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Assessment of Land Use-land Cover Change in Irga River Catchment Using Object-based Image Classification Technique

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Authors' contributions

This work was carried out in collaboration among all authors. Author SY designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors RKS and SP managed the analyses of the study. All authors read and approved the final manuscript.

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ABSTRACT

Land use-land cover (LULC) change analysis is essential for understanding the spatial and temporal change of landscape during a known long period for sustainable management of natural resources. The main objective of this study was to assess land use-land cover change using an object-based image classification technique which is a recent image classification technique with better accuracy than traditional pixel based image classification. The study was conducted in the catchment area of the Irga River, a tributary of the Barakar River, which falls in the Giridih district of Jharkhand (India). The catchment of the study area was delineated using SRTM DEM data (30 m spatial resolution). LANDSAT images (TM and OLI-TIRS) were used to develop the land use- land cover maps of 1997, 2007, and 2017 using object-based image analysis (OBIA). The images were

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classified and analyzed using ArcGIS and eCognition Developer 64 software. The accuracy of the classified images for each year was assessed by preparing the error matrix and calculating the Kappa coefficient. The overall accuracies of classified images were computed to be 88%, 83% and 91% while Kappa coefficients were found to be 0.8455, 0.7706 and 0.8796 for year 1997, 2007 and 2017 respectively. Over the 20 years (1997-2017), agricultural land increased by 12.23%, settlement increased by 76.62%, wasteland decreased by 39.59%, vegetation increased by 14.83%, water-bodies increased by 26.29%, and river area decreased by 16.66%. The analysis indicated an increasing trend in agricultural land, settlement, and vegetation while decreasing trends in wasteland and river areas. However, no definite trend was observed in the extent of the water-bodies.The results indicated that waste land greatly reduced and converted into settlement and agricultural land in the catchment.

Keywords: Land use-land cover; eCognition; remote sensing; GIS; OBIA; LULC change.

1. INTRODUCTION

Land use -land cover (LULC) change is one of the major components of environmental change which affects climate, land, and biodiversity [1-3]. Several changes in land use -land cover, such as long-term changes, are due to climate, natural causes, and human activity which play a significant role in changing this LULC [4]. As LULC change has an impact on global warming and natural ecosystems, therefore, its assessment and monitoring are essential. It is also needed by local agencies, state and federal for water- resource inventory (quantity, quality, management, and threats), flood control, and water-supply policies. In addition, natural or human-induced LULC change affects soil erosion, acidification, and soil organic depletion [4,5]. As vegetation cover increases, soil loss from the area decreases, which is considered adequate for reducing the energy of erosion driving forces [6]. Remote sensing and Geographic Information systems (RS & GIS) are potentially excellent and efficient techniques for analysing the spatial and temporal patterns of LULC. Moreover, it improved the convenience and accuracy of spatial data of land resource inventory and more productive analysis [5,7].

Over the world, considerable research has been done on image classification using a pixel-based image. Dewan and Yamaguchi (2009) evaluated land use/cover changes and urban expansion in Greater Dhaka, Bangladesh, between 1975 and 2003 using LANDSAT (MSS, TM, and ETM+) [3]. Abushnaf et al. (2015) prepared a land use/land cover map for Giridih district [8]. Sharma et al. (2011) to study the impact of land use and land cover change on soil erosion potential of a Maithon reservoir catchment, Jharkhand state [5]. Similarly, more researchers conducted studies using the pixel-based technique for different purposes and areas across the globe [9-14].

The object-based image analysis (OBIA) technique is a recently developed image classification technique that classifies images based on the object in place of a pixel as a traditional method [15,16]. Like pixel-based analysis, many researchers nowadays are interested in the OBIA technique. For example, Conchedda et al. (2008) used an object-based image classification approach to mangrove mapping [17]. Kindu et al. (2013) analysed land use-land cover changes for the Munessa-Shashemene area of the Ethiopian highlands over 39 years using Landsat MSS (1973), TM (1986), ETM+ (2000), and RapidEye (2012) data [18]. Deka et al. (2014) studied land use and land cover spatial change in the Kamrup district of Assam [19]. Alqurashi and Kumar, 2014 [20] have reported similar works; Gudex-Cross et al., 2017; Toure et al., 2018 [21-22] and many others. Several researchers reported that OBIA provides more accurate results than the traditional pixel classification [23-25]. For providing the latest and comprehensive information on various aspects for efficient and scientific planning of an area, monitoring and assessing LULC change is particularly important. Knowing the importance of LULC change assessment, the present research paper focuses on determining a change in LULC in the Irga catchment using the object-based image classification method.

2. MATERIALS AND METHODS

2.1 Study Area

Irga river catchment is situated in the South-West part of Giridih district of Jharkhand, India, between 24° 10' 08" and 24° 28' 04" N latitudes and 85° 52' 04" and 86° 08' 11" E longitudes. The elevation of the catchment ranges from 257 to 411 m above sea level. It covers 479 km^2 of the total geographical area. The catchment receives an annual rainfall of 1,100-1,350 mm. The soil pH ranges from 4.5 to 7.2 [26]. The location map of the study area is shown in Fig. 1.

2.2 Data and Software

Datasets used in the present study are shown in Table 1. The segmentation and classification of the satellite images have been done with eCognition developer 64 (V 9.0.1). ArcGIS 10.1 software has been used for handling, analysing and assessing various data types and final map preparation.

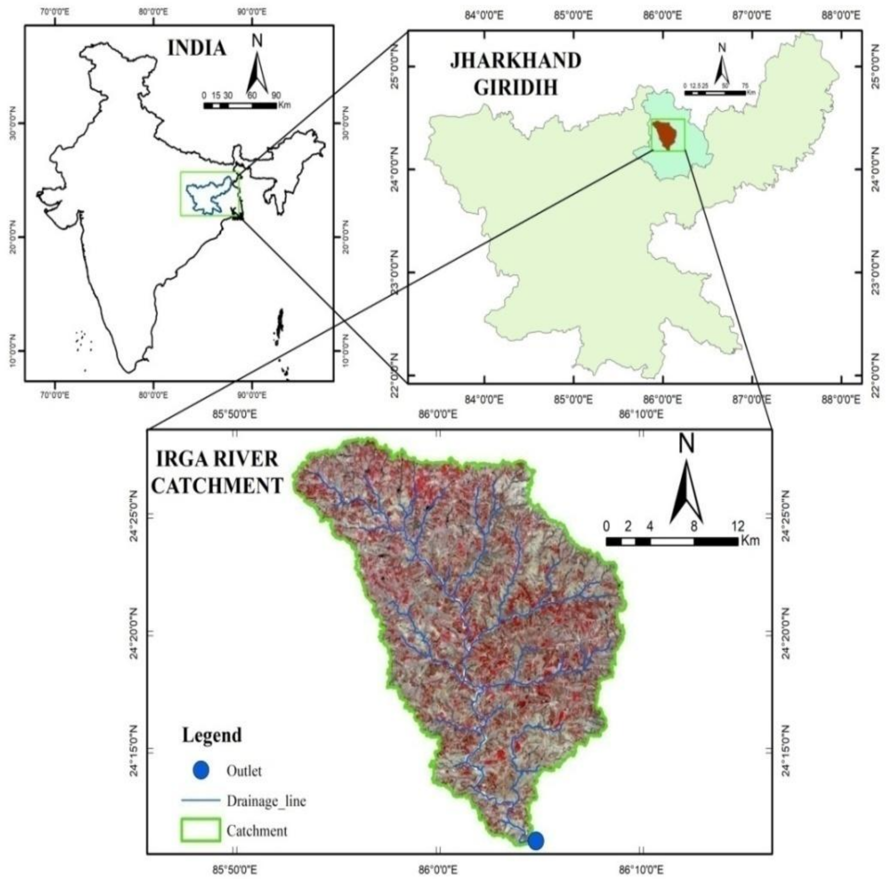

Fig. 1. Location map of Study area

Table 1. Different datasets used in the study

S.No.	Datasets used	Path/Row	Source
1.	SRTM DEM data		https://earthexplorer.usgs.gov [27]
2.	LANDSAT images		https://earthexplorer.usgs.gov [27]
	a) Thematic Mapper (TM) for the years 1997 and 2007	140/43	
	b) Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) for the year 2017	140/43	
3.	Google Earth images		Google Earth
4.	Field observations		Handheld GPS

2.3 Image Classification for LULC Mapping

The object based image classification method has been adopted in the study which is a newly developed image classification technique for all three year LANDSAT data. An image has been classified into six classes (i.e. Agricultural land, Vegetation, Water, River, Wasteland and Settlement area) as presented in Table 2. In object-based image analysis segmentation is primary step before an analyst can analyses and use the images. During selection of training sample Normalised Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were used to extract various features shown in Table 2.

NDVI [28] is a well-known vegetation index in LULC image analysis to distinguish between vegetated and non-vegetated areas and is as follows:

$$NDVI = (NIR - RED)/ (NIR + RED) \quad (1)$$

NIR and RED are the mean values of Near Infrared and Red bands, respectively, for a given object of segmentation. It varies from -1 (bare soil or water bodies) to 1(healthy green vegetation).

NDWI [29] is utilised to extract open water features in satellite imagery. It is also used as a metric for masking out black bodies – water and shadows. It is given by:

$$NDWI = (GREEN - NIR)/ (GREEN + NIR) \quad (2)$$

GREEN and NIR are the mean values of Green and Near Infrared bands, respectively, for a given object of segmentation, the values range from -1 to 1. High values of NDWI indicate the presence of extensive deep water bodies, whereas lower values indicate vegetation.

2.3.1 Segmentation

In object-based image analysis, segmentation is primary step before an analyst can analyse and use the images. Often proper image segmentation improves the classification result [30]. Segmentation is the process of grouping pixels of same spectral, pixel and textual values from an image into objects [31]. In the present study, the multi-resolution logarithm was performed for image segmentation. The multi-resolution logarithm is often used with good results for the segmentation of images [32]. The Segmentation criterion (parameters) used for all three year images is presented in Table 3.

The algorithm starts at the one-pixel level in an image and works bottom-up based. During the process, more and more pixels are grouped together in larger segments [33]. Pixels are grouped together if the heterogeneity of the spectral and spatial values does not exceed a minimum [34]. Determining the appropriate parameters for segmentation is often achieved by 'trial and error' and a visual inspection of the segmentation result [32,35]. In present study, the multi-resolution logarithm was performed for image segmentation. The Segmentation parameters shape and compactness factor used 0.2 and 0.8 for all three year images, respectively, whereas scale parameter and weightage of bands were assigned by visual checking.

2.3.2 Classification

After segmentation, classification was performed using Classification window under process tree in eCognition main window. Using class hierarchy window all six LULC classes i.e. Agricultural Land, Settlement, Waste Land, Vegetation, Water bodies and River were added. Further, image classification was performed by Standard Nearest Neighbor Object based method for all three year. After classification, classified map was exported in vector format (Shape file).UndereCognition main window with process tree, image object information, feature view and class hierarchy window were used for classification.

Exported map of 1997, 2007 and 2017 were added in ArcGIS and using symbology vector file was labelled and Colour is added to every class. By using various GIS techniques like overlay, integration, change detection and area calculation, various land use/land cover classes pertaining to different classes were determined. Wherever the classification was not good, the classification was performed again after Classification change detection was performed by cross-tabulation and overlay-intersection.

2.4 Accuracy Assessment

The classification accuracy assessment was done by computing overall accuracies and Kappa coefficients and using reference test pixel data [36, 37 and 38]. An accuracy assessment of the

Table 2. Different classes of land use- land cover adopted for the study

Land use- land cover Classes	Definition
Agricultural land	Land with crops or empty agricultural lands
Vegetation	All tree and shrub-covered surfaces
Water bodies	Reservoir, pond, and swamp
River	rivers
Wasteland	Open areas with low vegetation such as bushes and grasses, as well as bare ground prone to erosion
Settlement/built-up area	Fields with residential houses, commercial or industrial buildings

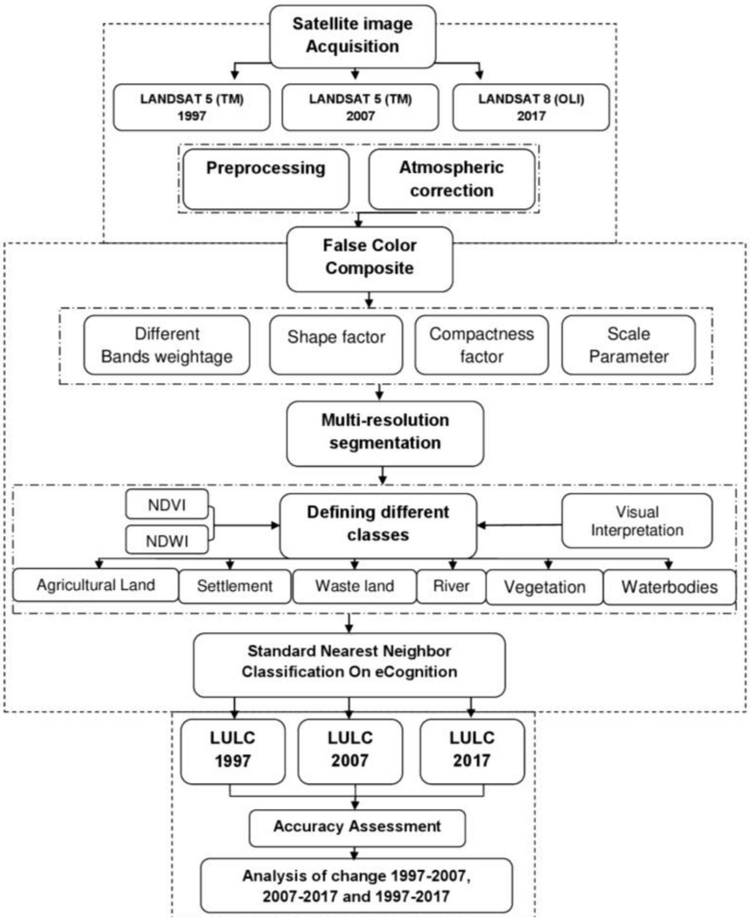

Fig. 2. The flow chart of the method followed for change analysis

classification results was performed using reference data taken from intensive field visits and satellite data. Reference data for the years 1997 and 2007 were collected with satellite data the same year different seasons by visual interpretation, while in-depth field visits for 2017. The overall accuracies and Kappa coefficients [39,40] were derived to assess the accuracy of the classification maps. The error matrix for each year was generated by comparing the predicted value from classified map to ground truth data. In addition, the Kappa coefficient as a discrete multivariate technique is also performed in the accuracy assessment. Kappa coefficient is computed as,

$$\mathrm{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \quad (3)$$

Where, r = Number of rows in the error matrix, x_{ii} =Number of observations in row i and column i (on the major diagonal), $x_{(i+)}$ =Total number of observations in rows i (shown as marginal total to right of the matrix), $x_{(+i)=}$Total number of observations in column i (shown as marginal total at the bottom of the matrix), N = total number of observations included in the matrix.

Kappa is an actual dimensionless number between -1 to 1: the value close to 1 shows maximum agreement, while the value of -1 is total disagreement. The ranges of Kappa coefficients for different levels of agreement [39,40] used for analysis of classified images.

2.5 Change Detection

Change detection can be assessed by using data from a single sensor as well as from multiple sensors at different acquisition dates. It was done by comparing changes in LULC in three time periods, viz. 1997-2007, 2007-2017 and 1997-2017. The flow chart of the method followed for image classification and change analysis is shown in Fig. 2.

3. RESULTS AND DISCUSSION

Irga river catchment and drainage map were generated using SRTM DEM and shown in Fig. 3. Land use and land cover classification for the years 1997, 2007 and 2017 were performed by applying the Standard Nearest Neighbor Object-based classification method in eCognition software.

3.1 Land Use and Land Cover Mapping

The prepared thematic classification maps for the study area's 1997, 2007 and 2017 are shown in Fig. 4a to 4c, respectively. The computed areas under different LULC classes for these years are presented in Table 3. From Table 3, it is observed that the study area contained 26246.34 ha (54.75 %) agricultural land followed by 15097.86 ha (31.50 %) waste land, 3280.77 ha (6.84 %) settlement, 2371.05 ha (4.95 %) vegetation, 134.55 ha (0.28%), waterbodies and 804.42 ha (1.68%) river area in the year 1997.The overall accuracy was 88.23%, and the kappa statistic was found to be 0.8455, indicating almost perfect agreement (Table 4). The reason behind such agreement is that the study used object-based image classification, which is more accurate than pixel based. This result is also supported by the work of Rahman and Saha (2008), and Adam et al. (2016).

The classification of the image of the year 2007 indicated that the study area consisted of 27093.33 ha (56.52%) agricultural land followed by 4529.43 ha (26.71%) waste land, 12802.23 ha (9.45%) settlement, 2533.14 ha (5.28%) vegetation, 232.38 ha (1.55%) river and 744.39 ha (0.48%) waterbodies. The overall accuracy was 83.92 %, and the Kappa statistic was 0.7706 (Table 5). The obtained value of the kappa statistic indicates that there is almost perfect agreement.

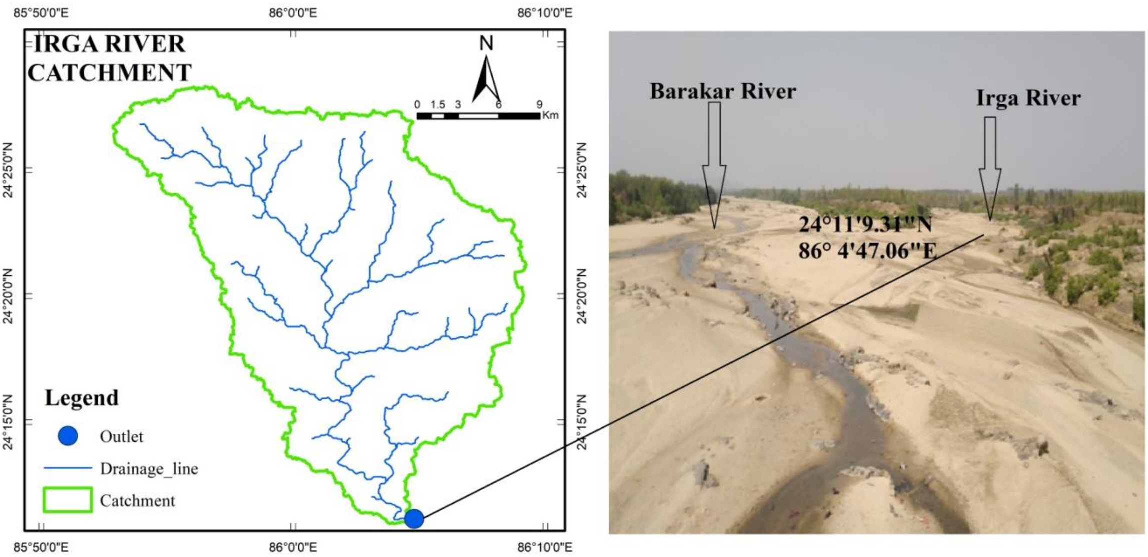

Fig. 3. Irga catchment with drainage lines and Outlet of Irga catchment

Table 3. Areal the extents of land use -land cover for the years 1997, 2007 and 2017

Class Name	Area in 1997		Area in 2007		Area in 2017	
	ha	%	ha	%	ha	%
Agricultural Land	26246.34	54.75	27093.33	56.52	29457.09	61.45
Settlement	3280.77	6.84	4529.43	9.45	5794.47	12.09
Waste land	15097.86	31.50	12802.23	26.71	9119.88	19.03
Vegetation	2371.05	4.95	2533.14	5.28	2722.59	5.68
Waterbodies	134.55	0.28	232.38	0.48	169.92	0.35
River	804.42	1.68	744.39	1.55	670.41	1.40

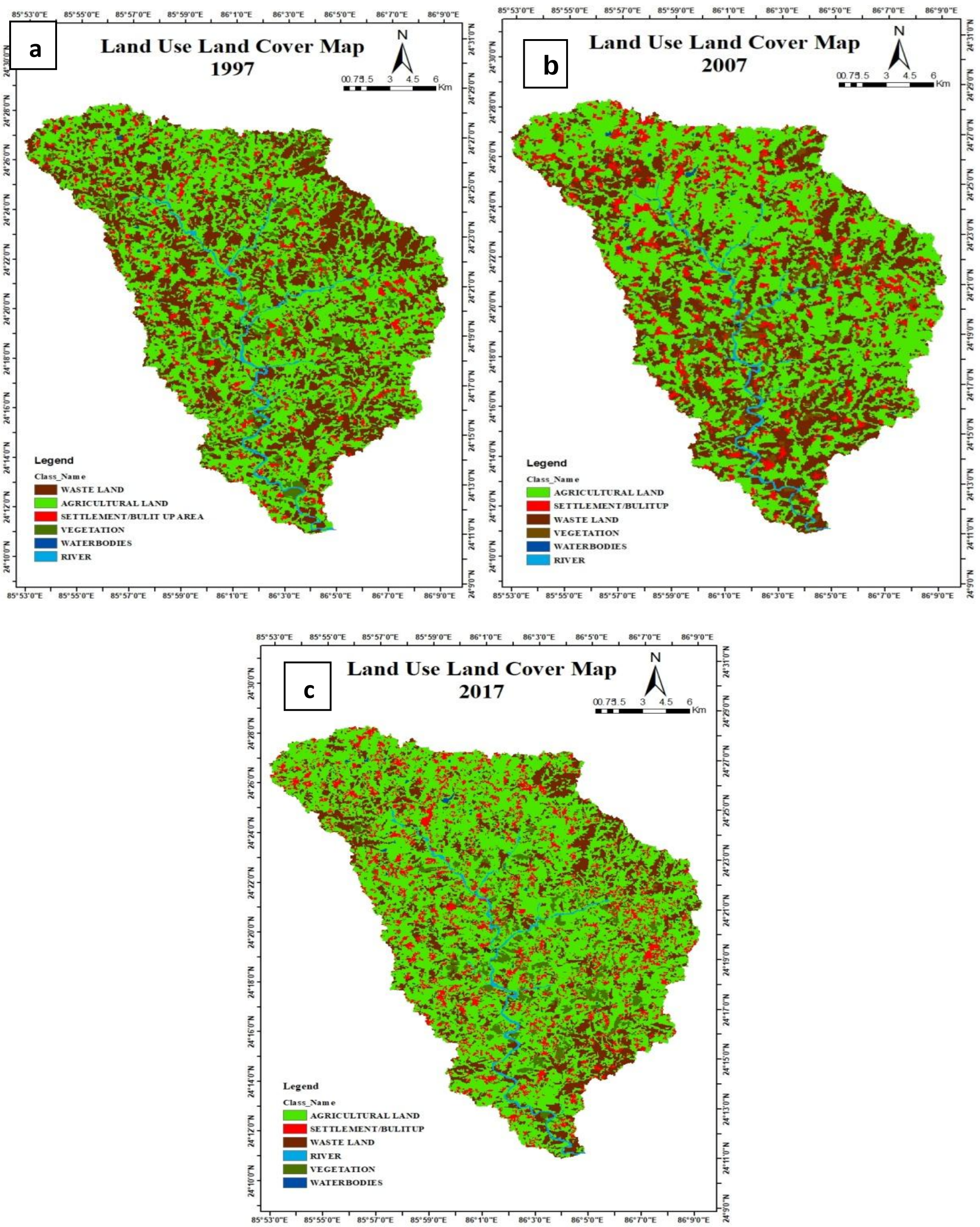

Fig. 4. Land use- land cover map of a) the year 1997, b) the year 2007, c) the year 2017

Table 4. Error matrix of LULC classification for the year 1997

		True LULC class								
		WL	**AL**	**S**	**V**	**W**	**R**	**Row Total**	**Users Accuracy (%)**	**Producer Accuracy (%)**
Predicted LULC class	**WL**	**13**	1	0	0	0	1	**15**	86.67	86.67
	AL	2	**16**	0	0	0	0	**18**	94.12	88.89
	S	0	0	**5**	1	0	0	**6**	83.33	83.34
	V	0	0	1	**4**	0	0	**5**	80.00	80.00
	W	0	0	0	0	**4**	0	**4**	100.00	100.00
	R	0	0	0	0	0	**3**	**3**	75.00	100.00
	Column Total	**15**	**17**	**6**	**5**	**4**	**4**	**51**		
	Kappa value	**0.8455**								
	Overall Accuracy	**88.23 %**								

AL-Agricultural Land, WL-Waste land, S-Settlement, V-Vegetation, W-Waterbodies and R-River

Table 5. Error matrix of LULC classification for the year 2007

		True LULC class								
		AL	**S**	**WL**	**V**	**W**	**R**	**Row Total**	**Users accuracy (%)**	**Producer accuracy (%)**
Predicted LULC class	**AL**	**44**	3	6	1	0	0	**54**	91.67	86.67
	S	1	**5**	1	1	0	0	**8**	55.56	88.89
	WL	3	0	**25**	1	0	0	**29**	78.13	83.34
	V	0	1	0	**5**	0	0	**6**	62.50	80
	W	0	0	0	0	**8**	0	**8**	100.00	100
	R	0	0	0	0	0	**7**	**7**	100.00	100
	Column Total	**48**	**9**	**32**	**8**	**8**	**7**	**112**		
	Kappa value	**0.7706**								
	Overall Accuracy	**83.92%**								

AL-Agricultural Land, WL-Waste land, S-Settlement, V-Vegetation, W-Waterbodies and R-River

Table 6. Error matrix of LULC classification for the year 2017

		True LULC class								
		AL	**S**	**WL**	**R**	**V**	**W**	**Row Total**	**Users accuracy (%)**	**Producer accuracy (%)**
Predicted LULC class	**AL**	**40**	0	2	0	0	0	42	97.56	95.24
	S	1	**10**	1	0	1	0	13	90.91	76.92
	WL	0	0	**18**	0	2	0	20	81.82	90
	R	0	0	0	**8**	0	0	8	100	100
	V	0	1	0	0	**8**	0	9	72	88.89
	W	0	0	1	0	0	**7**	8	100	87.50
	Column Total	41	11	22	8	11	7	100		
	Kappa value	0.8796								
	Overall accuracy	91%								

AL-Agricultural Land, WL-Waste land, S-Settlement, V-Vegetation, W-Waterbodies and R-River

Table 7. Comparison of LULC classes and the change during the period 1997 to 2017

Class Name	Changes (1997-2007)		Changes (2007-2017)		Changes (1997-2017)		Average rate of change(1997-2017)	
	Area (ha)	Percent	Area (ha)	Percent	Area (ha)	Percent	Ha/yr	Percent
Agricultural Land	846.99	3.23	2363.76	8.72	3210.75	12.23	160.5375	0.6115
Settlement	1248.66	38.06	1265.04	27.93	2513.70	76.62	125.685	3.831
Waste land	-2295.63	-15.21	-3682.35	-28.76	-5977.98	-39.59	-298.899	-1.9795
Vegetation	162.09	6.84	189.45	7.48	351.54	14.83	17.577	0.7415
Waterbodies	97.83	72.71	-62.46	-26.88	35.37	26.29	1.7685	1.3145
River	-60.03	-7.46	-73.98	-9.94	-134.01	-16.66	-6.7005	-0.833

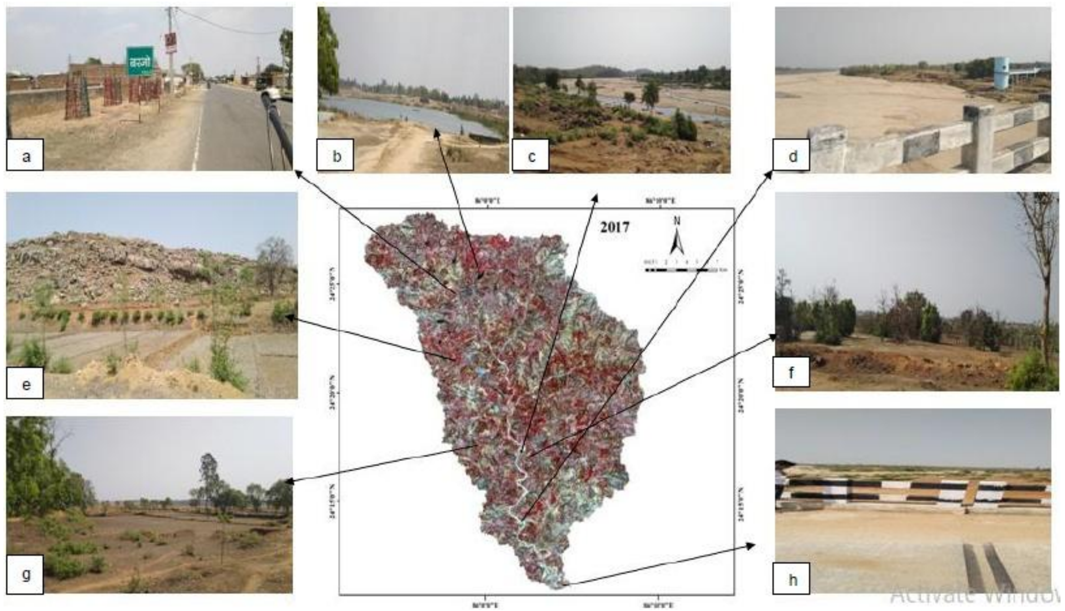

Fig. 5. Various classes of Irga catchment a) settlement, b) water body, c) waste land, d) river, e) agricultural Land, f) Vegetation, g) waste land, h) River outlet

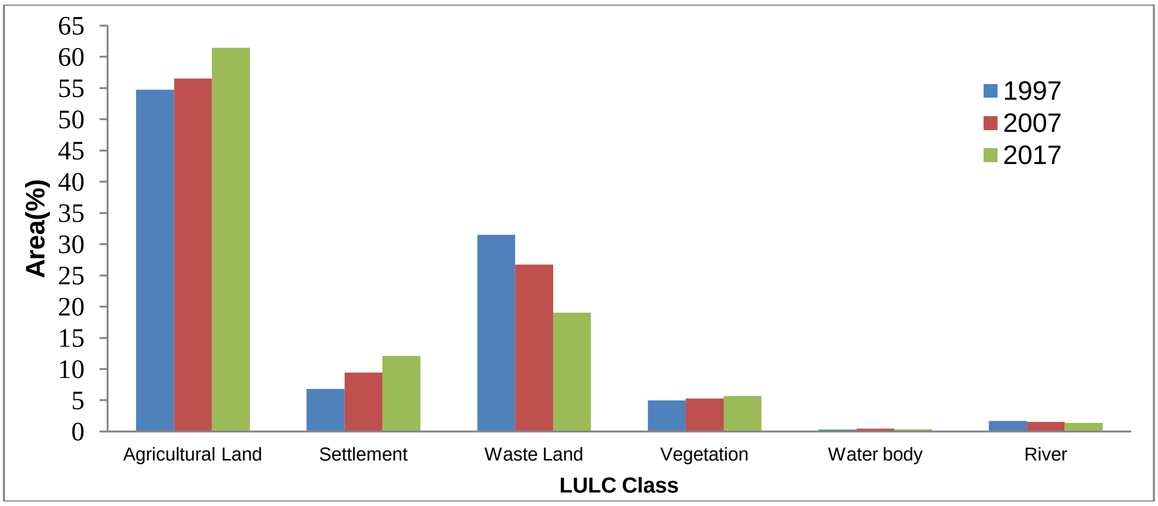

Fig. 6. Comparison of LULC areas for the years 1997, 2007 and 2017

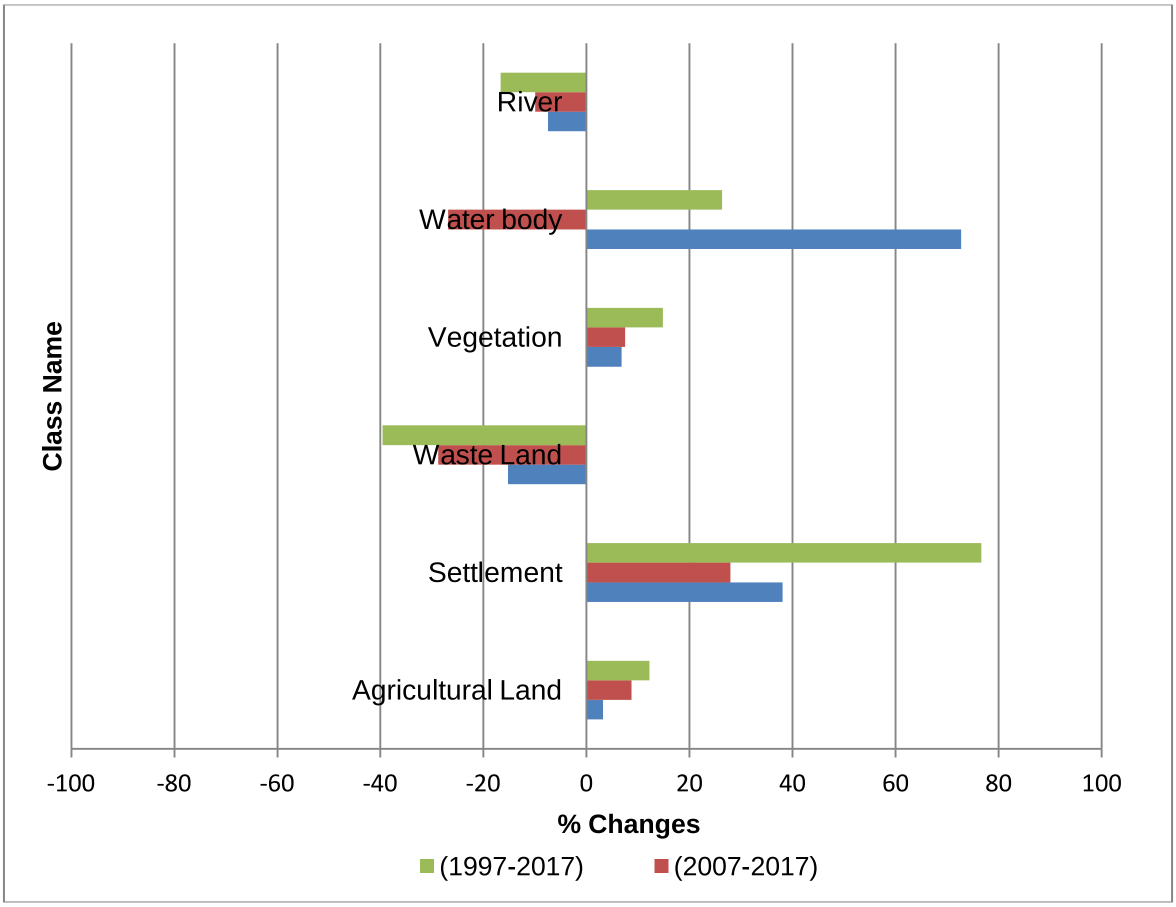

Fig. 7. Land use-land cover change during 1997-2007, 2007-2017, 1997-2017

Similarly, in the year 2017, the study area consisted of 29,457.09 ha (61.45 %) agricultural land followed by 5,794.47 ha (19.03 %) waste land, 9119.88 ha (12.09 %) settlement, 2,722.59 ha (5.68 %) vegetation, 169.92 ha (1.40 %) river and 670.41 ha (0.35 %) waterbodies. The overall accuracy was 91 %, and the Kappa statistic was found to be 0.8796, which indicates that the agreement is almost perfect (Table 6). During the site visit, photographs of different LULC classes were taken for ground verification which is shown in Fig. 5.

3.2 Land Use and Land Cover Change Analysis

The LULC changes have been summarised in Table 7. The results of the change detection analysis exhibit considerable changes in LULC in the study area in three different periods (from 1997 to 2007, from 2007 to 2017 and 1997 to 2017). This table indicates that significant changes in LULC classes have occurred over 20 years.

During 1997-2007 the areal extent of waterbodies increased highly by 72.71 % (97.83 ha) followed by the settlement area by 38.06% (1,248.66 ha), vegetation area by 6.84% (162.09 ha) and agricultural land by 3.23 % (846.99 ha) while the decreasing trend was found in vegetation 15.21 % (2,295.63 ha) followed by river 7.46% (60.03 ha) in this period. The high increase in the waterbodies area might be attributed to the construction of the Naulakha reservoir nearby Rajdhanwar and some new ponds in the catchment during this period. On the other hand, over the next decade (2007-2017), an increasing trend was found in settlement by 27.93% (1,265.04 ha), followed by agricultural land by 8.72% (2,363.76 ha), vegetation by 7.48% (189.45 ha) while drastic decrease found in wasteland 28.76% (3,682.35 ha) and waterbodies 26.88% (62.46 ha). The river also showed a decrease of 9.94% (73.98 ha), which is higher than the previous decade (Table 7).

A considerable change in aerial extent has been noticed in agricultural [12.23% (3,210.75 ha)] and vegetation [14.83% (351.54 ha)] land use during the period 1997 to 2017. The extent of settlement increased by 76.62% (2,513.70 ha), while waste land highly decreased by 39.59% (5,977.98 ha). A considerable part of the wasteland has converted into agricultural land, settlement and vegetation. The waterbodies area increased by 26.29% (35.37 ha), while the river area decreased by 16.66% (134.01 ha) over two decades. The reasons behind the increase in waterbodies area might be the construction of water harvesting structures and other water-based structures by the Government and other agencies through watershed development projects.

Further, the graphical comparison of LULC areas for the three years (1997, 2007 and 2017) is shown in Fig. 6, while Fig. 7 show changes over the period 1997-2007, 2007-2017 and 1997-2017, respectively. These figures, as well as Table 7, reflect an increasing trend in agricultural land, settlement and vegetation while decreasing in wasteland and river areas. However, no definite trend is observed in the extent of the waterbodies.

4. CONCLUSION

Land use -land cover (LULC) change is one of the major components of environmental changes which affect soil erosion. The land use-land cover information is essential for proper management, planning and monitoring of natural resources available in a particular region. This study's main objective is to examine LULC changes and their dynamics that occurred in the Irga catchment between 1997 and 2017 using remote sensing and GIS. The LULC maps of the 1997, 2007 and 2017 years were developed using LANDSAT images (TM and OLI/TIRS) by the OBIA technique, which has better accuracy than traditional pixel-based image classification. The land use land cover were classified into six classes viz. agricultural land, settlement, vegetation, waste land, water body and river. Accuracy assessment of prepared maps was made based on the error matrix and kappa coefficient. Change detection was done by comparing changes in LULC in three time periods, viz. 1997-2007, 2007-2017 and 1997-2017. The overall accuracy and kappa statistics for 1997, 2007 and 2017 are 88.23% and 0.8455; 83.92% and 0.7706; and 91% and 0.8796, respectively. Over the period 1997 to 2017, the area under agricultural land, settlement, natural vegetation and increased by 12.23%, 76.62%, 14.83% and 26.29%, respectively, while wasteland and river decreased by 39.59% and 16.66%, respectively. The study area had undergone a significant LULC change over the preceding 20 years, according to a field survey, digital image classification results, and change detection results. As a result, in order to avoid negative effects brought on by LULC changes in the study area, sustainable land use planning and management, proper implementation of soil, and water conservation measures, and provision of alternative livelihood strategies for local communities should all be implemented. The generated LULC map from the present study can be used for hydrological modelling and soil erosion assessment of the Irga river catchment.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Agarwal C, Green GM, Grove JM, Evans TP, Schweik CM. A review and assessment of land-use change models: dynamics of space, time, and human choice', Gen. Tech. Rep. NE-297. Newton Square, PA: US Department of Agriculture, Forest Service, Northeastern Research Station. 2002;61:297.
2. Jain, Atul K, Xiaojuan Yang. Modeling the effects of two different land cover change data sets on the carbon stocks of plants and soils in concert with CO2 and climate change." Global Biogeochemical Cycles. 2005;19.2.
3. Dewan, Ashraf M, Yasushi Yamaguchi. Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. Applied Geography. 2009; 29(3):390-401.
4. Leh M, Bajwa S, Chaubey I. Impact of land use change on erosion risk: an integrated remote sensing, geographic information system and modeling methodology. Land Degradation & Development. 2013;24.5: 409-421.
5. Sharma, Arabinda, Kamlesh N. Tiwari, Bhadoria PBS. Effect of land use land cover change on soil erosion potential in an agricultural watershed. Environmental Monitoring and Assessment. 2011;173.1: 789-801.
6. Pacheco, FAL, Varandas SGP, Sanches Fernandes LF, Valle Junior RF. Soil losses in rural watersheds with environmental land use conflicts. Science of the Total Environment. 2014;485:110-120.
7. Weng, Qihao. Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling. Journal of Environmental Management. 2002;64.3: 273-284.
8. Abushnaf AM, Pandey RK, Lal D, Kumar M. Land use / land cover mapping of Giridih District of Jharkhand by using Remote Sensing &GIS'. International Journal of Modern Engineering Research. 2015;1.5:14.
9. Rawat JS, Manish Kumar. Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. The Egyptian Journal of Remote Sensing and Space Science. 2015;18.1:77-84.
10. Ramteke, IK, Reddy GP. Obi, Sen TK, Singh SK, Chaterjee S, Rajankar PB, Das SN. Land use/land cover change dynamics in coastal ecosystem of Sundarban Delta, West Bengal-A Case Study of Bali Island. 2017;6.6:3565-3577.
11. Islam, Kamrul, et al. Land use classification and change detection by using multi-temporal remotely sensed imagery: The case of Chunati wildlife sanctuary, Bangladesh. The Egyptian Journal of Remote Sensing and Space Science. 2018;21.1:37-47.
12. Sushanth, Kallem, et al. Temporal land-use change analysis of Patiala-Ki-Rao watershed in Shivalik Foot-Hills using Remote Sensing and GIS. Journal of Agricultural Engineering. 2019;55.4:57-65.
13. Kumar, Kunal, Sahu, RK, Yadav S. Assessment of land use/land cover change using Geo-informatics in catchment of BurhiGandakriver, Bihar. Journal of Agricultural Engineering. 2020;53.3:377-385.
14. Rao, J. Himanshu, et al. Land use Land Cover Classification of Burhner River Watershed Using Remote Sensing and GIS. 2022;12(7):119-132.
15. Modi, Mohit, et al. Land cover change detection using object-based classification technique: a case study along the Kosi River, Bihar. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences. 2014;40.8:839-843.
16. Kar, Rajmita, et al. Monitoring spatio-temporal dynamics of urban and peri-urban landscape using remote sensing and GIS– A case study from Central India. The

Egyptian Journal of Remote Sensing and Space Science. 2018;21.3:401-411.

17. Conchedda, Giulia, Laurent Durieux, Philippe Mayaux. An object-based method for mapping and change analysis in mangrove ecosystems. ISPRS Journal of Photogrammetry and Remote Sensing. 2008;63.5:578-589.
18. Kindu, Mengistie, et al. Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands. Remote Sensing. 2013;5.5:2411-2435.
19. Deka, Jyotishman, Om Prakash Tripathi, Mohamed Latif Khan. Study on land use/land cover change dynamics through remote sensing and GIS–A case study of Kamrup District, North East India." Journal of Remote Sensing and GIS. 2014;5.1:55-62.
20. Alqurashi, Abdullah F, Lalit Kumar. Land use and land cover change detection in the Saudi Arabian desert cities of Makkah and Al-Taif using satellite data. Advances in Remote Sensing. 2014;3.03 :106.
21. Gudex-Cross, David, Jennifer Pontius, Alison Adams. Enhanced forest cover mapping using spectral unmixing and object-based classification of multi-temporal Landsat imagery. Remote Sensing of Environment. 2017;196:193-204.
22. Toure, Sory I, et al. Land cover and land use change analysis using multi-spatial resolution data and object-based image analysis. Remote Sensing of Environment. 2018;210:259-268.
23. Adam HE, Csaplovics E, Elhaja ME. A comparison of pixel-based and object-based approaches for land use land cover classification in semi-arid areas, Sudan. IOP Conference Series: Earth and Environmental Science. 2016;37(1). IOP Publishing,.
24. Rahman, Rejaur, Saha SK. Multi-resolution segmentation for object-based classification and accuracy assessment of land use/land cover classification using remotely sensed data." Journal of the Indian Society of Remote Sensing. 2008;36.2:189-201.
25. Yan G, Mas JF, Maathuis BHP, Xiangmin Z, Vandijk PM. Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing. 2006;27.18:4039-4055.
26. CGWBR. Ground Water Information Booklet Giridih District, Jharkhand State', Central Ground Water Board (CGWB), Ministry of Water Resources (Govt. of India); 2013.
27. Anonymous. USGS. Available:https://earthexplorer.usgs.gov/ Accessed 11 January 2019.
28. Jensen, John R. Remote sensing of the environment an earth resource perspective Prentice Hall. Upper Saddle River (NJ), USA; 2000.
29. McFeeters, Stuart K. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. International Journal of Remote Sensing. 1996;17.7:1425-1432.
30. Blaschke, Thomas. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing. 2010;65.1:2-16.
31. Hussain, Masroor, et al. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of Photogrammetry and Remote Sensing. 2013;80: 91-106.
32. Yan, Gao, et al. Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing. 2006;27.18:4039-4055.
33. eCognition User Guide, Trimble eCognition® Developer User Guide (Munich, Germany: Trimble Germany GmbH); 2014.
34. Baatz, Martin. Multi resolution segmentation: an optimum approach for high quality multi scale image segmentation. Beutragezum AGIT-Symposium. Salzburg, Heidelberg. 2000;12-23.
35. Dingle Robertson, Laura, Douglas J. King. Comparison of pixel-and object-based classification in land cover change mapping. International Journal of Remote Sensing. 2011;32.6:1505-1529.
36. Mather PM. Computer processing of remotely-sensed images. An introduction, (1st ed.). Chichester: Wiley; 1987.
37. Jensen JR. Introductory digital image processing: A remote sensing perspective. Prentice Hall, New Jersey; 1996.
38. Richards, John A. Error correction and registration of image data. Remote sensing

digital image analysis. Springer, Berlin, Heidelberg. 1986;33-68.

39. Cohen J. A coefficient of agreement for nominal scales. Educ. and Psychol. Meas. 1960;20(1): 37-46.

40. Landis, J. Richard, Gary G. Koch. The measurement of observer agreement for categorical data. Biometrics. 1977;159-174.

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