International Journal of Innovation and Applied Studies
ISSN 2028-9324 Vol. 41 No. 1 Nov. 2023, pp. 197-207

http://www.ijias.issr-journals.org/

Main Explanatory Factors of the Degradation of the Vegetation Cover of the Galangashie Classified Forest in North Togo: An Analysis Approach Using Spatial Statistics and GIS

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ABSTRACT: The Galangashie Classified Forest is facing a degradation of its vegetation cover due to anthropogenic factors. This research aims to identify the main explanatory factors of the dynamics of land use in order to propose a development plan for the sustainable management of this protected area. To achieve this, data was collected initially on the basis of survey forms by questionnaire and then by processing satellite images to determine the points of vegetation fires and the burned areas. The results show that four main factors explain this degradation of the classified forest. These are logging according to 37% of the households surveyed, agricultural practices for 36%, overgrazing according to 23% and wildfires according to 4% of the households surveyed. The annual distribution of wildfire points shows high fire activity in the forest. From 2001 to 2019, the areas burned in the sector evolved from 6139 to 5058 ha. On average 53% of the forest area was affected by the fires. The late fire points evolved from 49 to 112 points between 2001 and 2019, hence the vulnerability of the reserve. The results obtained constitute a database for the development of a development and management plan for the Galangashie Classified Forest.

KEYWORDS: Explanatory factors, degradation, Spatial statistics, Galangashie Classified Forest.

1 INTRODUCTION

The Galangashie classified forest, like most other protected areas in Togo, is experiencing a decline in its vegetation cover. Indeed, [10], p.32 has shown that, between 1987 and 2019, the average annual rate of regression of open and dry forests is -7.12%, while that of wooded savannahs is -6.80%. However, tree savannahs, shrub savannahs and grass savannahs grew by 2.25% and 1.22% respectively. Studies carried out by [1], p. 167 on the Fazao-Malfakassa National Park and the Oti-Kéran reserve in Togo have shown the state of degradation of these environments. In the Oti-Mandouri fauna and flora reserve, [9], p.51 has shown that this protected area is experiencing a worrying deterioration in its flora and fauna. Indeed, gallery forests, open forests, tree and shrub savannahs have fallen from 107691 ha in 1990 to 86382 ha in 2020, a reduction of 21309 ha. On the other hand, fields and fallow land increased from 10495 ha to 31804 ha, an increase of 21309 ha over the same period.

In Benin, [18], p.52 has shown that changes in the way people use the land have a direct impact on the quality of life. In the Savannah region of northern Togo, [4], p.31) states that many biotopes and biocenoses have been disturbed by human activities. In his view, people cut down or uproot hectares of forest every year. In addition, [6], [1], [9] have shown that the factors that degrade plant cover in protected areas include agriculture, transhumance, hunting and, above all, late vegetation fires. Like the other factors that degrade plant cover, uncontrolled vegetation fires, especially those recorded in protected areas, are harmful to vegetation because they occur at a time of water stress. The hypothesis of this research is that the Galangashiese classified forest is degrading as a result of human actions. The aim of this study is to determine the main factors explaining this degradation of the vegetation cover in the reserve, using spatial statistics and Geographic Information Systems (GIS).

2 Methodological Approach

2.1 Presentation of the Study Area

The Galangashie classified forest is located in the Savannah region, more precisely in the Oti prefecture. It covers an area of 10555 ha. The cantons bordering this classified forest are Barkoissi, Galangashie in the commune of Oti 1 and Mango in the commune of Oti 2 (Fig. 1). The classified forest is located between latitudes 10° and 10° 21' N and longitudes 0° and 0° 32' E. The environment is a lowland zone with a predominance of tropical ferruginous soils and shrubby and grassy savannahs in a Sudanian-type climate. The average population density is 224 inhabitants/km2. The main activities of local residents are farming, livestock rearing and fishing.

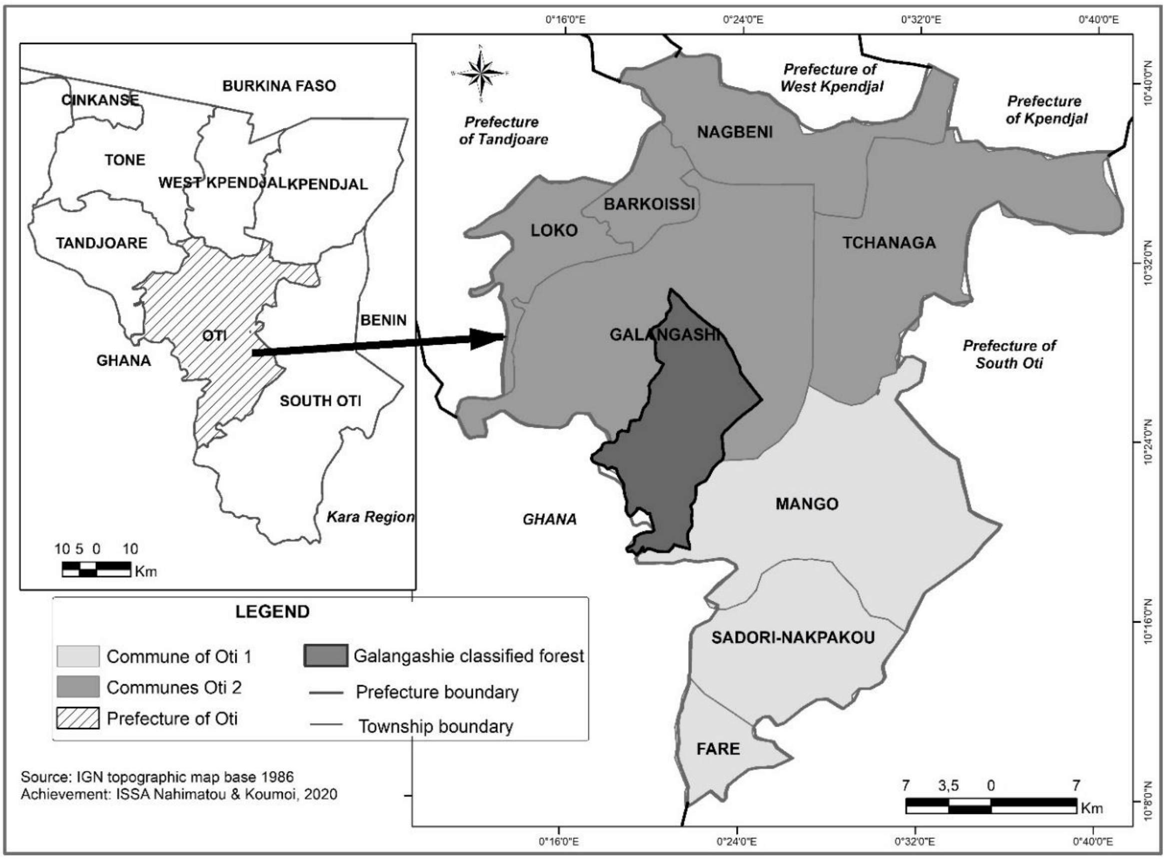


Fig. 1. Geographical location of the study area

2.2 Materials Used

Spatial Data: These are:

- IGN topographic maps (1: 200,000 scale, 1986) and maps from the Japan International Cooperation Agency (JICA) and the Togolese government (1: 500,000 scale, 2013);
- Landsat TM satellite images from 1987, ETM+ from 2001 and OLI-TIRS from 2019, each with 30m resolution, downloaded from the website: http://glovis.usgs.gov, to determine burnt areas.
- Active fire points (late fire points recorded during the months of March, April and May in particular) in MODIS images from 2001 to 2019, detected by the TERRA and AQUA observation systems (http://terra.nasa.gov). These two orbital satellites are equipped, among other things, with the MODIS instrument, which is particularly well suited to detecting active fires [8] p. 730. The data are provided in vector format (.shp) as part of the FIRMS project at the University of Maryland (USA). These fire points have a resolution of 1000 m.

Software: These are:

- ENVI 5.3 for digital processing of satellite images (determination of burnt areas);
- ArcGIS 10.5 for mapping and spatial statistics;
- Microsoft Excel spreadsheet for producing graphs.

Questionnaire and Interview Guide: A household questionnaire was administered to each farmer and/or stockbreeder in the selected riverside localities.

2.3 DATA COLLECTION METHOD

The secondary data collected consisted of data from satellite image processing. Satellite images of the Landsat TM type from 1987 and ETM+ from 2001 and 2019 have been used in previous studies to map land cover dynamics. For the present study, the areas derived from the remote sensing processing of these images were used. Next, population and household data by locality and by canton from the RGPH4, 2010 were used. This data was used to produce semi-structured interview guides and field questionnaires.

The primary data were collected from a structured questionnaire survey conducted in the cantons bordering the Galangashie Classified Forest. The localities involved in the study were: Akpossou, Bigou, Galagashie, Poloti in the canton of Galangashie and Mantchè in the canton of Mango. The sample adopted for this study is based on a study of households in the localities bordering the Galangashie classified forest. Within each locality, a sub-sample of individuals was chosen for the study according to the principle of exhaustive drawing without remittance. The number of households to be surveyed was determined using the formula of [7] with a confidence level of 95% and a margin of error of 5%:

$$n = \frac{N}{1 + N \times e^2}$$

n: number of households to be surveyed; N: total number of households in the sampled villages, e: margin of error.

On this basis, 222 households were selected. However, in order to have a sample that was more appropriate to the capacities available and representative of the target population, a margin of error of 8% was set with a confidence level of 92%. The number of households to be surveyed is therefore:

$$n = \frac{626}{1 + 626 \times 0.08^2}$$

$$\mathbf{n = 125}$$

Knowing that: n = T × N, which means $T = \frac{n}{N}$. *N: size of the target population, corresponding to the total number of households; n: sample size, corresponding to the households to be surveyed and T: sampling* rate.

$$T = \frac{125}{626} \times 100$$

$$T = 20\ \%$$

This rate, applied to the number of households in each village, is used to determine the total number of households to be surveyed per village (Table 1).

Table 1. Summary of the parameters of the sampling technique used

Prefecture	*Commune*	*Canton*	*Village*	*Households of 2010*	*Sample*
OTI	Oti 1	Mango	Mantche	111	23
			Akpossou	42	8
	Oti 2	Galangashie	Bigou	139	28
			Galangashie/Poloti	334	66
			TOTAL	**626**	**125**

Source: RGPH4 data, 2010

An empirical (random) survey was carried out, setting the minimum age of respondents at 30. This age was chosen on the basis that, by the age of 30, people are already beginning to pay attention to their environment and can distinguish any action likely to harm their surroundings. With at least 30 years' experience, he will therefore be able to accurately retrace the history of the evolution of his landscape. This approach was used by [2] in northern Togo, and the data obtained was supplemented by informal interviews with elderly people, village chiefs, ODEF branch managers in Mango and the Regional Environment Directorate of the Savannas Region.

2.4 DATA PROCESSING

- *Calculation of the Average Annual Rate of Spatial Expansion*

In previous studies, Landsat satellite images from 1987, 2001 and 2019 were processed using remote sensing principles. The areas and average annual expansion rates of all the land cover units were calculated between these periods [10]. This rate is calculated as the ***dependent variable (Y)*** in the simple linear regression method. This rate is calculated by canton (administrative grouping of several villages) between the two reference years (1987 and 2019).

- *Processing of Survey Data*

The data collected in the field were processed using EpiDATA, SPSS and Microsoft EXCEL software. Two types of analysis were carried out as part of this work. These were descriptive analyses and multivariate analyses.

The descriptive analysis was based on frequency tables, percentages for the variables, and graphs.

The bivariate analysis was carried out using a simple linear regression model (weighting). This method is used to determine the weight of each factor in the dynamics of land use. It is a set of statistical methods adapted to the analysis of the organisation of geographical space and its differentiations. It is executed by the "spatialstatistics tool" of the ArcGIS 10.5 software. According to [13], the use of these techniques requires a somewhat systematic organisation of geographical information in the form of a spatial information matrix. To this end, for the purpose of this study, the Galangashie Classified Forest is divided into the two riparian townships. Each section is described by a series of indicators (variables) relating to the problem being analysed. This requires two types of variable: the "dependent variable" and the "explanatory variables". The first variable here is the rate of land use dynamics (TD_OS) between 1987 and 2019 [10]. The explanatory factors selected are shown in Table 2.

Table 2. Description of Useful Variations

Type of variable	Nature	Description	Data Source
dependent variable	Rate of dynamics land cover (1987 to 2019)	State of land cover and its trend over time, in short the rate of change of land cover	satellite images Landsat TM and ETM+
Variables explanatory Or independent	Area exploited	Proportion of people farming more than 4 ha	surveys Data of land
	Availability of land	Proportion of those who state that land is not available	
	Fuelwood	Proportion of people who use fuel wood	
	Charcoal	Proportion of people who use charcoal	
	Population density	Number of inhabitants per km2 Population data from the RGPH4 were related to the surface area of each canton in (ArcGIS 10.5)	Data from RGPH4, 2010
	Household	Number of households per canton	

Source: field data and laboratory work, 2021

This simple or multiple linear regression method makes it possible to obtain a certain number of parameters that make it possible to justify the validity of the overall model [13]. These are:

- *R2/Rsquared:* the multiple R squared and adjusted R squared values are two statistics derived from the regression equation to quantify the performance of the model. The value of R-squared is between 0 and 100%.
- *Regression coefficients (β):* These are calculated by the regression tool. These values represent the strength and type of relationship between the explanatory variable and the dependent variable. When the relationship is positive, the sign

of the associated coefficient is also positive. Coefficients corresponding to negative relationships are negative. When the relationship is strong, the coefficient is relatively large (in relation to the units of the explanatory variable with which it is associated). Weak relationships are associated with coefficients close to zero; β0 is the coordinate at the origin of the regression. It represents the expected value for the dependent variable if all the independent (explanatory) variables are zero.

- *Multiple correlation coefficient*: This measures the link between the dependent variable and the k explanatory variables. If it is not zero, the link is non-existent.
- *Coefficient of multiple determination*: This indicates the proportion of the marginal dependent variance Y that is explained by the multiple regression.
- *Significance test*: The simple or multiple linear regression model is significant if the multiple regression coefficient calculated is greater than the corresponding value of the coefficient read from the Fisher coefficient test table (1953). This coefficient is 0.88 for a precision of 95% (margin of error of 5%), [5].
- *Model performance*: According to the null hypothesis H0 for this parameter, there is an independent relationship between the dependent variable and the explanatory variable. The adjusted R^2 and R^2 are measures of model performance. The adjusted R2 value is always lower than the R2 value, as it reflects the complexity of the model (number of variables) in its relationship to the data and therefore represents a more accurate measure of model performance.
- *Interpretation of the value of the regression coefficient*: When the regression coefficient is positive, this means that the two variables are moving in the same direction: when the slope, for example, becomes steeper, the erosion rate also increases. With a coefficient equal to 0.41, we can say that when Y varies by one unit, X varies by 0.41 units.

• *Processing of Vegetation fire Points and Determination of Burnt Areas*

The late fire points from the Modis images from 2001 to 2019 were projected into the working system (WGS 84, UTM 31N). These fire points were then super imposed on other information layers in a GIS. They were then selected according to the study area using the "select by attributes" and "Data - Export data" tools in ArcGIS 10.5 GIS software for processing and spatialization.

Burnt areas were determined by unsupervised classification of Landsat satellite images using ENVI 5.3 software. The process involved applying an unsupervised classification to these images after a 7-5-6 colour composition. This composition consists of applying the two short-wave infrared bands (2.08-2.35 µm; 1.55-1.75 µm) and the thermal infrared band (10.4-12.5 µm) to the colours Red, Green and Blue. This method was used by [11], [15]. The burnt areas extracted from Landsat satellite images by unsupervised classification were converted into vector format (.shp). They were then imported into ArcGIS 10.5 software to produce the maps. Areas were calculated for analysis purpose.

3 RESULTS

3.1 MAIN FACTORS IN THE DEGRADATION OF VEGETATION COVER

Four main factors which are responsible for this degradation: logging (37% of households surveyed), agricultural practices (36%), overgrazing (23%) and wildfire (4%) (Fig. 2). These factors were analysed by cross-referencing perceptions of these determinants according to socio-professional and socio-cultural categories.

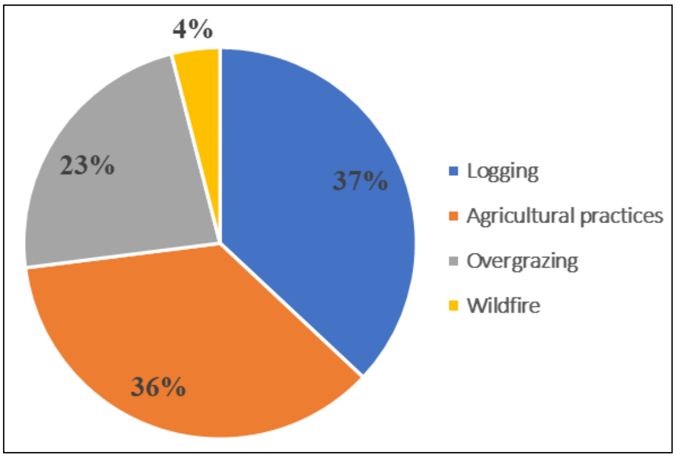


Fig. 2. Riparian population's perception of the causes of the degradation of the plant cover

Source: Field data, 2021

- *Logging (firewood and charcoal)*

According to 37% of households surveyed, firewood and charcoal remain the population's main sources of cooking energy.

The simple regression model between the rate of land use dynamics (TD_OS) and the use of fuelwood shows the performance of the model with a coefficient of multiple determination equal to 0.90 (Table 3). This calculated value is higher than the 0.88 found in the correlation coefficient test table for a precision of 95% (margin of error of 5%) showing that the model is statistically significant.

Table 3. Regression statistics for fuelwood use

Coefficient of multiple determination	**0,900690645**
Coefficient of determination R^2	0,7581022
Adjusted coefficient of determination R^2	**0,4518978**
Standard error	2,323209762
Observations	2
Regression coefficient for fuelwood use	**0,044728324**

Source: field data and laboratory work, 2021

The regression coefficient for fuelwood use is 0.04. This means that a variation of 1% in the number of households using fuelwood from the Galangashie reserve leads to a variation in the average annual expansion rate of 0.04%. In contrast, for charcoal use, the coefficient of multiple determination is 0.89. The model is also statistically significant (Table 4).

Table 4. Regression statistics for charcoal use

Coefficient of multiple determination	**0,890888702**
Coefficient of determination R^2	0,252897047
Adjusted coefficient of determination R^2	**0,347102953**
Standard error	5,840257851
Observations	2
Coefficient of regression for charcoal use	**0,043374613**

Source: field data and laboratory work, 2021

The regression coefficient R2 for charcoal use is 0.04. This means that the variation of 1% of households using firewood from the Galangashie reserve results in a variation of 0.04% in the average annual expansion rate. In fact, around 59% of households surveyed admit that they draw their energy resources from within the Galangashie Forest Reserve (Plate 1).

Plate 1: Logging and sale of charcoal along the RN1 in Bigou (village bordering the Galangashie Forest Reserve).

Source: authors, 2021

- *Agricultural Activities*

The main activity of people living near the Galangashie Forest Reserve is farming. This shows that 23% of households surveyed farm less than 2 ha, 13% farm between 2 and 3 ha and 64% farm more than 4 ha. According to 86% of them, there is not enough arable land.

The simple linear regression model by weighting the rate of land-use dynamics (TD_OS) and households declaring that land is insufficient due to the presence of the reserve shows a multiple coefficient of determination equal to 0.90 (Table 5). This calculated value is higher than the 0.88 found in the correlation coefficient test table for a precision of 95% (margin of error of 5%).

Table 5. Regression statistics for households reporting insufficient land

Coefficient of multiple determination	**0,90879948**
Coefficient of determination R^2	0,8259165
Adjusted coefficient of determination R^2	**0,1740835**
Standard error	2,8191657
Observations	2
Regression coefficient for households reporting insufficient land	**0,05281065**

Source: field data and laboratory work, 2021

The regression coefficient for households reporting that land is insufficient is 0.05. This means that the variation of 1% of households that declares land to be insufficient leads to a variation in the average annual expansion rate of 0.05%.

- *Vegetation Fires*

Vegetation fires are also a major factor in the degradation of vegetation, especially when they occur late in the season. They were cited by 4% of survey respondents. The figure 3 shows that 29% of households cite late vegetation fires, compared with 34% who cite both types of fire.

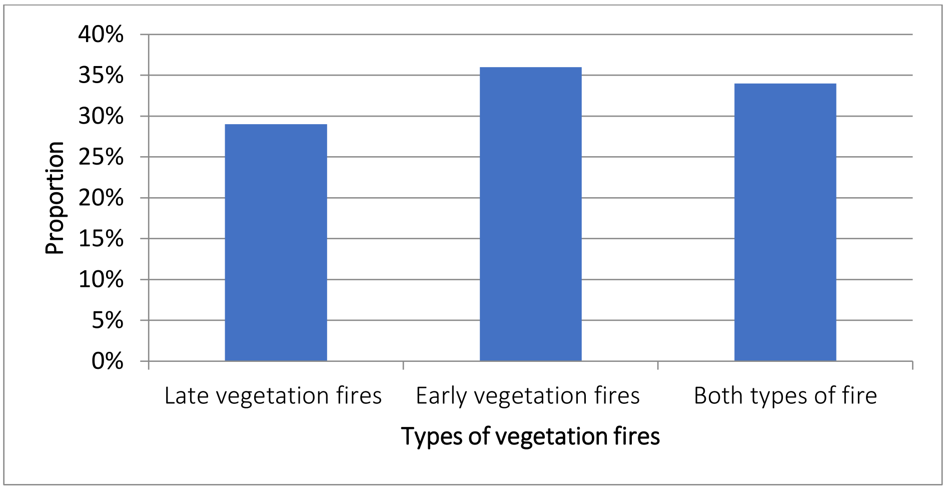


Fig. 3. Types of vegetation fires in the Galangashie Classified Forest

Source: Field data and laboratory work, 2021

It is therefore important to determine the areas burnt and the occurrence of late vegetation fires in the Galangashie classified forest.

The fig. 4 shows the spatiotemporal distribution of late vegetation fires in 2001 and 2019.

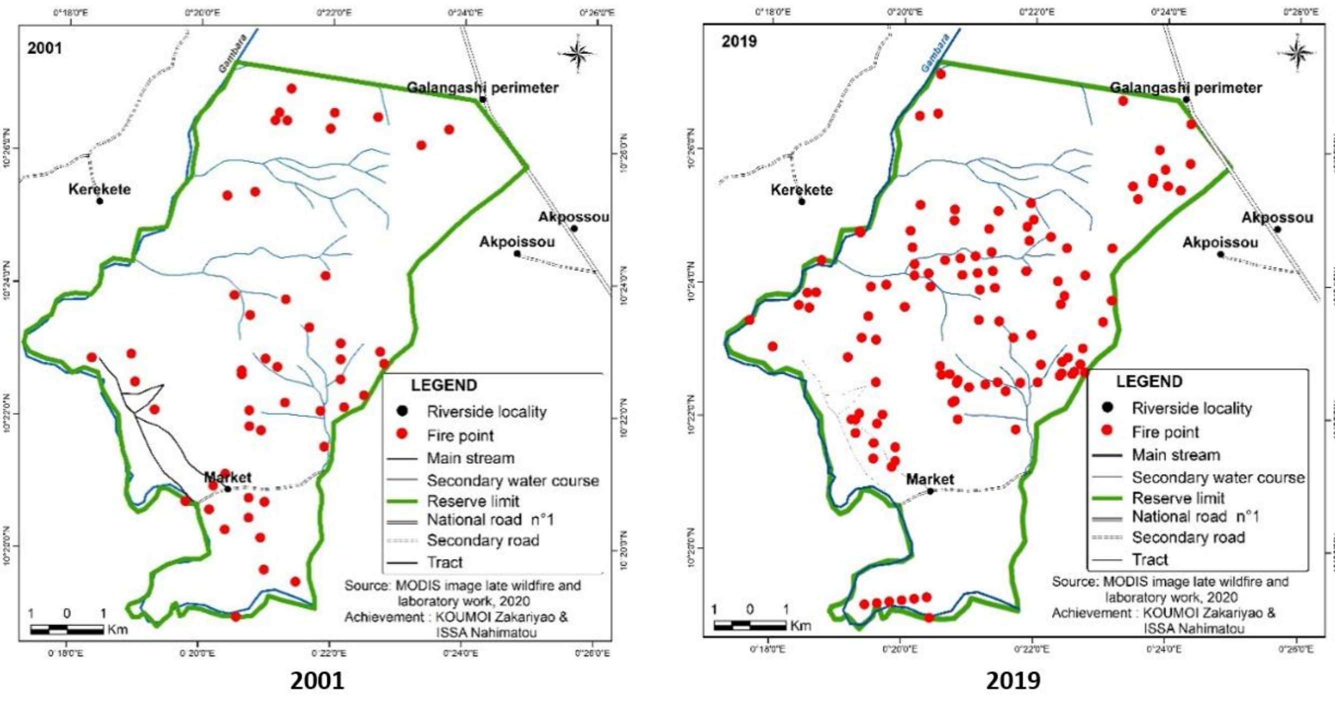
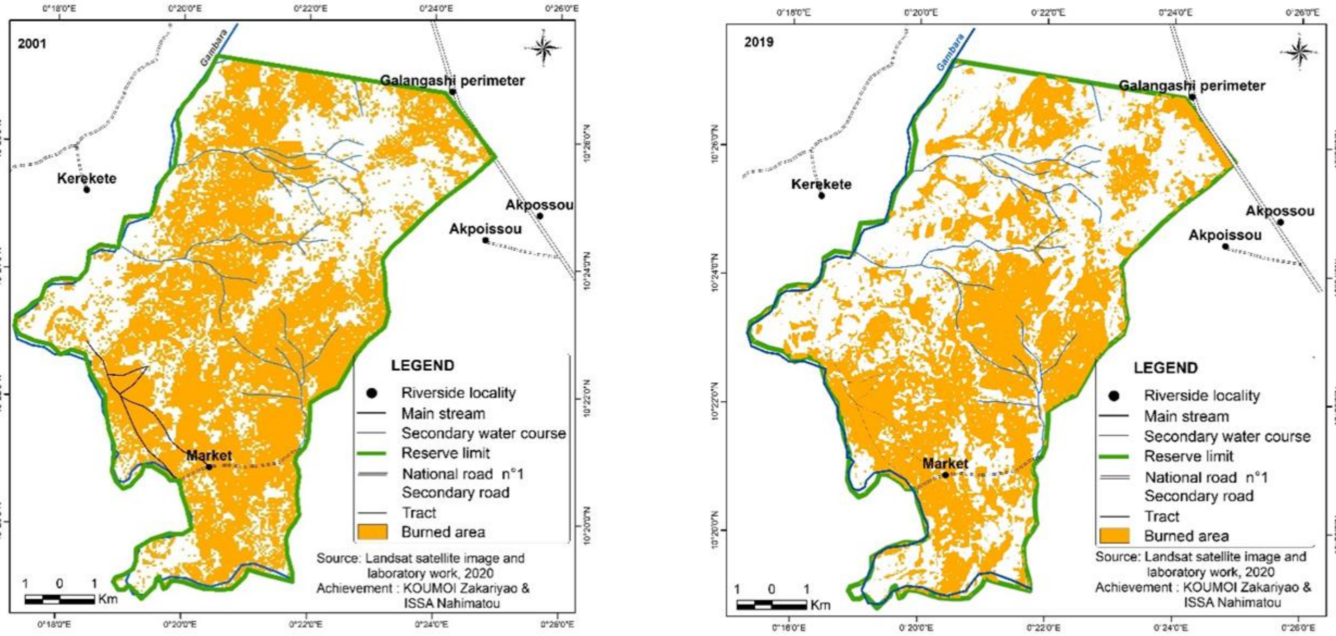


Fig. 4. Spatial distribution of late wildfires in 2001 and 2019

Source: based on MODIS image data of late vegetation fire point

The Figure 4 shows that the number of late wildfire points detected in the forest was 49 in 2001 and 112 in 2019. Analysis of their spatial distribution shows that the south and center-east were regularly covered by late wildfires in 2001. In 2019, the center and north-east were affected. The occurrence of fires in the north and center can be explained by the existence of riverside localities. These riverside communities carry out activities within the forest. Particular attention should be paid to late fires in this zone.

Analysis of the distribution of burnt areas shows an increase in vegetation fires. The Fig. 5 shows the spatial and temporal evolution of burnt areas in the study area between 2001 and 2019.



2001 **2019**

Fig. 5. Spatial and temporal trends in burnt areas between 2001 and 2019

Source: Based on data from Landsat satellite image processing, 2021

From 2001 to 2019, the area burnt has changed from 6139 to 5058 ha, i.e. an average of 53% of the park's surface area is covered by fires. In November 2001, the park recorded fewer late fires. The area burnt in the sector reached 6139 ha, i.e. 58% of the total area. These fires occurred mainly in shrub and grass savannah. On average, 5,599 ha were burnt, i.e. 53% of the total area. Within the forest, it is the south-eastern and central parts that have been most affected by these fires. By March 2019, these fires had decreased by 5058 ha in the sector, or 48% of the total area.

4 DISCUSSION

The dynamics of land cover can be explained by the factors associated with it. This study identified agricultural practices, farming, overgrazing and wildfires as the main drivers of vegetation degradation. These same factors were identified by [17]. Population growth, overexploitation of forest resources, fishing and urban sprawl are the main factors driving changes in the environment.

It should be noted that the degradation of natural formations has become much more pronounced over the period 2000 to 2015, with increased anthropisation of forest areas. In this region, agricultural practices, charcoal production, farming and vegetation fires, which are carried out in an uncontrolled manner, are largely responsible for the reduction in forest area and the impoverishment of the flora. This result is in line with research by [18], who have shown that human activities play a major role in the fragmentation of patches of dense forest in the Monts Kouffé classified forest. Other studies, such as those by [14], p. 143 in Central Togo and [3] on the Adele plateau have shown that plant formations are degraded by human intervention.

The particularity of this study is the determination of the share of each explanatory variable retained in the explanation of the average annual expansion rate of land cover dynamics. A bivariate analysis using the simple linear regression method between the dependent variable (TD_OS) and each explanatory variable was used to determine the weight of each explanatory factor. This same method was used by [15], p. 134 in south-east Togo. However, the study did not perform a multiple linear regression analysis by weighting all the explanatory factors with the dependent factor as [13] in Centre Togo. This is explained by the fact that the Galangashie Classified Forest crosses only two cantons. In spatial statistics, however, it is the vegetation formations, broken down by canton, that constitute the entity for regression analysis (observation numbers). For multiple regression to be possible, at least 4 observations are required. Nevertheless, the bi-variate analysis adopted enabled us to show the weight of each factor and the importance of spatial statistics in determining the factors that explain vegetation dynamics.

The burnt areas extracted from Landsat satellite images from 2001 and 2019 showed the effectiveness of fires in the study area. The high frequency of fires in the forest is due to hunting and the clearing of fields in the study area, where slash-and-burn agriculture and grazing are still the most widespread practices. Sometimes, these fires get out of hand and can set the park ablaze. The same observation was made by [12] in the prefecture of Oti in North Togo, where the Oti-Kéran Park is located. [16], p. 256 made the same observation in the Bassila and Mont Koufé forests and in part of the Wari-Maro forest.

In the light of these analyses, vegetation fires merit particular attention given that the high proportion of late fires and their damaging effects on the plant cover. The problem of fire in the study area, and especially in the PNFM, must be at the center of any analysis aimed at gaining a better understanding of how it works and improving its management. Remote sensing now appears to be a valuable and inexpensive tool for observing terrestrial ecosystems. In Togo, it can be used to monitor vegetation fires in order to help decision-makers take environmental decisions.

5 Conclusion

The main factors identified were logging (37%), farming practices (36%), overgrazing (23%) and wildfires (4%). The activities carried out by the riparian population (logging, farming, grazing and vegetation fires), which are increasing rapidly, are held responsible for these changes in the forest (retreat of the forest and strong savannisation). The annual distribution of fires shows a jagged pattern. Late fires are no less numerous and are harmful to vegetation because they occur at a time of water stress. Spatial analysis of burnt areas showed a high level of fire activity in the study area between 2001 and 2019. This study also enabled fire outbreaks and burnt areas to be spatialised and estimated. All this information, coupled with previous studies on the spatio-temporal dynamics of land use, is necessary in the process of drawing up development and management plans for this classified forest. But long before that, there is an urgent need to step up the monitoring of laws banning the felling of timber to ensure sustainable management of biodiversity in this environment, which is heavily influenced by human activity.

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