Affect on Climate due to COVID-19 Lockdown

Depiction of Aerosol Optical Depth (AOD) values from MODIS data

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Introduction

"Tiny solid and liquid particles suspended within the atmosphere are called aerosols". Aerosols come from various sources such as windblown dust, sea salts, volcanic ash, smoke from fires, and pollution from factories. Since aerosols affect weather and human health in a great amount they are important elements of the environment. The effect of aerosols on the disruption of solar radiation is called aerosol radiative forcing ("Climate Change," 2001). There are both direct and indirect effects of atmospheric aerosols. The direct effects include absorbing and backscattering of the sunlight, depending on the type of aerosol, and in an indirect way aerosols help in the alteration of the cloud particle size in the lower atmosphere(Lenoble et al., 2010). Aerosols also can act as sites for chemical reactions to take place (heterogeneous chemistry) (Ginoux et al., 2012). The most significant of these reactions are those that lead to the destruction of stratospheric ozone (Allen, 2015). These particles are important environmental elements because they can affect climate, weather, and people's health.

One of the major type of the aerosols are anthropogenic aerosols, Anthropogenic aerosols are the aerosols formed due to human activities, which in current times outweigh the natural aerosols. Majority of these aerosols are formed due to the burning of coal and oil, some of these also come from smoke generated by burning wood. These aerosols help in making more cloud droplets but decrease the size of the droplet, as a result, they tend to reflect more sunlight and trap the remaining sunlight inside. Consequently, this cools and heats the Earth's surface at odd times (Verma et al., 2019). Due to COVID-19 pandemic there was strict lockdown from the last week of March 2020, which decreased the anthropogenic activities to a bare minimum. This project focuses on the positive impacts of this lockdown and assesses the change in aerosol content and air pollution.

Study Area

Indian Gigantic plain:

The Indo-Gangetic Plains (IGP) are one of the main food-producing regions of India. Encompassing the northern part of the Indian subcontinent, the IGP region includes the Indian states of Punjab, Haryana, Uttar Pradesh, Bihar, and West Bengal. The region is characterized by mostly flat topography and includes the adjacent fluvial plains of the Indus and Ganges river systems. Today the IGP is extensively cultivated and densely populated. The area contains many urban cities and industrial hubs due to the abundance of water and food supplies in this region. As a result the area has high air pollution rates. Indian Gigantic Planes(IGP) is a major hotspot because of the desert dust traveling from the west and the high anthropogenic activities around the region (Srivastava et al., 2012).

Delhi:

Delhi is a hub for air pollution as there are many power plants, factories and an intense vehicular population in Delhi. There are various studies and assessments already done inDelhi which shows the urban development over Delhi.

Further to verify that the urban region in Delhi is very high, a map in Bhuvan portal representing Land use land cover classification of Delhi region was analyzed, Hence provingthat the study of AOD for this region should be done so as to determine if the air qualityfor people in that region is not drastic. The figure below represents the land use land cover mapfrom Bhuvan portal.

Figure 1 Map of Indo Gaigantic Plains used in this project

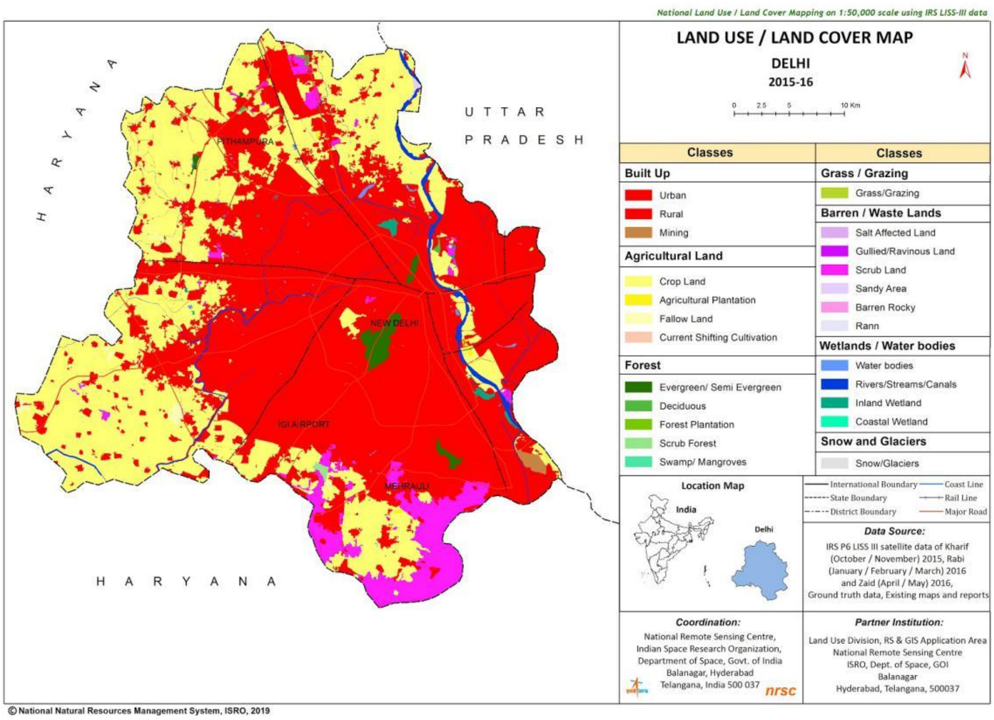

Figure 2 Delhi LULC map from Bhuvan portal

Objective

Illustrate the effect of lockdown due to COVID-19 lockdown in the IGP and Delhi region

Dataset used

Aerosol optical thickness: It is a measure of how much light the airborne particles prevent from traveling through the atmosphere. Aerosols absorb and scatter incoming sunlight, thus reducing visibility and increasing optical thickness. An optical thickness of less than0.1indicates a crystal clear sky with maximum visibility, whereas a value of 1 indicates the presence of aerosols so dense that people would have difficulty seeing the Sun, even at mid-day!

Hence, Modis terra 550nm AOD(8 day) data set is used for the assessment done in this project. The data sets are taken from NASA Earth Observation site. The resolution of this dataset is 0.01 degrees.

Methodology

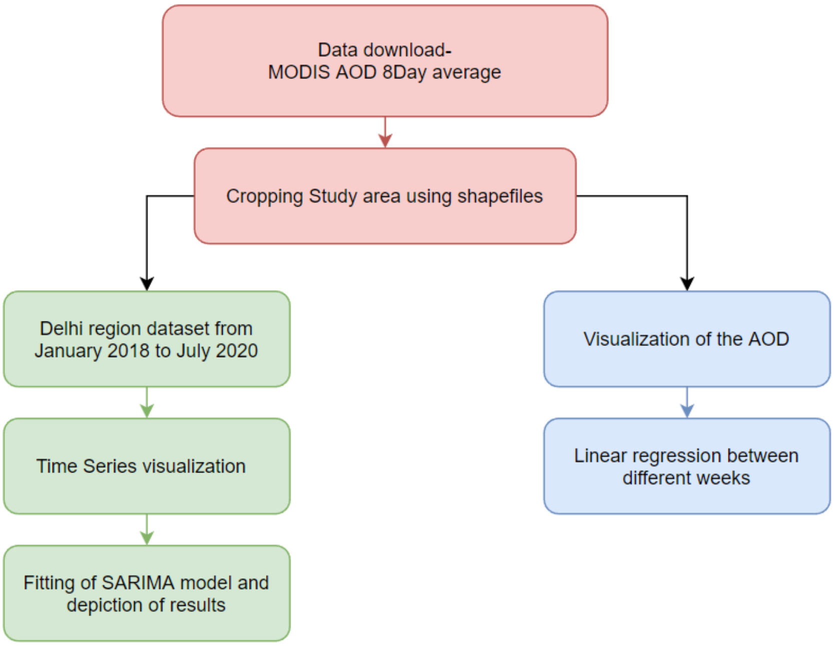

Figure 3 Flowchart explaining the methodology used in this project

Visualization

Due to the COVID-19 pandemic, there was a nationwide lockdown in 2020, consequently, a decrease in the air pollution caused by anthropogenic activities was observed (Mehta et al., 2021a; Mehta et al., 2021b) (Soni, 2021). We could capture this decrease in the aerosol content in the AOD estimated from the MODIS sensor. To be specific, depending on the data availability, we have observed prominent aerosol changes in the IGP region in the last and first weeks of March and April, the selected regions usually receive aerosol loading due to anthropogenic activities along with the transported dust from the Arabian Sea. Also, the increased solar illumination combined with hot winds results in the uplifting of particles from the local sources. After the imposition of lockdown, the anthropogenic sources were reduced, which could lead to a reduction in overall aerosol loading. Fig. 4 depicts the comparison for pre-and post- COVID-19 lockdown weeks for 2018, 2019 and 2020. Since the lockdown period started from the end of March and continued up to June, the reduction in the aerosol loading is significant enough that it can be observed in the heatmaps for 8 day average AOD values. It could be clearly seen that the values for the lockdown weeks are significantly lower than that of the years 2019 and 2020.

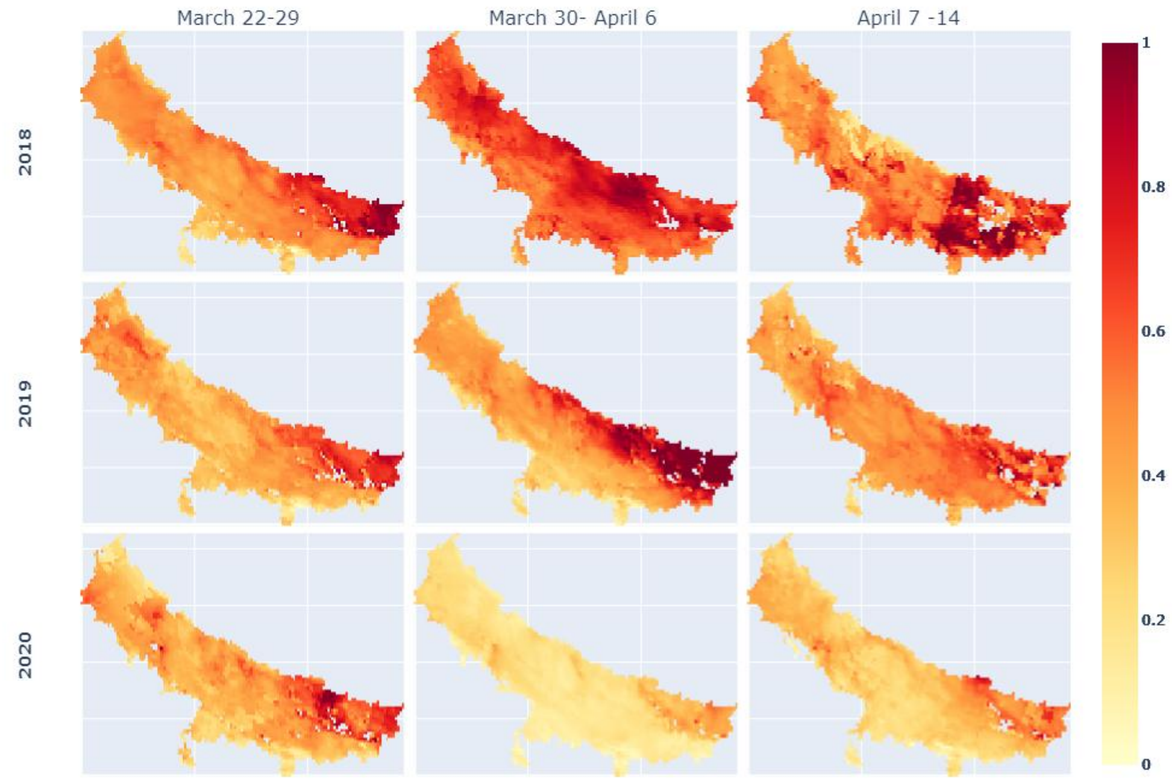

Figure 4 Figure depicting the drastic change in AOD values in lockdown period in IGP region

Linear Regression:

This form of analysis estimates the coefficients of the linear equation, involving one or more independent variables that best predict the value of the dependent variable. Linear regression fits a straight line or surface that minimizes the discrepancies between predicted and actual output values. There are simple linear regression calculators that use a “least squares” method to discover the best-fit line for a set of paired data. You then estimate the value of X (dependent variable) from Y (independent variable). It also approximates for correlation between two variables, the higher the value the more correlation between the variables.

Further to quantify the changes in the Fig 4 linear regression between the lockdown weeks of 2018 -2019 and 2019- 2020 was done. It can be clearly seen in the bottom right graph of Fig 5 that the AOD values for 2020 have significantly lowered in the lockdown week.

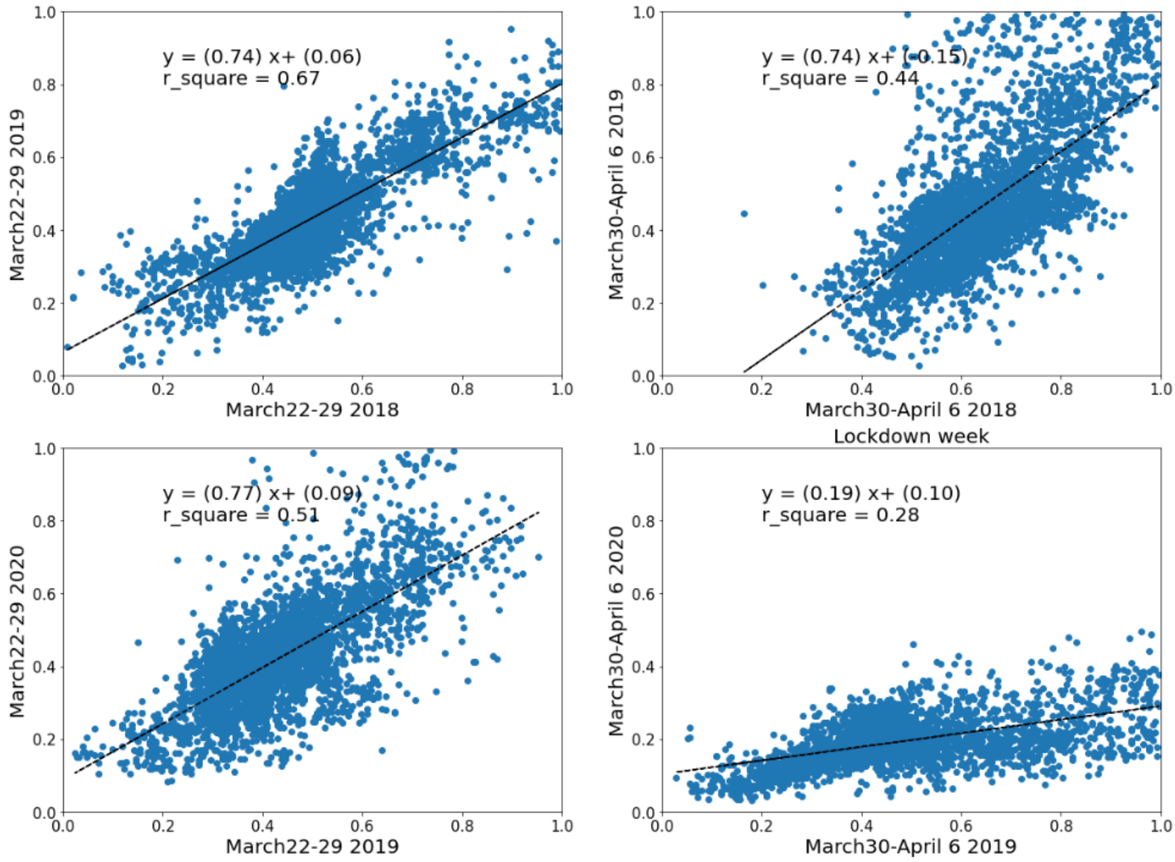

Figure 5 Linear regression analysis of the IGP region

Time Series Analysis

To demonstrate that the AOD values have decreased for the lockdown months of, A time series forecast model is prepared, that proves that the forecasted values without the assumption of lockdown is higher than the actual values. The study area chosen for this exercise is Delhi.

ARIMA(Auto Regressive Integrated Moving Average):

ARIMA model is a forecasting model whose value depends on the past values based on time lags and errors in time lag model. The ARIMA model includes both Auto Regressive(AR) and Moving Average(MA) component. If the data is seasonal a Seasonal-ARIMA model is implemented. Hence the expression of ARIMA model combines both AR model and MA model expressions. The condition for applying ARIMA model is the time series data should be stationary.(Prabhakaran, n.d.). The expression of AR(Auto Regressive) model is:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \epsilon_1$$

Here β are the coefficients of the data p are the no. of terms taken into consideration. And ϵ_t, ϵ_{t-1} refers to errors in the model. The expression for Moving Average(MA) model is:

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

Here q are the no. of terms of the MA model and the value of ϵ is taken from the equations below.

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_0 Y_0 + \epsilon_t$$

$$Y_{t-1} = \beta_1 Y_{t-2} + \beta_2 Y_{t-3} + .. + \beta_0 Y_0 + \epsilon_{t-1}$$

Hence the Expression for ARIMA model is:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q}$$

From the above equation it can be inferred that the parameters needed to define a ARIMA model is p, q; here p represents the AR component and q represents MA component. Also another component d is needed; which represents the no. of differencing needed to make the time series stationary.

The value of p,d,q can be tentatively set using ACF and PACF plots; based on the number of positive lags in both plots.

SARIMA Model

Seasonal Autoregressive Integrated Moving Average, SARIMA or Seasonal ARIMA, is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component.(Brownlee, 2018)When the time series has a defined seasonality, seasonal ARIMA model is applied. In this model seasonal differencing is used with usual differencing. It adds Four more parameters P,D,Q and S as seasonal component. Hence the model consist of p,d,q,P,D,Q and S parameters; where p,d,q are trend components and P,D,Q,S are seasonal components.

The training dataset were chosen from 1-January 2018 to 14 March 2020, and the data was predicted from 14- March 2020 to 30 July 2020. In Fig 6 the orange line depicts the actual value, the blue line depicts the training data and the green line depicts the forecasted values. It is clearly seen in the figure that actual values for most of the weeks were lower than the forecasted values. Hence, it shows that stopping of various anthropogenic activities affects the pollution content in the region.

Table 1: SARIMA model fitting coefficients

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.3493	0.107	3.273	0.001	0.140	0.558
ar.L2	0.2918	0.116	2.518	0.012	0.065	0.519
ar.S.L4	-0.7810	0.122	-6.392	0.000	-1.021	-0.542
ar.S.L8	-0.2305	0.133	-1.733	0.083	-0.491	0.030
sigma2	0.0286	0.004	6.697	0.000	0.020	0.037

Ljung-Box (L1) (Q):	0.03	Jarque-Bera (JB):	0.21
Prob(Q):	0.87	Prob(JB):	0.90
Heteroskedasticity (H):	1.69	Skew:	-0.10
Prob(H) (two-sided):	0.16	Kurtosis:	3.14

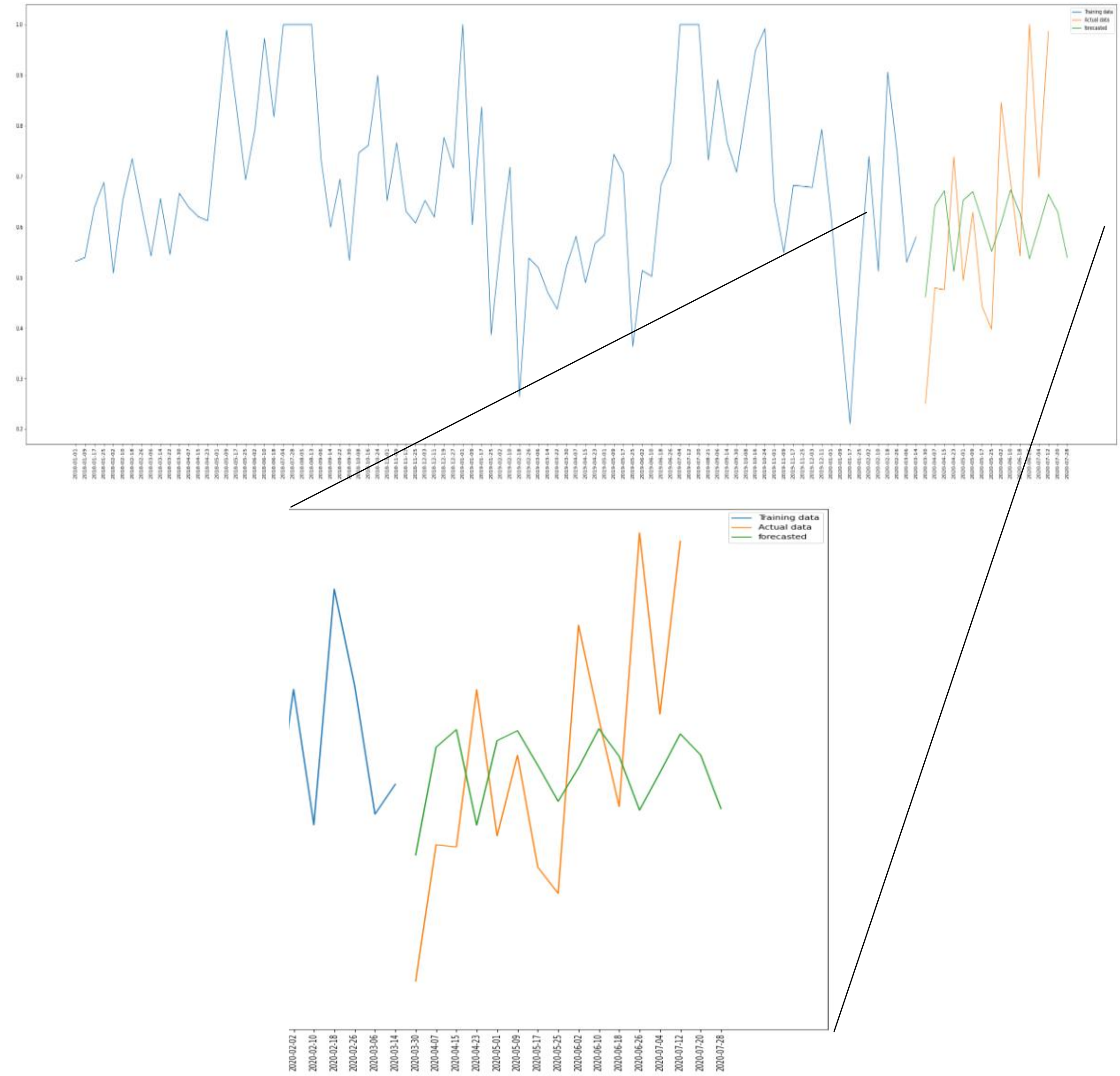

Figure 6 Time series visualization and forecasting for Delhi region.

Conclusion

There is a clear dip in the value of AOD for the period 30 March- 14 April. The further increase in the AOD values is because of summer dust and burning of the farm fields. Various data models on different type of variables could be applied and the same conclusion can be reached: By limiting the dangerous affect on climate by the anthropogenic activities could replenish and nourish the natural resources.

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