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Spatiotemporal dynamics of land use/land cover change and landscape fragmentation in the Chittagong Hill Tracts, Bangladesh: implications for ecological connectivity

Asib Ahmed[*1], Hriday Dey[1], and Md. Juhayr Akbar [1]

[1]Department of Geography and Environment, University of Dhaka, 1000 Dhaka, Bangladesh

***Corresponding e-mail:** asib01geo@du.ac.bd

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Abstract

To evaluate ecological sustainability, it is not only important to quantify land-use/land-cover (LULC) change, but also to understand how landscape configuration influences fragmentation patterns and structural connectivity. But traditional LULC mapping based on area often fails to capture structural fragmentation, which can mask ecological degradation. This study combined multi-temporal Landsat data with class-level landscape metrics to examine the spatiotemporal changes in LULC and landscape fragmentation in the ecologically sensitive Chittagong Hill Tracts (CHT), Bangladesh, between 2010 and 2025. Supervised maximum likelihood classification was used to create LULC maps, and six complementary metrics (NP, PD, ED, LPI, AI, and COHESION) were used to quantify fragmentation. The classifications were highly reliable, with overall accuracy of 89–90% and Kappa coefficient of 0.86–0.87. The built-up area grew by 442.95 km² and the vegetation by 502.71 km² during the study period. Although this vegetation recovery appeared to be present, fragmentation metrics showed significant structural degradation. The vegetation LPI dropped significantly from 92.40% to 47.16%, while ED, NP and PD increased, reflecting the trend of larger, continuous habitat patches being subdivided into smaller, more fragmented patches. Built-up landscapes, on the other hand, showed simultaneous growth in LPI, AI, and COHESION, indicating the progressive urbanization of the landscape and the creation of a more connected anthropogenic matrix. The contrasting trajectories showed that increases in vegetation extent was not necessarily reflect improvements in habitat configuration. The findings suggest that landscape configuration is a more sensitive measure of ecological change than traditional area-based LULC statistics and emphasize the importance of incorporating fragmentation metrics into ecological assessment frameworks. This holistic approach offers a solid foundation for ecological monitoring and for landscape-scale planning strategies that focus on the conservation and protection of large core vegetation patches, potential connectivity pathways, and sustainable urban development, core habitat patches, and sustainable urban development in rapidly changing mountainous landscapes.

Keywords: Ecological connectivity, landscape fragmentation, land use/ land cover, urban consolidation.

Introduction

The alteration of land use and land cover (LULC) by humans has changed landscapes globally, resulting in habitat loss, fragmentation and degradation of ecological connectivity (Haddad *et al.* 2015, Yang *et al.* 2025, Sobhani *et al*. 2021, Yang *et al.* 2022). Habitats have been fragmented by deforestation and agricultural development, creating large amounts of "edge" habitat and a loss of interior core habitat. These alterations reduce species dispersal and gene flow, directly impacting biodiversity and ecosystem function (Haddad *et al.* 2015, Kumar *et al.* 2022, Edwards *et al.* 2019 and Hughes *et al.* 2000). For instance, Haddad *et al.* (2015) compiled fragmentation experiments from around the world and found that species richness can be reduced by 13-75% and ecosystem services can be degraded due to habitat fragmentation (Haddad *et al.* 2015). Although forest area is not decreasing, fragmentation can still occur, as a recent global analysis revealed that tropical forests, despite being relatively intact in terms of cover, were the most fragmented from 2000 to 2020, highlighting the need to "curb deforestation and increase connectivity among forest fragments" (Ma *et al.* 2023). Likewise, almost one-third of the world's forests are within 100 m of a forest edge, which results in widespread edge effects on biodiversity and biomass (Yang *et al.* 2025). These results underscore the need for fragmentation and connectivity to be studied at a global scale and investigated at a regional level to guide conservation planning. South Asia has experienced high population growth and development,

resulting in high land change. Bangladesh is not an exception: although there has been some reforestation in recent decades, much of the upland forests in the country have been lost or degraded due to agricultural expansion, fuelwood collection and infrastructure development (Sarkar and Mukul 2024). The Chittagong Hill Tracts (CHT) is a hilly border region of southeast Bangladesh, which contains almost one-third of the national state forest area and rich biodiversity (Sarkar and Mukul 2024). The indigenous people of these hills are engaged in shifting cultivation and agroforestry (Rasul and Thapa 2006) and these hills are also important wildlife corridors linking Indo-Burma biodiversity hotspots. But, due to institutional issues and land conflicts, the CHT forest is highly degraded and fragmented (Sarkar and Mukul 2024). The CHT has been studied for mixed forest cover trends, with some reporting an increase in overall forest area (which is related to community forestry) and others documenting the continued fragmentation of forest, grassland and other classes (Chakma *et al.* 2023). The apparent decoupling of cover and configuration is consistent with global findings that forest cover increases do not necessarily lead to a decrease in fragmentation (Ma *et al.* 2023). Importantly, there are few studies that explicitly connect multi-year LULC change to fragmentation and connectivity metrics in this area. A finer scale analysis is required to quantify not only the extent of forest or agriculture change, but also the changes in landscape structure (patch size, edge density, isolation). Such analysis is timely given global and national conservation commitments (e.g. the UN Decade on Ecosystem Restoration 2021-2030 and Bangladesh's pledge to restore 0.75 M ha under the Bonn Challenge) that hinge on understanding and improving connectivity (Sarkar and Mukul 2024). To address these gaps, we use multi-temporal Landsat imagery (2010-2025) processed in Google Earth Engine (GEE) to produce annual land cover maps for the CHT. The Landsat archive (TM, ETM+, OLI) offers a consistent medium-resolution time series that is ideal for regional LULC monitoring and has been freely available since 2008, leading to a growing number of time-series change-detection studies (Zhu and Woodcock 2017). We produce annual cloud-free composites to capture representative land surface signals (as in the Landsat change-detection literature; Zhu and Woodcock 2017) and use supervised classification (maximum likelihood) to classify water, urban infrastructure, urban green, and barren land. The use and interpretability of this method in LULC mapping (Wulder *et al.* 2019) and its compatibility with the computational framework of GEE (Gorelick *et al.* 2017) justify this approach. Google Earth Engine enables efficient processing of large Landsat time series and on-the-fly compositing (Gorelick *et al.* 2017). The Maximum Likelihood Classifier (MLC) is a widely used supervised classification method that has a strong statistical foundation (Jensen 2005, Lu and Weng 2007) and has been applied to similar landscape analyses with success (Chakma *et al*. 2023, Wulder *et al.* 2019). We use existing landscape ecology tools (McGarigal *et al.* 2012) to quantify landscape fragmentation and infer connectivity impacts, both at the class level and at the landscape level. Patch density, largest patch index, edge density, mean patch area, and aggregation index are all measures of fragmentation (Turner 2018, McGarigal *et al*. 2012). The metrics are commonly employed in regional LULC studies to quantify the intensity of habitat loss and fragmentation (MacLean and Congalton 2015, Vogt *et al*. 2007). We also apply the Landscape Fragmentation Tool (LFT) to create a map of morphological fragmentation classes (core, edge, perforated, patch) at 100 m edge buffer width. The LFT approach (Vogt *et al*. 2007) can be used to distinguish between interior (core) and edge habitats and is suitable for ecological connectivity analyses (Vogt and Riitters 2017). We use a 100 m edge definition based on ecological considerations, as empirical studies have shown that approximately 30% of the world's forest area is within 100 m of an edge, which leads to changes in microclimates and biomass near forest edges (Yang *et al*. 2025). The edge depth of 100 m is used to ensure that the significant zone of fragmentation influence identified by global analyses (Yang *et al*. 2025, Haddad *et al.* 2015) is captured. To address several objectives, this study analyses trends in LULC extent and fragmentation metrics over 2010-2025. First, quantify the changes in areas of water, infrastructure, green space and bare land, extending from previous CHT analyses that were conducted at the level of forest and broad LULC classes (Chakma *et al.* 2023). Second, we monitor the changes in fragmentation statistics for these classes (e.g., whether forest patch density increased or core forest area decreased), giving a

temporal fragmentation profile. Third, examine the relationship between LULC transitions and changes in landscape connectivity metrics to assess changes in structural connectivity associated with land-cover transformation. This integrative analysis addresses a critical gap in the knowledge base: previous studies have reported on forest cover trends or forest fragmentation in Bangladesh separately (Chakma *et al*. 2023, Sarkar and Mukul 2024), but few studies have explicitly connected time-series LULC change to fragmentation and connectivity outcomes. We take a holistic view of cover change and fragmentation dynamics, as cover increases can be accompanied by increased isolation (Ma *et al*. 2023, Zhu and Woodcock 2017). Lastly, the spatiotemporal interaction between land cover change and fragmentation is directly relevant to conservation. The forests of the CHT play an important role in the region's biodiversity and carbon storage, and fragmentation threatens these values (Haddad *et al*. 2015). Our study quantifies the impacts of recent land use trends on connectivity, and can inform landscape planning, such as identifying critical corridors or where afforestation may have the greatest connectivity benefits (Taylor *et al*. 2006, Ma *et al*. 2023). The integration of LULC monitoring with fragmentation mapping provides insights into progress toward global biodiversity commitments, such as ecosystem restoration and protected area connectivity (Sarkar and Mukul 2024). To sum up, this study highlights the use of strong remote-sensing and landscape-metric approaches to shed light on the current landscape transformation of the CHT and its implications for evidence-based approaches to maintaining connectivity in the hill forests of Bangladesh.

Methodology

Study area: The CHT in the south-eastern part of Bangladesh was chosen because of its high ecological value and the high rate of land use change (Figure 1). The area includes the three administrative districts of Rangamati, Khagrachari and Bandarban. It geographically lies between 21.025′ N to 23.045′ N latitude and 91.045′ E to 92.050′ E longitude and covers an area of approximately

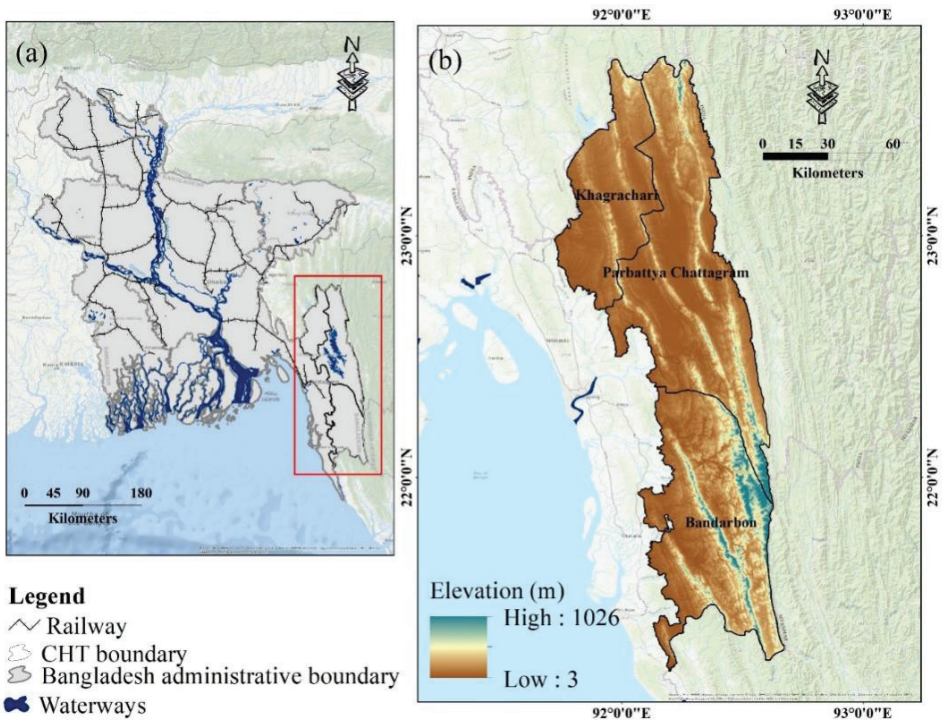


Figure 1. Study area map of the Chittagong Hill Tracts (CHT), Bangladesh. (a) Location of the CHT within Bangladesh. The red inset indicates the geographical position of the study area. (b) Elevation of the CHT.

13198.16 Km2, almost 40% of the total forest land area, and 8% of the total land area in Bangladesh (BFD 2017). Two-thirds of the area is characterized by steep slopes; the remaining area comprises of undulating topography (Rasul *et al*. 2004). The traditional landscape of Chittagong Hill Tracts is a blend of land uses, with over 70% of land area in three districts being covered by natural forests and plantation forests. The main plant species found in the area are tropical wet evergreen/ semi-evergreen and deciduous, which are referred to as 'hill forests'. The large area is mixed natural and planted forests (Rasul *et al*. 2007). The climate of this area is tropical monsoon type with three major seasons, dry winter season (November to March), pre-monsoon season (April to May) and monsoon season (June to October). The rainfall usually starts to increase from March to June. The annual rainfall varies from 2540 mm in the north to 2450 mm in the east, and almost 3810 mm in the south and west (Chakma *et al*. 2023). The CHT is an ideal place to study the effects of urbanization on landscape structure, due to its ecological significance and rapid landscape change. The aim of this study is thus to analyze the spatiotemporal dynamics of land-use change and landscape fragmentation by land-use class between 2010 and 2025, and to provide scientific information for sustainable land-use planning and biodiversity conservation in this ecologically sensitive mountain area.

Data sources: The primary data set used for LULC mapping a was multi-temporal Landsat imagery. Landsat 5 Thematic Mapper (TM) Collection 2 Level-2 Surface Reflectance imagery was used for 2010, while Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) Collection 2 Level-2 Surface Reflectance imagery was used for 2015, 2020, and 2025. The data sets were all retrieved from the archive of the United States Geological Survey (USGS) and processed in the GEE cloud-computing platform, which offers radiometrically consistent image collections and efficient processing of long-term satellite time series. All available Landsat observations from January to December of each study year were used to create annual image composites to ensure temporally representative and cloud-free datasets. Images were spatially filtered to the study area and quality assessed using the QA_PIXEL band before compositing. The quality assurance bitmask was used to exclude pixels affected by cloud, cloud shadow, cirrus contamination and other low-quality observations. Landsat Collection 2 Level-2 products were atmospherically corrected to surface reflectance, so no further atmospheric correction was needed. After quality masking, annual median composite images were created by computing the median reflectance value for each spectral band on a pixel-by-pixel basis. The median compositing method is found to be effective in reducing residual cloud contamination, atmospheric noise, sensor-related anomalies and other spectral outliers while maintaining stable annual land surface characteristics when compared to single-date imagery. The resulting composites are therefore able to produce strong and temporally representative spectral signatures for the heterogeneous urban landscape, which enhances the reliability and consistency of the supervised LULC classification. These annual median composite images, at 30 m spatial resolution, were then used as the main input data for supervised LULC classification and all further analyses.

Table 1. Datasets used in this study.

Dataset	Sensor	Processing Level	Spatial resolution	Temporal coverage	Pre-processing	Purpose	Data provider
Landsat 5 TM	TM	Collection 2 Level-2 Surface Reflectance	30 m	January–December 2010	QA_PIXEL cloud, cloud-shadow and cirrus masking; annual median composite generation	LULC classification	https://developers.google.com / earthengine/datasets/catalog/landsat
Landsat 8 OLI/TIRS	OLI/TIRS	Collection 2 Level-2 Surface Reflectance		January–December 2015, 2020 and 2025			

LULC classification: LULC maps were generated within the GEE using the supervised classification method with the MLC algorithm. The MLC algorithm estimates, for each pixel, the probability of belonging to a specific class based on its spectral attributes, assigning it to the class with the highest likelihood. This technique is widely used for its robustness, simplicity, and efficiency, as it evaluates spectral similarity through probabilistic and cost functions (Liu *et al*. 2014). In the present study LULC was divided into four categories; water bodies, buit-up, vegetation and barren land (Table. 2). These four classes are effective in presenting the major land transformation processes (Asadi *et al.* 2022, Li *et al.* 2015). For visualization and spatial interpretation, the classified maps were exported from GEE to ArcMap 10.8 for post-processing and analysis.

Table 2. The description and characteristics of the four LULC classes used in this study.

Class	Description
Waterbodies	River, canal, lakes, wetland.
Built -up	urban residential, commercial, institutional and industrial.
Vegetation	Park, garden, green roofs and walls.
Barren land	Bare soil, bare rock, sand.

Concluding the analytical workflow, an accuracy assessment was performed to quantitatively evaluate the reliability of the classification results, ensuring that each pixel was correctly assigned to its respective land cover category in accordance with established validation standards (Table 3). The reference data of ground truth were developed based on high-resolution historical imagery which is found on Google Earth Pro. Time-specific imagery in Google Earth was thoroughly cross-checked with the Landsat acquisition dates to be sure that the content is time consistent.

Landscape fragmentation metrics: Class-level landscape metrics were calculated using the landscape metrics package in R (version 4.4.3) which uses standardized algorithms that are consistent with the FRAGSTATS framework (Hesselbarth *et al.* 2019). All LULC maps were reprojected from the original geographic coordinate system to the Universal Transverse Mercator (UTM) Zone 46N (EPSG:32646) using the nearest-neighbor resampling method in the terra package. Reprojection into a projected coordinate system ensured accurate area- and distance-based metric calculations by preserving linear and areal measurements. The LULC rasters were then processed using the calculate_lsm() function to calculate class-level landscape metrics for each land-cover class (waterbodies, barren land, built -up and vegetation). Since this study is mainly concerned with built- up and vegetations fragmentation, only built- up and vegetations class metrics were used for subsequent analysis. Six commonly used landscape metrics were chosen to represent various aspects of landscape composition and configuration NP, PD, LPI, ED, AI, and COHESION (Figure 2) (Table 4 and 5). Overall study flow is illustrated in Figure3.

Table 3. This accuracy assessment framework ensures statistical reliability and robustness of the LULC classification results.

Metrics	Formula
Kappa co-efficient	$\frac{(TS \times TCS) - (Columntotal \times Rowtotal)}{(TS)2 - F\ (Columntotal \times Rowtotal)} \times 100$
Overall Accuracy (OA)	$\frac{TCP}{TS} \times 100$
User Accuracy (UA)	$\frac{\text{Correctly classified pixels in class}}{\text{Total pixels classified in class}} \times 100$
Producer Accuracy (PA)	$\frac{\text{Correctly classified pixels in class}}{\text{Total pixels in ground truth class}} \times 100$

Table 4. Metrics and equation used in this study.

Metric	Equation
NP	$NP = n_i$
PD	$PD = \frac{NP}{A} \times 1000 \times 100$
LPI	$LPI = \frac{\max(aij)}{A} \times 100$
ED	$ED = \frac{E}{A} \times 100$
AI	$AI = \frac{gii}{\text{Max}(gii)} \times 100$
COHESION	$COHESION = \left(1 - \frac{\sum p_{ij}}{\sum p_{ij\sqrt{a_{ij}}}}\right)\left(1 - \frac{1}{\sqrt{Z}}\right)^{-1} \times 100$

Here,
ni = Total number of patches of class i.
A = Total landscape area (m).
aij = Area of patch j belonging to class i.
max (aij) = Area of the largest patch of class i.
E = Total edge length of all patches of class i (m).
gii = Number of like adjacencies (shared cell edges) between pixels of class i.
max (gii) = Maximum possible number of like adjacencies for class i (used to standardize aggregation).
Pij = Perimeter of patch j in class i (m).
Z = Total number of raster cells in the landscape.

Note: Equations for NP, PD, LPI, and ED follow the FRAGSTATS v4 mathematical definitions (McGarigal et al. 2023), whereas AI and COHESION follow He et al. (2000) and Schumaker (1996), respectively.

Table 5. Description, ecological significance, and justification of the landscape metrics used to quantify vegetation fragmentation.

Metric and unit	Description
NP (No.)	NP quantifies the total number of discrete built- up and vegetations patches within the study area. It is one of the most widely used indicators of habitat subdivision and landscape fragmentation.
PD (100 ha^{-1})	PD standardizes the number of built- up and vegetations patches by the landscape area, allowing comparison among landscapes of different sizes.
ED (m/ha)	ED measures the total length of built- up and vegetations edges per unit landscape area. It represents the intensity of edge development within the landscape.
LPI (%)	LPI represents the percentage of the landscape occupied by the largest built- up and vegetations patch. It measures the dominance of the largest contiguous built- up and vegetations area.
AI (%)	AI measures the degree of spatial aggregation or clustering among patches of the same built- up and vegetations class based on cell adjacencies.
COHESION (%)	COHESION quantifies the physical connectedness of built- up and vegetations patches across the landscape and reflects habitat structural connectivity.

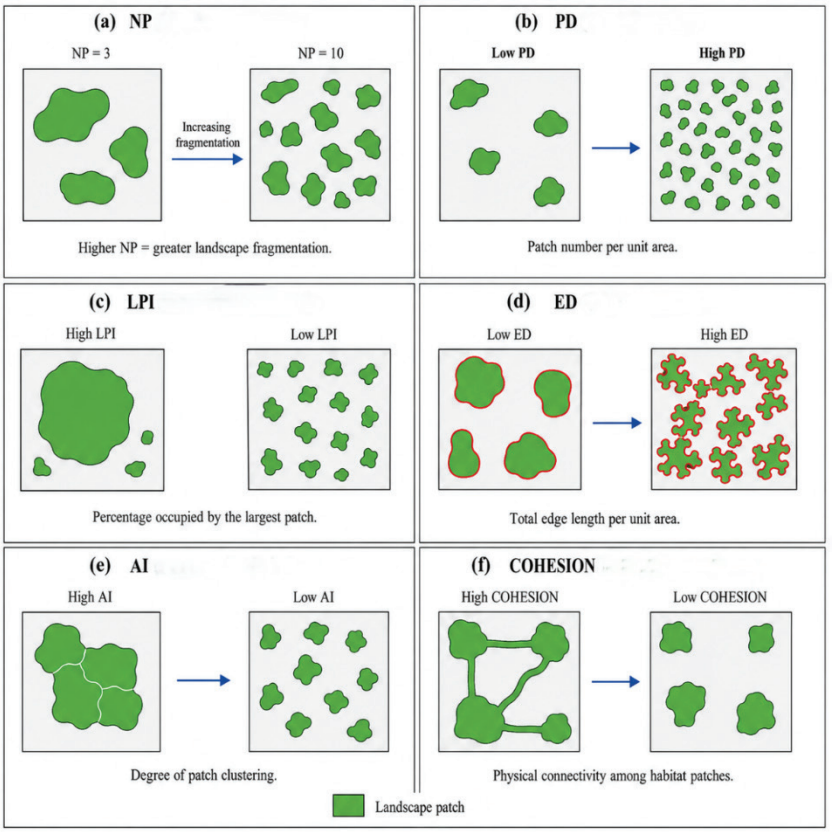


Figure 2. Conceptual illustration of six commonly used landscape fragmentation metrics: (a) NP, showing increased landscape fragmentation with a higher number of patches; (b) PD, representing the number of patches per unit area; (c) LPI, indicating the percentage of the landscape occupied by the largest patch; (d) ED, representing the total edge length per unit area; (e) AI, describing the degree of patch clustering; and (f) COHESION, illustrating the physical connectivity among habitat patches.

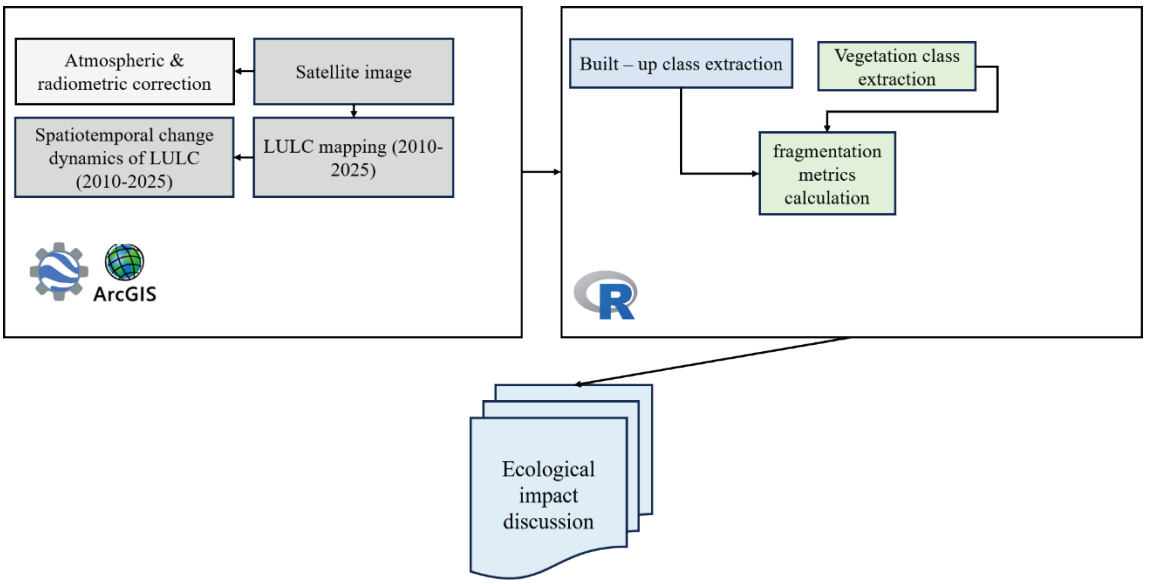


Figure 3. Methodological framework adopted for the study.

Result and Discussion

Accuracy assessment: The classification accuracy assessment showed high accuracy in all study years (Table. 6). The OA was between 89% and 90%, and the kappa coefficient was between 86% and 87%, which shows good agreement between the classified data and the reference data. The overall UA and PA for each class were generally high (above 0.82), indicating that the LULC maps were reliable for further spatiotemporal analysis, with waterbodies and urban areas having the highest classification accuracy.

Spatiotemporal change dynamics of LULC: The LULC analysis showed significant changes in the landscape of the CHT from 2010 to 2025, with the main changes being rapid urbanization and dynamic vegetation change (Figures 4-6). Vegetation remained the dominant land-cover class throughout the study period, increasing slightly from 12370.63 km² in 2010 to 12700.65 km² in 2015, declining to 12400.59 km² in 2020, and subsequently recovering to 12873.34 km² in 2025 (Figure 4). overall, the net gain of vegetation was 502.71 km² (Figure 5). But greater extent of vegetation does not always mean ecological improvement; changes in landscape configuration can also increase habitat fragmentation and reduce structural connectivity, which can decrease ecological connectivity even as areal extent increases. This distinction has been much highlighted in landscape ecology, where spatial configuration is also seen as important as landscape composition in maintaining the integrity of the ecosystem. The largest change was in built-up land, which grew by almost ten times from 51.35 km² in 2010 to 494.30 km² in 2025 (Figure 4), a total increase of 442.95 km² (Figure 5). About 87% was during 2015-2020, with built-up land growing by 384.26 km², marking an accelerated urbanization period. This intensive urbanization is typical of the rapid urbanization trends observed in other rapidly developing regions of South and Southeast Asia, where infrastructure development, population growth and economic expansion are the main drivers of natural ecosystem to impervious surface conversions (Liu *et al.* 2023, Li *et al.* 2023, Morya *et al.* 2022). Habitat loss, fragmentation, and loss of ecosystem services, especially in environmentally sensitive mountainous areas, are often linked to rapid urbanization (Belay *et al.* 2022, Peng *et al.* 2019, Yang *et al.* 2024). For instance, Xiao *et al.* (2020) found that ecosystem health in Qiannan Prefecture, Guizhou Province, China, has decreased from 1990 to 2015, particularly in the eastern and northern parts of the province. The study also showed that urbanization negatively impacted ecosystem health, and that the most significant driver between 1990 and 2005 was the growth of construction land. On the other hand, waterbodies showed a steady long-term decrease from 406.83 km² in 2010 to 334.45 km² in 2025, reflecting a net loss of 72.38 km² (Figs. 4 and 5). The greatest decrease was in 2015-2020 (−79.18 km²), indicating significant changes in the hydrological characteristics during the period of intensive urban development. In rapidly urbanizing landscapes, wetland degradation and river modification due to urban encroachment have been documented to have similar impacts on surface water, which decrease hydrological resilience and aquatic ecosystem functioning. The contrasting trends of vegetation and built-up land suggest that urban development has become

Table 6. Accuracy assessment of the classified LULC maps for 2010, 2015, 2020, and 2025 based on UA, PA, OA and the Kappa coefficient.

LULC Classes	2010		2015		2020		2025	
	UA	PA	UA	PA	UA	PA	UA	PA
Waterbodies	0.91	0.86	0.91	0.93	0.98	0.96	0.92	0.96
Barren land	0.87	0.97	0.86	0.94	0.82	0.85	0.84	0.75
Built - up	0.92	0.82	0.94	0.91	0.95	0.87	0.89	0.86
Vegetation	0.91	0.9	0.92	0.84	0.83	0.88	0.91	0.94
Kappa coefficient	86%		87%		86%		86%	
OA	90%		90%		89%		90%	

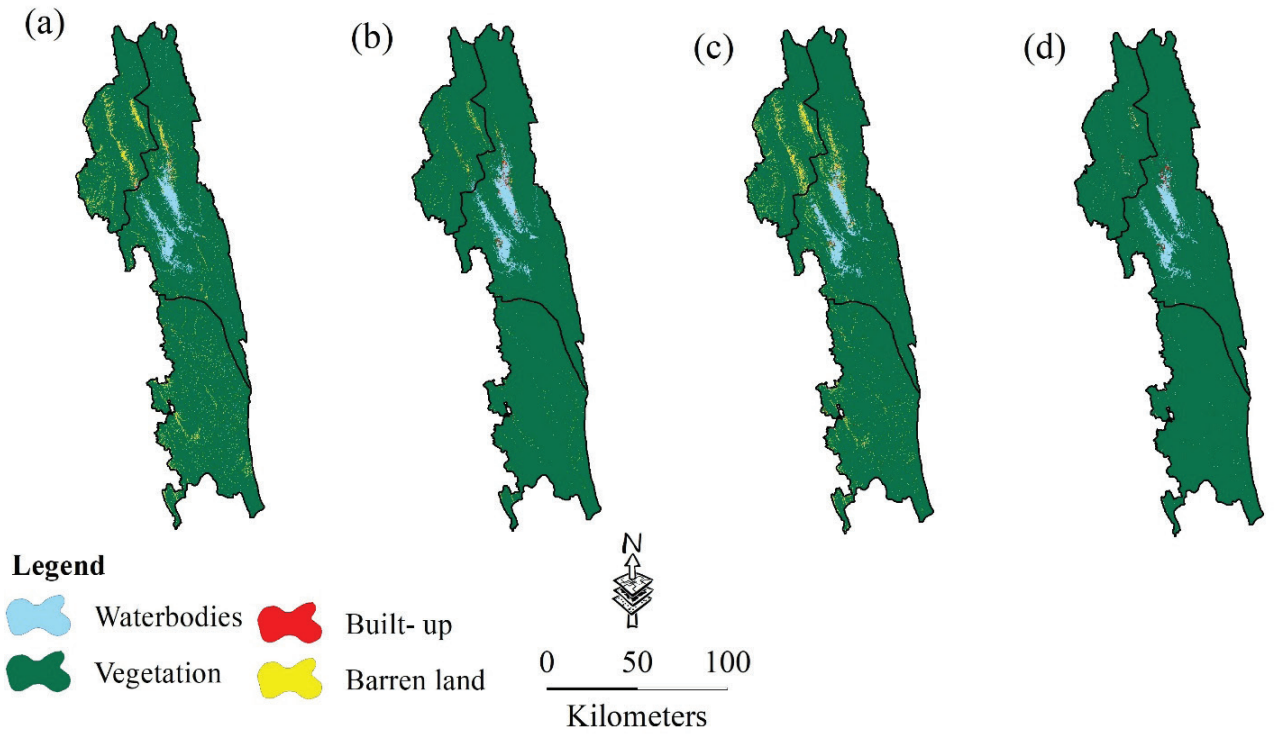


Figure 4. Spatiotemporal change dynamics LULC; (a) 2010, (b) 2015, (c) 2020 and (d) 2025.

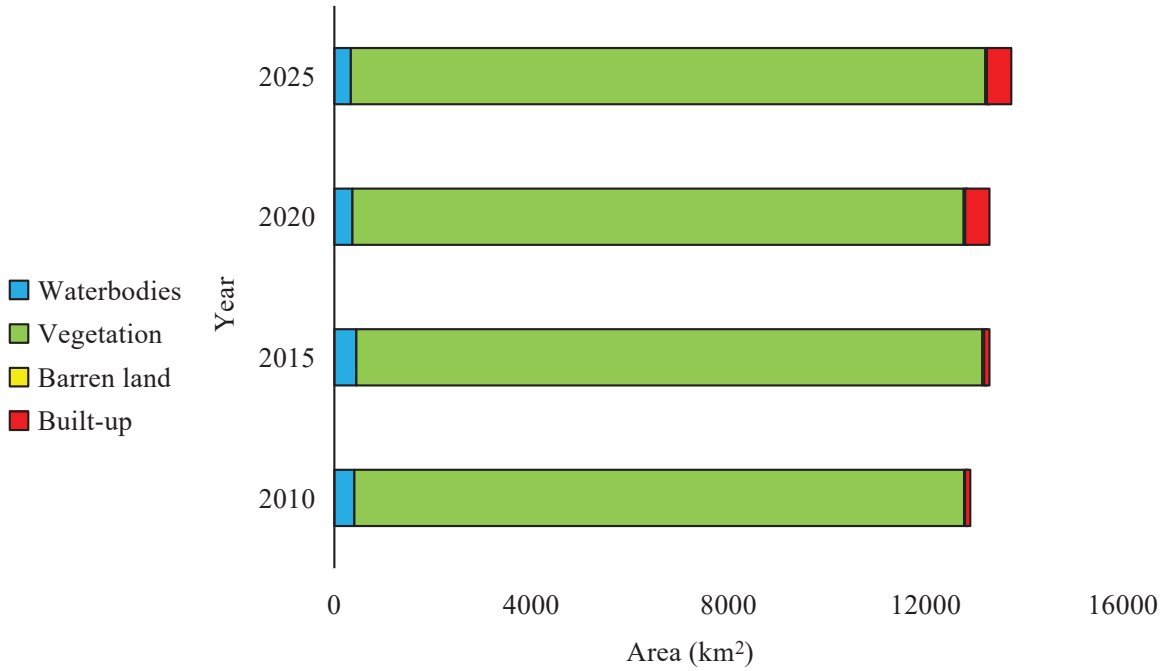


Figure 5. Quantification of land-use class change during the study period (2010-2025).

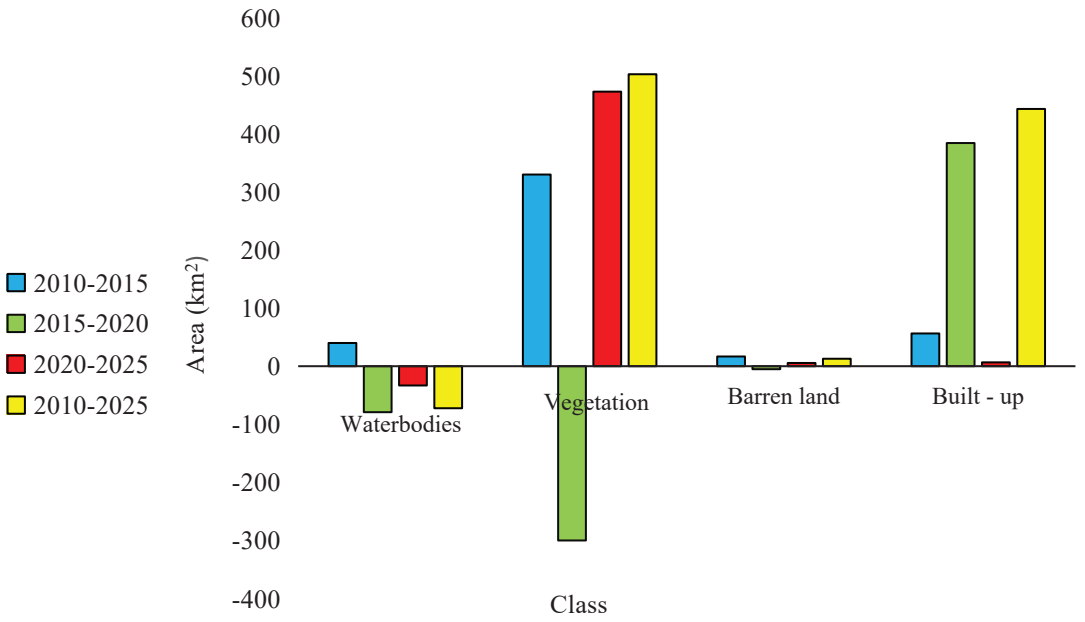


Figure 6. Gain and loss of Land-use classes across the time period (2010-2025).

the primary driver of landscape composition change in the CHT, with a slight increase in barren land area (+12.84 km²) over the study period. The results show that the area of land cover is not enough to assess the ecological impacts. Urban development can significantly change landscape structure without a corresponding increase in the amount of vegetation. Thus, landscape fragmentation metrics are needed to distinguish between increases in vegetation extent and changes in the structural condition and connectivity of vegetation patches. The next section examines this structural perspective with class-level landscape metrics (Figure 7).

Although the LULC analysis indicated a net increase of 502.71 km² in vegetation between 2010 and 2025. Class-level landscape metrics indicate that this expansion was not associated with an increase in ecological integrity. Rather, there was significant structural reorganization of vegetation, with progressive fragmentation of areal extent as vegetation increased, suggesting that large contiguous patches of vegetation were not preserved. The most obvious structural change was a dramatic decrease in the LPI from 92.40% in 2010 to 48.20% in 2015, with relatively low and stable values (47.17–47.16%) through 2025 (Figure 7a). The AI was consistently high (97.98–98.93%) while COHESION was always above 99.98% (Figure 7b–c). Collectively, these metrics indicate that vegetation patches largely retained physical connectivity but lost their spatial dominance as the original vegetation matrix was progressively subdivided into smaller interconnected patches. Thus, the fragmentation observed was not total habitat isolation but rather the breaking up of large habitat patches. This interpretation is also supported by the post-2015 increase in fragmentation metrics. ED was initially reduced from 24.42 to 12.20 m ha^{-1} but then rose to 17.69 m ha^{-1} by 2025. Likewise, NP increased from 2,220 to 3,042, while PD rose from 0.16 to 0.23 patches per 100 ha (Figure 7d–f). The concurrent rise in ED, NP and PD suggests a progressive fragmentation of vegetation into smaller and more irregular patches, which will lead to a rise in habitat edges and a decrease in interior habitat. These structural changes can be ecologically significant, as they increase edge effects, change microclimatic conditions, and increase edge exposure and alter the spatial conditions of interior vegetation. These results indicate that landscape composition and landscape configuration had different trends over the study period. Vegetation area grew, but the structural integrity of the vegetation decreased due to fragmentation of dominant habitat patches. This distinction is well known in landscape ecology, where the configuration of habitat is as important as the quantity of habitat in determining ecosystem

functioning. Large, continuous vegetation patches generally provide greater spatial continuity and may offer more favorable conditions for ecological processes than highly fragmented patches, and enhance ecosystem resilience, whereas fragmented landscapes restrict movement, reduce gene flow, and increase vulnerability to environmental disturbances (Shi *et al.* 2017, Cui *et al.* 2013, Geng *et al.* 2019, He *et al.* 2021). Therefore, the apparent improvement in vegetation cover should be taken with a grain of salt, because fragmentation indices indicate that the structural configuration of vegetation became more fragmented despite the increase in vegetation extent. The fragmentation pattern observed is similar to that found in rapidly urbanizing mountain landscapes where vegetation may still be the predominant land cover type but is increasingly fragmented by growing settlements, transportation corridors and associated infrastructure. The high AI and COHESION values in the CHT suggest that structural connectivity has not yet been lost, but the significant decrease in LPI and increase in edge formation suggest that as urban development continues, functional connectivity may become increasingly compromised unless large vegetation patches and ecological corridors are effectively conserved. Thus, it is recommended to keep core vegetation patches and enhance ecological corridor networks to ensure long-term biodiversity and landscape resilience.

Fragmentation and urban consolidation: The most significant landscape change was seen in built-up land, which increased by 442.95 km² between 2010 and 2025, of which almost 87% was in 2015-2020 (Figures. 4-6). The expansion was associated with a progressive urban consolidation, as suggested by landscape metrics (Figure 7). The AI grew significantly from 37.82% to 87.83% between 2010 and 2025 (Figure 7b–c), suggesting that isolated settlements gradually became more connected to each other. The AI increased significantly from 37.82% to 87.83% between 2010 and 2025 (Figure 7b–c), indicating that initially isolated settlements gradually became more connected to each other. Likewise, the LPI rose from 0.002% to 0.21%, indicating the appearance of larger and more prominent urban patches (Figure 7a). The concurrent increases in ED (1.29-5.12 m ha^{-1}), NP (5762-6973), and PD (0.4366-0.5283 patches per 100 ha) further indicate that urban growth occurred through both the expansion of existing settlements and the formation of new urban patches (Figure 7d-f). Together, these trends represent a typical diffusion-coalescence process, in which growing urban patches are increasingly spatially connected. Ecologically, the greater the aggregation and cohesion of urban areas, the more the landscape becomes cohesive and homogeneous, and the more it is likely to impede ecological flows. While compact urban development is more efficient than dispersed sprawl, its continued growth in the ecologically sensitive CHT could exacerbate habitat isolation and edge effects by replacing natural corridors with impervious surfaces. In rapidly urbanizing mountain landscapes, urban connectivity has been reported to be closely linked to loss of ecological integrity, as in other urban areas. For example, Zhang *et al.* (2025) found that urban expansion in Chongqing, China, showed a significant upward trend on the slope. The expansion advantage slope range (EASR) rose from 1.17°-8.25° to 1.42°-8.48°, meaning that built-up land was more likely to be on steeper slopes. In addition, ecosystem health was significantly reduced if urban development was added on slopes steeper than 12°. Thus, future urban development should be planned to combine compact growth with ecological corridor protection and green infrastructure to reduce fragmentation and ensure landscape connectivity and ecosystem resilience.

Structural Connectivity and Landscape Implications: The integrated assessment of LULC dynamics and landscape metrics shows that the spatial configuration of the CHT has been more affected by urbanization than its overall land-cover composition. Although vegetation increased by 502.71 km² during 2010-2025. This apparent recovery, however, was associated with a decrease in LPI and an increase in ED, NP, and PD (Figure 7), suggesting that large vegetation patches were becoming increasingly subdivided. On the other hand, the gradual rise of built-up LPI, AI and COHESION indicates the gradual merging of urban patches into a more connected anthropogenic matrix. The contrasting trends indicate a gradual shift from a vegetation-dominated landscape toward a more urbanized and structurally consolidated anthropogenic matrix, accompanied by increasing fragmentation of vegetation patches, but with smaller and narrower vegetation patches and more urbanized areas

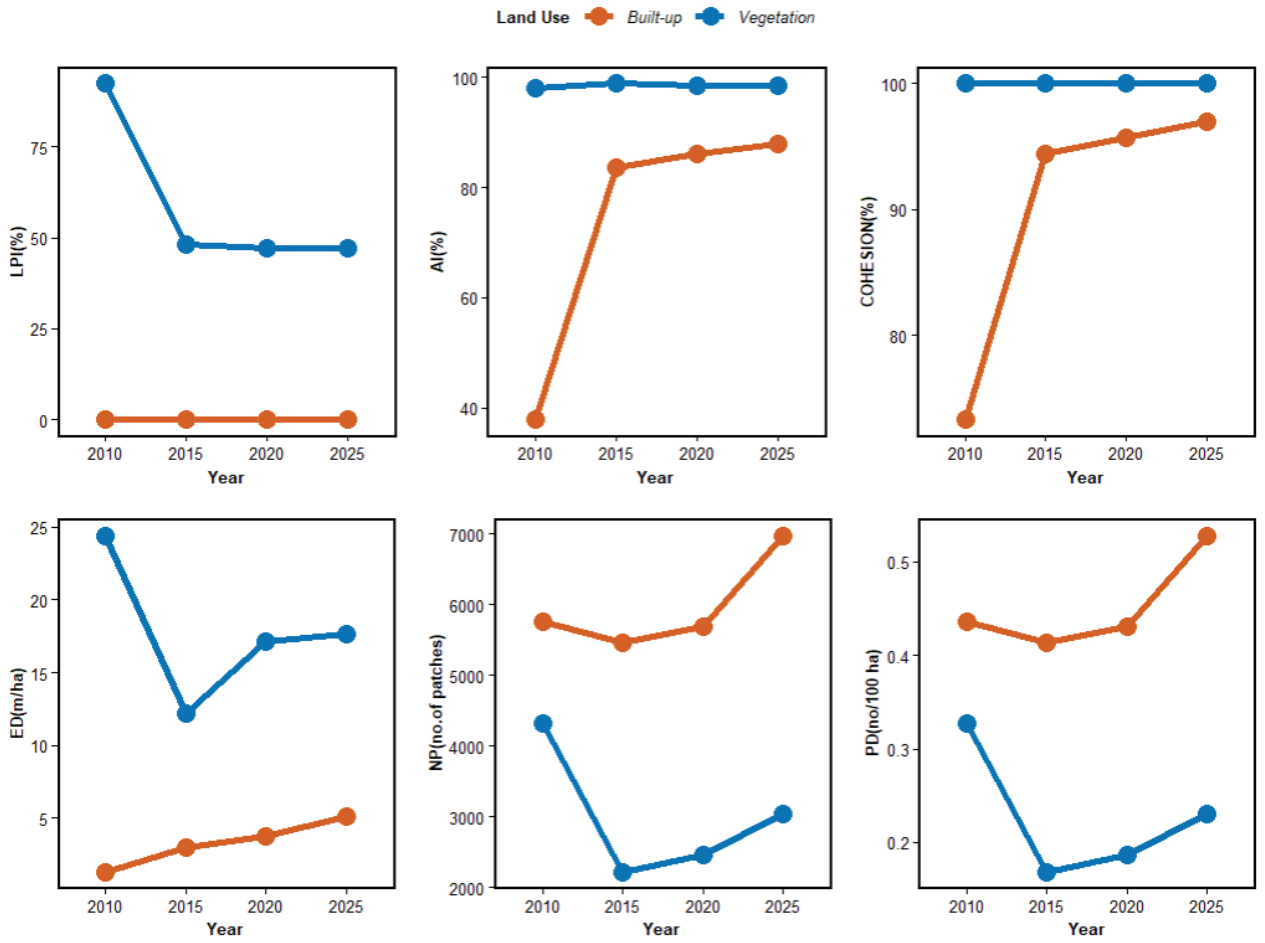


Figure 7. Temporal variation in class-level landscape fragmentation metrics for Vegetation and Built-up land-use classes from 2010 to 2025. The metrics include (a) LPI, (b) AI, (c) Patch Cohesion Index (COHESION), (d) ED, (e) NP, and (f) PD.

becoming more cohesive. This structural reorganization can decrease landscape permeability, break up ecological corridors, and limit species movement even though vegetation connectivity indices remain relatively high. Therefore, the configuration of the landscape is a more sensitive indicator of ecological degradation than the extent of vegetation change, especially in ecologically sensitive mountain environments. The results highlight the need for sustainable urban development in the CHT to go beyond just managing land-cover change to ensuring functional ecological connectivity from a management perspective. Therefore, protecting large core vegetation patches, conserving riparian and forest corridors and incorporating green infrastructure into future urban development are critical to reduce habitat fragmentation, maintain biodiversity and improve long-term landscape resilience. The findings show that the use of LULC analysis in conjunction with fragmentation metrics at the class level offers a more comprehensive framework for assessing ecological sustainability than traditional area-based assessments.

Limitations and future research directions: The results of this study are comprehensive assessment of land-use change and landscape fragmentation in the CHT, but there are some limitations and uncertainties in the interpretation of the results. The analysis was conducted on four temporal snapshots (2010, 2015, 2020, and

2025) that provide a good representation of long-term landscape dynamics, but may not fully reflect short-term land-cover changes related to seasonal variability or episodic disturbances. Second, the fragmentation analysis was based on class-level landscape metrics calculated from categorical LULC maps. These metrics are good indicators of landscape structure, but they are mostly measures of structural connectivity and not measures of ecological functions, species-specific habitat suitability, or functional connectivity. The main source of uncertainty is the accuracy of the LULC classification, because small errors in the classification of vegetation, barren land and built-up classes can lead to errors in the fragmentation metrics. Furthermore, the spatial resolution of the input raster can underrepresent small habitat patches and narrow ecological corridors, which can affect metrics like LPI, ED, NP, and PD. Moreover, the present analysis was limited to biophysical landscape features and did not explicitly account for socioeconomic drivers, such as population growth, road network expansion, tourism development, land-use policies, or topographic constraints, which can significantly shape urban growth patterns and landscape fragmentation in the CHT. Even with these restrictions, the temporal trends were very similar for several landscape metrics. The overall reduction in vegetation LPI, coupled with the rise in ED, NP and PD, and the simultaneous rise in built-up AI and COHESION, is a consistent signal of vegetation fragmentation and urban consolidation. The combination of these independent landscape metrics increases the confidence in the strength of the landscape change observed and the ecological interpretation. The current framework should be expanded in future studies by incorporating functional connectivity modelling, habitat quality assessment, biodiversity indicators and ecosystem service evaluation to gain a deeper understanding of the ecological impacts of landscape change. The addition of socioeconomic data, transportation infrastructure, and topographic data, in addition to high-resolution remote sensing data (e.g., UAV, LiDAR, or very-high-resolution satellite imagery), would enhance the ability to detect fine-scale landscape changes and identify fragmentation drivers. These multi-disciplinary approaches would offer a more holistic foundation for the creation of sustainable land use strategies that would consider the balance between urban development and biodiversity conservation and ecological resilience in the Chittagong Hill Tracts.

Conclusion

This study quantified the spatiotemporal dynamics of land-use change and landscape fragmentation in the CHT between 2010 and 2025 using class-level landscape metrics. The results demonstrated that the landscape was undergone substantial structural transformation driven primarily by rapid urban expansion. Built-up land increased by 442.95 km², whereas vegetation exhibited a net gain of 502.71 km². However, fragmentation analysis revealed that the increase in vegetation extent did not correspond to improved structural integrity. The marked decline in vegetation LPI, together with increasing ED, NP, and PD, indicates progressive subdivision of large habitat patches despite persistently high AI and COHESION, suggesting that vegetation connectivity is increasingly maintained through smaller and narrower habitat remnants.

Conversely, built-up land exhibited continuous increases in LPI, AI, and COHESION, reflecting a transition from dispersed settlements to an increasingly consolidated urban network. The simultaneous increase in urban ED, NP, and PD further indicates that urban growth occurred through both the expansion of existing settlements and the establishment of new urban patches. Collectively, these findings reveal a gradual shift from a vegetation-dominated landscape toward a more connected anthropogenic matrix. The integrated assessment demonstrates that landscape configuration provides a more comprehensive understanding of ecological change than conventional LULC area statistics alone. While vegetation cover appeared relatively stable, fragmentation metrics revealed declining habitat integrity and increasing structural fragmentation. These findings underscore the importance of incorporating landscape ecological indicators into regional planning and environmental monitoring.

From a policy perspective, sustainable land-use planning in the CHT should prioritize the conservation of large core vegetation patches, protection of ecological corridors, and integration of green infrastructure within future urban development. Such measures are essential to maintain landscape connectivity, enhance ecosystem resilience, and balance urban growth with biodiversity conservation. The methodological framework presented in this study provides a transferable approach for assessing landscape fragmentation in other ecologically sensitive mountainous regions experiencing rapid land-use transformation.

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