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Landscape dynamics and analysis of anthropogenic factors of deforestation and forest degradation in Lodja and Lomela territories in Sankuru Province, DRC

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Abstract

The Sankuru province, in its Lodja and Lomela territories, constitutes a vast forest province, rich in biodiversity. However, the province's forest ecosystems are undergoing changes because of human activities. This study uses remote sensing, cartography and landscape ecology analysis tools to quantify landscape dynamics and analyze the anthropogenic drivers behind these dynamics in Lodja and Lomela. Evolutionary trends in land use were quantified through the proportion of classes in the study area. The results obtained indicate a loss of 9.23% of dense forest between 2013 and 2023, with a significant increase in degraded forest and the rural complex. However, the landscape studied remains predominantly forest-dominated, although human impact is beginning to make itself felt. The main deforestation factors identified in the region are tree felling, vegetation fire, agriculture (slash-and-burn) and hunting. These factors are variably distributed in relation to villages in the landscape, so that agriculture, logging and fire are generally practiced in areas close to villages, while hunting is practiced far from villages. Our observations imply the need for land-use policies and actions that can involve all stakeholders in forest ecosystem management.

Keywords Deforestation, Degradation, Anthropization, Landscape dynamics, Sankuru

1 Introduction

Deforestation is one of the major environmental challenges facing the planet [12]. It is a complex and multifactorial phenomenon, which depends on the geographical, socio-economic and political conditions of each region [10]. Among the countries of the Congo Basin, the Democratic Republic of Congo (DRC) has the largest forest area, with around 155 million hectares, or almost 10% of the world's tropical forests [31]. However, this natural heritage of the DRC is under increasing pressure from agricultural

expansion, logging, hunting and poaching, infrastructure construction, urbanization and artisanal mining [1]. The province of Sankuru, located in the heart of the Democratic Republic of Congo, is home to exceptional natural wealth, particularly in terms of forest biodiversity. The region is home to a portion of the Salonga National Park, the largest protected tropical forest reserve on the African continent, as well as the Sankuru Nature Reserve [42]. However, deforestation and forest degradation are major issues threatening this unique ecosystem. In particular, the Lodja and Lomela territories are at the heart of this dynamic landscape, where anthropogenic factors are exerting increasing pressure on forest resources [17]. In tropical regions, the use of remote sensing and landscape metrics has greatly contributed to analyzing forest dynamics and assessing anthropogenic pressures on ecosystems [49]. These approaches not only allow for the characterization of land-use and land-cover changes but also enable the quantification of habitat fragmentation and connectivity, which are essential for sustainable forest management [24]. However, despite the abundance of studies conducted in the Amazon, Southeast Asia, and parts of the Congo Basin, very few have specifically focused on Sankuru Province. This province is characterized by unique socio-political constraints and poorly studied forest ecosystems. Significant scientific gaps remain, particularly in understanding the local dynamics of deforestation and forest degradation. To address this gap, our study stands out by combining satellite imagery analysis with field-based inventories of anthropogenic drivers of deforestation. This integrated approach not only provides a comprehensive view of landscape changes but also sheds light on local forest governance challenges, thereby offering a relevant scientific framework for sustainable forest planning and management in Sankuru (Mobunda Tiko et al. 2025).

To reconcile nature conservation with human development, several strategies have already been attempted in the Democratic Republic of Congo, including the establishment of protected areas such as Salonga National Park and the Sankuru Nature Reserve, as well as community forestry initiatives supported by national policies and international donors. While these approaches were designed to safeguard biodiversity and provide alternative livelihoods, they have often proved insufficient due to weak enforcement, limited financial and technical resources, and inadequate involvement of local communities in decision-making processes. As a result, slash-and-burn agriculture, timber harvesting, and hunting continue to exert pressure on forest ecosystems. In this study, we contribute new empirical evidence by combining remote sensing with field-based inventories to document both the spatial patterns and the underlying drivers of forest loss in Lodja and Lomela. This integrated approach provides critical insights for designing land-use policies that better align conservation goals with the socio-economic realities of local populations.

Despite the limited number of studies focusing specifically on Sankuru Province, the relevance of this research extends beyond filling a geographic gap. It aims to provide an integrated analytical framework for understanding how human activities reshape forested landscapes in Central Africa through combined remote sensing and field-based ecological data. Most existing studies on deforestation in the Congo Basin rely primarily on satellite-derived landcover change detection, often neglecting fine-scale field evidence of anthropogenic pressures. Our approach therefore bridges this gap by coupling spatially explicit forest dynamics with quantitative measures of human disturbance along

village gradients. This dual perspective allows us to link spatial patterns of deforestation to underlying socio-ecological processes.

Specifically, this study addresses three central research questions:

1. What are the spatial and temporal patterns of forest cover change in the Lodja and Lomela territories between 2013 and 2023?
2. How do anthropogenic activities such as agriculture, logging, vegetation fires, and hunting contribute to forest degradation and fragmentation?
3. What landscape-structural processes (e.g., fragmentation, dissection, aggregation) characterize the transition from natural to anthropized areas?

By articulating these questions, the study contributes to the broader field of tropical landscape ecology by operationalizing a replicable framework that quantifies both the extent and configuration of anthropization processes in under-documented forest regions like Sankuru.

We hypothesize that slash-and-burn agriculture and lack of land-use planning are leading to measurable forest loss and structural simplification in Lodja and Lomela.

2 Study area

This study was carried out in the central region of the Democratic Republic of Congo, more precisely in the province of Sankuru. This province, which resulted from the division of the former Kasaï Oriental province, comprises six territories: Lusambo (provincial capital), Lubefu, Katako-Kombe, Kole, Lodja and Lomela [48]. The territories of Lodja and Lomela (LL) were selected for this study due to their accessibility and proximity to green areas already identified and mapped in the region, such as Salonga National Park and Sankuru Nature Reserve (Fig. 1). The landscape of Lodja and Lomela has an Am (for Lodja) and Af (for Lomela) climate, characterized by average annual rainfall

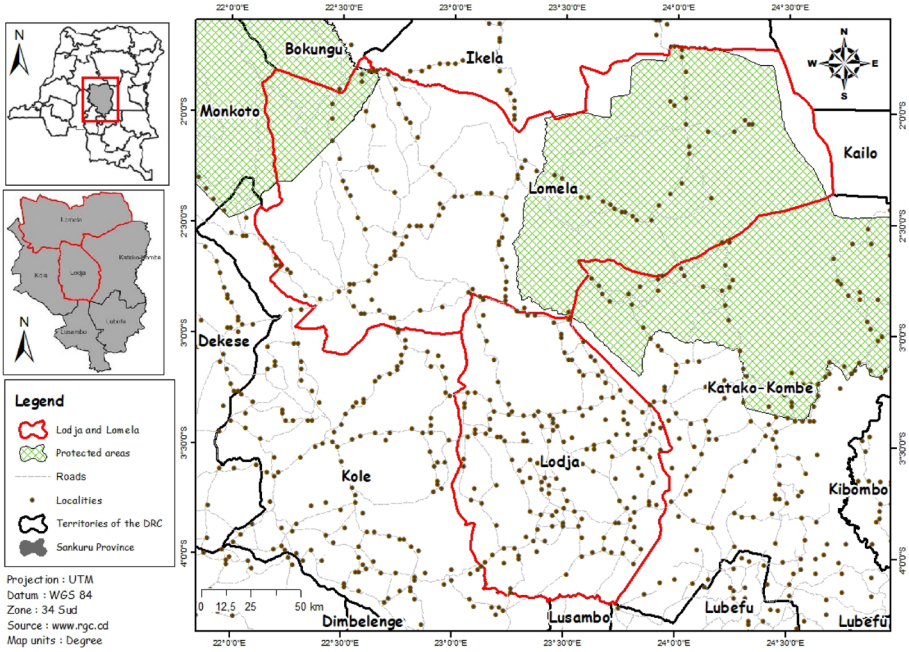


Fig. 1 Geographical location of the study area (Lodja and Lomela territories) and outlying territories in Sankuru province, central DR Congo

of 1700–1800 mm. There are two seasons in the area: the rainy season from August to April and the dry season from May to July [36]. Soil is predominantly sandy, highly degraded sandy-clay and hydromorphic clay. The average annual temperature is around 25 °C, while annual rainfall varies between 1600 and 2000 mm [23]. Agriculture is the province's main activity, followed by hunting, fishing, livestock breeding and, to a lesser extent, handicrafts. Trade, transport and financial transactions are also present, but concentrated in the urban centers [29].

3 Materials and methods

3.1 Satellite data acquisition and processing

Our methodological framework was designed to combine remote sensing and landscape ecology tools to capture both the extent and the structure of forest change. We selected Landsat imagery because it provides a long-term, consistent, and cost-effective record of land-cover dynamics, with spatial and temporal resolutions suitable for detecting major changes in tropical forest landscapes over decadal scales. To complement this, we employed landscape metrics, which enable the quantification of fragmentation, configuration, and anthropization processes that cannot be captured by area statistics alone. This integration of land-cover change detection with spatial pattern analysis allows us to assess not only how much forest has been lost, but also how the spatial structure of forest patches has evolved under anthropogenic pressures.

We selected three Landsat images acquired during the dry season between 2013 and 2023, with an interval of five years. Our selection was primarily based on image availability, seasonality, and quality, particularly ensuring low cloud cover. We then used these images to analyze spatio-temporal changes in the landscape, following approaches that have been successfully applied in previous studies [18, 35, 39]. The satellites used varied according to the study period, including Landsat 9 with the OLI-2 sensor, Landsat 8 with the OLI sensor, and Landsat 7 with the ETM + sensor. Considering the persistent cloud cover in the study area, we opted to use pre-processed Landsat surface reflectance products, which were downloaded via the SEPAL (System for Earth Observation Data Access, Processing and Analysis for Land Monitoring)[1] platform. SEPAL provides user-friendly access to massive Earth observation archives and facilitates the selection of the most suitable cloud-free scenes [11]. It is important to note that SEPAL was only used as a data access and download platform; the actual pre-processing steps (surface reflectance correction verification, cloud and shadow masking, and radiometric normalization), as well as the supervised classification, were carried out in Google Earth Engine (GEE). Final cartographic layouts and map editing were then produced in QGIS 3.32. For field validation, we used a Garmin 65s **GNSS receiver** (multi-constellation), with a nominal horizontal accuracy of approximately **3.65 m** as specified in the manufacturer's manual. The positioning data collected with this device was employed to validate the different land-use classes identified during the supervised classification.

3.2 Supervised classification of Landsat images

Satellite image pre-processing was carried out in two complementary environments. In this study, SEPAL was used solely as a data access portal, and not for image

[1] https://sepal.io/.

pre-processing or compositing. The subsequent and more detailed pre-processing steps were performed in Google Earth Engine (GEE), including atmospheric correction to surface reflectance, cloud and shadow masking (using the Fmask algorithm), and radiometric normalization across years [11]. Supervised classification and all accuracy assessments were also conducted in GEE to ensure consistency and reproducibility. To better differentiate the different land use classes, a false color composition was performed by combining the red, near infrared and mid-infrared bands [33]. This method was also used to identify training sites corresponding to the land-use classes observed in the field. Training areas for each class were delineated from 451 GPS points collected, creating at least 75 polygons per class. Supervised classification was carried out using the "Random Forest" algorithm, based on the local knowledge and reliability of this method [43]. Five land-use classes were selected for the study: dense forest, secondary forest, rural complex, savannah and water, of which the first two are considered natural and the others anthropogenic (Table 2).

To avoid confusion between land-cover categories, we refined the definitions of the two classes that were initially overlapping. Degraded forest refers to areas that were originally dense forest but have undergone partial canopy loss due to human activities (e.g., selective logging, fuelwood harvesting, fire damage) or natural disturbances. This class also includes abandoned plantations and long-term fallows where a significant proportion of tree cover remains visible. In contrast, the rural complex class groups actively managed or permanently converted areas, including cultivated fields, built-up zones, bare soils, and short-term fallows (<3 years) where tree cover is absent or negligible. Field photographs collected during ground-truthing were used to illustrate and validate these criteria, ensuring a clear operational distinction between the two categories.

To validate the classification, 224 GPS points collected in the field, independent from those used for supervised classification, were used. Classification accuracy was assessed using the kappa coefficient and overall accuracy [25]. Despite some criticism of the Kappa index, it was chosen for this study because the number of pixels in the training sites for each land-use class was similar for the different dates considered [38, 44]. To evaluate the accuracy of the supervised classifications, we reported multiple complementary indicators, including overall accuracy, user's and producer's accuracies for each land-cover class, and associated confidence intervals, following the best practices outlined by. While the Kappa coefficient was also calculated for comparability with previous studies, we acknowledge its limitations and therefore do not rely on a single threshold to determine classification acceptability. Instead, we interpret accuracy as a process that combines several measures to provide a more robust and transparent assessment of classification performance (Tables 1 and 2).

3.3 Landscape dynamics assessment

3.3.1 Landscape composition dynamics

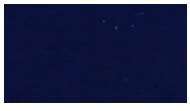
The spatio-temporal evolution of different land cover types was measured using the transition matrix [46]. The extent of deforestation (Ed) was assessed using the annual deforestation rate, determined by applying the formula proposed by Puyravaud [40].

$$\mathrm{Ed}\,(\%) = \left[\frac{1}{T2-T1} \times \ln\frac{A2}{A1} \times 100\right]$$

Table 1 Accuracy assessment results for the supervised classifications (2013–2023)

Year	Land-cover class	User's accuracy (UA, %)	Producer's accuracy (PA, %)	95% CI (± %) (confidence intervals)	Overall accuracy(OA, %)	Kappa
2013	Dense forest	95.2	93.8	± 2.1	96.1	0.94
	Degraded forest	92.7	91.4	± 2.6		
	Rural complex	94.5	92.8	± 2.3		
	Savannah	93.6	91.9	± 2.8		
	Water	99.1	98.6	± 1.0		
2018	Dense forest	97.5	96.8	± 1.5	97.3	0.96
	Degraded forest	95.2	94.5	± 1.8		
	Rural complex	97.1	96.3	± 1.6		
	Savannah	96.7	97.0	± 1.7		
	Water	99.4	99.1	± 0.5		
2023	Dense forest	99.0	98.5	± 1.0	99.1	0.98
	Degraded forest	97.8	98.2	± 1.2		
	Rural complex	98.9	98.7	± 1.1		
	Savannah	98.6	98.9	± 1.1		
	Water	99.9	99.8	± 0.2		

Table 2 Description of land cover classes. Small images are Quick Bird images available free of charge on Google Earth from June 2023.

Land use class	Description
Dense forest 	This class is characterized by vegetation with a complex vertical structure (several strata), with a canopy that is often high (between 30–50 m) and closed (dense). Human activities are limited or absent (MEDD, 2018).
Degraded forest 	This category includes forests resulting from the disturbance of the "dense forest" class. It has a heterogeneous canopy height of up to 30 m, depending on the age of the stand (MEDD, 2018). It also includes old fallow land and abandoned rubber plantations. They are often located close to fields.
Rural complex 	This class comprises a set of anthropized areas present in the landscape. These include cultivated fields, fallow land, bare areas, roads and inhabited areas along roads.
Savannah 	Savannah zones with low vegetation, and sometimes shrubs characterized by a low density of trees, with a canopy cover < 30% (MEDD, 2018). They are found mainly in the south, in Lodja, and in the northeast, in the RNSA.
Water 	Surface water, including rivers (For example the Lomela and Lukenie rivers) and ponds.

A1 is the area of the land-cover class at the initial date (ha), A2 is the area of the same class at the final date (ha), and T1-T2 is the time interval in years between the two observations. In this study, the term forest refers exclusively to the dense forest class, which is the best proxy for intact ecosystems. To complement this analysis, we constructed

transition matrices for each time interval (2013–2018 and 2018–2023). Each matrix records the area (in ha) of land that transitioned from one class to another, thereby identifying dominant conversion pathways (e.g., dense forest: degraded forest; degraded forest: rural complex). This approach allows us to quantify not only net changes in area but also the specific trajectories of forest cover dynamics.

3.3.2 Landscape structural dynamics

To assess the relationship between landscape configuration and related ecological processes in a measurable way, spatial structure indices were calculated using FRAGSTATS 2.0 software, chosen for compatibility with earlier landscape studies conducted in the Democratic Republic of Congo, which facilitates comparison of results across different regions and time periods. All analyses were performed on classified raster maps at a spatial resolution of 30 m, corresponding to the native resolution of Landsat imagery. This free software, developed by the U.S. Department of Agriculture's Forest Service, can be used to analyze landscape structure [27]. These indices include:

The three-landscape metrics presented in Table 3 were selected because they capture complementary and ecologically meaningful dimensions of landscape transformation under human pressure. The Number of patches (Nt) quantifies spatial subdivision and is one of the most direct indicators of fragmentation intensity, allowing us to detect whether forest continuity is being disrupted into smaller units. The Anthropization index (U) expresses the balance between anthropogenic and natural land-cover types and thus provides a synthetic measure of human dominance within the landscape as a key concern in studies of deforestation and land-use conversion in tropical regions [6]. Finally, the Fractal dimension (Df) characterizes the complexity and shape irregularity of patches, distinguishing natural, irregular forest forms (Df → 2) from human-modified, regularized patches (Df → 1) [8]. These three indices were chosen because together they summarize the extent, intensity, and geometric expression of anthropogenic disturbance. Other metrics (e.g., edge density, contagion, or Shannon diversity) were considered but not retained, as they tend to be highly correlated with Nt or U and provide limited additional interpretive value for landscapes dominated by binary transitions between natural and anthropogenic covers. This concise set therefore ensures analytical efficiency while maintaining ecological interpretability and comparability with previous studies conducted in Central Africa.

In addition, to identify spatial landscape transformation processes, particularly with regard to natural and anthropogenic land use, the decision tree algorithm was used [6]. To this end, comparisons were made between the number of patches, area and perimeter of patch type before and after transformation [19, 46]. A value of $t = 0.75$ was used to distinguish the process of fragmentation from that of dissection, with values greater than 0.75 indicating dissection, while values less than or equal to 0.75 signaling a prevalence of fragmentation [8].

3.4 Analysis of anthropogenic drivers of deforestation and forest degradation

3.4.1 Village selection

Based on purposive sampling, ten villages (Kalema, Mukumari, INERA, Lomela Centre, Vango, Lokolo, Lohalo ya Donga, Lukavukavu, Hyoka and Okonga) were selected along the Lodja-Lomela axis (± 140 km). In this study, we conceptualize **anthropization** as the

Table 3 Spatial structure indices

Metric	Formula	Description	Ecological interpretation / References
Number of patches (Nt)	–	Counts the number of patches present in class *i*.	An increase generally indicates fragmentation of that class, although other processes may also contribute (Bogaert et al., 2008).
Anthropization index (U)	$\mathrm{U} = \frac{A\ Anthropic}{A\ natural}$	Ratio of total anthropogenic areas (croplands, settlements, degraded forest) to natural areas (dense forest, savannah, water).	High values indicate landscapes dominated by anthropogenic classes [6].
Fractal Dimension (Df)	$\log\ (pf) = \log\ (\mathrm{k}) + \frac{Df}{2} \log\ (af)$	Derived from regression of log(perimeter) vs. log(area).	Indicates patch shape complexity: Df→2Df \to 2 for natural patches (irregular forms), Df→1Df \to 1 for anthropogenic patches (regular forms). Reflects degree of fragmentation and human influence [6, 8].

set of human-induced transformations of natural ecosystems, measured both through land-cover conversion and through direct disturbance indicators observed in the field (tree cutting, vegetation fires, agriculture, hunting, settlement, and fish farming). To investigate these processes, we purposively selected ten villages along the Lodja–Lomela axis based on three criteria: (i) relatively high population density, (ii) accessibility via National Road 7, and (iii) proximity to protected areas such as the Sankuru Nature Reserve. This allowed us to focus on sites where anthropogenic pressures are particularly pronounced.

3.4.2 Data collection

Based on the study carried out by Rakotondrasoa et al. [41], a multidisciplinary approach was applied: (i) four 500 m × 10 m transects were established in each village (oriented along the four cardinal directions) [41], where quantitative indicators of disturbance were systematically recorded in 50 m² plots; and (ii) informal interviews with local stakeholders were conducted to provide qualitative context on land-use practices and forest resource exploitation. In total, 400 plots were inventoried, covering an area of 20 ha. Data collection took place between March and June 2023, during the dry season, when anthropogenic activities such as slash-and-burn are most visible. Ethical considerations were respected: the study protocol received approval from the Institutional Review Board of ERAIFT (Protocol N° ERAIFT/CAR/BM/12/03/2025, dated 12 March 2025), and informed consent was obtained from all interview participants (Table 4).

3.4.3 Data analysis

Data analysis was based on a model describing the disturbance process in terms of various characteristics, such as disturbance type (classification of events or observations), frequency (extent of disturbance) and the spatial structure of the disturbance, notably distance from the village. The relative frequencies of each type of anthropogenic disturbance were calculated from the presence-absence data [14, 41].

To formally analyze the relationship between anthropogenic pressures and spatial patterns, we developed a simple analytical model in which the frequency of disturbance indicators (FD) was expressed as a function of the distance from the village (DV):

$$FDi = \beta\, o + \beta\, 1DVi + \epsilon$$

Where FDi represents the relative frequency of disturbance indicators recorded in plot i, DVi is the distance from the center of the village to the plot, β0 is the intercept, β1 the slope, and ε the error term. Disturbance indicators included tree cutting, vegetation fires, agricultural plots, hunting traces, settlements, and fishponds, each treated as a binary presence/absence variable at the plot level. Relative frequencies were then computed as the proportion of plots affected within each transect. We first calculated descriptive statistics of disturbance frequencies across villages, then tested associations between FDi and DVi using Pearson correlation tests. For indicators showing significant correlations, we applied linear regression models to quantify the effect of distance on disturbance frequency. All analyses were performed in R version 4.3.2. This approach allowed us to evaluate both the strength and direction of spatial gradients of anthropogenic influence (Table 5).

Table 4 Typology of anthropogenic forest degradation factors identified in the Lodja and Lomela landscape

Types of factors	Indicators
Agriculture	Presence of crop fields and fallow land
Carbonization	Charcoal remains, active or inactive ovens
Cutting	Presence of tree stumps or cut trunks,
Hunting	Presence/traces of traps, animal tracks or remains
Vegetation fire	Observation of black spots, charred trunks
Human settlement	Presence of human dwellings
Fish farming	Presence of fish ponds

Table 5 Variables used in the analysis of anthropogenic drivers of forest degradation

Variable	Type	Definition	Measurement/Unit	Source
FD (Frequency of disturbance indicators)	Dependent	Proportion of plots affected by a given disturbance type (tree cutting, vegetation fire, agriculture, hunting, settlement, fish farming)	Relative frequency per transects (%)	Field transects (400 plots, 20 ha total)
DV (Distance to village)	Independent	Distance from village center to each plot along transects	Meters (measured with GNSS receiver, ± 3.65 m accuracy)	Field GNSS data
Tree cutting	Explanatory (binary)	Presence of stumps or cut trunks in plot	0 = absent, 1 = present	Field observations
Vegetation fire	Explanatory (binary)	Presence of burnt vegetation or charred trunks	0 = absent, 1 = present	Field observations
Agriculture	Explanatory (binary)	Presence of active crop fields or short fallows	0 = absent, 1 = present	Field observations
Hunting	Explanatory (binary)	Presence of traps, animal remains, or tracks	0 = absent, 1 = present	Field observations
Settlement	Explanatory (binary)	Presence of houses or human infrastructure	0 = absent, 1 = present	Field observations
Fish farming	Explanatory (binary)	Presence of fishponds in the plot	0 = absent, 1 = present	Field observations

4 Results

4.1 Classification and mapping of land use from 2013 to 2023

Assessment of the quality of supervised classifications of Landsat images, based on the Random Forest algorithm, reveals overall accuracy rates ranging from 96.16% to 99.15%, with Kappa coefficients (k) varying between 0.94 and 0.98. These results are satisfactory and demonstrate a good ability to discriminate between different land-use classes. A visual analysis of the maps (Fig. 2) shows a progressive decrease in dense forest cover (shown in dark green) and an increase in degraded forest areas and the rural complex (fields, fallow land, built-up areas and bare soil). The loss of dense forest is particularly visible in the northeast, where the Sankuru Nature Reserve is located (Fig. 3).

4.2 Landscape composition dynamics

The Sankey diagram (Fig. 4) illustrates the quantitative transitions between land-cover classes from 2013 to 2018 and 2023. In 2013, dense forests (FD) covered 65.84% of the landscape; this proportion slightly increased to 69.76% in 2018 before dropping sharply to 60.54% in 2023. A large share of the dense forest area observed in 2013 remains in the same class in 2018, but a noticeable portion transitions into degraded forests (Fdeg) and the rural complex (CR). Degraded forests, which represented 14.02% in 2013, decreased to 10.97% in 2018, then increased significantly to 18.23% in 2023, indicating a dynamic

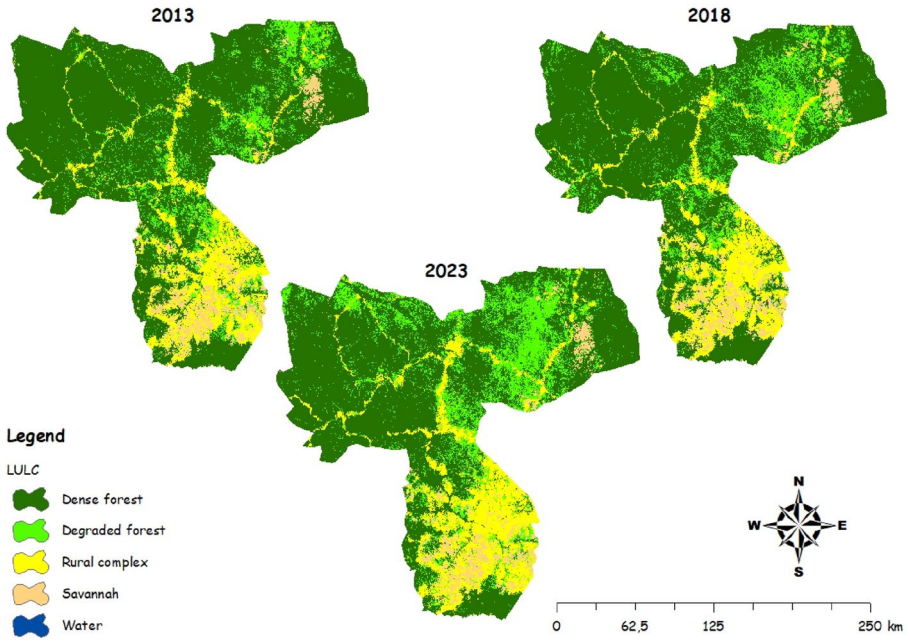


Fig. 2 Multitemporal land cover mapping of the Lodja and Lomela landscape in central DR Congo, based on supervised classification of Landsat images using the Random Forest algorithm

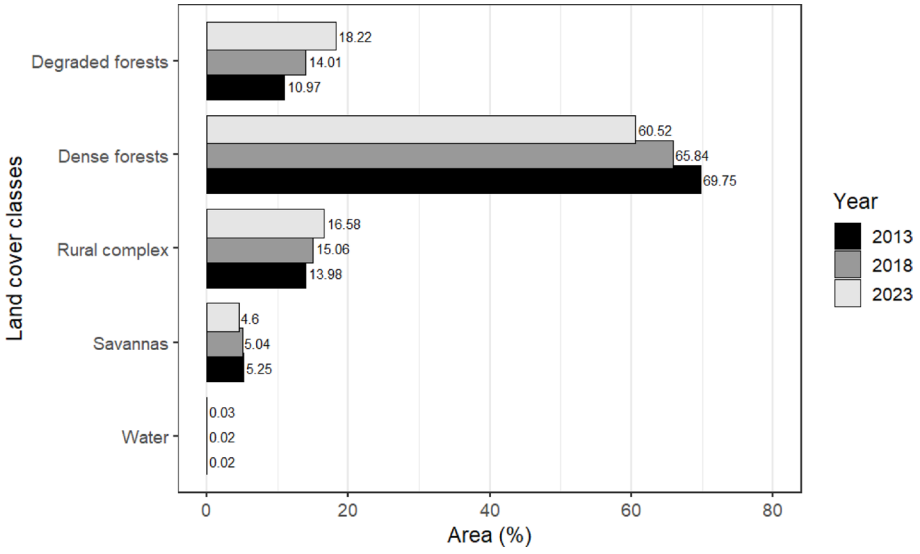


Fig. 3 Land use statistics for the years under review

process where some areas originate from dense forests while others shift toward the rural complex. The rural complex moves from 15.07% in 2013 to 13.99% in 2018, then rises to 16.59% in 2023, supported by inflows from degraded forests and savannas. Savannas (SA) display more limited fluctuations, shifting from 5.04% in 2013 to 5.26% in 2018, and then to 4.61% in 2023, with minor transitions toward the rural complex and degraded forests. Finally, water surfaces, which are extremely marginal, remain almost constant: 0.03% in 2013, 0.01% in 2018, and 0.03% in 2023. The annual deforestation rate from 2013 to 2023 is estimated at 0.25%.

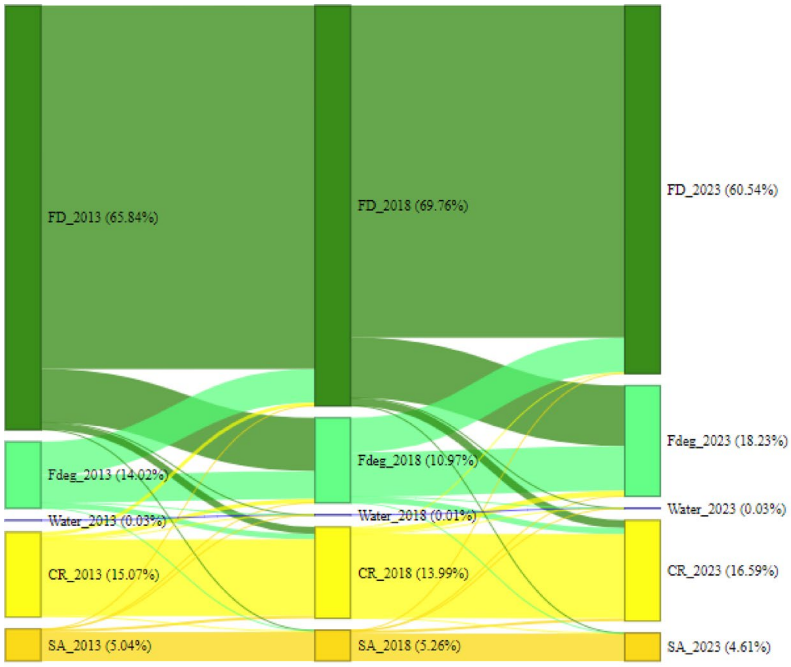


Fig. 4 Sankey diagram in percentages, with FD, dense forest; Fdeg, degraded forest; CR, rural complex; SA, Savannah

Table 6 Spatial structure indices calculated for the years 2013, 2018, and 2023, and identification of Spatial transformation processes (STPs) based on the decision tree algorithm of Bogaert et al. [6]. Nt: number of patches per class, at: total class area in km^2

Index	Dense forest	Degraded forest	Rural complex	Savannah	Water
2013					
Nt	8161	26,112	7827	127	2281
At	28,726	4518	5761	2165	10
D	33,02	0,95	3,39	0,11	0,69
Df	1,20	1,23	1,19	1,18	1,21
STP 2013–2018	Dissection	Creation	Aggregation	Creation	Deletion
2018					
Nt	11,124	30,513	5062	376	1437
At	27,113	5772	6202	2076	12
D	30,87	2,46	4,35	0,16	0,68
Df	1,19	1,21	1,18	1,18	1,19
STP 2018–2023	Dissection	Creation	Creation	Aggregation	Deletion
2023					
Nt	14,840	30,446	6828	357	1372
At	24,923	7505	6831	1897	14
D	28,47	3,36	5,44	0,14	0,57
Df	1,16	1,18	1,17	1,17	1,17

4.3 Landscape structural dynamics

Between 2013 and 2023, the dense forest experienced a phenomenon of patch dissection, resulting in a decrease in the total area of the class, in parallel with an increase in the number of zones (Table 6). As regards the dominance index, indicating the portion of surface occupied by the largest patch, dense forest shows the highest values for all years, although this trend is downward. It should be noted, however, that the dissection

of dense forest has led to the formation of patches of degraded forest, leading to an increase in the total area occupied by this class over time. This is accompanied by an increase in the number of patches and in the dominance index, highlighting a process of aggregation of degraded forest patches after their creation.

The other classes show similar trends, as is the case for the rural complex and water, which have also seen changes in their surface areas and spatial structure indices, reflecting the creation or aggregation processes that ensue. The savannah class, for its part, has seen a steady decline in the number of tasks and its surface area throughout the periods studied, justifying the process of suppression it has undergone over time. From 2013 to 2023, the human impact on the landscape is generally reflected in the fragmentation of dense forest areas, the creation of new patches in degraded forests and the rural complex (fields, fallow land, built-up areas and bare soil), followed by their aggregation.

As shown in Table 6, the dominance index (*D*) provides insight into how much of the landscape is controlled by the largest patch of each land-cover class, while the fractal dimension (*Df*) reflects the geometric complexity of these patches. A decline in *D* over time indicates a loss of spatial dominance of dense forest areas, consistent with increasing fragmentation, whereas a decrease in *Df* toward values closer to 1 suggests simplification of patch shapes due to anthropogenic modification such as logging, agriculture, and settlement expansion.

We can see a regressive trend in the fractal dimension for all forest types, with dense forests showing lower values than degraded forests. Despite this, fractal dimension values approaching 1 for all classes and periods analyzed suggest an evolution towards increasingly regular shapes. This reflects an increase in human impact on the Lodja and Lomela forest landscape (Fig. 5). It should be noted that, overall, according to the different indices presented in this section, the landscape of Lodja and Lomela in Sankuru is less anthropized. However, although the anthropization index remains below 1, indicating that dense forest, considered as the natural class, still occupies a significant part of

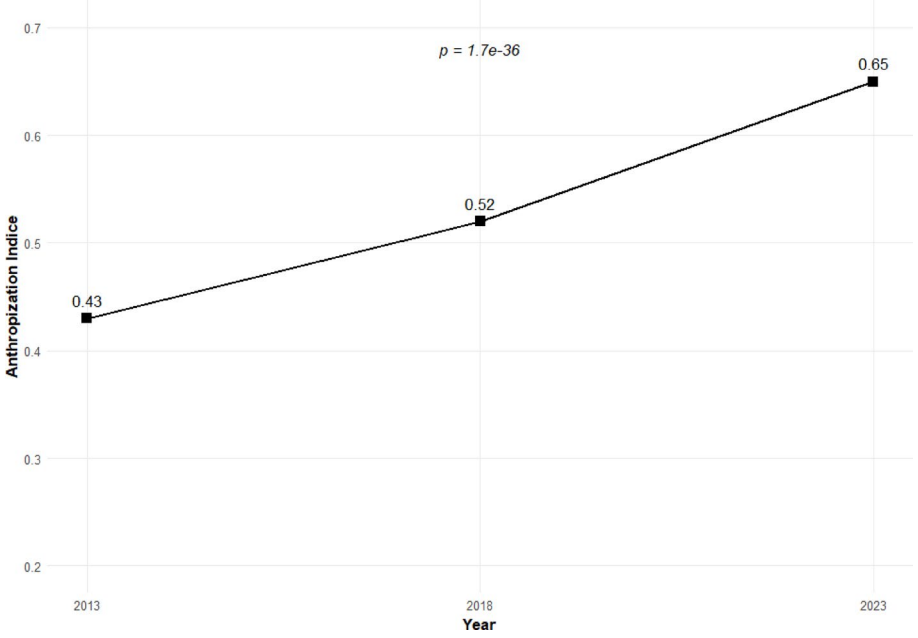


Fig. 5 Anthropization indice. An increase in the value of this index reflects an expansion or predominance of anthropogenic classes in the landscape

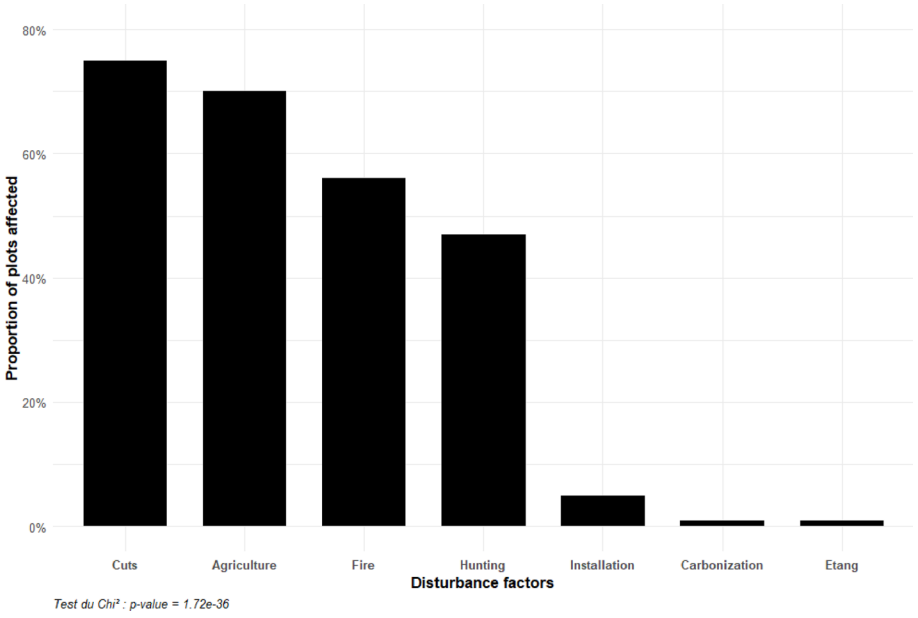


Fig. 6 Proportion of plots affected by type of disturbance. These data come from inventories carried out in 400 plots of 500 m^2 in the Lodja and Lomela landscapes

Table 7 Anthropogenic drivers of forest degradation

Disturbance factor	Pearson *r*	*p*-value	Regression slope	R^2	Direction
Tree cutting	−0.97	< 0.001	−0.65 per 100 m	0.94	Negative
Vegetation fire	−0.96	< 0.001	−0.39 per 100 m	0.92	Negative
Agriculture	−0.91	< 0.001	−0.08 per 100 m	0.87	Negative
Hunting	+0.81	0.009	+0.05 per 100 m	0.66	Positive

the Lodja and Lomela landscape, it is necessary to reflect now on the strategies to be put in place for the preservation of these ecosystems.

4.4 Anthropogenic factors of degradation and deforestation

The inventory of indicators of anthropogenic factors revealed four major disturbances identified in the Lodja and Lomela landscape, namely tree cutting, agriculture, vegetation fire and hunting (Fig. 6 and Table 7).

The inventory of anthropogenic disturbance indicators (tree cutting, vegetation fires, agriculture, hunting, settlements, fish farming) was not limited to a descriptive listing but rather served as the basis for our statistical analyses. Each indicator was recorded in binary form (presence/absence) at the plot level, then aggregated into relative frequencies per transect and per village. These frequencies were subsequently used as the dependent variables in correlation and regression analyses, with distance from the village center serving as the independent variable. Pearson correlation tests revealed significant negative associations for tree cutting ($r = -0.97$, $p < 0.001$), vegetation fires (r = –S0.96, $p < 0.001$), and agriculture ($r = -0.91$, $p < 0.001$), while hunting showed a significant positive association with distance ($r = 0.81$, $p < 0.01$). Linear regression models confirmed these trends, quantifying the rate of decline or increase of each indicator as a function of distance (Fig. 7).

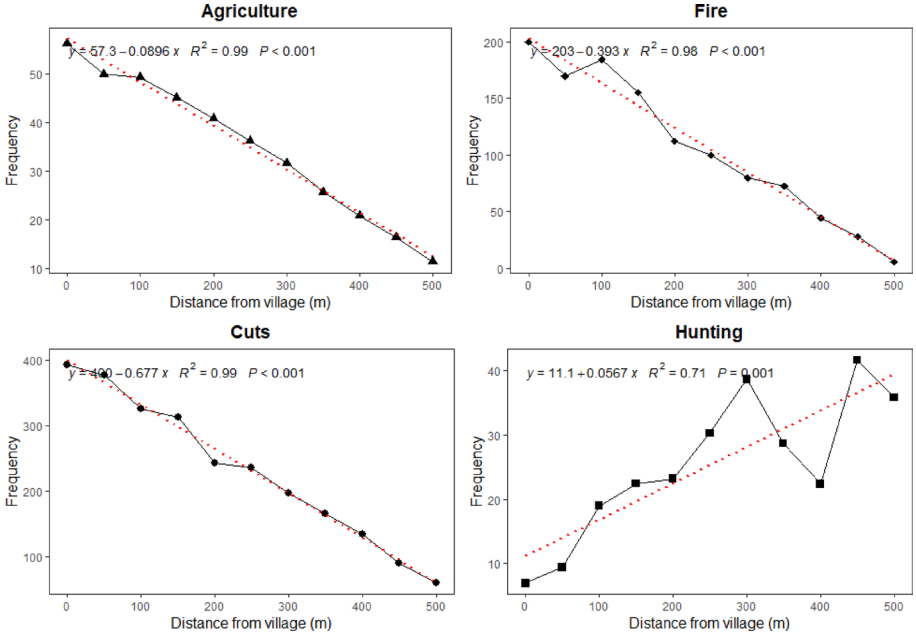


Fig. 7 Effect of distance from the village on the frequency of degradation factors. These data come from inventories carried out in 400 plots of 500 m^2 in the Lodja and Lomela landscapes

5 Discussion

5.1 Dynamics of anthropization in the Lodja and Lomela forest landscape

One limitation of our study is the relatively low temporal resolution of the imagery, as only three Landsat composites were analyzed over a 10-year period. This temporal spacing may underestimate short-term disturbances such as selective logging, shifting cultivation cycles, or small-scale clearings that occur between acquisition dates. Our choice was primarily constrained by persistent cloud cover in the region and the availability of cloud-free scenes during the study period, which limited the number of usable images. Despite this limitation, Landsat remains a robust data source for detecting major trends in forest cover dynamics at the landscape scale. Nevertheless, we recommend that future research build on our results by incorporating higher temporal resolution datasets such as Sentinel-2 (5-day revisit) or PlanetScope imagery, which would allow for a more detailed monitoring of fine-scale forest disturbances.

The results of this study show an evolution over time of land use in the study area. There has been a gradual reduction in the area occupied by dense forest, from 69.75% in 2013 to 60.52% in 2023. At the same time, the surface area of anthropogenic zones such as degraded forests and the rural complex (fields and fallow land, built-up areas and bare soil) is increasing. This phenomenon of change in the landscape is also observed in other research carried out in Central Africa, highlighting a regression of dense forests in favor of an expansion of anthropogenic zones [3, 32, 39].

Analysis of the land-use maps highlights several significant aspects of deforestation and the expansion of rural areas in the region studied (Fig. 2). Firstly, it is observed that the loss of dense forest cover and the expansion of the rural complex are most marked along main roads, as well as secondary roads, where most villages and human dwellings are concentrated, reflecting high population density. This correlation between the presence of roads and deforestation is consistent with the road effect theory, corroborated by various studies in DR Congo[4, 19, 22, 26].

On the other hand, deforestation is more pronounced in the north-eastern part of the study area, notably around the Sankuru Nature Reserve, exposed to various threats such as population expansion, growing demand for agricultural land, logging and mining, as well as poaching [15–17].

Furthermore, the expansion of the rural complex is particularly noticeable in the southern part of the region, notably in the Lodja territory. This predominantly agricultural area is densely populated and constitutes a major economic hub of the Sankuru province[9]. The presence of an airport in Lodja facilitates the marketing of agricultural produce to the surrounding urban centers, while Lomela, which is landlocked, is limited to subsistence farming. These observations underline the challenges of biodiversity conservation and sustainable natural resource management in the region, requiring concerted action by local stakeholders and the relevant authorities [5].

This study shows an annual deforestation rate of 0.25% between 2013 and 2023, in line with national estimates of 0.2% to 0.4% according to various sources [3, 21, 39]. These rates remain relatively low in relation to the classification of [7], but contrast with studies carried out in other DR Congo provinces with much higher deforestation rates [21, 33, 34, 46]. Sankuru's isolation and low population density seem to explain this trend. The anthropization of Lodja and Lomela is also corroborated by spatial structure indices highlighting negative transformation processes. These results underline a transition from dense forest landscapes to anthropogenic zones, notably through forest dissection.

5.2 Anthropogenic drivers of deforestation and forest degradation

This study, carried out in the Lodja and Lomela landscape, identified several factors of forest disturbance, including agriculture, tree cutting, carbonization, hunting, vegetation fire, human settlement and fish farming. The frequency of factors revealed that tree cutting was the main disturbance factor, although it can only be considered an abundant factor in the area in association with other factors. Indeed, tree-cutting is practiced for a variety of uses, mainly for agriculture (slash-and-burn), fish farming, construction, energy, etc. [2, 4, 47]. Its high frequency in our study area is explained by the methodology used, which consisted of counting the number of trees or stumps encountered.

Agriculture is the main activity of the Congolese rural population, with over 70% of the national population involved. Due to growing demographic pressure and saturation of the most fertile land, forest areas are threatened with conversion to farmland [20]. Agriculture, focused on rice and manioc, is the main activity of the rural populations of Lodja and Lomela [16]. Vegetation fires are linked to agriculture, particularly slash-and-burn agriculture, which is the main driver of deforestation in the DRC according to several studies [19, 32, 37, 45].

Hunting, mainly for small games, is also a major disturbance factor. It should be emphasized that, according to field observations, bushmeat is a quality food highly appreciated by the population of Lodja and Lomela, often preferred to meat from cattle. This confirms the study.

of [50], according to which bushmeat is the main source of animal protein available to Congolese rural populations living in forested areas.

Overall, the results found for this research objective are similar to those of Rakotondrasoa et al. [41], who found that logging, fire, species invasion and agriculture were the main anthropogenic factors in the degradation of Tapia (*Uapaca bojeri*) woodlands in

Arivonimamo, Madagascar. Kabemba et al. [15–17], also found that in Sankuru, precisely at RNSA level, slash-and-burn agriculture and hunting are the anthropogenic factors driving forest degradation. The multidimensional methodological approaches used, as well as the almost identical local conditions, explain the similarity of the results of these studies.

It is important to note that the villages included in this study were selected purposively, based on population density, accessibility, and proximity to the Sankuru Nature Reserve. As such, the results are not statistically representative of the entire province but should instead be interpreted as case studies that highlight typical dynamics of anthropogenic pressures in areas of high human–forest interaction. The insights generated from these focal sites provide valuable guidance for local and provincial land-use planning, but further studies with broader spatial coverage are needed to generalize these findings across Sankuru Province.

6 Conclusion

This study was carried out in the province of Sankuru, more precisely in a forest landscape encompassing the territories of Lodja and Lomela, home to a portion of the Salonga National Park (SNP) and the Sankuru Nature Reserve (SNR). Its main objective was to analyze, for the period 2013 to 2023, landscape changes within the forest ecosystems of this region. Using methods based on geographic information systems combined with remote sensing, statistics and landscape ecology analysis, forest losses were observed. The area of dense forest has been lost to that of degraded forest, in parallel with the rural complex. The result has been a reduction in dense forest zones and a simplification of the shape of these natural areas, which can be explained by a reduction in the fractal dimension. These changes in forest cover are the result of human activities identified in the area, mainly tree-cutting, agriculture, vegetation fires and hunting. Tree-cutting and vegetation fires are the starting point for agriculture and other human activities, exposing the forest and its biodiversity to significant losses. It is therefore important to put in place a land-use policy and measures that should take a systemic approach, considering the enhancement of other ecosystem services, and the improvement of the socio-economic conditions of the population, thus requiring a diversification of sustainable activities.

Author contributions

J.M.M, O.R.L and J.P.M.T.H, Conceptualization, methodology, formal analysis; J.M.M Wrote the first draft of the article; L.A.B, J.M.T, E.N, S.M.M, O.M.K, C.M.M were responsible for proofreading the text,

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board (IRB) of the Ecole Régionale Postuniversitaire d'Aménagement et de Gestion Intégrés des Forêts et Territoires Tropicaux (ERAIFT/UNESCO), which serves as an official ethics committee for research approval (Protocol code N° ERAIFT/CAR/BM/12/03/2025, dated 12 March 2025). The authors attest that informed consent was obtained from the participants and from the parents or legally authorized representatives of subjects under 16 years of age, for participation in the study and for the publication of images in an open-access online publication.

Consent for publication
All participants provided written informed consent for participation and publication of their anonymized data in this study.

Competing interests
The authors declare no competing interests.

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