# ANALYSIS OF LAND USE/LAND COVER CHANGE AND ITS PREDICTION IN THE MAMBASA SECTOR, DEMOCRATIC REPUBLIC OF CONGO

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**Abstract.** Current information on land use/land cover change and its future evolution is required to support land management planning and policymaking in most developing countries experiencing deforestation and land degradation. Here, we explore the land use/land cover change occurring between 1987 and 2019 in the Mambasa sector, located in the Democratic Republic of Congo, and used the cellular automata model to predict the 2035 land use/land cover. The results have shown that during the last 32 years, dense forest has lost approximately 5121.54 ha, while secondary forest, fallow land and fields and, built-up area have gained 1786.23 ha, 3140.46 ha and 194.85 ha respectively. The predicted land use/land cover for the year 2035 revealed that dense and secondary forests will continue to experience a decrease of 3.85% and 13.65% respectively, while built-up area and fallow land and fields will experience an increase of 6.9% and 34.25% respectively. However, the study revealed that the unsustainable agriculture system combined with wood energy and artisanal logging have led to land use/land cover change in Mambasa. To reduce deforestation in the region, it would be necessary to improve agricultural production system, diversify the income and provide others timber product sources.
**Keywords:** *land cover, CA-ANN model, remote sensing, Mambasa*

## Introduction

For centuries, human beings have been destroying the natural resources in order to satisfy their food needs through agricultural activities (Houghton, 1994). It is true that, for several years, the increase of human populations leads to the increase of the demand in natural resources, resulting in land degradation (Wondie et al., 2011).

Ouedraogo et al. (2010) has reported that, in tropical regions, the conversion of the natural forest areas to farmlands for the purpose of satisfying the increasing human population demand for natural resources makes agricultural activities one of the main causes of land degradation. Currently, land use/land cover change has been known for their negative effects on the survival of humankind. Indeed, in most cases, Land use/ land cover change strongly impacts crucial aspects of the functioning of the Earth (Lambin et al., 2001), especially with regard to their negative consequences on climate change (Song et al., 2018; Fan, 2015; Salazar et al., 2015; Houghton et al., 2017), degradation of soil (Alemu, 2015), global biogeochemical cycles such as carbon, nitrogen and water quality (Jain et al., 2013; Copeland et al., 1996; Schönhart et al., 2018; Le Maire et al., 2014; Spera et al., 2016; Sterling et al., 2013) as well as


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biodiversity loss (Haines-Young, 2009; Mantyka-Pringle et al., 2015; Wanger et al., 2010). Consequently, land use/land cover change has become one of the key environmental issues, specifically in tropical regions where deforestation is taking place at a rapid rate (Scholes and Van Breemen, 1997). Thus, performing studies on land use/ land cover change issues in these regions is important to reduce their negative consequences on humankind, and to assure the long-term persistence of natural resources.

According to Lambin et al. (2001), land cover points to the actual biophysical attributes of the Earth's surface (vegetation type, presence of water, rocks) whereas land use refers to the way in which the land cover is used. Thus, for numerous applications such as vegetation and farmland monitoring, analysis of the Earth's surface and atmosphere interactions, information on the current status of the land use/land cover is necessary (Townshend, 1992). Therefore, for the purpose of establishing sustainable land use policy with regard to natural resources, understanding the dynamics of the landscape is most important for development planners to suggest some good strategies to the current land-use for better management of natural resources and, to avoid some future unwanted negative consequences on humankind. In this context of spatiotemporal analysis, remote sensing technology can play a leading role in the frame of land use/land cover change monitoring.

Remotely sensed data, especially landsat images, have been extensively used in the frame of modeling land use/land cover change for different purposes (Ranagala et al., 2019; Song et al., 2018; Han et al., 2015; Simwanda et al., 2018; Rogan and Chen, 2004; Wu et al., 2006; Zhuravleva et al., 2013; Potapov et al., 2012; Chen et al., 2018). Indeed, for several decades, remote sensing combined with field measurements have been used with success to monitor the loss of forest cover all over the world (Defries et al., 2006). In addition, remote sensing technology possesses not only the capability to capture land use/land cover change information using different change detection techniques (Roy et al., 2002), but also, the ability to offer spatial information and repeated coverage of large areas (Lillesand et al., 2004).

Among numerous tools used for the purpose of modelling and predicting land use/land cover change, the Markov chain has not only been proved to be one of the powerful tools, but also delivered accurate results in the frame of land use/land change prediction (Halmy et al., 2015; Agarwal et al., 2002). Being a stochastic model, the Markov chain approach predicts the future evolution of one system based on the state of the initial time (Sinha and Kimar, 2013; Muller and Middleton, 1994). Numerous studies have used the Markov Cellular automata (CA) approach to predict land use/land cover change (Basse et al., 2014; Saputra et al., 2019; Li and Yeh, 2002; Nouri et al., 2014; Kumar et al., 2014; Mubea et al., 2010; Rendana et al., 2015). From these studies, it has been shown that Markov chain constitutes one of the most essential tools for land use planning and environmental change research over different regions of the world. The use of both stochastic Markov techniques and the cellular automata model seems to predict land use change better than the regression based models (Ye and Bai, 2008; Pontius and Malanson, 2005).

There are numerous tools used to model and predict land use/land cover change, but it seems that no research has been carried out to examine the land use/land cover change of the Mambasa sector, even though this region, located in amongst forested areas of the Democratic Republic of Congo, where pressures on forests are ever increasing, still experience accelerated land degradation, biodiversity loss, and climate change. And yet,


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accurate and current information on land use/land cover change is important to provide valuable information to decision-makers for elaborating good policies and strategies of sustainable forest management in Mambasa. Indeed, the assessment of the landscape dynamic due to human activities can provide the status of each land use/land cover type and its recent evolution so that further decision making processes can be initiated to undertake sustainable land use management Thus, the objectives of this study are (i) to analyze the spatio-temporal change of land use/land cover change of Mambasa sector from the year 1987 to 2019 and, (ii) to predict the future land use/land cover of the year 2035 using CA-ANN model.

## Materials and methods

### *Study area*

This study was conducted in Mambasa, an administrative sector of the Democratic Republic of Congo. It is located between 1°7′0″-1°29′0″N in latitude and 28°53′0″-29°7′0″E in longitude (*Fig. 1*). Its total land area is estimated at 45669.24 ha, entirely located in the Congolese central basin. The region is dominated by dense rainforest and equatorial climate. This climate is characterized by two dry seasons, notably the long dry season (between January and February) and the small dry season (between June and August). Over the two last decades, Mambasa has experienced considerable population growth that has negatively impacted its natural resources. Consequently, careful assessment of land use/land cover change is required to help decision makers for the purpose of elaborating sustainable land management planning of natural resources.

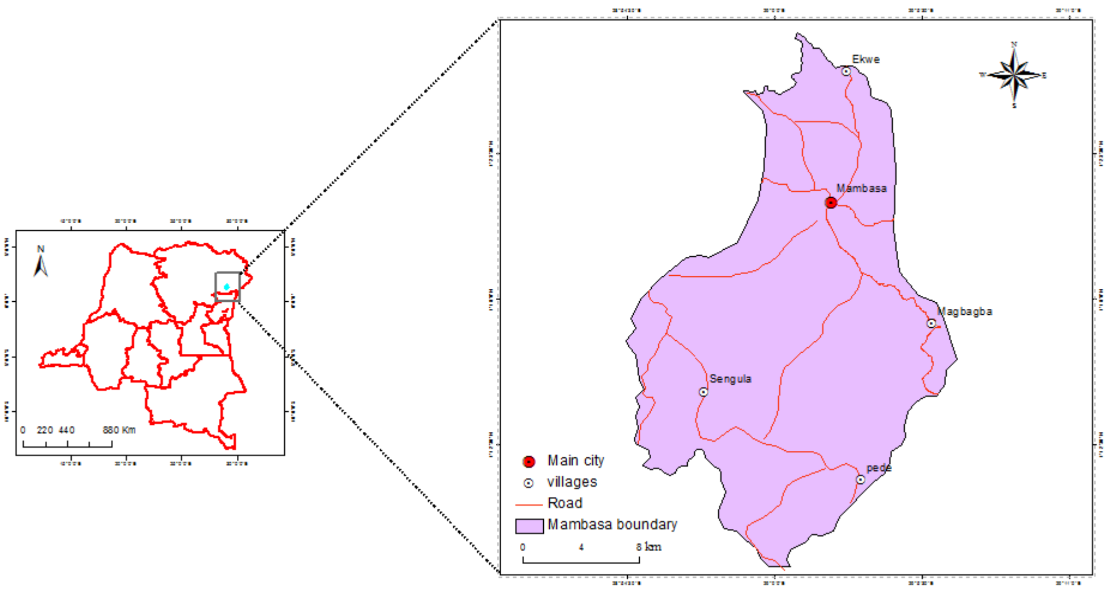


***Figure 1.*** *Location of Mambasa sector in the Democratic Republic of Congo*

### *Data collection*

According to the Landsat Worldwide Reference System (WRS), Mambasa is located at the Path and Row position of 174 and 59, respectively. Thus, Landsat images of the year 1987, 2003 and 2019, were freely downloaded from the website of the US


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Geological Survey National Center for Earth Resources Observation and Science (http://glovis.usgs.gov/), in order to extract crucial information on land use/land cover change in the Mambasa sector. In addition, as it requires to better know the region before performing supervised classification, field observations were carried out during March 2019 for the purpose of understanding the characteristics of each land use/land cover category. Thus, for each land use/land cover class, 150 training reference points were collected using the GPS receiver. The three landsat images were acquired in March and February because of cloud free images or clear sky during that period (*Table 1*). Indeed, using satellite images acquired almost in the same period remains an important advantage of land use/land cover change study. This removes the effects of change in season when investigating year-to-year change, and also minimizes the discrepancies in reflectance caused by seasonal vegetation fluxes, climatic differences and sun angle differences (Singh, 1989).

***Table 1.*** *Characteristics of remotely sensed data used for the study*

| Sensors | Acquisition date | Spatial resolution | Path/row | Band combination | Source |
|---|---|---|---|---|---|
| LT05 | March 1987 | 30 m | 174/59 | 5, 4, 3 | http://glovis.usgs.gov/. |
| LE07 | February 2003 | 30 m | 174/59 | 5, 4, 3 | http://glovis.usgs.gov/. |
| LC08 | March 2019 | 30 m | 174/59 | 6, 5, 4 | http://glovis.usgs.gov/. |

### *Land use/land cover classification and change detection*

After performing the image preprocessing (radiometric calibration and atmospheric correction using the FLAASH method), we then carried out supervised classification of the 1987, 2003 and 2019 satellite images following the Yangambi vegetation classification system. Firstly, field data was collected for each land use/land cover class in order to identify the spectral signature of each one (*Fig. 2*). In addition, using the maximum likelihood algorithm, satellite images were classified into four categories, namely dense forest, fallow land and fields, secondary forest and built-up area. In fact, the maximum likelihood algorithm is a parametric decision whose rule is based on the probability that has a certain pixel belonging to a certain category. It has been reported that this algorithm provides the higher classification accuracy in land use/land cover study (Vadrevu, 2013). Ultimately, post-classification operations were applied to improve the classified images. For our research, different software were applied as each one has its strength in certain operations needed for analysis. All image processing (image preprocessing and classification, change detection and accuracy assessment) were performed in ENVI 5.3 software and QGIS, while ArcGIS 10.1 was used to produce the final map.

To describe land cover change occurring between 1987 and 2019, the transition matrix method was applied. The transition matrix corresponds to a squared matrix describing changes occurring on different elements of a system during a certain period (Bell, 1974). Cells of matrix contain values of the variable which changed the state from initial time to final time. Values of column and rows represent the proportion of an area occupied by each land cover class at the corresponding time.

*Figure 3* shows the overall workflow of the study, including all the different steps from data collection to the production of the predicted land use/cover map.


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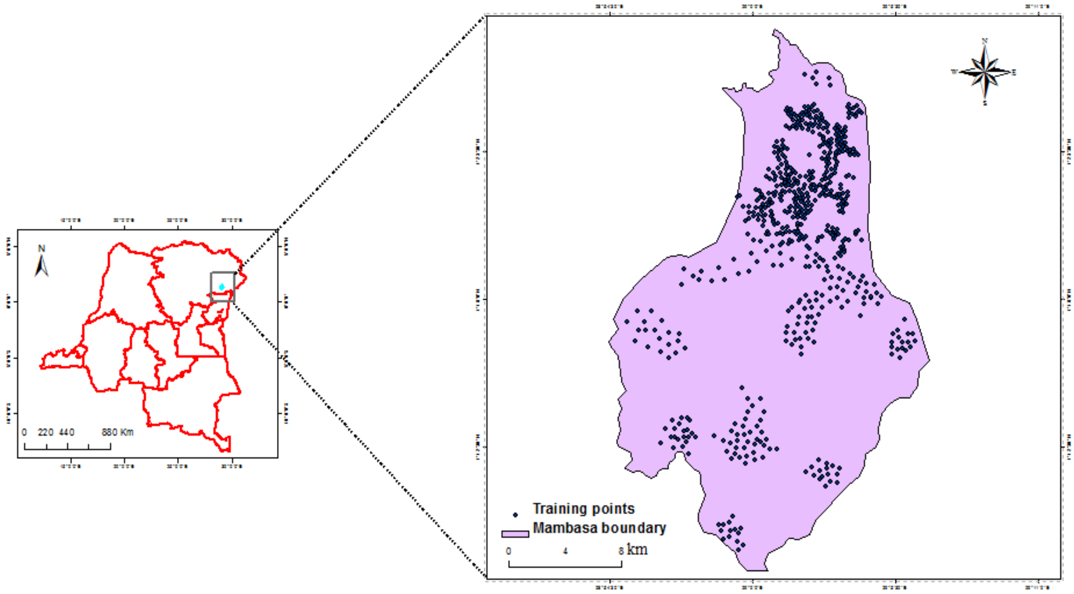


***Figure 2.*** *Location of training reference points collected during the field survey in the Mambasa sector*

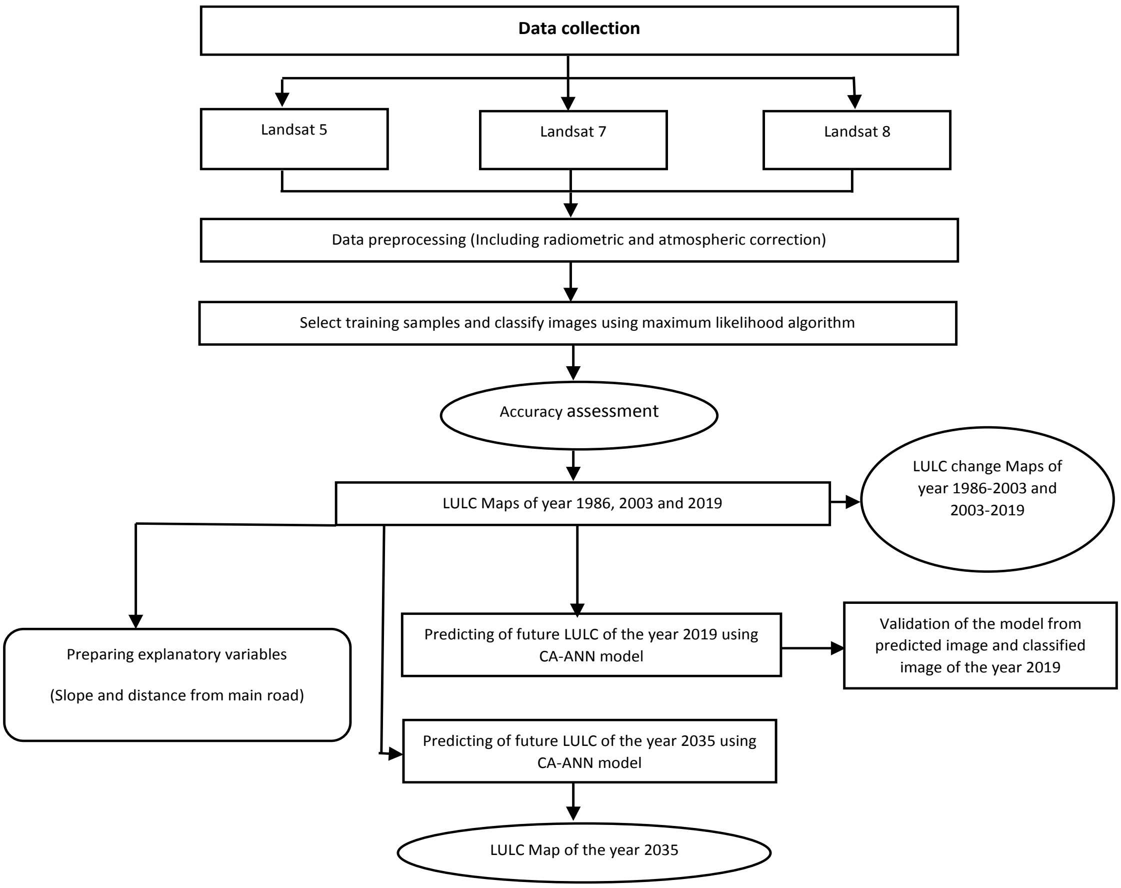


***Figure 3.*** *Schematic diagram of the research approach*

## *Prediction of future land use/land cover change*

For the purpose of predicting land use/land cover change in the Mambasa sector, MOLUSCE plugin imbedded in QGIS software was used. The cellular automata (CA) model was then applied, and the artificial neural network (ANN) algorithm was used in the model. Indeed, Jogun (2019) has stated that the use of the machine learning algorithm such as ANN to predict land cover change, is better than other methods like linear regression. Thus, two explanatory variables namely slope and distance from main roads in the Mambasa sector, were used in order to predict the future change. Firstly, the 1987 and 2003 classified images were used to predict the 2019 land use/land cover. Then, the three map comparison method was performed for the validation of the prediction results. As the validation results have shown high accuracy, the 2035 land use/land cover was predicted by means of 2003 and 2019 classified images.

*Figure 4* describes the structure of the CA-ANN model. Neurons in the input layers are considered as a set of cellular attributes, which are explanatory variables (slope and distance from main roads). It was reported that these variables explained the land use/land cover change probabilities. In the output layer, a neuron relates to a land use/land cover category. Each neuron value in the output layer represented the transition probability from the existing class to the corresponding land use class.

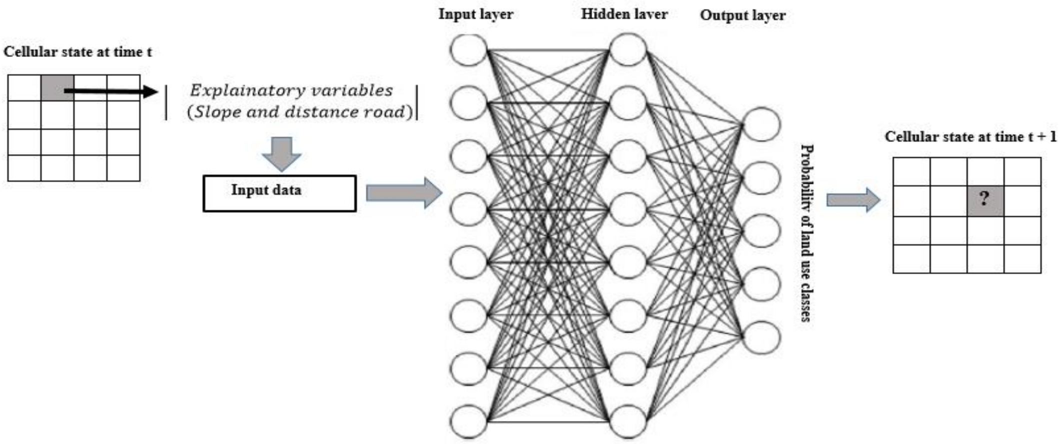


***Figure 4.*** *Processing architecture of ANN-CA model*

### *Accuracy assessment*

To use a land use/land cover map, it is crucial to know the accuracy of the map (Plourde and Congalton, 2003; Smits et al., 1999). Thus, accuracy assessment for the 1987, 2003 and 2019 maps was performed to appreciate the quality of information resulting from the image classification process. The confusion matrix method, which is the most common approach for appreciating image classification accuracy, was applied (Congalton, 1991). In this article, the reference data (ground truth points) were collected in March 2019 to perform the accuracy assessment of the 2019 classified image, while Google earth was used to carry out accuracy assessment for the 1986 and 2035 classified images. We then compared the observed pixels (ground truth points) of every land use/land cover class to the map pixel. The results were generated into the confusion matrix in order to assess the 1987, 2003 and 2019 final land use/land cover map accuracy. The overall user's and producer's accuracies were calculated from the confusion matrix. According to Pontius and Millones (2011), the producer's accuracy is


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used for determining how well an image is classified. In addition, the Kappa coefficient, one of the most statistic parameter for assessing image classification accuracy, was also computed (Rosenfield and Fitzpatrick-Lins, 1986).

Therefore, the overall accuracy of classification for the 1987, 2003 and 2019 map are 88.16% (kappa value 0.85), 89.16% (kappa value 0.86) and 93.6% (kappa value 0.91), respectively. As noted by (Weng, 2002), the minimum level for accuracy assessment in identification of land use/ land cover categories in the field of remote sensing should be at least 85%.

## Results

### *Accuracy assessment of satellite image classification*

The land use/land cover classification was successfully carried out with a high accuracy level. The overall accuracy of the 2019, 2003 and 1987 maps are 93.6% (kappa value 0.91), 89.15% (kappa value 0.86) and 88.16% (kappa value 0.85), respectively.

For the 2019 map, error matrix has been presented in *Table 2*. 159 of 170 field samples were correctly classified. The main confusion was observed between dense forest and secondary forest, with four validation points on secondary forest classified as dense forest, while two validation points on dense forest were classified as secondary forest. In addition, two validation points in secondary forest were classified as fallow land and field, while one validation point in the built-up area was classified as secondary forest.

For the 2003 map, error matrix has been presented in *Table 3*. A total of 218 reference points were checked against Google Earth image.196 of 218 validation samples were correctly classified. The main confusion was observed between dense forest and secondary forest, with seven validation points on secondary forest classified as dense forest, while six validation points in dense forest were classified as secondary forest. In addition, one validation point in secondary forest was classified as fallow land and field, while two validation points in fallow land were classified as secondary forest. Three validation points in fallow land were classified as built-up area, and three validation points in the built-up area were classified as fallow land and fields.

***Table 2.*** *Error matrix of land cover map produced by supervised classification of 2019 image*

| **Number of pixels** | **Reference data** | | | | | **User's accuracy (%)** |
|---|---|---|---|---|---|---|
| **Classified image** | **DF** | **SF** | **FF** | **BA** | **Row total** | |
| DF | 61 | 2 | 0 | 0 | 63 | 96.3 |
| SF | 4 | 42 | 2 | 0 | 46 | 91.3 |
| FF | 0 | 0 | 34 | 2 | 39 | 92.3 |
| BA | 0 | 1 | 0 | 22 | 24 | 91.7 |
| Column total | 65 | 45 | 36 | 24 | | |
| Producer's accuracy (%) | 93.9 | 93.3 | 94.7 | 91.7 | | |

Overall accuracy: 93.6, Kappa statistic: 0.91

***Table 3.*** *Error matrix of land cover map produced by supervised classification of 2003 image*


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| Number of pixels | Reference data | | | | | |
|---|---|---|---|---|---|---|
| **Classified image** | **DF** | **SF** | **FF** | **BA** | **Row total** | **User's accuracy (%)** |
| DF | 68 | 6 | 0 | 0 | 74 | 91.9 |
| SF | 7 | 52 | 1 | 0 | 60 | 86.7 |
| FF | 0 | 2 | 48 | 3 | 53 | 90.6 |
| BA | 0 | 0 | 3 | 28 | 31 | 90.3 |
| Column total | 75 | 60 | 52 | 31 | | |
| Producer's accuracy (%) | 90.7 | 86.7 | 92.3 | 90.3 | | |

Overall accuracy: 89.16, Kappa statistic: 0.86
DF: dense forest, SF: secondary forest, FF: fallow land and fields, BA: built-up area

### *Spatial and temporal changes in land use/land cover*

Summary statistics of Land use/land cover change for the Mambasa sector for the years 1987, 2003 and 2019 developed from supervised classification are listed in *Table 4*.

***Table 4.*** *Evolution of land use/cover in Mambasa sector from 1987 to 2019*

| Land use/cover classes | Spatial area coverage | | | | | | Annual rate of change |
|---|---|---|---|---|---|---|---|
| | **1987** | | **2003** | | **2019** | | **1987-2019** |
| | **Area (ha)** | **%** | **Area (ha)** | **%** | **Area (ha)** | **%** | **ha/year** |
| Built-up area | 302.76 | 0.66 | 412.02 | 0.9 | 497.61 | 1.09 | 6.09 |
| Fallow land and fields | 2763.99 | 6.05 | 4149.36 | 9.09 | 5904.45 | 12.93 | 98.14 |
| Secondary forest | 3753.54 | 8.22 | 5804.01 | 12.71 | 5539.77 | 12.13 | 55.82 |
| Dense forest | 38848.95 | 85.07 | 35303.85 | 77.3 | 33727.41 | 73.85 | -160.05 |
| Total | 45669.24 | 100 | 45669.24 | 100 | 45669.24 | 100 | |

During our survey, Mambasa sector's landscape was classified into four land cover/land use types including dense forest, Secondary forest, Fallow land and fields, and built-up area (*Fig. 5*). On the basis of analysis carried out in 1987, it was noted that approximately 85.07%, 8.22%, 6.05% and 0.66% of the total area subject to analysis were calculated as dense forest, Secondary forest, Fallow land and fields, and built-up areas, respectively; while, in 2003, around 77.3%, 12.71%, 9.09% and 0.9% of the total area was calculated as dense forest, Secondary forest, Fallow land and fields, and built-up areas, respectively. In 2019, 73.85%, 12.13%, 12.93% and 1.09% were classified as dense forest, Secondary forest, Fallow land and fields, and built-up areas, respectively. Consequently, the land use/land cover change from 1987 to 2019 have shown an increasing in Secondary forest, Fallow land and fields, and built-up areas, by 1786.23 ha, 3140.46 ha, and 194.85 ha respectively; while in the same period dense forest underwent significant negative change. Indeed, dense forest land has strongly declined in the same period. Approximately 160.05 ha of dense forests were converted every year into other land use/land cover categories during the study period. However, the main change during the study period in the Mambasa sector was observed in the area converted from dense forest into Fallow land and fields.


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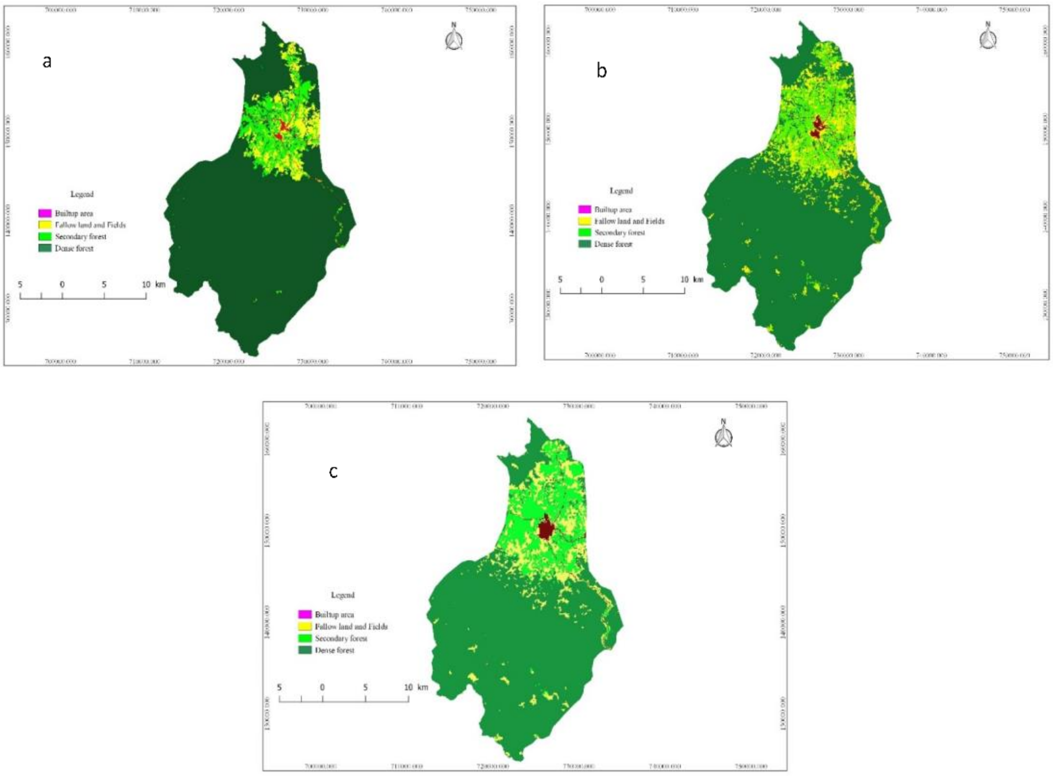


***Figure 5.*** *Land use/land cover map for the year (a) 1987, (b) 2003 and (c) 2019*

### *Transition among land use/land cover types from 1987 to 2019*

From the transitional probability matrix, it is easy to understand the trend in land use/land cover change occurring in the Mambasa sector during the study period. Indeed, the transitional probability matrix shows the probability of each cell of a certain land use/land cover type to be transformed into other types. Using the Markovian approach, the transitional probability matrix between the years 1987 to 2003, 2003 to 2019, and 1987 to 2019 has been performed in the MOLUSCE plugin. From *Table 5*, it can be revealed that, between 1987 and 2003, the probability of each land use/land cover category to be converted into fallow land and fields was higher than any other transition (third column). Moreover, it should be noted that, the conversion from dense forests to secondary forests is seen firstly as a conversion of dense forest into fallow land and fields; but when this land use/land cover class (fallow land and fields) is abandoned, it progresses into secondary forest by the natural process of vegetation succession. In addition, the no conversion from built-up area into dense forest was represented by zero values between 1987 and 2003, while, from 2003 to 2019, zero values represent no conversion of dense forest into built-up area. *Figure 6* represents the change maps that shows the transformation from one land use/land cover class to the others during 1987 to 2019. From the change maps, it was shown that the major part of the Mambasa landscape was converted into fallow land and fields. A total of 37426.05 ha of our study area did not change between 1987 and 2019. Among them, 33495.56 ha persisted as dense forest, 2356.01 ha as secondary forest, 1381.44 ha as fallow land and fields and 192.95 ha as built-up area. On the other hand, around 3325.47 ha, 1117.80 ha, and 81.26 ha of our study area


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were converted from dense forest, secondary forest, and built-up area respectively into fallow land and fields during 1987 to 2019.

***Table 5.*** *Transition matrix of land use/cover changes in Mambasa sector from 1987 to 2019*

| | Land cover category | | | | |
|---|---|---|---|---|---|
| | **From \ To** | **Built-up area** | **Fallow & fields** | **Secondary forest** | **Dense forest** |
| 1987-2003 | Built-up area | 0.7155 | 0.1813 | 0.1031 | 0.0000 |
| | Fallow and fields | 0.0440 | 0.4007 | 0.5314 | 0.0239 |
| | Secondary forest | 0.0112 | 0.2032 | 0.6717 | 0.1139 |
| | Dense forest | 0.0008 | 0.0573 | 0.0459 | 0.8960 |
| 2003-2019 | Built-up area | 0.8746 | 0.0799 | 0.0443 | 0.0011 |
| | Fallow and fields | 0.01997 | 0.9290 | 0.0292 | 0.0216 |
| | Secondary forest | 0.0092 | 0.1809 | 0.7377 | 0.0722 |
| | Dense forest | 0.0000 | 0.0274 | 0.0317 | 0.9409 |
| 1987-2019 | Built-up area | 0.6373 | 0.2684 | 0.0859 | 0.0083 |
| | Fallow and fields | 0.0559 | 0.4998 | 0.4251 | 0.0193 |
| | Secondary forest | 0.0280 | 0.2978 | 0.6277 | 0.0465 |
| | Dense forest | 0.0012 | 0.0856 | 0.0510 | 0.8622 |

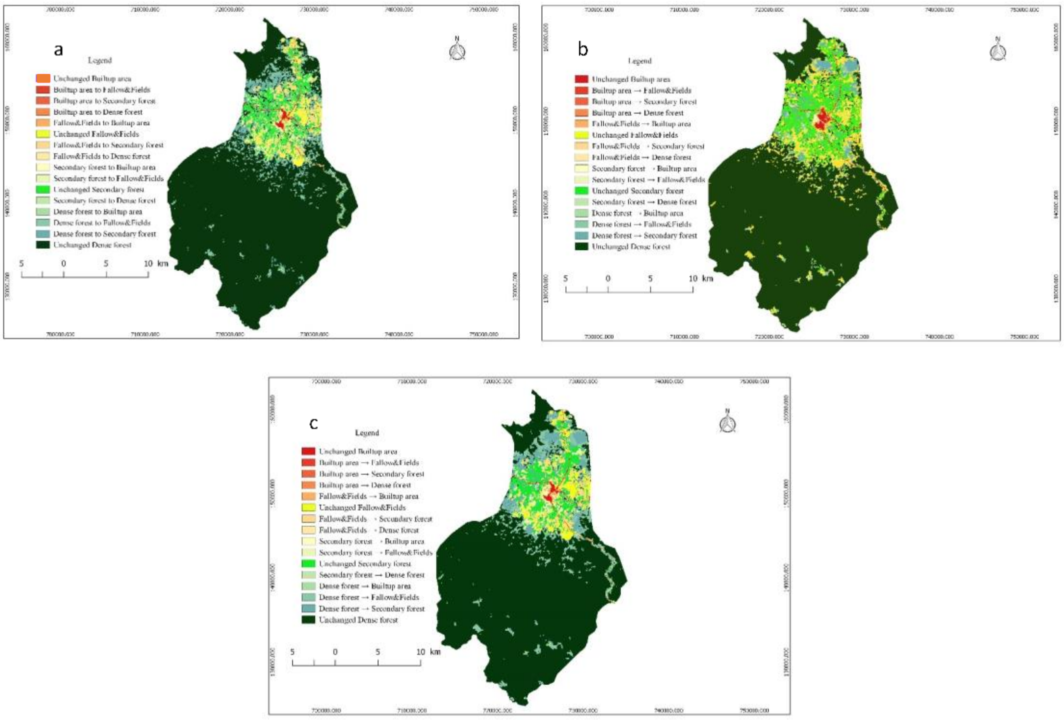

***Figure 6.*** *LULC transformation of Mambasa sector during (a) 1987 to 2003, (b) during 2003 to 2019 and (c) during 1987 to 2019*

***Prediction of the future land use change 2035***

After performing the change detection analysis, the next step of this study was focused at forecasting the future land use/land cover for the year 2035. Thus, the simulated map of 2035 as shown in *Figure 7* was carried out using two spatial drivers


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including slope and distance from main roads. Firstly, the land use/land cover for the year 2019 was predicted by using both land use/land cover maps of the year 1987 and 2003, by means of the Cellular automata Artificial Neural Network (CA-ANN) algorithm. Then, the three map comparison method was applied to validate the prediction results. It has been demonstrated that the model, by its strong performance measured by the percentage of component agreement at 97.3%, was able to predict the future land use/land cover change almost correctly. After the validation of the model, the land use/land cover for the year 2035 was predicted from the year 2003 to 2019. In 2035, Mambasa sector will have an increase in Fallow land and fields (34.25% ha) and built-up area (6.9% h), while dense and secondary forest will lose 3.85% and 13.65% respectively (*Table 6*).

***Table 6.*** *Summary of LULC change statistics between 2019 and 2035*

| **LULC classes** | **Area in hectare** | | **Area change from 2019 to 2035 in (%)** |
|---|---|---|---|
| | **2019** | **2035** | |
| Built-up area | 497.61 | 531.90 | 6.9 |
| Fallow & fields | 5904.45 | 7926.48 | 34.25 |
| Secondary forest | 5539.77 | 4783.50 | -13.65 |
| Dense forest | 33727.41 | 32427.36 | -3.85 |

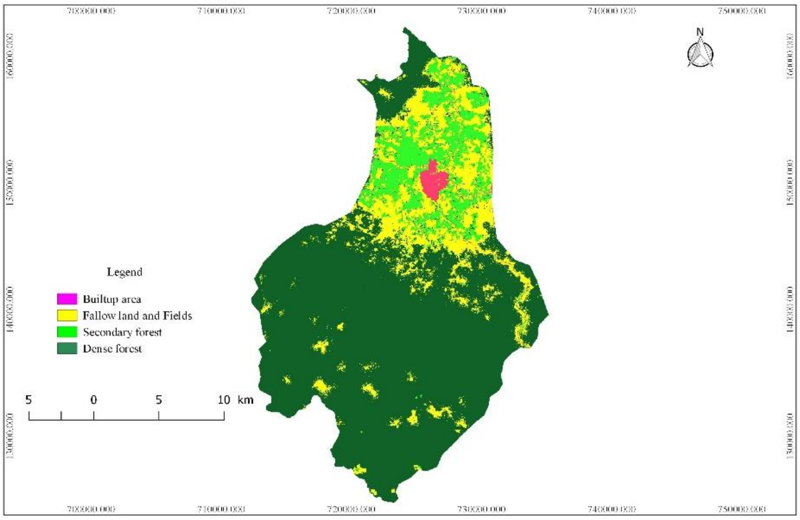


***Figure 7.*** *Predicted LULC for the year 2035*

## Discussion

### *Land use/land cover change from the year 1987 to 2019 and future prediction of 2035*

The present study aimed to assess the land use/land cover change in the Mambasa sector from 1987 to 2019, and predict the spatio temporal change by 2035 using the Cellular automata Artificial Neural Network (CA-ANN) algorithm. The results revealed significant change in Mambasa's landscape during the study period. Indeed, Mambasa's landscape was classified into four categories namely dense forest, secondary forest, built-up areas as well as fallows and fields. During the last 32 years, dense forest has approximately lost 5121.54 ha, while secondary forest, fallow land and fields, built-up


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area have gained 1786.23 ha, 3140.46 ha and 194.85 ha respectively. The ratio of dense forest in the landscape declined from 85.07% in 1987, to 73.85% in 2019. Thus, the annual rate of deforestation observed in dense forest was estimated at 0.41. This rate is well above the national average, estimated between 0.2 and 0.3% over the last three decades (UN-REDD, 2012; de Wasseige et al., 2014). As for secondary forest, its area has also increased during the last three decades, from 3753.54 ha in 1987 to 5539.77 ha in 2019. Note that most of its area comes from dense forest that has been converted into fallow land and fields and, after being abandoned, it evolved to secondary forest through the natural process of succession vegetation. Fallow land and fields showed a positive evolution following the acquisition of areas mainly lost in dense and secondary forests, respectively 3325.47 ha and 1117.8 ha. Its proportion in the landscape increased from 6.05% in 1987, to 12.93% in 2019. This can be explained by the expansion of agricultural activities in this region and the increase of population in the region (*Table 7*). As reported by (Aweto, 2012), in the humid and sub-humid tropics, several hundred million people depend on agriculture system based on shifting cultivation or rotational bush fallowing for their livelihood. Indeed, agriculture system in Mambasa is based on shifting cultivation that consists in clearing primary or secondary forest to install fields. These fields can be cultivated for one or two years before soil fertility is exhausted. The field is then abandoned and the farmers move on to clear a new field elsewhere in the forest. Bamba (2010) has stated that, agriculture of DRC based on the slash-and-burn agriculture system has always been practiced for several decades. In addition, (Mpoyi et al., 2013) noted that the agriculture system in this region is based on unimproved varieties and unsustainable practices of soil fertility management. Consequently, several hectares of forest are lost every year for the benefit of crop land. Our results corroborate the findings of (Ngabinzeke et al., 2016) that reported that the expansion of slash-and-burn agriculture in the region is leading to a conversion of natural habitats. According to the study, significant changes occurred during a period of one year in the area under study. Forest and savanna areas declined by 6.5 ha (86.6 to 80.1 ha) while agricultural areas (cleared land and seasonal crops) increased from 7.3 ha to 21.8 ha. Similar results were obtained in a study conducted in the Kongo central province. In this study, it has been reported that fallow land and fields increased from 22.72% in 1960 to 54.61% in 2005; while forest land, the landscape's matrix in 1960, declined from 49.95% of the total area of landscape to 5.67% in 2005. The study has revealed that the decrease in forest area was due to the unsustainable agriculture system and demographic pressures (Bamba, 2010). In a study conducted in Isangi region, it was found that due to human activities, notably agriculture and forest logging for wood energy, the percentage of forest land decreased by 20.9% (59 004 ha to 46675 ha) during 2002–2010, while mosaic habitat-agriculture land increased by 24% (23191 ha to 28768 ha) during 2002-2010 (Ciza et al., 2015).

However, the predicted change in 2035 shows that, there will still be an increase in Fallow land and fields and Builtup area, while dense and secondary forest will experience a decrease by 1300.05 ha and 756.27 ha, respectively. The decrease in secondary forest can be attributed to the expansion of agriculture in that land cover category. In fact, after several years, secondary forest appear to be suitable for developing agriculture as well as dense forest. The decrease in dense forest can also be explained by the expansion of human activities such as agriculture, wood energy and logging.


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***Table 7.*** *Evolution of population of the Mambasa sector from 1987 to 2019*

| Year | Population |
|---|---|
| 1987 | 55000 |
| 2003 | 128000 |
| 2019 | 249369 |

### *Model validation*

The present study used the three map comparison method to evaluate the model performance for land use/land cover change simulation in Mambasa sector. This approach was proposed by Pontius et al. (2011), and consists of two components of agreement and three components of disagreement (Bayes and Raquib, 2012). Indeed, the components of agreement include persistence simulated correctly (correct rejection) and change simulated correctly (hits), while the components of disagreement contain change simulated as persistence (misses), persistence simulated as change (false alarm), and change simulated as change to wrong category (Wrong hits). After implementing the three-map comparison method, it has been revealed that the simulated map yields the best result in terms of the percentages of component disagreement (2.3%) and component agreement (97.7%), as presented in *Table 8*.

***Table 8.*** *Components of agreement and disagreement of three map comparison method*

| Name of component | % |
|---|---|
| Persistence simulated correctly | 96.13406 |
| Change simulated correctly | 1.534867 |
| Total agreement | 97.66893 |
| Change simulated as persistance | 0.423469 |
| Persistence simulated as change | 0.737927 |
| Change simulated as to wrong category | 1.169677 |
| Total disagreement | 2.331073 |

## Conclusions

The land use/cover change caused by direct and indirect human activities has negative consequences at spatial and temporal scales. Understanding those changes provides relevant knowledge that is most important for decision-makers and civil society. This study examines land use/cover change in the Mambasa sector between 1987 and 2019, and uses CA-ANN to predict the future land cover change by 2035. During the last 32 years, It was shown that dense forest has approximately lost 5121.54 ha, while secondary forest, fallow land and fields, built-up area have gained 1786.23 ha, 3140.46 ha and 194.85 ha, respectively. The ratio of dense forest in the landscape declined from 85.07% in 1987, to 73.85% in 2019. Thus, the annual rate of deforestation observed in dense forest was estimated at 0.41%. From the change occurred in Mambasa landscape, it was revealed that the major part for the Mambasa landscape was converted into fallow land and fields. A total of 37426.05 ha for the Mambasa landscape were considered as persistence between 1987 and 2019. Among them, 33495.56 ha persisted as dense forest, 2356.01 ha as secondary forest, 1381.44 ha


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as fallow land and fields and 192.95 ha as built-up area. However, around 3325.47 ha, 1117.80 ha, and 81.26 ha were converted from dense forest, secondary forest, and built-up area into fallow land and fields during 1987 to 2019. The study revealed that the unsustainable agriculture system combined with wood energy and artisanal logging led to land use/cover changes in the Mambasa landscape. The predicted change in 2035 shows that, there will still be an increase in Fallow land and fields and built-up area, while dense and secondary forest will experience a decrease by 1300.05 ha and 756.27 ha, respectively. The decrease in secondary forest can be attributed to the expansion of agriculture in that land cover category. Hence, the present results should be taken into account to support sustainable management of Mambasa forest ecosystems and efficient use of natural resources. However, further studies on the effects of land use/land cover change on biodiversity composition, and the effects of climate change on it as well, should be undertaken to provide the whole vision of the phenomenon in the Mambasa sector.

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