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Long-Term Habitat Dynamics in the Greater Kafue Ecosystem of Zambia Using Multi-Temporal Landsat Data (1984–2024).

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Abstract

The Greater Kafue Ecosystem (GKE) in central-western Zambia, comprising Kafue National Park and nine surrounding Game Management Areas (GMAs), covers approximately 66,000 km² and ranks among southern Africa's largest conservation landscapes. Despite its ecological significance, long-term ecosystem-wide assessments of cumulative habitat transformation remain limited. This study employed multi-temporal Landsat imagery (1984–2024), processed in ArcGIS Pro and classified using Random Forest with object-based refinement, to quantify four decades of land-cover change. Classification performance was robust, with overall accuracies of 82–90% ($\kappa = 0.73$ – 0.86), macro-averaged F1-scores of 81.4–90.0%, and a 2024 overall accuracy confidence interval of $\pm 2.6\%$ (95% CI, $n = 600$). Natural habitat declined from 98.31% (9.65 million ha) in 1984 to 83.96% (8.24 million ha) in 2024, representing a net loss of approximately 1.41 million ha. Agricultural expansion was the dominant driver, with cropland increasing from 0.86% to 14.53%, accounting for 83% of total conversion. Conversion rates accelerated from 10,209 ha yr⁻¹ (1984–1994) to 57,269 ha yr⁻¹ (2014–2024). Spatial patterns were highly heterogeneous: Kafue National Park retained 98.87%, compared with 84.08% across GMAs, with retention ranging from 96.62% (Lunga Luswishi) to 37.77% (Bilili). Habitat loss exhibited strong spatial structuring, with edge effects extending up to 10 km beyond park boundaries and a 14.4 percentage-point gradient associated with proximity to roads. These findings underscore the effectiveness of strict protection while identifying road-accessible buffer zones as priorities for spatially targeted conservation planning.

Keywords: Habitat loss; Land cover change; Protected areas; Greater Kafue Ecosystem; Zambia; Google Earth Engine; Landsat; Miombo woodland.

1. Introduction

Habitat loss remains the dominant driver of global biodiversity declines in the Anthropocene. Between 2001 and 2020, terrestrial ecosystems lost approximately 1.3 million km² of forest cover annually, with species extinction rates estimated to be 100–1,000 times background levels [1–4]. Protected areas now cover roughly 17% of the world’s terrestrial surface and are widely regarded as the cornerstone of biodiversity conservation [5]. However, their effectiveness in preventing habitat loss varies and depends on governance regimes, management intensity, and pressures from surrounding landscapes [6–8]

Sub-Saharan Africa (SSA) presents a distinctive conservation context. The region supports globally significant large mammal assemblages, yet faces rapid demographic growth, agricultural expansion, and infrastructure development [9,10]. Unlike Southeast Asia and Latin America, where industrial agriculture drives large-scale deforestation, habitat loss in Africa is predominantly associated with smallholder agricultural expansion and livelihood pressures [11–14]. These dynamics necessitate conservation strategies that integrate biodiversity protection with rural development and sustainable land management.

The Greater Kafue Ecosystem (GKE) in central-western Zambia exemplifies these conservation challenges. Spanning approximately 66,000 km², the GKE comprises Kafue National Park (KNP; ~22,400 km²), one of Africa’s largest national parks, and nine surrounding Game Management Areas (GMAs; ~43,600 km²) that permit regulated resource use [15,16]. This dual-management structure creates a natural landscape experiment, contrasting a strictly protected core with multiple-use buffer zones. The ecosystem supports substantial elephant and lion populations, endangered African wild dogs, and endemic species such as the Kafue lechwe [17–19], while providing critical ecosystem services including carbon sequestration, hydrological regulation, and tourism revenue [20,21].

Despite GKE’s ecological importance, a systematic understanding of long-term patterns of habitat transformation across the entire GKE remains limited. Existing studies in Zambia have largely focused on district or provincial-scale assessments, individual GMAs, or short temporal windows that capture snapshots rather than multi-decadal trajectories [22,23]. The absence of ecosystem-wide, long-term analysis constrains the evaluation of cumulative habitat transformation, comparison of protection effectiveness across management regimes, and understanding of spatial gradients of change extending from protected cores into buffer zones.

Advances in remote sensing technologies and cloud computing platforms have significantly improved the feasibility of conducting large-scale, multi-temporal land-cover analyses [24–26]. Google Earth Engine (GEE), a cloud-based computing platform, provides access to vast archives of satellite imagery and powerful computational resources, enabling consistent analysis across broad spatial and temporal scales [27,28]. Such capabilities are particularly beneficial for conservation landscapes in Africa, where limited resources and logistical challenges often restrict field-based monitoring. Despite these advantages, the application of GEE in related studies remains relatively limited.

This study addresses critical knowledge gaps by providing the first comprehensive ecosystem-wide analysis of habitat transformation in the GKE over 40 years (1984–2024). Specifically, the study aims to: (1) classify and map land cover across five decadal time points using multi-temporal Landsat imagery; (2) quantify the magnitude, rate, and spatial distribution of habitat change at ecosystem, management zone, and individual GMA scales; (3) analyse transition pathways and dominant conversion processes; and (4) assess spatial gradients of transformation pressure related to protected area boundaries and infrastructure. The findings provide an empirical foundation for understanding habitat dynamics in one of Africa's most significant conservation landscapes and offer insights applicable to protected area management across the region.

2.0 Materials and Methods

2.1 Study Area

The GKE is located in central-western Zambia, spanning approximately 14°S to 17°S latitude and 24°E to 27°E longitude (Fig.1) [29]. The ecosystem encompasses approximately 66,000 km² (9.82 million ha) and comprises two distinct management zones: KNP, established in 1950 as a strictly protected area where human settlement and agriculture are strictly prohibited; and nine surrounding GMAs: Bilili, Kasonso Busanga, Lunga Luswishi, Mufunta, Mulobezi, Mumbwa, Namwala, Nkala, and Sichifulo, which permit regulated hunting, settlement, and agricultural activities[15,16,30,31]. The region is characterised by a sub-tropical climate with distinct wet (November–April) and dry (May–October) seasons. Mean annual rainfall ranges from approximately 750 mm in the south to 1,200 mm in the north, supporting extensive Miombo woodland (dominated by *Brachystegia* and *Julbernardia* species), mopane woodland, and seasonally flooded grasslands [32–34]. Elevation ranges from approximately 900 m to 1,400 m above sea level, with generally flat to gently undulating terrain dissected by the Kafue River system.

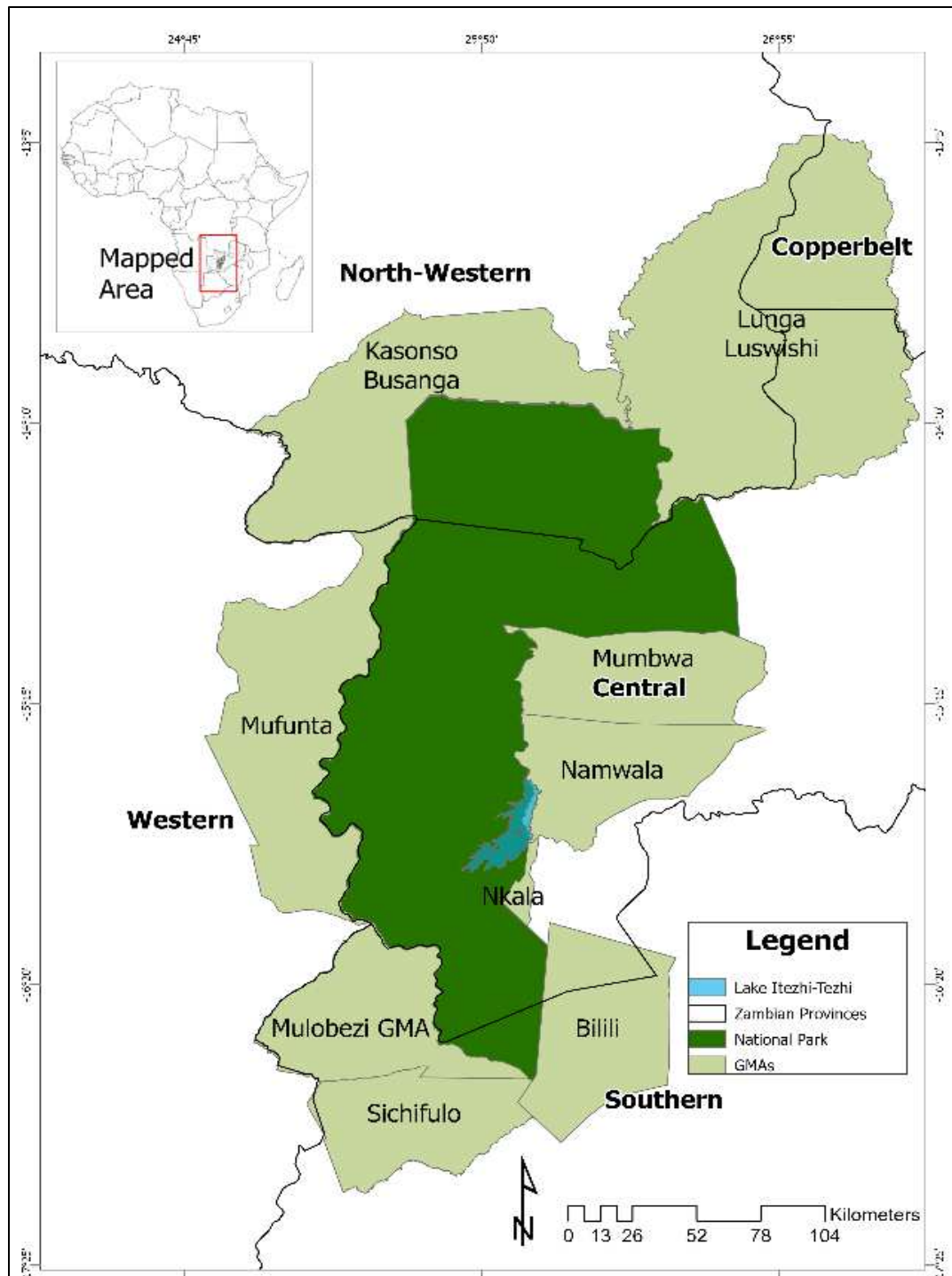


Fig. 1 Study area map showing KNP and surrounding GMAs. The nine GMAs include Bilili, Kasonso Busanga, Lunga Luswishi, Mufunta, Mulobezi, Mumbwa, Namwala, Nkala, and Sichifulo.

2.2 Overall workflow

Fig. 2 illustrates the methodological workflow adopted to achieve the study objectives. The approach followed a structured, sequential framework, ensuring a clear progression from data acquisition through analysis and interpretation. The study integrated remote sensing, Geographic Information System (GIS), and spatial analytical techniques to assess habitat dynamics in the GKE over 40 years (1984–2024). The methodology was organised into four main phases: (1) data acquisition and preprocessing; (2) land cover classification using a combined pixel-based and object-based post-classification refinement (OBPR) approach; (3) habitat change detection and spatial pattern analysis; and (4) results interpretation.

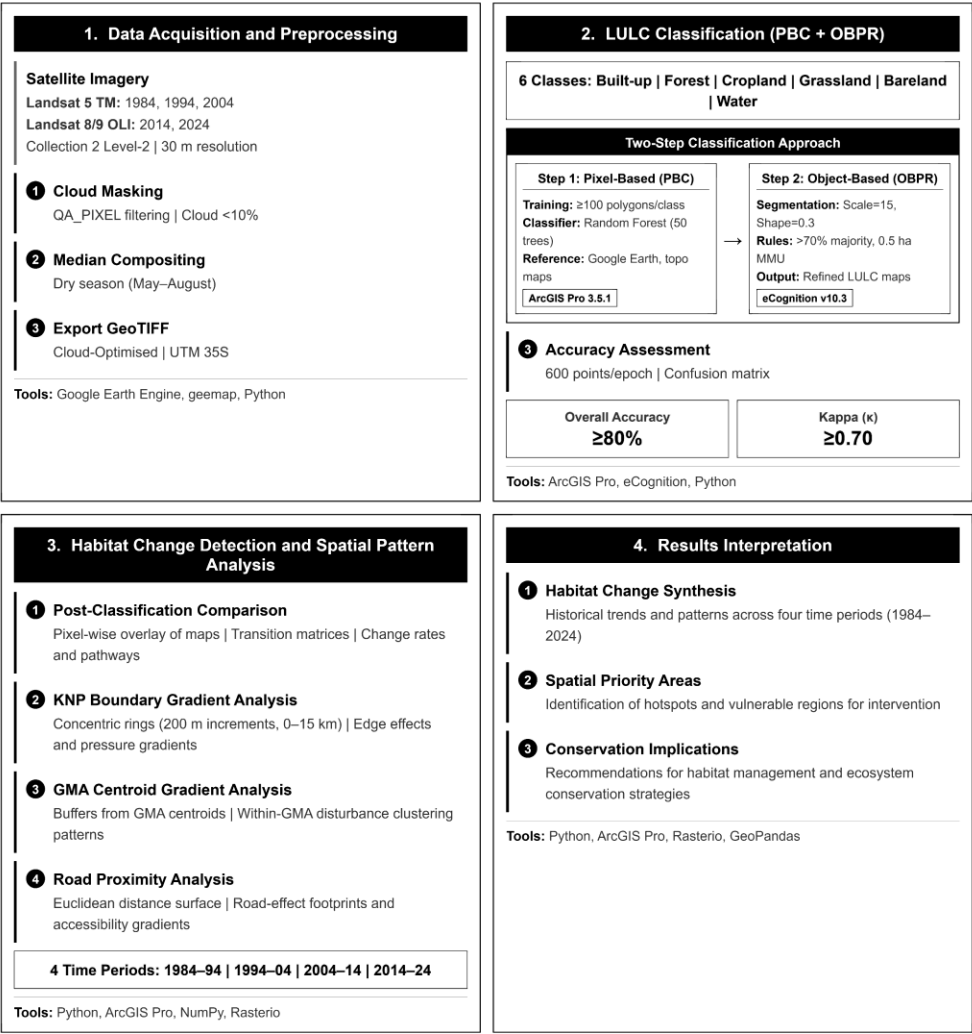


Fig. 2. Methodological workflow employed in assessing historical habitat dynamics in the Greater Kafue Ecosystem (1984–2024).

2.3 Data Acquisition and Preprocessing

2.3.1 Satellite Imagery

Multi-temporal Landsat Collection 2 Level-2 surface reflectance imagery was used to generate land cover maps for five reference years (1984, 1994, 2004, 2014, and 2024). Landsat 5 TM data were used for 1984-2004 epochs, Landsat 8 OLI for 2014 and Landsat 9 OLI-2 for 2024. Spectrally equivalent reflective bands were selected across sensors to maintain radiometric consistency and ensure reliable multi-decadal comparison [35,36]. Data acquisition and preprocessing were conducted in GEE using the *geemap* Python package [24,25]. The GKE boundary was buffered by 20 km to capture radial changes, and imagery was filtered to the dry season (May–August) [37,38]. Cloud and shadow masking was applied to the QA_PIXEL bands, followed by radiometric scaling parameters (scale factor = 0.0000275; offset = -0.2). Median composites were generated for each epoch and exported as 30 m Cloud-Optimised GeoTIFFs (UTM Zone 35S) [39].

2.3.2 Auxiliary datasets

Auxiliary spatial datasets were used to support land-cover classification, analysis, and interpretation of habitat dynamics. These included boundary shapefiles for the study area, digital elevation models (DEMs), topographic maps, and high-resolution imagery from Google Earth. Settlement extent data were obtained from the GRID3 Zambia Settlement Extents v3.0 dataset(<https://data.grid3.org/datasets/GRID3::grid3-zmb-settlement-extents-v3-0>). All auxiliary datasets were harmonised to a common projection system (UTM Zone 35S) and integrated to provide contextual information on topography, accessibility, and human settlement patterns within the study area[40].

Table 1 Datasets used in the study

Dataset	Source	Temporal coverage	Resolution
Landsat	Landsat TM/ETM+/OLI	1984–2024	30 m
DEM	SRTM	Static	~30 m
Roads	OSM	Static	Vector
Boundaries	KNP, GMAs	Static	Vector

2.4 Land-Cover Classification

2.4.1 Land-Cover Classes

Land cover was mapped consistently across all epochs using six classes: Forest, Grassland/Wetland, Cropland, Built-up, Bare land, and Water.

2.4.2 Habitat grouping

For subsequent analyses, classes were grouped into natural habitat and disturbed land: Natural habitat: Forest, Grassland/Wetland, Water; Disturbed land: Cropland, Built-up, Bare land.

2.4.3 Classification scheme

A hierarchical classification scheme (Level II), adapted from a land-use and land-cover classification system for remote sensing data [41], was used to reflect the ecological characteristics of the GKE and the study's conservation-oriented focus (Table 2). The scheme distinguishes natural habitat types from anthropogenically disturbed land uses that are directly relevant to habitat-loss assessment.

Table 2 Land cover classification scheme used in this study

ID	Level II	Level I	Description
1	Built-up/Settlements	Disturbed land	Urban areas, rural settlements, roads, and infrastructure
2	Forest	Natural habitat	Mature indigenous forest with a closed canopy (>60%) and minimal disturbance. Regenerating or partially disturbed woodland with an open canopy (40–60%)
3	Cropland	Disturbed land	Cultivated and fallow agricultural land
4	Grassland/Wetland	Natural habitat	Natural grasslands, dambos, and seasonally flooded areas
5	Bare Ground	Disturbed land	Exposed soil, rock, sand, heavily degraded areas, and recent burns
6	Water Bodies	Aquatic habitat/Natural	Rivers, lakes, reservoirs, and permanent water surfaces

2.4.3 Classification algorithm

Land-cover classification was performed in ArcGIS Pro 3.5.1 using the Random Trees (RT) classifier (Random Forest) within the Image Analyst environment. The ensemble consisted of 100 decision trees trained on bootstrap samples, with random subsets of predictors evaluated at each split. The final class assignment was determined by majority voting across trees (Eq. 1):

$$\hat{y}(x) = \arg \max_{c \in \mathcal{C}} \sum_{t=1}^T \mathbf{1}(h_t(x) = c) \quad (1)$$

Where:

- $\mathcal{C}$ is the set of land-cover classes
- $h_t(x)$ is the predicted class from tree t
- $\mathbf{1}(\cdot)$ is the indicator function (1 if true, 0 otherwise)
- T is the number of trees (100)

Node splitting was based on the Gini impurity index. Model parameters included a maximum of 100 trees, a maximum tree depth of 30, and a minimum of 2,000 samples per class. These parameters were determined through iterative, data-driven testing to optimise classification accuracy and model stability. At each split, $\sqrt{p}$ predictors were considered. The RT classifier was chosen for its robustness to non-linear relationships and strong generalisation in heterogeneous remote-sensing landscapes [42–45].

2.4.4 Classification implementation

A two-step workflow combining pixel-based classification (PBC) and object-based post-classification refinement (OBPR) was applied to reduce salt-and-pepper noise and improve thematic consistency in Landsat-scale LULC mapping[45–49].

Phase 1: Pixel-based classification

For each epoch (1984, 1994, 2004, 2014, and 2024), training polygons were digitised for all land-cover classes using multi-source reference information. High-resolution ESRI Hybrid imagery-based maps and Google Earth were used for post-2004 epochs, while Landsat composites, 1:50,000 topographic maps, and local ecological knowledge were used for earlier periods. A minimum of 100 training polygons per class was delineated, typically covering 20–200 pixels per polygon, with larger homogeneous patches containing up to about 2,000 pixels to capture within-class spectral variability [50,51]. Although robust, pixel-based classification alone resulted in localised misclassification due to spectral similarity, particularly between agricultural land and built-up areas, and between grassland/wetlands and bare land, a known limitation of medium-resolution imagery.

Phase 2: Object-based refinement

To address errors arising from spectral overlap, object-based post-classification refinement (OBPR) was applied to the initial PBC outputs [23,45,49,52]. Object-based analysis was

implemented in eCognition Developer v10.3 using multiresolution segmentation to generate homogeneous image objects for each epoch (Blaschke, 2010). Segmentation parameters were set to scale = 15, shape = 0.3, and compactness = 0.5. Refinement involved: (i) majority reassignment for objects with >70% pixel agreement; (ii) contextual correction of implausible class placements based on neighbourhood relationships; and (iii) enforcement of a 0.5 ha minimum mapping unit, with very small objects merged into adjacent dominant classes. Misclassified pixels were identified through overlay analysis, integrating object segments, ancillary spatial datasets, and expert visual interpretation [45]. Corrected classifications were reintegrated into the original maps, producing the final refined LULC datasets for all five epochs [49].

2.5 Accuracy assessment

Classification accuracy was evaluated according to best-practice guidance for land-cover validation [53]. For each epoch, 600 validation points were generated, with at least 100 per class. Reference labels were assigned through visual interpretation of high-resolution imagery (where available), Landsat time-series composites, topographic maps, and field knowledge from 2023 visits, which supported verification of the 2024 map and improved consistency in interpretation across epochs. An error (confusion) matrix was used to compute standard metrics (Eq. 1 – Eq. 5) :

Overall Accuracy (OA):

$$OA = \frac{\sum_{i=1}^C n_{ii}}{N} \quad (2)$$

Producer's Accuracy (PA):

$$PA_i = \frac{n_{ii}}{n_{i+}} \quad (3)$$

User's Accuracy (UA):

$$UA_i = \frac{n_{ii}}{n_{+i}} \quad (4)$$

216 **Cohen's Kappa (κ):**

217
$$\kappa = \frac{N \sum_{i=1}^C n_{ii} - \sum_{i=1}^C (n_{i+} n_{+i})}{N^2 - \sum_{i=1}^C (n_{i+} n_{+i})} \quad (5)$$

218

219 Where:

220 n_{ii} = correctly classified samples for class i

221 n_{i+} = row total for class i (reference total)

222 n_{+i} = column total for class i (classified total)

223 N = total validation samples

224 C = number of land-cover classes

225 Kappa values were interpreted according to Landis & Koch(1977).

226 Classification outputs were considered acceptable for subsequent change detection and
227 modelling only if they achieved an Overall Accuracy (OA) of at least 80% and a Cohen's Kappa
228 (κ) of at least 0.70. These thresholds are consistent with commonly adopted standards for reliable
229 land-cover mapping and change analysis [55,56], ensuring sufficient class-level and landscape-
230 scale reliability for multi-temporal comparison

231 To provide additional insight into per-class reliability, particularly for minority classes (e.g., Built-
232 up and Water Bodies), the F1-score was computed as the harmonic mean of Producer's and
233 User's Accuracy:

234
$$F1_i = \frac{2 \times PA_i \times UA_i}{PA_i + UA_i} \quad (6)$$

235

236 The macro-averaged F1-score was calculated as:

237

238
$$Macro-F1 = \frac{1}{C} \sum_{i=1}^C F1_i \quad (7)$$

239

240 This approach assigns equal weight to all classes and is appropriate for imbalanced land-cover
241 datasets [57–59].

242 **2.6 Habitat Change Detection (1984–2024)**

243 Habitat change was quantified using a post-classification comparison approach, whereby land-
244 cover maps from two epochs (t_1 and t_2) were overlaid to identify persistence, gains, losses, and
245 from-to transitions. This approach was selected because it produces explicit transition pathways
246 (e.g., Forest → Cropland) and supports both ecosystem-wide accounting and zone-based
247 summaries (GKE, KNP, GMAs). For each epoch, class areas were first computed from pixel
248 counts and then compared between time steps to estimate net change and annualised rates of
249 change.

250 Class area in hectares was computed as:

$$251 \quad A_c = N_c \times \frac{r^2}{10,000} \quad (8)$$

252 where A_c is the area of class c (ha), N_c is the number of pixels assigned to class c , and r is the
253 spatial resolution (m). With Landsat-derived maps at 30 m resolution, each pixel represents
254 0.09ha.

255 Net change between epochs was calculated as:

$$256 \quad \Delta A_c = A_{c,t_2} - A_{c,t_1} \quad (9)$$

257

258 and the annualised rate of change was derived as:

$$259 \quad R_c = \frac{\Delta A_c}{t_2 - t_1} \quad (10)$$

260

261 To characterise conversion pathways, transition matrices were derived from pixel-wise overlays
262 of t_1 and t_2 . These matrices quantify the number of pixels moving from class i to class j (n_{ij}), and
263 were used to compute transition probabilities for projection modelling:

$$264 \quad P_{ij} = \frac{n_{ij}}{\sum_{j=1}^k n_{ij}} \quad (11)$$

266

265 Where k is the number of land-cover classes.

267 **2.7 Spatial Pattern Analysis**

268 Beyond total change magnitudes, the study assessed the spatial structure of habitat
269 transformation to determine whether change was concentrated near protected-area boundaries,
270 transport corridors, or internal settlement cores within GMAs. Three complementary spatial
271 analyses were conducted: Two complementary spatial analyses were conducted: (i) KNP
272 boundary gradient analysis and (ii) road proximity analysis. Together, these analyses provided an
273 interpretable spatial diagnosis of pressure gradients and accessibility effects.

274 **2.7.1 KNP boundary gradient analysis**

275 To evaluate edge effects and pressure gradients outward from the protected core, concentric
276 rings were created outward from the KNP boundary into surrounding GMAs. Rings were defined
277 at 200 m increments up to a maximum of 15 km. For each ring r and epoch t , class composition
278 and natural habitat proportion were computed [49,60].

279 Let Ω_r be the set of pixels within the ring r . The proportion of natural habitat within Ω_r is:

280 Natural habitat proportion in the ring r

$$281 \quad H(r, t) = \frac{\sum_{x \in \Omega_r} I(LC(x, t) \in \mathcal{H})}{|\Omega_r|} \quad (12)$$

282 where $I(\cdot)$ is an indicator function and $|\Omega_r|$ is the number of valid pixels in ring r .

283 **2.8 Road proximity analysis**

284 Road accessibility was quantified using a Euclidean distance surface computed for each pixel:

$$285 \quad d(x) = \min_{s \in S} \|x - s\| \quad (13)$$

286 Where $d(x)$ represents the distance from the pixel x to the nearest road segment, and S denotes
287 the set of all mapped road locations. Euclidean distance has been widely applied in spatial
288 accessibility and land-use change analyses to represent gradients of anthropogenic influence
289 associated with transport infrastructure [62].

Land-cover composition and habitat retention were subsequently summarised within discrete distance bands to quantify the *road-effect footprint* defined as the spatial extent over which roads elevate habitat conversion, fragmentation, and edge effects relative to background conditions [41,63].

3.0 Results

3.1 Classification Accuracy

Overall classification accuracy ranged from 82% to 90% across the five reference years, with Kappa coefficients ranging from 0.73 to 0.86. The 2024 classification achieved high accuracy (OA = 89%, $\kappa = 0.86$). Macro-averaged F1-scores ranged from 81.4% to 90.0%, indicating consistent performance across classes. The 1984 classification achieved the lowest macro F1-score (81.4%), largely due to lower performance on Bare Ground (F1 = 62.9%). In 2004, reduced F1-scores were observed for Water Bodies (63.7%) and Grassland/Wetland (78.2%). Classification performance was highest in 2014 (macro F1 = 90.0%), with all classes achieving F1-scores above 85%. The 2024 classification maintained strong performance (macro F1 = 88.0%), with high F1-scores for Water Bodies (92.7%) and Bare Ground (92.0%). Detailed confusion matrices are provided in the supplementary materials.

Table 3 Per-class F1-scores (%) for LULC classification accuracy assessment

Year	Built-up	Forest	Grassland	Cropland	Bare Ground	Water Bodies	Macro F1	OA (%)	κ
1984	89.4	84.9	93.3	82.9	62.9	75.2	81.4	82	0.78
1994	91.2	86	82.3	91.3	90.9	91.8	88.9	89	0.87
2004	92.3	82.9	78.2	77.8	95.2	63.7	81.7	82	0.78
2014	89.6	96.2	91.5	85.7	88.7	88.1	90	90	0.88
2024	82.1	91.6	82.4	87.1	92	92.7	88	88	0.86

3.2 Land Cover Composition and Change (1984–2024)

The results indicate that GKE underwent a progressive transformation over the 40-year study period (Table 4, Fig. 3). Natural habitat (forest and grassland combined) dominated the landscape throughout but declined from 98.31% (9,649,526 ha) in 1984 to 83.96% (8,241,524 ha) in 2024, resulting in a net loss of approximately 1.41 million ha (4). Over the same period, disturbed habitat (cropland, built-up, and bareland) expanded from 1.69% (165,520 ha) to 16.04% (1,574,020 ha).

313 Forest cover showed the largest absolute decline, decreasing from 85.22% (8,364,796 ha) in
 314 1984 to 50.93% (4,999,146 ha) in 2024, resulting in 2024, a net loss of 3,365,544 ha (−40.24%).
 315 Grassland increased from 12.66% to 32.68%, partly offsetting forest losses within the natural
 316 habitat category through internal reconfiguration between woody and open vegetation types.
 317 Cropland exhibited the most pronounced proportional expansion, increasing from 0.86% (84,553
 318 ha) to 14.53% (1,426,472 ha), representing a 16-fold increase. Built-up areas increased from
 319 0.01% (1,173 ha) to 0.40% (39,501 ha), while water and bareland remained minor components
 320 of the landscape.

321 **Table 4** Land cover area and percentage composition for the GKE (1984–2024).

Land Cover Class	1984 Area (ha)	1984 (%)	2004 Area (ha)	2004 (%)	2024 Area (ha)	2024 (%)	Net change (ha)	Net change (%)
Built-up	1,173	0.01	6,166	0.06	39,501	0.40	+38,314	+3,265
Forest	8,364,796	85.22	6,346,698	64.66	4,999,146	50.93	−3,365,544	−40.24
Cropland	84,553	0.86	560,419	5.71	1,426,472	14.53	+1,341,633	+1,587
Grassland	1,242,710	12.66	2,665,627	27.16	3,207,925	32.68	+1,964,966	+158
Bareland	79,794	0.81	188,323	1.92	108,047	1.10	+28,201	+35
Water	42,021	0.43	47,943	0.49	34,453	0.35	−7,570	−18
Natural Habitat	9,649,526	98.31	9,060,268	92.31	8,241,524	83.96	−1,408,148	−14.59
Disturbed	165,520	1.69	754,908	7.69	1,574,020	16.04	+1,408,148	+851

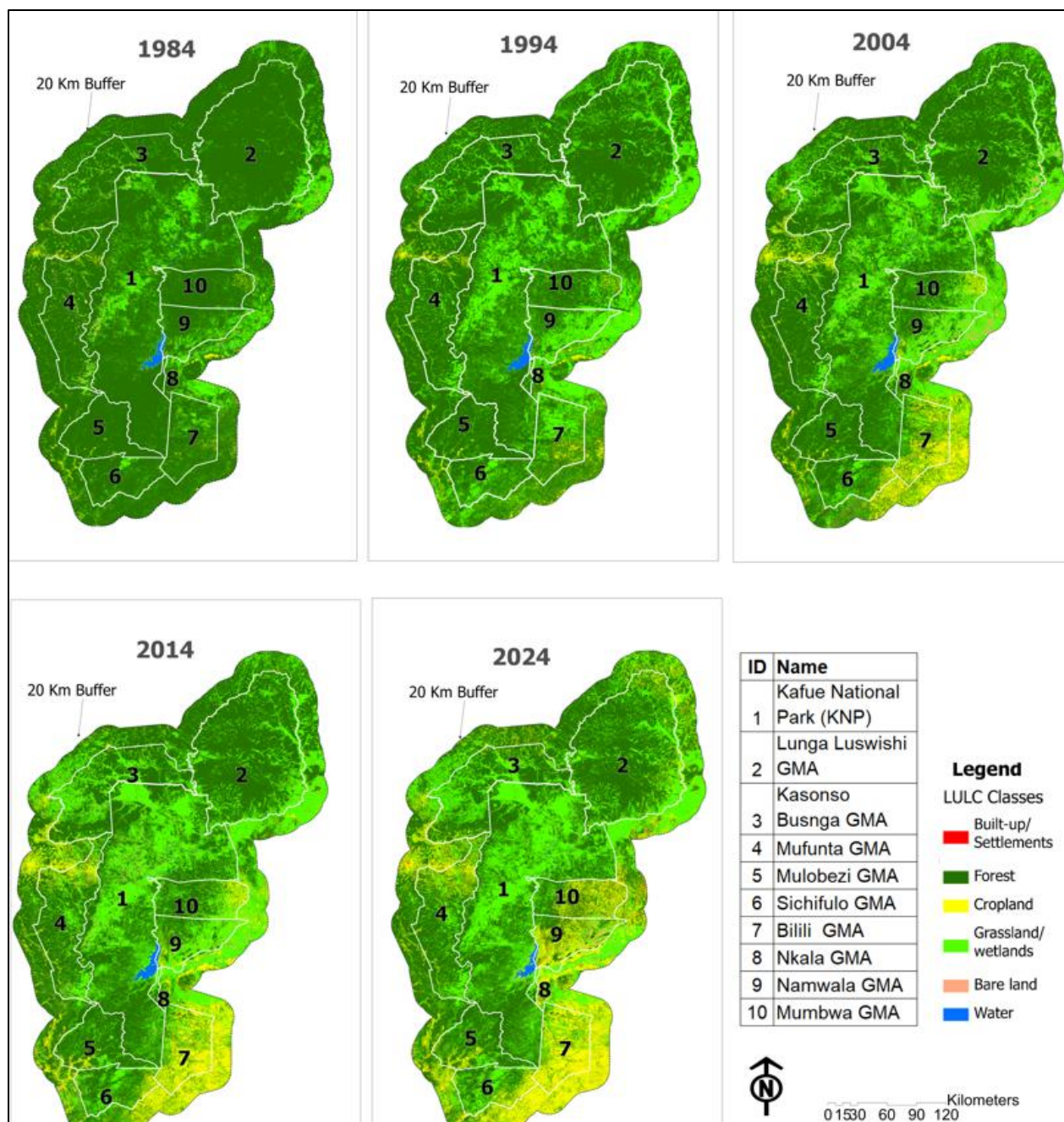


Fig. 1 Land cover maps for five epochs:1984, 1994, 2004, 2014, and 2024.

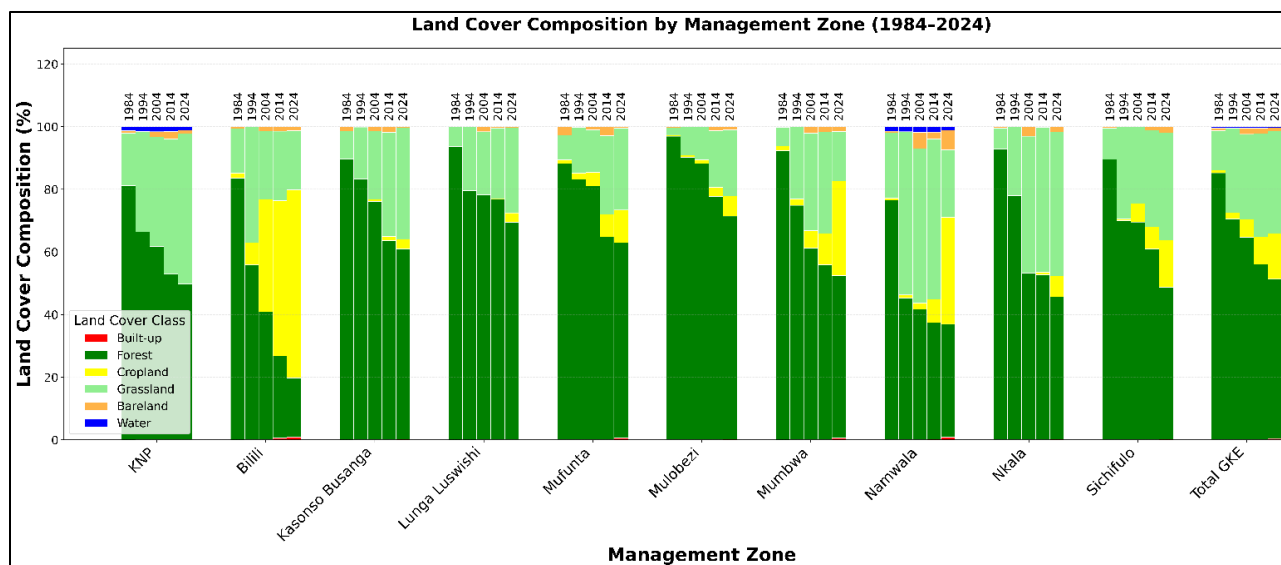


Fig. 2 Temporal land cover trends by Management Zones for the period 1984 and 2024.

3.3 Temporal Patterns and Acceleration of Change

Habitat loss accelerated over the study period. The rate of natural-to-disturbed conversion increased nearly seven-fold, from 12,271 ha yr⁻¹ in 1984–1994 to 83,876 ha yr⁻¹ in 2014–2024 (Table 5.3). Cropland expansion drove this acceleration, increasing from 10,209 ha yr⁻¹ (1984–1994) to 57,269 ha yr⁻¹ (2014–2024). The most substantial single-decade conversion of natural to disturbed habitat occurred in 2014–2024 (838,762 ha), accounting for 41% of the entire 40-year cumulative conversion.

Table 5 Great Kafue Ecosystem decadal change rates (1984-2024).

Period	Natural → Disturbed (ha)	Rate (ha yr ⁻¹)	Cropland Gain (ha)	Cropland Rate (ha yr ⁻¹)
1984–1994	122,705	12,271	121,455	10,209
1994–2004	565,712	56,571	374,268	37,365
2004–2014	530,665	53,067	388,203	29,330
2014–2024	838,762	83,876	754,549	57,269
1984–2024 Total	2,057,844	51,446	1,638,474	33,541

3.4 Spatial Heterogeneity Across Management Zones

Sharp contrasts in habitat retention emerged between KNP and the surrounding GMAs (Table 6; Fig. 5). Kafue National Park maintained consistently high natural habitat coverage, declining only marginally from 99.23% (1984) to 98.87% (2024), a net change of just −0.36 percentage points. Within KNP, forest cover shifted substantially from 81.16% to 49.71%, while grassland increased from 16.78% to 48.03%, indicating internal reconfiguration between woody and open vegetation types rather than conversion to disturbed land uses. Cropland and built-up areas remained negligible in KNP, together accounting for ≤0.07% in 2024. In contrast, GMAs experienced pronounced habitat loss, with natural habitat declining from 98.68% to 84.08%, a net reduction of 14.60 percentage points. Forest cover in GMAs decreased from 90.01% to 57.54%, while cropland expanded sharply from 0.52% to 14.46%. This KNP–GMA divergence demonstrates the effectiveness of strict protection in maintaining habitat integrity relative to multi-use management zones.

Substantial heterogeneity was observed among individual GMAs (Table 5.4). By 2024, natural habitat retention ranged from 96.62% in Lunga Luswishi to 37.77% in Bilili, a spread of 58.85 percentage points. The most severe declines occurred in Bilili (−59.91 pp), Namwala (−40.06 pp), Mumbwa (−30.59 pp), and Sichifulo (−16.71 pp), all characterised by higher accessibility and market connectivity. In contrast, relatively strong retention was observed in Kasonso Busanga (96.39%; −2.19 pp), Lunga Luswishi (96.62%; −3.35 pp), and Mufunta (88.46%; −7.59 pp), reflecting their relative remoteness and lower agricultural pressure.

Table 6 Natural habitat retention across management zones (1984–2024).

Management Zone	Total Area (ha)	1984 (%)	1994 (%)	2004 (%)	2014 (%)	2024 (%)	Change (pp)
Kafue National Park	2,251,490	99.23	99.95	98.30	97.60	98.87	−0.36
Nkala GMA	20,338	99.50	99.99	96.87	99.04	91.42	−8.08
Namwala GMA	316,597	98.88	98.96	92.73	90.17	58.82	−40.06
Bilili GMA	368,905	97.68	92.85	62.51	48.34	37.77	−59.91
Mufunta GMA	638,073	96.05	97.80	94.57	89.94	88.46	−7.59
Kasonso Busanga GMA	681,246	98.58	99.75	97.87	96.88	96.39	−2.19
Lunga Luswishi GMA	1,335,757	99.97	99.95	98.36	99.42	96.62	−3.35
Sichifulo GMA	302,867	99.44	99.41	93.97	91.67	82.73	−16.71
Mulobezi GMA	358,534	99.26	99.26	98.77	95.68	92.37	−6.89
Mumbwa GMA	341,088	98.34	97.93	92.47	88.29	67.75	−30.59
All GMAs	4,361,850	98.68	98.68	93.55	90.93	84.08	−14.60

Management Zone	Total Area (ha)	1984 (%)	1994 (%)	2004 (%)	2014 (%)	2024 (%)	Change (pp)
Total GKE	9,815,046	98.31	98.02	92.31	89.42	83.96	-14.35

3.5 Change by Management Zone (KNP vs GMAs)

Natural habitat loss varied dramatically across management zones (Fig. 5.3). Kafue National Park lost only 0.4% of its 1984 natural habitat, maintaining coverage at 98.87% by 2024. The combined GMAs lost 14.8%, declining from 98.68% to 84.08%.

Individual GMA losses ranged from 2.2% to 61.3%. Bilili experienced the most severe degradation (61.3%), followed by Namwala (40.5%), Mumbwa (31.1%), and Sichifulo (16.8%). In contrast, Kasonso Busanga (2.2%), Lunga Luswishi (3.4%), and Mulobezi (6.9%) retained most of their natural habitat. This pattern reflects an accessibility gradient: heavily impacted GMAs are proximate to roads and markets, while well-retained GMAs are located in remote areas. The 170-fold difference between KNP and Bilili demonstrates the effectiveness of strict protection relative to multi-use management.

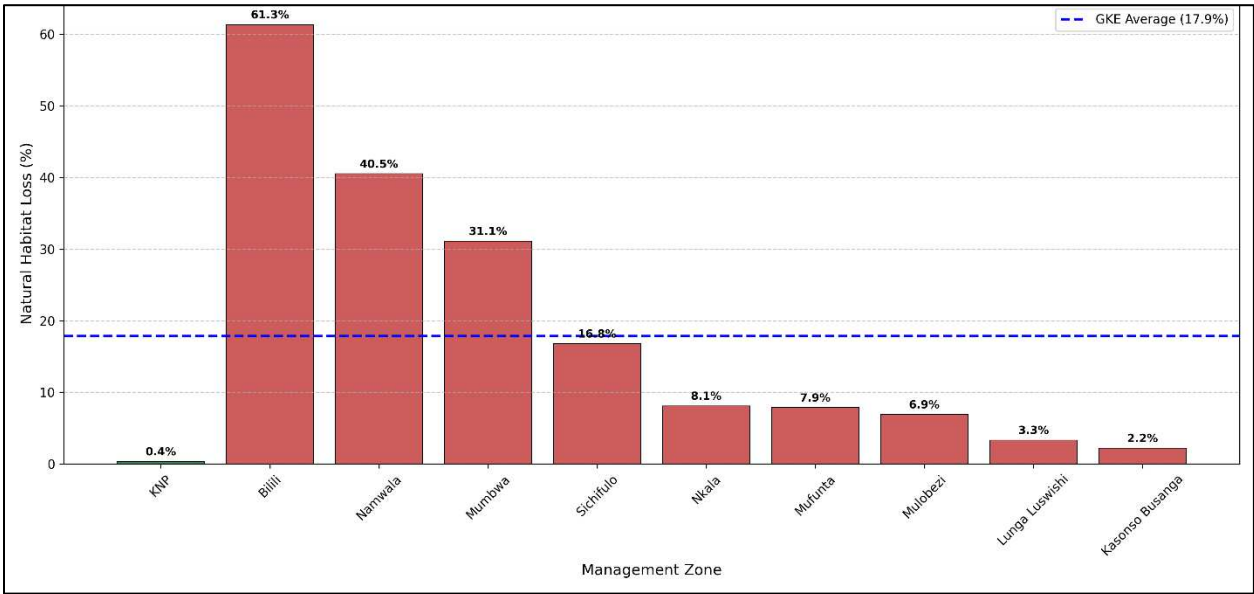


Fig. 3 KNP vs GMA habitat loss. The blue line indicates the GKE average of 17.9%.

3.6 Transition analysis

Transition analysis revealed that land cover change was concentrated in a small number of dominant, directional pathways. Forest → Cropland was the principal habitat loss pathway (954,169 ha; 9.72% of total landscape), followed by Grassland → Cropland (369,331 ha; 3.76%). Together, these two pathways accounted for most of the net decline in natural habitat. The single largest transition overall was Forest → Grassland (1,812,667 ha; 18.47%), indicating extensive internal reconfiguration within natural habitat classes. Cropland exhibited high persistence (75,554 ha remained cropland), indicating that agricultural conversion was largely irreversible once established. Zone-based transition comparisons confirmed that conversion to cropland was overwhelmingly concentrated in the GMAs: within KNP, Forest → Cropland totalled just 756 ha compared to over 953,000 ha in GMAs

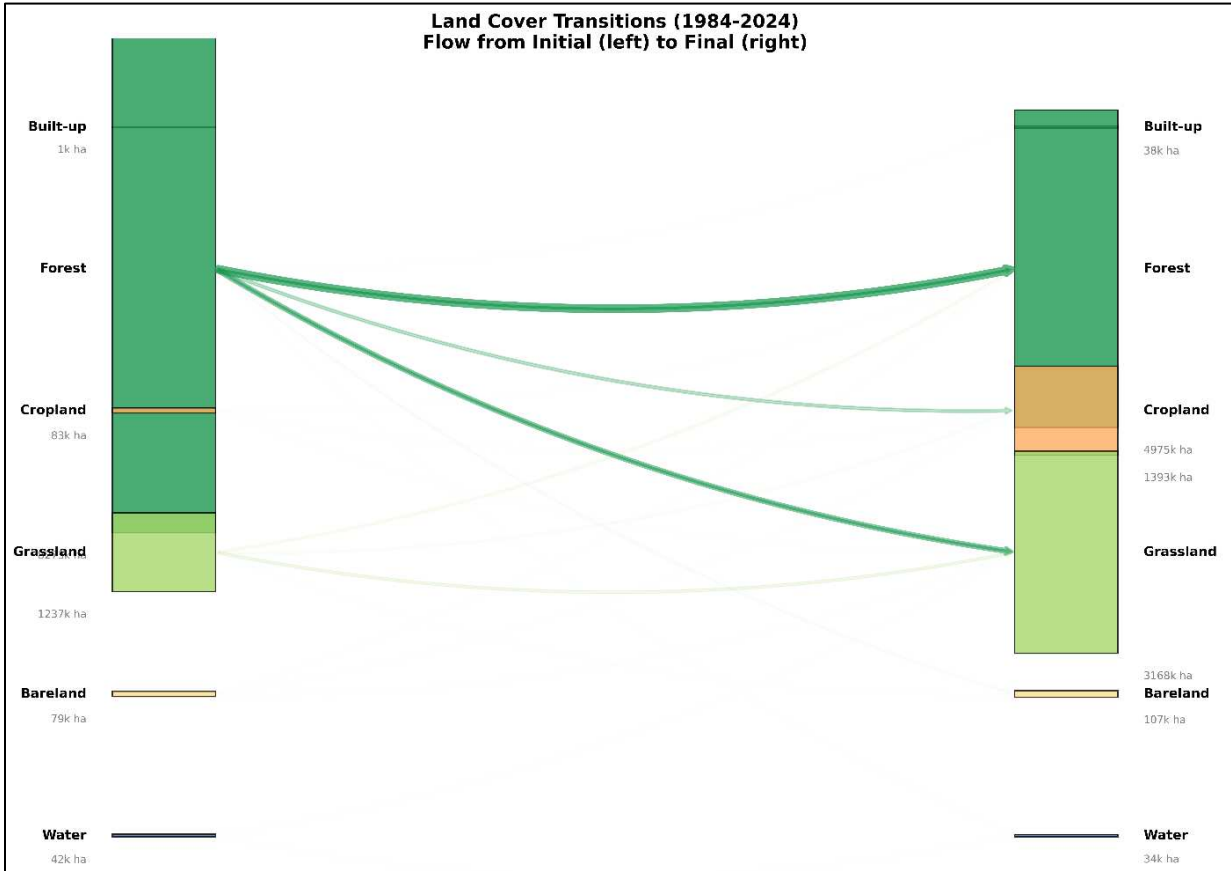


Fig. 4: Top transition pathways in the GKE (1984–2024), ranked by total area converted.

3.6 Boundary and Road Proximity Effects

Systematic spatial gradients characterised the patterns of habitat transformation across the GKE. Analysis of distance from the Kafue National Park (KNP) boundary revealed that natural habitat declined with increasing distance into surrounding Game Management Areas (GMAs) (Fig. s 5.5-5.6). In 2024, natural habitat averaged 90.9% within 0–1 km of the boundary, declining to 83.8% at 5 km, representing a 7.1 percentage-point gradient, with the steepest decline occurring within the first 5 km (-1.66 pp km^{-1}). Beyond this zone, natural habitat stabilised at approximately 81–82%, indicating an edge-influence depth of ~ 10 km.

Temporal analysis indicated that boundary effects strengthened substantially between 1984 and 2024 (Fig. 7b). In 1984, natural habitat declined only slightly from 99.2% within 0–1 km to 97.5% at 5 km, corresponding to a 1.7 percentage-point gradient (-0.32 pp km^{-1}). By 2024, the magnitude of habitat declines across the same distance increased markedly, representing a 427% increase in edge-effect strength.

Road proximity analysis revealed similarly strong spatial structuring of habitat loss within GMAs (Table 7; Fig. 8a). Natural habitat retention increased non-linearly with distance from major roads, rising from 77.0% within 0–2 km to 91.4% beyond 10 km, yielding a 14.4 percentage-point difference between road-adjacent and remote areas. The steepest habitat gradient occurred within the first 2 km of roads. Cropland exhibited the inverse pattern, declining from 20.8% (0–2 km) to 7.7% (>10 km), indicating that roads function as primary conduits for agricultural expansion into natural habitats (Fig. 8b).

Table 7: Natural habitat retention by distance from roads in GMAs (2024).

Distance Zone (km)	Natural Habitat (%)	Forest (%)	Grassland (%)	Cropland (%)	Built-up (%)	Bareland (%)	Change from 0-2 km (pp)
0–2	77.0	45.3	31.4	20.8	0.6	1.56	0.0
2–4	84.2	50.5	33.3	14.3	0.3	1.14	7.2
4–6	85.8	51.2	33.9	13.0	0.28	0.93	8.8
6–8	87.4	51.7	35.1	11.5	0.23	0.92	10.4
8–10	89.6	54.0	35.2	9.2	0.2	0.94	12.6
>10	91.4	55.8	35.6	7.7	0.14	0.67	14.4

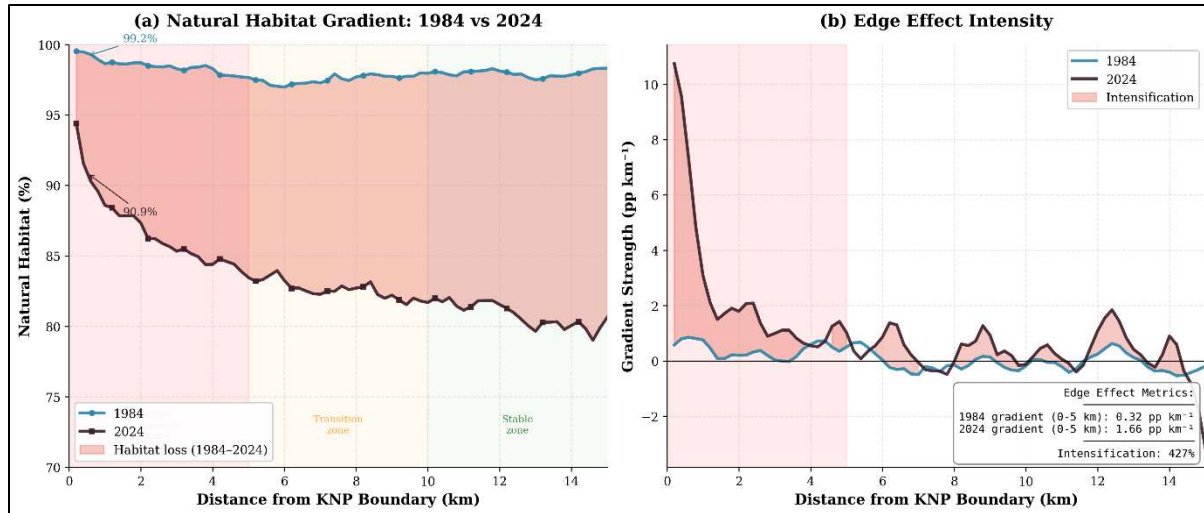


Fig. 5: Natural habitat gradient from KNP boundary (1984 vs 2024). (a) Habitat declined more steeply in 2024 (-1.66 pp km^{-1}) than in 1984 (-0.34 pp km^{-1}). (b) Edge effect intensity increased by 386% over 40 years.

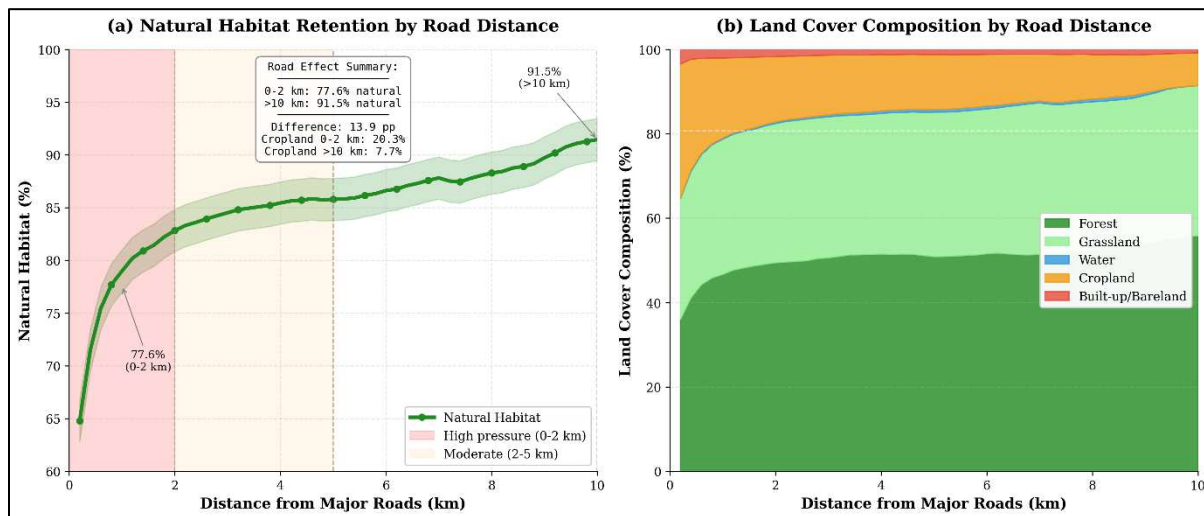


Fig. 6: Road proximity effects on natural habitat in GMAs (2024). (a) Habitat retention: 77.0% near roads (0–2 km) versus 91.4% in remote areas (>10 km). (b) Cropland decreases from 20.8% to 7.7% with distance from roads.

4.0 Discussion

4.1 Magnitude and Rate of Habitat Loss in Regional Context

The Greater Kafue Ecosystem experienced substantial habitat transformation over the 40-year study period, with natural habitat declining from 98.31% (9,649,526 ha) in 1984 to 83.96% (8,241,524 ha), representing a net loss of approximately 1.41 million hectares. Although classification accuracy met accepted standards (OA = 82–90%; κ = 0.73–0.86), uncertainty in the 2024 map (OA = 88%, n = 600) implies a $\pm 2.6\%$ confidence interval for overall accuracy. When translated to habitat area, this corresponds to an estimated $\pm 215,000$ ha of uncertainty in the 2024 natural habitat estimates. While this does not alter the clear trajectory of decline, it contextualises absolute area estimates within a bounded confidence range.

The magnitude of loss observed in the GKE aligns with broader regional patterns across sub-Saharan Africa. FAO (2020) reports annual deforestation rates of approximately 3.9 million ha yr^{-1} . At the national level, Zambia experienced net forest loss averaging approximately 250,000–300,000 ha yr^{-1} during the 2010s [64]. The peak cropland expansion rate within the GKE (57,269 ha yr^{-1} during 2014–2024), therefore, represents a substantial localised contribution within the national context.

Agricultural expansion accounts for approximately 83% of total natural habitat loss, confirming smallholder-driven agricultural conversion as the dominant transformation pathway. This finding is consistent with continental-scale analyses that identify subsistence and smallholder agriculture as the primary drivers of forest loss across Africa [11,65]. Recent work in Zambia further supports this pattern, demonstrating that the expansion of smallholder agriculture and settlement growth dominate land-cover transitions in mixed-use conservation landscapes [66]. In contrast, deforestation in Latin America and Southeast Asia is more strongly associated with large-scale commercial agriculture and plantation forestry [11,65].

The acceleration in cropland expansion from 10,209 ha yr^{-1} (1984–1994) to 57,269 ha yr^{-1} (2014–2024) indicates intensifying pressure rather than stabilisation. Comparable acceleration patterns have been observed in the Serengeti-Mara ecosystem and other African buffer zones [67], suggesting that the GKE reflects broader regional frontier-expansion dynamics.

4.2 Effectiveness of Strict Protection

The divergence between management regimes is striking. Kafue National Park retained 98.87% of its natural habitat in 2024, a decline of only -0.36 percentage points over four decades, whereas the combined GMAs declined from 98.68% to 84.08% (-14.60 percentage points). This stark contrast provides strong empirical support for the effectiveness of strict protection in maintaining habitat integrity. These findings align with global evidence demonstrating that well-managed protected areas significantly reduce deforestation compared to unprotected areas [68,69]. However, the divergence must be interpreted within Zambia's governance framework. National parks are administered by the Department of National Parks and Wildlife (DNPW) under strict protection mandates that prohibit settlement and cultivation. In contrast, GMAs operate under a mixed governance model involving Community Resource Boards, regulated hunting concessions, and legally permitted settlement and agricultural use [70]. Differences in tenure systems, enforcement intensity, and livelihood dependence on agriculture likely contribute substantially to the observed ecological divergence.

Although KNP is also less accessible and characterised by lower road density than many GMAs, the near absence of cropland conversion within the park compared to extensive expansion across GMAs strongly indicates that institutional enforcement has played a decisive role in preventing agricultural encroachment.

4.3 The Buffer Zone Challenge

The concentration of habitat loss within GMAs underscores the critical importance of buffer-zone governance in landscape-scale conservation. GMAs were designed to serve as transitional zones that reconcile wildlife conservation with local livelihoods through regulated resource use [71]. However, the findings indicate that agricultural expansion is progressively transforming portions of the buffer system into predominantly agrarian landscapes.

Substantial heterogeneity was observed among GMAs, with natural habitat retention in 2024 ranging from 37.77% (Bilili) to 96.62% (Lunga Luswishi). Severe declines occurred in Bilili (-59.91 pp), Namwala (-40.06 pp), and Mumbwa (-30.59 pp), whereas northern GMAs such as Kasonso Busanga (-2.19 pp) and Lunga Luswishi (-3.35 pp) retained high habitat integrity. This variability suggests that accessibility, historical settlement patterns, and market connectivity strongly mediate transformation trajectories. Spatially differentiated management strategies may therefore be more appropriate than uniform policy approaches across all GMAs.

4.4 Edge Effects and Infrastructure Influence

Spatial gradient analyses reveal systematic structuring of habitat transformation. Natural habitat declined with increasing distance from the KNP boundary into surrounding GMAs, with the steepest decline occurring within the first 5 km. This intensification of edge-associated loss is consistent with agricultural frontier-expansion theory, in which conversion radiates outward from established settlements as accessible land becomes saturated [11,72]. Road proximity exerted an even stronger influence. Natural habitat retention increased from 77.0% within 0–2 km of roads to 91.4% beyond 10 km, representing a 14.4 percentage-point difference. Cropland displayed the inverse pattern, declining from 20.8% near roads to 7.7% in remote areas. These findings confirm the central role of transport infrastructure in mediating land-use change by reducing transaction costs, enabling migration, and facilitating market access [63]. A substantial proportion of the GMA area lies within proximity to roads, indicating that much of the buffer landscape is already exposed to elevated anthropogenic pressure.

4.5 Implications for Conservation

The findings have several implications for conservation management in the GKE. First, the effectiveness of strict protection within KNP argues for maintaining and strengthening enforcement of existing regulations, particularly amid intensifying peripheral pressure. Second, the accelerating conversion trajectory suggests that current management approaches in GMAs are insufficient to stem agricultural expansion, warranting exploration of alternative strategies, including community-based conservation, payment for ecosystem services, and sustainable intensification of existing farmland. Third, the spatial prioritisation suggested by the heterogeneous GMA outcomes indicates that conservation investments should be strategically targeted. GMAs approaching but not yet exceeding critical transformation levels (e.g., Mufunta, Sichifulo) may offer higher returns on investment in interventions than either heavily transformed areas requiring restoration (Bilili) or well-retained areas requiring minimal intervention (Lunga Luswishi). Fourth, the documented gradient effects suggest that landscape connectivity between KNP and intact GMA areas should be prioritised, particularly corridor protection in areas experiencing rapid conversion.

4.6 Limitations

The 30m Landsat resolution may not detect fine-scale degradation processes preceding full conversion. Although classification accuracy met established reliability thresholds, the area estimates are subject to moderate uncertainty. Broad land-cover categories do not capture within-class ecological condition or habitat quality. Furthermore, the study documents spatial patterns but does not directly model socio-economic drivers.

Future research should integrate higher-resolution imagery (e.g., Sentinel-2) to detect early-stage degradation, incorporate demographic and economic datasets to model causal drivers, and apply landscape-fragmentation metrics to evaluate connectivity dynamics. Integrating governance and livelihood datasets would further clarify the institutional determinants of buffer-zone outcomes.

5.0 Conclusions

This study provides the first ecosystem-wide, multi-decadal assessment of habitat transformation in the Greater Kafue Ecosystem. Over four decades, natural habitat has declined substantially, driven primarily by accelerating agricultural expansion in surrounding GMAs. The trajectory of change indicates intensifying land-use pressure rather than stabilisation.

A pronounced divergence between management regimes emerged. The strictly protected core of Kafue National Park has maintained high ecological integrity, while multi-use buffer zones have absorbed most transformation. This contrast underscores the effectiveness of strict protection but also reveals the structural vulnerability of buffer systems that permit settlement and cultivation. The marked heterogeneity among GMAs further demonstrates that accessibility, infrastructure, and market connectivity strongly mediate conservation outcomes.

Spatial analyses confirm that habitat conversion is structured by boundary and road effects, reinforcing the role of infrastructure as a catalyst of landscape transformation. These findings highlight the need to extend conservation planning beyond protected-area boundaries to address broader socio-ecological processes.

Although the ecosystem retains substantial conservation value, continued agricultural expansion in buffer zones risks eroding landscape connectivity and long-term resilience. The evidence presented here provides a robust foundation for spatially targeted, governance-sensitive conservation strategies in one of Africa's most significant conservation landscapes.

541 **6.0 Declarations**

542 **Ethical Approval:** Not applicable. This study used publicly available satellite imagery and did not
543 involve human participants, human data, or animal subjects.

544 **Consent to Publish:** Not applicable.

545 **Consent to Participate:** Not applicable.

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548 **Author Contribution:** **G.M.:** Conceptualisation, analysis, writing – original draft. **D.P and K.K.:**
549 Conceptualisation, writing – review & editing. **M.S and V.R.N.:** Writing – review & editing. All
550 authors approved the final manuscript.

551 **Competing Interests:** The authors declare no competing interests.

552 **Clinical Trial Number:** Not applicable.

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556 to Landsat imagery through the Google Earth Engine platform.

557 **Availability of Data and Materials:** The classified land-cover maps (1984–2024) generated
558 during this study are available from the corresponding author upon reasonable request. The
559 Google Earth Engine and Python scripts used for classification and analysis are publicly available
560 in the supplementary materials.

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