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Analysis of land use and land-cover pattern to monitor dynamics of Ngorongoro world heritage site (Tanzania) using hybrid cellular automata-Markov model

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ABSTRACT

Assessment of land-use and land-cover (LULC) change of any region is one of the prominent features used in environmental resource management and its overall sustainable development. This study analyzed the LULC changes of Ngorongoro Conservation Area (NCA) and its surroundings using Remote Sensing and Geographical Information System integrated with Cellular Automata-Markov model. The LULC maps for the years 1995, 2005, and 2016 were classified using unsupervised and supervised classification procedure, and projected for 2025 and 2035 under business-as-usual scenario using the CA–Markov model. The results indicated maximum gains and losses in cultivated land and woodland in the study duration, respectively. The projected LULC for the period 2025 to 2035 showed a reduction in bushland, forest, water, and woodland, but an intensification in cultivated land, grassland, bare land, and the built-up area. The natural forests with high environmental values were found to be continuously declining under the current land management trend, causing the loss in the NCA's ecological values. For sustainable management, the authorities must reach conciliation between the existing LULC patterns change and ecosystem services monitoring. A rational land use plan must be made to control the increase of cultivated land and built-up area counting a rational land use plan and ecosystem services protection guidelines. Decision makers should involve stakeholder to support improved land use management practices for balanced and sustainable ecosystem services strategies.

1. Introduction

Globally variations in land-use and land-cover (LULC) are the key anthropogenic drivers of ecological change on all time-based and spatial scales (Lambin et al., 2003; Näschen et al., 2019). These changes are complex and caused by many factors, including physical and human factors (Huang et al., 2008). Furthermore, they encompass ecological fears, including; biodiversity loss, climate change, and natural resource pollution such as soils, water and air (Slingenberg et al., 2009; Twisa et al., 2020). LULC change has developed unique concerns in natural resource control and sustainable development in the local and global scale (Foley et al., 2005; Wei et al., 2015; Yirsaw et al., 2017). Furthermore, monitoring and mitigating the adverse effects of LULC while supporting fundamental resource production has become a key priority for policymakers and researchers worldwide (Ansari and Golabi, 2019).

Impacts of LULC change on ecological changes commonly studied in several areas using multi-temporal image methods (Basommi et al., 2016). The studies revealed that human actions and natural disturbances are the fundamental drivers of LULC dynamics (Lamichhane, 2008; Mishra et al., 2014; Singh et al., 2015; Singh et al., 2018; Varga et al., 2019). Also, findings acknowledged agricultural development and population growth as the major drivers for LULC dynamics (Serneels and Lambin, 2001; Chomitz et al., 2007; DeFries et al., 2010; Kindu et al., 2015; Pullanikkatil et al., 2016; Mannan et al., 2018; Solomon et al., 2018). Stress on changed land uses are rising worldwide, and examining

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the consequences of LULC change patterns on natural resources is necessary for future generations (Munthali and Murayama, 2014). Tanzania like many other countries experienced LULC changes over the past decades, while very few studies conducted to predict future LULC in the country (Näschen et al., 2019; Twisa and Buchroithner, 2019). Studies that assess LULC pattern to monitor land dynamics with focus in conservation of ecosystem services are urgently needed. These will benefit the country to monitor natural resource and strategies toward sustainable development to ensure ecosystem service wellbeing in future.

The NCA was established in 1959 as East Africa's first versatile protected area to conserve wildlife and natural resources and uphold Masai pastoralists' interests (Estes et al., 2006). It is recognized as an International Biosphere Reserve and World Heritage Site. It includes much of the Crater Highland in the NCA and surrounding lands between the Serengeti Plains and Gregory Rift Valley (Tarver et al., 2019). NCA is habitat to the world's predator animals (lions, leopards, cheetahs, and spotted hyenas) and major herds, such as wildebeest, gazelles, and zebras which attracts the tourism activities (Estes and Small, 1981; Kabigumila, 1993). However, the NCA's attraction and economic potential due to organized safari tourism come with its challenges, including increasing human activities (Charnley, 2005; Nyahongo et al., 2007). Several human activities result in increased environmental degradation (Nyahongo et al., 2007) by causing competition among different land users. The LULC change and future NCA pattern study are crucial for successful management strategies of ecosystem services in this World Heritage Site.

Different models have been established to forecast and simulate LULC change, including artificial neural network, statistical analysis, cellular automata, and Markov chain (Koomen and Beurden, n.d.; Subedi et al., 2013). Several studies indicate that the CA–Markov model when combined with RS and GIS; the combination creates a suitable method for studying dynamics of LULC change (Li and Reynolds, 1997; Myint and Wang, 2006; Guan et al., 2011; Riccioli et al., 2013; Roose and Hietal, 2018). A CA–Markov model is a robust method in modeling LULC changes since RS can be well incorporated (Kamusoko et al., 2011). The CA–Markov model understands the temporal succession and spatial projections of the Markov and CA theory, and it can be used to conduct out pattern simulation (Sang et al., 2011). The CA–Markov model similarly reflects the LULC changes' suitability and the influence of natural, economic, and societal factors concerning land use/cover changes. Numerous studies used CA-Markov, including GIS and RS techniques in land use/cover modeling and simulation (i.e., (Subedi et al., 2013; Kityuttachai et al., 2013; Nurmiaty et al., 2014; Sayemuzzaman and Jha, 2014; Nejadi et al., 2015; Gong et al., 2015)).

Based on the previous investigation and the current trend toward LULC change projection, this paper examined the LULC changes using the CA–Markov model. The objective of this study is to look into the LULC change pattern and monitor dynamics at NCA in order to support informed decision making. The output of this research will contribute to the existing or assist build a new scientific knowledge base on the spatial-temporal change of LULC and link to ecosystem services of NCA. This will benefit the all stakeholders including natural resource professionals, policymakers, researchers as well as community regarding sustainable management and monitoring of land use and ecosystem services.

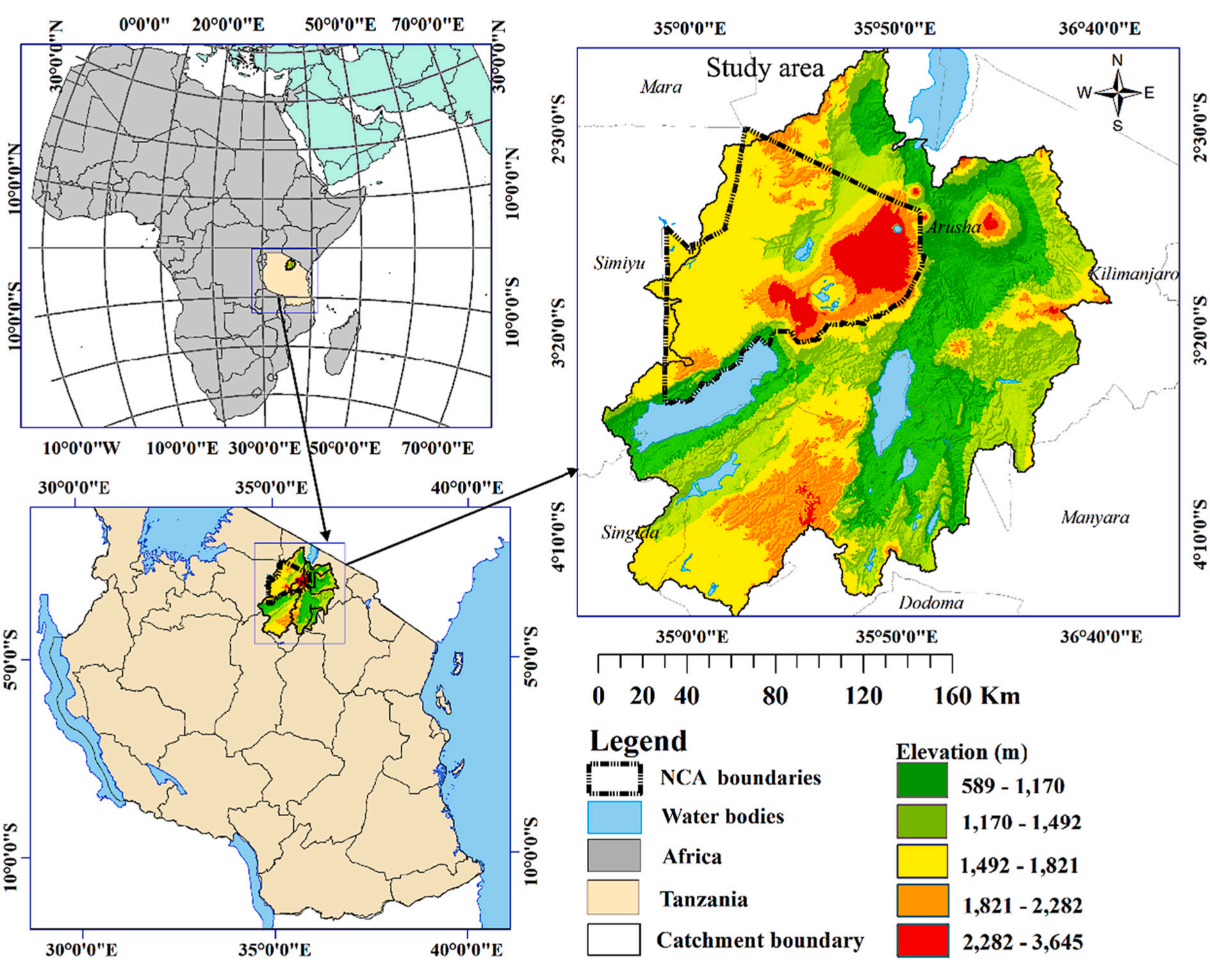

Fig. 1. The study area of Ngorongoro Conservation Area and Surrounding.

2. Materials and methods

2.1. Study area

The Ngorongoro Conservation Area (NCA) is located in the northern part of Tanzania between latitudes 2.5°–3.6° S and longitudes 34.0°–36.0° E with area coverage of 8283 km2. The area is surrounded by watersheds covering about 33,452 km2 from latitude 2.2° to 4.5° S and longitude 34.0° to 36.7° E (Fig. 1). Climatologically, the NCA is in the uplands with humid and misty conditions, where temperatures in the semi-arid zone can fall to 2 °C, and frequently rise up to 35 °C (Niboye, 2010). Rainfall in this area is seasonal with variations, ranging from 400 to 600 mm/y in arid lowland plains in the west and 1000 to1200 mm/y in highland forested areas in the east (Aisia Lawuo et al., 2014; Galvin et al., 2006). The NCA experiences bimodal conditions in which two wet and two dry seasons are distinguished. The wet season normally occurs between October and December and between March and May (MAM); the short dry season between January and February (JF) and between June and September (JJAS) (Bachofer et al., 2018). The NCA is very diverse ecologically, categorized into five different zones: the Salei plains, Crater Highlands, Gol Mountains, Kakesio/Eyasi Mountain, and Serengeti plains (Masao et al., 2015).

2.2. LULC classification and change detection

LULC maps were produced using three Landsat images; Landsat-5 TM 1995, Landsat-5 TM (BUMPER) 2005, and Landsat-8 OLI_TIRS 2016 (Table 1) using Path/Row 168/62, 168/63, 169/62 and 169/63 which covered study area by 19.6%, 10.8%, 40.6% and 29.1%, respectively. The 30 m resolution images with less than 10% cloud cover were collected from U.S Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS). The hybrid classification method (Teferi et al., 2010; Solomon et al., 2014), which includes unsupervised and supervised classification methods, was used to classify the images. The Iterative, Self-Organizing Data Analysis (ISODATA) clustering algorithm, performed the unsupervised classifications (Teferi et al., 2010; Boakye et al., 2008); while the Maximum Likelihood Classification (MLC) algorithm executed the supervised classifications (Solomon et al., 2014; Larbi et al., 2019; Temesgen et al., 2017). The LULC classes formed include forest, woodland, bushland, grassland, water, wetland, cultivated land, built-up area, and bare land (Table 2).

For accurate assessment of LULC maps produced from the satellite images, the stratified random method for each of the three classified LULC maps was used to represent the different LULC class of the study area. The accuracy was assessed using 90 pixels per category and was based on visual interpretation and ground truth data. The reference data for ground-truthing was obtained from a high-resolution Google Earth and field visit using GPS (Larbi et al., 2019) and previously classified LULC (Masao et al., 2015). A cross-tabulation was achieved between the class values and the ground truth, and the results were as an error matrix. In addition, the non-parametric Kappa test was performed to measure the magnitude of the classification accuracy to account for diagonal elements and in the confusion matrix (Rosenfield and Fitzpatirck-Lins, 1986). Change analysis was carried out using the classified (1995, 2005 and 2016) and the predicted LULC (2025 and 2035) maps to establish the pattern of LULC changes. To calculate the extent of changes occurred during the subsequent periods; 1995–2005, 2005–2016, 2016–2025 and 2025–2035 the percentage change was computed.

Table 1
Detailed data on the Landsat images used in this study.

Year	Satellite	Sensor	Path/Row	Acquisition Date	Cloud Cover (%)
1995	Landsat 5	TM (SAM)	168/62	30/01/1995	8
			168/63	27/09/1995	0
			169/62	02/06/1995	2
			169/63	17/10/1994	2
2005	Landsat 5	TM (BUMPER)	168/62	11/04/2005	3
			168/63	09/06/2005	2
			169/62	06/04/2005	0
			169/63	25/08/2004	1
2016	Landsat 8	OLI_TRIS	168/62	22/10/2016	4.82
			168/63	22/10/2016	1.9
			169/62	13/10/2016	0.16
			169/63	13/10/2016	0.53

Table 2
LULC descriptions.

Class	Descriptions
Bushland	Mainly comprised of plants that are multi-stemmed from a single root base.
Woodland	An assemblage of trees with canopy ranging from 20% to 80% but which may, or rare occasions, is closed entirely.
Wetland	The low-lying, uncultivated ground where water collects; a bog or marsh.
Cultivated land	Crop fields and fallow lands.
Built up area	Residential, commercial, industry, transportation, roads, mixed urban.
Grassland	Mainly composed of grass.
Forest	The continuous stand of trees, many of which may attain a height of 50 m including natural forest, mangrove and plantation forest.
Water	River, open water, lakes, ponds and reservoirs.
Bare land	The land area of exposed soil and barren area influenced by a human.

2.3. LULC prediction

The study applied Cellular Automata-Markov (CA-Markov) model to predict the 2025 and 2035 LULC status. CA-Markov is a robust model in predicting the patterns and the spatial arrangement of different LULC change categories which is available in IDRISI 17.0 (Arsanjani et al., 2011; Wang et al., 2012; Li et al., 2015). The model operates with reference to the historical LULC status image, transition probability matrix, and suitability images as a group file (Clark Labs, 2012; Eastman, 2012). The model is also commonly realistic in several countries (Singh et al., 2015; Omar et al., 2014; Mosammam et al., 2016) and comprises two components, the Cellular Automata model and Markov model. The mathematical expression of the Markov model is as presented in Eq. (1).

$$S(t+1) = P_{ij} \times S(t) \tag{1}$$

Where, $\boldsymbol{S(t+1)}$ represents the status of LULC at a time$(\boldsymbol{t+1})$, $\boldsymbol{P_{ij}}$ represent a transitional Matrix (2)

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \dots & P_{1n} \\ P_{21} & P_{22} & P_{23} & \dots & P_{2n} \\ P_{31} & P_{32} & P_{33} & \dots & P_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & P_{n3} & \dots & P_{nn} \end{bmatrix} \tag{2}$$

$(\boldsymbol{0 \le P_{ij} < 1})$, and $\sum_{j=1}^{n} \boldsymbol{P_{ij}} = \boldsymbol{1}$. Where$(\boldsymbol{i,j = 1,2,\dots,n})$. $\boldsymbol{i}$ **and** $\boldsymbol{j}$, are the land uses and $\boldsymbol{P_{ij}}$ represents the transition probability between any pair of land uses. From the matrix, the rows and columns represent historical and current LULC classes, respectively. Furthermore, the mathematical expression of the cellular automata is as presented in Eq. (3).

$$\boldsymbol{S(t, t+1) = f(S(t), N)} \tag{3}$$

The CA Markov model is a combination between the Markov model and cellular automata, which predicts LULC; by adding the spatial distribution element and possible LULC transition and distribution (Myint and Wang, 2006). The CA-Markov applies a standard filter with a 5 × 5-size Kernel pixel and Multi-Objective Land Allocation (MOLA) dynamic procedures for LULC prediction. The process then accomplishes the cellular automata component by reducing the weight of the suitability of pixels that are far from the considered LULC types. However, the reduced weighted suitability should not exceed 90% of the original value to ensure the proximate areas' conditional probability (Roose and Hietal, 2018). In this study, the 2025 and 2035 LULC maps were predicted using 2016 LULC classified map as a base map and a transition potential map. The transition potentials were generated based on the main transitions that occurred between the year 2005 and 2016 among the LULC classes. The model validation was performed by comparing the simulated 2016 LULC map which was based on the 1995 and 2005 classified images, with the classified 2016 LULC map. The "Relative Operating Characteristic (ROC)" and "Kappa indexes" were used to compare the agreements between the simulated and classified 2016 LULC status maps. The kappa indexes used includes Kappa for no information (Kno), Kappa for location (Klocation), Kappa for location stratum level (KlocationStrata), and Kappa for standard (Kstandard) (Clark Labs, 2012; Omar et al., 2014; Mosammam et al., 2016; Schneider and Gill Pontius Jr, 2001).

3. Results

3.1. Accuracy assessment

Table 3 shows the accuracy assessment for the classified maps for 1995, 2005, and 2016. The accuracy assessments founded on error matrices presented an overall accuracy of 98.01%, 99.71%, and 99.98% for 1995, 2005, and 2016. The Kappa coefficients of those periods were 0.98, 0.99, and 0.99, respectively.

3.2. LULC change pattern

The areas of land under different LULC types and percentage rate of change are given in Table 4. The LULC percentage graph and maps for the years 1995, 2005, and 2016 are presented in Figs. 2 and 3. LULC of the year 1995 indicated that the area 43.975% was covered by bushland, 34.914% by grassland, 9.038% by woodland, 4.275% by forest, 3.103% by cultivated land, 3.088% by water, 1.528% by wetland, 0.071% by bare land and 0.008% by built-up area. While land use/cover of the year 2005, the area was covered by 42.387% by bushland, 39.467% by grassland, 7.631% by cultivated land, 3.322% by forest, 3.261% by water, 2.474% by woodland, 0.818% by wetland, 0.631% by bare land and 0.01% by built-up area. The distribution of LULC in the year 2016 shows that about 44.452% was covered by bushland, 37.599% by grassland, 9.657% by cultivated land, 2.851% by water, 2.751% by forest, 1.891% by bare land, 0.661% by woodland, 0.118% by wetland and 0.021% by built-up area.

The changes in LULC for the study period (1995–2005, 2005–2016, and 1995–2016) are given in Table 5 and Fig. 4. During the study period 1995–2005, woodland decreased by 6.564%, bushland by 1.588%, forest by 0.953%, and wetland by 0.71%. The grassland experienced an increase of 4.553%, cultivated land by 4.528%, bare land by 0.56%, and water by 0.173%. While during 2005–2016, the decrease was observed in the grassland by 1.868%, woodland by 1.813%, wetland by 0.7%, forest by 0.571%, and water by 0.41%. The result showed an increase of bushland by 2.065%, cultivated land by 2.026%, bare land by 1.26%, and built-up area by 0.011% in the period 2005–2016. The results reveal that the highest net gain during the study period 2000–2016 was in cultivated land (6.554%), followed by grassland (2.685%), bare land (1.82%), bushland (0.477%), and built up are (0.013%), while net loss was in woodland (8.377%), forest (1.524%), wetland (1.41%), and water (0.237%) (Table 5).

Table 3
Accuracy assessment of the LULC classification at Ngorongoro Conservation Area and surrounding.

Land use/cover	1995		2005		2016	
	PA	UA	PA	UA	PA	UA
Forest	98.76	98.18	98.10	98.10	99.94	99.17
Woodland	98.91	99.06	97.91	97.93	100	99.20
Bushland	99.39	99.42	98.08	98.07	100	99.17
Grassland	99.91	99.93	99.98	98.10	99.98	99.18
Water	100	100	99.00	98.10	99.00	100
Wetland	99.98	100	98.10	98.10	99.80	99.20
Cultivated land	96.81	99.75	100	98.10	99.41	100
Built up area	100	100	96.20	96.20	100	99.20
Bare land	100	100	100.00	98.10	100	99.20
Overall	98.01		99.71		99.98	
Kappa	0.98		0.99		0.99	

Note: PA-Producer's Accuracy, UA—User's Accuracy.

3.3. LULC change pattern (transition) matrix

Tables 6, 7, and 8 show the change matrix cross-tabulation for the areas, and percentages changed from one LULC class to another compared to each LULC class's overall area for period 1995–2005, 2005–2016 and 1995–2016. During the study period 1995–2016 (Table 6), 61.09% of water remained unchanged, followed by bushland land (51%), grassland (50.46%), built up land (48.14%), forest (36.67%), bare land (29.88%), cultivated land (22.29%), woodland (1.55%) and wetland (0.49%). Although bushland and grassland maintain 50% of unchanged LULC, the largest share was gained from other LULC. Furthermore, wetland faced the maximum change, with 99.51% of its area converted to bushland (34.47%), water (30.73%), grassland (20.08%), bare land (12.71%), cultivated land (1.25%), forest (0.23%) and woodland (0.03%).

The cross-tabulation matrix for the study period between 1995 and 2005 showed that 68.48% of water remained unchanged, followed by built up land (58.75%), grassland (57.84%), forest (50.75%), bushland land (50.24%), cultivated land (39.03%), bare land (25.84%), wetland (16.81%) and woodland (9.25%). This suggests that woodland experience the maximum alteration, with 90.25% of its total area converted to bushland (57.86%), grassland (23.32%), cultivated land (4.9%), forest (4.16%), wetland (0.27%), water (0.19%), bare land (0.05%) and built-up area (0.01%).

Furthermore, for the period between 2005 and 2016, 66.69% of built-up land persisted changes, followed by bushland land (58.42%), water by (55.55%), bare land by (51.86%), forest by (51.98%), grassland (51.33%), cultivated land (24.85%), woodland by (5.04%) and wetland (0.85%). This means that woodland and wetland faced the maximum change, with 94.96% and 99.15% of its total area respectively converted to other LULC.

3.4. Predicted LULC patterns

CA-Markov model was applied to forecast LULC changes based on LULC change trends between 1995 and 2016. CA–Markov validation was succeeded, with 87.5% of ROC value. These results provided a basis for the following analysis of LULC changes. The values for Kappa statistics such as Kno (85.95%), Klocation (86.57%), KlocationStrata (86.57%), and Kstandard (82.05%) were also above 80%, which shows the high model capacity to simulate the 2025 and 2035 land use (Singh et al., 2015; Mosammam et al., 2016). Tables 9, 10 and Fig. 5 shows the extent of projected LULC types from 2016 to 2025 and 2035. Also, Fig. 5 shows the predicted LULC maps for the years 2025 and 2035. LULC of the projected the year 2025 indicated that the area 39.36% will be covered by bushland, 37.65% by grassland, 12.85% by cultivated land, 4.88% by bare land, 2.29% by forest, 1.99% by water, 0.37% by woodland, 0.32% by built-up area and 0.30% by the wetland. Moreover, the projected LULC for the year 2035 shows that; grassland will cover 39.47% of the area followed with 34.48% by bushland, 15.58% by cultivated land, 6.67% by bare land, 1.47% by forest, 1.23% by water, 0.45% by built-up area, 0.31% by woodland and 0.27% by the wetland.

Table 4
LULC classification results for 1995, 2005 and 2016.

Year	LULC					
	1995		2005		2016	
Unit	Ha	%	Ha	%	Ha	%
Forest	143,204	4.275	111,277	3.322	92,152	2.751
Woodland	302,766	9.038	82,860	2.474	22,151	0.661
Bushland	1,473,057	43.975	1,419,863	42.387	1,489,040	44.452
Grassland	1,169,535	34.914	1,322,070	39.467	1,259,488	37.599
Water	103,441	3.088	109,233	3.261	95,489	2.851
Wetland	51,185	1.528	27,411	0.818	3962	0.118
Cultivated land	103,960	3.103	255,619	7.631	323,484	9.657
Built up area	265	0.008	322	0.010	698	0.021
Bare area	2385	0.071	21,143	0.631	63,332	1.891
Total	3,349,797	100	3,349,797	100	3,349,797	100

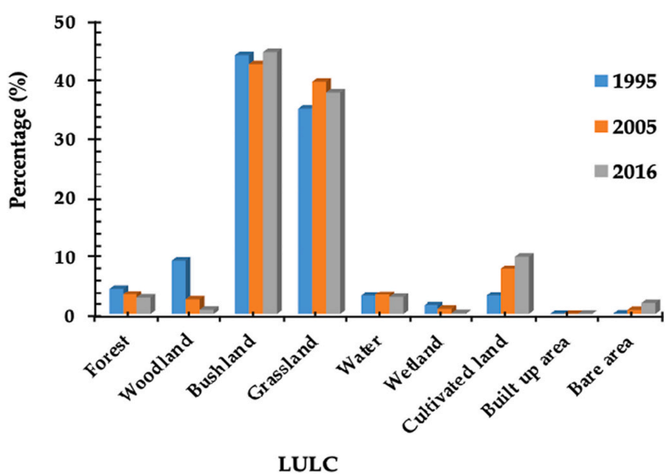

Fig. 2. LULC change graph for 1995, 2005, and 2016 at Ngorongoro Conservation Area and surrounding.

Net loss between 2025 and 2035 is expected in the forest, woodland, bushland, water, and wetland, while net gain is anticipated in grassland, cultivated land, built up area, and bare land. The bushland is expected to decrease by 4.88%, followed by forest 0.82%, water 0.77%, woodland 0.07%, and the wetland by 0.02%. Further, the cultivated land is expected to increase by 2.73%% followed by grassland 1.91%, bare land 1.79%, and built-up area 0.14%.

Table 11 and Fig. 6 show transitional probability matrix and maps respectively that express each pixel's probability to belong to the designated class in the year 2035 from 2016. Thus, these maps are a cartographical presentation of the transition probability matrix. During the period 2016 and projected 2035, 52% of built-up land and water will remain unchanged, followed by bushland (49%), bare land (46%), grassland (45%), forest (39%), cultivated land (26%), wetland (6%) and woodland (1%). This suggests that woodland will face the biggest change, with the probability of 63% to be converted to bushland (34%), followed by grassland (25%), forest (6%), and cultivated land (5%). The projection results revealed that water and built-up land would maintain above 50% of unchanged LULC, while the largest share will be gained from bushland and grassland. Furthermore, the expectation for one land use/cover class's enormous contribution to another is 53% of forest to bushland, 42% of cultivated land to grassland, 38% of grassland to bushland. Also, 38% of bare land was converted to grassland, 37% of wetland to bushland, 36% of bushland to grassland, 25% of woodland to grassland, 25% of water to bushland and 23% of built-up area to grassland.

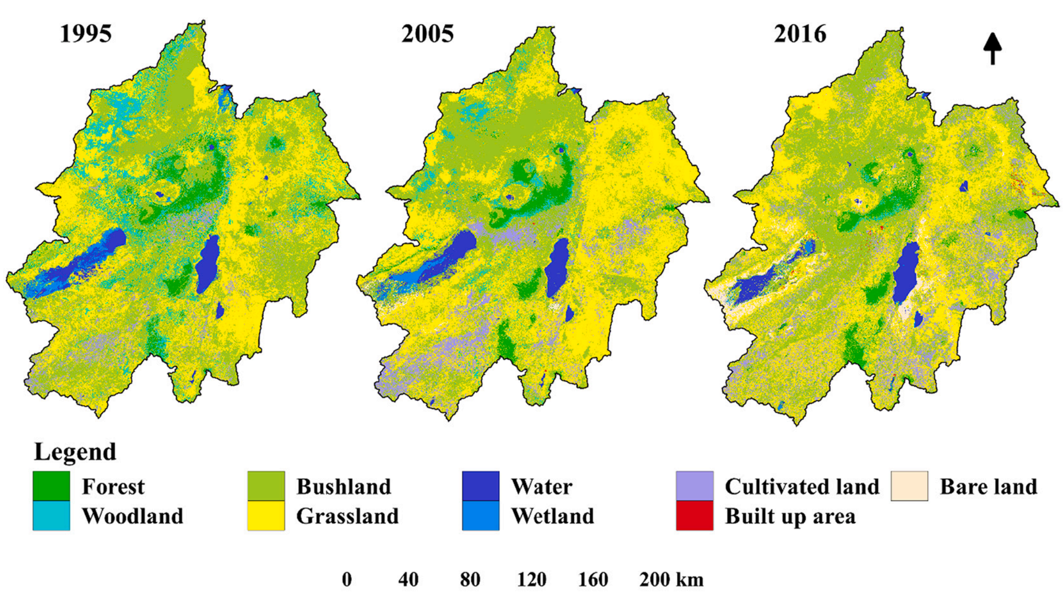

Fig. 3. LULC maps for 1995, 2005, and 2016 at Ngorongoro Conservation Area and surrounding.

Table 5
Changes in LULC for the period between 1995 and 2016.

Year	LULC Changes					
	1995–2005		2005–2016		1995–2016	
Unit	Ha	%	Ha	%	Ha	%
Forest	−31,927	−0.953	−19,125	−0.571	−51,052	−1.524
Woodland	−219,906	−6.564	−60,709	−1.813	−280,615	−8.377
Bushland	−53,194	−1.588	69,177	2.065	15,983	0.477
Grassland	152,535	4.553	−62,582	−1.868	89,953	2.685
Water	5792	0.173	−13,744	−0.41	−7952	−0.237
Wetland	−23,774	−0.71	−23,449	−0.7	−47,223	−1.41
Cultivated land	151,659	4.528	67,865	2.026	219,524	6.554
Built up area	57	0.002	376	0.011	433	0.013
Bare area	18,758	0.56	42,189	1.26	60,947	1.82

Fig. 4. Net LULC change from 1995 to 2016.

4. Discussion

To monitor LULC changes, 21 years period was considered, and LULC maps were generated for 1995, 2005, and 2016 using remote sensing data and ground-truthed information collected from the study area. A difference in the LULC change pattern of the altered land use types was observed. The results for the study period (1995–2016) on different classes of LULC indicate that maximum gains and losses occurred in cultivated land and woodland, respectively. In addition, bushland and grassland gain much of the share from other LULC, and the change matrix supported the findings of the study. The predicted LULC maps for 2025 and 2035 using CA-Markov, assuming the persistence of the study region's existing management (i.e., business as usual scenario), revealed that bushland, forest, water bodies, and woodland are expected to decrease while an increase is expected in cultivated land, grassland, bare land and built-up area. In NCA, these LULC trends may increase human-wildlife conflict, declines in habitat productivity, illegal resource extraction, and natural resource degradation (DeFries et al., 2007).

The change reflects and identifies the interaction between biodiversity conservation and economic development. Managing ecosystems services cannot rely on short term restoration plans assumed without coordination across the entire watershed. These plans when conducted in isolation are less likely to result in watershed-scale benefits than logical harmonized targets that are likely to restore the most ecosystem function. Managing ecosystems services cannot operate without monitoring or adaptive management. If the NCA communities want sustainable ecosystem services, they must manage land use and, for this, diverse sectors of the scientific community and the society must work together. Moreover, managing resource cannot succeed if the people living within the NCA watershed do not value the ecosystem services that may not meet their ideals of natural attraction, but may nevertheless be entirely

Table 6
Transition matrix showing LULC change at Ngorongoro Conservation Area between 1995 and 2016.

Area (Ha)		2016								
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
1995	FR	52,519	9944	70,609	7279	297	213	1737	5	602
	WL	12,016	4681	172,065	93,098	1347	252	18,410	74	825
	BUL	22,941	6357	751,212	498,744	7642	1557	157,387	172	27,047
	GL	4049	915	424,070	590,163	6964	968	121,164	246	20,994
	WT	311	19	19,072	13,903	63,188	465	792	11	5679
	WET	120	15	17,641	10,278	15,728	253	641	2	6506
	CL	163	219	33,994	44,906	229	249	23,174	59	967
	BLT	15	1	85	28	1	0	8	128	0
	BL	18	1	291	1090	94	6	172	0	712

Percentage (%)										2016
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
1995	FR	36.67	6.94	49.31	5.08	0.21	0.15	1.21	0.00	0.42
	WL	3.97	1.55	56.83	30.75	0.44	0.08	6.08	0.02	0.27
	BUL	1.56	0.43	51.00	33.86	0.52	0.11	10.68	0.01	1.84
	GL	0.35	0.08	36.26	50.46	0.60	0.08	10.36	0.02	1.80
	WT	0.30	0.02	18.44	13.44	61.09	0.45	0.77	0.01	5.49
	WET	0.23	0.03	34.47	20.08	30.73	0.49	1.25	0.00	12.71
	CL	0.16	0.21	32.70	43.20	0.22	0.24	22.29	0.06	0.93
	BLT	5.64	0.47	31.90	10.49	0.24	0.00	3.12	48.14	0.00
	BL	0.76	0.03	12.22	45.71	3.94	0.24	7.20	0.02	29.88

FR-Forest, WL—Woodland, BUL—Bushland, GL—Grassland, WT—Water, WET-Wetland, CL—Cultivated land, BLT-Built up land, BL- Bare land.

Table 7
Transition matrix showing land use/cover change at Ngorongoro Conservation Area between 1995 and 2005.

Area (Ha)		2005								
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
1995	FR	72,669	8789	53,060	5186	169	57	3271	0	1
	WL	12,604	28,002	175,175	70,594	573	805	14,849	18	147
	BUL	24,079	30,931	740,088	530,138	10,381	2040	122,479	55	12,866
	GL	1518	14,504	386,390	676,457	9683	1670	73,876	62	5375
	WT	339	59	12,879	3891	70,841	14,188	343	0	902
	WET	45	61	21,201	3010	17,262	8606	148	2	851
	CL	17	500	30,448	31,659	310	37	40,575	28	385
	BLT	0	0	76	11	0	0	21	156	0
	BL	5	14	545	1124	13	9	58	0	616

Percentage (%)										2005
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
1995	FR	50.75	6.14	37.05	3.62	0.12	0.04	2.28	0.00	0.00
	WL	4.16	9.25	57.86	23.32	0.19	0.27	4.90	0.01	0.05
	BUL	1.63	2.10	50.24	35.99	0.70	0.14	8.31	0.00	0.87
	GL	0.13	1.24	33.04	57.84	0.83	0.14	6.32	0.01	0.46
	WT	0.33	0.06	12.45	3.76	68.48	13.72	0.33	0.00	0.87
	WET	0.09	0.12	41.42	5.88	33.73	16.81	0.29	0.00	1.66
	CL	0.02	0.48	29.29	30.45	0.30	0.04	39.03	0.03	0.37
	BLT	0.03	0.17	28.63	4.31	0.00	0.10	8.01	58.75	0.00
	BL	0.23	0.57	22.87	47.14	0.56	0.37	2.42	0.01	25.84

FR-Forest, WL—Woodland, BUL—Bushland, GL—Grassland, WT—Water, WET-Wetland, CL—Cultivated land, BLT-Built up land, BL- Bare land.

Table 8
Transition matrix showing land use/cover change at Ngorongoro Conservation Area between 2005 and 2016.

Area (Ha)		2016								
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
2005	FR	57,845	11,805	37,699	2598	277	200	192	18	642
	WL	3672	4175	46,663	25,564	65	82	2439	10	191
	BUL	23,842	4869	829,494	423,103	12,668	1195	101,785	237	22,671
	GL	5933	1085	459,236	678,586	6599	1012	152,399	186	17,033
	WT	233	8	21,799	16,406	60,683	977	873	11	8242
	WET	60	2	4739	6265	13,768	233	171	0	2175
	CL	511	203	88,632	100,292	777	243	63,526	22	1415
	BLT	33	0	56	15	1	0	3	215	0
	BL	25	3	723	6661	651	20	2097	0	10,964

Percentage (%)										2016
		FR	WL	BUL	GL	WT	WET	CL	BLT	BAL
2005	FR	51.98	10.61	33.88	2.33	0.25	0.18	0.17	0.02	0.58
	WL	4.43	5.04	56.32	30.85	0.08	0.10	2.94	0.01	0.23
	BUL	1.68	0.34	58.42	29.80	0.89	0.08	7.17	0.02	1.60
	GL	0.45	0.08	34.74	51.33	0.50	0.08	11.53	0.01	1.29
	WT	0.21	0.01	19.96	15.02	55.55	0.89	0.80	0.01	7.55
	WET	0.22	0.01	17.29	22.85	50.23	0.85	0.62	0.00	7.93
	CL	0.20	0.08	34.67	39.23	0.30	0.09	24.85	0.01	0.55
	BLT	10.11	0.11	17.49	4.53	0.28	0.00	0.78	66.69	0.00
	BL	0.12	0.01	3.42	31.50	3.08	0.10	9.92	0.00	51.86

FR-Forest, WL—Woodland, BUL—Bushland, GL—Grassland, WT—Water, WET-Wetland, CL—Cultivated land, BLT-Built up land, BL- Bare land.

functional.

The suitable equilibrium between LULC change to improve human welfare and secure areas to sustain other ecosystem services is eventually a societal decision at the argument between development and conservation (Aveling et al., 2004; DeFries et al., 2004). A good starting point would be to effectively change the mindset toward ecosystem services and resources use by considering to 'use it wisely regardless of priority rights. Such a change can only occur if there is more widespread recognition that natural resources including land which are endangered. If the communities want the watershed to provide ecosystem services, they have to move beyond narrowly focused management that reflects sectorial interlinkage. This shift in approach is intellectually difficult because it requires more integrated and complex understanding than relying on a set of frameworks that describe ecosystem service only.

The tradeoffs among human practices and longtime management of ecosystem amenities become difficult. These requires adaptive management of ecosystems and natural resources (Singh et al., 2015), which in turn lays a foundation to bring different stakeholders together to help accommodate different opinions and interests. These changes need to be monitored and managed at the catchment scales to manage trade-offs between different ecosystem services and to balance losses and gains of land cover within the same. Simultaneously, multiple goals and various strategies should aim to structure and promote synergies or reduce tradeoffs among them (Tesfaw et al., 2018). Furthermore, better management of land resources for improved ecosystem services and community livelihoods must be assured.

Table 9
Areas of individual land use/cover change in the projected years 2025 and 2035.

Year	Land Use/Cover					
	2016 (Modelled)		2025		2035	
Unit	Ha	%	Ha	%	Ha	%
Forest	103,949	3.10	76,753	2.29	49,152	1.47
Woodland	14,092	0.42	12,548	0.37	10,218	0.31
Bushland	1,494,416	44.61	1,317,775	39.36	1,154,386	34.48
Grassland	1,200,979	35.85	1,262,030	37.65	1,325,857	39.55
Water	92,361	2.76	66,679	1.99	41,049	1.23
Wetland	10,577	0.32	9989	0.3	9207	0.27
Cultivated land	324,823	9.70	430,211	12.85	521,632	15.58
Built up area	6072	0.18	10,563	0.32	15,100	0.45
Bare area	102,528	3.06	163,249	4.88	223,196	6.67
Total	3,349,797	100	3,349,797	100	3,349,797	100

5. Conclusions

This study analyzed and forecasts LULC patterns to monitor LULC change using the hybrid CA–Markov model combined with GIS. The validation results reveal that CA–Markov is a suitable technique for predicting future LULC change. From the temporal patterns, changes between 1995 and 2016, woodland decreases at a maximum while the maximum increase was observed at a cultivated land. The forecast future (2016–2035) LULC changes reveal a reduction in the forest, woodland, bushland, and water, but expansions in grassland, wetland, grassland, cultivated built-up area, and bare land. A low-cost change analysis based on remote sensing imagery from different sensors made it possible to measure LULC changing pattern and predicting the future. With a time-series maps, change analysis showed the overall LULC change, including the inclusive finding of an area diverse forms of variations. However, the use of very high-resolution multispectral satellite imagery may offer even more details of changes in the area.

As an outcome, the current trend in land management, natural forests with high environmental values, is continuously declining, leading to the loss of the NCA's ecological values. The tourism sector may face a severe challenge due to the adverse impacts of the wildlife environment resulting from LULC change trends. The adverse effects on wildlife and their surroundings may decrease visitors' number and reduce the revenue from tourist's industries, which will affect the NCA wellbeing and livelihood of Maasai communities around the NCA. For sustainable management, the authorities must reach conciliation between the existing LULC patterns change and ecosystem services monitoring. A rational land use plan must be made to control the increase of cultivated land and built-up area counting a rational land use plan and ecosystem services protection guidelines. Moreover, the authorities must follow the guidelines of ecological protection in land use management to reserve

Table 10
Changes in LULC between 2016 and 2035.

Year	LULC Changes					
	2016 (Modelled) - 2025		2025–2035		2016–2035	
Unit	Ha	%	Ha	%	Ha	%
Forest	27,196	0.81	−27,601	−0.82	−43,000	−1.28
Woodland	1544	0.05	−2330	−0.06	−11,933	−0.35
Bushland	176,641	5.25	−163,389	−4.88	−334,654	−9.97
Grassland	−61,051	−1.80	63,827	1.9	66,369	1.95
Water	25,682	0.77	−25,630	−0.76	−54,440	−1.62
Wetland	588	0.02	−782	−0.03	5245	0.15
Cultivated land	−105,388	−3.15	91,421	2.73	198,148	5.92
Built up area	−4491	−0.14	4537	0.13	14,402	0.43
Bare area	−60,721	−1.82	59,947	1.79	159,864	4.78

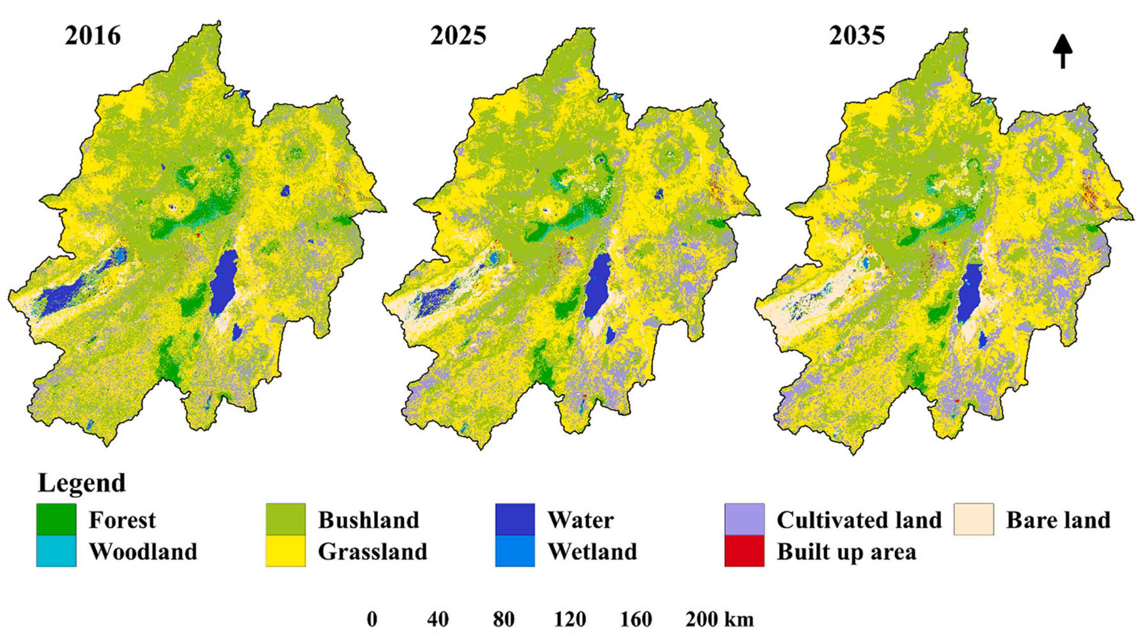

Fig. 5. Map showing projected LULC for the year 2016, 2025 and 2035.

Table 11
Transitional probability matrix of individual land use/cover at for the period 2016 and projected 2035.

Percentage		2035								
		FR	WL	BUL	GL	WT	WET	CL	BLT	BL
2016	FR	39	03	53	3	0	0	2	0	0
	WL	6	1	63	25	0	0	5	0	0
	BUL	2	0	49	36	0	0	9	0	4
	GL	0	0	38	45	0	0	13	0	4
	WT	0	0	25	10	52	6	0	0	7
	WET	0	0	37	15	28	6	0	0	14
	CL	0	0	30	42	0	0	26	0	2
	BLT	0	1	18	23	0	0	6	52	0
	BL	0	0	9	38	01	0	6	0	46

FR-Forest, WL—Woodland, BUL—Bushland, GL—Grassland, WT—Water, WET-Wetland, CL—Cultivated land, BLT-Built-up land, BL- Bare land.

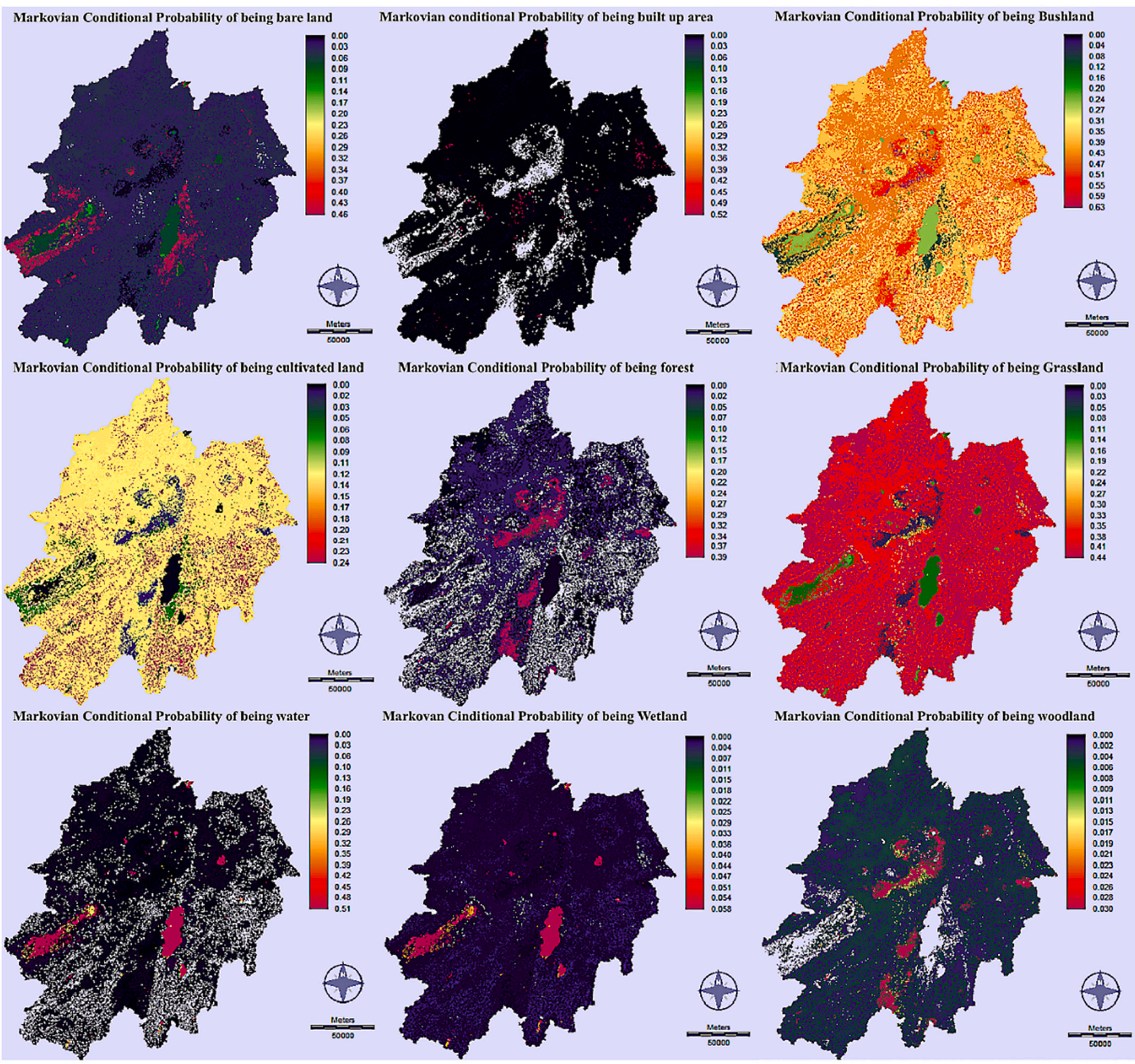

Fig. 6. Markovian transitional Probability of individual land use/cover.

conservation resources and benefit society within NCA a surrounding. Therefore, decision makers and stakeholders should plan to support improved land use management practices for balanced and sustainable ecosystem services strategies. However, further study which integrate very high-resolution remote sensing and participatory approaches are recommended to analyze LULC change patterns due different social economic factors and changes in climate.

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Author contributions

Mohamed Mwabumba:Conceptualization, Methodology, Writing-original draft. Prof. Brijesh K Yadav: Supervision, Writting-review & editing.Dr. Mwemezi Rwiza: Supervision, Writting-review & editing. Dr. Isaac Larbi: Visualization, Writting-review & editing. Dr Sekela Twisa: Methodology, Writting-review & editing

Declaration of Competing Interest

Authors declares that no conflict of interest in submitting this research paper to the Journal of Current Research in Environmental sustainability.

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