



## COVID-19 transmission due to interplay between $PM_{2.5}$ and weather conditions

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### ABSTRACT

**Background:** The association of air pollution with the COVID-19 pandemic majorly caused respiratory diseases among the major outcomes of COVID-19 infection. In addition, meteorological factors play an important role in spreading COVID-19 infection in humans who have been exposed to air pollutants.

**Objectives:** This study aims to estimate and comprehend the linkages between the contribution of  $PM_{2.5}$  concentrations and meteorological parameters to the spreading coronavirus infection in Gurugram, a badly affected city in India due to the COVID-19 pandemic.

**Materials and methods:** We employed some statistical analysis on daily average data of  $PM_{2.5}$  concentrations and meteorological conditions with daily COVID-19 cases from March 2020 to February 2022. To optimize  $PM_{2.5}$  concentrations linked with COVID-19 instances, a time series analysis was performed. The Pearson correlation test investigated the relationships between  $PM_{2.5}$  levels, meteorological data, and COVID-19 instances. The PCA was applied to reveal the most significant factor attributable to affecting the rate of COVID-19 transmission in Gurugram.

**Results:** The highest cases of COVID-19 (250,000) were observed in February 2022 when  $PM_{2.5}$  concentration was  $286.6\mu\text{g}/\text{m}^3$ ,  $12.64^\circ\text{C}$  temperature, 73.81% RH, and 68.265 km/h wind speed while minimum cases (3125) were found in March 2020 with the  $18.18\mu\text{g}/\text{m}^3$   $PM_{2.5}$  concentration,  $10.62^\circ\text{C}$  temperature, 50.05% RH, and 83.295km/h wind speed.

**Conclusion:** The principal component analysis helped conclude the results, which revealed that the daily COVID-19 cases were significantly positively correlated with  $PM_{2.5}$  concentrations, RH, and temperature. However, daily COVID-19 cases were negatively or poorly correlated with wind speed. COVID-19 pandemic is prominently affected by  $PM_{2.5}$ , while RH and temperature were found to be important meteorological factors significantly affecting its human-to-human transmission. This study may provide useful indications to regulatory bodies to modify environmental health policies.

### Introduction

Recently, a novel coronavirus disease (COVID-19) caused by severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) appeared in December 2019 and spread rapidly across the world.<sup>1</sup> Later, the World Health Organization (WHO) confirmed the disease as a pandemic.<sup>2</sup> The HCoVs (human coronaviruses) are coined in rodents and bats which are transmitted to human beings through zoonotic interactions. The people infected with SARS-CoV-2 were found with a similarity of 79.5% genetic sequence to SARS-CoV.<sup>3</sup>

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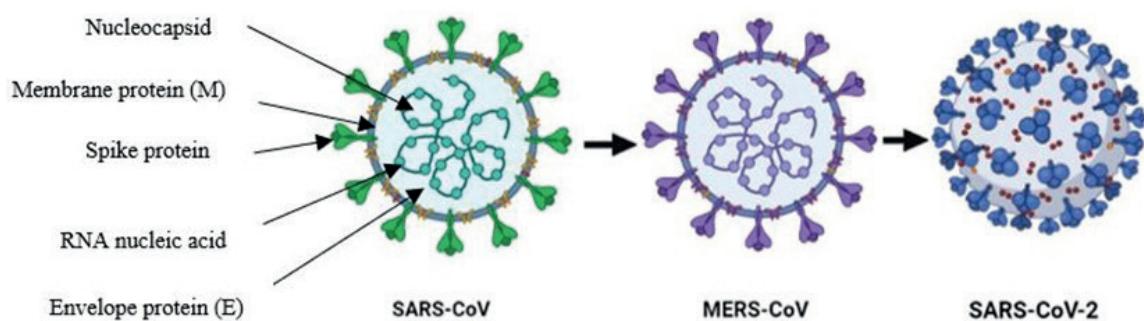
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**Figure 1.** Evolution of coronavirus.

The SARS-CoV-2 is structured with long RNA polymers surrounded by nucleocapsid proteins- membrane protein, spike protein, and envelope protein (Figure 1). The Coronavirus is transmitted through contaminated droplets from an infected person, enters cells through spike protein, and interacts with extracellular domains of the transmembrane angiotensin converting enzyme2 (ACE2) proteins for cell surface binding and internalization and subsequently to downregulation of surface ACE2 expression.<sup>4,5</sup> ACE2, a genetic risk factor, acts as a host receptor for SARS-CoV-2 infection and is also responsible for post-infection regulation, such as immune response, cytokine secretion, and viral genome replication.<sup>6</sup> The symptoms of COVID-19 infection include fever, dry cough, tiredness, loss of smell and taste, and mild to severe respiratory illness.

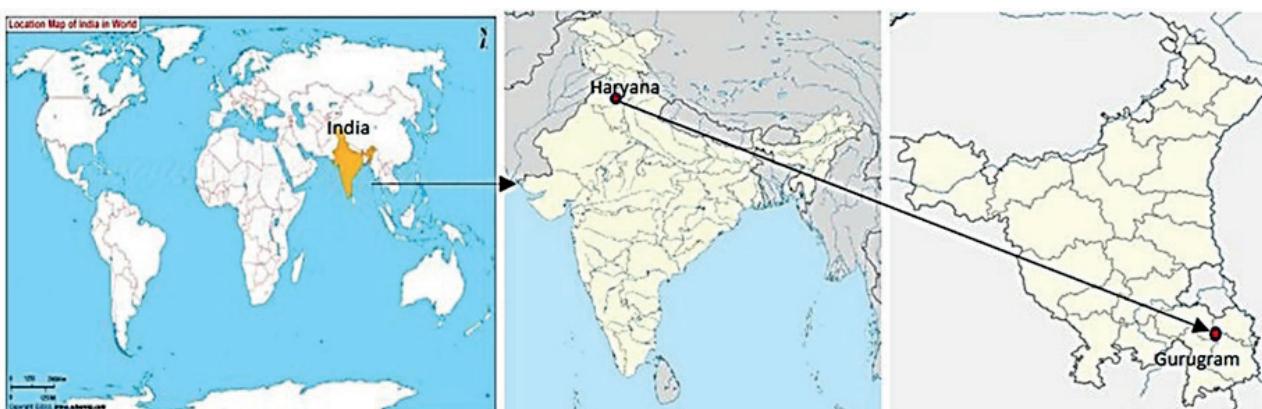
When COVID-19 infection is combined with comorbid conditions, it may cause blood clots or failure of the respiratory system, hypoxemia, renal failure, septic shock, multiple organ failure, and cardiogenic shock, consequent to mortality.<sup>7,8</sup> Gurugram, a highly polluted city in India, was significantly impacted by the COVID-19 pandemic. Previous studies have highlighted the association between PM<sub>2.5</sub> and respiratory illnesses.<sup>9-11</sup> The air quality index (AQI) across the National Capital Region (NCR) cities of Gurugram stayed mostly between 321 and 426  $\mu\text{g}/\text{m}^3$  levels in October 2020. Several hospitals were witnessing a spike in recovered COVID patients reporting respiratory complications caused by pollution, such as chronic obstructive pulmonary disease (COPD),

recurrence of cough, and breathlessness. With their lungs weakened by COVID-19 infection, the poor air quality has solitary compounded the problem.<sup>5</sup> Hence, we studied the variability of COVID-19 and its relationship between temperature, PM<sub>2.5</sub> concentrations, relative humidity, and wind speed to evaluate the transmission of coronavirus infection in humans.

### Methodology

#### Site description

Gurugram is a northern Indian city of Haryana state situated at 28.4595° N, 77.0266° E. This satellite city is part of the Delhi NCR of India (Figure 2) and has an area of 232 km<sup>2</sup> with 1,726,452 estimated population.<sup>12</sup> The hot of Gurugram contains distinct seasons, namely pre-monsoon (March-May) with approx. 45% humidity & 27 °C temperature; Monsoon (June-August) is a hot and humid season with approx. 67% humidity & 31 °C temperature; Post-monsoon (September-November) season is pleasant and mild seasons have 36% humidity & 33 °C temperature; and winter (December-February) has 74% humidity and average temperature 22 °C are foggy and cool with few sunny days. Thunderstorms are common during monsoons, with an average annual rainfall of approximately 714 mm.<sup>13</sup> We have considered PM<sub>2.5</sub> concentrations of the location of sector 51 in Gurugram for our study. One of the main reasons behind the high air pollution level in Gurugram's Sector-51 is dust comes in from various sources, mainly from the intensive construction activities as the city is developing rapidly.



**Figure 2.** World map showing India followed by Gurugram and Sector-51.

Nationwide lockdown is a major factor in distinguishing the impact of  $PM_{2.5}$  and weather conditions on COVID-19 cases. The nationwide lockdown was forced four times in

the year 2020 to stop the transmission of COVID-19 infection. The phase-wise lockdown periods were based on varied restrictions (Table 1).

**Table 1.** Different phases of lockdown periods and COVID-19 cases (%) in Gurugram.

Phase	Duration	COVID-19 cases (%) of total population in Gurugram
Phase 1	25 March 2020 - 14 April 2020 (21 days)	1%
Phase 2	15 April 2020 - 03 May 2020 (19 days)	2%
Phase 3	04 May 2020 - 17 May 2020 (14 days)	5%
Phase 4	18 May 2020 - 31 May 2020 (14 days)	11%

#### **Data availability, collection, and processing**

Daily average  $PM_{2.5}$  data for Sector-51, Gurugram, was obtained from the website of the Central Pollution Control Board from 01 March 2020 to 28 February 2022.<sup>14</sup> Meteorological data in the metropolitan region, viz. temperature, relative humidity, and wind speed were also downloaded from the website of the central pollution control board for the same period. Daily COVID-19 cases in Gurugram from 01 March 2020 to 28 February 2022 were obtained from the Health Bulletin of Govt. of India.<sup>15</sup> Unlock 1.0 began on 01 June 2020, while Unlock2.0 on 01 March 2022 in India. Both lockdown and normal periods were analyzed separately to compare the effects.

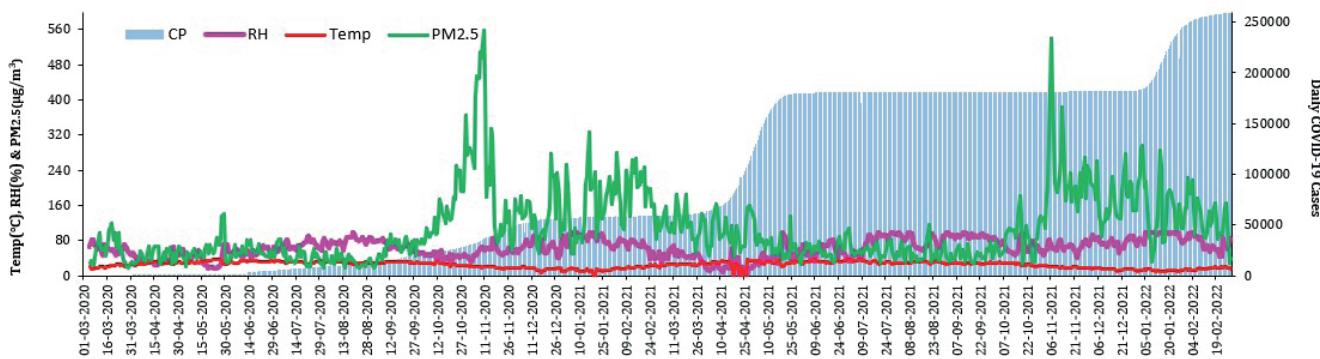
Time series analysis was conducted to examine the variability of COVID-19 confirmed cases and  $PM_{2.5}$  concentrations, along with their monthly linkages, i.e., the meteorological parameters. The variability was observed in four seasons; namely, pre-monsoon includes months of March-May (MAM); monsoon=June-August (JJA); post-monsoon=September-November (SON); winter= December-February (DJF). The relationship between  $PM_{2.5}$  and COVID-19 cases were determined by analyzing the daily mean  $PM_{2.5}$  concentrations and daily COVID-19 confirmed cases using the Pearson correlation test. The statistical analyses and Pearson correlation tests were performed using SPSS 22.0 (IBM SPSS Statistics 22.0). The significance threshold was set at  $p<0.05$  and  $p<0.01$ . Further, to understand the effect of meteorological variables on COVID-19 transmission in Gurugram, which is surrounded by diverse geographical situations, we have conducted Principal Component Analysis (PCA) by using R-software.

PCA accentuates the variation and carries out the significant patterns of the data concerned. PCA is mostly employed to lessen the dimensions of the dataset, which contains interrelated variables, by transforming it into a new set of independent variables called Principal Components (PCs). The PCs are further rotated by PCs varimax rotation to obtain a better relationship between the variables and the original dataset. When varimax rotation is performed, it ensures that each variable is maximally associated with one single component and has zero correlation with other components.<sup>16</sup>

#### **Results and Discussion**

##### **Time series analysis of $PM_{2.5}$ concentrations, COVID-19 cases, and meteorological variables**

Time series of COVID-19 cases, relative humidity, temperature, and correlated  $PM_{2.5}$  pollutants are shown in Figure 3 to better comprehend the variability in COVID-19 cases due to daily  $PM_{2.5}$  concentrations and meteorological variables across the region over the study period. At the onset of the COVID-19 pandemic in March 2020, the number of cases was lower than in September. However, in the last month of 2020, the average rise in COVID-19 cases was noted. A linear increase in COVID-19 cases was observed over the year. Additionally, the  $PM_{2.5}$  variability is influenced, and a modest decrease in  $PM_{2.5}$  is noticed till August 2020 due to the obvious reason of lockdown. However, there was a steady increase in  $PM_{2.5}$  concentrations during the winter- December, January, and February (DJF) months. The linear trend of  $PM_{2.5}$  for 2020 indicates that  $PM_{2.5}$  levels in the region continue to



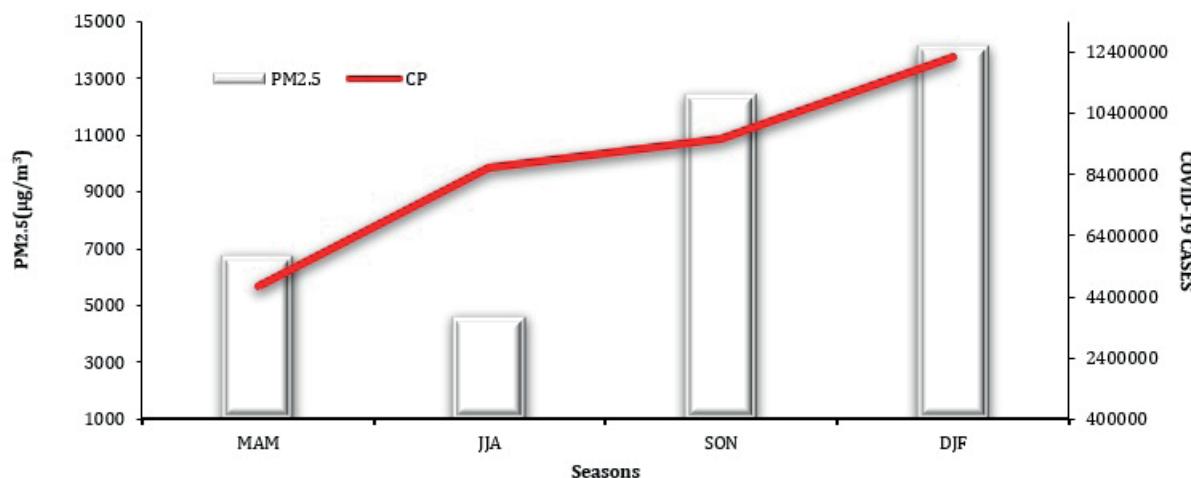
**Figure 3.** Time series analysis of  $PM_{2.5}$ , COVID-19 cases, and meteorological variables in Gurugram.

rise in the peak months. In the second wave of COVID-19 in 2021, the meteorological parameters also exhibited seasonal variability throughout the year, whereas  $PM_{2.5}$  showed sharp peaks in October and November for 2020 and 2021. In 2020, there may be a statistically significant link between the COVID-19 number of cases and  $PM_{2.5}$  concentrations for the study region. From April to May, due to lockdown, the cases were diminished. Most of the cases were reported in November and December 2020. In August, the cases crossed 10,000 trademarks. There is a sharp increase in  $PM_{2.5}$  concentration ( $559.31 \mu g/m^3$ ), lowering the temperature ( $20.23 ^\circ C$ ) and RH (33.41), indicating the correlation with rising cases of COVID-19 (39933) on 27 October 2020. A similar sharp increase can also be seen on 06 November 2021 with ( $539.34 \mu g/m^3$ ) level of  $PM_{2.5}$ , temperature ( $19.41 ^\circ C$ ), and RH (55.13). With increasing  $PM_{2.5}$  concentration in Gurugram, due to dust coming from different sources, coronavirus cases have also been rising. Pati also reported the average air quality index (AQI) of Gurugram for November was higher this year (2021) compared to the previous two-357 (upper levels of very poor) this time, up from 303 (very poor threshold level) in November 2020 and 273 (poor) in November 2019.<sup>17</sup> Wind direction and local sources also play an important part in spreading the virus. A recent study has found that the virus can remain viable in the air for multiple hours. Thus, the spread of the virus can be affected by wind conditions such as wind speed and direction. Ambient wind will enhance the complexity of the secondary flows with recirculation between the two virtual humans. Microdroplets follow the airflow streamlines well and deposit on human bodies and head regions, even with the 3.05 m (10 ft) separation distance.<sup>18</sup> The rest of the microdroplets can transport in the air farther than 3.05 m

(10 ft) due to wind convection, causing a potential health risk to nearby people.<sup>16</sup> According to the Haryana State Pollution Control Board (HSPCB), the city was witnessing the worst AQI level in the past five years.<sup>15</sup>

#### **Seasonal variations between $PM_{2.5}$ concentrations, COVID-19 cases, and meteorological variables**

Further, we investigated the association between COVID-19 cases and the variability of  $PM_{2.5}$  concentrations during all seasons for Gurugram. To understand the seasonal contribution towards  $PM_{2.5}$  concentrations and associated COVID-19 cases, the cumulative seasonal mean was computed and plotted (Figure 4). During the monsoon (JJA) season, a smaller number of COVID-19 cases (619) was observed whereas, post-monsoon and winter seasons are dominated by the increased number of COVID-19 cases (250000) with elevated ( $559.31 \mu g/m^3$ )  $PM_{2.5}$  concentrations. The analysis was compared with another location of Gurugram, i.e., Teri Gram, where no linear variability was noted in the COVID-19 cases at both locations. Although the concentration of  $PM_{2.5}$  differs in post-monsoon and winter seasons, the highest  $PM_{2.5}$  ( $467.28 \mu g/m^3$ ) concentrations were observed at the Teri gram location compared with Sec 51 (figure not shown). Prime Minister of India, Mr. Narendra Modi announced the Janta curfew in March 2020. Due to this, the  $PM_{2.5}$  reduction was 8% on the curfew day but declined to 34% the next day, owing to negligible combustion activities in March 2020 in and around the city, resulting in a decline in COVID cases. The COVID positivity rate rages when Unlock 1.0 begins in June 2020. High humidity accelerates the release of hazardous substances into the atmosphere. Rising temperatures also contribute to increased ground-level ozone smog, which worsens air pollution.<sup>3,19</sup>



**Figure 4.** Seasonal variations of  $PM_{2.5}$  concentrations and COVID-19 cases.

**Table 2.** Seasonal regression values of COVID-19 patients and PM<sub>2.5</sub> concentrations.

Seasons	R-values
March, April, May (MAM2020)	0.215
June, July, August (JJA2020)	-0.536**
September October November (SON2020)	0.131
December January February (DJF2020-21)	0.233*
March, April, May (MAM2021)	-0.558**
June, July, August (JJA2021)	0.013
September, October, November (SON2021)	0.716**
December, January, February (DJF2021-22)	-0.355**

\*\* Significant at 0.01 level \* Significant at 0.05 level

In the year 2021, the number of COVID-19 cases decreased in the first months of the year due to several government-imposed restrictions, and as the second wave of COVID-19 was seen in the pre-monsoon (MAM) season and consistent daily cumulative values throughout the year. In JJA, there was a decrease in PM<sub>2.5</sub> concentrations and COVID-19 instances. During the summer, meteorological conditions such as increased temperature, higher wind speeds, and improved atmospheric dispersion can contribute to lower PM levels, resulting in lower COVID-19 cases. A slight peak of COVID-19 cases and PM<sub>2.5</sub> levels is observed in SON 2021 ( $r=0.716^{**}$ ), followed by an exponential rise in DJF ( $r=-0.355^{**}$ ), as mentioned in Table 2. COVID-19 cases have risen in winter because colder weather often drives people indoors, with less ventilation and increased proximity to others. Indoor settings, especially in poorly ventilated spaces, can facilitate the spread of the virus through close contact and respiratory droplets.

PM<sub>2.5</sub> levels increased slightly in the winter and pre-monsoon seasons of 2020 and 2021, which could be owing to a relaxation in the strict lockdown. PM<sub>2.5</sub> seasonality was seen in both years, with less PM<sub>2.5</sub> concentration (19.97  $\mu\text{g}/\text{m}^3$ ) in the season of monsoon and more (559.31  $\mu\text{g}/\text{m}^3$ ) in the post-monsoon and in winter seasons (326.28  $\mu\text{g}/\text{m}^3$ ).

#### **Correlations between PM<sub>2.5</sub> concentrations, COVID-19 cases, and meteorological variables**

We employed the Pearson correlation technique for the study area to identify the relation between daily cases of COVID-19 and PM<sub>2.5</sub> concentrations. Further, we divided the number of COVID-19 cases into different seasons to know the seasonal variability and their association with PM<sub>2.5</sub>. As COVID-19 hit India in March 2020, we obtained the data of COVID-19 cases from March 2020 to February 2022. Correlations were tested at 0.01 and 0.05 levels of significance.

A negative correlation ( $r=-0.536$ ) between the number of COVID-19 cases and PM<sub>2.5</sub> was noted in the monsoon season (JJA) of the year 2020 for Gurugram, which could be due to the reduction of PM<sub>2.5</sub> level by precipitation and subsequent removal of the pollutants. On the other hand, PM<sub>2.5</sub> and COVID-19 cases were correlated as positively significant ( $r=0.233$ ) in the winter season (DJF) of the year 2020 (Table 2). During the winter

season, a lot of biomass burning is practiced in the North-western parts of the state, increasing pollutant levels over the neighboring regions. This could be the major factor in finding a positive association between COVID-19 cases and PM<sub>2.5</sub> concentrations. However, Zoran *et al.* observed the strong influence of daily average particulate matter concentrations with the positive association of average surface air temperature and inversely related to air relative humidity on the COVID-19 cases outbreak in Milan. Being a novel pandemic coronavirus version, COVID-19 might be ongoing during summer conditions associated with higher temperatures and low humidity levels.<sup>11,20</sup> In the second wave of the COVID-19 pandemic in the pre-monsoon (MAM) season in 2021, we noticed a seasonal shift of relation in comparison with the year 2020. A significant negative relation ( $r=-0.558$ ) was observed in the pre-monsoon season. In contrast, the post-monsoon season showed strong positive relations ( $r=0.716$ ) between COVID-19 cases and PM<sub>2.5</sub> concentrations, and surprisingly, negative correlations were noted in the winter season of 2021. An early lockdown was associated with a lower-case count in this season.

Recent evidence corroborates our results, such as the daily cases of COVID-19 infection were significantly positively correlated ( $r=0.46$ ) with absolute humidity in Delhi, Mumbai, and Pune. At the same time, a strong negative correlation was found with the minimum temperature in Ahmedabad ( $r=0.38$ ).<sup>21</sup> Thus, lower temperatures and high humidity were responsible for the increased rate of COVID-19 spread throughout the city. Particulate matter pollution is positively correlated with a rise in cases of COVID-19 and increased mortality rates.<sup>20</sup> Additionally, our study also reveals that PM<sub>2.5</sub> concentrations are significantly associated with COVID-19 cases in Gurugram. Cole *et al.* also observed that a 1  $\mu\text{g}/\text{m}^3$  rise in PM<sub>2.5</sub> concentrations is 9.4 times more COVID-19 cases and 2.3 times more deaths.<sup>21</sup> Chinese people living in a highly polluted zone were more prone to die from SARS as compared to someone living in a region with cleaner air.<sup>22</sup> Researchers analyzed that several viruses, including influenza and adenovirus, can be loaded on air particles.<sup>16</sup> Zhao *et al.* concluded that particulate matter was a reason behind the spread of 2015 avian influenza.<sup>23</sup> Particulate pollution can accelerate the spread of respiratory infections and elevate the mortality risk.<sup>12</sup> Higher PM

concentrations of air pollution may favor the SARS-CoV-2 spread. Untangling the role of particulate matter in air contamination in the spread of the virus is thus crucial and urgent.<sup>23</sup>

#### Principal component analysis (PCA)

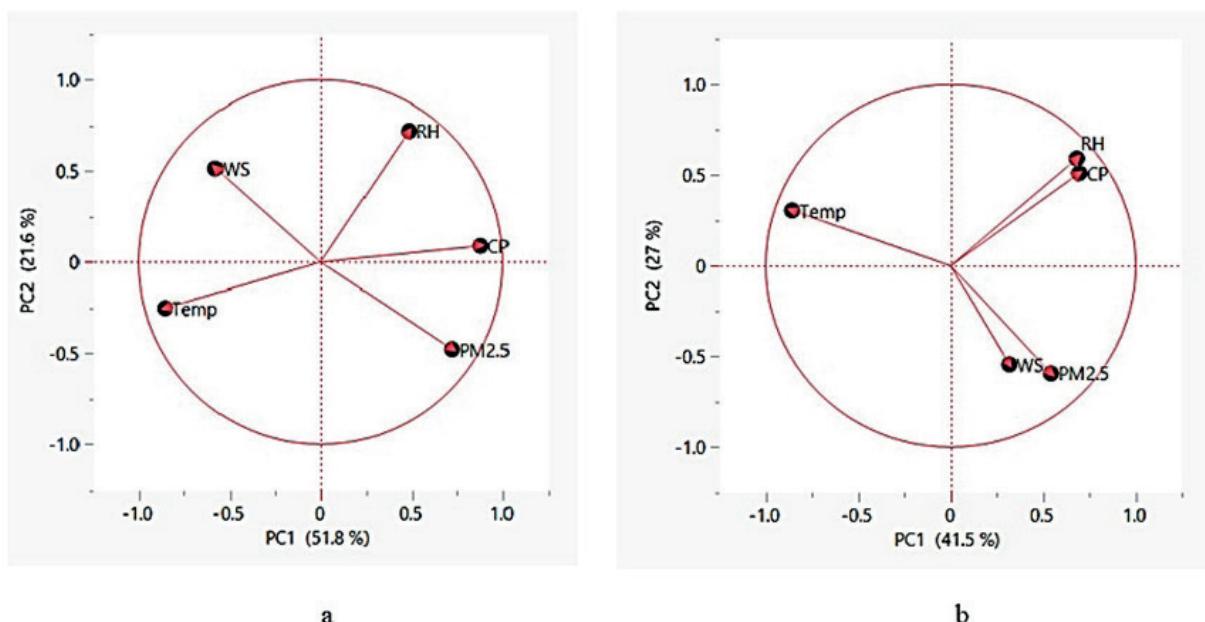
We have determined the Pearson correlations between COVID-19 cases and  $PM_{2.5}$  concentrations and meteorological parameters. Still, a robust and critical analysis is required to understand year-to-year seasonal variability and accountable attributes. Therefore, we applied principal component analysis (PCA) and visualized the patterns and correlations between the daily COVID-19 cases,  $PM_{2.5}$  concentrations, and meteorological variables (temperature, RH, wind speed). The PCA was performed on a correlation matrix after measuring the data sets on varying scales, and variables were standardized before the PCA was applied.<sup>22</sup> Eigenvalues of all principal components (PCs) were determined for both years. Eigenvalues assist in establishing the number of PCs carried out for interpretation. As per Kaiser's Rule, PCs having an eigenvalue less than one cannot be interpreted due to carrying insignificant information.<sup>23</sup> Therefore, out of 5 PCs, only two having eigenvalues of more than one

was selected for further processing. The Eigenvalues and accumulated variance of selected PCs for the years 2020 and 2021 are mentioned in Table 3. Further, the PCs were imperiled to varimax rotation and generated factor loadings matrix for interpretation. The rotation of PCs ensures equal spreading of the significance between the factors (Figure 5).

We have visualized the patterns and correlations between the daily COVID-19 cases,  $PM_{2.5}$  concentrations, and meteorological variables- temperature, RH, and wind speed. The summary plots show the collective variance of the PCs through loading factors for the years 2020 and 2021 (Figure 5). In 2020, the eigenvalue (2.59) of PC1 with 51.78% variance indicates strong positive factor loadings for  $PM_{2.5}$ , RH, and daily COVID-19 cases. However, PC1, having a 2.08 eigenvalue with 41.5% variance for the year 2021, shows obvious positive factor loadings for  $PM_{2.5}$ , RH, and daily cases of COVID-19 but slight positive factor loadings for wind speed also observed (Figure 6). A significant correlation was seen between relative humidity, temperature, and daily cases of COVID-19 in November and December 2020. Figure 5a and Figure 5b depicts the strongly correlated variables with each other. It could be interpreted that the daily COVID-19 cases were

**Table 3.** Eigenvalue and variability of Principal components (PC) reflecting  $PM_{2.5}$  concentrations, meteorological parameters, and daily cases of COVID-19 infection.

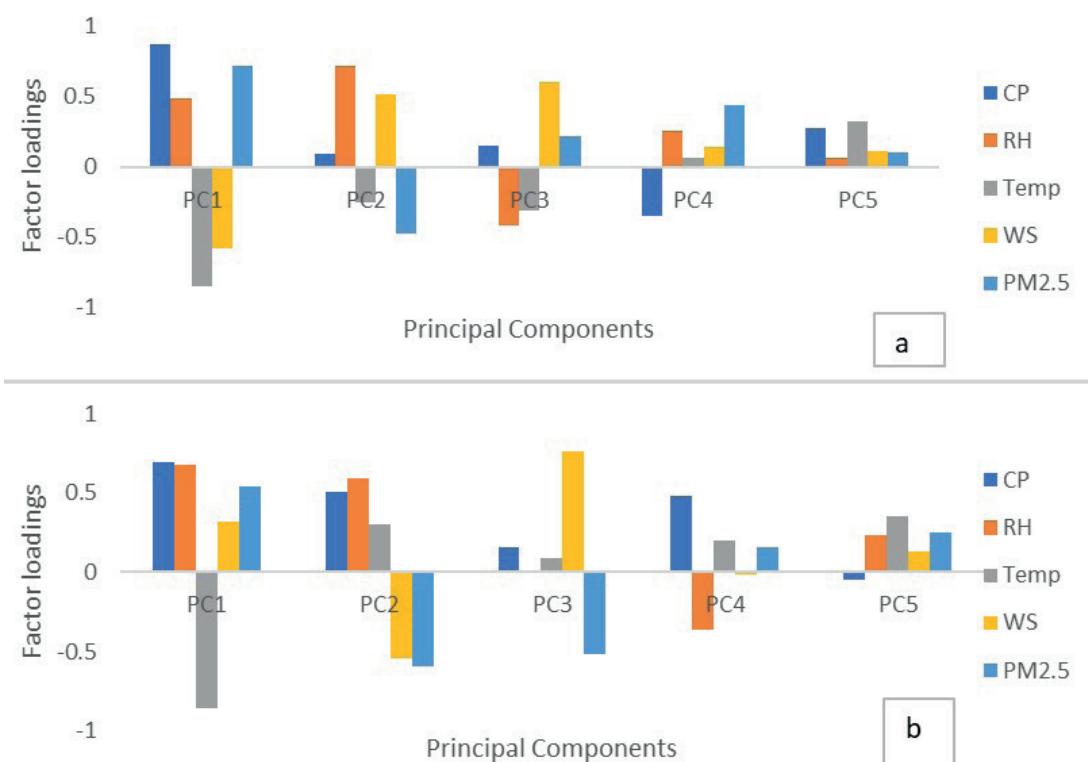
Year	2020		2021	
	PC1	PC2	PC1	PC2
Eigenvalue	2.5892	1.0809	2.0774	1.3515
Variability (%)	51.784	21.619	41.547	27.03
Cumulative variability %	51.784	73.403	41.547	68.577



**Figure 5.** Summary plots showing projections of  $PM_{2.5}$  concentrations, meteorological parameters, and COVID-19 cases based on PC1 and PC2 for the (a) year 2020 and (b) year 2021.

significantly correlated with  $PM_{2.5}$  concentrations, RH, in both years and poorly correlated with wind speed in the year 2021. However, a negative correlation was noticed between daily cases of COVID-19 and wind speed. In an ambient environment, wind speed plays an important role in diluting and removing the droplets that may reduce the viral load in the air, consequently reducing COVID-19 transmission.<sup>24</sup> Zoran et al. also reported that  $PM_{2.5}$  and wind speed show a weak association with respiratory diseases but a strong correlation with increasing temperature and decreasing humidity.<sup>11</sup> The temperature in 2021 was positively correlated with COVID-19 cases, but

there was a negative correlation observed in 2020, which implies that lower temperature enhanced transmission. Anand et al. also suggested that the meteorological variables, such as relative humidity and absolute humidity, showed a moderate positive correlation with the daily COVID-19 cases in three cities.<sup>12</sup> PCA analysis revealed that COVID-19 cases are closely correlated with humidity.<sup>25</sup> The same pattern was seen in the year 2021. Thus, PCA concluded that daily cases of COVID-19 were strongly correlated with the  $PM_{2.5}$  concentrations, temperature, and relative humidity in the years 2020 and 2021.



**Figure 6.** Factor loadings after varimax rotation for the years (a) 2020 and (b) 2021.

### Conclusion

Our results indicate that exposure to high levels of  $PM_{2.5}$  pollutants in association with meteorological factors may enhance vulnerability. Consequently, people may be affected by the COVID-19 infection. The maximum COVID-19 cases (33%) were observed with  $286.6 \mu g/m^3$   $PM_{2.5}$  concentration,  $68.265 \text{ km/h}$  wind speed,  $73.81\%$  RH, and  $12.64^\circ\text{C}$  temperature in the winter season. Minimum COVID-19 cases (1.39%) were reported in the pre-monsoon season with  $18.18 \mu g/m^3$   $PM_{2.5}$  concentration,  $83.295 \text{ km/h}$  wind speed,  $50.05\%$  RH, and  $10.62^\circ\text{C}$  Temperature. Hence, this study reveals the positive significant association between high  $PM_{2.5}$  concentrations, meteorological factors, and COVID-19 cases in Gurugram.

The consequences of  $PM_{2.5}$  indicate that the limited  $PM_{2.5}$  exposure will contribute to defeating the COVID-19 pandemic. Green environmental strategies should be encouraged as these would safeguard human beings who are vulnerable to the COVID-19 pandemic. Also, it is

suggested that further analyses with subsequent clinical studies should be conducted in other parts of India, applying robust techniques to identify the contribution of other pollutants in spreading the COVID-19 pandemic.

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### Conflict of interest

The authors have no conflict of interest relevant to this article.

### References

- [1] Satarker S, Nampoothiri M. Structural proteins in severe acute respiratory syndrome coronavirus 2. Arch Med Res. 2020; 51(3): 482-91. doi: 10.1016/j.

arcmed.2020.05.012.

[2] World Health Organization (WHO). Daily cases and deaths by date reported to WHO. 2023 [cited 2023 January 03]. Available from: <https://covid19.who.int>.

[3] Malik YA. Properties of coronavirus and SARS-CoV-2. *Malays J Pathol.* 2020; 42(3): 5-11. PMID: 32342926.

[4] Guruprasad L. Human coronavirus spike protein-host receptor recognition. *Prog Biophys Mol Biol.* 2021; 161(9): 39-53. doi: 10.1016/j.pbiomolbio.2020.10.006.

[5] Choudhary A, Sreenivasulu K, Mitra P, Misra S, Sharma P. Role of genetic variants and gene expression in the susceptibility and severity of COVID-19. *Ann Lab Med.* 2021; 41(2): 129-38. doi:10.3343/alm.2021.41.2.129.

[6] Upadhyay E, Mohammad AA, Dasgupta N, Rahman S, Kim J, Datta M. Assessment of occupational health hazards due to particulate matter originated from spices. *Int J Environ Res Public Health.* 2019; 16(6): 15-9. doi: 10.3390/ijerph16091519.

[7] Biswas, K. Chatterjee, A. Chakraborty, J. Comparison of air pollutants between Kolkata and Siliguri, India, and its relationship to temperature change. *J Geovis Spat Anal.* 2020; 4(7): 1-15. doi:10.1007/s41651-020-00065-4.

[8] Kumar A, Rana S. Population abundance of Greater Flamingo *Phoenicopterus roseus* (Aves: Phoenicopteridae) in district Gurugram of Haryana, India. *J Threat Taxa.* 2022; 14(7): 20821-7. doi:10.11609/jott.2785.8.7.8953-8969.

[9] Travaglio MY, Popovic R, Selley L, Leal NS, Martins LM. Links between air pollution and COVID-19 in England. *Environ Poll.* 2021; 268(2): 115855-9. doi: 10.1016/j.envpol.2020.115859.

[10] Upadhyay E. An Introduction to Air Quality Index and Health Concerns. *Bio Evolution.* 2014; 1(4): 51-4. ISBN 978-81-925781-3-2.

[11] Zoran MA, Savastru RS, Savastru DM, Tautan MN. Assessing the relationship between surface levels of  $PM_{2.5}$  and  $PM_{10}$  particulate matter impact on COVID-19 in Milan, Italy. *Sci Total Environ.* 2020; 738: 139825. doi: 10.1016/j.scitotenv.2020.139825.

[12] Anand V, Korhale N, Tickle S, Rawat MS, Beig G. Is Meteorology a factor to COVID-19 Spread in a Tropical Climate? *Earth Syst Environ.* 2021; 5(2): 939-48. doi:10.1007/s41748-021-00253-2.

[13] Climate & weather averages in Gurgaon, Haryana, India. [cited 2023 April 29]. Available from: [www.timeanddate.com/weather/india/gurgaon/climate](http://www.timeanddate.com/weather/india/gurgaon/climate).

[14] CPCB. Air quality monitoring, emission inventory and source apportionment study for Indian cities, New Delhi. 2022: 1-658. [cited 2022 December 12]. Available from: <http://cpcb.nic.in/Delhi.pdf>.

[15] Health Bulletin District Gurugram for COVID-19. National Informatics Centre, Ministry of Electronics & Information Technology, Government of India. 2022. [cited 2022 April 29]: 1-702. Available from: <https://gurugram.gov.in/health-bulletin>.

[16] Wang B, Li R, Lu Z, Huang Y. Does comorbidity increase the risk of patients with COVID-19: evidence from meta-analysis. *Aging.* 2020; 5(12): 60-49. doi: 10.18632/aging.103000.

[17] Pati. City's average AQI in November this year worse than last two years. 2022. [cited 2022 September 21]. Available from: [http://timesofindia.indiatimes.com/articleshow/88017474.cms?utm\\_source=contentofinterest&utm\\_medium=text&utm\\_campaign=cpst](http://timesofindia.indiatimes.com/articleshow/88017474.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cpst).

[18] Feng Y, Marchal T, Sperry T, Yi H. Influence of wind and relative humidity on the social distancing effectiveness to prevent COVID-19 airborne transmission: A numerical study. *J Aerosol Sci.* 2020; 147: 105585. doi: 10.1016/j.jaerosci.2020.105585.

[19] Kim KH, Kabir E, Ara JS. A review of the consequences of global climate change on human health. *J Environ Sci Hlth, Part C.* 2014; 32(3): 299-318. doi:10.1080/10500501.2014.941279.

[20] Liu Y, Gayle A, Smith A, Rocklöv J. The reproductive number of COVID-19 is higher compared to SARS coronavirus. *J Travel Med.* 2020; 115(3): 55-80. doi: 10.1093/jtm/taaa021.

[21] Cole MA, Ozgen C, Strobl E. Air pollution exposure and COVID-19 in Dutch municipalities. *Environ Resour Econ.* 2020; 76(2): 581-610. doi: 10.1007/s10640-020-00491-4.

[22] Ortiz A, Fernández L, Sawalha AH. Genetic variability in the expression of the SARS-CoV-2 host cell entry factors across populations. *Genes Immun.* 2020; 21(3): 269-72. doi: 10.1038/s41435-020-0107-7.

[23] Zhao P, Yang XL, Wang XG, Hu B, Zhang L, Zhang W, Shi ZL. A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature.* 2020; 579(2): 270-3. doi:10.1038/s41586-020-2012-7.

[24] Chen PM, Hemmen TM. Evolving healthcare delivery in neurology during the coronavirus disease 2019 (COVID-19) pandemic. *Front Neurol.* 2020; 28(11): 571-8. doi: 10.3389/fneur.2020.00578.

[25] Daraei H, Toolabian K, Kazempour M, Javanbakht M. The role of the environment and its pollution in the prevalence of COVID-19. *J Infect.* 2020; 8(2): 168-9. doi: 10.1016/j.jinf.2020.06.019.