Dynamics of Land Use in the City of Abidjan from 1986 to 2017: Contribution of Remote Sensing and GIS

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Abstract

The city of Abidjan is located in the south-east of Côte d'Ivoire knows a spatio-temporal dynamics of the occupation of its soil. Anthropogenic activities and the increase of the population contribute strongly to this situation. The objective of this study is to follow the evolution of land use in the Abidjan zone from 1986 to 2017. The study was conducted using satellite data and field observations. It is based on the diachronic analysis of Landsat satellite images from 1986, 2000, 2015 and 2017. The different Landsat images were processed by the classification methods supervised using the maximum likelihood algorithm. The thematic maps produced made it possible to highlight the spatio-temporal dynamics of the land use from 1986 to 2017 in the Abidjan area. The results obtained showed a negative overall evolution of the types of occupation of the territory of our study area. Thus, over this period, there is an annual increase of 1.16% of the habitat/bare soil class against a regression of the other units of land occupation.

Keywords: Abidjan; GIS; Ivory Coast; Land cover dynamics; Remote sensing

Introduction

Man manages, exploits most of the land and puts pressure on natural resources. The city of Abidjan is not immune to this change in its space given the strong anthropic pressures that it has been facing for decades. Economic capital of Ivory Coast, it is confronted like all major African cities with an accelerated spatial and demographic growth. Some authors have previously highlighted the impact of population growth on the degradation of natural resources [1-4]. This is why monitoring and quantifying the dynamics of land use in this densely populated area is necessary.

Land use is a fundamental variable for urban planning as well as for the study and understanding of the environment. This theme has become unavoidable in most cartographic and monitoring inventories of environmental phenomena. Land cover mapping is a major concern for space actors and managers as well as for urban planning. Today, the contribution of earth observation tools is important for detecting and analyzing the different changes in land use [5-10]. The applications of satellite imagery, coupled with GIS are very diverse. Indeed, several studies have shown the importance of space tools for measuring forest cover changes, to characterize and quantify urban sprawl, to simulate and predict changes in land use [1]. Satellite images are the only available tools that allow, at relatively low cost, and in a short time, to obtain images of a large territory and to follow its evolution over time [8]. In fact, satellite imagery, thanks to its synoptic view, makes it possible to understand and map dynamic phenomena such as land use, in particular that of the city of Abidjan.

Study area

The city of Abidjan is located in southeastern Côte d'Ivoire between 4° 10 and 5° 30 north latitude and 3° 50 and 4° 10 west longitude. It enjoys a wide opening on the Atlantic Ocean in its southern part. This opening allowed him to start an economy turned towards the outside. Its surface area is about 58 000, of which 9 000 ha are lagoons or 16% and 49 000 ha of land is 84% [11].

Material and Methods

Data

The main data used consists essentially of a satellite image database containing four Landsat images covering the period 1986 to 2017 from the TM (Thematic Mapper), ETM+(Enhanced Thematic Mapper Plus) and Landsat 8 Oli (Operational Land) sensors. Imager). A georeferenced digital vector layer of the Abidjan district and its communes and another vector layer relating to the boundaries of the Ebrié lagoon were used. The latter allowed the extraction of the study area. In addition, population volume data for the Abidjan district from the last census of 2014. They will be used to show the evolution of the Abidjan population.

Methods

Pretreatments: Image preprocessing is a set of operations that aim to increase the readability of images and to facilitate their interpretation for better extraction of spatial information [3]. The radiometric corrections were carried out using the "Radiometric calibration" algorithm of the ENVI 5.1 software for the correction of irregularities of the sensor and then the atmospheric corrections of the effects of the atmosphere thanks to the "FLAASH Correction" algorithm integrated under the ENVI 5.1 software.

Process of classification of satellite images

Definition of thematic classes: Training areas must be identified as a reference for classification. The choice of training plots was made on the basis of the visual interpretation of the images in colored

composition as well as the knowledge of our study area. Thus, from the training plots, we identified five themes that represent the types of land use. These are: dense forest, degraded forest, crop/fallow, water and habitat/bare soil (Figures 1 and 2).

Supervised classification of images

There are two main categories of classification, the so-called supervised classification is used in the work. This is justified by the more or less easy access to a study area. Beforehand, a calculation of the class separability index is done in order to evaluate the reliability of the training sites that will be used for classifications. The method of class separability chosen is the Jefferies-Matusita distance. It highlights the probability of a pixel to belong to a class. The Jefferies-Matusita distance is between 0 and 2. The closer the value is to 2, the more spectral separability ensures good classification accuracy. A value greater than 1.8 or 1.7 is generally used to agree that two classes are distinct [5]. The maximum likelihood method based on the Bayes classifier is used. The research is done on a space of models based on probabilistic hypotheses. The principle of this Bayesian classification is to partition an image by a calculation of the probability of belonging to a given region of each pixel of the image. Indeed, it calculates the probability of a pixel to belong to a given class. The algorithm classifies the image based on the spectral information from the training areas [6]. Finally, a validation mission is carried out in the field.

Evaluation of the classification

The evaluation of the quality of the classifications obtained was possible thanks to the calculation of a matrix of confusion or matrix of error. It is a double entry table. The results of the classification are online and those observed in the field, in columns [6]. Thus, the accuracy of the classifications was evaluated by the confusion matrix. The calculation of the confusion matrix made it possible to generate two indices:

- The global precision: it is a measure that takes into account the accuracy of the entire classification by calculating the number of correctly classified pixels according to the reference pixels (the diagonal in the error matrix). It varies between 0 and 100%.

- The kappa coefficient: it is an index that makes it possible to evaluate overall the results of the classification compared to the reference data. It incorporates the diagonal elements of the confusion matrix, including unclassified pixels [6]. It varies between 0 and 1. A value of 0 indicates that the classification result is random and a value of 1 indicates that the classification is perfect.

Diachronic mapping of land use from 1986 to 2017

It is to realize the map of occupation of the ground of the four years (1986, 2000, 2015 and 2017) covering the time of study (1986 to 2017) is a period of 31 years. The results of the land use classifications for the years 1986, 2000, 2015 and 2017 are compared to see the proportion of each class per year. Such a visual representation makes it possible to interpret the changes that have occurred between the classified images.

Results and Discussion

Results

Mapping of the land use of the city of Abidjan from 1986 to 2017: From 1986 to 2017, five classes of land use were identified. This is the dense forest class, degraded forest, crop and/or grassy area, built/bare soil and water class. Figures 3a-3d below and the circular diagrams that accompany them make it possible to see the distribution of the surface
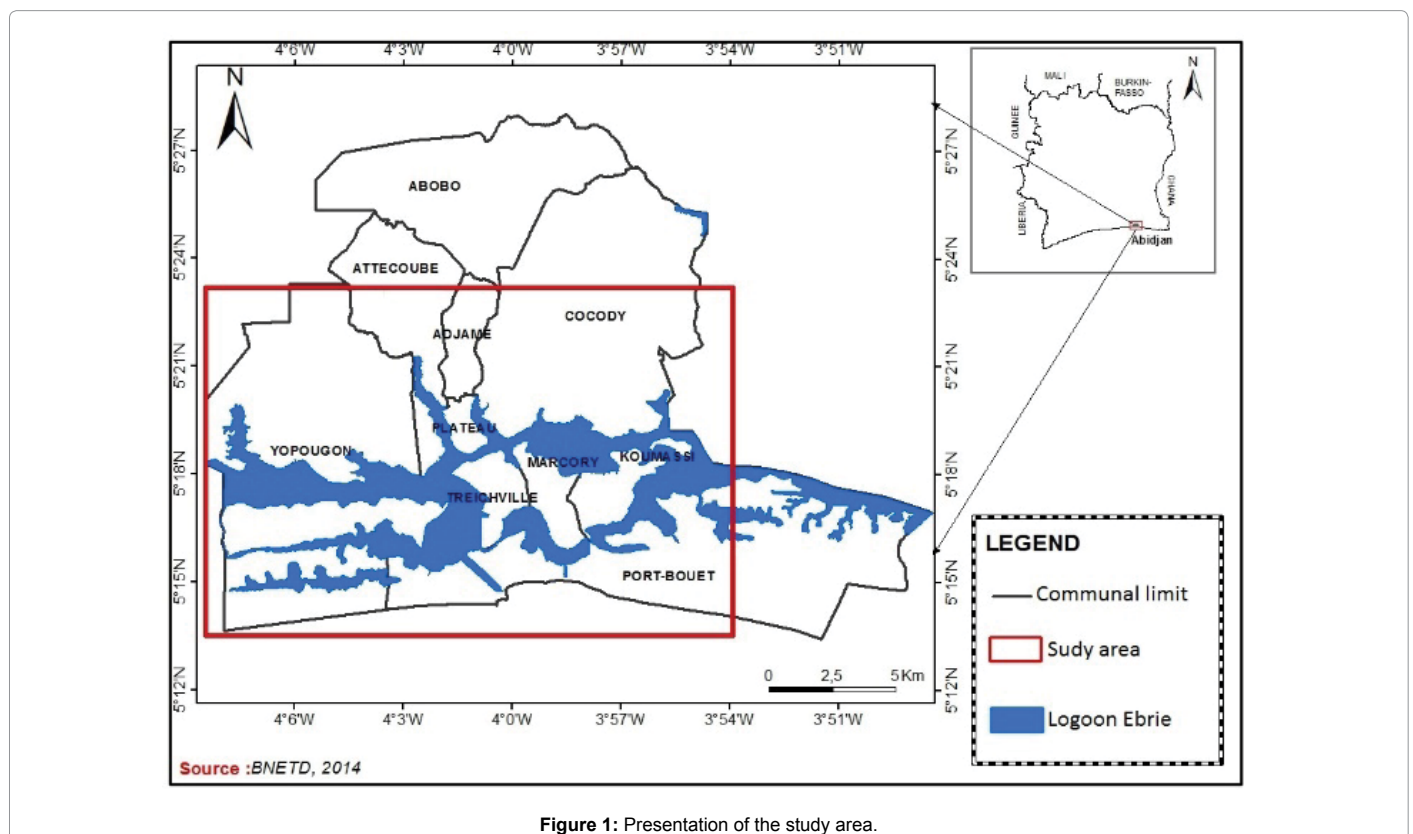

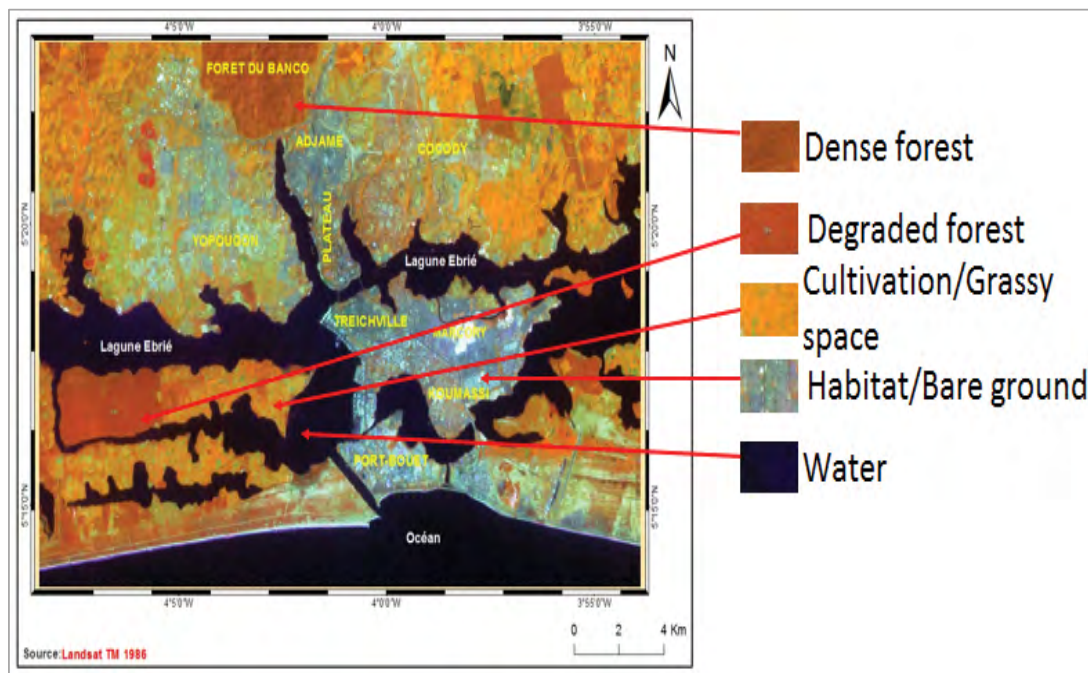**Figure 1:** Presentation of the study area.

Figure 2: Identification of land use classes.

area of the types of occupation of the soil of the city of Abidjan in order to appreciate its evolution.

Indeed, in 1986, the dense forest had an area of 3.73%, 12.90% for the degraded forest, 9.45% for crops/grassland, 46.10% for the habitat class/bare soil and 27.78% for water (Figure 3a). In 2000, the class size of dense forest, degraded forest, crop/grassland, habitat/bare soil and water increased to 3.14%, 8.95%, 5, 35%, 53.45% and 27.51% (Figure 3b). At this level, there is a decrease in the proportion of the area of thematic classes except that of the habitat/bare soil. In 2015, this same observation is made. The proportion of the area of the other types of occupation is decreasing while that of the habitat/bare soil category has increased and is estimated at 61.71% (Figure 3c). This same trend continued in 2017 when only the proportion of the habitat/bare soil area increased by 65.81%. This can be seen on the 2017 map where the habitat/bare soil category occupies most of the surface of our study area (Figure 3d). The graphs in Figure 4a-4c show the evolution of the land use classes between 1986 and 2017. They show the different changes that took place during these years in the environment.

Dynamics of land use between 1986 and 2000: Figure 4a shows two evolutionary trends. Firstly, a decrease in the areas of dense forest, degraded forest, crop/grassland classes and water. They increased from 1,788 ha, 6,192 ha, 4,556 ha and 13,330 ha in 1986 to 1,505 ha, 4,294, 3,339 ha and 13,200 ha in 2000. Second, there is an increase in the area of habitat/bare soil which increased from 22 119 to 25 647 during the same period.

Dynamics of land use between 2000 and 2015: The observation of the graph in Figure 4b indicates a general decline in the area occupation classes except the dense forest class. Indeed, the class size of dense forest, degraded crop/soil and water has increased from 1505 ha, 4294 ha, 3339 ha and 13200 ha in 2000 to 1420 ha, 4113 ha, 2566 ha and 10273 ha in 2015. At this level, the types of land use that have

undergone more regression are the crop/grassland class and the water class. The increase in the habitat/bare soil class, which is estimated at 25647 ha in 2015 against 22119 ha in 2000, was followed by a decrease in the area of the other classes.

Dynamics of land use between 2015 and 2017: Figure 4c shows that the evolutionary trend is always the same as previous periods. There is a slight decrease in the area of dense forest, which goes from 1420 ha in 2015 to 1345 ha in 2017. It tends to remain constant in our study area and this is the fact, perhaps, of the forest Banco, which because of its protection has not been significantly affected. The area of other types of land use that has declined is 4113 ha, 2566 ha, and 10273 ha in 2015 against 2894 ha, 2110 ha, and 10057 ha in 2017 respectively for the classes degraded forest, crop/grassland and water. This decrease is still due to the increase in the habitat/bare soil category, which increased from 29,613 ha in 2015 to 31,579 ha in 2017.

Overall change in land cover types between 1986 and 2017: Figure 5 shows the changes made between the different land cover classes between 1986 and 2017 in Abidjan. From 1986 to 2017 the area of dense forest has increased from 1788 ha to 1345 ha, the degraded forest has gone from 6192 ha to 2894 ha, the area of cultivation/grassland has increased from 4556 ha to 2110 ha ha and the water has gone from 13330 ha to 10057 ha. However, there is a significant increase in habitat from 22,119 ha in 1986 to 31,579 ha in 2017. Table 1 summarizes the different transformations of the units of land use calculated in each of the five classes between 1986 and 2017.

The analysis in Table 1 shows that the degraded forest and the cropping space/grassland have a similar regression rate respectively of -2.42% and -2.45%. The dense forest rate is estimated at -0.91% similar to that of water which is -0.90%. The occupancy rate of the bare-land/bare-land category, on the other hand, increased (+ 1.16%) between 1986 and 2017. This increase mainly occurred to the detriment of the
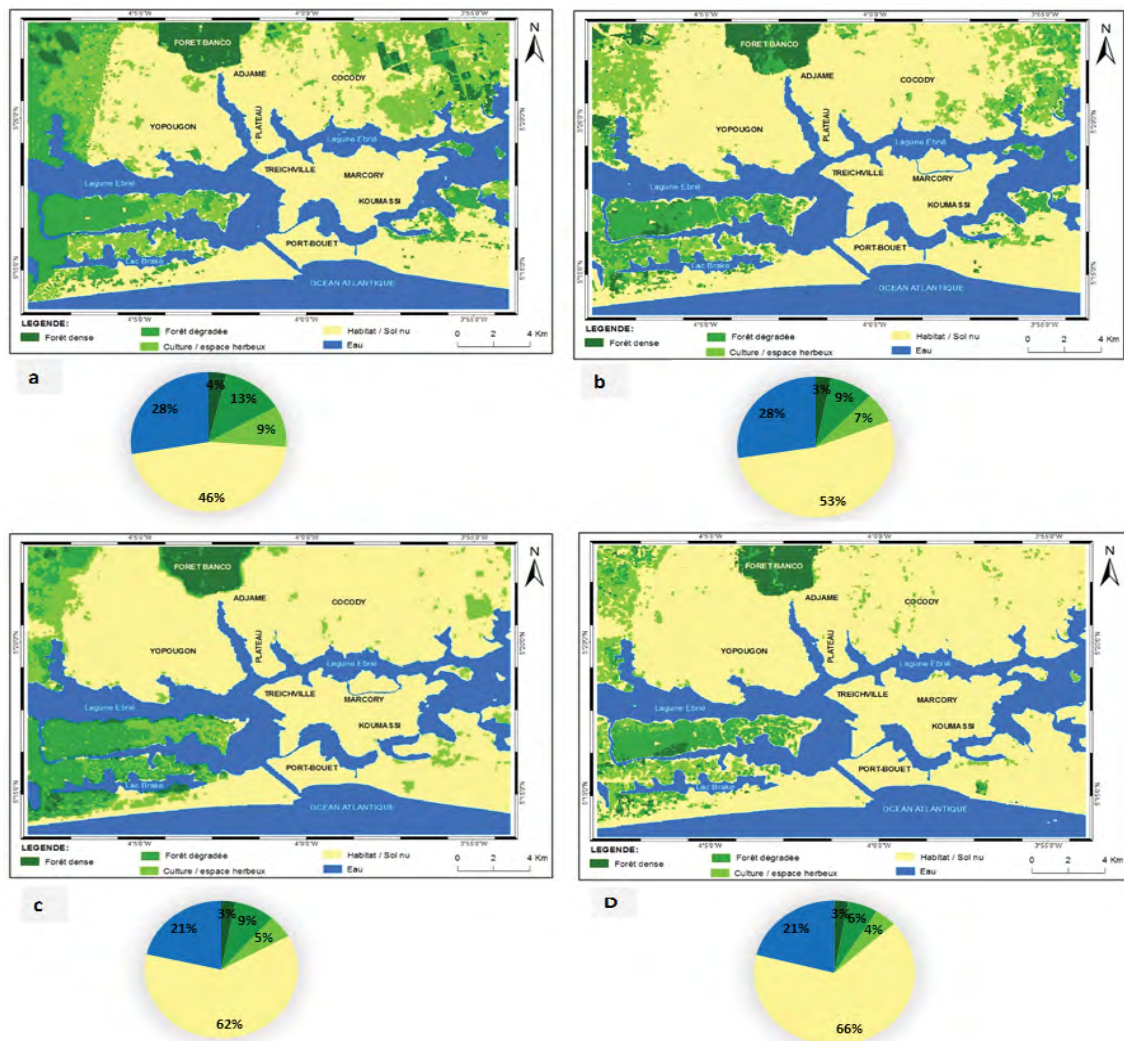
Figure 3: (a) Land cover in 1986; **(b)** Land cover in 2000; **(c)** Land cover in 2015; **(d)** Land cover in 2017.
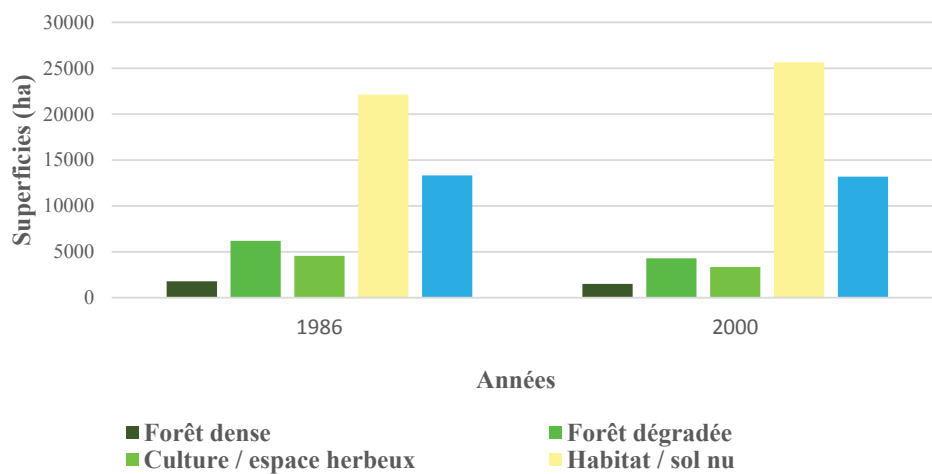

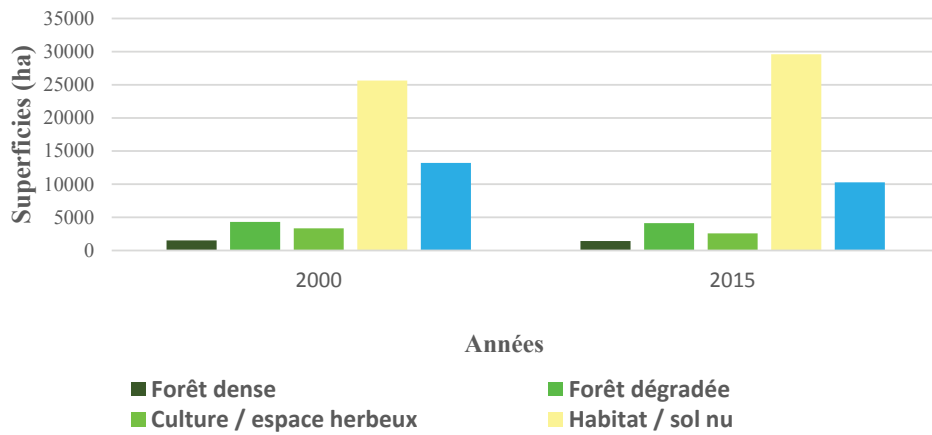**Figure 4a:** Land cover from 1986 to 2000.
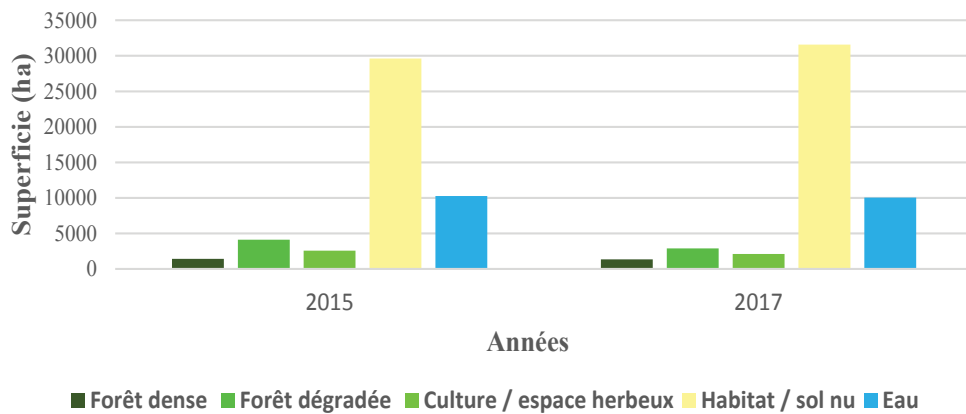
Figure 4b: Land cover from 2000 to 2015.

Figure 4c: Land cover 2015-2017.

Figure 5: Overall land use between 1986 and 2017.

Classes	Tg (%)	Tc (%)
Dense forest	-24.78	-0.91
Degraded forest	-53.26	-2.42
Cultivation/Grassy space	-53.69	-2.45
Habitat/bare ground	+42.77	+1.16
Water	-24.55	-0.90

Tg: Global rate of change; Tc: Annual average change rate

Table 1: Rate of change of land cover classes between 1986 and 2017.

other classes. It could therefore be said that habitat is the main space-hunter in the study area.

Discussion

The method used for the production of land cover maps was based on supervised classification using the maximum likelihood algorithm. Landsat imagery has been used to map land cover. The use of 5 land cover classes was sufficient to implement a landscape mapping analysis [7]. These different maps were used to follow the spatio-temporal evolution of our study area. The maximum likelihood algorithm uses spectral information to extract types of land cover. This could explain the confusion between certain classes such as the dense forest and the degraded forest on the one hand and the degraded forest on the other hand with the grassy culture/space class.

These confusions could be explained by the fact that these types of occupancy have a similar reflectance at times in certain places in the image. However, the shortcomings of this method are offset by the field mission and accuracy in the selection of training plots. In addition, the calculation of the confusion matrix allowed a kappa coefficient of 0.87 for the TM image, 0.74 for the ETM+, 0.72 for the Oli 2015 and 0.81 for the 2017 Oli. Since a land cover study can be validated if the kappa index is between 50% and 75% [9], we can say that the results of our classifications are good. The results showed that habitat is the only type of land use that has undergone a surface evolution to the detriment of other types of land use. These results are consistent with those found [12-14] in a study of land-use dynamics in lagoon systems of south-eastern Togo that show that the steady increase is largely responsible for changing the occupation of space.

Conclusion

Landsat data from satellite imagery have yielded results and achieved the objectives of the study. Thus, the analysis of Landsat images from 1986 to 2017 made it possible to follow the spatio-temporal evolution of the land use of our study area. The different land cover maps made on the basis of Landsat images (TM, ETM+and OLI) between 1986 and 217, showed a decrease in the areas of the dense forest, degraded forest, crop/grassland and water classes, respectively, 73% to 2.80%, 12.90% to 6.03%, 9.45% to 4.40%, 27.78% to 20.96%. In addition, there is an increase in the area of habitat/bare soil from 46.10% to 65.81%. It emerges from this study that anthropogenic pressures, namely population growth and rapid urbanization, mainly explain the regression and the degradation of the vegetation cover.

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