POLITECNICO DI MILANO

Geoinformatics Engineering Master of Science

School of Civil Environmental and Land Management Engineering

School of Industrial and Information Engineering

Ten years analysis of Mau Forest degradation: forest cover and ecosystem transformation

Supervisor: Prof.ssa Giovanna Sona

Thesis by:

Phesto Osano – ID: 941690

Anno Accademico 2021-2022

JULY 2022

ABSTRACT

Land use and land cover change is driven by human actions and drives changes that limit availability of products and services for human and livestock, and it can undermine environmental health as well. In the last three decades, global forest area decreased from 32.5% to 30.8%. Despite the many drivers causing forest degradation, the most important for Africa is agricultural expansion. To reverse this trend, many interventions have been initiated locally and on a global scale. In this study, we attempted to understand how Mau Forest, one of the major ecosystems in Kenya is transforming over the period of 10 years from 2010 to 2020. Overall, this study was to assess land use land cover transformation with specific interest in forest degradation analysis within in the Mau Forest Complex using Remote sensing and Geographical Information System (GIS). Specifically, the study was aiming to determine the trend in forest cover change for the study period. In addition, the study was seeking to determine and compare forest cover change with other land use classes e.g., agriculture, settlements within the ecosystem. Lastly, this projected will provide an application and data that will form the basis for future reference and may support the Kenyan Forest Service and Kenyan Wildlife Service in the planning of patrols, especially when operationalized as a near real-time (NRT) monitoring system. Knowledge on the spatial extent and the location of degrading areas may additionally inform policy makers to prioritize main intervention areas. Using GEE, an image collection, or data stack, were be generated for the study period comprising all images intersecting the study area to produce a cloud-free composite of scenes for the whole ecosystem. In this study, classification schema comprises of five Land cover classes namely Forest, Agriculture, Grassland, Bareland, Build-up, and water bodies were considered as they are the dominant land uses within the ecosystem. Using Random Forest algorithm, all the images were classified, and accuracy assessment conducted. The overall mean accuracy was 87.64%, slightly above the minimum allowable value according to Anderson et al (1976).

From the analysis, Forest cover has been decreasing through the study period at annual rate of 0.5% with highest loss in 2017 (0.87%) translating to 1885.16 ha and lowest in 2014 (0.19%) which is about 403.88 ha. The agricultural land has been on the increase at an average annual rate of 3.14% which translate to 1254.5 ha/year. Unlike Forest and Agriculture which have one direction of land cover transformation, Grassland experience both increase and decrease.

Averagely, over the 10 years analysis, Grassland cover reduced by approximately 0.23 % in terms of cover. The greatest loss occurred in 2019 by 12.99% which is approximately 837.91 ha with the highest gain in 2018 by about 9.09%. Like Grassland, both Bareland and Water experienced both positive and Negative trend within the 10 years of analysis. For water, the highest increase was in 2016 by about 4 ha. Land Use Land Cover transformation results from the composite interface of numerous factors such as culture, human behavior, policy, economics, management, and the environment. To understand and quantify such transformation, remote sensing and GIS has proven to very fundamental technology in providing such information. If used in conjunction with deforestation monitoring, this approach could be the base for precise forest monitoring in Kenya.

Key words: Landsat image, GIS, Remote sensing, Land Use and land Cover Change, Forest degradation

Table of Contents

LIST OF TABLES

LIST OF FIGURES

1.0 INTRODUCTION

1.1 Problem Description

In the last three decades, global forest area decreased from 32.5% to 30.8%. However, this decrease was not uniform for all continents and more specifically varied between countries. For instance, while South America reported a decrease in the rate of forest loss in the last decade, Africa actually reported an increase in the rate of net loss during the same period. Despite the many drivers causing forest degradation, the most important for Africa is agricultural expansion. To reverse this trend, many interventions have been initiated locally and on a global scale. Significant goals, legal and policy reforms have been drawn up and applied in various parts of the world in order to ensure sustainable management of forests. It is obvious that most of these interventions still face challenges that are varied in nature, and therefore their effectiveness is strongly reduced. One of the most critical challenges is the lack of timely and relevant information to inform decision makers. Regular and precise monitoring of forest cover is critical for observation of changes and in examining the underlying causes to provide sufficient information that can support decisions making, formulate policies and strategies to manage forest ecosystems sustainably (MacDicken, 2015; Romijn et al., 2015).

In the recent years, the use of remote sensing data has revolutionized and supported forest cover monitoring studies. The old methods of detecting land use and cover changes like ground-based approaches are expensive and only cover small areas. Remote sensing technologies provide some of the most accurate methods of measuring the degree and pattern of change in cover conditions over a given space and period. Satellite data have become a very important application in forest change recognition because of the recurring coverage of the satellites at short intervals. Further, monitoring land cover changes through remote sensing technology, is beneficial since it provides information regarding areas that have little or no access as well as enable more efficient and cost-effective land cover mapping. Ground mapping and physical analysis is too costly and time-consuming, and thus, remote sensing technologies have made it more feasible and cost effective to ascertain hotspots of deforestation (Chakravarty et al., 2012). Technology in its very nature is dynamic as it undergoes improvements over time. Remote sensing technology has been utilized for many years and has undergone major improvements both in execution and utility. The employment of latest technology in Remote sensing and GIS will be crucial for sustained management of forests at the global and local level. The production of spatial data of better resolution is key for decision making. The use of globally acceptable methods or standardized methods of analysis will improve comparability, consequently improving the decision making and management strategies in forest conservation. In most developing countries such as Kenya, there exists inadequate data coupled with ineffective platforms for information of changes in forest cover monitoring. This situation renders the use of updated technology in remote sensing and GIS as the most essential means of acquiring and analyzing geospatial information that cannot be captured by field-based methods (Romijn et al., 2015).

1.2 Forest Cover Dynamics

The exponential growth in population in most African countries has put persistent pressure on natural resources, especially forests. This is despite the important role forests play both in societal development and environmental functions. Forests act as a source of raw materials and many other products important for human survival. Other indirect benefits such as carbon sequestration and protection of soil and water supplies are also acquired from forests. The increasing need for agricultural and living space has seen forest coverage reduce significantly. A recent report by FAO and UNEP (2020) has established that in the last three decades, the global forest cover has reduced by 2.3 per cent which represents a loss of 178 million hectares of forest cover.

Despite the important role played by forests in Kenya, deforestation and forest degradation remain a major challenge. Recent reports by the government of Kenya, have estimated a deforestation rate of 50,000 ha per year translating to a loss to the economy of up to $19 million. Previous literature has mentioned that deforestation was initiated by the European settlers during colonization and has never stopped to date. The demand for high value agricultural land by the colonialist led to high rates of deforestation that did not change even after independence. (GoK, 2014)(Kogo et al., 2019)

Currently, the forest cover in Kenya is only a meagre 7.4 per cent of the total land area. This is below the global average which stands at 21.4 per cent. In the last three decades Kenya has seen a decline in forest cover of 25 per cent per year (WWF, 2015). This reduction has impacted among other areas, the water reserves which has had a tremendous economic impact on the country (Ministry of Environment, 2018). Forest loss also has had a direct impact on communities that directly depend on forest products for their livelihoods. For instance, continuous deterioration of forest lands results to a reduction in non-timber forest products (NTFP) such as honey and fruits. This in return means that community members have to travel a longer distance to collect these products. This situation impacts on the general economy of an area as more time that would have been used in other productive activities is wasted searching for NTFP (Boafo, 2013). Following these impacts, the need for maintaining and increasing forest cover in Kenya cannot be overstated.

1.3 Drivers and Impacts of forest degradation

Deforestation can be looked at as the abrupt transition from land with trees to land without trees with no plans for subsequent regrowth (Curtis et al., 2018). Deforestation can occur naturally through wildfires or human induced through clearcutting or selective logging, transitional subsistence farming or small holder agroforestry systems. In the developed countries like the USA and some countries in Europe including Russia, forest loss due to wildfires is the most dominant while urbanization represent the least fraction. Contrariwise, in sub-Saharan Africa, shifting agriculture and commodity driven deforestation showed more dominance (Curtis et al., 2018).

Swart (2016) categorized drivers of land use change into underlying drivers and proximate drivers. According to the author proximate (direct) drivers encompass the human activities and actions that produce an effect on the land cover. Most studies have reported that the most important direct driver is commercial agriculture that causes forest loss. Wood extraction for commercial and domestic use, urban expansion and development of infrastructure have also been mentioned to contribute directly to forest loss. On the other hand, underlying drivers have been defined as the social process that underlie the direct cause and can act either locally or globally. These drivers can be orientated either socially, economically, political, culturally or technologically indirectly affecting forest cover change. Further, these factors do not act independently, rather they are interconnected concepts that operate on multiple scale. This classification shows that it is imperative to consider forest cover change and its drivers not only on a local or national scale, but also on a global scale (Swart, 2016).

Population pressure has been noted as one of the most important driver of deforestation and forest degradation. This is due to increased demand of land for agriculture and settlement. In Kenya, the population is growing at an annual rate of 3 per cent. Consequently, the projection is that the country will have a population of 60 million by 2030 (Imo, 2012). Additionally, government data shows that currently more than half of the Kenyan population is comprised of younger individuals. Coupled with the high rates of poverty and unemployment being experienced in Kenya, the population will look to natural resources such as land to earn a living. All this implies that unless appropriate measures are taken, deforestation will only grow from bad to worse. Migration of people from low potential to high potential areas is also a major driver of deforestation in Kenya. In Kenya, more than 75% of the population is concentrated on high potential areas that make up approximately 20% of the total land mass (Imo, 2012) and just like many African countries, Kenya is experiencing high levels of rural-urban migration. This means that with concentrated population, people are bound to seek new areas of settlement increasing the risk on deterioration of natural lands. Another driver of forest destruction is the increasing demand for energy sources which is also tied to population growth. According to government reports, up to 67% of the country's population are dependent on firewood, while 17% are dependent on charcoal. This makes more than 80% of the country dependent on wood biomass for energy sources. This pressure exerted on forest resources has largely contributed to deforestation. The push for green energy such as solar or wind will greatly absorb the shock on forest resources and thus slow down the rates of deforestation (Moses, 2012).

Over the years, deforestation and forest destruction has been attributed to factors like population pressure and encroachment by smallholder farmers. However Klopp (2012) in his paper attempted to argue differently by examining the role of power and politics on forest destruction. He argues that corrupt politicians and powerful elites have also played a bigger role in destroying forests for selfish ends. This situation is normally exacerbated by electoral competition characterizing political liberalization of authoritarian regimes resulting to increased rate of deforestation. Despite the challenge posed by this kind of driver, the author suggests decentralization of governance as a solution and thus curb the unaccountable power held by abusive leaders (Klopp, 2012).

In many cases, humans believe they will eventually benefit from destruction of natural areas. For instance, when communities clear forest lands for agriculture they intent to increase food production. Agricultural expansion may increase food production in the short term, but the negative effects of forest destruction will overtake the community members including the ones who never participated may end up losing. Converting natural lands to agricultural lands will have negative environmental effects. Firstly, the radiation balance of a unit area is changed. Since most crops are not annual, there is a period during which the land is bare which increases its albedo. This increases the solar energy reflected back to space increasing the effect of global warming. Removal of vegetation on land decreases the water holding capacity through the reduction of soil porosity by soil compaction. This decreases the infiltration capacity consequently increasing the risks of soil erosion. The reduced water holding capacity of the soil will cause problems for the land both during the dry season and wet season. During the rainy season the risks of erosion are higher while during the dry season there is increased risks of hydrological drought. These two effects will in turn have negative impacts on agriculture and other economic activities (Pellikka et al., 2018). Precipitation in an area may also be affected due to forest degradation. As forests are cleared, the rate of evapotranspiration is also reduced subsequently affecting cloud formation. This may result to reduced precipitation (Pellikka et al., 2018).

A study to measure effect of forest degradation and deforestation on ecosystem services on a 50-year time scale showed that the overall landscape capacity to deliver ecosystem services dropped by 16%. This was carried out by considering three unique aspects namely, the change in forest area, the composition of change and the initial state of the environment. On these three, agriculture has the highest effect causing the greatest decline in ecosystem services (Balthazar et al., 2015). Additionally, land cover change, specifically the loss of forested lands, has direct impact on carbon stocks. A study carried out by Pellika et al. (2018) showed that clearance of forest land significantly reduced carbon sequestration.

1.4 Interventions against Forest Degradation and Challenges Encountered

In order to curb the high rates of deforestation and forest degradation, various institutions including local and national governments together with international bodies have come up with different strategies. Significant legal and policy reforms have been drawn up and applied in various parts of the country in order to ensure sustainable management of forests (Imo, 2012).

Several goals and targets set by relevant bodies to enhance forest conservation are worth a mention. The SDG15.1 outlines the importance of forest conservation. It intimates that "by 2020 countries should ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements" (FAO and UNEP, 2020).

On the other hand, the United Nations Strategic plan for forests Goal 1 intimates that countries should endeavor to "Reverse the loss of forest cover worldwide through sustainable forest management, including protection, restoration, afforestation and reforestation, and increase efforts to prevent forest degradation and contribute to the global effort of addressing climate change". The goal further states that Forest area is increased by 3 percent worldwide by 2030. Lastly, the New York Declaration on Forests Goal 1 insinuates that "At least halve the rate of loss of natural forests globally by 2020 and strive to end natural forest loss by 2030"(FAO and UNEP, 2020).

Following increased pressure from the international community coupled with the realization of the importance of forests to the wellbeing of the people as well as the glaring threats from climate change, the Government of Kenya (GoK) has directed more resources towards protecting the country's forest resource base. This has been done mainly through the formulation of relevant policy and setting of sustainability goals. One good example is Kenyan Government intention to achieve the noble objectives of Vision 2030 (GoK, 2007a). Through this goal the Government of Kenya is committed to enhance the protection of critical “water towers" in the country including Mau Forest Complex (MFC).

Likewise, the Kenyan Government has initiated a series of reforms in Forestry and Environmental Sectors through policies and legislations. Through the National Forest Policy of Kenya, and the revised Forest Conservation and Management bill 2015 the government intends to achieve decentralization of management roles and allow for the active participation of local community members in forest management (Langat, 2016). This paved way for the introduction of Participatory Forestry Management (PFM) which subsequently led to the formation of Community Forest Associations (CFAs). This act states that "the community, through a legally formed entity referred to as the community forest association (CFA) shall enter into an agreement with the Kenya Forest Service (KFS) to assist in the safeguarding of forest resources through protection and conservation activities (GoK 2015)." The community subsequently is supposed to benefit through the sustainable utilization of forest resources. A win-win situation is supposed to be attained where equitable distribution of resources, biodiversity conservation, poverty reduction and conflict resolution is achieved through the inclusion of local community members in the management of forests (Mogoi et al., 2012).

In recent years, the number of interventions, through policies and projects, in the forestry sector has gone up. Nevertheless, this is not reflected in the positive results seen in improving forest cover. One author notes that the number of interventions in terms of policies and projects should not be used to determine the level of success in conservation (Arevalo & Ladle, 2018). It is imperative that local realities be taken into consideration and integrated in the conservation policies and strategies (Shahbaz et al., 2011). A good point in case is where, despite their involvement in forest management, local communities still feel that there is very little usefulness of the interventions in terms of socio-cultural, environmental, and economic aspects. The economic aspect is especially an important area for the local communities where a majority do not feel a change in their livelihoods. The exclusive focus on conservation, has rendered most of the economic problems of society to be ignored by most players (Shahbaz et al., 2011).

1.5 Study Objectives

Overall, this study was to assess land use land cover transformation with specific interest in forest degradation analysis within in the Mau Forest Complex using Remote sensing and Geographical Information System (GIS). Specifically, the study was aiming to determine the trend in forest cover change for a period of 10 years from 2020 to 2020. In addition, the study was seeking to determine and compare forest cover change with other land use classes e.g., agriculture, settlements within the ecosystem. Lastly, this projected will provide an application and data that will form the basis for future reference and may support the Kenyan Forest Service and Kenyan Wildlife Service in the planning of patrols, especially when operationalized as a near real-time (NRT) monitoring system. Knowledge on the spatial extent and the location of degrading areas may additionally inform policy makers to prioritize main intervention areas.

1.6 Economic and social importance of the Mau Forest Complex

The Mau Forest Complex (MFC) is the largest water catchment area in East Africa. According to recent estimates, the MFC is the largest indigenous montane forest covering an area of about 2700

km^2Following the serious degradation facing the forest complex, several studies have reported a notable decline in discharge and a reduction in quality of water from the ecosystem (Olang & Kundu, 2011).

Vegetation in the MFC varies largely from grasslands with scattered trees in the plains, to shrubland and forests in the hilly uplands. In the higher mountain ranges, bamboo forests are largely predominant. The vegetation around the rivers and lakes mainly comprises Acacia trees and dense bush and shrubs. Studies have shown that before the extensive degradation of the MFC, the area was mainly covered by rich evergreen forests and woodland dominated by Acacia trees in the plains (Olang & Kundu, 2011).

The population density around the MFC varies according to many factors. However, this population has been growing in a consistent manner. For instance, it is estimated that up to 11, 000 households live within two kilometers of the South-western Mau and Transmara forests. Up to 75% of these households derive their subsistence from the forest. They use it for firewood, poles, fibers, honey collection and game hunting as well harvesting of medicinal plants. Some of these activities such as livestock grazing and fuelwood collection have put a constant pressure and led to further degradation of the forest (Obati & Breckling, 2015).

2.0 LITERATURE REVIEW

2.1 Forest Cover Trends

Forests currently cover 30.8% of the global land area (FAO and UNEP, 2020). The total forest area is 4.06 billion hectares but these are not equally distributed around the globe. Up to more than 50% of the world's forests are found in only five countries (Canada, Russia, Brazil, the United States of America and China) and 66% of forests are found in ten countries (FAO and UNEP, 2020).

Forest area as a proportion of total land area, which serves as SDG Indicator 15.1.1, decreased from 32.5% to 30.8% in the three decades between 1990 and 2020. This represents a net loss of 178 million hectares of forest, an area about the size of Libya. However, the average rate of net forest loss declined by roughly 40% between 1990–2000 and 2010–2020, the result of reduced forest area loss in some countries and forest gains in others (FAO and UNEP, 2020). Forest loss is primarily caused by agricultural expansion, while an increase in forest area may occur through natural expansion of forests, e.g. on abandoned agricultural land, or through reforestation or afforestation (FAO and UNEP, 2020).

In the recent decade, Africa had the highest net loss of forest area, with a loss of 3.94 million hectares per year, followed by South America with 2.60 million hectares per year. For the last consecutive decades, Africa has reported an increase in the rate of net loss, while South America's losses have decreased substantially, more than halving since 2010 relative to the previous decade (FAO and UNEP, 2020).

Kenya's forest cover is estimated to be about 7.4% of the total land area, which is a far cry from the recommended global minimum of 10%. On the other hand, Kenya's closed canopy forest cover currently stands at about 2% of the total land area, compared to the African average of 9.3% and a world average of 21.4 per cent(Ministry of Environment, 2018). Most of the closed canopy forests in Kenya are montane forests that are also the nation's water towers. By assuming the year 1990 as the baseline and the year 2015 as our current context we observed a decline in forest cover in the country by 25% (824,115 hectares) or a rate of 33,000ha forest loss per year. Put in context this is same as losing forest cover equaling the size of 100 football pitches or over 200,000 tree stamps daily (WWF, 2015).

In recent years, Kenya's forests have been depleted at an alarming rate of about 5,000 hectares per annum. This is estimated to lead to an annual reduction in water availability of approximately 62 million cubic metres, translating to an economic loss of over USD 19 million. The depletion has the potential to rollback achievements made in attaining Vision 2030 and the Government's Big Four Agenda of food and nutritional, security, affordable and decent housing, universal healthcare and manufacturing, if it is not urgently addressed (Ministry of Environment, 2018).

2.2 Background of the MFC

2.2.1 The History of Mau Forest Degradation

In the last three decades, the Mau Forest Complex (MFC) has undergone significant land use changes due to increased human population requiring more land for settlement and subsistence agriculture. The encroachment has led to far-reaching land fragmentation, deforestation of the headwater catchments and destruction of wetlands hitherto existing within the fertile upstream areas. Today, the effects of the human activities are slowly taking a toll as is apparent from the diminishing river discharges through periods of low flows, and deterioration of river water qualities through pollution from point and non-point sources (Baldyga et al., 2007) (Olang & Kundu, 2011). Despite the aforementioned crucial functions, the Mau Forest Complex has been impacted by widespread irregular and ill-planned settlements coupled with illegal forest resource harvest that has reduced the cover by more than 7% in the past 21 years [21]. To reverse these negative trends, the government has enhanced forest management through the exploitation of various interventions incorporating both policy and restoration measures (Tarus & Nadir, 2020).

In most African countries, most resources are a source of conflict between local communities thus drawing political nuances. In Kenya for instance, the MFC represents the ancestral land of the Ogiek tribe (Sang, 2001). Even though they started farming from the 1930s-1940s, their traditional livelihood was based on beekeeping, wildlife hunting and gathering of food and medicines from the forest. (Kimaiyo Towett, 2004). Up until the formation of the colonial government, the forest land was jointly held by several lineages, whose members sustained devoted relationships of exchange and marriage with the neighbouring Maasai and Kipsigis tribes (Blackburn, 1974). After the arrival of the British, the Ogiek were evicted from the forest and their land declared Crown Land or allocated to white settlers or other tribes. Their identity was not recognized, with repeated attempts to assimilate them into the largest ethnic groups, such as Maasai or Kalenjin. First under the colonial rule, later under the independent government, they were sidelined and discriminated against because of their small population and insignificant political power (Sang, 2001). (Albertazzi et al., 2018).

2.2.2 Mau Forest Complex Degradation Trends

In an archetypal forest transition of a third world country at the edge of a globalized system, the MFC degradation started and relentlessly continued with loss of flora and fauna. Indiscriminate felling of trees for timber and charcoal resulted to destruction of the diverse forest plant life. Furthermore, the wildlife including elephant and buffalo, that were abundant in the Mau were reduced to a portion of the original due to human-wildlife conflict and loss of habitat. The cleared forest land was then used for several uses including; settlement, agriculture and livestock farming. Of particular significance was the excision of land that is at present under tea production that makes the Mau Catchment zone the largest tea growing area in Kenya undertaken both by large scale local and foreign corporations as well as local small holder farmers (Mutugi & Kiiru, 2015).

The destruction of the MFC is a typical example of varying local, national and international interests. In the MFC, the population of the Ogiek people drastically declined. Those remaining have either been incorporated into other ethnic groups or adopted different lifestyles incompatible with conserving the forest (Kimaiyo 2004). The satellite image assessments show that there was a decrease of 180,000 ha of forest land. The forested land reduced from 520,000 ha in 1986 to 340,000 ha (Hesslerová and Pokorný 2010). Between 1998 and 2004, the Government of Kenya revealed intentions to excise 10% of the gazetted forests. The earlier excision of 1,812 ha was reserved for the resettlement of the Ogiek. However, this never happened as most of the area was allocated to politicians, bureaucrats, businessmen and professionals with political and economic power (Ndungu Report, 2004). Altogether, the forest excision and extensive human encroachments led to a total loss of about 25% over and above the 107,000 ha of the Mau between 1989 and 2009 (Mutugi & Kiiru, 2015).

Reports produced by the Regional Centre for Mapping of Resources for Development (RCMRD) entailing time series analysis of satellite based remote sensing data have revealed substantial land cover changes in the MFC. By the year 1986, the dominant pre-change land cover types were about 75% of forests, 12% of woodlands and 13% of farms. By 1989, the landscape had changed tremendously giving rise to about 60 % of forest and woodland, and 40 % of agriculture and built-up area. (Olang & Kundu, 2011).Another study revealed from the observed land use patterns that the MFC underwent deforestation ranging from about 18% to 25% between 1973 and 2010 with the peak deforestation rate witnessed in the early years of 2000s. (Rwigi, 2014).

2.2.3 Management of the Mau Forest Complex

In recent years, the Mau Forest Complex has received a lot of attention from local and international organizations due to its ecological importance. Most forest areas in Kenya are under the management of the Kenya Forest Service (KFS), which has made considerable advances towards tackling the deforestation and degradation threat to the major water towers in the country. One of their major achievement includes the new forest policy and law 2005. The law emphasizes on a participative approach to forest resource management by all stakeholders especially the local communities. The Government of Kenya also took a further step in establishing the Task Force for the Mau Forest Complex whose mandate was to recommend strategies for restoring the MFC in line with Vision 2030. The KFS also established a very important scheme of restoration of forests through tree planting. (Olang & Kundu, 2011).

The Mau Forests Complex Authority (MFCA) was to be established to organize and supervise the management of the forest. The authority was to be guided by board of directors made up of stakeholders, including the economic sectors directly reliant on the goods and services of the Mau Forests Complex such as forestry, water, tourism and wildlife, energy and agriculture. The MFCA identified immediate areas of concern to enhance the protection of Mau Forest. They saw the need for assessment studies on the critical catchment areas and biodiversity hotspots, which demand immediate and appropriate conservation strategies. Additionally, there was need for frequent monitoring to avert further deterioration of the forest through tree felling, charcoal burning and new encroachment. Demarcation and fencing of hydrological and biological hotspots or where significant human-wildlife conflicts could occur was hence vital in this context. (Olang & Kundu, 2011).

2.2.4 Social-political Aspects and Conflicts Surrounding the MFC

The Mau Forest Complex represents ancestral land of the Ogiek tribe, making it an area of political struggle (Sang, 2001). The traditional livelihood of the Ogiek was a hunter-gatherer although from 1930s-1940s they embraced farming (Kimaiyo Towett, 2004). Up until the creation of the colonial government, the forest land was communally held by more than a few lineages, whose members maintained frequent relationships of exchange and marriage with the neighboring Maasai and Kipsigis tribes (Blackburn, 1974). The arrival of the British settlers saw the Ogiek community get evicted from the forest and their land declared Crown Land (1930s) or allocated to white settlers or other tribes. The Ogiek were marginalized and discriminated against because of their low number and irrelevant political power both by the colonial and later the independent government (Sang, 2001). This instance in the Mau Forest underlines the fact that African governments' power is strictly connected with natural resource management. This assessment confirms similar points developed for extractive resources and should adapt the strategies to fight against forest degradation, controlling the impact of national strategies while focusing on initiatives driven by the community. (Albertazzi et al., 2018).

2.3 Methods of Detecting Forest Cover Change

2.3.1 Application of Remote Sensing and GIS

In the recent years, the use of remote sensing data has revolutionized and supported forest cover monitoring studies. It has provided some of the most accurate methods of measuring the degree and pattern of change in cover conditions over a given period. Satellite data have become a very important application in forest change recognition because of the recurring coverage of the satellites at short intervals. Forest cover today is transformed primarily by anthropogenic activities and any concept of global change must include the widespread influence of human action on land surface conditions and processes.

The orthodox methods of detecting land use and cover changes are expensive, not precise and only cover a small area. However, remote sensing provides valuable information on land use and cover dynamics because of its capability of synoptic observations and repetitive coverage, (Sharma et al., 1989). Detection of changes in the land use and cover involves use of a minimum of two period data sets (Jenson, 1986). The changes in land use and cover due to natural and anthropogenic activities can be observed using present and archived remotely sensed data (Luong, 1993)(Jaiswal et al., 1999).

In most cases, land cover changes involve small areas and develop over extended time scales (Lambin, Geist, & Lepers, 2003). As a result, successful monitoring of changes demands longer-term data sets with detailed spatial resolution. Furthermore, the accuracy of analyses based on these data is depended upon consistency of the temporal and spatial definition of “forest” versus “non-forest” (Sexton, Urban, Donohue, & Song, 2013b). Despite there being several geospatial data sets representing forest cover on a global scale, none have both the spatial and temporal scale required for longer-term monitoring of change at fine spatial resolution. In the past, the delivery of suitably scaled data has faced two challenges. First, the access to sizeable volumes of satellite imagery. Secondly, the real-time reference observations needed to translate image pixels into estimates of cover. Considering the aforementioned the archive of Landsat data with spatial resolution (30m to 60m) and temporal extent (1972–present) is the best source of information for retrieving historical baselines of forest cover factors (Olander et al., 2008). (Kim et al., 2014).

Change detection is a “process of identifying changes in the state of an object or phenomenon by observing images at different times”. Producing land cover maps for tropical zones using satellite imagery poses several challenges. Moreover, it is widely asserted that spectral signatures obtained from Landsat imagery for tropical forest display minimal band separability between vegetation types (Tole, 2002; Tottrup, 2004). For instance, after large torrents, areas adjacent to tropical forests are often fuzzy due to the resulting vegetation densification triggering these areas to blend with densely vegetated tropical forest cover (Campbell, 1981). As a result, boundaries between classes may be incomprehensible except for dry season imagery. Moreover, where landscapes comprise a high level of heterogeneity, for instance in indigenous tropical systems, mixed pixels signifying multiple land cover types in a particular pixel often dominate a remotely sensed image (Smith et al., 2003). There are several technical hurdles when using remotely sensed imagery for a comprehensive land cover classification in fragmented and tropical environments (Baldyga et al., 2007).

2.3.2 Forest Cover Change in Mau Forest Complex

Various studies have been carried out to determine the forest cover change in MFC. For instance, Baldyga et al. (2007) attempted to test the efficacy of raw and transformed Landsat bands in mapping land cover units in the Mau Forest Complex and bordering region and also evaluate the rate of land cover change at multiple spatial scales (Baldyga et al., 2007). In their methodology, the authors acquired three Landsat scenes (Path 169, Row 60) on 28 January 1986, 06 February 1995 and 04 February 2003. The dates were chosen to capitalize on pronounced disparities in reflectance between forested and nonforested areas, reducing confusion at forest edges between dense forest vegetation and small-scale agricultural plots. An important distinction was sought between forested and nonforested areas in an attempt to isolate the rapid conversion of forest to small-scale subsistence farming and managed pasture. Further, the study identified nine thematic classes, excluding shadow and cloud cover, as relevant for quantifying the range of vegetation types and associated spatial and temporal transitions. These thematic classes represent coarse data aggregates corresponding to basic land management practices occurring within the River Njoro watershed. A combination of unsupervised and supervised image classification methods was used to classify digitally the pixels in all three Landsat images (Baldyga et al., 2007).

This study revealed considerable losses in forest areas associated with increases in small-scale agriculture. It was shown that changes in land cover are present across the landscape while the analysis disclosed the intensity and type of change as a function of the geographical position. The use of spatially distributed approach enables the location of areas within the watershed that will most benefit from conservation practices. In a developing nation such as Kenya where financial resources for conservation are scarce, the use of GIS and remote sensing tools provide a cost-effective of improving land management decision-making (Baldyga et al., 2007).

Another study by Ayuyo & Sweta (2014) examined the Mau complex by adopting four approaches. These included; detecting the changes that have taken place, classifying the nature of the change, determining the spatial extent of the change and evaluating the spatial pattern of the change (Ayuyo & Sweta, 2014). The study applied the use of Remote Sensing and GIS to evaluate the land cover and land use changes, trends, magnitudes and the consequent environmental impacts for a period of about 37 years.

The study used satellite imageries and topographical maps of the area combined with geographical coordinates of designated ground control points for recording and image matching, classification and processing. ENVI 4.8 and ArcGIS 10 processing software were used for the development of land cover and land use classes and displaying and subsequent processing and improvement of the images. To achieve its aims, this study used three classes namely; forestland, other vegetation, and Non-vegetated land from which training sites were described after the developing the classification scheme. (Ayuyo & Sweta, 2014).

This study reported that from 1973 and 1986, forest cover reduced by 4.2%, area under other vegetation decreased by 1.86% while area under non-vegetation had an increase of 7.00%. The next period of 1986 and 2000 showed a minor growth of forest land implying that forest land was not disturbed in this period while other vegetation converted to none-vegetation. Specifically, area under forest cover increased by 1.2% while area under other vegetation decreased by 6.00% and area under non-vegetation increased by 7.2%. Between 2000 and 2010, forest cover decreased by 8.7% while the area under other vegetation increased by 20.4% and the area under none-vegetation for the decreased by 12.3%. The study concluded that there were both desirable and undesirable changes, although the changes that has a negative impact on forest cover were more than compared to those that impacted positively (Ayuyo & Sweta, 2014).

Ndubi (2018) carried out a study with the goal to determine the possible locations of the drivers of land cover change in MFC by pinpointing the changes happening in various land cover types and the anthropogenic activities causing those changes. The method followed involved downloading images and radiometrically and geometrically correcting them before processing. The images were radiometrically processed using ENVI 5.1 to remove the distortions that occur when electromagnetic radiations interact with atmospheric materials. Geometric correction was done using ArcGIS 10.3 software to eliminate the shift that occurs between images, a consequence of different sensor flight heights for images of the same place captured at varying times. The authors were able to identify six distinct features on all images whose corresponding positions were then located on the ground. The geographic coordinates of the six points were recorded by means of a handheld GPS unit at the exact ground positions. The logged coordinates were then used in the geo-rectification process (Ndubi, 2018).

This study showed that cropland and spread out of built-up area were the main drivers for land cover change in Eastern Mau Forest area. This was especially accompanied with the decline of indigenous and plantation forest land cover types. The author concluded that sustainable use of forest resources in Eastern Mau Forest area would only be possible if expansion of drivers of land cover change in Eastern Mau Forest area were checked or reduced (Ndubi, 2018).

3.0 METHODOLOGY

3.1 Study Area

The study will be carried out in the Mau Complex Forest, which is the largest almost continuous montane indigenous forest in East Africa as well as the most extended natural water tower in Kenya. The study area is located in the Rift Valley region in Kenya, between latitudes 0° 91' N - 1° 49' S and longitudes 34° 9' - 36° 6' E. It covers a total area of about 24,000 km² and 13 counties: Baringo, Bomet, Elgeyo Marakwet, Kericho, Kiambu, Kisumu, Nakuru, Nandi, Narok, Nyamira, Nyandarua and Uasin Gishu (Swart, 2016). The forestry complex is part of the upper water catchment area of the twelve main rivers of West Kenya that flow into the lakes Victoria, Turkana, Natron, Baringo and Nakuru. The Mau Complex is composed of 22 blocks – all but one of them (the Maasai Mau) declared forest reserves. The altitude ranges between 1000 to 3200 meters above sea level, with the most highly elevated areas located in the middle part of the study area: the northern part of the county Narok and western areas of Nakuru (Albertazzi et al., 2018).

The study area falls into different climate zones: equatorial tropical rainforest climates with high monthly rainfalls and tropical savannah climates with dry seasons. In the study area, the rainfall pattern is bimodal and the long rainy season is from March to May, and short rainy season October to December (Swart, 2016). Depending on the exact location in the area, dry season generally runs from January to March, and May to September. Annual monthly temperatures vary spatially as well: the highly elevated parts show low annual temperatures (minimums of 10.6 °C), while the most northern parts in Elgeyo Marakwet and Baringo have high annual temperatures (maximum temperatures of 24.6 °C) (Swart, 2016).

3.2 General steps of LULC mapping in the GEE environment

GEE is a platform for processing a multi-petabyte catalog of global-scale satellite imagery and geospatial datasets with planetary-scale with analysis capabilities, and makes it available for scientists, researchers, and developers to detect changes, map trends, and quantify differences on the Earth's surface dating back up to 40 years (Google, 2012). It allows users to download and upload global satellite imagery, as well as allowing them to perform complex calculations on the same. Currently, GEE is gaining popularity within the scientific community due to its powerful free cloud processing and Planetary-scale datasets, flexible APIs for development, Git functionality, ability to upload your own data, dynamic easy user interface, among others. However, despite the advantages, GEE is not designed for large Vector data processing, limited Cartographic capability. In addition, there is user limitation on data processing and data exporting, lack of all GIS functionality and limited for noncoding users. In conducting 10 years analysis for Mau Forest ecosystem, the classification process was divided into four major steps that is data collection, classification, accuracy assessment and change detection. With one year interval, the surface reflectance data from 2010 as the base year to 2022 as the final year were collected within GEE platform.

Using GEE, an image collection, or data stack, were be generated for the study period (2010-2020) comprising all images intersecting the study area to produce a cloud-free composite of scenes for the whole ecosystem. In this study, classification schema comprises of five Land cover classes namely Forest, Agriculture, Grassland, Bareland, Build-up, and water bodies were considered as they are the dominant land uses within the ecosystem. Using High resolution satellite images and Google earth, Ground truth samples were collected for each class, randomly distributed within each land use class as by guided by an expert knowledge. The collected samples were divided into 'Training sample' 70% and Testing sample 30% which was necessary for accuracy assessment. Because tree-based algorithms such as Random Forest are sensitive to class imbalance (Hossein S. M. et al., 2021), efforts were made to avoid large differences between the numbers of samples, although some classes such as Water bodies and Bareland covered a small area in the ecosystem, and relatively fewer samples were taken. Together with expert knowledge in training sample point distribution, normalized difference vegetation index (NDVI) also assisted as it was easy to create a visual segmentation of the images to identify land use type.

3.3 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index is a simple indicator of photosynthetically active biomass that helps to differentiate vegetation from other types of land cover and determine its overall state. The chlorophyll pigment in a healthy plant absorbs most of the visible red light, while the cell structure of a plant reflects most of the near-infrared light. It implies that high photosynthetic activity, commonly related to dense vegetation, will have fewer reflectance within the red band and better reflectance within the near-infrared one. This difference in reflection and absorption of EM radiation enables reliably detection of vegetation cover separately from other land cover types. NDVI value ranges between -1.0 and +1.0. The NDVI is calculated from these individual measurements as follows:

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

3.4 Image classification using Random Forest algorithm

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. To date, RF is considered one of the most widely used algorithms for land cover classification using remote sensing data (Li, X. et al 2016, Jin, Y. et al 2018). According to Mahdianpari et al. (2017) and Xia et al. (2018), the reasons for RF receiving considerable interest over the last two decades are first, good handling of the outliers and noisier datasets, secondly, good performance with high dimensional and multi-source datasets. In addition, RF is more preferred than other popular classifiers, such as SVM, kNN or MLC in many applications due to its higher accuracy (Rodriguez-Galiano, V.F et al 2012); and increasing the processing speed by selecting important variables (van Beijma, S. et al., 2014). According to Tamiminia, H. et al. (2020), analysis of over the last 10 years peer-reviewed articles shows that the RF algorithm is the most frequently used classification algorithm for satellite imagery (Tamiminia, H. et al. 2020); considering all these reasons, we chose RF for the present study.

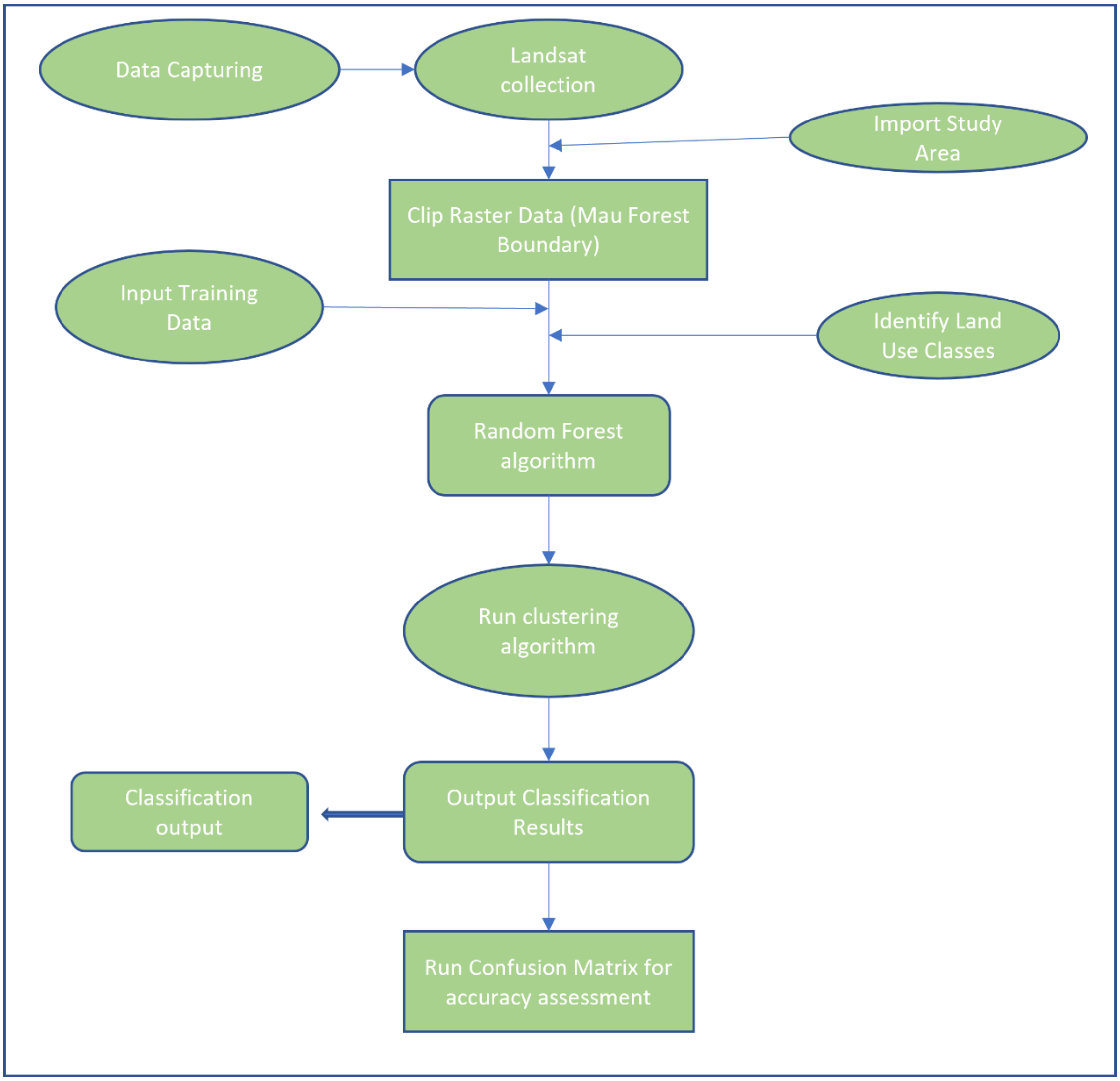


Figure 1: General Work-flow in GEE

3.5 Accuracy assessment

According to Congalton and Green (2019), error matrix is the most applied technique to determine accuracy of a classification process in land use land cover development. The classification accuracy can be evaluated to produce an overall measure of the map's quality, which can then be used to compare alternative change detection systems (Foody 2002; Sabah S. Aljenaid et al., 2022). As proposed by Anderson et al (1976), the minimum allowable level of accuracy in interpreting remote sensing data to identify land use land cover classes should be at least 85%. To compute the components of overall accuracy, producer's accuracy, user's accuracy, error of omission (EO), error of commission (EC), and kappa coefficient, these standards error matrices (accuracy assessment statistics) are computed based on the same data references for each image (Aljenaid et al., 2022). However, according to Foody (2020), a confusion matrix (i.e., OA, PA and UA) only provides information for an "estimate" of classification accuracy, thus only a tentative conclusion can be made. This is especially the case when we compare different classification results with small accuracy differences.

Due to large amount of dataset involved in the study, only Overall accuracy and User accuracy was considered as it is very informative about quality of the outcome of a classification process. Overall accuracy (OA) is the total number of successes compared to the total number of samples in the categorized image (Aljenaid et al., 2022). It is calculated by summing the number of correctly classified values and dividing it by the total number of values in the confusion matrix using the below equation:

$$\text{Overal Accurracy} = \frac{Sum\ of\ Diagonal\ Correctly\ Tallied}{Total\ Number\ of\ Samples} \times 100$$

User's accuracy (UA) is the probability of classified pixel on each map representing the actual class on the ground or real-world location (Congalton 1991; Jensen 2005; Campbell 2007) and it was calculated using below equation:

$$\text{User Accurracy} = \frac{Correctly\ Identified\ Sample\ in\ a\ Row}{Row\ Total} \times 100$$

3.6 Change Detection and Final Computation

This sage of the analysis was caried out using a combination tool and approaches. First, the output of the classification were exported from GEE to QGIS for final statistical and change detection computation using Orfeo ToolBox in QGIS. Secondly, the results were further exported to ArcMap 10.8 due to its capabilities in overlay analysis using spatial analyst tool and good Maps production. Orfeo Toolbox, OTB, is a remote sensing image processing library developed by CNES, the French Space Agency, with the goal of enabling the user to process remote sensing images from different sources (satellite, image provider) with different levels of preprocessing (ortho-rectification, radiometric corrections). The tool is distributed as Open-Source software and is therefore available for any remote sensing scientist or processing chain developer. The tool performs change detection between two successive images by using Multivariate Alteration Detector (MAD) (Nielsen, A. A., and Conradsen, K. 1997) algorithm. The MAD algorithm produces a change map through the application of statistical method which can handle different modalities (Nielsen, A. A., and Conradsen, K. 1997).

4.0 RESULTS

In conducting forest cover analysis of Mau complex ecosystem, combination of different approaches, data sources and tools were explored to improve the accuracy of the result. The land cover classification results from 2010 to 2020 were calculated. Having trained every possible feature signature for each LULC class (678 training sites and 292 validation sample) as well as the image pre-processing analysis, the object-based classification was implemented to extract the LULC from Landsat satellite images in Google Earth Engine. For further analysis and detection of changes, the classified images were exported to QGIS. Using Orfeo ToolBox in QGIS, change detection between two successive images were computed using Multivariate Alteration Detector (MAD) (Nielsen, A. A., and Conradsen, K. 1997) algorithm. The MAD algorithm produces a change map through the application of statistical method which can handle different modalities (Nielsen, A. A., and Conradsen, K. 1997). The total Area of the study covers approximately 268690.107 ha, with forest occupying 80% (216591 ha), Agriculture 14.86% (39927.35 ha), Grassland 2.4% (6448.563 ha), Build-Up 1.3% (3492.971 ha), Bareland 0.8% (2149.521 ha) and lastly Water bodies 0.03% (80.60703 ha) in 2010 as shown in the figure above.

4.1 Data used and Processing

In this study, a collection of both Landsat 5, 7 and 8 sensors were used in the Google engine platform. Using GEE, an image collection, or data stack, were generated for the study period (2010-2020) comprising all images intersecting the study area to produce a cloud-free composite of scenes for the whole ecosystem. The table below shows date of data acquisition, the sensor and image identification number.

Table 1: Satellite data used for the analysis

Sensor (Landsat)	Date	Image ID
5	2010/01/30	LT05_L2SP_169060_20100130_20200825_02_T1
5	2011/01/17	LT05_L2SP_169061_20110117_20200823_02_T1
7	2012/03/16	LE07_L1TP_169061_20120316_20200909_02_T1
8	2013/05/30	LC08_L2SP_169060_20130530_20200913_02_T1
8	2014/01/25	LC08_L2SP_169060_20140125_20200912_02_T1
8	2015/02/13	LC08_L2SP_169060_20150213_20200909_02_T1
8	2016/02/16	LC08_L2SP_169060_20160216_20200907_02_T1
8	2017/01/17	LC08_L2SP_169060_20170117_20200905_02_T1

8	2018/02/05	LC08_L2SP_169060_20180205_20200902_02_T1
8	2019/03/12	LC08_L2SP_169060_20190312_20200829_02_T1
8	2021/01/28	LC08_L2SP_169060_20210128_20210305_02_T1
8	2020/02/11	LC08_L2SP_169060_20200211_20200823_02_T1

GEE provided algorithms for Landsat collection processing. Surface reflectance improves comparison between multiple images over the same region by accounting for atmospheric effects such as aerosol scattering and thin clouds, which can help in the detection and characterization of Earth surface change. Landsat surface reflectance (SR) data are available in Earth Engine as a copy of the USGS Collection 2. Google Earth Engine provides several algorithms that allows users to process the images based on user requirements. The ‘raw’ scenes in Earth Engine contain imagery with digital numbers (DNs) that represent scaled *radiance*. The conversion of DNs to at-sensor radiance is a linear transformation using coefficients stored in scene metadata (Chander et al. 2009). The `ee.Algorithms.Landsat.calibratedRadiance()` method performs this conversion. Conversion to TOA (or at-sensor) *reflectance* is a linear transformation that accounts for solar elevation and seasonally variable Earth-Sun distance. The TOA conversion is handled by the `ee.Algorithms.Landsat.TOA()` method. The TOA method converts thermal bands to brightness temperature.

4.2 Classifications and accuracies

After processing the stacked image collection, classification was carried on each single image producing land cover for the ecosystem from 2010 to 2020. During the classification process, five land cover classes namely Forest, Agriculture, Grassland,

Bareland, Build-up, and water bodies were considered since they are the dominant land covers within the ecosystem. Random classifier algorithm provided by GEE was applied since it performs better in handling of the outliers and noisier datasets, secondly, it offers good performance with high dimensional and multi-source datasets.

	2010
Land Cover	Area (Ha)
Forest	216591.1
Agriculture	39927.35
Grassland	6448.563
Bare-land	2149.521
Buildup	3492.971
Water	80.60703

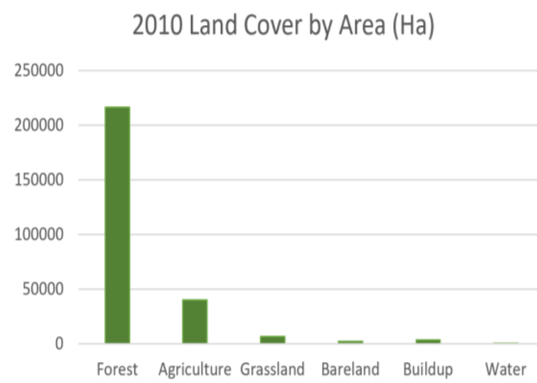


Figure 2: Initial (2010) Land Use Land Cover distribution by Class

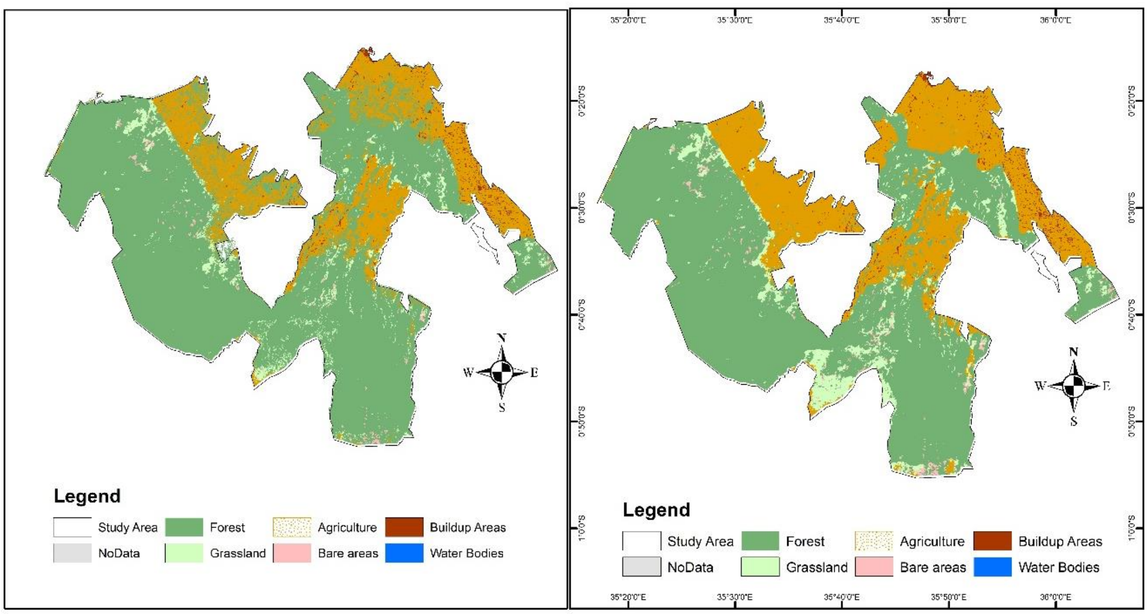


Figure 3:Initial Land Use Land of 2010 (Left) and the final Land Use Land Cover of 2020(Right) (the orange color in the maps is not well represented in the legend)

The results of the classification indicate that in 2010, Forest occupies larger portion of the ecosystem with 80% translating to approximately 216591 ha, with water occupying the least portion of about 0.03%.

With approximately 968 sampling points, the classification outputs were further subjected to accuracy assessment using error matrixes, most applied technique to determine accuracy of a classification process in land use land cover development. The Random Forest algorithm provides an automated classification accuracy validation using the out-of-bag error, where approximately 30% of selected training samples were left out during classification. After the classification was complete, the model took the 30% 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.

Table 2: Training and Validation sample distribution among the LULC classes

Land Cover Class	Total sample	Training Samples (70%)	Validation Samples (30%)
Forest	242	169	73
Agriculture	180	126	54
Grassland	178	125	53
Bareland	136	95	41
Buildup	142	99	43
Water	92	64	28
Total	**968**	**678**	**292**

In conducting the accuracy assessment, we applied the same training sample and validation data points to classify and assess the accuracy of the land cover maps. 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. As reported by Chander et al. (2009), 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.

For this study the overall mean accuracy was 87.64%, slightly above the minimum allowable value according to Anderson et al (1976), as he indicated that the minimum accuracy value for reliable Land cover classification is 85%. The maximum Overall Accuracy was obtained for year 2020 dataset, with an OA value of 90.43%. From the analysis and visual examination of the data, it had 0% cloud cover and every land cover class could be easily identified from the image. I attribute the good performance to data quality. The lowest OA was archived in 2014 with an accuracy of 85.36% as shown in Table 3.

Table 3: Overall Accuracy for the 10 years period

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average
OA	86.89	89.36	88.23	86.23	85.36	88.51	86.23	87.36	86.36	87.32	90.43	87.48

In calculating User Accuracy, vegetation attained highest the value among the land use classes with average value of 91.23% with Bareland attaining the lowest of an average of 84.32%. Agriculture, Grassland and Water obtained a mean User Accuracy of 89.74%, 89.24% and 87.56 respectively as shown in the table below. However, the results of classification accuracy assessment can be improved by introducing additional auxiliary data or variables (Thanh N. P. 2020) for example the effect of altitude, slope among others.

Table 4: User Accuracy for each land cover class for the 10 years period

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average
Forest	88.95	90.12	95.23	89.57	94.61	92.32	93.12	90.55	91.25	90.12	93.74	**91.23**
Agriculture	90.75	85.25	90.23	88.58	93.24	90.47	89.36	87.28	89.56	87.24	95.23	**89.74**
Grassland	87.63	90.69	89.58	87.58	91.98	92.12	85.23	88.98	89.89	89.25	88.79	**89.24**
Bareland	83.25	89.69	82.03	85.55	81.21	84.63	80.23	89.23	80.25	86.25	85.2	**84.32**
Water	88.32	85.69	84.98	89.78	85.36	87.65	88.21	84.12	85.36	89.93	90.76	**87.56**

4.3 Change Detection

To understand the trends, change detection was carried out in QGIS using Orfeo ToolBox. Orfeo Toolbox, OTB, is a remote sensing image processing library developed by CNES, the French Space Agency, with the goal of enabling the user to process remote sensing images from different sources (satellite, image provider) with different levels of preprocessing (ortho-rectification, radiometric corrections). The tool is distributed as Open-Source software and is therefore available for any remote sensing scientist or processing chain developer. The tool performs change detection between two successive images by using Multivariate Alteration Detector (MAD) (Nielsen, A. A., and Conradsen, K. 1997) algorithm. The MAD algorithm produces a change map through the application of statistical method which can handle different modalities (Nielsen, A. A., and Conradsen, K. 1997).

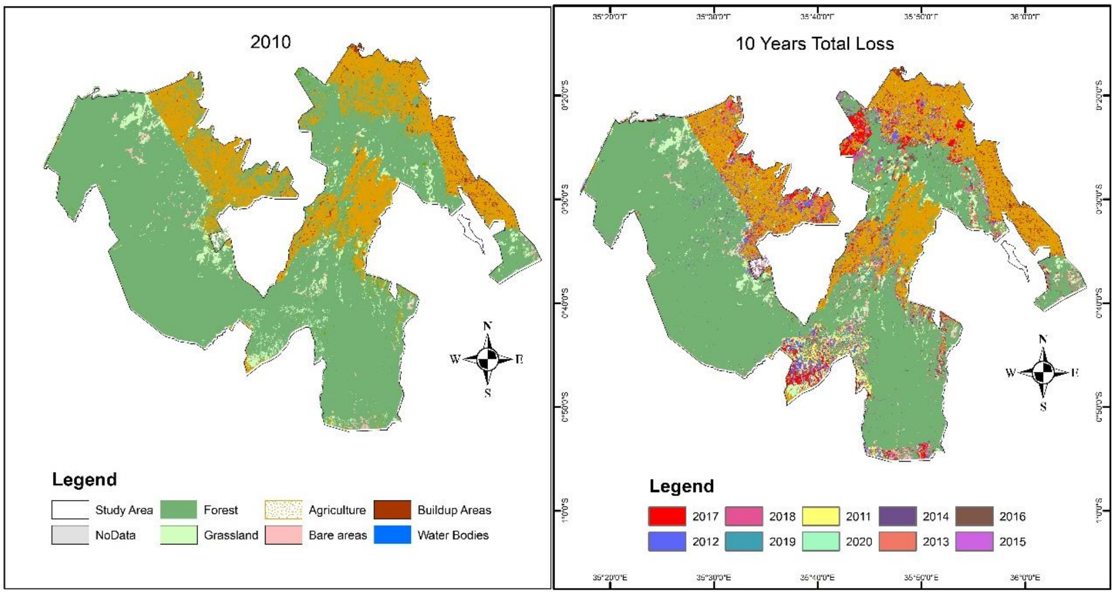


Figure 4:Yearly Forest cover loss

As shown in the figure

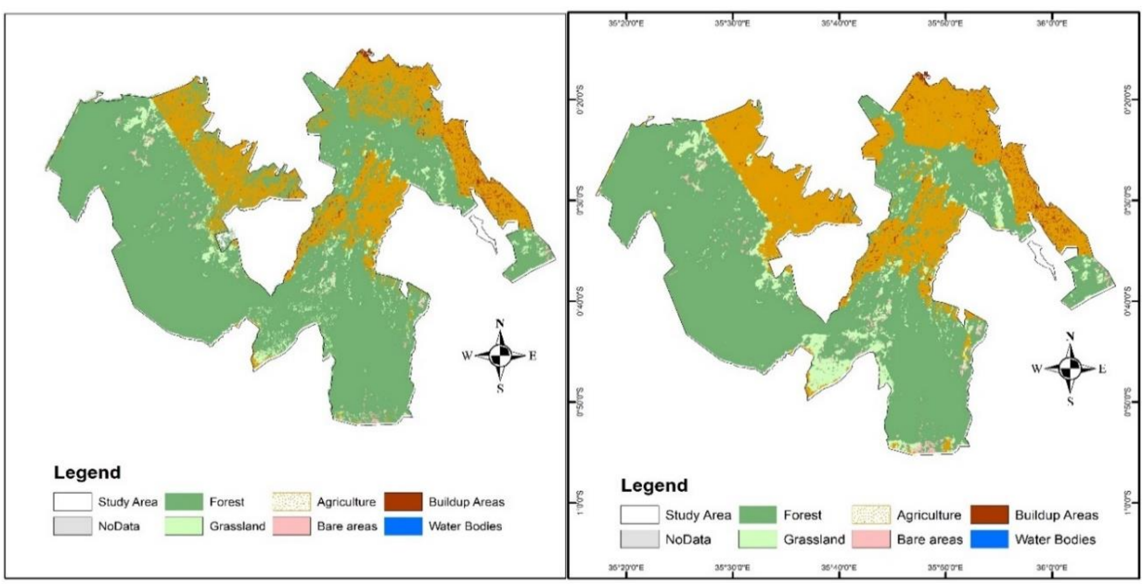


Figure 5:Forest lost between 2010 and 2011 shown in Red

above, using OrfeoTool, it was possible to compute yearly forest loss from 2010 to 2020.

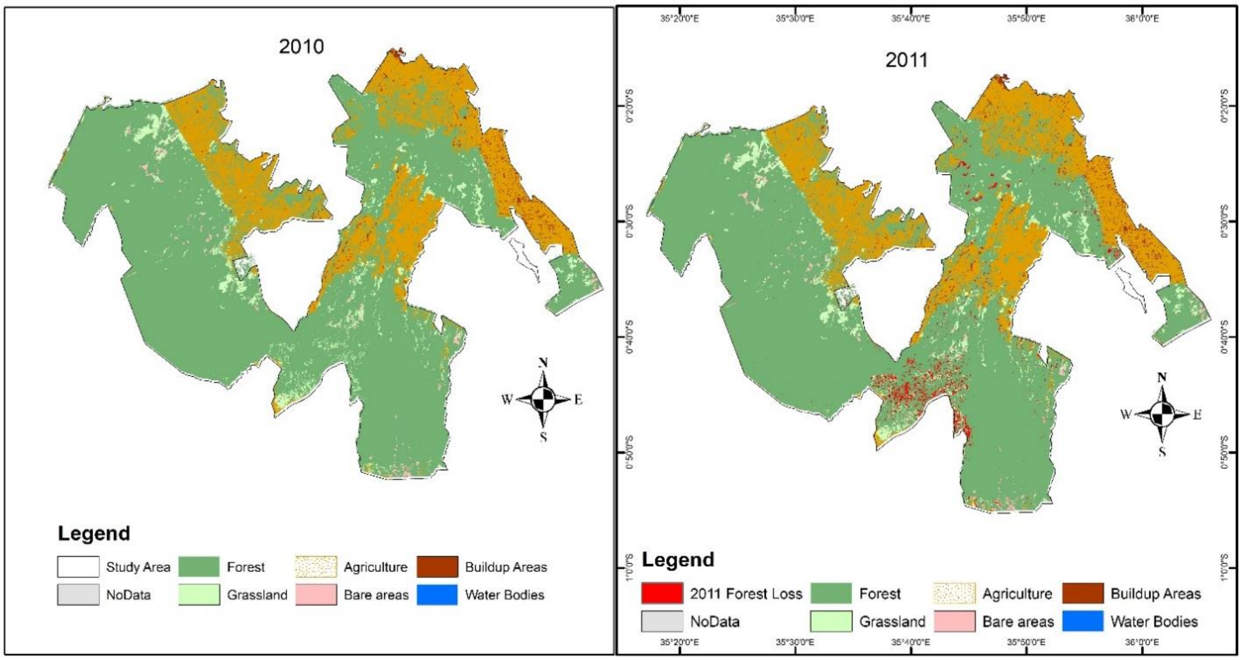


Figure 6: Initial Land Use Land of 2010 (Left) and the final Land Use Land Cover of 2020 (Right)

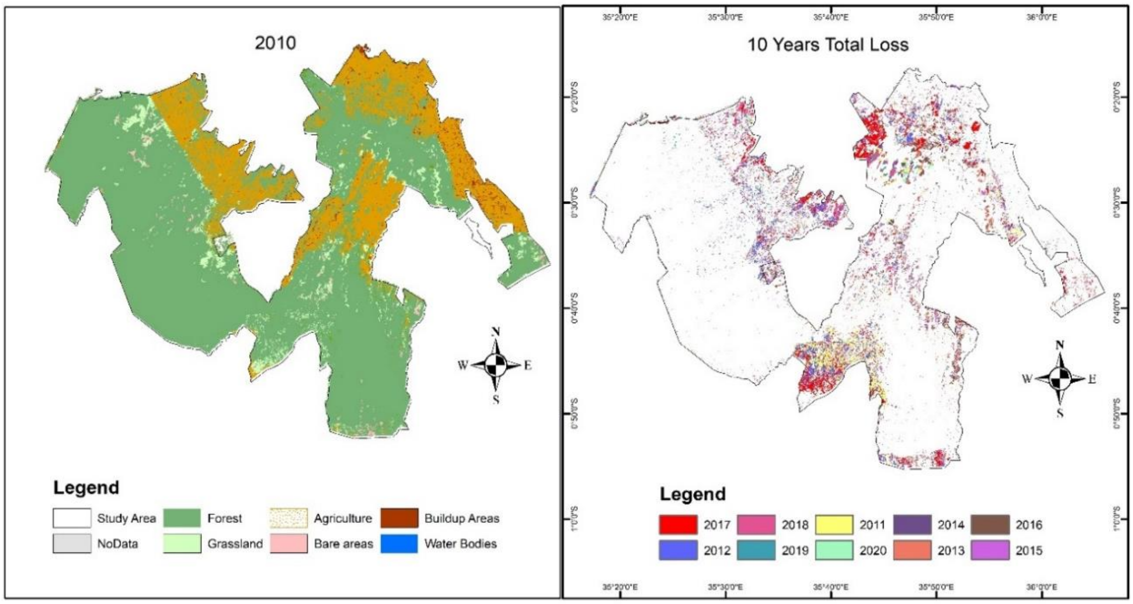


Figure 7: Total Forest loss for the 10 Years period

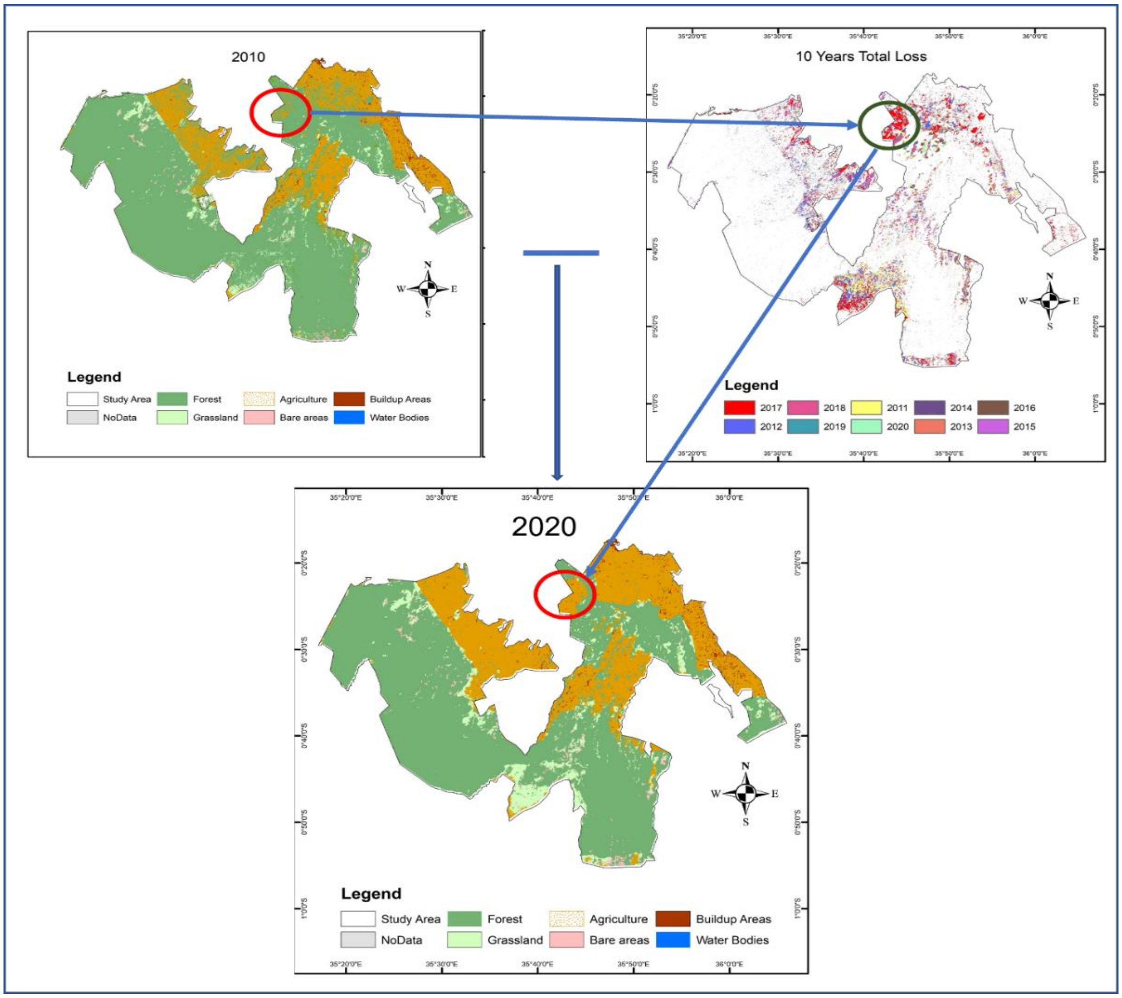
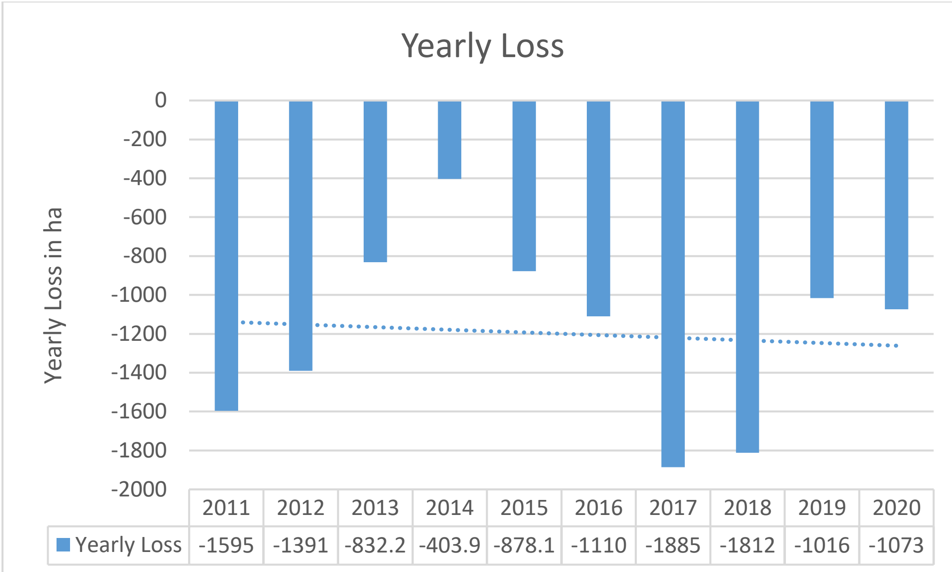


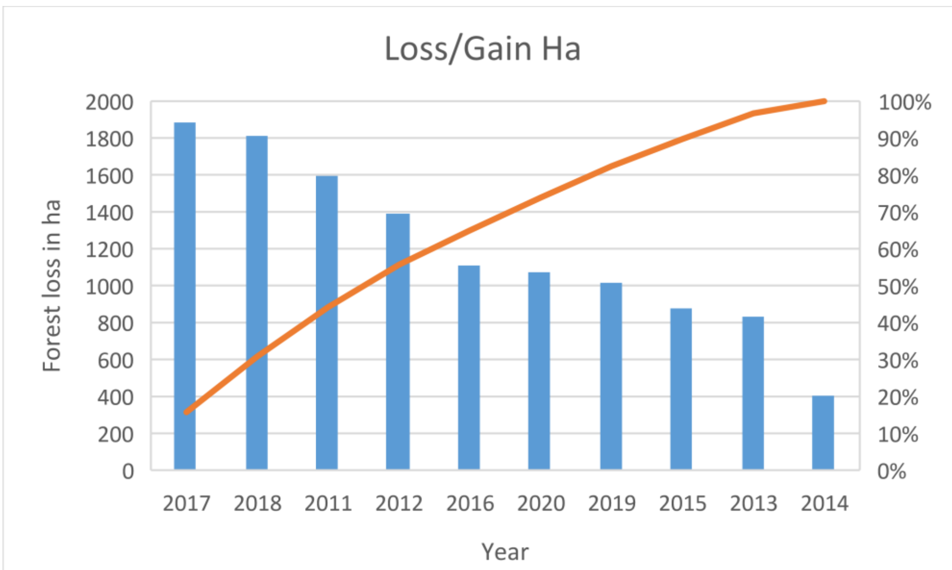
Figure 8: Areas affected by forest degradation

4.4 Trends and discussion

4.4.1 Forest Trend

From the analysis, Forest cover has been decreasing through the study period at annual rate of 0.5% with highest loss in 2017 (0.87%) translating to 1885.16 ha and lowest in 2014 (0.19%) which is about 403.88 ha. A similar study done by Alice Jebiwott *et al* (2021), also noticed a negative forest cover trend in Mau Forest with an increasing trend in Agricultural land.

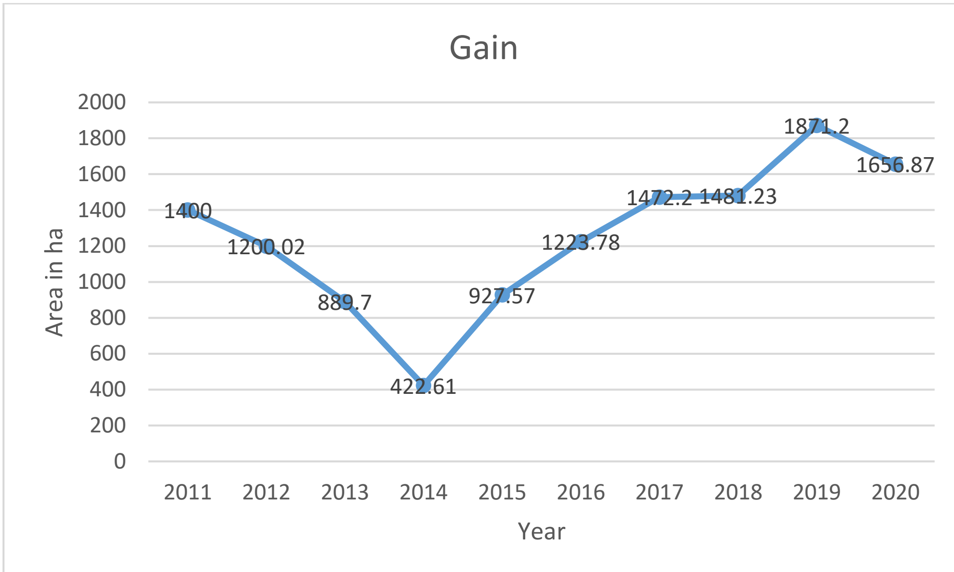




	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Area ha	2165 91.1	2149 95.8	2136 05	2127 72.8	2123 68.9	2114 90.8	2103 81	2084 95.9	2066 84.2	2056 68.5	2045 95.2

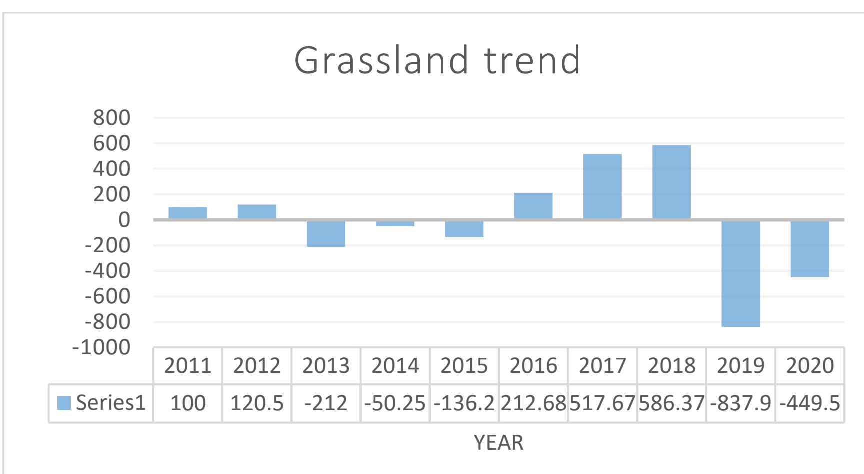
4.4.2 Agriculture

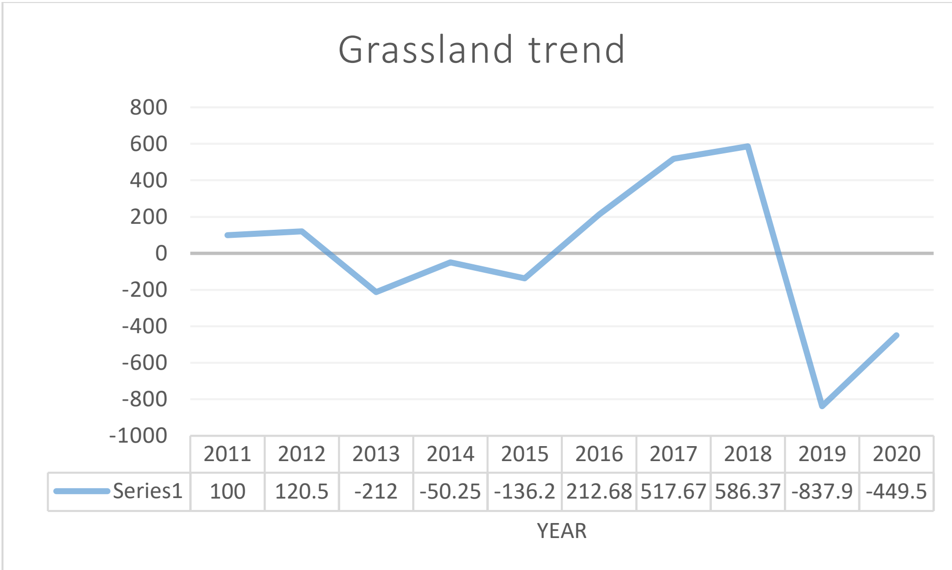
Over the 10-year time period analysis, we observed continuous decrease trends in total forested area with an opposite trend in farmland within the ecosystem. The agricultural land has been on the increase at an average annual rate of 3.14% which translate to 1254.5 ha/year. The rate increase is in agreement with population increase as seen in the increase in build environment. The highest expansion of farmland was experienced in 2019 with 4.68% while the lowest was in 2014 by 1.06% rate.



4.4.3 Grassland

Unlike Forest and Agriculture which have one direction of land cover transformation, Grassland experience both increase and decrease. Averagely, over the 10 years analysis, Grassland cover reduced by approximately 0.23 % in terms of cover. The greatest loss occurred in 2019 by 12.99% which is approximately 837.91 ha with the highest gain in 2018 by about 9.09%. As shown in the picture below.

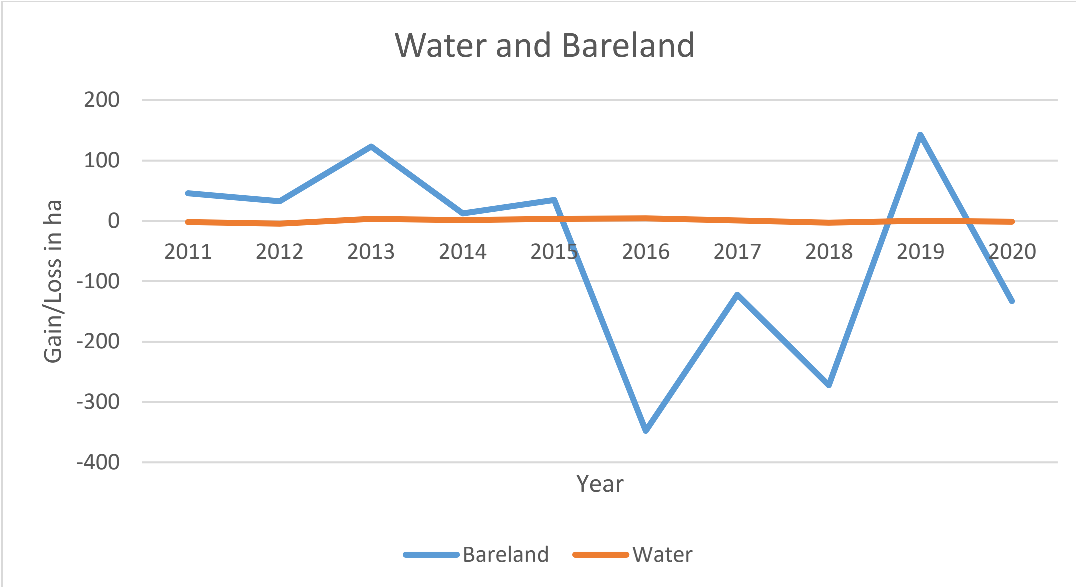


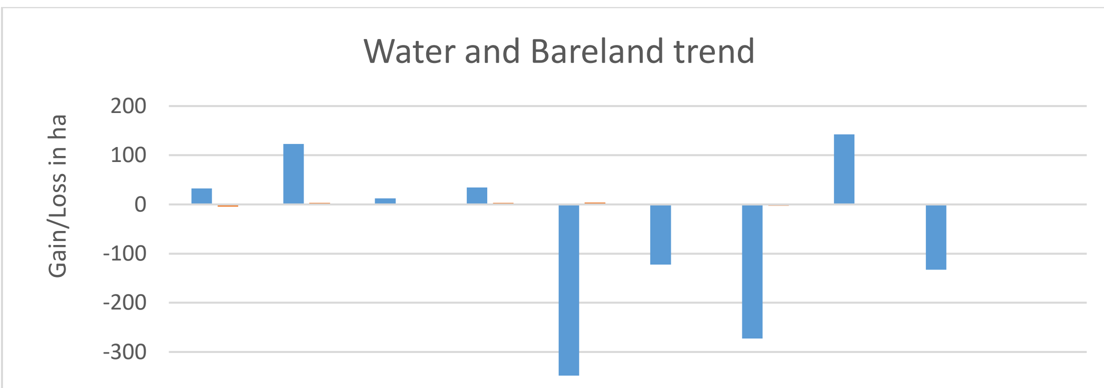


	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Series1	100	120.5	-212	-50.25	-136.2	212.68	517.67	586.37	-837.9	-449.5

4.4.4 Bareland and water cover trend

Like Grassland, both Bareland and Water experienced both positive and Negative trend within the 10 years of analysis. For water, the highest increase was in 2016 by about 4 ha. This high increase could be attributed to collection of water ponds after a long rain since there are very little water bodies within the upper part of the ecosystem, with the lowest decrease in 2012 by almost similar quantity. Bareland on the other hand experienced sharp fluctuations in terms of loss and gain. The highest gain by was in 2019 by approximately 142.8 ha with the lowest decrease in 2016 by approximately 347.81 ha. Since the data was captured during planting season, land prepared for farming could be easily classified as Bareland, this could explain the sharp fluctuation in terms of cover.





	2012	2013	2014	2015	2016	2017	2018	2019	2020	
Bareland	32.6	123	12.2	34.55	-347.81	-122.45	-272.34	142.8	-132.88	
Water	-4.6	3.358	1.02	3.26	4.22	0.85	-2.78	0	-1.23	

5.0 CONCLUSION

Land Use Land Cover transformation results from the composite interface of numerous factors such as culture, human behavior, policy, economics, management, and the environment (Wilder, 1985). To understand and quantify such transformation, remote sensing and GIS has proven to very fundamental technology in providing such information. If used in conjunction with deforestation monitoring, this approach could be the base for precise forest monitoring in Kenya. This study integrated remote sensing and GIS to quantify and analyze the LULC changes in Mau Forest ecosystem. Forest degradation from 2010 to 2020 were analyzed and visualized using statistics and maps diagrams. In addition to Forest, the other identified classes like Agriculture, Grassland and Bareland revealed substantial change patterns in the study area except for Water. Compared to other studies on forest degradation monitoring with earth observation data and different approaches, this study achieved lower overall accuracy. In Brazil and Indonesia, forest degradation has been mapped with an accuracy of about 94 and 95%, respectively (Sofan et al. 2016, Souza et al. 2005). These studies used one clear frame per year and a simple frame difference algorithm for consecutive time steps. However, such an approach is far less promising in Mau than in tropical rainforests, since Mau Forest is characterized by a mix of evergreen, semi-deciduous and deciduous trees (Obare and Wangwe 1998). Here, cloud-free images are only available during the dry season, when degradation activities are less distinguishable from canopy senescence (Miettinen, Stibig, and Achard 2014). In particular, the leaf-off configuration of some trees, which is absent in tropical rainforests, results in considerable variation in the RS signal. The combination of high signal variation and very few non-cloudy observations in the rainy season poses an additional challenge to distinguish noise from actual disturbances or seasonal vegetation dynamics. Furthermore, the complex mix of different forest types (evergreen, semi-deciduous, bamboo) and degradation drivers in the Mau Forest may require higher resolution satellite images which are very expensive and require high computational computer that were not available in this study. However, despite the technological and data limitation in the study, the changes in LULC were effectively captured by the remote sensing Landsat satellite sensors with different spectral, spatial, and temporal resolutions with GIS analysis. The change detection analysis using GIS and remote sensing delivers valuable information to understand the annual patterns of land use dynamics in Mau Forest ecosystems for planners and decision-makers; therefore, sustainable forest and land management planning is possible. The expansion of the Agricultural activities within the Mau ecosystem is mainly at the expense of Forest land. The findings indicate ongoing disturbances in both at the edge and the interior of the forest, resulting in the continuous fragmentation of the Mau Forest. To slow down or reverse this process adequate forest monitoring tools are needed. As human activities progressively shift into the interior of the forest, currently degrading areas cannot be reached within one day. For the environment's long-term sustainability and monitoring of forest disturbance in Mau Forest, LULC changes should be constantly monitored in the future. The presented data and results may support the Kenyan Forest Service and Kenyan Wildlife Service in the planning of patrols, especially when operationalized as a near real-time (NRT) monitoring system. Knowledge on the spatial extent and the location of degrading areas may additionally inform policy makers to prioritize main intervention areas. Moreover, Landsat TM5, ETM+7, and OLI8 images archives and the newly invented remote sensing satellite imagery for example Sentinel 2 optical images should be used to create and monitor accurate maps of forest cover changes in Mau. The advent of the Sentinel satellites (S1 and S2) with higher spatial resolution and revisit time

marks an interesting opportunity to improve the forest monitoring activities. New spectral bands, particularly in the red spectrum, of Sentinel 2 may enhance the distinguishability of tree canopy and understory vegetation. Therefore, the calibration of Spectral Mixture Analysis (SMA) models may be more accurate than with Landsat bands.

6.0 REFERENCES

Albertazzi, S., Bini, V., Lindon, A., & Trivellini, G. (2018). Relations of power driving tropical deforestation : a case study from the Mau Forest (Kenya). *Belgeo. Revue Belge de Géographie*, *2*, 0–19. https://doi.org/10.4000/belgeo.24223

Arevalo, J., & Ladle, R. (2018). *Challenges of Forest Conservation* (pp. 172–195). https://doi.org/10.1201/9781315367170-7

Ayuyo, I. O., & Sweta, L. (2014). *Land cover and land use mapping and change detection of Mau Complex in Kenya using geospatial technology*.

Baldyga, T. J., Miller, S. N., Driese, K. L., Gichaba, C. M., & Valle, L. (2007). Assessing land cover change in Kenya ’ s Mau Forest region using remotely sensed data. *African Journal of Ecology*, *46*(1), 46–54.

Balthazar, V., Vanacker, V., Molina, A., & Lambin, E. F. (2015). Impacts of forest cover change on ecosystem services in high Andean mountains. *Ecological Indicators*, *48*, 63–75.

Boafo, J. (2013). *The impact of deforestation of forest livelihoods in Ghana*.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Chrisphine, O. M., Maryanne, O. A., & Mark, B. K. (2016). Assessment of Hydrological Impacts of Mau Forest , Kenya. *Hydrol Current Res*, *7*(223), 2. https://doi.org/10.4172/2157-7587.1000223

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science*, *1111*(September), 1108–1111.

E Nyland, K., E Gunn, G., I Shiklomanov, N., N Engstrom, R., & A Streletskiy, D. (2018). Land cover change in the lower Yenisei River using dense stacking of landsat imagery in Google Earth Engine. *Remote Sensing*, *10*(8), 1226.

FAO and UNEP. (2020). *The State of the World’s Forests 2020. Forests, biodiversity and people.*

Google. (2012). *Google Earth Engine*. https://earthengine.google.org/#intro

Hesslerová, P., & Pokorný, J. (2010). Effect of Mau forest clear cut on temperature distribution and hydrology of catchment of Lakes Nakuru and Naivasha: preliminary study. In *Water and nutrient management in natural and constructed wetlands* (pp. 263–273). Springer.

Imo, Moses, and M. I. (2012). Forest Degradation in Kenya : Impacts of Social , Economic and Political Transitions For the exclusive use of Moses Imo. *African Political, Economic and Security Issues*, *1*(1).

Imo, M. (2012). Forest Degradation in Kenya: Impacts of Social, Economic and Political Transitions. *African Political, Economic and Security Issues*.

Jaiswal, R. K., Saxena, R., & Mukherjee, S. (1999). Application of Remote Sensing Technology For Land Use / Land Cover Change Analysis. *Journal of the Indian Society of Remote Sensing*, *27*(2), 123.

Jiang, W., Yuan, L., Wang, W., Cao, R., Zhang, Y., & Shen, W. (2015). Spatio-temporal analysis of vegetation variation in the Yellow River Basin. *Ecological Indicators*, *51*, 117–126.

Kim, D., Sexton, J. O., Noojipady, P., Huang, C., Anand, A., Channan, S., Feng, M., & Townshend, J. R. (2014). Remote Sensing of Environment Global , Landsat-based forest-cover change from 1990 to 2000. *Remote Sensing of Environment*, *145*, 178–193. https://doi.org/10.1016/j.rse.2014.08.017

Kinyanjui, M. J., Shisanya, C. A., Nyabuti, O. K., Waqo, W. P., & Ojwala, M. A. (2014). Assessing tree species dominance along an agro ecological gradient in the Mau Forest Complex, Kenya. *Open Journal of Ecology*, *2014*.

Kipkoech, A., Mogaka, H., Cheboiywo, J., & Kimaro, D. (2011). *The total economic value of Maasai Mau, trans Mara and Eastern Mau forest blocks, of the Mau forest, Kenya*. Environmental Research and Policy Analysis (K).

Klopp, J. M. (2012). Deforestation and democratization: patronage, politics and forests in Kenya. *Journal of Eastern African Studies*, *6*(2), 351–370.

Kogo, B. K., Kumar, L., & Koech, R. (2019). Forest cover dynamics and underlying driving forces affecting ecosystem services in western Kenya. *Remote Sensing Applications:*

Society and Environment, *14*, 75–83.

Langat, D K, Maranga, E. K., Aboud, A. A., & Cheboiwo, J. K. (2016). Role of forest resources to local livelihoods: The case of East Mau forest ecosystem, Kenya. *International Journal of Forestry Research*, *2016*.

Langat, D K, Maranga, E. K., Aboud, A. A., & Cheboiwo, J. K. (2018). The Value of Selected Ecosystem Services: A Case Study of East Mau Forest Ecosystem, Kenya. *Journal of Forests*, *5*(1), 1–10.

Langat, David Kipkirui. (2016). *Economic valuation of forest ecosystem services and its implications on conservation strategies in East Mau forest, Kenya*. Egerton University.

Mbugua, M. W. (2011). *Environmental degradation as a cause of conflict: a case study of the Mau Forest Degradation in Kenya (1963-2010)*. University of Nairobi, Kenya.

Ministry of Environment. (2018). *Taskforce Report on Forest Resources Management and Logging Activities in Kenya* (Issue April).

Mogoi, J., Obonyo, E., Ongugo, P., & Oeba, V. (2012). Communities , Property Rights and Forest Decentralisation in Kenya : Early Lessons from Participatory Forestry Management. *Conservation and Society*, *10*(2), 182–194. https://doi.org/10.4103/0972-4923.97490

Mutugi, M., & Kiiru, W. (2015). Biodiversity, Local Resource, National Heritage, Regional Concern and Global Impact: The Case of Mau Forest, Kenya. *Europian Scientific Journal*, *1*, 681–691.

Ndubi, A. O. (2018). Using land cover change to predict forest degradation pressure points, Eastern Mau Forest, Kenya. *International Letters of Natural Sciences*, *71*.

Obati, G. O., & Breckling, B. (2015). Socio-ecological characterization of forest ecosystem health in the south-western Mau Forest Reserve, Kenya. *Eastern Africa Social Science Research Review*, *31*(1), 89–118.

Olang, L. O., & Kundu, P. M. (2011). Land degradation of the Mau forest complex in Eastern Africa: a review for management and restoration planning. *Environmental Monitoring*, 245–262.

Ongugo, P. O., Mogoi, J. N., Obonyo, E., & Oeba, V. O. (2008). *Examining the roles of community forest associations (CFAS) in the decentralization process of Kenyan forests*. *July*.

Pellikka, P. K. E., Heikinheimo, V., Hietanen, J., Schäfer, E., Siljander, M., & Heiskanen, J. (2018). Impact of land cover change on aboveground carbon stocks in Afromontane landscape in Kenya. *Applied Geography*, *94*(September 2017), 178–189. https://doi.org/10.1016/j.apgeog.2018.03.017

Rwigi, S. K. (2014). *Analysis of Potential Impacts of Climate Change and Deforestation on Surface Water Yields from the Mau Forest Complex Catchments in Kenya*. University of Nairobi.

Shahbaz, B., Ali, T., & Suleri, A. Q. (2011). Forest Policy and Economics Dilemmas and challenges in forest conservation and development interventions : Case of Northwest Pakistan. *Forest Policy and Economics*, *13*(6), 473–478. https://doi.org/10.1016/j.forpol.2011.05.002

Sidhu, N., Pebesma, E., & Câmara, G. (2018). Using Google Earth Engine to detect land cover change: Singapore as a use case. *European Journal of Remote Sensing*, *51*(1), 486–500.

Swart, R. (2016). Monitoring 40 years of land use change in the mau forest complex, kenya. *A Land Use Change Driver Analysis.*

Tarus, G. K., & Nadir, S. W. (2020). Effect of Forest Management Types on Soil Carbon Stocks in Montane Forests: A Case Study of Eastern Mau Forest in Kenya. *International Journal of Forestry Research*, *2020*.

WWF. (2015). *State of Forests in Kenya*. https://www.wwfkenya.org/keep_kenya_breathing_/state_of_forest_in_kenya/