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Analysing role of airborne particulate matter in abetting SARS-CoV-2 outbreak for scheming regional pandemic regulatory modalities

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ABSTRACT

The mutating SARS-CoV-2 necessitates gauging the role of airborne particulate matter in the COVID-19 outbreak for designing area-specific regulation modalities based on the environmental state-of-affair. To scheme the protocols, the hotspots of air pollutants such as $PM_{2.5}$, PM_{10}, NH_3, NO, NO_2, SO_2, and and environmental factors including relative humidity (RH), and temperature, along with COVID-19 cases and mortality from January 2020 till December 2020 from 29 different ground monitoring stations spanning Delhi, are mapped. Spearman correlation coefficients show a positive relationship between SARS-COV-2 with particulate matter ($PM_{2.5}$ with $r > 0.36$ and PM10 with $r > 0.31$ and p-value $<0{\cdot}001$). Besides, SARS-COV-2 transmission showed a substantial correlation with NH_3 ($r = 0.41$), NO2 ($r = 0.36$), and NO ($r = 0.35$) with a p-value <0.001, which is highly indicative of their role in SARS-CoV-2 transmission. These outcomes are associated with the source of PM and its constituent trace elements to understand their overtone with COVID-19. This strongly validates temporal and spatial variation in COVID-19 dependence on air pollutants as well as on environmental factors. Besides, the bottlenecks of missing latent data, monotonous dependence of variables, and the role air pollutants with secondary environmental variables are discussed. The analysis set the foundation for strategizing regional-based modalities considering environmental variables (i.e., pollutant concentration, relative humidity, temperature) as well as urban and transportation planning for efficient control and handling of future public health emergencies.

1. Introduction

The rapidity and unpredicted outbreak of Severe Acute Respiratory Syndrome (SARS) and coronavirus disease (SARS-CoV-2) have stressed the importance of combating and regulating modalities (WHO, 2020; Yamamoto et al., 2020). Since the appearance of COVID-19 in 2019, a

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large number of research studies have been conducted on the disease (Domingo, 2021; Taha et al., 2023; Cherusseri et al., 2022; Maurya et al., 2022; Royal et al., 2021). The severity of COVID-19 has challenged the state-of-the-art healthcare services and raised the need to understand the origin, diagnosis and pathogenesis of causative virus (Chaudhary et al., 2021, 2023a; Cherusseri et al., 2022; Chugh et al., 2022; Park et al., 2023; Singh et al., 2022; Upasham et al., 2022). Moreover, the origin of SARS-CoV-2 is still a matter of debate. While most studies point to a zoonotic origin, with bats and pangolins being possible intermediate hosts, the intermediate source species has not yet been confirmed (Domingo, 2021). Some researchers have also suggested an unnatural origin, but their conclusions are yet to be experimentally evaluated (Domingo, 2021). As a consequence, many areas worldwide are highly impacted by the covid infections as well as deaths and are therefore identified as SARS-CoV-2 hotspots (Desai, 2020; World Health Organization, 2020). Furthermore, the varying character of SARS-CoV-2 virus with the accessibility of various transmission pathways and its interaction with environmental features resulted in the emergence of various variants; all of which significantly challenged prevention and rapid control (Chaudhary et al., 2021; Gage et al., 2021; Paliwal et al., 2020; Sadique et al., 2021; Chaudhary et al., 2022; Taha et al., 2023) (see Table 1).

Toxicological analysis have revealed the role of air contamination (i.e. due to anthropogenic sources, traffic-related air pollution and internal combustion engines) in causing airborne hyper-responsiveness and contagion, which results in the severity of respiratory and cardiovascular diseases (Manisalidis et al., 2020; Schraufnagel et al., 2019; Suzuki et al., 2020; World Health Organization, 2019). For instance, the presence of air contaminants and the persuasive and infectious nature of COVID-19 virus have been related to chronic diseases such as cardiopulmonary failures (van Doremalen et al., 2020). Furthermore, various research investigations further revealed that inhaling air pollutants further reduces the immune reaction and facilitates virus growth, survival, and replication (Ali and Islam, 2020a; Karan et al., 2020).

In many research investigations, the role of numerous air contaminants, such as particulate matter (PM), nitrogen dioxide (NO_2), ammonia (NH_3), sulfur dioxide (SO_2) and ozone (O_3), has been evaluated using epidemiological, toxicological, and regression analyses (Ali and Islam, 2020a; Becchetti et al., 2021; Nor et al., 2021a; Suzuki et al., 2020; Chaudhary et al., 2023a, 2023b). Since PM contributes to 7·6% of global mortality(Schraufnagel et al., 2019), it has been anticipated as the most prominent factor for aggravating COVID-19 severity and abating the prognosis of the disease. The PMs can be classified as fine particles (PM_{10} are particulate matter with size $\leq$10 μm) and ultrafine particles ($PM_{2\cdot5}$ are particulate matter with size $\leq$2·5 μm) with primary and secondary origins (Bo et al., 2017; Das et al., 2015; Manisalidis et al., 2020). Therefore, particulate matter and air pollutants are anticipated as a reinforce to the transmission of SARS-CoV-2, its penetration, and its severity in humans.

Many scientific reports documented by U.S. Environmental Protection Agency (EPA), have studied and evaluated the role of particulate matter in various adverse human health issues (Brook et al., 2010; US EPA, 2019; Wu et al., 2020). Setti et al. (2020) reported primary analysis of the existence of relation of airborne particulate matter in particular atmospheric conditions with COVID-19 virus, which anticipated a potential application as an indicator of COVID-19 recurrence. The SARS-CoV-2 particles bound to airborne PM (Nor et al., 2021a) were likely to be more profound in the alveolar and tracheobronchial parts of the vulnerable host subject (Ali and Islam, 2020a; Nor et al., 2021a). Furthermore, PM indirectly weakens the host's immune response, which increases the host's susceptibility towards COVID-19 and worsens its severity (Yang, et al, 2020; Zhao et al., 2013). PM causes SARS-CoV-2 to bind with vulnerable cells, thus causing overexpression of ACE-2 receptors(Borro et al., 2020).

The pathogenicity of PM is crucially evaluated in terms of its constituents and chemical composition, especially trace elements. Various trace elements like cadmium (Cd), arsenic (As), lead (Pb), chromium (Cr), and mercury (Hg) characterize a very small trace of the total PM mass(Das et al., 2015; Dominici et al., 2015; Sharma and Mandal, 2017). However, these are enough to induce adverse human health issues such as lung damage, cardiopulmonary conditions and low birth weight. Numerous studies have revealed the role of inhalable airborne trace elements relatable to COVID-19 symptoms such as lung and cardiopulmonary morbidity, failure and mortality (Das et al., 2015; Dominici et al., 2015; Mo et al., 2021; Zhao et al., 2013; Markandan et al., 2022). In all the studies, it has been consistently highlighted those airborne trace elements present in the PM result in decreased immune efficacy and chronic inflammation among COVID-19 patients.

Moreover, humans residing in polluted sites are additionally prone to SARS-COV2, where most hotspots of COVID-19 happen to be the most polluted megacities (Desai, 2020). For instance, Delhi, the capital of India, has been listed in the world's top ten polluted cities consecutively for last three years and was devastated majorly due to COVID-19 (Greenpeace y IQAir, 2020). Primary sources of PM in Delhi's atmosphere are vehicular emissions, industries, construction, episodic agricultural burning and waste burning. (Dhaka et al., 2020; Saraswati et al., 2019; Sharma and Mandal, 2017).

Previous studies examined the relation between COVID-19 spread and air quality index (AQI) in different megacities(Ali and Islam, 2020a; Dutta and Jinsart, 2021; Karan et al., 2020; S. Kumar, 2020; Tello-Leal and Macías-Hernández, 2021a; Chaudhary et al., 2022). Yet, according to our survey, no analysis directly evaluates the impact of PM and its secondary causatives (NH_3, NO, NO_2, SO_2, RH) on growth and intensity of SARS-COV2 infection in Delhi. Besides, AQI-COVID-19 correlation studies primarily lack addressing missing data issues, analysing the significance of the correlation, catering to the monotonous correlation amongst variables, and were multivariate analyses (Anand et al., 2021; Bontempi, 2021; Milicevic et al., 2021; Villeneuve and Goldberg, 2020). Owing to these limitations, the current analysis examines the potential role of airborne trace elements in terms of PM and its secondary sources (NH_3, NO, NO_2, SO_2, RH) in COVID-19 spread and mortality by utilizing the Spearmen correlation with significance evaluation. Moreover, Spearmen rank correlation has been employed to investigate the relation between COVID-19 with air pollutants and environmental factors during the first COVID-19 wave in Delhi. The study aims to establish a groundwork for designing area-based approaches (depending on environmental factors and airborne trace elements, PM, RH, and NH3) to regulate COVID-19 intensity and future infectious threats.

2. Methodology & analysis

2.1. Study area

Delhi, which is located at 28·61° N 77·23° E, is the capital city and a

Table 1
Statistical data on environmental parameters, deaths, and cases reported in Delhi.

	PM2·5	PM10	NH_3	NO_2	NO	SO_2	Temperature	Humidity	Deaths	Cases
Mean	93·35	180·59	35·81	38·51	26·91	13·15	30·79	31·75	34·39	2041·81
std	83·48	123·09	10·39	19·53	30·66	3·23	6·55	15·51	37·95	1945·05
min	11·85	29·66	20·48	14·35	3·91	7·42	14·22	7·73	0·00	0·00
max	523·31	729·31	72·47	96·95	145·50	23·82	42·70	75·38	437·00	8593·00

union territory of India, was selected for analysis in the present study. It is one of the most populated (population: 15 million; population density: 11297 people/km (Commissioner and Road, 2011)) metropolitan capitals, maintains the 2nd position as the world's top megacities (UN/DESA, 2018). Investigations have shown that biomass and automobile emissions significantly contribute PM to the Delhi environment. (Saraswati et al., 2019). In contrast, the agricultural sector has been identified as a significant contributor to airborne ammonia (Chaudhary et al., 2021; Sharma et al., 2014).

2.2. Data Collection and Processing

The concentrations of the various air pollutants such as PM2.5, PM10, NH_3, SO_2, NO_2, and NO recorded from 29 different air monitoring stations spanned across Delhi, established under "*Central Pollution Control Board*" (CPCB), under the "*Ministry of Environment, Forests and Climate Change, Government of India*". Similarly, day-to-day COVID-19 cases and casualties during the analysis duration were obtained World Health Organization, WHO (HTTPS://covid19.who.int/) data from January 1, 2020 to December 31, 2020.

2.3. Processing of missing data

One of the major concerns while performing air quality analysis is catering for the missing observations (Hadeed, O'Rourke, Burgess, Harris and Canales, 2020; Khan et al., 2021a). For instance, air quality data can be influenced by power failure, filter replacement, mechanical deterioration, undetectable contaminant concentration, and/or crashing of computer systems (Khan et al., 2021b). Therefore, it is essential to address the issue of missing data effectively since it is pervasive and affects data analysis significantly. Previous reports on air quality have categorized missing data into three cases (i) Missing at random (MAR), (ii) Missing completely at random (MCAR), and (iii) Not missing at random (NMAR) (Khan et al., 2021b; Little and Rubin, 2014).

In the current study, the MAR benchmark was 7%. To address the issue associated with missing data, we used the "last observation carried forward (LOCF)" method, where missing data is superseded by a prior observation assuming the variable remains unaffected during the period (Hamer and Simpson, 2009).

In the present study, the first section emphasizes a statistical and comparative investigation of air pollutants from 29 sites across Delhi from January to December 2020, focusing on the air quality index (AQI) and its temporal variation. The Delhi AQI index was estimated as the mean AQI across these 29 locations. Second part of the study focuses on COVID-19 infectivity, mortality, movement restriction, and lockdown on the AQI of various locations in Delhi. The duration from January to November 2020 was divided into three stages (i) Pre-lockdown stage: 1st January- March 23, 2020, (ii) Lockdown stage: 24th March- May 31, 2020, (iii) Unlock stage: 1st June- November 30, 2020.

2.4. Methodology: Spearmen correlation coefficient

Spearman's rank correlation coefficient, a nonparametric measure of rank correlation which shows the statistical dependency among two variables, was used in the present study (Sedgwick, 2014). However, previous studies have employed the Pearson correlation coefficient for similar analysis. The significant difference between the two analyses lies in the fact that the Pearson correlation coefficient estimates only the linear dependence among the variables. (Hauke and Kossowski, 2011). However, Spearman's rank correlation measures a monotonic dependence between two variables. If the Spearman coefficient is higher than the Pearson then it indicates that the relationship between variables is not linear but monotonic. As the data used for the current study is not normally distributed, we expect the Spearman coefficient to produce results with greater significance.

Suppose, we have variables (A_i, B_i) transformed to rank variables (R(A_i), R(B_i)), then we can define the Spearman rank coefficient (ρ_s) between these variables as:

$$\rho_s = \frac{cov(R(A), R(B))}{\left[\sigma_{R(A)}\sigma_{R(A)}\right]}$$

where Cov(R(A), R(B)) estimates the covariance between R(A) and R(B) $\sigma_{R(A)}$ and $\sigma_{R(B)}$ defines the standard deviations of R(A) and R(B) If we have a sample such that all the ranks are different, then the Spearman rank coefficient (ρ_s) can be simplified as:

$$\rho_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

with $d_i = R(A_i) - R(B_i)$ as the deviation between each observation of R (A) and R(B). The correlation coefficient is bounded between −1 as anti-correlation to +1 indicating a full positive correlation.

2.5. Significance test

The significance of statistical correlation for all variables was ascertained using the probability value (p-value) analysis(Dahiru, 2011; Shih and Aisner, 2021), which estimates the degree of random relation among the variables while lies in ranges between 0 and 1. For example, a p-value of 1 implies a complete chance that the relationship between variables is random. At the same time, a "null hypothesis" portrays no significant correlation between variables, indicating a random relationship. Therefore, a near-zero P-value indicates that the null hypothesis can be discarded and there exists a substantial pure correlation among the variables. While the p-value advances towards zero, the chances that the estimated results are due to a sampling error decrease.

3. Results and discussion

3.1. Analysis to map hotspots of environmental risk factors

Fig. 1 shows a pie-chart illustrating the area-wise distribution of pollutants (i.e., NH_3, NO, NO_2, SO_2, $PM_{2.5}$, and PM_{10}) monitored across various regional or sub-station levels where it is seen that the distribution of pollutants varies significantly across the monitored region. For instance, the sectors in a darker shade of red and a darker shade of blue from the pie chart represent the highest and lowest percentage of pollutants recorded in the monitored sub-station. Fig. 1 also shows the pollutant contribution from all sub-station locations arranged in the form of ranking. For example, the average pollutant contribution of atmospheric $PM_{2.5}$ was highest in Jahangirpuri (122.8 μg/cm^3) and lowest in Shadipur (70.2 μg/cm^3), respectively. In contrast, the pollutant contribution of atmospheric PM_{10} was highest in Bawana (227 μg/cm^3) and lowest in Sri Aurobindo Marg (117.4 μg/cm^3), respectively. On the other hand, the pollutant contribution of NO and NO_2 was highest in Pusa (64.1 μg/cm^3) and Jahangirpuri (68.1 μg/cm^3), respectively, while the contribution of SO_2 was highest in Vivek Vihar (24.9 μg/cm^3). Rohini (63.3 μg/cm^3) and Mandir Marg (18.1 μg/cm^3) reported the highest and the lowest NH_3 pollutant contribution among all other sub-station locations. These findings ascertain that the pollutant distribution (and the type of pollutant) varies geographically across the investigated sub-station locations. Based on the findings mentioned above, it can be concluded that:

a) The three highest contributors of atmospheric $PM_{2.5}$ (Jahangirpuri, Bawana, and Rohini) are industrial areas of Delhi surrounded by agricultural regions, contributing towards the release of particles such as sulfate and nitrate particles, elemental and organic carbon, and soil (Goyal et al., 2021; Taneja et al., 2020). $PM_{2.5}$ is is mainly originated from chemical reactions in the fuel ignition and atmosphere. Therefore, power plants, industrial facilities, and agricultural

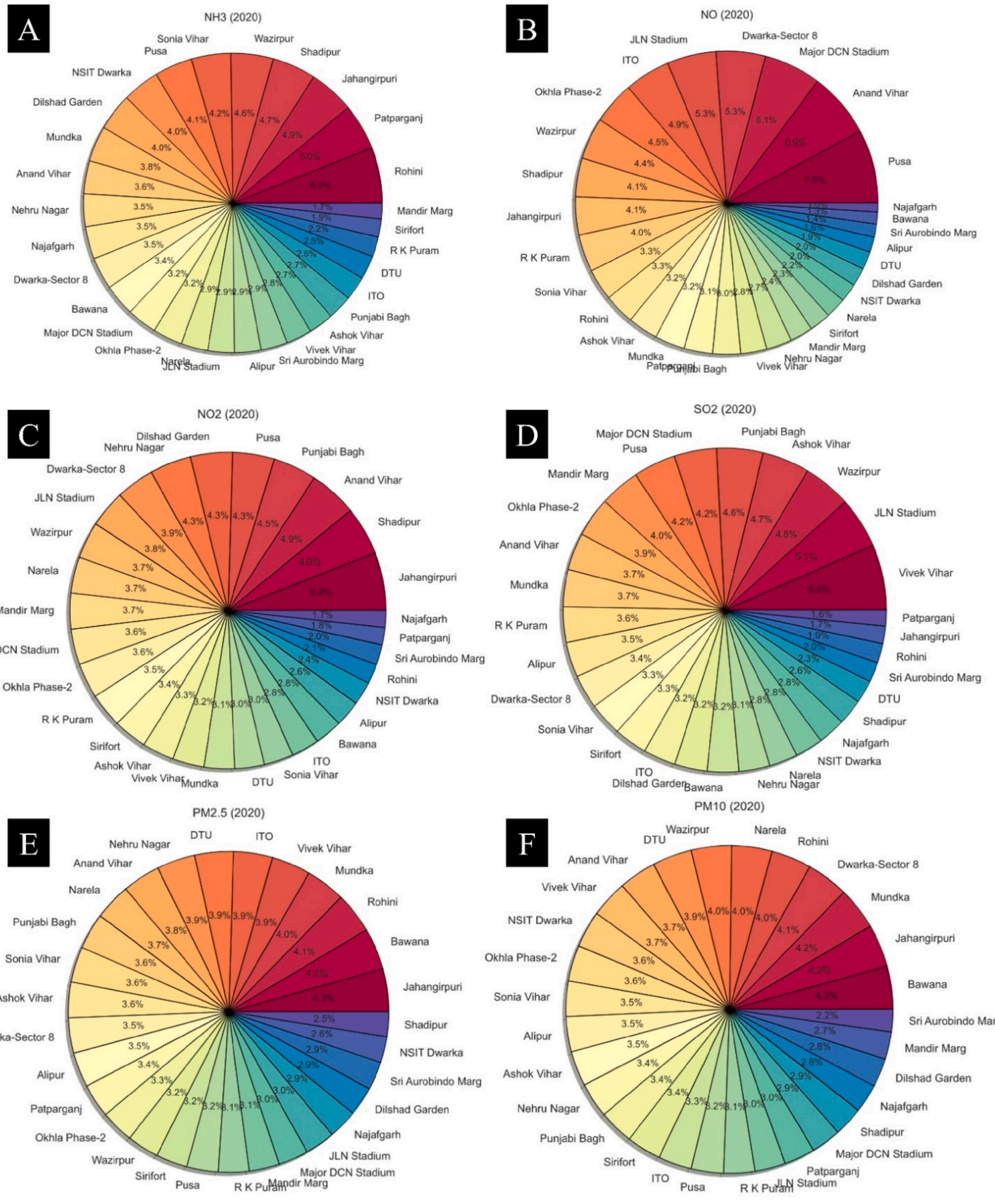

Fig. 1. Pie chart illustrating the area-wise percentage distribution of pollutants from all sub-station across Delhi.

burning in these locations can be considered major sources of atmospheric $PM_{2.5}$.

b) The three highest contributors of PM_{10} (Jahangirpuri, Bawana, and Mundka) are the industrial areas of Delhi. A study by Gargava et al. highlighted that construction and paved road dust are major contributing factors to PM_{10} (Gargava et al., 2014). Investigation of major PM10 components such as sulfates, nitrates, and toxic trace metals (i.e., Pb, Ni, V, As, and Hg) revealed that while paved road dust is the principal source of PM10, power plants (coal and natural gas-fired) are largest contributing sources of primary NO^3, Ni and V whereas industrial boilers (heavy-duty diesel fuel) contribute majorly to SO_4^{2-}, V and Ni. Besides, other studies have reported that the prevalence of PM_{10} can be associated with vehicular emissions or suspended aerosols from agricultural practices (Nigam et al., 2021).

c) Among all Delhi sub-stations, Rohini, Patparganj, and Jahangirpuri are top contributors to airborne ammonia. Primary sources of atmospheric NH_3 are from agricultural activities such as animal husbandry, nitrogenous fertilizers, manure management, and/or the different soil and water management practices (Adams et al., 2001). Other studies have reported that biomass combustion may produce an unprecedented amount of nitrogen element, which appears to be the second-largest contributor of atmospheric NH_3 after agriculture (Kuttippurath et al., 2020). Since agricultural fields surround Rohini, Patparganj, and Jahangirpuri regions, it is plausible to claim that the high contribution of atmospheric NH_3 can be attributed to the abovementioned factors.

d) The burning of fuels in vehicles at high temperatures causes nitrogen and oxygen from the air to produce nitrogen monoxide. In contrast, when the released NO from the vehicle exhaust system combines with oxygen from the air, nitrogen dioxide (NO_2) will be formed (Arshad et al., 2020). As such, it is plausible to claim that NO_2 is mainly emitted from anthropogenic emissions such as fuel combustion in traffic and industrial sectors. In the present study, regions such as Jahangirpuri, Shadipur, Pusa, and Anand Vihar contributed mainly to NO and NO_2, indicating the high vehicle dependency in these regions compared to other locations.

e) Vivek Vihar, JLN Stadium, and Wazirpur contributed mainly to SO_2 pollutants compared to other Delhi locations. The largest source of SO_2 in the atmosphere is burning fossil fuels in power plants or in vehicles and heavy equipment that burn fuel with high sulfur content. Therefore, the high SO_2 pollutants in the aforementioned regions are justifiable since they are active industrial sites (D. N. Kumar and Priyanka, 2021; Srivastava et al., 2020).

3.2. Correlation analysis

Fig. 2 shows the Spearman correlation among different variables over the pre-lockdown, lockdown, and unlock phase. From Fig. 2b, it can be seen that during the pre-lockdown phase the confirmed, COVID-19cases shows a high positive correlation with temperature (0.41, p-value $\approx 10^{-2}$) and SO_2 (0.54, p-value $\approx 10^{-2}$) with a small positive correlation with $PM_{2.5}$ (0.19), PM_{10} (0.10), NO (0.13), NO_2 (0.22) and NH_3 (0.19) and a negative correlation with relative humidity (−0.28). For the observation it can inferred that the environmental factor specially temperature and SO_2 may contributes towards the rise of, COVID-19cases. Besides, we observe that the number of COVID-19 deaths shows a negative correlation with temperature (−0.29) and SO_2 (−0.26) during the pre-lockdown phase, showing these factors although contributes towards the increase in number of covid cases but has little impact on, COVID-19deaths. During the pre-lockdown phase, we observe a positive correlation of humidity with the number of, COVID-19deaths. The magnitude of correlation of humidity with,

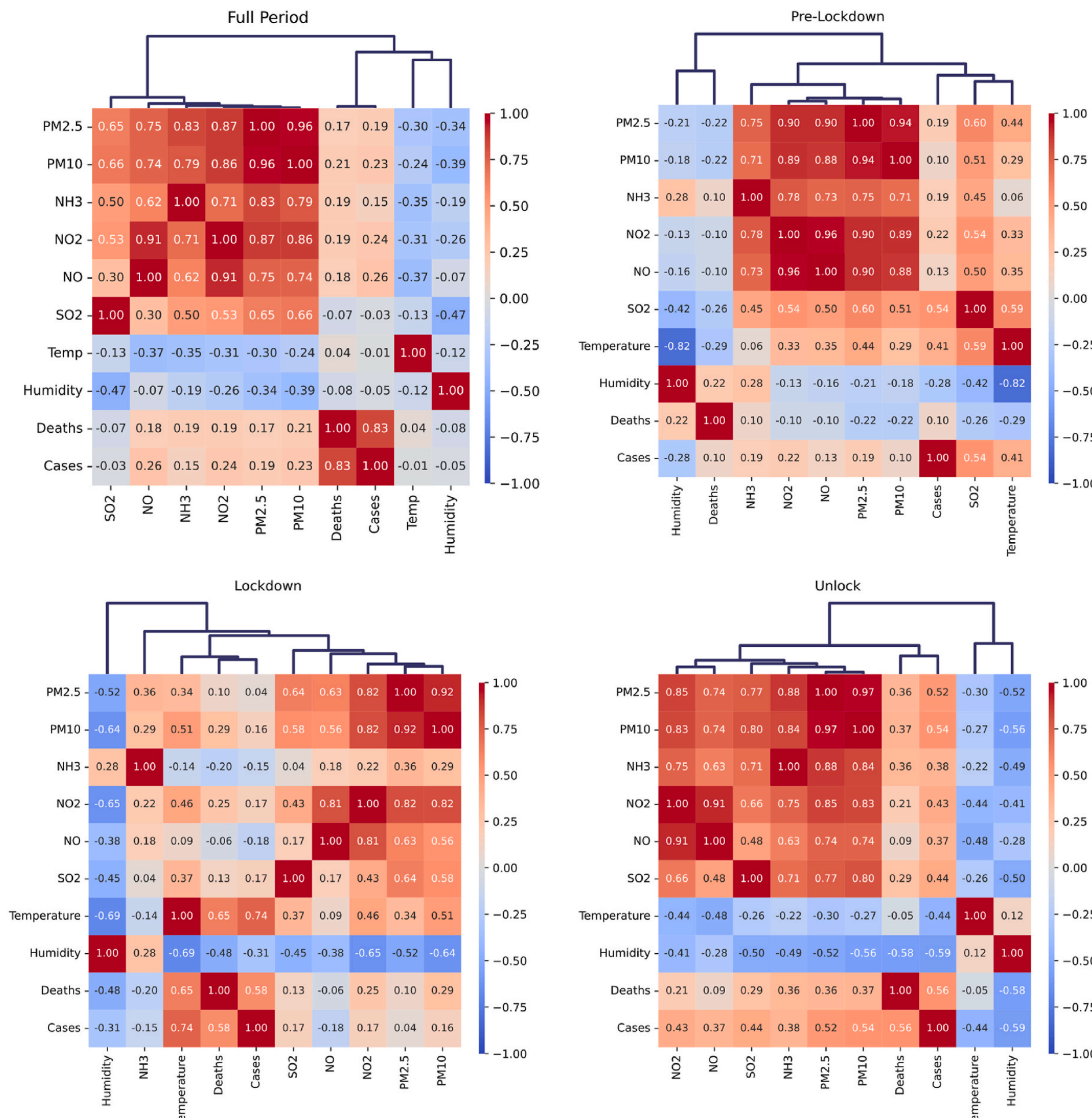

Fig. 2. Comparison of Correlation heatmap and dendrogram between variables during the pre-lockdown, lockdown, and the unlock phase along with results of full period.

COVID-19cases and deaths increases during the lockdown and unlock phase. Previous studies have reported on the role of relative humidity in the transmission of COVID-19 (Božič and Kanduč, 2021a; Mecenas et al., 2020; Salom et al., 2021; Tello-Leal and Macías-Hernández, 2021a). Secondary pollutants such as ammonia alkalize the atmosphere, which favours the transmission of COVID-19 by supporting the virus to fuse with the plasma membrane of target cells, all of which indicate the correlation between pollutant concentration and the impact during the pre-lockdown phase of COVID-19 in Delhi.

Temperature plays an important role in COVID-19cases and

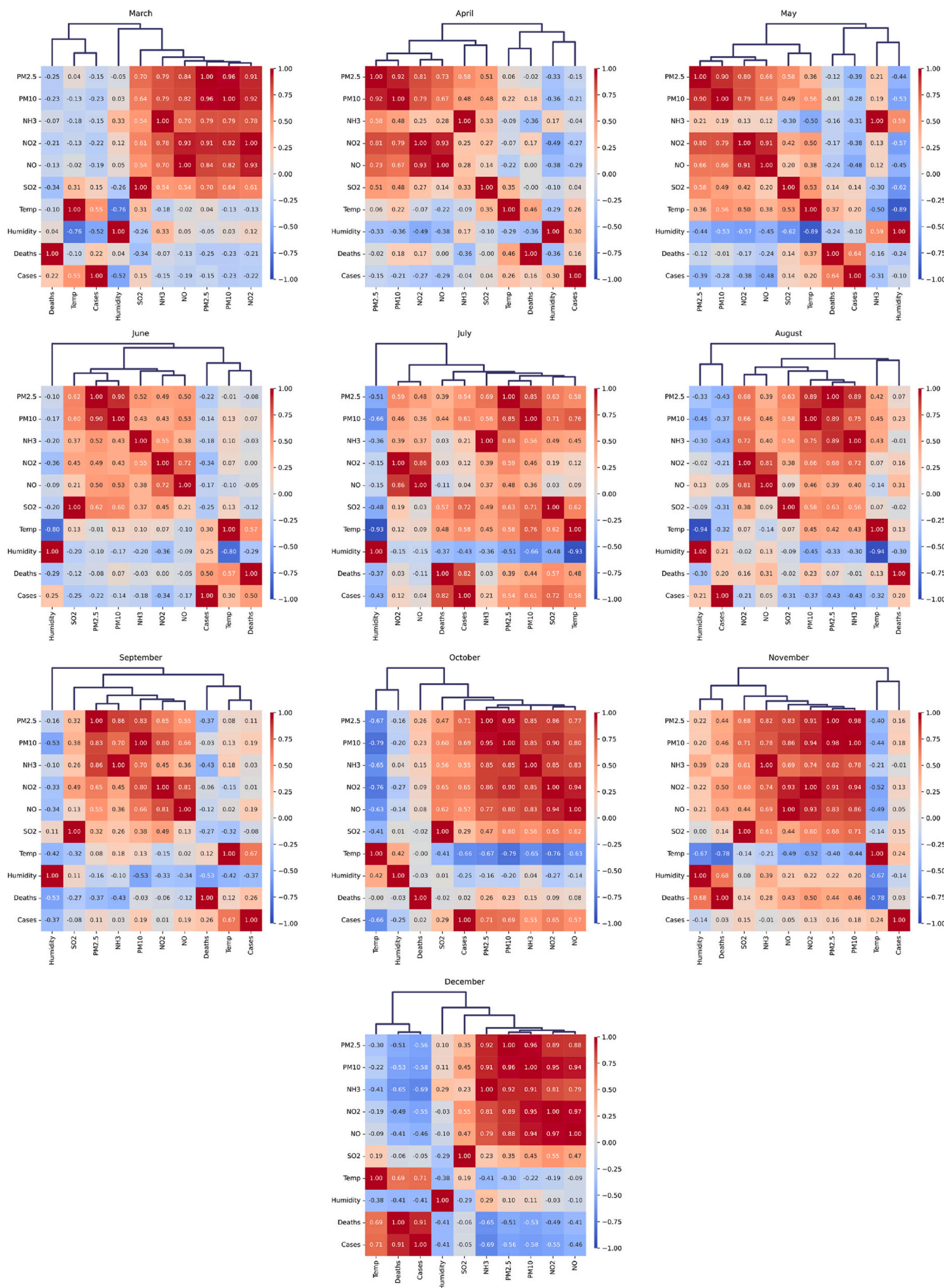

Fig. 3. Correlation heat map and dendrogram between variables for every month during the period of analysis.

mortality during the pre-lockdown and lockdown period. We observe a moderately high correlation of temperature with, COVID-19cases (0.41, p-value $\approx 10^{-2}$) during the pre-lockdown phase (January 2020 to March 2020). This is the winter period in Delhi, with a relatively low temperature. The correlation of temperature with, COVID-19 cases (0.74 p-value $\approx 10^{-10}$) and deaths (0.65 p-value $\approx 10^{-8}$) becomes highly positive during the lockdown phase. Delhi observes a moderately higher temperature during this time. Lastly, correlation of temperature with, COVID-19 cases during the unlock phase becomes highly negative (-0.44, p-value $\approx 10^{-10}$). Fig. 2c shows that during the lockdown period, COVID-19 mortality shows significant positive correlation with PM_{10} (0.29, p-value $\approx 10^{-2}$) and NO_2 (0.22, p-value $\approx 10^{-2}$). However, relative humidity and NH_3 show a negative correlation with the number of deaths during the lockdown period with correlation of -0.48 (p-value $\approx 10^{-5}$) and -0.20 (p-value $\approx 10^{-1}$) and respectively. These negative correlations, in particular of relative humidity, ascertains the hypothesis made by previous researchers that low relative humidity leads to a higher transmission and penetration rate of the viruses, which subsequently weakens human immunity (Božič and Kanduč, 2021b; Tello-Leal and Macías-Hernández, 2021b). On the other hand, virus droplets bound to $PM_{2.5}$ are highly favourable for deeper penetration in the alveolar range of susceptible individuals, leading to higher respiratory failures (Ali and Islam, 2020b; Nor et al., 2021b). As such, the substantial correlation among the pollutants and COVID-19 is justifiable.

Fig. 2d shows the correlation analysis during an un-lock period where a small significant correlation was observed between COVID-19 cases and mortality with PM, NH_3, NO_2, NO, SO_2, and relative humidity. The correlation between COVID-19 mortality with $PM_{2.5}$, PM_{10}, NH_3, NO_2, SO_2, and relative humidity are 0.46, 0.37, 0.36, 0.21, 0.29 and -0.58 respectively. However, the correlation is moderate and cannot be considered random since p-values for these correlations were less than 0·001. We also observe a high positive correlation still exists between COVID-19 cases with $PM_{2.5}$, PM_{10}, NH_3, NO_2, NO, SO_2 with correlation of 0.52, 0.54, 0.38, 0.43, 0.37, 0.44 (with p-value $\approx 10^{-10}$), which indicates that COVID-19 transmission is dependent on the PM and the pollutant concentration of Delhi environment.

3.3. Hierarchical clustering

We construct metric distances based on the Spearman correlation matrix. The metric distance between two variables (*i* and *j*) is defined as $D_{ij} = \sqrt{2(1 - Cij)}$ where C_{ij} is the correlation matrix. The elements of the distance matrix lie between 0 and 2. This distance matrix is used to create the dendrogram Fig. 2, using an average linkage hierarchical clustering algorithm. A dendrogram is a tree-like structure that shows the hierarchical clustering between the variables. It is a branching diagram showing the similarity and dissimilarity between the variables, where the variables in the same branch are similar, implying a cluster. We divide the investigation into two parts: In the first part, we analyse the effect of the restriction imposed by the government. In this case, the full period is divided into three parts: pre-lockdown, lockdown and unlock period. Dendrogram plots, along with the correlation heat maps for three periods and the full period, are shown in Fig. 2. The second part takes the monthly data and compares the monthly dendrograms in Fig. 3. It is found that the dendrogram of the full period Fig. 2a shows that there are three clusters based on the properties of the variable. These clusters depend on the variable class as the most prominent cluster is the pollutant cluster, including all pollutants (such as $PM_{2.5}$, PM_{10}, SO_2, NO_2, NO, and NH_3). The second cluster is the weather variables (Temperature and Humidity), and the third cluster is the COVID variables (Cases and Deaths). It can be observed that:

- There is a change in cluster structure during the three time-periods.
- The Pre-lock down, the pollutants are still in one cluster except for SO_2, with temperature and COVID cases forming the second cluster. The deaths and humidity are in the third cluster. Indicating, COVID deaths are closely linked with the relative humidity, whereas as there is a relation between the rise in COVID cases and temperature.
- In the lockdown phase, COVID-19 cases and mortality are in the same cluster as temperature, implying that temperature significantly correlates with COVID-19 cases and mortality, possibly making the infection more contagious.
- During the unlock phase, the cluster structure is restored as the full period, and clusters are again based on the variable class (pollutant, weather or COVID).

In the second part of the hierarchical clustering, we perform monthly analysis of the system, and we observe that:

- During March (Fig. 3a), death and cases are closely related to temperature, and to some extent with humidity Therefore, the system can be divided into two clusters: the first cluster contains all pollutants, whereas the second cluster contains the weather and COVID variables.
- In April (Fig. 3b), when the first COVID wave hit Delhi, we got three clusters, where the COVID cases and humidity were in one cluster, deaths and temperature were in the second, and the pollutant in the third. It can be concluded that temperature affects deaths, whereas humidity significantly affects COVID cases.
- There is a change in the cluster structure in May which is the lockdown period (Fig. 3c), where the COVID-19 cases and mortality are in a separate cluster from pollutants. The separation of COVID-19 cases and deaths as an independent cluster can be attributed to the strong lockdown restrictions imposed on the public, where they were constrained to remain at their home, thus terminating the chain of transmission.
- During June (Fig. 3d), lockdown was lifted partially, we observe that role plays a vital role in COVID deaths and cases. During this time Delhi, observe a high temperature period.
- During July (Fig. 3e), we observed that some of the pollutants, such as SO_2, $PM_{2.5}$, and PM_{10} are closest to the COVID variables. However, after July, the pollutant as well as the COVID variable again separates from each other.
- From August till December (except the month of October), we see that the COVID variables are closely related to the weather conditions and forms a cluster with each other. Temperature is considered closely related with COVID variables.
- During the month of October, we observe that the COVID cases as well as COVID related deaths are clustered with the pollutant. During this period, Delhi suffers a high pollutant due to the excess of stubble burring around the around the farmland in Delhi. Stubble burning which is a seasonal problem contributes about 20%–50% of the Delhi air pollution.

3.4. Correlation threshold network

The threshold method uses the threshold to construct the threshold network from the Spearman correlation matrix. The variables in the system are represented as nodes, whereas the correlation represents the connection among variables. When correlation coefficient exceeds a given threshold value, we connect the variables by a link. In our construction, the variables in the system (pollutants, weather and COVID) define the set of Vertices/Nodes (V = {$PM_{2.5}$, PM_{10}, SO_2, NO, NO_2, NH_3, temperature, humidity, COVID cases, and COVID deaths}). The links (E) in the network G(V, E) are based on the threshold values ($0 \leq \theta \leq 1$), where we add a link between the nodes, say *i* and *j* , if $C_{ij} > \theta$. Mathematically the edges E are defined as

$$E = \begin{cases} e_{ij} = 1, if\ i \neq j\ and \left|C_{ij}\right| \geq \theta \\ e_{ij} = 0, otherwise \end{cases}$$

Different threshold values generated a different network, with the same nodes but a different set of connections between the nodes. With the increase in the threshold, the network becomes more and more sparse, and links with strength less than the threshold are dropped.

We constructed the network using four different thresholds [θ = (0.1, 0.3, 0.5, 0.7)] for three time-periods: pre-lockdown, lockdown, and unlock. The comparison between the three periods at different thresholds is shown in Fig. 4. It can be observed that:

- At all thresholds and time periods, pollutants show a high connectivity level, with $PM_{2.5}$ and PM_{10} playing the central role.
- At low thresholds, COVID deaths and cases show a relation with the pollutants, especially $PM_{2.5}$, PM_{10}, SO_2, humidity, and temperature.
- In the pre-lockdown period, at intermediate thresholds (0.3, 0.5), COVID-19 mortality seems isolated and unrelated to any other variables. The same is observed for the unlock period at the 0.5 threshold. However, during the lockdown period, COVID-19 mortality shows a good dependence on the temperature and humidity.

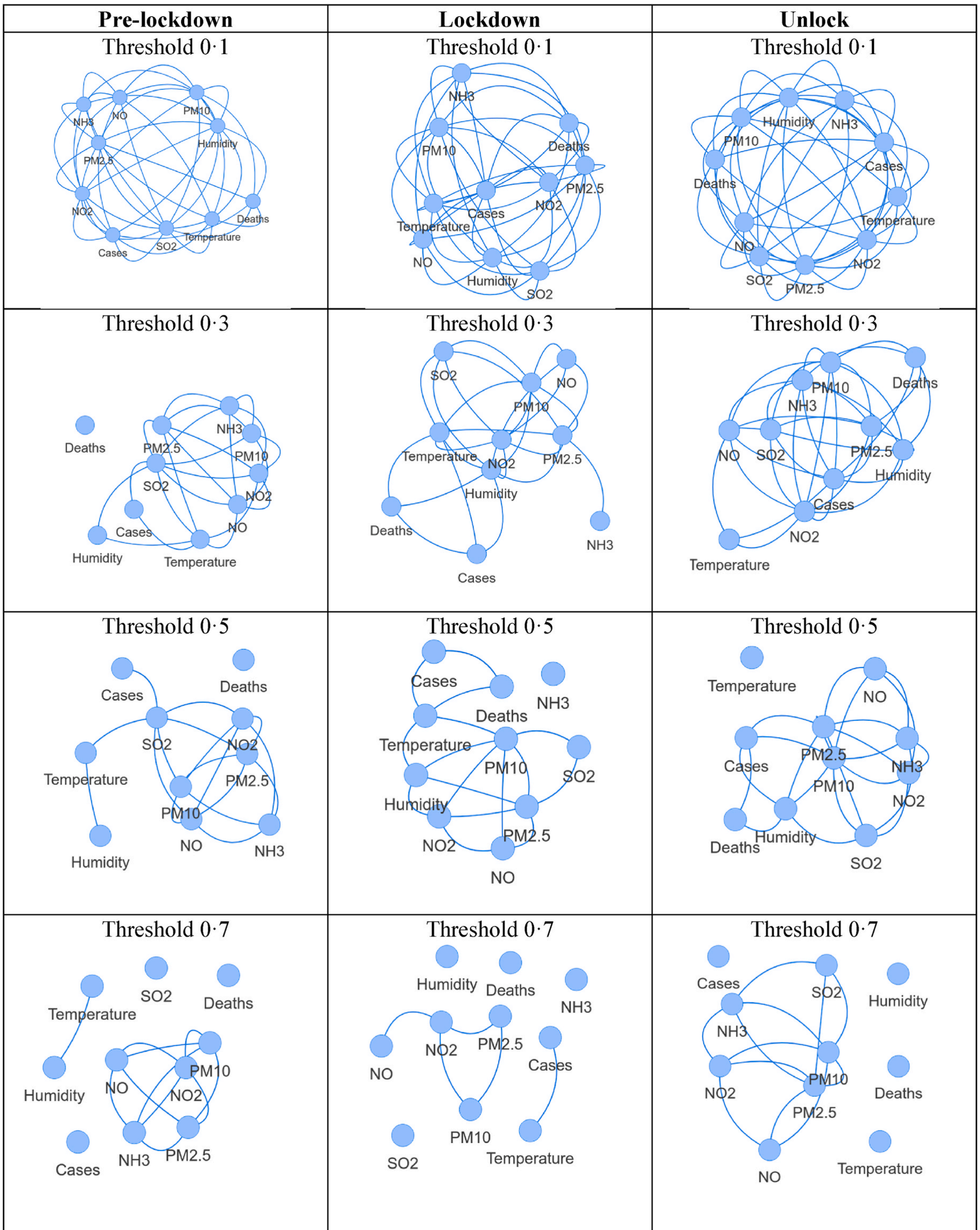

Fig. 4. Network at different threshold during pre-lockdown, lockdown and unlock phase.

- COVID-19 cases always show a relation with the temperature and humidity at low and intermediate thresholds. This relation disappears at higher thresholds ($\theta \geq 0.7$). However, COVID-19 cases also show a relation with SO_2 at the low and intermediate threshold for the pre-lockdown period. The reason for such a relationship is not yet known.
- We can see only two components for most of the threshold range for all three periods. The most significant component is made up of pollutants, and the other component is made up of COVID-19 and weather variables. This observation shows that climatic conditions significantly impact the spread and lethality of the SARS-CoV-2.

4. Conclusions

- In conclusion, the present study employed statistical correlation analysis to establish connections between various environmental variables, including pollutant concentration, relative humidity, and secondary contaminants, with the transmission, reported cases, and mortality during the COVID-19 wave. The study yielded several key findings, which are summarized as follows:The study successfully identified hotspots of airborne pollutants in different locations in Delhi, India, by mapping ambient pollutant concentrations. Major construction work, vehicle exhaust emissions, and industrial activities were associated with primary pollutant hotspots, while ammonia hotspots were linked to agricultural activities. Additionally, the hotspots of particulate matter (PM) were found to be related to the constituent trace elements.
- During the pre-lockdown period, there was a moderate positive correlation (>0.4, p-value $\approx 10^{-2}$) between the intensity of COVID-19 and temperature, which increased during the lockdown phase, demonstrating a very high correlation (correlation value of 0.74) with higher statistical significance (p-value $\approx 10^{-10}$). Relative humidity showed a small negative correlation (−0.28) with COVID cases and a positive correlation (0.22) with COVID deaths during the pre-lockdown phase. However, during the lockdown phase, the correlation between humidity and COVID cases and deaths increased in magnitude (−0.31 and −0.48, respectively). This suggests that relative humidity may play a potential role in SARS-CoV-2 transmission, possibly through its impact on immunity, receptor cell binding, and aerosol formation for secondary transmission.
- . Significant correlations (r = 0.29 and 0.22) were found between COVID-19 cases and mortality with PM10 and NO2, respectively, during the unlock phase, highlighting PM as a significant risk factor that exacerbates the severity of the COVID-19 outbreak. The trace elements comprising PM were also identified as potential contributors to increased COVID-19 morbidity and mortality.
- The study's demonstrated the effectiveness of lockdown and movement restrictions in reducing ambient pollutant concentrations in Delhi. This reduction was attributed to decreased emissions from transportation, industrial sectors, and agricultural activities during the lockdown period.
- Hierarchical clustering and threshold network analyses were used to explore the relationships between variables, dividing them into three categories: COVID variables, weather variables, and pollutants. A close association was observed between weather and COVID variables, which was visually evident through the Dendrogram and threshold network. The significance of these relationships was quantified by the network's threshold, with links present at higher thresholds indicating higher significance
- The study revealed the significant contribution of pollutants to COVID cases and deaths, particularly during the high air pollution season in Delhi, such as the period of stubble burning in October.
- Nevertheless, the resulting economic crisis and the degrading mental health of confined people are the foremost associated concerns.

Although the decline in air pollutants was observed in one of the most highly polluted cities globally, it is worth noting that the livelihoods of many people were affected significantly due to the lockdown measures in response to the COVID-19 pandemic. Nevertheless, the study outcomes highlight the importance of strategizing techniques to reduce vehicular, industrial, and agricultural emissions to improve air quality levels and sustain better public health globally. Moreover, it is the first attempt to understand airborne trace element role as particulate matter constituents in COVID-19 morbidity and mortality. The study opens new prospects for understanding the spatial and temporal variation of COVID-19 severity and mutations in SARS-CoV-2 in interaction with airborne trace elements as particulate matter constituents.

Author's contribution statement

P.B., Analysis, V.C., Writing - Review & Editing, K.M.: Conceptualization and methodology, R.K.T.: Editing, S.A. investigation, K.N., Editing., M.T., supervision and validation., A.K.: Formal analysis and resources., supervisions, S.R.: Conceptualization, M.K.: Writing - Review & Editing.,and All authors have reviewed and accepted the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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