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Original Research Paper

A Multi-Scale Feature Extraction Approach to Improve Land Use / Land Cover Classification Accuracy using IRS LISS-IV Imagery

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Abstract

The study presents an approach to map Land Use / Land Cover Change (LULCC) at large scale and processing techniques that permit higher accuracy. IRS RESOURCESAT-2 LISS-IV images of Nellore district of Andhra Pradesh were used to apply the classification technique. In multi-scale feature extraction approach LULCC takes two forms i.e. conversion from one category of LULCC to another and modification of condition within a category. Thus, major LULCC classes were extracted using object based approach and uncertain classes were identified using onscreen knowledge based method. The results shown in 2009, the accuracy of cropland, water body and built-up segments were 99.3%, 94.79% and 89.72%, respectively, whereas, in 2013 the accuracies were 94.31%, 88.26% and 81.20%, respectively. Hence, this classification approach can be useful in different landscape structure over the time, which can be quantified and assessed to achieve a better understanding of the land cover.

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1 INTRODUCTION

Precise and timely land use / land cover (LULC) information is essential to many government and private organizations at local, regional, national and global levels for different applications such as environmental monitoring and planning, LULC change modeling, transportation planning, urban development planning, urban modeling, etc. Remotely sensed data have been the major sources of prepared LULC maps (Chen and Stow, 2003). For preparing updated LULC information at different scales, remote sensing image classification techniques have been developed since 1980s. During 1980s and 1990s, most classification techniques were employed by keeping image pixel as the basic unit of analysis, in which each pixel is labeled as a single LULC class. Although a large number of remote sensing classification techniques have been developed in recent decades (Lu and Weng, 2007), based on spectral variables; whereas spatial information was more or less ignored. Spectra-based classification approaches are conceptually simple and easy to be implemented, but they neglect the spatial components, which are inherited in real-world remote sensing imagery (Moser *et al*, 2013). A number of LULC types cannot be effectively separated with spectral information and thereby less than desired accuracy has been reported with spectra-only classifiers (Tso and Mather, 1999; Stuckens *et al*, 2000). For example, there has been a consensus that impervious surfaces and bare soil (e.g. bright urban impervious surfaces and dry soil, and dark impervious surfaces and moist soil) cannot be effectively separated only with spectral information. These issues become severe with the continued advancements in satellite sensor technologies to capture images at high spatial resolution (i.e. LISS-IV and CARTOSAT-1, 2A, 2B). With higher spatial resolutions, images are likely to have higher within-class spectral variability. As a result,

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less than satisfactory results have been reached with spectral classifiers (Myint *et al,* 2011). In remote sensing literature, such approaches have been generally called "spatio-contextual" image classification, indicating the relationship between a "target" pixel and its neighboring pixels is incorporated into analyses (Tso and Mather, 1999). These spatio-contextual image classification approaches can be grouped into three categories, including 1) texture extraction, 2) Markov random fields (MRFs) modeling and 3) image segmentation and object-based image analysis (Stuckens *et al*, 2000; Blaschke, 2010; Thoonen *et al*, 2012; Moser *et al,* 2013). Compared to traditional per-pixel and sub-pixel classification methods, object-based models provide a new paradigm to classify remote sensing imagery (Blaschke, 2010; Myint *et al,* 2011). As the high spatial resolution images convey more ground information and allow Earth observations with enhanced accuracy of digital information (Aksoy *et al.* 2010) and thus efficient and accurate extraction of objects from these data is attracting greater attention from remote sensing researchers (Baltsavias, 2004). Hence, object-based approaches are more appropriate for high resolution remote sensing images since they assume that multiple image pixels form a geographic object. So, instead of considering an image as a collection of individual pixels with spectral properties, object-based methods generate image objects through image segmentation (Pal and Bhandari, 1992). Accordingly, object-based image analysis can simultaneously take the spectrum, shape, texture, and semantic relation into the feature space to improve interpretation accuracy (Benz *et al* 2004; Zhang *et al* 2013); hence, the use of object-based classification of high resolution image shows a thriving upbeat in innovation of new and novel techniques.

Meaningful objects always exist over a certain range of scales in segmentation of remote-sensing images (Yuan *et al,* 2014). Hence, to overcome the limitation of the object-based classification an approach has been adopted to enhance the accuracy of the satellite image classification incorporating onscreen modification of post classified image segments. This approach has been taken after observing heterogeneity of the study area, where, built-up areas are with urban, rural, industrial and infrastructure, discriminate water bodies from numerous aqua ponds and partial wetland, discriminate bare lands from vegetated open areas, coastal sand from riverine sand and abandoned aqua ponds. Earlier studies on object-based classification approaches have shown significant higher accuracy (Benz *et al,* 2004; Wang *et al,* 2004; Myint *et al,* 2011). The objective of the present study is to use optimal combinations of object-based and visual LULC classification to obtain higher classification and post-classification change detection accuracies. This hybrid method was applied to IRS RESOURCESAT-2 LISS-IV satellite images of the coastal region of Andhra Pradesh, India. The focus of our study is on LULCC because of rapid industrialization is taking place along the coastal part of this region along with urban expansions.

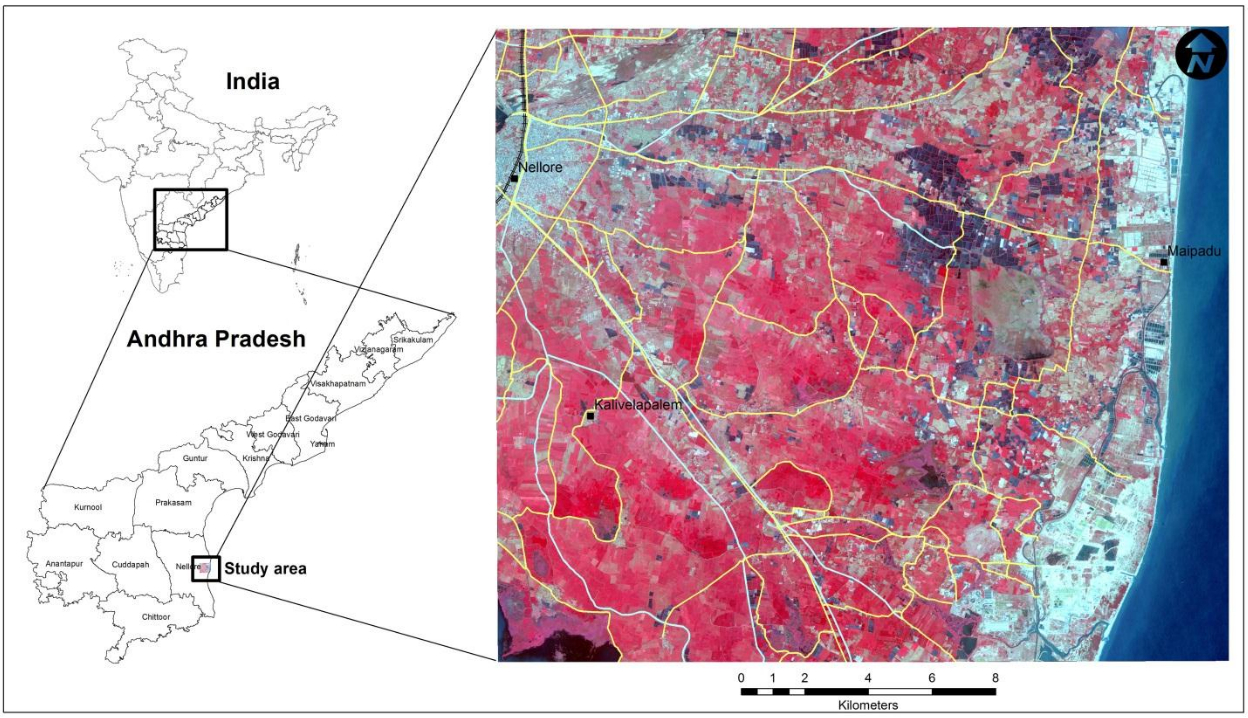

Figure 1. Location map of the study area

2 STUDY AREA

The part of Eastern coastal belt of India, which is a part of Nellore district of Andhra Pradesh has been selected as the study area for present study. The study area covers an area of 404.46 km^2 and located between 14º 18' 45" N to 14º 29' 30" N and 79º 58' 55" E to 80º 10' 20" E (Figure 1). The terrain is nearly plain to gently sloping area characterized by agricultural land in most of the region. River Penner flows through Northern part. The mean minimum temperature ranges from 19.9ºC to 28.1ºC and maximum from 28.9ºC to 39.4ºC and normal rainfall is 1080.5mm. The soil is characterized by sandy clay loam.

3 MATERIALS AND METHODS

3.1 Data Processing

Two cloud-free IRS RESOURCESAT-2 LISS-IV datasets, one from March 22, 2009 and one from March 13, 2013 (WGS 84) with a pixel size of 5.8m x 5.8m were used (Table 1). These images were selected on the basis of their availability and the quality of datasets for the study area. Although different LULC classes for each of the two RESOURCESAT-2 LISS-IV images were conducted separately. Atmospheric correction was also performed.

ERDAS Imagine (2015) was used to process the atmospheric correction of LISS-IV images using the ERDAS Model maker. Image segmentation was performed using eCognition developer 9.0 (2015). Post segmentation rectification and classification accuracy assessment was performed using ArcGIS 10.2.2. Thirteen level-2 LULC classes were selected for the classification process of 2009 and 2013 datasets following the classification scheme of NRSC (2011) (Table 2).

3.2 Ground Validation

The locations of these training sites were captured using GPS enabled geotagged camera. Additional training samples for each land cover class (190 in total) were derived from high resolution imagery available in Bhuvan Geo-portal (Bhuvan, 2016). The training samples were used as inputs for the classification analysis and accuracy assessment.

3.3 Image Classification

The steps for preparing a LULC map that includes the combination of the object-based and onscreen LULC classification is presented in the map (Figure 2). In the object-based classification method, the LISS-IV images were segmented into image objects. This segmentation process creates image objects that reflect group of spatially homogeneous neighboring pixels are iteratively clustered until a preset threshold is exceeded. If more weight is assigned to particular spectral layers, these layers have more influence on the resulting segmentation boundaries. The parameters used during the segmentation process are scale, shape and compactness. The scale parameter determines the maximum size of the created object, the shape factor controls for the spectral information and shape, and the compactness factor determines compactness of the objects' edges/borders (Definiens, 2010). In the present study merging technique has been successfully applied on satellite images to extract the major LULC classes. In this study a visual resemblance to potential objects were recognized following a 'trial and error' approach (Im *et al.* 2008; Robertson and King, 2011). Hence, major LULC classes like built-up, cropland and water bodies were clipped out separately from the segmented layers to avoid redundancy (Figure 2).

In this study, to bring out a satisfactory visual match between image objects and landscape features, the segmentation parameters (scale- 5, shape- 0.1 and compactness- 0.5; a weight of 2 for the infra-red layer) were selected on the basis of assigned value of Gutiérrez *et al.* (2012), which proved satisfactory during field visits in the summer of 2015.

Table 1. Satellite image specifications

Satellite	Sensor	Dates of pass	Spatial resolution	Spectral Resolution	Radiometric Resolution
IRS R-2	LISS-IV	22 March, 2009	5.8 m	3 bands (2,3,4)	8 bit
		13 March, 2013			16 bit

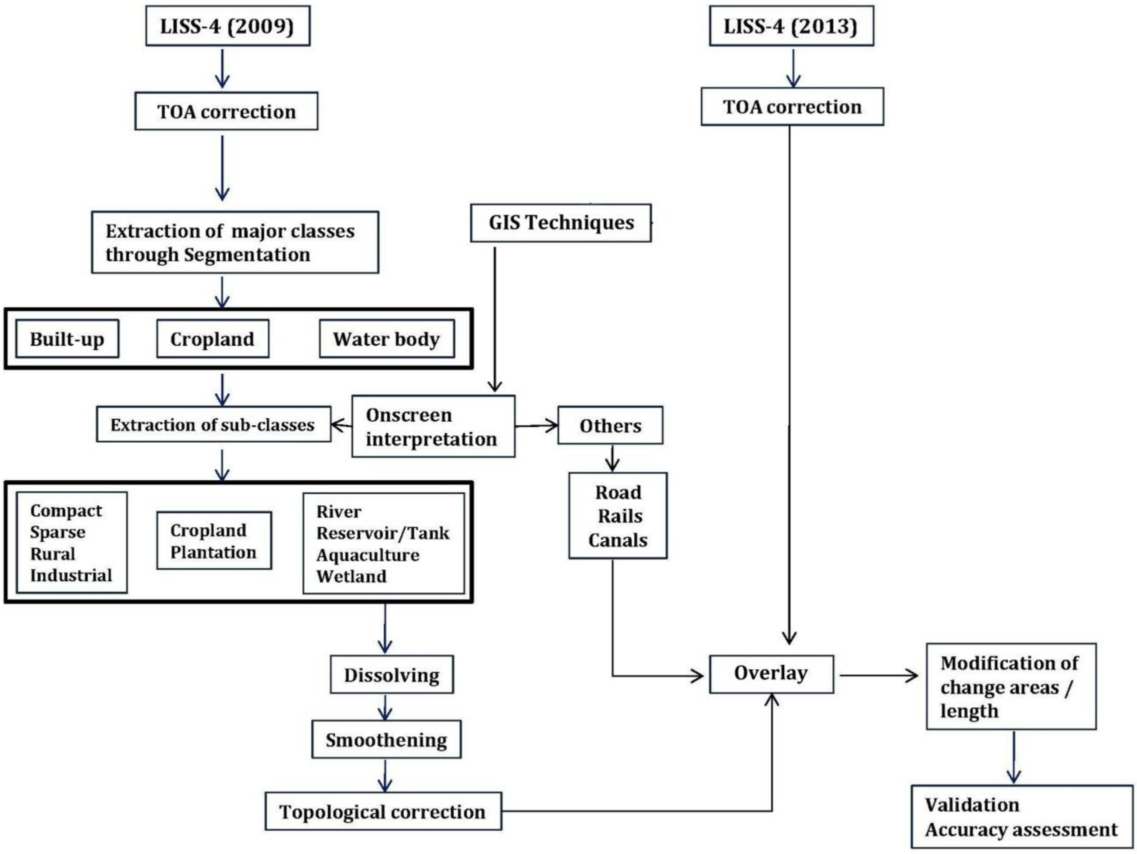

Figure 2. Schematic Preparation

3.4 Segmentation and Overlay

Segmentation was performed on LISS-IV image of 2009. After segmentation, output layers were used for onscreen modification and extraction of sub-classes using ArcGIS software. Advantage of updating and converting level-1 segments into level-2 sub-classes using onscreen value addition lies in its simplicity and error less interpretation. All the value added data was bring into one database using union method. It has also been noticed that the union layer has increased the no of features, which were further dissolved according to classes and to reduce feature number. Slivers were also eliminated through merging with adjacent bigger polygons. To remove the staircase geometric shape of the segments using 25m smoothening process was implied and finalized through topological correction. In the next step of image classification we have used the total classified vector dataset of 2009 and overlaid on 2013 satellite image to identify the LULC changes using onscreen interpretation (Roy *et al*, 2015). Thus, same dataset of 2009 has been updated with additional field contained 2013 LULC classes. Accuracy assessment reports for individual class categories and overall classification accuracies were performed for classified image of 2013.

3.5 Change Detection

A multi-date post classification comparison change detection technique was used to determine changes in LULC between 2009 and 2013. This is perhaps the most common approach to change detection (Jensen, 2004) and has been successfully used by NRSC (2011) to monitor LULC changes at 1: 50000 scale for entire India. The post-classification approach provides ‘From–To” change information and the kind of landscape transformations that can be easily calculated and mapped (Yuan *et al*, 2005). A change detection map with 62 combinations of ‘From-To’ change information were derived from prepared for 2009 and 2013.

Table 2. Land use / land cover classification schemes (NRSC, 2011)

Level 1 classes	Level 2 classes	LUCODE	Description
Built up	Compact	1	All places with a municipality, corporation or cantonment or notified town.
	Sparse	2	Areas where discrete uses are not distinguishable or separable.
	Vegetated/open area	3	Includes vegetation cover midst urban areas, play grounds, stadium, racecourse, golf course, gardens, parks, zoo, beaches and skiing areas.
	Rural	4	Built up areas smaller in size, mainly associated with agriculture and allied sectors and non-commercial activities.
	Industrial	5	Human activity is observed in the form of manufacturing along with other supporting establishments of maintenance. Heavy metallurgical industry and thermal cement, petrochemical, engineering plants.
Agriculture	Cropland	6	Areas with standing crop as on the date of satellite overpass. It appears bright red to red in color with varying shape and size in a contiguous to non-contiguous pattern.
	Fallow land	7	Cropland areas, which are uncropped during the agricultural year under consideration as on the date of satellite overpass during all cropping seasons.
	Plantation	8	Includes tea, coffee and rubber, which are normally grown in the hilly regions and closely associated with forest cover.
	Aquaculture	9	Located mostly along the coast or in lakes, river and estuaries where fish are bred and reared for commercial purposes.
Wasteland	Scrub land	13	The land which is generally prone to deterioration due to erosion.
	Sandy	15	Areas that have stabilized accumulation of sand, in coastal, riverine or inland areas.
Wetland	Wetland	16	All submerged or water saturated lands, natural or man-made, inland or coastal, permanent or temporary, vegetated or non-vegetated, which necessarily have a land-water interface.
Water body	Water body	17	Surface water in the form of rivers, canals, ponds, lakes and reservoirs.

3.6 Classification and Change Detection Accuracy Assessment

Assessments of the classification accuracy of the LULC maps were conducted by comparing samples of the classified layer and reference layer following Congalton (1991). Fifty reference points were verified by field visits, and 190 reference points were verified through comparison with recent Bhuvan imagery dated between 2009 and 2014 (Bhuvan, 2016). The class and overall accuracies, which provide an indication of the classification agreement between two maps (the classified and the ground-truth maps) that is not attributable to chance, were calculated and are presented as error matrices. The change detection accuracy was obtained by random sampling method to calculate an error matrix for obtained classes (Fuller *et al*, 2003; Yuan *et al*, 2005). Classification of the polygons as 'change' and 'no change' in the resulting LULC change layer was conducted. A total of 24282 polygons were used in the change detection assessment: 12748 polygons for the 'change' and 11534 for the 'no change' category. All reference polygons were validated through field visits and an inspection of Bhuvan imagery.

4 RESULTS AND DISCUSSIONS

4.1 Segmentation Accuracy

Extraction of major LULC dominant classes separately through segmentation shows higher accuracy to identify objects with homogenous spectral and textural characteristics. In the present study, the built-up, cropland and water body were having higher dominance over the study area (Saxena *et al*, 2014) hence, were segmented separately (Figures 3, 4 and 5). The results of the segmentation accuracy are presented in table (Table 3). The accuracy assessments with respect to the post classified segments of 2009 show overall accuracy of cropland, water body and built-up segments were 99.3%, 94.79% and 89.72%, respectively.

It was noticed from the accuracy of the built-up segment that due to complexity of LULC of the study area (Lu and Weng, 2007), it has achieved a comparatively less than water body and cropland. More specifically the presence of abandoned aqua ponds and adjacent built-up areas have created similar textural and spectral identity which were reduced the efficiency to extract segments precisely.

Table 3. Accuracy assessment for segmentation

Segments	Accuracy
Built-up	89.72%
Cropland	99.30%
Water body	94.79%

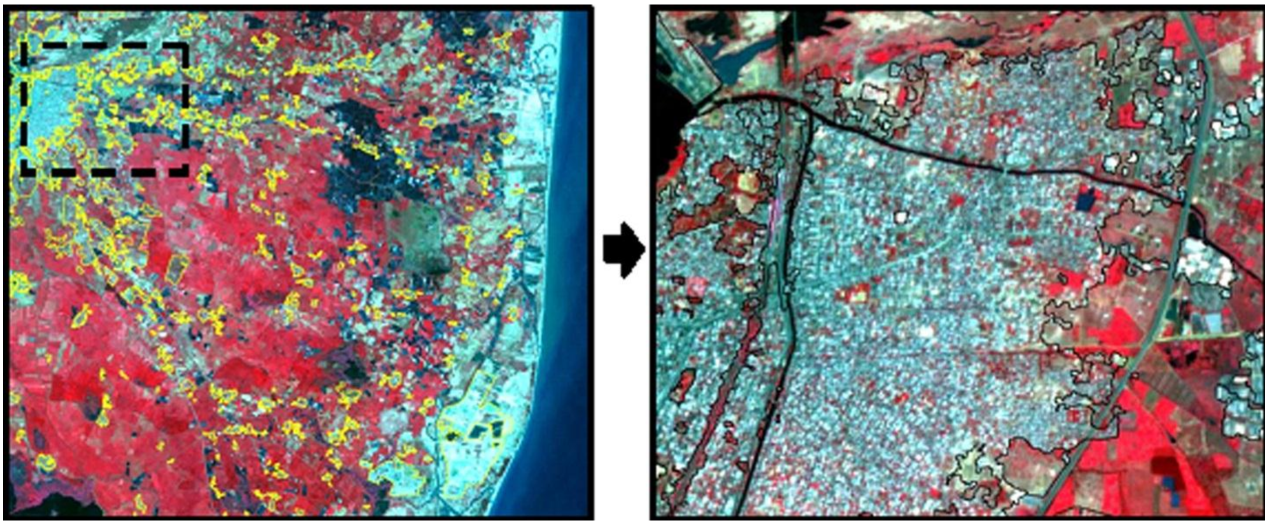

Figure 3. Extraction of built-up segment

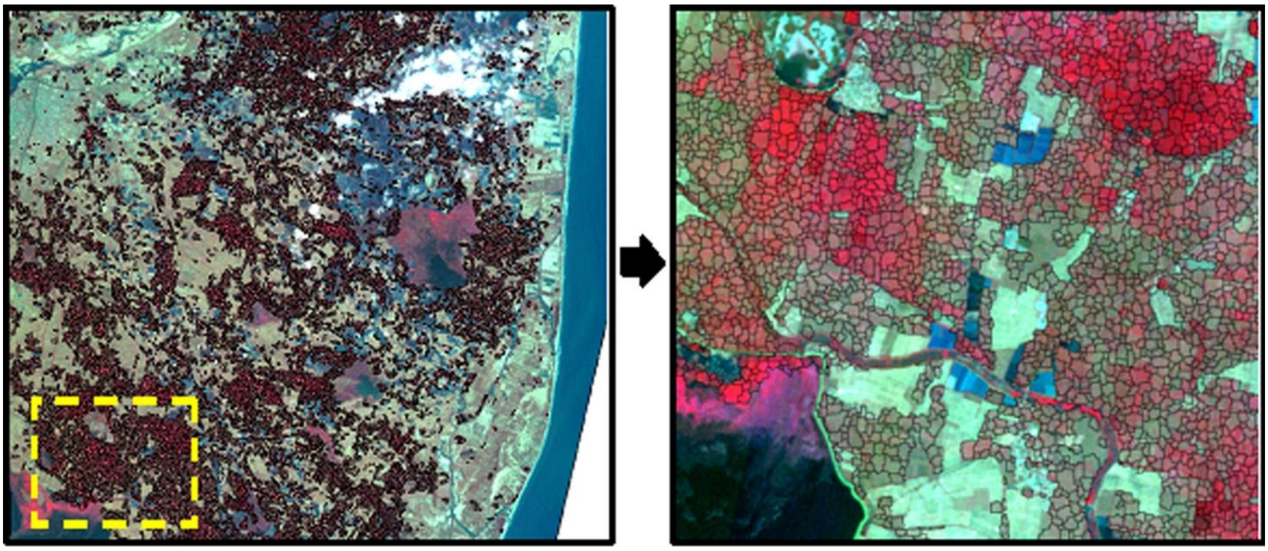

Figure 4. Extraction of cropland segment

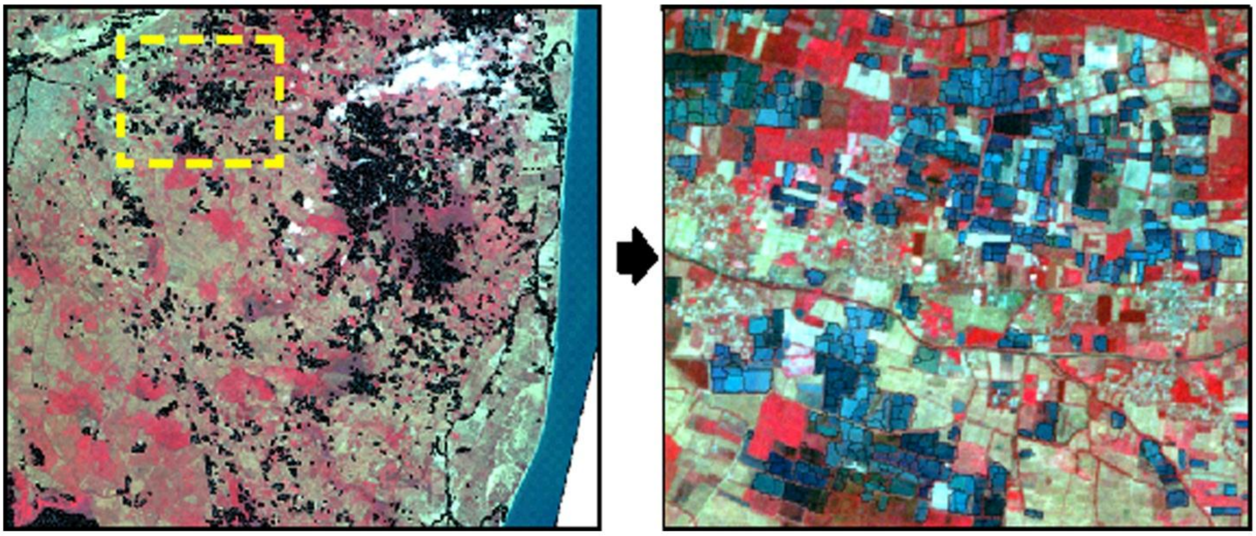

Figure 5. Extraction of water body segment

4.2 Modification and Extraction of Sub-Classes

Extraction of major LULC classes and many sub-classes cannot be depicted either object based or pixel based method. Thus, through onscreen value addition to the extracted segmented layer, thirteen level-2 classes were brought out. Table (Table 4) shows total number of segments was classified at level-1, which were further sub-divided into thirteen LULC classes at level-2.

It has also been noticed from the LISS-IV satellite image that, the study area is covered by few irrigation canal which is covering an area about 2.9 sq. km. Similarly, the study area is covered by few major roads and rails which are covering an area about 0.73sq.km. These segments have been extracted onscreen to incorporate in LULC mapping (Figure 6 and Table 5).

Table 4. Modification of extracted segments at level-2

Level-1	Level-2	Segments	Total	Extraction type
Built-up	Compact	129	559	Automatic
	Sparse	67		Value addition to compact
	Vegetated	94		Value addition to compact
	Rural	210		Value addition to compact
	Industrial	59		Value addition to compact
Agriculture	Cropland	2532	5238	Automatic
	Fallow land	814		Manually
	Plantation	126		Value addition to cropland
	Aquaculture	1766		Value addition to water body
Wasteland	Scrubland	425	428	Manually
	Sandy area	3		Value addition to built-up
Wetland	Wetland	62	62	Value addition to water body
Water body	Water body	203	203	Automatic

Table 5. Modification of extracted segments at level-2

Type	Mappable No.	Length (km)	Area coverage (km^2)
Roads	2	4	0.73
Canals	8	104	2.9

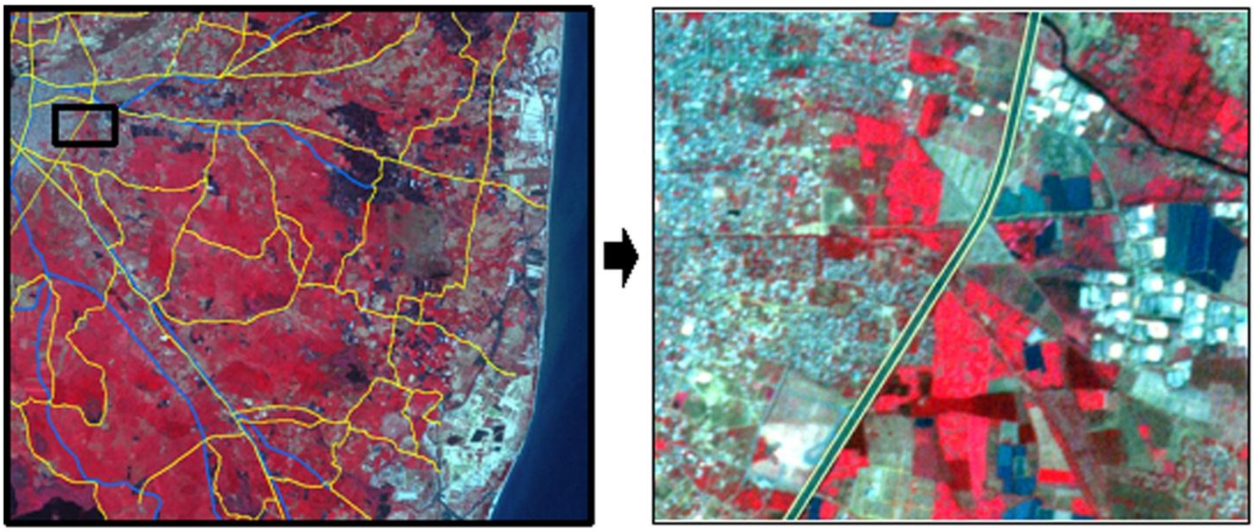

Figure 6. Extraction of rail, roads and canals

4.3 Classification Accuracy

The overall accuracy achieved for the LULC map shows the capabilities of combined classification approach. The Kappa statistic (0.89) also shows a good classification agreement. Kappa values were 0.88 for combined method, showing that the classification agreement between images ranged from good to very good (Monserud and Leemans, 1992). A 'From-To' change analysis in the present study introduced more accurate results applying a combined classification approach, delivering greater insight into actual and LULC change increase in 'urban', 'agriculture', 'aquaculture' and 'industrial' areas. The results of the classification accuracy assessment showed in table (Table 6). These results show that the extraction and merging of the best- classified classes from object-based and onscreen methods produces a LULC map with improved accuracy in comparison to individual object-based or pixel based classification methods.

4.4 Land Use / Land Cover Change

It has been observed (Figure 7) in comparing both the classification output that there has been a major transformation from scrubland to industrial expansion along the coast of study area. The map also depicted the major transformation of aquaculture to agriculture during 2009-2013. A total of 61 possible LULC changes were detected (Table 7), of which 24 are larger than 1 km^2. Most of LULC changes are the result of agriculture intensification, industrialization and urban expansion.

A summary of the LULC change results is provided in table (Table 8). Approximately 230 km^2 (56.9%) of the total study area (404.46 km^2) remained unchanged, and 174.46 km^2 (43.1%) changed. LULC classes, viz. cropland, scrubland, aquaculture and industry are more dynamic in nature (Table 7). Hence, all the classes have major contribution in 2013 LULC change. The study investigated that there was a considerable increase of cropland, industry and built-up vegetated area by 12.78 %, 2.16% and 1.83%, respectively in 2013. Simultaneously, decrease in fallow land, aquaculture and scrubland by 12.25%, 4.99% and 0.69%, respectively in 2013 has also been observed (Table 8). It has been noticed that, 'Aquaculture' class was lost between 2009 and 2013 and mostly transformed into 'cropland' and 'urban built-up vegetated' (Table 9). It has found that majority of the urbanization primarily occurred in the cropland areas (Tian *et al*, 2014). 'Industrial' area replaced almost 8.74 km^2 of scrubland, cropland, fallow land and aquaculture in total, which is an increase of 2.16% of TGA. The 'Urban' class replaced nearly 9.29 km^2 of the 'cropland' and 'fallow land' and 'scrubland' class which is 2.29 % of TGA.

Table 6. Classification accuracy for 2013

Level-1	Level-2	User's accuracy	Producer's accuracy
Built-up	Compact	0.96	0.96
	Sparse	0.80	0.89
	Vegetated	0.83	0.86
	Rural	0.93	0.95
	Industry	0.92	0.95
Agriculture	Cropland	0.88	0.91
	Fallow land	0.91	0.83
	Plantation	0.89	0.91
	Aquaculture	0.95	0.96
Wasteland	Scrubland	0.80	0.84
Wetland	Wetland	0.89	0.94
Water body	Water body	0.84	0.86
Overall accuracy		0.89	
Kappa statistic		0.88	

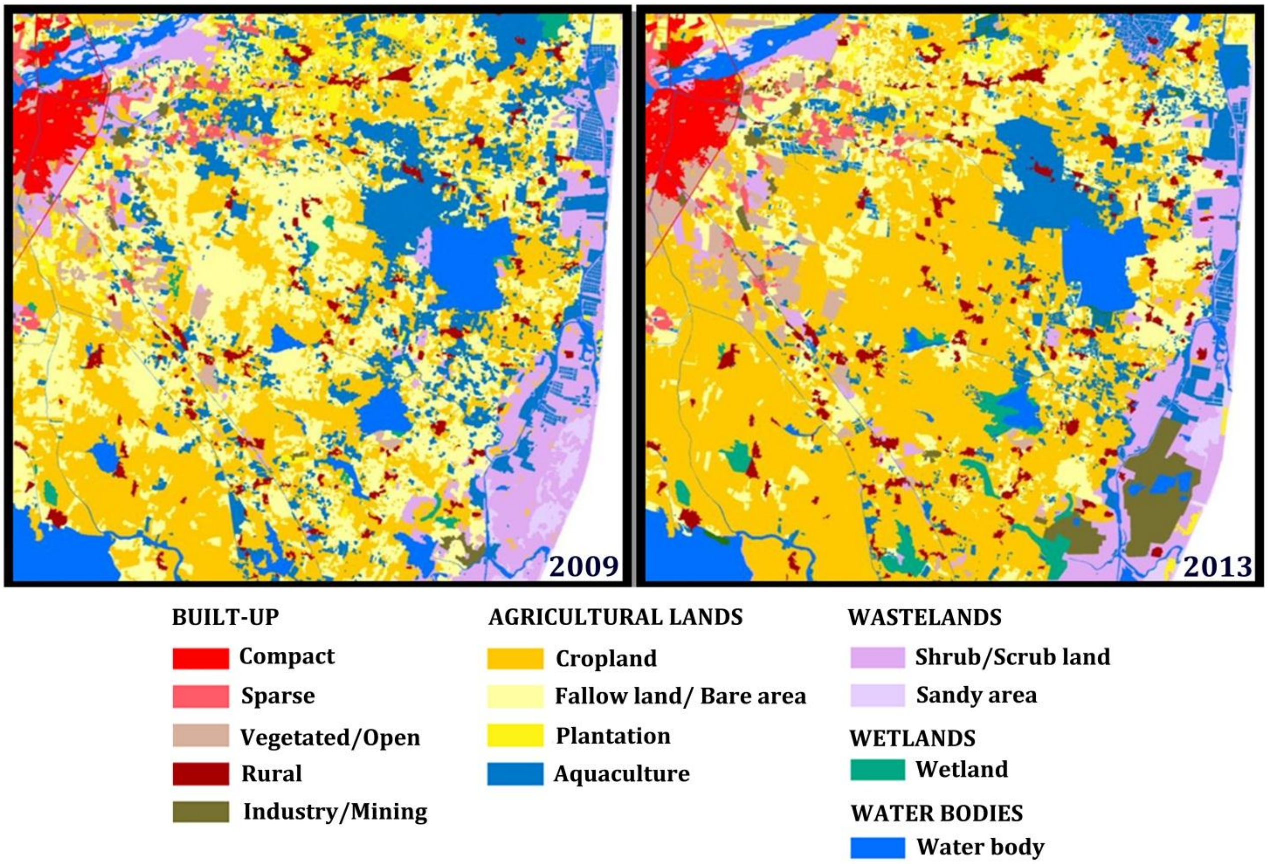

Figure 7. Land use / land cover map of study area (2009 and 2013)

The classified map is showing that there was a substantial interclass change about 12% of TGA between cropland and fallow land, but it was found as not considerable due to unavailability of multi season data. The most striking findings were that the largest patch of aquaculture field and scrub land has been decreased to approximately 12 km^2 due to industrial development after 2011 along the coastal track (Figure 8 and Figure 9).

Table 7. Land use / land cover change combinations and converted area

No.	'From – To' Classes	Area (sq.km)	No.	'From – To' Classes	Area (sq.km)
1	Aquaculture to Cropland	14.19	32	Plantation to Built-up Industries	0.04
2	Aquaculture to Fallow land	9.44	33	Plantation to Built-up Rural	0.13
3	Aquaculture to Built-up Industries	0.98	34	Plantation to Built-up Vegetated	0.15
4	Aquaculture to Built-up Rural	0.2	35	Plantation to Wasteland-Scrubland	0.36
5	Aquaculture to Built-up Vegetated	0.81	36	Built-up Vegetated to Built-up Compact	0.27
6	Aquaculture to Wasteland-Scrubland	3.02	37	Built-up Vegetated to Built-up Sparse	0.18
7	Aquaculture to Water body	0.27	38	Wasteland Sandy to Aquaculture	0.13
8	Aquaculture to Wetland	0.12	39	Wasteland Sandy to Fallow land	0.09
9	Cropland to Aquaculture	2.68	40	Wasteland Sandy to Agri. Plantation	0.09
10	Cropland to Fallow land	20.11	41	Wasteland Sandy to Built-up Industries	0.94
11	Cropland to Agri. Plantation	2.03	42	Wasteland Sandy to Built-up Sparse	0.04
12	Cropland to Built-up Compact	0.16	43	Wasteland Sandy to Wasteland-Scrubland	1.52
13	Cropland to Built-up Industries	0.55	44	Wasteland Sandy to Water body	1.11
14	Cropland to Built-up Rural	1.64	45	Wasteland Scrubland to Aquaculture	2.34
15	Cropland to Built-up Sparse	0.27	46	Wasteland Scrubland to Plantation	0.58
16	Cropland to Built-up Vegetated	2.2	47	Wasteland Scrubland to Built-up Compact	0.35
17	Cropland to Wasteland-Scrubland	2.8	48	Wasteland Scrubland to Built-up Industries	5.3
18	Cropland to Water body	0.47	49	Wasteland Scrubland to Built-up Rural	0.54
19	Cropland to Wetland	1.23	50	Wasteland Scrubland to Built-up Sparse	0.15
20	Fallow land to Aquaculture	3.7	51	Wasteland Scrubland to Built-up Vegetated	1.97
21	Fallow land to Cropland	68.54	52	Wasteland Scrubland to Wasteland Sandy	0.91
22	Fallow land to Agri. Plantation	0.98	53	Wasteland Scrubland to Water body	1.28
23	Fallow land to Built-up Compact	0.08	54	Wasteland Scrubland to Wetland	0.13
24	Fallow land to Built-up Industries	0.93	55	Water body to Cropland	0.87
25	Fallow land to Built-up Rural	0.83	56	Water body to Fallow land	0.46
26	Fallow land to Built-up Sparse	0.36	57	Water body to Wasteland-Sandy	1.32
27	Fallow land to Built-up Vegetated	2.74	58	Water body to Wetland	4.1
28	Fallow land to Wasteland-Scrubland	3.06	59	Wetland to Cropland	0.66
29	Fallow land to Water body	0.2	60	Wetland to Fallow land	0.52
30	Plantation to Cropland	1.54	61	Wetland to Water body	0.48
31	Plantation to Plantation	1.25			

Table 8. LULC change statistics for 2009 and 2013

Level-1 Classes	Level-2 Classes	Area in sq. km			Change (%) w.r.t TGA
		2009	2013	Change	
Built up	Compact	9.12	9.97	0.86	0.21
	Sparse	4.64	5.65	1.01	0.25
	Vegetated / open area	5.57	12.99	7.42	1.83
	Rural	9.36	12.71	3.35	0.83
	Industrial	2.34	11.08	8.74	2.16
Agriculture	Crop land	125.06	176.74	51.68	12.78
	Fallow land	110.9	61.34	-49.56	-12.25
	Plantation	6.96	7.17	0.21	0.05
	Aquaculture	57.93	37.74	-20.19	-4.99
Wasteland	Scrubland	35.51	32.71	-2.8	-0.69
	Sandy area	6.41	4.7	-1.71	-0.42
Wetland	Wetland	2.46	6.39	3.94	0.97
Water body	Water body	28.21	25.27	-2.95	-0.73

Table 9. LULC change matrix (2009-2013)

Land Use / Land Cover- 2009	Land Use / Land Cover- 2013														
	LU Codes	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**13**	**15**	**16**	**17**	**2009 Total**
	1	9.12													**9.12**
	2		4.64												**4.64**
	3	0.27	0.18	5.11											**5.57**
	4				9.36										**9.36**
	5					2.34									**2.34**
	6	0.16	0.27	2.2	1.64	0.55	90.92	20.11	2.03	2.68	2.8		1.23	0.47	**125**
	7	0.08	0.36	2.74	0.83	0.93	68.54	29.48	0.98	3.7	3.06			0.2	**111**
	8			0.15	0.13	0.04	1.54	1.25	3.48		0.36				**6.96**
	9			0.81	0.2	0.98	14.19	9.44		28.89	3.02		0.12	0.27	**57.9**
	13	0.35	0.15	1.97	0.54	5.3			0.58	2.34	21.97	0.91	0.13	1.28	**35.5**
	15		0.04			0.94	0.01	0.09	0.09	0.13	1.52	2.47	0.01	1.11	**6.41**
	16						0.66	0.52					0.8	0.48	**2.46**
	17						0.87	0.46				1.32	4.1	21.46	**28.2**
	2013 Total	**9.97**	**5.65**	**12.99**	**12.70**	**11.10**	**176.70**	**61.34**	**7.17**	**37.70**	**32.70**	**4.70**	**6.39**	**25.30**	**404**

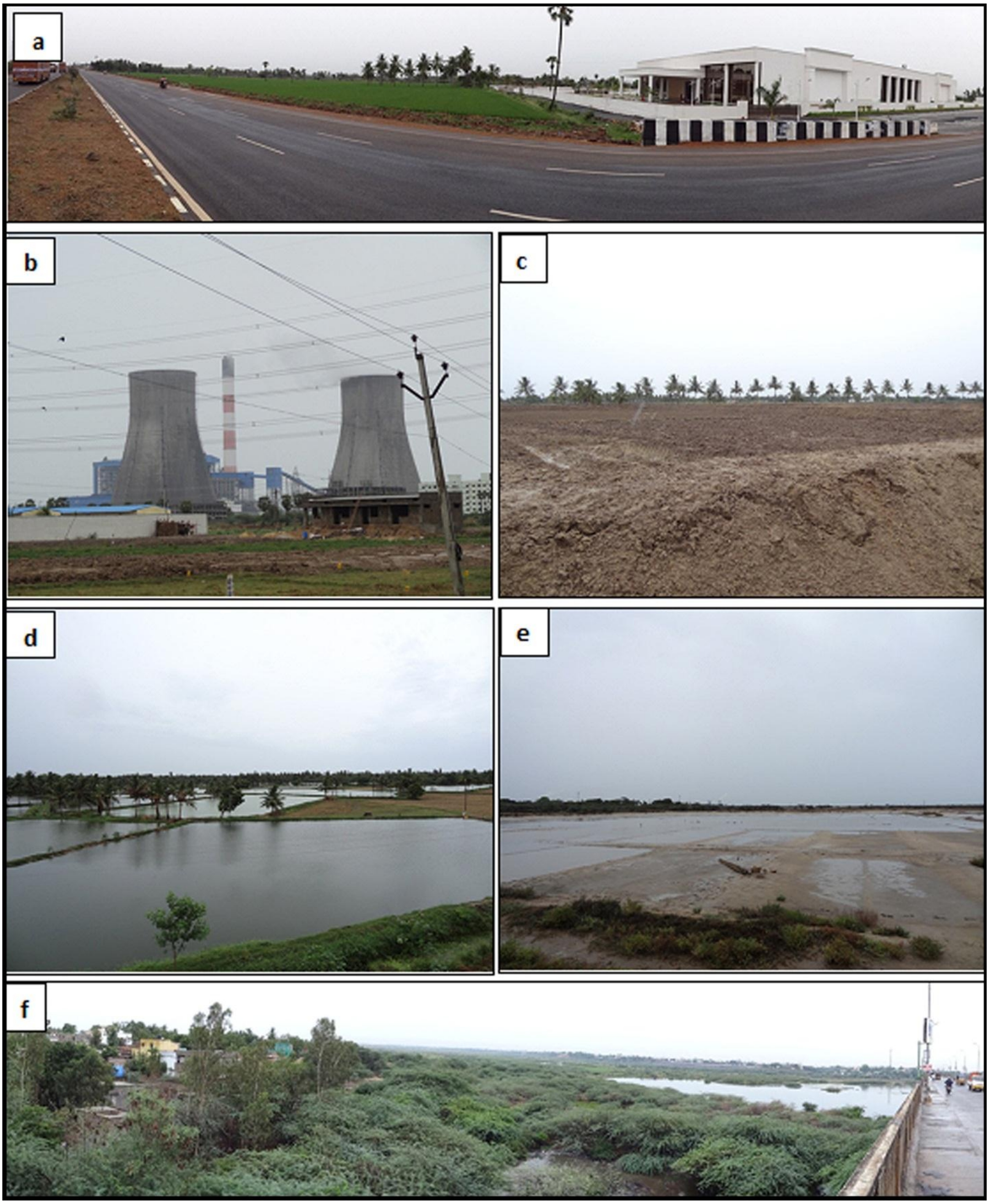

Figure 8 Ground validation of (a) conversion of cropland to urban built-up, (b) conversion of scrubland to industry, (c) conversion of agriculture land to aquaculture, (d) aquaculture practices, (e) abandoned aqua ponds and (f) chocking of river bed due to encroachment of urban built-up.

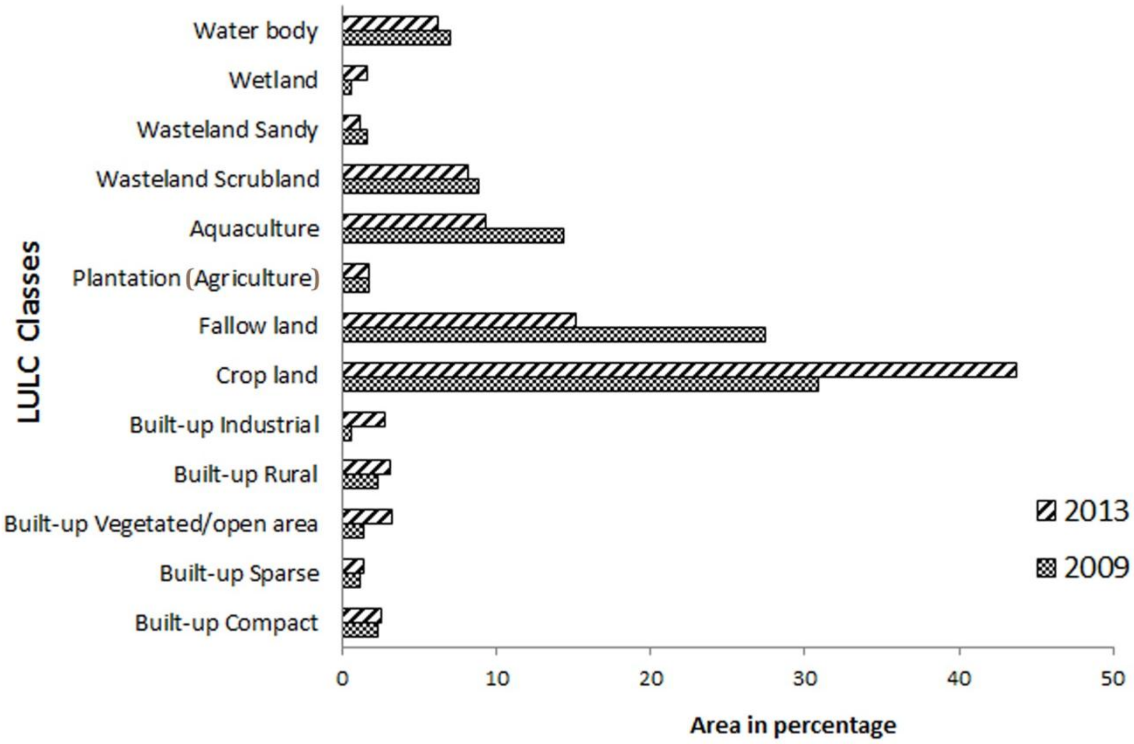

Figure 9. Change in LULC

An objective of the study was to establish a method for mapping LULC that can be applied at large scale mapping. We were interested to develop a methodology to classify high resolution satellite image with maximum accuracy. We performed a combined object based and onscreen classification techniques together. The combined classification approach has the advantage that only classes with the highest classification accuracies contribute to the final LULC map, resulting in a higher overall classification accuracy (Gutiérrez *et al*, 2012). Other authors have also obtained higher classification accuracies when applying a combination of classification methods, including Bhaskaran, Paramananda and Ramnarayan (2010). Minimal errors introduced during classification of imagery can be overcome by applying query based onscreen rectification. We were used the same database to update the change using satellite image of 2013, hence, it did not require further topological correction and simultaneously it reduces the classification error .

5 CONCLUSIONS

Object and onscreen based classification present a promising mode to improve classification of remotely sensed images. Discrimination of LULC classes with different spectral, textural, and topographical characteristics using combined object-based and onscreen classification approaches may lead to advance workflows for classifying past, present and future LULC. This technique is very useful for a complex LULC, where LULC class change rate is very high. As the accuracy for the present study is very high, so we recommend this classification approach for region with different characteristics. However, significance research is still required to reduce the subjectivity and human bias of onscreen rectification procedure.

Operational GIS projects related to LULC needs highly accurate datasets on timely basis, which can further be integrated with other datasets during decision making processes. The classification approaches in this study have produced highly accurate datasets which can be maintained and updated within GIS environment. Furthermore, it will be beneficial for researchers and decision makers to execute the development plan for certain LULC.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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ABBREVIATIONS

GIS: Geographical Information System**; GPS:** Global Positioning System**; IRS:** Indian Remote Sensing Satellite**; ISRO:** Indian Space Research Organization**; LU:** Land Use; **LULC:** Land Use/ Land Cover**; LULCC:** Land Use/ Land Cover Change**; MRFs:** Markov Random Fields**; NRSC:** National Remote Sensing Centre**; R2:** RESOURCESAT-2**, TGA:** Total Geographical Area**; TOA:** Top of Atmosphere**; WGS 84**; World Geodetic Survey 1984.

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