

Diachronic Analysis of Land-Use and Forest-Cover Changes in the Irobo Classified Forest (Sikensi, Côte d'Ivoire)

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Abstract

The decline in forest cover is a major conservation challenge in Côte d'Ivoire, where agricultural expansion exerts considerable pressure on forest ecosystems. The objective of this study is to analyze spatiotemporal changes in land use and forest cover in the Irobo Classified Forest between 1988 and 2026 and to assess a trend-based scenario of forest-cover change by 2050. The study used Landsat 4 TM and Landsat 8 OLI/TIRS satellite imagery processed in Google Earth Engine, supplemented by GIS data and field observations. Supervised classification using the Classification and Regression Trees (CART) algorithm was used to distinguish four land-use classes: water bodies, forest, cropland/fallow land, and settlements/bare land. Forest cover decreased from 19,105.81 ha (46.67%) in 1988 to 8,278.17 ha (20.22%) in 2026, representing a loss of 10,827.64 ha, or 56.67% of the initial forest cover. The average annual forest loss was estimated at 284.94 ha/year, corresponding to an annual deforestation rate of 2.20%. Meanwhile, cropland and fallow land

increased from 50.69% to 79.10% of the classified forest area. Spatial analysis indicates that the remaining forest areas became more scattered and less spatially continuous between 1988 and 2026. Under the trend-based scenario, forest area could decline to approximately 4,881.19 ha by 2050, representing 11.92% of the classified forest area. These findings demonstrate the usefulness of combining remote sensing, GIS, and field observations to quantify long-term land-use changes and identify forest areas potentially exposed to future conversion. They provide a spatial basis for forest monitoring, conservation, and restoration planning in the Irobo Classified Forest.

Keywords: Côte d'Ivoire, Irobo Classified Forest (Sikensi), deforestation, land use, remote sensing, GIS, spatial projection

Introduction

Tropical rainforests play a major role in ecosystem functioning, particularly through carbon storage, water cycle regulation, soil protection, and biodiversity conservation (Tao et al., 2022). However, these ecosystems have experienced significant decline over the past several decades due to the combined effects of human activities and environmental changes. Across tropical rainforest regions, forest loss has been estimated at approximately 220 million hectares since 1990 (Vancutsem et al., 2021; Bourgoin et al., 2024).

In Côte d'Ivoire, this trend is particularly pronounced. Dense rainforests, once widespread, have declined considerably, from approximately 16 million hectares in the 19th century to 2.97 million hectares in 2020 (Aké-Assi & Boni, 1990; Cuny et al., 2023). Despite their role in biodiversity conservation, protected areas and classified forests in Côte d'Ivoire face increasing pressure from human activities (Kouassi, 2008; Kouassi et al., 2023; Malan et al., 2023).

These pressures are mainly associated with agricultural expansion, bushfires, illegal logging, illegal gold mining, and other forms of natural resource exploitation. Other contributing factors include population growth, urbanization, and challenges related to the sustainable management of forest areas (Kouassi, 2008; Koné et al., 2014; Andrieu et al., 2016; BNETD, 2016; N'Dri Ehikpa et al., 2020; Kobenan & N'Guéssan, 2021; Cuny et al., 2023).

The Irobo Classified Forest, located in southern Côte d'Ivoire, illustrates the pressures affecting classified forests in the country. It faces increasing pressure from agricultural land clearing, forest resource exploitation, and the gradual settlement of populations engaged in cash crop farming, particularly cocoa and rubber. These activities contribute to changes in vegetation cover and highlight the challenges of conserving and sustainably managing classified forests in Côte d'Ivoire (Gueulou et al., 2020; N'Dri Ehikpa et al., 2020; Kouassi et al., 2023; Malan et al., 2023).

In response to forest degradation, Côte d'Ivoire has adopted a national strategy for forest preservation, rehabilitation, and expansion to restore degraded forest ecosystems and promote sustainable forest management (Ministère des Eaux et Forêts, 2019). The Irobo Classified Forest has also been included in previous forest development initiatives, notably two World Bank/CDC-funded reforestation projects (1979–1985 and 1986–1990), which established mechanized hardwood plantations for timber production at Irobo, Mopri, Téné and Sangoué, and a CCCE-funded project (1989–1991) supporting the preparation of their management plans (SODEFOR, n.d.). Despite these efforts, continued human pressure highlights the need to assess long-term changes in forest cover to support conservation and restoration decisions. In this context, diachronic land-use analysis, combined with remote sensing, geographic information systems (GIS), and field observations, provides a means of identifying changes in forest cover and areas converted to other land uses. This information can help identify areas requiring priority conservation or restoration measures, while the analysis of potential forest-cover changes by 2050 can provide further guidance for long-term forest management.

This study aims to analyze spatiotemporal changes in land use in the Irobo Classified Forest between 1988 and 2026. More specifically, it seeks to: (i) map the main land-use classes for the study years; (ii) quantify changes in forest cover; (iii) identify the main forms of human pressure observed in the classified forest; and (iv) analyze, based on trends observed between 1988 and 2026, the potential evolution of forest cover by 2050.

2. Study Area

The Irobo Classified Forest is located in southern Côte d'Ivoire, between the Sikensi Department and the Bandama River (Figure 1). Covering an area of 40,940 hectares, it extends across the departments of Dabou, Grand-Lahou, Sikensi, and Tiassalé. Its geographical extent ranges from 962021.52 to 983830.31 m for the X coordinate (Easting) and from 600680.47 to 637907.91 m for the Y coordinate (Northing), in the WGS 84 / UTM Zone 29N coordinate system (EPSG:32629). It is accessible by a main road connecting Bécédi to Ahouanou, passing through Bakanou A and Bakanou B, as well as the forest camps of Brikisso and Pikinou. A road to the north provides access to Akalékro, on the banks of the Bandama River, while an old road west of Bécédi provides access to the northeastern part of the forest area.

The Irobo Classified Forest lies within the humid tropical zone. It is mainly characterized by two types of soil: sandy-clay soils rich in quartz and developed on schist, and soils derived from granitic formations with a coarser texture (De Boissezon, 1967; Perraud, 1971). The terrain is gently rolling and consists of small hills with slopes generally ranging from 5 to 10%. These hills

are 20 to 30 m high, with elongated forms and semi-interfluvies ranging from 500 to 800 m in width (De Boissezon, 1967). The area has a humid equatorial climate. Annual rainfall ranges from 1600 to 1800 mm, while the average temperature is approximately 26.5 °C. These climatic conditions favor the development of dense, humid vegetation adapted to the ecological conditions of southern Côte d'Ivoire. The area is mainly inhabited by populations engaged in agriculture. These include the indigenous Abidji people as well as migrant communities, including the Baoulé, Agni, and Lobi. Agriculture is one of the main activities in the area, particularly through the development of cocoa, rubber, oil palm, and coffee plantations.

Since it was classified in 1962, the Irobo Classified Forest has been subject to increasing pressure, particularly from the expansion of agricultural activities and the gradual occupation of certain parts of the forest. Land clearing for plantations and conflicts over land occupation contribute to the gradual transformation of the forest landscape. These pressures represent an important challenge for forest conservation and justify the analysis of long-term changes in land use.

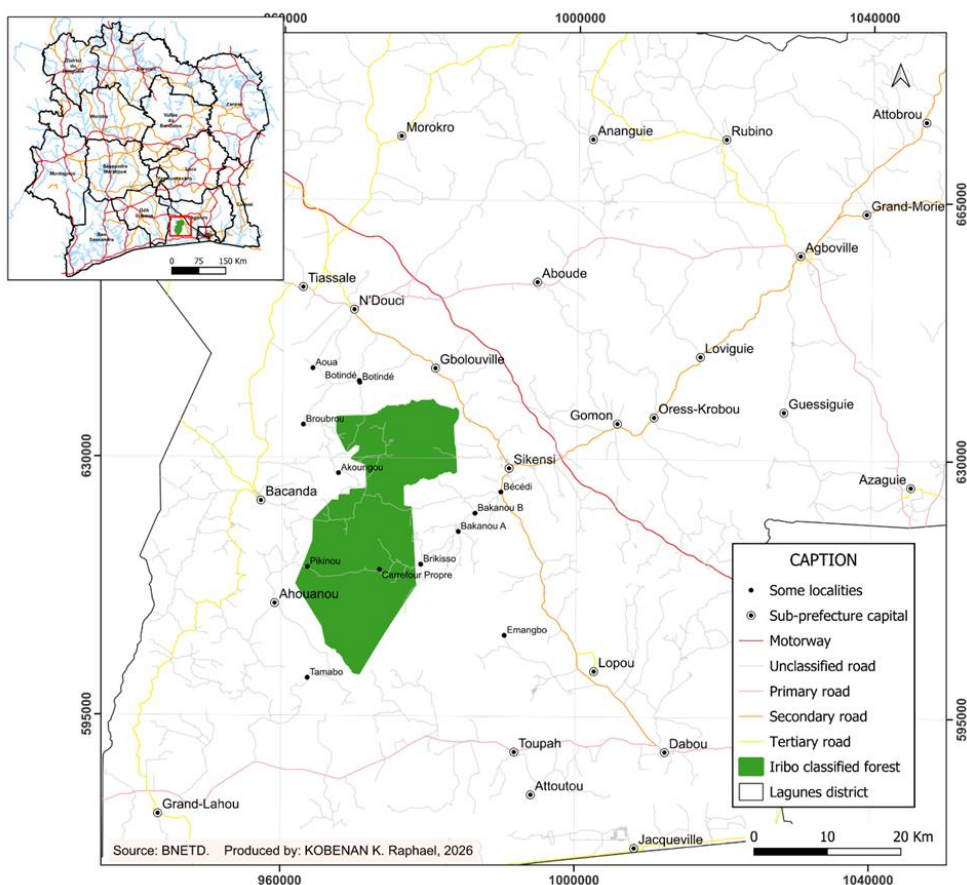


Figure 1: Location of the Irobo Classified Forest

3. Materials and Methods

3.1. Data

The analysis of land-use dynamics in the Irobo Classified Forest is based mainly on Landsat satellite imagery, vector data delineating the classified forest, and reference data used for training and validating the classifications. Two dates were selected to assess changes in land use over a 38-year period: 1988 and 2026. Two Landsat satellite images acquired in 1988 and 2026 were used to analyze land-use and forest-cover changes in the Irobo Classified Forest. Their main characteristics are presented in Table 1.

Table 1: Characteristics of the Landsat satellite images used in the study

Characteristics	1988 image	2026 image
Satellite	Landsat 4	Landsat 8
Sensor	TM	OLI/TIRS
Acquisition date	December 24, 1988	March 12, 2026
Collection	Collection 2	Collection 2
Processing level	Level-2	Level-2
WRS-2 Path/Row	196/056	196/056
Product identifier	LT04_L2SP_196056_19881224_20200917_02_T1	LC08_L2SP_196056_20260312_20260314_02_T1
Cloud cover (%)	5.00	1.19

Both images were acquired during the main dry season, which extends from December to April in the study area. Within this period, priority was given to scenes with low cloud cover over the classified forest in order to reduce atmospheric effects and seasonal differences that could affect the land-use analysis. This approach led to the selection of the December 1988 image and the March 2026 image.

For land-use classification, six spectral bands were selected from both Landsat 4 TM and Landsat 8 OLI: blue, green, red, near-infrared (NIR), short-wave infrared 1 (SWIR1), and short-wave infrared 2 (SWIR2).

The map data were obtained from the Center for Geographic and Digital Information of the National Office for Technical Studies and Development (BNETD). They include administrative boundaries, the road network, localities, and other elements needed to delineate and map the study area. The boundary of the Irobo Classified Forest was provided in vector format and used to delineate the analysis area. It covers an area of 40,940 ha.

The field data consist of georeferenced points recorded using a GPS and photographs. They were used to identify the main land-use classes observed in the classified forest and to support the interpretation of satellite imagery, as well as the training and validation of the classifications.

3.2. Preprocessing of Satellite Images

The satellite images were preprocessed in the Google Earth Engine (GEE) environment using Landsat Collection 2, Level-2 surface reflectance products. The scale factors associated with these products were applied to the optical bands to obtain the reflectance values used for subsequent processing. Pixels that could affect data quality were masked using the QA_PIXEL and QA_RADSAT quality bands. The mask excluded fill pixels, clouds, dilated clouds, cloud shadows, and pixels affected by radiometric saturation. For the Landsat 8 image, pixels identified as cirrus clouds were also excluded. This step was used to reduce the influence of atmospheric and radiometric effects on the spectral values used for classification. Processing was performed at a spatial resolution of 30 m for both dates to ensure spatial comparability. A false-color composite combining the short-wave infrared 1 (SWIR1), near-infrared (NIR), and blue bands was also generated to facilitate visual interpretation of the satellite imagery. This band combination helped distinguish vegetation cover, agricultural areas, and other land-cover features based on their spectral responses, thereby supporting the identification and delineation of training samples.

3.3. Sampling and Land-Use Nomenclature

The land-use classification is based on a supervised approach (Bonn & Rochon, 1992; Kobenan & N'Guéssan, 2021). Four classes were defined based on the main land-use types observed in the classified forest (Table 2).

Table 2: Nomenclature of land-use classes used for classification

Code	Class
1	Water bodies
2	Forest
3	Cropland/Fallow land
4	Settlements/Bare land

Reference samples were derived from GPS points collected during field surveys, visual interpretation of satellite imagery, and available information on the study area. For each study year, 250 reference points were used to delineate reference polygons representing the four land-use classes: 50 points for water bodies, 90 for forest, 65 for cropland/fallow land, and 45 for settlements/bare land.

The reference polygons were sampled at a spatial resolution of 30 m to extract spectral values corresponding to the four land-use classes. Because the polygons differed in size and could therefore generate unequal numbers of pixels among classes, the number of extracted pixels was limited to a maximum of 3,000 pixels per class. This procedure was used to reduce class imbalance and prevent classes represented by larger polygons from disproportionately influencing classifier training.

For each study year, the resulting dataset was randomly divided into two independent subsets. Seventy percent (70%) of the samples were used exclusively to train the Classification and Regression Trees (CART) classifier, while the remaining 30% were reserved exclusively for accuracy assessment. Thus, the validation samples were not used during classifier training, ensuring independence between the training and validation datasets.

The “Water bodies” class was included in the supervised classification and represented by 50 reference points used for classifier training. However, no pixels were assigned to this class in the final classified maps for either 1988 or 2026. This may be explained by the limited spatial extent and seasonal variability of temporary watercourses within the Irobo Classified Forest, as well as the 30 m spatial resolution of Landsat imagery. Furthermore, both satellite images were acquired during the main dry season in Côte d’Ivoire (December 1988 and March 2026), when some small streams and temporary water bodies may dry up or experience substantially reduced water levels, making them more difficult to detect in satellite imagery. Therefore, the absence of this class from the final maps should not be interpreted as evidence of a complete absence of surface water within the study area.

3.4. Supervised Classification and Validation

Land-use mapping was performed using the Classification and Regression Trees (CART) algorithm available in Google Earth Engine. For each of the two dates, the balanced samples were randomly divided into two distinct subsets: 70% were used to train the classifier, while the remaining 30% were reserved for validation. The samples used for validation were therefore not used to train the model. After training, the CART model was applied to the selected spectral bands of each image to produce land-use maps based on the four initially defined classes, although only three classes were represented in the final maps. A 3×3 -pixel majority filter (focal_mode) was then applied to the classified images to reduce the “salt-and-pepper” effect and improve the spatial continuity of the mapped units.

The quality of the classifications was evaluated using the samples reserved for validation and a confusion matrix. Classification performance was assessed mainly using overall accuracy and the Kappa coefficient (Congalton, 1991; Konan et al., 2016), calculated using the equations presented below. The 1988 classification had an overall accuracy of 97.79% and a Kappa coefficient of 0.971, while the 2026 classification had an overall accuracy of 98.01% and a Kappa coefficient of 0.966. These results indicate a high level of agreement between the classes assigned by the model and the reference data used for validation, highlighting the importance of accuracy assessment in satellite image classification (Congalton, 1991; Panchal et al., 2009).

$$\hat{k} = \frac{a - b}{1 - b} \quad a = \frac{1}{N} \sum_{i=1}^{N_c} x_{ii} \quad b = \frac{1}{N^2} \sum_{i=1}^{N_c} (x_{+i} x_{i+})$$

Where:

N_c = Number of classes

N = Total number of observations

x_{ii} = Number of observations in column i , row i (diagonal of the matrix)

x_{+i} = Total number of observations in column i

x_{i+} = Total number of observations in row i

3.5. Calculation of Areas and Change Analysis

The area occupied by each land-use class was calculated from the classified pixels. The area of each pixel was converted to hectares and then aggregated within the boundaries of the classified forest. Given the slight difference between the geometric area of the vector file (41,118.29 ha) and the official area of the classified forest (40,940 ha), the calculated areas were normalized to the official area.

This process preserves the relative proportions obtained from the classifications while ensuring that the sum of the areas of the different classes corresponds exactly to 40,940 ha for each study year. Forest dynamics between 1988 and 2026 were assessed based on changes in forest area. Total forest loss (P), expressed in hectares, was calculated using the following equation:

$$P = S_{1988} - S_{2026}$$

Where S_{1988} and S_{2026} represent the forest areas in 1988 and 2026, respectively. The average annual forest loss (P_m), expressed in hectares per year, was calculated as follows:

$$P_m = \frac{(S_{1988} - S_{2026})}{(2026 - 1988)}$$

The annual deforestation rate (θ), expressed as a percentage per year, has sometimes been estimated by dividing the deforestation rate observed over a given period by the duration of that period (Menon & Bawa, 1997; Narendra Prasad, 1998). However, this approach does not adequately represent the annual rate of change in forest cover (Puyravaud, 2003; Vieilledent et al., 2013). In this study, the annual rate of change in forest cover was calculated over the 38 years between the two observations using the approach proposed by Puyravaud (2003). To express deforestation as a positive value when forest area decreases, the sign of the rate of change was reversed. The annual deforestation rate was therefore calculated using the following equation:

$$\theta = -\frac{1}{38} \ln \left(\frac{S_{2026}}{S_{1988}} \right) * 100$$

Where $\ln$ denotes the natural logarithm. Thus, a positive value of θ indicates a decrease in forest area over the study period. This approach provides an estimate of the average annual rate of forest cover loss over the entire study period.

3.6. Projection of Forest Cover by 2050

The potential change in forest cover by 2050 was estimated based on the dynamics observed between 1988 and 2026. The projection was based on an exponential extrapolation of forest-cover change, consistent with the relative annual rate of forest-cover change described by Puyravaud (2003), and was considered a trend-based scenario. First, the ratio between the forest areas observed in 2026 and 1988 was calculated using the following equation:

$$R = \frac{S_{2026}}{S_{1988}}$$

The forest cover retention coefficient between 2026 and 2050 was then determined by considering the duration of the historical period (1988–2026) and the projection period (2026–2050):

$$R_{2050} = R^{\frac{2050-2026}{2026-1988}}$$

The theoretical forest area by 2050 was then estimated as follows:

$$S_{2050} = S_{2026} \times R_{2050}$$

This projection represents a trend-based scenario rather than a forecast. It assumes that the relative rate of forest-cover change observed between 1988 and 2026 remains constant through 2050. The approach does not explicitly incorporate future changes in agricultural practices, population dynamics, forest-management policies, conservation interventions, restoration programs, climatic conditions, or other socioeconomic and environmental drivers. Therefore, the projected forest area should be interpreted as an indication of the potential trajectory of forest cover if the historical trend persists, rather than as a deterministic prediction of forest conditions in 2050.

Spatial factors, including proximity to previously deforested areas, have been used in GIS-based deforestation modelling (Mas et al., 2004). In the present study, the projected forest loss was spatially allocated in Google Earth Engine to produce a land-use map for 2050. This allocation was applied to pixels classified as forest in 2026 using a vulnerability index combining proximity to non-forest areas and local human pressure.

First, a mask distinguishing forest pixels from non-forest pixels was created from the 2026 classification. The distance from each forest pixel to non-forest areas was then calculated at a spatial resolution of 30 m. This distance was converted into a proximity index using the following equation:

$$P_r = \frac{1}{d + 1}$$

Where d represents the distance to the nearest non-forest pixel. This transformation assigns the highest values to forest pixels located close to areas that are already non-forest. The proximity index was then normalized between 0 and 1 based on the minimum and maximum values observed within forest areas:

$$P = \frac{P_r - P_{\min}}{P_{\max} - P_{\min}}$$

Local human pressure (A) was estimated as the average proportion of non-forest pixels within a 300 m circular neighborhood around each pixel. This variable ranges from 0, corresponding to an entirely forested neighborhood, to 1, corresponding to an entirely non-forest neighborhood. The vulnerability index (V) was calculated using a weighted linear combination of the two components, following the general multicriteria evaluation principle discussed by Malczewski (2000). Equal weights were assigned to proximity to non-forest areas and local human pressure:

$$V = 0.5P + 0.5A$$

Where P represents the normalized proximity to non-forest areas and A represents local human pressure. High values of V therefore correspond to forest pixels considered most exposed to potential conversion.

Equal weights were assigned to the two components because no empirical evidence was available to support a greater influence of either proximity to non-forest areas or local anthropogenic pressure in the study area. The 0.5/0.5 weighting was therefore adopted as a parsimonious and transparent assumption that avoids giving arbitrary priority to either component. The vulnerability index should consequently be interpreted as a spatial allocation tool for the trend-based scenario rather than as an independently calibrated predictive model of future deforestation.

To spatially allocate the forest area expected to be lost between 2026 and 2050, a vulnerability threshold was identified using a binary search procedure with 30 iterations.

For each threshold tested, the area of forest pixels with a vulnerability value greater than or equal to the threshold was calculated and compared with the theoretical forest loss obtained from the exponential projection.

The final threshold was selected to minimize the difference between the area to be converted on the map and the projected theoretical loss. A very small random value was added to the index only when ranking the pixels to separate pixels with identical vulnerability values. Forest pixels selected as potentially deforested were then reclassified as “Cropland/Fallow land” to produce the projected land-use map for 2050.

Finally, the forest area obtained from the projected 2050 map was compared with the theoretical forest area obtained from the exponential extrapolation. The difference between these two values was calculated to assess the agreement between the quantitative projection and its spatial allocation.

After preprocessing, classification, and analysis, the resulting spatial data were imported into the GIS environment (ArcGIS) for formatting and map production. This step was used to produce the land-use maps for 1988 and 2026, as well as the projected map for 2050. The map layout involved organizing the different information layers and adding the elements needed to read and interpret the maps.

4. Results

4.1. Classification Performance

The supervised classifications performed for 1988 and 2026 showed high levels of accuracy. For 1988, the overall accuracy was 97.79%, with a Kappa coefficient of 0.971. For 2026, the overall accuracy was 98.01%, with a Kappa coefficient of 0.966. These results indicate a high level of agreement between the classes obtained from the classification and the reference data used for validation.

4.2. Status and Changes in Land Use Between 1988 and 2026

The results show substantial changes in land use within the Irobo Classified Forest between 1988 and 2026 (Table 3; Figure 2). In 1988, forest covered 19,105.81 ha, representing 46.67% of the study area. Cropland and fallow land constituted the largest land-use class, covering 20,753.18 ha, or 50.69% of the total area. Settlements and bare land occupied 1,081.01 ha, representing 2.64% of the classified forest.

In 2026, forest cover had decreased to 8,278.17 ha, accounting for 20.22% of the study area. In contrast, cropland and fallow land expanded to 32,384.58 ha, representing 79.10% of the total area. Settlements and bare land occupied 277.25 ha, corresponding to 0.68% of the classified forest.

Overall, forest cover declined by 10,827.64 ha between 1988 and 2026, corresponding to a decrease of 26.45 percentage points. Over the same period, cropland and fallow land increased by 11,631.40 ha, while settlements and bare land decreased by 803.76 ha. These changes indicate a marked reduction

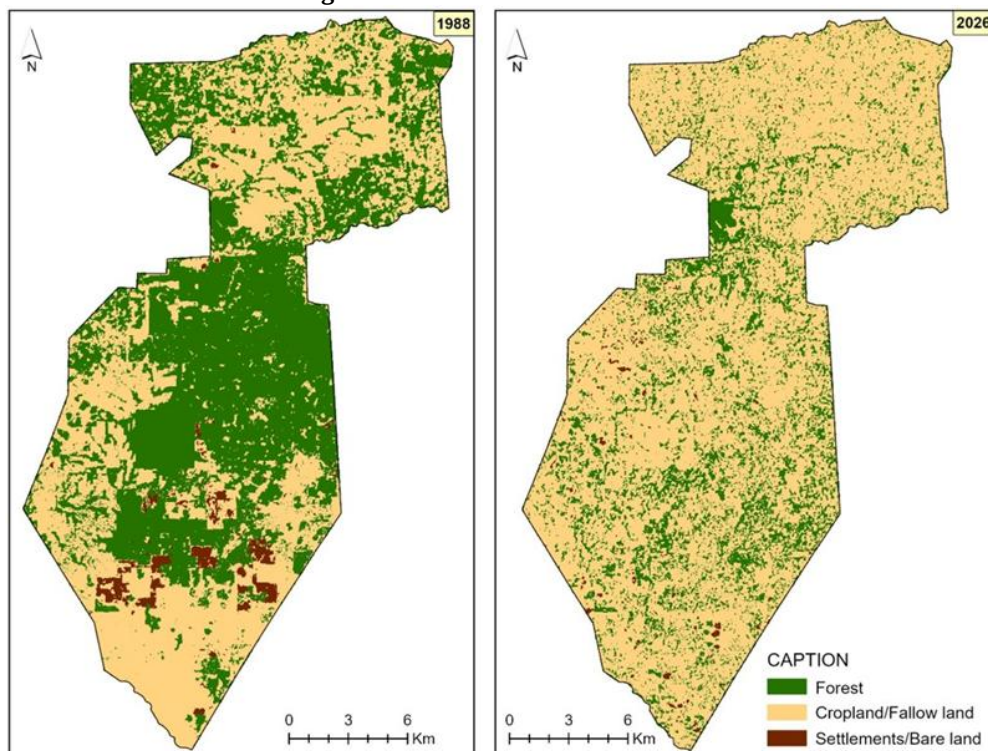
in forest cover alongside an expansion of agricultural and fallow areas within the classified forest.

No water bodies were identified in the final classified maps for either year. However, this result does not necessarily indicate the absence of surface water within the study area, as small or seasonal water features may not have been detected at the 30 m spatial resolution of Landsat imagery.

Table 3: Changes in land use in the Irobo Classified Forest between 1988 and 2026

Land Use Classes	1988 (ha)	1988 (%)	2026 (ha)	2026 (%)	Change (ha)
Forest	19,105.81	46.67	8,278.17	20.22	-10,827.64
Cropland/Fallow land	20,753.18	50.69	32,384.58	79.10	11,631.40
Settlements/Bare land	1,081.01	2.64	277.25	0.68	-803.76
Total	40,940	100	40,940	100	-

Figure 2: Land Use in 1988 and 2026



Source : Google Earth Engine (GEE).

Produced by : KOBENAN K. Raphael, 2026.

The observed changes were mainly characterized by a substantial decline in forest cover and a marked increase in cropland and fallow land. Between 1988 and 2026, forest area decreased by 10,827.64 ha, representing a 56.67% reduction relative to its 1988 extent. Over the same period, cropland and fallow land increased by 11,631.40 ha. Field observations revealed the presence of agricultural plantations within the classified forest, including cocoa plantations associated in some areas with banana plants and other trees

(Photo 1). Other perennial crops, such as oil palm, kola, orange, and rubber trees, may also occur within agricultural areas. Camps and dwellings were observed near or within cultivated areas (Photo 2). These observations highlight the presence of agricultural activities and human settlements within the Irobo Classified Forest.

The “Cropland/Fallow land” class encompasses different agricultural land uses and fallow areas rather than cocoa plantations alone. Some perennial crop plantations, particularly cocoa plantations associated with shade trees, may constitute agroforestry systems that differ structurally from annual cropland and fallow vegetation. However, these agricultural systems were not mapped as separate classes in this study.

At the 30 m spatial resolution of Landsat imagery, relatively small or heterogeneous plantations may produce mixed spectral responses, while the presence of trees within cultivated plots can make some plantations spectrally similar to forest vegetation. Furthermore, the exact boundaries and areas of individual plantations were not available, and no dedicated reference dataset was established to distinguish and validate the different plantation types. Consequently, cocoa-based agroforestry systems and other perennial crop plantations could not be reliably mapped or quantified separately using the classification approach adopted in this study. These agricultural systems were included in the broader “Cropland/Fallow land” class where identified as cultivated land, although some tree-covered plantations may have been confused with forest vegetation. More detailed mapping would require higher-resolution imagery and dedicated field reference data.

Photo 1: Cocoa and banana plantations observed near camps in the Irobo Classified Forest (January 2026)



Source : Photographs by KOBENAN K. Raphaël, January 2026

Photo 2: Examples of camps observed in the Irobo Classified Forest (January 2026)



Source : Photographs by KOBENAN K. Raphaël, January 2026

Over the 38 years between the two observations, the average annual forest loss was estimated at 284.94 ha/year, while the annual deforestation rate was 2.20% per year. These results show the significant decline in forest cover during the study period.

The “Settlements/Bare land” class also decreased, from 1,081.01 ha (2.64%) in 1988 to 277.25 ha (0.68%) in 2026, representing a reduction of 803.76 ha.

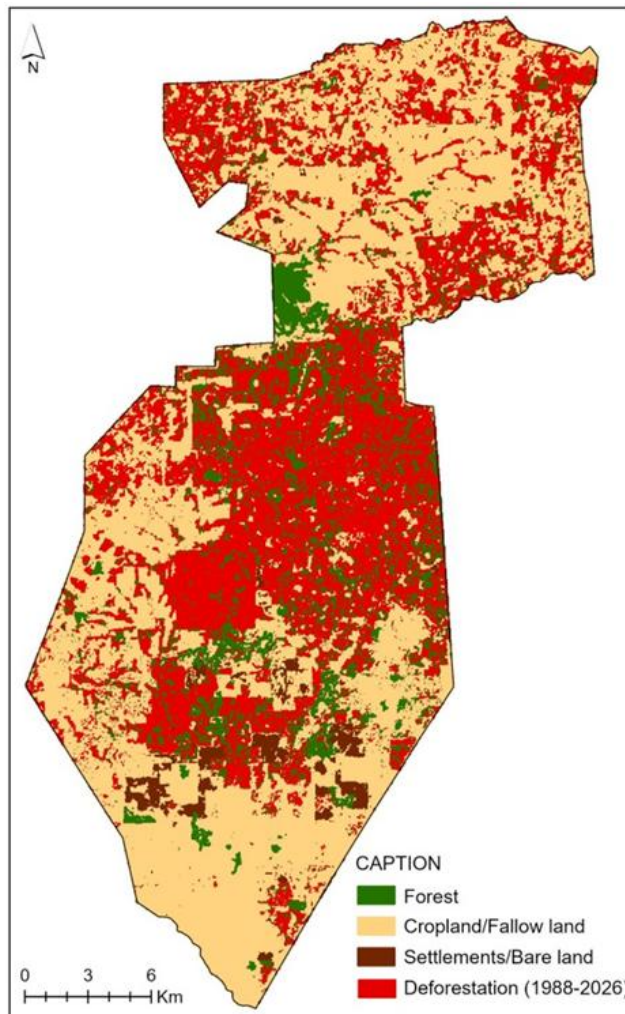
This change may be linked to clearance operations that led to the removal of several camps within the classified forest. However, field observations indicate that some camps remain within the plantations. Due to their small size and their location within areas covered by vegetation, these settlements may be difficult to detect in Landsat images at a spatial resolution of 30 m. The mapped decrease in the “Settlements/Bare land” class therefore does not necessarily mean that all human settlements within the classified forest have disappeared.

4.3. Spatial Dynamics of Deforestation Between 1988 and 2026

The analysis of the spatial distribution of deforestation between 1988 and 2026 shows a decline in forest cover in different parts of the Irobo Classified Forest (Figure 3). Deforested areas are found both along the edges and within the classified forest, showing that forest loss was not limited to peripheral areas. In the central part of the classified forest, deforested areas are particularly extensive and cover large areas in some places. The remaining forest areas appear as smaller and more spatially scattered patches than in 1988, indicating a reduction in the spatial continuity of forest cover. Because specific landscape fragmentation metrics were not calculated in this study, these patterns should not be interpreted as a quantitative assessment of forest fragmentation. In the northern part, deforested areas are also numerous but more widely dispersed. Some forest areas remain in this part of the classified forest, but they are often separated from one another. Overall, the map shows

that deforestation between 1988 and 2026 led to a substantial reduction in forest cover and a decrease in its spatial continuity within the Irobo Classified Forest. The remaining forest areas are now more scattered and largely surrounded by non-forest areas.

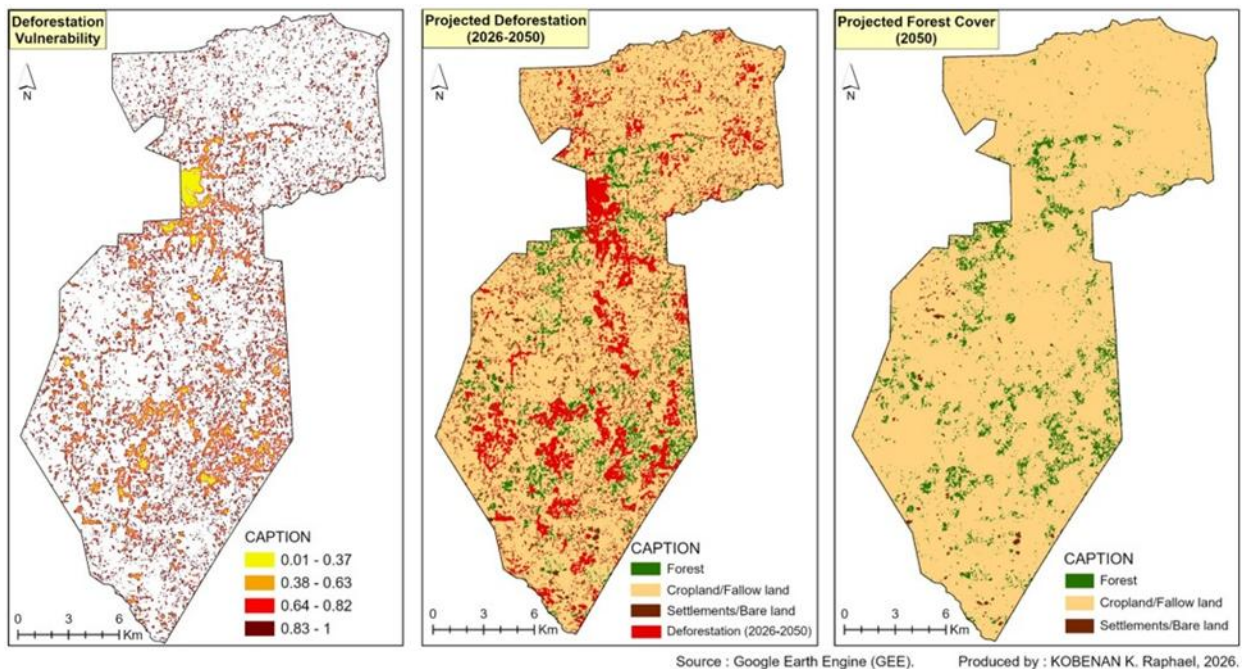
Figure 3: Spatial Dynamics of Deforestation in the Irobo Classified Forest Between 1988 and 2026



4.4. Projected Changes in Forest Cover by 2050

The trend-based projection indicates a continued decline in forest cover by 2050 (Figure 4). The theoretical forest area would decrease from 8,278.17 ha in 2026 to 4,881.19 ha in 2050, representing 11.92% of the total area of the Irobo Classified Forest. This change would correspond to an additional loss of approximately 3,396.98 ha between 2026 and 2050, representing a 41.04% reduction in the forest cover present in 2026.

Figure 4: Vulnerability to deforestation, projected deforestation between 2026 and 2050, and projected forest cover by 2050 in the Irobo Classified Forest



The spatial allocation of this loss results in a mapped forest area of 4,858.16 ha in 2050. The difference from the projected theoretical forest area is 23.03 ha, or approximately 0.47%. This small difference indicates good agreement between the area obtained from the quantitative projection and that obtained after spatial allocation.

The vulnerability map shows an uneven distribution of areas that could be affected by deforestation. The highest vulnerability levels are scattered across different parts of the remaining forest areas. They are particularly present in the central and southern parts of the classified forest, but also appear in several areas in the northern part. The presence of high or moderate vulnerability levels within some forest areas shows that the potentially affected areas are not limited to the edges of the classified forest.

Projected deforestation between 2026 and 2050 also shows a wide spatial distribution. Areas that could lose their forest cover are found near cropland and fallow land, but also within some forest areas still present in 2026. The central part, which connects the two main sections of the classified forest, has a high concentration of areas projected to be deforested. In the southern part, potential losses appear more scattered and are associated with the remaining forest areas.

By 2050, cropland and fallow land would occupy most of the classified forest, while the remaining forest cover would consist of areas of different

sizes scattered throughout the classified forest. Some forest areas would remain mainly in the central and southern parts, while the projected forest areas in the northern part would be smaller and more isolated.

Thus, assuming that the trend observed between 1988 and 2026 continues, deforestation could lead to a further reduction in forest area and a decrease in the spatial continuity of the remaining forest cover. Under this scenario, areas with the highest levels of vulnerability could require particular attention for monitoring and conservation.

However, these results should be interpreted as a trend-based scenario and not as a certain prediction of the state of the classified forest in 2050.

The actual change in forest cover may depend on conservation and restoration measures, agricultural practices, management of the classified forest, and, more broadly, changes in human pressures.

5. Discussion

The diachronic analysis of land use shows a sharp decline in forest cover in the Irobo Classified Forest between 1988 and 2026. Forest area decreased from 19,105.81 ha in 1988 to 8,278.17 ha in 2026, representing a loss of 10,827.64 ha, or 56.67% of the initial forest cover. This change represents an average loss of 284.94 ha/year and an annual deforestation rate of 2.20%. At the same time, cropland and fallow land increased from 20,753.18 ha (50.69%) to 32,384.58 ha (79.10%) of the classified forest area. These results show a significant decline in forest cover accompanied by a marked increase in agricultural land.

This change is consistent with field observations, which showed the presence of plantations, particularly cocoa and banana plantations, as well as camps within the classified forest. It suggests that agricultural activities are an important source of pressure on forest areas. This situation is similar to the findings of Malan et al. (2023) in the Goin-Débé Classified Forest, where a significant reduction in forest areas was observed between 1988 and 2020, along with the expansion of agricultural plantations and fallow land. Despite differences in the study sites and observation periods, these results show the importance of changes related to agricultural land use in several classified forests in Côte d'Ivoire.

Similar changes have also been reported in other tropical regions. Nourtier and Grinand (2016a) reported changes in forest cover in Mikea National Park in Madagascar, while Kimvula et al. (2023) showed the importance of agricultural activities in land-use dynamics at the INÉRA Kiyaka forest station in the Democratic Republic of the Congo. In Côte d'Ivoire, studies by Cuny et al. (2023), N'Dri Ehikpa et al. (2020), Kobenan & N'Guéssan (2021) and Konan et al. (2016) also report changes in forest areas due to human activities, particularly the expansion of agricultural land.

The changes observed in the Irobo Classified Forest are therefore part of a broader pattern of pressure on tropical forests.

Beyond the reduction in forest area, the spatial analysis conducted in Irobo shows that forest loss occurred in different parts of the classified forest and was not limited to its edges. The forest areas still present in 2026 appear more scattered and less continuous than in 1988, suggesting a reduction in the spatial continuity of forest cover. However, because specific landscape fragmentation metrics were not calculated in this study, these spatial patterns should not be interpreted as a quantitative assessment of forest fragmentation. Further research using landscape metrics would be necessary to quantify changes in forest configuration and fragmentation more precisely.

The decrease in the “Settlements/Bare land” class observed between 1988 and 2026 should be interpreted with caution. Field observations show that camps remain within the classified forest, particularly within or near plantations. Their small size and location within areas covered by vegetation may make them difficult to detect in Landsat images at a spatial resolution of 30 m.

The decrease in this class on the maps therefore does not necessarily reflect a similar decrease in human presence within the classified forest. This limitation shows the importance of combining satellite analysis with field observations when interpreting land-use changes.

The results of the projection to 2050 follow the same trend. Assuming that the relative rate observed between 1988 and 2026 continues, the theoretical forest area could reach approximately 4,881.19 ha in 2050, representing 11.92% of the classified forest area.

This would represent an additional loss of approximately 3,396.98 ha compared with 2026. The spatial allocation of this loss also shows that several forest areas still present in 2026 are vulnerable to conversion, particularly in the central and southern parts of the classified forest. If this trend continues, the remaining forest areas could become more spatially scattered and their spatial continuity could be further reduced.

However, this projection should be considered a trend-based scenario rather than a certain prediction. It is based on the assumption that the relative trend observed between 1988 and 2026 will continue through 2050. It therefore does not directly take into account possible future changes in conservation policies, agricultural practices, forest restoration activities, or, more broadly, human pressures. Its main purpose is to identify a possible future trend and the areas that could be particularly exposed if current trends continue.

In this context, the results show the importance of strengthening conservation measures and the sustainable management of the Irobo Classified Forest. The observed decline in forest cover, the expansion of agricultural

areas, and the vulnerability of some remaining forest areas show the importance of regular land-use monitoring, protecting the remaining forest areas, and strengthening restoration activities. It is also important to consider agricultural activities and the populations living in and around the forest when developing management strategies that combine forest conservation with local uses.

Conclusion

This study analyzed spatiotemporal changes in land use in the Irobo Classified Forest between 1988 and 2026 using Landsat satellite imagery, remote sensing and GIS tools, supplemented by field observations. The results show a sharp decline in forest cover over the 38-year study period. Forest area decreased from 19,105.81 ha in 1988, representing 46.67% of the total area of the classified forest, to 8,278.17 ha in 2026, representing 20.22%. This change corresponds to a loss of 10,827.64 ha, or 56.67% of the 1988 forest cover, with an average annual loss of 284.94 ha/year and an estimated annual deforestation rate of 2.20%.

Along with the decline in forest cover, cropland and fallow land increased significantly, from 50.69% of the study area in 1988 to 79.10% in 2026. Field observations, particularly the presence of agricultural plantations and camps within the classified forest, support the results of the satellite analysis and show the importance of human activities in the current land use of this area. The spatial analysis also shows that forest loss was not limited to the edges of the classified forest but occurred in different parts of the area. The forest areas still present in 2026 appear more scattered and less continuous than in 1988, indicating a reduction in the spatial continuity of forest cover. However, because specific landscape fragmentation metrics were not calculated, this pattern should not be interpreted as a quantitative assessment of forest fragmentation. The trend-based projection for 2050 indicates that, if the trend observed between 1988 and 2026 continues, forest area could reach approximately 4,881.19 ha, or 11.92% of the total area of the classified forest. This would correspond to an additional loss of approximately 3,396.98 ha compared with 2026.

However, this projection should be considered a trend-based scenario rather than a certain prediction, as future changes in forest cover may be influenced by conservation policies, agricultural practices, restoration activities, and changes in human pressures.

These results demonstrate the usefulness of combining Landsat imagery, GIS, and field observations for long-term monitoring of land-use and forest-cover change in the Irobo Classified Forest. However, the study has several limitations. The 30 m spatial resolution of Landsat imagery may limit the detection of small settlements, temporary water bodies, and small forest

patches, while the 2050 projection assumes the continuation of the relative rate of forest-cover change observed between 1988 and 2026. Moreover, no specific landscape fragmentation metrics were calculated; consequently, changes in forest spatial structure are interpreted primarily in terms of the distribution and continuity of the remaining forest cover. Future research could integrate higher-resolution imagery, landscape metrics, additional observation dates, and socioeconomic and environmental drivers to improve the characterization and modeling of forest-cover dynamics. Despite these limitations, the study provides a quantitative and spatial baseline for monitoring the Irobo Classified Forest and identifying areas requiring particular attention for conservation and restoration.

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