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Research Article

An empirical analysis of Delhi's air quality throughout different COVID-19 pandemic waves

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Abstract
Delhi was one of India's COVID-19 hotspots, with significant death rates during the year 2021. This study looked at the link between COVID-19 cases in Delhi, and key meteorological variables. The study found that COVID-19 cases during the second wave (P2-March- May 2021) were much higher than during the first wave (P1-Jan-Feb 2021) in Delhi. During P1 (Jan-Feb 2021) the mean $PM_{2.5,}$ $PM_{10,}$ NO_2 and CO concentrations were greater than that of P2 (March-May 2021) while the reverse happened for SO_2 and O_3. Spearman correlation test indicated that COVID-19 cases maintained a significant positive correlation with the high temperature of P2 (March-May 2021) and high humidity of P1 (Jan-Feb 2021) in line with the accepted notion that COVID-19 transmitted favourably in hot and humid climates. The Multilayer perceptron (MLP) model indicated that COVID-19 spread was supported by air pollutants and climate variables like $PM_{2.5}$, NO_2, RH, and WS in P1(Jan-Feb 2021) and $PM_{2.5}$ and O_3 in P2 (March-May 2021). Owing to chemical coupling, across all six monitoring stations, O_3 maintained an inverse relationship with NO_2 throughout the COVID-19 phases in Delhi. The city dwellers had health risks also due to PM pollution at varying degrees, indicated by high hazard quotients (HQs), requiring lowering of air pollution concentrations on an urgent basis.

Keywords: COVID-19, Delhi, Air pollution, Hot spots, Respiratory infection, Spatial regression

INTRODUCTION

The SARS-CoV-2 or COVID-19 pandemic has become a growing menace, with waves following waves hurting the human population. According to WHO, as of May 25, 2021, coronavirus has infected over 167 million individuals and caused more than 3 million fatalities globally (https://covid19.who.int/). Due to the multiple waves of the COVID-19 pandemic, Indian cities are also facing significant issues, with the number of positive cases growing since the first case was found on January 27, 2020 (Andrews *et al*., 2020). The second wave of COVID-19, which began in March 2021 in India, witnessed a substantially larger increase in confirmed cases than the first wave. As of April 30 2021, India recorded more than 400,000 confirmed cases in a single day, the largest of any country (https://en.wikipedia.org/wiki/COVID-19 pandemic in India). The capital city of Delhi similarly recorded surges and plateaus in the number of daily cases, with 175 cases reported on March 1 2021, 28,395 instances reported on April 20 2021, and 3,231 cases reported on May 20 2021 (http://health.delhigovt.nic.in/wps/wcm/connect/DoIT_Health/health/home/). The government of India and the city of Delhi are battling several waves of COVID-19 with tactics such as total lockdown, increas-

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ing the rate of virus discovery through quick testing, building confinement, and launching a rapid vaccination push.

The ever-increasing air pollution and its health impacts are a huge concern to the global population; in 2016, 4.2 million fatalities were documented globally as a result of ambient air pollution (WHO, 2016). Many cities have reported an increase in respiratory ailments due to a rise in particulate matter pollution, such as $PM_{2.5}$ and PM_{10}. Respiratory mortality rose by 0.58 % for every 10 μg m^{-3} rise in particulate matter 10 m in diameter (PM_{10}) concentration (Analitis *et al*., 2006). Some studies have shown that increasing the concentration of daily particulate matter 2.5 m in diameter ($PM_{2.5}$) by 10 μg m^{-3} increases the incidence of respiratory illness by 2.07 percent, and hence the hospitalization rate by 8 %. Dominici *et al*., 2006; Zanobetti *et al*., 2009). Similarly, additional research discovered that for every 10 μg m^{-3} rise in ambient particulate matter $PM_{2.5}$ concentration, the cardiopulmonary mortality rate increases by 6% to 13%. (Beelen *et al*., 2008; Krewski *et al*., 2009). The annual PM_{10} (60 μg m^{-3}) and $PM_{2.5}$ (40 μg m^{-3}) levels in many Indian cities, including Delhi, had surpassed the National Ambient Air Quality Standard (NAAQS). In terms of airborne particle pollution, India is home to eight of the world's top 10 most polluted cities, with Delhi being among the most polluted megacities (WHO, 2018). $PM_{2.5}$ is regarded as the most dangerous pollution, causing health concerns all over the world (Dutta and Jinsart, 2021 a). Similarly, the capital city of Delhi experienced $PM_{2.5}$ and PM_{10} values of more than 250 μg m^{-3} in 2019 (CPCB, 2019).

Several studies have found that, in addition to particulate matter pollution, ozone (O_3) is a major polluter in Delhi (Chen *et al*., 2020; Ghude *et al*., 2009). Prior to the COVID-19 era, rising O_3 concentrations in Delhi raised worries, and the Central Pollution Control Board (CPCB) started formulating strategies to address the health issues. O_3 levels increased as well during the COVID-19 shutdown. Due to the role that NO_X plays in the synthesis of NO_2, the creation of NO_X from industrial activities and vehicular emissions may be what caused the increase in O_3 during the lockdown period. When exposed to sunlight, NO_2 degrades further to nitric oxide (NO) and an oxygen atom (O), which combine with ambient oxygen, i.e., (O_2), to generate ozone (O_3). As a result, O_3 and NO_2 are related to this process (Han *et al*., 2011; Monks *et al*., 2015). Furthermore, there were limits on transportation movements, rubbish burning, industrial activity, and so on throughout the COVID-19 lockdown period, making Volatile organic carbon (VOC) generation less predictable. An inverse link between ozone (O_3) and nitrogen oxide (NO_2) concentrations were discovered. Because Delhi had low NO_2 levels and high ground-level ozone, there was less NO available to react with ozone (O_3) and produce oxygen (O_2) (Chameides *et al*., 1992; Dutta and Jinsart, 2021 b). Changing environmental conditions such as sun radiation, temperature, and humidity can all impact O_3 formation and the movement of precursors for O_3 creation (Lu *et al*., 2019). However, according to a study conducted in Delhi, there was a reduction of 10% ,18% , 31% , and 43% of CO, NO_2, PM_{10} and $PM_{2.5}$ in India, and unfavourable meteorological conditions may have a significant improvement in air quality if proper control plans are implemented, as $PM_{2.5}$ increased by only 33 % during the COVID-19 lockdown (Sharma *et al*., 2020).

The first wave (P1) of COVID-19 began in Delhi on March 4, 2020, with the discovery of the first COVID-19 infected patient, and reached its peak on November 11, 2020, with 8,593 daily infection cases. During the first wave of the COVID-19 pandemic, Lockdown procedures enhanced Delhi's and other Indian cities' air quality, but with its enormous population, India could not give up on the goal of rapid economic progress (Dutta and Jinsart, 2021c; Dutta and Jinsart, 2021d; Dutta and Jinsart, 2022). Following that, new infection cases fell precipitously, and by December 31, just 574 new infected COVID-19 cases had been recorded, signalling the end of the first wave. In the time of COVID-19 second wave (P2), the escalating coronavirus infections in India and the state capital have presented significant issues for both the national and state governments. Following the COVID-19 shutdown, Delhi's air quality has decreased once more, posing a health risk. This study aimed to examine Delhi's air quality and climatic characteristics during two COVID-19 stages and also to examine the health risk of city people caused by $PM_{2.5}$ and PM_{10} inhalation.

MATERIALS AND METHODS

Study location

According to the 2011 census, Delhi had a land area of 1,483 km^2 and a population of around 11 million people. In terms of commerce, industry, medical care, and education, Delhi has grown to be one of the most significant cities in the country. Delhi's five-season climate is classified as extreme by the Köppen climatic classification system. (April–June) Summer is scorching, whereas winter is extremely frigid (December-January). In the summer, temperatures range from 25 to 45 degrees Celsius, while in the winter, they range from 22 to 5 degrees Celsius. While autumn lasts from mid-September to late November, spring lasts from February to March, and is the most pleasant season. The wet monsoon season, which starts in July, lasts roughly three months. The impact of climatic conditions causes seasonal fluctuations in air pollution. Delhi, the capital of India, is one of the most polluted cities in the world and has been the subject of most studies in India regarding air pollution (Guttikunda *et al*., 2019). It is quite concerning that the second wave of COVID-19 has seen an increase in coronavirus disease cases in a heavily populated and polluted metropolis.

Methodology

The low ebb, COVID-19 first-wave infectivity peaked in Delhi in January and February 2021, with monthly average per day infected cases of 314 and 150, respectively. However, in March and April 2021, the monthly average of new infections per day jumped to 746 and 16,230 cases, respectively. Daily infected cases reduced somewhat in May 2021, yet there were still 13,030 new cases registered between May 1 and May 20, 2021. As a result, Delhi experienced a real high tide (P2) phase of COVID-19 second wave infectivity from March 1 to May 20 2021. This study examined Delhi's air quality over two periods: the first wave's "low ebb" and the second wave's "high tide," with variable COVID -19 infectivity concentrations. The first phase (P1) of COVID-19 first wave infection in Delhi lasted 59 days, from January 1 to February 28, with an average of 236 positive cases per day. COVID-19 cases grew from March 1 to May 20 2021 (81 days), with an average of over 9,500 reported cases; as a result, this period has been defined as the high tidal second phase (P2) of COVID-19's second wave (http://health.delhigovt.nic.in/wps/wcm/connect/doit_health/Health/Home/Covid19/Bulletin+May+2021).

Daily data on air quality ambient concentrations of PM_{10}, $PM_{2.5}$, SO_2, NO_2, CO, and O_3 (24-hour average data) and meteorological parameters (ambient temperature (T), relative humidity (RH), and wind speed (WS) were collected for the city of Delhi (P1 and P2) Six Delhi monitoring sites were used to collect the data as part of the NAAQS program run by Central Pollution Control Board (CPCB, 2009). Main two factors for selection of these monitoring stations were considered: first, they were situated in both residential and commercial districts, and second, they provided coverage for Delhi's four corners (North, South, East, West, and Central), as can be seen in Fig. 1. Relative humidity (RH) in (%), wind speed (WS) in, and temperature (T) in degrees Celsius (m s-1) were collected daily (24-hour average) from the above-mentioned monitoring sites for the city of Delhi for P1 and P2.

Spearman's non-parametric correlation coefficient was employed to understand correlation between air contaminants, climatic data, and COVID-19 instances since variables could not be assumed to be normally distributed. The coefficient of correlation was calculated using SPSS 25. With a p-value of less than .01, the correlation coefficients were statistically acceptable (Hara *et al*., 2013). Equation 1 below demonstrates how to get Spearman's correlation coefficient:

$$\rho = 1 - \frac{6\sum d_i^2}{n\,(n^2-1)} = \frac{\sum_i (X_i-\bar{X})\,(y_i-\bar{y})}{\sqrt{\sum_i (X_i-\bar{X})^2)\sum_i (y_i-\bar{y})^2\,)}} \qquad \text{Eq. 1}$$

where ρ is variation in the ranks of the associated variables, where n is the number of observations.

The relative significance of contaminants and environmental conditions in the spread of COVID-19 in Delhi throughout the two phases analyzed was determined

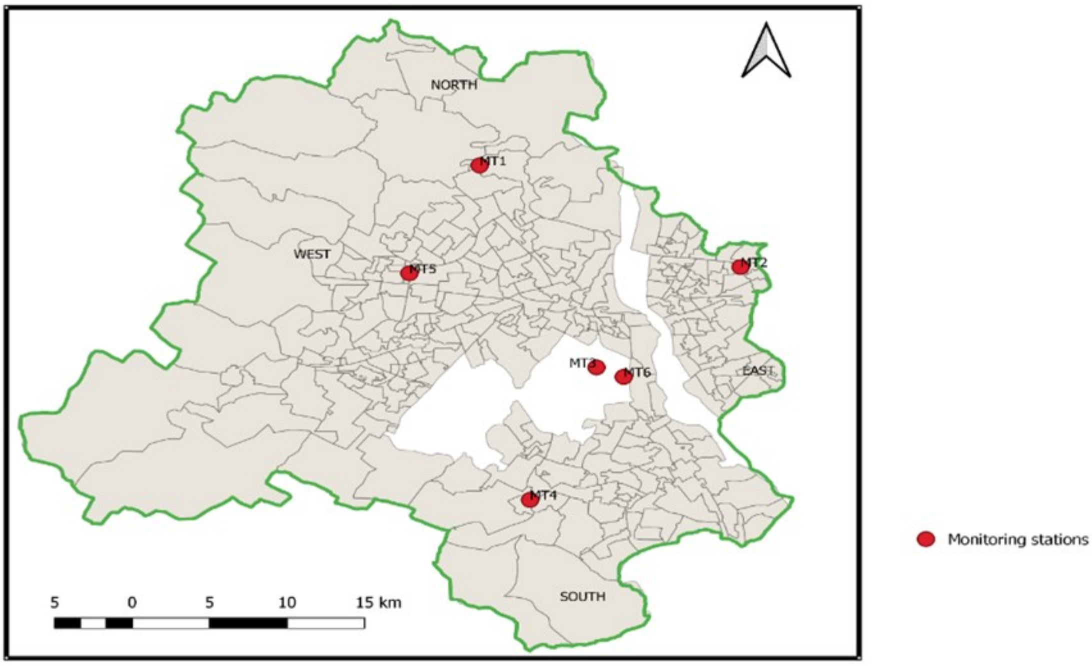

Fig. 1. *Locations of the monitoring stations at Delhi MT1- Jahangirpuri (North), MT2- Patparganj (East), MT3 and MT6- Jawahar Lal Nehru Stadium and Major Dhyan Chand National Stadium (Central), MT4- Siri fort (South), MT5- Punjabi Bagh (West)*

Table 1. Particulate matter reference concentrations (RfC)

Pollutants	Hourly average ($\mu g\ m^{-3}$)		Annual average ($\mu g\ m^{-3}$)	
	WHO (2018)	NAAQS	WHO (2018)	NAAQS
PM_{10}	50	100	20	60
$PM_{2.5}$	25	60	10	40

using the multilayer perceptron (MLP), a well-known feed-forward neural network design of the Artificial Neural Network (ANN).

In this study, the health risk assessment (HRA) was calculated using Delhi city's hazard quotient (HQ) on the basis of ambient particulate matter concentrations ($PM_{2.5}$ and PM_{10}) inhalation at non-cancer endpoints; USEPA, 2016). The inhalation exposure values (ECinh) for P1 and P2 were calculated using the reference concentrations (RfC) of particulate matter (PM) reported in Table 1.

The concentration of inhaled exposure (ECinh) was measured in accordance with Equation (2).

$$EC_{inh}\ (\mu g\ m^{-3}) = \frac{C\ x\ ET\ x\ EF\ x\ ED}{AT} \quad \text{Eq. 2}$$

Equation (2) calculates the actual and projected values for the ambient $PM_{2.5}$ concentrations; ET stands for exposure time (for non-carcinogenic substances), which is 24 hours per day; EF for exposure frequency, which is 350 days per year; ED for exposure duration (for non-carcinogenic substances), which is 30 years; and AT for average time (for non-carcinogenic substances);

$$(AT = ED\ (in\ years)\ x\ 365\ days\ x \frac{24 hours}{day}).$$

A quantified hazard quotient was used to characterize risk in the non-carcinogenic risk assessment (HQ). Equation 3 depicts the computation.

$$HQ = \frac{EC}{RfC} \quad \text{Eq. 3}$$

A risk analysis would anticipate unfavourable health impacts if the HQs were larger than one (HQs>1), and If the HQs were less than one, there were no substantial negative health impacts (HQs1). The WHO established the HQ values for assessing the danger to human health for vulnerable populations, including the elderly, children, and those who are unwell. Additionally, NAAQS derived the HQs values of the Pollution Control Board (PCB) were used to calculate the health risk for demographics of regular citizens, such as adults.

The hazard index (HI) is the summation of HQ,

$$HI = \sum HQ \quad \text{Eq. 4}$$

The total risk of non-carcinogenic problems brought on by various substances is estimated using HI. There is little risk of non-carcinogenic repercussions if the HI is less than one. If HI is more than one, non-carcinogenic repercussions should be possible, with the likelihood increasing as HI value rises (USEPA, 2013).

RESULTS

COVID-19 cases during P1 and P2

During P1, the per day average case number of COVID -19 was 236; during P2, the number increased to 9,514 cases per day. The largest number of instances recorded per day during P1 occurred on January 6, 2021, when 654 cases were reported. The largest number of cases per day reported during P2 occurred on April 20, 2021, with 28,395 instances, as shown in Table S1 and Fig.2.

Air pollution during P1 and P2 across Delhi

During P1 (Jan-Feb 2021) and P2 (March-May 2021) the mean $PM_{2.5}$ concentrations seen from all monitoring stations were 186.92 $\mu g\ m^{-3}$ and 78.91 $\mu g\ m^{-3}$, correspondingly, whereas mean PM_{10} concentrations detected were 297.84 $\mu g\ m^{-3}$ and 206.91 $\mu g\ m^{-3}$. Table 2 shows that the mean $PM_{2.5}$ and PM_{10} concentrations were greater at the time of P1 than the time of P2 . According to ARAI-TERI, vehicles and industry were the largest sources of ambient $PM_{2.5}$ (33%) and PM_{10} (28%) in Delhi, followed by building activities 15% and 31%, respectively, reported by ARAI-TERI (2018). The mean $PM_{2.5}$ concentration at MT1 (north) was significantly higher (241.18 $\mu g\ m^{-3}$) than at the other Delhi monitoring sites included in the research. The much higher $PM_{2.5}$ content in the air at MT1 (north) might be attributed to big industrial sites located (northwest) within 10 kilometers of this monitoring station. The mean concentration of $PM_{2.5}$ in MT1 (north) was 241.18 $\mu g\ m^{-3}$ and 99.88 $\mu g\ m^{-3}$ for P2. The mean PM_{10} concentration at MT1 (north) was also greater than at other monitoring sites in Delhi chosen for the study. According to Table S2 and the boxplot in Fig. 3, the mean concentration of PM_{10} of MT1 (north) was 376.07 $\mu g\ m^{-3}$ and 262.30 $\mu g\ m^{-3}$, respectively. Significantly lower PM concentrations during P2 than P1 might be attributed to the partial lockdown enforced by the Delhi government in response to growing COVID-19 cases, which encompasses all industrial, vehicular, and commercial activity (e.g., restaurants) in Delhi.

Table 2 shows that the mean NO_2 concentrations observed during P1(Jan-Feb 2021) and P2(March-May 2021) from all monitoring sites were 57.35 $\mu g\ m^{-3}$ and

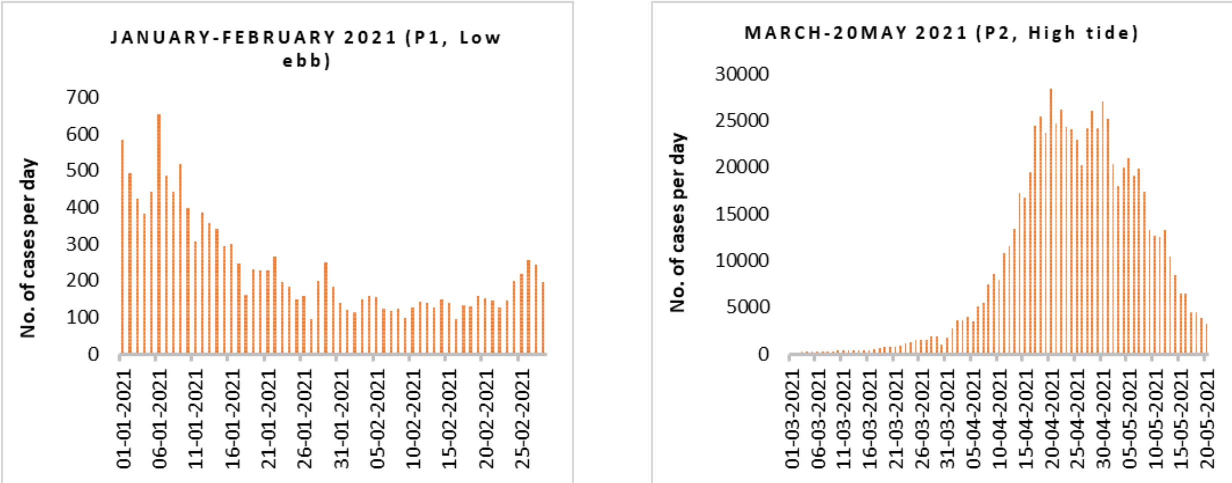

Fig. 2. *Cases per day during the low ebb (P1-Jan-Feb 2021) and high tide (P2-March- May 2021) period*

36.95 µg m^{-3}, in that order. Mean NO_2 content at MT5 (west) was significantly higher than at the other Delhi monitoring sites included for the research. Table S2 and the boxplot from Fig. 3 reveal that the mean NO_2 content of MT5 (west) was 73.63 µg m^{-3} for P1 and 50.34 µg m^{-3} for P2. This shows that there may have been some local sources of NO_2 pollution near the MT5 (West) monitoring station during P1, which may have resulted in considerably higher NO_2 readings in the area compared to all other Delhi monitoring stations.

Table 2 shows that the mean SO_2 concentration recorded was 12.35 µg m^{-3} and 13.52 µg m^{-3}, respectively. The mean SO_2 concentration of MT3 (central) 19.46 µg m^{-3} was greater than other monitoring stations during P1 considered for the study in Delhi, according to Table S2 and the boxplot in Fig. 3. For P2, the mean SO_2 concentration at MT5 (west) was 24.94 µg m^{-3}, which was higher than at other monitoring stations.

The average CO content at MT5 (west) was much greater than at the other Delhi monitoring sites included for the research. According to Table 2, the mean CO content was 1.90 µg m^{-3} and 0.96 µg m^{-3}. According to Table S2 and the boxplot in Fig. 3, the mean concentration of CO in MT5 (west) was 2.48 µg m^{-3} for P1 and 1.37 µg m^{-3} for P2.

As shown in Table 2, the mean concentration of O_3 measured was 29.59 µg m^{-3} and 43.84 µg m^{-3}. The mean O_3 concentration of MT4 (south) was significantly greater than that of the other monitoring stations used for the study in Delhi. According to Table S2 and the boxplot in Fig. 3, the mean concentration of O_3 of MT4 (south) was 52.14 µg m^{-3} for P1 and 72.67 µg m^{-3} for P2. MT4 (South) was placed in the city's downwind direction (Fig. 1). Precursor pollutants for O_3 generation may have been delivered down to MT4 (South) from upwind city areas, contributing to a large rise in ambient O_3 concentration at this location.

Meteorological factors during P1 and P2 across Delhi

Table S3 and boxplots of Fig. 4 indicate the recorded average temperature (°C), relative humidity (RH%), and wind speed (WS ms^{-1}) for both the phases of P1 and P2. During P1 i.e., from January to February 2021, the average temperature recorded was 18±2.80 °C, phase P1was under the influence of the winter and spring seasons. For phase P2 i.e., from March to May 20 2021, the average temperature recorded was 28±2.64 ° C, phase P2 was under the influence of spring and summer seasons. The average RH recorded during

Table 2. Mean values of ambient concentrations of all the stations in Delhi

Statistics	$PM_{2.5}$		PM_{10}		NO_2		SO_2		CO		O_3	
	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
No. of observations	59	81	59	81	59	81	59	81	59	81	59	81
Mean	186.92	78.91	297.84	206.91	57.35	36.95	12.35	13.52	1.90	0.96	29.59	43.84
Variance (n)	6698.54	1038.70	9372.63	5603.41	238.96	126.26	4.68	13.30	0.46	0.15	42.33	129.21
Standard deviation (n)	81.84	32.23	96.81	74.86	15.46	11.24	2.16	3.65	0.68	0.39	6.51	11.37

P1: Jan-Feb 2021; P2: March- May 2021

Fig. 3. *Box plot of $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO of each station for the period P1 (Jan-Feb 2021) and P2 (March-May 2021)*

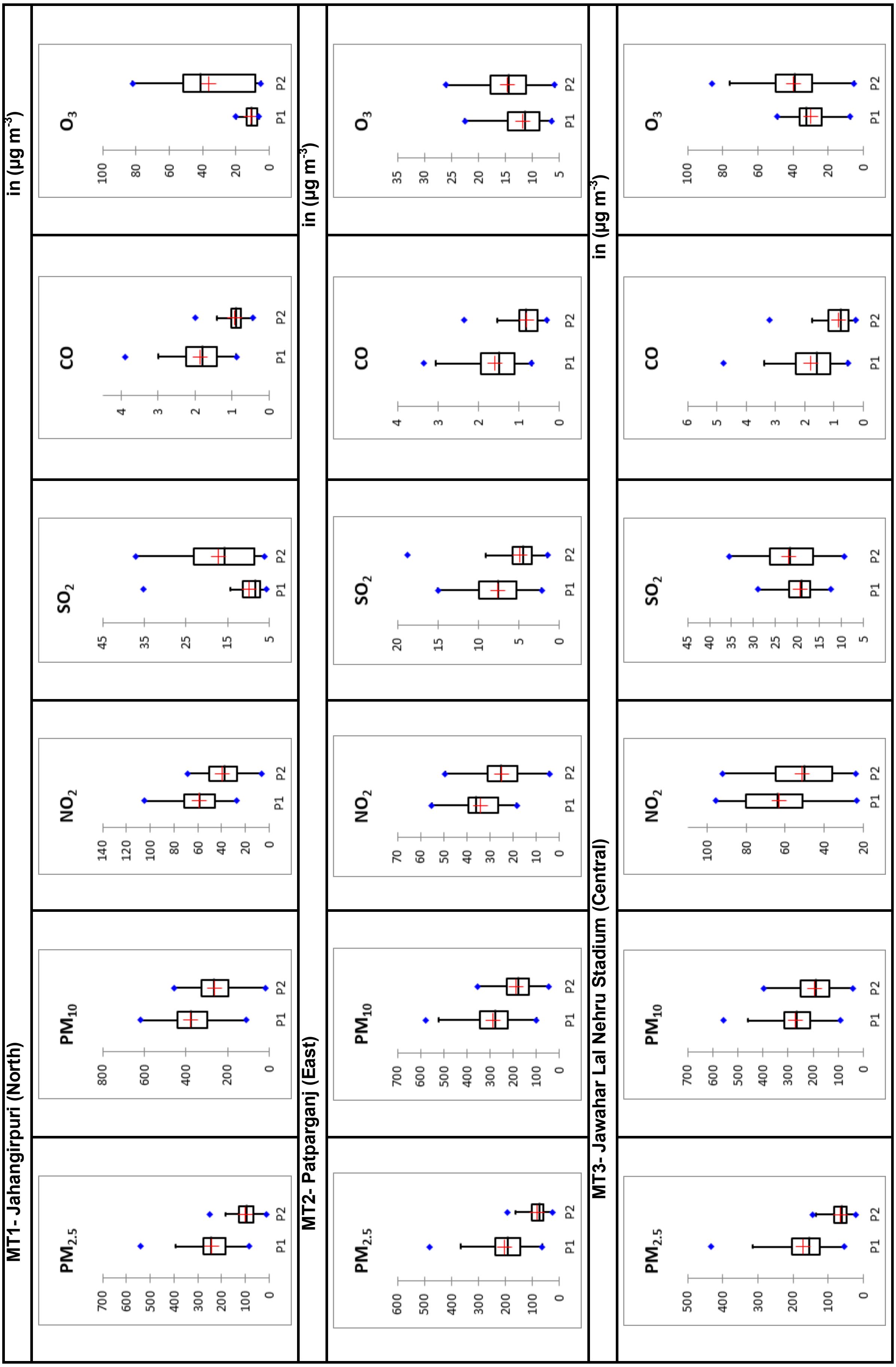

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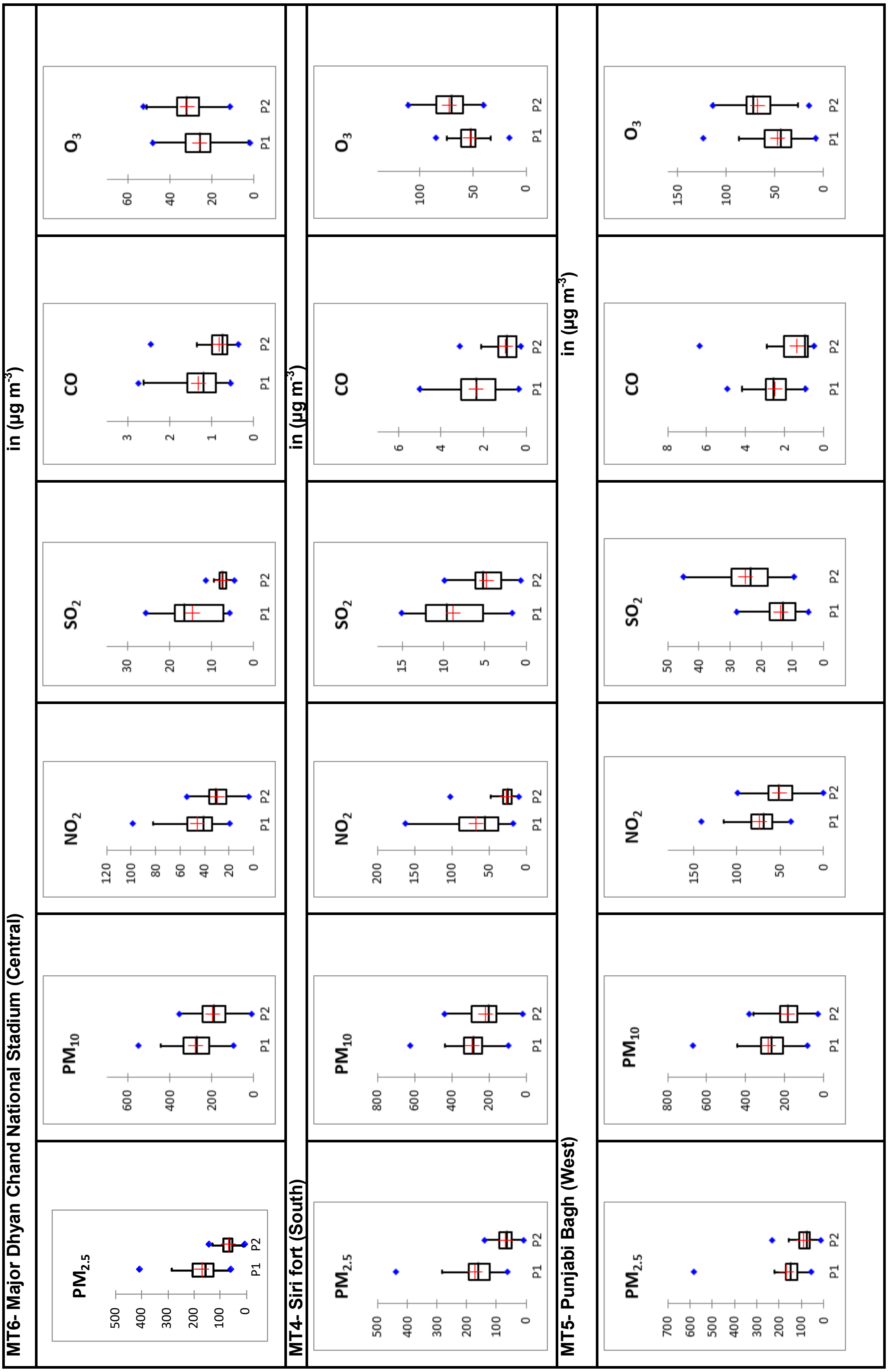
Fig. 3. Contd….



MT6- Major Dhyan Chand National Stadium (Central)
in (µg m-3)
MT4- Siri fort (South)
in (µg m-3)
MT5- Punjabi Bagh (West)
in (µg m-3)
PM2.5
PM10
NO2
SO2
CO
O3
P1
P2

Table 3. Results from the normality test

	Kolmogorov-Smirnov[a]						Shapiro-Wilk					
	P1			P2			P1			P2		
	Statistic	df	Sig.	Statistic	df	Sig.	Statistic	Df	Sig.	Statistic	df	Sig.
No. of cases per day	0.186	59	0.000	0.186	81	0.000	0.840	59	0.000	0.840	81	0.000

[a]Lilliefors Significance Correction; P1: Jan-Feb 2021; P2: March- May 2021

Table 4. Spearman correlation test results for P1 (N=59) and P2 (N=81)

Variables	Phase	$PM_{2.5}$	PM_{10}	NO_2	SO_2	CO	Ozone	Tem-perature °C	Humid-ity (%)	Wind speed (ms^{-1})	No. of cases per day
$PM_{2.5}$ ($\mu g\ m^{-3}$)	P1	1.00	0.87**	0.17	0.11	0.58**	-0.04	-0.54**	0.19	-0.12	0.02
	P2	1.00	0.80**	0.49**	0.65**	0.68**	-0.21	-0.15	0.22*	-0.03	-0.27*
PM_{10} ($\mu g\ m^{-3}$)	P1	0.87**	1.00	0.40**	0.19	0.74**	0.06	-0.23	-0.17	-0.27*	-0.15
	P2	0.80**	1.00	0.38**	0.64**	0.57**	-0.13	-0.08	-0.07	0.08	-0.29**
NO_2 ($\mu g\ m^{-3}$)	P1	0.17	0.40**	1.00	-0.09	0.63**	0.22	0.45**	-0.57**	-0.52**	-0.67**
	P2	0.49**	0.38**	1.00	0.52**	0.67**	-0.36**	-0.31**	0.20	-0.22*	-0.41**
SO_2 ($\mu g\ m^{-3}$)	P1	0.11	0.19	-0.09	1.00	0.12	-0.03	-0.14	-0.07	0.02	0.28*
	P2	0.65**	0.64**	0.52**	1.00	0.70**	0.00	-0.32**	-0.08	0.11	-0.35**
CO ($\mu g\ m^{-3}$)	P1	0.58**	0.74**	0.63**	0.12	1.00	0.09	0.07	-0.29*	-0.38**	-0.36**
	P2	0.68**	0.57**	0.67**	0.70**	1.00	-0.17	-0.27*	0.11	-0.08	-0.45**
Ozone O_3 ($\mu g\ m^{-3}$)	P1	-0.04	0.06	0.22	-0.03	0.09	1.00	0.22	-0.38**	-0.12	-0.27*
	P2	-0.21	-0.13	-0.36**	0.00	-0.17	1.00	0.44**	-0.60**	-0.07	0.47**
Temperature °C	P1	-0.54**	-0.23	0.45**	-0.14	0.07	0.22	1.00	-0.66**	-0.38**	-0.47**
	P2	-0.15	-0.08	-0.31**	-0.32**	-0.27*	0.44**	1.00	-0.57**	-0.51**	0.68**
Humidity (%)	P1	0.19	-0.17	-0.57**	-0.07	-0.29*	-0.38**	-0.66**	1.00	0.30*	0.52**
	P2	0.22**	-0.07	0.20	-0.08	0.11	-0.60**	-0.57**	1.00	0.12	-0.49**
Wind speed ($m\ s^{-1}$)	P1	-0.12	-0.27*	-0.52**	0.02	-0.38**	-0.12	-0.38**	0.30*	1.00	0.41**
	P2	-0.03	0.08	-0.22*	0.11	-0.08	-0.07	-0.51**	0.12	1.00	-0.34**
No of cases per day	P1	0.02	-0.15	-0.67**	0.28*	-0.36**	-0.27*	-0.47**	0.52**	0.41**	1.00
	P2	-0.27*	-0.29**	-0.41**	-0.35**	-0.45**	0.47**	0.68**	-0.49**	-0.34**	1.00

**. Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed).
Note: P1: Jan-Feb 2021; P2: March- May 2021

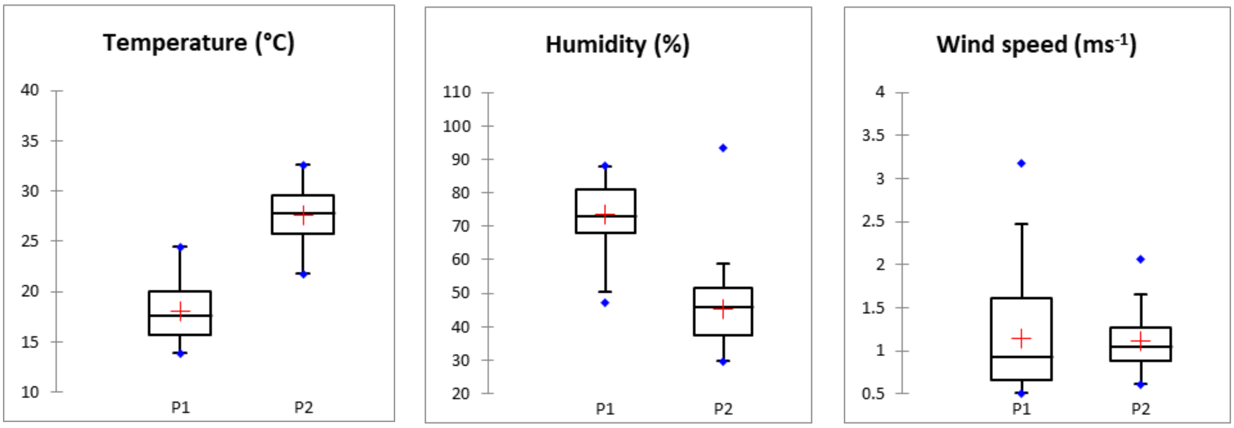


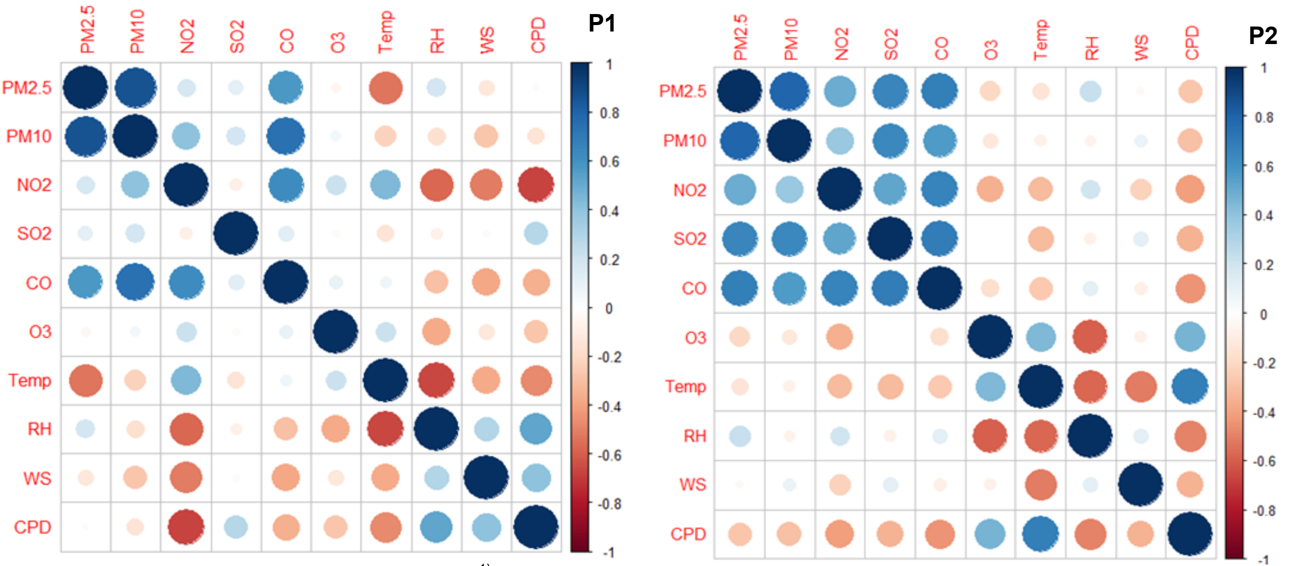
Fig. 4. *Box plots of temperature (°C), humidity (%), and wind speed (ms^{-1}) during P1 and P2*

phases P1 and P2 were 73.52±9.16 % and 45.96±10.51 %, respectively. This shows that the average RH decreased considerably during phase P2. The average WS recorded during phases P1 and P2 were 1.14±0.62 (m s^{-1}) and 1.11±0.33 (m s^{-1}), respectively. This shows that the average WS was marginally higher during phase P1 than P2.

Correlation of air pollutants and meteorological variables during P1 and P2

The assumption of a normal distribution of daily confirmed COVID-19 cases during P1 and P2 was untrue, as shown by the normality test results in Table 3. Kolmogorov-Smirnov normality test p-values were 0.000, less than 0.05, and Shapiro-Wilk p-values were also 0.000, less than 0.05. In order to examine and establish the associations between air quality data, climatic variables, and COVID-19 validated instances during P1 (Jan-Feb 2021) and P2 (March- 20 May 2021) the Spearman correlation test, a non-parametric correlation estimation approach, was used.

Table 4 shows the results of a Spearman correlation test correlation study between COVID-19 verified cases and environmental and meteorological variables. Fig. 5 presents the correlation test results for the periods P1 (N=59) and P2 (N=81) to better understand the correla-



CPD- No. of cases per day; WS- Wind speed (ms^{-1}); RH- Relative Humidity (%); Temp- Temperature °C; $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, O_3 (in µg m^{-3})

Fig. 5. *R program was used to produce the P1 (January to February 2021) and P2 (March to May 20 2021) Spearman correlation matrices. Positive correlations are denoted by the color blue, whereas negative correlations are denoted by the color red. The R program was used to produce the P1 (January to February 2021) and P2 (March to May 20 2021) Spearman correlation matrices. Positive correlations are denoted by the color blue, whereas negative correlations are*

Table 5. Importance of the independent variables of P1 (N=59) and P2 (N=81)

Independent Variable Importance (**P1**)			Independent Variable Importance (**P2**)		
	Importance	Normalized Importance		Importance	Normalized Importance
$PM_{2.5}$	0.146	98.6%	$PM_{2.5}$	0.166	100.0%
PM_{10}	0.112	75.6%	PM_{10}	0.087	52.3%
NO_2	0.149	100.0%	NO_2	0.078	47.3%
SO_2	0.086	58.1%	SO_2	0.109	65.6%
CO	0.110	74.1%	CO	0.118	71.3%
O_3	0.066	44.5%	O_3	0.135	81.4%
Temp °C	0.070	46.9%	Temp °C	0.096	58.2%
R H (%)	0.130	87.3%	R H (%)	0.101	61.1%
W S (mph)	0.131	88.2%	W S (mph)	0.109	65.9%

P1: Jan-Feb 2021; P2: March- May 2021

tion between different variables plotted with R software. According to Table 4 and Fig. 5, the number of confirmed cases per day during P1 exhibited a significant positive association with SO_2, Humidity, and Wind speed and a significant negative correlation with NO_2, O_3, and temperature. During P2, the number of verified cases per day correlated significantly with O_3, while temperature correlated significantly negatively with $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, humidity, and wind speed.

Important variables influencing COVID-19 spread during (P1) and (P2)

Multilayer perceptron (MLP)

The best model, with R^2 = 77.18% for the P1 phase and R^2 = 63.29% for the P2 phase of COVID-19 transmission, was created using the MLP approach with 10 hidden neurons, with 70% of the data utilized for training and 30% for testing (Fig. 6). Table 5 also shows the normalized significance of the independent variable. The findings show that for phase P1, NO_2, $PM_{2.5}$, RH, and WS are the most important factors for COVID-19 infection rate (above 80%), and for phase P2, $PM_{2.5}$ and O_3 are also important factors for COVID-19 contamination rate (above 80%), with O_3 and temperature being the least significant factors for P1 and NO_2, and PM_{10} being the least significant factors for P2.

Health risk assessment due to $PM_{2.5}$ and PM_{10} during P1 and P2

Evaluation of the health risks associated with exposure to $PM_{2.5}$ and PM_{10}

Table 6 shows ambient $PM_{2.5}$ and PM_{10} levels measured at Delhi's MT1 (north), MT2 (east), MT3 and MT6 (centre), MT4 (south), and MT5 (west) monitoring sites. Furthermore, compared to the NAAQS standard, all monitoring stations throughout phases P1 and P2 exhibit high $PM_{2.5}$ and PM_{10} average concentrations. Table shows the HQs of $PM_{2.5}$ and PM_{10} exposure. The HQs values are calculated using the Indian NAAQS standard for calculating health risk for Delhi inhabitants and the WHO air quality criteria for determining health risk for sensitive citizen cases.

Table 7 shows that the HQ values for health risk assessment for Delhi inhabitants were not below the permitted limit in all regions since the HQs were more than one (HQs>1). Furthermore, $PM_{2.5}$ and PM_{10} levels recorded at Delhi MT1 (north), MT2 (east), MT3 and MT6 (central), MT4 (south), and MT5 (west) indicate HQs greater than one (HQs>1) throughout both phases of P1 and P2. This means that city people in Delhi were exposed to a high level of potential risk at all these sites. Fine particle matter exposure might endanger sensitive populations such as youngsters, the elderly, and the sick. During high $PM_{2.5}$ and PM_{10} concentration occurrences, the affected people should wear personal protective equipment or avoid high-risk regions.

Equation 4 was used to determine the hazard indices (HI). The HI values are presented in Fig.7 using heat maps for P1 and P2. For phase P1, the HI of $PM_{2.5}$ and PM_{10} was larger than one at all measured sites, and the HI of MT1 was substantially higher than at other monitored locations. In phase P2, HI was more than 1 at all measured sites for both $PM_{2.5}$ and PM_{10}, however the HI values were lower when compared to P1. Furthermore, for the P2, MT1 had greater HI values than the other monitored locations. Different sizes of HI values of $PM_{2.5}$ and PM_{10} were used to identify danger locations, as illustrated in Fig. 7.

DISCUSSION

COVID-19 is a respiratory ailment, and airborne transmission is the primary mode of transmission across various populations, particularly in congested areas (Zhang *et al.*, 2020). If individuals take precautions, the spread of coronavirus illness is likely to be reduced

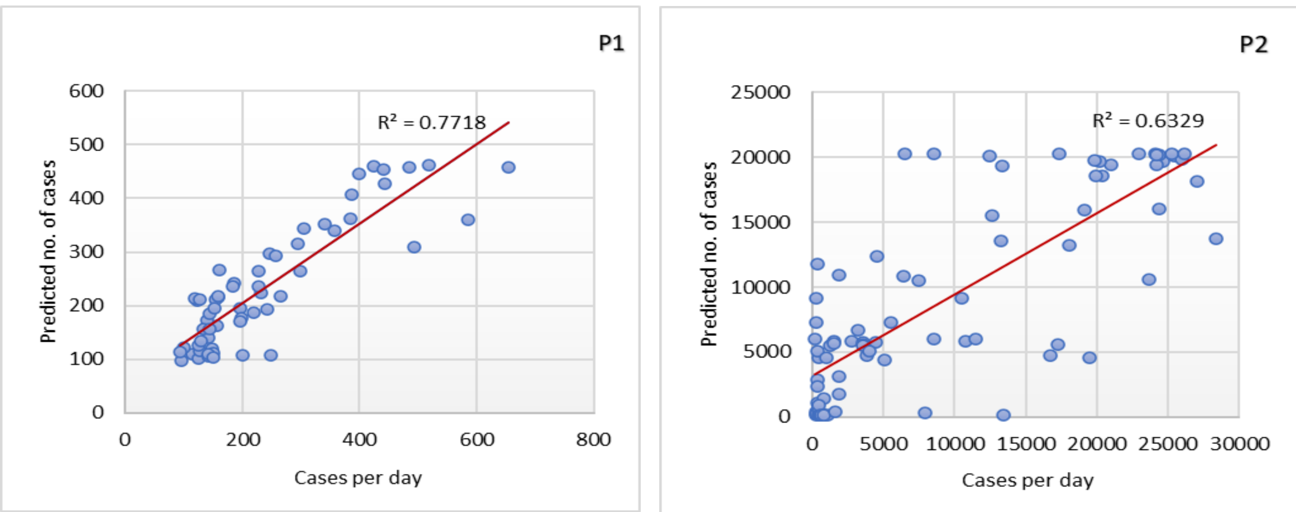


Fig. 6. *Regression plot for the MLP model during P1 and P2) showing predicted values against cases per day*

Table 6. $PM_{2.5}$ and PM_{10} average ambient concentrations in ($\mu g\ m^{-3}$)

Stations	January 2021 - February 2021 (P1)		March 2021- May 2021 (P2)	
	EC $\mu g\ m^{-3}$		EC $\mu g\ m^{-3}$	
	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}
MT1- (North)	241.18	376.07	99.88	262.3
MT2- (East)	201.94	288.35	81.93	187.87
MT3- (Central)	170.93	271.8	66.13	194.19
MT6- (Central)	168.66	278.07	66.67	193.17
MT4- (South)	171.47	290.76	70.16	216.06
MT5- (West)	167.33	281.97	88.69	187.89

(Lahiri *et al*., 2020). The second wave of COVID-19 had an influence on several countries (Cacciapaglia *et al*., 2020; Cousins, 2020; Looi, 2020; Tayech *et al*., 2020; Vaid *et al*., 2020; Xu and Li, 2020). Air pollution may be one of the elements driving COVID-19 distribution; however, the variables influencing COVID-19 spread are not restricted to the air pollution mentioned in this work. Lung inflammation caused by persistent NO_2, O_3, and PM exposure causes a variety of respiratory problems. Air pollution, according to published research, acts as a means for viral transmission in locations where individuals have been exposed to severely polluted air for an extended length of time, significantly exacerbating the COVID-19 outbreak and its spread in Europe and the United States (Ali and Islam, 2020; Bashir *et al*., 2020; Berman and Ebisu, 2020; Fattorini and Regoli, 2020). COVID-19 has a greater negative impact on urban areas in India than on rural ones. In this regard, Delhi has been severely afflicted. The difficulties that Delhi is having with COVID-19 administration are quite worrying. Because Delhi typically has low to very bad and dangerous air quality, it is critical to conduct studies to learn how air pollution influences the spread of COVID-19 and its mortality. Policymakers should also develop plans and measures to prevent pollution from worsening and thereby reduce health concerns (Meo *et al*., 2022).

The main public health problem is caused by a number of air pollutants, including ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), particulate matter with an aerodynamic width of less than 2.5 µm ($PM_{2.5}$) or less than 10 µm (PM_{10}), and carbon monoxide (CO) (Cheong *et al*., 2019; Brunekreef *et al*., 2002). The present looked at the correlations between air quality and COVID-19. It was discovered that SO_2 for four stations and O_3 were favourably related to the occurrence of health problems.

According to the World Health Organization, low- and middle-income nations incur a disproportionately large load, and the Pacific and South-East Asia areas are especially sensitive to the detrimental impacts of air pollution on human health. According to the Global Bur-

Table 7. Comparison of headquarters is based on the WHO and India NAAQS air quality criteria for Delhi's six ambient monitoring stations

Stations	January 2021 - February 2021 (P1)						March 2021- 20th May 2021 (P2)					
			HQ (P1)						HQ (P2)			
	EC $\mu g\ m^{-3}$		NAAQS	WHO	NAAQS	WHO	EC $\mu g\ m^{-3}$		NAAQS	WHO	NAAQS	WHO
	$PM_{2.5}$	PM_{10}	$PM_{2.5}$		PM_{10}		$PM_{2.5}$	PM_{10}	$PM_{2.5}$		PM_{10}	
MT1- (North)	241.18	376.07	3.85	9.25	3.61	7.21	99.88	262.3	1.60	3.83	2.52	5.03
MT2- (East)	201.94	288.35	3.23	7.75	2.77	5.53	81.93	187.87	1.31	3.14	1.80	3.60
MT3- (Central)	170.93	271.8	2.73	6.56	2.61	5.21	66.13	194.19	1.06	2.54	1.86	3.72
MT6- (Central)	168.66	278.07	2.70	6.47	2.67	5.33	66.67	193.17	1.07	2.56	1.85	3.70
MT4- (South)	171.47	290.76	2.74	6.58	2.79	5.58	70.16	216.06	1.12	2.69	2.07	4.14
MT5- (West)	167.33	281.97	2.67	6.42	2.70	5.41	88.69	187.89	1.42	3.40	1.80	3.60

P1: Jan-Feb 2021; P2: March- May 2021

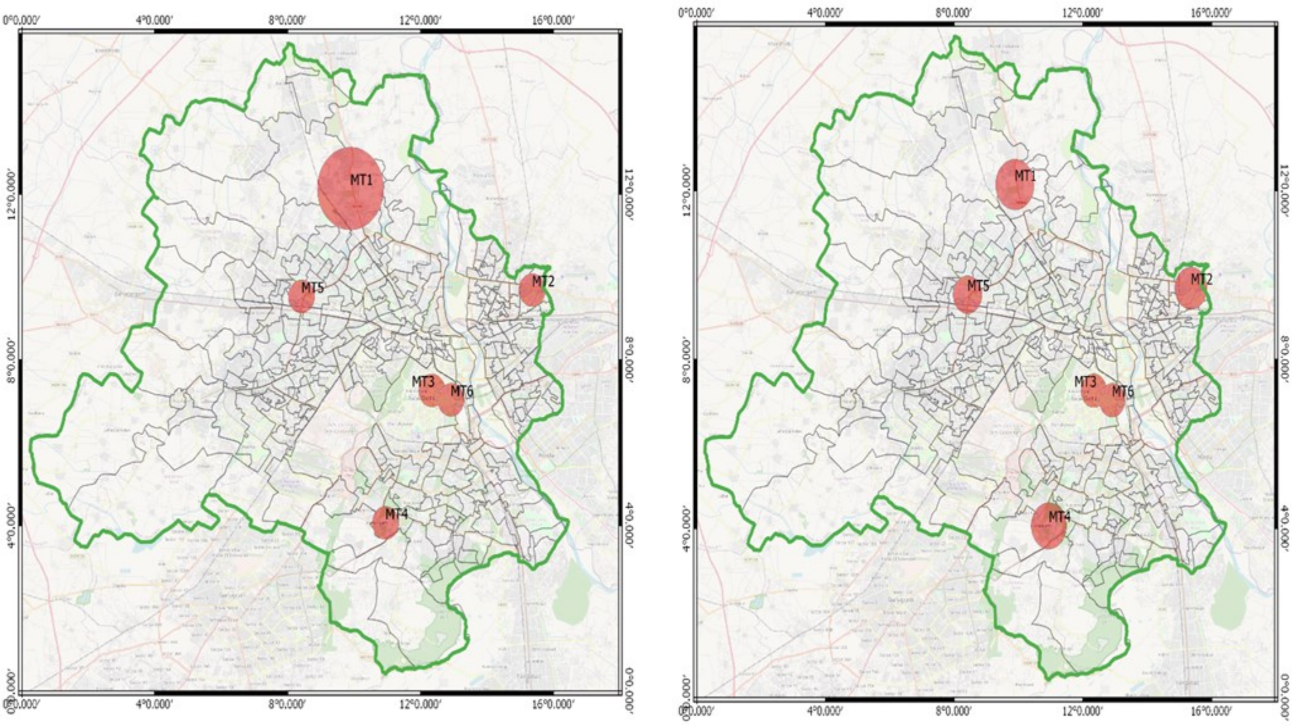


Fig. 7. *Hazard indices during the 2 phases P1 and P2, of the study*

den of Disease Study, ambient air pollution considerably influences ischemic heart illness, cerebrovascular disease, and the associated loss of years of life owing to disability (Cohen *et al*., 2017). COVID-19 patients' circumstances worsen when the patient's heart is already compromised by another illness. The majority of them need ICU services. However, in an emergency circumstance like the covid-19 epidemic, the ICU is insufficient in Delhi. The majority of the patients are unable to live. As a result, the area AQI is an issue in this sort of circumstance, such as COVID-19. This component also influences the number of crucial instances.

Different substances are to blame for various ailments. Despite the fact that only pollutants such as SO2 and O3 have an increasing effect, the air quality in Delhi is detrimental, and it is a passive approach that progressively impacts human health in the long run. It was noted that the O_3 and SO_2 levels have not decreased despite the lockdown, which is concerning for Delhi residents. Many countries are striving to solve the problem of air pollution, which severely impacts the health of billions of people globally. In addition to mitigating measures, patients with pre-existing risk factors for cardiovascular disease may be persuaded to explore initiatives to minimize air pollution emissions. As air pollution concentrations grow, doctors and patients who are more vulnerable should be more aware of early warning signs of health hazards. Tertiary healthcare institutions may organize their resource distribution around predicted periodic peaks in CO and O_3 concentration levels.

Strengths and limitations

Delhi is a sprawling city with consistent land use, a dense population, and fluctuating air quality. The physical characteristics of the area, as well as rigorous ambient air quality monitoring, provide the most up-to-date real-world data for investigating how air pollution impacts people's health. If public hospitals are included in this research, the findings will be generalizable to the whole community. The present study could not ascertain the precise health risk each participant experienced because the COVID-19 exposure and outcome components were analyzed at the population level rather than the individual level.

Conclusion

The study found that the per day average case number of COVID-19 during the second wave (P2) was much higher than during the first wave (P1) in Delhi. The mean $PM_{2.5,}$ $PM_{10,}$ NO_2 and CO concentrations were greater at the time of P1 than at the time of P2. However, SO_2 and O_3 mean concentrations were greater at the time of P2 than that of P1. Both SO_2 and NO_2 concentrations in western Delhi were found to be higher due to contributions from local sources while O_3 concentrations in south Delhi also remained on the higher side. Precursor pollutants for O_3 generation went down drastically during P2 leading to a large rise in ambient O_3 concentration (72.67 µg m^{-3} mean) in south Delhi. Owing to chemical coupling, across all six monitoring stations, O_3 maintained an inverse relationship with

NO_2 but in a nonlinear way. P1 was unleased in Delhi at a comparatively low temperature (17.99 °C) and high humid (75.32%) season than P2 (27.54°C, 45.3%). Spearman correlation test indicated that COVID-19 cases maintained a significant positive correlation with the high temperature of P2 and high humidity of P1 in line with the accepted notion that COVID-19 transmitted favourably in hot and humid climates. The Multilayer perceptron (MLP) model indicated that COVID-19 spread was supported by air pollutants and climate variables like $PM_{2.5}$, NO_2, RH, and WS in P1 and $PM_{2.5}$ and O_3 in P2. The total health risk (non-carcinogenic), assessed for P1 and P2, due to the higher presence of PM pollution in the ambient air highlighted an important understanding for the policymakers. Apart from COVID-19, the city dwellers were also at health risk due to PM pollution at varying degrees across the six monitoring stations covered in this study of Delhi. However, both during P1 and P2, the health risk was much higher for people living in MT1 covered area i.e., the northern part of Delhi. Therefore, the priority is to gain control over PM pollution in the city so that a pandemic like COVID-19 cannot intensify human health problems.

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Supplementary Information

The author(s) is responsible for the content or functionality of any supplementary information. Any queries regarding the same should be directed to the corresponding author. The supplementary information is downloadable from the article's webpage and will not be printed in the print copy.

Conflict of interest

The authors declare that they have no conflict of interest.

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