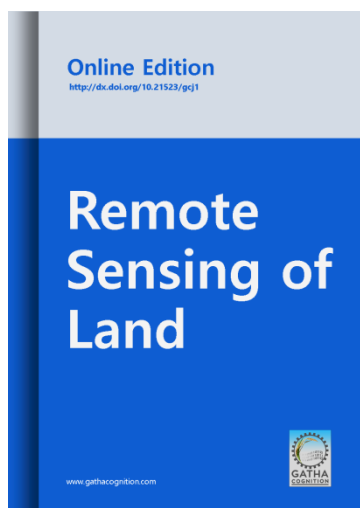




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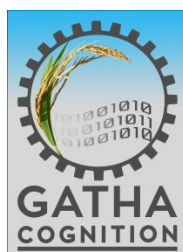
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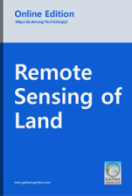
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Original Research Paper



Geospatial Assessment of Spatiotemporal LULC Dynamics in the Mula and Pravara River Basins

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Abstract

Land Use and Land Cover (LULC) dynamics provide essential insights into landscape transformation and its implications for environmental sustainability, agricultural development, and watershed management. The present study investigates temporal changes in LULC within the Mula and Pravara River Basins (MPRBs), located in the eastern region of the Western Ghats in Ahilyanagar District, Maharashtra, India. Together, the two basins cover approximately 5,551.3 km² and form part of the larger Godavari River basin. LULC changes during 1994–2025 were assessed using multi-temporal Landsat imagery, including Landsat-5 Thematic Mapper (TM) for 1994 and Landsat-9 Operational Land Imager-2 (OLI-2) and Thermal Infrared Sensor-2 (TIRS-2) for 2025. The classified imagery was grouped into six major classes: barren land, cropland, natural vegetation, roads and settlements, scrubland, and water bodies. The results revealed distinct LULC trajectories between the two basins. In the Pravara River Basin, cropland increased from 36.3% to 40.3%, while barren land decreased from 25.3% to 14.6% and scrubland increased from 18.1% to 24.7%. In the Mula River Basin, cropland increased substantially from 15.5% to 31.0%, whereas barren land declined from 25.1% to 15.7% and roads and settlements increased from 0.9% to 4.6%. Transition-matrix analysis using the ArcMap Combine tool quantified the direction and magnitude of class-to-class conversions and identified substantial transitions involving barren, scrub, cropland, and developed land. The 2025 classification achieved an overall accuracy of 89%, with a Kappa coefficient of 0.8959. The findings demonstrate spatially heterogeneous LULC transformation, with more pronounced agricultural and developed-land expansion in the Mula Basin. The study provides a quantitative baseline for future LULC monitoring and supports integrated land, water, and watershed management in the Deccan Trap region of Western Maharashtra.

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1 INTRODUCTION

Land is a constantly evolving natural resource that supports human survival and maintains the delicate balance of terrestrial ecosystems (Chen *et al.*, 2021; Ennouri *et al.*, 2021). Changes in the Earth's surface system are typically influenced by population growth (Lambin *et al.*, 2003), economic development, and geographic factors

such as landscape characteristics, slope gradient, weather conditions, and soil groups (Yalew *et al.*, 2016; Tewabe and Fentahun 2020). LULC represent the ways in which human beings utilize and transform natural resources, including vegetation, land, and aquatic resources, over time (Ahmad *et al.*, 2020; Tewabe and Fentahun 2020). Human-induced activities directly affect the surrounding environment, particularly surface-water resources, groundwater levels, and evapotranspiration processes (Hurni *et*

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al., 2005; Akpoti et al., 2016). Socio-economic activities, changes in climate patterns, and natural vulnerability are also closely associated with LULC dynamics at the global scale (Sewnet 2015; Chakilu and Moges 2017). Increasing population and urban expansion can result in substantial conversion of natural and forested areas to other land uses, contributing to soil-loss problems in parts of the Himalayan states of India (Sharma et al., 2007). Therefore, monitoring LULC changes is important for understanding landscape transformation and supporting sustainable natural-resource management.

Over the past few decades, numerous methods have been developed and applied worldwide to monitor and map LULC and assess land-cover changes (Zhu and Woodcock 2014; Jin et al., 2017; Wu et al., 2017). Change detection is particularly important for research and policy formulation in areas such as urban planning, environmental management, and agriculture, especially for understanding land-use and land-cover transformations (Solaimani et al., 2010; Hegazy and Kaloop 2015). Thus, LULC change assessment provides an important baseline for sustainable planning and management of natural resources.

Satellite data are widely recognized as an important source of information for generating LULC maps and assessing landscape changes (Mishra et al., 2020; Sambe et al., 2025; Yasin et al., 2025). Remote Sensing (RS) and Geographic Information Systems (GIS) have substantially improved the accuracy and efficiency of assessing the spatiotemporal dynamics of LULC in a cost-effective manner (Serra et al., 2008; Gaikwad et al., 2023). Improvements in remote sensing technology and digital image-processing algorithms have further increased the use of satellite data, particularly Landsat imagery, for monitoring LULC changes across different spatial and temporal scales (Talukdar et al., 2021). Owing to its repetitive data acquisition, suitability for digital processing, and precise georeferencing, remote sensing provides an effective source for identifying, evaluating, and mapping LULC patterns (Jensen 1996; Chen et al., 2005). The integration of satellite data with RS and GIS has consequently enhanced the precision and efficiency of LULC analysis and established these techniques as important tools for monitoring spatial and temporal changes in land use and land cover.

LULC change assessment at different spatial scales involves the application of various image-classification algorithms. These include unsupervised methods such as K-means and ISODATA, supervised techniques such as minimum distance, parallelepiped, and maximum likelihood classification, and non-parametric approaches including fuzzy classification, nearest-neighbor classification, and machine-learning algorithms such as random forest, support vector machines, and neural networks (Al-Doski et al., 2013; Zhang et al., 2014). Among these approaches, supervised classification is one of the most widely employed techniques for LULC mapping because it enables land-cover classes to be identified using representative training samples. Large areas in India have also

been transformed into ravine lands because of the removal of vegetation cover and inappropriate land-use practices (Singh and Dubey 2000). Although LULC-related environmental changes have been investigated in different parts of India, comparatively limited attention has been given to similar landscape transformations within the Deccan Trap region, particularly in Western Maharashtra.

In India, where agriculture plays a significant role in the economy and livelihoods of millions of people, land is one of the most important natural resources. The growing needs of people and their jobs have led to the heavy use of available land for a variety of purposes. Over the past few decades, the conversion or reclamation of land for agricultural purposes has become a prevalent trend in various parts of the country (Joshi and Nagare, 2009). These transformations are particularly relevant in the MPRBs of Western Maharashtra, where agricultural activities, irrigation development, settlement expansion, and associated human activities have contributed to changes in the landscape.

Despite the application of remote sensing and GIS techniques in several regions of India, a basin-scale comparative assessment of long-term LULC changes in the Mula and Pravara River Basins remains limited. In particular, there is a need to quantify the changes in major LULC classes and to identify the direction and magnitude of conversions between different land-cover categories over time. The Mula and Pravara River Basins represent an important Deccan Trap landscape in Western Maharashtra and have undergone considerable changes in agricultural land, barren land, scrub land, natural vegetation, settlements, and water bodies. However, the spatial and temporal patterns of these transformations have not been adequately evaluated through a consistent multi-temporal satellite-based framework covering both basins. Addressing this gap is important for understanding the changing landscape characteristics of the region and for providing a baseline for future land and natural-resource management.

The present study therefore focuses on the comparative assessment of LULC dynamics in the Mula and Pravara River Basins using multi-temporal Landsat satellite data for 1994 and 2025. The novelty of the study lies in its comparative basin-scale analysis of six major LULC classes—barren land, cropland, natural vegetation, roads and settlements, scrub land, and water bodies—using a consistent classification and change-detection framework. In addition to quantifying changes in the area and percentage of individual LULC classes, the study employs post-classification change detection and a transition matrix to identify the major class-to-class conversions between 1994 and 2025. This approach provides a detailed understanding of the magnitude, direction, and spatial pattern of LULC transformation in the MPRBs.

Accordingly, the primary objective of the present investigation is to assess the spatial and temporal changes in LULC in the Mula and Pravara River Basins during the

period 1994–2025. The specific objectives are: (1) to prepare LULC maps of the MPRBs for 1994 and 2025 using multi-temporal Landsat satellite data and supervised classification; (2) to quantify the spatial and temporal changes in major LULC classes between 1994 and 2025; (3) to identify and quantify major LULC class-to-class conversions using post-classification change detection and transition-matrix analysis; and (4) to comparatively evaluate the major spatial and temporal patterns of LULC transformation in the MPRBs during the study period.

The study provides a spatially explicit assessment of three decades of LULC transformation in the MPRBs and establishes a baseline for understanding landscape changes in this important Deccan Trap river-basin system. The findings may support future land-use planning, agricultural management, and sustainable natural-resource management in the region.

2 STUDY AREA

The MPRBs are located in the eastern sector of the Western Ghats within Ahilyanagar District, Maharashtra, India, and form an integral part of the upper Godavari River system. Extending approximately between 19°25'–19°45' N latitude and 74°00'–74°30' E longitude, the two adjoining basins cover a total area of about 5,551.3 km², with the Pravara River Basin (PRB) occupying 2,650.7 km² and the Mula River Basin (MRB) covering 2,900.6 km² (Figure 1). Physiographically, the region represents a transitional landscape moving from the high-relief Western Ghats in the west to the subdued, semi-arid terrain of the Deccan Plateau in the east. Elevation across the study area spans from 404 to over 1,400 m above mean sea level. The climate is tropical to semi-arid because the area lies predominantly within the rain-shadow zone, east of the Western Ghats. Rainfall exhibits a steep west-to-east gradient with most of the mean annual precipitation (~501.8 mm) occurring during the Southwest Monsoon (June–September) followed by extended dry conditions with high evapotranspiration rates.

Rather than serving purely as a static background, these distinct environmental and physiographic gradients directly dictate the spatial patterns, constraints, and trajectories of Land Use and Land Cover (LULC) transitions across the MPRBs. In the western highland sector (>900 m elevation), steep slope gradients, rugged basaltic topography, and high seasonal rainfall foster rapid surface runoff and soil erosion. These physical limitations restrict agricultural expansion and urban development, effectively locking the land cover into persistent Natural Vegetation and forest refuges, while exposed steep slopes remain preserved as Barren or Scrub Land.

Moving eastward into the central plateau and pediment zone (550 to 900 m elevation), moderate slopes and dissected denudational basaltic surfaces present favorable conditions for land transformation. Improved drainage accessibility and irrigation development in this intermediate zone have actively driven the systematic conversion of unutilized Scrub Land and degraded surfaces into intensified Cropland. In contrast, the lower-relief eastern

sector (<550 m elevation) consists of thick alluvial terraces, floodplains, and depositional terrain. Despite receiving lower rainfall, the flat topography, fertile alluvial soils, and proximity to drainage river channels make this eastern zone the primary spatial driver for socio-economic development, directly facilitating high-density Cropland expansion, settlement growth, and infrastructure development. By linking highland slopes to vegetation persistence, central pediments to scrub-to-crop conversion, and eastern floodplains to urban and agricultural intensification, the physical environment provides the structural framework for the observed LULC dynamics.

Climatically, the study area falls within the tropical and semi-arid climatic domain and lies predominantly within the rain-shadow region east of the Western Ghats. Rainfall exhibits a strong west–east gradient, with substantially higher precipitation in the western hilly sector and progressively lower rainfall toward the eastern plateau. The region receives most of its annual precipitation during the Southwest Monsoon season (June–September), while the period from October to May is comparatively dry. The mean annual precipitation is approximately 501.8 mm. Seasonal temperature variability is pronounced, with the highest temperatures generally occurring during the summer months, whereas winters are relatively mild and dry (Gaikwad et al., 2026b). This combination of seasonal rainfall concentration, high evapotranspiration, and semi-arid conditions exerts a strong influence on vegetation dynamics, agricultural practices, surface-water availability, and land degradation processes.

The MPRBs provide a representative semi-arid watershed environment in which topographic gradients, basaltic geology, drainage characteristics, climatic variability, and anthropogenic land-use pressures interact to produce substantial spatial and temporal LULC variability. The contrasting landscape conditions between the western highlands, central denudational plateau, and eastern depositional plains provide an appropriate natural framework for assessing long-term LULC transformations.

3 METHODOLOGY

3.1 Data acquisition

The methodology involves data acquisition, preprocessing, validation through ground surveys, and generating thematic maps for the present study area analysis (Samarinas et al., 2023). The toposheet data acquired from the Survey of India (SOI) (<https://surveyofindia.gov.in>) toposheets (1:50,000) (47 E/10, 47 E/11, 47 E/14, 47 E/15, 47 I/1, 47 I/2, 47 I/3, 47 I/4, 47 I/6, 47 I/7, 47 I/8, 47 I/10, 47 I/11, 47 I/12, 47 I/14, 47 I/15, and 47 I/16) were georeferenced via ArcMap 10.8.1. The spatial datasets were projected to the WGS 1984 UTM Zone 43 N coordinate system. Georeferencing accuracy was assessed with a minimum of 8 GCPs per toposheet, with an RMSE of no more than 0.5 pixels. These toposheets were then mosaicked to generate a continuous spatial dataset to extract watershed boundaries (Legese et al., 2026). For

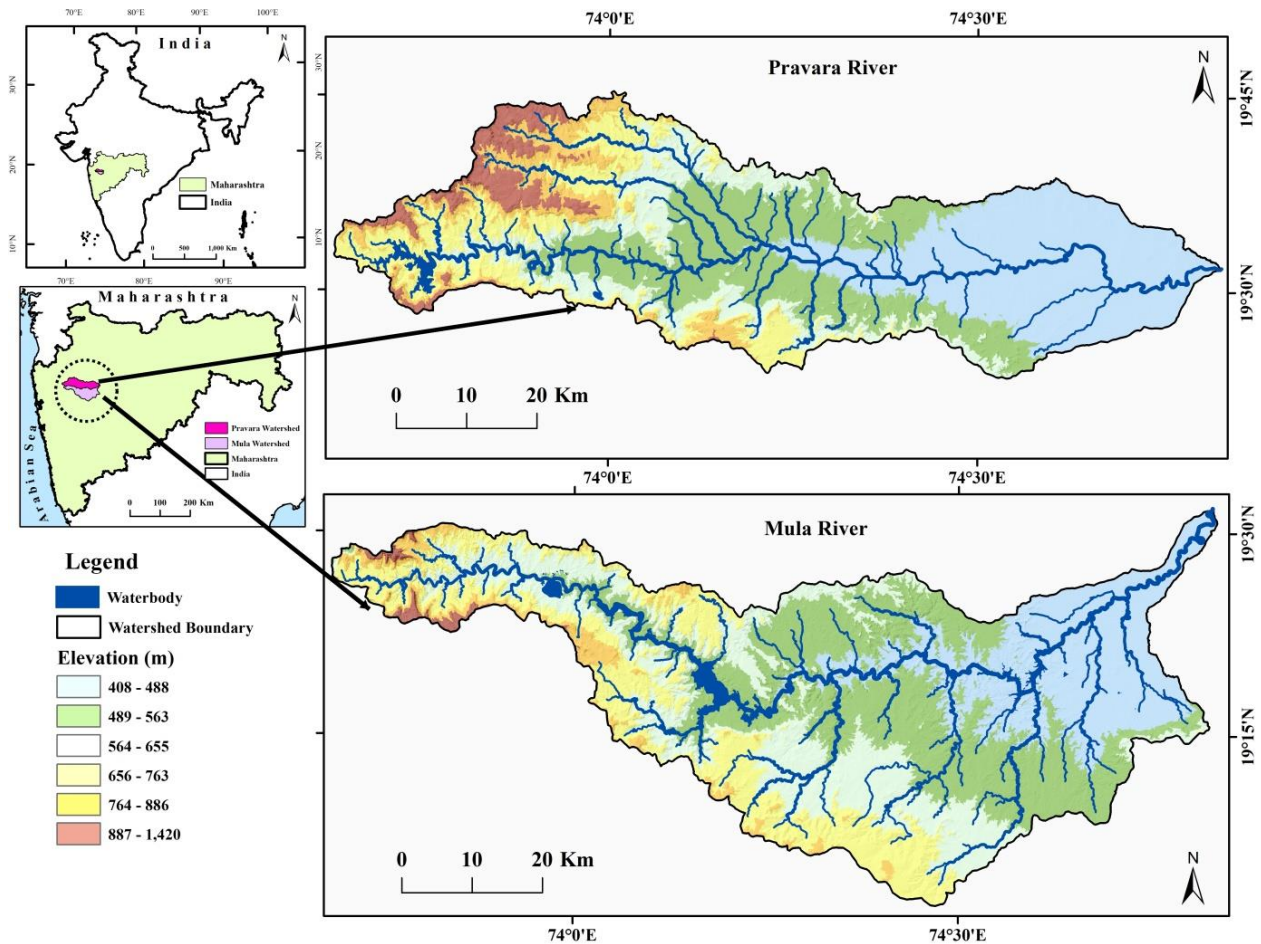


Figure 1. Study area MPRBs

the multi-temporal LULC analysis, the necessary satellite images were selected from the USGS Earth Explorer online geospatial portal (<https://earthexplorer.usgs.gov>). Landsat satellite images from 1994 and 2025 were utilized to assess temporal changes in LULC within the study area.

The images from the Landsat 4-5 Thematic Mapper (TM) satellite were selected for the year 1994, whereas images acquired by the Landsat-9 Operational Land Imager-2 (OLI-2) and Thermal Infrared Sensor-2 (TIRS-2) sensors were used for 2025. The image selected for 1994 dates back to February (2 and 9 February 1994) and had a cloud cover of less than 10% (Murad et al., 2024). For 2025, Landsat-9 OLI-2/TIRS-2 imagery acquired on January 29 and 30, 2025 comprising a total of 11 spectral bands. Out of these, the initial seven bands essential for LULC classification were utilized (Figure 2). The study area was covered by Landsat scenes corresponding to WRS-2 Paths 146–147 and Rows 46–47. The satellite imagery for the month of July exhibits the maximum water-logged area, while the image data for March reveals the maximum vacant land surface, attributed to the harvesting of all crops during the summer season (Ferrant et al., 2017).

Therefore, the periods of March and July are deemed unsuitable for clear-cut delineation of LULC changes (Sohl et al., 2025). Both the TM and MSI sensors find their primary applications in forest management, agricultural monitoring, coastal studies, inland water resource assessment, and the mapping and monitoring of LULC. The pixel-based radiometric measurements are provided in Top of Atmosphere (TOA) reflectance along with the parameters to transform them into radiance (Gupta and Gupta, 2026).

3.2 Data analysis

3.2.1 Image classification

The satellite images were downloaded from the USGS and georeferenced using the SOI toposheets and corresponding ground control points (Manjunatha, 2021). The projection of both images were UTM 43 N with WGS 84 datum. The Earth Resource Data Analysis System (ERDAS 2014) Imagine was utilized for image pre-processing, band combination, and LULC analysis. False Color Composites (FCC) were generated using band combinations of 3-2-1 for the 1994 Landsat 4-5 TM image and 5-4-3 for the 2025 Landsat-9 OLI-2 image. Based on these images, various LULC classes were identified and classified. (USGS, 2020; Singh and Vyas, 2022). Multispectral satellite imagery was effectively utilized to

classify LULC. A ‘supervised classification’ method was adopted, based on the spectral reflectance characteristics of various land cover elements within the imagery (Reddy, 2018). To facilitate the classification, “training sites” representing different land cover classes were identified (Maury et al., 2026). Among the available classification algorithms, the Maximum Likelihood Classification (MLC) method was employed to classify the satellite imagery. This method operates on the assumption that training samples for each land cover class follow a normal distribution, classifying pixels into their respective categories based on their spectral characteristics. The classification includes six major classes, i.e., water body, roads and settlement, natural vegetation, barren land, agricultural land, and scrub land (Waza et al., 2026). For each class, more than fifty training sites were used. Accuracy represents how close the results are to the true values and determines the quality of information obtained from remotely sensed data (Wang et al., 2024). The researcher assessed accuracy by visually interpreting images with support from ground truth data collected during fieldwork. The assessment of image classification involved using an error matrix, which compares referenced

and classified data (Congalton and Green 2019). It helped determine user accuracy, producer accuracy, overall accuracy, and the Kappa coefficient. Overall accuracy is calculated by dividing the total correctly classified pixels on the diagonal by the total samples (Barman et al., 2026). The Kappa coefficient offers a more comprehensive assessment by considering off-diagonal observations in the error matrix, providing a robust evaluation compared to overall accuracy measures (Tokluoglu et al., 2026).

3.2.2 LULC Change Detection

In this study, temporal changes in LULC were analyzed using the Post-Classification Change Detection method, based on supervised classified satellite imagery from 1994 and 2025. This method enables the determination of how an area belonging to a specific LULC class in 1994 transformed into a different class by 2025. Consequently, it enables the precise identification of changes in the total area of individual LULC classes as well as specific class-to-class conversions and their respective areas.

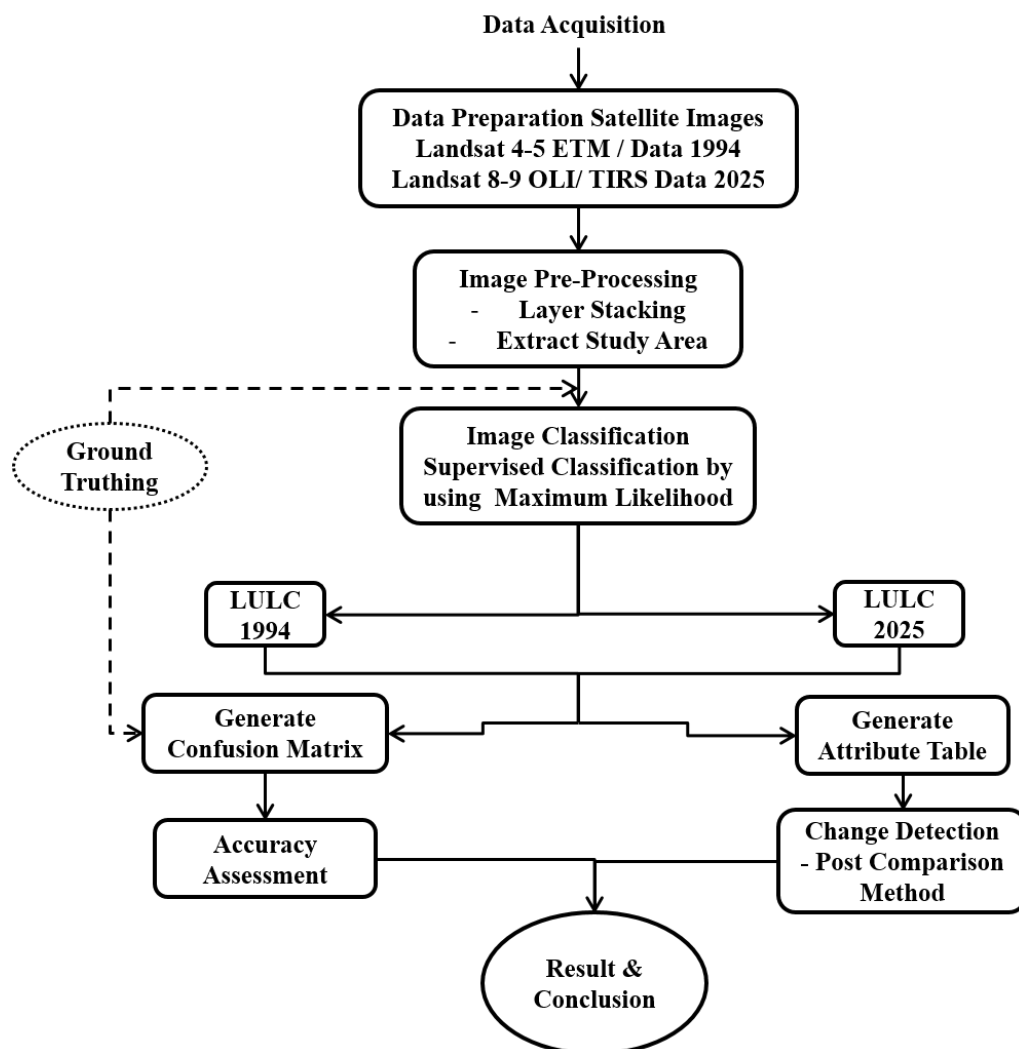


Figure 2. Methodology

The analysis utilized the ‘Combine’ tool (located under Spatial Analyst Tools → Local) in ArcMap 10.8.1. By using the ‘Combine’ tool to merge the classified raster images from 1994 and 2025, a unique combination of LULC classes for both time periods was obtained for each pixel. This process made it possible to determine whether a class from 1994 remained unchanged by 2025 or transformed into a different class. For instance, if an area classified as agricultural land in 1994 was converted into a settlement, barren land, or any other category by 2025, that specific conversion was identified, and its area was quantified. Thus, a quantitative analysis was conducted regarding the direction of change, the nature of class conversion, and the associated area for each land use and land cover class during the 1994–2025 period. Several scholars have used the Equation (1) to perform the change detection (Hassen and Assen, 2018; Bagwan and Gavali 2023).

$$C = [(A_{t2} - A_{t1}) / A_{t1} \times 100] \quad (1)$$

A_{t1} = Area of one type of land cover at t^1 time

A_{t2} = Area of one type of land cover at t^2 time

C = Rate of change.

3.2.3 Transition matrix for LULC conversion monitoring

‘Transition Matrix for Landscape Conversion Monitoring’ is an effective method for the quantitative assessment of land-use changes within a specific geographic area over a defined period, utilizing multi-temporal LULC imagery (Bektas and Goksel 2005; Kalpana, 2018). This method enables the identification of “from-to” transitions, indicating how the LULC class changes from an initial time period to a subsequent period. Based on classified data derived from multi-temporal satellite imagery, the nature, direction, and magnitude of land-use changes can be clearly established.

In the analysis of LULC changes, the transition matrix serves as a systematic table where rows represent LULC classes from the initial stage, and columns represent the corresponding classes from the final stage. Diagonal values within the matrix indicate areas where no change occurred in the respective LULC class during the period, whereas off-diagonal values represent the transition or conversion from one class to another (Suleiman et al., 2017; Bagwan and Gavali 2023). Consequently, it is possible to clearly identify which land-use class transformed into another and the extent of the area involved in such a conversion. Mishra et al., (2020) and Naikoo et al., (2020) have adopted similar methods. Through this process, the area of transition for each LULC class was determined, and a ‘LULC Conversion Transition Matrix’ was generated. The resulting transition matrix was visualized as a heat map using the Python programming language. Recently, similar studies were also carried out to

analyze LULC using the ‘Conversion Transition Matrix’ heat map (Arsiso, 2025; Hussain et al., 2025; de Bodas et al., 2026). This heat map visually illustrates the magnitude and nature of transitions across various LULC classes.

3.3 Land use land cover analysis

3.3.1 Landsat 4-5 (TM) Image (February 1994):

The Landsat 4-5 Thematic Mapper (TM) image from 1994 was utilized to generate the LULC map for the study area (Rigala et al., 2026). Figure 3 illustrates the spatial distribution of LULC classes for 1994. The northern and southern regions are predominantly characterized by barren land, while cropland is primarily concentrated in the eastern and central zones. Scrub land exhibits a scattered distribution (Zhai et al., 2026), while cropland and scrub land predominantly occupy areas adjacent to water bodies. The presence of built-up land is minimal across the study area (Arif and Toersilowati, 2024).

The LULC classification statistics, as presented in Table 1, indicate that the total study area PRB encompasses 2,650.7 km². The dominant land cover categories include cropland (36%) and barren land (25%), followed by scrub land (18%), natural vegetation (15.5%), and built-up land (3.6%) (Hussien and Woyessa, 2026). Water bodies constitute only 1.2% of the total area, specifically along the Pravara River (Yamazaki et al., 2015). In the case of the Mula River basin, the study area extends over 2,900.6 km², where scrub land (43%) and barren land (25%) are the prevailing land cover types. The remaining area comprises cropland (15.5%), natural vegetation (12.8%), and built-up land (0.9%). The absence of remarkable urban settlements results in a negligible proportion of built-up areas within both watersheds (Table 1) (Waqas et al., 2026).

3.3.2 Landsat 8-9 (OLI / TIRS) Image (January 2025):

The Landsat 9 Operational Land Imager (OLI-2) and Thermal Infrared Sensor 2 (TIRS-2) imagery was utilized to generate the LULC map for the year 2025. Figure 4 is highlighting considerable land cover transformations over time (Głowienka and Maj, 2026; Zahrani et al., 2026). A noticeable increase in settlements is observed, particularly in the central and eastern regions, which may be attributed to urban expansion and favorable topographic conditions (Kong et al., 2026; Tripta et al., 2026). Cropland, depicted in yellow, remains the dominant land cover, indicating the region's continued reliance on agriculture (Cui et al., 2026). Additionally, water resources are distinctly visible, contributing to agricultural sustainability. Vegetation is predominantly concentrated along water bodies, forming a natural buffer, and is also dispersed across other parts of the study area (Maceseanu et al., 2026; AbdelRahman, 2026; Das, 2026).

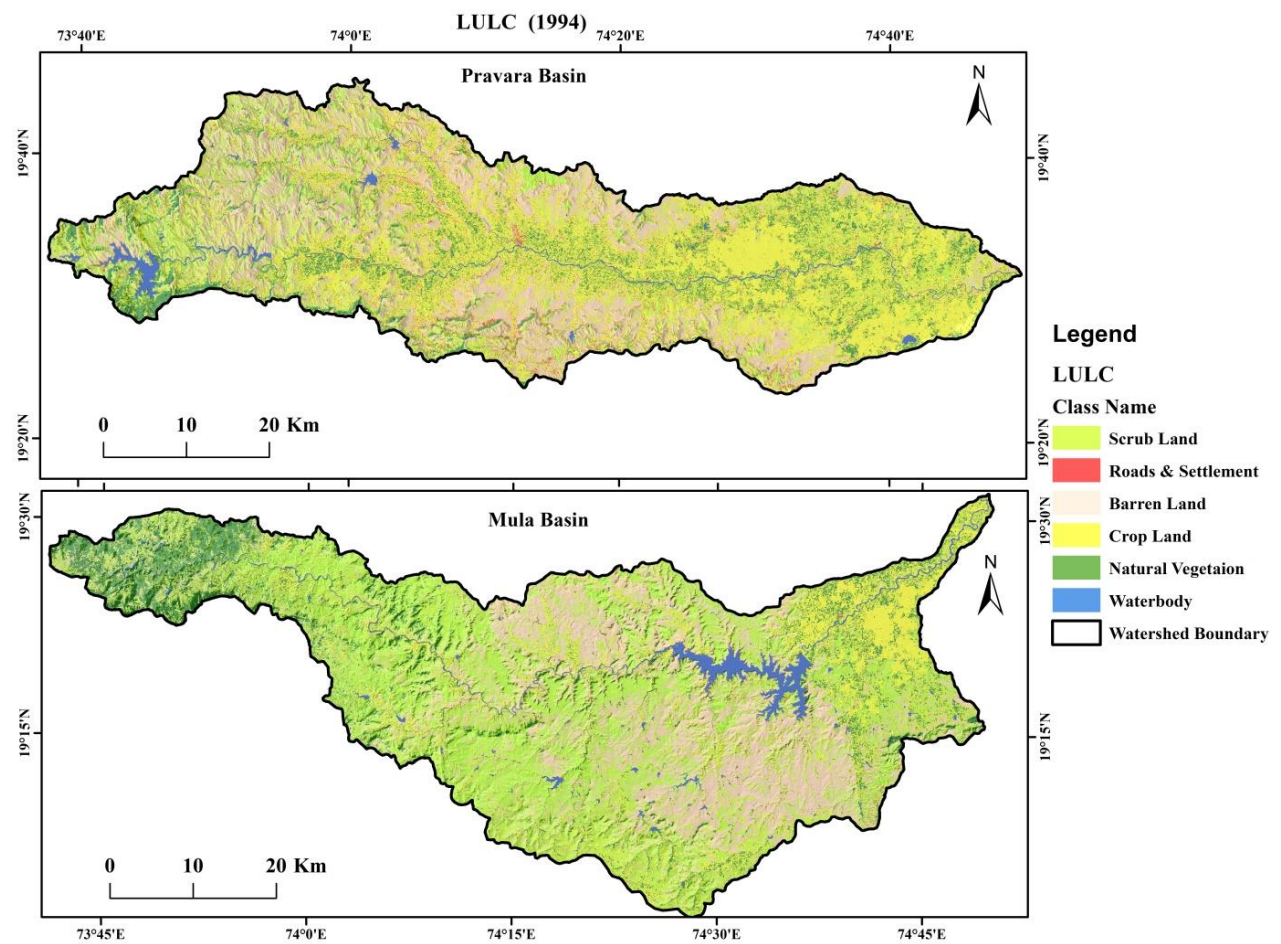


Figure 3. LULC (1994)

Table 1. LULC (February 1994)

Class Name	Pravara River		Mula River	
	Area (km ²)	Area (%)	Area (km ²)	Area (%)
Barren Land	670.6	25.3	728.1	25.1
Cropland	962.2	36.3	449.6	15.5
Natural Vegetation	410.9	15.5	371.3	12.8
Roads and Settlement	95.4	3.6	26.1	0.9
Scrub Land	479.8	18.1	1250.1	43.1
Water body	31.8	1.2	75.4	2.6
Total	2650.7	100.0	2900.6	100.0

The LULC classification statistics for 2025, as detailed in Table 2, indicate that cropland occupies the largest proportion of the study area at 40.3%, reflecting its agricultural significance (Blissag et al., 2026). Vegetation and built-up areas account for 14.6% and 3.9%, respectively. Scrub land and barren land cover 24.7% and 14.6%, respectively (Hussien and Woyessa, 2026), while water bodies constitute 1.9% of the Pravara River basin.

In the Mula River basin, scrub land remains the dominant land cover, occupying 35.6% of the total area, followed by cropland (31%), indicating extensive agricultural practices (Belete et al., 2023; Molla et al., 2026). Vegetation and built-up areas account for 11.2% and 4.6%, respectively. Barren land covers 15.7%, while water bodies make up 1.9% of the total area.

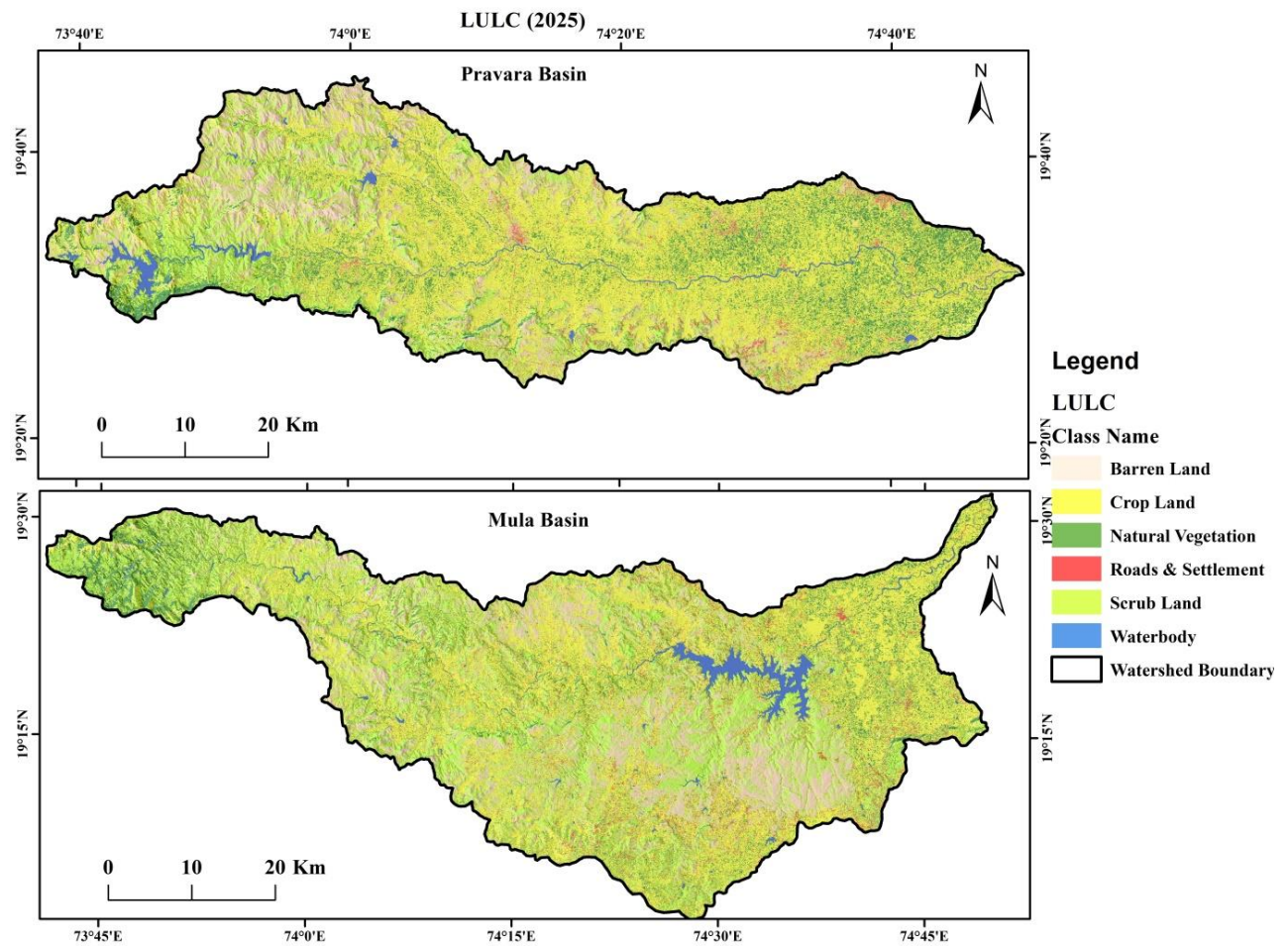


Figure 4. LULC (2025)

Table 2. LULC (January 2025)

Class Name	Pravara River		Mula River	
	Area (km ²)	Area (%)	Area (km ²)	Area (%)
Barren Land	387.0	14.6	455.4	15.7
Cropland	1068.2	40.3	899.3	31.0
Natural Vegetation	387.0	14.6	324.6	11.2
Roads and Settlement	103.4	3.9	133.4	4.6
Scrub Land	654.7	24.7	1032.6	35.6
Water body	50.4	1.9	55.2	1.9
Total	2650.7	100.0	2900.6	100.0

4 RESULT VALIDATION

Fieldwork plays a crucial role in providing ground truth data, enabling a deeper understanding of land use and land cover changes in the study area (Ekka et al., 2026). During this stage, the study area is visited at various times or seasons using Global Positioning System (GPS) surveys, and digital photographs are taken (Fretwell et al., 2017). This helps in understanding the current land use and land cover, as well as the actual changes that have

occurred (Tahir et al., 2025) in the study area from 1994 to 2025.

4.1 Field Verification

4.1.1 Built-up Land

During the field survey, built-up areas were identified and validated using fifty GPS coordinates and photographs, based on the presence of houses, roads, and related infrastructure that indicate significant anthropogenic expansion (NRSC, 2006; Utomo et al., 2025).

4.1.2 Cropland

Cropland covers areas dedicated to the cultivation of crops such as grains, vegetables, fruits, and nuts, as well as land used for livestock grazing (Bringezu et al., 2021). It consists of varied agricultural practices, including irrigated and unirrigated agriculture, fallow fields, and plantations, which jointly support farming, manufacturing, and rural living (Sivaraman et al., 2023). Field verification was conducted using GPS coordinates and photographic documentation, supported by observations of crop characteristics, cultivation patterns, and land-management practices (Photo 1) (Anderson, 1976).

4.1.3 Scrub Land

Scrub land is characterized by shallow and skeletal soils, rare chemical degradation (Wielgos and Kulik, 2026), steep slopes, severe erosion, and extreme aridity, which favor the expansion of sparse scrub vegetation (NRSC 2006; Zubair et al., 2026). These areas are generally characterized by elevated, relatively level terrain and are distinct from hilly or mountainous terrain (Gujar et al., 2025). Field verification was conducted using GPS coordinates and geotagged photographs to validate these features and support the accuracy assessment of the LULC classification (Photo 2) (Ganga et al., 2026).

4.1.4 Natural Vegetation

Vegetation was defined as land with >10% tree canopy cover, an area >0.5 ha, and trees ≥ 5 m in height (NRSC, 2006; Goparaju and Ahmad, 2020). It included evergreen/semi-evergreen, deciduous, plantation, and scrub forests (Jara et al., 2017). Field observations and GPS-referenced photographs were used to verify vegetation type, canopy cover, and spatial characteristics at selected locations, supporting the satellite-based LULC classification. (Photo 3) (Sarun and Nat, 2025).

4.1.5 Water body

Water bodies include natural water features such as rivers and streams, which carry water through defined channels either continuously or seasonally (Singh et al., 2026). They also include ponds, lakes, tanks, and reservoirs (Ninawe et al., 2026). During the field survey, these water features were directly observed and verified, including the Bhojapur Dam and other water bodies, based on their presence, flow conditions, and spatial distribution (Photos 4 and 5) (Manandhar et al., 2024).

4.1.6 Barren Land

Barren land is characterized by little or no vegetation and generally poor soil fertility, limiting its suitability for agricultural activities (Naik et al., 2025). Barren land may include rocky terrain, sand dunes, exposed surfaces, and other sparsely vegetated areas (Singh and Sharma, 2025).

Field verification was conducted using GPS-referenced observations and geotagged photographs at selected locations, based on vegetation cover, surface characteristics, and agricultural use (Photo 6).

4.2 Accuracy assessment

Accuracy is defined as the degree of proximity between the obtained results and the true values (Zhang et al., 2026). It serves as a measure of the quality of the information extracted from remotely sensed data. Accuracy assessment relied on visual interpretation of images supplemented by ground truth data gathered from fieldwork. The accuracy assessment of the classified images was conducted using the ERDAS Imagine application (Othow et al., 2017). For each of the identified images in 2025, the accuracy evaluation tool of the supervised classifier randomly generated 100 reference points using stratified random sampling. The error matrix and kappa statistics for all classified images were also generated using the ERDAS Imagine software (Foody, 2002). Due to the unavailability and unclear nature of Google Earth images, the accuracy assessment of the images from 1994 was not feasible. The classified image attained an overall classification accuracy of 89% for the year 2025 (Table 3). Subsequent sections present the individual producer's accuracy and user's accuracy values for all classes.

4.2.1 User's and Producer's Accuracy

Another procedure derived from the error matrix includes the "error of omission" and the "error of commission" (Bhat et al., 2026). Omission error refers to the proportion of reference pixels belonging to a specific class that are incorrectly classified into other classes. Commission error refers to the proportion of pixels classified as a specific class that actually belong to other classes. Omission and commission errors are complementary to Producer's Accuracy and User's Accuracy, respectively, and can be calculated as 100 minus the corresponding accuracy value (Rwanga and Ndambuki, 2017).

4.2.2 Kappa statistics

Kappa statistics were produced to assess class accuracy within the broader context of classifier accuracy. According to the criteria outlined by Landis and Koch (1977), agreement is considered poor if Kappa is below 0.4, satisfactory if it falls between 0.4 and 0.7, and excellent if it exceeds 0.75. Table 4 shows the kappa statistics for the 2025 LULC classification.

For the year 2025, the overall Kappa statistics value is 0.8959. Remarkably, the water body category exhibits a kappa value of 1 for 2025, signifying an outstanding agreement. All other classes have kappa values exceeding 0.5, indicating good to excellent agreement.



Photo 1. Agricultural practices



Photo 2. Scrub Land Near (Sakur Mandve)



Photo 3. Natural Vegetaion in Kalsubai Harishchandragad wildlife sanctuary



Photo 4. Water body (Bhojapur Dam)



Photo 5. Water body (Randha Falls)



Photo 6. Barren Land (Near Sakur)

Table 3. Accuracy assessment for classified Landsat image (2025) of the Mula-Pravara basin

Class Name	Referenced Total	Classified Total	Number of correct	Producer's Accuracy (%)	User's Accuracy (%)
Barren Land	17	17	17	100	100
Cropland	45	48	42	93.33	87.50
Natural Vegetation	14	11	10	78.57	90.91
Roads and Settlement	8	8	6	100	75
Scrub Land	12	12	10	100	83.33
Water body	4	4	4	100	100
Total	100	100	89		
Overall Classification Accuracy = 89%					

Monitoring and managing natural resources and urban development rely on change detection, which provides a quantitative analysis of how the population and other environmental activities are distributed spatially (Huang *et al.*, 2008).

4.3 LULC Change Detection and Dynamics

By comparing the classified LULC images from 1994 and 2025, the area of each category was determined in terms of both km² and percentage. Subsequently, to quantify the temporal changes in the area of each LULC category, the percentage increase or decrease for the respective category was calculated (Desalegn *et al.*, 2014; Hailu *et al.*, 2020). For this purpose, the percentage change in land use and land cover was determined using the following Equation (2), based on a comparison of the category-wise areas from 1994 and 2025.

$$\text{Percentage LULC change} = \frac{\text{Area final year} - \text{Area initial year}}{\text{Area initial year}} \times 100 \quad (2)$$

4.3.1 Pravara Basin

The LULC change analysis of the PRB reveals remarkable land cover transitions over time. Barren land has decreased by 10.7%, indicating conversion to more productive land uses, likely cropland (+4.0%) and scrub land (+6.6%) (Table 5, Figure 5). The increase in cropland suggests agricultural expansion, possibly driven by improved irrigation and farming practices. A minor fall in natural vegetation (-0.9%) implies limited deforestation, while the growth in scrub land may indicate land degradation. Built-up areas (roads and settlements) have in-

creased slightly by 0.4%, reflecting limited urban expansion. Additionally, water bodies have expanded by 0.7%, possibly due to improved watershed management or seasonal water retention. Overall, the observed changes suggest a shift toward agricultural intensification, natural regeneration, and infrastructure expansion, with a potential impact on land sustainability and hydrological balance in the region.

A transition matrix was prepared to quantify the changes in LULC classes between 1994 and 2025. The matrix records the area of each LULC class in 1994 that was subsequently classified into the same or a different LULC class in 2025. The rows represent the LULC classes of 1994, while the columns represent the corresponding LULC classes of 2025. The diagonal elements indicate areas that remained under the same LULC class, whereas the off-diagonal elements represent conversions from one LULC class to another. The transition matrix was generated using the classified LULC maps in GIS and was used to quantify the magnitude and direction of landscape transformation during the study period.

An analysis of LULC changes in the PRB between 1994 and 2025 reveals considerable transformations driven by human intervention and environmental factors. The barren land decreased by 41.9%, with its area dropping from 670.6 km² to 387.0 km² (Figure 6). This barren land was primarily converted into cropland (171.4 km²) and scrub land (180.4 km²). Key drivers behind this shift include the expansion of irrigation facilities, water conservation and watershed management measures, and agricultural

Table 4. Overall Kappa Statistics for classified Landsat image of the Mula-Pravara basin

Class Name	Overall Kappa Statistics = 0.8959
	Kappa Value (2025)
Barren Land	1.00
Cropland	0.9092
Natural Vegetation	0.8078
Roads and Settlement	0.8263
Scrub Land	0.8967
Water body	0.9356

Table 5. LULC (Pravara basin)

Class Name	2025		1994		Change (%)
	Area (km ²)	Area (%)	Area (km ²)	Area (%)	
Barren Land	387.0	14.6	670.6	25.3	-10.7
Cropland	1068.2	40.3	962.2	36.3	4.0
Natural Vegetation	387.0	14.6	410.9	15.5	-0.9
Roads and Settlement	103.4	3.9	95.4	3.6	0.4
Scrub Land	654.7	24.7	479.8	18.1	6.6
Water body	50.4	1.9	31.8	1.2	0.7

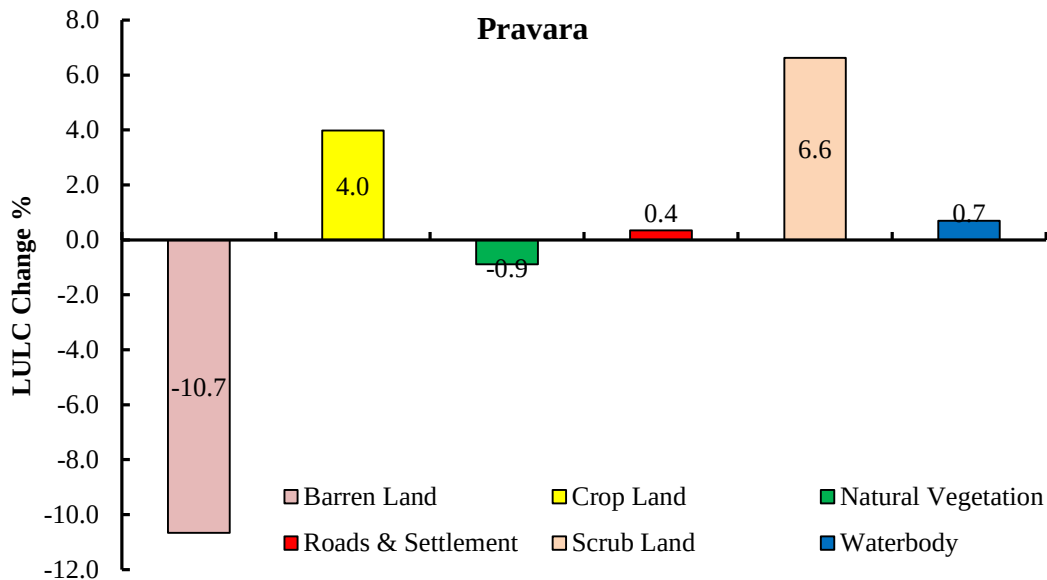


Figure 5. Overall LULC change in Pravara basin (1994–2025)

expansion. Consequently, the cropland area saw a significant increase, rising from 962.2 km² in 1994 to 1,067.1 km² (40.3% increase) by 2025 (Figure 7). This highlights the expansion of agriculture and improved water resource availability within the river basin.

Concurrently, changes have occurred in areas covered by natural vegetation and scrub land. Due to increasing urbanization, population growth, and infrastructure development, the area occupied by roads and settlements expanded by approximately 103.6 km² (11%). Specifically, a conversion of cropland and scrub land into built-up areas is evident. However, the water surface area shows relatively minimal change.

Overall, it is evident that agricultural expansion, irrigation, water conservation, watershed management, and increasing urbanization are the primary drivers of LULC changes in the PRB.

4.3.2 Mula Basin

The LULC change analysis of the Mula River Basin (MRB) indicates significant land cover transitions, reflecting shifts in land utilization patterns. Table 6 and Figure 8 show a prominent decline in barren land (-9.4%) and scrub land (-7.5%), suggesting large-scale land conversion, primarily into cropland (+15.5%), indicating intensified agricultural expansion, likely driven by improved irrigation practices and increasing food demand. The increase in built-up areas (roads and settlements) by +3.7% signifies urban growth and infrastructure development, potentially influenced by population expansion and economic activities. A marginal decline in natural vegetation (-1.6%) suggests minimal deforestation, while the slight decrease in water bodies (-0.7%) may be attributed

to seasonal hydrological variations. These LULC changes highlight a transition from fallow and degraded lands to more productive agricultural and urban landscapes, which may have implications for land productivity, ecological stability, and watershed hydrology in the MRB.

Anthropogenic activities and intensive agricultural practices have led to significant changes in LULC within the MRB between 1994 and 2025. A major shift observed is the expansion of agricultural land, with the area increasing from 449.6 km² to 899.2 km² (Figure 9).

Against the backdrop of this agricultural expansion, barren land decreased by 37.4%, dropping from 728.1 km² to 456.0 km². Furthermore, rapid infrastructure development and urbanization have resulted in a substantial increase in the area covered by roads and settlements, rising from 26.1 km² to 134.4 km².

The impact of human and economic development is also evident in the natural ecosystem. The area under natural vegetation declined from 371.3 km² to approximately 324 km², while scrub land saw a reduction of 17.5%. Similarly, a decline of approximately 26% was recorded in the area covered by surface water bodies (Figure 10).

Overall, the LULC changes in the MRB highlight the mounting pressure that agricultural expansion, urbanization, and infrastructure development exert on the natural ecosystem. This situation highlights the importance of sustainable land and water resource management alongside socio-economic progress.

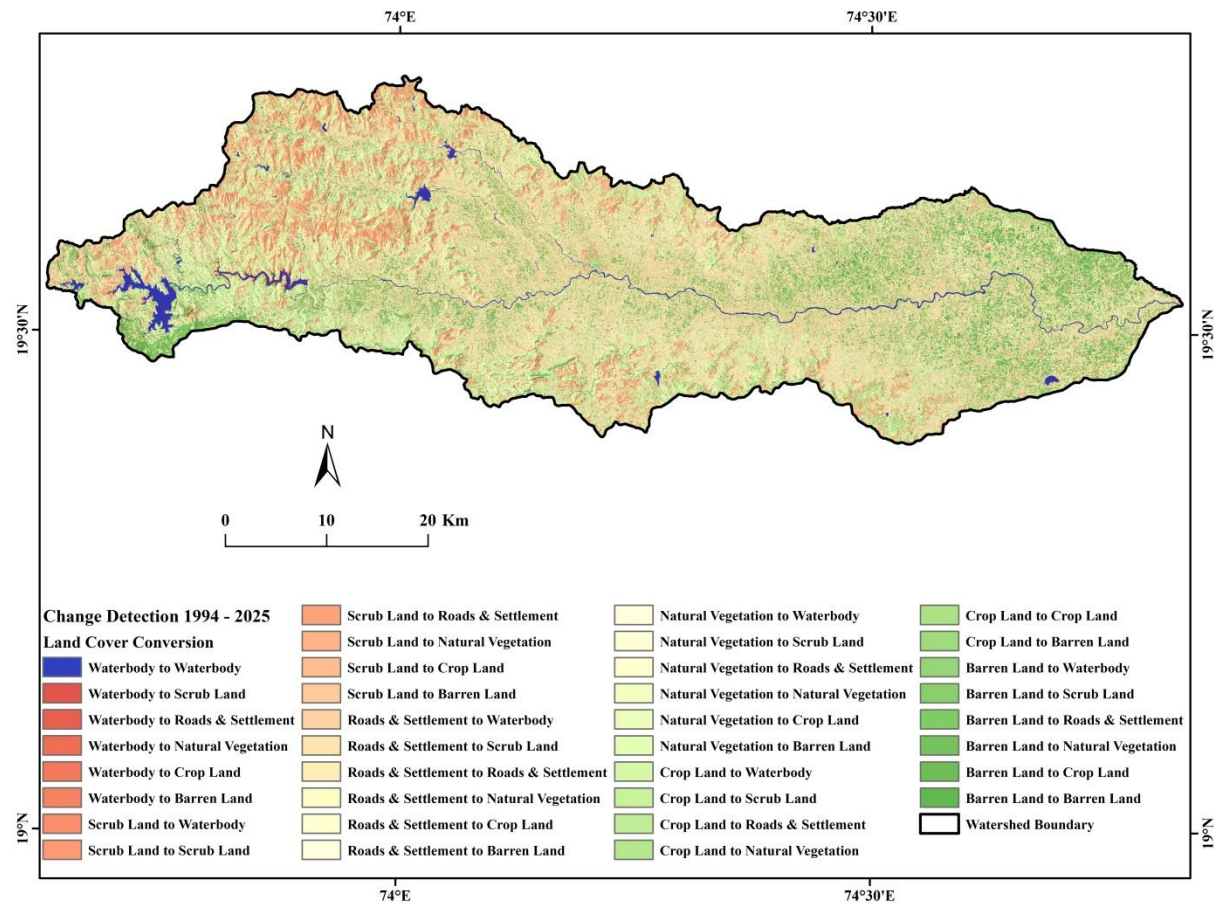


Figure 6. LULC dynamics by confusion matrix in PRB (1994–2025)

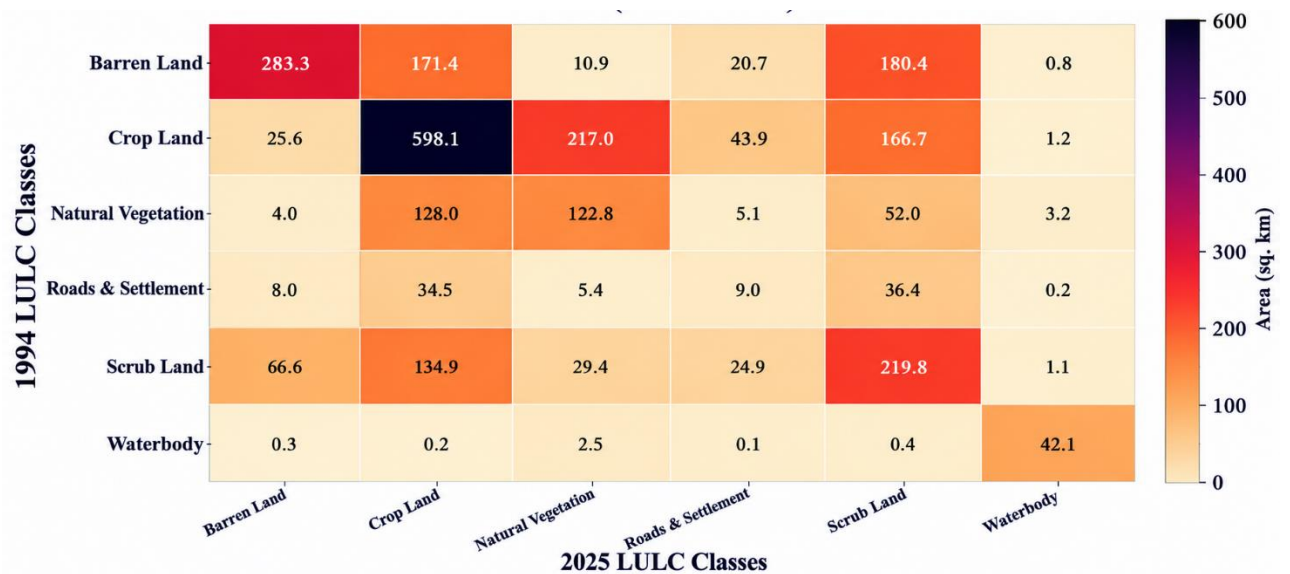


Figure 7. LULC Transition Matrix (Pravara Basin)

Table 6. LULC (Mula basin)

Class Name	2025		1994		Change (%)
	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	
Barren Land	456.0	15.7	728.1	25.1	-9.4
Cropland	899.2	31.0	449.6	15.5	15.5
Natural Vegetation	324.6	11.2	371.3	12.8	-1.6
Roads and Settlement	134.4	4.6	26.1	0.9	3.7
Scrub Land	1033.4	35.6	1250.2	43.1	-7.5
Water body	55.7	1.9	75.4	2.6	-0.7

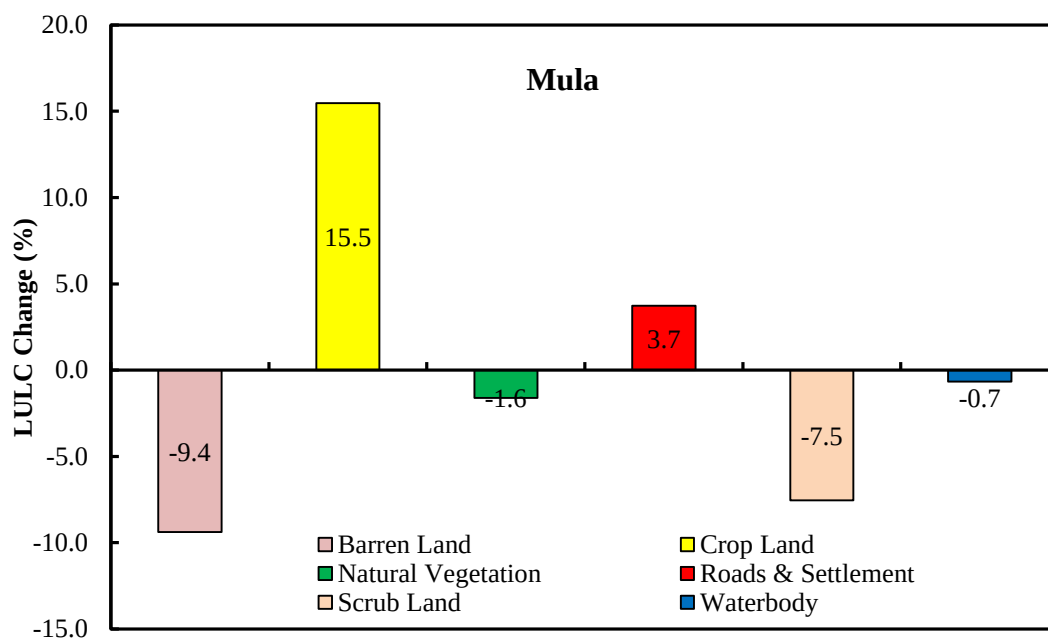


Figure 8. Overall LULC change in the MRB (1994–2025)

5 CONCLUSION

The present study demonstrates substantial and spatially heterogeneous LULC changes in the MPRBs during 1994–2025. In the PRB, cropland increased by 4.0% and scrubland by 6.6%, whereas barren land decreased by 10.7%. In the MRB, cropland showed a more pronounced increase of 15.5%, while barren land and scrubland decreased by 9.4% and 7.5%, respectively. Roads and settlements increased by 3.7% in the MRB, indicating a notable expansion of developed land.

The transition-matrix analysis provided further insight into the direction and magnitude of these changes. Using the ArcMap 10.8.1 Combine tool, the 1994 and 2025 classified LULC maps were integrated on a pixel-by-pixel basis to identify class-to-class transitions. The analysis indicated substantial conversion of barren land toward cropland and scrubland in the PRB, while the

MRB showed considerable conversion of barren and scrubland toward cropland and developed land. Thus, the transition analysis complemented the overall area-based comparison by identifying the specific pathways of landscape transformation. The 2025 LULC classification achieved an overall accuracy of 89%, with a Kappa coefficient of 0.8959, indicating good agreement between the classified map and reference information. The integration of multi-temporal Landsat imagery, supervised classification, GIS-based spatial analysis, the Combine tool, transition-matrix analysis, and field observations provided an effective framework for assessing long-term LULC dynamics.

Overall, the findings demonstrate contrasting LULC trajectories between the two basins, characterized mainly by agricultural expansion, reduction of barren and semi-natural surfaces, and increasing developed land,

particularly in the MRB. The results provide a quantitative baseline for future land and water-resource planning. Continued monitoring using higher-resolution satellite imagery, field observations, and GIS-based techniques is

recommended to identify emerging agricultural, settlement, vegetation, and hydrological change hotspots and to support sustainable watershed management.

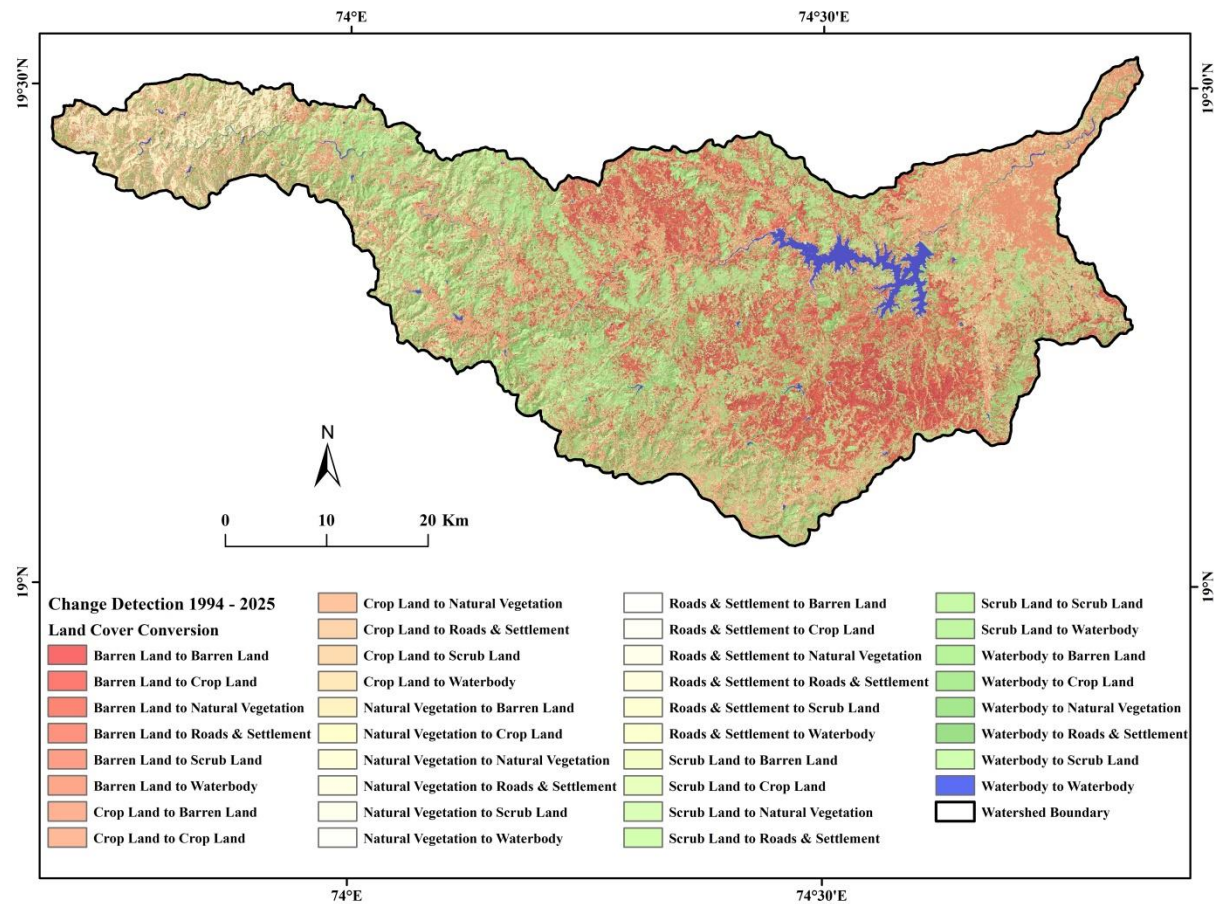


Figure 9. LULC dynamics by confusion matrix in MRB (1994–2025)

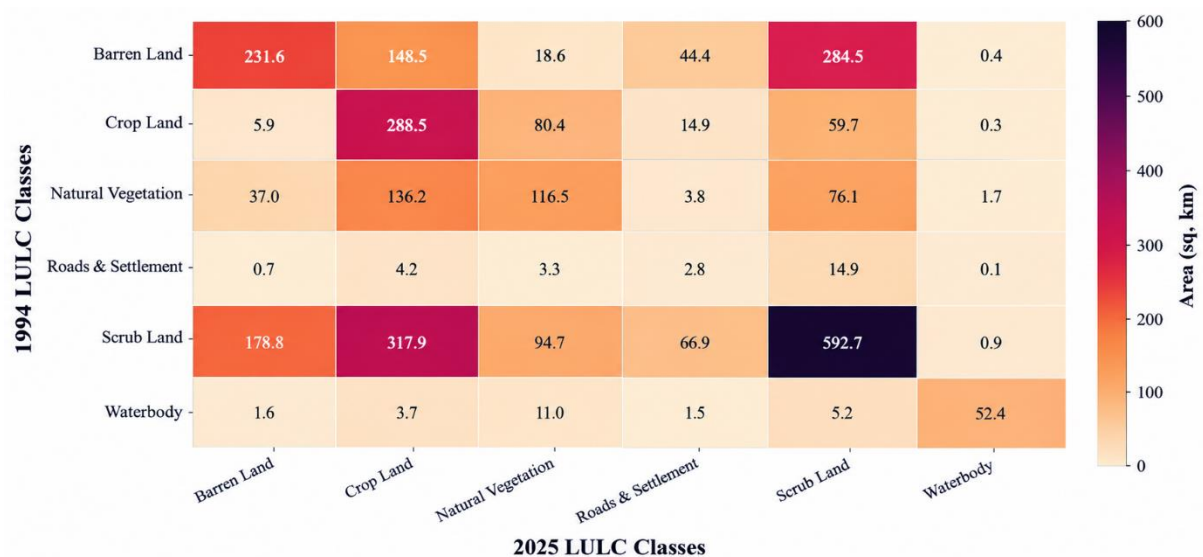


Figure 10. LULC Transition Matrix (Mula Basin)

6 LIMITATIONS

1. Reliable and temporally consistent historical reference data for 1994 were unavailable; therefore, conventional accuracy assessment was not performed for the 1994 LULC classification.
2. Differences in sensor characteristics between Landsat-5 TM (1994) and Landsat-9 OLI-2/TIRS-2 (2025) may influence the comparability of LULC classifications.
3. The analysis uses only two temporal datasets (1994 and 2025) and therefore does not capture intermediate or short-term LULC changes.
4. Similar spectral responses among cropland, scrubland, barren land, and sparsely vegetated areas may introduce classification uncertainty.
5. The transition matrix identifies spatial changes between LULC classes but does not independently establish the specific socioeconomic or environmental drivers responsible for those changes.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ABBREVIATIONS

ERDAS 2014: The Earth Resource Data Analysis System 2014; **GIS:** Geographic Information Systems; **GPS:** Global Positioning System; **LULC:** Land Use and Land Cover; **MPRBs:** Mula and Pravara River Basins; **MRB:** Mula River Basin; **OLI-2:** Operational Land Imager-2; **PRB:** Pravara River Basin; **RS:** Remote Sensing; **SOI:** Survey of India; **TIRS-2:** Thermal Infrared Sensor-2; **TM:** Thematic Mapper.

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