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Land-Use and Land Cover Changes on the Slopes of Mount Meru-Tanzania

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Abstract

Environmental transitions analysis was done in part of the land on the slopes of the foothills of Mount Meru in thirty (30) years' time from 1986 to 2016 using satellite-derived land use/cover maps and a Cellular Automata (CA) spatial filter under IDRISI software environment and assessed the important land use changes. Also, the future land use for 2026 which is the next ten (10) years was simulated based on Cellular-Automata Markov model. The results showed significant land use transitions whereby there is a huge land use change of bush land (BL) and agriculture land (AG) into human settlement (ST) which resulted into conversion of Arusha town into a City. In addition, the changes have caused slight changes in water bodies into mixed forest. Moreover, the future land use/land cover (LULC) simulations indicated that there will be unsustainable LULC changes in the next ten years since most of bush land and part of agriculture land will be used for building different structures thus interfering with fresh water sources and food availability in the City. These changes call upon the relevant planning authorities to put in place the best strategies for good urban development.

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Land Use Change,
Markov Chain,
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Remote Sensing,
Spatial Modeling.

Introduction

In the modern world, LULC is inevitable since human use their environment for their development. Human may use the atmosphere, surface and underground of the earth for development and on doing so they may affect the environment. Such changes occur as a result of complex processes that involve modifications in land-cover and land use,[1] and they

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are determined by the interaction in space and time between biophysical and humans endeavors.[2] Such processes include but not limited to expansion of agriculture, infrastructures, settlements, development of industries and natural disasters. In several areas on the earth, river ecosystems and land cover have changed as a result of various forces persisting on them which have led to modification of the flow regime[3,4] and change in ecology. Such forces include deforestation, overgrazing, expansion of agriculture, and infrastructure development. Moreover, the increased competition for water use and conversion in land use in the upstream of many rivers are said to have contributed to change in hydrological regimes of many rivers and wetlands.[5,6] Different government policies, political influences as well as technological changes can also lead to land use/land cover changes which can affect the watersheds and catchment areas.[3,7,8] The above-mentioned issues are among of the several activities degrading large environment in many developing countries including Tanzania.

The study on impacts of land-use and land cover change has been a point of interest of many researchers. For example, [2,9–11] in their studies attempted to provide the insights and understanding of the causes and effects of land-use and land cover change with most emphasis of their studies on biophysical aspect of land-use and land cover change. Currently, large areas in Nothern Tanzania are said to have been converted to agricultural land and other uses, including the cultivation of food and cash crops, overgrazing, expansion of settlements and development of infrastructures such as irrigation scheme systems, mining and other industries as a result of increased migrations and internal population. Such areas include the slopes of Mount Meru in Tanzania which is among the important Pangani River Basin (PRB) sub catchment feeding the Pangani River.[12,13] This area is facing deforestation and forest degradation, poor agricultural expansion which includes increased furrow irrigation technology, establishment of new large commercial farms from virgin land, overgrazing, rapid increase in human population due to immigration and natural process threatened the land use and land cover of the area hence affecting the hydrological system of the area.[6,13,14] Currently, there has been a significant increase of farming and livestock activities in the PRB sub catchment. This has raised the dramatic conversion of grassland, woodland and forest into cropland and pasture which eventually results into negative changes in the wetlands size and river regimes.[6]

Knowing the main drivers of land use and land cover change on rivers and its aspects is vital, such understanding includes both assessments of the expected rate and spatial pattern of land-use and land-cover change (LULC) as well as familiarity of the principal human and biophysical drivers.[2] These complex questions can be answered through modeling the land use land cover change in GIS environment. Also, the process of analysis, forecasting and evaluating future land-use change of any place involves a complicated set of tasks, and should be performed using better scientific knowledge of the physical extent, character and consequences of land transformation.[15] In analysis and modeling of LULC dynamics, remote sensing and GIS tools are widely used to study both quantitatively and qualitatively using Cellular Automata and Markov Chain (CA-MC) spatial models and predicting the future LULC scenario basing on historical land cover data.[10,16–19] Apart from that, Normalized Difference Vegetation Index (NDVI), principal component analysis (PCA), image rationing, image differencing, change vector analysis in terms of magnitude and direction, deviation and regression, are among the techniques which can be used in GIS environment to study the LULC changes.[17,20,21] In this study, CA-MC has been used to assess the land use change and model the future LULC in the upper part of the PRB catchment.

Land Cover Change and Drainage

Land cover plays a vital role in drainage system and conservation of any catchment. Different studies have shown the land covered with different types of vegetations in relation to soil type can affect the drainage and sustainability of a particular catchment.[22,23] Further studies by different researchers have shown that the pressure for change in a land cover can particularly cause changes in the hydrological regime of an area especially when extensive deforestation has taken place.[24] While this happen, the catchments study shows that the hydrological regime of an area can change with no significant changes of precipitation over long time.[25] Other studies show stream annual flow to be high in forested areas than deforested area but does not show the season in which such events occurs.[26]

Cellular Automata

CA is one of the methods used to model land change in terms of geospatial location of development as well as quantity of change. In this model, the geospatial dynamics are controlled by local rules determined either by the CA spatial filter or transition potential maps.[27] The CA model is defined as a one or two-dimensional grid of identical automata cells of which each automata cell processes respective information, and proceeds in its actions based on data received from its environment and following rules that it stores or holds internally.[28] A simple CA have five components which are the grid space on which the model operates, cell states in the grid space and transition rules, which determine the spatial dynamic process. Others include status of neighborhoods that influences the central cell and iteration numbers.[29] In addition, a grid of automata must be defined by a set of inputs from the states of neighbouring cells to become a CA. Moreover, two-dimensional CA must be considered on a grid lattice with the influencing neighborhoods containing four (von Neumann function) or eight (Moore function) adjacent cells.[30] The most important advantage of the CA models is based on its ability to control complex spatially distributed processes, as well as affording insights into a wide variety of local behaviors and global patterns. Furthermore, temporal and spatial complexities of many phenomena can be well simulated and represented by properly defining transition rules in CA models.[29] With such vital advantages, CA models have been increasingly used for simulating different spatial phenomena including LULC[31] and urban growth.[32] These features give most significant concern in CA modeling which requires defining appropriate transition rules based on training data which control the model. Furthermore, linear boundaries have been used to define the rules; however, land-use dynamics, and many other geospatial phenomena, are extremely complex and require non-linear boundaries for the definition of rules.[29]

Markov Chain Model

The Markov Chain premise is a stochastic series that depicts the probability of how one state is altered to another state. The Markov Chain produces a key descriptive outcome that determines the probability of change from one category to another category thus managing the temporal dynamics among the land use/cover categories, based on transition probabilities (e.g. conservation to built-up area), which is a also called transition probability matrix.[10,33] This model is highly used for studies of water resource systems and simulation of precipitation sequences, particularly to describe and predict lithological transition,[34] plant succession [35] and land use change.[36] The model works under assumption of several mathematical probability theories of transition probabilities calculated through the Chapman-Kolmologov equation. In this study, such mathematical manipulations are omitted since GIS softwares are used for the same purpose.

CA- Markov Chain Model

The CA-MC model is an integrated system which plays a great role in multi-criteria evaluation of LULC changes. It is among the best method and technique for quantity estimation, spatial and temporal dynamic modeling of LULC changes since GIS and remote sensing data can be well integrated to give a meaningful outcome.[33] In this model, the MC tool is used to produce transitional probabilities statistics, transitional area statistics and conditional transition images data which are used as inputs to predict the later state of the particular pixels over space basing on the condition, location and proximity of the neighboring pixel in CA model.. [10,16,18,19,37–40] In this paper, studies on the impacts of land use and land cover changes on water resources on the slopes of mount Meru is assessed using CA-MC spatial models. The two models will be used to estimate and project the future land cover land use changes of the study area.

Materials and Methods

Description of Study Area

The study area involved the foothills of the eastern and south west parts of Mount Meru which is part of the entire Pangani basin sub catchment located

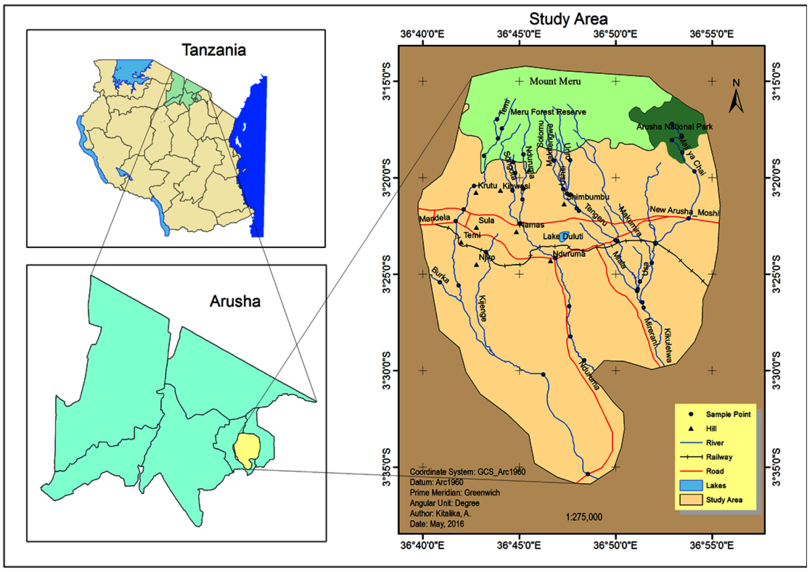


Fig. 1: Location of the study area

in the Nothern part of Tanzania sub catchment (Figure 1).[41] The natural vegetation in this area is typically tropical forest to savannah and topography is dominated by the Mount Meru volcanic cone of Pleistocene to recent origin. The local climate of the area is temperate Afro-Alpine with minimum and maximum daily temperature of 20.6 °C and 28.5 °C, respectively. The rainfall is irregularly distributed between a main wet season from February to mid May and a minor one from September to November both giving the mean annual rainfall of 535.3 mm.[42,43] The catchment area of the river (headwater) is characterized by both artificial coniferous trees and mixed natural forest conservation; middle area of the river consists of mixed agriculture and urban settlement. The floodplain (downstream) region is characterized by bare land, intensive grazing, large scale agriculture, treated municipal sewage disposal and serious flooding in wet season.[44]

Sources of Data and Data Collection

In this study, both primary and secondary data were used. The primary data used include precipitation and water levels in rivers within the sub catchment for 2016, and the secondary data for precipitation in 1989, 1996 and 2006 were collected from the Pangani Basin Water Office (PBWO) (Table 1). Other secondary data includes the Landsat Thematic Mapper (LTM) images downloaded from United States Geological Survey (USGS) Earth Explorer, as shown in Table 2. The collected satellite images were used to determine the change in land use/ land cover of the area over time within thirty years (1986-2016). The classified satellite images were also used to predict the condition of land use /land cover condition in 10 years to come in the Markov-Cellular Automata dynamic model (MCA).[16,18,19,37–40]

Data Analysis

The collected satellite images were pre-processed first before analyzing them, the process involved projecting them to UTM zone 36 S which corresponds to Arusha Region, and then the red green and blue (RGB) composite images were created for each year. RGB were created by layer stacking which involved Band 2, 3 and 4 for Landsat TM 4-5 and Band 3, 4 and 5 for Landsat 8. Each image with composite colour was extracted to cover the study area by using the study area map. Images were analyzed by using IDRISI-Selva software and the results were assessed basing on the changes occurred in the land uses and associating them with water reservoirs. The satellite images were preprocessed then converted into composite images with false colors which could help to identify clearly the areas with different land uses like vegetation, settlements and water sources through supervised classification.[16,18] Maximum likelihood (MAXLIKE) algorithm was used to classify the images for change detection analysis. Analysis of the net gain and loss of various land uses like forest cover, settlements and agricultural having a time step satellite images were performed and interpreted basing on Kappa Index of Agreement (KIA)[10] for the best image representative image of the future land use land change prediction model. The whole procedural activities are summarized in Scheme 1. Also, the rainfall and river water levels for some years were used to evaluate any correlation in relation to land use/land cover change if any.

Satellite Image Classification, Training, Signature Development and Classification

Supervised image classification was adopted due to the fact that the whole process is controlled by the user especially on deciding the number of classes to be identified, creation of training samples and detailed knowledge about the real study area land use and land cover distribution.[45] The training samples representing the pixels with particular land covers for 1986, 1996, 2006 and 2016 were created by using polygons with the aid of GPS points with support from Google earth image. In addition, the land use topographic maps for similar years representing the study area for Quarter Degree Square (QDS) 55-3 and 55-4 collected from the Cartography Department of the Ministry of Land were also used for the same purpose. Six classes of land LULC were identified which involved Mixed forest (MF), Bush land (BL), Agriculture (AG), Settlements (ST), water bodies (WB) and rocks (RK). Twenty five (25) pixels were used for training and validation in each WB and RK land use class whereas for MF, AG and ST fifty (50) pixels were used for the same purpose in each land use class. The same training samples were stored and used to create signature file for entire image supervised classification process. Table 3 describes the land use classes identified in the study area.

Supervised image classification was done after creation of signature file; each composite image was supplied in the maximum likelihood classification Algorithm as input together with the associated signature file. After running the Algorithm, the Land use and Land cover maps with trained classes were produced and was ready for classification accuracy assessment process. All these processes were performed on each individual image in ArcGIS 10.3 software.

Accuracy Assessment and Change Detection Analysis

The assessment of classification accuracy was performed on each classified map by comparing the land use classes with 33 ground truth GPS points then creating an error matrix table; the producers, users and overall accuracy were calculated from the table in Microsoft Excel sheet, as suggested by Coppin and Bauer (1996), which requires acceptable classification results to be at least from 70% and above. The overall accuracy was determined by the relation given in (1) to (3). Table 2.5 gives a summary of accuracy assessment for year 1986 to 2016 which all qualified for further adoption.

$$\text{Overall Overall accuracy} = \Sigma \frac{\text{Correct classified}}{\text{Number of observations}} \times 100 \quad ...(1)$$

$$\text{User's accuracy} = \Sigma \frac{\text{Correct classified pixels in the row}}{\text{Pixels in the row}} \times 100 \quad ...(2)$$

$$\text{Producer's accuracy} = \Sigma \frac{\text{Correct classified pixels in the column}}{\text{Pixels in the column}} \times 100 \quad ...(3)$$

Table 1. Annual precipitation and Discharge in the year 1986 to 2016

Year	Ann. Prec. (mm)	Discharge (m^3/s)				
		Temi	Nduruma	Tengeru	Maji ya Chai	Av. Level
1986	503.3	0.67	0.75	0.66	0.30	0.60
1996	225.4	0.29	0.34	0.28	0.13	0.26
2006	229.6	0.31	0.35	0.31	0.14	0.28
2016	464.3	0.61	0.75	0.38	0.19	0.48

Source: Pangani Basin Water Office (PBWO) 2016, **Ann. Prec.** - Annual Precipitation, **Av.** - Average

Table 2: USGS Collected Landsat TM Characteristics used for LULC

Satellite Image	Resolution	Path	Row	Collection date
Landsat TM 4-5	30m × 30m	168	062	Sep-1986
Landsat TM 4-5	30m × 30m	168	062	Sep-1996
Landsat TM 4-5	30m × 30m	168	062	Sep-2006
Landsat ETM 8 TIR/OLI	30m × 30m	168	062	Oct-2016

Table 3: Description of Land Use Classification of the Study Area

Land Use	Description
Mixed Forest (MF)	Areas with plantation and natural forest, firewood, charcoal, pole wood and timber
Bush land (BL)	Areas with shrubs, agro forest, pasture and thickets
Agriculture (AG)	Areas with land for commercial and peasant agriculture
Settlements (ST)	All forms and types of buildings
Water bodies (WB)	All areas covered with water (rivers, snow, lakes floods and wastewater treatment sites)
Rocks (RK)	All areas with rocks and mining

Change Detection Analysis

The statistics from classified land use and land cover maps of 1986, 1996, 2006 and 2016 were used to detect the changes occurred in the period of 30 years. Change detection involved finding the quantities of the land use land cover changed, locations where the changes occurred and the type of changes occurred at a certain defined time interval.[10,46] In post classification process; quantitative changes were detected by comparing the successive pairs of classified maps by subtracting the quantities of the current land use class from the quantities of the past land use class; the differences obtained from each pair were converted to percentage of change by using relation (4).

$$\text{Percentage change} = \frac{\text{Observed change}}{\text{Total area}} \times 100 \quad ...(4)$$

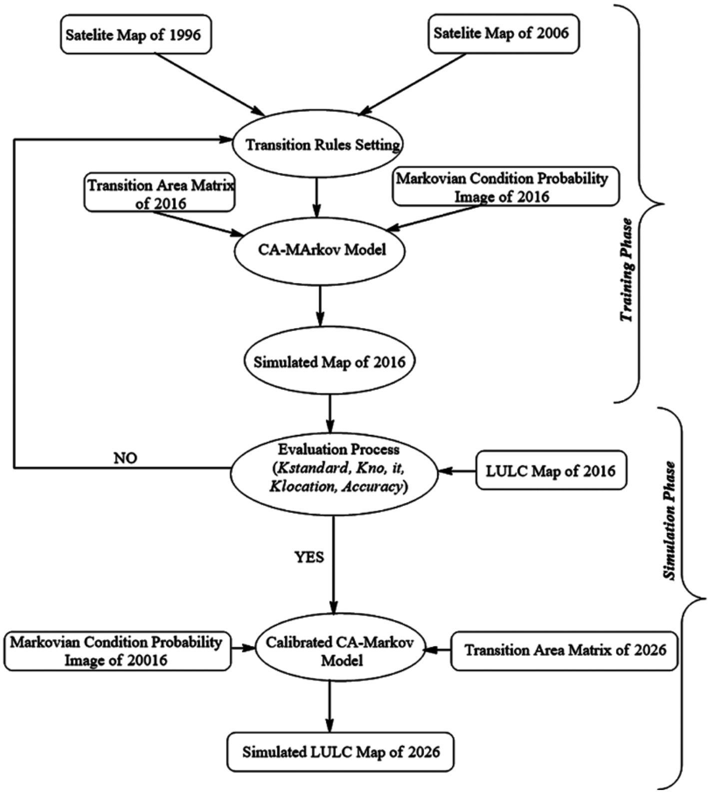
Through change detection the deep understanding in terms of anthropogenic interference in the land use and land covers of an area will be possible hence this can facilitate in understanding the protection strategy of the environment.

Results and Discussion

Analysis of LULC

Figures 2 (a) and (b) through 3 (c) and (d) are LULC maps of the study area for 1986, 1996, 2006 and 2016 and their statistics are summarized in Tables 4 through 8. The study shows that agriculture land increased from 46.85% in 1986 of the total land use to 50.42% in 1996 with land use of 545.8 km^2 to 587.4 km^2, respectively. While this happened, the bush land decreased from 31.5% to 24.19% meaning that rise in agriculture occurred in a sacrifice of conversion of bush land. Also within similar years the mixed forest increased from 139.7 km^2 to 174.9 km^2 meaning that maybe part of the bush land was a result of forest clearance which was recovered in the 1996 (Table 4 and 8). In addition, areas inhabited by human settlement increased in the ten years from 74.3 km^2 in 1986 to 110.4 km^2 in 1996 that being the result of conversion of bush land and part of agriculture land (Table 8). The areas inhabited by water bodies decreased to 0.45% in 1996 from 1.2% for the year 1986. Several reasons may explain as why this happened due to the fact that water bodies are contributed in environment as a result of rainfall, precipitations, soil type and the extent of canopy cover which accounts for evaporation index. Rainfall being the main source of surface water, then it is anticipated that fluctuation of rainfall could be the best reason explaining the extent and existence of water bodies on surfaces.

The agriculture land decreased in 2006 with only 42.8% being used up compared to 50.42% in 1996. The cross-tabulation study shows that the agriculture land was partly converted to bush land (15.5 km^2 uncultivated for long time and changed to bush land) and 90.6 km^2 was converted to settlement as a result of urbanization. Generally, settlements increased by 96.8 km^2 and 53.9 km^2 in 2006 and 2016, respectively (Table 7 and 8). However, in ten years later (2016) agriculture and raised to 45.62 % (increase by 2.82% with a net gain of 32.8 km^2) due to decreased rates of settlements constructions and part of the bush land was reconverted into agriculture land (Figure 3(d) and 10, Table 4 and 8). More analysis shows mixed forest (MF) conservation decreased consecutively between 1996 and 2016 but in a decreasing rate by 8.2 km^2 for the year 1996 to 2006 and 0.7 km^2 in ten years later. That means between 2006 and 2016 forest conservation was strongly put in place to rehabilitate parts of the bush land into forest or to increase the plantation forest in bush lands. Such improved forest plantations include the Midawe and Temi waterfalls catchment areas where big estates of coniferous (pines) trees were raised. Also, the water bodies (WB) continued to decrease up to 10.6 km^2 by 2006 whereas in 2016 it increased by 0.8 km^2. That being a change in ten years case, generally the water bodies have decreased in 30 years (1986-2016) by 9.8 km^2 which can be an alarming situation. It should be noted that most rivers running in Arusha City have their main catchment sources being within the top hills of Mount Meru which is part of the study area and therefore it is an area of profound importance in terms of fresh water sources. A close examination of LULC maps of the study area from Figures 2 and 3 show a progressive decrease of water bodies at



Scheme 1: Flowchart for CA-Markov Model process as explained by Arsanjani *et al.,* 2011 and modified by Kitalika *et al.,* 2018

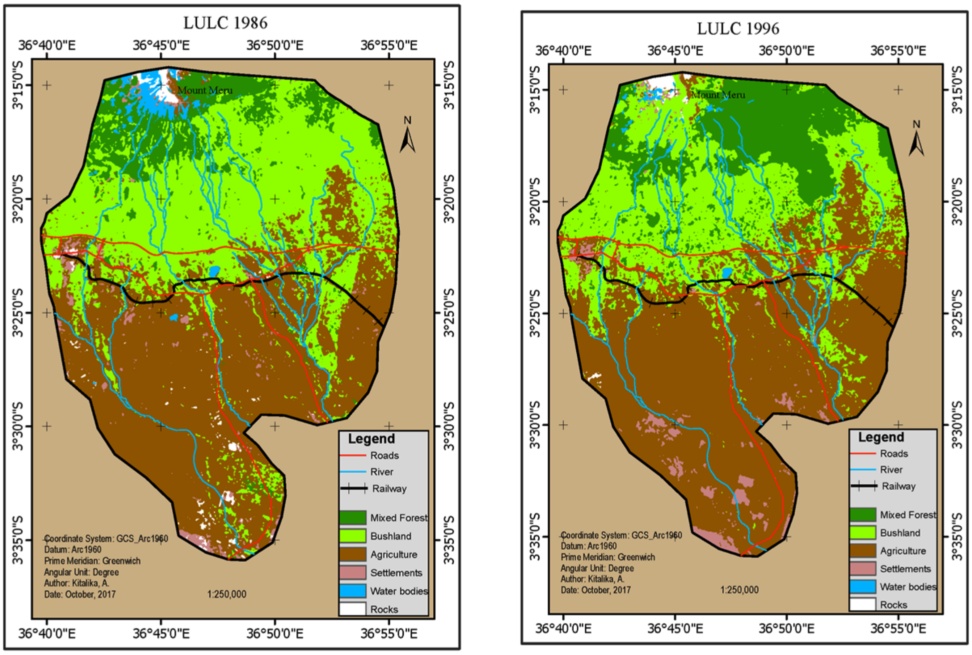
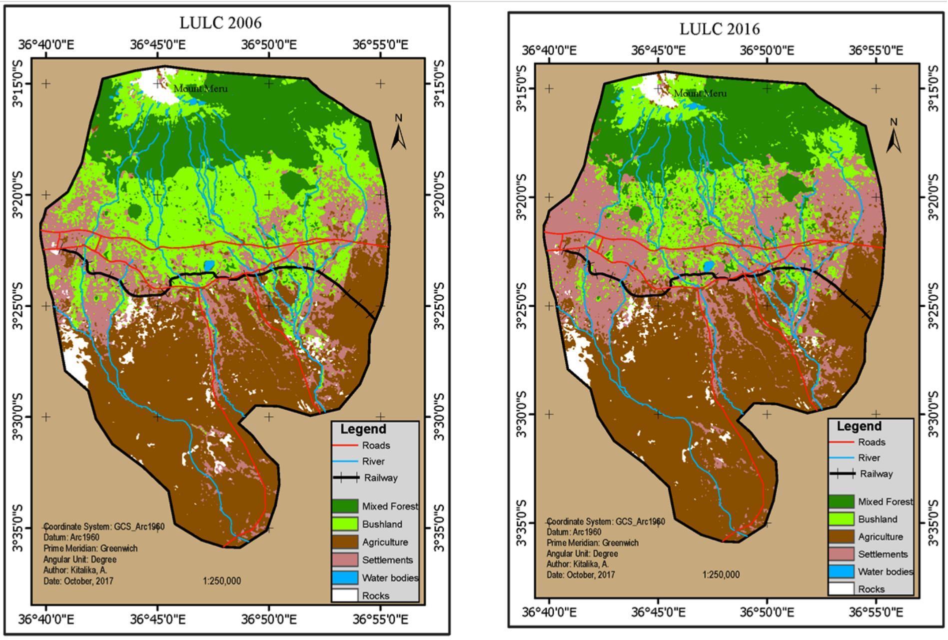


Fig. 2: LULC Change detection for (a) 1986 (b) 1996 on the slopes of Mount Meru



(c) (d)

Fig. 3: LULC Change detection for (c) 2006 (d) 2016 on the slopes of Mount Meru

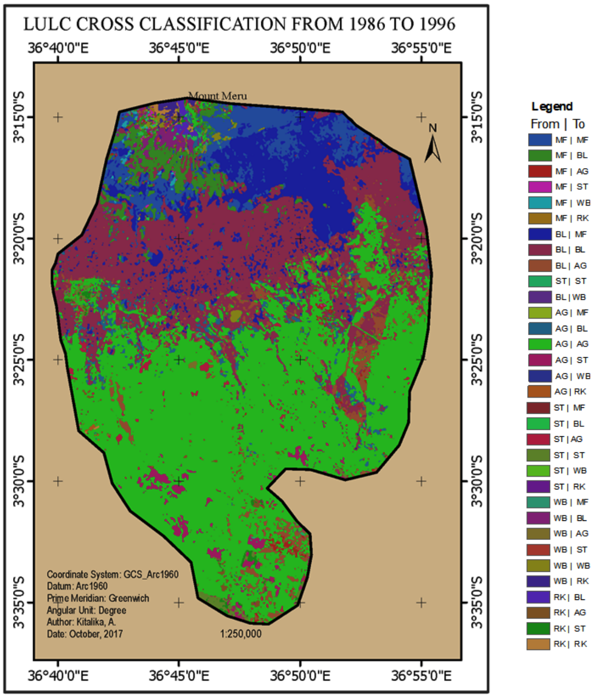


Fig. 4: Cross tabulation for LULC change detection on the slopes of Mount Meru from 1986 to 1996

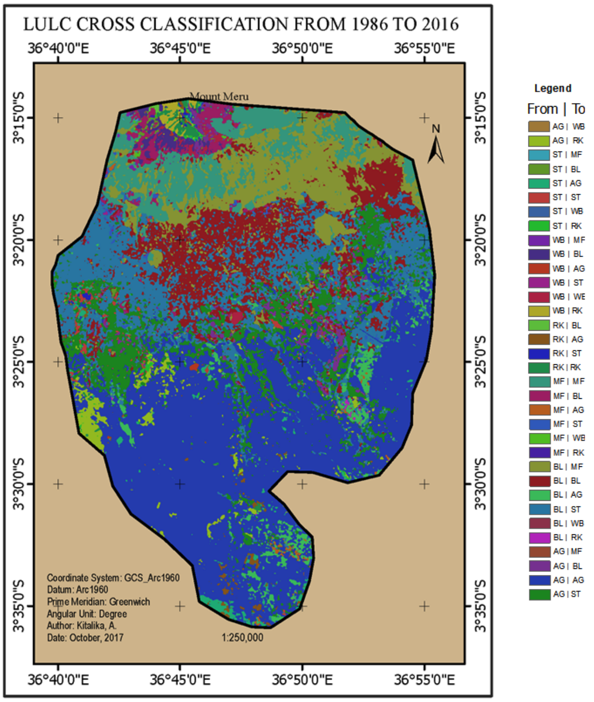


Fig. 5: Cross tabulation for LULC Change detection on the slopes of Mount Meru from 1996 to 2006

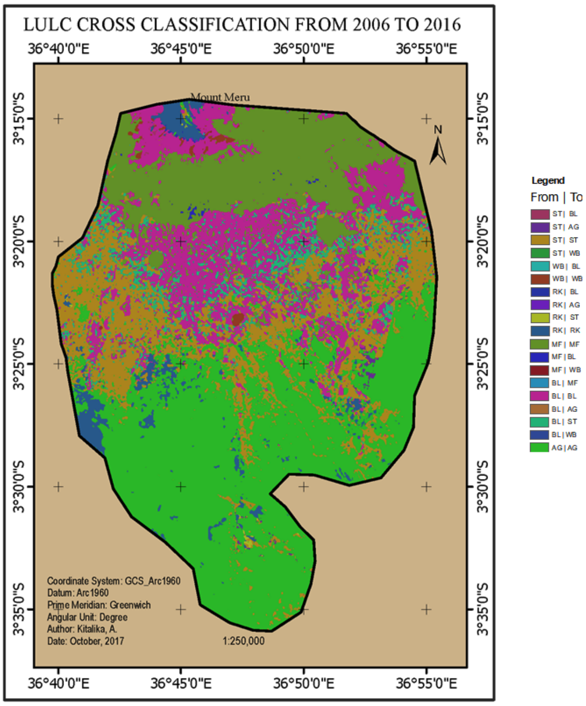


Fig. 6: Cross tabulation for LULC Change detection on the slopes of Mount Meru from 2006 to 2016

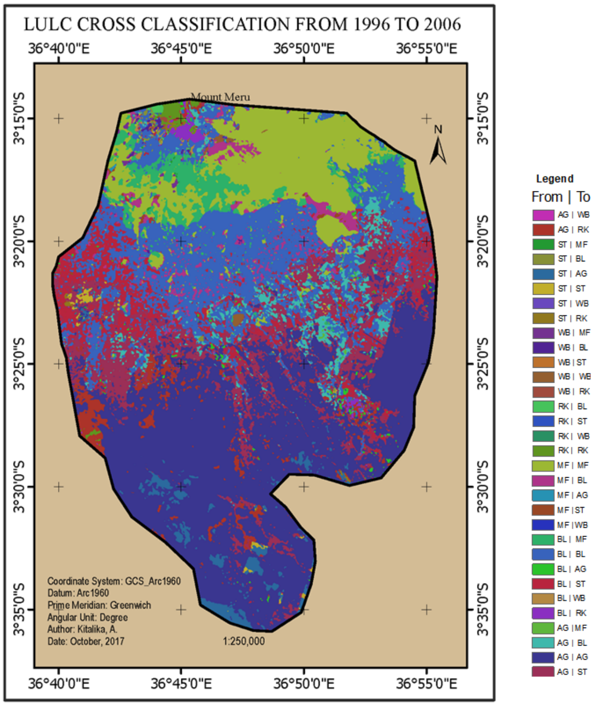
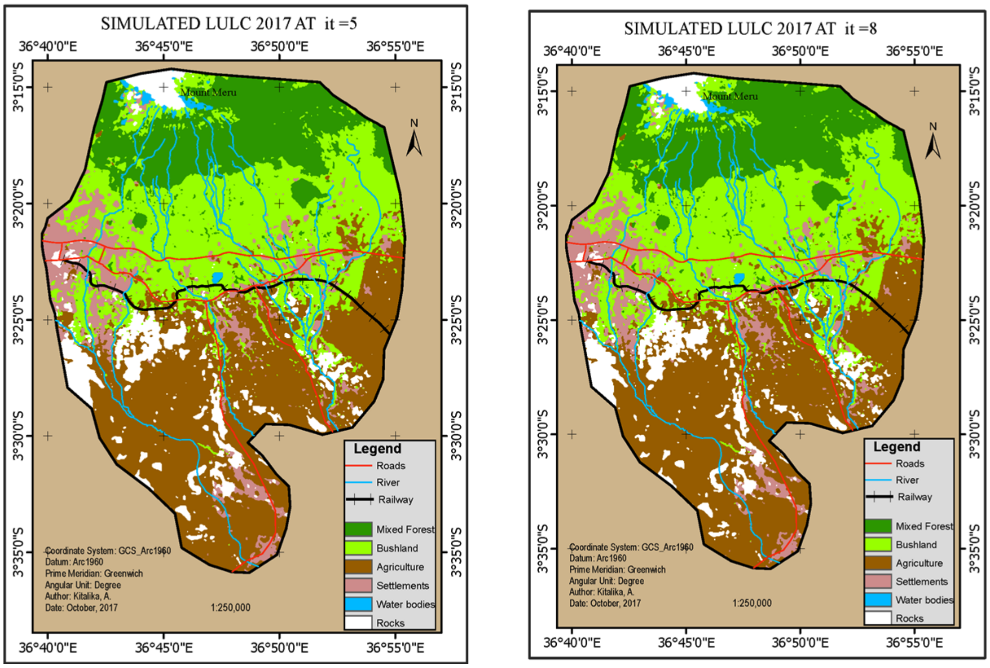
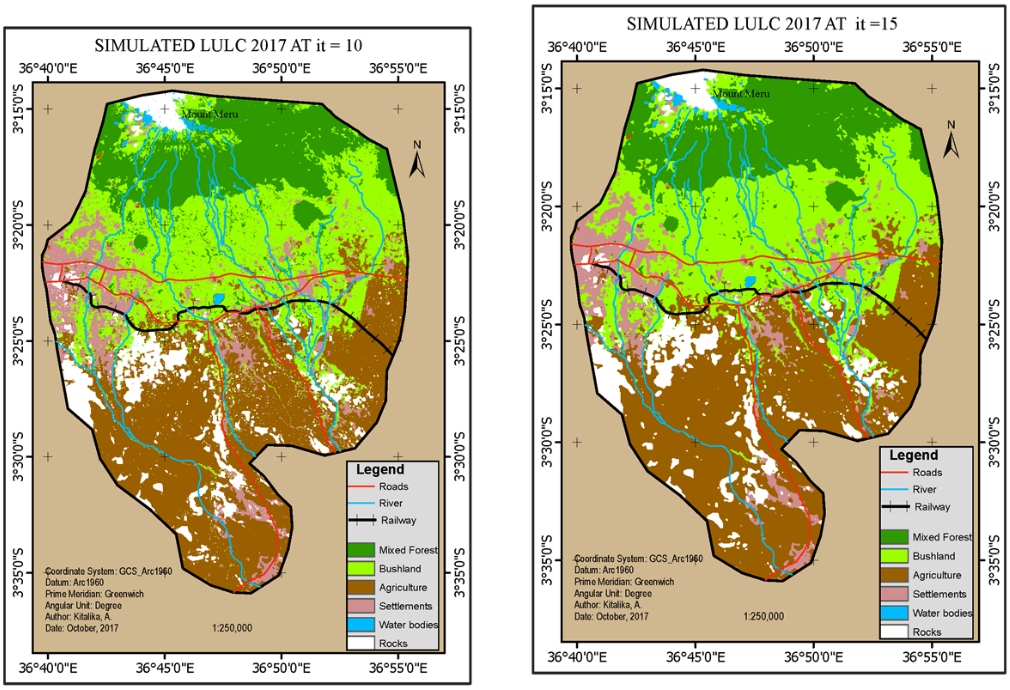


Fig. 7: Cross tabulation for LULC Change detection on the slopes of Mount Meru from 1986 to 2026



(a) **(b)**

Fig. 8: Simulated LULC C on the slopes of Mount Meru at (a) it = 5 (b) it = 8



(c) **(d)**

Fig. 9: Simulated LULC C on the slopes of Mount Meru at (c) it = 10 (d) it = 15

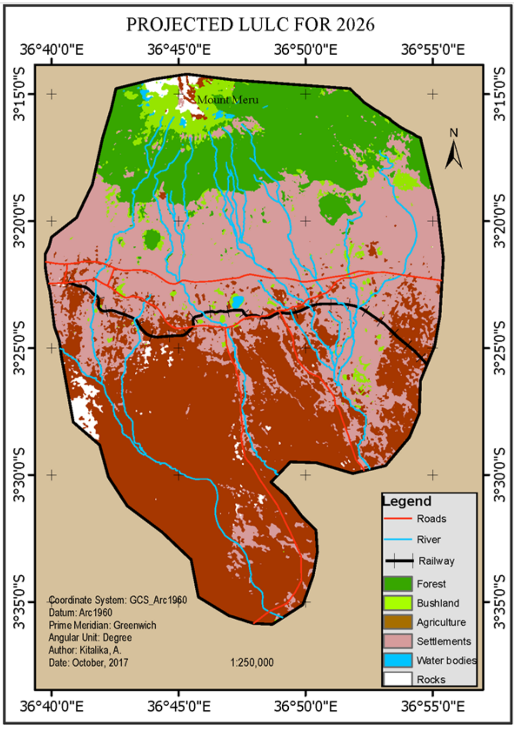


Fig.10: Projected LULC on the slopes of Mount Meru for 2026 at it = 10

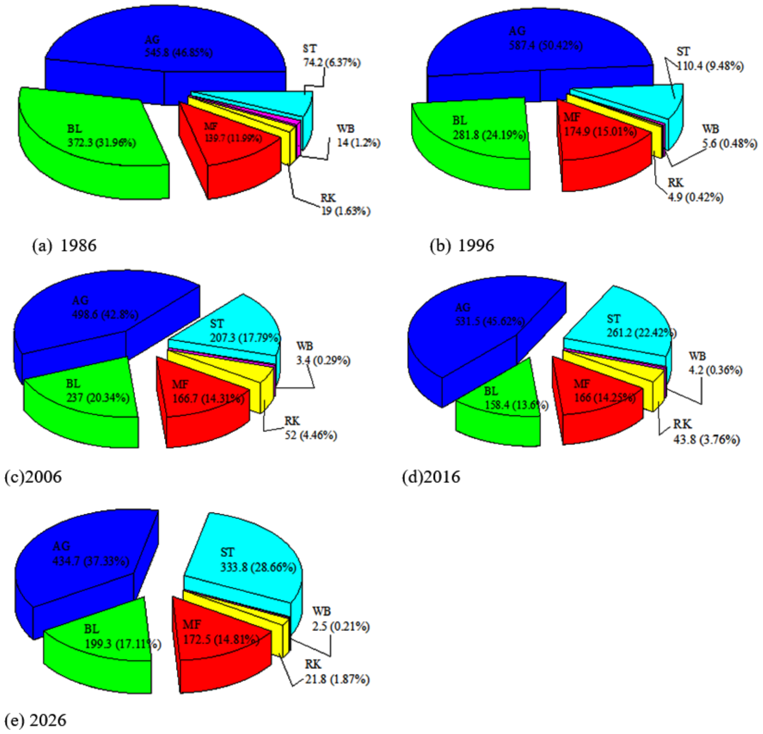


Fig. 11: Analysis of LULC from 1986 to 2016.

Table 4: Actual LULC detection values and its projection from 1986 to 2026

LULUC	AREA (km²)					NET GAIN AND LOSS (km²)					NET GAIN AND LOSS (%)				
	1986	1996	2006	2016	2026*	1996-1986	2006-1996	2016-2006	2016-1986	2026*-2016	1996-1986	2006-1996	2016-2006	2016-1986	2026*-2016
MF	139.7	174.9	166.7	166.0	172.5	35.2	-8.2	-0.7	26.3	6.5	3.0	-0.7	-0.1	2.3	0.6
BL	372.3	281.8	237.0	158.4	199.3	-90.5	-44.9	-78.5	-213.9	40.9	-7.8	-3.9	-6.7	-18.4	3.5
AG	545.8	587.4	498.6	531.5	434.7	41.6	-88.8	32.9	-14.3	-96.7	3.6	-7.6	2.8	-1.2	-8.3
ST	74.2	110.4	207.3	261.2	333.8	36.2	96.8	53.9	187.0	72.6	3.1	8.3	4.6	16.1	6.2
WB	14.0	5.6	3.4	4.2	2.5	-8.4	-2.2	0.8	-9.8	-1.7	-0.7	-0.2	0.1	-0.8	-0.1
RK	19.0	4.9	52.0	43.8	21.8	-14.1	47.1	-8.2	24.8	-22.0	-1.2	4.0	-0.7	2.1	-1.9

*Projected, +ve - net gain, -ve - net loss.

Table 5. Classification Accuracy Assessment for 2016 and Other Overall Accuracy

LULC	MF	BL	AG	ST	WB	RK	Total	Accuracy (%)		Overall Accuracy (%)			
								User's	Producer's	Year	Total test points	Correct points	Accuracy
MF	4	1	0	0	0	0	5	80	100	1986	25	20	80
BL	0	4	1	0	0	0	5	80	80	1996	25	21	84
AG	0	0	5	1	0	0	6	83	63	2006	25	20	80
ST	0	0	1	6	0	0	7	86	75	2016	33	27	81.5
WB	0	0	0	0	5	0	5	100	100				
RK	0	0	1	1	0	3	5	60	100				
Total	4	5	8	8	5	3	33	81.5					

Table 6. Markov Transition Probability Matrix from 1996 to 2006

	MF	BL	AG	ST	WB	RK	Model Validation	
MF	0.7434	0.2178	0	0.032	0.003	0.004	Kstandard	0.87
BL	0.1243	0.5867	0	0.270	0.004	0.015	Kno	0.88
AG	0.0003	0.0638	0.7	0.192	0	0.057	Klocation	0.91
ST	0.0051	0	0.9	0.106	0.002	0.002	it	10
WB	0.3431	0.2284	0	0.014	0.303	0.112		
RK	0	0.2311	0	0.025	0.023	0.721		

the top hills which can be associated with melting of the ice caps, decreased precipitation, increased atmospheric temperature and evaporation. It is very unfortunate that different researchers had different ideas on the effect of canopy cover towards the water bodies whereby some researchers advocates increase in rivers discharge with increased deforestations[25] and others arguing differently.[26] While these arguments remain contradictory, it should be remembered that runoff always increase with deforestation due to decrease of water breaks hence infiltrations. Also, soil conditions (sandy, clay, loamy or rocks) account for water infiltration as a main source of rivers and aquifer recharge (Soil and Water Analysis Tool, SWAT). Loose soil is likely to allow more infiltration than compact soil and the vice versa is true. The proportions of change of each LULC category for the year 1986 to 2016 are summarized in Table 7.

Model validation

It was necessary to validate the customized CA-Markov model and assess whether it could be used for simulation of the 10 years (2026) prediction LULC. The process was done through comparison of several simulated maps of 2006 at iteration 5, 8, 10 and 15 (Figure 8 and 9) with the actual LULC map of 2006 and assessment of their Kappa Indices (KIA) optimal values with their respective iterations. The validated model was observed at iteration 10 with satisfying required minimum value for model validation Kappa of 0.80 in which under this study Kstandard, Kno and Klocation of 0.87, 0.88 and 0.91 were obtained, respectively (Table 6) and therefore the model was adopted.[47–50] Similar model validation for future land use in Tehran was done by Arsanjani *et al.,* in their study and found a strong correlation between the actual, map and predicted model map at Kstandard of 0.91 and Klocation of 0.97 at iterations 3000.[10]

Land-use change prediction

The validated model was executed to project the LULC for the next 10 years (2026). The process was done together with the 2006 land-use map, the 1996–2006 transition area matrixes, as well as the 2006 transition potential maps. The resulting values for various land use changes are summarized in Table 4 and Figure 11. From figure 11(e) it is seen that the total land for agriculture (AG) will decrease by 8.29% which will be replaced by human settlement (ST) and bush land (BL) which will also increase by 6.2% and 3.51% by 2026, respectively. It is obvious that the increased human settlement will be caused by increased population which is among the expected major land use change for the urbanization process of an area. It is also anticipated that in the next 10 years there will be a very little increase of mixed forest (MF) by 0.56% which is a good sign of good forest conservation strategy by the government. It should be noted that the increase in urbanization process normally is associated with increase in demand of land for construction which can involve clearance of natural resources in some conserved areas such as forest and water which in this study if the present government laws and rules will continue to be strictly followed the conserved forest will continue to survive. Also the status of water body will be in a bad situation in relation to increased population since the demand for fresh water will be high if no other water sources will be invented. The study shows decrease in fresh water bodies (WB) by 0.15% from 2016 to 2026 which is highly alarming for the rapid growing population of Arusha City. In addition, the area covered by rocks will decrease in the next 10 years by1.89% which will

Table 7: Cross Tabulation Proportions of Change

	1986 LULC	MF	BL	AG	ST	WB	RK	Total	Kappa Index (KIA) 1986	1996
1996	MF	0.059	0.088	0.001	0.001	0.002	0.000	0.150	0.401	0.309
	BL	0.036	0.165	0.030	0.005	0.005	0.002	0.242	0.361	0.532
	AG	0.020	0.062	0.386	0.029	0.001	0.007	0.504	0.645	0.560
	ST	0.004	0.005	0.051	0.029	0.001	0.006	0.095	0.389	0.253
	WB	0.002	0.000	0.000	0.000	0.002	0.000	0.005	0.181	0.460
	RK	0.000	0.000	0.001	0.000	0.002	0.001	0.004	0.074	0.293
	Total	0.120	0.320	0.469	0.064	0.012	0.016	1.000	Overall	0.459
	1996 LULC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**	**Kappa Index(KIA) 1996**	**2006**
2006	MF	0.102	0.037	0.002	0.001	0.002	0.000	0.143	0.627	0.663
	BL	0.038	0.123	0.039	0.002	0.001	0.001	0.203	0.383	0.478
	AG	0.001	0.013	0.336	0.078	0.000	0.000	0.428	0.417	0.567
	ST	0.008	0.063	0.094	0.012	0.000	0.000	0.178	-0.060	-0.029
	WB	0.001	0.001	0.000	0.000	0.001	0.000	0.003	0.227	0.372
	RK	0.001	0.005	0.034	0.002	0.001	0.003	0.045	0.626	0.056
	Total	0.150	0.242	0.504	0.095	0.005	0.004	1.000	Overall	0.393
	2006 LULC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**	**Kappa Index (KIA) 2006**	**2016**
2016	MF	0.138	0.005	0.000	0.000	0.000	0.000	0.143	0.956	0.961
	BL	0.005	0.127	0.000	0.003	0.000	0.001	0.136	0.564	0.915
	AG	0.000	0.000	0.428	0.024	0.000	0.005	0.456	1.000	0.892
	ST	0.000	0.071	0.000	0.151	0.000	0.002	0.224	0.806	0.604
	WB	0.001	0.000	0.000	0.000	0.003	0.000	0.004	0.914	0.750
	RK	0.000	0.000	0.000	0.000	0.000	0.037	0.038	0.832	0.996
	Total	0.143	0.203	0.428	0.178	0.003	0.045	1.000	Overall	0.837
	1986 LULC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**	**Kappa Index (KIA) 1986**	**2016**
2016	MF	0.061	0.078	0.001	0.001	0.002	0.000	0.143	0.425	0.349
	BL	0.024	0.085	0.018	0.004	0.005	0.001	0.136	0.150	0.446
	AG	0.017	0.038	0.347	0.043	0.001	0.010	0.456	0.522	0.549
	ST	0.016	0.117	0.078	0.012	0.001	0.001	0.224	-0.053	-0.013
	WB	0.001	0.000	0.000	0.000	0.002	0.000	0.004	0.159	0.540
	RK	0.001	0.001	0.025	0.004	0.002	0.004	0.038	0.223	0.095
	Total	0.001	0.320	0.469	0.064	0.012	0.016	1.000	Overall	0.311

Table 8: Cross tabulation by quantitative change (km^2)

	1986 LULUC	MF	BL	AG	ST	WB	RK	Total
1996	MF	68.6	102.5	1.2	0.9	1.7	0.0	174.9
	BL	41.6	192.0	34.7	6.2	5.6	1.7	281.8
	AG	22.7	71.8	449.9	33.4	1.0	8.6	587.4
	ST	4.4	5.5	59.4	33.2	0.9	7.0	110.4
	WB	2.1	0.5	0.1	0.2	2.6	0.0	5.6
	RK	0.2	0.0	0.6	0.3	2.2	1.5	4.9
	Total	139.7	372.3	545.8	74.2	14.0	19.0	1165.0
	1996 LULUC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**
2006	MF	118.9	42.6	2.4	0.6	2.0	0.0	166.7
	BL	43.7	143.2	45.0	2.4	1.4	1.3	237.0
	AG	0.9	15.5	391.4	90.6	0.0	0.0	498.6
	ST	9.7	73.6	109.2	14.2	0.2	0.2	207.3
	WB	0.6	1.2	0.1	0.1	1.3	0.1	3.4
	RK	1.0	5.6	39.3	2.4	0.6	3.1	52.0
	Total	174.9	281.8	587.4	110.4	5.6	4.9	1165.0
	2006 LULUC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**
2016	MF	160.4	5.6	0.0	0.0	0.0	0.0	166.0
	BL	5.7	147.6	0.0	3.7	0.2	1.2	158.4
	AG	0.0	0.3	498.5	27.4	0.0	5.2	531.5
	ST	0.1	82.9	0.0	176.1	0.0	2.0	261.2
	WB	0.6	0.3	0.0	0.0	3.1	0.0	4.2
	RK	0.0	0.0	0.1	0.1	0.0	43.6	43.8
	Total	166.7	237.0	498.6	207.3	3.4	52.0	1165.0
	1986 LULUC	**MF**	**BL**	**AG**	**ST**	**WB**	**RK**	**Total**
2016	MF	70.8	91.2	1.5	0.7	1.9	0.0	166.0
	BL	27.7	98.8	20.9	4.2	6.1	0.9	158.4
	AG	19.8	44.6	404.0	50.6	0.7	11.7	531.5
	ST	18.4	136.2	90.6	13.6	0.6	1.6	261.2
	WB	1.4	0.1	0.2	0.2	2.2	0.0	4.2
	RK	1.5	1.4	28.7	5.0	2.6	4.8	43.8
	Total	1.5	372.3	545.8	74.2	14.0	19.0	1165.0

Table 9. Position Model Validation for 2016

LULC	MF	BL	AG	ST	WB	RK	Total	Accuracy (%)
MF	7	1	0	0	0	0	8	87.5
BL	0	6	1	1	0	0	8	75
AG	0	1	6	1	0	0	8	75
ST	0	0	0	7	0	1	8	87.5
WB	0	0	0	0	8	0	8	100
RK	0	0	1	1	0	4	6	66.7
Total	7	8	8	10	8	5	46	82

mostly be expected to be converted into settlements due to the fact that there is minimum possibility of areas covered with rocks to be converted in any of the remaining land use categories.

Despite the anticipated land use changes expected to occur in the next 10 years, some challenges occurred in the process of image and land use classifications hence in the projected model. For example, the study area has rocks on the mountain peak and other areas which its reflectance somehow resembled that of iron and white corrugated plastic sheets, other white plastic coverings and several other greenhouses in the flower farms. This must have led some confusion for actual land use category classification. It is unfortunate that the most common worldwide method for validation of the projected LULC map saves to use the validated model at stated three (3) Kappa values as stated at model validation section. On the other side, comparison between the projected and real image after the specified time lapse can also be used to observe what has happened in real environment. The second alternative is worthless since the aim of projecting the future LULC change of environment resides on protecting them from alarming current observed changes. However, there are some features which are necessary in any correct mapping process, such as scale and location which are sensitive to any feature presentations.[51,52] In this study, this feature has been taken care of by assuring similar scale is used for all analysis images through windowing and correct georeferencing is done in addition to inspection for correct LULC classification in comparison with the simulated and real map. Difficulties appear in validation of simulated and projected maps since there are no true references as there is inexistence. Therefore, the best validation method in this study was designed in order to ensure that the model predicted reasonably, the locations and land use of the predicted cells for development and assessed their feasibilities in comparison to the real map.[10] The comparisons were done with true features based on the predictor model map of 2006 in relation to the true map of the same year and their outcomes were as summarized in Table 9. From this table the comparison showed correctness by 82% which can also account for similar percentage correctness of the project LULC map for 2026.

LULC and Discharge

A study was done to evaluate whether there is any effect on change of canopy cover in relation to river discharge when other parameters remained constant. The analysis shows that there was very weak correlation between the two ($r \leq 0.3$, n = 4, p $\leq$ 0.03, Figure 12). These results suggest that the presence of good canopy cover feature around any catchment area is not the only cause for maximized recharge potential of any watershed rather it can add potentials for long term discharge and recharge of the river. Therefore, a combination of factors such as soil structure and texture, terrain and weather conditions of a place may account in addition to canopy cover. Further analyses were needed to find out other contributing factors for discharge potentials of the river whereby the correlation analysis was done between precipitations of an area in relation to the discharge patterns of rivers for thirty (30) years in ten (10) years intervals. The analysis showed that there is a strong positive correlation between the two [(a) $r = 0.99$, n = 4, p $\leq$ 0.003, (b) $r = 0.97$, n =

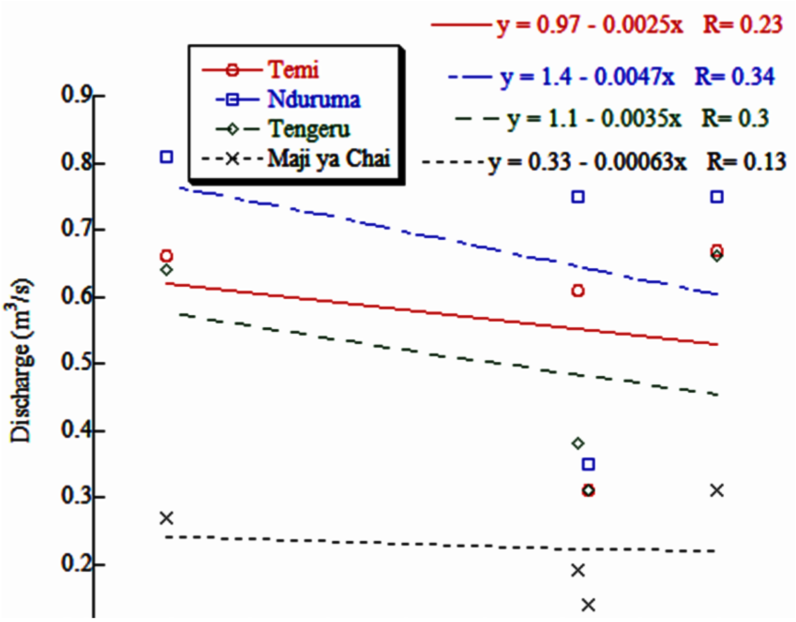


Fig. 12: Correlation Analysis for Discharge in Rivers and Precipitation from 1986 to 2016

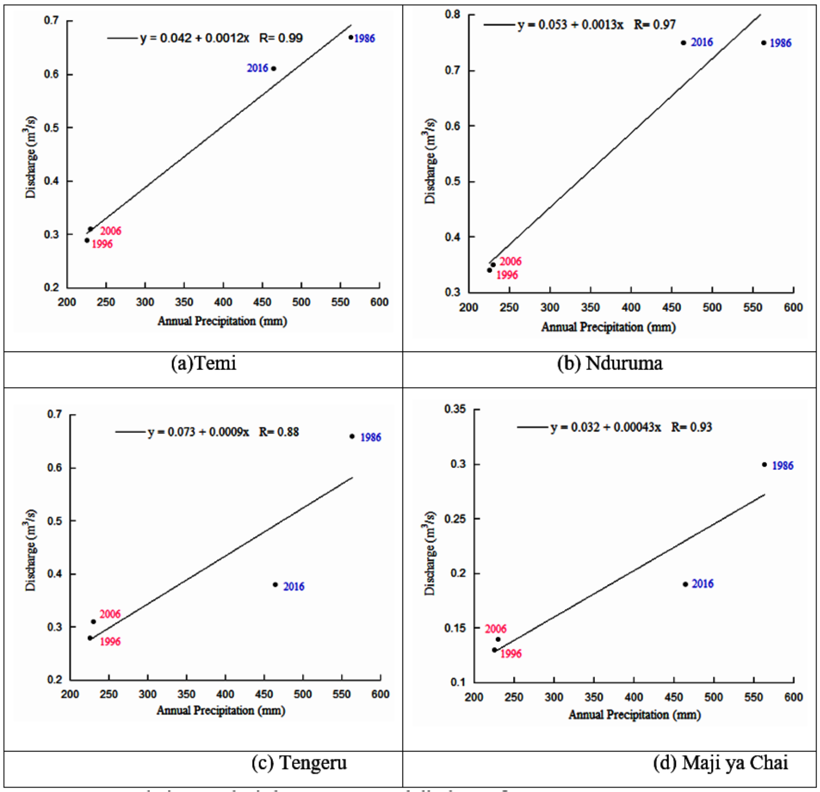


Fig. 13: Correlation Analysis between MF and discharge from 1986 to 2016

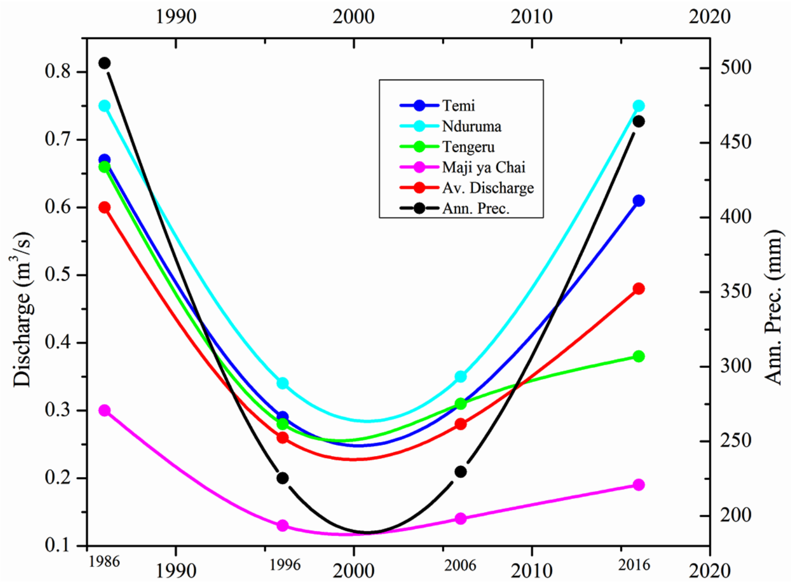


Fig. 14: Precipitation and discharge patterns for Rivers from 1986 to 2016

4, $p \leq 0.01$ (c) $r = 0.88$, n = 4, $p \leq 0.05$, (d) $r = 0.93$, n = 4, $p \leq 0.04$), Figure 13 and 14)] suggesting that the main water sources from rivers is precipitation. While this positive correlation is promising for the two relationships it should be remembered that the feasibility of the holding capacity of precipitated water is much more pronounced when there is good canopy cover of an area in order to minimize the runoff, evaporation and increase the soil holding capacity for water and porous aquifers which in turn will give a good recharge potential of any watershed. It should also be made clear that this assessment was done in the assumption that other confounding factors for discharge such as soil type, water, agriculture and transpiration (SWAT) remained constant throughout the year otherwise the analysis could be invalid. It should be noted that most rivers from this study area originates from the top hills of mount Meru which the LULC study shows that water bodies from the mountain peak have been decreasing continuously from 1986 to 2016 (Figure 3 and Table 3). These calls upon Tanzanian country and the world as a whole to put in place all necessary environmental protection practices such as reducing the greenhouse gases emission which are the main cause of the global climate change such as increase in atmospheric temperature which has accelerated the melting of ice caps all over the world including Mount Meru which is within the study area.

In addition, analysis from Figure 14 indicates that Temi and Tengeru Rivers had almost similar and higher discharge pattern and levels compared to Nduruma and Maji ya Chai Rivers. Further, close analysis shows that the discharge potential of Nduruma River resembles much that of Temi and Tengeru Rivers but the low measured discharge capacity of the former is attributed by higher water abstraction in the source by AWSA for domestic use and the process is accelerated much more by the irrigation practices in the downstream. A combination of two have caused drying off of the river in the floodplain area specifically during the dry season hence causing massive deaths of aquatic creatures and the riparian vegetations. Also the illustration shows higher precipitation than discharge capacity of the rivers suggesting that not all water coming from precipitations is free from discharge, rather part of it is vulnerable for other factors such as evaporation, plants and animals utilization, soil water and other domestic uses.

Conclusion

This study indicates a significant land use changes of the area which might have caused even changes in other environmental parameters such as the natural vegetation cover, living organisms, and water characteristics. The study has shown a rapid conversion of bush and agriculture land into human settlement which is likely to be a common case for any area in transition into urbanization. However, the challenge arises when there is an increase in human settlements which reflects the increasing in human population at the expense of reduced agriculture land (AG). That means while the population is increasing, the capacity to be fed by the same environment is minimized meaning that the sustainability of such urban population must involve importation of food and food products from others areas which will eventually increase the living cost. In addition, the present study has assessed the LULC of the area using only the features presented in the satellite images which are the outcomes of the influencing factors. Such factors which can affect the environment include social, political, scientific, technological, socioeconomically and biophysical factors which if they were integrated in the CA-Markov model, could improve the accuracy of simulation thus giving the actual situation of the land use change which could be higher than 82% accurate. Furthermore, errors must have happened in rock classification since in the study area there are greenhouses and roads which could show similar reflectance with rocks and therefore some of the classification could have included in either settlements or rocks. Such errors may account for the 18% inaccuracy. Lastly, the observed continuous land use changes in the area attracts attention to further studies of other associated environmental features which are also likely to have been affected.

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