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Delineation of Peri-urban Area using Modern Techniques — a case study of North 24 Parganas district, West Bengal, India

Jhantu Saradar[1]
Dr. Sukla Hazra[2]
[1]UGC-SRF, East Calcutta Girls' College, Kolkata, West Bengal
[2]Principal, East Calcutta Girls' College, Kolkata, West Bengal,

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Abstract

The current paper presents a method to delineate the Peri-urban areas near Kolkata, a megalopolis of West Bengal, India. Landuse and land cover (LULC) classification has been done using Optimum Index Factor (OIF). Seven different indices (viz. NDPI, NDVI, NDBI, NDBaI, SAVI, MNDWI and UBI) have been applied to depict different landuse components in the study area as no single index is sufficient to explain the existing design. In order to identify the peri-urban areas Principal Component Analysis has been undertaken and 'maximum likelihood classification algorithm' has been used for classification followed by ground truthing. Peri-urban regions are analysed using the spectral plots and dendrograms are used in grouping the categories. To evaluate the classifications, overall accuracies and Kappa statistics are also computed.

Introduction

The landscape of North 24 Parganas district is undergoing a rapid change because of its proximity to the city of Kolkata. It is a bordering district of West Bengal, where a large number of refugees were rehabilitated after the partition of Bengal. It thus caused dynamism in landuse pattern. Since the early days of the 20th century, a 'conurbation' has been formed based on Kolkata as an elongated stretch along the Hugli river in the western part of this district. A significant change in urbanization took place after 1980, when Barasat, away from this conurbation, became the district headquarters of North 24 Parganas leading to major change in the landuse characteristics. Rapid economic expansion was accompanied with several environmental challenges caused mostly by the anthropogenic activities. The severity of the problem has been aggravated due to non-execution of the rules and regulations by urban municipalities. Environmental condition of rural areas changed mostly near the urban centres. These are called 'peri-urban' or 'rural-urban fringe' or 'urban sprawl' areas. The landuse land cover (LULC changes in these transitional areas may be monitored at short time interval using satellite images. The advantage is that a change in status of an object, must result in a change in radiance value (Mas, 1999; Yeung and Lo, 2002). They used either 'ISODATA unsupervised classification' or 'maximum likelihood algorithms' in supervised classification. During the last three decades, a large number of landuse classification methods have been suggested for classification of wide, robust and complex region (Hall and Hay 2003).

Study Area

The district of North 24 Parganas lies between 22º05′54″N to 23º16′39″N of latitude and 88º20′03″E to 89º06′34″E of longitude covering a total area 4168.86 km^2. The Hugli river flows along its western boundary and Ichhamati river makes the international border with Bangladesh in the east. Besides, there are a number of rivers like, Jamuna, Padma, Bidyadhari and canals like Noai, Haroa, Sunti and also paleo-channels, oxbow lakes etc. The region experiences tropical monsoon climate with temperature ranging between 10° C (December) to 41°C (June) and an annual rainfall of about 142 cm (restricted in the months of July

September). The soils are generally hydromorphic in nature and are mostly poorly drained. The pristine vegetation has been reduced and replaced by secondary re-growth of arable lands of paddy, mango orchards and bamboo trees. In the south there is a small patch of mangrove vegetation along with saline wetlands. Most of the tidal inlets are blind channels and survive as carriers of passage of rainwater of the watershed region of the main channel (Hunter, 1998; Majumder, 2001).

The district consists of 22 blocks with 27 municipalities and 200 Gram Panchayats. It has good connection with the other parts of West Bengal by Eastern Railway, Barrackpur Trank Road, National Highways (NH 34 and 35) and Expressways. The central business district (CBD) of Kolkata city is only 10 km away from the western part of the district and urbanization started during the British period when Kolkata was the capital of India and urbanization based on industrialization took place along the river Hugli and Eastern Railway line. Later in the 1980s, Barasat became the administrative headquarter of the district that resulted another spurt of urbanization (Fig. 1).

Objectives

The major objectives of this study is to determine the best band combinations for landuse classification of the study area and to prepare a method to delineate the peri-urban area with the application of remote sensing images and GIS application.

Data and Methodology (Fig. 2)

Image Rectification

The area of North 24 Parganas are covered by two Landsat images of path 138 and row 44 and 45. These images were downloaded from GLCF website (http://glcf.umd.edu/). The acquisition date of the images was 2nd February 2010. The images were rectified with UTM projection using WGS 1984 datum. These two scenes are then mosaiced to finally extract the entire area of North 24 Parganas.

Image Subset

The boundary polygon layer of North 24 Parganas district has been prepared from rectified district administrative map. From this, the same area has been subset. Software like, TNT MIPS, Arc GIS, and ERDAS were used for image processing and thematic mapping.

Optimum Index Factor

Combination of R.G.B. band is very complex and changeable, by which the visual interpretability of the images differ (Tsagaris and Anastassopoulos, 2005, Liang et al. 2008, Muntshry, 2011). For this purpose, optimum index factor (OIF (Chavez et al. 1982) technique has been applied to select the possible three-bands which will be rendered as R-G-B. This method has been developed to designate the most favorable band combination for LULC classification. It is based on the amount of total variance and correlation between various bands. High value of OIF indicates the bands contain much information (e.g. high standard deviation) with little duplication (e.g. low correlation) between the bands (Ali and Basavarajappa, 2008, Yueming et al 2007). They used algorithm to compute the OIF for any subset of three bands as follows:

$$\text{OIF} = \sum_{i=1}^{3} SDi \,/\, \sum_{j=1}^{3} |CCj|$$

Where, SDi = standard deviation, |CCi| = absolute value of correlation coefficient.

For larger OIF values, more information will be covered than the standard False Colour Composite (BeauchemIn and Fung, 2001). From Landsat TM5 image, 35 combinations are obtained, from which the combination of band 5, 4, 1 achieved highest OIF value (Table 1).

Selection of Indices

The complexity and variety of landuse in this district can not be detected by a single index. However, different objects can be made more visible and interpretable by enhancing bands with different ratios. Different object-oriented image enhancement has been applied to regionalize the study area. Altogether 7 different kinds of enhancement have been used, viz., normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), urban built-up index (UBI), soil adjusted vegetation index (SAVI), modified normalized difference water index (MNDWI), normalized difference pond index (NDPI), and normalized difference bareness index (NDBaI) (Rahman and Syakur, 2012; Lee et al, 2010; Huete, 1988; Xu, 2007; Lacaux*et et al*. 2007; Gardelle et al 2009; Ling et al, 2006).

The NDBI denotes the built-up area and also the bare lands. Therefore, NDBaI is used to recognize the bare soil with low moisture content and higher temperature. It is used here to eliminate those pixels having higher NDBI values and also higher NDBaI values. This method extracts the built-up area more correctly. The NDVI classifies the region on vegetative area while the MNDWI and NDPI can identify different types of water bodies (Lunetta et al. 2006). SAVI is another index which identifies the soil and its moisture with different vegetation content. UBI has been taken to extract the built-up area and also the peri-urban areas on its surroundings (Table 2).

Principal Component Analysis (PCA)

PCA is a common technique for finding patterns in multi-dimensional data and is done to reduce its dimensionality and improve the spectral information of the band combinations. It is applied here to compress the multi-channel data into new set of variables as peri-urban region is not well represented by any one of the indices. PCA of these indices has been done for pattern recognition and image compression (Yueming et al 2007, Ehsani and Quiel. 2010). PCA aids in elimination of redundant information due to inter-band correlation (Lillesand et al. 2004).

The first principal component (PC1) usually contains the largest amount of information from the original data set. Transformation of the bands give rise to the new co-ordinate system orthogonal to the previous ones. To avoid the problem of linearity caused by similarity among indices, the first three results from PCA (PC1, PC2 & PC3) are used as band combinations for the purpose of creating sample sets. On this new image supervised classification is done for LULC classification. Sample sets are then created based on field work and peri-urban area are extracted from landuse map (Fig. 8B). A large area shows peri-urban or rural-urban fringe, reflecting rapid changes inA large area shows peri-urban or rural-urban fringe, reflecting rapid changes in landuse (Table 3 and 4).

Results and Discussion

The maximum value of OIF is obtained for the combinations of 5, 4, 1 bands (Table- 1). The OIF value for 5, 4, 1 band combinations is 26.69. The best combination (5, 4, 1) consists of middle infra red, infra red and one visible (Blue-Green) band; it has the lowest correlation value of 1.38. The ranking of second and third of OIF values are 22.99 and 22.34 for the combinations of 5, 4, 2 (Mid IR, NIR and Green) and 5, 4, 3 (Mid IR, NIR and Red) respectively. The lowest OIF value (4.64) is derived for the combinations of 3, 2, 1 (Red, Green and Blue-Green) bands with highest correlation value 2.81. This 3, 2, 1 band combination consists very low interpretability. Supervised classification technique with maximum likelihood classification algorithm has been carried out to prepare the required LULC map of the study area on OIF combination (Fig. 3A).

For further improvement of the band combination, all these indices are used in PCA. First three PCs of indices form the new False Colour Composite (FCC) images. On this new FCC images, supervised classification is done (Fig. 3B) and nine LULC categories have been identified using training sets (Table 9 and Fig. 7). On these PCs, the eigenvector represents in the PC1 is 59.56% of the total variance (Table 5). The total variance of PC2 accounts for 39.91 % and PC3 accounts 0.45%. The first three components were bringing the total variance of 99.92%. Pc2 contains useful information about the vegetation cover while PC1 and PC2 together contain information about the built-up and bare area (Table 6).

On the basis of three PCs, a supervised classification has been done yielding nine landuse classes (urban, peri-urban and rural areas along with cultivable waste land, arable lands, mangrove vegetation and wetlands). The overall accuracy is 94.52% with Kappa statistics as 93.60% (Table 8). Here the result of accuracy to LULC based on PCA is better than OIF (90.34% (Table 7). The peri-urban areas are then extracted from LULC, based on OIF bands (Fig. 8A) and PCAs band combinations (Fig. 8B).

It is interesting to note that areas which are cultivable including both fallow and arable land in the rural and in peri-urban areas are grouped or linked, whereas urban areas are linked with bare ground (Fig. 5). It may be due to the fact that such areas are lying bare for further planned urban expansion e.g. in Rajarhat New Town area. Brickfields are also categories as bare ground, which are far away from the towns and cities. On the other hand, in case of LULC based on OIF bands, arable land, current fallow land , rural areas and wetlands are grouped under urban areas which are actually mutually exclusive (Fig. 4).

Conclusion

This study has therefore revealed the uses of different ratio based indices for mapping or enclosing an environmental region, i.e. the peri urban area. Here Landsat TM 7 bands with high spatial resolution satellite data are used for this type of mapping. It is observed that plain land with paleo channels, urban settlement with dense road network, rural settlement with wetland, waste land and arable lands, mangrove vegetation, and salt covered marshy lands may be identified by spectral values of the images. Those spectral values carry unique information on landuse classes even revealing the small brick fields, marshy lands etc. The spectral plots show that in some cases, only slight spectral differences could be deployed effectively in discriminating urban areas, bare grounds and peri urban with cultivable lands etc. Spectral signatures of three PC's are also used for such landuse classification. Based on field observations, it is found that there are some physical barriers in the expansion of the peri urban area, e.g., wetlands, low lands, paleo channels and water-logged areas and natural hazard prone areas are not suitable for settlement. In the study area, the expansion of urban or peri urban settlement area took place toward northeast along the Sealdah - Bongaon railway line. Wetland or bheries are the seat of pisiculture in the east and southeastern part of the district which do not favour the growth of urban settlement. In such a complex region with multidimensionality, this type of analysis is ideal for environmental regionalization. Further research is needed for improving our knowledge about landuse-land cover classification using image based data.

Acknowledgement

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Table - 1: OIF Values of different Band Combinations

Combination	$\sum \sigma$	Sum of Correlation Values	$OIF = \sum_{i=1}^{3} \frac{SDi}{\sum_{j=1}^{3} \lvert CCj \rvert}$
1,4,5,	36.815022	1.3819963	26.63901633
2,4,5,	35.605251	1.5480763	22.9996745
3,4,5,	37.897202	1.6960424	22.34448974

Source: All computations done by the authors

Table - 2: Different Indices using Landsat Image Bands

Index	Formula
NDPI	(B5-B2)/(B5+B2)
NDVI	(B4-B3)/(B4+B3)
NDBI	(B7-B4)/(B7+B4)
NDBaI	(B5-B6)/(B5+B6)
SAVI	{(B4-B3)*(1+0.5)}/{(B4+B3)+0.5}
MNDWI	(B2-B7)/(B2+B7)
UBI	(NDBI-NDVI)

Table - 3: Correlation Matrix of 7 Indices dated February, 2010 of North 24 Parganas District, 2010

Raster	NDPI	NDVI	NDBI	NDBaI	SAVI	MNDWI	UBI
NDPI	1.0000	0.4446	0.8437	0.9737	0.4446	-1.0000	0.3587
NDVI	0.4446	1.0000	-0.0928	0.5191	1.0000	-0.4446	-0.6726
NDBI	0.8437	-0.0928	1.0000	0.7596	-0.0928	-0.8437	0.7992
NDBaI	0.9737	0.5191	0.7596	1.0000	0.5191	-0.9737	0.2513
SAVI	0.4446	1.0000	-0.0928	0.5191	1.0000	-0.4446	-0.6726
MNDWI	-1.0000	-0.4446	-0.8437	-0.9737	-0.4446	1.0000	-0.3587
UBI	0.3587	-0.6726	0.7992	0.2513	-0.6726	-0.3587	1.0000

Table - 4: Eigenvectors of the 7 Components of the 7 Indices of North 24 Parganas District, 2010

PCA's	NDPI	NDVI	NDBI	NDBaI	SAVI	MNDWI	UBI
PC1	0.5395	0.1361	0.3799	0.3923	0.2041	-0.5395	0.2438
PC2	0.0424	0.3957	-0.2508	0.0819	0.5936	-0.0424	-0.6465
PC3	0.0726	0.1941	0.3474	-0.8502	0.2912	-0.0726	0.1533
PC4	-0.4493	0.2321	0.4887	0.3415	0.3482	0.4493	0.2565
PC5	-0.0000	-0.8448	0.2582	0	0.3911	0	-0.2582
PC6	0.7071	0	0	0	0	0.7071	0
PC7	-0.0000	-0.1400	-0.6055	0	0.4970	0	0.6055

Table - 5: Principal Component Analysis of 7 Indices

Image 2010	PCA1	PCA2	PCA3	PCA4	PCA5	PCA6	PCA7
	59.56	39.91	0.45	0.08	0	0	0

Table - 6: The Calculated Variance of 7 Indices, 2010

Raster	NDPI	NDVI	NDBI	NDBaI	SAVI	MNDWI	UBI
NDPI	0.0493	0.0143	0.0333	0.0340	0.0214	-0.0493	0.0190
NDVI	0.0143	0.0209	-0.0024	0.0125	0.0313	-0.0143	-0.0232
NDBI	0.0333	-0.0024	0.0316	0.0224	-0.0036	-0.0333	0.0340
NDBaI	0.0359	0.0125	0.0224	0.0276	0.0187	-0.0359	0.0100
SAVI	0.0214	0.0313	-0.0036	0.0187	0.0469	-0.0214	-0.0349
MNDWI	-0.0493	-0.0143	-0.0333	-0.0359	-0.0214	0.0493	-0.0190
UBI	0.0190	-0.0232	0.0340	0.0100	-0.0349	-0.0190	0.0572

Source: All computations done by the authors

Table - 7: LU LC Classification Error Matrix based on OIF Bands of North 24 Parganas, 2010

LULC	Urban	Peri Urban	Rural	Water bodies	Wetland	Arable Land	Current Fallow	Bare Area	Mang rove	Total	Accuracy (%)
Urban	170	17	0	0	0	0	0	0	0	187	90.91
Peri urban	42	134	7	0	2	0	0	0	0	185	72.43
Rural	0	33	45	0	0	2	0	1	0	81	55.56
Water bodies	0	0	0	449	0	0	0	0	0	449	100
Wetland	0	1	0	0	492	0	0	0	0	493	99.80
Arable	0	0	0	0	0	473	10	0	0	483	97.93
Current Fallow	0	0	0	0	0	128	158	0	0	286	55.24
Bare area	0	0	0	0	0	0	0	228	0	228	100
Mangrove	0	0	0	0	0	0	0	0	532	532	100
Total	212	185	52	449	494	603	168	229	532	2924	
Accuracy (%)	80.19	72.43	86.54	100	99.60	78.44	94.05	99.56	100		
Overall Accuracy = 91.69 %						Khat Statistics = 90.34%					

Table - 8: LU LC Classification Error Matrix based on PCA's of 7 Indices of North 24 Parganas, 2010

LULC	Urban	Peri urban	Rural	Arabl e land	Current fallow	Bare area	Water bodies	Wetla nd	Mang rove	Total	Accuracy (%)
Urban	246	8	0	0	0	5	0	2	0	261	94.25
Peri urban	8	359	49	0	1	0	0	28	0	445	80.67
Rural	0	74	138	7	22	0	0	6	10	257	53.70
Arable	0	0	3	614	3	0	0	0	0	620	99.03
Current fallow	0	12	18	25	327	0	0	13	0	395	82.78
Bare area	0	1	0	0	0	597	0	0	0	598	99.83
Water bodies	0	0	0	0	0	0	1180	2	0	1182	99.83
Wetland	0	5	2	0	0	0	0	1202	3	1212	99.17
Mangrove	0	0	0	0	0	0	0	9	792	901	98.88
Total	254	459	210	646	353	603	1180	1262	805	5771	
Accuracy (%)	96.85	78.21	65.71	95.0	92.63	99.17	100	95.25	98.39		
Overall Accuracy = 94.52%					Khat Statistics = 93.60%						

Table - 9: LULC Categories of North 24 Parganas district, 2010

LULC	LULC on OIF Band (5,4,1)		LULC on PCA's of 7 Indices	
	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
Urban	300.71	7.21	340.1487	8.15
Peri urban	333.99	8.01	782.5014	18.77
Rural	860.45	20.64	513.7623	12.32
Water bodies	268.31	6.43	183.204	4.39
Wetland	775.66	18.60	1033.2999	24.78
Arable	491.26	11.78	31.5396	0.75
Current fallow	728.68	17.47	821.1834	19.69
Bare area	370.12	8.87	434.5398	10.42
Mangrove	39.64	0.95	28.7055	0.6
Total	4168.8	100	4168.88	100

Source: All computations done by the authors

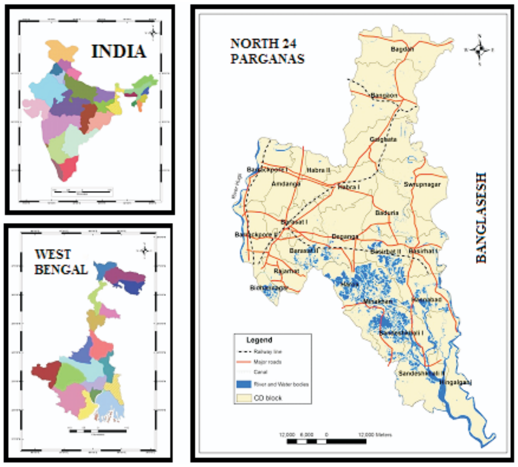

Fig.1: Location Map of the Study Area

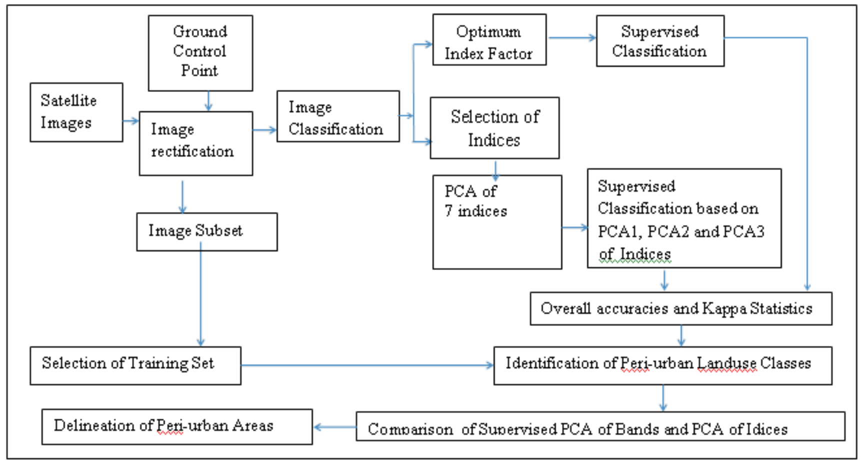

Fig. 2: Flow Diagram of Methodology

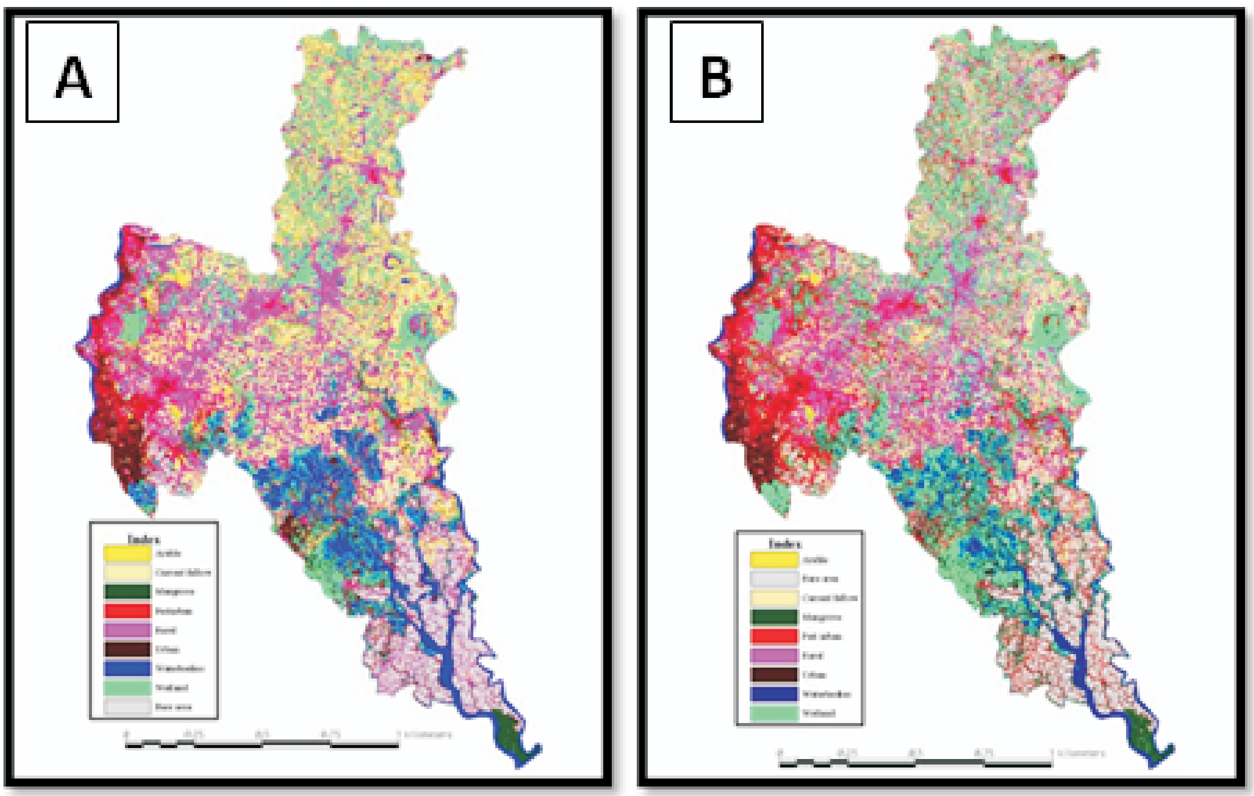

Fig. 3: Supervised LULC Map using (A) OIF Band Combination (B) PCA's of 7 Indices, North 24 Parganas District, 2010

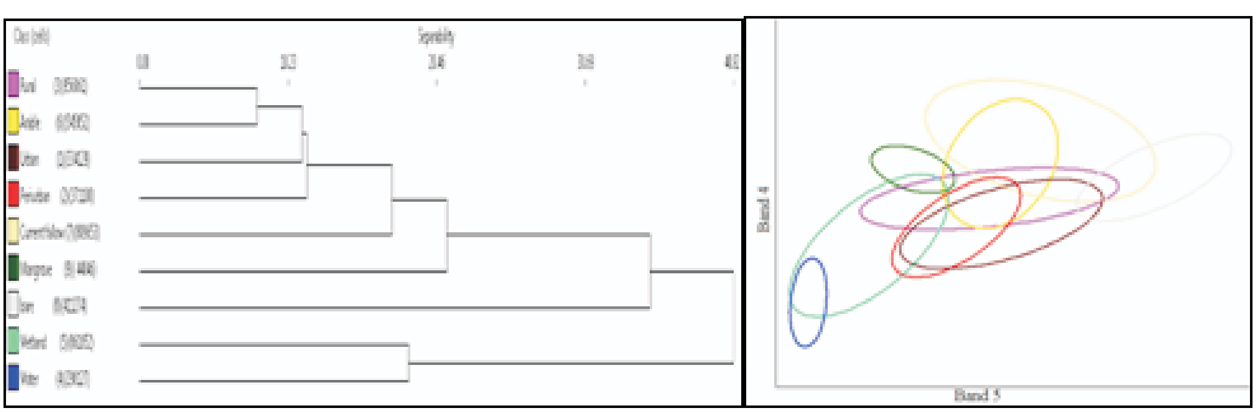

Fig. 4: Dendrogram and Spectral Plot of LULC based on OIF bands, 2010

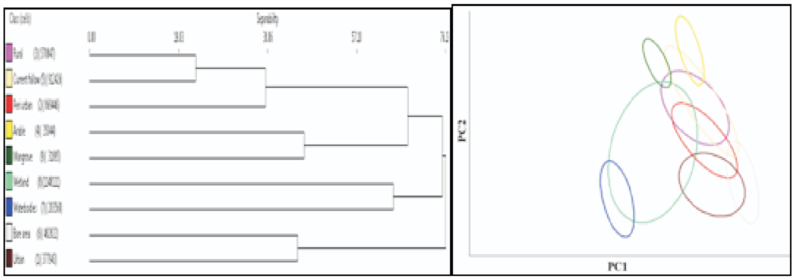

Fig.5: Dendrogram and Spectral Plot of LULC based PCA's of 7 Indices, 2010

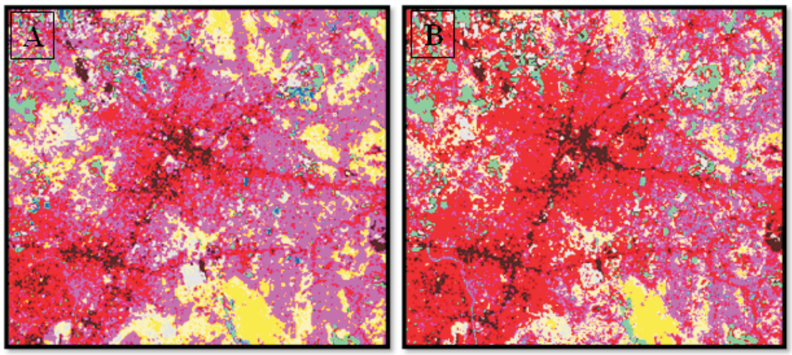

Fig. 6: Different LULC of Barasat (A) OIF Bands and, (B) PCA's of Indices, 2010

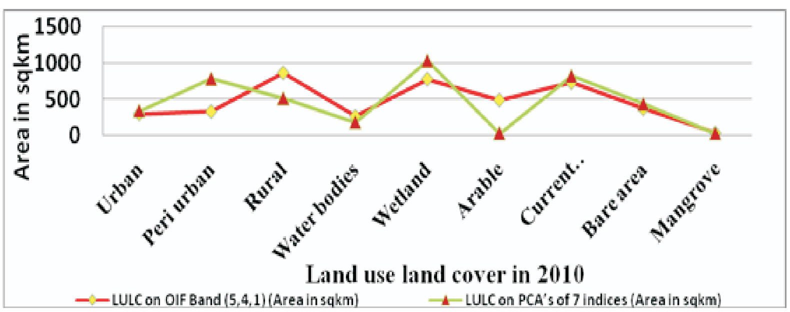

Fig. 7: LULC based on OIF and PCAs Combination, 2010

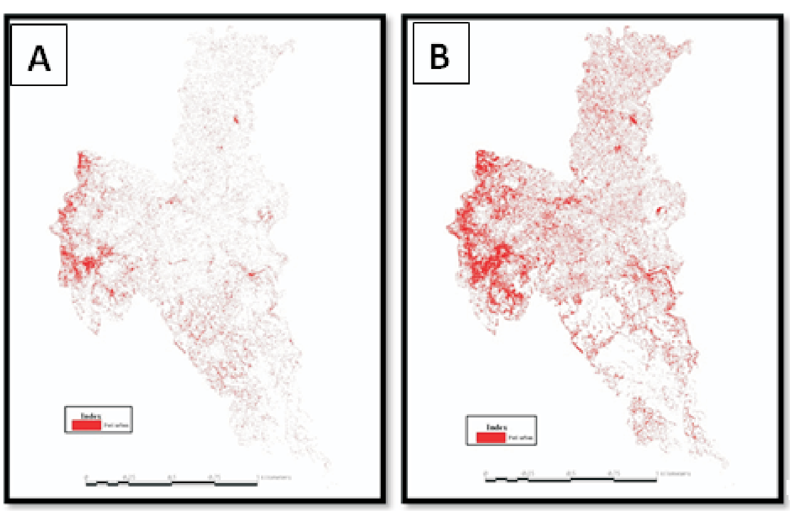

Fig. 8: Peri-urban Areas based on (A) OIF Bands, (B) PCA's of Indices, 2010

Jhantu Saradar
UGC-SRF
East Calcutta Girls' College
Kolkata, India - 700 089
Email: jhantusaradar@gmail.com

Dr. Sukla Hazra
Principal
East Calcutta Girls' College
Kolkata, India - 700 089
Email: ecgc_principal@rediffmail.com