Multi-temporal Land cover Mapping of the Kakamega Forest utilizing Landsat imagery and GIS

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MULTI-TEMPORAL LAND COVER MAPPING OF THE KAKAMEGA FOREST UTILISING LANDSAT IMAGERY AND GIS

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ABSTRACT
Forest resources contribute significantly to the Kenyan economy. However, due to pressures exerted by the growing population, this scarce resource is seriously endangered. In particular, the Kakamega Forest has experienced serious degradation in the past, though some restoration efforts have also been put in place. In this research, we utilise time series Landsat imagery to characterise the changes and capture the trends in land cover changes. Three epochs are utilised, namely, 1986, 1995 and 2005.
Pre-processing involved georeferencing and radiometric corrections. As a first step the time series imageries were evaluated via a threshold analysis distinguishing between 'forest' and 'non-forest'. Subsequently, a supervised multispectral classification was performed distinguishing various land cover classes. Ground truthing for the historical imagery was done using aerial photographs, topographic maps and site visits. Actual land cover verification was based on amateur photographs taken in 1999 from an aircraft, and ground observations in 2008. For classification the maximum-likelihood decision rule was applied considering bands 3, 4, 5, 7 plus 7/2 for thematic mapper (TM)/enhanced thematic mapper plus (ETM+) imagery and 1, 2, 3 and 4 for Multi-spectral scanner (MSS) data, respectively. The classification results form a solid basis for a consistent and detailed evaluation of forest history between 1986 and 2005. Analysis results presented include graphs and pie charts of change in land cover class areas over time as well as such allowing for true change detection with transitions between the different classes. In this study, maximum likelihood supervised classification change detection techniques were applied to Landsat images acquired in 1986, 1995 and 2005 respectively. To map land cover changes in kakamega forest, a supervised classification was carried out on the six reflective bands for the three images individually with the aid of ground truthing data. Changes among different land cover classes were assessed. During the study period, a very severe land cover change had taken place as a result of agricultural and settlement. These changes in land cover led to vegetation degradation. The effects of restoration efforts are also captured in the research findings.

Key words: Land-cover mapping, image classification, change detection

1.0 INTRODUCTION

Forest resources contribute significantly to Kenya's economy. The agricultural sector, the tourism sector, manufacturing and processing industry which are the backbone of the country's economy, directly or indirectly, rely on the dwindling forest resources. Kenya's major river systems (Tana, Athi, Ewaso Nyiro, Nzoia, and Yala) source their water from mountain forest catchment areas. These rivers traverse the country, providing fresh water for domestic use, industrial processing, irrigation and hydro-electricity generation. River Tana alone supplies water for the Seven Folk hydro-electric power stations, providing more than half of the country's electricity. In addition, forests provide building and weaving materials, pulp for the paper industry, herbal medicine, wild fruits and honey. They regulate rainfall patterns, reduce sedimentation load in our rivers and provide environmental stability.

The monitoring of land cover/land use (LCLU) using satellite imagery has been adequate for general extensive synoptic coverage of large areas (Lillesand *et al.,* 2004; Jensen, 2000). As a result, this has reduced the need for expensive and time consuming ground surveys conducted for validation of data. In general, satellite imagery has been able to provide frequent data collection on a regular basis, unlike aerial photography which provides more geometrically accurate maps, but are limited with respect to extent of coverage and expense.

In this paper, the term 'land cover' relates to the type of feature present on the surface of the earth such as agriculture fields, lakes, rivers, trees and buildings. On the other hand, the term land use relates to the human activity or economic function associated with a specific piece of land, with examples being a tract of land on the fringe of a forested area that may be used for family housing or agriculture. Depending on the level of mapping detail, its land use could be described as, residential or agricultural use. The same tract of land would have a land cover consisting of roofs, pavement, grass, and trees (Lillesand *et al.,* 2004). For simplicity, we adopt the term 'land-cover' in the rest of the paper to refer to both terms since land cover can be inferred from imagery but land use may need further verification.

Digital change detection is the process of determining and/or describing changes in land-cover and landuse properties based on co-registered multi-temporal remote sensing data. The basic premise in using remote sensing data for change detection is that the process can identify change between two or more dates that is uncharacteristic of normal variation. Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use change in a wide variety of environments (Srivastava and Gupta, 2003; Künzer *et al.,* 2005; Bhattacharya *et al.,* 2005, Herold *et al.,* 2002). There are many techniques available to detect and record differences (e.g., image differencing, ratios or correlation) and these might be attributable to change (XiaoMei and RongQing 1999). However, the simple detection of change is rarely sufficient in itself: information is generally required about the initial and final land cover or types or land uses. Furthermore, the detection of image differences may be confused with problems in phenology and cropping, and such problems may be exacerbated by limited image availability and poor quality in temperate zones, and difficulties in calibrating poor images. Post-classification comparisons of derived thematic maps go beyond simple change detection and attempt to quantify the different types of change.

The degree of success depends upon the reliability of the maps made by image classification. Broadly speaking, large-scale changes such as widespread logging or major urban development might be mapped reasonably easily, while in the case of evolutionary changes such as erosion, succession, colonisation or degradation, boundaries may be indistinct and the class-labels uncertain (Mitchell *et al.,* 2006; Schaab *et al.,* 2005).

Remote sensing is a powerful tool in the provision of such information. It involves the acquisition of information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, phenomenon or area under investigation (Lillesand *et al.,* 2004). Sensors aboard satellites in space record the amount of electromagnetic energy reflected from various objects on the earth's surface at various wavelengths. From the spectral response patterns, information about the objects is derived. Through the analysis of remotely sensed data for different epochs, change detection is possible. With time change analysis and monitoring of forest destruction can be done. The knowledge acquired from this information forms a basis for decision making in efforts to address the deforestation menace. It is in this vein that this research was carried out to establish factual information on the state of Kakamega Forest which is reportedly in danger of extinction and has attracted attention from the public and many environmental organisations.

This research aims at mapping the forest resources for the purpose of determining and assessing the rate at which the forest is depreciating by the finding the most affected areas so that necessary corrective actions may be taken to curb deforestation of the forest. Inadequate forest statistics and maps are a limiting factor in many tropical countries including Kenya. Quite often, the available forest data are outdated and of little help in the planning and management of forest resource. The problem facing high and medium potential areas of Kenya with regard to forest management is that of a rapidly growing population, leading to increased pressure on land as a source of livelihood. To determine the right formula of allocating land to settlements, agriculture, forestry, or any other land uses without making one aspect suffer presents a great challenge. For forest-based resources, an essential requirement is to establish the types, extent and present condition of these forests.

The main objective of this research was therefore to provide information and generate a database on the status of the Kakamega Forest resource and land cover changes to facilitate sustainable management geared towards conservation of both the forest and its habitat. To achieve this broad objective, the task was split into several sub-tasks, namely :

(i) To provide maps showing changes in forest cover for the period between 1986,1995 and 2005,

(ii) To provide land cover map within the forest for the years 1986, 1995 and 2005, and,

(iii) Build a framework for facilitating further research in the forest.

2.0 STUDY AREA, DATA AND METHODOLOGY

2.1 The Study Area

Kakamega Forest is situated in Western Province in Kenya (34° 37’ 5” - 35° 9’ 25” East and 0° 32’ 24” North - 0° 2’ 52” South) as shown in Figure 1, North-West of the capital Nairobi, 15 km from Kakamega Town along the Kakamega - Eldoret Highway. Along the North Eastern edge of the Lake Victoria basin at an altitude of 1,500-1,600 metres above the sea level, Kakamega Forest is a remnant of rain-forest which once spanned the Equator from the West to East coasts of Africa. Gazetted as a Trust Forest in 1933, it covered an area of 240 km^2, a little less than half of which currently remains as indigenous forest. The forest is closely associated both geographically and biologically with other two smaller forest blocks namely Kisere (484 ha) located 6 km to the north and Malava (718 ha) also located 12 km to the north (Kenya Wildlife Service, 2007).

Kakamega Forest covers an area of about 240 km^2 and was established to protect the only mid altitude tropical rain-forest in Kenya, a remnant and eastern limit of rain-forests of Zaire and West Africa. The forest contains many species found nowhere else in the country and Africa. It was established as a protected area by the Government of Kenya (GoK) (KIFCON, 1994). The forest lies in the Lake Victoria catchment basin, about 50 km north of Kisumu City and just West of the Nandi Escarpment that forms the edge of the central highlands.

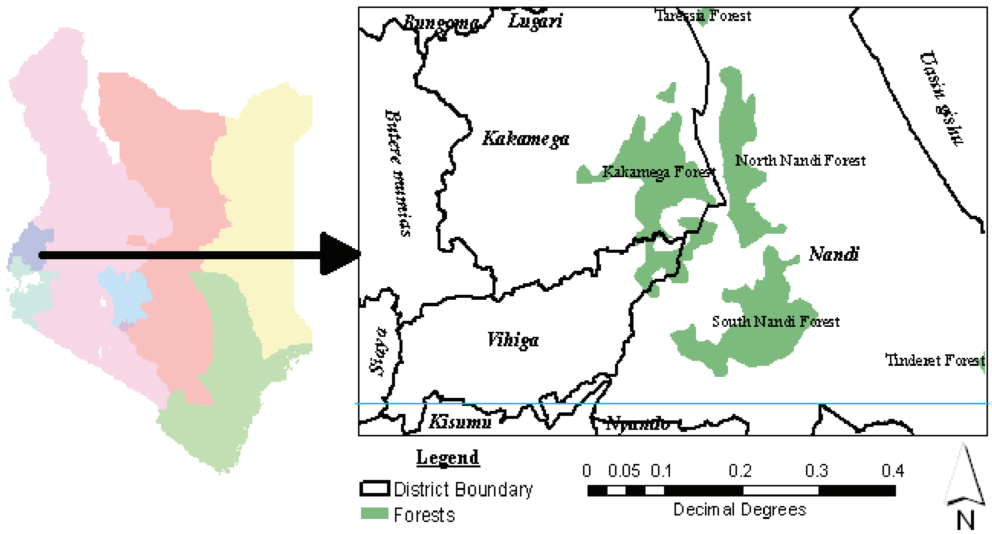


Figure 1: Location of the study area (Kakamega Forest) in western Kenya

The average annual rainfall is about 2000 mm. The long rains fall between March and May, with a short rain season from October to November. Rain falls mostly in the afternoon or early evening and is often accompanied by heavy thunderstorms. Average temperatures remain almost similar throughout - between 15° C and 28° C.

It was first gazetted as a Trust Forest in 1933 and two small nature reserves, Yala and lsecheno were established within the forest in 1967. In 1985, nearly 4400 ha of the northern portion of the forest together with the adjacent Kisere Forest were gazetted as Kakamega Forest National Reserve (KIFCON, 1994). The forest is a high biodiversity area, including over 300 species of birds, and over 350 species of plants (Köhler 2004). The terrain is undulating, with often steep sided river valleys.

In efforts to maintain and preserve wildlife diversity, the importance of preserving a fragile ecosystem like forests cannot be overstated. With their unique flora and fauna, forests are important resource reserve for genetic banks, the medicine industry, nutrient recycling and carbon dioxide sequestration. The loss of such systems would therefore be a great loss to humanity (Blackett, 1994).

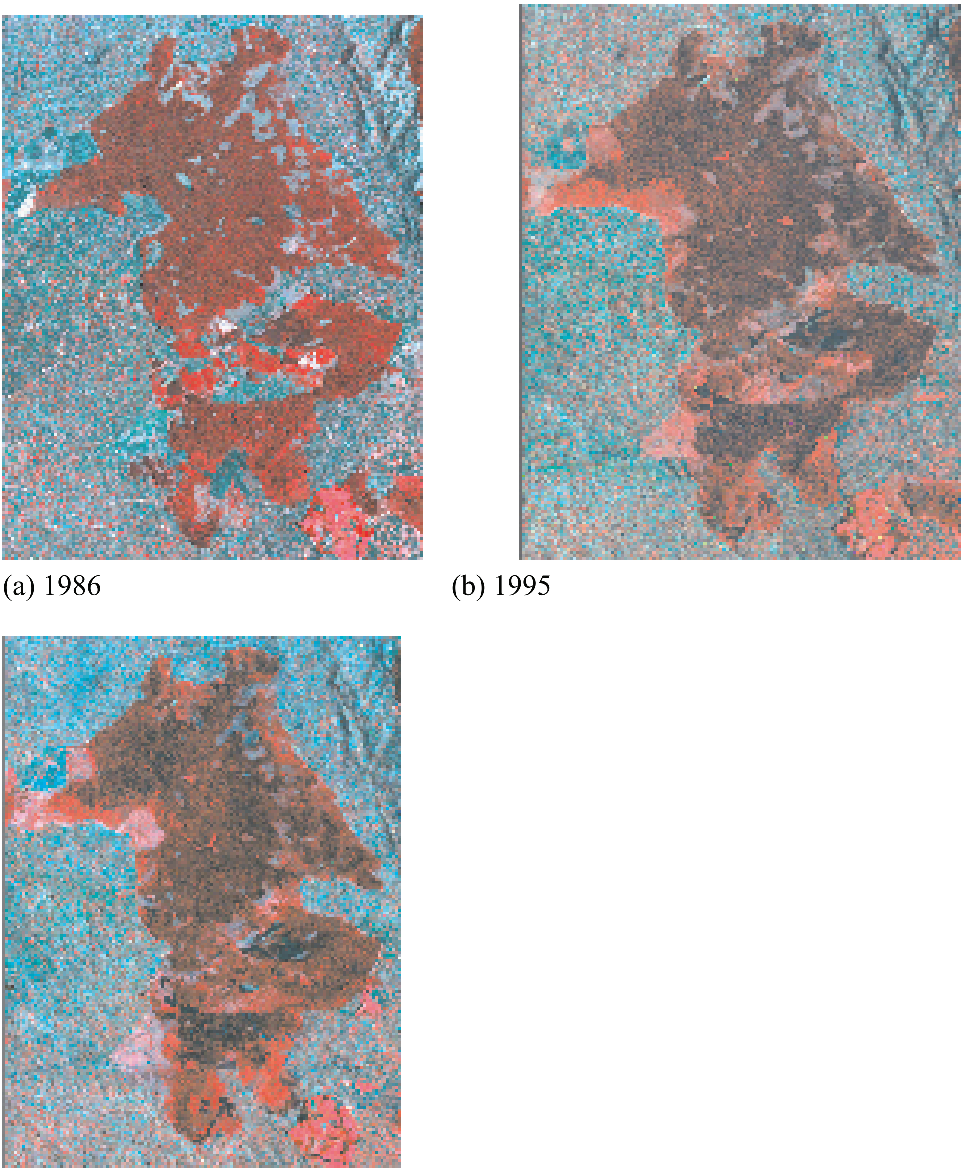
2.2 Data

This research aims to map and assess Kakamega Forest resources from 1986 to 2005 at a 10-year interval and determine the changes in forest cover (increase and/or decrease) that have taken place. Various sets of data were used to map and carry out analysis on the study area. The data used are given in Table 1.

Table 1:Characteristics and sources of data used in the research

Satellite imagery	Landsat series -30 m resolution	Regional Centre for Mapping of the resources for Development (RCMRD)
Rainfall data		Raingauge records
Kenya Meteorological Service		
Economic activities	Census records	Central Bureau of Statistics
Population data	Census records	Central Bureau of Statistics
Topographical maps	scale 1/50000	Geomatic Engineering and Geospatial Information System department
Aerial photographs	Kakamega forest air photographs	Kenya Forest Service

Figure 2 shows georeferenced false colour composite images used for the three epochs used in this research. Combinations of Landsat bands are combined using RGB (red-green-blue) colours to obtain false colour composites with various combinations being suited for particular applications. Table 2 lists some of these false colour composites and typical applications areas.



(a) 1986

(b) 1995

(c) 2005

Figure 2: False color composite Landsat satellite imageries for the 3 time periods- band 4 (red), band 3 (green) and band 2 (blue)

Table 2: Colour composite combinations and viable application areas

Composite	*Application*
True colour (1,2,3)	Mainly used to water study
False colour (2,3,4)	Vegetation and water distintion
False colour (2,4,5)	Built up and cleared areas distinction
False colour (2,4,7)	Vegetation distinction

2.3 Methodology

The methodology adopted in this research is as follows:

Step 1 Coordinate transformation (georeferencing) to WGS 84 UTM 36 South

Topographical maps were georeferenced prior to digitisation. This formed the base upon which subsequent image georeferencing could be tied to.

Step 2 Digitisation of topographic maps of Kakamega Forest.

The gazetted forest boundary, topographic features and other key features within a stretch of about 50 km around the forest was digitized from the georeferenced Kakamega and Kaimosi topographic sheets (Figure 3). This formed the base map for geo-referencing interpreted data and overlaying the images from Landsat satellite.

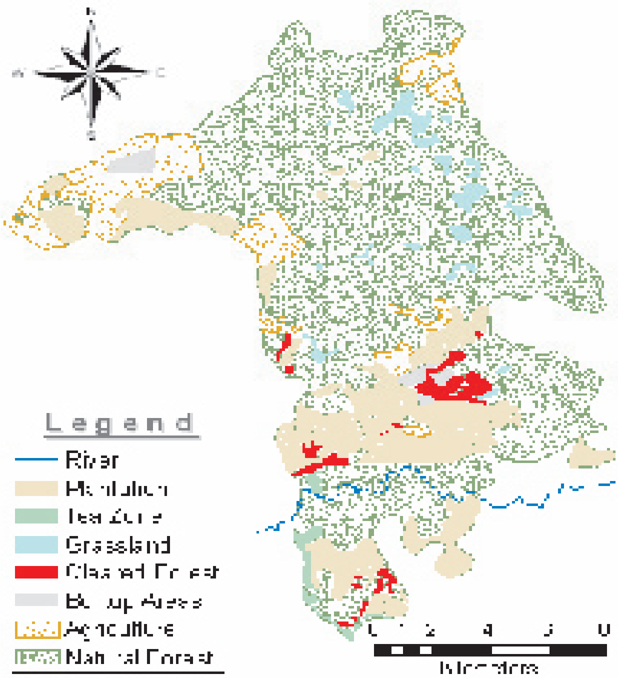


Figure 3: Digitised land cover classes

Step 3 Layer stacking of all bands for the 3 epochs
Kakamega area had portions imaged in different scenes. Prior to stacking, the images were compared and variations in contrast addressed by contrast enhancement and histogram equalisation (where feasible). These scenes were then layer stacked to prepare a mosaic of the entire area.

The Kakamega Forest land cover mapping mainly used satellite remote sensing data with 30 m ground resolution from Landsat satellite series. Bands 1, 2, 3, 4, 5, 7 were layer stacked to form a colour composite. This was done on all the images for the different years, 1986, 1995 and 2005. The scenes used were as follows: Landsat Multi Spectral Scanner (MSS) scene of 22nd September 1986, Landsat Thematic Mapper (TM) scene of 22nd February 1995 and Landsat Enhanced Thematic Mapper Plus (ETM+) scene of 22nd September 2005.

Step 4 Image to map geometric correction
The geographically correct digitised features (forest cover) were used to perform image to map registration. This was done for each mosaic for the three epochs.

Step 5 Image to image geometric correction
Residual geometric distortion (small amounts) was addressed through image to image registration. In both Step 4 and Step 5 cubic convolution was used as the resampling method, with the pixel resolution being retained as 30 m.
Linear resampling was performed using four well defined and distributed control points. The result was refined by iteratively recomputing the root mean squares (RMS) with improved correspondence file coordinates until an acceptable RMS of below 0.5 was obtained for all control points. False colours (red, green and blue) composites were generated from these scenes (see table 2). The Landsat satellite scenes used had a spatial resolution of 30 m x 30 m, each scene covering 185 km x 185 km. Total-cover panchromatic aerial photographs of scale 1:10000 taken along the forest edge in 1986, 1995 and 2005.

Stereo viewing of the photographs gave detailed impression of the cover classes on the forest. Aerial photographs were used to provide information missing out in parts of the forest.

Step 6 Image subsetting
These scenes were then clipped for an area of about 20 km x 20 km (UTM zone 36 S: 680,000 - 740,000 E by -5,000 - 60,000 N; ellipsoid Clarke 1880, datum Arc 1960). Atmospheric and terrain shading effects were corrected based on a digital terrain model derived from the 1:50,000 topographic maps contours. For an improved visual interpretation of the scenes on the screen a piece-wise linear transformation (via breakpoints) was applied for band combination 5/4/3 (ETM+ and TM) and 2/4/1 (MSS), respectively. The images were subset to focus on the forested portion. This smaller image has the added advantage of being processed fairly fast compared to processing of the entire mosaic.

Step 7 Classification of the images

The first step towards a classification of the landscape was a threshold analysis aimed at generation of binary images distinguishing ‘forest’ from ‘non forest’. This distinction was made by performing multispectral classifications independently for these two major land-covers. The different spectral channels were evaluated to assess their suitability. Band 2 (green) for TM and ETM+, and Band 1 (green) for MSS, were found to be best for separating ‘forest’ and ‘no forest’. At first, forested areas were derived by overlay techniques combining the resulting threshold images and raster layers of the official forest areas digitised from topographic maps. However, though temporal changing patterns of forest losses and replanting were observed, in total there was no major change in forest-cover utilizing this single band thresholding approach.

What was needed for describing forest fragmentation and disturbances in detail was to distinguish between more land cover classes in order to separate natural forest from secondary forest, or even young forest plantation. Furthermore, the results of the threshold analysis demonstrate that a truly satisfying separation of ‘forest’ and ‘no forest’ was not possible when considering just one spectral band.The rationale underlying the traditional approaches to computer-assisted land cover classification using multispectral digital remote sensing data is that pixels from within the same land cover class tend to group together or cluster in multi-spectral feature space, and that pixels from different cover classes tends to be separate from one another in multi-spectral feature space. The tendency of pixels from within the same land cover class to form spectrally distinct clusters is the foundation of the algorithm employed in this work for thematic feature extraction and classification. Computer-assisted classification of digital multi-spectral remote-sensing data can be partitioned into two general approaches: supervised and unsupervised. We adopted supervised classification in this work. In this, an analyst selects ‘training areas’ that are spectrally representative of the land cover classes of interest.

From these training areas, univariate and multivariate statistics, such as mean vector, standard deviation, variance and covariance, are first calculated and then used to classify each independent pixel of the entire image being examined. Decision rules can be non-parametric, such as minimum Euclidean distance to means, or parametric, such as Gaussian maximum likelihood (Lillesand *et al.,* 2004; Sabins, 1978). Supervised training area selection and classification requires a priori decisions on the part of the analyst before resorting to computer-assisted classification. Because of its strong theoretical and statistical soundness, the maximum likelihood classification algorithm was chosen in this work. Signature data was derived for each of the epochs based on features identifiable per epoch during the training stage. This approach addresses possible problems that are encountered using multi-date imagery.

Step 8 Accuracy assessment

To verify the quality of the classification exercise, accuracy evaluation was done. This was done using ground truth data collected from the field for a sample comprising of fifty (50) locations (targets).

Step 9 Change matrix calculations

This was done to obtain the amounts of change for the various feature classes. In the post classification comparison approach two or more images were independently classified and registered, and through the use of a pixel-by-pixel comparison algorithm, those pixels that indicate changes between images were determined (Lillesand, *et al.,* 2004). Further, change maps and change matrix statistics were computed to quantify and explain the specific changes.

2.4 Analysing Land Cover Changes

A geographical information system (GIS) is an appropriate tool for the assessment of land degradation and as an aid to conservation planning since it allows the simultaneous examination of attribute data for the same geometric feature, thus enabling interpretation of a range of interrelated geospatial information for the same area (Korte 1993). GIS is particularly suitable for comprehensive storage of data at different geographical scales and permits cross analysis of data especially involving time series analysis and spatial statistics (Lyon, 2003). GIS can be used to provide not only important information on vegetation patterns in time, but also information on the spatial variation of management variables themselves in relation to land attributes and management decisions (Worboys, 1995). Exploratory spatial data analysis is used to describe and visualise spatial distributions and to identify typical locations, thus patterns of spatial association can be recognized (Usery, 1996).

The simplest landscape metric for assessing changes in landscape composition over a period of time is the proportion metric. This tends to assess the composition ratio on the different land covers in a landscape. The proportion metric is expressed as a percentage of the spatial extent of the landscape being considered. A proportion value of a land cover category close to zero percent implies that the land cover category is almost non-existent in the landscape. While a proportion close to 100 % implies that the land cover dominates the entire landscape. GIS capabilities allow for the computation of proportion metrics alongside visualisation of trends.

In this research the above approach was used to get dynamics of land covers beginning from 1986, 1995 and 2005. Changes in terms of areas and percentages were obtained as well as rates of change. Seven land cover classes of the Kakamega forest were decided upon based on knowledge of the area and the shapes, colour, tones and patterns of the false color composite satellite images. The classes were namely, natural forest; grassland; built-up areas; plantation (hardwood); plantation (softwood); tea zone and agriculture.

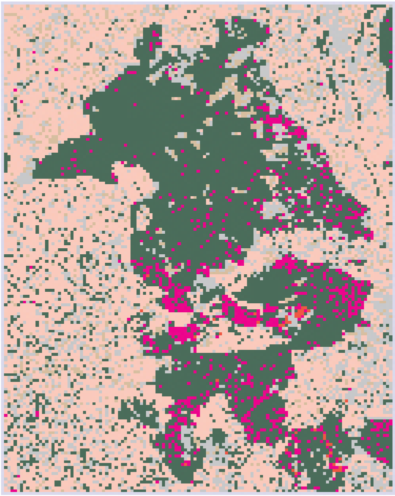
Table 3: Visual characteristics of identified classes

Interpretation class	*Image charateristics*
Natural forest	Dark brown/dark red with black mottled coarse texture
Grassland	Isolated patches of green/blue occuring as large islands in thedark brown shades
Tea zones	Purple elongated areas along the forest edge
Softwood plantations	Dark brown shades smooth to fine texture occasionally separated by bluish/greenish strips
Hardwood plantations	Bright red shades with smooth textures
Agriculture	Greenish shades with dense mottles of purple, brown rough texture or bluish shade light mottled medium texture
Cleared forest/built up areas	Black expansive patches

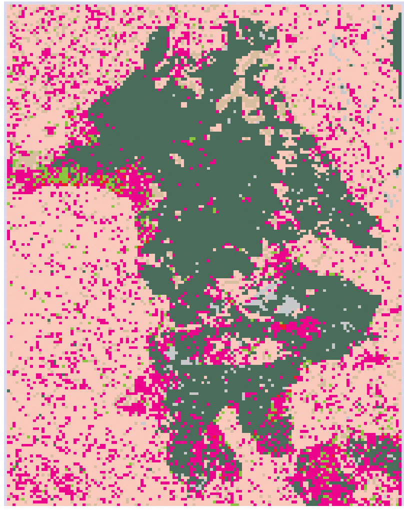
In identifying these classes, their characteristic appearance on the satellite imagery was used. These characteristics are summarised in Table 3. These spectral classes I were validated using information classes derived from aerial photographs and field visits.

3.0 RESULTS AND DISCUSION

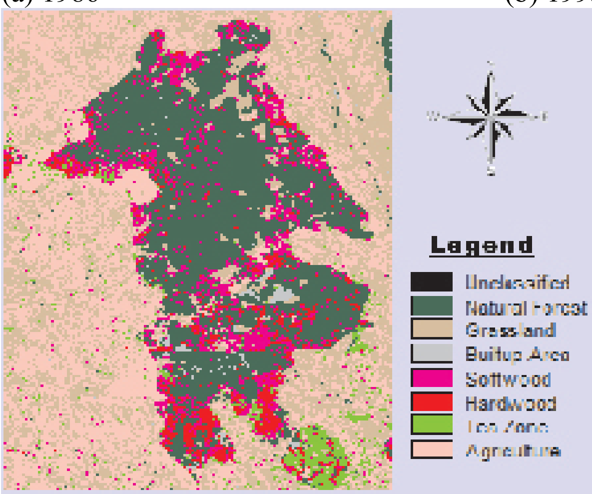
Figure 4 shows the classified images. Shown here are the seven identified classes.



(a) 1986



(b) 1995



(c) 2005

Figure 4: Classification results for the three epochs

Figure 5 shows the various proportions allocated to each of the classes for the three epochs considered. In this figure, hardwood plantation and softwood plantation classes have been merged into one plantation class. GIS provided functionalities for generation of thematic maps as products of and cover analysis. GIS enabled map overlays where different themes can be overlaid with other data e.g. socio-economic data to get certain information.

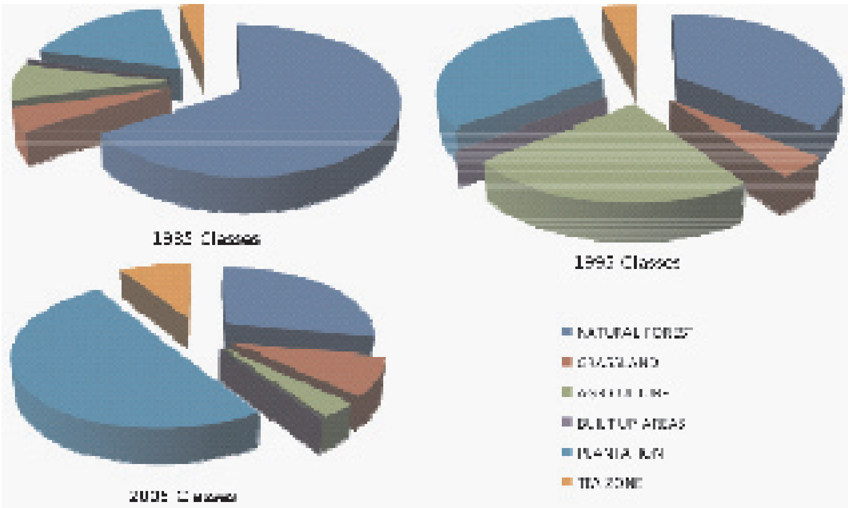


Figure 5: Proportionate land covers in the forest for each of the 3 epochs

The spatial distribution of human induced classes namely agriculture, plantations and built up areas depict a clear relation between population density, accessibility and forest interference. The classes are situated along accessible areas within the forest along forest roads and on the forest edge. The classes are also pronounced on the Western and Southern parts adjacent to densely populated locations and with good road network. On the eastern part, there is little forest interference since it is shielded by the steep terrain of the Nandi escarpment that harbour lower population.

Land cover trends obtained from the images indicate that there was enormous destruction of Kakamega Forest over the period between 1986 and 1995, but the forest recovered substantially over the period between 1995 and 2005. Increased agricultural activities were registered during this period, and increased agriculture implies deforestation. Over the period 1995 - 2005, there was a general recovery of the forest as evidenced by reduced agricultural activities and increased forest plantations.

To analyse and assess the quality of the classification steps, error matrices were generated based on maximum likelihood classifier for each of the three epochs. In this part, the seven original classes are considered (i.e. , prior to merging of the plantation classes). Statistics generated included overall accuracy, producer's accuracy, user's accuracy and Khat statistic. These results are tabulated below in tables 4 - 6.

Table 4: Classification error matrix for 1986 imagery

Grassland	*Natural*	*Agriculture*	*Hardwood forest*	*Softwood*	*Built-up*	*Tea*	*Row*	*User accu*		
area	*zones*	*total*	*racy (%)*							
Grassland	206	0	0	0	0	3	0	209	98.6	
Natural forest	0	792	4	0	2	0	0	798		
99.3										
Agriculture		0		0	435		1	1	9	0
446	97.5									
Hardwood		0		0		1	133	4	0	1
139	95.7									
Softwood		0		29		0	3	206	0	0
238	86.6									
Built-up areas		10		0		14		0	0	322
0	247	90.3								
Tea zones	0		0	0		0	0	0	201	102
100										
Column total		216		821		454		137	213	
235	202	2278								
Producer acc	95.4	96.5		95.8		97.1	96.7	94.9	99.5	

Overall Accuracy=96.40%

Table 5: Classification error matrix for 1995 imagery

	Grassland	*Natural*	*Agriculture*	*Hardwood forest*	*Softwood*	*Built-up*	*Tea*	*Row*	*User accu*	
	area	*zones*	*total*	*racy (%)*						
Natural forest	1549	0	3	8	0	0	0	1560	99.3	
Grassland	0	160	0	1	0	0	64	225	71.1	
Built-up area	7		0	203	0		0	0		0
210 96.7										
Softwood	1		0	0	249		0		0	
4	254	98.0								
Hardwood	0		0	0	0		45		1	
0	46	97.8								
Tea zones	0		0	0	21		1	14		2
38	36.8									
Agriculture	0		25	0	86		0	0		052
361	69.3									
Column total	1557	185	206		365		46	15		023
2694										
Producer	99.5	86.5	98.5		68.2		97.8	93.3		
78.1										
ac uracy (%)										

Overall Accuracy=91.69%

Table 6. Classification error matrix for 2005 imagery

	Natural forest	Grassland	Softwood	Hardwood	Tea	Built-up	Agriculture	Row zones	User accu [illegible]
	Total	racy (%)							
Natural forest	1224	0	0	0	0	3	0	1227	99.8
Grassland	0	49	2	0	0	0	0	51	96.1
Grassland	0	49	2	0	0	0		0	51
96.1									
Hardwood	0	0	2		0	104	0	0	106
98.1									
Built-up areas	2	0	0		0		0	116	0
118	98.3								
Agriculture	0	0	3		0		0	0	543
546	99.5								

After the merging of the plantation classes, statistics were calculated using standard GIS cross tabulation functions. These statistics show changes in area of individual cover types between the two epochs of interpretations. These results are shown in Table 7.

Table 7: Land cover in the three different years derived from the analysis of the satellite images

Year	*1986*		*1995*		*2005*	
Cover type	Area (Ha	%	Area (Ha)	%	Area (Ha)	%
Natural forest	16558.2	66	9000.6	36	7223.6	28
Agriculture	1235.9	5	6035.5	24	2136.9	8.6
Built-up areas	18.6	0.1	22.3	0.1	30.5	0.1
Plantation	4562.3	18	7886.5	31.5	12985.9	50
Tea zones	723.8	2.9	986.7	3.9	2235.6	8.8
TOTAL	24995.1	100	25037.8	100	25468.8	100

Actual change can be obtained by a direct comparison between validated classification results of the image series from epoch to epoch. Land cover/use changes that occurred during the period under consideration were measured by computing change matrices. Land cover change detection is necessary for updating land cover maps and the management of natural resources (Brandt *et al*. 2002, Lunetta *et al*. 2004). The change is usually detected by comparison between two multi-date images, or sometimes between an old map and an updated remote sensing image. Change detection is obtained in remote sensing through operations which allow for subtraction of two images with the final result being an image which can further be vectorized capturing the changes.

Tables 8 and 9 show the inter-conversion between the various land cover types over the periods 1986 - 1995 and 1995 - 2005. Columns represent the later epoch's data while rows represent the earlier epoch's data. These values indicate the areas that were previously and the cover that is represented in the row that now been converted to the cover represented in the column.

Table 8. Change matrix for 1986-1995

Year		*1995*					
		Natural forest	*Agriculture*	*Plantation*	*Build-up areas*	*Grassland*	*Tea zones*
1986	Natural forest	12370.9	1644.4	2803	2.5	860.5	968.3
	Agriculture	148.2	1486.3	60.8	0	0	42.2
	Plantation	192.5	748.2	1900.9	0	58.3	420.2
	Build-up areas	7.4	0	0	10.2	0	0
	Grassland	452.3	125.2	0	6.2	923.1	3.7
	Tea zones	153.8	280.9	122.8	1.2	36.2	485.3

Table 9: Change matrix for 1995-2005

Year		*2005*					
		Natural forest	*Agriculture*	*Plantation*	*Build-up areas*	*Grassland*	*Tea zones*
1995	Natural forest	11548.2	222.2	236.8	6.2	125.2	311.1
	Agriculture	331.1	2484.9	1119.7	0	95.5	274.1
	Plantation	5.5	520.3	1501.6	0	2.5	5.8
	Build-up areas	2.5	9.8	0	6.2	0	0
	Grassland	766.2	99.6	86.8	0	885.3	0
	Tea zones	120.5	590.3	853.1	1.2	1.2	275.3

Figure 6 captures the trends for each land cover over the 3 epochs. It can be seen that the natural forest cover has continually reduced, though the largest reduction occurred between 1986 and 1995.

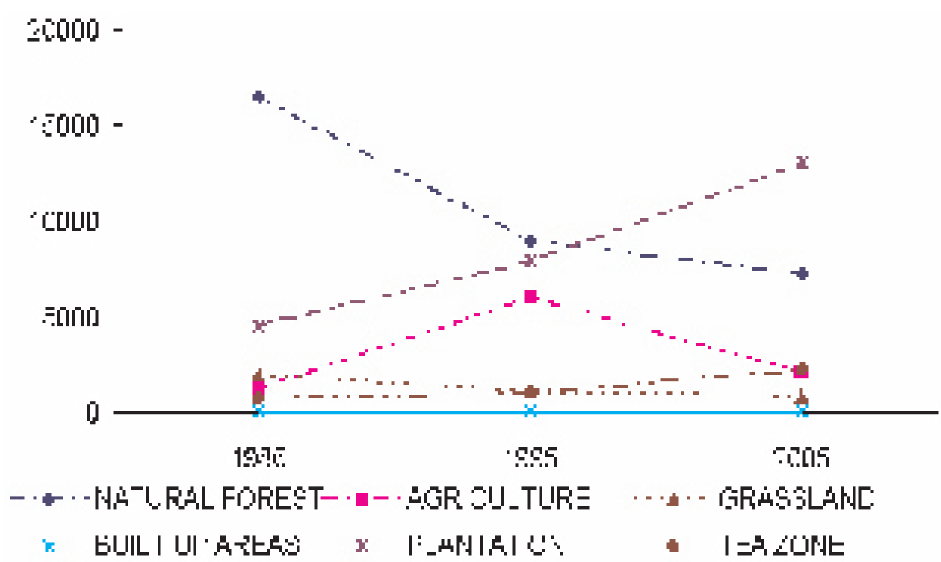


Figure 6: Kakamega land cover trends

Artificial efforts of reforestation can also be noted with large increases in areas under plantations. It can also be seen that area cleared for agriculture increased between 1986 and 1986 but some of these lands were converted back to plantations between 1995 and 2005.

4.0 CONCLUSION

From the results obtained, it has been shown that Kakamega Forest was enormously deforested between 1986 and 1995, but there was significant recovery over the period between 1995 and 2005. This trend can be attributed to the work done through several projects initiated in the region to enhance forest conservation in line with Government's policy of poverty reduction as well as empowerment of the local people through community participatory approach. Such project include: community based cultivation of medicinal plants, promotion of environmental protection, energy saving technologies, promotion of ecotourism, development of apiculture and sericulture among others.

This research has confirmed the utility of remote sensing and GIS in mapping and highlighting worrying trends and quantifying these trends in land cover changes. It has also demonstrated that they can be used to assess the impact of any remedial measures taken to avert negative changes as evidenced by the increased forest cover registered between 1995 and 2005 through increase in forest plantations.

Due to the activities going on in Kakamega Forest, it is recommended that the time duration between monitoring epoch might be reduced to at least biennial or triennial basis so that any change can be documented and the necessary corrective steps taken towards the right direction to avert further negative effects.

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