"Use of remote sensing technique in Air Quality Modeling of Delhi Region"

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Abstract:

In developing countries like India, urbanization and development usually start and proceeds in an unplanned way. This unplanned and uncontrolled urbanization leads to ecological imbalance, and ultimately, ecological collapse. Of all the hazards that our ecology is prone to in today's environmental scenario, air pollution has become a major concern. Deterioration of air quality in most of the large cities in India has majorly been a condition driven by industrialization, uncontrolled growth of population, and increased dependence on automobiles. Keeping this in view, an attempt has been made to develop a GIS model which will help conveniently obtain air quality information directly from remotely sensed data. The paper demonstrates the potentiality of remote sensing for air quality monitoring and methods of linking satellite derived data with the ground truth data, by using GIS as the aiding tool.

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1. Introduction

The core objective of this study is to analyze the performance of the projected model for mapping air quality parameters using Landsat 8 OLI and TIRS satellite data. In-situ measurements were needed for model generation and calibration. For this study, the ground truth data of all the major criteria pollutants, which was needed for in-situ measurements for the generating the model, were collected from eighteen CAAQM (continuous ambient air quality monitoring) station of CPCB (Central Pollution Control Board) throughout Delhi (industrial, commercial and residential area). These stations are measuring the amount of air pollutants daily on a continuous basis. Satellite data and ground-truth data were collected in accordance to each other. Further, models were developed to determine the concentration of different pollutants over the study area. The efficiency of different models were determined based on different statistical measures like MSE, RMSE. Finally, air quality maps were generated using the proposed models.

2. Study Area

Delhi, which is the capital of India, is the area of study for this research. Delhi is in Northern India between the latitudes of 28°24’17” and 28°53’00” North and longitudes of 76°50’24” and 77°20’37” East. The city has an area about 1483 sq. km. Delhi faces extremes of climatic conditions. In summer season (April - July), the climate is very hot, while it is cold in the winter season (December - January). The average temperature can vary from 25°C to 45°C during the summer and 22°C to 5°C during the winter. The city witnesses an average rainfall of 714 mm (http://delhi.gov.in/DoIT/DES/Publication/abstract/SA2012.pdf).

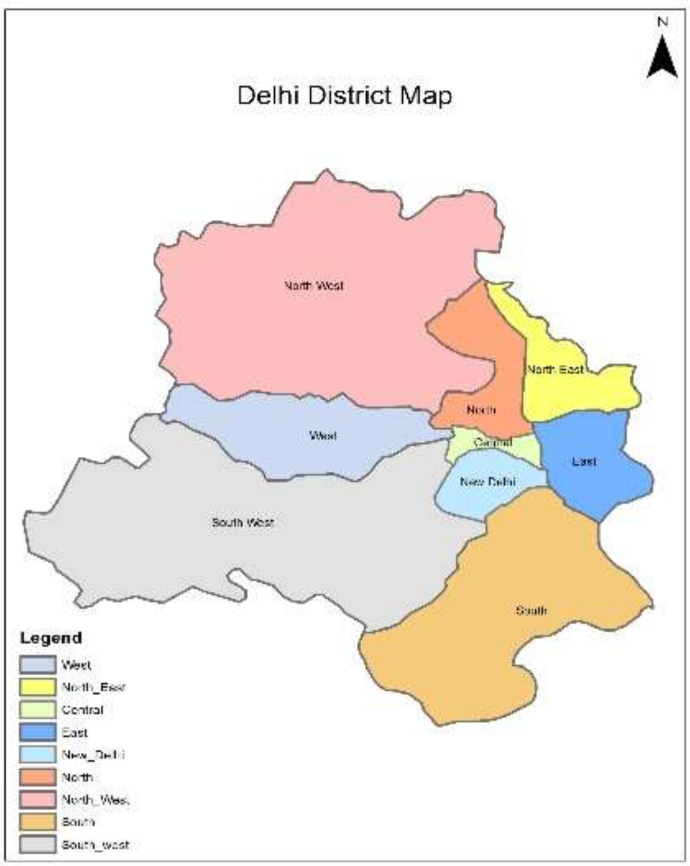


Fig: 1 – Administrative boundaries of state of Delhi

3. Methodology

3.1. Data acquisition

The ground truth air quality monitoring data for various CAAQM monitoring stations was collected for April month of year 2013, 2015, and 2017. Remote sensing data for the same duration of time was extracted from USGS Earth Explorer website.

3.2. Calculating atmospheric reflectance

Remote sensing satellite detectors exhibit linear response to incoming radiance, whether from Earth's surface radiance or internal calibration sources. This response is quantized into 16-bit values that represent brightness values commonly called Digital Number (DN). Digital numbers can be converted to at-aperture radiance as well as to at sensor reflectance using simple formulas. In case of Landsat 8 OLI & TIRS the reflectance is calculated as mentioned below:

$\rho\lambda = (M_P * Q_{CAL} + A_P) / \cos(\theta_{SZ})$

Where,

$\rho\lambda$ = TOA planetary reflectance

M_ρ = Band-specific multiplicative rescaling factor from the metadata

A_ρ = Band-specific additive rescaling factor from the metadata

Q_{cal} = Quantized and calibrated standard product pixel values (DN)

θ_{SZ} = Local solar zenith angle

Landsat 8 OLI and TIRS satellite data set was selected corresponding to the ground truth measurements of the pollution levels. Arc GIS 10.1 software were used for all the analysis. The images were acquired on 17th April 2015 and 22nd April 2017. All the images were geometrically rectified. Sample locations were then identified on these geo coded images.

The signals measured in each of these visible bands represent a combination of surface and atmospheric effects, usually in different proportions depending on the condition of the atmosphere. Therefore, it is required to determine the surface contribution from the total reflectance received at the sensor. In this study, we extracted surface reflectance from all the bands, using a simple form of equation. This equation is also used by other researcher in their study (Popp, 2004).

Rs – Rr = Ratm

Where,

Rs = Reflectance recorded by Satellite Sensor

Rr = Reflectance from surface references

Ratm = Reflectance from atmospheric components

It should be noted that the reflectance values at the top of atmosphere was the sum of the surface reflectance and atmospheric reflectance. In this study we used Arc GIS for creating TOA reflectance image. Surface reflectance images for all the bands were ordered from USGS. Then the TOA reflectance measured was subtracted from the surface reflectance image to obtain the atmospheric reflectance.

3.3. Image pre-processing

The image pre processing techniques include all those methods which are required to execute before we can extract the correct features and information from the downloaded raster image. These necessary pre processing techniques include –

A. Image subsetting

Image subsetting is done to extract the exact area of study out of the whole acquired remote sensing image. Our study area was Delhi city, which was a small portion of the acquired satellite image, so it was necessary to crop out the area of our interest for further manipulation. This helps in proper data management and processing as this displays only the information that is required for further processing. The satellite image was subsetted with the Delhi state boundary using Arc GIS. Both the satellite image and the site boundary were exported as layers in arcmap. Using the "Extract by mask" tool of Arc Map, the Delhi region was cropped out of the satellite image.

B. GPS LOCATION IDENTIFICATION AND LINKING

After the images have been subsetted, they can be manipulated for further processing. The next step after subsetting the images is to link the GPS locations of various air quality monitoring stations onto the images for defining the location of monitoring sites on the site map. The GPS locations for various monitoring stations were extracted from google earth, and then, these were linked to the subsets of satellite images using Arc Map.

Table 1: List of CAAQM stations with their GPS locations and figures of all criteria pollutants of study for the year 2015

STATION NAME	X	Y	NO2	PM_{10}	$PM_{2.5}$	CO
Anand Vihar	**77.302524**	**28.691159**	58.33	267.00	100.00	70.20
CRRI, Mathura Road	**77.130056**	**28.667028**	15.85	146.11	91.96	40.50
IHBAS, Dilshad Garden	**77.297791**	**28.652737**	61.00	280.00	98.00	100.40
ITO, New Delhi	**77.147306**	**28.651472**	40.00	272.00	99.00	68.00
NSIT, Dwarka	**77.249528**	**28.631639**	75.00	320.00	66.00	114.00
Punjabi Bagh, Delhi	**77.200556**	**28.637278**	56.00	107.00	70.20	42.00
RK Puram, New Delhi	**77.032500**	**28.609028**	74.00	113.00	89.00	79.00
Shadipur, New Delhi	**77.167000**	**28.564583**	78.00	150.00	110.00	37.00
Mandir Marg, New Delhi	**77.273552**	**28.551144**	111.00	106.00	67.00	20.00

3.4. Extracting dn values for gps locations

After the GPS locations for all the CAAQM monitoring sites of interest had been linked to the subsetted images, DN values or pixel values for the linked GPS locations is extracted. This is done using "extract multi values to points" tools in the spatial analyst toolbox of Arc Map. These pixel values denote atmospheric reflectance at various air quality monitoring sites. The DN values thus obtained for each of the eight bands of the satellite image is then correlated with the monitoring data of each criteria pollutant.

3.5. Correlation, multiple linear regression analysis, and regression modeling

Finally, the atmospheric reflectance was correlated with air quality parameters. Further, multiple linear regression models were used to quantify the relationships between the various air quality parameters and most correlated bands of Landsat 8 OLI and TIRS band values. Linear regression model was carried out on different air quality parameters and top few spectral variables separately and then both were combined together by gradually increasing the number of variables in order of ranking till the R square was stabilized. The coefficients for selected variables were used to make a regression equation for prediction of air quality parameters. The multiple correlation coefficients (R^2), the standard error of the mean Y estimate (SE (Y)), F-ratio values, and probability (P) at 95 percent confidence level were used to establish the statistical significance of the regression models. Air quality maps for all the dependent variables (air quality parameters) were generated using the regression algorithms filtered by using a 3 X 3 pixel smoothing filter to remove the random noise. Further, the proposed algorithms were validated using the extracted atmospheric reflectance from Landsat OLI & TIRS satellite image acquired on 22nd April 2017 along with corresponding ground truth data. The generated maps were color coded for visual interpretation. Generally, the concentrations above industrial and urban area were higher compared to other area.

3.6. Validation of regression model

The model thus obtained needs to be validated to determine its accuracy and precision before its application in predicting air quality trends. This is done using "root mean square error" approach. Emissions of all the criteria pollutants from various monitoring stations are extracted from the maps produced using the regression model. This is done using "extract multi values to points" tools in the spatial analyst toolbox of Arc Map. The values thus extracted are the predicted air quality trends for 22nd April 2017.

On MS Excel, both predicted and observed values were then fed and root mean square error was determined in order to understand how much does the predicted values derived differ from the actual air quality monitoring data.

4. Results and Discussion

The statistical results of the developed regression models are summarized in Table 9, showing how well spatial variation in air pollutants can be predicted by applying the different developed regression models. All the developed regression models for particulate matters were highly significant. First model which combines band 2, 3 and 4 provided the best fit for predicting PM_{10}. It had the high R^2 value i.e. 0.676, signifying a good linear relationship between estimated and predicted PM_{10} and indicated that 67% of the variance in the PM_{10} values could be explained by this model. Each of these variables had significant *p*-values, indicating a strong correlation with PM_{10}. On the other hand, second model, which combines band 1, 2 and 5 provided the best fit for predicting $PM_{2.5}$ with R^2 value of 0.916. Similarly third model which combines band 3, 4 and 7 with R^2 value of 0.76 was used for predicting CO. The proposed algorithms were validated using the extracted atmospheric reflectance from Landsat OLI & TIRS satellite image acquired on 22nd April 2017 along with corresponding ground truth data. Validation results showed that models developed using Landsat OLI & TIRS data are significant for particulate matter, whereas the mentioned satellite data cannot be used for predicting gaseous pollutants accurately.

Table 2. Recommended Models for different air quality parameters

POLLUTANT	BANDS MOST CORRELATED	WAVELENGTH (MICROMETERS)	REGRESSION MODEL
PM_{10}	Band 2 (B2)	0.452 - 0.512	$= \beta_0 + (\beta 1 * B2) + (\beta 2 * B3) + (\beta 3 * B4)$ Where: β_0 = 653.8134, β_1 = (-1.459), β_2 = 4.3 and β_3 = (-3.68)
	Band 3 (B3)	0.533 - 0.590	
	Band 4 (B4)	0.636 - 0.673	
$PM_{2.5}$	Band 1 (B1)	0.435 - 0.451	$= \beta 0 + (\beta 1 * B1) + (\beta 2 * B2) + (\beta 3 * B5)$ Where: β_0 = 48.939, β_1 = 0.0355, β_2 = (-0.0798) and β_3 = 1.182
	Band 2 (B2)	0.452 - 0.512	
	Band 5 (B5)	0.533 - 0.590	
Carbon Monoxide	Band 3 (B3)	0.533 - 0.590	$= \beta 0 + (\beta 1 * B3) + (\beta 2 * B4) + (\beta 3 * B7)$ Where: β_0 = 83.659, β_1 = (-0.427), β_2 = 0.22 and β_3 = (-0.461)
	Band 4 (B4)	0.636 - 0.673	
	Band 7 (B7)	2.107 - 2.294	

Further air quality maps for all the dependent variables (air quality parameters) were generated using the regression algorithms filtered by using a 3 X 3 pixel smoothing filter to remove the random noise. The generated maps were color coded for visual interpretation. Generally, the concentrations above industrial and urban area were higher compared to other area.

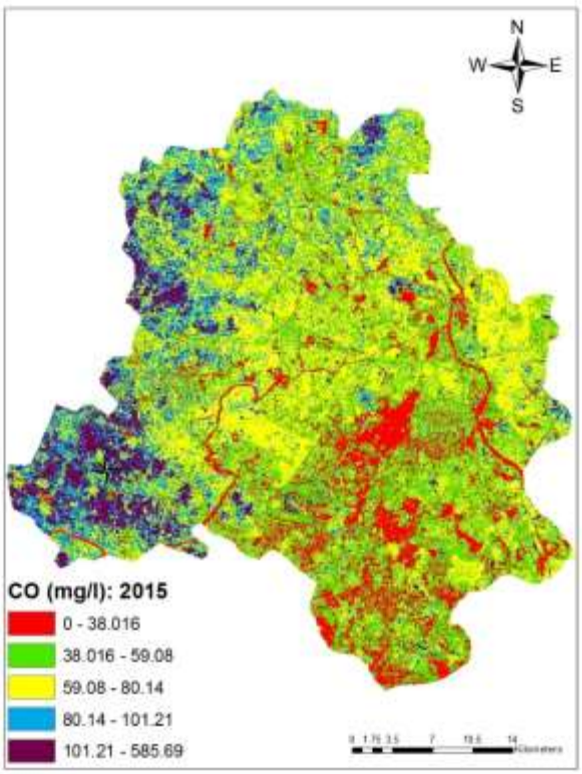


Fig 2. Map showing concentration of Carbon Monoxide over the study area (Delhi) in 2015

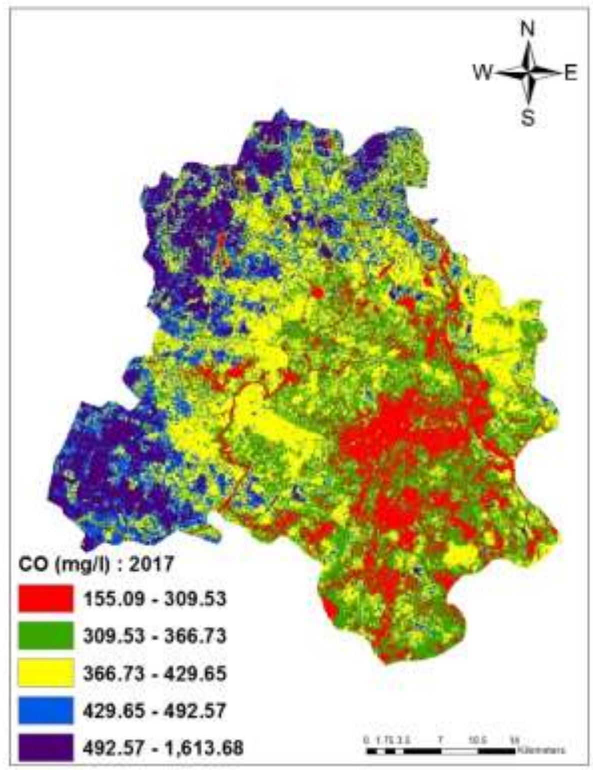


Fig 3. Map showing concentration of Carbon Monoxide over the study area (Delhi) in 2017

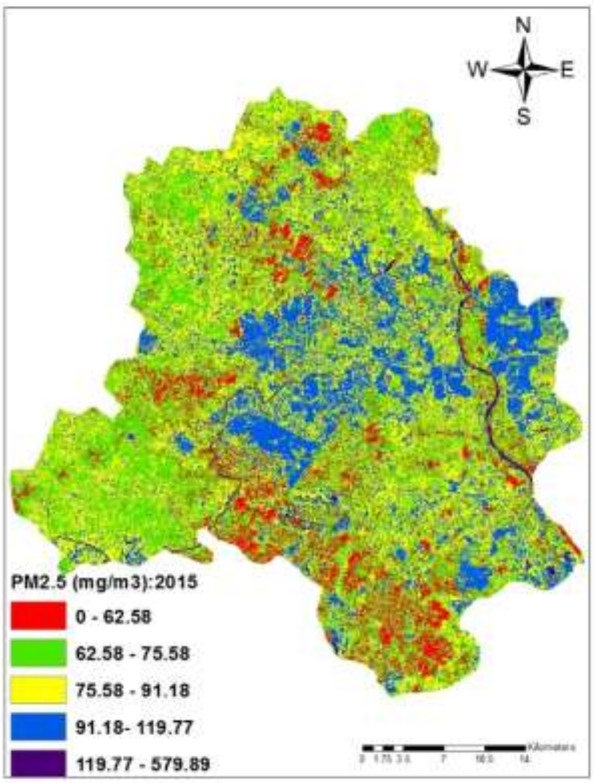


Fig 4. Map showing concentration of $PM_{2.5}$ over the study area (Delhi) in 2015

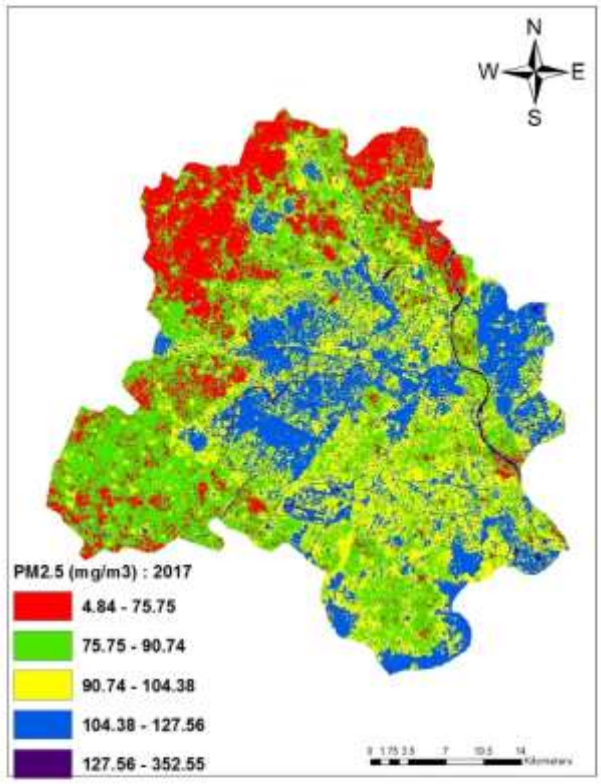
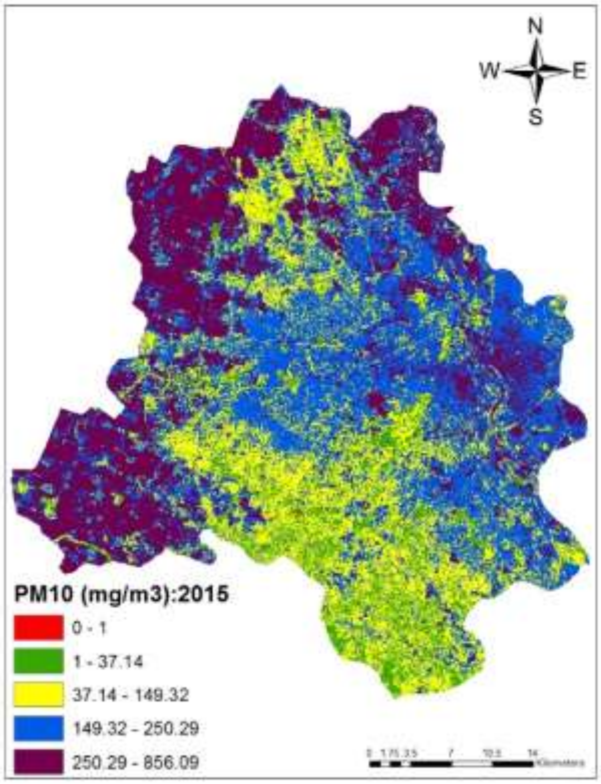


Fig 5. Map showing concentration of $PM_{2.5}$ over the study area (Delhi) in 2017



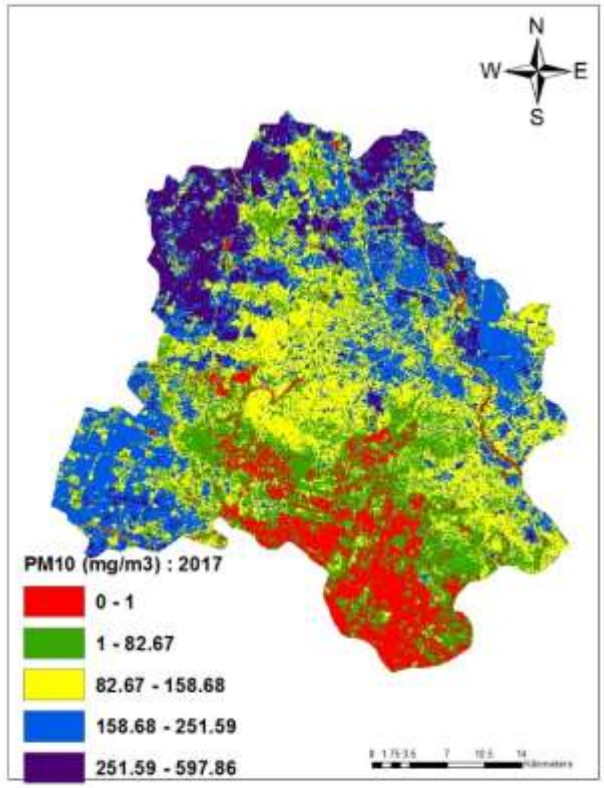


Fig 6. Map showing concentration of PM_{10} over the study area (Delhi) in 2015

Fig 7. Map showing concentration of PM_{10} over the study area (Delhi) in 2017

5. Conclusion

The study indicated that remote sensing and GIS technology can provide useful information for air pollution. Another crucial conclusion made in the study is that Landsat 8 OLI & TIRS data can be used for estimating, modelling, mapping and predicting pollution level of particulate matter (PM_{10} and $PM_{2.5}$). On the other hand, the mentioned satellite data is appropriate for the quantitative estimation of gaseous pollutants. As per the results of study, most parts of Delhi are experiencing high levels of PM_{10} concentrations, ranging between 149-857 mg/m^3. Current research is a crucial study as it will allow us to draw information on air from a wide variety of sources, each potentially measured at different resolutions, with different error structures and with different levels of uncertainty. It will lead to more precise measurement of air quality together with measures of uncertainty.

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