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Spatial Modeling for Air Quality Index Using Remote Sensing Technique

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Abstract—*In progressing nations like India, urban sprawl and development normally begins and continues in a spontaneous and haphazard way. Decay of air quality in the majority of the expansive urban areas in major cities has significantly been a condition driven by industrialisation, uncontrolled development of populace, and expanded reliance on vehicles. There is a need for timely information about changes in the air pollution levels in cities for adopting precautionary measures. Keeping this in view, an attempt has been made to develop a model which will be useful to obtain air quality information directly from remotely sensed data easily and quickly. This paper depicts the possibility of remote sensing for ambient air quality monitoring and techniques for linking satellite inferred information with the ground truth information, by utilizing GIS as the supporting tool. For this study pixel values, vegetation index and urbanization index from Landsat 8 OLI & TIRS image were used to develop regression based model with Air Pollution Index (API), which were calculated from in-situ air pollutant information. It was found that among the 13 parameters of Landsat, highest correlation exists between pixel values in NIR (Near Infra-Red) band (Pearson correlation -0.692) and Normalized Difference Vegetation Index (NDVI) (Pearson correlation -0.685) and both have inverse relationship with API. Regression model was developed for API with R2 value 0.52. Vegetation indices, and NIR can be taken as indicators for the air quality information. However, the reliability of the model can be improved through inclusion of more sample points and integrating with traffic related parameters and population density.*

1. INTRODUCTION

Air contamination is a major issue in any prospering country, like India. The increase in air contamination level with urban land use denseness which tends to escalate towards the downtown area [14]. Consequently, to keep air standards in admissible limits there is dependably a requirement for timely information regarding changes in air contamination levels in urban communities. Making use of remote sensing expertise in air contamination studies started in 1970's with the appraisal of the state of air contamination as stated by the change in reflectance of ground entities on air photos [12]. Although, due to comparatively weak and fuzzy border, which is because of blending of this data with the message of ground, the extraction of air contamination data from remotely detected information is troublesome. A portion of the exploration studies carried out in this direction have uncovered the connection between Land Use/Land Cover (LU/LC) just as satellite reflectance and air contaminations [12, 1]. Among the distinctive components, it was likewise discovered that vegetation can be considered as a negative factor for air toxins and vegetation indices are assessed as criteria and pointers for urban air contamination contemplate [6, 5].

In addition, Geographic Information System (GIS) interpolation strategies are generally used to convert the point data to surface data to study spatial dissemination of air contaminants [2, 15]. Among various interpolation techniques, the techniques used for air contamination contemplates are IDINT, IDW and Kriging [2]. It likewise helps in managing tremendous database in a basic and speedy way. This paper is an attempt to relate air contamination guidelines with vegetation indices also with some other image extracted guidelines. The air pollution parameters considered is overall API (Air Pollution Index) or AQI (Air Quality Index) which can be characterized as a plan that changes the weighted estimations of individual air contamination related parameters ($PM_{2.5}$, PM_{10}, CO, NO_2 and O_3.) into single number or set of numbers [9]. The image specifications considered are one vegetation indices NDVI (Normalized Difference Vegetation index) and one urbanization index NDBI (Normalized Difference Urbanization/Built-up Index) along with all other eleven bands of Landsat OLI and TIRS satellite data.

2. MATERIALAND METHODS

2.1 Study Area

Mumbai is the capital city of the Indian state of Maharashtra. The Mumbai Metropolitan Region is the second most crowded metropolitan zone in India, with a populace of 21.3 million as in 2016. The whole territory of Mumbai is 603.4 km2 (233 sq. mi). Of this, the island city traverses 67.79 km2 (26 sq. mi), while the rural region traverses 370 km2 (143 sq. mi), together representing 437.71 km2 (169 sq. mi) under the organization of Municipal Corporation of Greater Mumbai (MCGM). Mumbai is bounded by the Arabian Sea to the west. Many parts of the city lie just above sea level, with the average elevation of 14 m (46 ft.). Mumbai has a tropical climate, explicitly a tropical wet and dry climate. The cooler season from December to February is trailed by the summer season from March to June. The period from June to about the end of September constitutes the south-west monsoon season, and October and November structure the post-monsoon season. The average total yearly precipitation is 2,146.6 mm (85 in) for the Island City, and 2,457 mm (97 in) for the suburbs. The average annual temperature is 27.2 °C (81 °F). The record high is 42.2 °C (108 °F) set on 14 April 1952, and the record low is 7.4 °C (45 °F) set on 27 January 1962.

Figure 1: Study Area

2.2 Field Data Collection

Choosing the formula to compute Air Pollution Index (API) corresponds to the type of major contaminants of the study region. For the research on this study area, the API was computed from the observed PM_{10}, $PM_{2.5}$, NO_2, CO andO_3 values making use of the following formula [10]:

$$API = \frac{1}{4} * (PM_{10} / S_{PM10} + PM_{2.5} / S_{PM2.5} + NO_2 / S_{NO2} + CO / S_{CO} + O_3 / S_{O3})$$

Where, PM_{10}, $PM_{2.5}$, NO_2, CO and O_3 stands for individual values of Particulate Matter of diameter less than 10µm and 2.5µm respectively, Nitrogen Dioxide, Carbon Monoxide and Ozone and S_{PM10}, $S_{PM2.5}$, S_{NO2}, S_{CO} and S_{O3} stands for standard values of atmospheric air quality of the respective pollutants [10].

The ambient air contaminants information of Mumbai required for the study was gathered from the website of System of Air Quality and Weather Forecasting and Research (SAFAR) developed by Ministry of Earth Science, Govt. of India and Indian Institute of Tropical Meteorology, Pune (http://safar.tropmet.res.in/map_data.php?city_id=3&for=current). There were 10 sample points of ground truth data collection. Inverse distance weighted (IDW) non-linear interpolation method was used to convert discrete data of these 10 sampling locations into continuous data over the entire study area. Values of different parameters were extracted using interpolated maps from 50 random locations, which were used for the development of the model. Data of similar sample points of different date were used for validation purpose.

2.3 Satellite Data

Landsat 8 OLI & TIRS satellite data acquired on 05th Feb 2019 and 12th Feb 2019 was obtained from United States Geological Survey (USGS) and used for the present study. Different bands along with the spatial resolution of the Landsat 8 OLI & TIRS satellite image is as mentioned in Table 1.

Table 1: Different bands of Landsat 8 OLI & TIRS satellite data

Bands	Wavelength (µm)	Resolution (m)
Band 1 (Coastal/Aerosol): B1	0.435 – 0.451	30
Band 2 (Blue): B2	0.452 – 0.512	30
Band 3 (Green): B3	0.533 – 0.590	30
Band 4 (Red): B4	0.636 – 0.673	30
Band 5 (NIR): B5	0.851 – 0.879	30
Band 6 (Shortwave IR-1): B6	1.566 – 1.651	30
Band 7 (Shortwave IR-2): B7	2.107 – 2.294	30
Band 8 (PAN): B8	0.503 – 0.676	15
Band 9 (Cirrus): B9	1.363 – 1.384	30
Band 10 (TIR – 1): B10	10.60 – 11.19	100
Band 11 (TIR – 2): B11	11.50 – 12.51	100

2.4 Data Analysis and Model Generation

2.4.1 DN (Digital Number) to Radiance Conversion

To expel the systematic errors and improvise the attributes, DN values of Landsat image were converted to radiance. The transformation of DN values to radiance depends on a calibration curve of DN [3, 8].

2.4.2 Image Processing (Spectral Enhancement)

Since the time satellite recording of spectral radiance of ground objects in visible and near-infrared bands became possible, many others have developed various indices based on the certain combinations (sum, difference, ratio, linearadditional) of bands [13]. These indices are used to identify and monitor the temporal variation of the object. Moreover, these combinations have the advantage of reducing the effect of external factors, such as solar irradiance, atmospheric influence etc.[4]. One vegetation based index, Normalized Difference Vegetation Index (NDVI), and one urbanization based index, Normalized Differential Built-up Index (NDBI) as shown in Table no. 2 were used for the present study.

Table 2: List of Spectral Indices used in the study

Indices	Formula	Reference
Normalized Differential Vegetation Index (NDVI)	(NIR – Red) / (NIR + Red)	[11]
Normalized Differential Built up Index (NDBI)	(NIR – SWIR) / (NIR + SWIR)	[16]

All the images produced after spectral enhancement were used for the development of models for monitoring and predicting air pollution parameters over the study area.

2.4.3 Model Generation

The statistical analysis was done using SPSS 20. Pearson correlation and multiple linear regression (MLR) were employed to discover the association within APIs (dependent variables) and pixel values of different bands and the indices developed through the satellite image (independent variables). Pearson correlation analysis between Landsat 8 OLI and TIRS band, and spectral indices with APIs was done to disclose the association between these variables and evaluate their effectiveness in predicting air quality of the study area. This statistical tool assisted in exclusion of insignificant independent variables; only those with the high correlation with dependent variables were selected.

Further, MLR models were used to measure the associations between the API and shortlisted bands and indices of the satellite data. The coefficients for selected variables were used to generate regression equation for simulation of overall API of the study area. After analyzing the regression coefficients (R^2), the standard error of the mean Y estimate (SE(Y)), and P - value at 95 percent confidence level, the developed regression model was used for developing unique class simulated map for air quality of the study area.

2.4.4 Model Validation

The developed regression model on the satellite data of 5th February 2019 was validated and quantified using the ground truth data and satellite image of 12th February 2019, to certify that not only it is applicable on a specific data set but also generated precise results on several data sets. In order to validate the models, two quantitative criteria R^2 and RMSE, were calculated between the measured and predicted values. R^2 values specify the strength of the statistical linear relationship between two values, and RMSE indicates absolute estimation errors [7].

3. RESULTS AND DISCUSSION

3.1 Correlation between APIs and Radiance values

Correlation study has been done between radiance values of all the eleven bands of Landsat 8 OLI & TIRS data, spectral indices (NDVI and NDBI) and APIof the 50 sample points (Table 4). There exists a negative correlation of API with reflectance in NIR, SWIR, TIR and vegetation index. The best correlation of API is with the radiance in NIR with a Pearson correlation coefficient of −0.692.

There is a strong correlation between overall API and API (PM_{10}), which shows that PM_{10} has major impact on overall air quality of the study area followed by NO_2 as shown in Table 3. After analyzing correlation matrix, most correlated bands and index were shortlisted and subjected to multiple linear regression (MLR) analysis.

3.1.1 Regression Models

The statistical results of the developed regression models are encapsulated in Table 5, describing how well spatial variation in air contaminants can be ascertained by applying the different developed regression models.

Table 3: Correlation between API and other pollution parameters

	PM10	PM2.5	NO2	CO	O3
API	0.965	0.555	0.668	0.29	-0.167

Table 4: Correlation matrix between APIs and Radiance values

Bands and Indices (Landsat 8 OLI & TIRS)	Air Pollution index (API)
B1	0.263
B2	0.228
B3	0.166
B4	0.104
B5	-0.692
B6	-0.240
B7	-0.111
B8	0.111
B9	0.057
B10	-0.127
B11	-0.167
NDVI	-0.685
NDBI	0.093

Table 5: Recommended Models for different air quality parameters

	REGRESSION MODEL	R^2
API	$\gamma = \beta_0 + (\beta1*NIR) + (\beta2*NDVI)$ Where: $\beta_0 = 189.818$, $\beta_1 = (-1.022)$, $\beta_2 = (-0.242)$	0.52

Model was developed for API using radiance values of NIR and NDVI with R^2 value of 0.52 showing an average correlation between variables and API. The proposed algorithms for API was used for the generation of simulated map for API (Figure 2).

3.1.2 Model Validation

The proposed algorithms for API were validated using the extracted atmospheric reflectance from Landsat OLI & TIRS satellite image acquired on 12th Feb 2019 along with corresponding ground truth data.Validation results showed that models developed using Landsat OLI & TIRS data are significant for API with R^2 value 0.6145 as shown in figure 3.

4. CONCLUSION

Through present study it can be concluded that vegetation indices (NDVI), and NIR can be taken as indicators for the air quality information. However, the reliability of the model can be improved through inclusion of more sample points and integrating with traffic related parameters and population density.

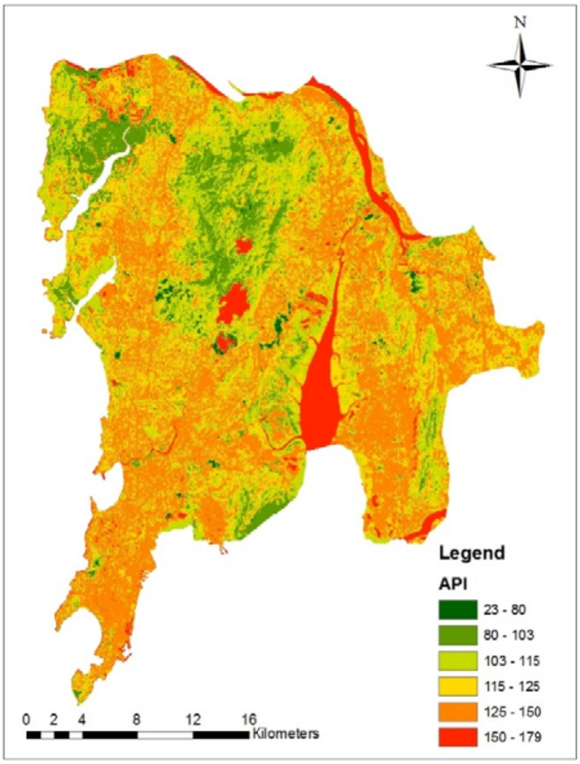

Figure 2: Simulated Map of API using model.

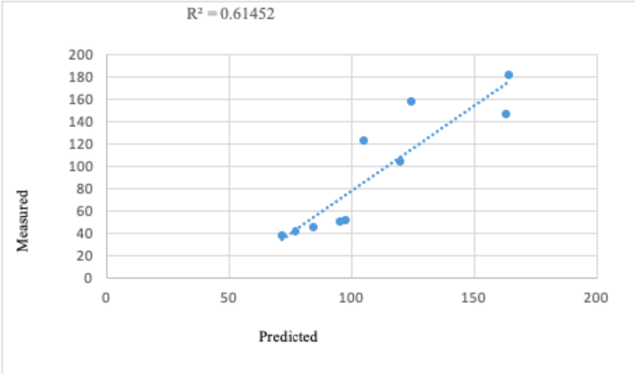

Figure 3: Scatter plot of predicted vs measured API

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