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Original Research

Repercussions of the COVID-19 Pandemic on the Air Quality of Chennai, India

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Abstract

COVID 19 Pandemic in India had demanded an imposition of lockdown for three weeks initially and was extended further. This has drastic effect on air quality making it better because of control of vehicle emissions. This study analyzed the air quality in Chennai city using the parameters of pollution (NH_3, $PM_{2.5}$, NO_2, SO_2, O_3 and CO) for air quality data for monitoring stations (three) spread over the city. National Air Quality Index (NAQI) has been used to present the quality of air spatially during lockdown and before lockdown. The concentrations of $PM_{2.5}$ among the pollutants selected showed a maximum reduction (-61%) compared to the pre-lockdown process. NO_2 (−40%) and CO (−32%) have also gone down when lockdown was in place, among other contaminants. In the different sections of the city, about 53% reduction in NAQI has been observed. Deep learning short-term predictions of various air pollutants are made in this study. The correlation between AQI and Pollutants (NH_3, $PM_{2.5}$, NO_2, SO_2, O_3 and CO) in the study area modelled in deep learning using PYTHON. The classification of AQI class has been created in python with AQI values of Good (0-50), Satisfactory (51-100), Moderate (101-200), Poor (201-300), Very poor (301-400) and severe (>401). The study shows the level of co-relation of $PM_{2.5}$ being the highest. A linear regression model was performed and metrics such mean absolute error, r^2 to check the model performance for training and testing data are calculated. These results can be coupled with social, economic and Cultural factors that could have common emission patterns and air quality especially in metropolitan cities. The present study would aid authorities as it clearly shows that the quality can be made better if sources of emission can be diminished. This will pave way to protect and make the surroundings and environment better.

Keywords: COVID 19, AQI, Chennai, air pollution

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Introduction

Chennai is regarded as "The Detroit of India" with the city being home to more than one third of India's automotive industry. It ranks sixth in population in India and fourth among metros. Travel demand was estimated on the basis of an increase in the number of per capita trips. The per capita travel in 2005, which was 1.44, is expected to be 1.6 by 2016 and 1.65 by 2026. [1]. Increased urbanization, atomization and industrialization have led to contamination of environment on a massive scale and necessitate the mitigation of environmental pollution. A decline in air quality is the most visible result encountered. Chennai ranks high on the $PM_{2.5}$ pollution list for 2011 and 2016 [2]. This increased level of pollution creates health issues like respiratory diseases, asthma. [3-4]. Tamil Nadu state government had come up with statue for minimizing health issues caused mainly by air pollution. Within the jurisdiction of Chennai polluting industries (on higher scale) have been listed out. Implementation of strict emission standards for vehicles, renovation of transport to CNG fuel, prohibition of heavy vehicles entry in the course of peak hours, etc. have been enforced. Despite these measures, air pollution level in Chennai has not been reduced significantly. In order to achieve success, however, the feasibility of these policy initiatives has raised several questions. Therefore, unless successful countermeasures are taken and enforced, there will be no restoration of ambient air quality. Wuhan, China reported COVID-19 On December 2019. Fatal cases reported are close to 28 million worldwide (Until February 5, 2021) infected rising day by day which demanded imposition of initial lockdown for three weeks initially from March and were extended further till may. [5] reported the decline of pollution in 88 cities within just four days starting from day of lockdown after standstill of all operations. In a way lockdown had fruitful with regard to air pollution control. This was the motivation for the study undertaken in the city of Chennai.

AQI is vital for making Environment sustainable, which otherwise would pose a threat to human race and it has a strong correlation with strategies that would be employed to prevent spreading because its incident with pandemic. Quarantine and restrictions on travel had reduced carbon emissions by 25% in china. [6]. The growth of renewable energy generation were forecasted and how climate were impacted due to COVID-19 were analyzed using machine learning [7]. Studies carried out to forecast Air Quality using Machine learning [8-14]. Comparative assessment of ML'S were done to forecast the Troposphere ozone levels [15]. Researchers outlined the Importance of Weather Normalized Models and the relationship with Meteorological temporal features and air pollutants. In addition, suggestions were made that further research are needed to explore and understand the correlations between traffic, air pollution and anthropogenic activities, and air pollution. [16]. As air quality will have impact wide range say health, agriculture, overall economy of country, accurate prediction by recent and reliable techniques both for short and long -term is the need of the hour.

Not all countries are economically good. AQI analysis from this study shows that indication of air quality of metropolitan city needs research to study the same for concentration level of air particles qualified for data reliability. The prediction of air quality using machine learning method is on higher level and worthier because of its flexibility in non- linear modelling as it depends on expert knowledge and engineering features to refine the prediction effect of the model.

Literature Background

Pollution problems in India is becoming a serious threat these days. Air quality was declining in many cities [17-19] and its impacts are more pronounced around the globe [20-22] causing economic loss and diseases [23-25]. Earlier researchers reported decreasing trend of air pollutants due to lockdown period, [26-33] reduced anthropogenic emissions [34], meteorological impacts on air concentration [35-36]. Many researchers have studied AQI in Chennai city [32, 37-38] but they have not done micro level analysis. Researchers used Air Pollution Index (API) as an indication [39] in contrast to earlier methods [40-41] has omitted many other contaminants, many of them can be detrimental to people with respiratory infection [42]. Later many indices propped up. No indices developed which would be apt for all scenarios. [33]. Earlier studies [44-45] had monitored major cities air quality. Out of National Air Quality Standards (INAQS) and National Air Quality Index (NAQI) developed by CPCB, the present study used National Air Quality Index (NAQI) since it eliminated earlier uncertainties.

Summing up, it shows the correlation and aftereffects of pandemic (lockdown) has a major effect upon restoring air quality and shown a better pathway for evaluating pollution quantitatively. The current research is an attempt to determine the effectiveness of the lockdown in Chennai as an uncommon method for decreasing air pollution intensity.

Research Significance

The main motto of this study is in regard of pollutant concentration in Chennai lockdown phases (during and before) and to measure the consolidated quality of air during enforcement of lockdown period. The present study can aid the government to identify and categorize the areas owing to land use and can come up with stringent rules for minimization of vehicular emissions and pollution caused due to industries thereby leading to sustainability and improving the health conditions. This study can be of additional value to decision makers for determining the effect of lockdown on air quality and can be an eye-opener for alternate plans with support of public. An attempt has been made to classify AQI with deep learning using Python. A comparative analysis is carried out for the corresponding period of time in 2019 for assessing the quantum of improvement during the lockdown periods. The prediction of air quality using machine learning method is on higher level and worthier because of its flexibility in non-linear modelling as it depends on expert knowledge and engineering features to refine the prediction effect of the model.

Study Area

Chennai, the capital of the Tamil Nadu state in Indian (Fig. 1), is located at 12°54'27''N, 80°23'07''E. Chennai City is located close to the southern coastal region of India and has a tropical savanna climate with dry summers and winters. In Chennai, Currently, there are three stations which monitors air with the capacity to track and document pollutants

Materials and Methods

Data

The study had used Air quality data from three monitoring stations for assessing the air quality of Chennai city (during lockdown phase) which includes Central pollution control board manual and Continuous Ambient Air Quality Monitoring Stations. The data were taken online [46] for Contaminants – Particulate Matter, Sulphur Dioxide, Nitrogen Dioxide (NO_2), Carbon Monoxide, ozone (O_3)

Methodology

Data generated from Continuous Ambient Air Quality Monitoring (CAAQM) network has been analysed for Chennai, One of the prime cities in southern zone.

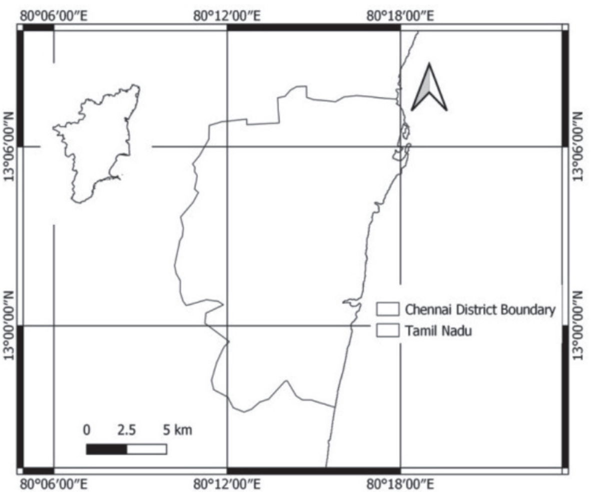

Fig. 1. Depiction of study area location.

AQI uses maximum sub-index approach - PM_{10} and $PM_{2.5}$, SO_2, NO_2 and CO. A sub-index for O_3found [45]. Indian Institute of Technology Madras (IITM) -AQI predicts air quality as extremely unhealthy, very weak, poor, moderate and decent. Indian National Air Quality Standards (INAQS) used parameters – particulate matter (PM) – N10 µm size and N2.5 µm size ($PM_{2.5}$), ozone (O_3), nitrogen dioxide (NO_2), ozone (O_3), lead (Pb), benzo(a)pyrene (BaP), benzene(C6H6), ammonia (NH_3), arsenic (As), carbon monoxide (CO), and nickel (Ni), Sulphur dioxide (SO_2), [47]. Out of this annual norm is exhibited by 4and remaining have short-term (Table 3). O_3 and CO exempted. This study investigated $PM_{2.5}$, SO_2, NO_2, O_3, CO and NH_3 parameters individually and as integrated index during the period of lockdown and had attempted for a comparison before lockdown period with health exposure determined as in Table 1 owing to approval of NAQS. The determinations of sub-indices were based on 24-hmean data [47]. Though not necessary for simultaneous tracking for all contaminants. Calculation process is done as per NAQI with two steps

Sub-indices Formulation for pollutants considered individually and the second: the sub-indices combination for obtaining NAQI.

I_1, I_2, I_3...., I_n - Sub-indices formulations for X_1, X_2, X_3...., n contaminants are evaluated through sub-index functions as presented below:
Scientifically-

$$I_i = f(X_i), i = 1,2, \dots., n \tag{1}$$

(I) - NAQI, (overall)

$$I = F(I_1, I_2, \dots \dots., I_n) \tag{2}$$

Step I- Sub-Indices

X_i (Pollutant concentration) and subsequent I (sub-index) relation
I-X relationship is given by:

$$I = \alpha X + \beta \tag{3}$$

α being slope
X intercept = 0is β

Pollutant concentration (Cp) calculated as below:

$$I_i = \left[\left\{ \frac{I_{HI} - I_{LO}}{B_{HI} - B_{LO}} \right\} * (C_P - B_{LO}) \right] + I_{LO} \tag{4}$$

Breakpoint concentration [BHI]≥known concentration;
Breakpoint concentration [BLO]≤known concentration;
BHI equivalent AQI value - IHI;
BLO equivalent AQI value - ILO
Cp - Pollutant Concentration

Table 1. CPCB - Indian National Air Quality Standards (INAQS). [17] CPCB (2014).

Pollutants ($\mu g/m^3$)	Time weighted average	Industrial, residential and others	Ecologically sensitive area (GOI)
		Concentration of ambient air	
$PM_{2.5}$	24 h	60	60
SO_2	24 h	80	80
NO_2	24 h	80	80
O_3	8 h	100	100
CO	8 h	02	02
	1 h	04	04
NH_3	24 h	400	400

Step II- Sub-Indices Combination

Weighted Additive form:

$$I = AggregatedIndex = \sum wiIi\ (ForI = 1\ to\ n) \quad (5)$$

$\Sigma wi = 1$;
I_i - pollutant I sub-Index;
n -pollutant variable number;
w_i – pollutant weight

Aggregation Form: [non -Liner] RMS Form

$$I = AggregatedIndex = [\sum I_i^p]^{\left(\frac{1}{p}\right)} \quad (6)$$

[p being positive real number greater than 1] RMS Form:

$$I = AggregatedIndex = [\frac{1}{k}(I_1^2 + I_2^2 + \cdots + I_k^2]^{1/2} \quad (7)$$

Operator form – Minimum or Maximum as per Ott, 1978:

$$I = MinorMax(I_1, I_2, I_3, \ldots\ldots.., I_n) \quad (8)$$

Prediction of AQI using Machine Learning

Modelling of AQI and its accurate prediction has its own significance. This section demonstrates the development of model for predicting the AQI using python.

The impact of pandemic variation in air quality due to pollutants have been modelled. Data for modelling using python had been taken from [36] for Contaminants - Particulate Matter, Sulphur Dioxide, Nitrogen Dioxide (NO_2), Carbon Monoxide, ozone (O_3)

Table 2. AQI classes and health Impact for the six pollutants.

AQI class	Range	Health impact	$PM_{2.5}$ 24 h ($\mu g/m^3$)	SO_2 24 h ($\mu g/m^3$)	NO_2 24 h ($\mu g/m^3$)	O_3 8 h ($\mu g/m^3$)	CO 8 h ($\mu g/m^3$)	NH_3 24 h ($\mu g/m^3$)
Good	(0-50)	Low Impact	0-30	0-40	0-40	0-50	0-1	0-200
Satisfactory	(51-100)	Low breathing discomfort	31-60	41-80	41-80	51-100	1.1-2	201-400
Moderate	(101-200)	Breathing discomfort	61-90	81-380	81-180	101-168	2.1-10	401-800
Poor	(201-300)	Breathing discomfort based on prolonged exposure of people	91-120	381-800	181-280	169-208	10-17	801-1200
Very poor	(301-400)	Respiratory illness based on prolonged exposure of people	121-250	801-1600	281-400	209-748	17-34	1200-1800
Severe	(401-500)	Respiratory effects -major population	N250	N1600	N400	N748	N34	N1800

Table 3. Pollutants mean concentration and variation (during 2nd March to 20th March and 25th March to 28th April) in Chennai, India.

Pollutants	Mean concentration avg.		Overall variation	
	Before lockdown	During lockdown	Net	%
$PM_{2.5}$	64.75	25.38	-39.36	-60.79
SO_2	15.85	14.89	-0.96	-6.079
NO_2	30.08	18.06	-12.01	-39.95
CO	1.62	1.10	-0.51	-31.95
O_3	52.54	43.33	-9.20	-17.52
NH_3	51.2	57.41	6.21	12.14

and analyzed for before lockdown and during lockdown period. Correlation between AQI with Pollutants (NH_3, $PM_{2.5}$, NO_2, SO_2, O_3 and CO) as dependent variables that affect the air quality has been studied and a pair plot performed.

The classification of AQI class has been created in python with AQI values of Good (0-50), Satisfactory (51-100), Moderate (101-200), Poor (201-300), Very poor (301-400) and severe (>401).

Statistical analysis. The significance of the statistical correlations was evaluated and compared with predicted and measured values using indices, R^2, and Mean Absolute Error (MAE)

$$R^2 = \left(\frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{N} (x_i - \bar{x}) + \sum_{i=1}^{N} (y - \bar{y})} \right) \tag{9}$$

x_i - predicted value; y_i is the measured value; N is the total number of samples; − x is the average value of the sampled value, and y − is the average sample forecast value

$$MAE = \frac{\sum_{i=1}^{n} |y_{i-} x_i|}{n} \tag{10}$$

Results and Discussion

Variation of Major Pollutants Concentration (Before and During-Lockdown)

The imposition of lockdown for a period of three weeks, there were pollutant reduction in city of Chennai has been substantially reduced by pollutants (Fig. 2 and Table 3) especially in concentration of $PM_{2.5}$, NO_2 and CO (Fig. 2f, a, e). $PM_{2.5}$ average concentrations have decreased by around -60.79%. NO_2 (-39.95%) and CO (-31.96%) are other contaminants that have shown clear variance (before and during lockdown). However, the decrease was very low for O_3(-17.53%) and SO_2(-6.08%) without any constant pattern (Fig. 2d, b). During period of study the 8 h NH_3 (Mean daily maximum concentration) (+12.14% total variation) shows increase in the trend (Fig. 2c). NAQI Prediction value for before and during-lockdown (Fig. 2g), the overall decrease in air quality was around -53.22% with a net decrease of -67.82.

NAQI Trend Spatially for Before and During-Lockdown Period

The pattern of air quality variance between March 3rd and April 14th during study period (Fig. 3).

The improvement even after a single day after lockdown is depicted in Fig. 3e) and Fig. 3f) indicates the change on April 14th showing 36% reduction in NAQI which was supposed to be the 20th day of lockdown.

NAQI increased marginally on 21st April and 28th April, respectively (Fig. 3h and i) due to norms of lockdown relaxed partially.

Statistical analysis (ANOVA) of measured air pollutants data had been carried out. Results of Chennai city show that the P values 0.86, 0.335, 0.422 and 0.482 of SO_2, NO_2, O_3 and NH_3 respectively were all more than the p value shown in table 4 (0.05), indicating no significant difference in their mean values, but $PM_{2.5}$ and CO at 0.015 and 0.018 being less (p value of 0.05), indicating that the difference is significant and there are changes.

Spatial Concentration Trend during the Lockdown and Pre-Lockdown Period of Major Pollutants

Since movement was curtailed, there was a drop down in number of vehicles and all offices and commercial places were shut down which paved way to air quality improvement especially, $PM_{2.5}$, CO and NO_2) (Figs 4 to 6). $PM_{2.5}$, Fig. 4 projecting major one. The concentration pattern (spatial) of this contaminant on different days (Before and During lockdown time) in the city of Chennai, road transport is the primary source of $PM_{2.5}$. The other causes are factory operation, construction work and dust re-suspension. Notably, the concentrations of contaminant decreased below the allowable level only within few days of the lockdown (Fig. 4f). NO_2 and CO are other major contaminants other than $PM_{2.5}$ showing downward trend (Figs 5 and 6). The emissions NO_2 and CO from vehicles especially diesel in urban areas and from manufacturing sectors as a result of combustion. All of these industries closed their operations during this lockdown phase, resulting in the reduction of contaminants such as NO_2 and CO. Average NO_2 and CO concentrations in the study areas have decreased by as much as-39.95 and-31.95%, respectively. The SO_2 and NH_3 concentration in Chennai is well below the limits specified (Figs 8, 9 respectively) and O_3 has decreased marginally (during Lockdown) in comparison to before-lockdown period.

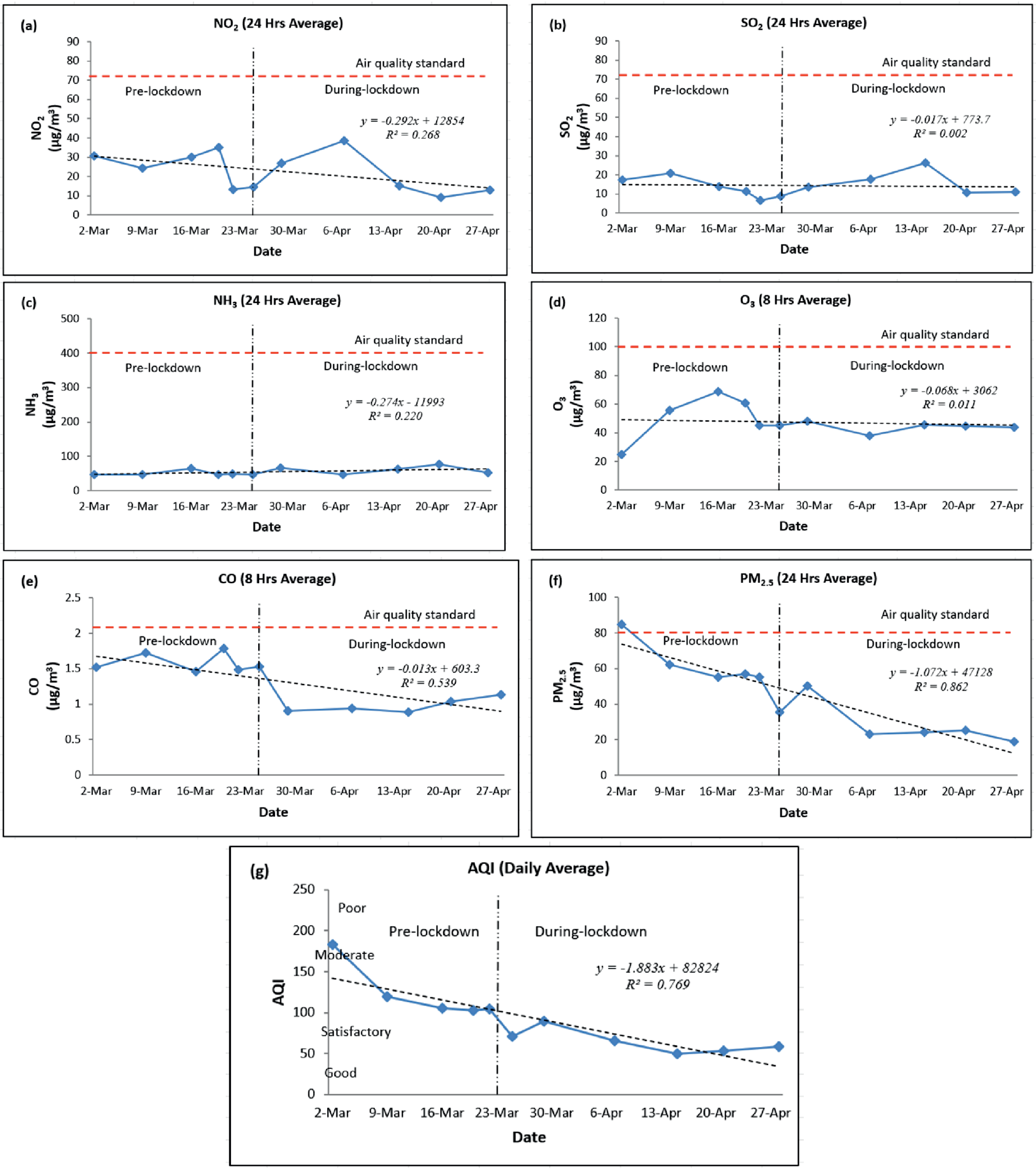

Fig. 2. Average concentrations Trend (24 h) of a) NO_2, b) SO_2, c) NH_3, f) $PM_{2.5}$ and g), f) AQI and 8 h average of d) O_3, e) CO between 3rdMarch and April 14thin Chennai, India.

(Fig. 7). From analysis, it is shown that NH_3 is well below specified limits as shown in Fig. 9.

Interdependence of Contaminants in the Ambient Atmosphere

The Interdependence of various concentrations of pollutants of air in Chennai falling between the study period (i.e., from March 3rd to April 28 th) are presented (Table 4). The $PM_{2.5}$ concentration (The average daily (24 h)) is closely linked to daily mean NO_2 (r = 0.51) and 8 h average CO (r = 0.77) concentrations. Similarly, the mean concentration (daily) of CO too is closely associated with the mean concentration (daily) – NO_2; with r = 0.35, and 8 hours O_3; with r = 0.39.Regional transport has been fully constrained by the lockdown period. It is evident that the increased regulation of local transport activities is the main parameter for reduction in pollutant concentration.

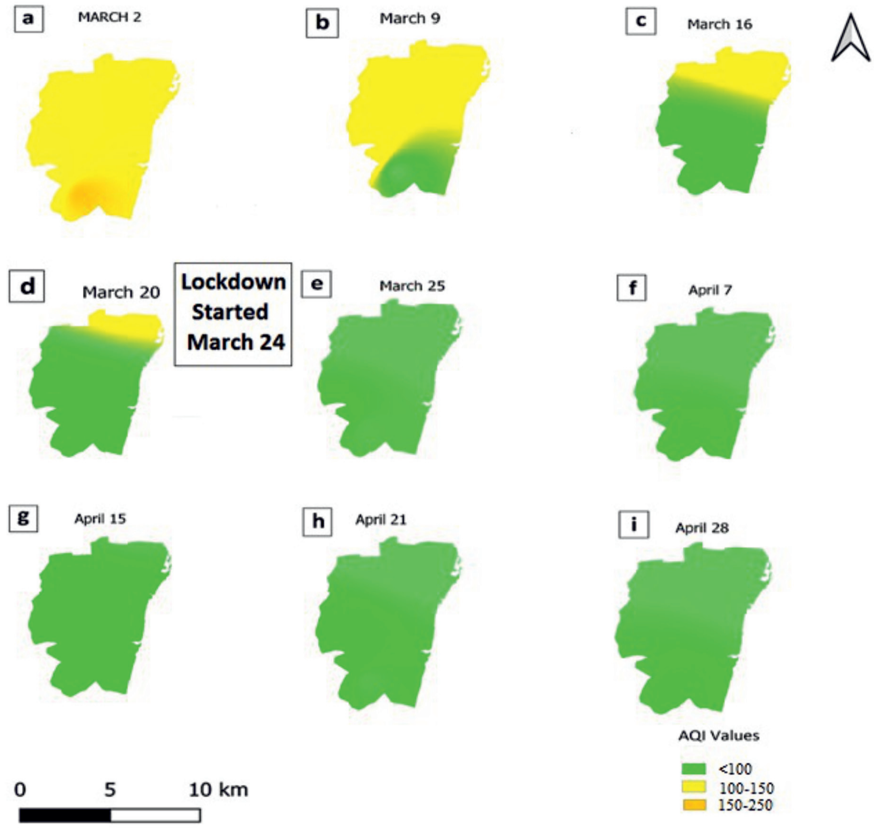

Fig. 3. NAQI value in the Chennai during 2rd March to 28th April 2020.

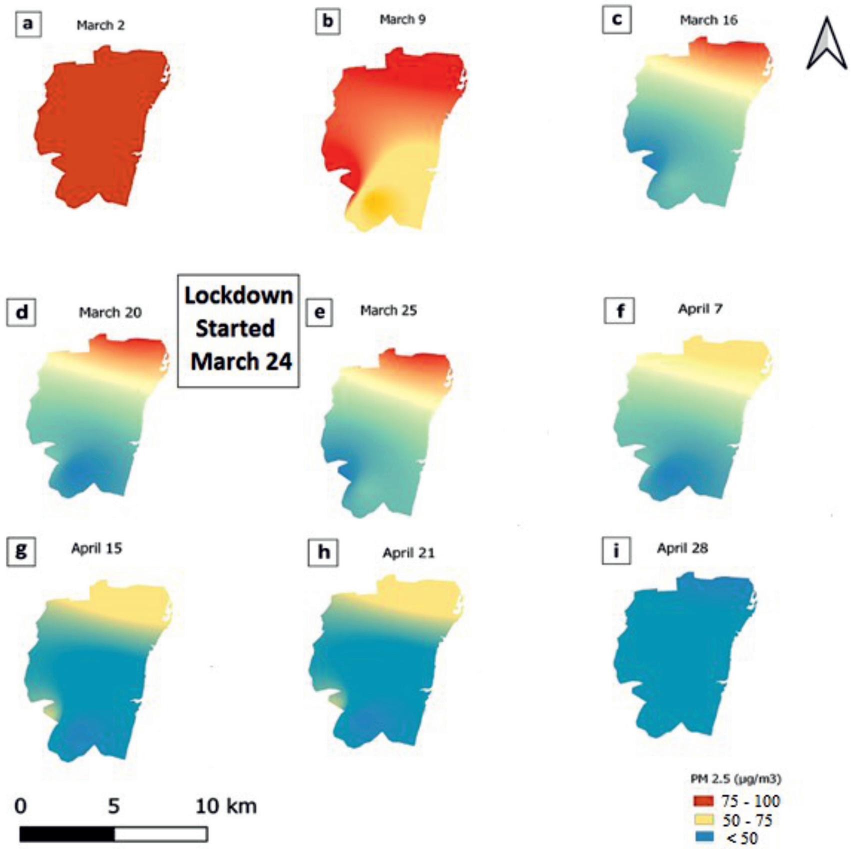

Fig. 4. $PM_{2.5}$concentrationin the Chennai during 2rd March to 28th April 2020.

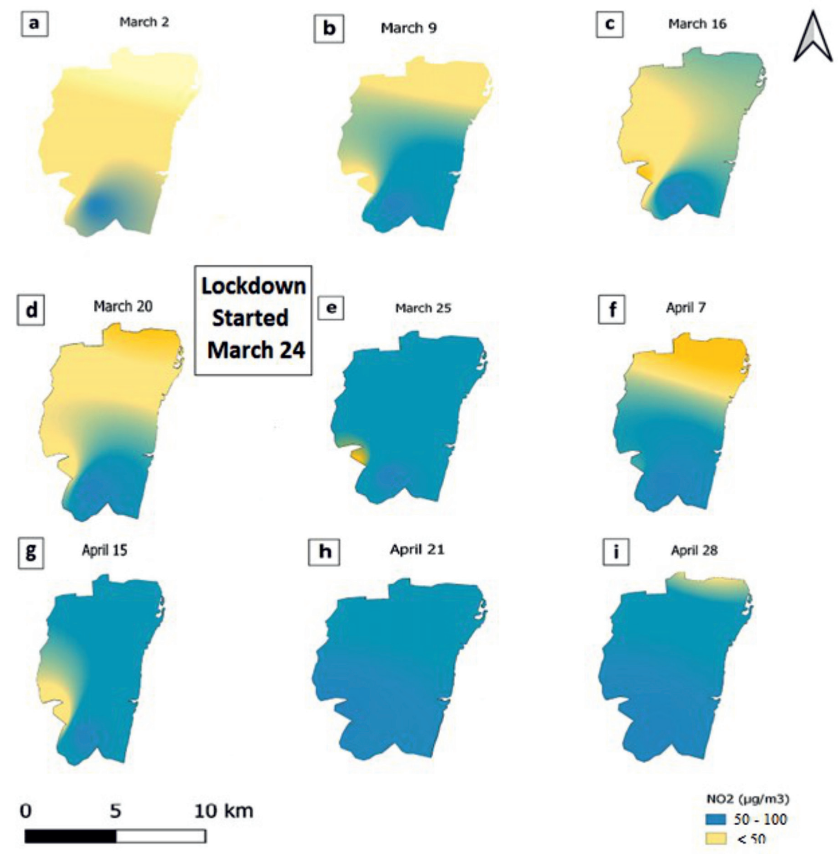

Fig. 5. NO_2concentration in the Chennai during 2rd March to 28th April 2020.

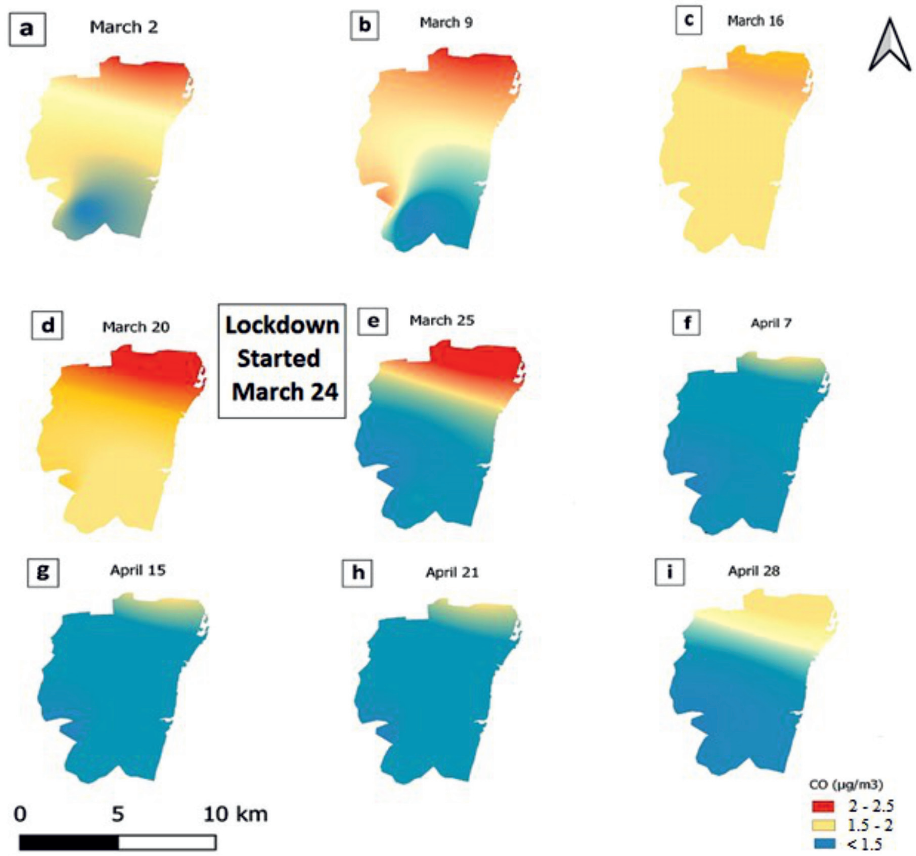

Fig. 6. CO concentration in the Chennai during 2rd March to 28th April 2020.

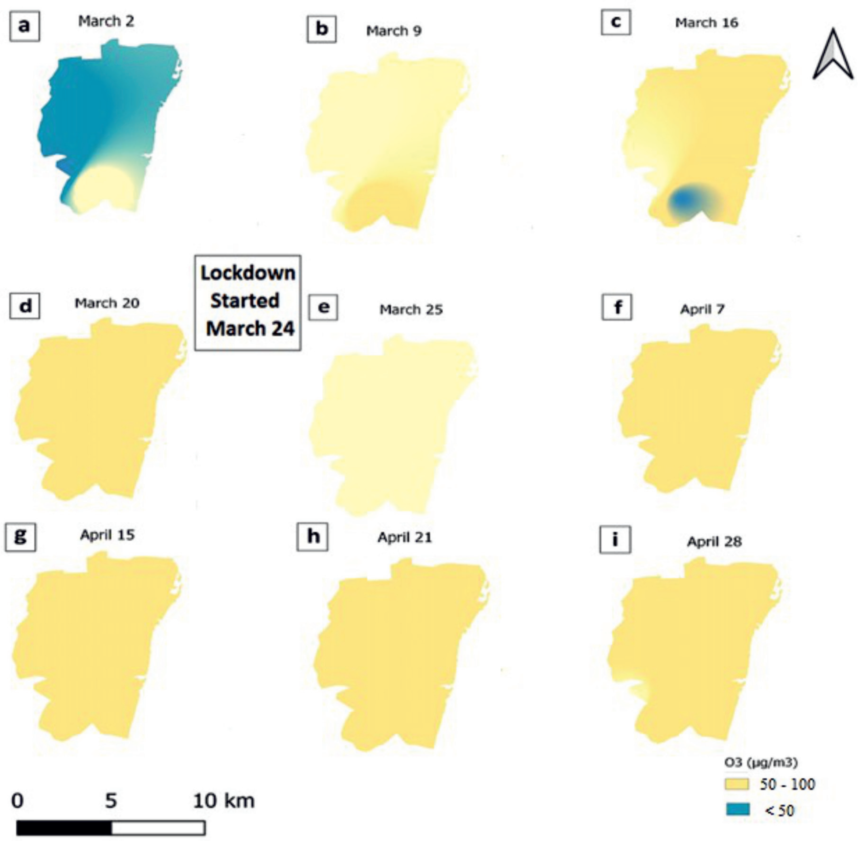

Fig. 7. O_3 concentration in the Chennai during 2rd March to 28th April 2020.

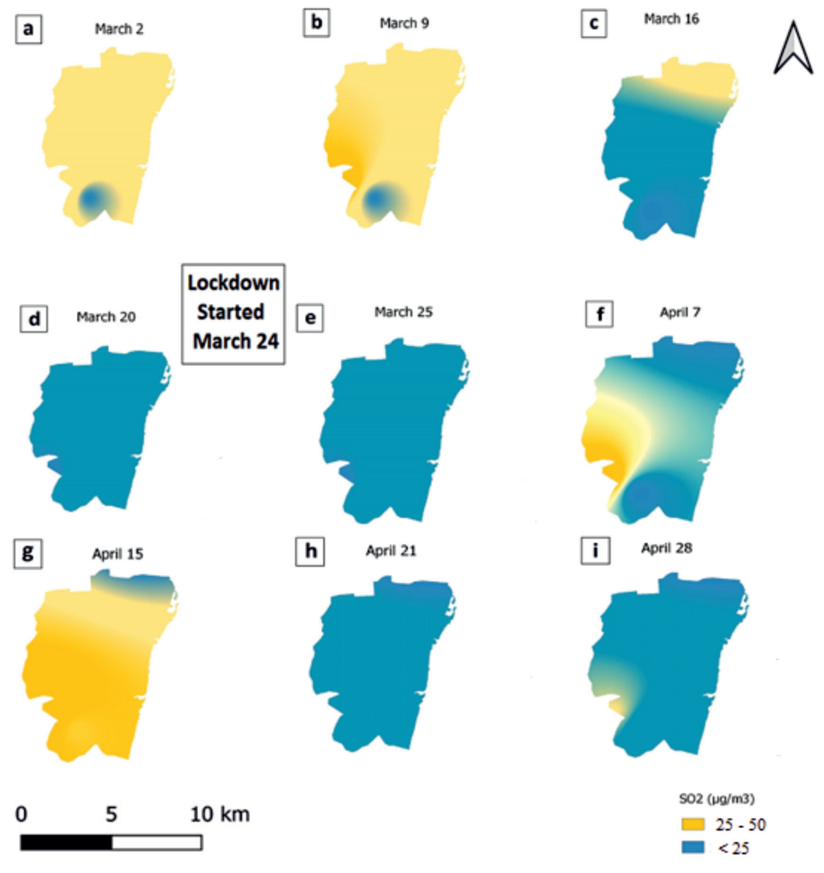

Fig. 8. SO_2 concentration in the Chennai during 2rd March to 28th April 2020.

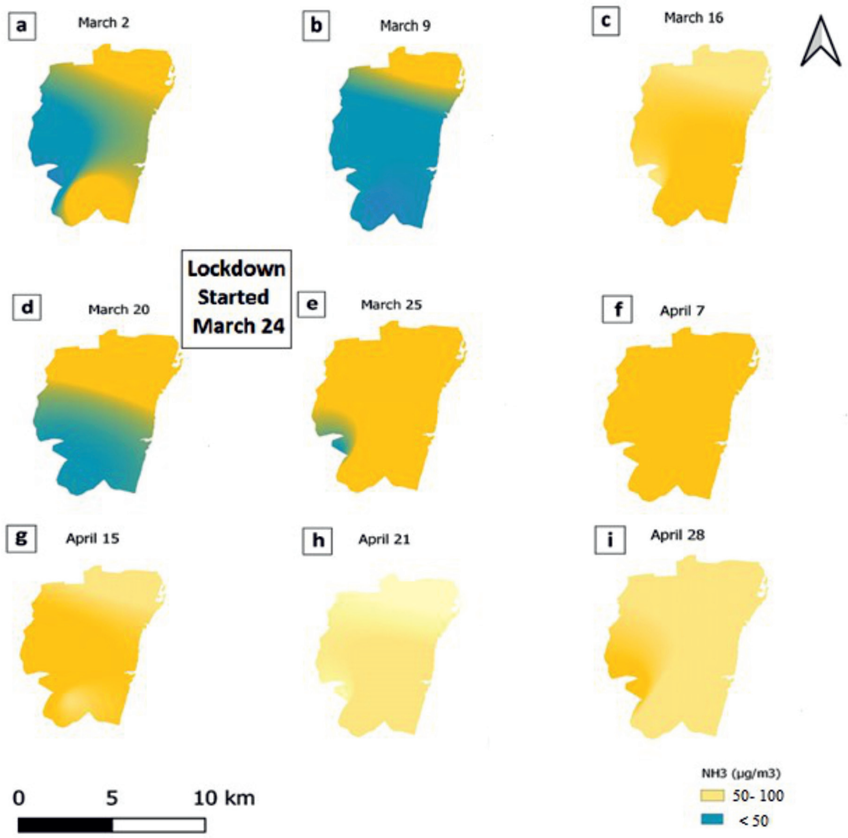

Fig. 9. NH_3 value in the Chennai during 2nd March to 28th April 2020.

Table 4. Statistical analysis (ANOVA) for Air Pollutants data during and pre-lockdown period in Chennai, India

Pollutants	Source of Variation	SS	df	MS	F	P-value
$PM_{2.5}$	Between Groups	1984.08	1	1984.08	11.52	0.0145
	Within Groups	1032.824	6	172.1374		
	Total	3016.904	7			
SO_2	Between Groups	1.188368	1	1.188368	0.032	0.8624
	Within Groups	218.0217	6	36.33695		
	Total	219.2101	7			
NO_2	Between Groups	80.18001	1	80.18001	1.09	0.3358
	Within Groups	439.6866	6	73.2811		
	Total	519.8666	7			
CO	Between Groups	0.625335	1	0.625335	10.42	0.0179
	Within Groups	0.359808	6	0.059968		
	Total	0.985143	7			
O_3	Between Groups	144.2451	1	144.2451	0.74	0.4222
	Within Groups	1167.12	6	194.5201		
	Total	1311.365	7			
NH_3	Between Groups	50.8032	1	50.8032	0.56	0.4819
	Within Groups	542.6618	6	90.44363		
	Total	593.465	7			

Table 4. Air pollutants co-correlation and its linking Pearson's correlation matrix.

	$PM_{2.5}$	SO_2	NO_2	CO	O_3	NH_3
$PM_{2.5}$	1.00					
SO_2	0.10	1.00				
NO_2	0.51	0.17	1.00			
CO	0.77	-0.27	0.35	1.00		
O_3	0.02	-0.14	0.11	0.38	1.00	
NH_3	-0.39	-0.01	-0.52	-0.52	0.21	1.00

Correlation between AQI and Pollutants (NH_3, $PM_{2.5}$, NO_2, SO_2, O_3 and CO) Using Deep Learning

Figs 10 and 11 demonstrate Seaborn Pair plot of AQI classification and the pollutants (PM_{10}, PM_{25}, NO_2, CO, and O_3) during lockdown and before lockdown respectively. The classification of AQI class has been created in python with AQI values of Good (0-50), Satisfactory (51-100), Moderate (101-200), Poor (201-300), Very poor (301-400) and severe (>401). The variable distribution and the relationship with

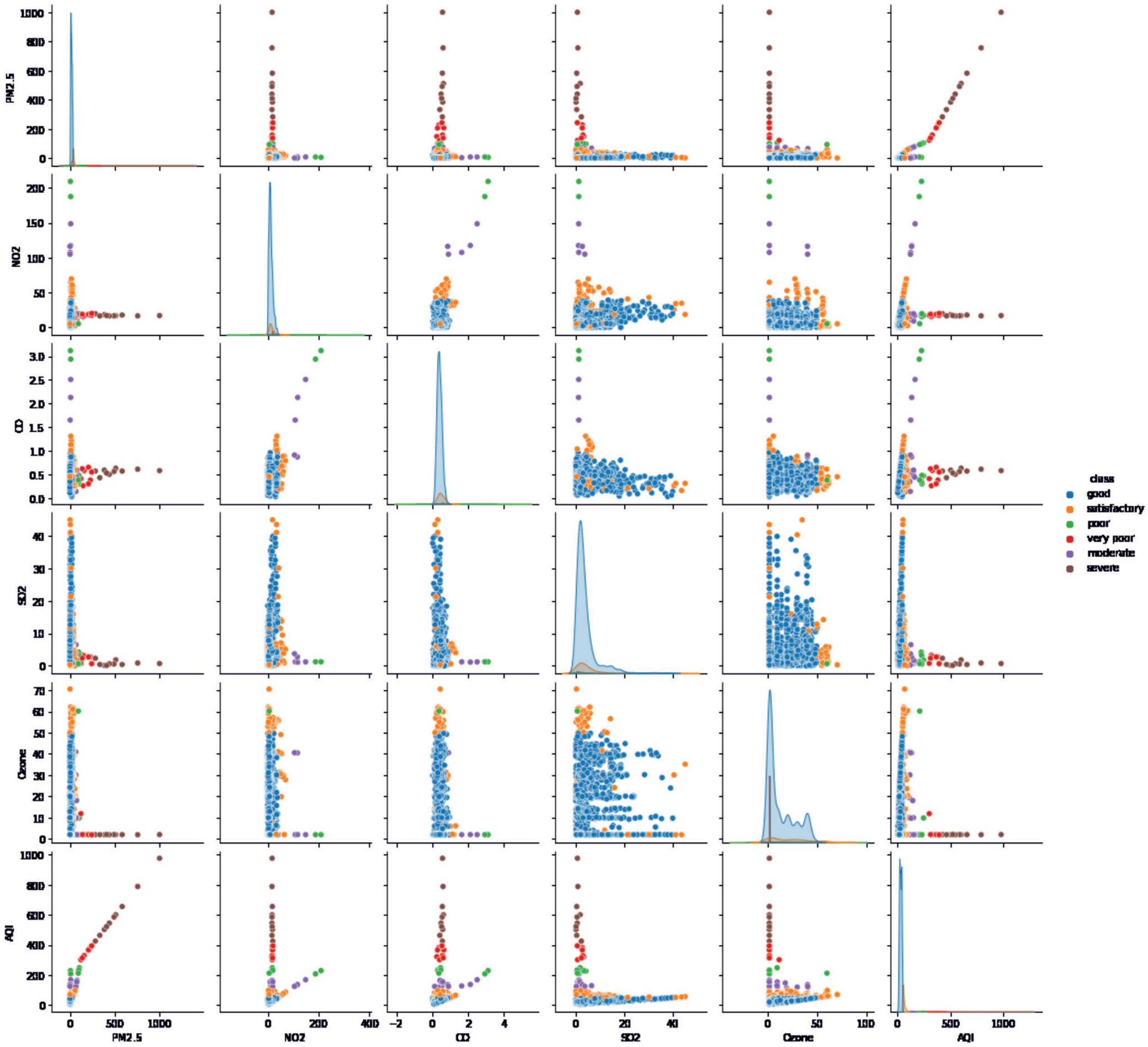

Fig. 10. AQI and Pollutants (Stack Model Heat Map - Seaborn) during Lockdown.

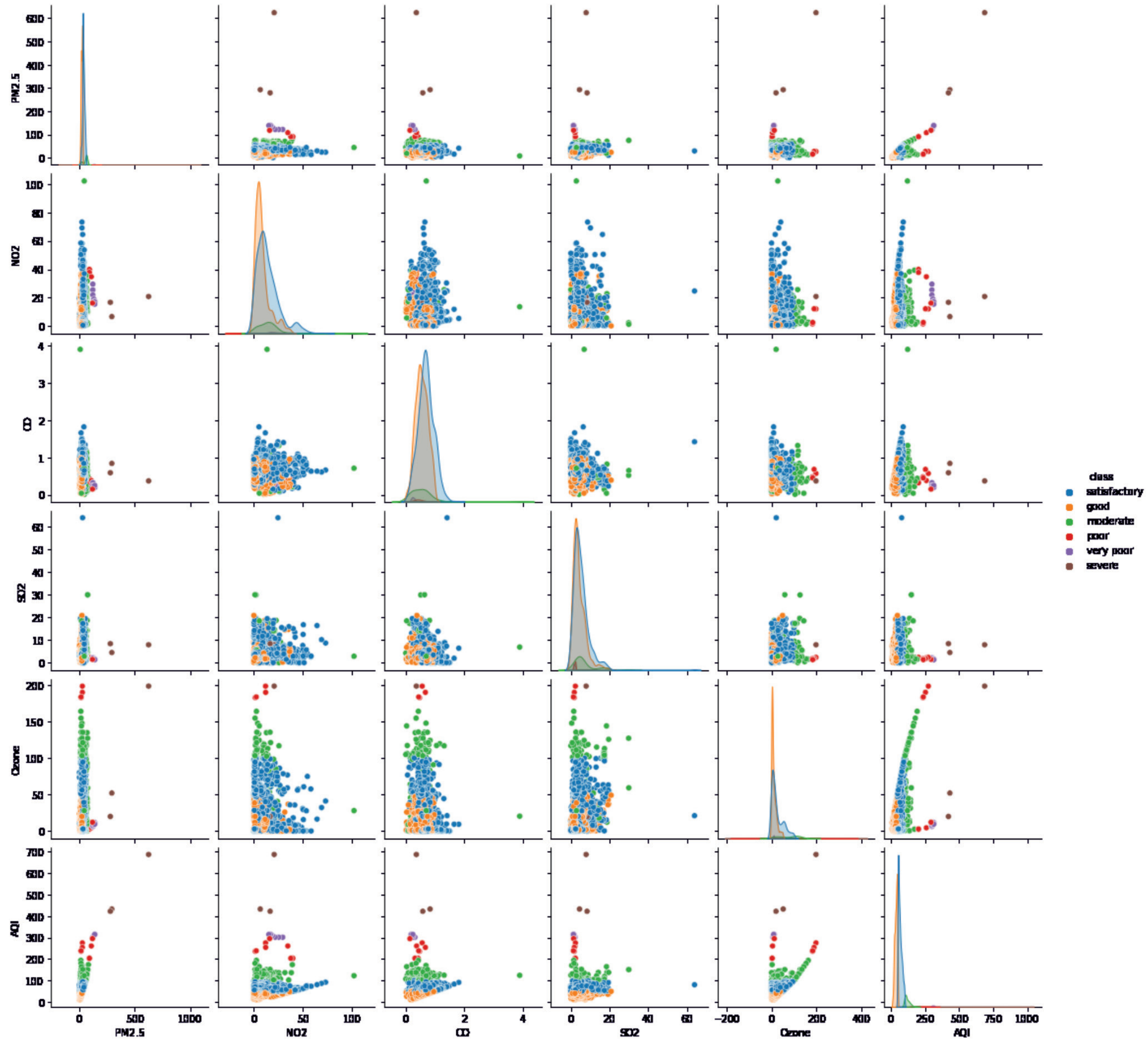

Fig. 11. AQI and Pollutants (Stack Model Heat Map - Seaborn) before Lockdown.

AQI are shown. From the figure it is evident that the pollutant variables $PM_{2.5}$ NO_2, CO, SO_2 and ozone are correlated positively. The level of co-relation of $PM_{2.5}$ being highest. The results show that the air quality in that area (Alandur) had been improved as evident from pair plot falling under good and satisfactory conditions. The improvement in quality of air been reported by other researchers [48-52] across the globe in different countries when compared with results before lockdown as shown in Fig. 11. The results also show that as industries and production centres were closed and due to reduced traffic (cut down of anthropogenic activities) because of continuous lockdown the pollutant $PM_{2.5}$ to a significant level.

The AQI values being improved as evident from class good being more pronounced in case during lockdown. The study demonstrates the benefit of Deep learning short-term predictions of various air pollutants. A linear regression model was performed

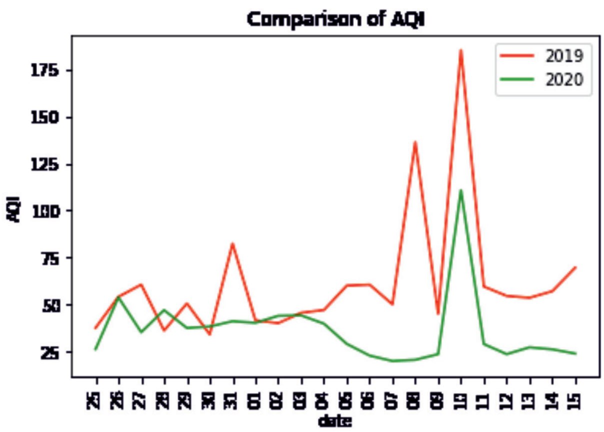

Fig. 12. Comparison of AQI of 2019 and 2020.

Table 5. Metrics to check the model performance.

Training performance		
MAE	R-squared	Adj.R- Squared
5.90	0.927	0.9278
Test performance		
MAE	R-squared	Adj.R- Squared
6.26	0.909	0.908

and metrics such mean_absolute_error, r^2 to check the model performance for training and testing data are presented in Table 5. A comparative analysis is carried out for the corresponding period of time in 2019 for assessing the quantum of improvement during the lockdown periods. Fig. 12 shows the comparison of AQI values of 2019 and 2020 and it is evident that AQI values of 2020 shows the reduced values and the peak values are also reduced. The reason being attributed to complete lockdown nation wide for 21 days from 24 March 2020 for 21 days (14 April 2020). These results can be coupled with social, economic and Cultural factors that could have the common emission patterns and air quality especially in metropolitan cities. Further, it can be extended to identify the sources associated with domestic coal combustion, vehicular emissions, incineration of waste and local policies and strategies can be framed accordingly to curb them. Also Change in technologies incorporating abatement of SOx and NOx and behaviour changes can aid the same.

Conclusion

– Big cities in India are recorded to be most polluted and have associated links for accounting for improvement in Chennai city internationally. This has pronounced positive effect on human and can facilitate to preserve the environment thereby improving the quality as well. There are global reports on reduction of NO_2 and carbon emissions. Urbanization had direct correlation with economic impact of a country but resulting in environmental degradation that leads to health risks also. Lockdown due to pandemic had resulted in reduction of emissions and had a positive impact in environmental restoration. This study has presented the pandemic impact on air quality (during lockdown) in Chennai, one of the prime cities in southern zone with the help of NAQI taking into consideration six pollutants concentration. It shows that there were decline in $PM_{2.5}$, by −61. This accounts for 30% change in air quality immediately after a day after imposition of lockdown. In addition, total of 51% decrease in NAQI over the full period of lockdown.
– The study would be a value addition for planning regulatory aspects and can be an eyeopener for imposition of strict enforcement locally for establishment of localized control policy and globally for preserving and saving our planet and improving the air quality.
– The government officials can monitor the atmospheric emissions continuously and can take necessary action against the persons who violate the same.
– More sort of such research works can be encouraged owing to the changes pertaining to climatic conditions as well.

Conflicts of Interest

The authors declare no conflict of interest.

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