GeoPlanning
Journal of Geomatics and Planning

Vol. 8, No. 2, 2021

e-ISSN: 2355-6544

Received: 10 August 2021;
Accepted: 10 December 2021;
Published: 30 December 2021.

Keywords:
Land use, land cover, spatial prospective, trend, Classified Forest, Upper Alibori.

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Original Research Open access

Prospective Mapping of Land Cover and Land Use in The Classified Forest of The Upper Alibori Based on Satellite Imagery

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DOI: 10.14710/geoplanning.8.2.115-126

Abstract

The dynamics of land cover and land use in the classified forest of the upper Alibori (FCAS) in relation to the disturbance of agro-pastoral activities is a major issue in the rational management of forest resources. The objective of this research is to simulate the evolutionary trend of land cover and land use in the FCAS by 2069 based on satellite images. Landsat images from 2009, 2014 and 2019 obtained from the earthexplorer-usgs archive were used. The methods used are diachronic mapping and spatial forecasting based on senarii. The MOLUSCE module available under QGIS remote sensing 2.18.2 is used to simulate the future evolution of land cover and land use in the FCAS. The land cover and use in the year 2069 is simulated using cellular automata based on the scenarios. The results show that natural land cover units have decreased while anthropogenic formations have increased between 2009 and 2014 and between 2014 and 2019. Under the "absence multi-criteria zoning (MZM)" scenario over a 50-year interval, land cover and use will be dominated by crop-fallow mosaics (88%). On the other hand, the scenario "implementation of a multicriteria zoning (MZE)", was issued with the aim of reversing the regressive trend of vegetation types by making a rational and sustainable management of resources.

1. Introduction

Africa had the highest net loss of forest area over the period 2010-2020, at 3.94 million hectares per year (FAO et PNUE, 2020). Forests managed with the support of forestry projects are not spared (Gbedahi et al., 2019). Sustainable forest management requires the ability to characterise and spatialise the resource within a forest massif (Munoz et al., 2015). Land cover and its evolution over time is a good indicator of these interactions, as it reflects the impacts of land cover and climate change on natural environments (Monier, 2010). Furthermore, modelling and projecting land cover changes is becoming a relevant tool for decision support (Thierry et al., 2018). It allows territorial planning policies to be analysed in order to assess and anticipate their environmental impacts (Samie et al., 2017). Exploring the future in a quantitative way is a scientific challenge. Taking into account the spatial dimension (in the quantitative sense) in foresight is relatively recent and remains delicate, calling on various skills in geomatics and remote sensing for the reconstruction of past trajectories, but also in modelling (Houet, 2015)

In Benin, forests are undergoing deforestation or degradation processes of varying severity, with negative impacts on ecosystems and the livelihoods of local populations in particular (Moumouni et al., 2019). The human activities directly responsible for forest destruction are commercial timber exploitation, the establishment of crops and plantations, the use of firewood and intensive livestock farming (overgrazing) (Sinsin et al., 2010). Nevertheless, deforestation, which was estimated at 150,000 ha/year between 1960 and 1980, fell from 70,000 ha/year between 1990 and 2000 to 50,000 ha/year from 2000. This regression is a testimony to the efforts of the Beninese state to curb the degradation of vegetation cover (FAO, 2015).

In relation to the national forest cover, the north of Benin concentrates nearly 92.5% of natural resources thanks to the presence of a series of protected areas (classified forests, hunting zones and national parks) (Mama et al., 2020). But with high population growth correlated with unsustainable land cover and land use, these reforestation efforts are being challenged. Furthermore, the increasing lack of fertile land, the inadequacy of grazing areas and the search for water in the lands bordering the FCAS are invoked to justify the unsustainable exploitation of the natural resources available in this area by the indigenous population (Mama et al., 2020). Agropastoral exploitation observed in the FCAS in 2000 by (Akindélé, 2000), in 2002 has continued and been reinforced (Issiako & Arouna, 2018; Mama et al., 2020; Seidou et al., 2017). Deforestation and forest degradation continue in the FACS despite the management plan developed with the participation of various stakeholders. The practice of agro-pastoral activities in the FCAS and forest dynamics are intimately linked, leading objectively to a restructuring of forest areas. The understanding and monitoring of land cover dynamics as well as the representation of changes affecting the territory are thus political, economic and social issues in the FCAS. What is the evolutionary trend of land cover in the FCAS in the current context of intense agropastoral practices? The objective of this paper is to simulate the evolutionary trend of land cover and land use in the FCAS by 2069 on the basis of scenarios. This research is based on the hypothesis that the evolutionary trends of the vegetation cover by 2069 will vary according to the scenarios put in place.

2. Material and Methods

2.1. Study Area

The FCAS straddles the Provinces of Atacora, Borgou and Alibori. It is located between 10°14 and 11°40 North latitude and between 1°54' and 2°55' East longitude. It is located in ecological zones 1 and 2 which include the Districts of Gogounou, Kandi, Banikoara, Kèrou, Ouassa-Péhunco and Sinendé, which are known to be major producers of cotton, maize and yams. This state forest estate is globally subject to degradation factors including agriculture, hunting, livestock, logging and various forms of encroachment related to the installation of housing and other infrastructure (Issiako & Arouna, 2018). Figure 1 shows the geographical location of the FCAS.

2.2. Rationale for the choice of dates

The participatory management plan for the FCAS was developed for the period 2010 - 2019. Thus, the use of spatial imagery before the plan (2009), during the implementation of the plan (2014) and after the implementation of the plan (2019).

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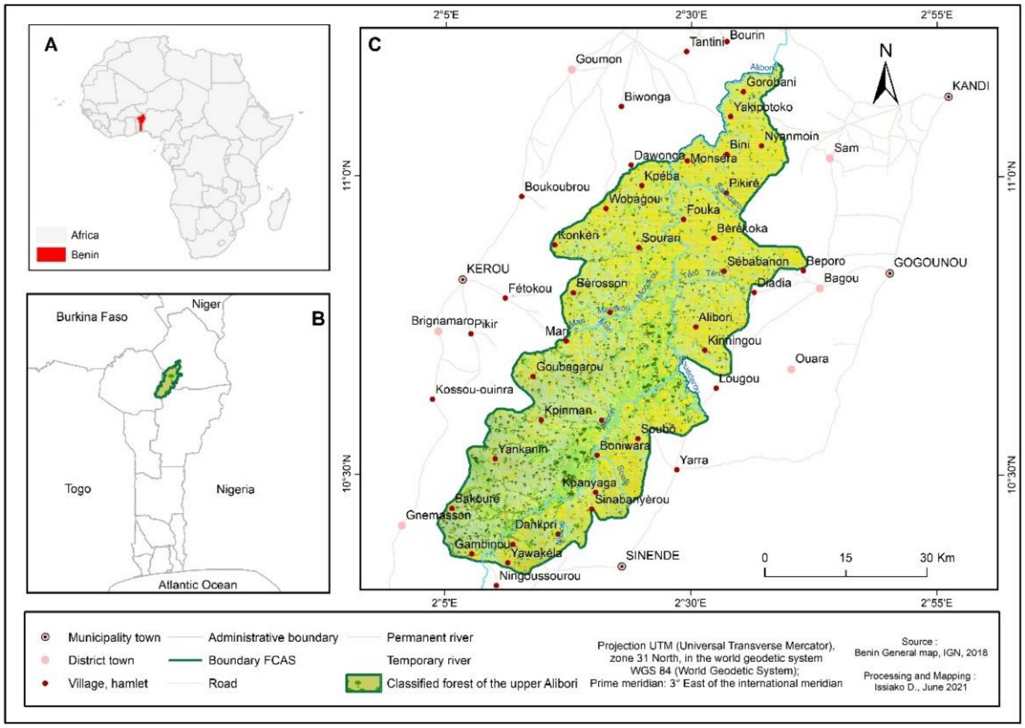
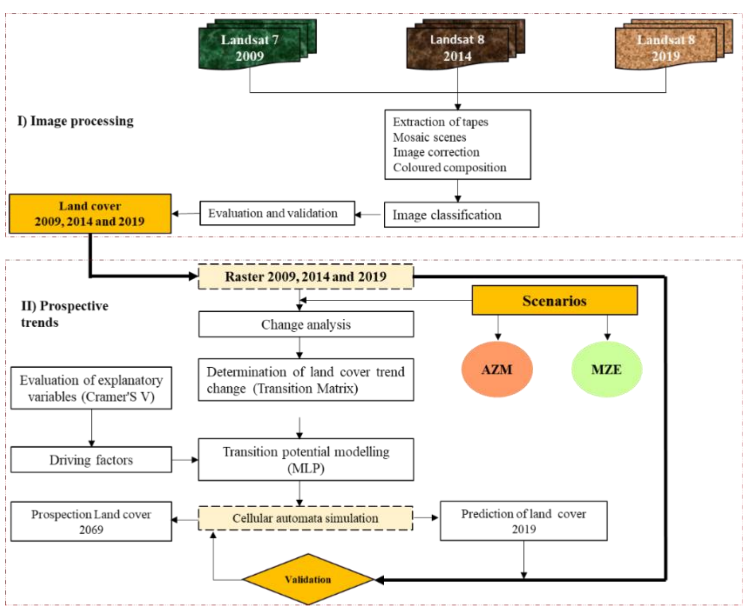


Data source: Benin general map, National Geographic Institute (IGN) of Benin, 2018

Figure 1. Geographical location of the Upper Alibori Classified Forest

2.3. Methodological flow chart

This research used methodology that can be seen at Figure 2.



Legend: AZM: Absence of multi-criteria zoning; MZE: Implementation of zoning with effectiveness

Source: inspired by (Hakim et al., 2019)

Figure 2. Flow chart of the research method

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2.4. Planimetric data used

The planimetric data used are topographic maps, at 1:50,000 scale, sheets of Bagou, Alibori Forest, Goumori, Kérou, Péhunco, Sinendé and Sonsoro produced by the Institut Géographique National (IGN) of Benin in 2018; Landsat 7 ETM+ multi-spectral images in Geotiff format from 22 december 2009: Path192 and Row 52; with a spatial resolution of 30 m; Landsat OLI-TIRS (Landsat 8) images in Geotiff format from 25 december 2014: Path192 and Row 52; with a spatial resolution of 30 m; and Landsat OLI-TIRS (Landsat 8) images in Geotiff format, of 20 december 2019; Path192 and Row 52;with a spatial resolution of 30 m. These images have been downloaded from www.earthexplorer-usgs.gov/usa. These images were radiometrically corrected before digital processing.

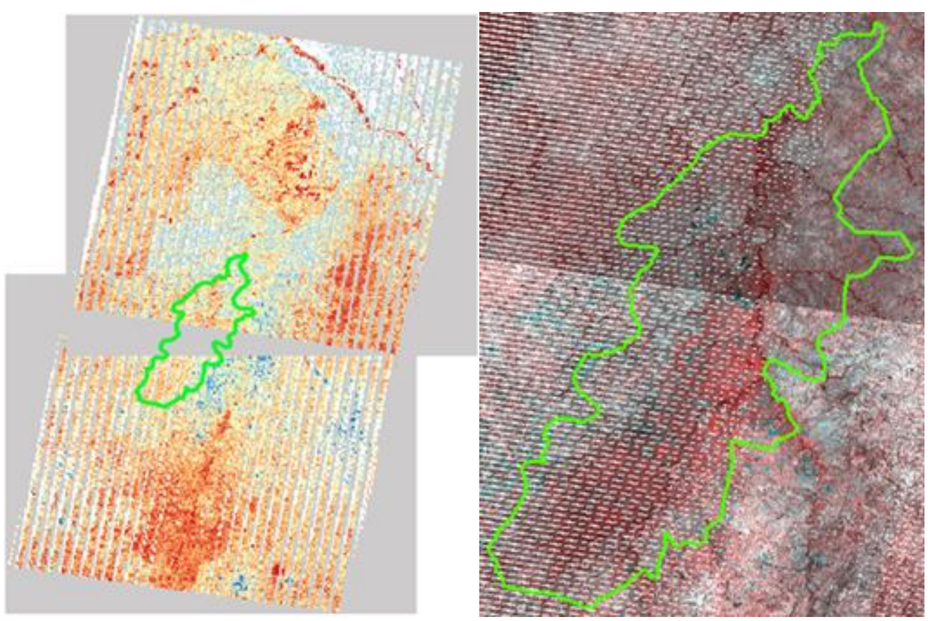
2.5. Digital processing of Landsat images

The mapping of spatio-temporal land cover and land use changes started with the digital processing of satellite images using QGIS2.18.2 software, in particular the Train Radom Forest Image Classifier module contained in the Orfeo toolkit. The "RandomForest" algorithm has already been used in previous studies on satellite image classification (Rodriguez-Galiano et al., 2012; Shao et al., 2016). This digital processing includes: importing Landsat images into QGIS software, clipping the area of interest, calculating the image pyramid, colour composition, choosing training areas and supervised classification by maximum likelihood.

Importing the images into QGIS. The different image scenes were imported into the QGIS software.

Mosaicing

A mosaic of two (02) scenes was made to cover the entire FCAS (Figure 3).



a. Image from 2009 before mosaic b. Image from 2009 after mosaic

Data source: Landsat 7 ETM+, December 2009, P.192 and R.52, 30 m

Figure 3. Mosaic of two (02) scenes covering the FCAS

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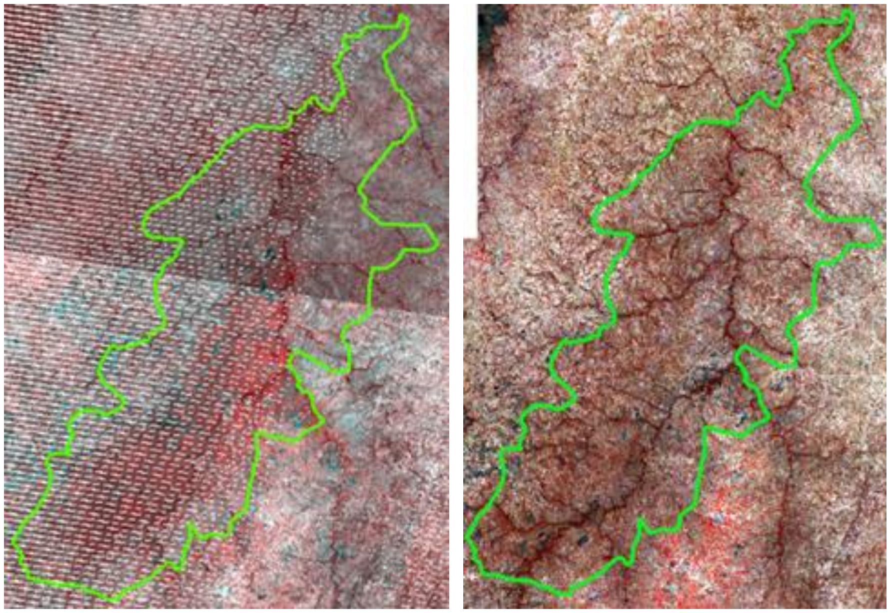
Correction of the 2009 image

The 2009 image has been corrected (Fill Gab); the strips have been filled in to allow further work. Figure 4 shows the 2009 image in the study area before and after treatment.



Data source: Landsat 7 ETM+, December 2009, P.192 and R.52, 30 m

Figure 4. Landsat 7 ETM+ image from 2009 before and after correction

Creation of ROIs (Region Of interest)

After a colour composite, the land-use units were identified and coded on the different scenes. For each land-use unit, training areas (ROIs) were delineated away from the transition zones to avoid including mixed pixels that could be classified in two distinct classes.

Creation of the classification model

In order to classify under Random Forest, a model was created to run the classification using the ROIs created previously. The Train Radom Forest Image Classifier module of the Orfeo toolbox was used to create the model. Once the model was validated through the value "Global performance", for each image (Olouloi et al., 2006; Toko Mouhamadou, 2014), the classification was done using the Image classifier module contained in the Orfeo toolbox.

Create Image Classification

This application performs a classification of the input image, based on the Model file created with the Train Random Image Image Classifier algorithm. The supervised classification was then performed. The training plots were used to establish a key numerical feature that could best describe the spectral attributes for each class type. In this case, the parametric algorithm chosen is maximum likelihood (Toko Mouhamadou, 2014).

In supervised classification, the image analyst supervises the pixel categorisation process by specifying to the computer algorithm numerical descriptors of various land cover types present in the scene. Thus, representative samples of known land cover sites (training plots) were used.

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Classification evaluation

The control points were geolocalised using a Garmin 62s GPS receiver at all homogeneous units across the FCAS. Two validation visits were carried out to confirm and reclassify the results of the satellite image interpretation. Of two hundred (195) sampled control points, 190 were found to be correctly classified, i.e. a proportion of 97 %. Table I shows the distribution of the ground control points by land cover unit.

Table I. Distribution of fieldwork points by land cover/landuse unit

Units of land cover	Traded points	Validated points	Percentage (%)
Field mosaic and fallow	45	44	23
Woodlands	14	13	7
Gallery forest / riparian formation	40	38	19
Plantation	1	1	1
Tree and shrub savannahs	95	94	48

Vectorisation and development of the transition matrix

The classified images were transformed into a shapefile in order to determine the areas of each land cover unit and to establish the transition matrix. The transition matrix is in the form of a square matrix and consists of X rows and Y columns. The number of rows in the matrix indicates the number of land-use units at time t 0; the number Y of columns in the matrix is the number of converted units at time t 1 and the diagonal contains the areas of the units that remain unchanged. The transformations are done from rows to columns.

2.6. Detecting changes

Average annual rates of spatial expansion (T)

The annual average rate of spatial expansion expresses the proportion of each land cover unit that changes annually (Zakari et al., 2018).

$$\mathbf{T} = \frac{(lnS_2 - lnS_1)}{(t_2 - t_1)} \mathbf{x\ 100} \qquad \text{[Eq :1]}$$

with T: average annual rate of spatial expansion; S1 and S2: area of a land-use unit at dates t1 and t2 respectively; t2 - t1: number of years of evolution; ln: natural logarithm; e: base of natural logarithm; (e = 2.71828 invariant coefficient).

Conversion rate of land cover units

The conversion rate of a land cover class is the degree to which the land cover class has changed by converting to other classes.

$$\mathbf{T_c} = \frac{S_{it} - S_{is}}{S_{it}} \mathbf{x\ 100} \qquad \text{[Eq :2]}$$

with Tc: conversion rate; Sit : Area of unit i at initial date t; Sis: Area of the same unit remaining stable at date t1.

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2.7. Forward-looking land cover mapping method

The 2014 and 2019 land cover maps were used to simulate the 2069 land cover. To estimate the reliability and predictive capacity of the simulation to 2069, the 2019 land cover was simulated from the transition of the land cover dynamics observed between 2009 and 2014 as a test. The reference map of 2019 and the one simulated in the same year were compared. Therefore, if the validated result reaches an acceptable accuracy (50%), then the simulation for 2069 will be valid. However, if the result is less accurate, the simulation will not be valid. The simulated map in 2019 was produced using QGIS remote sensing 2.18.2 software including the MOLUSCE (Model for Land cover Change Evaluation) module (Mienmany, 2018).

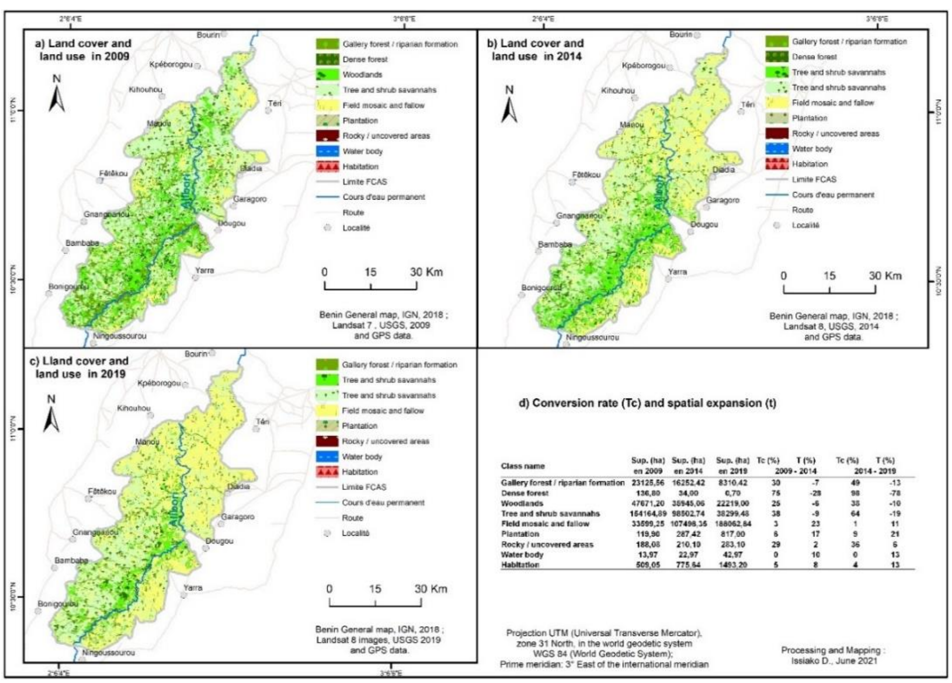
Several factors influencing land cover change were incorporated into this model. These are distance to settlements, distance to fields, distance to roads and population density. Cramer's V index was calculated for each explanatory factor and used to select those that best contribute to land cover dynamics. This is the Cramer's V coefficient, which is a correlation coefficient that varies from 0.0 (no correlation) to 1.0 (perfect correlation).

Two scenarios were developed to project the future of land cover in order to facilitate decision-making. These are: Scenario 1 Absence of multi-criteria zoning (AZM), trend (2014-2019) maintained, the AZM scenario is a trend scenario that assumes no new forest management policies; and Scenario 2 Implementation of zoning with effectiveness Sustainable Management 2069, the main objective of the "Sustainable Management" scenario is to manage the remaining forest resource through the implementation of an integrated forest management plan.

3. Results

3.1. Land cover dynamics of the FCAS

Land cover in 2009, 2014, 2019 in the FCAS can be seen in Figure 5.



Data source : Landsat 7 ETM+, Landsat 8 OLI-TIRS, P.192 and R.52; resolution : 30 m ; method supervised classicification : Train Radom Forest of the Orfeo

Figure 5. Land cover in 2009, 2014 and 2019 in the FCAS

These three units have respectively -28%, -9% and -7% spatial expansion rates between 2009 and 2014. Between 2014 and 2019, units such as dense dry forest (98%), tree and shrub savannahs (64%), gallery forest (49%) and open forest and wooded savannahs (38%) experienced a high conversion rate with a negative average annual spatial expansion rate.

3.2. Probability of change of land-use units in scenario 1

The transition probabilities provide information on the likelihood of conversion of units to other land-use units between 2019 and 2069 (scenario 1).

Scenario 1 transition probability matrix (AZM)

Table II. Transition probability matrix of land cover and land use units

Class name 2019	Class name 2069								TOTAL
	Gallery forest / riparian formation	Woodlands	Tree and shrub savannahs	Field mosaic and fallow	Plantation	Rocky / uncovered areas	Water body	Habitation	
Gallery forest / riparian formation	0.7209	0	0	0.2061	0.0691	0	0	0	1
Woodlands	0	0.2646	0.1503	0.5766	0	0	0	0.01	1
Tree and shrub savannahs	0	0	0.12	0.8796	0	0	0	0	1
Field mosaic and fallow	0	0	0	0.9981	0	0	0	0	1
Plantation	0	0	0	0	0.8185	0	0	0.18	1
Rocky / uncovered areas	0	0	0	0	0	0.0111	0	0.99	1
Water body	0	0	0	0	0	0	1	0	1
Habitation	0	0	0	0	0	0	0	1	1

Data source : Landsat 8 OLI-TIRS, LCLU, 2019, cell transmission rules, Simulation sotfware MOLUSCE (QGIS Remote Sensing)

Based on Table II, it can be deduced that by 2069, open forests and wooded savannahs and tree and shrub savannahs will no longer exist and the other vegetation formations if the evolutionary trends observed between 2014 and 2019 are maintained.

Scenario 2 transition probability matrix (MZE)

Table III. Transition probability matrix from anthropogenic to natural formations

Class name 2019	Class name 2069									Total
	Gallery forest / riparian formation	Dense forest	Woodlands	Tree and shrub savannahs	Field mosaic and fallow	Plantation	Rocky / uncovered areas	Water body	Habitation	
Gallery forest / riparian formation	0.9959	0	0	0	0	0.0041	0	0	0	1
Dense forest	0	1	0	0	0	0	0	0	0	1
Woodlands	0	0.0402	0.9551	0	0	0.0048	0	0	0	1
Tree and shrub savannahs	0	0.1326	0.3106	0.5531	0.0014	0.0022	0	0	0	1
Field mosaic and fallow	0.0267	0.0227	0.0791	0.8671	0.0037	0.0008	0	0	0	1
Plantation	0.0073	0.0045	0.0139	0.106	0.0071	0.8607	0	0	0.0005	1
Rocky / uncovered areas	0	0	0.3939	0.6061	0	0	0	0	0	1
Water body	0.8718	0	0	0	0	0	0	0.1282	0	1
Habitation	0	0.001	0.0036	0.9894	0	0	0	0	0.0059	1

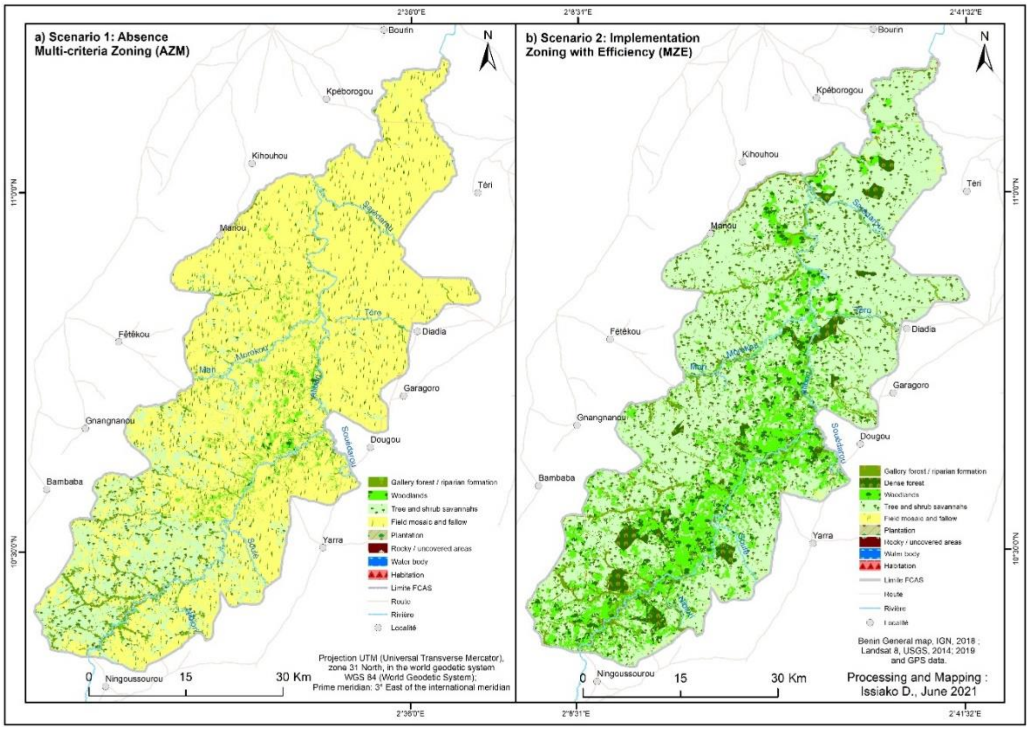
Data source: Landsat 8 OLI-TIRS, LCLU, 2019, cell transmission rules, Simulation sotfware MOLUSCE (QGIS Remote Sensing)

DOI: 10.14710/geoplanning.8.2.115-126

Based on Table III with the implementation of multi-criteria zoning, there will be more anarchic installation of fields; the probability of reconstitution and stability of natural vegetation by 2069 will be high.

3.3. Prospective states of land cover units by 2069

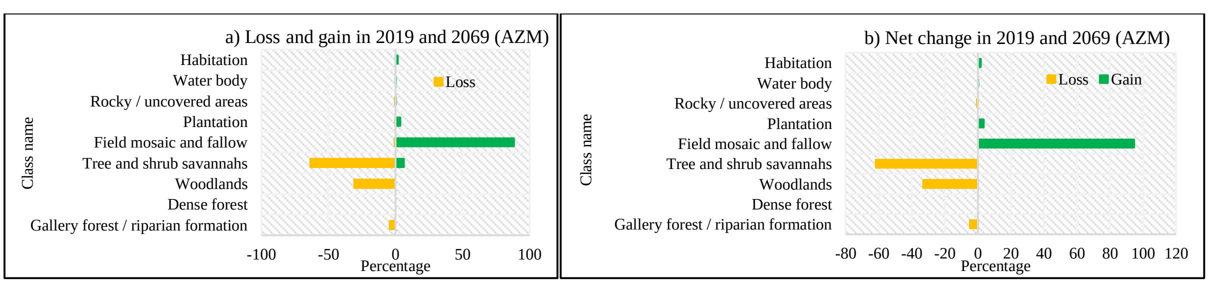
Land use by 2069 based on the "Absence Multi-Criteria Zoning (AZM)" and "Implementation Multi-Criteria Zoning" scenarios can be seen in Figure 6.



Data source : Landsat 8 OLI-TIRS, LCLU, 2019, cell transmission rules, Simulation sotfware MOLUSCE (QGIS Remote Sensing)

Figure 6. Land use by 2069 based on the "Absence Multi-Criteria Zoning (AZM)" and "Implementation Multi-Criteria Zoning" scenarios

Changes observed with "Absence Multi-Criteria Zoning (AZM)" scenario

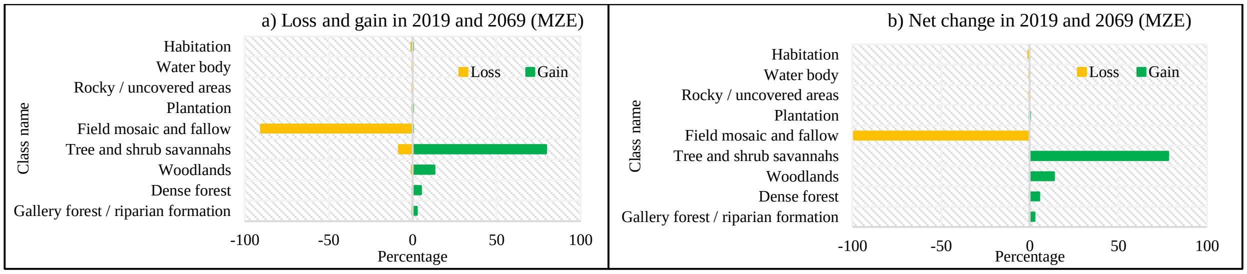


Data source: Landsat 8 OLI-TIRS, LCLU, 2019, cell transmission rules, Simulation sotfware MOLUSCE (QGIS Remote Sensing)

Figure 7. Changes observed between 2019 and 2069 in the Absence Multi-criteria Zoning scenario

Indeed, in this scenario, gallery forests, dense dry forests, woodlands, tree and shrub savannahs and water bodies will lose 4%, 31% and 63% respectively by 2069 compared to the base year 2019 (Figure 7). The area of fields and fallow land will increase by 88%.

Changes observed with "Implementing Multi-criteria Zoning with Efficiency (MZE)" Scenario



Data source: Landsat 8 OLI-TIRS, LCLU, 2019, cell transmission rules, Simulation sotfware MOLUSCE (QGIS Remote Sensing)

Figure 8. Observed changes between 2019 and Implementation Multi-Criteria Zoning" scenarios

The exam of the Figure 8 shows that this loss is likely to be in favour of gallery, dense forest, woodlands and plantations, which will gain 2%, 5%, 13% and 79% respectively in area, or 207,359 ha (Figure 8a). This indicates that the establishment of fields in the FCAS will be regulated by a new forest management policy in the period 2019-2069. In contrast, gallery, dense forest, woodlands, plantations will experience a net positive change of 23.25% (Figure 8b).

4. Discussion

The diachronic analysis with the combination of the transition matrix allowed to highlight the different forms of conversion that the land cover units in the Forêt Classée de l'Alibori Supérieur underwent between 2009, 2014 and 2019. This concerns the regression of natural vegetation formations in favour of anthropogenic formations. Anthropogenic pressures on natural resources through these activities have favoured the transformation of natural formations (Issiako & Arouna, 2018; Mama et al., 2020). Knowledge of recent dynamics is essential to understand future evolution and its modelling (Paegelow et al., 2004).

The MOLUSCE method is used for the spatial survey in 2069. This method is implemented on the Quantum GIS software in which there is a Modules for land cover Change Simulations (MOLUSCE) plugin (Hakim et al., 2019). The land cover change was predicted using a MOLUSCE analysis method based on the Cellular Automata method by Mirici et al. (2018) and Subiyanto & Suprayogi (2019). The Multi-Layer Perceptron (MLP) Cellular Automata Simulator tool simulates the land cover data for the period 2019 and the actual referenced 2019 land cover map obtained from the satellite image in 2019 was used to validate the model and the performance of the model. The overall accuracy indices of the land cover survey in 2069 are 87% (AZM) and 85% (MZE). This shows that the land cover survey based on the scenarios can be continued as the overall precision value is high. The results of the trend scenario1 (AZM), show that the most likely evolutionary trend will be the conversion of gallery forest, dense dry forest, woodlands and shrub and tree savannah into field and fallow mosaic. Thus, the areas of crop-fallow mosaics, settlements and plantations will increase by 2069. This increase could be explained by population growth and the lack of arable land in village areas. Deforestation due to selective logging will lead to the loss of plant biodiversity. Faced with these anthropogenic disturbances in these protected natural landscapes, which impart a change in composition and spatial configuration, biodiversity is in permanent danger in Benin and Africa (Mama et al., 2020). This is in line with the work of Thierry et al. (2018) and Seko et al. (2018) who conducted their research in the North-West and North-East of Benin respectively and who explain the high demand for cultivated land by the increase in population.

In the framework of the implementation of the Multicriteria Efficiency Zoning (MZE) which is nothing else than the implementation of an integrated forest management plan that can combine both environmental conservation and agropastoral activities. The results obtained show that with the implementation of a new management policy, there will be no more anarchic installation of fields inside the forest. The probability of reconstitution and stability of natural vegetation formations by 2069 will be very high. The hypothesis that the evolutionary trends of the vegetation cover by 2069 vary according to the scenarios implemented is verified.

5. Conclusion

At the end of the spatial and temporal evaluation of the FCAS land use and land cover units, it appears that natural formations have regressed in favour of anthropogenic formations between 2009 and 2014 and between 2014 and 2019, despite the status of protected area with a management plan for this geographical space. Thus, the ecological balance of natural vegetation types has been severely disrupted. The projection of current land cover trends using cellular automata has made it possible to assess the dynamics of land cover and land use for the period 2019 - 2069. During this period, the cultivated area will increase significantly by almost 88% compared to the total forest area if the current trend is maintained with little implementation of the management plan. On the other hand, the implementation of an effective zoning system will allow the control of anthropic pressures, which will in turn allow the restoration of degraded areas. The maps translate into forward-looking trend scenarios and will allow the identification of degraded management areas on the one hand and favourable areas for the conversion of forest resources on the other. This research can provide decision-makers with the necessary data for the elaboration of a future spatial management plan for the conservation and rational exploitation of forest resources. Therefore, the prospective study of potential areas for plant biodiversity conservation deserves to be done to further inform decision makers.

6. Acknowledgements

Thank you to all those who have helped in this research.

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