Temporal variation analysis, impact of COVID-19 on air pollutant concentrations, and forecasting of air pollutants over the cities of Bangalore and Delhi in India

Bala Naga Manikanta Meda1 · Aneesh Mathew1

Received: 9 November 2021 / Accepted: 25 March 2022 / Published online: 9 April 2022 © Saudi Society for Geosciences 2022

Abstract
Indian cities are highly vulnerable to atmospheric pollution in recent years, due to exponential growth in urbanisation and industrialisation, and the increased pollution has been made to focus on the temporal variation analysis and forecasting of air pollutants over major Indian cities like Delhi and Bangalore. PM2.5 concentrations are nearly 60.5% less than the annual average value during monsoon season while 76.3% more during the winter months. Ozone concentrations increase during the summer months (~46.3% more than the annual average) in Delhi, whereas in Bangalore, ozone concentrations are more (~75% more than the annual average) during the winter months. Variations of carbon monoxide and nitrogen oxides are significantly less comparatively. COVID-19 lockdown has a substantial positive impact on air pollution. Air pollutant concentrations are reduced during phase I and phase II of the lockdown. Pollutants, especially NOx and PM2.5 concentrations, are drastically reduced compared to the previous years. NOx concentrations are reduced by ~20% in Bangalore, whereas ~50% in Delhi. PM2.5 concentrations are reduced by ~41% in Delhi and ~55% in Bangalore. Forecasting of pollutants will be helpful in providing the valuable information for the optimal air pollution control strategies. It has been observed that linear model gives better results compared to ARIMA and Exponential Smoothening models. By forecasting, the concentration of NO2 is 115.288 µg/m3, the ozone is 30.636 µg/m3, SO2 is 11.798 µg/m3, and CO is 2.758 mg/m3 over Delhi in 2021. All the pollutants during forecasting showed a rising trend except sulphur dioxide.

Keywords Air Pollution · Temporal variations · COVID 19 · Forecasting · Linear model

Introduction
Air pollution is the presence in the ambient atmosphere of substances, generally resulting from human activities, in sufficient concentrations, for long enough periods, and under conditions that obstruct people’s comfort or enjoyment of property (Indian Standard Institution IS–4167 1980). It is the presence of one or more contaminants in the outdoor atmosphere, their characteristics, concentration, time duration affecting human health, vegetation, damages properties, and interference to the comfortable enjoyment of life (Wark et al. 1999).

The concentration of air pollutants is primarily determined by the total amount of pollution released into the environment and the atmospheric conditions that influence the pollutants’ fate. Vehicles, smokestacks, and other industrial emissions into the air and wind erosion of soil are significant sources of air pollution (Brusseau et al. 2019). Anthropogenic and natural source emissions over long periods with enhanced concentrations alter pollutants’ physical and chemical properties. For example, when oxides of nitrogen and volatile organic compounds (VOCs) in car exhaust have been emitted into warm, sunlight air experiences the immediate formation of O3. Hence, air pollution can be caused due to both physical and chemical actions. Air pollutants can fluctuate greatly, even when emissions are pretty consistent, in response to fluctuations in atmospheric conditions. When atmospheric conditions are very stable, even tiny emissions can lead to extreme levels of pollution (Ahammed et al. 2006). Carbon monoxide, lead, ground-level ozone, particulate matter, nitrogen dioxide, and sulphur...
Its oxidation leads to troposphere whose significance has been well recognised. Plants are the primary sources of anthropogenic precursors. Vehicles and power plants are the primary sources of anthropogenic NOx concentrations (Rai et al. 2011). In the lower troposphere, the NOx sources are anthropogenic such as the combustion of fossil fuels. Biomass burning and microbial emissions from agricultural soils can be substantial contributors to rural regions (Van der A et al. 2008). VOCs, one of the major precursors of ozone, contribute to formation of ozone at ground level at a major level through photochemical oxidation reactions. Quantitative assessment of VOCs impact on ozone will be helpful in emission reduction strategies of ozone in cities (Zhang et al. 2020). The major sources of VOCs emissions are vehicles, petrochemical industries, paints, cooking gas usage, and fossil fuel burning (Lyu et al. 2016). The quantities of non-methane hydrocarbons (NMHCs) which are emitted from vegetation mainly also contribute to the ozone formations (Trainer et al. 1987).

Carbon monoxide (CO) is another trace element in the troposphere whose significance has been well recognised. Its oxidation leads to O3 formation or destruction, depending upon the NO concentration. The reaction of CO with hydroxyl radicals is the primary removal process from the atmosphere. Through this mechanism, CO acts as a significant precursor to photochemical ozone (Ahammed et al. 2006).

During hot and sunny summer episodes, ambient concentrations were found to be at their highest (Luna et al. 2014; Biancofiore et al. 2015). Due to high relative humidity, there is a reduction in photochemical production efficiency and an increase in wet deposition, which reduces concentrations of O3 (Lelieveld and Crutzen 1990; García et al. 2011). Atmospheric movements of the air spread concentrations of pollutants like ozone and its precursors. Hence, wind speed and direction are also highly correlated with variations in ozone level concentrations (Revlett 1978; García et al. 2011).

Van der A et al. (2008) derived trends of NOx globally over the period of 1996–2006 and found 7% declined emission annually. Peshin et al. (2017) have conducted spatio-temporal variation of atmospheric pollutants and anthropogenic effects on the ozone formation across the Delhi region during 2010–2014 and found that ozone is > 65% during October–February compared to other months. COVID-19 lockdown measures had resulted in a considerable change in air pollution worldwide. The complete shutdown of many industries and minimal usage of vehicle reduce pollution worldwide (Singh et al. 2020). There is a huge positive impact on the air pollution due to lockdown during this global pandemic (Dales et al. 2021; Liu et al. 2021; Barua and Nath 2021; Tian et al. 2021; Othman and Latif 2021).

Singh et al. (2020) have conducted a study over different regions of India and found significant reduction in particulate matter during lockdown. The highest decrease in particulate matter (~50–70%) was found for the northwest and Indo-Gangetic Plains. A significant reduction (~30–70%) in NO2 was found except for a few sites in the central region. Similar reductions were observed for CO having a 20–40% reduction. Kerimray et al. (2020) have investigated the effects of traffic-free urban settings on air quality in big cities during the COVID-19 lockdown in Almaty, Kazakhstan, and found PM2.5 concentrations were lowered by 20% during the lockdown, variations ranging from 7 to 34% in various regions, compared to the average on the same days in 2018–2019. Many pollutant concentrations declined in during lockdown while few studies (Kerimray et al. 2020; Singh et al. 2020) reported ozone concentrations actually increased during lockdown due to suitable meteorological conditions.

The present study primarily focusses on the temporal variations of air pollution, the impact of COVID-19 lockdown on air quality, and forecasting of pollutant concentrations for 2021. Atmospheric pollutants exhibit spatio-temporal variations. Spatial variations are generally due to variations in emissions in various locations. While temporal variations are mainly due to seasonal climatic changes. It is very important to study temporal variations to assess the behavioural pattern of pollutants for making strategies in reducing air pollution. Also, the study aims to analyse the effect of lockdown due to COVID-19 on the air pollutant concentration over the cities of Bangalore and Delhi. The formation of the various primary and secondary pollutants is very much complex in the atmosphere. Hence, it is required to develop forecasting model using advanced statistical models. Various air pollutants are also highly variable temporally as well as spatially. So, another objective of the present study is to perform forecasting modelling of various air pollutants using time-based regression models in terms of performance efficiency.

**Study areas**

The present work mainly focussed on two study areas: Bangalore and New Delhi. Bangalore is a south Indian city, while New Delhi is a north Indian city with extreme climates.
comparatively. Difference in climatic conditions and pollution level made me choose the cities for the study.

**Bangalore**

Bangalore is a metropolitan city in Karnataka state. Being most significant information technology (IT) industry in India is in Bangalore; it is called Silicon city. The population of Bangalore is about 11 million. Bangalore has a tropical savanna climate as per Koppen climatic classification ‘Aw’ with distinct wet and dry seasons. Bangalore usually has a more moderate climate throughout the year because of its higher elevation. The average annual rainfall is about 974.5 mm (http://www.bangalore.climatemps.com/). Bangalore is home to a wide range of heavy and light industries and high-tech and service industries, including IT and electronics, telecommunications, aerospace, and many other industries.

Vehicular emissions account for 60–70% of Bangalore’s pollution (Karnataka State Pollution Board). One of the most significant sources of air pollution is vehicular pollution. Inadequate urban governance also affects Bangalore, causing waste treatment and the use of diesel generators for electricity. Figure 1 shows the geographic location of Bangalore study area.

**Delhi**

New Delhi, India’s capital city, is a cosmopolitan city with 30.29 million people and a land area of about 42.7 km². Delhi’s climate mixes monsoon-influenced humid subtropical (Koppen climate classification Cwa) and semi-arid (Koppen climate classification BSh), with significant differences in summer and winter temperatures and precipitation. The average annual rainfall is about 800 mm (http://www.newdelhi.climatemps.com/). Figure 2 represents the geographic location of Delhi.

IT, telecommunications, banking, hotels, media, and tourism are among the key industries. Delhi’s manufacturing industries have also grown as many consumer goods companies have established manufacturing units and offices in the region. Apart from industries, animal agriculture contributes to Delhi’s pollution problem, as smog and other harmful

---

![Fig. 1 Geographic location of Bangalore study area](image-url)
particles are produced by farmers burning their crops in other states. Animal agriculture accounts for approximately 80% of agricultural land. Animal agriculture is also a contributing factor to Delhi’s air pollution.

**Data and methodology**

The data required for the study have been collected for both cities, i.e. Bangalore and New Delhi. The data have been collected from all India CAAQMS (Continuous Ambient Air Quality Monitoring Station) portal (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing). For Delhi, the data have been collected from four CAAQM stations. They are Mandir Marg, Anandvihar station, R K Puram, and Shadipur stations. For Bangalore, the data have been collected from BTM Layout, City Metro Station, and Silk Board stations.

For temporal variations, the daily average concentrations of various pollutants, viz., carbon monoxide, oxides of nitrogen, ozone, and particulate matter, are collected for years 2017, 2018, and 2019 from all the above stations. For forecasting analysis, the annual average of various pollutants is collected from 2013 to 2019 and forecasted for 2021.

Pre-processing of data has been carried out after the collection of data. Data pre-processing helps to deal with missing data and inconsistent data. Data pre-processing includes cleaning, normalisation, transformation, and deletion of noisy data. The removal of out of range data is an essential task in data pre-processing. For example, due to errors, the concentration value may be negative in the data. Such data must be removed. This is called out of range data removal. Conversion of pollutant concentration values into required units is also done in this step.

Figure 3 shows the flowchart of methodology which illustrates the step by step procedures of methodology adopted for the present study. The collected data is pre-processed and then transformed into categories of interest. For temporal variation in the pollution, the daily average concentrations are clustered according to the months for further analysis. To analyse hourly variations, each hour data over the period is clustered separately, and various graphs have been plotted.

![Geographic location of Delhi study area](image)

**Fig. 2** Geographic location of Delhi study area
Then, categorised data is used for finding temporal variation analysis and variations in pollutants due to COVID-19 lockdowns. The annual average data of pollutants are collected, and using various predictive analysis techniques, forecasting of pollutants has been conducted.

**Time-based regression analysis**

Time series regression is a statistical method for predicting future responses using previous experiences and the transfer of dynamics from relevant predictors. From observational or experimental data, time series regression can help understand and predict the behaviour of dynamic systems (Ibrahim et al. 2009). Various models address time-based regression like the linear model, the Auto-Regressive Integrated Moving Average model, and Exponential smoothening.

**Linear model**

A line equation drives a linear model. Time series analysis is done by building the equation with dependent and independent variables.

\[
y = \sum_{i=0}^{n} \beta_i x_i + \theta.
\]

Here,

- \(y\) dependent variable
- \(x_i\) \(i^{th}\) independent variable or predictor variable
- \(\theta\) intercept or bias variable
- \(\beta\) coefficient of predictor variable

The Ordinary Least Squares technique is used to optimise the error in the linear model. The function to be optimised is

\[
S(\varepsilon) = \left| y_i - \sum_{j=1}^{p} x_j \beta_j \right|^2 = \|y - \beta x\|^2
\]

where,

- \(S(\varepsilon)\) error function
- \(p\) no of observations

**ARIMA model**

ARIMA is an acronym that stands for Auto-Regressive Integrated Moving Average. This acronym is descriptive, capturing the key aspects of the model itself (Hyndman and Khandakar 2008). Briefly, they are:

- **AR**: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations.
- **I**: Integrated. The use of differencing of raw observations (e.g. subtracting an observation from an observation at the previous time step) in order to make the time series stationary.
- **MA**: Moving Average. A model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

It is a type of model that explains a time series based on its past values, lags, and forecast errors. As a result, that equation can be used to forecast.

A standard notation is used of ARIMA \((p, d, q)\) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used. The parameters of the ARIMA model are defined as follows:

**Fig. 3** Flowchart of methodology
Exponential smoothening

Exponential Smoothening is one of the forecasting methods which is helpful in forecasting the data of no clear trend or seasonal pattern. In simple exponential smoothening, forecasts are calculated using weighted averages, where the weights decrease exponentially as observations come from further in the past the smallest weights which are associated with the oldest observations:

\[ y_{T+1} = \alpha y_T + (\alpha - 1)y_{T-1} + (\alpha - 1)^2 y_{T-2} + \ldots \]  

(3)

where,

- \( y_{T+1} \) forecasted value for \( T+1 \) observation from \( T \) observation
- \( \alpha \) smoothening parameter and \( 0 \leq \alpha \leq 1 \)

Performance evaluation of models

The model performance has been evaluated by calculating various error standards, correlation coefficient (\( R \)), and determination (\( R^2 \)). \( R^2 \) value determines the goodness of fit between actual model predicted values. Also, various error standards for a model like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) will give a better view of how the actual and predicted values vary. Also, the correlation plot (actual vs. predicted) shows a clear relation between actual and predicted.

The coefficient of determination (\( R^2 \)) value gives the proportion of the variance in the dependent variable that is predictable from the independent variable.

\[
R^2 = \frac{n[\sum_{i=1}^{n} p_i a_i - \sum_{i=1}^{n} p_i \sum_{i=1}^{n} a_i]^2}{\left[ n \sum_{i=1}^{n} a_i^2 - (\sum_{i=1}^{n} a_i)^2 \right] \left[ n \sum_{i=1}^{n} p_i^2 - (\sum_{i=1}^{n} p_i)^2 \right]} \]

(4)

MAE gives the average difference between actual and predicted values.

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |p_i - a_i| 
\]

(5)

MAPE tells the percentage deviation of the prediction value from the actual value.

\[
MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{p_i - a_i}{a_i} \right| \]

(6)

MSE is a combined measurement of the mean and variance of the error.

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (p_i - a_i)^2 
\]

(7)

RMSE is the square root of MSE

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - a_i)^2} 
\]

(8)

where,

- \( a_i \) actual observation of \( i^{th} \) observation in data
- \( p_i \) predicted observation of \( i^{th} \) observation in data

Results and discussions

Temporal variation analysis of air pollution

Various air pollutant concentration data have been collected from CAAQMS for Delhi and Bangalore cities for carrying out temporal and seasonal variation analysis from 2017 to 2019. The data have been pre-processed, and the average monthly pollutant concentrations are tabulated.

Temporal variation analysis for Delhi

The monthly and annual average pollutant concentrations of \( \text{NO}_x \), ozone, \( \text{PM}_{2.5} \), and CO have been tabulated for Delhi city. Various charts have been developed for analysing temporal variations of pollutant concentrations in Delhi city. Various graphs have been developed showing different trend analyses in Delhi as depicted in Fig. 4.

Annual average particulate matter (\( \text{PM}_{2.5} \)) concentrations have been 121.48, 145.27, and 145.56 \( \mu g/m^3 \), respectively, for the years 2019, 2018, and 2017. The particulate matter concentrations were high up to 245 \( \mu g/m^3 \) in December 2019, 295.26 \( \mu g/m^3 \) in December 2018, and 327.06 \( \mu g/m^3 \) in November 2017. The lowest \( \text{PM}_{2.5} \) concentrations were 41.12 \( \mu g/m^3 \) in August 2019, 47 \( \mu g/m^3 \) in August 2018, and 46 \( \mu g/m^3 \) in August 2017. It has been observed that \( \text{PM}_{2.5} \) concentrations are very high during winter months and least during monsoon months. The \( \text{PM}_{2.5} \) has been following a trend with a higher value in January, and it keeps reducing up to September, i.e. completing summer and monsoon, and then hikes up to the end of the year, i.e. winter in Delhi.
Fig. 4 Monthly variation of pollutants (a) PM$_{2.5}$, (b) NO$_x$, (c) CO, (d) ozone over Delhi.
Annual average concentrations of NO$_x$ have been 126.98, 133.20, and 206.25 ppb for the years 2019, 2018, and 2017, respectively. Monthly NO$_x$ concentrations were high up to 179.59 ppb in January 2019, 246.48 ppb in January 2018, and 297.27 ppb in October 2017. The trend has followed almost similar throughout the year with lesser values during June, July, and August. The least monthly average values were 72.50 ppb in June 2019, 74.41 ppb in May 2018, and 98.48 ppb in August 2017. The NO$_x$ concentrations are high during winter months, moderate during summer, and least during monsoon months. Concentrations have been reduced from 2017 to 2019 in Delhi.

The annual average concentrations of CO have been 2.15, 2.42, and 2.26 mg/m$^3$ for the years 2019, 2018, and 2017, respectively. The highest monthly average concentrations were 3.22 mg/m$^3$ in January 2019, 3.51 mg/m$^3$ in December 2018, and 3.42 mg/m$^3$ in November 2017. The least monthly average values were 1.43 mg/m$^3$ in August 2019, 1.67 mg/m$^3$ in August 2018, and 1.48 mg/m$^3$ in September 2017. The CO values are high during October, November, and December, i.e. during winter period. CO concentrations are less during the monsoon months. No much difference in concentrations has been recorded between winter and summer.

One of the significant secondary pollutant ozone trends is quite different compared to other pollutants. The annual average concentrations in Delhi were 31.59, 29.14, and 28.96 µg/m$^3$ for the years 2017, 2018, and 2019, respectively. The higher ozone concentrations were 39.21 µg/m$^3$ in March 2019, 43.34 µg/m$^3$ in April 2018, and 66.52 µg/m$^3$ in May 2017. The least average monthly ozone concentrations were 18.85 µg/m$^3$ in March 2019, 20.08 µg/m$^3$ in February 2018, and 14.79 µg/m$^3$ in February 2017. The trend of ozone has behaved quite differently compared to other pollutants. The ozone has encountered higher concentrations in summer and least during the winter months of December and August. The reason behind this trend variation is because of the ozone dependence on the meteorology of the area. In summer, due to higher solar radiations, higher ozone concentrations are formed.

**Temporal variation analysis for Bangalore**

The monthly and annual average pollutant concentrations of NO$_x$, ozone, PM$_{2.5}$, and CO have been tabulated for Bangalore city. Various charts have been developed for analysing temporal variations in Bangalore. Various graphs have been developed and showing trend analysis in Bangalore as depicted in Fig. 5.

The annual average PM$_{2.5}$ concentrations have been found to be 43.45, 38.08, and 41.55 µg/m$^3$ for the years 2019, 2018, and 2017, respectively, in Bangalore. In 2019, the highest concentration was occurred in January and was 74.75 µg/m$^3$, while the least concentration was 20.9 µg/m$^3$ in August. In 2018, the highest and the least were 73.29 and 14.59 µg/m$^3$ in December and August, respectively. During monsoon, the least concentrations have been recorded, and the highest was recorded in the winter months. The difference in concentrations between the summer months and winter months is pretty less. The trend has started with higher values in January and continued at a steady pace until April and has been falling until September (i.e. up to monsoon season) and again raised until December (due to winter).

The trend of PM$_{2.5}$ in both Delhi and Bangalore cities is similar in comparison. The concentrations of PM$_{2.5}$ in Delhi have been found to be 3 to 4 times higher than those in Bangalore. The concentrations in Bangalore are mostly under permissible limits, while in Delhi, PM$_{2.5}$ is one of the primary pollutants that is devastating the environment.

The annual average concentrations of NO$_x$ pollutants have been observed to be 22.83, 22.80, and 11.00 ppb for the years 2019, 2018, and 2017, respectively. The highest concentrations were 33.97 ppb in May 2019, 43.97 ppb in October 2018, and 13.41 ppb in May 2017. The least monthly average concentrations were 10.05 ppb in December 2019, 14.19 ppb in August 2018, and 7.39 ppb in March 2017. NO$_x$ trend is similar throughout the year. The concentrations of NO$_x$ are not much varied throughout the year. NOx concentrations are not varied seasonally because most of the NO$_x$ pollution is due to vehicles, and vehicular pollution is similar throughout the year.

The NO$_x$ pollution in Delhi is very much higher than that of Bangalore. The trend analysis in Delhi shows a seasonal variation, while Bangalore is not showing any seasonal variations. The pollutant concentrations in Delhi have been found to be 10–12 times higher than those in Bangalore.

The annual averages of carbon monoxides were 0.88, 0.75, and 0.49 mg/m$^3$ for the years 2019, 2018, and 2017, respectively. The highest concentrations recorded monthly were 1.15 mg/m$^3$ in March 2019, 1.25 mg/m$^3$ in November 2018, and 0.79 mg/m$^3$ in January 2017. The lowest concentrations recorded were 0.22 mg/m$^3$ in July 2017, 0.67 mg/m$^3$ in April 2018, and 0.713 mg/m$^3$ in November 2019. The seasonal variation of CO is comparatively less. The CO concentrations have been observed to be higher during summer in 2019, while during 2017 and 2018, CO concentrations are higher during the winter months. No proper trend was observed for CO in Bangalore.

The CO concentrations have been reduced from 2017 to 2019 in Delhi, while it was observed that there is an increase in CO concentrations in Bangalore, which is an adverse effect. Seasonal variations have also been noticed in Delhi for CO, while no such trend has been observed in Bangalore. The CO concentrations in Delhi have been observed to be 2 to 5 times more than those in Bangalore.
Fig. 5 Monthly variation of pollutants (a) PM$_{2.5}$, (b) NO$_x$, (c) CO, (d) ozone over Bangalore
The annual average concentrations were 35.52, 36.53, and 34.94 µg/m³ for the years 2019, 2018, and 2017, respectively. The monthly highest concentrations were recorded as 61.53 µg/m³ in January 2019, 76.41 µg/m³ in January 2018, and 73.64 µg/m³ in February 2017. The least monthly concentrations were 17.09 µg/m³ in August 2019, 15.59 µg/m³ in August 2018, and 14.26 in August 2017. There is a strong trend followed by the ozone in Bangalore with higher concentrations during winter and least during monsoon.

Higher concentrations of ozone have been recorded in winter in Bangalore, while in Delhi, the higher concentrations are found in summer. Meteorology may also influence the air pollutants’ concentration variations in both cities. The ozone formation is influenced by meteorology. Even though pollutant concentrations are higher in Delhi, it has been observed that ozone concentrations are higher in Bangalore.

Compared to Delhi city, the correlation of meteorological parameters with mean ozone concentrations in Bangalore is much higher. The meteorology in Bangalore city has a higher impact on ozone concentration at the ground level than in Delhi city. Wind speed and wind direction affect the mixing and spread of pollutant concentrations (Revlett 1978) and its correlation with ozone in Bangalore is higher than that in Delhi city.

### Percentage variation analysis

However, the amount of the variations of pollutant concentrations is also needed to find. By making yearly average as a benchmark for the pollutant concentration over the year, the percentage of pollutant concentration varied with the average value has been calculated. The charts have been developed showing percentage variations for different years and have been depicted in Figs. 6 and 7.

\[
\% \text{Variation} = \frac{\text{concentration in a month} - \text{Average value in that year}}{\text{Average value in that year}} \times 100
\]

(9)

All the pollutant concentrations have been found to be higher than the annual average concentrations during the winter months. The monthly variation of carbon monoxide over the years for both cities is less compared to other pollutants. The highest positive and negative variation has been found to be 61.73% and −55.16% during months of January and July, respectively for the year 2019 in Bangalore. While in Delhi, it has been noticed to be 53.01% and −43.25% during November and June, respectively, for the year 2017. Other pollutants like ozone have experienced more than 100% variations. The highest positive and negative percentage variation of ozone was 109.19% during Jan 2017 and −55.168% during July 2019 in Bangalore, and it was 110% during April 2017 and −33.31% during August 2019 for Delhi. Ozone is the only pollutant among the considered pollutants whose trend is varied between the two cities because ozone is regulated by meteorology. Oxides of nitrogen did not show significant variations over the period. Even though the highest positive variation in NOx in Bangalore was 92.79%, the variation of more than 50% never happened over 3 years. The highest negative variation that happened in Bangalore was −55.94%. Particulate matter (PM2.5) is one of the pollutants which follow a strong trend for both cities. Monsoon is the season with the least PM2.5 pollution, but during the winter, PM2.5 pollution is at the worst level. The average monthly variation is higher than the annual average values during winter, with a highest of 92.47% in Bangalore and 103.24% in Delhi, while the highest negative is −67.13% and −69.89%, respectively for Bangalore and Delhi cities. Simply considering annual data is not advised and temporal variations must be taken into consideration in order to analyse the pollutant concentration variations.

### Impact on pollution due to COVID-19 lockdowns

During the COVID-19 lockdown period in India, due to the shutdown of industries, minimal traffic and lessened anthropogenic activities accounting for pollution helped to improve the urban cities’ air quality. The phase I lockdown was put in place from 25th March 2020 with a complete shutdown of all services and factories for 21 days, i.e. up to 14 April 2020. At the end of phase 1, it was announced by the Government of India to extend the lockdown up to 3rd May 2020, i.e. for 20 more days as phase II of lockdown. How the COVID-19 lockdown influenced the reduction in air pollution has been carried out by comparing pollution during the lockdown period with the previous years (2019 and 2018) which is tabulated, for Delhi and Bangalore cities, respectively. Along with the period of lockdown, the comparison in air pollution variations has also been made for 25 days before and after lockdown.

The analysis has been made featuring the impact of COVID-19 lockdown on air pollution in Delhi and Bangalore cities. Various graphs have been developed showing the comparison of daily average concentrations of various air pollutants like NO₂, ozone, PM2.5, and CO during lockdown period and the same period’s pollutant concentrations during 2018 and 2019. Also 10 days before and after lockdown, the pollutant concentration variations are also depicted in Figs. 8 and 9 for Delhi and Bangalore, respectively.

In Delhi, all the pollutants show a reduction during lockdown period. During COVID-19 period (i.e. 25 March 2020 to 5 May 2020), the concentrations of NO₂ have reduced drastically. The concentrations had not reached value of 30 µg/m³ during this period, while during same days in 2018 and 2019, NO₂ concentrations were as high as 100 µg/m³. No days during lockdown have exceeded the concentrations of respective day in 2018 and 2019.
The concentrations of PM$_{2.5}$ have been reduced drastically during lockdown in comparison with previous years. The daily average concentrations have not reached 100 µg/m$^3$ during lockdown and the highest was 72.18 µg/m$^3$. In 2018 and 2019, during the same period of time, the concentrations on some certain days had reached the higher values up to 217.87 µg/m$^3$ which was quite higher than daily average standard value of 60 µg/m$^3$ as per NAAQS (National Ambient Air Quality Standards) standards. During the lockdown period, the concentrations of PM$_{2.5}$ were highly controlled and under NAAQS standards for most of the days, while during the same period in previous years, the concentrations were quite higher than daily average standard value.

The concentrations of ozone were also reduced during the lockdown period. The concentration has reached as low as 50 µg/m$^3$ during lockdown, while in previous years during...
the same period, the daily average concentrations have reached as high as 94.68 µg/m³. During phase II of lockdown, the concentrations of ozone have been on higher side compared to previous years. During phase I, the daily average ozone concentrations exceeded those of previous year which was two, while during phase II, it was 15 days. Even though the concentrations of NO₂ have been reduced significantly, ozone concentrations did not reduce. This is because of the regulation of ozone not only by ozone precursors but also due to meteorology (Feng et al. 2019).

The concentrations of CO also have been reduced but not as drastically as NO₂ and PM₂.₅ in Delhi. This has happened even though anthropogenic emissions reduced because natural source emissions were higher in Delhi. The daily average CO concentrations were reduced up to 0.7 mg/m³, and in previous years, it was about 2.5 µg/m³.
The air pollution concentrations were reduced in Bangalore also due to lockdown. The air quality has been increased gradually during lockdown. The daily average PM$_{2.5}$ concentrations in Bangalore have been reduced drastically compared to previous years 2018 and 2019. The highest daily average concentration during lockdown was less than 47.02 µg/m$^3$, while in 2019, it was 114.07 µg/m$^3$ and in 2018, it was 231.38 µg/m$^3$.

The concentrations of NO$_2$ have been reduced slightly during lockdown in Bangalore. The NO$_2$ concentrations were very high during 2018 and 2019; the concentrations have reduced compared to 2018. The reductions in daily
Fig. 9 Comparison of various pollutant concentrations during the lockdown, 10 days before and after the lockdown (a) PM$_{2.5}$, (b) NO$_2$, (c) CO, (d) ozone in Bangalore

(a) PM$_{2.5}$

(b) NO$_2$

(c) CO

(d) Ozone
average pollutant concentrations during lockdown are low compared with the daily average concentrations of the same period of 2019, while these reductions are pretty high compared with 2018. The highest daily average concentration during lockdown was 22 µg/m³, while in 2019, it was 34.03 µg/m³ and in 2018, it was 85.34 µg/m³.

The concentrations of CO have been reduced significantly and the concentrations are pretty constant throughout the lockdown period. The highest concentration during lockdown was 0.96 mg/m³, while during 2019 and 2018, CO concentrations were 3.63 and 2.12 mg/m³, respectively.

The daily average concentrations of ozone have reduced slightly during the lockdown. The concentrations of ozone have reached a least value of 25.01 µg/m³ during lockdown period. The highest daily average concentration during lockdown was 49.87 µg/m³, while during 2018 and 2019 were 68.38 and 81.07 µg/m³, respectively. Many days during lockdown have exceeded the average concentrations compared to previous years.

Analysing the various pollutant concentrations during COVID-19 with previous years (2018 and 2019), concentrations of the same day show the significant reduction in pollution over both cities. Overall pollution has been reduced in 2020 when compared to 2019. The percentage reduction of air pollution during lockdown phases I and II is depicted in Table 1 and Table 2. So, to know the extent of reduction during the lockdown, the comparison also included 25 days prior to and later the lockdown and is depicted in Figs. 10 and 11. Twenty-five days before lockdown, the concentrations during 2020 were likely a little less than those in 2019. However, during the lockdown, the concentration has reduced more than before the lockdown. After lockdown, some of the pollutant concentrations have increased more, even a partial lockdown was imposed. The daily average concentrations of CO in Bangalore and Delhi were reduced by 37.06% and 13.23%, respectively, during phase I and 21.95% and 20.12% during phase II. The daily average concentrations of CO were 0.69 mg/m³ and 1.26 mg/m³ during 25 days before lockdown, and during lockdown in Bangalore, average concentrations of CO were 1.12 mg/m³ and 0.88 mg/m³. There is almost 50% reduction in daily average concentrations in comparison to 25 days before and during lockdown. PM$_{2.5}$ is one of the major pollutant concentrations which were also reduced drastically during the lockdown. There was 60.43% reduction in Bangalore, and it was 45.57% in Delhi during phase I. During phase II, the reduction was lesser than that during phase I and was 50.14% and 36.21% in Bangalore and Delhi, respectively. The daily annual average concentrations were reduced by 18.5% and 25.13% in Bangalore and Delhi cities during phase I. It was observed that the ozone concentrations rather than reduced were actually increased by 4.13% which is due to favourable meteorology in Delhi especially due to increase in solar radiation, and in Bangalore, it was reduced by 10.12% during phase II. The oxides of nitrogen were also reduced by 14.05% during phase I in Bangalore and there is drastic reduction of 44.25% in Delhi. During phase II of lockdown, the reduction in Bangalore was 15.96%, and in Delhi, it was 55.62%. Unlike other pollutants, NO$_2$ concentrations were reduced more during phase II than phase I. On an overall scrutiny, lockdown has shown an impeccable reduction in pollution. The results show that PM$_{2.5}$, CO, and ozone reductions in Bangalore are more compared to Delhi, while NO$_2$ reductions in Delhi are more compared to Bangalore.

### Table 1
| Lockdown | Avg. % reduction in Bangalore | Avg. % reduction in Delhi |
|----------|------------------------------|--------------------------|
| CO       | PM$_{2.5}$                   | Ozone                    | NO$_2$       | CO       | PM$_{2.5}$ | Ozone | NO$_2$ |
| Phase I  | 37.06                        | 60.43                    | 18.50        | 14.05    | 61.31      | 45.57 | 25.13 | 44.25 |
| Phase II | 21.95                        | 50.14                    | 10.12        | 15.96    | 48.52      | 36.21 | -4.13 | 55.62 |
| Overall  | 29.69                        | 55.41                    | 16.23        | 14.98    | 54.89      | 40.89 | 10.50 | 49.93 |

### Table 2
|Lockdown | Avg. % reduction in Bangalore | Avg. % reduction in Delhi |
|---------|------------------------------|--------------------------|
| CO      | PM$_{2.5}$                   | Ozone                    | NO$_2$       | CO       | PM$_{2.5}$ | Ozone | NO$_2$ |
| Phase I | 33.38                        | 56.22                    | 17.97        | 21.22    | 50.06      | 52.32 | 46.37 | 65.60 |
| Phase II| 5.15                         | 51.21                    | 2.44         | 18.79    | 35.66      | 48.72 | 21.01 | 65.11 |
| Overall | 19.97                        | 53.45                    | 10.59        | 20.07    | 43.22      | 50.61 | 43.227| 65.37 |
in modelling compared to other models with very good $R^2$ values ranging from 0.8 to 0.9. Table 3 depicts the $R^2$ values of various models used in forecasting of various pollutants, viz., NO$_2$, SO$_2$, ozone, and CO.

Comparison of forecasted concentrations with actual concentrations for year 2020 in Delhi city is shown in Table 3. Based on $R^2$ values found for models used for forecasting and comparison of actual concentrations in 2020 with forecasted values of various models, it has been found that linear models are best fit for forecasting. The forecasted pollutant concentrations for 2021 are depicted in Table 4.

For forecasting, the data of annual averages of pollutants from years 2015 to 2019 is only used due to availability of limited data. Average data of year 2020 is used for validation. Being the data is limited, the forecasting is done for year 2021 only. All the models show good correlation between time and annual averages. There was an increase in pollution levels from 2015 to 2017 and has been found the trend of pollution levels started decreasing from 2018 for all the pollutants of interest which is a good sign for the cities. The reduction in pollution levels in Delhi is due to few pollution control programmes launched by Delhi government. Table 5 shows the forecasted pollutant levels in Delhi.

Figure 12 shows the linear trend followed by the annual averages of pollutants and forecasted value for year 2021 with 95% and 85% confidence limits.

Forecasted pollutant concentrations for the year 2021 for Delhi are shown in Fig. 12. The forecasted pollutant concentrations of NO$_2$, SO$_2$, ozone, and CO are 115.266 µg/m$^3$, 11.798 µg/m$^3$, 30.636 µg/m$^3$, and 2.758 mg/m$^3$, respectively. This shows that pollution is not increasing rapidly for the past 5 years. This has shown the pollution control programmes taken place in the recent years are successful which is a positive sign.

Conclusions

The monthly variations in the various pollutants over Delhi and Bangalore cities have been analysed, along with the impact of COVID-19 lockdown on air pollution. Forecasting analysis has also been carried out for various pollutants to find the air pollutants concentrations in the years 2020 and 2021. In Bangalore, from 2017 to 2019, annual average concentrations of CO were increased by 79.6%, PM$_{2.5}$ by 4.910%, and NOx by 105%. In contrast, ozone concentration was reduced by 1.7%. In Delhi, the annual average of many...
pollutants showed a negative trend. Annual average concentrations were reduced by 38.1%, 11.4%, and 4.9% from 2017 to 2019 for NOx, PM$_{2.5}$, and CO, while ozone concentrations were increased by 9%. NOx concentrations showed a steady monthly average over the years with 1 or 2 months with slightly elevated values which may be due to biomass or agricultural waste burning. The monthly average values of ozone concentrations in Bangalore were higher than the annual average by 70–100%. In comparison, the ozone in Delhi was higher during the summer months.

Table 3 Comparison of $R^2$ values of various models used for forecasting

| Pollutant | Linear model | ARIMA model | Exponential smoothing |
|-----------|--------------|-------------|----------------------|
| NO$_2$ (µg/m$^3$) | 0.91 | 0.72 | 0.65 |
| SO$_2$ (µg/m$^3$) | 0.86 | 0.65 | 0.76 |
| Ozone (µg/m$^3$) | 0.81 | 0.59 | 0.69 |
| CO (mg/m$^3$) | 0.82 | 0.72 | 0.84 |

Table 4 Comparison of forecasted concentrations with actual concentrations for year 2020 in Delhi city

| Pollutant | Actual | Linear model | ARIMA model | Exponential smoothing |
|-----------|--------|--------------|-------------|----------------------|
| NO$_2$ (µg/m$^3$) | 105.36 | 110.26 | 125.62 | 116.23 |
| SO$_2$ (µg/m$^3$) | 14.06 | 13.92 | 13.65 | 16.23 |
| Ozone (µg/m$^3$) | 35.62 | 32.41 | 39.62 | 41.26 |
| CO (mg/m$^3$) | 2.441 | 2.632 | 2.756 | 2.102 |

Table 5 Forecasted average pollutant concentrations over Delhi for 2021

| Pollutant | Average | 85% confidence limits | 95% confidence limits |
|-----------|---------|-----------------------|-----------------------|
| NO$_2$ (µg/m$^3$) | 115.266 | 70.47886 | 150.0531 | 32.95208 | 187.5799 |
| SO$_2$ (µg/m$^3$) | 11.798 | −4.98267 | 28.57867 | −20.81 | 44.40601 |
| Ozone (µg/m$^3$) | 30.636 | 21.26666 | 40.00534 | 12.4296 | 48.8424 |
| CO (mg/m$^3$) | 2.758 | 1.612715 | 3.90385 | 0.5324952 | 4.983505 |

pollutants showed a negative trend. Annual average concentrations were reduced by 38.1%, 11.4%, and 4.9% from 2017 to 2019 for NOx, PM$_{2.5}$, and CO, while ozone concentrations were increased by 9%. NOx concentrations showed a steady monthly average over the years with 1 or 2 months with slightly elevated values which may be due to biomass or agricultural waste burning. The monthly average values of ozone concentrations in Bangalore were higher than the annual average by 70–100%. In comparison, the ozone in Delhi was higher during the summer months (~46.3%) more than the annual average. Carbon monoxide concentrations
were almost steady in other months of the year. PM$_{2.5}$ concentrations showed many variations during the months of the year in both Bangalore and Delhi. PM$_{2.5}$ concentrations were nearly 60% less than the annual average value during the monsoon season, while it was nearly 75% more during the winter months in both cities. In Bangalore, various pollutants, viz., CO, NO$_2$, PM$_{2.5}$, and ozone concentrations, during lockdown were reduced by 29.9%, 55.4%, 16.2%, and 14.9%, while in Delhi, concentrations were reduced by 16.7%, 40.9%, 10.5%, and 49.9%, respectively, compared to the previous year. In contrast, meteorology is almost similar to the previous year. In Delhi, during phase 2, the ozone concentration increased by 4.1% while NO$_2$ concentrations decreased by 49.93%, which shows ozone formation does not solely depend on NOx concentrations. Time-based regression models have been used to predict various air pollutants and it has been observed that linear model gives better results compared to ARIMA and Exponential Smoothening models. Linear models show a good correlation in modelling compared to ARIMA and Exponential Smoothening models with $R^2$ values ranging from 0.8 to 0.9. By forecasting, the concentration of NO$_2$ is 115.288 µg/m$^3$, the ozone is 30.636 µg/m$^3$, SO$_2$ is 11.798 µg/m$^3$, and CO is 2.758 mg/m$^3$ over Delhi in 2021. For further scope of research, forecast studies using various machine learning techniques can be conducted, and thus, the potential of new models can be exploited for predicting pollutant concentrations and thereby giving continuous ambient air quality predictions.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12517-022-09996-2.

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations Conflict of interest The authors declare no competing interests.

References

Ahammad YN, Reddy RR, Gopal KR, Narasimhulu K, Basha DB, Reddy LSS, Rao TVR (2006) Seasonal variation of the surface ozone and its precursor gases during 2001–2003, measured at Anantapur (14.62°N), a semi-arid site in India. Atmos Res 80(2–3):151–164

Barua S, Nath SD (2021) The impact of COVID-19 on air pollution: Evidence from global data. J Clean Prod 298
Baur D, Saisana M, Schulze N (2004) Modelling the effects of meteorological variables on ozone concentration - A quantile regression approach. Atmos Environ 38(28):4689–4699

Bazhanov V, Rodhe H (1997) Tropospheric Ozone at the Swedish Mountain Site Areskutan: Budget and Trends. In Journal of Atmospheric Chemistry (Vol. 28). Kluwer Academic Publishers

Beig G, Gunthe S, Jadhav DB (2007) Simultaneous measurements of ozone and its precursors on a diurnal scale at a semi urban site in India. J Atmos Chem 57(3):239–253

Biancofiore F, Verdeccchia M, di Carlo P, Tomassetti B, Aruffo E, Busilacchio M, Bianco S, di Tommaso S, Colangeli C (2015) Analysis of surface ozone using a recurrent neural network. Sci Total Environ 514:379–387

Brauer M, Freedman G, Frostdt J, van Donkelaar A, Martin RV, Dincăten F, Coccon M, Ramirez-Andreotta M, Pepper IL, Maximillian J (2019) Comparison of ozone concentration: A multifractal analysis. Atmos Environ 145:365–375

Bouarar I, Ynoue RY (2016) Prediction of ground-level ozone concentration estimation and Monte Carlo analysis. Atmos Environ 138:1–6

Brusseau ML, Ramirez-Andreotta M, Pepper IL, Maximilian J (2019) Environmental Impacts on Human Health and Well-Being. Environmental and Pollution Science, pp 477–499

Carbone-Cabestrane R, Ariza-Villaverde AB, Gutiérrez de Rave E, Jiménez-Hornero FJ (2019) Visibility graphs of ground-level ozone time series: A multifractal analysis. Sci Total Environ 661:138–147

Dales R, Bianco-Vidal C, Romero-Meza R, Schoen S, Lukina A, Cakmak S (2021) The association between air pollution and COVID-19 related mortality in Santiago, Chile: A daily time series analysis. Environ Res 198

Fan H, Zhao C, Yang Y (2020) A comprehensive analysis of the spatio-temporal variation of urban air pollution in China during 2014–2018. Atmos Environ 220

Feng R, Zheng Hjnn, Zhang Aran, Huang C, Gao H, Ma Ycheng (2019) Unveiling tropospheric ozone by the traditional atmospheric model and machine learning, and their comparison: A case study in hangzhou, China. Environ Pollut 252:366–378

Fuhrer J, Sk L, Irby, Ashmore MR (1997) Critical levels for Ozone concentration in São Paulo, Brazil: Deterministic versus statistic approaches. Environ Res 198

Gao M, Yin L, Ning J (2018) Artificial neural network model for ozone concentration estimation and Monte Carlo analysis. Atmos Environ 194:129–139

Garcia I, Rodríguez JG, Tenorio YM (2011) Artificial Neural Network Models for Prediction of Ozone Concentrations in Guadalajara, Mexico. Sci Total Environ 601:128–139

Hoshiyaripur B, Brasseur G, Andrade MF, Gavidia-Caldérón M, Bouarar I, Ynoeu RY (2016) Prediction of ground-level ozone concentration in São Paulo, Brazil: Deterministic versus statistic models. Atmos Environ 145:365–375

http://www.bangalore.climatetemps.com/
http://www.new-delhi.climatetemps.com/
https://app.cpcbccr.com/ccf/#/caaqm-dashboard-all/caaqm-landing
https://kspcb.karnataka.gov.in/

Hyndman RJ, Khandakar Y (2008) Automatic time series forecasting: The forecast package for R. J Stat Softw 27(1):1–22

Ibrahim MZ, Zailan R, Ismail M, Lola MS (2009) Forecasting and Time Series Analysis of Air Pollutants in Several Area of Malaysia. Am J Environ Sci 5(5):625–632

Indian Standards Institutions: IS 4167 (1980): Glossary of terms relating to air pollution

Jenkin ME (2008) Trends in ozone concentration distributions in the UK since 1990: Local, regional and global influences. Atmos Environ 42(21):5434–5445

Kerimray A, Baimatova N, Ibragimova OP, Bukanov B, Kenessov B, Plotitsyn P, Karaca F (2020) Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in Almaty, Kazakhstan. Sci Total Environ 730:139179

Lelieveld J, Crutzen PJ (1990) Influences of cloud photochemical processes on tropospheric ozone. Nature 343(6255):227

Li K, Jacob DJ, Liao H, Shen L, Zhang Q, Bates KH (2019) Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China. Proc Natl Acad Sci 116:422–427

Liu H, Liu S, Xue B, Lv Z, Meng Z, Yang X, Xue T, Yu Q, He K (2018) Ground-level ozone pollution and its health impacts in China. Atmos Environ 173:223–230

Liu Q, Harris JT, Chiu LS, Sun D, Houser PR, Yu M, Duffy DQ, Little MM, Yang C (2021) Spatiotemporal impacts of COVID-19 on air pollution in California, USA. Sci Total Environ 750:141592

Luna AS, Paredes MLL, de Oliveira GCG, Corrêa SM (2014) Prediction of ozone concentration in tropospheric levels using artificial neural networks and support vector machine at Rio de Janeiro, Brazil. Atmos Environ 98:98–104

Lyu XP, Chen N, Guo H, Zhang WH, Wang N, Wang Y, Liu M (2016) Ambient volatile organic compounds and their effect on ozone production in Wuhan, central China. Sci Total Environ 541:200–209

Munir S, Chen H, Ropkins K (2013) Quantifying temporal trends in ground level ozone concentration in the UK. Sci Total Environ 458–460:217–227

National Research Council (1991) Rethinking the Ozone Problem in Urban and Regional Air Pollution. National Academies Press

Ohman M, Latif MT (2021) Air pollution impacts from COVID-19 pandemic control strategies in Malaysia. J Clean Prod 291:125992

Paoletti E, De Marco A, Beddows DC, Harrison RM, Manning WJ (2014) Ozone levels in European and USA cities are increasing more than at rural sites, while peak values are decreasing. Environ Pollut 192:295–299

Park YS, Lek S (2016) Artificial Neural Networks: Multilayer Perceptron for Ecological Modeling. Developments in Environmental Modelling (Vol. 28). Elsevier B.V., pp 123–140

Prybutok VR, Yi J, Mitchell D (2018) Comparison of neural network models with ARIMA and regression models for prediction of Houston’s daily maximum ozone concentrations. Dev Environ Model 162

Rai R, Rajput M, Agrawal M, Agrawal SB (2011) Gaseous air pollutants: a review on current and future trends of emissions and impact on agriculture. J Sci Res 55:77–102

Ramos Y, Requa WI, St-Onge B, Blanchet JP, Kestens Y, Smargiassi A (2018) Spatial modeling of daily concentrations of ground-level ozone in Montreal, Canada: A comparison of geostatistical approaches. Environ Res 166:487–496

Revlett GH (1978) Ozone Forecasting Using Empirical Modeling. J Air Pollut Control Assoc 28(4):338–343

Peshin SK, Ashima Sharma SK, Sharma MN, Mandal TK (2017) Spatio-temporal variation of air pollutants and the impact of anthropogenic effects on the photochemical buildup of ozone across Delhi-NCR. Sustain Cities Soc 35:740–751

Sekar C, Ojha CSP, Gjuric BR, Goyal MK (2016) Modeling and Prediction of Hourly Ambient Ozone (O₃) and Oxides of Nitrogen (NOₓ) Concentrations Using Artificial Neural Network and Decision Tree Algorithms for an Urban Intersection in India. J Hazard Toxic Radioact Waste 20(4)

Shen J, Chen J, Zhang X, Zou S, Gao Z (2017) Outdoor and Indoor Ozone Concentration Estimation Based on Artificial Neural Network and Single Zone Mass Balance Model. Procedia Eng 205:1835–1842

Singh V, Singh S, Biswal A, Kesarkar AP, Mor S, Ravindra K (2020) Diurnal and temporal changes in air pollution during COVID-19 strict lockdown over different regions of India. Environ Pollut 266:115368
Tian J, Wang Q, Zhang Y, Yan M, Liu H, Zhang N, Ran W, Cao J (2021) Impacts of primary emissions and secondary aerosol formation on air pollution in an urban area of China during the COVID-19 lockdown. Environ Int 150:106426

Trainer M, Williams EJ, Parrish DD, Buhr MP, Allwine EJ, Westberg HH, Fehsenfeld FC, Liu SC (1987) Models and observations of the impact of natural hydrocarbons on rural ozone. Nature 329(6141):705

Van der A RJ, Eskes HJ, Boersma KF, van Noije TPC, van Roozendael M, de Smedt I, Peters DHMU, Meijer EW (2008) Trends, seasonal variability and dominant NOx source derived from a ten year record of NO2 measured from space. J Geophys Res Atmos 113(4)

Wang T, Wei X, Ding A, Poon SC, Lam K, Li Y, Chan L, Anson M (2009) Increasing surface ozone concentrations in the background atmosphere of Southern China, 1994–2007. Atmos Chem Phys 9(16):6217–6227

Wark K, Warner CF, Davis T (1999) Air Pollution: its origin and control. Pearson. ISBN: 978–0673994165

Yi J, Prybutok VR (1996) A neural network model forecasting for prediction of daily maximum Ozone concentration in an industrialized urban area. Environ Pollut 92(3):349

Zhang K, Li L, Huang L, Wang Y, Huo J, Duan Y, Wang Y, Fu Q (2020) The impact of volatile organic compounds on ozone formation in the suburban area of Shanghai. Atmos Environ 232:117511