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Land use/land cover dynamics in an arid and semi-arid landscape: A 24-year analysis of Baringo County, Kenya (2000–2024)

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ABSTRACT

Assessing land use and land cover (LULC) changes in arid and semi-arid lands (ASALs) is essential for promoting environmental conservation, improving ecosystem functionality, and formulating sustainable land use plans. This study examined LULC changes in Baringo County, Kenya, over a 24-year period (2000–2024). Landsat imagery from 2000, 2014, and 2024 were processed and analyzed using the random forest (RF) algorithm on the Google Earth Engine (GEE) platform. Data processing and analysis were done using ArcGIS Pro (version 3.4.0), and R software (version 4.3.2). The analysis revealed significant LULC changes, including expansions in cropland (+1196.24 km²), shrubland (+418.44 km²), built-up areas (+96.21 km²), and water features (+81.62 km²), alongside reductions in forestland (-1057.08 km²), grassland (-406.54 km²), and bareland (-328.90 km²). The observed LULC dynamics were driven by deforestation, agricultural expansion, alien species invasion, population growth, and weak policy enforcement. These LULC changes have had profound environmental, social, and economic impacts. Forest loss has diminished ecosystem services, accelerated soil erosion, and undermined climate change mitigation efforts. The proliferation of *Prosopis juliflora* has provided some benefits, such as soil stabilization and fuelwood, but has adversely affected biodiversity, livelihoods, and traditional agro-pastoral systems. While cropland expansion has enhanced food security, it has also exacerbated soil erosion, sedimentation, and hydrological alterations in local lakes. Furthermore, the increase in water features has led to flooding, displacing communities, damaging infrastructure, and disrupting tourism and local economies. The findings of this study highlight the urgent need for sustainable land management strategies to mitigate the negative impacts of LULC changes on ecosystems and livelihoods while maximizing the positive outcomes of these dynamics in Baringo County.

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1. Introduction

The world has witnessed a multitude of changes in land use and land cover (LULC), both of anthropogenic and natural origin (Kindu et al., 2013; Winkler et al., 2021). Approximately one-third of the earth's terrestrial surface has undergone alterations in LULC over the past six decades. In the Global North, the predominant trends have been afforestation and the abandonment of cropland, whereas in the Global South, widespread deforestation and agricultural expansion have been the most significant occurrences (Winkler et al., 2021). Such changes have a direct or indirect impact on local, regional, and global ecological processes. For instance, they disrupt the interaction of land and atmospheric fluxes of carbon, water, and energy (Das et al., 2022; Oki et al., 2013; Otieno et al., 2025; Umair et al., 2019). The disruption of these processes affects the prevailing weather and climatic conditions, thereby inducing deleterious environmental effects (Niyogi et al., 2009; Rotich et al., 2025). In response, the disruptive effects can result in the loss of vegetation cover, the extinction of plant species, changes in biodiversity, an increase in desertification, and land barrenness (Gallego-Zamorano et al., 2022; Hansen et al., 2004). Additionally, alterations in climatic conditions influence human activities and can trigger shifts in environmental utilisation for economic gains (Lameck et al., 2025a). The environmental consequences include a reduction in the value of ecological environments due to the degradation of soils, climate change effects, and loss of habitats. Furthermore, LULC changes affect rural livelihoods that depend on the natural environment for socioeconomic well-being (Baffour-Ata et al., 2021; Demissie et al., 2017; Kindu et al., 2015; Kullo et al., 2021; Lameck et al., 2025a).

Developing sustainable solutions and ensuring sustainable human and environmental interactions is vital (Di Baldassarre et al., 2019; Joshi et al., 2023; Kindu et al., 2018). Part of the process is to ensure that humankind derives sustainable benefits from the environment and contributes positively to enhancing the existing ecosystems (Hounkpati et al., 2024; Masterson et al., 2019). The establishment of stable environments results in the creation of productive landscapes and has beneficial impacts on ecosystem functions, including nutrient cycling, hydrological balance, flood regulation, and erosion control (Bennett et al., 2021; Kindu et al., 2016). However, the intensified exploitation of resources has lowered the environmental and economic benefits derived across diverse agroecological habitats globally (Lameck et al., 2025b; Lampert, 2019). The effects are rampant in ecologically vulnerable arid and semiarid lands (ASALs) (Han et al., 2022; Villani et al., 2021). Like high-potential regions, ASAL areas have gained increased focus on implementing nature-based solutions, environmental conservation and restoration, and climate change mitigation efforts (Chausson et al., 2020; Jenkins et al., 2021). Globally, these areas support over 2 billion people and cover almost half of the world's terrestrial environments (Prăvălie, 2016; UNEP, 2007). Restoration efforts targeting these areas are central to targets aimed at mitigating climate change and its effects. These areas are highly vulnerable and have continued to experience increased exploitation compared to other high-potential regions, rendering them more fragile (Magalhães, 1994). Nevertheless, ASAL areas present significant opportunities for livelihood improvement and ecosystem conservation.

Baringo County is among Kenya's ASAL counties, which supports a diverse range of pastoral and agro-pastoral livelihoods. Additionally, the county plays a significant role in Kenya's economy through its contribution to the tourism sector, which is supported by the presence of numerous tourist attractions (Baringo County Government, 2013). Like other regions, the county has experienced varied dynamics of LULC changes. Despite the changing dynamics in land uses in the county, their magnitude and implications have been scarcely evaluated. Additionally, the existing studies focused on parts of the county with no analysis considering the LULC dynamics in the entire Baringo County. Against this background, the present study sought to investigate the dynamics of LULC changes and their implications in Baringo County, Kenya. Specifically, the study aimed to (1) quantify the LULC changes in Baringo County from 2000 to 2024 and (2) Investigate the environmental and socio-economic implications of LULC changes in Baringo County. This study provides evidence-based insights that can guide land use policies and adaptive management strategies to mitigate environmental degradation while enhancing socio-economic resilience in the study area. Its findings can directly inform the County Integrated Development Plans (CIDPs), National Land Use Policy, Vision 2030 implementation strategies, and Kenya's commitments to the Sustainable Development Goals (SDGs) and the UN Decade on Ecosystem Restoration.

2. Materials and methods

2.1. Study area

The study was conducted in Baringo County, geographically located along the Great Rift Valley of Kenya, between longitudes 35°30′ and 36°30′ E and latitudes 0°10′ and 1°40′ S (Fig. 1). The county covers an area of approximately 10,951.61 km^2 with an estimated population of approximately 666,763 people as of 2019 (Baringo County Government, 2018; KNBS, 2019). The mean annual rainfall of Baringo County ranges from 300–700 mm in the lowlands and 1000–1500 mm in the highlands, with a characteristic bimodal rainfall distribution pattern. Long rains occur in March-July, while short rains occur during September-November, with peaks occurring in April and November (Juma et al., 2016). The climate of Baringo varies from humid highlands to arid lowlands, with temperatures ranging between 10 °C and 35 °C (Baringo County Government, 2018). The altitudinal variation of the county is from 715 m above the mean sea level in the lowland Njemps flats to 3014 m above the mean sea level at the Lake Baringo catchment. The land uses in Baringo County are significantly shaped by the topographical and climatic conditions. Agriculture is practised mainly in the highland regions, especially along the Tugen hills, transcending from the southern to the northern parts of the county. Pastoralism, apiculture, dryland farming, fishing, and tourism are concentrated in the lowland plains located in the eastern and western parts of the county (Baringo County Government, 2014). The dominant soil types in the study area include Lithic Leptosols, Calcaric Regosols, and Chromic Luvisols (Juma et al., 2016). The county is rich in flora and fauna, having a woody mixture of indigenous and exotic vegetation species, while a variety of wild animals and more than 450 bird species are also found in the county (Baringo County Government, 2018). Approximately 165 km^2 of the county comprises surface water from Lakes Baringo, Bogoria, and Kamnarok, which form important tourist attraction sites and sources of livelihood for the local communities bordering these sites. The beautiful sceneries in the Tugen Hills, Eldama Ravine, Simot waterfalls, and Laikipia escarpment attract regular visitors (Baringo County Government, 2018).

2.2. Data and data sources

The present study employed both ancillary and satellite data. The ancillary data included topographic maps, county land use plans, and ground survey points, which were used to aid the classification and verification process. The study area's topographical maps were acquired from the Survey of Kenya (SOK) office. The maps were georeferenced, and various land use classes were digitised and saved in vector format. The data obtained from the topographical maps were used to derive the actual reference data for analysing the LULC of 2000. The data from the county land use plans were supplemented with Google Earth images and discussions with land use planners and surveyors to create the reference data for the 2014 and 2024 LULC classifications. The locals also provided historical LULC information on the different parts of the study area based on their understanding. The responses on LULC types from the residents were considered for those who had lived in their current place of residence for more than 20 years (Asante-Yeboah et al., 2022).

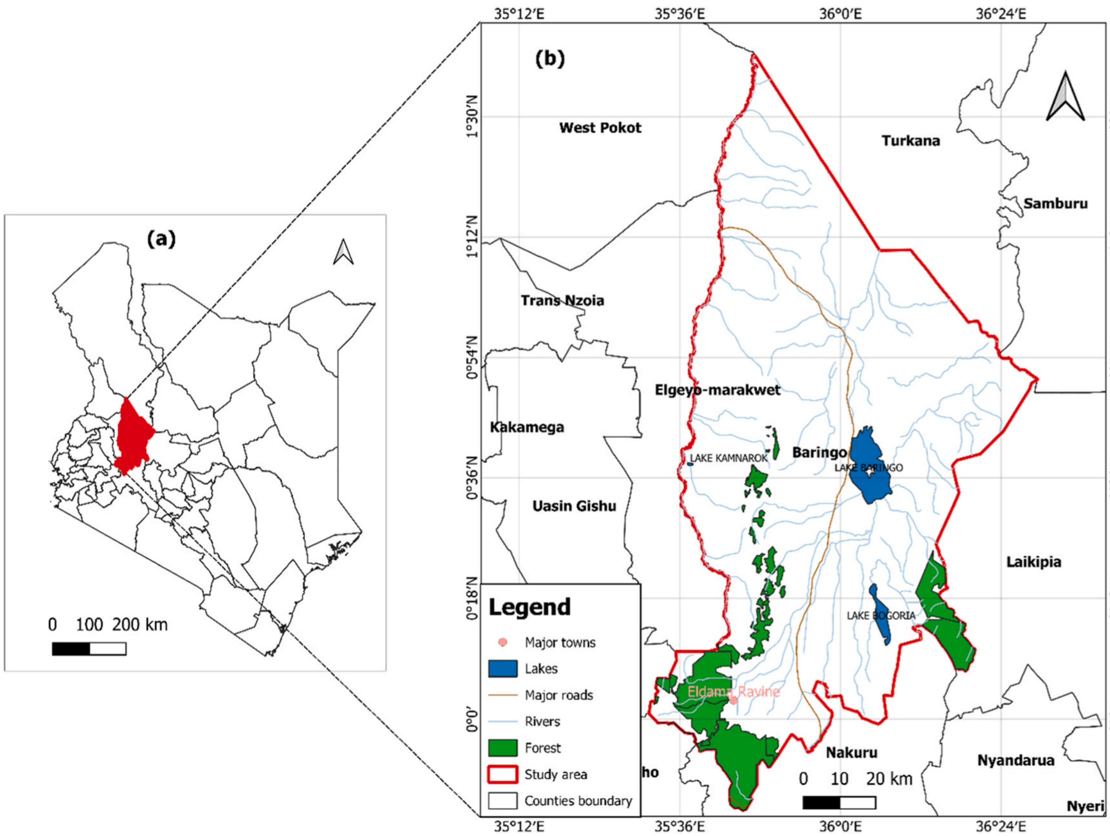

Fig. 1. Map of the study area (a) location of Baringo County in Kenya, (b) map of Baringo County.

The acquisition of information was made in conjunction with high-resolution Google Earth imagery to guide the navigation and understanding of the local environment. The three data sources were combined to generate 1084 samples for major LULC types in the context of the study area. Seven classes of LULC, including shrubland, grassland, forestland, cropland, bareland, water features, and built-up areas, were successfully classified as described in Table 1.

The satellite data comprised multispectral data obtained from Landsat 7 (Enhanced Thematic Mapper Plus, ETM+) and Landsat 8 (Operational Land Imager/Thermal Infrared Sensor, OLI/TIRS). The surface reflectance products of these sensors, which were readily corrected for radiometric and atmospheric artefacts, were accessed from the Google Earth Engine (GEE) platform. The platform archives temporal satellite data series from various sensors and missions in a cloud computing platform, which can be filtered and accessed via an internet-based application programming interface (API) and a web-based interactive development environment (Amani et al., 2020). The platform also enables automated processing and analysis of satellite image data and exports the final LULC product to Google Drive for subsequent download and processing. The implementation of automated tasks has been demonstrated to significantly enhance the processing of satellite images while simultaneously optimizing the utilization of storage space (Gorelick et al., 2017). Another advantage of the platform is that it permits free access, processing, and downloading of satellite data products by registered users. The satellite images were acquired in 2000 to cover the early years, in 2014 to cover the middle of the study period, and in 2024 to cover the current period.

Table 1
Description of the various LULC classes in the study area.

Class ID	LULC class	Description
1	Forestland	Land > 0.5 ha with trees > 2 m (m) and a canopy cover > 15 %, or trees able to reach these thresholds in situ
2	Shrubland	Land dominated by shrubs, mainly *Prosopis juliflora.*
3	Grassland	Land with temporary or permanent grass cover
4	Cropland	Tilled land and/or land under cultivation of crops
5	Water features	Open waters, including lakes, rivers, streams, and dams
6	Built-up area	Settlements, paved roads, and industrial facilities
7	Bareland	Land without vegetation, land covered by rocks, or degraded lands

2.3. Images and classification of the satellite images

The Landsat images used in the present study were already in the surface reflectance format. However, in the acquisition and filtering process, the cloud cover threshold for the three satellite images was set to a value below 10 %. Additionally, the images were acquired between March and August of each representative season. This window enabled the maximum spectral separation between different class features, as the features depict distinctive phenological properties. The period also coincides with low cloud cover, thus allowing for relatively high-quality images to be acquired. The LULC classification on GEE was conducted using the random forest (RF) algorithm developed by Breiman (2001). Machine learning algorithms are frequently used to solve classification and regression problems. This study utilised supervised learning to robustly analyse complex functional spatial characteristics from the sample training data. Additionally, the classifier is robust in handling outliers and noisier datasets and overcomes the overfitting problem common in other machine learning approaches. The classifier creates independent and unrelated decision trees based on a random split of the training data (Pal, 2005). Each decision tree then evaluates the likely class to which the pixel belongs. In the present study, the training and validation data were split into ratios of 70 % and 30 %, respectively. The parameters required for the RF algorithm include the number of decision trees to be created (ntrees) and the number of predictors taken into consideration at each fork of the tree (mtry). The ntree parameter was set to 500, as any value above this threshold did not improve the overall classification accuracy (Duro et al., 2012). The mtry parameter was set to the square root of the number of overall variables. The RF classification was implemented using ee.Classifier.smile.RandomForest is an in-built function within the GEE platform. The input bands for the classification process included the blue, green, red, near-infrared, and shortwave-infrared bands.

2.4. Accuracy assessment and change detection

The assessment of accuracy is a fundamental component of the evaluation of the classification process, both in terms of its precision and reliability. The ground reference data digitised from topographical maps and land use information provided by land planning experts facilitated the accuracy assessment process. In each year of study, random samples constituting 30 % of reference data were used for the accuracy assessment using the confusion matrix. Assessment metrics such as user accuracy, producer accuracy, overall accuracy, and kappa coefficient were used to assess the accuracy of the classification. The producer accuracy (Eq. (1)) depicts how often actual features in the study area are correctly shown on the classification map, while the user accuracy (Eq. (2)) represents how often the class in the classification map will be present on the ground. The overall accuracy (Eq. (3)) gives the proportion of the correctly mapped class types; that is, it shows the extent to which the classified map reflects the actual ground features. An overall accuracy of 1 indicates that the classification perfectly corresponds with actual ground features. The kappa coefficient (Eq. (4)) demonstrates the performance of the actual classification using the reference data compared to an agreement expected by chance or by randomly assigning values. A value close to 1 indicates that the classification is better than a random assignment of classes (Congalton, 1991).

$$\text{Producer accuracy} = \frac{X_{ig}}{\mathrm{R}} * 100 \tag{1}$$

$$\text{User accuracy} = \frac{X_{ic}}{\mathrm{P}} * 100 \tag{2}$$

$$\text{Overall accuracy} = \frac{X_{ii}}{N} * 100 \tag{3}$$

$$\text{Kappa coefficient} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} (X_{ic} * X_{ig})}{C^2 - \sum_{i=1}^{r} (X_{ic} * X_{ig})} \tag{4}$$

where N refers to the total number of samples, C is the total number of correctly classified pixels, P is the total number of points in each class that agree with the classified map, and R is the total number of reference points in the reference class category. X_{ic} indicates the number of correctly classified points in each class by the user. X_{ii} is the total number of times samples are classified correctly, and X_{ic} is the total number of times samples are expected to be classified correctly.

2.5. LULC patterns, trends, and magnitudes

The classified LULC maps were subjected to further analysis and post-classification processes, including change detection, to identify the LULC compositions, trends, changes, and magnitude and intensities of LULC transitions. The process involved the overlay of independently classified maps and the detection of changes between different LULC classes in the three periods. The post-classification analysis was implemented in ArcGIS Pro (version 3.4.0) and R statistical software (version 4.3.2). Maps, graphs, and Sankey plots were used to visualise the patterns, trends, and intensities of LULC. The R packages *raster*, *networkD3*, and *dplyr* were used to create the 3D Sankey plots in R statistical software (Allaire et al., 2017; R Core Team, 2020; Wickham et al., 2015).

2.6. Implications of LULC changes

Available literature was reviewed to ascertain the implications of LULC changes in Baringo County. The literature comprised peer-reviewed research articles, review articles, and book chapters sourced from Scopus and Web of Science databases and the Google Scholar search engine. We further reviewed national and county government reports, policy documents, and strategic development plans relevant to our study to substantiate our findings. Fig. 2 provides a graphical depiction of the study methodology workflow summary.

3. Results

3.1. LULC classes and accuracy assessment

The classification accuracies for different reference years revealed that, in general, the various class types in the study area were mapped accurately (Table 2). The producer accuracies were above 78 %. Similarly, the user accuracy for the different LULC classes in the study area was relatively high, except for that of the grassland and built-up areas classes that depicted low user accuracies below 70 %. The overall accuracies and the kappa statistics were also above 83 % (Table 2).

3.2. LULC statistics, distribution, and changes

3.2.1. LULC statistics and distribution

The area statistics and percentages of the major LULC types were generated and are summarised in Table 3. The spatial distribution of the major LULC classes that define the study area was also mapped, as shown in Fig. 3. Grassland and shrubland were the two dominant LULC classes in the study area, while built-up areas exhibited the lowest area coverage in all three study years (Table 3). The grasslands were primarily located in the central and the northern part of the study area, while the shrublands were dominant in the western belt and northwestern region of Baringo County (Fig. 3). The forestland was mainly situated in the southwestern part of the study area, while water features were found in the central (Lake Baringo) and southeastern (Lake Bogoria) part of the study area. The southern and eastern parts of the study area were dominated by croplands (Fig. 3).

3.2.2. LULC changes

Between the study years, the areas of the respective LULC classes experienced both positive and negative dynamics. From 2000–2014, cropland (+709.34 km^2), shrubland (+266.24 km^2), water features (+63.08 km^2) and built-up areas (+39.60 km^2) increased in area coverage while grassland (-545.45 km^2), forestland (-474 km^2) and bareland (-58.81 km^2) decreased. The study area continued to experience LULC changes between 2014 and 2024, with increased area under croplands (+486.90 km^2), shrubland (+152.20 km^2), grassland (+138.91 km^2), built-up areas (+56.61 km^2) and water features (+18.54 km^2). Within the same period, forestland and bareland area declined by −583.08 km^2, and −270.09 km^{2,} respectively. Overall (2000–2024), there was an expansion in cropland (+1196.24 km^2), shrubland (+418.44 km^2), built-up (+96.21 km^2) and water features (+81.62 km^2) areas and a decline in forestland (-1057.08 km^2), grassland (-406.54 km^2) and bareland (-328.90 km^2) areas in Baringo County (Table 4).

3.3. LULC transitions

The assessment of LULC changes revealed that the study area experienced various LULC transitions in the study period. Tables 5 and 6 summarise the multiple LULC transitions and their magnitudes between the study years. The results show that between 2000 and 2014, much of

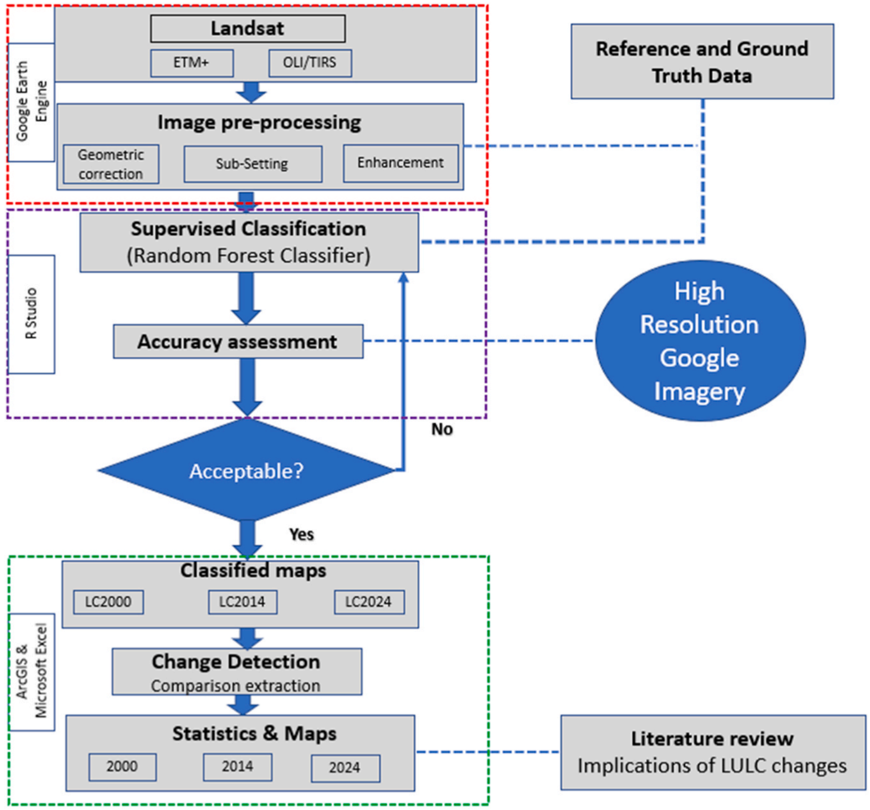

Fig. 2. Summary of the study methodology workflow.

Table 2
Summary of the classification accuracies for the 2000, 2014 and 2024 LULC maps. Where PA = producer's accuracy, UA = user's accuracy.

LULC class	2000		2014		2024	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Bareland	85	99	82	96	91	99
Cropland	87	71	68	83	89	88
Forestland	97	96	95	100	100	100
Grassland	85	63	95	66	83	68
Shrubland	78	74	94	81	87	93
Built up areas	88	91	100	74	100	52
Water features	100	93	100	100	100	100
Overall Accuracy	90		88		89	
Kappa statistic	86		83		86	

the grassland was converted to shrubland (1234.64 km^2) and cropland (478.47 km^2). Forestland similarly experienced transitions into other classes like shrubland (532.84 km^2) and grassland (235.02 km^2), reflecting forest degradation and deforestation. Water features (133.68 km^2) and built-up areas (0.55 km^2) exhibited relatively small changes, indicating higher stability over the study years (Table 5).

From 2014–2024, a notable 1100.85 km^2 transitioned from shrubland to grassland. Forestland also significantly transitioned to shrubland (568.77 km^2) and grassland (105.87 km^2). Cropland gained 145.15 km^2 from bareland but lost 579.06 km^2 to grassland. Built-up areas increased slightly to 97.51 km^2, reflecting gradual urban expansion (Table 6).

A Sankey plot (Fig. 4) was plotted in R software to depict the overall LULC transitions (2000–2024) in the study area. The bands represent the actual proportion of land that changed class over time.

4. Discussion

4.1. LULC categories and accuracy assessment

In the present study, remote sensing data, GIS analysis, and empirical literature were integrated to assess the LULC changes and their implications in Baringo County over 24 years. The remote sensing analysis was able to accurately characterise the LULC classes in the study based on the accuracy indicators. The LULC mapping revealed excellent accuracies except for the built-up and grassland classes, which showed low

Table 3
Area coverage of major LULC classes in Baringo County.

Class	2000		2014		2024	
	km^2	(%)	km^2	(%)	km^2	(%)
Water Features	178.90	1.63	241.98	2.21	260.52	2.38
Grassland	5084.46	46.43	4539.01	41.45	4677.92	42.71
Shrubland	2721.54	24.85	2987.78	27.28	3139.98	28.67
Forestland	1876.21	17.13	1402.21	12.80	819.13	7.48
Bareland	596.08	5.44	537.27	4.91	267.18	2.44
Cropland	493.12	4.50	1202.46	10.98	1689.36	15.43
Built up area	1.30	0.01	40.90	0.37	97.51	0.89
Total	10,951.61	100.00	10,951.61	100.00	10,951.61	100.00

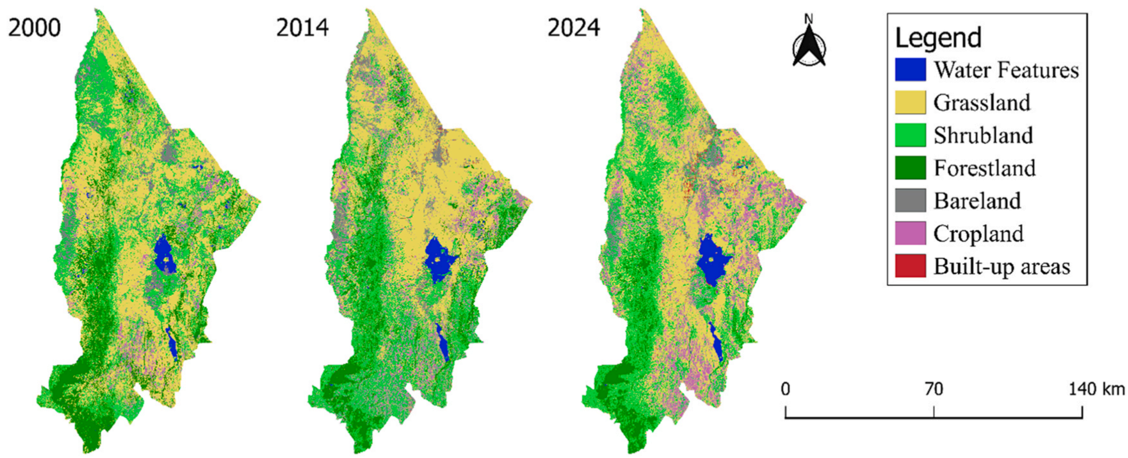

Fig. 3. LULC maps of Baringo County for the years 2000, 2014, and 2024.

Table 4
LULC changes in the study area.

	2000–2014		2014–2024		2000–2024	
	km^2	%	km^2	%	km^2	%
Water Features	63.08	35.26	18.54	7.66	81.62	45.62
Grassland	−545.45	−10.73	138.91	3.06	−406.54	−8.00
Shrubland	266.24	9.78	152.2	5.09	418.44	15.38
Forestland	−474	−25.26	−583.08	−41.58	−1057.08	−56.34
Bareland	−58.81	−9.87	−270.09	−50.27	−328.9	−55.18
Cropland	709.34	143.85	486.9	40.49	1196.24	242.59
Built up area	39.6	3046.15	56.61	138.41	96.21	7400.77

Table 5
LULC change matrix of Baringo County showing the transition in land use classes from 2000 to 2014 (km^2).

		2014							
		Water features	Grassland	Shrubland	Forestland	Bareland	Cropland	Built-up	Total
	Water features	133.68	13.78	7.60	17.03	3.27	3.17	0.37	178.90
	Grassland	41.62	2987.24	1234.64	271.90	56.52	478.47	14.06	5084.46
2000	Shrubland	38.33	995.08	1032.11	65.76	146.65	433.72	9.90	2721.54
	Forestland	7.90	235.02	532.84	1038.45	11.45	49.76	0.78	1876.21
	Bareland	20.25	164.73	67.58	6.27	293.55	28.67	15.02	596.08
	Cropland	0.18	142.86	112.99	2.80	25.43	208.66	0.21	493.12
	Built-up	0.02	0.31	0.02	0.00	0.40	0.01	0.55	1.30
	Total	241.98	4539.01	2987.78	1402.21	537.27	1202.46	40.90	10,951.61

Table 6
LULC change matrix showing the transition in land use classes from 2014 to 2024 in Baringo (km^2).

		2024							
		Water features	Grassland	Shrubland	Forestland	Bareland	Cropland	Built-up	Total
	Water features	214.15	5.16	14.00	1.52	0.16	6.16	0.83	241.98
	Grassland	14.76	2846.40	756.61	18.14	100.64	723.87	78.57	4539.01
2014	Shrubland	18.59	1100.85	1375.08	109.25	10.68	369.92	3.39	2987.78
	Forestland	12.19	105.87	568.77	680.92	0.42	33.29	0.75	1402.21
	Bareland	0.28	35.94	200.84	3.50	145.73	145.15	5.83	537.27
	Cropland	0.30	579.06	206.62	5.55	4.64	404.80	1.49	1202.46
	Built-up	0.25	4.63	18.06	0.25	4.91	6.15	6.64	40.90
	Total	260.52	4677.92	3139.98	819.13	267.18	1689.36	97.51	10951.61

user accuracies. The user, producer, and overall accuracies for most LULC classes were high (above 85 %), which is above the acceptable accuracy in most remote sensing analyses (Ahmed et al., 2024; Foody, 2008). In some years, grasslands and built-up areas had lower user accuracies than the recommended threshold. A possible explanation for the low accuracy for the grassland class is due to the few spectral bands and the individual NDVI used in the classification process. Other studies in Kenya that mapped grasslands with relatively higher accuracies used more indices and other landscape features, such as elevation (Wei et al., 2021). Other studies have also mapped grasslands and built-up areas with relatively lower thresholds than other LULC classes, such as water features and forestlands (Wei et al., 2020). Our study also showed that

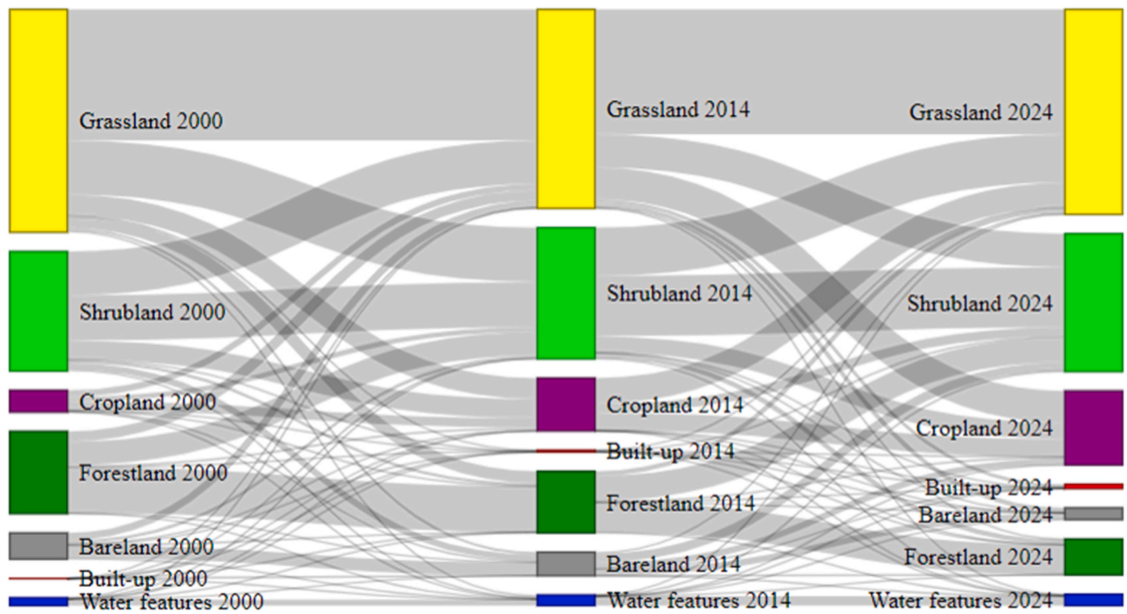

Fig. 4. Sankey plot showing the LULC transitions between 2000,2014 and 2024.

forestlands and water features were mapped with higher producer and user accuracies. The high performance of these LULC classes can be attributed to their distinct and well-defined characteristics.

4.2. LULC statistics and changes

Generally, grassland and shrubland dominated the largest percentage of the study area during the study period. The results of the LULC analysis showed that the study area underwent different anthropogenic and natural alterations. Key changes included expansions of cropland, shrubland, water features, built-up areas and decline of forestland, grassland and bareland areas (Table 4). The increase in cropland areas over the study period is due to agricultural expansion (Boitt et al., 2022; Ochuka et al., 2019). Baringo's livelihoods depend on economic activities such as agriculture, pastoralism, and beekeeping (Baringo County Government, 2014). Agricultural expansion (both rainfed and irrigated) can be linked to increased population in the study area. In 1989, the population of Baringo County was approximately 347,000 people (GOK, 1994). The population has since doubled to 667,000 in 2019 (KNBS, 2019). The increased population means that more food and production land is needed. Another driver of cropland expansion pointed out in other studies is the increased climate variability in the study area that has triggered changes in how land is managed (Becker et al., 2016). Our analyses corroborate other studies that demonstrated an increased expansion of croplands and a subsequent reduction of forest cover in different parts of Kenya (Kipkulei et al., 2022; Kogo et al., 2021; Rotich et al., 2022; Rotich and Ojwang, 2021).

Expansions in shrublands results from invasive species, including alien Prosopis and native *Dodonaea viscosa,* among others (Becker et al., 2016; Mbaabu et al., 2019). Prosopis, locally referred to as 'Mathenge', is a small, invasive, fast growing, evergreen, drought-resistant tree species of tropical American origin that has aggressively colonised many ASAL areas in Kenya, including Baringo County (Adoyo et al., 2022; Clement et al., 2020; Maundu et al., 2009; Mbaabu et al., 2019; Mwangi and Swallow, 2005). Prosopis was introduced in Baringo County, Kenya, in the early 1980s for fuelwood provision and desertification control, but since then, it has spread rapidly from the original plantations to new areas (Ng et al., 2017). In Baringo County, the species alone has spread to over 18,000 ha since its introduction in the region (Mbaabu et al., 2019). Similarly, other studies in the area found prevalent invasions of grasslands by the native *Dodonaea viscosa* woody vegetation (Becker et al., 2016). Other studies in Kenya and the East Africa region have also established Prosopis invasion as a primary driver of rangeland degradation and grassland and bare land conversion to shrublands (Abebe et al., 2022; Mekuyie et al., 2018; Tadese et al., 2020).

Deforestation and forest degradation are the primary causes of forest losses in the study region as exhibited by the conversion of forestland to shrubland and grassland (Fig. 4). The exploitation of natural forests for timber, settlement, charcoal and firewood has increased in the study region (Odada et al., 2006). Our study shows that intensive forest losses have occurred in the Lembus forest, part of the Mau Forest complex in the southern region and along the Tugen Hills escarpment extending to the north. Causes of escalated forest losses include cropland and grazing land expansions, charcoal production, and illegal logging. Increased population has elicited deforestation, forcing people to explore forested landscapes for occupation. Additionally, Kimutai and Watanabe (2016) found increased illegal logging activities and timber extraction in the Lembus forest. Intensive human activities have played a significant role in the drastic reduction in forest cover in the southern part of the county. The overall reduction in grassland areas in Baringo County can be linked to the expansion of shrublands, particularly the invasive Prosopis, which has altered grassland ecosystems, displacing native grass species (Mbaabu et al., 2019). The conversion of grasslands to cropland (Table 6) also contributed to the decrease of grassland areas.

The study findings further indicated a steady ascend in water features (Table 4). This can be attributed to the increase in water volumes in Lakes Baringo and Bogoria. The increased water features in the study area align with the observed expanding fluctuations in lake water levels within the Kenyan Rift Valley, as reported by Gebreegziabher et al. (2024) and Muita et al. (2021), which are primarily driven by LULC changes, geological processes, and climate change. The rise in water volumes in the study area lakes is attributed to the combined effect of increased mean annual precipitation, land use changes, and sedimentation (Kiage and Douglas, 2020). These factors collectively influence the hydrological dynamics of the region, leading to significant changes in the extent and volume of the lakes over time. The area has also experienced growth in water infrastructures such as dams and ponds sponsored by the county and national governments (Baringo County Government, 2018).

The LULC dynamics also revealed a steady increase in built-up areas in Baringo County (Table 4). This observation is primarily attributed to an increase in human settlements and the expansion of urban markets in the county as a result of population growth (Boitt et al., 2022). The development of urban markets since the advent of devolution has been remarkable in Kenyan counties, which has opened up marginalised areas. Services have been more decentralised, and business opportunities have expanded in small and large towns (BTI, 2022). Over the 24-year study period, most towns in the study area, such as Kabarnet, Eldama Ravine, Marigat, and Mogotio, expanded, leading to increased coverage of built-up areas. Similarly, other small markets such as Chemolingot, Kabartonjo, and Tenges have experienced increased expansion. The growth of the markets has been contributed by recent infrastructural projects such as upgrading existing roads to bitumen standards, e.g., the road linking Oinobmoi junction and Barwessa and other minor roads in major market centres of the county. This opening up of roads reduces remoteness and acts as a focal point for economic development and businesses (Greiner et al., 2021). Furthermore, an increase in built-up areas can be linked to the development of tourism in Lake Baringo, which has led to the increased establishment of tourist lodges on the shores and the adjacent islands (Baringo County Government, 2018). Conversely, previous research has shown that rapid urban growth and unplanned construction negatively impact natural resources including water catchment areas and water quality (Sharma et al., 2022).

4.3. Implications of LULC changes

The dynamics of LULC changes in the study area have had direct and indirect environmental, social and economic implications. For instance, Jebiwott et al. (2020) observed that the decline in forest cover in the Katimok area has resulted in the reduction and loss of ecosystem services, including the destruction of habitats and a decline in the abundance of mushrooms and medicinal plants. The significant forestland losses might further hinder climate change mitigation efforts. Forestland losses are predominant in the slopy and hilly regions, potentially increasing the risk of landslides and soil erosion. In the recent past, Baringo County has experienced periodic landslides, resulting in the loss of life, property, and livestock (Baringo County Government, 2014). It is expected that further cultivation on hilly slopes will continue to subject the soil to erosive agents such as wind and water. The practice, compounded with the high precipitation in the mountainous areas and the poor vegetation cover, will increase the runoff and reduce soil fertility in these environments.

The impact of Prosopis invasion in the study area has been mixed. It has become a principal source of shade, fodder, fuel wood, charcoal, timber, fencing poles and an enhanced microclimate in the area, in addition to increasing soil stability (Mbaabu et al., 2019; Mwangi and Swallow, 2005). However, it has conversely had serious negative consequences for the delivery of traditional ecosystem services provided to agro-pastoralists. The plant has also invaded grasslands, *Vachellia tortilis*-dominated land, and croplands, impacting the livelihoods of local people. Furthermore, the extent and speed of invasive species spread in the study area have exceeded the capacity of local communities to adapt their production systems, thereby destabilising the socio-ecology of the dryland savannahs around Lake Baringo and placing them in imminent danger of collapse. According to the local communities, their primary livelihood options of livestock keeping and farming are threatened by the expansion of the invasive Prosopis alien species (Mwangi and Swallow, 2005). There are also reported cases of serious injuries by Prosopis on both livestock and humans associated with Prosopis thorns, loss of livestock and ulceration of livestock teeth and mouth (Huho and Omar, 2020). If unchecked, future scenarios indicate that the further expansion of Prosopis will not only affect people's livelihoods but also spill over to other key economic sectors, such as tourism.

The expansion of cropland and intensive farming practices in Baringo County have contributed to enhanced food security alongside improved livelihoods and diversification, as a variety of horticultural crops, cereals, and tubers have been established via irrigation agriculture in recent decades for subsistence and commercial purposes. However, changes in land cover in the Lake Baringo catchment area, mostly from cropland expansion, have led to increased soil erosion and sediment transport to the lake, consequently changing the hydrologic pattern of the lake (Johansson and Svensson, 2002). Intensive farming in the study area characterised by increased water abstractions from the Perkerra, Molo and Ol Arabel Rivers for the Perkerra Irrigation Scheme has also led to periodic reduced inflows of Lake Baringo, thereby negatively affecting the biodiversity in the water body, as a limited number of aquatic organisms can survive under such conditions (Ochuka et al., 2019). Omondi et al. (2014) noted that anthropogenic activities such as farming, deforestation and keeping a large number of livestock in the catchment areas of Baringo introduced pollutants in the form of silt, nutrients and ions in the water body through the tributaries, leading to increased turbidity and algal blooms. The reduced forest cover in the study area associated with the clearance of trees for charcoal production also renders the water bodies vulnerable to sedimentation and flooding as deforestation increases the area's vulnerability to agents of erosion, such as wind and water (Ochuka et al., 2019).

The rise in water levels between 2000 and 2024 in Lakes Baringo and Bogoria has led to the flooding of the riparian areas. This has had significant negative impacts on the surrounding local communities and the local economy, since schools, homes, hospitals, agricultural areas, roads, and tourism infrastructure such as hotels and lodges have been submerged in water and rendered unusable.

Climate change exacerbates LULC change effects through erratic rainfall patterns, prolonged droughts, and extreme weather events, which reduce the resilience of both natural systems and human communities (Tamang and Joshi, 2025). Simultaneously, anthropogenic drivers such as population growth, settlement expansion, deforestation, and weak enforcement of land use policies intensify the pace and scale of LULC changes. These human-induced pressures reduce the land's ability to adapt to climatic shifts, creating a feedback loop of degradation and vulnerability.

5. Conclusions

The present study investigated LULC changes in the ASAL Baringo County, Kenya, from 2000 to 2024, and analyzed the implications of these changes. The results revealed significant LULC dynamics over the 24 years. Grasslands and shrublands were the dominant LULC classes, while built-up areas consistently occupied the smallest area across all three study years. The observed LULC change patterns included the expansion of croplands, shrublands, water features, and built-up areas, alongside a reduction in forestland, grassland, and bareland. These transformations were driven by a combination of anthropogenic and natural factors. The LULC changes have had notable ecological and socio-economic consequences, affecting landscapes, soil health, livelihoods, and hydrological resources in the region. Strict enforcement of forest resource management legislation, such as Baringo County's Charcoal Production Act of 2016, is essential to curtail deforestation and forest degradation. Additionally, implementing afforestation initiatives can aid in restoring degraded forest landscapes and ensuring the continued provision of critical ecosystem services. Farmers in Baringo County are encouraged to adopt sustainable agricultural practices to optimize production while mitigating agricultural expansion and the conversion of natural habitats into croplands. A multidisciplinary approach that incorporates the perspectives of stakeholders across environmental, governance, policy, and land use management sectors is critical for addressing the potential benefits and risks associated with *Prosopis juliflora*. This will enable effective management and utilization of the species within the county. The study highlights the vital role of remote sensing and GIS technologies in providing timely and accurate data to inform decision-making. The findings can guide both county and national governments in natural resource management by identifying priority areas for restoration and enhanced conservation efforts.

6. Recommendations

Based on the findings of this study, the following recommendations are proposed to guide policy and decision-making for sustainable land use in Baringo County.

- There is a need to strengthen land governance through the enforcement of land use regulations and the integration of long-term LULC monitoring into county-level planning frameworks. This will ensure land use decisions are informed by current and accurate data.
- Promoting sustainable agricultural practices, including conservation agriculture and agroforestry, can help minimize environmental degradation while enhancing food security and climate resilience.
- The management of invasive species such as *Prosopis juliflora* requires targeted strategies that balance ecological control with economic utilization, particularly for fuelwood and soil stabilization.
- Ecosystem restoration should be prioritized, particularly through reforestation and grassland rehabilitation programs that protect biodiversity, prevent soil erosion, and preserve water catchments.
- Given the increase in water features and related flooding, investments in flood risk mitigation such as the development of early warning systems, proper drainage, and resilient infrastructure are critical.
- Public awareness and community engagement through educating local communities on sustainable land management practices and involving them in conservation efforts to foster ownership and long-term commitment.
- The adoption of remote sensing and GIS technologies for continuous environmental monitoring should be institutionalized to support data-driven policy development and adaptive management.

CRediT authorship contribution statement

Stefan Sieber: Writing – review & editing. **Mengistie Kindu:** Writing – review & editing. **Harison Kipkulei:** Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Brian Rotich:** Visualization, Methodology, Formal analysis, Conceptualization. **Abdalrahman Ahmed:** Writing – review & editing. **Azaria Lameck:** Writing – review & editing. **Jocelyn Burudi:** Writing – review & editing. **Kossi Hounkpati:** Writing – review & editing. **Stanley Makindi:** Writing – review & editing. **Mark Boitt:** Writing – review & editing.

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Data availability

Data will be made available on request.

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