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RESEARCH ARTICLE

Air Pollution Modeling from Remotely Sensed Data Using Regression Techniques

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Abstract 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. For this study pixel values, vegetation indices and urbanization index from IRS P6 LISS IV and Landsat ETM+ images were used to develop regression based models with Air Pollution Index (API), which were calculated from in-situ air pollutant information. It was found that among the 12 parameters of IRS, highest correlation exists between pixel values in NIR (Near Infra-Red) band (Pearson correlation −0.77) and Normalized Difference Vegetation Index (NDVI) (Pearson correlation −0.68) and both have inverse relationship with API. In case of Landsat, the highest correlation was observed in SWIR (Short Wave Infra-Red) band (Pearson correlation −0.83) and NIR (Pearson correlation −0.78). Both single and multivariate regression models were calibrated from best correlated variables from IRS and Landsat. Among all the models, multivariate regression model from Landsat with four most correlated variables gave the most accurate air pollution image. On comparison between the API modeled and API interpolated images, 90.5 % accuracy was obtained.

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Introduction

In a developing country like India, air pollution is a serious problem. The pollution level rise with urban land use density which tends to increase towards the city center (Weng and Yang 2006). Hence, to keep air quality in acceptable limits there is always a need for timely information about changes in air pollution levels in cities. The use of remote sensing techniques in air pollution studies started in 1970's with the estimation of the state of air pollution according to the change in reflectance of ground objects on air photos (Ruru and Shouping 2005). However, because of relatively weak and fuzzy border, which is due to mixing of this information with the message of ground, the extraction of air pollution information from remotely sensed data is very difficult. Some of the research studies carried out in this direction have revealed the relationship between Land Use/Land Cover (LU/LC) as well as satellite reflectance and air pollutants (Ruru and Shouping 2005; Ahmad et al. 2006). Among the

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different factors, it was also found that vegetation can be considered as a negative factor for air pollutants and vegetation indices are evaluated as criteria and indicators for urban air pollution study (Manawadu and Samarakoon 2005; Hogda et al. 1995). Also, Geographic Information System (GIS) interpolation techniques are widely used to convert the point data to surface data to study spatial distribution of air pollutants (Bell 2006; Wong et al. 2004). Out of the various interpolation techniques, the methods used for air pollution studies are IDINT and Kriging (Bell 2006). It also helps in dealing with vast database in a simple and quick manner.

This paper is an attempt to relate air pollution parameter with vegetation indices as well some other image extracted parameters. The air pollution parameter considered is API (Air Pollution Index) or AQI (Air Quality Index) which can be defined as a scheme that transforms the weighted values of individual air pollution related parameters (e.g., SO_2 concentration or SPM) into single number or set of numbers (Rao and Rao 2001). The image parameters considered are NDVI (Normalized Difference Vegetation Index), VI (Vegetation Index), TVI (Transformed Vegetation Index) and UI (Urbanization Index).

Method and Materials

ERDAS Imagine 9.1 has been used for rectification, layer stacking, NDVI image preparation, image classification and API model building while Arc Map 9.3 has been used for buffering, zonal mean calculation and interpolation. The data used, mathematical expressions and other techniques required for the model development has been explained in the following sections. The correlation and regression analysis has been done in IBM SPSS version 20.

Data Used

IRS P6 (LISS IV)

The data used for the present study is a mosaic image of the remotely sensed data of IRS P6 (Resourcesat 1) LISS (Linear Imaging Self-scanning Sensor) IV obtained on February and March, 2007. The spatial resolution of the imagery is 5.8 m with three spectral bands, green and red in visible and NIR (Near Infra Red) region.

Landsat ETM+

The earth observing instrument onboard this spacecraft is the Enhanced Thematic Mapper Plus (ETM +). The system is designed to collect 15 m resolution panchromatic data and six bands of data in the visible, NIR, and MIR (Middle Infra Red) spectral regions at a resolution of 30 m and 60 m resolution data at Thermal Infra Red (TIR) band. The data which is used in the present study was acquired in March, 2007.

Image Pre-processing

DN (Digital Number) to Radiance Conversion

To remove the systematic errors and improve the quality, DN values of IRS and Landsat image were converted to radiance. The conversion of DN values to radiance is based on a calibration curve of DN (Chander and Markham 2003; Negi et al. 2009). Complete details of the conversion from DN to radiance can be seen in the above mentioned references.

Landsat Image Gap Filling

Landsat image gap filling was done to correct the Scan Line Corrector (SLC) error on images acquired after May 2003. A gap filling utility in ENVI developed by Scaramuzza et al. (2004) was used to fill the gaps on one Landsat scene using another Landsat scene. For this procedure, the Landsat image acquired on 4th March 2007 was used as a base image while the image acquired on 20th March 2007 as the gap filler. Although few gaps could not be filled with this method, the buffer zones used in this study did not fall on those gaps.

Land Use/Land Cover (LU/LC)

The knowledge of LU/LC is important to justify the relationships between the API and image characteristics used in this study. The LU/LC map of the study area has been prepared from the IRS P6 (LISS IV) data using supervised Maximum Likelihood Classification (MLC) technique in ERDAS software. The training pixels are chosen based on fieldworks, maps and personal experience. Six LU/LC classes which have impact on air pollution were extracted from the IRS (LISS IV) image. Those are barren land, open scrub, salt affected land, settlement (built up areas), vegetation and water bodies.

Vegetation Indices

Three different vegetation indices were used for the present study, namely NDVI, TVI and VI. NDVI is calculated per pixel value obtained in red and NIR band of different LU/LC classes (Boken et al. 2008):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

Where, NIR and R stand for the pixel values in NIR and red wavelengths respectively.

To avoid the negative values of NDVI and hence to stabilize the variance, Deering et al. (1975) proposed the TVI by adding 0.5 and taking square root of the result (Lautenschlager and Perry 1981).

$$TVI = \sqrt{(NDVI + 0.5)} \tag{2}$$

A simple vegetation index can be obtained by taking difference of pixel values in R from NIR, as follows (Lautenschlager and Perry 1981):

$$VI = NIR - R \tag{3}$$

Air Pollution Index (API)

The choice of the formula to calculate API depends on the type of major pollutants of the study area. For the present study area, the API/AQI is calculated from the observed TSPM (Total Suspended Particulate Matter), RSPM (Respirable Suspended Particulate Matter), NO_x and SO_2 values using the following formula (Rao et al. 2004):

$$API = \frac{1}{4} * \left(\frac{TSPM}{S_{TSPM}} + \frac{RSPM}{S_{RSPM}} + \frac{SO_2}{S_{SO2}} + \frac{NO_x}{S_{NOx}} \right) * 100 \tag{4}$$

Where, TSPM, RSPM, SO_2, NO_x stands for individual values of TSPM, RSPM, Sulphur Dioxide and Oxides of Nitrogen and S_{SPM}, S_{RSPM}, S_{SO2} and S_{NOx} stands for standards value of ambient air quality of the

Table 1 Comparison between correlations between of API of combined and single pollutants with image parameters from IRS for 100 and 250 m buffers

Var	API		API (NO_x)		API (RSPM)		API (SO_2)		API (TSPM)	
	Pearson Corr	Sig. (2-tailed)	Pearson Corr	Sig. (2-tailed)	Pearson Corr	Sig. (2-tailed)	Pearson Corr	Sig. (2-tailed)	Pearson Corr	Sig. (2-tailed)
Green 100	0.042	0.891	−0.004	0.99	0.007	0.982	−0.185	0.545	0.079	0.798
Red 100	−0.141	0.647	−0.116	0.707	−0.163	0.595	−0.239	0.431	−0.083	0.787
NIR 100	−.760[a]	0.003	−0.528	0.064	−.595[b]	0.032	−0.478	0.099	−.730[a]	0.005
NDVI 100	−0.441	0.131	−0.318	0.29	−0.29	0.336	−0.144	0.638	−0.467	0.108
VI 100	−0.357	0.231	−0.231	0.448	−0.229	0.452	−0.079	0.797	−0.393	0.184
TVI 100	−0.449	0.124	−0.326	0.277	−0.295	0.328	−0.148	0.63	−0.474	0.102
Green 250	0.225	0.46	0.142	0.643	0.065	0.833	0.075	0.808	0.311	0.301
Red 250	−0.029	0.924	−0.03	0.923	−0.164	0.593	0.024	0.938	0.086	0.78
NIR 250	−.773[a]	0.002	−.632[b]	0.021	−0.533	0.061	−0.476	0.1	−.764[a]	0.002
NDVI 250	−.679[b]	0.011	−.570[b]	0.042	−0.373	0.209	−0.437	0.136	−.740[a]	0.004
VI 250	−.646[b]	0.017	−0.524	0.066	−0.351	0.24	−0.426	0.147	−.715[a]	0.006
TVI 250	−.673[b]	0.012	−.571[b]	0.041	−0.364	0.221	−0.431	0.141	−.735[a]	0.004

[a] Correlation is significant at the 0.01 level (2-tailed)

[b] Correlation is significant at the 0.05 level (2-tailed)

respective pollutants. The API is also calculated individually for all the sample points. The algorithm to calculate the API of the single pollutants is (Rao and Rao 2001):

$$API_{Pollutant} = \left(\frac{Pollutant}{S_{Pollutant}}\right) * 100 \tag{5}$$

where, *Pollutant* and $S_{Pollutant}$ stands for individual values and standard value of ambient air quality of single pollutant. The air pollutant information required for the study has been collected from the website of Andhra Pradesh Pollution Control Board (APPCB) (http://appcb.ap.nic.in). There are 17 sample points out of which 13 are taken for calibration of the model and rest are used for validation purpose. This criterion for splitting the data was taken from the study of Mourad et al. (2005) where he concluded that 15 % of the available data should be taken for validation purpose in multiple regression analysis for data size less than 20.

Urbanization Index (UI)

In this study, UI was estimated using LANDSAT ETM + data to quantitatively evaluate urbanization. It assumes high and positive values for all other LU/LC surfaces, while strongly negative values for vegetated pixels. The algebraic expression for the Index is (Villa 2007):

$$UI = \frac{SWIR - NIR}{SWIR + NIR} \tag{6}$$

where, *SWIR* and *NIR* stand for pixel values given in *SWIR* and *NIR* wavelengths respectively.

Interpolation Techniques

Interpolation is the procedure of predicting the value of attributes at non-sampled sites from measurements made at point locations within the same area or location. Several techniques of interpolation are available in literature. The techniques that are best suited for air pollution studies are Kriging, Inverse Distance Interpolation (IDINT) and Natural Neighbor Interpolation (NNINT) (Bell 2006; Wong et al. 2004). The IDINT with different variances is used in the present study for spatial prediction of API.

Regression Analysis

In the present study, the dependent variable is the API and the independent variables are the images extracted parameters from IRS and Landsat images. Once a regression model has been constructed, it is important to confirm the goodness of fit of the model and the statistical significance of the estimated parameters. Root Mean Squared Error (RMSE) is a good measure of accuracy. It is calculated by the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum (APIcalculated - APImeasured)^2} \tag{7}$$

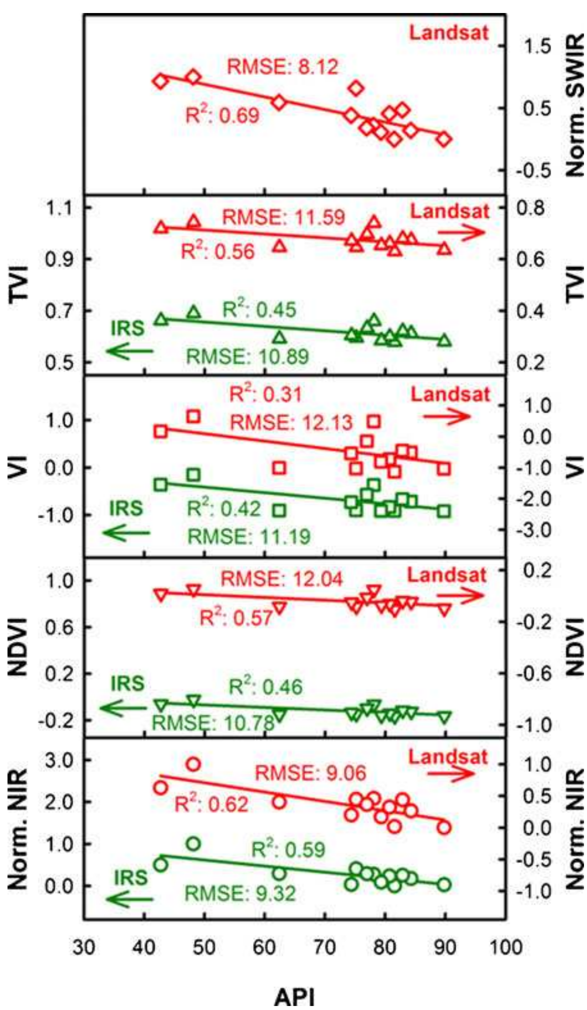

Fig. 1 Linear regression trend between normalized NIR, NDVI, VI and TVI (IRS and Landsat) and API in 250 m buffer

Table 2 Comparison between R^2 and RMSE values of the single variable and multiple variables IRS and Landsat regression models

Model		R^2	RMSE
IRS	NIR	0.59	9.32
	NDVI	0.46	10.78
	VI	0.42	11.19
	TVI	0.45	10.89
	NIR-VI-TVI	0.62	8.12
Landsat	SWIR	0.69	8.12
	NIR	0.62	9.06
	NDVI	0.57	12.04
	VI	0.31	12.13
	TVI	0.56	11.59
	SWIR-NIR-VI-TVI	0.79	7.77

Where, n, $API_{calculated}$ and $API_{measured}$ stands for number of variables, calculated and measured API respectively.

Study Area

Hyderabad is a metropolitan city in the state Andhra Pradesh in India. It lies between the latitude of 17°18′N and 17°30′N and longitude of 78° 22′E and 78°35′E about 536 m above mean sea level. It is the fifth largest city in India with an area of 275 km^2. There are several agents that cause pollution in the city which includes industry, vehicles, disposal of bio-degradable waste, burning of non-degradable waste such as plastics and PVC pipes, modern agricultural inputs, building activity etc. APPCB is assessing the ambient air quality in the state which has the monitoring network with 60 ambient air quality-monitoring stations. In addition to these, continuous ambient air quality monitoring station has also been installed in Hyderabad.

Database Preparation

API interpolated map, vegetation indices images, UI image and LU/LC map for the study area have been prepared. Zonal means of IRS and Landsat image parameters (radiance, NDVI etc.) are calculated in 250 m, 100 m, 50 m and 25 m buffers at those locations where field air pollution data is available.

Results and Discussions

IRS API Model

Correlation analysis has been carried out between reflectance in green, red, NIR, NDVI, TVI and VI from all the buffer zones with API of the 13 sample collection locations (Table 1). There exists a negative correlation of API with reflectance in NIR, NDVI, VI and TVI. Moreover, the data from 250 m buffer were having more correlation than the smaller buffer zones. The best correlation is with reflectance in NIR in 250 m buffer with a Pearson correlation coefficient of −0.77. However, TVI being a transformed form of NDVI shows almost same correlation as NDVI.

Correlation between NDVI and reflectance values are analyzed with APIs calculated from single pollutant individually. From the results, it is observed that, there is comparatively a better correlation in case of image parameters and API of TSPM than all other pollutants (Table 1). The less correlation between RSPM and API is believed due to the particle size of RSPM which ranges from 0.3 to 10 μm. RSPM is

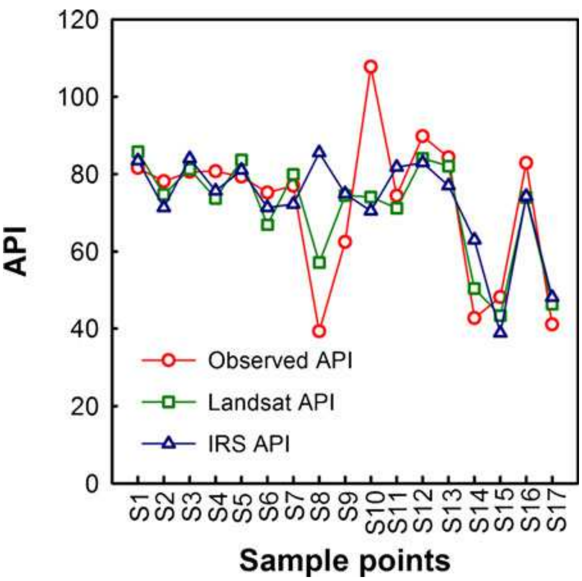

Fig. 2 Comparison between observed and modeled API at sample location points

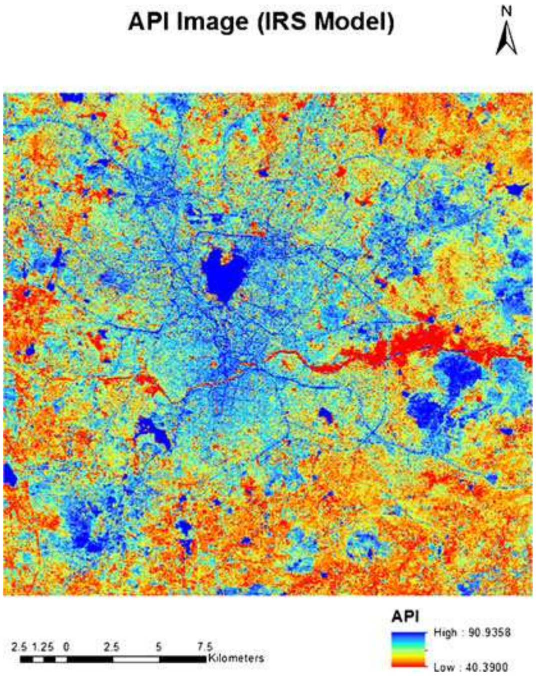

Fig. 3 API image from IRS model

mostly found in road side areas and being very small in size are less affected by vegetation.

Single and multivariate regression models were developed between API of all pollutants and image parameters and compared to find the most optimum model to produce the API image. Figure 1 shows the plots for 250 m buffer. The highest coefficient of determination (R^2) value for single variable regression model is 0.59 for NIR (Table 2). The RMSE for all the cases is found to be approximately 9 to 11. To observe the combined effect of multiple variables and to improve the quality of the model results, several other API models were developed using 2, 3 and all 4 variables together. The best model was found using 3 variables together viz. NIR, VI and TVI with R^2 of 0.62 and RMSE of 8.12; the modelled results are shown in Fig. 2 at all sample points and discussed later in detail.

Landsat API Model

Similar analysis was done with Landsat data extracted parameters. In this case, there were 3 extra bands for analysis viz. blue, SWIR 1 and 2. UI was also used for the correlation analysis. The best correlation is with reflectance in SWIR in 250 m buffer with a Pearson correlation coefficient of −0.833.

Similar to IRS model, single and multivariate regression models were developed between APIs of all pollutants and image parameters and compared to find the most optimum model to produce the API image (Fig. 1). A comparison of R^2 values of single and multiple variables are shown in Table 2. The coefficient of determination (R^2) value for single variable regression models of SWIR is 0.69. The best model in case of Landsat was found using 4 variables together viz. SWIR, NIR, VI and TVI with R^2 of 0.79 and RMSE of 7.77. In both models, when combined, TVI showed better results than NDVI.

UI is an indicator of urban morphology of an area. The UI was also analyzed with API since it is derived from pixel values of SWIR and NIR. It shows a positive linear trend between UI and API with a Pearson correlation of only 0.37 for 250 m buffer. Air pollution is not only the function of urban morphology but also a function of traffic density and several other man made factors which were out of scope of this study.

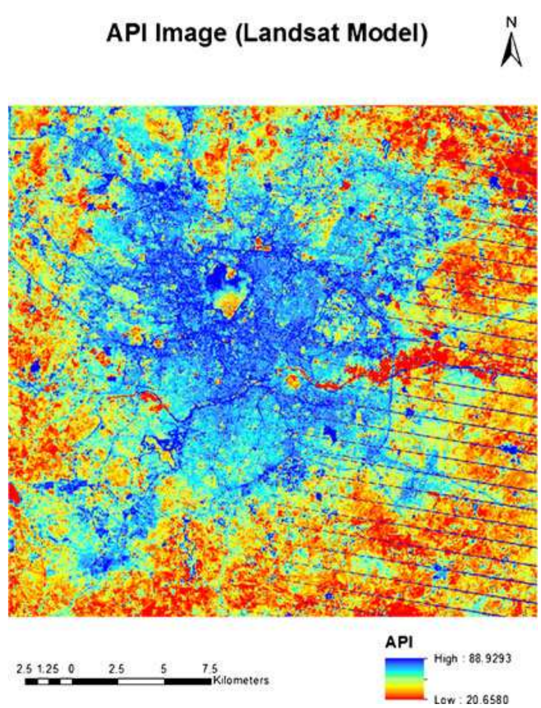

Fig. 4 API image from Landsat model

API Model in ERDAS Model Maker

The multiple linear regression models developed for IRS (LISS IV) and Landsat (ETM+) data are given below:

$$API_{IRS} = 35.8 - 46.7 * NIR - 34.8 * VI + 213.7 * TVI \quad (8)$$

$$API_{Land} = -460.0 - 10.4 * SWIR + 1.0 * NIR - 6.4 * VI + 851.6 * TVI \quad (9)$$

API images have been shown in Figs. 3 and 4. It is displayed in air quality categories using the API ranges given by Rao et al. (2004) specifically for the study area. These ranges are clean air (0–25), light air pollution (26–50), moderate air pollution (51–75), heavy air pollution (76–100) and severely polluted (>100).

Accuracy Assessment of API Models

The applicability of a model depends on its validation. To quantify the accuracy of the developed multivariate API models from IRS and Landsat data, the observed and calculated values are compared (Fig. 2). Out of 17 sample sites, 14 are comparable in case of IRS and 15 in case of Landsat model, giving accuracy of the model as 82 % and 88 % respectively. The RMSE of the validation points BPPA, KBRN Park, Paradise and Zoo Park were 23 and 9 for IRS and Landsat model. The high RMSE in case of IRS model was due to high difference of observed and calculated data of KBRN Park and Langar House. To analyze the reasons behind the anomalous points the image was classified by supervised technique after collecting ground truth for Level III classification (column 4, Table 3). Though KBRN Park is classified as an orchard (vegetated area), the vegetation indices were found very low compared to other orchard area such as Zoo Park. This caused the estimation of API higher than the desired. The field verification entailed the low vegetation indices because of the density of trees present in the orchards. However, the observed API was less due to low traffic areas around the Park. The second anomalous point Langar House, which is classified as the high dense mixed urban. The observed API at this site is unexpectedly higher than the other areas of same LU/LC. This was found to be one limitation of this study where only vegetation was considered. With inclusion of other factors like

Table 3 Comparison between observed and calculated API

Location	$API_{irs} - API_{cal}$	$API_{lan} - API_{cal}$	LU/LC characteristics
Abids	-1.90	4.19	Commercial (High Dense)
Balanagar	6.83	−3.41	Industrial (restricted)
BPPA	−3.44	0.72	Mixed Urban(Medium Dense)
Charminar	5.12	−7.03	Commercial (High Dense)
Chikkadpally	−1.67	4.31	Mixed Urban(Medium Dense)
Jeedimetla	3.84	−8.31	Residential (High Dense)
Jubilee Hills	4.77	2.93	Mixed Urban (Medium Dense)
KBRN Park	−46.17	17.80	Orchard
Kukatpally	−12.48	12.02	Mixed Urban(Medium Dense)
Langar House	37.31	−33.66	Mixed Urban(High Dense)
Nacharam	−7.38	−3.24	Industrial
Paradise	6.88	−5.73	Commercial (High Dense)
Punjagutta	7.31	−2.23	Commercial (High Dense)
Rajendrnagar	−20.23	7.62	Residential (Sparse)
Sainikpuri	9.29	−4.72	Residential (Medium Dense)
Uppal	8.64	−8.96	Mixed Urban (High Dense)
Zoo Park	−7.01	5.22	Orchard

urban morphology, traffic density, time of day etc. the accuracy can be improved.

Comparison between Interpolated and Calculated API

Air pollution study is commonly done using interpolation techniques in GIS (Pummakarnchana et al. 2005; Patil et al. 2003; Rahmatizadeh et al. 2006). For this study, API obtained from the regression models have been compared with API obtained from interpolation. The interpolation for the present work has been done by IDINT (variance 2) (Fig. 5). Twenty one arbitrary locations (test points) within the image have been selected to compare the interpolated values and the APIs calculated from the regression models. Landsat and IRS modeled API values are compared with interpolated API values at these test points with the help of range and mean error plots (Fig. 6). The confidences of the Landsat API values are more with respect to interpolated values than IRS API values. All points are found comparable except 2, which were found in low dense urban area. Although regression model estimated a low API, the value from interpolation technique were more because of high air pollution in the nearby areas.

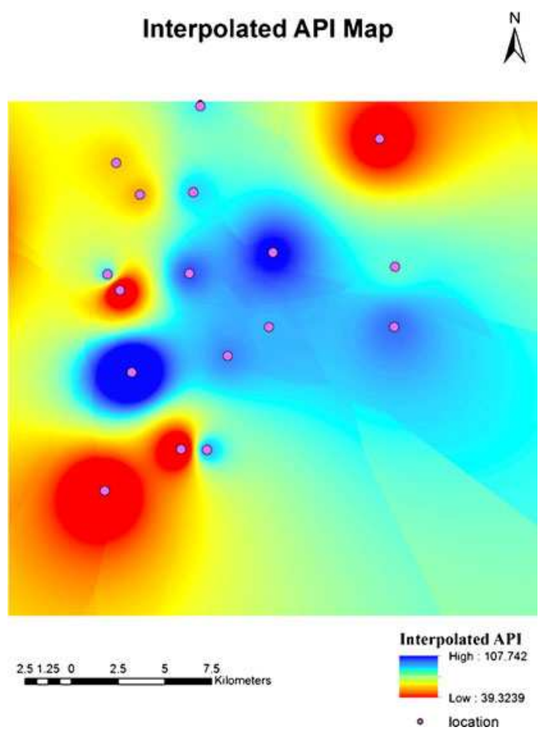

Fig. 5 Interpolated API map using Inverse Distance Weighing method with location of sample points

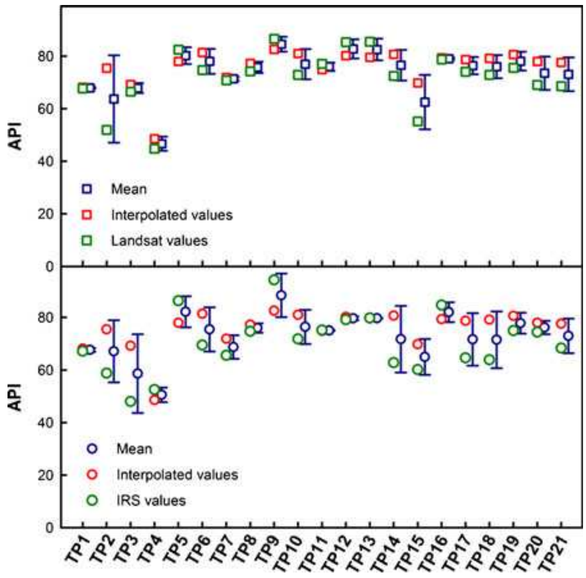

Fig. 6 Comparison between calculated and interpolated API with range and mean error plot at test points

Conclusion

In this paper, air pollutant information has been converted to an index, API and regression based models have been developed between API and several image extracted parameters from IRS LISS IV and Landsat ETM+ images. API varies inversely with respect to vegetation indices and reflectance values of red, NIR and SWIR. The highest correlation was observed for Landsat SWIR wavelength with Pearson correlation of 0.83. For single pollutants, TSPM being larger in size has more correlation with image parameters than other pollutants.

Multivariate regression models are more promising and yielded better results for both the cases of IRS and Landsat. The combined effect improved the R^2 value from 0.59 (NIR) to 0.62 (NIR, VI, TVI) in case of IRS model and from 0.69 (SWIR) to 0.79 (SWIR, NIR, VI, TVI) in case of Landsat model. The validation of API calculated with observed values implied that due to availability of more number of bands, specifically SWIR, Landsat is better than IRS in providing air pollution information of the study area. The best R^2

(0.79) and lowest RMSE (7.77) was found for Landsat using 4 variables NIR, SWIR, VI and TVI. Also, the calculated values from API models were comparable with the interpolated values with accuracy of 80 % and 90 % for IRS and Landsat model respectively.

Although interpolation techniques are widely used for air pollution studies, this paper described a methodology to obtain air pollution from images directly. Vegetation indices, NIR, SWIR 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.

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