DEFORESTATION IN HUMID TROPICAL AREAS: SPATIO-TEMPORAL DYNAMICS AND FACTORS OF FOREST COVER LOSS IN THE OUMÉ DISTRICT (CENTRAL-WESTERN CÔTE D'IVOIRE)

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Résume

Deforestation in humid tropical zones poses a major threat to biodiversity and ecosystem services. In Côte d'Ivoire, this issue is particularly concerning, with a drastic reduction in forest cover over the past century. The district of Oumé, located in the pre-forest zone of the country's central-western region, exemplifies this alarming trend. This study analyzes the spatio-temporal dynamics of deforestation between 1988 and 2023, highlighting the anthropogenic and environmental factors that drive forest area loss. The findings reveal an acceleration of the phenomenon, especially within protected areas, and emphasize the impact of agricultural activities, logging, and demographic pressure. The objective is to contribute to a better understanding of deforestation mechanisms in order to guide conservation policies and the sustainable management of forest resources in ecologically vulnerable zones.

Keywords: Deforestation, spatio-temporal dynamics, agricultural activities, sustainable management.

Introduction

Since 1972, environmental issues—including those concerning ecosystem destruction—have risen to the forefront of international concern. Conferences, reports, and summits have proliferated ever since. At the heart of these discussions, the disappearance of forest reserves and its consequences continue to shake the scientific community. Forests absorb atmospheric CO_2 through photosynthesis and release oxygen, which is essential to life. Yet, despite providing numerous resources and ecological services, forests remain among the most threatened ecosystems.

According to INPE (2008), approximately 17% of the Amazon rainforest—equivalent to 60 million hectares—has been converted to other land uses over the past 30 years. In terms of forest loss, Côte d'Ivoire experienced one of the highest deforestation rates in the 2000s, with an annual rate of around 6%, compared to the global average of 0.5% (Yedmel, 2004). Ivorian forests, which covered about 16 million hectares at the beginning of the 20th century, had shrunk to roughly 3 million hectares by the late 1990s (DCGTX, 1993). Protected areas (classified forests and national parks) have not been spared. According to OIBT (2009), the occupancy rate of classified forests, which ranged from 10% to 33% in 1996, had risen to between 30% and 80% by 2009, depending on the region.

While forest loss across the national territory shows a steady trend, the disappearance of reserves in the central pre-forest zone is particularly pronounced. This study aims to analyze the dynamics and key drivers of deforestation in Côte d'Ivoire's pre-forest region over three decades marked by significant forest cover decline. The general objective is to highlight the patterns and causes of deforestation in the central part of the country. To achieve this, the study focuses on two main axes: first, the spatio-temporal dynamics of deforestation in the pre-forest zone from 1988 to 2023; and second, the identification of the dominant factor driving forest cover loss in the central region.

I- Study Area Description

Côte d'Ivoire is located in West Africa and covers an area of 322,462 km². The country is divided into 19 regions, which are further subdivided into 58 departments. The department of Oumé, which constitutes our study area, is situated in the central-western part of Côte d'Ivoire, between 6°00 and 6°40 North latitude and between 5°10 and 5°50 West longitude.

It is bordered to the east by the department of Toumodi, to the west by Sinfra, to the north by Yamoussoukro and Sinfra, and to the south by Lakota and Divo. The regional capital is Gagnoa. The department of Oumé spans approximately 4,400 km² and includes the sub-prefectures of Oumé, Diégonéfla, Tonla, and Guépahouo (see Figure 1).

Strategically located, the department lies at the phytogeographic boundary between deciduous dense forest and the southwestern edge of the "Baloué V" zone—an ecological transition area between the forest zone and the Ivorian savanna region.

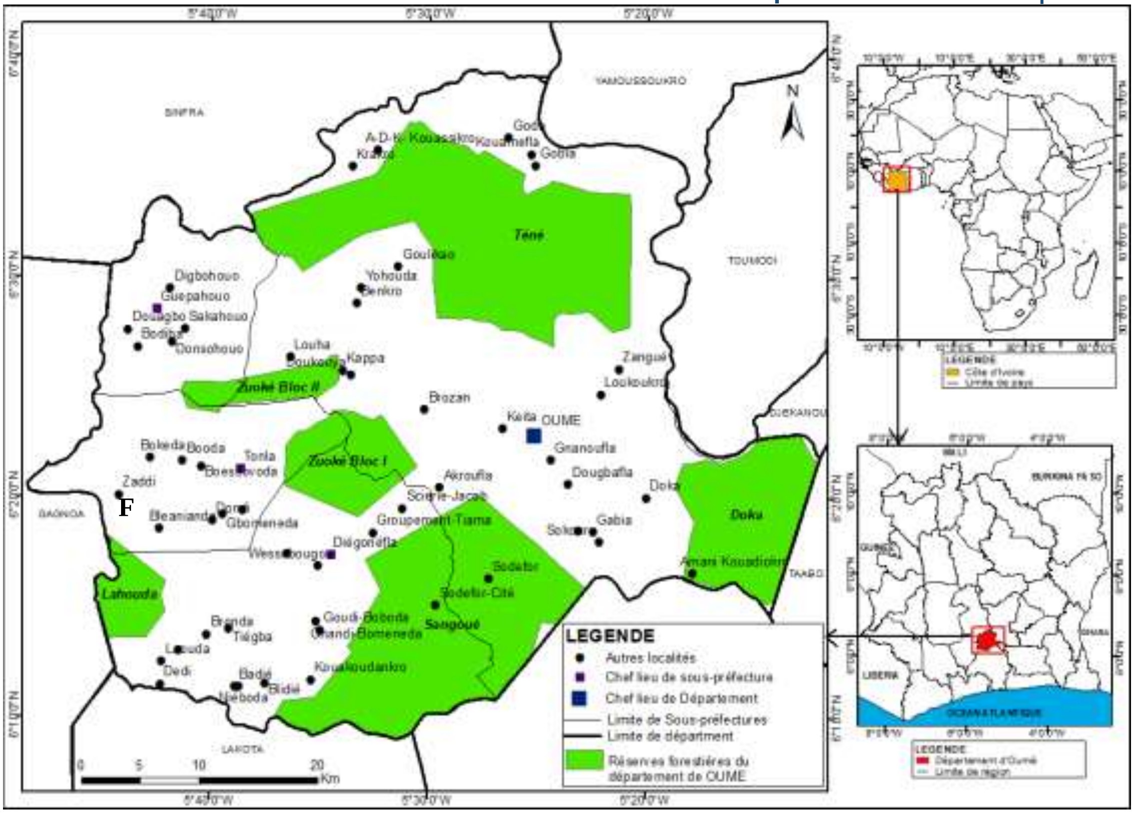


Figure 1: Overview of the Oumé Department (Source: BNEDT–SODEFOR, 2014)

With a population of 274,020 inhabitants, of which nearly 85% are youth (RGPH, 2014), the department has a large labor force. However, unemployment affects a significant portion of the youth population. Most residents are engaged in agricultural activities, artisanal gold mining, and other practices that threaten local ecosystems.

The vegetation in the Oumé department belongs to the mesophilic sector of the Guinean domain (Guillaumet & Adjanohoun, 1969). The forest cover is disturbed, featuring semi-deciduous types dominated by Celtis and Triplochiton scleroxylon Schumann (Koulibaly et al., 2010). There are some forest galleries and isolated forest patches. Riparian forests along the Bandama River are also present, flooded from September to October by the river's silty waters—an extension of the semi-deciduous dense forest (Lauginie, 2007).

Instead of a continuous dense forest cover, the landscape now consists of a mosaic of forest fragments and artificial plantations of species such as Tectona grandis (OIBT, 2004). However, due to climate change, especially in the northeastern zone, savanna-type vegetation is increasingly spreading across the area.

The fauna of the Oumé department includes several animal species. Large mammals are mainly the African forest buffalo (Syncerus caffer nanus) and a few hippopotamuses along the Bandama River. Other species include the royal antelope (Neotragus pygmaeus), the scaled pangolin (Manis tricuspis), and long-tailed pangolins. Numerous rodent species have also been recorded (Bourlière et al., 1974; Lauginie, 1995).

Oumé experiences a tropical climate with an average annual temperature of 26.72°C, ranging from a minimum of 24.77°C in July to a maximum of 28.12°C in February. The total annual rainfall is 1,100.74 mm. According to Lecomte (1990), the climate is classified as subequatorial with bimodal rainfall patterns.

The department belongs to the Bandama River watershed, which forms its natural eastern boundary with the department of Toumodi (Girard, 1971). It is traversed by two major basins: the Téné and the Bouba. The area is well irrigated, with a dense drainage network composed of several tributaries flowing west-east, north-south, or south-north. Two of these tributaries feed into the Bandama River, themselves supplied by smaller streams.

Geologically, the Oumé department is underlain by an ancient basement composed mainly of ortho-metamorphic rocks, including orthogneiss and green rocks—orthogneiss or granito-gneiss. These rocks have undergone dynamic processes and partial recrystallization, forming a continuum between orthogneiss and granite. Depending on their mineral composition, they may be alkaline or calc-alkaline. Their appearance varies widely: sometimes only mica is oriented, while in other cases the rock exhibits true bedding. The alkaline feldspar is microcline, and the plagioclase ranges from acidic oligoclase to andesine. Colored minerals may include muscovite, biotite, amphibole, epidote, sphene, and zircon.

Topographically, the department consists of low granite plateaus, with altitude decreasing from west to east, dominated by Birimian chains. Most granite plateaus resemble hills connected by broad convex slopes with gentle gradients, leading to flat lowlands covered with sandy colluvium. In the western part of the department, plateaus reach elevations of 200–250 meters, with relatively rugged terrain. Toward the east, near the Bandama River, elevation gradually drops to around 150 meters. The Birimian chains, composed of isolated hills or mounds, are aligned in a general northeast–southwest direction, with altitudes ranging from 260 to 320 meters. The summits of these hills are typically armored, with steep flanks covered in debris from summit erosion. At lower altitudes, hills extend into zones of detrital material deposition, eroded from the Birimian hills. These are found in the southwest, around Oumé, extending toward the Bandama River, and consist of very red, gravelly clay soils. In the northwest corner, the first slopes of the large Vanvoua hill emerge, with elevations exceeding 400 meters.

II- Materials and Methods

2.1 Materials Used

The use of appropriate materials in scientific research is essential to achieving the study's objectives. For this research, both field equipment and software tools were employed for data collection and processing. These include:

- A table listing the geographic coordinates (longitude, latitude) of inventory points and ground-truth sites for validating the land use map
- A 10-meter measuring tape to define the radius of inventory plots, and other metric tapes for tree measurements
- Inventory sheets and pencils for recording collected data

• An experimental setup of 20m × 20m plots, preselected from satellite image pixels, with a field team assisting in plot installation and DBH (Diameter at Breast Height) measurements

➢ **The equipment used includes geomatics and botanical tools, such as:**

• A Garmin GPS receiver (Etrex 20) for recording coordinates (X, Y). It was used during field missions to validate land cover classes, locate preselected points from satellite imagery for above-ground biomass quantification, and identify sites of anthropogenic activity and geospatial features that may threaten forest ecosystems in the Oumé department. It also helped locate surveyed households

• A digital "Canon" camera for capturing field images

• A detailed map showing localities, watercourses, reserves, roads, infrastructure, and various exploitation sites

The software and analytical tools used include:

• ArcGIS 10.5.1, licensed through a partnership with IRD, for analyzing, overlaying, interpolating, and producing maps from downloaded data, documentation, surveys, and other sources

• ENVI and IMPACT Toolbox, for processing Landsat and Sentinel-2A satellite images

• Sphinks and XLSTAT, for survey data analysis and statistical computations

• IDRISI, for predictive simulation of vegetation cover status

2.2- Data Used

Various types of data were used in this study, including cartographic data, satellite imagery, land use maps, meteorological data, woody biomass data, socio-economic survey data, and population data.

• Cartographic data included a georeferenced digital layer of reserve boundaries produced and updated by SODEFOR, and the BNEDT database containing vector layers (boundaries, roads, hydrographic network, and infrastructure) in shapefile format. These layers were used to extract the study area

• Satellite meteorological data included temperature, rainfall, and relative humidity from 1988 to 2023 for the Oumé department. These were used to analyze spatio-temporal climate variability. Data were acquired from NOAA (www.noaa.org) and validated using SODEXAM records

• Land use maps were derived from processed Landsat images and validated through field observations. These maps support predictive simulations of deforestation under various scenarios

• Survey data were collected during field missions and include socio-economic information related to forest exploitation in the department. A sample of individuals was selected for the study

• Population data were obtained from the INS to assess the correlation between population growth and the reduction of carbon stock reserves.

2.3 Analytical Method

The spatio-temporal dynamics of deforestation in the Oumé department from 1988 to 2023 were analyzed using remote sensing and GIS-based vegetation cover mapping. The goal was to produce land use maps to better understand the distribution of vegetation types. Landsat TM, ETM, and OLI 8 satellite images were processed at multiple levels.

Preprocessing of Landsat TM, ETM, and OLI 8 Images

The Landsat images were already geometrically corrected, so radiometric correction was applied directly.

Radiometric Correction

Radiometric correction converts pixel values into reflectance values, enabling physical interpretation of the data. This was done using the Radiometric Calibration tool in ENVI 5.1.

Atmospheric Correction

The atmospheric correction method used was FLAASH, which incorporates sensor parameters at the time of image capture. The FLAASH Atmospheric Correction tool in ENVI 5.1 allows integration of the following parameters:

- Input radiance image
- Output reflectance file
- Output directory for FLAASH files
- Root name for FLAASH files

Additional parameters such as date, time of capture, satellite altitude, and pixel size were entered. This correction improves image clarity and enhances subsequent processing steps.

Study Area Extraction

The study area (Oumé department) was extracted from the images using the Region of Interest tool in ENVI 5.3, matching the department’s boundaries.

Landsat OLI 8 Image Processing

Only relevant image processing techniques were applied to extract the desired information. These included:

- Image Enhancement: To improve visual interpretation, contrast stretching was applied to distinguish tones between scene elements. Spatial filters were used to remove spatial patterns, followed by a 2% linear stretch
- Color Composition: This technique uses three channels corresponding to specific spectral bands to optimize interpretability. According to Sarr (2009), it enhances discrimination between geographic features

- Vegetation Index: Using Red (R) and Near Infrared (NIR) bands, vegetation indices increase contrast for chlorophyll-rich vegetation while reducing contrast for other themes. NDVI (Normalized Difference Vegetation Index), ranging from -1 to +1, was used to measure vegetation characteristics (Toney et al., 1999)

- Principal Component Analysis (PCA): PCA reduces the number of spectral bands by compressing information into fewer components. These new bands, called principal components, retain the most significant data variations.

Training plots representing all land cover types were identified using the color composition of bands 5-7-4 and Principal Component Analysis (PCA) based on the first three bands. These approaches enabled the selection of training sites based on accessibility and spatial distribution.

In essence, the goal was to establish control points for various land cover types, based on field research and documentary analysis of the study area. These types include: Dense Forest, Degraded Forest, Open Forest, Bare Soil, Perennial Crops, Annual Crops, Fallow Land, and Built-up Areas—each serving as a site for confirming or rejecting land cover units.Mission de terrain et collecte de données

The field validation mission aimed to support the interpretation of satellite images for land cover and land use mapping. It was conducted from March 1 to March 31, 2023. Given the temporal resolution of Landsat OLI 8 imagery, this data collection period was appropriate for overlaying GPS field data with land cover and land use elements, and for pixel characterization to ensure high classification accuracy. Photographs were also taken to document vegetation types within and outside reserves, as well as land use driven by human activities in the Oumé department. These data are essential for producing accurate land cover maps.

Classification, Evaluation, and Validation

Image classification is a key transformation method that groups image entities into thematic classes based on spectral properties. It can be supervised or unsupervised, with several classification techniques available.

This study employed Random Forest classification in QGIS, along with the production of transition matrices for the years 1988, 2003, and 2023. Satellite image classification is crucial for analyzing land cover changes over time. Using Landsat imagery from these three years, changes over a 35-year period were detected. The Random Forest algorithm, integrated via the Semi-Automatic Classification Plugin (SCP) in QGIS, enabled precise and reproducible classification:

- Data Preparation

Before classification, rigorous preparation was required:

- Load satellite images from 1988, 2003, and 2023 (e.g., Landsat missions)

- Apply atmospheric and radiometric corrections

- Create training samples or Regions of Interest (ROIs) to represent each land cover class (e.g., forest, agriculture, urban, water);

- Random Forest Classification in QGIS

Random Forest is a supervised classifier based on ensembles of decision trees. It is well-suited for multispectral image classification due to its robustness against noise and heterogeneous data.

Steps in QGIS:

- Activate the SCP plugin
- Load satellite images into SCP
- Define land cover classes using representative samples
- Run the classification using Random Forest
- Generate classified maps for 1988, 2003, and 2023.

- Validation of Results

For each year:

- Compare classified maps with control points or validation data
- Generate confusion matrices to assess model performance
- Calculate metrics such as overall accuracy, Kappa coefficient, recall, and F1-score

- Transition Matrix Production (1988–2003, 2003–2023, 1988–2023)

Transition matrices analyze land cover changes between two dates, showing how each initial class evolved over time.

Steps:

- Overlay classified maps from two years (e.g., 1988 vs. 2003)
- Use the MOLUSCE plugin or QGIS raster tools to cross-reference maps
- Generate transition matrices showing:
- Persistence (e.g., forest remaining forest)
- Change (e.g., forest converted to agriculture or urban area)
- Conversion rates between classesResult Analysis

Transition matrices help:

- Quantify spatial dynamics (deforestation, urbanization, agricultural expansion)
- Identify the most stable or vulnerable classes
- Support decision-making in land use planning, conservation, and territorial management.

- **Methodology Summary: Random Forest Classification and Transition Matrices (1988–2023)**

To analyze land cover evolution over 35 years, a rigorous methodology was implemented using satellite images from 1988, 2003, and 2023. The main objective was to perform thematic classification using the Random Forest algorithm in QGIS and produce transition matrices to identify spatio-temporal dynamics.

Image Sources:

- Landsat 5 TM (1988)
- Landsat 7 ETM+ (2003)
- Landsat 8 OLI (2023)

Images were downloaded from the USGS portal, selected for quality (cloud-free, dry season), corrected atmospherically, reprojected, and clipped to the study area.

Training Data: Polygons or points representing land cover classes were created using field knowledge, high-resolution imagery (e.g., Google Earth), and existing maps.

Classification: Using SCP in QGIS, Random Forest was applied. Each tree votes for a class, and the majority vote determines the pixel's classification. The algorithm is robust to spectral noise and correlations, offering strong performance without complex tuning.

Evaluation: Confusion matrices were generated by comparing predicted classes with independent validation points. Metrics such as overall accuracy, Kappa index, recall, precision, and F1-score were calculated. According to Skupinski et al. (2009), the Kappa index reflects the ratio of correctly classified pixels to the total sampled pixels.

Expected Separability: Kappa values ranged from 1.80 to 1.99 for 2023 imagery, and around 1.80 for 2003 and 1988, indicating good class separability.

Classified Image Filtering

Isolated pixels were removed using the Sieve Classes function in ENVI, based on spectral neighborhood analysis.Digitization and Cartographic Rendering

Digitization is the final step, converting classified raster images into vector format (polygons) for GIS management in software like ArcGIS. The final land cover map includes essential cartographic elements: orientation, legend, scale, and geographic coordinates.

III- Results and Analysis

3.1- Spatio-Temporal Dynamics of Deforestation in the Oumé Department from 1988 to 2023

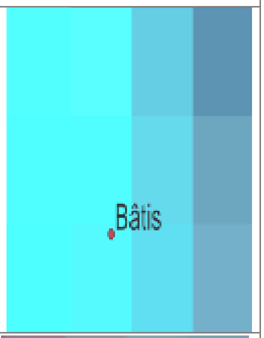
3.1.1- Description of Land Cover Elements in 2023

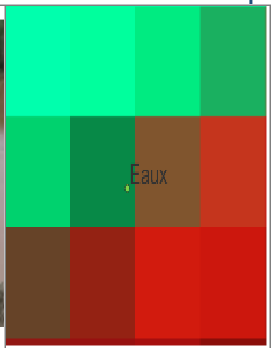
The 30-day field mission conducted in the Oumé department enabled the validation of pixel-to-land cover correspondences observed in the 2023 satellite imagery, based on color composition analysis (see Plate 1).

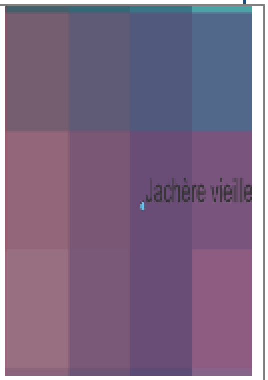
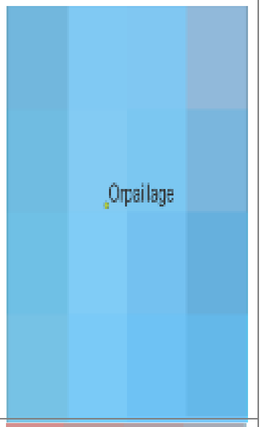
The collection of various spatial data related to land cover allowed for the verification of predefined control points on the satellite images prior to the mission, as well as the identification of new ground points. These efforts supported the description of vegetation types, crop types, and activities contributing to the reduction of carbon stock reserves throughout the Oumé department.

Georeferenced control points and their overlay on satellite imagery provided a spatial framework for analysis. Reference photographs taken at ground control points for each land cover class helped assess how the natural environment is being exploited in the region.

Plot 1: Descriptive points of land cover in the Oumé department

Department Points (X = Longitude; Y = Latitude)	**Land Cover Description**	**Land Cover Image**	**Band Composition (5-3-2)**
P1 X= 864015 Y= 716758	Built-up Areas		
P2 X= 867363 Y= 717041	Annual Crops		
P3 X= 875906 Y= 712882	Perennial Crops 1		
P4 X= 862610 Y= 713128	Perennial Crops 2		

P5 X= 908024 Y= 726702	Water		
P6 X= 894692 Y= 729746	Tree-Dominated Forest		
P7 X=863575 Y= 691075y	Dense Forest		
P8 X= 887104 Y= 729924	Semi-Deciduous Forest		
P9 X= 894442 Y= 729841	Young Fallow Land		

P10 X= 877443 Y= 712412	Old Fallow Land		
P11 X= 870094 Y= 711477	Artisanal Mining Sites		
P12 X=892254 Y= 715457	Bare Soil 1		
P13 X= 898238 Y= 712040	Bare Soil 2		

This mission also enabled the characterization of satellite images for the production of land cover maps for the year 1988, followed by those for 2003 and 2023. The high accuracy of the collected data facilitated the generation of confusion matrices, which were essential for evaluating the reliability and precision of the image classifications.

3.1.2- Land Cover Characterization for 1988

➢ Validation of Supervised Classification

The confusion matrix derived from the classification of the most recent Landsat satellite image (2023) indicates excellent performance, with an overall accuracy of 91% and a Kappa coefficient of 0.90.

- Overall Accuracy (91%): This represents the proportion of correctly classified pixels, weighted by the number of pixels in each class relative to the total number of training pixels. It reflects the general reliability of the classification and its close alignment with real-world conditions.

- Kappa Coefficient (0.90): This value indicates an excellent level of agreement, as it exceeds the threshold of 0.81, confirming the robustness of the classification model.

The confusion matrix also demonstrates strong class separability. However, the tree savanna class shows a lower accuracy of 73.44%, indicating a high omission rate, with many pixels misclassified into other categories.

In summary, these results confirm the reliability of the land cover maps produced for the Oumé department and validate the methodological approach used in the classification process

➢ **Land Cover Map of the Oumé Department – 1988**

Forest degradation in the Oumé department in 1988 was primarily concentrated within the core areas of classified forests. The dominant vegetation within these reserves consisted largely of occupied plantations, indicating early signs of anthropogenic pressure and land conversion.

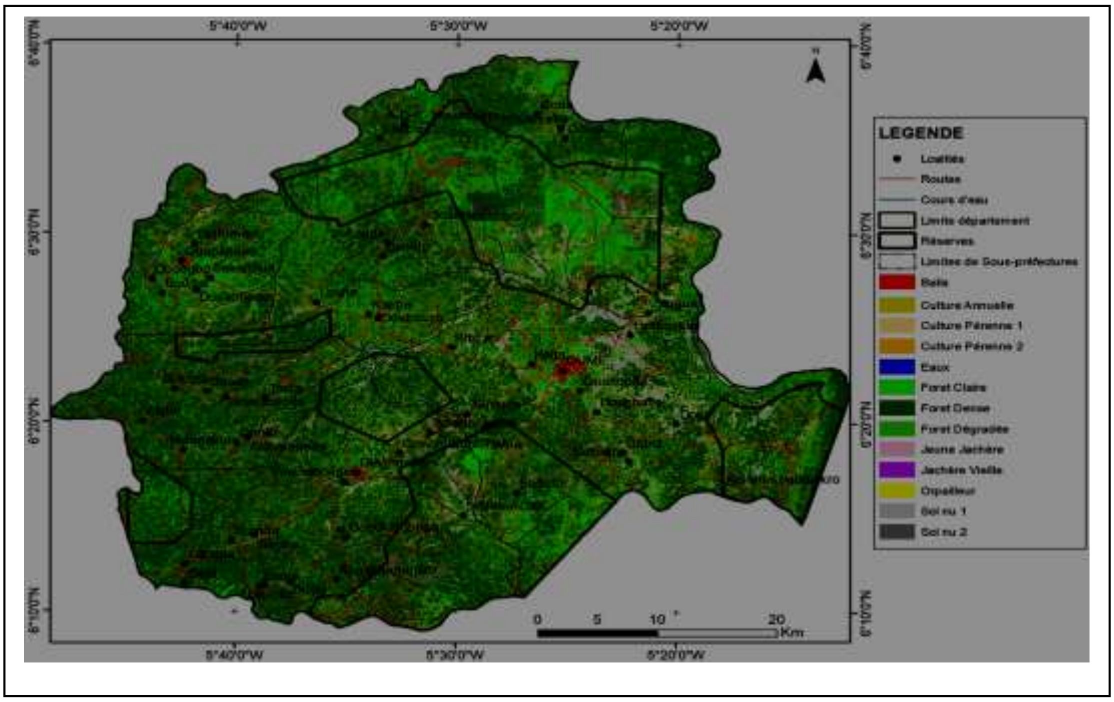


Figure 2: Land Cover Maps of the Oumé Department 1988

Forest areas occupied the largest share of land in terms of surface area. Perennial and annual crops also covered a significant portion of the territory. In contrast, bare soils and built-up areas represented relatively small surfaces—approximately 550 hectares. The various forest vegetation types had an average coverage of around 200 hectares.

3.1.3- Land Cover Characterization of the Oumé Department 2003

➢ **Validation of Supervised Classification**

The confusion matrix derived from the supervised classification of the 2003 Landsat satellite image yielded an overall accuracy of 89% and an excellent Kappa coefficient of 0.90.

- Overall Accuracy (89%): This represents the percentage of correctly classified pixels, weighted by the number of pixels in each class relative to the total number of training pixels. It reflects the general reliability of the classification.

- Kappa Coefficient (0.90): This value indicates excellent agreement, as it exceeds the threshold of 0.81.

Notably, the built-up areas and annual crop classes showed strong pixel correlation and spatial consistency. However, it is important to acknowledge that producing land cover maps with 100% spatial accuracy remains nearly impossible due to the complexity and variability of landscape elements.

➢ **Land Cover Map of the Oumé Department 2003**

During the 2003 period, forest degradation intensified significantly, largely due to the 2002 crisis involving displaced populations and rapid demographic growth within the department. In response to these pressures, agricultural expansion became a primary strategy for livelihood, leading to widespread land conversion. As a result, carbon stock reserves experienced substantial losses, particularly in forested zones that were cleared or degraded to accommodate farming activities.

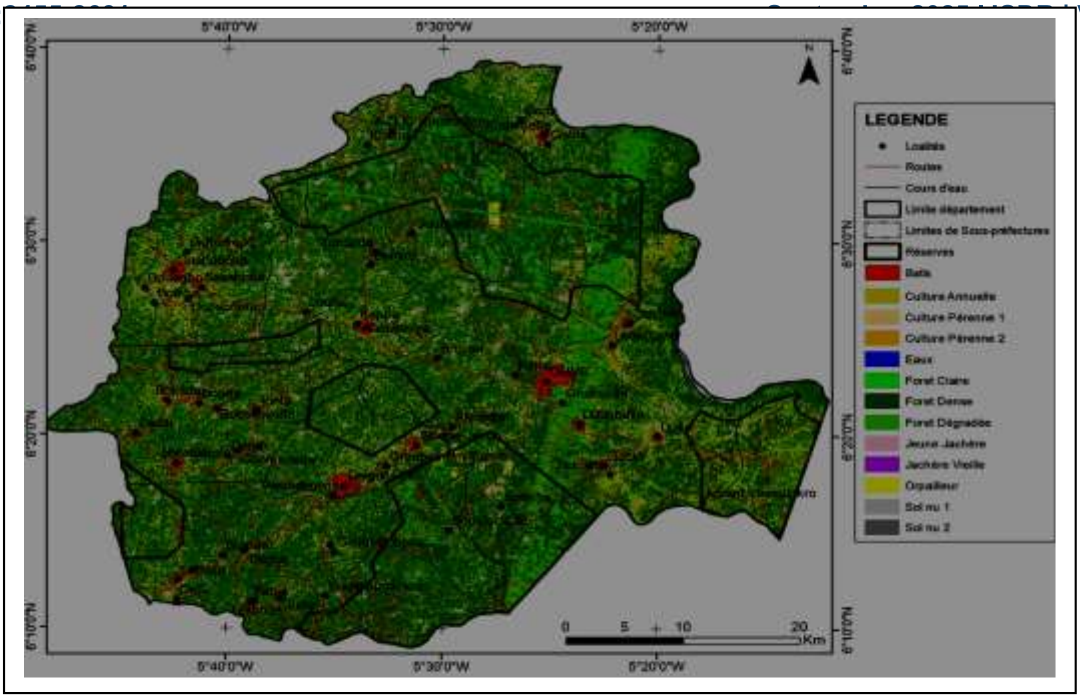


Figure 5: Land Cover Map of the Oumé Department 2003

The land cover analysis reveals a significant presence of dense and degraded forests, alongside a notable extent of old fallow lands, as indicated by the referenced graph. These patterns reflect the persistence of forest formations in certain zones, despite ongoing anthropogenic pressures, and suggest a landscape shaped by both natural vegetation and long-term agricultural cycles.

3.1.3- Land Cover Map of the Oumé Department 2003

- **Validation of Supervised Classification**

The confusion matrix resulting from the supervised classification of the 2023 Landsat satellite image shows an overall accuracy of 91% and an excellent Kappa coefficient of 0.91. Ground control points confirmed nearly all land cover classes, demonstrating strong class separability and high classification reliability.

Among the classified categories, dense forest and water bodies stood out as the most accurately identified classes. This matrix, compared to those from previous years, is the closest to real-world conditions and served as the reference for generating the earlier land cover maps of 1988 and 2003.

3.1.4- ***Land Cover Map of the Oumé Department* 2023**

The ground control points describing land use and land cover in the Oumé department reveal a significant loss of vegetation cover, and consequently, a decline in forest carbon stock reserves. The 2023 land cover map (OCS) clearly illustrates the severe degradation of forest reserves across the region.
Anthropogenic activities such as agriculture, artisanal mining, and settlement expansion—have played a major role in this decline. The statistical data presented in the accompanying graph aligns closely with the visual interpretation of land cover classes in the 2023 OCS map, confirming the extent of environmental pressure and land transformation.

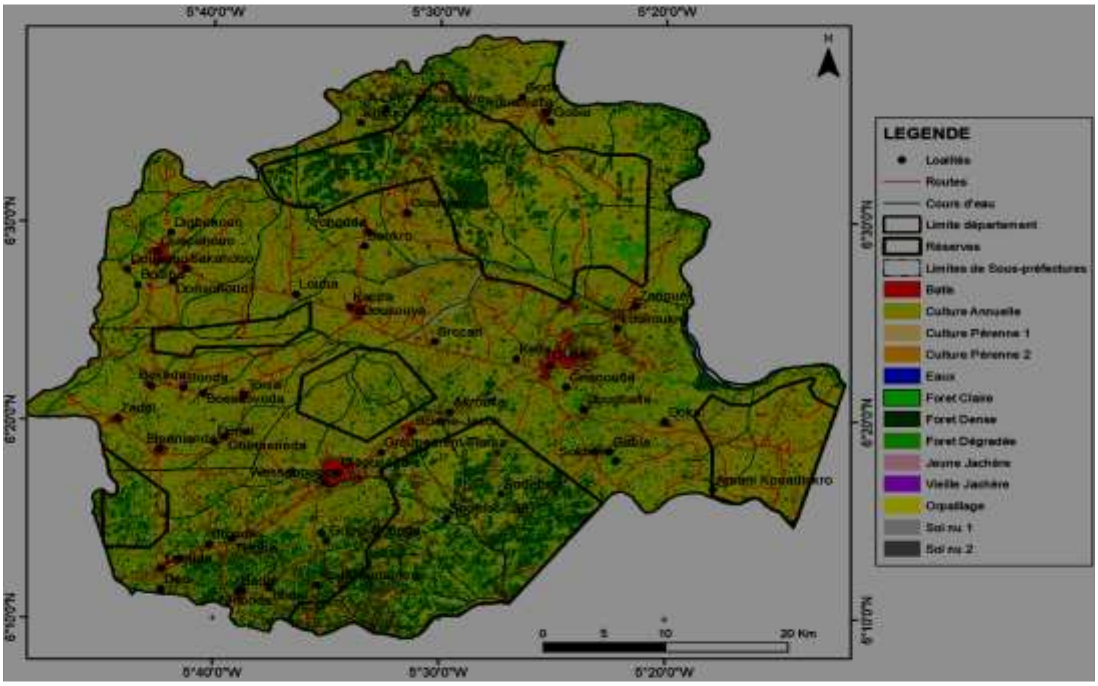


Figure 7: Land Cover Maps of the Oumé Department 2023

Savanna zones occupy the largest portion of land area in the Oumé department. The remaining patches of dense and degraded forest are primarily located within partially preserved reserves, although these areas have been heavily impacted by anthropogenic pressures. Notably, the reserves of DOKA, ZOUKOUE (1 and 2), and LAHOUDA have collectively lost nearly 90% of their forest cover. Only the forests of TENE, SANGUE, and parts of LAHOUDA remain in relatively good condition.

➢ NDVI Spatial Analysis

The Normalized Difference Vegetation Index (NDVI) result is presented as a single-band image enhanced with a gradient color palette. This visualization technique helps isolate areas of dense vegetation within forest reserves.

- High NDVI values (0.45 to 0.75), shown in yellow, indicate zones of very dense vegetation.
- Low NDVI values (−1 to −0.85) correspond to areas with minimal or no vegetation cover.

This NDVI spatialization provides a clear visual representation of vegetation health and density across the department, supporting assessments of forest degradation and carbon stock loss.

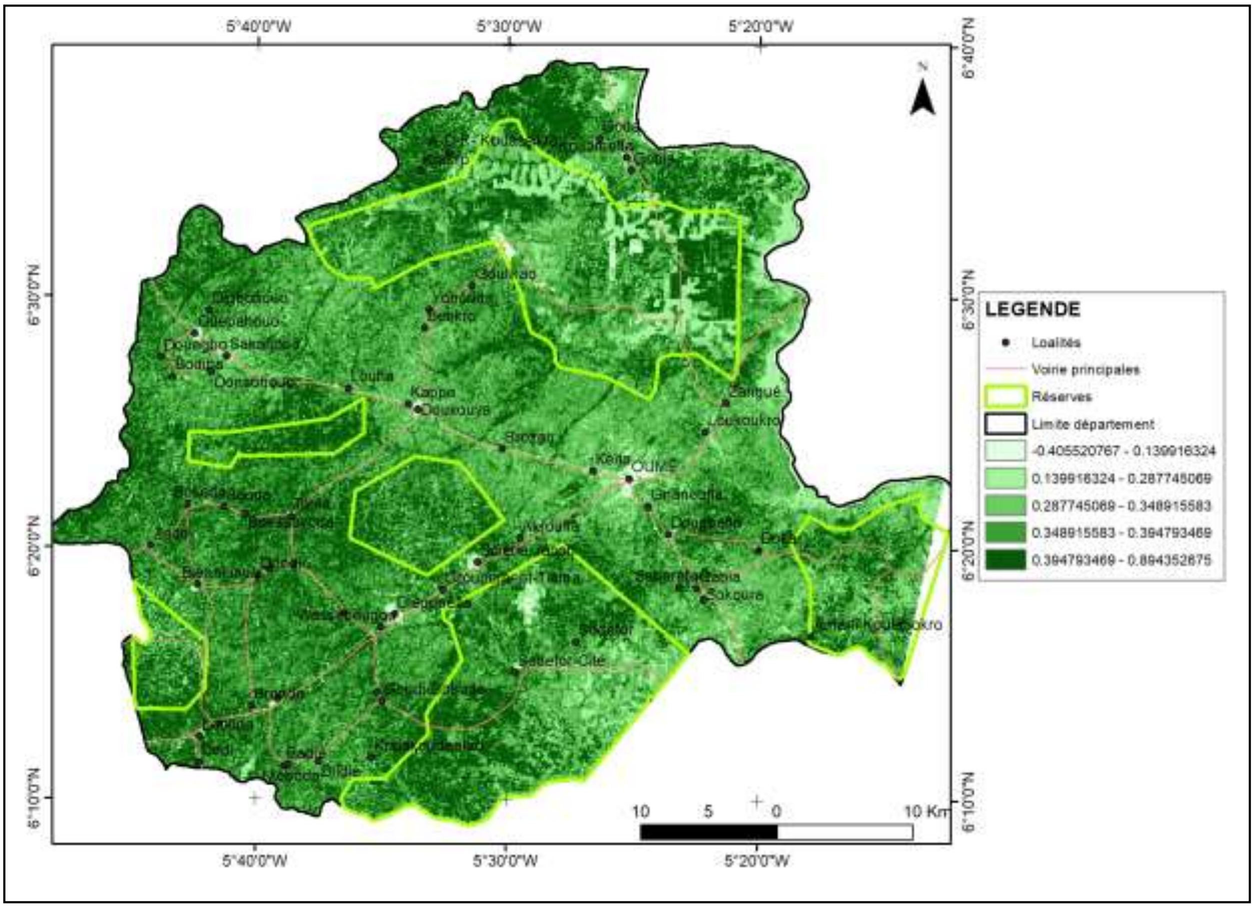


Figure 6: NDVI Values of the Oumé Department 1988

The Normalized Difference Vegetation Index (NDVI) is represented as a single-band image enhanced with a green-toned color palette. This palette effectively isolates areas of dense vegetation within forest reserves, while also distinguishing between dense and sparse vegetation outside the reserves.

- Very dense vegetation appears in dark green, with NDVI values ranging from 0.394 to 0.894.
- Low vegetation density is indicated by values between −0.405 and −0.139, typically associated with bare soil, degraded zones, or senescent vegetation.

NDVI responds to the chlorophyll content in plant leaves, which is directly influenced by nitrogen availability. As such, NDVI serves as a proxy for measuring photosynthetic activity across the landscape.

Since chlorophyll levels determine the "greenness" of vegetation, NDVI in remote sensing can also detect areas with yellowing or falling leaves, signaling stress or senescence. NDVI values are most informative during the active vegetative growth phase, particularly within reserves, but are less suitable during harvest periods when vegetation cover is reduced.

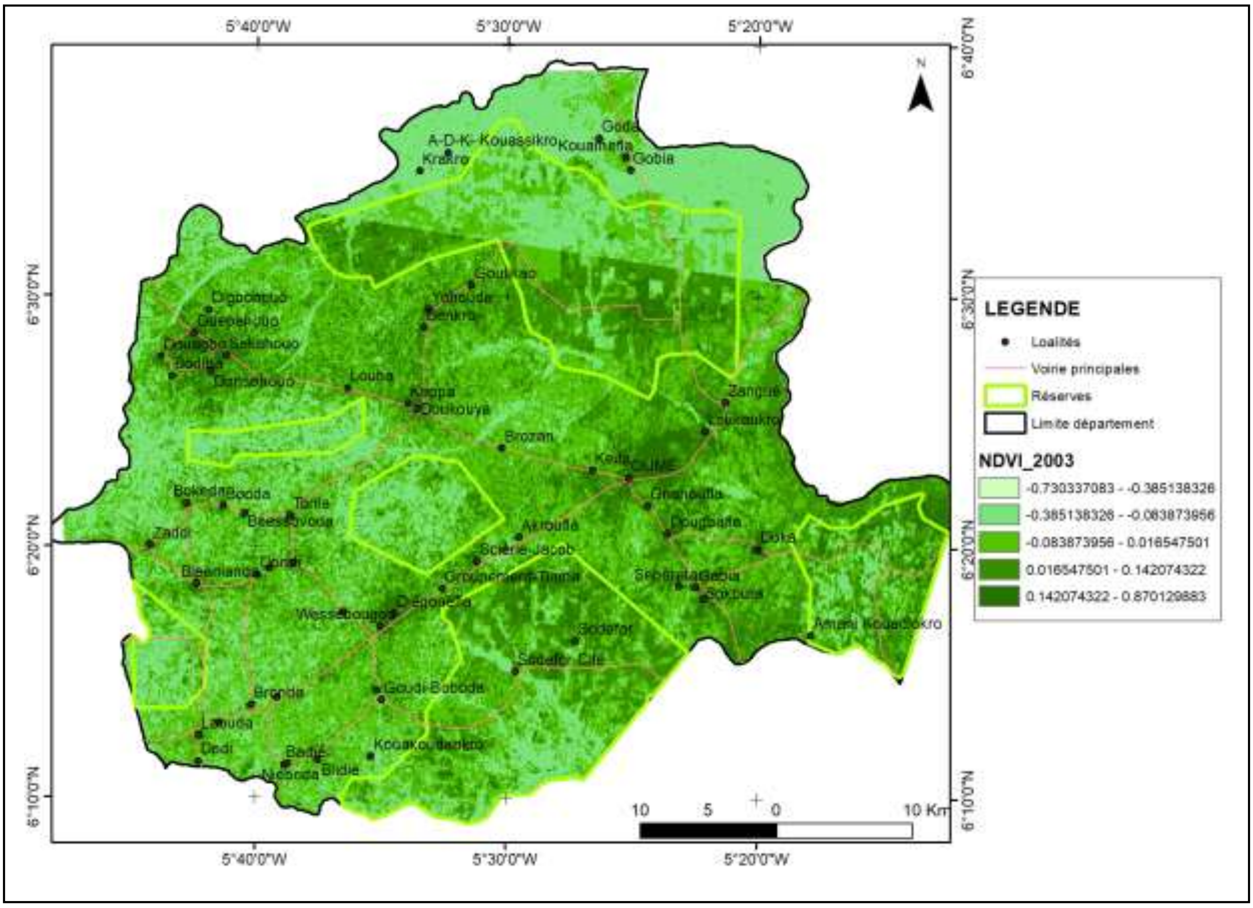


Figure 7: NDVI Values of the Oumé Department 2003

In the NDVI formula, NIR and Red refer to the reflectance values of the near-infrared and red spectral bands, respectively. Interpreting NDVI values can be challenging without a basic understanding of what they represent. NDVI values range from −1 to +1:

- Values close to +1 indicate dense and healthy vegetation, as observed in parts of the Oumé department.
- Values close to −1 suggest sparse or unhealthy vegetation, or the presence of non-vegetated elements such as water bodies or bare soil.

General Guidelines for NDVI Interpretation:

- High NDVI values (0.45 to 0.75) typically represent very dense vegetation, shown in yellow on the NDVI image (Figure 14).
- Low NDVI values (−1 to −0.85) correspond to sterile zones with little or no vegetation cover.
- Intermediate values indicate moderately vegetated areas or transitional zones.

The 2003 NDVI analysis highlights the presence of non-vegetated areas, including water bodies and degraded lands. It also reveals the growth of planted trees in the TENE and SANGE reserves, initiated in the 1980s. These areas show varying degrees of vegetation density, with some zones remaining sparse.

NDVI is sensitive to chlorophyll content, which is directly influenced by nitrogen availability in plants. Therefore, NDVI serves as a proxy for photosynthetic activity and can detect areas with yellowing or senescent leaves. It is most effective during the active vegetative growth phase, especially within forest reserves, but less reliable during the harvest season when vegetation cover is reduced.

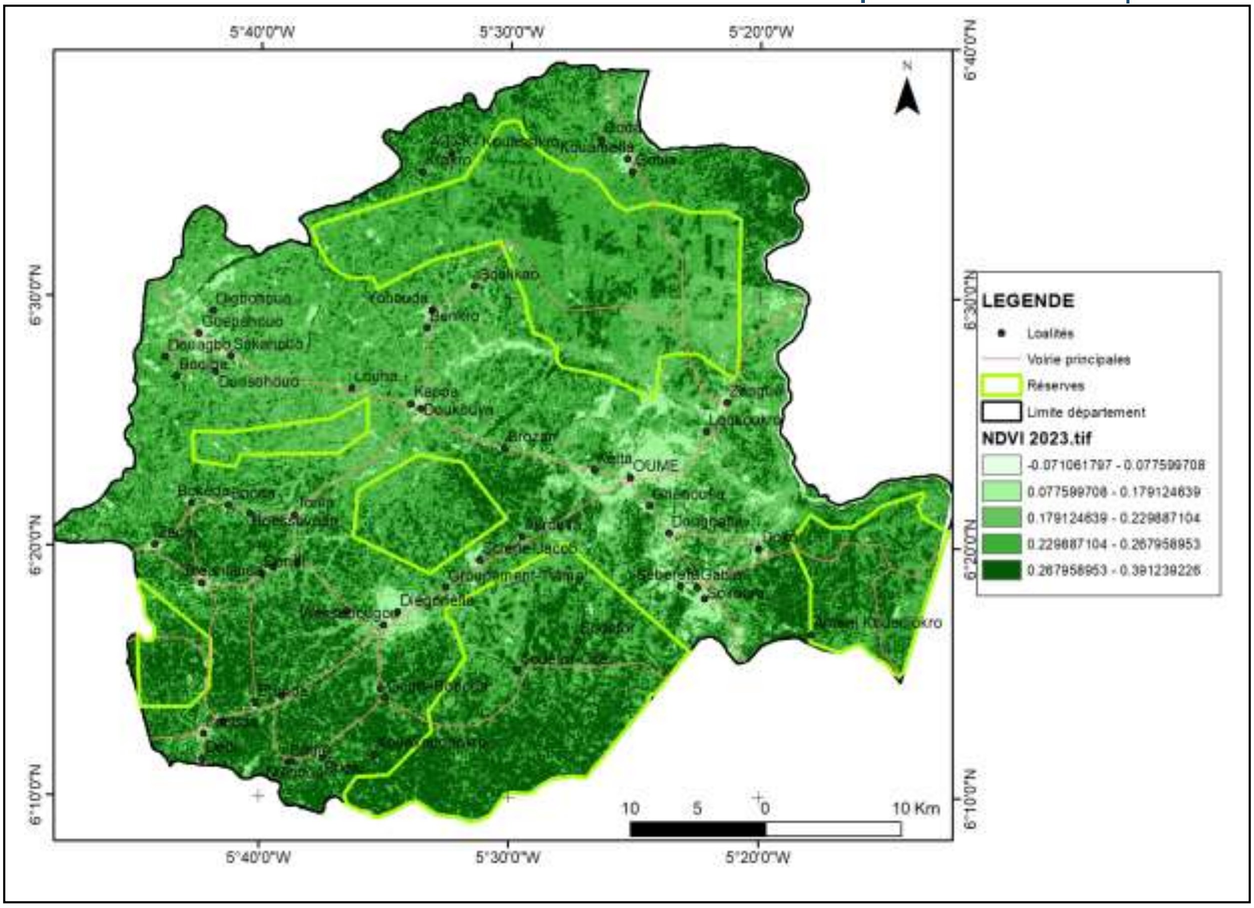


Figure 8: NDVI Values of the Oumé Department 2023

The 2023 NDVI image reveals a significant distribution of vegetation index values, which can be categorized into different vegetation formations such as low, moderate, or high vegetation cover based on predefined thresholds. These categories help confirm the presence or absence of forest carbon stock reserves. Areas with low NDVI values typically indicate weak or absent carbon stocks, while higher values suggest healthier vegetation and greater biomass potential.It is important to note that interpreting NDVI values can be complex, as they are influenced by several factors including soil type, climatic conditions, and crop species. Therefore, NDVI analysis should be complemented with other data sources, such as dendrometric field measurements particularly DBH (Diameter at Breast Height) collected both inside and outside forest reserves.

NDVI images are generated by processing reflectance values from the near-infrared (NIR) and red bands of Landsat satellite imagery. The correlation between NDVI values and biomass data collected from sample plots allows for the estimation of carbon stock across different vegetation classes. This integrated approach enhances the accuracy of carbon mapping and supports sustainable land management strategies.

IV- Drivers of Deforestation and Forest Degradation in the Oumé Department

4.1- Statistics on Land Cover Change: Gains and Losses

A marked transformation in land cover has been observed in the Oumé department over a 35-year period, revealing three major trends:

- **Decline of Dense Forests**: The proportion of dense forest has drastically decreased, falling from 44.3% in 1988 to just 13% in 2023—a loss of over 70%. This sharp decline highlights the intensity of deforestation in the region, despite a slight increase between 1988 and 2003.

- **Expansion of Annual and Perennial Crops**: Annual crops have experienced dramatic growth, reaching 42.9% in 2023 compared to 8.1% in 1988, reflecting strong agricultural pressure on forested areas. Perennial crops have followed a similar trend, with their surface area increasing more than ninefold between 1988 and 2023.

- **Urbanization and Land Artificialization**: Built-up areas have gradually expanded, rising from 0.5% to 1.9%, indicating moderate but steady urban development. The increase in both young and old fallow lands may reflect an intensification of agricultural cycles.

As shown in Table 1, these changes illustrate a clear dynamic of forest land conversion toward agricultural and urban uses, resulting in a net loss of biodiversity and ecosystem services.

Tableau 1: Summary of Land Cover Change Dynamics in the Oumé Department (1988–2023)

Land Cover Class	Area in 1988 (ha)	Area in 2003 (ha)	Area in 2023 (ha)	1988 (%)	2003 (%)	2023 (%)	Trend
Built-up Areas	1,132.70	2,940.80	4,386.30	0.54	1.29	1.92	Moderate urban growth
Annual Crops	18,639.67	30,285.60	97,852.70	8.15	13.30	42.88	Strong agricultural expansion
Perennial Crops 1	7,190.36	6,006.21	9,148.05	3.14	2.60	4.01	Slight increase
Perennial Crops 2	3,450.84	5,872.68	31,744.90	1.51	2.60	13.91	Significant growth
Water Bodies	100.95	510.23	546.07	0.04	0.20	0.24	Stable
Open Forest	423.46	1,740.25	4,009.63	0.19	0.80	1.76	Gradual increase
Dense Forest	101,331.46	108,704.00	29,602.90	44.30	47.70	12.97	Sharp decline
Degraded Forest	38,476.47	37,750.50	34,514.30	16.82	16.60	15.13	Slight decline
Young Fallow	1,288.42	2,665.96	6,294.25	0.56	1.20	2.76	Increasing
Old Fallow	326.86	1,088.73	2,209.91	0.14	0.50	0.97	Increasing
Mining Sites	2,801.59	3,146.42	430.01	1.23	1.40	0.19	Decline
Bare Soil 1	14,216.94	10,336.10	1,690.63	6.22	4.50	0.74	Sharp decline
Bare Soil 2	21,710.31	6,693.59	5,765.82	9.49	2.90	2.53	Decline

4.2- **Population Growth Analysis**

The population growth in the Oumé department mirrors the demographic trends observed in medium-sized cities across Côte d'Ivoire. The graph below illustrates the evolution of the department's population from 1988 to 2021, highlighting a steady increase over the decades.

This demographic expansion has had direct implications on land use, contributing to:

- Increased demand for agricultural land
- Expansion of built-up areas and infrastructure
- Greater pressure on forest reserves and natural ecosystems

Understanding population dynamics is essential for interpreting land cover changes and planning sustainable development strategies in the region.

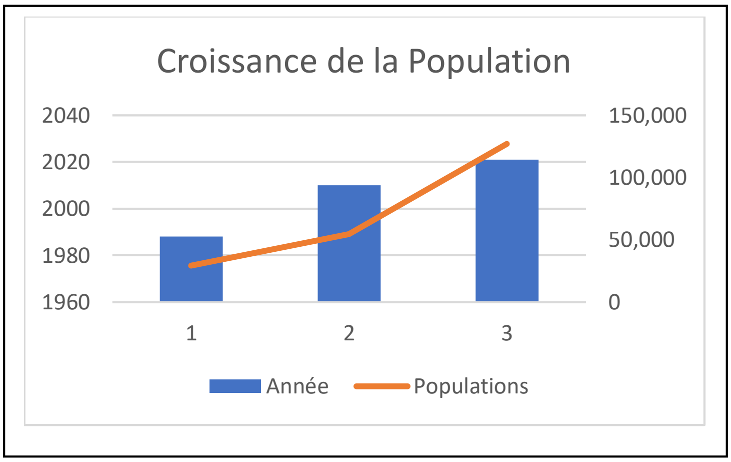
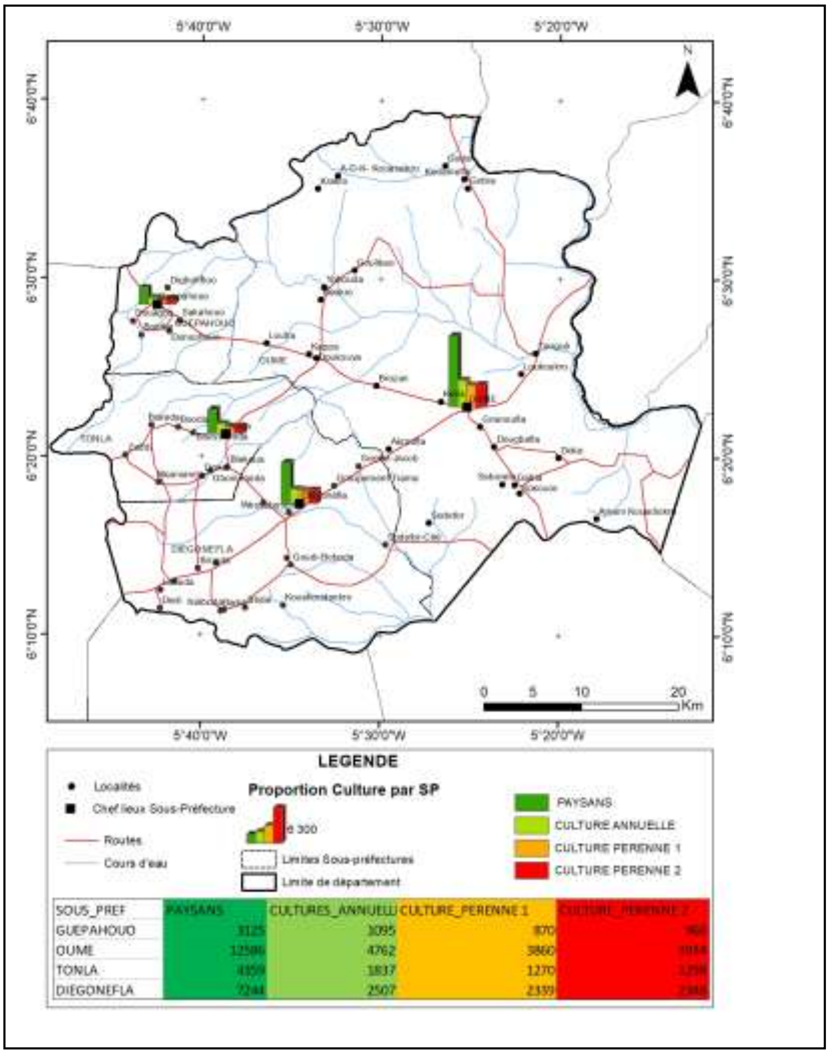


Figure 9: Histogram of Population Growth in the Oumé Department

Population growth in the Oumé department has directly influenced deforestation activities, particularly within forest carbon stock reserves. A comprehensive field mission across the department revealed that agricultural policy is largely driven by export-oriented crops such as cocoa, rubber (hévéa), and oil palm. The demand for agricultural land surged following two major crises: the 2002 conflict and the post-electoral crisis of 2011, both of which led to significant population displacement. This influx of non-native populations, primarily engaged in subsistence farming, has contributed to land pressure and forest conversion. Today, Oumé records one of the highest population growth rates in Côte d'Ivoire, with the population nearly doubling since the early 2000s, as illustrated in the corresponding graph.

4.3- Analysis of Agricultural Activities in the Oumé Department

Field surveys conducted across households in various sub-prefectures reveal a strong prevalence of anthropogenic activities, particularly agriculture, which stands out as one of the leading drivers of deforestation in the region. Both perennial and annual crops are cultivated extensively in areas that benefit from favorable rainfall patterns and a well-developed hydrographic network, including rivers and streams that support year-round farming. The sub-prefectures of Oumé and Diégonéfla record the highest levels of agricultural activity in the department, with 12,586 and 4,359 active farming households respectively. These figures underscore the intensity of land use and the growing pressure on forest ecosystems, especially in zones with high agricultural potential.



4.4- Forest Exploitation in the Oumé Department

Forest exploitation in the Oumé department has deep historical roots, dating back to the colonial period. The production of timber and cabinet-grade wood experienced significant growth after independence, with logging volumes increasing substantially since the early 2000s. The TENE and SANGOUE forests are particularly known for their high timber output. Following the forestry reform introduced by Decree No. 94-368 of July 1, 1994, efforts were made to improve forest management, promote value-added wood processing, and rehabilitate forest lands through reforestation. As a result, the profession of forest operator became central to the sector, and forest reserves in the department gained strategic importance.

The main products of forest exploitation include wood energy, such as charcoal and firewood, which are widely used in Oumé due to the high cost of gas. However, accurate assessment of forest exploitation remains challenging, as survey data are often underreported in official statistics. The private forest-wood sector in Oumé comprises three main categories of actors:

1. Forest Operators – Responsible for sustainable management of forest areas and wood processing units.

2. Wood Traders and Artisans – Involved in the commercialization of timber and the production of furniture and other finished wood products.

3. Local Farmers – Utilize ecosystem services and forest resources for community-based activities and subsistence needs.

IV- Discussion of Land Cover Mapping Results

The analysis of land cover dynamics based on Landsat imagery reveals a significant difference in classification accuracy between 1988 and 2023. The comparison of SPOT satellite images from 2000 and 2015 enabled the quantification of deforestation in the study area (DeFries et al., 2007). Supervised classifications conducted in QGIS yielded statistically acceptable accuracy levels (Kabba & Li, 2011; Landis & Koch, 1977), partly due to the grouping of vegetation formations (N'Guessan et al., 2006).

The land cover change analysis highlights a continuous regression of forest formations, both outside and within reserves, particularly in SANGOUÉ and the LAHOUDA zones 1 and 2, where forest areas have been replaced by mosaics of fields and fallows (Arouna, 2002; Orékan, 2007; Bogaert et al., 2011; Diallo et al., 2011).

The transition matrix reveals:

- Degradation of forest formations
- Marked anthropization, with expansion of perennial and annual crop mosaics
- Weak vegetation recovery between 2003 and 2023

The low rate of forest restoration signals a shift in carbon stock reserves, driven by accelerated land clearing for agriculture. Between 2003 and 2023, the area of fields and fallows doubled, indicating a transformation of forest ecosystems into anthropogenic formations.

These findings align with previous studies in the Sudanian zone of northern Benin (Mama et al., 2013), and with research by Arouna (2002), Orékan (2007), Sounon-Bouko et al. (2007), Bogaert et al. (2011), and Diallo et al. (2011), which document a steady decline in forest cover in favor of agriculture, bare soils, and urban expansion.

In the southern region of W National Park in Benin, Houessou et al. (2013) identified agriculture as the primary driver of vegetation change. These results are consistent with broader findings across sub-Saharan Africa (Wood et al., 2004; Mama et al., 2013; Avakoudjo et al., 2014), confirming agriculture as the main factor influencing vegetation cover transformation.

However, land cover dynamics may vary by region. For example:

- In central Benin, Arouna et al. (2011) found charcoal production to be the leading cause of vegetation change.
- In Sine Saloum, Senegal, Lykke (2000) identified frequent fires and declining rainfall as key drivers of vegetation shifts.

In the Oumé department, demographic growth acts as an indirect driver of degradation. Rising population levels increase pressure on vegetation resources, leading to the expansion of agricultural plots for food, housing, and commercial use.

The size of agricultural assets per household significantly influences decisions to open new plots (Houessou et al., 2013). The growing needs of farmers and the increasing burden on households support findings by Orékan (2007) and Ouédraogo et al. (2010), which show a strong correlation between population growth and land and vegetation degradation.

Conclusion

The spatio-temporal analysis of deforestation dynamics in the Oumé department reveals a profound and accelerated transformation of forest landscapes over the past three decades. Despite ongoing conservation efforts, Ivorian forests—particularly those in the pre-forest central zone—continue to face intense pressure from agricultural expansion, urbanization, and unsustainable exploitation of natural resources.

The data highlight an alarming regression of dense forest cover, increasingly replaced by annual and perennial crops. This shift in land use threatens the ecological resilience of the region and signals a critical turning point in forest sustainability.

This study underscores the urgent need for strengthened environmental governance, built on:

- Sustainable land management policies
- Continuous spatial monitoring
- Active community engagement

Preserving forest ecosystems requires a nuanced understanding of local dynamics and the socio-economic drivers behind land transformation. Immediate action is essential to halt biodiversity loss and restore the vital ecological functions of Côte d'Ivoire's tropical rainforests.

BIBLIOGRAPHIE

1. **Girard, M. C., & Girard, C. M.** (1999). *Traitement des données de télédétection.* Paris : Dunod, 544 p.
2. **Lagabrielle, E.** (2003). *Cartographie de la végétation tropicale par télédétection.* Revue XYZ, n°95, 67–78.
3. **Bonn, F.** (1996). *Systèmes d'information géographique et analyse spatiale.* Presses de l'Université du Québec, 302 p.
4. **Zanin, C., & Tremelo, M. L.** (2003). *Sémiologie graphique et cartographie numérique.* Armand Colin, Paris.
5. **BNEDT.** (1974). *Étude cartographique et de télédétection de la couverture forestière.* Bureau National d'Études Techniques et de Développement, Côte d'Ivoire.
6. **Atta, K.** (1978). *Dynamique de l'occupation du sol urbain : cas de la ville de Bouaké.* Mémoire de Maîtrise, Université de Bouaké, Côte d'Ivoire.
7. **Couret, D., et al.** (1999). *Dynamique urbaine d'Abidjan de 1989 à 1998 par télédétection.* IRD/CCT, France.