STM JOURNALS

Research & Reviews: Journal of
Space Science & Technology

https://journals.stmjournals.com/rrjosst

ISSN: 2321-2837 (Online)
ISSN: 2321-6506 (Print)
Volume 14, Issue 2, 2025
May–August
DOI (Journal): 10.37591/RRJoSST

Research RRJoSST

Geospatial Assessment of Land Use and Land Cover Changes in Debrigarh Wildlife Sanctuary, Odisha: A Twenty-Year Perspective

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Abstract

Among the recorded dynamic processes on the surface of the earth is the change in land use and land cover (LULC) pattern as an outcome of several anthropogenic practices. Planning, development, and management of land for sustainable usage of land depend on plotting and tracing the vagaries in LULC. Anthropogenic activity, generally for forestry and food production, is altering the land surface. The steadily diminishing landscape also has tragic implications for biodiversity and critically important ecosystem services like carbon storage. The protection of areas of land provides a solution, together, these areas can work to save natural and social resources, guard human well-being, and deliver sustainable livelihoods which encourages sustainable development when effectively managed and equitably governed. Thus, this study is an attempt to track changes in LULC patterns of Debrigarh Wildlife Sanctuary (DWS) in Bargarh District of Odisha over a period of 20 years (2004 to 2024) by channels of Remote Sensing (RS) and Geographic Information System (GIS) systems. A total of 346.91 km^2, the entire territory of the DWS is being studied. The study centres on determining variations in LULC and assessing vegetation based on the well-known ration NDVI using data from satellites. Nevertheless, during the period that was examined for the study area, Landsat 4-5 TM and Landsat 8-9 OLI/TIRS imageries sufficiently supported the detection of changes brought about by nature or human activity throughout time. LULC classification was efficiently done with substantial accuracy and it has been found that forest cover has increased while other LULC classes seem to decline.

Keywords: Land use land cover, anthropogenic practice, wildlife sanctuary, remote sensing (RS), and Geographic Information System (GIS)

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Received Date: May 21, 2025
Accepted Date: May 27, 2025
Published Date: June 21, 2025

Citation: Niti Parashar, Harshita Jain, Maya Kumari, Praveen Kumar Rai. Geospatial Assessment of Land Use and Land Cover Changes in Debrigarh Wildlife Sanctuary, Odisha: A Twenty-Year Perspective. Research & Reviews: Journal of Space Science & Technology. 2025; 14(2): 12–27p.

INTRODUCTION

The complex interactions between human activity and natural ecosystems are exemplified at the Debrigarh Wildlife Sanctuary in Odisha. Due to both natural and human forces, this sanctuary's LULC patterns have changed significantly during the last 20 years. Comprehending these dynamics is pivotal to the efficient preservation and enduring administration of the sanctuary's ecological services and biodiversity. Several studies have revealed that the assessment of LULC plays a vital role in understanding the dynamics of landscape [1–5]. LULC maps deliver knowledge to assist users in knowing the current landscape. Understanding LULC is essential because it provides insight into both the existing and bygone settings of Earth's exterior. Although they are two different concepts, LULC is frequently used synonymously. The standard definition of land cover is the superficial biospheric cover of Earth's exterior that might comprise inland water, soil, flora, artificial structures, and rock. The method by which land has been utilized by humans for commercial endeavours is referred to as land use [6, 7]. The fundamental metric used to evaluate the settings of Earth's exterior and trace the condition and efficiency of the ecological system is called LULC. Natural and human resource-induced LULC fluctuations have typically led to deforestation, global warming, biodiversity loss, and an increase in flooding during natural disasters [8–10]. The main inputs for hydrology, global climate change, carbon cycle studies, and environmental modelling and monitoring are LULC data sets. LULC mapping and remote sensing offer valued visions into the Earth's surface, enabling better supervisory for sustainable development, ecological protection, and disaster response. These technologies continue to evolve, offering increasingly detailed and timely information for an extensive variety of applications.

Understanding the scope and impressions of LULC changes in natural and cultural landscapes on the exterior of the Earth at numerous geographical scales benefits from regular monitoring of LULC changes [11]. Since the 1990s, the combination of remote sensing data with field estimates has been crucial in assessing the loss of forest cover [12]. To detect LULC and provide estimates of their respective areas, remote sensing data and GIS domains are frequently employed as they offer a useful source of data that covers the earth's surface at a spatial and spectral resolution that allows easier land use and land cover classification than traditional approaches [13, 14]. A large variety of satellites and sensors are made available with continued advancement for better assessment of landscape dynamics [15]. Optical sensors with enhanced resolution helped plot LULC at varied scales because of their broad sensing array and greater frequency signal dispensation [16]. The combination of remote sensing (RS), geographic information systems (GIS), and global positioning systems (GPS) which are known as geo-informatics technology are proving to be the most inventive and dynamic tool for environmental researchers and geoscientists for mapping, monitoring, modelling, assessment, and defensible management of various environmental issues and natural resources [17].

So far, two types of approaches for land use land cover classification have evolved: supervised classification (Human guided), and unsupervised techniques (Calculated by software) [12]. Also, many techniques have been developed in the literature for LULC change detection, including manual on-screen digitization of multi-temporal satellite images, post-classification comparison, image ratio, image regression, and orthodox image variation [6]. Post-categorization comparison is widely acknowledged as the most accurate method with the benefit of revealing the type of alterations [18]. The current study used a pixel-by-pixel comparison approach with the help of supervised maximum likelihood classification technique to detect changes in the land use and land cover maps derived from satellite images as it is considered to be one of the most robust techniques of land use classification [19–24]. Numerous scholars from diverse nations acknowledged the leads of using geospatial tools for plotting, tracking, and identifying variations in LU/LC. However, derived LULC maps are so often taken as inefficient eminence for further implementation until they are assessed contrary to reference data [25]. Disagreements between the two data sets are typically interpreted as errors in the land cover map derived from the remotely sensed data [26]. The most extensively encouraged classification accuracy is the procedure of error matrix which can be used to acquire a chain of descriptive and systematic statistics [13, 26, 27].

This study focuses on mapping the LULC pattern and LULC change in Debrigarh Wildlife Sanctuary during the study period (2004–2024). Debrigarh Wildlife Sanctuary actively contributes to the preservation of the state's natural environment. Various wildlife species inhabiting a variety of habitats are necessary to sustain the equilibrium of the global carbon cycle and the ecological balance. The current study details how shifting farming, forest fires, built-up areas, and other factors have changed LULC. Moreover, using multi-temporal Debrigarh Wildlife Sanctuary satellite imagery, an effort has been made to determine a relationship between the expanse of forest and the amount of built-up, agricultural, or bare land. The findings will also elaborate on the results of efforts made to date for the conservation of the Debrigarh Wildlife Sanctuary and further suggestions can be drawn for sustainable management practice.

STUDY AREA

The Orissan district of Bargarh is home to the Debrigarh Wildlife Sanctuary (DWS). The sanctuary spreads over an area of 346.91 km^2 and is sited between 21°28' and 21°43'N latitudes and 83°30' and 83°46'E longitudes (Figure 1). The Orissan government declared it a wildlife sanctuary with notice No. 2409/FFAH/dated February 8, 1985. The Lohara and Debrigarh Reserved Forests, located in the renowned

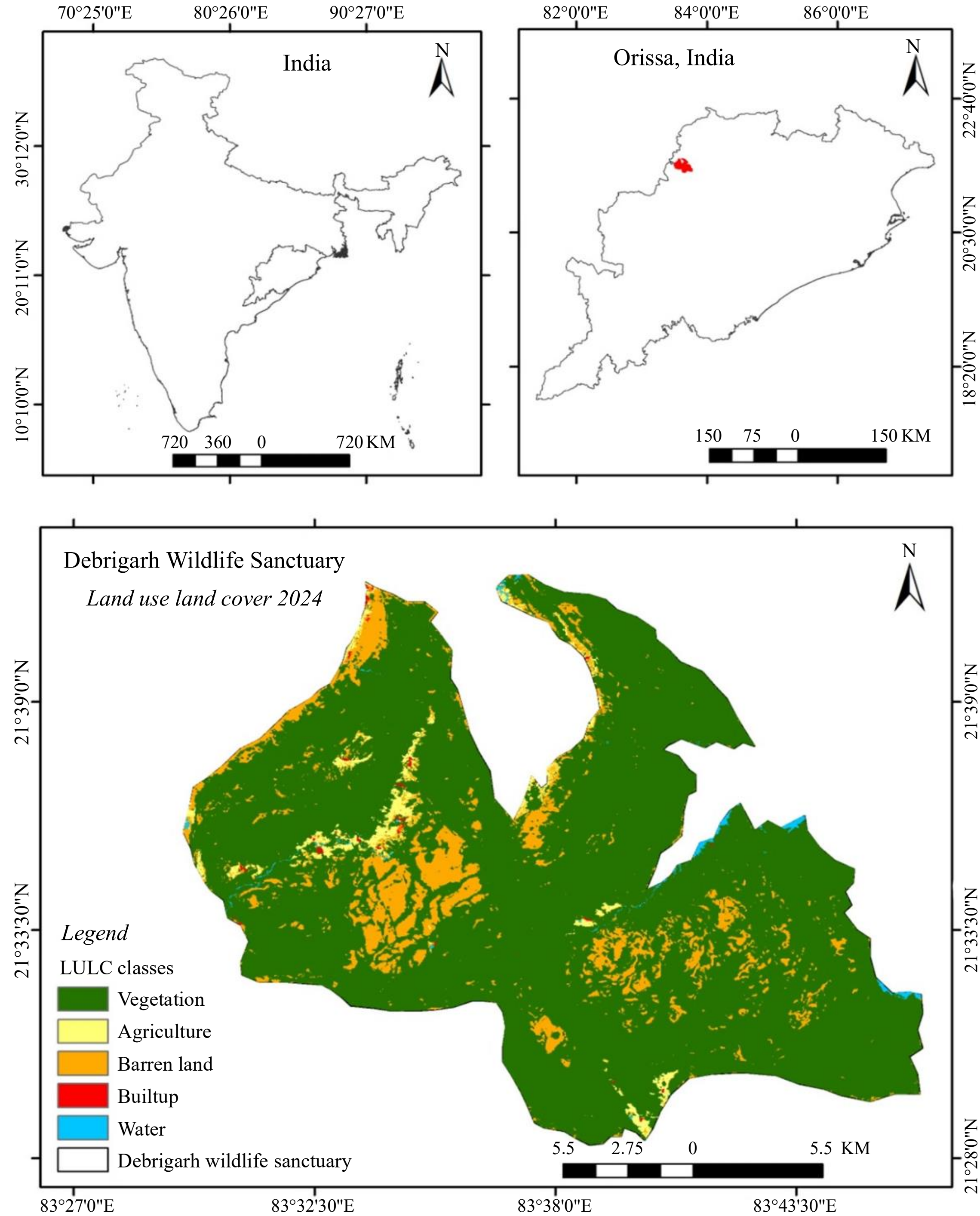


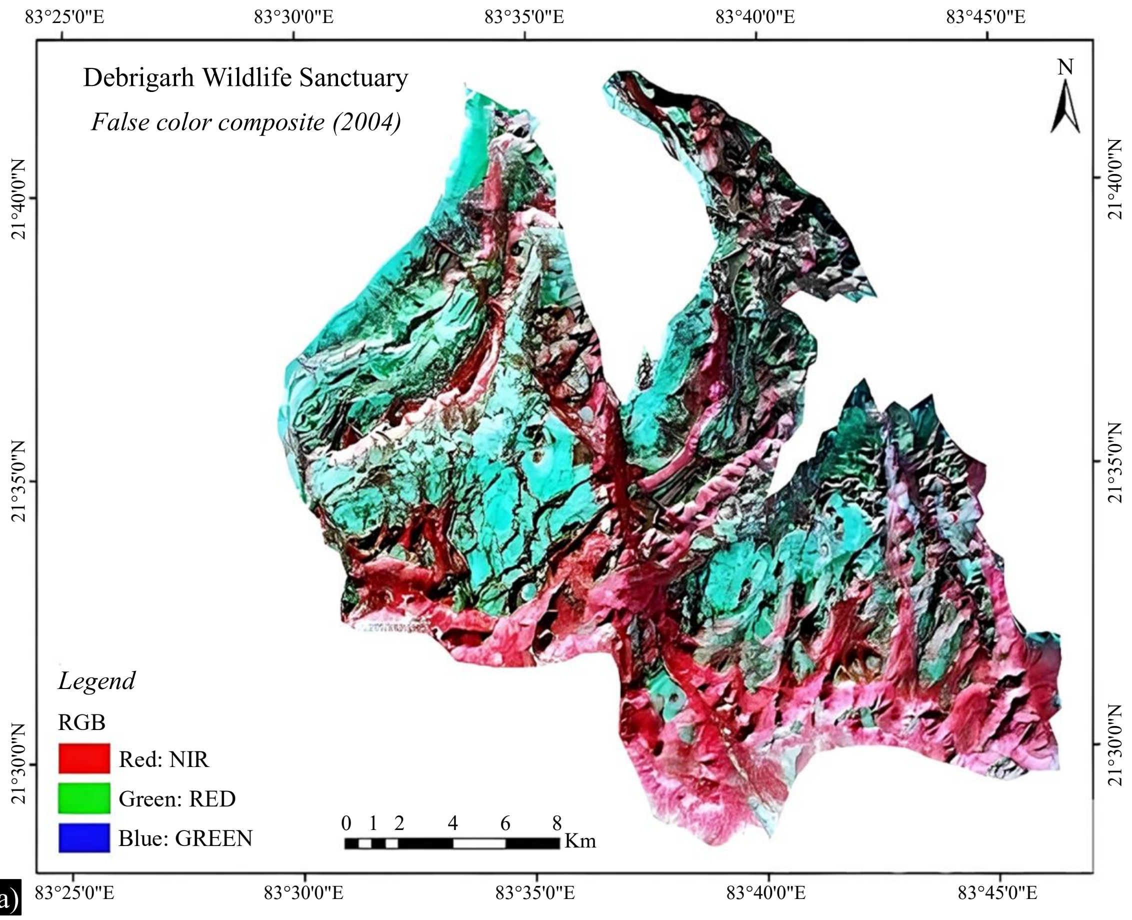
Figure 1. Location map, Debrigarh wildlife Sanctuary.

Barapahad Hills of the Bargarh district, make up the sanctuary. This sanctuary is well-known for its abundant biodiversity in addition to its sylvan beauty and breathtaking waterfalls. The sanctuary region is dominated by a dry deciduous forest with a diverse range of plants. A portion of the woodland is also covered in grasslands. Rainfall typically relies on the southwest monsoon. In summer (April–May), the maximum temperature reaches 46°C, while in winter (December–January), the minimum temperature drops to 10°C. Relatively high humidity is present. Mixed vegetation, including Bija, Sal, Bandhan Sisoo, Karada, Mahul, Dhaura, Ainla, Harda, Domkurdu, Bahada, etc., can be found in the Debrigarh sanctuary. The refuge is dotted with Salia bamboo. The main fauna comprises the following: Sloth bear, Langur, Wild boar, Porcupine, giant squirrel, Malabar Common Civet, Four-horned antelope, Tiger, Leopard, Gaur, Sambar, and Spotted Deer. Peafowl, Blue Jays, Spur Fowl, Jungle Crows, Eagle Varieties, and Owls are among the Avifauna. Several migratory species can be seen, including the Brahminy, Great crested grebe, duck, Pintail, Godwal, Tufted pochard, and Shoveller.

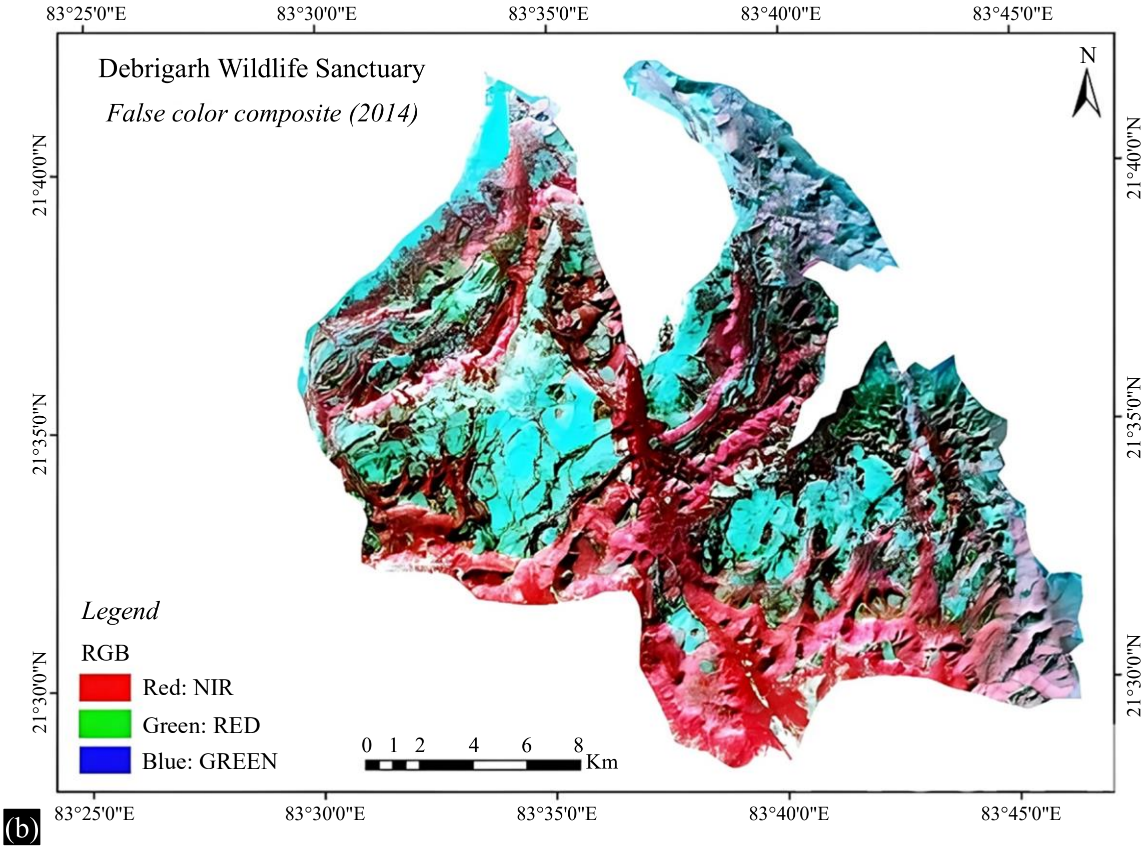
MATERIALS AND METHODS

Dataset

In contemporary work, variations on grounds of time and space in LULC of Debrigarh Wildlife Sanctuary are studied using satellite data from Landsat 4-5 TM for the year 2004 and Landsat 8-9 OLI and TIRS for the years 2014 and 2024 (Figure 2(a)–(c)). The above data are made available jointly by the National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS). Landsat 4-5 TM consists of seven spectral bands with a 30 m spatial resolution for visible, near-infrared, and shortwave infrared (band 1–5 and band 7) and a 120 m resolution for thermal band (band 6). Landsat 8-9 OLI/TIRS provide a spatial resolution of 30 m for visible, near-infrared, and shortwave infrared and cirrus (band 1–7 and 9); 100 m for thermal (band 10 and 11) and 15 m for panchromatic (band 8). Details of dataset are elaborated in Table 1.



(a)



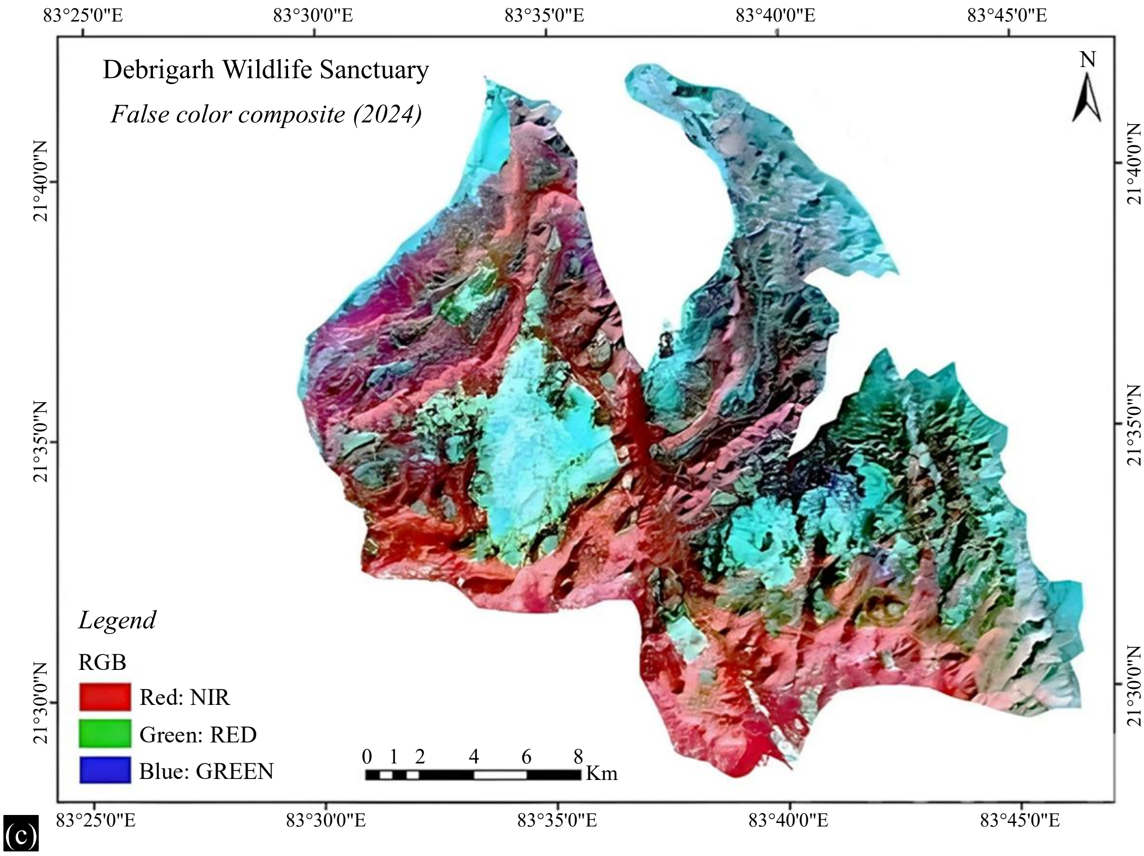


Figure 2. (a) FCC Landsat image (2004). (b) FCC Landsat image (2014). (c) FCC Landsat image (2024).

Table 1. Dataset.

Satellite/sensor	Source	Date of acquisition	Band used	Spatial resolution
Landsat 4-5 TM	United States Geological Survey https://earthexplorer.usgs.gov/.	27/12/2004	Blue, green, red, near-infrared, shortwave infrared 1 and 2 (bands 1, 2, 3, 4, and 5 respectively)	30 m
Landsat 8-9 OLI/TIRS	United States Geological Survey https://earthexplorer.usgs.gov/.	23/12/2014, 21/12/2024	Blue, green, red, near-infrared, shortwave infrared 1 and 2 (band 2, 3, 4, 5, 6 and 7 respectively)	30 m

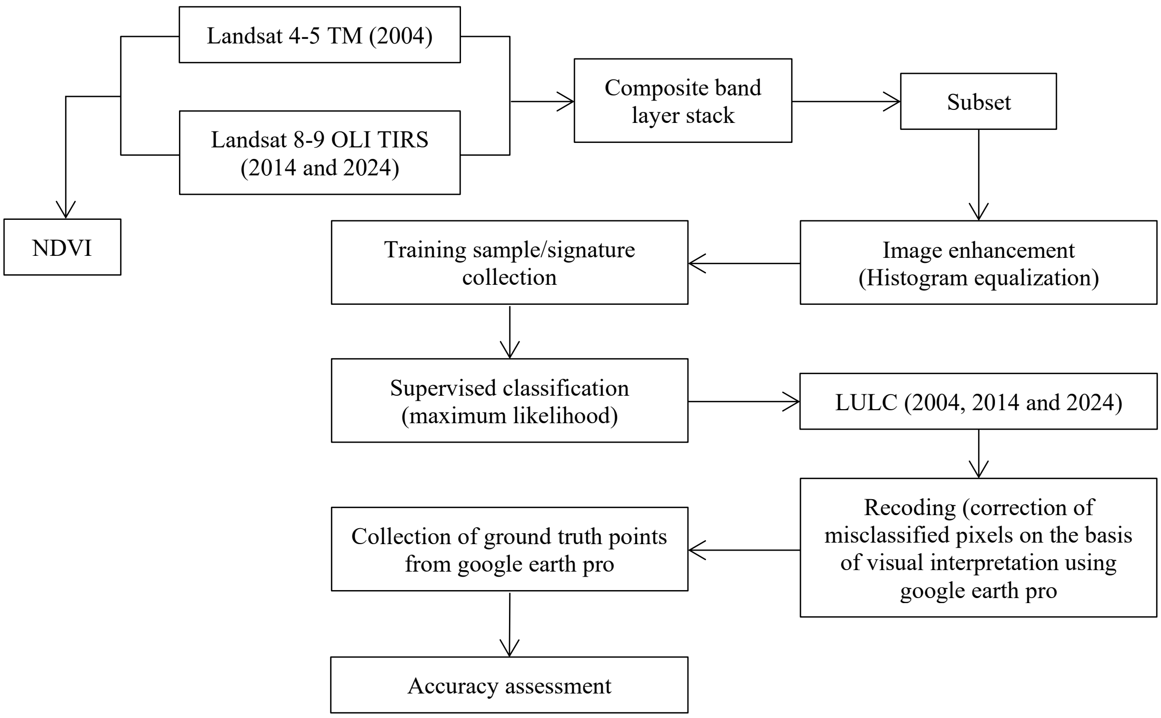


Figure 3. Methodology flow chart.

Methodology

Figure 3 elaborates the step-on-step method utilized in the study of LULC. LULC is the classification or categorizing of physical elements and anthropological activities on the terrestrial surface across time, utilizing accepted systematic and statistical techniques of study of relevant data. Efficient land use land cover classification involves pre-processing, categorization, post-processing, and lastly, accuracy assessment of the map. Pre-processing of the acquired Landsat images involves layer stacking (band composition of visible, NIR, and SWIR), and image enhancement with the help of geometric and radiometric corrections and histogram equalization. Further, the study region was extricated out of the Landsat tile using subset tool. Later, with the aid of signature files, the supervised classification was completed using the maximum likelihood classification technique. Based on Bayesian theory, MLC is a supervised classification technique [28]. The likelihood that a pixel falls into one of multiple classes is the foundation of MLC. The mean vector and covariance metrics are the two most crucial elements of maximum likelihood classification that may be derived from training data [29]. LULC maps for 2004, 2014 and 2024 are generated using this procedure. The land LULC maps are categorized into five classes viz., agriculture, vegetation, barren land, settlement, and water body. Table 2 represents the details about land use types [30]. All the LULC data produced were then compared with the observed data provided by high-resolution spatiotemporal imagery of Google Earth for accuracy assessment, forest area was visited in person for ground truth points. 300 points were taken for each classified data corresponding to 60 points for each class. Further values from classified images were extracted to these points and subsequently frequency table was created to make a confusion matrix. Lastly, computation

Table 2. Details of land use land cover.

Land use land cover type	Description
Vegetation	Dry deciduous mixed forest (reserved forest)
Agriculture	Paddy, sugarcane, groundnuts and vegetable
Barren land	Parts of the eastern plateau and hills
Built-up	Settlement of villagers (now been relocated)
water	Hirakud reservoir (Mahanadi river)

Table 3. Calculation of NDVI.

Satellite/sensor	Band used	Formula	Results
Landsat 4-5 TM	NIR and RED (band 4 and band 3)	NDVI=(Band4–band3)/(band 4+band 3)	NDVI 2004 (–0.36–0.59)
Landsat 8-9 OLI/TIRS	NIR and RED (band 5 and band 4)	NDVI=(Band5–band4)/(band 5+band 4)	NDVI 2014 (–0.06–0.41), NDVI 2024 (0–0.38)

of the areal expanse and percent cover of each LULC category, the results were examined and reported along with the change discovery investigation. In addition to LULC maps, Normalized Difference Vegetation Index (NDVI) is calculated using the formula as revealed in Table 3.

RESULTS AND DISCUSSION

Accuracy Assessment

Accuracy assessment of the classified land use land cover image is an important measure of the research as it is vital to make a quantitative assessment of how efficiently the pixels are sampled and classified into land cover classes [15]. So far, several accuracy assessment methods are discussed but the most common and efficient is creation of confusion or error matrix based on some factors such as collection of ground control points (GCPs), classification scheme, sampling type, spatial auto correlation and size and unit of sample [31]. Error matrix can be used to acquire a chain of descriptive and systematic statistics [26, 27]. This technique is capable of effectively presenting the accuracy of each category, also omission and commission errors present in classification are reported. Producer's accuracy, user's accuracy, overall accuracy, and kappa statistics are generally testified [26, 27, 13, 15, 32, 33]. Omission errors are an example of producer accuracy, which is the likelihood that forecasted values truly belong to the specified class, while commission errors are an example of user accuracy, which is the likelihood of correctly categorized values in a given class. While overall accuracy is ratio of correctly classified values to total values. To eliminate the impact of chance on user, producer, and overall accuracy assessments, kappa estimation can be performed using coefficient of agreement. Kappa value ranges between 0 and 1, it has been categorized as >0 (poor), 0–0.2 (slight), 0.21–0.4 (fair), 0.41–0.6 (moderate), 0.61–0.8 (substantial), 0.81–1 (perfect) and referenced by several researchers [15, 34, 35]. Substantial accuracy as detailed in Table 4 of the classified satellite imagery was achieved proving it to be appropriate for further analysis.

LULC Pattern 2004–2014

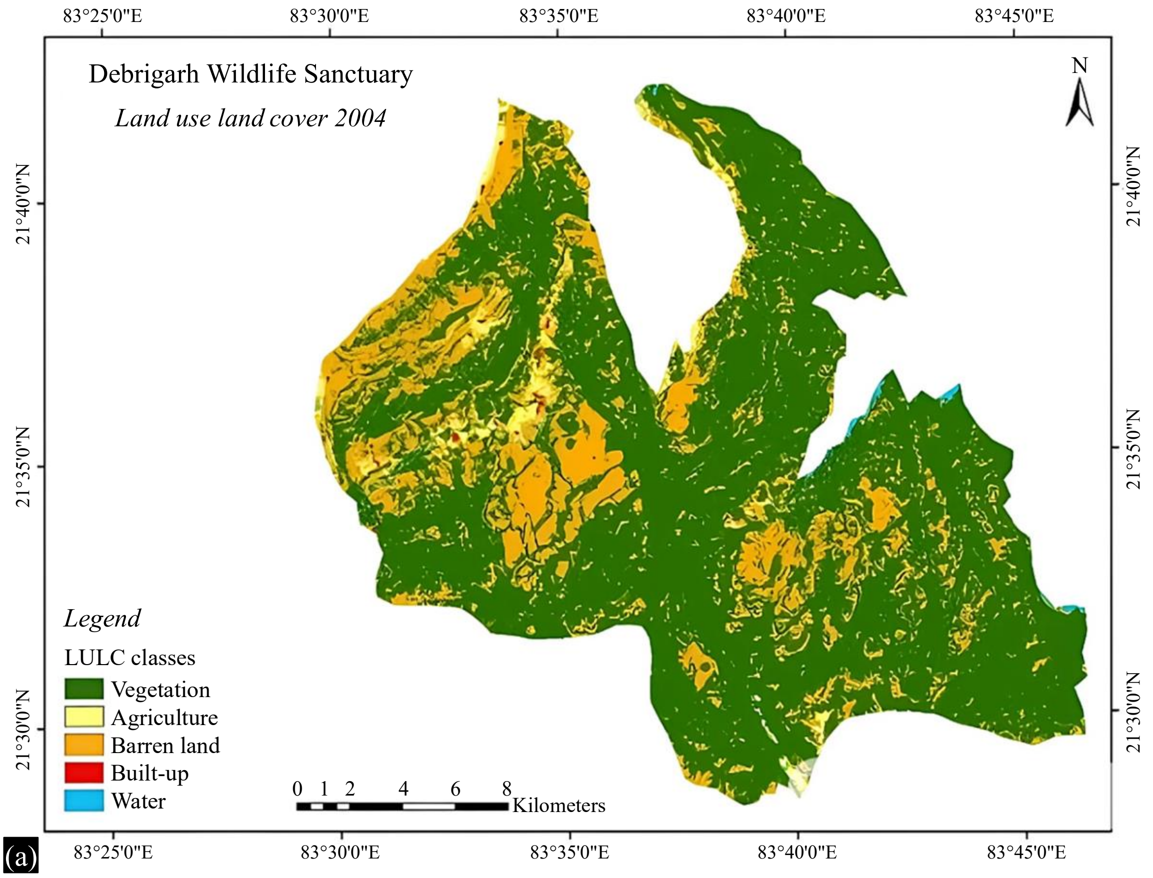
Examination of the temporal LULC design of Debrigarh Wildlife Sanctuary is essential in finding the changes occurring as a result of conservation projects. The research demonstrates the LULC design in the years 2004 and 2014 as well as the spatial and time-based variations in each class reflected (Table 5, and Figures 4(a)–(c) and 5). The preserved area is dominated by forest cover as it is spreading over an area of 290.70 km^2 which constitutes 74.05% of the total study area in 2004 while significant expansion by 32.81 km^2 leading to coverage of 323.52 km^2 was observed by year 2014. Another dominant class is barren lands which are parts of eastern hills and plateaus covering an area of 92.76 km^2 which holds 23.63% of the total area, this land cover class declined by 34.73 km^2 and the remaining barren land covered 58.02 km^2 in 2014. It is evident from Figure 4(a)–(c) that barren land is encroached upon by vegetation cover and many developmental changes happening in the sanctuary to promote tourism. Also, patches of agricultural field are found in the area which occupied an area of 6.96 km^2 in 2004 and increased by 1.52 km^2 till 2014, and finally, 8.48 km^2 area was recorded under agricultural practice. Small built-up was found i.e. 0.56 km^2 which slightly increased to 0.71 km^2 by 2014. The water body adjacent to the study area is the Hirakud dam reservoir on the Mahanadi River which shows slight changes over the study period.

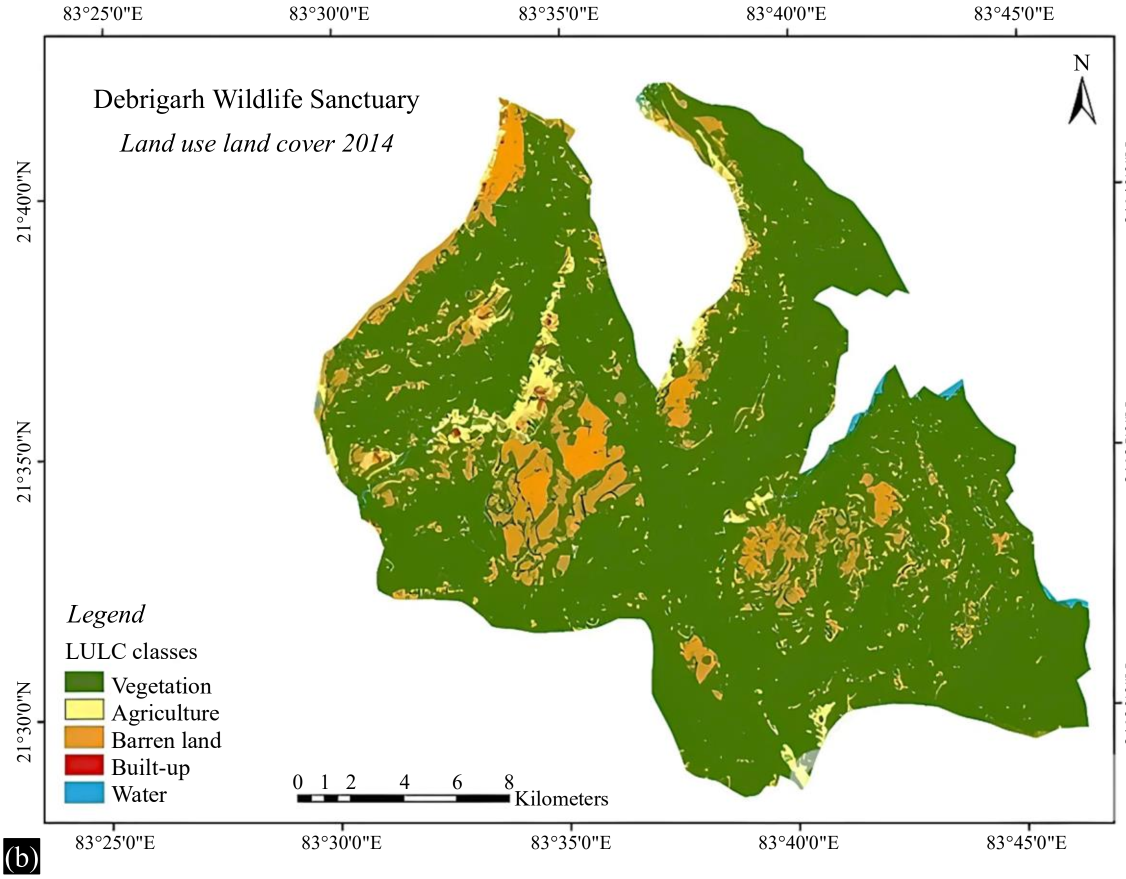
Table 4. Accuracy Assessment of LULC.

	2004		2014		2024	
	PA (%)	*UA (%)*	*PA (%)*	*UA (%)*	*PA (%)*	*UA (%)*
Vegetation	93.75	100	85.71	100	85.71	100
Agriculture	96.67	96.67	96.77	100	96.43	90
Barren land	90.63	96.67	100	93.33	85.29	96.67
Built-up	100	100	100	100	100	90
water	100	86.67	100	86.67	100	86.67
Overall accuracy	96%		96%		92.67%	
Kappa value	0.95		0.95		0.91	

Table 5. Area covered by each LULC class and change (2004–2014).

LULC classes	Land use land cover area					
	2004 (km^2)	*2014 (km^2)*	*Δ (km^2)*	*2004 %*	*2014 %*	*Δ %*
Vegetation	290.70	323.52	32.81	74.05	82.41	8.35
Agriculture	6.96	8.48	1.52	1.77	2.15	0.38
Barren land	92.76	58.02	-34.73	23.63	14.78	–8.84
Built-up	0.56	0.71	0.16	0.14	0.18	0.04
Water	1.57	1.82	0.25	0.40	0.46	0.06





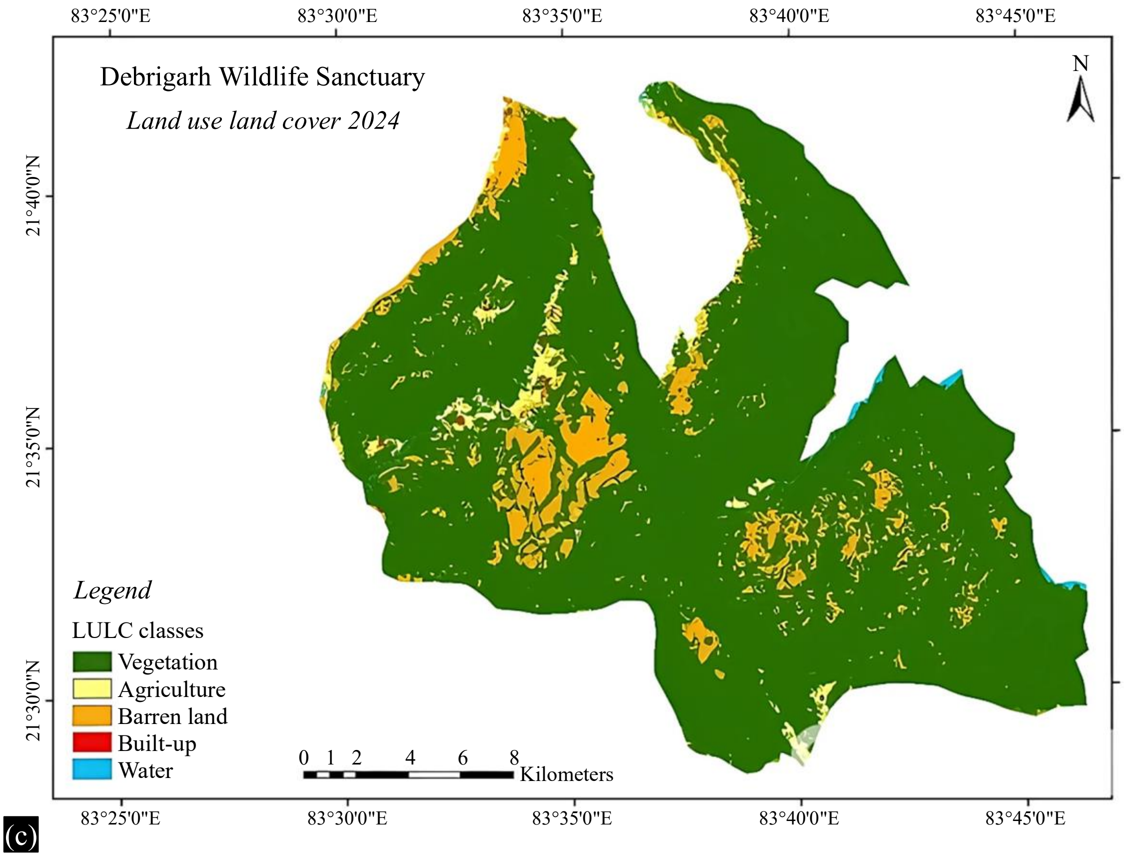


Figure 4. (a) LULC map, 2004. (b) LULC map, 2014. (c) LULC map, 2024.

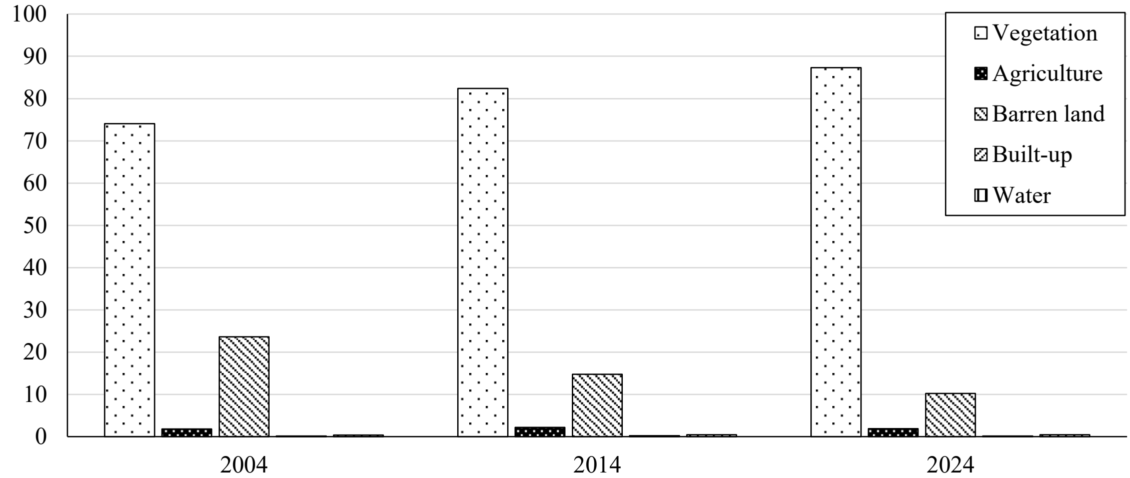


Figure 5. Percentage of area under each land use land cover class.

Table 6. The area under each LULC class and change (2014–2024)

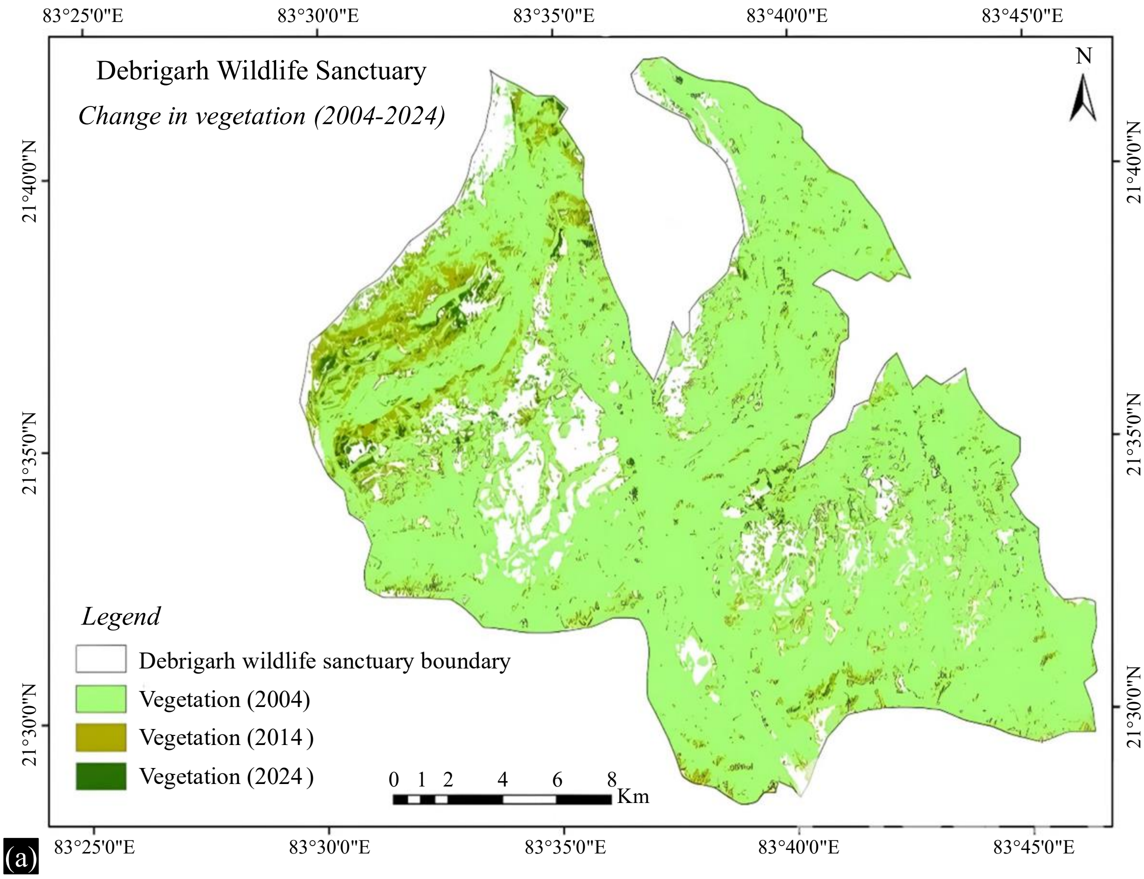
LULC classes	Land use land cover area					
	2014 (km^2)	*2024 (km^2)*	*Δ (km^2)*	*2014 %*	*2024 %*	*Δ %*
Vegetation	323.51	342.81	19.30	82.41	87.33	4.91
Agriculture	8.48	7.35	–1.13	2.15	1.87	–0.28
Barren land	58.02	40.17	–17.85	14.78	10.23	–4.54
Built-up	0.71	0.58	–0.13	0.18	0.14	–0.03
Water	1.82	1.62	–0.19	0.46	0.41	–0.04

LULC Pattern 2014–2024

In the past decade, the rising trend is only found in the vegetation class of the Debrigarh sanctuary whereas lesser areas under agriculture, built-up, barren land, and water classes are found (Table 6 and Figures 4(a)–(c) and 5). The forest cover of 323.51 km^2 constituting 82.41% of the total area in 2014 increased by 19.30 km^2 by 2024 and the present forest cover expands over an area of 342.81 km^2 accounting for 87.33% of the total area. Other LULC categories in Debrigarh Wildlife Sanctuary show a declining trend because, a year ago, the authorities converted a 300 ha area into a verdant meadow following the villagers' relocation from the sanctuary's core region. The highest percentage of decline is observed in barren land; it reduced from 58.02 km^2 in 2014 by 17.85 km^2 to 40.71 km^2 in 2024. Agricultural land has shrunken from 8.48 km^2 in 2014 by 1.13 km^2 to 7.35 km^2 area under agricultural practice at present. As a result of the relocation of about 420 families from Debrigarh Wildlife Sanctuary, the built-up portion was reduced from 0.71 km^2 in 2014 to 0.58 km^2 in 2024. A slight waning of water cover is observed.

Change Detection (2004–2024)

Land use land cover (LULC) change detection based on remote sensing data is an important source of information for various decision support systems [36]. The importance of change detection is to determine which land-use class is changing to the other [37]. Figure 6(a)–(c) elaborates change detection analysis of the LULC between years 2004 and 2024. Table 7 shows the section of area (km^2) of each class. It represents the transformation of land from one LULC class to another. It is found that a major proportion of vegetation/forest cover has continued unaffected throughout the study era as out of 290.70 km^2 of forest, 288.25 km^2 of forest remains unchanged while little transformation is found from forest to barren land i.e. 1.73 km^2 and transformation of forest to other class in insignificant. Agriculture shows significant changes as out of 6.96 km^2 of agricultural land 0.86 km^2 of it changed into vegetation 1.99 km^2 into barren land and 4.03 km^2 remains unchanged. Although agricultural land changed to another land use/land cover, still overall area occupied under agriculture has enlarged.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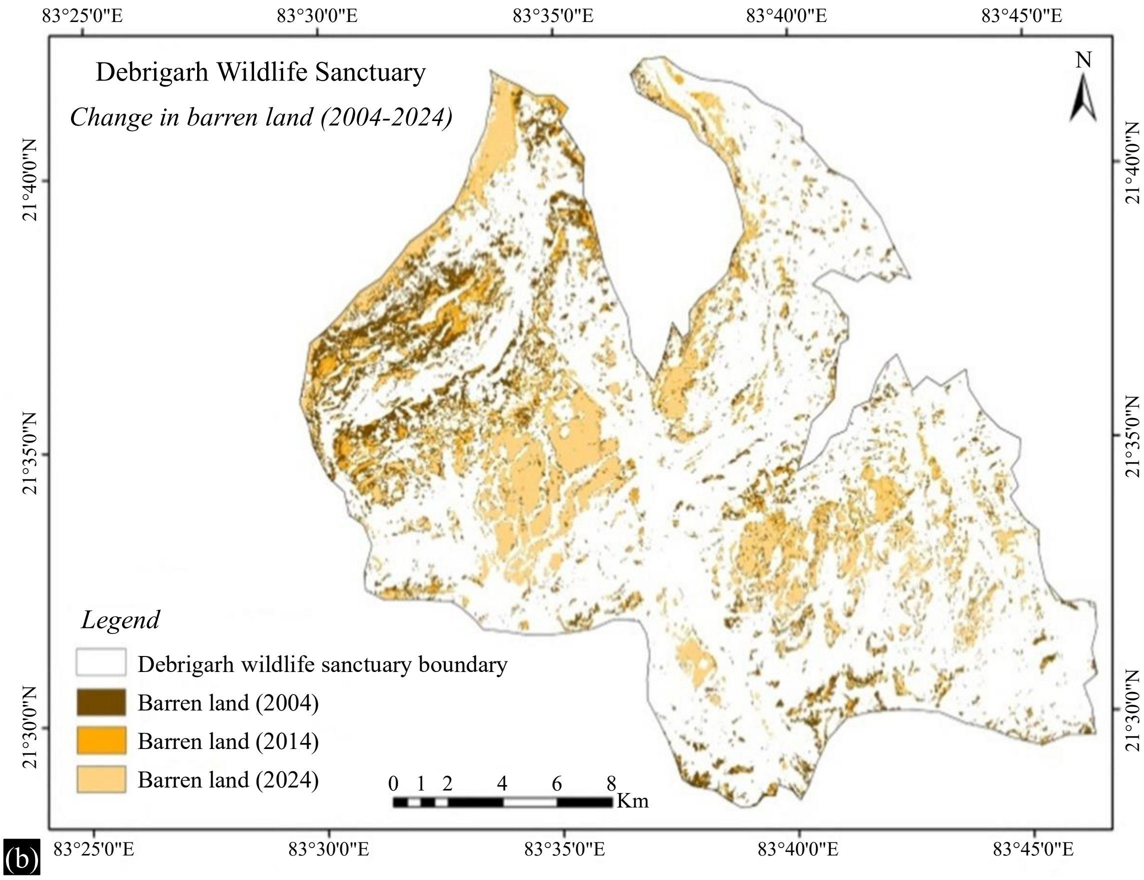
83°40'0"E
83°45'0"E
21°40'0"N
21°35'0"N
21°30'0"N
Debrigarh Wildlife Sanctuary
Change in vegetation (2004-2024)
N
Legend
Debrigarh wildlife sanctuary boundary
Vegetation (2004)
Vegetation (2014)
Vegetation (2024)
0 1 2 4 6 8
Km
(a)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21°30'0"N
Debrigarh Wildlife Sanctuary
Change in barren land (2004-2024)
N
Legend
Debrigarh wildlife sanctuary boundary
Barren land (2004)
Barren land (2014)
Barren land (2024)
0 1 2 4 6 8
Km
(b)

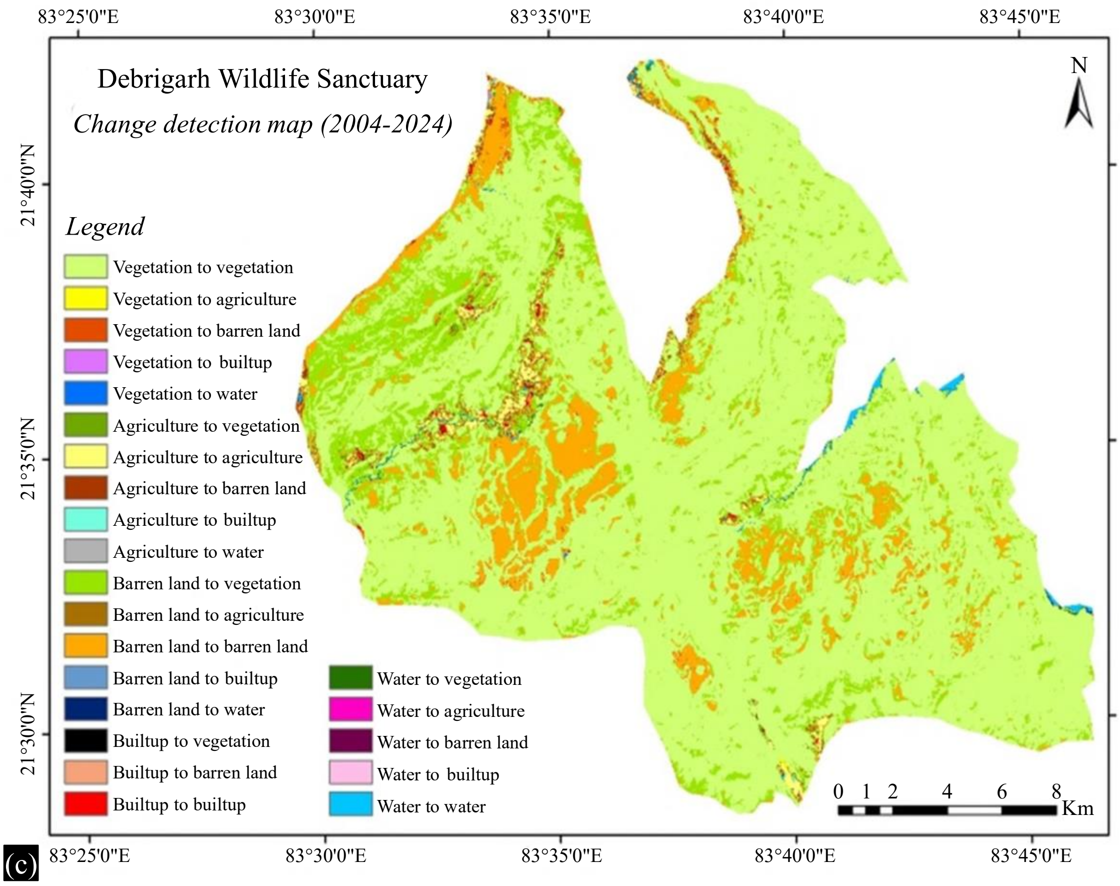


Figure 6. (a) Change in land use land cover class between 2004 and 2024. (b) Change in land use land cover class between 2004 and 2024. (c) Change in land use land cover class between 2004 and 2024.

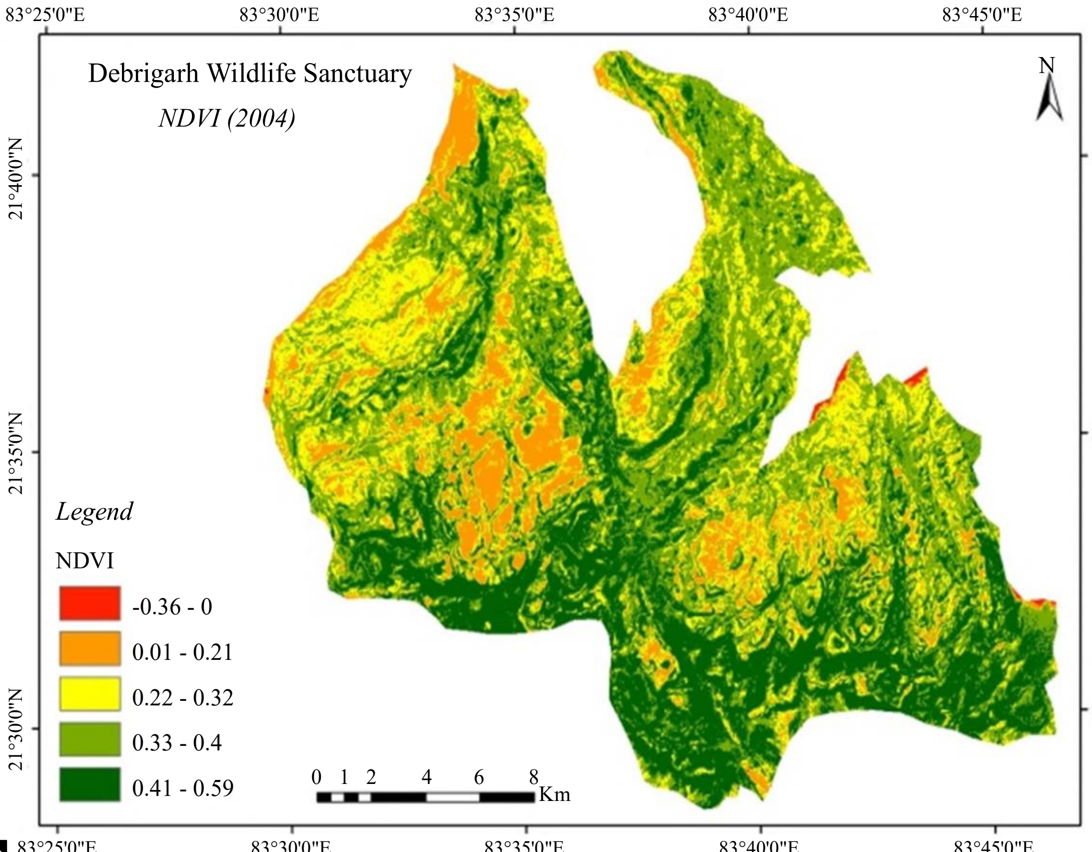
Table 7. Change matrix (2004–2024).

	2024						
	LULC Classes	***Vegetation***	***Agriculture***	***Barren land***	***Built-up***	***Water***	***Total***
2004	Vegetation	288.25	0.32	1.73	0.03	0.36	*290.70*
	Agriculture	0.86	4.03	1.99	0.05	0.03	*6.96*
	Barren land	53.10	2.98	36.39	0.06	0.23	*92.76*
	Built-up	0.07	0.00	0.04	0.45	0.00	*0.56*
	Water	0.53	0.01	0.03	0.00	1.00	*1.57*
	Total	*342.81*	*7.35*	*40.17*	*0.58*	*1.62*	*392.54*

About half of the barren land shifted into vegetation between 2004 and 2024. Out of 92.76 km^2, area 53.10 km^2 area of barren land turned into forest/vegetation, 2.98 km^2 into agriculture and 36.39 km^2 remained unchanged, the shift of barren land into built-up and water is minor. At the beginning of the study period, built-up covered 0.56 km^2, of which 0.45 km^2 remained unchanged while minimal shift has taken place to vegetation and barren land. The study area is adjacent to Hirakud reservoir and the changes detection analysis stated that the line between water and Debrigarh Wildlife Sanctuary is turning into vegetation [38].

Normalized Difference Vegetation Index (NDVI)

Vegetation greenness is quantified using the Normalized Difference Vegetation Index (NDVI) and it can be useful for understanding vegetation density plus alterations in the health of plants. It is computed as the ratio of the Red (R) and Near Infrared (NIR) in the usual way. Overall, the NDVI values range between –1.0 and +1.0: NDVI<0: this range shows that clouds and water are present,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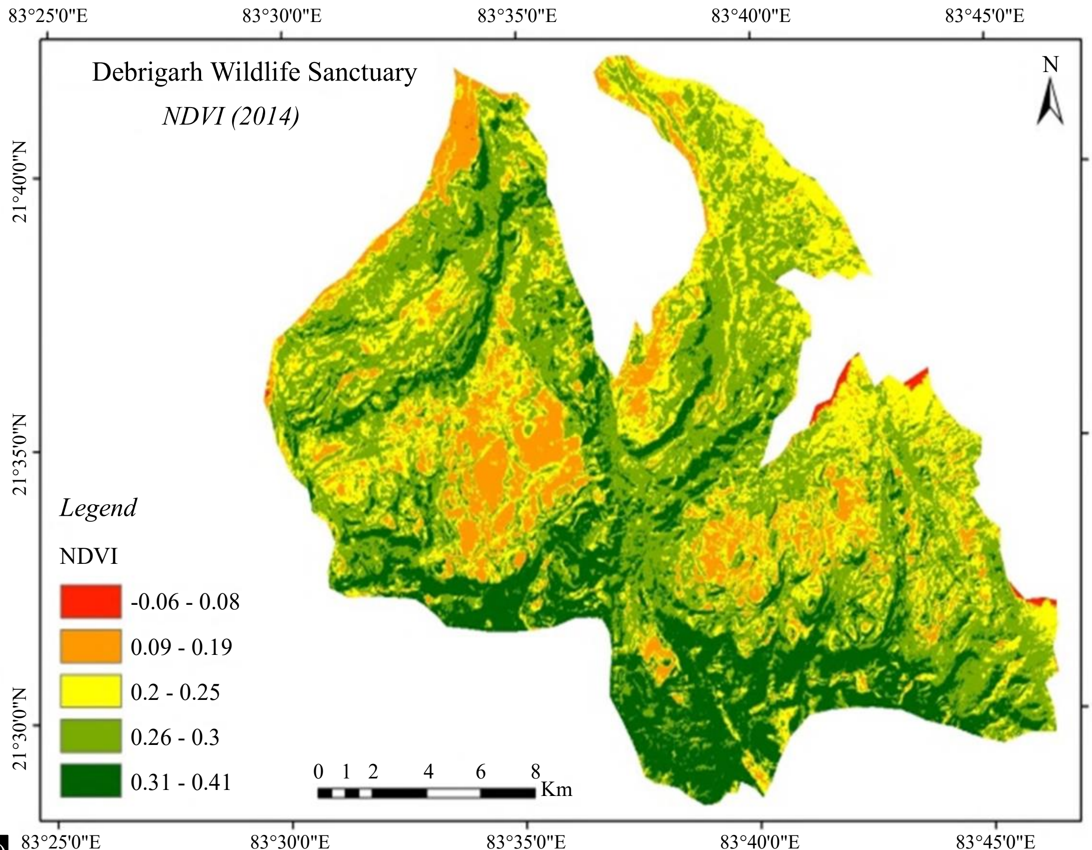
83°45'0"E
21°40'0"N
21°35'0"N
21°30'0"N
Debrigarh Wildlife Sanctuary
NDVI (2004)
N
Legend
NDVI
-0.36 - 0
0.01 - 0.21
0.22 - 0.32
0.33 - 0.4
0.41 - 0.59
0 1 2 4 6 8 Km

(a)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83°35'0"E
83°40'0"E
83°45'0"E
21°40'0"N
21°35'0"N
21°30'0"N
Debrigarh Wildlife Sanctuary
NDVI (2014)
N
Legend
NDVI
-0.06 - 0.08
0.09 - 0.19
0.2 - 0.25
0.26 - 0.3
0.31 - 0.41
0 1 2 4 6 8 Km

(b)

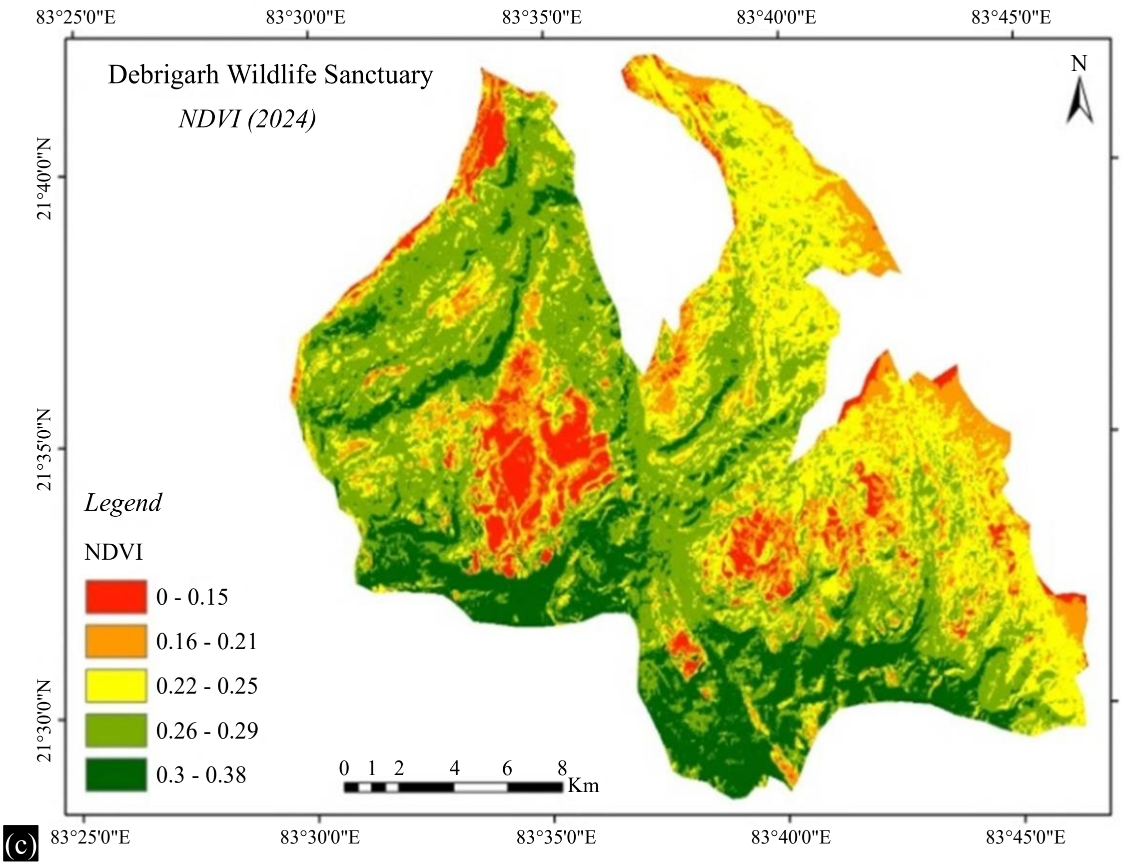

Figure 7. (a) Normalized Difference Vegetation Index (NDVI), 2004. (b) Normalized Difference Vegetation Index (NDVI), 2014. (c) Normalized Difference Vegetation Index (NDVI), 2024.

NDVI~0: it shows the soil (bare) land, NDVI>0: it is known as the vegetated area, NDVI=1: greater than changes in one value mean dense vegetation, High sensor radiation is absorbed and the leaves can undergo photosynthesis process.

It is observed that the vegetation index between 2004 and 2024 shifts towards more positive values and hence represents vegetation growth about quality and measure (Figure 7(a)–(c)). In the year 2004, the NDVI value ranged between –0.36 and 0.59 where an area in the range of –0.36–0 shows water, 0.01–0.32 shows barren land and patches of built-up while an area under a range of 0.33–0.4 and 0.41–0.59 shows sparse and dense vegetation respectively. The scenario changed in the year 2014 when the NDVI value shifted towards more positive values which range between –0.06 and 0.0.41, where areas having values between –0.06 and 0.08 are a water cover, areas holding values 0.09–0.19 show barren land while NDVI class 00.2–0.25, 0.26–0.3 and 0.31–0.41 shows agriculture and varied health and density of forest. During recent years, i.e., 2024, no negative values are extracted and NDVI values range between 0 and 0.38. Areas under 0–0.15 class show patches of barren land while all other classes under 0.16–0.38 are representations of forest cover.

CONCLUSION

Debrigarh Wildlife Sanctuary stands as a vital natural asset, showcasing the beauty of Odisha's wilderness and serving as a stronghold for biodiversity conservation. It is noteworthy that throughout the study phase, the area covered by vegetation has amplified, however part concealed by built-up, agricultural, and barren land has diminished. The tourist areas and the tourist's accommodation entail mainly the forest cover changes as concluded by the land use change analysis of Debrigarh WLS which was carried out on the physical data and satellite image. These changes could also be categorized into different clusters of causes such as timber livelihood dependence of locals, agricultural expansion (plantation), forestry operations, forest fire, and different kinds of infrastructure developments. This is a result of the government's efforts to reallocate 420 families from the sanctuaries and turn the spared land into grasslands for the benefit of herbivores. It has been determined through analysis using both *in-situ* and remotely sensed data that the vegetation area has risen which is a sign of positive ecological equilibrium. Through concerted efforts in conservation and sustainable management, the sanctuary can continue to thrive as a haven for wildlife and a source of inspiration for future generations.

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