Inspecting Satellite Data for Surface Air Quality Monitoring and, Prediction of Surface AQI using ML models and Prophet

Vatsal Patel[1], Dr. S. D. Dhiman[2], Dr. Reshma .L Patel[3]

[1]MTech Environmental Engineering Student, [2]Associate Professor, [3]Associate Professor
[1, 2, 3] Department of Civil Engineering,
[1, 2, 3]BVM Engineering College, Anand, Gujarat, India.

Abstract: Rapid urbanization and industrialization have caused Indian urban regions to suffer severe air pollution issues; insufficient ground monitoring data and incomplete air pollution source characterization impedes putting policy measures to overcome this issue, remote sensing and GIS can tackle this hurdle to some extent. The necessity of monitoring and preserving air quality has now become an essential priority in many industrial and urban areas today. The air quality is skeptically affected due to multiple forms of pollution caused by fossil fuel burning, stubble burning, electricity, etc. The accumulating deposition of harmful gases is creating a serious threat to the quality of life in urban areas and their surroundings. The quality of air is affected by multi-dimensional factors including location, time, and meteorological factors. This study focuses on the current and future advancing techniques of monitoring and predicting air quality for Ahmedabad city by scrutinizing the use of remote sensing data for surface air quality monitoring which includes acquiring the satellite image data using python for NO2 and SO2, correlating ground and satellite data. And using ground data, predicting air quality index using machine learning tools like Random Forest Regressor, Adaboost Regressor, and times series model Prophet.

***Index Terms* – Air quality Index, Satellite data, Machine Learning Models, Prophet.**

I. INTRODUCTION

Ahmedabad city of Gujarat has emerged as an important economic and industrial hub in India and one of the hundred Indian smart cities. The areas in Ahmedabad city and Sabarmati river banks are better known for the best Infrastructure and Transport. Ahmedabad district's major industries include Textile, Pharmaceutical, Construction, and Chemical. Some of the major contributing sources of air pollutants in Ahmedabad city consist because of road dust, vehicular emissions, open domestic fuel burning, waste burning, construction activities, industrial activities, etc. Gujarat Pollution Control Board regularly monitors the ambient air quality of Ahmedabad by Continuous Ambient Air Quality Monitoring Station (CAAQMS) installed at Maninagar, Kankariya Dhor Bajar, and GIDC Vatva and other14 manual stations operated under NAMP & SAMP under CPCB guidelines.

The conventional method of monitoring urban air quality has been to use a network of ground monitoring stations and models that measure emissions and forecast changes in the air quality at discrete points. Satellite remote sensing may be able to provide a comprehensive image of air quality in an urban air shed, as well as knowledge on the origin of isolated incidents. The use of remote sensing data could aid air quality experts in determining peak concentrations and concentration gradients between surface monitoring stations. Compared to ground-based monitoring, satellite sensors have only provided limited quantitative information for air quality, but the potential for quantitative applications exists. The combined use of these two data and model sources could allow for better policy decisions and scientific understanding of an urban air shed than either approach alone. A study on air quality by environmental researchers over the last thirty years shows that the proliferation of cities and improper maintenance of automobiles aren't just the causes of air pollution but the pollution level is greatly modified by metrological factors as well (M. A. Pohjola et.al 2002). Air pollutants are classified, primary pollutants: substances which are directly discharged from the source into the atmosphere and secondary pollutants which are discharged through natural events or by man-made activities, such as vehicular emissions and industries. Primary pollutants are particulate matter (PM), nitrogen dioxide (NO2), sulfur dioxide (SO2), and carbon monoxide (CO), while secondary pollutants are compounds in the atmosphere that are formed due to a chemical or physical reaction with primary pollutants like ozone, nitric acid, etc.

Currently, there are two state-of-the-art methods for predicting air quality: (i) statistical models and (ii) artificial intelligence techniques. Statistical models based on single variable linear regression (Y. Li, Q. Chen et.al 2015) have shown a negative correlation between different variables that influence prediction. Meanwhile, artificial-intelligence-based approaches can include several parameters to facilitate better forecasting. (J. Zhang and W. Ding, 2017) forecasted pollution from meteorological data with the help of artificial neural network-based classifiers. Further, a trend study (X. Xi, Z. Wei, and R. Xiaoguang, 2015) revealed that machine learning models are more reliable in solving forecasting problems. Therefore, most air quality prediction models (M. Castelli, F. Clemente et.al 2020) are designed on AI platforms. (R.Mangayarkarasi et. al, 2021) predicted AQI using SARIMA and machine learning model Random Forest in junction with Facebook's Prophet library which had better precision as well as lower RMSE values indicating the use of Prophet features for better accuracy. This study scrutinizes the use of remote sensing data as a replacement for air quality monitoring of the ground. Ground data are used in Random Forest Regressor and Adaboost Regressor for prediction, more features are added using Prophet Library and checked for an increase in accuracy of the models.

1.1 Air Quality Index

The National Air Quality Index (AQI) was launched in New Delhi on September 17th, 2014, under the Swachh Bharat Abhiyan. The air quality index (AQI) was developed by government agencies to communicate to the public about the extent of how polluted the air is; the Higher the value higher the risk for health. Two steps are involved in calculating AQI (1) Calculating the sub-index for each pollutant using the Standard Indian Breakpoint values for each parameter. (2)The sub-index with the maximum value is the AQI of that particular day.

According to India's National Ambient Air Quality Standards (2009), the tolerable values of pollutants such as PM2.5, PM10, NO2, SO2, and CO are as follows: 60 µg/m3 (24-h mean), 100 µg/m3 (24-h mean), 80 µg/m3 (24-h mean), 80 µg/m3 (24-h mean), and 02 µg/m3 (8-h mean).

1.2 Random Forest Regressor

It is an ensemble technique which performs regression task with the use of multiple decision trees and bagging technique. The hypothesis for the random forest is that when models with weak performance are correctly combined we can achieve a more robust or accurate model; here every base learner model has high variance and low bias (random selection of row dataset and features with replacement) but when combined all of them together the resultant is with low bias and low variance as all decision trees (base learner models) are perfectly trained on that particular dataset and hence the output doesn't depend on one decision tree but multiple decision trees.

1.3 Adaboost Regressor

Adaptive Boosting is an iterative ensemble method. Adaboost Regressor builds a strong Regressor by combining multiple poorly performing Regressor to achieve high accuracy strong Regressor. The concept of Adaboost is to assign weights to the datasets and training the data sample in each iteration which ensures the accurate predictions of wrong or unusual observations. Decision trees are used as base learners, the wrongly classified dataset are given higher weights then based on error, the performance of the base learner is calculated from which weights are updated where correct datasets are given lower weights, normalized and further higher weight datasets move to next base learner and so on until accuracy is achieved or estimators are specified.

1.4 Prophet

Facebook's Prophet is an open-source algorithm for generating time-series models. It is particularly good at modelling time series that have multiple seasonality. At its core is the sum of three functions of time plus an error term: growth g (t), seasonality s (t), holidays h (t), and error e_t. The growth function models the overall trend of data. The seasonality function approximates the cyclic pattern in data. The holiday function identifies dates that may cause major changes to the data. It offers a tool for time series analysis and forecasting for some contexts. The Prophet is built using a probabilistic coding language (STAN). Prophet provides the same advantages of the Bayesian statistics which includes seasonality. Prophet uses Python or R to develop the forecasting prototype by adding more features to the data after detecting all the growth, seasonality, events, and errors. The built-in API uses cutting-edge forecasting methods to obtain good-quality forecasting data.

II. METHODOLOGY

This study comprises of investigating if satellite data would be a reliable source to monitor surface air quality for locations where ground monitoring stations aren't available. To achieve this air quality parameter data for NO2 and SO2 were selected for satellite data as these were available in a higher resolution of 5.5 X 3.5 km2 for the duration of the year 2020-2021; for the same duration, ground data was procured from Maninagar station which was selected because of its data availability. Goggle Colaboratory was used to get the datasets from the netCDF file while ground data was procured from the CPCB website. For the prediction of AQI for ground data machine learning models; Random forest Regressor and Adaboost Regressor were used. Time series analysis model: Prophet was also used to predict AQI. Predictions of all models were further compared to select an accurate model.

2.1 Study Area:

The site selected as per the daily 24-hour average data availability is The Continuous Ambient Air Quality Monitoring Station installed at Maninagar, Kankariya Dhor Bajar, Ahmedabad (Latitude, longitude =23.002657,72.591912) in the state of Gujarat, India.

2.2 Dataset Description:

The data for ambient air quality parameters for NO2 and SO2 is taken into consideration for collection. The ground surface data of the CAAQMS at Maninagar (23.002657, 72.591912) is been acquired from the Central Pollution Control Board's website (www.cpcb.nic.in) from 01-01-2020 to 01-01-2021 was acquired.

The Satellite data was acquired from Earth Data's website (https://earthdata.nasa.gov) for the parameters of NO2 and SO2 from Sentinel 5P's TROPOMI Instrument of 5.5x3.5 km2 resolution. A total of 367 granule file links were obtained and processed in a python script using Goggle COLAB.

For the prediction of AQI, surface data was collected from the CPCB website for Maninagar station, Ahmedabad for the duration of 01-01-2017 to 01-01-2021 and the parameters selected to calculate AQI were NO2, SO2, PM10, PM2.5 & CO. The data for the same was also collected for the duration of 2020-2021 for comparison.

After calculating the AQI these datasets were further fed to Random Forest Regressor, Adaboost Regressor, and Prophet Model to predict AQI; for improving the accuracy of models more features were added using prophet parameters and later were compared with accuracies of previous models.

2.3 Data Pre-Processing:

In the pre-processing step, data gaps in ground data were replaced with null values. While in satellite data the column density values for all the locations in a swath were present so only Maninagar station's location datasets were circumscribed with 3x3 average pixel grid values and 5x5 average pixel grid values as representative of the area for all 367 granules.

2.4 Feature Selection:

Satellite datasets for NO2 and SO2 are only selected as they are available in higher resolution for the duration of one year (1st Jan 2020-1st Jan 2021) for the same duration ground data are collected for Maninagar Station. For Prediction five pollutant data are collected for the duration of one year and four years.

The AQI calculation considered here are five pollutant data measures: NO2, SO2, PM2.5, PM10, and CO. The average values in the last 24 hours are used and for CO the maximum values in the last 8 hours are used. Each measure is converted into a Sub-Index based and AQI is calculated from the maximum operator formula.

III. **DATA VISUALIZATION**

1. Ground Data collected for the duration of 01-01-2020 to 01-01-2021 for Maninagar Station.

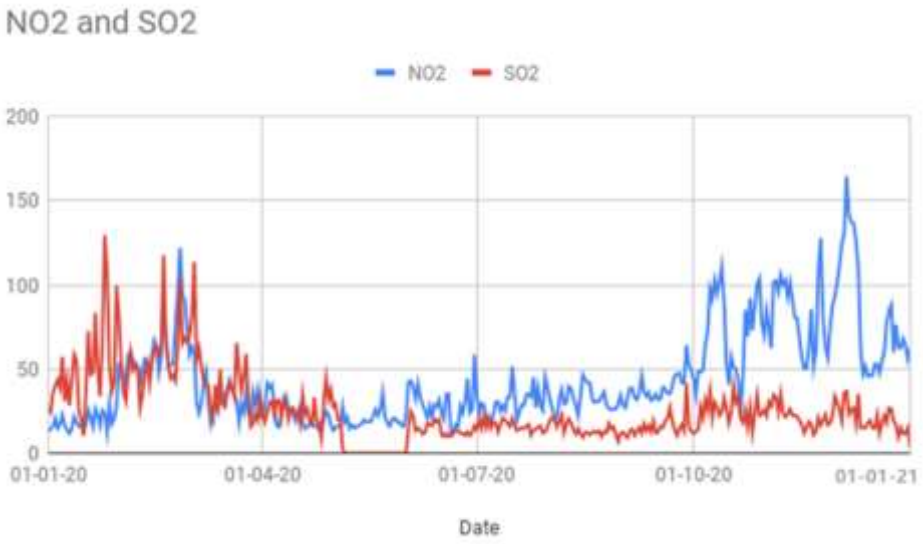

Figure 1 Ground NO2 & SO2 data (2020-21)

2. The graph below represents satellite data collected for NO2 for 3X3 pixel grid average values and 5X5 pixel grid average values at the location of Maninagar Station.

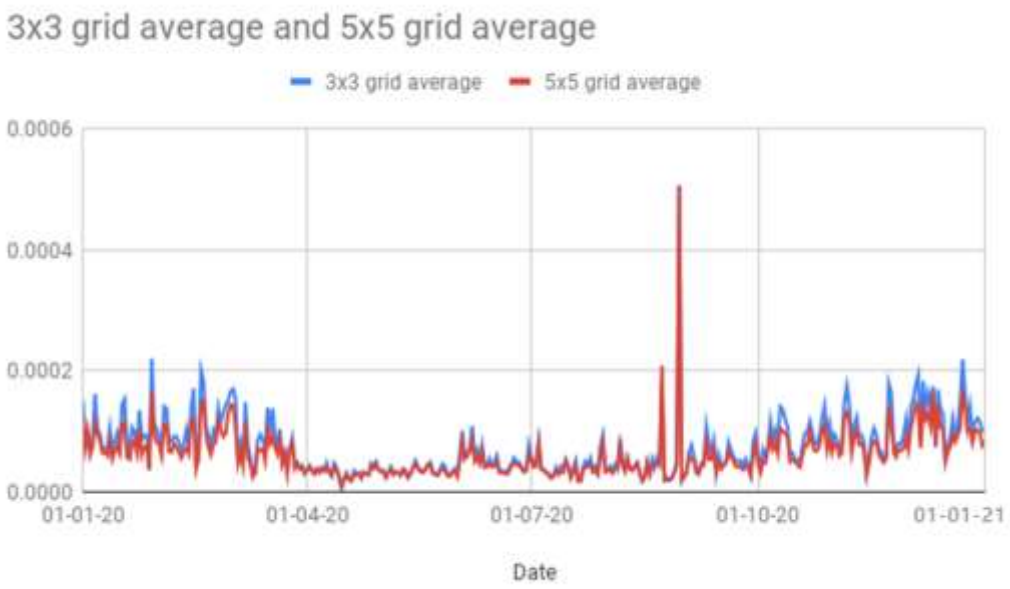

Figure 2 Satellite NO2 3x3 & 5x5 average grid values (2020-21)

3. The graph below represents satellite data collected for SO2 for 3X3 pixel grid average values and 5X5 pixel grid average values detected around the location of Maninagar Station.

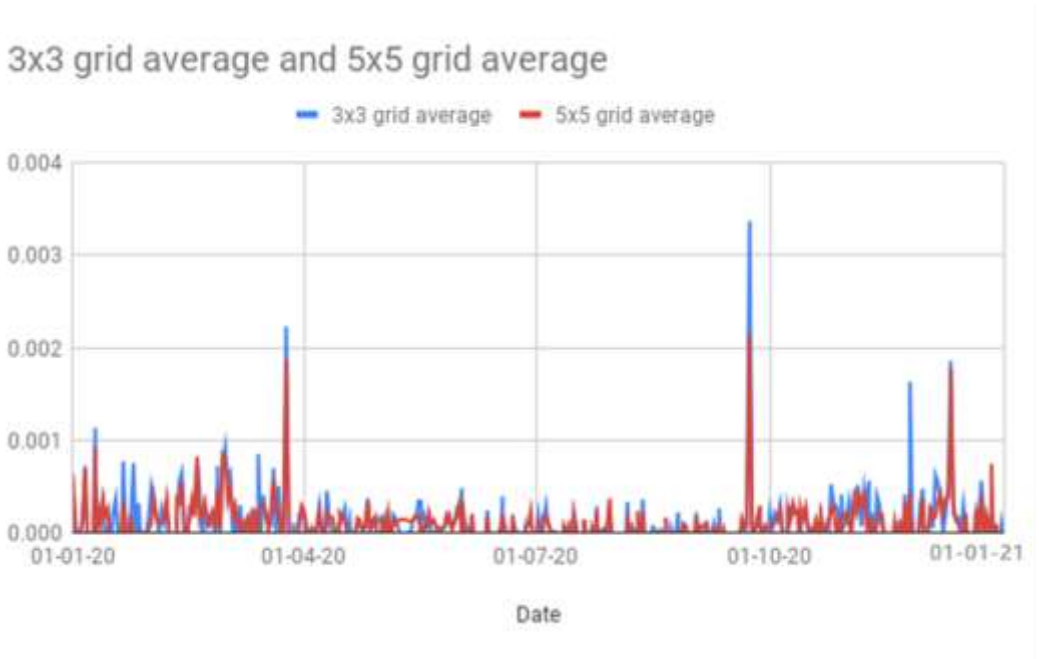

Figure 1 Satellite SO2 3x3 & 5x5 average grid values (2020-21)

4. The graphs below represents ground data collected for the duration of 2017-2021 and 2020-2021 for Maninagar Station of parameters including NO2, SO2, PM2.5, PM10 & CO which will further be used for prediction.

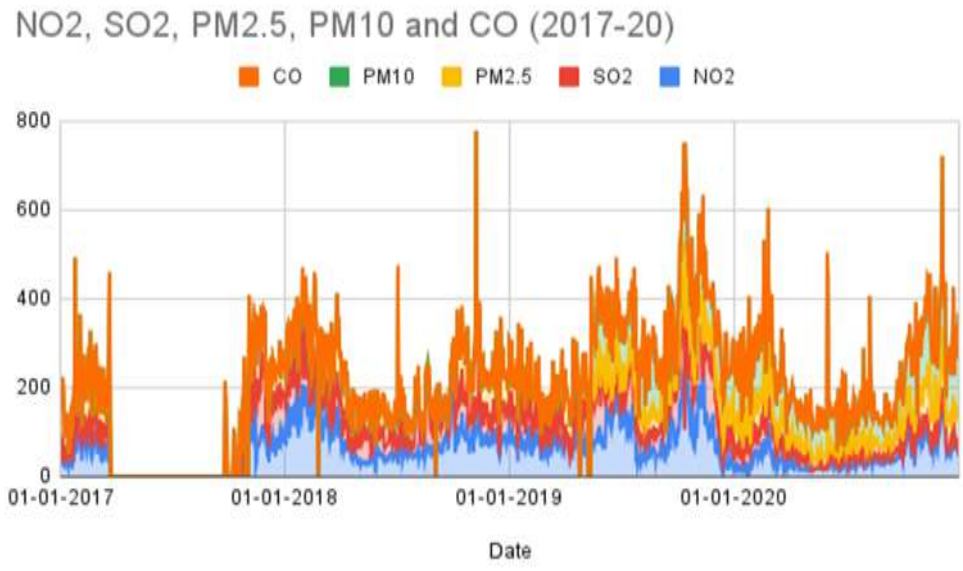

Figure 4 Ground Air quality parameters (2017-21)

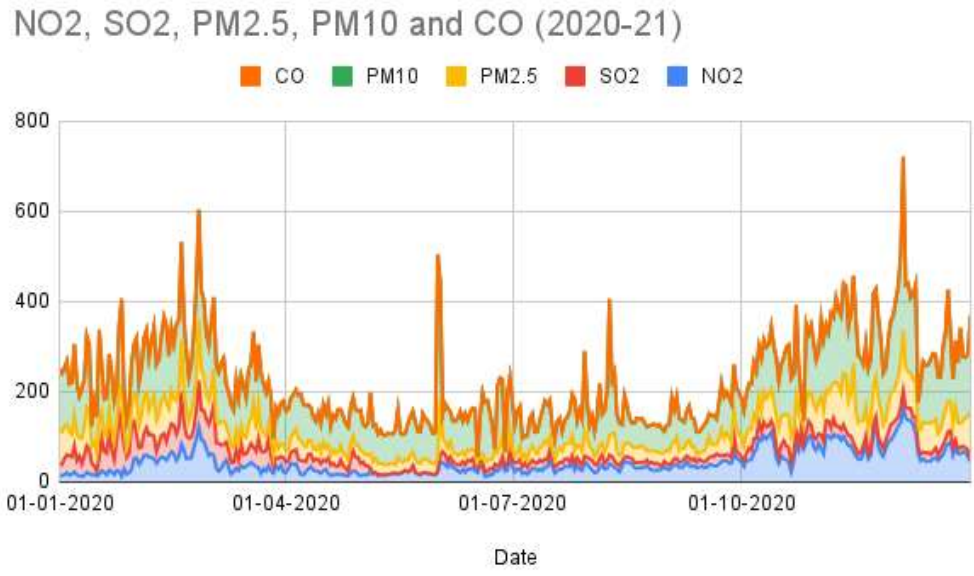

Figure 2 Ground Air quality parameters (2020-21)

IV. RESULTS AND DISCUSSION

1. The Ground data and Satellite data obtained for the air quality parameters NO2 and SO2 were correlated in order to validate if the satellite data were viable to monitor surface air quality. To get an idea of parameter concentrations in the area around the station a grid of 3x3 and 5x5 was selected in which all the column density data would be averaged for that particular day ad ground data were also of a daily average concentration.

Table 1 Correlation between Ground data and Satellite data.

Data	Coefficient of Correlation (r)	Rounded r value	Relationship
G-NO2 with S-NO2 (3x3 grid)	0.511511592	0.51	Moderate Positive
G-NO2 with S-NO2 (5x5 grid)	0.448996729	0.45	Moderate Positive
G-NO2 with S-SO2 (3x3 grid)	0.234446518	0.23	Weak Positive
G-NO2 with S-SO2 (5x5 grid)	0.187099237	0.19	Weak Positive

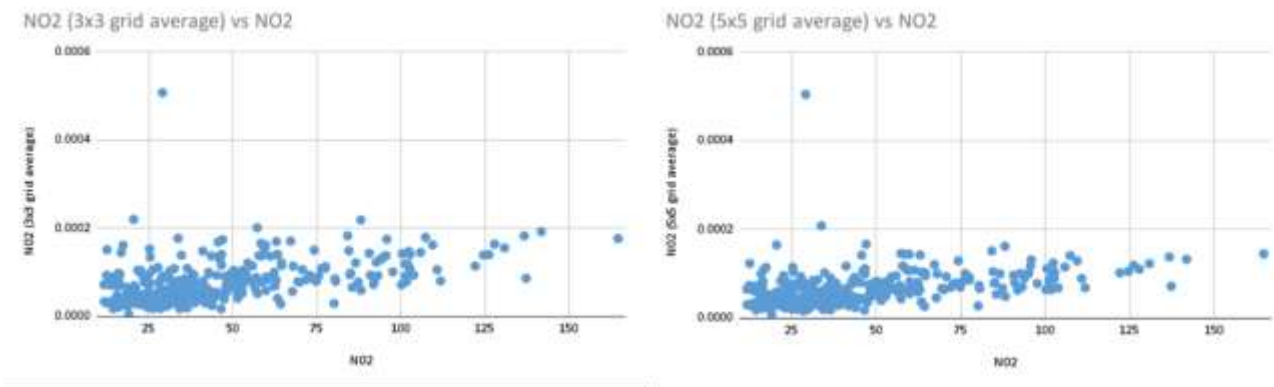

Figure 6 Scatter plot for correlation of G-NO2 with 3x3 grid and G-NO2 with 5x5 grid values.

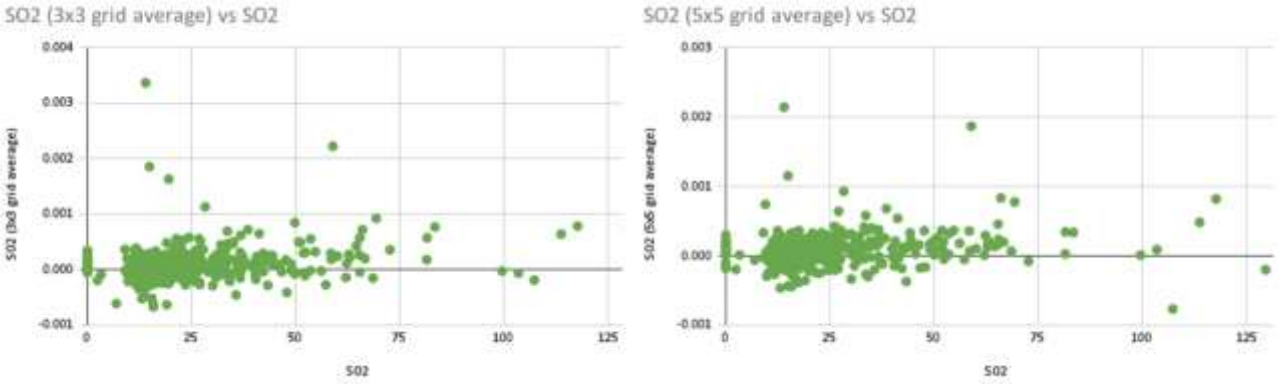

Figure 3 Scatter plot for correlation of G-SO2 with 3x3 grid and G-SO2 with 5X5 grid values.

The G-NO2 with S-NO2 3x3 grid average values and G-NO2 with S-NO2 5x5 grid average values showed moderate positive correlation while SO2 datasets showed weak positive correlation. A strong positive correlation would have indicated feasible usage of satellite data for air quality monitoring. Further ground air quality monitoring is demonstrated as Air Quality Index which is calculated using standard breakpoint values into Indices to achieve it; for satellite data there aren't any standard breakpoint values developed to generate an AQI from the parameters. So as of now Satellite data cannot be used in replacement of surface air quality monitoring also because the unit of average column density levels (Satellite data) was moles/m^2 while for the ground data it was µg/m^3 because the satellite data does not provide the concentration of a definite altitude.

4.1 Prediction of Air Quality Index

The parameters used to calculate AQI were NO2, SO2, PM10, PM2.5 and CO. The sub-indices calculation and the maximum operator function all were executed using python in Google Colaboratory.

1. The graphs below shows Air Quality Index calculated for 2017-2021 & 2020-2021 ground data.

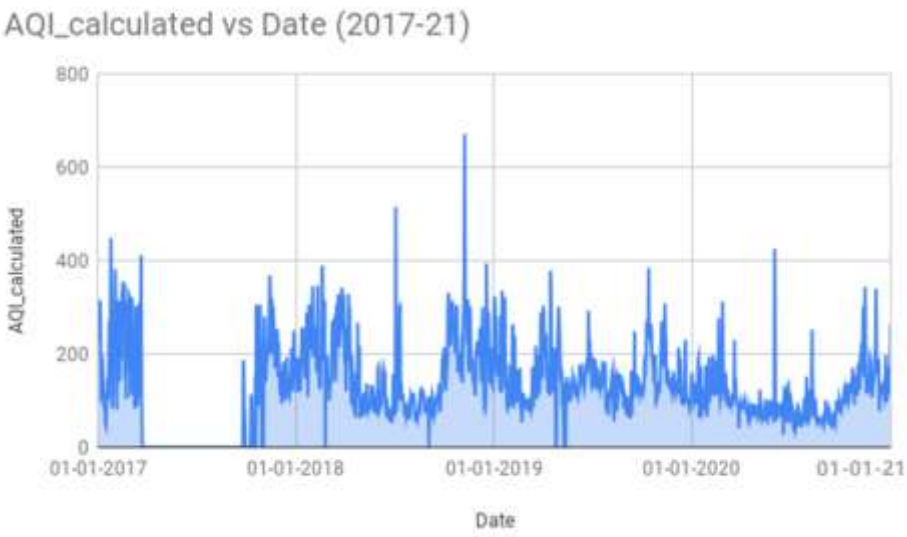

Figure 4 AQI calculated (2017-21)

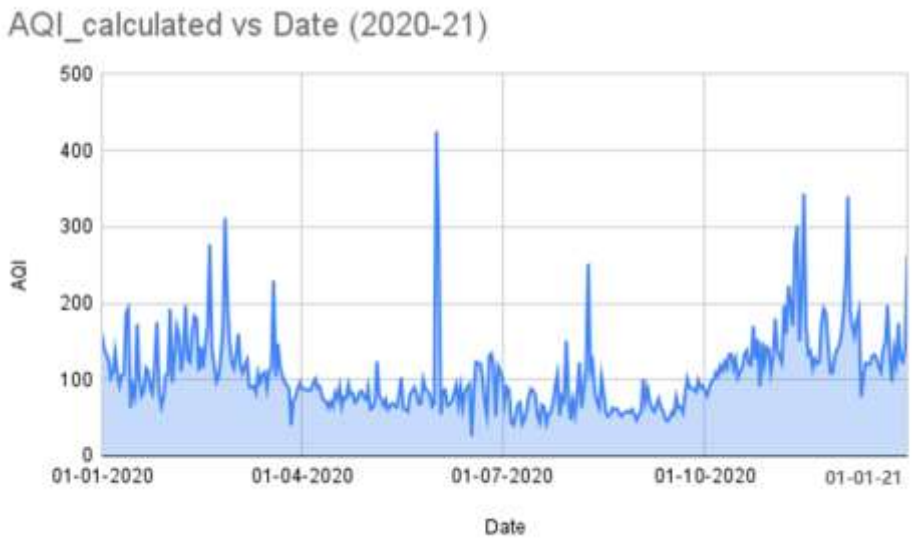

Figure 5 AQI calculated (2020-21)

4.2 AQI Prediction Models

4.2.1 Random Tree Regressor

Random Tree Regressor model was used first with one year data for 1st Jan 2020 to 1st Jan 2021 and later with data of duration 1st Jan 2017 to 1st Jan 2021.The R2 value of both models were less 0.15 and 0.35 respectively which shows weak fit for the model.

Prophet forecasting model creates more features using growth function (change points), seasonality function, event function and error. The feature values added are: trend, yhat lower, yhat upper, trend lower, trend upper, additive terms, additive terms, lower additive terms, upper daily, daily lower, daily upper, weekly lower, weekly upper, yearly lower, yearly upper. These features were added to the data to check for accuracy.

The addition of more features into the data made the model more accurate with R2 value for one year duration as 0.98 and for the duration of four years as 0.99 indicating strong fit for the model. Also lower MAE and RMSE values were seen compared to the model without prophet parameters.

Table 1 Performance and error metrics of RF model

	2017-2021		2020-2021	
	Without Prophet parameters	With Prophet parameters	Without Prophet parameters	With Prophet parameters
Score(R^2)	0.36	0.99	0.15	0.98
MAE	47.65	1.53	27.74	1.22
MSE	5361.77	3.91	1545.65	2.31
RMSE	73.22	1.97	39.31	1.52

1. For the duration of (2017-2021)

(a) RF without Prophet Parameters (b) RF with Prophet Parameters

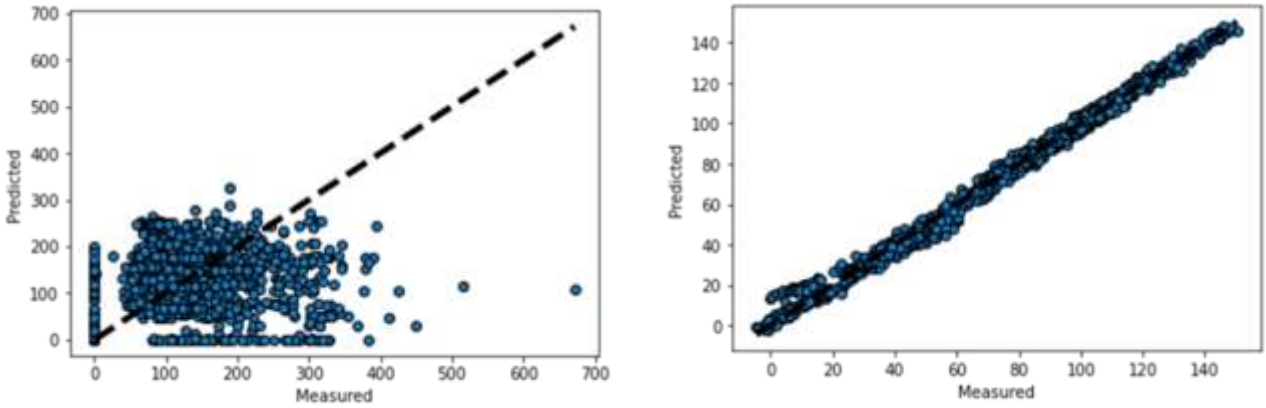

Figure 6 Graphs of prediction vs measured values of (a) RF without Prophet Parameters and (b) RF with prophet parameters (2017-21)

2. For the duration of (2020-2021)

(a) RF without Prophet Parameters (b) RF with Prophet Parameters

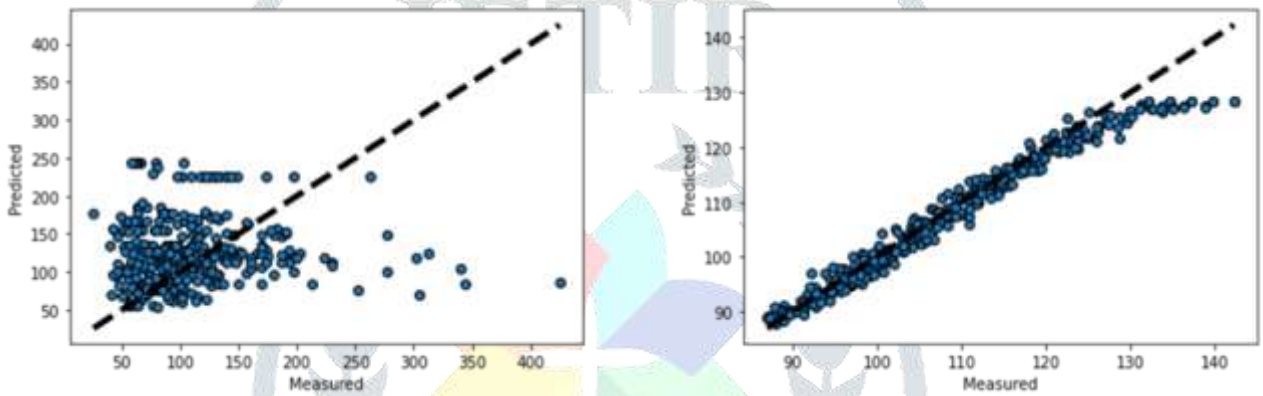

Figure 7 Graphs of prediction vs measured values of (a) RF without Prophet Parameters and (b) RF with prophet parameters (2017-21)

4.2.2 Adaboost Regressor

Adaboost Regressor model was fed with one year data for 1st Jan 2020 to 1st Jan 2021 and later with data of duration 1st Jan 2017 to 1st Jan 2021.The R2 value of both models were less 0.44 and 0.13 respectively which shows weak fit for the model.

When Prophet Parameters for the data of both one year and four years duration were applied into the models they showed better R2 values 0.99 for four years of data while 0.96 for one year of data; RMSE and MAE values were also drastically decreased compared to the models used without prophet parameters.

Table 2 Performance and error metrics of AR model

	2017-2021		2020-2021	
	Without Prophet parameters	With Prophet parameters	Without Prophet parameters	With Prophet parameters
Score(R^2)	0.13	0.99	0.44	0.96
MAE	70.35	1.83	39.94	1.910
MSE	7347.27	5.29	2610.21	5.57
RMSE	85.72	2.30	51.09	2.36

1. For the duration of (2017-2021)

(a)AR without Prophet Parameters (b) AR with Prophet Parameters

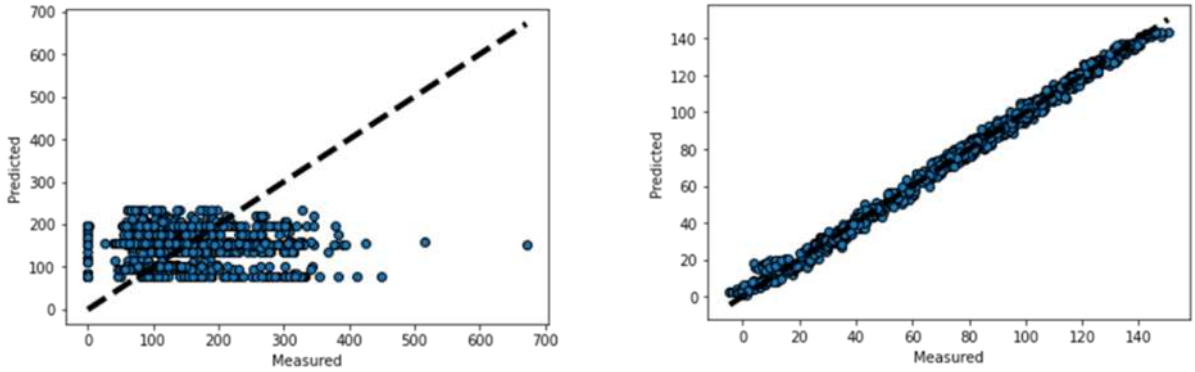

Figure 12 Graphs of prediction vs measured values of (a) AR without Prophet Parameters and (b) AR with prophet parameters (2017-21)

2. For the duration of (2020-2021)

(a) AR without Prophet Parameters (b) AR with Prophet Parameters

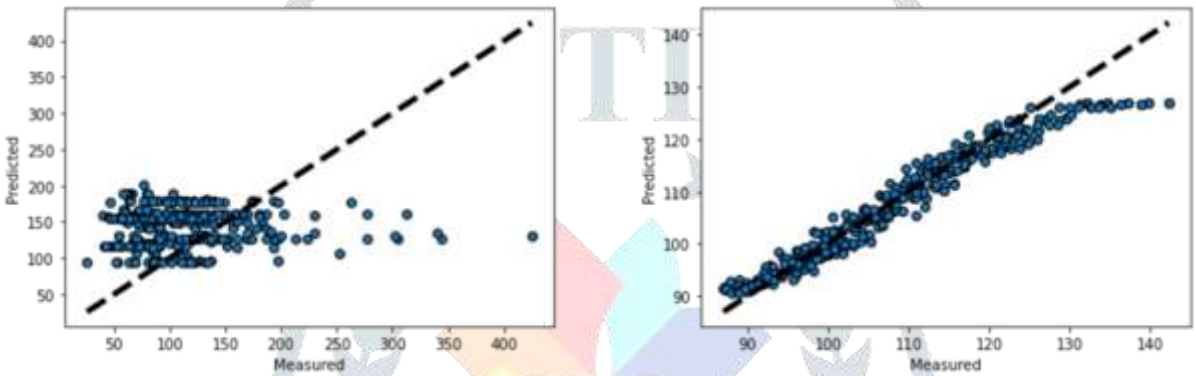

Figure 13 Graphs of prediction vs measured values of (a) AR without Prophet Parameters and (b) AR with prophet parameters (2020-21)

4.2.3 Prophet (Time series model)

The graph below is generated using date and AQI value for the duration of four years (2017-2020) using prophet library which detects trends, seasonality, events and adds features to the data. There can be visually seen a cyclic pattern over the years with lower values during the months of monsoon and higher values at the end and beginning months of the year.

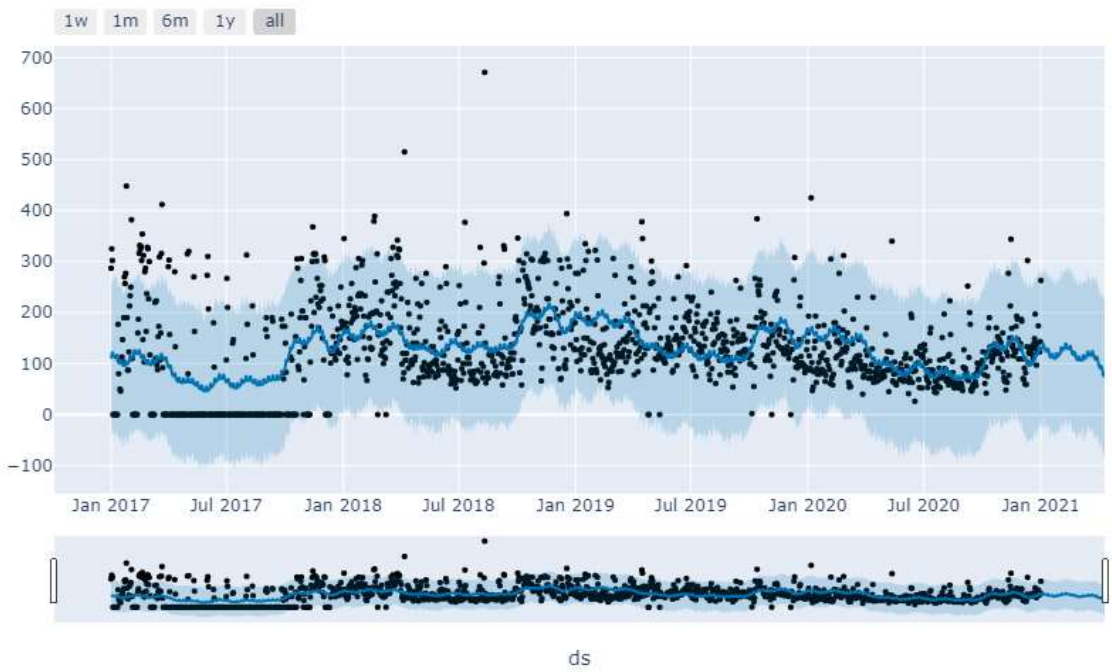

Figure 8 Timeline Graph of Ground data (2017-21)

Prophet Prediction: Using Prophet the prediction was made for a year ahead till 2022 using just the date and AQI values as data input in the prophet model; data for the duration of four years (2017-2021) and the duration of a year (2020-2021) were used to predict AQI and later compared to see the benefit of including long term data.

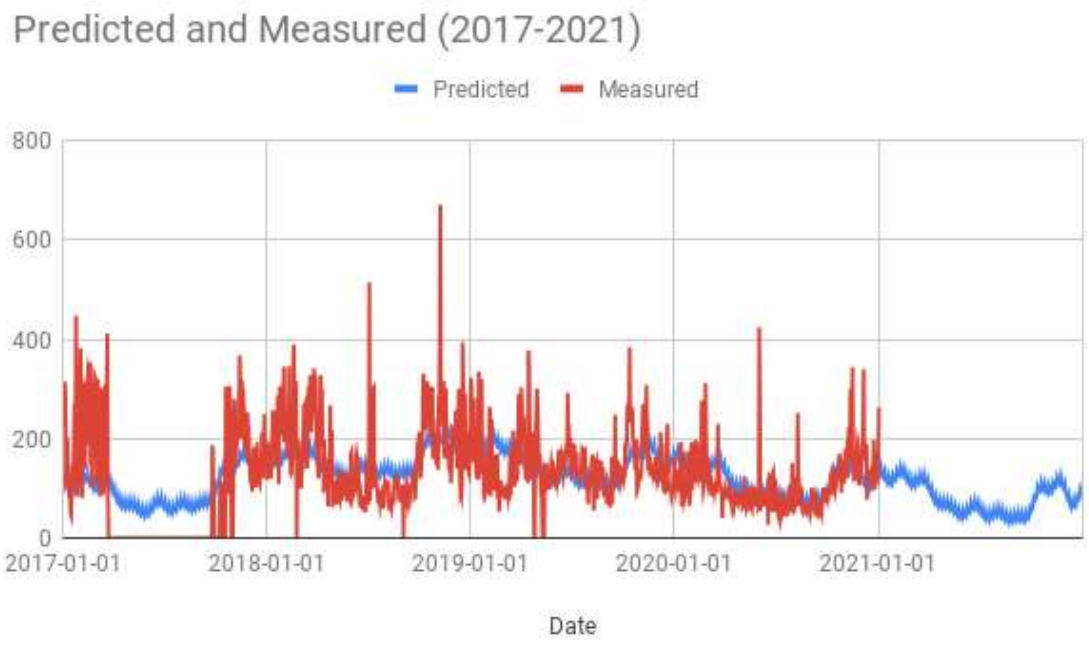

Figure 15 AQI Prediction graph till 2022 using (2017-21) 4 years of data.

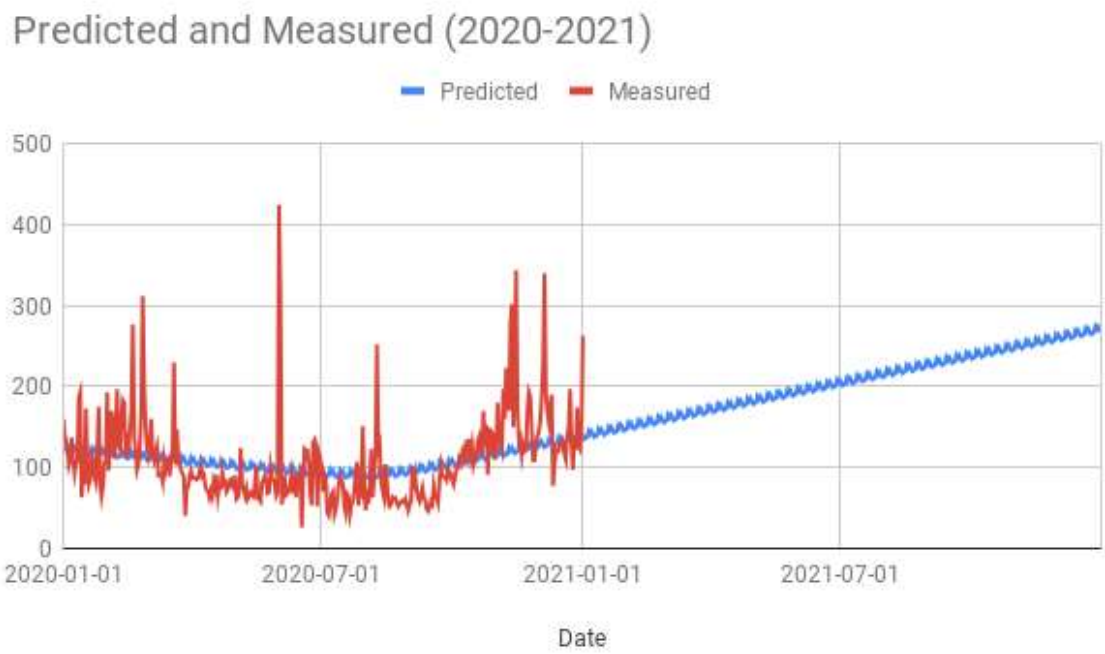

Figure 9 AQI Prediction graph till 2022 using (2020-21) a year of data.

Fig.15, 16 shows the model with four year data predicts accurate AQI compared to one year data. This is also because with more data available; events, seasonality & change points can be detected by the model more accurately.

Comparison of predicted values.

1. The duration of 1st Jan 2017-1st Jan 2021

Table 4 Comparison of Predicted AQI of models

Date	Random Forest Regressor	Adaboost Regressor	Prophet
	Without Prophet parameters	Without Prophet parameters	
01-01-2021	214.66	139.42	263
01-02-2021	214.66	139.42	123.84
01-03-2021	214.66	139.42	108.44
01-04-2021	214.66	139.42	99.36
01-05-2021	214.66	139.42	65.26
01-06-2021	214.66	139.42	52.43
01-07-2021	214.66	139.42	55.02
01-08-2021	214.66	139.42	47.19
01-09-2021	214.66	139.42	41.42
01-10-2021	214.66	139.42	54.34
01-11-2021	214.66	139.42	94.38
01-12-2021	214.66	139.42	98.10

2. The duration of 1st Jan 2020 to 1st Jan 2021

Table 5 Comparison of Predicted AQI values of Models

Date	Random Forest Regressor	Adaboost Regressor	Prophet
	Without Prophet parameters	Without Prophet parameters	
01-01-2021	226.87	184.55	138
01-02-2021	226.87	184.55	147.71
01-03-2021	226.87	184.55	157.86
01-04-2021	226.87	184.55	175.28
01-05-2021	226.87	184.55	178.31
01-06-2021	226.87	184.55	198.12
01-07-2021	226.87	184.55	208.29
01-08-2021	226.87	184.55	212.29
01-09-2021	226.87	184.55	227.76
01-10-2021	226.87	184.55	237.85
01-11-2021	226.87	184.55	246.74
01-12-2021	226.87	184.55	260.77

The models when used without prophet parameters having less accuracy can be seen having same predicted values for all the dates in the table which is because the model provides the average value of the cluster which can be seen in Fig. 10 (a), 11(a) for Random Forest Regressor Fig. 12 (a), 13 (a) for Adaboost Regressor without prophet parameters.

Selection of best model

The criteria for the selection of best model for prediction lies with the R2 value also known as coefficient of determination while it also shows the score of the model suggesting the percentage accuracy achieved by a model.

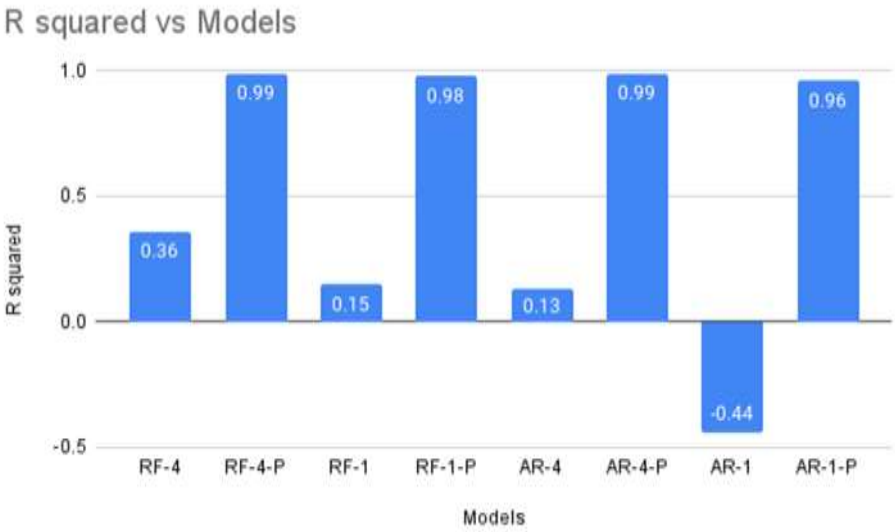

Figure 17 Comparison of accuracy achieved by all models

- In the graph above RF-4-P (Random Forest Regressor with 4 years of data using prophet parameters) and AR-4-P (Adaboost Regressor with 4 years of data using prophet parameters) shows the best accuracy achieved which is 99% further from these models which have the lowest RMSE (Root Mean Squared Error) would be preferred.
- RMSE penalizes large errors in the dataset while MAE is less biased for large errors in the dataset so RMSE values are preferred to choose the best model. Lower the RMSE value, lower the error in the said model.

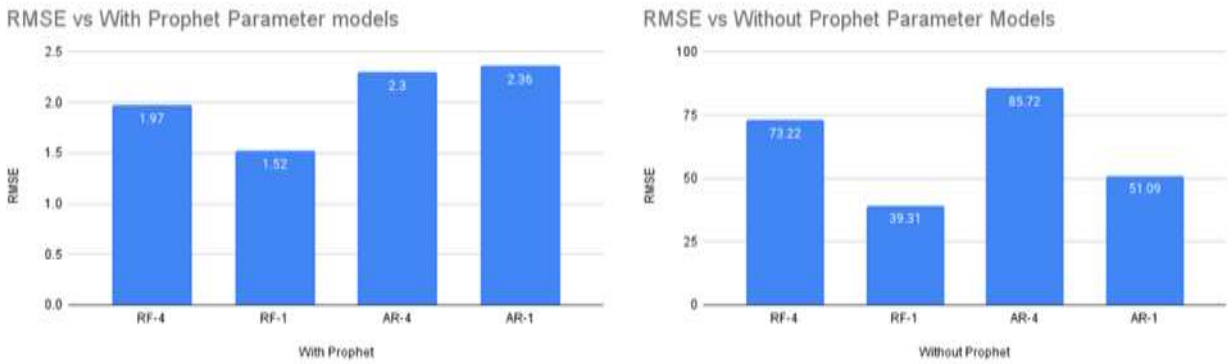

Figure 18 Comparison of RMSE values of all models with prophet parameters and without prophet parameters.

In the graphs above RMSE vs Models with and without prophet parameters are plotted. The lowest RMSE value amongst RF-4 with prophet parameter and AR-4 with prophet parameters is of the RF-4-P model with its value being 1.97. Hence RF-4-P model is suggested as the best model for prediction among the other models.

V. CONCLUSION AND FUTURE WORK

Continuous Air quality monitoring is required to make people aware about air pollution and it's health risks while there are limited number of monitoring stations in India; This study investigates if the remote sensing data can be used for surface air quality monitoring while remote sensing data for PM2.5 isn't available (which dominates in affecting surface air quality) researchers have used aerosol optical depth to relate to it. The limitation of Satellite data is also that it provides column density values whose units are moles/m2 meaning it doesn't provide concentration of a particular altitude for which AQI cannot be generated. When correlated to the ground data only NO2 parameter showed moderate positive relation (r=0.51) which is still not fit for further analysis. Hence, Sentinel 5 data in the future will provide the data of a said altitude.

Several statistical tools and semi-automated tools help researchers predict air quality by considering several pollutants and meteorological parameters. However, Machine learning models to forecast and to monitor air quality are required, especially in urban areas. In this study the models were performed on two durations of datasets from which we conclude that the more the data

provided more accurate prediction, for this prophet library was used to generate more features as well to include in datasets for the model to perform better with even 4 years of data. The Random Forest Regressor Model with prophet parameter showed the best accuracy of 99% with RMSE value 1.97 for 4 years of data, while Adaboost Regressor showed 99% accuracy but with RMSE value 2.3. When the models were run without the prophet parameters they showed the least accuracy with high error from which we can learn that more the features provided to the models, the better accuracy can be achieved. For further study instead of adding prophet features one should consider adding meteorological factors such as temperature, wind speed etc. with the air quality parameters by which better accuracy can be achieved.

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