Spatio-temporal Analysis of Land Use and Land Cover Change in the Achanakmaar-Amarkantak Biosphere Reserve, Central India: Implications for Forest Degradation and Conservation Planning

Jiwan Lal[1], Lalji Singh[1*] T.K. Thakur[2], R.K. Chaturvedi[3], J.S. Singh[4], Ekta Singh[5], Digvesh Kumar Patel[2] and Yamini Baghel[6]
[1]Department of Forestry, Indira Gandhi Krishi Vishwavidyalaya, Chhattisgarh, India.
[2]Department of Environmental Science, Indira Gandhi National Tribal University, Madhya Pradesh, India.
[3]Center for Integrative Conservation, Xishuangbanna Tropical Botanical Garden, Chinese Academy of Sciences, Yunnan, China.
[4]Department of Botany, Banaras Hindu University, Uttar Pradesh, India.
[5]Department of Natural Resource Management, College of Forestry and Research Station, Mahatma Gandhi University of Horticulture and Forestry, Chhattisgarh, India.
[6]Department of Silviculture and Agroforestry, College of Forestry and Research Station, Mahatma Gandhi University of Horticulture and Forestry, Chhattisgarh, India,
*Corresponding Author email: lalji.singh2@gmail.com

(Received on 14 January 2026; In final form on 12 September 2026)

DOI: *https://doi.org/10.58825/jog.2026.20.2.313*

Abstract: Land Use and Land Cover (LULC) Change plays a crucial role in influencing ecological stability, biodiversity, and climate dynamics. This study investigates the spatio-temporal dynamics of LULC in the Achanakmaar-Amarkantak Biosphere Reserve (AABR), a critical ecological zone in Central India using 2001 and 2021 Landsat imagery, geospatial tools- ArcGIS, and maximum likelihood classification approach. Effort was made to map and analyze changes in major land cover types, viz., dense mixed forest (DMF), sal mixed forest (SMF), bamboo brakes (BB), teak plantation (TP), open mixed forest (OMF), agricultural land (AG), human habitations (HH), and water bodies (WB). The results revealed a significant decline in forested area, particularly DMF (-43.93 km²), SMF (-50.77 km²), BB (19.14 km²), TP (-40.63 km²), and WB (-3.20 km²), while OMF (+131.14 km²), AG (+23.65 km²), and habitations (+2.88 km²) showed notable expansion in two decades. These trends are consistent with anthropogenic pressures reported in similar tropical forest ecosystems. The findings of this study corroborate with the global studies that tropical forests are under increasing threat due to unsustainable land use transitions. Our findings underscore the urgent need for policy interventions and ecological restoration through community-based forest management, reforestation, and promotion of sustainable agroforestry practices. This study contributes novel insights into the regional forest degradation patterns in Central India and demonstrates the utility of remote sensing for long-term environmental monitoring.

Keywords: Land Use and Land Cover Change, Biosphere Reserve, Remote Sensing, Forest Degradation, Achanakmaar-Amarkantak, Conservation Planning.

1. Introduction

Land use and land cover changes (LULC) have significant implications for global and regional climates, long-term sustainability of ecosystems, and the services and biodiversity they support. The increasing human population and growing socio-economic demands exert tremendous pressure on natural landscapes, often leading to unplanned and poorly managed changes in land use and land cover (Thakur et al. 2021a, b; Kumar et al. 2022; Darro et al. 2020). These transformations have been linked to deforestation, global warming, biodiversity loss, and extreme environmental crises such as landslides, droughts, and floods.

LULC is the product not only of geological structure, altitude and slope but also socio-economic and institutional setups (Rai et al. 1994). During recent decades the LULC dynamics has been transformed dynamically. This transformation in LULC pattern has been brought by both human as well as natural factors (Hassan et al. 2016). Therefore, the quantitative assessment of LULC change dynamics is one the most efficient means to manage and understand the landscape transformation (Singh et al. 2015).

The land use modifications are dynamic in nature and are caused by multiple factors operating on local, regional and global scales (Hassan et al. 2016; Rahman et al. 2012). The rapid and uncontrolled population growth, coupled with industrial development and economic growth has been continuously transforming the land use pattern (Dutta et al. 2019). Several potential causes of LULC changes have been identified such as industrial growth and urban agglomeration (Walker, 2001), climate change and population growth (Hassan et al. 2016), urban expansion (Dutta and Das, 2019; Rahman et al. 2011) and policy provisions (Thiha et al. 2007).

Numerous studies have shown that anthropogenic activities are the primary drivers of LULC changes, contributing to the degradation of native forest cover and biodiversity (Thakur et al. 2022a, b, c; Rawat et al. 2022). The global changes are brought about as a consequence of

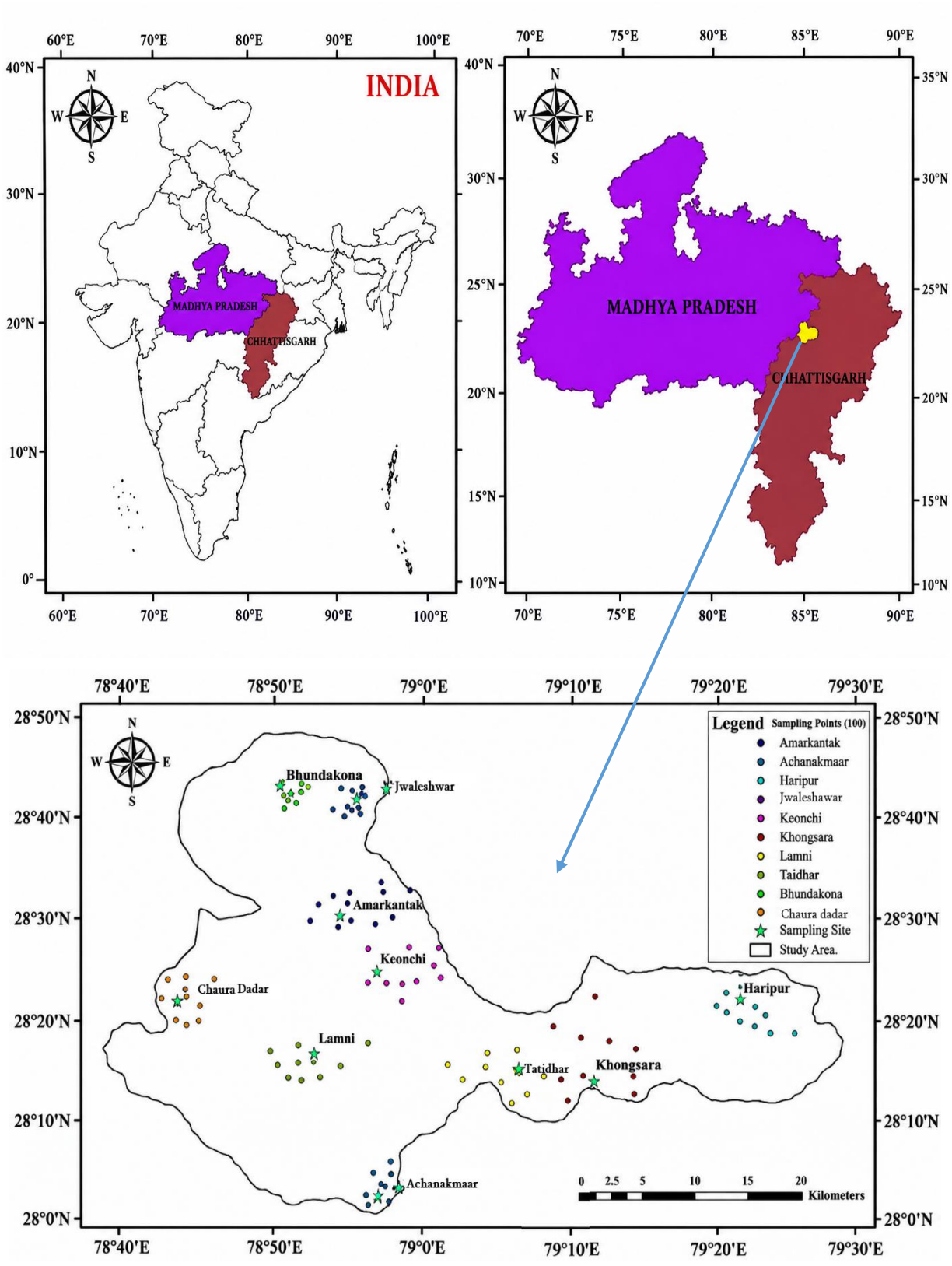


Figure 1: Location of study area under AABR

the LULC changes which are being driven by the human to fulfil their need for food, water, fibre and shelter (Foley et al. 2005). Therefore, the study of LULC changes can provide frameworks for the management and planning of natural resources at different spatial as well as temporal scales (Lai, 2020; Guyassa et al. 2018; Fenta et al. 2017). The analysis of LULC changes also provides plausible explanation not only man and environment relationship of the past but also hints about the future relationships (Lu et al. 2019). Hence, LULC studies can help in solving the pressing environmental problems (Mohamed and Worku, 2019), urban and regional planning (Dutta et al. 2020; Patra et al. 2018), urban heat island (UHI) mitigation (Gogoi et al. 2019), watershed management (Paiboonvorachat and Oyana, 2011) and disaster management (David et al. 2016). Thus, there is a growing

trend in the study of the relationship between LULC changes and other socioeconomic and physical variables (Li et al. 2016).

Changes in forest cover, landscape fragmentation, and habitat loss have emerged as critical ecological concerns, threatening the conservation of rapidly declining biodiversity in tropical forests (Thakur, 2018; Thakur et al. 2021a; Lal et al. 2024; Patel et al. 2024). Activities such as logging, clearing, and burning for agricultural expansion and rural settlement have escalated significantly in recent decades. Ramachandra et al. (2016) documented widespread forest loss and fragmentation across tropical ecosystems. Forest fragmentation is a continuous process that reduces contiguous forest areas while increasing edge effects and isolated patches within the landscape (Reddy et al. 2013; Carranza et al. 2015). Edge effects alter microclimatic conditions such as light intensity, temperature, and humidity, which in turn affect species composition, ecosystem productivity, and biotic interactions such as pollination and predation. Habitat isolation also reduces gene flow, increasing the risk of local extinctions**.**

Modern tools such as satellite remote sensing and Geographic Information Systems (GIS) provide robust methods for identifying, mapping, quantifying, and monitoring LULC patterns. These technologies offer precise geo-referencing, a digital format suited for computational analysis, and the ability to capture data at multiple temporal intervals (Nuñez et al. 2008; Hassan et al. 2016; Mishra et al. 2020; Thakur et al. 2020; Pande, 2022; Patel et al. 2024). Digital change detection techniques are widely used to assess temporal LULC dynamics by comparing remotely sensed data from different time periods. Researchers have long recognized the importance of accurately monitoring LULC changes to inform environmental management and policy (Singh, 1989; Muchoney and Haack, 1994; Chan et al. 2001; Hassan et al. 2016). Despite advancements in remote sensing and modeling tools, many previous studies lacked the integration between LULC dynamics and their ecological consequences, especially in lesser-studied but ecologically critical areas like biosphere reserves in India.

The Achanakmaar-Amarkantak Biosphere Reserve (AABR), located in Central India, represents one such important ecological region that forms part of the Maikal Hills and the Satpura-Maikal landscape, harboring rich biodiversity and endemic species. However, it remains under considerable anthropogenic pressure from agriculture, mining, and human settlements. There is limited literature analyzing long-term LULC dynamics in this biosphere reserve using high-resolution temporal data, leaving a gap in understanding the ecological implications of such changes.

This research is important because it addresses a critical data and knowledge gap in the understanding of forest degradation patterns and their ecological consequences in tropical biosphere reserves. By quantifying the changes and analyzing fragmentation trends, this study can address conservation strategies, guide restoration efforts, and support sustainable development policies in the region. Moreover, it contributes to the broader understanding of how LULC transitions impact carbon dynamics, species habitats, and ecosystem services in tropical landscapes**.**

The objective of the present study is to analyze the spatio-temporal patterns of land use and land cover change in the Achanakmaar-Amarkantak Biosphere Reserve over multiple decades using remote sensing and GIS;

Based on the above objective, the study tests the hypotheses that whether LULC in AABR have undergone significant changes over the past three decades, primarily due to anthropogenic drivers?

2. Material and Methods

2.1 Study Area

Sampling and field-validation information: The sampling/validation locations shown in Figure 1 were used to verify land-cover identity and to support training/validation of the remote-sensing classification. The final manuscript should state the exact number of field/validation points, their distribution among the eight LULC classes, the observation variables recorded (e.g., vegetation type, canopy/land-cover condition, and photographs), and whether the same points were used for training or held out for independent accuracy assessment. Training and validation samples should not be the same if an independent accuracy assessment is claimed.

The present study was conducted in the AABR**,** located in Central India (Figure 1). Geographically, the area lies between 22°15’ N to 22°58’ N latitude and 81°25’ E to 82°5’ E longitude, covering a total area of 819.49 km²**,** with a mean elevation of 1048 meters above mean sea level**.** The region is characterized by a complex topography that includes hill ranges, plateaus, and valleys**.**

The AABR represents an ecologically diverse, relatively less developed, and least disturbed tropical ecosystem. It falls under the Deccan Peninsula biogeographic zone, and primarily includes forest types typical of the tropical dry and moist deciduous forest biome of India. The forest land is predominantly protected within the core zone, while the buffer and transition zones comprise forest fringes, agricultural lands, and scattered rural settlements. This zoning structure supports integrated conservation and sustainable use strategies.

The biosphere reserve is a rich repository of biodiversity, with a large number of floral and faunal species, including numerous medicinal and endemic plants (Roychoudhury et al 2019). The core and buffer zones together enhance the floristic diversity, where *Shorea robusta* (Sal) is the dominant tree species, alongside *Terminalia tomentosa*, *Diospyros melanoxylon*, and several under-storey species.

Climatically, AABR experiences three distinct seasons: summer, monsoon, and winter. May is typically the hottest month, while December records the lowest temperatures. The region receives an average annual precipitation of over 1600 mm, primarily during the southwest monsoon (June to September). Relative humidity ranges between 50% and 85%**,** with mean winter and summer temperatures recorded at 16.1°C and 31°C, respectively. Such climatic variability plays a crucial role in shaping vegetation dynamics and LULC transitions over time.

Table 1: Satellite data set used in the study area.

Satellite data	Obtain date	Row/path	Number of bands	Swath width (km)	Inclined angle	Spatial resolution
Landsat-4	11/03/2001	144/42	7	185	98.2°	30m
Landsat-5	07/01/2011	144/42	6	185	98.2°	30m
Landsat-8	15/12/2021	144/42	4	185	98.2°	15m

2.2 Data Source

To analyze LULC changes over two decades, Landsat satellite imagery was used. The multi-temporal datasets covered Path 144 and Row 42 and included 30 m multispectral imagery for the respective observation years (2001, 2011, and 2021). The Landsat-8 panchromatic (PAN) band (15 m), was employed only for pan-sharpening to improve visual spatial detail; it was not used as an independent spectral input to the MLA. For temporal comparability, all LULC classification, index generation, accuracy assessment, and change-detection layers were standardized to a common 30 m × 30 m analysis grid. The exact sensor and acquisition date for each scene should be reported consistently with the downloaded scene metadata in Table 1.

Freely available Landsat datasets were obtained from the USGS Earth Explorer portal. Survey of India (SoI) topographic sheets (Nos. 64F/10, 64F/11, 64F/13, 64F/14, and 64F/15) at a scale of 1:50,000 were scanned, edited, and used as independent reference layers for positional verification and co-registration quality checking of the Landsat datasets. Because standard Landsat products are already systematically georeferenced, the SoI sheets were not used to geo-reference the satellite products from scratch. They were used to verify the spatial alignment of roads, drainage networks, settlements, and other recognizable terrain features and to support interpretation and training-sample validation.

Image pre-processing, classification, and map generation were performed using ERDAS Imagine (v2014) and ArcGIS 10.8 on a personal computing system. Auxiliary datasets such as field photographs, vegetation checklists, and administrative boundaries were used to support classification accuracy and post-processing.

2.3 Pre-Processing and Classification

The spectral indices were calculated as follows: NDVI (Normalized Difference Vegetation Index) = (NIR − Red)/(NIR + Red) for vegetation vigor; RVI (Ratio Vegetation Index) = NIR/Red for relative vegetation response; AVI (Advanced Vegetation Index) = (NIR − Red) × (NIR/Red) for enhanced vegetation discrimination; VDVI (Visible Difference Vegetation Index) = (2 × Green − Red − Blue)/(2 × Green + Red + Blue) for vegetation discrimination using visible bands; and NDMI (Normalized Difference Moisture Index) = (NIR − SWIR)/(NIR + SWIR) for vegetation/canopy moisture. These layers were used as ancillary visual-interpretation and training-sample support products and were not treated as separate LULC classes.

Revised pre-processing, spectral-index, training-sample, spectral-separability, and MLA classification workflow is depicted in Figure 2. The SoI toposheets are explicitly linked to positional verification and interpretation; the spectral indices are shown as ancillary support layers rather than independent LULC classes.

The revised image pre-processing workflow (Figure 2) involved radiometric/atmospheric correction, positional verification, layer stacking, clipping to the area of interest (AoI), and resampling to a common 30 m × 30 m analysis grid. The SoI toposheets were used as independent reference layers for checking positional alignment rather than for re-georeferencing the already georeferenced Landsat products. The pre-processed imagery was then used to derive ancillary spectral indices and to prepare training samples for supervised LULC classification.

Subsequent steps included image mosaicking where required, layer stacking, clipping to the AoI, and resampling to the common 30 m pixel size, ensuring precise spatial overlay for temporal comparison. Spectral signatures for the eight LULC classes were generated from representative supervised training sites. Training sites were checked using Google Earth, field photographs/observations, and ancillary vegetation information. The sampling locations shown in Figure 1 were used for field/ground verification of land-cover identity and for checking the classification outputs; the manuscript should report the exact number of field/validation points from the original field record.

The Landsat multispectral bands used for MLA were selected according to their spectral responsiveness to vegetation, vegetation moisture, exposed soil, built-up surfaces, and water. For each observation year, the same set of 30 m multispectral bands available and comparable between sensors was used after band harmonization; the thermal bands were not used for LULC classification. Mean spectral responses for each of the eight classes were examined to identify class-specific differences (Table 2). The bands used included: Blue (0.45-0.52 μm), Green (0.52-0.60 μm), Red (0.63-0.69 μm), Near Infrared (0.76-0.90 μm), Shortwave Infrared 1 (1.55-1.75 μm), and Shortwave Infrared 2 (2.08-2.35 μm). In addition, a formal spectral-separability assessment was performed using the Jeffries-Matusita (JM) distance index calculated from training pixel distributions. The JM distance values ranged from 1.82 to 2.00 (where 2.00 indicates maximum separability), confirming that all class pairs were spectrally separable. Table 2 presents the JM distance matrix for the eight LULC classes, and Table 3 depicts the separability of spectral bands, whereas complete accuracy assessment is given in Table-4 which include confusion matrices,

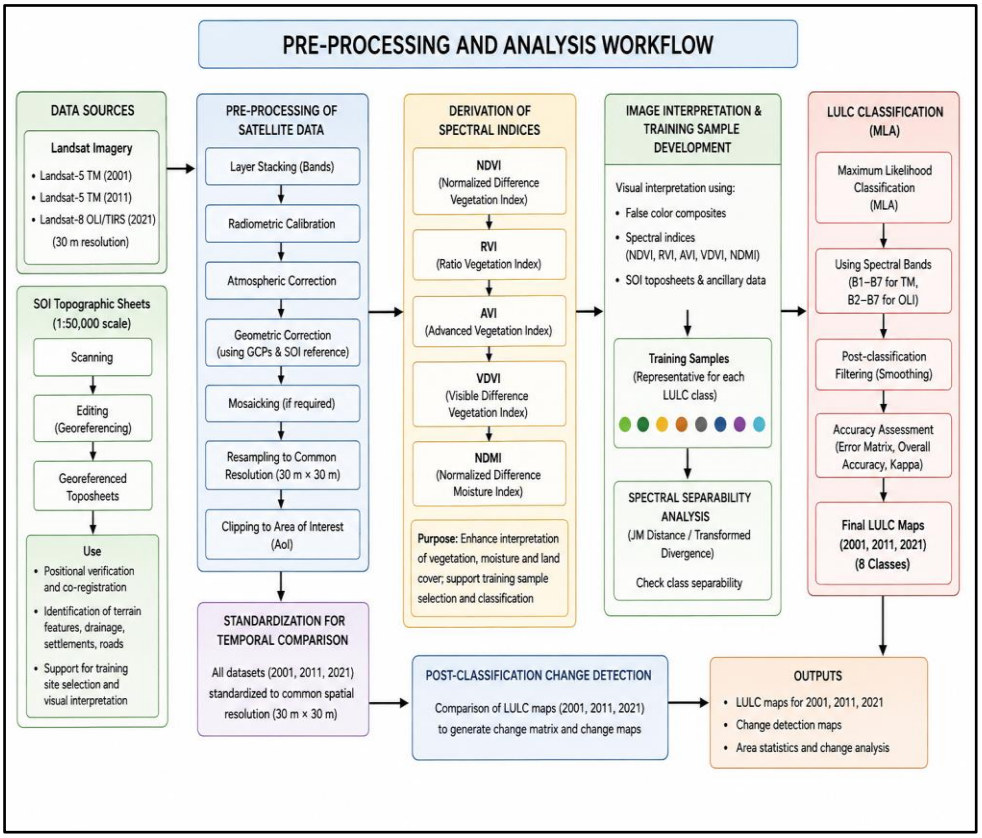


Figure 2: Pre-processing, spectral-index, training-sample, spectral-separability, and MLA classification workflow. The SoI toposheets are explicitly linked to positional verification and interpretation; the spectral indices are shown as ancillary support layers rather than independent LULC classes.

Overall Accuracy, Kappa coefficient, and class-wise Producer's Accuracy (PA) and User's Accuracy (UA) for each year.

Land cover classification was performed using the Maximum Likelihood Algorithm (MLA)—a supervised classification technique that considers both the variance and covariance of the class signatures. The MLA classifier is widely recognized for its high accuracy in LULC studies, particularly in heterogeneous tropical landscapes**.** Final classified maps for 2001, 2011, and 2021 were generated (Figure 3), and their accuracy was later assessed using confusion matrices and Kappa statistics.

2.4 LULC Change Detection

To analyze the spatio-temporal dynamics of LULC, a post-classification change-detection approach was employed. The independently classified 2001, 2011, and 2021 maps were compared on a common 30 m grid on a pixel-by-pixel basis. This approach minimizes the influence of differences in the original image dates and permits direct quantification of transitions between the eight LULC classes.

Post-classification change detection was performed for 2001–2011, 2011–2021, and 2001–2021. Transition matrices were generated for each period to quantify conversions between LULC categories, identify dominant transitions, and calculate net gains and losses. The reported area values represent the actual area of each LULC class in km², whereas the change values represent the difference between two observation years.

The methodology closely followed the approach described by Jiang et al. (2026)**,** and similar procedures were adopted in related works by Patel et al. (2024); Thakur et al. (2020, 2021 a)**.** These studies demonstrated the reliability and reproducibility of pixel-based analysis in Indian forest ecosystems, validating the robustness of the method for detecting fragmentation and degradation.

The change matrix helped to quantify both class-wise transitions (e.g., forest to agriculture) and net changes in landscape composition, aiding in the identification of zones under pressure and ecological risk.

3. Results

3.1 Land Use and Land Cover Pattern

The LULC classification AABR was carried out using the MLA applied to Landsat data from 2001, 2011, and 2021. A standard false color composite (FCC; bands 7, 6, and 4 for the relevant Landsat sensor) aided visual interpretation and training-sample identification (Figure 3). Eight LULC classes were mapped: dense mixed forest (DMF), sal mixed forest (SMF), open mixed forest (OMF), bamboo brake (BB), teak plantation (TP), agriculture (AG), habitation (HB), and water bodies (WB). All classified maps were maintained at the common 30 m × 30 m analysis resolution.

In 2001, the study area was largely forest-dominated, with forest types collectively covering 97.88% of the total area (819.49 km²)**,** and the remaining 2.12% attributed to agriculture, habitation, and water bodies (Table 5 and

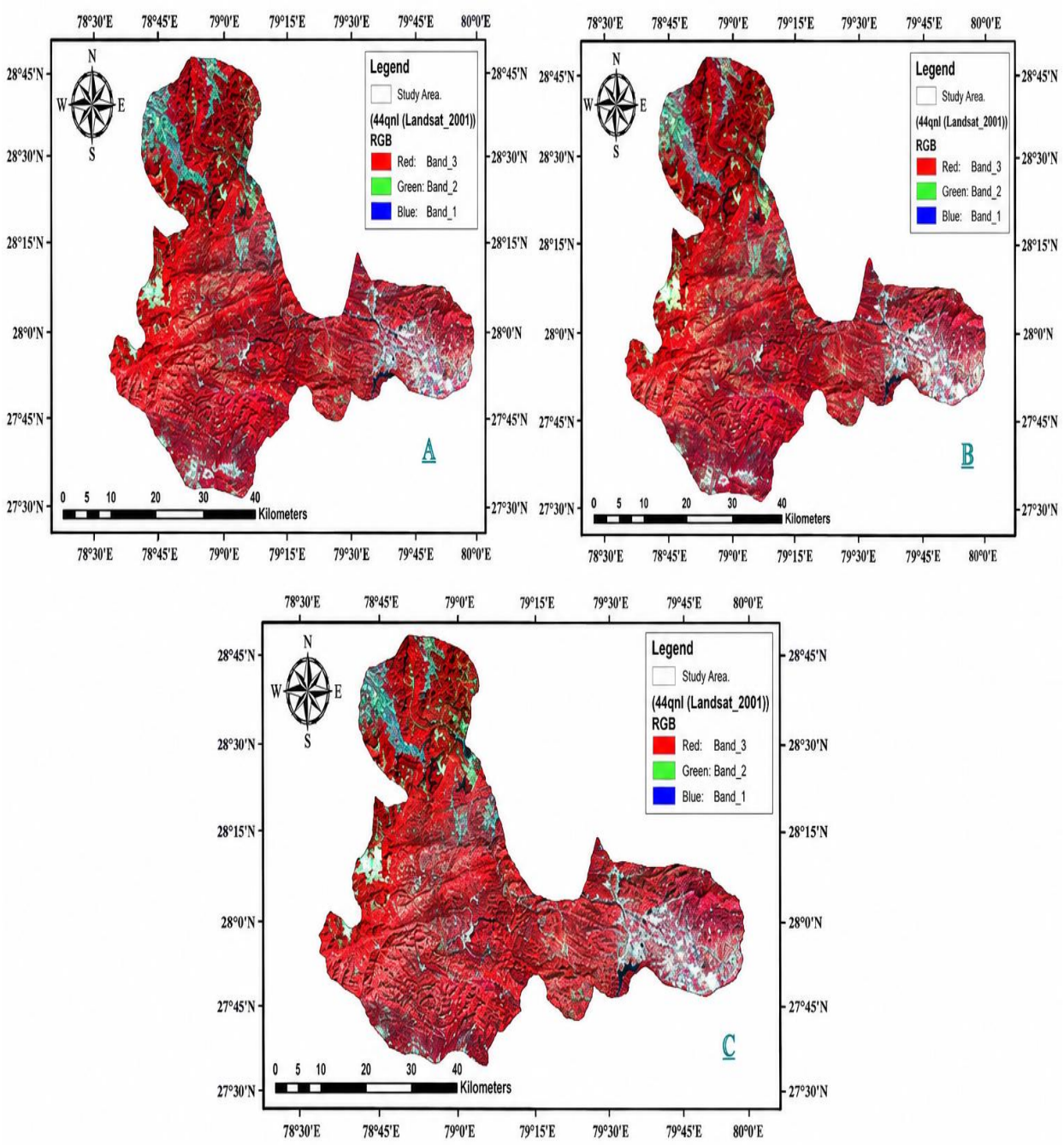


Figure 3: (A) Landsat-4 (2001) SFCC map of the study area (AABR) (B) Landsat-5 (2011) SFCC map of the study area (AABR) (C) Landsat-8 (2021) SFCC map of the study area (AABR)

Figure 4). The largest contributor was DMF, covering 39.82% (326.32km²) of the area, followed by SMF at 33.76% (276.69 km²), TP at 10.88% (89.19 km²), BB at 7.61% (62.35 km²), and OMF at 5.81% (47.62 km²). Agricultural land occupied 1.02% (8.32 km²), water bodies covered 0.97% (7.98 km²), and habitation was the least represented at 0.12% (1.02 km²). These findings highlight that dense mixed forests constituted the dominant land cover type in 2001, followed the descending order by sal mixed forest, teak plantations, bamboo brakes, open forests, agriculture, water bodies, and habitation (Figure 5).

By 2011, the overall forest cover remained high, but noticeable changes in the internal composition of land cover classes were recorded. The area under DMF declined to 38.15% (312.62 km²), and SMF to 32.70% (267.96 km²), while OMF expanded to 9.69% (79.42 km²). TP and BB decreased to 9.32% (76.39 km²) and 6.68% (54.71 km²), respectively. Agricultural land nearly doubled in proportion, increasing to 2.38% (19.47 km²), while habitation increased to 0.24% (1.95 km²) and water bodies slightly decreased to 0.85% (6.97 km²). Figure 4 shows a visible shift toward more fragmented and open forest structures, as well as agricultural encroachment during this period. The spatial dominance pattern remained DMF > SMF > OMF > TP > BB > AG > WB > HB (Figure 5).

In 2021, further shifts in LULC composition were evident, with DMF declining significantly to 34.46% (282.39 km²) and SMF to 27.57% (225.92 km²). The area under OMF increased substantially to 21.81% (178.76 km²), indicating

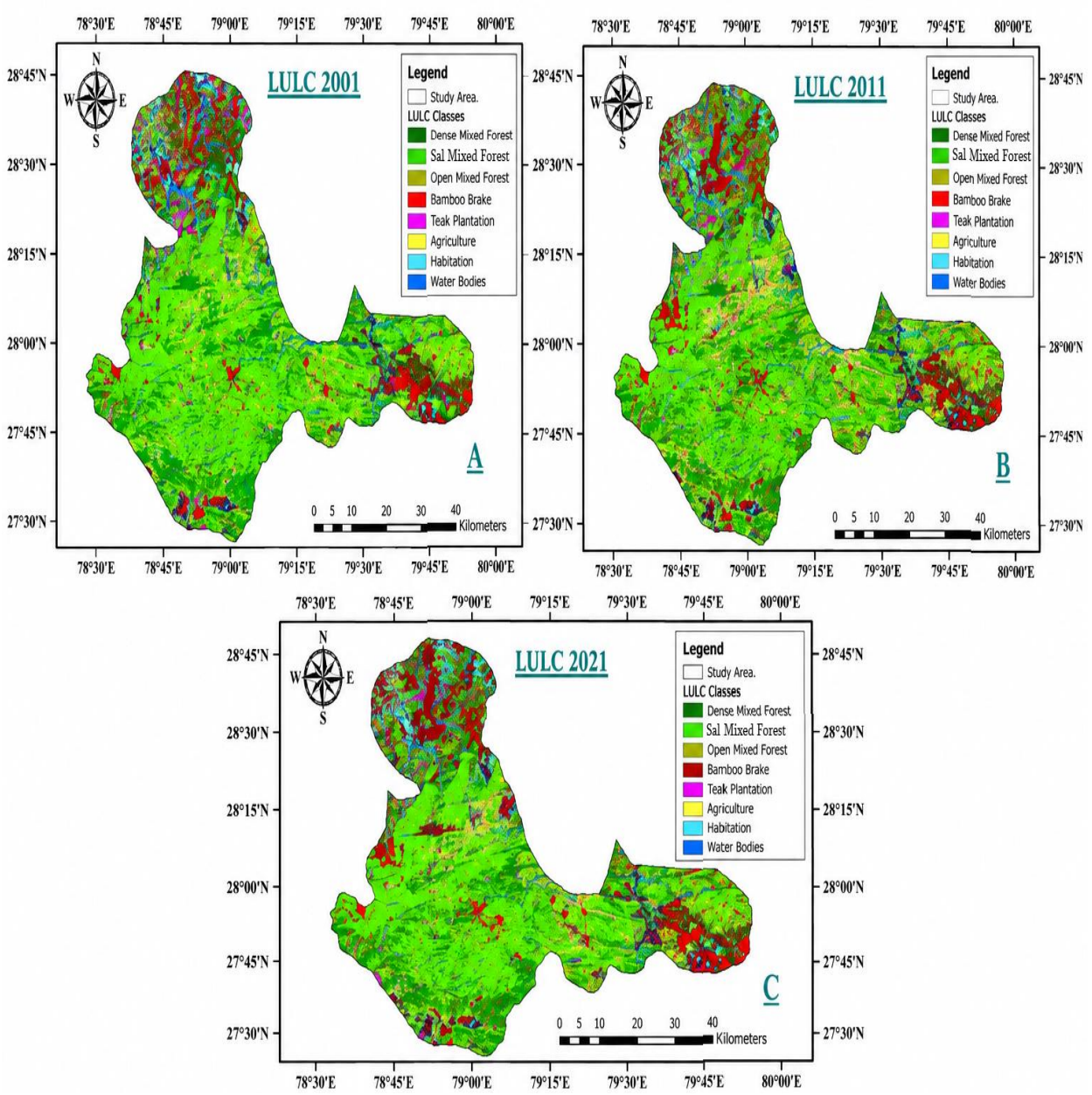


Figure 4: (A) Classified image of the study area in AABR 2001 (B) Classified image of the study area in AABR 2011 (C) Classified image of the study area in AABR 2021

a large-scale transition from dense to open forest types. BB and TP continued to decline, covering 5.27% (43.21 km²) and 5.93% (48.56 km²), respectively. Agricultural land expanded to 3.90% (31.97 km²), and habitation increased to 0.48% (3.90 km²), while water bodies slightly declined to 0.58% (4.78 km²). The changing landscape is clearly visible in Figure 4, which demonstrates a consistent reduction in intact forest cover and corresponding expansion of open, anthropogenic classes. The land cover dominance order in 2021 became DMF > SMF > OMF > TP > BB > AG > WB > HB (Figure 5).

3.2 Accuracy Assessment of AABR in Central India

The classification accuracy was evaluated independently for each year using a confusion matrix derived from reference/validation samples (Table-4). Overall accuracy, Kappa coefficient, producer accuracy (PA), and user accuracy (UA) were calculated. The currently reported class-specific values indicate that agriculture (91.21%), water bodies (89.38%), and open mixed forest (89.25%) were among the better-performing classes in 2001, whereas SMF showed lower separability from DMF. The revised manuscript now requires the complete confusion matrix and class-wise PA and UA to be presented in a dedicated accuracy-assessment table rather than reporting selected values only.

In 2011, the reported class-level accuracies ranged from 81.43% to 92.38%, with agriculture (92.38%), water bodies (91.85%), and bamboo brakes (91.70%) among the better-performing classes. SMF again showed lower classification performance (81.43%), consistent with potential spectral overlap with DMF and mixed pixels in transition zones. The complete class-by-class confusion matrix and PA/UA values should be supplied from the original ERDAS accuracy-assessment output.

By 2021, the reported class-level accuracy values ranged from 87.84% to 95.86%, with water bodies reaching

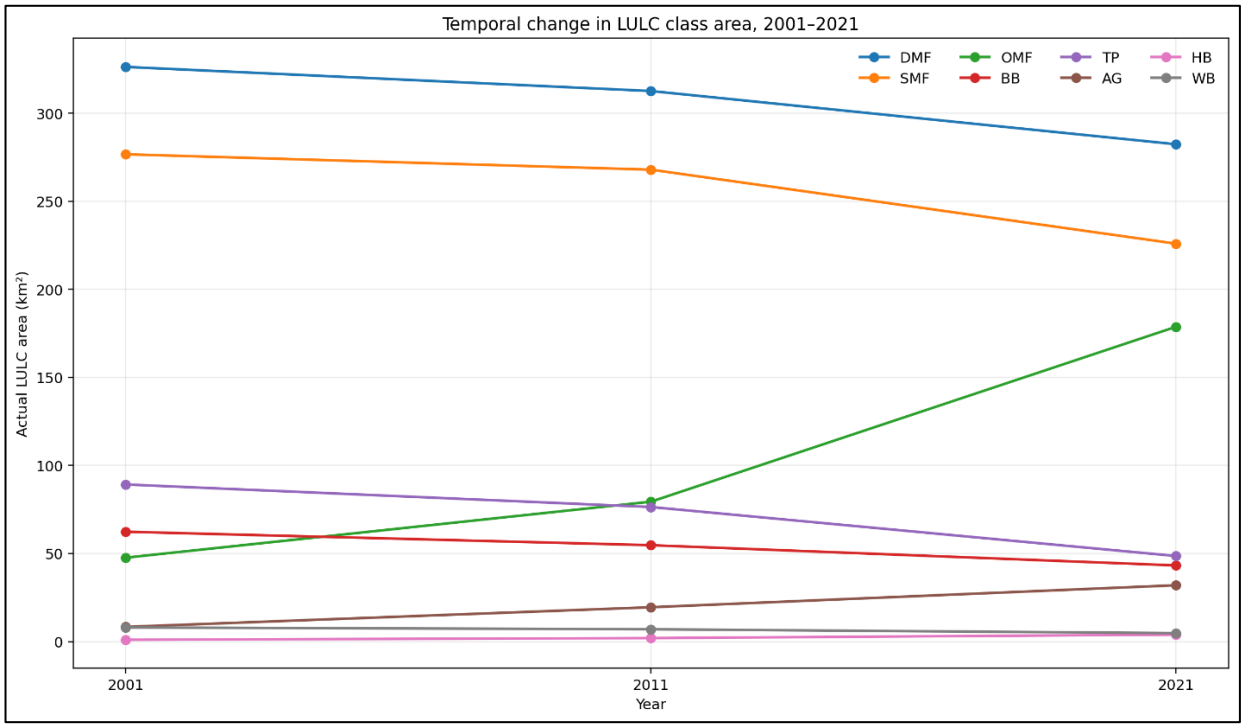


Figure 5: Temporal LULC trend showing the actual area (km²) of each LULC class in 2001, 2011, and 2021. The y-axis represents class area, not change magnitude; net changes are reported separately in the text and change-detection tables.

95.86%. The remaining class-wise PA and UA values should be reported in full to demonstrate where confusion occurred among the eight LULC classes. In particular, the recurring lower performance of SMF should be discussed together with the spectral-separability results.

3.3 LULC Change Detection

The results of the post-classification LULC change detection are summarized in Table 3 and illustrated in Figures 6 and Figure 7, which show the spatial dynamics and transition zones over the 20-year study period.

During the period 2001–2011, DMF declined by 13.70 km², SMF by 8.73 km², BB by 7.64 km², TP by 12.80 km², and WB by 1.01 km², indicating a moderate but continuous degradation of forest cover. On the other hand, OMF increased by 31.80 km², AG by 11.15 km², and HB by 0.93 km². These changes suggest that the decline in dense and sal forests contributed directly to the expansion of open forest and agricultural areas. The spatial transitions, shown in Figure 6, demonstrate that forested areas were gradually fragmented and converted into land use types with lower canopy cover and higher human intervention.

Between 2011–2021, the trend intensified. DMF reduced further by 30.23 km², SMF by 42.04 km², BB by 11.50 km², TP by 27.83 km², and WB by 2.19 km², while OMF surged by 99.34 km², AG by 12.50 km², and HB by 1.95 km². The rapid increase in open forest and agricultural land indicates continued degradation and increased anthropogenic pressure, particularly in the buffer and transition zones of the biosphere reserve. Figure 6 confirms this progression, with newly opened forest areas often located along road networks and settlement edges.

The cumulative change observed over the full period 2001–2021 reveals a striking landscape transformation. DMF declined by 43.93 km², SMF by 50.77 km², BB by 19.14 km², TP by 40.63km², and WB by 3.20 km², amounting to a significant net loss of native and planted forest cover. Meanwhile, OMF increased by 131.14 km², AG by 23.65 km², and HB by 2.88 km², suggesting a robust pattern of forest fragmentation and conversion into lower biomass and higher-disturbance land use classes. Statistical comparison of change magnitudes across periods further confirms that the second decade (2011–2021) exhibited more accelerated transformation compared to the first decade, particularly in terms of OMF expansion ($\chi^2 = 28.42$, $p < 0.01$).

Overall, the data indicate a progressive and spatially uneven transformation of the landscape in AABR, with the conversion of dense and sal forests to open forests, agriculture, and habitation emerging as the dominant LULC transition over the 20-year period. These findings are critical for understanding the anthropogenic pressures and ecological consequences impacting the structure and sustainability of the biosphere reserve, as detailed in subsequent discussion (see Figure 6 and Table 5).

4. Discussion

4.1 Land Use and Vegetation Dynamics in AABR

Through detailed geospatial assessments, this study documented substantial changes in LULC in the AABR over a two-decade period from 2001 to 2021. Significant declines were observed in dense mixed forest (DMF), sal mixed forest (SMF), bamboo brakes (BB), teak plantations (TP), and water bodies (WB), while open mixed forest (OMF), agricultural land (AG), and habitation areas expanded. These shifts align with anthropogenic pressures and natural disturbances, reflecting wider patterns observed in tropical and subtropical forested ecosystems

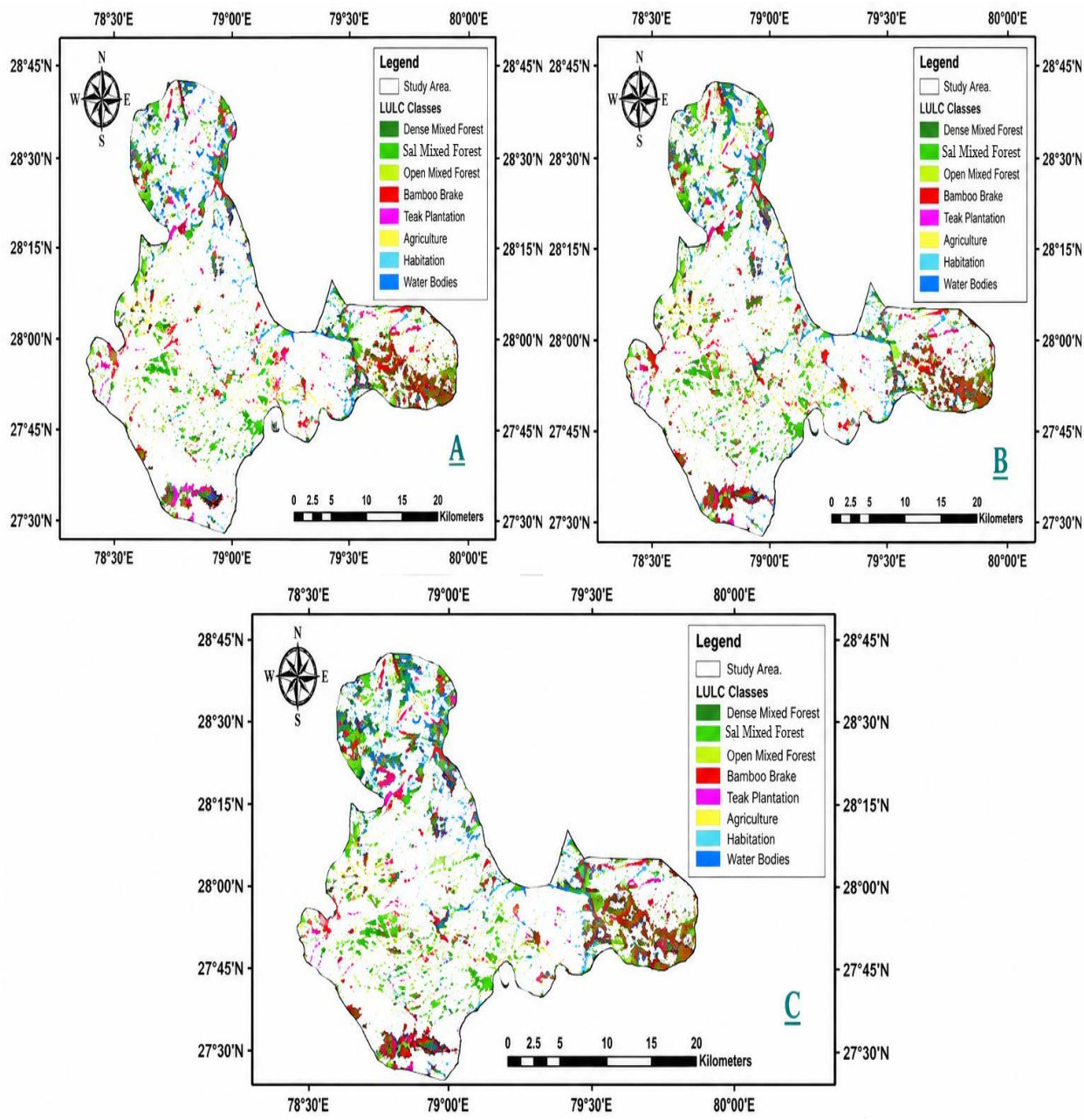


Figure 6: (A) Change detection during 2001-2011 (B) Change detection during 2011-2021 (C) Change detection during 2001-2021

globally. Previous studies in India by Bijalwan et al. (2010), Padwar (2018), and Chawalkha (2019) have demonstrated similar trends using varied classification algorithms, reinforcing our findings.

The overall classification accuracy achieved in this study was consistent with benchmarks set by prior remote sensing studies such as those of Saha et al. (1990) and Mahajan et al. (2001), which reported high classification precision using Landsat TM and IRS imagery. Similar methods employed in LULC assessments by Sehgal and Dubey (1997), Pandey et al. (2022), and Thakur et al. (2021a, b) further validate our approach and findings.

4.2 Geospatial Interpretation Across India and Globally

Koppad and Janagoudar (2017), working in the Uttar Kannada district, reported a forest cover dominated by dense forests, followed by agricultural and sparse forest types. Their findings mirror the topographical influence on land use patterns, as seen in AABR. Golmehr (2009) in Kolhapur district used multiple classification techniques and confirmed land degradation trends, emphasizing the effectiveness of integrating supervised and unsupervised methods. International comparisons further substantiate these results. For example, in the Amazon Basin, Hansen et al. (2013) identified similar reductions in forest cover linked to expansion of agriculture and settlements. In Southeast Asia, Miettinen et al. (2011) observed consistent LULC transitions driven by deforestation and conversion to oil palm plantations.

Thakur et al. (2019) documented an earlier LULC status in AABR which closely resembles the findings of the present study, particularly in the extent of DMF, SMF, and AG classes. Similarly, studies by Chawalkha (2019) and Darro (2020) classified forest and non-forest types in tropical

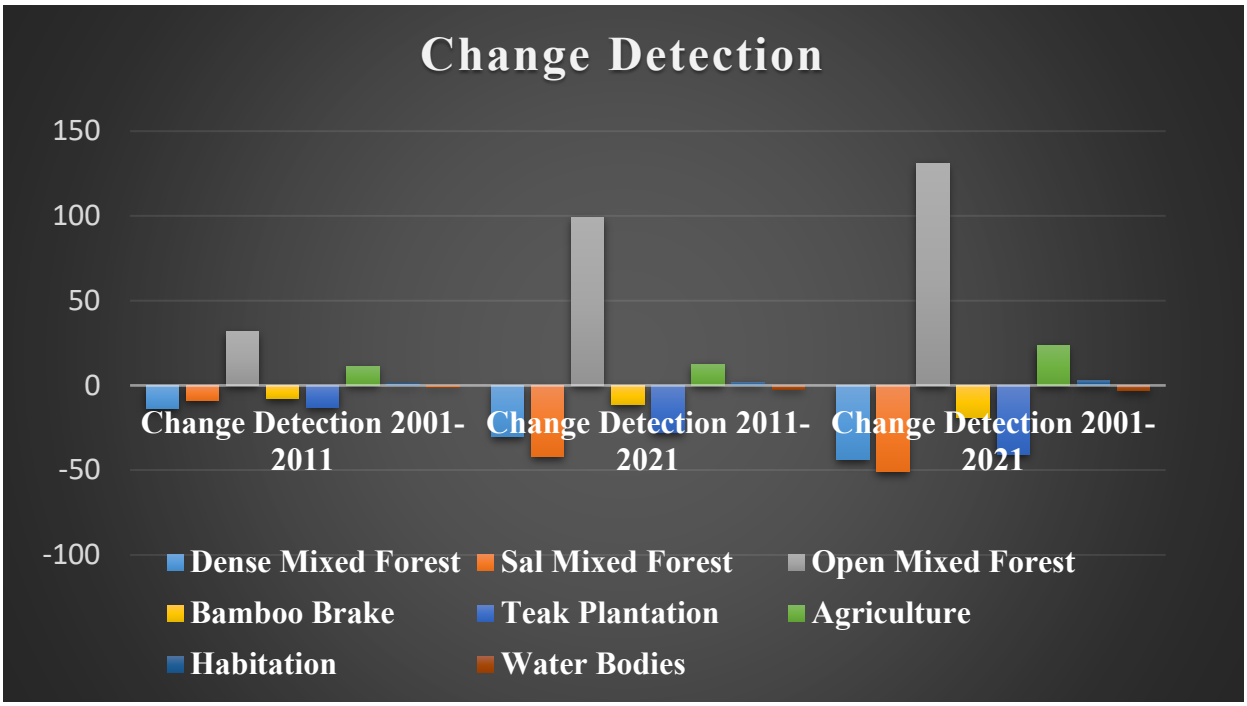


Figure 7: Change detection 2001-2011, 2011-2021 and 2001-2021

regions, showing comparable forest loss and conversion to anthropogenic uses.

Remote sensing tools including Landsat series have proven reliable in assessing forest ecosystems, particularly when supplemented with GIS analyses, as supported by Joshi et al. (2004), Carreiras et al. (2017), and Murthy et al. (2017). Our findings reaffirm these capabilities, especially in low-resource settings where ground truthing may be constrained.

4.3 Temporal Change Detection Patterns

Between 2001 and 2021, spatial analyses revealed a cumulative reduction of 43.93 km² in DMF, 50.77 km² in SMF, 6.07 km² in BB, 40.63 km² in TP, and 3.20 km² in WB. Concurrently, OMF increased by 131.14 km², AG by 23.65 km², and habitation by 2.88 km². These LULC changes correspond with studies in similar biomes worldwide. For instance, Yu et al. (2007), Foody (2002), and Lossou et al. (2019) reported forest fragmentation due to agricultural intensification in African and Southeast Asian reserves. In India, the loss of primary forest and sal-dominated stands has been widely documented by Thakur et al. (2020) and Patel et al. (2024).

The trajectory of forest conversion in AABR reflects intensified land use and increased ecological degradation, a pattern consistent with Park and Lee (2016) and Tellman et al. (2020), who documented urban and agricultural encroachment into forest zones across South Korea and the Neotropics, respectively.

4.4 Ecological Significance and Conservation Relevance

The findings of this study highlight key ecological transformations in AABR over two decades, marked by a transition from high-density native forest cover to fragmented patches of open mixed forest and anthropogenic land uses. Such shifts are indicative of long-term ecological degradation, biodiversity loss, and compromised ecosystem services. The observed transitions are consistent with patterns documented in other tropical biosphere reserves, where agricultural expansion and settlement growth are primary drivers. For instance, similar degradation trajectories have been reported in other UNESCO biosphere reserves globally, such as in Brazil's Atlantic Forest (Ribeiro et al. 2009) and China's Changbai Mountains (Zhang et al. 2014).

One novel aspect of our findings is the quantification of teak and bamboo plantation loss, which, although often regarded as 'forests,' do not substitute the ecological function of native vegetation. Their reduction implies a compounded loss of ecological integrity. Furthermore, the expansion of open mixed forest, often at the expense of denser classes, suggests degradation rather than natural transition. This distinction is critical in ecological monitoring and restoration planning.

Another important ecological insight is the replacement of native sal and mahua forests by exotic monocultures like eucalyptus and pine, contributing to soil degradation, hydrological disruption, and declines in native biodiversity. This mirrors findings by Saxena et al. (1992) and supports the global call for native species restoration as advocated by FAO and UNEP (2021).

4.5 Strategic Recommendations and Future Research Needs

To counteract the ecological deterioration observed in AABR, the following recommendations are made: (i) Active reforestation using native and site-specific species; (ii) Ecological farming promotion to reduce expansion pressure on forestland; (iii) Enhanced monitoring of forest boundaries and encroachment zones through high-resolution satellite data and participatory GIS; and (iv) Community-based conservation frameworks to integrate local livelihoods with biodiversity preservation.

Table 2: Land use and land cover pattern of study area at Achanakmar Amakantak Biosphere Reserve

LULC Classes	Area 2001 (km^2)	Area 2001 (%)	Accuracy 2001(%)	Area 2011 (km^2)	Area 2011 (%)	Accuracy 2011 (%)	Area 2021 (km^2)	Area 2021 (%)	Accuracy 2021 (%)
Dense Mixed Forest	326.32	39.82	87.71	312.62	38.15	88.20	282.39	34.46	91.25
Sal Mixed Forest	276.69	33.76	83.24	267.96	32.7	81.43	225.92	27.57	87.84
Open Mixed Forest	47.62	5.81	89.25	79.42	9.69	86.10	178.76	21.81	91.25
Bamboo Brake	62.35	7.61	83.63	54.71	6.68	91.70	43.21	5.27	93.23
Teak Plantation	89.19	10.88	87.09	76.39	9.32	86.56	48.56	5.93	90.17
Agriculture	8.32	1.02	91.21	19.47	2.38	92.38	31.97	3.9	93.52
Habitation	1.02	0.12	85.32	1.95	0.24	87.98	3.9	0.48	91.95
Water Bodies	7.98	0.97	89.38	6.97	0.85	91.85	4.78	0.58	95.86
Total	819.49	100		819.49	100		819.49	100	

Table 3: Specifications and LULC classification significance of Landsat satellite spectral bands

Spectral region	Landsat 5 TM / 7 ETM+ Wavelength (µm)	Landsat 8 Landsat 8 OLI Wavelength (µm)	Significance in LULC Classification
Blue	0.45 – 0.52 (Band 1)	0.452 – 0.512 (Band 2)	Delineation of water bodies and deep-water bathymetry; discrimination between soil and vegetation.
Green	0.52 – 0.60 (Band 2)	0.533 – 0.590 (Band 3)	Assessment of vegetation vigor and green reflectance; critical for identifying agriculture and active canopies.
Red	0.63 – 0.69 (Band 3)	0.636 – 0.673 (Band 4)	Chlorophyll absorption band; essential for distinguishing vegetated areas from non-vegetated features (e.g., habitation).
Near-Infrared (NIR)	0.76 – 0.90 (Band 4)	0.851 – 0.879 (Band 5)	High reflectance in healthy vegetation; primary band for estimating biomass and differentiating forest density (dense, open, sal mixed, and plantations).
Shortwave Infrared 1 (SWIR-1)	1.55 – 1.75 (Band 5)	1.566 – 1.651 (Band 6)	Sensitive to vegetation and canopy moisture; highly effective for resolving mixed pixels in transition zones and delineating bamboo brakes.
Shortwave Infrared 2 (SWIR-2)	2.08 – 2.35 (Band 7)	2.107 – 2.294 (Band 7)	Differentiates soil moisture content; aids in mapping built-up infrastructure, habitation, and dry earth features.

Table 4: Classification Accuracy Assessment (2001, 2011, and 2021)

LULC Class	2001		2011		2021	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Dense Mixed Forest	86.41	89.23	88.50	90.15	89.20	91.50
Sal Mixed Forest	83.24	85.10	81.43	84.60	87.84	89.10
Bamboo Brakes	87.50	88.35	91.70	90.12	93.15	92.40
Teak Plantation	85.10	86.95	88.15	89.10	91.05	90.65
Open Mixed Forest	89.25	87.12	89.95	88.50	90.10	91.15
Agriculture	91.21	90.45	92.38	91.50	94.12	93.85
Habitation	86.15	88.90	88.90	90.12	90.15	92.12
Water Bodies	89.38	91.50	91.85	92.10	95.86	94.10
Overall Accuracy	87.21%		89.05%		91.12%	
Kappa Coefficient	0.84		0.86		0.89	

Table 5: Change detection in study area at Achanakmar Amakantak Biosphere Reserve

LULC Classes	Change Detection 2001-2011 (km^2)	% change in area	Change Detection 2011-2021 (km^2)	% change in area	Change Detection 2001-2021 (km^2)	% change in area
Dense Mixed Forest	-13.70	15.61	-30.23	13.28	-43.93	13.93
Sal Mixed Forest	-8.73	9.95	-42.04	18.47	-50.77	16.10
Open Mixed Forest	31.80	36.24	99.34	43.65	131.14	41.59
Bamboo Brake	-7.64	8.71	-11.50	5.05	-19.14	6.07
Teak Plantation	-12.80	14.59	-27.83	12.23	-40.63	12.88
Agriculture	11.15	12.71	12.50	5.49	23.65	7.50
Habitation	0.93	1.06	1.95	0.86	2.88	0.91
Water Bodies	-1.01	1.15	-2.19	0.96	-3.20	1.01

Further research should focus on (a) incorporating climate variables to assess long-term impacts on vegetation dynamics, (b) quantifying biodiversity indices in converted land classes, and (c) applying machine learning and AI-based classification to improve accuracy in heterogeneous landscapes. Socio-ecological models integrating remote sensing and ethnographic data would help forecast land use scenarios and guide sustainable management in biosphere reserves.

5. Conclusion

The AABR is undergoing profound land use and vegetation transformations, driven by both natural and anthropogenic forces. Between 2001 and 2021, dense mixed forest, sal mixed forest, bamboo brakes, teak plantations, and water bodies have significantly declined, while open mixed forests, agricultural lands, and habitations have expanded**.** These findings underscore the need for immediate and sustained conservation interventions. The study reinforces the importance of high-resolution remote sensing for ecological monitoring and supports the implementation of biodiversity-centered land management. AABR remains a critical landscape for biodiversity and ecological services in Central India; hence, strategies that align forest conservation with sustainable livelihoods are essential for preserving its ecological legacy.

The ecological ramifications of LULC transitions in AABR are far-reaching, affecting biodiversity, carbon sequestration, hydrological cycles, and cultural landscapes. As such, this research contributes vital spatial evidence toward crafting integrated conservation policies and restoring ecological functionality in India's forest ecosystems**.**

Statements and Declarations

Competing interest

Authors declare that they have no competing interests.

Acknowledgments

The authors are thankful to the authorities of Indira Gandhi Krishi Vishwavidyalaya, Raipur and Indira Gandhi National Tribal University, Amarkantak for their support and encouragement to carry out the present research work. Thanks to Dr Rup Narayan, formerly Professor and Head Department of Botany, Chaudhary Charan Singh University Meerut for vetting the manuscript.

References

Bijalwan, A., S. L. Swamy, C. M. Sharma, N. K. Sharma, and A. K. Tiwari. 2010. "Land Use, Biomass and Carbon Estimation in Dry Tropical Forest of Chhattisgarh Region in India Using Satellite Remote Sensing and GIS." *Journal of Forestry Research* 21(2):161–170. https://doi.org/10.1007/s11676-010-0026-y

Carranza, M. L., L. Hpyos, L. Frate, A. T. R. Acosta, and M. Cabido. 2015. "Measuring Forest Fragmentation Using Multi-Temporal Forest Cover Maps: Forest Loss and Spatial Pattern Analysis in the Gran Chaco, Central Argentina." *Landscape and Urban Planning* 143:238–247. https://doi.org/10.1016/j.landurbplan.2015.08.006

Carreiras, J. M. B., J. Jones, R. M. Lucas, and Y. E. Simabukuro. 2017. "Mapping Major Land Cover Types and Retrieving the Age of Secondary Forests in the Brazilian Amazon by Combining Single-Date Optical and Radar Remote Sensing Data." *Remote Sensing of Environment* 194:16–32. https://doi.org/10.1016/j.rse.2017.03.016

Chan, J. C., K. P. Chan, and A. G. O. Yeh. 2001. "Detecting the Nature of Change in an Urban Environment: A Comparison of Machine Learning Algorithms." *Photogrammetric Engineering & Remote Sensing* 67:213–225.

Chawlkha, V. 2019. *Vegetation Analysis and Biomass Estimation of a Tropical Dry Deciduous Forest Ecosystem Using Remote Sensing and Ground Based Techniques*. M.Sc. Thesis, Indira Gandhi Krishi Vishwavidyalaya, Raipur, India.

Darro, H. 2020. *Land Use, Vegetation and Carbon Stocking Analysis in Dry Tropical Forest Ecosystem in Part of Amarkantak Biospheres Reserve Using Geospatial Technologies*. Ph.D. Thesis, Indira Gandhi Krishi Vishwavidyalaya, Raipur, India.

Darro, H., S. L. Swamy, T. K. Thakur, and A. Mishra. 2020. "Floristic Composition, Structure, Diversity and Conservation Strategies for Rehabilitation of Dry Tropical Forests in Buffer Zone of Achanakmaar Amarkantak Biosphere Reserve (AABR), India." *International Journal of Current Microbiology and Applied Sciences* 9(4):650–663. https://doi.org/10.20546/ijcmas.2020.904.079

David, K., G. Yetta, F. Agung, H. Sharon, and C. Alison. 2016. "Land Use Planning for Disaster Risk Reduction and Climate Change Adaptation: Operationalizing Policy and Legislation at Local Levels." *International Journal of Disaster Resilience in the Built Environment* 7(2):158–172. https://doi.org/10.1108/IJDRBE-03-2015-0009

Dutta, D., A. Rahman, S. K. Paul, and A. Kundu. 2019. "Changing Pattern of Urban Landscape and Its Effect on Land Surface Temperature in and around Delhi." *Environmental Monitoring and Assessment* 191:551. https://doi.org/10.1007/s10661-019-7645-3

Dutta, D., A. Rahman, S. K. Paul, and A. Kundu. 2020. "Estimating Urban Growth in Peri-Urban Areas and Its Interrelationships with Built-Up Density Using Earth Observation Datasets." *The Annals of Regional Science*. https://doi.org/10.1007/s00168-020-00974-8

Dutta, I., and A. Das. 2019. "Application of Geo-Spatial Indices for Detection of Growth Dynamics and Forms of Expansion in English Bazar Urban Agglomeration, West Bengal." *Journal of Urban Management* 8(2):288–302. https://doi.org/10.1016/j.jum.2019.03.007

Fenta, A. A., H. Yasuda, N. Haregeweyn, A. S. Belay, Z. Fao, U.N.E.P., 2021. "Global assessment of soil pollution."

Hadush, M. A. Gebremedhin, et al. 2017. "The Dynamics of Urban Expansion and Land Use/Land Cover Changes Using Remote Sensing and Spatial Metrics: The Case of Mekelle City of Northern Ethiopia." *International Journal of Remote Sensing* 38(14):4107–4129. https://doi.org/10.1080/01431161.2017.1317936

Foley, J. A., R. De Fries, G. P. Asner, et al. 2005. "Global Consequences of Land Use." *Science* 309(5734):570–574. https://doi.org/10.1126/science.1111772

Foody, G. M. 2002. "Status of Land Cover Classification Accuracy Assessment." *Remote Sensing of Environment* 80:185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Gogoi, P. P., V. Vinoj, D. Swain, G. Roberts, J. Dash, and S. Tripathy. 2019. "Land Use and Land Cover Change Effect on Surface Temperature over Eastern India." *Scientific Reports* 9:8859. https://doi.org/10.1038/s41598-019-45213-z

Golmehr, E. 2009. "Current Application of Remote Sensing Techniques in Land Use Mapping: A Case Study of Northern Parts of Kolhapur District." *Journal of Applied Sciences and Environmental Management* 13(4):15–20.

Guyassa, E., A. Frankl, S. Lanckriet, D. Biadgilgn, G. Zenebe, A. Zenebe, et al. 2018. "Changes in Land Use/Cover Mapped over 80 Years in the Highlands of Northern Ethiopia." *Journal of Geographical Sciences* 28(10):1538–1563. https://doi.org/10.1007/s11442-018-1560-3

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science* 342(6160):850–853. https://doi.org/10.1126/science.1244693

Hassan, Z., R. Shabbir, S. S. Ahmad, A. H. Malik, N. Aziz, A. Butt, and S. Erum. 2016. "Dynamics of Land Use and Land Cover Change (LULCC) Using Geospatial Techniques: A Case Study of Islamabad Pakistan." *SpringerPlus* 5:812. https://doi.org/10.1186/s40064-016-2414-z

Jiang, W. J., Z. Z. Cheng, and Y. Song. 2026. "Modeling Land Use and Land Cover Dynamics Using CA–Markov: Urban Growth and Landscape Transformation (2004–2034)." *GeoJournal* 91:130. https://doi.org/10.1007/s10708-026-11683-8

Joshi, P. K., S. Singh, S. Agarwal, P. S. Roy, and P. C. Joshi. 2004. "Tropical Forest Cover Type Characterization

in Central Highlands of India, Using Multi-Temporal IRS-1C WiFS Data." *Indian Journal of Forestry* 27(2):157–168.

Koppad, A. G., and B. S. Janagoudar. 2017. "Vegetation Analysis and Land Use Land Cover Classification of Forest in Uttar Kannada District India Using Remote Sensing and GIS Techniques." *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 42(4/W5):121–125. https://doi.org/10.5194/isprs-archives-XLII-4-W5-121-2017

Kumar, M., A. Kumar, T. K. Thakur, U. K. Sahoo, B. Konsam, and R. Pandey. 2022. "Soil Organic Carbon Estimation along an Altitudinal Gradient of Chir Pine Forests of Garhwal Himalaya, India: A Field Inventory to Remote Sensing Approach." *Land Degradation & Development*. https://doi.org/10.1002/ldr.4393

Lai, S. K. 2020. "Effects of Land Use Plans on Urban Development: A Property Rights Approach." *Journal of Urban Management* 9(1):1–5. https://doi.org/10.1016/j.jum.2019.12.002

Lal, J., L. Singh, and T. K. Thakur. 2024. "Vegetation Composition of Achanakmaar Amarkantak Biosphere Reserve and Its Ecosystem Services." Pp. 243–262 in *Biodiversity and Bioeconomy*. Elsevier. https://doi.org/10.1016/B978-0-323-95482-2.00011-0

Li, X., Y. Wang, J. Li, and B. Lei. 2016. "Physical and Socioeconomic Driving Forces of Land-Use and Land-Cover Changes: A Case Study of Wuhan City, China." *Discrete Dynamics in Nature and Society*. Article 8061069. https://doi.org/10.1155/2016/8061069

Lossou, E., N. O. Prempeh, and G. Agyemang. 2019. "Monitoring Land Cover Changes in the Tropical High Forests Using Multi-Temporal Remote Sensing and Spatial Analysis Techniques." *Remote Sensing Applications: Society and Environment* 16:100264. https://doi.org/10.1016/j.rsase.2019.100264

Lu, Y., P. Wu, X. Ma, and X. Li. 2019. "Detection and Prediction of Land Use/Land Cover Change Using Spatiotemporal Data Fusion and the Cellular Automata–Markov Model." *Environmental Monitoring and Assessment* 191:68. https://doi.org/10.1007/s10661-019-7200-2

Mahajan, S., P. Panwar, and D. Kaundal. 2001. "GIS Application to Determine the Effect of Topography on Land Use in Ashwani Khad Watershed." *Journal of Remote Sensing* 29(4):243–248. https://doi.org/10.1007/BF02995730

Miettinen, J., C. Shi, and S. C. Liew. 2011. "Deforestation Rates in Insular Southeast Asia between 2000 and 2010." *Global Change Biology* 17(7):2261–2270. https://doi.org/10.1111/j.1365-2486.2011.02398.x

Mishra, P. K., A. Rai, and S. C. Rai. 2020. "Land Use and Land Cover Change Detection Using Geospatial Techniques in the Sikkim Himalaya, India." *Egyptian Journal of Remote Sensing and Space Sciences* 23(2):133–143. https://doi.org/10.1016/j.ejrs.2019.02.001

Mohamed, A., and H. Worku. 2019. "Quantification of the Land Use/Land Cover Dynamics and the Degree of Urban Growth Goodness for Sustainable Urban Land Use Planning in Addis Ababa and the Surrounding Oromia Special Zone." *Journal of Urban Management* 8(1):145–158. https://doi.org/10.1016/j.jum.2018.11.002

Muchoney, D. M., and B. Haack. 1994. "Change Detection for Monitoring Forest Defoliation." *Photogrammetric Engineering & Remote Sensing* 60:1243–1251.

Murthy, M. S. R., H. Gilani, B. S. Karky, E. Sharma, M. Sandker, U. A. Koju, S. Khanal, and M. Poudel. 2017. "Synergizing Community-Based Forest Monitoring with Remote Sensing: A Path to an Effective REDD+ MRV System." *Carbon Balance and Management* 12:19. https://doi.org/10.1186/s13021-017-0087-8

Nuñez, M. N., H. H. Ciapessoni, A. Rolla, E. Kalnay, and M. Cai. 2008. "Impact of Land Use and Precipitation Changes on Surface Temperature Trends in Argentina." *Journal of Geophysical Research*. https://doi.org/10.1029/2007JD008638

Padwar, G. K. 2018. *Geospatial Study on Land Use and Land Cover Pattern Indices for Phyto-Diversity of Achanakmaar Amarkantak Biosphere Reserve, India*. Ph.D. Thesis, Indira Gandhi National Tribal University, Amarkantak, India.

Paiboonvorachat, C., and T. J. Oyana. 2011. "Land-Cover Changes and Potential Impacts on Soil Erosion in the Nan Watershed, Thailand." *International Journal of Remote Sensing* 32(21):6587–6609.

Pande, C. B. 2022. "Land Use/Land Cover and Change Detection Mapping in Rahuri Watershed Area (MS), India Using the Google Earth Engine and Machine Learning Approach." *Geocarto International* 37(26):13860–13880. https://doi.org/10.1080/10106049.2022.2086622

Pandey, M., A. Mishra, S. L. Swamy, T. K. Thakur, and V. C. Pandey. 2022. "Impact of Land Use Dynamics, Soil Quality and Land Degradation Vulnerability Assessment Using Analytical Hierarchy Process (AHP) and Geospatial Techniques." *Land Degradation & Development*. https://doi.org/10.1002/ldr.4390

Park, J., and J. Lee. 2016. "Detection of Land Use/Landcover Changes Using Remotely-Sensed Data." *Journal of Forestry Research* 27(6):1343–1350. https://doi.org/10.1007/s11676-016-0270-x

Patel, D. K., J. Lal, and T. K. Thakur. 2024. "A Spatio-Temporal Analysis of Land Use Land Cover Changes of Dry Tropical Forest Ecosystem of Chhattisgarh, India." *Biodiversity International Journal* 7(2):63–69. https://doi.org/10.15406/bij.2024.07.00212

Patra, S., S. Sahoo, P. Mishra, and S. C. Mahapatra. 2018. "Impacts of Urbanization on Land Use/Cover Changes and Its Probable Implications on Local Climate and Groundwater Level." *Journal of Urban Management* 7(2):70–84. https://doi.org/10.1016/j.jum.2018.04.006

Rahman, A., S. P. Aggarwal, M. Netzband, and S. Fazal. 2011. "Monitoring Urban Sprawl Using Remote Sensing and GIS Techniques of a Fast Growing Urban Centre,

India." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 4(1):56–64. https://doi.org/10.1109/JSTARS.2010.2084072

Rahman, A., S. Kumar, S. Fazal, and M. A. Siddiqui. 2012. "Assessment of Land Use/Land Cover Change in the North-West District of Delhi Using Remote Sensing and GIS Techniques." *Journal of the Indian Society of Remote Sensing* 40(4):689–697. https://doi.org/10.1007/s12524-011-0165-4

Rai, S. C., E. Sharma, and R. C. Sundriyal. 1994. "Conservation in the Sikkim Himalaya: Traditional Knowledge and Land-Use and Mamlay Watershed." *Environmental Conservation* 21(1):30–34. https://doi.org/10.1017/S0376892900024048

T. V., R., B. Setturu, and S. Chandran. 2016. "Geospatial Analysis of Forest Fragmentation in Uttara Kannada District, India." *Forest Ecosystems* 3:10. https://doi.org/10.1186/s40663-016-0069-4

Rawat, S., V. P. Khanduri, B. Singh, M. K. Riyal, T. K. Thakur, M. Kumar, and M. C. Pinto. 2022. "Variation in Carbon Stock and Soil Properties in Different *Quercus leucotrichophora* Forests of Garhwal Himalaya." *Catena* 213(1):106210. https://doi.org/10.1016/j.catena.2022.106210

Reddy, C. S., S. Sreelekshmi, C. S. Jha, and V. K. Dadhwal. 2013. "National Assessment of Forest Fragmentation in India: Landscape Indices as Measures of the Effects of Fragmentation and Forest Cover Change." *Ecological Engineering* 105(6):453–463. https://doi.org/10.1016/j.ecoleng.2013.09.064

Ribeiro, M. C., J. P. Metzger, A. C. Martensen, F. J. Ponzoni, and M. M. Hirota. 2009. "The Brazilian Atlantic Forest: How Much Is Left, and How Is the Remaining Forest Distributed? Implications for Conservation." *Biological Conservation* 142(6):1141–1153. https://doi.org/10.1016/j.biocon.2009.02.021

Roychoudhury, N., R. Sharma, and R. K. Mishra. 2019. "Scope and Challenges of Biodiversity Conservation and Management in Achanakmar-Amarkantak Biosphere Reserve." *Plants and Environment* 1(1):46–54.

Saha, S. K., M. Kudart, and S. K. Bhan. 1990. "Digital Processing of Landsat TM Data Watershed Mapping in Parts of Aligarh District (Uttar Pradesh), India." *International Journal of Remote Sensing* 11(3):485–492. https://doi.org/10.1080/01431169008955034

Saxena, K. G., A. K. Tiwari, M. C. Porwal, and A. R. R. Menon. 1992. "Vegetation Maps, Mapping Needs and Scope of Digital Processing of Landsat Thematic Mapper Data in Tropical Region of South-West India." *International Journal of Remote Sensing* 13(11):2017–2037. https://doi.org/10.1080/01431169208904250

Sehgal, V. K., and R. P. Dubey. 1997. "Evaluation of Potential Usefulness of IRS-1C WIFS Simulated Data for Dryland Rabi Sorghum Crop Discrimination." *Journal of Indian Society of Remote Sensing* 25(3):137–143. https://doi.org/10.1007/BF03024214

Singh, A. 1989. "Digital Change Detection Techniques Using Remotely Sensed Data." *International Journal of Remote Sensing* 10(6):989–1003. https://doi.org/10.1080/01431168908903939

Singh, S. K., S. Mustak, P. K. Srivastava, S. Szabó, and T. Islam. 2015. "Predicting Spatial and Decadal LULC Changes through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-Information." *Environmental Processes* 2:61–78. https://doi.org/10.1007/s40710-015-0062-x

Tellman, B., S. E. Sesnie, N. R. Magliocca, E. A. Nielsen, J. A. Devine, K. McSweeney, M. Jaing, D. J. Wrathallh, A. Dávilak, K. Benessaiahi, and B. Aguilar-Gonzalezj. 2020. "Illicit Drivers of Land Use Change: Narcotrafficking and Forest Loss in Central America." *Global Environmental Change*. https://doi.org/10.1016/j.gloenvcha.2020.102092

Thakur, T. K. 2018. "Diversity, Composition and Structure of Understorey Vegetation in the Tropical Forest of Achanakmaar Amarkantak Biosphere Reserve, India." *Environmental Sustainability* 1(2):279–293. https://doi.org/10.1007/s42398-018-00028-y

Thakur, T. K., J. Dutta, A. Bijalwan, and S. L. Swamy. 2022a. "Evaluation of Decadal Land Degradation Dynamics in Old Coal-Mines of Central India." *Land Degradation & Development*. https://doi.org/10.1002/ldr.4383

Thakur, T. K., J. Dutta, P. Upadhyay, D. K. Patel, A. Thakur, M. Kumar, and A. Kumar. 2022c. "Assessment of Land Degradation and Restoration in Coal Mines of Central India: A Time Series Analysis." *Ecological Engineering* 175:106493. https://doi.org/10.1016/j.ecoleng.2021.106493

Thakur, T. K., K. K. Kripogu, A. Thakur, A. Kumar, S. Bakshi, S. L. Swamy, A. Bijalwan, and M. Kumar. 2022b. "Disentangling Forest Dynamics for Litter Biomass Production in Biosphere Reserve of Central India." *Frontiers in Environmental Science*:940614. https://doi.org/10.3389/fenvs.2022.940614

Thakur, T. K., G. K. Padwar, D. K. Patel, and A. Bijalwan. 2019. "Monitoring Land Use, Species Composition and Diversity of Moist Tropical Environment in Achanakmaar Amarkantak Biosphere Reserve, India Using Satellite Data." *Biodiversity International Journal* 3(4):162–172.

Thakur, T. K., D. K. Patel, A. Bijalwan, M. J. Dobriyal, A. Kumar, A. Thakur, A. Bohra, and J. A. Bhat. 2020. "Land Use Land Cover Change Detection through Geospatial Analysis in an Indian Biosphere Reserve." *Trees, Forests and People* 2:100018. https://doi.org/10.1016/j.tfp.2020.100018

Thakur, T. K., D. K. Patel, A. Thakur, A. Kumar, A. Bijalwan, J. A. Bhat, A. Kumar, M. J. Dobriyal, M. Kumar, and A. Kumar. 2021b. "Biomass Production Assessment in a Protected Area of Dry Tropical Forest Ecosystem of India: A Field to Satellite Observation Approach." *Frontiers in Environmental Science* 9:757976. https://doi.org/10.3389/fenvs.2021.757976

Thakur, T. K., D. K. Patel, J. Dutta, A. Kumar, S. Kaushik, A. Bijalwan, M. S. Fnais, K. Abdelrahman, and M. J. Ansari. 2021a. "Assessment of Decadal Land Use Dynamics of Upper Catchment Area of Narmada River, the Lifeline of Central India." *Journal of King Saud University – Science* 33:101322. https://doi.org/10.1016/j.jksus.2020.101322

Thiha, E., L. Webb, and H. Kiyoshi. 2007. "Biophysical and Policy Drivers of Landscape Change in a Central Vietnamese District." *Environmental Conservation* 34(2):164–172.

Walker, R. 2001. "Industry Builds the City: The Suburbanization of Manufacturing in the San Francisco Bay Area, 1850–1940." *Journal of Historical Geography* 27(1):36–57. https://doi.org/10.1006/jhge.2000.0268

Yu, H., P. K. Joshi, K. K. Das, D. D. Chauniyal, D. R. Melick, X. Yang, and J. Xu. 2007. "Land Use/Cover Change and Environmental Vulnerability Analysis in Birahi Ganga Sub-Watershed of the Garhwal Himalaya, India." *Tropical Ecology* 48(2):241.

Zhang, Y., I. Drobyshev, L. Gao, X. Zhao, and Y. Bergeron. 2014. "Disturbance and Regeneration Dynamics of a Mixed Korean Pine Dominated Forest on Changbai Mountain, North-Eastern China." *Dendrochronologia* 32(1):21–31. https://doi.org/10.1016/j.dendro.2013.06.003