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Protected area creation and its limited effect on deforestation: Insights from the Kiziba-Baluba hunting domain (DR Congo)

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ABSTRACT

The study examines the spatiotemporal dynamics of landscape anthropization in the Kiziba-Baluba Hunting Domain (KBHD), near Lubumbashi in southeastern Democratic Republic of Congo, facing increasing human threats. It assesses these dynamics from 1989 to 2023 using remote sensing, Geographic Information Systems (GIS), and landscape ecology principles. The results reveal a significant decrease in forest cover, declining from 70.33 % in 1989 to 26.22 % in 2023, with an annual deforestation rate of -1.84 %. This deforestation has led to the expansion of savannas (63.93 %), agriculture (5.76 %), and built-up and bare soil (0.93 %) through patch creation and aggregation. The level of landscape disturbance has increased sixfold over 34 years, from 0.42 in 1989 to 2.81 in 2023. The reduction in the size of the largest forest patch and increased spatial isolation show rising fragmentation and dissection, often followed by the attrition of residual patches. These findings highlight the inefficiency of current conservation measures in KBHD, indicating a need for restructuring management, redefining protected area boundaries, developing a suitable management plan, implementing reforestation programs, strengthening enforcement of environmental laws, and actively involving local communities.

1. Introduction

Tropical forests, vital for the biosphere, house over half of global biodiversity and provide essential ecosystem services, including carbon storage for climate regulation (FAO, 2020; Karsenty, 2019). However, these ecosystems face growing human impact, leading to accelerated deforestation and degradation, especially in tropical regions (Hansen et al., 2013). Land cover changes have reduced global forest area from 19.65 million km^2 in 1990 to 17.70 million km^2 in 2015 (Keenan et al., 2015). Projections suggest that by 2030, a quarter of the Amazon rainforest could vanish, and half of Southeast Asia's remaining forests may disappear (WWF, 2015).

Sub-Saharan Africa is not spared from the phenomena of deforestation and forest degradation, despite its forests covering 13.85 % of the global forest area in 2020. These forests are crucial for the survival of over two-thirds of the population (Masolele et al., 2024). Forest fragmentation is significant, especially in the Congo Basin, home to ecologically vital tropical forests (De Wasseige et al., 2014). The Democratic Republic of the Congo (DR Congo) also experiences these issues, given its importance in context of climate change and deforestation (Potapov et al., 2012).

The DR Congo is known for its large, forested areas, covering about 145 million hectares. These forests include dense humid forests, mountain forests, dry forests, and savanna-forest mosaics (Lawson, 2014). However, they face serious issues of deforestation and degradation (Potapov et al., 2012). This is due to activities like commercial agriculture, charcoal production, and mining (Masolele et al., 2024; Ministère de l'Environnement, Conservation de la Nature et Tourisme,

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2012; Potapov et al., 2012). Nearly 70 % of the Congolese population lives in rural areas, where agriculture and charcoal production are key livelihoods (Mbuangi et al., 2021). These practices, combined with population growth, poverty, and poor governance, put heavy pressure on the forests. This creates major environmental problems and highlights the need for sustainable management strategies to protect these resources.

To mitigate human impact on forest resources, about 12 % of the DR Congo's land is designated as protected areas to preserve ecosystems (Butsic et al., 2015). However, conservation efforts face challenges due to weak enforcement of environmental laws and local socio-economic issues (Kipute et al., 2021). Rather than just improving existing protected areas, the government aims to raise this proportion to 15 % by creating new ones since the early 21st century (Kyale et al., 2019), following Lomami National Park's example. However, expanding without proper planning poses management difficulties, especially in areas heavily influenced by human activity, like the Kiziba-Baluba Hunting Domain (KBHD) near Lubumbashi in southeastern DR Congo.

KBHD is in a region where *miombo* woodland covered about 23 % of the national territory in 2010 (Malaisse, 2010; Potapov et al., 2012). This forest, dominated by *Brachystegia, Julbernardia*, and *Isoberlinia* genera, is crucial for local populations (Chidumayo and Gumbo, 2013). However, as a mining region, *miombo* faces significant human pressures (Khoji et al., 2023; Cabala et al., 2022; Useni et al., 2017), even in protected areas like KBHD (Useni et al., 2023, 2020).

Deforestation in KBHD is driven by several factors. After the mining sector in DR Congo was liberalized in 2002, mining extraction increased, causing rural exodus and urban growth, especially in Lubumbashi (Khoji et al., 2022; Useni et al., 2018). This population growth increased food demand, leading the local government to support farmers, which expanded agricultural activities. To meet urban food demand, villagers in KBHD clear forests for agriculture, contributing to deforestation.

Population growth has also increased energy needs, worsened by electricity production and distribution issues (Banza et al., 2016). As a result, charcoal, being cheaper, has become the main cooking energy source (Kabulu et al., 2018). Villagers cut down trees to produce charcoal, which is lucrative due to high urban demand. Additionally, they exploit non-timber forest products (NTFPs) like fruits and medicinal plants, whose overharvesting for urban markets further exacerbates deforestation (N. D. N'tambwe et al., 2023).

Despite these challenges, protected areas like KBHD play a crucial role in preserving biodiversity, maintaining ecosystems, and promoting environmental awareness (Levin et al., 2017). Studying forest ecosystem evolution within KBHD is vital to understand ongoing spatial changes and evaluate existing conservation strategies. Technological advancements, especially in machine learning, enable analysis using tools like Google Earth Engine, which provides remote sensing data for multi-scale landscape assessment (Gorelick et al., 2017). Additionally, integrating landscape ecology approaches helps to understand interactions between different landscape components and design more effective conservation strategies. However, recent studies have primarily focused on landscape dynamics in protected areas of the DR Congo that are distant from major cities (Musavandalo et al., 2024; Useni et al., 2023; Cirezi et al., 2022; Useni et al., 2020; Kyale et al., 2019), neglecting the impact of proximity to cities on landscape dynamics within protected areas.

This study aims to evaluate the spatiotemporal dynamics of landscape anthropization in the KBHD between 1989 and 2023. We assess the hypothesis that the establishment of the KBHD in an anthropized region has failed to preserve the forest due to the persistence of human activities within it, resulting from inadequate enforcement of environmental laws. This situation is shown by a decrease in the total forest area and an increase in the number of forest patches, leading to spatial fragmentation and isolation.

2. Materials and methods

2.1. Study area

The KBHD, found in southeastern DR Congo, covers an area of 1460 km^2, spanning 11°28′54.00"- 11°50′48.26"S and 27°41′48.88"- 28°10′51.86"E, near the city of Lubumbashi (Fig. 1). This region, at an average altitude of 1200 meters, experiences Köppen Cw climate type with an annual average temperature of 20°C. This climate is characterized by a rainy season (November to March), with an annual average rainfall exceeding 1000 mm, and a dry season (May to September), separated by a two transitional months (Kalombo, 2016; Malaisse, 2010; Kottek et al., 2006).

Dominant soils are ferralsols (Baert et al., 2009), and the terrain is relatively flat. The vegetation is primarily composed of *miombo* woodlands, but human activities are gradually replacing them with savannas (Cabala et al., 2017; Malaisse, 2010). This transformation disrupts habitats, affecting plant and animal species and compromising ecosystem services (Green et al., 2013). KBHD hosts 76 villages, each with around 250 inhabitants engaged in agriculture, charcoal production, and collecting NTFPs (N'tambwe et al., 2023; United Nations, 2022; Kabulu et al., 2018; Kasongo et al., 2018; Useni et al., 2017). Anthropogenic pressure leads to deforestation as new forested lands are sought.

2.2. Landsat images acquisition and processing

2.2.1. Data choice and acquisition

The KBHD landscape has been systematically mapped using Landsat satellite imagery, including TM sensors (1989 and 1998), OLI-TIRS-1 (2014), and OLI-TIRS-2 (2023) with a spatial resolution of 30 meters, allowing detailed analysis. The years were chosen for their availability and low cloud cover (<5 %).

Specifically, 1989 and 1998 were selected to characterize the landscape before the KBHD was established in 2006. 1989 represents the period before the country's democratization following the 1990 National Conference, marked by socio-political crises. 1998 was chosen to analyze the impact of the 1997 political regime change. 2006 marks the official creation of the KBHD. 2014 is before the dismantling of Katanga province, and 2023 is eight years after this event. The dismantling of Katanga significantly impacted regional landscape dynamics (Khoji et al., 2022).

The Landsat images were captured during the dry season (June and July) to ensure consistency in the spectral response of different vegetation covers (Oszwald et al., 2010). These images were downloaded and analyzed using Google Earth Engine (GEE), a cloud platform for large-scale geospatial data analysis, visualization, and storage (Gorelick et al., 2017).

2.2.1. Preprocessing and supervised classification

Radiometric corrections were applied to the images using the Landsat Ecosystem Disturbance Adaptive Processing System algorithm (Hua et al., 2021). This step minimizes registration errors and ensures radiometric consistency. To address Landsat sensor variability, we implemented a normalization method based on slope and intercept (Verbesselt et al., 2012). Scenes covering KBHD were mosaicked, reprojected into the WGS 84/UTM 35s coordinate system, and resampled onto a pre-defined pixel grid using bilinear interpolation (Potapov et al., 2012). Next, a false-color composite image combined near-infrared, red, and green spectral bands to distinguish vegetation types (Gutman et al., 2021).

Subsequently, a supervised classification was undertaken to define four main land cover classes, namely forest, savannas, agriculture, as well as built-up and bare soil. Training areas were delineated on the ground during field campaigns (conducted between June and July 2023) and projected onto the composite image. In inaccessible areas, high-

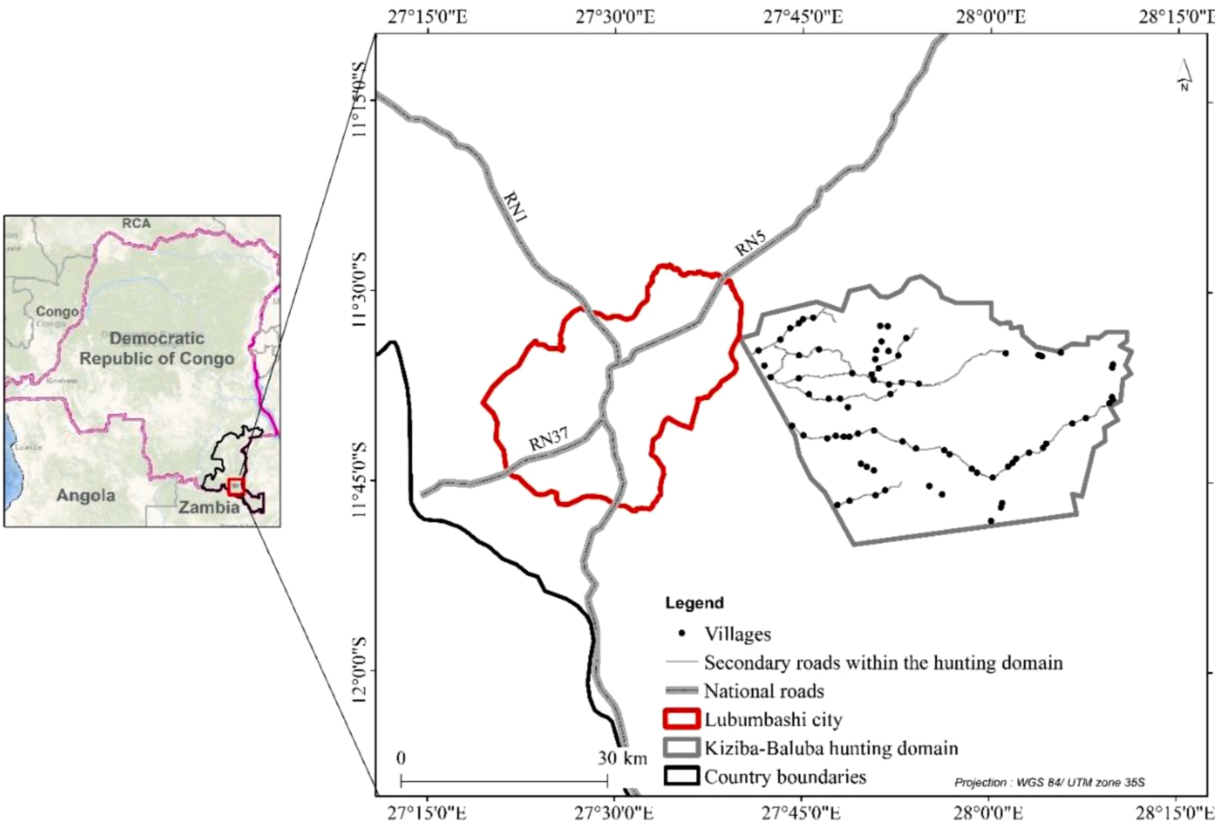

Fig. 1. Location of the KBHD on the outskirts of the city of Lubumbashi, in the Upper Katanga province, DR Congo. The region is traversed by national roads, and a string of villages is situated within the KBHD. This proximity to major transportation roads eases access and economic activities, which in turn contribute to anthropogenic pressures on forest ecosystems.

resolution images from Google Earth Engine and Google Earth Pro supplemented training data. The Random Forest classifier, known for robustness and flexibility, was used with adjusted parameters (Mtry = 2, total trees = 100) for optimal accuracy (Phan et al., 2020).

2.2.3. *Accuracy assessment and area estimation*

We rigorously evaluated the obtained classifications for accurate area estimation and land cover change assessment (Olofsson et al., 2014). Random sampling points were selected across eight land cover for each period (1989-1998, 1998-2006, 2006-2014, and 2014-2023). These land cover included stable categories (forest, savannas, agriculture, fallows, built-up, and bare soil) and change categories. Cochran (1997)'s equation was used to determine 1050 sampling points per period. Furthermore, proportional weighting accounted for land cover importance: 200 points for >30 % coverage, 150 points for 20-30 %, and 100 points for <20 %. These sampling points were then used to calculate the error matrix, expressed in terms of proportion of estimated areas. Adjustments were made to minimize biases in the measurement of areas and land cover changes, thus obtaining more accurate estimates (Nelson et al., 2021).

Measurement accuracies, including overall accuracy, user's and producer's accuracies, were calculated using the accuracy assessment Eqs. (1) and (3) from Olofsson et al. (2014). Adjustments of area estimates for each land cover class and associated standard errors were also made using the area estimation Eqs. (10) and (11) from Olofsson et al. (2014), with standard error calculated using a 95 % confidence interval to assess the reliability of these estimates. Finally, quantity and allocation disagreements were assessed using the accuracy assessment Eqs. (2)-(5) from Pontius and Millones (2011), thus measuring discrepancies between the obtained classification and reference data. All spatial analysis were conducted using ArcGIS 10.8.1.

2.3. *Landscape dynamics analysis*

Landscape composition evaluation relies on three metrics: class area (CA), percentage of landscape (PLAND), and number of patches (NP). These allow both quantitative and qualitative assessment of landscape heterogeneity evolution (McGarigal, 2015). Furthermore, the change in landscape composition was assessed using transition matrices, from which a stability index was calculated. This index measures the unchanged proportion of a land cover class relative to lost and gained proportions (Bogaert et al., 2004). Moreover, the rate of periodic deforestation was estimated and converted into an annual deforestation rate considering the total number of study years (Kyale et al., 2019; Useni et al., 2020). To assess forest disturbance, an index of forest disturbance (U) was calculated, representing the ratio between cumulative anthropogenic land cover classes area (savannas, agriculture, as well as built-up and bare soil) and forest cover, with values below 1 suggesting a landscape predominantly dominated by forest (Khoji et al., 2022).

The ecological processes underlying the observed landscape composition dynamics were identified through metrics such as CA and PN, through a decision tree (Bogaert et al., 2004). These processes include creation, aggregation, enlargement, shift, attrition, perforation, shrinkage, deformation, dissection, and fragmentation of patches (Fig. 2).The differentiation between dissection and fragmentation was achieved using a specific reference value (0.75), a ratio of final to initial area ≤ 0.75 indicates fragmentation, while > 0.75 suggests dissection (de Haulleville et al., 2018). Additionally, the largest patch index (LPI) was computed for each land cover class, quantifying the percentage of CA composed of the largest patch. LPI approaches 0 when largest patch become smaller and LPI approaches 100 when total landscape consists of a single patch of corresponding land cover type (Bamba et al., 2008).

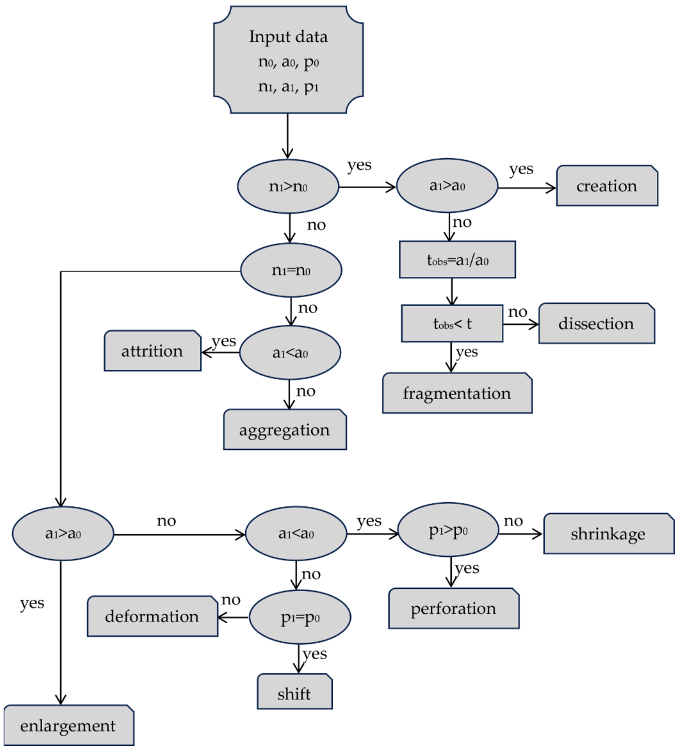

Fig. 2. The decision tree algorithm used to show spatial transformation processes that change the spatial structure of landscapes. The parameters a_0, p_0, and n_0 represent the class area, perimeter, and number of patches before the transformation, respectively, while a_1, p_1, and n_1 represent the values after the change in spatial structure (Bogaert et al., 2004).

Furthermore, the degree of patch isolation was assessed through the proximity index (PROX), considering both the size and proximity of patches. PROX = 0 means no patches of the same type within a specific radius, while an increase reflects closer patch distribution (McGarigal, 2015).

3. Results

3.1. Validation of Landsat images classification and mapping

The results of the classification accuracy analysis reveal high values (≥80 %) for producer's accuracy, user's accuracy, and overall accuracy (Table 1), suggesting precise classification of land cover classes compared to ground truth data. Additionally, the analysis of quantity disagreement (QD) and allocation disagreement (AD) revealed relatively low overall differences between the map class and the reference class. For the periods 1989-1998 and 2006-2014, discrepancies were primarily attributable to allocation disagreement, as indicated by AD/QD ratios of 3.29 and 1.70, respectively. In contrast, for the periods 1998-2006 and 2014-2023, differences were mainly due to quantity disagreement, as evidenced by AD/QD ratios of 0.17 and 0.51, respectively. These findings suggest that, despite the presence of disagreements, the low values of AD and QD indicate that the change classifications were generally reliable.

Furthermore, all area estimates were significant, with no margin of error at the 95 % confidence interval threshold (Table 1). Visual analysis of Landsat image classifications indicates a notable reduction in forest cover, especially in the western region of the KBHD. Concurrently, there has been an increase in savanna and agricultural areas in this same region (Fig. 3).

3.2. Landscape composition dynamics

In 1989, the forests, which formed the primary landscape, experienced a substantial decline in coverage. It dropped from 70.33 % in 1989 to 22.61 % in 2023, resulting in an annual deforestation rate of 1.84 %. During the same period, the proportion of savannas nearly tripled, rising from 29.51 % to 63.38 %, making them the dominant land cover. The expansion of agriculture was remarkable during the same period, with their proportion increased ninefold. Additionally, built-up areas and bare soil nearly doubled, growing from 0.23 % of the landscape in 1989 to 0.45 % in 2023 (Table 2). These findings highlight a significant and rapid transformation of the KBHD landscape, characterized by pronounced deforestation and substantial savanna and agricultural expansion.

Overall, the forests regression observed between 1989 and 2023 were supported by a notable transfer of area to savannas (14.19 %, 15.60 %, 12.26 %, and 21.88 % during 1989-1998, 1998-2006, 2006-2014, and 2014-2023, respectively), as did agriculture (0.28 %, 0.60 %, 1.27 %, and 3.61 %) and built-up/bare soil (0.07 %, 0.30 %, 0.38 %, and 0.18 %). However, despite this regression, a trend of forests regeneration from savannas was observed (7.09 %, 7.61 %, 8.23 %, 3.42 % for the same periods, respectively).

Furthermore, savannas were converted to agricultural land, built-up areas, and bare soils. Agricultural expansion largely originated from forests (0.28 %, 0.60 %, 1.27 %, 3.61 % for the same periods, respectively) and savannas (0.78 %, 0.22 %, 2.81 %, 5.18 % for the same periods, respectively). Finally, the expansion of built-up areas and bare soils was also due to significant conversion from forests (0.07 %, 0.30 %, 0.38 %, 0.18 % for the same periods, respectively) and savannas (0.08 %, 0.39 %, 0.48 %, 0.16 % for the same periods, respectively), as illustrated in Table 2.

The analysis of land cover stability showed that forests were the most stable class from 1989 to 2014, as indicated by the stability index. However, this stability decreased significantly between 2014 and 2023, with savannas becoming the most stable class by 2023. In contrast, agriculture and built-up/bare soil remained unstable from 1989 to 2023 (Table 2). These results reveal a shift in land cover dynamics, with forests becoming less stable and savannas more stable.

This trend is further supported by the forest disturbance index, which tripled from 0.42 in 1989 to 2.81 in 2023. Initially below 1, the index surpassed this threshold in 2014 and increased further in 2023, indicating a growing prevalence of human-induced land cover changes (Fig. 4). These findings highlight the increasing extent of forest disturbance and the dominance of anthropogenic land cover over time.

3.3. Spatial pattern dynamics of the landscape

The structural dynamics of the KBHD landscapes from 1989 to 2023 were analyzed using a decision tree algorithm (Bogaert et al., 2004). Between 1989 and 1998, forest areas exhibited a decrease in patch area (CA) and an increase in patch number (PN) (Table 3), indicating dissection ($t=0.89>0.75$). Conversely, savannas, agriculture, and built-up/bare soil experienced increases in both CA and PN, indicating a creation process.

From 1998 to 2006, forests and agriculture faced attrition process, with decreases in both CA and PN (Table 3). In contrast, savannas showed an increase in CA and a decrease in PN, reflecting patch aggregation. Built-up and bare soil exhibited increased CA and PN, indicating a creation process.

Between 2006 and 2014, forests underwent a dissection process ($t=0.89>0.75$), marked by decreased CA and increased PN (Table 3). In contrast, savannas, agriculture, and built-up/bare soil all underwent creation processes, evident from increases in both CA and PN.

Finaly, from 2014 to 2023, forests exhibited fragmentation, with a decrease in CA and an increase in PN ($t=0.54<0.75$). Savannas and built-up/bare soil showed increases in CA and decreases in PN,

Table 1
Evaluation of classification accuracy and estimation of areas for land cover and land cover change classes from 1989-1998, 1998-2006, 2006-2014, and 2014-2023, based on supervised classification of Landsat images using the Random Forest classifier. F: forest; S: savannah; AF: agriculture; BBS: built-up and bare soil; PA: producer accuracy; UA: user accuracy; OA: overall accuracy; QD: quantity disagreement; AD: allocation disagreement; CI: confidence interval. The classifications performed are statistically dependable, with significant area estimates and no error margin.

1989-1998								
	F	S	AF	BBS	F loss	S gain	AF gain	BBS gain
Accuracy measure								
PA	**100.00 %**	**95.24 %**	**100.00 %**	**100.00 %**	**85.16 %**	**80.68 %**	**99.95 %**	**100.00 %**
UA	**100.00 %**	**91.19 %**	**83.65 %**	**100.00 %**	**85.47 %**	**93.51 %**	**100.00 %**	**100.00 %**
OE	**0.96**							
QD	**0.01**							
AD	**0.03**							
AD/QD ratio	**3.29**							
Stratified estimators of area ± CI [% of total map area]								
Area	55.78 %	21.44 %	0.01 %	0.01 %	10.43 %	11.30 %	0.97 %	0.06 %
95 % CI	0.00 %	1.20 %	0.00 %	0.00 %	1.21 %	0.81 %	0.00 %	0.00 %
1998-2006								
	F	S	AF	BBS	F loss	S gain	AF gain	BBS gain
Accuracy measure								
PA	**100.00 %**	**100.00 %**	**100.00 %**	**0.95 %**	**98.86 %**	**92.00 %**	**84.31 %**	**100.00 %**
UA	**100.00 %**	**95.48 %**	**89.80 %**	**100.00 %**	**96.10 %**	**99.17 %**	**95.83 %**	**100.00 %**
OE	**0.98**							
QD	**0.02**							
AD	**0.004**							
AD/QD ratio	**0.17**							
Stratified estimators of area ± CI [% of total map area]								
Area	46.38 %	26.53 %	0.02 %	0.96 %	15.77 %	8.45 %	1.14 %	0.75 %
95 % CI	0.00 %	0.91 %	0.00 %	0.78 %	0.61 %	0.53 %	0.35 %	0.00 %
2006-2014								
	F	S	AF	BBS	F loss	S gain	AF gain	BBS gain
Accuracy measure								
PA	**97.32 %**	**100.00 %**	**86.49 %**	**82.93 %**	**92.80 %**	**83.58 %**	**90.46 %**	**84.22 %**
UA	**98.41 %**	**99.00 %**	**89.29 %**	**95.59 %**	**87.32 %**	**94.20 %**	**95.77 %**	**98.04 %**
OE	**0.97**							
QD	**0.01**							
AD	**0.02**							
AD/QD ratio	**1.70**							
Stratified estimators of area ± CI [% of total map area]								
Area	39.98 %	33.03 %	0.15 %	0.08 %	10.36 %	4.02 %	11.71 %	0.68 %
95 % CI	0.84 %	0.72 %	0.01 %	0.03 %	0.89 %	0.28 %	0.74 %	0.14 %
2014-2023								
	F	S	AF	BBS	F loss	S gain	AF gain	BBS loss
Accuracy measure								
PA	**100.00 %**	**100.00 %**	**81.30 %**	**100.00 %**	**97.30 %**	**81.66 %**	**86.28 %**	**100.00 %**
UA	**100.00 %**	**99.33 %**	**100.00 %**	**97.00 %**	**91.72 %**	**97.14 %**	**92.71 %**	**90.57 %**
OE	**0.97**							
QD	**0.02**							
AD	**0.01**							
AD/QD ratio	**0.51**							
Stratified estimators of area ± CI [% of total map area]								
Area	20.50 %	33.82 %	1.18 %	0.04 %	20.53 %	10.63 %	5.46 %	7.83 %
95 % CI	0.00 %	0.44 %	0.25 %	0.00 %	1.09 %	0.96 %	0.63 %	0.48 %

indicating aggregation. Agriculture displayed a creation process, with increases in both CA and PN.

The LPI for forests dropped significantly from 91.60 % in 1989 to 37.11 % in 2023, indicating more fragmentation. In contrast, the LPI for savannas rose from 33.83 % to 87.17 % over the same period. The LPI for agriculture increased from 0.66 % to 4.32 %, and for built-up/bare soil areas, it went up from 1.00 % to 3.77 % (Table 3). These changes show that the largest patches for savannas, agriculture, and built-up/bare soil areas are getting bigger.

These trends illustrate a shift in the landscape: forests are becoming more fragmented, while savannas, agriculture, and built-up/bare soil areas are expanding. Additionally, the Proximity Index (PROX) for forests decreased, meaning forest patches are becoming more isolated (Table 3). On the other hand, savannas, agriculture, and built-up/bare land have higher PROX values, suggesting that their patches are starting to merge.

4. Discussion

4.1. Methodological approach

The rise of machine learning has greatly advanced environmental monitoring with tools like Google Earth Engine (GEE), which offers free access to satellite images and large-scale spatial analysis (Zhang et al., 2021; Phan et al., 2020). However, GEE requires an internet connection, which can be a limitation in developing countries (Amani et al., 2020). Landsat images, while having medium resolution, are cost-effective and useful for monitoring large areas in agriculture, forestry, and environmental studies (Singh et al., 2021).

The use of local environmental knowledge and quality field data has improved the accuracy of Landsat image classification with the Random Forest classifier (Xia et al., 2017). In this study, land cover validated by field data are dominant in the region and were selected for comparison (Khoji et al., 2023; Cabala et al., 2018b; Munyemba and Bogaert, 2014). However, wetlands and some natural savannas were grouped with anthropogenic savannas due to similar reflectance, but this did not affect

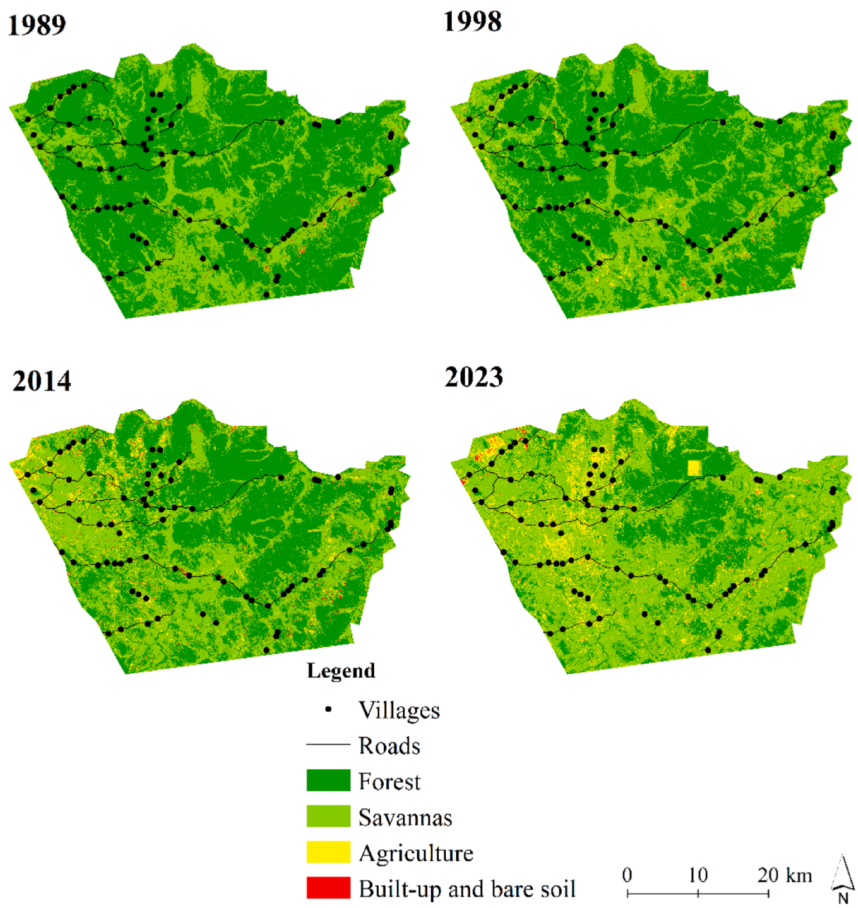

Fig. 3. Land cover maps of the KBHD derived from supervised classification of Landsat images from 1989, 2006, 2023, 2040, and 2060 using the Random Forest classifier. Forest cover shows a remarkable regression between 1989 and 2023, while savannas, agriculture, as well as built-up and bare soil, are characterized by a spatial expansion within the KBHD.

overall land cover trends.

Landscape dynamics were analyzed using transition matrices to identify major landscape changes, which are essential for linking pattern to process (Pontius et al., 2004). These matrices highlighted landscape transitions in the Lufira Biosphere Reserve, DR Congo (Useni et al., 2020). The stability index from these matrices shows how resistant different land cover are to change, reflecting their resilience to human impacts. Spatial Transformation Processes (STP) were analyzed using Bogaert et al. (2004) decision tree algorithm to understand landscape configuration changes and their causes.

The study selected metrics for their ecological relevance (Bogaert et al., 2002), using CA and PN as bases for further metrics (McGarigal, 2015). Among these, the forest disturbance index, used in this study to assess forest landscape disturbance in the KBHD, revealed similar trends in the Kasenga territory in the same region (Mpanda et al., 2022). Similarly, LPI was employed in this study to prove forest fragmentation in the KBHD. This index was used to highlight forest fragmentation in the Katangan Copperbelt Area (Cabala et al., 2018b). Additionally, the proximity index assessed the spatial isolation of forest patches, contributing to the understanding of landscape connectivity and ecological interactions. This metric was also used in protected areas in the Amazon (Cabral et al., 2018).

The Principal Component Analysis (PCA) (see Appendix 1) of forest indices showed a strong positive correlation between CA, LPI, and PROX, linking total area, fragmentation, and landscape connectivity. These are negatively correlated with NP and the disturbance index, indicating that as forest area shrinks, patches become smaller, less connected, and more disturbed. For anthropogenic savannas, a positive correlation between CA, LPI, and PROX, and a negative correlation with NP, suggests that larger savanna areas create better-connected patches, reducing isolation. For agricultural land, fallow, built-up areas, and bare soil, positive correlations among CA, PN, LPI, and PROX reflect organized human planning, enhancing connectivity and patch size, while controlled fragmentation increases patch numbers.

The study did not account for all variables affecting deforestation, such as socio-economic factors, which may limit the overall understanding of the processes. Nonetheless, the study linked land cover changes to key anthropogenic activities using decision tree analysis, providing insights into the interactions between human activities and landscape changes (Bogaert et al., 2014).

4.2. Anthropogenic pressure and associated spatiotemporal landscape dynamics within the KBHD

The KBHD has seen major land cover changes from 1989 to 2023, with significant forest loss. Over this period, the forest has experienced a net loss of over half of its coverage, highlighting the crucial role of deforestation in this region. These results confirm trends observed both in unprotected areas (Cabala et al., 2022; Khoji et al., 2023, 2022; Mpanda et al., 2022; Useni et al., 2024) and in protected areas (Useni et al., 2020) of the Katanga region in DR Congo, where forest cover is declining alarmingly. These findings also confirm the trends observed in protected areas on the Copperbelt Province of Zambia (Phiri et al., 2022) and in half of the protected areas within the Kilombero waterment in Tanzania (Thonfeld et al., 2020).

The deforestation rate in KBHD (-1.84 %) is much higher than the national average of -0.38 % (2001-2019) (Eba'a Atyi et al., 2022) and exceeds that of the Lubumbashi charcoal production basin (-1.51 %,

Table 2
Transition matrices highlighting the percentage of change in land cover classes between 1989-1998, 1998-2006, 2006-2014, and 2014-2023, derived from Landsat images classification using the Random Forest classifier. 1 % corresponds to 14.57 km^2. Forest has shown a significant decrease in favor of savannas, agriculture, as well as built-up and bare soil.

1989-1998	Forest	Savannas	Agriculture and fallows	Buit-up and bare soil	Total
Forest	55.78	14.19	0.28	0.07	70.33
Savannas	7.09	21.44	0.78	0.08	29.40
Agriculture and fallows	0.00	0.03	0.01	0.00	0.04
Buit-up and bare soil	0.02	0.17	0.03	0.01	0.23
Total	62.89	35.84	1.10	0.16	100
Stability index	2.58	0.96	0.01	0.02	
1998-2006	Forest	Savanes	Agriculture and fallows	Buit-up and bare soil	Total
Forest	46.39	15.60	0.60	0.30	62.89
Savanes	7.61	27.62	0.22	0.39	35.84
Agriculture and fallows	0.00	1.01	0.02	0.07	1.10
Buit-up and bare soil	0.01	0.14	0.01	0.01	0.16
Total	54.01	44.37	0.85	0.77	100
Stability index	1.92	1.11	0.01	0.01	
2006-2014	Forest	Savannas	Agriculture and fallows	Buit-up and bare soil	Total
Forest	39.98	12.26	1.27	0.38	53.89
Savannas	8.23	33.02	2.81	0.48	44.54
Agriculture and fallows	0.05	0.58	0.14	0.04	0.81
Buit-up and bare soil	0.00	0.45	0.23	0.07	0.75
Total	48.27	46.32	4.45	0.96	100
Stability index	1.80	1.33	0.03	0.04	
2014-2023	Forest	Savannas	Agriculture and fallows	Buit-up and bare soil	Total
Forest	22.61	21.88	3.61	0.18	48.27
Savannas	3.42	37.55	5.18	0.16	46.32
Agriculture and fallows	0.14	3.19	1.06	0.06	4.45
Buit-up and bare soil	0.06	0.66	0.20	0.04	0.96
Total	26.22	63.28	10.05	0.44	100
Stability index	0.77	1.09	0.09	0.03	

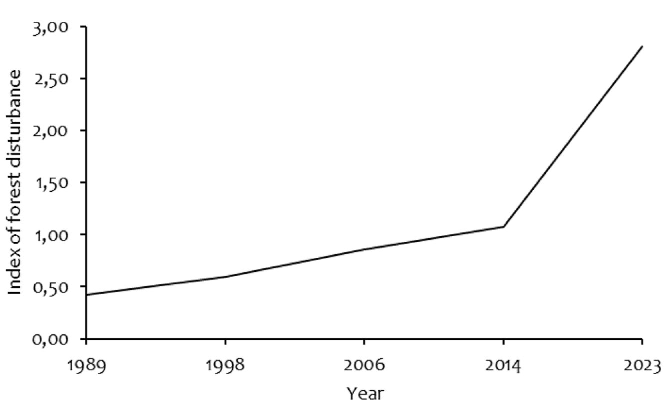

Fig. 4. Variation in the forest disturbance index within the KBHD from 1989 to 2023, derived from Landsat images classification using the Random Forest algorithm. Forest cover has experienced increasing disturbance, with acceleration saw between 2014 and 2023.

Table 3
Evolution of metrics characteristic of landscape spatial pattern dynamics in the DCKB in 1989, 1998, 2006, 2014, and 2023 derived from supervised classification of Landsat images using the Random Forest classifier. PN: patch number, CA: class area, LPI: largest patch index, PROX: proximity index. The forest is experiencing processes of dissection, attrition, and fragmentation of its patches. This spatial evolution leads to increased landscape heterogeneity, resulting in decreased connectivity within the forest, where patches become increasingly isolated.

	Forest	Savannas	Agriculture and fallows	Built-up and bare soil
1989				
n	10537	19699	253	1092
a	1023,00	434,10	0,74	2,34
LPI	91,60	33,83	0,66	1,00
PROX	73785,67	4761,45	0,52	0,32
1998				
n	19307	30531	5480	1110
a	915,34	525,47	16,00	3,31
LPI	78,94	40,92	1,19	1,81
PROX	55846,66	5990,06	1,92	0,36
2006				
n	14749	16710	4911	3425
a	783,68	658,31	12,03	6,52
LPI	74,63	72,20	2,05	2,94
PROX	25605,57	24326,73	0,58	0,91
2014				
n	21866	24029	19758	9420
a	702,55	681,49	65,56	11,13
LPI	56,12	53,84	2,69	2,63
PROX	10138,42	44019,21	3,97	0,94
2023				
n	26126	20362	37028	1648
a	382,65	919,61	144,37	13,51
LPI	37,11	87,17	4,32	3,77
PROX	2113,49	90162,69	42,66	1,67

1990-2022) (Khoji et al., 2023). It is also higher than the rate in Mozambique's Quirimbas National Park, in the Zambezi region, which experienced 41.67 % forest loss over 38 years (Mucova et al., 2018). Disparities in deforestation rates can be explained by differences in spatial scale, highlighting the need to tailor analyses to specific local contexts (Wu, 2004).

Human activities have profoundly altered the landscape of the KBHD, resulting in the conversion of significant forest into savannas, which increased from 29.51 % in 1989 to 63.38 % in 2023. This major landscape transformation is largely attributed to charcoal production (Khoji et al., 2023). This phenomenon is exacerbated by persistent challenges related to energy production and distribution in the city of Lubumbashi, compounded by rapid population growth (Dibwe, 2009; Kabulu et al., 2018). Consequently, over 90 % of the urban population relies on charcoal for cooking (Kabulu et al., 2018). Additionally, inefficient charcoal production and scarce forest resources (Kasanda et al., 2024; Khoji et al., 2023) lead to mass logging, increasing savanna areas around the city (Useni et al., 2019, 2017). Similar trends were seen in the Lufira Biosphere Reserve, Kundelungu National Park, and Virunga National Park (Udahogora et al., 2021; Useni et al., 2023, 2020).

Hunting, which provides protein in rural areas, also contributes to the increase of savannas (Fargeot, 2013). Indeed, hunting methods, like fire use, harm wildlife and disrupt *miombo* tree regeneration (Useni et al., 2023). Furthermore, the collection of NTFPs also contributes to the savannization of the KBHD forest, even though these products are vital for livelihoods (Chirwa et al., 2008). For illustration, in the rural area of Lubumbashi, tree felling is sometimes practiced easing the collection of certain species of non-timber forest products (NTFPs) such as caterpillars. Additionally, honey extraction often involves the debarking of specific tree species, thereby disrupting the ecological balance.

Furthermore, agriculture is another major factor driving deforestation, with the proportion of agriculture land increasing from 0.04 % in

1989 to 10.05 % in 2023. While agriculture is crucial for DR Congo's communities (Kasongo et al., 2013), practices like slash-and-burn expand agriculture and impact soil nutrients (Ribeiro et al., 2020). Moreover, urban population growth increases demand for agricultural products, leading to expansion even in protected areas. Agricultural trends in KBHD mirror those in the Lubumbashi charcoal basin (Khoji et al., 2023), Lufira Biosphere Reserve (Useni et al., 2020), and Yangambi Biosphere Reserve (Kyale et al., 2019). Similar patterns are observed in Zimbabwe's Midlands Black Rhino Conservancy, where agricultural land increased by 20 % over 40 years (Kunedzimwe et al., 2023).

The expansion of built-up and bare soil in KBHD, doubling from 0.23 % in 1989 to 0.44 % in 2023, threatens ecosystems and disrupts ecological balance. This is due to village growth from migrations and expanding existing villages. Similar trends are seen in protected areas like Yangambi Biosphere Reserve (Kyale et al., 2019) and the Maze National Park in southwestern Ethiopia (Simeon and Wana, 2024).

Forest cover decline in KBHD is accompanied by low regeneration and deforestation, reducing the forest stability index by nearly threefold from 1989 to 2023. This trend aligns with observations in the Lubumbashi charcoal basin (Khoji et al., 2023) and the Kasenga territory (Mpanda et al., 2022), due to similar analytical methods.

The analysis of landscape transformation highlighted processes such as forest attrition, dissection, and fragmentation. Forest attrition, typical of natural land cover (Bogaert et al., 2011), mainly results from the conversion of forests into savannas and built-up areas. This phenomenon was particularly pronounced between 1998 and 2006 due to political changes and economic growth. Dissection and fragmentation result from road construction to connect emerging villages and agricultural road rehabilitation (2006-2023) (Mufuta et al., 2022). These findings align with Useni et al. (2024), in the Kasenga municipality, located in the same region.

In contrast, savannas as well as built-up and bare soil showed processes of aggregation and creation, typical of anthropogenic land covers (Bogaert et al., 2011). Savannas creation is driven by deforestation and increased light penetration, supporting herbaceous growth. These trends are consistent with previous observations in the Lufira Biosphere Reserve (Useni et al., 2020) and in the Lubumbashi plain (Cabala et al., 2018b; Munyemba and Bogaert, 2014). The increase in built-up areas is due to villages expansion and new settlements within protected areas. Agricultural land creation meets high food demand, while patch attrition occurs due to instability and vegetative recolonization of abandoned lands. Similar results have been highlighted in the Lubumbashi plain and in the Katangan Copperbelt (Cabala et al., 2018a, 2017).

Finally, forest fragmentation in KBHD is marked by a threefold reduction in the largest patch index, indicating major changes in forest structure. Similar trends are observed in Lufira Biosphere Reserve (Useni et al., 2020). The decrease in the proximity index suggests reduced ecological connectivity and increased habitat isolation, which could impact wildlife(Reddy et al., 2013).

The presence of anthropogenic practices in a protected area is a consequence of the absence of a specific management plan, a gap also observed in other protected areas in the DR Congo (Boketshu et al., 2021; Wilondja et al., 2020). The absence of a management plan leads to inefficient natural resource management and increases vulnerability to anthropogenic pressures, compromising conservation aims and ecological viability. Furthermore, although laws regulating protected areas exist in the DRC, their applicability stays problematic.

4.3. Implications for landscape management

The analysis of land cover dynamics in the KBHD from 1989 to 2023 showed significant forest regression, instability, and disturbance. The forest experienced attrition, fragmentation, and dissection, leading to isolated patches. This change resulted in the expansion of savannas, agriculture, and built-up areas, impacting biodiversity and ecosystem services. Immediate action is needed to reverse these trends and manage natural resources sustainably.

To counteract forest regression, the Congolese Institute for Nature Conservation should establish a new boundary for the KBHD, as Lubumbashi's rapid expansion threatens the area (Useni et al., 2018). They should also create a monitoring service with eco-guards to patrol the new boundaries. Examples of successful protected area management include the Lwama-Kivu hunting domain in DR Congo (Wilondja et al., 2020) and the Bururi forest nature reserve in Burundi (Havyarimana et al., 2017).

Our results reveal a decrease in forest spatial connectivity due to the isolation of its patches. Connectivity, which facilitates or constrains species movement between habitats (Avon et al., 2014), is essential for animal movement. Concurrently, significant savannization is altering natural habitats for species. To address this, the Congolese Institute for Nature Conservation should implement a reforestation plan and support assisted natural regeneration to reverse the decline in forest connectivity and the spread of savannas. Successful reforestation initiatives in other regions of the world show promising results (Fagan et al., 2016). The KBHD restoration strategy needs funding from the Congolese government and support from national and international partnerships, similar to the efforts for the Lubumbashi zoological garden.

Furthermore, the rise of agriculture in the KBHD highlights the need for a management plan by the Congolese Institute for Nature Conservation. This plan should establish management blocks, as seen in the Lwama-Kivu hunting domain (Wilondja et al., 2020), defining protection and buffer zones with specific activities allowed in each. Promoting agroforestry in key areas, especially near existing villages, is crucial for supporting ecosystem services and reducing pressure on the remaining habitats. Agroforestry is a sustainable development approach with significant benefits, especially in Africa (Mbow et al., 2014), as demonstrated in Cameroon (Awazi and Avana-Tientcheu, 2020).

Additionally, the expansion of villages requires relocating those established after the hunting domain's creation. This should involve local Indigenous communities in the planning and management of the protected area. Successful co-management with local communities, like in Cameroon, has reduced deforestation and degradation (Bruggeman et al., 2015). Co-management will be accepted if the benefits are clear, which can be achieved through support to local farmers by the Congolese Institute for Nature Conservation, reducing pressure on forest land (Moukouyou et al., 2015).

5. Conclusion

The aim of this study was to evaluate the spatiotemporal dynamics of landscape anthropization in the KBHD from 1989 to 2023 using remote sensing, Geographic Information Systems, and landscape ecology approaches. The results showed that the creation of the KBHD in 2006 did not preserve the forest due to ongoing human activities and weak enforcement of environmental laws. This led to a significant decline in forest cover, which decreased about threefold from 1989 to 2023, with an annual deforestation rate of -1.84 %, higher than regional and national averages. Deforestation transformed the forest into savannas, agricultural land, and built-up areas, resulting in landscape degradation, as indicated by stability and disturbance indices. This anthropization has led to fragmentation and isolation of forest patches, confirmed by the proximity index evolution. Suppression, dissection, and fragmentation were the main spatial transformation processes, while agriculture and built-up areas mainly experienced patch creation. Our results, although limited to landscape evolution without socio-economic and dendro-floristic data, confirm that establishing a protected area in an anthropized region did not stop deforestation.

These findings highlight the need for urgent corrective measures. In the short term, the Congolese Institute for Nature Conservation should redefine the protected area boundaries, set up a permanent monitoring service, and develop a management plan supported by reforestation and assisted natural regeneration, with active participation from local communities. Additionally, strict enforcement of environmental laws and funding for further research to analyze the situation in depth are essential.

Ethical Compliance

The authors confirm that this study was conducted in compliance with ethical standards and that all necessary approvals were obtained.

CRediT authorship contribution statement

Héritier Khoji Muteya: Conceptualization, Data curation, Formal analysis, Methodology, Software, Resources, Writing – original draft. **Médard Mpanda Mukenza:** Software, Methodology. **Ildephonse Kipili Mwenya:** Software, Methodology. **François Malaisse:** Writing – original draft. **Dieu-donné N'tambwe Nghonda:** Writing – original draft. **Nathan Kasanda Mukendi:** Writing – original draft. **Jean-François Bastin:** Software, Methodology. **Jan Bogaert:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Yannick Useni Sikuzani:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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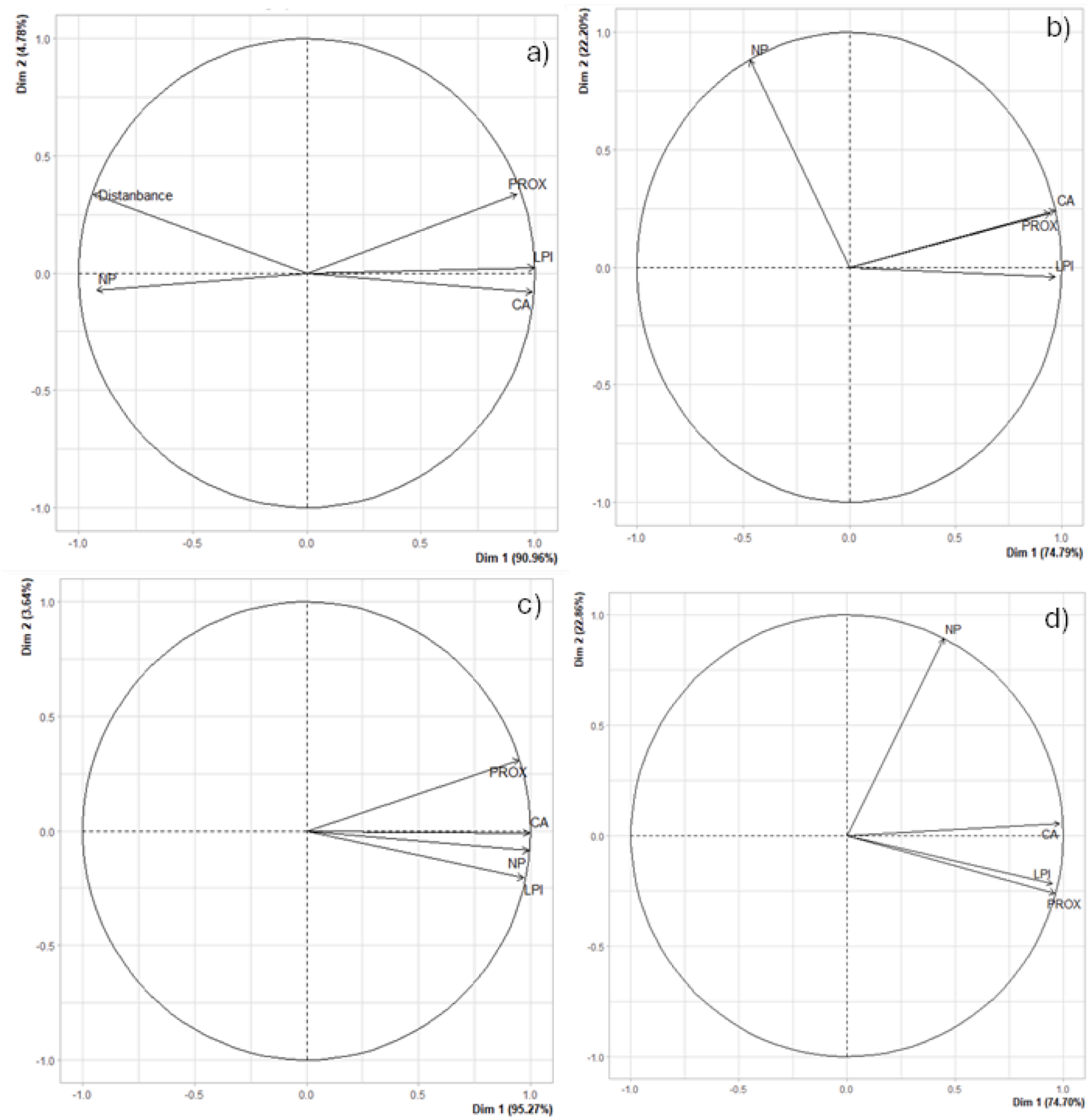
Appendix 1

The elucidation of relationships between structural indices was conducted through Principal Component Analysis (PCA). This technique was chosen for its ability to reduce the dimensionality of datasets, thereby enhancing interpretability while minimizing information loss (Greenacre et al., 2022). The analysis steps included constructing a correlation matrix and calculating its determinant to verify whether the matrix was an identity matrix. Subsequently, the maximization index (Kaiser-Meyer-Olkin adequacy factor) was computed to find the suitability of a factorial solution for our dataset. Creating a correlation circle of variables with different dimensions highlighted each variable's contribution to axis (dimension) construction (Jolliffe and Cadima, 2016).

The results showed strong positive correlations between changes in CA, LPI, and PROX for forests and savannas. For forests, CA, LPI, and PROX all decreased together, while for savannas, these indices increased together. PN showed a negative correlation with CA, NP, and PROX for both land cover types and a positive correlation with forest disturbance. This confirms that as total forest area shrinks, LPI and patch proximity decrease, while NP and disturbance levels rise. Conversely, as savanna area expands, LPI and patch proximity increase, and the number of patches decreases. For agricultural lands, fallows, built-up areas, and bare soil, all four indices were positively correlated, indicating that an increase in these land cover types is linked to more patches, a larger largest patch, and greater landscape connectivity.



Appendix 1. Principal Component Analysis (PCA) illustrating the relationships between spatial structure indices of forests (a), savannas (b), agricultural lands and fallows (c), as well as built-up areas and bare soil (d). The first two axes of the PCA explain 95,74 % of the total variation in (a), 96.99 % in (b), 98.91 % in (c), and 97.56 % in (d). Overall, class area (CA), largest patch index (LPI), and proximity index (PROX) exhibit significant positive correlations for both forest and savanna. The number of patches (NP) and disturbance index also show positive correlations for forest. These four indices are all positively correlated for agriculture and fallows as well as built-up and bare soil.

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