SPATIO-TEMPORAL DYNAMICS OF LAND USE AND LAND COVER IN ELGEYO ESCARPMENT, KENYA

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ABSTRACT

The Elgeyo Escarpment has undergone land use and land cover (LULC) changes over the last five decades. However, past LULC change assessments focused on forests and river basins and little on LULC changes and their drivers in the escarpment. This paper, therefore assesses spatio-temporal dynamics of LULC and their drivers. Satellite images were analyzed to assess LULC changes using remote sensing and geographical information system (GIS) techniques; and validated using ground-truthing. Structured questionnaires were administered to 180 household heads, eight focus group discussions and key informant interviews conducted to determine LULC change drivers. The survey participants were over fifty-five years of age, to provide historical LULC change trends. The images were pre-processed and classified using the maximum likelihood algorithm in Environment for visualizing images (ENVI), with images overall classification accuracies being over 70%. The results indicate LULC conversions varied in trends and magnitude. Between 1995 and 2014, grassland and shrubland decreased by 78.15% and 24.41%, respectively. Conversely forest, built-up and cropland gained by 411.82%, 200.95% and 13.62%, respectively. In 2014-2020, forest cover increased by 63% while grassland, built-up, shrubland and cropland decreased by 79.69%, 39.14%, 21.57% and 11.80%, respectively. Overall, forest, built-up and cropland gained while shrubland and grassland decreased. Notably, forest gained by 734.52% while shrubland decreased by 40.72%. Population growth is the primary LULC driver triggering increased demand for food (88.9%), settlements (52.2%) besides cattle rustling (44.4%) and forest evictions. Periodic LULC assessments are crucial to guide policies and guidelines formulation for the sustainable management of the escarpment.

Keywords: Escarpment, land use/cover change, degradation, Landsat, remote sensing

INTRODUCTION

About three-quarters of the earth's land surface has been altered by humans within the last millennium (Luyssaert *et al.*, 2014). This has seen a fivefold increase in agricultural land from the 17th century to 1990, while forest cover and grasslands decreased during the same period (Ramankutty *et al.*, 2018). These land use land cover (LULC) changes have been attributed to the increase in the global population, which has grown to approximately seven billion people currently and is projected to increase to over nine billion by 2050 (FAO, 2015). Europe was largely naturally covered by forests, but nowadays it is a mosaic of landscapes with the largest farmlands found in Eastern Europe, (Ramankutty *et al.*, 2018). Similarly, in northern Africa, a significant gain in agricultural, urban and built-up land was observed in Libya at the expense of the natural forests (Ahwaidi, 2017). The same trend was observed in sub-Saharan Africa, where agricultural and barren land increased between 1975 and 2000 while forest land diminished during the same period owing to overstocking and deforestation (Brink and Eva., 2009). In eastern Africa, pasture land notably decreased and was attributed to overstocking from 1992 to 1999 (Lambin *et al.*, 2003).

Kenya has continued to experience notable and varied LULC changes over the last three decades (Campbell *et al.*, 2005) with predominant LULC types being savannah grassland, agricultural land and forestland (Njoka *et al.*, 2016). Kiambu County registered significant increase in the urban areas at the expense of agricultural land between

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1984 and 2013 (Musa and Odera 2015). In western Kenya, the built-up and agricultural areas increased while forestland and grassland reduced significantly between 1995 and 2017 (Kogo *et al.*, 2021).

In Elgeyo Marakwet County, similar LULC change trends were observed where bushland and forest cover of Rimoi wildlife protected area declined resulting in a corresponding increase in, agricultural land, shrubs and acacia trees cover between 1986 and 2006 (Togoch, 2018). Further, the encroachment of Embobut forest as well as the escarpment extending into sections that had previously never been settled has been observed (Kilimo, 2014). This resulted in the loss of huge chunk of forest to farmland (Kipkemoi, 2018) that significantly affected the Arror River basin negatively (Chebet *et al.*, 2017). This is manifested by low tree diversity in the Embobut River Basin (Wanjohi, 2019) jeopardizing goal 15 of the Sustainable Development Goals (SDGs) that advocate for the protection and restoration of sustainable use of terrestrial ecosystems (Morton *et al.*, 2017).

The human encroachment of the Embobut forest ecosystem led to a protracted back and forth eviction and encroachment (Kilimo, 2014), culminating in the formation of Embobut forest taskforce. Although majority of the people were compensated, they squandered the cash and migrated into the escarpment (Amnesty, 2018). Meanwhile, the cattle rustling problem in the Kerio valley between the residents of Baringo and the Elgeyo Marakwet Counties since 1992 escalated (NCCK, 2009) forcing a huge population to settle in the escarpment (Pkalya *et al.*, 2003), thereby degrading the fragile ecosystem (Kiprono, 2018).

In response to these developments, some studies were carried out on land use and cover changes in sections of the escarpment. However, these studies were limited to particular river basins of Arror river (Chebet *et al.*, 2017) and Embobut river, that flow across the escarpment, Embobut forest (Kipkemoi, 2018; Wanjohi, 2019), Kibonge (Chirchir *et al.*, 2018) and Kimwarer (Kiptanui, 2015) forests. Therefore, understanding land use and cover spatio-temporal dynamics is critical in formulating conservation measures for the escarpment. This paper aimed to determine LULC changes and their respective drivers over a 25-year period.

MATERIALS AND METHODS

Study area

The Elgeyo Escarpment is located in Elgeyo Marakwet County, Kenya (Figure 1) and is bounded by Latitudes $00^{o}10'00''$ N and $01^{o}17'\ 00''$N and Longitudes $35^{o}30'00''$E and $35^{o}\ 43'00''$E (Figure 1). It covers an area of approximately 815.71 km^2. The escarpment runs 140 km long and approximately five kilometers wide on average extending from a height of 1200 m.a.s.l to 2800 m.a.s.l and cuts across all the four sub-counties of the Elgeyo Marakwet County (KNBS, 2019). The Elgeyo Escarpment is inhabited by approximately 126,000 people, with over 91% of the Escarpment constituting the rural areas (KNBS, 2019). The Elgeyo Escarpment is conspicuous in nature as characterized by its rugged terrain (CGoEM, 2018; Kipkiror *et al.*, 2021). It is endowed with fertile soils and reliable rainfall (Sombroek *et al.*, 1982). The temperature in the Escarpment ranges between 17 °C and 30 °C during the rainy and dry seasons, respectively. It receives rainfall ranging from 1000 mm to 1400 mm per annum (KMS, 2020).

The Elgeyo Marakwet County hosts Cherangany and Elgeyo water towers. These ecosystems are sources of several rivers that form the main watershed running alongside the Escarpment. The Kerio catchment area lies to the eastern side of the watershed and drains into Lake Turkana while the Lake Victoria Basin that drains into Lake Victoria lies to the Western of the watershed (Sombroek *et al.*, 1982).

Datasets acquisition

The paper is based on three time period multispectral Landsat images from the United States Geological Survey (USGS) Earth explorer Website (https://earthexplorer.usgs.gov/). Landsat 5 TM satellite image for 6th February, 1995 located in WRS - path 169 and WRS-rows 60 and 59. Landsat 8 operational land imager (OLI) satellite image for 25th January, 2014 from WRS-path 169 and WRS-rows 59 and 60. Finally Landsat 8 OLI satellite image for 11th February, 2020 from WRS-path 169 and WRS-rows 59 and 60 are used (Table I). The acquisition period was meant to enable a sustained phenology in all the images. The area shapefile is from contour interpolation and tracing contour value from elevation of 1200 m to 2800 m.

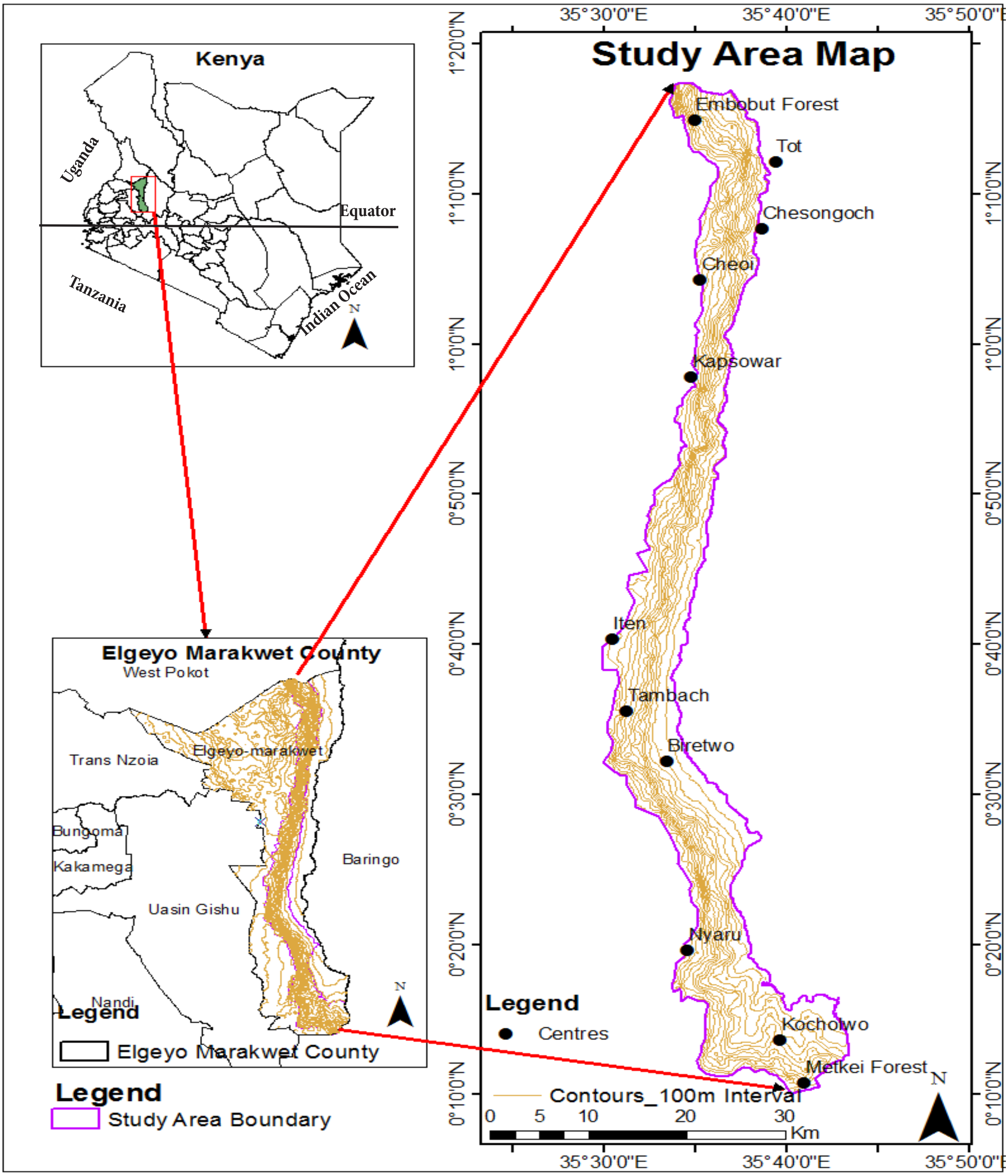

Figure 1: Location and extent of Elgeyo escarpment

TABLE I- SPECIFICATIONS OF THE SATELLITE IMAGERIES FOR ELGEYO ESCARPMENT

Year	Date of acquisition	Level-1 sensor	Spatial resolution (m)
2020	11th February 2020	Landsat 8	30
2014	25th January 2014	Landsat 8	30
1995	6th February 1995	Landsat 5	30

Digital maps of the study area and topographic maps (scale of 1:50,000) were acquired from Survey Department of Kenya. 1995 and 2020 is the initial and final study years, respectively. This sufficiently represents the period when remarkable LULC conversions happened in the area (Alliance, 2015). The images were processed and analyzed using digital image processing software ArcMap version 10.4.1.

Pre-processing of satellite images

The first action was to augment the grade of the image data to reduce radiometric and geometric flaws that arise while obtaining images (Bruce and Herbert, 2006) to rectify the atmospheric interference (Duggin and Rubinove,1990; Song *et al.*, 2001). Dark subtraction were performed to eliminate the effects of atmospheric dispersion from the distantly sensed data to enhance reparability of the spectral classes (Song *et al.*, 2001). The Landsat images from diverse locations were mosaicked into a sole flawless blended image and clipped using the escarpment's boundary map digital shapefile representing the area of interest (AOI).

Image classification

All the pixels in the satellite image were grouped into LULC information classes (Kadavi *et al.*, 2018). Training sites from the pre-processed images were constructed by drawing training samples about the area of interest (AOI) to constitute the main LULC classes explicitly discriminable and devoid of effects arising from period interim differences of the images deployed. Identification of numbers of training sites for distinct LULC classes were determined by their distinct spectral reflectance. The objects in the various images were visualized through the distinction of the color bands (Red-Green-Blue bands). The spectral signatures of the generated return on investment (ROI) were analyzed for satisfactory separability to guarantee minimum confusion amongst the land cover classes (Gao *et al.*, 2010). Once the ROIs were satisfactory, supervised classification was done in ArcMap 10.4 software using the maximum likelihood algorithm (Hassan *et al.*, 2016). The described LULC classes are depicted in Table II.

Accuracy assessment

Prior to the application of image classification outputs in change detection, an accuracy assessment was done. This was meant to validate the potency of the categorization by establishing how acceptable the resultant LULC correlate

TABLE II - LAND USE LAND COVER (LULC) CLASSIFICATION SCHEME

No	LULC class	Description
1	Forest	Lands dominated by woody plants with a cover >15% and height exceeding five meters.
2	Shrubland	Woody perennial plants with persistent and woody stems and without any defined main stem being less than five meters tall.
3	Grassland	Plants without persistent stem or shoots above ground and lacking definite firm structure. Tree and shrub cover is less than 10%.
4	Cropland	Cultivated and managed vegetation/agricultural lands. Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems).
5	Built up	Land covered by buildings and other manmade structures.

LULC = Land use land cover

with the existing land cover on the ground (Muriithi, 2016). The classification precision was evaluated using ground truth ROIs sample from topographic maps and ground truthing. Collation of classification outputs and the area's ground reference test pixels were statistically analyzed using assessment tables. The overall, producer and users' accuracies were derived for each of the classified image. Further, the Kappa coefficient for each image was extracted to scrutinize the concurrence of the remotely-sensed categorization and the ground truth pixels. The overall accuracies and Kappa coefficients realized exceeded 0.7 consequently permitting thorough examination and change detection according to Lea and Curtis (2010).

Change detection

Change detection was performed on the images using ArcMap 10.4 to determine any conversions that may have happened over time (Lu *et al.*, 2004). This was done by calculating the changes in land cover between two consecutive images that is 1995-2014 and 2014-2020 to ascertain the magnitude of change among land cover classes. Each of the three classified images; 1995, 2014 and 2020 was converted from raster to polygon and in the attribute table, the classes were labeled and their areas auto generated using calculate geometry tool. Using geoprocessing intersect tool, two successive images i.e., 1995-2014, 2014-2020 and 1995-2020 were intersected to establish LULC conversions.

Field survey

A household survey, key informant interviews and focus group discussions were conducted to obtain primary data. A structured questionnaire was administered to 180 respondents who had resided in the area for at least fifty-five years deemed to have deep understanding and memory of the LULC and change patterns over time. This entailed, identifying a respondent who would refer the enumerator to the subsequent respondent until no more suitable respondents could be traced, a technique referred to as snowball sampling (Naderifar *et al.*, 2017). This method is often applied when it is difficult to access subjects with target attributes. Existing study subjects recruit future subjects among their acquaintances and sampling continues until saturation (Grove *et al.*, 2012). Eight focus group discussions were held to collect data from eight-member focus groups. The groups comprised of men and women aged 55 years and above. These members were believed to have historical knowledge on LULC change trends in their respective areas. Additionally, a key informant interview schedule was used to collect data from the Ministry of Agriculture, Lands and Forestry and other government agencies comprising Kerio Valley Development Authority (KVDA), National Environment Management Authority (NEMA), Kenya Forest Service (KFS) and Kenya Meteorological Department (KMD).

The surveys were carried out in Soy South, Tambach, Kapsowar, Embobut and Endo Wards representing Keiyo South, Keiyo North, Marakwet West and Marakwet East four sub-Counties, respectively, that the escarpment runs through. Survey data were analyzed using statistical package for social scientists (SPSS) software. Descriptive analysis was done to determine the respondents' profile including gender, age, marital status, literacy levels and occupation. Further, LULC change drivers were derived using frequencies, percentages and standard errors. Relationship and extent of influence of population parameters and LULC and changes was established using correlation and regression techniques.

RESULTS

Classification accuracies and LULC classes

The overall accuracies for the three study years; 1995, 2014 and 2020 were 78.4%, 76.91% and; 84.58% respectively while the Kappa coefficients for 1995, 2014 and 2020 were 0.71; 0.70 and 0.79, respectively (Table III). Within the study period, the five main LULC classes in the area were; shrubland, forest and cropland, with grassland and built-up areas being minor (Figure 2).

TABLE III- CONFUSION MATRICES FOR LULC MAPS FOR 1995, 2014 AND 2020 FOR ELGEYO ESCARPMENT

Classification	1995						2014						2020					
	CL	GL	SL	FL	BU	Total	CL	GL	SL	FL	BU	Total	CL	GL	SL	FL	BU	Total
Cropland (CL)	92	6	18	0	0	116	102	5	22	0	0	129	74	2	16	0	0	92
Grassland (GL)	3	17	3	0	2	25	8	31	4	0	3	46	0	38	5	0	2	45
Shrubland SL)	22	0	114	8	0	144	17	0	117	13	0	147	12	0	122	16	0	150
Forest (FL)	0	0	28	94	0	122	0	0	33	89	0	122	0	0	9	112	0	121
Built-up (BU)	0	2	0	0	17	19	0	4	0	0	24	28	0	6	0	0	27	33
Total	117	25	163	102	19	426	127	40	176	102	27	472	86	46	152	128	29	441
UA (%)	78.6	70.0	71.9	92.2	89.5		78.6	68.0	69.9	92.2	89.5		78.6	68.0	69.9	92.2	89.5	
PA (%)	79.3	70.0	79.2	77.1	89.5		80.3	77.5	70.5	87.3	88.9		86.1	82.6	80.3	87.5	93.1	
OA (%)	78.4						76.9						84.6					
KC	0.7						0.7						0.8					

UA=user accuracy, PA = producer accuracy, OA = Overall accuracy, KC = Kappa coefficient (dimensionless).

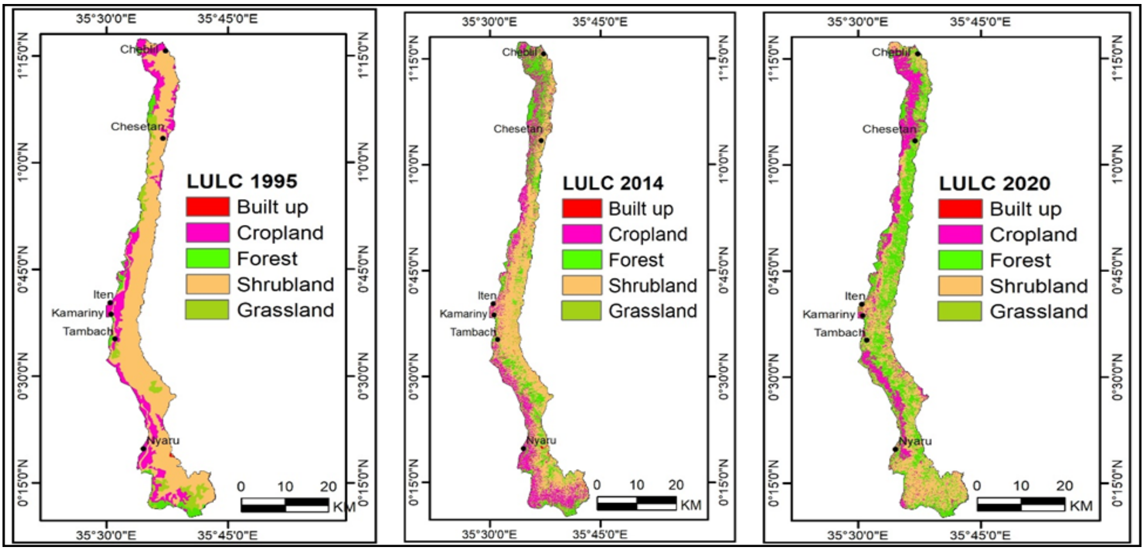

Figure 2: Land use land cover maps for 1995, 2014 and 2020 of Elgeyo Escarpment

Land use land cover trends and magnitude

Supervised classification shows that the most dominant LULC classes are shrubland, cropland and forest, with the three constituting a combined coverage of over 90%. Forests depicted a continuous growth while built-up remained constant over the period (Table IV). In 1995, shrubland, cropland, grassland, forests and built-up covered 67.23%, 20.18%, 7.73%, 4.72% and 0.14%, respectively. By 2014, major LULC changes had occurred resulting in a fivefold increase in forest cover to 24.14% while cropland and built-up areas increased slightly to 22.93% and 0.4%, respectively. Shrubland and grassland decreased significantly to 50.82% and 1.96%, respectively (Table IV). In 2020, forest cover had grown to 39.36% while shrubland had decreased drastically to 39.82%. Cropland and built-up areas decreased marginally to 20.23% and 0.26%, respectively. Grassland decreased significantly to 0.43% (Table IV).

Between 1995 and 2014, major LULC changes occurred in all the LULC classes with grassland and shrubland decreasing significantly by 78.2% and 24.4%, respectively. Conversely, forest and built-up gained tremendously by 411.8% and 200.9%, respectively. Further, cropland increased by 13.6% during this study period (Table V). In the period 2014-2020, forest cover continued to increase by more than 63% while grassland and built-up declined drastically by 79.7% and 39.1%, respectively. Additionally, shrubland and cropland areas decreased by 21.6% and 11.8%, respectively (Table V). Overall, forest, built-up and cropland areas increased while shrubland and grassland decreased over the study period. Forest area gained 277.7 km^2, representing an increase of 734.5%. Built-up increased by 83.3% while cropland gained marginally by 0.2 %. Conversely, grassland and shrubland areas decreased by 95.9 % and 40.7 %, respectively (Table V).

TABLE IV- LAND USE LAND COVERAGE AND CHANGES IN ELGEYO ESCARPMENT: 1995-2020

LULC	1995		2014		2020	
	km^2	%	km^2	%	km^2	%
Cropland	161.77	20.18	183.80	22.93	162.12	20.23
Grassland	61.99	7.73	13.54	1.96	2.75	0.34
Shrubland	538.86	67.23	407.32	50.82	319.45	39.82
Forest	37.80	4.72	193.46	24.14	315.45	39.36
Built-up	1.14	0.14	3.43	0.43	2.09	0.26
Total	801.56	100.00	801.56	100.00	801.56	100.00

TABLE V- LAND USE LAND COVER TREND AND RATE OF CHANGE IN ELGEYO ESCARPMENT

LULC	1995-2014		2014-2020		1995-2020	
	km^2	%	km^2	%	km^2	%
Cropland	22.03	13.62	-21.68	-11.80	0.35	0.22
Grassland	-48.45	-78.16	-10.79	-79.69	-59.24	-95.56
Shrubland	-131.54	-24.41	-87.87	-21.57	-219.41	-40.72
Forest	155.66	411.80	121.99	63.06	277.65	734.52
Built-up	2.29	200.88	-1.34	-39.07	0.95	83.33

LULC = land use land cover

The LULC transition statistics for 1995-2014, 2014-2020 and 1995-2020 are presented in Tables VI to VIII. The changes are in the form of the unchanged LULC category and the conversion from one class to another during the study (Table VI). Between 1995 and 2014, cropland gained about 110.03 km^2 through the conversion of other land uses mostly from shrubland (74.36 km^2) and grassland (29.3 km^2) and a small portion (6.27%) from forest. Conversely, cropland lost 3.47 km^2, 54.22 km^2 and 29.53 km^2 to grassland, shrubland and forest, respectively having a net gain of 22.03 km^2. Grassland lost heavily during this period by 48.45 km^2 to cropland, forest and shrubland. Forest, gained 155.58 km^2 with most of it (128.78 km^2) being converted from shrubland (Table VI).

Between 2014 and 2020, 64.63 km^2, 45.63 km^2 and 0.67 km^2 of cropland was converted to shrubland, forest and built up in that order. About 6.64 km^2 and 3.16 km^2 of grassland was converted to shrubland and forest, respectively, while 157.43 km^2, 50.52 km^2 and 1.04 km^2 of shrubland was converted to forest, cropland and built-up in that order. Built-up was converted to shrubland, cropland and forest by 1.68 km^2 0.87 km^2 and 0.48 km^2 in that order (Table VII). Overall, there was a net gain in forest cover (121.99 km^2) at the expense of cropland, grassland, shrubland and built-up by 20.88 km^2, 10.79 km^2, 88.19 km^2 and 1.34 km^2, respectively (Table VII).

TABLE VI- LULC TRANSITION STATISTICS (1995-2014) OF ELGEYO ESCARPMENT

LULC	LULCC (km^2)					
	Cropland	Grassland	Shrubland	Forest	Built-up	Total 1995
Cropland	73.78	3.47	54.22	29.53	0.77	161.77
Grassland	29.30	0.90	22.71	8.92	0.17	61.99
Shrubland	74.36	8.02	325.58	128.78	2.12	538.86
Forest	6.27	1.16	4.19	26.10	7.02	37.80
Built-up	0.09	0.0	0.38	0.05	0.29	0.81
Total 2014	183.80	13.54	407.08	193.38	3.43	801.23
Change (2014-1995)	22.03	-48.45	-131.78	155.58	2.62	-

LULC = land use land cover

TABLE VII- LULC TRANSITION STATISTICS (2014-2020) IN ELGEYO ESCARPMENT

LULC	Coverage (km2)					
	Cropland	Grassland	Shrubland	Forest	Built-up	Total 2014
Cropland	72.87	0.61	64.63	45.63	0.67	183.80
Grassland	3.62	0.09	6.64	3.16	0.03	13.54
Shrubland	50.52	1.42	201.00	157.43	1.04	407.33
Forest	37.87	0.39	46.63	108.76	0.20	193.46
Built-up	0.87	0.24	1.68	0.48	0.17	3.43
Total 2020	162.12	2.75	319.14	315.45	2.09	801.56
Change (2020 - 2014)	-20.88	-10.79	-88.19	121.99	-1.34	

LULC = land use land cover

Between 1995 and 2020, 59.76 km^2, 49.92 km^2 and 1.22 km^2 of cropland was converted to shrubland, forest and built-up in that order. Further, 22.44 km^2 and 25.54 km^2 and 14.84 km^2 of grassland was converted to cropland, shrubland and forest, respectively. Additionally, 227.67 km^2 and 84.21 km^2 of shrubland was converted to forest and cropland, respectively. Moreover, built-up lost to cropland, grassland, shrubland, and forest by 0.05 km^2, 0.08 km^2 and 0.29 km^2 and 0.035 km^2, respectively. During the entire study, forest gained immensely by 281.31 km^2. Built-up and cropland gained albeit marginally by 1.28 km^2 and 0.68 km^2, respectively. Shrubland and grassland lost drastically by 219.67 km^2 and 60.26 km^2, respectively (Table VIII).

Respondents' attribute

The survey results revealed that all the respondents were married and most engaged in agriculture both crop farming (94.4%) and livestock keeping (90%) for a living (Table IX). Other occupations are business (9%) and formal employment (4.4%). The level of education among the target respondents was fairly low since 33.3% and 30.6% constituted illiterate and primary education levels, respectively.

TABLE VIII- LULC TRANSITION STATISTICS (1995-2020) IN ELGEYO ESCARPMENT

LULC	LULCC (km^2)					
	Cropland	Grassland	Shrubland	Forest	Built-up	Total 1995
cropland	53.44	1.01	59.76	49.92	1.22	165.35
Grassland	22.44	0.18	25.54	14.84	0.11	63.09
Shrubland	84.21	1.55	230.95	227.67	0.71	545.07
Forest	4.54	0.04	6.86	29.09	0.01	40.52
Built-up	0.05	0.08	0.29	0.035	0.09	0.85
Total 2020	164.68	2.83	323.40	321.86	2.13	814.90
Change (2020 -1995)	0.67	-60.26	-219.67	281.34	1.28	-

LULC = land use land cover

TABLE IX- RESPONDENTS' ATTRIBUTE IN THE ELGEYO ESCARPMENT

Respondent attribute	Description	Frequency	Percentage (%)
Gender	Female	52	28.9
	Male	128	71.1
Age	<50	9	5
	>50	171	95
Marital status	Married	180	100
Education level	Illiterate	60	33.3
	Primary	55	30.6
	Secondary	40	22.2
	Tertiary	15	8.3
	University	10	5.6
Occupation	Crop farming	170	94.4
	Livestock keeping	162	90
	Business	9	5
	Formal employment	8	4.4

Land use and cover change drivers

Land use and cover changes across the globe are driven by various factors. Survey results show that in the 1995-2014 period, LULC changes across the Elgeyo escarpment were mainly driven by population growth (97.2%) setting off increased demand for food (87%), settlement areas (45%) and pursuance of income (5%) (Table X). The increased food demand encompasses both human and animal feeds. Additionally, disease outbreaks (40%), particularly malaria was the main factor driving the Kerio Valley residents to the escarpment. Further, infrastructural development (5%) has emerged as a motivation that resulted in people moving to areas with improved road network, schools, churches and health facilities.

XI, corroborates the survey results. Kenya and housing census reports indicate that the area's human population more than doubled between 1989 and 2019. The 1989 report, indicates that the population was 68,558 people. This figure grew to 76,190 people by 1999. During the following two census cycles (2009 and 2019), human population had grown to 99,889 and 126,504 people, respectively (Figure 3a).

This growth in human population brought forth a corresponding increase in the number of households. In 1989, there were 12,684 number of households. In 1999 and 2009 there were 16,581 and 20,940 number of households respectively. By 2019, the number of households had more than doubled to 26,762 (Figure 3a).

TABLE X- LAND USE LAND COVER CHANGE DRIVERS IN ELGEYO ESCARPMENT

LULC change driver	1995 - 2014		2014 - 2020		1995 - 2020	
	Frequency	%	Frequency	%	Frequency	%
Population growth	175	97.2	177	98.3	176	97.8
Increased food demand	157	87	163	90.6	160	88.9
Settlement	81	45	107	59.4	94	52.2
Income	9	5	62	34.4	36	20.0
Cattle rustling	90	50	70	39.0	80	44.4
Infrastructural development	9	5	51	28.3	30	16.7
Disasters	18	10	46	25.6	32	17.8
Disease outbreak (Malaria)	72	40	10	6.0	41	22.8
Forest eviction	25	13.9	32	17.8	29	16.1

Cattle rustling caused 50% of the movements from the valley to the escarpment. This is prevalent particularly in the Tot and Tunyo divisions of the County (Table X). Forest evictions and disasters contributed to the occupation and LULC changes in the escarpment by 13.9% and 10%, respectively. During the 2014-2020 study period, LULC changes were driven largely by the same factors albeit differently. For instance, increased demand for; food, settlement, income, improved infrastructure and landslides occurrence contributed to LULC changes by 90.6%, 59.4%, 34.4%, 28.3% and 25.6% ,respectively. Conversely, cattle rustling and malaria outbreaks as LULC change driving forces declined to 39% and 6%, respectively.

A review of Kenya's population growth as a key LULC change driver as depicted in Figures 3a and 3b and Table

Population density exhibited a similar trend with 1989 population density being 85 Persons/km^2 and more than double (155 persons/km^2) by 2019 (Figure 3b).

The correlation analysis results indicate that forest cover has a significant positive correlation with population, households and density. Built-up has a non-significant positive correlation. On the converse, grassland and shrubland have a significant negative correlation with population, household and density. Cropland has a non-significant negative correlation with population, households and density (Table XI). The results further show that the total population, number of households and density significantly contributed to the decline in grassland, shrubland and increase in forest cover. However, they had insignificant impact on cropland and built-up (Table XI).

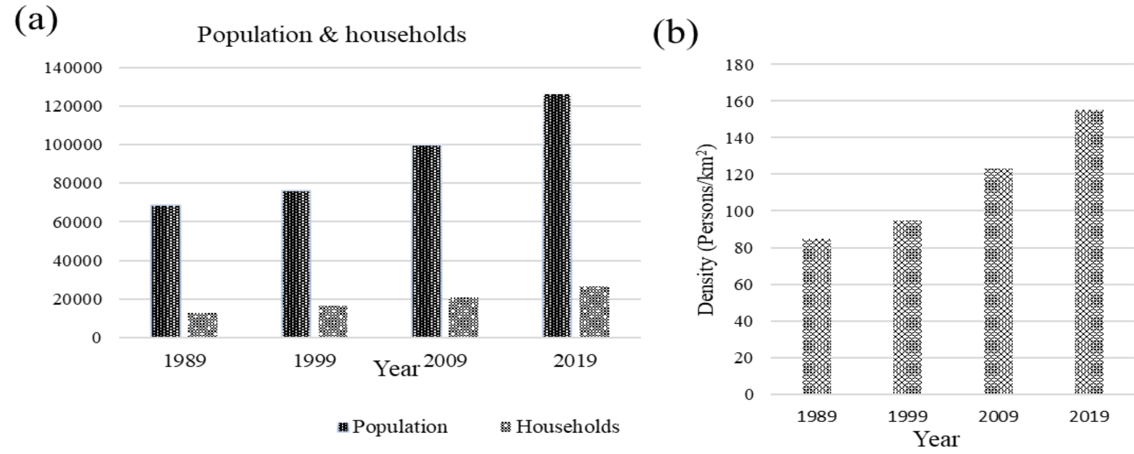

Figure 3: Population, households (a) and density (b) in Elgeyo escarpment

TABLE XI- RELATIONSHIP BETWEEN LULC AND POPULATION PARAMETERS IN ELGEYO ESCARPMENT

LULC Class	Population		Households		Density	
	R-Squared (R^2)	Corr. Coeff (r)	R-Squared (R^2)	Corr. Coeff (r)	R-Squared (R^2)	Corr. Coeff (r)
Cropland	0.058	-0.058	0.069	-0.069	0.025	-0.025
Grassland	0.912	-0.912	0.907	-0.907	0.925	-0.925
Shrubland	0.983	-0.983	0.981	-0.981	0.988	-0.988
Forest	0.99	0.99	0.988	0.988	0.994	0.994
Built-up	0.346	0.346	0.336	0.336	0.378	0.378

LULC = land use land cover

DISCUSSION

The results in this paper show that Elgeyo escarpment underwent land use land cover change over the last 25-years. The changes varied in trends and magnitude both spatially and temporally. They also varied in terms of land use and cover classes. The major change between 1995 and 2014 was the eightfold increase in forest cover and a significant increase in cropland. Built-up areas almost doubled. The increase in forest areas, cropland and built-up saw an almost corresponding decrease in shrubland and grasslands during the same period. This can be attributed to conversion of shrubland and grassland into cropland for food production and timber for constructing houses and thus consistent with other past studies. In particular, Kanianska (2016) noted that human societies begun to modify natural ecosystems, resulting in drastic reduction in the earth's vegetation cover (KWTA, 2020).

The decline in shrubland and grassland cover between 1995 and 2014 in the study area is also consistent with Kissinger *et al.* (2012) who observed that global vegetation cover conversion was most profound between 2000 and 2010. This is the period when large portions of vegetation, worldwide were converted to agricultural land (Ramankutty *et al.*, 2018). Further, (Ayuyo *et al.*, 2014), observed that reduction in vegetation cover could be related to the cutting down of trees for various reasons including encroachment for agricultural purposes. This finding is also consistent with that of Sang *et al.* (2022) who found a decline in shrubland and grassland cover along the Kenya's standard gauge railway corridor. Further, bush fires have been blamed for decimating shrubs and grasses (Rotich *et al.*, 2020). This, clearing of vegetation for farming purposes would extensively degrade the soils since the ecologically sensitive parameters for the habitat cannot buffer the resultant impacts (Zewdu *et al.*, 2016).

Forest cover continued to gain tremendously while shrubland and grassland drastically declined between 2014 and 2020 because the shrubs grew taller and wider converting the area to forest land. Cropland and built-up declined minimally during this period. This can be related to routine eviction exercises that were carried out by the Republic of Kenya that climaxed in 2013 (Amnesty, 2018). It can also be attributed to forest conservation efforts through legal, policy and community sensitization on forest protection benefits. For example, compulsory establishment of farm forestry that is legally provided by the agriculture (farm forestry) rules; section 5(1). This rule prescribes that every person owning or occupying agricultural land shall establish and maintain a minimum of 10 percent of the land under farm forestry.

Additionally, trees growing culture campaigns including instilling tree growing culture in young generations including school going children to plant trees in their farms and in school compounds have contributed to increased forest cover in the escarpment (KWTA, 2020). Moreover, the improved concept of plantation establishment and livelihood improvement scheme (PELIS); a non-resident cultivation within a state forest or the already harvested areas with the desire to establish a plantation improved forest cover substantially (KFS, 2021; KWTA, 2020).

During the study, there was a net minimal increase in built-up areas. This can be attributed to population growth. The 1989 census found that the Kenyan population was 21.4 million people. This increased to 28.7 million people in 1999, 38.6 million people in 2009 and 47 million people in 2019 (KNBS, 2019). In the Elgeyo Escarpment, human population grew from 68,558 to 126,504 people between 1989 and 2019. This translates to a population growth rate of approximately 3% per annum (KNBS, 2019). The increase in population follows that the families' land is inherited; shared among the male children who will have come of age to start their own families. This is demonstrated by the steady increase in the number of households rising from 12, 684 to 26,762 between 1989 and 2019 (KNBS, 2019).

As a result of population growth, resources such as land and vegetation are over-utilized. It is therefore not surprising that shrubland and grasslands decreased in the area during the study (Tables IV and V). This is demonstrated by the negative relationship between population, shrubland and grassland (Table XI). These results are consistent with Demetriou *et al.* (2013) who found that land inheritance, land markets and historical or cultural perspectives cause land use and cover changes. They are also in agreement with Kogo *et al.* (2021) who found that population increase caused the decline in grassland that was due to unsustainable land use practices. Further, insecurity caused by the conflict between the residents of Baringo and Elgeyo Marakwet Counties residing in Kerio valley (NCCK, 2009) that forced over 32,000 people to move to higher areas considered safer (Pkalya *et al.*, 2003) and probably degrading the fragile escarpment (Kiprono, 2018).

Additionally, the overall marginal increase in built-up areas during the study can be attributed to the increased roads networks. This is particularly those murram roads done by the County Government of Elgeyo Marakwet across the Escarpment (Kilimo, 2014). For instance, the earth-surfaced roads cover a total of 564.4 km, of which 258.4 km were roads newly opened by the County Government (CGoEM, 2018). This finding is in agreement with Sang *et al.* (2022) who found increase in bare land, cropland and built-up and drastic reduction in shrubland land and grassland. They attributed the changes to the construction of the Standard Gauge Railway and the advent of devolution which catalysed development to grassroots leading to mushrooming of urban areas and settlements.

Malaria outbreak as LULC change drivers declined between 2014-2020 (Table X). This can be attributed to a deliberate and robust campaigns by the Republic of Kenya's Ministry of Health and development partners including the World Health Organization (WHO) and the United States of America (MoH, 2016; Noor *et al.*, 2012). Although the programme had begun in the year 2004, they only targeted children under five years old, pregnant women and the elderly in the society (Noor *et al.*, 2007). They were later expanded to all members of the society. These programme entailed sensitization, mass distribution of insecticides treated mosquito nets, spraying mosquitoes breeding areas and encouraging people to sleep under the insecticides treated mosquito nets (Ng'ang'a *et al.*, 2021).

CONCLUSIONS

The Elgeyo Escarpment has undergone profound changes that vary spatially and temporally and among the various LULC classes during the study. Forest cover increased substantially while shrubland and grasslands decreased profoundly during the study. There was a net increase in forest, cropland and built-up areas and a net decline in shrubland and grassland. Besides, cattle rustling, forest evictions and infrastructural development encouraged people to settle in the escarpment, exerting immense pressure on the landscape. The recovery of forest cover highlights the importance of a timely government intervention in the management of natural resources. Population growth is a key LULC change driver triggering increased demand for food and housing. Therefore, this paper is important since it will inform planning and regulation of land use and decision making on appropriate policies, strategies and regulations formulation as well as resource allocation in the escarpment.

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