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Land Use Dynamics in the Department of Séguéla, Northwestern Côte D'Ivoire

Arthur Brice Konan-Waidhet*, Kouakou Hervé Kouassi, Kouamé Elyass Kanga

Laboratory of Science and Technology of Environment, Jean Lorougnon Guédé University, Daloa, Côte d'Ivoire
Email: *konanwab@yahoo.fr, konanwaidhet@ujlg.edu.ci

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Abstract

Land use monitoring occupies a very important place in the analysis of the dynamics of the earth system. It helps to understand the organization and helps to provide relevant elements for the establishment of diagnoses and the development of environmental forecasts. The objective of this study is to follow the evolution of the agricultural landscape in the department of Séguéla from 1988 to 2020 and to make a prediction for 2050, in order to manage the spaces reasonably. The methodology adopted is based on the one hand on the processing of satellite images for the analysis of land cover and on the other hand on predictive modeling (LCM model) by 2050. The results obtained show that the land use maps produced after processing the satellite images made it possible to highlight the dynamics of the agricultural landscape in this part of the Worodougou region. During the period 1988 to 2020, we witness an increase in the area of cultivated territory as well as a slight reduction in wooded savannas which are largely made up of perennial crops (cashew trees, cocoa trees, coffee trees, etc.). These two aforementioned classes have respective annual rates of change of 2.42% and −0.44%. A scenario modeling land cover changes in 2050 with an overall accuracy of 80.35% revealed a continued growth of crops and fallows to the detriment of natural forests and wooded savannas.

Keywords

Satellite Images, Land Use, LCM Model, Land Cover Change, Séguéla

1. Introduction

In Côte d'Ivoire, the use of land for agriculture is the main factor of deforestation. Indeed, the economic choice of Côte d'Ivoire, based on agriculture has favored the creation and extension of large agricultural areas to the detriment of forest formations. Thus, in 50 years of independence the country has lost nearly 90% of its natural forests to agricultural activities with an annual deforestation rate estimated at 250,000 ha/year between 1990 and 2015 [1]. The department of Séguéla is not immune to this reality. In this area, as in other localities in the country, agriculture remains the culprit of direct impacts on land use and landscape configuration.

Indeed, food crops combined with cash crops have disrupted the process of vegetation succession and caused the breakup of large farming households, leading to the multiplication of agricultural farms [2]. In addition, landscape changes made during land use affect climate, biodiversity, and soil change [3]. Indeed, these changes contribute to global climate change and, in turn, are controlled by it, whether at the global, regional or local scale [4]. Thus, analyses of land cover and land use changes have become essential components for studies of land cover change and assessment of land cover degradation [5]. Also, it should be emphasized that for several years, modeling and projection of land use change have emerged as a relevant tool for decision support. It allows the analysis of land use policies in order to evaluate and anticipate their environmental impacts [6]. The originality of this research lies in the fact that the modeling of land use dynamics will make it possible to follow the evolutionary trend of the landscape and to find acceptable rules to preserve natural resources, such as forest and water resources. We can therefore ask ourselves about the spatial translation of this landscape degradation. Land use changes therefore have a direct impact on land use and on the landscape configuration of this environment [7]. Given the worrying situation and the importance of agriculture in the Ivorian economy, studies must be undertaken to provide solutions to this problem. Such a study requires a global view of the study site. It is within this framework that this study aims to assess the dynamics of the agricultural landscape in the department of Séguéla, in order to predict their future changes. The aim is to simulate land use changes in the year 2050. Indeed, according to [8], detecting and predicting changes in land use and land cover are crucial to guide land resource management, planning and sustainable development. Thus, to simulate land cover and land use changes, several models are used. However, in this study, the Markov Cellular Automata model was applied to simulate and predict future land use maps. This model has in fact been used by other authors [8] [9] [10]. To conduct such a study, it is important to use reliable quantitative and qualitative data [7]. To this end, satellite imagery has become an excellent source of wide-area data revealing the historical and intra-seasonal dynamics of crop performance, as well as agricultural yield under the influence of local growing conditions combined with current weather patterns. As a result, remote sensing has become the mainstay of many agricultural consulting firms. Many times, these providers combine data collected at certain checkpoints with predictive models to optimize agricultural inputs [11]. Thus, remote sensing is the most suitable method to conduct this study, as its synoptic aspect, and repeatability allow the distinction of the totality of land occupations.

2. Material and Methods

2.1. Study Area

The department of Séguéla is located in the northwest of Côte d'Ivoire, between longitudes 7˚12' and 6˚17' West and latitudes 8˚30' and 7˚45' North (**Figure 1**). It is bordered to the north by the department of Kani, to the west by the departments of Koro, Touba and Biankouma, to the south by the department of Vavoua and to the east by the department of Mankono. Administratively, it belongs to the region of Woroudougou and the district of Woroba, of which Séguéla is the chief town. It covers an area of 6511 km^2 and includes 8 sub-prefectures, including Bobi, Diarabana, Dualla, Kamalo, Massala, Séguéla, Sifié, Worofla [12].

The department of Séguéla is located in the forest-savanna transition zone with increasingly sparse vegetation from south to north. The vegetation is made up of savannah dotted with forest galleries. Today, due to the progressive degradation of the vegetation and the natural wildlife habitat, the ecological balance is broken and has forced the large fauna to migrate to more receptive areas (what is called more receptive area). However, some small rodent and reptile type wildlife species are present [13].

2.2. Materials

The satellite data used are Landsat 5, 7 and 8 images from the TM, ETM+ and OLI sensors respectively. The different scenes covering the study area vary according to the sensors, so for the TM and ETM+ sensors, the study area overlaps four scenes including 197-54, 197-55, 198-54 and 198-55 and only two scenes

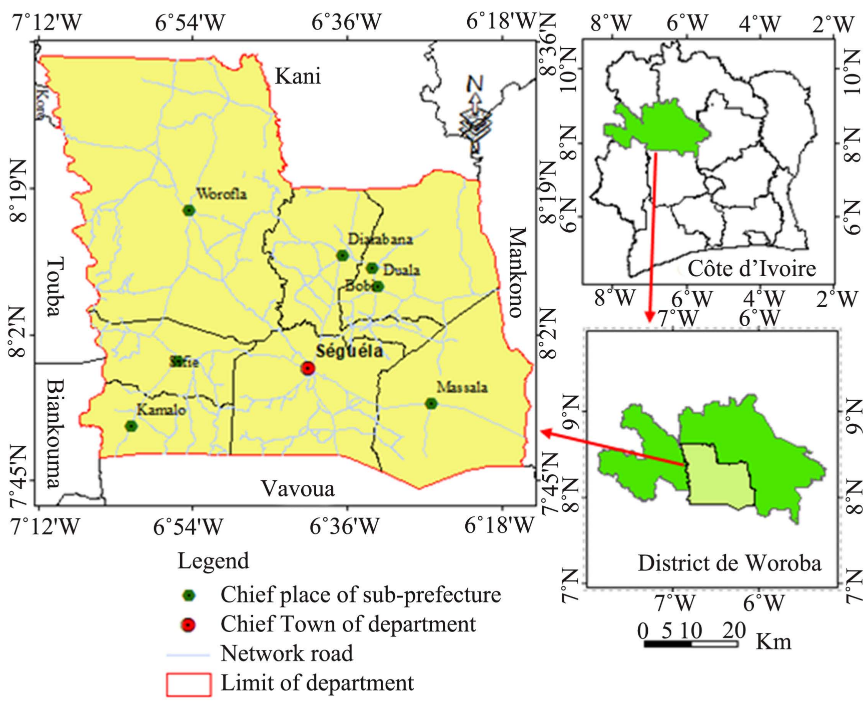

Figure 1. Location of the study area.

with the OLI sensor (197-55 and 198-54). These images were acquired at different dates including: for the TM images on 06/12/1998, 07/12/1988, 31/12/1988 and 09/12/1988; ETM+ 07/01/2004, 14/01/2004 and 23/01/2004 and for the OLI sensor on 14/01/2020 and 06/02/2020 (**Table 1**). All these images are available free of charge at http://glovis.usgs.gov/.

All the images used are recorded by the sensors during the long dry season (December to January), *i.e.* the period of the year when the cloud cover and cloud cover rates are lowest [14]. Moreover, this choice helps to reduce possible seasonal effects. The different years chosen are: 1988, 2004 and 2020.

The data were selected with an interval of 16 years in order to be able to perceive the changes in the vegetation.

The software used in this study are: 1) ENVI 4.7 for satellite image processing; 2) IDRISI 17.0 for change detection and land use modeling; 3) ArcGIS Desktop 10.5 for map production; 4) Google Earth to identify the various agricultural sites; 5) Excel for graph production.

2.3. Methods

2.3.1. Satellite Image Pre-Processing

The images were enhanced in order to homogenize the hues of the spectral bands of the different images. In addition, we performed a local contrast enhancement in two steps: first, the radiometric distribution was homogenized for each image through radiometric stretching, and second, a dynamic adjustment was performed between several images. The radiometry of the image to be corrected was adjusted to the reference image.

2.3.2. Color Composition

Each image from a channel is in grayscale. We used the color composition to produce a color image from the combination of three spectral bands. This combination is based on the principle of assigning spectral bands, chosen according to the objectives of the study, to the three primary colors red, green and blue [15].

Table 1. Radiometric characteristics of Landsat images.

Satellite	Sensor	Spectral resolution used (μm)	Channel	Spatial resolution (m)	Year
Landsat 5	TM	Band 3: 0.63 - 0.69 Band 4: 0.76 - 0.90 Band 5: 1.55 - 1.75	Rouge Proche IR Moyen IR	30 30 30	1988
Landsat 7	ETM+	Band 3: 0.63 - 0.69 Band 4: 0.76 - 0.90 Band 5: 1.55 - 1.75	Rouge Proche IR Moyen IR	30 30 30	2004
Landsat 8	OLI	Band 4: 0.64 - 0.67 Band 5: 0.85 - 0.88 Band 6: 1.57 - 1.65	Rouge Proche IR Moyen IR	30 30 30	2020

The objective of this operation is to have a synthesis of information in order to make a good discrimination of the types of objects to study. In our case, these are the different land uses (water, forest, wooded savannah, crops and fallow land, and built-up and bare soil). At the end of several combinations two types of colored compositions were retained: 4-3-5 for images from the TM and ETM+ sensors and 4-5-6 for images from the OLI sensor because it presents the best discrimination of land use types. These colored compositions allowed us to:

- Select sites to visit and orientation in the field;
- To choose training plots for the realization of the directed classifications;
- To choose control plots for the evaluation of the classifications.

2.3.3. Interpretation of the Color Composition Maps

The different colored compositions were interpreted from the knowledge of the characteristics of each of the spectral bands used, those of the behavior of the different types of land use present and the use of Google Earth software. The interpretation of the colored compositions was also verified by field observations.

2.3.4. Supervised Classification and Evaluation

The good knowledge of the study area allowed us to opt for a supervised classification. It consists in applying the same treatment to each pixel, independently of the neighboring pixels. The Maximum Likelihood algorithm was chosen for the classification of the different bands of the colored composition. This method calculates the probability of a pixel belonging to a given class. The pixel will be assigned to the class for which the probability is the highest. However, if this probability does not reach the expected threshold, the pixel is classified as "unknown". Then, the quality of the classification obtained was evaluated using the parameters calculated by the confusion matrix, which are the global precision and the Kappa coefficient [16]. Also called contingency table, the confusion matrix is a table displaying the statistics of the classification accuracy of an image, including the degree of misclassification among the various classes. It is computed with values expressed in pixels and in percentage. In addition, other synthetic measures of classification reliability can be computed: user accuracy, director accuracy, omission and commission errors.

2.3.5. Analysis of Land Use Dynamics

The analysis of changes over the entire study period was done by a post-classification comparison. It produces a change detection matrix derived from the comparison between pixels of two classifications between two dates [16]. From this, the global rate of change (T_g) and the average annual rate of spatial expansion (T_c) were calculated. The changes at the global scale were determined by extracting the areas of the different land use units for each year. The changes were determined over the period 1988-2020. This consisted of the ratio between the difference in areas and the initial areas for each period. In a second step, we moved on to an in-depth analysis, evaluating the changes that occurred within each land use unit in isolation. This analysis is done by calculating the rate of change (T_c) or average annual rate of spatial expansion, commonly used in land use change studies [17] [18]. These rates of change are estimated from the formulas in the following Equations (1) and (2):

$$T_c = \left[\left(\frac{S_2}{S_1}\right)^{\frac{1}{t}} - 1\right] \cdot 100 \tag{1}$$

$$T_g = \left[\left[S_2 - S_1\right]/S_2\right] \cdot 100 \tag{2}$$

where:

T_g = overall rate of change (%);

T_c = annual rate of change (%);

S_1 = land area at date t_1;

S_2 = land area at date t_2 ($t_2 > t_1$);

t = number of years between the two dates.

Analysis of the rate of change values shows that positive values indicate "progression" and negative values indicate "regression." Values close to zero indicate that the class is relatively "stable".

2.3.6. Simulation of Land Use Dynamics

1) Choice of the model

There are several models for land cover simulation of which the most widely used are CA-Markov, LCM, Dinamica EGO and CLUE-S. Among a wide range of land cover simulation model approaches, we chose the LCM model for its performance, multi-scale potential, spatially explicit procedure based on raster data, and the fact that it has been successfully applied multiple times in tropical regions. According to the work of [19], the LCM model performed better in simulating land cover compared to other models (CA-Markov, Dinamica and CLUE-S). Also, it is available for free with the trial version of IDRISI 17.0. This model uses artificial neural networks to model complex ecological systems. The Markov chain analysis predicts future land use patterns based on knowledge of past and present land use patterns. It is also complemented by the application of cellular automata and a multi-criteria evaluation of a number of change criteria to spatialize and better understand change.

2) Model calibration and validation

In order to simulate the dynamics of land use at a later date (2050), the model must first be calibrated on known data. The 2020 image being the most recent, it will be the subject of a first test-simulation, calibrated by two earlier dates (1988 and 2004). The 1988 and 2004 images are used as a basis for extrapolating the quantities of future land use. This is a linear extrapolation, as the simulation is based on two points in time to calibrate the model. According to [20], calibration is the estimation and adjustment of model parameters and constraints to improve the fit between model outputs and a data set. This step is fundamental, as the quality of the results obtained will depend on the correct parameterization of the model. For validation, the result of the 2020 land use simulation is compared to the 2020 land use map resulting from the classification.

In sum, all these different steps leading to the analysis of land use dynamics are summarized in Figure 2.

3. Results and Discussion

3.1. Results

3.1.1. Maps of Land Use Dynamics

Figure 3(a) presents the land use map of Seguela Department in 1988, based on supervised classification. The results of this classification reveal that forests and wooded savannahs are mostly surrounded by crops and fallows and cover almost the entire territory. The northwest and southwest peripheries are essentially dominated by forests and wooded savannahs. Crops and fallow land are less dense and concentrated in the eastern part. Built-up areas and bare soil are

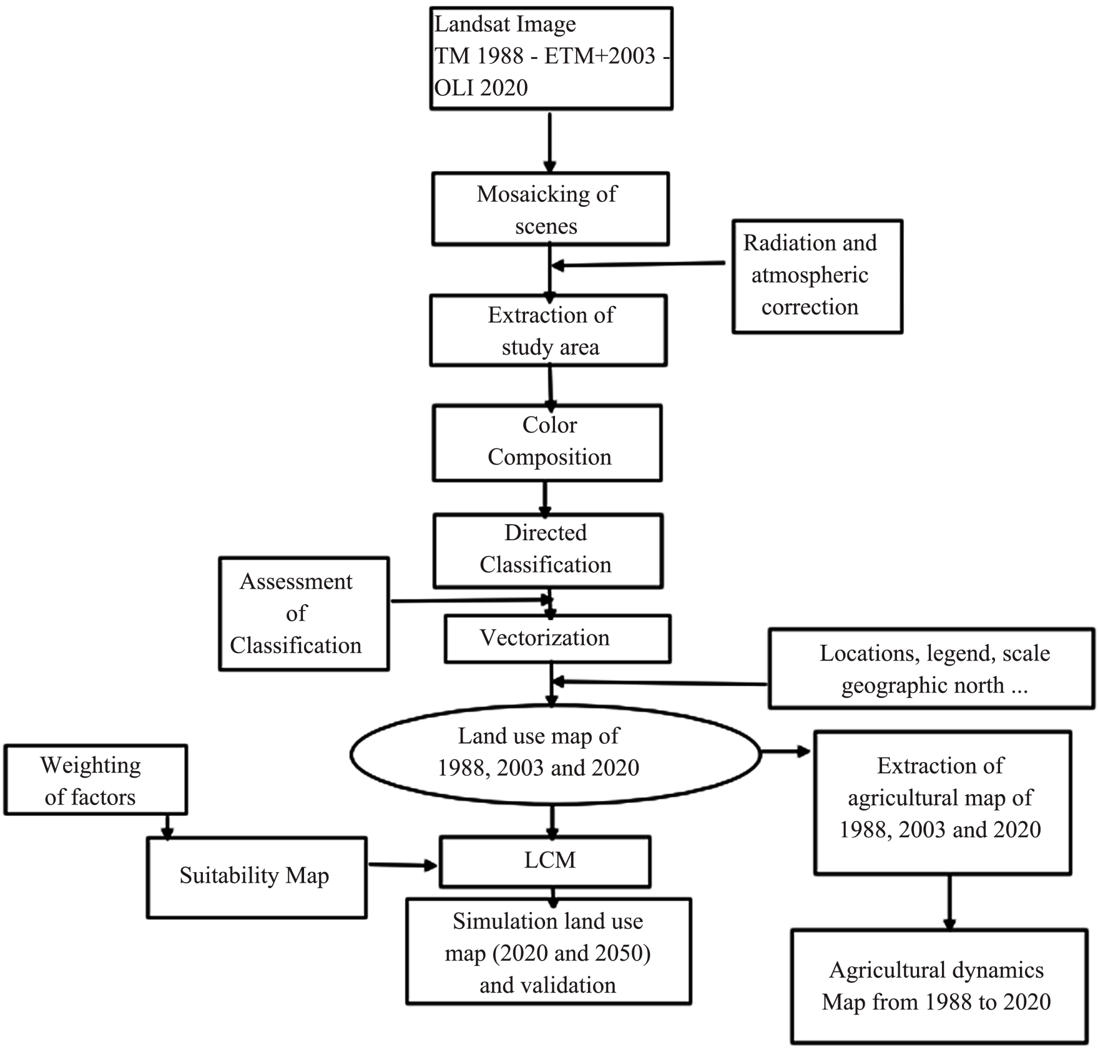

Figure 2. Synthesis of the methodology used for the monitoring of land use.

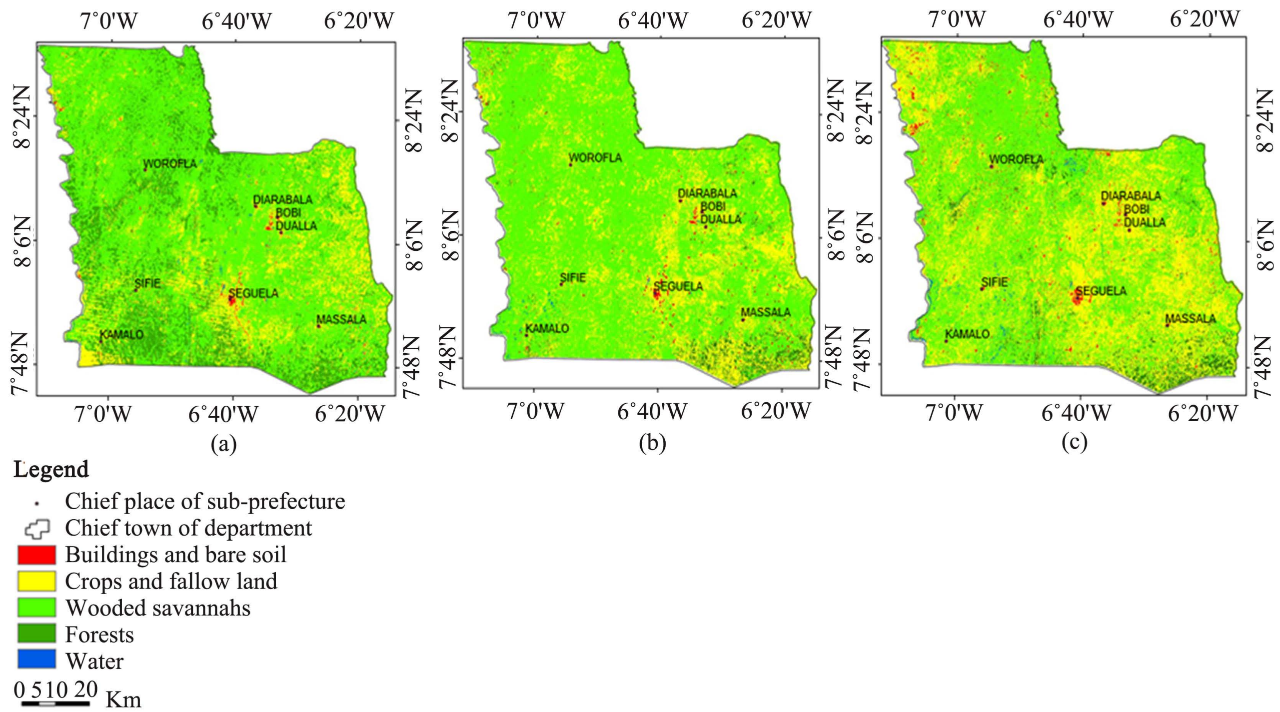

Figure 3. Land use maps in Séguéla department: (a) 1988; (b) 2004; (c) 2020.

essentially present in the eastern part of the department and consist of burned areas, dwellings, wastelands and rocky outcrops.

The land use map for 2004 (**Figure 3(b)**) shows a gradual disappearance of forest formations throughout the study area, giving way to wooded savannas. These wooded savannahs are present throughout the territory of the department of Séguéla. Crops and fallow land are distributed throughout the territory with a strong concentration in the central east and southeast. The images taken during the dry season, a period when bush fires are intense, show a remarkable presence of buildings and bare soil, although they occupy a small part of the territory with a more pronounced concentration in the east.

Observation of the land use map for the year 2020 (**Figure 3(c)**) shows a disappearance of forest formations throughout the study area. These formations are represented by a few forest patches corresponding to sacred woods or preserved forest islands. They are mostly located in the north. The wooded savannahs are distributed throughout the territory, but they are more concentrated in the southwest and the north. The central parts are dominated by crops and fallow land. Buildings and bare soil are less dense and spread over the entire territory. This is due to the fact that the image was taken during the dry season, the period of bush fires. Bare soil is a surface where the influence of the soil is important, despite the presence of some woody or herbaceous plants.

The confusion matrix (**Table 2**) and its Kappa coefficient (0.94) show a good classification of the image. However, some confusions were observed. The most important of these confusions are the following cases:

Table 2. Confusion matrix of the 1988 image classification.

Classes	Buildings and bare soil	Crops and fallow land	Forests	Wooded savannahs	Water body
Buildings and bare soil	94.86	6.15	0	0	0
Crops and fallow land	5.14	86.43	0	1.36	0
Forests	0	0	99.54	0	2.26
Wooded savannahs	0	7.43	0.19	97.17	3.55
Water body	0	0	0.28	1.47	94.19
Total	100	100	100	100	100

Overall accuracy = 95.42%; Kappa coefficient = 0.94.

- 6.17% of buildings and bare soil confused with crops and fallow land;
- 7.43% of wooded savannahs confused with crops and fallows.

The confusion matrix (**Table 3**) with a Kappa coefficient around 0.88 allows us to state that the classification obtained is very good. However, some confusions occurred. The most important of these confusions are the following cases:

- 8.54% of the Savannah trees confused with Crops/Fallow land;
- 5.74% of Buildings/Bare Soils confused with Crops/Fallow lands.

The Kappa coefficient shows a good classification of the image. However, **Table 4** shows that the crop and fallow land class has strong confusions with some classes. These are:

- 13.45% of Buildings and Bare Soil confused with Crops and Fallow Land;
- 3.96% of wooded savannahs confused with crops/fallow.

3.1.2. Analysis of Land Use Dynamics 1988 to 2020

The analysis in **Figure 4** shows that in 1988 the landscape was dominated by forest. In 2004, we see a balanced growth of forests and crops and fallow land. In 2020, forests have intensified in the department and built-up and bare soil also experience an increase in 2004 and a regression in bare soil in 2020.

The evolution of the surface areas of the different types of land use is represented by **Figure 4**.

This figure shows two trends in evolution. Between 1988 and 2020, those that stand out are wooded savannahs and crops and fallow land. We note an increase in the area of wooded savannahs, as well as an increase in the area of crops and fallow land, which rose from 10% of the total area of the department of Séguéla to 49% and from 31% to 43%, respectively.

The evolution of the land use classes observed during the period 1988-2020 is represented in **Table 5**.

- Analysis of this table shows an average annual increase of 3.79% and 2.42% in the area of built-up and bare soil and crop and fallow land in the study area, respectively. In sum, there are three major processes that have taken place in the landscape over 32 years. These are:

Table 3. Confusion matrix of the 2004 image classification.

Classes	Water	Buildings and bare soil	Crops and fallow land	Wooded savannahs	Forests
Water	92.50	0	0	1.99	3.60
Buildings and bare soil	0	94.26	5.49	0	0
Crops and fallow land	0	5.74	85.98	1.72	0
Wooded savannahs	2.5	0	8.54	97.41	5.05
Forests	5	0	0	0.86	91.35
Total	100	100	100	100	100

Overall accuracy: 92.09%, Kappa Coefficient: 0.87.

Table 4. Confusion matrix of the 2020 image classification.

Classes	Buildings and bare soil	Crops and fallow land	Forests	Wooded savannahs	Water
Buildings and bare soil	86.55	0	0	0	0
Crops and fallow land	13.45	95.14	2.64	3.73	3.52
Forests	0	4.86	97.37	0	0
Wooded savannahs	0	0	0.53	93.38	3.96
Water	0	0	0	2.89	92.51
Total	100	100	100	100	100

Overall accuracy: 86.11 %; Kappa Coefficient: 0.83.

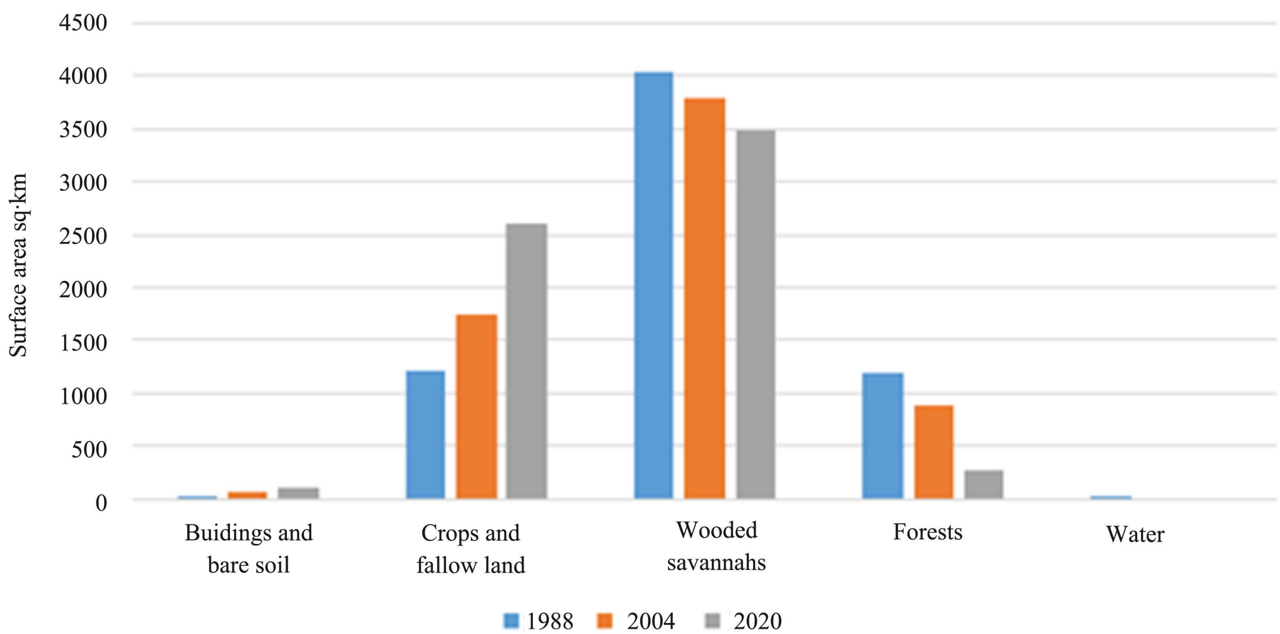

Figure 4. Evolution of land use class areas from 1988 to 2020.

Table 5. Evolution of land use classes between 1988-2020.

Land use	T_g	T_c
Buildings and bare soil	+229.06	**+3.79**
Crops and fallow land	+115	**+2.42**
Forests	−13.42	**−0.45**
Wooded savannahs	−76.93	**−4.48**
Water	**−35.61**	**−1.37**

T_g: Overall rate of change; T_c: Average annual rate of change.

- A dramatic increase in built-up and bare ground and crops and fallow land at the expense of the other classes;
- The natural or anthropogenic regeneration of the forest cover that has led to the restoration and formation of wooded savannahs;
- The silting up and eutrophication of water bodies.

3.1.3. Simulation of the State of Land Use

1) Model calibration and validation

Thus, for the calibration, a transition probability matrix (Table 6) was generated from the land cover classes between 1988 and 2004, in order to use it as base data for the land cover projection in 2020. From the analysis of this table, we notice an overall stability with a maximum for the built-up areas/bare ground and the wooded savannahs. For model calibration, the simulated 2020 land cover map was validated by comparing it to the 2020 land cover map from the classification as shown in Figure 5.

The comparative analysis of the simulated and observed 2020 land use resulted in the confusion matrix shown in Table 7.

This analysis shows that the simulation predicted 0.12% of water areas, 10.83% of forest areas, 37.83% of wooded savannah areas, 3% of built-up areas and 47.9% of crop and fallow areas.

2) Simulation of land use in 2050

After calibrating the model and assessing its validity, it was of interest to examine the structure and trend of change at a later date (2050). The prediction of the land cover in 2050 was made on the basis of the transition between the land covers of 2004 and 2020. The result of the land cover prediction for the year 2050 is shown in Figure 6.

The visual analysis of the result of this simulation indicates that the crops and fallows and the bare soil buildings will have a very high growth rate. The wooded savannahs will experience a strong decrease towards their disappearance. Forests and water will disappear as shown in Figure 7.

To better understand this large increase in the area of crops and fallow land, we assessed the dynamics of these crops in one of the areas heavily dominated by cultivated land.

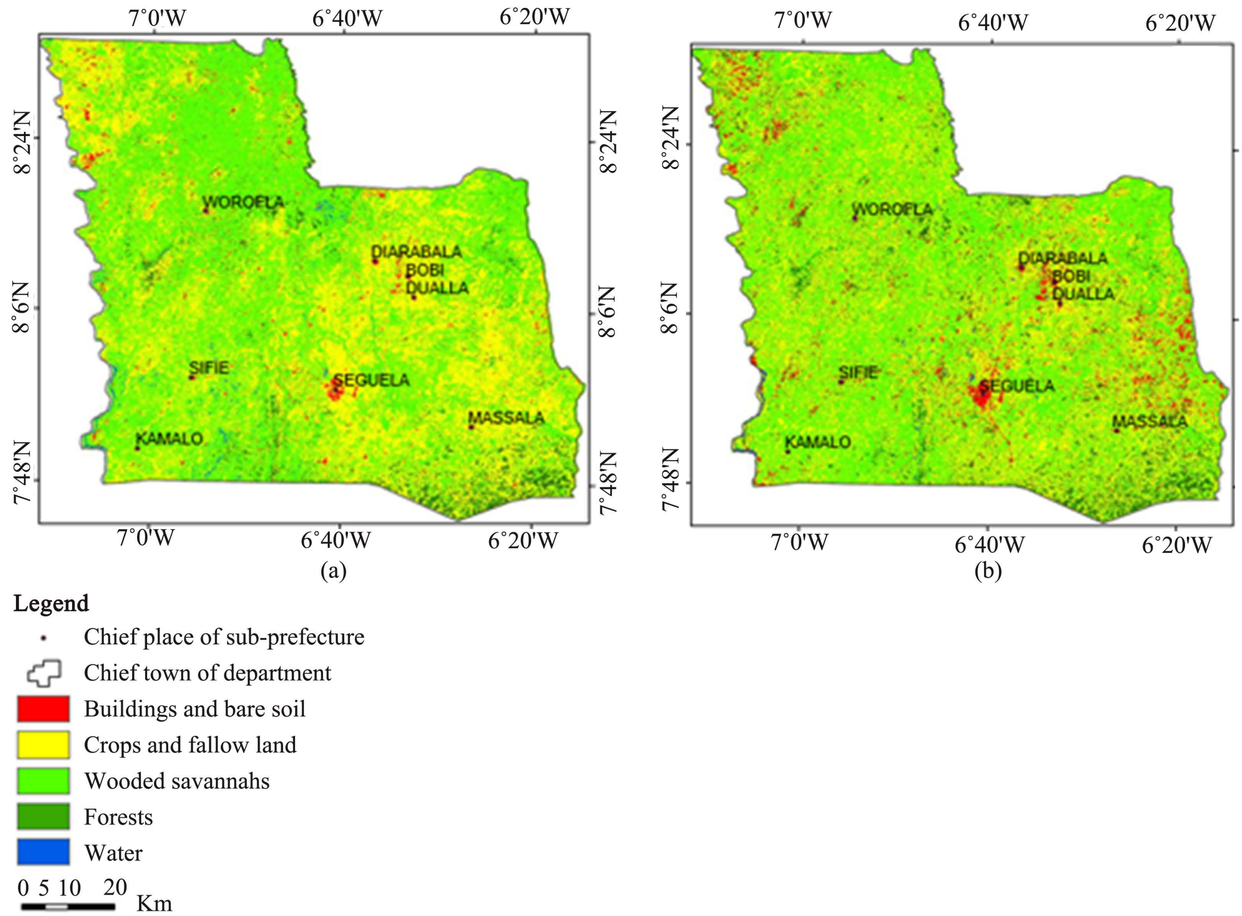

Figure 5. Comparison of land use maps (observed and simulated) 2020: (a) Observed land use map in 2020; (b) Simulated land use map in 2020.

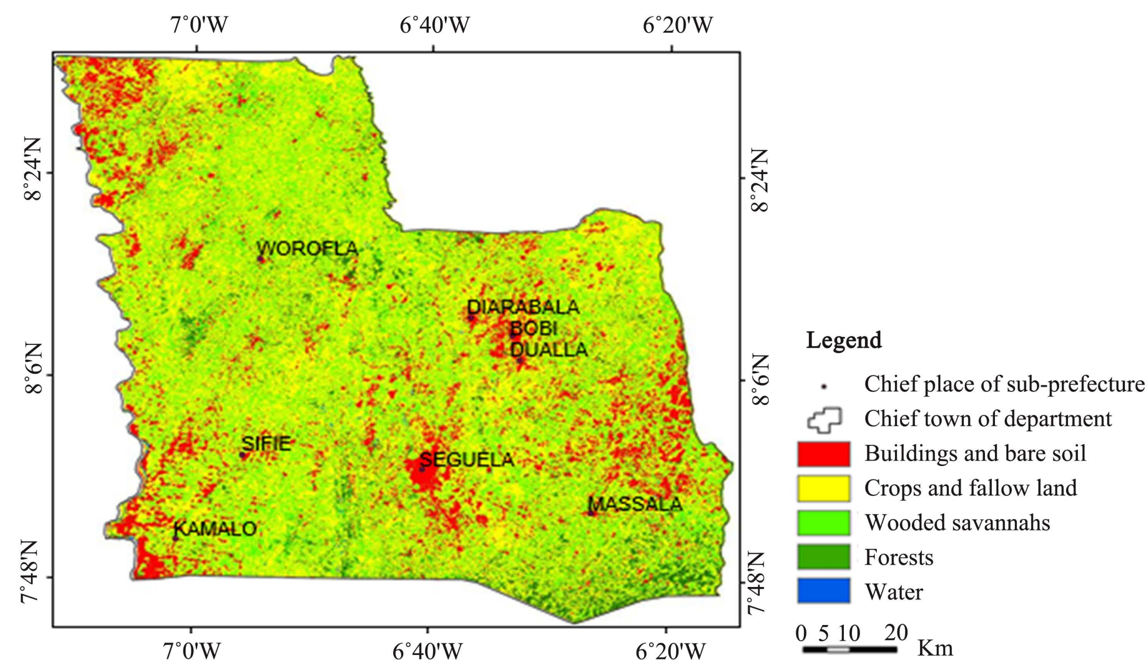

Figure 6. Simulated land use map of the year 2050.

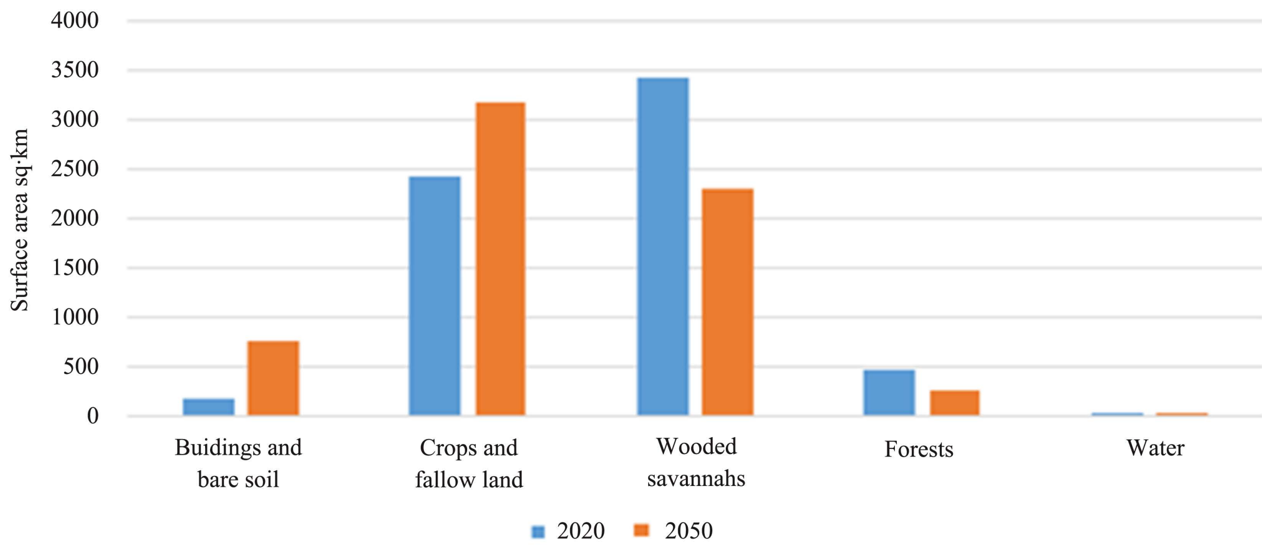

Figure 7. Change in the area of land use classes between 2020 and 2050.

Table 6. Transition probability matrix for the 2020 simulation.

2004 1988	Water	Buildings/ bare soil	Wooded savannahs	Forest	Crops/ fallow land
Water	0.5678	0.0386	0.0523	0.2476	0.0937
Buildings/bare soil	0.060	0.705	0.0225	0.0403	0.1738
Wooded savannahs	0.001	0.0267	0.7381	0.0528	0.1814
Forest	0.0056	0.1872	0.2320	0.4249	0.1403
Crops/fallow land	0.0002	0.0343	0.0992	0.2694	0.5969

Table 7. Confusion matrix between observed and simulated land use in 2020.

Simulated Observed	Water	Buildings/ bare soil	Wooded savannahs	Forest	Crops/ Fallow land
Water	4.6332	0.32	0.427	2.0228	0.7655
Buildings/bare soil	29.54	148.78	25.853	8.505	15.575
Wooded savannahs	0.68	60.57	1220.648	165.1425	865.18
Forest	0.450	8.2879	338.72	426.918	126.39
Crops/Fallow land	0.6247	107.1527	0.0992	216.80	2489.506
Prediction (%)	0.12	3	37.83	10.83	47.9

Overall accuracy: 80.35%; Kappa Coefficient: 0.69.

3.2. Discussion

The present study made it possible to map land use from satellite images (TM 1988, ETM+ 2004 and OLI 2020). These different maps have highlighted five types of land use in the department of Seguela: forests, wooded savannahs, water bodies, built-up areas and bare soil as well as crops and fallow land. However, the results obtained show that each of the land use maps had an overall accuracy rate of over 90% and a Kappa coefficient of over 87%. However, some confusion was observed during the different classifications. These confusions could be explained by the heterogeneity of the study area. Variation in woody cover and the passage of bushfires provide a diversity of spectral signatures relatively close to certain formations during the dry season ([7] [21] [22] [23]), these authors have conducted similar studies to ours in different areas and have also reported these difficulties. They argue that, the confusions are due to a similarity of spectral responses of some woody formations. Despite these confusions, we can state that the values (the Kappa coefficients) obtained are satisfactory and indicate that the different classifications are correct because, according to [20], a classification is considered acceptable when the Kappa coefficient is greater than 50%.

The study of the dynamics of land use between 1988 and 2020 reveals that the areas of water and forests as well as wooded savannahs have undergone regressions with estimated annual loss rates of 1.37%, 4.48% and 0.45% respectively. These regressions were made to the benefit of crops and fallows, wooded savannahs and built-up areas and bare soil. This situation could be explained by several factors, including population growth. This population which was 88,379 in 1988 has increased to 239,171 in 2020 [12]. In addition to population growth, the various policies put in place by the Ivorian government have also favored the development of agriculture. Indeed, the policy of returning to the land and the 2012-2015 national development plan adopted by the Ivorian government, aiming to make Côte d'Ivoire an emerging country by 2020. It has set the following objectives: improving competitiveness, particularly by increasing productivity, seeking self-sufficiency and food security. As well as, the increase in agricultural products such as cashew nuts which rose from 0.15 US dollars/kg to 0.75 US dollars/kg between 1991 and 2017 [24]. All of these reasons have pushed farmers to take an interest in agriculture. Unfortunately, given the low rate of yield in the farming environment and the cultivation techniques that have not yet been improved, the increase in their income forces them to increase the cultivated areas. This has led to a progressive increase in cultivated land between 1988 and 2020. These cultivated areas are estimated at 5556.09 km^2, although some of the cultivated areas have been abandoned (916.41 km^2) over time in favor of other types of land use. Agriculture remains the main occupant of this part of northern Côte d'Ivoire.

As for the results of the 2020 and 2050 simulations, they indicate the same trends in land cover and land use. Built-up and bare land as well as crops and fallow land are expected to grow considerably at the expense of natural forests and wooded savannahs. This leads to an increase in agricultural land and a loss of natural vegetation. These same observations were made by [7] in their respective studies of the Lobo River watershed in Nibehibe and the RAMSAR of Grand-Bassam. Indeed, projections made according to the [12] predict a population of 597,680 inhabitants in 2050, which is more than double the current population of the department of Seguela. In a few years, in regions with high population density all available space will be converted to agriculture. This will lead to a very high rate of deforestation in the department of Seguela.

4. Conclusions

The use of remote sensing using the classification method, more precisely the maximum likelihood method, has made it possible to highlight the general dynamics of land use, particularly the transformations of the agricultural landscape of the department of Seguela between 1988, 2004 and 2020. The results obtained show that the department of Seguela is highly anthropized and has undergone significant changes. It also appears that, despite this high land use since the 1980s, food crops and fallow land have slowed down in favor of perennial crops. This is particularly true of cashew nuts, which have grown incredibly in this part of Côte d'Ivoire. This growth in perennial crops was at the expense of forest areas, with an overall decrease of 115%. The LCM simulation of land use has made it possible to predict land use for the 2050 horizon with an accuracy of 80.35%. It shows that the current trends of decreasing forest areas and expanding crops will continue in the future.

In the perspective, it will be judicious to conduct studies to estimate the yield of perennial and food crops per unit of land in the department of Séguéla with the aim of proposing perennial and food crops per unit of land in the department of Séguéla in order to propose new cultivation techniques to maximize the yield to avoid the destruction of natural forests.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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