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Modeling of landscape dynamics in the Djibi watershed by 2050

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Summary: Many practices observed in land occupation and use, such as urbanization and population growth, lead to the degradation of natural resources (water, forest) in the autonomous district of Abidjan. The Djibi watershed, tributary to the Aghien lagoon watershed, located on the outskirts of the city of Abidjan, is no exception to this phenomenon. Thus, the objective of this study is to simulate, using a remote sensing and GIS model, the future dynamics of land use in the Djibi watershed. The study method was based, on the one hand, on the processing of satellite images and GIS, for the analysis of land use dynamics and, on the other hand, on the LCM (land change modeler) model, for the prediction of land use. Thematic maps produced from satellite image processing highlighted the landscape dynamics of land use in the Djibi watershed. Between 2000 and 2020, all land use categories decreased in favor of concentrated habitats. However, there was an annual reduction of 0.43% in the areas devoted to food crops / fallow land, in favor of concentrated habitats. The Land Change Modeler model generated the scenarios (urbanization and non-urbanization) of land use changes by 2050 based on explanatory variables (altitude, slope, distance to roads, distance to localities, distance to watercourses). In addition, the study revealed that socio-economic factors (population density, distance from localities and roads) are the main underlying causes of the decline in food crops and fallow land. The regressive trend of natural resources (water and forest) seems to continue into the future with current land use practices.

1. Introduction

Changes in land use and occupation are an important factor in sustainable development (Judge, 2019). They strongly impact the balance between human needs and environmental preservation. These changes, particularly linked to human influences, constitute the major environmental issue that dominates our time. Environmental degradation is a major problem facing several regions (Debbarh & Badraoui, 2001). Over the years, like all major cities, Abidjan, the economic capital of Côte d'Ivoire, has experienced rapid urbanization and agricultural intensification due to population growth, the construction of infrastructure (roads, buildings, schools, etc.) and the search for food security (Etienne *et al* ., 2010). The Djibi watershed, a tributary of the Aghien lagoon watershed, located on the northern outskirts of the city of Abidjan, has urban and agricultural areas (Diallo et al., 2019). Furthermore, Scheren *et al*., (2004), Macary *et al*. (2006), Belghiti *et al*., (2014), N'Guessan *et al*., (2011) and EL

Ouali *et al.*, (2011) showed that any activity carried out or exercised on the watershed influences in one way or another the surface water resources. Faced with this situation, knowledge of a territory and its development is necessary. It is therefore important to monitor changes in land use over time and predict the future scenario. Thus, the processing of satellite data through a diachronic analysis is essential for the evolution of the surface states of the Djibi watershed. The general objective of this study is to simulate, using the LCM model, the future dynamics of land use in the Djibi watershed.

2. Materials and Methods

2.1. Study area

The study area is the Djibi River watershed, one of the main tributaries of the Aghien Lagoon. Located in the south of Côte d'Ivoire, in the Abidjan district between latitudes 5°26' and 5°38' N and longitudes 3°59' and 4°21' W; this watershed covers an area of 78 km², with a perimeter of 77 km and a compactness index KC =2.46 indicating an elongated shape. It includes part of the Abobo commune and is part of the Abidjan lagoon network associated with the Aghien Lagoon watershed (**Figure 1**). The altitudes vary between 12 and 135 m (Diallo *et al.* , 2018).

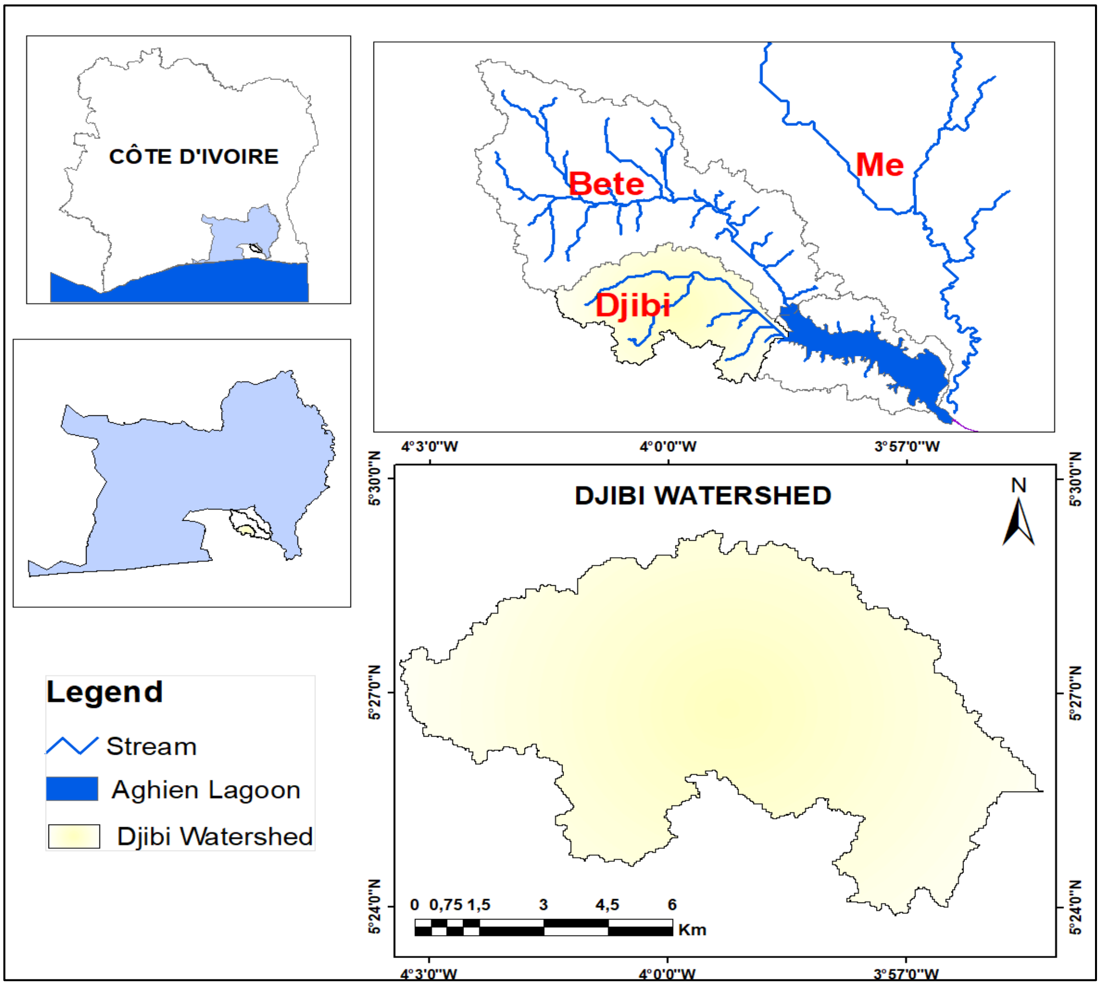


Figure 1. Location of the study area

The Djibi River watershed is under the influence of a transitional equatorial climate, characterized by four seasons (Noufé, 2019). This climate is fairly representative of the rainforests (now heavily degraded) that extend to the south, below the 1600 mm isohyet. From a geological point of view, the Djibi watershed is housed in the continuous aquifer of the sedimentary basin made up of the Quaternary and MioPliocene aquifers (Continental Terminal). The Quaternary sedimentary formations consist of sands, gravelly sands, muds or clays, muddy sands and sandy or silty muds (Soro N. *et al.* , 2004, Koffi *et al.* , 2023). Given its agricultural vocation, this basin is planted with rubber trees, oil palms, corn and banana trees associated with market gardeners (eggplants, okra, tomatoes, cabbages, etc.). Pig, sheep and poultry farming are also noted, as well as the presence of a few fish ponds. The area is under pressure both in terms of urbanization and cultivable areas, due to the increase in population at a rate of 2.61% per year.

2.2. Study data

For landscape dynamics modeling, the data used are essentially satellite images. They are of two types

-Two Landsat images: Enhance Thematic Mapper Plus (ETM+) from 2000 and Operational Landsat Imager (OLI) from 2020. Each image with a spatial resolution of 30 m × 30 m pixels was geometrically corrected before being made available. These cloud-free images allow good monitoring of environmental dynamics. Scenes 195/056 and 196/056 cover the study area.

-A 30 m resolution digital terrain model (DTM) was used to determine the elevation, slope and hydrographic network maps.

2.3 Methods

2.3.1 *Detection of changes in land use units*

For change analysis, a quantitative assessment of gains and losses, net changes and transitions is required. These changes can be materialized by change maps and in graph form (Eastman, 2009). The generation of change graphs is an important step in the modeling process. Two land cover maps at different dates are used as a basis for understanding the nature of change. Land cover changes that occurred between the years 2000 and 2020 were identified and integrated into the transition sub-model, while taking into account static or dynamic variables (Diallo, 2022).

2.3.2 *Choice of transitions to model*

The LCM model allows the selection of specific transitions to be modeled (Aguejdad, 2009). The principle is to build models grouping the different transitions. Based on land use maps produced at earlier dates (2000 and 2020), the selected transitions are those that transform cash crops into food crops and fallow land and then into housing. These transitions are a function of urban sprawl in the area and intensive agriculture for food self-sufficiency.

2.3.3 Integration of explanatory variables

Land cover modeling at future horizons depends on several explanatory variables. The number of variables to be integrated into the model is constrained by their availability, spatialization, and influence on the location and changes in land cover types (Roy *et al* ., 2014; Megahed *et al.* , 2015). In this study, the number of variables used is limited compared to the range of potentially explanatory variables (environmental, socio-edaphic, political-economic, biophysical, etc.) listed by (Geist and Lambin, 2001). Thus, distance to roads, distance to built-up areas, distance to waterways, slope and altitude were used. They are selected not only based on their high use in land cover change studies, but also based on their explanatory capacities (Mwanjalolo *et al.* , 2018; Shade and Kremer, 2019). The explanatory power of these variables is tested using Cramer's V index which calculates the correlation between the variables and varies between 0 and 1. The stronger the correlation, the more the coefficient will approach 1 and vice versa (Eastman, 2015).

2.3.4 Creating the transition sub-models

The first step is devoted to constructing the transition sub-model which will allow the introduction of variables on which potential transitions will occur. Two options for modeling potential transitions are proposed: neural networks (the Multi-Layer Perceptron (MLP) or Logistic Regression (ReLog) (Nghiem, 2014). The neural network was favored because it is more efficient than the multiple regression model, especially in complex and non-linear systems (Eastman, 2015).

2.3.5 How the Transition Submodel Works

In this last step, the transition submodel models the defined transitions using the Multi-Layer Perceptron (MLP) option. The operation of the transition submodel will be considered acceptable if its accuracy rate reaches at least 75% (Eastman, 2009). However, by default an accuracy rate of 50% is accepted (Rodriguez *et al.*, 2013). The potential transition maps will be created once the operation of the transition submodel is finished.

3. Results and Discussion

3.1 Analysis of classification accuracy

The average accuracy for the producer and user of each maximum likelihood classification and its overall accuracy are presented in **Table 1**. The accuracy values reported in the table indicate that the classification of the 2000 and 2020 land cover maps are quite accurate. For all classifications, the average overall accuracy is above 96%. The lowest accuracy is observed in 2000 with a value of 90.41%. For the year 2020, the overall accuracy is 99.69%. **Table 1** shows that the kappa coefficients of the classifications are 0.87 and 0.99 for the 2000 and 2020 images, respectively.
In sum, the average of the overall accuracies and kappa coefficients exceed 96% and 0.95, respectively, which makes the processing acceptable and the modeling of land cover maps possible.

Table 1: Different percentages of classification accuracies

	Classification		
Value	2000	2020	Average
Overall accuracy (%)	90.41	99.69	96.63
Kappa coefficient	0.87	0.99	0.95
Producer (%)	86.64	99.6	95.35
User (%)	91.59	99.83	97.09

3.2 Analysis of changes in land use

3.2.1 Occupation status in 2000 and 2020

The land use maps of the Djibi watershed, from 2000 and 2020, resulting from the supervised classification of Landsat ETM+ and OLI satellite images (**figure 2**) highlight: water, concentrated habitats, dispersed habitats and bare soil, rubber plantations and degraded forest, palm plantations and degraded forest and food crops and fallow land. In 2000, the vegetation cover of the Djibi watershed was entirely represented by food crops/fallow land and rubber/plantation/degraded forest from south to north, to the west by concentrated habitats, from west to south by water and dispersed habitat/bare soil and to the south by palm grove/plantation/degraded forest. In 2020, the basin is entirely dominated from west to south by concentrated habitats, from north to south by food crops/fallow; scattered habitat/bare soil and rubber/plantation/degraded forest and to the southeast by water and palm grove/plantation/degraded forest.

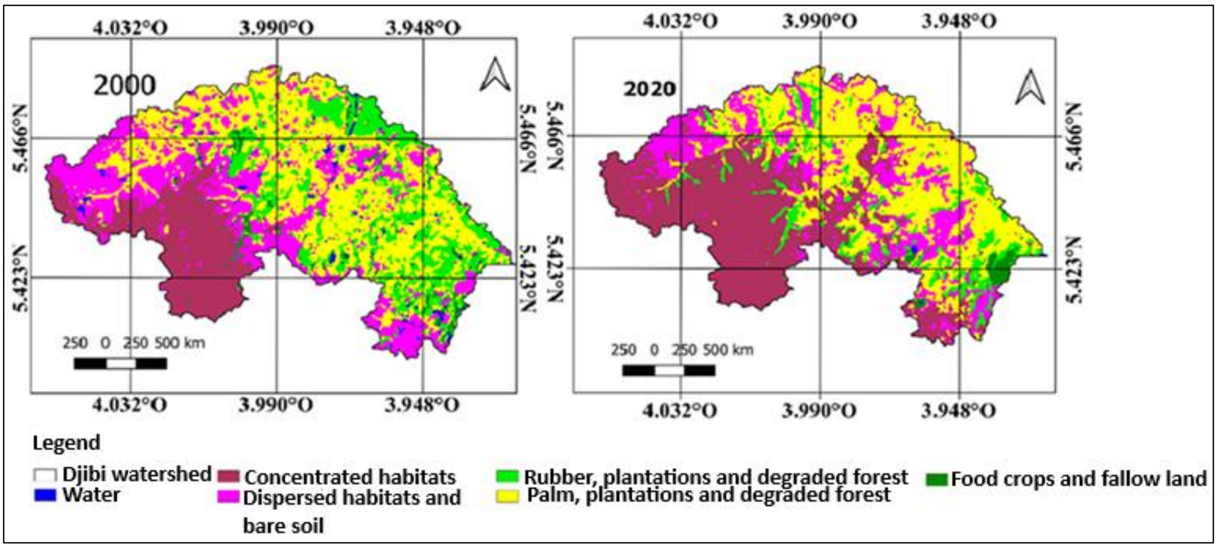


Figure 2. Land use mapping from 2000 to 2020

3.2.2. Land use dynamics from 2000 to 2020

The variation rates of the different types of land use in the Djibi watershed are shown in **Table 2**. These rates reflect the significance of the changes that occurred during the 2000s and 2020s. The evolution of the areas of each class represented by Table 2 indicates two trends of evolution. On the one hand, there is a decrease in the total areas. Indeed, waters went from 1.7 km² in 2000 to 0.2 km² in 2020, scattered habitats and bare soil from 19.9 km² in 2000 to 15.5 km² in 2020; rubber plantations and degraded forest from 13.7 km² in 2000 to 7.9 km² in 2020; Food crops and fallow land from 27.3 km² in 2000 to 25 km² in 2020 and palm plantations and degraded forest from 2.7 km² in 2000 to 1 km² in 2020. On the other hand, we observe at the level of concentrated habitats, an increase in the surface area which went from 12.7 km² in 2000 to 28.41 km² in 2020. Table 3 also provides information on the overall rates of change in land use between 2000 and 2020 based on land use maps. Concentrated habitats increased by 123.31% between 2000 and 2020. This increase was made to the benefit of water bodies, scattered habitats and bare soil, rubber plantations and degraded forest, food crops and fallow land, and palm plantations and degraded forest respectively by 88.63; 21.96; 42.17; 8.42; 64.7.

Table 2: Area and percentage of land use types in the Djibi watershed

BV DJIBI	2000		2020		2000 to 2020	2000 to 2020
OCS Classes	Area (km²)	Proportion (%)	Area (km²)	Proportion (%)	Progression/Regression (%)	Rate of change (%)
EA	1.7	2.2	0.2	0.25	-10.30	-88.63
HC	12.7	16.3	28.4	36.4	4.10	123.31
HDSN	19.9	25.5	15.5	19.9	-1.23	-21.96
HPFD	13.7	17.5	7.9	10.12	-2.70	-42.17
CVJ	27.3	35	25	32.05	-0.43	-8.42

PPFD	2.7	3.4	1	1.2	-5.07	-64.7
TOTAL	78	100%	78	100%	-	-

OCS=Land use, BV=Watershed

Land Change Modeler is used for the detection of gains and losses of land cover units over the period from 2000 to 2020 (**Figure 3**). During this period, concentrated habitats gained 16.2 km² and lost 0.05 km², or a gain of 16.1 km². Water lost 1.06 km² and gained 0.09 km², or an estimated loss of 0.97 km². Also, scattered habitats and bare soil lost 15.47 km² and gained 10.22 km², or a loss of 5.25 km². Similarly, rubber plantations and degraded forest lost 10.28 km² and gained 4.50 km², or a loss of 5.78 km². Food crops and fallow land also lost 14.12 km² and gained 11.09 km², a loss of 3.03 km². Finally, palm plantations and degraded forest lost 1.99 km² and gained 0.94 km², a loss of 1.05 km² from 2000 to 2020.

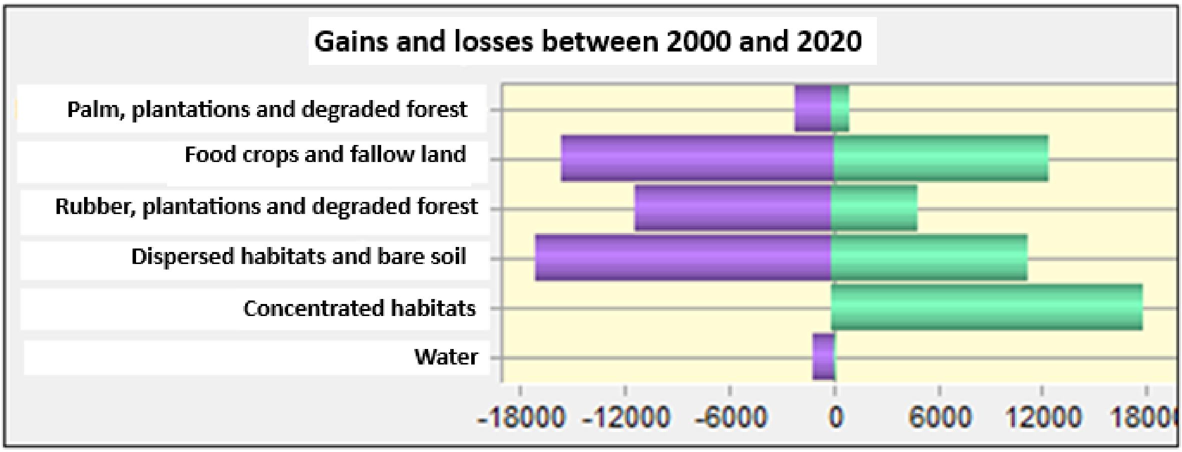


Figure 3. Gains and losses of land use types between 2000 and 2020.

It is clear that there are significant changes and transitions in the Djibi watershed from 2000 to 2020. These main transitions concern the shift from dispersed habitats and food crops and fallow land to concentrated habitats, from rubber plantations and degraded forest to dispersed habitats.

3.3 Relationship between explanatory variables and land use changes

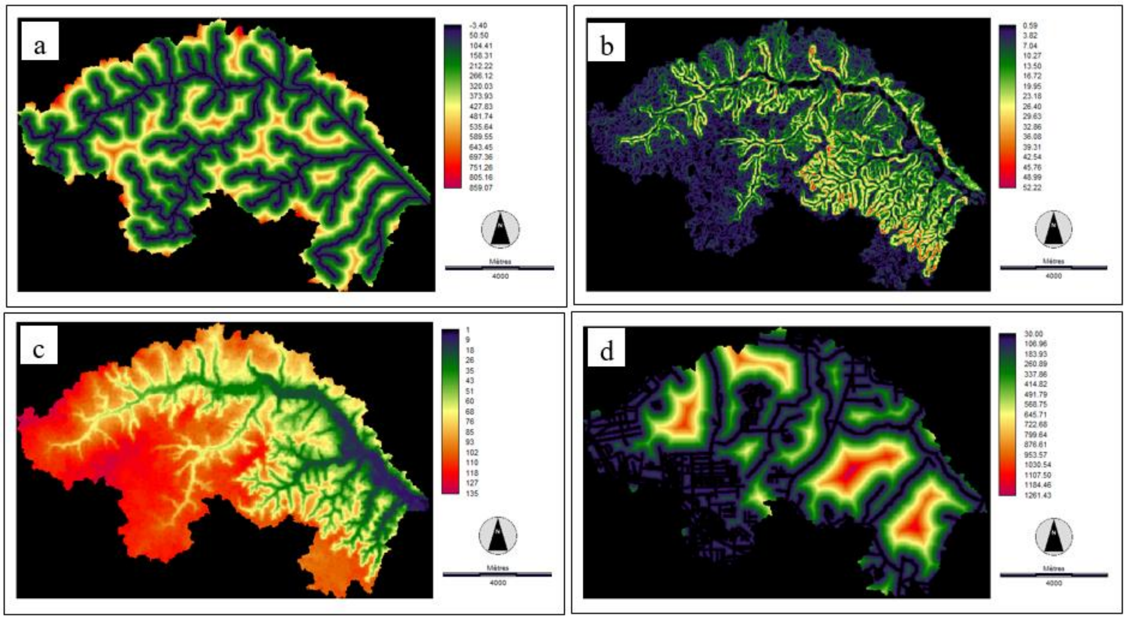
The variables used in the LCM model concerned distances to localities, distances to roads, distances to watercourses and distances to altitudes and slopes. **Table 3** presents the different links between the explanatory variables and the different types of land use in the Djibi watershed. These links are measured through Cramer's V coefficient. At the altitude variable level, Cramer's V coefficients are greater than 0.15 with all land use classes except water. The watercourse variable has Cramer's V coefficients less than 0.15 with the different land use classes except concentrated habitats. The slope variable has Cramer's V coefficients less than 0.15 with all classes except concentrated habitats; rubber plantations and degraded forest and food crops and fallow land. The locality variable has Cramer's V coefficients greater than 0.15 with all classes except palm plantations and degraded forest and water. Finally, the road variable has Cramer's V coefficients less than 0.15 with all classes except concentrated habitats; rubber plantations and degraded forest; and food crops and fallow land.

Despite the low Cramer's V coefficients, all explanatory variables were accepted for the modeling of the different transitions because this test is approximate and does not recognize the effects of interactions. The modeling tool chosen for the potential transitions is the neural network through which there is a robust evaluation procedure that allowed to retest these explanatory variables. **Figure 4** presents the spatial representation of these explanatory variables. The altitude and slope variables are variables common to the two scenarios of the study (urbanization and non-urbanization).

Table 3: Cramer's V coefficient (relationships between land use changes and explanatory variables).

Classes	Altitude	Watercourse	Slope	Locality	Road
HC	0.6788	0.1540	0.3696	0.6225	0.3382
HPFD	0.4847	0.1252	0.2329	0.5055	0.2366
CVJ	0.2400	0.0944	0.2041	0.2124	0.1850
HDSN	0.1783	0.0840	0.0995	0.1677	0.0681
PPFD	0.1711	0.0301	0.0567	0.1435	0.0640
EA	0.0984	0.0240	0.0193	0.1145	0.0295

HC: Concentrated habitats; HPFD: Rubber trees, plantations, degraded forest; CVJ: Food crops and fallow land; HDSN: Dispersed habitats and bare soil; PPFD: Palm groves, plantations, degraded forest; EA: Water



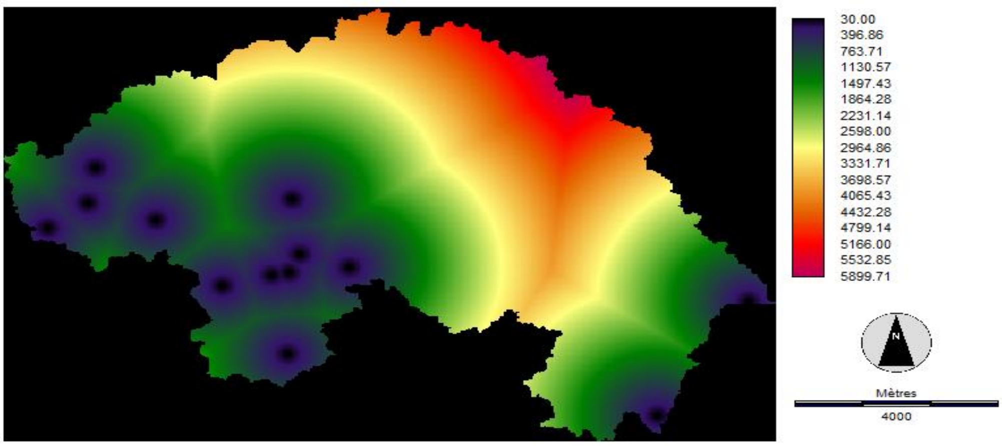


Figure 4. Spatial representation of explanatory factors (a= watercourse (m), b= slope (%), c= altitude (m), d= road distances (m), locality (m)).

3.4 Accuracy rate of potential transitions

The accuracy rate of the potential transitions used in the Djibi watershed is presented in **Table 4.** The accuracy rate represents an agreement between a particular transition and the selected explanatory variables. The accuracy rates of the different potential transitions (**Table 4**) are less than 80%. The highest accuracy rate (54.5%) is observed at the transition from scattered habitats and bare soil to concentrated habitats. And the lowest accuracy rate (50.05%) is observed at the transition from rubber, plantations and degraded forest to food crops and fallow land; the accuracy rates are greater than 50%. They are therefore acceptable.

Table 4: Accuracy rate of potential transitions

Scenarios	Potential transitions	Accuracy rate (%)
Urbanization	Scattered habitats and bare soil to concentrated habitats	54.45
	Food crops and fallow land towards concentrated habitats	50.66
No Urbanization	Scattered habitats and bare soil towards food crops and fallow land	51.09
	Rubber, plantations and degraded forest towards Food crops and fallow land	50.05
	Food crops and fallow land towards Hevea, plantations and degraded forest	53.10

3.5 Transition probability matrix

The transition matrix from one land use class to another is presented in **Table 5**. The rows of this **table** represent the land use classes of 2000 and the columns represent the land use classes of 2020. This is the transition matrix from one land use to another. In this matrix, the values vary from 0.001 to 0.9873. Values very close to 0 indicate that the transition has no chance of occurring. Values tending towards 1 indicate that the mutation is certain. The land use status is reflected by the values at the diagonal. Water has a probability of 0.0010 of remaining stable and has a probability of 0.4437 of changing respectively to concentrated habitats. This is explained by the presence of wetlands. Concentrated habitats have a probability of 0.9873 of remaining stable. Dispersed habitats and bare soil have a probability of 0.1296 of remaining stable and a probability of 0.6425 of converting to concentrated habitats. Rubber plantations and degraded forest have a probability of 0.1334 of remaining stable and have probabilities of 0.2303 and 0.4736 of converting to dispersed habitats and bare soil and to food crops and fallows, respectively. Food crops and fallows have a probability of 0.4247 of remaining stable and have probabilities of 0.2413 and 0.2253 of changing to concentrated habitats and to dispersed habitats and bare soil, respectively. Palm plantations, degraded forest have a probability of 0.0187 of remaining stable and have probabilities of 0.2179 and 0.4103 of changing to concentrated habitats and to food crops and fallows, respectively.

Table 5: Transition matrix to establish the probability of transition from one land use to another (between 2000 and 2020 in the Djibi watershed).

Classes	**EA**	**HC**	**HDSN**	**HPFD**	**CVJ**	**PPFD**
EA	**0.0010**	0.4437	0.1806	0.0718	0.2900	0.0129
HC	0.0001	**0.9873**	0.0067	0.0017	0.0038	0.0004
HDSN	0.0006	0.6425	**0.1296**	0.0450	0.1729	0.0093
HPFD	0.0017	0.1467	0.2303	**0.1334**	0.4736	0.0143
CVJ	0.0013	0.2413	0.2253	0.0948	**0.4247**	0.0125
PPFD	0.0020	0.2179	0.1938	0.1573	0.4103	**0.0187**

3.6. Spatial allocation of land use by 2050 in the Djibi watershed

Figure 5 presents the modeling of land use changes in the two scenarios (urbanization and non-urbanization) of the Djibi watershed. In this study, in the Urbanization scenario, the area of concentrated habitats will occupy the largest area of 44 km² and will be followed by that of food crops and fallow land with an area of 20 km². The area of rubber plantations and degraded forest will be in third position with 7.23 km². Finally, the area of dispersed habitats and bare soil will come last with 5.25 km². For the non-Urbanization scenario, food crops and fallow land will increase and occupy the largest area with 29.8 km², then the area of concentrated habitats will be followed, which will undergo a reduction to occupy second place with 28.7 km². The area scattered habitats and bare soil will increase to occupy the third position with 12.2 km². Finally, the area of rubber plantations and degraded forest will be reduced and will occupy the last position with 6.3 km². These two scenarios will provide relative information on the changes in land use that could be expected by 2050.

The land use areas of these scenarios are presented in **Table 6 .** In both scenarios, water and palm grove and degraded forest plantations will experience a stability of their respective areas of 0.93 km² and 0.94 km² because the transitions linked to water and palm grove and degraded forest plantations have not been taken into account.

Table 6: Land use scenarios for 2050

Classes	Urbanization (km²)	No Urbanization (km²)
EA	0.93	0.93
HC	44	28.7
HDSN	5.25	12.2
HPFD	7.23	6.3
CVJ	20	29.8
PPFD	0.94	0.94

The statistics of the areas of the different types of land use from 2000 to 2020 and of the Urbanization and Non-Urbanization scenarios are shown in **Figure 5**. It emerges from the analysis of **Figure 6** that urbanization will be marked in 2050 with the dominance of concentrated habitats.

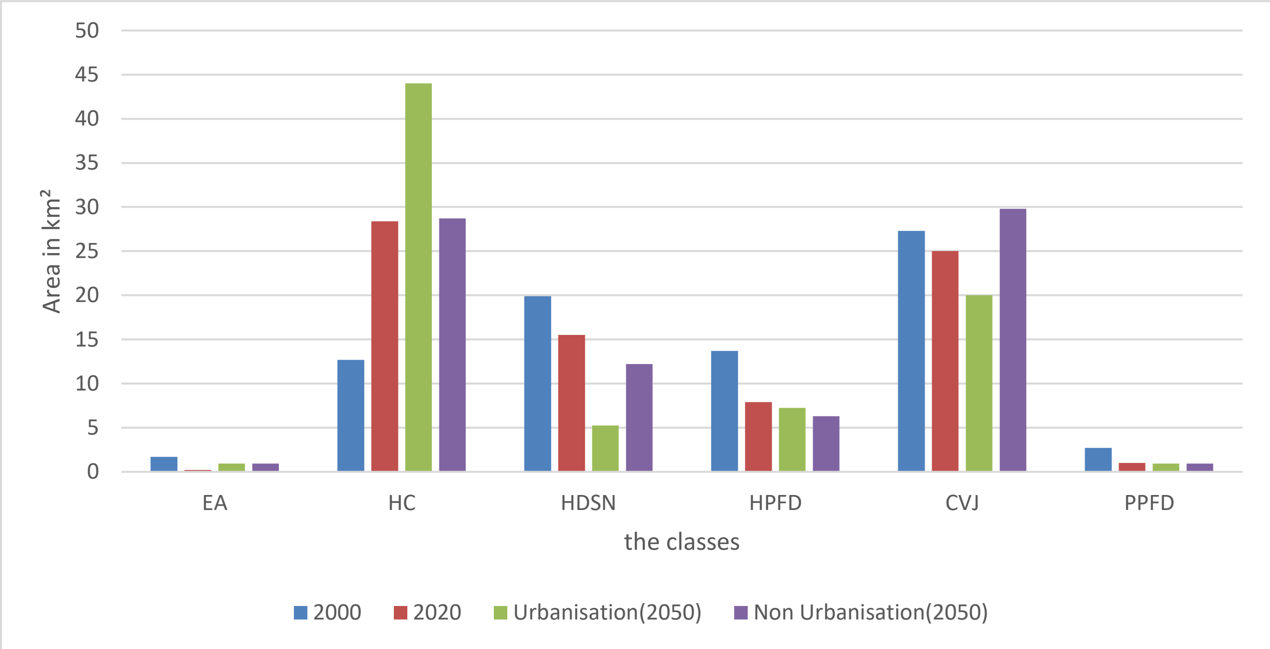


Figure 5. Statistics on the areas of different types of land use in 2000, 2020 and 2050

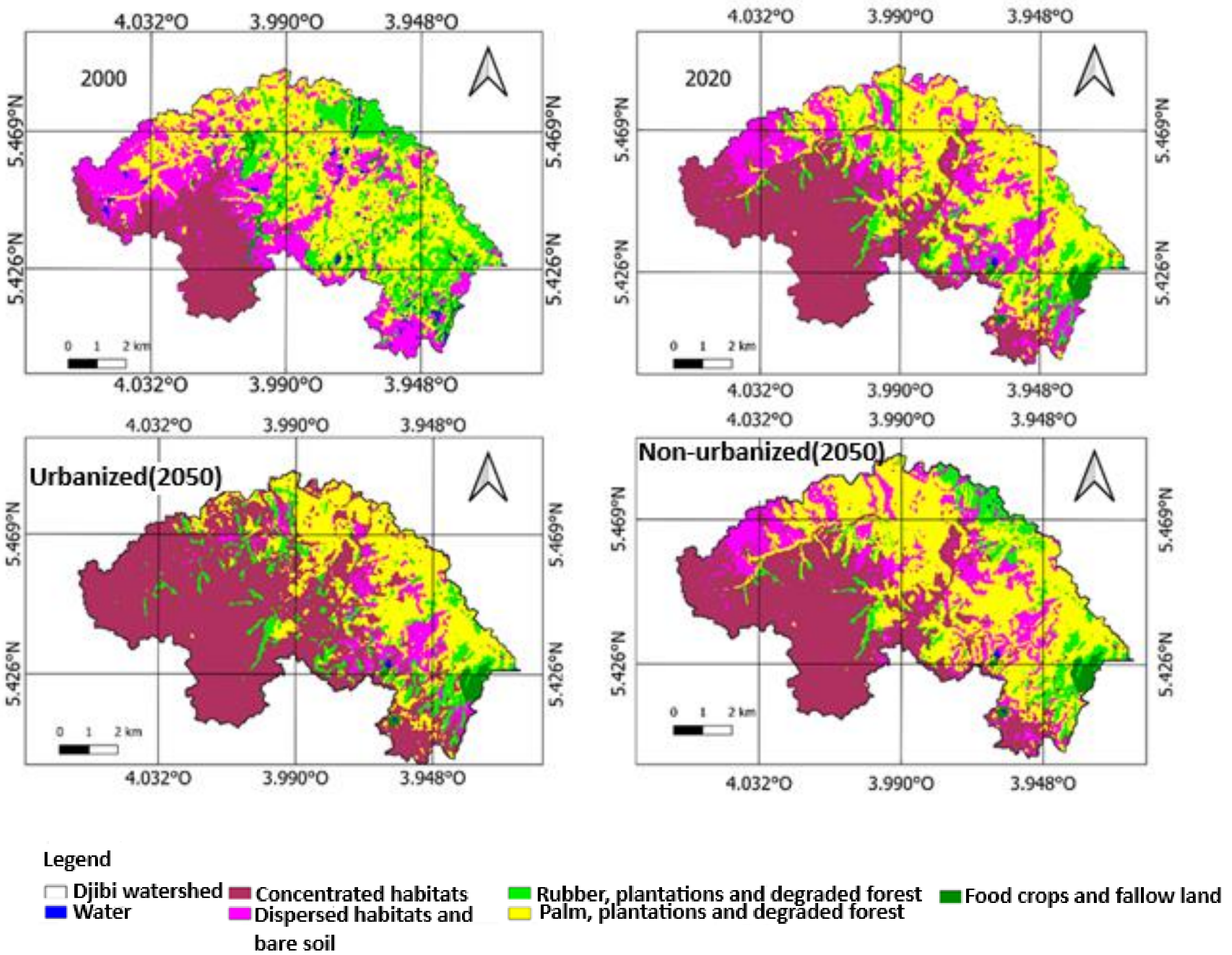


Figure 6. Land cover maps for 2050 based on land cover maps from 2000 and 2020

4. Discussion

4.1 Satellite image processing

The land cover mapping approach based on the supervised classification of two Landsat ETM+ (2000) and OLI (2020) satellite images made it possible to establish land cover maps and analyze landscape dynamics in the Djibi watershed. These classifications using the maximum likelihood algorithm made it possible to obtain overall accuracy values of 96,25% for 2000 and 95,82% for 2020. This classification obtained is good insofar as a classification is considered acceptable when the overall accuracy is around 80% (Congalton, 1991 ; Girard and Girard, 1999) These details corroborate those obtained by other authors such as Koné *et al* .,(2007)**,** during a study carried out in the Ivorian Guinean savannah zone with overall precisions of 91% and 93.21%; N'guessan *et al.,* (2006) ; the same is true in a study carried out at the level of the Badénou classified forest with overall precisions of 88% and 91%.

4.2 Analysis of land use dynamics

The analysis of land use dynamics highlighted the different evolution processes that occurred within the landscape during the period 2000 and 2020 in the Djibi watershed. It shows a regression in the area of forest formation in favor of anthropized formations. The results obtained show the extent and rate of evolution of habitats concentrated in the basin between 2000 and 2020. Indeed, the evolution of population density will lead to housing needs. According to Diallo *et al*., (2018), these housing needs have resulted since the 1990s in the conquest of peri-urban spaces by individuals and private real estate operators. During this same period, a decline in perennial rubber and oil palm crops of 6% and 5% respectively was observed. This regressive dynamic is due to the spatial extension of the Abidjan district. A study conducted by Sako (2013) on the impact of urbanization on the conservation of the Banco National Park in Abidjan showed a significant occupation of the space of this protected forest of 7% in 1998.

4.3 Modeling of land use dynamics

The use of the LCM (Land Change Modeler) model allowed us to generate scenarios of land use changes by 2050. Urbanization and non-urbanization are the scenarios that were named. The basic principle used in the LCM model is to analyze changes in land use between the different classes over the period 2000 and 2020, to evaluate the impact of the explanatory variables and finally to predict the land use model based on the choice of potential transitions. A strong conversion of rubber plantations, palm groves, degraded forest, food crops and fallow land and scattered habitats and bare soil was observed during the period 2000 to 2020, these results are similar to those of Kouamé (2017) in the impact of climate change and land use dynamics. This can be explained by various reasons which are anthropogenic activities such as the abusive exploitation of wood for housing, the creation of factories. The level of association between the explanatory variables and the different land use classes, was evaluated using Cramer's V coefficient which calculates the correlation between variables and varies between 0 and 1. Some explanatory variables used in this study have Cramer's V coefficients that are equal to or greater than 0.4, but also are less than 0.15. Although some of the variables have Cramer's V coefficients less than 0.15, they are acceptable. Indeed, a strong correlation does not take into account the complexity of the relationships between the variables (Maestripieri and Paegelow., 2013)**.** Cramer's V coefficient is an approximate test and does not recognize the effects of interactions (Eastman., 2015).

Indeed, a robust evaluation procedure is incorporated in the model development process when the modeling tool is the neural network. Thus, the level of association between the explanatory variables and the different land use classes is also evaluated through the accuracy rates of the different potential transitions. The accuracy rates of the different potential transitions are less than 80%. The highest accuracy rate (54.45%) is observed at the level of the transition from dispersed habitat and bare soil to concentrated habitat. And the low accuracy rate (50.05%) is observed on the side of the transition from rubber tree / plantation / degraded forest to food crop / fallow. The accuracy rates are higher than 50%. They are therefore acceptable because according to Rodriguez *et al.* , (2013) accuracy rates higher than 50% are acceptable by default. The results of the accuracy rates have a similarity with the results of Islam and Ahmed., (2011) who mentioned the absence of variables having influence on land use classes

The land cover change scenarios were run up to 2050. These two scenarios provide the extremes of land cover changes that could be expected up to 2050. There are always ambiguities in the acceptability of the results especially when the results of the predicted future are based on uncertain variables **(**Islam and Ahmed, 2011 Mishra *et al.*, 2014**)**. 1000 iterations were considered sufficient for the data run and the accuracy rates are acceptable.

5. Conclusion

At the end of this study, it appears that image processing techniques and GIS have made it possible to analyze the dynamics of land use between the years 2000 and 2020 and to predict the state of land use by 2050. The study of the dynamics of land use has shown that the Djibi watershed has dynamic environments that are undergoing significant change. The hydrological balance of the basin massifs has been significantly disrupted by the increase in population combined with human activities. The cartographic results indicated rates of food crops and fallow land estimated at 0.43% respectively between 2000 and 2020. This decrease in the areas of food crops and fallow land has benefited human environments that are constantly conquering new inhabited lands.

The land use status modeling by LCM allowed to generate the land use scenarios for 2050 based on the explanatory variables; altitude, slope, distance to roads, distance to localities, distance to waterways. The Urbanization scenario is considered as the bad case in which there is no conservation of natural resources (water, forest, etc.). The non-Urbanization scenario is the best case that considered a sustainable environment with a reversal of environmental resource losses. The validation of the model was based on the assessment of the accuracy rate that represents an agreement between a particular transition and the explanatory variables. All accuracy rates were less than 80% and greater than 50%. They were accepted by default. These low rates are due to the absence of variables that have influence on the land use classes.

Based on the results and limitations of this study, recommendations should be made to managers, decision-makers and non-governmental organizations (NGOs) with a view to sustainably using the natural resources (water, forest, etc.) available in the Djibi watershed.

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