

**CHANNEL MIGRATION AND RESULTANT LAND USE DYNAMICITY
OF AN ALLUVIAL CHANNEL USING GEOSPATIAL TOOLS: A STUDY
ON THE RAIDAK-I RIVER BUFFER ZONE, COOCH BEHAR, WEST
BENGAL**

Md Hasanuzzaman^{1*} and Professor Sujit Mandal²

¹Research Scholar, Department of Geography, University of Gour Banga

²Professor and Head, Department of Geography, Diamond Harbour Women's University.

*Corresponding Author

ABSTRACT

Changes in Land use Land cover is a dynamic process taking place on the surface and it become a central component in current strategies in managing natural resources and monitoring environmental changes. Remote sensing data under GIS domain were utilized to evaluate the changes in land-use/land-cover (LU/LC) spanning a period of 1975 to 2016 along the Raidak-I River channel, Cooch Behar, West Bengal. In this paper, LANDSAT 2 MSS and LANDSAT 5 data for 1975 and 1996 and also LANDSAT 8 OLI 2016 have been used. Seven different types of LU/LC were categorized and out of them open forest was evident as the most important landuse/landcover practices followed by agriculture land in 1975 and the settlement in 2016. Significant reduction (0.29%) in open forest area to agriculture land and builtup area were observed. The change rate of the sandbar is -0.034% which indicates the land use extension due to agriculture and human constructions. It is believed that the present study will help to contribute towards sustainable land-use planning and management towards protection of extremely rich biodiversity of the North East India with mighty Brahmaputra River system.

Keywords: Channel Migration, Geospatial Tools, Land Use, Land Cover, Agriculture Land, Cooch Behar, West Bengal

1. INTRODUCTION

The land is the most significant natural phenomena which are based on all activities. Land use without geology is seasonally dynamic and in fact, it is more changing variable. With the increase of population and human activities, the demand for limited land and soil resources for

urban and industrial land, agriculture, pasture, and forestry is increasing. Land resource usage rates and types of changes related data and knowledge are essential for proper management, planning, and development. Different techniques have been effectively used in the land use and land cover classification and identification of changes, e.g., pixel-based classification (Foody, 1996; Duda et al., 2001), artificial neural network classification (Kanellopoulos et al., 1992; Liu et al., 2004), object-oriented classification (Geneletti and Gorte, 2003; Elmqvist et al., 2008), visual interpretation (Liu et al., 2005) and post-classification comparison change detection (Serra et al., 2003). Remotely sensed data is useful to study the land use and land cover change in less time, with low cost and good accuracy. Remote sensing and GIS provide efficient methods and tools for analyzing land use planning and modeling land use dynamicity. Satellite data analysis, including data on drainage, lithology, and LULC are used for the functional evaluation of landform. This dataset is the core of GIS which provides an excellent way to analyze and interpret spatial data. This data also provides a strong mechanism that is not only for the observation of degradable land and environmental changes but also allows the analysis of other environmental changes.

India is facing an important problem of natural resource crisis, especially in view of population growth and economic development. LULC defines quantity and territorial distribution of land and is understood to be a very importance in the study of environmental changes at various scales. Also, such a research provides a significant tool to increasing land use ability and reduces the negative environmental and social impact to LULC. In this study, the introduced approach was applied to investigate the LULC changes for a 41 year period at Raidak-I River sounding area in the Himalayan foothill. The study area is characterized by rapid constriction, deforestation, river migration and as a result, LULC change. Remote sensing images and GIS, recent land use and land cover changes have the main opportunities to highlight the current trends for the transfer of different types of land feature. This study seeks to contribute to an informative background of future researchers' work, the impact of policies and strategies, directing, leading to a sustainable management of the area.

2. STUDY AREA

The Raidak River is one of the main right bank tributaries of the Brahmaputra River. It is a trans-boundary river and flows through countries like Bhutan, India and Bangladesh. The river rises in the Himalayas and is known as Thimphu Chhu in its upper reaches. It passes through various mountains and valleys in Bhutan. In its journey it is joined by several small tributaries flowing from nearby mountains. The river is known as the Wong in its upper course in Bhutan. The river after traversing through the mountainous terrain in Bhutan comes back to the plains in India, into the plains in Alipurduar district and then flows through Cooch Behar district in the

state of West Bengal. After flowing in the Indian subcontinent, the river enters Bangladesh. The Raidak River merges with the Brahmaputra River within the nation limits of Bangladesh. The confluence takes place at the chainage of 327 km.

Among the three course of river Raidak, middle one is old Raidak, western flow is named as Raidak-I or Deepa Raidak and lastly the eastern one is named as Raidak-II. The name of middle flow signifies that old Raidak is the ancient course of the Raidak River. The study area river Raidak-I is located in between two district of West Bengal, which are Cooch behar and New Alipurduar. The region is situated between 26° 34' 30.18'' to 26° 12' 57.58'' North latitude and 89° 43' 12.12'' to 89° 41' 38'' East longitude. Length of the river in the study area is 81.9 km.

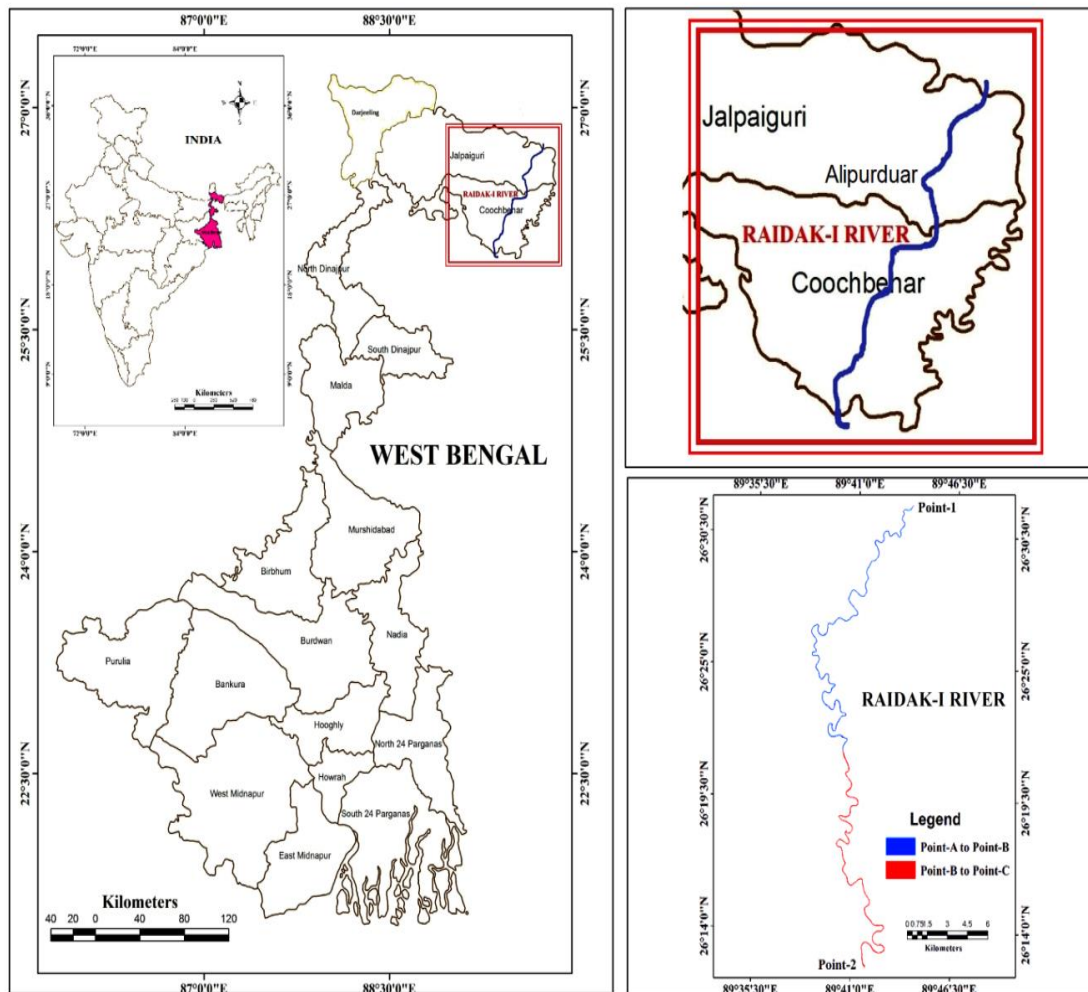


Fig. 1: Location map of Raidak-I River.

3. DATA AND METHODOLOGY

In this study, LANDSAT 2 MSS and LANDSAT 5 data for 1975 and 1996 and also LANDSAT 8 OLI 2016 have been acquired from the US Geological Survey (<http://earthexplorer.usgs.gov/>). The acquired satellite data were already georeferenced to Universal Transverse Mercator (UTM) zone 46 N projection using WGS-84 datum (Table 1). For geometric error correction and ground truth verification of the satellite images and classification have done using 135 points collected with the help of Global Positioning System (GPS), and secondary data from Google Earth Pro software and topographic maps. In this work, for image analysis have been used two commercial software’s Arc GIS 10.2 and ERDAS 9.2 software.

Table 1: Landsat satellite data specifications.

Satellite images	Years	Spatial Resolution	Source
LANDSAT_2- MSS	1975	60x60 meter	(http://earthexplorer.usgs.gov/)
LANDSAT_5-TM	1996	30x30 meter	(http://earthexplorer.usgs.gov/)
LANDSAT_8-OLI-TIRS	2016	30x30 meter	(http://earthexplorer.usgs.gov/)

3.1 Image classification

In this study, to assess LULC changes a modification of the Anderson Scheme Level I approach has been applied (Anderson, Hardy, Roach, & Witmer, 1976). Seven separate LULC types were identified: water body, sand bar, dense forest, open forest, agriculture land, built-up area, and lowland (Table 2).

Table 2: Classes delineated on the basis of supervised classification

Class no.	Land use/Cover Types	Description
1	Water body	River, permanent open water, lakes, ponds and reservoirs.
2	Sand bar	Point bar and char land along the river.
3	Dense forest	Very deep forest area.
4	Open forest	Trees, grassland and scrub area.
5	Agriculture land	Cropland, orchards, vineyards, nurseries.
6	Built-up area	Residential, commercial and services, transportation, roads.

7	Lowland/wetland	Abandoned meandering channel, seasonal wetlands, low-lying areas, marshy land, rill and gully, swamps.
---	-----------------	--

Pre-classification of the satellite images and all the satellite images were studied using spatial and spectral profiles to determine digital numbers (DNs) of different LULC classes. Forty to fifty training sites, between in size from 120 to 4900 pixels, were used to train the satellite images. The training samples were then renamed, refined, merged and deleted after class histograms and statistical parameters. The maximum likelihood classification was incorporated for performing supervised classification. Post-classification synthesis was used to improve the accuracy of the image classification because it is an easy and effective method.

3.2 Accuracy Assessment

Accuracy assessment was made through an error or confusion matrix. A confusing matrix formulation data’s about the ground truth and predicted classifications done by a classification system (Czaplewski, 1992; Prisley and Smith, 1987; Yuan, 199; Hay, 1988; Van Deusen, 1996; Jupp, 1989). Total 135 sample points from ground verification and Google Earth were selected for accuracy evaluation. The classified pixel from the satellite image was compared to the same point in the field. The accuracy evaluation results generally formulate users with an overall accuracy of the map and the accuracy for each class in the map. The following formula used for accuracy assessment:

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels (diagonal)}}{\text{Total number of refernce pixels}} \times 100 \dots\dots\dots 6.1$$

In addition to overall accuracy, the classification accuracy of the separate class is calculated in the same manner. The two techniques are user’s accuracy and producer’s accuracy (Story and Congalton, 1986; Lunetta et al., 2001; Khorram, 1999; Zhou et al., 1998). Producer’s and user’s accuracy evaluated using following formula:

$$\text{User’s accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the row total)}} \times 100 \dots\dots\dots 6.2$$

$$\text{Producer’s accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of refernce pixels in that category (the column total)}} \times 100 \dots\dots 6.3$$

Another measurement used in this work is the Kappa coefficient (Ma and Redmond, 1995; Foody 1992). It is calculate by following formula:

$$\text{Kappa Coefficient} = \frac{(\text{Total no. of Sample} \times \text{Total number Correct Sample}) - \sum(\text{Column total} \times \text{Row total})}{\text{Total no.of Sample}^2 - \sum(\text{Column total} \times \text{Row total})} \times 100$$

.....6.4

The kappa values ranging between 0 to 1. The values 0.4 represent poor/very poor classification, 0.4 to 0.55 represent fair classification, 0.55 to 0.7 represent good classification, 0.7 to 0.85 represent very good classification, and above 0.85 represent the excellent classification of satellite images (Monserud and Leemans, 1992).

3.3 Change detection

Between 1975 and 1996 and 1996 and 2016, cross-tabulation was used to compare two different time-level classified images to determine the qualitative and quantitative aspects of the change of time (Weng, 2001). The mathematical information of overall LULC change with the profit and loss in every class between 1975 and 1996 and 1996 and 2016 were then compiled.

4. RESULT AND DISCUSSION

According to dominant LULC and the interest of study, seven classes have been developed. Some other LULC classes could have been developed but their proportions are not clearly reflected. The unnecessary pixel is included in the neighbouring category within the system. Finally, classification of the images became seven major LULC features classes of Raidak-I river buffer zone and its circumference for the year 1975, 1996 and 2016 (Fig.2).

Table 3: Total areas (Hectares) of land use and land cover different classes.

LULC classes	1975	1996	2016
Water body	14.652	9.086	7.878
Sand bar	9.202	4.274	5.572
Dense forest	9.17	5.424	3.057
Open forest	80.92	108.184	112.042
Agriculture land	40.162	52.049	50.103

Built-up area	53.388	60.97	62.452
Lowland/lowland	54.439	25.704	20.586

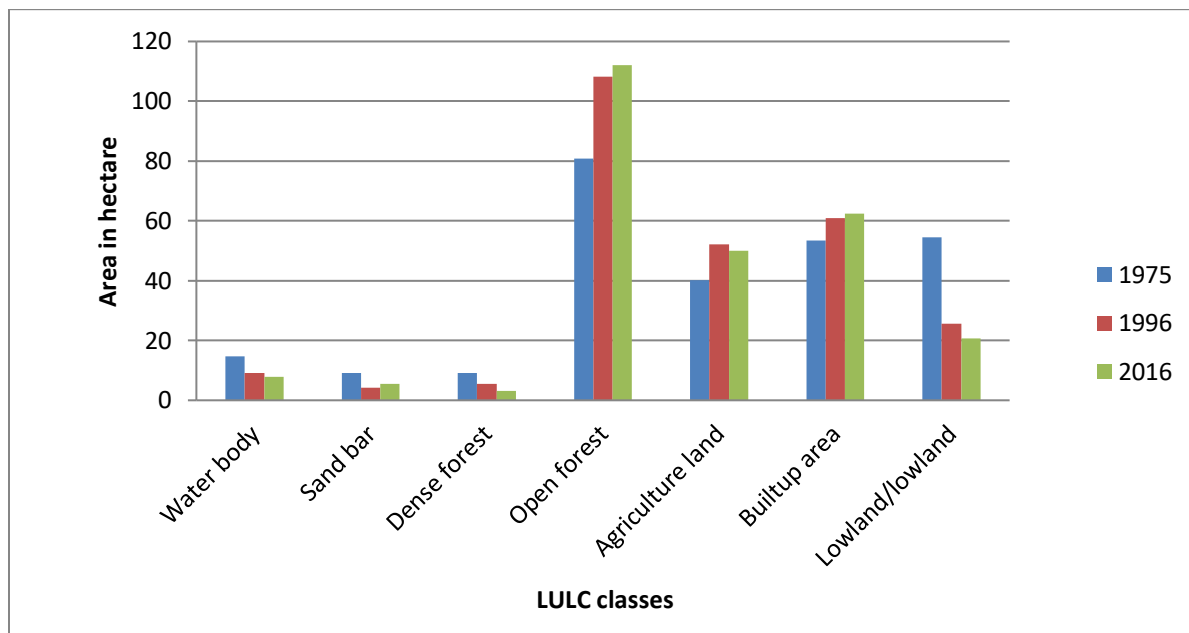
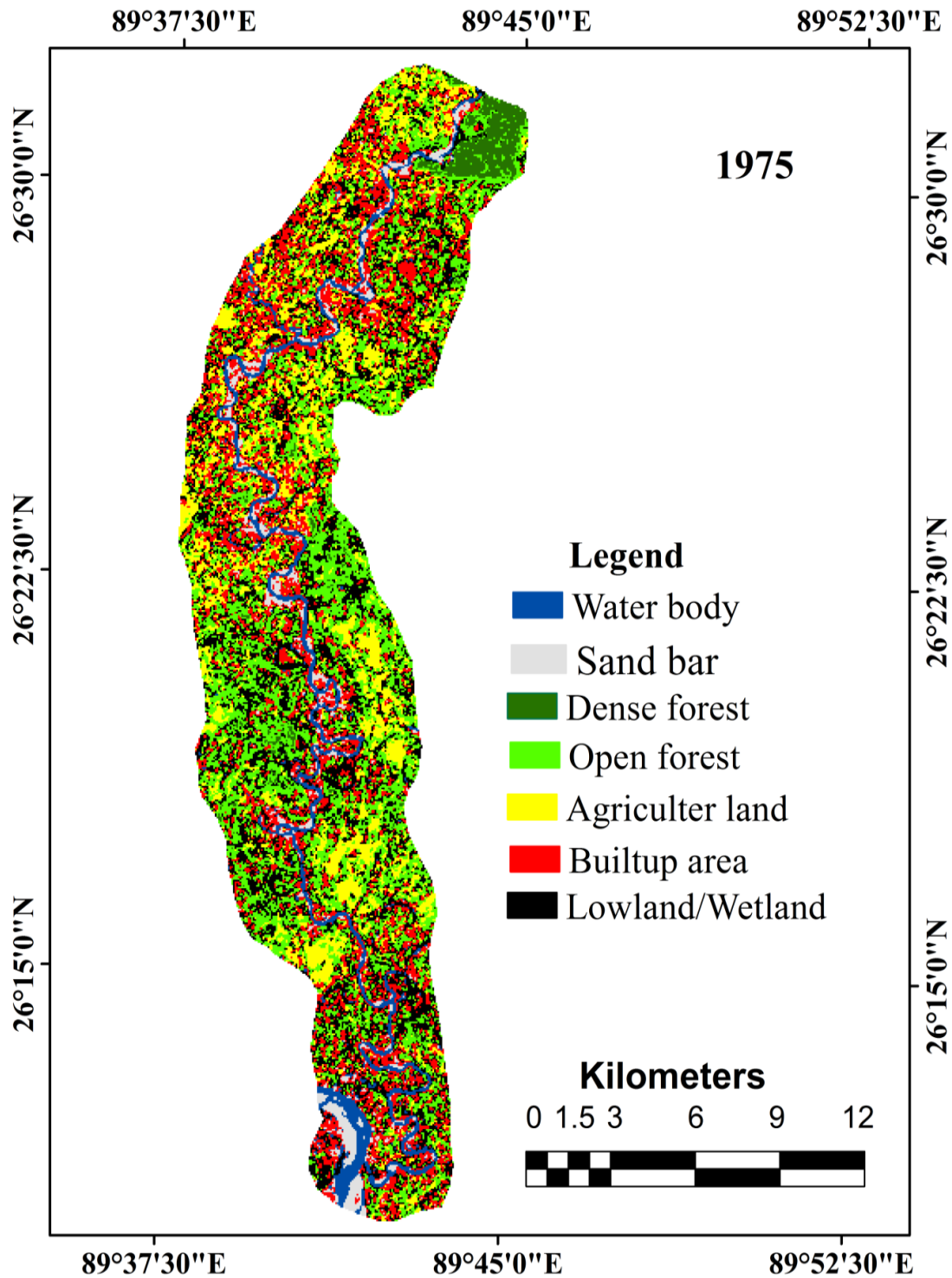
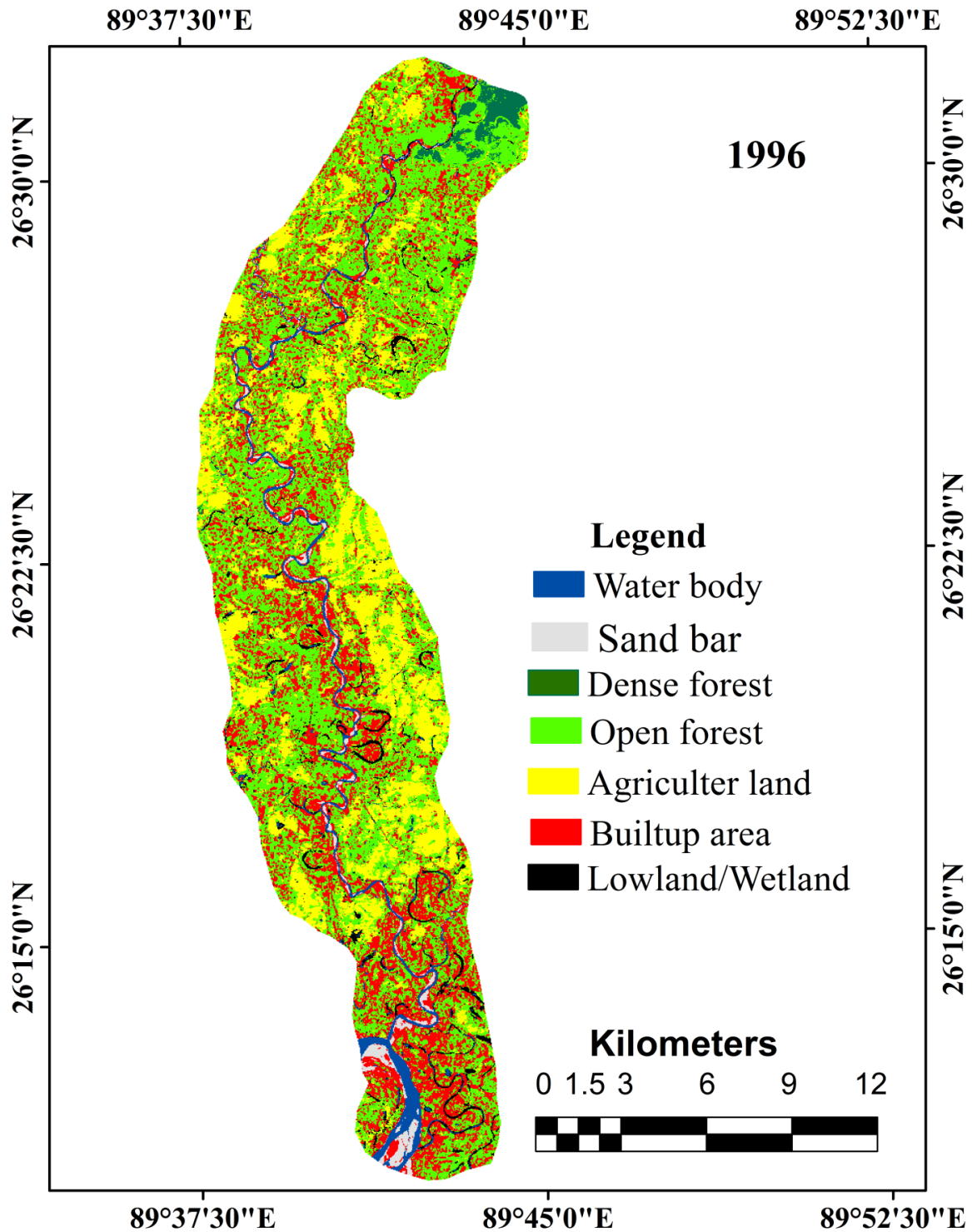


Fig. 2: Classes delineated on the basis of supervised classification.

The tabulations and area calculations depict an extensive data set and information area under various LULC, area transformation of LULC, transformation rate, increasing and decreasing trend of LULC (Table 3). The LULC in an area gives an idea of overall spatial utilization of natural and cultural resources. In this study, changes in LULC of Raidak-I River buffer area were assessed from the differences between 41 years of period (1975-2016). The table 6.2 depicts seven classes of LULC i.e. Water body, sand bar, dense forest, open forest, agriculture land, built-up area, and low/wetland. It is calculated from the table 6.4 that in the year 1975 the area was dominated by open forest (30.89%), followed by lowland/wetland (20.78%), built-up area (20.38%), agriculture land (15.33%), water body (5.59%), sand bar (3.51%), and dense forest (3.50%). In the year 1996, open forest covered 40.72%, built-up area 22.95%, agriculture land 19.59%, lowland/wetland 9.67%, water body 3.41%, dense forest 2.04%, and sand bar 1.61%. Moreover in the recent year 2016, open forest covered 42.81%, built-up area 23.86%, agriculture land 19.15%, lowland/wetland 7.87%, water body 3.01%, sand bar 2.13%, and dense forest 1.17%.





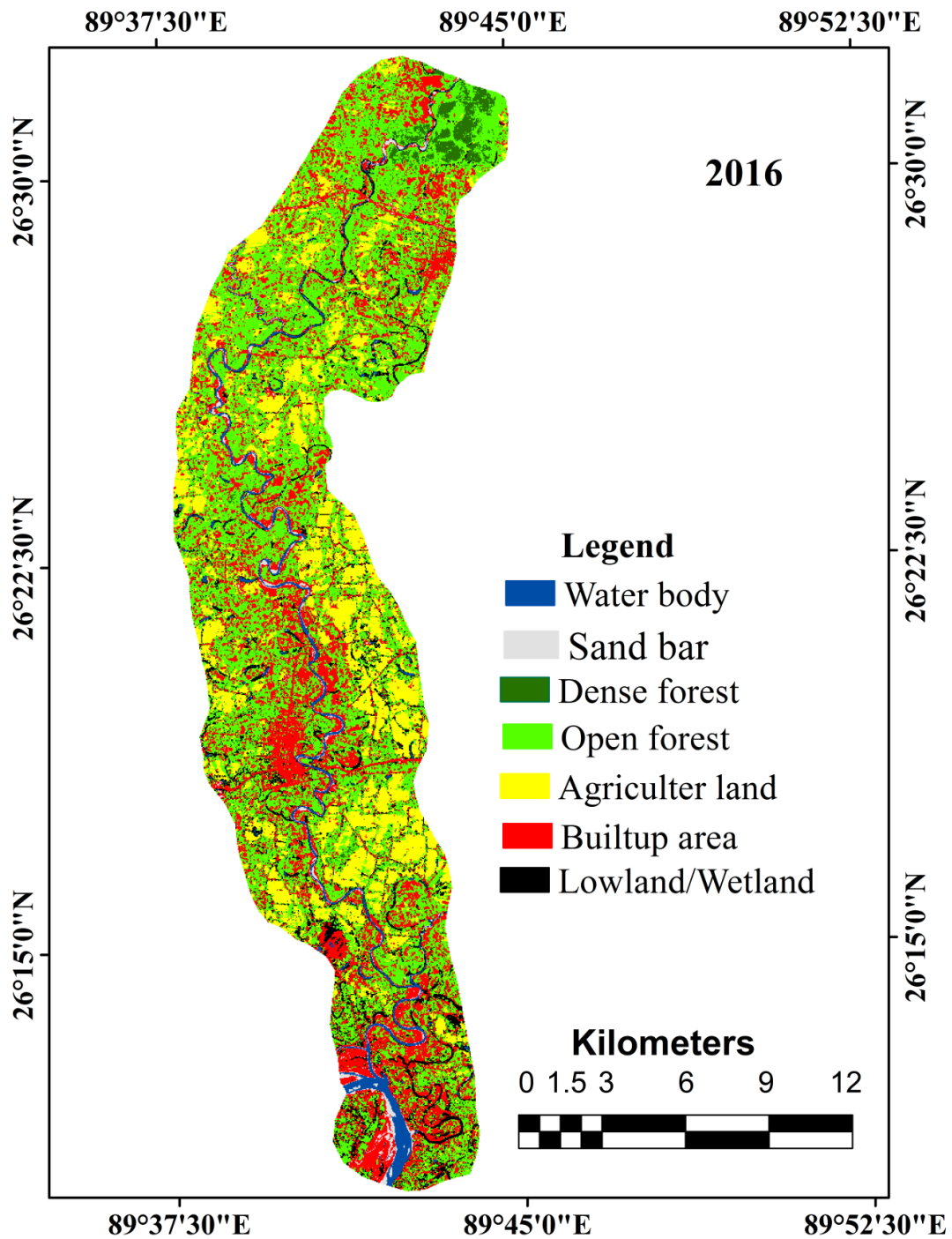


Fig. 3: Classified land use and land cover maps of Raidak-I River buffer zone in 1975, 1996 and 2016.

Table 4: Land use and land cover change detection of different classes.

LULC classes	1975 (Area in ha)	% of total area	1996 (Area in ha)	% of total area	Change 1996- 1975	2016 (Area in ha)	% of total area	Change 2016- 1996	Change rate 2016- 1975
Water body	1465.2	5.59	908.6	3.41	-2.18	787.8	3.01	-0.4	-0.06
Sand bar	920.2	3.51	427.4	1.61	-1.9	557.2	2.13	0.52	-0.034
Dense forest	917	3.5	542.4	2.04	-1.46	305.9	1.17	-0.87	-0.057
Open forest	8092	30.89	10818.4	40.72	9.83	11204.2	42.81	2.09	0.29
Agriculture land	4016	15.33	5204.9	19.59	4.26	5010.3	19.15	-0.44	0.093
Built-up area	5338.8	20.38	6097	22.95	2.57	6245.2	23.86	0.91	0.085
Lowland/wetland	5443.9	20.78	2570.4	9.67	-11.11	2058.6	7.87	-1.8	-0.31

The study area is not an urbanized region. It is a blending area of open forest, lowland/wetland, and agriculture land. Open forest is the dominant feature class and it is also gradually increasing (rate of change 0.29%) because dense forest and lowland are converted into open forest.

Table 5: Rate of change of LULC classes in 2016-1975.

LULC Classes	Change Rate 2016-1975 (%)
Water body	-0.06
Sand bar	-0.034
Dense forest	-0.057
Open forest	0.29
Agriculture land	0.093

Built-up area	0.085
Lowland/Wetland	-0.31

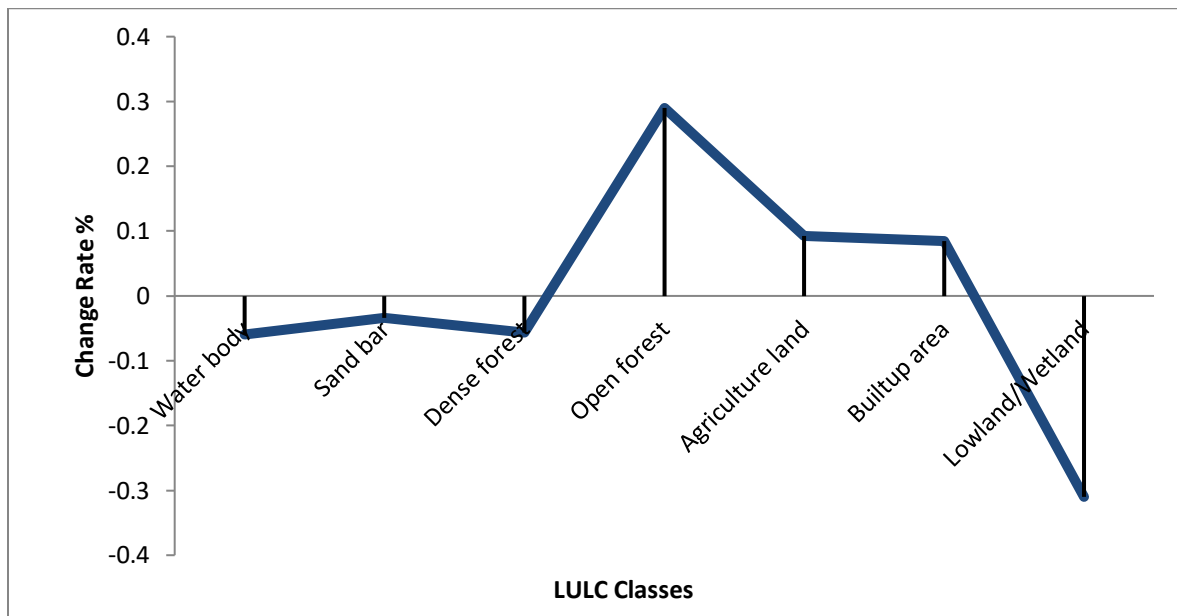


Fig. 4: Rate of change of LULC classes in 2016-1975.

During the last 41 years, the change in other LULC features classes is demarcating. The percentage of the water body, dense forest and lowland are gradually decreasing (Table 4, Fig. 3) because of human population growth and transformation of dense forest and lowland into agricultural land and built-up area. Agriculture land is an important economic indicator in this area. The increase in percentage (0.093%) of agricultural land is a good sign from the point of view of the economic development of study area. Built-up area increased by the rate of 0.085%, which is good evidence due to human population growth. The main towns of this study area are Tufanganj. The dense forest covered 917 hectares in 1975. Water is one of the most essential resources. Water bodies cover only 5.59% of the total study area in the year 1975 which decreased to the rate of -0.06% during 1975-2016 probably due to human intervention and seasonal variation. The change rate of the sandbar is -0.034% which indicates the land use extension due to agriculture and human constructions.

Based on a random selection of 135 reference pixels for each time, the classified images were evaluated for the accuracy, which was compared to the collected land use maps (Ahmed and Ahmed 2012). The kappa coefficients of classified images (1975, 1996, and 2016) were, respectively found to 80.09 %, 82.66%, and 87.57%, with the overall accuracies of 87.59%,

85.01%, and 89.63% (Table 8). On the other hand, the accuracy of the user measures the proportion of each land cover class is accurate. Moreover, the user's accuracy was calculated with respect to each LULC classes, which is appropriate whereas producers' accuracy calculated using Google Earth and land base, which is exactly classified. It is seen that LULC image accuracy increased in the study period. Because in the present time satellite images having higher resolution and more accurate.

Table 6: User's accuracy assessment of the six main classes for the classified Landsat satellite images

Years	User's Accuracy (%)						
	Water body	Sand bar	Dense forest	Open forest	Agriculture land	Built-up area	Abandoned channel
1975	90.00	80.23	90.12	80.18	86.67	86.67	85.32
1996	90.00	80.00	80.23	90.00	83.41	86.67	85.43
2016	95.00	86.67	90.00	90.24	90.12	86.67	90.00

Table 7: Producer accuracy assessments of the six main classes for the classified Landsat satellite images

Years	Producer's Accuracy (%)						
	Water body	Sand bar	Dense forest	Open forest	Agriculture land	Built-up area	Abandoned channel
1975	81.81	85.71	100	72.73	86.02	86.02	89.47
1996	85.71	92.31	100	69.35	83.10	83.87	89.00
2016	90.21	92.00	100	69.89	90.00	92.10	90.00

Table 8: overall accuracy assessment and Kappa coefficient of the six main classes for the classified Landsat satellite images.

Years	Overall Accuracy (%)	Kappa Coefficient (%)
1975	87.59	80.09
1996	85.01	82.66
2016	89.63	87.57

5. CONCLUSIONS

The LULC trend of an area is a result of both natural and socio-economic factors and their utilization in time and space by the human. In this work, using landsat satellite images of 1975, 1996 and 2016 land use/land cover changes were the assessed in the study area. The research expressed open forest as most dominant (30.89%- 42.81%) and dense forest as the minor (3.50%- 1.17%) classes of LULC types in the Raidak-I buffer zone. The percentage of the water body, dense forest and lowland gradually decreased, because of human population growth and transformation of dense forest and lowland into agricultural land and built-up area. Agriculture land is an important economic indicator in this area. The increase in percentage of agricultural land (0.093%) is a good indication from the point of view of the economic development of the study area. Built-up area was also increased which is good evident. Accurate LULC change data is essential for understanding landform characteristics of a geographical area.

REFERENCES

- Anderson, R., Hardy, E. E., Roach, J. T., & Witmer, R. E., A land use and land cover classification system for use with remote sensor data. USGS Professional, Washington, DC, 1996.
- Czaplewski, R.L., Misclassification bias in areal estimates. Photo-gramm. Eng. Remote Sens. 58, 1992, 189–192.
- Duda, R.O., Hart, P.E., Stork, D.G., Pattern Classification. John Wiley & Sons, New York, 2001.
- Foody, G.M., On the compensation for chance agreement in image classification accuracy assessment. Photogramm. Eng. Remote Sens. 58, 1992, 1459–1460.

- Foody, G.M., Approaches for the production and evaluation of fuzzy land cover classifications from remotely sensed data. *International Journal of Remote Sensing* 17 (7), 1996, 1317–1340.
- Geneletti, D., Gorte, B.G.H., A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. *International Journal of Remote Sensing* 24 (6), 2003, 1273–1286.
- Hay, A.M., The derivation of global estimates from a confusion matrix. *Int. J. Remote Sens.* 9, 1988, 1395–1398.
- Jupp, D.L.B., The stability of global estimates from confusion matrices. *Int. J. Remote Sens.* 10, 1989, 1563–1569.
- Kanellopoulos, I., Varfis, A., Wilkinson, G.G., Megier, J., Land-cover discrimination in SPOT HRV imagery using an artificial neural network-a 20-class experiment. *International Journal of Remote Sensing* 13 (5), 1992, 917–924.
- Liu, Zhengjun, Liu, Aixia, Wang, Changyao, Niu, Zheng, Evolving neural network using real coded genetic algorithm (GA) for multispectral image classification. *Future Generation Computer Systems* 20 (7), 2004, 1119–1129.
- Liu, J.Y., Tian, H.Q., Liu, M.L., Zhuang, D.F., Melillo, J.M., Zhang, Z.X., China's changing landscape during the 1990s: large-scale land transformations estimated with satellite data. *Geophysical Research Letters* 32, 2005.
- Ma, Z., Redmond, R.L., Tau coefficients for accuracy assessment of classification of remote sensing data. *Photogramm. Eng. Remote Sens.* 61, 1995, 435–439.
- Monserud, R.A., Leemans, R., Comparing global vegetation maps with the Kappa statistic. *Ecol. Model.* 62, 1992.
- Prisley, S.P., Smith, J.L., Using classification error matrices to improve the accuracy of weighted land-cover models. *Photogramm. Eng. Remote Sens.* 53, 1987, 1259–1263.
- Serra, P., Pons, X., Saurr, D., Post-classification change detection with data from different sensors: some accuracy considerations. *International Journal of Remote Sensing* 24 (16), 2003, 3311–3340.
- Van Deusen, P.C., Unbiased estimates of class proportions from thematic maps. *Photogramm. Eng. Remote Sens.* 62, 1996, 409–412.

Weng, Q., A remote sensing-GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. *Int. J. Remote Sens.* 22, 2001.

Yuan, D., A simulation comparison of three marginal area estimators for image classification. *Photogramm. Eng. Remote Sens.* 63,1997, 385–392.