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Forest dynamics and carbon stocks in the Santchou wildlife reserve from 2000 to 2022 and projections for 2050

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Abstract

Protected areas are vital spaces for biodiversity conservation, but their balance is increasingly threatened by human activities. This study focuses on the Santchou Wildlife Reserve (RFS) in western Cameroon to analyse vegetation cover dynamics, assess carbon storage capacity and use a Markov predictive model to project changes in land use classes between now and 2050. We start from the hypothesis that anthropogenic pressures, particularly agricultural expansion and land occupation, are the main factors contributing to forest degradation in the RFS, leading to a significant reduction in carbon stocks and a lasting transformation of ecosystems. To explore this issue, several research questions have been formulated: What are the rates and trends of forest degradation and deforestation observed in the reserve between 2000 and 2022? How do human activities, such as agriculture and urbanisation, influence these dynamics? What is the carbon storage capacity of different types of forests, and how does it change with degradation? Finally, what projections can be made for land use in 2050, and what strategies could mitigate these changes? The results of this study, based on satellite image analysis, reveal a gradual loss of forest cover over the study period, with an annual degradation rate of 7.5% and a deforestation rate of 1%. Secondary forests of medium age stand out for their ability to store the most carbon (0.534 tC/ha), followed by high-altitude forests (0.280 tC/ha). The main causes of this degradation are attributed to agriculture, which accounts for 46% of losses, and human occupation, which accounts for 34%. In light of these findings, concrete measures are proposed to reverse this trend. These include promoting sustainable agricultural practices by encouraging farmers to adopt environmentally friendly methods and launching reforestation initiatives to restore degraded areas. The involvement of local communities, through training and awareness programmes, is also essential to promote participatory management of natural resources. Finally, strengthening land use regulations and integrating conservation objectives into public policy would help align economic incentives with biodiversity protection. A comprehensive approach, combining these different actions, is essential to reduce degradation and ensure the sustainability of the Santchou Wildlife Reserve.



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Keywords Anthropization, Satellite images, Spatiotemporal dynamics, Forest cover, Carbon stock spatialization

1 Introduction

Around the world, forests harbor the majority of Earth's terrestrial biodiversity. Since 1990, the world has lost approximately 420 million hectares of forest cover, although the rate of deforestation has shown signs of slowing [1, 2]. The Congo Basin, the second-largest tropical rainforest after the Amazon, is particularly affected by this issue. In Cameroon, forests initially covered 22 million hectares, but this area has since declined to 20.2 million hectares [1, 3]. Globally, forest area decreased by 178 million hectares between 1990 and 2020 [1].

The primary drivers of deforestation include agricultural activities and firewood collection [4]. In Cameroon, the deforestation rate was estimated at 0.27% between 2015 and 2020 [5], affecting nearly all regions of the country [6]. These anthropogenic pressures significantly contribute to climate change. According to the IPCC's Sixth Assessment Report [7], global warming could exceed + 1.5 °C by 2035, with projections ranging up to + 1.8 to 4 °C by 2100 [8]. Rising temperatures disrupt precipitation patterns, leading to prolonged droughts and habitat destruction. These changes impact tree health and biodiversity while promoting invasive species and increasing the risk of forest fires, thereby compromising carbon sequestration capacity [9].

To mitigate these impacts, several initiatives have been implemented. At the 1992 Rio Conference, Cameroon committed to strengthening environmental protection and sustainable natural resource management, leading to the adoption of laws such as Law No. 94/01 of January 20, 1994. Despite these efforts, deforestation persists, reducing carbon sequestration capacity in both protected areas (PAs) and their surroundings [10]. Numerous studies highlight that anthropogenic pressures accelerate the degradation of PAs, undermining their role in biodiversity conservation [11]. Nevertheless, these areas remain critical for climate issues due to their carbon stocks [12], and many studies emphasize their potential to optimize carbon sequestration [13–15].

In West and Central Africa, research has explored the use of remote sensing to monitor land-use dynamics, assessing its effectiveness in capturing vegetation changes influenced by climate variability and human activities [16]. In Cameroon, these applications have been studied in areas such as the Santchou Wildlife Reserve and the Mounjo region, where anthropogenic pressures threaten biodiversity and forest ecosystems.

The Santchou Wildlife Reserve, located in western Cameroon, faces similar challenges, including habitat destruction and biodiversity loss. While remote sensing is an essential tool for sustainable forest management [17], data on land-use dynamics remain scarce in this region [18–20]. Modern remote sensing tools can capture detailed changes in vegetation cover, thereby guiding more sustainable forest resource management [8, 21, 22].

Previous studies, such as [23], have assessed forest cover changes in the Santchou Wildlife Reserve, identifying cash crop agriculture as a major cause of degradation. However, these studies have significant limitations, including: (i) a lack of longitudinal data to analyze long-term trends. (ii) insufficient analysis of local dynamics, particularly community practices and the effectiveness of conservation policies. (iii) an absence

of future projections to anticipate land-use trajectories and their impacts on carbon sequestration.

This study aims to analyze forest cover dynamics and assess carbon sequestration potential in the Santchou Wildlife Reserve, using remote sensing to evaluate degradation dynamics and project land cover changes by 2050.

2 Materials and methods

2.1 Study site

The Santchou Wildlife Reserve (X:10.035939 Y:5.257411) is located in western Cameroon (Fig. 1), covering 7,000 hectares [24] and encompassing eight villages, including Mbongo, Mbokou, and Mogot, primarily inhabited by the Mbo'o and Bamiléké tribes, along with populations from the Haut-Nkam department and the South-West and North-West regions [25].

The commune's relief is divided into three zones: (i) low-altitude (≤ 700 m); (ii) medium-altitude (700–1000 m); and (iii) high-altitude ($> 1,000$ m). A diverse hydrographic network, including the Menoua and Nkam rivers, flows through the low-altitude zone, while the high-altitude zone features numerous springs that provide potential water resources. Dominant economic activities include agriculture, commerce, forest product exploitation, artisanal quarrying, handicrafts, and transport [26]

Wildlife in the reserve includes various species such as primates, aulacodes, rats, pangolins, deer, and monitor lizards. However, species like elephants and panthers have disappeared due to human activities. These animals are protected within the Santchou forest and wildlife reserve [24]. According to [27], the SWR vegetation belongs to the Congo-Guinean domain and features remnants of significant mountain forest systems. Santchou's vegetation comprises three strata: (i) *herbaceous*, dominated by grasses like *Imperata cylindrica*; (ii) shrub, including *Musa* sp. and *Coffea* sp.; and (iii) tree, featuring species such as *Cola* sp and *Milicia excelsa*, along with exotic fruit trees.

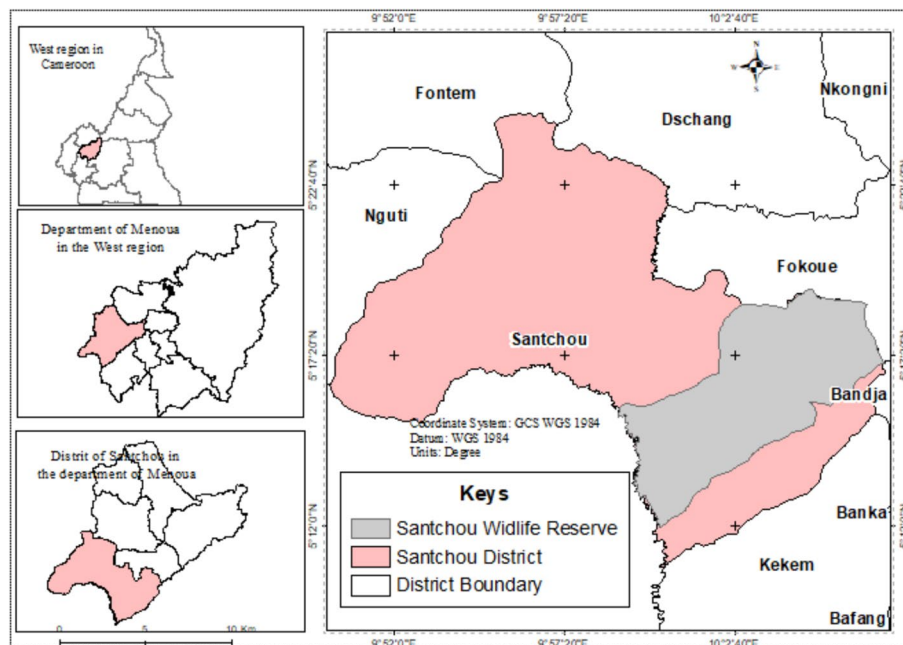


Fig. 1 Location map of the Santchou wildlife reserve. This reserve is in the western region of Cameroon

The soils of the Santchou commune vary by altitude: (i) hydroorphic soils in the low-altitude zone; (ii) ferralitic soils in the high-altitude zone, characterized by a reddish color and silty or sandy-clay texture; and (iii) humus-bearing soils in the mid-altitude zone, suitable for robusta coffee, cocoa, oil palm, and various food crops [24].

3 Methods

This section highlights the tools and methods used to collect, process and analyse the data used to write this article. This methodological approach is multi-faceted, integrating remote sensing approaches, field surveys, observations and botanical surveys.

3.1 Satellite image collection

Spatial dynamics of forest cover were mapped using images from Landsat satellites [28]. The satellite images used are from the Landsat ETM, ETM+, and Landsat 8 sensors, covering the scenes of February 2000, March 2010, December 2014, and January 2022. These data were downloaded via the USGS (United States Geological Survey) Earth Explorer platform, which offers a wide range of freely accessible satellite data [29]. Table 1 shows the characteristics of the Landsat images collected.

Satellite images from December and February were selected for this study in Cameroon because they correspond to the dry season, a period when cloud cover is minimal and ground visibility is optimal, thus allowing for a more accurate analysis of land use dynamics.

3.1.1 Image processing

The images were processed in several stages:

- **Color composition (multispectral image) and photo-interpretation**
This stage involved combining information from the red, blue, green, near-infrared, mid-infrared, and far-infrared bands to produce a multispectral image. This operation aimed to obtain a synthesis of information enabling effective differentiation of plant formation types through photo-interpretation. True and false color compositions were used to determine which best facilitated the visualization of land use classes.
- **Radiometric correction**
Radiometric corrections applied to Landsat images are an essential step in ensuring data quality and comparability. These corrections aim to eliminate distortions caused by atmospheric variations, differences in solar illumination, and sensor noise. For processed Landsat images, this procedure includes converting digital values (stretching) to top-of-atmosphere (TOA) reflectance, followed by atmospheric correction to obtain surface reflectance, given that this is a mountainous area. These corrections ensure temporal and spatial consistency of the data, improved contrast,

Table 1 Characteristics of satellite images

Sensors	Date	Path and row	Spatial resolution (m)	Number of bands	Radiometry (bits)
Landsat enhanced thematic mapper (ETM)	26-02-2000	p186r56	30, 15	8	8
Landsat enhanced thematic Mapper+ (ETM+)	12-03-2010	p186r56	30, 15	8	8
Landsat 8	18-12-2014	p186r56	30, 15	11	16
Landsat 8	22-01-2022	p186r56	30, 15	11	16

and the spread of information dynamics between 0 and 256 values, which are essential for analysing land use dynamics and environmental changes.

- Extraction of area of interest

Following color composition and visual interpretation, the study area was extracted from the SWR shapefile. This operation extracted only the area of interest from the Landsat scene.

- Supervised classification

Supervised classification of satellite images was performed using the Maximum Likelihood algorithm, a classic and robust method for land cover studies, particularly in contexts where land use classes are well defined and the available reference data are representative [30]. Although newer machine learning algorithms (such as Random Forests or neural networks) often offer superior performance, Maximum Likelihood was chosen for its transparency, ease of interpretation, and suitability for the specific objectives of this study, particularly the temporal comparability of results over an extended period (2000–2022).

For the image from the year 2000, taken by the Landsat 7 ETM+ sensor, a true colour composite (4,3,2) was used, corresponding respectively to the near infrared (NIR), red (R) and blue (B) bands. This combination allows for optimal distinction between vegetation, bare soil and wetlands. For images from subsequent years, acquired by the Landsat 8 and 9 OLI/TIRS sensors, bands 5, 4 and 3 were selected to reproduce an equivalent spectral combination (NIR, R, B), thus ensuring methodological consistency throughout the study period.

The sampling of reference points was adapted to the specific characteristics of each year, taking into account data availability and landscape variability. Thus, 3,215 points were sampled for the year 2000, 10,685 for 2010, 14,000 for 2014, and 31,103 for 2022 (Fig. 2). Although the number of points varies significantly between years, particular attention was paid to the spatial and thematic representativeness of the samples in order to limit classification bias. The confusion matrices, presented in the appendix, were restructured according to standard conventions (rows = reference classes, columns = predicted classes) to facilitate the interpretation of the results. The Kappa coefficients, which are consistently above 0.85, confirm the overall reliability of the classifications, while highlighting the need for critical analysis of residual errors, particularly for minority classes.

This method calculates the probability of a pixel belonging to a given class rather than another, independently of neighboring pixels [31]. In all, five land-use classes were defined: medium-aged secondary forests, highland forests, shrub-savannahs, agrosystems, and built-up areas. Figure 2 opposite illustrates the SWR landscape.

3.1.2 Land use prediction model

The CA-Markov prediction model simulates land cover changes based on transition probabilities between land cover classes, calculated from historical data. The CA-Markov chain model was run using the Idrisi Selva software. This model considers past trends to anticipate future changes, offering a flexible approach adaptable to different contexts and spatial scales. However, it assumes that transition probabilities remain constant over time and are sensitive to the quality of data input. Despite these limitations,

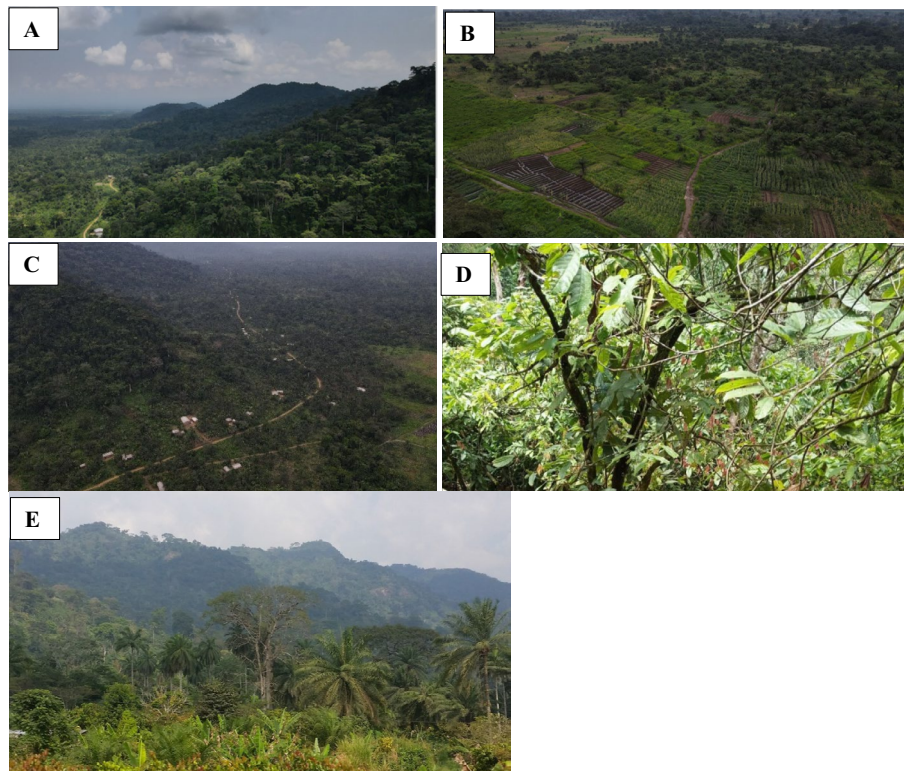


Fig. 2 SWR landscape, showing: **A** highland forests, **B** shrub-savannahs, **C** built-up areas, **D** agrosystems and **E** medium-aged secondary forests. Credit photo: Photo credit: Djiha, March 2023

the Markov model is a powerful tool for simulating and predicting changes in land use [33].

The mathematical formula of the CA-Markov model for predicting changes in land use can be represented as follows:

$$P(t+1) = P(t) * M \quad (1)$$

where

- $P(t)$ is the land-use probability matrix at time t
- M is the transition matrix representing the transition probabilities between the different land cover classes.

Validating the simulations produced by the CA-Markov model was a crucial step in assessing the reliability of the land use projections made for 2050. This validation is based on a comparison between the simulated results and actual land use data, a method known as hindcasting. By recalculating the transitions observed between two past dates and comparing the results with available land use maps, we assessed the model's ability to reproduce actual dynamics. Statistical indicators, such as the Kappa index or overall accuracy, were used to quantify the agreement between simulated and observed data. This robust validation not only strengthens the credibility of future projections, but also identifies the limitations of the model, particularly with regard to the assumption of stationarity of transition processes [34].

3.1.3 Classification validation

This is done on two levels: by calculating the Kappa coefficient and by field observations. The Kappa coefficient is a measure classically used to assess the accuracy of the classification algorithm in the context of Land and Land Cover Analysis [35, 36]. It compares the observed agreement between classifications with the agreement expected by chance, providing a more robust assessment of accuracy than other measures, such as the simple accuracy rate.

Kappa coefficient formula:

The formula for the Kappa coefficient (κ) is :

$$K = \frac{Po - Pe}{1 - Pe} \quad (2)$$

where:

- PoPo is the proportion of agreement observed (i.e. the overall accuracy rate).
- PePe is the proportion of agreement expected by chance, calculated from the margins of the confusion matrix.

The Kappa coefficient values obtained are given in Tables 2, 3, 4 and 5.

3.1.4 Vectorization and cartographic representation

The final step in image processing was vectorization, the conversion from raster to vector format [32]. This stage involved the conversion of classified images from raster to vector (polygon) mode, using ArcGIS 10.7[®] software.

At field level, validation consisted of a survey of ground truth points (GPS points), enabling the classification to be corrected by reassigning certain blocks of misclassified pixels to the appropriate land use classes [37]. A total of over 110 points were surveyed. Figure 3 shows the methodological path followed in processing the images.

3.2 Field data collection

A series of activities was carried out in the field, lasting a total of 20 days. It consisted of field reconnaissance, interviews with the Santchou forest station chief, botanical surveys, photography and dendrometric surveys. Indeed, field surveys guarantee the authenticity of the observations made and reveal realities that other scientific investigation strategies (remote sensing) cannot [38].

3.2.1 Sampling design

Following the recommendations of [39] for tropical formations, the sampling setup consisted of square temporary plots (Fig. 4). Four 30 m × 30 m plots were randomly installed in each vegetation type: medium-aged secondary forests, shrub-savannahs, highland forests, and agrosystems. This distinction, inspired by [40], is based on parameters such as the biophysical environment, forest type, stand development stage, undergrowth structure, and canopy characteristics (Fig. 4). The geographical coordinates of each plot were recorded at the center using a Garmin 73s GPS, resulting in a total of 30 plots defined by land-use type [41].

Table 2 Kappa coefficient values for the 2000 classification, from the confusion matrix

Catégorie	High altitude forest	Building	Agrosystem	Shrubby savannahs	Medium-aged secondary forest	Total	Type	F
High altitude forest	7420	25	12	1	0	7458	ICP	980
Building	80	1600	30	40	0	1750	CCP	60,000
Agrosystem	120	10	4000	250	0	4380	CCP-ICP	59,000
Shrubby savannahs	30	8	500	1800	5	2343	CCP-ICP/CCP*100	97.52
Medium-aged secondary forest	0	0	0	0	42,000	42,000		
Column total	7650	1643	4542	2091	42,005	57,931		

CCP Correctly classified pixels, /ICP Incorrectly classified pixels

Table 3 Kappa coefficient values for the 2010 classification, from the confusion matrix

Catégorie	High altitude forest	Building	Agrosystem	Shrubby savannahs	Medium-aged secondary forest	Total	Type	F
High altitude forest	8000	20	10	2	0	8032	ICP	862
Building	100	1500	25	30	0	1655	CCP	57,100
Agrosystem	150	20	3900	200	0	4270	CCP-ICP	56,238
Shrubby savannahs	40	10	250	1700	5	2005	CCP-ICP/CCP*100	98.49
Medium-aged secondary forest	0	0	0	0	42,000	42,000		
Column total	8290	1550	4185	1932	42,005	57,962		

CCP Correctly classified pixels, /ICP Incorrectly classified pixels

Table 4 Kappa coefficient values for the 2014 classification, from the confusion matrix

Catégorie	High altitude forest	Building	Agrosystem	Shrubby savannahs	Medium-aged secondary forest	Total	Type	F
High altitude forest	7500	30	15	3	0	7548	ICP	1158
Building	90	1550	35	35	0	1710	CCP	57,908
Agrosystem	130	15	3950	220	0	4315	CCP-ICP	56,750
Shrubby savannahs	25	5	550	1750	5	2335	CCP-ICP/CCP*100	98.03%
Medium-aged secondary forest	0	0	0	0	42,000	42,000		
Column total	7745	1600	4550	2008	42,005	57,908		

CCP Correctly classified pixels, /ICP Incorrectly classified pixels

Table 5 Kappa coefficient values for the 2020 classification

Catégorie	High altitude forest	Building	Agrosystem	Shrubby savannahs	Medium-aged secondary forest	Total	Type	F
High altitude forest	7600	28	18	4	0	7650	ICP	1814
Building	85	1620	32	5	0	1742	CCP	57,834
Agrosystem	320	12	3880	421	0	4633	CCP-ICP	56,020
Shrubby savannahs	35	7	842	1600	5	2489	CCP-ICP/CCP*100	96.34%
Medium-aged secondary forest	0	0	0	0	42,000	42,000		
Column total	7860	1667	4450	1852	42,005	57,834		

CCP Correctly classified pixels, /ICP Incorrectly classified pixels

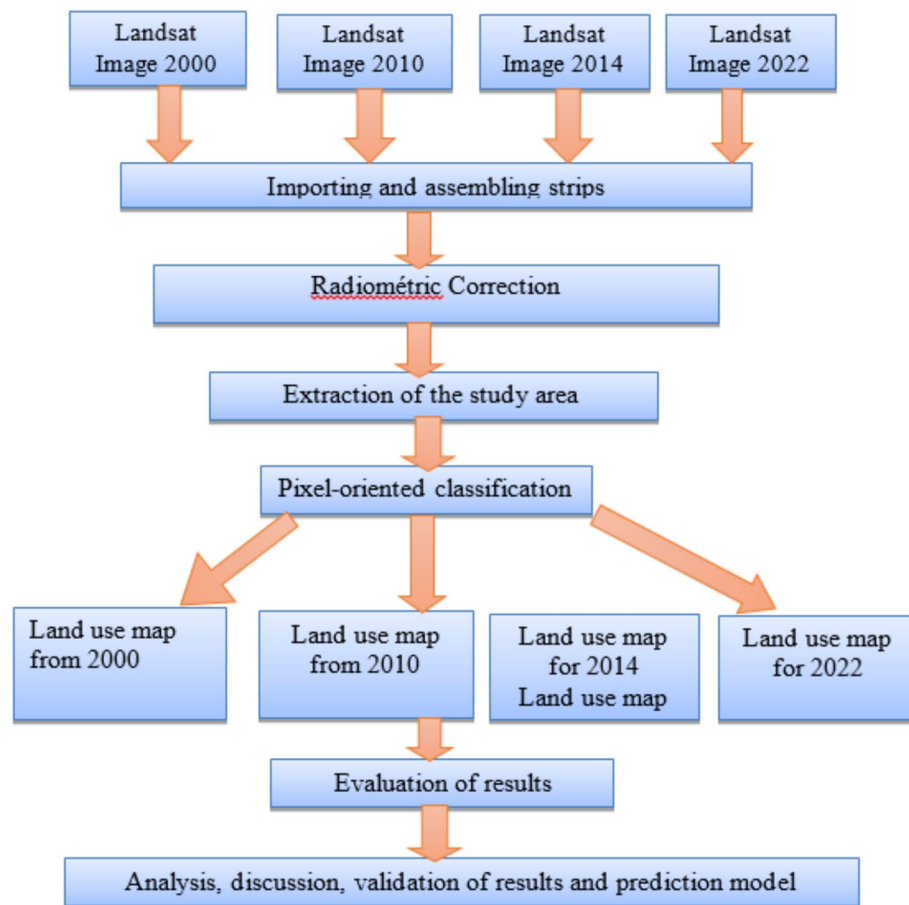


Fig. 3 Satellite image processing method

3.2.2 Method for identifying drivers of degradation in the Santchou reserve

To identify the factors contributing to degradation in the Santchou Wildlife Reserve, a combined methodology was used. Analysis of satellite images (Landsat) made it possible to quantify changes in land use between 2000 and 2022, revealing an expansion of cash crops (cocoa, coffee) and urbanised areas. Finally, field observations identified intensive agricultural practices, illegal logging and bush fires as the main drivers of degradation. They also confirmed these trends and identified illegal activities such as selective logging and slash-and-burn agriculture. This integrated approach provided an understanding of anthropogenic pressures and land use conflicts in the reserve.

3.2.3 Method for recording botanical and dendrometric parameters of trees

In each plot, all trees are identified and measured in terms of their diameter in the different vegetation types as recommended by [42]. Measurements are taken (Fig. 5), and the geographical coordinates of each individual are recorded. According to [43], the scientific and local names of the sampled trees are recorded to establish taxonomic correspondences. Unidentifiable individuals are collected and stored for later identification at the Cameroon National Herbarium.



Fig. 4 Grid of sample plots. Photo credit: Djiha, March 2023



Fig. 5 Measuring the diameter of a tree. **A** Tree marked at 1.30 m; **B** diameter measurement. Photo credit: Mbevo, March 2023

3.3 Estimation of potential reforestation areas

In forestry, potential reforestation areas refer to regions where environmental conditions are favourable to tree growth and where reforestation could be beneficial, both ecologically and economically [44]. These areas are generally identified based on several criteria:

- Climate: Temperature, rainfall and seasons favourable to tree growth;
- Soil: Quality and type of soil, including fertility and drainage;

- Topography: Slope and exposure, which influence humidity and sunlight;
- Biodiversity: Presence of plant and animal species, and impact on the ecosystem;

These potential reforestation zones have been rigorously identified by comparing high-altitude forest classifications for the years 2000 and 2022. This approach highlights areas that have changed from forest to non-forest. It is therefore these areas that are considered as potentially suitable for reforestation [45]. To carry out this analysis, we first extracted the two land-use classes corresponding to high-altitude forests for the two reference years. This operation was carried out using ArcMap 10.5® software.

To precisely identify areas where changes have taken place, i.e. spaces where forest cover has decreased, we used the “Eraser” operator integrated into ArcMap®. This operator subtracts the areas corresponding to forests present in 2022 from those observed in 2000, thus revealing areas deforested or degraded over time. This process has enabled us to pinpoint areas of forest cover loss, which are the main targets for potential reforestation projects.

Once the areas of change had been identified, we assessed the surface areas. This step was crucial to assess the extent of the areas to be reforested and to plan future interventions (whether by planting native species or by assisted natural regeneration, while taking into account local ecological specificities).

3.4 Data analysis

3.4.1 Rate of land use change rate

Analysis of changes over the entire study period was carried out using a post-classification comparison, producing a change detection matrix between two dates [46]. The land cover class areas obtained were calculated using the Global Rate of Change (TG) proposed by the FAO in 1996. This rate is defined by the formula:

$$T = S2 - S1, \quad (3)$$

where **S1** and **S2** represent respectively the percentage proportion of the area of a land cover class for the oldest and the most recent year. On this basis, the Global Rate of Change was calculated [47].

Changes on a global scale were determined by extracting the areas of the different land-use classes for each year. This assessment was carried out over three distinct periods: 2000–2010, 2010–2014 and 2014–2022. The evaluation of the land cover rate measures the degree of conversion of a given unit into other landscape units between two dates t1 and t2. This rate was determined according to the following formula:

$$Tg = \frac{S2 - S1}{S} * 100 \quad (4)$$

Tg = Overall rate of change

S1= area of a land-use unit at date t1

S2 = area of the same land use at date t2

S= Number of years between the two dates

Thus, if $S2 - S1 < 0$, this corresponds to a regression in vegetation cover from year 1 to 2. If $S2 - S1 > 0$, this corresponds to an increase in vegetation cover from year 1 to 2. If $S2 - S1 = 0$, this corresponds to stability in vegetation cover from year 1 to 2.

3.4.2 Calculating the deforestation rate

The deforestation rate represents the fraction of forest transformed by other types of land use other than forest. It was calculated using the formula proposed by [48]. Its mathematical equation is as follows:

$$R = \frac{1}{t_2 - t_1} \ln \left(\frac{A_2}{A_1} \right) * 100 \quad (5)$$

With **R**: deforestation rate;

A1 and **A2** represent the sum of the share of occupancy units.

ln: natural logarithm; **t1**: year 1; **t2**: year 2.

3.4.3 Calculating the annual degradation rate

The degradation rate represents the fraction of the forest disturbed at a given time. It was evaluated using the formula developed by [49].

$$ARL = \frac{\frac{S_2}{S_1}}{t} * 100 \quad (6)$$

With **S1**: initial forest area;

S2: forest area lost;

ARL: annual rate of loss by degradation (%);

t: number of years between two dates.

3.4.4 Estimating carbon stocks

In this study, biomass was assessed using the non-destructive or indirect method based on regression equations. This relies on allometric equations to estimate biomass in an ecosystem. In this study, only above-ground biomass was taken into account. The parameters collected were introduced into the equations below in order to estimate the carbon stock.

3.4.4.1 II.2.4.4.1. Estimation of above-ground biomass The allometric equation developed by [50] to estimate the site-specific biomass of trees in the tropical moist forests of Cameroon for diameter classes of $10 < \Phi < 121$ was used to estimate the above-ground biomass. The mathematical expression of this allometric equation is as follows:

$$BA = \exp(-1,836 + 2,619 * \ln(D) + 1,268 * \ln(\rho)) \quad (7)$$

With **BA**: estimated above-ground biomass in Kg;

ρ : specific density of a species expressed in g/cm³.

and **D**: diameter (cm).

On the other hand, the allometric equation developed by [51] was used for species in diameter classes $1 < \Phi < 10$. This equation is used to estimate the above-ground biomass of different compartments (trunk, crown and leaves) of understocked trees in the semi-deciduous rainforest of Cameroon. The mathematical expression of this allometric equation is as follows:

$$BA = \exp(-2811 + 2474 * \ln(D)) * CF \quad (8)$$

CF = expansion factor = 0.11

The specific wood densities of each species sampled were collected from the global wood density database [52].

3.4.4.2 Sequestered carbon stock The total biomass estimated from the various equations was converted to carbon stock by multiplying by a carbon fraction [13]. Knowing that carbon constitutes 0.47% of woody matter, the formula used for this purpose is as follows:

$$\text{Carbonstock (kg)} = \text{biomass(kg)} * 0,47 \quad (9)$$

They were converted to tones (t) using the conversion table, and the parameters calculated were extrapolated to the hectare using the formula $FE = 10,000/\text{sampled area}$. Carbon stocks for each pool and stratum are thus presented in t C/ha.

3.4.5 Carbon spatialization

The spatialization of carbon stock data in the SWR was carried out using the method of [53, 54]. It uses the geographical coordinates of each parcel and its carbon stock as input data. Then it extrapolates to the extent of the land cover map, following the principle that a parcel corresponds to a pixel class, and all identical pixel classes correspond to assessed carbon stocks.

4 Results

4.1 Land use changes in the SWR

Analysis of the four images (2000 to 2022) reveals that the Santchou Wildlife Reserve is made up of five (05) thematic classes. Over the period observed, these classes showed both regressive and progressive spatio-temporal dynamics. The class that underwent a regressive dynamic was that of the high-altitude forests, while the class of secondary forests of medium age showed a progressive dynamic. The latter is followed by shrub savannahs, agrosystems, and finally built-up areas (Fig. 6).

In terms of validation, for the whole of the study area, the Kappa coefficient obtained for the year 2000 was 97.17%, indicating an accurate classification. The agrosystem class was the most difficult to classify, with 2241 pixels misclassified, representing 9% of the total. This difficulty is attributed to the similarity between certain areas of degraded forest. In 2010, the Kappa coefficient was 92.87%, confirming the reliability of the classification. For 2014, the Kappa coefficient obtained for Landsat images is 98.69%, which can be explained by the good quality of the image (low cloud cover) and its satisfactory radiometric resolution. The margins of error are small between the different occupancy classes, particularly between water bodies and degraded forests, with only 102 misclassified pixels, representing 0.13%. Finally, in 2022, a Kappa coefficient of 97.12% was determined. Overall, these Kappa coefficients attest to the reliability of the classification algorithm.

4.2 Land use between 2000 and 2022

In 2000, the distribution of land use classes in the Santchou Faunal Reserve consisted of 66% high forest, 13% medium-aged secondary forest, 15% shrub savannah, 3% agrosystems and 3% built-up areas (Fig. 7).

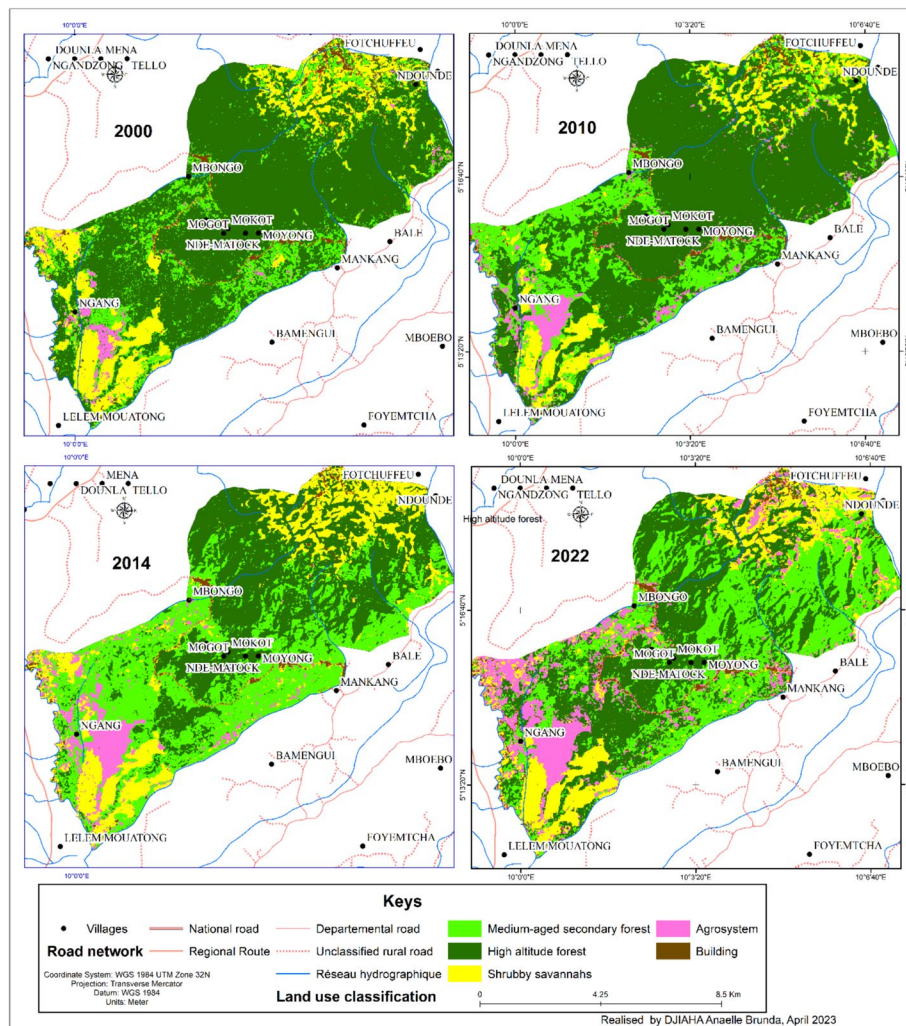


Fig. 6 Spatial and temporal trends in the SWR over 22 years

In 2010, the proportion of high-altitude forest fell from 66 to 63%, while medium-aged secondary forest gained ground, increasing from 13 to 19%. Shrub savannah decreased from 15 to 11%. Agrosystems increased from 3 to 5%, while built-up areas decreased slightly, from 3 to 2% (Fig. 7).

In 2014, high-altitude forest underwent a significant reduction, falling to 39%. In contrast, mid-age secondary forest doubled, reaching 39%. Shrub savannah increased to 15%, while the share of agrosystems rose slightly from 5 to 6%. The built-up area continued to decrease, reaching 1% (Fig. 7).

In 2022, the highland forest recorded a slight loss, falling to 38%. Medium-aged secondary forest has decreased to 35%. Agrosystems have increased significantly, from 6 to 14%. Shrub savannah fell to 8%, and built-up areas increased to 5% (Fig. 7).

The land use transition matrix [55] in the SWR between 2000 and 2022 shows that over these 22 years, 6030.72 ha of secondary forest were converted to other land use classes, namely secondary forest, savannah, agrosystems and built-up areas. 1412.04 ha of savannah and 1254.93 ha of mature forest were converted to other land use types. The lowest conversions were recorded in agrosystems and built-up areas (Table 6). The percentages correspond to the percentage change in land use for each land cover class.

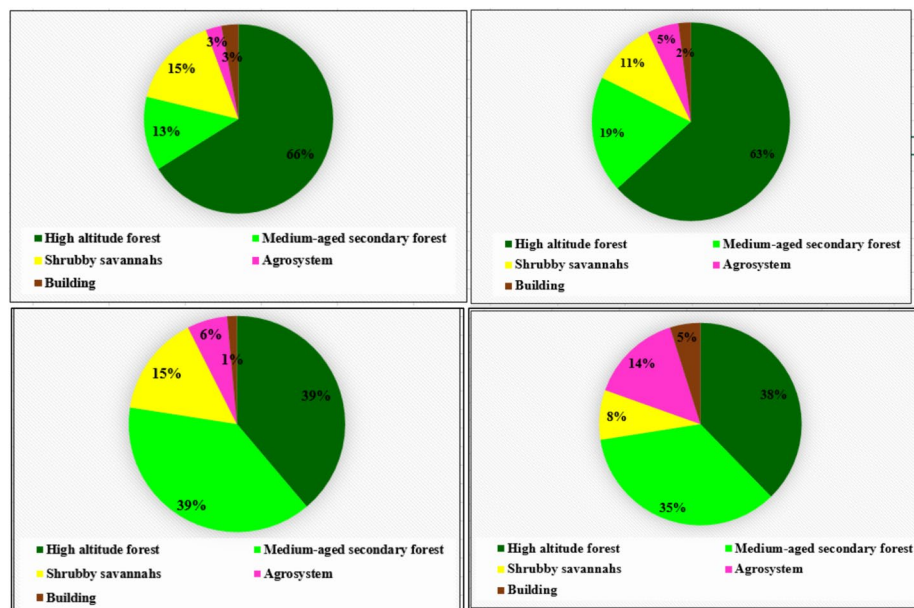


Fig. 7 Variation in occupancy rates in the Santchou forest reserve between 2000 and 2022. Land cover statistics are derived from the classification of Landsat images

Table 6 Matrix of land use changes in the SWR between 2000 and 2022

Land use classification		2022				
		Highland forest (%)	Secondary forest (%)	shrub-savannahs (%)	Agrosystem (%)	Buildings (%)
2000	Highland forest	28.3	37.8	4.4	26.1	7.6
	Secondary Forest	0.5	43.5	5.6	59.9	1.5
	Savanna	0.01	5.4	63.3	31.5	10.4
	Agrosystem	0.3	1.2	10.9	79.9	8.7
	Buildings	0.03	0.05	3.6	20.3	75.9
	Total (%)	28.84	88	87.8	217.7	104.1
Stability						
Changes in the forest						
Conversion of savannah into mature forest						
Conversion of savannah to secondary forest						
Converting the savannah into an agrosystem						
Converting the savannah into buildings						
Conversion of the agrosystem to mature forest						
Conversion of the agrosystem to secondary forest						
Conversion of the agrosystem to savannah						
Conversion of the agrosystem into buildings						
Conversion of mature forest to savannah						
Converting mature forest into an agrosystem						
Converting mature forest into buildings						
Conversion of secondary forest to savannah						
Converting secondary forest into an agrosystem						
Conversion of secondary forest to buildings						
Converting buildings into mature woodland						
Conversion of built-up areas into secondary forest						
Conversion of buildings into savannah						
Converting buildings into agrosystems						

4.3 Annual rate of deforestation and degradation in different land use classes

The results obtained for the calculation of the rate of deforestation between the reference year 2000 and the last year of observation, 2022, reveal that the high-altitude forest shows a deforestation rate of -2.56% , while the medium-old secondary forest shows a deforestation rate of 4.60% . The overall annual deforestation rate is thus estimated at 1.03% , equivalent to an annual rate of 0.04% , for a period of 22 years. This is slightly lower than the national deforestation rate of 0.05% [1].

About the rate of degradation, the results comparing the reference year with the last year of observation show that the highland forest has a degradation rate of 2.59% , while the medium-aged secondary forest has a degradation rate of 12.52% . This corresponds to an annual rate of degradation of 7.56% .

4.4 Evolution of land use classes in the Santchou forest reserve from 2000 to 2022

4.4.1 Dynamics of land use between 2000 and 2010

The statistical results relating to land use over the period 2000 to 2010 reveal significant variations in the different classes. High-altitude forests decreased from 6198.6 to 5932.4 ha, which represents a regression of 266.2 ha over 10 years, or an annual loss of 26.6 ha. Medium-aged secondary forests, on the other hand, increased from 1184.3 to 1780.9 ha, an increase of 596.6 ha, equivalent to an annual increase of 59.6 ha.

Shrub savannah also declined, from 1461.6 to 988.4 ha, representing a loss of 473.2 ha, or an annual loss of 47.3 ha. Conversely, agrosystems grew from 253.5 to 479.3 ha, an increase of 225.8 ha over the period, corresponding to an annual increase of 22.5 ha. Finally, the built-up area decreased from 273.4 to 189.8 ha, representing a decline of 83.6 ha, equivalent to an annual loss of 8.3 ha.

4.4.2 Dynamics of land use between 2010 and 2014

Between 2010 and 2014, the Santchou Wildlife Reserve experienced a significant loss in its area of high forest, which fell from 5932.4 to 3693 ha, a regression of 2239.4 ha, corresponding to an annual loss of 559.8 ha over these four years. On the other hand, medium-aged secondary forests increased from 1780.9 to 3619.4 ha, representing an increase of 1838.5 ha, or $+459.6$ ha per year. The shrub savannah also increased, from 988.4 to 1412 ha, an increase of 423.6 ha, equivalent to $+105.9$ ha per year. Agrosystems grew from 479.3 to 563.7 ha, an increase of 84.5 ha, equivalent to an annual increase of 21.1 ha. Finally, built-up areas declined from 189.8 to 136.6 ha, a decrease of 53.2 ha, equivalent to an annual loss of 13.3 ha.

4.4.3 Dynamics of land use between 2014 and 2022

This analysis revealed that the area of high forest decreased from 3639 to 3533.2 ha, representing a decline of 105.8 ha, equivalent to an annual loss of 13.2 ha. Medium-aged secondary forests have also decreased, from 3619.4 to 3262.4 ha, a decline of 357 ha, equivalent to an annual loss of 44.6 ha. The shrub savannah also declined significantly, from 1412 to 743.9 ha, with a reduction of 668.1 ha, equivalent to an annual loss of 83.5 ha. Agrosystems, on the other hand, increased from 563.7 to 1374.8 ha, an increase of 811 ha, representing an annual increase of 101.3 ha. Built-up areas also rose, from 136.6 to 456.4 ha, an increase of 319.8 ha, equivalent to an annual increase of 39.9 ha.

The results show that the most significant changes occurred between 2010 and 2014. The periods from 2000 to 2010 show slightly regressive forest cover dynamics. These observations also show that the high-altitude forests experienced a significant regression over the four periods, indicating a major loss of forest cover in the Santchou Wildlife Reserve. Analysis of the images shows an increasing deterioration in the Reserve's forest cover. The diagram below illustrates the dynamics of land cover in the reserve between 2000 and 2022 (Fig. 8). Values below the x-axis indicate losses, while those above the axis represent gains.

4.5 Projection of land cover dynamics in 2050 in the SWR

The simulations conducted using a CA-Markov predictive model allow us to explore potential trends in land cover evolution within the Santchou Wildlife Reserve (SWR) by 2050, based on historical dynamics observed between 2000 and 2022. It is crucial to emphasize that these results do not constitute strict predictions, but rather exploratory scenarios grounded in the strong assumption of stationarity in land cover transition processes. This assumption, central to Markov models, posits that past trends will persist into the future, without accounting for potential disruptions caused by major socio-economic or political changes.

According to these simulations, a significant expansion of agricultural land is projected, with a 30% increase expected by 2050, primarily at the expense of primary forests and savannas. Urban areas and agroecosystems are also anticipated to experience rapid growth, with estimated increases of 40% and 25%, respectively. Secondary forests, which have already expanded in recent decades, are expected to continue growing, particularly in areas previously occupied by degraded primary forests (Fig. 9). These trends primarily reflect the increasing demographic and economic pressures in the region, driving demand for agricultural land and housing. Current policies, which promote the expansion of arable land and agroforestry systems, as well as the growing demand for wood products, also contribute to these dynamics. While climatic factors (such as variations

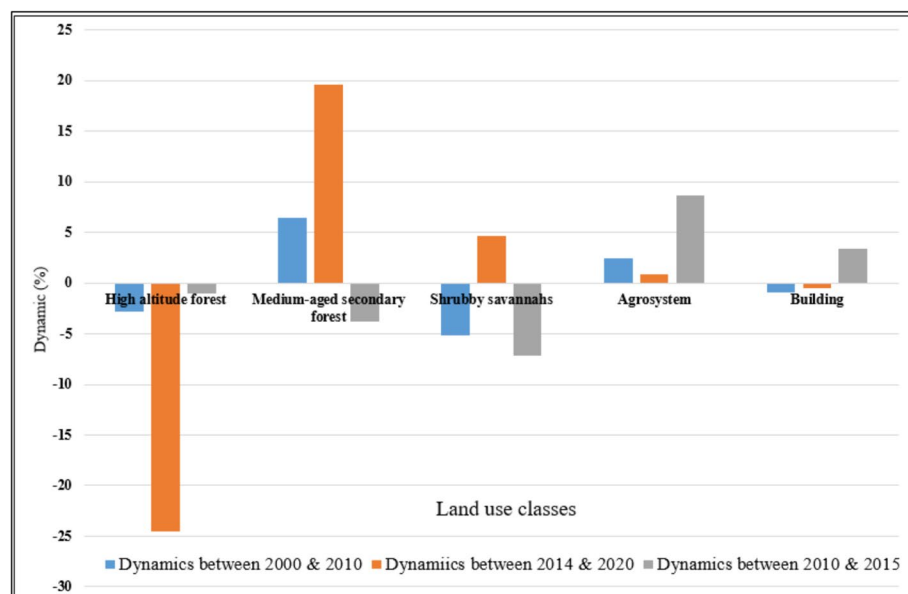


Fig. 8 Dynamics of land use in the reserve between 2000 and 2022

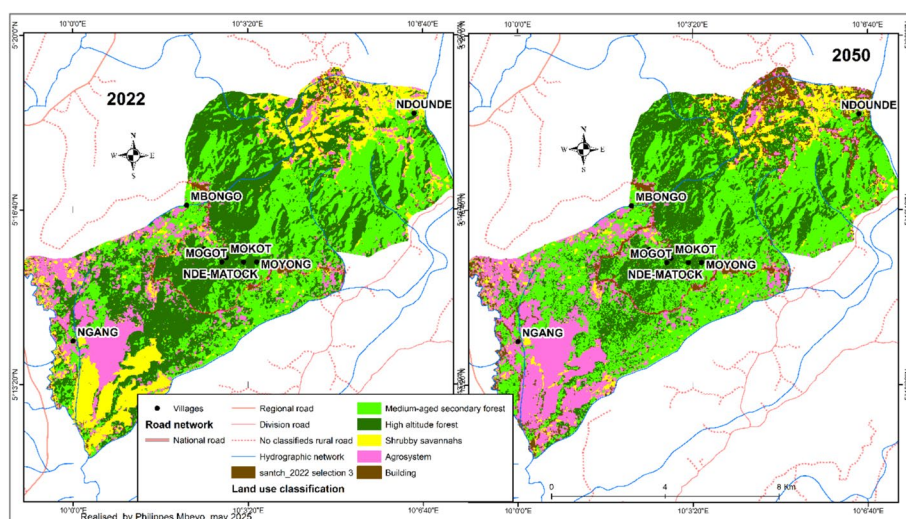


Fig. 9 Predictive model of land use obtained from the Markov model

Table 7 Carbon stocks in the different vegetation strata

Strate	Number of plots by class	Area in-ventoried (ha)	Σ aerial biomass (kg)	Carbon sequestration (kg)	Carbon sequestration(t)	Stocks de Carbon (tC/ha)
Highland forest	30	2.7	53.682	25.23	0.025	0.28
Mid-age secondary forests	30	2.7	102.437	48.145	0.0481	0.534
Shrubby Savannah	30	2.7	11.193	5.261	0.005261	0.058
Agrosystem	30	2.7	0.432	0.203	0.0002	0.0022
Total carbon SWR						0.8742

in precipitation and temperature) may locally influence land use, their impact remains secondary compared to socio-economic drivers in this scenario.

5 Estimation and specialization of carbon stocks

5.1 Estimation of carbon stocks

The carbon rate recorded for the SWR is estimated at 0.874 tC/ha (Table 7). Mid -age secondary forest is the land cover type with the highest carbon content (0.534 tC/ha), followed by highland forest (0.280 tC/ha). Agrosystems and shrub savannahs are land cover types with the lowest carbon content, at 0.002 tC/ha and 0.058 tC/ha respectively.

5.2 Spatialization of carbon stocks

Spatialization of carbon stocks within the Santchou Wildlife Reserve reveals variations between the different land-use classes. Mid-age secondary forests have a higher carbon content, with an average of 0.4075 tC/ha, followed by savannahs (0.0305 tC/ha). Agro-systems have an average of 0.001 tC/ha, while high-altitude forests have an average of 0.1695 tC/ha (Fig. 10).

5.3 Main factors of SWR degradation and estimate of potential reforestation area

Following data analysis and satellite image processing, four main degradation factors were identified in the Santchou Faunal Reserve. These are: agriculture, which accounts

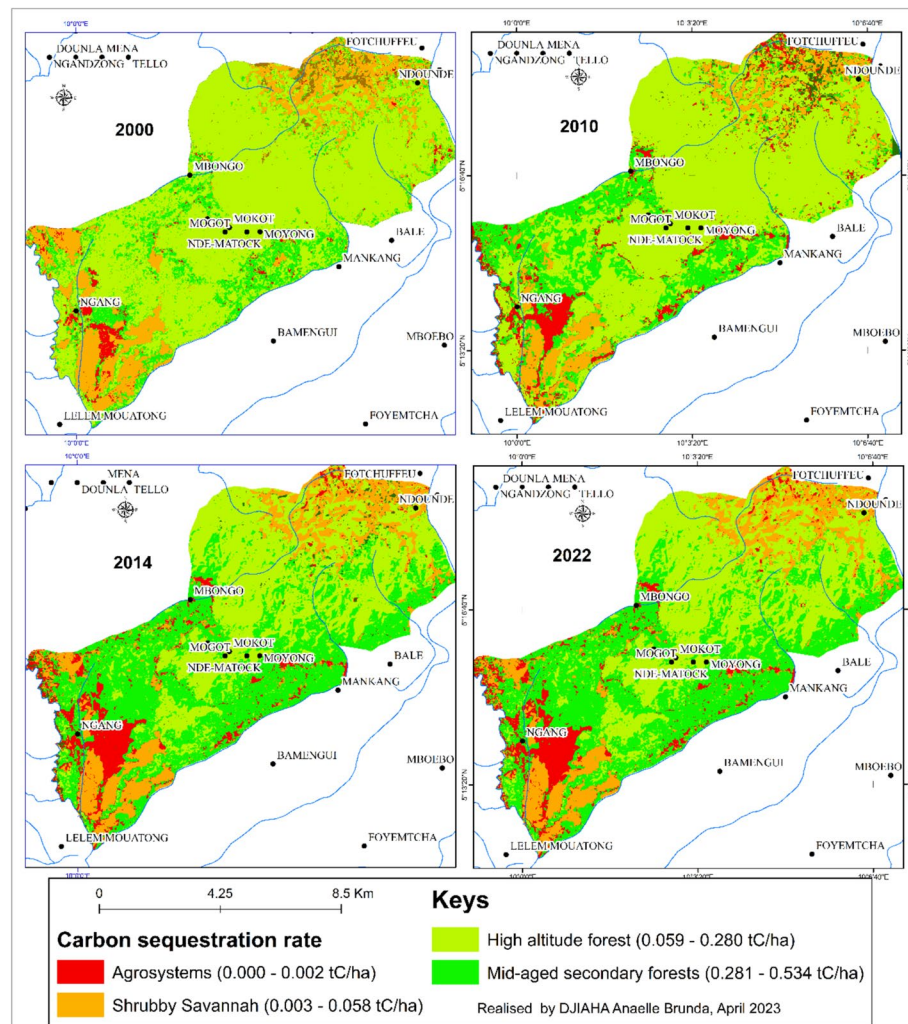


Fig. 10 Spatial distribution of carbon in the SWR

Table 8 SWR degradation rate

No.	Degradation factors	Duration	Percentages (%)
1	Agriculture	22 years	46
2	Human occupation		34
3	Illegal logging		14
4	Bushfires		6
	Total		100

The statistics were defined after discussions with SWR staff

for 46% of deforestation; human occupation, 34%; illegal logging, 14%; and bushfires, 6% (Table 8).

After processing Landsat images from 2000 to 2022, degraded areas were quantified and designated as priority reforestation zones. These zones correspond to areas where forests have been partially or fully converted to other land uses. We identified 3703 ha for reforestation out of a total of 7000 ha in the Santchou Wildlife Reserve (SWR), representing 53% of the reserve's total area (Fig. 11). The land-use classes with high conversion rates included highland forests, which lost 2559.6 ha, and medium-aged secondary

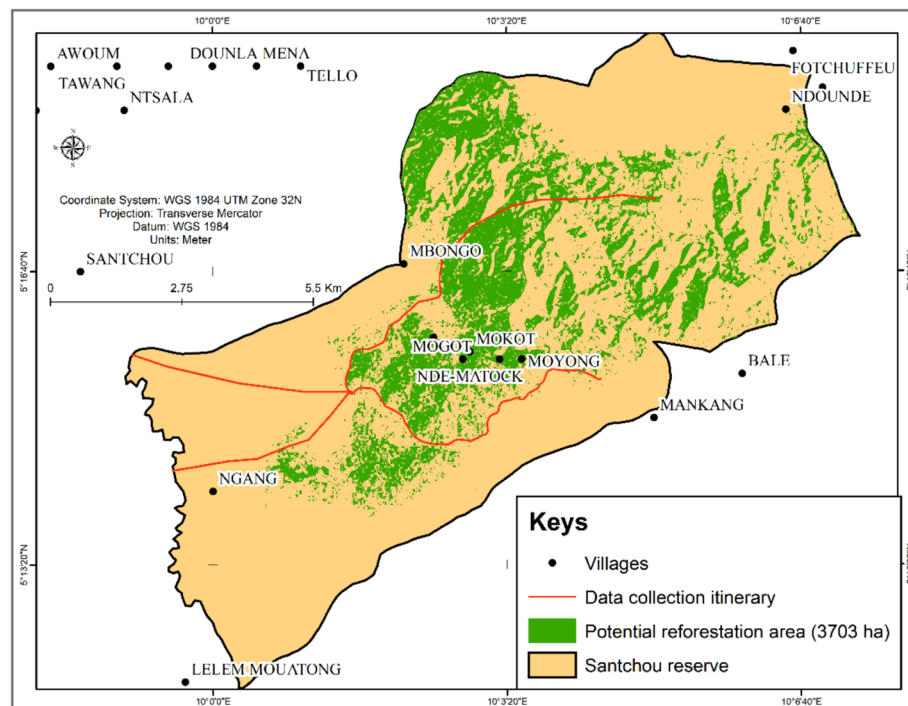


Fig. 11 Potential reforestation areas in the SWR4

forests, which gained 2434.7 ha. This 3703 ha area corresponds to a carbon storage capacity of 0.83 tC/ha.

6 Discussion

6.1 Land use dynamics of the SWR from 2000 to 2022

Analysis of land use dynamics in the Santchou Wildlife Reserve has identified five main classes: mature forest, secondary forest of medium age, shrub savannah, agrosystem and urbanised areas. A diachronic analysis of satellite images over 22 years (2000–2022) revealed two major trends: a decline in mature forests and an increase in secondary forests and agrosystems. Between 2010 and 2014, there was a marked decrease in mature forests, while secondary forests increased. These changes can be explained mainly by agricultural expansion, with local communities clearing forests to grow food and cash crops [56, 57]. Indeed, agriculture is responsible for 80% of forest loss in Cameroon, with 41.33% of forest conversions attributed to agricultural practices [57].

In the Santchou Reserve, shrub savannahs declined in 2022, while agrosystems increased. These results corroborate the observations of [58–60], which highlight a decline in forests and savannahs in favour of agricultural land. Urbanised areas also experienced significant growth, increasing from 136.6 to 456.4 ha between 2014 and 2022, reflecting increased demographic pressure. Tazo [61] had already noted the presence of more than 2000 people in the reserve in 1994, a figure supported by [62].

The rates of deforestation and degradation observed between 2000 and 2022 reveal an annual deforestation rate of 1.025%, well above the national average of 0.08% [63]. This high rate can be explained by intense anthropogenic pressures, particularly agriculture, urbanisation and logging. The degradation rate is estimated at 7%, comparable to the 13.28% observed in northern Benin [64]. These results highlight the combined

impacts of population growth, slash-and-burn agriculture and infrastructure expansion, as pointed out in [8, 65]. These factors, coupled with the effects of climate change, contribute to increasing ecosystem instability.

The implications of these findings are significant. Loss of forest cover and habitat fragmentation threaten biodiversity and reduce carbon sequestration capacity, thereby compromising conservation and climate change mitigation efforts. Furthermore, the expansion of agricultural and urbanised areas, while meeting immediate socio-economic needs, risks exacerbating land use conflicts and limiting the resources available to future generations. These findings highlight the urgent need to implement sustainable land management policies that integrate both the needs of local communities and conservation imperatives.

6.2 Degradation factors in the Santchou forest reserve

The primary illegal activities in the Santchou Wildlife Reserve (SWR) include agriculture, illegal logging, and bushfires. Cash crops like cocoa and coffee, along with maize and cassava, significantly contribute to forest degradation (Fig. 12). Population growth exacerbates these issues as locals increasingly encroach on forested land for farming, the main economic activity. A 20 km secondary road linking Fouban to Bale further intensifies anthropization. Reference [67] notes that population increases, driven by high birth rates and declining mortality, lead to farmland expansion and global deforestation.

Surrounded by eight villages, the SWR has seen built-up areas expand from 2% in 2000 to 5% in 2022, impacting vegetation cover. In response to rising demands, locals establish new plantations, altering the landscape. Illegal logging, including artisanal sawmilling, and bushfires degrade the SWR, with communities harvesting trees indiscriminately for heating, lighting, and medicinal purposes. Reference [68] highlight transhumant livestock farming as an additional land use, while [66] identify extensive livestock farming as a primary cause of deforestation.

In the SWR, agriculture and illegal exploitation of forest resources have led to significant anthropization and ecosystem degradation. Cash crop farming, particularly cocoa, coffee, and oil palm cultivation, provides substantial income for many residents. Reference [23] note that cash crop agriculture is a key factor in forest cover change within the reserve. Reference [10] report that intensified logging has fragmented forests around Boumba-Bek National Park, similar to those in the Santchou Forest Reserve. Reference [69] demonstrate that peasant agriculture is the leading cause of deforestation in tropical areas [70], contributing to 35% of forest destruction in Africa [63]. This situation escalates the conflict between conservation efforts and the well-being of communities near protected areas [71].

7 Carbon sequestration potential of the Santchou forest reserve

In the Santchou Faunal Reserve (SWR), mid-age secondary forests exhibit the highest carbon stock at 0.534 tC/ha, followed by highland forests at 0.280 tC/ha. This difference is attributed to the higher density and larger diameter of trees in secondary forests, which are often composed of fast-growing pioneer species. In contrast, agrosystems have the lowest carbon stock at 0.0022 tC/ha, primarily due to the replacement of woody vegetation with annual crops, drastically reducing stored biomass.



Fig. 12 SWR degradation factors. Photo credit: Djiha, March 2023

Field-collected carbon data were extrapolated across the reserve, revealing that carbon classes ranging from 0.281 to 0.534 tC/ha, associated with mid-age secondary forests, cover a large area. This extrapolation method, validated by [67] in the Ngog-Mapubi forest massif, has proven effective in mapping biomass and informing land-use change perspectives.

The low carbon sequestration rates in SWR's agrosystems and savannahs result from intense anthropogenic pressure. [68] noted that in Laf Madjam Park, changes in forest cover are mainly driven by the collection of non-timber forest products and wood exploitation for energy and construction by local populations, leading to significant carbon sequestration loss. Similarly, [72] identified factors such as poverty, rapid population growth, and agricultural intensification as the primary causes of natural vegetation fragmentation in tropical regions. These pressures not only reduce the carbon sequestration potential of forests but also contribute to climate change.

These findings highlight the importance of strengthening sustainable land management practices and promoting less destructive agricultural alternatives to preserve

carbon stocks and maintain essential ecosystem services. They also underscore the need to raise awareness among local communities about the impact of their activities on ecosystems and to develop policies that integrate conservation with socio-economic development.

The estimation of carbon stocks in the Santchou Wildlife Reserve (RFS) was conducted using field inventories combined with allometric equations specific to tropical ecosystems. For each vegetation stratum (high-altitude forests, mid-age secondary forests, shrub savannahs, and agroecosystems), 30 inventory plots were established, covering a total area of 2.7 hectares per class. Tree measurements, including diameter at breast height (DBH) and height, were converted into aboveground biomass using pan-tropical allometric equations [73]. Biomass was then converted into carbon stocks by applying a conversion factor of 0.47 [74], representing the average carbon content of plant biomass.

The values obtained are significantly lower than those reported in the literature for similar ecosystems. For example, [75] estimate that tropical secondary forests typically store between 30 and 50 tC/ha, even in early regeneration stages. Several hypotheses may explain this discrepancy: (1) underestimation of stocks due to inadequate extrapolation of plot data to the hectare scale, (2) selection of plots that are not representative of high-biomass areas, or (3) advanced degradation of the studied ecosystems, reflecting intense anthropogenic pressures. To address these uncertainties, a reevaluation of extrapolation procedures was undertaken and deemed necessary. We compared the allometric equations used with models specific to Central African forests [76] and integrated sensitivity analyses to assess the impact of measurement errors on final estimates. Additionally, cross-validation with independent data, such as those derived from remote sensing, helped strengthen the robustness of the results [77].

Regarding the spatialization of carbon stocks, it was carried out by combining field inventory data with high-resolution satellite imagery (Landsat). The carbon values estimated for each plot were extrapolated across the entire reserve using ordinary kriging, a spatial interpolation method commonly used for environmental variables [78]. This technique accounts for the spatial variability of carbon stocks while minimizing estimation errors. The resulting maps were then validated through cross-validation (leave-one-out), yielding a coefficient of determination (R^2) of 0.78 and a root mean square error (RMSE) of 0.045 tC/ha.

However, this methodology has certain limitations. The heterogeneity of landscapes within the RFS, characterized by a mosaic of forests, savannahs, and agricultural areas, can introduce biases in the interpolation, particularly in transition zones between strata. Additionally, the spatial resolution of Landsat images (30 m) may not capture fine variations in biomass, especially in degraded or fragmented areas. To address these limitations, a multi-scale approach integrating LiDAR data or very high-resolution images (e.g., Sentinel-2 or drones) would be necessary to refine the accuracy of carbon maps [79].

Finally, transparency regarding uncertainties is a critical aspect often overlooked in spatialization studies. In this study, uncertainties were estimated by propagating errors from field inventories and interpolation models, resulting in an average margin of error of $\pm 15\%$ for carbon stocks. A thorough discussion of error sources, including potential biases related to sampling methodology and model assumptions, is provided to ensure the credibility of the results [80].

8 Comparative analysis with previous work (Meli and Meli 2015)

Both studies address conservation and resource management in the Santchou Wildlife Reserve, highlighting distinct strengths and weaknesses. The present study focuses on forest cover changes through satellite imagery and floristic inventories, providing precise quantitative data on carbon sequestration and allowing for the assessment of cover change impacts on climate. The use of remote sensing techniques offers a comprehensive view of forest dynamics across extensive geographical areas, essential for understanding ecosystem evolution.

In contrast, [23] employ an integrated approach, combining satellite image analysis with land use indices and socio-economic data from field surveys. While this method enhances the understanding of deforestation drivers, it presents challenges. The complexity of integrating diverse data can lead to less clear results, and the focus on socio-economic factors may divert attention from immediate ecological changes.

The current study thus provides a rigorous assessment of forest cover dynamics and carbon sequestration, critical for conservation strategies. By concentrating on quantitative data, it establishes clear baselines for future interventions, forming a robust foundation for evidence-based management policies, although incorporating socio-economic dimensions could enhance its findings. This work is notable for its analytical rigor and capacity to provide essential conservation data, even as it could benefit from socio-economic considerations.

Ultimately, the complementarity of these two approaches suggests that they could be synergistically employed to improve the management of the Santchou Wildlife Reserve.

9 Estimation of errors associated with the biomass-to-carbon conversion method using land cover classes

Estimating carbon stocks from land cover classes is subject to multiple sources of error, which can significantly undermine the accuracy of results and compromise decision-making in forest management and climate policy. This section critically examines key methodological biases and suggests improvements based on recent findings.

9.1 Inaccuracies in biomass estimation

One of the most common errors stems from the use of inappropriate conversion coefficients to estimate biomass from land cover classes. These coefficients, often derived from regional or global studies, can vary significantly depending on ecosystem type, successional stage, and local edaphoclimatic conditions [75]. For example, regenerating tropical secondary forests generally store less carbon than mature forests, but their biomass is often overestimated or underestimated if the coefficients used are not specific to their developmental stage [81]. A recent meta-analysis has shown that using generic coefficients can lead to errors of up to 40% in carbon stock estimates, with major implications for conservation strategies and climate financing mechanisms [82]. To address this bias, it is recommended to use allometric equations specific to local ecosystems, such as those developed for Central African forests [78], and validate them through targeted field campaigns.

9.2 Ecological heterogeneity within land cover classes

Land cover classes, often broadly defined (e.g., "secondary forest" or "savanna"), conceal significant ecological heterogeneity that directly affects biomass and carbon storage. For instance, a study in the Congo Basin revealed that intra-class biomass variability can reach 30%, depending on species composition, soil structure, and disturbance regimes [83]. Ignoring this variability leads to biased estimates, particularly in ecological transition zones (e.g., between forests and savannas), where biomass gradients are most pronounced [73]. To improve accuracy, approaches that combine very high-resolution remote sensing (e.g., LiDAR or Sentinel-2) with stratified field inventories can be used to capture this heterogeneity [77].

9.3 Temporal dynamics of land cover changes

Static biomass-to-carbon conversion models, which do not account for dynamic changes in land cover, are particularly problematic in regions experiencing intense anthropogenic pressure. For example, deforestation, urbanization, or the conversion of forests to agricultural land can drastically alter carbon stocks within a few years [84]. A study in the Amazon showed that models neglecting these dynamics underestimate carbon emissions by 20 to 50%, depending on the intensity of disturbances [85]. To address this bias, it is essential to integrate temporal data (e.g., Landsat or MODIS time series) and use dynamic models (e.g., Markov models or cellular automata) to capture transitions between land cover classes [86].

9.4 Use of outdated data

Using outdated or unupdated data to estimate biomass and carbon is a major source of error, particularly in the context of rapid climate change and anthropogenic transformation. For example, a comparative study showed that carbon estimates based on biomass data older than 10 years could be underestimated by 15 to 25% in tropical regions due to tree growth and land-use changes [87]. To ensure the relevance of estimates, it is crucial to regularly update reference data and incorporate complementary sources, such as recent satellite products (e.g., ESA's GEDI or Biomass CCI) [88].

9.5 Neglect of environmental factors

Biomass-to-carbon conversion models often overlook environmental factors that directly influence carbon sequestration capacity. For example, soil quality, water availability, and local climatic conditions can cause carbon stocks to vary by more than 50% within the same land cover class [89]. A study in West Africa found that humid savannas store up to three times more carbon than dry savannas due to differences in primary productivity [90]. To improve the accuracy of estimates, it is essential to integrate environmental variables (e.g., precipitation, temperature, soil type) into conversion models using multivariate or mechanistic approaches [91].

9.6 Implications of the findings for conservation policy, REDD+ initiatives, or protected area management in Central Africa

The findings of this study on ecosystem degradation and the decline in carbon stocks within the Santchou Wildlife Reserve offer critical insights for conservation policies, REDD+ initiatives, and protected area management in Central Africa. First, they

highlight the crucial importance of adopting inclusive and participatory governance, as advocated by [92, 93], who demonstrate that active involvement of local communities in natural resource management significantly enhances sustainability. In Central Africa, where conflicts between conservation and socio-economic development are common, a participatory approach could mitigate anthropogenic pressures while strengthening ecosystem resilience [94].

Second, these findings underscore the need to rethink REDD+ strategies so that they not only focus on reducing emissions from deforestation but also incorporate incentive mechanisms for sustainable agricultural practices and ecological restoration. Studies by [95, 96] have shown that the most effective REDD+ initiatives are those that combine payments for ecosystem services (PES) with local development programs, such as agroforestry or community forest management. For instance, in the Congo Basin, projects like WWF-CARPE have demonstrated that integrating agroforestry systems can reduce deforestation while improving local livelihoods [97].

Finally, this study highlights the urgency of strengthening the institutional capacities of protected area managers, a point also emphasized by [98, 99]. This involves not only better resource allocation for monitoring and law enforcement but also the adoption of adaptive management strategies capable of adjusting to changing environmental and socio-economic dynamics. Programs such as TRIDOM (Tri-National Dja-Odzala-Minkébé) have shown that cross-border cooperation and the use of advanced technologies (such as remote sensing and geographic information systems) can enhance the management of protected areas in Central Africa [100].

By integrating these approaches, conservation policies could not only preserve biodiversity and carbon stocks but also contribute to the sustainable socio-economic development of local communities, while aligning global climate change mitigation goals with local realities.

9.7 Study limits

Limitations of the study on forest cover dynamics and carbon stock assessment in the Santchou Wildlife Reserve include access difficulties to certain areas. Geographical constraints and potential restrictions may hinder field observations and limit the collection of accurate and complete data.

Setting up plots for floristic inventories is further complicated by dense vegetation and species diversity, making tree identification and measurement challenging, which can affect result accuracy. Additionally, the quality of the Landsat images used may be a limiting factor; cloud cover can obscure clarity, impacting classification and temporal analysis. The unavailability of satellite images for certain years can also restrict the analysis of changes over specific intervals.

The Markov model employed to predict land cover changes assumes constant transition probabilities over time, potentially overlooking rapid changes driven by socio-economic or environmental factors, which could undermine the validity of forecasts. Several methodological limitations must be considered for a rigorous interpretation of these projections:

Stationarity Assumption: Markov models assume that the probabilities of transition between land cover classes remain constant over time. However, this assumption is unrealistic in contexts of rapid change, such as demographic shifts, land reforms, or

economic shocks. For example, strengthened conservation policies or changes in agricultural subsidies could radically alter the projected trajectories.

Lack of Hindcasting Validation: The model was not validated by testing its ability to "predict" past states using earlier data (for example, by simulating land cover in 2022 based on data from 2000). Such validation would have allowed for an assessment of the reliability of the projections and adjustments to the transition probabilities.

Absence of Sensitivity Analysis: No systematic evaluation of the impact of variations in model parameters (for example, transition rates) on the results was conducted. A sensitivity analysis would have helped identify the most influential transitions and estimate the robustness of the scenarios in the face of uncertainties.

In conclusion, while these simulations provide a useful exploratory framework for anticipating land cover trends, they must be interpreted with caution, keeping in mind their inherent limitations. A complementary approach, integrating qualitative data (such as interviews with local stakeholders) and more dynamic models, would be necessary to refine these projections and guide sustainable land-use policies.

10 Conclusion

This study aimed to analyze the dynamics of forest cover and assess the carbon sequestration potential of the Santchou Wildlife Reserve (SWR). It examines land use changes over the past 22 years, identifies the most affected areas, assesses degradation factors, pinpoints regions suitable for reforestation, and quantifies changes in carbon stocks between 2000 and 2022. The results reveal five land use classes: high forest, mid-age secondary forest, shrub savannah, agrosystem, and built-up area. Mid-age secondary forests, agrosystems, and built-up areas are increasing, while shrub savannah and highland forest are decreasing. The SWR has experienced significant deforestation and degradation, primarily driven by agriculture, expansion of built-up areas, and illegal logging. The most affected land-use types likely to benefit from regeneration are highland forests and agrosystems. In terms of carbon sequestration potential, mid-age secondary forests, followed by highland forests, exhibit the greatest capacity. Despite significant degradation over the past 22 years, the SWR retains considerable carbon sequestration potential, currently threatened by human activities. Thus, implementing reforestation and monitoring measures is crucial for conserving this essential reserve. Enhancing community engagement in conservation efforts and integrating conservation objectives into public policy are vital. Establishing stricter land use regulations and promoting sustainable land management practices will help preserve the reserve's ecological integrity. Future research should focus on targeted conservation strategies for vulnerable species, considering the impacts of habitat loss. In-depth soil analyses are also essential to assess ecological health and regeneration capacity, guiding reforestation and soil restoration initiatives. Strengthening community involvement in conservation and aligning public policy with conservation goals will be critical for preserving biodiversity and enhancing the reserve's carbon sequestration potential.

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Author contributions

Anaëlle Brunda DJIAHA contributed to the conceptualization, mapping, analysis, and writing of the article following his fieldwork. Marlène NGANSOP TOUNKAM's and Philippes MBEVO FENDOUNG'S role consisted of constructing the

methodology, revising, editing, and mapping. All the authors read and approved the version. All authors have read and agreed to the version of the manuscript.

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Data availability

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

Declarations

Ethics approval and consent to participate

The prior informed consent of the participants was obtained in accordance with the guidelines for the application of the Nagoya protocol and more precisely, the newly adopted ABS law of Cameroon. In this case, we obtained verbal consent from the Reserve Manager (who is an agent of the Ministry of Forestry and Wildlife of Cameroon) and those of the different participants (Field's guides). This was done by the principal investigator. We obtained this oral consent after having explained in detail the objectives of the survey, the procedures, the risks and the potential benefits. The participants had the opportunity to ask questions and to withdraw at any time they wanted. We didn't consider people of ages lower than 21 years in the study. The field's guides below this age are still in secondary school and early university and assumed it not knowledgeable to provide the information researched. So, we did not need any parental authorization.

Consent for publication

Informed consent for publication has been obtained from all participants for the use of identifiable data or images, and no data or images that could identify participants are included in this manuscript.

Competing interests

The authors declare no competing interests.

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