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Land Use/Land Cover Dynamics and Future Changes Using a CA-Markov Model in the Mount Nlonako Forest and Peripheries (Littoral, Cameroon)

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Abstract

Forests are facing several challenges related to forest deforestation mostly due to the actions of man. The study used a CA-Markov model to examine land use/land cover dynamics from 1986 to 2022, as well as estimate future changes from 2022 to 2052 in the Mount Nlonako forest and peripheries. Three types of Landsat images (Landsat 4 - 5 Thematic Mapper (TM) images of 1986 and 2004, and Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS) image of 2022) were used for diachronic analysis. The results revealed six major land use/land cover classes namely: Dense forest, Clear forest, Farmland, Savannah, Built-up Area and Bare floor. Accuracy rates for land use/land cover classification ranged from 89.85% to 93.11%. The prediction model was accepted with an overall satisfaction rate of 84.08%. The Dense Forest class has been steadily decreasing from 138320.94 ha (75.42%) in 1986 to 84161.34 ha (45.89%) in 2022, corresponding to a total loss of 54159.6 ha (29.53%) over the 36-year period and is projected to reach 39028.34 ha (21.28%) in 2052 corresponding to a future loss of 45133 ha (24.61%) over a period of 30 years. Anthropogenic factors (mainly agriculture and industrial logging) and natural factors (excess rainfall) were responsible for the degradation of the area. Regardless of the limitations of the CA-Markov model due to the non integration of socio-economic factors, this study is a crucial alert to decison and policy makers to undergo protection procedures for this area to be protected, thereby involving the local communities in the management and restoration of the area through participatory management.

Keywords

Mount Nlonako Forest, Spatio-Temporal Change, Future Changes, CA-Markov Model, Degradation, Deforestation

1. Introduction

Land is one of the most essential natural resources on Earth, as life and several developmental activities depend on land surface (Karimi et al., 2018). Presently, 90% of tropical regions globally are undergoing significant alterations in their structure due to both natural and manmade influences, including deforestation and the intensification of agriculture (Saputra & Lee, 2019; Aniah et al., 2023). Furthermore, this has resulted in modifications to Land Use and Land Cover (LULC) (Leta et al., 2021). The decline in forest land has led to various negative outcomes or changes such as habitat loss and fragmentation, local extinction, increased susceptibility to alien species invasion, decreased soil infiltration rate, altered species diversity, local, regional, and global climate change, unstable soil carbon stock, and other greenhouse gases emitted from human activities (Rittenhouse et al., 2012). The geoenvironment and natural ecosystems have changed as an outcome of these changes (Aniah et al., 2023; Feudjio et al., 2023). According to several studies (Momo et al., 2018; Thangavelu et al., 2021), one of the key factors influencing changes in ecosystems and the services they provide is land use/land cover change (LULCC). Increases and declines in agriculture and forests, respectively, have been the hallmarks of the recent global shifts in the Land Use and Land Cover (LULC) trajectory (Saputra & Lee, 2019; Leta et al., 2021). Since the 19th century, fast population increase, urbanization, and industrialization have resulted in a major loss of biodiversity due to changes in land cover (Zapfack et al., 2002; Krauss et al., 2010). The FAO estimates that between 1900 and 2000, changes in land use and land cover on the African continent were primarily responsible for the loss of over 52 million hectares of forest, or 56% of the world's total forest cover (FAO, 2020). Changes in land use and land cover constitute the primary cause of changes in ecosystems and services in Cameroon (Momo et al., 2018; Temgoua et al., 2021; Feudjio et al., 2023). According to the report by FAO 2020, Cameroon forests constitute around 19 million hectares, (about 11% of the Congo Basin). This countrys' forest ecosystems account for close to 46.27% of the country's total land (Ngomin & Mvongo, 2015). Given the remarkable biodiversity of these forests, Cameroon is the second richest country in Central Africa's Atlantic region (Djomo & Chimi, 2017). Ndobe & Mantzel (2014) estimated that the forest land of the country (Cameroon) declined by approximately 400,000 hectares of the total forest cover between 1900 and 2000.

Globally, there are 4.06 billion hectares of forest cover, or roughly 0.5 hectares per person. However, these forests are not dispersed equitably throughout the earth and only make up 31% of the land area (Ngueguim, 2013; FAO, 2014;

Tchatchou et al., 2015). Tropical rainforests are among the world's most significant biomes with a high species diversity (Hill & Hill, 2001). Despite being regarded as the world's richest ecosystems, they have the highest rates of degradation and deforestation (Momo, 2009; Temgoua et al., 2018a, 2018b). Over the 2015-2020 period, the rate of deforestation was estimated at 16 million hectares per year, compared to 10 million hectares per year in the 1990s. Since 1990, there has been a decline of over 80 million hectares in the global area of primary forests. (FAO, 2020). The majority of the world's forests, or over 44% (1770 million hectares), are found in tropical regions. Over 60,000 tree species are listed in the Global Tree Search database, with over 20,000 of those species being placed on the IUCN Red List (De Wasseige et al., 2012) and approximately 8000 are considered threatened worldwide (De Wasseige et al., 2012). Nowadays, tropical forests are at the heart of international issues on climate change and conservation of biodiversity.

LULC mapping and change detection approaches have been created and put into practice globally over the last few decades (Akamba Bekono et al., 2023; Feudjio et al., 2023; Lum-Ndob et al., 2024). For analyzing the spatial and temporal dynamics of LULC changes over several decades and at different scales, remote sensing (RS) and geographical information systems, or GIS, have shown to be indispensable low-cost and effective technologies (Zekeng et al., 2019; Djiongo et al., 2020; Fokeng et al., 2020; Tsewoue et al., 2020; Temgoua et al., 2021; Chisanga et al., 2022; Liliane et al., 2022; Feudjio et al., 2023). This method aids in setting up and putting into practice conservation strategies and land use policies (Jin & Fan, 2018). These techniques provide more precise and timely monitoring of land use and change (Shojaei et al., 2018; Kermani & Rohrbach, 2018; Aliabad & Shojaei, 2019; Achu et al., 2019; Forozan et al., 2020; Lum-Ndob et al., 2024).

Despite the fast-growing population, which may be one of the primary causes of land degradation to meet rising demand for food and urban development, little or no research has been conducted to quantify forest loss and predict future changes in the Mount Nlonako forest area. The current study therefore is aimed to analyze temporal and spatial LULCC as well as quantify land cover changes over the last thirty years using satellite images and predict LULCC in the area from 2022 to 2052 using a CA-Markov model. Finally, the work will provide a solid scientific database to assist government officials and land use planners for the management of forests in general and Mount Nlonako forest in particular.

2. Material and Methods

2.1. Study Site

This study was carried out in the Mount Nlonako forest area, found in the Moungo division of Littoral region of Cameroon. The area is located between latitudes 4˚36'05" - 4˚57'05" North and longitudes 9˚54'10" - 10˚14'20" East, south of Nkongsamba town and east of Mount Kupe Muanengouba as seen in **Figure 1**. Mount Nlonako forest covers around 3500 hectares and has a peak of 1825 metres

(Mahmoud et al., 2020). Mount Nlonako is a wildlife forest with high level of faunal endemism, yet hunting and poaching are prevalent (Fonkwo et al., 2011). Mount Nlonako forest is a nature reserve home to the world's largest amphibian species (*Conraua goliath*), the majority of which are critically endangered and peculiar to this region (Hermann et al., 2005; Bergl, 2007; Fonkwo et al., 2011). Fast-growing population and land reclamation have significantly contributed to meeting the increasing demand for food and urban development in the Moungo division, which shares a border with the Nkam division in the Littoral region of Cameroon (Tsewoue et al., 2020; Mathaus et al., 2023). The vegetation is a dense humid semi-deciduous forest dominated by plants from the families Myristicaceae, Fabaceae, Olacaceae, Bombacaceae, and Anacardiaceae (Sainge et al., 2018). Subsistence farming is the primary activity of local populations. Cash crops such as cocoa and coffee are widely grown (Tsewoue et al., 2020).

The climate is humid pseudotropical with an unimodal rainfall regime. There are two seasons: a lengthy rainy season from March to October and a brief dry season from November to February. Precipitation is plentiful and varies by altitude: Nkongsamba (877 m, 2684 mm), Nlonako (1825 m, 3000 mm), and Nkondjock (339 m, 2000 mm). The average temperature is 26˚C at Nkongsamba, 20˚C at the top of the mountain and 27˚C at Nkondjock (Lacatuce et al., 2023).

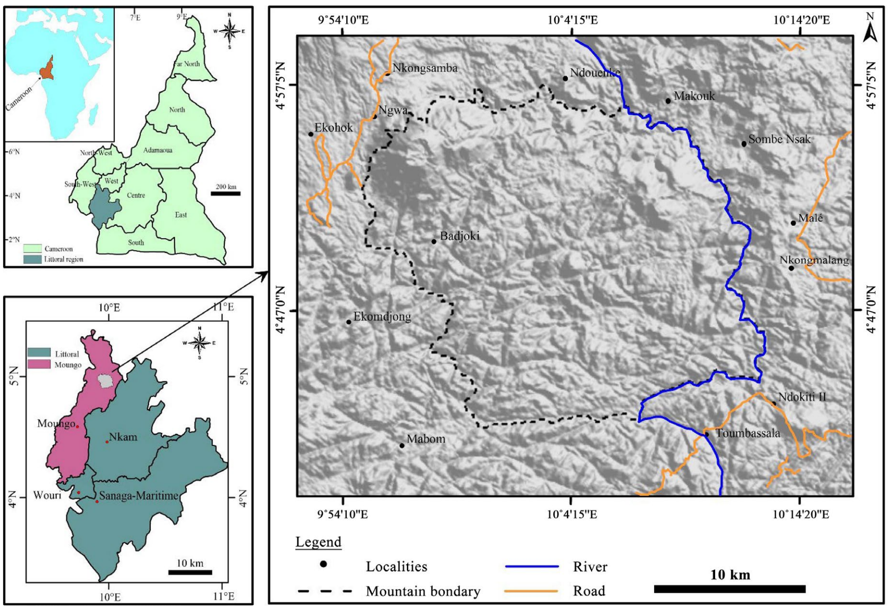


Figure 1. Location of Mount Nlonako study area in Littoral Cameroon, Central Africa.

2.2. Data Acquisition and Processing

Freely available landsat images were downloaded from United States Geological Survey (USGS) Glovis data archive (http://glovis.usgs.gov/) and registered using the Universal Transverse Mercator (UTM) projection of World Geodetic System (WGS) 1984 zone 32. The data includes Thematic Mapper (TM, 1986), Thematic Mapper (TM, 2004), and Operational Land Imager and Thermal Infrared Sensor

(OLI-TIRS, 2022) with a compatible spatial resolution of 30 m (Table 1). In addition, these photographs were in good condition, with no cloud cover or rain. Figure 2 summarizes all the methods and analyses used in this work to quantify forest loss and provide predictions.

Table 1. Characteristics of the Landsat data sources used in this study.

Missions	Sensors	Date of acquisition	Number of bands	Spatial resolution	Projection	Cloud cover
Landsat 4 - 5	TM	February 1986	7	30 m	WGS84 UTM Zone 32N	0.002%
Landsat 4 - 5	TM	May 2004	7	30 m	WGS84 UTM Zone 32N	0.001%
Landsat 8	OLI-TIRS	November 2022	9	30 m	WGS84 UTM Zone 32N	0.002%

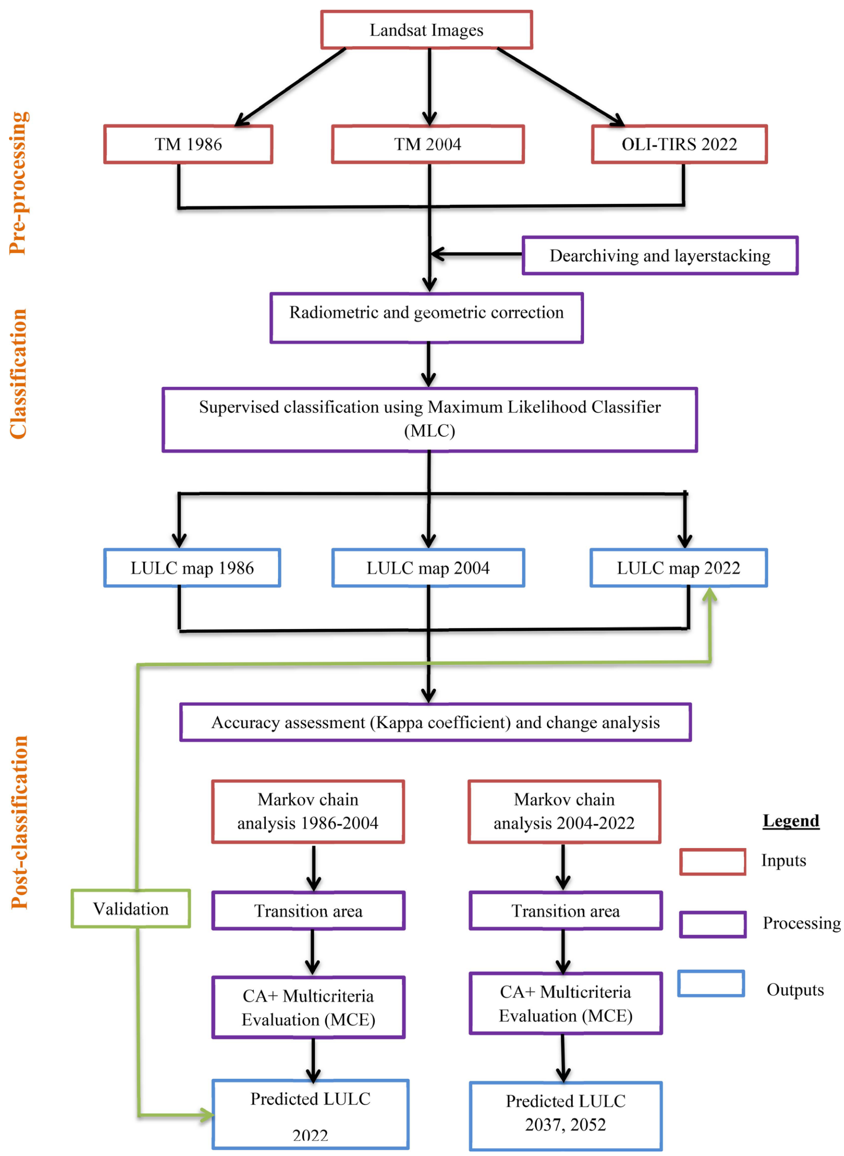


Figure 2. Methodological flowchart used for the production and prediction of LULC maps.

For the processing of images, obtained strips were constructed using the ERDAS IMAGINE program 2018, version 16.5. After the strips had been assembled, image preprocessing was performed. This included dearchiving and relocating the 1 m pixel offsets, as well as conducting radiometric and geometric adjustments. The radiometric upgrade consisted of fixing sensor errors, atmospheric veil, and redistributing color levels in order to make the best use of the available palette. The geometric adjustment involved correcting the landsat images so that they overlapped with other images. After the changes were done, it was essential to mosaic the several photographic sets to create a continuous panorama of the research area.

2.3. Image Classification Using Maximum Likelihood Classifier

Photographic images were interpreted and classified using a supervised classification technique, allowing evidence of land use/land cover change (LULCC) to be obtained from multi-band and multi-temporal raster images. Maximum Likelihood Classifier (MLC) was used for the classification of images since it takes less time to compute than any other supervised classification approach (Al-Ahmadi & Hames, 2009; Mondal et al., 2016). The MLC approach relies on the assumption that all pixels will be assigned to one of the classes. However, MLC method only works efficiently provided that the spectrum information is properly distributed as an effect of its parametric approach (Abdullah et al., 2019). This issue is addressed during post-classification correction with auxiliary data. In this study, Erdas Imagine software was used to execute MLC after geo-referencing, pre-processing, mosaicking, and sub-setting the Mount Nlonako forest. Six land use/land cover (LULC) classes were identified following the first visual image interpretation by incorporating sensor spatial resolution. As a result, sample pixels were extracted from satellite images by making appropriate adjustments to band combinations. Colored compositions (4-3-2) for 1986 image scenes, (4-3-2) for 2004 image scenes, and (4-3-2) for 2022 image scenes were also used, with the sample spectral signatures (180 for each class) later used in LULC classification. False color composite pictures of Landsat Thematic Mapper (TM) (1986), Landsat TM (2004), and Landsat Operational Land Imager with Thermal Infrared Sensor (OLI-TIRS) (2022) were created. When developing training signatures, spectral separation of features was ensured using scatter plots of each spectral value. An identification file was thus generated by choosing pixels with homogeneous surface types and combining them with six LULC classes: Dense forest (DF), Farmland (FL), Clear forest (CF), Savannah (SV), Built-up area (BUA), and Bare floor (BF) (**Table 2**).

Table 2. Classes delineated on the basis of supervised classification.

LULC Classes	Description
Dense forest	All naturally occurring lands in which trees cluster together to produce a thick and permanently leafy canopy throughout the year, with a density greater than 60%. The forest here is intact with relatively little or no disturbance.

Continued

Clear forest	Forestland with a crown cover of 15% - 60%. Their low crown-cover canopy indicates degradation caused by planned or uncontrolled logging, mining, and agricultural operations. This can also be know as degraded forest.
Farmland	Areas used for cultivation of both annual and perennial crops, as well as juvenile cash crop plantations.
Savannah	Areas characterized by grass, regardless of woodland savannah or shrub.
Bare Floor	Areas with little or no vegetation cover, including open fields, bare slopes, and exposed rocks.
Built-up-area	Dedicated to residential and commercial sectors, as well as infrastructure (roads, buildings, cities, and villages).

2.4. Change Detection and Accuracy Assessment

After classifying land use and land cover, a post-comparison of changes was performed, allowing for the determination of LULC changes. A confusion or error matrix was used to test the accuracy of the production of the classified maps of 1986, 2004 and 2022. This matrix integrates a number of statistical methods to remove errors generated during the development of the output map. These errors include omission error, producer accuracy, commission error, and overall correctness (Alam et al., 2019). In this work, 440 randomly selected ground truth points for 1986, 2004, and 2022 LULC classified maps were chosen during a field survey and paired with geographical features, morphological maps, and high-resolution Google Earth images to assess accuracy. In addition, a nonparametric Kappa coefficient (K) was calculated for classification precision using Equation (1):

$$K = \frac{\sum_{i-1}^{r} Xa - \sum_{i-1}^{r} (Xb)(Xc)}{N^2 - \sum_{i-1}^{r} (Xb)(Xc)} \tag{1}$$

where r is the number of rows/columns in the confusion matrix, Xa is the number of observations in row i and column i, Xb is the total number of rows, Xc is the total number of columns, and N is the number of observations.

The annual change was quantified using the annual rate of change (R) formula proposed by Peng et al. (2008) and used by Temgoua et al. (2021).

$$R = \frac{A2 - A1}{A1} \times \frac{1}{T} \times 100 \tag{2}$$

where R is the yearly rate of land cover dynamic, measuring the change rate of the target land cover type; $A1$ and $A2$ are the area of the target land cover type at the beginning and end of the study period, respectively; and T is the study period, which is commonly defined in years.

Land use/land cover prediction using Cellullar Automata-Markov chain model

The "Cellular Automata" "Markov Chain" models (CA-Markov model) are thought to be useful for predicting land use changes (Mishra & Rai, 2016). The CA-Markov model is one of the most commonly used methods for LULCC forcasting (Wang et al., 2019). This model is the result of integrating the CA and

Markov chain models. Markov chain model was introduced in 1970 and first used by Burnham for simulation of land use (Mishra & Rai, 2016). It is a statistical technique that uses a transition probability matrix to anticipate the next state and all subsequent states depending on the current state (Wang et al., 2019). It accurately measures the projected change in land surface area from the most recent date to the anticipated date (Mondal et al., 2016). The outcome of this process is the transition probability file, which is a matrix that records the probability for each LULC class to change to another class. In addition, the analysis of two different periods from the LULC map produces the transition matrices, a transition area matrix, and a set of conditional probability images (Mishra et al., 2019). The Markov chain model uses the evolution from date t − 1 to t to project LULCC probability to a future date t + 1, where t stands for time (year). Nonetheless, the Markov chain model is inadequate for modeling and predicting LULC dynamics because it ignores the spatial distribution of each LULC class (Wang et al., 2019). To address this gap, the Cellular Automata (CA) model was incorporated with the Markov chain model so as to account for the spatial structure and geographic orientations of LULCC (Feudjio et al., 2023). The Markov Chain model was used in this study to calculate the transition probability matrix (conversion probability) and transition area matrix (conversion area matrix) of the LULC classes from 1986 to 2004 and 2004 to 2022, respectively while CA model was used to determine the spatial distribution and geographic directions of each LULC classes within the same time frame. The proportional error was set at 15% while creating the transition probability matrix. Later, this matrix was used to generate a data set with conditional probability for each LULC class. Finally, the transition probability matrices and conditional probability data were produced using the IDRISI Selva 17.0 software's CA spatial operator, based on Markov chain analysis and Multi Criteria Evaluation (MCE), to simulate LULC maps of 2037 and 2052. Additionally, a 5 × 5 pixel contiguity filter was used to construct spatially explicit contiguous weighting factors that prioritize pixels closer to the existing LULC class over pixels further away. Although the number of iterations is determined by the number of years the prediction is executed, it was set to 15 for this study, reflecting the years 2022 to 2037 and 2037 to 2052. On the other hand, Markov chain analysis was used to approximate the transition probability matrix from 2022 to 2037, as well as from 2037 to 2052.

2.5. Model Validation

To confirm the accuracy of the CA-Markov model, a comparison was done between the classified and forecasted LULC maps for 2022. The estimated LULC map for 2022 is based on the 2004 LULC data and the transition area matrix during an 18-year period. To further assess the correctness of the CA-Markov model in this work, Kappa indices of agreement were calculated using the "Validate" tool in IDRISI Selva software with a resolution of 30 m × 30 m. These indices include Kappa for no information (Kno), Kappa standard (Kstandard), Kappa for grid-cell location (Klocation) and Kappa for stratum-level location (KlocationStrata), which are well-described by Khwarahm et al. (2021). When the calculated Kappa values are above 80%, the model is validated.

3. Results

3.1. Accuracy Assessment of 1986, 2004 and 2022 Classified Maps

Accuracy assessment indicates the precision with which (land use/land cover) LULC classes of classified maps for various years were established. Table 3 summarizes this study's findings. The overall accuracy ratings for 1986, 2004, and 2022 classified LULC maps were 89.85%, 91.48%, and 93.11%, respectively, which exceeded 85%. The classified map from 1986 had the lowest accuracy, while the classified map from 2022 had the best overall accuracy. In the classified LULC maps studied, the highest user's and producer's accuracy values were recorded for Farmland (96.6%) and Bare Floor (94.3%) for the 1986 map, Dense forest (94.7%) and Savannah (97.1%) for the 2004 map, Bare Floor (96.77%) and Clear Forest (96.2%) for the 2022 map, while the lowest user's and producer's values were recorded for Built-up Area (82.6%) and Dense Forest (84.9%) in the 1986 map, Farmland (71.1%) and Bare Floor (87.1%) in the 2004 map, Farmland (85.71%) and Savannah (90.6%) in the 2022 map. The 2022 classified LULC map and the 1986 classified LULC map had the greatest and lowest overall Kappa values, 0.90 and 0.85, respectively (Table 3). In general, the accuracy and Kappa values for practically all LULC classes increased gradually and approached the reference value of one, suggesting a very significant agreement with reference data (Table 3).

Table 3. Accuracy assessment of LULC classification maps of 1986, 2004 and 2022.

Image	Accuracy	Classes						Overall accuracy	Overall kappa
		Dense forest	Clear forest	Farmland	Savannah	Built-up-area	Bare Floor		
Landsat TM 1986	Reference total	53	48	32	51	21	35	**89.85**	**0.8583**
	Classified	49	46	29	48	23	37		
	Correctly classified	45	42	28	45	19	33		
	User's accuracy (%)	91.8	91.3	**96.6**	93.8	82.6	89.2		
	Producer's accuracy (%)	84.9	87.5	87.5	88.2	90.5	**94.3**		
	Kappa	0.83	0.85	0.83	**0.89**	0.88	0.87		
Landsat TM 2004	Reference total	56	51	30	48	33	31	**91.48**	**0.8817**
	Classified	57	53	38	52	32	29		
	Correctly classified	54	50	27	47	30	27		

Continued

	User's accuracy (%)	**94.7**	94.3	71.1	90.4	93.8	93.1		
	Producer's accuracy (%)	96.4	98.0	90.0	**97.9**	90.9	87.1		
	Kappa	0.88	0.85	**0.91**	0.85	0.89	**0.91**		
Landsat OLI 2022	Reference total	59	52	33	53	36	32	**93.11**	**0.9017**
	Classified	58	53	35	50	39	31		
	Correctly classified	56	50	30	48	34	30		
	User's accuracy (%)	96.55	94.34	85.71	96.00	87.18	**96.77**		
	Producer's accuracy (%)	94.9	**96.2**	90.9	90.6	94.4	93.8		
	Kappa	0.91	0.92	0.89	0.84	0.92	**0.93**		

3.2. Land Use Land Cover Changes between 1986 and 2022

3.2.1. Change Detection of the Various Land Use Land Cover Classes

In 1986, Mount Nlonako forest and peripheries (MNFP) were primarily Dense forest (138320.94 ha) and Clear forest (36790.80 ha), accounting for almost 95% of the total surface area of MNFP (Figure 3), with Dense forest accounting for 75.42% and Clear forest for 20.06%, respectively (Table 4). Meanwhile, Farmland, Savannah, Built-up-area, and Bare floor accounted for almost 5% of the total surface area, with proportions of 0.93% (1697.97 ha), 3.14% (5757.94 ha), 0.43% (788.07 ha), and 0.03% (56.65 ha), respectively (Table 4).

Table 4. Land use/land cover type changes in the study area between 1986 and 2022.

LULC classes	1986		2004		2022	
	ha	%	ha	%	ha	%
Dense forest	138320.94	75.42	117320.55	63.97	84161.34	45.89
Clear forest	36790.80	20.06	44347.44	24.18	63114.57	34.41
Farmland	1697.97	0.93	4783.31	2.608	11742.06	6.40
Savannah	5757.94	3.14	14126.67	7.702	19165.26	10.45
Built-up-area	788.07	0.43	1324.81	0.722	2023.32	1.10
Bare Floor	56.65	0.03	1509.57	0.823	3205.8	1.75
Total	183412.35	100	183412.35	100.00	183412.35	100.00

Between 1986 and 2004, the dense forest lost -21000.39 ha (−11.45%) of its surface area (Table 5; Figure 4), falling from 138 320.94 ha (75.42%) in 1986 to 117320.55 ha (63.97%) in 2004 (Table 4). The loss of Dense forest during this time period resulted in an increase in Clear forest and Savannah of 7556.64 ha (4.72%) and 8368.93 ha (4.56%), respectively. Clear forest area grew from 36790.80 ha

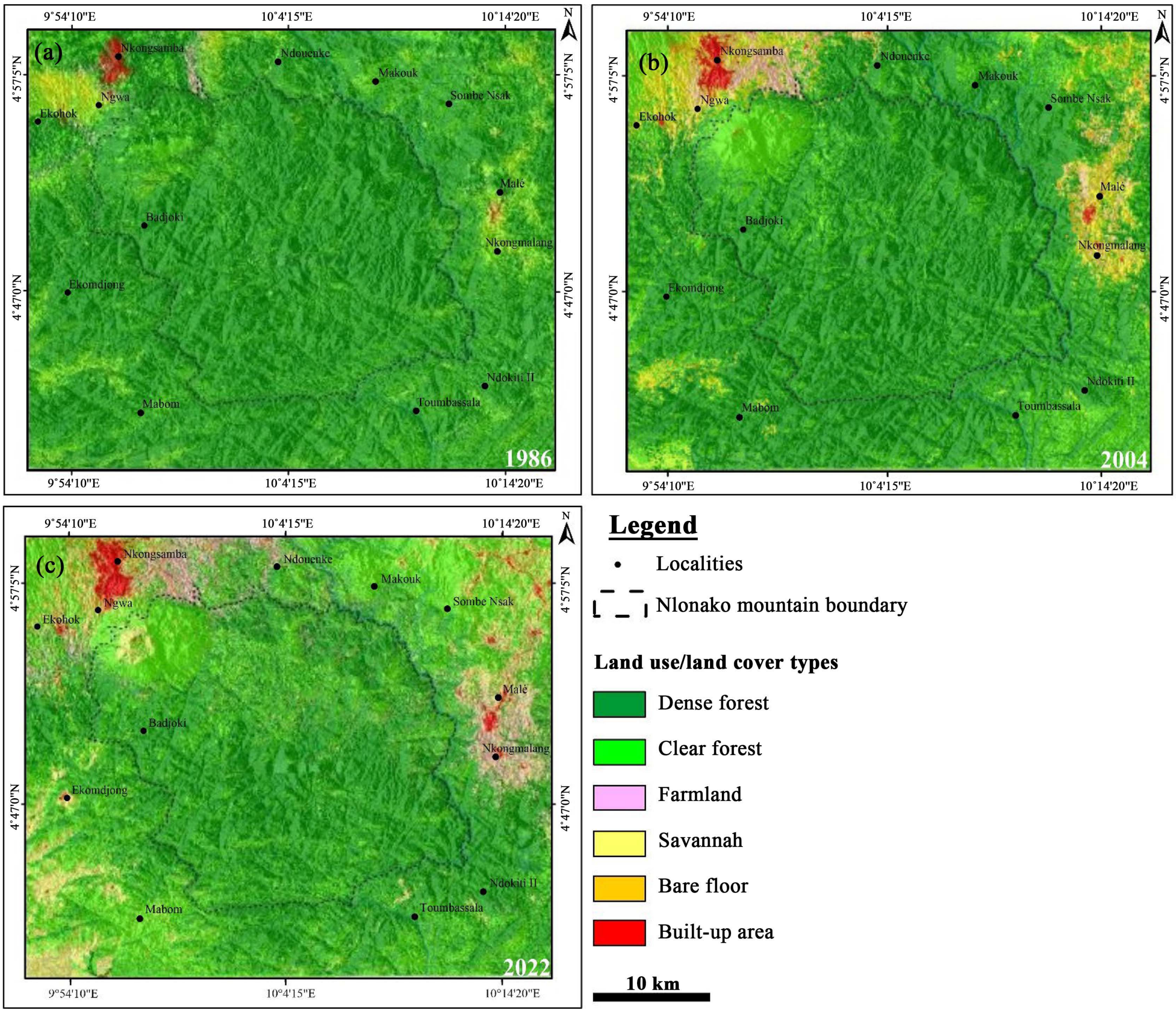


Figure 3. Classified maps of the Mount Nlonako forest and peripheries; (a) map of 1986, (b) map of 2004 and (c) map of 2022.

(20.06%) to 44347.44 ha in 2004. Savannah's surface area also increased, rising from 5757.94 ha (3.14%) in 1986 to 14126.67 ha (7.70%) by 2004. (Table 4; Figure 3 and Figure 4). Farmland rose by 1.67% (3085.47 ha) (Table 5; Figure 4), from 1697.97 ha in 1986 to 4783.31 ha in 2004. Between 1986 and 2004, Built-up area and Bare floor increased by 0.29% (536.74 ha) and 0.79% (1452.92 ha), respectively (Table 5).

From 2004 to 2022, the evolution of all LULC classes is about double that of 1986 to 2004, with the exception of Savannah, which had a smaller rise of 5038.59 ha (2.75%) compared to 8368.93 ha (4.56%) from 1986 to 2004 (Table 5; Figure 4). The Dense forest's surface area decreased from 117 320.55 ha (63.97%) in 2004 to 84 103.34 ha (45.89%) in 2022 (Table 4). This significant decrease in Dense forest surface area resulted in an exponential increase in all other LULC classes except Savannah. The Clear forest, Farmland, Built-up area, and Bare floor expanded by 18763.13 ha (10.23%), 6958.75 ha (3.8%), 698.51 ha (0.38%), and

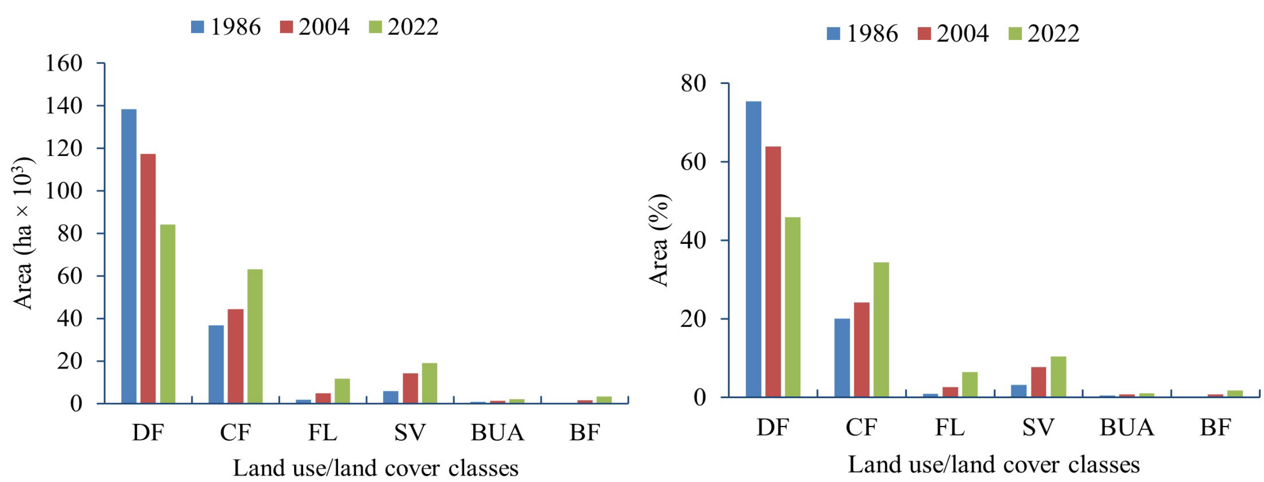
1696.23 ha (0.93%), respectively. This increase in size corresponds to an increase in surface area of Clear forest from 44347.44 ha (24.18%) in 2004 to 63114.57 ha (34.41%) in 2022; Farmland from 4783.31 ha (2.6%) in 2004 to 11742.06 ha (6.4%) in 2022; and Built-up area from 1324.81 ha (0.72%) in 2004 to 2023.32 ha (1.1%) in 2022. In addition, Bare Floor expanded from 1509.57 ha (0.82%) in 2004 to 3505.8 ha (1.75%) in 2022, while Savannah increased from 14 126.6 ha (7.7%) in 2004 to 19 165.26 ha (10.45%) in 2022 (Table 4). This rise in surface area is seen on the classified maps of 2004 and 2022 (Figure 3).

In general, the MNFP underwent significant change between 1986 and 2022. Between 2004 and 2022, there was a significant amount of change. From 1986 to 2022, the Dense Forest class lost 54 159.6 ha (29.53%) of its surface area (Table 5), from 138 320.94 ha (75.42%) in 1986 to 84 161.34 ha (45.89%) in 2022. This loss significantly contributed to the overall increase in the other five LULC classes. From 1986 to 2022, the surfaces of Clear forest, Farmland, Savannah, Built-up area, and Bare floor increased by 26323.77 ha (14.35%), 10044.09 ha (5.47%), 13407.32 ha (7.31%), 2022.89 ha (0.67%), and 3149.15 ha (1.72%), respectively, as shown in Table 6 and visualized on Figure 3 and Figure 4.

Table 5. Surface area changes of LULC from 1986 to 2022.

Land use/land cover classes	Surface area changes in the past					
	1986-2004		2004-2022		1986-2022	
	ha	%	ha	%	ha	%
Dense forest	−21000.39	−11.45	−33159.21	−18.08	−54159.6	−29.53
Clear forest	7556.64	4.12	18767.13	10.23	26323.77	14.35
Farmland	3085.47	1.67	6958.75	3.8	10044.09	5.47
Savannah	8368.93	4.56	5038.59	2.75	13407.32	7.31
Built-up-area	536.74	0.29	698.51	0.38	2022.89	0.67
Bare Floor	1452.92	0.79	1696.23	0.93	3149.15	1.72

(-) indicates a decrease in change



(a) (b)

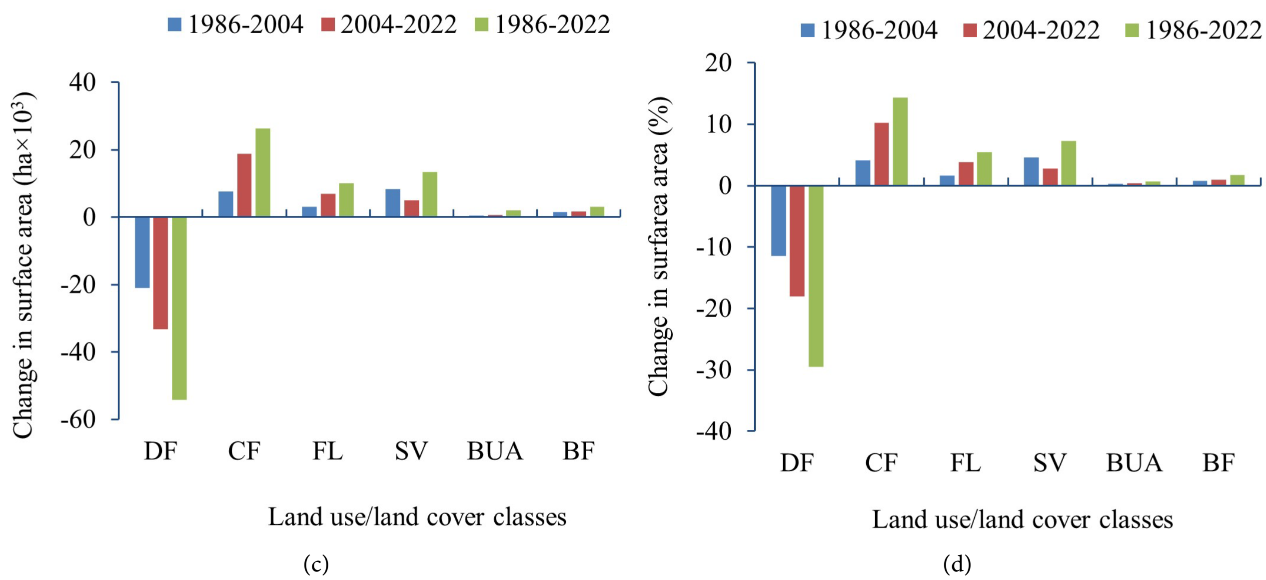


Figure 4. Past land use/land cover dynamics in the Mount Nlonako forest and peripheries. (a) Area of each LULC class in ha; (b) Area of each LULC class in percentage; (c) Gain or loss in ha; (d) Gain or loss in percentage. (DF: Dense forest, CF: Clear forest, FL: Farmland, SV: Savannah, BU: Built-up-area, BF: Bare floor).

The annual rate of change per land use land cover class in the MNFP shows that for all periods (from 1986 to 2004 and from 2004 to 2022), Dense forest regressed in its surface area at an annual regression rate of −0.84% and −1.577%, respectively, and at an overall annual regression rate of −1.08% over a 36-year period (Table 6). This regression in Dense forest resulted in an increase in the surface areas of Clear forest, Farmland, Savannah, Built-up area, and Bare floor at yearly rates of 1.988%, 16.43%, 6.466%, 4.35%, and 154.41%, respectively (Table 6; Figure 5). Bare Floor had a very strong yearly expansion rate of 154.41% from 1986 to 2022; its total surface was 56.65 ha (0.03%) in 1986 and increased by 3149.15 ha (1.72%) to 3205.8 ha (1.75%) in 2022 (Table 4). Within the periods analyzed, the annual change rate was high from 2004 to 2022, with the exception of the classes Farmland and Savannah, which had substantial annual increases from 1986 to 2004 (10.09% and 8.07%, respectively), compared to 8.08% and 1.98% from 2004 to 2022 (Table 6).

Table 6. Annual rate of change of LULC from 1986 to 2022 in the MNFP.

Land use/land cover classes	Annual rate of change from 1986-2022 (%)		
	1986-2004	2004-2022	1986-2022
Dense forest	−0.84	−1.57	−1.08
Clear forest	1.14	2.35	1.98
Farmland	10.09	8.08	16.43
Savannah	8.07	1.98	6.46
Built-up-area	3.78	2.92	4.35
Bare Floor	142.48	6.24	154.41

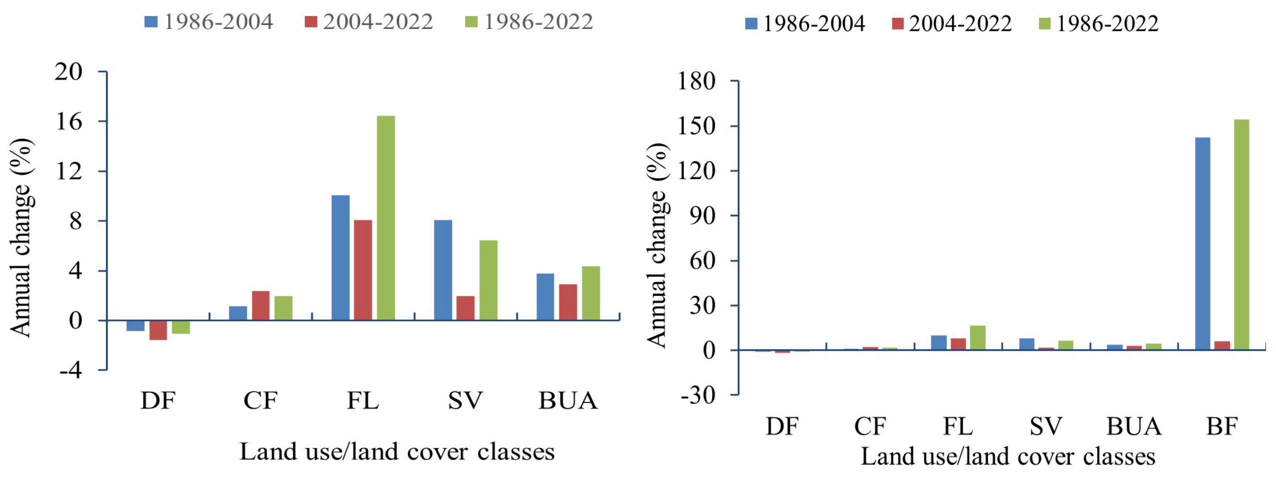


Figure 5. Annual rate of change of land use/land cover classes from 1986 to 2022, (a) without Bare Floor class in order to visualize the changes in other classes; (b) with Bare Floor class in order to visualize the high change rate of Bare floor class. ((DF: Dense forest, CF: Clear forest, FL: Farmland, SV: Savannah, BUA: Built-up-area, BF: Bare floor).

3.2.2. Functional Transition or Conversion of LULC Classes

The transformation of the different classified land use/land cover classes in the MNFP between 1986-2004 and 2004-2022 is outlined in Table 7 and Table 8. The transitional matrix within the periods discloses high diagonal values, which represent the preserved or no-changed surface areas for each LULC class.

Between 1986 and 2004, the most significant change was the conversion of Dense forest to Clear forest (22674.31 ha), Farmland (610.83 ha), Savannah (3075.73 ha), Built-up area (102.97 ha), and Bare floor (17.32 ha). The Dense forest class decreased from 138 320.94 ha (1986) to 117 320.55 ha (2004), whereas 90 839.39 ha remained unchanged (Table 7). In addition, a significant change was observed in the conversion of 3075.73 ha of Dense forest and 1559.45 ha of Clear forest to Savannah. Savannah's surface area expanded from 5757.94 ha in 1986 to 14126.67 ha in 2004 (Table 7) as a result of the conversion of other LULC types and the remaining 787.79 ha of Savannah. Furthermore, 610.83 ha of Dense forest, 369.87 ha of Clear forest, 383.28 ha of Savannah, 21.64 ha of Built-up area, and 22.80 ha of Bare floor were transformed into Farmland. The transitional matrix also shows that 3131.34 ha, 1051.01 ha, 267.62 ha, and 43.80 ha of Farmland were transformed to Dense forest, Clear forest, Savannah, and Built-up area, respectively, with 289.54 ha remaining unchanged. Furthermore, 17.32 ha of Dense forest, 19.31 ha of Clear forest, and 20.01 ha of Savannah were reduced to Bare floor (Table 7). During this time, agriculture and urban areas were not converted to Bare floors (Table 7). As the surface area of Dense forest decreased, that of the other five classes increased within this period.

From 2004 to 2022, it was discovered that Dense forest (DF) contributed more to the establishment of land use/land cover types than other classes (Table 8). A total of 20569.92 ha of Dense forest, 1574.95 ha of Dense forest, 4562.71 ha of Dense forest, 224.82 ha of Dense forest, and 332.07 ha of Dense forest were

Table 7. Land use/land cover transition matrix between 1986 and 2004 in the Mount Nlonako forest and peripheries.

Land use/land cover classes		1986 (area in hectares)						
		Dense forest	Clear forest	Farmland	Savannah	Built-up-area	Bare Floor	Total
2004(area in hectares)	Dense forest	90839.39	22674.31	610.83	3075.73	102.97	17.32	**117320.55**
	Clear forest	33175.76	9108.18	369.87	1559.45	114.86	19.31	**44347.44**
	Farmland	3131.34	1051.01	289.54	267.62	43.80	0.00	**4783.31**
	Savannah	9298.60	3220.39	383.28	787.79	416.59	20.01	**14126.67**
	Built-up-area	891.21	347.71	21.64	21.67	42.57	0.00	**1324.81**
	Bare Floor	984.64	389.19	22.80	45.66	67.27	0.00	**1509.57**
	Total	**138320.94**	**36790.80**	**1697.97**	**5757.94**	**788.07**	**56.65**	**183412.35**

The shaded figures are the surface areas which remained unchanged for each LULC class.

converted to Clear forest, Farmland, Savannah, Built-up area, and Bare floor, respectively, with 56896.88 ha remaining intact (Table 8). Farmland experienced a significant growth in surface area, nearly tripling from 4783.31 ha (2004) to 11742.06 ha (2022). In all, 1574.95 ha of Dense forest, 1285.22 ha of Clear forest, 432.34 ha of Savannah, 89.20 ha of Built-up area, and 208.38 ha of Bare floor were converted to Farmland, whereas 1193.22 ha of Farmland remained intact throughout this time period. We also noticed that the conversion of Clear forest (339.35 ha), Farmland (186.34 ha), Savannah (285.33 ha), and Built-up area (198.37 ha) to Bare floor was higher in 2004-2022 than in 1986-2004 (Table 7 and Table 8). In general, there was a greater conversion of LULC types to other land uses in the second period (2004-2022) than in the first period (1986-2022).

Table 8. Land use/land cover transition matrix between 2004 and 2022 in the Mount Nlonako forest and peripheries.

Land use/land cover classes		2004 (area in hectares)						
		Dense forest	Clear forest	Farmland	savannah	Built-up-Area	Bare Floor	Total
2022 (area in hectares)	Dense forest	56896.88	20569.92	1574.95	4562.71	224.82	332.07	**84161.34**
	Clear forest	40193.05	16387.14	1285.22	4667.99	241.82	339.35	**63114.57**
	Farmland	6497.19	2039.33	1193.22	1502.19	323.79	186.34	**11742.06**
	Savannah	12264.65	4117.88	432.34	1812.35	252.70	285.33	**19165.26**
	Built-up-Area	575.58	308.34	89.20	752.94	98.89	198.37	**2023.32**
	Bare Floor	893.21	924.84	208.38	828.49	182.78	168.10	**3205.80**
	Total	**117320.55**	**44347.44**	**4783.31**	**14126.67**	**1324.81**	**1509.57**	**183412.35**

The shaded figures are the surface areas which remained unchanged for each LULC class.

3.3. Predicting and Mapping Land Use/Land Cover Changes from 2022 to 2052

3.3.1. Evaluation and Validation of the Model

a) Evaluation of the model

To evaluate the model used to anticipate future land use and land cover changes in the MNFP from 2022 to 2052, the classified land use land cover map of 2022 was compared to the predicted land use/land cover for the same year (2022), as shown in **Figure 7**. **Table 9** summarizes the surface area differences across the various LULC classes, which are represented in **Figure 6**. In general, the six LULC classes had very low relative errors of less than 5% (**Table 9**). The best agreement was observed for Built-up area and Bare floor, which exhibit classified areas of 2023.32 ha and 3205.8 ha and predicted areas of 2053.01 ha and 3143.95 ha, respectively, with an error of 0.01% and 0.04% for Built-up area and Bare floor, respectively (**Figure 6**). Farmland also had a low error rate (0.33%) but a considerable change in area, 595.97 ha (**Table 9**). Looking at both maps, we noticed a difference in the surface area of the Built-up region, specifically in Ekomdjong village on the 2022 predicted map.

Nonetheless, visual analysis revealed that simulated (predicted) LULC maps and modern (classified) maps are relatively similar (**Figure 7**). The simulated LULC map revealed that Farmland, Clear Forest, Savannah, and Bare Floor were all underestimated. Dense forest and Built-up areas were overestimated. It enables the calculation or evaluation of the models' precision in predicting LULC changes at any given point in time.

Table 9. Areas (in ha and %) of the Classified and predicted LULC classes in 2022.

Land use/land cover Classes	LULC Classified map 2022		LULC Predicted map 2022		Surface variation	
	Area		Area		Area	
	ha	%	ha	%	ha	%
Dense forest	84161.34	45.89	88164.08	48.06	−4002.7	−2.17
Clear forest	63114.57	34.41	60850.92	33.18	2263.65	1.23
Farmland	11742.06	6.4	11146.09	6.07	595.97	0.33
Savannah	19165.26	10.45	18054.3	9.84	1110.96	0.61
Built-up-area	2023.32	1.1	2053.01	1.11	−29.69	−0.01
Bare Floor	3205.8	1.75	3143.95	1.71	61.85	0.04
Total	183412.35	100	183412.35	100		

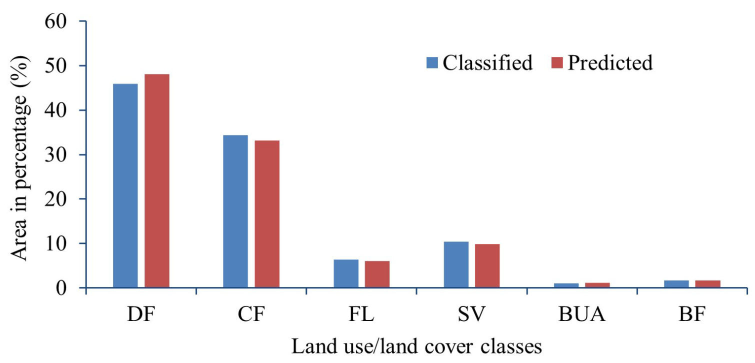


Figure 6. Change variation of land use/land cover classes between the classified and the predicted maps of 2022. (DF: Dense forest, CF: Clear forest, FL: Farmland, SV: Savannah, BUA: Built-up-area, BF: Bare floor)

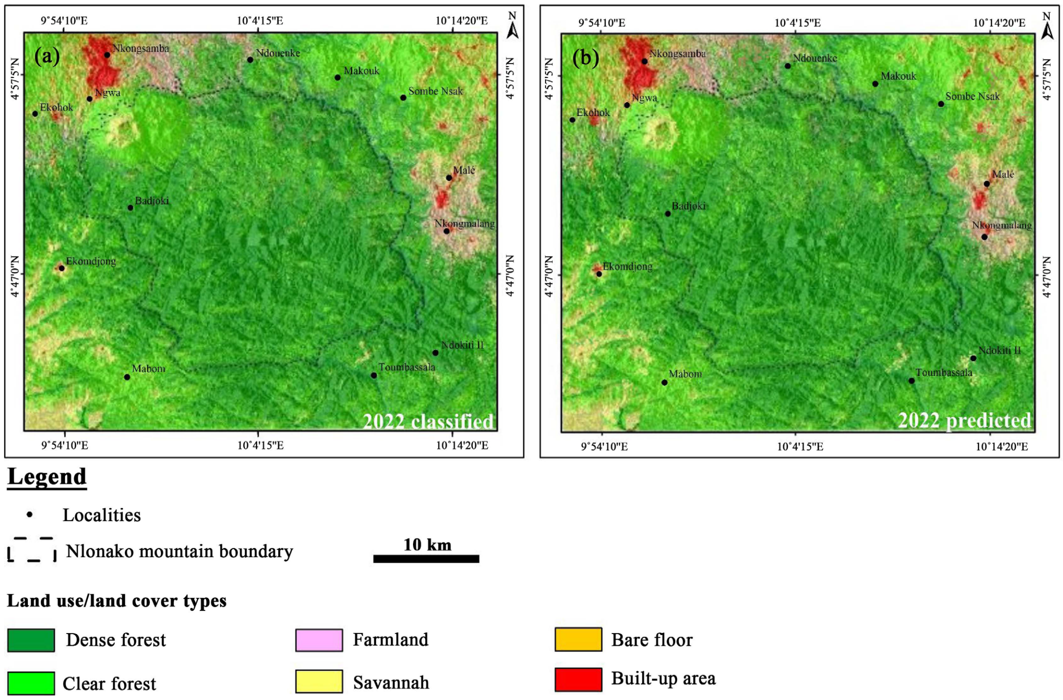


Figure 7. Classified map (a) and predicted map (b) of the different LULC classes in 2022.

b) Validation of the Model

The IDRISI Selva environment v.17's VALIDATE module was used in order to complete accuracy assessment. The results suggest that K values (Kno = 0.8521 (85.21%), Klocation = 0.8308 (83.08%), KlocationStrata = 0.8169 (81.69%), Kstandard = 0.8247 (82.47%)) above 0.8 (80%) provide satisfactory levels of accuracy (Table 10). When the findings for each kappa index agreement exceed 0.8 (80%), the K statistics are considered accurate. The Kno value of 0.85 suggests that the 2022 classified and forecasted LULC maps are in agreement. The Klocation was nearly perfect, indicating the spatial accuracy of the aggregate LULC in each category between the anticipated and classified maps. As a result, CA-Markov modeling is appropriate for making reliable predictions for future LULC classes.

Table 10. Kappa statistics for 2020 classified versus 2022 predicted LULC map.

Information of Location	Information of quantity		
	No[n]	Medium[m]	Perfect [p]
Perfect[P(x)]	P(n) = 0.4781	P(m) = 0.9822	P(p) = 1.0000
PerfectStratum[K(x)]	K(n) = 0.4781	K(m) = 0.9822	K(p) = 1.0000
MediumGrid[M(x)]	M(n) = 0.3276	M(m) = 0.8652	M(m) = 0.8564
MediumStratum[H(x)]	H(n) = 0.1537	H(m) = 0.2932	H(m) = 0.2942
No[N(x)]	N(n) = 0.1537	N(m) = 0.2932	N(n) = 0.2942
Agreement chance		0.1539	
Agreement quantity		0.3826	

Continued

Agreement grid cell	0.4271
Disagreement grid cell	0.0263
Disagreement quantity	0.0101
Kappa statistics	Index
Kno	0.8521
Klocation	0.8308
KlocationStrata	0.8169
Kstandard	0.8247

3.3.2. Future Land Use/Land Cover Change Patterns

Future changes in LULC classes were calculated across the MNFP from 2022 to 2052 using the predicted LULCC patterns and distribution in 2022 (Table 11, Figure 8). The estimated LULC maps for 2037 and 2052 revealed that the various LULC classes will face major changes, as shown in Figure 9 and Table 12, particularly in the north-west and eastern parts, but also at the forest's edges and center (Figure 8). According to model forecasts, only the Dense forest class will experience surface regression between 2022 and 2037, while the other five classes (Clear forest, Farmland, Savannah, Built-up area, and Bare floor) will continue to expand. The Dense forest will lose −22566.5 ha (−12.31%), from 84161.34 ha (45.89%) in 2022 to 61594.84 ha (33.58%) in 2037 (Table 11 and Table 12). From 2022 to 2037, Clear forest, Farmland, Savannah, Built-up area, and Bare floor would increase by 5.59% (10968.24 ha), 2.28% (4885.04 ha), 3.05% (5586.38 ha), 0.28% (514.69 ha), and 0.71% (1312.15 ha), respectively (Table 12, Figure 9). From 2022 to 2037, the clear forest will increase from 63114.57 ha (34.41%) to 74082.81 ha (40.39%), Farmland from 11742.06 ha (6.40%) to 15927.10 ha (8.68%), Savannah from 19165.26 ha (10.45%) to 24751.64 ha (13.50%), Built-up area from 2023.32 ha (1.10) to 2538.01 ha (1.38%), and Bare floor from 3205.8 ha (1.75%) to 4517.95 ha (2.46%), respectively (Table 11 and Table 12).

Table 11. Predicted areas of land use/land cover types between 2022 and 2052.

Land use/land cover classes	2022		2037		2052	
	ha	%	ha	%	ha	%
Dense forest	84161.34	45.89	61594.84	33.58	39028.34	21.28
Clear forest	63114.57	34.41	74082.81	40.39	85051.05	46.37
Farmland	11742.06	6.40	15927.10	8.68	20112.14	10.97
Savannah	19165.26	10.45	24751.64	13.50	30338.03	16.54
Built-up-area	2023.32	1.10	2538.01	1.38	3052.70	1.66
Bare Floor	3205.8	1.75	4517.95	2.46	5830.10	3.18
Total	183412.35	100.00	183412.35	100.00	183412.35	100.00

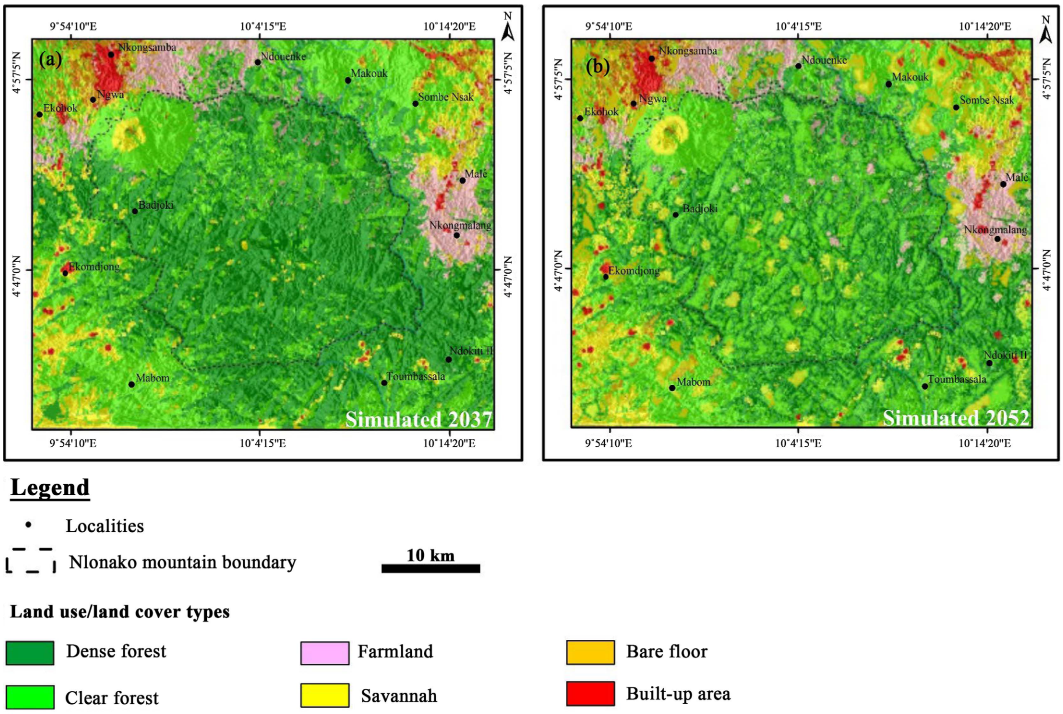


Figure 8. Predicted land use/land cover maps of Mount Nlonako forest and peripheries for the years 2037 (a) and 2052 (b).

Between 2037 to 2052, the same pattern of change will be observed. Thus, the steady rise of Clear forest, Farmland, Savannah, Built-up area, and Bare floor will result in gains of 10968.24 ha (5.98%), 4185.04 ha (2.29%), 5586.39 ha (3.05%), 514.69 ha (0.28%), and 1312.15 ha (0.71%) respectively. The continual decrease in Dense forest will result in a loss of −22566.5 hectares (−12.31) (Table 12, Figure 9).

Table 12. Surface changes of land use land cover from 2022 to 2052.

Land use/land cover Classes	Surface area changes in the future					
	2022-2037		2037-2052		2022-2052	
	ha	%	ha	%	ha	%
Dense forest	−22566.5	−12.31	−22566.5	−12.3	−45133	−24.61
Clear forest	10968.24	5.98	10968.24	5.98	21936.48	11.96
Farmland	4185.04	2.28	4185.04	2.29	8370.08	4.57
Savannah	5586.38	3.05	5586.39	3.04	11172.77	6.09
Built-up-area	514.69	0.28	514.69	0.28	1029.38	0.56
Bare Floor	1312.15	0.71	1312.15	0.72	2624.3	1.43

With respect to the transition matrix of projected land use/land cover classes between 2022 and 2052, Dense forest will continue to decline, from 84161.34 ha (45.89%) in 2022 to 39028.34 ha (21.28%) in 2052. This loss of forest area is likely

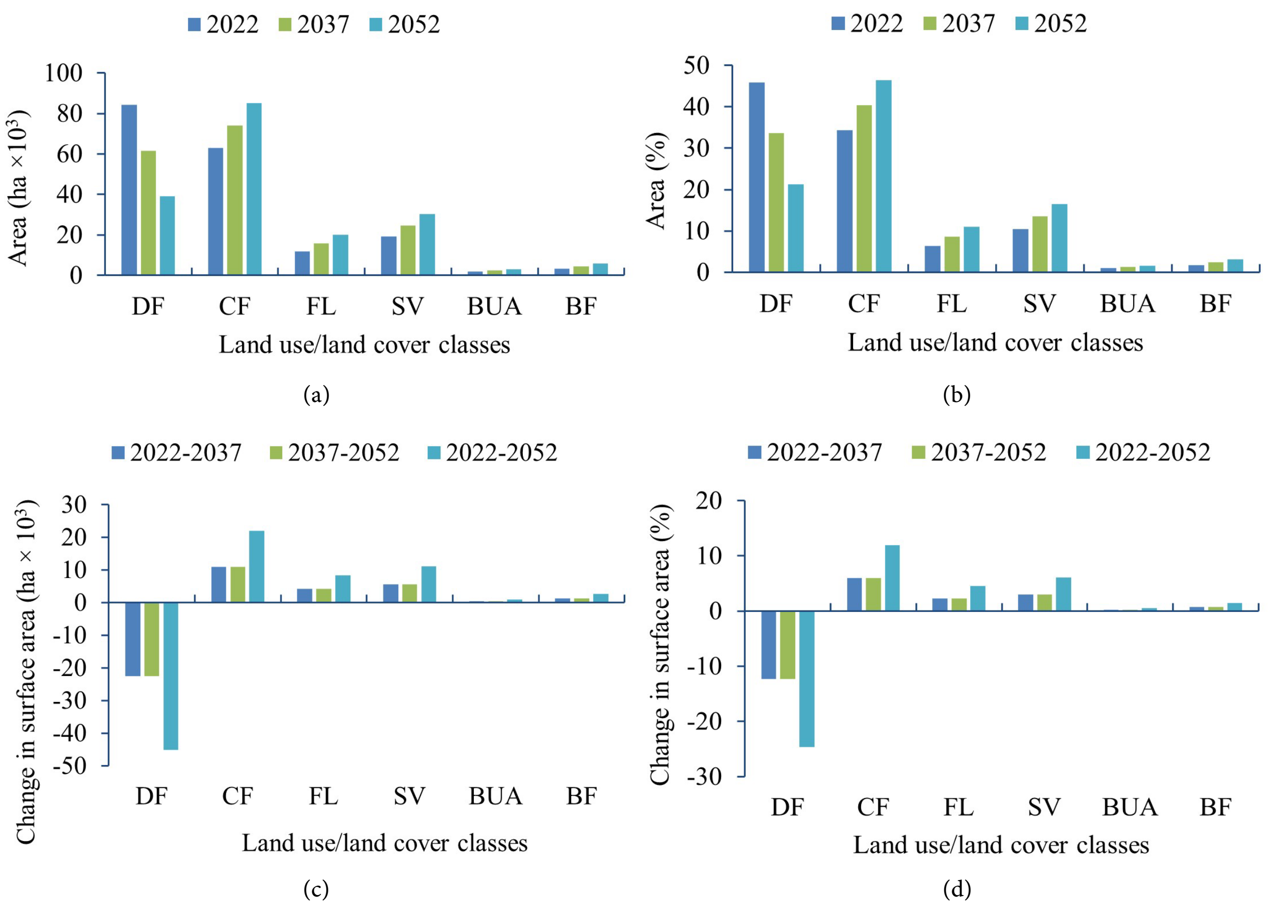


Figure 9. Future land use/land cover dynamics in the Mount Nlonako forest and peripheries. a) Area of each LULC class in ha; b) Area of each LULC class in percentage; c) Gain or loss in ha; d) Gain or loss in percentage. (DF: Dense forest, CF: Clear forest, FL: Farmland, SV: Savannah, BUA: Built-up-area, BF: Bare floor).

to be converted into other land use/cover types. Between 2022 and 2037, 22080.43 ha, 4786.65 ha, 3969.29 ha, 293.54 ha, and 326.03 ha will be converted into Clear forest, Farmland, Savannah, Built-up area, and Bare floor, respectively (Table 13).

Table 13. Predicted land use/land cover type transition matrix between 2022 and 2037.

	Land use/land cover classes	2022 (area in hectares)						
		Dense forest	Clear forest	Farmland	Savannah	Built-up	Bare Floor	Total
2037 (area in hectares)	Dense forest	30138.90	22080.43	4786.65	3969.29	293.54	326.03	**61594.84**
	Clear forest	35127.92	26534.95	2808.57	8077.20	635.85	898.32	**74082.81**
	Farmland	6913.88	4023.17	2218.52	2179.60	339.20	252.73	**15927.10**
	Savannah	10345.61	8122.18	1117.36	3540.50	383.10	1242.90	**24751.64**
	Built-up-area	446.23	986.57	287.89	444.47	124.05	248.80	**2538.01**
	Bare Floor	1188.80	1367.28	523.07	954.20	247.59	237.01	**4517.95**
	Total	**84161.34**	**63114.57**	**11742.06**	**19165.26**	**2023.32**	**3205.79**	**183412.35**

The shaded figures are the surface area which will remain unchanged for each LULC class.

Between 2037 and 2052, 16990.82 ha, 6032.97 ha, 3515.06 ha, 186.00 ha, and 206.58 ha of Dense forest are predicted to be converted into Clear forest, Farmland, Savannah, Built-up area, and Bare floor, respectively (Table 14).

Table 14. Predicted Land use/land cover type transition matrix between 2037 and 2052.

	Land use/land cover classes	2037 (area in hectares)						
		Dense forest	Clear forest	Farmland	Savannah	Built-up	Bare Floor	Total
2052 (area in hectares)	Dense forest	12096.91	16990.82	6032.97	3515.06	186.00	206.58	**39028.34**
	Clear forest	35288.74	34463.55	4134.39	9403.06	729.99	1031.32	**85051.05**
	Farmland	4780.58	8081.66	3191.46	3312.31	427.08	319.04	**20112.14**
	Savannah	7680.59	11515.72	1466.35	6614.57	716.39	2344.41	**30338.03**
	Built-up-area	476.75	1186.69	377.27	553.31	159.20	299.48	**3052.70**
	Bare Floor	1271.27	1844.37	724.66	1353.32	319.35	317.12	**5830.10**
	Total	**61594.84**	**74082.81**	**15927.10**	**24751.64**	**2538.01**	**4517.96**	**183412.35**

The shaded figures are the surface area which will remain unchanged for each LULC class.

Between 2022 and 2052, 42 235.81 hectares (total surface area in Table 13 and Table 14) of Dense forest will stay intact. Between 2022 and 2052, Farmland is expected to increase from 11742.06 ha in 2022 to 15927.10 ha in 2037 and from 15927.10 ha in 2037 to 20112.14 ha in 2052, owing primarily to the sum-up transformation of 10819.62 ha of Dense forest, 6942.96 ha of Clear forest, 2583.71 ha of Savannah, 665.16 ha of Built-up area, and 1247.73 ha of are floor (Table 13 and Table 14). It is also observed that a larger area of Dense forest will be converted to Farmland between 2037 and 2052 (6032.97 ha) than between 2022 and 2037 (4786.65 ha), whereas the other LULC classes will be converted more to Farmland between 2022 and 2037 than between 2037 and 2052. From 2022 to 2052, 5409.98 hectares of Farmland and 60998.3 ha of Clear forest will remain unaltered. Built-up area will rise from 2023.32 ha in 2022 to 3052.70 ha in 2052. Clear forest will be converted more to Built-up area between 2037 and 2052 (729.99 ha) than between 2022 and 2037 (635.85 ha). The yearly increase or decrease of each land use/land cover class from 2022 to 2052 is depicted in Figure 10. The yearly change for each LULC class shows that Dense forest (Figure 10) will decrease annually by 1504.43 ha, while Clear forest, Farmland, Savannah, Built-up area, and Bare floor, will increase annually by 731.21 ha, 279 ha, 372.42 ha, 34.32 ha, and 87.47 ha, respectively, from 2022 to 2052 (Figure 10).

Almost identical annual changes were observed from 1986 to 2022 and 2022 to 2052 (Table 15), confirming the effectiveness of the CA-Markov model utilized in this investigation. It reveals that Dense forest will regress at a rate of 1504.43 ha/year, whereas Clear forest will increase at a rate of 731.21 ha/year, followed by Savannah, Farmland, Bare floor, and Built-up Area, which will expand at rates of 372.42 ha/year, 279 ha/year, 87.47 ha/year, and 56.19 ha/year, respectively (Table

15). Between 2022 and 2052, the built-up will expand at a rate of 34.31 ha/year, as opposed to 56.19 ha/year between 1986 and 2022.

Table 15. Annual change rate (Δ/year) of Land use/land cover in the Mount Nlonako forest and peripheries.

Land use/land cover classes	Past changes			Future changes		
	Δ1986-2022	Year	Δ/year	Δ2022-2052	Year	Δ/year
Dense forest	54159.6	36	1504.43	45133	30	−1504.43
Clear forest	26323.77	36	731.21	21936.48	30	731.21
Farmland	10044.09	36	279.00	8370.08	30	279.00
Savannah	13407.32	36	372.42	11172.77	30	372.42
Built-up-area	2022.89	36	56.19	1029.38	30	34.31
Bare Floor	3149.15	36	87.47	2624.3	30	87.47

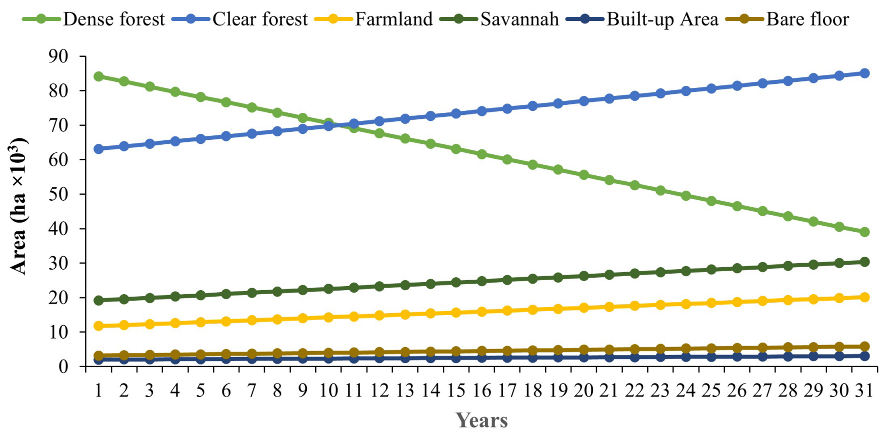


Figure 10. Yearly evolution of each land use/land cover class from 2022 to 2052 as predicted by CA-Markov model (the numbers represent the years from 2022 to 2052).

4. Discussion

Geospatial approaches and applied modeling are now widely used for mapping and monitoring land use/land cover changes (LULCC) in geoenvironmental ecosystems, particularly in and around non-protected and protected areas (Eludoyin & Iyanda, 2019; Feudjio et al., 2023; Lum-Ndob et al., 2024). Classification of land use/land cover classes using Landsat imagery is one of the most effective remote sensing applications, and the majority of algorithms have been created for this purpose. This study used the Maximum Likelihood Classifier (MLC) algorithm to classify satellite images. The MLC approach is based on the principle that all pixels will fall into their respective classes, as described by Al-Ahmadi and Hames (2009).

The study employed the CA-Markov model to assess the trend of land use changes from 1986 to 2022 and forecast this trend for the Mount Nlonako forest region and periphery from 2022 to 2052. This was made possible by describing LULCC using remote sensing (RS) and geographic information system (GIS) approaches. The overall accuracy for all identified images was greater than 85%, regardless of the year of consideration. Mansour et al. (2020) define an acceptable limit for land use/land cover (LULC) classification as an overall accuracy of 85%. From this overall accuracy, the handling of Landsat images allowed the identification of six classifications (Dense forest, Clear forest, Farmland, Savannah, Built-up area, and Bare floor). This result shows that natural formation (Dense forest) were converted to anthropisized formations (Human settlement, Farmland and Bare floors). This result was similar to that of Feudjio et al. (2023) in the Santchou forest reserve, who also identified 6 classes (mountain forest, lowland forest, degraded mountain forest, degraded lowland forest, cultivated lands, and built-up area). The similarity in the number of classes could be due to the types of human activities carried out in these areas. An overall Kappa coefficient was also observed, ranging between 0.85 and 0.90. The Kappa coefficient indicates the higher capability of the CA-Markov model for simulation of land use changes in the MNFP. In this regard, the present classification of images in the MNFP and the research period are satisfactory and reliable. This Kappa coefficient is nearly identical to that obtained by Feudjio et al. (2023) (0.82 to 0.92 in the Santchou forest reserve) and Forozan et al. (2020) (0.89 to 0.91 in Yazid city, Morocco). These Kappa values were all thought to be effective for the classification of landsat images in their respective areas of study. To effectively anticipate future changes in research, the accuracy of the CA-Markov model is tested using kappa indices (Lum-Ndob et al., 2024).

The Kappa Index of Agreement (KIA), Kno (Kappa for no information), Klocation (Kappa for location), Kstandard (Kappa for standard), and KlocationStrata (Kappa for stratum-level location) all reflect prediction accuracy (Mosammam et al., 2016). The Kno agreement refers to the agreement between the 2022 categorized and forecasted LULC maps (Chisanga et al., 2022). According to certain authors, Kstandard is used to assess the accuracy of the CA-markov model (Huang et al., 2020). For this investigation, the Kstandard value was 0.82, which is higher than the standard value of 0.75, indicating a reasonable model for predicting future LULCC. Furthermore, the data show that the model is better at predicting LULCC in terms of location than quantity, and it also demonstrates its ability to anticipate future changes with accurate location indicators. The CA-Markov model does not account for many socioeconomic factors (land-use policies during the anticipated period and population growth), which reduces its forecasting capacity. However, if all of these factors are included in the CA-Markov model, its performance improves significantly.

The results of the land use/land cover change research revealed that deforestation is still taking place in the Mount Nlonako forest region and surrounding areas. Between 1986 and 2022, the Dense forest class lost 54159.6 hectares, or 29.53% of its original surface area in 1986 (75.42%). There was a greater loss of forest land between 2004 and 2022 (33159.21 ha) than between 1986 and 2004 (21000.39 ha). Tsewoue et al. (2020) reported that between 2005 and 2014, there was a significant rise in population in the Moungo division, which could be one of the factors contributing to vegetation loss due to the creation of farmland and buildings. This vegetation lost could also be due to logging activities carried out by industrial logging companies (SEFACAM and SIENCAM) established in the Nkam division that exerts pressure on the forest (Lacatuce et al., 2023). Analysis of deforestation rates for the considered time periods 1986-2004 and 2004-2022 discloses deforestation rates of 0.84% per year and 1.57% per year respectively and an overall deforestation rate of 1.08% (1504.43 ha) per year between the period 1986 and 2022. This high rate of deforestation, mostly observed in the second period, shows that the forest reserve is under increasing pressure over time. This increasing pressure could be due to the establishment of plantations and intense exploitation activities conducted by these industrial logging companies. Temgoua et al. (2021) noticed the same trend of continuous deforestation in their research in the Melap forest reserve as a result of plantation development and construction of roads that cut across the reserve. The rate of deforestation observed in our study area is higher than that reported by Liliane et al. (2022), who found a deforestation rate of 0.89% (233.1 ha) per year in Cameroon's Mbalmayo forest reserve, and Rogers (2011), who noticed a deforestation rate of 0.05% in the Republic of Central Africa. This deforestation rate is also higher than the 0.26 percent reported by Ernst et al. (2013) in the Congo basin between 2000 and 2005. However, this rate is lower than that reported by Momo et al. (2012), who found a 50.9% deforestation rate in the Kilum-Ijim forest in the North-west of Cameroon. While the surface area of Dense forest decreased, other land use types increased. The surface area of the five other classes rose in decreasing order: Clear forest (731.31 ha/year), Savannah (372.42 ha/year), Farmland (279 ha/year), Bare floor (87.47 ha/year), and Built-up area (56.19 ha/year). In terms of expansion rate per year, Bare Floor increased at an exponential rate of 308.83% over a period of 36 years, followed by Farmland (32.86%), Savannah (12.93%), Built-up Area (8.7%), and Clear Forest (3.97%). This high increase observed in Bare Floor class from 1986 (56.65 ha) to 2022 (3205.8 ha) could be as a result of abandoned buildings or farmlands. This trend of regression in forest cover in favor of other land use types was also observed by many authors in other forest areas in Cameroon. Some of these authors are Wafo et al. (2005) in Laf-Madjam forest reserve; Momo et al. (2018) in the Koupa matapit gallery forest, Temgoua et al. (2018b) in the teaching and research forest of Dschang's University in Belabo, Eastern Cameroon, Djiongo et al. (2020) in Bouba Ndjidda national park, Fokeng et al. (2020) in Metchie-Ngoum forest reserve, Temgoua et al. (2021) in the Melap forest reserve, Liliane et al. (2022) in the Mbalmayo forest reserve, Feudjio et al. (2023) in the Santchou forest reserve, Lacatuce et al. (2023) in Forest Management Unit (FMU) 00-004 and Lum-Ndob et al, (2024), in the Eseka alluvial gold mining district in the Centre region of Cameroon. This high rate of deforestation could be attributed to the local inhabitants destroying large areas of forest land in order to establish plantations employing the slash and burn method. Megevand (2013) found that deforestation in the

Congo basin is associated with increased slash-and-burn agricultural activities, artisanal timber extraction, firewood gathering, and charcoal production. Rapid population increase in Nlonako and Nkondjock necessitated the clearing of forest areas to make way for urbanization. These settlements pose significant concerns to biodiversity and habitat degradation for wildlife. The same results were reported by Momo et al. (2018) in the Koupa-Matapit forest where most of the forest were converted into cropland. Cameroon woods are being modified by both internal and external population increase, as well as settlement-related activities such as firewood collection, logging, farming, and grazing (Fokeng et al., 2020; Lum-Ndob et al., 2024). Deforestation in the Congo Basin is linked to population density and related subsistence activities (agriculture and energy), which often deplete the forest. The authors identified agricultural activities as the primary source of deforestation and degradation in those areas. Mount Nlonako Forest is not a protected area, unlike the majority of the protected sites described above, suggesting that Cameroon's protection regulations need to be updated. However, this decreasing trend of forest cover is not specific to Cameroon, as similar observations have also been made in other African countries. Some of these are: the Yangambi biosphere reserve in the Democratic Republic of Congo by Kyale et al. (2019); and the Katimok forest reserve in Kenya by Jebiwott et al. (2020). Nevertheless, changes were more significant in the second period (2004-2022) than in the first period (1986-2004). Farmland and Built-up area are projected to reach 20112.14 ha and 3052.7 ha, respectively, in 2052, which corresponds respectively to 10.97% and 1.66% of the total surface area of the MNFP. However, Dense forest will continue to decline while the other classes will rise over time, as predicted by landsat images in 2037 and 2052. Based on information obtained from the local populations and field observations, deforestation in the MNFP is historically associated with agriculture and in particular, with the expansion of agricultural land through the slash-and-burn technique, as it is common in the Congo basin (Momo et al., 2023; Tchatchou et al., 2015). According to Kissinger et al. (2012), agriculture is the main cause of deforestation in tropical areas, contributing to 35% of forest loss and destruction in Africa. Agricultural activities, as shown by the increase of Farmland area in satellite images, are also involved in the decrease of natural formations (Madjigoto et al., 2015). This rapid rise of Farmland between 1986 and 2004 and continuous increase between 2004 and 2022, as shown by Landsat images could be due to the fact that, in the 1990s, there was a decline in the salaries of civil servants, added to it by the ongoing world economic crisis, which is seriously affecting the country and local population through an increase in the poverty rate, favoring the search of land for agricultural practices. It was noticed that many farmers open large areas of farmlands for the production of cash crops like cocoa, coffee, and palm, which considerably promotes biodiversity loss. Feudjio et al. (2023) reported the same practices around the Santchou forest reserve. It was also discovered that locals engage in illicit logging, whereas industrial firms engage in legal logging. The creation of these logging firms in the research region

(Nkam division) increases population growth, resulting in biodiversity loss (Brun et al., 2018). Other sources of forest degradation noted by respondents included household energy, excess rainfall, bushfires, and an increase in population, which has a minor impact on the forest landscape (Lacatuce et al., 2023). Knowing that this massif is a rich animal and plant biodiverse environment that is home to animal species that are unique to Cameroon, the Cameroonian government must undertake management measures to limit forest damage, which is primarily caused by human activity.

5. Conclusion

Land use/land cover (LULC) dynamics between 1986 and 2022, as well as the prediction of future LULCC from 2022 to 2052 in the Mount Nlonako forest and peripheral regions, was based on historical LULC using the CA-Markov model. This showed a significant and continuous regression of Dense forest area in favor of other types of land use, primarily Farmland, Built-up area, and Savannah. A rise in Built-up area and Farmland LULC classes was expected to accommodate rising population demands for food and housing production. Over a 36-year period, forest area decreased by 1504 ha (1.08%) per year. The change is mainly due to the lack of state control over the forest, which has led to its anarchic invasion by local communities. The CA-Markov model allowed the possibility to identify a more critical degradation over the next thirty years. The efficacy of this model has also been denoted for predicting land use/land cover changes in the study area. However, the execution of the model could be improved by integrating many socio-economic factors in order to obtain better results. Because of the importance of this area at the local, regional, and global levels, this study serves as a critical reminder to decision-makers and policymakers to follow protection protocols to ensure its protection. Decision-makers and politicians should consider an increase in population and land-use demand, as well as include local residents in the area's management and restoration through participatory management.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdullah, A. Y. M., Masrur, A., Adnan, M. S. G., Al Baky, Md.A., Hassan, Q. K., & Dewan, A. (2019). Spatio-Temporal Patterns of Land Use/Land Cover Change in the Heterogeneous Coastal Region of Bangladesh between 1990 and 2017. *Remote Sensing, 11*, Article 790. https://doi.org/10.3390/rs11070790

Achu, A. L., Aju, C. D., Suresh, V., Manoharan, T. P., & Reghunath, R. (2019). Spatiotemporal Analysis of Road Accident Incidents and Delineation of Hotspots Using Geospatial Tools in Thrissur District, Kerala, India. *KN-Journal of Cartography and Geographic Information, 69,* 255-265. https://doi.org/10.1007/s42489-019-00031-1

Akamba, B. J. C., Assam, E. M. T., Biondokin, A., & Abossolo, S. A. (2023). La REDD + comme outil de la gestion durable: Cas de la foret communale de Yoko (Centre-Cameroun) et de la reserve foresti'ere de Bapouh-Bana (Ouest-Cameroun). *Espace Géographique et Société Marocaine, 1,* 157-179.

Al-Ahmadi, F., & Hames, A. (2009). Comparison of Four Classification Methods to Extract Land Use and Land Cover from Raw Satellite Images for Some Remote Arid Areas, Kingdom of Saudi Arabia. *Journal of King Abdulaziz University-Earth Sciences, 20,* 167-191. https://doi.org/10.4197/ear.20-1.9

Alam, A., Bhat, M. S., & Maheen, M. (2019). Using Landsat Satellite Data for Assessing the Land Use and Land Cover Change in Kashmir Valley. *GeoJournal, 85,* 1529-1543. https://doi.org/10.1007/s10708-019-10037-x

Aliabad, F. A., hakimzadeh, M. a., & Shojaei, S. (2019). The Impact of Drought and Decline in Groundwater Levels on the Spread of Sand Dunes in the Plain in Iran. *Sustainable Water Resources Management, 5,* 541-555. https://doi.org/10.1007/s40899-017-0204-6

Aniah, P., Bawakyillenuo, S., Codjoe, S. N. A., & Dzanku, F. M. (2023). Land Use and Land Cover Change Detection and Prediction Based on Ca-Markov Chain in the Savannah Ecological Zone of Ghana. *Environmental Challenges, 10,* Article ID: 100664. https://doi.org/10.1016/j.envc.2022.100664

Bergl, R. A. (2007). *Conservation Biology of the Cross River Gorilla (Gorilla Gorilla Diehli)* (p. 207). PhD Thesis, University of New York.

Brun, L. E., Gaudence, D. J., Gibigaye, M., & Tente, B. (2018). Land Cover Dynamics in the Humid Zones of the Community of d'Allada, South Benin, (Sites Ramsar 1017 and 1018). *European Scientific Journal, ESJ, 14,* 59-77. https://doi.org/10.19044/esj.2018.v14n12p59

Chisanga, C. B., Shepande, C. C., & Nkonde, E. (2022). CA-Markov Approach in Dynamic Modelling of LULCC Using ESA CCI Products over Zambia. In Y. Z. Zhang, & Q. M. Cheng (Eds.), *Geographic Information Systems and Applications in Coastal Studies* (pp. 9, 34-46). IntechOpen.

De Wasseige, C., de Marcken, P., Bayol, N., Hiol Hiol, F., Mayaux, P., Desclée, B., Nasi, R., Billand, A., Defourny, D., & Eba'a Atyi, R. (2012). *The Forests of the Congo Basin-State of the Forests 2010.* Publications Office of the European Union.

Djiongo, B. J. E., Desrochers, A., Avana, M. L. T., Khasa, D., Zapfack, L., & Fotsing, É. (2020). Analysis of Spatio-Temporal Dynamics of Land Use in the Bouba Ndjidda National Park and Its Adjacent Zone (North Cameroun). *Open Journal of Forestry, 10,* 39-57. https://doi.org/10.4236/ojf.2020.101004

Djomo, A. N., & Chimi, C. D. (2017). Tree Allometric Equations for Estimation of Above, Below and Total Biomass in a Tropical Moist Forest: Case Study with Application to Remote Sensing. *Forest Ecology and Management, 391,* 184-193. https://doi.org/10.1016/j.foreco.2017.02.022

Eludoyin, A. O., & Iyanda, O. O. (2019). Land Cover Change and Forest Management Strategies in Ife Nature Reserve, Nigeria. *GeoJournal, 84,* 1531-1548. https://doi.org/10.1007/s10708-018-9936-6

Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Christophe, M., & Defourny, P. (2013). National Forest Cover Change in Congo Basin: Deforestation, Reforestation, Degradation and Regeneration for the Years 1990, 2000 and 2005. *Global Change Biology, 19,* 1173-1187. https://doi.org/10.1111/gcb.12092

FAO (2014). *Methodology Proposed for the Analysis of the Agents and Causes of Deforestation in the Pilot Sites Component 4 of the French Fund for the Global Environment*

Project. Working Paper 365.

FAO (2020). *Global Forest Assessment* (p. 46).

Feudjio, F. L., Tiomo, I. F., Kamga, B.Y., Kpoumie, H. M., Tanougong, A. D. N., Nguetsop, V. F., & Zapfack, L. (2023). Predicting Land Use/Land Cover Changes in the Santchou Wildlife Reserve (Santchou, West-Cameroon) Using a CA-Markov Model. *Trees, Forests and People, 14,* Article ID: 100438. https://doi.org/10.1016/j.tfp.2023.100438

Fokeng, M. R., Forje, W. G., Meli, M. V., & Bodzemo, B. N. (2020). Multi-Temporal Forest Cover Change Detection in the Metchie-Ngoum Protection Forest Reserve, West Region of Cameroon. *The Egyptian Journal of Remote Sensing and Space Science, 23,* 113-124. https://doi.org/10.1016/j.ejrs.2018.12.002

Fonkwo, N. S., Angwafo, T. E., & Mbida, M. (2011). Abundance and Distribution of Large Mammals in the Bakossi Landscape Area, Cameroon. *Journal of Soil Science and Environmental Management, 2,* 43-48.

Forozan, C., Elmi, M. R., Talebi, A., Mokhtari, M. H., & Shojaei, S. (2020). Temporal-Spatial Simulation of Landscape Variations Using Combined Model of Markov Chain and Automated Cell. *Journal of Cartography and Geographic Information, 4,* 12-27.

Herrmann, H., Böhme, W., Euskirchen, O., Hermann, P. A., & Schmitz, A. (2005). African Biodiversity Hotspots: The Reptiles of Mt Nlonako, Cameroon. *Revue Suisse de Zoologie, 112,* 1045-1069. https://doi.org/10.5962/bhl.part.80336

Hill, J. L., & Hill, R. A. (2001). Why Are Tropical Rain Forests So Species Rich? Classifying, Reviewing and Evaluating Theories. *Progress in Physical Geography, 25,* 326-354. https://doi.org/10.1191/030913301680193805

Huang, Y., Yang, B., Wang, M., Liu, B., & Yang, X. (2020). Analysis of the Future Land Cover Change in Beijing Using CA-Markov Chain Model. *Environmental Earth Sciences, 79,* Article No. 60. https://doi.org/10.1007/s12665-019-8785-z

Jebiwott, A., Ogendi, G. M., Makindi, S. M., & Esilaba, M. O. (2020). Forest Cover Change and Its Impacts on Ecosystem Services in Katimok Forest Reserve, Baringo County, Kenya. In W. Leal Filho (Ed.), *Handbook of Climate Change Resilience* (pp. 515-536). Springer International Publishing. https://doi.org/10.1007/978-3-319-93336-8_155

Jin, Y., & Fan, H. (2018). Land Use/Land Cover Change and Its Impacts on Protected Areas in Mengla County, Xishuangbanna, Southwest China. *Environmental Monitoring and Assessment, 190,* Article No. 16. https://doi.org/10.1007/s10661-018-6891-0

Karimi, H., Jafarnezhad, J., Khaledi, J., & Ahmadi, P. (2018). Monitoring and Prediction of Land Use/Land Cover Changes Using Ca-Markov Model: A Case Study of Ravansar County in Iran. *Arabian Journal of Geosciences, 11,* 50-92. https://doi.org/10.1007/s12517-018-3940-5

Kermani, H., & Rohrbach, A. (2018). Orientation-Control of Two Plasmonically Coupled Nanoparticles in an Optical Trap. *ACS Photonics, 5,* 4660-4667. https://doi.org/10.1021/acsphotonics.8b01145

Khwarahm, N. R., Najmaddin, P. M., Ararat, K., & Qader, S. (2021). Past and Future Prediction of Land Cover Land Use Change Based on Earth Observation Data by the CA-Markov Model: A Case Study from Duhok Governorate, Iraq. *Arabian Journal of Geosciences, 14,* 15-44. https://doi.org/10.1007/s12517-021-07984-6

Kissinger, G., Herold, M., De, & Sy., V. (2012). *Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD + Policymakers* (p. 93). Lexeme Consulting.

Krauss, J., Bommarco, R., Guardiola, M., Heikkinen, R. K., Helm, A., Kuussaari, M. et al. (2010). Habitat Fragmentation Causes Immediate and Time-Delayed Biodiversity Loss at Different Trophic Levels. *Ecology Letters, 13,* 597-605.

https://doi.org/10.1111/j.1461-0248.2010.01457.x

Kyale, J. K., Wardell, D. A., Mikwa, J.-F., Kabuanga, J. M., Monga, N. A. M., Oszwald, J., & Doumenge, C. (2019). Dynamics of Deforestation in the Biosphere Reserve of Yangambi (Democratic Republic of Congo): Spatial and Temporal Variability over the Last 30 Years. *Trees and Forests of the Tropics, 341,* 5-28. https://doi.org/10.19182/bft2019.341.a31752.

Lacatuce, K. T., Momo Solefack, M. C., Tanougong, D. A., Dong Etchike, A. B., Monthe, S. R., & Tchokomeni, A. (2023). Analysis of the Dynamics of Vegetation Cover and Land Use in Forest Management Unit 00-004 and Its Surroundings on the Coast of Cameroon. *Anuário do Instituto de Geociências, 46,* Article No. 56870. https://doi.org/10.11137/1982-3908_2023_46_56870

Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability, 13,* Article No. 17.

Liliane, M. D., Romain, N. J., Caroline, M. S. M., Abigaelle, T., & Loic, T. T. A. (2022). Quantifying Forest Loss in the Mbalmayo Forest Reserve (Center Region, Cameroon). *Journal of Geoscience and Environment Protection, 10,* 271-288. https://doi.org/10.4236/gep.2022.109016

Lum-Ndob, S. V., Ambo, F. B., Neba, A. G., Ijunghi, A. K., Tata, E., & Suh, C. E. (2024). Land Use and Land Cover Dynamics in the Eseka Alluvial Gold Mining District, Centre Region, Cameroon. *Journal of Geographic Information System, 16,* 289-305. https://doi.org/10.4236/jgis.2024.164018

Madjigoto, R., Ouya, B., Libar, J., Djim-Assal, D., Kemsol, A. & Dénénodji, A. (2015). *Degradation of the Forest Areas of Eastern Logone, Issues and Perspectives: What Strategies for Sustainable Conservation* (pp. 5159-5103). Zinder University Presses of Societies and Environment.

Mahmoud, M. I., Campbell, M. J., Sloan, S., Alamgir, M., & Laurance, W. F. (2020). Land-cover Change Threatens Tropical Forests and Biodiversity in the Littoral Region, Cameroon. *Oryx, 54,* 882-891. https://doi.org/10.1017/s0030605318000881

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring Land Use and Land Cover Changes in the Mountainous Cities of Oman Using GIS and Ca-Markov Modelling Techniques. *Land Use Policy, 91,* Article ID: 104414. https://doi.org/10.1016/j.landusepol.2019.104414

Mathaus, D. D. F., Ndumbe, L. N., Borel, K. Y., Ingram, V. J., & François, N. V. (2023). Socio-Economic and Ethnobotanic Characteristics of Plant Use in Mount Nlonako, Cameroon. *Journal of Medicinal Plants Studies, 11,* 48-60. https://doi.org/10.22271/plants.2023.v11.i6a.1606

Megevand, C. (2013). *Deforestation Trends in the Congo Basin: Reconciling Economic Growth and Forest Protection* (p. 64). World Bank Publications. http://www.worldbank.org/en/news/press-release/2013/05/14/

Mishra, V. N., & Rai, P. K. (2016). A Remote Sensing Aided Multi-Layer Perceptron-Markov Chain Analysis for Land Use and Land Cover Change Prediction in Patna District (Bihar), India. *Arabian Journal of Geosciences, 9,* 1-18. https://doi.org/10.1007/s12517-015-2138-3

Mishra, V., Rai, P., & Mohan, K. (2019). Prediction of Land Use Changes Based on Land Change Modeler (LCM) Using Remote Sensing: A Case Study of Muzaffarpur (Bihar), India. *Journal of the Geographical Institute Jovan Cvijic, SASA, 64,* 111-127. https://doi.org/10.2298/ijgi1401111m

Momo, S. M. C. (2009). *Influence of Anthropogenic Activities on the Vegetation of Mount Oku (Cameroon)* (p. 197). Doctorate Thesis, University of Yaounde I.

Momo, S. M. C., Chabrerie, O., Gallet-Moron, E., Nkongmeneck, B. A., Leumbe, L. O. N., & Decocq, G. (2012). Analyse de la Dynamique de Déforestation par Télédétection Couplée aux Modèles d'Equations Structurales: Exemple de la Foret Nepheliphile du Mont Oku (Cameroun). *Acta Botanica Gallica*, *159*, 451-466.

Momo, S. M. C., Mingang, D. L., Ngueguim, J. R., & Christian, K. Y. P. (2023). Diversity and Floristic Composition of Woody Plants in the Mbalmayo Forest Reserve (Centre, Cameroon). *Journal of Biodiversity and Environmental Sciences, 22,* 104-117. http://www.innspub.net

Momo, M. C. S., Njouonkou, A. L., Temgoua, L. F., Zangmene, R. D., Taffo, J. B. W., & Ntoupka, M. (2018). Land-Use/Land-Cover Change and Anthropogenic Causes around Koupa Matapit Gallery Forest, West-Cameroon. *Journal of Geography and Geology, 10,* 56-65. https://doi.org/10.5539/jgg.v10n2p56

Mondal, M. S., Sharma, N., Garg, P. K., & Kappas, M. (2016). Statistical Independence Test and Validation of CA Markov Land Use Land Cover (LULC) Prediction Results. *The Egyptian Journal of Remote Sensing and Space Science, 19,* 259-272. https://doi.org/10.1016/j.ejrs.2016.08.001

Mosammam, H. M., Nia, J. T., Khani, H., Teymouri, A., & Kazemi, M. (2016). Monitoring Land Use Change and Measuring Urban Sprawl Based on Its Spatial Forms: The Case of Qom City. *The Egyptian Journal of Remote Sensing and Space Sciences, 20,* 103-116. https://doi.org/10.1016/j.ejrs.2016.08.002

Ndobe, S. N., Mantzel, K. (2014). *Deforestation and REDD in the Takamanda National Park, South West Cameroon* (34 p.). https://www.forestpeople.org

Ngomin, A., & Mvongo, N. M. N. (2015). *Second Generation of Silviculture in Cameroon: Conceptual Basis, Operational Procedure and Design* (p. 86). MINFOF-GIZ.

Ngueguim, J. R. (2013). *Productivity and Floristic Diversity of Woody Plants in Dense Humid Forests of Africa in Cameroon: Site of Mangombe, Bidou and Campo* (p. 213). Doctorate Thesis, Natural History Museum.

Peng, J., Wu, J., Yin, H., Li, Z., Chang, Q., & Mu, T. (2008). Rural Land Use Change during 1986-2002 in Lijang, China, Based on Remote Sensing and GIS Data. *Sensors, 8*, 8201-8223. https://doi.org/10.3390/s812801

Rittenhouse, C. D., Pidgeon, A. M., Albright, T. P., Culbert, P. D., Clayton, M. K., Flather, C. H. et al. (2012). Land-Cover Change and Avian Diversity in the Conterminous United States. *Conservation Biology, 26,* 821-829. https://doi.org/10.1111/j.1523-1739.2012.01867.x

Rogers, J. (2011). *The Effectiveness of Protected Areas in Central Africa: A Remotely Sensed Measure of Deforestation and Access* (p. 128). Thesis Submitted to the Graduate School of Arts and Sciences, Columbia University.

Sainge, M. N., Lyonga, N. M., & Jailuhge, B. (2018). *Floristic Diversity across the Cameroon Mountains: The Case of Bakossi National Park, and Mt Nlonako* (p. 96). Technical Report to the Rufford Small Grant Foundation UK, by Tropical Plant Exploration Group (TroPEG) Cameroon.

Saputra, M. H., & Lee, H. S. (2019). Prediction of Land Use and Land Cover Changes for North Sumatra, Indonesia, Using an Artificial-Neural-Network-Based Cellular Automaton. *Sustainability, 11,* Article No. 3024. https://doi.org/10.3390/su11113024

Shojaei, S., Alipur, H., Ardakani, A. H. H., Nasab, S. N. H., & Khosravi, H. (2018). Locating Astragalus Hypsogeton Bunge Appropriate Site Using AHP and GIS. *Spatial*

Information Research, 26, 223-231. https://doi.org/10.1007/s41324-018-0166-2

Tchatchou, B., Sonwa, D. J., Ifo, S., & Tiani, A. M. (2015). *Deforestation and Degradation of Forests in the Congo Bassi: Inventory, Actual Causes and Perspectives* (p. 60). Occasional Paper 120, CIFOR.

Temgoua, L. F., Allaissem, B., Tchamba, M., Saradoum, G., Osée, M. M., & Solefack, M. C. M. (2018a). Spatio-Temporal Dynamic of Land Use and Land Cover in the Classified Forest of Djoli-Kera, South-Eastern, Chad. *Open Journal of Forestry, 8,* 283-296. https://doi.org/10.4236/ojf.2018.83019

Temgoua, L. F., Meyabeme Elono, A. L., Mfonkwet Njiaghait, Y., Ngouh, A., & Nzuta Kengne, C. (2021). Land Use and Land Cover Dynamics in the Melap Forest Reserve, West Cameroon: Implications for Sustainable Management. *Geology, Ecology, and Landscapes, 6,* 305-315. https://doi.org/10.1080/24749508.2021.1923269

Temgoua, L. F., Momo Solefack, M. C., Nguimdo Voufo, V., Tagne Belibi, C., & Tanougong, A. (2018b). Spatial and Temporal Dynamic of Land-Cover/Land-Use and Carbon Stocks in Eastern Cameroon: A Case Study of the Teaching and Research Forest of the University of Dschang. *Forest Science and Technology, 14,* 181-191. https://doi.org/10.1080/21580103.2018.1520743

Thangavelu, A., Ram, L. Y., & Sapna, K. (2021). *Assessment and Predicting of LULC by Kappa Analysis and CA Markov Model Using RS and GIS Techniques in Udham Singh Nagar District, India*.

Tsewoue, M. R., Tchamba, M., Avana, M. L., & Tanougong, A. D. (2020). Spatio-Temporal Dynamic of Land Use Change in the Moungo Division, Littoral Region, Cameroon: Influence on the Expansion of Banana-Based Agroforestry Systems. *International Journal of Biological and Chemical Sciences, 14,* 486-500. https://doi.org/10.4314/ijbcs.v14i2.15

Wafo, T. G., Fotsing, J. M. & Huaman, D. (2005). Evolution du couvert végétal dans la réserve forestière de Laf-Madjam (Extrême nord du Cameroun) de 1976 à 2003. In *Anais XII Simposio Brasileiroo de Sensoriamento Remoto* (pp. 3379-3386), INPE (Instituto Nacional de Pesquisas Espaciais).

Wang, M., Cai, L., Xu, H., & Zhao, S. (2019). Predicting Land Use Changes in Northern China Using Logistic Regression, Cellular Automata, and a Markov Model. *Arabian Journal of Geosciences, 12,* Article No. 790. https://doi.org/10.1007/s12517-019-4985-9

Zapfack, L., Engwald, S., Sonke, B., Achoundong, G., & Madong, B. A. (2002). The Impact of Land Conversion on Plant Biodiversity in the Forest Zone of Cameroon. *Biodiversity and Conservation, 11,* 2047-2061. https://doi.org/10.1023/a:1020861925294

Zekeng, J. C., Sebego, R., Mphinyane, W. N., Mpalo, M., Nayak, D., Fobane, J. L. et al. (2019). Land Use and Land Cover Changes in Doume Communal Forest in Eastern Cameroon: Implications for Conservation and Sustainable Management. *Modeling Earth Systems and Environment, 5,* 1801-1814. https://doi.org/10.1007/s40808-019-00637-4