Remote Sensing Applications: Society and Environment 23 (2021) 100586

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

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

Mapping the trends of forest cover change and associated drivers in Mau Forest, Kenya

Alice Jebiwott[a,*], George Morara Ogendi[b], Busuyi Olasina Agbeja[c], Abiodun Akintunde Alo[c], Ronald Kibet[a]

[a] Pan African University Life and Earth Sciences Institute (PAULESI), Private Bag, University of Ibadan, Nigeria
[b] Department of Environmental Science, Egerton University, P.O Box 536-20115, Egerton, Kenya
[c] Department of Forest Resource Management, University of Ibadan, Private Bag, Ibadan, Nigeria

ARTICLE INFO

Keywords:
Forest cover
Land use
Mau forest
Trend analysis
Driving forces

ABSTRACT

Mau Forest in the Rift Valley in Kenya is the largest of the five major water towers in the country and also the largest indigenous montane forest in Eastern Africa. As such, the forest is an important natural resource base not only to the local economy but to the East African region at large. In spite of this, the forest has been highly degraded owing to immense anthropogenic pressure from the forest surrounding communities. The aim of this study was to assess the trends in forest cover and the driving forces leading to its change. Landsat TM images of 1984 and 1995, ETM+ of 2008, and OLI/TIRS of 2020 were used to depict the trend in forest cover for the period between 1984 and 2020. Focus Group Discussions (FGD) and in-depth interviews were also used to get the perceptions and experiences of the local people regarding the trend in forest cover and the associated driving forces. The results from the qualitative data were integrated with those of remote sensing for assessment of trend in forest cover. The study findings indicate a decline of 25.2% of forest cover within the Mau Forest complex in a period four years shy of four decades, amounting to approximately 699 km^2 of tree cover. This trend was fueled by an increasing demand for agricultural land where farmlands increased by 69.9%, as well as logging-legal or illegal-where grassland area increased by 37.2%. Three major drivers of forest cover change identified by the participants include human settlements, logging and expansion of farmlands. We recommend that forest policymakers and managers involve the local community, as the main stakeholders, in all levels of decision making and management so as to promote sustainable use of forest resources and improved management of the forest.

1. Introduction

Forests play a major role not only in environmental protection but also in improving the livelihoods of many communities around the world. Despite this role in environmental protection, forest degradation is still a major problem especially in the developing world (German et al., 2010). This is mainly attributed to lack of understanding and recognition on the benefits of forests on environmental and human wellbeing hence, many anthropogenic practices have contributed to deteriorating water quality and quantity, soil erosion, poor air quality and climate change among many other effects (Douglas and Simula, 2010). According to Owens and Lund (2009), Japan is one of the earliest countries to experience environmental problems due to the destruction of forest cover. The wanton logging of the montane Cryptomeria japonica forests led to the increased incidence of flooding in low-lying areas. In Portugal, forest degradation mostly in the northern part of the Tagus River, was as a result of overgrazing and conversion to wheat farms. This led to soil erosion and eventually decreased soil fertility in the region. Later on, afforestation was carried out to recuperate the eroded soils (Spiecker et al., 2012). Forests have continued to be cut in headwater areas since then, often with disastrous consequences downstream.

The importance of forests in environmental management has long been recognized especially in the developed world where they have been designated as protected areas European Alps (Evans, 2008). In the developing world, forests are also gradually being acknowledged though deforestation and forest degradation are still some major issues affecting its conservation (Temu et al., 2008). With the introduction of the World

* Corresponding author.
E-mail addresses: aliciaphil.chebby@gmail.com (A. Jebiwott), gmorara2009@gmail.com (G.M. Ogendi), olasinagbeja@yahoo.com (B.O. Agbeja), danielakintundealo@gmail.com (A.A. Alo), ronaldlangatkip@gmail.com (R. Kibet).

https://doi.org/10.1016/j.rsase.2021.100586
Received 18 April 2021; Received in revised form 7 July 2021; Accepted 14 July 2021
Available online 30 July 2021

Conservation Strategy in 1980, environmental protection and sustainable development was increasingly connected and has led to a variety of Community Conservation Approaches (Sletten et al., 2008). Different countries have adopted various approaches to conserve forests. For instance, Nepal has different strategies to conserve and utilize its natural resources, and Community Forestry is one of the successful strategies through the active and meaningful involvement of rural communities in forests management. So far, Kenya has adopted several initiatives as a step towards recognizing protection of forests. The country has launched and adopted various initiatives including the REDD programme, Voluntary Partnership Agreement (VPA), AFR100 and Intended Nationally Determined Contributions (INDCs) among others. The REDD + aims to sensitize people on the role of forest cover in protecting our water resources, the atmosphere, control of pollutants and climate change in general. Therefore, there has been an increasing acknowledgement on the importance of forests in global environmental protection (DeShazo et al., 2016).

In Africa, populations are mostly concentrated in the rural areas and most of them are dependent on the forest resources. Approximately 300 million people live in forests, including 60 million indigenous people (FAO, 2010). As such, encroachment of the forests for subsistence farming and settlement is common especially in the sub-Saharan Africa. Other forest degrading activities include livestock grazing, timber production and the extraction of fuel wood. The majority of these activities, if unsustainably managed or left uncontrolled can lead to forest destruction. These anthropogenic activities have negative effects on the global environment, predominantly the emissions of carbon into the atmosphere and loss of biodiversity. Moreover, these human activities may result in the decrease of ecosystem goods and services, decline in land productivity and loss of livelihoods (FAO, 2010). Geist and Lambin (2002), suggest that human responses to changing economic opportunities both at national and international levels is one of the most important determinants of forest cover change. According to FAO (2015), 129M ha of global forest cover was lost between 1990 and 2015 with agricultural expansion as the main driver. The destruction of the forest as an ecosystem will have adverse consequences on both the present and the future generations (Palo and Mery, 2012).

In East Africa, forested mountains are frequently referred to as 'water towers.' Such is the case because they contain many streams and springs that are the sources of major rivers that eventually drain into lakes. The Mau Forest Complex, the largest montane forest in East Africa, is one of such water towers as it is the main water source for twelve rivers that feed into lakes Natron, Victoria and Turkana. The Mau Forest Complex supports the livelihoods of more than 3 million rural people who live in the Lake Victoria Basin and up to 2 million more in urban areas (UNEP, 2012). However, this water tower is facing intense pressures from the anthropogenic activities being undertaken in and around the forest complex. Deforestation and conversion to other land uses, logging, charcoal burning and encroachment for settlement have undermined the ability of this forested landscape to provide critical ecosystem services (Ministry of Forestry and Wildlife, 2013). UNEP's earlier valuation of the ecosystem services of Mau forest and its importance to the economy of Kenya, acted as a catalyst in realizing that this vital ecosystem needed urgent rehabilitation measures to curb further losses (UNEP, 2012). This shows that the country has already acknowledged the significance of forests.

To save this ecosystem from further destruction and collapse, the government of Kenya recently embarked on forceful evictions of thousands of families who had settled in the forest for decades. It is more than fifteen years since the first eviction took place (2004–2006) following the Ndung'u Report (Southall, 2005) and again in 2008 and 2017 following the Mau Forest Task Force report, making it relevant to evaluate the impacts of such evictions on forest cover. It is against this background that this study aimed to assess the forest cover trends, and the associated drivers of change in the Mau Forest ecosystem.

2. Materials and methods

2.1. Study area description

The Mau Complex forests when combined cover an area of over 400,000 ha (KFWG, 2018) and is the largest remaining closed canopy forest block in Eastern Africa. It lies between 0.6114°S and 35.7407°E in the Rift Valley Province of Kenya and spans across four counties: Narok, Nakuru, Bomet and Kericho. Mau Forests constitutes several forests generally classified into seven blocks that include Eastern Mau, Ol'donyo Purro, South-West Mau, Transmara, Maasai Mau, Southern Mau and Western Mau. The Mau Forest Complex is one of the five major catchment areas in Kenya, and is a source of many rivers, including Nzoia, Nyando, Yala, Sondu, Molo, Mara, Kerio, Njoro, Ewaso Ngiro, Njoro, Nderit, Makalia, and Naishi. These rivers in turn drain to major lakes that include Nakuru, Natron, Victoria, Baringo and Turkana (Chrisphine et al., 2016; Odawa and Seo, 2019). Fig. 1 shows the map of the study area.

2.2. Data collection

To assess the trend in forest cover, Landsat satellite images from 1984 to 2020 were used. GIS allows one to visualize, question, analyze, and interpret spatial data and their attributes in order to understand relationships, patterns, and trends. Landsat 5 & 7 imageries for 1984, 1995 and 2008, and Landsat 8 for 2020 were acquired from the web-based data archives of the USGS (Path 169, and Rows 060 & 061) and Google Earth Engine. All images were acquired during the dry seasons when the cloud coverage was minimal. Data specifications are described in Table 1(see Table 4).

Focus group discussion and in-depth interviews were conducted to gather the participants views and perceptions about the forest cover change and the related driving forces. The focus group discussion participants comprised of the local community members who were conveniently selected based on their knowledge of the study area and their willingness to participate in the discussion. The in-depth interviewees were community leaders and the Kenya Forest Service officials as well as Community Forest Association leaders. These participants were considered knowledgeable and experienced enough to provide us with accurate and reliable information regarding the use, changes and management of the forest. The data was used to augment the geospatial information.

2.3. Data analysis

2.3.1. Land cover classification

Areas of interest on the earth's surface have been for decades studied and classified into different land covers using multi-temporal remote sensing data (Butt et al., 2015). Landsat images (5, 7 and 8) were classified across four epochs at twelve-year intervals from 1984 to 2020 using the RandomForest (RF) algorithm. However, the image of the study area for the year 1996 was not available on freely available repositories, hence the study opted for the 1995 image that was closest to the year 1996. Fig. 2 illustrates the land cover classification process.

Training samples were created to represent four land cover classes using ArcGIS. There is no rule of thumb when it comes to selection of the size of training samples for land use and land cover classification. While (Stehman, 2005) noted that it is difficult to perfectly adhere to probability sampling protocols, this study was able to concur with the standard sampling scale for localized classification in remote sensing applications (Praveen et al., 2019). states that is advisable to have a sample size within the range of 80–120 for classes not exceeding five when conducting land cover classification in a small-scale area. The total number of training samples used were 98, 78, 110, and 78 for years 1984, 1995, 2008, and 2020 images respectively. The four distinctive land cover classes selected for this study were:

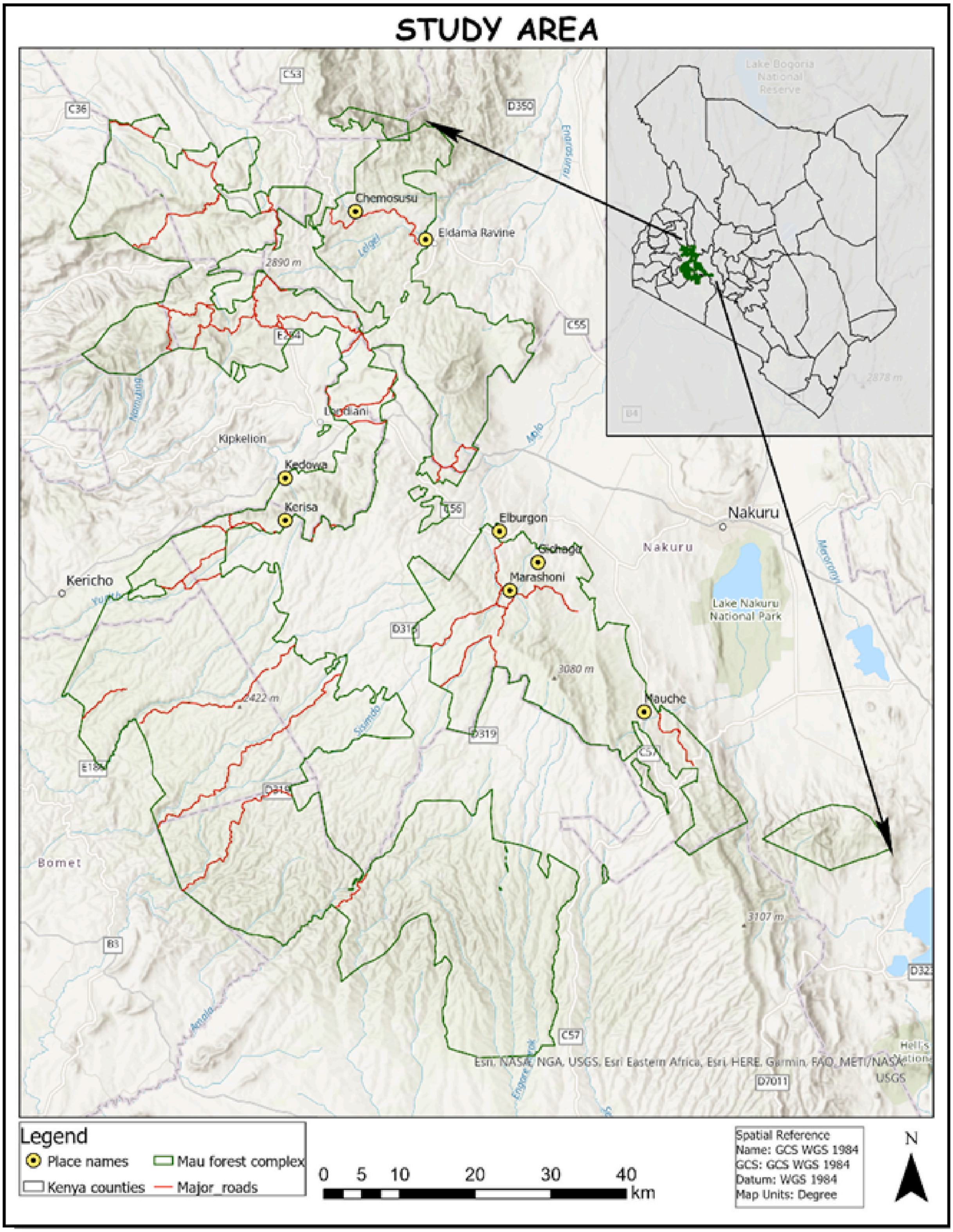

Fig. 1. Map of Mau Forest (Source; author).

Forest cover: This land cover category represented the area covered with mature trees forming clear canopies.

Farmlands: This category represented the area with cultivated crops and ploughed agricultural land. It ranges from personal farmlands to recently established tree plantations with no distinctive trees with visible canopies.

Grassland: This category includes glades, uncultivated lands, and small shrubs.

Other land: This category represented all other classes not falling within the above-mentioned categories. They included bare land, rock outcrops, and water bodies.

Table 1
Secondary data and their specifications.

Data model	Data type	Data source	Date
Landsat 5 & 7	Raster	https://earthexplorer.usgs.gov/	01/07/1984, 06/02/1995 & 31/10/2008
Landsat 8	Raster	Google Earth Engine	27/12/2020
Mau forest boundary	Vector	KFS	2020
Climate data (rainfall and temperature)	Raster	KMD	1984-2020

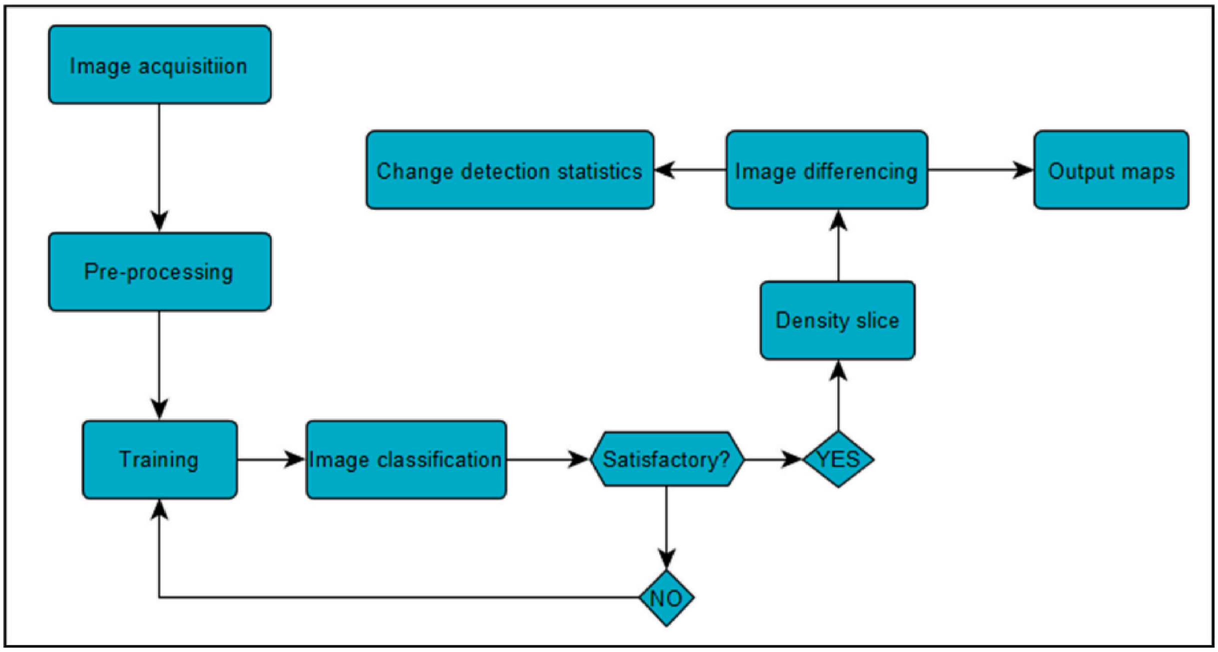

Fig. 2. Land cover classification flowchart.

Supervised classification was then conducted using RandomForest (RF) algorithm outlined in Equations (2.1) to (2).5 (Rodriguez-Galiano et al., 2012). RF is highly recognized for improved accuracy through its capabilities to provide exemplary outputs from small sample sizes (Belgiu and Drăgu, 2016). The input sample size for the training site had to be managed well since the RF algorithm is very sensitive to input data. The number of pixels to be used for training the classification has to be managed properly because the larger the number the bigger the classification tree grows for each land cover class. The repercussion for this is a low-quality classification as the algorithm tries to match too many distinctive pixel values from a big sample size. Several iterations guided by expert judgement, were conducted to ensure the classification output represented features accurately.

RF incorporates distinct classifiers where each classifier contributes one vote in assigning the most intermittent class to the input vector (**Z**),

$$(Z)C^{D}_{rf} = majority\ \ vote\left\{\widehat{C}_n(z)\right\}_1^D \tag{2.1}$$

where $\hat{C}^{D}_{rf}$ is the most intermittent class and $\hat{C}_n(\mathbf{Z})$ is the class probability of the n_{th} tree of the random forest. The RF classification employs base classifiers using trees,

$$\{f(x,\ \Theta_k),\ k=1,\ \ldots,\}, \tag{2.2}$$

Where f is the decision tree, x is the input vector and $\{\Theta_k\}$ the random vectors that are uncontrolled and evenly distributed.

Suitable attribute selection is mandatory for the tree design to augment dissimilarity measurement between classes. Direct feature elimination is achieved using the RF's Gini feature importance (Breiman, 2001), commonly referred to as Gini index. This capability allows for direct elimination of irrelevant features unlike traditional regression methods such as, principal component or partial least squares technique that can only perform well in complex dimensional spectral data learning exercises, but does not offer direct feature expulsion.

The RF classifier achieves direct feature selection hence high-level performance regarding complex data dimensions. It applies a small subset of 'sound variables' used for training reasons only. Therefore, spectral features can be ranked profoundly by distinctively indicating feature relevance. At each node τ, within the binary trees T of the RF, the Gini impurity $i(\tau)$ searched for an optimal split which measure how well the potential split between samples of the two classes in that specific node separates.

$Pk = \frac{nk}{n}$, which is a fraction of n_k samples from class $k = \{0, 1\}$ out of the total n samples at node τ, the Gini impurity $i(\tau)$ is calculated using Equation (2.3).

$$i(\tau) = 1 - p_1^2 - p_0^2 \tag{2.3}$$

with respect to sample fractions $Pl = \frac{nl}{n}$ and $Pr = \frac{nr}{n}$, equation (2.4) defines how a decrease Δi results from splitting and sending the samples to two sub-nodes τ_l and τ_r by a threshold t_θ on variable θ.

$$\Delta i(\tau) = i(\tau) - p_l i(\tau_l) - p_r i(\tau_r) \tag{2.4}$$

Maximum Δi is ascertained by an exhaustive search of the pair $\{\theta, t\theta\}$ from all variables θ at the node, in addition to all probable thresholds $t\theta$. The decrease in Gini impurity emanating from this optimal split Δi_θ (τ, T) is reported independently for all variables θ, and accrued for all nodes τ in all trees T in the forest, as defined in Equation 2.5

$$I_G(\theta) = \sum_T \sum_t \Delta i_\theta(\tau, T) \tag{2.5}$$

The Gini importance I_G, finally shows the number of times a particular feature has been assigned for a split and the size of its general favorable value for the classification topic under study.

2.4. Post classification comparison and change detection

Classified Landsat images were analyzed using ENVI and ArcGIS to enable the assessment of the Mau Forest cover changes over time. For forest cover change, independently classified images for the different time intervals were compared. The classification outputs were coded by color, a process commonly known as density slicing. The color-coded outputs are the input data for image differencing. This comparison showed a complete matrix of land cover used to detect forest cover change. It helped in identifying the percentages and the rates of changes that had occurred within the selected years.

To achieve this, the area in hectares and percentage change of each of the selected year was first determined. The percentage change and the rate of changes that have occurred were then calculated by dividing observed change by absolute sum of change as shown in equations (2.6) to (2).9;

$$\%\Delta = OC/_{ASC} \times 100 \tag{2.6}$$

$$\%\Delta in \ \ year = \frac{Y_2 - Y_1}{Y_1} \times 100 \tag{2.7}$$

$$Average \ \ Rate \ of \Delta = \frac{Y_2 - Y_1}{T_2 - T_1} \times 100 \tag{2.8}$$

$$\% \ average \ \ rate \ \ of \ \ change = \frac{Average \ \ Rate \ \ of \ \ Change \left(ha/_{yr} \right)}{Difference \ \ in \ \ year} \times 100 \tag{2.9}$$

where;

OC is the observed change
ASC is absolute sum of change i.e., fixed year (starting year)
Y_2–Y_1 is the observed change
Y_2 is the ending year
Y_1 is the starting year
T_2-T_1 is the periodic interval between the initial period and the final period.

From the land cover matrix table, relevant statistics were thereafter calculated for the different land cover classes to determine the rate of change and the size of area affected.

2.4.1. Accuracy assessment

Many factors impart classification accuracy hence its assessment is vital for any remote sensing tasks for thematic mapping (Strahler et al., 2006). Variations occur regarding the sample sizes employed for accuracy assessment in remote sensing (RS). As such, they weigh in on issues such as differing project aims and needs of a given project, considering reasonable limitations and restraints, for example image resolution and quality (Foody, 2009).

Bagging is a technique embedded in the RF algorithm that separates 1/3 of the sampled dataset (training sites) into a subset called out-of-bag error. The other 2/3 of the samples are selected to make every n_{th} tree grow (see Equation (2.2)). This technique of intentional omission of some samples is for the purpose of performance evaluation of the classification. The estimated error is as a result of the overall number of out-of-bag elements and misclassifications to guarantee candid assessment of generalization error (Breiman, 1996). Tables 2 and 3 show the results of the error estimation from the classification performance for the 1984, 1995, 2008, and 2020 Landsat images.

3. Results and discussion

3.1. Land cover classification output

At present, no comprehensive critique on the factors that drive land use change in the Mau complex exists. Many studies have been conducted to bridge this gap which is necessary for future modelling and policy making processes. The forest acts as a unique biodiversity hotspot in addition to its fulfilment of socio-economic purposes supporting the livelihoods of millions of Kenyans surrounding the complex.

Four land cover classes were selected and coded as 1-Forest, 2-Farmland, 3- Grassland and 4-Other, whereby other land cover represented waterbodies, built-up areas and bare land. The class code 4 was grouped together for the purpose of consistency because they were not present across all the study periods, and could not be individually discerned for change. For example, there were no built-up areas nor water bodies detected in the base year, 1984, whereas they were visible in other study periods. Four land cover maps were produced as shown in Fig. 3.

Table 2
Confusion matrices for years 1984 and 1995 classifications.

	1984						1995					
	Class	1	2	3	4	class.error	Class	1	2	3	4	class.error
	1	1014	0	0	0	0	**1**	1017	0	1	0	0.000982318
	2	0	1019	0	1	0.00098039	**2**	0	1005	4	0	0.003964321
	3	0	1	812	0	0.00123001	**3**	0	2	806	0	0.002475248
	4	0	1	5	198	0.02941176	**4**	0	0	0	202	0
Sample size	98						78					

Table 3
Confusion matrices for years 2008 and 2020 classifications.

	2008						2020					
	Class	1	2	3	4	class.error	Class	1	2	3	4	class.error
	1	1018	0	0	0	0	**1**	1010	0	0	0	0
	2	0	1007	8	1	0.008858268	**2**	0	1003	7	4	0.010848126
	3	0	13	802	0	0.015950920	**3**	0	3	810	0	0.003690037
	4	1	4	0	199	0.024509804	**4**	0	11	1	191	0.059113300
Sample size	110						78					

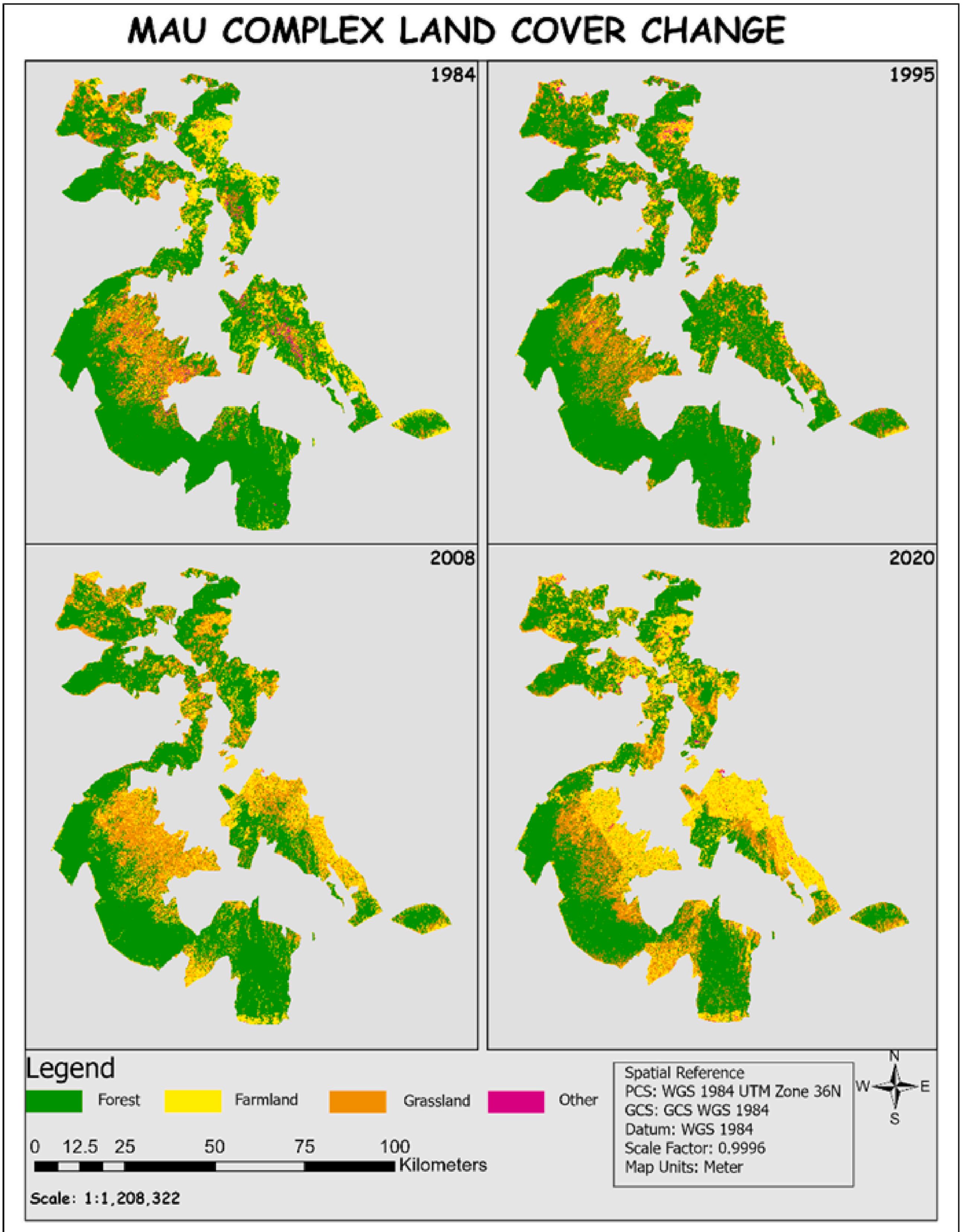

Fig. 3. Mau complex land cover maps.

Table 4
1984–1995 land cover change matrix (T2-T1).

Area (Km^2)	Forest	Farmland	Grassland	Other	Row Total	Class Total
Forest	**2634.29**	329.44	339.1	1.3	3304.13	9740.64
Farmland	62.84	**162.13**	95.77	1.58	322.32	2070.43
Grassland	74.4	116.83	**218.02**	3.39	412.65	1036.7
Other	0.83	1.36	2.17	**0.21**	4.57	898.46
Class Total	2772.36	609.76	655.06	6.49	0	34.91
Class Changes	138.07	447.64	437.04	6.28	0	0
Image Difference	531.77	−287.44	−242.42	−1.91	0	0

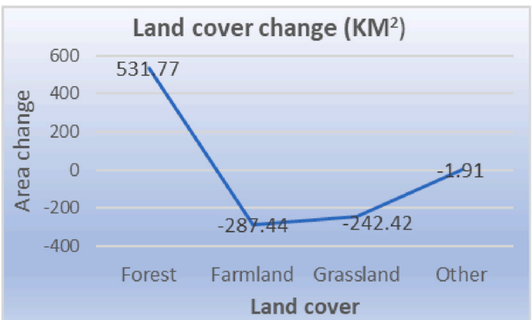

Fig. 4. Area of land cover change between 1995 & 2008.

3.2. Accuracy assessment

The RandomForest algorithm provides an automated classification accuracy validation using the out-of-bag error (Breiman, n.d.), where approximately 37% of selected training samples were left out during classification. After the classification was complete, the model took the 37% of unused samples and conducted a cross check of the resultant land cover class against what was discerned by expert judgment and gave an error estimate. Tables 3 and 4 show the resultant class error from the classification. The tables depict the results of classified pixels from the third fraction of training samples set aside by the classification algorithm for accuracy assessment. From these isolated samples, misclassifications are recorded and output as class error percentages from each land cover class defined in the study.

The random forest's decision trees function exceptionally when their depth is small since a larger depth is likely to result to overfitting hence higher model variance. The bootstrap samples, which are random small subsets of the data, are bolstered as training datasets for the decision trees. The bootstrap samples are incorporated into every decision tree separately and the majority vote in every tree is counted to determine the classification output. Martínez-Muñoz and Suárez (2010), note that the final output from aggregating all decision trees is not impacted by the original training deviations since they take different training datasets as input. Variance is therefore reduced without changing the bias of the aggregated decision trees though bagging.

Despite random forest popularity as a classification engine, Rodriguez-Galiano et al (2012), highlight that it has not been thoroughly evaluated for its split rules for classification by the remote sensing community. In this regard, their study was conducted to explore RF classifier's performance in land cover classification of a complex area and to analyze its sensitivity to noise and dataset size. In their findings, they noted that the RF algorithm for land cover classification yielded accurate results where 92% overall accuracy was established and a 0.92 Kappa index.

In comparison to this study's classification accuracy, the level of accuracy witnessed can be justified as the confidence level of the results is high. The out-of-bag score presents a good trade-off where the dataset is not too large, like the case of this research's study area, and is preferred to validation score, which is calculated using all the ensemble's decision trees. However, the computation of the validation score and out-of-bag score differs completely and should not be compared.

3.3. Post-classification comparison and land cover change trends

3.3.1. Land cover change between 1984 and 1995

Table 4 shows the 1984–1995 land cover change matrix where in 1984, forest cover stood at approximately 2772 km^2, farmland at 610 km^2, grassland at 655 km^2, and other land at 6 km^2. In the year 1995, the forest cover had increased by 19.2% while the farmland, grassland, and other land reduced by 47.1%, 37%, and 19.5%, respectively, as shown in Fig. 4.

3.3.2. Land cover change between 1995 and 2008

By the year 2008, there was a significant decrease in tree cover by approximately 23.9%, whereas the farmland, grassland, and other land increased tremendously by 103.8%, 109.1%, and 87.9% respectively. Table 5 shows the land cover change matrix and Fig. 5 shows the area in

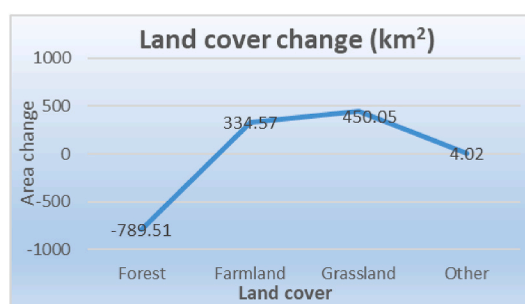

Fig. 5. Area of land cover change between 1995 & 2008.

Table 5
1995–2008 land cover change matrices (T3-T2).

Area (Km^2)	Forest	Farmland	Grassland	Other	Row Total	Class Total
Unclassified	3.28	1.97	1.6	0.01	6.87	9738.33
Forest	**2407.97**	47.37	57.09	0.38	2512.82	2514.62
Farmland	399.03	**132.64**	121.38	1.54	654.59	656.89
Grassland	489.79	137.5	**231.03**	2.52	860.84	862.7
Other	4.05	2.83	1.54	**0.12**	8.54	8.59
Class Total	3304.13	322.32	412.65	4.57	0	0
Class Changes	896.16	189.68	181.62	4.45	0	0
Image Difference	−789.51	334.57	450.05	4.02	0	0

Table 6
2008–2020 land cover change matrices (T4-T3).

Area (Km^2)	Forest	Farmland	Grassland	Other	Row Total	Class Total
Unclassified	0.29	0	0	0.01	0.31	9765.32
Forest	**1908.84**	65.28	98.28	1.9	2074.29	2074.29
Farmland	229.56	**379.01**	423.76	3.25	1035.58	1035.58
Grassland	370.91	196.3	**330.38**	0.94	898.52	898.52
Other	5.93	16.36	10.16	**2.49**	34.94	34.94
Class Total	2515.52	656.95	862.58	8.6	0	0
Class Changes	606.69	277.94	532.2	6.11	0	0
Image Difference	−441.23	378.63	35.95	26.35	0	0

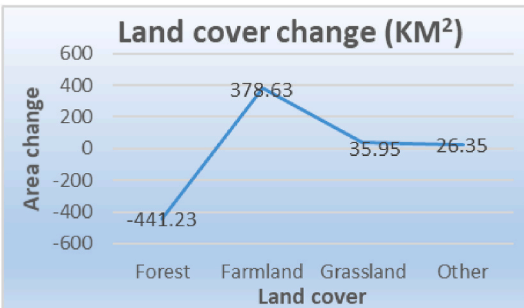

Fig. 6. Area of land cover change between 2008 & 2020.

square kilometers of land cover changes from 1995 to 2008. This is evidence that encroachment was rampant within the forest boundary where there was an increased demand for agricultural land. On the other hand, the area under grassland increased as a result of a shift in the famously known shamba system which allowed the community members around forest ecosystems to grow crops on a previously clear-cut forest area as they tended to young trees in order to establish tree plantations. The changing regime saw the system abandoned and with it, most of the plantations, and probably grass grew and replaced the farmlands.

3.3.3. Land cover change between 2008 and 2020

The classified image statistics for the 2020 Landsat image indicated land use changes that had taken place since 2008 as shown in Table 6. The statistics revealed that the negative trend of tree cover loss in the Mau Forest did not reduce as depicted in Fig. 6. It further suffered approximately 17.5% decline in areas that were covered by trees. Logging however seemed to have reduced and the resultant increase in grassland stood at 4.2%. Conversion of forest into farmlands continued to be rampant leading to an increase by 57% of area under farmlands. The area classified as other lands also extensively increased by 306.5% as compared to the year 2008 which was at 87.9%. Built-up areas and bare surfaces constituted the largest percentage of the increased other lands.

3.3.4. Land cover trend between 1984 and 2020

The study established a decline of 24.86% of forest cover within the Mau Forest complex in a period four years shy of four decades, amounting to approximately 689 km^2 of tree cover. Table 7 shows the overall changes from 1984 to 2020. The declining trend was fueled by an increasing demand for agricultural land where farmlands increased by 69.9%, as well as logging-legal or illegal-where grassland area increased by 37.2%.

According to the study, the total area under farmland and grassland was found out to be approximately 669 km^2, aggregating to 96% of the total area where tree cover was lost and the remaining 4% covering other land. Fig. 7illustrates the trend in changes of areas of different land cover classes across the study periods.

In the base year 1984, the area under forest cover was 2772 km^2 which increased to 3304 km^2 in the year 1995. In the year 1975, there was a change in the way forests were managed in Kenya shifting from forest department between 1910 and 1975 to Non-residential cultivation (NRC), commonly known as *Shamba System*, from 1976 (Gichuru, 2015). This regime change saw extensive establishment of tree plantations that saw the increase in tree cover between 1984 and 1995 as established in this study. From the year 1995 onwards, tree cover loss became rampant reducing from the promising 3304 km^2 to 2527 and further down to 2083 in the years 2008 and 2020 respectively. The reduction in tree cover, as highlighted by Gichuru, (2015), had negative impacts on the livelihoods of the people around the Mau complex ecosystem. Forests are known to support humans through the ecological benefits that ooze from them including water catchment, biodiversity conservation and favorable climatic conditions.

Recent studies on land cover changes within Kenya's forests have reported tremendous decline in tree cover over the past three decades. A study by Odawa and Seo (2019), focusing Mau water tower land cover change reported a 22% decline of tree cover in the Mau complex, a rate comparable to this study's results. The current study findings revealed that the most significant land use change from forest cover was farmlands, a fact supported by Odawa and Seo (2019), where such changes were witnessed on the forest periphery where humans had easy access to the forest.

From this study, tree cover loss in the Mau complex became severe from 1995 onwards where the largest percentage loss of approximately 24% was recorded in a 13-year period (1995–2008). This is consistent with the findings of Baldyga et al (2008), who observed that extreme land cover transitions were experienced from the year 1995 in the Mau complex region. Massive forest losses characterized by a mix of subsistence agriculture, degraded areas and managed pasture were recorded.

Table 7
1984–2020 land cover change matrices (T4-T1).

Area (Km^2)	Forest	Farmland	Grassland	Other	Row Total	Class Total
Unclassified	2.95	2.37	1.83	0.03	7.18	9738.64
Forest	**1780.76**	157.73	132.55	0.95	2071.99	2073.43
Farmland	486.03	**293.54**	250.1	3.07	1032.74	1035.7
Grassland	489.15	142.21	**263.65**	2.02	897.02	898.46
Other	13.46	13.91	6.95	**0.41**	34.74	34.91
Class Total	2772.36	609.76	655.06	6.49	0	0
Class Changes	991.6	316.22	391.42	6.07	0	0
Image Difference	−698.93	425.93	243.39	28.42	0	0

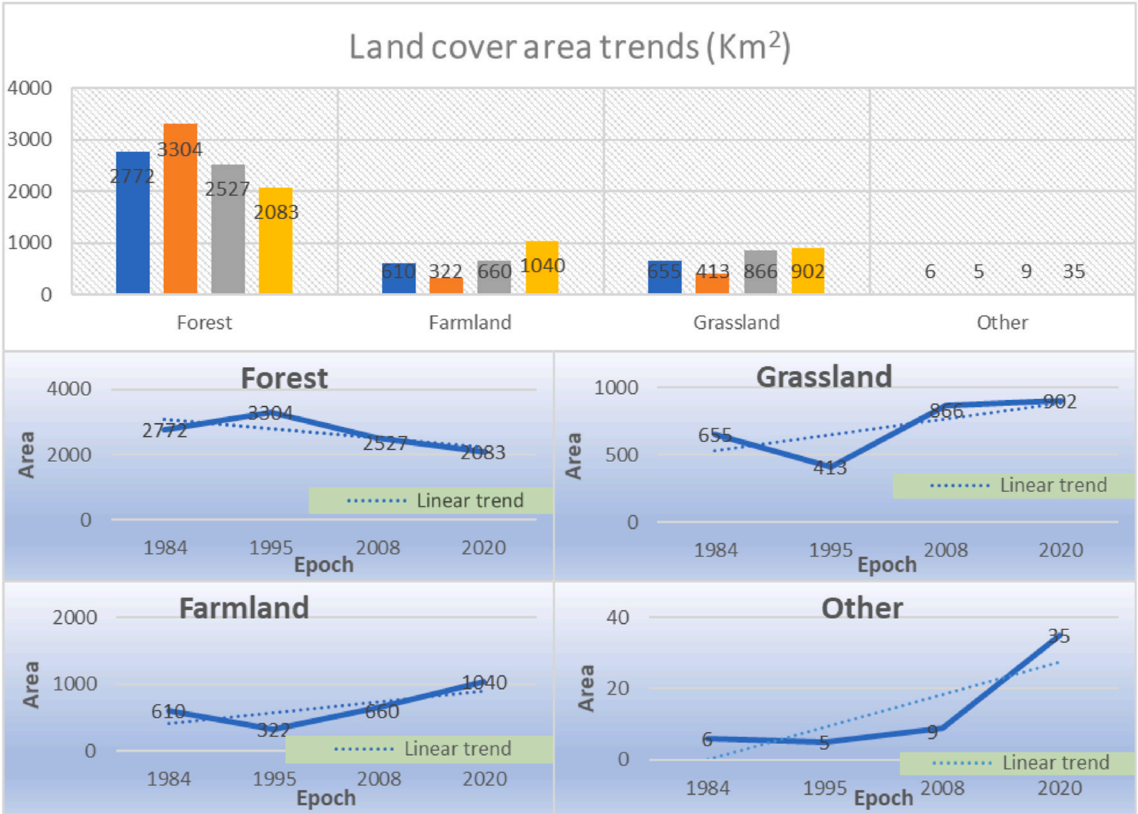

Fig. 7. Trend in land cover area changes.

As a consequence, significant effects on hydrological and ecological systems were felt which are well known to accompany harsh implications on environmental sustainability.

A similar analysis on land use change in the Mau complex as presented by Ongong and Sweta (2014), recorded a decline in tree cover in all 22 forests that make up the Mau Forest Complex. The researchers also highlighted those significant changes in tree cover were witnessed more in the eastern, central and northern parts of the forest which is evident in the land cover maps presented in Fig. 3 in this study. Their study revealed an existing relationship between forest cover loss and population increase where steep slopes were mostly affected. They further singled out illegal land allocation and land grabbing as the primary drivers of forest degradation which, led to reduced rainfall and therefore reduced flows in the rivers and streams flowing from the Mau Forest Complex.

Moreover, agricultural-related activities were the major drivers of land-use change resulting to degradation of forest area. A study conducted by Swart (2016), revealed that there was a 0.6% annual increase of small-scale farmlands from forested areas for a period of 40 years, beginning from 1973. This change was high from the year 1994–2003, a finding similar to our study's findings where the highest land use change occurred between the year 1995 and 2008. We can therefore conclude that small-scale farming was the greatest driver of forest loss in the Mau complex.

In Kenya, only 20% of the total land area is considered arable for agriculture and the remaining 80% categorized as arid and semiarid lands (ASALs) (Campbell et al., 2005). The Mau complex has been exposed to anthropogenic activities, especially since close to 75% of Kenya's population is concentrated in arable land, as it is among the most fertile regions in the country which is highly suitable for agriculture. This is the reason there was a sharp increase in area under agriculture between 1984 and 2020 evident from this study's findings.

3.4. Perceptions of change in forest cover and associated drivers

The narrations of the FGD participants support the findings of the satellite imagery. According to the participants, the forest has been declining over the years and the three major driving forces attributed to this decline are clearing of forests for settlement, expansion of agricultural lands and logging. They noted that, initially the forest was covered with indigenous trees but nowadays, most parts have been converted into plantation forest due to reforestation with exotic trees. They argued that agriculture was the main economic activity in the area and owing to the increasing populations, the lands outside the forests have been subdivided into smaller portions rendering them inadequate for food production. The forests then are seen as alternatives lands where the adjacent communities can carry out their subsistence farming activities. Moreover, they indicated that tea plantations by multinational companies and the Nyayo Tea Zones also contributed to decline in forest cover.

In addition, the FGD participants and key informants pointed out that there are licensed saw millers that operate within the forest. These, together with the illegal loggers have contributed to forest degradation even though the licensed logging companies carry out reforestation in the areas where they have clear felled trees. Clearing of the forest for settlement was another driver mentioned in the discussion. The participants cited poverty and landlessness as factors that have driven illegal settlers into settling in the forest. The settlements led to a major decline in forest cover as the families that moved into the forest would clear huge tracts of forest land to accommodate their homesteads, rearing of livestock and cultivation land. According to the FGD participants, as more people moved into the forest, there was need for infrastructural developments such as schools, health facilities, churches and roads leading to further reduction in forest cover. Other drivers, perceived as minor by the participants, include overgrazing, charcoal production, collection of fuelwood and construction material.

4. Conclusion

The integration of satellite data with social data proved effective as there was concurrence in observations and understanding as to the drivers and causes of Mau forest cover change. Both sets of data indicated that indeed the trend in forest cover has been declining. Between 1984 and 2020, the forest cover had declined by 25.2% with the largest percentage loss of 24% observed between 1995 and 2008. Meanwhile, Farmland land use had increased by 69.9% and grassland 37.2% within the same period. Agriculture and logging were major driving forces of forest cover decrease, a fact supported by the FGD and in-depth interview information. Another major driving force mentioned by the participants was clearing of forest for settlement. The assessment of the drivers of forest cover change based on the perceptions of the community members exposes some vital information that need to be addresses by the forest management authorities. It highlights some loopholes that have led to ineffective implementation of forest management policies and strategies in maintaining the forest cover. It is imperative that the forest management authorities involve the forest dependent communities, who are the main stakeholders, in coming up with intervention measures and implementation strategies in order to promote sustainable use of the forest resources and protect the forest from further loss.

Funding

This work was supported by the African Forest Forum (AFF) and the Pan African University Life and Earth Sciences Institute (PAULESI).

Ethical statement

I, Alice Jebiwott, on behalf of all co-authors, hereby testify that our manuscript entitled 'Mapping the Trends of Forest Cover Change and Associated Drivers in Mau Forest, Kenya' submitted to 'Remote Sensing Applications: Society and Environment', has fulfilled the following:

1) This material has not been published previously
2) The paper is not under consideration for publication elsewhere,
3) The publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out
4) If accepted, the paper will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.
5) Agree to the statement below;
   To verify originality, your article may be checked by the originality detection service Crossref Similarity Check.

CRediT authorship contribution statement

Alice Jebiwott: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Resources, Funding acquisition. **George Morara Ogendi:** Project administration, Reviewing and Editing, Supervision. **Busuyi Olasina Agbeja:** Reviewing, Supervision. **Abiodun Akintunde Alo:** Reviewing, Supervision, Funding acquisition. **Ronald Kibet:** Data Acquisition, Reviewing and Editing.

Declaration of competing interest

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

Acknowledgements

This paper is part of a doctoral research for the first author. Sincere thanks to the Pan African University Life and Earth Sciences Institute (PAULESI) for providing the research grant for this study. The authors are also deeply indebted to the African Forest Forum (AFF) for awarding the first author a fellowship under the theme '*Assessment of Trends of Impacts of Climate Change on Forest and Tree-Resources and Coping Mechanisms in Africa*' in which the authors were able to fully fund and conduct this study.

References

Baldyga, T.J., Miller, S.N., Driese, K.L., Gichaba, C.M., 2008. Assessing land cover change in Kenya's Mau Forest region using remotely sensed data. Afr. J. Ecol. 46 (1), 46–54. https://doi.org/10.1111/j.1365-2028.2007.00806.x.
Belgiu, M., Drăgu, L., 2016. Random forest in remote sensing: a review of applications and future directions. ISPRS J. Photogrammetry Remote Sens. 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011.
Breiman, L.. https://www.stat.berkeley.edu/pub/users/breiman/OOBestimation.pdf.
Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32. https://doi.org/10.1023/A:1010933404324.
Butt, A., Shabbir, R., Ahmad, S.S., Aziz, N., 2015. Land use change mapping and analysis using Remote Sensing and GIS: a case study of Simly watershed, Islamabad, Pakistan. Egyptian Journal of Remote Sensing and Space Science 18 (2), 251–259. https://doi.org/10.1016/j.ejrs.2015.07.003.
Campbell, D.J., Lusch, D.P., Smucker, T.A., Wangui, E.E., 2005. Multiple methods in the study of driving forces of land use and land cover change: a case study of SE Kajiado District, Kenya. Hum. Ecol. 33 (6), 763–794. https://doi.org/10.1007/s10745-005-8210-y.
Chrisphine, O.M., Maryanne, O.A., Mark, B.K., Kenyatta, J., 2016. Assessment of hydrological impacts of Mau forest, Kenya. https://doi.org/10.4172/2157-7587.1000223.
DeShazo, J.L., Pandey, C.L., Smith, Z.A., 2016. Why REDD will fail. In: Why REDD Will Fail. Taylor and Francis Inc. https://doi.org/10.4324/9781315851105.
Douglas, J., Simula, M., 2010. The Future of the World's Forests, 7. Springer Netherlands. https://doi.org/10.1007/978-90-481-9582-4.
Evans, J., 2008. The forests handbook. In: Applying Forest Science for Sustainable ... - Google Books, 2. John Wiley & Sons. https://books.google.co.ke/books/about/The_Forests_Handbook_Volume_2.html?id=I7zMclbITXUC&printsec=frontcover&source=kp_read_button&redir_esc=y#v=onepage&q&f=false.
FAO, 2010. Global Forest Resources Assessment 2010.
FAO, 2015. Global forest resources assessment 2015. www.fao.org/publications.
Foody, G.M., 2009. Sample size determination for image classification accuracy assessment and comparison. Int. J. Rem. Sens. 30 (20), 5273–5291. https://doi.org/10.1080/01431160903130937.
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.
German, L., Karsenty, A., Tiani, A.-M., 2010. Governing Africa's forests in a globalized world. In: German, L. (Ed.), Choice Reviews Online, 47. Routledge. https://doi.org/10.5860/choice.47-6855. Issue 12.
Gichuru, I.I., 2015. Factors contributing to the success of Pelis strategy in forest plantation establishment: case study of Mucheene forest. Int. Acad. J.Soc. Sci.Educ. 1 (4), 15–43.
KFWG, 2018. Monitoring of water towers. https://www.kenyaforests.org/index.php/what-we-do/monitoring-of-water-towers.
Martínez-Muñoz, G., Suárez, A., 2010. Out-of-bag estimation of the optimal sample size in bagging. Pattern Recogn. 43 (1), 143–152. https://doi.org/10.1016/j.patcog.2009.05.010.
Ministry of Forestry and Wildlife, 2013. Analysis of Drivers and Underlying Causes of Forest Cover Change in Various Types of Forests in Kenya, 33. Kenya Forest Service. http://www.kenyaforestservice.org/documents/redd/Analysis of Drivers of Deforestation &forest Degradation in Kenya.pdf.
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. Sustainability 11 (13), 3524. https://doi.org/10.3390/su11133524.
Ongong, I., Sweta, L., 2014. Land cover and land use mapping and change detection of Mau complex in Kenya using geospatial technology. Int. J. Sci. Res.
Owens, J.N., Lund, G.H., 2009. Forests and forest plants. In: Forests and Forest Plants, I. UNESCO-EOLSS.
Palo, M., Mery, G., 2012. Sustainable Forestry Challenges for Developing Countries. Springer Science & Business Media. https://books.google.co.ke/books?id=cGDxCAAAQBAJ&redir_esc=y.
Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M., Rigol-Sanchez, J.P., 2012. An assessment of the effectiveness of a random forest classifier for land-cover classification. ISPRS J. Photogrammetry Remote Sens. 67 (1), 93–104. https://doi.org/10.1016/j.isprsjprs.2011.11.002.
Sletten, M., Vedeld, P., Kaboggoza, J., 2008. To co-operate or not to co-operate? : a study of collaborative management planning in Mount Elgon National Park, Uganda. NORAGRIC Work. Pap. Working Paper. https://agris.fao.org/agris-search/search.do?recordID=NO2009005698.
Southall, R., 2005. The ndungu report: land & graft in Kenya. Rev. Afr. Polit. Econ. 142–151.
Spiecker, H., Mielikainen, K., Kohl, M., Skovsgaard, J., 2012. In: Growth Trends in European Forests: Studies from 12 Countries. Springer Science & Business Media. https://books.google.co.ke/books/about/Growth_Trends_in_European_Forests.html?id=CtnnCAAAQBAJ&printsec=frontcover&source=kp_read_button&redir_esc=y#v=onepage&q&f=false.

Strahler, A.H., Boschetti, L., Foody, G.M., Friedl, M.a., Hansen, M.C., Herold, M., Mayaux, P., Morisette, J.T., Stehman, S.V., Woodcock, C.E., 2006. Global land cover validation: recommendations for evaluation and accuracy assessment of global land cover maps. Change. https://doi.org/10.1080/01431160512331326521.

Swart, R., 2016. Monitoring 40 Years of land use change in the Mau forest complex, Kenya. https://edepot.wur.nl/404611.

Temu, A.B., Chamshama, S.A.O., Kung'u, J., Kaboggoza, J.R.S., Chikamai, B., Kiwia, A. M., 2008. New perspectives in Forestry education. In: First Global Workshop on Forestry Education, September 2007.

UNEP, 2012. Deforestation costing Kenyan economy millions of dollars each year and increasing water shortage risk. https://www.unep.org/news-and-stories/press-release/deforestation-costing-kenyan-economy-millions-dollars-each-year-and.