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Remote sensing and GIS-based assessment of spatio-temporal land use and land cover dynamics in Churachandpur district, Manipur, Northeast India

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Abstract

Land use and land cover (LULC) change is a key indicator of environmental transformation, particularly in ecologically fragile mountainous regions. This study examines the spatio-temporal dynamics of LULC in Churachandpur district, Manipur, Northeast India, over a 30-year period (1994-2024) using multi-temporal Landsat datasets and GIS techniques. Landsat 5 TM (1994, 2009) and Landsat 8 OLI (2024) imagery were classified into five categories—vegetation cover, fallow land, agricultural land, built-up area, and water bodies—using the Maximum Likelihood supervised classification algorithm. Classification accuracy assessment based on a confusion matrix yielded satisfactory overall accuracy and kappa statistics across all time periods. Results indicate that vegetation cover remained dominant throughout the study period, while fallow land showed strong temporal variability associated with shifting cultivation practices. Agricultural land exhibited a gradual decline, whereas built-up areas expanded significantly, particularly after 2009, reflecting increasing urbanization and infrastructure development. Water bodies showed a slight but consistent increase. Post-classification change detection revealed pronounced bi-directional transitions between vegetation cover and fallow land, highlighting dynamic land-use cycling. The study underscores significant landscape restructuring driven by socio-economic and environmental processes and provides a baseline for sustainable land management in Northeast India.

Keywords: Land use and land cover (LULC), Remote sensing, Geographic Information System (GIS), Spatio-temporal analysis, Change detection, Churachandpur district, Northeast India, Landsat imagery

1. Introduction

Land cover refers to the physical and biophysical attributes of the Earth's surface, including vegetation, water bodies, soil, and built-up areas, whereas land use describes the manner in which humans utilize and manage these resources. As land use directly influences land cover, both concepts are intrinsically linked and are commonly analysed together in environmental and geographical studies.

Land use and land cover (LULC) change is a key driver of environmental transformation, significantly affecting ecosystem structure, hydrological processes, biodiversity, soil quality, and local to regional climate systems. Rapid population growth, anthropogenic pressure, urban expansion, infrastructural development, and shifting agricultural practices have accelerated LULC change globally. These changes are particularly pronounced in ecologically fragile mountainous regions, where livelihoods are closely dependent on natural resources and land systems are highly sensitive to disturbance.

Remote sensing and Geographic Information System (GIS) technologies have emerged as powerful tools for monitoring and quantifying LULC dynamics. Remote sensing provides repetitive, synoptic, and cost-effective Earth observation data, while GIS enables efficient spatial analysis, modelling, and visualization. The integration of these technologies has therefore become a standard approach in environmental monitoring, land resource management, and regional planning studies.

Numerous studies have applied geospatial techniques to assess LULC dynamics across different regions. For instance, Juliev *et al.* (2019)^[7] examined LULC change in Uzbekistan, while Yang *et al.* (2017)^[22] investigated its role in urban heat island intensification in China. In South Asia, rapid urban expansion and associated environmental impacts have been

widely reported in Pakistan. In India, LULC studies have been conducted in regions such as the Sikkim Himalaya, Dhanbad district, and Imphal city, while in Manipur, research has focused on forest fragmentation and landscape dynamics in Ukhrul and Senapati districts.

Churachandpur district, located in the southern part of Manipur, is characterized by rugged terrain, dense forest cover, and widespread shifting cultivation practices. In recent decades, the district has experienced notable land use changes driven by population growth, urbanization, infrastructure development, and increasing pressure on natural resources. Despite its ecological importance, systematic district-level studies on long-term LULC dynamics in Churachandpur remain limited.

Therefore, the present study aims to analyse the spatio-temporal dynamics of LULC in Churachandpur district over a 30-year period (1994-2024) using remote sensing and GIS techniques. The study further identifies major land transformation trends and provides baseline information to support sustainable land management and regional planning in this ecologically sensitive region.

2. Study Area

Churachandpur district is located in the southern part of Manipur, Northeast India, between 23°56'N to 24°37'N latitude and 93°21'E to 93°53'E longitude (Figure.1). The district forms part of the Manipur Western Hills within the

Indo-Myanmar orogenic belt and is characterized by highly dissected mountainous terrain, steep slopes, and narrow valleys. Elevation ranges from approximately 900 to 1000 m above mean sea level, with local variation controlled by structural deformation and fluvial incision.

2.1 Physiography

The district exhibits rugged physiography dominated by parallel hill ranges oriented in a north-south direction. The terrain is highly unstable in several locations due to steep slopes, active erosion, and frequent mass-wasting processes. Valley bottoms are relatively narrow and are mainly occupied by settlements and agricultural land, while upland areas are dominated by forest cover and shifting cultivation (jhum) landscapes.

2.2 Geology

Geologically, the district is composed predominantly of Tertiary sedimentary formations belonging to the Surma and Barail groups. Lithological units include sandstone, shale, siltstone, and occasional conglomerates. These formations are intensely folded and faulted due to tectonic activity associated with the Indo-Myanmar subduction zone. The region lies in a seismically active belt, and ongoing crustal deformation significantly influences slope instability, drainage evolution, and landform development.

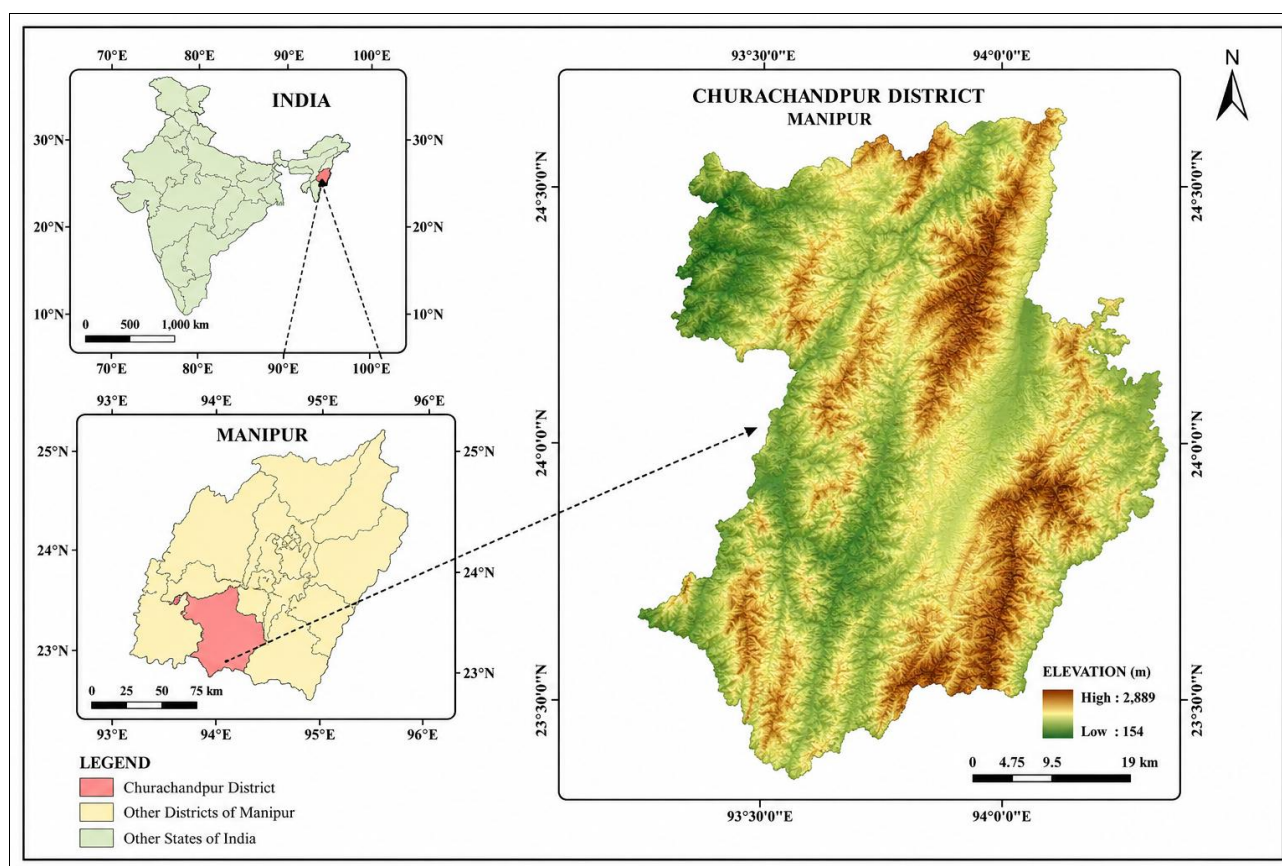


Fig 1: Churachandpur district, Manipur

2.3 Soils

Soils in the district are mainly derived from sedimentary parent materials and are generally classified as deep to moderately deep, acidic, and well-drained upland soils. Red and yellow loamy soils dominate the hill slopes, while

valley regions contain relatively more fertile alluvial soils. Soil texture varies from sandy loam to clay loam depending on topographic position. However, soil fertility is generally low to moderate due to intense leaching under heavy monsoonal rainfall and continuous shifting cultivation

practices, which contribute to soil erosion and nutrient depletion.

2.4 Climate

The district experiences a humid subtropical monsoon climate characterized by warm, humid summers, intense rainfall during the monsoon season, and cool, dry winters. The southwest monsoon contributes the majority of annual rainfall, making the region highly prone to soil erosion, landslides, and rapid geomorphic changes.

2.5 Drainage

The drainage system is primarily controlled by structurally guided rivers, including the Khuga, Tuivai, Tuitha, Leimatak, and Manipur rivers. These rivers exhibit dendritic to sub-dendritic drainage patterns in valley regions and are highly responsive to seasonal rainfall variability. The Khuga River system is particularly significant due to the presence of the Khuga Dam, which has also influenced local hydrological and land use conditions.

2.6 Vegetation and Land Use

The district is largely covered by dense subtropical hill forests. Vegetation patterns are strongly influenced by altitude, slope, and human intervention. Shifting cultivation (jhum) is widely practiced in upland areas, resulting in a mosaic of forest, secondary vegetation, and fallow land. Increasing anthropogenic pressure has led to gradual conversion of forested areas into agricultural and settlement zones in recent decades.

2.7 Socio-economic Profile

According to the Census of India (2011), the district has a population of 226,884 with a literacy rate of 82.78% and a sex ratio of 975 females per 1000 males. Agriculture and forest-based activities form the primary livelihood base. Rapid population growth, infrastructure development, and urban expansion—particularly around Churachandpur town, the district headquarters—have significantly influenced land use dynamics.

3. Methodology

3.1 Data preparation and processing

Cloud-free (cloud cover <10%) multi-temporal Landsat satellite imagery was utilized to analyse the spatial and temporal dynamics of land use and land cover (LULC) in Churachandpur district, Manipur, over a 30-year period (1994-2024). Landsat 5 Thematic Mapper (TM) imagery was employed for the years 1994 and 2009, whereas Landsat 8 Operational Land Imager (OLI) imagery was used

for 2024. All satellite datasets were obtained from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre, which provides freely accessible and radiometrically calibrated Earth observation data.

To ensure temporal consistency, satellite images corresponding to Path 135 and Row 43 were selected for all three years. Each dataset has a spatial resolution of 30 m, making Landsat imagery suitable for regional-scale LULC mapping and long-term environmental monitoring. Images were acquired during comparable seasons to minimize the influence of seasonal vegetation variability and phenological differences on classification accuracy.

Prior to classification, the satellite images underwent a series of standard pre-processing procedures to improve data quality and ensure consistency among the multi-temporal datasets. Radiometric correction was applied to reduce sensor-related noise and convert the digital numbers into standardized reflectance values. Atmospheric correction was subsequently performed to minimize atmospheric scattering and absorption effects, thereby improving spectral consistency between the different acquisition dates.

Following radiometric and atmospheric corrections, all images were geometrically corrected and accurately registered to the Universal Transverse Mercator (UTM) coordinate system, WGS 84 datum, ensuring precise pixel-to-pixel correspondence among the three temporal datasets. Accurate geometric registration is essential for reliable change detection, as even minor positional errors can significantly affect the interpretation of land-cover transitions.

Subsequently, individual spectral bands, including the Blue (B), Green (G), Red (R), Near-Infrared (NIR), and Shortwave Infrared (SWIR) bands, were stacked to generate multispectral composite images suitable for visual interpretation and supervised classification. These spectral bands were selected because they provide valuable information for discriminating vegetation, agricultural land, built-up areas, water bodies, and fallow land.

The administrative boundary of Churachandpur district was then used to clip the satellite images, thereby restricting the analysis exclusively to the study area. This step reduced computational requirements and eliminated unnecessary information outside the district boundary.

A summary of the satellite datasets, including sensor type, acquisition date, spatial resolution, and path/row information, is presented in Table 1, while the overall methodological framework adopted for image pre-processing, supervised classification, accuracy assessment, and change detection is illustrated in Figure 2.

Table 1: Details of data sources and datasets used in the study

Sl. No.	Satellite Data	Date of acquisition	Path	Row	Resolution(m)
1	Landsat 5 TM	21/Feb/1994	135	43	30
2	Landsat 5 TM	14/Feb/2009	135	43	30
3	Landsat 8 OLI	11/Mar/2024	135	43	30

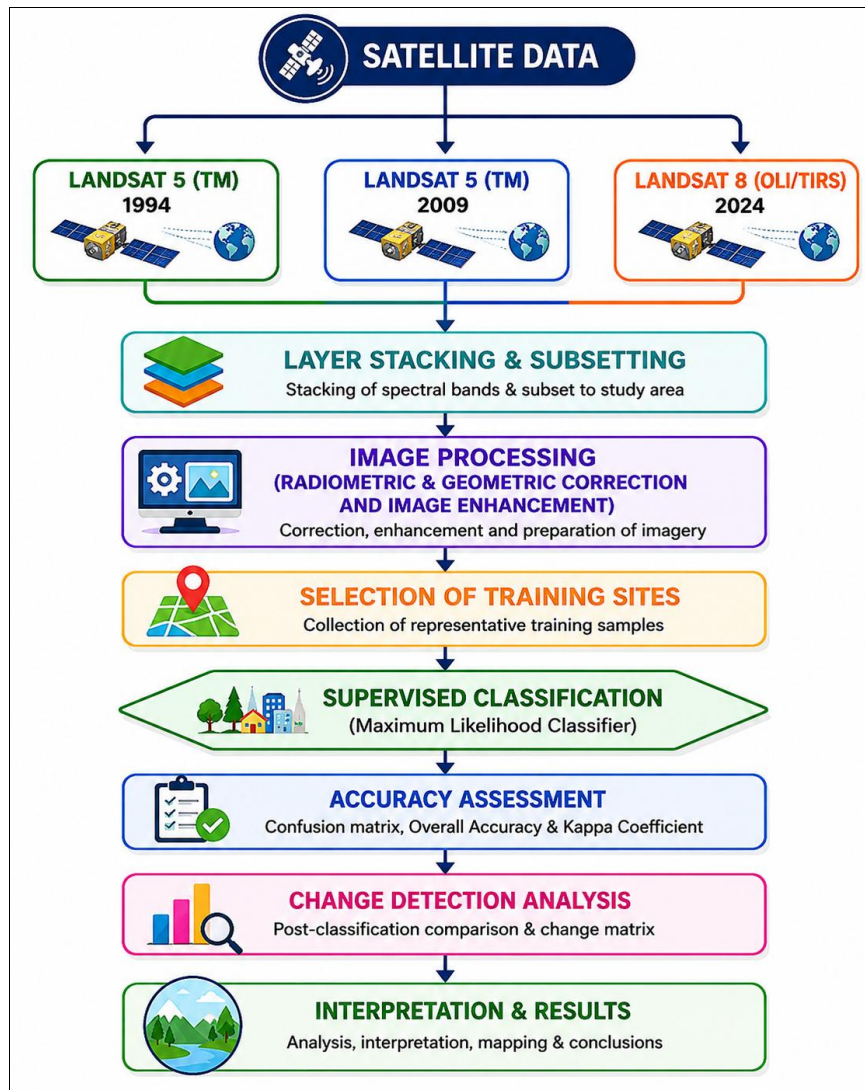


Fig 2: Methodological flow chart of the study

3.2 Land Use and Land Cover Classification and Change Detection

The pre-processed Landsat images were imported into ArcGIS 10.8 for land use/land cover (LULC) classification and change detection. Initially, the individual spectral bands (blue, green, red, near-infrared (NIR), and shortwave infrared (SWIR)) were stacked to generate multispectral composite images. The study area was subsequently extracted by clipping the composite images using the administrative boundary of Churachandpur district.

To facilitate visual interpretation and improve the discrimination of different land-cover features, standard False Colour Composite (FCC) images were generated using the NIR, red, and green bands. The FCC images enhanced the contrast between vegetation, agricultural fields, settlements, water bodies, and other land-cover types, thereby assisting in the selection of representative training samples for supervised classification.

Supervised classification was performed for the years 1994, 2009, and 2024 using the Maximum Likelihood Classifier (MLC), one of the most widely adopted parametric classification algorithms in remote sensing. The classifier assigns each pixel to the class with the highest probability based on the statistical characteristics of the training samples. Training samples for each class were selected using field knowledge, high-resolution satellite imagery,

Google Earth, and visual interpretation of the FCC images. Based on their spectral characteristics and land-use patterns, the study area was classified into five major LULC categories: vegetation cover, fallow land, agricultural land, built-up area, and water body.

Following classification, post-classification change detection was carried out to evaluate spatial and temporal changes in LULC between 1994-2009, 2009-2024, and the overall period 1994-2024. A cross-tabulation (change matrix) technique was employed to quantify the conversion of one land-cover class into another, thereby identifying the dominant land-use transitions during the study period. The area and percentage change for each LULC class were subsequently calculated to assess long-term landscape dynamics.

The annual rate of change for each LULC class was estimated using the following equation (1):

$$C = \frac{A_2 - A_1}{T} \quad (1)$$

where

- C = annual rate of change of the LULC class ($\text{km}^2 \text{ year}^{-1}$),
- A_1 = area of the LULC class in the initial year (1994),

- A_2 = area of the LULC class in the final year (2024), and
- T = time interval between the two observations (30 years).

The combination of supervised classification, post-classification comparison, and change matrix analysis enabled a comprehensive assessment of the magnitude, direction, and rate of LULC changes in Churachandpur district over the 30-year study period.

3.3 Accuracy Assessment

Accuracy assessment and error matrix analysis are widely used to evaluate the reliability of classified remote sensing outputs (Reis, 2008) [12]. In this study, classification accuracy was assessed for each LULC map to validate the reliability of the results (Devi and Shimrah, 2022) [3]. Accuracy assessment is a fundamental component of remotely sensed data analysis as it determines the quality and robustness of the classification output (Congalton, 2001; Sharma *et al.*, 2016) [2, [15].

A confusion matrix (error matrix) was constructed by comparing classified data with reference data to evaluate classification performance. High-resolution imagery from Google Earth Pro was used as the reference dataset for validation. From the confusion matrix, overall accuracy, kappa coefficient, producer's accuracy (omission error), and user's accuracy (commission error) were derived.

Overall accuracy represents the proportion of correctly classified pixels to the total number of reference pixels within the error matrix (Anand, 2017) [1]. The kappa coefficient provides a statistical measure of agreement between classified and reference data beyond chance agreement. Producer's accuracy indicates the probability that a reference pixel is correctly classified, whereas user's accuracy represents the probability that a classified pixel actually corresponds to the real-world category.

The kappa coefficient and overall accuracy were computed using Equations (2) and (3), respectively. Producer's and user's accuracies were calculated using Equations (4) and (5) following Shimrah *et al.* (2022) [3].

$$\hat{K} = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \cdot x_{+i})} \quad (2)$$

Where, $\hat{K}$ = kappa co-efficient

N = total number of samples

r = number of classes

X_{ii} = diagonal values in the matrix

x_{i+} = total samples in row i

x_{+i} = total samples in column i .

Overall Accuracy (OA),

$$OA = \frac{1}{N} \sum_{i=1}^r n_i \quad (3)$$

Where, N = total number of pixels

r = number of classes

n = correctly identified pixels in each class.

Producer accuracy (PA),

$$PA = \frac{n_i}{n_i c_{0l}} \quad (4)$$

Where, n_i = correctly identified pixels in the class

$n_i c_{0l}$ = column total for the considered class.

User accuracy (UA),

$$UA = \frac{n_i}{n_{irow}} \quad (5)$$

Where, n_i = correctly identified pixels in the class

n_{irow} = row total for the considered class.

4. Results

4.1 Accuracy Assessment

Accuracy assessment is an essential step in land use/land cover (LULC) classification, as it evaluates the reliability and quality of the classified maps by comparing the classified data with reference (ground truth) information. In the present study, the accuracy of the supervised classification was assessed using a confusion (error) matrix, from which the Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa coefficient (κ) were calculated. These statistical measures provide a comprehensive evaluation of classification performance by quantifying both omission and commission errors.

The classification results demonstrated a high level of accuracy for all three study years (Table 2). The overall accuracy values were 89.25%, 94.57%, and 87.16% for 1994, 2009, and 2024, respectively. Among these, the 2009 classification achieved the highest overall accuracy, indicating excellent agreement between the classified image and the reference data. The relatively lower overall accuracy observed in 2024 may be attributed to increased landscape heterogeneity, rapid urban expansion, and spectral similarity among vegetation, fallow land, and built-up areas, which are common challenges in medium-resolution satellite image classification.

The Kappa coefficient (κ) further confirmed the reliability of the classification results, with values of 0.85, 0.92, and 0.83 for 1994, 2009, and 2024, respectively. According to the classification proposed by Landis and Koch (1977), Kappa values greater than 0.80 represent almost perfect agreement between the classified map and the reference data. Therefore, the obtained Kappa statistics indicate that the classification results are highly reliable and suitable for subsequent change detection and temporal analysis.

Producer's Accuracy (PA) and User's Accuracy (UA) varied among the individual LULC classes. Agricultural land and water bodies consistently achieved the highest accuracy values throughout the study period. Water bodies recorded 100% Producer's Accuracy in all three years, demonstrating that all reference water pixels were correctly identified, while User's Accuracy reached 100% in 2009 and 98.44% in 2024, indicating minimal commission errors. These high accuracies are mainly due to the distinctive spectral characteristics of water in Landsat imagery, which facilitate accurate discrimination from surrounding land-cover types. Similarly, agricultural land exhibited consistently high Producer's and User's Accuracy values, exceeding 94% in

all study years. The distinct spectral response of cultivated fields during the image acquisition period contributed to the reliable identification of agricultural areas.

In contrast, vegetation cover and fallow land exhibited comparatively lower accuracies, particularly in the 2024 classification. Vegetation cover recorded a Producer's Accuracy of 67.07% in 2024 despite achieving a User's Accuracy of 100%, indicating that while all pixels classified as vegetation were correctly identified, a considerable number of actual vegetation pixels were misclassified into other classes. Likewise, fallow land showed lower Producer's and User's Accuracy values in 2024 due to spectral overlap with regenerating vegetation and agricultural land. These findings highlight the influence of seasonal vegetation conditions and the heterogeneous nature of shifting cultivation landscapes on classification performance.

The built-up area class displayed an interesting pattern. Although Producer's Accuracy reached 100% in 2024, User's Accuracy decreased to 59.74%, indicating that while all reference built-up pixels were successfully detected, a significant proportion of pixels classified as built-up actually belonged to other land-cover classes. This overestimation is likely caused by spectral confusion between built-up surfaces, exposed soil, barren land, and construction sites, which exhibit similar reflectance characteristics in medium-resolution Landsat imagery.

Overall, the accuracy assessment demonstrates that the supervised classification approach adopted in this study produced highly reliable LULC maps for all three study years. The overall accuracy values exceeded the commonly accepted threshold of 85%, while the Kappa coefficients consistently remained above 0.80, confirming strong agreement between the classified maps and the reference data. These results validate the suitability of the classification methodology and provide confidence in the subsequent LULC change detection and spatial analysis conducted for Churachandpur district

Table 2: Overall accuracy and Kappa coefficient for the classified maps of 1994, 2009 and 2024.

Sl. No.	Year	Overall Accuracy	Kappa Coefficient
1	1994	89.25%	0.85
2	2009	94.57%	0.92
3	2024	87.16%	0.83

The 2009 LULC classification achieved the highest accuracy among the three study years, with an overall accuracy of 94.57% and a Kappa coefficient (κ) of 0.92, indicating excellent agreement between the classified map and the reference data. Although the overall accuracies for 1994 (89.25%; $\kappa = 0.85$) and 2024 (87.16%; $\kappa = 0.83$) were comparatively lower, they remained well above the widely accepted threshold of 85% for reliable LULC classification. The comparatively lower accuracy in 2024 may be attributed to increased landscape heterogeneity, rapid urban

expansion, and greater spectral similarity among vegetation, fallow land, agricultural land, and built-up areas. Nevertheless, the consistently high overall accuracy and Kappa coefficient values obtained for all three years demonstrate the robustness of the supervised classification approach and confirm the suitability of the generated LULC maps for subsequent change detection and spatio-temporal analysis.

Table 3 presents the class-wise producer's and user's accuracies for vegetation cover, fallow land, agricultural land, built-up area, and water body. Agricultural land and water bodies exhibited consistently high classification accuracies across all study years, whereas vegetation cover and fallow land showed comparatively lower accuracies due to spectral similarities and seasonal variations associated with shifting cultivation. The relatively lower user accuracy observed for built-up areas in 2024 may be attributed to spectral confusion between built-up surfaces, exposed soil, and barren land.

Overall, the high overall accuracies and Kappa coefficients demonstrate that the supervised classification produced reliable and consistent LULC maps. Therefore, the classified datasets are considered sufficiently accurate for subsequent change detection analysis and assessment of long-term land use and land cover dynamics in Churachandpur district.

4.2 Land Use and Land Cover Status in 1994, 2009, and 2024

Multi-temporal Landsat satellite imagery was used to assess the spatial and temporal distribution of land use and land cover (LULC) in Churachandpur district over a 30-year period. Historical LULC patterns were derived from Landsat 5 Thematic Mapper (TM) imagery for 1994 and 2009, while Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) imagery was used for 2024. Using a supervised classification approach based on the Maximum Likelihood algorithm, the study area was classified into five major LULC categories: vegetation cover, fallow land, agricultural land, built-up area, and water body.

The classified LULC maps for the three study years are presented in Figure 3, illustrating the spatial distribution and temporal evolution of the major land-cover classes. Vegetation cover remained the dominant land-cover category throughout the study period, occupying a substantial proportion of the district. Fallow land was mainly distributed along the central and eastern parts of the district, reflecting the widespread practice of shifting cultivation. Agricultural land was concentrated in valley bottoms and relatively gentle slopes, whereas built-up areas were primarily confined to Churachandpur town and surrounding settlements, showing noticeable expansion over time. Water bodies occupied the smallest proportion of the study area, with a marked increase after 2009 following the impoundment of the Khuga Dam reservoir.

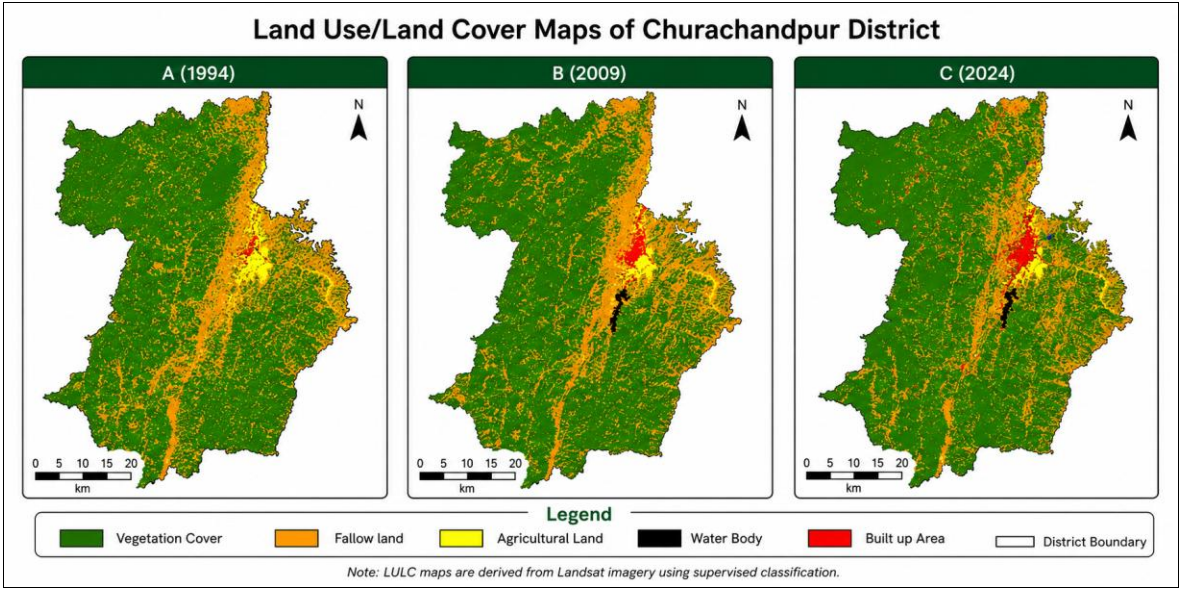


Fig 3: Land Use and Land Cover map of Churachandpur District of Manipur

Visual comparison of the classified maps reveals considerable changes in the spatial distribution of LULC classes between 1994 and 2024. The most notable changes include the expansion of built-up areas, fluctuations in fallow land associated with shifting cultivation, regeneration of vegetation in several parts of the district, and a slight increase in water bodies. These observations indicate that

both anthropogenic activities and natural landscape processes have significantly influenced the land-use dynamics of Churachandpur district over the past three decades. The quantitative changes in area and percentage of each LULC class are presented and discussed in the following sections.

Table 4: Land Use/Land Cover (LULC) Change Statistics

LULC Classes	Area Change (km ²)			Percentage Change (%)			Rate of Change (km ² /year) C 1994-2024
	1994-2009	2009-2024	1994-2024	1994-2009	2009-2024	1994-2024	
Vegetation Cover	-49.44	84.05	34.61	-2.04	3.48	1.43	1.15
Fallow Land	52.80	-127.55	-74.75	2.18	-5.28	-3.09	-2.49
Agricultural Land	-17.93	3.69	-14.24	-0.74	0.15	-0.59	-0.47
Built-up Area	10.32	39.19	49.51	0.43	1.62	2.05	1.65
Water Body	4.25	0.62	4.87	0.18	0.03	0.20	0.16

The positive (+) and negative (-) signs denote inter-period increases and decreases in values, respectively

Table 4 presents the area change (km²), percentage change (%), and annual rate of change (km²/year) for the five major land use/land cover (LULC) classes in Churachandpur district during the periods 1994-2009, 2009-2024, and the overall period 1994-2024. Positive values indicate an increase in area, whereas negative values indicate a decrease.

4.2.1 Vegetation Cover

Vegetation cover experienced a decline of 49.44 km² (-2.04%) between 1994 and 2009. However, during 2009-2024, it increased substantially by 84.05 km² (3.48%), resulting in a net gain of 34.61 km² (1.43%) over the entire study period. The average annual rate of change was 1.15 km²/year, indicating an overall recovery of vegetation, likely due to natural regeneration, afforestation, and the abandonment of some shifting cultivation areas.

4.2.2 Fallow Land

Fallow land increased by 52.80 km² (2.18%) during 1994-2009, reflecting the widespread practice of shifting cultivation. In contrast, it declined sharply by 127.55 km² (-5.28%) between 2009 and 2024. Consequently, the overall change from 1994 to 2024 was a decrease of 74.75 km² (-

3.09%), with an annual rate of -2.49 km²/year. This reduction suggests that many fallow areas were converted into vegetation, agricultural land, or built-up areas.

4.2.3 Agricultural Land

Agricultural land decreased by 17.93 km² (-0.74%) during the first period but showed a slight increase of 3.69 km² (0.15%) during 2009-2024. Overall, agricultural land recorded a net loss of 14.24 km² (-0.59%), corresponding to an annual decline of 0.47 km²/year. This trend indicates a gradual reduction in cultivated land, possibly due to urban expansion, land abandonment, and changing agricultural practices.

4.2.4 Built-up Area

Built-up area exhibited continuous growth throughout the study period. It increased by 10.32 km² (0.43%) between 1994 and 2009 and expanded more rapidly by 39.19 km² (1.62%) during 2009-2024. Overall, the built-up area increased by 49.51 km² (2.05%), with the highest annual growth rate of 1.65 km²/year among all LULC classes. This substantial increase reflects rapid urbanization, population growth, infrastructure development, and expansion of settlements across the district.

4.2.5 Water Body

Water bodies increased by 4.25 km² (0.18%) between 1994 and 2009, primarily due to the impoundment created by the Khuga Dam. A further but marginal increase of 0.62 km² (0.03%) occurred during 2009-2024. Overall, water bodies expanded by 4.87 km² (0.20%), with an annual rate of change of 0.16 km²/year, indicating that the water surface remained relatively stable after the dam became operational.

4.2.6 Overall Interpretation

The results indicate that Churachandpur district experienced significant land use transformations over the last three decades. The most notable changes include the rapid expansion of built-up areas, reflecting increasing urbanization and infrastructure development, and the

marked decline in fallow land, suggesting changes in shifting cultivation practices and land conversion. Vegetation cover showed a net increase over the entire study period, indicating partial ecological recovery despite earlier losses. Agricultural land experienced a slight overall decline, while water bodies remained relatively stable following the construction of the Khuga Dam. These findings highlight the combined influence of anthropogenic activities and natural processes on landscape dynamics and emphasize the importance of sustainable land-use planning for conserving natural resources and supporting balanced regional development.

4.3 Change detection of LULC classes from 1994 to 2009, 2009 to 2024 and 1994 to 2024

Table 5: LULC changes of Churachandpur district from 1994 to 2009, 2009 to 2024 and 1994 to 2024

LULC Classes	Area Change (km ²)			Percentage Change (%)			Rate of Change (km ² /year) C 1994-2024
	1994-2009	2009-2024	1994-2024	1994-2009	2009-2024	1994-2024	
Vegetation Cover	-49.44	84.05	34.61	-2.04	3.48	1.43	1.15
Fallow Land	52.80	-127.55	-74.75	2.18	-5.28	-3.09	-2.49
Agricultural Land	-17.93	3.69	-14.24	-0.74	0.15	-0.59	-0.47
Built-up Area	10.32	39.19	49.51	0.43	1.62	2.05	1.65
Water Body	4.25	0.62	4.87	0.18	0.03	0.20	0.16

The positive (+) and negative (-) signs denote inter-period increases and decreases in values, respectively

The Table 5 and figure 4 together illustrate the magnitude and trend of land use/land cover (LULC) changes in Churachandpur district during 1994-2009, 2009-2024, and the overall period 1994-2024. While the graph provides a visual comparison of percentage changes among different LULC classes, Table 5 presents the corresponding changes in area (km²), percentage change (%), and annual rate of change (km²/year). Together, they provide a comprehensive understanding of the temporal dynamics of land-use change in the district.

Vegetation cover experienced contrasting trends during the study period. Between 1994 and 2009, it declined by 49.44 km² (-2.04%), indicating the conversion of forested land into fallow land, agricultural land, and settlements. However, during 2009-2024, vegetation cover increased substantially by 84.05 km² (3.48%), resulting in a net increase of 34.61 km² (1.43%) over the entire study period, with an average annual gain of 1.15 km²/year. The graph clearly shows this reversal, suggesting vegetation recovery through natural regeneration, plantation activities, and reduced pressure from shifting cultivation in some areas.

Fallow land showed the greatest fluctuation among all LULC classes. It increased by 52.80 km² (2.18%) during 1994-2009, reflecting the widespread practice of shifting cultivation (jhum). However, it decreased sharply by 127.55 km² (-5.28%) between 2009 and 2024, leading to an overall decline of 74.75 km² (-3.09%), with the highest annual rate of decrease (-2.49 km²/year). The graph highlights this dramatic decline, indicating that large areas of fallow land were converted into vegetation, agricultural land, and built-up areas.

Agricultural land showed relatively minor changes compared to the other classes. It declined by 17.93 km² (-0.74%) during the first period, followed by a slight increase of 3.69 km² (0.15%) during 2009-2024. Despite this recovery, the overall change remained negative, with a net loss of 14.24 km² (-0.59%) and an annual decline of 0.47 km²/year. The graph reflects these modest fluctuations, suggesting that agricultural land remained comparatively

stable, although some cultivated land was converted for other purposes.

Built-up area recorded the most consistent and rapid increase throughout the study period. It expanded by 10.32 km² (0.43%) between 1994 and 2009 and accelerated considerably by 39.19 km² (1.62%) during 2009-2024. Overall, built-up land increased by 49.51 km² (2.05%), representing the highest positive percentage change and the highest annual growth rate (1.65 km²/year). The graph clearly demonstrates this upward trend, reflecting rapid urbanization, population growth, infrastructure development, and the expansion of residential and commercial areas in Churachandpur district.

Water bodies exhibited only minor changes during the study period. They increased by 4.25 km² (0.18%) between 1994 and 2009, primarily due to the formation of the Khuga Dam reservoir, followed by a marginal increase of 0.62 km² (0.03%) during 2009-2024. Consequently, water bodies showed an overall increase of 4.87 km² (0.20%), with an annual growth rate of 0.16 km²/year. The graph indicates that most of the increase occurred during the first period, after which the extent of water bodies remained largely stable.

Overall, both the graph and Table 5 demonstrate that Churachandpur district has undergone significant landscape transformation during the past three decades. The most prominent changes include the rapid expansion of built-up areas, the substantial decline in fallow land, and the recovery of vegetation cover after 2009. Agricultural land experienced only a slight overall decline, whereas water bodies remained relatively stable following the construction of the Khuga Dam. These patterns indicate that urbanization, infrastructure development, shifting cultivation practices, and natural vegetation regeneration have been the primary drivers of land-use change. The combined graphical and tabular analysis provides valuable information for sustainable land-use planning, natural resource management, and environmental conservation in Churachandpur district.

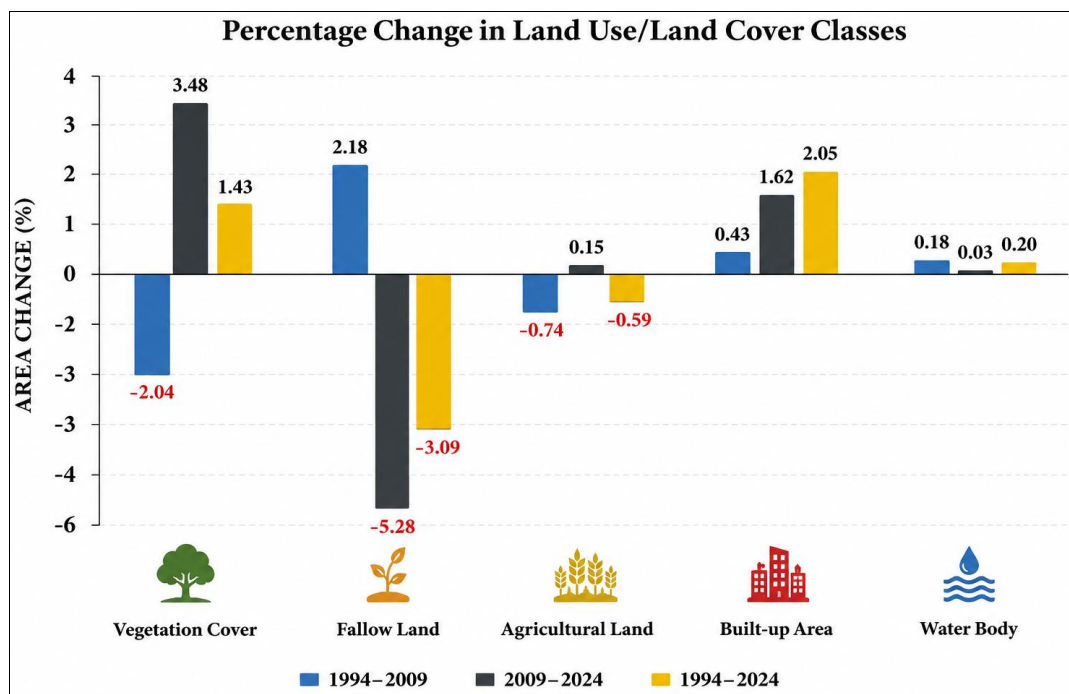


Fig 4: Graphical representation of LULC change during the study period

Table 6: Summary of Land Use/Land Cover (LULC) Changes in Churachandpur District (1994–2024)

LULC Class	Area Change (km ²)			Percentage Change (%)			Rate of Change (km ² /year) 1994–2024	Overall Trend	Major Reason
	1994–2009	2009–2024	1994–2024 (Overall)	1994–2009	2009–2024	1994–2024 (Overall)			
Vegetation Cover	–49.44	84.05	34.61	–2.04	3.48	1.43	1.15	↑ Increased	Natural regeneration, afforestation, abandonment of shifting cultivation
Fallow Land	52.80	–127.55	–74.75	2.18	–5.28	–3.09	–2.49	↓ Decreased	Conversion to vegetation, agriculture and built-up land
Agricultural Land	–17.93	3.69	–14.24	–0.74	0.15	–0.59	–0.47	↓ Slight Decrease	Urban expansion and changing agricultural practices
Built-up Area	10.32	39.19	49.51	0.43	1.62	2.05	1.65	↑ Rapid Increase	Urbanization, infrastructure development and population growth
Water Body	4.25	0.62	4.87	0.18	0.03	0.20	0.16	↑ Slight Increase	Construction of Khuga Dam and reservoir stabilization

Note: The positive (+) and negative (–) signs denote inter-period increases and decreases in values, respectively

5. Conclusion

The present study assessed the spatio-temporal dynamics of Land Use/Land Cover (LULC) in Churachandpur district, Manipur, over a period of thirty years (1994–2024) using multi-temporal Landsat satellite imagery and Geographic Information System (GIS) techniques. The summary presented in Table 6 provides an integrated overview of the major changes observed in the five LULC classes, including area change, percentage change, annual rate of change, overall trend, and the possible driving factors responsible for these transformations.

The results indicate that the landscape of Churachandpur district has undergone substantial changes during the study period owing to the combined influence of anthropogenic activities and natural ecological processes. Among the five LULC classes, built-up area exhibited the most significant increase, recording a net expansion of 49.51 km² (2.05%) with an average annual growth rate of 1.65 km²/year. The continuous increase in built-up land, particularly after 2009, reflects rapid urbanization, population growth, infrastructure

development, and expansion of residential and commercial establishments. This trend clearly indicates increasing developmental pressure on available land resources.

Vegetation cover remained the dominant land-cover class throughout the study period and recorded an overall increase of 34.61 km² (1.43%), corresponding to an annual increase of 1.15 km²/year. Although vegetation cover declined during the period 1994–2009, a remarkable recovery was observed between 2009 and 2024. This positive trend suggests that natural forest regeneration, plantation programmes, and the gradual abandonment of shifting cultivation in some areas have contributed to the restoration of vegetated landscapes. The increase in vegetation cover represents a positive ecological outcome that may enhance biodiversity conservation and ecosystem stability.

In contrast, fallow land experienced the largest overall decline, decreasing by 74.75 km² (3.09%) at an annual rate of 2.49 km²/year. The substantial reduction in fallow land indicates extensive conversion into vegetation, agricultural land, and built-up areas. This pattern reflects changing land-

use practices and suggests a gradual reduction in traditional shifting cultivation systems. The decline also signifies increasing utilization of previously unused or temporarily abandoned land for productive and developmental purposes. Agricultural land exhibited relatively minor fluctuations during the study period. The class showed an overall decline of 14.24 km² (0.59%), with an average annual loss of 0.47 km²/year. Although some recovery occurred after 2009, the overall decreasing trend suggests that portions of agricultural land have been converted to settlements and other non-agricultural uses. The relatively small magnitude of change indicates that agriculture continues to play an important role in the district's economy despite increasing developmental activities.

Water bodies showed the least variation among all LULC classes, with a net increase of 4.87 km² (0.20%) and an annual growth rate of 0.16 km²/year. The increase was primarily associated with the construction of the Khuga Dam, which significantly expanded the water surface during the first study period. After the reservoir reached its operational level, the extent of water bodies remained relatively stable, indicating minimal hydrological changes during the later years.

Overall, the findings summarized in Table 6 demonstrate that urban expansion, infrastructure development, changing agricultural practices, shifting cultivation, and natural vegetation regeneration have been the principal drivers of land-use and land-cover change in Churachandpur district. The simultaneous increase in built-up areas and vegetation cover, together with the decline in fallow and agricultural lands, reflects the evolving interaction between socio-economic development and environmental processes.

The study confirms that remote sensing and GIS provide an efficient and reliable approach for monitoring long-term landscape dynamics. The generated LULC database and change analysis offer valuable baseline information for understanding land transformation patterns and their environmental implications. These findings can support evidence-based decision-making for sustainable land-use planning, forest conservation, watershed management, biodiversity protection, and balanced regional development. In conclusion, the observed LULC changes emphasize the importance of implementing sustainable land management strategies that balance developmental needs with environmental conservation. Continuous monitoring using geospatial technologies, combined with appropriate policy interventions, will be essential for ensuring the sustainable utilization of natural resources and maintaining ecological integrity in Churachandpur district in the future.

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