollutant concentration (Fig. 4a–l) and fire events (Figures S5). It was also observed that the vehicle movement was very less during lockdown in 2020 and 2021 (Fig. 3) which also confirms the reduction in pollutant concentration, AQI values and ER% in response to the reduced anthropogenic activities. However, the lockdown during May 2021 have not showed an effective reduction in the pollution level (Table 4) probably due to the relaxed measures of lockdown and compensation from stubble burning.

Other air pollutants have significant relation with metrological parameters such as relative humidity (RH), temperature, wind speed (WS) and wind direction (WD). When WS is high, pollutants get dispersed in the atmosphere and air quality gets improved; however, in our study area, the WS remains low (ranges between 1.70 and 2.9 m/s) during whole time period (January to June) taken to study the effect of lockdown. There were no major changes in the temperature (23.87 and 22.27 degree in 2019 and 2020, respectively) of the year 2019 and 2020 as presented in Fig. S9 and Table A3 (supplementary material). RH was little high in the year 2020 as shown in Figure S10 (Table A3 Supplementary material) and thus AQI was less. This shows the reciprocal relationship between AQI and RH following earlier study by Jayamurugan et al. (2013) who reported that the RH is highly correlated with PM which is considared as one of the important factor in deciding AQI of an area. Average WS was 1.8 m/s in the year 2019 and 2.27 m/s in the year 2020 and 2.00 m/s in 2021 (supplementary material Fig. S11 and Table A3). The pattern of the WD was also found to be similar (SW direction) for the year 2019, 2020 and 2021 (supplementary material Fig. S12 and Table A3) following the findings of Sharma et al. (2020). Temperature, WS, and WD is almost same in all the three years but the RH is little high in 2020. This analysis clearly shows that the metrological conditions have less effect on the concentration of air pollutants or AQI over the region during lockdown period following earlier finding by Bhawre (2020) and Navinya et al. (2020). However, during rainy season and in winter season, the pollutant concetration is controled majorly by meteorology of the study area (Fig. 4a–l).

Discussion

This study explains the condition of the air quality in different states of northern India viz. Delhi, Punjab, Haryana, part of Eastern Uttar Pradesh, and part of Northern Rajasthan mainly during January 2020 to June 2021. Assessment of effects of lockdown on the pollutant concentration, AQI, and ER% is the major focus of discussion, and done in three scenarios during 2020 including pre-lockdown, lockdown, and post-lockdown. $PM_{2.5}$, PM_{10}, NO_2, NH_3, and CO concentration was significantly decreased during lockdown when compare with pre-lockdown. $PM_{2.5}$, PM_{10}, NO_2, NH_3, and CO decreased by 46%, 31%, 39%, 24%, and 34% during lockdown scenario as compared to the pre-lockdown scenario. But SO_2 concentration remained similar during lockdown and pre-lockdown may be due to the operational thermal power plants and other sources. O_3 concentration was increased during lockdown due to the reduced vehicular movement (Figs. 3) and clear sky conditions.

The concentration of these parameters shows significant decrease because of lockdown similar to the earlier reported studies of Srivastava et al., (2020); Siddiqui et al., (2020); Sur et al., (2021) and Singh and Nanda et al. 2021c among others. However after that the concentration decreased significantly during the rainy season (except for O_3) due to the settling of pollutants through rain and other meteorological controls (Fig. 4a–l). Overall scenario showed highest concentration in the pre-lockdown (including winters viz. January and February), low during lockdown (especially first lockdown during from 24 March to 14 April) and medium in post-lockdown (Tables 5 and 6). Little increase in the level of pollutants in May month is again due to crop stubble burning (Fig. S5) and allowed anthropogenic activities in relaxed lockdown.

Table 7 Correlation between the pollutants, metrological parameters, AQI and Excess Risk in 2019

	$PM_{2.5}$	PM_{10}	NO_2	NH_3	CO	Ozone	SO_2	WS	WD	RH	Temp	AQI	ER%
$PM_{2.5}$	1	0.732**	0.279**	0.218**	0.399**	−0.060**	0.132**	−0.016	−0.150**	−0.015	0.052**	0.895**	0.220**
PM_{10}		1	0.209**	0.196**	0.275**	0.048**	0.129**	−0.004	−0.140**	−0.192**	0.275**	0.868**	0.210**
NO_2			1	0.146**	0.324**	−0.156**	0.088**	−0.067**	−0.064**	−0.003	−0.128**	0.271**	0.117**
NH_3				1	0.240**	−0.097**	−0.064**	−0.052**	0.007	0.133**	−0.097**	0.234**	0.050**
CO					1	−0.140**	0.086**	−0.122**	−0.135**	0.061**	−0.082**	0.382**	0.491**
Ozone						1	0.270**	0.116**	−0.209**	−0.358**	0.356**	−0.023	−0.005
SO_2							1	−0.058**	−0.070**	−0.101**	0.071**	0.146**	0.061**
WS								1	0.002	−0.015	−0.002	−0.025	−0.012
WD									1	0.002	−0.034*	−0.167**	−0.063**
RH										1	−0.676**	−0.079**	0.001
Temp											1	0.110**	0.011
AQI												1	0.236**
ER%													1

** = significant at $p = 0.001$, * = significant at $p = 0.005$

Table 8 Correlation between the pollutants, metrological parameters, AQI and Excess Risk in 2020

	$PM_{2.5}$	PM_{10}	NO_2	NH_3	CO	O_3	SO_2	WS	WD	RH	Temp	AQI	ER%
$PM_{2.5}$	1	0.837**	0.382**	0.265**	0.453**	−0.161**	0.03	−0.071**	−0.025	−0.210**	−0.069**	0.935**	0.550**
PM_{10}		1	0.483**	0.225**	0.460**	−0.133**	0.124**	0.019	−0.034*	0.072**	−0.039*	0.907**	0.580**
NO_2			1	0.322**	0.223**	−0.027	0.158**	0.075**	−0.031	0.106**	−0.057**	0.436**	0.373**
NH_3				1	0.136**	−0.182**	−0.048**	−0.119**	−0.048**	0.104**	−0.034*	0.267**	0.166**
CO					1	−0.166**	0.062**	0.084**	−0.064**	0.095**	−0.031	0.469**	0.954**
O_3						1	0.155**	−0.098**	−0.046**	−0.346**	0.042*	−0.165**	0.150**
SO_2							1	0.053**	0.022	−0.01	−0.017	0.089**	0.143**
WS								1	0.039*	−0.056**	−0.018	−0.014	0.066**
WD									1	−0.040*	0.001	−0.024	−0.057**
RH										1	−0.070**	0.179**	0.121**
Temp											1	−0.053**	−0.038*
AQI												1	0.569**
ER%													1

*Significant at $p = 0.005$, **significant at $p = 0.001$

Findings of current study regarding the pollutants level were also compared with reference concentrations reported by other researchers for earlier years in the same region. The concentrations of pollutants (with respect to earlier concentration in bracket) like $PM_{2.5}$, PM_{10}, NO_2, CO, O_3, and SO_2 for 2020 were 53.39 μg/m^3 (77 μg/m^3 in 2019), 117.01 μg/m^3 (200 μg/m^3 in 2017–2019), 22.39 μg/m^3 (31.5 μg/m^3 in 2017), 0.82 mg/m^3 (1.1 mg/m^3 in 2019), 34.28 μg/m^3 (44 μg/m^3 in 2019), 13.53 μg/m^3 (15 μg/m^3 in 2019) (Sharma et al., 2020; Singh & Nanda et al., 2021c). These figures clearly show the significant reduction in pollutants concentration in 2020 as compared to previous years because of lockdown. However, 2021 showed less effect of lockdown on the concentration of air pollutants (Table 4).

Average AQI during the lockdown period was 94 while in pre-lockdown and post-lockdown AQI was 154 and 100, respectively (Table 6). This reduction in AQI again confirmed the effect of lockdown on air quality improvement amid COVID-19. ER % from the pollutants $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO were also calculated and mean and SD of total ER% were 16.9 ± 5.1, 6.7 ± 4.9, and 3.3 ± 2.0 during pre-lockdown, lockdown and post-lockdown, respectively (Fig. 7a, b). Less ER% post-lockdown is due to the variable magnitude of pollutant specific risk and their settling due to meteorological controls in the rainy season. This shows that the ER % due to air pollution was lowered in lockdown scenario of 2020 amid COVID-19. Delhi was found to be highly polluted and thus very high ER % was obtained.

Meteorological parameters were found to be less correlated with the pollutants in 2019 and 2020 and thus it may be said that there is very less influence of meteorology on the pollutants distribution over the study area during 2020 lockdown following the earlier findings of Navinya et al. (2020). Decrease in the mobility during the lockdown in 2021 was also seen; however, improvement in the pollution level was little less as compared to the improvement seen during 2020 lockdown.

Conclusion

Variation in the air pollutants ($PM_{2.5}$, PM_{10}, NO_2, CO, O_3, and SO_2) and the effect of lockdown on criteria air pollutants, AQI and Excess Risk (ER %) were examined in the Northern part of India taking ground-based data ($n = 47$) from January 2020 to June 2021 and GIS techniques. Meteorological data for 2019 were also used for the comparison due to the continuous availability. $PM_{2.5}$, PM_{10}, NO_2, CO, O_3, and SO_2 concentration were less in 2020 as compared to the concentration of these pollutants in the year 2019 and 2021. Daily pattern showed this phenomenon over the Delhi, Haryana, and Punjab where the highest pollution level was observed during October and November (stubble burning control), medium during winter months (December- February) and lowest during summer and monsoon. In pre-lockdown period $PM_{2.5}$ concentration was greater (71 μg/m^3) than CPCB standards (40 μg/m^3) but during lockdown period the concentration was less (38.7 μg/m^3) and falls in good air quality category. $PM_{2.5}$, PM_{10}, NO_2, NH_3, and CO decreased by 46%, 31%, 39%, 24% and 34% in lockdown scenario as compared to the pre-lockdown scenario. SO_2 concentration was not declined because of no restriction on coal-based thermal power plants and crop residue burning in this part of north India, considered as major source of SO_2. Ozone (O_3) concentration was increased in lockdown period because of clear sky conditions in response to the reduction in pollutants concentration which resulted in to higher sunlight passing through atmosphere that resulted in to high rate of photo-reactions and thus high O_3 formation. Decreasing trends of concentrations of pollutants just after lockdown in 2020 clearly show the effect of lockdown on air quality. However, lockdown during May 2021 was not effective much. AQI was in good to satisfactory category during lockdown.

The ER% get reduced significantly in the year 2020 which may have possibly reduce the deaths due to air pollution and increased the life expectancy of inhabitants. However, assessing the exact increase in life expectancy is the subject of future research. Anthropogenic activities are the main causes of increasing the air pollutants in this region mainly in the months of May and October–November. The blocks (other than the blocks situated at the boundary) identified under high ER % may be considered for air quality improvement and management sites. Meteorology has very less influence on pollutants concentration over the study area during the lockdown period. However, during monsoon and winter, the meteorology plays important role as seen in the daily data pattern of pollutants during the study period.

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Data Availability and Materials Data will be provided by the corresponding author on request.

Declarations

Conflict of interest No conflict of interest.

References

Banarjee, T., Singh, S. B., & Srivastava, R. K. (2011). Development and performance evaluation of statistical models correlating air pollution and metrological variables at Pantangar India. *Atmospheric Research, 99*, 505–517. https://doi.org/10.1016/j.atmosres.2010.12.003.

Bao, R., & Zhang, A. (2020). Does lockdown reduce air pollution? Evidence from 44 cities in northern China. *Science of the Total Environment, 731*, 139052.

Bhawre P. (2020). Study of air quality index over indian region during lockdown research article study of air quality index over indian region during lockdown period COVID19. *International Journal of Current Research* https://doi.org/10.24941/ijcr.38710.06.2020

Dantas, G., Siciliano, B., França, B. B., da Silva, C. M., & Arbilla, G. (2020). The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro Brazil. *Science of the Total Environment, 729*, 139085. https://doi.org/10.1016/j.scitotenv.2020.139085

Dhaka, S. K., Kumar, V., Panwar, V., Dimri, A. P., Singh, N., Patra, P. K., & Kajino, M. (2020). PM 2.5 diminution and haze events over Delhi during the COVID-19 lockdown period: An interplay between the baseline pollution and meteorology. *Scientific reports, 10*(1), 1–8.

Filonchyk, M., Hurynovich, V., Yan, H., Gusev, A., & Shpilevskaya, N. (2020). Impact Assessment of COVID-19 on Variations of SO2, NO2, CO and AOD over East China. *Aerosol and Air Quality Research, 20*(7), 1530–1540.

He, J., Gong, S., Yu, Y., Yu, L., Wu, L., Mao, H., & Li, R. (2017). Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environmental Pollution, 223*, 484–496. https://doi.org/10.1016/j.envpol.2017.01.050

Huang, Y., Yan, Q., & Zhang, C. (2018). Spatial–temporal distribution characteristics of in China in 2016. *Journal of Geovisualization and Spatial Analysis, 2*(2), 12.

Ilten, N., & Selici, A. T. (2008). Investigating the impacts of some meteorological parameters on air pollution in Balikesir Turkey. *Environmental Monitoring and Assessment, 140*(1–3), 267–277. https://doi.org/10.1007/s10661-007-9865-1

Jayamurugan, R., Kumaravel, B., Palanivelraja, S., & Chockalingam, M. P. (2013). Influence of temperature, relative humidity and seasonal variability on ambient air quality in a coastal urban area. *International Journal of Atmospheric Sciences*. https://doi.org/10.1155/2013/264046

Kanchan, K., Gorai, A. K., & Goyal, P. (2016). A review on air quality indexing system. *Asian Journal of Atmospheric Environment, 9*(2), 101–113. https://doi.org/10.5572/ajae.2015.9.2.101

Kant, Y., Mitra, D., & Chauhan, P. (2020). Space-based observations on the impact of COVID-19-induced lockdown on aerosols over India. *Current Science, 119*(3), 539–544.

Kumar, A., Gupta, I., Brandt, J., Kumar, R., Dikshit, A. K., & Patil, R. S. (2016). Air quality mapping using GIS and economic evaluation of health impact for Mumbai city, India. *Journal of the Air and Waste Management Association, 66*(5), 470–481. https://doi.org/10.1080/10962247.2016.1143887

Lal, P., Kumar, A., Kumar, S., Kumari, S., Saikia, P., Dayanandan, A., Adhikari, D., & Khan, M. L. (2020). The dark cloud with a silver lining: Assessing the impact of the SARS COVID-19 pandemic on the global environment. *Science of the Total Environment, 732*, 139297. https://doi.org/10.1016/j.scitotenv.2020.139297

Mahato, S., Pal, S., & Ghosh, K. G. (2020). Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi India. *Science of the Total Environment, 730*, 139086.

Muhammad, S., Long, X., & Salman, M. (2020). COVID-19 pandemic and environmental pollution: A blessing in disguise? *Science of the Total Environment, 728*, 138820.

Nakada, L. Y. K., & Urban, R. C. (2020). COVID-19 pandemic: impacts on the air quality during the partial lockdown in São Paulo state Brazil. *Science of the Total Environment, 730*, 139087.

Navinya, C., Patidar, G., & Phuleria, H. C. (2020). Examining effects of the COVID-19 national lockdown on ambient air quality across urban India. *Aerosol and Air Quality Research, 20*(8), 1759–1771. https://doi.org/10.4209/aaqr.2020.05.0256

Otmani, A., Benchrif, A., Tahri, M., Bounakhla, M., El Bouch, M., & Krombi, M. H. (2020). Impact of Covid-19 lockdown on PM10, SO2 and NO2 concentrations in Salé City (Morocco). *Science of the Total Environment, 735*, 139541.

Pathakoti, M., Muppalla, A., Hazra, S., Dangeti, M., Shekhar, R., Jella, S., Mullapudi, S. S., Andugulapati, P., & Vijayasundaram, U. (2020). An assessment of the impact of a nation-wide lockdown on air pollution—A remote sensing perspective over India. Atmospheric Chemistry and Physics. https://doi.org/10.5194/acp-2020-621

Ranjan, A. K., Patra, A. K., & Gorai, A. K. (2020). Effect of lockdown due to SARS COVID-19 on aerosol optical depth (AOD) over urban and mining regions in India. *Science of the Total Environment, 745*, 141024.

Sharma A. (2020). Invest India, 2020. What constitutes essential services during lockdown? https://www.investindia.gov.in/team-india-blogs/what-constitutes-essential-services-during-lockdown (accessed on 7 August 2020).

Sharma, S., Zhang, M., Gao, J., Zhang, H., & Kota, S. H. (2020). Effect of restricted emissions during COVID-19 on air quality in India. *Science of the Total Environment, 728*, 138878. https://doi.org/10.1016/j.scitotenv.2020.138878

Shehzad, K., Sarfraz, M., & Shah, S. G. M. (2020). The impact of COVID-19 as a necessary evil on air pollution in India during the lockdown. *Environmental Pollution, 266*, 115080. https://doi.org/10.1016/j.envpol.2020.115080

Siddiqui, A., Halder, S., Chauhan, P., & Kumar, P. (2020). COVID-19 Pandemic and city-level nitrogen dioxide (NO2) reduction for urban centres of India. *Journal of the Indian Society of Remote Sensing, 48*(7), 999–1006. https://doi.org/10.1007/s12524-020-01130-7

Singh, D., & Nanda, C. (2020). Aerosol optical depth (AOD) variation over haryana due to lockdown amid Covid-19 as an indicator of air quality. In *2020 IEEE India GEOSCIENCE and Remote Sensing Symposium (InGARSS)* pp. 170–172. IEEE. https://doi.org/10.1109/InGARSS48198.2020.9358971.

Singh, D., Dahiya, M., Kumar, R., & Nanda, C. (2021a). Sensors and systems for air quality assessment monitoring and management: A review. *Journal of Environmental Management, 289*, 112510.

Singh, D., Kundu, N., & Ghosh, S. (2021b). Mapping rice residues burning and generated pollutants using Sentinel-2 data over northern part of India. *Remote Sensing Applications: Society and Environment, 22*, 100486.

Singh, D., Nanda, C., & Dahiya, M. (2021c). State of air pollutants and related health risk over Haryana India as viewed from satellite platform in COVID-19 lockdown scenario. *Spatial Information Research*. https://doi.org/10.1007/s41324-021-00410-9

Srivastava, S., Kumar, A., Bauddh, K., Gautam, A. S., & Kumar, S. (2020). 21-Day Lockdown in India Dramatically Reduced Air Pollution Indices in Lucknow and New Delhi, India. *Bulletin of*

Environmental Contamination and Toxicology. https://doi.org/10.1007/s00128-020-02895-w.

Sur, K., Verma, V. K., & Pateriya, B. (2021). Variation of tropospheric NO2 over Indo-Gangetic plain during COVID-19 outbreak in India. *Spatial Information Research*. https://doi.org/10.1007/s41324-021-00399-1.

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M. C., Alastuey, A., & Querol, X. (2020). Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. *Science of the Total Environment, 726*, 138540. https://doi.org/10.1016/j.scitotenv.2020.138540

Wai, T., Wai, W., Tam, S., Tak, I., Yu, S., Kai, A., Lau, H., Wing, S., & Wong, A. H. S. (2013). Developing a risk-based air quality health index. *Atmospheric Environment, 76*, 52–58. https://doi.org/10.1016/j.atmosenv.2012.06.071

World Health Organisation (WHO). (2021). WHO Coronavirus (COVID-19) Dashboard, available at https://covid19.who.int/ accessed on 18 Jan 2022.