Trees, Forests and People 2 (2020) 100018

Contents lists available at ScienceDirect

Trees, Forests and People

journal homepage: www.elsevier.com/locate/tfp

Land use land cover change detection through geospatial analysis in an Indian Biosphere Reserve

Tarun Kumar Thakur[a], Digvesh Kumar Patel[a], Arvind Bijalwan[b], Mammohan J. Dobriyal[c], Anirudh Kumar[a], Anita Thakur[a], Abhishek Bohra[d], Jahangeer A. Bhat[c,*]

[a] Indira Gandhi National Tribal University, Amarkantak, Madhya Pradesh 484 887, India
[b] College of Forestry, VCSG Uttarakhand University of Horticulture and Forestry, Ranichauri-249199, Tehri Garhwal, Uttarakhand, India
[c] College of Horticulture and Forestry, Rani Lakshmi Bai Central Agricultural University, Jhansi - 284003 (U.P.) India
[d] ICAR-Crop Improvement Division, Indian Institute of Pulses Research (IIPR), Kanpur, India

ARTICLE INFO

Keywords:
Land use land cover (LULC)
Temporal-spatial change
Tropical forest
Remote sensing
GIS
Achanakmaar Amarkantak Biosphere Reserve

ABSTRACT

The present study examines the land use land cover (LULC) and change detection impacts on forest ecosystem in Achanakmaar Amarkantak Biosphere Reserve (AABR – area 626.76 km^2) of Central India. Results revealed that there has been a change in AABR land use pattern from 2008 to 2018. The major changes include loss of 19.72 km^2 of vegetation cover in various forest types due to increasing biotic interference and over grazing, conversion of 14.77 km^2 of Dense Sal mixed forest to open mixed forest and cultivable land, and 5.0 km^2 teak plantation and Bamboo brakes to agricultural land. Despite losing many plant species due to anthropogenic pressure, the present study found that the AABR as a unique repository of plant species rich in biodiversity. Many spots of this area are invaded or replaced by exotic species which is causing the loss of ecology and diversity of this region. Based on our study Sal mixed forest reduced by 2.88% (5.23 km^2), Dense mixed forest 4.02% (9.54 km^2), Teak plantation 6.77% (2.61 km^2) and Bamboo brakes reduced by 7.66% (2.34 km^2). The study concludes that the Landsat 7 TM and Resourcesat 2A satellite images are the most suitable for studying the LULC change on forest ecosystem of AABR. We advocate that by adopting the rigorous conservation measures, especially in open & dense forest and young under-stocked teak forests can restore the vegetation density and diversity in the area. Moreover, Sal natural regeneration of vegetation would remain crucial, and invasion of exotic species over native species needs to be restored in the forest area. Such findings on major changes occurring in forest ecosystem hold tremendous implications in relation to the welfare of the resource-poor tribal communities who are greatly dependent on the natural resources available in AABR for their livelihood.

Introduction

Undulating geography with anecdotal slopes covered with different forest type's viz. Dense mixed and Sal mixed forests, Bamboo plantations, Teak forest, Open mixed forest and manmade plantations harbor huge amount of diversity in and around the Achanakmaar Amarkantak Biosphere Reserve (AABR). There are many plant species endemic to this area such as *Cupressus torulosa, Araucaria bidwilli, Thuja oreintalis, Pinus caribbea* etc and are well distributed (https://www.indianetzone.com/40/achanakmar_amarkantak_biosphere_reserve.htm). It is a storehouse of many medicinal and aromatic plants, edible plants, non-timber forest products and many other useful plants and harbors different animals which reflect the rich heritage of natural resources (Roychoudhury et al., 2016; Tiwari et al., 2014). AABR is one of the least disturbed and less developed area of two adjoining states of Madhya Pradesh and Chhattisgarh. It comprehends unique natural and cultural characteristics and hence, it was declared as 14th Biosphere reserve of the country in the year 2005 (Joshi et al., 2010). However, species diversity in most part of AABR is being alarmingly reduced to endangered levels due to various anthropogenic factors (Reid et al., 2005). Ecological degradation by increasing biotic interferences, construction of permanent structure in the sensitive zone has obstructed pathway of many of the small perennial stream, forest fire, illicit cutting of trees put severe pressure on natural resources leading to destruction of habitats of flora and fauna (Geist and Lambin, 2001; Thakur et al., 2019). These losses are irreversible and create threat to well-being of local indigenous communities. Safeguarding AABR biodiversity is of paramount importance as it is intricately linked to the livelihoods and economy of indigenous people of the region.

A number of primitive tribes such as, Gond, Baiga, Panika, Pradhan, Kols etc. are living amidst the thick forests of AABR. Forest based ac-

* Corresponding author.
E-mail address: jahan191@gmail.com (J.A. Bhat).

https://doi.org/10.1016/j.tfp.2020.100018
Received 18 June 2020; Received in revised form 27 July 2020; Accepted 28 July 2020
Available online 1 August 2020

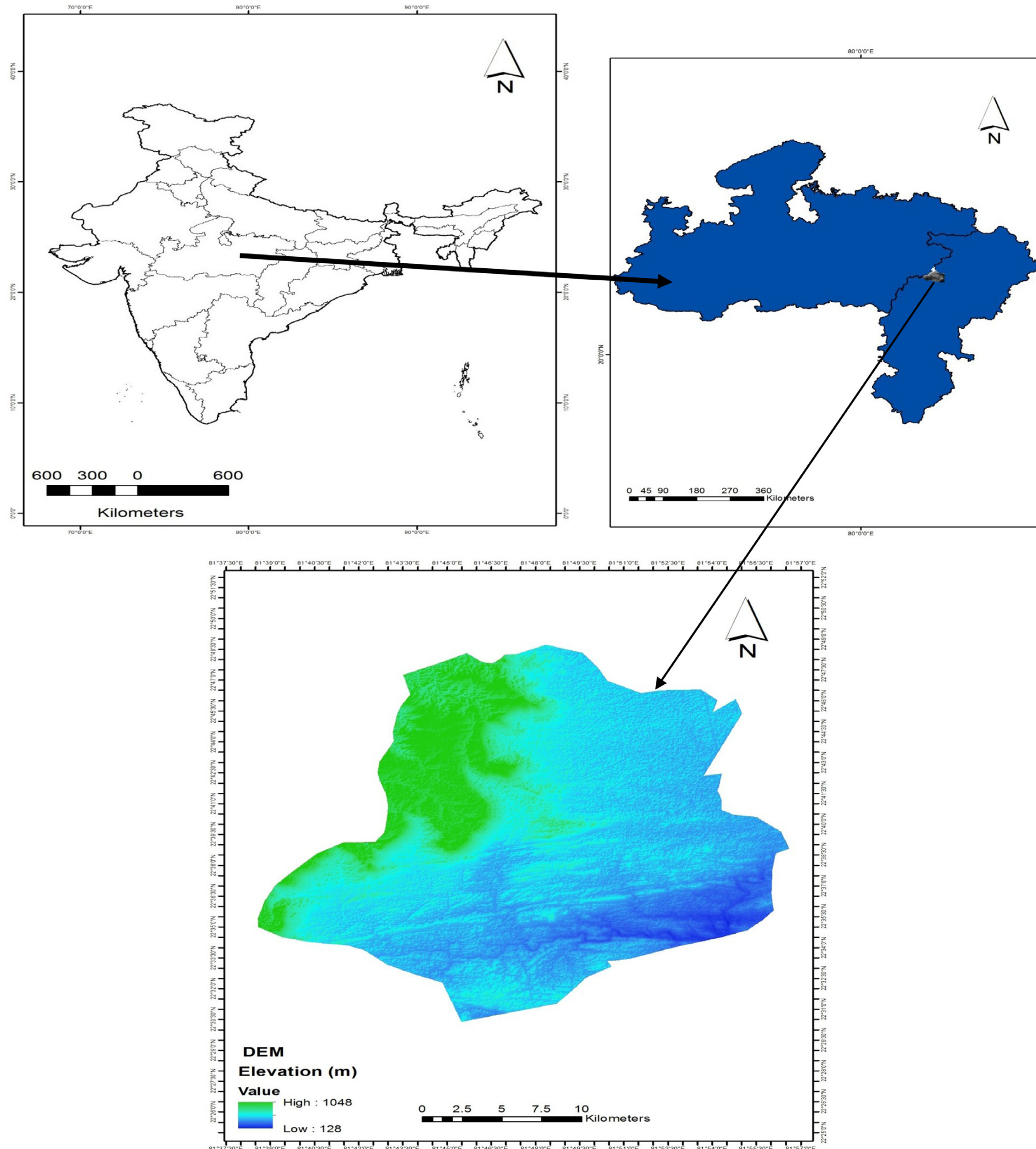


Fig. 1. Layout map with elevation model of the AABR.

tivities and agriculture is the main sources of livelihood and income of these poor tribal populations in-habiting the AABR (Thakur et al., 2017). The communities collect NTFPs, medicinal and aromatic plants species, leafy vegetables, dry fruits, resins, dyes, fuel, fodder, flosses, fiber, edible and medicinal mushrooms etc. to utilize for domestic purpose and some of them are locally marketed (Thakur et al., 2017). The overexploitation and unsustainable usage of natural resources has led to ecological imbalance and biodiversity crisis. Therefore, documentation of biological resources, their utilization and indigenous knowledge are important for conservation and sustainable utilization of biological resources. The data on land use and change will provide useful insights for planning future strategies and developing resources as per the domestic and commercial requirements (Thakur, 2018). Ground based measurements are quite cumbersome, uneconomical and time consuming for quantifying the biological diversity. In recent years, the geospatial tools generate large-scale and accurate information on the LULC changes and

Table 1
Description of the satellite image used in the study.

Satellite	Sensor	Acquisition date	BAND USED	Spatial Resolution	Processing
Resorcesat-2A	AWiFS (Advanced Wide Field Sensor)	03/04/2018	Visible and Near Infrared band	5.8m	Level 1
Landsat 7	Thematic Mapper (TM)	22/04/2008	Visible (B1, B2, B3,) NIR (B4) SWIR (B5)	30 m	Level 1

land detection analysis (Sudhakar 1994; Yuan et al., 2005; Saadat et al., 2011; Zhang et al., 2014; Wu et al., 2018 Mishra et al., 2019). The remote sensing and GIS techniques have immense potential in determining and assessing the spatial variability of the LULC. Systematic mapping of species occurrence in a given area provides distributional pattern related to ecological parameters and their quantum of availability. Identification of rare, endangered and threatened species is essential for prioritization of conservation in the area.

The research on natural resources assessment of AABR remains limited both qualitatively and quantitatively. In this context, application of the modern geospatial techniques underpins the spatial database that is quite necessary for planning for conservation and sustainable development. Additionally field surveys of the selected areas, the dataset offers ground realities of LULC status and traditional uses of biological resources. Satellite Remote sensing (RS) techniques and ground measurements will provide clear advantages for the LULC pattern in AABR. Park and Lee (2016) compared actual LULC classification using Landsat 7 and IKONOS images. Further, use of geospatial techniques was applied for the development of spatial database on forest vegetation for devising suitable science and technology-based interventions was necessary for the forest ecosystem management in the present study.

Material and methods

Study area

The UNESCO natural heritage site AABR was chosen for research as the biotic interferences have notably increased in the last two decades, causing deforestation and conversion of forest areas to agricultural and open forest area. The study area lies between 22° 15'N to 22° 58' N and 81° 25' E to 82° 5' E which covers 626.76 km^2 area of the watershed with a mean altitude of 1048 m from ASL. The AABR region is a vast reservoir of biodiversity including a variety of medicinal plants. Besides, this area holds unique geological formations where water resources are created and conserved due to interaction of forest and rocks. For example, interaction between the extensive root network of Sal tree and lime stone bauxite holds water during rainy season and the water is then released slowly through aquifers or minor rivers of this region. Reserve forest and different forest types in the core and buffer zones of AABR enrich the floral diversity of this region. The typical climate of the reserve has summer, rainy and winter. The maximum temperature is recorded in the month of May, while the December month registers the minimum temperature. The south-western monsoons carries rainfall during the months of June to September and mean annual precipitation

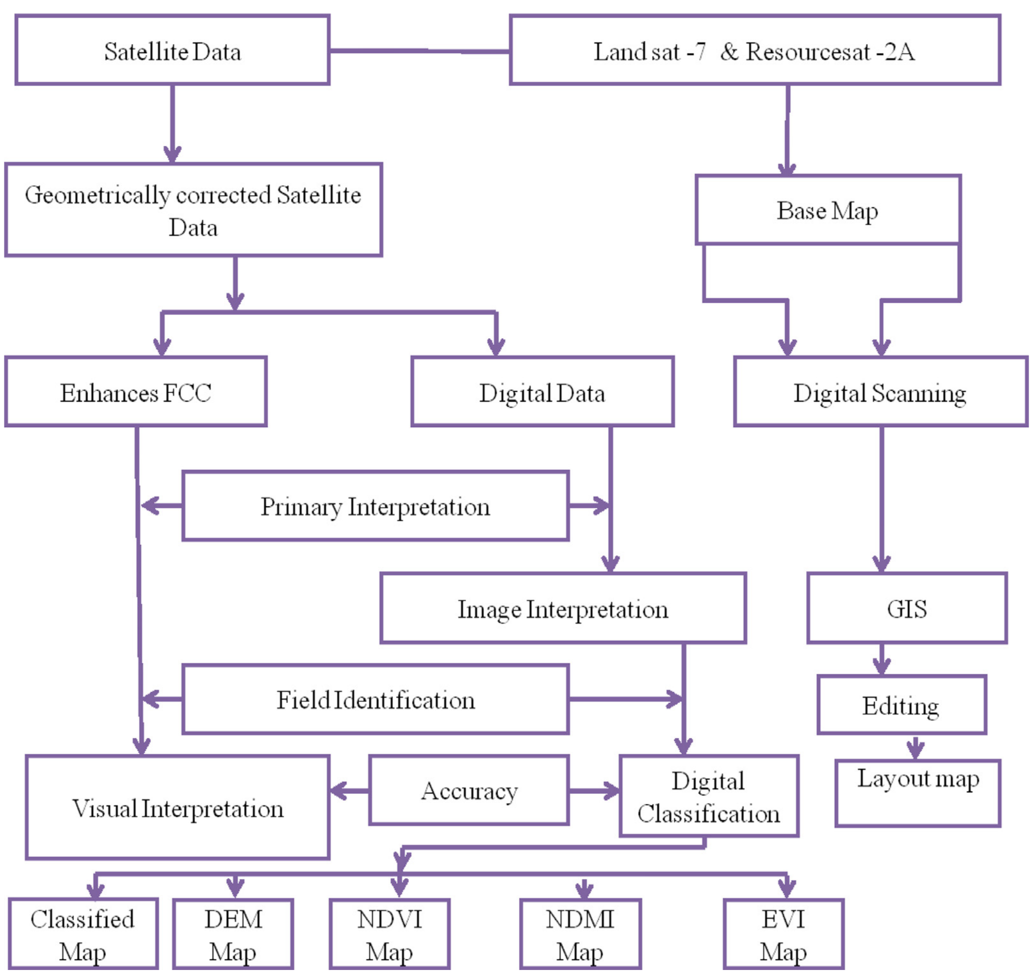


Fig. 2. Methodology for the generation of thematic maps.

Table 2
Vegetation indices used in this study.

Vegetation index	Equations	References
Normalized difference vegetation index (NDVI)	$\frac{NIR-Red}{NIR+Red}$	Rouse et al. (1973)
Enhanced vegetation index (EVI)	$G * \frac{NIR-Red}{NIR+C1*Red-C2*Blue+L}$ G (Gain factor)=2.5, C1=6, C2=7.5, L=1	Huete and Justice (1999)
NDMI (Normalized difference Moisture index)	$\frac{NIR-SWIR}{NIR+SWIR}$	Hardisky et al. (1983)

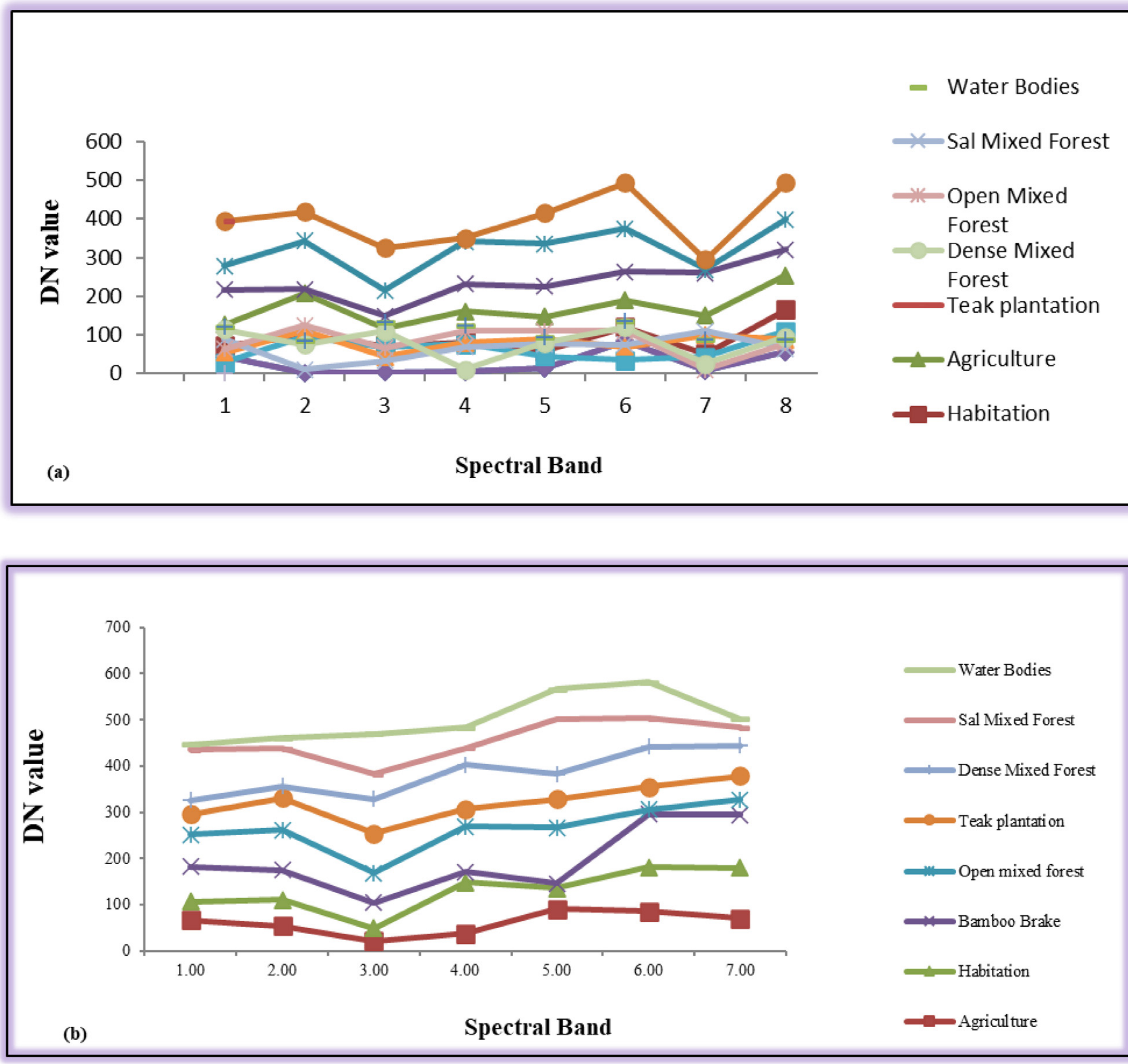


Fig. 3. Mean spectral values (DN: digital number) of different land use/land cover classes in the study area (a) Satellite images of Landsat-7 (2008) and (b) Satellite image of Resourcesat 2A (2018).

is more than 1600 mm. The average of relative humidity is found between 50 to 85%, whereas, the mean temperatures of the area in winter and summer remain 16.1°C and 31°C, respectively. The layout map with an elevation model of the study area is depicted in Fig. 1.

Data source

Medium resolution of 30 m in Landsat-7 TM of 2008 image and Resourcesat 2A level-1C at 5.8 m high resolution of 2018 image was used for mapping LULC and change detection of Achanakmaar Amarkantak Biosphere Reserve from 2008 to 2018 (Table 1). Landsat 7 (2008) image obtained freely from The United States Geological Survey (USGS) website (http://glovis.usgs.gov/) and Resourcesat 2A (2018) satellite data procured from NRSC, NDC, Hyderabad, India. Image analysis of the procured data was analyzed in ERDAS Imagine in personal computer and the auxiliary data collected from Survey of India topomaps. Ancillary data included the ground truthing data for the LU/LC classes.

Pre-processing and classification

The detailed methodological framework and analysis for the entire study are illustrated in Fig. 2. Geometric distortions were removed by georeferencing the image to map registration using the Survey of India toposheets (64F/10, 64F/11, 64F/13, 64F/14& 64F/15) on 1:50000

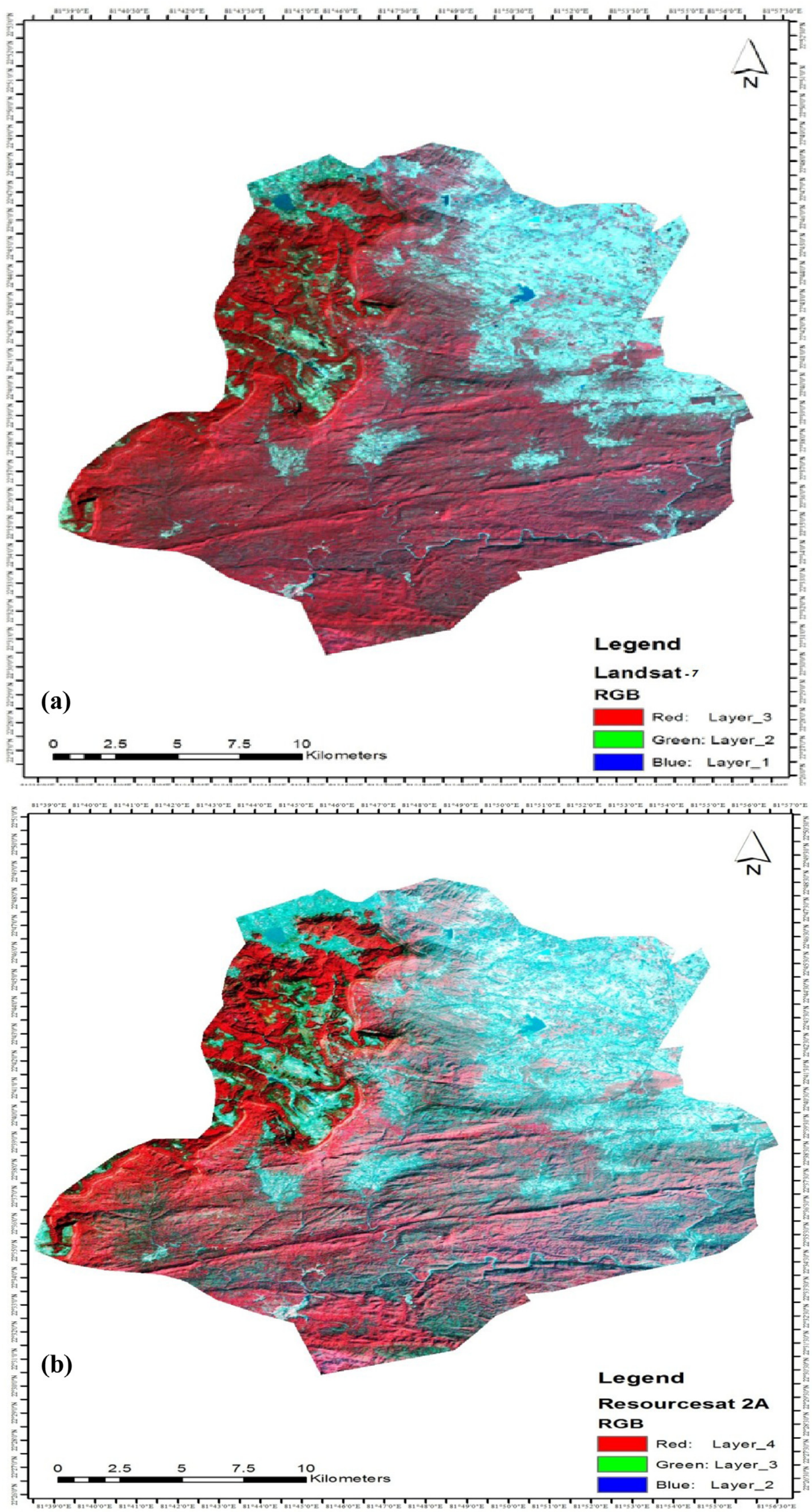


Fig. 4. False colour composite (FCC) map of the study area: (a) during 2008 image and (b) 2018 image.

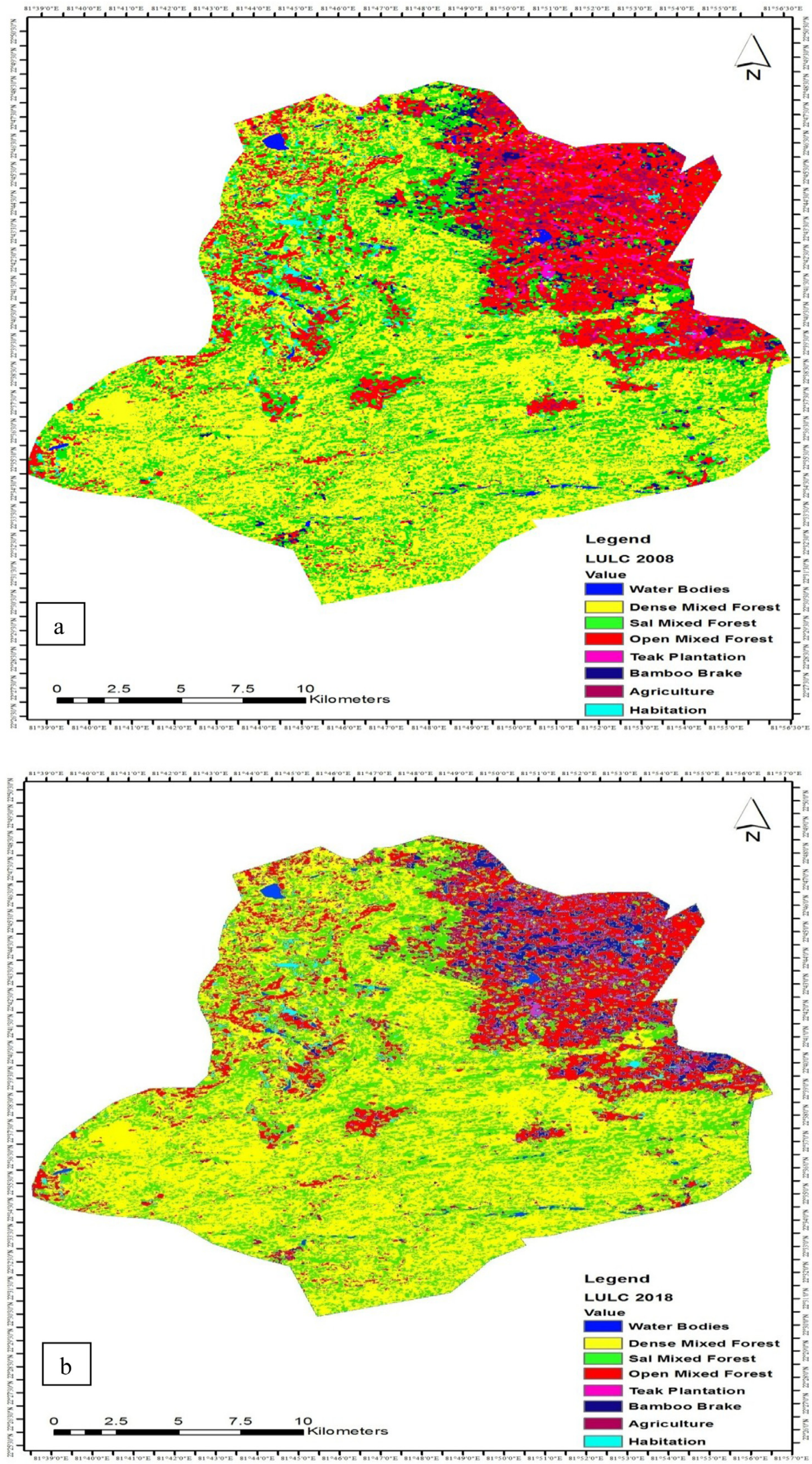


Fig. 5. Classified map of Achanakmaar Amarkantak Biosphere Reserve: (a) LULC map during 2008 and (b) LULC map of 2018.

Table 3
Sample points used in the study area.

Sample points	Forest Type	Latitude	Longitude
1	DMF (Dense mixed forest)	22°37′37.920"N	81°42′42.970"E
2	DMF	22°37′37.360"N	81°45′45.645"E
3	DMF	22°40′40.960"N	81°53′53.102"E
4	DMF	22°38′38.180"N	81°45′45.660"E
5	DMF	22°37′37.860"N	81°43′43.323"E
6	DMF	22°37′37.484"N	81°46′46.687"E
7	DMF	22°38′38.686"N	81°51′51.566"E
8	DMF	22°37′38.700"N	81°43′51.931"E
9	DMF	22°38′40.700"N	81°50′51.931"E
10	DMF	22°38′39.700"N	81°471′51.931"E
11	SMF (Sal mixed forest)	22°45′45.258"N	81°44′44.102"E
12	SMF	22°45′45.240"N	81°44′44.820"E
13	SMF	22°45′45.215"N	81°44′44.681"E
14	SMF	22°45′45.238"N	81°44′44.692"E
15	SMF	22°45′45.258"N	81°44′4.903"E
16	SMF	22°45′45.102"N	81°44′44.667"E
17	SMF	22°45′45.440"N	81°44′44.997"E
18	SMF	22°44′44.383"N	81°46′46.743"E
19	SMF	22°44′44.852"N	81°46′46.362"E
20	SMF	22°42′44.852"N	81°44′46.362"E
21	OMF (Open mixed forest)	22°37′37.107"N	81°44′44.25"E
22	OMF	22°37′37.104"N	81°44′44.993"E
23	OMF	22°40′40.947"N	81°53′53.135"E
24	OMF	22°37′37.293"N	81°46′46.686"E
25	OMF	22°42′42.120"N	81°45′45.546"E
26	OMF	22°39′39.94"N	81°51′51.339"E
27	OMF	22°44′44.532"N	81°47′47.689"E
28	OMF	22°44′44.507"N	81°47′47.670"E
29	OMF	22°44′44.493"N	81°47′47.656"E
30	OMF	22°44′44.522"N	81°47′47.643"E
31	TP (Teak plantation)	22°39′39.380"N	81°59′59.688"E
32	TP	22°38′38.681"N	81°51′51.696"E
33	TP	22°38′38.675"N	81°51′51.646"E
34	TP	22°38′38.670"N	81°50′50.6580"E
35	TP	22°38′38.655"N	81°51′51.770"E
36	TP	22°38′38.605"N	81°51′51.280E
37	TP	22°38′38.665"N	81°51′51.120E
38	TP	22°38′38.740"N	81°50′50.910E
39	TP	22°39′39.490"N	81°55′55.910E
40	TP	22°39′39.390"N	81°55′55.310E
41	BB (Bamboo brakes)	22°39′39.380"N	81°59′59.688"E
42	BB	22°39′39.318"N	81°59′59.683"E
43	BB	22°39′39.293"N	81°59′59.686"E
44	BB	22°39′39.223"N	81°59′59.626"E
45	BB	22°39′39.273"N	81°59′59.486"E
46	BB	22°39′39.293"N	81°58′59.686"E
47	BB	22°39′35.293"N	81°59′55.646"E
48	BB	22°39′39.203"N	81°59′59.186"E
49	BB	22°39′39.235"N	81°59′59.386"E
50	BB	22°39′39.292"N	81°59′59.653"E

scale. Pre-processing of selected satellite data follows the vital procedure to analyse LULC change detection and maintains the unique structure to associate with the biophysical phenomena in the ground and the acquired images. Georeferencing and mosaicking of acquired data in the ERDAS imagine software on the basis of Area of Interest (AoI). Classification of images was accomplished with the help of various assign spectral signatures by the Landsat – 7 TM and Resourcesat 2A data to different land use. Satellite images were used to generate the vegetation indices map. The following vegetation indices are derived from different spectral bands and mean spectral values (DN) of various LU classes a represented in Table 2 and Fig. 3, respectively. For each of the encoded LU/LC class, training samples were chosen by delineating polygons around envoy area. To prepare the land use and cover change map from remote sensing data, animage classification of LULC and vegetation changes was done by using the MLA possibility procedure.

Field survey and accuracy assessment

The reference/ground and ancillary data were collected through the field survey as ground control point with the help of GPS and direct local field measurements for ground verification and which was performed for image classification. The coordinates of the sample points in the field were taken and a total of 50 sample plots were selected for ground survey and 10 sample plots in each forest type. The sample points used in the study area are mentioned in Table 3. '*Confusion matrix*' of Story and Congalton (1986), and '*Kappa*' analysis of Lea and Curtis (2010) were followed for the overall accuracy assessment and evaluation of images of 2008 to 2018.

LULC change detection and analysis

LULC map of 2018 was resampled to the spatial and high resolution of 5.8 m for the classified map and for performing LULC and change detection analysis. A comparison in a pixel-based technique was performed to generate changes on pixel basis for more efficient enchanting the advantages of all the categories. Pairs of two different time series classified images (2008 and 2018) were compared using cross – tabulation in order to find out the information of LULC changes for the periods from 2008 to 2018. Change matrix presents significant information about the spatial extent of vegetation changes in LULC (Shalaby and

Table 4
LULC and change detection distribution in Achanakmaar Amarkantak Biosphere Reserve, India.

Class Name	Area (km^2) 2018	Area in (%) 2018	Area (km^2) 2008	Area in (%) 2008	Difference 2018 Vs 2008 (km^2)
Water bodies	5.29	0.84	6.45	1.02	-1.16
Sal mixed forest	181.26	28.92	186.49	29.75	-5.23
Dense mixed forest	236.96	37.80	246.5	39.32	-9.54
Open mixed forest	104.54	16.67	92.8	14.80	+11.74
Teak plantation	38.54	6.14	41.15	6.562	-2.61
Bamboo brake	30.55	4.87	32.89	5.24	-2.34
Agriculture	27.48	4.38	18.6	2.96	+8.88
Habitation	2.14	0.34	1.88	0.29	+0.26
Total	**626.76**	**100**	**626.76**	**100**	

Fig. 6. Pictorial illustration of the various forest types of AABR, Central India (A) Sal Mixed Forest, (B) Teak Plantation, (C) Bamboo Brakes, (D) Dense Mixed Forest, (E) Open mixed forest.

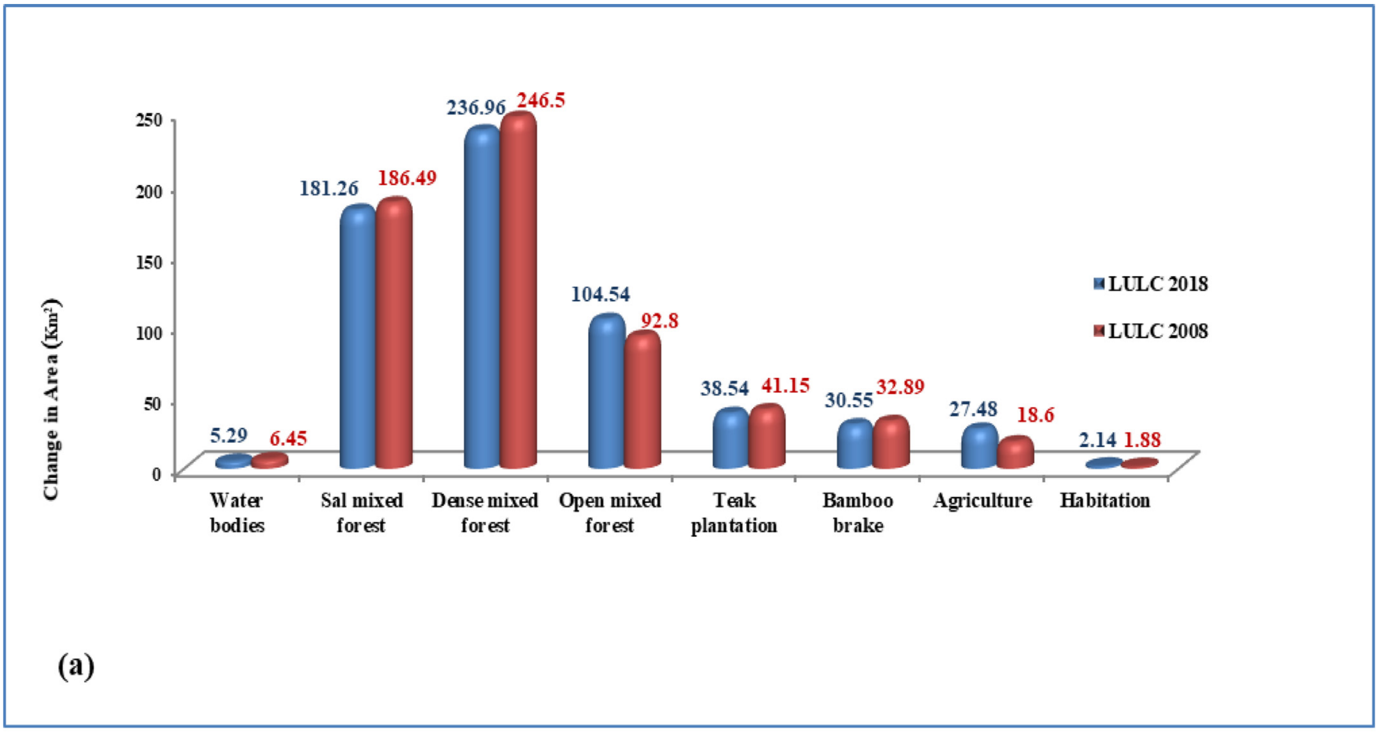
Tateishi, 2007). Change matrix viewing the LULC changes in both images was generated from 2008 to 2018 classified images to evaluate the entire changes in LULC and it was performed under ERDAS Imagine software in PC environs (Weng, 2001; Yang and Wen, 2011; Rawat and Kumar, 2015; Yang et al., 2017).

Results and discussion

Land use and land cover status

The LULC and change detection analysis was performed in a study area of AABR of India by using MLA. Before classifying, the Standard False Colour Composite (SFCC) is generated with the band combinations of 4, 3, and 2 to help in identifying few training areas for classification. An overview of SFCC of the study area during 2008 and 2018 is shown in Fig. 4. The multi-temporal data, eight LULC classes, *viz*. Dense and Sal mixed forest, Teak plantation, Open mixed forest, Bamboo Brakes, Agriculture, Habitation and Water bodies of 2008 and 2018 are registered in Fig. 5. The distribution of different LULC categories is given in Table 4 and pictorial depiction of different forest types is mentioned in Fig. 6.

The results on spatial distribution of different forest types and change detection during 2008-2018 is presented in Table 4 and contribution of changes in different vegetation classes during 2008 to 2018 are shown in Fig. 7. Results from classified image in 2008 indicated that the area occupied by different classes viz; habitation areas comprise 1.88 km^2 (0.30%), Water bodies was about 6.45 km^2 (1.03%), Agriculture 18.6 km^2 (2.96%), Bamboo Brakes 32.89 km^2 (5.24%), Teak forest area covered 41.15 km^2 (6.56%), Open mixed forest was 92.8 km^2 (14.8%) while, Dense mixed forest and Sal mixed forest had maximum part of the watershed and occupied about 246.5 km^2 (39.32%), and 186.49 km^2 (29.49%) area, respectively. A comparison of the latest classified maps (2018) with that of (2008) suggested crop land, habitation and open mixed forest increasing from 2.96 to 4.38%, 0.30 to 0.34% and 14 to 16.67%, respectively over the last ten years. Interestingly, in 2018 map water bodies was less than 1% (5.29 km^2) of the total geographical area, 4.87% area was covered by Bamboo Brakes, and Teak forest area was covered 38.54 km^2 (6.14%) which is reduction in the area with respect to 2008. Similarly, Dense mixed forest and Sal mixed forest



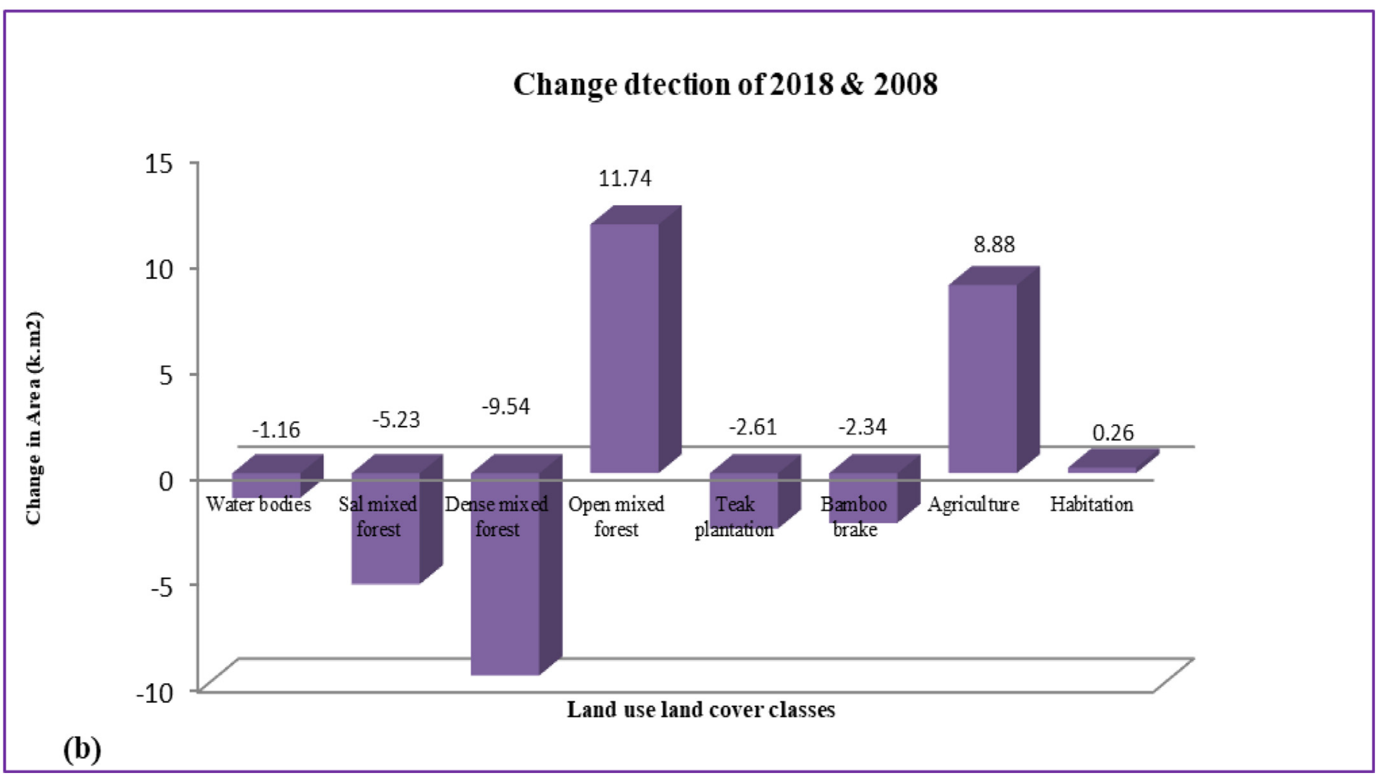


Fig. 7. LULC and change detection maps of 2008 and 2018 images (a) and (b).

types reduced to 66.72% in 2018 against 69% in 2008 due to increasing biotic interference inside the biosphere reserve (Table 4). Results showed that the threats are increasing on water bodies due to the silt, filth, and shortage of water, destruction of tanks, reservoirs, stop-dams and encroachment. Agriculture and habitation areas are increasing due to conversion of dense forest and Sal mixed forest area. Similar trends were also reported in the recent past by Tellman et al., (2020), Yu et al., (2020), and Lossou et al., (2019).

The classified images of 2008 and 2018 (Fig. 5) show that the spatial extent of different land use categories.The total study area comprises of 626.76 km^2 of which interestingly green vegetation cover, accounted 95.71% (591 km^2) and agriculture, grassland, water bodies, other classes etc. cover the remaining 4.29% (34.91 km^2) of the total area. In 2018 among the different classes, Dense mixed forest occupied the largest area accounting for 37.80%, while habitation occurred only in 0.34% of the total area. The other prominent vegetation classes fol-

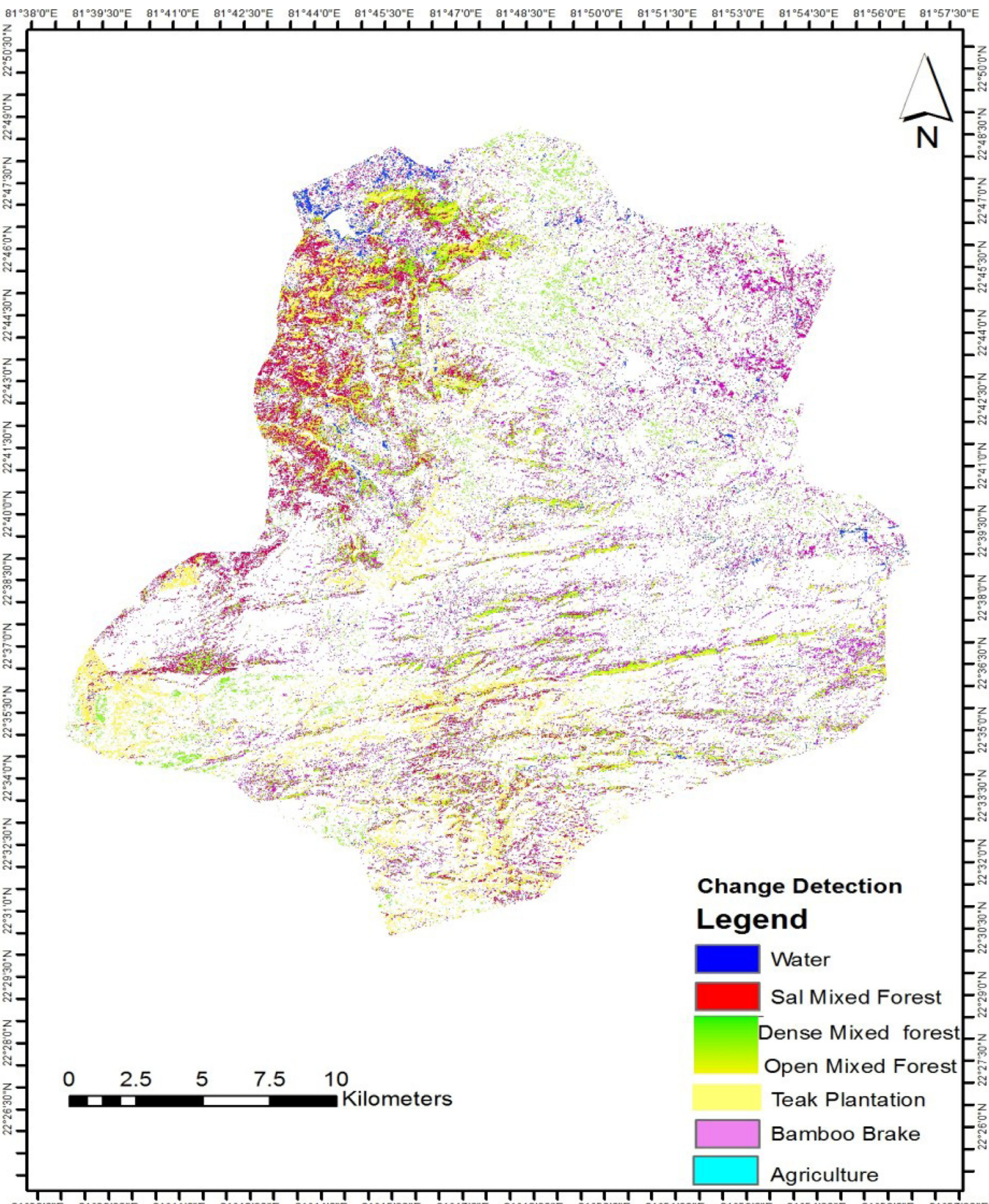


Fig. 8. LULC change in different classes of LULC in AABR from 2008 to 2018.

lowed by Dense mixed forest were Sal mixed forest, Open mixed forest, Teak forest, Bamboo Brakes, Agriculture and Water bodies, which covered 28.92%, 16.67%, 6.14%, 4.87%, 4.38% and 0. 84% of the total area, respectively and similar proportional distribution of classes with 1 to 4 % variation were also found in 2008. Dense mixed forest covered the largest area followed by Sal mixed forests, Open mixed forest, Bamboo Brakes, Agriculture and water bodies, while the minimum area covered by the habitation in the entire study area in 2008. Dense and Sal mixed forest are the predominant LULC in the study area for a decade, followed by Open mixed, Teak plantation and Bamboo brakes. Habitation change appears relatively insignificant due to the small area. Open mixed forest and Agricultural areas have increased, while Dense mixed, Sal mixed, Teak plantation and Bamboo brakes have decreased significantly. Young under-stocked teak forests can restore the vegeta-

Table 5
List of the RET species in the AABR region.

S. No.	Botanical name	Family	Local name	Plant habit	Part used	Mode of utilization	Diversity of uses
1	*Adina cordifolia* (Roxb.) B & H	Rutaceae	Haldu, Karma	T	Fruit	Timber, Leaves and fruits	Timber, Medicinal uses
2	*Feronia elephantum* Corr.	Rutaceae	Kaith	T	Fruit	Ripe fruits eaten & pickled	Edible food
3	*Ficus infectoria* (Miq.)	Moraceae	Pakar	T	Leaves	Cold beverage,	Medicinal
4	*Semecarpus anacardium Linn.*	Anacardiaceae	Bheluva	T	Fruits& seeds	Roasted fruits are eaten	Medicinal. Marking of clothes
5	*Phoenix sylvestris* (L.) Roxb.	Arecaceae	Wild kajur	T	Fruit	Ripe fruits eaten	Medicinal (Fruit/Seed/Root), Food, Fodder, Fuelwood
6	*Cochlospermum religosum* (L.) Alston	Bixaceae	Kumbi	T	Flowers & Seeds	Flowers cooked as Vegetable	Medicinal
7	*Abelomoshcus moschatus* Medik.	Malvaceae	Jungli bhendi	H	Fruits	Vegetable	Medicinal
8	*Alternanthera sessilis* Mart.	Amaranthaceae	Garundi	H	Twigs	Cooked as vegetable	Medicinal
9	*Bauhinia purpurea* Linn.	Fabaceae	Koelar-Kachnar	T	Tender leaves & Flower	Cooked as vegetable	Firewood & fodder Bark dyes
10	*Phyllocephalum indicum* (Less) Kirkman	Zingiberaceae	Vanjeera	H	Young leaves	Spice	Medicinal
11	*Smithia conferta* Sm.	Fabaceae	Duthi	H	Leaves	Cooked as vegetable	Medicinal
12	*Mentha arvensis*	Lamiaceae	Pudina	H	Leaves	Spices & pickled	Medicinal
13	*Chlorophytum arundinaceum* (Roxb.)	Asparagaceae	Safed musli	H	Suckers	Root	Medicinal
14	*Urginea indica* (Roxb.) Kunth	Liliaceae	Jangli-piyaz	H	Bulb	Bulbs cooked as vegetable	Edible and Medicinal values
15	*Eryngium foetidum* Linn.	Apiaceae	Van dhania	H	Leaves/Stem	Spices	Edible and medicinal
16	*Curcuma caesia* Roxb	Zingiberaceae	Kalihaldi	H	Rhizomes	Rhizomes used as Spice and flavour ing.	Medicinal
17	*Dioscorea pentaphylla L.*	Dioscoreaceae	Suwarkanda,	C	tuber	Tubers cooked as vegetable	Medicinal
18	*Amorphophallus paeoniifolius* (D.) N.	Araceae	Suran kand	H	Corn	Corms, and stem eaten and cooked as vegetable	Medicinal
19	*Antidesma diandrum* Roxb.	Euphorbiaceae	Saroti	S	Leaves & fruits	Leaves	Medicinal
20	*Woodfordia floribunda* (L.). Kurz.	Lytharaceae	Dhavai	S	Flowers	Flowers are eaten as food	
21	*Bahunia villi* (L.) Benth.	Fabaceae	Mahul	C	seeds	Roasted seeds are eaten	Medicinal & NTFPs
22	*Sisymbrium nigrum* Prantl	*Cruciferae*	Jungli rye	H	Seeds	Vegetable	Edible
23	*Ocimum gratissimum* L.	*Lamiaceae*	Jangli Tulsi	H	Seeds, Leaves, Inflorescences	Leaves	Medicinal
24	*Bacopa monnieri* L Wettst.	*Plantaginaceae*	Brahmi	H	Whole plants	Plant parts are eaten	Medicinal
25	*Cyperus gracilis* R. Br.	*Poaceae*	Nagar motha	H	Leaves, roots	Leaves	Fodder and Commercial products
26	*Zingiber cassumunar* Roxb.	Zingiberaceae	Jangali Adrak	H	Rhizome	Rhizome is used to treat	Medicinal
27	*Allium tuberosum* Roxb.	Liliaceae	Van lasun	H	Leaves and bulb	The leaves and bulbs are used for treatment	Medicinal
28	*Asparagus racemosus* Willd.	Liliaceae	Satavar	H	Roots	Roots extracts	Medicinal
29	*Lepidium sativum* Linn.	Brassicaceae	Chandrasur	H	Young leaves	Leaves extract	Medicinal

Note: T- Tree, S- Shrub, H-Herb, C-climber.

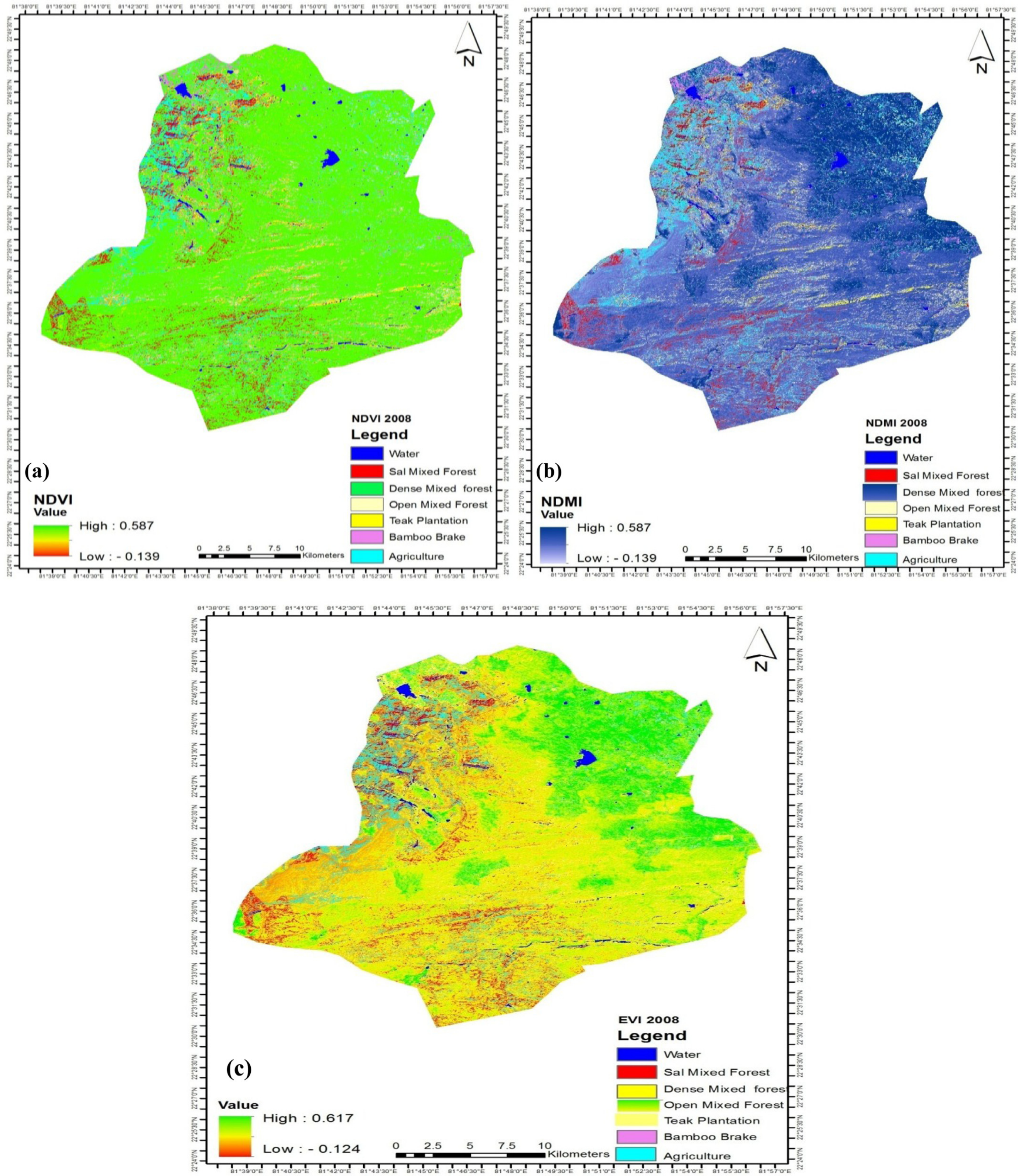


Fig. 9. (a) Distribution of Land use using NDVI for 2008. (b) Distribution of Land use using NDMI for 2008. (c) Distribution of Land use using EVI for 2008.

tion density and diversity in the area. Moreover, Sal regeneration by assisted natural regeneration would remain crucial, and replacement of native species by exotic ones should be kept in check in order to restore native forests. The area of water bodies has also decreased significantly from 2008 to 2018 and data on change detection is illustrated in Figs. 7 and 8. Indigenous communities of AABR uses different forest products such as leafy vegetables, tubers, rhizomes, fruits, seeds, nuts and pods. Other than edibles, AABR has been the source of several herbal, medicinal, ornamental, sacred and economically useful plants (Sundriyal and Sundriyal, 2001; Aryal et al. 2018; Chauhan et al. 2018).

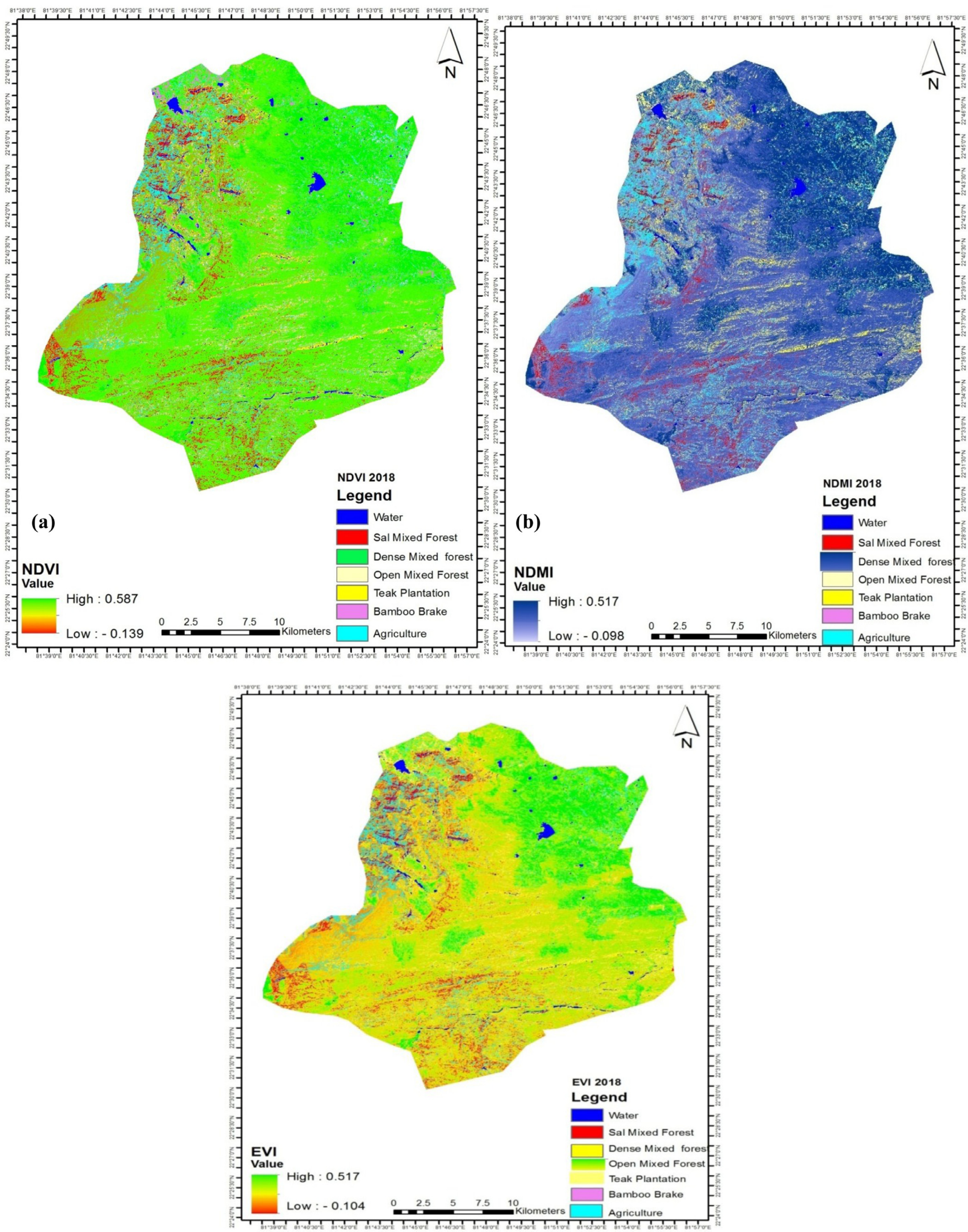


Fig. 10. (a) Distribution of Land use using NDVI for 2018. (b) Distribution of Land use using NDMI for 2018. (c) Distribution of Land use using EVI for 2018.

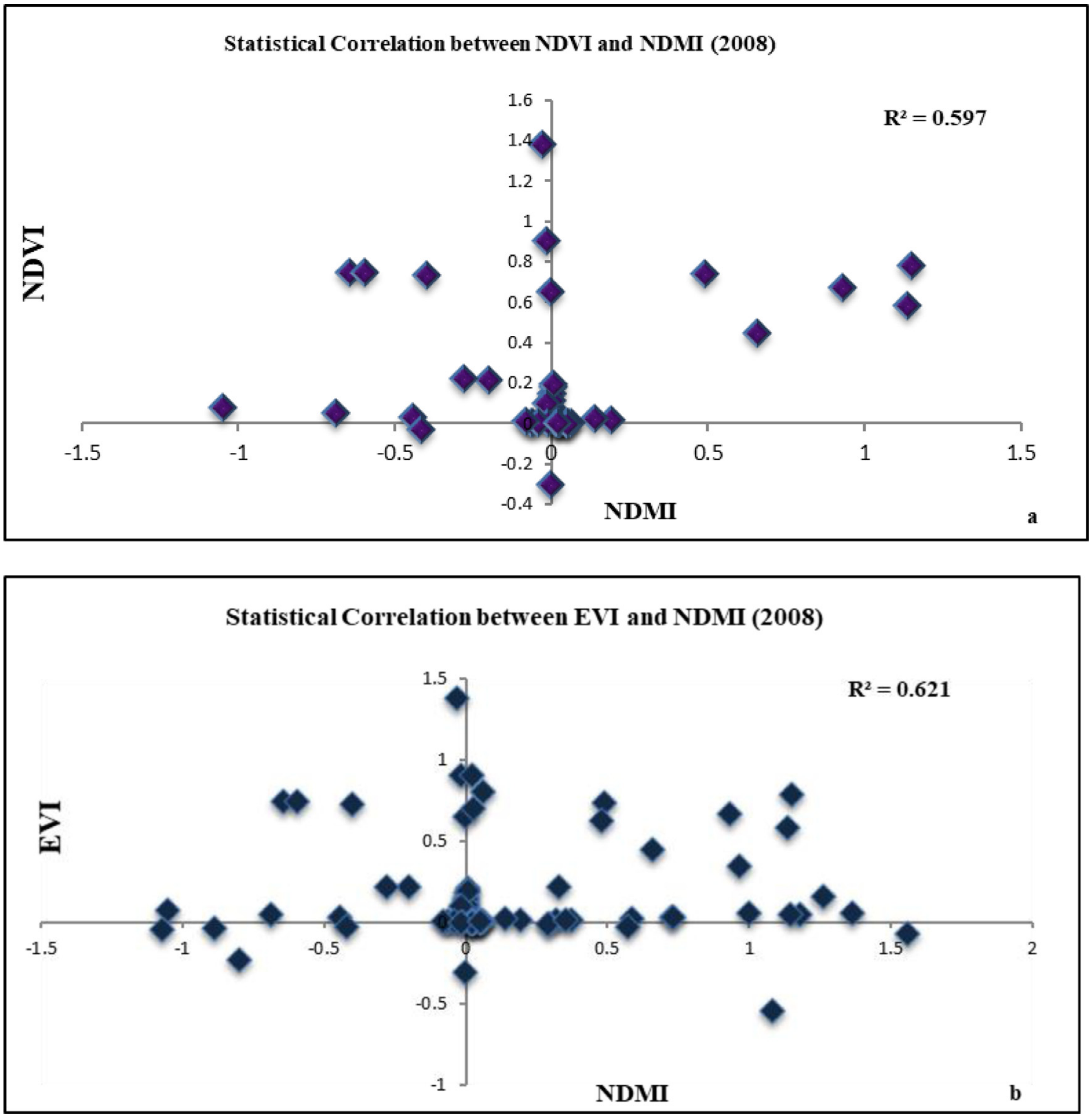


Fig. 11. (a) Statistical correlation between NDVI and NDMI. (b) Statistical correlation Between EVI and NDMI (2008).

This study has attempted to provide useful insights into traditional food habits and its modern alternatives. Hence, this study will be useful for policy interventions for judicious utilization, improving livelihoods, conservation and sustainable management of forest resources for addressing livelihood problems among indigenous communities of AABR.

Medium resolution (Landsat 7 image) and high-resolution satellite images (i.e. Resourcesat 2A image) have been used for LULC changes from 2008 to 2018 of AABR. LULC and changes monitoring and mapping has gradually more standard as few of the most efficient tools for LULC and natural resource management applications. As demonstrated earlier by Aslami and Ghorbani (2018) and Aggarwal et al. (2016), the present study approves the trustworthiness and accuracy of SRS imaging technology for monitoring and mapping of LULC and change detection in diverse areas.

Overall accuracy, using LULC classification in the current study varies from 87.69% to 92.4%, which is in agreement of Aslami and Ghorbani (2018) and Chetan et al. (2017) who reported overall accuracy varying from 91.76% to 93% and 80% to 93%, respectively. Furthermore, Omlanson and Bauer (2016) reported in sequence for overall accuracy varied from 92.2% to 96.4%. Several researchers worked on LULC and change detection in the tropical region were noted in a similar manner (Yu et al., 2007; Petropoulos et al., 2012; Omlanson and Bauer, 2016; Park and Lee, 2016; Soha and El-Raey, 2019; El-Tantawi et al., 2019; Mishra et al., 2019). Moreover, results are comparison with previous studies, such as Foddy (2002) and Saxena (1992), which used MLC pixel-based image analysis for LULC and change detection and similar kind of results were reported by Azizi et al. (2016) and Mirzaei et al. (2018).

Following the LULC change from 2008 to 2018 in AABR, we could discern notable changes that occurred over the 10-year duration; such as conversion of Dense and Sal mixed forest covers to Open mixed forest and Agricultural land, ecological degradation by anthropogenic activities like slash and burn, overgrazing, overexploitation of MAPs in ground & underground vegetation, encroachment etc., The construction of permanent structure, mining, settlements, water crisis also pose severe pressure on biological resources leading to destruction of habitats of flora and fauna. Many native species are replaced by non-native or exotic species which is affecting the ecology of this region e.g. Sal and Mahua were replaced by tropical Pines and Eucalyptus which is damaging the diversity of AABR. Shalaby and Tateishi (2007) also recorded similar results, the maximum changes in land use associated with human develop-

Table 6
Accuracy assessment using confusion matrix generated for 2008 Landsat 7 image and 2018 Resourcesat 2A images.

Maps	2008	2018
Overall accuracy (%)	87.69	92.4
Kappa Coefficient	0.876	0.924

ment. Human interferences put pressure on both biotic and abiotic components of the local environment of AABR which ultimately has resulted in the disturbed ecological balance of this region. A list of rare, endangered and threatened species of AABR is mentioned in Table 5. Moreover, Kwon et al. (2005) and Korea forest service (2010) also revealed the same cause, thus showing the same trend as in the present study. Similar research on LULC change of protected areas also proved in previous studies of the sustainable natural resource management (Qian et al., 2019).

Disturbed ecological balance in turn may yield several adverse consequences. Severe anthropogenic pressure being experience in this region is putting the local environment under great risk. Interestingly, the enhancing vegetation and improved rainfall may provide better ecosystem services to the protected areas (Jiang et al., 2018). This issue requires greater attention from forest villagers, forest officials, foresters and forest managers for proper land use planning for the sustainable development of natural resources. The major changes include loss of 19.72 km^2 of vegetation cover in various forest types due to increasing biotic interference and over grazing, leading conversion of 14.77 km^2 of dense Sal mixed forest to open mixed forest and cultivable land, and also conversion of 5.0 km^2 teak plantation and Bamboo brakes to agricultural land. Despite loss of various plant species due to anthropogenic pressure, the study found many species are replaced by exotic species which is affecting the ecology and diversity of this region e.g. Sal and Mahua are replaced by tropical Pines and Eucalyptus.

Direct field measurement and accuracy assessment

The reconnaissance survey was done for direct field measurements and the LULC maps in 2008 and 2018 were derived from Landsat 7 and Resourcesat 2A satellite data (Fig. 5), and their overall classification accuracy and Kappa statistics are given in Table 6. Overall accuracy assessment for the classified images of 2008 and 2018 were chosen with 'Kappa accuracy assessment technique'. This technique was done by using medium and 5.8 m resolution satellite data which has been generated from each forest class. Image classification accuracy assessment of 2008 and 2018 images were very constructive and overall accuracy for the LULC image of 2008 was found 87.67%, while in 2018 was found 92.4% accuracy with the overall Kappa statistics of 0.8769 and 0.924 for 2008 and 2018 images, respectively (Table 6). Moreover, Hossen and Negm (2016) reported the error matrix and implemented over the LULC classification based on the reference/ancillary data. The change matrix in the studied periods 2008-2018 is illustrated in Table 7. Results revealed from the LULC and change matrix indicate that the most important changes on vegetation in the Dense mixed forest and Sal mixed forest.

Establishing correlations among NDMI with NDVI and EVI

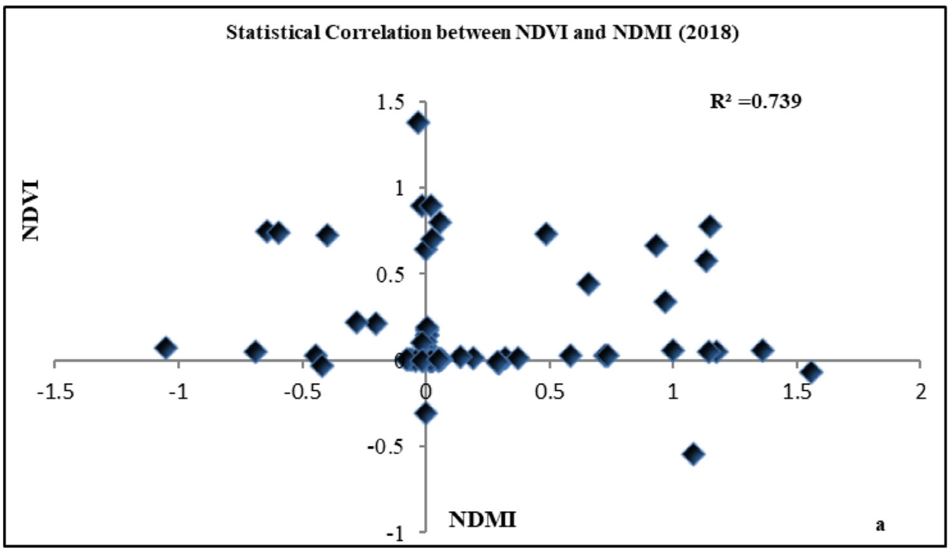
Data on LULC using vegetation indices are represented in Figs. 9 and 10. The results of change detection as per Normalized difference moisture index (NDMI) revealed in the study area decreased by almost 1.42% (Table 8). Also, a 1.9% decrease in the value of Dense mixed forest was observed during the period under examination (Figs. 9 and 10). For the purpose of statistical validation, sample coordinates were distributed in the selected area, and the raster values of all the vegetation indices

Table 7
Change matrix calculation of AABR.

2018		Water bodies	Sal mixed forest	Dense mixed forest	Open mixed forest	Teak plantation	Bamboo brake	Agriculture	Habitation	Total
2008	**Water bodies**	0	4	1,667,884	15	0	0	0	4489	1,672,392
	Sal mixed forest	1254	358,634	0	227	0	316,860	5863	170,940	853,778
	Dense mixed forest	0	589	0	342	252,693	59	47	308,262	561,992
	Open mixed forest	6521	1,412,223	560,594	8009	145,468	2043	0	37	2,134,895
	Teak plantation	40,977	757	514	204,761	74	42	5581	3	252,709
	Bamboo brake	0	174	9549	302	31	0	3540	424,183	437,779
	Agriculture	944	92,492	222,291	5407	4795	9571	60	4	335,564
	Habitation	3247	0	2214	440	7095	295	5191	50	18,532
	Total area (histogram Value)	52,943	1,864,873	2,463,046	219,503	410,156	328,870	20,282	907,968	6,267,641
	Total area (km^2)	**5.29**	**181.26**	**236.96**	**104.54**	**38.54**	**30.55**	**27.48**	**2.14**	**626.76**

Table 8
Distribution of land use classes using various vegetation indices for the year 2008 and 2018.

	NDVI Area in km^2			NDMI Area in km^2			EVI Area in km^2		
Classes	2008	2018	Change%	2008	2018	Change%	2008	2018	Change%
Sal mixed Forest	189.3	179.54	1.56	320.42	318.15	0.36	179.44	176.23	0.51
Dense mixed forest	201.55	189.65	1.89	210.46	201.56	1.42	199.89	193.59	1
Open mixed forest	120.96	118.97	0.31	69.24	74.89	0.90	175.66	178.45	-0.44
Teak plantation / Bamboo Brake	86.78	81.78	0.80	13.87	15.98	0.33	55.60	62.89	−1.15
Agriculture	28.17	56.82	4.57	12.77	16.55	0.66	16.17	15.76	0.06



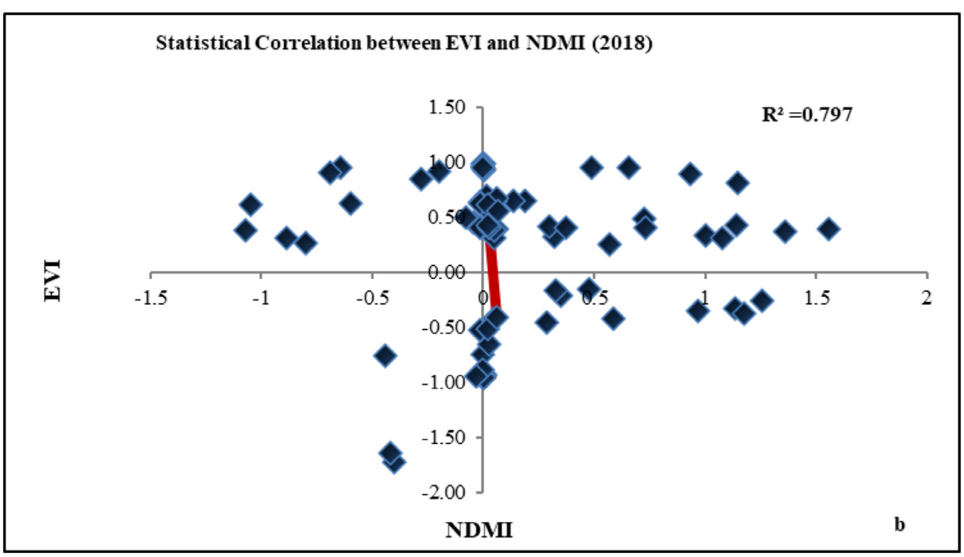


Fig. 12. (a) Statistical correlation between NDVI and NDMI. (b) Statistical correlation Between EVI and NDMI (2018).

were computed with ArcGIS. Later on, given values were extracted for statistical regression analysis. As evident from Figs. 11 and 12, linear regression analysis of the AABR areas revealed that NDMI is highly correlated with the enhanced vegetation index (r2 > 0.797) and NDVI (r^2 > 0.739). Similar mythologies were adopted earlier by Karan et al. 2016. Tillack et al. (2014) established NDVI coupled with NDMI as the best index to analyze vegetation/LULC dynamics when compared to other satellite vegetation indices.

Conclusion

AABR has vast forest area with high anthropogenic pressure for resource utilization by tribes and other forest dwelling communities. The decadal LULC changes in the AABR covering an area of 626.76 km^2 in temporal scale from 2008 to 2018. LULC patterns are important in identifying limited resources, and environmentally critical areas from land conversion or human exploitation. The area is predominantly covered with forest vegetation but substantial conversion witnessed in different vegetation classes such as Dense mixed forest and Sal mixed forest in fringe areas of cultivable land and habitation. The field survey in combination with interaction with local communities' reveals that the forest resources are the main source of livelihood which put intense pressure without proper forest management regulations.

We advocate that by adopting the rigorous conservation measures, especially re-vegetation of open forest with indigenous species & augmentation of dense forest by the respective species. To check cultivable land expansion forest farming or ecological farming concepts need to taught to tribals for better livelihood options. Current findings hold tremendous implications in framing biodiversity based livelihood plan for socio economic upliftment of forest dwelling communities. The ethos of ensuring sustainable utilization of the natural diversity in the forest ecosystem is key to mitigate climate change impact.

Author's contribution statement

TKT: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Resources, Writing - original draft, Writing - review & editing. **AB**: Conceptualization, Investigation, Writing - review & editing. **MJRD**: Investigation, Writing - review & editing. **DKP**: Conceptualization, Methodology, Validation, Formal analysis. **AK**: Writing - review & editing, Supervision. **AT**: Methodology, Data curation, Review & editing. **AB** and **JAB**: Writing - review & editing.

Declaration of Competing Interest

Authors declare that they have no competing interests.

Acknowledgments

We thankfully acknowledge the financial support provided by the Ministry of Environment, Forests and Climate Change (MoEF&CC), Government of India, New Delhi, vide its project Sanction No. F.13/4/2013-NNRMS/RE.

References

Aggarwal, N., Srivastava, M., Dutta, M., 2016. Comparative analysis of pixel-based and object-based classification of high resolution remote sensing images - a review. Int. J. Eng. Trends. Technol. 38, 5. doi:10.14445/22315381/IJETT-V38P202, 11.

Aryal, K.P., Poudel, S., Chaudhary, R.P., Chettri, N., Ning, Wu., Kotru, R., 2018. Diversity and use of wild and non-cultivated edible plants in the Western Himalaya. J. Ethnobiol. Ethnomed. 14, 10.

Aslami, F., Ghorbani, A., 2018. Object-based land-use/land-cover change detection using Landsat imagery: a case study of Ardabil, Namin, and Nir counties in northwest Iran. Environ. Monit. Assess. 190, 376. doi:10.1007/s10661-018-6751-y.

Azizi, A., Malakmohamadi, B., Jafari, H.R., 2016. Land use and land cover spatiotemporal dynamic pattern and predicting changes using integrated CA-Markov model. Glob. J. Environ. Sci. Manag. doi:10.7508/gjesm.2016.03.002.

Chetan, M.A., Dornik, A., Urdea, P., 2017. Comparison of object and pixel-based land cover classification through three supervised methods. J. Geo. Geoinfor. Land Manag. doi:10.12902/zfv-0165-2017.

Chauhan, S.H., Yadav, S., Takahashi, T., Luczaj, L., Cruz, L.D., Okada, K., 2018. Consumption patterns of wild edibles by the Vasavas: a case study from Gujarat, India. J. Ethnobiol. Ethnomed. 14, 57.

El-Tantawi, A.M., Bao, A., Chang, C., Liu, Y., 2019. Monitoring and predicting land use/cover changes in the Aksu-Tarim River Basin, Xinjiang-China (1990–2030). Environ. Monit. Assess. 191, 480. doi:10.1007/s10661-019-7478-0.

Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201.

Geist, H.J., Lambin, E.F., 2001. What drives tropical deforestation? A meta analysis of proximate and underlying causes of deforestation based on sub-national case study evidence. Louvain-la-Neuve (Belgium): LUCC International Project Office, LUCC Report Series no. 4.

Hardisky, M.A., Klemas, V., Smart, R.M., 1983. The influence of soil-salinity, growth form and leaf moisture on the spectral radiance of Spartina altemiflora canopies. Photogramm. Eng. Remote Sens. 49, 77–83.

Hossen, H., Negm, A., 2016. Change detection in the water bodies of Burullus Lake, Northern Nile Delta, Egypt, using RS/GIS. In: Proceedings of the twelfth International Conference on Hydro informatics, HIC 2016. Procedia Engineering, 154, pp. 936–942.

Huete, A.R., Justice C., 1999. MODIS vegetation index (MOD13) algorithm theoretical basis document. Ver. 3.

Jiang, C., Nath, R., Labzovskii, L., Wang, D., 2018. Integrating ecosystem services into effectiveness assessment of ecological restoration program in northern China's arid areas: insights from the Beijing-Tianjin sandstorm source region. Lan. Use. Policy 75, 201–214.

Joshi, K.C., Negi, M.S., Tiple, A.D., 2010. Achanakmar-Amarkantak Biosphere Reserve. Biosphere Reserve Information Series (BRIS), 2(1–2): 1–158.

Karan, S.K., Samadder, S.R., Maiti, S.K., 2016. Assessment of the capability of remote sensing and GIS techniques for monitoring reclamation success in coal mine degraded lands. J. Environ. Manag. 182, 272–283.

Korea Forest Service., 2010. Statistical Yearbook of Forestry. Korea Forest Service, Daejeon http://www.forest.go.kr.

Kwon, S.D., Seo, J.H., Son, Y.M., Park, Y.K., 2005. Biomass carbon emissions according to conversion of forest land in Korea. For. Bioeng. 24, 10–15.

Lea, C., Curtis, A.C., 2010. Thematic accuracy assessment procedures: national park service vegetation inventory, version 2.0. Natural Resource Report NPS/NRPC/NRR—2010/204 National Park Service, Fort Collins, Colorado, USA

Lossou, E., Prempeh, N.O., Agyemang, G., 2019. Monitoring land cover changes in the tropical high forests using multi-temporal remote sensing and spatial analysis techniques. Remote Sens. Appl.: Soc. Environ. 1–14 (16) article 100264.

Mirzaei, M, Ghorbani, A., Keivan, B.F., 2018. Land use/cover change detection using Landsat and IRS imagery: a case study, Khalkhal County. Irani. J. Geog. Space 60, 101–116 In Persian.

Mishra, P.K., Rai, A., Rai, S.C., 2019. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. Egypt. J. Remote Sens. Space Sci. doi:10.1016/j.ejrs.2019.02.001.

Olmanson, L.G., Bauer, M.E., 2016. Improved land cover classification by integrating Landsat imagery with Lidar and object-based image analysis for land cover classification of the international lake of the woods/rainy river basin. http://lps16.esa.int/posterfiles/paper2097/Landcoverposter32_40_final.pdf.

Park, J., Lee, J., 2016. Detection of land use / land cover changes using remotely-sensed data. J. For. Res. doi:10.1007/s11676-016-0270-x.

Petropoulos, G.P., Kalaitzidis, C., Vadrevu, K.P., 2012. Support vector machines and object-based classification for obtaining land-use/cover cartography from Hyperion hyperspectral imagery. Comput. Geo. 41, 99–107. doi:10.1016/j.cageo.2011.08.019.

Qian, D., Cao, G., Du, Y., Li, Q., Guo, X., 2019. Impacts of climate change and human factors on land cover change in inland mountain protected areas: a case study of the Qilian Mountain National Nature Reserve in China. Environ. Monit. Assess. 191, 486. doi:10.1007/s10661-019-7619-5.

Rawat, J.S., Kumar, M., 2015. Monitoring land use/cover change using remote sensing and GIS techniques: a case study of Hawalbagh block, district Almora, Uttarakhand, India. Egypt. J. Rem. Sens. Space. Sci. 18, 77–84.

Reid, W.V., Mooney, H.A., Cropper, A., Capistrano, D., Carpenter, S.R., Chopra, K., Dasgupta, P., Dietz, T., Duraiappah, A.K., Hassan, R., Kasperson, R., Leemans, R., May, R.M., McMichael, A.J., Pingali, P., Samper, C., Scholes, R., Watson, R.T., Zakri, A.H., Shidong, Z., Ash, N.J., Bennett, E., Kumar, P., Lee, M.J., RaudseppHearne, C., Simons, H., Thonell, J., Zurek, M.B., 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, District of Columbia, p. 155.

Rouse J.W., Haas R.H., Schell J.A., Deering D.W., 1973. Monitoring vegetation system in the great plains with ERTS; pp. 3010–3017.

Roychoudhury, N., Sharma, R., Mishra, R.K., 2016. Ethnobotanical uses of plant species in Achanakmar-Amarkantak biosphere reserve. Van Sangyan 7–19 ISSN 2395 - 468X.

Saadat, H., Adamowski, J., Bonnell, R., Sharifi, F., Namdar, M., Ale-Ebrahim, S., 2011. Land use and land cover classification over a large area in Iran based on single date analysis of satellite imagery. ISPRS J. Photogram. Rem. Sens. 66, 608–619.

Shalaby, A., Tateishi, R., 2007. Remote sensing and GIS for mapping and monitoring land cover and land use changes in the northwestern coastal zone of Egypt. App. Geog. 27, 28–41. doi:10.1016/j.apgeog.2006.09.004.

Soha, A.M., El-Raey, E.M., 2019. Land cover classification and change detection analysis of Qaroun and Wadi El-Rayyan lakes using multi-temporal remotely sensed imagery. Environ. Monit. Assess. 191, 229. doi:10.1007/s10661-019-7339-x.

Story, M., Congalton, R.G., 1986. Accuracy assessment: a user's perspective photogramm. Eng. Remote Sens. 52 (3), 397–399.

Sudhakar, 1994. Stratification approach for forest cover type and land use mapping using IRS-1A LISS-II data – a case study. J. Ind. Soc. Rem. Sens. 22 (1), 21–29.

Sundriyal, M., Sundriyal, R.C., 2001. Wild edible plants of Sikkim Himalayas: nutritive value of selected species. Econ. Bot. 55 (3), 377–390.

Tellman, B., Sesnie, S.E., Magliocca, N.R., Nielsen, E.A., Devine, J.A., McSweeney, K., Jaing, M., Wrathallh, D.J., Dávilak, A., Benessaiahi, K., Aguilar-Gonzalezj, B., 2020. Illicit drivers of land use change: narcotrafficking and forest loss in central America. Glob. Environ. Change doi:10.1016/j.gloenvcha.2020.102092.

Thakur, T.K., 2018. Diversity, composition and structure of understorey vegetation in the tropical forest of Achanakmaar Biosphere Reserve, India. Environ. Sustain. 1 (2), 279–293.

Thakur, T.K., Kumar, Y., Bijalwan, A., Dobriyal, M.J.R., 2017. Traditional uses and sustainable collection of ethnobotanicals by aboriginal communities of the Achanakmaar Amarkantak Biosphere Reserve of India.. Fron. Environ. Microb. 3 (3), 39–49.

Thakur, T.K., Swamy, S.L., Bijalwan, A., 2019. Assessment of biomass and net primary productivity of a dry tropical forest using geospatial technology. J. For. Res. 30 (1), 157–170.

Tillack, A., Clasen, A., Kleinschmit, B., F€orster, M., 2014. Estimation of the seasonal leaf area index in an alluvial forest using high-resolution satellite-based vegetation indices. Remote Sens. Environ. 141, 52e63.

Tiwari, A.P., Sikarwar, R.L.S., Dubey, P.C., 2014. Documentation of ethnomedical knowledge among the tribes of Achanakmar-Amarkantak biosphere reserve, Central, India. Indian J. Nat. Prod. Resour. 5 (4), 345–350.

Wu, T., Luo, J., Fang, J., Ma, J., Song, X., 2018. Unsupervised object-based change detection via a Weibull mixture model-based binarization for high-resolution remote sensing images. IEEE Geosci. Rem. Sens. Lett. 15, 63–67.

Yang, C.B., He, X.Y., Yan, F.Q., Yu, L.X., Bu, K., Yang, J.C., Chang, L.P., Zhang, S.W., 2017. Mapping the influence of land use/land cover changes on the urban heat island effect-a case study of Changchun, China. Sustainability 9, 312.

Yang, X., Wen, X., 2011. Post classification comparison change detection of Guangzhou Metropolis, China. Key. Engi. Mat. 467 (469), 19–22. doi:10.4028/www.scientific.net/KEM.467-469.19.

Yu, H., Joshi, P.K., Das, K.K., Chauniyal, D.D., Melick, D.R., Yang, X., Xu, J., 2007. Land use/cover change and environmental vulnerability analysis in Birahi Ganga sub-watershed of the Garhwal Himalaya, India. Trop. Ecol. 48 (2), 241.

Yu, J., Li, F., Wang, Y., Lin, Y., Peng, Z., Cheng, K., 2020. Spatiotemporal evolution of tropical forest degradation and its impact on ecological sensitivity: a case study in Jinghong, Xishuangbanna, China. Sci. To. Environ., 138678 doi:10.1016/j.scitotenv.2020.138678.

Yuan, F., Sawaya, K.E., Loeffelholz, B., Bauer, M.E., 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sens. Environ. 98, 317–328.

Zhang, P., Lv, Z., Shi, W., 2014. Local spectrum-trend similarity approach for detecting land-cover change by usingspot-5 satellite images. IEEE Geosci. Rem. Sens. Lett. 11, 738–742.