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Research Article

Keywords: COVID-19, Air quality index, Lockdown, Mortality, Analytical Neural Network

Posted Date: April 6th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-283652/v1

Version of Record: A version of this preprint was published at Soft Computing on July 13th, 2021. See the published version at https://doi.org/10.1007/s00500-021-06012-9.

Weather Indicators and Improving Air Quality in Association with COVID-19 Pandemic in India

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Abstract

The COVID-19 pandemic enforced nationwide lockdown, which has restricted human activities from March 24 to May 3 2020, resulted an improved air quality across India. The present research investigates the connection between COVID-19 pandemic imposed lockdown and its relation with present air quality in India; besides, relationship with climate variables and daily new affected cases of Coronavirus and mortality in India during the lockdown period has also been examined. The selected seven air quality pollutant parameters (PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2, NH_3 and O_3) at 223 monitoring stations and temperature recorded in New Delhi were used to investigate the spatial pattern of air quality throughout the lockdown. The results showed that the air quality has improved across the country and average temperature and maximum temperature were connected to the outbreak of the COVID-19 pandemic. This study will assist the policy practitioner, researcher, urban planner, and health expert to make suitable strategies against the spreading of COVID-19 in India and abroad.

Keywords: COVID-19; Air quality index; Lockdown; Mortality; Analytical Neural Network

1. Introduction

The Coronavirus-induced lockdown has a remarkable influence on pollution in the world's second-largest populated country, India. Soon after the nationwide lockdown[1], the scientific community raised ed a question: Does the COVID-19 pandemic lockdown situation improve air quality, especially in cities and industrial corridors? (Wright 2020). The scattered empirical evidences have been suggested that, paradoxically, the impact of the COVID-19 pandemic has improved air quality around the world, for instance, China, France, and Italy (Yunus et al. 2020) (ESA, 2020). The National Aeronautics and Space Administration (NASA) has first reported that lockdown has reduced the aerosol and nitrogen dioxide over Wuhan in China (NASA 2020). Then, the European Space Agency (2020) had been continuously reported that in Italy, Spain, and France emissions reduced by 20 to 30% during the month of March 2020 due to the lockdown situation (ESA 2020). (Tobías et al. 2020) found that air pollutant materials decreased significantly during the two-week lock-down period for example, PM10 decreased by 28 percent to 31.0 percent and nitrogen dioxide decreased by 45 percent to 51 per cent; on the contrary, Ozone gas increased by 33 percent to

[1] Indian lockdown is the world larges lockdown because of its population size and entire country wide lockdown at a time on 24th March to 3th May, 2020. It is also the lockdown in world largest democracy.

57 percent in Barcelona.During the pre-locked down period, India had the top twenty polluted cities in the world (Majumdar et al. 2020) with the maximum cities that crossed the tolerant breathing limit of pure air in India (Central Pollution Control Board, 2019). (Majumdar et al. 2020) also found that both particulate matters and gaseous pollutant have caused serious health problems in various cities in India, especially in Delhi, Kanpur, Kolkata, Bengaluru and Mumbai. (Balakrishnan 2019) found that in India, more than one million premature deaths have occurred due to various air pollutants. India has one of the utmost rates of respiratory problems and the world's maximum number of tuberculosis (Wright 2020). (Garaga et al. 2018) estimated the regional average concentration of $PM_{2.5}$ in India and found that north has 3.3 $\mu g/m^3$ and, east, west, and south India has respectively 3.3, 3.7, 2.3, and 1.6 $\mu g/m^3$. Moreover, as a developing country, India has experienced large scale urbanization; therefore, pollution is a clear result of urbanization and its associated phenomena.

The COVID-19 pandemic driven lockdown has changed the air quality in India. All cities in India , experienced a decline the concentration of particulate matter during the lockdown phase. This is mainly contributed due to the less number of motor vehicles and roadside food-vendors who use coal cook stoves which are the important sources of pollutant in Indian cities. In a recent paper, (Sharma et al. 2020) found that there is a 43% decrease in $PM_{2.5}$ and 18% decrease in NO_2 in India during the first half of lockdown stage compared to earlier years. (Mahato et al. 2020) established that the intensities of PM_{10} and $PM_{2.5}$ maximum reduction is . more than 50% during this lockdown period. They also observed that the air quality is improved by 40% to 50% during the four days of the lockdown.Moreover, (Huang et al. 2020) found that NO_2 in the atmosphere over the eastern parts of China had decreased by approximately 65% in comparison to the previous year.

However, it has been noticed that COVID-19 affected patients have similar symptoms to other affected illnesses, e.g. cough, fever, respiratory disorder, and pneumonia. It has been found that the growth of other Coronavirus has significant relation with increase or decrease in temperature in the region. (Bashir et al. 2020b) analyzed the COVID-19 outbreak in the New York City with daily temperature, humidity, wind speed, and air quality; and according to their finding ingrowth of COVID-19. The affected people has positive correlation with minimum temperature and air quality. (Dalziel et al. 2018a) found the similar results that the influenza health epidemic follows a seasonal pattern of the climatic parameter; after the end of rainy and summer season's infection related health epidemic generally followed the

increasing trend. Dalziel et al. (2018a) also found that the spatial variation of humidity differentiation in the incidence of influenza in the USA. The seasonal fluctuation of humidity leads to the seasonal outbreak of influenza, especially in winter. (Tan et al. 2005) analyzed the relationship of SARS outbreak and daily temperature in the major cities of China and they found that 16˚C to 28˚C, was the suitable condition for the growth for SARS virus. A sharp decrease in average temperature or towards cold weather lead an increase or outbreak of SARS virus to affect patients. Therefore, it has the high probability to other SARS group virus which would follow the same kind of spread in dynamically related to temperature and humidity. Moreover, the weather phenomena have a close relationship with the human immune system. However, meteorological parameters such as wind speed and direction also affect the increase and transition of transferable syndromes (Ma et al. 2020). In recent work, (Ahmadi et al. 2020) found that the sensitivity of COVID-19 epidemic in Iran is associated with the wind speed, humidity, solar radiation, and population density. The authors also revealed that suitable climatic condition, particularly humidity in Tehran and Mazandaran province increase the virus affected populations compared to the rest of Iran. Incidentally, (Van Doremalen et al. 2020, p. 1) found that SARS virus can remain active for three hours on aerosol, thereby there is a high chance of transmitting the virus with the direction of wind flow. Similarly, (Chen et al. 2020) found that the climatic model with relative humidity, wind speed and temperature were highly associated with COVID-19 pandemic. Further, (Contini and Costabile 2020) stated that the concentration of $PM_{2.5}$ and PM_{10} in the air with biological, physical and chemical analysis could explain the observed mortality in various parts of the World.

Considering the close relationship with different climatic indicators with Coronavirus along with nationwide lockdown's impact on air quality in India,the aim of the present research is to critically explore the connection between COVID-19 imposed lockdown and air quality across India during the pre-lockdown and lockdown period.

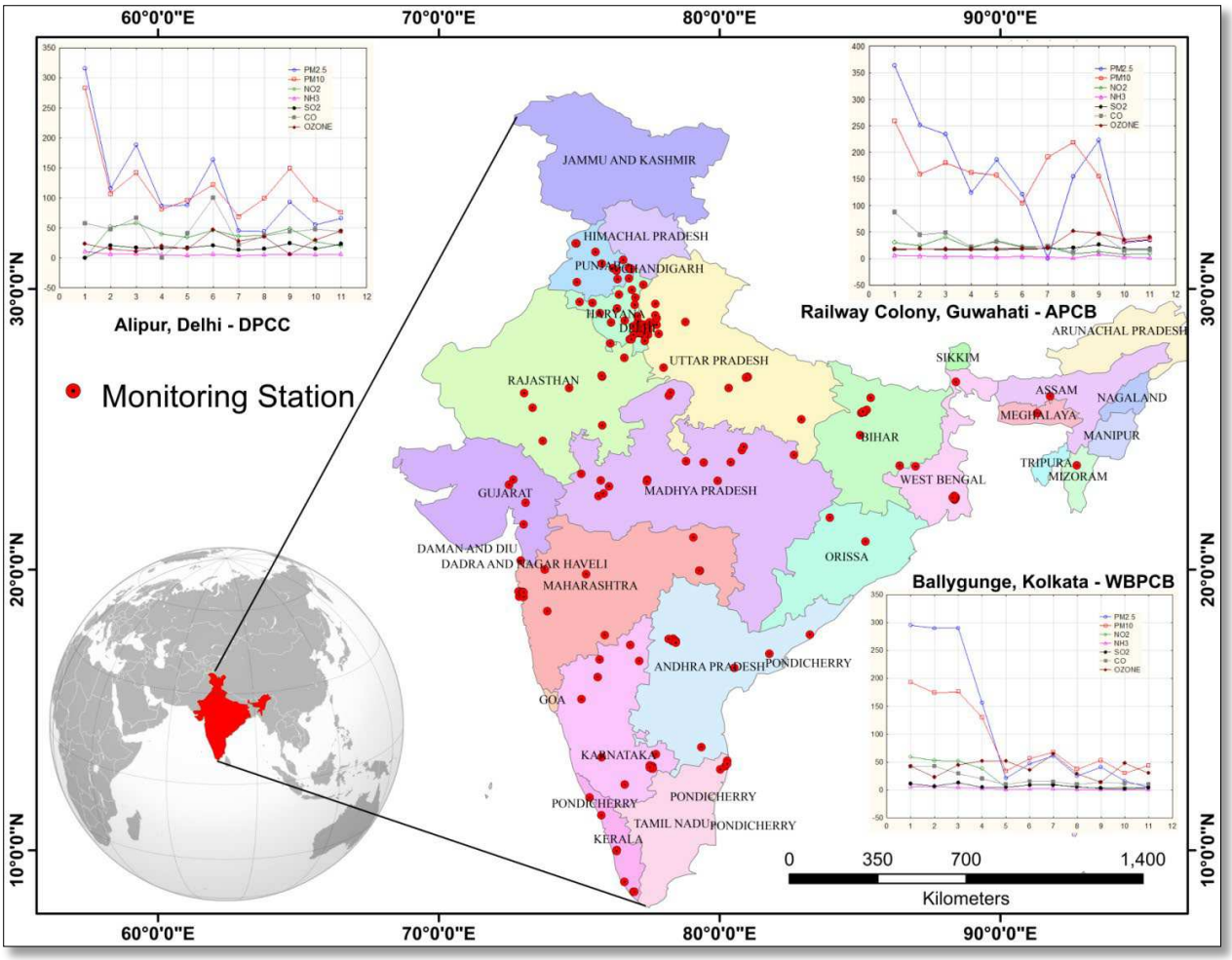
2. Study area

The present study has focused in India; due to the huge variations of latitude (8°4'N to 37°6'N), longitude (68°7'E to 97°25'E) and varying physiography, India's climate has a broad variety of weather conditions. The climate of India differs from tropical to subtropical humid, with most of the area's average temperature varies from 10°C to 40°C throughout the year.

The rainfall of the country varies about 100 to150 cm and the country received the maximum amount of rain during the monsoon season. It is well known fact that subtropical climatic conditions are also responsible for different types of diseases.

Moreover, India has 1.3 billion populations and 31.16% lives in fifty-three urban agglomerations spreading across the country, whereas the rest of the population (68.16%) lives in the rural areas (Census of India 2011). In the recent decade, India has been experienced a positive increase of urbanization and economic growth (Gurjar et al. 2016), which combinedly make the country one of the largest greenhouse gas emitters, therefore, people are facing air pollution-induced problems in everyday life. (Pant et al. 2020, p. 19) mentioned that air quality always remains as significant environmental and health hazard problems in Indian megacities.

In addition, being a highly populated developing country, the country's health infrastructure does not have that much capacity to facilitate this huge population. Whereas, India suffers from poverty and a large number of families without access to basic health care services, which hinders people's health condition. The poor infrastructures lack of medicine, beds and limited resources are common phenomena in the government-aided hospitals throughout the nation. On the other hand, private hospitals have better infrastructure that is too expensive and almost inaccessible for a low-income group of poor families. According to WHO's (WHO) guidelines, doctor population ratio should be 1:1000 but in India, it is 1: 1457. Therefore, the number of doctors is far less than that is required in India. As a result of this, India is suffering to overcome the new challenges in medical and health sciences. Figure 1 shows the map of the study area with point location of data sources.



< Figure 1. Map of the study area with point location of data sources >

3. Materials and Methods

3.1. Analytical Neural Network (ANN)

The ANN is a machine learning technique, connectionist system motivated by the research of biological neurons (Hewitson and Crane 1994; Levine et al. 1996). A self-learning method employs the ANN model to self analyze the associations among multi-source data (such as combines of qualitative and quantitative information) and to determine the region more likely to trigger air quality index under certain predetermined geo-environmental circumstances. Furthermore, this method may create links to linear or nonlinear projection methods to a satisfactory precision (Licznar and Nearing 2003). ANN's are commonly used in their capability to model the dynamic process and identify the trends in science and technological problems (Jain et al. 1996; Cracknell and Reading 2014).

An *ANN* method was constructed with considering different air quality parameters as input or covariates, and air quality index (AQI) observed dependent factors. Here a multi-layer

perceptron neural network classifier has been developed using the covariates referred e.g. PM 2.5 (μg/m^3), PM 10 (μg/m^3), NO_2 (μg/m^3), NH_3 (μg/m^3), SO_2 (μg/m^3), CO (mg/m^3) and Ozone (μg/m^3) were considered. Hyperbolic tangent was considered for the development of the model for hidden layer initialization, and identity function was considered for the activation of the output layer. Hyperbolic tangent function takes real-valued arguments of inputs ($x_1, x_2, \ldots, x_n$) and transforms them to the range (–1, 1) through Eq. 1.

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (1)$$

The identity function is a linear function (Eq. 2) that obtains real-valued arguments of hidden layer and precedes them unaffected.

$$f(x) = x \qquad (2)$$

There is also a supplementary neuron component, named w_0, identified as the bias that can be taken as a synapse connected with an input $Aqf_0 = -1$. The output of the neuron AqI_n(air quality index) is supported on the creation among input vector $Aqf\ (Aqf_0, x_1, x_2, \ldots, x_n)$ and vector $w\ (w_0, w_1, w_2, \ldots, w_n)$ composed of synapses, with the bias (w_0), The following equations (Eq. 3 and Eq. 4) were considered to make the *ANN* method.

$$Aqf \times w = \sum_{n=0}^{i} Aqf_n \times w_n \qquad (3)$$

Where; Aqf are the components of air quality ($Aqf_n = Aqf_0 \ldots\ldots Aqf_i$), w is the synaptic influence allocated for individual Aqf($w_n = w_0 \ldots\ldots w_i$).

$$AqI_n = \varphi(Aqf \times w) \qquad (4)$$

Where, φ is the establishment role value and AqI_n is the air quality index.

3.2. Air Quality Index (AQI)

According to the Millennium Development Goals, sustainable management is essential for a nation to progress under crucial conditions.As a measure, AQI records pollutants from the monitoring station in the surrounding air. AQI make awareness on the public by providing information about the risk of daily pollution level and on the other hands helps to take immediate measure for this impact on the environment (Ghorani-Azam et al. 2016). It represents the consistency of the air using colour schemes, graphics and graded as , good, satisfactory, moderate, poor, very poor and severe.Maximum air pollution and related diseases are indicated by the high value of AQI. Removing complexity, eclipse and stiffness,

traditional measurement of AQI based on individual contaminants to the norm using the effective aggregation process. (Swamee and Tyagi 1999). (Sharma et al. 2020) stated, AQI used maximum sub-indices using such five pollutants (PM_{10}, $PM_{2.5}$, SO_2, NO_2, and CO). The National Ambient Air Quality Monitoring Programme includes seven new parameters which included $PM_{2.5}$, Ozone (O_3), Ammonia (NH_3), Benzene (C_6H_6), Benzo (a), pyrene (BaP), Arsenic (As) and Nickel (Ni). And rests of parameters are Sulfur dioxide (SO_2), Nitrogen Di Oxide (NO_2), particulate matter size less than 10 microns (PM_{10}), Lead (Pb) and Carbon Monoxide (CO) respectively. Among twelve parameters, the three parameters have the annual standard (annual avg.), six parameters have annual standard and short term (annual avg./24hr) and O_3, CO has only short term (1hr/8 hr/24hr). The current research work has aimed by presenting an integrated index of analyzing on seven pollutants ($PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO and O_3) individually in the lockdown period compared to pre-lockdown period and also indicate future condition depending on this trend.

For estimating AQI, an established method by the Central Pollution Control Board (CPCB), Govt. of India has been followed throughout the study. The AQI has been estimated by considering the major pollutants ($PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO and O_3). All monitoring stations across India and its recorded pollutant have been considered in the present study.

There are two steps to calculate AQI i.e. the first one is to formulate the sub-indices and the second one is the amalgamation of sub-indices to acquire AQI.

Further the sub-index functions were used to formulate sub-indices for n numbers of pollutants; mathematically it is expressed as,

$$I_i = f(X_i), i = 1,2,\ldots.,n \qquad (5)$$

Amalgamation of sub-indices to acquire AQI is done using some numerical function, i.e. expressed as,

$$I = F(I_1, I_2, \ldots., I_n) \qquad (6)$$

The relationship between sub-index (I_i) and pollutants concentration (X_i) expressed as,

$$I = \alpha X + \beta \qquad (7)$$

Here, α indicates slope of the line and β indicates intercept at X=0

On the other hand, sub-indices (I_i) for a identified pollutant attentiveness (C_p) are expressed as,

$$I_i = [\{(I_{HI} - I_{LO}) / (B_{HI} - B_{LO})\} \times (C_P - B_{LO})] + I_{LO} \quad (8)$$

Here, B_{HI} indicates cut-off point attentiveness ≥ known attentiveness; B_{LO} indicates cut-off point attentiveness ≤ known attentiveness; I_{HI} means AQI value equal to B_{HI}; I_{LO} means AQI value equivalent to B_{LO} and Cp specify pollutant concentrations.

Thereafter, weighted additive value was calculated to amalgamation of sub-indices and expressed as,

$$I = Aggregated\ Index = \sum W_i I_i (for\ I = 1, \ldots, n) \quad (9)$$

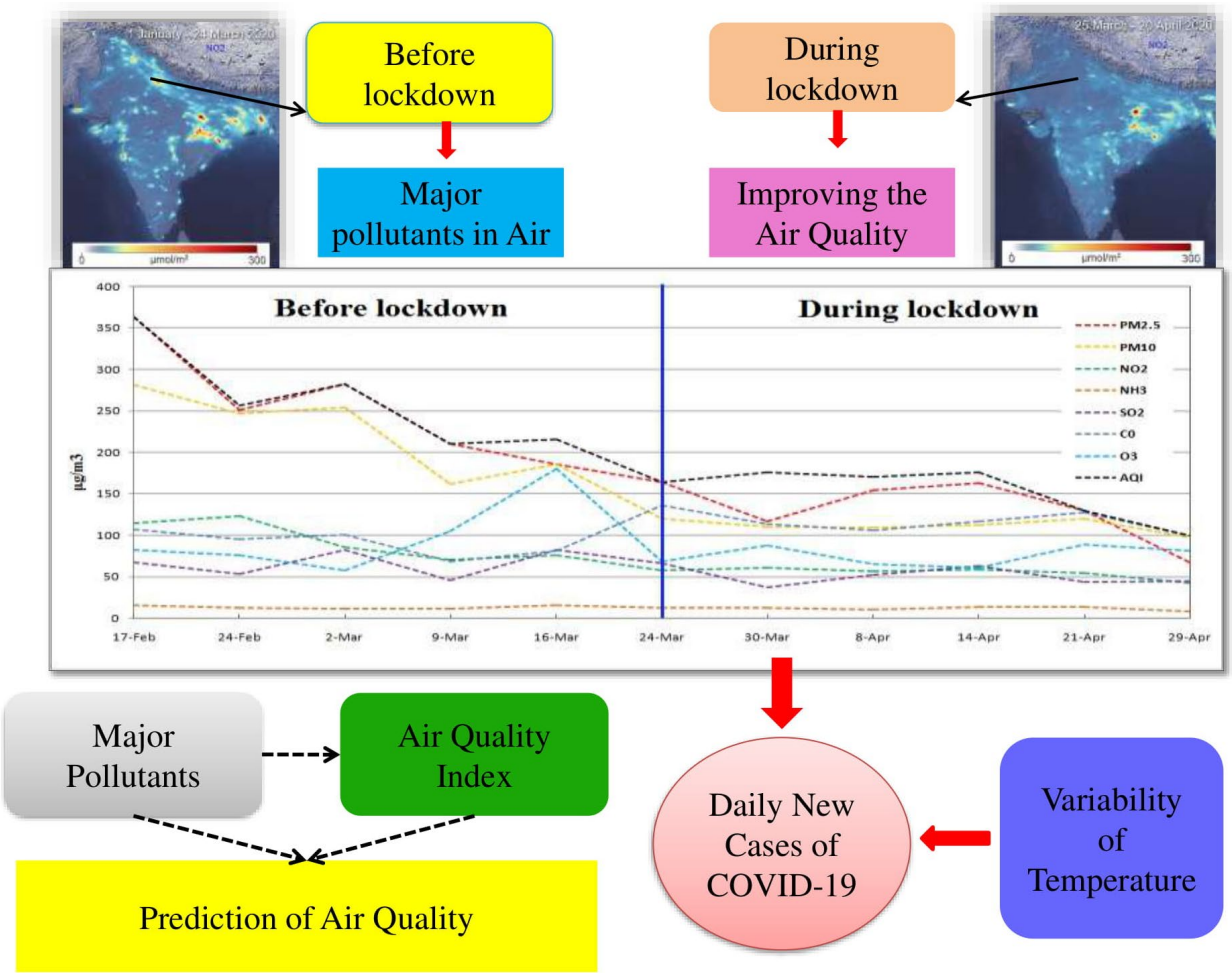
Here, $\sum W_i$ equals 1, I_i indicates sub-index of pollutant I, n indicates amount of different pollutants, and W_i means influence of the pollutant .

Minimum or maximum operator form are expressed as (Ott 1978):

$$I = Minimum\ or\ Maximim\ (I_1, I_2, I_3, \ldots n) \quad (10)$$

3.3. Kendall and Spearman Rank Test

We have done the probability distribution of various climatic condition and definite cases of COVID 19 with the help of Kendall test and Spearman correlation. This non-parametric method has also been applied because the distribution has followed the normal probability distribution (Taylor 1987). Finally, the Figure 2 shows the methodology flow chart used in this research.

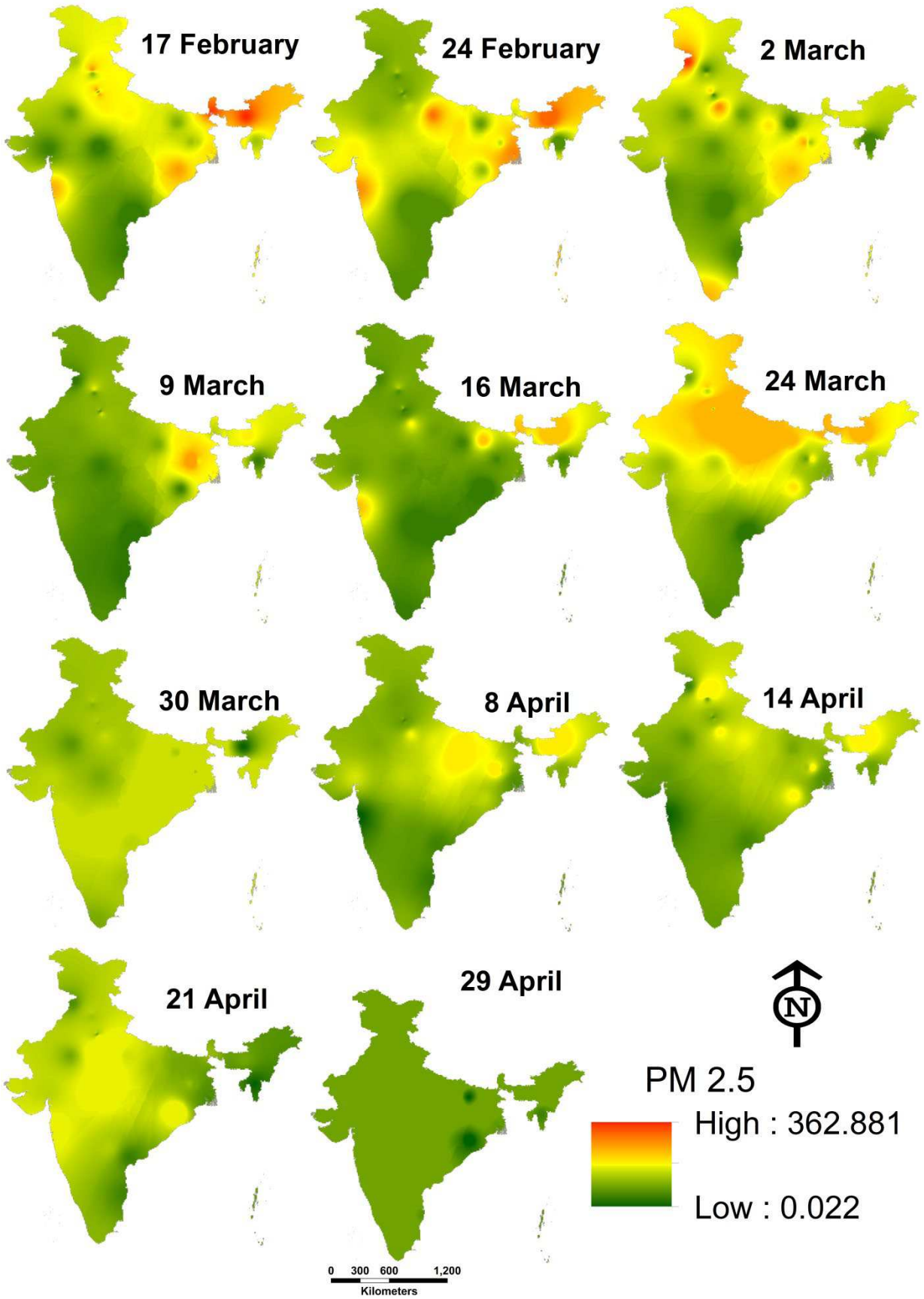


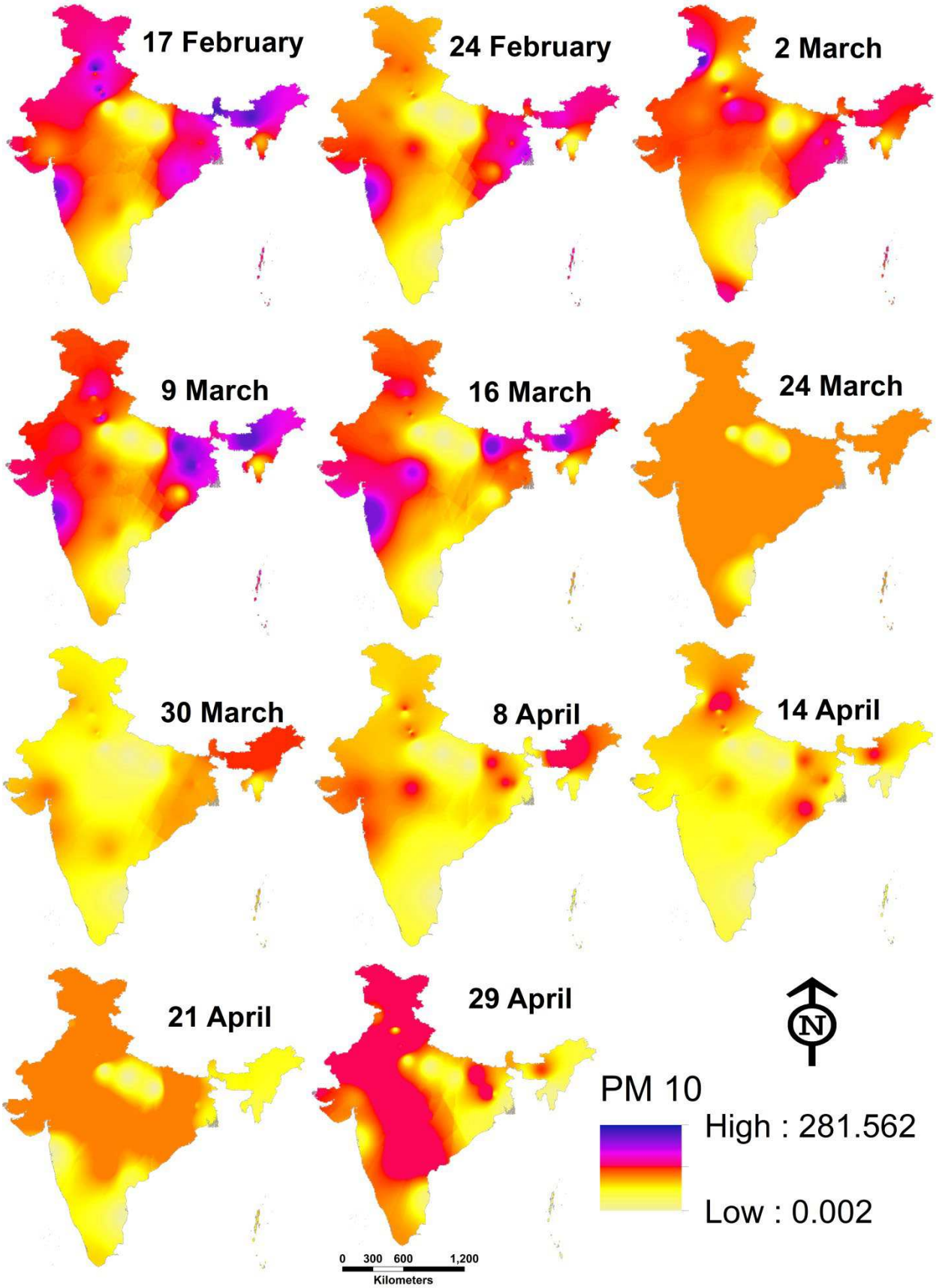
< Figure 2.Methodology flow chart.>

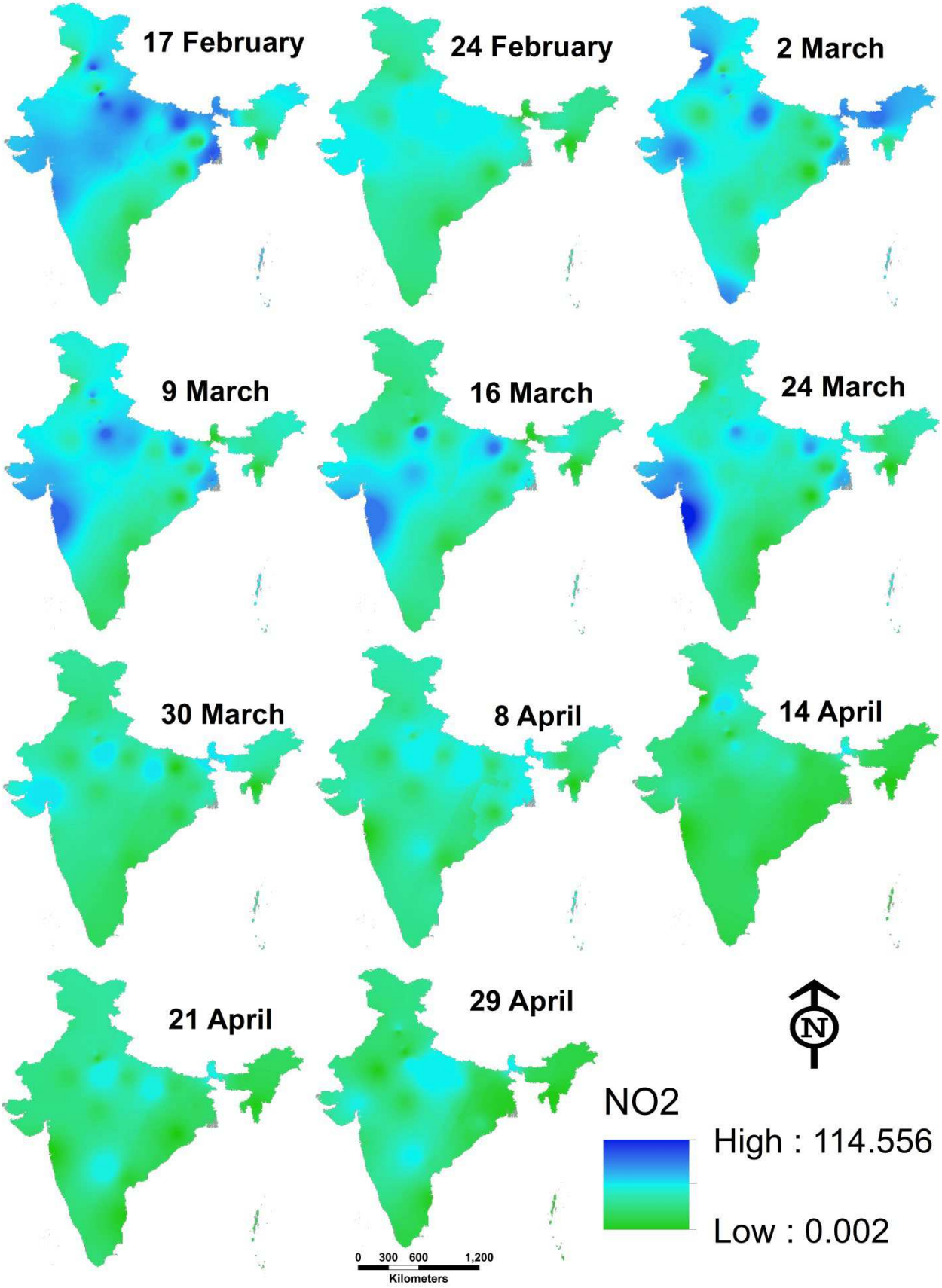
4. Results

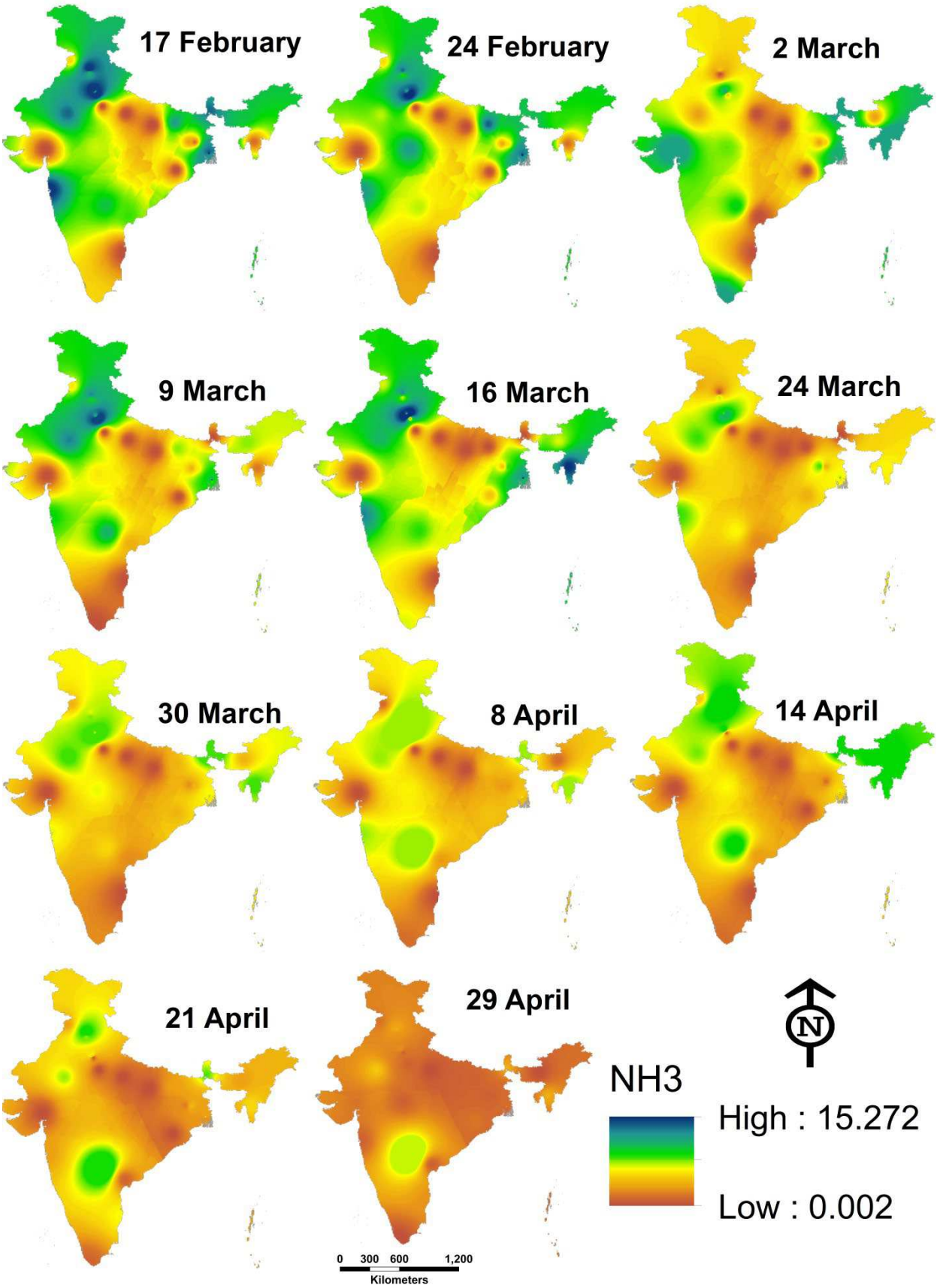
4.1 Spatial mapping of major pollutants during pre-lockdown, lockdown The Lockdown Policy was introduced by the Indian Government in order to mitigate and monitor the COVID-19 pandemic. It was a collective decision to maintain a social distancing policy and to avoid mass gathering. Along with the above strategy, strict measures have been taken to put an end to transport systems (road, rail, air) and to the closure of major industries.As a result of a total closure of traffic flow, factories, hotels, stores, and government offices brought a massive change in air pollution, especially among the key prevalent elements, such as PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2, NH_3 and O_3 (Figure 3).This can be clearly seen from the spatial distribution of the accumulatedPM_{10}, $PM_{2.5}$, CO, NO_2, SO_2 and NH_3contaminants at various pre-lockdown days, lockdown and predicted post-lockdown period (Figure 3). Particularly, the amounts of the pollutants only decreased below the permissible limit within one week of the shutdown (March 24, 2020 to March 31, 2020), whereas the absorption of O_3 increases in manufacturing and transport conquered region. Later, the central government has

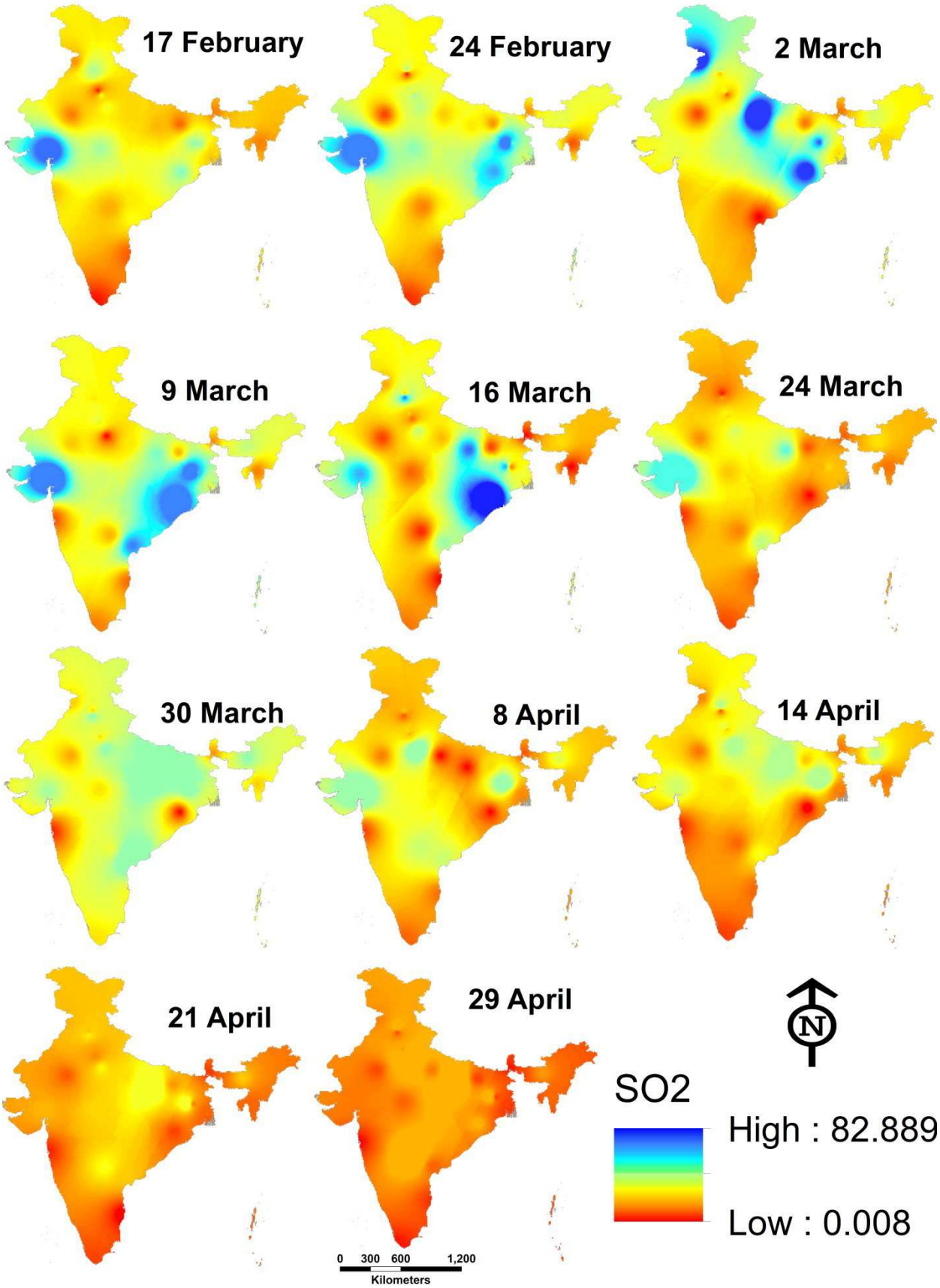
given a limited relaxation (April 14, 2020) of the lockdown measures of COVID-19 for the necessary vehicles and human activities beyond the red zone, with a marginal effect on air pollutants. Owing to COVID-19 lockdown steps, the emissions declined dramatically in the vehicular traffic and the shutdown of factories, restaurants, shops, government offices and several other human-induced activities (Figure 3).

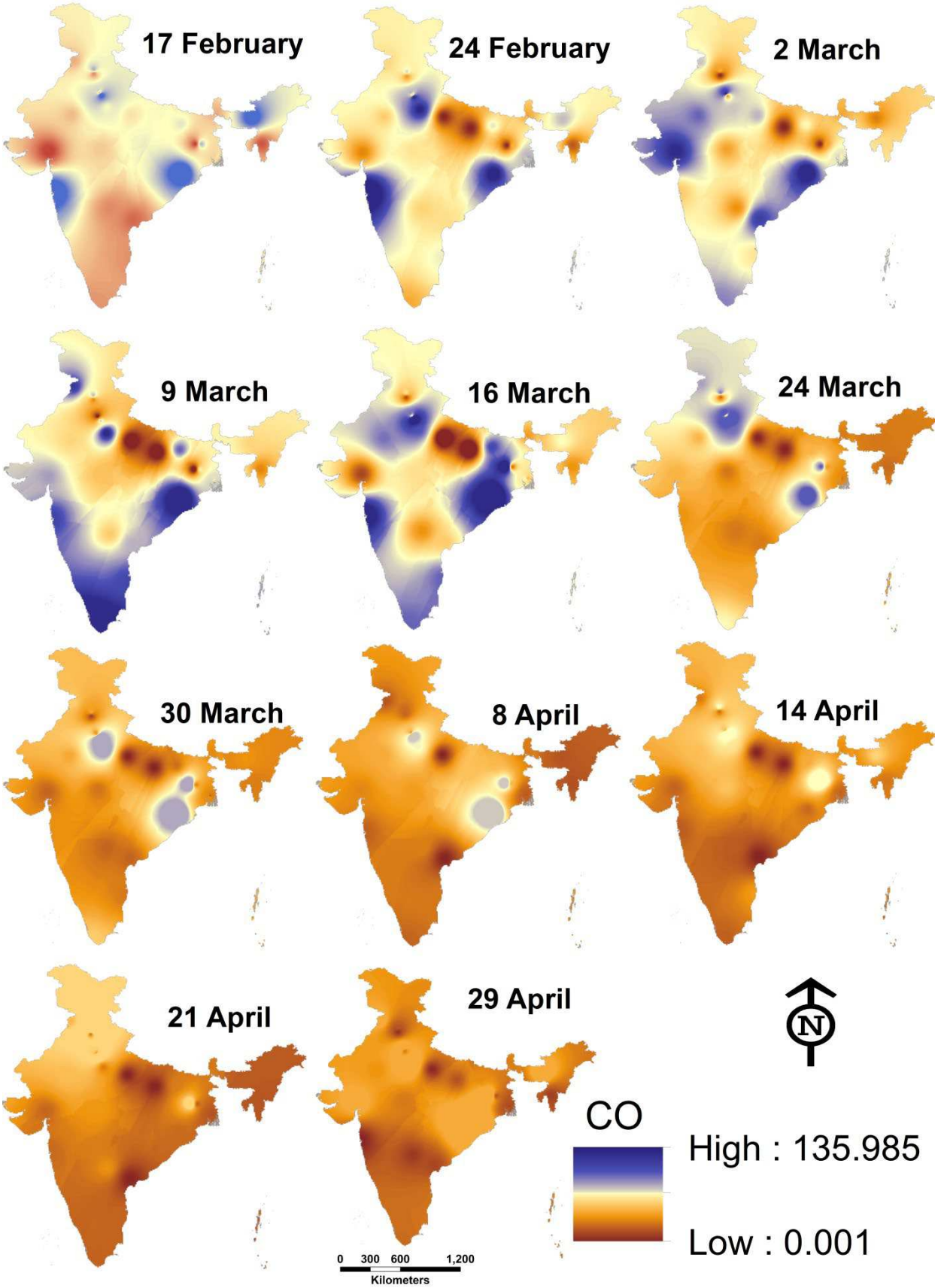

17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
PM 2.5
High : 362.881
Low : 0.022
0 300 600 1,200
Kilometers

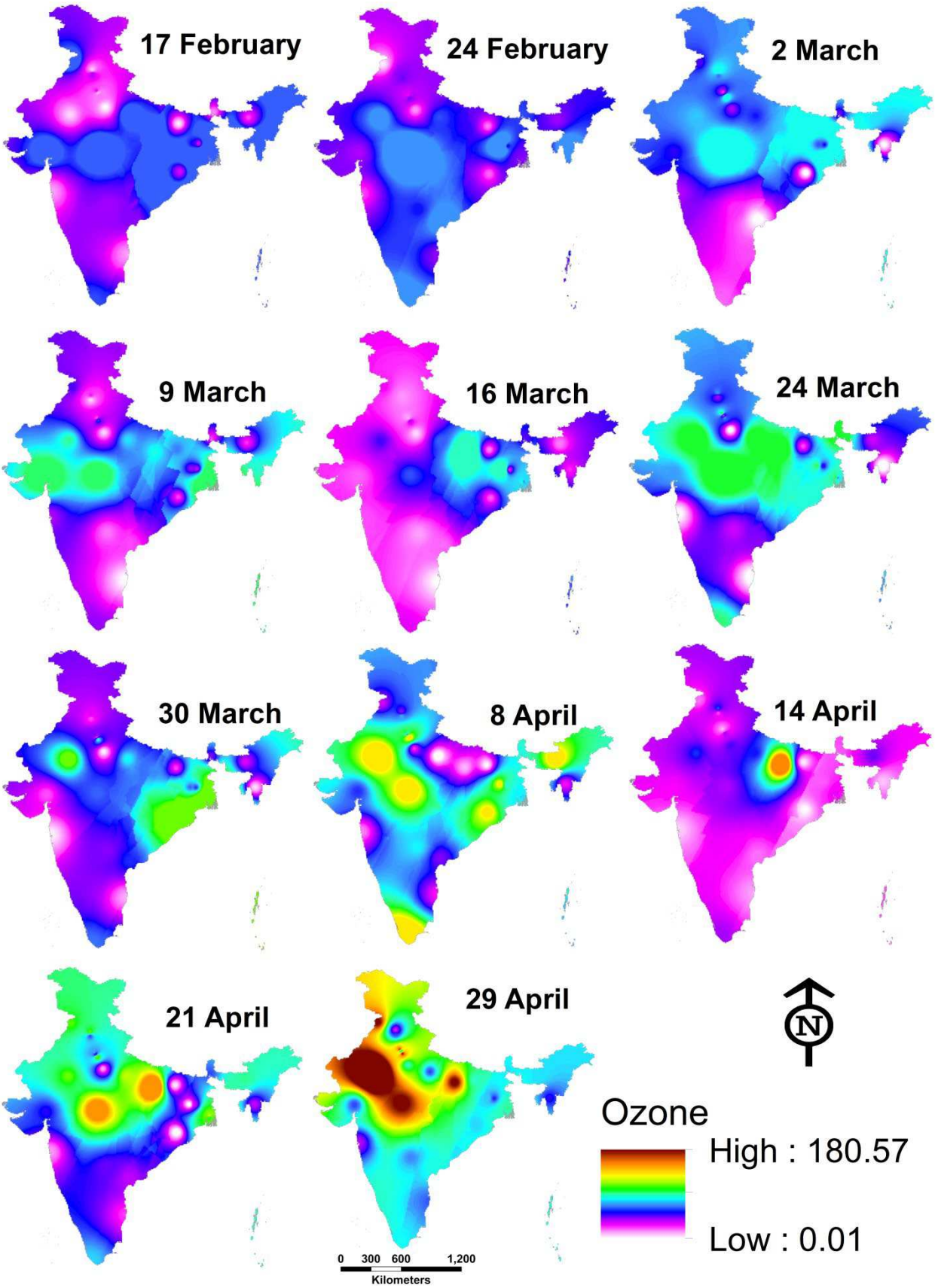

17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
PM 10
High : 281.562
Low : 0.002
0 300 600 1,200
Kilometers

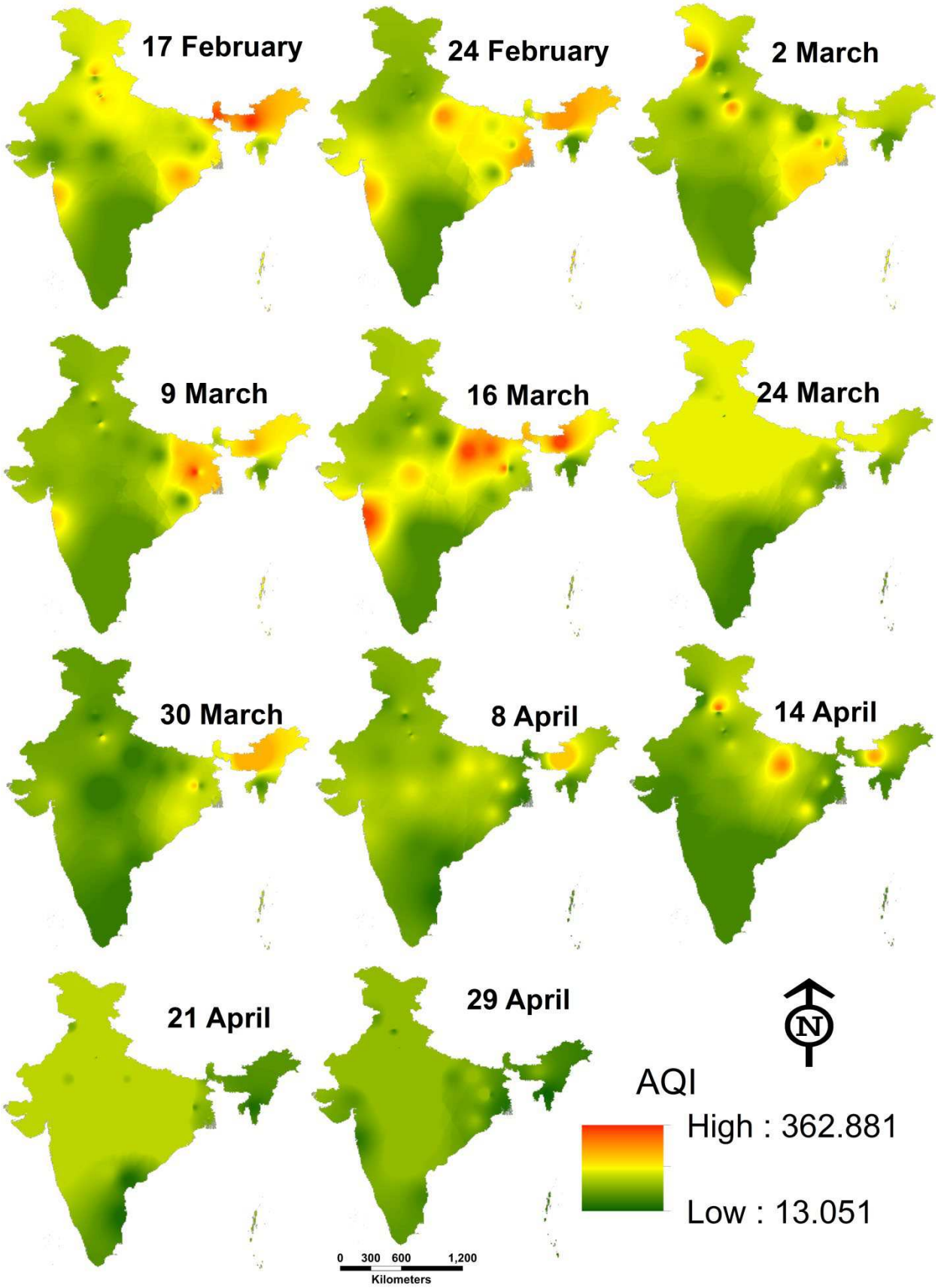

17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
NO2
High : 114.556
Low : 0.002
0 300 600 1,200
Kilometers


17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
NH3
High : 15.272
Low : 0.002
0 300 600 1,200
Kilometers


17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
SO2
High : 82.889
Low : 0.008
0 300 600 1,200
Kilometers


17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
CO
High : 135.985
Low : 0.001
0 300 600 1,200
Kilometers


17 February
24 February
2 March
9 March
16 March
24 March
30 March
8 April
14 April
21 April
29 April
N
Ozone
High : 180.57
Low : 0.01
0 300 600 1,200
Kilometers



< Figure 3. Spatial distribution of PM 2.5 (µg/m3) in before and during lockdown period (a), Spatial distribution of PM 10 (µg/m3) in before and during lockdown period

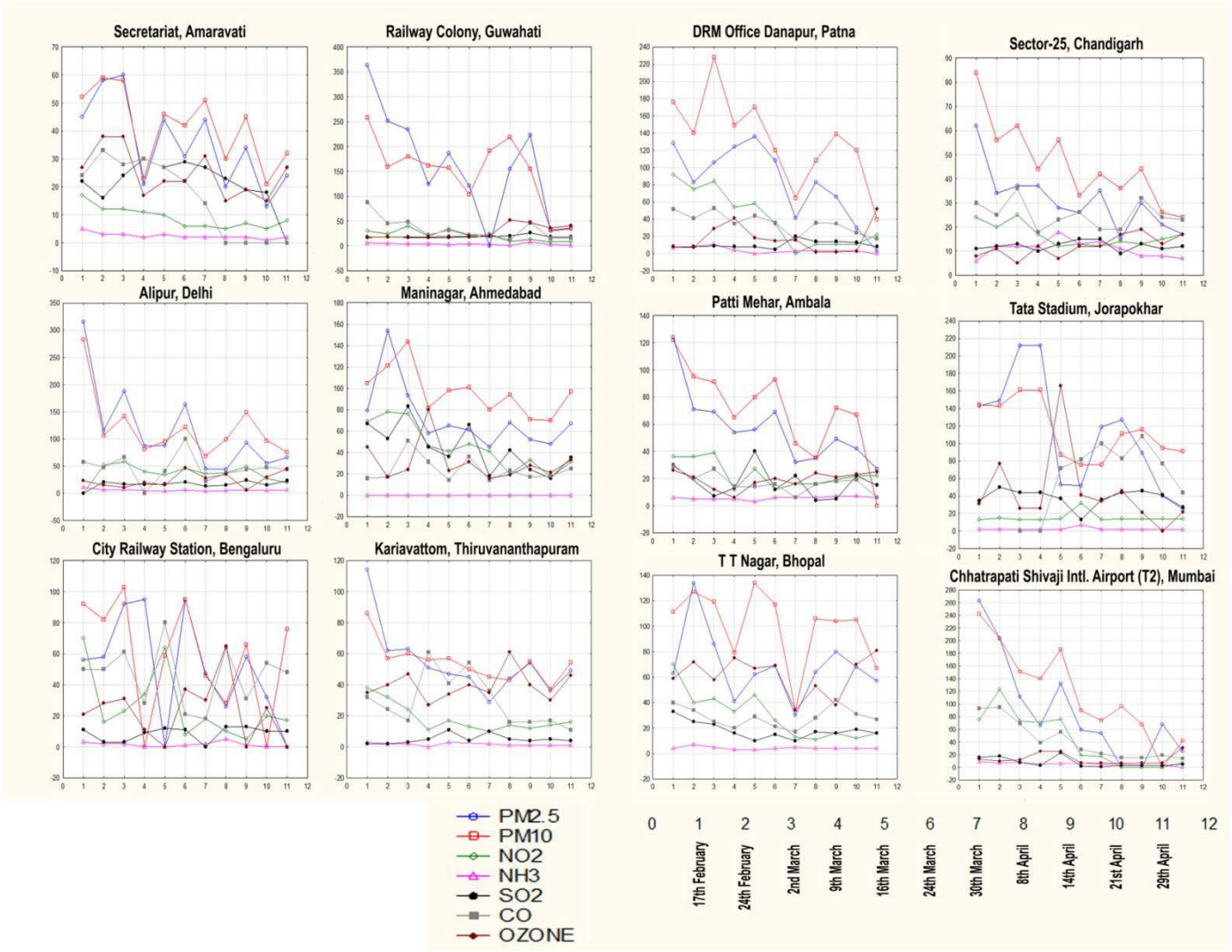
(b), Spatial distribution of NO2 (µg/m3) in before and during lockdown period (c), Spatial distribution of NH3 (µg/m3) in before and during lockdown period (d), Spatial distribution of SO2 (µg/m3) in before and during lockdown period (e), Spatial distribution of CO (µg/m3) in before and during lockdown period (f), Spatial distribution of Ozone (µg/m3) in before and during lockdown period (g) and Spatial distribution of Air Quality Index in before and during lockdown period (h). >

It was observed that air quality is improved drastically during the pre-lockdown period (24thMarch, 2020) of the COVID-19 extended lockdown phase (3rdMay, 2020) and air quality is deteriorated slightly after the government gave a minor relaxation (April 14, 2020) to the necessary vehicles and other human activities beyond the red zone. On average, there is a significant improvement in air quality (-26.99% with the net reduction of -39.16) throughout three weeks lockdown duration (24thMarch, 2020 to 14thApril, 2020) relative to the standard air quality over three weeks pre-lockdown period (Figure 3h). During the predicted post-lockdown phase (after May 3, 2020), air quality dropped dramatically, this is like at the value similar to the start of the lockdown period (March 24, 2020).

4.2 Changes in major pollutants concentration during pre-lockdown, lockdown and post-lockdown

The change in the intentness of major air pollutants is very clear from the predicted outcomes that during the pre-lockdown period of COVID-19 (before March 24, 2020) the country witnessed massive air pollutants as in the previous months or years. However, after the lockdown (March 24, 2020); a major reduction in pollutants was observed throughout the country as a result of the COVID-19 pandemic (Figure 4). Especially significant decreases in quantity of pollutants such as PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2 and NH_3 have been estimated during the lockdown period (Figure 4). The average assemblies of ambient air pollutants such as PM_{10} and PM2.5 have reduced by -40.84 per cent and -45.38 per cent respectively. The decline rate of PM_{10} and $PM_{2.5}$ is directly linked with automobile emissions, industrial dust and cooking smoke or to complicated reactions with chemicals such as SO_2 and NO. Apart from these, the outcomes of the decline in PM_{10} and $PM_{2.5}$ came from forest fires, wood burners, agricultural burning, industrial smoke, and dust produced from various work sites (Majumdaret al., 2020). Other pollutants that have displayed a significant difference between pre-lockdown and lockdown are CO (-19.76%) and NO_2 (-37.80%), whereas in SO_2 (-33.81%) and NH_3 (-17.06%), the decline was very low compared to the others pollutants, and there was also no strong trend of regression. The accumulation of O_3 increases in

manufacturing and transport dominated region, in particular,> 10% rise. The source of this increased in O_3, particularly in industrial and transport dominated areas, is decline in NO, which contributes to reduce in O_3 consumption ($NO+O_3=NO_2+O_2$) and causing a raise in O_3 levels. The study also predicts that the assemblage of major air pollutants during post-lockdown of COVID-19 pandemic would take at least 180 days to archive the concentration of major air pollutants, such as pre-lockdown levels across the country. It is a good sign that a significant perfection in air quality might be probable if the strict accomplishment of emissions control policies such as lockdown is enforced.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Railway Colony, Guwahati
DRM Office Danapur, Patna
Sector-25, Chandigarh
Alipur, Delhi
Maninagar, Ahmedabad
Patti Mehar, Ambala
Tata Stadium, Jorapokhar
City Railway Station, Bengaluru
Kariavattom, Thiruvananthapuram
T T Nagar, Bhopal
Chhatrapati Shivaji Intl. Airport (T2), Mumbai
PM2.5
PM10
NO2
NH3
SO2
CO
OZONE
0 1 2 3 4 5 6 7 8 9 10 11 12
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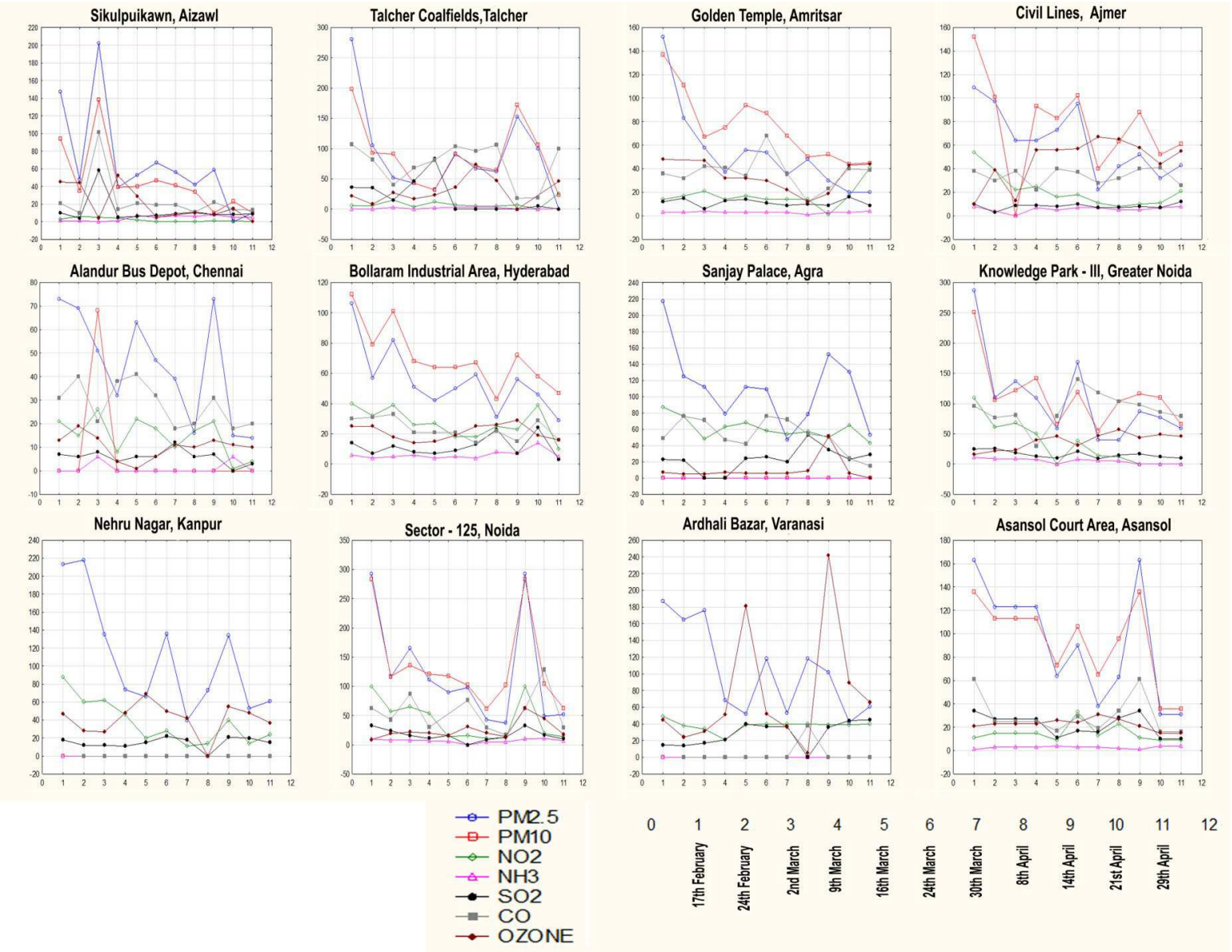
24th February
2nd March
9th March
16th March
24th March
30th March
8th April
14th April
21st April
29th April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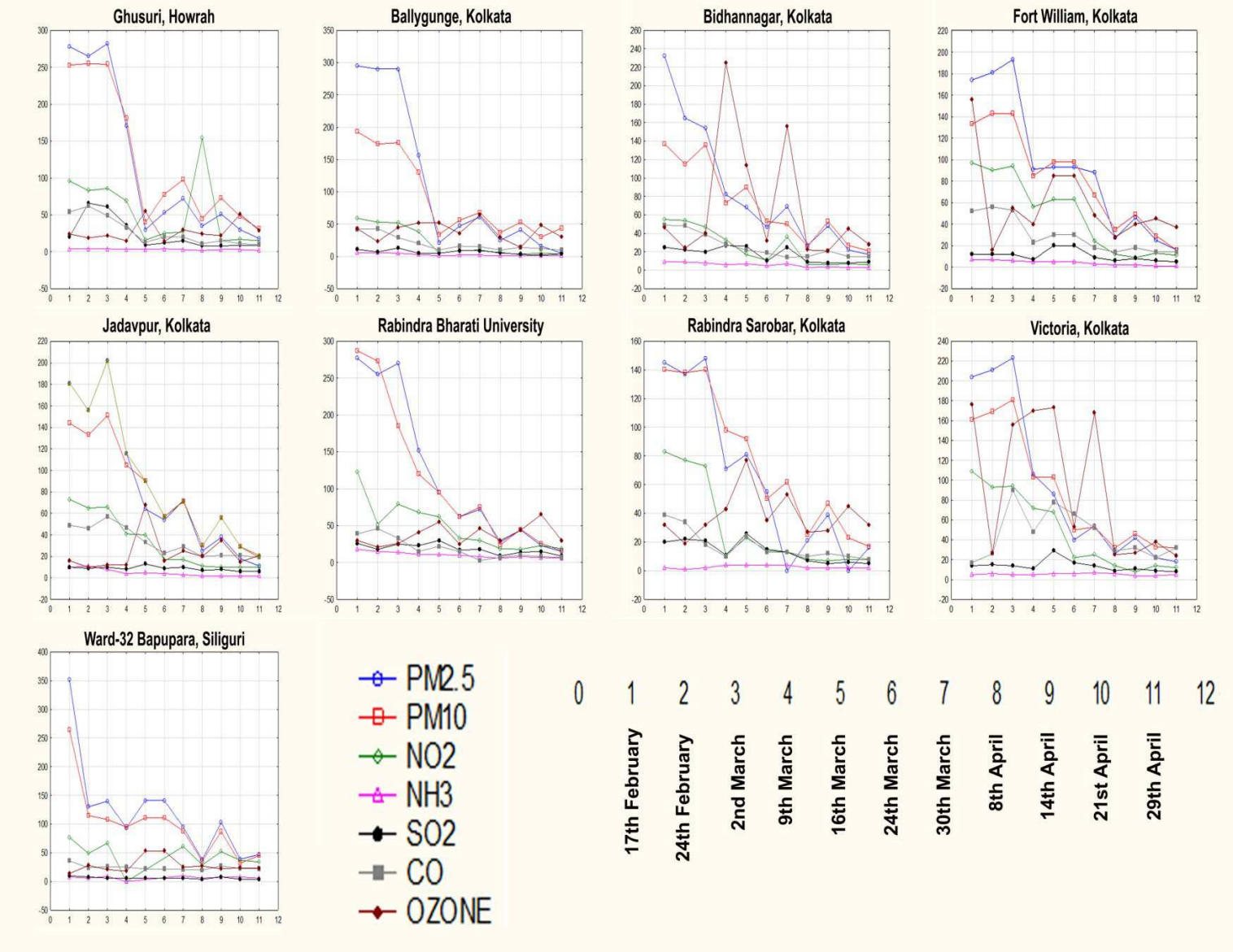
Talcher Coalfields,Talcher
Golden Temple, Amritsar
Civil Lines, Ajmer
Alandur Bus Depot, Chennai
Bollaram Industrial Area, Hyderabad
Sanjay Palace, Agra
Knowledge Park - III, Greater Noida
Nehru Nagar, Kanpur
Sector - 125, Noida
Ardhali Bazar, Varanasi
Asansol Court Area, Asansol
PM2.5
PM10
NO2
NH3
SO2
CO
OZONE
0 1 2 3 4 5 6 7 8 9 10 11 12
17th February
24th February
2nd March
9th March
16th March
24th March
30th March
8th April
14th April
21st April
29th April


Ghusuri, Howrah
Ballygunge, Kolkata
Bidhannagar, Kolkata
Fort William, Kolkata
Jadavpur, Kolkata
Rabindra Bharati University
Rabindra Sarobar, Kolkata
Victoria, Kolkata
Ward-32 Bapupara, Siliguri
PM2.5
PM10
NO2
NH3
SO2
CO
OZONE
0 1 2 3 4 5 6 7 8 9 10 11 12
17th February
24th February
2nd March
9th March
16th March
24th March
30th March
8th April
14th April
21st April
29th April

<Figure 4.Trend of major pollutants in some selected monitoring station.>

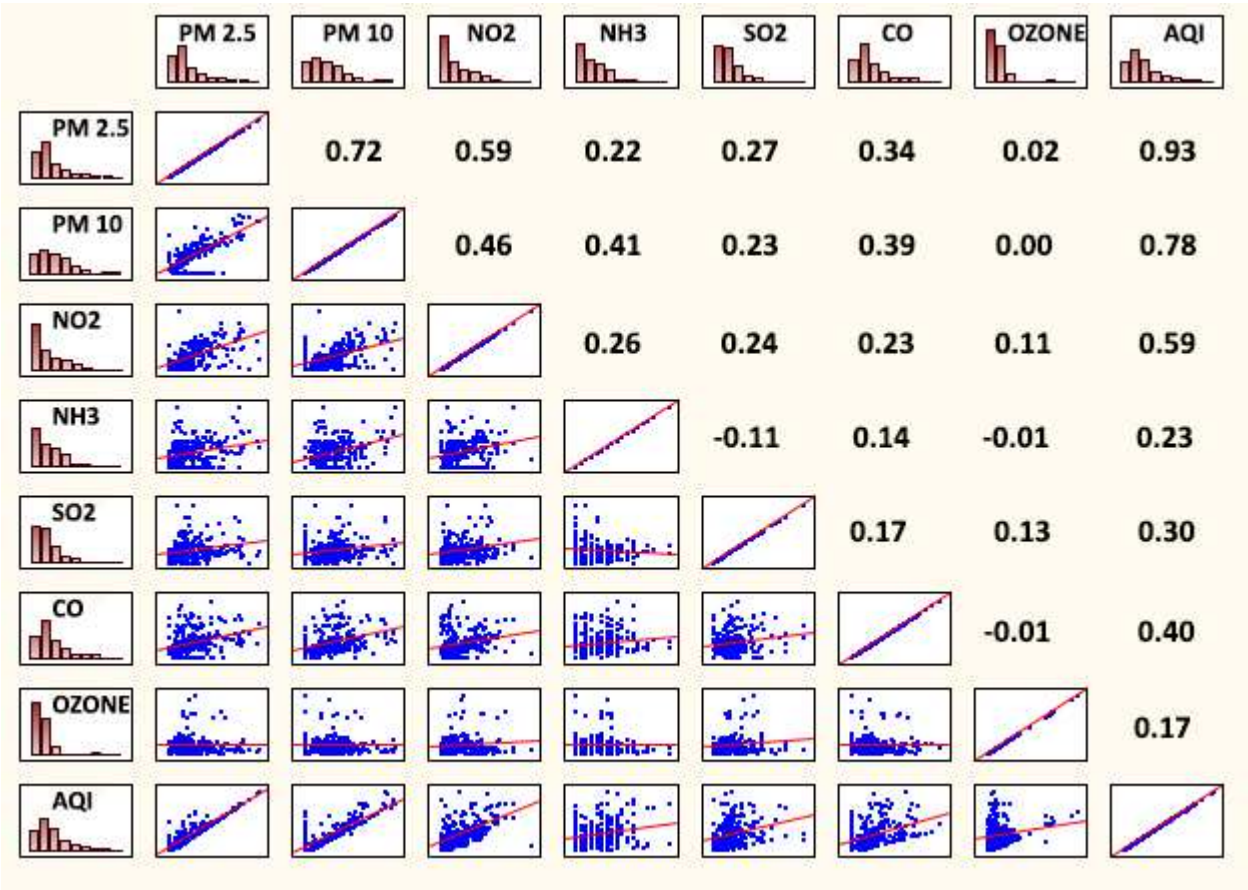
4.3 Spatial variation of PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2, NH_3, and O_3, concentration

In the last five years (2016 to 2020), we have observed the seven contaminants' 24 hours accumulation phase during the same two months span (i.e. March and April). Continuous measurements of PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2 and NH_3 pollutants was acquired from the air quality monitoring station of India (Kamyotra and Sinha 2016). Here, we used air quality monitoring data for 223 monitoring stations across India as a collective station for the analysis. The figures suggest a significant decrease in air quality levels across India after the lockdown was implemented. In contrast to PM_{10} and $PM_{2.5}$ which have decreased dramatically (-40.84% and -45.38%) during lockdown phase, NO_2 and CO have decreased drastically (-37.80% and -19.76%), while pollutants such as SO_2 and NH_3 may have slight declination trends (-33.81% and -17.06%) compared to others. The maximum PM_{10} and $PM_{2.5}$ were noticed in 2019 were as high as 264.82μg/m^3 and 344.07μg/m^3, respectively. This net decreased to -113.10.44μg/m^3 (-59.86% maximum reduction) and -57.56μg/m^3 (-45.05% maximum reduction) respectively in 2020. The amount of O_3 increases in manufacturing and transport dominated region. The results indicate that the accomplishment of the lockdown would lead to a significant improvement in air quality and should be placed into practice as an additional way of reducing pollution. The spatial distribution of all the pollutants except Ozone are maximum in some pockests, i.e., National Capital Region (NCR), Mumbai metropolition region, Kolkata , Guahati and its surrounding regions. There are similar spatial allocatoion has been associated in the case of air quality index. The gradual decelining tendency has been associated among pollutant materials and its areultant air quality in lockdown period.

4.4 Correlation between pollutants in the atmosphere

The correlation between various concentrations of air pollutants in India during the study period (i.e. from 17th February, 2020 to 29th April, 2020) is shown in Figure 5. The mean daily accumulation of $PM_{2.5}$ is directly linked to the average daily concentration of PM_{10} (r = 0.73), NO_2 (r = 0.58), CO (r = 0.34) and AQI (r = 0.92). Similarly, the average daily concentration of PM_{10} is directly correlated with the maximum daily concentration of $PM_{2.5}$ (r = 0.73), NO_2 (r = 0.48), NH_3 (r = 0.41), CO (r = 0.39) and AQI (r = 0.80). The mean daily accumulation of NO_2 is directly linked to the average daily concentration of $PM_{2.5}$ (r = 0.58),

PM_{10} (r = 0.48) and AQI (r = 0.58). NH_3 by the mean daily aggregation is directly linked to the average daily concentration of PM_{10} (r = 0.41). Similarly, the average daily aggregation of SO_2 is linked with AQI (r = 0.30). The daily concentration of CO has a positive relation with $PM_{2.5}$ (r = 0.34), PM_{10} (r = 0.39) and AQI (r = 0.40). The daily aggregation of AQI is also directly linked to the average daily concentration of $PM_{2.5}$ (r = 0.92), PM_{10} (r = 0.80), NO_2 (r = 0.58), SO_2 (r = 0.30) and CO(r = 0.40).

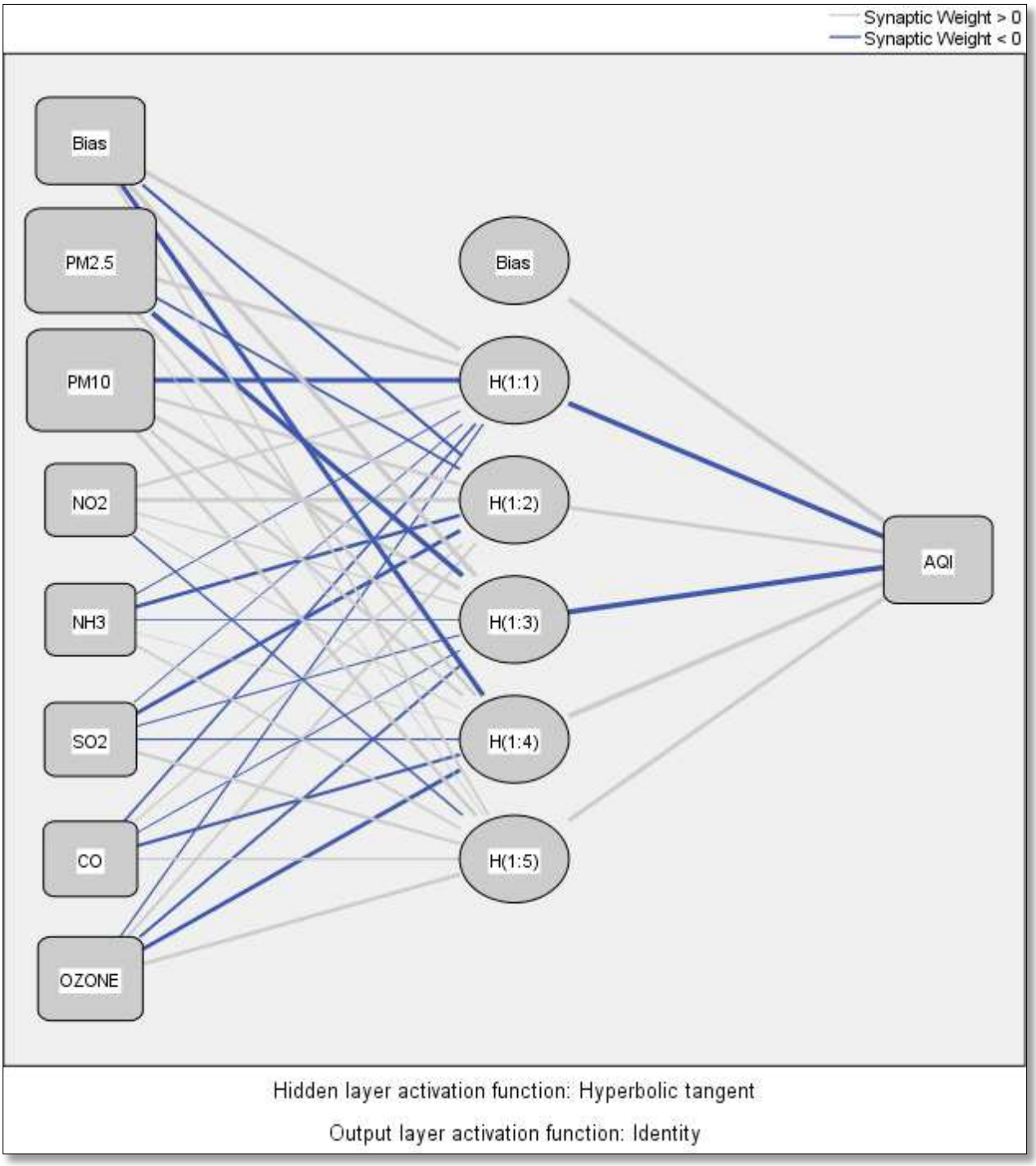


<Figure 5.Correlation of different pollutants in India during lockdown.>

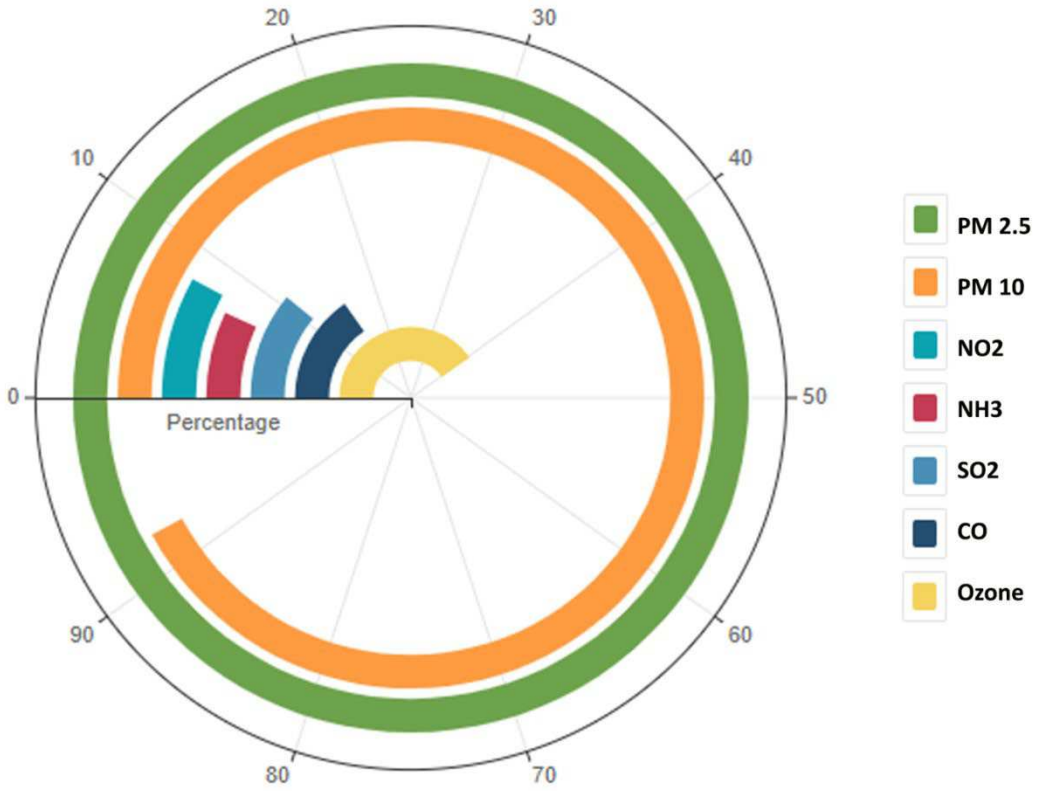
4.5. Results of ANN modelling

After several years of experience, we got an integrated network structure with a minimum error rate for both training and testing. It used 69.1% of total data to train the network and rest 30.9% for testing the model. There were one hidden layer with 5 hidden node (Fig: 6) in the network structure. The Sum of Squares Error (*SSE*) was 1.548 for training and 1.055 for testing with a relative error 0.012 and 0.021 respectively. Observed values were well correlated with predicted values (Fig: 8) with a high degree of explainability (R^2 linear = 0.985). Among the predictor covariates PM 2.5 contributed most (0.366) for AQI prediction, followed by PM 10 (0.337). NH_3 has just minimal accountability (0.029) for this result

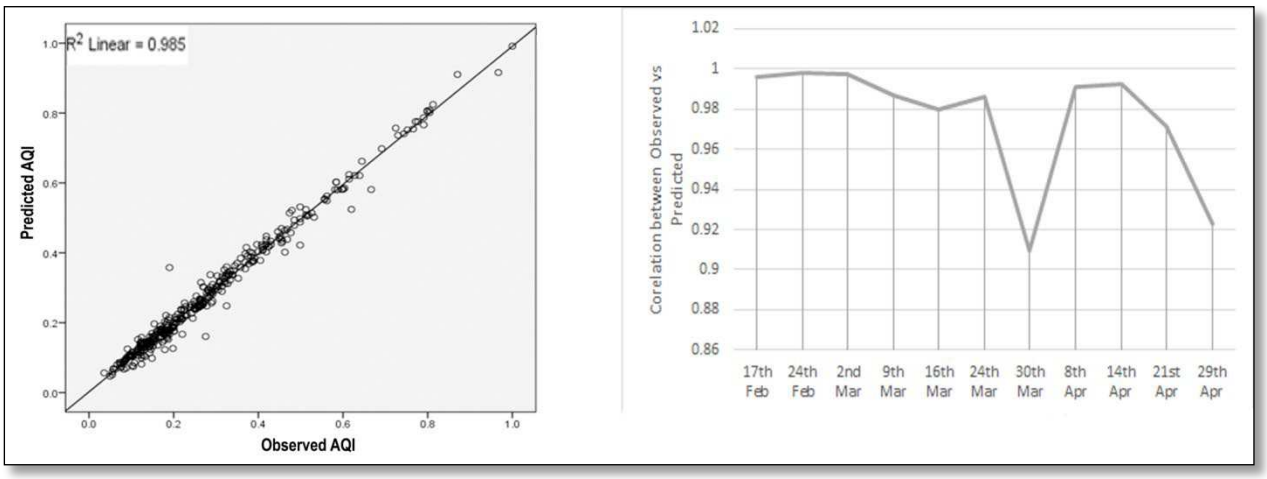
(Figure 7). Normalized importance of input variables are given in (Figure 7). Synaptic weights in between input variables- hidden node and hidden node-output (Table: 5) are the weighing factor for prediction through Equations 3 and 4.



<Figure 6.Structure of the network in ANN model.>



<Figure 7.Importance of the variable in ANN model.>



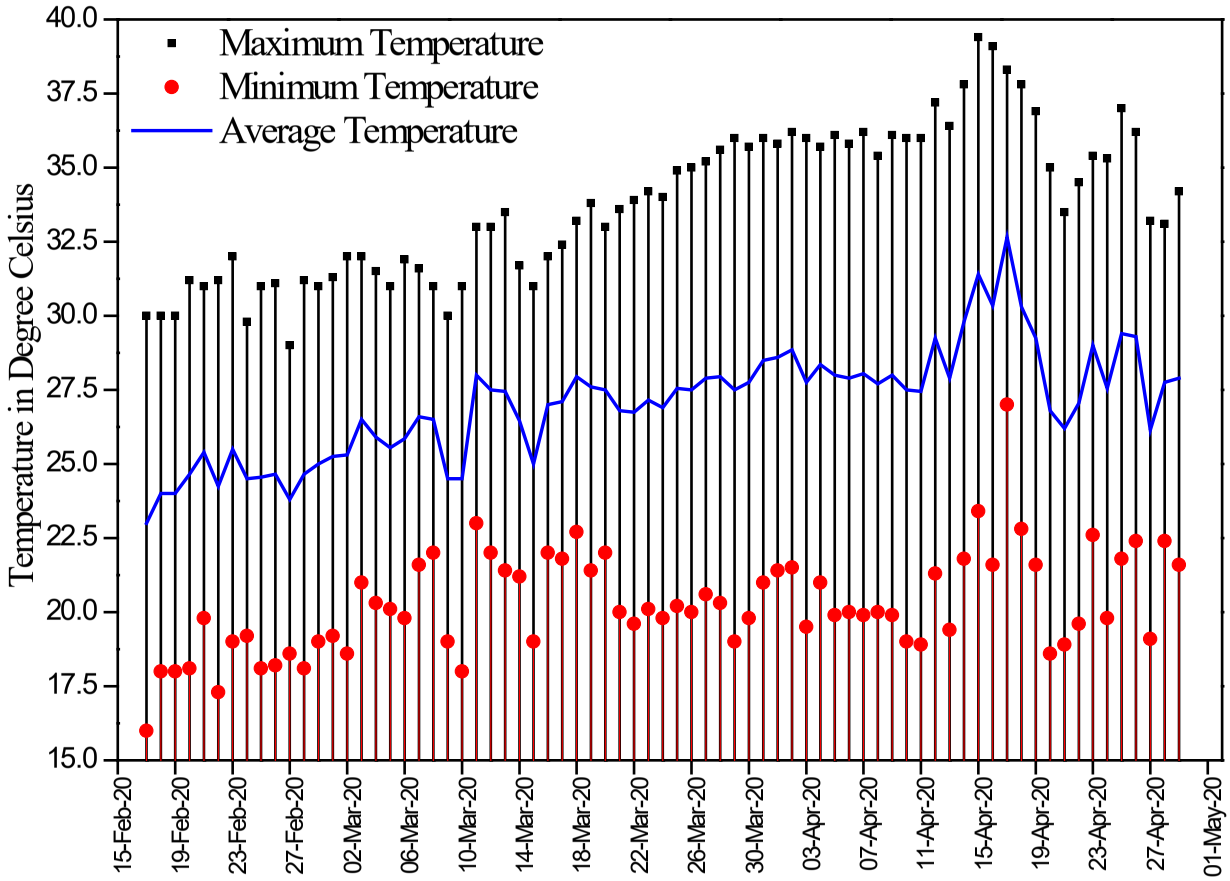
<Figure 8. Accuracy of the model using observed vs. predicted values.>

4.6. Influence of climate indicators on mortality

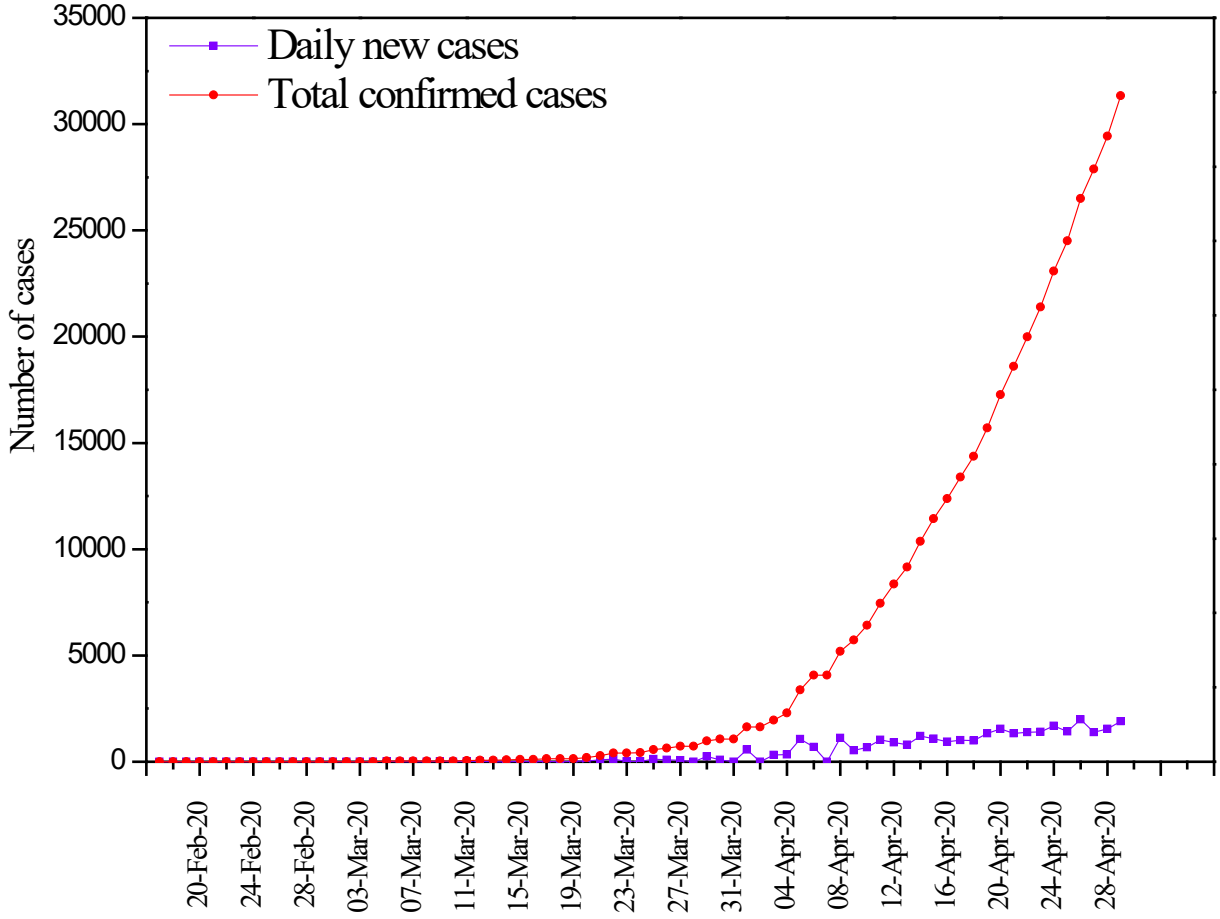
The empirical results of seven atmospheric factors are presented in Tables 2 and 3using the Kendal and Spearman rank correlation analysis. Results indicated that, the average air quality and maximum temperature are relevant for COVID-19 positive new cases (Figure 9 and 10). The variation of temperature from high to low influences the spreading of virus in nationwide. Though India faces mortality and positive cases, but by comparison it is quite

low than other non- tropical countries which has the similar range of temperature i.e. from 3^0C -17^0C. In addition, according to Spearman test, average air quality and mean temperature indicates the positive case and mortality of COVID-19. The changing climate patterns for existing research have been examined for COVID-19 pandemic in highly populated countries like India. Our experiments showed that the maximum temperature and the average temperature are connected to the regional distribution of COVID-19 during lockdown period. Shi et al.

(2020); Bashir et al. (2020a) supported our outcomes, which examined at climate changes and claimed that temperature was the controlling factor behind COVID-19. Apart from this, humidity and temperature play a important role in the spreading of COVID-19 (Sajadi et al. 2020). The Wuhan incidence of COVID-19 revealed a close relation between diseases spread and weather patterns, with projections that warmer weather can control the virus (Wang et al. 2020). (Dalziel et al. 2018b) predicted that growing magnitude of seasonal variations in specific humidity contributes to more severe pandemics. Apart from this, meteorological parameters like air quality, humidity and wind speed also accelerated the spread of COVID-19. In fact, air temperature also leads to the spread of the virus (Chen et al. 2020). In those areas where absolute humidity varies between 3 and 9 g / m^3 and the atmosphere is hot in nature, the MIT community has previously confirmed 90 per cent events. In this regard, (Poole 2020) has also corroborated this by stating that humidity and climate indicators are associated with the COVID-19 spread. .Therefore, it can be said that the maximum temperature and humidity have altered the mortality trend in India than American and European countries. So there are very close connection between climate indicators and the distribution of COVID-19.



<Figure 9.Variability of temperature in before and during lockdown period.>



<Figure 10.Trend of positive COVID-19 cases in different temporal period.>

5. Discussion

India ranks fifth in the world's most polluted countries and is the home to the 21 most polluted cities in the world, based on concentrations of $PM_{2.5}$ and PM_{10}. In a recent decade, numerous suggestive measures have failed to maintain the standard air quality across Indian cities. However, the scenario has changed due to COVID-19 pandemic, the environment and air quality have improved significantly. The particulate matter ($PM_{2.5}$, PM_{10}) which is related to automobile emissions, industrial emissions, dust, cooking smoke are one of the most dangerous air pollutants reduced drastically from 138.85 $\mu g/m^3$ to 75.84 $\mu g/m^3$ in India. However, due to relaxation permitted after April 14 2020 by the government beyond the red zone has resulted in the smaller fluctuation on the prediction of selected air pollutants. As well as the spatial prediction of the AQI during pre-lockdown and lockdown period indicates a significant improvement in air quality, but the reduction of air quality was observed in the post-lockdown phase. This also indicates the chance of an increase in the air pollutants with

increasing relaxation in the coming days. Decreasing air pollutants due to lockdown for restricting of COVID19 community spread has been observed around the world (Huang et al. 2020).

However, the highly transmissible COVID-19 has forced the world to shutdown mode and responsible for 238,650 deaths in all over the world (WHO, 2020). Whereas in India at present the number 1323 deaths and it is going on. The nature of COVID-19 is still not known completely (Van Doremalen et al. 2020). Primary statements from WHO clearly stated there were signs of human to human transmission (Twitter handle of WHO, on January 14 2020, but after some days it was found the COVID-19 is highly transmissible from human to human contact. The present study indicates that the mortality rate significantly related to the maximum temperature, minimum temperature, average temperature and air quality (Table: 1 and 2). The increasing daily new cases have always increased the mortality rate in India. Although, the higher amount of correlation values for daily new deaths, cumulative deaths and mortality rate were associated positively with maximum temperature and negatively with air quality. Similar results were also observed over the USA by (Bashir et al. 2020a) although the correlation values with maximum temperature were much lower.

Further, previous studies have found that deaths from asthma attack, acute respiratory inflammation, and cardio respiratory diseases is associated with prolonged interaction with polluted air (Schwartz and Dockery 1992; Dockery and Pope 1994) and causing 4.6 millions of deaths per year around the world (Lelieveld et al. 2015, 2019; Cohen et al. 2017). Besides this medical profile and the patients' age structure died from COVID-19 found that all the age categories are susceptible to COVID-19 but the mortality rate increases with increasing age combined with pre-existing medical conditions related to heart disease diabetes and asthma (WHO, 2020). As well as, (Wu et al. 2020) found that in the United States, COVID-19 death is related to prolonged exposure to the $PM_{2.5}$. Therefore, (Contini and Costabile 2020) rightly mentioned that air quality can be considered as a factor affecting the respiratory system of the human body and increasing mortality rates. Besides this, the quality of air is severely related to human activities (Donahue 2018) and we can infer that the interaction among the people is also very high in this area, thereby the probability of high infected people as well as high mortality rate around the polluted areas. So, it can be said that climate indicators and air quality are not significantly connected with COVID-19 death cases.

Table: 1 Kendal tau correlation coefficient of selected variables

	Daily new cases	Daily new deaths	Total deaths	Mortality rate	Maximum temperature	Minimum temperature	Average temperature	Average rainfall	Air quality
Daily new cases	1.000	.772**	.761**	.772**	.506**	.259**	.472**	.204*	-.689**
Total deaths	.772**	1.000	.812**	1.000**	.535**	.226**	.467**	.181*	-.691**
Daily new Deaths	.761**	.812**	1.000	.812**	.659**	.265**	.579**	.244**	-.824**
Mortality Rate	.772**	1.000**	.812**	1.000	.535**	.226**	.467**	.181*	-.691**
Maximum Temperature	.506**	.535**	.659**	.535**	1.000	.341**	.773**	.264**	-.571**
Minimum temperature	.259**	.226**	.265**	.226**	.341**	1.000	.584**	.113	-.279**
Average temperature	.472**	.467**	.579**	.467**	.773**	.584**	1.000	.231**	-.542**
Average rainfall	.204*	.181*	.244**	.181*	.264**	.113	.231**	1.000	-.266**
Air quality	-.689**	-.691**	-.824**	-.691**	-.571**	-.279**	-.542**	-.266**	1.000

***, **, and * are the significant at the 1%, 5%, and 10% level of significance respectively.

Table:2 Spearman rho correlation coefficient of selected variables

	Daily new cases	Daily new deaths	Total deaths	Mortality rate	Maximum temperature	Minimum temperature	Average temperature	Average rainfall	Air quality
Daily new cases	1.000	.885**	.863**	.885**	.651**	.379**	.603**	.284*	-.804**
Total deaths	.885**	1.000	.901**	1.000**	.682**	.315**	.608**	.259*	-.826**
Daily new Deaths	.863**	.901**	1.000	.901**	.817**	.376**	.744**	.360**	-.916**
Mortality Rate	.885**	1.000**	.901**	1.000	.682**	.315**	.608**	.259*	-.826**
Maximum Temperature	.651**	.682**	.817**	.682**	1.000	.477**	.914**	.376**	-.760**
Minimum temperature	.379**	.315**	.376**	.315**	.477**	1.000	.748**	.153	-.413**
Average temperature	.603**	.608**	.744**	.608**	.914**	.748**	1.000	.328**	-.719**
Average rainfall	.284*	.259*	.360**	.259*	.376**	.153	.328**	1.000	-.391**
Air quality	-.804**	-.826**	-.916**	-.826**	-.760**	-.413**	-.719**	-.391**	1.000

***, **, and * are the significant at the 1%, 5%, and 10% level of significance respectively.

Table:3 Pollutant matter and gases before and after lockdown in India 2020

Types of Pollutants	Before Lockdown												After Lockdown										overall variation	
	17-Feb-20		24-Feb-20		02-Mar-20		09-Mar-20		16-Mar-20		24-Mar-20		30-Mar-20		08-Apr-20		14-Apr-20		21-Apr-20		29-Apr-20		Net	%
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low		
PM2.5	66.000	45.004	250.869	44.89	281.917	37.285	209.849	21.002	185.852	32.064	163.655	31.001	117.316	0.085	154.839	0.022	289.776	0.029	129.258	0.055	66.972	0.029	-63.0118	-45.3812
PM10	281.562	0.02	247.435	0.017	253.908	0.004	281.057	0.012	218.757	0.013	190.831	0.011	185.95	0.013	161.907	0.011	161.907	0.011	119.696	0.008	96.943	0.008	-50.1569	-40.8436
NO2	114.556	3.151	122.967	6.091	85.977	5.078	99.252	0.087	75.98	0.074	57.729	0.052	60.903	0.056	56.627	0.008	70.983	0.087	64.506	0.008	42.726	0.026	-17.9898	-37.8074
NH3	15.272	0.009	13.001	0.007	11.95	0.002	11.253	0.005	15.745	0.006	12.168	0.006	12.764	0.005	10.159	0.006	9.968	0.005	13.985	0.003	7.995	0.004	-1.12927	-17.0618
SO2	66.946	1.586	52.958	0.62	82.917	0.008	45.954	0.124	82.889	6.003	65.94	0.023	36.935	0.03	52.605	0.025	45.482	0.027	43.908	0.003	44.891	0.003	-11.4398	-33.8148
C0	106.885	16.043	127.022	0.001	100.888	0.131	99.856	0.001	106.526	0.001	135.985	0.069	113.814	0.051	105.86	0.001	94.971	0.051	80.917	0.001	67.923	0.027	-11.4224	-19.7674
O3	82.752	7.133	75.695	0.01	57.94	4.068	104.955	4.004	180.57	1.007	68.933	5.064	88.126	6.253	64.963	0.029	241.282	0.045	88.778	0.058	80.915	0.071	7.70775	15.62036
AQI	362.812	52.004	257.106	48.376	281.918	60.753	210.122	30.002	185.956	46.002	163.885	42.001	190.852	34.058	218.76	20.006	289.997	45.002	129.509	18.005	99.895	13.051	-39.1646	-26.9955

Source: National Air quality Index portal, Central Pollution Control Board, Govt. of India, 2020.

Table:4 comparative analysis of pollutant matter in India 2016, 2017, 2018, 2019 and 2020

	Before Lockdown								After Lockdown										overall variation	
	17-Feb-16		17-Feb-17		17-Feb-18		17-Feb-19		30-Mar-20		08-Apr-20		14-Apr-20		21-Apr-20		29-Apr-20		Net	%
Types of pollutants	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low		
PM2.5	340.231	36.027	341.881	36.98	343.003	37.131	340.231	36.027	117.316	0.085	154.839	0.022	289.776	0.029	129.258	0.055	66.972	0.029	-113.101	-59.861
PM10	263.81	0.013	263.814	0.687	263.817	1.687	263.818	0.013	185.95	0.013	161.907	0.011	161.907	0.011	119.696	0.008	96.943	0.008	-59.562	-45.0519
NO2	114.311	3.285	114.808	3.13	114.719	3.152	114.724	3.157	60.903	0.056	56.627	0.008	70.983	0.087	64.506	0.008	42.726	0.026	-29.3178	-49.7664
NH3	13.189	0.007	15.227	0.009	15.228	0.009	15.291	0.009	12.764	0.005	10.159	0.006	9.968	0.005	13.985	0.003	7.995	0.004	-1.88173	-25.5283
SO2	66.945	1.583	66.934	1.856	66.945	1.551	66.946	2.003	36.935	0.03	52.605	0.025	45.482	0.027	43.908	0.003	44.891	0.003	-11.9545	-34.8067
C0	106.891	16.053	106.892	16.054	106.914	16.054	107.92	16.054	113.814	0.051	105.86	0.001	94.971	0.051	80.917	0.001	67.923	0.027	-15.2424	-24.7425
O3	83.251	7.191	84.451	7.228	85.813	7.213	85.981	7.256	88.126	6.253	64.963	0.029	241.282	0.045	88.778	0.058	80.915	0.071	11.004	23.8968
AQI	362.812	73.011	362.803	73.012	362.784	73.012	361.134	73.342	190.852	34.058	218.76	20.006	289.997	45.002	129.509	18.005	99.895	13.051	-111.825	-51.3575

Source: National Air quality Index portal, Central Pollution Control Board, Govt. of India, 2020.

Table: 5 Network Information of ANN

Input Layer	Covariates	1	PM2.5
		2	PM10
		3	NO2
		4	NH3
		5	SO2
		6	CO
		7	OZONE
	Number of Units[a]		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		5
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	AQI
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

6. Conclusion

It can be stated that the COVID-19 pandemic-induced lockdown imposed significant restriction on human activities which has reduced emissions of the pollutants from commercial sectors in India. The much-needed lockdown effect on concentrations of seven air pollutants and climate indicators from February 17 to April 29, 2020 at 223 locations in different stations across the country shows significant reductions. The study has found that among all pollutants, PM_{10} and $PM_{2.5}$ recorded the highest decline accompanied by NO_2, SO_2, NH_3 and CO. The concentrations of PM_{10} and $PM_{2.5}$ is declined by approximately -40.84% and -45.38% respectively relative to the previous four years across the country. Besides, an improvement in O_3 has been observed (15.62%) in most regions, which can be due to the drop in particulate matter in relation to the decline in NO_x. It is obvious from the outcomes that the lockdown implementation has

contributed to a major change in air quality and could be placed into action as an additional way of decreasing emissions from different sources. Moreover, the findings will be the key issue for decision-makers to implement necessary measures to control the air pollutants and mortality rate.

The present study would have a huge impact on post-pandemic crisis management of air quality, especially for megacities. The policymakers would have the opportunities to redesign the existing air quality regulatory mechanism. The study would provide concrete evidence on how the human anthropogenic activity has affected the composition of the lower atmosphere.

Ethics declarations

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest: The authors declare that they have no conflict of interest.

Authorship contributions: All the authors have substantial contributions to the conception and design of the work.

References

Ahmadi M, Shari A, Dorosti S, et al (2020) Investigation of effective climatology parameters on COVID-19 outbreak in Iran. Science of the Total Environment 729:. https://doi.org/10.1016/j.scitotenv.2020.138705

Balakrishnan K (2019) The impact of air pollution on deaths , disease burden , and life expectancy across the states of India : the Global Burden of Disease Study 2017. Lancet Planet Health 3:26–39. https://doi.org/10.1016/S2542-5196(18)30261-4

Bashir MF, Ma B, Bilal, et al (2020a) Correlation between climate indicators and COVID-19 pandemic in New York, USA. Science of The Total Environment 728:138835. https://doi.org/10.1016/j.scitotenv.2020.138835

Bashir MF, Ma B, Komal B, et al (2020b) Science of the Total Environment Correlation between climate indicators and COVID-19 pandemic in New. Science of the Total Environment 728:138835. https://doi.org/10.1016/j.scitotenv.2020.138835

Census of India (2011) West Bengal Census Handbook

Chen B, Liang H, Yuan X, et al (2020) Roles of meteorological conditions in COVID-19 transmission on a worldwide scale. MedRxiv

Cohen AJ, Brauer M, Burnett R, et al (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. The Lancet 389:1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6

Contini D, Costabile F (2020) Does Air Pollution Influence COVID-19 Outbreaks?

Cracknell MJ, Reading AM (2014) Geological mapping using remote sensing data: A comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. Computers & Geosciences 63:22–33

Dalziel BD, Kissler S, Gog JR, et al (2018a) Urbanization and humidity shape the intensity of influenza epidemics in U.S. cities. Science 79:75–79

Dalziel BD, Kissler S, Gog JR, et al (2018b) Urbanization and humidity shape the intensity of influenza epidemics in US cities. Science 362:75–79

Dockery DW, Pope CA (1994) Acute respiratory effects of particulate air pollution. Annual review of public health 15:107–132

Donahue NM (2018) Air Pollution and Air Quality. In: Green Chemistry. Elsevier, pp 151–176

ESA (2020) Coronavirus lockdown leading to drop in pollution across Europe

Garaga R, Sahu SK, Kota SH (2018) A review of air quality modeling studies in India: local and regional scale. Current Pollution Reports 4:59–73

Ghorani-Azam A, Riahi-Zanjani B, Balali-Mood M (2016) Effects of air pollution on human health and practical measures for prevention in Iran. Journal of research in medical sciences: the official journal of Isfahan University of Medical Sciences 21:

Gurjar BR, Ravindra K, Singh A (2016) Air pollution trends over Indian megacities and their local-to-global implications. Atmospheric Environment 142:475–495. https://doi.org/10.1016/j.atmosenv.2016.06.030

Hewitson BC, Crane RG (1994) Neural nets: applications in geography: applications for geography. Springer Science & Business Media

Huang X, Ding A, Gao J (2020) Enhanced secondary pollution offset reduction of primary emissions during COVID-19 lockdown in China

Jain AK, Mao J, Mohiuddin KM (1996) Artificial neural networks: A tutorial. Computer 29:31–44

Kamyotra J, Sinha D (2016) CPCB Bulletin

Lelieveld J, Evans JS, Fnais M, et al (2015) The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525:367–371

Lelieveld J, Klingmüller K, Pozzer A, et al (2019) Cardiovascular disease burden from ambient air pollution in Europe reassessed using novel hazard ratio functions. European Heart Journal 40:1590–1596. https://doi.org/10.1093/eurheartj/ehz135

Levine E, Kimes D, Sigillito V (1996) Classifying soil structure using neural networks. Ecological modelling 92:101–108

Licznar P, Nearing M (2003) Artificial neural networks of soil erosion and runoff prediction at the plot scale. Catena 51:89–114

Ma Y, Zhao Y, Liu J, et al (2020) Effects of temperature variation and humidity on the death of COVID-19 in Wuhan , China. Science of the Total Environment 724:138226. https://doi.org/10.1016/j.scitotenv.2020.138226

Mahato S, Pal S, Ghosh KG (2020) Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Science of the Total Environment 139086. https://doi.org/10.1016/j.scitotenv.2020.139086

Majumdar D, Purohit P, Bhanarkar AD, et al (2020) Managing future air quality in megacities : Emission inventory and scenario analysis for the Kolkata Metropolitan City , India 1. Atmospheric Environment 222:117135. https://doi.org/10.1016/j.atmosenv.2019.117135

NASA (2020) Airborne nitrogen dioxide plummets over China. NASA Earth Observatory

Ott WR (1978) Environmental indices: theory and practice

Pant S, Singh M, Ravichandiran V, et al (2020) Peptide-like and small-molecule inhibitors against Covid-19. Journal of Biomolecular Structure and Dynamics 1–10

Poole L (2020) Seasonal Influences on the Spread of SARS-CoV-2 (COVID19), Causality, and Forecastabililty (3-15-2020). Causality, and Forecastabililty (3-15-2020)(March 15, 2020)

Sajadi MM, Habibzadeh P, Vintzileos A, et al (2020) Temperature, Humidity, and Latitude Analysis to Estimate Potential Spread and Seasonality of Coronavirus Disease 2019 (COVID-19). JAMA Network Open 3:e2011834–e2011834

Schwartz J, Dockery DW (1992) Increased Mortality in Philadelphia Associated with Daily Air Pollution Concentrations. Am Rev Respir Dis 145:600–604. https://doi.org/10.1164/ajrccm/145.3.600

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

Shi P, Dong Y, Yan H, et al (2020) Impact of temperature on the dynamics of the COVID-19 outbreak in China. Science of The Total Environment 138890

Swamee PK, Tyagi A (1999) Formation of an air pollution index. Journal of the Air & Waste Management Association 49:88–91

Tan Y-J, Lim SG, Hong W (2005) Characterization of viral proteins encoded by the SARS-coronavirus genome. Antiviral research 65:69–78

Taylor JM (1987) Kendall's and Spearman's correlation coefficients in the presence of a blocking variable. Biometrics 409–416

Tobías A, Carnerero C, Reche C, et al (2020) Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. Science of the Total Environment 726:138540. https://doi.org/10.1016/j.scitotenv.2020.138540

Van Doremalen N, Bushmaker T, Morris DH, et al (2020) Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. New England Journal of Medicine 382:1564–1567

Wang Y, Wang Y, Chen Y, Qin Q (2020) Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control measures. Journal of medical virology 92:568–576

Wright R (2020) The world's largest coronavirus lockdown is having a dramatic impact on pollution in India. CNN

Wu X, Nethery RC, Sabath BM, et al (2020) Exposure to air pollution and COVID-19 mortality in the United States. medRxiv

Yunus AP, Masago Y, Hijioka Y (2020) COVID-19 and surface water quality: Improved lake water quality during the lockdown. Science of The Total Environment 731:139012. https://doi.org/10.1016/j.scitotenv.2020.139012

Figures

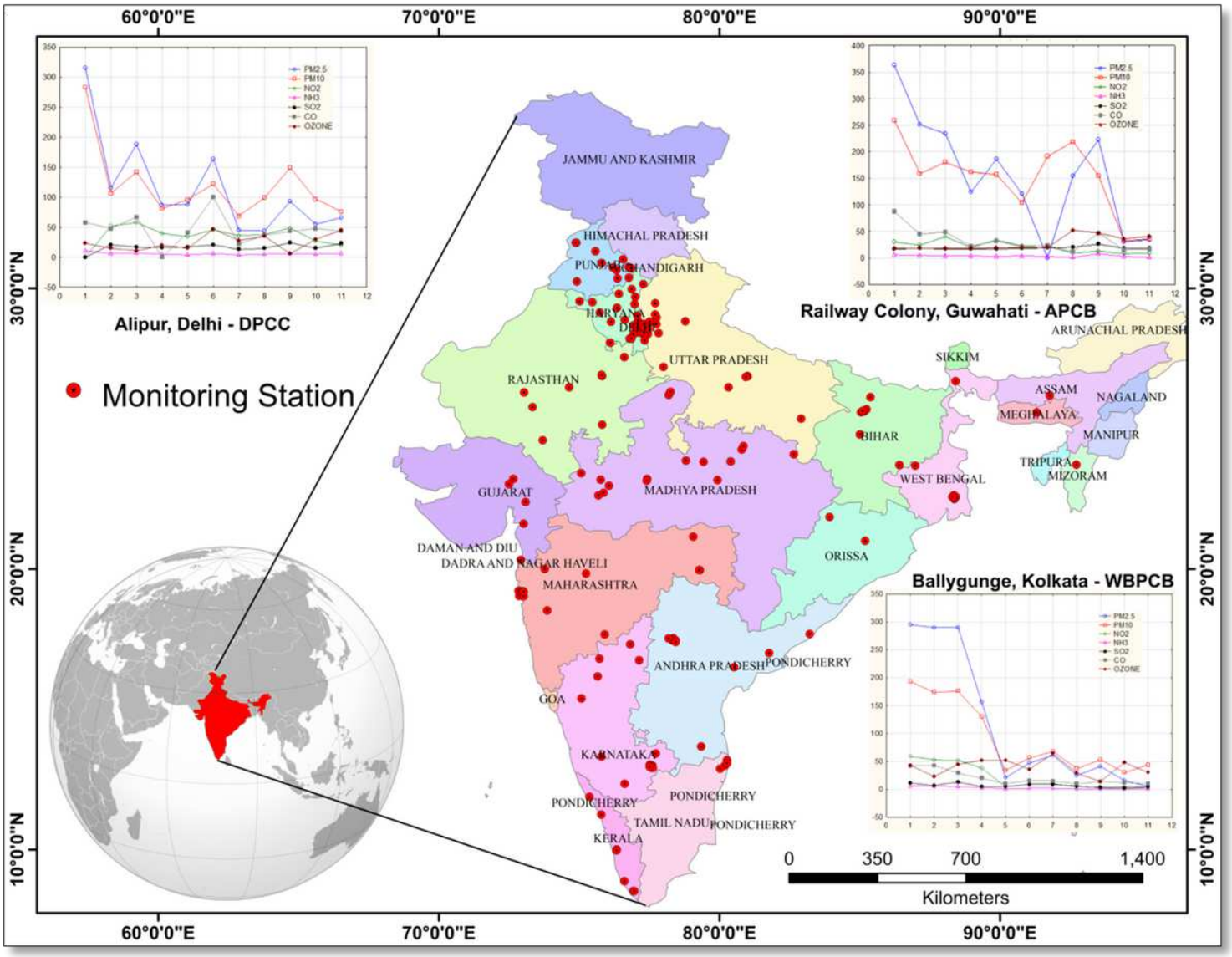


Figure 1

Map of the study area with point location of data sources. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

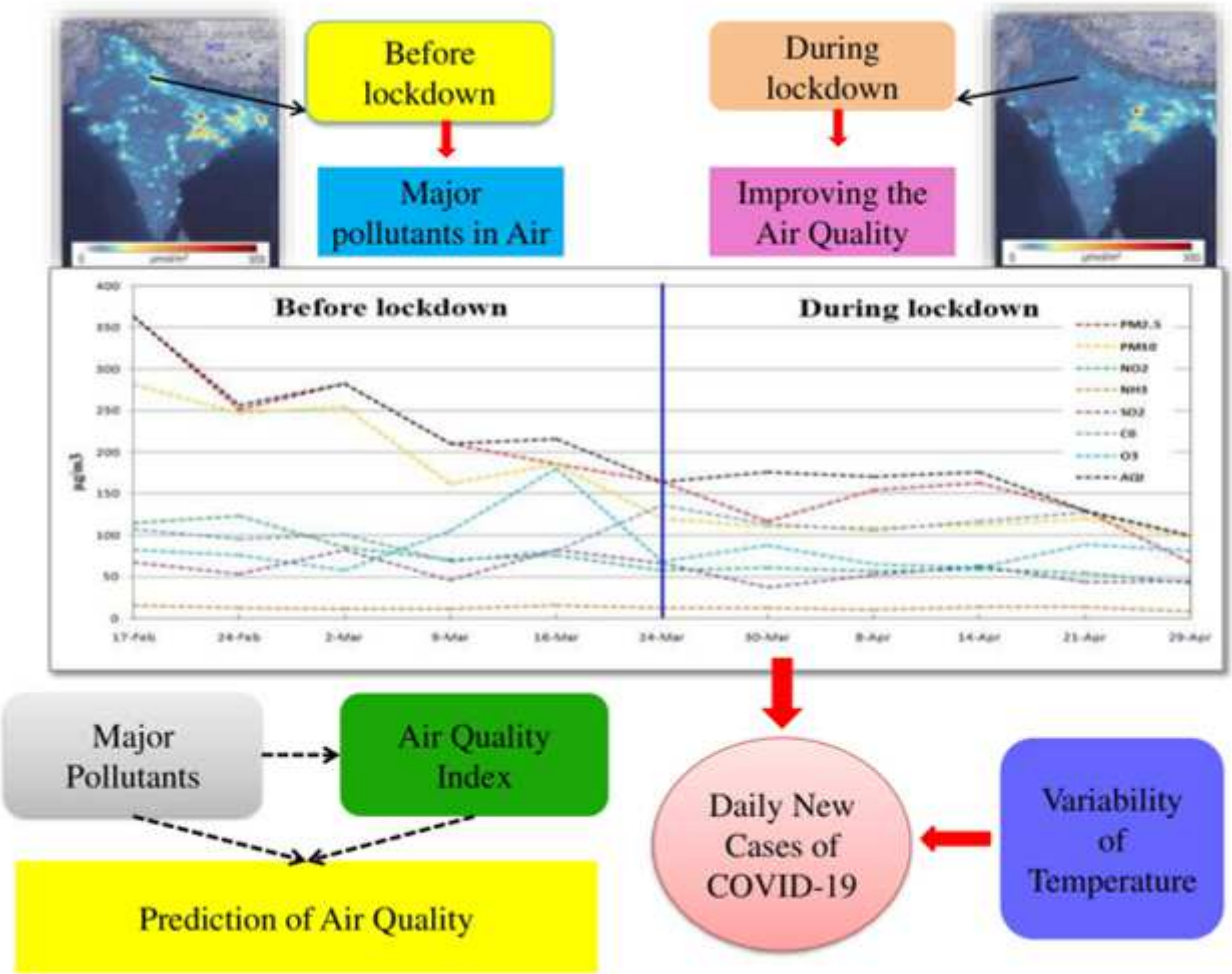


Figure 2

Methodology flow chart.

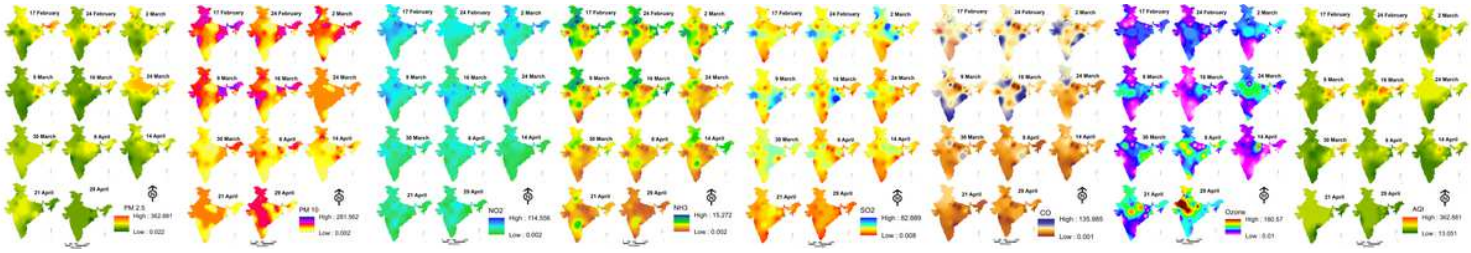


Figure 3

Spatial distribution of PM 2.5 (µg/m3) in before and during lockdown period (a), Spatial distribution of PM 10 (µg/m3) in before and during lockdown period (b), Spatial distribution of NO2 (µg/m3) in before and during lockdown period (c), Spatial distribution of NH3 (µg/m3) in before and during lockdown period (d), Spatial distribution of SO2 (µg/m3) in before and during lockdown period (e), Spatial distribution of CO (µg/m3) in before and during lockdown period (f), Spatial distribution of Ozone (µg/m3) in before and during lockdown period (g) and Spatial distribution of Air Quality Index in before and during lockdown period (h).

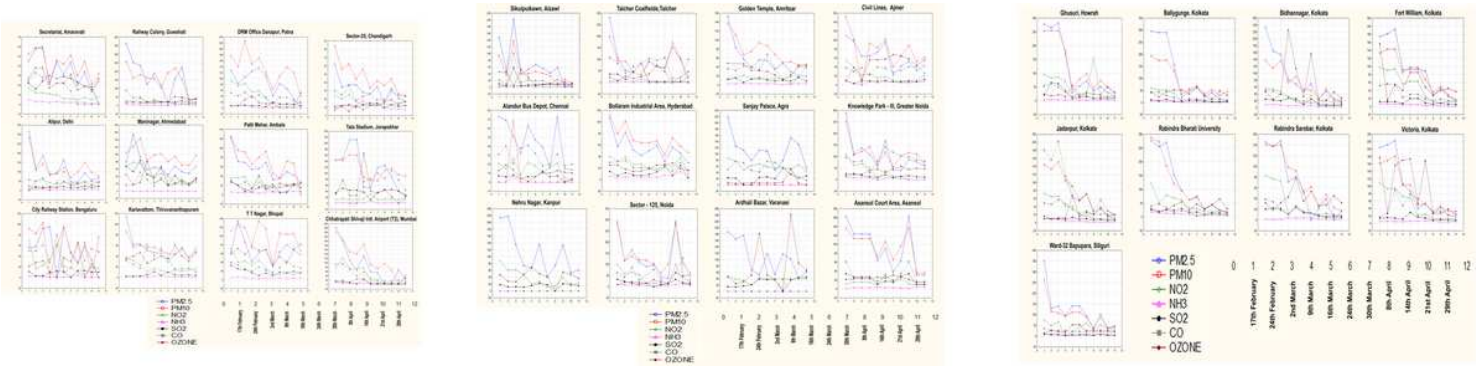


Figure 4

Trend of major pollutants in some selected monitoring station.

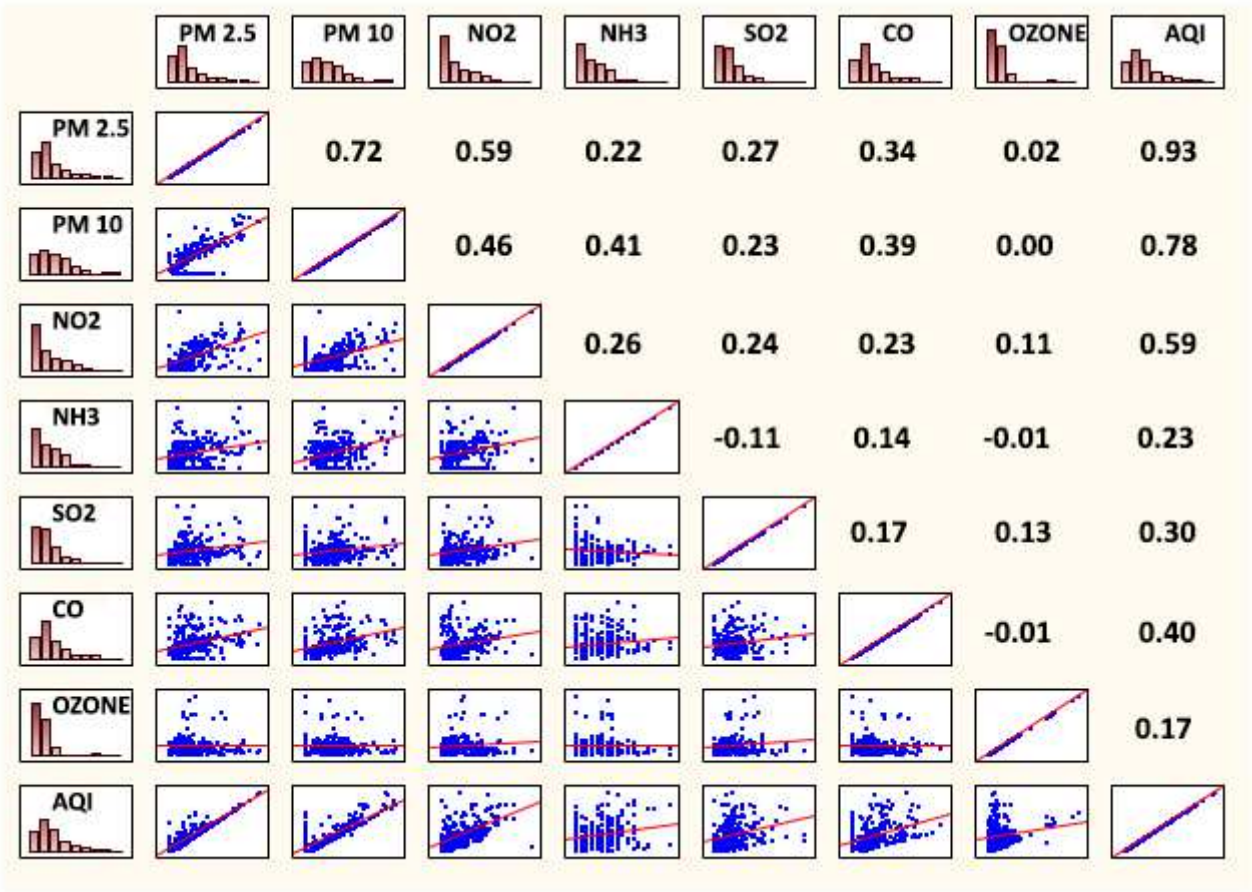


Figure 5

Correlation of different pollutants in India during lockdown.

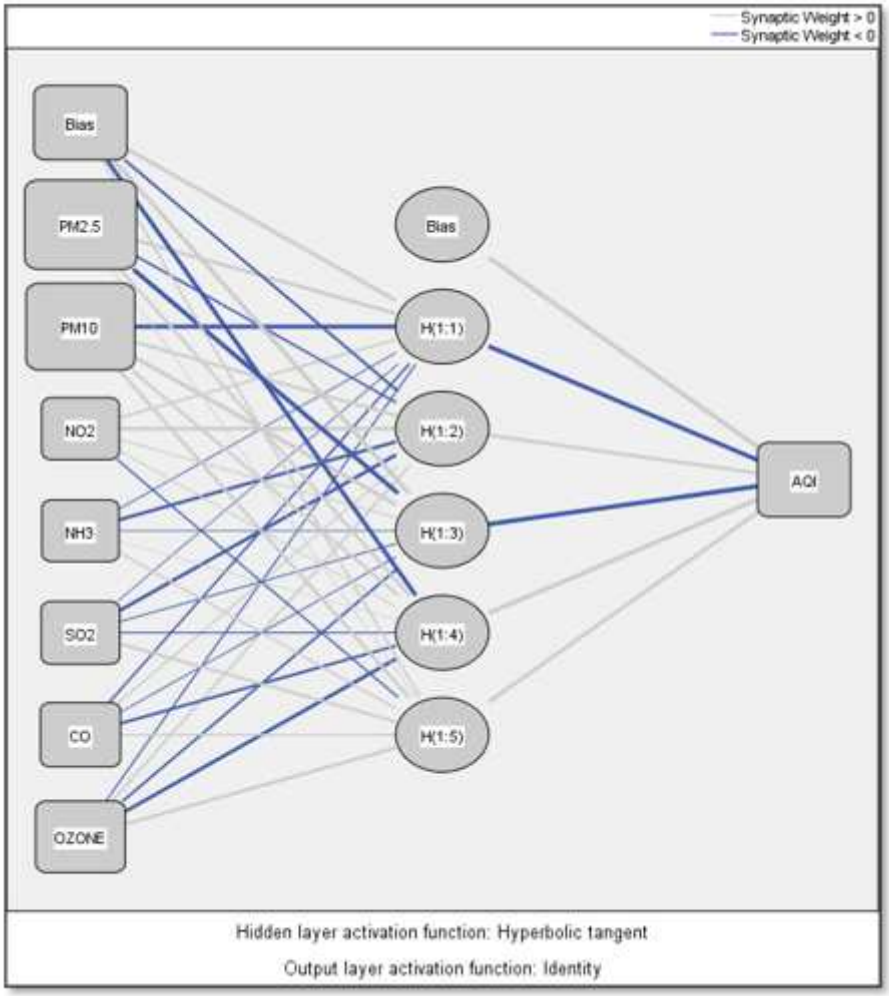


Figure 6

Structure of the network in ANN model.

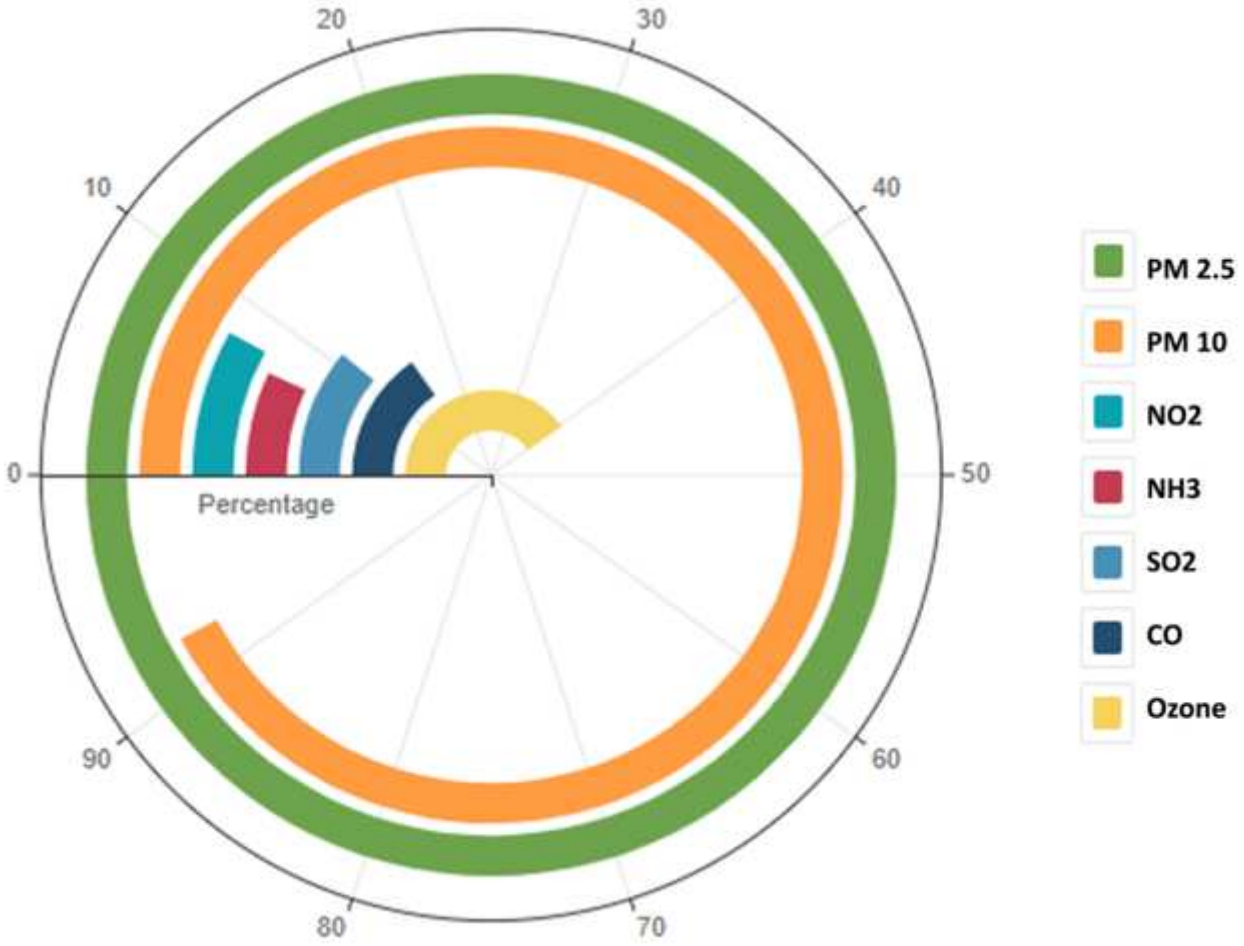


Figure 7

Importance of the variable in ANN model.

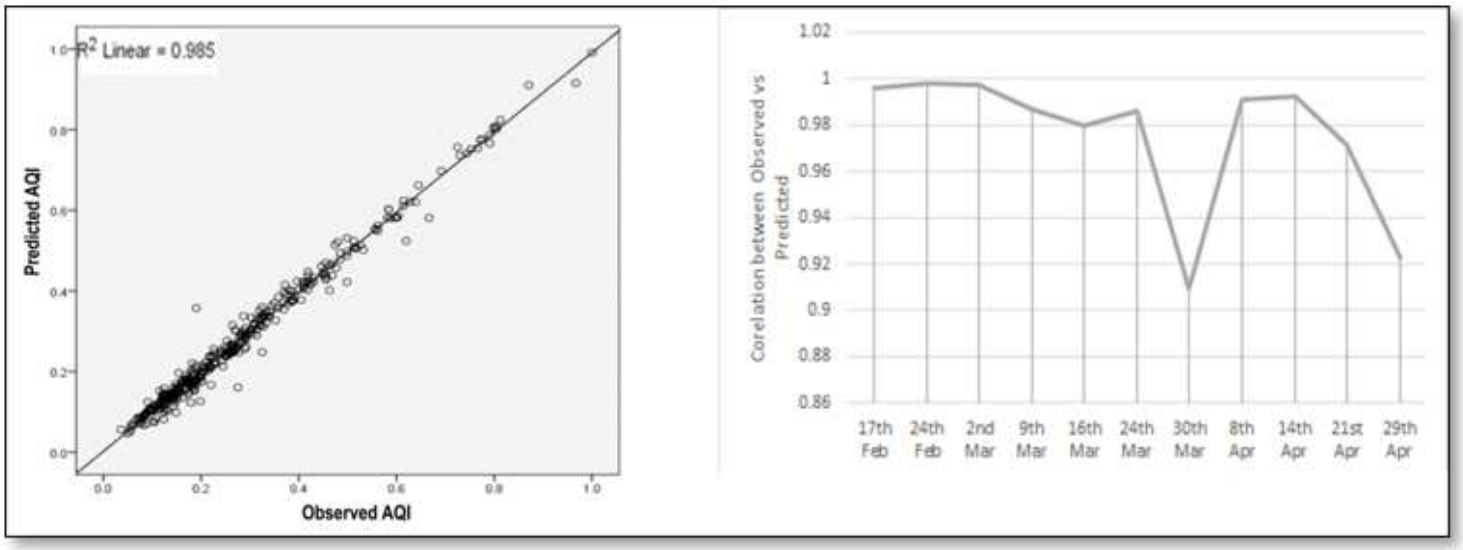


Figure 8

Accuracy of the model using observed vs. predicted values.

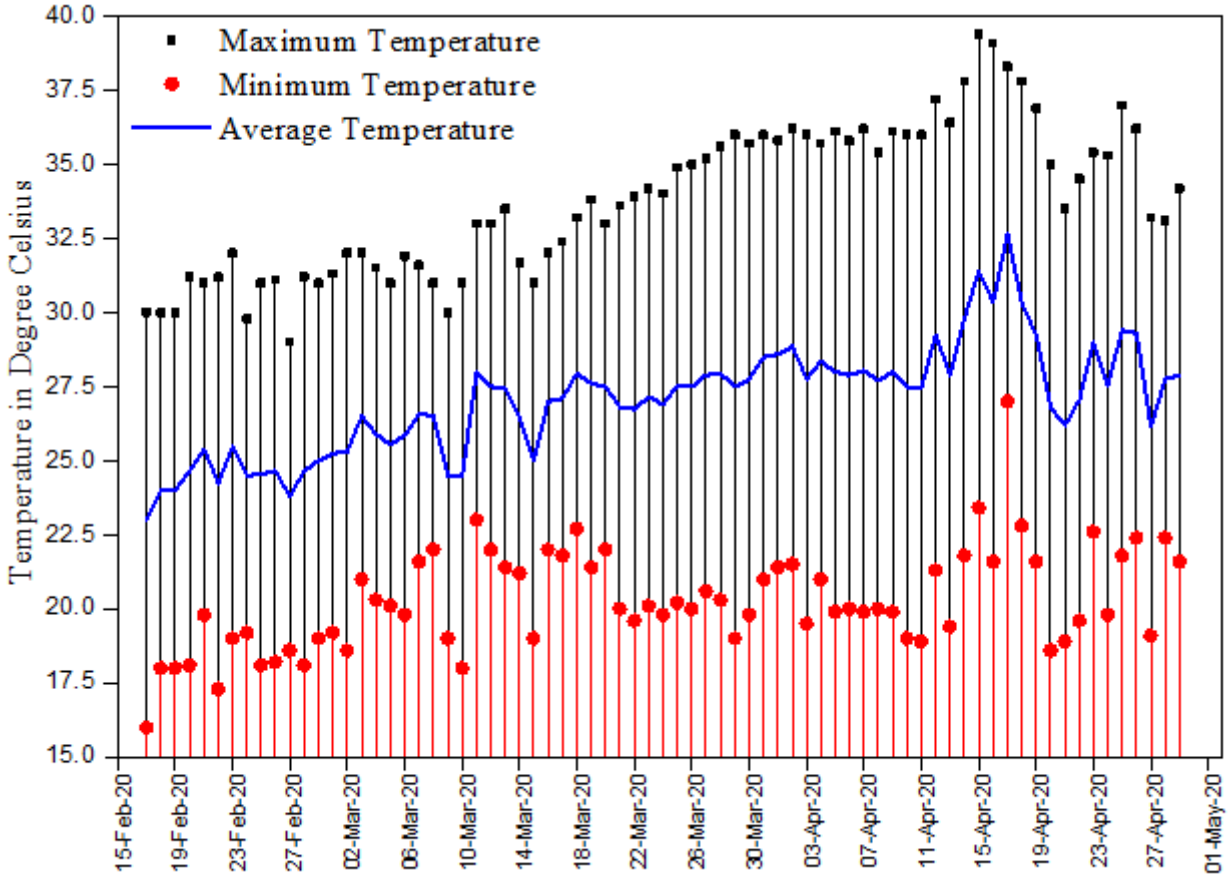


Figure 9

Variability of temperature in before and during lockdown period.

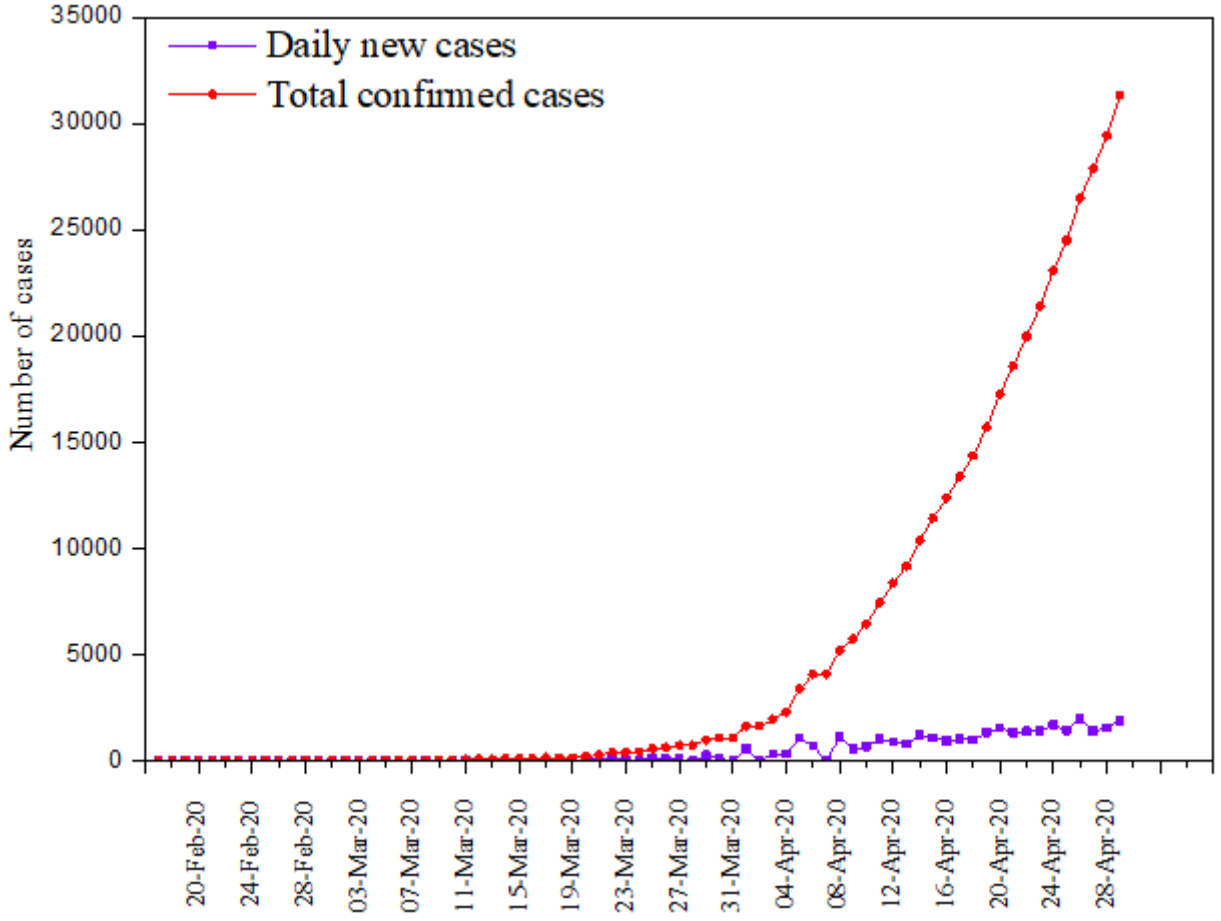


Figure 10

Trend of positive COVID-19 cases in different temporal period.

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