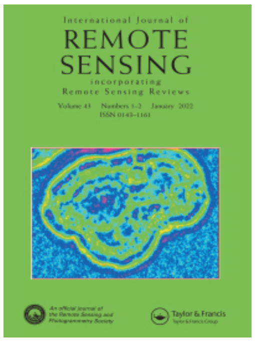

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Contribution of 'human induced fires' to forest and savanna land conversion dynamics in the Luki Biosphere Reserve landscape, western Democratic Republic of Congo

N. C. Cirezi[a,b,c,d], J-F. Bastin[c], E. Tshibasu[e], E. T. Lonpi[a], G. B. Chuma[b,f], Y. Mugumaarhahama[b,d], K.R. Sambieni[a], K. C. Karume[b], R.S. Lumbuenamo[a,g] and J. Bogaert[a,c]

[a]Department of protected areas management, Ecole Régionale Post-universitaire d'Aménagement et de Gestion intégrés des Forêts et Territoires tropicaux (ERAIFT), Kinshasa, Democratic Republic of Congo; [b]Department of Environment and Land Resources Management, Faculty of Agriculture and Environmental Sciences, Université Evangélique en Afrique, Bukavu, Democratic Republic of Congo; [c]TERRA Teaching and Research Centre, Gembloux Agro-Bio Tech, University of Liège, Gembloux, Belgium; [d]Environmental management, Insitut supérieur de développement rural(ISDR/KAZIBA), Kaziba, Democratic Republic of Congo; [e]Forest and Agriculture Program, World Wildlife Fund (WWF), Kinshasa, Democratic Republic of Congo; [f]Laplec, UR SPHERES, University of Liège, Belgium; [g]Department of Natural Resources Management, Faculty of Agriculture, Université de Kinshasa, Kinshasa, Democratic Republic of Congo

ABSTRACT

Human-induced fire is one of the most important determinants of forest cover and change in tropical and subtropical regions of the world. Yet its impact on forest cover and forest cover change remains unclear, as fires in Africa generally do not spread over very large area. This is particularly the case in the Democratic Republic of Congo (DRC), a region of the world that is still poorly investigated. Here, we propose to study the effect of human-induced fire on land use and land cover change in a protected area of the DRC, i.e. the Luki Biosphere Reserve (LBR). We investigate tree cover changes in and around the reserve between 2002 and 2019 using Landsat 7 ETM+, Landsat 8 OLI/TIRS and MODIS MCD12Q1 images and quantify human induced fires using MODIS MCD64A1 images. The study combines land use and land cover (LULC) change detection analysis of four images, two acquired in 2002 and two acquired in 2019, with multi-temporal assessment of annual burnt area acquired between 2002 and 2019 from MODIS MCD64A1 to assess the role of fire in LULC changes and the sensitivity of different LULC types to fire. The results show a dynamic conversion of primary forest to secondary forest over about 16% of the area, the evolution of savanna to secondary forest over 9.6% (Landsat image) and the replacement of secondary forest by savanna over 8.1% (MODIS image) of the total area of Luki Reserve. Of the total area undergoing land use change, 34.1% (Landsat image) and 35.7% (MODIS image) were caused by fire, which however did not cause a significant LULC change. For the LULC types that experienced fire events, the least stable type was

KEYWORDS
Land use and land cover; forest fire; slash and burn agriculture; remote sensing; MODIS; Landsat; spatial correlation; logistic regression model; Luki Biosphere Reserve

CONTACT N. C. Cirezi nadegecirezi@gmail.com Department of protected areas management, Ecole Régionale Post-universitaire d'Aménagement et de Gestion intégrés des Forêts et Territoires tropicaux (ERAIFT), Kinshasa 15 373, Democratic Republic of Congo

primary forest, which had the lowest stability rate (34.2% and 23% for Landsat and MODIS image analysis, respectively) compared to others. This result illustrates the importance of fire as a driver of primary forest loss and degradation in the region. Despite the high exposure of savannas to fire events, they were not significantly destabilized by fire (stability rates of 86.3 and 97% for Landsat and MODIS analysis, respectively). Future analyses should focus on discriminating between different fire types to better understand the complex relationship between fire and ecosystem conditions.

1. Introduction

According to data published by the Global Forest Watch (GFW), approximately 12.2 million hectares of tree cover were lost in the tropics in 2020 (Anders 2020). Among the countries most affected by primary forest loss in the last year (2020), the Democratic Republic of Congo (DRC) is in second place, after Brazil, with an average loss of about 500,000 ha (Global Forest Watch 2021). From 2002 to 2020, the total area of primary rainforest in DRC decreased by 5.1% (Anders 2020). Since the last decade, the country is placed at the top of the list of countries in terms of primary forest area lost (de Wasseige et al. 2012, 2014).

Compared to other tropical regions of the world, where deforestation is mainly a result of commodity cultivation (palm plantation in Southeast Asia, soy and grazing in America), in tropical Africa, deforestation and forest degradation are mainly dominated by shifting cultivation on bushland at a rate of approximately 92% leading to either replacement of primary forest by other land use types or its degradation into secondary forest (Curtis et al. 2018; Tyukavina et al. 2018).

In the DRC, deforestation and forest degradation are mainly the result of the expansion of slash-and-burn agriculture (the main form of agriculture in the country) (Ickowitz et al. 2015; Katembera et al. 2015) combined with fuelwood extraction, mining, logging and urbanization (Paluku 2005; Duveiller et al. 2008; Sikuzani et al. 2017; MECNT 2012; Megevand 2013; Deklerck et al. 2019). Although mainly practiced on a small scale, shifting cultivation can range from a few hectares to hundreds of hectares (Harris et al. 2017; Potapov et al. 2012; de Wasseige et al. 2014). Contributing to up to 92% of the deforestation in the DRC (Tyukavina et al. 2018), slash-and-burn agriculture is supported by the high population growth rate (currently estimated at 3.1% in DRC (World Bank 2021) and expected to double by the end of the century), accelerated urbanization and high levels of poverty (Megevand 2013). The lack of alternative sources of income leads the population to depend mainly on natural resources for basic commodities and household energy needs (Lubalega et al. 2018; Potapov et al. 2012).

Indigenous communities have been managing landscapes with fire over several millennia (Peltier et al. 2014; Klimaszewski-Patterson et al. 2018). Fire is widely used as a low-cost and effective tool to manage and transform land for agriculture and grazing, to improve hunting conditions, to clear dense vegetation and to control pests (Kim, Sexton, and Townshend 2015; FAO 2020; Deklerck et al. 2019). Among the various categories of fires, forest fire, mainly of human origin (voluntary or accidental), is used for domestic activities such as the opening fields for agriculture, honey harvesting, brush clearing,

Figure 1. Opening of fields by slash-and -burn in the Kisavu enclave of Luki Biosphere Reserve in the western part of Democratic Republic of Congo.

livestock and hunting (FAO 2010; Posner, Maercklein, and Overton 2009; Zhao et al. 2021; Tyukavina et al. 2022). Forest fires are most documented in Africa and in DRC as one of the main causes of land cover and land use change leading to landscape fragmentation (FAO 2020; Bogaert et al. 2008; Zhao et al. 2021). Savanna fires, which also occur several times a year, penetrate the surrounding fields and lead to savannisation of the environment and a reduction in traditionally slash-and-burn arable land (Peltier et al. 2014). As illustrated in Figures 1 and 2, fire is mainly used for two purposes in the LBR landscape, either for preparing lands for agriculture degrading the forest cover from primary to secondary forest or for savanna regeneration.

Globally, several studies have been conducted to assess the contribution of fire to forest loss (Tyukavina et al. 2022; Zhao et al. 2021). Locally, few studies have documented the contribution of these practices to land cover and land use changes, which is important for sustainable planning. In this paper, we combine medium and high-resolution remote

Figure 2. Setting fire to a savanna in the the Kibuya enclave of the Luki Biosphere Reserve in the western part of the Democratic Republic of Congo.

sensing datasets to study the effect of human-induced fires on land use and land cover (LULC) in the landscape of the LUKI Biosphere Reserve (LBR), one of the three biosphere reserves in the DRC, a relic of the Mayombe forest that has been exposed to several cycles of degradation (WWF-RDC 2009). The reserve is located between two main roads with heavy traffic (Matadi-Boma and Boma-Tshela) and is close to the megacity of Kinshasa, which exposes the reserve to overexploitation (Pendje and Mbaya 1992; Michel et al. 2021; Cizungu et al. 2021). Several studies (Rageade 2014; Michel et al. 2021; Cizungu et al. 2021) have highlighted the role of fire regimes in LULC changes and potentially explanatory causes without properly quantifying their contribution or their behaviour in the different types of LULC. We propose here to quantify the contribution of fire to LULC, based on methods used to characterize fire originally developed in Zhihua, Ballantyne, and Annie Cooper (2019) and van Wees et al. (2021) but adapted to the case and the scale of the Luki Biosphere Reserve and highlighting 2 forest types (primary and secondary forests) often combined in many studies. Specifically, this study aimed to:

(1) Produce LULC maps using Landsat 7 ETM+(2002), Landsat 8 OLI/TIRS (2019), MODIS MCD12Q1 (for 2002 and 2019) and compare the results obtained at these 2 resolution levels;
(2) Analyse the changes in LULCfor Landsat and MODIS images using a transition matrix;
(3) Analyse fire dynamics using MODIS Collection 6 MCD64A1 burnt areas from 2002 to 2019;
(4) Evaluate the sensitivity of different land uses and land covers to fire, and the effect of fire through correlation tests.

2. Materials and methods

2.1. Study area

This study was conducted in the Luki Biosphere Reserve (LBR) (WWF-RDC 2009). The LBR is located in the south-western part of the Democratic Republic of the Congo (5.3–5.9° N – 12.8–13.8° E) and about 120 km east of the Atlantic coast (Figure 3). This reserve is subdivided into three major zones: the core zone dedicated to integral protection, the buffer zone and the transition zone where community activities are allowed (WWF-RDC 2009). The reserve also has four enclaves including Kimbuya, Kyobo, Kisavu and Tsumba-Kituti. According to the Köppen-Geiger classification, the reserve has a tropical climate of the AW5 type (tropical savanna or tropical wet and dry climate) marked by a significant maritime influence with an average annual rainfall of 1095.66 mm and annual mean temperature of 24.65°C (Harris et al. 2020). The dry season holds for about 5 months from mid-May to mid-October and alternates, with a rainy season covering the rest of the year. There is also a short dry season during January and February. The vegetation of the Luki area is a mosaic of habitats consisting of dense forests, savannas and degraded forests (Nsenga 2001; Lubini 1997). The inhabitants of the Mayombe area around the LBR depend mainly on the forests for hunting, agriculture and fuelwood collection. They also depend on the savannas for grazing livestock and growing certain types of crops (Deklerck et al. 2019).

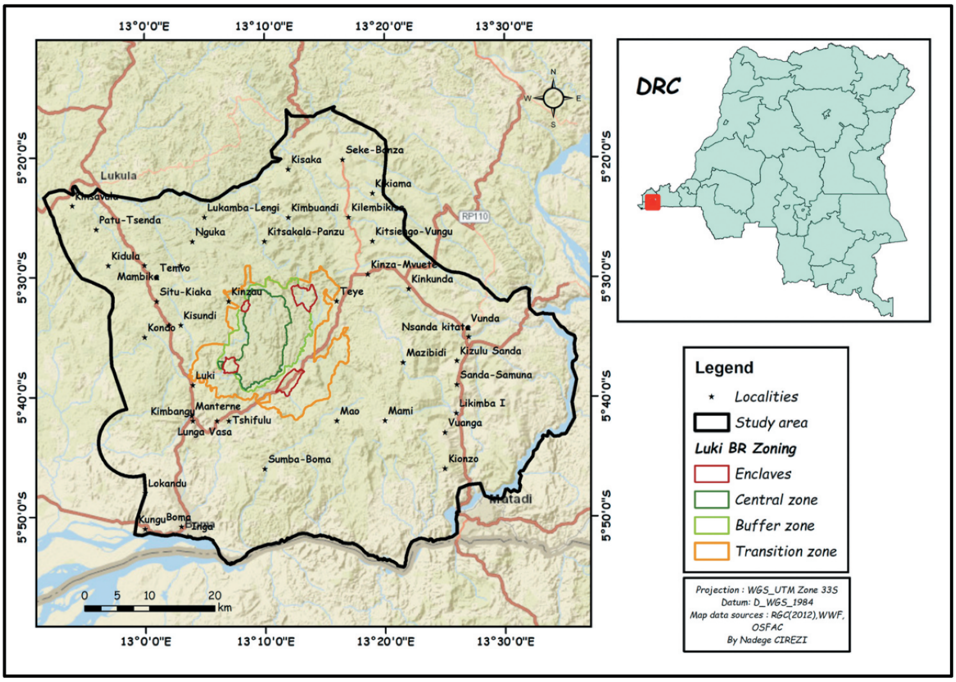

Figure 3. Study area: Luki Biosphere Reserve, western Democratic Republic of Congo (DRC).

As argued in other studies (Allan et al. 2017; Laurance et al. 2012), considering buffer zones when assessing protected areas degradation provides a better understanding of degradation processes. The LBR was considered with its surroundings extending to 20 km over the reserve. Being also part of the European Union project 'Strengthening the resilience of local communities in Luki and Mai-Ndombe in the DRC to climate change', the boundaries of the study area under consideration correspond to the project intervention area that was drawn following the natural and administrative boundaries.

2.2. Data sources

2.2.1. Land use and land cover data

The assessment of land use and land cover dynamics (LULC) from 2002 to 2019 is carried out using Landsat 7 ETM+ (2002), Landsat 8 OLI/TIRS (2019) and MODIS Land Cover Type

Table 1. Characteristics of the images used for LULC analysis.

Sensor	Acquisition date	Identification	Cloud cover	Used bands	Resolution(m)
Landsat 7 ETM+	11 April 2002	Path/Raw:183/64	<10%	B4/NIR	30
				B3/RED	30
				B2/GREEN	30
Landsat 8 OLI/TIRS	18 June 2019	Path/Raw:183/64	<10%	B5/NIR	30
				B4/RED	30
				B3/GREEN	30
MODIS Land Cover Type MCD12Q1	2002–2019	Tile h9v9	-		500

Product (MCD12Q1 for 2002 and 2019) images. The characteristics of the images used are presented in Table 1.

Landsat images were downloaded free of charge from https://earthexplorer.usgs.gov/ and MODIS product from https://ladsweb.modaps.eosdis.nasa.gov/search/order/. For the Landsat images, the two dates were chosen to maximize image quality (low cloud cover: 6%) and to maximize the period covered by MODIS burnt area products (starting in 2001) used to assess the bush fire occurrence. The 2002 image corresponds to the transition period between the dry and rainy season and the 2019 image corresponds to the beginning of the dry season. For both dates, the phenology of the vegetation is not very different. The MODIS MCD12Q1 images cover the period from 2002 to 2019 and data are annual time span.

2.2.2. Burnt areas data

Fires were identified using annual burnt areas covering the period from 2001 to 2019. The burnt area data were downloaded free of charge from https://firms.modaps.eosdis.nasa.gov/ in shapefile format. The shapefile was derived from the monthly version of GeoTIFF image with the same projection and geographical extent as the GeoTIFF windows of the subcontinent (Giglio et al. 2018). The burnt area estimation was based on the burnt areas of the MODIS 6 MCD64A1 collection from Aqua and Terra at 500 m resolution. This collection offers better detection of small fires, a significant reduction in unmapped areas, and a reduction in the temporal uncertainty of fire date comparing to previous collections and fire points (Giglio et al. 2018). The data used were produced by the University of Maryland and distributed by NASA’s Fire Information for Resource Management System (FIRMS) (Giglio et al. 2006; Müller and Suess 2011). For this study burnt areas were chosen overactive fires because, as shown by van Wees et al. (2021), burnt areas perform better than active fires when assessing the contribution of fires to forest loss.

2.3. Data processing

2.3.1. Land use and land cover analysis

To determine the different land use and land cover types for the 2 years (2002 and 2019) two types of images were analysed and compared.

2.3.1.1. Landsat images. The LULC types for the years 2002 and 2019 and the change map were produced following several steps:

- **Image pre-processing** was essential and aimed to establish a more direct link between the data and biophysical phenomena it represents. As the images acquired from USGS were geometrically corrected in advance with pixels geolocated precisely based on the UTM WGS84 zone 33S projection; the radiometric processing consisted of the radiometric calibration (for the conversion of the original numerical values into reflectance values), dark subtraction and atmospheric correction using Quick Atmospheric Correction algorithm (Bernstein 2012) in Envi 5.1. A cloud mask (6% cloud cover) was then applied to both images to obtain comparable images for the 2 years. After performing the basic operations of image enhancement, to adjust and improve the specific visual qualities of the image using histogram equalization, a false colour composition (Near Infrared Red (NIR)-Red (R)-Green (G) corresponding to R (Red) G (Green) Blue (B) channels) was created (Cotonnec et al. 2005). These bands correspond to bands 5/4/3 for Landsat 8 image and 4/3/2 for Landsat 7 image.

- **Pre-stratification and nomenclature establishment**: The aim was to define the different land use and land cover classes and their spectral characteristics before running the classification. It was carried out through the false colour composition and the unsupervised classification that allowed to highlight the principal patterns corresponding to major groups of land uses. This was completed by a quick verification of LULC types by interpreting Very High Resolution (VHR) Google Earth image (July 2012 and July 2015), by collecting training reference points from field observations (June 2019) and by consultation with previous studies on vegetation in the region(Lubini 1997). The units presented in Table 2 have been selected for classification.
- **Classification**: After identification and spectral recognition of the classes of land use, map derivation from the images was done using supervised classification with the 'Maximum Likelihood' algorithm. This algorithm is based on Bayes' rule and uses the statistics of training plot samples to calculate the probability that each pixel belongs to one of the land use and land cover classes (Cotonnec et al. 2005). The model was calibrated using 80% (640 points) of the training data collected on field in 2019 and combined VHR Google Earth images (July 2012 and July 2015) interpretation. For both images (2002 and 2019), five LULC types (primary forest, secondary forest, savanna, anthropogenic zone and waterbody) were differentiated using ENVI 5.1. Figure 4 presents the distribution of control points in the study area.
- **Accuracy assessment**: To assess the reliability of the classification, the remaining 20% (160 points) of the training samples collected were used to test the predictive performance of the model using the confusion matrix. For each image, the overall accuracy and the Kappa Coefficient (K) were generated using formula described in (Congalton 1991).

2.3.1.2. MODIS MCD12Q1 images. The MODIS Land Cover Type (MCD12Q1) product acquired from the NASA website maps the global land cover at 500-m spatial resolution at annual time step for five different land cover legends: International Geosphere-Biosphere Programme (IGBP) legend, University of Maryland (UMD) legend, Leaf Area Index (LAI)

Table 2. Identity and definition of selected units for the supervised classification.

N°	Classes	Description	Appearance on "False color" composition
1	Primary forest (PF)	Dense forest where the human footprint is nowhere noticeable. This forest is characterized by a closed canopy	Dark Red
2	Secondary forest (SF)	Degraded forest (Where agricultural activities are generally carried out)	Light red
3	Savanna (S)	Vegetation mainly grassy	Dark red with a fine texture
4	Anthropogenic zone (AZ)	Built-up areas and bare soil	Greenish
5	Water body (WB)	Watercourses (Rivers)	No colour

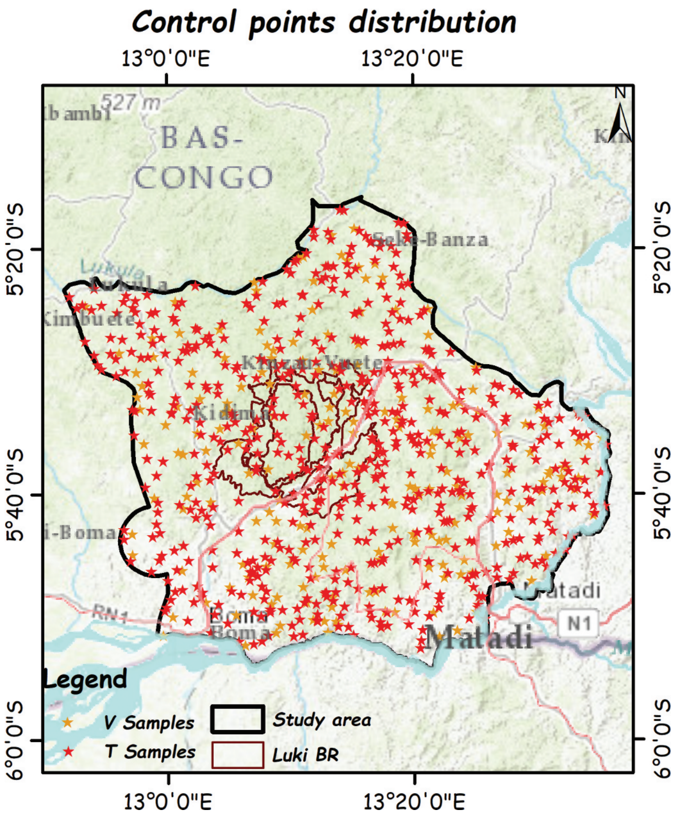

Figure 4. Control points distribution. Legend: V samples: validation samples; T samples: training samples.

legend,
BIOME-Biogeochemical Cycles (BGC) legend and Plant Functional Types (PFT) legend (Sulla-Menashe and Friedl 2018). Of these legends, the University of Maryland (UMD) classification legend was selected to determine the LULC types. Data are provided in HDF4 format and are already classified using supervised classification of MODIS reflectance data. The classification considers 15 land cover types of which 10 have been identified in the study area (deciduous evergreen forest, closed shrublands, wooded savannas, savannas, grasslands, permanent wetlands, croplands, urban and built-up areas, croplands and natural vegetation mosaic). The downloaded h9V9 tile was clipped to the study area, and the classes were combined to be consistent with those already considered in Table 2 for Landsat images. Their area was then determined to be ha and %. To obtain comparable results for both types of images, the 6% cloud mask considered for the Landsat images was applied. Classification maps for the years 2002 and 2019 were thus produced and the areas for each class were determined.

2.3.2. Change analysis

Using ArcGIS 10.7.1, changes were highlighted through a transition matrix generated using intersect function. The transition matrix was created to identify the transition frequencies between classes over the study time span for the two types of images

(Bogaert, Colinet, and Mahy 2018; Bamba et al. 2008). To analyse the evolution of the surfaces of the different classes during the study period, a curve representing the annual trend of the surfaces of the classes has been drawn.

2.3.3. Burnt areas

The annual burnt areas obtained from FIRMS were used to produce a cumulative burnt area map covering the period 2002–2019. The result is a shapefile with values ranging from 0 to 18 representing the observed annual fire frequency for the last 19 years. Each surface has burned at least once between 2002 and 2019.

2.4. Assessment of human made fire contribution to observed changes

To correlate fires with observed changes (2002–2019) and determine the proportion of fire in the observed changes, intersections between burnt areas and transition classes initially converted into shapefile format were performed for Landsat and MODIS LULC change detection results. To have the same spatial resolution, before their conversion into shapefiles, the Landsat images were aggregated to the pixel size of the burnt area (500 m) using the 'Resample' function (Zhihua, Ballantyne, and Annie Cooper 2019) in ArcMap 10.7.1. The stability rate of the classes was also determined by assessing the proportion of the area that remained stable despite the passage of fire relative to the total area occupied by the class (combining stable and transitional areas).

To assess the impact of LULC on fire occurrence, the binary logistic model was used. The burnt areas collected by the MODIS sensor on board the Aqua and Terra platforms were considered as the dependent variable and the LULC as the explanatory variable. The binary logistic model was also used to evaluate the effects of fire occurrence on changes in the LULC. In the latter model, the occurrence of a change in LULC served as the dependent variable, while the occurrence of fire served as the explanatory variable. All of these analyses were performed using R 4.0.5.

Figure 5 summarizes the methodology used for the data analysis.

3. Results

3.1. Land use/land cover maps and precision assessment

The overall classification accuracy obtained from the confusion matrix for each LULC classification map ((a) and (b)) was estimated at 81% for 2002 and 85.0% for 2019. The overall statistical Kappa values were 0.72 and 0.77, respectively. The percentage and coverage of major LULC types in and around Luki BR are presented in Figure 6 and the proportions for each class in Table 3. Image classification of 2002 and 2019 results showed five distinct LULC classes: primary forest, secondary or degraded forest, savanna, anthropogenic areas and waterbodies. For Landsat image analysis, in 2002 the study area showed a dominance of 2 classes: savanna, which covered 37.9% of the total area equivalent to 117,960.6 ha and primary forest, which covered 30.2% of the area equivalent to 93,959.2 ha. The secondary forest (degraded forest) class represented 29.5% corresponding to 91,687.1 ha of land. The water body class and the anthropogenic zone were the least represented classes, with 1.2% and 1.1% respectively corresponding to 3583.2 ha

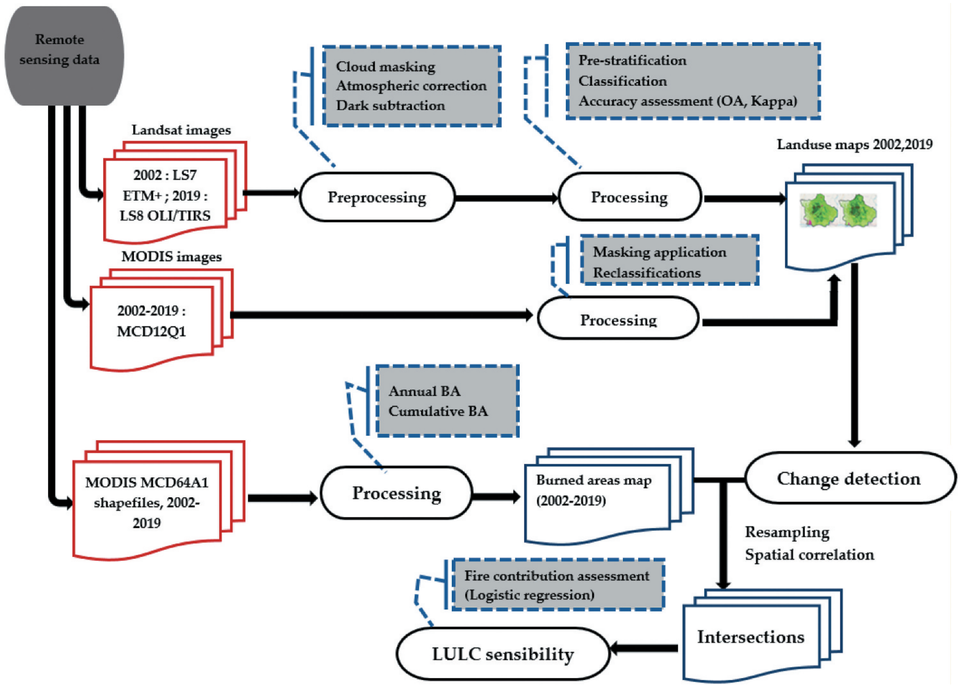

Figure 5. Data processing workflow.

and 3465.1 ha. In 2019, 51.9% of the study area was covered by secondary forest, which corresponds to 161,148.7 ha of land. It was followed by the savanna at 24.5% (76191.8 ha). The primary forest showed a considerable decrease in surface area(51504.1 ha corresponding to 16.6%). The anthropogenic zone covered 4.6% (15238 ha). The water body class represents 1.1% of the study area corresponding to 3465.1 ha. The result synthesis is presented in the Table 3 below.

For MODIS MCD12Q1 image analysis, the landscape is dominated by three land cover types in 2002: secondary forest, savanna and primary forest representing 115,255.1 ha, 100425 ha and 90,000 ha, respectively, which correspond to 37.1%; 32.3% and 29%. Water bodies and anthropogenic zones, respectively, represent 3600 ha (1.2%) and 1375 ha (0.4%). In 2019, the secondary forest occupied the first position, with 174,900 ha corresponding to 43.7% followed by the savanna that covered 121,805 ha (39.2%) and the primary forest class, with 47,000 ha (15,1%).

For the two sensors, the results showed a continuous decreasing trend of the primary forest area. The class lost 13.6% and 13.8% of its area for the Landsat and MODIS images, respectively. For savannas, the results of Landsat image analysis indicate a reduction of 8,4% in their area. MODIS images, on the other hand, indicate a slight increase in the area occupied by savannas (growth of 6.9%).

For the secondary forest, the two sensors indicated the increase of its area at different rates: 22.3% for Landsat Images and 6.6% for MODIS Images. The same trend was observed for the anthropogenic zone class. The water class, on the other hand, did not experience any change in area.

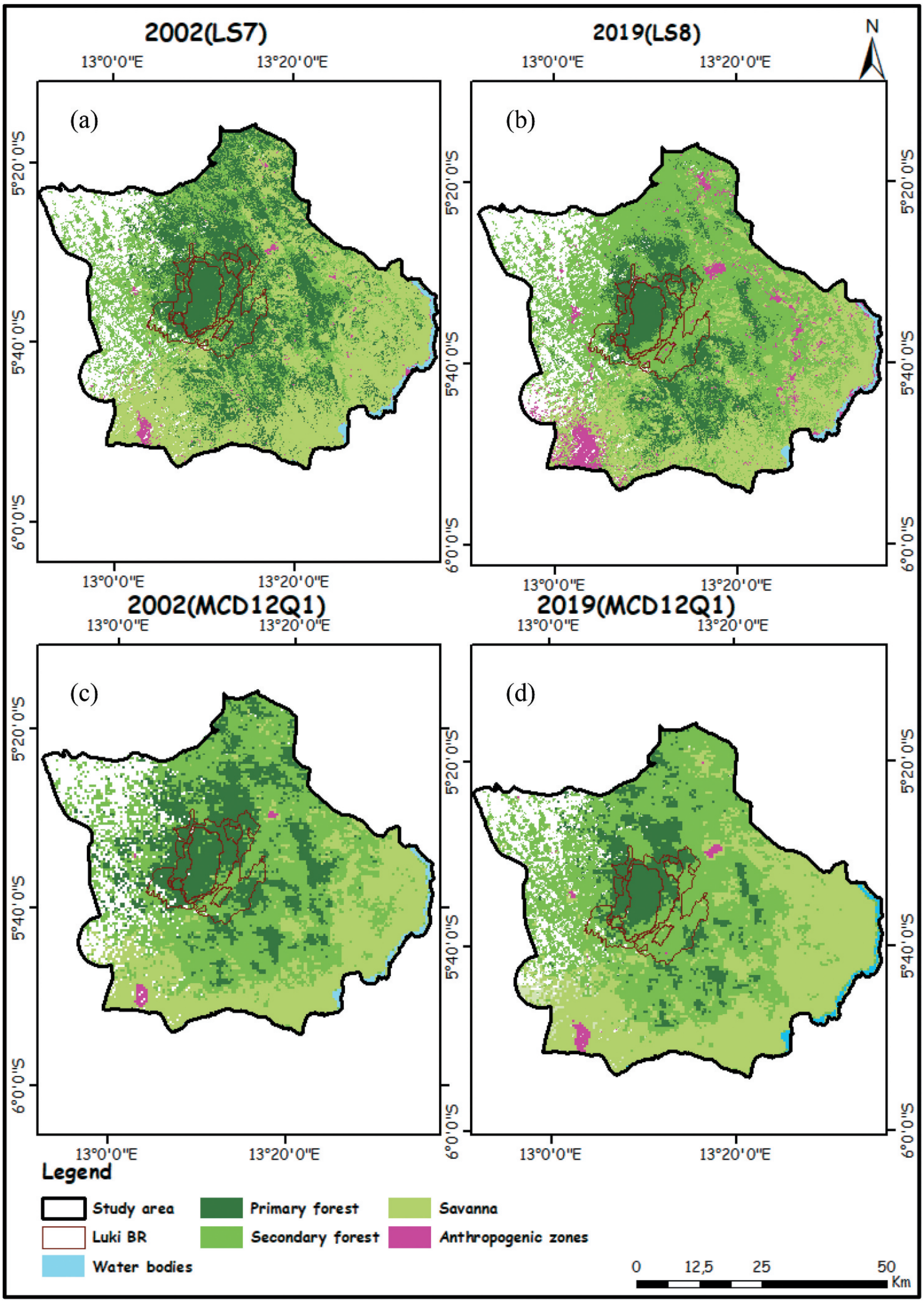

Figure 6. Land use and land cover maps for the years 2002 and 2019 in Luki biosphere reserve landscape, western Democratic Republic of Congo. Legend: 2002(LS7): LULC map of 2002 obtained from Landsat 7; 2019(LS8): LULC map of 2019 obtained from Landsat 8; 2002(MCD12Q1): LULC map of 2002 obtained from MODIS MCD12Q1, 2019(MCD12Q1): LULC map of 2019 obtained from MODIS MCD12Q1. White pixels represent no-data values generated with cloud mask.

Table 3. Land use and land cover class areas (ha and %) for 2002 and 2019 and change occurred between 2002 and 2019 in the Luki Biosphere Reserve landscape for MODIS and Landsat Image analysis. Positive change values represent an increase in the area of a class and negative values represent a decrease in the area of the class.

	Years								Change	
	2002				2019				2002–2019	
	LS7		MCD12Q1		LS8		MCD12Q1		LS	MCD12Q1
LUCL classes	ha	%	ha	%	ha	%	ha	%	%	%
Primary forest(PF)	93959.2	30.2	90000	29.0	51504.1	16.6	47000	15.1	−13.6	−13.8
Secondary forest(SF)	91687.1	29.6	115255.1	37.1	161148.7	51.9	174900	43.7	22.3	6.6
Savanna(s)	117960.6	37.9	100425	32.2	79299.3	29.5	121805	39.2	−8.4	6.9
Anthropogenic zones (AZ)	3583.2	1.2	1375	0.4	15238	4.6	2350.1	0.8	3.4	0.3
Water bodies (WB)	3465.0	1.1	3600	1.2	3465	16.6	3600	1.2	0	0.0
	310655.1	100	**310655.1**	**100**	**310655.1**	**100.0**	**310655.1**	**100**		

Legend: LULC: Landuse Landcover. LS7: Landsat 7. LS8: Landsat 8. LS: Landsat. ha: hectare.

3.2. LULC change analysis

The transition matrix presented in Table 4 indicates that for Landsat image analysis, out of the 30.2% of the landscape that was occupied by the PF class in 2002, 13.6% remained PF and 16.4% was converted into SF in 2019. The savanna class underwent a positive evolution due to the conversion of 9.6% of its area into SF and 3.1% into anthropogenic zones. The SF has also experienced gains due to the conversion of 16.4% of PF and 9.6% of savannas in 2019. The class of Anthropogenic Zones also experienced gains due to the conversion of 3.1% of savannas. 0.5% of SF and 0.1% of PF. The most stable class was the WB; there was no variation in this class. The major part of the changes is located at the top of the diagonal and represent negative changes. The most important positive change has been the conversion of savannas into secondary forest. The transition matrix obtained from MODIS MCD12Q1 image analysis presented in Table 5 indicates that out of the 29.0% of the landscape that was occupied by the PF class in 2002, 12.5% remained PF and 16.2% was converted into SF by 2019. The SF has experienced gains due to the conversion of 16.2% of PF and 1.2% of savannas into SF in 2019. The savanna class has also gained of area due to the conversion of 8.1% of SF. The AZ class experienced gains due to the conversion of 0.2% of secondary forests and savannas. The most

Table 4. Transition matrix obtained from Landsat 7/8 image analysis and representing changes and conversions among classes in the Luki Biosphere Reserve from 2002 to 2019.

		2019					
LULC Conversions		Primary forest (%)	Secondary forest (%)	Savannas (%)	Anthropogenic zones (%)	Water bodies (%)	Total (%)
2002	Primary forest (%)	**13.6**	16.4	0.2	0.1	0.0	**30.2**
	Secondary forest (%)	2.7	**25.9**	0.5	0.5	0.0	**29.6**
	Savanna (%)	0.3	9.6	**24.9**	3.1	0.0	**37.9**
	Anthropogenic zone (%)	0.0	0.1	0.2	**0.9**	0.0	**1.2**
	Water bodies (%)	0.0	0.0	0.0	0.0	**1.1**	**1.1**
	Total (%)	**16.6**	**51.9**	**25.8**	**4.6**	**1.1**	**100**

Table 5. Transition matrix obtained from MODIS MCD12Q1 image analysis representing changes and conversions among classes in the Luki Biosphere Reserve from 2002 to 2019.

	LULC Conversions	2019 Primary forest (%)	Secondary forest (%)	Savanna (%)	Anthropogenic zones (%)	Water bodies (%)	Total (%)
2002	Primary forest (%)	**12.5**	16.2	0.3	0.0	0.0	29.0
	Secondary forest (%)	2.5	**26.3**	8.1	0.2	0.0	37.1
	Savanna (%)	0.0	1.2	**30.8**	0.2	0.0	32.2
	Anthropogenic zones (%)	0.1	0.0	0.0	**0.4**	0.0	0.5
	Water bodies (%)	0.0	0.0	0.0	0.0	**1.2**	1.2
	Total (%)	15.1	43.7	39.2	0.8	1.2	100

stable class was that of the water bodies, which did not experience a transition. A large number of changes are located at the top of the diagonal and represent negative changes. The most important positive change has been the conversion of savannas into secondary forest (1.2%).

3.3. Evolution of land use classes and distribution of burnt areas

The results presented in Figure 6 show the variation in annual areas of land use classes obtained from MODIS MCD12Q1 as well as the burnt areas obtained from MODIS MCD64A1 between 2002 and 2019.

By analysing Figure 7, we notice that the secondary forest and savanna classes are experiencing an increase in their surface area to the detriment of the primary forest class, which is decreasing in area over the years. The classes of anthropogenic areas and water surfaces do not experience significant changes. The burnt areas, however, show a random trend. While the years 2012 and 2013 recorded more burnt areas during the studied period, the opposite situation was observed for the years 2002 and 2015 for which fewer burnt areas were recorded. The distribution of burnt areas shown in Figure 8 indicates that the south-eastern, the north-eastern and south-western zones were the most affected by fires. The same map also shows a significant span of the LBR. That is, 150132 ha has also been affected by fires between 2002 and 2019. Only the north-western zone appears less affected by fires.

3.4. Fire impact assessment on LULC

3.4.1. Burnt areas and LULC transitions

The results presented in Table 6 indicate that fire alone accounted for approximately 34.1% of the transitions in the study area for the results obtained from Landsat image analysis and 35.7% for MODIS image analysis. For the Landsat image analysis, the transitions were mainly noticed by the replacement of primary forests (58.7%) and savanna (28.7%) by secondary forests. The proportion of secondary forests and anthropogenic zones that have transitioned is reduced; it represents less than 5% of all transitions. Fire was responsible for the transition of several classes including primary forest to water surface for which it is the cause at 100%. A similar situation is noticed for the transition of anthropogenic areas into waterbody (85.8%) those of primary forest into secondary forest (66.5%) and those of savanna into waterbody (52.2%) for which the values exceed half. The contribution of fires to the conversion of savanna into secondary forest (44.5%). Of anthropogenic area into savanna (42.2%) as well as savanna

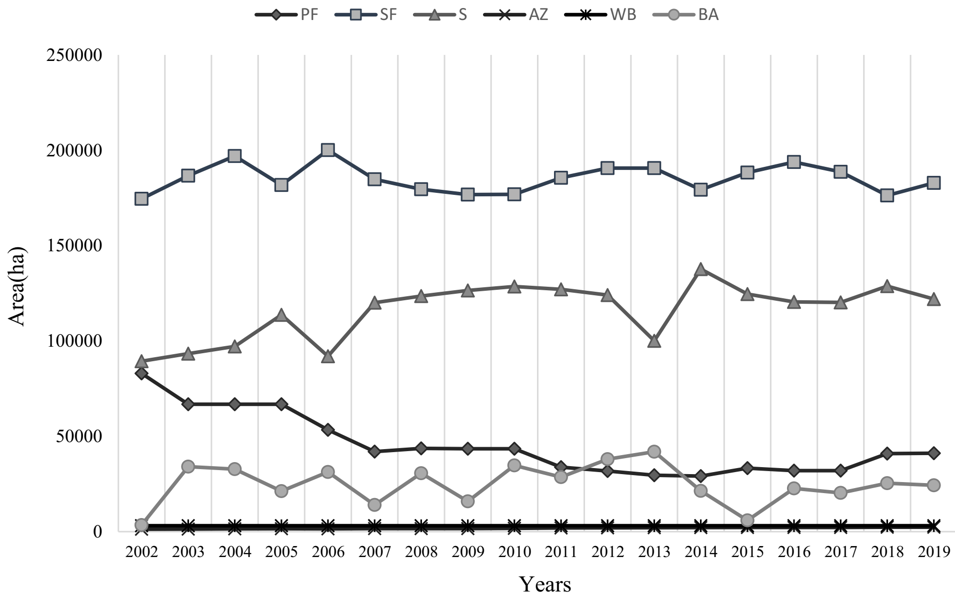

Figure 7. Land use classes and BA evolution. Legend: PF: primary forest, SP: secondary forest, S: Savanna, AZ: anthropogenic zones, WB: water bodies, BA: burnt areas.

into anthropogenic area (36.9%) is also significant. Fire, on the contrary, had no role to play in the transition of waterbodies into other land use classes. For the MODIS image analysis, the main transitions were the conversion of primary forest to secondary forest (48.6%) and the conversion of secondary forest into savanna (37.9%). Fire was most involved in the conversion of secondary forest to savanna, savanna to secondary forest and primary forest to savanna. The rate of fire involvement in the conversion of savanna to anthropogenic area, secondary forest to anthropogenic area and primary forest to secondary forest did not exceed 30%. For the other conversions, fire did not play a major role.

The statistical analysis performed and presented in Table 7 indicates the contribution of fire occurrence to the observed changes.

The results in Table 7 show that fire occurrence is not a driver of LULC change. In fact, fire occurrence multiplies the probability of LULC change by 0.94.

3.4.2. LULC sensitivity to human induced fires

The results in Table 8 indicate that despite the use of fire in the area the LULC remained stable at 75% (MODIS) and 67.2% (Landsat). The savanna class experienced important fire episodes of fire (58.5% and 50.1%, respectively, for Landsat and MODIS image analysis) but was not significantly affected (stability rates 97% and 73.2%, respectively, for Landsat and Modis image analysis). Compared to the savanna class, the primary forest class had a fire rate of 21.8% (MODIS) and 8.5% (Landsat) which strongly affected the stability of the class (34.2% for Landsat image analysis and 23% for MODIS image analysis). The secondary forest class had fire on 18.8% of its cover and was the most stable (86.3%) for Landsat image analysis. It also had fire on 39.6% of its cover with a stability of 57.0% for the MODIS

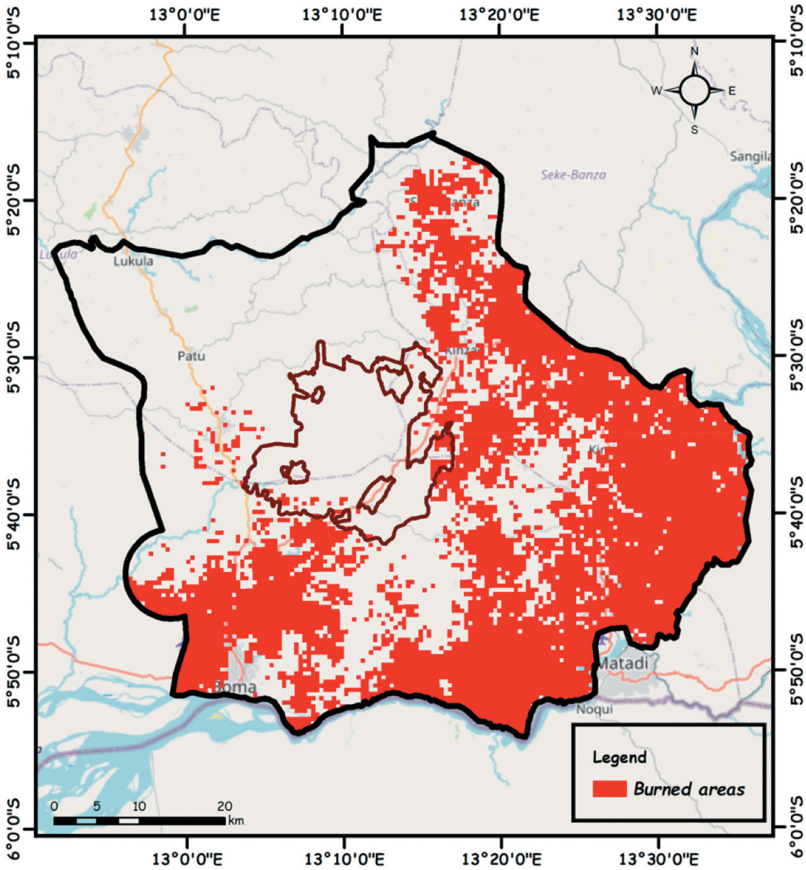

Figure 8. Cumulative burnt areas distribution in the Luki Biosphere Reserve landscape from 2002 to 2019.

image analysis. The influence of man-made fires on anthropogenic areas and water surfaces was not very noticeable. The stability rate was 100% for these two classes (MODIS image analysis) and, respectively, 0% and 80.8% (Landsat image analysis).

The statistical analysis presented in Table 9 indicates the association of fire occurrence f to the initial LULC.

The results in Table 9 highlight that fire occurrences are more associated with the other classes of LULC compared to PF. Overall, the probability of fire occurrence in PF is 11.5 times lower than in savannas. After savannas, fires occur more in anthropogenic areas (2.4 times higher probability of occurrence than in PF). Fires are 1.4 times more likely to occur in SF than in PF.

4. Discussion

4.1. Data and methodology

This study aimed to assess LULC change from 2002 to 2019 in the LBR landscape and to quantify the contribution of human-induced fires in the observed changes using

Table 6. Transitions and contributions of human induced fires to transitions observed in the Luki Biosphere Reserve landscape from 2002 to 2019.

	Total coverage				Proportion due to fire			
	LS		MDC12Q1		LS		MDC12Q1	
Transition classes	ha	%	ha	%	ha	%	ha	%
PF-SF	50730.1	48.7	50225.0	48.6	15084.8	29.7	9189.4	18.3
PF-S	524.3	0.5	900.0	0.9	348.5	66.5	417.8	46.4
PF-AZ	406.7	0.4	25.0	0.0	108.7	26.7	0.0	0.0
PF-WB	2.3	0.0	0.0	0.0	2.3	100.0	0.0	0.0
SF-PF	8150.7	9.2	8025.0	7.8	2499.2	53.6	392.5	4.9
SF-S	1455.8	1.4	39200.0	37.9	219.6	15.1	24645.5	62.9
SF-AZ	0.5	0.0	300.0	0.3	0.1	20.0	77.5	25.8
S-PF	965.8	0.9	125.0	0.1	271.6	28.1	0.0	0.0
S-SF	29548.9	28.4	3850.0	3.7	13139.7	44.5	2010.4	52.2
S-AZ	9731.3	9.3	650.0	0.6	3592.0	36.9	189.4	29.1
S-WB	14.4	0.0	0.0	0.0	7.5	52.2	0.0	0.0
AZ-PF	20.2	0.0	0.0	0.0	5.0	24.7	0.0	0.0
AZ-SF	143.4	0.1	0.0	0.0	30.4	21.2	0.0	0.0
AZ-S	504.1	0.5	0.0	0.0	212.9	42.2	0.0	0.0
AZ-WB	56.5	0.1	0.0	0.0	48.5	85.8	0.0	0.0
WB-PF	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WB-SF	8.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WB-S	24.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WB-AZ	394.4	0.4	0.0	0.0	0.6	0.2	0.0	0.0
Total	**104187.9**	**100.0**	**103300.0**	**100.0**	**35571.5**	**34.1**	**36922.5**	**35.7**

Legend: PF: primary forest; SF: secondary forest; S: Savanna; AZ: anthropogenic zone; WB: water body.

Table 7. Logistic regression associating LULC change with fire occurrence.

	β	SE	Z value	*P*(>|z|)	
Reference = No fire					
Intercept	−0.606	0.002	−389.98	<2e-16	***
Fire	−0.059	0.002	−25.84	<2e-16	***

Legend: β: estimate, SE: standard error, P: *p*value.
*** highly significant at $\alpha = 0.05$ (At $\alpha = 0.05$, this coefficient is statistically different from 0).

a combination of Landsat Images (2002 and 2019), MODIS Land Cover Type Product (MCD12Q1 2002–2019) and MODIS Burnt Area MCD64A1 (2002–2019). This study assumes that all the identified fires are human induced fires since there are almost no documented wildfires in the region (Verhegghen et al. 2016; Curtis et al. 2018; van Wees et al. 2021; Tyukavina et al. 2022). This is an acceptable source of uncertainty given the results obtained in the above-mentioned research and interviews with local communities in the region (illustrative figures in introduction). The human-induced fires include fires used for agricultural purposes as well as bush fires used for savanna regeneration.

LULC has been assessed using a supervised classification based on the Maximum Likelihood algorithm for Landsat images and the classified MCD12Q1 product based on the UMD classification legend(Sulla-Menashe and Friedl 2018).

To validate the quality of Landsat image classifications, the Kappa coefficient was calculated (0.72 and 0.77 for 2002 and 2019 respectively). These values are considered statistically acceptable according to the scale previously provided by Skupinski et al. (2009). The maximum likelihood algorithm is reported to give better results in LULC studies (Vadrevu 2013). The reduced number of classes considered and the definition of homogeneous plots when choosing the training sites have allowed to explain the precisions obtained for the

Table 8. Sensitivity of LULC classes to human induced fires from 2002 to 2019 in the Luki Biosphere reserve landscape.

	Burnt areas (2002–2019)									
	LS		MCD12Q1		LS		MCD12Q1			
	Stable areas		Converted areas		Total area		Fire proportion/Class		Stability rate/Class	
LULC types	LS ha	MCD12Q1 ha	LS ha	MCD12Q1 ha	LS ha	MCD12Q1 ha	LS %	MCD12Q1 %	LS %	MCD12Q1 %
Primary forest	8093.6	2864.36	15544.3	9607.6	23637.9	12471.96	21.8	8.5	***34.2***	***23***
Secondary forest	17173.8	33289.6	2718.9	25115.5	19892.7	58405.1	18.3	39.6	***86.3***	***57***
Savanna	46490.7	71773.1	17010.8	2199.84	63501.5	73972.95	58.5	50.1	***73.2***	***97***
Anthropogenic zones	1251.8	99.6	296.8	0	1548.6	99.6	1.4	0.1	***80.8***	***100***
Water bodies	0	2554.84	0.6	0	0.6	2554.84	0	1.7	***0***	***100***
Total BA	**73009.9**	**110582**	**35571.5**	**36922.9**	**108581**	**147504.5**	**100**	**100**	*67.2*	**75**

Legend: LS: Landsat, BA: burnt area.

Table 9. Logistic regression associating fire occurrence with initial LULCs.

	β	SE	Z value	P(>|z|)	
Reference = PF					
Intercept	−1.174	0.002	−509.26	<2e-16	***
SF	0.3110	0.003	97.89	<2e-16	***
S	2.438	0.003	780.06	<2e-16	***
AZ	0.892	0.010	85.31	<2e-16	***

Legend: PF: primary forest, SF: secondary forest, S: Savanna, AZ: Anthropogenic zones, β: estimate, SE: standard error, P: *p* value.
*** highly significant at $\alpha = 0.05$ (At $\alpha = 0.05$, this coefficient is statistically different from 0).

classifications. The study conducted by Bouetou-Kadilamio, Averti Ifo, and Binsangou (2017) revealed considerable confusion between the degraded forest, crop-fallow and plantation classes. In their classifications, 31.1% and 34.11% of pixels in the crop-fallow and plantation classes in 1986 were assigned to the degraded forest class. This situation is noticed in regions where agriculture is mainly practiced in secondary forests and on a small scale (de Wasseige et al. 2014) as is the case for the Luki Biosphere landscape. The classes of crop-fallow and secondary forests were thus merged because of the difficulty of discriminating at a resolution of 30 m. However, as reported by Michel et al. (2021), considering a high number of training samples can help to reduce the confusion between the two classes.

Two data sources (Landsat 7/8 and MODIS MCD12Q1) were used to analyse the state of LULCs and their changes over time to increase the accuracy of the results obtained from two sources at different levels of resolution. The presence of significant cloud cover in the region (Potapov et al. 2012; Tyukavina et al. 2018) did not allow acquisition of Landsat images at annual steps. This led to the use of MODIS images to complete the data, albeit at medium resolution.

4.2. LULC change assessment

The results obtained revealed important changes in the LBR landscape from 2002 to 2019 for both Landsat and MODIS data. The primary forest has lost 13.7% (Landsat) and 13.6% (MODIS) of its area essentially to the benefit of the secondary forest. The same result has been obtained by Michel et al. (2021) in the Luki BR where he founded the decreasing of 13.26% for the primary forest from 1987 to 2002 considering only the LBR extent. The same trend was observed by Potapov et al. (2012) who found an increase in gross forest cover loss of 13.8% between the period 2000–2010 in DR Congo.

For the savanna class, two trends were noticed. For the Landsat image analysis, the savanna has experienced a decrease in its surface (12.4%) to the benefit of the secondary forest and anthropogenic class. For the MODIS image analysis, the savanna increased at the expense of the secondary forest. Due to the medium resolution of MODIS images, changes over small areas of land may not be noticeable. This is the case of efforts that are undertaken to regenerate anthropogenic savannas into secondary forest state in the Luki region, mostly in small areas. An example is the Manzoni savanna, which was left to regenerate and has been able to evolve into a secondary forest (Deklerck et al. 2019).

The secondary forest recorded the greatest gain in surface followed by the anthropogenic zones that gained surface area both for Landsat and MODIS images but at various rates. The results found by Michel et al. (2021) showed a decrease in the secondary forest class as this was considered separately from the fields and fallows. The fallow crop and built-up areas gained surface area significantly. These results corroborate those found by other authors (Bamba 2010; Dejace 2019; Rageade 2014) in the Luki region and elsewhere (Katembera et al. 2015; Opelele et al. 2020; Useni et al. 2020; Ngabinzeke et al. 2016; Megevand 2013; Potapov et al. 2012) who argue that population growth and expansion increase cultivated area expansion as well as the degradation of natural ecosystems leading to the conversion of primary forest into a mosaic of secondary forest and savanna. The research conducted by Bamba (2010) also mentioned that the decrease in forest area is due to the unsustainable agricultural system and demographic pressure. The low growth rate of secondary forest for MODIS images during the study period can be explained by the fact that in tropical Africa, agriculture is essentially small scale, and this may not be perceptible at such a low-resolution level. The same is true for anthropogenic areas, which often cover small areas in the region. Indeed, in the Luki Biosphere Reserve region a significant increase in population has been noticed in the form of the installation of new villages along the national road that crosses the reserve. This has been followed by an important need for land for agriculture and vital space. It is also important to mention that the high level of poverty that already affects more than 60% of the population in DRC (World Bank 2021) has pushed the population to depend essentially on natural resources for its survival that has consequently increased the demand for and pressure on such resources.

4.3. Human-induced fire impacts on LULC changes

Among the transitions in LULC as observed during the study period. Fire was an explanatory factor of about 34.1% (for Landsat image analysis) and 35,7% (for MODIS image analysis) of the observed changes. This corroborates the results found by van Wees et al. (2021) and Tyukavina et al. (2022)on a global scale. They found that fire was, respectively, the cause of $34 \pm 14\%$ and 26 to 29% of the observed forest losses.

The conversion of secondary forest to savanna, savanna to secondary forest, primary forest to secondary forest, and other minor conversions are explained, on the one hand, by fire (whose contribution rate is generally below 75%) and on the other hand by other factors not investigated in this study. Based on the available literature, these factors include industrial and artisanal logging, hunting, and charcoal production that also contributes to forest degradation (Lubalega et al. 2018; Rageade 2014; Dejace 2019; Katembera et al. 2015). It is also important to notify that some values noted for the contribution of fire to transitions such as the transition of primary forest to waterbodies, waterbodies to primary forest, anthropogenic zones to waterbodies for Landsat image analysis can be due to the often-unexpected behaviour of some pixels during analysis. This does not put into question the results obtained because the confusion matrix shows more than satisfactory results at the reserve scale. The generalization applied also to Landsat images for analysis could also influence the results obtained (Lubalega et al. 2018; Rageade 2014; Dejace 2019; Katembera et al. 2015; Decklerck et al. 2015).

As for the behaviour of the main land use types in relation to fire, 67.2% (for Landsat images) and 75% (for MODIS images) of the area remained stable despite the use of fire in the different LULC. The primary forest class was the most destabilized by fire (only 34.2% and 23% of stability rate, respectively, for Landsat and MODIS image analysis). This caused an important transition in the class due to the conquest of new lands for agriculture involving the use of fire. Slash and burn agriculture is reported to be the main deforestation driver in the DRC contributing up to 92% of forest loss (Tyukavina et al. 2018; Curtis et al. 2018). The increase in population also leads to an increase in the demand of land for agriculture leading to the clearing of more and more land (Megevand 2013). The high level of stability in the secondary forest class can also be explained by anthropogenic actions in the class not leading to the change in land use. The clearing in the secondary forests being partial. Agriculture is essentially practiced in the undergrowth while maintaining the status of secondary forest (Ickowitz et al. 2015; Ngabinzeke et al. 2016). This leads more to degradation than deforestation of the secondary forest impeding its evolution towards a mature forest and a significant encroachment into the primary forest (Peltier et al. 2014). In the savanna class, the high 'stability' observed (73.2% and 97%, respectively, for MODIS and Landsat images) can also be explained by periodic fire that occur in savanna without leading to its conversion to other land use types. Bucini and Lambin (2002) argued that fires maintain savanna ecosystems by preventing the invasion of woody species, especially in the savanna/forest transition zone.

Although fire has a role to play in LULC change, statistical tests performed on the analysis of fire occurrence on observed changes revealed that fire is not a driver of LULC change. These results are different from those found globally by Tyukavina et al. (2022) which highlighted the role of fire in forest degradation and the increasing trend of this menace. Regarding LULC sensitivity to fire, primary forest is less affected by fire compared to other LULC classes.

5. Conclusions

The assessment of the contribution of human-induced fires and the dynamics of forest cover and savanna in the Luki area provided an understanding of the changes in the environmental patterns of this landscape between 2002 and 2019. To achieve the initial objectives, a methodology combining the joint use of Landsat (7/8) and Modis MCD12Q1 images for LULC and burnt areas extracted from Modis MCD61A1 was used. The reliability of the results obtained for the classification of Landsat images was assessed using the Kappa index. The results showed that in the Luki BR landscape, primary forest has decreased to the benefit of secondary forest, while savanna has increased in area at the expense of secondary forest. The causes of this dynamic are partially explained by the use of fire in land clearing and other activities such as logging and hunting documented in the area. The primary forest class has been the most affected by deforestation, and secondary forests have experienced more degradation than land-use change. For savannas, the passage of fire has less influence on its stability. In fact, the results indicate that fire is not the driving force for LULC change and that it affects different types of LULC differently, which are therefore due to the combination of several other factors. The research highlights the main danger to be feared, namely the risk of primary forest loss and conversion to secondary forest through the conquest of new land for agriculture. This is only possible if the pressure on natural resources is reduced by the development of alternative income-generating opportunities for the economically weak living in the area. This study highlights the fact that fire use is an important factor in the non-evolution of secondary forest to primary forest. In addition to deforestation, fire is an important factor in forest cover degradation and is only considered in a few large-scale studies. Among the actions needed to restore the Luki Biosphere Reserve landscape, the protection of anthropogenic savannas can also contribute to the increase of forest cover increasing. This study aims to contribute to the understanding of the process of forest degradation in protected areas in DRC and in the LBR landscape.

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ORCID

N. C. Cirezi http://orcid.org/0000-0002-0133-2619
J-F. Bastin http://orcid.org/0000-0003-2602-7247
G. B. Chuma http://orcid.org/0000-0002-9023-2395
Y. Mugumaarhahama http://orcid.org/0000-0002-4690-502X

Author contributions

Conceptualization. N. C. Cirezi. J-F. Bastin and E. Tshibasu; Data processing. N. C. Cirezi; Formal analysis. N. C. Cirezi. G. B. Chuma. J-F. Bastin and Y. Mugumaarhahama; Funding acquisition. E.L. Tipi; Methodology. N. C. Cirezi. E. Tshibasu. G. B. Chuma. Y. Mugumaarhahama. K. Karume and J.-F. Bastin; E.LTipi; Supervision. J-F. Bastin. R. S. Lumbuenamo and J. Bogaert; Validation. K. R. Sambieni. K. Karume. R. S. Lumbuenamo. J-F. Bastin and J. Bogaert; Visualization. R. S. Lumbuenamo. J-F. Bastin and J. Bogaert; Writing – original draft. N. C. Cirezi and J.-F. Bastin; Writing – review and editing. E. Tshibasu. G. B. Chuma. E. L.Tipi. Y. Mugumaarhahama. K. R. Sambieni. K. Karume. J-F. Bastin.

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