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Impact of COVID-19 lockdown on the particulate matter over Perungudi, Chennai, India

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ABSTRACT

The nationwide lockdown of Phase-1 in India was started from March 25 to April 14, 2020 and Phase-2 from April 15 to May 3, 2020 with severe restrictions on public activities in India. Utilizing the particulate matter PM_{10} and $PM_{2.5}$ data recorded during this adverse time, the present study is undertaken to assess the impact of phase 1 and 2 lockdown on the air quality of Perungudi, Chennai, India. The data obtained from the Tamil Nadu Pollution Control Board was assessed for lockdown phase. We compared particulate matter data for the unlock phase with a coinciding period in March 2020 to determine the changes in pollutant concentrations during the lockdown period of April 2020. The descriptive analysis of PM continuous data was performed to determine the mean, standard deviation, variance, skew and kurtosis to identify the nature of data. Correlogram analysis gives the information that the data under study has non-stationary behaviour and not random. Along with this linear regression analysis were performed to determine the relationship and trend for the data. The results revealed decreasing trend in the concentrations (PM_{10} , $PM_{2.5}$).

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1. Introduction

The first lockdown imposed on India which was Phase-1 started from March 25 to April 14, 2020, with severe restrictions on all public activities. The Phase-2 lockdown lasted for 19 days from April 15th to May 3rd 2020. During this period various parts of the cities were color-coded into green, orange, and red zones depending on the number of COVID-19 positive cases. The red zones were marked as drastic increasing cases and had total lockdown, orange zones had moderately increasing cases were provided with partial lockdown having some relaxations and the green zone which had low positive cases had least restrictions among all of them.

The vital air pollutants in cities and industries are NO_2 , SO_2 , PM_{10} which are responsible for cardiovascular and respiratory diseases [1,2]. The main sources of these pollutants are vehicular exhaust, road dust, and mainly metal processing industries [3,4]. The Ministry of Earth, Forest, and Climate change (MoEF) under

its National Clean Air Programme (NCAP) launched a five-year action plan in 2019 to reduce by 30% the nationwide concentration of particulate matter [5]. Due to the mandatory lockdown imposed across the country, 88 Indian cities have observed a drastic reduction in air pollution. The rapid industrial growth is one of the main reasons for the release of different gaseous emissions and particulate matter (PM_{10} , $PM_{2.5}$). The various harmful air pollutants are being emitted into the environment by human activities as primary pollutants which in turn lead to the formation of secondary pollutants by their chemical reactions in the atmosphere. A drop of 43% and 31% in PM_{10} and $PM_{2.5}$ concentration during the lockdown period and past 4-year values for different regions of India has also been reported [6]. India, bonded their regular presence in the list of top 20 polluted cities of the world [7–9]. Continuous degradation of air quality in some of the Indian metropolitan cities like New Delhi, Mumbai, Kolkata and Chennai that often exceed the standards set by WHO and Central Pollution Control Board (CPCB).

The prominent air quality improvement was noticed from the reduction in Particulate Matter, NO_2 , SO_2 and CO, during the COVID-19 lockdown period was observed in the Hangzhou megac-

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ity [10]. A positive effect of the social distancing measures is investigated [11] on the concentrations of the three main primary air pollutants PM_{10} , NO_2 and CO of the São Paulo and Rio de Janeiro. The air quality changes during COVID-19 lockdown over the Yangtze River Delta Region shows that the reduced human activity and industrial operations lead to significant reduction in $PM_{2.5}$, NO_2 , and SO_2 [12]. Several countries like France, Germany, Italy, Spain, and China imposed COVID-19 lockdown led to suspension of power plants, transportation, and other industrial operations which resulted in extreme decrease in concentration levels of NO_2 , $PM_{2.5}$, PM_{10} and CO [13–17].

This present study is undertaken to determine the concentration of air pollutants PM_{10} and $PM_{2.5}$ for the pre and post lockdown period of phase 1 and 2 (March 1, 2020 to May 3, 2020) to find the impact of air quality in Perungudi of Chennai, India.

2. Study area

Chennai city, situated on the shores of the Bay of Bengal, is the capital of Tamil Nadu and the fourth largest metropolis in India [18]. Perungudi lies in the neighborhood of Chennai in the state of Tamil Nadu. It is amidst the IT Estate India expressway. It is bordered on two sides by the famous Old Mahabalipuram road and Perungudi Lake. Perungudi is primarily located at $12.97^\circ N$ $80.25^\circ E$ and an average elevation of 9 m (29 feet). The strategic location of Perungudi had made the place to transform from a small village to a vibrant commercial and residential hub. Being one of the two major landfills in Chennai, the Perungudi dump yard is always in news for its frequent fires. This causes complaints from the residents about the air pollution and health issues. Tamil Nadu Pollution Control Board has installed real time continuous air quality monitoring station at Perungudi. The dump yard in Perungudi also extends its hands till Pallikaranai marsh land which is aesthetically a beautiful home for rare and local migratory birds. It is desirable to analyze the concentration of particulate matter in this area during the lockdown period. The location of Perungudi in Chennai, India is shown in (Fig. 1).

3. Methodology

3.1. Basic descriptive statistics

The time series plot of PM_{10} and $PM_{2.5}$ before and after lockdown is shown in (Figs. 1a and 1b) respectively. Phase 1 lockdown

started from March 25, 2020 and the remaining 7 days in that month do not show any significant changes in the data. So March is considered as Pre-lockdown data and April month includes phase 1 and 2 lockdown, considered as Post-lockdown data set.

Chennai Perungudi time series data of PM_{10} and $PM_{2.5}$ are subjected to the descriptive statistical analysis which includes mean, variance, standard deviation, skewness, kurtosis and coefficient of variation are shown in Table 1. Skewness is a measure of the asymmetry of the distribution. A distribution is asymmetric when one tail is longer than the other. If the skewness is positive, then the distribution is said to be skewed to the right while a negative skewness denotes a distribution skewed to the left. Zero skewness implies a perfectly symmetric distribution [19].

Kurtosis is a measure of degree of the peakedness of the probability distribution. The normal distribution is used as reference for interpreting kurtosis. A positive kurtosis suggests that a distribution with more extreme possible data values (outliers) than a normal distribution thus, fatter tails (Leptokurtic distributions). A negative kurtosis indicates a distribution with less extreme possible data values than a normal distribution thus, thinner tails (Platykurtic distributions). A zero kurtosis has roughly the same outlier character as a normal distribution (Mesokurtic distributions)

3.2. Test for normality and stationarity

The normal distribution test and stationarity test can be judged from skew and kurtosis values and correlogram respectively. The skewness value should be close to zero and kurtosis is to be -3 to $+3$ for a normal distribution. Stationary test is performed using Correlogram or autocorrelation function is used to find whether the data under study has the property of stationarity or non-stationarity. The autocorrelation function is a tool used to identify the periodicities in the given time series. The correlation of time series data within itself is known as autocorrelation plot or autocorrelation function plot ACF. It can have positive, negative or zero correlation. The dotted lines represent 95% confidence level. Lag 1 is always at 1 since the data is correlated within itself. Mostly autocorrelations are done to check the randomness in the time series data. This randomness is calculated at various time lags in the autocorrelation plot. If the data is random then the autocorrelations should be close to zero at all or any time lags. If it is not random, then one or more autocorrelations will represent non-zero in the time lag [20].

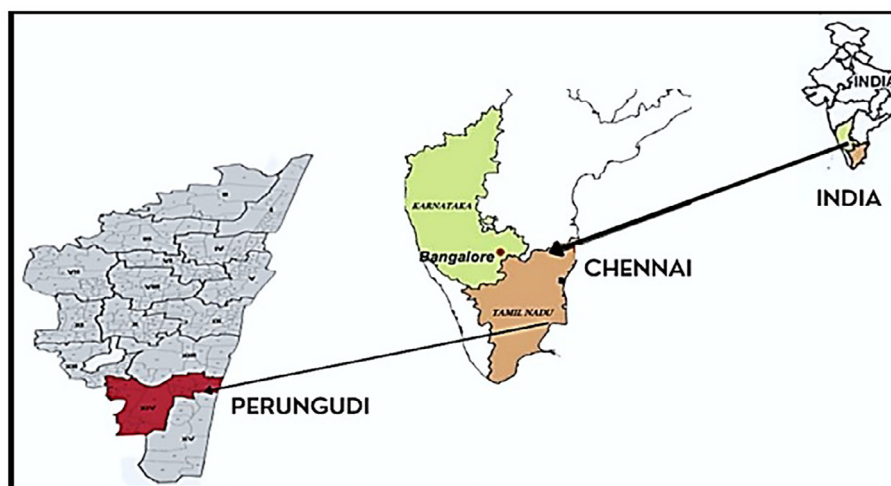


Fig. 1. Location of Perungudi in Chennai, India.

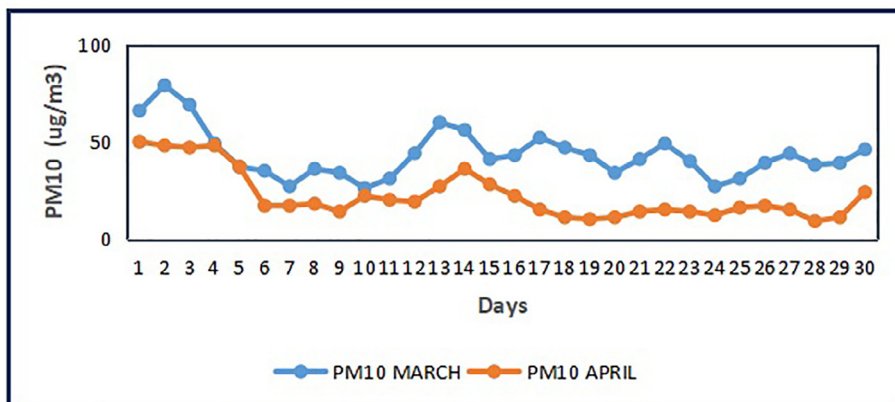


Fig. 1a. Time series plot of PM₁₀ before and after lockdown.

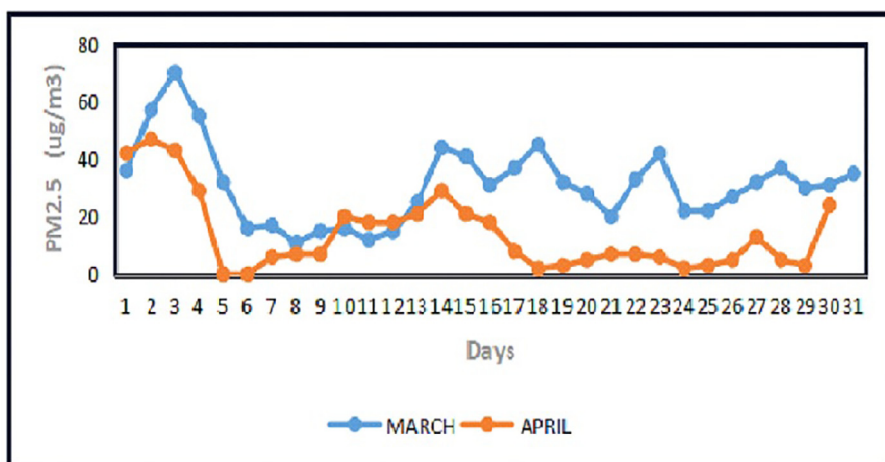


Fig. 1b. Time series plot of PM_{2.5} before and after lockdown.

Table 1
Statistics of PM₁₀ and PM_{2.5} before and after lockdown.

Statistics	Before lockdown		After lockdown	
	PM ₁₀	PM _{2.5}	PM ₁₀	PM _{2.5}
Mean	43.43	31.161	22.133	13.967
Standard deviation	12.604	13.835	12.459	13.252
Maximum	79	70	50	47
Minimum	26	1	9	0
Variance	158.875	191.407	155.222	175.619
Skewness	1.096	0.810	1.246	1.173
Kurtosis	1.214	0.841	0.362	0.564

The Auto correlation Function (ACF) or Correlogram plot was drawn on the PM₁₀ and PM 2.5 values before and after lockdown. It is shown in (Figs. 2a and 2b).

The plots give useful information to determine the correlation in the values of a time series data. The correlogram decays quickly within 4 or 5 lags for the stationary time series. For the non-stationary time series, the correlogram decays rather slowly [21].

From (Figs. 2a and 2b), the ACF plots show a very slow exponential decay with an increasing lag. The slow decay in ACF values shows that the PM concentration in time series is dependent on each other which are known as persistence. Based on Rodriguez Iturbe et al. [22] these phenomena may be related to the fractal properties. The slow decay in ACF values also shows that self-similarity is present in the PM time series. Self-similarity is the

property of fractal where an object looks and behaves the same regardless of any scales.

3.3. Linear regression

Linear regression is the method of fitting a function to a set of data is shown in (Figs. 3a and 3b) for before and after lockdown for PM₁₀ and PM_{2.5} respectively. Simple linear regression is the most widely used parametric method for identifying monotonic trend in a time series. It is used to evaluate the relation between one variable with another or other variables. It is usually performed to identify the slope of variables on time. Positive slope signifies an increasing trend while negative slope shows declining trend [23]. Generally used metric for finding goodness of fit is R

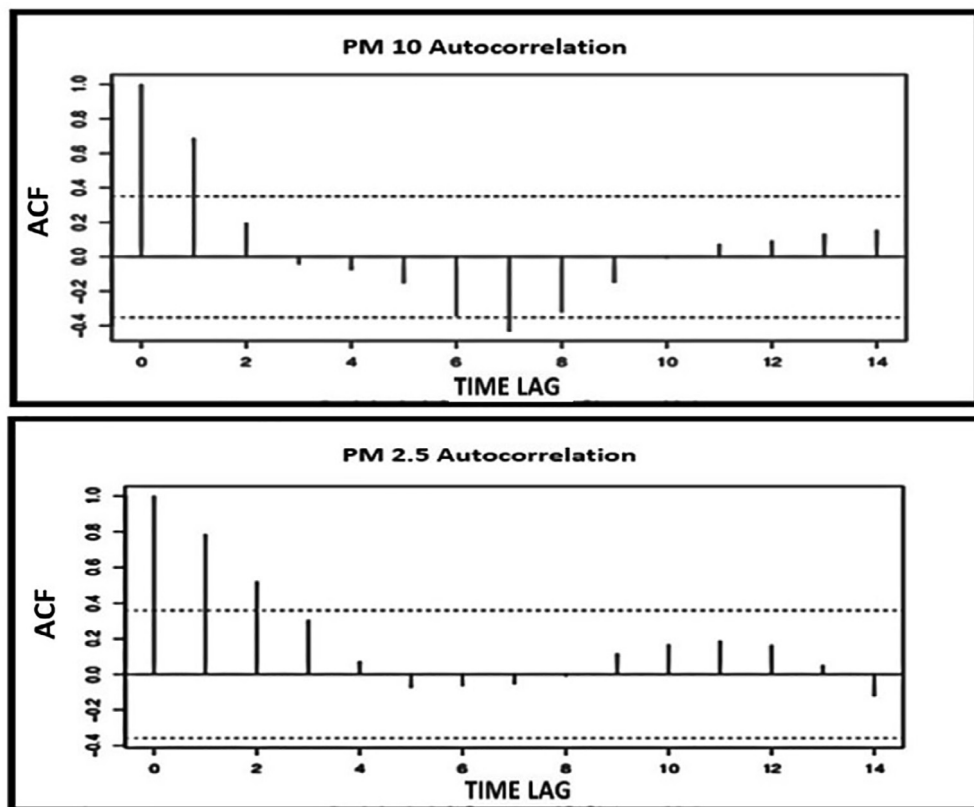


Fig. 2a. Before lockdown autocorrelation function (ACF) for PM₁₀ and PM_{2.5} respectively.

squared or coefficient of determination. R-squared evaluates the scatter of the data points around the fitted regression line. When the R-squared value is higher it represents small differences between the observed data and the fitted values.

4. Results and discussion

In the descriptive statistics, the mean value decreases in April when compared with March. Standard deviation is important because the shape of a normal curve can be found by using its mean and standard deviation. The mean gives the information where the middle highest part of the curve should go. Standard deviation gives the width of the curve. The data before the lockdown has the highest mean of 43.43 for PM₁₀ and 36.161 for PM_{2.5}. Standard deviation do not vary much before and after lockdown period which informs that the width of the curve remains almost the same. Variance gives the information about the degree of spread in the data set. Pre and post lockdown data has large variance which shows that the spread of data is more. The skewness value is not very close to zero so the pre and post data is not normally distributed exactly but little skewed. For pre lockdown PM_{2.5} the skewness lies between 0.5 and 1, the distribution is moderately skewed. For pre lockdown PM₁₀ and post lockdown PM₁₀ and PM_{2.5} the skewness is greater than 1 which shows the distribution is highly skewed. Kurtosis gives the information about the height and sharpness of the central peak, relative to that of standard bell curve. The kurtosis value lies between -3 to +3 for both the data set which identifies presence of normal distribution.

The correlogram is a widely used tool for checking the randomness in a data set. Autocorrelations should be near to zero for any and all time lag separations if the data is random. One or more of the autocorrelations will be significantly non zero if the data is

not random. The Autocorrelation at lag 1 is very high but the other values at lags greater than 1 are relatively small but not zero. It can be confirmed that the data is not random and stationary. The time lag do not fall to zero within few lags rather decays slowly which shows non stationarity in it. Correlogram shows slow decrease as the lags increase is due to the presence of trend while the shape is due to seasonality. The maximum peaks are found at lag 1 and 7 in both the pre lockdown data. In post lockdown notable peak is observed at only in lag 1 in both the data.

After identifying the presence of trend in correlogram, the nature of trend is tested using linear regression method. This shows decreasing trend for both the pre and post lockdown period. Before lockdown PM₁₀ has 12% and PM_{2.5} has 2% R- squared reveals the data fit in the model. After lockdown PM₁₀ has 48% and PM_{2.5} has 26% R- squared reveals the data fit in the model. Generally higher R squared is the best fit for the model. R-squared value increases when compared for before and after lockdown. The slope of the line is negative in all cases which shows there is a negative linear relationship.

5. Conclusion

It is definite that there is clear reduction in the mean values of particulate matter concentrations due to COVID-19 lockdown. Even though skewness is observed, kurtosis value significantly proves that data under study is normally distributed. Standard deviation remains almost same in both the cases. Correlogram analysis confirmed the presence of non-stationarity and trend in the data. Regression analysis show declining trend in particulate matter (PM_{2.5} and PM₁₀) levels during the COVID-19 lockdown period, as compared to the pre-COVID-19 month. Further, we also note that the linear regression analysis exhibited a negative corre-

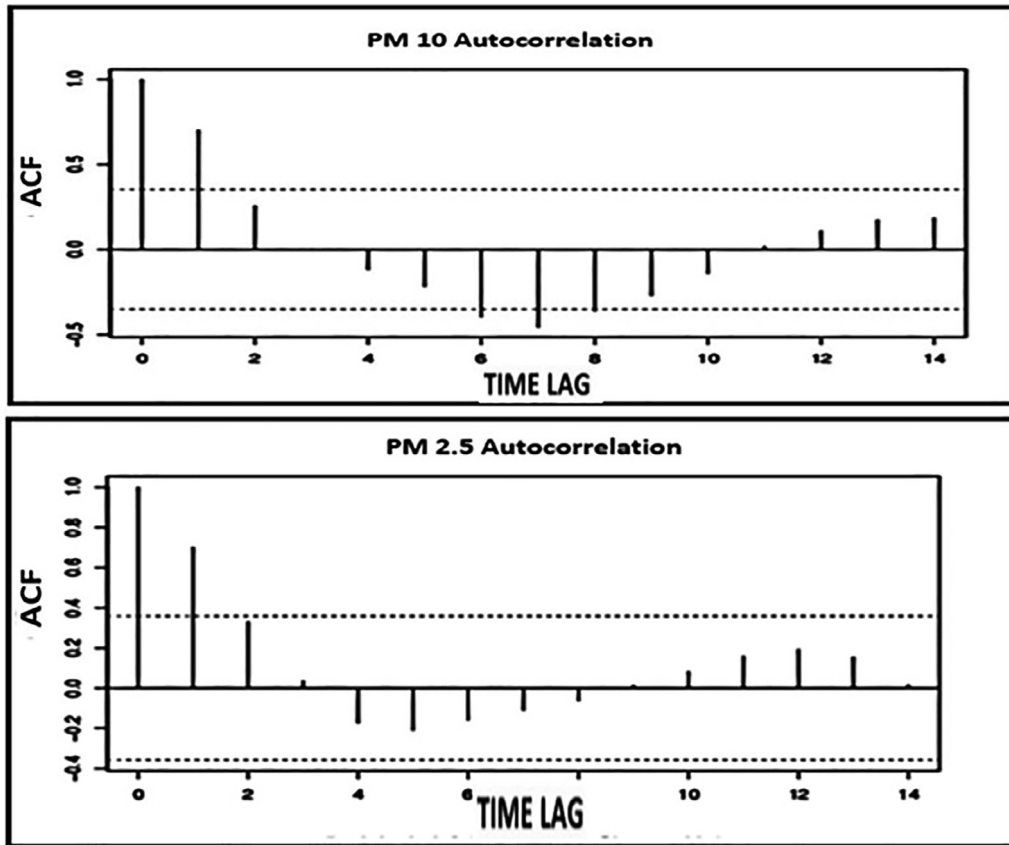


Fig. 2b. After lockdown autocorrelation function (ACF) for PM₁₀ and PM_{2.5} respectively.

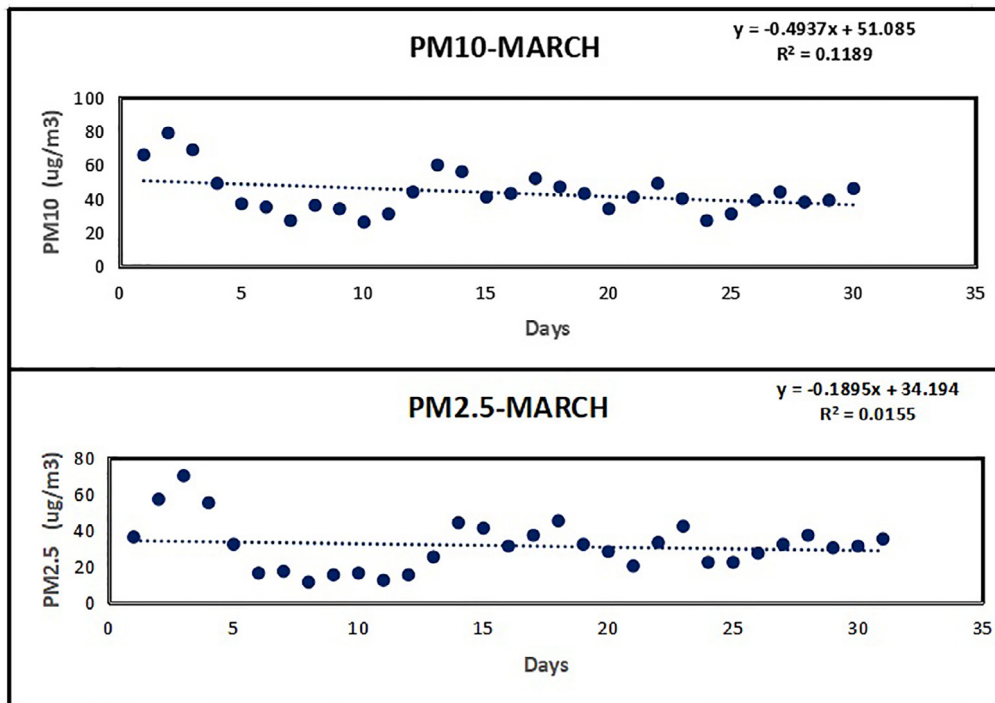


Fig. 3a. Before lockdown regression analysis for PM₁₀ and PM_{2.5} respectively.

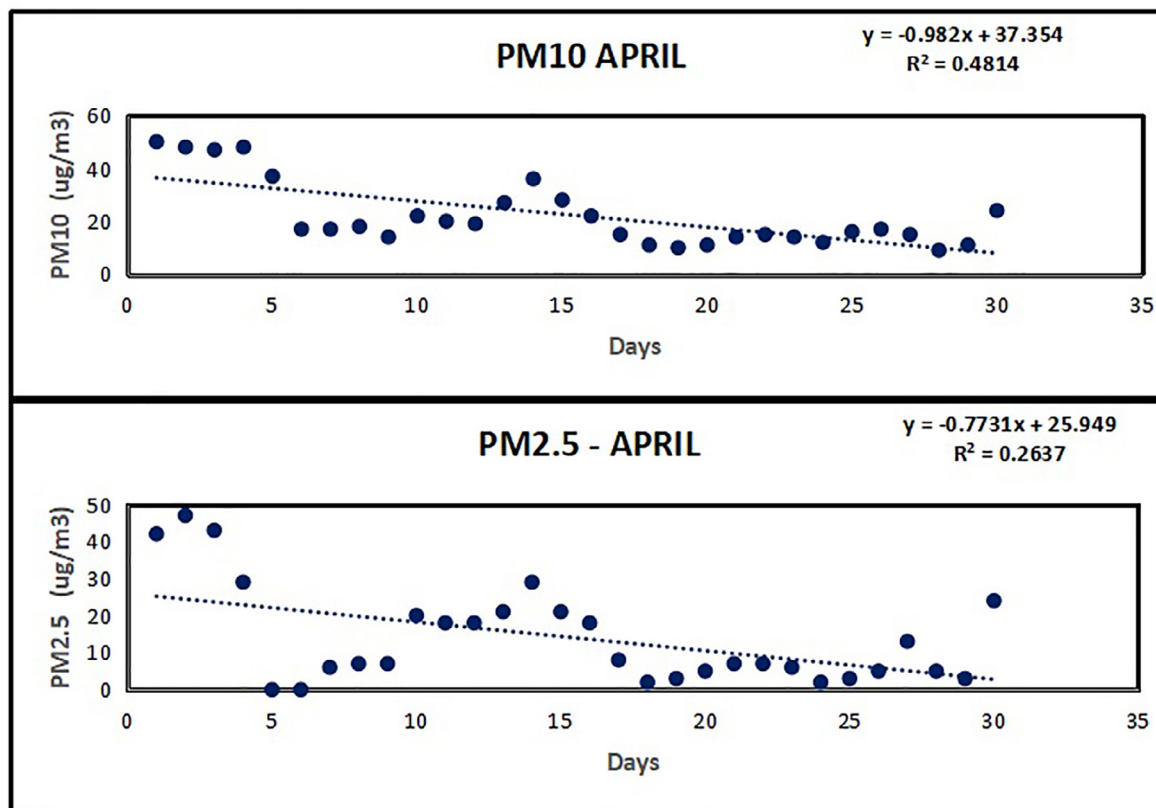


Fig. 3b. After lockdown regression analysis for PM_{10} and $PM_{2.5}$ respectively.

lation between the daily particulate matter and the growing number of days. The main reason behind the negative correlation could be the meteorological conditions prevailing in the region. The meteorological conditions are always meant to be the saviour, the impacts from it which is not to be ignored. It should be reckoned in the future for the same by understanding the trend in the particulate matter. Phase 1 and 2 lockdown brought significant improvement in the quality of air in Perungudi.

CRediT authorship contribution statement

S. Tamil Selvi: Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft
S. Najma Nikkath: Writing - review & editing.
N. Mahalakshmi: Writing - review & editing.

Declaration of Competing Interest

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

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