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Application of Integrated Image Classification (IIC) Method for the Analysis of Urban Landuse Pattern of Kolkata Municipal Corporation, West Bengal, India

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Abstract

Application of remote sensing techniques for landuse/land cover analysis is increasingly evolving as the best option for approaching land management. Categorization of pixels of a raw image forms the fundamental basis of digital image analysis. However, a single process of categorization, either using supervised or unsupervised method, is not sufficient to delineate the complex landuse patterns, especially in urban areas. Researchers have found some mismatch errors with the real world domain features. The integration of these two methods has the potential to bring about more classifier accuracy in the study of landuse. This article is an attempt to apply the integrated method in landuse / land cover classification and find out whether or not the levels of accuracy improve. The study has been undertaken to analyse the pattern of landuse changes within Kolkata Municipal Corporation.

Introduction

Changes in landuse / land cover (LU/LC) is a common phenomenon, occurring with an increasing momentum in urban regions. On the other hand, urbanised areas are characterized by a complex mosaic in terms of LU/LC components. The fact that the urban landscape is characterized by non-homogenous features, poses a challenge for the researcher using remotely sensed data for the analysis of its land character. Again, in many places of a big city, features are often found in an overlapping condition with others. For instance it is like the visibility of roads being blocked by flyovers, tree canopies blocking road, rivers being bounded by concrete banks, wetlands and canals surrounded by kuchha structures of slums or marshy lands used for garbage dumping, etc. Such overlap or mix of uses poses a problem for landuse analysis with help of remotely sensed data. This problem has led to continuous attempts at finding the way out. Literature reveals (Burnicki, 2011; Wang & Feng, 2011; Turner et al., 2007; Parker et al., 2003) that classifiers for land use and land cover analysis have been used in different permutations and combinations to achieve better accuracy.

The Problem of Integration of Methods

The intensity and pattern of landuse in the urban areas has a traditional character of heterogeneity (Kaplan et al., 2009). Literature abounds on the problems of using classifiers for land use mapping. Although there are several practical barriers in image processing (Dai et al., 2010, Woodcock et al., 1987) for urban areas, Digital Image Classification (DIC) is an important and popular method for extracting geo-spatial data. It is the process of sorting of pixels into number classes through statistical techniques by using computer aided software (Lillesand et al., 2009, Jindal & Josan, 2007, Jain et al., 2001). After classification, any number of thematic maps can be created and data and information can be processed scientifically. Due to complexities created by the non-homogenous character of urban land, it is more difficult to achieve accuracy in comparison to the non-urban areas. Several inherent confusions are created by the following factors —

1. In the urban area, the spectral values of one pixel can be mixed up with the adjacent corresponding land uses and their functions (Banzhaf, 2007). In this case the relation between land classes and its spectral values does not match accurately (Froster, 1984, Baraldi. 1990).
2. On the other hand, the spatial extent of pixels does not match with the ground coverage of the surface features (Aplin et al., 2008).
3. Again, a pixel in the satellite image can represent more than a single type land cover and landuse (Fisher, 1997, Aplin et al., 2008) category.
4. It may also be difficult to get cloud free images for the proposed temporal window and for the area of interest.

It is evident from literature, that classification is entirely accurate through any one particular method. Marfai et al., (2003, 2008) used the multi-dimensional image classification technique for the assessment of environmental problems in the coastal zone. Of late, Bhatta (2010) has measured the traditional matrices, spatial matrices and spatial statistics to analyse the growing pattern of urban centres. User knowledge plays a greater role especially in complex regions. Combined decision making modalities in DIC have been established to achieve better results (Alkoot et al., 1999, Kuncheva, 2002, Lepisto et al., 2010).

In recent years, the integrated method of unsupervised and supervised classification has been widely used by scientists, researchers and planners and is popularly called the Integrated Image Classification (IIC) method. Jenerette and Wu (2001), Luck and Wu (2001), Weng (2007) and Schneider and Woodcock (2008) have scientifically evaluated the various consequences of urban dynamics and landscape heterogeneity on the environment, with the use of the IIC method. In the study of natural features also, the IIC method has been applied by the scientists in a variety of fields. For instance, Kittler et al. (1996 and 1998) used this method for pattern analysis and recognition, Lu et al., (1992 and 2003) and Jain (1999) for human body feature identification while Lepisto et al., (2010) identified the nature of rocks from natural images. Evidently, digital image classification (DIC) with IIC method produces a more accurate classification of urban landuse and serves to effectively assess the temporal changes in LU/LC. An accurate LU/LC map plays a vital role in change detection analysis and thereby becomes an important tool of the urban planners.

Study Area

The city of Kolkata, the second largest metropolis of India, has evolved from a small agglomeration of three villages of Sutanuti, Kolikata and Gobindapur to its present sprawling urban region over more than three centuries (Sinha, 1990). The Corporation area is located between 22º 26' 53.64" N and 22º 38' 07.28"N latitude and 88º14'30.77" E and 88º27' 37.56"E longitude and covers an area of 187.33 sq km (including Fort William) on the left bank of Hooghly river. The Kolkata Municipal Corporation (KMC) has a population of more than 4,572,876 (GoWB, 2004).

Methodology

For DIC, the common classification methods in Remote Sensing (RS) and Geo-spatial study are either supervised or unsupervised. The first one is a more regulated and controlled image classification method from user's perspective. Here pixel classes can be grouped and tested with the help of 'ground truth verification', 'overlay analysis' and others.

This DIC method involves three distinct stages a) training, b) classification and c) output (Lillesand et al., 2009). In this selection of the training area and the classification procedures need a prior decision (Angel et al - 2005). Based on the previous information of pixel spectral character, the user gives computer the required command to identify the features classes (Joseph, 2003).

In unsupervised method, spectrally separable classes (known as *spectral classes*) are generated at first and then their information utilities emerged. Here, the classifier demarcates the spectral classes from the image (Lillesand et al., 2009). Different clustering algorithms are used for the natural grouping of the data. Pre-determined classes are not necessary. This method is inefficient for large and multiple image classification (Jindal & Josan, 2007).

Database: LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) image dataset of 17th November, 2000 was acquired from the open access site of Global Land Cover Facilities (GLCF) for the analysis as a sample data. This data set is more useful for the study of urban heterogeneity milieu from the old urban core to the relatively young urban fringe (Hipple et al., 2006, Banzhaf et al., 2007). Spectral and spatial properties of this data set are given in Table No. 1 and Fig. 1).

Digital Operations and Analysis: From these vast images, the study area has been extracted from the KMC Ward map on 1:5,000 scale, using the subset system in ERDAS IMAGINE 9.0. The salient features of integrated (unsupervised to supervised) method of DIC are shown in Fig. 2.

Apart from these, overlay analysis between the raw image and the combined output image and intensive ground truth verification (GTV) performs a vital role in identifying the inaccurate classes and confused features. After the GTV, all the pixels of confused features are then converted to actual classes using 'recoding operation' in the software that needs the user's knowledge about the landuse characteristics of the area concerned. After recoding, the final output is created through filtering.

Finally, for accuracy assessment, conditional Kappa coefficient (K^) has been used. It is a measure of the difference between the *original agreement* of reference data and automated classifier *and change agreement* of reference data and a random classifier (Lillesand et al., 2009).

Result and Discussions

Two classified output images have been generated with four different classes as — 1) water body, 2) vegetation cover, 3) urban built-up area and 4) grass land with shrubs. The spatial pattern of these LU/LC classes in unsupervised and IIC method of ETM+ data is shown in Table - 2, Fig. 3(A and B) and Fig. 4 (A and B).

1. ***Urban Built-up Area:*** It includes buildings, roads, concrete pavements, flyovers, and other concrete structures. In the unsupervised methods, some confused features of landuse, shown by yellow colour in Fig. 4 A, have been clubbed separately. These have been converted to the urban built-up class in IIC output by integrated process. It now covers 68.46% of the area. Urban built-up area is considered as a predominant landuse category in the central, southern and northern area of KMC due to the development of intensive '*urban jungles*' and skyscrapers.
2. ***Vegetation Cover:*** This includes various types of vegetated areas like orchards, wooded areas, and other vegetation patches and covers about 13.15% of the total area. It is mainly found in the west, south-west, south and eastern fringes of KMC. On the other hand, the result of unsupervised classification shows this class to be nearly 26% of the total area.
3. ***Water Body:*** Water bodies include canals, wetlands and ponds, which together comprise 6.74% of the area after IIC method, whereas it was 6.75% in unsupervised classification.
4. ***Grassland with Shrub:*** As the data is captured during the post-monsoon period, this class became dominant over open land and vegetated area. It covers about 11.64% of the area and predominantly surrounds the wetlands and fringe area of the KMC. But in the unsupervised method the spread of this class is estimated at 16. 75 % of the total area.

The accuracy of classification has been shown in Table Nos. 3 and 4 with values of individual and overall Conditional Kappa (K^) Statistic of the

LU/LC classes of LANDSAT ETM+ data. It is found that every class in unsupervised method has a lesser value of Conditional Kappa Statistics compared to those in IIC output.

For the classified image of ETM+ in IIC method, the overall accuracy is 93.41% which is better than the observed level of 62.87% in unsupervised method. In the IIC classified image, urban built-up area is spread over the south-eastern and southern parts covering about 69.52% of the total area. For this class the producer accuracy is 99.39%, but the user accuracy is 95.56%. The coverage of land under water bodies has slightly increased and covers 6.29% of the total area. Here both the producer and user accuracy level of 100% is observed. The vegetated tract is found over 12.09% of the total area with 84.62% producer accuracy and 91.67% user accuracy. However, grassland with shrubs shows a decline in coverage (11.64%) with an accuracy level of over 85%. Conditional Kappa (K^) Statistics for each LU/LC category is found to be 0.90.

Concluding Remarks

The analysis, ut supra, presents an overview of some critical aspects of image processing with reference to urban studies. Some early works (Schulthes et al., 2005; Angel et al., 2005; Dey, 2009 and Lillesand et al., 2009) show that the quality of both the supervised and unsupervised methods of image classification is a function of image quality, user skill and software efficacy. Dey et al., (2009) has identified the operational errors of supervised and unsupervised image classifications on the basis of computational logic and operator's efficiency (Table - 5)

In the present study better accuracy has been obtained by applying IIC method (Tables - 2 and 3). As it has also reduced the level of output error, this overlay approach strongly corroborates its efficiency of LU/LC analysis in spatial scale The thematic maps prepared were satisfactorily tested/ verified by ground truthing. However, further addition of data from different sources for geo-processing would definitely improve the quality of the image analysis to a great extent.

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Table – 1: Spectral and Spatial Properties of Landsat Data (TM and ETM +)

BANDS	LANDSAT 4/5 TM		LANDSAT 7 ETM+	
	Spectral (µm)	Spatial (m)	Spectral (µm)	Spatial (m)
1 Blue	0.45 - 0.52	30	0.45 - 0.52	30
2 Green	0.52 - 0.60	30	0.52 - 0.60	30
3 Red	0.63 - 0.69	30	0.63 - 0.69	30
4 Near Infrared	0.76 - 0.90	30	0.76 - 0.90	30
5 Middle Infrared1	1.55 - 1.75	30	1.55 - 1.75	30
6 Thermal Infrared	10.40 - 12.50	120	10.40 - 12.50	60
7 Middle Infrared 2	2.08 - 2.35	30	2.08 - 2.35	30
Panchromatic	n/a	n/a	0.50 - 0.90	15

Source: Angel, S. et al (2005)

Table – 2: Classification of LANDSAT ETM+ data, KMC Area.

LU/LC Class	After Unsupervised Method		After IIC Method	
	Area (ha)	%	Area (ha)	%
Water Body	1266.66	6.75	1266.66	6.75
Vegetation Cover	4870.35	25.94	2470.34	13.15
Urban Built-up Area	9496.60	50.57	12854.63	68.46
Grassland with shrub	3143.61	16.74	2185.59	11.64
Total	18777.22	100.00	18777.22	100.00

Source: *Computed by the authors*

Table – 3: Conditional Kappa (K^) Statistic for each LU/LC Category (based on Landsat ETM+ data)

Class Name	Kappa (K^) Statistics	
	After Unsupervised Method	After IIC Method
Grassland with Shrub	0.5005	0.8312
Natural Vegetation	0.4749	0.8833
Urban Built up Area	0.5122	0.9157
Water Body	0.7501	1.0000
Overall Kappa Statistics	0.4835	0.9000
Overall Accuracy (%)	**62.87**	**93.41**

Source: *Computed by the authors*

Table – 4: Accuracy of LU/LC Classification Output by IIC Method

Class Name	Reference Total	Classified Total	Number Correct	Producers Accuracy (%)	Users Accuracy (%)
Urban Built Up	43	45	43	99.39	95.56
Vegetation	26	24	22	84.62	91.67
Grassland with Shrub	14	14	12	85.71	85.71
Water Body	8	8	8	100.00	100.00
Total:	91	91	85		

Overall Classification Accuracy = 93.41%

Table – 5: Experimental Result of Soft Computation on Different Spectral Resolutions

Items of Assessment	Clustering	Density Slicing	Maximum Likelihood
Type of classification	Unsupervised	Supervised	Supervised
Material	Radiometric Spectral	Radiometric Spectral	Multispectra l
Observed Computational / Operational Error (%)	5	20	45
Level of Logical Perfection from General Digital Image Classification Perspective	Very high	Medium	Low
Level of Logical Perfection from Remote Sensing and GIS Image Classification Perspective	Low	Medium to high	Very high

Source: Dey (2009)

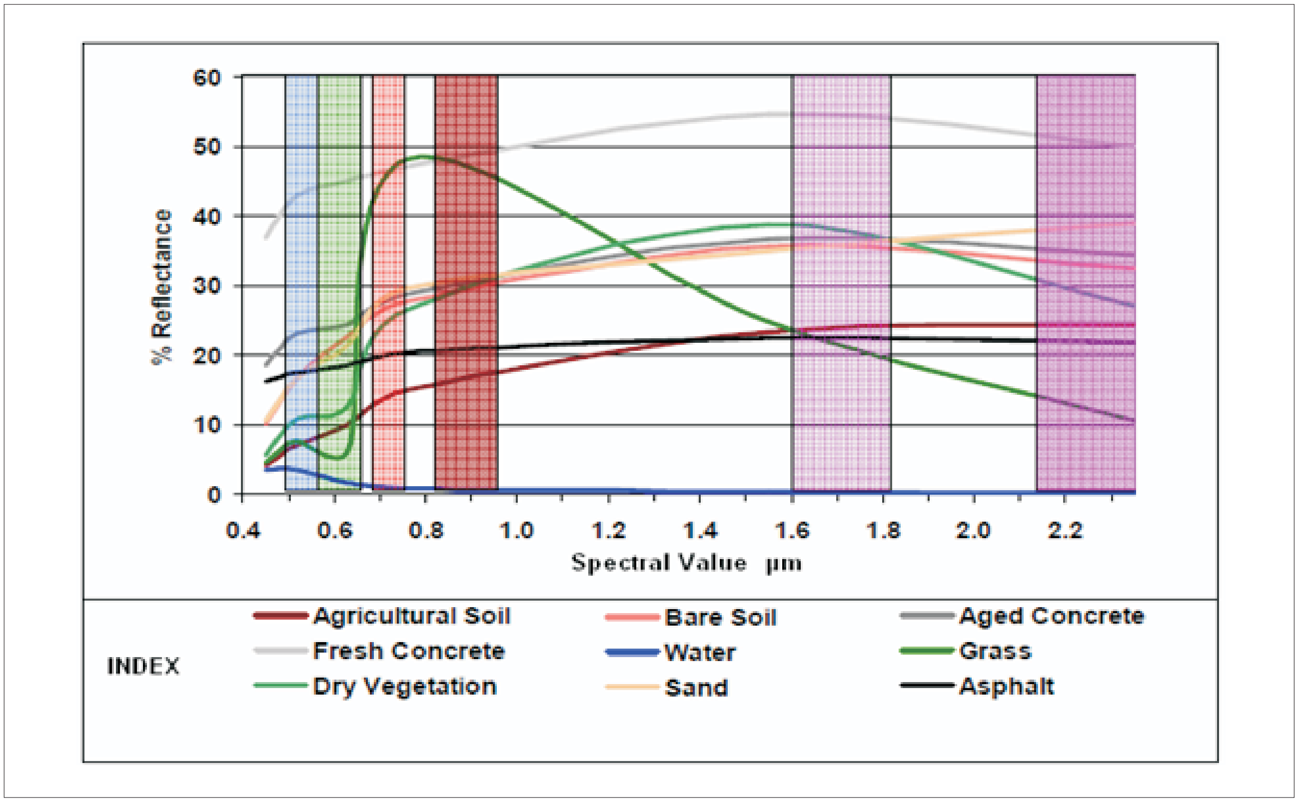

Fig. 1: Spectral Characteristics of various land cover and land use categories of LANDSAT TM & ETM+ Bands (after *Angel, S. et al, 2005*).
a) agricultural soil, bare soil, and grass are merged together in grass with shrub class, b) signatures of fresh concrete, aged concrete, and asphalt are unified in urban built up class, c) water and sand are considered in water body category, and d) vegetation cover for the dry vegetation signatures for the KMC

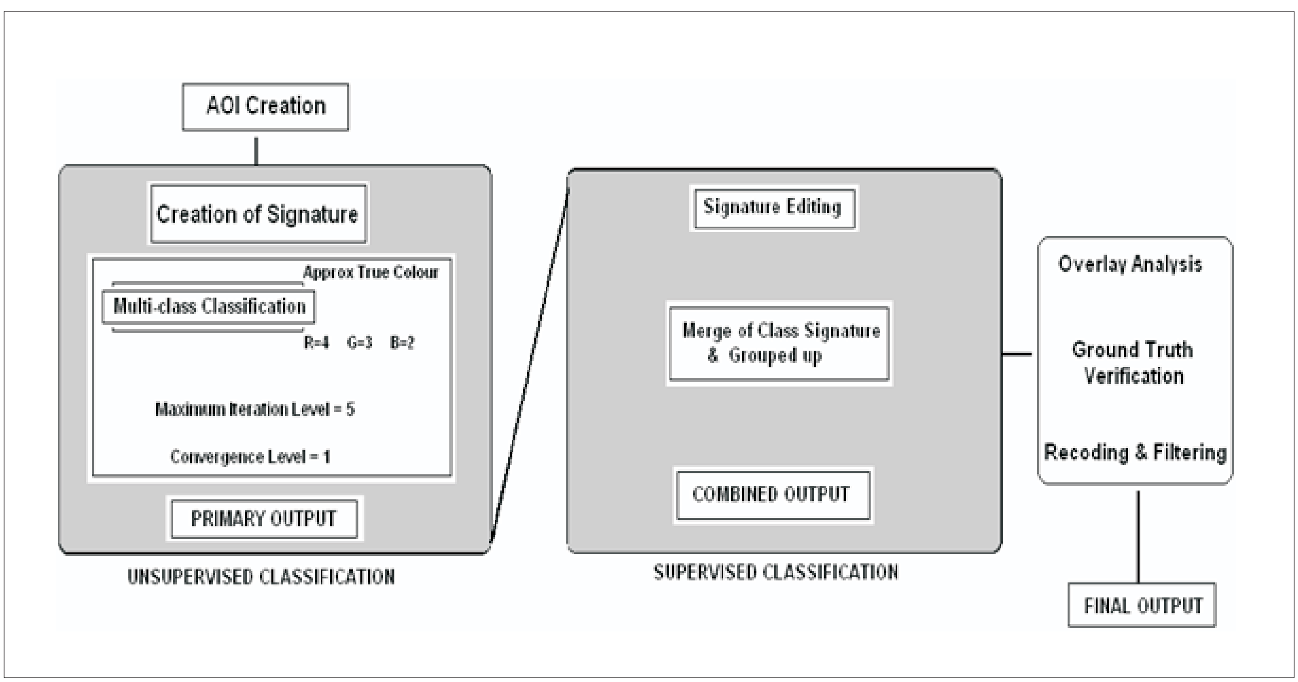

Fig. 2: Operational Stages for Integrated Image Classification (IIC) Method

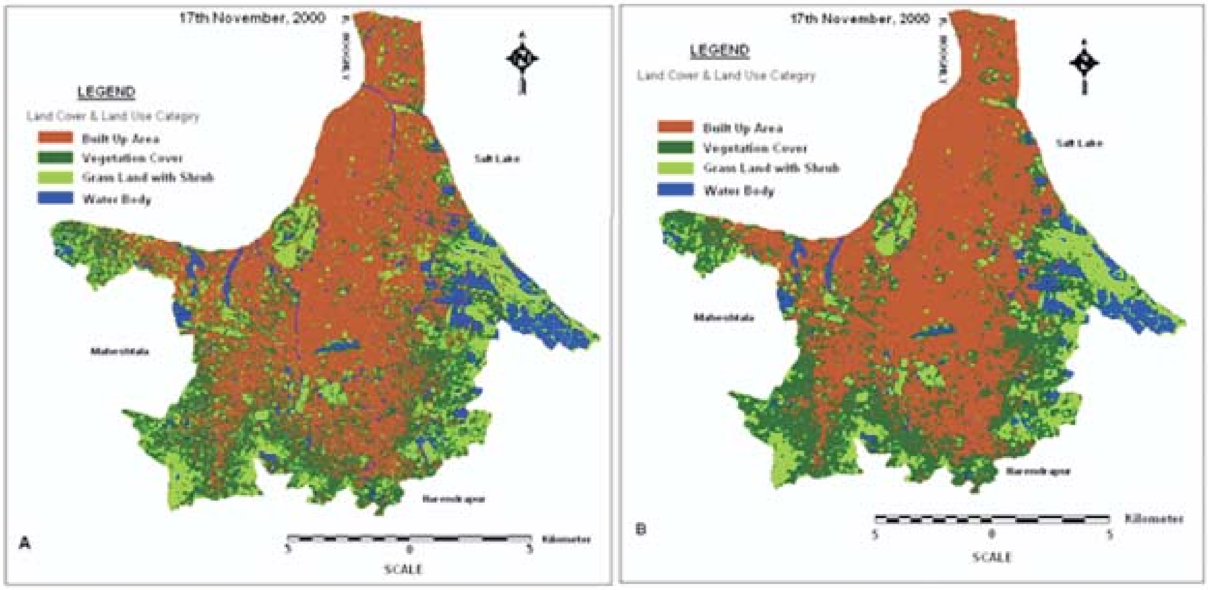

Fig.3: The classification results of LANDSAT ETM+ data by Integrated Image Classification method
A = The Integrated Image Classification output of KMC with different classes,
B = Landuse / Land Cover output of same data using median function filtering (3 x 3)

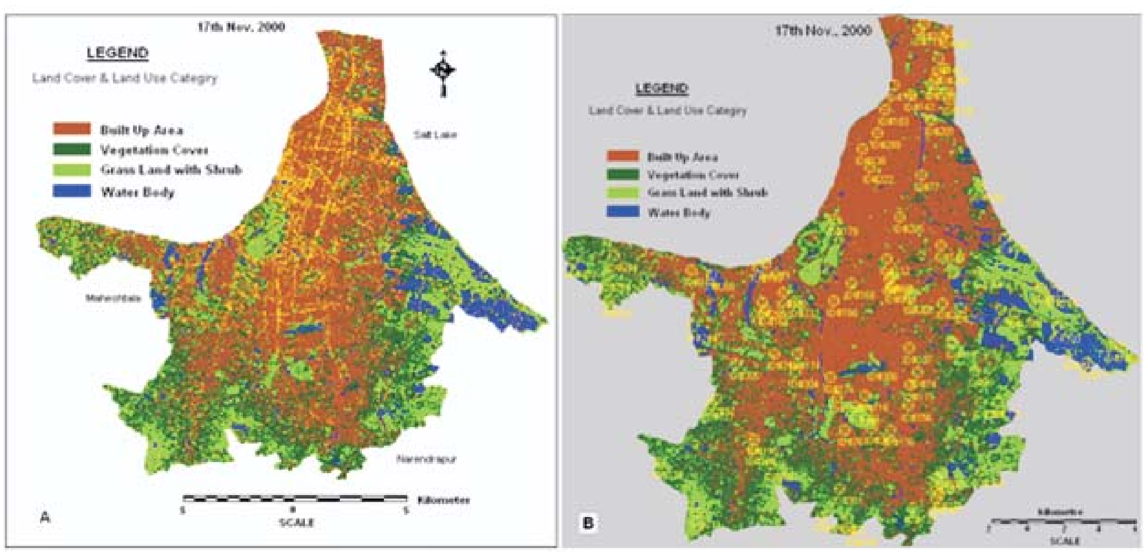

Fig. 4: A = Classified Output of ETM+ data by Unsupervised Method (confusion area shown by yellow colour), and
B = Location of Accuracy Assessment Points in different parts of the Study Area

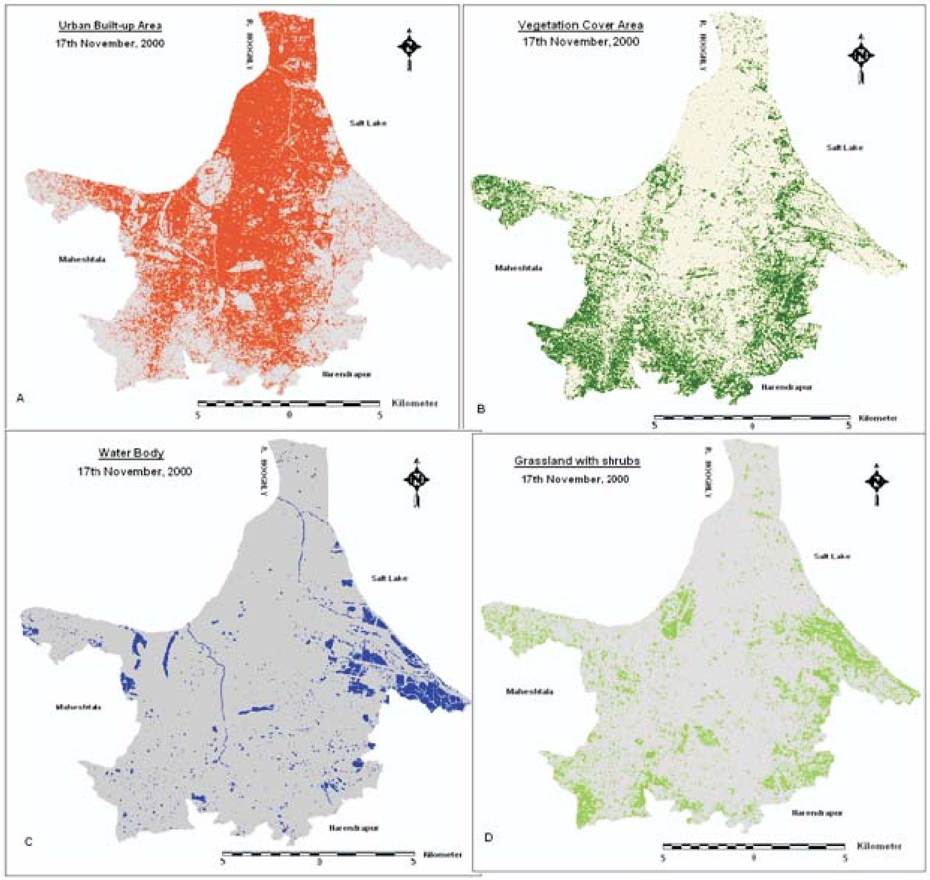

Fig. 5: Thematic Maps of different LU/LC Classes after Integrated Image Classification (IIC) Method

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