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Research Article

Land use/land cover dynamics using support vector machine in the area of Lambaréné, Gabon, from 1988 to 2022

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Abstract
Land use dynamics depict territorial changes, which include conversions and adjustments to landscape units caused by natural and human-induced processes. Human pressures impact landscape changes and various degradation in Lambaréné, which was established as a fully-fledged commune in 1963. The present study aimed to assess several Land Satellite (LANDSAT) pictures from 1988, 2000, 2013, and 2022 was utilized to map land use. The study generated data on land use changes in Lambaréné by cross-referencing these multiple maps. The supervised technique was utilized, and the Support Vector Machine algorithm (SVM) was used to study land-use changes over the last three decades. The resulting transition matrices were used to study the spatial and temporal dynamics of built-up areas, vegetation, and water bodies. The findings showed that urban areas had grown significantly, from 204.73 hectares in 1988 to 736.54 hectares in 2022, a 14.22 % rise, while vegetation dropped from 4057.40 hectares to 3488.86 hectares, a 67.36 % loss during the same time. This trend emphasized the disturbing influence of development on the region's already fragile ecosystems. Nonetheless, there was a slight recovery in the area's vegetation cover between 2013 and 2022, which was most likely due to the area's vulnerability to flooding disasters and thus low investment in infrastructural development during this time, particularly on the left bank of River Lambaréné compared to the right bank. Although these findings looked noteworthy, the use of higher-resolution images might be better for clearly understanding the complexity of land use change in Lambaréné.

Keywords: Dynamics, Change, Support Vector Machine (SVM), Land use, Lambaréné

INTRODUCTION

The ability to continuously observe the Earth's surface and develop massive databases for prospective use of information on the health of natural resources, local ecosystems, and their evolution is a spatially explicit assessment opportunity made available by remote sensing (Crouzat *et al*., 2017). At a time when the World is witnessing fast urbanisation and expansion, which have drastically transformed the urban environment, (Li *et al*., 2019), Land cover dynamics research is gaining popularity among scientists in general, and environmentalists in particular due to its relevance in the process of adopting environmental management strategies (Essono *et al*., 2019).
According to the United Nations (2018) Economic Commission for Africa, the world's urban population will reach 2.5 billion over the next four decades, with Asia and Africa accounting for 90 % of this rise. This growing urbanisation endangers the supply of Ecosystem

Services (ES) both locally and internationally. To this end, the African Union (2021), in its Green Recovery Action Plan 2021-2027, acknowledged that climate change and environmental degradation in general (including land degradation, ecosystem degradation, habitat destruction, water and air pollution, and biodiversity loss, among other things), exacerbate the challenges that countries face during the post-COVID-19 recovery. Given the increasing frequency of urban disasters, national and local governments, municipal authorities, and decentralised institutions such as city planning units, environmental management units, and other social service providers will need to understand, commit to, and consider long-term investments.

Furthermore, changes in land use and land cover (LULC) linked with the rapid urbanisation and abandonment of rural regions have significantly affected the supply and demand dynamics for ES (González-García *et al*., 2020). Territorial changes, in turn, are the outcome of land use dynamics, which are characterised by conversions and alterations of landscape units caused by both natural and human processes that have been extensively studied (Essono *et al*., 2019). These pressures are caused by the increase in agricultural, timber extraction, infrastructural development, including urban expansion, and other economic, institutional, and demographic issues in the Congo Basin (Fonteyn *et al*., 2021; Okanga-Guay *et al*., 2019; Tchatchou *et al*., 2015). These modifications are often characterized by uncontrolled development. Remote sensing is making it easier to monitor these changes.

Gabon has tropical rainforests spanning 89 % of its country and is home to around 18 % of the forests in the Congo and Ogooué basins. Gabon's diverse animal population includes species found in Central African woodlands. Agriculture, urbanization, forestry, mining, poaching, and other human influences increasingly jeopardise this unique biodiversity (Cornélis *et al*., 2022).

Indeed, there is growing interest among Gabonese scientists, particularly geographers and environmentalists, in studies of land cover change using remote sensing, though, according to Simba (2022), few studies on the dynamics of changes in land cover using satellite images have been conducted. Few studies have been conducted to assess land use changes in the Lambaréné region. However, several studies on land use change in Gabon have already raised the alarm that human activities are putting pressure on natural ecosystems, with deforestation, infrastructure growth, and urban development as the primary reasons for the deterioration (Boucka *et al*., 2021; Okanga-Guay *et al*., 2019; Essono *et al*., 2019).

The present study aimed to estimate the various changes in land use of Lambaréné observed by mapping and quantifying the landscape dynamics and describing the land use classes using a diachronic analysis of Landsat images from 1988 to 2022.

MATERIALS AND METHODS

Study area

Lambaréné, the administrative headquarters of Moyen-Ogooué province, is situated in central-western Gabon (Fig. 1), 275 kilometres from Libreville, the country's capital. It has 38775 residents (2013). According to the Lambaréné Town Hall, it has a total land area of 5,230 hectares, which is split into two districts: the first district has 3,090 hectares and the second district has 2,140 hectares. Already established as a fully-fledged commune in 1963 by Order No 224/PR/MITC of 13 August 1963 specifying the borders of the urban perimeter of

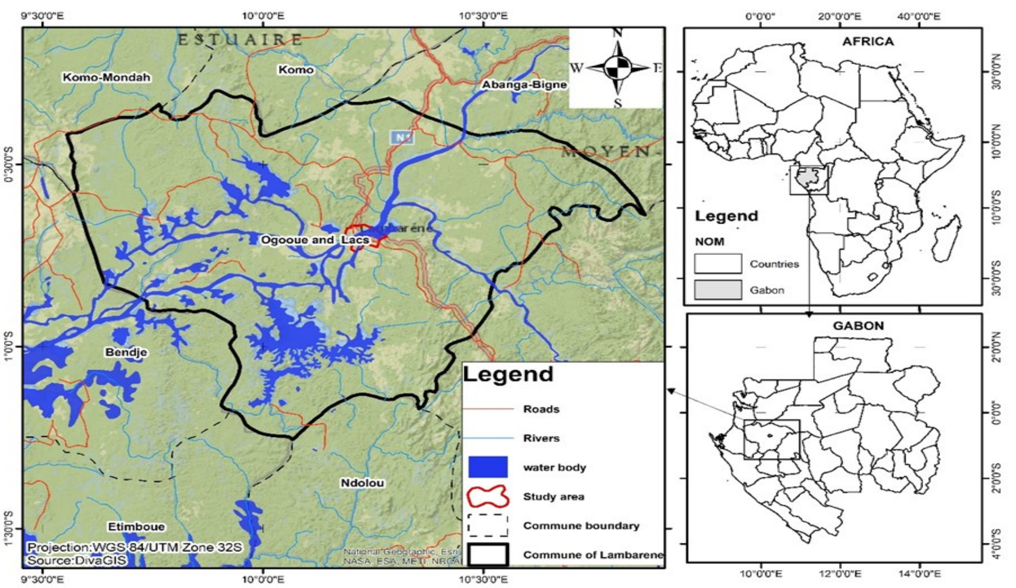

Fig. 1. *Map of the study area of Lambaréné*

the two divisions of the Commune of Lambaréné, the town's area was expanded at the cost of the Department of Ogooué and Lakes by the decree N°000665/PR/MIDDSM of 23 June 1995. The two main districts are divided into 24 neighborhoods with 13 on the right bank, and 11 on the second, the left bank. Because of its location in tropical Africa, the Ogooué Basin in Lambaréné (Gabon) gets substantial quantities of rainfall, averaging 1,600-2,200mm per year (Dongue *et al*., 2022). This has two wet seasons and two dry seasons (Gil *et al*., 1990) Lambaréné's average annual temperature is 27°, influenced by the equator.

Lambaréné is distinguished by its lowlands, which mark the beginning of the immense sedimentary plain that extends to the sea (except for a few hill chains). As is typical across the province, the natural forest vegetation predominates. Its hydrographic network is dominated by the River Ogooué, which runs through the province and significantly impacts the local hydrographic network. It is cut by rapids, widens in the lowlands, and then branches out into numerous arms and lakes from Lambaréné and increasingly towards the mouth. Rainfall and periodic flooding of the river create vast semi-aquatic areas, primarily downstream of Lambaréné, as well as the marshy areas of the Mbiné and Abanga upstream, occupying nearly a quarter of the surface area of the Province of Moyen-Ogooué and half of the Department of Ogooué and Lac (UNDP ART Initiative, 2016).

The settlement of Lambaréné, which is wholly inside Gabon's coastal sedimentary basin, sprang up around the Ogooué watershed, where the river divides into two arms, encircling the island on which the town center is situated. The Oremb'Owango separates to the north at the site's upstream end. The major river, the Oremb'Owango, runs to the south, explaining the existence of several wetlands on the site.

The topography of Lambaréné and its surrounding region is mostly low-lying ground with a few minor plateaux above it. The right bank is a plateau severely fragmented by watercourses, giving it a hilly shape with an average height of 100m. However, the tallest point (157 m) lies to the northwest of this bank.

Due to cultural richness, the Ogooué et des Lacs department is one of Gabon's most cosmopolitan. This is why Lambaréné, its capital, is sometimes described as "Gabon in miniature". Yet, it also has great and diverse economic prospects. To that end, the summary report on the Province of Moyen-Ogooué, PROGRAMME ART GOLD GABON, produced by the UNDP (2016) in collaboration with the provincial departments of the Ministry of the Environment, provides a non-exhaustive table of this economic potential, which is supported by the richness of its fishing resources; the richness and diversity of its fauna and flora; the high potential of its soil and subsoil in terms of natural resources; and its human resources. In addition to the above, Lambaréné, along with neighbouring cities such as Ndjolé and Port-Gentil, is the site of the junction of the major watersheds, with an 800 km^2 opening into the Atlantic Ocean, as described by Maloba-Makanga (2011). Since 1970, these towns have played an important role in logging in production and as transportation routes for forest goods.

The lakeside area was at the epicentre of this activity, which stopped in 2010 when the export of logs was prohibited. This act sought to revitalise the forestry sector, particularly its industry, to provide the forest an important role in the national economy, and to persuade operators to honour management and industrialisation pledges they made some years ago, notwithstanding government incentives. There will be no logs leaving the port of Owendo. All cut wood must be treated on-site before being sold on the open market (Moumbongoyo and Kombila-Mouloungui, 2020).

The city of Lambaréné, like most of Gabon's provincial capitals, is undergoing significant population increase, pointing to the human indicator as the primary source of the vulnerability of anarchic land use in Lambaréné. Although data on Lambaréné's population was unavailable in the early 1980s, censuses in 1993, 2003, and 2013 show that the city's population increased from 15,033 in 1993 to 24,275 in 2003 and 38,157 in 2013, with a density of 1206 inhabitants per km^2, which is the main human indicator of Lambaréné's vulnerability to uncontrolled land use (Hmidi, 2019). This paper examines the consequences of population increase over the years on land use in Lambaréné.

Methodology

Data collection

To study LULC changes in the area of Lambaréné, four multispectral satellite images

of the area were acquired for four periods: 1988, 2000, 2013 and 2022. Landsat images were obtained from the United States Geological Survey (USGS) https://earthexplorer.usgs.gov/. Specifications of the satellite data acquired for change analysis are given in Table 1. The grounds for this approach stem from the difficulties of gathering high-quality photographs that span a sufficiently extended period in the research region. The data spans 1988, 2000, 2013, and 2022. The selection of these dates was mostly influenced by the quality of the available and useable data. There was relatively little cloud cover.

Image processing and classification

Pre-processing satellite images prior to change detection phenomena is critical in developing a more direct relationship between the obtained data and biophysical phenomena (Abd El-Kawy *et al*., 2011). Remotely sensed data from aircraft or satellites are often geomet-

Table 1. Characteristics of the Landsat images used

Description	Sensors	Acquisition date	Cloud Cover %	Comment	System projection	Resolution (m)
LT04_L1TP_186060_19880202_20170209_01_T1	LANDSAT4 TM	02/02/1988	20.00	Moderate level	WGS84	30
LE07_L1TP_186060_20000407_20170212_01_T1	LANDSAT7 TM+	07/04/2000	23.00	Moderate level	WGS84	30
LC08_L2SP_185061_20130802_20200912_02_T1	LANDSAT8 OLI_TIRS	02/08/2013	5.74	High Degree of Visibility	WGS84	30
LC09_L2SP_185061_20220123_20220225_02_T1	LANDSAT8 OLI_TIRS	23/01/2022	20.00	Moderate level	WGS84	30

rically deformed owing to acquisition system and platform motions (Hassan *et al*., 2016).

As a result, Landsat images were atmospherically adjusted using the FLASH algorithm in the ENVI software tools to get surface reflectance data. L4 TM and Landsat 7 ETM + data were registered to their matching Landsat 8 OLI image utilizing automated image-to-image registration algorithms and a set of ground control points to integrate time series image data sets for change detection at the pixel level (GCPs). The spatial enhancement approach (i.e. focus analysis) was used to increase the image resolution of a Landsat 7 ETM + image. The data set supplier georeferenced the imagery (Universal Transverse Mercator-UTM, WGS84). The Landsat images from each research year were then separately categorized with a supervised classification algorithm using existing LULC employing ground truth data. However, due to the spatial and spectral resolution of the satellite images, categorisation mistakes in area estimations may arise (Gebeyehu *et al*., 2022). Thus, assessing the correctness of categorized images is critical in determining the dependability of retrieved information from classification (Olofsson *et al*., 2013). Consequently, the classification findings' correctness was validated using the data. Finally, using individually classified Landsat images, a post-classification comparison was performed for the LULC maps of 1988-2000, 2000-2013, and 2013-2022.

To evaluate the land use and land cover changes, Support Vector Machine classification algorithm was utilised. This is the supervised classification step, with the Support Vector Machine algorithm being employed. Because of the benefits of vector sampling, SVM is a technique that best classifies validation regions, allowing for better separation of established classes and avoiding misunderstanding.

This capacity can be fully used by sampling coverage changes more extensively. If no training samples are available for a specific class, the option to hide them is provided. The results obtained, generally in areas with higher sampling density for different classes during the documented tests, demonstrated the possibility of discriminating mixed classes in the feature space by bringing them to higher-dimensional spaces provided by SVM, thus becoming a very powerful tool and improving the quality of the results obtained (Medina and Atehortúa, 2019).

Furthermore, in diverse landscape classification experiments with Landsat TM images, the performance of SVM has been significantly proven (Bouaziz *et al*., 2017; Paneque-Gálvez *et al*., 2013). Earlier, a study by Pal and Mather (2005) showed that SVM outperforms the Maximum Likelihood Classification (MLC) and Artificial Neural Networks (ANN) classifiers in classification accuracy when applied to Landsat ETM+ and hyperspectral images, and it may be employed with short training datasets and dimensional data.

Delimitation and land cover class

The main benefit of this form of processing is that it allows the spectral signatures produced by the ROIs (Region of Interest) to be utilised to automatically, swiftly, and reliably identify and classify the components of the space. However, implementing this approach requires extensive knowledge of the area to be mapped to discover appropriate classes, which explains the method's selection. Supervised classification is a multistage iterative procedure. Three main classes are identified from the images. Table 2 described the identified classes.

This step seeks to extract the research regions based on their borders to speed up the procedure. Landsat images are around 180x180 kilometres in size and have a ground resolution of 30m. (Allen *et al*., 2013; Yan *et al*., 2016). With such a large surface area, extracting the study area (scene) beforehand is advisable to speed up the image processing process (Dembélé *et al*., 2018).

RESULTS

The present study information depicts land use and cover changes from 1988 to 2022. The maps indicated considerable changes in the research region, characterized by either progressive or regressive spatial development of land cover classes. In general, the changed dynamics of land cover between 1988 and 2022 was characterized by urbanization and deforestation (Table 3). The geographical development of anthropogenic landscape was significantly delayed. This was during the recurrence of heavy rains followed by catastrophic floods (between 2013 and 2022).

Overview of Land Use/Land Cover Dynamics using Support Vector Machine in Lambaréné, Gabon, from 1988 to 2022

Significant changes in land distribution were observed during the analysed time periods (1988, 2000, 2013, and 2022) (Fig. 2). In 1988, urbanised areas covered just 204.73 hectares, or 3.95 % of the overall area, but have progressively increased to 770.72 hectares, or 14.88 % of the studied area, in 2013. However, in 2022, this increase has been reduced somewhat to 736.54 hectares, or 14.22 % of the study area. In comparison, vegetation cover has steadily dropped from 4057.40 hectares (78.33 %) in 1988 to 3470.43 hectares (67.00 %) in 2013 before stabilising at roughly 3488.86 hectares (67.36 %) in 2022. Meanwhile, aquatic areas have risen from 917.48 hectares (17.71 %) in 1988 to 954.30 hectares (18.42 %) in 2022, demonstrating relative consistency over time, as illustrated in Table 3, and Fig. 3.

Trends and patterns of land use change from 1988 to 2022

The trends and patterns of land use change showed significant changes during the time period investigated. Built up areas increased progressively from 204.73 hectares in 1988 to 770.72 hectares in 2013, before significantly dropping to 736.54 hectares in 2022. This constant rise until 2013 amounts to an average increase of 10.27 % per year, whereas the modest decline from 2013 to 2022 suggests a loss of 0.48 % per year on average. Vegetation cover, on the other hand, has shown a negative trend, declining from 4057.40 hectares in 1988 to 3470.43 hectares in 2013, before stabilising at around 3488.86 hectares in 2022. This initial decline continued at an annual rate of -0.94 % until 2013, before stabilising between 2013 and 2022, as shown in Graph 4, with an annual minimum gain of 0.05 %. Water body areas have remained generally steady, ranging from 917.48 hectares in 1988 to 954.30 hectares in 2022, with annual changes of less than 0.1 % on average.

This depicts changes in built-up areas, vegetation cover, and water bodies from 1988 to 2022 (Table 4), as well as % age changes for each land cover category between years . The '+' symbol represents an increase, the '-' symbol represents a decrease, and 'stagnation' signifies little or no change.

Transition matrices for land use/land cover change between 1988 and 2022

Change in land use/land cover 1988-2000

The numbers reveal a significant growth in built-up area between 1988 and 2000, from 204.73 ha to 341.40 ha, a 67.67% increase (Table 5). The change from 204.73 ha to 341,40 ha resulted from the conversion of 192.33 ha of Vegetation and 0.27 ha of water body. This trend is replicated in the transition matrix, where the built-up area expanded from 148.80 ha to 341.40 ha, followed by a significant decrease in vegetation from 55.66 ha to 3815.80 ha. The accompanying percentages show that built-up area increases from 3.95 % to 6.59 %, while vegetation decreases from 78.33 % to 74.92 %. This transition depicts how urbanisation is increasing at the expense of vegetation.

Change in land use 2000-2013

Between 2000 and 2013, built-up areas rose dramatically, increasing by 125.66 % from 341.40 ha to 770.72 ha (Table 6). Furthermore, urban regions have expanded

Table 2. Land use description of Lambaréné area

Land use	Description
Built-up	Human-made structures; significant road and rail networks; huge homogeneous impervious surfaces, such as parking structures, office buildings, and residential dwellings; examples include homes, dense villages, towns, and cities, paved roads, and asphalt. Human-made structures; significant road and rail networks; huge homogeneous impervious surfaces, such as parking structures, office buildings, and residential dwellings; examples: homes; dense villages, towns, and cities; paved roads; asphalt
Vegetation	Examples of dense vegetation clusters with closed or dense canopy include woodland areas, savannas, plantations, swamps, and mangroves.
Water body	Areas where water was largely present throughout the year; may not include areas with occasional or ephemeral water; includes little to no sparse vegetation, no rock outcrops, or built-up structures such as docks; examples: rivers, ponds, lakes, oceans, flooded salt plains

Table 3. Land use Land cover change of Lambaréné from 1988 to 2022

Class	1988		2000		2013		2022	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Buit-up	204.73	3.95%	341.40	6.59%	770.72	14.88%	736.54	14.22%
Forest	4057.40	78.33%	3880.63	74.92%	3470.43	67.00%	3488.86	67.36%
Water body	917.48	17.71%	957.58	18.49%	938.54	18.12%	954.30	18.42%

Table 4. Inter-census rate of change in land use/land cover dynamics

Year	Built-up Area (ha)	Vegetation Cover (ha)	Water Bodies (ha)	% Change Built-up	% Change Forest	% Change Water
1988	204.73	4057.40	917.48	-	-	-
2000	341.40	3880.63	957.58	+136.67	-4.39	+4.29
2013	770.72	3470.43	938.54	+125.24	-10.61	-1.98
2022	736.54	3488.86	954.30	-4.42	+0.44	+1.71

Table 5. Transition matrix 1988-2000

	Class 2000			
Class 1988	**Buit-up (ha)**	**Vegetation (ha)**	**Water body (ha)**	**Total**
Buit-up (ha)	148.80	192.33	0.27	341.40
Vegetation (ha)	55.66	3815.80	9.17	3880.63
Water body (ha)	0.27	49.26	908.05	957.58
Total	204.73	4057.40	917.48	5179.61

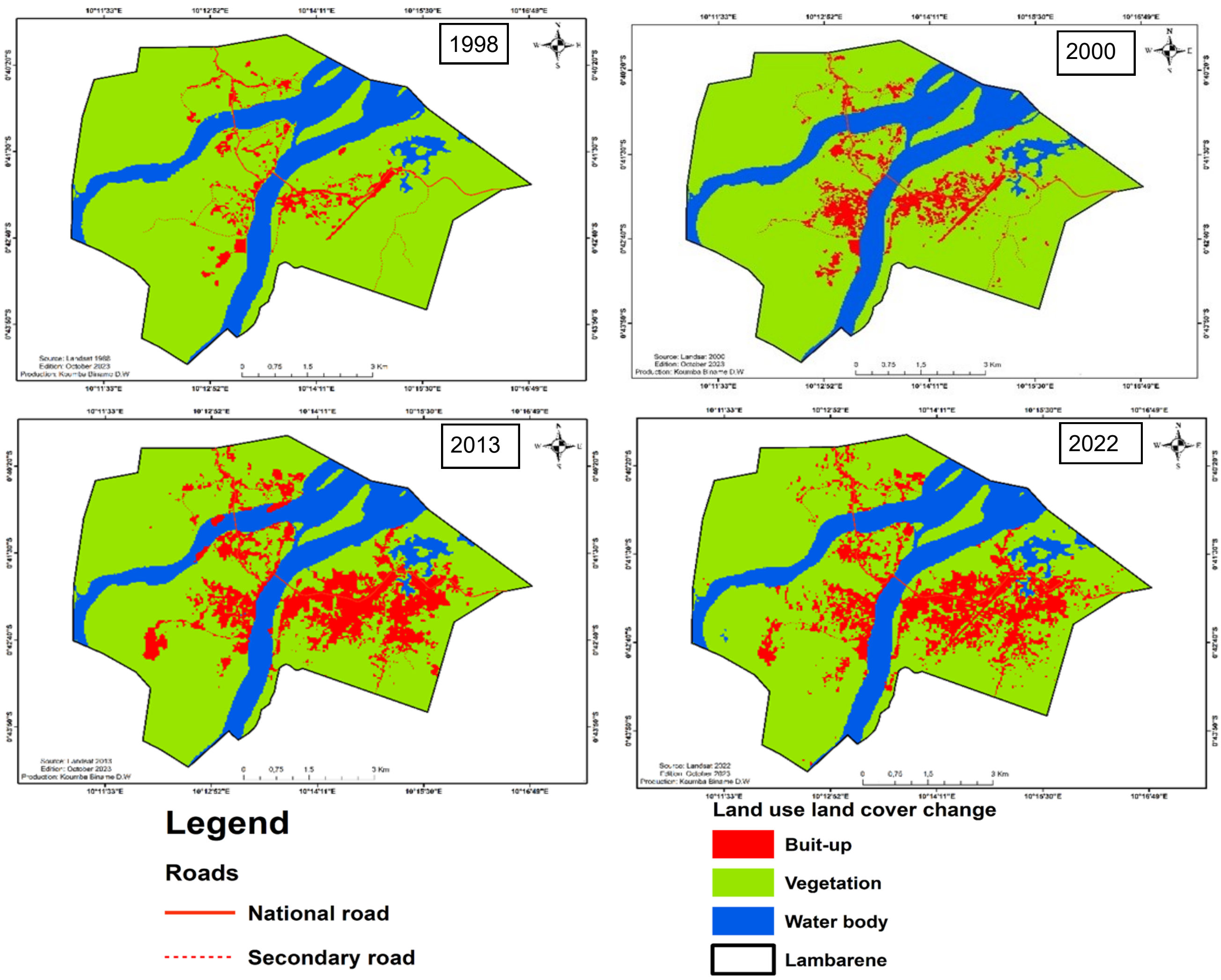

Fig. 2. *Land Use / Land Cover classes change in the Lambaréné area (Gabon) during 1988, 2000, 2013 and 2022*

tremendously. This trend is reflected in the transition matrix, which shows a significant increase in built-up areas and a reduction in vegetation. The vegetation area decreased from 79.87 to 3336.18 ha. The %ages coincide with built-up area increasing from 6.59 % to 14.88 % and vegetation decreasing from 74.92 % to 67.00 %, showing strong pressure on vegetation.

Change in land use 2013-2022

Although the built-up area is expected to rise between 2013 and 2022, statistical data indicate a little deceleration, from 770.72 ha to 736.54 ha. The built-up area share has declined somewhat, from 14.88 % to 14.22 % (Table 7). The transition matrix between these two periods demonstrates this trend, with a decreased

Table 6. Transition matrix 2000-2013

	Land use 2013			
Land use 2000	**Buit-up (ha)**	**Vegetation (ha)**	**Water body (ha)**	**Total**
Buit-up (ha)	259.29	484.52	26.91	770.72
Vegetation (ha)	79.87	3336.18	54.30	3470.35
Water body (ha)	2.24	59.93	876.37	938.54
Total	341.40	3880.63	957.58	5179.61

Table 7. Transition matrix 2013-2022

	Class 2022			
Class 2013	**Buit-up (ha)**	**Forest(ha)**	**Water body (ha)**	**Total**
Buit-up (ha)	589.28	144.57	2.70	736.54
Forest (ha)	160.74	3310.52	17.59	3488.86
Water body (ha)	20.70	15.35	918,25	954.30
Total	770.72	3470.43	938.54	5179.70

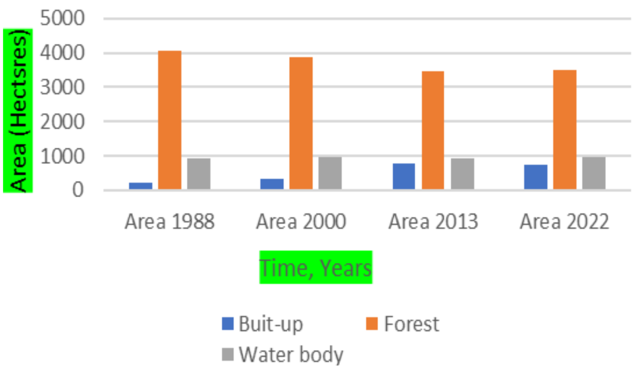

Fig. 3. *Situation of land use (1988 to 2022)*

growth in built-up area and a little increase in vegetation. The built-up's area decreased from 770.72 ha to 736.54 ha, while vegetation increased from 160.74 ha to 3310.52 ha. Despite this modest increase, the data obtained suggests that vegetation has decreased from 67.00 % to 67.36 % overall.

DISCUSSION

Analysis of built-up area growth

Statistics show that built-up areas have continuously increased from 204.73 ha in 1988 to 736.54 ha in 2022 (Table 3). The transition matrices 1988-2000, 2000-2013, and 2013-2022 show these positions increasing in a row (Table 7). This confirms the observed increase in urbanisation and demonstrates the clear association between static values and changes in the transition matrices.

The decrease in vegetation surface area and the growth in built-up areas show an inverse relationship. The static data show that the amount of vegetation has declined over time (from 4057.40 ha in 1988 to 3488.86 ha in 2022) (Table 3 and Fig. 3), whilst the transition matrices show that there has been a significant conversion of vegetated areas to built-up areas during the last three decades. Previous studies in many parts of Gabon focused on spatial and environmental changes. Findings of other land use land cover studies are consistent with studies on Gabon's spatiotemporal variability and pattern. These studies generally reported a warming trend in environmental degradation due to anthropogenic activities. For example, Essono *et al.*, 2019 investigated territorial changes in Owendo city, which are marked by conversions and alterations of landscape units as a consequence of natural and man-made processes. From 1990 to 2018, there was an 81 % rise in bare soil, a 390 % increase in manganese, a 37 % increase in road network, a 389 % increase in built-up areas, and a 63 % increase in river network.

In contrast, thick woodland dropped by 67 % and mangroves decreased by 16 %. Whereas Okanga-Guay *et al*. (2018) implemented a GIS-based method for temporal dynamic modelling of land use and land cover based on changes observed between 2000 and 2014.In another study of modelling land use dynamics and their effects around protected areas in the northern zone of Libreville (Gabon), the study proposes a projective analysis between 2020 and 2028. The procedure determined the areas that are expected to change at the prediction dates (2020 and 2028). The simulated changes demonstrate that the classes most influenced by a regressive dynamic are sparse forest, thick forest, and mangrove, with artificial surfaces benefiting from this. Artificial surfaces benefit from mangroves. Plant structures have the greatest conversion probability: 57.58 % in sparse forest, 21.17 % in thick forest, and 17.68 % in mangrove. The transition probability matrices show that the probability of the built environment occupying low-density forest ranges from 33% to 41%, while the probability of colonizing dense forest ranges between 0.72 and 7 %.

A recent study by Boucka *et al*. (2021) on mapping land use in Gabon in 2015 demonstrated that changes between 2010 and 2015 confirmed the trend in pattern change in Gabon. It highlighted ten land use classes: forests, savannas, agricultural land, and artificial surfaces are the most active land use classifications. The biggest forest losses are associated with the conversion of forests to artificial surfaces, cultivated land, and bare soils, while the most substantial forest gains are recorded at forest road closure. In Gabon, the investigation by Boucka *et al*. (2021) revealed a match between the land use map created and the reference data with an overall accuracy of 95 %. Indeed, the findings of this study demonstrated a significant trend toward growing urbanization, resulting in a significant growth of built-up areas to the detriment of vegetation. The trend observed in Lambaréné follows a similar pattern of Boucka *et al*. (2021). It focused on the continual rise of urban areas, which increased from 204.73 ha in 1988 to 736.54 ha in 2022, while vegetation decreased from 4057.40 ha to 3488.86 ha over the same period, as seen in Table 4. This transition is reflected in the % of built-up areas expanding from 3.95 % to 14.22 % and vegetation decreasing from 78.33 % to 67.36 % (Table 3).

At the level of the spatial sample, the use of remote sensing is beneficial for understanding changes in land cover. The present study used the supervised method to map land use dynamics from 1988 to 2022. The results of the processed remote sensing data show a building boom between 2000 and 2013, followed by a slight decrease between 2013 and 2022. Based on Table 1, describing the data obtained, 3 out of 4 images were taken during rainy periods (1988, 2000, and 2022). In other words, in January, February, and April, cloud cover varied between 20 and 22 % (moderate resolution). But also, an image with an excellent spatial resolution of 5 % in the year 2013 in August, which corresponds to the dry season period, with a dry season of 3 months (July to September) and a long rainy season of 9 months marked by frequent thunderstorms and heavy rain, from October to June (Koumba *et al*., 2018). This being the case, there may be some confusion in the obtained results. Indeed, in a hot, humid tropical environment, there is a very high level of cloud cover every month of the year. As a result, optical images with very low cloud cover are rare, as the cloud cover limits the number of usable satellite images in coastal and tropical regions (Akoma *et al*., 2019; Boucka *et al*., 2021; Wasseige *et al*., 2014). In Gabon, for example, only 20–30 % of images are analyzable (Maloba-Makanga, 2011b). These factors must be considered when determining the accuracy of the results.

Relative stability of aquatic areas despite increasing urbanization

The statistics data suggest that aquatic regions have remained relatively stable throughout time, varying between 17 and 18 % of the total surface area. A review of the transition matrices demonstrates that these regions have remained relatively stable despite urban growth, with minor variations in conversions between aquatic areas and the other class groups (Table 3).

Trends in change and development policies

The transition matrices showed periods of greater urban growth (1988-2000 and 2013-2022) and periods of less rapid urban expansion (2000-2013) (Table 6). These variances are linked to shifts in development methods and eras when measures to conserve or limit urbanization were put in place. Gabon is one of the few nations in the world that has long included the subject of sustainability in its growth trajectory and planning frameworks and whose policies have contributed to the development of the country's natural and cultural assets (Cornélis *et al*., 2022). However, urbanization and economic activities that have a long-term influence on natural habitats (oil palm and hevea plantations, logging, mining sector expansion, etc.) are accelerating. They may endanger Gabon's flora (Tropicos, 2019).

Between 2013 and 2022, the urbanized (built-up) area decreased somewhat, dropping from 770.72 hectares to 736.54 hectares, a 4.42 % decline, while forest cover increased slightly, from 3470.43 hectares in 2013 to 3488.86 hectares in 2022, a 0.44 % rise as described in Table 7. This rise is ascribed to government measures to prohibit log exports, the institutionalization of Forest Stewardship Council (FSC) certification, and the French business Rougier's abandoning of a substantial portion of its operations in Central Africa (Chalmin and Jégourel, 2016), particularly on the left bank of Lambaréné, where it had vast facilities. These methods have made conservation strategies and natural regeneration more successful in particular sections of Lambaréné.

The water body area has also expanded somewhat, rising 1.71 % from 938.54 hectares in 2013 to 954.30 hectares in 2022 (Table 7). These changes can be attributed to changes in hydrological systems, but also to natural variations in aquatic ecosystems and seasonal rainfall, which create favourable conditions for flooding, as documented by previous land-use studies by Loubamono and Faugères (1993), Maloba-Makanga (2011), and Mbadinga *et al*. (2019), all in central Africa mainly Gabon.

The present research region, Lambaréné, is developed in a flood-prone physical setting, owing to copious rainfall and diverse terrain. These include moderately high plateaux with views of a wide, gradually sloping alluvial plain dotted with marshes. Populations and some strategic structures or networks have been established in an anarchic way in this location despite its natural characteristics that are barely suitable for human settlement (Mbadinga *et al*., 2019). Many research on rainfall variability variables in equatorial Africa in general, and flooding risk in the Ogooué catchment region at Lambaréné in particular, have been conducted, resulting in a comparatively high frequency of floods (Loubamono and Faugères, 1993; Maloba-Makanga, 2011; Mbadinga *et al*., 2019).

define flood-prone morpho-climatic circumstances as an indicator representing the dangers of multiple-cause flooding. Although not all floods are caused by weather, the topographical component is a determinant factor in the characterization and location of the flood (Defossez *et al*., 2017), since a mix of natural forces causes floods. Natural elements that influence the nature of the danger include geomorphological predispositions, the breadth of the urban drainage network, and ample and consistent rainfall (Menie and Pottier, 2019).

According to Mbadinga *et al*. (2019) the Left Bank of the Ogooué features a wide, gently sloping area with a low height of roughly 30 metres, multiple watercourses, extensive marshes, and a few lakes. Based on these variables, the minor decrease in the number of structures in 2022 may be attributed to a progressive understanding of the hazards of flooding among people repeatedly exposed and incur considerable material loss over time. This drop results from a possible strong abstention on the part of the population regarding long-term investments in specific sites or even their abandonment of areas deemed prone to flooding, particularly on the left bank of the Lambaréné compared to the right bank. This shift in viewpoint might be related to a slowdown in Lambaréné's urban expansion, spurred by worries about flood safety, and could increase the avoidance of flood-prone regions. This pattern might account for the decline in built-up areas between 2013 and 2022. Other reasons, such as the inadequate execution of decentralization legislation, rural migration, and the isolation of specific rural districts, might also impact this trend. The ART GOLD GABON 2009 PROGRAMME had already highlighted the region's difficulties, which could have significant ramifications, notably by encouraging the establishment of new urban centres in higher-lying areas to ensure greater safety from flooding, particularly on the road towards Canton Biweni -Diala, known as the Fougamou road, and upstream of Lambaréné, known as the Libreville road, to limit urban sprawl in potentially flood-prone areas to ensure the safety of residents (Menie and Pottier, 2019).

Conclusion

The results obtained from this study revealed a notable tendency towards increased urbanization in Lambaréné, resulting in a large expansion of built-up areas to the disadvantage of vegetation between 1988 and 2000, then between 2000 and 2013. Despite evidence of stabilization or minor recovery in vegetation between 2013 and 2022, these shifts highlight the need for balanced urban development plans that include effective conservation measures to conserve forest ecosystems while encouraging sustainable urban expansion. Informed environmental and urban policies are required to strike a balance between economic growth and long-term protection of key natural resources. The results of this study will contribute to sustainable land management by development managers and related agencies involved in the decision-making process. These outcomes will also be an important step for further LULC study regarding the probable increase in flooding. A continuous decrease in forest cover in the area may affect population vulnerability. Known for its abundant pluviometry, the area is tied to the unique characteristics of the main river (Ogooué) and other water bodies surrounding the city, including wetlands.

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Conflict of interest

The authors declare that they have no conflicts of interest.

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