

ASSESSMENT AND DETECTION OF LAND COVER CHANGES IN THE SOUTHERN FRINGE OF KOLKATA USING REMOTELY SENSED DATA

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ABSTRACT. Continual, historical, and precise information about the land use and land cover (LULC) changes of the Earth's surface is extremely important for any kind of sustainable development program, in which LULC serves as one of the major input criteria. In this study, a supervised classification was applied to five types of Landsat images collected over time (1980, 1990, 2000, 2010 and 2015) that provided recent and historical LULC conditions for the area. Four LULC categories were identified and mapped. Post-classification comparisons of the classified images indicated that the major change consisted of barren land changing into agricultural land. This analysis revealed that substantial growth of built-up areas in the south eastern part of Kolkata over the study period resulted in significant decrease in the area of water bodies, cultivated land, vegetation and wetlands. Urban land transformation has been largely driven by large number of population and high population growth rate with rapid economic and infrastructural development like the extension of metro railway, flyovers and hence huge real estate development.

KEY WORDS: Detection of Land Use and Land Cover Change, Sustainable Development, Urban Land Transformation, Substantial Growth

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INTRODUCTION

Urbanization is an inexorable process due to economic development and rapid population growth of an area. Encroachment of urban development in the agricultural areas may pose dire consequences such as land degradation and desertification (Shalaby et al. 2004). Urban growth is the movement of residential areas or commercial areas to the semi urban or rural areas. It has long been considered a sign of regional economic sustainability. Its benefits are increasingly balanced against the ecosystem impacts, including degradation of air and water quality and loss of agricultural tracts and socio-economic effects of economic disparities as well as regional disparities, social fragmentation and the cost of infrastructure (Squires 2002).

The rate of population growth is very high in developing countries rather than the developed countries. The population of urban areas is expected to exceed 60% by 2030, with 90% of the projected increase occurring in low income countries i.e. developing or under developed countries, which have urban settlements that are growing five times the rate of those in developed countries. The rapid changes of land use and cover, in the developing countries, are often characterized by rapid urban growth, land degradation, or the transformation of agricultural land to shrimp farming ensuing huge cost to the environment (Sankhala and Singh 2014). Land cover is dynamic and varies at different spatial and temporal scales (Cihlar 2000). Therefore, determining the trend and the rate

of land cover conversion are necessary for the development and planning in order to develop rational land use policy. For this purpose, the temporal dynamics of remote sensing data can play an important role in monitoring and analyzing land cover changes.

Geographic Information Systems (GIS) and Remote Sensing (RS) are very powerful and cost-effective tools for assessing the spatial and temporal dynamics of LULC (Lambin, et al. 2003; Serra et al. 2008). In case of developing countries satellite data are particularly useful due to the cost and time associated with traditional survey methods (Dong et al. 1997), and these techniques have become viable alternatives to conventional survey and ground-based urban mapping methods (Jensen et al. 2004). It is also the most common data source for detection, quantification, and mapping of LULC patterns and changes because of its repetitive data acquisition, digital format suitable for computer processing, and accurate geo-referencing procedures (Chen et al. 2005; Jensen 1996; Lu et al. 2004). Satellite data provide valuable multi-temporal data on the processes and patterns of LULC change, and GIS is very much essential for mapping and analyzing the patterns of LULC (Zhang et al. 2002). Retrospective and consistent synoptic coverage from satellites is particularly useful in areas where changes have been rapid (Blodget et al. 1991). Pre and post-classification comparisons have been extensively used (Coppin et al. 2004; Singh 1989). In the pre classification approach, procedures such as image differencing (Toll et al. 1980; Cohen and

Fiorella 1998); band rationing (Eastman et al. 2005), change vector analysis (Johnson and Kasischke 1998); Lu et al. 2005) vegetation index differencing (Townshend and Justice 1995). Post-classification comparisons of derived thematic maps go beyond simple change detection and attempt to quantify the different types of change. The degree of success depends upon the reliability of the maps made by image classification. Broadly speaking, large-scale changes such as widespread logging or major urban development might be mapped reasonably easily. Whereas evolutionary changes such as erosion, succession, colonization or degradation, the boundaries may be indistinct and class-labels uncertain (Foody and Boyd 1999); Khorram et al. 1999).

Change detection and monitoring by remote sensing involves the use of several multi-date images to evaluate the differences occurring in LULC between the acquisition dates of images that are due to various environmental conditions and human actions (Singh 1989). The successful use of satellite remote sensing for LULC change detection depends upon an adequate understanding of landscape features, imaging systems, and methodology employed in relation to the aim of analysis (Yang and Lo 2002). Many change detection techniques have been developed and used for monitoring changes in LULC from remotely sensed data. There are many techniques available to detect and record differences (e.g. image differencing, ratios or correlation) and these might be attributable to change (Singh 1989; Stow et al. 1996; Yuan et al. 1999). However, the simple detection of change is rarely sufficient in itself: information is generally required about the initial and final land cover or types or land uses, the «from-to» analysis (Khorram et al. 1999). Furthermore, the detection of image differences may be confused with problems in phenology and cropping, and such problems may be exacerbated by limited image availability and poor quality in temperate zones, and difficulties in calibrating poor images.

Change detection is useful in many applications related to land use and land cover (LULC) changes, such as shifting cultivation and landscape changes (Imbernon 1999; Serra et al. 2008), land degradation, land suitability and desertification (Adamo and Crews-Meyer 2006); Majumdar 2020); Gao and Liu (2010), coastal change and urban sprawl (Shalaby and Tateishi 2007), urban landscape pattern change (Batisani and Yarnal 2009); Dewan and Yamaguchi (2009); Long-qian et al. (2009), deforestation (Schulz et al. 2010; Wyman and Stein 2010), quarrying activities (Mouflis et al. 2008), and landscape and habitat fragmentation and other cumulative changes (Munroe et al. 2005; Nagendra et al. 2006).

Accurate and up-to-date land cover change information is necessary to understanding and assessing the environmental consequences of such changes (Giri et al. 2005). While remote sensing has the capability of capturing such changes, extracting the change information from satellite data requires effective and automated change detection techniques (Roy et al. 2002). Digital change detection is the process of determining or describing changes in land cover and land-use properties based on co-registered multi-temporal remote

sensing data. The basic premise in using remote sensing data for change detection is that the process can identify change between two or more dates that is uncharacteristic of normal variation. Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use change in a wide variety of environments (Chan et al. 2001; Muchoney and Haack (1994); Singh 1989).

In this article remote sensing and GIS techniques was applied with the aim of answering the question how the land use and land cover has changed in Rajpur Sonarpur Municipality from 1980 to 2015, 10 years interval.

STUDY AREA

Rajpur Sonarpur Municipality (Fig. 1) lies on the delta of the Hooghly River with a gentle slope. It is bounded in the north by the Kolkata Municipal Corporation, to the south by Baruipur Community Development (C.D.) Block, to the east and west by Sonarpur C.D. Block. This municipality is well connected with the head quarter of eastern railway of India (i.e. Sealdah station) by the different railway stations one of them (i.e. Sonarpur) is a junction station. Other important stations are Garia, Narendrapur, and Subhasgram. By these railway stations the commuters from south 24 parganas come to city for their daily work. This town is also well connected with the Eastern-Metropolitan By pass and it also provides easy connectivity from the Netaji Subhash International Airport. The Metro Railway line connects the municipality on the northern side through Kavi Subhash metro station, which is also terminal station of the existing metro railway route at present time. Rajpur Sonarpur Municipal area is surrounded by five outfalls viz. Adi Ganga, Kurigachhi Irrigation Channel, Tolly's Nullah, Srinagar Panchanna Gram Drainage Channel, and Rania Keorapukur Khal.

Rajpur Sonarpur Municipality comprises of 37 mouzas namely Harinavi, Kodalia, Rajpur, Malancha, Mahinagar, Jagaddal, Dhamaitala, Mallikapur, Baikunthapur, Bansidharpur, Ellachi, Ukhila-Paikpara, Barhans-Fartabad, Kumrakhali, Nischintapur, Chak-Harinavi, Manikpur, Balia, Kandarapur-Boalia, Tentulberia, Dhalua, Panchapota, Kusumba, Garagachha, Lashkarpur, Sripur-Bagher Ghola, Boral, Rania, Paschim-Nishintapur, Sonarpur, Ghasiara, Gorkhara, Kamrabad, Noapara, Tegharia, Chowhati, Jagannathpur. Total population of this municipality is 424368 comprising 35 wards with a growth rate of 26.03 between the years 2001–2011. In comparison with the Kolkata Metropolitan Area (KMA) the population growth rate of entire KMA is 10.30 according to Census 2011. This municipality is located in the suburbs of Kolkata city which has experienced very high growth rate i.e. 26.03 per cent (Majumdar and Sivaramakrishnan (2020). People from the surrounding areas migrate into this area which is the major cause of high growth rate of population. In order to provide better citizen services, amenities and infrastructural services for the inhabitants of this municipality, it has been divided (Table 1) into five local offices. Those are as listed below.

Table 1. Composition of Municipal Administration in Rajpur Sonarpur Municipality

Name of the Local Offices	Ward Number
Garia	1 to 7
Sonarpur	8 to 15
Rajpur	16 to 26
Mahamayatala	27 to 31
Baral	32 to 35

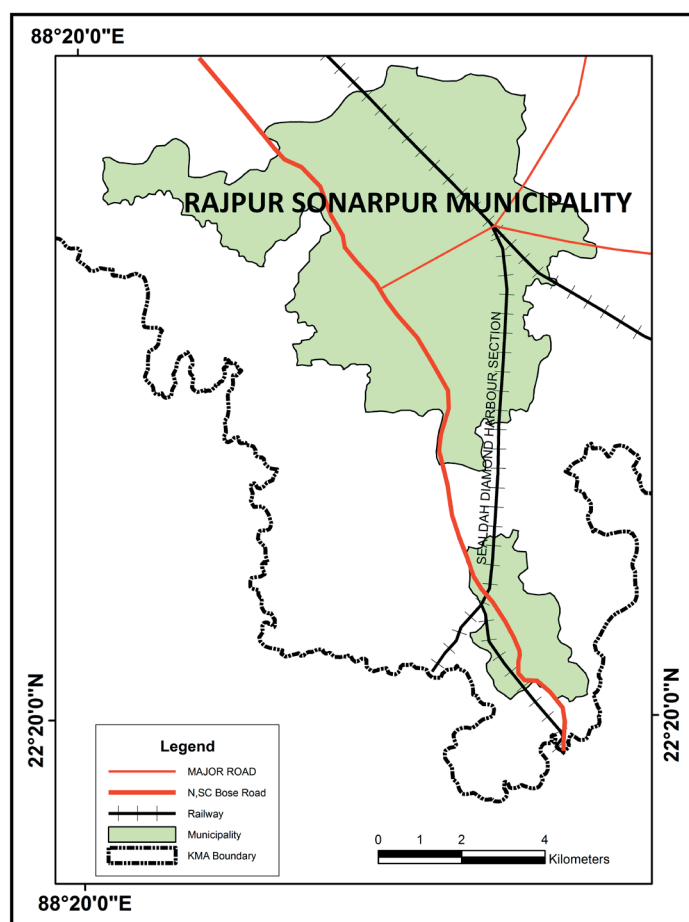


Fig. 1. Location Map of RajpurSonarpur Municipality

MATERIAL AND METHODS

The data set for this study is comprised of five Landsat images recorded from 1980 to 2015. Detailed description of those images discussed below (Table 2). The data has been chosen for 10 years interval because the Census of India is calculated in the interval of 10 years. By calculating 10 years interval time the researcher can easily correlate demographic characteristics (like population growth rate, density etc.) and land use land cover change of this area.

Five sets of landsat satellite images were used here. First, Landsat MSS, Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) images and two sets of OLI 8 images (with path/row 138/45). At the time of layer stacking of those images thermal band was excluded. Digital maps published from the RajpurSonarpur Municipality, has been digitized and geo-referenced from digital topographic maps with scale of 1:50,000 which has been published by the Census of India in 2010 under the Government of India. This map has been used as a reference image only for the geometric correction and geo-referencing of the municipal area. It has also been used for geometric correction of those satellite images

and to collect some ground truth information of that time period. Finally, ground information (for cross checking of the produced maps (like various types of land use and land cover information, number of water bodies or wetland in municipal area from 1980 to 2015) was collected between the years 1980 until 2015 to get land use/land cover information. Then supervised classification algorithm was used to scrutinize the land cover types.

Image Processing

The images were geometrically corrected and geo-referenced to the Universal Transverse Mercator (UTM) coordinate system by using a reference image which has been geo-referenced previously by the topographical sheets which were provided by the Survey of India (SOI). This minimum of 30 randomly distributed ground control points (GCPs) were selected from the topographical sheets for geo-referencing the image. Re-sampling technique was performed using a nearest neighbour algorithm technique. Image transformation technique was used with root mean square (RMS) error of 0.1 pixels indicating that the image was accurate to within one pixel.

Table 2. Detailed Information of Utilized Satellite Imagery

Satellite	Acquisition Date	Sensor	Spatial Resolution	Projection
Landsat 8	08-03-2015	OLI-TIRS	30m	WGS 84 UTM 45 N
Landsat 7	21-01-2010	TM	30m	
Landsat 7	17-11-2000	ETM+	30m	
Landsat 5	14-11-1990	TM	30m	
Landsat 3	21-02-1980	MSS	60m	

Source: US Geological Survey, 2015

Image Enhancement and Visual Interpretation

Image enhancement is basically the modification of image by improving clarity and visual interpretability of the remotely sensed image. The process of visually interpreting digitally enhanced imagery attempts to optimize the complementary abilities of the human mind and the computer. The mind is excellent at interpreting spatial attributes on an image and is capable of identifying obscure or subtle features. Generally these images are used for visual analysis while original images used for automated analysis. (Lillesand and Kiefer 1994; Eastman 2006). By the process of supervised classification five land use and land cover maps were produced. Some of the classes were spectrally confused in the image of 1980 because of very low resolution of image which is MSS imagery in nature. So it could not be separated well by supervised classification. For this reason visual interpretation technique has been used to separate them properly.

Image classification

Land cover classes are typically mapped from digital remotely sensed data through the process of a supervised digital image classification (Campbell 1987; Thomas et al. 1987). The overall objective of the image classification procedure is to automatically categorize all pixels in an image into land cover classes or themes (Lillesand and Kiefer 1994). The maximum likelihood classifier has been used because it quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel so that it is considered to be one of the most accurate classifier since it is based on statistical parameters.

Supervised Classification

Researcher used ERDAS IMAGINE 2014 software for digital image processing and image classification of the Landsat images described above. Training samples were selected for each of the predetermined LULC types by delimiting polygons around representative sites with the help of feature space tool. Using those polygons the researcher derived spectral signatures for the respective land cover types which are recorded on the satellite images. A spectral signature is considered to be satisfactory when confusion among the land covers to be mapped [is] minimal' (Gao and Liu 2010). After collecting spectral signatures image classification was done using maximum likelihood as a classification method.

Maximum likelihood algorithm is one of the common parametric classifiers used for especially in case of supervised classification. This algorithm is used for computing the weighted distance or likelihood (D) of unknown measurement vector (X) belonging to one of the known classes (M_c) which is based on the Bayesian equation (Mukhopadhyay et al. 2013).

$$D = \ln(a_c) - [0.5 \ln(\text{cov}_c)] - [0.5(X - M_c)T(\text{cov}_c^{-1})(X - M_c)]$$

The class is assigned with the unknown measurement vector in which it has the highest probability of belonging. The advantage of maximum likelihood algorithm is that it considers the variance covariance matrix with in the class distributions.

In case of normally distributed data, this performs better than the other known parametric classifiers, though the results may be unsatisfactory for the data not having normal distributions (Mukhopadhyay et al. 2013). It may be of two types parametric and non-parametric. By the supervised classification a raster layer i.e. the classified image and a distance file originates. Both the thematic layer and the distance file were used for post-classification thresholding. Four initial LULC maps were produced. Because these are the major land use land cover types of this area (Table 3).

Classification Improvement

Some LULC classes were spectrally confused because of mixing of different colours of pixels. So it could not be properly separated by supervised classification especially in the images of 1980. For instance, confusion between the deep water bodies and wetland in some portions of the area. Because in areas of discontinuous free water bodies, significant numbers of pixels were misclassified to the fallow class due to the existence of aquatic plants which are hydrophytes in nature. To improve the level of accuracy of the classified image and to reduce misclassifications, the researcher integrated the initial LULC maps resulting from supervised classification with the maps resulting from visual interpretation. Visual interpretation was very important for increasing classification accuracy and, consequently, the quality of the LULC maps produced. In case of MSS Landsat images, due to the low resolution image correction techniques were used. Finally, the researcher produced accurate LULC maps which was also compared with the reference data (the archived data, historical maps, topographic maps, and ground control points).

Classification Accuracy Assessment

Accuracy assessment method is very useful for individual classification when resulting data are used for the change detection analysis (Owojori and Xie 2005). Accuracy assessment technique was performed based on using a random sample method of more than 150 check points i.e. ground control points, old sketch maps, topographic maps as a referenced map in ERDAS Imagine 9.2 software to scrutinize the land use or land cover classes of the area.

Detection of LULC changes

Post Classification Comparison (PCC) method and change detection analysis were applied to compare and analyze the LULC maps resulting from the integration of the results of visual interpretation and supervised classification. PCC was employed to detect the differences between each pair of LULC maps (i.e., 1980 to 1990, 1990 to 2000, 2000 to 2010 and 2010 to 2015).

Fig.2. shows an overlay of Rajpur Sonarpur Municipality administrative boundaries in 1980, 1990, 2000, 2010 and 2015. The total urban areas for the five respective periods were estimated at 8.21, 10.80, 15.92, 21.67 and 23.22 (Table 4). Analysis of annual rate of change between the four periods (1980–1990), (1990–2000), (2000–2010), (2010–2015) showed that the area expanded by 52.5%, 84.5%, 136.1%, 62.8% respectively, with an average rate of 84% for the whole study period, from 1980 to 2015.

Table 3. Identified Classes by Supervised Classification

No	Land Use Classes	Description
1	Built-up Area	Residential, Commercial, Industrial, Roads, Railway, mixed urban or built-up area
2	Vegetation	Vegetative areas, Agricultural areas
3	Water body	Pond, Canal, Reservoir
4	Fallow land	Waste land, Fallow land

Change detection

Following the classification of imagery from the individual years, a multi-date post-classification comparison change detection algorithm was used to determine changes in land use and land cover in four intervals, 1980–1990, 1990–2000, 2000–2010, and 2010–2015. This is perhaps the most common approach to change detection (Jensen 2004) and has been successfully used by (Yang 2002) to monitor land use changes in the Atlanta, Georgia area.

Change detection accuracy assessment

Change detection presents unique problems for accuracy assessment since it is difficult to sample areas that will change in the future before they change. A concern in change detection analysis is that both position and attribute errors can propagate through the number of multiple dates. This is especially true when more than the two dates are used in the analysis. The simplest method of accuracy assessment of change maps is to multiply the individual classification map accuracies to estimate the expected accuracy of the change map (Yuan et al. 1999). A more rigorous approach is to randomly sample areas classified as change and no-change and determine whether they were correctly classified (Fuller et al. 2003).

Overall accuracy was calculated from the error matrix by dividing the sum of the entries that make major diagonal by the total number of examined pixels. Kappa co-efficient of agreement was also calculated by using following equations (Afify2011).

$$\hat{K} = p_o - p_c \div 1 - p_c$$

$$p_o = \sum_{i=1}^r P_{ii}$$

$$p_c = \sum_{i=1}^r P_i + P + i$$

Here,

r = The number of rows in the error matrix.

P_{ii} = The proportion of pixels in row 'i' and column 'i'.

P_{i+} = The proportion of the marginal total of row 'i'.

P_{+i} = The proportion of the marginal total of column 'i'.

RESULTS

Land use pattern in 1980

To scrutinize the land use pattern in 1980, the researcher first tried to focus on the Landsat MSS imagery for the year 1980. Different land use categories had been identified and used as past reference for the year 1980. Those identified land use pattern was verified in the ground truth verification. Because Prior ground verification knowledge is crucial to recognize the pattern of land use classes during supervised image classification. By applying the ground truth knowledge the researcher identified the pixel along with their color tone, texture to verify each land use category during the classification of image. The land use pattern which were categorized into four classes for the year are listed in Table 3 and shown in Fig. 2A total of 49.26 Sq.km. of land area was estimated for this municipality after the supervised classification. From the identified land use categories, the highest category was vegetation (53% of the total land area) and it is followed by fallow land (16.93% of the total land area), built up area (16.67% of the total land area) and waterbody (12% of the total land area) shown in Table 4.

In figure 2a, brownish patches indicates built up area which was more prominent in this municipal areas. The yellow color indicates fallow land which was high in this time period. In the eastern side the percentage of fallow land is relatively high than the other areas (Fig. 2a). In this period the percentage of fallow land is relatively high than the other periods which is because of low resolution of the image.

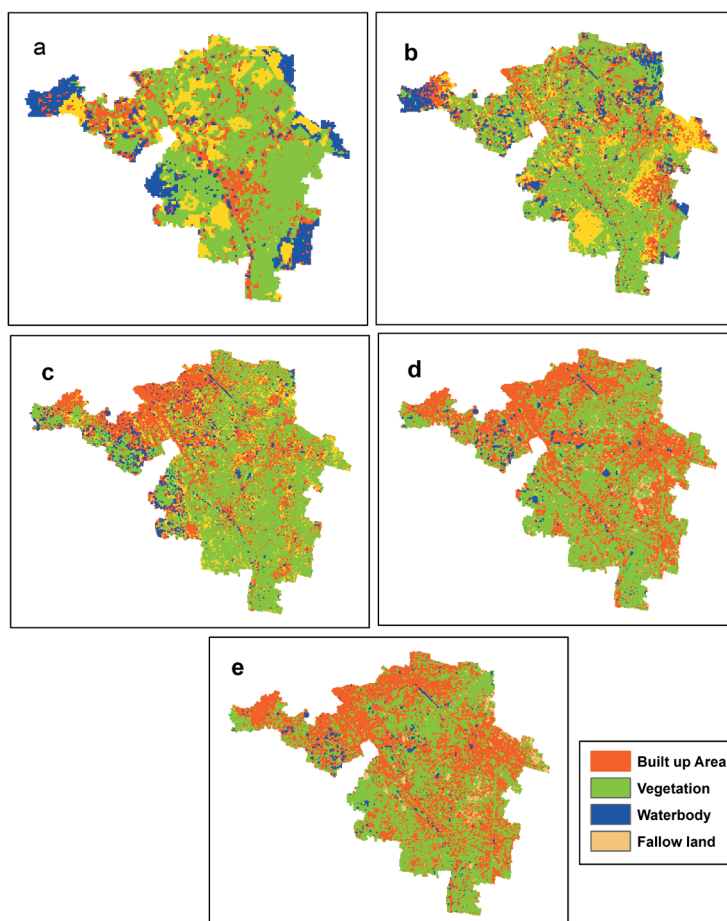


Fig. 2a. to 2e. LULC of RajpurSonarpur Municipality 1980–2015

Land use pattern in 1990

After 1990 land use classification, land use pattern of 1990 (Fig. 2b) was visually interpreted. A total of 4 land use categories were identified during 1990 image classification. Based on 1990 image classification results, the highest category was vegetation (24.72 sq.km. sharing 50% of total land area) followed by built up area, 10.80 sq.km. (22%) and fallow land 7.89 sq.km. (16%) and water body sharing 4.28 sq.km. (9%) respectively (Table 3 and 4). Advantageous location of the municipality, nearness to adjacent railway station i.e. Sonarpur and Subhasgram railway station, good market facility, both type of well-connected roads (Metalled and arterial roads) and good infrastructure facility were the main causes behind the growth of built up area.

Land use pattern in 2000

In 2000 (Fig 2c), built up area covered 32% of the study area, whereas vegetation, water bodies and fallow land accounted for 47%, 11% and 6% of the area respectively (Table 4). In this figure built up area is high in the north west portion. It is relatively high than the other areas which are because of accessibility from the city core areas by the N.S.C. Bose road. Beside these factors metro railway is another factor behind the huge population density of the region.

After the year 1993 different mouzas were added under this municipality's jurisdiction. After the addition of those panchayats, it has seen that right side of the railway track is denser than the left side. Because left side portion of the railway track is already highly dense from the past years. Land use pattern in 2010 and 2015

In 2010 (Fig. 2d), vegetation area accounted for 45.92% of the study area, whereas built up area, water bodies and fallow land covered 44.99%, 4.66% and 4.26% of the study area. But after the five years i.e. in the year 2015 (Fig. 2e),

majority (47%) of the study area was categorized as built up area and it is followed by vegetation, water bodies and fallow land i.e. 44%, 2% and 3% respectively (Table 4). The observed difference of the LULC classes of RajpurSonarpur area as shown in Table 5.

Relative Changes in Land Use in RajpurSonarpur

Relative change in land uses (percentage) of this municipality was assessed based on data presented in Table 6. The relative changes showed some irregular pattern in this study area from 1980 to 2015. Land use change from 1980–2015 showed negative changes in most of the categories except the built up area.

Around 6% of Natural vegetated area had decreased between 1990 to 2000 time period, while 30% of the wetlands or water bodies has been converted built up areas between these time period. Between the year 2000 to 2010 the percentage of Built up area has been increased into 36% while 55% of the wetlands or water bodies has been converted into fallow land or built up area. In the year 2015, 32% of the fallow land has been decreased due to urban growth. These are the consequences of huge urban growth in this area.

Classification and Change Detection Accuracy

Error matrices were used to assess classification accuracy and are summarized for all five years in Table 7a-7e. The overall accuracies for 1980, 1990, 2000, 2010 and 2015 were, respectively, 92.5%, 85%, 87.5%, 90% and 92.5%, with Kappa statistics of 87%, 77%, 78%, 81% and 86%. Users and producer's accuracies of individual classes were consistently high, ranging from 85% to 92%. Specially 1980, the resolution of the image was very low. To minimize the errors of the image, post classification comparison has been done among the classified images of 1990 and 1980.

Table 4. Trend of Land use and Land cover (sq.km.) in RajpurSonarpur Municipality

Year	1980	1990	2000	2010	2015
Built up area	8.21	10.80	15.92	21.67	23.22
Vegetation	26.02	24.72	23.23	22.62	21.86
Waterbody	6.14	4.28	2.96	1.31	1.21
Fallow land	8.34	7.89	5.67	2.10	1.42

Table 5. Trend of Land Use and Land Cover in RajpurSonarpur Municipality

Year	Percentage of Area in Sq.km					Changes of Area in Percentage			
	1980	1990	2000	2010	2015	1980–1990	1990–2000	2000–2010	2010–2015
Built up area	16.85	22.65	33.53	45.43	48.67	5.79	10.88	11.90	3.24
Vegetation	53.42	51.83	48.93	47.42	45.82	-1.58	-2.91	-1.50	-1.60
Waterbody	12.61	8.97	6.23	2.75	2.54	-3.63	-2.74	-3.49	-0.21
Fallow land	17.12	16.54	11.94	4.40	2.98	-0.58	-4.60	-7.54	-1.43

Table 6. Relative changes in the land use and land cover from 1980 to 2015

Land Use Categories	Changes in Area (Percentage)			
	1980–1990	1990–2000	2000–2010	2010–2015
Built up area	31.47	47.35	36.14	4.77
Vegetation	-4.99	-6.04	-2.61	-3.35
Water body	-30.37	-30.65	-55.59	-47.10
Fallow land	-5.42	-28.06	-62.86	-32.39

Table 7. Error matrix of LULC Classification

Sub-table 7a							
Error matrix showing accuracy and Kappa statistics of 1980 supervised land use classification							
Reference Data						PA (%)	UA (%)
Classified Data	Built up Area	Vegetation	Water Body	Fallow Land	Total		
Built up Area	9	0	0	0	9	100	100
Vegetation	0	22	0	0	22	100	80
Water Body	0	0	4	3	7	100	100
Fallow Land	0	0	0	0	0	40	100
Total	9	22	4	3	38		
Overall Accuracy = 92.50%, Kappa Statistics = 0.87							
Sub-table 7b							
Error matrix showing accuracy and Kappa statistics of 1990 supervised land use classification							
Reference Data						PA (%)	UA (%)
Classified Data	Built up Area	Vegetation	Water Body	Fallow Land	Total		
Built up Area	7	2	0	2	11	78	63
Vegetation	2	18	0	0	20	90	90
Water Body	0	0	3	0	3	100	100
Fallow Land	0	0	0	6	6	75	100
Total	9	20	3	8	40		
Overall Accuracy = 85%, Kappa Statistics = 0.77							
Sub-table 7c							
Error matrix showing accuracy and Kappa statistics of 2000 supervised land use classification							
Reference Data						PA (%)	UA (%)
Classified Data	Built up Area	Vegetation	Water Body	Fallow Land	Total		
Built up Area	0	0	0	2	2	87	87
Vegetation	13	0	0	1	14	100	87
Water Body	2	20	1	0	23	100	100
Fallow Land	0	0	0	1	1	25	100
Total	15	20	1	4	40		
Overall Accuracy = 87.50%, Kappa Statistics = 0.78							
Sub-table 7d							
Error matrix showing accuracy and Kappa statistics of 2010 supervised land use classification							
Reference Data						PA (%)	UA (%)
Classified Data	Built up Area	Vegetation	Water Body	Fallow Land	Total		
Built up Area	18	2	0	0	20	95	90
Vegetation	1	17	1	0	19	90	90
Water Body	0	0	0	0	0	-	-
Fallow Land	0	0	0	1	1	100	100
Total	19	19	1	1	40		
Overall Accuracy = 90%, Kappa Statistics = 0.81							
Sub-table 7e							
Error matrix showing accuracy and Kappa statistics of 2015 supervised land use classification							
Reference Data						PA (%)	UA (%)
Classified Data	Built up Area	Vegetation	Water Body	Fallow Land	Total		
Built up Area	0	3	0	0	3	100	87
Vegetation	19	17	0	0	36	85	100
Water Body	0	0	1	0	1	100	100
Fallow Land	0	0	0	0	0	-	0
Total	19	20	1	0	40		
Overall Accuracy = 92.50%, Kappa Statistics = 0.86							

Classification and Change Maps and Statistics

Change detection maps were generated for all five years (Fig. 3a to 3d) and the individual class area and change statistics for the five years are summarized in Table 4 and Table 5.

From 1980 to 2015, urban area increased approximately 15.01 Sq.km. while vegetation area decreased 4.17 Sq.km. (%), water body 4.93 Sq.km., and fallow land decreased 6.92 Sq.km. Relatively, urban and developed areas increased 8.21 Sq.km. to 23.22 Sq.km. from 1980 to 2015, with the greatest increase occurring from 1990 to 2000 i.e. 47% of the total change, while vegetation, water bodies and wetland decreased, respectively, 6%, 30% and 28%. But changes in vegetation, water bodies and fallow land was intensive from the year 2000 to 2010 i.e. 1.50%, 3.49% and 7.54% respectively (Table 5). To reduce this error image correction techniques was used. To further evaluate the results of land cover conversions, matrices of land cover changes from 1980 to 1990, 1990 to 2000, 2000 to 2010, and 2010 to 2015 were created (Table 8a to 8d). In the table, unchanged pixels are located along the major diagonal of the matrix. Conversion values were sorted by area. These results indicate that increases in urban areas mainly came from conversion of vegetated land and water bodies to urban uses during the twenty five year period, 1980–2015 (Table 8a to 8d).

From 2000 to 2010, 7.32 Sq.km. was converted from vegetated area and 2.97 Sq.km. from fallow land. While in 2010 to 2015, 5.26

Sq.km area was converted into built up area from the vegetated area, while at the same time, some portion of urban area was converted to forest. These changes may seem to be classification errors. But vegetated areas are among some of the most sought after areas for developing new housing. Roads and railway lines were generally classified as urban, but when urban trees along the streets grow and expand, the associated pixels may be classified as vegetation. The researcher notes that the changes from urban to forest occurred almost entirely near city streets and railway. This same thing also happened in some cases of water body areas. Because some time it falls under the vegetation areas because of the cover by hydrophytes. Classification errors may also cause other unusual changes.

In Table 8 the researcher examines more specifically the changes in cover type between 1980 and 2015 for the random sample of the correctly classified 200 change samples from the 300 change sites evaluated. Maximum percentage of land use change was «vegetation to urban» and «water bodies to urban». These percentages of change are similar to the results of the change detection from the Landsat classifications of the entire area. Relatively rare and unlikely types of conversions, such as fallow land to water body, and then to urban areas and urban to vegetation, and then to urban area, totaling 5%, are assumed to largely be classification errors.

Table 8. Matrices of LULC changes from 1980–2015

Matrices of Land Cover and Changes (Sq.Km.) from 1980 to 1990					
a. 1980–1990 1990	1980				
	Built up Area	Vegetation	Water Body	Fallow Land	1990 Total
Built up Area	1.84	0	0.7	0.8	10.81
Vegetation	5.18	14.66	1.44	4.33	24.73
Water Body	1.55	1.93	1.41	0.91	4.28
Fallow Land	2.21	3.37	0.71	1.84	7.89
1980 Total	8.22	26.03	6.15	8.34	49.26
Matrices of Land Cover and Changes (Sq.Km.) from 1990 to 2000					
b. 1990–2000 2000	1990				
	Built up Area	Vegetation	Water Body	Fallow Land	2000 Total
Built up Area	5.42	3.55	0.33	1.44	15.92
Vegetation	5.9	15.25	1.23	2.21	23.24
Water Body	1.1	1.83	0.88	0.42	2.97
Fallow Land	2.4	3.75	0.12	1.57	5.68
1990 Total	10.81	24.73	4.28	7.89	49.26
Matrices of Land Cover and Changes (Sq.Km.) from 2000 to 2010					
c. 2000–2010 2010	2000				
	Built up Area	Vegetation	Water Body	Fallow Land	2010 Total
Built up Area	10.84	3.53	0.14	0.46	21.68
Vegetation	7.32	15.91	0.92	0.93	22.63
Water Body	0.55	1.27	0.76	0.03	1.32
Fallow Land	2.97	1.92	0.09	0.7	2.11
2000 Total	15.92	23.24	2.97	5.68	49.26

Matrices of Land Cover and Changes (Sq.Km.) from 2010 to 2015					
d. 2010–2015 2015	2010				
	Built up Area	Vegetation	Water Body	Fallow Land	2015 Total
Built up Area	16.9	4.19	0.19	0.39	23.23
Vegetation	5.26	16.34	0.39	0.64	21.87
Water Body	0.23	0.41	0.64	0.04	1.21
Fallow Land	0.83	0.93	0	0.35	1.42
1990 Total	21.68	22.63	1.32	2.11	49.26

DISCUSSION

Although similar statistics could be generated for other units such as county, township, or census tract, etc., the above change statistics shed little light on the question of where land use changes are occurring. However, by constructing a change detection map (Fig. 3a to 3d), the advantages of satellite remote sensing in spatially disaggregating the change statistics can be more fully appreciated. Fig. 3a to 3e shows a map of the major land cover types and the conversion from semi urban to urban uses. Built up area, vegetation and water bodies representing maximum percentage of the total area, are the three major land cover types in this municipality. Conversions involving these three classes also represent the most significant changes. Urban growth and the loss of vegetation land were the most important conversions in this area. Although Fig. 3a to 3e only displays the changes from vegetation, water bodies and fallow land to urban, other changes can also be

mapped. The urban growth occurred to the west (Harinavi area), towards eastern side (towards the railway station), and south (Subhashgram railway station area) directions. Whereas growth towards the northern side was limited by the influence of Kolkata Municipal Corporation (Fig. 1). The southward expansion and the westward expansion was the highest and is attributed to the presence of the Sonarpur and Subhashgram railway station and because of the availability of abundant flat vacant land which was suitable for housing construction. A major road named Eastern Metropolitan By pass connecting the airport with Kolkata city is also passing through the Rajpur Sonarpur Municipality in this area.

In summary, information from satellite remote sensing can play a significant role in quantifying and understanding the nature of changes in land cover and where they are occurring. Such information is essential to planning for urban growth and development.

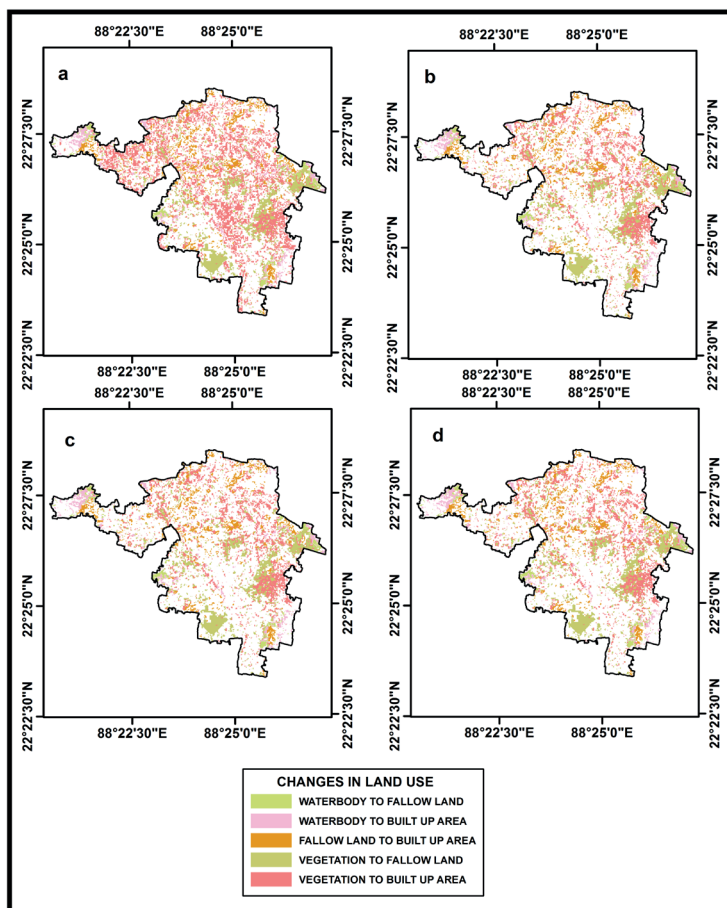


Fig. 3a. to 3d. showing changes in the LULC from 1980 to 2015; Fig. 3a showing the changes of land use between 1980 to 1990, Fig. 3b showing the changes of land use between 1990 to 2000, Fig. 3c showing the changes of land use between 2000 to 2010, Fig. 3d showing the changes of land use between 2010 to 2015

Fig. 3a to 3d showing changes in the LULC from 1980 to 2015; Fig. 3a showing the changes of land use between 1980 to 1990, Fig. 3b showing the changes of land use between 1990 to 2000, Fig. 3c showing the changes of land use between 2000 to 2010, Fig. 3d showing the changes of land use between 2010 to 2015.

CONCLUSION

The objective of the study were to provide multi-temporal land cover map and its change analysis in the last twenty five years. The study area has undergone a very severe land cover changes as a result of large residential projects and good infrastructural facilities. It leads into high population growth which results into the increases in built up areas. Due to this reason vegetation, wetland and fallow land decreases rapidly. This also demonstrates that supervised classifications of the landsat imageries can be used to produce accurate landscape change maps and future planning of the area. General patterns and trends of land use change in Rajpur Sonarpur Municipal Area were evaluated by: (1) classifying the land, it has been found

that agricultural tracts, vegetation and wetland were converted into urban land during the periods from 1980 to 2015; (2) comparing the results of multi temporal Landsat-derived statistics to estimates from other inventories; (3) quantitatively assessing the accuracy of change detection maps by kappa statistics or khat statistics. By this study the changes and pattern of land use and land cover has been identified. After land use and land cover analysis, it has been found that most of the land use and land cover in this area has been transformed in to urban area or built up area in this time period which creates extreme pressure in the local land resources and ecosystem. This study will help to identify the major urban land use change patterns in relation to policy making and planning, transportation and population growth for the sustainable development of the area. The results quantify the land cover change patterns of this municipal area and demonstrate the potential of multi temporal Landsat data to provide an accurate, economical means to map and analyze changes in land cover over time that can be used as inputs to land management and policy decisions. ■

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