

Changes in Land Use Land Cover in Equatorial Coastal Forest of Kilifi County, Kenya

Lewis Mjomba NDUNGU¹, László ZENTAI²

¹ ELTE Eötvös Loránd University, Doctoral School of Earth Sciences

² ELTE Eötvös Loránd University, Faculty of Informatics, Institute of Cartography and Geoinformatics

E-mail: lewismjomba@gmail.com

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Absztrakt

A földhasználat és a felszínborítás (LULC) változásai befolyásolják az emberi tevékenységeket és a környezetvédelemmel és -megóvással kapcsolatos eljárásokat. Ezek a változások általában antropogén jellegűek, mivel a népesség növekedése urbanizációt és mezőgazdasági terjeszkedést eredményez. Ezek a változások környezeti leromláshoz vezethetnek, hozzájárulva ezzel olyan problémákhoz, mint a globális felmelegedés. Ez a tanulmány a kenyai Arabuko Sokoke-erdő (ASF) és az Arabuko Sokoke-erdő régió (ASFR) területén 2001 és 2023 között bekövetkezett LULC-változások elemzésére, a LULC-átalakulások azonosítására és az erdőirtás mértékének meghatározására összpontosított. A Landsat 7 ETM+ és a Landsat 8 OLI/TIRS műholdas képeket a Google Earth Engine segítségével elemeztük, hogy elkészítsük a 2001-es, 2012-es és 2023-as LULC térképeket. A képek osztályozásához Random Forest algoritmust használtunk. A változástérképeket a QGIS MOLUSCE eszközzel hoztuk létre. Hét LULC osztályt (erdő, kopár terület, vizes élőhely, erdős terület, beépített terület, termőterület és vízfelület) hoztunk létre, ahol az osztályozás általános pontossága és Kappa-együtthatója meghaladta a 93%-ot, illetve a 91%-ot. A 22 éves időszakban az ASF és az ASFR éves erdővesztése 629 ha/év, illetve 289 ha/év volt. Ezen felül 6682 ha erdő vált erdős területté az ASF-ben, míg 8399 ha az ASFR-ben. A szakirodalom szerint ezeket a változásokat elsősorban a nemzeti és helyi szintű társadalmi, gazdasági, technikai és politikai tényezők kölcsönhatása okozza. A folyamat hatékony mérsékléséhez több érdekelt fél bevonásával végrehajtott beavatkozásokra van szükség.

Abstract

Land Use Land Cover (LULC) changes influence human activities and policies related to environmental protection and conservation. These changes are usually anthropogenic in nature with population increase driving urbanization and agricultural expansion. These changes may result in environmental degradation thereby contributing to global problems like global warming. This study focused on analysing LULC change in Arabuko Sokoke Forest (ASF) and Arabuko Sokoke Forest Region (ASFR) in Kenya, between 2001 and 2023, identifying the LULC conversions, and determining the rate of deforestation. Landsat 7 ETM+ and Landsat 8 OLI/TIRS satellite images were analysed using Google Earth Engine (GEE) to create 2001, 2012, and 2023 LULC maps. Random Forest algorithm was used for image classification. Conversion maps were generated using QGIS MOLUSCE tool. Seven LULC classes (forest, bareland, wetland, woodland, built-up, cropland, and water) were classified with overall accuracies and Kappa coefficients of above 93% and 91%, respectively. For the 22-year period ASF and ASFR experienced an annual forest loss of 629 ha (hectares)/year and 289 ha/year respectively. Additionally, 6682 ha and 8399 ha of the forests were converted into woodlands within ASF and ASFR respectively. Existing literature suggest that these changes are largely driven by the interplay of social, economic, technical, and policy factors at national and local levels. Therefore, multi-stakeholder interventions are required for effective mitigation.

1. Introduction

The concept of sustainable development emerged in the 1980s, but it was the implementation of the Sustainable Development Goals (SDGs), adopted by consensus by the United Nations at the 2015 General Assembly, that made it more widely known. Putting the world on a sustainable development path is one of the UN's biggest undertakings to date and perhaps also has the potential to reduce the gap between developed and developing

countries. Africa is the least developed region in the world, but there are also significant differences in natural and social conditions between African countries. The colonial past also plays a major role in African countries because the policies and economic role of the colonial countries still have a significant impact on the development of countries that have been independent for decades.

The loss of biodiversity in Africa is threatening the livelihoods of tens of millions of people, reducing food security, leading to

conflict as arable land shrinks, and increasing the likelihood of animal-to-human transmission of infections. Forests cover 26% of Africa's land area, most of which is in South Africa, Ethiopia and Nigeria, but the forest cover is steadily decreasing (Food and Agriculture Organization of the United Nations [FAO], 2021). Agriculture is the main direct cause of deforestation, accounting for about three quarters of deforestation in Africa. To make matters worse, the continent's growing population clearly causes an increase in demand for food. Twentieth-century colonisation has in many cases replaced natural vegetation with cocoa, coffee, oil palm and tea plantations.

Tropical Africa has lost about 22% of its forest cover since 1900, comparable to the losses in South America (Amazon Basin). Even less attention is paid to the shrinkage of dry forests in West, East and Southern Africa, despite the historically much greater rate of deforestation in these areas. This is another reason why it can be instructive to look at land use and land cover change in Kenya. From a global perspective, it is estimated that over six decades (1960-2019) a third (32%, approximately 43 million km²) of the global land area has been affected by land use changes (Winkler et al., 2021). Moreover, during the same period global net forest area loss was 0.8 million km², while global agriculture had an expansion of 1.0 and 0.9 million km² for cropland and pasture/rangeland respectively. These statistics underscore the significance of these land use changes.

Land use describes people's activities, their inputs, and arrangements of how they utilize land, while land cover describes features that are observed on the earth's surface which can be anthropogenic or natural (Tadese et al., 2021). Land Use Land Cover (LULC) as a concept and a research area had been applied to various fields of studies. It can be applied in study areas such as erosion, landslides, global change and land planning (Liping et al., 2018). Additionally, evaluation of LULC change is vital in resource management, sustainable development, environmental conservation (Alam et al., 2020), water management climate-resilient strategies (Mekonnen & Manderso, 2023), water resource planning and watershed management (Waithaka, 2023).

The effects of land use changes have also been captured on a local scale in various parts of the world. In the Kashmir Valley, India, between 1992 and 2001, there was a decrease in forest and pasture areas and an increase in shrubs, plantations, marshy areas, barren land, and built-up areas. However, between 2001 and 2015, forest and pasture areas increased (Alam et al., 2020). In the Taliha North watershed of DR Congo, forest cover decreased from 253.11 km² in 1987 to 201.12 km² in 2001 and further to 123.04 km² in 2020 (Kapiri et al., 2023). In the Bafing area of Senegal, between 1986 and 2020, there was a significant increase in water bodies, vegetated areas, agricultural land, and settlements, while bare ground decreased (Sambou et al., 2023). In Ethiopia, construction and cropland areas increased by 46.95% and 15% respectively while vegetation, grassland, and waterbodies decreased by 70.02%, 38.1%, and 62.7% respectively (Mekonnen & Manderso, 2023). In Western Uganda, there was an increase in forest (0.1%), agriculture (0.1%), and urban (0.1%), while wetland, grassland, and

shrubland cover decreased by 0.05%, 0.22%, and 0.01% respectively (Kishaija et al., 2024).

Kenya as a country has also experienced LULC changes which have been researched at a localized level. In the watershed of River Ruiru, Kiambu County perennial crops (coffee and tea), annual crops, and built-up areas increased by 11.43%, 35.84% and 3.068% respectively, while forestland, shrubland, and grassland decreased by 29.79%, 13.25%, and 7.48% respectively, between 1976 and 2017 (Waithaka, 2023). In Makueni County, results showed that built up areas had the highest increase from 160.7 km² to 644.5 km², while evergreen forests had the highest decrease in area from 3105.8 km² to 1372 km² between 2000 and 2016 respectively (Cheruto et al., 2016).

Land cover change analysis reveals substantial forest loss in both the Mau Forest Complex and Mt. Elgon complex in Kenya. The Mau Forest Complex experienced a 21.9% loss (88,493 ha) of forest cover between 1986 and 2017, while the Mt. Elgon complex experienced a 12.5% loss (27,201 ha) between 1984 and 2017 (Ojoatre et al., 2023). Further analysis by Masayi et al. (2021) specifically focusing on the Kenyan side of Mt. Elgon Forest ecosystem from 1973 to 2019, revealed specific changes in forest types. Natural forests declined by 18%, bamboo forests by 15.19%, and plantation forests by 15.6%, while mixed farming, fallow land, and tea plantations increased by 29%, 10%, and 0.13%, respectively. These findings highlight pressure on forest ecosystems largely attributed to human activities.

Drivers and causes of LULC change are a major global concern, prompting numerous investigations worldwide. One such study in Pakistan identified several key drivers (Anwar et al., 2022). Perceived and proximate drivers included natural conditions, increased infrastructure, unplanned urbanization, and agricultural decline, while underlying drivers were poor marketing, inadequate financial resources, and weak governance. Socioeconomic factors and climatic factors such as drought and rainfall can also drive the change (Cheruto et al., 2016). Furthermore, natural conditions such as frost and drought can also damage forests, as observed in the Nagyerdő forest in Debrecen, Hungary (Molnár & Király, 2023). Human activity has a long history of influencing forest cover. For example, Zentai (2013) notes that forest conversion into farmlands and grazing land resulted in wood shortages in Europe, contributing to the development of silviculture and forestry practices. These studies illustrate the diverse range of factors contributing to LULC change including both natural and anthropogenic activities factors.

However, anthropogenic activities are widely recognized as key drivers of extensive land transformations (Alam et al., 2020) largely attributed to rapid population growth. For instance, a study in Ethiopia showed that population increase leads to high food demands causing conversion of natural forests into grasslands, urbanized, and agricultural land (Mekonnen & Manderso, 2023). Also in Uganda, Kishaija et al. (2024) showed that population growth has a positive relationship with the extent of urban areas, contributing to their increase. The relationship between population growth and forest changes, however, is

complex and context dependent. Sambou et al. (2023) demonstrated a contrasting trend: while increased population in Bafing was associated with an increase in tree cover, likely due to the presence of a large dam and supportive policies, population growth in Faleme coincided with increased deforestation, likely due to different land use pressures and management strategies

Generally, conversion of natural vegetation to grazing land, farmland, urban centres, and human settlements in East Africa is associated with land degradation, deforestation and loss of biodiversity (Maitima et al., 2009). Other activities such as conversion of wetlands into settlement and agricultural land were the main drivers of LULC changes in Nyando River Basin in Kisumu County, Kenya (Odaro et al., 2023). Statistically, Ojoatre et al. (2023) documented that agriculture was the main cause of deforestation as it accounted for 81.5% (70,612 ha) and 63.2% (24,077 ha) of the deforestation in Mau Forest and Mt. Elgon Forest respectively.

Different studies employ different LULC classification schemes depending on the research objectives, location, and researcher preferences. For example, Ojoatre et al. (2023) used seven LULC classes: forest, moorland, agriculture large-scale, agriculture small-scale, rangeland, settlement/urban, and water. Kapiri et al. (2023) employed four classes: including forest, savannah, bare lands and buildings, and croplands and fallows. Masayi et al. (2021) classified land cover into natural forest, bamboo forest, grassland, mixed farming, and fallow land. Similarly, Kruasilp et al. (2023) used six classes were used including forest, built-up area, agricultural land, maize, para rubber trees, and water. Cheruto et al. (2016) used seven classes: evergreen forests, grassland, bushlands, built-up areas, croplands, bare land, and water bodies. While the specific LULC classes vary across studies, a common broad categorisation of vegetation (natural and semi natural) and human activities is evident.

Arabuko Sokoke Forest (ASF) was first gazetted as a forest reserve in 1943 as Crown Forest, and later the reserve was subsequently expanded with additional forest land gazetted in 1968 and 1979 (Wekesa, 2017). The management and governance of ASF has deteriorated since the colonial era.

Several factors are responsible for this decline, including insufficient incentives for local community participation in forest management, widespread poverty, occurrences of unauthorized forest resource access, firewood overexploitation, and poaching of construction materials. Based on the background, this paper aims to (a) analyse LULC changes for ASF and Arabuko Sokoke Forest Region (ASFR) between 2001 and 2023; (b) identify conversions between the LULC classes for the period; (c) determine the annual deforest loss rate.

2. Materials and Methods

2.1. Study Area

ASF is the largest remaining fragment of East African coastal dry forest with high density of endemic species making it a global

biodiversity hotspot (Cuadros-Casanova et al., 2018; Glenday, 2008). It covers an area of approximately 41,846 ha, located along the Kenyan coast in Kilifi County. However, other scholars have documented it to have an area of 41,600 ha (103,740 acres) (Arabuko-Sokoke Forest Management Team [ASFMT], 2002; Glenday, 2008; Wekesa, 2017).

The elevation within ASF ranges from 40m to 160m above sea level, with three major vegetation type including mixed forest, Brachystegia Forest, and Cynometra Forest (Arabuko-Sokoke Forest Management Team [ASFMT], 2002). It experiences long rains between April and June, and short rains in November and December. The climate is hot and humid with an average temperature of 29°C (Muriithi & Kenyon, 2002). The soil texture generally ranges from sandy to sandy loam.

ASF management has four forest regions; Gede, Jilore, Kararacha, Sokoke, with three forest stations in Gede, Jilore and Sokoke (Habel et al., 2017). Administratively, ASF is shared between Malindi, Ganze and Bahari Constituencies. Its boundaries extend to seven locations: Jilore, Mwachera, Vitengeni, Sokoke, Roka, Gede, and Ngerenya, which make up the ASFR (154160 ha), along longitude 40°E and latitude 3°S (Figure 1). Indian Ocean borders the east of Gede, Roka, and Ngerenya Locations. Several villages surrounding the reserve are mostly inhabited by small-scale farmers with the Giriama tribe who are primarily dependent on forest resources. They also grow subsistence crops including cow peas, cassava, and maize, while cash crops include mango, coconut, and cashew-nut.

2.2. Data collection

Top-of-atmosphere (TOA) reflectance calibrated Tire 1 collection 2 images of Landsat 7 Enhanced Thematic Mapper plus (ETM+) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) were used in this study. Median composite images were generated using 46 images from 2000-2001, 49 images from 2011-2012, and 42 images from 2023. The study period 2001-2023 was selected based on the availability of a sufficient number of satellite images with minimal cloud cover in the study area.

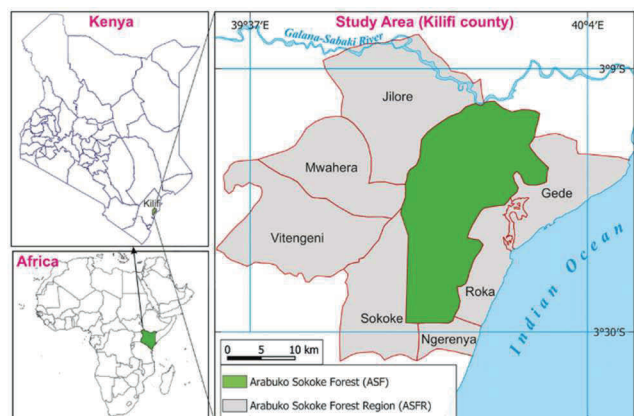


Figure 1 Study Area Map

2.3 Image processing, accuracy assessment, and classification

Spectral indices were calculated in the Google Earth Engine (GEE) platform for the 2001, 2012, and 2023 median composite images and added as additional bands to improve classification accuracy. Training samples were derived from user-defined polygons, with 1442, 1736, and 2017 pixels used for training the 2001, 2012, and 2023 image datasets, respectively. High resolution Google Earth Images was used as reference to digitize the training sample polygons with a total of seven LULC types as shown in Table 1. LULC type and description is adapted from the Kenya Forest Service, (2021). Figure 2 shows the field photos depicting the LULC types.

The sampling data was randomly split into groups of 70% training data and 30% testing data. The Random Forest (RF) algorithm, a built-in classifier in GEE, was used to perform supervised classification on the 2001, 2012, and 2023 images using the training data. This process produced LULC maps for the selected time periods.

Table 1 LULC types and description

LULC types	Description
Forest (FO)	Land area covering over 0.5 ha with trees above 2m height, and a crown cover greater than 15%. Not used for agriculture or other non-forest purposes
Bareland (BL)	Land area without vegetation covered by bare soil, rocks, rough roads, or degraded lands
Wetland (WE)	Wetland, vegetated wetland (Mash, Bogs, Papyrus)
Woodland (WL)	Woodland scrubs, thickets, open and wooded grass
Built-up (BU)	Lands dominated by huts, houses, industrial facilities and paved houses.
Cropland (CL)	Area under crop cultivation or tilled land.
Water (WA)	Water bodies including streams, rivers, ocean, and lakes.

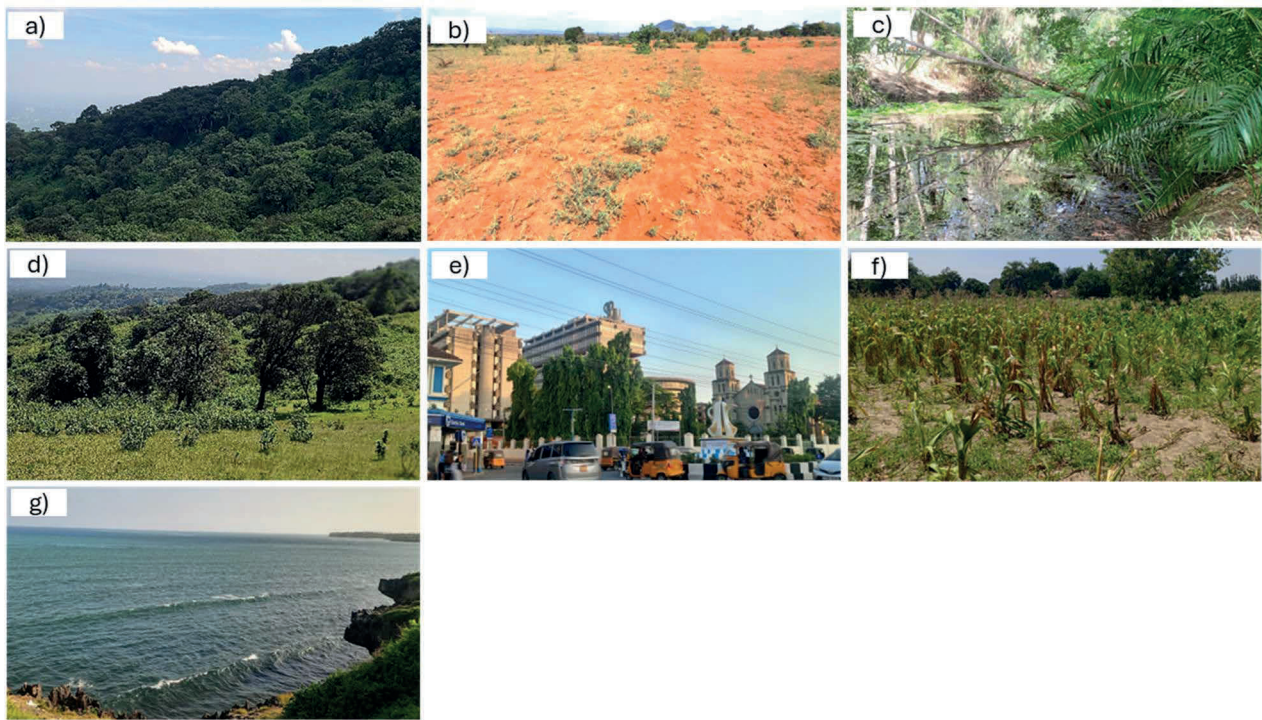


Figure 2 Photos showing the LULC types: a) forest, b) bareland, c) wetland, d) woodland, e) built-up, f) cropland, and g) water.

Evaluation of the supervised classification utilized GEE built-in accuracy assessment techniques. The overall accuracy (OA), kappa coefficient (K), consumer accuracy (CA), and producer accuracy (PA) were calculated for the classified images. Equations 1, 2, 3, and 4 represent the formulas used. The value obtained from the GEE function was multiplied by 100 for presentation purposes.

LULC values were reclassified, and LULC and conversion maps were generated and visualized using QGIS. Conversion maps were specifically generated using the MOLUSCE (Modules for Land Use Change Simulations) tool in QGIS (NextGIS, 2024). A summary of the methodology flow and steps is shown in Figure 3.

$$OA = \frac{\text{Number of Correctly Classified Samples}}{\text{Number of Total Samples}} \times 100 \quad (1)$$

$$K = \frac{\text{Overall Accuracy} - \text{Estimated Chance Agreement}}{1 - \text{Estimated Chance Agreement}} \times 100 \quad (2)$$

$$CA = \frac{\text{Number of Correctly Classified Samples in each Class}}{\text{Number of Samples Classified to that Class}} \times 100 \quad (3)$$

$$PA = \frac{\text{Number of Correctly Classified Samples in each Class}}{\text{Number of Samples from Referenced data in each Class}} \times 100 \quad (4)$$

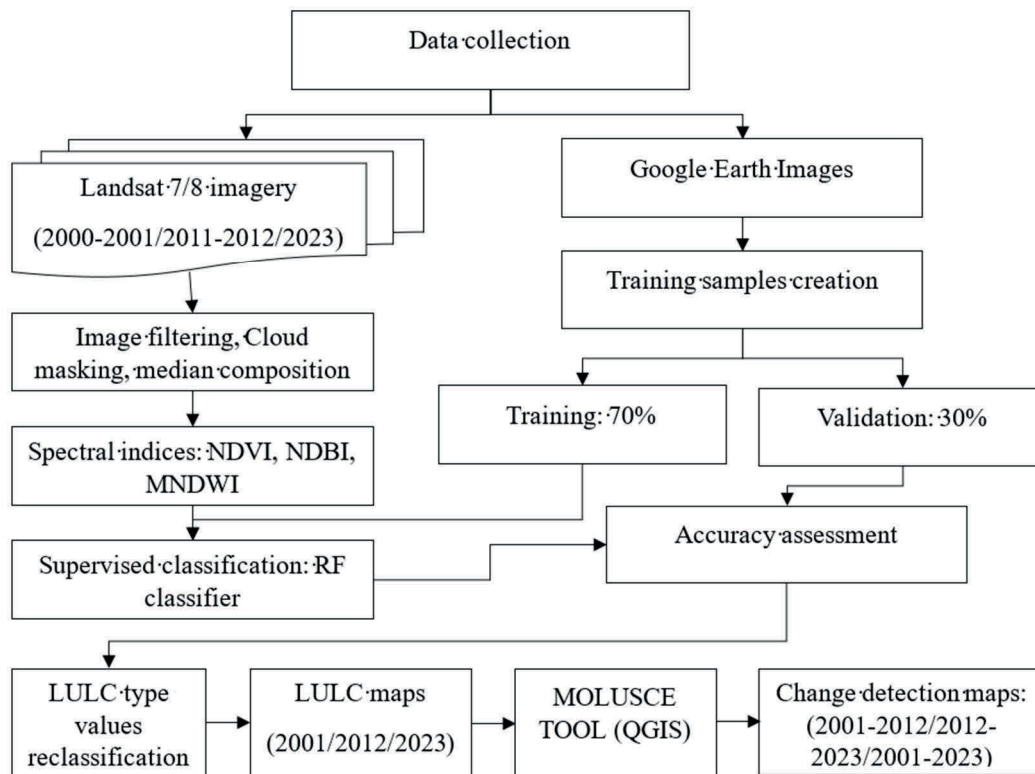


Figure 3 Methodology flow chart

2.4 Limitations of the study

The ASFR is located near the equator along the Kenyan Indian coast, thus experiences persistent cloud cover throughout the year. This scarcity of suitable cloud-free images necessitated the use of a two-year period of satellite data to generate each median image composite. Combining two years of data improved the generation of a clearer, higher-quality composite. Generally, adding satellite image extracts alongside the figures for individual LULC types would unnecessarily complicate the figure content and would not increase their interpretability.

3. Results

3.1 LULC Maps classification Accuracy

The results of confusion matrices, OA, PA, CA, and K calculations are shown in Table 2. 2001, 2012, and 2023 classified maps had an OA of 93%, 99%, and 94% respectively.

The K was 91%, 98%, and 92% for 2001, 2012, and 2023 images. Urban and cropland classes for 2001 image had the lowest PA of 27% and 22% due to the scarcity of reference data for accurate training data identification. However, the high OA and K of the image allowed for the results to be used for change analysis.

3.2 LULC maps

Mapping and displaying the spatial distribution of the seven LULC types is shown in Figure 4. Spatially cropland has been spreading on the eastern side of ASFR, specifically Gede and Roka locations from 2001 to 2023. The water inlet from the Indian Ocean is seen shrinking over the years. Galana-Sabaki river is visible in the northern side of the 2001 and 2012 map while in 2023 its size has significantly reduced. Bareland has increased rapidly on the eastern side of ASFR. Within the ASF, the ratio of woodland areas has increased, with a decrease in forest.

Table 2 Accuracy Assessment for 2001, 2012, and 2023 classified images

		Forest	Bareland	Wetland	Woodland	Built-up	Cropland	Water	OA	K
2001	CA	92%	85%	99%	30%	100%	50%	100%	93%	91%
	PA	96%	95%	90%	100%	27%	22%	100%		
2012	CA	100%	89%	100%	100%	96%	86%	100%	99%	98%
	PA	100%	100%	100%	53%	96%	96%	99%		
2023	CA	100%	93%	100%	85%	100%	96%	85%	94%	92%
	PA	94%	97%	82%	96%	74%	100%	100%		

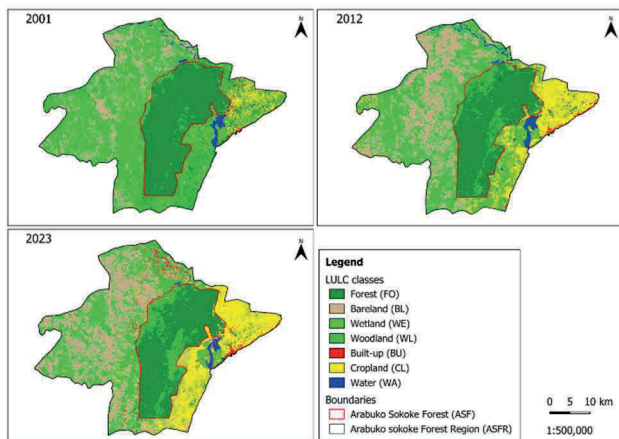


Figure 4 LULC maps for 2001, 2012, and 2023.

3.3 LULC Analysis and changes for ASF and ASFR

3.3.1 LULC analysis for ASF

Throughout the examined period forest was the most dominant class, showing a declining trend from 2001 to 2023 (Figure 5). Forest class was the dominant type covering 39,348 ha (94.0%), 35,240 ha (84.2%), and 33,000 ha (78.9%) in the year 2001, 2012, and 2023 respectively. Woodland, cropland, built-up, and bareland classes increased steadily throughout the period. Woodland had the highest increase from 2,345 ha to 8,245 ha. However, wetland showed a decreasing trend from 82 ha to 4 ha.

The 2001-2012 period had a larger forest loss of 4,108 ha (10%), compared to 2,240 ha (6%) loss in the 2012-2023 period. On the other hand, woodland had a higher gain of 3790 ha (162%) in the 2001-2012 period compared to 2110 ha (34%) in the 2012-2023 period. There was also a large cropland area increase of 320 ha between 2001-2012 with a small decrease of 13 ha in 2012-2023 period.

3.3.2 LULC analysis for ASFR

LULC analysis for ASFR is shown in Figure 6. Woodland class was the highest with 73,368 ha (47.6%), 57,952 ha (37.6%), and 47,726 ha (31%) of the area for 2001, 2012, and 2023 respectively. Generally, woodland, and grassland class have been

decreasing throughout the 2001-2023 period while bareland, built-up, and cropland classes show an increasing trend. Wetland showed a slight decreasing trend, while water class increased and then decreased. Generally, the 2001-2012 period had the largest decrease in forest and woodland classes as 11,495 ha (23%) and 15416 ha (21%) was lost respectively. Additionally, the 2001-2012 period saw the largest increase of bareland, cropland, and water classes with a gain of 13210 ha (62%), 12918 ha (214%), and 499 ha (32%) respectively.

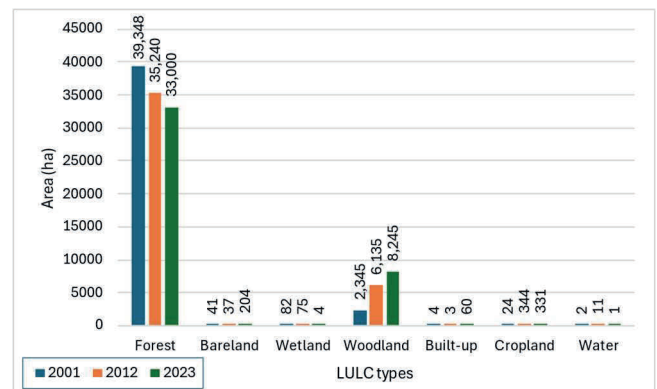


Figure 5 LULC Analysis for ASF

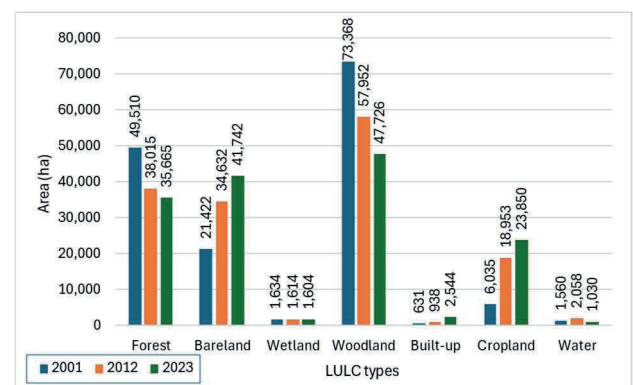


Figure 6 LULC Analysis for ASFR

3.4 LULC Changes

3.4.1 Total LULC Changes for 2001-2023 period

The largest decline within ASFR was woodland class losing 25,642 ha, followed by forest with a loss of 13,846 ha within the 22 years study period (Figure 7). On the other hand, the coverage of bareland and cropland classes increased by 20,320 ha and 17,815 ha respectively for ASFR. ASF had a woodland increase of 5,900 ha, while forest decreased by 6,348 ha.

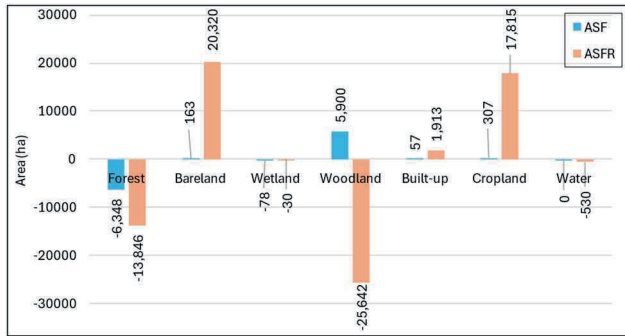


Figure 7 Total LULC change in ha (2001-2023)

3.4.2 Annual LULC changes

The mean annual year gain and loss rates are shown in Figure 8. Within the ASFR, bareland had the highest yearly increase of 924 ha/year followed by cropland (810 ha/year) while woodland and forest had net annual losses of 1,166 ha/year and 629 ha/year respectively. Moreover, ASF has an annual woodland gain of 268 ha/year and an annual forest loss of 289 ha/year for the 2001-2023 period. During the study period both wetland and water classes had minor changes annually. ASFR experiences an annual built-up growth 87 ha/year during the 22-year period.

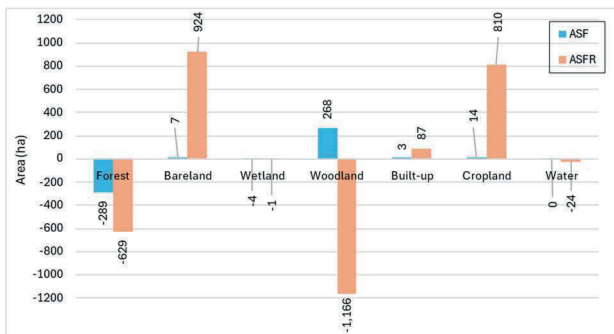


Figure 8 Annual LULC Change rates in ha (2001-2023)

3.5 Land use land cover conversions in ASF

Several LULC conversions were observed in the ASF over the 2001-2023 period (Table 3). Forest class had the largest conversion as 6682 ha, 183 ha and 43 ha was converted to

woodland, cropland, and bareland respectively. On the other hand, 494 ha, 71 ha and 9 ha of woodland, wetland, and bareland respectively was converted to forest. Water and built-up areas experienced the least conversions.

3.6 Land Cover conversions in ASFR

Within the larger area of ASFR woodland had the largest conversion with 56% (41,167 ha) being converted into bareland (26950 ha), cropland (11514 ha), forest (1556 ha), built-up (1115 ha), water (26 ha) and wetland (6 ha) areas. 31.9% (15,801 ha) of the forest area was converted into woodland (8399 ha), cropland (6150 ha), bareland (762 ha), wetland (209 ha), and water (8 ha) (Table 4). On the other hand, 19% (1,203 ha) of the cropland was converted into bareland (404 ha), built-up (274 ha), woodland (271 ha), and forest (254 ha).

3.7 Spatial distribution of the LULC conversions

Figure 9 shows the LULC conversions between different classes for ASF and ASFR for 2001-2012, 2012-2023, and 2001-2023 period. Generally, the ASF area experienced relatively larger conversions in the 2001-2012 period compared to 2012-2023 especially in the northwestern and eastern part. Large conversion of woodland to bareland is observed in Jilore, Mwashera, Vitengeni, and Sokoke locations while Gede, Roka, and Ngerenya

locations experienced conversion of woodland into cropland and other land uses.

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Table 3 Land Cover conversions in ASF (2001-2023)

		2023							
	LULC type	Forest	Bareland	Wetland	Woodland	Built-up	Cropland	Water	Grand Total
2001	Forest	32421	43	0	6682	19	183	1	39348
	Bareland	9	15	0	10	2	6	0	41
	Wetland	71	1	4	7	0	0	0	82
	Woodland	494	143	0	1544	38	126	0	2345
	Built-up	2	0	0	0	0	1	0	4
	Cropland	4	3	0	2	1	14	0	24
	Water	1	0	0	0	0	0	0	2
	Grand Total	33000	204	4	8245	60	331	1	41846

Table 4 Land Cover conversions in ASFR (2001-2023)

		2023							
	LULC type	Forest	Bareland	Wetland	Woodland	Built-up	Cropland	Water	Grand Total
2001	Forest	33709	762	209	8399	274	6150	8	49510
	Bareland	44	13171	4	6595	549	1039	20	21422
	Wetland	74	34	1373	89	19	8	37	1634
	Woodland	1556	26950	6	32201	1115	11514	26	73368
	Built-up	25	46	3	19	239	300	0	631
	Cropland	254	404	0	271	274	4832	0	6035
	Water	3	376	9	152	74	7	939	1560
	Grand Total	35664	2544	1030	47725	23850	41742	1604	154160

4. Discussion

This study analyzed LULC changes within the Arabuko Sokoke Forest (ASF) and the broader Arabuko Sokoke Forest Region (ASFR) between 2001 and 2023. Generally, the 22-year period saw significant LULC variation and conversions within ASF and ASFR. The ASF experienced a forest loss of 6348 ha with a 5900-ha woodland and 307-ha cropland increase. Consequently, the larger ASFR had a forest loss of 13,846 ha and a woodland decrease of 20,320 ha. This is largely contributed by increase in bareland and cropland of 20,320 ha and 17,815 ha. This shows forest loss was largely caused by expansion of woodland, bareland, and cropland area in ASFR while ASF loss was mainly cropland. The increase in woodlands and bareland areas may arise from the harvesting of trees by local communities. Built-up, wetland, and water areas had minimal effects on forest loss.

These findings coincide with other LULC change studies confirming forest loss in Kenya including Cherengany hills forest ecosystem (Rotich & Ojwang, 2021), Mau Forest and Mt. Elgon Forest (Ojoatre et al., 2023). Forest decrease is also a common occurrence as observed by studies in other African countries such as Tanzania (Käyhkö et al., 2011), Uganda (Kishaija et al., 2024), Ethiopia (Mekonnen & Manderso, 2023),

and Democratic Republic of Congo (Kapiri et al., 2023). Additionally, these studies concede large cropland expansion.

LULC changes observed within ASFR are closely linked to demographic and socio-economic factors. The study region is within Kilifi County which has seen an increase in population over the years despite administrative boundary system changes which were instituted by the new constitution in 2010. Census reports show a growing population trend within the region of 544,303 (1999), 1,109,735 (2009), and 1,440,958 (2019) (Central Bureau of Statistics [CBS], 2001; Kenya National Bureau of Statistics [KNBS], 2010, 2019). This study showed a 214% (12918 ha) cropland increase in the 2001-2012 period which may have been attributed to the 103.9% increase in population in the 1999-2009 period, that results in a growing need for agricultural products. Moreover, timber demand has increased as it is required for carving which contributes to further reduction in forest area (Arabuko-Sokoke Forest Management Team [ASFMT], 2002).

Notwithstanding the significant demographic and socio-economic influence, Kenya has a long history of implementing policies and legal frameworks to address forest-related challenges. The 1964 forest Master Plan, 1969 Forest Act, Forest

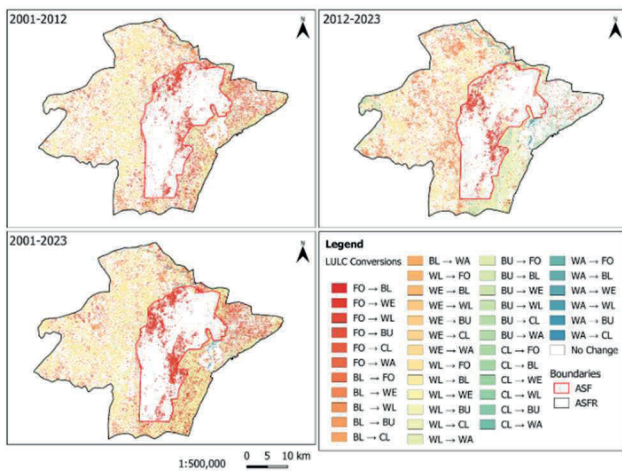


Figure 9 LULC conversion Maps for 2001-2012, 2012-2023, and 2001-2023.

Act of 2005, 2010 Constitution of Kenya, and the national forest policy of 2014, are some of the policy documents that have promoted conservation and management of forests in Kenya (Chisika & Yeom, 2024). Specifically, Forest Act of 2005, legally recognised Participatory Forest Management (PFM), which was first introduced in ASF in 1997 as a pilot project (Ongugo et al., 2008). Additionally, the act established the Kenya Forest Service (KFS) which manages and administers all state forests in Kenya. The KFS works alongside other state institutions such as National Museum Kenya (NMK), Kenya Wildlife Service (KWS), and Kenya Forest Research Institute (KFRI) to ensure collective efforts in forest protection (Adinoyi, 2015).

The state led institutions have tried their best to address various forest related challenges, however most forest communities felt marginalized in this process. The Forest Act of 2016 addressed this challenge by allowing the formation of Community Forest Associations (CFAs) thus enhancing community participation in forest management (Ndalila et al., 2024). CFAs function similarly to Community Based Organisations (CBOs) with a one-time membership subscription (Mutune & Lund, 2016). CFAs and CBOs within ASF include Arabuko Sokoke Forest Adjacent Dwellers Association (ASFADA), Arabuko Sokoke Forest Management Team (ASFMT), Arabuko Sokoke Forest Guide Association (ASFGA), and Friends of Arabuko Sokoke Forest (FoASF) (Adinoyi, 2015). It is estimated that there are about 300 user groups involved in the management under ASFADA (Ongugo et al., 2008).

Despite having such a strong management institutions, structures, and support systems, ASF conservation and protection effort face various challenges. These challenges are centred around elite capture, limited resources, unequal representation, conflicting stakeholders' interests and institutional mandates (Chisika & Yeom, 2024). This can lead to marginalization of local communities and unequal distribution of socio-economic benefits derived from the forest. For instance, there are low survival rates of trees planted by the county government due to insufficient technical support and

collaboration from organisations such as KEFRI and KFS (Mbuvi et al., 2018). Weak government structures and unclear stakeholder roles hinder effective implementation of conservation strategies (Habel et al., 2017). This ambiguity undermines conservation goals due to confusion and possible duplication of efforts. Inadequate financial, technical and human expertise regarding the management of the forests has resulted in challenges such as encroachment, agricultural expansion, and indiscriminate tree cutting for charcoal (Mbuvi et al., 2018). The severe resource gap significantly undermines the capacity of relevant organisations to effectively monitor and enforce regulations.

Additionally, the identified key drivers of destruction are illegal logging and natural resource exploitation, charcoal burning, and local elephant population exceeding the carrying capacity (Habel et al., 2017). Cuadros-Casanova et al. (2018) identified the demand for poles, carvings, and timber by the surrounding community as key drivers of illegal logging. From an international perspective, Báder et al. (2023) emphasize that agroforestry focusing on high-value trees produces high-quality logs, which can help mitigate regional timber shortages. The natural environmental challenge of frequent droughts, especially in Ganze constituency, leads to tree desiccation (County Government of Kilifi, 2023b, 2023a), which is a contributing factor to large conversion of woodland to bareland in Mwahera, Vitengeni, and Sokoke locations.

Addressing these issues requires a multi-faceted approach, combining community engagement, habitat management and law enforcement. Locally, Kilifi County has advocated for community engagement in nature-based enterprises, strict forest laws enforcement, establishing tree nurseries and woodlots and the development of forest management plans (County Government of Kilifi, 2023b). They also plan to train and equip additional 30 forest guards and rehabilitation of degraded lands. Such efforts can improve institutional capacity, reduce overdependence of forest products and poverty levels and expansion of sources of livelihoods (Adinoyi, 2015). Electric fencing of ASF has helped to reduce human-wildlife conflict, which has been instrumental in reducing illegal settlement and deforestation (Habel et al., 2017).

CBOs have, to some extent, incorporated measures to reduce forest vulnerability and hazards, such as implementing anti-logging practices and policy, adhering to forest resource utilization zones, community educational and financial empowerment, and creating forest sustainability awareness programs (Adinoyi, 2015). The challenge of limited resources can be addressed through innovative funding models, formulation of partnerships, and increasing budget allocations (Chisika & Yeom, 2024). Continuous monitoring and evaluation of these strategies can ensure long term sustainability of conservation measures in ASF. Moreover, success of these strategies requires a strong political will and adaptive management.

5. Conclusion

LULC studies generally provide a key insight on the interactions of human activities and the natural environment. Quantifying these interactions spatially and temporally is an effective way of monitoring hotspot areas requiring intervention and gaps in mitigation measures enforcement. Temporally there is an annual decrease of forest area of 629 ha/year (ASFR) and 289 ha/year (ASF) for the 2001-2023 period. Spatially, Jilore, Mwahera, Vitengeni, region experienced the largest conversion of woodland to bareland. These changes highlight the need for enacting and enforcing balanced mitigation measures for long-term sustainability.

Socio-economic pressures, inadequate governance and poor management practices have resulted in shifts and conversion in land cover uses within ASF and ASFR. Poverty and unemployment create local community overdependence on the forest for energy and food supply. This is evident from the increasing demand for agricultural land, firewood, and charcoal which leads to illegal logging and encroachment. These adverse effects are further encouraged by weak law enforcement, poor governance structure, and lack of coordinated efforts between forest related organisation. Chisika & Yeom, (2024) suggests that such challenges can be overcome through fostering transparent and inclusive stakeholder engagement, enhancing equitable representation and robust governance reducing elite capture, and amplifying marginalized groups voices in decision making. The insights from this study can guide local and national policymakers and practitioners in developing tailored interventions to address forest degradation hotspots and contribute to the achievement of global biodiversity conservation goals.

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