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Landscape Configuration Dynamics Reveal Woody Encroachment and Emerging Human Pressure in the Katavi Heterogeneous Landscape

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Abstract

The Katavi Region in western Tanzania harbours one of the country's most ecologically significant protected area landscapes, yet faces exceptional demographic pressure, with a 104.2% population increase recorded between 2012 and 2022. Despite documented agricultural expansion and hydrological degradation, there remains limited understanding of how these pressures are reshaping landscape structure and ecological connectivity across the broader protected-area landscape.. This study quantified land-cover composition and configuration dynamics across the Katavi landscape over 2017–2024 using the Sentinel-2 10m land-cover time series. Landscape and class metrics (FRAGSTATS definitions) were computed in PyLandStats under both 4- and 8-neighbour connectivity rules, and a pixel-wise transition matrix identified with dominant conversion pathways. Tree cover (61–69%) and rangeland (25–33%) dominated the landscape throughout the study period. The most pronounced trend was a net tree-cover increase of 4.42 percentage points coupled with a rangeland decline of 5.80 percentage points. Transition analysis confirmed that rangeland-to-tree conversion (~ 459,404 ha) was the dominant transition, nearly double the reverse flow, indicating a sustained shift toward woody dominance consistent with woody encroachment processes. Tree patches coalesced into fewer, larger stands (patch count − 30.5%; Aggregation Index 98.2), while rangeland fragmented progressively (Splitting Index + 51.4%). Anthropogenic classes, though occupying small absolute areas, exhibited large relative increases (built area + 159.7%, crops + 22.2%) proliferating as scattered patches characteristic of early-stage peripheral encroachment. All findings were robust to the connectivity rule employed. These results provide one of the first high-resolution, multi-year landscape pattern analyses for Katavi and demonstrate that landscape configuration metrics can reveal emerging conservation risks that are not evident from land-cover composition alone. The observed trade-offs between woodland expansion, rangeland fragmentation, and peripheral human encroachment highlight the need for integrated land-use planning that considers not only changes in habitat extent, but also changes in landscape configuration and ecological connectivity.

1. Introduction

Land-cover change is a leading driver of biodiversity loss and ecosystem degradation in tropical landscapes, particularly where agricultural expansion and settlement growth intersect with protected area boundaries (Foley et al., 2005; IPBES, 2019). Although protected areas remain central to global biodiversity conservation, their effectiveness increasingly depends not only on how much habitat they retain, but also on how that habitat is spatially configured in landscapes experiencing growing human pressure. Land-cover change contributes to habitat fragmentation, which in turn leads to habitat loss. Fragmentation can act as a barrier that limits gene flow, dispersal, species movement, and population persistence, while increasing isolation and edge-related pressures, with ecological effects that may persist for decades (Haddad et al., 2015). Recent global evidence further shows that protected areas vary widely in their ability to resist surrounding habitat loss, reinforcing the value of place-based, spatially explicit assessment to identify where protection is effective and where pressures are intensifying (Li et al., 2024).

The Katavi landscape is heterogeneous consisting a network of protected and unprotected areas with different conservation statuses, including national parks (e.g., Katavi National Park), game reserves (e.g., Rukwa Game Reserve), game-controlled areas (e.g., Mlele Game Controlled Area), forest reserves (e.g., Mulele Hills Forest Reserve), wildlife management areas (WMAs) (e.g., Mpimbwe Wildlife Management Area), and open areas (Mtuy et al., 2026). National parks are strictly protected and permit only non-consumptive activities, including tourism, research, and environmental education. Game reserves are also strictly protected but allow regulated consumptive uses, including trophy hunting under permits issued by the Tanzania Wildlife Management Authority (TAWA) (URT, 2022).

The presence of protected areas has largely contributed to maintaining the state of the art of resources in this landscape. However, increasing human population has intensified pressure on these resources. According to the 2012 and 2022 Population and Housing Census regional profile reports, Katavi's population increased from 564,604 to 1,152,958, representing a 104.2% increase over the decade (URT, 2024). This population growth has increased the demand for agricultural land, forest resources, water, and space for infrastructure and other development activities. As a result, encroachment into protected areas has intensified, resulting in vegetation clearing, overexploitation of natural resources, habitat loss and fragmentation, and increasing pressure on biodiversity. These changes threaten ecosystem integrity and reduce the capacity of the landscape to sustain both wildlife populations and the livelihoods of local communities.

Understanding how heterogeneous landscapes respond structurally to increasing human pressure is important for assessing ecosystem change and supporting effective land-use management. This requires quantifying changes in landscape composition and configuration driven by human activities. Previous studies have shown that woody plant encroachment results from interacting drivers, including changing fire regimes, climate variability, herbivory, and land management practices (Stevens et al., 2017; Venter et al., 2018). Recent studies have shown that increasing woody cover alters forage availability and other ecosystem services, creating trade-offs among livestock production, biodiversity conservation, and carbon storage (Skhosana et al., 2025; Venter et al., 2018).

Woody encroachment, habitat fragmentation, and agricultural expansion should therefore be considered interconnected processes of landscape restructuring rather than independent phenomena. In the Katavi landscape, where habitats such as rangelands, woodlands, and wetlands collectively support wildlife movements and local livelihoods, identifying whether landscape change is primarily driven by agricultural expansion, woody thickening, or habitat fragmentation is critical for conservation planning and sustainable land-use management. Distinguishing which of these drivers, from fire regime and herbivory shifts to climate variability and demographic pressure, dominates the change is essential for describing changes experienced within landscapes.

Recent advances in remote sensing provide powerful tools for monitoring these landscape changes over time (Crowley & Cardille, 2020). Detecting structural changes requires spatially explicit datasets capable of capturing both land-cover transitions and landscape configuration. The Sentinel-2 10 m Land

Use/Land Cover time series available through the ArcGIS Living Atlas provides annual global land-cover maps derived from Sentinel-2 imagery using deep-learning algorithms (ESRI, 2026). Independent evaluations have shown that the Esri 10 m land-cover product achieved the highest overall accuracy among comparable global datasets for 2020, although classification uncertainty remains, particularly along woody–herbaceous transition zones (Venter et al., 2022). More recent validation studies have similarly shown that classification accuracy varies among land-cover classes and landscape contexts, highlighting the importance of acknowledging uncertainty and conducting robustness assessments when interpreting landscape change (Xu et al., 2024; Naboureh et al., 2025).

Although annual land-cover maps effectively describe the spatial distribution and temporal dynamics of ecosystems, they do not fully capture the structural characteristics of landscapes that influence ecological processes. To convert land-cover information into decision-relevant evidence, landscape ecology provides a suite of metrics that quantify landscape composition and configuration, including patch aggregation, edge complexity, fragmentation, and connectivity. Open-source tools such as PyLandStats enable the computation of FRAGSTATS-equivalent landscape metrics within reproducible, script-based workflows, facilitating consistent multi-year comparisons (Bosch, 2019). However, landscape metrics are sensitive to methodological decisions, particularly spatial grain and patch connectivity definitions. Recent studies have shown that metric responses vary with grain size, land-cover type, and the metric selected, emphasizing the need to clearly justify scale selection and carefully interpret patch-based analyses (Fu et al., 2021; Kato & Motobe, 2024). Similarly, evaluating alternative neighbourhood rules for defining patch connectivity improves confidence that observed fragmentation or aggregation patterns reflect real landscape changes rather than methodological assumptions.

Despite Katavi's ecological importance and accelerating demographic pressure, there remains limited understanding of how the broader protected-area landscape is responding structurally to increasing human influence and what these changes imply for long-term conservation. Although previous studies have documented aspects of land-cover change within the ecosystem, few have simultaneously examined land-cover composition, transition pathways, and landscape configuration to evaluate emerging conservation risks across the wider protected-area landscape.

This study therefore asks: *How is the Katavi protected-area landscape responding to increasing human pressure, and what do changes in landscape configuration reveal about emerging conservation risks?* To answer this question, this study uses annual 10 m land-cover maps for 2017 to 2024 to quantify (i) inter-annual composition trends, (ii) dominant endpoint conversion pathways via pixel-wise transition analysis, and (iii) multi-year landscape and class configuration dynamics using a reproducible metric workflow implemented under alternative connectivity rules. The observed patterns are then interpreted in relation to anthropogenic pressure, ecological integrity, and conservation management.

2. Materials and Methods

2.1 Study Area

This study was conducted within the Katavi region of western Tanzania. The region is one among 31 administrative regions of Tanzania, covering approximately 45, 843 Km^2 lying at longitude 30° and 33° E and Latitudes 5° to 7° S at 1,000 to 2,500 meters above sea level (URT, 2024). The region forms the Katavi landscape and the greater Rukwa-Katavi ecosystem, which adjoins the Rungwa-Kizigo-Muhesi ecosystem, which connects to the famous Greater Ruaha ecosystem. This whole landscape provides a home to wildlife and humans with more than 65% of the land covered by woodland and protected areas. The region receives 700 to 1200 mm of rainfall per year, the average annual temperature ranges between 25 and 30°C (Mulder et al., 2007).

The landscape is situated within the shallow western arm of the East African Rift Valley, south-east of Lake Tanganyika, and is dominated by miombo woodland (mainly Brachystegia, Julbernardia, and Isoberlinia genera) (Banda et al., 2008). Open savannah grassland, and seasonally inundated floodplains associated with the Katuma River, and the ephemeral Lakes Katavi and Chada also cover large part of the landscape (TAWIRI, 2020). These wetlands support some of the highest dry-season concentrations of large mammals in East Africa, including African savanna elephants (*Loxodonta africana*), buffalo (*Cyncerus caffer*), hippopotamus (*Hippopotamus amphibius*), and large carnivores such as African lion (*Panthera leo*), African leopard (*Panthera pardus*), spotted hyena (*Crocuta crocuta*), wild dogs (*Lycaon pictus*) and Crocodiles (WWF, 2021). Agriculture, which is conducted in small-scale crop farming, is the main human activity followed by livestock keeping. Other activities such as fisheries, beekeeping and small business centres are conducted on a small scale daily (URT, 2024).

2.2 Land-Cover Data Source

Annual land-use/land-cover (LULC) maps were sourced from the Sentinel-2 10 m Land Use/Land Cover Time Series, a global product made available through the ArcGIS Living Atlas of the World. The dataset is produced through a collaboration between Esri, Impact Observatory, and Microsoft, wherein a proprietary deep learning classification model, trained on billions of human-labelled image pixels curated by the National Geographic Society, is applied to the full archive of European Space Agency (ESA) Sentinel-2 Level-2A surface reflectance imagery on the Microsoft Planetary Computer (Venter et al., 2022). Each annual map represents a composite of LULC predictions aggregated across the calendar year to minimise seasonal and cloud-related artefacts.

An independent cross-comparison by Venter et al. (2022) found that, among three major 10 m global LULC products for the year 2020, the Esri product achieved the highest overall accuracy at 75%, with water (92%) and tree cover among the most reliably classified categories. Temporal consistency improvements in later releases have further reduced spurious year-to-year classification noise (Esri, 2024). The product employs a nine-class legend; within the Katavi study extent, seven classes were observed (Table 1). The dataset properties and analysis parameters are summarised in Table 2.

Table 1
LULC class legend and descriptions for the Katavi landscape.

Code	Class	Description
1	Water	Open water bodies including rivers, lakes, and reservoirs
2	Trees	Woody vegetation with canopy cover; includes miombo woodland and riparian forest
4	Flooded vegetation	Herbaceous vegetation intermixed with standing water; seasonal wetlands and marshes
5	Crops	Cultivated cereals, grasses, and crop fields not at tree height
7	Built area	Impervious surfaces, buildings, roads, and settlements
8	Bare ground	Exposed soil, rock, or sand with minimal vegetation cover
11	Rangeland	Grassland and open savannah with scattered shrubs; combined grass and scrub class

Table 2
Summary of raster dataset properties and analysis parameters.

Property	Value
Data source	Esri / Impact Observatory Sentinel-2 10 m LULC Time Series
Temporal coverage	2017–2024 (8 annual maps)
Native spatial resolution	10 m
Analysis grain	~ 30 m (mode resampling, scale factor = 3)
Coordinate reference system	WGS 84 / UTM zone 36S (EPSG: 32736)
Raster dimensions	29,292 rows × 30,746 columns
Common analysis window	29,132 rows × 30,596 columns
NoData convention	0 (background; absent from official legend)
Thematic classes observed	7 (codes 1, 2, 4, 5, 7, 8, 11)

2.3 Raster Preprocessing

2.3.1 Spatial subsetting and alignment

For each year (2017–2024), the corresponding global LULC tile was downloaded from the ArcGIS Living Atlas - Sentinel-2 Land Cover Explorer and imported into ArcGIS Pro (version 3.6) for initial spatial subsetting. Each annual raster was clipped to the study area boundary using the Extract by Mask geoprocessing tool with a vector polygon delineating the Katavi landscape extent. The masked outputs were exported as single-band GeoTIFF files in the WGS 84 / UTM zone 36S projected coordinate system

(EPSG: 32736), preserving the native unsigned 8-bit integer encoding of the class codes. A diagnostic check confirmed that all eight annual rasters shared an identical pixel grid geometry (29,292 rows × 30,746 columns at 10 m resolution), ensuring direct year-to-year comparability without additional co-registration or reprojection.

2.3.2 NoData treatment

The clipped rasters did not carry an explicit NoData tag in their internal metadata. Inspection of the unique pixel values across all years revealed that the value 0 was not part of the official class legend (which begins at code 1) and occurred at a stable proportion in every annual raster, corresponding to the masked background area outside the valid landscape footprint. The value 0 was therefore designated as NoData throughout the analysis. All compositional calculations were performed on valid (non-zero) pixels only, and pixels were included in the transition matrix only when both the 2017 and 2024 rasters contained non-zero class codes at that location.

2.3.3 Common analysis window

To guard against spurious change signals arising from minor differences in valid-pixel extent between years, a single common analysis window was computed from the bounding extent of all non-zero pixels in the 2017 reference raster. This rectangular window (29,132 rows × 30,596 columns) was applied uniformly to all subsequent years, ensuring that every annual metric was derived from an identical spatial footprint.

2.3.4 Spatial grain aggregation

Landscape metrics are recognised to be sensitive to the spatial grain of the input data (Turner et al., 2001; Wu, 2004). At the native 10 m resolution, the analysis window comprised approximately 891 million pixels per year, rendering exhaustive patch delineation and landscape metric computation computationally prohibitive in terms of processing time and memory requirements. To balance analytical tractability with thematic fidelity, the rasters were aggregated to an effective grain of approximately 30 m by applying a scale factor of 3 (i.e., 3 × 3 pixel blocks) with mode resampling. Mode resampling assigns the most frequent class value within each block, which is the standard aggregation method for categorical data (McGarigal, 1995). This approach may underrepresent very small patches (area < 900 m^2); accordingly, the effective minimum mapping unit of the analysis should be interpreted as approximately 30 m when evaluating patch count and shape metrics.

2.4 Landscape Pattern Analysis

2.4.1 Software implementation and patch delineation

All landscape metrics were computed in Python (version 3.13.5) using the PyLandStats library (Bosch, 2019), which provides reproducible, FRAGSTATS-equivalent algorithms within the scientific Python ecosystem. Patches were delineated under two alternative connectivity rules to evaluate the sensitivity of spatial pattern metrics to adjacency assumptions: (a) 4-neighbour (rook) connectivity, where pixels

are considered connected only if they share a common edge; and (b) 8-neighbour (queen) connectivity, where pixels sharing either an edge or a corner are treated as connected. Both rules were applied to every year and every metric set, and differences between the two were interpreted as connectivity sensitivity.

2.4.2 Landscape-level metrics

Four landscape-level metrics were computed annually across the valid (non-background) area to capture complementary aspects of landscape configuration:

Contagion (CONTAG) quantifies the degree to which patch types are aggregated or clumped within the landscape. It is derived from the probability of adjacent cell pairs belonging to the same versus different classes (Li & Reynolds, 1993). Higher CONTAG values indicate landscapes dominated by a few large, contiguous patches; lower values indicate greater intermixing and fragmentation (McGarigal & Marks, 1995).

Edge Density (ED) measures the total length of edge between all patch types per unit landscape area (m ha^{-1}). By standardising edge to a per-area basis, ED facilitates comparisons across landscapes of different extent and permits inter-annual tracking of boundary complexity.

Shannon's Diversity Index (SHDI) captures landscape compositional diversity as a function of the number of classes and the evenness of their proportional representation. SHDI approaches zero when the landscape is dominated by a single class and increases with the number and equitability of classes present.

Splitting Index (SPLIT) expresses the degree of landscape subdivision and is computed as $SPLIT = A^2 / \sum(a_{ij}^2)$, where A denotes total landscape area and a_{ij} represents individual patch areas (Jaeger, 2000). Higher SPLIT values indicate a more fragmented landscape in which area is distributed among many small, disjunct patches.

CONTAG, ED, and SHDI were computed directly through PyLandStats. SPLIT was derived from the patch-area table exported for each year using the published FRAGSTATS formula, as the metric is not natively available in the library.

2.4.3 Class-level metrics

To identify which individual cover types were responsible for driving landscape-level change, five class-level metrics were computed annually for all non-background classes:

Proportion of Landscape (PLAND) - the percentage of valid area occupied by the focal class; equivalent to compositional share.

Number of Patches (NP) - the total count of discrete patches belonging to each class under the specified connectivity rule.

Class Edge Density (ED $_{class}$) - the edge length contributed by the focal class, normalised to a per-unit-area basis.

Aggregation Index (AI) - computed as AI = (g_{ii} / max g_{ii}) × 100, where g_{ii} is the observed number of like-adjacencies and max g_{ii} is the theoretical maximum for the given class abundance (He et al., 2000). Values near 100 indicate highly compact, aggregated patches.

Mean Shape Index (SHAPE $_{MN}$) - the arithmetic mean of patch-level shape index values, where a value of 1 corresponds to a maximally compact (square) patch and increasing values indicate greater boundary complexity.

Class-level metrics were evaluated for the six primary cover types observed in the study area: Trees, Rangeland, Water, Crops, Built area, and Flooded vegetation. Bare ground was excluded from the class-level narrative owing to its negligible extent (< 0.01% in all years).

2.5 Change Detection

2.5.1 Annual composition time series

For each year, class composition was expressed as the percentage of valid (non-zero) pixels belonging to each class: $\%Class_i = 100 \times n_i / \sum n_{valid}$. This normalisation ensured internal consistency between the composition table and the PLAND values derived from the landscape analysis.

2.5.2 Endpoint change summaries

Change between the study endpoints was quantified for every metric as: (i) absolute change, $\Delta = Value_{2024} - Value_{2017}$; and (ii) relative change, $100 \times \Delta / Value_{2017}$. These endpoint summaries provided a concise characterisation of both direction and magnitude for each metric and class.

2.5.3 Pixel-wise transition matrix

A transition matrix was constructed by cross-tabulating pixel-level class assignments between 2017 and 2024 across the common analysis footprint. Only pixels classified as valid in both years were included. Transition counts were converted to area (hectares) using the pixel area at the analysis grain (~ 30 × 30 m = 900 m²). The matrix distinguished persistence (diagonal entries representing pixels that retained their class) from class-to-class conversions (off-diagonal entries), enabling identification of the dominant conversion pathways, separation of net from bidirectional exchange, and attribution of donor and recipient classes.

2.6 Robustness and Uncertainty Considerations

Three principal sources of methodological uncertainty were addressed. First, all metrics were computed under both 4-neighbour and 8-neighbour connectivity to ensure that ecological conclusions were robust to the definition of patch adjacency. Second, the use of a ~ 30 m aggregated grain was documented and interpreted with caution; while mode resampling preserves the dominant class within each block, very

small patches may be suppressed, and patch-count metrics should be regarded as conservative estimates. Third, thematic uncertainty inherent to any global LULC product was acknowledged. Spectral confusion between trees and rangeland; the two dominant classes in miombo ecosystems and between water and flooded vegetation can be exacerbated by seasonal phenology and cloud contamination (Venter et al., 2022). Accordingly, large bidirectional exchanges between spectrally similar classes were interpreted conservatively, and pronounced inter-annual fluctuations in minor classes (particularly flooded vegetation) were flagged as potentially reflecting classification variability rather than genuine conversion, unless independently corroborated.

2.7 Data Analysis

For each year, valid mapped pixels were tabulated by class and converted to percent of valid mapped area. Patch-based metrics were computed under both 4-neighbor and 8-neighbor connectivity rules; the 4-neighbor rule is used as the primary reporting convention because it is more conservative for patch merging.

Endpoint change detection paired 2017 and 2024 pixels on the aligned grid to build a class-to-class transition matrix. Transition counts were converted to area using the analysis-grain cell size (~ 30 × 30 m = 0.09 ha). Gross gains, gross losses and net change were then summarized for each land-cover class. Raster QA checks confirmed that the annual grids shared the same CRS, shape and resolution, that valid-area composition sums were internally consistent, and that net class change balanced to zero.

The entire workflow was implemented as a scripted, reproducible pipeline in Python: raster I/O via Rasterio, array processing via NumPy, tabulation via Pandas, landscape metrics via PyLandStats, and visualisation via Matplotlib.

3. Results

3.1 Overall Land-Cover Composition

Katavi remained dominated by trees and rangeland throughout the study period (Fig. 2A). Tree cover increased from 61.03% of valid mapped area in 2017 to 65.45% in 2024 (+ 4.42 percentage points), while rangeland declined from 33.22% to 27.42% (-5.80 percentage points) (Fig. 2B). Water increased modestly to 5.13%, and built area expanded from 0.12% to 0.32%, indicating a small but directionally consistent expansion of anthropogenic cover.

3.2 Landscape Configuration

Landscape configuration changed more subtly than composition (Fig. 4). CONTAG remained high, showing that the landscape was still organized around large contiguous tree and rangeland blocks. ED declined slightly, consistent with some coalescence of dominant cover types, while SHDI increased

marginally as minor classes became more represented. The strongest structural signal was SPLIT, which increased by 51.4%, indicating greater subdivision of the mapped landscape by 2024 (Table 3).

Table 3
Landscape-level configuration metrics for the Katavi landscape, 2017 versus 2024.

Metric	2017	2024	Change	Change (%)
CONTAG	74.52	74.14	−0.39	−0.52
Edge density (m ha⁻¹)	17.87	17.27	−0.60	−3.38
SHDI	0.866	0.882	+ 0.016	+ 1.83
SPLIT	3.09	4.68	+ 1.59	+ 51.4

Note: 4-neighbour connectivity. CONTAG, contagion (%); ED, edge density (m ha⁻¹); SHDI, Shannon's diversity index; SPLIT, splitting index. Values rounded for display; changes computed from unrounded metrics. 4- and 8-neighbour results were effectively identical.

3.3 Class-Level Pattern Shifts

Class-level metrics showed divergent trajectories (Fig. 5). Trees gained area while losing patches, a coalescence pattern consistent with expansion and merging of woody cover. Rangeland lost area and became less spatially dominant. Crops, built area and flooded vegetation expanded from small baselines, with increases in patch number that point to scattered, fine-grained proliferation rather than large consolidated blocks (Table 4).

Table 4
Class-level pattern metrics for the principal land-cover classes, 2017 versus 2024.

Class	PLAND 2017 (%)	PLAND 2024 (%)	NP 2017	NP 2024	ΔNP (%)	AI 2017	AI 2024
Trees	61.03	65.45	26,306	18,295	−30.5	97.94	98.24
Rangeland	33.22	27.42	30,046	27,048	−10.0	95.98	95.41
Water	4.61	5.13	803	1,690	+ 110.5	99.65	99.30
Crops	0.96	1.17	3,176	5,519	+ 73.8	93.60	91.79
Built area	0.12	0.32	330	882	+ 167.3	94.46	94.41
Flooded vegetation	0.05	0.51	345	2,113	+ 512.5	91.64	93.99

Note: 4-neighbour connectivity. PLAND, percentage of landscape; NP, number of patches; AI, aggregation index. Bare ground (< 0.01% throughout) omitted. Values rounded for display; ΔNP computed from unrounded counts.

3.4 Endpoint Transitions and Net Change

The transition analysis identified rangeland-to-trees conversion as the dominant off-diagonal pathway, covering 459,404 ha. The reverse pathway, trees to rangeland, covered 234,617 ha. Across all transition pathways, trees showed a net gain of 216,350 ha and rangeland a net loss of 284,691 ha. Rangeland also supplied the largest transitions into crops, water, flooded vegetation and built area, confirming that rangeland was the principal donor class across the landscape (Fig. 6A-B and 7).

4. Discussion

4.1 Landscape configuration dynamics reveal increasing woody dominance amid localized anthropogenic pressure

The observed landscape dynamics indicate that the Katavi heterogeneous landscape is undergoing gradual structural reorganization rather than widespread degradation. Although changes in overall land-cover composition were relatively modest, the configuration metrics revealed substantial shifts in the spatial organization of landscape elements. Tree cover increased while rangelands declined, accompanied by increasing aggregation, reduced edge density, and the coalescence of woody patches. Conversely, localized expansion of cropland and built-up areas occurred primarily along the landscape margins, reflecting emerging anthropogenic pressure without fundamentally altering the dominant landscape matrix. These findings demonstrate that landscape configuration metrics provide a more sensitive indicator of ecological change than land-cover composition alone, revealing structural transformations that would otherwise remain undetected.

The increase in tree cover, coupled with declining patch density and reduced edge density, suggests progressive woody encroachment through patch expansion and consolidation rather than the establishment of numerous isolated patches. Similar patterns have been reported across East African savanna ecosystems, where reduced fire frequency, altered herbivore dynamics, increasing atmospheric CO_2 concentrations, and localized land-use changes have promoted woody expansion into formerly open rangelands. Such structural changes may enhance habitat continuity for woodland-associated species while simultaneously reducing the extent and connectivity of open habitats required by grazing herbivores and other savanna specialists. Consequently, the ecological implications extend beyond changes in land-cover proportions to encompass shifts in habitat suitability, movement pathways, and ecosystem functioning. These relationships illustrate a fundamental principle of landscape ecology, whereby changes in spatial pattern influence ecological processes beyond changes in habitat extent alone (Turner, 2005; Turner & Gardner, 2015).

The relatively stable Contagion Index should not be interpreted as evidence of landscape stability. Rather, it indicates that the dominant landscape matrix has remained intact while undergoing internal structural reorganization. This distinction is important because ecological degradation often begins through changes in spatial configuration before substantial habitat loss becomes apparent. Landscape ecological theory recognizes that habitat configuration can influence ecological processes independently of habitat quantity, making spatial metrics particularly valuable for detecting early

ecosystem change (Fahrig, 2003; Turner, 2005). The persistence of a continuous landscape matrix therefore reflects structural resilience at the regional scale, even as ongoing reorganization modifies habitat composition, patch arrangement, and ecological processes operating within that matrix.

The marked increase in the Splitting Index, together with contrasting responses among land-cover classes, further demonstrates that fragmentation processes were spatially heterogeneous. Fragmentation intensified primarily within rangelands and localized human-modified areas, whereas woody vegetation became increasingly consolidated. These contrasting trajectories illustrate that protected landscapes may simultaneously experience ecological recovery in some components and emerging anthropogenic pressure in others. Such spatial heterogeneity would be overlooked if interpretation relied solely on net changes in land-cover area.

Together, these findings indicate that the Katavi landscape is transitioning toward increased woody dominance through gradual structural reorganization rather than abrupt land-cover replacement. Such transitions can modify habitat permeability, alter disturbance regimes, and reshape the balance between woodland and open-savanna ecosystems, with important implications for biodiversity conservation, herbivore movement, and long-term ecosystem resilience. More broadly, the results demonstrate the importance of integrating landscape composition, configuration, and transition analyses when assessing protected-area dynamics. While changes in habitat extent describe where land cover has changed, landscape configuration reveals how ecological structure is reorganizing. This distinction is particularly valuable in heterogeneous conservation landscapes, where emerging risks to ecological integrity may develop through fragmentation, patch coalescence, or connectivity changes long before substantial habitat loss becomes evident. Integrating landscape composition with configuration metrics therefore provides a more comprehensive understanding of ecosystem dynamics and strengthens the scientific basis for adaptive conservation planning in heterogeneous protected landscapes (Turner & Gardner, 2015).

4.2 Contrasting landscape trajectories reflect heterogeneous ecological and anthropogenic processes

The class-level landscape metrics demonstrate that the observed changes were not uniform across land-cover types but instead reflected contrasting ecological and anthropogenic processes operating simultaneously within the Katavi heterogeneous landscape. Tree cover exhibited increasing aggregation, declining edge density, and fewer but larger patches, indicating progressive consolidation of woody vegetation. In contrast, rangelands became increasingly fragmented, with reductions in area, patch size, and connectivity. Cropland and built-up areas expanded primarily along landscape margins, reflecting localized human pressure rather than widespread transformation of the protected landscape. These contrasting responses highlight the heterogeneous nature of landscape dynamics, where different land-cover classes follow distinct structural trajectories despite occurring within the same regional landscape.

The expansion and consolidation of woody vegetation are consistent with increasing woody encroachment reported across many African savanna ecosystems. Woody encroachment has frequently been associated with interacting drivers such as altered fire regimes, changes in herbivore communities, increasing atmospheric CO_2 concentrations, and localized reductions in disturbance. While greater woodland continuity may benefit woodland-dependent species by increasing habitat availability and structural connectivity, continued expansion into open rangelands may reduce habitat suitability for grazing wildlife and alter ecological interactions that maintain savanna ecosystem structure and function. Consequently, the ecological consequences of woody expansion depend not only on changes in vegetation cover but also on the balance maintained between woodland and grass-dominated habitats. Evaluating these contrasting trajectories therefore requires consideration of both habitat amount and habitat configuration, which together determine ecological functioning across heterogeneous landscapes (Fahrig, 2013; Turner & Gardner, 2015).

The fragmentation of rangelands has equally important ecological implications. Open habitats provide essential foraging areas for many large herbivores characteristic of the Katavi ecosystem, and progressive subdivision of these habitats may reduce landscape permeability, alter movement pathways, and increase the energetic costs associated with seasonal resource use. Although fragmentation remained spatially localized during the study period, continued expansion of agriculture and settlements around protected-area boundaries could progressively weaken ecological connectivity between core habitats and surrounding multiple-use landscapes if left unmanaged. Similar patterns have been documented in modified conservation landscapes, where incremental land-use change gradually erodes habitat connectivity despite relatively limited reductions in overall habitat extent (Fischer & Lindenmayer, 2007).

Conversely, the relatively limited expansion of cropland and built-up land suggests that anthropogenic pressure remains concentrated rather than pervasive. This finding indicates that the protected-area network continues to buffer much of the landscape from extensive human modification. Nevertheless, the rapid proportional increase in these land-cover classes signals emerging pressures that warrant continued monitoring because localized development often represents the initial stages of broader landscape transformation. Detecting such changes early is particularly important in heterogeneous conservation landscapes, where cumulative impacts may become ecologically significant long before they are reflected in substantial losses of natural habitat.

Overall, the contrasting trajectories among landscape classes demonstrate that protected landscapes cannot be adequately assessed using a single measure of habitat gain or loss. Instead, integrating class-specific landscape metrics provides a more comprehensive understanding of how different ecological processes reshape landscape structure simultaneously. Such an approach improves the capacity to distinguish between natural ecological reorganization and localized anthropogenic disturbance, thereby providing a stronger scientific basis for adaptive conservation planning and long-term landscape management. More broadly, these findings reinforce one of the central principles of landscape ecology:

understanding ecosystem dynamics requires evaluating not only changes in habitat extent but also changes in the spatial configuration through which ecological processes operate (Turner, 2005).

4.3 Rangeland contraction, fragmentation, and implications for landscape function

The decline and progressive fragmentation of rangelands represent one of the most ecologically significant structural changes observed across the Katavi landscape. Although rangelands remained the second most extensive land-cover class throughout the study period, they experienced substantial reductions in area together with increasing subdivision and declining aggregation. These changes indicate that rangelands are becoming increasingly fragmented and spatially isolated despite continuing to occupy a considerable proportion of the landscape. Such patterns suggest that ecological change within the Katavi landscape is occurring through gradual modification of habitat configuration rather than abrupt habitat loss, emphasizing that changes in landscape structure often precede major changes in landscape composition (Turner, 2005).

The dominant conversion of rangelands to woody vegetation indicates that fragmentation is closely linked to ongoing woody encroachment, while localized conversion to cropland and built-up areas further contributes to the subdivision of remaining open habitats. These interacting processes progressively reduce the size, continuity, and structural integrity of rangelands, potentially altering ecological processes that depend on extensive open landscapes. As fragmentation increases, the remaining rangeland patches become more irregular and isolated, reducing landscape permeability for species adapted to open savanna environments. Such structural changes are widely recognized as important drivers of biodiversity responses because fragmentation influences species persistence through both habitat configuration and habitat availability (Fahrig, 2003).

The ecological implications extend beyond changes in habitat extent. Rangelands within the Katavi ecosystem provide critical grazing resources for both wildlife and livestock and contribute to seasonal wildlife movements between protected areas and surrounding multiple-use landscapes. Progressive fragmentation may therefore constrain movement pathways, reduce access to forage, and increase pressure on the remaining continuous grazing areas. Although the present study did not directly evaluate wildlife movement or functional connectivity, the observed structural changes are consistent with landscape ecological theory, which predicts that increasing fragmentation can reduce functional connectivity, alter species movement, and disrupt ecological processes long before habitat availability becomes critically limited (Haddad et al., 2015; Fischer & Lindenmayer, 2007). Consequently, the observed landscape reorganization may represent an early indication of emerging constraints on ecological function within the broader protected landscape.

Importantly, fragmentation should not be interpreted solely as a reduction in habitat area. Landscape ecology recognizes that habitat amount and habitat configuration are complementary components of landscape structure, both of which influence biodiversity, ecological processes, and functional connectivity (Fahrig, 2003, 2013; Turner, 2005). Consequently, evaluating habitat extent alone provides

only a partial understanding of ecological change within heterogeneous landscapes. In the Katavi landscape, the marked increase in the Splitting Index, together with declining rangeland aggregation, indicates that habitat configuration is changing in ways that may influence species movement, disturbance dynamics, and ecosystem resilience even where substantial areas of natural vegetation remain. These findings reinforce the importance of integrating habitat amount with configuration metrics when assessing the ecological condition of protected landscapes.

The results also highlight the value of detecting fragmentation at an early stage. Although cropland and built-up land still occupy relatively small proportions of the landscape, continued population growth and incremental land conversion around protected-area boundaries could progressively intensify fragmentation of the remaining open habitats. Monitoring changes in rangeland configuration therefore provides an opportunity to identify emerging conservation risks before widespread habitat degradation occurs, allowing management interventions to maintain landscape connectivity and the ecological functions supported by open savanna systems. Maintaining functional connectivity before fragmentation reaches ecological thresholds is widely recognized as one of the most effective strategies for sustaining biodiversity and long-term landscape resilience within protected-area networks (Haddad et al., 2015; Turner & Gardner, 2015).

4.4 Peripheral anthropogenic expansion under demographic pressure

Although cropland and built-up land occupied relatively small proportions of the Katavi landscape throughout the study period, their spatial trajectories provide important evidence of emerging anthropogenic pressure. Built-up land more than doubled (+ 159.7%), while cropland increased by 22.2%, with both classes exhibiting marked increases in patch number but little change in aggregation. This pattern indicates dispersed rather than consolidated expansion, suggesting that landscape modification is occurring through the establishment of numerous small settlements and cultivated fields rather than large, contiguous areas of conversion. Such spatial signatures are characteristic of the early stages of landscape transformation, where localized development progressively alters landscape structure before substantial changes in overall land-cover composition become evident.

The observed pattern is consistent with the demographic changes occurring within the region. Katavi's population increased from 564,604 in 2012 to 1,152,958 in 2022, representing a 104.2% increase (United Republic of Tanzania, National Bureau of Statistics, & Office of the Chief Government Statistician, 2024). Population growth inevitably increases demand for agricultural land, settlement, fuelwood, transport infrastructure, and other natural resources, placing increasing pressure on protected-area boundaries and adjacent village lands. Although the spatial footprint of these land-cover classes remains relatively limited, their dispersed distribution suggests that human influence is expanding through incremental encroachment rather than extensive landscape conversion.

This interpretation is consistent with previous studies from the Katavi–Rukwa ecosystem, which have identified surrounding land-use change as an important factor influencing the long-term effectiveness of

protected areas, wildlife distribution, and ecological connectivity (Giliba et al., 2022). Similar patterns have been reported globally, where protected areas substantially reduce habitat loss within their boundaries but remain vulnerable to increasing anthropogenic pressure along their peripheries (Li et al., 2024). The dispersed expansion of cropland and settlements observed in Katavi therefore represents more than a simple increase in land-cover area; it reflects an emerging reorganization of the landscape matrix that can progressively increase fragmentation, edge effects, and interactions between human activities and natural ecosystems.

From a landscape ecological perspective, the spatial arrangement of these small anthropogenic patches may be more consequential than their current extent. Numerous scattered patches introduce new habitat edges, increase landscape heterogeneity, and reduce the continuity of surrounding natural habitats. Over time, these incremental changes can modify ecological flows, increase disturbance frequency, and reduce the permeability of the landscape for wide-ranging species, even when the total area converted remains relatively small (Turner, 2005; Fischer & Lindenmayer, 2007).

The environmental consequences of peripheral expansion extend beyond landscape structure. Agricultural expansion and settlement development along protected-area boundaries frequently intensify edge-related disturbances, including altered fire regimes, illegal resource extraction, invasive species establishment, and increased human–wildlife interactions. Where these activities occur near the Katuma floodplain and associated wetlands, they may also contribute to greater nutrient and sediment inputs and intensify competition for water resources. These interacting pressures illustrate how localized anthropogenic expansion can influence both terrestrial landscape configuration and broader ecosystem processes, reinforcing the need for integrated monitoring of land-use change across protected-area boundaries.

4.5 Water and flooded vegetation dynamics and links to basin processes

Changes in water and flooded vegetation were comparatively modest relative to those observed for terrestrial land-cover classes, yet they remain ecologically important because the Katuma River–Lake Katavi floodplain functions as a key organizing feature of the broader landscape. Open water increased slightly from 4.61% to 5.13%, while flooded vegetation exhibited greater temporal variability with an overall increase during the study period. Given the dynamic nature of floodplain ecosystems, these patterns should be interpreted cautiously because wetland extent is strongly influenced by seasonal inundation, vegetation phenology, and classification uncertainty associated with annual satellite composites.

Although the present analysis was not designed to evaluate hydrological processes directly, previous basin-scale studies have demonstrated that water abstraction, irrigation infrastructure, and river regulation influence the hydrological functioning of the Katuma River–Lake Katavi wetland system, while management interventions such as the removal of illegal weirs have contributed to partial hydrological

recovery (Elisa et al., 2021). Consequently, changes in water-related land-cover classes should be interpreted within the broader context of basin processes rather than as isolated landscape phenomena.

From a landscape ecological perspective, wetlands perform functions that extend beyond the water bodies themselves. They contribute to habitat heterogeneity, maintain ecological connectivity, regulate seasonal resource availability, and support the movement of wildlife across the landscape. Consequently, even relatively small changes in floodplain dynamics may influence ecological processes disproportionately to their spatial extent by altering habitat availability and the connectivity of aquatic and terrestrial ecosystems (Turner & Gardner, 2015).

The modest increase in mapped open water observed in this study may therefore reflect interannual hydrological variability, management interventions, or a combination of both. However, the available evidence does not permit attribution of these changes to specific drivers. Resolving these mechanisms will require the integration of multi-season satellite observations with rainfall records, river discharge, groundwater dynamics, and time-series analyses capable of distinguishing permanent water from seasonal inundation.

Future research would also benefit from combining optical imagery with Synthetic Aperture Radar (SAR), which is less affected by cloud cover and can improve the detection of seasonal flooding and floodplain connectivity. Such approaches would provide a more comprehensive understanding of hydro period dynamics and strengthen assessments of how hydrological variability interacts with landscape configuration to influence ecosystem resilience within the Katavi protected landscape.

4.6 Robustness, uncertainty, and interpretation boundaries

The consistency of the observed landscape patterns across multiple analytical approaches increases confidence in the principal findings. The sensitivity analysis demonstrated that metrics describing overall landscape configuration were largely robust to alternative connectivity definitions, whereas patch-area-dependent metrics such as the Splitting Index showed the expected sensitivity to changes in neighbourhood rules. This behaviour is consistent with landscape metric theory, where diagonal connectivity influences patch delineation without substantially altering broader spatial trends. Importantly, the principal conclusions-including the progressive consolidation of woody vegetation, fragmentation of rangelands, and localized expansion of anthropogenic land uses-remained consistent irrespective of the connectivity definition adopted. Likewise, the asymmetric transition matrix independently corroborated the observed net increase in woody vegetation, providing complementary evidence that the detected landscape changes reflect coherent ecological patterns rather than methodological artefacts.

Despite this consistency, several interpretation boundaries should be acknowledged. First, thematic uncertainty remains an inherent limitation of global land-cover products. Although the ESA WorldCover dataset provides high overall classification accuracy, confusion between woody and herbaceous vegetation remains a recognized challenge within heterogeneous savanna–woodland mosaics, where

gradual vegetation transitions complicate class discrimination (Venter et al., 2022). Consequently, small changes affecting individual vegetation classes should be interpreted with appropriate caution.

Second, landscape metrics are inherently scale dependent. Aggregating the original 10 m data to an effective 30 m grain improved computational efficiency and reduced pixel-level noise but inevitably reduced the representation of very small landscape features. As a result, metrics based on patch number and patch size are likely conservative estimates of fine-scale fragmentation. Nevertheless, because all analyses were performed using a consistent spatial resolution, the temporal trends reported here remain directly comparable and provide a robust basis for evaluating long-term landscape dynamics.

Finally, landscape metrics describe how landscape structure changes but do not, on their own, identify the processes responsible for those changes. While the observed patterns are consistent with woody encroachment, localized agricultural expansion, and demographic growth, establishing causal relationships requires the integration of additional datasets describing fire regimes, rainfall variability, grazing intensity, hydrological dynamics, accessibility, and land-use policy. Future studies combining landscape ecological analyses with these complementary drivers will provide a more comprehensive understanding of the mechanisms shaping landscape change within the Katavi ecosystem.

4.7 Management implications and priorities for integrated landscape conservation

The landscape changes observed in Katavi indicate that conservation management should focus not only on preventing habitat loss but also on maintaining the spatial structure and ecological functioning of the landscape. Although the protected landscape remains dominated by natural vegetation, the combined effects of woody expansion, progressive rangeland fragmentation, and localized anthropogenic development suggest that ecological integrity is increasingly influenced by changes in landscape configuration rather than by extensive land-cover conversion alone. Consequently, landscape configuration metrics can provide valuable early-warning indicators of ecological change, allowing management interventions before degradation becomes widespread.

A first management priority is to maintain the integrity of open rangeland systems. While rangelands continue to occupy a substantial proportion of the landscape, the increasing Splitting Index indicates progressive subdivision that may reduce habitat continuity and ecological connectivity for species dependent on open savanna habitats. Conservation efforts should therefore extend beyond protecting the total area of rangelands to maintaining the size, connectivity, and spatial arrangement of remaining habitat patches. Protecting large contiguous rangeland blocks and safeguarding movement corridors between grazing areas and wetlands will help sustain ecological processes that depend on landscape connectivity.

A second priority is the early management of peripheral anthropogenic expansion. The proliferation of small cropland and settlement patches suggests that landscape modification remains relatively localized, providing an opportunity for proactive intervention before scattered developments coalesce

into larger, more fragmented landscapes. Tanzania's framework for integrated and participatory village land-use planning provides an appropriate mechanism for guiding settlement expansion, clarifying land-use boundaries, and reducing conflicts between conservation and local development objectives (National Land Use Planning Commission, 2020). Previous studies further demonstrate that incorporating geospatial information into participatory planning improves decision-making but requires sustained institutional capacity and long-term implementation to achieve meaningful conservation outcomes (Eilola et al., 2021).

A third priority is to strengthen integrated monitoring of terrestrial and wetland ecosystems. Although changes in open water and flooded vegetation were relatively modest, the ecological importance of the Katuma River–Lake Katavi floodplain extends far beyond its spatial extent. Coordinated monitoring of landscape configuration together with hydrological dynamics would improve understanding of how land-use change, water management, and seasonal flooding interact to influence habitat availability, floodplain connectivity, and ecosystem resilience. Such integrated monitoring would provide a stronger evidence base for adaptive management across the wider Katavi ecosystem.

More broadly, this study demonstrates the value of landscape ecological approaches for protected-area management. While conventional land-cover assessments identify where change has occurred, landscape configuration metrics reveal how ecological structure is reorganizing and where emerging pressures are beginning to alter landscape function. Incorporating these complementary perspectives into long-term monitoring programmes would strengthen the capacity of conservation agencies to detect early ecological change, prioritize management interventions, and maintain landscape resilience under increasing environmental and demographic pressures.

4.8 Future research directions

Three research extensions would materially strengthen inference and management relevance.

1. Zonal stratification by protection and land-tenure: Disaggregate metrics inside Katavi National Park, buffer zones, and village lands to identify where coalescence, fragmentation, and anthropogenic proliferation are concentrated. This would directly connect patterns to governance regimes and enforcement realities.
2. Driver attribution: Combine land-cover transitions with burned area products, rainfall anomalies, and accessibility variables to test whether woody expansion aligns more closely with fire suppression, climate variability, or localized land management, consistent with regional patterns reported across Africa (Venter et al., 2018).
3. Independent validation: Use targeted field checks or very high-resolution imagery sampling in rangeland–tree ecotones and wetland margins to quantify class confusion rates and refine uncertainty bounds, building on known performance characteristics of 10 m global products (Venter et al., 2022).

5. Conclusion

This study demonstrates that the Katavi heterogeneous landscape underwent significant structural reorganization between 2017 and 2024 despite relatively modest changes in overall land-cover composition. The integration of landscape composition, configuration, and transition analyses revealed a clear ecological trajectory characterized by progressive woody expansion, increasing rangeland fragmentation, and localized anthropogenic development concentrated around landscape margins. These findings show that important ecological change can occur through the reorganization of landscape structure long before substantial losses of natural habitat become apparent.

The contrasting responses of individual land-cover classes highlight the complexity of ecological processes operating within protected landscapes. While increasing woody connectivity may enhance habitat continuity for woodland-associated species, the fragmentation of open rangelands and the dispersed expansion of cropland and settlements have the potential to alter habitat permeability, ecological connectivity, and the functioning of savanna ecosystems. The observed landscape dynamics therefore reflect the simultaneous influence of natural ecological processes and emerging human pressures rather than a single, uniform pattern of landscape change.

From a conservation perspective, the results demonstrate that monitoring habitat extent alone is insufficient for understanding landscape condition. Landscape configuration metrics provide complementary information on fragmentation, aggregation, connectivity, and spatial organization, offering early indications of ecological change before these are reflected in substantial habitat loss. Incorporating these metrics into routine protected-area monitoring would strengthen the capacity to identify emerging conservation risks, prioritize management interventions, and evaluate the effectiveness of long-term landscape management.

More broadly, this study illustrates the value of landscape ecological approaches for understanding and managing heterogeneous conservation landscapes. By linking changes in landscape pattern with ecological processes and management implications, it provides a stronger scientific basis for conserving ecosystem resilience, maintaining functional connectivity, and supporting adaptive conservation planning in Katavi and other savanna protected-area systems experiencing increasing environmental and demographic pressures.

Declarations

Author Contribution

J.O.R.: Conceptualization, methodology, investigation, formal analysis, data curation, visualization, writing—original draft. M.L.D.: Methodology, investigation, data curation, writing—review and editing. D.J.K.: Investigation, validation, writing—review and editing. G. S. Melitha: Methodology, formal analysis, writing—review and editing. G. S. Malley: Conceptualization, supervision, interpretation of results, writing—review and editing. All authors read and approved the final manuscript.

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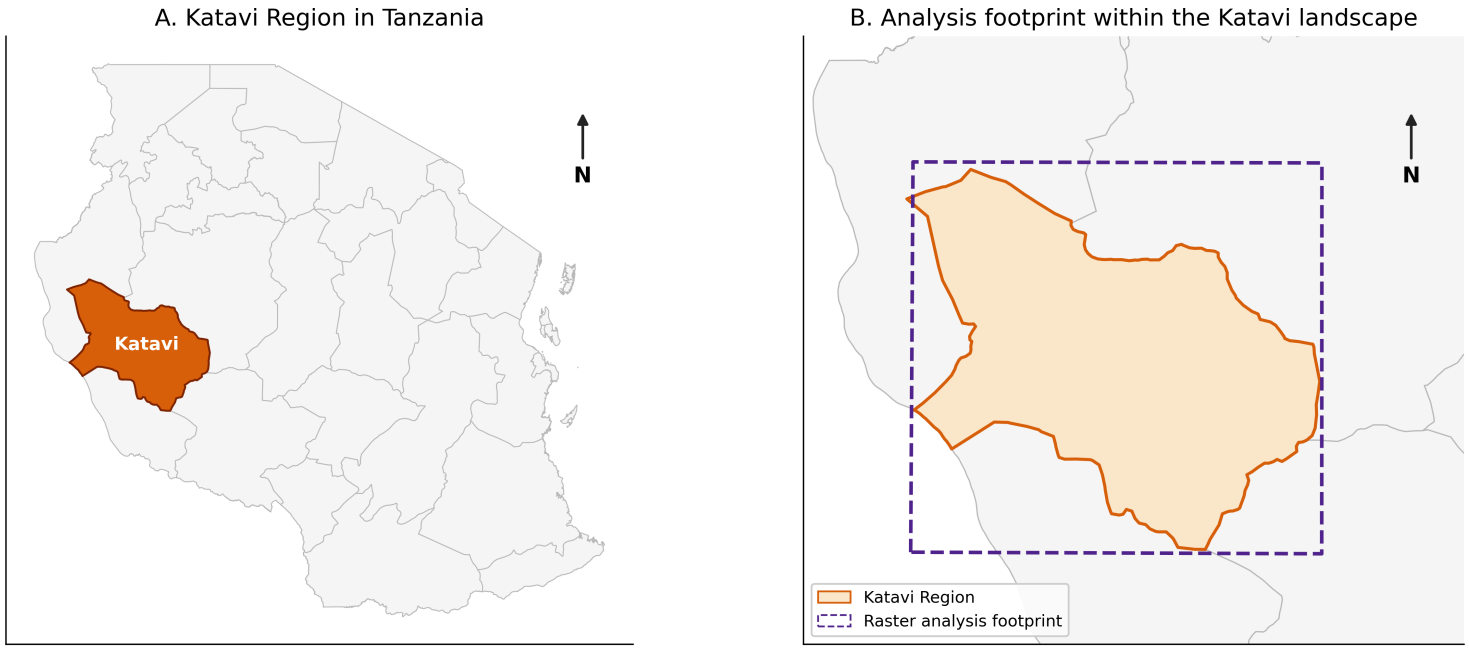
References

1. Banda, T., Mwangulango, N., Meyer, B., Schwartz, M. W., Mbago, F., Sungula, M., & Caro, T. (2008). The woodland vegetation of the Katavi-Rukwa ecosystem in western Tanzania. *Forest Ecology and Management*, *255*(8–9), 3382–3395. https://doi.org/10.1016/j.foreco.2008.01.079
2. Bosch, M. (2019). PyLandStats: An open-source Pythonic library to compute landscape metrics. *PLOS ONE*, *14*(12), e0225734. https://doi.org/10.1371/journal.pone.0225734
3. Crowley, M. A., & Cardille, J. A. (2020). Remote Sensing's Recent and Future Contributions to Landscape Ecology. *Current Landscape Ecology Reports*, *5*(3), 45–57. https://doi.org/10.1007/s40823-020-00054-9
4. de Jonge, I. K., Olff, H., Mayemba, E. P., Berger, S. J., & Veldhuis, M. P. (2024). Understanding woody plant encroachment: A plant functional trait approach. *Ecological Monographs*, *94*(3). https://doi.org/10.1002/ecm.1618
5. Eilola, S., Muro, J., Käyhkö, N., & De Vries, W. T. (2021). Lessons learned from participatory land use planning with earth observation and community mapping in rural Africa. Environmental Science & Policy, 124, 403–415.
6. Elisa, M., Kihwele, E., Wolanski, E., & Birkett, C. (2021). Managing wetlands to solve the water crisis in the Katuma River ecosystem, Tanzania. Ecohydrology & Hydrobiology, 21(2), 211–222. https://doi.org/10.1016/j.ecohyd.2021.02.001
7. Esri. (2024). Global land cover updates. *ArcGIS Blog*. https://www.esri.com/arcgis-blog/products/arcgis-living-atlas/imagery/global-land-cover-updates
8. ESRI. (2026). *Sentinel-2 10-Meter Land Use/Land Cover. ArcGIS Living Atlas of the World*.
9. Fahrig, L. (2017). Ecological responses to habitat fragmentation per se. Annual Review of Ecology, Evolution, and Systematics, 48, 1–23. https://doi.org/10.1146/annurev-ecolsys-110316-022612
10. Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., … Snyder, P. K. (2005). Global consequences of land use. Science, 309(5734), 570–574.

11. Fu, G., Wang, W., Li, J., Xiao, N., & Qi, Y. (2021). Prediction and selection of appropriate landscape metrics and optimal scale ranges based on multi-scale interaction analysis. *Land*, *10*(11), 1192. https://doi.org/10.3390/land10111192
12. Giliba, R. A., Fust, P., Kiffner, C., & Loos, J. (2022). Multiple anthropogenic pressures challenge the effectiveness of protected areas in western Tanzania. *Conservation Science and Practice*, *4*(6), e12684. https://doi.org/10.1111/csp2.12684
13. Haddad, N. M., Brudvig, L. A., Clobert, J., Davies, K. F., Gonzalez, A., Holt, R. D., … Townshend, J. R. (2015). Habitat fragmentation and its lasting impact on Earth's ecosystems. *Science Advances*, *1*(2), e1500052. https://doi.org/10.1126/sciadv.1500052
14. He, H. S., DeZonia, B. E., & Mladenoff, D. J. (2000). An aggregation index (AI) to quantify spatial patterns of landscapes. Landscape Ecology, 15(7), 591–601.
15. IPBES. (2019). *Global assessment report on biodiversity and ecosystem services*. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. https://doi.org/10.5281/zenodo.3831673
16. Jaeger, J. A. (2000). Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. Landscape Ecology, 15(2), 115–130.
17. Kato, S., & Motobe, A. (2024). Landscape metric sensitivity to grain size in rural Japan. *Landscape and Ecological Engineering*. https://doi.org/10.1007/s11355-024-00611-y
18. Kimaro, H. S., Asenga, A. M., Munishi, L., & Treydte, A. C. (2019). Woody Encroachment Extent and Its Associated Impacts on Plant and Herbivore Species Occurrence in Maswa Game Reserve, Tanzania. *Environment and Natural Resources Research*, *9*(3), 63. https://doi.org/10.5539/enrr.v9n3p63
19. Li, G., Fang, C., Watson, J. E. M., Sun, S., Qi, W., Wang, Z., & Liu, J. (2024). Mixed effectiveness of global protected areas in resisting habitat loss. *Nature Communications*, *15*, 8389. https://doi.org/10.1038/s41467-024-52693-9
20. Li, H., & Reynolds, J. F. (1993). A new contagion index to quantify spatial patterns of landscapes. *Landscape Ecology*, *8*(3), 155–162.
21. McGarigal, K., & Marks, B. J. (1995). FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure (General Technical Report PNW-GTR-351). USDA Forest Service, Pacific Northwest Research Station.
22. Mtui, D. T., Lepczyk, C. A., Chen, Q., Miura, T., & Cox, L. J. (2017). Assessing multi-decadal land-cover–land-use change in two wildlife protected areas in Tanzania using Landsat imagery. *PLoS One*, *12*(9), e0185468. https://doi.org/10.1371/journal.pone.0185468
23. Mtuy, E. T., Kavana, D. J., Kipangula, D. C., & Makindara, J. R. (2026). Habitat Heterogeneity Shapes Bee Species Diversity and Community Structure in an East African Protected Ecosystem. *African Journal of Ecology*, *64*(2). https://doi.org/10.1111/aje.70157
24. Mulder, M. B., Caro, T., & Msago, O. A. (2007). The role of research in evaluating conservation strategies in Tanzania: The case of the Katavi-Rukwa ecosystem. *Conservation Biology*, *21*(3), 647–658. https://doi.org/10.1111/j.1523-1739.2007.00703.x

25. Naboureh, A., Li, A., Bian, J., Moharrami, M., Ebrahimy, H., Lei, G., Nan, X., Zhang, Z., Feizizadeh, B., Dabove, P., Makki, M., Sauter, T., Attarchi, S., & Amani, M. (2025). Accuracies, discrepancies, and challenges of the 10 m global land cover products in mountains. GIScience & Remote Sensing, 62(1), 2556064. https://doi.org/10.1080/15481603.2025.2556064
26. National Land Use Planning Commission. (2020). Guidelines for integrated and participatory village land use management and administration (3rd ed.). United Republic of Tanzania.
27. Skhosana, F. V., Stevens, N., Archibald, S., & Lehmann, C. E. R. (2025). The impacts of woody encroachment on nature's contributions to people in North America and Africa: A systematic review. People and Nature. https://doi.org/10.1002/pan3.70134
28. Stevens, N., Lehmann, C. E. R., Murphy, B. P., & Durigan, G. (2017). Savanna woody encroachment is widespread across three continents. Global Change Biology, 23(1), 235–244.
29. Tanzania National Parks Authority. (n.d.). Katavi National Park brochure (KA-ENG).
30. TAWIRI. (2020). Aerial survey of large animals in the Katavi–Rukwa ecosystem. Tanzania Wildlife Research Institute.
31. Turner, M. G., Gardner, R. H., & O'Neill, R. V. (2001). Landscape ecology in theory and practice: pattern and process.
32. URT. (2024). The United Republic of Tanzania, National Bureau of Statistics, & Office of the Chief Government Statistician. (2024). The 2022 Population and Housing Census: Katavi Region basic demographic and socio-economic profile report.
33. URT. (2022). The Wildlife Conservation Act (Cap. 283 Revised Edition 2022). Government Press, Dodoma, Tanzania.
34. Venter, Z. S., Barton, D., Chakraborty, T., Simensen, D., & Singh, G. (2022). Global 10 m land use land cover datasets: A comparison of Dynamic World, WorldCover and Esri Land Cover. *Remote Sensing*, *14*(16), 4101. https://doi.org/10.3390/rs14164101
35. Venter, Z. S., Cramer, M. D., & Hawkins, H. J. (2018). Drivers of woody plant encroachment over Africa. Nature Communications, 9, 2272. https://doi.org/10.1038/s41467-018-04616-8
36. Wu, J. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. Landscape Ecology, 19(2), 125–138.
37. WWF. (2021). Eastern Africa: Katavi–Rukwa landscape conservation. World Wildlife Fund.
38. Xu, P., Tsendbazar, N. E., Herold, M., De Bruin, S., Koopmans, M., Birch, T., … Zanaga, D. (2024). Comparative validation of recent 10 m-resolution global land cover maps. Remote Sensing of Environment, 311, 114316.

Figures



Administrative boundaries: geoBoundaries gbOpen Tanzania ADM1; raster footprint from the aligned Katavi LULC stack.

Figure 1

Figure 1.1: Study area map. Location of Katavi Region within Tanzania and the raster analysis footprint used for the 2017-2024 land-cover analysis. Tanzania ADM1 boundary source: geoBoundaries.

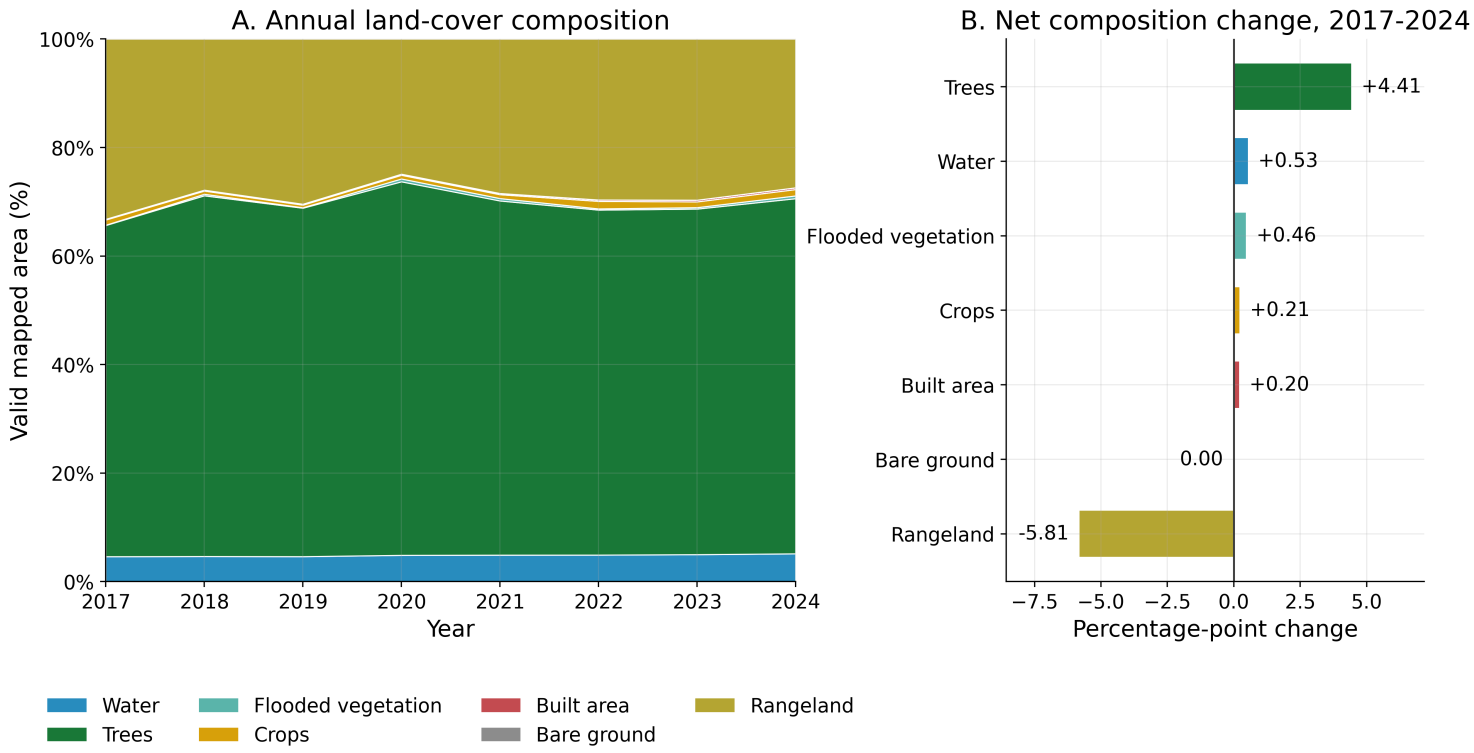


Figure 2

Annual land-cover composition as percent of valid mapped area and endpoint percentage-point change from 2017 to 2024.

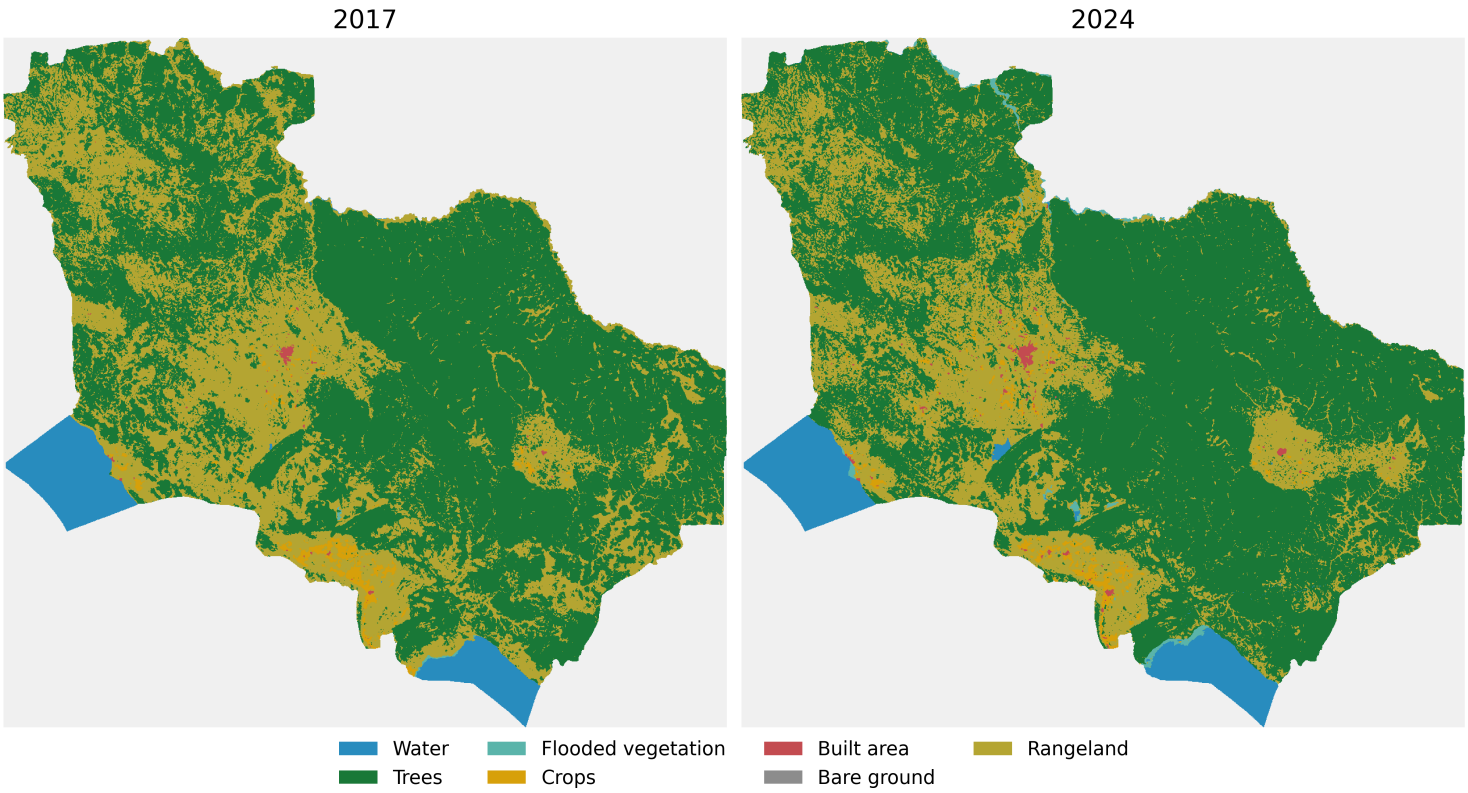


Figure 3

Endpoint classified land-cover maps for 2017 and 2024, displayed at approximately 240 m grain for spatial context.

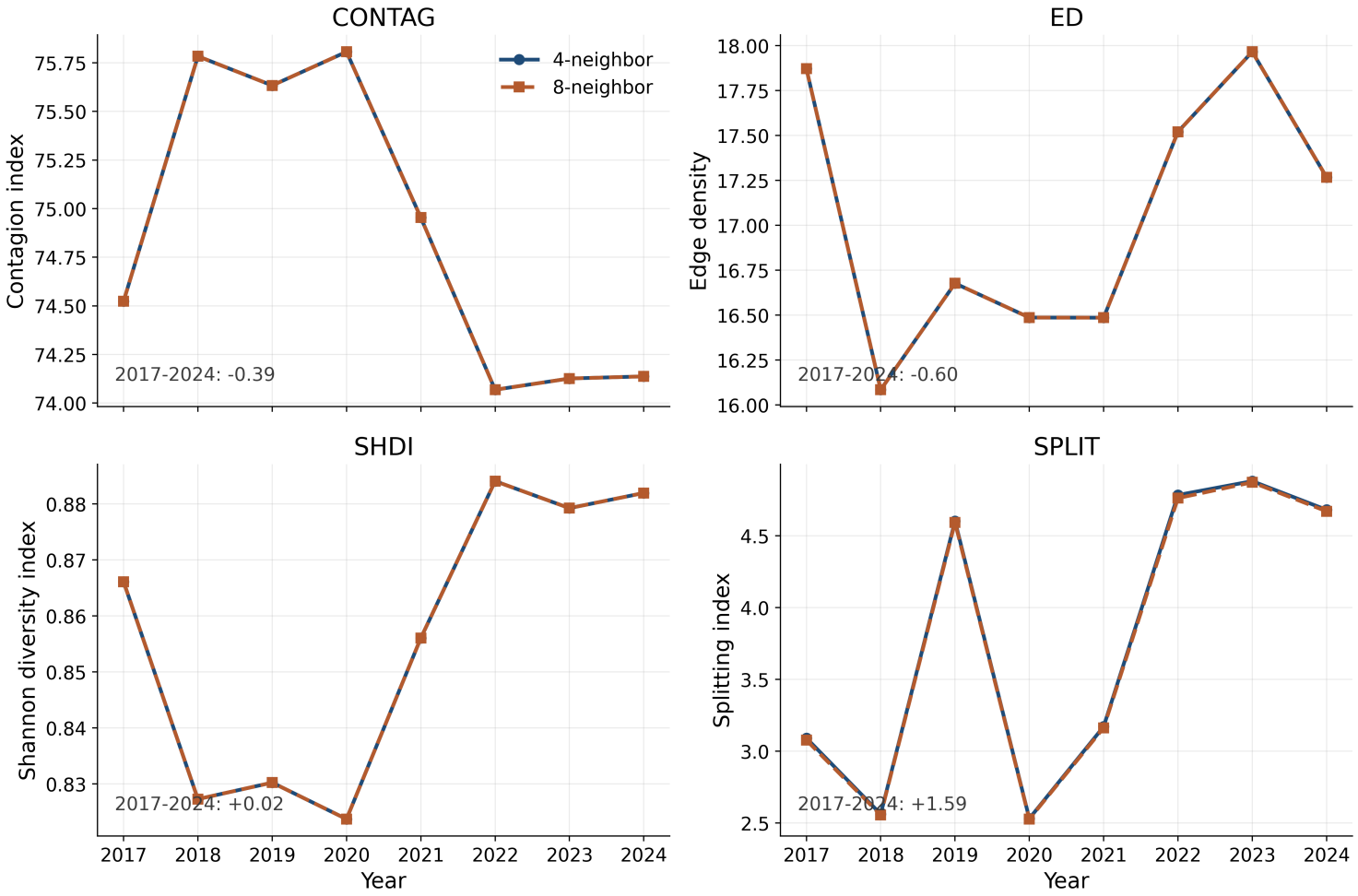


Figure 4

Landscape-level configuration metrics for 4- and 8-neighbor patch definitions, showing stable contagion/diversity and a marked increase in SPLIT.

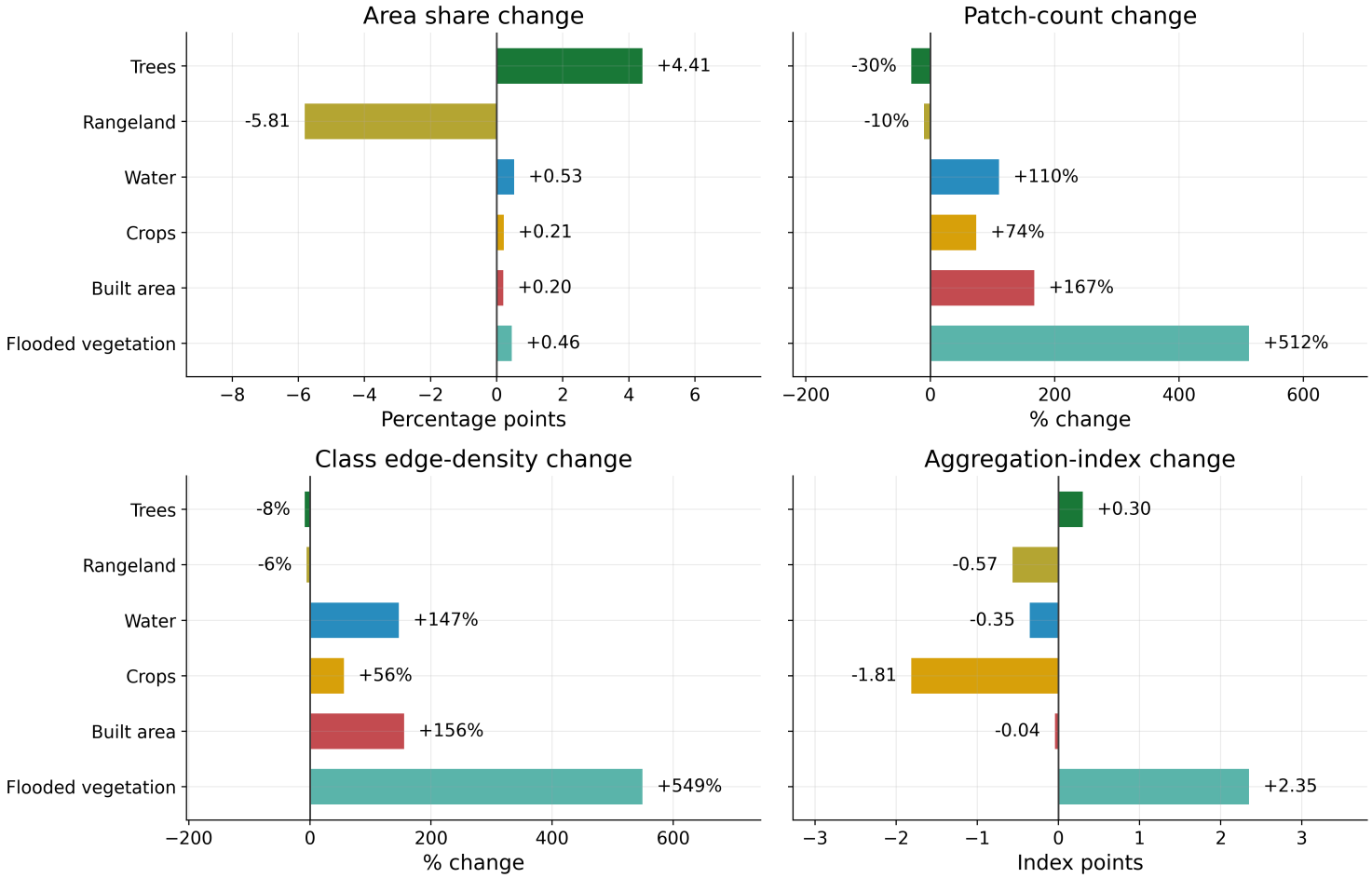


Figure 5

Endpoint class-level changes under the 4-neighbor rule for area share, patch count, edge density, and aggregation index.

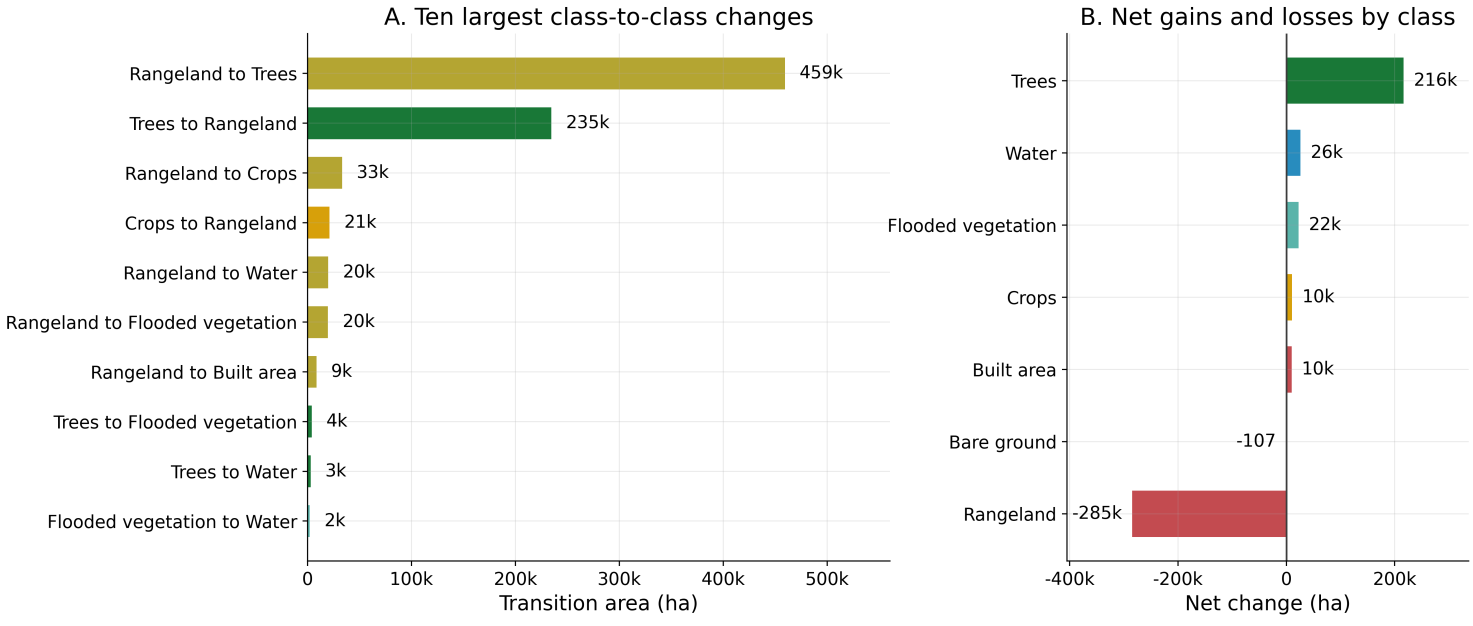


Figure 6

Largest class-to-class changes and net gains/losses by class between 2017 and 2024.

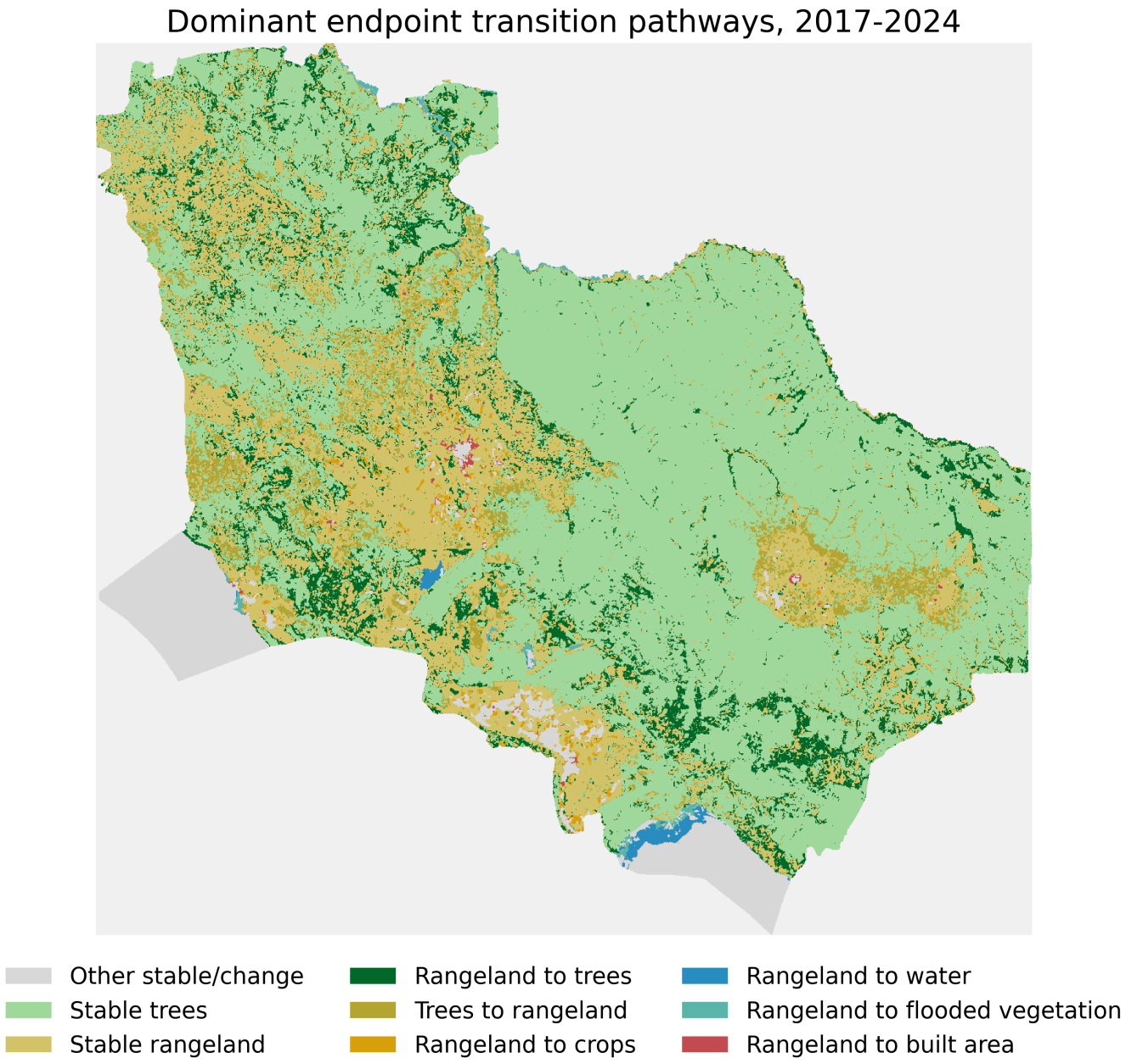


Figure 7

Display-scale map of stable tree/rangeland areas and the largest rangeland/tree/anthropogenic transition pathways