Forestry carbon sequestration and trading: a case of Mau Forest Complex in Kenya

Forest Change detection and carbon trading

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Abstract
The global temperature is at an all-time high, the polar ice is melting, the sea levels are rising and the associated disasters are a time bomb. These variations in temperature are thought to trace roots to anthropogenic sources. In order to mitigate these changes and slow down the rate of warming, several efforts have been made locally and internationally. One of the agreed up-on way to do this is by using forests as reservoirs for carbon since carbon is one of those greenhouses gasses responsible for the warming. Mau forest, in Kenya, is one of those ecosystems where degradation has happened tremendously, though still viewed as a potential site for reclamation.

Using GIS and remote sensing analysis of Landsat images, the study sought to compare various change detection techniques, find the amount of biomass lost or gained in the forest and the possible income accrued in case the forest is placed under the Kyoto protocol’s Clean Development Mechanism (CDM). Various vegetation ratios were used in the study ranging from NDVI, NDII to RSR. The results obtained from these ratios were not quite convincing as setting threshold for the ratios to separate dense forest from other forms of vegetation was not straightforward. As a consequence, the three ratios NDVI, NDII and RSR were combined and substituted for RGB bands respectively. A classification was done using this combination and the results compared to classifications based on tasselled cap and principal component analysis (PCA).

The results of the various methods showed that the forest has lost its biomass over time. The methods indicated that the section of the forest studied lost between 8088 ha and 9450 ha of dense forest land between 1986 and 2010. This is between 29% and 35% of forest cover lost depending on the various methods of change detection used. This acreage when converted into forest biomass at a rate of 236 Mg.ha\(^{-1}\) gives a value of between 1908768 tons and 2230200 tons of carbon. If the Mau forest were registered as Kyoto compliant, then in the carbon market, this would have been a loss of between $24.1m and $ 28.2m according to California carbon dashboard (28th, May 2015). This is a huge sum of money if paid to a rural community as benefits from carbon sequestration via forestry. Such are the amounts that a community can earn by protecting a forest for the purposes of carbon sequestration and trading.

Keywords: carbon, indices, NDVI, change detection, biomass, remote sensing
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Dedication
This piece of work is dedicated to Jacob Alex Otieno K’Achila - Lihudu. You have been an oasis of hope in my deserts of calamities. I might have grown into a silent young man, but in my silence I do admire your approach to life. As a family, your support over the years has been tremendous. Mum and dad, I wish you could see eye to eye once again. An old tree spells miseries to the nesting birds when it is uprooted. Your stubbornness is messing us up. It is tearing down the morale and our moral standings grow shakier with time. I cannot raise my head in a crowd anymore!

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1 INTRODUCTION

1.1 Background

Sequestering carbon is seen as one way of slowing down the pace at which global warming is happening. There are many ways of sequestration, using both artificial and natural sinks which stores carbon for a long period of time (van Kooten, Eagle, Manley, & Smolak, 2004). The Kyoto protocol, signed in 1997, gave targets to the well-off countries to cut down carbon production or support carbon sink projects elsewhere to compensate for their carbon production (Jindal, Swallow, & Kerr, 2008). This was to be done through afforestation and reforestation (carbon sinks), emissions trading and to sponsor carbon reducing projects in other countries. This flexible mechanism provides a framework for emissions control in almost all parts of the world including the developing countries that are not signatories to the Kyoto protocol (Halsnæs, 2002). The developed countries being heavily industrialised were seen to be releasing a lot of carbon dioxide into the atmosphere.

One of the means for sequestration identified in the protocol is by using the natural sinks. Forests are the largest natural sinks for carbon (Pan et al., 2011). Plants absorb and use carbon dioxide for photosynthesis – to generate food. As a result, carbon forms most of the plant (tree) tissue. Estimating the amount of biomass in the plant will therefore relate to the amount of carbon the plant contains. These estimates are done using allometric equations which relates certain aspects of a tree to its biomass (Bombelli et al., 2009). The procedure involves taking measurements on the tree and then feeding the measurements into the allometric equation. However, where there is thick undergrowth, rough terrain or a large tract of forests, such methods seems rudimentary.

GIS and remote sensing have been used extensively in mapping land cover and land uses (Shalaby & Tateishi, 2007; Weng, 2002) and the changes in them, a process called change detection. Remote sensing satellites provide data that covers even the most inaccessible places on earth. This data has a high temporal resolution (NOAA, four hours) and spatial resolution (SPOT, GEOEYE, QuickBird, and IKONOS). GIS on the other hand provides an environment for analysis of these images for easier interpretation. There are various possible operations in a GIS environment like overlays, subtraction of pixel values to detect changes etc. for analysis purposes. In this breadth, GIS and remote sensing have been used to estimate biomasses of forests around the world (Foody et al., 2001; Kinyanjui et al., 2014; Roy & Ravan, 1996; Shalaby & Tateishi, 2007; Weng, 2002) and the changes in the biomasses.

1.2 Aims and objectives of the study

Mau forest complex (MFC) in Kenya is one important catchment in the Kenyan hydrological system. It is a source of several rivers that feeds many lakes in the country and other neighbouring countries. However, this water tower is under threat of extinction due to deforestation through illegal logging and encroachment into the forest reserve (Müller & Mburu, 2009). The main objective of this study is to establish the magnitude of deforestation in Mau forest between 1980s and 2010, and to compare various methods of detecting the changes in the forest biomass. It is also desired that
the forest be included under the Kyoto protocol as one of the natural carbon sinks. In this way, the amount of biomass lost over the years under study is to be approximated and their monetary equivalent obtained as per carbon emissions trading.

The specific study questions to be answered by the study include;

i. What is the change in biomass between 1980s and 2010, and how much is it in monetary values?

ii. Are there significant variations when different change detection methods are used?

iii. How does NDVI compare with other indices?
2 CARBON TRADING AND CHANGE DETECTION

The mean temperature of the world, over the years, have shown significant rise (Diaz & Bradley, 1997), a trend which is worrying to the climate scientists and everyone else. The worry that comes with it is tied to the foreseen consequences that the trend is likely to elicit (Fujisawa & Kobayashi, 2010). A higher temperature rise will lead to the melting of the Arctic and Antarctic ice, as a result of which most coastal cities will be displaced and property flooded. The general precipitation patterns globally, are also influenced by the temperatures and thus the subsequent changes will follow suit. The rise in temperatures also affects plant and animal habitat, meaning, those animal species that resides in the colder niche will have to migrate or face extinction altogether. This whole hullaballoo will take the human - animal conflict to the next level in the spirit of survival for the fittest. Intense heat waves, hurricanes and prolonged droughts are other foreseeable effects (Edmunds, 2004).

The global warming is being hastened because more heat is being reflected back to the earth surface. The sun is responsible for heating the earth in the form of shortwave solar radiations. These shortwaves are scattered, absorbed, reflected and transmitted by the atmospheric elements. Naturally, a small percentage that is absorbed by the earth warms it and some are released back into the space in form of long-wave terrestrial radiation. There are atmospheric components in the atmosphere that ensures the temperatures do not fluctuate too much. They absorb some of the space-bound long-wave radiations and warms up our sky to a manageable temperature. These absorbers are mainly water vapour, carbon dioxide and methane. However, the concentration of carbon dioxide is on the rise due to human activities (Philipona, Dürr, Marty, Ohmura, & Wild, 2004). This means more heat than necessary is continually trapped contributing to the global warming phenomenon.

The carbon dioxide absorbs in the thermal wavelength which happens to coincide with the atmospheric window. A high concentration of carbon dioxide is therefore capable of blocking the window. The queer thing about carbon dioxide concentration in relation to the temperature is that the high temperatures in turn, increases the amount of carbon dioxide in the atmosphere (Murphy, 2014). A high temperature increases the chances of carbon dioxide trapped in the oceans to leaking out, just like warming a coke bottle would (Fearnside, 2004). This therefore increases the amount of carbon dioxide in the atmosphere further. This unending cycle can only be stopped by reducing the amount of carbon dioxide in the atmosphere. Many efforts have been made to reduce the amount of carbon dioxide in the atmosphere owing to the fact that human activities are responsible for the increase.

Since the realization that increases in carbon dioxide within the atmosphere is exacerbated by anthropogenic sources, several summits have been held to ponder on the issue and discuss mitigation measures. In 1997, a milestone was reached by the signing of the Kyoto protocol. This is a binding agreement which was signed by developed countries to stabilize greenhouse gas emissions – one of which is carbon dioxide. It provided three mechanisms in which these emissions could be stabilized and reduced cost effectively. The three mechanisms included Joint Implementation (JI), Emissions Trading (ET) and Clean Development Mechanism (CDM) (Jindal et al., 2008). These mechanisms provide the developed nations with an opportunity to reduce their emissions anywhere in the world where the costs are manageable and then count
those reductions as part of their national target. JI and CDM support projects that are geared towards emission reductions. While JI functions in Europe (Eastern) and former USSR, CDM operates wholly in the developing countries (Jindal et al., 2008).

Therefore, CDM is the only Kyoto mechanism that directly involves the developing countries in fighting for greenhouse gas emission reductions. Basically, the CDM works like an investor from a developed country investing in a developing country, where the investments are projects geared towards reducing greenhouse gas emissions (Reyes & Gilbertson, 2010). The motive behind such project is to ensure that the emissions are lower than they would have been in a business-as-usual state without the project. At the end, the investor gets the credits – carbon credits – and uses them to meet his Kyoto target (Sridhar, 2010). A simple example would be like in an attempt to reduce her emissions; Germany funds a solar power project in Sudan – which would have not been possible without the funding. The solar energy caters for the fossil fuel that would have been used. Germany therefore takes the carbon credits and uses it to offset her Kyoto targets.

Common projects undertaken under CDM involve carbon sinks. These are either man made or natural reservoirs that stores carbon compounds over a long period of time (van Kooten et al., 2004). The process by which these sinks siphon carbon from the atmosphere is called sequestration. The artificial sinks include landfills and carbon capture and storage from chimneys in factories. Among the natural sinks include forests and oceans. The CDM approves sequestration via afforestation and reforestation (Pacala & Socolow, 2004). In this scenario, the plants in the forests absorb carbon in the form of carbon dioxide for photosynthesis purposes. A developed country commits to fund reforestation or afforestation in the developing countries, whereupon completion, the total amount of carbon sequestered by the project is credited to the developed nation (Reyes & Gilbertson, 2010). This method has numerous advantages to the host country and the donor alike.

2.1 Benefits of carbon sequestration

Other than reducing carbon in the atmosphere, mechanisms like agroforestry increases productivity, income and guarantees food security for the producers. Agroforestry in dry lands enhances the ecological value of the land and serves as a source of livelihoods to the communities that adopt it as a carbon sequestration technique (R. Lal, 2001). Afforestation, reforestation and other efforts to conserve forests are geared towards preserving and protecting endangered species of flora and fauna (Thomas, Dargusch, Harrison, & Herbohn, 2010; R. J. Zomer, Trabucco, Bossio, & Verchot, 2008). Besides, forests are naturally an integral part of hydrological cycle. They are mostly catchment areas of rivers and other hydrological features. Mau forest, for example, is a significant water tower in the Kenyan hydrological system (Baldyga, Miller, Driese, & Gichaba, 2008; Mango, Melesse, McClain, Gann, & Setegn, 2011). The Amazon River for instance has its catchment in the Amazon forest.

The sequestration system also provides employment to the local communities, a move which contributes to economic emancipation of the locale (Jindal et al., 2008). Forest guards, awareness campaigners and the extension service providers serve effectively when outsourced from within the surrounding community. Once conceived and properly implemented, the carbon sequestration scheme provides revenue to the community through payments for sequestered carbon (Ferraro, 2001; Jindal et al.,
In most cases, a lump-sum is normally paid at the initial stage. Microenterprises also crops up as spill-over benefits, for instance tree nurseries which provide income. The surrounding community equally benefits from other non-woody products like picking fruits besides monitored firewood collections within the forests.

Given the poverty conditions in Africa, such projects could help alleviate poverty. However, such projects are not so common in Africa. The literature available on carbon trading conditions in Africa is scanty (Jindal et al., 2008). So far there are few projects in Africa, across the continent from far West Africa in Senegal to East Africa in Kenya, and from Sudan to South Africa. The projects are, however, sparse and cover small land area. Besides, most of the projects are not Kyoto compliant projects, while others are more concerned on profit maximization with little or no regard to the surrounding communities (Lang & Byakola, 2006). The distribution of the projects is equally imbalanced with most of them found in East Africa (Jindal et al., 2008).

2.2 Potential in Africa

The advent of CDM relaxed the emission restrictions on the major emitters – developed nations. It implies that the developed nations can look for a cheaper place and options to reduce or provide a means of compensating for their emissions. This has made the developing countries and Africa in particular, a potential target for such emission trading ventures (Jindal et al., 2008). The land value is relatively cheaper in most parts of Africa and this means large track of lands can be easily acquired and put under carbon trading schemes (R. Lal, 2002). A less strict land use planning policies, or non – existence at all, makes the conversion to agroforestry and other form of carbon sequestering schemes easier in the sub – Saharan Africa.

Climate is another issue that drives the carbon trading. As much as the trading schemes aim to mitigate climate, afforestation and reforestation processes can only be well practised in favourable climates and soils (R. Zomer, Trabucco, van Straaten, & Bossio, 2006). The sub – Saharan tropical climate is ideal for afforestation and reforestation processes. Generally, the rainfall is enough to sustain forest growth and regrowth, in cases of reforestations. However, most parts of Africa, other than the regions close to the equator, lack adequate rainfall to sustain large scale tree plantations for carbon sequestration (R. Zomer et al., 2006). These regions include the Sahel region and the Southern Africa, mostly within the Kalahari and Namib deserts.

The other drive for the movement to Africa is the poverty. A considerable population in the sub – Saharan Africa lives in poverty. This means that an alternative income generating scheme is more than welcome to them (Jindal et al., 2008). This state makes the integration of carbon trading into the system much easier as an alternative means for earning a livelihood. Besides providing income, it creates sustainable development incorporated in environmental management thus appears as a single shop with solution to several problems (Ferraro, 2001). However, there are some challenges facing the full and speedy implementation of these projects in Africa and elsewhere.

2.3 Challenges

For registration and acceptance of a project under CDM, there are numerous procedures. These procedures are done for every piece of land committed for the
sequestration projects. In case of small land holdings, it means there has to be several of such small holdings for a feasible project to be carried out (Thomas et al., 2010). This normally discourages the suppliers that supply the carbon offsets. Land tenure and security of tenure is another issue that impedes the process (Unruh, 2008). Many pieces of land in Africa are either governed by customary laws or a mixture of customary and statutory laws of land. This is normally tricky in terms of conducting transactions involving these lands since the different jurisdictions have varying opinion concerning land use priorities. Most free lands are communally owned and committing a community land to such project is not easy.

The long procedure undertaken in order to receive the payment is not encouraging especially to the poor small holders who might have taken an opportunity cost and favoured the project over their subsistence farming (Perez, Roncoli, Neely, & Steiner, 2007). The forests also take long time to mature, during which the land might seem idle and tempting to the land owner. This might lead to land use change in the process and leads to more carbon released into the atmosphere. Besides all these, there are also the threats of fire and deforestation which can release more carbon than foreseen. Such practices might lead to a decrease in the amount earned from the project and subsequent withdrawal by the farmers who are participating. The lucrative timber business might reverse the gains made by sequestration if there is no adequate monitoring.

2.4 Methods of change detection

The changes that happen to the environment are mostly attributed to the human activities on earth. These changes in the environment have to be measured accurately in order to adequately quantify the effects of human activities on the environment (Berberoglu & Akin, 2009). Due to improvements in the computing world and data abundance, remote sensing and GIS offers reasonable tools for detecting, analysing and quantifying changes in the land uses. Courtesy of remote sensing, changes on the earth surface can be analysed even for those remote - inaccessible areas of earth due to the airborne way of capturing the information (Baiocchi, Brigante, Dominici, Milone, & Radicioni, 2013). The repetitive nature of the satellites with the long history of Landsat - in particular, ensures that data is available in abundance (Jensen, 1983). The improved temporal and spatial resolution enables scientists to notice even the slight changes in the land uses.

GIS provides an ample environment for analysing multi-dated data and overlaying different layers to discern changes. It also accommodates data from different sources and provides mathematical and statistical tools for data modelling and manipulation (Lu, Mausel, Brondizio, & Moran, 2004). Another major benefit from the GIS is that it allows for output in different data formats. Some GIS software have user friendly graphical user interface for interaction with the data and the ultimate display. GIS and remote sensing together are widely used for change detection analysis. Several studies have been carried out on change detection using GIS and remote sensing (Brondizio, Moran, Mausel, & Wu, 1994). Below, I discuss some of the methods used to detect and quantify changes in land uses.
2.4.1 Rationing

Rationing uses digital numbers (DN) to divide the pixels of one band by another (Berberoglu & Akin, 2009). The main reason for the division is twofold; one is to magnify the difference between the two bands compared. The second reason is that the illumination intensity of the scene may vary, and thus the radiance, but the ratio between the illuminated and non-illuminated area of the same scene will remain the same. This therefore makes rationing a lucrative option with little biases brought about by time of the image capture, sun angle and even atmospheric effects to some extent. The DN value is a function of several aspects including the object imaged, the time, radiometric resolution and the sensor system used to acquire the image (Chander, Markham, & Helder, 2009).

Reflectance of the object influences the value of the DN in an image. Some objects will reflect higher than others in certain bands/wavelengths. For instance, vegetation reflects highly on the near infrared (NIR) and low in the visible (R) reflectance of Landsat images (Pickup, Chewings, & Nelson, 1993). This makes the two bands ideal for segregating and studying vegetation since no other natural feature shows such consistent spectral pattern in the two bands. Different types of vegetation also reflect differently depending on their health, vigour and other states (Lyon & McCarthy, 1995). The time of the year affects the amount of energy from the sun that reaches the earth (Chander et al., 2009). This is because the amount of energy changes with season where there is low energy during winter and high during summer. This means that other factors held constant, the DN value will be low in winter and high in summer.

Other than the seasonal variations, the amount of solar energy varies during the day too. The energy is higher in the midday than mornings and evenings. This implies that a high energy per square area is expected at noon than at any other time of the day. Therefore reflectance and the subsequent DN obtained will be influenced by the time of the day the image was taken. The radiometric resolution of the sensor also affects the range of DN values that can be measured by the sensor. An 8-bit sensor will have a wider range of measurements than a 7-bit sensor. For instance, Landsat MSS is a 7-bit sensor while ETM+/TM are 8-bit sensors. This largely affects the range of DN value recorded by the sensor (Irish, 2000).

For studying vegetation, the NIR band and the R band are ideal (Anderson & Hanson, 1992). There are several ratios that have been formulated to study vegetation based on these two bands (A. R. Hue, 1988; A. Hue, Liu, Batchly, & Van Leeuwen, 1997; Richardson & Everitt, 1992). These ratios are better called spectral indices which is a term used to describe a combination of the reflectance of two or more wavelengths. These ratios are designed to highlight the difference in radiance between surfaces (Short, 1982). The indices supresses the solar illumination difference caused by topography and aspect (Elvidge & Lyon, 1985; Singh, 1989). This allows for a consistent comparison between images both spatially and temporally. Moreover, an ideal vegetation index would be insensitive to soil changes in the background and have just slight influence by the path radiance of the atmosphere (A. Hue, 1989; Jackson, Slater, & Pinter, 1983). Indices have been used in studying several phenomena ranging from forest fires, spread of drought to estimating the amount of green vegetation (Asrar, 1989; Myneni, Keeling, Tucker, Asrar, & Nemani, 1997).
2.4.2 Normalised Difference Vegetation Index – NDVI

The most commonly used index is the normalised difference vegetation index (NDVI) (Hayes & Sader, 2001). It relates the NIR and the R band and the relationship is computed as in equation (1).

\[ \text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \]  

The RED band shows the absorption of the red wavelengths by the greenness in plants - chlorophyll, a low value of R indicates a lot of chlorophyll in the plants imaged. The NIR shows the reflection of the near infrared wavelengths by the leaf cell structure. A higher value of NIR indicates healthy vegetation (Holm, Burnside, & Mitchell, 1987). The NDVI values ranges from – 1 to 1. The higher values shows high vegetation content while lower values, especially in the negative region, signify non-vegetation features like water, bare land, ice and snow, or clouds (Lillesand, Kiefer, & Chipman, 2004; Rouse Jr, Haas, Schell, & Deering, 1974). The ratio is an indicator for greenness in the scene and can be used to predict productivity and leaf area index in the vegetation. The ratio normalizes the effects of the zenith angle of the sun, thus called normalized.

2.4.3 Simple ratio - (NIR / R)

Remote sensing provides an avenue for estimating the leaf area index (LAI), a ratio of the area covered by the leaves to the corresponding land area. This kind of ratio shows the photosynthetic capabilities of plants within the area concerned (Jarvis & Leverenz, 1983). Consequently, the ratio can be used to infer changes that have taken place on the plants. This ratio is estimated based on vegetation indices like the NDVI discussed above and simple ratio (SR) which both relates spectral reflectance of plant leaves at different wavelengths as seen in equation (2).

\[ \text{SR} = \frac{\text{NIR}}{\text{R}} \]  

The value of SR is high for vegetation and low for other land uses (Lillesand et al., 2004). It also reduces the effects of the atmosphere and topography on the reflectance. The equation partly cancels irradiances and transmittances thereby reducing topographic differences and atmospheric effects respectively. However, as an algebraic rule, the ratio is rendered useless when a division involves zero. There is also a wide range of values possible depending on the amount of the red reflectance. Some of these problems are addressed by the NDVI. The changes in the ratio in a scene over a time period can be used to infer the changes that have occurred on the vegetation covered in the scene over time.

In a study on Finnish pine and spruce stands (Stenberg, Rautiainen, Manninen, Voipio, & Smolander, 2004), the revised simple ratio (RSR) was found to correlate with LAI better than the NDVI. RSR is a modified version of SR and is calculated according to equation (3).

\[ \text{RSR} = \frac{\rho_{\text{Band} 4}/\rho_{\text{Band} 3}}{(\rho_{\text{Band} 5_{\text{MAX}}} - \rho_{\text{Band} 5})/(\rho_{\text{Band} 5_{\text{MAX}}} - \rho_{\text{Band} 5_{\text{MIN}}})} \]  

In equation (3), \( \rho_{\text{Band} 3, 4, 5} \) respectively are the reflectance of bands 3, 4 and 5. The \( \rho_{\text{Band} 5_{\text{MAX}}} \) and \( \rho_{\text{Band} 5_{\text{MIN}}} \) are the maximum and minimum reflectance on the MIR band (band 5 of the Landsat 5). These ratios are used to measure the amount of vegetation at time 1 and compared to the amount at time 2 in order to make inferences about change.
2.4.4 Normalized difference infrared index – NDII

This index is positively correlated to the water content in the leaves hence used to measure the water content of plants. The shortwave infrared (band 5 on Landsat TM/ETM +) reflectance is inversely proportional to the leaf water content because it is strongly absorbed (Ceccato, Flasse, Tarantola, Jacquemoud, & Grégoire, 2001; Gao, 1995). Therefore, it is a good indicator of how much vegetation is present in a scene by sensing their water content. However, the band 5 alone is inadequate and must be contrasted with a near infrared band to estimate the water content since other leaf parameters, like structure, also influences the band 5 reflectance. In order to compute the index, the following equation (4) is used (Klemas & Smart, 1983).

$$\text{NDII} = \frac{(\text{NIR} - \text{SWIR})}{(\text{NIR} + \text{SWIR})}$$ (4).

Where, NIR is the near infrared band 4, and SWIR is the short wave infrared band 5 of the Landsat data used. NDII has been studied by many scientists under different names to monitor the vigour and amount of water in vegetation, the different names mostly arising from the bands of the various sensors used or the intended purpose of study (Yilmaz, Hunt, & Jackson, 2008).

2.4.5 Image differencing

Image differencing subtracts a band from another to infer the changes or the state of health of the vegetation (Elvidge & Lyon, 1985). The distinction here is that the same band is used but with two scenes from different time period. The first band from time 2 is subtracted from the first band from time 1. For an 8 – bit image, this can give results ranging from ~ 255 to 255. A value of zero or thereabout will signify no change whereas low values or high values will indicate that significant change has taken place (Hayes & Sader, 2001). These changes are observable on the difference histogram. However, these changes might not be too reliable since the differencing does not take into account the scene illumination conditions which might be the only difference in the two images. Furthermore, selecting a working threshold to make the boundary between the change and non-change pixels is not straightforward. Although the differencing is simple and easy to interpret, it only uses a single band at a time.

2.4.6 Change vector analysis – CVA

When land cover undergoes changes, its spectral response on the satellite sensor changes accordingly. If spectral variables are observed on the land cover before the change and after the change, and the variables plotted on a graph, change can be observed in both magnitude and direction. This is the change vector analysis (Malila, 1980). This method has been used in various applications including detecting changes around the Chernobyl (Schopmann & Tyler, 1996), tree ecosystems (Allen & Kupfer, 2000), land use changes (Berberoglu & Akin, 2009), among many others. In all these applications, change vector analysis (CVA), has shown a relatively superior quality in detecting and quantifying changes in the land uses involved. The change magnitude is calculated as per equation (5).

$$\text{CM} = \sqrt{(\text{DN}_{11} - \text{DN}_{21})^2 + (\text{DN}_{12} - \text{DN}_{22})^2 + \ldots + (\text{DN}_{16} - \text{DN}_{26})^2 + (\text{DN}_{17} - \text{DN}_{27})^2}$$ (5)

Where CM is the magnitude of change and DN$_{ij}$ is the digital number recorded in band j for the date i. The CM is computed by finding the Euclidean distance between the two images compared across all the available bands. After the CM, the direction of change is calculated.
2.4.7 Classification – post classification

Change detection has been achieved through classification of satellite images (Fan, 2008; Fichera, Modica, & Pollino, 2012). Images of the same scene captured at different dates are classified into the different land uses identifiable from the image. These classified images are then exposed to post-classification comparisons to check whether there is any change and to quantify the change if there is (Lillesand et al., 2004). In a GIS environment, methods like “intersect” and “union” are handy in evaluating the amount of change, even at pixels levels. In order to ascertain the accuracy of the changes obtained, an accuracy assessment is carried out on the change detection procedure. Just like the usual accuracy assessment, an error matrix is generated only that this matrix is modified to accommodate the two dates and the changes (Fichera et al., 2012).

2.4.8 Principal component analysis – PCA

While handling remote sensing images, quite often we meet multispectral images whose bands are highly correlated statistically. This means that the information carried by the bands overlap and thus some of the bands are redundant to some extent (Lillesand et al., 2004). The quality of extractable information is therefore compromised by the redundancy. To visualize such correlation and the subsequent redundancy, a scatterplot of two suspected redundant bands on a two-dimensional space will reveal a tight cluster. This suggests redundancy of the spectral information contained in the two bands.

Principal component analysis (PCA) is a remote sensing technique that compresses the information from several bands of the image into few bands, called principal components (PCs). These principal components capture the variance in nearly the whole image and therefore represent the most useful information in the image (Estornell, Martí-Gavliá, Sebastiá, & Mengual, 2013). They highlight the information in the image, differentiate noise from signals and reduce the dimension of the data (Hayes & Sader, 2001). In this breadth, principal component analysis serves to compress the data, i.e. reduce the dimension (Liu, Nishiyama, & Yano, 2004).

It involves assigning new axes to the data by translation and rotation of the original axes to new axes governed by correlation in the datasets. The first axis, PC1, is set perpendicular to the second axis, PC2 and represents the vector of the greatest variance in the dataset. The second axis, orthogonal to the first one, represents the second greatest variance in the data (Hayes & Sader, 2001; Lillesand et al., 2004). The third, fourth and so on are ordered in decreasing variance of the data. Generally, the first few PCs contain the greatest amount of useful information in the data and are therefore enough for analysis and coherent conclusions on the data.

Since they contain the most information on the image, one can therefore use them as a basis for classifying an image instead of the original image bands. By this, the amount of data for analysis is considerably reduced (Estornell et al., 2013). The storage space is equally smaller than the original image, thus the PCA serves to compress the data in the process. The procedure for obtaining PCs from a dataset is a three step process, i.e. obtaining the covariance matrix, solving for the eigenvalues and the eigenvectors, and finally projecting the data where each PC comes out orthogonal to each other (Zabalza et al., 2014). The resulting attributes in the new axes are not correlated.
2.4.8.1 Covariance matrix

Mathematically, covariance is variance measured in two dimensions. This can be extended to several dimensions to represent multidimensional datasets and generate a covariance matrix (Jeffrey, 2001). When the variables increase together, we get a positive covariance, a negative covariance is obtained when one variable increases as the other decreases and a zero value for a covariance symbolizes independent variables. In the context of remote sensing images, the variables under consideration are spectral bands and the items of consideration are the DN values within the pixels (Zabalza et al., 2014). These forms the matrix elements. An image (Landsat) can be represented in a matrix format as follows (Estornell et al., 2013).

\[ Z_{n,b} = \begin{pmatrix} z_{1,1} & \cdots & z_{1,n} \\ \vdots & \ddots & \vdots \\ z_{7,1} & \cdots & z_{7,n} \end{pmatrix} \]

where \( n \) is the number of pixels while \( b \) is the number of bands.

When the bands are taken as vectors, we have \( Z_{k} = \begin{pmatrix} z_{1} \\ \vdots \\ z_{7} \end{pmatrix} \), where \( k = 7 \), the no. of bands in a Landsat (TM and ETM+) image. The covariance matrix is calculated as follows to reduce the dimensionality of the image.

\[ C_{b,b} = \begin{pmatrix} \alpha_{1,1} & \cdots & \alpha_{1,7} \\ \vdots & \ddots & \vdots \\ \alpha_{7,1} & \cdots & \alpha_{7,7} \end{pmatrix} \]

where \( \alpha_{i,j} \) is the covariance of each pair of bands. The value entered on row 5 and column 4 for example, is the covariance between the 5th and the 4th dimension (Jeffrey, 2001). Along the leading diagonal, (where \( i = j \)), the covariance value is equivalent to the variance of that band.

2.4.8.2 Eigenvalue and eigenvectors

From the matrix, the eigenvalues (\( \lambda \)) are calculated as the solution to the following characteristic equation (6)

\[ \text{Det} (C - \lambda I) = 0, \quad (6) \]

Where \( C \) represents the covariance matrix of the Landsat data bands, \( I \) is a diagonal identity matrix, Det is the determinant of the matrix. The identity matrix is introduced since we can only subtract a matrix from another matrix, not a constant like \( \lambda \) (Jeffrey, 2001). The eigenvalues computed indicate the amount of the original information retained in each PC (Zabalza et al., 2014). Those eigenvalues (PCs) with minimal values can be discarded altogether (Estornell et al., 2013). The PCs can be expressed as a matrix in the following way

\[ A_{7} = \begin{pmatrix} w_{1,1} & \cdots & w_{1,7} \\ \vdots & \ddots & \vdots \\ w_{7,1} & \cdots & w_{7,7} \end{pmatrix} (z_{1}) \]

where \( A \) is the vector of PCs, \( W \) is the matrix of transformation and \( z \) is the vector of the original data. The coefficients of the transformation matrix are eigenvectors and they can be computed as \( (C - \lambda k I) W_k = 0 \). For Landsat datasets (TM and ETM+), \( k = 7 \).

2.4.8.3 Projection

The eigenvectors matrix is transposed and multiplied with the original band vector to obtain uncorrelated dataset (Zabalza et al., 2014).
2.4.9 Tasselled cap indices

Tasselled cap transforms the image data in such a way that most of the valuable information in the image is contained in two components - brightness and greenness (Lillesand et al., 2004). The components, brightness and greenness, are related to reflections from the soil and vegetation respectively. Tasselled cap is a method of enhancing the spectral variability in the Landsat data and specifically optimizes data viewing for vegetation. They measure soil reflectance, vegetative content and relationship between soil and canopy moisture respectively (Crist & Cicone, 1984).

The direction of the principal variation in the soil reflectance is perpendicular to that of the vegetation. The third index, called wetness, relates to the canopy of the vegetation and moisture in the soils. These indices rely on a linear combination of the 6 bands of (Landsat) data to generate the wetness, greenness and brightness per pixel. Each of the indices can be computed according to equation (7).

\[
TC_i = (k_1 \cdot \text{band}_1) + (k_2 \cdot \text{band}_2) + (k_3 \cdot \text{band}_3) + (k_4 \cdot \text{band}_4) + (k_5 \cdot \text{band}_5) + (k_7 \cdot \text{band}_7)
\]

In the equation (7), the \(TC_i\) is the desired index (wetness, greenness or brightness), \(k_i\) are constants (coefficients) which depend on the index to be calculated. The coefficients are obtained from Huang et al. (2002).

2.4.10 Soil Adjusted Vegetation Index

The soil adjusted vegetation index (SAVI) is a vegetation index similar to the NDVI except for the adjustment for background reflectance from soil. Here, the top of atmosphere reflectance are used in the index (Huete, 1988) according to equation (8).

\[
SAVI = \frac{[(1 + L) \cdot (\text{Band}_4 - \text{Band}_3)]}{(\text{Band}_4 + \text{Band}_3 + L)}
\]

\(L\) is a correction factor to the soil brightness, and its value is 0.5 (Huete, 1988).

2.5 Allometric equations

Traditionally, the aboveground tree biomass was determined for the purposes of sustainable utilization and the management of forest and woody resources. This was done in order to check and harvest wood for fuel and timber production (Henry et al., 2011). Of late, the forest biomass estimation has gained momentum for the purposes of carbon content estimation (Bombelli et al., 2009) in the wave of carbon trading especially on the CDM front (Pacala & Socolow, 2004). There is a growing interest in the global carbon, therefore aboveground biomass estimation with high accuracy to check the increase or decrease in carbon is highly essential.

Forests serves as a large carbon sink in the world’s ecosystem and influences many lives, of plants and animals, human being included. Managing forests is therefore an essential way of climate change mitigation (van Kooten et al., 2004). As a result, allometric equations are necessary to estimate the changes in the carbon biomass resulting from either afforestation, deforestation or reforestation (Henry et al., 2011). Allometric equations uses tree parameters like height and trunk diameters to estimate the mass of the tree (Kangas & Maltamo, 2006). Allometric equations specific for a species are the most favoured (Ketterings, Coe, van Noordwijk, & Palm, 2001), however, some forests have hundreds of species together (Gibbs, Brown, Niles, & Foley, 2007). Therefore, an allometric equation selected for such a mixed forest should capture the variability. Using a generalized allometric equation has been effectively tried within the tropics (Brown, 2002).
There are many allometric equations that have been proposed and used for biomass estimations within the sub Saharan Africa (Henry et al., 2011). Out of these, there are some which were tailored specifically for the tree species in Kenyan forests. However, these equations do not show significant differences when used for biomass estimation and therefore it should not consume much of a time modelling a different equation (Kinyanjui et al., 2014). The equations relate the biomass as a function of diameter at breast height (D1.3) and the height (h) of the tree in various forms.

### 2.6 Carbon trading

The CDM as one of the flexible mechanisms of the Kyoto protocol provides for a trading in carbon emitted to or sequestrated from the atmosphere (Hepburn, 2007), guided by some carbon trading policies (Sorrell & Sijm, 2003). The amount of carbon that is possible to be sequestered within an area over a given period of time is estimated and this value is converted to a monetary value depending on the rates in the carbon market (Bebbington & Larrinaga-Gonzalez, 2008; Reyes & Gilbertson, 2010). In this way, the carbon stored in a forest can be traded in the carbon markets to generate income for the surrounding communities and inspire other activities geared towards protection and even forest expansion. Forest guarding, tree seedling programs, among others can all be funded by revenues generated from such kind of trading.
3 STUDY AREA

3.1 Mau Forest Complex

The Mau forest complex is located between 0° 0’ 19″N and 0° 0’ 93″S and 35° 0’ 29″E and 36° 0’ 10″E in the south western part of Kenya, within the Great Rift Valley (figure 1). It is one of the five major catchment areas in Kenya, also called water towers. Mau forest is the most important water tower of the five due to its roles (Gichuhi, 2014). It serves as a catchment area to several lakes in Kenya including lakes Baringo, Nakuru, Turkana and the Trans-boundary Lake Victoria. It is made up of seven forest blocks and a source to 12 rivers in the country (Gichuhi, 2014). The waters from Mau support several socio-economic activities downstream ranging from domestic use to hydroelectric power production, industrial and agricultural activities.

Figure 1: A section of Landsat TM image of 1986 showing Mau forest complex and the lakes in the Rift Valley region of Kenya, and inset is the location of the forest in Kenya.

The forest has an area of approximately 400,000 ha and is regarded as the largest closed-canopy montane ecosystem in Eastern Africa. It rests at an average altitude of 2500 m above sea level, though this height is not evenly distributed (Olang & Kundu, 2011). Some parts of the forest are steep escarpments, rolling terrain and plains, mostly the rolling topography dominates. Geologically, the area is composed of quaternary and tertiary volcanic deposits. On average, the area receives an annual rainfall of 1300 mm. It has long rains in the months of May and June and short rains between September and November, with mean monthly ranging between 30 mm and 120 mm. the temperatures greatly depend on the altitude ranging from 6 °C to 30°C (Olang & Kundu, 2011).
The forest is a part of flow regulation and flood mitigation downstream and reduces soil erosion, besides regulating the microclimate. Hydrology of Lake Nakuru, for example, which is fed by Rivers Makalia, Nderit and Njoro, all from the Mau catchment, is greatly dependant on the condition of the catchment (Gichuhi, 2014). The deforestation and subsequent agricultural practices on the catchment have led a load of sediments into the lake which compromises both the aquatic life and the lake volume. The changing nutrient levels in the lake attributed to agricultural chemicals have caused a reduction in the algal content of the lake which is the main food for the flamingos, a renowned tourist attraction to the lake (Olang & Kundu, 2011). There are different types of soils in the catchment area giving rise to various forms of vegetation (Olang & Kundu, 2011).

The forest complex has many tree species as listed elsewhere (Mutangah, Mwangangi, & Mwaura, 1993). Despite the complex vegetation structure within the forest, there is an apparent grouping in terms of altitude with lower altitudes (below 2300 m) having the montane forests, bamboo above 2300 m and Juniperus procera forest at higher peaks in the escarpment. The forests provide several environmental services including relief/orographic rainfall, nutrient cycling and soil formation. Additionally, its role in carbon sequestration as a sink makes it a significant ecosystem globally for the climate change mitigation (Gichuhi, 2014).

The forest area has seen a lot of encroachment, both legal and illegal. Between 1995 and 2008, it is estimated that some blocks of the forest cover had declined by about 40% (Atela, Denich, Kaguamba, & Kibwage, 2012). The decline is due to human activities and the high population pressure around the forest (Müller & Mburu, 2009). Generally, the forest has had an average decrease in acreage by 25% over the period 1990 to 2010 (Olang & Kundu, 2011). The rising population around the forest, and the type of farming practiced have contributed to siltation and pollution of the waters downstream. There is deforestation to clear land for cultivation, construction and charcoal burning as population surges.

3.2 Government’s efforts to protect the Mau

The forest is home to the Ogiek community, who are hunters and relies on the forest for food, medicine and ritual or spiritual traditions (Rambaldi, Muchemi, Crawhall, & Monaci, 2007). The Ogiek community used to protect the forest; however, with the population growth and more demand for forest products, they are slowly adopting other means of living like subsistence agriculture. Hence, they have cleared parts of the forest to meet their agricultural needs. Other communities living adjacent to the forest have also cleared forest edges, gone deep into the forest for logging due to timber demand, or cleared forests for settlement purposes as the population grows (Kinjanjui, Karachi, & Ondimu, 2013). There were also instances of allocation of forest lands by the government to the landless communities displaced by ethnic violence.

As a consequence of the forest degradation, the volumes of rivers from this forest has been dropping, this drop led to the delay in commissioning of a dam project along River Sondu/Miriu, one of the rivers from the Mau. Due to these tangible effects, the government resorted to resettle the forest dwellers and protect the forest (Kinjanjui et al., 2013). The communities around the forest have been engaged in forest management activities through incentives, all geared towards protecting the water tower (Atela et al., 2012).
4 METHODS

4.1 Data pre-processing

A series of Landsat 5TM and Landsat ETM+ images of path 169/row 60 were used for the years considered in the study. The datasets were chosen around the same dates to reduce chances of differences in phenology due to seasonal variations. The images were LT51690601986028XXX11, LT51690601995037XXX01, LE71690602000027EDC00 and LT51690602010030MLK00. These images were for 28th January, 1986, 21st January, 1995, 27th January 2000 and 30th January, 2010. The 2000 image was pan sharpened to improve its spatial resolution and then used as a reference for geometric registration of the other images.

Pan sharpening means using a high resolution band to improve the spatial resolution of a multispectral image (Laben & Brower, 2000). In this study, band 8 (Panchromatic Band) was used to sharpen the 6 bands of the Landsat data excluding the thermal band. After this, the pan sharpened image was used to register others. The registration was done through a nearest neighbour sampling method with 12 control points in each image. An average root mean square error of 0.33 pixels was obtained with the images registered to a WGS84 datum in zone 36 and the horizontal distances measured in meters.

Due to the intended use in calculating tasselled cap indices, the digital numbers (DNs) had to be converted into reflectance (Crist, 1985). There are constants and coefficients provided for computing tasselled cap indices like wetness, brightness and greenness (Huang, Wylie, Yang, Homer, & Zylstra, 2002). These coefficients are readily usable for Landsat 7 ETM+ top of atmosphere reflectance. This means that for the Landsat 5 data used in this study, a conversion into an equivalent of Landsat 7 was necessary (Vogelmann et al., 2001). To achieve this, several procedures were carried out (Crist, 1985). The image was reclassified in such a way that all the zero values were replaced with “NoData” because there is no need of calculating reflectance and indices on areas where data is missing. The DNs were then converted into a Landsat 7 equivalent using equation (9).

\[
DN = (\text{slope} \times \text{DN5}) + \text{intercept} (9)
\]

In the equation, the slope and the intercept are unique for each band given by the reciprocal of the values used in Vogelmann et al., (2001) as shown in table 1. The DN output is the Landsat 7 ETM+ equivalent and DN5 is the data fed in. This operation was only done on the 6 bands needed for the indices.

<table>
<thead>
<tr>
<th>Band</th>
<th>Slope</th>
<th>Intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.943</td>
<td>4.21</td>
</tr>
<tr>
<td>2</td>
<td>1.776</td>
<td>2.58</td>
</tr>
<tr>
<td>3</td>
<td>1.538</td>
<td>2.50</td>
</tr>
<tr>
<td>4</td>
<td>1.427</td>
<td>4.80</td>
</tr>
<tr>
<td>5</td>
<td>0.984</td>
<td>6.96</td>
</tr>
<tr>
<td>7</td>
<td>1.304</td>
<td>5.76</td>
</tr>
</tbody>
</table>
Before converting the DNs into reflectance, they are turned into radiance, which is a measure of the energy recorded by the sensors. The following equation (10) is used for the conversion,

\[ L = (\text{gain} \times \text{DN7}) + \text{bias} \] (10)

L is the computed radiance in Watts / (sq. meter * mm * steradians), DN7 are the Landsat 7 ETM+ equivalents calculated previously. The gain and bias are wavelength specific (band specific) and the latest values of gains and biases for ETM+ were used (Chander et al., 2009). After obtaining the radiances, they were converted to reflectance values to enhance comparison among different scenes. Reflectance achieves this by eliminating apparent differences caused by the variations in the aphelion and perihelion and the differing amount of energy output per band (Irish, 2000). The reflectance is calculated as per equation (11), where R is the reflectance, a unit-less quantity, L is the radiance calculated in the previous step, d is the distance between the earth and sun at the time of image capture, it is measured in astronomical units (Chander et al., 2009).

\[ R = \frac{\pi \times L \times d^2}{E_{\text{SUN}} \times \cos(\theta)} \] (11)

\( E_{\text{SUN}} \) is band specific sun radiance while \( \theta \) is the sun elevation angle obtained from the image metadata file. The \( E_{\text{SUN}} \) values used in the calculation were according to Chander et al., (2009). The variables \( d \) and \( \theta \) greatly depends on the scenes and the time of the image acquisition. They are derived from the header file in the image metadata. The last step was to convert the angles to radians. More information on how the sun – earth distance is related to the date, and specifically the Julian calendar, was found from Chander et al., (2009). In the process of conversion, it was possible to have some negative values for reflectance; these were eliminated as negative reflectance is impractical.

After performing the image registration, preliminary tests were done on the image to test the accuracy of the registration. The results of the tests showed that the average mean root square error of 0.33 pixels obtained in the process was not good enough to use in processes like image differencing and most change detection techniques. A method was then applied to clip the portions of the forests from the images using a circle of radius 51 km, with the centre on a feature common in the images.

### 4.2 Indices

Various ratios and indices for the scene were computed in order to better understand the chronology of changes in the extent of forest. NDVI has been used in many studies as listed earlier, to estimate yields in crops, pasture performance, among others (Hayes & Sader, 2001; Holm et al., 1987). It is related to the percentage of ground cover by vegetation, photosynthetic activity in plants and amount of the biomass. In this study, NDVI was calculated in an attempt to find the amount of forest cover over the four years under study. The NDII correlates well with the leaf water content. It was calculated to check the abundance of the leaves and the forest cover by extension. RSR which is an improved simple ratio by introducing reflectance of band 5 was also calculated to check the extent of the vegetation cover (Stenberg et al., 2004).

These indices were used to classify the images; however, setting the threshold to capture the different classes of vegetation was not easy with the indices. Therefore, the classification produced two classes, forest and non-forest. This was too coarse for
meaningful interpretation. Besides, there were anomalies with some indices, for instance, the NDII puts water bodies in the same category as forests and the distinction cannot be made between the two by entirely relying on it. Some background reflectance from the soil are indispensible on the NDVI, therefore, the acreage on forests as per the NDVI is unreasonably high. The RSR equally showed progressive changes in the vegetation cover; however the boundaries were not clear between the vegetation types.

The resulting indices showed a general decrease in the size of greenness progressively. However, the indices have their shortcomings (Stenberg et al., 2004). For instance, the NDII which measures moisture in the leaves of the vegetation seemed to measure water and categorised the water bodies as green plants. The NDVI also is susceptible to various forms of defects ranging from seasonal changes to background reflectance from the soils. Since these indices have strong features which are desirable for vegetation analysis, a combination of the three (NDVI, NDII and RSR) was used to represent the RGB respectively, for classification purposes. This improved the variability between the features and made classification easier.

In order to discern the various vegetation components clearly, the NDVI, NDII and RSR were layer-stacked together to enhance the image interpretation. The resulting image was more distinct spectrally than the original image and obviously better than the indices individually, for instance, water is distinctly red in the resulting image as shown below in figure 4, dense forest was whitish and remarkably different from sparse forests – light green.

![Figure 4: Layer-stacked image (left) and the original image band 432 (right) for the year 2000](image)

The combined ratio was then used for a more detailed classification. A supervised classification algorithm was used where training sites were identified from the image with the help of Google Earth images at times and spectral variability. With the combination, it was possible to classify the image into 4 distinct classes of water, dense forest, sparse forest and others. The “others” category included settlement, urban areas and bare lands.
4.3 PCA

A principal component analysis was performed on the image where 3 components were generated. The main aim was to reduce redundancy in the data and enhance the differences between features in the scene (Estornell et al., 2013). In this way, classification could be done easier because reducing the image to 3 bands (principal components) increases spectral variation between the features in the imagery. With the three principal components, a supervised classification was done which yielded 4 classes of dense forest, sparse forest, water and others.

4.4 Tasselled cap

The tasselled cap indices were calculated for brightness, greenness and wetness. The three indices (brightness, greenness and wetness) were calculated. After generating these indices separately, they were used as three bands for the image (RGB) and used for classifying the image into 4 land use classes – dense forest, sparse forest, water and others.

4.5 Allometric equations

The allometric equations relates the forest biomass to the tree characteristics like diameter at breast height, height and tree species. Theses equations are of the form of a power function like equation 12 (Zianis & Mencuccini, 2004).

\[ M = aD^b \] (12)

Where a, and b are scaling coefficients, M is the biomass and D the diameter at 1.3 m. There was no forest inventory for the tree biomasses and species. Therefore, the average forest biomass of 236 Mg.ha\(^{-1}\) was used (Kinyanjui et al., 2014). This value was multiplied by the areal coverage of the forest to obtain the total biomass of the forest. The sparse forest cover was not used in the biomass estimations for the area covered in the study. Only the dense forest mass was used for the biomass estimations.

4.6 Carbon trading

The change in dense forest cover – hence change in carbon – was calculated. This was done by merely subtracting the acreages of a later year from an earlier year since they showed a general decrease in acreage over time. The amount of carbon biomass lost over the years was therefore obtained using an average biomass density of 236 Mg.ha\(^{-1}\) (Kinyanjui et al., 2014) over the dense forest area. This amount of biomass was estimated using the different methods of change detection and a monetary value computed for each, using the prevailing exchange rates in the carbon market. The carbon exchange rates used were from the California carbon dashboard.
5 FINDINGS

5.1 Results and discussions

The results obtained for the various indices used (NDII, NDVI and RSR) were as shown in figure 5 below.

The NDII captures water bodies as vegetation, figure 5. This makes it difficult to separate the vegetation from water bodies. Besides, setting a threshold for the indices to separate forest from the other land covers is not straightforward. For the NDVI, even
the backscattering or reflectance from the soil is captured as vegetation. This compromises the effectiveness of the index in computing the amount of vegetation. The acreage under vegetation might therefore be unnecessarily high owing to reflectance from the soils in the background. The introduction of band 5 in the RSR adjusts for the closure in canopies and reduces the background reflectance associated with the NDVI. However, setting a threshold is still challenging and not straightforward.

When the indices were independently used to classify the images, it was only possible to classify them into two classes – forested areas and non-forested areas as figure 6 illustrates. This is because setting thresholds to discriminate between the different land uses and land covers was not straightforward.

Figure 6: A two-class classification based on the indices (NDII, NDVI and RSR).
An automatic Jenks classification was used with two classes. The red regions are regions of lower values of the various indices due to no vegetation cover or limited vegetation. The green regions are of relatively high vegetation cover. However, it is important to note that the NDII classified the lakes as high vegetation. This was the other tricky issue with these indices, besides setting the thresholds to separate the vegetation and other land uses. It should also be noted that NDVI is affected by soil reflectance in the background to some extent.

Figure 7: A supervised classification based on the principal component analysis (PCA) for the 4 years of study.
The principal component analysis (PCA) was used to reduce the image into 3 principal components before a supervised classification was performed. The supervised classification was used to generate 4 classes – dense forest, sparse forest, water and others. The “others” group consisted of settlements, urban areas and bare lands. The classification had an overall accuracy of 82% averagey.

Figure 8: Classification based on the combined ratios (NDVI, NDII and RSR) as the RGB bands.
Due to the shortcomings of the individual indices and the difficulty in setting the threshold, the three ratios were layer-stacked together to form an RGB image which was then used for classification. As previously shown in figure 4, the result of the combination of the ratios enhanced the separation of various land uses. The resulting image was then used to perform a supervised classification which had an overall accuracy of 88%. The results were as shown in figure 8 above.

The three indices obtained in the tasselled cap were stacked (layer-stacked) to form the RGB bands of the image and used for classification. Some of the spectral signatures for the training samples used in the supervised classification are shown in figure 9 below. The results for classification based on tasselled cap indices were as shown in the figure 10.

![Signature Mean Plot](image1)

**Figure 9:** Signatures used for classification based on the tasselled cap. Top row from left to right are 1986 and 1995 image signatures, 2000 and 2010 image signatures in the lower row.

The supervised classification based on the tasselled cap indices was done with an overall accuracy of 82%. All the methods showed a general decrease in dense forest over the years.
Figure 10: Classification based on the Tasselled Cap indices

The amount of dense forest obtained with the various methods was quantified in terms of hectares as shown in table 2 below. These values were converted into biomasses as table 3 illustrates. Using the average biomass of 236 Mg.ha$^{-1}$, the changes in biomass were estimated based on the methods of classification adopted. Based on the resulting figures, the monetary values of the biomass was approximated based on California carbon dashboard rates (http://calcarbondash.org/), transaction rates on the 28 of May, 2015. The resulting figures are shown in table 4.
Table 2: Different acreages of dense forest obtained from different methods used.

<table>
<thead>
<tr>
<th>Year/Method</th>
<th>Ratios (ha)</th>
<th>PCA (ha)</th>
<th>Tas. Cap (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>27820</td>
<td>27333</td>
<td>27549</td>
</tr>
<tr>
<td>1995</td>
<td>26431</td>
<td>25591</td>
<td>25984</td>
</tr>
<tr>
<td>2000</td>
<td>23413</td>
<td>22292</td>
<td>22860</td>
</tr>
<tr>
<td>2010</td>
<td>19732</td>
<td>17883</td>
<td>18370</td>
</tr>
</tbody>
</table>

Table 3: Loses in tonnes of carbon from the forest over the years

<table>
<thead>
<tr>
<th>Year/Method</th>
<th>Ratios</th>
<th>PCA</th>
<th>Tas. Cap</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986 – 1995</td>
<td>327804</td>
<td>411112</td>
<td>369340</td>
</tr>
<tr>
<td>1995 – 2000</td>
<td>712248</td>
<td>778564</td>
<td>737264</td>
</tr>
<tr>
<td>2000 – 2010</td>
<td>868716</td>
<td>1040524</td>
<td>1059640</td>
</tr>
</tbody>
</table>

Table 4: The biomass loses in dollars

<table>
<thead>
<tr>
<th>Year/Method</th>
<th>Ratios</th>
<th>PCA</th>
<th>Tas. Cap</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986 – 1995</td>
<td>4143442.56</td>
<td>519655.68</td>
<td>4668457.6</td>
</tr>
<tr>
<td>1995 – 2000</td>
<td>9002814.72</td>
<td>9841048.96</td>
<td>9319016.96</td>
</tr>
<tr>
<td>2000 – 2010</td>
<td>10980570.24</td>
<td>13152223.36</td>
<td>13393849.6</td>
</tr>
</tbody>
</table>

With these huge figures, it is clear that income can be generated through carbon trading if the forest is registered under the CDM of Kyoto protocol. The surrounding communities would therefore be paid according to the amount of carbon that the forests sequester.

The different methods performed well in classifying the image. The ratios would have given a larger area because setting thresholds for the forests in ratios like NDVI, NDII and RSR is not outright clear. It is a trial and error therefore the indices were combined to analyse the vegetation extensively. NDVI alone could not yield a workable classification results since it is affected by among others, the background soil reflectance and saturation at high vegetation. Hence, presence of vegetation could be detected even in areas where none existed at times. However, the NDVI showed a general change in the vegetative cover from the 80s to 2010.

NDII measures the moisture content in the plant cells. However, it was possible to observe that the lakes and other water bodies in the image were classified as vegetation because of higher moisture content. This shows that, independently, NDII should not be used on an unfamiliar territory. Nevertheless, it also captured the general decrease in acreage of dense forests from the 80s to 2010. The RSR performed exemplarily well, even though setting a threshold was equally a challenge too. The inclusion of the middle infrared band (5) adjusts for the closure in the canopies and reduces the background reflectance associated with the NDVI.

When combined, the ratios showed a greater improvement in terms of contrasts among the land uses in the image. More land use types were discernible in the resulting image than it was for the ratios individually. This facilitated the classification process and the 88% accuracy obtained was the highest of all the other methods tried. This shows that combining these indices is better than using them individually as they tend to compensate and cancel out some unforeseeable errors in the process. As can be seen
from the image in figure 4, the combined ratios produced an image in which features are distinct. The PCA and the tasselled cap each produced an accuracy of 82%. This was seen as good enough to use for interpretation and analysis. Both methods showed a general decrease in the vegetative cover in the study area over the years. The combined ratio, PCA and tasselled cap showed that the forest cover, since 1986, has decreased by 29%, 35% and 33% respectively. There were slight variations in the resulting acreage of forest lost over the years with the various methods used.

5.2 Limitations

There was no forest inventory for the Mau forest. The closest to an inventory obtained was the work done by (Kinyanjui et al., 2014). The data used in the study was not available so the tree density obtained was assumed for this study. Otherwise, an accurate biomass would have demanded data per specie since the biomass is specie dependent. Instead, the generalised form was used to complete the study. The other limitation is the coarse resolution used for the study. With a 30 m resolution Landsat, the canopies and different forest species are not conceivable. Therefore, the whole forest was balkanised and handled as a single entity. In the real case, the forest has different canopies at different sites and species.

There was limited ground truth data to enhance the classification accuracies. Unlike in (Kinyanjui et al., 2014) where several samples were taken at 10 m intervals within plots well distributed in the forest, this study relied on published literature and maps for classification. The absence of ground data also meant that the carbon sequestered by undergrowth in the forest could not be accounted for.

5.3 Conclusions and recommendations

Global warming is a threat to humanity everywhere and any method feasible for mitigation should be embraced. The study explored one of the numerous methods available, carbon trading, and it is evident that forest ecosystems can be reclaimed through such method in conjunction with all the other stakeholders in unison. With more forests reclaimed, the size of the natural reservoir (sink) for carbon will increase and this improves the biodiversity besides influencing positively the hydrological cycle, as in the case of Mau forest complex.

GIS and remote sensing have demonstrated tenacity and handiness in matters pertaining environmental conservation. There are many means of analysing the images to understand the changes in the environment. NDVI, NDII and RSR are just but a few besides the others that have been tested. These methods when used on an image of a higher resolution could give more dependable estimates of the actual state of the ground. Higher resolution images could reveal more convincing findings to the global warming debate.

A future study should encourage using two or more of the indices together as this seems to give more insight into the image than the indices independently. A higher resolution image with ample ground data collection would also enhance classification accuracies. The ground measurements would make it possible to account for the undergrowth in the forests and the higher resolutions makes it possible to detect
various canopies and species. With these, a species dependent allometric equation can comfortably estimate the biomasses to a higher level of accuracy.
6 REFERENCES


Diaz, H. F., & Bradley, R. S. (1997). Temperature variations during the last century at high elevation sites. *Climatic change at high elevation sites* (pp. 21-47) Springer.


