Dynamics and Drivers of Land Use and Land Cover Changes in Migori River Watershed, Western Kenya Region

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Dynamics and drivers of land use and land cover changes in Migori River Watershed, western Kenya region

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ABSTRACT

Understanding land use and land cover (LULC) change dynamics and their contributing factors are critical for developing sustainable land management strategies. Therefore, this paper assesses the trends and patterns of LULC changes and their drivers in the Migori River watershed in Kenya from 1980 to 2020. The spatial analysis is based on remote sensing data based on the maximum likelihood classifier algorithm; whereas the analysis of the drivers is based on index-based ranking and logistic regression of 318 households' survey data. The results show that between 1980 and 2020, the watershed experienced a considerable decline in shrub lands by 40.63% (−235.97 km^2), grasslands by 84.86% (−59.14 km^2), forests by 52.90% (−98.36 km^2), water by 82.03% (−39.27 km^2) and wetlands by 38.44% (−3.69 km^2); whereas cultivated land, bare land and built-up areas expanded over the same period by 34.25% (+347.42 km^2), 132.28% (+60.95 km^2) and 461.20% (+25.32 km^2), respectively. The results of the household survey revealed that the perceptions of the locals tended to corroborate these observed LULC patterns obtained from spatial analysis, with 60.50% (n = 192) of the respondents reporting a significant expansion in agricultural land use (at $p < 0.05$), and 75.80% (n = 241) observing a significant decline in forest areas in the watershed (at $p < 0.05$). Fuel wood collection, timber/poles production, agricultural expansion, population pressure, and high poverty are the major drivers of these LULC changes. The findings also revealed that educational level significantly influenced the survey participants' perceptions concerning these drivers. The paper concludes that the watershed's natural landscapes have been undergoing destruction at the expense of human settlement and infrastructural developments driven by anthropogenic activities. Therefore, there is a need, among others, for land use zoning to regulate conflicting land uses on the watershed between settlement, conservation, and agricultural lands.

Introduction

Since the 1970s, land use and land cover (LULC) change has been an important research topic, receiving significant attention from the scientific world (Brown et al., 2013). This is attributed to the global recognition of land use and land cover change as a major factor impacting various environments in the world and its escalation from local, regional to global scales over the last decades (Oliver and Morecroft, 2014; Xu et al., 2020). These changes can be gradual or abrupt such as the ones influenced by natural catastrophes or even political intrigues (Kariyeva & van Leeuwen, 2012). In the pursuit of livelihoods, the competing human demands for exploitation, management, and conservation of land resources drive changes in land use and land cover (Magige, 2018). Human-induced causes of LULC are classified into two major groups, namely proximate drivers and underlying drivers (Munthali et al., 2019). The proximate drivers are factors linked to human undertakings that directly transform the land cover e.g. urbanization or agriculture, while the underlying drivers are forces that trigger the proximate causes and indirectly increase their effect on the environment e.g. government policies and technological advancement (Kindu et al., 2015; Song et al., 2018). The underlying drivers cut across the biophysical, demographic, social, cultural, technological, economic, political, and institutional factors (Xu et al., 2020). Several studies indicate that it is the synergy of several drivers that results in land use and land cover changes (Dewan et al., 2012; Meshesha et al., 2016; Munthali et al., 2019). Du et al. (2014) opined that the drivers of land use and land cover are dynamic and their impact depends on the context, which could be socio-economic, ecological, historical, and political.

Land use and land cover change have significant effects on the functioning of socio-economic and ecosystems with important tradeoffs for sustainability, biodiversity, food security, and

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socio-economic vulnerability of communities and ecological systems (Guzha et al., 2018; Alawamy et al., 2020). A growing volume of the literature shows that LULC change has devastating impacts on natural resources, food security, climate change, and energy (Rutten et al., 2014; de Castro et al., 2016; Xu et al., 2016). Watersheds are one of the fragile natural resources most impacted by changes in LULC over the last few decades (Hassen & Assen, 2018). De-Castro et al. (2016) observe that the effects of pervasive LULC on watersheds are multi-faceted and cut across hydrology, water chemistry, and biodiversity among others. Researchers have shown that changes in the condition and composition of land cover in watersheds affect the quantity and quality of water resources available in the watershed altering the sediment regime, the volume of runoff discharge, and the rate of the peak flow of the runoff, and the way pollutants move through the drainage basin (Chiwa, 2012; Mekonnen et al., 2015; Kipkorir, 2017). Like any other country in Sub-Saharan Africa, Kenya's watersheds face immense pressure from rapid and extensive LULC changes caused by human-environment interactions (Muriithi, 2016; Onyango et al., 2021). Even though various studies on LULC changes in a diversified range of landscapes have been done in Kenya, research on LULC dynamics of watersheds within the larger Lake Victoria Basin as well as the factors contributing to these changes remains scanty.

The present study focuses on the Migori River watershed, one of the hotspots of biodiversity situated in the Kenyan Lake Victoria basin. This region has been continuously experiencing extensive vegetation loss and fragmentation of its natural landscapes over the last few decades due to agricultural expansion, infrastructural development, and increased occurrence of natural hazards such as floods and landslides (Magige, 2014; Sirengo et al., 2018; Onyango & Opiyo, 2022), but data and documentation detailing the nature and extent of these landscape changes are limited. Estimating the rate, nature, type, and pattern of LULC changes in any landscape, as well as understanding factors that influence these changes, are fundamental for decision-making by policymakers, planners, and other stakeholders (Kamwi et al., 2015; Liping et al., 2018). Therefore, this study aims at quantifying LULC changes and assessing the key drivers contributing to these changes in the Migori River watershed between 1980 and 2020. Thus, the study captured local communities' perceptions of LULC change trends and the drivers of these changes in the study area. Various studies have pointed out that LULC change dynamics observed on any landscape are a reflection of aggregated decisions at the household level in response to policy and an institutional background over a particular period (Hassen & Assen, 2017; Munthali et al., 2018). The findings of this study are envisioned to offer a foundation for systematic and effective land use planning, management, and ecological restoration for socio-economic development in the Migori River watershed.

Materials and methods

Description of the study area

The Migori River watershed (Fig. 1) hereafter referred to as the watershed, is located within Migori County and covers approximately 2,597 km^2 of land area in the Western Kenya region. Migori River originates from Chepalungu Forest in Emuria-Dikiri Sub-county of Narok County, from where it flows 70 km through Migori County to Lake Victoria. The entire catchment for the Migori River is found at an altitude of 1500 m above sea level. It enjoys an inland equatorial climate that is heavily influenced by its proximity to Lake Victoria. It receives mean annual rainfall in the range of 700 mm to 1800 mm with two wet seasons and two dry seasons. Average temperatures in the region range from 13 °C to 24 °C depending on the seasons.

The watershed is divided into six agro-ecological areas, ranging from Upper Midland 1–3, which covers sections of Rongo, Uriri, Kuria East, and Kuria West Sub-Counties, to Lower Midland 1–5, which covers sections of Rongo, Uriri, Nyatike and Suna East Sub-Counties (Sirengo, 2018). This watershed's land use is dominated by extensive agricultural and deforestation practices for charcoal production in the upstream, urbanization and agricultural practices - especially tobacco, cotton, maize, and sugarcane farming among others- in the midstream, and, mining and urban development activities are rampant in the downstream region because of its arid and semi-arid climatic conditions consisting of extensive savanna grasslands. Geologically, the watershed lies within the Migori Greenstone Belt, which is a system of Archaean rocks containing mineral deposits such as gold, copper, zinc, and galena which are being mined artisanally in the region (Odumo et al., 2011).

Satellite imagery data acquisition

A combination of remote sensing and geographical information system (GIS) is used to assess the trends and patterns of land use and land cover changes in the Migori River watershed between 1980 and 2020 at the recommended 10-year intervals (Alawamy et al., 2020). The paper utilizes datasets of multi-temporal and spectral satellite imageries of Landsat 3 Multispectral Scanner (1980), Landsat 4, 5 Thematic Mapper (1990, 2000, and 2010), and Operational Land Satellite - Thematic Infrared Sensor (2020) obtained from the United States Geological Survey (USGS) earth explorer website (https://www.earthexplorer.usgs.gov). The features of these imageries are summarized in Table 1. To minimize phonological variations, all images selected were for the dry month of December; when both the moisture content and cloud coverage in Migori County are at their lowest.

Data pre-processing

After the acquisition, the raw satellite images were imported into ERDAS Imagine 2020 Version by Hexagon Geospatial for standard pre-processing procedures undertaken before classification to improve their visualization and interpretability. First, radiometric/atmospheric correction was performed to reduce the effects of haze captured on the Landsat images following the approach described by Lillesand and Keifer (2015). In this procedure, the metadata of the raw Landsat imageries of the five years under investigation was exported into the ERDAS Imagine software which then utilized the information contained in the metadata to automatically correct the datasets, eliminating all the atmospheric impurities such as cloud cover that might adversely impact image classification (Onyango et al., 2021). The radiometrically corrected images were then subjected to an image mosaicking procedure whereby images of similar paths but different rows were joined together into one single image so as to retrieve the exact area of the imageries covered by the watershed (Nguyen et al., 2019). Due to the vastness of the Migori River watershed, the entire shape of the watershed could not be captured in a single satellite row, hence separate Landsat images that hold portions of the watershed had to be joined (mosaicked) into one single image covering the entire watershed in order to ease processing. Image sub-setting (described by Samrat et al., 2022) was then performed to extract and clip the area of interest (i.e. the Migori River watershed) from the mosaic using the extent of the Migori County in Kenya. Noteworthy, satellite images usually cover extensive landscapes that often extend beyond the region required for the project/research hence the need for sub-setting (Samrat et al., 2022). After sub-setting, layer stacking was

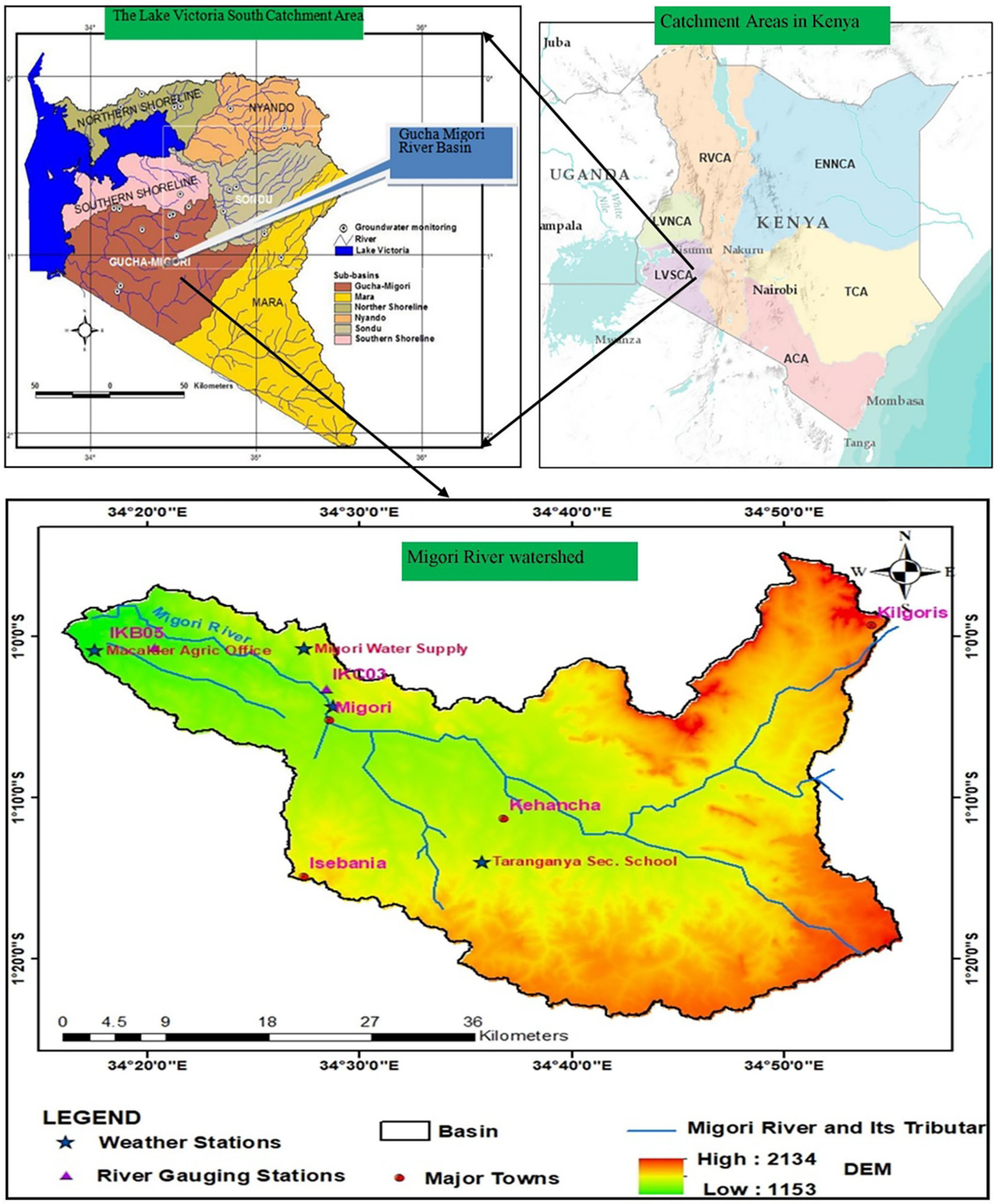


Fig. 1. Location map of Migori River watershed.

Table 1
Features of multi-temporal Landsat imageries.

YEAR	Sensor	Path/ Row	Acquisition Date	Resolution (m)	Cloud cover (%)	Season	Source
1980	Landsat 3 MSS	170/60	11/12/1980	60	0	Dry	USGS
1990	Landsat 4,5 TM	170/60	17/12/1990	30	1	Dry	USGS
2000	Landsat 4,5 TM	170/60	09/12/2000	30	1	Dry	USGS
2010	Landsat 4,5 TM	170/60	12/12/2010	30	0	Dry	USGS
2020	Landsat 8 OLI-TIRS	170/60	15/12/2020	30	0	Dry	USGS

performed in which appropriate bands (with exception of the thermal bands) were layer-stacked/combined together to form one single composite image to bring out the true color image of the scene (Lillesand & Keifer, 2015). Finally, the images were subjected to pan-sharpening to enhance the visualization of panchromatic images (USGS, 2020).

Data processing and analysis

After successful pre-processing and prior to classification, the training and validation datasets of different periods used for classification and accuracy assessment, respectively, were collected from the Google Earth desktop application as described by Doyog et al. (2021). Google Earth is available free of charge and offers very high spatial resolution images with historical and up-to-date details of the Earth's surface (Midekisa et al., 2017; Doyog et al., 2021), allowing multi-temporal analysis of landscape changes over time (Eggen et al., 2016; Sidhu et al., 2018). Next, the corrected images were subjected to a supervised classification based on the Maximum Likelihood Classification (MLC) algorithm to define LULC classes (Munthali et al., 2019). Previous studies have shown that MLC is the most common, successful, and widely adopted algorithm for LULC classification (Ikiel et al., 2013; Ariti et al., 2015; Onyango & Opiyo, 2022). Eight classes were developed based on ancillary data, visual analysis of the locations on Google Earth Pro maps, and ground truthing (Anwar et al., 2022). The LULC classes of interest were therefore defined as cultivated land, shrub land, grasslands, forests, bare land, built-up areas, water, and wetlands (Table 2). For each class, 6 ground-truth polygons were sampled randomly and digitized using aerial photographs and visual inspection of the locations on Google Earth maps. In line with Jensen (2007), each training sample polygon used in the classification process contained not<50 pixels. The training sample polygons which were found with unwanted pixels were thrown out and replaced with the new ones with desired spectral signatures. After successful image training with the signature editor, the Maximum Likelihood algorithm was run a couple of times to produce class signatures and classify the imageries into meaningful land use and land cover categories. Finally, the ArcGIS Desktop by Esri (Version 10.2) was used to generate cartographically appropriate LULC maps for the years 1980, 1990, 2000, 2010, and 2020.

Post-processing analysis

Accuracy assessment was done through the generation of confusion/error matrices in which the data from LULC classification are compared to the ground-truthing data acquired from fieldwork. This study used 160 ground reference points (20 reference points for each LULC class) and reference data extracted from Google Earth images for accuracy assessment. The positions of the reference points were automatically identified on the classified images and their class values were defined to determine the accuracy of a pixel. The statistical components of the confusion matrix namely, producer's accuracy, user's accuracy, overall accuracy, kappa statistics, and overall kappa coefficient were calculated for all the classified LULC images based on the algorithms provided in Congalton and Green (2019). Change detection analysis was then carried out using the change matrix tool. During this automated process, classified LULC data of the initial year under consideration is compared to the one for the final year under consideration. Once, the areal coverages are computed, the software produces a change detection matrix that shows the net changes for the respective classes over a given period. The data for 1980, 1990, 2000, 2010, and 2020 obtained from the change matrix is expressed in square kilometers and percentages. Finally, the LULC change-transition matrix through the overlay technique in ArcGIS to estimate the area converted from every LULC category to the other over the period between 1980 and 2020. Moreover, the annual rate of change of each LULC category was computed as percentages using equation (1) proposed by Puyravaud (2003).

$$r = \left(\frac{1}{t_2 - t_1}\right) \times \text{In}\left(\frac{A_2}{A_1}\right) \quad (1)$$

where r is the annual rate of change for each LULC category (in percentage), and A_2 and A_1 are areas of each LULC category at the end (t_2) and the beginning (t_1), respectively, for the period under review.

Household survey

Sample size and sampling procedure

A descriptive cross-sectional survey was conducted between January and February 2022, among 318 randomly selected households in the Migori River watershed, using pre-tested, interviewer-administered semi-structured questionnaires. The household questionnaires consisted of various questions designed to get information on the perceptions of the local communities on LULC changes and the drivers in the Migori River watershed from 1980 to 2020. The questionnaire was initially pretested in 30 households in the Awendo Sub-county, which neighbors the watershed and isn't part of the actual survey after which the adjustments were effected before the actual household survey. Prior to the survey, village elders and local administration officials were consulted to explain the purpose of the study, understand the local realities (which helped in developing questionnaire items), and obtain permission to visit the selected households. During the exercise, the questionnaires were administered to household heads or other senior members of the selected households who had lived in the watershed for at least ten years, upon obtaining verbal consent. Cultural norms dictated that the male be interviewed as the head of the household unless absent then the spouse or adult (over 21 years) family member who understands the family and area well. Each interview lasted about 35 min on average.

Characteristics of the sampled households

A summary of the socio-economic characteristics of the respondents is presented in Table 3. The age of the participants ranges from 21 to 83 years, with an average of 38.60. Approximately 57.80% lived in the watershed throughout the period under review

Table 2
Land Use and Land Cover categories used in the Migori River watershed.

LULC class	Description
Cultivated land	Areas occupied by crops, fruits, and vegetables
Shrub land	Degraded forest land or areas under woody vegetation dominated by young trees and shrubs that are<5 m tall
Grassland	Landscapes covered by herbaceous vegetation and are not cultivated or have<10% coverage of shrubs and trees
Forests	Landscapes are mostly made up of mature natural or planted trees, and there are no obvious signs of severe disruption of ecological processes
Bare land	Open rocky or soil surfaces that are devoid of any vegetation
Built-up area	Areas comprising human settlements, transportation, industrial and commercial infrastructure
Water	Water surfaces of rivers, ponds, flood plains, wells, or lake
Wetland	Landscapes that are soaked by water for the majority of the year i.e. swamps

Table 3
Summarized attributes of the sampled household in the study area (N = 318).

Household Characteristic	Value
Ethnic group (Luo, %)	50.90
The average age of household heads (years)	38.60
Male-headed households (%)	70.80
Marital status (married, %)	77.70
Education (literate, %)	72.10
Occupation (Farming, %)	80.00
Average household size (no)	6.10
Average landholding size (acres)	2.91
Average household income (Kshs/year*)	57,552.29
Income sources (agriculture, rank)	1
Household cooking stove (three-stone open fire, %)	93.50

Key: * The exchange rate for Kshs at the time of the study was 1 USD = 115.40.

for LULC changes. The majority (77.70%) is married, 70.80% of the households are male-headed and 29.20% are female-headed. Household sizes in the watershed range from 1 to 12 persons, with an average of 6.10. About 84.30% own land and 15.70% are landless, with landholding size ranging from 0.50 to 9.00 acres, with an average of 2.91 acres. Regarding educational attainment, 72.10% are literate – 23.00%, 25.50%, and 23.60% - had attained primary education, secondary education, and college education, respectively, with 27.90% having no formal schooling. About 80.00% of the surveyed households were involved in crop farming and a small proportion of the participants (20.00%) were engaged in various off-farm and non-farm activities. The average household income of the participants was USD 498.72 (Kshs 57,552.29) per annum. Agriculture is ranked as an important income source for households in the watershed, followed by non-farm activities (employment in non-farm sectors like healthcare, education, mining, and tourism), which are ranked second, then off-farm self-employment activities (such as processing, packaging, transport or sale of farm produce, and lastly remittances).

Statistical analyses

The LULC change analysis was conducted using ArcGIS Desktop by Esri (Version 10.2) and ERDAS Imagine 2020 by Hexagon Geospatial, in a process that combined GIS and remote sensing techniques. The socio-economic survey data was analyzed using the IBM SPSS Statistics for Windows (Version 24.0) in which both descriptive statistics and regression analyses were conducted. After obtaining the descriptive statistics, ranking the LULC change drivers for the watershed based on the weighted average was computed using the Relative Importance Index (RII) equation (2) adopted by previous studies (Musa et al., 2006; Aziz et al., 2016).

$$RII = \frac{R_n C_1 + R_{n-1} C_2 \cdots + R_1 C_n}{A \times N} \quad (2)$$

where R_n = value of the lowest/last rank e.g. if the lowest/last rank is 5 in the Likert-scale used, then R_n = 5 and $R_n - 1$ = 4; R_1 = value of the highest/first rank in the Likert-scale used, usually 1; C_n = counts/number of observations on lowest/last rank; C_1 = counts/number of observations on highest/first rank; A = the highest value in the overall ranking scale, and N = total number of respondents.

Logistic regression analysis is carried out using equation (3) to determine the drivers of LULC changes at the household level in the Migori River watershed. In this model, the independent variables comprised the socio-economic attributes whereas the dependent variables are the respondent's perceptions of the driving forces of LULC change. The logistic regression analysis at the household level approximated the probability of the effects of the independent variables on the dependent variables (Munthali et al., 2019).

$$Logit\ (Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \quad (3)$$

where Y = dependent variable indicating the likelihood that Y = 1, α = the intercept, $\beta_1 \ldots \beta_n n$ = coefficients of associated independent variables, and $X_1 \ldots X_n$ = independent variables.

Results and discussion

Accuracy assessment of the LULC classification

The classified imageries have an overall accuracy of over 86.00% (Table 4). Since an overall accuracy of over 80.00% is acceptable and recommended (Turan & Günlü, 2010), the LULC classification is thus acceptable and hence reliable. Furthermore, the overall kappa coefficient for all the classified images ranged between 0.77 and 0.81, which when compared to the Landis and Koch (1977) ratings shows that the classification carried out for the study has a strong agreement with the ground-truthing reference data. The kappa coefficient is a measurement of the precision or agreement between data from classified imageries and data from ground reference locations (Ikiel et al., 2013). Although there are small differences in producer and user accuracies of specific LULC categories, the classification registered high overall accuracy (Table 4). These accuracy assessment results provided the basis for subsequent examination of LULC changes.

LULC change dynamics in Migori River watershed from 1980 to 2020

LULC changes have been investigated for the years 1980, 1990, 2000, 2010, and 2020 using three-generation Landsat time-series data considering eight different classes, namely cultivated land, shrub land, grasslands, forests, bare land, built-up areas, water, and wetlands. The classified LULC maps for the corresponding years, showing the spatial representation of these LULC types, are shown in Fig. 2.

Overall trend analysis of LULC changes (1980–2020)

The proportionate coverage area of each of the eight classes extracted in the watershed from 1980 to 2020 of LULC change trends is summarized in Table 5 and Fig. 3. Table 5 indicates that shrub land, grassland, forests, water, and wetland shrunk while cultivated land, bare land, and built-up area expanded over the past 40 years in the watershed. The cultivated land was the most dominant LULC class in the watershed in 1980, accounting for approximately 51.86% of the total landscape; but it has since then increased by about 347.42 km^2 (8.69 km^2/year). Since the 1980s, cultivated land initially fell sharply in 1990 before taking a steady increasing trend over the following decades. While the cause of the decline in cultivated land in 1990 is unknown, the trend of farmland expansion over the years could be attributed to the high rate of population increase (UN Department of Economic and Social Affairs, 2019); which might have increased the demand for food and consequently resulted in the conversion of other natural landscapes like grasslands, wetlands and forests and shrub lands into farmlands. Bare land accounted for 2% of the watershed in 1980 but has since risen by 132.28% (0.1 km^2/year). This is a reflection of the effect of increased unsustainable utilization of grasslands and forests through overgrazing and deforestation. This is consistent with the conclusions of Hassen and Assen (2018) about land-use change in the Lake Tana watershed in Ethiopia. The built-up area constituted<3% of the watershed in 1980 but has since expanded by 461.20% (0.6 km^2/year). This exponential expansion demonstrates the rapid rate of conversion of natural landscapes into settlement areas to accommodate the ever-burgeoning population.

Forest cover in the watershed seems to have declined by about 52.90% (1.48 km^2/year) notwithstanding the forest conservation efforts since the 1980s championed by the Permanent Presidential Commission on Soil Conservation and Afforestation. This can be attributed to the expansion of rural and urban settlements and farmlands, weak enforcement of conservation laws, and increased demand for timber as raw materials for construction and fuel wood for household usage. Although grasslands exhibited an irregular pattern of spatio-temporal changes across the five reference periods, it has experienced a decline of approximately 84.86% (1.48 km^2/year) over the past 40 years. This substantial decline in grasslands is an indication of the increasing demand for agricultural lands and the development of forests in some of the grasslands. Moreover, the irregular pattern of changes observed in grasslands from 1980 to 2020 can be attributed to the destruction by constant incidences of fire outbreaks that usually occur in the

Table 4
Accuracy-assessment results for the 1980, 1990, 2000, 2010 and 2020 LULC change maps.

LULC Type	1980			1990			2000			2010			2020		
	PA (%)	UA (%)	k	PA (%)	UA (%)	k	PA (%)	UA (%)	k	PA (%)	UA (%)	k	PA (%)	UA (%)	k
Cultivated Land	93.51	87.80	0.75	96.04	84.35	0.76	99.49	82.63	0.50	98.15	88.33	0.75	97.33	91.92	0.79
Forest	72.73	94.12	0.94	87.10	90.00	0.89	75.00	93.75	0.93	76.00	95.00	0.95	84.62		0.84
Wetland	–	–	0.00	50.00	66.67	0.66	–	–	0.00	–	–	0.00	–	–	0.00
Grassland	56.00	100.00	1.00	88.24	81.08	0.79	40.00	100.00	1.00	66.67	100.00	1.00	86.36	100.00	1.00
Shrub Land	92.05	82.65	0.75	89.11	93.75	0.91	71.05	96.43	0.96	85.86	92.39	0.89	92.98	94.64	0.93
Bare Land	71.43	83.33	0.83	73.91	100.00	1.00	43.75	100.00	1.00	57.14	100.00	1.00	72.73	80.00	0.79
Water	33.33	100.00	1.00	40.00	100.00	1.00	71.43	100.00	1.00	100.00	100.00	1.00	100.00	100.00	1.00
Built-up Area	100.00	100.00	1.00	82.70	88.80	0.83	96.00	86.90	0.75	50.00	100.00	1.00	66.67	100.00	1.00
Overall Accuracy	87.00%			88.33%			85.67%			90.33%			92.33%		
Overall Kappa	0.79			0.84			0.69			0.83			0.86		

Note: PA = producer's accuracy; UA = User's accuracy; k = kappa statistic.

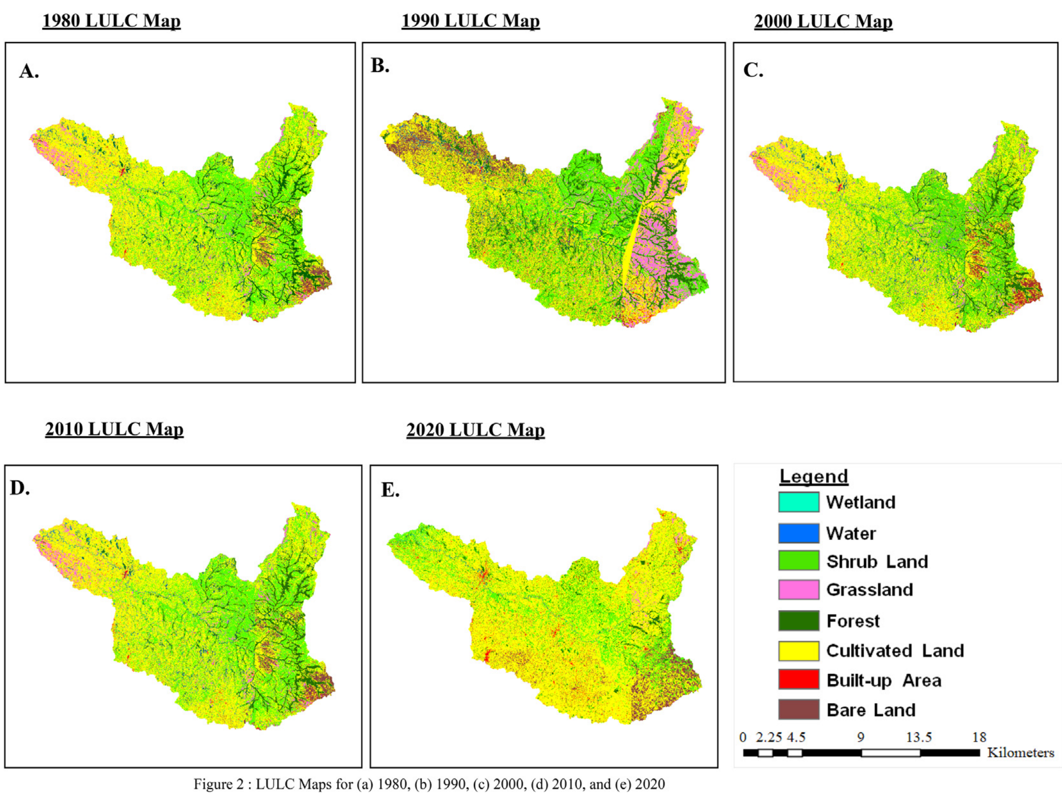


Fig. 2. LULC Maps for (a) 1980, (b) 1990, (c) 2000, (d) 2010, and (e) 2020.

Table 5
Land Use and Land Cover patterns of Migori River Watershed between 1980 and 2020.

LULC type	1980		1990		2000		2010		2020	
	Area (km^2)	%	Area (km^2)	(%)	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Cultivated land	1014.36	51.86	766.54	39.19	1421.17	72.66	1445.28	73.89	1361.78	69.62
Shrub land	580.81	29.69	488.67	24.98	203.38	10.40	233.70	11.95	344.84	17.63
Grassland	69.69	3.56	209.79	10.73	54.58	2.79	80.87	4.13	10.55	0.54
Forests	182.15	9.32	298.19	15.25	122.98	6.60	102.07	5.22	83.79	4.28
Bare land	46.04	2.35	162.31	8.30	110.25	5.64	63.25	3.23	123.02	5.57
Built-up area	5.49	0.28	6.50	0.33	9.83	0.50	8.27	0.43	30.81	1.58
Water	47.87	2.45	21.01	1.07	22.15	1.13	17.23	0.88	8.60	0.44
Wetland	9.97	0.49	2.95	0.15	8.93	0.46	5.34	0.27	5.91	0.34
Total	1955.98	100.00	1955.98	100.00	1955.98	100.00	1955.98	100.00	1955.98	100.00

area during periods of droughts (Odeny, 2015) or by the droughts themselves (Oyugi, 2016). The entire Migori County where the watershed lies is a drought prone region characterized by unreliable rainfalls, poorly distributed throughout the year and constantly fluctuating temperatures (Oyugi, 2016), and has been known to be constantly threatened by fire outbreaks, following

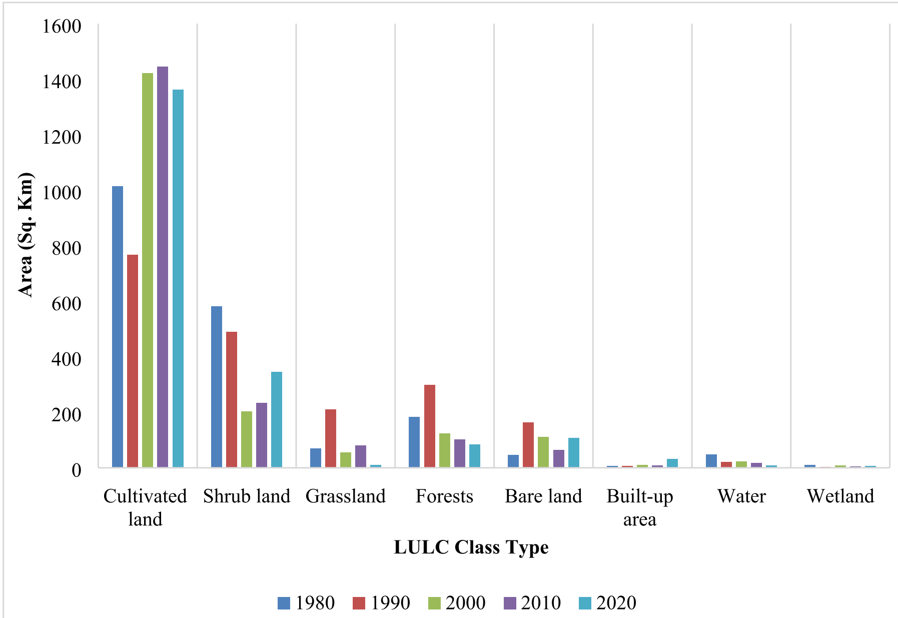


Fig. 3. Trends of Land use/cover changes in the Migori River watershed between 1980 and 2020.

prolonged drought conditions (Odeny, 2015). The frequent destruction of grasslands by both fire or drought incidences and the successive regenerations contributes to the irregular pattern of spatio-temporal changes over time.

Similar to grasslands, the patterns of spatio-temporal changes in shrub lands showed that it has declined by 40.63% (5.90 km^2/year) over the four-decade period, which was largely attributed to the conversion to cultivated lands and settlements due to population pressure. Since 1980, water declined by 82.03% (0.98 km^2/year) while the wetlands shrunk by 38.44% (0.1 km^2/year). This declining trend in areas under water and wetlands could be attributed to the emergence and growth of aquatic vegetation and invasive species in these areas, frequent occurrence of droughts in the area (Magige, 2014), and probably the depletion of water through domestic usage, canal irrigation, and livestock watering. Further, the decline suggests the existence of unsustainable land management practices like the reclamation of these lands to create spaces for agriculture and settlement, coupled with mining in the area.

Decadal trend analysis of LULC changes

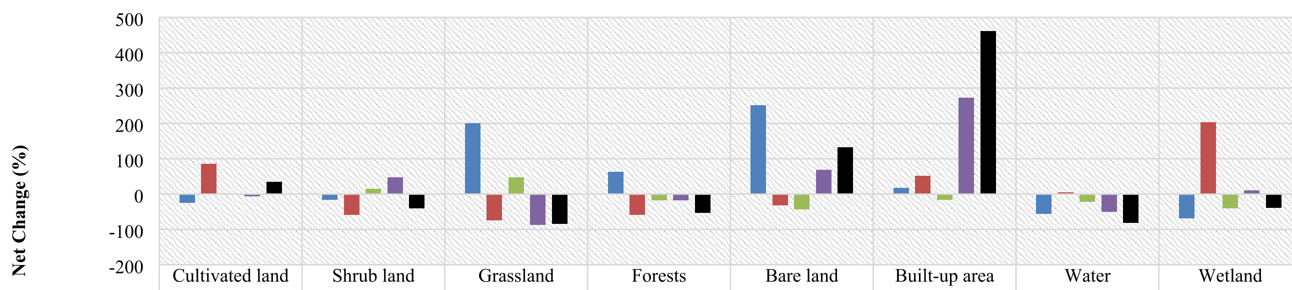
A decade-by-decade analysis of the rates of change in LULC between 1980 and 2020 in the watershed revealed specific net changes in the form of gains and losses for each class during the 1st period (1980–1990), 2nd period (1990–2000), 3rd period (2000–2010) and 4th period (2010–2020) as shown in Table 6 and Fig. 4.

(I) The pattern of LULC changes between 1980 and 1990.

From 1980 to 1990, the watershed experienced considerable positive and negative transformations in the LULC coverage (Table 6 and Fig. 4). Spatial analysis indicated that cultivated land was the dominant LULC in the watershed in 1980, covering around 1014.36 km^2 (51.86%) of the entire land area (Table 5). However, it decreased to 766.54 km^2 (39.19%) in 1990 (Table 5), resulting in a net loss in coverage of about 24.43% over that decade (Table 6). Shrub lands, water, and wetlands also showed negative trends during this decade, with net losses of 15.86%, 56.11%, and 69.27% from their original coverage, respectively (Table 6). On the contrary, the remaining LULC categories experienced positive trends from 1980 to 1990 i.e. there is an increase in grasslands by 201.03%, forests by 63.71%, bare land by 252.00%, and built-up area by 18.40%. These findings imply that, during this era, the land areas under cultivation, shrubs, water, and wetlands shrunk because they became bare, got covered by grasslands and forests, or were converted to settlements for the growing population. This phenomenon could be attributed to a government policy by the new government in the early 1980s which established the Permanent Presidential Commission on Soil Conservation and Afforestation (PPCSCA) in 1981 to champion environmental conservation efforts in the entire country (Nasong'o, 2012). This policy instituted protective and

Table 6
Decadal Rate of Change in Land Use and Land Cover between 1980 and 2020 in Migori River watershed.

LULC Type	1980–1990		1990–2000		2000–2010		2010–2020		1980–2020		
	Area (km^2)	% Change	Area (km^2)	% Change	Area (km^2)	% Change	Area (km^2)	% Change	Area (km^2)	% change	Annual Rate of Change (km^2/year)
Cultivated land	−247.82	−24.43	654.63	85.40	24.11	1.69	−83.50	−5.78	347.42	34.25	8.69
Shrub land	−92.14	−15.86	−285.29	−58.38	30.32	14.91	111.14	47.56	−235.97	−40.63	−5.90
Grassland	140.10	201.03	−155.21	−73.98	26.29	48.17	−70.32	−86.95	−59.14	−84.86	−1.48
Forests	116.04	63.71	−175.21	−58.76	−20.91	−17.00	−18.28	−17.91	−98.36	−52.90	−2.46
Bare land	116.27	252.00	−52.06	−32.07	−47.00	−42.63	43.74	69.15	60.95	132.38	1.52
Built-up area	1.01	18.40	3.33	51.23	−1.56	−15.87	22.54	272.55	25.32	461.20	0.63
Water	−26.86	−56.11	1.14	5.43	−4.92	−22.21	−8.63	−50.09	−39.27	−82.03	−0.98
Wetland	−6.65	−69.27	5.98	202.71	−3.59	−40.20	0.57	10.67	−3.69	−38.44	−0.09



	Cultivated land	Shrub land	Grassland	Forests	Bare land	Built-up area	Water	Wetland
1980 - 1990	-24.43	-15.86	201.03	63.71	252.00	18.40	-56.11	-69.27
1990 - 2000	85.40	-58.38	-73.98	-58.76	-32.07	51.23	5.43	202.71
2000 - 2010	1.69	14.91	48.17	-17.00	-42.63	-15.87	-22.21	-40.20
2010 - 2020	-5.78	47.56	-86.95	-17.91	69.15	272.55	-50.09	10.67
1980 - 2020	34.25	-40.63	-84.86	-52.90	132.38	461.20	-82.03	-38.44

Fig. 4. LULC decadal net changes in the Migori River watershed for the period of 1980 – 2020.

preservation measures for natural forests and grasslands, with farmlands inside forested areas being reclaimed by the government, leading to the encroachment of wetlands and shrub lands due to increased demand for new farmlands and settlement areas (Nasong'o, 2012).

(II) The pattern of LULC changes between 1990 and 2000.

In this decade, the LULC categories of cultivated land, water, and wetlands, which had recorded net losses during the previous decade showed substantial gains in their land coverage whereas those of grasslands, forests, and bare land, which had registered substantial net gains recorded net losses (Table 6). Cultivated land increased by 85.40%, the water rose by 5.43% and wetlands grew twofold (202.20%). Conversely, grasslands were reduced by 73.98%, forests by 58.76%, and bare land by 32.07%.

During the same period, shrub land continued to show a negative trend with a 58.38% net loss while built-up lands continued to experience a positive trend with a net gain of 51.23%. These environmental transformations could generally be attributed to the high rate of population growth observed in Kenya from the late 1980s towards the new millennium, which was estimated to be between 3.20 and 3.60% per annum (UN Department of Economic and Social Affairs, 2019). During the same period, the population growth rate of the entire Lake Victoria basin, under which the watershed is located, was touted to be among the highest in the country at 2.85% per year (Rakama et al., 2017). This massive population growth might have led to the conversion of bare lands to settlement areas or farms; and the destruction of forests and grasslands in the quest for new croplands or settlement areas, raw materials for construction works, and fuel wood for domestic consumption.

(III) The pattern of LULC changes between 2000 and 2010.

Fig. 4 and Table 6 reveal that five of the LULC categories recorded net losses with two recording net gains. Forests, bare land, water, wetland, and built-up registered net losses of 17.00%, 42.63%, 22.21%, 40.20%, and 15.87% respectively; whereas shrub land and grassland grew by 14.91% and 48.17% respectively. Unlike the previous decades, cultivated land remained relatively constant during this decade (2000–2010), only rising by 1.69%. Generally, the transformations suggest that during this period grasslands and shrub lands expanded largely at the expense of other natural landscapes - forests, bare land, water, and wetlands - due to the existence of unsustainable land management practices. The built-up area lost a small portion as cultivated lands saw little change in their coverage; which indicates no acquisition of new lands for settlement or farming. These occurrences could be attributed to the coming to power of a new regime that oversaw policies that not only spurred strong economic development and created employment opportunities in urban areas of the country but also enacted new conservation laws and policies like the Environmental Management and Coordination Act of 1999 and Forest Act of 2005, that may have impacted land management approaches causing an uncoordinated transition from old practices.

(IV) The pattern of LULC changes between 2010 and 2020.

Between 2010 and 2020, grasslands declined by 86.95%, forests by 17.91%, and water by 50.09% unlike other categories that increased - shrub land by 47.56%, bare land by 69.15%, built-up area by 272.55%, and wetlands by 10.67%, with cultivated land remaining fairly constant (Table 6). The substantial expansion of bare lands and shrub lands is a reflection of the effect of unsustainable utilization of grasslands and forests through overgrazing and deforestation respectively. Moreover, the substantial increment of the built-up areas reflects the high rate of conversion of natural landscapes like forests and grasslands into settlement areas for the burgeoning population. Of the four epochs, this period stands out as the one in which the environment of the watershed suffered considerable negative transformation.

Land use and land cover change matrix

Table 7 present the cross-tabulation change matrix illustrating how the coverages of various LULC classes have changed over time from one class to another from 1980 to 2020. Conversions of one LULC to the other occurred across the entire watershed. Results show that during the period between 1980 and 2020, 81.41% of built-up areas (12.61 km^2), 74.34% of cultivated land (756.84 km^2), 56.26% of water (26.93 km^2), 22.59% of bare land (10.40 km^2), 20.33% of shrub lands (118.09 km^2), 15.96% of forests (29.08 km^2), 4.08% of grasslands (2.84 km^2), and 0.60% of wetlands (0.06 km^2) remained unchanged. This demonstrates that while the original areas of built-up lands, cultivated lands, and water remained largely unchanged, the rest of the LULC categories experienced high conversion with over 80% of their total land areas converted to other LULC classes. A large portion of cultivated land was converted to shrub land (15.30%) whereas a large proportion of bare land became cultivated land (58.36%). Also, the majority of shrub lands turned into cultivated land (66.12%) whilst major sections covered by grasslands became either cultivated land (68.59%) or shrub land (18.12%). Forests lost a large part of their coverage to cultivated land (54.95%) as water and wetland lost large chunks to shrub land (18.70%) and cultivated land (66.20%) respectively. Although the original built-up areas remained largely unchanged, 18.16 km^2 and 6.69 km^2 were gained from cultivated land and shrub land respectively.

Table 7
Land Use/Land Cover change matrix of Migori River watershed from 1980 to 2020.

	LULC Class	2020 (Area in km^2)								
		Cultivated land	Shrub land	Grassland	Forests	Bare land	Built-up area	Water	Wetland	Total (1980)
1980 (Area in km^2)	Cultivated land	***756.84***	155.56	1.18	31.76	44.85	18.16	2.52	3.49	**1014.36**
	Shrub land	384.03	***118.09***	5.44	14.92	50.66	6.69	0.55	0.43	**580.81**
	Grassland	47.80	12.63	***2.84***	0.89	3.11	1.47	0.16	0.79	**69.69**
	Forests	100.10	38.39	0.31	***29.08***	12.05	0.96	1.11	0.15	**182.15**
	Bare land	26.87	7.61	0.28	0.34	***10.40***	0.47	0.05	0.02	**46.04**
	Built-up area	12.61	1.78	0.15	0.29	0.94	**2.34**	0.22	0.07	**15.49**
	Water	26.93	8.95	0.01	5.73	0.89	0.62	***3.85***	0.89	**47.87**
	Wetland	6.60	1.83	0.34	0.78	0.12	0.10	0.14	***0.06***	**9.97**
	Total (2020)	**1361.78**	**344.84**	**10.55**	**83.79**	**123.02**	**30.81**	**8.60**	**5.91**	**1955.98**

Note: The bold and italicized entries along the diagonal represent the LULC areal coverages that remained unchanged between 1980 and 2020.

Watershed community perceptions on trends and drivers of LULC changes

Local community perceptions concerning the trends of LULC changes and distances to infrastructure

Survey participants' perceptions of LULC trends in the Migori River watershed are presented in Fig. 5. The study observed significant differences ($p < 0.05$) among the surveyed households in perceptions concerning the trends of LULC changes and proximity to various infrastructures like commercial centers and markets, educational centers, health facilities, and roads. The study participants perceived that farmlands have significantly expanded ($p < 0.05$) in the watershed while forests and vegetation cover have significantly declined ($p < 0.05$) over the years under review; a confirmation of the observed LULC trends interpreted from remotely sensed data in the period of 1980 – 2020. About 60.50% and 75.80% of watershed communities accurately perceived that farmlands and forests had expanded and shrunk respectively (Fig. 5). This is consistent with the fact that 80.00% of the households in the watershed are involved in crop farming and that agriculture is considered the most important source of income for the watershed community (Table 3). Farming of crops like tobacco, cotton, maize, and sugarcane is widely practiced in the watershed and this expands farmlands while reducing forest cover through the clearing of vegetation. Nearly-two-thirds of the households (65.20%) perceived that the distance to natural water sources didn't change from 1980 to 2020. Also, the distances to infrastructures like health facilities and major roads largely remained unchanged over the same period. On the other hand, distances to commercial centers and markets, portable drinking water, and education centers were perceived to have significantly decreased over the same period ($p < 0.05$). These results are consistent with the findings of Munthali et al. (2019) in the Dedza watershed of Malawi and they show that the accelerated urban development observed in the spatial analysis prioritized the expansion of residential areas for commercial, settlement, and academic purposes at the expense of health centers and road networks. This perceived expansion of infrastructure in the study area confirms the observed built-up area trends in the period of 1980–2020 interpreted from remotely sensed data.

In general, the study observed that the watershed communities are sufficiently aware of changes in natural resources and changes related to infrastructure development. Moreover, the usage of older respondents (≥21 years), of which half had lived in the watershed throughout the period under review for LULC changes, yielded an accurate historical account of LULC changes in the watershed, corroborating the observed LULC trends interpreted from remotely sensed data in the period of 1980–2020. This local attention to LULC changes including infrastructure development can provide valuable input for government strategies to execute a suitable spatial plan for the watershed. Combining LULC maps with local perceptions of LULC changes enables enhanced interpre-

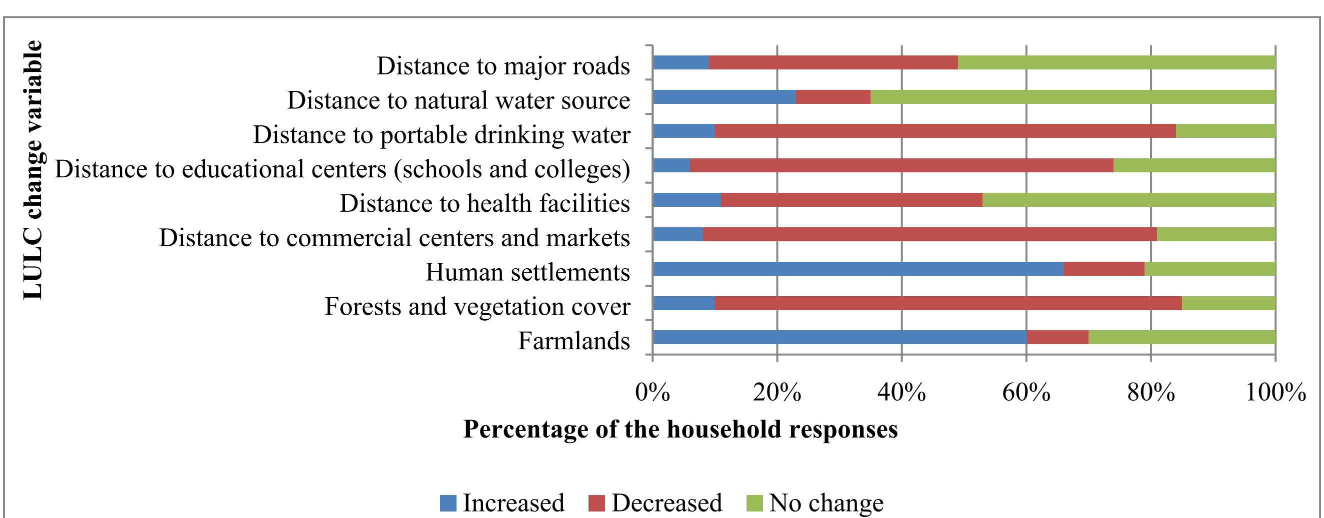


Fig. 5. Survey participants' perceptions of LULC trends in the Migori River watershed.

tation of the land use information, which can help the government to develop a spatial plan that considers socio-economic and ecological circumstances and engages local people in decision-making.

Ranked drivers of land use and land cover changes in the watershed

The survey identified 11 major proximate/direct drivers of LULC change in the watershed (Table 8); these are factors linked to human undertakings that directly transform the land cover (Lambin & Meyfroidt, 2011). Fuel wood collection, timber/poles production, shifting cultivation, agricultural expansion, and charcoal production were the top five ranked proximate causes of LULC changes in the watershed, with fuel wood collection and timber/poles production ranking first and second respectively. Other notable factors included settlements and artisanal mining. The results of this study resonate with other similar studies in the developing world where anthropogenic activities were reported as the contributory factors for LULC changes. For instance, Munthali et al. (2019) study identified firewood collection, charcoal production, settlement construction, and agricultural expansion as the four major proximate drivers of LULC changes in the Dedza watershed in Malawi. A study by Kleemann et al. (2017) identified agricultural intensification and extensification, livestock production, fuel wood utilization, mining, and bushfire as the top proximate drivers of LULC trends in the Upper Eastern Region of Ghana. In Indonesia, Juniyanti et al. (2021) show that direct causes of LULC in most watersheds in the country include the expansion of agricultural areas, wood extraction for fuel, and timber production. However, the study found that shifting cultivation is not a dominant direct cause. Guarderas et al. (2022) study in Ecuador shows that the major pressure on watershed ecosystems in northern Ecuador is the continued expansion upwards of the agricultural-livestock frontier and deforestation; however, contrary to our findings, it also ranked unplanned urbanization expansion and natural reforestation as one of the most important LULC drivers.

Concerning the underlying/indirect drivers, that is the forces that indirectly trigger the proximate causes (Geist & Lambin, 2002), the survey participants perceived population growth and poverty as the two main drivers of LULC change in the watershed, followed by limited access to alternative sources of energy, demand for timber, and lack of law enforcement (Table 9). This essentially means that the top five proximate causes of LULC changes in the watershed i.e., fuel wood collection, timber/poles production, shifting cultivation, agricultural expansion, and charcoal production, are triggered by population pressure and high poverty levels. This is consistent with similar studies conducted in the developing world. For instance, in Sub-Saharan Africa, population growth and high poverty levels have been reported to be the main contributory factors for LULC changes in natural ecosystems in the Zambezi region of Namibia (Kamwi et al., 2015), Dedza watershed in Malawi (Munthali et al., 2019), rangelands in the Afar region of Ethiopia (Mekuyie et al., 2018), Pugu and Kazimzumbwi Forest Reserves in Tanzania (Mdemu et al., 2012). The same trend has also been observed in the destruction of natural ecosystems in the highlands of Northern Ecuador (Guarderas et al., 2022), and the deforestation of deciduous and mangrove forests in Bangladesh (Reza & Hasan, 2019). Contrary to our study and the mentioned studies, a study by Juniyanti et al. (2021) found that the institutional/political driver is by far the leading underlying cause of LULC in various ecosystems in Indonesia as opposed to population growth or high poverty levels.

In the survey, approximately 95% agreed that the population of the area has increased over the period under review, which corroborated with population data that indicate that the population of the Migori County where the watershed is situated has grown by 180% between 1980 and 2019 (KNBS, 2019). Earlier studies in the larger Lake Victoria basin, the region which encompasses the Migori River watershed, had also identified population pressure as one of the drivers of landscape alterations (Odada et al., 2009; Onyango et al., 2021). Indirectly, population growth in the watershed leads to LULC changes by causing increased local demand for food which drives agriculture expansion; increased timber and energy (fuel wood and charcoal) consumption which drives deforestation, and increased demand for settlement and associated amenities which drives deforestation to create space for housing units and infrastructure development in terms of residential, commercial, health, transport and educational facilities (Kamwi et al., 2015; Reza & Hasan, 2019; Munthali et al., 2019).

Poverty is pervasive in the Kenyan Lake Victoria Basin in which the Migori River watershed occurs, as most households live below the poverty line (Onyango & Opiyo, 2021). Evidence of the widespread poverty in the watershed was observed in the survey results which revealed that the average household daily income in the watershed is <2 USD (Table 3). This low level of income obtained majorly from agricultural activities is what the watershed household heads rely on to sustain and support an average family of 6 persons (Table 3), a household size that is beyond the 4-members national average (KNBS, 2019). Poverty in the watershed is exacerbated by the landlessness of some households who are unable to engage in the most important source of income in the study area, agriculture (Table 3). Also noteworthy is that the low level of participation in non-farm and off-farm activities (Table 3) also contributes to the high poverty levels in the watershed as it exposes them to livelihood vulnerabilities associated with overreliance on climate-sensitive rainfed agriculture.

Due to the high poverty levels, about 93% of the watershed households use three-stone open fire for cooking (Table 3) resulting in increased utilization of fuel wood which not only causes indoor air pollution but also accelerates deforestation. An Association between poverty and the usage of three-stone open fire has been established in the western Kenya region by Njenga et al.

Table 8
Perceived proximate drivers of LULC changes in the Migori River watershed.

LULC Proximate Driver	Distribution of Respondents per Rank					Weight	Index	Rank
	1	2	3	4	5			
Firewood collection	139	114	38	11	16	1303	0.82	1
Timber or poles production	118	86	94	13	7	1249	0.79	2
Shifting cultivation	57	49	128	64	20	1013	0.64	3
Agriculture expansion	45	53	78	89	53	902	0.57	4
Charcoal production	21	35	95	132	35	829	0.52	5
Rural infrastructure expansion	14	34	48	201	21	773	0.49	6
Settlements	9	17	113	43	136	674	0.42	7
Brick production	2	10	56	167	83	635	0.40	8
Artisanal gold mining	0	2	35	205	76	599	0.38	9
Unplanned urban expansion	3	13	16	62	224	463	0.29	10
Bush fires	0	0	0	60	258	378	0.24	11

Table 9
Perceived underlying drivers of LULC changes in the Migori River watershed.

LULC Underlying Driver	Distribution of Respondents Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Population growth	272	25	5	12	4	1503	0.95	1
Poverty	162	106	31	18	1	1364	0.86	2
Poor access to alternative-energy supply	38	47	192	24	17	1019	0.64	3
Demand for timber	35	48	79	105	51	865	0.54	4
Lack of law enforcement	34	15	95	136	38	825	0.52	5
High cost of agriculture inputs	23	29	48	186	32	779	0.49	6
Weak government policies	10	13	111	37	147	656	0.41	7
Natural topographic conditions	5	0	28	199	86	593	0.37	8
Urbanization	1	5	19	177	116	552	0.35	9
Political interferences	0	1	1	24	292	347	0.22	10

(2017). Also, poverty has made watershed communities to be involved in charcoal burning as a source of income; they seem to burn the charcoal and sell it in urban areas rather than use it in their households. The over-dependence of rural communities on fuel wood and urban dwellers on charcoal has been widely documented in Kenya by previous studies (Kituyi, 2004; Njenga et al., 2017). Timber/pole production was identified as one of the drivers because it is used by the rural communities for constructing settlements for the ever-burgeoning population. The high utilization of fuel wood, charcoal, and timber/poles for construction in this region explains the decline in forest cover between 1980 and 2020. Overall, the findings imply that the watershed community derives its income from shifting cultivation and the extraction and sale of forest products like poles, lumber, firewood, and charcoal and that they are also driven to clear forested areas for additional farmlands or settlement areas to accommodate the growing population.

Although weak government policies regarding natural resources conservation didn't come out strongly among the top underlying drivers of LULC changes in the watershed identified by the survey, weak law enforcement did; which implies that appropriate government policies are in place but their enforcement is weak and ineffective and therefore may not curtail unsustainable land management practices. The various protected areas such as forest blocks, wetlands, cultural sites, and water sources in the watershed are governed by various government policies developed over the years such as the Environmental Management and Conservation Act 1999 (which mandates environmental management with the goal of attaining sustainable land-based natural resources like forests, wetlands, and water catchment landscapes), Forest Conservation and Management Act 2016 (which provides for the establishment, protection, conservation, and sustainable utilization and management of forests and forest resources for maintenance and conservation of water catchment areas), Water Act 2016 (which tackles the.

utilization of water resources to meet human and animal needs, the sustainable management protection of watershed ecosystems), and Land Act 2012 (which emphasizes sustainable conservation, management, and protection of land resources including critical biodiversity, forests, and fragile ecosystems), and Wildlife Conservation and Management Act 2013 (provides for the sustainable protection, conservation, and management of water catchment areas including forests and wetlands existing within the game parks, reserves and protected areas). These government policies generally prohibit logging for timber or deforestation for fuel wood collection, settlement, or agricultural expansion within these protected areas, the government has been lax in providing the enforcement required to curtail such practices from continuing in the watershed, which may be due to the recognition of the high poverty levels experienced by the rapidly growing population. Therefore law enforcement continues to be an important trigger for these anthropogenic-induced causes of LULC changes.

Household-level logistic regression of perceived drivers of land use and land cover changes

Logistic regression analysis was carried out to determine the drivers of LULC changes at the household level in the Migori River watershed (Table 10). According to Munthali et al. (2019), the logistic regression analysis of LULC drivers at the household level approximates the probability of the effects of the respondents' socio-economic attributes (independent variables) on the respondent's perceptions of the driving forces of LULC change (dependent variables). Regression analysis (Table 10) showed that education attainment level significantly and negatively impacted (at $p < 0.05$) the perceptions of watershed households on timber/poles production, agricultural expansion, and poverty as drivers of LULC change. This finding is consistent with the conclusions reached by Munthali et al. (2019) and Anwar et al. (2022) studies which both generally showed that, among main socio-economic determinants, the education level of rural communities has a significant influence on their perceptions of LULC change and its drivers. This implies that education can be used to bring behavior change among rural communities in terms of their interaction and utilization of natural resources (Onyango & Opiyo, 2021). The results also revealed that the landholding size, educational level, and duration of residency in the watershed significantly influenced the perceptions of the watershed community concerning fuel wood collection, timber/poles production, population growth, and poverty (Table 10). Shifting cultivation was not significantly influenced by any of the determinants. The age of household heads significantly influenced their perceptions of fuel wood collection, population growth, and poverty.

Conclusions and recommendations

The study established that the major land use in the watershed during the period under review is cultivated land with an average of 61.44% overall coverage of the total land area during the entire period hence the livelihoods of the watershed inhabitants have been historically agriculture-dependent. The decline in shrub lands by 40.63%, grasslands by 84.86%, forests by 52.90%, water by 82.03%, and wetlands by 38.44%; coupled with increased cultivated land by 34.25%, bare land by 132.28%, and built-up areas by 461.20% over the period under review indicate that the natural landscapes in the watershed are undergoing destruction at the expense of human settlement and infrastructural developments. Fuel wood collection, timber/pole production, shifting cultivation, agricultural expansion, charcoal production, population pressure, and high poverty level are the topmost drivers perceived by the watershed communities to be contributing to the land use and land cover changes in the watershed. Since all these identified drivers are still active in the watershed, the natural landscapes are likely to decline further, with negative implications on watershed ecosystem services, biodiversity, and community livelihoods. Gen-

Table 10
Socio-economic determinants influencing perceived drivers of LULC change.

Perceived drivers	Determinants	Coefficient	Std. Error	Wald	p-value
Fuel wood collection	Age	0.015	0.023	4.553	0.033*
	Household size	0.089	0.103	0.749	0.387
	Land holding size	−0.531	0.231	5.297	0.021*
	Gender (1 = Male)	−0.122	0.526	0.054	0.817
	Education (1 = No formal education)	0.982	0.673	2.131	0.044*
	Education (2 = Primary education)	0.241	0.532	0.205	0.651
	Duration of residency (1 = 11–20 years)	2.3	0.621	13.733	0.033*
	Duration of residency (2 = above years)	1.497	0.617	5.894	0.015*
Timber/poles production	Age	0.053	0.024	4.785	0.474
	Household size	0.078	0.108	0.514	0.029*
	Land holding size	−0.07	0.216	0.106	0.744
	Gender (1 = Male)	−0.474	0.586	0.653	0.419
	Education (1 = No formal education)	−1.263	0.704	3.212	0.013*
	Education (2 = Primary education)	−0.134	0.613	0.048	0.027*
	Duration of residency (1 = 11–20 years)	1.415	0.817	3.003	0.036*
	Duration of residency (2 = above years)	1.234	0.73	2.861	0.091
Shifting cultivation	Age	0.073	0.031	5.614	0.088
	Household size	−0.011	0.147	0.005	0.943
	Land holding size	0.023	0.302	0.006	0.939
	Gender (1 = Male)	−1.321	0.782	2.854	0.091
	Education (1 = No formal education)	1.16	0.836	1.923	0.165
	Education (2 = Primary education)	0.253	0.715	0.125	0.224
	Duration of residency (1 = 11–20 years)	3.245	1.219	7.089	0.082
	Duration of residency (2 = above years)	0.946	1.517	0.388	0.533
Agricultural Expansion	Age	0.084	0.046	3.37	0.066
	Household size	0.362	0.154	5.497	0.019*
	Land holding size	−0.781	0.619	1.592	0.984
	Gender (1 = Male)	−0.433	0.997	0.189	0.664
	Education (1 = No formal education)	−0.826	1.373	0.362	0.547
	Education (2 = Primary education)	−0.773	1.064	0.528	0.002*
	Duration of residency (1 = 11–20 years)	−0.174	0.585	0.088	0.766
	Duration of residency (2 = above years)	−0.304	0.492	0.381	0.537
Population growth	Age	0.073	0.025	8.658	0.003*
	Household size	0.033	0.111	0.085	0.77
	Land holding size	−0.004	0.225	0	0.027*
	Gender (1 = Male)	−1.022	0.602	2.877	0.09
	Education (1 = No formal education)	0.738	0.708	1.088	0.297
	Education (2 = Primary education)	−0.121	0.566	0.045	0.31*
	Duration of residency (1 = 11–20 years)	3.201	0.739	18.765	0.001*
	Duration of residency (2 = above years)	1.497	0.785	3.637	0.057
Poverty	Age	−0.052	0.017	8.917	0.003*
	Household size	−0.124	0.078	2.519	0.113
	Land holding size	−0.337	0.181	3.446	0.043*
	Gender (1 = Male)	0.02	0.42	0.002	0.962
	Education (1 = No formal education)	−0.045	0.512	0.008	0.929
	Education (2 = Primary education)	−0.341	0.491	0.483	0.011*
	Duration of residency (1 = 11–20 years)	−3.628	1.058	11.754	0.041*
	Duration of residency (2 = above years)	−1.994	1.151	3.004	0.083

Note: * represents statistical significance at $p \leq 0.05$.

erally, the study observed that the watershed communities are sufficiently aware of changes in natural resources and changes related to infrastructure development. This local attention to land use and land cover changes including infrastructure development can provide valuable input for government strategies to execute a suitable spatial plan for the watershed. Integration of spatial LULC analysis with local perceptions of LULC changes enables enhanced interpretation of the land use information, which can help the government to develop a spatial plan that considers socio-economic and ecological circumstances and engages local people in decision-making.

The paper recommends land use zoning on the watershed area to demarcate land areas into settlement areas, conservation, and protected areas, and agricultural lands as well as regulate physical development and use of fragile conservation areas like forests, wetlands, and water sources. Efforts should be directed towards the adoption of alternative cooking energy types by watershed households to reduce the overall demand for fuel wood and consequently ease pressure on forests. The government should also harmonize the existing conservation policies to align them with the interests and priorities of the local watershed communities to balance competing goals for effective management and conservation of the watershed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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