Trends and drivers of forest cover change in the Cherangany hills forest ecosystem, western Kenya

Article *in* Global Ecology and Conservation · August 2021

DOI: 10.1016/j.gecco.2021.e01755

2 authors:

Brian Rotich
Chuka University College

Dennis Ojwang
University of Twente

Global Ecology and Conservation 30 (2021) e01755

Contents lists available at ScienceDirect

Global Ecology and Conservation

journal homepage: www.elsevier.com/locate/gecco

Trends and drivers of forest cover change in the Cherangany hills forest ecosystem, western Kenya

Brian Rotich[a,c,*], Dennis Ojwang[b]

[a] *Faculty of Agricultural and Environmental Sciences, Hungarian University of Agriculture and Life Sciences, Páter Károly u. 1, Gödöllő 2100, Hungary*
[b] *Leaf Magnet Research and Development Ltd, PO Box 34109-00100, Nairobi, Kenya*
[c] *Faculty of Agriculture and Environmental Studies, Chuka University, PO Box 109-60400, Chuka, Kenya*

ARTICLE INFO

Keywords:
Deforestation
Remote sensing
Land cover
Forest degradation
Water tower

ABSTRACT

Detecting and monitoring forest cover change and its drivers has become a vital component of forest management globally as it helps in decision-making and policy development. The objective of this study was to analyze the spatio-temporal trends of forest cover change and its drivers from 1985 to 2020 in the Cherangany hills forest ecosystem, Kenya. Landsat satellite data and Google Earth Engine (GEE) algorithms were used for land cover mapping and change detection. In addition, a literature review was undertaken to establish the drivers of forest cover change over time in the study area.

The results show an overall decline in the forest, water features, and built-up areas land cover categories in the study area while croplands, grasslands, and bareland registered gains. The percentage area under forests declined by about 14.1% (13,782 ha) during the 35 years. This loss translates to an annual average forest loss of 0.40% or 394 ha. Conversely, cropland and grassland registered an increase of about 8.1% (7944 ha) and 5.8% (5616 ha) respectively over the 35-year study period. The drivers of forest cover change in the ecosystem comprised the conversion of forests to croplands and grasslands, grazing, encroachment, illegal logging, firewood harvesting, charcoal production, forest fires, excisions, climate change, population growth, policy, and institutional failures.

The findings of this study will help the relevant forest managers re-evaluate the past conservation and management strategies and focus the rehabilitation efforts on the forest ecosystem's degradation hotspots for sustainable forest management.

1. Introduction

The Food and Agricultural Organization (FAO) of the United Nations estimates the entire forest area of the world at 4.06 billion hectares or 31% of the total land area. The tropical domain has the most forests, followed by the boreal, temperate, and subtropical climate (FAO, 2020). Forests are vital for protecting land and water resources, provision of renewable raw materials and natural amenities, biodiversity conservation, and climate change mitigation (Aju et al., 2015; Miura et al., 2015). Between 1990 and 2020, the globe has lost a net area of 178 million hectares of forest, majorly from deforestation and forest degradation. However, the rate of net

* Corresponding author at: Faculty of Agricultural and Environmental Sciences, Hungarian University of Agriculture and Life Sciences, Páter Károly u. 1, Gödöllő 2100, Hungary.
E-mail address: Kanyongi.Brian.Rotich@phd.uni-szie.hu (B. Rotich).

https://doi.org/10.1016/j.gecco.2021.e01755
Received 21 June 2021; Received in revised form 13 August 2021; Accepted 13 August 2021
Available online 14 August 2021

forest loss has slowed significantly over this period due to a reduction in deforestation in some countries and increases in forest area in others due to afforestation and natural forest extension (FAO, 2020; Keenan et al., 2015). For instance, the global annual rate of net forest loss reduced by half over 25 years from an area of 7.3 million ha per year in the 1990 s to about 3.3 million ha per year in 2015 (FAO, 2015).

Tropical deforestation and forest degradation occur due to proximate/direct drivers or underlying/indirect drivers (Geist and Lambin, 2002). Direct drivers include anthropogenic activities or immediate actions that directly impact forest cover and loss of carbon like agriculture, urban expansion, mining, logging, livestock grazing, and forest fires. The indirect drivers encompass complex interactions of fundamental political, socio-economic, cultural, and technological processes. Examples of indirect drivers of deforestation include corruption, poor governance, population growth, and land tenure uncertainties. The proximate and underlying drivers are usually interlinked, resulting in land cover and land-use changes (Geist and Lambin, 2002; Millennium Ecosystem Assessment, 2005). In most developing countries of Asia, Latin America, and Africa, the key driver of deforestation is agriculture (commercial and subsistence). At the same time, forest degradation occurs due to timber extraction and logging, charcoal production, fuelwood collection, forest fires, and livestock grazing (Hosonuma et al., 2012).

Africa currently has 16% of the world's forests. Small-scale logging and timber extraction are the main threats to African forests, with severe long-term consequences. The net forest loss in Africa has increased in three decades since 1990, with the highest annual net forest loss occurring between 2010 and 2020, at 3.9 million ha (FAO, 2020; Hosonuma et al., 2012). Kenya's forest cover is estimated at 7.4% (4.31 million hectares) of the total land area (58.26 million hectares). Although this is an improvement from the cover in the early 2000 s, which was under 2%, it is still below the recommended global and constitutional minimum of 10% (Republic of Kenya, 2018). Kenya's closed-canopy forests, which also double as the water towers cover, currently stand at about 2% of the entire nation's land area compared to the African average of 9.3% and a world average of 21.4%. Kenya lost roughly 5000 ha of forest per year in just one decade (2000–2010), resulting in an annual reduction in water availability of around 62 million cubic meters, which translated to a loss of about United States Dollars (USD) 19 million to the country's economy. Clearance for agriculture, unsustainable exploitation (including timber harvesting, charcoal production, and forest grazing), institutional failures, and poor governance in the forest sector in the past are the key drivers of deforestation in Kenya. (Ministry of Forestry and Wildlife, 2013; Republic of Kenya, 2018).

Changes in forest area over time reflect changes in land use demands. The use of Remote Sensing (RS) and GIS (Geographical Information System) in mapping and monitoring forest cover changes over time is critical as it provides adequate information for identifying conservation hotspots to support restoration strategies, decision making and policies for conservation, and sustainable management of forest ecosystems (Martinez del Castillo et al., 2015; Masek et al., 2015; Zafar et al., 2021). Several studies have been carried out in Africa and Kenya using remote sensing techniques to monitor forest cover change trends (Kimutai and Watanabe, 2016; Kogo et al., 2019; Kweyu et al., 2020; Muhati et al., 2018; Teucher et al., 2020; Tuffour-Mills et al., 2020; Wekesa et al., 2020; Zvobgo and Tsoka, 2021).

The Cherangany (Cherangani) hills forest ecosystem is among Kenya's five main water towers, contributing significantly to the national economy since it provides numerous economic, environmental, social, and cultural benefits. The annual Total Economic Valuation (TEV) of Cherangany Hills Water Tower was estimated at Kenyan Shillings (KES) 47 billion (USD 470 million) in the year 2020 (Kenya Forest Service, 2015; Kenya Water Towers Agency, 2020). Like other tropical montane forests, the Cherangany forest ecosystem has experienced forest cover disturbances in the past, yet there is a limited comprehensive spatio-temporal analysis of its forest cover dynamics, with most studies focusing on socio-economic aspects and short-term forest cover changes.

Therefore, it is against the above background that this paper investigates forest cover change in the Cherangany hills forest ecosystem, western Kenya. Specifically, we aimed to: (1) Analyze the spatio-temporal trends of forest cover change in the ecosystem from 1985 to 2020 using GIS and RS techniques, and (2) Conduct a literature review to understand further the drivers of forest cover change in the study area. This study will help the relevant forest managers re-evaluate the conservation strategies during the evaluated period and inform future management decisions in the study area and other similar ecosystems to achieve sustainable forest management goals.

2. Materials and methods

2.1. Study area

Cherangany hills forest ecosystem is located within an area defined by 1°16′ N, 35°26′ E. It traverses three administrative counties: West Pokot, Trans-Nzoia, and Elgeyo-Marakwet, covering about 97,397 ha (Kenya Water Towers Agency, 2020). The forest ecosystem comprises 14 forest blocks (Fig. 1), mainly indigenous forests with a few continuous forest plantations. The western blocks of the forest consist of Kapkanyar, Kapolet, Kamatira, and Kiptaberr, while Embobut, Chemurkoi, Kaisungor, Kererr, kapchemutwa, Lelan, Kipkunur, Sogotio, Cheboyit, and Toropket, which are less connected, make the eastern blocks. These forest blocks are about 60,500 ha of a closed-canopy forest, which is approximately 52.9% of the total area. The rest is made up of pockets of bamboo, moorland, grasslands, scrub, and rock outcrops. About 4000 ha of land in the forest ecosystem is under cultivation and plantations of exotic tree species

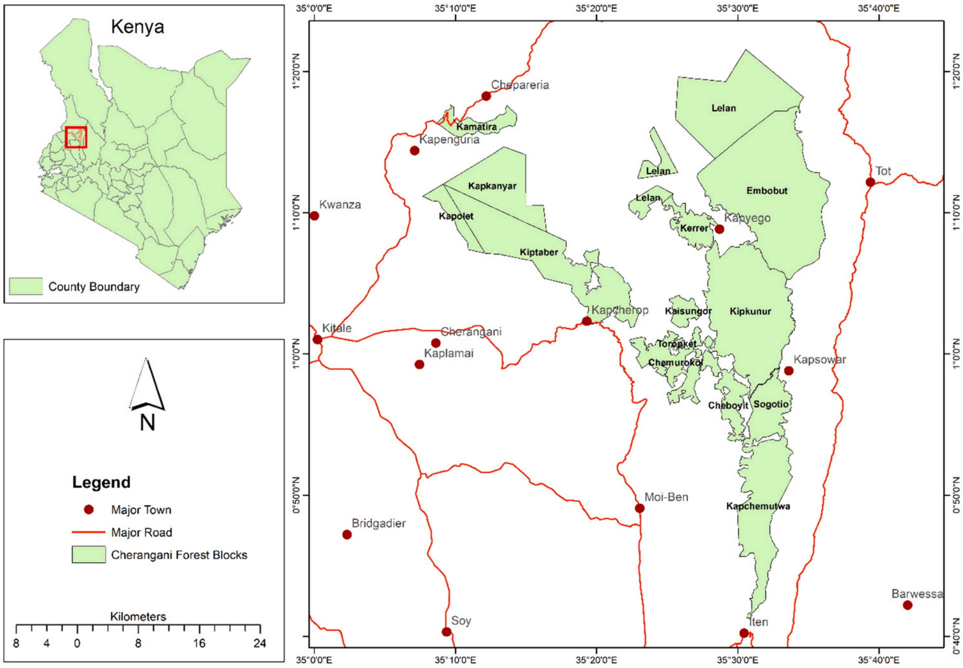

Fig. 1. Map of Cherangany forest ecosystem in Kenya, showing the 14 forest blocks.

(Kenya Forest Service, 2015).

The Cherangany forest ecosystem is an undulating upland plateau on the western side of the Great Rift Valley formed by an old fault-block formation. The geology is composed of metamorphic rocks, with conspicuous quartzite ridges and occasional marble veins, while the soils are mainly well-drained Cambisols, with varied acidity, good structure, and a high organic matter content (Kenya Water Towers Agency, 2020). The ecosystem's altitude ranges from 2000–3365 m above sea level. The area receives bi-modal rainfall with long rains occurring during April – June and short rains in July – October, while the dry season typically occurs from December to February. The mean annual rainfall in the Cherangany hills ranges from around 800 mm in the North to about 1500 mm in the west. The area is relatively cool with a minimum temperature of 14 °C, a mean temperature of 18.6 °C, and a maximum temperature of 24 °C. The Cherangany forest ecosystem is an important water catchment in Kenya. It is a source of several streams that combine to form river Nzoia that drains to Lake Victoria while rivers Turkwel and Kerio drain into lake Turkana (Kenya Forest Service, 2015).

The Cherangany forest ecosystem is rich in biodiversity. It is a significant biodiversity hotspot as it is home to several endangered faunal species such as the African crowned eagle, red chested owlet, lammergeyer, Sitatunga, thick-billed honeyguide, and the critically endangered mountain bongo. Common tree species in the ecosystem include the common yellowwood, while tree ferns mainly occur in stream valleys, with some patches of bamboo (Kenya Water Towers Agency, 2020).

Ethnic groups living around and within the forest ecosystem include the Marakwet, Pokot, Luhya, and the indigenous Cherang'any/Sengwer communities. Their livelihoods are supported by economic activities like mixed farming (crop production and livestock keeping), beekeeping, lumbering, wage labor, and small businesses (Kenya Water Towers Agency, 2020; Mbuni et al., 2020; Petersen et al., 2021a; Rotich, 2019).

2.2. Data

RS coupled with GIS is convenient in monitoring temporal land-use change trends based on freely available data. These tools are essential, especially in tropical montane environments where conducting a field survey over large areas is often challenging due to time and costs constraints (Sidhu et al., 2018). Remote sensing is a powerful tool for global processes studies such as global warming and forest cover change due to its cost-effectiveness and accuracy over large areas compared to traditional techniques, which were based on fieldwork or only in geographical information systems (Kumar, 2011; Pôças et al., 2011; Townshend et al., 2012). The Landsat archive, available through Google Earth Engine (GEE), is a database for historical optical information dating back to 1973 (Sidhu et al., 2018). The database stores images from various passive sensors belonging to the Landsat program of the National Aeronautics and

Space Administration (NASA), which provides the longest spatially continuous record of Earth's observations free of charge. Data collected by Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Operational Land Imager (OLI) are available free for use in any research work. This study explored and used historical data from Landsat satellite for land cover mapping. Specifically, TM was a satellite instrument onboard Landsat 4 and 5, acquiring images continuously from July 1982 to November 2011. The data released from this instrument includes six spectral bands at 30 m spatial resolution and one thermal band at 120 m resolution (resampled at 30 m). The ETM+ was on board of Landsat 7, collecting images dating back to July 1999. The ETM+ data consists of seven reflective bands at 30 m spatial resolution and one panchromatic band at 15 m (Vittek et al., 2013).

This study selected six reference years for analysis that nearly splits the study period into a 5-year time interval for change analysis with 1985 as the base year (2000; 2005; 2010; 2015; 2020). We considered images from the period 1985 as the baseline for the change detection analysis because it was the year with the best quality satellite image data we could find close to 1964, the period Cherangany forest was gazetted as a forest reserve (Kenya Forest Service, 2015). The subsequent selected periods between 2000 and 2020 provided an opportunity to compare the rate of forest cover changes under different management regimes.

Data filtering was done in GEE for cloud-free imagery relative to these years from the Landsat image collection. Another set of information we used was training and testing samples, which defined different spatial categorical information. Spatial categorical data for land cover in the study area was determined from visually dominant land cover types. We visually discerned four main categories dominant in the study area (forest, cropland, grassland, bare-land), and other minor categories such as water features and built-up formed a category for "others"(see Table 1 below). The land cover category of interest in this study is forest. Visual interpretation of Landsat TM and ETM backed by a field survey over Google Earth helped produce the different land-cover categories as shown in Fig. 2 below.

Table 1
Description of land cover classes applied in image classification.

Code	Definition	Description
1	Cropland	Includes small-scale agriculture, horticulture, rain-fed maize farms, small (< 2 ha) tea orchards intercropped with food crops, garden-size tree/shrub orchards intercropped with herbaceous crops.
2	Grassland	Includes grassland and shrubland, trees may be present, but < 30% of crown coverage may be suitable for pasture.
3	Forest	Tree height >2 m; crown coverage > 30%; this class includes Bamboo Forest
4	Bare-land	Vegetation cover of <10%
5	Others	Includes pockets of water features, built-up, and any other visible cover.

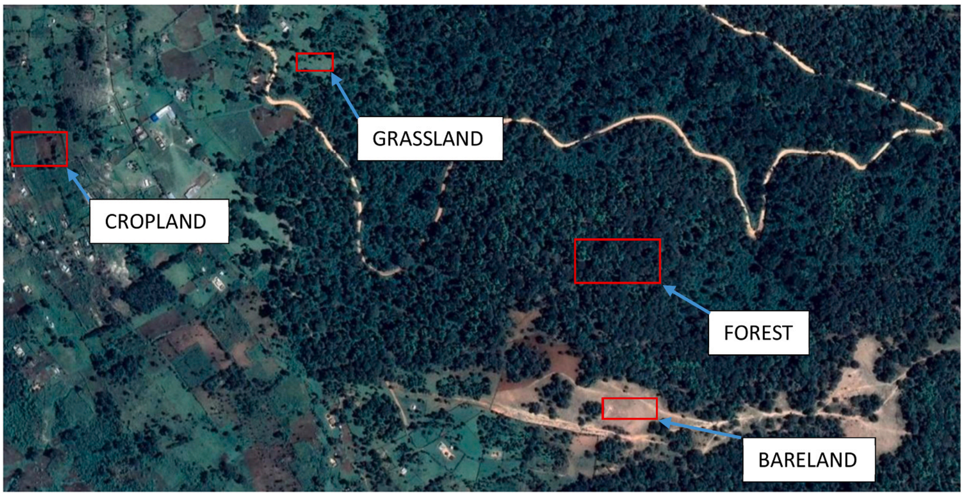

Fig. 2. Sampling in Google Earth.

The study area covers part of a raster mosaic of four Landsat scenes, row 059 and 060, and path169 and 170 for each year under study. Spectral bands of the Landsat mosaics used for analysis include band1, band2, band3, band4, and band5. Normalized Difference Vegetation Index (NDVI) was calculated and used as part of the covariates for image classification. NDVI is a derivative of Band3 (red band) and Band4 (Near Infrared band). This index takes and quantifies vegetation's reflective difference between the near-infrared (NIR) and visible red (RED) wavelengths (Elmore et al., 2000). The formula used to generate the NDVI data is shown in Eq. (1) below:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

2.3. Data analysis in GEE

GEE is a cloud-based platform with high performance in terms of data retrieval and processing, available for any researcher (Shelestov et al., 2017). GEE database consists of huge imagery data collection, including MODIS (Moderate Resolution Imaging Spectroradiometer), Landsat, and Sentinel-2 data accessible through JavaScript code within GEE's code editor. The editor allows users to develop algorithms, test and preview the code results in real-time without actually downloading the satellite images (Tsai et al., 2018). The GEE as an analysis tool provides many statistical classifiers for pixel-based image classification useful for land-use mapping. Classifiers are Machine Learning Algorithms (MLAs), including Support Vector Machine (SVM), Classification and Regression Tree (CART), Random Forest (RF), and many more. This study explored and applied the RF technique because it has the strength of overcoming the problem of overfitting compared to other MLA. It overcomes this problem by constructing an ensemble of Decision Trees (DTs).

2.3.1. Cloud masking and generation of median composite

GEE allows for various multitemporal methods for cloud detection and masking for Landsat imagery (Mateo-García et al., 2018). In this study, we used a function to detect and handle clouds in a multi-temporal image collection. The function for masking out clouds is based on the "pixel_qa' band of Landsat 8 RS data. Once the cloud masking was complete, we generated the median composite image from the image collections for each year and then added NDVI from the greenest pixels. This formed the final image composite for classification.

2.3.2. Training random forest classifier

The study implemented and tested Random Forest, a pixel-based supervised machine-learning algorithm. To train and test random forest classifier, we used the survey data collected over Google Earth. Manual digitization of cropland, grasslands, forest, bare-land, and other sample areas was done based on high spatial resolution satellite imagery available through the google earth application. We generated 223 samples for training and 106 for testing purposes. Of the 223 testing samples, 56 represented cropland, 40 grassland, 87 forest, 22 bare-land, and 18 represented other land cover types. In the testing samples, 25 represented cropland, 16 grassland, 39 forest, 14 bare-land, and 12 represented other land cover types. The training and testing samples were prepared in a Google Earth Engine Asset then imported into our analysis script. We then extracted corresponding input pixel values at the Landsat image pixel level for both training and testing samples.

Random Forest is an ensemble classifier that the GEE platform performs supervised image classification for land use mapping. It was the most appropriate for this study based on its strength to overcome overfitting and being the most widely used classifier that can manage hundreds of input variables (Shelestov et al., 2017). It integrates a bagging method and randomly selects subsets of features from training samples provided for each tree. In this analysis, we set the main input parameter for the random forest classifier: the number of trees as 1000. We put this large number to improve the accuracy of classification. Belgiu and Drăgu (2016) suggest that about 500 trees are an optimal number of tree counts to achieve accurate results. We performed Random Forest classification in the GEE platform using *ee.Classifier.smileRandomForest* function and then trained it. The function is freely available in the earth engine library of tools.

2.3.3. Accuracy assessment and Image classification

This study performed an accuracy assessment for the trained RF classifier then applied it to make predictions for map generation. We then generated a confusion matrix for each year's image data in GEE. Other parameters for accuracy assessment generated include user and producer accuracy and overall accuracy. Therefore, we used overall accuracy to assess the performance of RF because it makes interpretation easy and is an effective accuracy estimation method (Plourde and Congalton, 2003). The overall accuracy method quantifies the correctly classified test data by the classifier as a percentage. To evaluate the class-level performance, we used the confusion matrix given by the classifier to calculate user and producer accuracies. GEE provides in-built techniques to produce the accuracy assessment for RF classifiers. The techniques used to generate accuracy statistics include *accuracy*, *producersAccuracy*, *errorMatrix,* and *consumersAccuracy* functions, which are provided freely in GEE. A producer's accuracy is a value that gives the probability that a particular area is correctly classified. On the other hand, the user's accuracy gives a chance that an area classified on the map is actually that land cover on the ground (Banko, 1998). The overall accuracy of the classification is the probability obtained by dividing the sum of the values in the main diagonal by the total number of pixels assessed, which in this study was 106 samples. Once we were satisfied with the accuracy results, we downloaded classified land cover maps from GEE for further analysis in ArcGIS software.

2.4. Temporal change detection

It is vital to assess the Spatio-temporal patterns of land cover change because they help understand land use processes (Lin et al., 2020). Land cover change patterns help policymakers adopt and implement appropriate management practices for sustainable environmental development (Tsai et al., 2018). Therefore, quantifying the gains and losses of major land cover types is essential to understand the study area trends better. We calculated land cover changes using equations adapted from Lin et al. (2020). The equations are as follows:

$$K_{gain} = S_b - S_a \tag{2}$$

$$K_0 = S_{b_i} = S_{a_i} \tag{3}$$

$$K_{loss} = S_a - K_0 \tag{4}$$

where S_a and S_b denote land cover types at the beginning and end year (time) in a given period (5 years), respectively. S_{ai} and S_{bi} denote land cover types with no change between the beginning and end year (time).

Change detection analysis was done in ArcGIS software through the ArcToolbox set of tools. Classified images were clipped to the boundary of the forest blocks then converted to vector format for geoprocessing through the intersection tool. The intersection process allowed the conversion of landcover information for all the years into one database in tabular form for change detection. We then calculated the total area covered by each class to detect a change and then summarized it into percentage change.

2.5. Literature review

The literature review was undertaken to supplement the findings of this study and establish the drivers of forest cover change over time from earlier studies conducted in the Cherangany forest ecosystem. The databases used for literature search include Google Scholar, ResearchGate, SpringerLink, Scopus, and ScienceDirect. The searches were performed in June 2021 for peer-reviewed articles and review articles. Only English language journals were selected for consideration as we focused our search on studies published after the year 2000.

We also reviewed government reports, policies, and strategic documents relevant to our study, including; The Forest Conservation and Management Act (2016), Kenya Forest Service Strategic Plan (2017), Cherangani Hills Forest Strategic Ecosystem Management Plan (2015), Kenya Water Towers Status Report for Cherangany Hills (2020) and the County Integrated Development Plans (Trans-Nzoia, 2018–2022; Elgeiyo-Marakwet, 2013–2017; West Pokot, 2018–2022).

The flowchart below (Fig. 3) shows a summary of our study methodology.

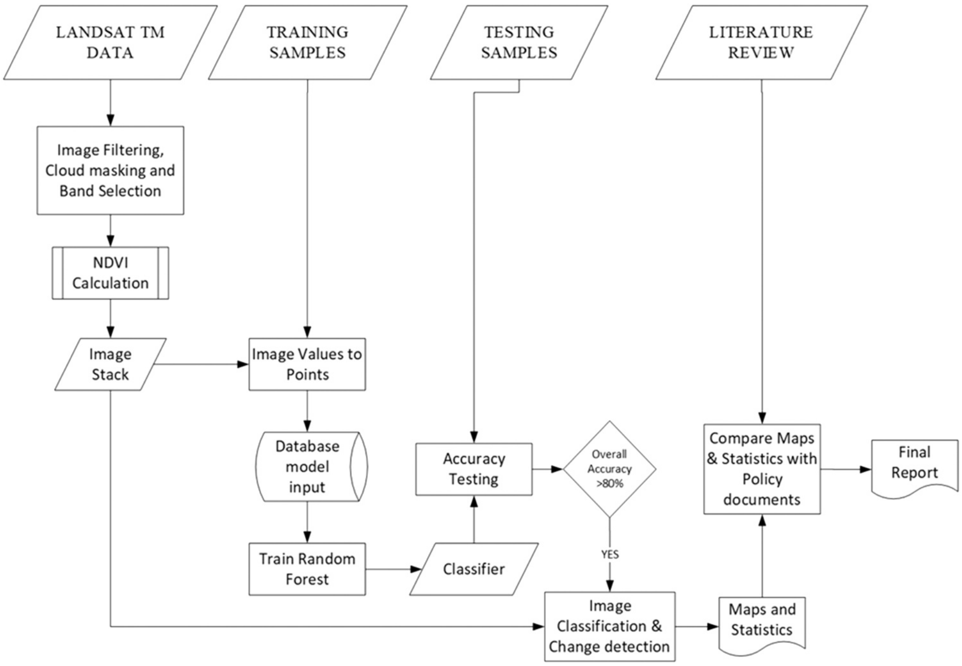

Fig. 3. Flowchart showing a summary of the study methodology.

3. Results

3.1. Classification accuracy

Confusion Matrix and Statistics were generated to assess the accuracy of the maps. Table 2 shows accuracy metrics, confusion matrix, test kappa, and overall accuracy results. The table presents calculations from the mapped land cover classes (columns) and reference data in the rows. The main diagonal of the matrix table shows the correctly classified pixels useful in the accuracy assessment. The study produced maps with an overall accuracy of about 82%, with kappa statistics of about 76%. It is evident from Table 2 that there is a classification mix between grassland and cropland classes with producer accuracy of 68.8% and 96%, respectively. There is also evidence of spectral mixture between cropland, bare-land, and others classes. Therefore, interpretation of these results was made with these spectral mixtures in consideration. The forest cover class had the highest producer accuracy (100%) compared to other classes. This being the class of interest for this study, the results allowed for change analysis.

Table 2
Confusion Matrix and Statistics.

	Cropland	Grassland	Forest	Bareland	Others	Total	Producer Acc
Cropland	**24**	1	0	0	0	25	96.0%
Grassland	3	**11**	1	0	1	16	68.8%
Forest	0	0	**39**	0	0	39	100.0%
Bareland	5	0	0	**8**	1	14	57.1%
Others	4	1	1	1	**5**	12	41.7%
Total	36	13	41	9	7	**106**	
User Acc.	66.7%	84.6%	95.1%	88.9%	71.4%		
Test Kappa	**75.8%**	Overall Acc.	**82.1%**				

3.2. Land cover maps

The land cover maps from the years 1985, 2000, 2005, 2010, 2015, and 2020 were produced using the random forest for supervised image classification. The land cover types include forest, cropland, grassland, Bareland, and others (water features and built-up). Forest was the dominant land cover type for all the years, but it is visible from the maps that a significant forest cover change occurred in the last decade of the selected years (2010–2020) compared to the preceding decades. The eastern forest blocks (Lelan, Embobut, Kipkunur, and Kapchemutwa) were the most affected by the change, as shown in Fig. 4 below.

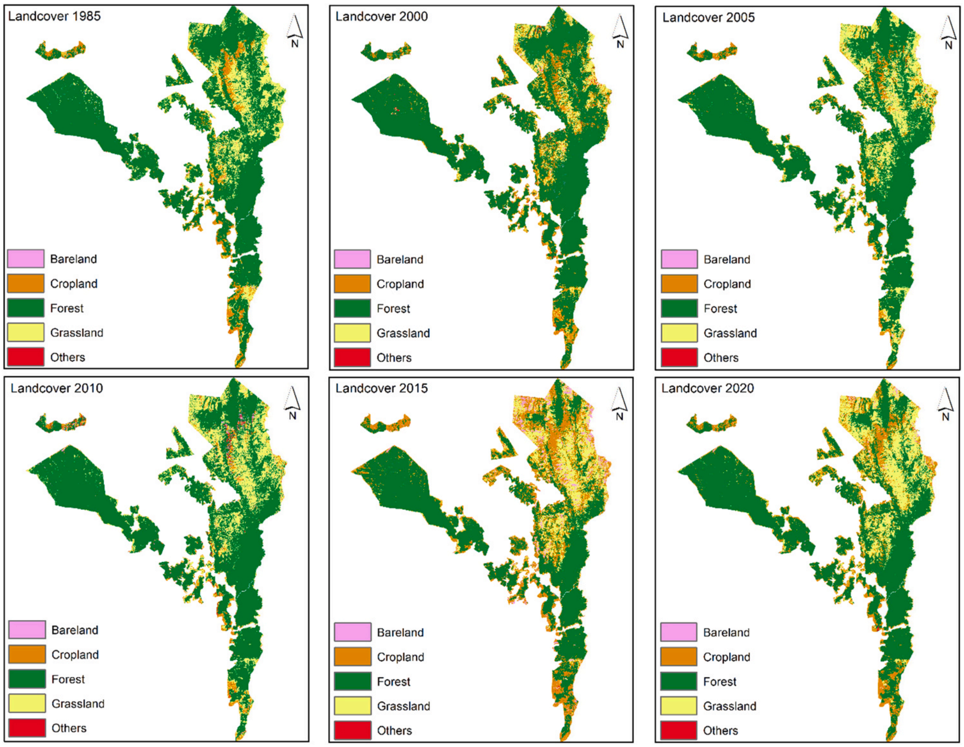

Fig. 4. Land cover maps of the Cherangany forest ecosystem for the years 1985, 2000, 2005, 2010, 2015 and 2020.

3.3. Land cover analysis

Though our main objective was to find out forest cover changes over time, we also considered other major land cover classes in the study area to get the comprehensive change in forest cover over other land cover classes. The area (ha) and proportion (%) of the different land cover categories in the study area for the selected years were analyzed and summarized as shown in Table 3 below.

Table 3
Area (ha) and proportion (%) of the land cover categories in the study area in 1985, 2000, 2005, 2010 and 2020.

	1985		2000		2005		2010		2015		2020	
Land cover	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
Bareland	283.0	0.3	472.6	0.5	500.5	0.5	1878.2	1.9	3560.8	3.6	668.3	0.7
Cropland	7593.3	7.8	13,270.8	13.6	8083.8	8.3	5537.0	5.7	25,697.9	26.3	15,537.7	15.9
Forest	75,818.8	77.7	71,960.9	73.7	69,766.3	71.5	67,586.5	69.2	53,029.3	54.3	62,036.5	63.6
Grassland	13,673.4	14.0	10,991.7	11.3	18,972.6	19.4	21,690.5	22.2	15,269.0	15.6	19,289.2	19.8
Others	237.4	0.2	909.9	0.9	282.8	0.3	913.8	0.9	49.1	0.1	74.2	0.1

3.4. Land cover patterns

The year 1985 had the highest forest cover area of 75,819 ha (77.7%), while 2015 recorded the lowest forest cover at 53,029 ha (54.3%). The area under croplands was highest in 2015 at 25,697 ha (26.3%) and lowest in 2010 at 5537 ha (5.7%). As for the grassland, the highest area was registered in 2010 at about 21,690 ha (22.2%), while the lowest area occurred in the year 2000 at about 11,000 ha (11.3%). Bareland and others land cover sizes were below 10,000 ha for all the years. On average, the forest had the highest cover at about 66,700 ha, followed by grasslands (16,648 ha), cropland (12,620 ha), Bareland (1227 ha), and others (411 ha). Fig. 5 below shows the patterns of the various land cover categories for the selected years.

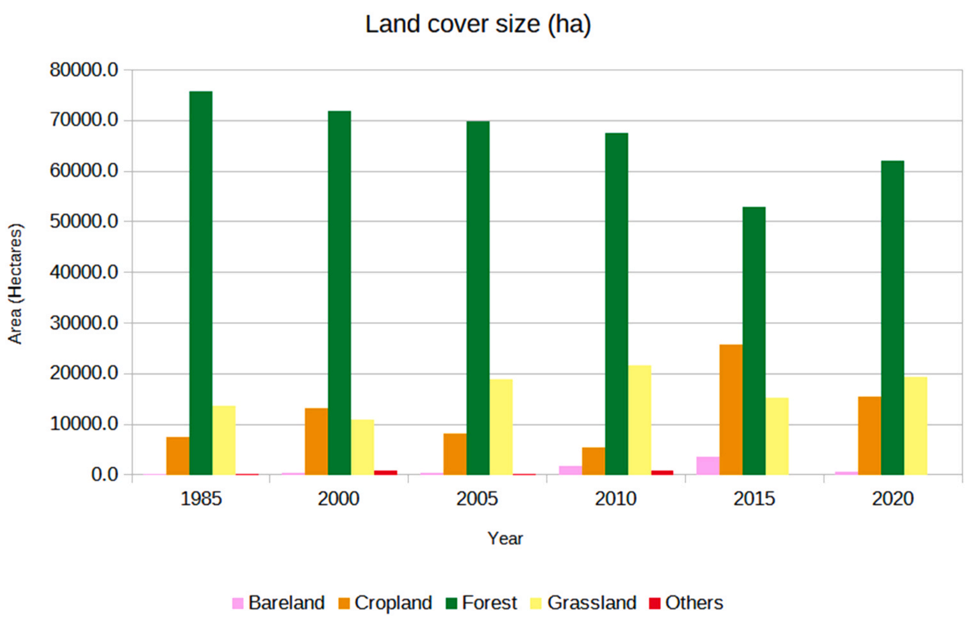

Fig. 5. A bar chart showing land cover areas in hectares in Cherangany forest ecosystem.

3.5. Land-cover change trends

The different land cover types changed with time, as shown in Table 4 below. Overall, there was a decline in forest and others (water features and built-up) land cover types while croplands, grasslands, and Bareland registered gains. The percentage area under forests declined by about 14.1% (13,782 ha) during the 35-year period (1985–2020). This decline translates to an annual average forest loss of 0.40% or 394 ha. The highest forest cover loss occurred between 2010 and 2015, where 14,557 ha (14.9%) of the forest was lost. It is worth noting that there was a constant decline in the forest cover from 1985 to 2015 resulting in an overall loss of 23.4% (22,790 ha), after which a positive gain of 9.3% (9007 ha) was registered between the years 2015 and 2020. Conversely, cropland and grassland registered an increase of about 8.1% and 5.8%, respectively, over the 35-year study period. Bareland had a low positive change of 0.4%, while others (water features and built-up) showed a minimal net loss of 0.1%.

Table 4
Land cover changes in Cherangany forest ecosystem for the period 1985–2020.

Land cover type	1985–2000		2000–2005		2005–2010		2010–2015		2015–2020		1985–2020			
	%	Ha	%	Ha	%	Ha	%	Ha	%	Ha	Net % change	Net area change (ha)	Mean Annual Change (%)	Mean Annual Change (ha)
Bareland	0.2	189.6	0	27.9	1.4	1377.7	1.7	1682.6	-2.9	-2892.5	0.4	385.3	0.01	11
Cropland	5.8	5677.5	-5.3	-5187	-2.6	-2546.8	20.6	20,160.9	-10.4	-10160.2	8.1	7944.4	0.231	227
Forest	-4	-3857.9	-2.2	-2194.6	-2.3	-2179.8	-14.9	-14557.2	9.3	9007.2	-14.1	-13782.3	-0.402	-393.8
Grassland	-2.7	-2681.7	8.1	7980.9	2.8	2717.9	-6.6	-6421.5	4.2	4020.2	5.8	5615.8	0.166	160.5
Others	0.7	672.5	-0.6	-627.1	0.6	631	-0.8	-864.7	0	25.1	-0.1	-163.2	-0.003	-4.7

3.6. Forest conversion to other land cover types

The results show that forest conversion to cropland and grassland were the key transitions in the Cherangany ecosystem over the stipulated study period. The trends of area conversion from forest to cropland and forest to grassland between 1985 and 2020 are shown in Fig. 6 below. Conversion of forest to cropland was highest between 2010 and 2015 (6000 ha), while forest to grassland peaked between 2000 and 2005 (4500 ha). The period between 2015 and 2020 recorded the lowest conversion of forest to both cropland and grassland at less than 1000 ha.

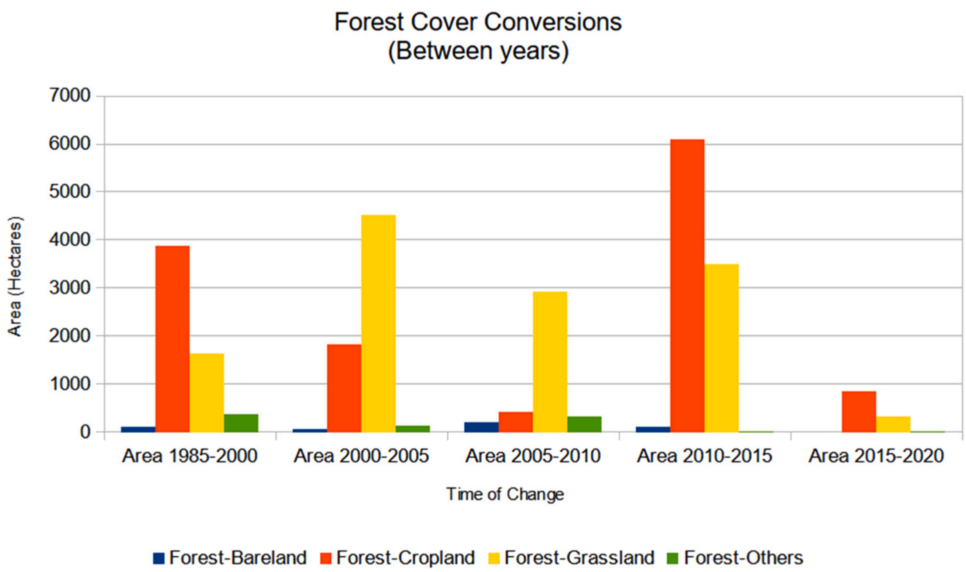

Fig. 6. A bar chart showing forest conversion trends in the Cherangany forest ecosystem between the years 1985 and 2020.

4. Discussion

4.1. Forest cover change

There was an overall decline in the forest cover over the 35-year study period resulting in a loss of about 13,782 ha of forest. Conversely, croplands and grasslands increased by 7944 ha and 5615 ha, respectively. This makes agricultural expansion and grazing the two most dominant direct causes of deforestation in the area. Our findings corroborate with previous results in the study area showing a decrease in forest cover, albeit over different time frames. Kenya's Ministry of Forestry and Wildlife (2013) reported a 49% reduction in forest cover over 36 years in the study area from 46,450 ha in 1973 to 23,850 ha in 2009. The area under crops increased from 49,950 ha to 99,800 ha over the same period. Similarly, a Land use and Land Cover analysis by the Kenya Water Towers Agency (2020) in the Cherangany forest ecosystem between 1990 and 2019 also showed a reduction in forestland by 15% (10,352 ha) while the croplands and grasslands increased by 7108 ha and 3223 ha respectively. Nationally, research has shown a similar trend of forest cover losses in Kenya's montane forests, especially the other prominent water towers (Akotsi et al., 2006; Masayi et al., 2021; Odawa and Seo, 2019).

Contrary to our findings, a LULC change detection analysis using a similar methodological approach in the drylands of Pokot Central over three decades (1986–2017) revealed an increase in woody vegetation at the expense of grassland as the most prevalent change despite both study areas being within the same administrative boundary of West Pokot County (Petersen et al., 2021a). This discrepancy in LULC change can be attributed to the underlying divergent livelihood pathways, climatic conditions, and socio-economic backgrounds between the two locations within the same County. A Similar trend of LULC changes was observed within two spatially proximate locations of Laikipia County, Kenya (Roden et al., 2016).

4.2. Drivers of forest cover change

Deforestation and forest degradation have been the root cause of the 23.4% decline in forest cover in the Cherangany ecosystem from 1985 to 2015. Settlement within the forest blocks and encroachments has escalated the conversion of forest to cropland and grazing land (Fig. 6), recurrence of forest fires in the ecosystem through arsonist, charcoal production, and illegal logging. This has impacted the well-being of the ecosystem and the forest cover. Overall, these findings are in accordance with findings reported by Hosonuma et al. (2012) in 100 developing countries within Africa, Asia, and Latin America, where they established that commercial and subsistence agriculture were the leading causes of deforestation while forest degradation was mainly due to timber logging, charcoal production, fuelwood extraction, forest fires and livestock grazing in the forests.

Excisions by the local authority government and politicians for agriculture and settlement purposes were rampant in Kenya in the 1980 s through1990s and early 2000 s, motivated by individual political interests or private gain (Government of Kenya, 2010). Affected forest blocks in the Cherangany forest ecosystem are the Lelan forest block and its constituent Kapkanyar block. Two major excisions were effected in 1988 where 13,786 ha was excised out of the originally gazetted 28,606 ha of Lelan forest block and 4563 ha excised out of 10,600 ha Kapkanyar forest block. In the ensuing years, encroachment by the settled communities further progressed into the remaining gazetted forested area and currently accounts for the loss of about 7600 ha (West Pokot County, 2018). There has also been a notable conversion of Kapolet forest reserve sections to farmland over 20 years, as reported by the Kenya Water Towers Agency (2020). Excision is not unique to the study area as they have occurred in other major water towers of Kenya in the past, including the Eastern (35,301 ha) and South Western (22,797 ha) blocks of the Mau Forest, Mount Kenya forest reserve (6361 ha) and the Chebyuk settlement scheme of Mount Elgon forest (8700 ha). Most excisions are politically motivated for purposes of settlement and agriculture in a bid to purchase communities' allegiance and maintain political support (Albertazzi et al., 2019; Kenya Wildlife Service, 2010; Laman et al., 2001). This often results in further encroachment by the settled communities beyond the allocated areas hence forest degradation and reduced forest cover.

Increased population also results in demand for more land for farming and settlement leading to encroachment into forested areas (County Government of Trans Nzoia, 2018; Elgeyo Marakwet County, 2013; West Pokot County, 2018). There has been a steady increase in the human population over time in the three administrative counties within which the Cherangany forest ecosystem lies from 903,131 people in the year 1989 to 1,611,582 people in the recently conducted national census of 2019. This translates to a 78.4% rise in population in the three counties combined (Kenya National Bureau of Statistics, 2019). The human population living within the Cherangany water tower was estimated at 530,287 people in 2009 (Kenya National Bureau of Statistics, 2009). Amongst the 14 administrative forest blocks, Kapolet had the highest population of 43,227 people, followed by Embobut (41,531) people, while Toropket recorded the least population (Kenya National Bureau of Statistics, 2019). Our findings are in agreement with that by Petersen et al. (2021a), who attributed deforestation and a decrease in canopy cover in Pokot Central to agricultural expansion and increased settlements. A study by Odawa and Seo (2019) in the Mau water tower in Kenya found a significant negative relationship between forest cover and population increase. The Kenya Forest Service (KFS) also notes that population growth exerts pressure on forests, agricultural land, and protected areas, leading to encroachment and eventually degradation (Kenya Forest Service, 2017). Changes in forest cover, forest fires, illegal logging, soil degradation, and biodiversity loss have all been linked to rapid population increase in a number of studies locally, regionally, and globally (Hunke et al., 2015; Lanz et al., 2018; Marchant et al., 2018; Odawa and Seo, 2019).

Embobut Forest block has experienced significant encroachments by the surrounding communities in the past, with the pinnacle of encroachment occurring between 2010 and 2014. A report by the Embobut Forest Task Force constituted by the Ministry of Forestry and Wildlife (2010) notes that by the year 2008, about 16,000 ha of the forest was under human encroachment. Approximately 19,500 people were living illegally in the forest. Large forest areas were extensively cleared for agricultural activities and settlements, which explains the momentous decline in forest cover within the said period. The trend was gradually reversed from the year 2014 when the communities who had invaded the forest were evicted to allow for its restoration. About 2874 community members were identified by the Embobut Task Force and compensated with KES 410,000 (4585 USD) to move out of the forest and find alternative areas of settlement (Ministry of Forestry and Wildlife, 2010). Encroachment has also been reported in Lelan, Kiptaberr, Kamatira, Kapkanyar, and Toropket forest blocks of the Cherangany forest ecosystem (Ministry of Environment and Forestry, 2020; Rotich et al., 2020). The encroachments have been worsened by a lack of clear forest boundary demarcation in some forest blocks (Embobut, Kapolet, Kapkanyar, Kiptaberr, Kaisungor) within the ecosystem.

Most of rural Kenya's communities livelihoods are anchored on mixed farming, where locals engage in crop production and livestock keeping (Ulrich et al., 2012). Livestock grazing and associated activities in the Cherangany hills forest ecosystem contribute to forest degradation. Free-range grazing practiced in Lelan, Embobut, and Kamatira forests are characterized by large numbers of livestock (cattle, sheep, and goats) herded in the forest, especially during the dry seasons. The large herds of livestock destroy the undergrowth by trampling and browsing on young trees and seedlings, hampering the natural regeneration process and reversing the rehabilitation efforts (Ministry of Environment and Forestry, 2020). The makeshift shelters constructed using tree products by some nomadic herders also contribute to forest degradation.

Unsustainable wood extraction is another key driver of forest cover changes in the study area and rural Kenya in general. Wood extraction occurs in the form of commercial logging in plantation forests and illegal logging in natural forests for timber, firewood harvesting, and charcoal production for both domestic use and commercial purposes (Bergmann et al., 2019; County Government of Trans Nzoia, 2018; Ministry of Forestry and Wildlife, 2013; Petersen et al., 2021b; Republic of Kenya, 2018). Increased demand for timber and building poles has led to illegal chainsaw logging of indigenous tree species. Our findings are directly in line with previous findings by Kimutai and Watanabe (2016), who report that illegal logging of Lembus forest in Western Kenya is among the leading causes of forest degradation. A socio-economic study conducted by the Kenya Water Towers Agency (2020) established that about 68% of the houses in the study area were built using materials acquired from the nearby state forest blocks. It is estimated that more than 90% of the poor rural populations in developing nations rely on fuelwood for energy, while about 80% of the urban poor rely on charcoal to meet their daily domestic energy needs (Remedio, 2002; Sampe and Pakiding, 2015). Garekae et al. (2019) further report that 75% of the rural households in Chobe enclave of Botswana are highly dependent on forests for the provision of household energy needs and construction materials. Charcoal production plays an integral role in most rural Kenya communities' livelihoods as it is a key income-generating activity for meeting basic family needs like food and clothing (Bergmann et al., 2019; Petersen et al., 2021b). Over-dependence on fuelwood and charcoal as a primary energy source at the household level in the Cherangany hills ecosystem has increased charcoal production and firewood collection (Rotich et al., 2020; West Pokot County, 2018). The availability of a ready market for timber, charcoal, and firewood in the nearby urban towns such as Kapenguria, Kitale, Kapcherop, Tot, and Iten has further aggravated the situation. These findings complement that of Bergmann et al. (2019), who note that while most charcoal consumers are located in urban and peri-urban settings, it is the rural populations who meet the ever-growing demand for charcoal and in doing so contribute to deforestation and land degradation in the rural areas through their production-end practices. A study by Petersen et al. (2021a) showed that local communities in Central Pokot perceived wood extraction for charcoal production as an important driver of tree cover loss in addition to increased settlements and farming, with the preferred tree species for charcoal production almost facing extinction.

Forest fires are frequent in the study area, especially during the dry seasons from December to February (Rotich, 2019). The fires emanate from slash and burn land preparation methods, use of fire during honey harvesting, wildfires, burning of grazing land to allow for pasture regeneration, and arsonists who use fire to divert attention from their illegal activities in the forest. In 1986, a forest fire in Cherangany forest destroyed hundreds of hectares in the Kapkanyar forest block, resulting in biodiversity loss and reduced forest cover. These findings are consistent with research by Nyongesa and Vacik (2018) who report arson, honey collection, and charcoal production as the leading causes of fires in Gathiuru forest, Mount Kenya leading to loss of wildlife habitat and wildlife, water and air pollution, and soil erosion.

Climatic conditions have changed over the years in the study area (County Government of Trans Nzoia, 2018). An analysis of the study area's historical climatic data by Mwangi et al. (2020) shows a decreasing rainfall trend during the March-April-May (MAM) primary rainy season and a subsequent reduction in length of the growing period by five days. Temperatures also showed a rising trend ranging from 0.3°C to 0.5°C per decade from 1981 to 2010 with a predicted rise of between 3.0°C to 3.5°C by the 2050 s. This could be the reason for reduced forest cover over the said period and could further affect the species composition, regeneration capacity, and ultimately the forest cover in the future. Many studies have reported climate change as a driver of forest cover change, especially in the tropics and subtropics (Brack, 2019; Kirilenko and Sedjo, 2007; Somorin, 2010).

Policy and institutional failures in the form of poor governance, administration, and management of forest resources contribute to deforestation and forest degradation in Kenya. Despite the existence of forest institutions in Cherangany forest, deforestation and forest degradation have continued over the years due to weak enforcement of existing forest laws as a result of limited institutional capacity in terms of staffing, equipment, and resources. Political interferences and integrity issues among the enforcing officers have further curtailed conservation efforts (Government of Kenya, 2010). Khuc et al. (2018), in their study, identified poor province-scale forest governance among the drivers of deforestation and forest degradation in Vietnam.

Reforestation coupled with enhanced protection for natural regeneration and rehabilitation has been at the forefront of restoration activities in the study area after the enactment of the new Forest Conservation and Management Act of 2016, which repealed and replaced the Forest Act of 2005. This accounts for the gain (9.3%) in forest cover between 2015 and 2020. The reforested Cherangany forest landscape area in the ensuing period is approximated at 2000 ha stretching from West Pokot to Elgeyo Marakwet counties.

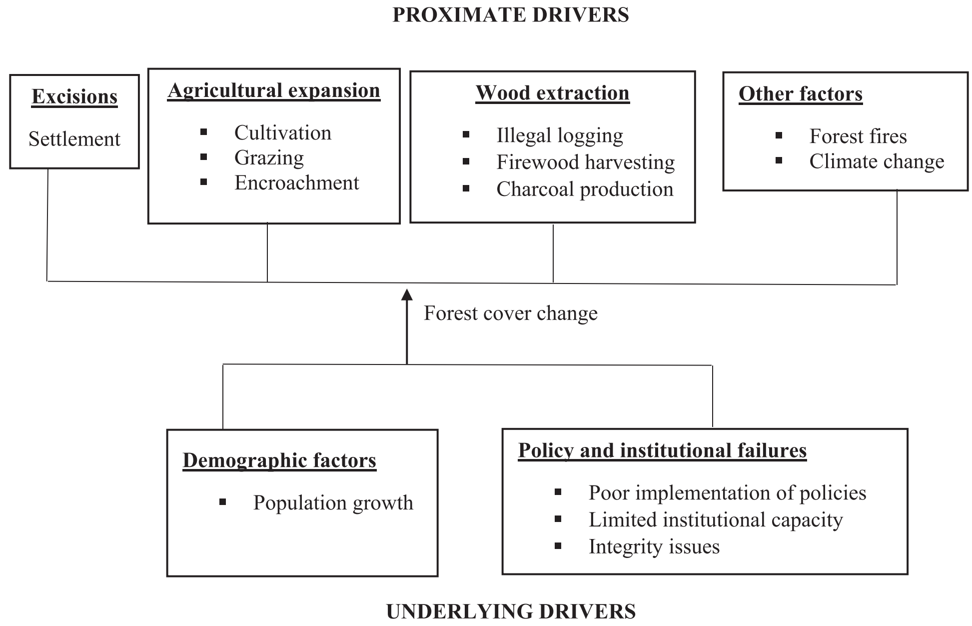

Fig. 7. Schematic diagram showing the proximate and underlying drivers of forest cover change in Cherangany hills forest ecosystem Adapted from Geist and Lambin (2002).

Enhanced community participation in forest activities through Community Forest Associations (CFAs) has improved conservation through reforestation, rehabilitation, and joint monitoring with KFS. Strengthened forest security personnel and multi-agencies security operations involving General Service Unit (GSU), Administration Police (AP), and regular police have further allowed for the natural regeneration of the previously degraded forest blocks. Other public and private actors in the region have also been actively involved in fostering environment security for the ecosystem to regain its health and integrity functions to supply ecosystem goods and services.

In summary, therefore, the drivers of forest cover changes in the Cherangany hills forest ecosystem can be categorized as either proximate/direct or underlying/indirect, as shown in Fig. 7.

5. Conclusion

This study establishes the use of RS and GIS combined with literature review as a cost-effective and time-efficient tool for monitoring forest cover change trends and their drivers. Our analysis reveals a general decline in the forest cover over the 35-year study period in the Cherangany hills forest ecosystem with varying magnitudes between the selected years. There was a continuous forest cover decline trend from the years 1985–2015, after which forest gain was realized from 2015 to 2020. Primarily, forest loss occurred as a result of conversion to croplands and grasslands. The hotspots of forest cover change in the study area are also visible from the generated land cover maps (Fig. 4). Forest cover change was a product of proximate and underlying drivers, which are typically interlinked. Proximate drivers of forest cover changes in the ecosystem include conversion of forests to croplands and grasslands, grazing, encroachment, illegal logging, firewood harvesting, charcoal production, forest fires, excisions, and climate change, while indirect drivers comprise population growth and institutional failures.

Restoration of the Cherangany forest ecosystem will require a multi-agency approach intervention, the Whole of Government (WoG) Approach, with the inclusion of Civil Societies forming the Whole of Nations (WoN) Approach. Collaboration with the adjacent forest communities and CFAs, investments in alternative sources of livelihoods and energy and Income Generating Activities (IGAs) to reduce forest dependency, enhanced seedling production *in-situ* and *ex-situ* targeted at increasing forest cover at large scale, adoption of integrated fire management to reduce the frequent forest fires and broader involvement of the international community (European Union, World Bank, United Nations Environment Program) in funding conservation programs will also go a long way in achieving the restoration goals.

This study's findings can guide the relevant government, community, and non-Governmental conservation agencies and organizations in their conservation and restoration efforts by focusing on the degradation hotspots.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Open access publishing funding provided by the Hungarian University of Agriculture and Life Sciences (Szent István University).

CRediT authorship contribution statement

Brian Rotich: Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Dennis Ojwang**: Conceptualization, Formal analysis, Methodology, Writing – review & editing.

Declaration of Competing Interest

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

Acknowledgments

The authors wish to express their gratitude to Dr. Benjamin Kinyili for proofreading the first draft of this paper and the anonymous reviewers for their valuable comments and suggestions.

References

Aju, P.C., Iwuchukwu, J.J.I., Ibe, C.C., 2015. Our forests, our environment, our sustainable livelihoods. Eur. J. Acad. Essays 2 (4), 6–19. www.euroessays.org.

Albertazzi, S., Bini, V., Lindon, A., Trivellini, G., Relat. Power Driv. Trop. deforestation: a case Study Mau For. (Kenya) 2019 0 19 doi: 10.4000/belgeo.24223.

Banko, G., 1998. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data and of Methods Including Remote Sensing Data in Forest Inventory. INTERIM REPORT IR-98–081 /November 1998.

Belgiu, M., Drăgu, L., 2016. Random forest in remote sensing: a review of applications and future directions. ISPRS J. Photogramm. Remote Sens. 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011.

Bergmann, C., Roden, P., Nüsser, M., 2019. Contested fuelscapes: producing charcoal in sub-Saharan drylands. Area 51 (1), 55–63. https://doi.org/10.1111/area.12394.

County Government of Trans Nzoia, 2018. County Integrated Development Plan 2018–2022 of Trans Nzoia County.

Elmore, A.J., Mustard, J.F., Manning, S.J., Lobell, D.B., 2000. Quantifying vegetation change in semiarid environments. Remote Sens. Environ. 73 (1), 87–102. https://doi.org/10.1016/S0034-4257(00)00100-0.

FAO, 2020. Global Forest Resources Assessment 2020: Main report.Rome. https://doi.org/10.4324/9781315184487-1.

FAO, 2015. Global Forest Resources Assessment 2015, Rome, Italy.

Garekae, H., Lepetu, J., Thakadu, O.T., 2019. Forest resource utilisation and rural livelihoods: Insights from Chobe enclave, Forest resource utilisation and rural livelihoods: insights from Chobe enclave, Botswana. South Afr. Geogr. J. 00 (00), 1–19. https://doi.org/10.1080/03736245.2019.1606730.

Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation. BioScience 52 (2), 143–150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2.

Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., Romijn, E., 2012. An assessment of deforestation and forest degradation drivers in developing countries. Environ. Res. Lett. 7 (4), 044009 https://doi.org/10.1088/1748-9326/7/4/044009.

Hunke, P., Mueller, E.N., Schröder, B., Zeilhofer, P., 2015. The Brazilian Cerrado: assessment of water and soil degradation in catchments under intensive agricultural use. Ecohydrology 8 (6), 1154–1180. https://doi.org/10.1002/eco.1573.

Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J.V., Grainger, A., Lindquist, E., 2015. Dynamics of global forest area: results from the FAO Global Forest Resources Assessment 2015. For. Ecol. Manag. 352, 9–20. https://doi.org/10.1016/j.foreco.2015.06.014.

Kenya Forest Service, 2017. Kenya Forest Service Strategic Plan. GoK Printers, pp. 2017–2022.

Kenya National Bureau of Statistics, 2009. The 2009 Kenya Population and Housing Census - Population and Household Distribution by Socio-economic Characteristics: Vol. II.

Kenya National Bureau of Statistics, 2019. Kenya population and housing census volume 1: Population by County and sub-County. In Kenya National Bureau of Statistics: Vol. I (Issue November). https://www.knbs.or.ke/?wpdmpro=2019-kenya-population-and-housing-census-volume-i-population-by-county-and-sub-county.

Kenya Water Towers Agency, 2020. Kenya Water Towers Status Report for Cherangany Hills.

Kenya Wildlife Service, 2010. Mt Kenya Ecosystem Management Plan, 2010–2020.

Khuc, Q. Van, Quang, B., Meyfroidt, P., Paschke, M.W., 2018. Forest policy and economics drivers of deforestation and forest degradation in Vietnam: an exploratory analysis at the national level. For. Policy Econ. 90 (February), 128–141. https://doi.org/10.1016/j.forpol.2018.02.004.

Kimutai, D.K., Watanabe, T., 2016. Forest-cover change and participatory forest management of the lembus forest, Kenya. Environ. - MDPI 3 (3), 1–18. https://doi.org/10.3390/environments3030020.

Kirilenko, A.P., Sedjo, R.A., 2007. Climate change impacts on forestry. Proc. Natl. Acad. Sci. U.S.A. 104 (50), 19697–19702.

Kogo, B.K., Kumar, L., Koech, R., 2019. Forest cover dynamics and underlying driving forces affecting ecosystem services in western Kenya. Remote Sens. Appl. Soc. Environ. 14 (January), 75–83. https://doi.org/10.1016/j.rsase.2019.02.007.

Kumar, D., 2011. Monitoring forest cover changes using remote sensing and GIS: a global prospective. Res. J. Environ. Sci. 5 (2), 76–88. https://doi.org/10.1201/9781420033564-12.

Kweyu, R.M., Thenya, T., Kiemo, K., Emborg, J., 2020. The nexus between land cover changes, politics and conflict in Eastern Mau forest complex, Kenya. Appl. Geogr. 114 (November 2019), 102115 https://doi.org/10.1016/j.apgeog.2019.102115.

Laman, M., Khamati, B., Milimo, P., 2001. Mount Elgon Integrated Conservation and Development Project (MEICDP): External Evaluation Final Report By (Issue March).

Lanz, B., Dietz, S., Swanson, T., 2018. The expansion of modern agriculture and global biodiversity decline: an integrated assessment. Ecol. Econ. 144, 260–277. https://doi.org/10.1016/j.ecolecon.2017.07.018.

Lin, L., Hao, Z., Post, C.J., Mikhailova, E.A., Yu, K., Yang, L., Liu, J., 2020. Monitoring land cover change on a rapidly urbanizing island using google earth engine. Appl. Sci. 10 (20), 1–16. https://doi.org/10.3390/app10207336.

Marchant, R., Richer, S., Boles, O., Capitani, C., Courtney-Mustaphi, C.J., Lane, P., Prendergast, M.E., Stump, D., De Cort, G., Kaplan, J.O., Phelps, L., Kay, A., Olago, D., Petek, N., Platts, P.J., Punwong, P., Widgren, M., Wynne-Jones, S., Ferro-Vázquez, C., Wright, D., 2018. Drivers and trajectories of land cover change in East Africa: human and environmental interactions from 6000 years ago to present. Earth Sci. Rev. 178 (January), 322–378. https://doi.org/10.1016/j.earscirev.2017.12.010.

Martinez del Castillo, E., García-Martin, A., Longares Aladrén, L.A., de Luis, M., 2015. Evaluation of forest cover change using remote sensing techniques and landscape metrics in Moncayo Natural Park (Spain). Appl. Geogr. 62, 247–255. https://doi.org/10.1016/j.apgeog.2015.05.002.

Masayi, N.N., Omondi, P., Tsingalia, M., 2021. Assessment of land use and land cover changes in Kenya's Mt. Elgon forest ecosystem. Afr. J. Ecol. 2020, 1–16. https://doi.org/10.1111/aje.12886.

Masek, J.G., Hayes, D.J., Joseph Hughes, M., Healey, S.P., Turner, D.P., 2015. The role of remote sensing in process-scaling studies of managed forest ecosystems. For. Ecol. Manag. 355, 109–123. https://doi.org/10.1016/j.foreco.2015.05.032.
Mateo-García, G., Gómez-Chova, L., Amorós-López, J., Muñoz-Marí, J., Camps-Valls, G., 2018. Multitemporal cloud masking in the Google Earth Engine. Remote Sens. 10 (7), 7–9. https://doi.org/10.3390/rs10071079.
Mbuni, Y.M., Wang, S., Mwangi, B.N., Mbari, N.J., Musili, P.M., Walter, N.O., Hu, G., Zhou, Y., Wang, Q., 2020. Medicinal plants and their traditional uses in local communities around cherangani hills, western Kenya. Plants 9 (3). https://doi.org/10.3390/plants9030331.
Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC. https://doi.org/10.5822/978-1-61091-484-0_1 (Island Press, Washington, DC).
Akotsi, E.F.N., Ndirangu, J.K., Gachanja M., Chang. For. Cover Ub. Kenya's Five "Water Tower 2003-2005 2006 45.
Brack, D. (2019). Forests and Climate Change Duncan Brack i the fourteenth session of the United Nations Forum on Forests (Issue c).
Elgeyo Marakwet County, 2013. County integrated development plan (CIDP) 2013–2017. In IMF Staff Country Reports (Vol. 20, Issue 156). https://doi.org/10.5089/9781513543284.002.
Government of Kenya, 2010. REDD readiness preparation proposal Kenya - Annexes to R-PP (Issue April).
Kenya Forest Service, 2015. Cherangani Hills Forest Strategic Ecosystem Management Plan. November, 2015–2040. http://www.kefri.org/wp-content/uploads/PDF/Publications/CheranganiHills Strategic Ecosytem Plan 2015_2040–1.pdf.
Ministry of Environment and Forestry, 2020. INTEGRATED MASTER PLAN FOR RESTORATION AND REHABILITATION OF ELGEYO-CHERANGANY HILLS ECOSYSTEM (Issue July).
Ministry of Forestry and Wildlife, 2010. Embobut Forest Restoration Taskforce Report.
Ministry of Forestry and Wildlife, 2013. Analysis of Drivers and Underlying Causes of Forest Cover Change in Various Types of Forests in Kenya. Kenya Forest Service, 33. http://www.kenyaforestservice.org/documents/redd/ Analysis of Drivers of Deforestation &forest Degradation in Kenya.pdf.
Miura, S., Amacher, M., Hofer, T., San-Miguel-Ayanz, J., Ernawati, Thackway, R., 2015. Protective functions and ecosystem services of global forests in the past quarter-century. For. Ecol. Manag. 352, 35–46. https://doi.org/10.1016/j.foreco.2015.03.039.
Muhati, G.L., Olago, D., Olaka, L., 2018. Land use and land cover changes in a sub-humid Montane forest in an arid setting: a case study of the Marsabit forest reserve in northern Kenya. Glob. Ecol. Conserv. 16, e00512 https://doi.org/10.1016/j.gecco.2018.e00512.
Mwangi, K.K., Musili, A.M., Otieno, V.A., Endris, H.S., Sabiiti, G., Hassan, M.A., Tsehayu, A.T., Guleid, A., Atheru, Z., Guzha, A.C., Meo, T., De, Smith, N., 2020. Vulnerability of Kenya" s water towers to future climate change: an assessment to inform decision making in watershed management. Am. J. Clim. Change 2020 (9), 317–353. https://doi.org/10.4236/ajcc.2020.93020.
Nyongesa, K.W., Vacik, H., 2018. Fire management in Mount Kenya: a case study of gathiuru forest station. Forests 9 (8), 481. https://doi.org/10.3390/f9080481.
Odawa, S., Seo, Y., 2019. Water tower ecosystems under the influence of land cover change and population growth: focus on mau water tower in Kenya. Sustain. (Switz.) 11 (13). https://doi.org/10.3390/su11133524.
Petersen, M., Bergmann, C., Roden, P., Nüsser, M., 2021a. Contextualizing land-use and land-cover change with local knowledge: a case study from Pokot Central, Kenya. Land Degrad. Dev. 32 (10), 2992–3007. https://doi.org/10.1002/ldr.3961.
Petersen, M., Kamurio, C.N., Kortom, C.D., Nüsser, M., 2021b. Charcoal producers and the pandemic: effects of COVID-19 in Pokot Central, Kenya. Erdkunde 75 (2), 121–137. https://doi.org/10.3112/erdkunde.2021.02.04.
Plourde, L., Congalton, R.G., 2003. Sampling method and sample placement: how do they affect the accuracy of remotely sensed maps? Photogramm. Eng. Remote Sens. 69 (3), 289–297. https://doi.org/10.14358/PERS.69.3.289.
Pôças, I., Cunha, M., Marcal, A.R.S., Pereira, L.S., 2011. An evaluation of changes in a mountainous rural landscape of Northeast Portugal using remotely sensed data. Landsc. Urban Plan. 101 (3), 253–261. https://doi.org/10.1016/j.landurbplan.2011.02.030.
Remedio, E.M., 2002. Wood energy and livelihood patterns: a case study from the Philippines. Unasylva 53 (211), 13–18.
Republic of Kenya, 2018. A report on Forest Resources Management and Logging Activities in Kenya: Ministry of Environment and Forestry.Nairobi: Government Printer. April, 131.
Roden, P., Bergmann, C., Ulrich, A., Nüsser, M., 2016. Tracing divergent livelihood pathways in the drylands: A perspective on two spatially proximate locations in Laikipia County, Kenya. J. Arid Environ. 124, 239–248. https://doi.org/10.1016/j.jaridenv.2015.08.004.
Rotich, B., 2019. Forest conservation and utilization in embobut, Cherangani Hills, Kenya. Int. J. Nat. Resour. Ecol. Manag. 4 (1), 7. https://doi.org/10.11648/j.ijnrem.20190401.12.
Rotich, B., Makindi, S., Esilaba, M., 2020. Communities" attitudes and perceptions towards the status, use and management of Kapolet Forest Reserve in Kenya. Int. J. Biodivers. Conserv. 12 (December), 363–374. https://doi.org/10.5897/IJBC2018.1448.
Sampe, F., Pakiding, D.L., 2015. Perception of Traditional Small Scale Brick-making owner on firewood usage for Brick-making process. Procedia Soc. Behav. Sci. 211 (September), 653–659. https://doi.org/10.1016/j.sbspro.2015.11.095.
Shelestov, A., Lavreniuk, M., Kussul, N., Novikov, A., Skakun, S., 2017. Exploring Google earth engine platform for big data processing: classification of multi-temporal satellite imagery for crop mapping. Front. Earth Sci. 5 (February), 1–10. https://doi.org/10.3389/feart.2017.00017.
Sidhu, N., Pebesma, E., Câmara, G., 2018. Using Google Earth Engine to detect land cover change: Singapore as a use case. Eur. J. Remote Sens. 51 (1), 486–500. https://doi.org/10.1080/22797254.2018.1451782.
Somorin, O.A., 2010. Climate impacts, forest-dependent rural livelihoods and adaptation strategies in Africa: a review. Afr. J. Environ. Sci. Technol. 4 (December), 903–912.
Teucher, M., Schmitt, C.B., Wiese, A., Apfelbeck, B., Maghenda, M., Pellikka, P., Lens, L., Habel, J.C., 2020. Behind the fog: forest degradation despite logging bans in an East African cloud forest. Glob. Ecol. Conserv. 22, e01024 https://doi.org/10.1016/j.gecco.2020.e01024.
Townshend, J.R., Masek, J.G., Huang, C., Vermote, E.F., Gao, F., Channan, S., Sexton, J.O., Feng, M., Narasimhan, R., Kim, D., Song, K., Song, D., Song, X.P., Noojipady, P., Tan, B., Hansen, M.C., Li, M., Wolfe, R.E., 2012. Global characterization and monitoring of forest cover using Landsat data: opportunities and challenges. Int. J. Digit. Earth 5 (5), 373–397. https://doi.org/10.1080/17538947.2012.713190.
Tsai, Y.H., Stow, D., Chen, H.L., Lewison, R., An, L., Shi, L., 2018. Mapping vegetation and land use types in Fanjingshan National Nature Reserve using google earth engine. Remote Sens. 10 (6), 927. https://doi.org/10.3390/rs10060927.
Tuffour-Mills, D., Antwi-Agyei, P., Addo-Fordjour, P., 2020. Trends and drivers of land cover changes in a tropical urban forest in Ghana. Trees For. People 2 (June), 100040. https://doi.org/10.1016/j.tfp.2020.100040.
Ulrich, A., Ifejika Speranza, C., Roden, P., Kiteme, B., Wiesmann, U., Nüsser, M., 2012. Small-scale farming in semi-arid areas: livelihood dynamics between 1997 and 2010 in Laikipia, Kenya. J. Rural Stud. 28 (3), 241–251. https://doi.org/10.1016/j.jrurstud.2012.02.003.
Vittek, M., Brink, A., Donnay, F., Simonetti, D., Desclée, B., 2013. Land cover change monitoring using landsat MSS/TM satellite image data over west Africa between 1975 and 1990. Remote Sens. 6 (1), 658–676. https://doi.org/10.3390/rs6010658.
Wekesa, C., Kirui, B.K., Maranga, E.K., Muturi, G.M., 2020. The fate of taita hills forest fragments: evaluation of forest cover change between 1973 and 2016 using landsat imagery. Open J. For. 10 (01), 22–38. https://doi.org/10.4236/ojf.2020.101003.
West Pokot County, 2018. West Pokot County Development Plan, 2018 - 2022.
Zafar, T.B., Ding, W., Din, S.U., Khan, G.M., Hao, C., He, L., 2021. Forest cover and land use map of the Chunati Wildlife Sanctuary based on participatory mapping and satellite images: insight into Chunati beat. Land Use Policy 103 (November 2020). https://doi.org/10.1016/j.landusepol.2020.105193.
Zvobgo, L., Tsoka, J., 2020. COVID-19 and the call for 'Safe Hands': challenges facing the under-resourced municipalities that lack potable water access - a case study of Chitungwiza municipality, Zimbabwe. Water Res. X 9 (December 2020), 100074. https://doi.org/10.1016/j.tfp.2021.100090.