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Original Article

Analysis of Community Forestry Impact on the Forest Communities Based Management Landscape Dynamics in Miombo Woodland Region of the Democratic Republic of the Congo

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ABSTRACT

Twenty local communities had received in Upper-Katanga their accreditation granting them perpetual management of their forest concession according to the Decree-Law No 14/018 of August 2nd, 2014, concerning the allocation of Forest Communities Based Management (FCBM). The objective is to reduce poverty, improve community livelihoods and reduce forest degradation and deforestation. Thus, community forestry serves as a management tool to address the numerous pressures on the Katangian open forest (Miombo Woodland), including deforestation and land cover changes which alter the structure and dynamics of vegetation cover and increase climate change effects. It also encourages the local communities to restore and conserve their forest heritage sustainably through FCBM. Consequently, the establishment of FCBM leads to changes in the spatial configuration of the Miombo landscape. To evaluate the impact of community forestry on the dynamic landscape of FCBM, Landsat images were used with a combined approach which integrated NDVI into the coloured composition to increase class separability for the final classification. The interpretation of the landscape dynamics was determinate by spatial indices (area, perimeter and number of patches). The accuracy and Kappa index were greater than 90% on all classifications carried out by spectral correspondence of 2021 image, for six defined land cover classes. The analysis shows that NDVI inclusion in the colour composition increases the separability of forest classes following its degradation gradient. Furthermore, spatial indices show that community forestry has greatly influenced spatial configuration, from 2017 to 2019. The trend becomes downward between 2019 to 2021, thus demonstrating the impact of Covid-19 on the Miombo project results. This is visible through the number of patches, perimeter and area in each FCBM and

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in turn, its landscape dynamics before Covid-19 forest area increased by more than 80% in each FCBM but after COVID-19 it decreased. However, this dynamic remains proportional to temporal fluctuations as the trends before and after COVID-19 are disproportionate. The community forestry project implementation in the Miombo woodland has led to a transformation in the forest areas and affected their extent, number, and type. Therefore, reassessing the project's broad strategies is essential to ensure the sustainability of its activities in these areas.

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INTRODUCTION

Forest degradation is a significant landscape-related issue in the Congo Basin (Cabala *et al*., 2018; Muteya *et al.*, 2023). Predominantly informal logging activities present a substantial limitation and major impediment to the effective management of forest resources (Mbarga, 2014). Several factors contribute to this situation such as charcoal production, timber exploitation, agriculture, urbanization, etc. (Nghonda et al., 2023), leading to forest impoverishment (Castillo *et al*., 2022) and diminishing the capacity of forests to maintain the ecosystem services productions (Godlee et al., 2020) through changes in land cover (Bustamante *et al.*, 2016; Sikuzani *et al.*, 2019a, 2023).

The forest management system in the Democratic Republic of Congo (DRC) is based on a colonial model that entrusts exclusive decision-making to the state and private industrial loggers (Baraka *et al*., 2021; Nghonda *et al.*, 2023), disadvantaging local communities. Additionally, there has been a significant population increase and the country's agriculture is insufficiently mechanized to satisfy the growing needs of the population (FAO, 2020). This observation indicates that centralist models are no longer suitable (Baraka *et al.*, 2021) in light of the increasing subsistence needs of rural and urban populations (Kpatinvoh *et al*., 2016; Megevand *et al.*, 2013) and suggests the necessity for transferring forest management to local communities (FAO, 2020).

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Following the Rio Earth Summit in 1992, researchers and civil society actors focused on no-timber forest products (NTFPs) and questioned the dominant role of public and private decision-makers in forest management (MEDD, 2018). Some have criticized the national and provincial government's failure (Lescuyer *et al.*, 2021), to ensure the sustainable management of forest ecosystems (Anantha *et al.*, 2021); which constitutes a livelihood stock for local communities (LC), highlighting their undisputed importance. Using the revise forestry code of 2002, DRC adopted community forestry as a model for managing forest resources. This was implemented in 2014 through the institutionalization of Local Community Based Management (FCBM) (Baraka *et al.*, 2022), aiming to empower LC in managing their territory while generating socio-economic benefits from forest resources management.

Through significant lobbying by stakeholders implementing the community forestry (CF) project in south-eastern DRC and support from the province's political and administrative authorities, approximately twenty FCBMs in Upper-Katanga have received perpetual accreditation after meeting the requirements of Decree-Law No 14/018 of August 2, 2014, concerning the allocation of forest concessions to local communities (MEDD, 2018). The objective is to reduce poverty, improve community livelihoods (Adebu *et al.*, 2019) and combat forest degradation and deforestation (FAO, 2016). CF thus serves as a management tool to address the numerous pressures on the Katangian open forest (*Miombo)*, including deforestation and land cover changes (Nghonda *et al.*, 2023), which alter the structure and dynamics of vegetation cover (Jiagho *et al.*, 2019). It also encourages LC to restore and conserve its forest heritage sustainably through FCBM. Consequently, the establishment of FCBMs leads to changes in the spatial configuration of the Miombo landscape.

Given the above, the change in landscape configuration following the installation of FCBMs is evident. Sustainable management of the *Miombo* forest ecosystems, with a high degree of efficiency and security, requires a comprehensive understanding of the context, problems and potential solutions, considering the participation of all relevant stakeholders. This study aims to assess the impact of community forestry on the landscape structure of FCBMs forest ecosystems in the south-eastern of the DRC, using remote sensing based on satellite images, according to the landscape transformation process based on spatial structure index, resulting from a supervised classification validated by control points describing the reality on the landscape. Throughout this study, the following questions will be examined and answered: Has the miombo project had an impact on the spatial configuration of FCBM in Miombo Woodland? Did covid-19 have any influence on the project's results?

MATERIALS AND METHODS

Study Area

Upper-Katanga province, an integral part of the Lubumbashi plain located in the southeast of the Democratic Republic of Congo, lies between latitudes 10 and 12 degrees south and longitudes 25 and 28 degrees east (Cabala *et al*., 2018). The study includes villages participating in the community forestry project piloted by the FAO in the *Miombo* open forest (MEDD, 2018). Three of these villages were visited: *Milando*, *Kyunga* and *Musoshi*, located 67km northeast, 80km north-east and 73km south of Lubumbashi city, respectively (Fig 1).

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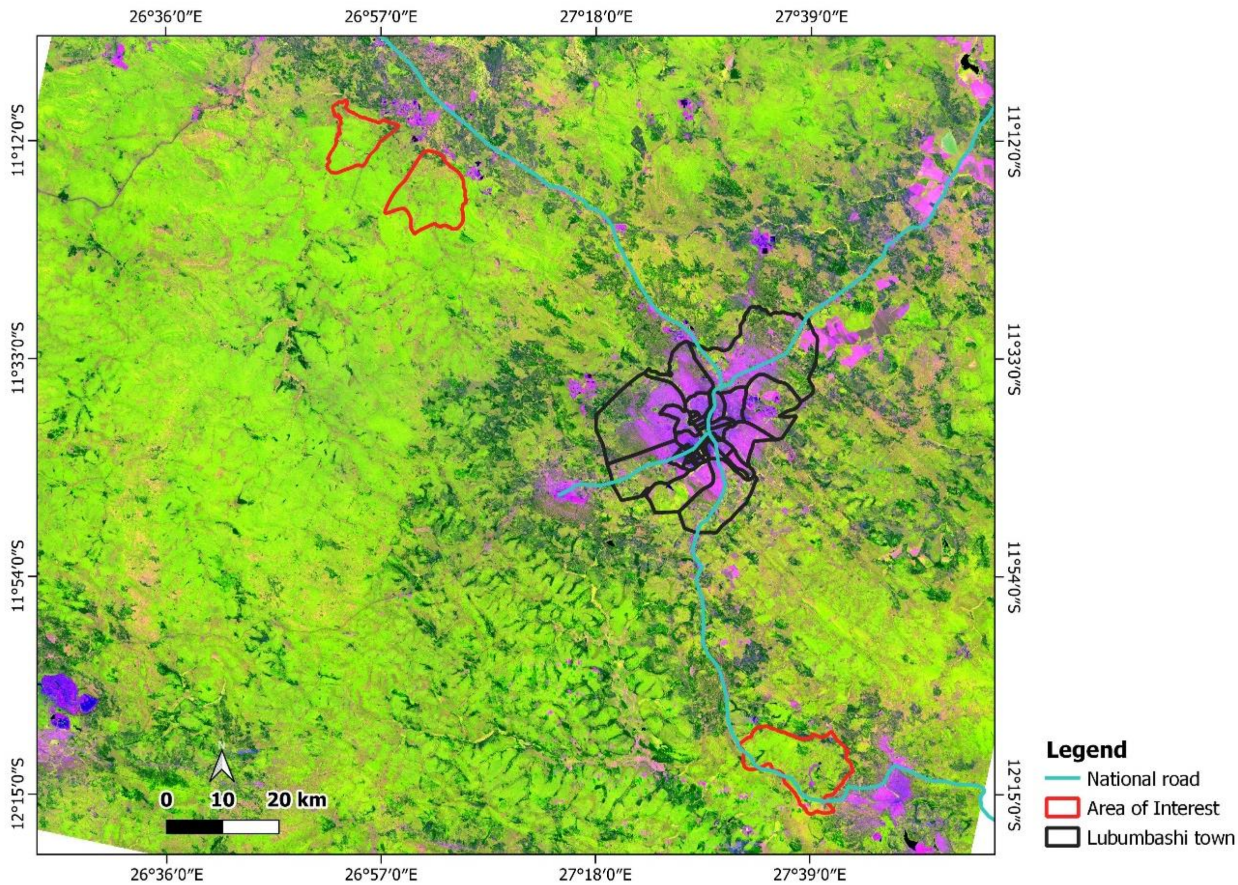
FIGURE 1. Geolocation of the Area of Interest in Upper Katanga, Southeastern of the Democratic Republic of Congo. It Comprises Three FCBMs in Red Colour: Milando (12,898 ha), Musoshi (17,411 ha) and Kyunga (7,970 ha) (FAO, 2023). Landsat Image 2021, in Colour Composition With NDVI Layer on Red Channel, Band 2 on Green Channel and Band 4 on Blue Channel.



These sites were selected due to their strategic location on main roads and their significance in supplying non-timber forest products and charcoal to Lubumbashi city Dubiez *et al.* (2020). These villages are situated near the RN2 trunk road, which experiences heavy traffic. They are part of the Katanga Copper Arc (KCA), as extensively described by Cabala *et al.* (2017). The local population primally engages in gathering, farming, charcoal production and artisanal mineral exploitation. Consequently, mining activities, carbonization and agricultural practices disrupt natural vegetation regeneration and succession processes, causing an imbalance in the landscape. The climate is divided into two seasons: the rainy season from November to March and the dry season from May to September. April and October are considered transitional months (Alexandre, 1977). The average rainfall is 1270 mm, while the average temperature and relative humidity are respectively around 20°C and 66% (Malaisse *et al.*, 1978). The most dominant vegetation type is open forest miombo type, with scattered patches of vegetation following anthropization (Sikuzani *et al.*, 2017; Cabala *et al.*, 2018; Muteya *et al.*, 2023).

Data Collection and Processing

Satellite Data

The LANDSAT8 satellite images, acquired via free download from the United States

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Geological Survey (USGS) on this link http://earthexplorer.usgs.gov/, were obtained on different dates. These four images were downloaded from October 23rd: September 15th, November 3rd and August 4th in 2015, 2017, 2019 and 2021 respectively. During these months, chlorophyll activity is at the threshold because it is a period across rainy and dry seasons or the beginning of the rainy season. Therefore, vegetation is practically distinguishable and without edge effects. The area covered by a scene was 185km², and all FCBMs studied were covered. The images have a panchromatic band resampled to 15-m pixels while eight bands are multispectral resampled to 30-m pixels. To avoid clouds, images were acquired at different times but having similar solar illumination. There is a notable difference in radiometric resolution between them. The images were successfully pre-processed using QGIS 3.20.

These four images were pretreated in order to calibrate their digital number values and converted on the absolute radiometric calibration factor and frequency range for each band (Lane et al., 2014); due to the difference in acquisition dates. Thus, the images obtained were converted into surface reflectance (TOC) based on solar spectral irradiance; and then georeferenced on Universal Transverse Mercator system zone 35S referenced to the WGS 84 ellipsoid.

Delimitation Area and Unsupervised Classification

A shapefile for each FCBM served as a mask layer to delimitate the study area (Oszwald *et al.*, 2011), using multiple raster clips in QGIS 20.3 software. The shapefile results from the participatory mapping of the Miombo project piloted by the FAO and centralized at the Open Forest Observatory of the DRC. A single composition utilizing bands NDVI layer, 4 and 2 for red, green and blue channels respectively, was adopted for all images (Lane *et al.*, 2014); as colour compositions. This multispectral configuration provides the best visual result for identifying sample areas for each soil unit (Tahinarivony *et al.*, 2017); as part of the reduction in contrast according to the degradation of forest evolution (fig 2).

Among the variety of unsupervised classification methods such as K-mean, random tree and ISODATA (Lane *et al.*, 2014); the ISO cluster classifier was selected in this research because of its straightforward and machine-based approach with minimized human intervention. Initial 10 clusters were created based on radiometric counts extracted from the red and near-infrared spectral bands, but classes exhibiting radiometric and thematic similarity were subsequently merged (Barima *et al.*, 2009). According to Bigot (2016), 4 to 6 land-use classes are sufficient for a cartographic analysis of this type of landscape. Finally, six classes were selected.

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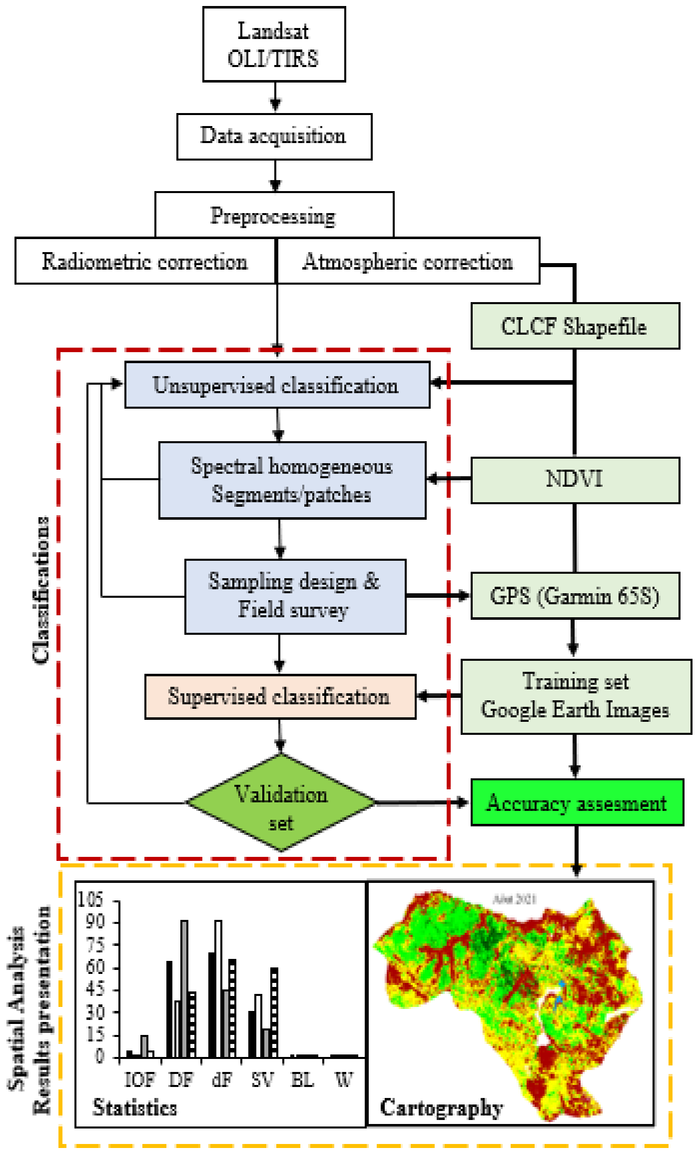
FIGURE 2. Representative Diagram of the Image Processing Methodology up to Classification Validation.



NDVI Index and Sampling Design

The Normalized Difference Vegetation Index (NDVI) specifically, was calculated to enhance the discrimination between different types of plant cover (Hountondji, 2017; Oszwald *et al.*, 2011). The NDVI was derived and included in the TOC to define the last map which served to create the sampling set (Fig 3). The NDVI has been scaled linearly to a numerical range like the surface reflectance of multispectral bands, and the unsupervised classification was used in the final supervised classification as explained below.

The NDVI provides an estimate of chlorophyll activity at various phenological stages (Djoufack, 2011), and a well-established indicator of the presence and condition of vegetation. Due to its inverse relationship between chlorophyll absorption of red radiant energy increased reflectance of near-

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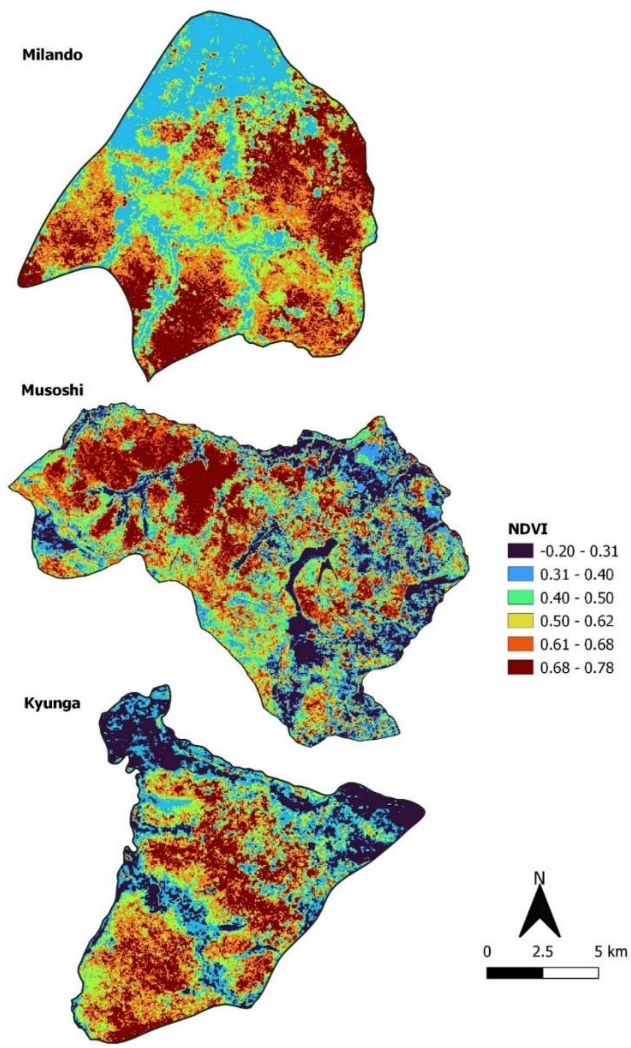
infrared energy for vegetation canopies. The NDVI is given by equation 1, its range of value goes from -1 (*i.e.*, no chlorophyll activity detected) to 1 (maximum chlorophyll activity). Vigor and abundant vegetation present high NDVI values due to a high reflectance in the near infrared spectrum channel which allows it to absorb more light in the red visible spectrum. However, very degraded, stressed or space vegetation has almost similar reflectance in both spectra (near-infrared and red). Therefore, their NDVI values are low or even zero. Water bodies yield negative values due to red reflectance larger than near-infrared reflectance. The NDVI values for bareland in rural areas are often above zero than in urban areas despite being close to zero, due to their similar reflectance in both bands. The difference in NDVI values between two years during the same season can indicate a change in land cover class (Tahinarivony *et al.*, 2017). Thus, the NDVI image would be expected to enhance the discrimination between the different stages of degradation of the plant cover of FCBMs (fig 2).

$$\text{NDVI} = \frac{NIR-R}{NIR+R} \text{ (Equation 1)}$$

Where NIR: Near infrared; R: Red.

FIGURE 3. Thresholds for NDVI Variation in the FCBM



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Field data collection was necessary for classification validating and realized using a Garmin 65S GPS. Indeed, a vector grid of 500 × 500 m² was projected onto the 6 clusters derived from the unsupervised classification were loaded into a GPS receiver as a vector data layer. The 6 clusters obtained were visited in each FCBM. Polygons < 0.5 ha were deleted to limit the errors of the unsupervised unsieved ISODATA classification. A total number (120) of sites surveyed due to 40 by FCBM was limited following the size of the research team (two scientists) and the limited financial means for five days of fieldwork. Access to the sampling location was on foot or by motorbike. The control points were modified depending on the polygon size and unsupervised classes. 25 × 25 m² plots were installed in each unsupervised forest class. The central point of the vector grid constitutes the centre of each plot. Thus, the floristic inventory was carried out in each plot to assess the canopy cover. Furthermore, other types of land cover were identified, geolocated and recorded using GPS (water point, bareland, dwelling). These were used in the final classification.

Training and Validation Datasets

The 40-field sampling retained in each LCFC made it possible to create regions of interest (ROIs), transformed into a training dataset to calibrate the supervised classifier and a validation dataset to evaluate the classification accuracy. Based on spectral characteristics, the training data was grouped into 6 classes using ArcGIS (ESRI, version 10.1). The spectral signature of training sites was examined using the *RasterDataPlotting* tool in QGIS 3.20 and determined that all cluster groups are separate.

The validation process consisted of two steps: firstly, the visual verification of non-forest classes, and secondly, the definition of degradation levels for legend attribution as adopted in the FAO-piloted *Miombo* project (2016),

The classifications were evaluated using the confusion matrix method (Pontius, 2000). This matrix allowed for the assessment of user accuracy calculated as a percentage of correctly classified pixels in class *i* ($P_u(i)$), according to equation 2.

$$P_u(i) = \frac{M_c(i)}{m_1} \times 100 \text{ (Equation 2)}$$

where $M_c(i)$ represents the number of pixels assigned to class i and m_1 is the total number of pixels of class *i* within the image.

The producer's accuracy (i) was determined using equation 3:

$$P_p(i) = \frac{M_c(i)}{m_2} \times 100 \text{ (Equation 3)}$$

where m_2 represents the number of pixels belonging to class i. A lower (i) value indicates confusion between classes, while a higher value denotes reliability in class selection compared to samples from other classes.

Overall accuracy (*MPCC*), representing the proportion of correctly classified pixels, was calculated using equation 4 (Congalton, 2001).

$$MPCC = \frac{1}{n}\sum_{i=1}^{n} P_u(i) \text{ (Equation 4)}$$

where n is the total number of pixels in the matrix.

The Kappa coefficient ($\hat{K}$equation 5), which indicates classification quality by comparing the accuracy of the pixel assignment to the total number of surveyed pixels (Landis & Koch, 1977; Pontius, 2000), was calculated using Equation 5.

$$\hat{K} = \frac{n\sum_{i=1}^{r} M_c(i) - \sum_{i=1}^{r} m_1 m_2}{n^2 - \sum_{i=1}^{r} m_1 m_2} \times 100 \text{ (Equation 5)}$$

where r is the number of rows in the matrix.

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Supervised Classification of the Landsat 2021 Image

The supervised classification of the Landsat 2021 image was conducted using the methodology outlined in Figure 3. These steps culminated in a supervised classification utilizing the maximum likelihood algorithm. This method creates a likelihood function and employs an optimization algorithm to maximize it, thereby assigning each pixel in the image to the land cover class with the highest probability of belonging (Collet, 2001; Congalton, 2001). However, due to the spatial resolution of the data (30 m), only six classes were discriminated in finally land cover classes for the three study areas. An accuracy assessment, which appeared as the user's and producer's accuracies, of the most refined classification level, was quantitatively assessed based on unsystematic sample validation pixels from ground-truth polygons.

Supervised Classification of Landsat OLI/TIRS Images from 2015, 2017 and 2019

The classifications of FCBMs for the years 2015, 2017 and 2019 were derived by spectral matching with the final land cover classes from the 2021 Landsat OLI/TIRS image, following the methodology outlined in Figure 2. In case of doubt, google Earth images were used for photo interpretation to confirm the class before final classification. These classes served as training areas for the maximum likelihood algorithm, which assigned each pixel to the land cover class with the highest probability of association. (Collet, 2001; Congalton, 2001). Additionally, each pixel was assigned a certainty index related to this classification choice (Barima *et al.*, 2009).

Assessment of Changes Detection

The evolution of land cover classes was evaluated using transition matrices between two periods (t_1 and t_0) (Bogaert *et al.*, 2008) after superimposing the two land cover maps in GIS software (ArcGIS 10.1) and manipulating them in Excel. The spatial structure of the landscape was quantified using three spatial indices: the number of patches (n), the area (a) and the perimeter of the patches (p). The number of patches provides information on the class fragmentation between two periods, while the perimeter provides information on its shape (Bogaert *et al.*, 2008; Castillo *et al.*, 2022). The interpretation of spatial dynamics was refined with the help of the decision tree suggested by Bogaert *et al.* (2004). A threshold of t = 0.5 was used in this study for decision evaluation based on the indices (n, a and p) (Cabala *et al*., 2018; Sikuzani *et al.*, 2024). The separation of the fragmentation and dissection processes was based on the value of t_{obs}, (t_{obs} = a /a_{10}); if $t_{obs} < 0.5$, fragmentation is detected and if $t_{obs} > 0.5$, dissection is detected. Changes between two dates were defined using the rate of change formula (*Te*) proposed by (Munyemba, 2010; equation 6).

$$Te = \frac{a_f - a_i}{a_i} \text{ (Equation 6)}$$

where a_i is the total area of the class in the initial year and a_f is the total area of the same class in the subsequent year. A positive *Te* indicates an increase in the area of the corresponding class, while a negative *Te* indicates a regression in the area of the class over time.

RESULTS

Definitions of Land Cover Classes

The heterogeneity of the land cover in the FCBMs and the gradual transition from one class to another, resulting from the density of the vegetation cover and the size of the individuals, led us to carry out an unsupervised classification of the OLI/TIRS image with six land cover classes (Intact Open Forest, Degraded Forest, Demoted Forest, wooded Savannah, Grassland. Field work and spectral

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characteristics of the classes enabled us to identify the similarity between classes and merge closely related ones. Despite the possibility of distinguishing many classes, six main classes were selected based on the FAO model and the group of practitioners involved in the *Miombo project* to implement the final classifications (Table 1). These classes are:

Table 1: Classes Description Table

Land Cover Class	**Description**
Intact Open Forest	
	Represents the climax stage of the open forest characteristic in Lubumbashi plain (Malaisse, 2010);
Degraded Forest	
	Characterized by a gradual reduction in contrast compared to the intact open forest (Muteya *et al.*, 2023), with small-scale human activities becoming visible;
Demoted Forest	
	Represents shrub and tree savannahs resulting from human activity and old fallow land or post-cultivation wasteland (Sikuzani *et al.*, 2020);
Savannah	
	Represents spring fallow land, flooded and exposed fields, meadows, or grassy savannah (Malaisse, 2018);
Bareland	
	This complex represents areas that have been heavily developed or rural constructions (Sikuzani *et al.*, 2024);
Water	
	Represents water reservoirs and temporary puddles.

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Validation of Land Cover Classifications from Landsat OLI Images

Validation of the land cover classifications was acquired by confusion matrices (Tables 1, 2 and 3) through an accuracy and Kappa index. Accuracy remained at 94.45%, 91.93% and 90.54% for Milando, Musoshi and Kyunga, respectively.

Milando: The classes were correctly chosen, as evidenced by the P_p with the lowest P_u of 90.26% corresponding to the intact open forest class; and the lowest ranked class is that of bare land with 87.88% of Pu (Table 2).

Table 2: FCBM Milando in Miombo Woodland of Democratic Republic of the Congo, Satellite Image Classification Validation Parameters in Absolute Values.

Milando		IOF	DF	dF	SV	BL	W
2015	***Pu***	99,5	95,14	86,9	100	95,45	100
	Pp	97,17	95,8	96,8	100	95,45	100
	MPCC	**93,35**					
	K	**96,16**					
2017	***Pu***	100	87,5	91,95	96,9	60,2	73,9
	Pp	100	81,27	95,44	91,72	92,9	100
	MPCC	**89,83**					
	K	**85,34**					
2019	***Pu***	99,42	97,04	90,8	98,28	100	100
	Pp	97,55	96,87	96,36	98,56	85,19	100
	MPCC	**97,6**					
	K	**96,76**					
2021	***Pu***	91,3	92,31	96,7	99,65	87,88	100
	Pp	90,3	92,44	98,7	98,72	93,55	100
	MPCC	**94,45**					
	K	**92,22**					

Pu: User accuracy, Pp: Producer accuracy, K: Kappa index and MPCC: Mean of correctly classified pixels (overall accuracy).

Musoshi: The P_p of classes have the best ranked with 100% accuracy scores for the 2021 classification. P_u followed by the demoted forest, intact open forest and savannah classes with a P_u 98.17%, 96.77% and 88.39% respectively, compared with 68.24% for the degraded forest. The savannah (P_p = 100%), degraded forest (P_p = 98.30%), bareland (P_p = 97.76 %) and Water (P_p = 96.67 %) are least affected by the samples from the other classes. Moreover, the intact open forest class (P_p = 67.80%) was more often chosen instead of the other classes (Table 3). The classification nevertheless remains valid given that all the P_p and P_u are beyond 60%. The accuracy decreased in 2021 because of the fragmentation date impact.

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Table 3: Validation Parameters for the Classification of FCBM Musoshi in Miombo Woodland of Democratic Republic of the Congo, Satellite Images in Absolute Values.

Musoshi		IOF	DF	dF	SV	BL	W
2015	***Pu***	99,29	99,64	96,69	100	100	100
	Pp	99,47	99,55	99,32	99,39	100	100
	MPCC	**98,51**					
	K	**97,76**					
2017	***Pu***	96,6	100	100	100	100	100
	Pp	100	99,3	100	100	100	100,0
	MPCC	**99,44**					
	K	**99,29**					
2019	***Pu***	98,36	98,38	100	99,27	100	100
	Pp	99,31	98,12	96,12	99	100	83,33
	MPCC	**99,35**					
	K	**99,15**					
2021	***Pu***	96,8	68,24	98,2	88,39	100	100
	Pp	67,8	98,3	81,4	100	97,76	96,7
	MPCC	**91,93**					
	K	**89,48**					

Pu: User accuracy, Pp: Producer accuracy, K: Kappa index and MPCC: Mean of correctly classified pixels (overall accuracy).

Kyunga: the intact forest class (P_p = 100%) was misclassified and more frequently selected in place of the other classes, while the bare land and water classes were often selected in place of the other classes, with respectively a P_p of 61.90% and 63.63% respectively. The bare land, very degraded forest and savannah classes were the best ranked respectively with a P_u of 100%, 93.44% and 92.92%, respectively, compared with 77.78% for the Water class (Table 4).

Table 4: Validation Parameters of the Classification of FCBM Kyunga in Miombo Woodland of Democratic Republic of the Congo, Satellite Images in Absolute Values.

Kyunga		IOF	DF	dF	SV	BL	W
2015	***Pu***	100	99,74	100	99,35	100	100
	Pp	99,86	100	100	100	69,23	100
	MPCC	**99,84**					
	K	**99,73**					
2017	***Pu***	100	100	99,59	98,07	100	100
	Pp	100	100	99,20	99,27	100	60,0
	MPCC	**99,61**					
	K	**99,41**					
2019	***Pu***	98,36	98,38	100	99,27	100	100
	Pp	99,31	98,12	96,12	99	100	83,33
	MPCC	**99,35**					
	K	**99,15**					
2021	***Pu***	87,95	91,12	93,44	92,92	100	77,78
	Pp	100	80,79	90,19	93,75	61,90	63,63
	MPCC	**90,54**					
	K	**88,51**					

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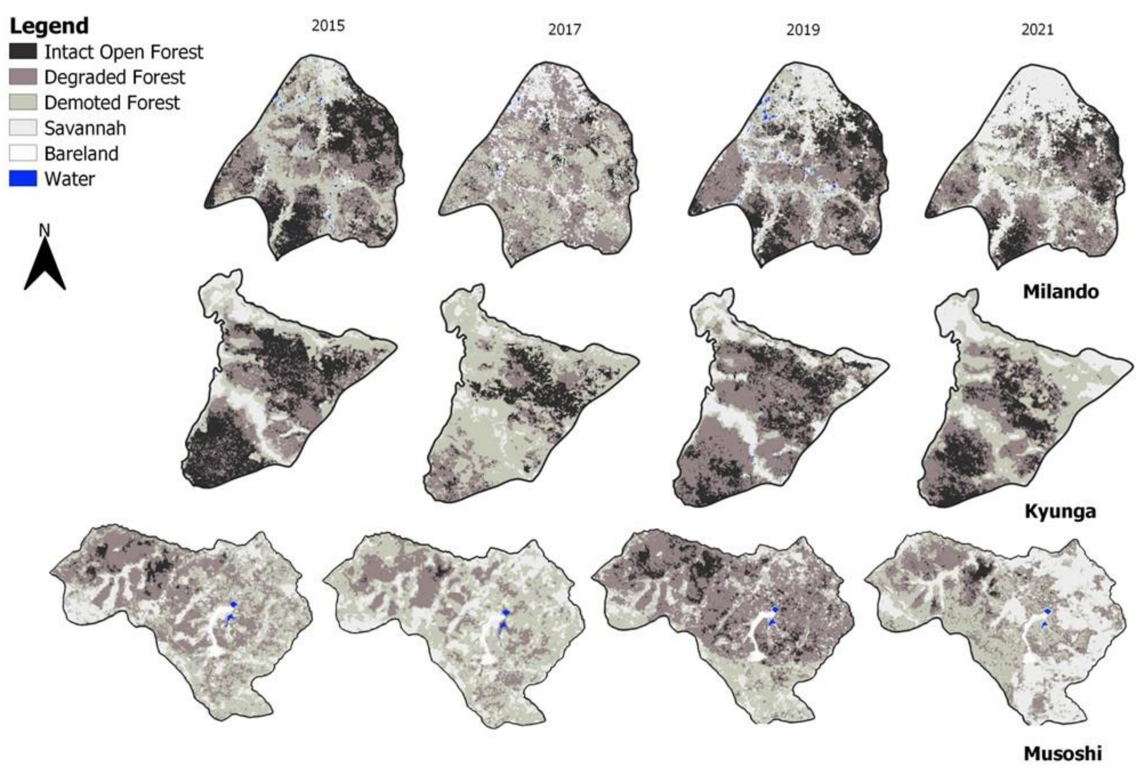
Pu: User accuracy, Pp: Producer accuracy, K: Kappa index and MPCC: Mean of correctly classified pixels (overall accuracy).

The Kappa coefficient (*K̂*) was 92.22%, 88.51% and 89.48% for Milando, Musoshi and Kyunga, respectively, indicating satisfactory classifications (Figures 3, 4 and 5). The validation results for the remaining classifications are correct, considering the overall accuracy and Kappa index which are above 88%; user accuracy and producer accuracy are also above 75% for all forest classes. However, to carry out the classifications of the Landsat OLI/TIRS 2015, 2017 and 2019 images, the NDVI values were combined in the image band to increase the separability of forest classes. The spectral correspondence of the land cover classes in the Landsat OLI/TIRS 2021 image shows good class separability across all the land cover classes from previous years achieving an *MPCC* (%) and *K̂* (%) of 97.60% and 96.76%, respectively. The 2015 and 2019 Google Earth images were integrated with the initial images for photointerpretation.

Land Cover Mapping in FCBMs

Six classes were retained for the last classifications of the FCBM landscape (Fig 4). The intact open forest is in continuous dynamics throughout the FCBMs as well as the savannah. The degradation of forest classes remains evident despite the installation of the Miombo project in 2017. The four apologia show the spectacular biannual change in land cover. Furthermore, the installation of the project shows an added value in the afforestation of forest classes and reducing anthropogenic classes. Community forestry has had a positive impact on forest class aggregation, which influenced FCBM landscape configuration.

Figure 4: FCBMs Land Cover Mapping in the Miombo Woodland of the Democratic Republic of the Congo (Milando, Kyunga and Musoshi). Landsat OLI/TIRS Images Downloaded Date October 2015, September 2017, November 2019, Août 2021. Maximum Likelihood Algorithm.



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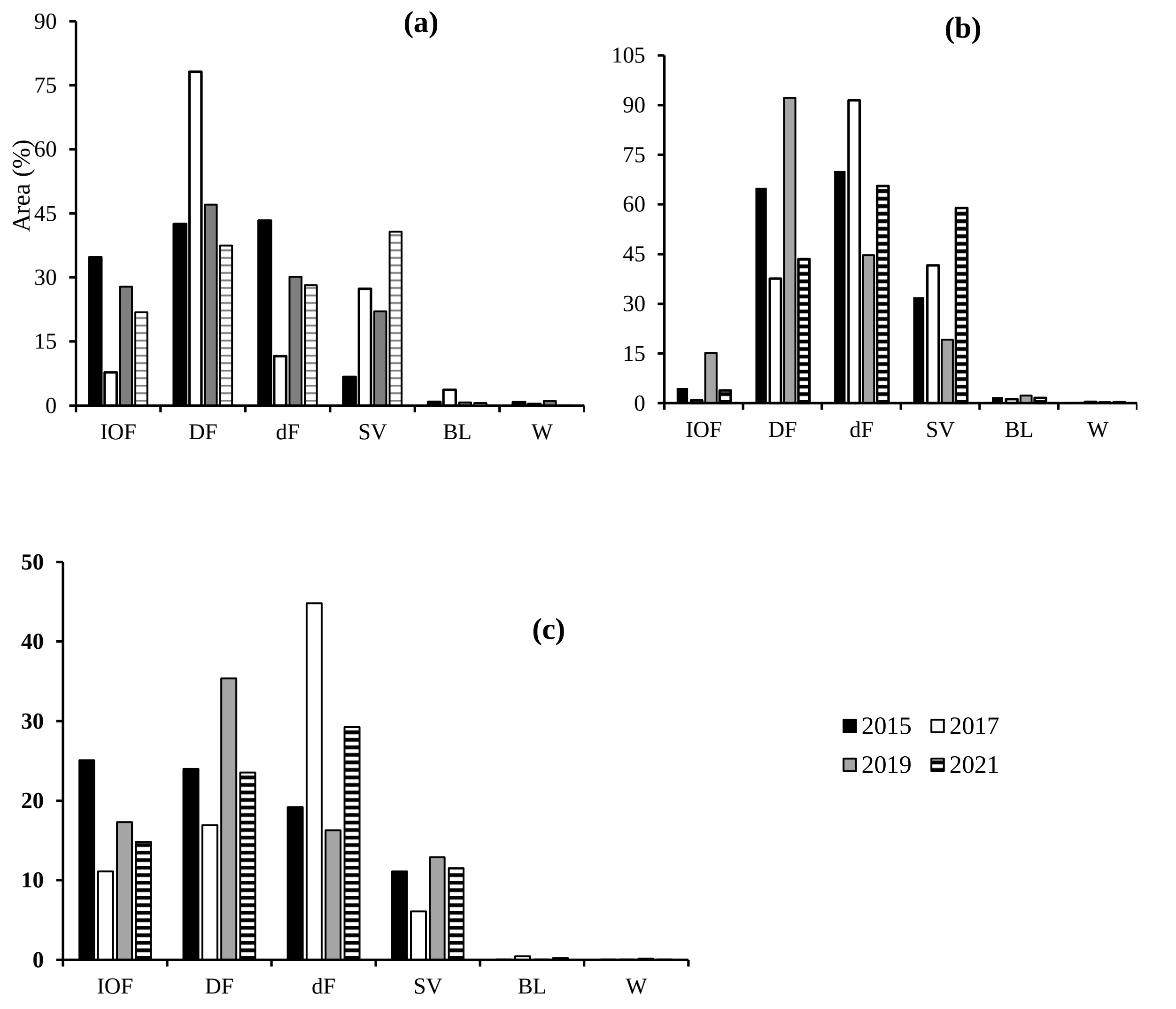
Dynamics of Land Cover Classes in FCBMs

Between 2015 and 2017, forest classes (intact open forest, degraded forest) experienced a loss of cover to savannah classes (demoted forest and savannah) and anthropogenic class (Bareland) in all FCBMs (Fig 5). Forest areas showed continuous decreases in cover until 2021. Notably, from 2017 to 2019, a net increase in forest areas was recorded across all FCBMs, accompanied by a decrease in savannah and anthropogenic areas, except in *Kyunga*, where the savannah class changed at the same rate as forest areas during this period. Between 2019 and 2021, forest areas experienced a modest decrease in surface area, with losses to savannah and anthropogenic areas. The water class remained static in *Kyunga* and *Musoshi*, where as in *Milando,* it was dynamic over the time intervals, reaching a peak between 2017 and 2019.

Figure 5: Assessment of Landscape Composition Elements at the scale of FCBMs in the Miombo Woodland of the Democratic Republic of the Congo. (a) Milando, (b) Musoshi and (c) Kyunga between 2015, 2017, 2019 and 2021; which IOF= Intact Open Forest; DF=Degraded Forest; dF= Demoted Forest; SV= Savannah; BL= Bareland and W= Water



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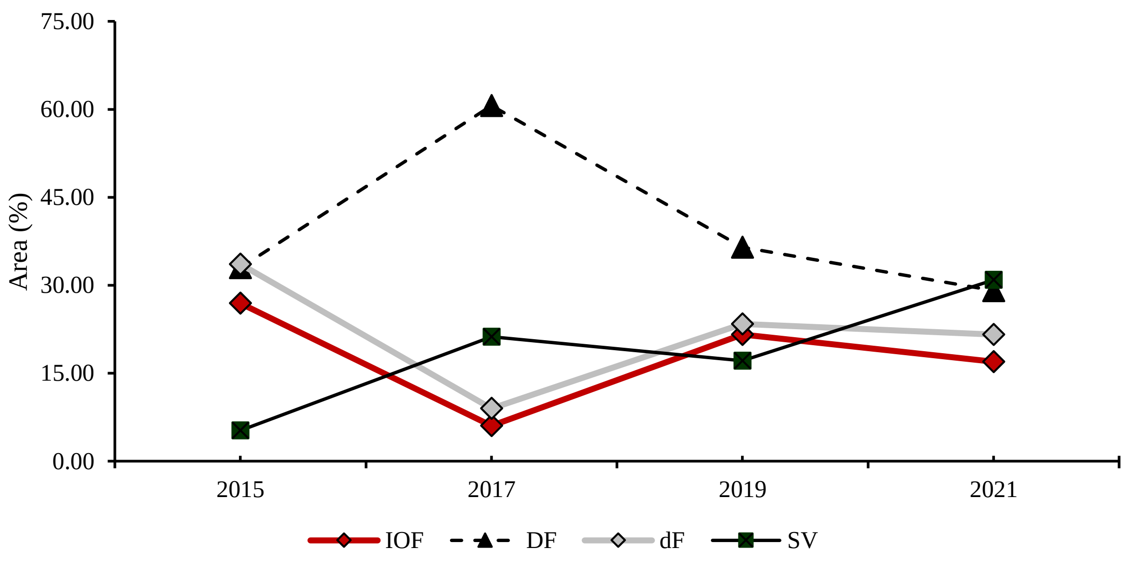
Land Cover Dynamics in FCBMs between 2015, 2017, 2019 and 2021

Land Cover Transition in the Milando FCBM between 2015 and 2021

Fig 6 below shows the types of land cover transitions in the Milando FCBM between 2015 and 2021. Some land-use changes in *Milando* are more pronounced than others. Between 2015 and 2017, savannah areas increased dramatically from 5.22% to 21.19%; however, between 2017 and 2019, it is destroyed by -3,06%. Paradoxically in 2021, the area occupied by the savannah is 30.9% with a notable growth of more than 13% at the scale of the FCBM between 2017 and 2019. On the other hand, degraded forests grew from 32.29% to 60.62% between 2015 and 2017. Almost the same area gained between the previous years is lost between 2017 and 2019 (-24.14%) and continues to decrease from 2019 to 2021 (-7.39%). A decrease in the demoted forest class is notable between 2015 and 2017 (33.60 – 8.98%), with a contrary trend between 2017-2019 (+14.41%), from 2019 to 2021 a modest decrease is remarkable (-1.78%). Intact open forests saw a decline of -20.08% between 2015 and 2017, compared with an increase of +15.56% between 2017 and 2019 and a decline of -4.64% between 2019 and 2021. The period from 2017 to 2019 shows an increasing in the areas of forest classes in their entirety. These constants show that the conversion dynamics in the *Milando* FCBM include deforestation, afforestation and savannization of forest areas. Anthropization and flooding are also important factors in *Milando*.

Figure 6: Illustration of the Conversion Dynamics of Landscape Elements in Milando FCBM in the Miombo Woodland in the Democratic Republic of the Congo between 2015 and 2021 between 2015 and 2021. IOF: Intact Open Forest, DF: Degraded Forest, dF: Demoted Forest, SV: Savannah



Land Cover Transition in Musoshi FCBMs between 2015 and 2021

The transitions between land cover over time are particular. There has been a steady increase and decrease in forest areas at *Musoshi* (Fig 7). Between 2015 and 2017, the intact (-2.1%) and degraded (-15.7%) open forest classes decreased, while the highly degraded forest class increased by 13.3% and the savannah class by 5.5%. The trend is reversed between 2019 and 2021, with an increase in forest areas, notably +8.2% for intact open forest and

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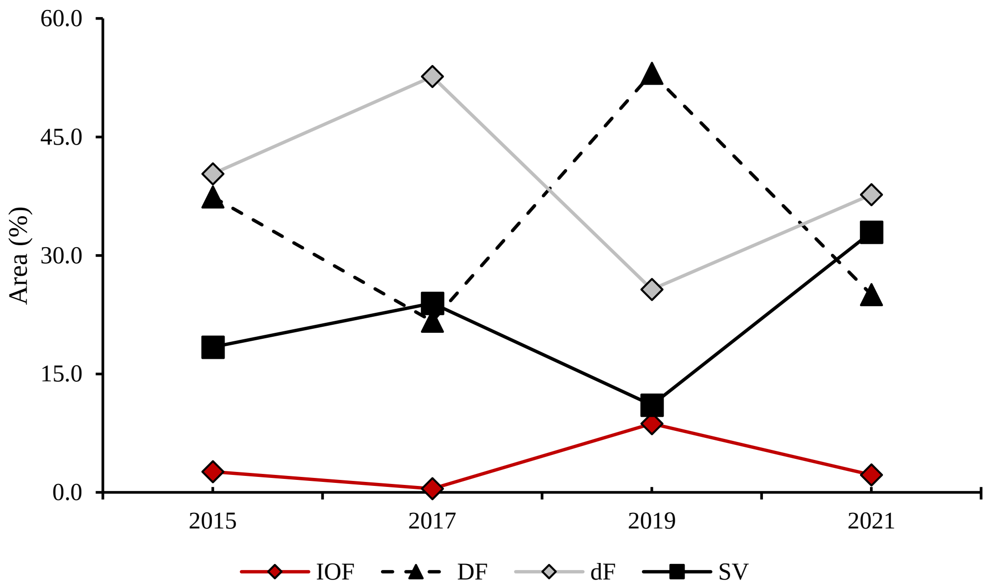
31.4% for degraded forest, compared with a reduction in the total area of the demoted forest class (-26.3%) and the savannah class (-12.8%). Furthermore, between 2019 and 2021, a reduction in forest area is recorded, with a drop of -6.5% in the total area of the intact light forest class and -28.1% in the total area of the degraded forest class, compared with an increase in the total area of the degraded forest and savannah classes, with growth of +12.1% and +21.8% respectively. Thus, the dynamics of conversion in the *Musoshi* FCMB include forest degradation, deforestation, afforestation and savannization.

Figure 7: Illustration of the Conversion Dynamics of Landscape Elements in Musoshi FCBM in the Miombo Woodland in the Democratic Republic of the Congo between 2015 and 2021 between 2015 and 2021. IOF: Intact Open Forest, DF: Degraded Forest, dF: Demoted Forest, SV: Savannah.



Land Cover Transition in the Kyunga FCBMs between 2015 and 2021

The transition between land-cover classes in *Kyunga* is as spectacular as in the other FCMBs assessed (Fig 8). Between 2015 and 2017, the total area of the demoted forest class increased by 32.28%, while the total area of forest decreased by 17.6% for intact open forest, -8.92% for degraded forest and 6.3% for savannah. Between 2017 and 2019, the situation is reversed, with an increase in the total area of forest spaces of +7.77% for intact open forest and +23.25% for the degraded forest class, against a decrease in the total area of savannah spaces with -40.14% for the demoted forest class. On the other hand, there is a paradoxical increase in the total area of the savannah class (+9.59). Between 2019 and 2021, a decrease in total area of -3.1% for intact open forest, -14.91% for degraded forest and -2.77% for savannah was recorded, compared with an increase of +20.53% for the demoted forest class. The dynamics of conversion in the Kyunga FCBM therefore include degradation, afforestation and degradation.

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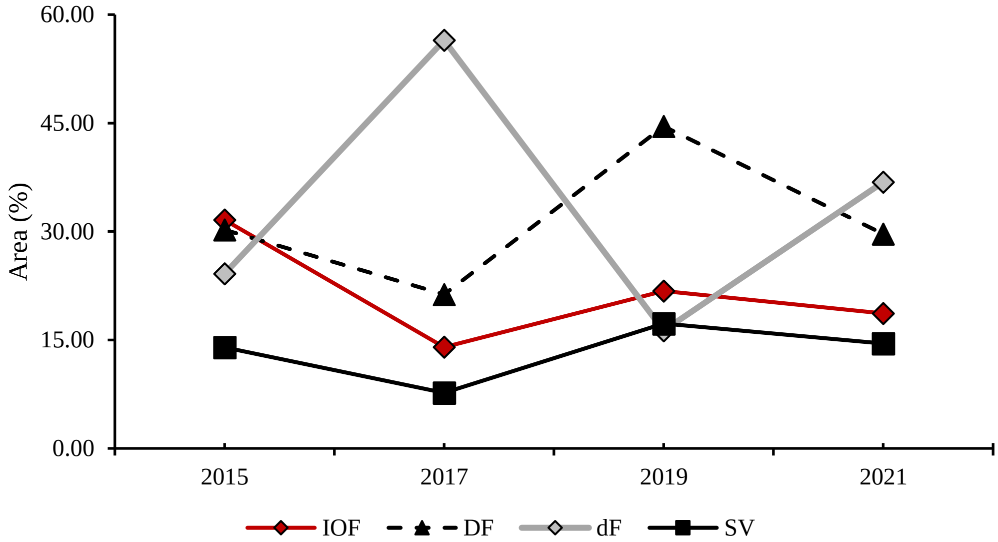
Figure 8: Illustration of the Conversion Dynamics of Landscape Features in Kyunga FCBM in the Miombo Woodland in the Democratic Republic of the Congo between 2015 and 2021. IOF: Intact Open Forest, DF: Degraded Forest, dF: Demoted Forest, SV: Savannah



Structural Dynamics of the Forest Landscape in FCBMs

Dynamics of Woodland Structures in Milando

Between 2015 and 2017, the number of patches decreased for all forest classes and increased for the other classes. In addition, the surface areas of all classes increased, except for intact forest and water, which decreased (Fig 9). The most notable transformation process for all classes during this period, apart from the intact forest and water classes, was creation. The intact forest class underwent suppression and the water class fragmentation, with $t_{obs.}$ = 0.46 less than t = 0.5.

Between 2017 and 2019, the number of patches will decrease for all classes except for the intact forest and water classes. Similarly, the surface areas of all classes are decreasing, except for the intact forest and water classes, which are increasing. Two transformation processes were notable during this period: creation for the intact forest and water classes, and deletion for the rest of the classes.

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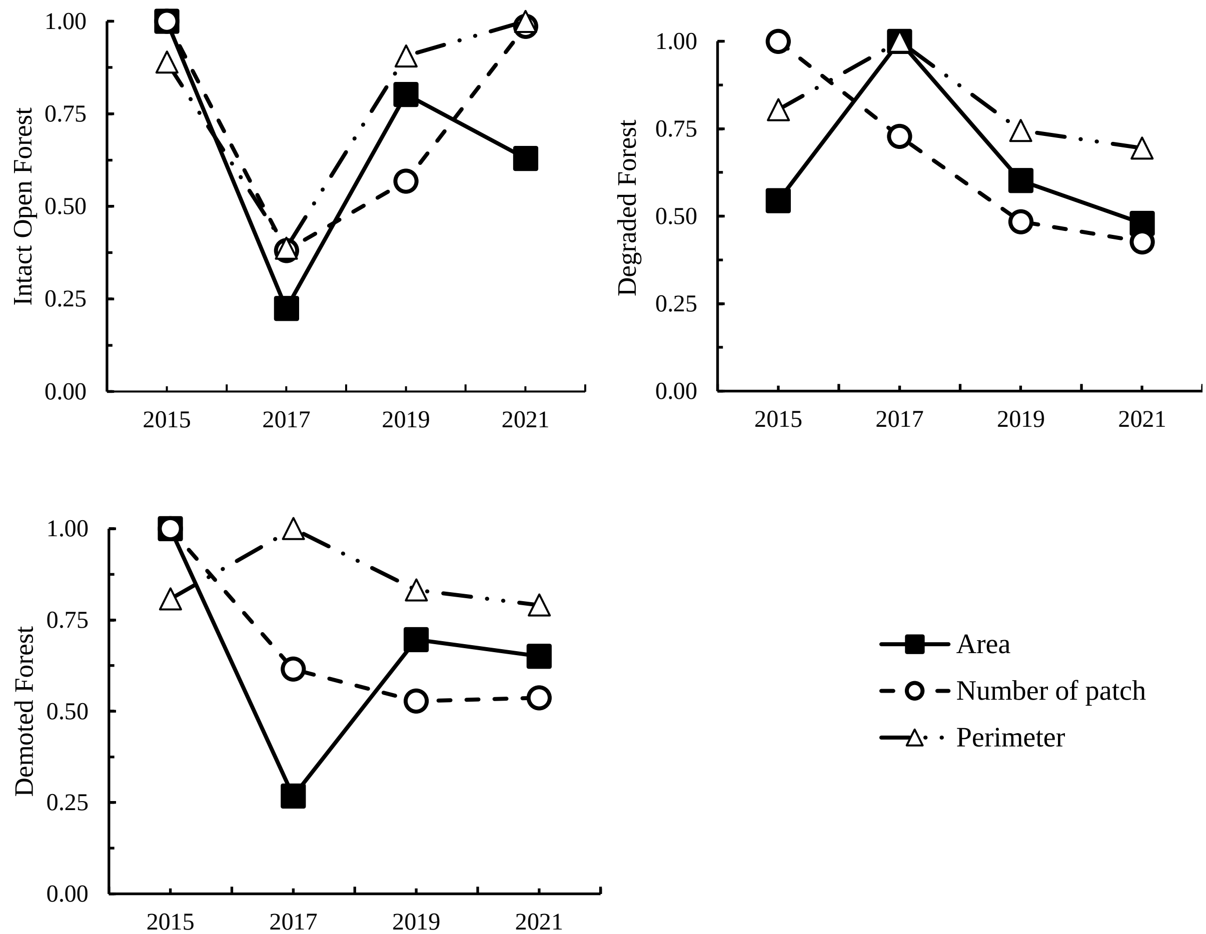
Figure 9. Illustration of Spatial Structure Indices Tendance in the Milando FCBM in FCBMs in the Miombo Woodland of the Democratic Republic of the Congo between 2015, 2017, 2019 and 2021.



Between 2019 and 2021, the number of patches decreased for the Degraded Forest, Very Degraded Forest and Water classes, while increases were recorded for the Intact Forest and Buildings & Bare Ground complex classes. At the same time, a decrease in the number of areas was observed in the forest classes, apart from the very degraded forest class. During this period, various transformation processes were noted, including aggregation for the highly degraded forest and savannah classes, creation for the degraded forest class and deletion for the water class. The intact forest class and the built-up & bare soil complex show an increase in the number of patches at the same time as a decrease in the total area of the classes. Given the respective values of $t_{obs.}$ = 0.93 and $t_{obs.}$ = 0.85, all greater than t = 0.5, the transformation process chosen is dissection.

Structural Dynamics of Forest Areas in Musoshi

Between 2015 and 2017, the number of patches decreased for all classes. The areas increase for three classes (highly degraded forest, savannah and the built-up & bare soil complex) and decrease for three others (intact forest, degraded forest and water). Two transformation processes were observed: aggregation and suppression (Fig 10).

Between 2017 and 2019, the number of patches increased for all classes except for the bare land complex and water. Furthermore, an increase in the

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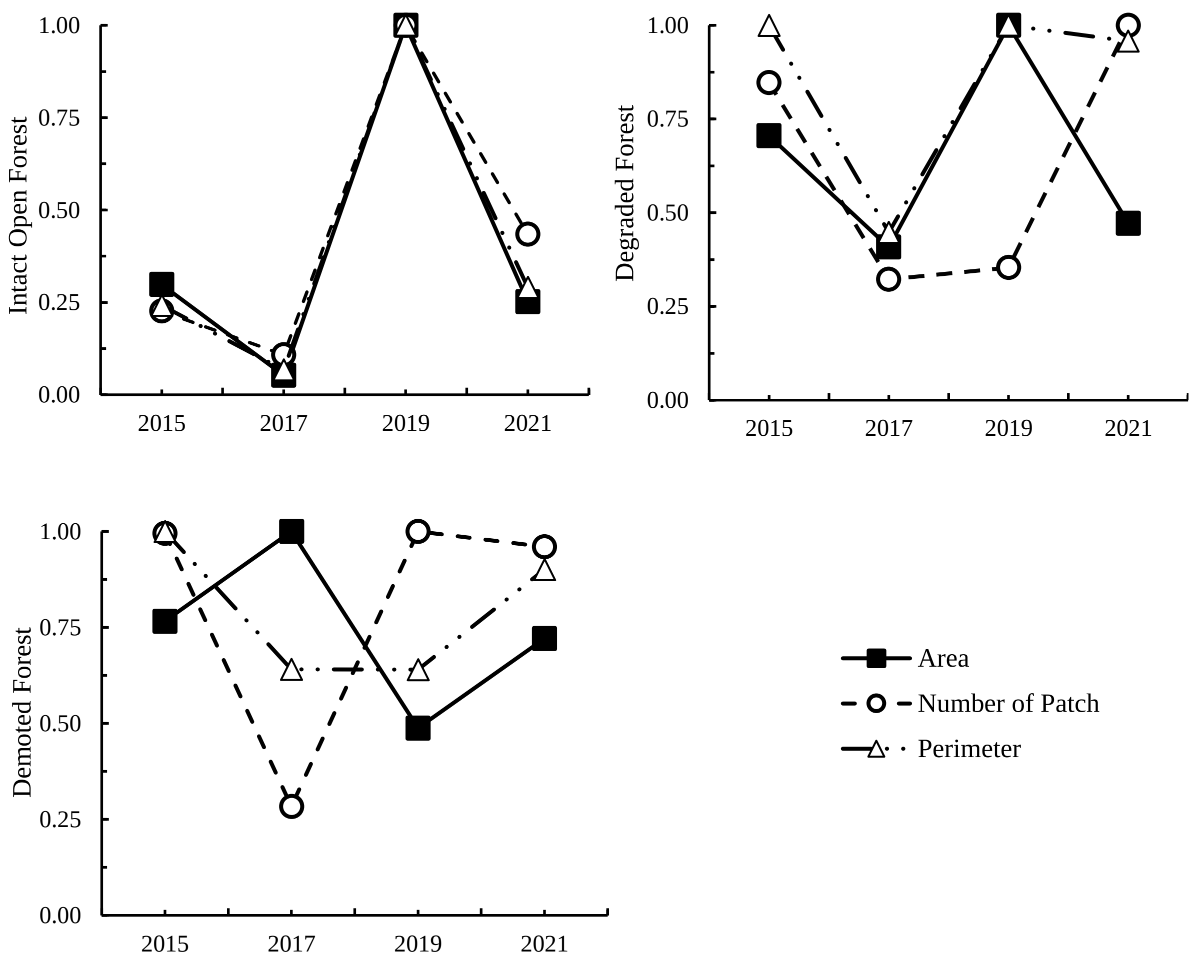
total area was observed for the intact forest, degraded forest and built-up & bare soil complex classes, compared with a decrease in the total area of the other classes. The notable transformation process during this period was the creation of the intact forest and degraded forest classes, suppression of the water class, aggregation of the built-up & bare soil complex, and fragmentation of the highly degraded forest and savannah classes, due to $t_{obs.}$ = 0.46 and $t_{obs.}$ = 0.47 respectively, all of which are greater than t = 0.5 (Figure X).

Figure 10. Illustration of Spatial Structure Indices Tendance in Musoshi FCBM in the Miombo Woodland of the Democratic Republic of the Congo between 2015, 2017, 2019 and 2021.



Between 2019 and 2021, the number of patches decreased for all classes except for the degraded forest class, which undergoes an increase, and the water class, which remains static. Similarly, the total area of the classes decreases for most of them; however, it increases for the highly degraded forest and savannah classes. The transformation processes retained include deletion (intact forest and buildings & bare soil), enlargement (water), aggregation (degraded forest and savannah) and fragmentation for degraded forest, given the value of $t_{obs.}$ = 0.47, which is lower than t = 0.5. During the period from 2015 to 2021, the transformation processes retained in the Musoshi FCBM were deletion, aggregation and dissection.

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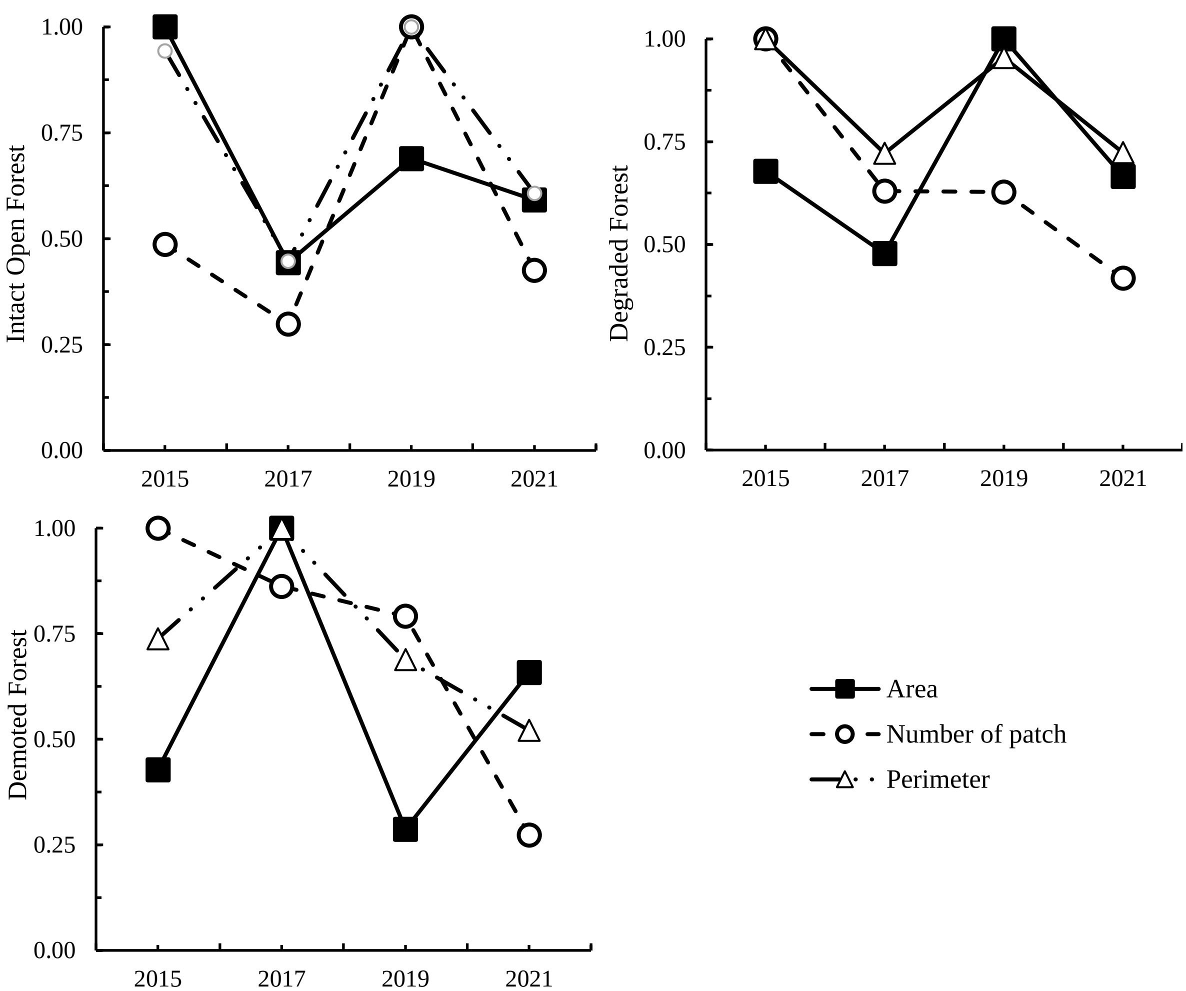
Dynamics of Forest Area Structures in Kyunga

Between 2015 and 2017, the number of patches decreased in all classes apart from the water class. At the same time, the total area in the forest classes, except for highly degraded forest, increased in the other classes, except for savannah, which decreased (Fig 11). The transformation processes that stand out during this period include suppression (intact forest, degraded forest and savannah), aggregation (highly degraded forest and built-up areas & bare soil) and dissection for the open forest class, given the value of $t_{obs.}$ = 1.25, which is higher than t = 0.5.

Between 2017 and 2019, the number of patches decreases in most classes, except for the intact forest and water classes. On the other hand, the total area increased in most classes, except for the highly degraded forest class and the built-up & bare soil complex. The transformation processes were creation (intact forest and water), aggregation (degraded forest and savannah) and deletion (highly degraded forest and the built-up & bare soil complex).

Figure 11. Illustration of Spatial Structure Indices tendance in the Kyunga FCBM in the Miombo Woodland of the Democratic Republic of the Congo between 2015, 2017, 2019 and 2021.



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Between 2019 and 2021, the number of patches decreases for all classes apart from the bare land complex. Similarly, the total area decreases in most classes except for the highly degraded forest class and the built-up & bare soil complex. The notable transformation processes were deletion (intact forest, degraded forest and water), aggregation (highly degraded forest) and creation for the bare land.

Between 2015 and 2021, considering the dynamics of the structures in the *Kyunga* FCBM. The most notable changes were deletion, aggregation and creation.

Table 5. Spatial Indices Between 2015, 2017, 2019 and 2021 and Identification of Transformation Processes (SPT) Based on the Decision Tree of Bogaert et al. (2004) in FCBMs in the Miombo Woodland of the Democratic Republic of the Congo.

FCBM Milando						
	IOF	**DF**	**dF**	**SV**	**BL**	**W**
CA_{2015}	34,71	42,55	43,34	6,74	0,85	0,8
NP_{2015}	3454	5704	5894	1579	144	120
CA_{2017}	7,78	78,2	11,58	27,33	3,73	0,37
NP_{2017}	1316	4152	3625	4016	1022	165
SPT2015-2017	Attrition	Aggregation	Aggregation	Creation	Creation	Fragmentation
CA_{2019}	27,85	47,05	30,17	22,09	0,75	1,08
NP_{2019}	1962	2763	3110	1442	310	379
SPT2017-2019	Creation	Attrition	Attrition	Attrition	Attrition	Fragmentation
CA_{2021}	21,86	37,52	28,2	40,76	0,63	0,01
NP_{2021}	3405	2435	3162	654	315	3
SPT2019-2021	Dissection	Attrition	Aggregation	Aggregation	Fragmentation	Attrition
FCBM Musoshi						
CA_{2015}	4,52	65,01	70,1	31,94	1,79	0,38
NP_{2015}	289	2362	2761	1723	15	7
CA_{2017}	0,8	37,63	91,46	41,6	1,91	0,34
NP_{2017}	138	899	787	888	59	5
SPT2015-2017	Attrition	Attrition	Aggregation	Attrition	Aggregation	Dissection
CA_{2019}	15,15	92,19	44,64	19,21	2,24	0,32
NP_{2019}	1276	987	2773	2453	216	4
SPT2017-2019	Creation	Aggregation	Attrition	Aggregation	Attrition	Creation
CA_{2021}	3,82	43,52	65,95	58,95	1,6	0,27
NP_{2021}	554	2789	2662	746	61	4
SPT2019-2021	Attrition	Attrition	Aggregation	Attrition	Creation	Attrition
FCBM Kyunga						
CA_{2015}	25,08	23,99	19,18	11,11	0,01	0,02
NP_{2015}	801	1761	1059	426	3	7
CA_{2017}	11,12	16,91	44,83	6,1	0,44	0,02
NP_{2017}	491	1109	913	285	221	15
SPT2015-2017	Attrition	Attrition	Aggregation	Aggregation	Aggregation	Attrition
CA_{2019}	17,29	35,38	12,87	13,72	0,04	0,14
NP_{2019}	1645	1105	838	238	10	105
SPT2017-2019	Creation	Creation	Fragmentation	Fragmentation	Aggregation	Attrition

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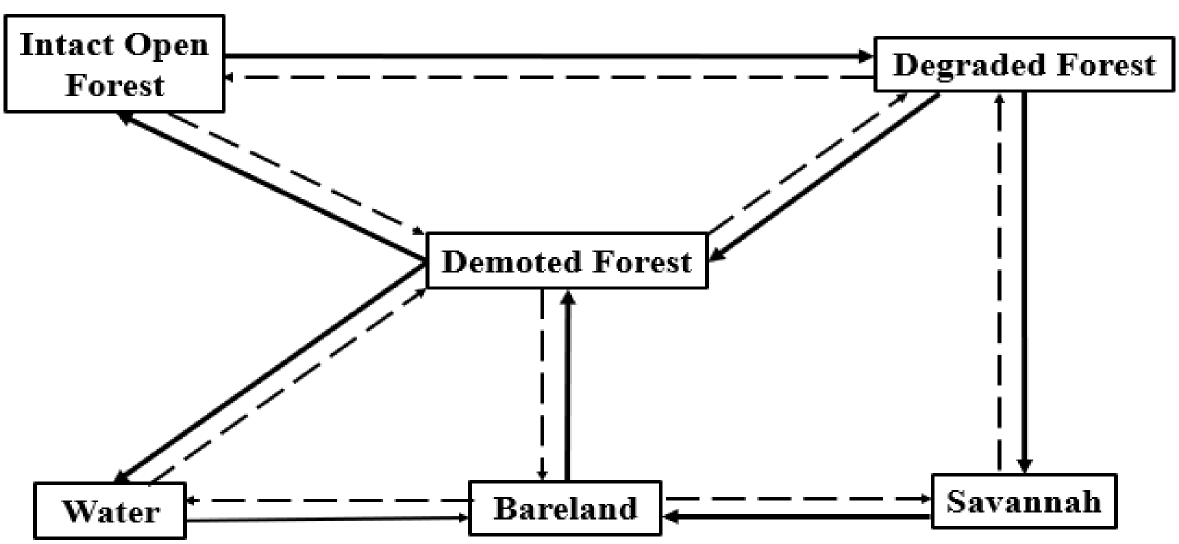
FCBM Milando						
	IOF	**DF**	**dF**	**SV**	**BL**	**W**
CA_{2021}	14,83	23,54	29,52	11,52	0,24	0,05
NP_{2021}	700	736	289	140	146	30
SPT2019-2021	Attrition	Fragmentation	Aggregation	Aggregation	Attrition	Elongation

ICF: Intact open forest, DF: Degraded Forest, dF: demoted forest, SV: Savannah, BL: Bareland and W: Water. CA: class area, NP: number of patches.

The indices in Table 5 made it possible to detect changes in the spatial structure of FCBMs landscape studies over 4 years. The number of patches for forest classes increased between 2017 and 2019 from 1317 to 1962; 138 to 1276 and from 491 to 1645 for intact open forests in Milando, Musoshi and Kyunga respectively. On the other side, the savannah classes decreased from 1442 to 654 and 285 to 238 in Milando and Kyunga respectively. Paradoxically, savannah areas increased in the same period from 888 to 2453. this indicates the creation of other dense forests and the fragmentation of savannah areas in the FCBMs. And creation trend is confirmed by the increase in the mean areas of intact open forest in all FCBMs. This demonstrates the impact of community forestry on the spatial structure of the miombo woodland. Below is the explicit diagram of existing conversions between classes within FCBMs (Fig 12). The degradation of higher forest classes (OIF and DF) goes from demoted forest to savannah. The intermediate element of distribution of portions of surface areas is the Demoted Forest class (very degraded forest). A conversion of 8.39% and 4.54% demoted forest to savannah is notable in 2021, in Musoshi and Kyunga respectively; which adds 12.12% conversion between savannah and bare land in Milando in the same year. Direct conversions between the Demoted Forest and water involve the establishment of settling basins for mining companies and temporary water slopes.

Figure 12. Diagram of the Conversion Dynamics of Landscape Elements in FCBMs in the Miombo Woodland of the Democratic Republic of the Congo. Solid Lines Show Primary Conversions While Dashed Lines Show Secondary Conversions.



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DISCUSSION

Definition of land cover classes: The use of remote sensing to monitor vegetation cover is essential because it quickly makes available information that can be used by decision-makers to properly manage forest areas (Sarr, 2009). This technology has been crucial for monitoring the landscape in the FCBMs. Taking into account the demographic growth recorded over the last few decades in the Lubumbashi plain (Sikuzani *et al.*, 2020) in conjunction with climatic variations, leading to major environmental upheavals (Bachinyaga *et al.*, 2022). The landscape structure in the FCBM has been influenced by community forestry, both in how it looks and in how it's composed. Defining the classes was not an easy task and required a combination of other layers, in this case NDVI, to clearly distinguish the land cover classes.

The fragmentation and degradation of forest classes since 2017 are the reason for the rarefaction of natural resources, accentuated in particular by the growing demand for charcoal (Dubiez *et al.*, 2020), the opening up of large areas to serve mining companies and the rapid conversion of natural vegetation into farmland to meet the food needs of local communities (Faucon *et al.*, 2018). It is therefore important to assess possible changes in land cover over time and space. Most of the landscape dynamics in the Lubumbashi plain have been studied using specific time intervals, which are often respected in the selection of satellite images (Cabala *et al.*, 2018; Munyemba, 2010; Sikuzani, 2019). The characterization of the evolution of these areas through satellite images taken at different seasonal dates has enabled the analysis and summary of the transformation processes of vegetation cover over time, highlighting any seasonal effects among the different variables.

The choice of images on different shooting dates did not affect the results. The only class cover to have suffered the effect of the dates is water, following the streams in the region. Thus, it could appear and disappear from one image to another because of the season effect. Furthermore, the heterogeneity of the classes, with their almost similar physiognomy, did not make it easy to establish definitive occupancy classes. To achieve this, the correspondence of spectral signatures allowed us to merge very similar classes. The same technique was used by Cabala *et al.*, (2018). who, after performing an unsupervised classification, merged the classes with the closest signatures to facilitate a diachronic study. As a result, only six classes were retained, making it possible to highlight the impact of community forestry on the landscape structure of FCBMs in the Miombo woodland. The selection of 2015 as the starting point was systematic because it shows the trend of forest cover before the start of the project activities and makes it possible to highlight the impact of the project on it. The decreasing trend in forest cover between 2015 and 2017 was even the additional motivation for the project´s establishment in this region.

Validation of land cover classifications from Landsat OLI images: The method used to analyse the transition modalities between different dates is based on transition matrices (Cabala *et al.*, 2018b). Although this method is simple to implement, it can lead to an accumulation of classification-specific errors, such as Pontius (2000). However, it remains robust with respect to variations in image conditions (Lefebvre *et al.*, 2011). In this study, it was applied to analyse images from the same sensor taken at different dates. We did not encounter significant issues when mapping land cover using Landsat imagery. While Landsat images have a medium spatial resolution, they do not capture all details in contexts where landscape transitions occur gradually and in mosaics (Cabala *et al.*, 2017). Nonetheless, they provide a general overview of land cover evolution in the FCBMs, this has allowed us to highlight the impact of the project on the latter while offering further opportunities to enrich the analysis. For detailed analysis, particularly along

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deforestation fronts, very high-resolution images (e.g. SPOT) are essential (Lane *et al.*, 2014). Despite this, the classifications in our study are satisfactory and statistically consistent, following Pontius's logic (2000) and Landis & Koch (1977). which shows that overall accuracy greater than or equal to 75% is sufficient to validate a classification. The same logic applies to the kappa index. On average, the overall accuracy is 93.8% for Milando FCBM and 97.3% for Musoshi and Kyunga (Table 2,3,4). The Kappa index was 92.6, 96.4 and 96.7% for *Milando*, *Musoshi* and *Kyunga* respectively. These values were higher than those previously found by (Cabala *et al.*, 2018) and almost identical to those later found by Sikuzani *et al.* (2024) in the same region. This shows that our classifications are acceptable and can be subjected to analysis.

Land cover mapping in FCBMs: The four landscape transition figures give a visual idea of the biannual changes between land use classes (Figure 3). This could be due to the upsurge in human activity resulting from the increased demand for charcoal in large urban areas without any policy to manage deforested areas. The densification of forest areas is clearly marked between 2017 and 2019, with a marked return of the intact open forest and degraded forest classes (Figure 4). This can be explained by the fact that the implementation phase of the Miombo Project will be in full swing during this period, and its achievements in the Lubumbashi region to date are by no means negligible (Murhula, 2021). The project focused on landscape restoration and the development of non-timber forest products, in this case, the development of the seed industry, other sources of income and so on.

These activities have been beneficial and have enabled many people to systematically abandon charcoal production, the main driver of deforestation and degradation of the Miombo woodland of the Lubumbashi region (Cabala *et al.*, 2018). From 2019 to 2021, there is a decrease in forest area in favour of savannah (Figure 4). This can be explained by the fact that the efforts of the project came to a halt with the outbreak of the covid-19 pandemic. During this period, most sources of income were suspended because of the curfew. To meet the needs of households in precarious situations, the forest areas were used as an element of production and charcoal-making became the preferred activity. This demonstrates the importance of this ecosystem to the local communities and the need to conserve it so that it can continue to provide the ecosystem services that are so important to both urban and rural communities. Later work in the same region by Lescuyer *et al.* (2021) and others supports this hypothesis, FAO (2010) and Dubiez *et al.* (2020). Also, shows that the landscape structure of the FCBMs has been significantly affected by human activity, and community forestry has been identified as one of the actions to support the recovery of the landscape structure. The impact of community forestry between 2017 and 2019 is a monitor to understand the impact of community forestry on the landscape structure of the FCBM in the Miombo woodland.

Dynamics of land cover classes in FCBMs: Despite the possibility of regenerating several spatial structure indices, only three were retained in this study, as suggested by Bogaert *et al.* (2008). The same indices had been used by Sikuzani *et al.* (2024) and Munyemba (2010) to assess the spatial structure in the Miombo woodland. There are the number of patches, area and perimeter. This also allowed us to assess the impact of community forestry on the spatial structure of FCBMs. The trends observed at *Milando*, *Musoshi* and *Kyunga* scales are similar, and highlight the major changes that the landscape has undergone since 2015 (Figure 4). An expansion of savannah areas (demoted forest and savannah) has been observed; this is taking place away from the dwellings of local communities, charcoal production sites and along the main roads.

Moreover, this is happening at the expense of dense forest areas (intact and degraded forest) which are

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undergoing continual regression (Sikuzani et al., 2023). On one hand, the use of these areas provides new fertile farmland, increasing agricultural production (Echezona *et al.,* 2011). On the other hand, it increases the percentage of bare land abandoned after charcoal production, accentuating exacerbating soil degradation (FAO, 2016) leaned to savannization (Chicouène, 2006; Faucon *et al.*, 2018). This is the reason for the spectacular changes that create illogical transitions between land cover classes, in this case from intact open forest to savannah (Figure 5,6,7). These transitions are rare, but they do exist in FCBMs. Similar observations were made by Barima *et al.* (2009) in the forest-savannah transition zone of Ivory Coast. They found that open forests decreased by 39% in favour of savannah classes. The increase in these factors is the result of the erratic supply of electrical energy, which is a limiting factor in efforts to conserve the Miombo woodland in the Lubumbashi region (Cabala *et al.*, 2018).

In addition, the use of improved fireplaces and bricks derived from ecological coal remains until now (Nge et al., 2020), practical solutions to reduce deforestation in miombo according to the social context of the country. This could reduce or even stabilise deforestation and forest degradation. In turn, the spatial structure of the Miombo woodland could be restored. The period from 2017 to 2019 shows a significant densification of forest areas (Figure 5,6,7). This is due to the impact of the Miombo project, which aims to restore DRCongo's Miombo ecosystems to reduce poverty and increase the income of local communities through the rational management of forest areas. However, the reverse trend between 2019 and 2021 is largely due to Covid-19. Indeed, during the pandemic, project activities were reduced to a minimum and local communities returned to their old habits at an exponential rate. This led to the over-exploitation of forest areas, thus counteracting the impact of the project in the region. Sikuzani *et al*. (2024) corroborate this fact by showing a negative trend in the development of forest areas as opposed to non-forest areas during the Covid-19 period.

Structural dynamics of the forest landscape in FCBMs: As observed by Munyemba (2010) and Sikuzani *et al.* (2019) in the Lubumbashi region, the results of this study align with the reported by Barima *et al*. (2009) in Ivory Coast, where significant changes in forest areas were noted in the Tanda transition zone, highlighting a substantial reduction in forest area in favour of savannah formations. Analysis of the spatial structure indices clearly shows the rapid degradation of forest areas in the FCBMs (Figure 8,9,10). The annual rate of degradation decreased from 39% between 2015 and 2017 to 11% between 2019 and 2021 in *Milando* (Figure 8); from 41% to 37.5% in *Musoshi* (Figure 9) and from 28% to 7% in *Kyunga* (Figure 10) over the same period. The trend is regressive and is attributable to the efforts made by the Miombo project between 2017 and 2019. In addition, the overall rate of degradation between 2015 and 2021, depending on the axis, was 5.8% on the Likasi axis compared with 2.14% on the *Kasumbalesa* axis, which is still much higher than the country's average deforestation rate, estimated at 0.2% (Sikuzani *et al.*, 2023).

Furthermore, analysis of the indices revealed that forest areas in the FCBMs are predominantly by degraded forest class (Figure 5,6,7), similar to findings in the Pama partial wildlife reserve in Burkina Faso by Soulama *et al.* (2015). In *Milando*, forest classes are highly fragmented compared to other FCBMs, akin to observations in the Amazon by Castillo et al. (2022), with transformation processes beginning with perforation or dissection, as demonstrated by Cabala *et al.* (2018) in the Lubumbashi region. In contrast, forest classes in *Kyunga* are compact, with continuous regression. This is probably because Kyunga is a new village, and human activity is still controlled. However, with mining companies already encroaching on the northern most part of the FCBM, this reality is likely

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to change soon. These findings are consistent with those of Bogaert *et al.* (2011), indicating that increased accessibility to the primary forest in *Milando* leads to landscape change (Bamba, 2012; Sikuzani *et al.*, 2020). Mining activities, remarkable in all the FCBMs, accelerate transformation processes by opening up roads that serve as corridors for transporting charcoal to large cities (Onguene *et al.*, 2018).

Furthermore, the Musoshi FCBM supports the thesis of Vranken *et al.* (2015). They show that the influence of human activities on surrounding natural resources depends on village size; this is evidence that community forestry is a useful element in the configuration and composition of land in the Miombo woodland. According to Mouhamadou (2019), these landscape indices make it possible to validate the detection changes by revealing three notable processes in the FCBMs. Initially, savannization is characterized by the degradation of intact and degraded open forest areas in favour of savannah areas (Figure 11). Consequently, the loss of intact and degraded open forest areas to other land-cover classes characterized deforestation. Finally, afforestation results in an increase in the relative density of woody species within forest classes, following the dynamics of natural succession combined with community forestry actions. This corroborates the results found by (Nkombe *et al.*, 2023) in the Mikembo sanctuary in Upper-Katanga.

The once compact forest areas are now opened in a matrix dominated by savannah areas (Sikuzani *et al.*, 2023). Customary land law dictates that the plant resources in a plot of land belong exclusively to the landowner and, by default, to the chief of the land (Forestier, 2002). This provision often leads to conflicts, as the reduction in plant production results in the exploitation of forest areas (Tchatchou et al., 2015). In the study area, customary decisions take precedence over those of the FCBM management committees, rendering the committee powerless to implement good governance practices (Baraka *et al.*, 2022; Nghonda *et al.*, 2023). Furthermore, the degradation of the vegetation cover in the FCBMs is primarily due to human activities (Muteya *et al.*, 2023; Sikuzani *et al.*, 2023) and climatic variations (Gansaonré, 2018; Hountondji, 2017).

Moreover, production systems in the study area are extensive (FAO, 2016), i.e. depending on the increase in cultivated area to increase yield. The nature of the agricultural dynamics observable in the FCBMs area is largely driven by the evolution of charcoal production. Nge *et al.*, (2020) found that the informal nature of charcoal production accelerates land cover changes in the Lubumbashi hinterland, due to easy access to wood resources (Barros *et al.*, 2022). Consequently, abandoned fields are increasingly converting to savannahs, further diminishing forest cover (Soulama *et al.*, 2015). This shift poses a threat to agriculture, as recent increases in agricultural production in the West African sub-region have been largely due to the expansion of cultivated land, as observed by Djoufack (2011). Miombo project implementation shows growth in spatial structure indices between 2017 and 2019, while this trend declines between 2019 and 2021, with an increase in the number of patches indicating forest fragmentation or dissection (Table 5).

Hence results, biodiversity is being lost due to the destruction of many natural habitats (Ndavaro *et al.*, 2021; Tshanika *et al.*, 2023), mining directly degrading biodiversity in the FCBMs through mineral extraction (Pa *et al.*, 2010), and permanent risk of amplification of environmental and public health problems due to the copper and cobalt surface soils contamination (Faucon *et al.*, 2018). In this sense, regular monitoring of changes in land use, as has been done in this work, shows that land cover is a fundamental variable in environmental management and in understanding how it works. Covid-19 has negatively affected the project's efforts as shown by the regressive trend in the period

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between 2019 to 2021 (Table 5). This finding corroborates the one found in the same area by (Sikuzani *et al.*, 2024). This would be due to the cessation of support activities for the local committees in the process of implementing and appropriating project objectives from May 2019 to November 2020 (Sikuzani *et al.*, 2024). This resulted in the return of charcoal production activities to serve large agglomerations with an exponential increase of actors looking for how to survive (Murhula et al., 2025). Land conflict is a second element that promotes the loss of biodiversity in FCBMs.

Mining companies are responsible for most of the conflicts (Messina, 2014). A topological study that can define the number of terminals for each FCBM according to its shape is necessary for their integral protection while prioritizing the restoration of positive relations between mining companies and local communities by developing a common centre of interest.

CONCLUSION

This study assessed the impact of community forestry on the landscape dynamics of FCBM in Upper-Katanga, using a diachronic analysis of land cover between 2015 and 2021. The results reveal significant changes in the FCBM forest areas. Trends observed in *Milando*, *Musoshi* and *Kyunga* indicate substantial degradation since 2015, leading to the expansion of demoted forest and savannah areas. The period between 2017 to 2019 highlights the impact of community forestry on FCBM's spatial configuration, with the densification of savannah areas promoting afforestation within the region. The transformation of forest areas has affected their extent, number, and type. The Miombo community forest management project has notably contributed to the regression of dense vegetation areas (intact and degraded open forest). Spatial analyses indicate that degraded forests are the dominant class in most FCBMs, with Intact Open Forests in continual decline. Therefore, reassessing the project's broad strategies is essential to ensure the sustainability of its activities in these areas.

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