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Research Paper

Post-classification corrections in improving the classification of Land Use/Land Cover of arid region using RS and GIS: The case of Arjuni watershed, Gujarat, India ☆

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ABSTRACT

Classifying Remote Sensing (RS) imagery for reliable and accurate Land Use/Land Cover (LU/LC) change information still remains a challenge in heterogeneous and arid landscapes due to spectrally similar LU/LC features. The aim of the present study is to extract reliable LU/LC information using ancillary data and change detection between 2001 and 2011 for Arjuni watershed from highly arid state Gujarat, India using RS and Geographic Information System (GIS). The Maximum Likelihood Classifier (MLC) was first applied to IRS LISS-III imagery of 2001 and 2011 and classified as: water body, forest, agricultural land, scrub forest/Prosopis, barren land, settlement/built-up land, river sand and quarry. Further, the study employed an innovative methodological framework of ancillary data (viz., texture imagery, Normalized Difference Water Index-NDWI and drainage network) for post-classification corrections. It has significantly improved overall classification accuracies from 67.84% to 82.75% and 71.93% to 87.43% for 2001 and 2011, respectively. The change detection study showed an increase in agricultural land, forest, water body classes and decrease in scrub forest/Prosopis and river sand classes over the period of ten years.

1. Introduction

The reliable and updated information on the LU/LC maps and their dynamics can help to provide base information for further decision making in watershed management activities (Alphan, 2003). Therefore, the LU/LC change is considered as an important measure to evaluate the impact of applied watershed management measures. Remote Sensing (RS) is a technology used to monitor and evaluate the LU/LC changes, which typically vary from global to regional scale (Csaplovics, 1998; Foody, 2002; Dutta et al., 2003; Shanwad et al., 2008). In addition, the Geographical Information System (GIS) technology provides a flexible environment for collecting, storing, displaying and analyzing digital data necessary for LU/LC change detection (Weng, 2002; DeMers, 2005; Wu et al., 2006; Reis, 2008). The integrated use of satellite RS and GIS have been proven to be a powerful and cost effective approach for monitoring LU/LC changes (Hathout, 2002; Herold et al., 2003; Lambin et al., 2003; Poyatos et al., 2003; Serra et al., 2008; López-Granados et al., 2013; Phukan et al., 2013; Singh et al., 2013; Hazarika et al., 2015). However, the automatic digital classification offers a challenge in getting accurate good classification accuracy for arid and heterogeneous landscapes (Manandhar et al., 2009), due to high inter-annual variability in climatic conditions. The major problems include the variety of spatial patterns, highly fragmented features, and variable vegetation cover (Barkhordari and Vardanian, 2012). The spectrally similar LU/LC classes are quite common in such regions. All these factors limit the accuracy of image classification.

Various researchers have made efforts to improve the accuracy of MLC (Chen and Stow, 2002; Pal and Mather, 2006; Lu and Weng, 2007). The most common approach is to incorporate the ancillary data before, during and after the classification and thereby infuse the ancillary knowledge (Hutchinson, 1982; Mesev, 1998; Rocha et al., 2005). Here, the ancillary data are any type of spatial or non-spatial information that may be of value in the image classification. It includes elevation, slope, aspect, geology, soil, hydrology, derived indices, vegetation maps, DEM etc. (Jensen, 1996). Various

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studies have been undertaken to improve the accuracy of classification using different RS and/or GIS based ancillary data at various stages of classification (Jones et al., 1988; Franklin and Wilson, 1992; Ricchetti, 2000; Shalaby and Tateishi, 2007; Yacouba et al., 2009). In particular, the ancillary data like urban mask (Mesev, 1998; Northcutt, 1991), DEM (Eiumnoh and Shrestha, 2000; Ricchetti, 2000; Fashi et al., 2000; Saha et al., 2005) and texture imagery (Alrababah and Alhamad, 2006; Franklin et al., 2000) have been proven to be quite successful. The visual image interpretation using GIS has also effectively been used to get the better classification accuracy (Abd El-Kawy et al., 2011).

Looking to the accuracy of specific LU/LC class like water body, its spectral signature is quite different from other land features. However, it is difficult to identify the water class pixels at the boundary region of water body due to high possibility of spectral mixing with other neighboring classes. Specifically, shallow water bodies can be mistaken for soil and saturated soil can be mistaken for water pixels along the periphery (Sarkar and Jain, 2008). The Normalized Difference Water Index (NDWI) was first proposed in 1996 to detect surface water and to allow for the measurement of surface water extent (McFeeters, 1996). The approach has been successfully used in applications where the measurement of the extent of open water body is required (Jain et al., 2005; Xu, 2006; Ganaie et al., 2013; McFeeters, 2013; El-Asmar et al., 2013).

The primary objective of the present study is to improve the classification accuracy in the arid heterogeneous landscape of Arjuni watershed, (from Gujarat, India) using RS and GIS ancillary data viz., texture imagery, NDWI and drainage network layers. The secondary objective of the present study is to assess the LU/LC changes in the study area from 2001 to 2011. The changes are mainly due to watershed management measures, which were undertaken by various watershed development activities in the last decade. Numbers of government and non-government agencies are involved in the watershed development measures of this underdeveloped region. The Desert Development Programme (DDP) has been extensively implemented in the upper northeastern part of watershed. In order to intensify the agricultural land, about 27.63% of the watershed area was already treated by the year 2011 through land reclamation from degraded land to agricultural land, horticulture etc. Therefore, the LU/LC change detection was applied to assess the impact of such watershed management measures.

2. Study site

The Arjuni watershed is located at the junction point of Mehsana, Patan and Banaskantha districts of Gujarat, India (Fig. 1). It extends about latitude of 23° 51′ 7.8″ N to 24° 19′ 18.9″ N and longitude of 72° 15′ 17.9″ E to 72° 50′ 16.3″ E, with a total area of 979.53 km^2. The Arjuni and Saraswati are the dominant ephemeral rivers of the watershed. It consists of the extreme arid climate condition and heterogeneous topography. The climate exhibits very hot summer, cold winter, high evaporation and a short rainy season (July-August). The normal annual rainfall is 625–875 mm. The region is rich in agricultural production, but it largely depends on groundwater, both for irrigation and drinking water requirements. However, its extensive withdrawal had led to large drops in groundwater level in many talukas/blocks of Mehsana district of the study area. Mining activities have also mainly contributed to the economic growth of the region. The Vadasand and Jasvantgadh villages are the main mining sites. These consist of the Granite quarries. Here, the quarries are areas with human-induced effects that result in exposing soil surface layers and/or changes in topsoil (Abd El-Kawy et al., 2011). The mean daily maximum temperature is of about 41 °C. Due to its unique geological and geomorphologic characteristics, the major environmental challenges of the watershed include erodible sediments, severe rainstorm events, rapid population increase, irrational land use, increased soil erosion rate etc. Moreover, the high temperature, sandy soil, water scarcity, poor quality of ground water and high wind velocity together make a very precarious situation in agriculture (Thakkar et al., 2015). Therefore, in last decade, the North Eastern part of the study area has been treated by various watershed development programmes viz., Desert Development Programme (DDP).

3. Data used and processing

Table 1 shows the description and sources of all the acquired primary and secondary data of the study area. The primary data of LU/LC classes were collected from the field by ground truthing. The secondary data viz., RS data, previously available LU/LC map and topographic sheets are collected from different sources.

3.1. Remote Sensing (RS) data

The acquired RS imagery have been pre-proceed using geometric corrections, radiometric corrections and sun angle corrections as describe below.

3.1.1. Geometric corrections

The geometric transformation can be quantified by selecting pairs of suitable Ground Control Points (GCPs) on RS imagery and an appropriate geometric model. The IRS 1C LISS-III image of 21st Oct 2001 geometrically corrected with reference to already rectified master image of IRS R2 LISS-III dated 29th Oct 2011. The geometric transformations were performed using second order polynomial and nearest neighborhood resampling algorithm. A total of 121 GCPs having the corresponding RMSE of 0.291 was considered the referencing of IRS 1C LISS-III image of 21st Oct 2001. To accommodate the lower small part of the watershed area, IRS 1D LISS-III image of 14th Dec 2001 was also geometrically corrected by 100 GCPs having corresponding RMSE of 0.233 and mosaic together in ERDAS IMAGINE 9.2.

3.1.2. Radiometric corrections

The radiometric corrections were applied to the obtained RS data of Arjuni watershed by converting Digital Number (DN) values into spectral radiance values using the external calibration coefficients provided in the satellite data header/metadata file.

3.1.3. Sun angle corrections

The position of the Sun relative to the Earth depends on the time of the day/year. Therefore, the Sun angle corrections were applied on at-sensor radiance imagery of RS data. The Sun elevation angles (α) were provided in the satellite data header/metadata file.

3.2. Ancillary data

In the present study, following three masks were generated using RS and GIS integrated ancillary data for the post-classification corrections:

3.2.1. Forest mask generation

Texture image refers to the pattern of brightness variations or gray-levels within an image (Carr, 1999). In the present study, 3×3 variance texture imagery were derived from NIR band of RS data of 2001 and 2011 individually and stacked with corresponding visual bands. The developed five layer imagery were applied

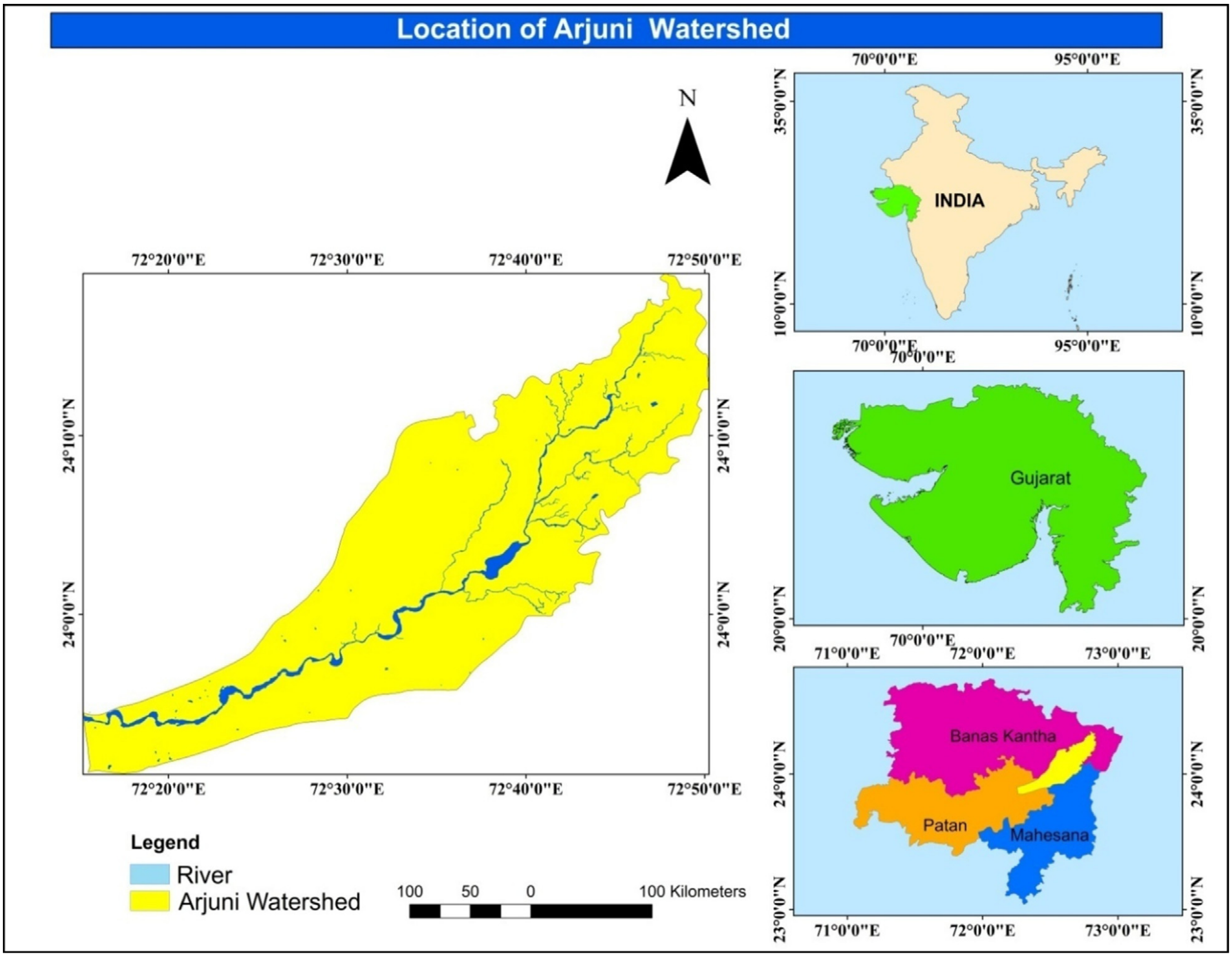


Fig. 1. Location map of the study area.

Table 1
Data used for LU/LC and biomass change detection for Arjuni watershed.

Data	Description	Source
IRS 1C LISS-III IRS 1D LISS-III IRS R2 LISS-III	Path: 93, Row: 55; Date of pass: 21st Oct 2001 Path: 92, Row: 55; Date of pass: 14th Dec 2001 Path:93, Row:55; Date of pass: 29th Oct 2011	Acquired from National Remote Sensing Centre (NRSC), Hyderabad, India, through Bhaskaracharya Institute for Space Applications and Geo-Informatics (BISAG), Gandhinagar, Gujarat, India
LU/LC map of May 2000	Developed by visual image interpretation of IRS data	BISAG, Gandhinagar, Gujarat, India
Field data of LU/LC classes	Using GPS of Garmin Terex Summit HC, v. 3.7	BISAG, Gandhinagar, Gujarat, India
Topographic sheets	Open series topographic sheets (surveyed in 2005 and published in 2011) No. 45D/8, 45D/1, 45D/12, 45D/15, 45D/16, 46A/5, 46A/9	Survey of India, Gandhinagar, Gujarat, India
LISS-IV data	Spatial resolution is 5.8 m	BISAG, Gandhinagar, Gujarat, India

for supervised classification and classified into eight LU/LC classes (viz., water body, forest, agricultural land, scrub forest/Prosopis, barren land, settlement/built-up land, river sand and quarry). The forest masks were extracted from classified maps of 2001 and 2011 as shown in Fig. 2.

3.2.2. Water body mask generation

The NDWI (McFeeters, 1996) index was generated for RS data of 2001 and 2011 individually using Eq. (1). The NDWI values greater than zero represent water surfaces, while values less than, or equal, to zero represent non-water surfaces. The next step is to determine what threshold value needs to be applied to the NDWI image so as to eliminate non-water surfaces which may have low reflectance, and possibly positive NDWI values. The appropriate threshold values were selected using the rule classifier by iterating different values in ENVI (v. 4.7) software. The threshold values of 0.26 and 0.28 were selected for water body masks development of corresponding 2001 and 2011 RS data (Fig. 3).

$$NDWI = (L_{Green} - L_{NIR})/(L_{Green} + L_{NIR}) \quad (1)$$

where L_{Green} is the radiance in Green channel and L_{NIR} is the radiance in NIR channel.

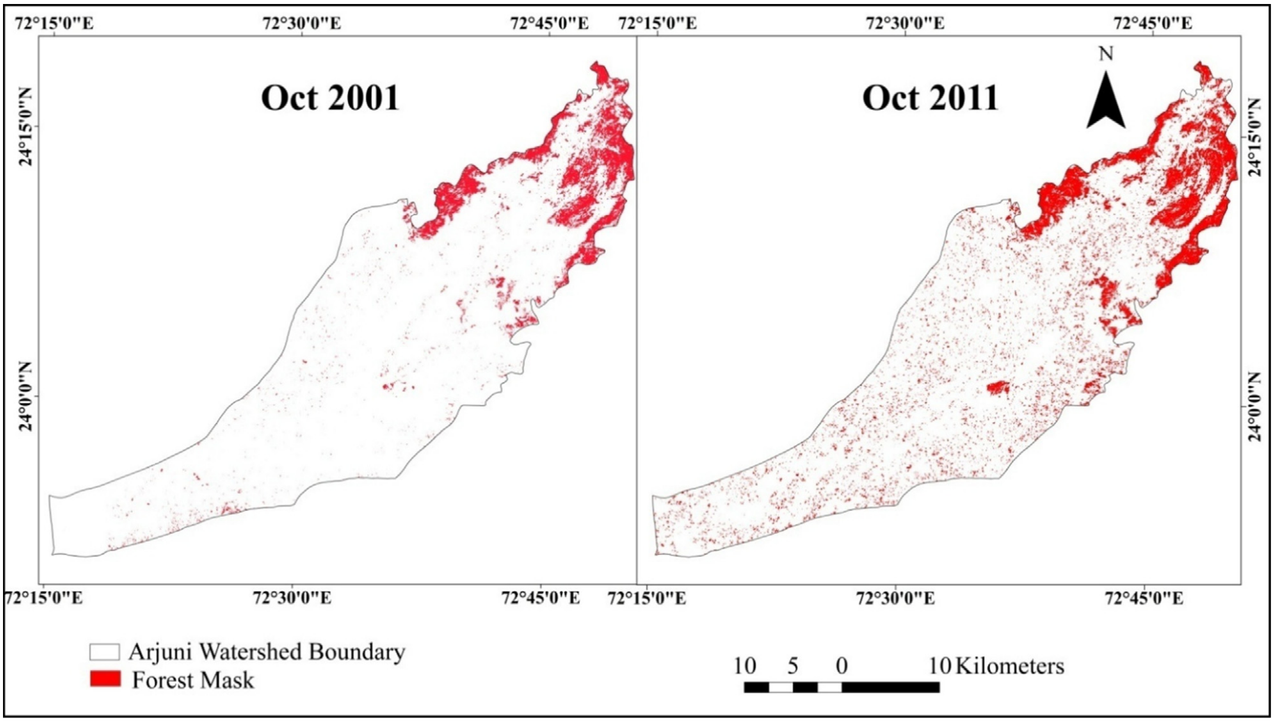


Fig. 2. Forest masks generated for 2001 and 2011.

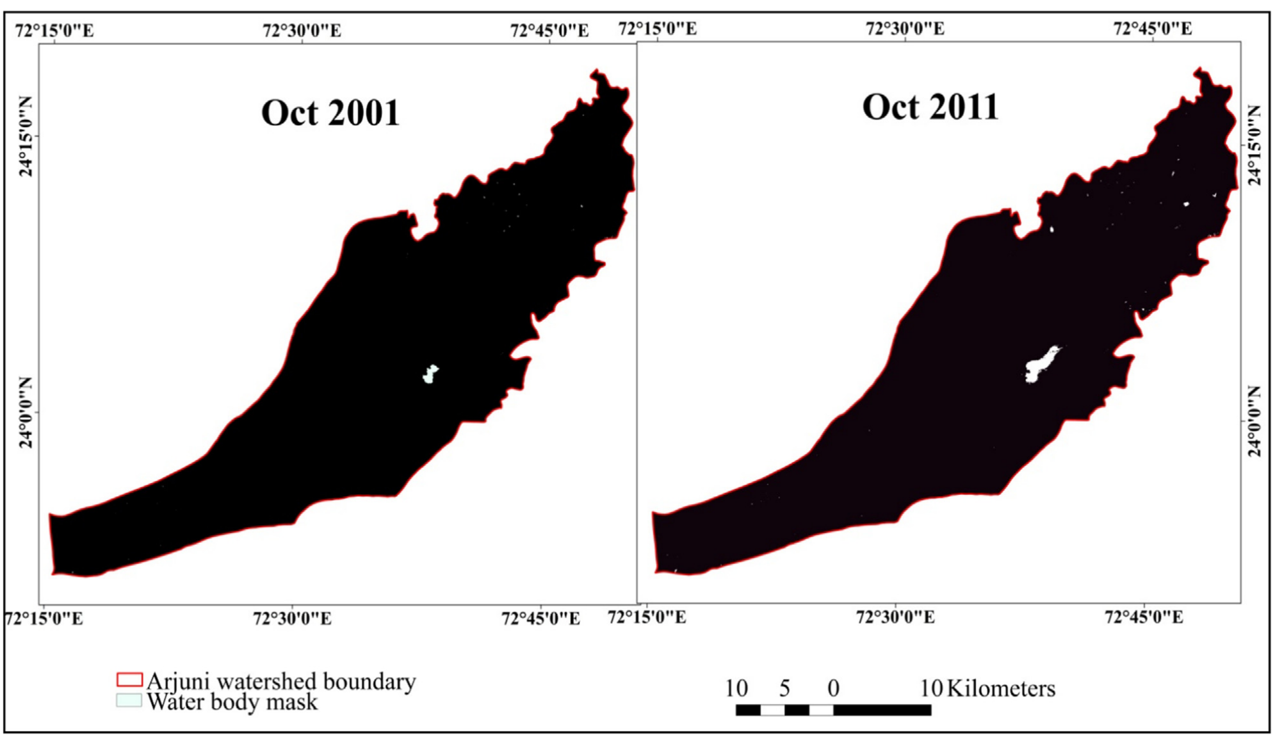


Fig. 3. Water body masks generated for 2001 and 2011.

3.2.3. Drainage network mask generation

The Arjuni and Saraswati are ephemeral rivers and hence in the post-monsoon season the drainage network path is full of sand except for the stored water bodies (viz., reservoir). Therefore, the on-screen digitization of drainage network, except stored water bodies was carried out based on visual image interpretation on the RS data of 2001 and 2011 individually (Fig. 4) and drainage network masks were developed

4. Methodology

A flowchart showing the RS data used, processing and the methodology adopted for the present study as described in detail below in Fig. 5. It includes the new four steps post-classification correction approach to improve the classification accuracy derived from MLC. Initially, the RS data of 2001 and 2011 were classified using MLC decision rule of supervised classification. They gave

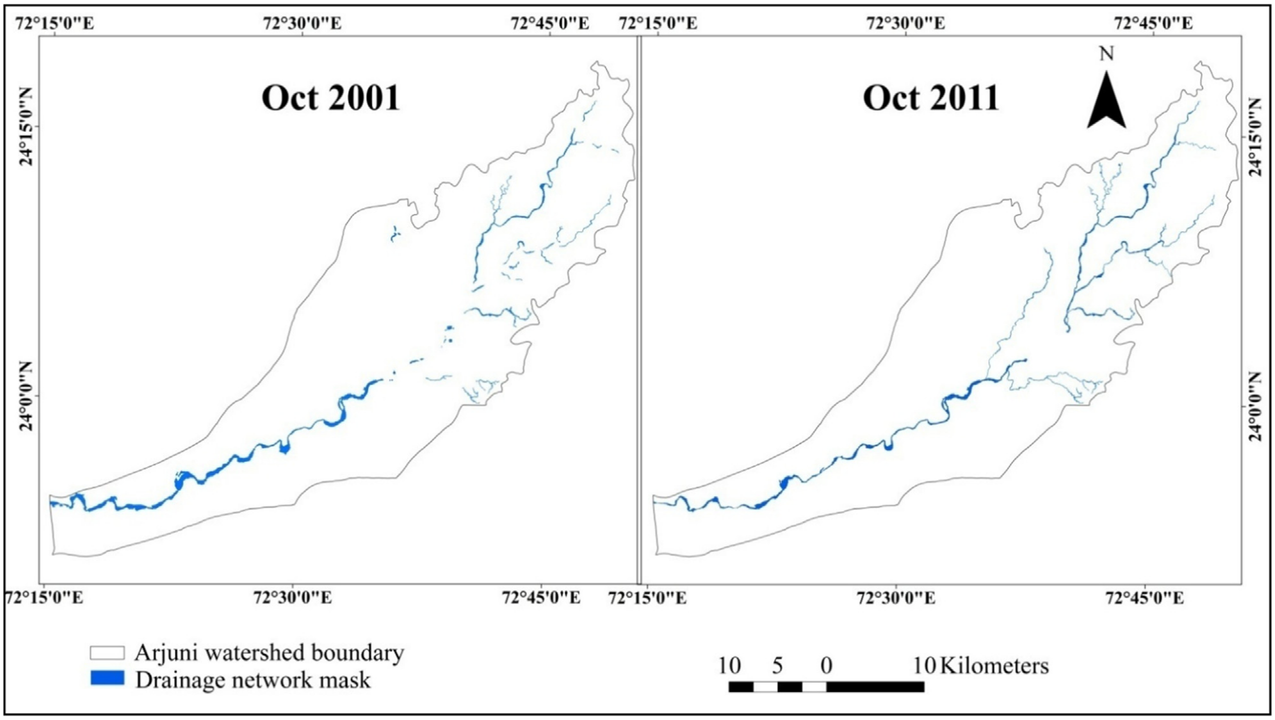


Fig. 4. Drainage network masks generated for 2001 and 2011.

unsatisfactory results caused by spectral confusion among some classes like; scrub forest/Prosopis and agricultural land (mainly harvested), forest and agricultural land (having natural vegetation), settlement/built-up land and river sand, water body with the other classes etc. In order to reduce such misclassifications, the integrated RS and GIS based ancillary data viz., (1) 3×3 variance texture images (2) NDWI, and (3) digitized drainage network based on visual image interpretation, were used at post-classification stage. Subsequently, the 3×3 majority filter was applied on scrub forest/Prosopis class and visual image interpretation of IRS LISS-IV data to further minimize the misclassifications. The accuracy assessment was carried out between the classified thematic LU/LC maps derived by MLC with and without post-classification corrections. It was followed by McNemar statistical significance test to check the significant difference of accuracies in proportion.

4.1. LU/LC classification

Maximum Likelihood Classifier (MLC) is the most widely adopted parametric classification algorithms. It has been extensively used for the LU/LC classification worldwide (El-Hattab, 2016; Rawat and Kumar, 2015). In the present study, the MLC is used for the LU/LC classification of acquired RS imagery data of 2001 and 2011. Taking into account the spectral characteristics of the satellite images and existing knowledge of land use of the study area, eight LU/LC categories were classified viz., water body, forest, agricultural land, barren land, scrub forest/Prosopis, settlement/built-up land, river sand and quarry.

4.2. Post-classification corrections using ancillary data

The post-classification correction technique was developed and used to refine the class assignment of a pixel after its initial MLC. The deerived LU/LC maps from MLC were noisy due to spectral similarity among different classes. For example, the forest class was misclassified as scrub forest/Prosopis and/or agricultural land. Similarly, the river sand class was misclassified into settlement/built-up land class. The post-classification correction technique is divided into four steps based on misclassified LU/LC class type. The Step1 was applied to minimize the misclassification of forest class. Initially, the forest class pixels were removed from classified LU/LC maps of 2001 and 2011 using reclassify function in ArcGIS 9.3 and the forest masks developed using ancillary data were overlaid in ERDAS IMAGINE (v 9.2) individually. The corrected thematic maps were further employed for water body class correction in Step 2. Here, the water body masks developed using ancillary data were overlaid on the output of Step 1 to remove the misclassification of water bodies (check dam, talav etc.) with other neighbouring classes at the boundary region. In step 3, to minimize the misclassification of river sand class with settlement/built-up land class, the developed masks of drainage network were overlaid on the resulted thematic maps from step 2. In step 4, the corrected thematic maps were applied by 3×3 majority filter on scrub forest class to reduce the salt and pepper effect. However, some noisy forest class pixels were still misclassified with agricultural land (having healthy crops) at southern part of the watershed in RS data of 2011. The visual image interpretation of high resolution IRS LISS-IV data was used to manually assign the forest class on misclassified pixels.

4.3. Accuracy assessment

The accuracy assessment was carried out on the classified thematic maps in two ways, as follows: (1) without post-classification corrections and (2) with post-classification corrections. The stratified random samples of 342 points were selected. The reference data of ground truth points and open series topographic sheets were proved helpful accuracy assessment of LU/LC maps of 2011. Similarly, the reference data of previously available LU/LC map of

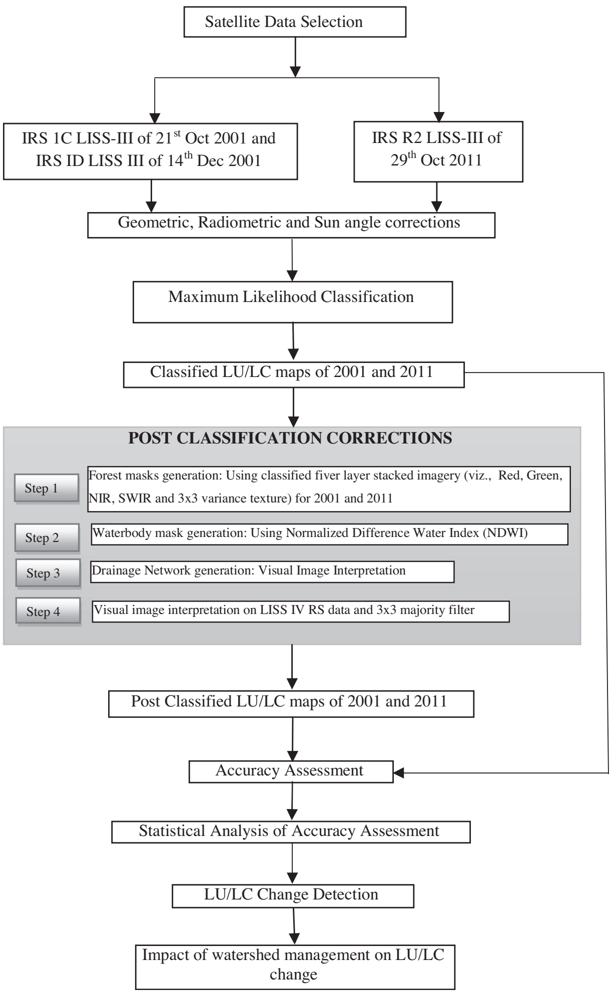


Fig. 5. The flowchart for the adopted methodology.

2000 and open series topographic sheets were proved helpful to accuracy assessment of LU/LC maps of 2001. The accuracy parameters viz., Producer's accuracy (a measure of omission error), User's accuracy (a measure of commission error) and Kappa statistics (overall and conditional) were estimated.

4.4. Statistical analysis of accuracy assessment

It is required to assess the statistical significance of accuracy between classified thematic LU/LC maps of without post-classification corrections and with post-classifications corrections. We have applied the McNemar non-parametric test, which basically compares the statistical significance of the difference between two proportions (Foody, 2004). It is based on Chi-square (χ^2) distribution as shown in Eq. (2). As Chi-square distribution is continuous and sample frequency of data are discrete (Dietterich, 1998), the continuity correction is applied using Eq. (3).

$$\chi^2 = \frac{b - c}{\sqrt{b + c}} \tag{2}$$

$$\chi^2 = \frac{(|b - c| - 1)^2}{\sqrt{b + c}} \tag{3}$$

where b is the number of categorical data having incorrect proportion in the LU/LC map without post-classification corrections and correct proportion in LU/LC map with post-classification corrections, and c is the number of categorical data having correct proportion in the LU/LC map without post-classification corrections and incorrect proportion in LU/LC map with post-classification corrections.

4.5. Change detection

The post-classified corrected LU/LC maps have been applied for change detection over the period of 2001–2011. The areal changes of classified LU/LC maps were assessed.

5. Results and discussions

As would be expected, the MLC without post-classification corrections did not produce satisfactory results. Figs. 6 and 7 represent the band wise mean radiance values of training pixels of LU/LC classes classified by MLC without post-classification corrections for 2001 and 2011, respectively. The difficulty with the signatures is the mean radiance values among LU/LC classes viz., forest, agricultural land, scrub forest/Prosopis, which are showing highest radiance values in band 3 (NIR). It represents that there is a high probability of misclassification among these four classes.

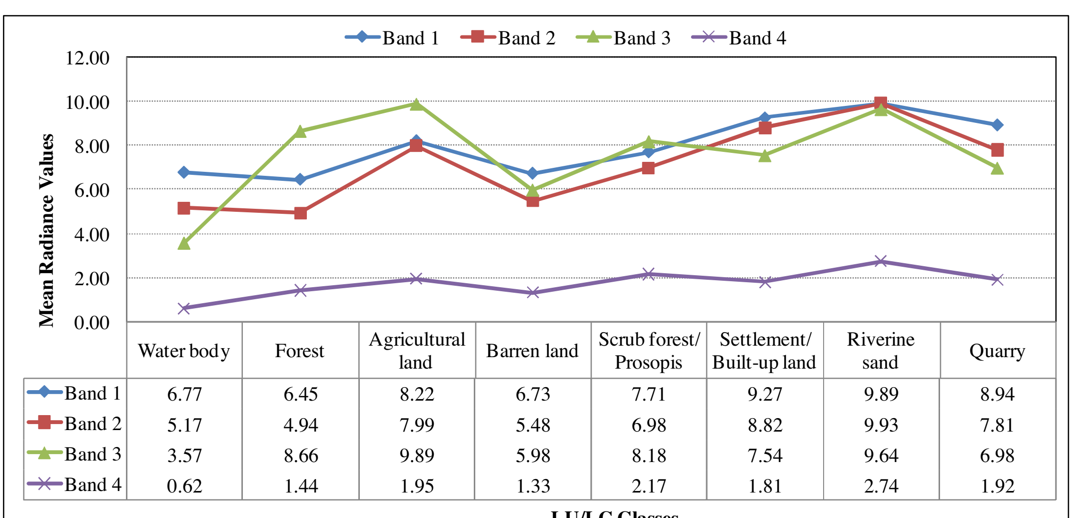
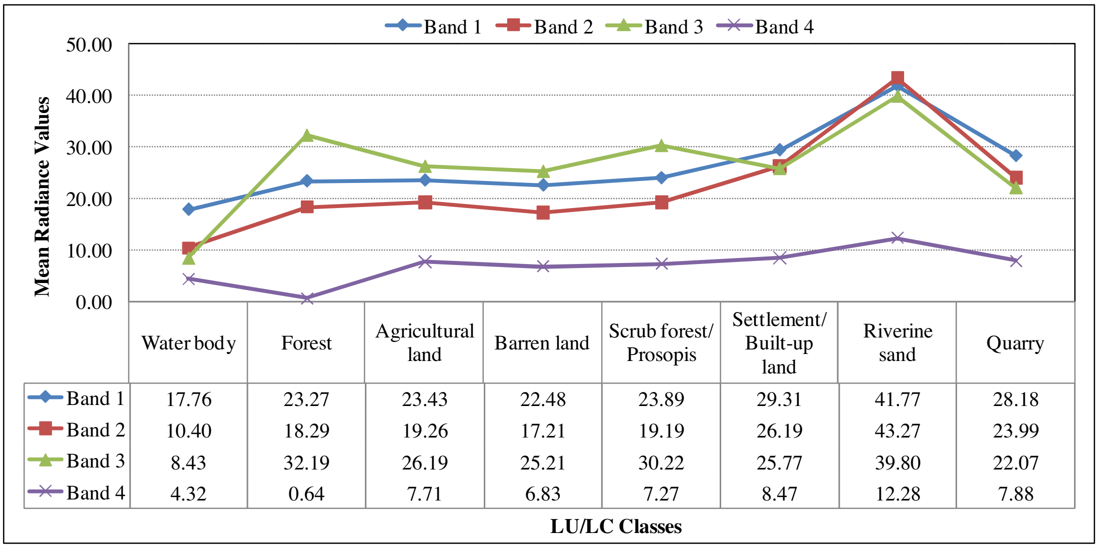


Fig. 6. Mean radiance values of traning pixels of the various LU/LC classes over band 1–4 for RS data of 2001.



	Water body	Forest	Agricultural land	Barren land	Scrub forest/ Prosopis	Settlement/ Built-up land	Riverine sand	Quarry
Band 1	17.76	23.27	23.43	22.48	23.89	29.31	41.77	28.18
Band 2	10.40	18.29	19.26	17.21	19.19	26.19	43.27	23.99
Band 3	8.43	32.19	26.19	25.21	30.22	25.77	39.80	22.07
Band 4	4.32	0.64	7.71	6.83	7.27	8.47	12.28	7.88

Fig. 7. Mean radiance values of traning pixels of the various LU/LC classes over band 1–4 for RS data of 2011.

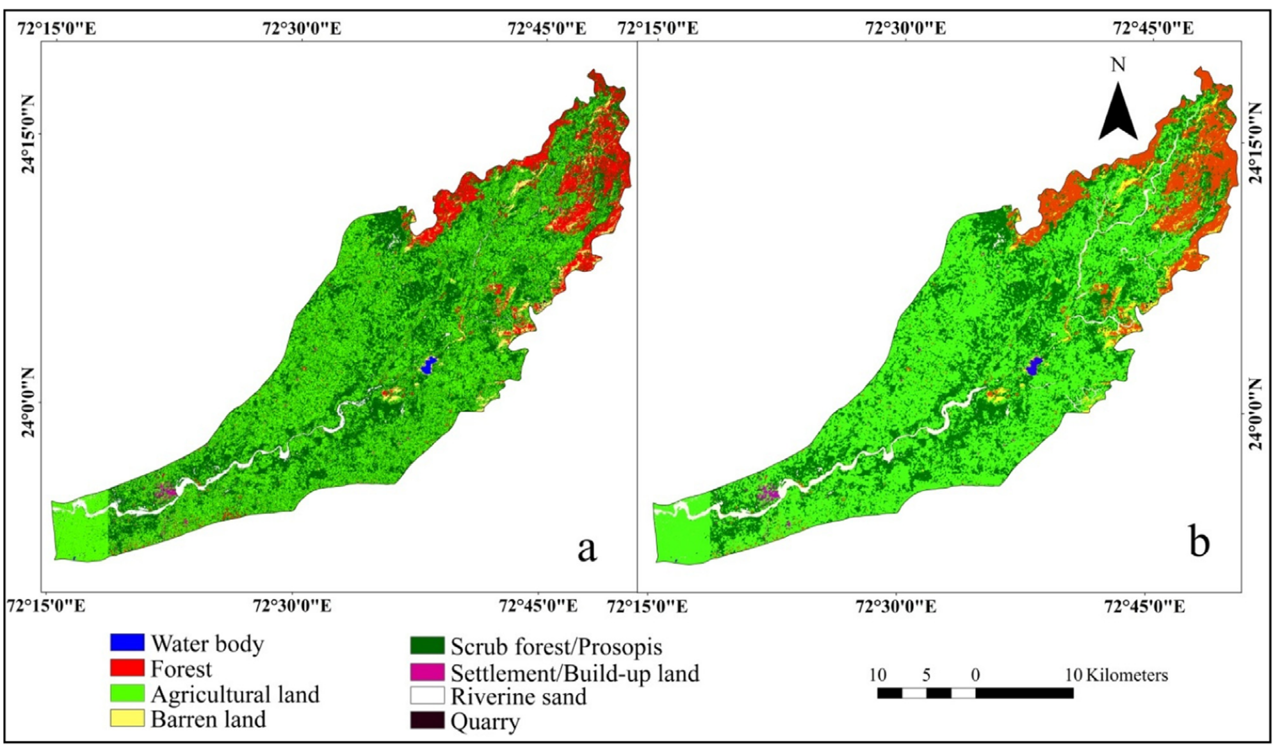


Fig. 8. LU/LC maps of Arjuni watershed for 2001 classified by MLC; (a) without post classification corrections (b) with post classification corrections.

The classified LU/LC maps by MLC without and with post-classification corrections are presented in Figs. 8 and 9 for 2001 and 2011, respectively. It is evident that each of the RS based classification products has undergone improvement after post-classification corrections.

The poor performance of MLC without post-classification corrections is confirmed by accuracy assessment results (error matrices) as shown in Tables 2–5. Table 2 indicated the high commission error (i.e., low user's accuracy) for the forest, agricultural land and settlement/built-up land classes for 2001. With the post-classification corrections, that involved integrating ancillary information to minimize the misclassification, the user's accuracy of water body, forest, agricultural land, settlement/built-up land and river sand classes were largely increased (Table 3). The values of user's accuracy for the corresponding classes have been increased from 85.00% to 95.00%, 68.57% to 82.86%, 56.34% to 78.87%, 66.67% to 83.33% and 74.07% to 96.3%, respectively. The user's accuracy of barren land has also increased from 80.95% to 95.24%, but the quarry and scrub forest/Prosopis classes have not showed any change.

Similarly, Table 4 indicated low user's accuracy for forest, agricultural land, scrub forest/Prosopis and river sand classes for 2011. With the post-classification corrections, the user's accuracy of forest, agricultural land and river sand have increased from 63.89% to

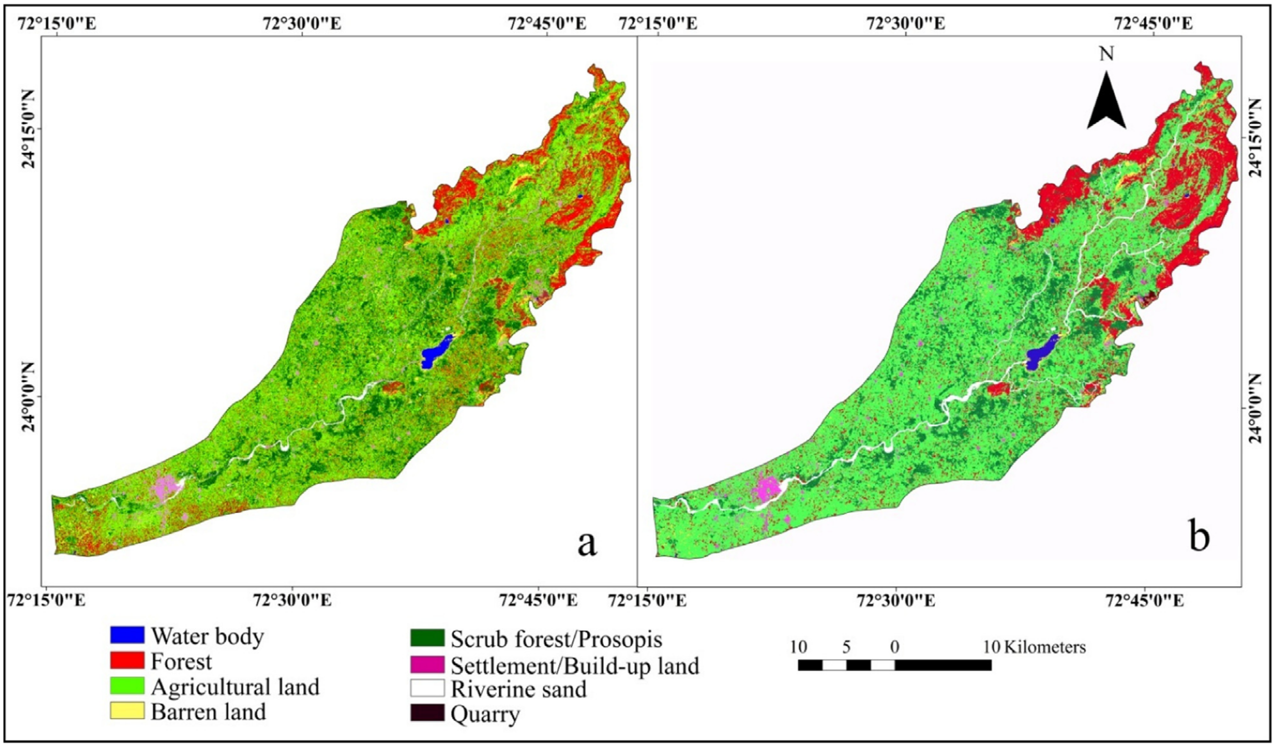


Fig. 9. LU/LC maps of Arjuni watershed of 2011 classified by MLC; (a) without post classification corrections (b) with post classification corrections.

Table 2
Error matrix for LU/LC map derived by MLC without post classification corrections using RS data of 2001.

LU/LC Classes	Reference Data								Total	Producer's Accuracy (%)	User's Accuracy (%)	Conditional Kappa
	Water body	Forest	Agricultural land	Barren land	Scrub forest/ Prosopis	Settlement/ Built-up land	River sand	Quarry				
Water body	17	0	1	2	0	0	0	0	20	85.00	85.00	0.84
Forest	0	24	2	2	7	0	0	0	35	100.00	68.57	0.66
Agricultural land	1	0	80	2	59	0	0	0	142	78.43	56.34	0.38
Barren land	0	0	1	17	2	0	0	1	21	70.83	80.95	0.80
Scrub forest/ Prosopis	0	0	11	0	55	0	1	1	68	42.31	80.88	0.69
Settlement/ Built-up land	2	0	2	1	1	12	0	0	18	100.00	66.67	0.65
River sand	0	0	3	0	4	0	20	0	27	95.24	74.07	0.72
Quarry	0	0	2	0	2	0	0	7	11	77.78	63.64	0.63
Total	20	24	102	24	130	12	21	9	342			
Overall Accuracy		67.84				Overall Kappa		0.60				

91.67%, 56.41% to 82.05%, and 64.86% to 100%, respectively (Table 5). Barren land has also increased from 89.47% to 94.74%. However, the user's accuracy of scrub forest/Prosopis class has marginally gone down from 76.60% to 65.96%. The water bodies such as check dams/talavs were correctly classified in boundary region and increased the user's accuracy for both 2001 and 2011.

The overall classification accuracies of LU/LC maps of 2001 and 2011 without post-classification corrections were 67.84% and 71.93%, whereas after post-classification corrections they increased by 82.75% and 87.43%, respectively. Similarly, the Kappa statistics of LU/LC maps of 2001 and 2011 without post-classification corrections were 0.60 and 0.67, respectively. Whereas, after post-classification corrections they increased by 0.78 and 0.85, respectively.

The statistical analysis using the McNemar test confirmed the above results. The null hypothesis of McNemar test is that the classification accuracy derived MLC classification without post classification correction are not significantly different from the one derived with post classification correction. The results of Mcnemar test has rejected the null hypothesis by achieving the p-value lower than the significance level of alpha level of 0.05. It inferred the significant difference between MLC classification with post-classification corrections and without post-classification corrections for both 2001 and 2011 by ($\chi^2 = 40.984,\ p < 0.0001$) and ($\chi^2 = 30.72,\ p < 0.0001$), respectively. Hence, the MLC with post classification correction resulted in a significantly more accurate LU/LC map as compated to the MLC without post classification corrections.

The data in Table 6 shows the total area of all the LU/LC categories resulted from MLC using post-classification corrections for each study year. The corresponding % changes are shown in Fig. 10. Over the period from 2001 to 2011, the area occupied by water body, forest, agricultural land, settlement/built-up land

Table 3
Error matrix for LU/LC map derived by MLC with post classification corrections using RS data of 2001.

LU/LC Classes	Reference Data								Total	Producer's Accuracy (%)	User's Accuracy (%)	Conditional Kappa
	Water body	Forest	Agricultural land	Barren land	Scrub forest/ Prosopis	Settlement/ Built-up land	River sand	Quarry				
Water body	19	0	1	0	0	0	0	0	20	95.00	95.00	0.95
Forest	0	29	2	2	2	0	0	0	35	100.00	82.86	0.81
Agricultural land	1	0	112	1	27	1	0	0	142	83.58	78.87	0.65
Barren land	0	0	1	20	0	0	0	0	21	86.96	95.24	0.95
Scrub forest/ Prosopis	0	0	11	0	55	0	1	1	68	64.71	80.88	0.75
Settlement/ Built-up land	0	0	3	0	0	15	0	0	18	93.75	83.33	0.83
Rive sand	0	0	1	0	0	0	26	0	27	96.30	96.30	0.96
Quarry	0	0	3	0	1	0	0	7	11	87.50	63.64	0.63
Total	20	29	134	23	85	16	27	8	342			
Overall Accuracy		82.75				Overall Kappa		0.78				

Table 4
Error matrix for LU/LC map derived by MLC without post classification corrections using RS data of 2011.

LU/LC Classes	Reference Data								Total	Producer's Accuracy (%)	User's Accuracy (%)	Conditional Kappa
	Water body	Forest	Agricultural land	Barren land	Scrub forest/ Prosopis	Settlement/ Built-up land	River sand	Quarry				
Water body	30	0	0	0	0	0	0	2	32	100.00	93.75	0.93
Forest	0	23	4	6	3	0	0	0	36	60.53	63.89	0.59
Agricultural land	0	13	66	7	25	2	0	4	117	76.74	56.41	0.42
Barren land	0	0	1	17	1	0	0	0	19	51.52	89.47	0.88
Scrub forest/ Prosopis	0	2	8	1	36	0	0	0	47	53.73	76.60	0.71
Settlement/ Built-up land	0	0	2	1	0	28	0	1	32	74.29	87.50	0.86
Rive sand	0	0	4	1	2	5	24	1	37	100.00	64.86	0.62
Quarry	0	0	0	0	0	0	0	22	22	73.33	100.00	1.00
Total	30	38	85	33	67	35	24	30	342			
Overall Accuracy		71.93				Overall Kappa		0.67				

Table 5
Error matrix for LU/LC map derived by MLC with post classification corrections using RS data of 2011.

LU/LC Classes	Reference Data								Total	Producer's Accuracy (%)	User's Accuracy (%)	Conditional Kappa
	Water body	Forest	Agricultural land	Barren land	Scrub forest/ Prosopis	Settlement/ Built-up land	River sand	Quarry				
Water body	32	0	0	0	0	0	0	0	32	100.00	100.00	1.00
Forest	0	33	1	2	0	0	0	0	36	97.06	91.67	0.91
Agricultural land	0	1	96	5	10	1	1	3	117	84.96	82.05	0.73
Barren land	0	0	1	18	0	0	0	0	19	66.67	94.74	0.94
Scrub forest/ Prosopis	0	0	14	1	31	0	0	1	47	75.61	65.96	0.61
Settlement/ Built-up land	0	0	1	1	0	30	0	0	32	96.77	93.75	0.93
River sand	0	0	0	0	0	0	37	0	37	97.37	100.00	1.00
Quarry	0	0	0	0	0	0	0	22	22	84.62	100.00	1.00
Total	32	34	113	27	41	31	38	26	342			
Overall Accuracy		87.43				Overall Kappa		0.85				

and quarry showed an increase, whereas the area occupied by scrub forest/Prosopis and river sand showed a decrease. The forest area mainly includes the deciduous forest at the north-eastern part of the watershed. Its area increased from 96.81 km^2 to 171.28 km^2. This increase is mainly due to increased dense vegetation or dense scrub area over the period of ten years The agricultural land is the largest class of total LU/LC categories assigned, occupying more than 50% of the study area. In 2011, the amount of farmland had increased significantly by occupying 59.72% (584.99 km^2) of the area. This may be due to conversion of the large portion of scrub forest/Prosopis vegetation into agricultural land (nearby the river bank of Arjuni). The result is

Table 6
LU/LC change at watershed level over 2001–2011.

Lu/lc classes	Area of 2001 (km^2)	% of Area Occupied	Area of 2011 (km^2)	% of Area Occupied	% of Change
Water body	2.16	0.22	5.76	0.59	166.67
Forest	96.81	9.88	171.28	17.49	76.92
Agricultural land	524.58	53.55	584.99	59.72	11.52
Barren land	26.29	2.68	31.48	3.21	19.74
Scrub forest/Prosopis	295.60	30.18	135.72	13.86	−54.09
Settlement/Built-up land	3.65	0.37	20.41	2.08	459.18
Riverine sand	29.92	3.05	27.66	2.82	−7.55
Quarry	0.52	0.05	2.23	0.23	328.85
Total	979.53	100.00	979.53	100.00	

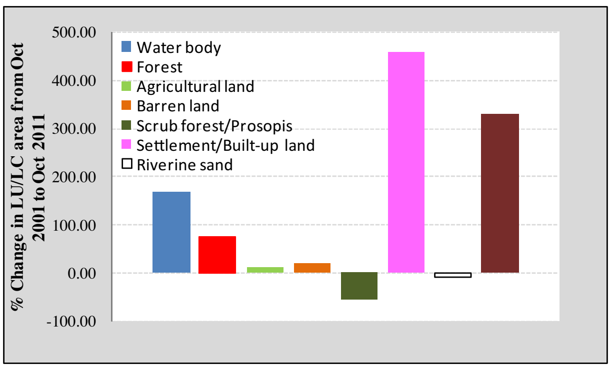


Fig. 10. % Change in areas of LU/LC classes for Arjuni watershed.

confirmed by the highest decline in scrub forest/Prosopis area by 54.09%. The settlement/built-up land rapidly increased from 3.65 km^2 to 20.41 km^2. This was most likely due to increased expansion rate in the residential allotment, industrial area and infrastructure in the Sidhpur city of Patan district. The area of riverine sand decreased from 29.92 km^2 to 27.66 km^2. This change may be due to area of riverine sand occupied by Prosopis over the period of ten years. The main mining spot located in Jasvantgadh and Vadasana villages showed a rapid increase in quarrying activities. The quarrying area accelerated from 0.52 km^2 in 2001 to 2.23 km^2 in 2011.

6. Conclusion

Although the MLC is widely used classifier, it could not perform satisfactorily to ensure the desired classification accuracy for heterogeneous and arid landscape. In the present study, it was possible to significantly improve MLC accuracy by incorporating ancillary data such as (1) texture image (2) NDWI and (3) drainage network based on visual image interpretation. Moreover, the high resolution IRS LISS-IV data and 3×3 majority filter have further helped to reduce the misclassification. The estimated overall classification accuracy of 82.75% (for 2001) and 87.43% (for 2011) indicate that the integration of ancillary data with MLC for RS imagery is an effective method for classification accuracy improvement and further change detection.

Erratic rainfall and frequent drought are commonly observed in rain-fed, arid and heterogeneous landscape of study area and hence the watershed management programmes in such regions have been assigned priority over the last decade. It has obviously affected LU/LC changes over the duration of 2001–2011. The key changes in LU/LC, which reflect regional policies and human induced impact on the area, are an increase in area under water body, forest, agricultural land and settlement/built-up land, whereas scrub forest/Prosopis and river sand have declined significantly. In addition, some undesirable changes are also identified such as increase in area under barren land and quarries.

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