Assessing Land Use/Cover dynamics of the Ngorongoro world heritage site in Tanzania using a hybrid CA–Markov model

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Abstract

Abstract: In this study, land-use/cover pattern of the UNESCO world heritage site, Ngorongoro Conservation Area; is analyzed using the CA–Markov model with the help of RS and GIS. Hybrid classification techniques ware used to monitor land use/cover changes, using Landsat images for 1995, 2005 and 2016. The CA-Markov model is then used to predict the land use /cover maps for 2025 and 2035. The highest net gain from 1995-2016 observed in cultivated land (6.55%), grassland (2.68%), bare land (1.82%), bushland (0.48%) and built-up area (0.01%), and the net loss found in woodland (8.38%), forest (1.52%), wetland (1.41%), and water cover area (0.24%). However, reduction is expected in bushland (4.88%), forest (0.82%), water (0.77%) and woodland (0.07%) during 2025-2035 with increase in cultivated land (2.73%), grassland (1.19%), bare land (1.79%) and built-up area (0.14%). As per the current trend in land use management, forest cover is significantly declining; leading to the loss in the ecological values of the Ngorongoro Conservation Area and its surroundings. The results of this study can be used directly by the policymakers to plan appropriate conservation schemes to endorse improved land use management practices for ecological protection of the heritage site.

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Abstract:

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Keywords: Land use/cover, Ngorongoro Conservation Area, CA-Markov model, Remote Sensing, GIS

1. Introduction

Change in land use/cover has become one of the major issues in achieving the goals of sustainable development (Guan et al., 2011; Halmy et al., 2015). These changes in the landscape are the main anthropogenic drivers of Spatio-temporal environmental variations in the form of climate change, biodiversity loss and the pollution of natural resources (Lambin et al., 2003; Näschen et al., 2019; Twisa et al., 2020). Thus, the change in land use/cover is one of the fundamental concerns in natural resource management of local, national, regional and global landscapes (Foley et al., 2005; Yirsaw et al., 2017). Monitoring the dynamics of land use/cover changes is crucial for policymakers in mitigating its adverse impacts in the long term (Ansari and Golabi, 2019). Land use/cover changes are investigated under changing environmental conditions using multi-temporal remotely sensed images (Basommi et al., 2016; Kindu et al., 2015; Solomon et al., 2018). These studies consistently demonstrate that natural extremes associated with human activities are the key drivers of land use/cover dynamics at spatial and temporal scales (Basommi et al., 2016; Singh et al., 2015; Varga et al., 2019).

Invariably it is identified that agricultural expansion and population growth are the major anthropogenic factors responsible for land use/cover dynamics at local and global scales (Defries et al., 2010; Kindu et al., 2015; Solomon *et* al., 2018). Understanding the implications of land-use change patterns is deemed crucial in the context of our natural resource management and planning (DeFries et al., 2007). Some studies focused on documenting the nature and extent of historical alterations responsible for these changes (Haack et al., 2015; Jagger and Perez-Heydrich, 2016; Munthali and Murayama, 2014). Like other countries, Tanzania is not exempted from land use/cover changes over the past decades (Näschen et al., . 2019; Twisa and Buchroithner, 2019). However, few studies have been conducted for monitoring the current and future land use/cover patterns in Tanzania. Notably, the world heritage Ngorongoro Conservation Area (NCA) and its surrounding region are mostly undocumented (Masao et al., 2015; Estes et al., 2006), which is considered as the study area of this research. Created in 1959 as East Africa's first multiple-use protected area, the NCA is intended to conserve the wildlife and other natural resources for safeguarding the interests of the resident pastoral Masai communities (Estes et al., 2006).

This UNESCO declared world heritage area and International Biosphere Reserve includes much of the Crater Highlands in the NCA and surrounding areas between the Gregory rift valley and the Serengeti plains (Tarver et al., 2019). This NCA is the home to the world's largest ungulate herds consisting of wildebeest, zebras, and gazelles. The predatory animal population includes lions, spotted hyenas, leopards, and cheetahs. The area also provides habitat for the endangered black rhinoceros along with >400 species of birds (Deocampo, 2004; Żaba and Gaidzik, 2011). Due to the economic potential of the NCA, many tourist activities are concentrated in this region responsible for many environmental issues (Charnley, 2005;Fyumagwa et al., 2013). As visitors to the area continuously increasing, and so does the congestion and exposure of wildlife to human activities (Fyumagwa et al., 2013). A continued increment in visitors numbers at NCA resulted in environmental degradation (Mkiramweni et al., 2016) and competing use of the existing land. Hence understanding of the land use/cover change and future pattern of NCA is essential for designing effective management strategies of this heritage site.

Different modelling frameworks are developed to predict land-use/cover changes, including cellular automata, statistical analysis, Markov chain and artificial neural network (Kityuttachai et al., 2013; Subedi et al., 2013). The Cellular Automata-Markov (CA–Markov) model integrated with Remote Sensing (RS) and Geographical Information system (GIS) techniques seemed an appropriate approach in dynamic modelling of spatial and temporal changes in land use/cover (Guan et al., 2011; Myint and Wang, 2006; Riccioli et al., 2013; Roose and Hietala 2018; Kityuttachai et al., 2013; Nurmiaty et al.2014; Sayemuzzaman and Jha, 2014; Subedi et al., 2013) and were found a robust approach (Kamusoko et al., 2011; Sang et al., 2011). Furthermore, the CA–Markov model considers the effect of natural, societal, and economic factors on land-use changes which suit the nature of the study area. Therefore, the present study analyzed the land-use changes for the NCA and its surrounding area using the CA–Markov model combined with RS and GIS; to generate vital information for effective management of this world heritage site.

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 8,283 km^2. The study area covers the NCA and surrounding biodiversity hotspot with the size of about 33,452 km^2 from latitude 2.2° to 4.5° S and longitude 34.0° to 36.7° E, as shown in figure 1. Climatologically, the area is in the highlands with moist and misty conditions, where temperatures fall as low as 2 °C, and often rise to 35 °C (Żaba and Gaidzik, 2011). Rainfall in this area is seasonal and highly variable, ranging from 400 to 600 mm/year in arid lowland plains in the west and 1000 to1200 mm/year in highland forested areas in the east (Lawuo et al., 2014; Galvin et al., 2006). The area experiences bimodal conditions in which two wet and two dry seasons are distinguished. The wet season start from October to December and March to May; the short dry season is observed from January to February and from June to September. The area is very diverse ecologically and categorized into five different zones namely the 1) Crater highlands, 2) Salei plains, 3) Gol Mountains, 4) Serengeti plains, and 5) Kakesio/Eyasi Mountain (Masao et al., 2015).

2.2. Land Use/Cover Classification and Change Detection

Assessments of land use/cover were undertaken using three Landsat images; Landsat-5 TM 1995, Landsat-5 TM (BUMPER) 2005 and Landsat-8 OLI_TIRS 2016 as listed in Table 1. The images with a spatial resolution of 30 m and less than 10% cloud cover were collected from the Center for Earth Resources Observation and Science (EROS) of the United States Geological Survey (USGS). The ERDAS Imagine 2011, Arc GIS 10.3, and QGIS 2.18 software packages were used for this analysis. The hybrid classification technique (Gebrehiwot et al., 2014; Teferi et al., 2010), which involves unsupervised classification followed by supervised classification technique, was employed in classifying the images. The unsupervised classification was carried out using Iterative Self-Organizing Data Analysis (ISODATA) clustering algorithm(Boakye et al., 2008; Teferi et al., 2010) while supervised classification was undertaken with Maximum Likelihood Classification (MLC) algorithm (Gashaw et al., 2017; Gebrehiwot et al., 2014). The selected land use/cover classes were bushland, woodland, wetland, cultivated land, built-up area, grassland, water, forest and bare land as listed in Table 2.

For accurate assessment of land use/cover maps produced from the satellite images, the stratified random method for each of the three classified land use/cover maps was used to represent the different land use/cover 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 Land use/cover (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 Fitzpatrick-Lins, 1986). Change analysis was carried out using the classified (1995, 2005 and 2016) and the predicted land use/cover (2025 and 2035) maps to establish the pattern of land use/cover changes. To calculate the extent of changes occurred during the subsequent periods; 1995–2005, 2005–2016, 2016-2025 and 2025–2035 the percentage change were computed.

2.3. Land use/cover Prediction

The CA-Markov model was used to determine the land use/cover status of 2025 and 2035. The CA-Markov model available in IDRISI 17.0; is a robust simulator that predicts the trend and spatial structure of different land use/cover categories (Arsanjani et al., 2011; Wang et al., 2012). The model is based on historical land use/cover status images, transition probability matrix and relevant images as reference material (Eastman, 2012). This model is also widely applied in many countries (Mosammam et al., 2016; Singh et al., 2015; Wang et al., 2012), where projections rely on past trends. The study employed the 2016 classified map as the base land use/cover status, and the 2005 and 2016 maps are used for assembly transition probability matrix. The process involves the application of Markov transition estimator first to determine the transition between 2005 and 2016. The relative area under consideration determined next using different suitability factors, and the constraints controlling the alternates to the factors (Gashaw et al., 2017).

The Boolean maps were developed in each class processing by assigning a value of unity for the areas under consideration and zero for the remaining areas. The factors used in this process are the distance from the road, distance from the town centre and distance from developed areas, slope and elevation. The area with high suitability for conversion to each class type was assigned a value from 0 (no chance for conversion) to 1 (high chance for conversion) to a certain land-use class (Gashaw et al., 2017). However, the slope was considered as obvious constant to build up and cultivated areas because high slopes inhibit this kind of activities (Eastman, 2012). For the forest, bushland, grassland and the bare land, slope were not considered as a constraint. The multi-criteria evaluation (MCE) decision support system was applied to integrate factors and constraints, using a weighted linear combination (WLC) fussy membership algorithm. This procedure develops a single map with suitability to each land use/cover class (Gashaw et al., 2017; Kamusoko et al., 2011). The suitability map for each land use/cover class then assigned the binary value of 0-255 with 0 indicating non-suitable and 255 for highly suitable land (Gashaw et al., 2017). The suitability maps for each land use/cover class areas are presented in figure 3.

The model was validated through the comparison of the simulated and classified 2016 land use/cover maps using the relative operating characteristic (ROC) and Kappa indices (Mosammam et al., 2016; Schneider and Gil Pontius, 2001). The kappa indices included Kappa for no information (K_{no}), Kappa for location ($K_{location}$), Kappa for stratum level location ($K_{locationStrata}$) and Kappa for standard ($K_{standard}$).

3. Results

This section summarizes results for the land use/cover change analysis and future prediction using the hybrid CA-Markov model, for the world heritage site in the NCA and the surroundings. It includes model accuracy assessment, historical and projected land use land cover patterns.

3.1. Accuracy Assessment

Table 3 shows the accuracy assessment of the land use/change classification in the form of producer's accuracy (PA), user's accuracy (UA), and Kappa coefficient for the classified maps of 1995, 2005, and 2016. The accuracy assessments based on confusion matrices showed an overall accuracy of 98.01%, 99.71%, and 99.98% for 1995, 2005, and 2016 respectively. The Kappa coefficients of those years are 0.98, 0.99, and 0.99, respectively. The producer and user accuracy of individual classes show slight differences, but the overall efficiency is observed for these results. These results provided a fundamental platform for subsequent analysis of land use/cover changes. CA–Markov validation was attained, with a ROC value of 87.5%. The Kappa statistics values are found as K_{no} (85.95%), $K_{location}$ (86.57%), $K_{locationStrata}$(86.57%) and $K_{standard}$ (82.05%). The observed accuracy tests of above 80% show the capability of the model to simulate the 2025 and 2035 land-use patterns effectively (Mosammam et al., 2016; Singh et al., 2015).

The area under different land use/cover and its change for the study period of 1995-2016 is listed in Tables 4. The land use/cover maps for the years 1995, 2005, and 2016 are presented in Figure 2. Land use/cover of the year 1995 indicates that 43.97% of the area was covered by bushland, 34.91% by grassland, 9.04% by woodland, 4.27% by forest and 3.10% by cultivated land. Also, 3.09% of the area was covered by water, 1.53% by wetland, 0.07% by bare land and 0.01% by built-up area. In the year 2005, the area was covered by 42.39% bushland, 39.47% grassland, 7.63% cultivated land, 3.32% forest and 3.26% water while, 2.47% of the area was covered by woodland, 0.82% wetland, 0.63% bare land and 0.01% built-up area. The distribution of land use/cover in the year 2016 showed that about 44.45% was covered by bushland, 37.60% by grassland, 9.66% by cultivated land, 2.85% by water and 2.75% by forest. However, 1.89% of the area was covered by bare land, 0.66% by woodland, 0.12% by wetland and 0.02% by built-up area.

The land use/cover change for the study period of 1995-2016 is listed in Table 4. During the study period of 1995-2005; decrease in woodland, bushland, forest, and wetlands cover occurred by 6.56%, 1.59%, 0.95% and 0.71% respectively. The grassland, cultivated land, bare land and water surface experienced an increase of 4.55%, 4.53%, 0.56% and 0.71% respectively. During 2005-2016, the decrease was observed in the grassland, woodland, wetland, forest and water cover by 1.81%, 0.70%, 0.57% and 0.41% respectively. The result also showed an increase of bushland, cultivated land, bare land and built-up area by 2.06%, 2.03%, 1.26 and 0.01%, respectively. The results show that the highest net gain during the study period of 1995-2016 was in cultivated land (6.55%), followed by grassland (2.68%), bare land (1.82%), bushland (0.48%) and built up is (0.01%), while net loss was in woodland (8.38%), forest (1.52%), wetland (1.41%), and water (0.24%) as listed in Table 4.

3.3. Land Use/Cover Change Pattern (Transition) Matrix

Tables 5-7 show the cross-tabulation change matrix for the changed areas and their corresponding percentages from one land use/cover class to another in comparison with the total area of each land use/cover class from 1995 to 2016. During the study period of 1995-2016, 61% of water remained unchanged, followed by bushland land (51%), grassland (50%), built-up land (48%) and forest (37%). Besides, unchanged classes were also observed in bare land (30%), woodland (2%) and wetland (0%) as listed in table 5. This change implies a complete loss of the environmentally sensitive areas such as wetlands, with its total area converted to bushland by 34%, water by 31%, grassland by 20%, bare land by 13% and cultivated land by 1%.

The cross-tabulation matrix for the study period between of 1995-2005 (table 6), shows that 68% of water remained unchanged, followed by built-up land (59%), grassland (58%), forest (51%), bushland land (50%) and cultivated land (39%). Also, the same was maintained for the bare land (26%), wetland (17%) and woodland (9%). These conditions suggest that wetland experienced the maximum alteration, with 83% of its total area converted to bushland (41%), water (34%), grassland (6%), and bare land (2%). Furthermore, for the period between 2005 and 2016 (table 7), 67% of built-up land persisted changes, followed by bushland land (58%), water by (56%), bare land by (52%), forest by (52%), grassland (51%), cultivated land (25%), woodland by (5%) and wetland (1%). This condition point towards the conversion of the wetland to the water body, grassland, bushland, bare land and cultivated land by 50%, 23%, 17%, 8% and 1%, respectively.

3.4. Conditional Probability Matrix for Predicted Land Use/Cover

Table 8 and Figure 3 show the conditional probability that expresses pixel's probability for each 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 year of 2035, 52% of built-up land and water remain unchanged followed by bushland (49%), bare land (46%), grassland (45%), forest (39%), cultivated land (26%), wetland (6%) and woodland (1%). These results suggest that woodland face the most significant 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 the built-up area would maintain above 50% of unchanged land use/cover, while the largest share will be gained from bushland and grassland, respectively. The expected contribution of the single land use/cover class would be 53% of forest to bushland; 42% of cultivated land to grassland and 38% of grassland to bushland. Furthermore, the contribution is expected to be 38% of bare land 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.

3.4. Predicted Land Use/Cover Patterns

The CA-Markov model was used to predict future land-use patterns based on the trends of land-use changes that took place between 1995 and 2016. Table 9 shows the extent of land-use types projected in 2025 and 2035. Also, Figure 4 shows the predicted maps of land use for the year 2025 and 2035. Land use/cover of the year 2025 indicated that the area would be covered by bushland, grassland cultivated land and bare land by 39.36%, 37.65%, 12.85% by, 4.88% and 2.29%; while the area would be covered by forest, water, woodland, built-up area and the wetland by 1.99%, 0.37% by, 0.32% and 0.30%, respectively. Moreover, for the land use/cover of the year 2035, the area is covered by grassland (39.47%), bushland (34.48%), cultivated land (15.58%), bareland (6.67%) and Forest (1.47%). The area will also be covered by forest (1.47%), water (1.23%), built-up area(0.45%), woodland(0.31%) and wetland by 0.27%. Net loss between 2025 and 2035 is expected in forest, woodland, bushland, water and wetland while the net gain is anticipated in grassland, cultivated land, built-up area and bare land. Bushland is likely to decrease by 4.88%, followed by forest 0.82%, water 0.77%, woodland 0.07% and wetland 0.02%. Furthermore, 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%.

4. Discussion

For monitoring of land use/cover changes over the historical period of 1995-2016 (21 years), land use/cover maps for 1995, 2005 and 2016 were developed for the study area. Significant variation in the pattern of land use/cover change of the different land-use types is observed. The results for the study duration of 1995–2016 on different classes of land use/cover indicated that maximum gain and loss occurred in cultivated land and woodland, respectively. Furthermore, according to the findings, bushland and grassland gain is quite higher from other land use/cover. These changes of different land use/cover into bushland and grassland are supported by the change matrix tables (Table 5-7), which showed that from 1995 to 2016, 57% of woodland, 49% of the forest, 36% of grassland, 34% of wetland and 33% of cultivated were concerted to bushland. Other land use/cover classes converted to bushland included 32% of built-up area, 18% of water and 12% of bare land. Moreover, the changes converted 46% of bare land, 43% of cultivated land and 34% of bushland to grassland. Similarly, notable changes have occurred in woodland (31%), wetland (20%), water (13%), built-up area (10%) and forest (5%). Then, land use/cover changes were predicted for 2025 and 2035 using the CA-Markov model, assuming the continuation of the current management trend in the study area. To simulate reasonable future land use/cover changes, the Markov chain model was carried out to estimate Markovian probability transition matrix using land use/cover maps of 1995 and 2016, and then the output was used to predict future land use/cover for the years 2025 and 2035. The results indicated that from 2025 to 2035, the reduction is expected in bushland (4.88%), forest (0.82%), water (0.77%) and woodland (0.07%) while and the increment is expected in cultivated land (2.73%), grassland (1.19%), bare land (1.79%) and built-up area (0.14%).

In 1995, the area was covered by bushland at large in the eastern, central and northern parts, forest and woodlands were mainly covered the central, northern parts and few areas of the southern parts. Cultivation land was mainly covered the eastern parts of the area. However, a high increase in cultivated land was observed during 1995-2016 in the eastern and southern parts, which is mainly out of conservation areas associated with little restrictions on human activities. In the northern and central parts, forest and woodland were reduced to bushland and grassland. These changes seem due to some human activities and recurrences of severe drought conditions as reported by Mkiramweni et al., 2016. More expansion of cultivation land is expected from 2016 to 2025 and 2035 over the eastern part, southern parts, and some parts of the northern areas. High expansion of buildup areas is expected from 2025 to 2035 around the central parts between Lake Manyara and the NCA, and eastern parts just outside the boundaries of the protected areas.

Overall, the built-up area expansion mainly caused by the rapid growth of population, which also suggested the expansion in agricultural land in the eastern and southern parts. These changes in land use/cover have significant impacts on biodiversity, ecosystem, health and protected area integrity, as stated by DeFries et al., 2007; Jones et al., 2009. These changes reflect and shape the global interplay between economic development and biodiversity conservation with multiple objectives, and policymakers aim to shape and foster synergies between them (Tesfaw et al., 2018). Although these changes occur outside the boundaries of existing protected areas, they impose potential negative consequences for the ecological functioning (DeFries et al., 2007).

The appropriate balance between land use/cover to improve human well-being and protected areas to conserve other ecosystem services is ultimately a societal decision at the argument between conservation and development (Adams et al., 2004; DeFries et al., 2007). In general, human activities are expected to increase having potential influences on protected areas (Sala et al., 2000). In NCA, where the population is expected to grow in the future, these land-cover trends may lead to increased human-wildlife conflict, illegal resource extraction, declines in habitat productivity, and degradation of the natural resource.

5. Conclusions

In this study, monitoring and prediction of land use/cover change of the UNESCO world heritage site, Ngorongoro Conservation Area and its surroundings are performed for an extended period of 1995-2035 using a CA–Markov model along with GIS and RS. The simulated land use/cover pattern of our model is compared well with the actual land use/cover condition of the reference year (2016), emphasizing that CA–Markov is capable for predicting the future land use/cover change of the study area. The results show that during 1995-2016, the highest net gain was in cultivated land (6.55%), grassland (2.68%), bare land (1.82%), bushland (0.48%) and built-up area (0.01%), and the net loss observed in woodland (8.38%), forest (1.52%), wetland (1.41%), and water (0.24%). The predicted land use/cover changes of years 2025 to 2035, show notable reduction in bushland (4.88%), forest (0.82%), water (0.77%) and woodland (0.07%). Increment in cultivated land (2.73%), grassland (1.19%), bare land (1.79%) and built-up area (0.14%) is observed for the selected future years.

Considering the current trend in land management of the NCA, natural forests are heading towards their loss along with a decline in their associated environmental values. A compromise between the current patterns of land use/cover change with environmental protection and management policy is thus essential for sustainable management of the ecological system present in and around the NCA. In order to avoid this compromise, a rational land use plan must be made for the NCA and its surrounding region with rigorous monitoring and increased restrictions on cultivated land and built-up areas. Moreover, the guidelines of ecological protection should be followed sincerely in land use management to preserve ecological resources for a long term benefit of society of NCA and its surrounding region.

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8. Author statement

The five authors contributed in a substantial way to the manuscript. All authors discussed the structure of the manuscript and approved the submitted manuscript.

9. Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1. *Detailed characteristics of Landsat images used in the study.*

Year	Satellite	Sensor	Path/Row	Acquisition Date	Cloud Cover (%)
1995	Landsat 5	TM (SAM)	168/62	30/01/1995	8.0
			168/63	27/09/1995	0.0
			169/62	2/6/1995	2.0
			169/63	17/10/1994	2.0
2005	Landsat 5	TM (BUMPER)	168/62	11/4/2009	3.0
			168/63	9/6/2005	2.0
			169/62	6/4/2009	0.0
			169/63	25/08/2004	1.0
2016	Landsat 8	OLI_TRIS	168/62	22/10/2016	4.8
			168/63	22/10/2016	1.9
			169/62	13/10/2016	0.2
			169/63	13/10/2016	0.5

Table 2. *Land use classification used for this study.*

Class	Descriptions
Bushland	It is mainly comprised of plants with multi-stem originating from a single root base.
Woodland	An assemblage of trees with 20% to 80% canopy cover which may, or rare occasions, is closed entirely.
Wetland	The low-lying areas, usually uncultivated ground with water collects; a bog or marsh.
Cultivated land	Crop fields and fallow lands.
Built-up area	Residential, mixed urban, transportation, roads, commercial, industry.
Grassland	It is a land which is mainly dominated by grasses.
Forest	The continuous stand of trees, many of them with a height of 50 which include natural forest, mangrove a

Class	Descriptions
Water	River, open water, lakes, ponds and reservoirs.
Bare land	The area of land with exposed soil and barren area influenced by a human.

Table 3. *Accuracy assessment of the land use/cover classification at Ngorongoro conservation area and its surrounding areas.*

	1995	**1995**	**2005**	**2005**	**2016**	**2016**
LULC	**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	98.01	99.71	99.71	99.98	99.98
Kappa	0.98	0.98	0.99	0.99	0.99	0.99

Table 4. *Land use/cover classification statistics and changes for 1995, 2005 and 2016 images*

Land Use/Cover

Year	**1995**		**2005**
Unit	**Ha**	%	**Ha**
Forest	143204	4.27	111277
Woodland	302766	9.04	82860
Bushland	1473057	43.97	1419863
Grassland	1169535	34.91	1322070
Water	103441	3.09	109233
Wetland	51185	1.53	27411
Cultivated land	103960	3.1	255619
Built up area	265	0.01	322
Bare area	2385	0.07	21143
Total	3349797	100	3349797
Land Use/Cover Change	**Land Use/Cover Change**	**Land Use/Cover Change**	**Land Use/Cover Change**
Year	**1995-2005**	**1995-2005**	**2005-2016**
Unit	**Ha**	%	**Ha**
Forest	-31927	-0.95	-19124
Woodland	-219906	-6.56	-60709
Bushland	-53194	-1.59	69177
Grassland	152535	4.55	-62581
Water	5792	0.17	-13744
Wetland	-23774	-0.71	-23449
Cultivated land	151659	4.53	67865

Built up area	57	0	376
Bare area	18758	0.56	42189

Table 5. *Transition matrix showing land use/cover change at Ngorongoro Conservation Area during 1995-2016.*

				2016	2016	2016				
Area (ha)	**Area (ha)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	52519	9944	70609	7279	297	213	1737	5	602
	WL	12016	4681	172065	93098	1347	252	18410	74	825
	BUL	22941	6357	751212	498744	7642	1557	157387	172	27047
1995	**GL**	4049	915	424070	590163	6964	968	121164	246	20994
	WT	311	19	19072	13903	63188	465	792	11	5679
	WET	120	15	17641	10278	15728	253	641	2	6506
	CL	163	219	33994	44906	229	249	23174	59	967
	BLT	15	1	85	28	1	0	8	128	0
	BL	18	1	291	1090	94	6	172	0	712
Percentage (%)	**Percentage (%)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	**37**	7	49	5	0	0	1	0	0
	WL	4	**2**	57	31	0	0	6	0	0
	BUL	2	0	**51**	34	1	0	11	0	2
1995	**GL**	0	0	36	**50**	1	0	10	0	2
	WT	0	0	18	13	**61**	0	1	0	5
	WET	0	0	34	20	31	**0**	1	0	13
	CL	0	0	33	43	0	0	**22**	0	1
	BLT	6	0	32	10	0	0	3	**48**	0
	BL	1	0	12	46	4	0	7	0	**30**

FR-Forest, WL—Woodland, BUL—Bushland, GL—Grassland, WT—Water, WET-Wetland,

CL—Cultivated land, BLT-Built up land, BL- Bare land

Table 6. *Transition matrix showing land use/cover change at Ngorongoro Conservation Area during 1995-2005.*

					2005	2005				
Area (ha)	**Area (ha)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	72669	8789	53060	5186	169	57	3271	0	1
	WL	12604	28002	175175	70594	573	805	14849	18	147
	BUL	24079	30931	740088	530138	10381	2040	122479	55	12866
1995	GL	1518	14504	386390	676457	9683	1670	73876	62	5375
	WT	339	59	12879	3891	70841	14188	343	0	902
	WET	45	61	21201	3010	17262	8606	148	2	851
	CL	17	500	30448	31659	310	37	40575	28	385
	BLT	0	0	76	11	0	0	21	156	0
	BL	5	14	545	1124	13	9	58	0	616
Percentage (%)	**Percentage (%)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	**51**	6	37	4	0	0	2	0	0
	WL	4	**9**	58	23	0	0	5	0	0
	BUL	2	2	**50**	36	1	0	8	0	1

					2005	2005				
1995	GL	0	1	33	**58**	1	0	6	0	0
	WT	0	0	12	4	**68**	14	0	0	1
	WET	0	0	41	6	34	**17**	0	0	2
	CL	0	0	29	30	0	0	**39**	0	0
	BLT	0	0	29	4	0	0	8	**59**	0
	BL	0	1	23	47	1	0	2	0	**26**

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 2005 and 2016.*

					2016	**2016**				
Area (ha)	**Area (ha)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	57845	11805	37699	2598	277	200	192	18	642
	WL	3672	4175	46663	25564	65	82	2439	10	191
	BUL	23842	4869	829494	423103	12668	1195	101785	237	22671
2005	GL	5933	1085	459236	678586	6599	1012	152399	186	17033
	WT	233	8	21799	16406	60683	977	873	11	8242
	WET	60	2	4739	6265	13768	233	171	0	2175
	CL	511	203	88632	100292	777	243	63526	22	1415
	BLT	33	0	56	15	1	0	3	215	0
	BL	25	3	723	6661	651	20	2097	0	10964
Percentage (%)	**Percentage (%)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	**52**	11	34	2	0	0	0	0	1
	WL	4	**5**	56	31	0	0	3	0	0
	BUL	2	0	**58**	30	1	0	7	0	2
2005	GL	0	0	35	**51**	0	0	12	0	1
	WT	0	0	20	15	**56**	1	1	0	8
	WET	0	0	17	23	50	**1**	1	0	8
	CL	0	0	35	39	0	0	**25**	0	1
	BLT	10	0	17	5	0	0	1	**67**	0
	BL	0	0	3	32	3	0	10	0	**52**

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

Table 8 *Transitional probability matrix of individual land use/cover for the period 2016 and projected 2035*

					2035					
Percentage (%)	**Percentage (%)**	**FR**	**WL**	**BUL**	**GL**	**WT**	**WET**	**CL**	**BLT**	**BL**
	FR	**39**	3	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
2016	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	1	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

Table 9. *Land use/cover statistics for projected 2025 and 2035 maps*

Land Use/Cover

Year	**2016**	**2016**	**2025**
Unit	**Ha**	**%**	**Ha**
Forest	92152	2.75	76753
Woodland	22151	0.66	12548
Bushland	1489040	44.45	1317775
Grassland	1259488	37.6	1262030
Water	95489	2.85	66679
Wetland	3962	0.12	9989
Cultivated land	323484	9.66	430211
Built up area	698	0.02	10563
Bare area	63332	1.89	163249
Total	3349797	100	3349797
Land Use/Cover Change	**Land Use/Cover Change**	**Land Use/Cover Change**	**Land Use/Cover Change**
Year	**2016-2025**	**2016-2025**	**2025-2035**
Unit	**Ha**	**%**	**Ha**
Forest	-15399	-0.46	-27601
Woodland	-9603	-0.29	-2330
Bushland	-171265	-5.09	-163389
Grassland	2542	0.05	63827
Water	-28810	-0.86	-25630
Wetland	6027	0.18	-782
Cultivated land	106727	3.19	91421
Built up area	9865	0.3	4537
Bare area	99917	2.99	59947

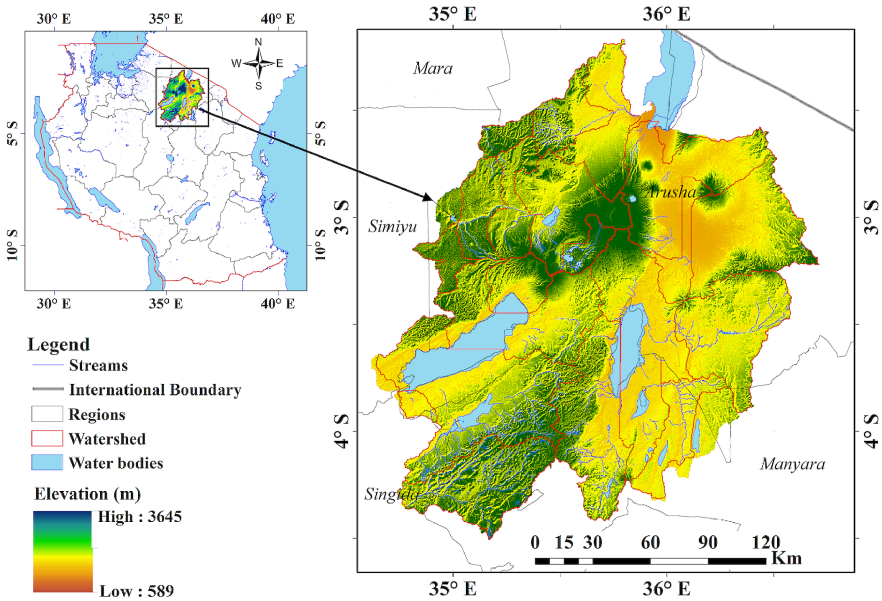
Figure legends

Figure 1. The study area of Ngorongoro Conservation Area (NCA) and its surrounding region

Figure 2. Land use/cover maps for 1995, 2005 and 2016 at Ngorongoro Conservation site and its surrounding area.

Figure 3. The Markovian conditional probability of individual land use/cover of the study area

Figure 4. Projected land use/cover for the year 2025 and 2035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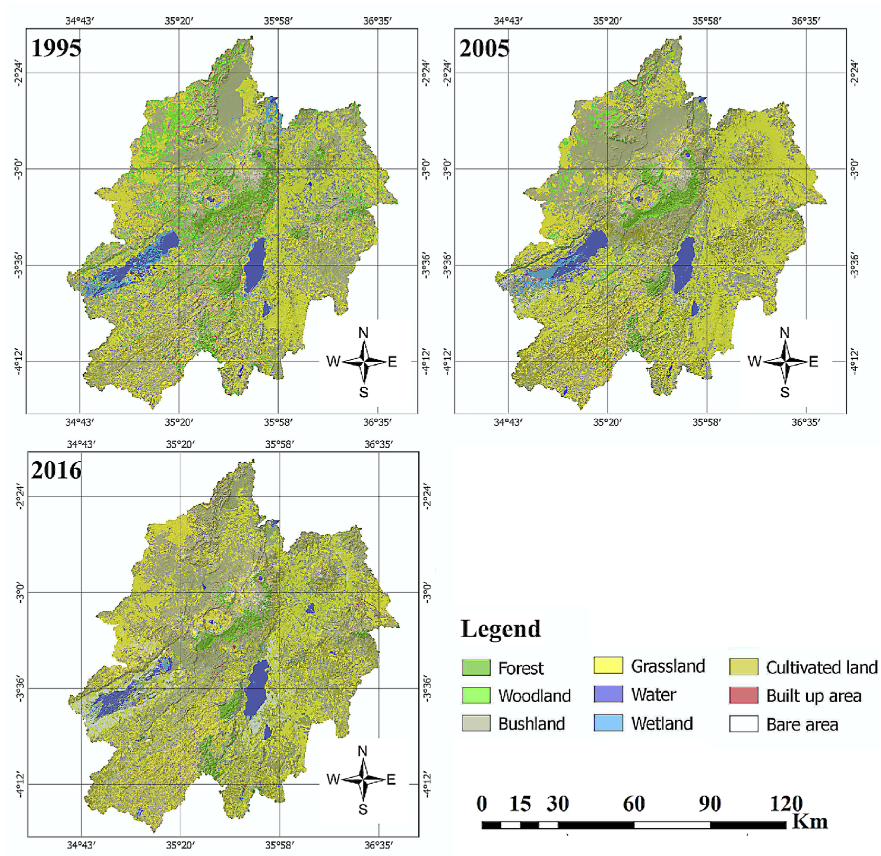
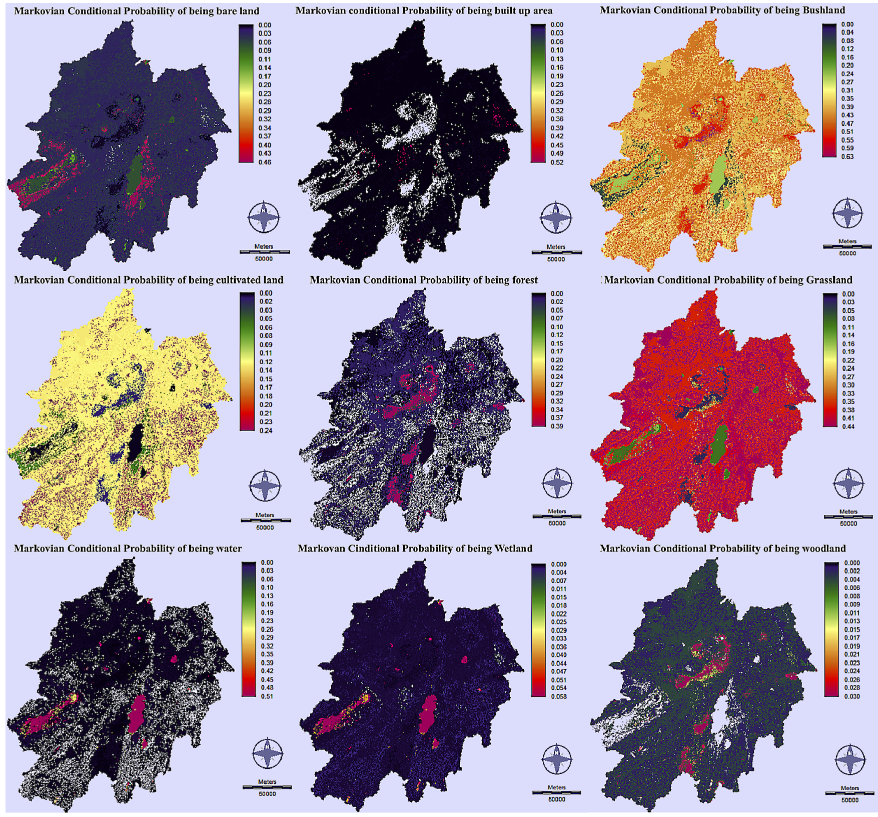
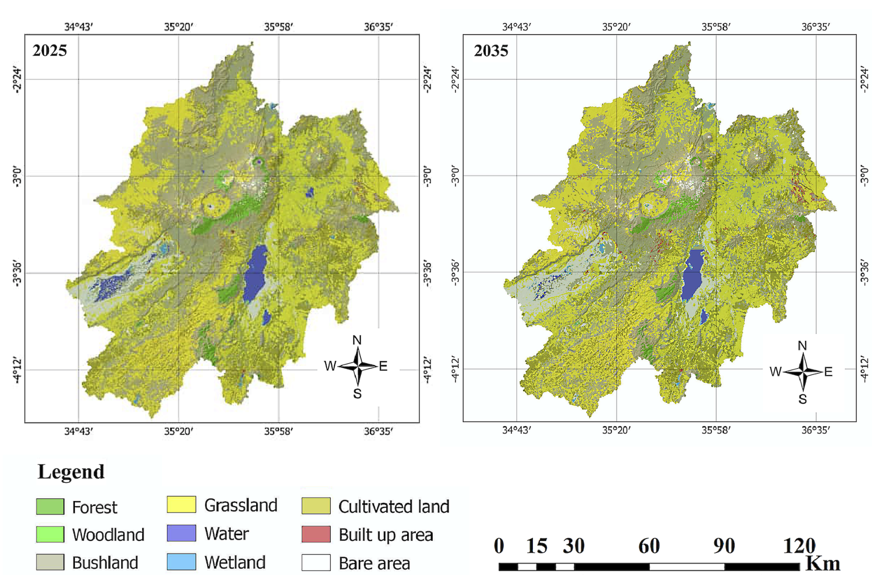
0 15 30 60 90 120
Km
Legend
Streams
International Boundary
Regions
Watershed
Water bodies
Elevation (m)
High : 3645
Low : 589


1995
2005
2016
34°43′
35°20′
35°58′
36°35′
-2°24′
-3°0′
-3°36′
-4°12′
N
W
E
S
Legend
Forest
Woodland
Bushland
Grassland
Water
Wetland
Cultivated land
Built up area
Bare area
0 15 30 60 90 120
Km


Markovian Conditional Probability of being bare land
Markovian conditional Probability of being built up area
Markovian Conditional Probability of being Bushland
Markovian Conditional Probability of being cultivated land
Markovian Conditional Probability of being forest
Markovian Conditional Probability of being Grassland
Markovian Conditional Probability of being water
Markovan Cinditional Probability of being Wetland
Markovian Conditional Probability of being woodland


2025
2035
34°43′
35°20′
35°58′
36°35′
-2°24′
-3°0′
-3°36′
-4°12′
N
W
E
S
Legend
Forest
Woodland
Bushland
Grassland
Water
Wetland
Cultivated land
Built up area
Bare area
0 15 30 60 90 120
Km