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# Land use/land cover dynamics and its future scenarios in Luando Reserve, Angola

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**Abstract:** Anthropogenic activities modify biophysical environment and affect ecological balance and the human population. The paper analysed the dynamic patterns and trend of land use/cover (LULC) changes in Luando Reserve (LR) for 45 years and predicted its future scenarios for the next 20 years. Remotely sensed data, particularly Landsat imageries for 1975, 1990, 2005 and 2020 were processed, classified and analysed using GIS. Markov-CA model was used to predict future scenarios of LULC dynamic for 2040. Major LULC classes identified included waterbody, wetland, forest, grassland, farmland and settlement. Findings indicated that LR underwent an increase in farmland, settlement, waterbody and wetland areas, and a significant decrease in forest area. The projection for 2,040 indicated that the actual LULCC trend will continue in the next 20 years, with a worrying decrease of 7.1% in the forest area. Settlement and agricultural expansion are the major threats to biodiversity expansion in LR.

**Keywords:** Angola; change detection; land use/land cover change; LULCC; Luando Reserve.

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**Biographical notes:** Edwin Imfumu is a researcher in Environmental Management and Agroforestry. He has two Masters' degrees, one in Environmental Management jointly conferred by Pan African University (Life and Earth Sciences Institute) and University of Ibadan (Ibadan, Nigeria); the other one in Agroforestry obtained from Institut Supérieur Agro-Vétérinaire Saint Pierre Canisius (Kinshasa, DR Congo). He received his Bachelor's in Agronomy from Université Pédagogique Nationale (Kinshasa, DR Congo). He is interested in forest ecology, and the relationship between human, environment and biodiversity.

Albert Orodena Aweto was a Professor of Geography at the University of Ibadan, Ibadan, Nigeria, where he lectured for over 40 years before retiring in 2021. He is the author of the book, *Shifting Cultivation and Secondary Succession in the Tropics*, published by CABI, Wallingford, UK (2013). He authored and co-authored over 60 scientific papers dealing mainly with soil and vegetation dynamics under bush fallow, soil dynamics under monocultural plantations of teak, gmelina, rubber, cashew, oil palm and eucalyptus. He was listed as a researcher and educator in the third edition of Marquis Who's Who in Science and Engineering (USA).

## 1 Introduction

Human activities impact the biophysical environment and cause changes that alter considerably its balance and dynamics and consequently affect the quality of life of the population. The modification of the terrestrial surface of the earth by human activities is commonly known around the globe as land use/land cover change (LULCC) (Hassan et al., 2016; Sang et al., 2019). Identifying the processes, patterns, rates, causes and consequences of LULCC is crucial for land use planning and management decision making (Arowolo and Deng, 2018). As LULC change has a major impact on biodiversity and ecosystems (Falcucci et al., 2007) it is of great importance to monitor these changes within protected areas (PAs) (Bailey et al., 2016).

In fact, PAs are created for biodiversity protection (Mascia et al., 2014; Rechciński et al., 2019). However, even PAs are subject to growing pressures from human activities as people live inside and near PAs and use the land, plants, and animals to meet their basic livelihood needs (Bailey et al., 2016). This is the case of Luando Reserve (LR), in Angola, which has a range of biodiversity, hosting currently about 200 individuals of Giant Sable antelope (*Hippotragus niger voriani*) and having an estimated population of 27,000 people living within the reserve. This is not without danger for biodiversity, given the large population. Unfortunately, there are still fundamental knowledge gaps concerning anthropogenic activities within LR, due to research difficulties and very limited investment in research in PAs (Huntley, 2019; Revermann et al., 2017). It is instructive to observe that documented studies on LULC change over time, in response to human activities, are lacking for the LR, which is a very large nature reserve that contains most of the biomes of Angola.

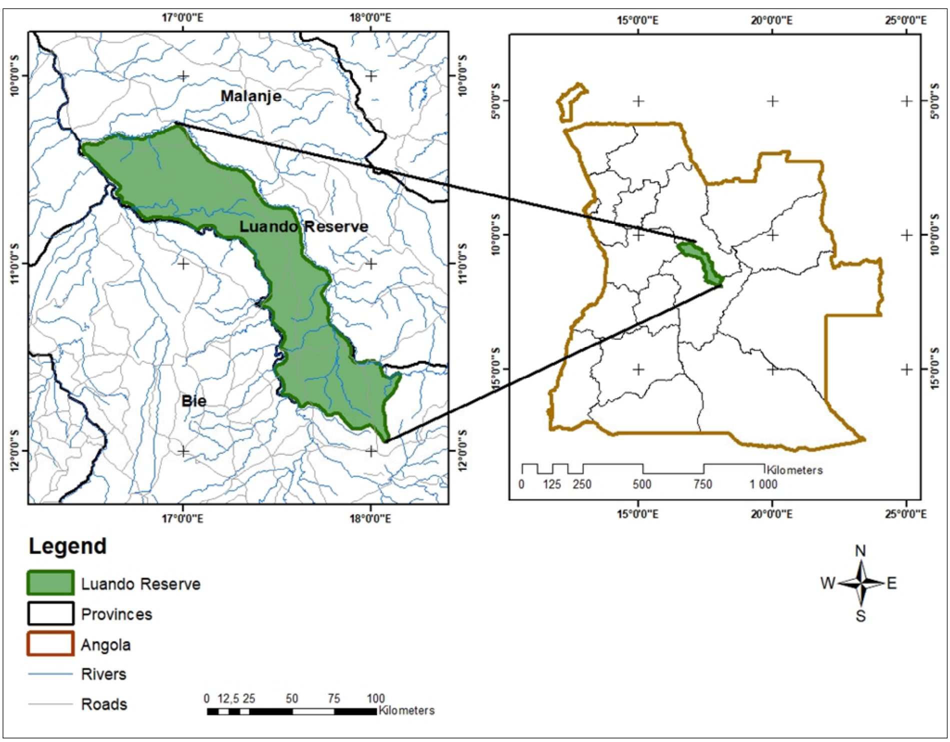
Some scholars including Estes and Estes (1974), Vaz Pinto et al. (2016) and Pinto (2019) undertook detailed studies of Giant Sable in LR. Despite this, no study has been conducted regarding LULCC inside the reserve. Therefore, there is a need to fill the gap of the lacking information on the state of the land use/land cover within the reserve since the country's independence. The aim of the current study is to map and quantify LULCC s in LR, Angola, specifically, time series analysis of LULCC s in LR for three different periods 1975, 1990, 2005 and 2020; and project future LULCC scenarios for the next 20 years.

## 2 Material and methods

### *2.1 Study area*

LR is positioned astride two provinces, Malanje (Luquembo municipality) and Bié (Cuemba municipality), with the larger proportion (80%) of the reserve being in Malanje Province as shown in Figure 1 (Elizalde et al., 2019). The reserve lies between latitudes 10°14’ and 11°56’ South and longitudes 16°26’ and 18°01’ East and covers an area of 8, 280 km$^2$. The altitude varies between 1000 and 1400m, with the highest points on the hills located in the southeast and the lowest point at the confluence of Luando and Cuanza rivers in the northwest. According to Köppen climate classification, LR falls in Cwa and Cwb category (Elizalde et al., 2019) with annual rainfall ranging between 1,100 mm and 1,400 mm, and annual mean minimum and maximum temperatures are 20°C and 22°C respectively (Elizalde et al., 2019).

**Figure 1** Map of LR (see online version for colours)




### *2.2 Methods*

#### *2.2.1 Data source*

This study used satellite imageries of 1975, 1990, 2005 and 2020, shown in Table 1. Imageries were downloaded free of charge from the USGS earth explorer website. A relatively short period during the dry season was chosen as the optimal time for image acquisition to avoid seasonal variation in LULC classes.

**Table 1** Summary of data source

| *Satellite* | *Sensor* | *Resolution* | *Year* |
|---|---|---|---|
| Landsat 5 | MSS | 60 metres | 1975 |
| Landsat 5 | TM | 30 metres | 1990 |
| Landsat 7 | ETM+ | 30 metres | 2005 |
| Landsat 8 | OLI | 30 metres | 2020 |

### 2.2.2 Data analysis

#### 2.2.2.1 Image preprocessing and classification

- *Image processing*: Images were subjected to the basic pre-processing enhancements. This pre-processing was necessary to adjust the data for use in quantitative analysis (Norovsuren et al., 2019) and it consisted of geometric and radiometric corrections. Radiometric and geometric errors of the Landsat satellite images were removed to ensure data quality using ArcGIS 10.5. Images were first converted to Top of Atmosphere (TOA) radiance, then from radiance to reflectance measures (Hao et al., 2021).
- *Image classification:* Maximum Likelihood algorithm was used in this study. It lies on the probability of a pixel fitting into a specific LULC class. The Bayesian equation for the maximum likelihood is as follows (Koko et al., 2020):

$$\mathrm{L}_i(x) = \ln p\left(a_c\right) - \left[0.5\ln\left(\left|Cov_c\right|\right)\right] - \left[0.5\left(X - M_c\right)T\left(Cov_c - 1\right)\left(X - M_c\right)\right] \tag{1}$$

where $\mathrm{L}_i(x)$ is the likelihood function. The class is $a_c$, $i = 1, 2, 3, 4, M$. $M$ is the total class number. $X$ is the n-dimensional pixel of a vector. $n$ represents the number of bands. $p(a_c)$ is the probability of the exact class at position X in *ac* for a pixel. The determinant of the covariance matrix of the data in class *ac* is $|Cov_c|$. The inverse of the covariance matrix is $Cov_c$ and the mean vector is *Mc*.

#### 2.2.2.2 Post-classification and change detection

- *Accuracy assessment*: in post-classification, we assessed the classification accuracy for classification is not complete until its accuracy is assessed (Dimobe et al., 2015). LULC classification accuracy, which is based on the confusion matrix, is presented in Table 2. It was used to determine the overall accuracy, user's and producer's accuracy.
- *Change detection*: Changes that occurred in LR over the study time were detected through post-classification using the change detection statistical tool of post-classification, from which, the matrix table of 'from-to' change class was obtained (Kafi et al., 2014). The annual average rate of change between two periods was calculated by a formula used by Dimobe et al. (2015):

$$\Delta = \left((A2 - A1)/A1 * 100\right)/(T2 - T1) \tag{2}$$

where

Δ average annual rate of change (%)

A1 amount of land cover type in time 1 (T1)

A2 amount of land cover type in time 2 (T2).

The magnitude of change is the degree of expansion or reduction in the LULC class size. It was calculated using the following equation:

$$MC = F - I \tag{3}$$

where

$MC$ magnitude of change

$F$ class area at the initial time

$I$ class area at the final time.

**Table 2** LULC classification accuracy

| *Category* | *1975* | | *1990* | | *2005* | | *2020* | |
|---|---|---|---|---|---|---|---|---|
| | *Pa (%)* | *Ua (%)* | *Pa (%)* | *Ua (%)* | *Pa (%)* | *Ua (%)* | *Pa (%)* | *Ua (%)* |
| Water body | 80 | 57 | 90 | 60 | 50 | 41 | 89 | 64 |
| Wetland | 70 | 70 | 80 | 88 | 75 | 54 | 95 | 87 |
| Forest | 97 | 98 | 99 | 99 | 97 | 99 | 91 | 98 |
| Grassland | 95 | 96 | 97 | 97 | 94 | 95 | 96 | 97 |
| Farmland | 82 | 70 | 97 | 93 | 93 | 89 | 94 | 95 |
| Settlement | 70 | 70 | 80 | 66 | 70 | 70 | 92 | 85 |
| *Overall accuracy (%)* | *95* | | *97* | | *94* | | *92* | |
| *Kappa coefficient* | *0.90* | | *0.97* | | *0.91* | | *0.95* | |

Notes: *Pa = Producer's accuracy
*Ua = User's accuracy

### *2.2.3 LULCC simulation*

Markov-CA model was used to predict LULCC in the next 20 years, that is for 2040, to understand the future variation in LULC in LR. Markov-CA chain is a combination of the Markov Chain and Cellular Automata developed to solve the limitation of the Markov chain by adding a spatial dimension to the model by CA (Ruben et al., 2020). The transition probability matrix and the transition probability areas were obtained from 1975, 1990, 2005 and 2020 maps. Then, the matrices were used in simulating future LULCC (Chu, 2020).

There was a necessity for the model to be validated to make sure of the accuracy and reliability of the projection. We first did a 2020 projection from 1975 and 2005 classified images and compared them with the actual 2020 state (Table 3). The similarity between the actual (2020) map and projected map together with the area extent allowed us to proceed with the 2040 projection which was done using 1975 and 2020 classified images. Validation was done using a chi-square statistical test.

**Table 3** Area statistics, magnitude and rate per annum

| *Year* | | *Forest* | *Grassland* | *Farmland* | *Wetland* | *Settlement* | *Waterbody* | *Total* |
|---|---|---|---|---|---|---|---|---|
| | | *Area statistics of LULC classes (ha)* | | | | | | |
| 1975 | Area | 741,222.09 | 201,232.26 | 22,226.13 | 8,511.93 | 5,280.03 | 3,605.58 | 982,078.02 |
| | % | 75.50 | 20.50 | 2.26 | 0.87 | 0.54 | 0.37 | 100 |
| 1990 | Area | 642,798.54 | 259,997.76 | 56,150.82 | 10,978.47 | 7,560.27 | 4,592.16 | 982,078.02 |
| | % | 65.50 | 26.50 | 5.72 | 1.12 | 0.77 | 0.47 | 100 |
| 2005 | Area | 560,296.17 | 286,456.68 | 98,315.01 | 16,713.45 | 14,658.48 | 5,638.23 | 982,078.02 |
| | % | 57.1 | 29.2 | 10.00 | 1.70 | 1.49 | 0.57 | 100 |
| 2020 | Area | 379,924.92 | 430,834.77 | 96,899.85 | 49,427.37 | 19,043.37 | 5,947.74 | 982,078.02 |
| | % | 38.7 | 43.86 | 9.87 | 5.03 | 1.94 | 0.61 | 100 |
| | | *Magnitude of change (ha)* | | | | | | |
| 1975–1990 | | –98,423.55 | 58,765.5 | 33,924.69 | 2,466.54 | 2,280.24 | 986.58 | - |
| 1990–2005 | | –82,502.4 | 26,458.92 | 42,164.19 | 5,734.98 | 7,098.21 | 1,046.07 | |
| 2005–2020 | | –180,371 | 144,378.1 | –1,415.16 | 32,713.92 | 4,384.89 | 309.51 | |
| 1975–2020 | | –361,297.8 | 229,602.51 | 74,673.72 | 40,915.44 | 13,763.34 | 2,342.16 | |
| | | *Rate per anum (%)* | | | | | | |
| 1975–1990 | | –8.88 | 1.94 | 10.17 | 1.93 | 2.87 | 1.82 | - |
| 1990–2005 | | –0.85 | 0.67 | 5.00 | 3.48 | 6.25 | 1.51 | |
| 2005–2020 | | –2.14 | 3.36 | –0.09 | 13.04 | 1.99 | 0.36 | |
| 1975–2020 | | –1.08 | 2.53 | 7.46 | 10.68 | 5.79 | 1.44 | |

## 3 Results

### *3.1 Land use/land cover*

#### *3.1.1 Accuracy assessment*

Land use classification accuracy based on confusion matrix is presented in Table 2. The overall accuracy classification report shows a percentage of 95%, 97%, 94% and 92% for 1975, 1990, 2005 and 2020, respectively. The kappa coefficient values for the same years were 0.90, 0.97, 0.91 and 0.95, respectively. From this result (Table 2 and Figure 2) we can conclude with confidence that the classification met the accuracy requirement of the data. The kappa coefficient values with a minimum of 0.90 express an excellent classification quality (Sang et al., 2019).

Producer's accuracy is the map accuracy from the point of view the maker, indicating the probability that a land cover class on the ground is correctly classified on the map. User's accuracy is the accuracy from the point of view of the map user, indicating how often a land cover class on the map is actually present on the ground.

#### *3.1.2 Pattern of LULCC*

##### *3.1.2.1 Change detection in LULC*

*Magnitude and rate of change*

The results of the spatial distribution of LULCC classes for all the years are shown in Table 3 and Figure 2 and those of magnitude and rate (per annum) of change are computed from area statistics in Table 3.

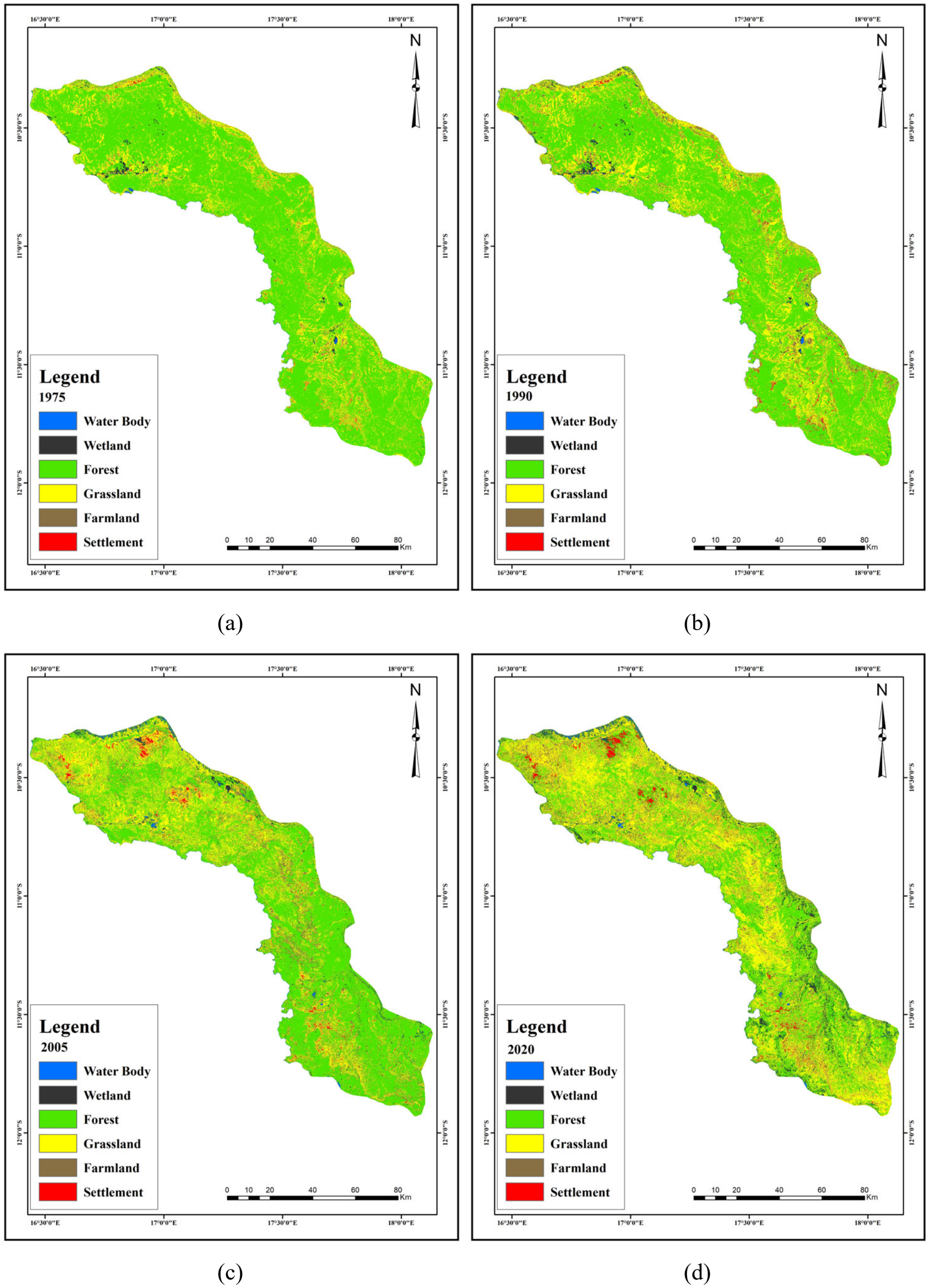
From 1975 to 1990, grassland had the highest magnitude of change (58,765.5 ha) and annual rate (1.94%), followed by farmland having 33,924.69 ha and 10.17% of magnitude and rate, respectively. Wetland with a magnitude of 2,466.54 ha and a rate of 1.93%, took the third position, followed by settlement with 2,280.24 ha and 2.87%. At the fifth position, waterbody had 986.58 ha and 1.82% of magnitude and rate, respectively. The last position was occupied by forest with a magnitude of –98,423.55 ha and a rate of –0.88%.

From 1990 to 2005, farmland with the largest magnitude (42,164.19 ha) and rate (5.00%) was at the first position, followed by grassland having 26,458.92 ha and 6.67% of magnitude and rate, respectively. Settlement with a magnitude of 7,098.21 ha and a rate of 6.25%, took the third position, followed by wetland with 5,734.98 ha and 3.48%. At the fifth position, waterbody had 1,046.07 ha and 1.51% of magnitude and rate, respectively. The last position was occupied by forest with a magnitude of –82,502.4 ha and a rate of –0.55%.

From 2005 to 2020, grassland had the largest magnitude (144,378.1 ha) and rate (3.36%), followed by wetland having 32,713.92 ha and 13.04% of magnitude and rate, respectively. Settlement with a magnitude of 4,384.89 ha and a rate of 1.99%, took the third position, followed by water body with 309.51 ha and 0.36%. At the fifth position, farmland had –1415.16 ha and –0.09% of magnitude and rate, respectively. The last position was occupied by forest with a magnitude of –180,371 ha and a rate of –2.14%.

Conclusively, the magnitude of change is either positive or negative, and forest land cover had the highest magnitude of change, although, the observed change is negative.

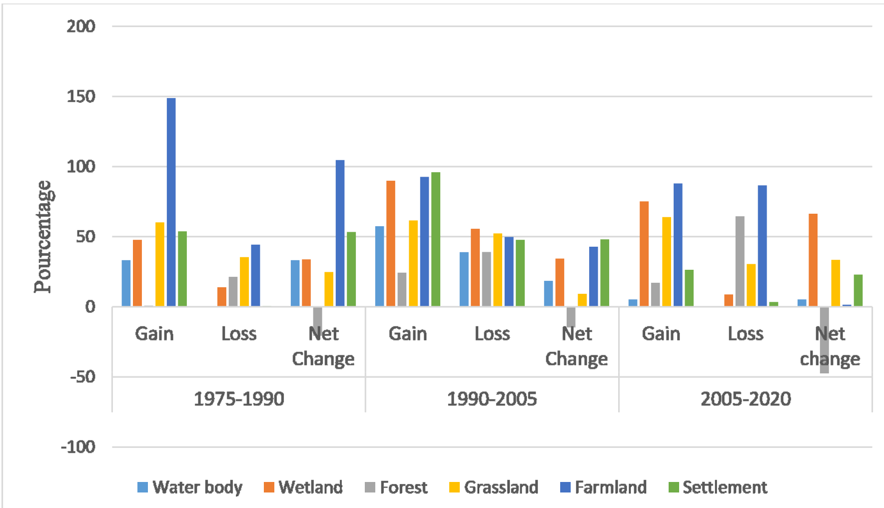
**Figure 2** Maps of LULC for, (a) 1975 (b) 1990 (c) 2005 and (d) 2020 (see online version for colours)



## *Gains, losses and net changes*

Gains, losses and net changes presented in Figure 3 are derived from the transition matrix in Table 4.

**Figure 3** Gains, losses and net changes of LULC for 1975–1990, 1990–2005, 2005–2020 (see online version for colours)




From 1975 to 1990, waterbody had a net change of 33.32% indicating a significant increasing trend of water body during this specific period. As for wetland, the net change being 33.85% signifies a remarkable increase in the wetland. Forest had the net change of –20.6%, which indicates that the forest cover decreased from 1975 to 1990. Concerning grassland, the net change is 24.77%, this means the grassland significantly increased for the specific interval of time. The net change of farmland is 104.59%, indicating that farmland area significantly increased for the specific period of study. Settlement area had a net change of 53.33% that shows an increasing trend settlement for that period.

From 1990 to 2005, for waterbody, the net change was 18.55%, which indicates an increase in water body during this specific period. Wetland had the net change of 34.32% points out a remarkable increase in the wetland. As for forest, the net change of –14.72% indicates that the forest cover had a significant decreasing trend. For grassland, the net change of 9.24% indicates that grassland increased for the specific time interval. Farmland had the change of 42.89% showing that farmland areas significantly increased for the specific period. Settlement area had the net change of 48.42% which indicates a significant increase in settlement for that period.

From 2005 to 2020, waterbody had a net change of 5.20%, which indicates an increasing trend of waterbody. Concerning wetland, the net change being of 66.29% signifies a remarkable increase in the wetland. Forest had the net change accounting for –47.48% indicating that the forest significantly decreased for that time. As for grassland the net change of 33.51% means grassland remarkably increased. Farmland had 1.46% of net change, indicating an increasing trend for farmland. Settlement a net change of 23.02%, this shows that settlement area significantly increased for this specific time interval.

**Table 4** Transition matrix

| *Year* | *Category* | *Waterbody* | *Wetland* | *Forest* | *Grassland* | *Farmland* | *Settlement* |
|---|---|---|---|---|---|---|---|
| 1975 to 1990 | Waterody | *7,050.06* | 0 | 0 | 0 | 0 | 0 |
| | Wetland | 1,530 | *10,996.65* | 0 | 0.45 | 0 | 0 |
| | Forest | 0 | 5,241.33 | *826,900.2* | 131,565.06 | 395.1 | 1.08 |
| | Grassland | 0.18 | 6.12 | 4,774.68 | *200,984.13* | 83,215.08 | 4,066.92 |
| | Farmland | 0 | 0 | 0 | 24,885.54 | *7,335.81* | 0.09 |
| | Settlement | 0 | 0 | 34.74 | 1.44 | 0 | *9,723.15* |
| 1990 to 2005 | Waterbody | *2,397.15* | 557.55 | 916.38 | 569.61 | 127.71 | 23.76 |
| | Wetland | 658.8 | *1,676.34* | 4333.5 | 3410.1 | 775.35 | 124.38 |
| | Forest | 1,232.55 | 6,006.69 | *423,915.3* | 149,499.09 | 56,472.21 | 5672.7 |
| | Grassland | 1,035.27 | 5,402.16 | 104,762.43 | *110,102.58* | 32,619.51 | 6,075.81 |
| | Farmland | 282.51 | 2,778.48 | 23,544 | 20,172.33 | *7,211.7* | 2,161.8 |
| | Settlement | 31.95 | 292.23 | 2,824.56 | 2,702.97 | 1,108.53 | *600.03* |
| 2005 to 2020 | Waterbody | *5,638.23* | 0 | 0 | 0 | 0 | 0 |
| | Wetland | 309.51 | *12,301.29* | 4,086.63 | 0.9 | 0 | 15.12 |
| | Forest | 0 | 37,126.08 | *314,885.25* | 199,903.41 | 8,373.6 | 7.83 |
| | Grassland | 0 | 0 | 50,825.97 | *155,088.18* | 75,534.3 | 5,008.23 |
| | Farmland | 0 | 0 | 10,124.46 | 75,198.78 | *12,990.15* | 1.62 |
| | Settlement | 0 | 0 | 2.61 | 643.5 | 1.8 | *14,010.57* |

Notes: The diagonal values (in italics) represent the area of each LULC class that remained stable from time T1 to time T2 while the off-diagonal values represent the changing area. The values along the row cells show the area converted from a particular LULC type *i* to other non-$i^{th}$ types and the sum gives its total loss while those of the column cells indicate the area gained to the $i^{th}$ type of LULC from the non-$i^{th}$ types and the sum gives its total gain. The rows display the categories of initial Time, and the columns display the categories of subsequent time.

**Table 5** Chi-square test

| *Category* | *Predicted 2020 (O) area (%)* | *Actual 2020 (E) area (%)* | *(O-E)²/E* |
|---|---|---|---|
| Water body | 0.61 | 0.61 | 0 |
| Wetland | 2.26 | 5 | 1.5 |
| Forest | 47.7 | 38.7 | 2.09 |
| Grassland | 34.6 | 43.9 | 1.97 |
| Farmland | 12.7 | 9.87 | 0.81 |
| Settlement | 2.17 | 1.94 | 0.02 |
| Total | 100 | 100 | 6.39 |

Note: $\chi^2 = \sum(O-E)^2/E = 6.39$; df = 5; $\chi^2_{0.05} = 11.07$.

## *3.2 Projection of LULCC for 2040*

### *3.2.1 Validation of the model*

We tested the hypothesis stating that the area statistics of the actual and the predicted images were the same. From the chi-square test result for model validation (Table 5, Figure 4, Figure 5 and Figure 6), we concluded that there is no significant difference between the predicted and the actual state.

**Figure 4** Actual and Projected 2020 LULC areas (see online version for colours)

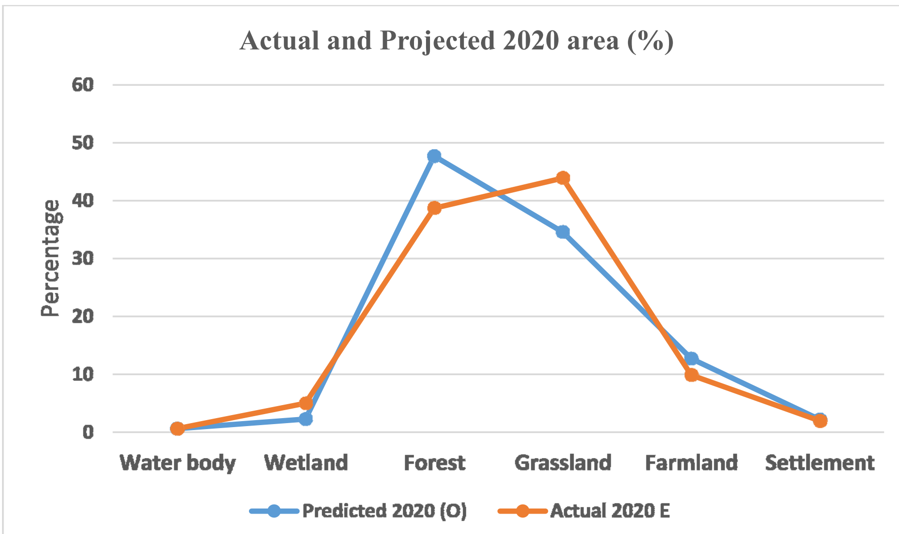



**Figure 5** Actual 2020 and projected 2040 areas (see online version for colours)

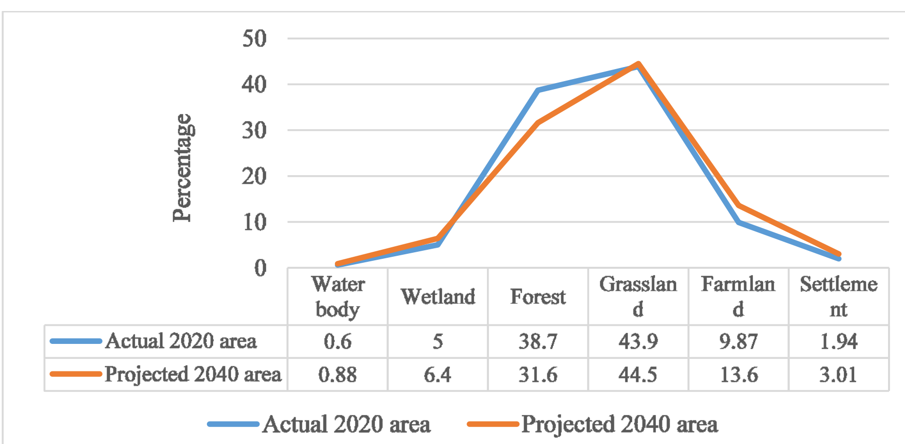
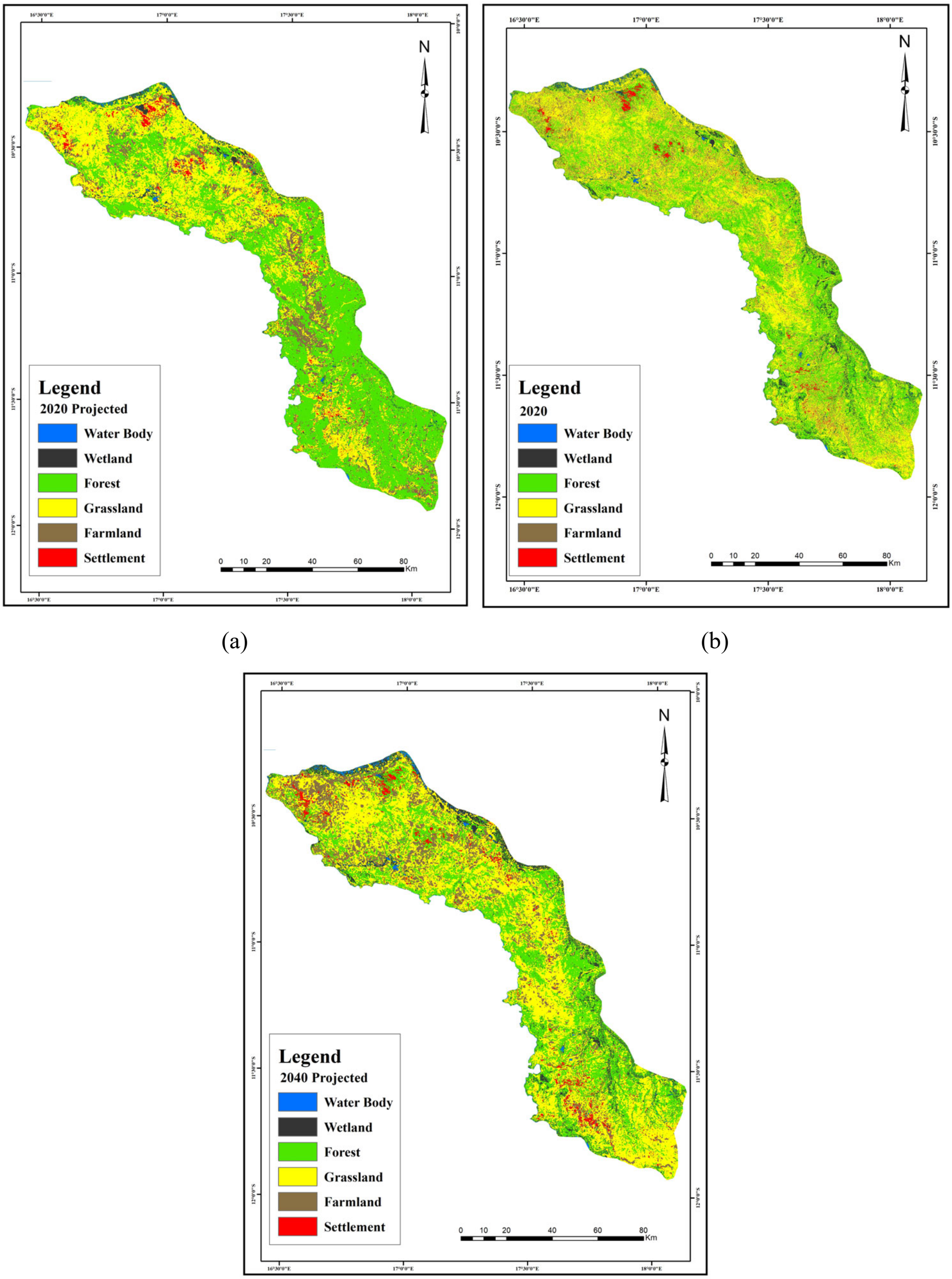


**Figure 6** (a) Projected 2020 (b) Actual 2020 (c) Projected 2040 LULC maps (see online version for colours)




(a) (b)

(c)

#### *3.2.1.1 LULC Prediction for 2040*

Results of the 2040 projection (Figure 6) indicated that waterbody will expand from 0.61% in 2020 to 0.88% in 2040. A continuous increase of wetland area will also be observed from 5.03% in 2020 to 6.4% in 2040. In contrast, there would be a decrease in forest cover from 38.7% (2020) to 31.6% (2040). For grassland area an increase will be observed from 43.9% and to 44.5% for 2020 and 2040, respectively. Farmland area will increase from 9.87% in 2020 to 13.6% in 2040. A continuous increase of settlement area from 1.94% to 3.01% for 2020 and 2040, respectively, will be observed.

## 4 Discussion

Classification is not complete until its accuracy is assessed (Forkuor and Cofie, 2011). Results revealed an overall classification accuracy and a kappa coefficient higher than 92% and 0.9, respectively for all classifications. That means the accuracy assessment requirement with a threshold of 85% was met and the classification quality was excellent as expressed by kappa coefficient values (Sang et al., 2019).

Results of change detection indicated an increase in waterbody over time. The net change was 33.2% (in 1990), 18.55% (in 2005), and 5.2% (in 2020). The reason can be the combination of abundant rainfall compared to previous years (Xu et al., 2020) and plains with poor drainage, which resulted in huge seasonal floods in wetlands (Elizalde et al., 2019). This also applies to wetland that had a net change of 33.8%, 34.32% and 66.29%, for 1975–1990, 1990–2005 and 2005–2020, respectively. This is in line with the results of a study conducted in Bauchi by Kafi et al. (2014) and Xu et al. (2020) who found that land cover by waterbodies including wetland increased due to a dramatic increase in rainfall compared to previous years.

A decrease in forest land was observed with a net change of –20.6%, –14.72% and –47.78%, for 1975–1990, 1990–2005 and 2005–2020, respectively. The analysis showed farmland and settlement expanded at the expense of forest. Reduction of the forest is mainly caused by an expansion of cropland for agriculture which is the major source of livelihood for most rural people (Tadese et al., 2020), particularly, in Angolan Miombo where the conversion of forests into agricultural lands has been demonstrated by Cabral (2007), Cabral et al. (2011), and Schneibel et al. (2016).

For all the time interval studied, results of net change pointed out an increase in grassland as follows, 24.77% (1975–1990), 9.24% (1990–2005) and 33.51% (2005–2020). Besides the natural grassland ecosystem in the reserve, the increase that was observed in this class may be due to the increased area of fallow, which is a transition state between agricultural land and secondary vegetation, as Miombo forest with woodland under-canopy vegetation is mainly composed of grass (Syampungani, 2009).

An increase in farmland was observed for the whole period of the study. The increase in farmland is normal as the population within the reserve keeps growing. On the other hand, the relative decrease in net change over time (especially for 2005–2020) may be explained by the recently strengthened administration that expanded the PA system and this makes it increasingly difficult for trespassers to encroach on the reserve (Huntley, 2019).

Change detection revealed that settlement expanded with a net change of 53.33%, 48.12% and 23.02%, for 1975–1990, 1990–2005 and 2005–2020. Settlement expansion is due primarily to population increase. Settlement expansion and population growth are positively correlated (Leyk et al., 2020; Nieves et al., 2020), that is the reason why the net change has been positive. However, the decrease in trend over time may be explained by the greater administrative control of the activities of settlers in the reserve through regular patrols.

LULC changes can reshape the entire ecosystem of a reserve (Hashim et al., 2020), by modifying its landscape and consequently, ecosystem balance and services. The 2040 predicted state of LULC in LR indicated a decrease in forest area and an increase in other LULC classes. If the actual policy governing the reserve remains unchanged, there will be a forest cover loss of 7.1% representing a loss of 69,334.2 ha in the next 20 years. The forest cover loss is directly induced by agricultural activities and indirectly by population growth. Results from studies in Nigeria by Pujiono et al. (2019) and in Romania by Kucsicsa et al. (2020) are in accord with ours. Lu et al. (2019) warned that there is a need for future policy plans in order to reduce pressure on the remaining vegetation by restricting the expansion of some activities like construction. This is because many uses of forests are incompatible with others – for example, total biodiversity protection and farming – and most of them are interlinked in a way or another (Douglas and Simula, 2011). Therefore, an increase of a particular use will exercise adverse effects on the availability of others.

## 5 Conclusions

This study was carried out in LR located in Malanje and Bié provinces in Angola. Six LULC classes were detected including waterbody, wetland, forest, grassland, farmland and settlement. Results of LULC analysis revealed remarkable changes in all the LULC classes, with an increase in all the classes, except forest area that had a tremendous decrease of –36.8% for the total area of study. An increase in water body (0.24%), wetland (4.16%), grassland (23%), farmland (7.61%), settlement (1.4%) was observed.

Findings from the 2040 projection indicated that the actual LULC change trend will continue in the next 20 years, with a worrying decrease of –7.1% in the forest cover. In contrast, expansion will be observed in waterbody (0.27%), wetland (1.37%), grassland (0.6%), farmland (3.7%) and settlement (1.07%). The expansion of water body and wetlands depends on the persistence of the climatic condition that is characterised by above average rainfall and the attendant flooding of rivers and their floodplains. On the contrary, a reversed trend of reduced rainfall will lead to the shrinking of water body and wetlands. Finally, it is important to observe that the trend of shrinking forest land cover is a major threat to the conservation of biodiversity in LR. This problem needs to be addressed by restricting the influx of illegal settlers into the reserve.

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