# ABSTRACT

## MAPPING LAND COVER LAND USE CHANGE IN MBEERE DISTRIC, KENYA.

The main goal of the study was mapping land cover land use change patterns in Mbeere District between 1987 and 2000.Two Landsat images acquired in 1987 and 2000; and MODIS data were used to map and quantify the patterns of change. The results revealed a complex land cover change pattern between the two dates; with both positive and negative changes. Grasslands increased by 29 %, settlement/agriculture by 31 %, while woodland reduced by 41%. The study also confirmed that digital change detection is still a viable change detection method in arid and semi-arid lands despite limitations associated with factors like high spectral similarities and phenology.

# MAPPING LAND COVER LAND USE CHANGE IN MBEERE DISTRICT, KENYA.

A Thesis

Submitted to the

Faculty of Miami University

in partial fulfillment of

the requirements for the degree of

Masters of Arts

Department of Geography

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2007.

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## Acknowledgement

I take this space to acknowledge the help of several people who made this study possible. First, I would like to express my gratitude to my advisor, Dr. Mary Henry, for her time and academic guidance through out the entire period of this thesis. I also would like to thank Dr. William Renwick and Dr. John Maingi my committee members, for their time and valuable input in every stage of this research.

I would also like to thank the Department of Geography and the Department of Botany for their financial assistance which made this study possible. My appreciation goes to all my friends for their moral support throughout the study, and everybody who contributed in making this research work a success.

# CHAPTER I

## Introduction

Monitoring environmental processes is becoming increasingly important wherever there is increasing population and development pressure placed on fragile arid and semi-arid environments (Sun *et al*, 2005). Globally, arid and semi-arid lands cover over 70% of total landmass (Weigand & Florian, 2000) and support approximately one sixth of the world's population (Veron, *et al*, 2006). Arid and semi-arid lands have been considered agriculturally and economically unimportant, and very few surveys on their biological productivity and dynamics have been carried out (Wellens, 1997). Degradation of arid and semi-arid lands has however occurred at a global scale, with over 70% of area affected in Africa, Asia and Americas, and about 54% in Australia (Wellens, 1997).

Controversy, both informed and uninformed, inevitably surrounds and confounds discussions of land degradation in the dry lands (Dregne, 2002).Local to national scale studies have demonstrated the importance and the socio-ecological significance of dryland degradation, though land cover change in these fragile zones is poorly documented, and its causes are not fully understood (Lambin *et al*, 2001). Single factor causation and irreducible complexity are the two theories, which are mutually exclusive but unsatisfactory explanations for dryland degradations (Geist & Lambin, 2004). Single factor causation proponents suggest various primary causes of degradation in the fragile arid environments including growing population and poor management of the same (Houerou, 2002). On the other hand, dryland degradation has been attributed to multiple causative factors that are specific to each locality, revealing no distinct pattern (Dregne, 2002).

A fundamental and continuing debate on arid land degradation has been over whether desertification actually exists, and if so, how it might be defined, measured and assessed (Herrmann & Hutchinson, 2005). Above the debate of whether the causes are socio-economic or biophysical, there is the question on the degree to which these causes are at local, and how they interact across organization levels at different regions of the world and at different time periods (Geist & Lambin, 2004).

Some scientists have argued that the figures of global land cover change and desertification are not accurate and they have talked of the ‘myth of desertification’ as a publicity tool (UNEP, 2002; Herrmann & Hutchinson, 2005). The argument is that dry land ecosystems might after all be adapted to disturbances and may exhibit good recovery characteristics. According to Wiegand & Florian (2000), vegetation changes generally occur unpredictably in the short term (years) in response to rainfall, and episodically over the long term (several decades) in response to rare events, or due to grazing pressure, climate change, or a combination of these factors. Arid and semi-arid ecosystems also exhibit complex non-equilibrium dynamics involving complicated non-linear processes and stochastic event-driven behavior (Pickup *et al.*, 1998). Brief, unpredictable and episodic events like rainfall in arid regions can be of crucial importance in understanding the ecology of organisms or communities, but these events can best be captured by continuous, long term monitoring (Henschel & Seely, 2000). Weigand & Florian (2000) argued that the complex nature and changes in arid and semi-arid ecosystems and especially the mismatch between the observation times and time scales of vegetation changes make it difficult to fully understand their long term dynamics. According to Rasmussen *et al* (2001), broad generalizations on land degradation process, based on local scale studies are risky, as they oversimplify the complex reality. The research, however, concluded that whereas regional or continental scale studies will be required in order to improve on the estimates of environmental change, local scale studies are required to understand the processes and causes involved.

Recent research into natural resources rehabilitation based on in-depth case studies has highlighted situations where population growth and agricultural intensification have been accompanied by improved rather than deteriorating environmental resources (Boyd & Slaymaker, 2000; Tiffen *et al*, 1994). Mazzucato & Niemeijer (2001), conducted research in eastern Burkina Faso, which had been experiencing high population growth and agricultural intensification, and concluded that there was no evidence that the land was being degraded. The research was aimed at establishing the relationship between population growth and agricultural intensification to environmental degradation. Land cover loss and soil erosion were used as the indicators of degradation. After analyzing land cover and soil erosion data covering a period of six years, they concluded that there was no land degradation evident.  However, Boyd & Slaymaker (2000) did a case study of arid and semi-arid lands within six countries in Africa and concluded that there were few examples of reversal of natural resources degradation and no evidence of a wider trend towards environmental recovery. Their research was initiated through regional and national literature reviews, and case study methodologies were developed and tested. The main objective was to examine how widespread the prospects for positive outcomes are by comparing increasing population with rates of erosions. The research concluded that there was no wide trend towards environmental recovery with increasing population. It is within these conflicting findings therefore that this research aims at mapping land use land cover (LULC) change in Mbeere using Landsat multitemporal data, and analyze the various factors responsible for the current LULC patterns.

## The Problem

Kenya is an agricultural country and depends entirely on land productivity for subsistence and socio-economic development (GOK & UNEP, 1997). In contrast, about 80% of Kenya's landmass is classified as arid and semi-arid, and occupied by 25% of country's population (GOK, 2005). However, despite their relative aridity, these lands support over 60% of the livestock population, and the largest proportion of Kenya's wildlife population (Ngugi, 2005). Arid lands in Kenya also account for 10% of country's GDP and more than 80% of eco-tourism interests, which are among the main earners of foreign exchange to the country (GOK, 2005).

Based on 2003 Kenya Demographic and Health Survey, arid and semi-arid lands are still facing socio-economic problems such as increasing poverty, acute food and water shortage, illiteracy and poor health (GOK, 2005). In addition, human population in these fragile environments has been increasing rapidly; causing environmental degradation and fragmentation. For example, Mbeere district which is arid and semi-arid has seen tremendous population growth (Kamau, 2004; Mbugua, 2002; Chira, 2003). According to 1989 population census, Mbeere district had a population density of 65 persons per square kilometer. By 1999 population census, the population density had increased to 85 persons per square kilometer with an average family size of 6 persons per household.

In 1950s and 1960s, Mbeere was sparsely populated and was covered by bush or grasslands that were used for raising large herds of goats and cattle (Olson, 2004). Mbeere people were originally pastoralists who kept large herds of animals and subsistence shifting cultivation was practiced as supplementary economic activity. Since land was communally owned, it was easy to move around in search of pasture and the shifting cultivation gave land time to recover making it less degraded. Increasing population with time however forced slow sedentarization of the once pastoralist community and this marked the beginning of rapid changes in land cover in the area.

Migration from the neighboring high potential agricultural districts due to population pressure in those areas has increased cultivation practices that are incompatible with the unstable and fragile arid environments (Southgate & Hulme, 1996). According to Olson (2004), in 1970s and 1980s, the Kenyan government implemented a land adjudication program in Mbeere district which caused rapid change in land cover due to increased sedentarization of the once predominantly nomadic community. The area which was once covered by bushland was cleared within first years of adjudication causing rapid change in land cover.

Though arid and semi-arid lands globally have been facing increasing pressure from growing human population, and degradation, LULC change in arid and semi-arid lands has been poorly documented (Lambin, *et al*, 2001). In Kenya, most research work has been concentrated in the high potential highland zones which are considered of high economic importance. However, the increasing population coupled with persisted drought and famine in these vast lands calls for constant monitoring and management to control degradation and ensure sustainable use of natural resources.

The current Mbeere District development plan aims at effective management, sustainable economic growth, and poverty reduction. The plan identifies drought and unreliable rainfall, and population growth as among the key development challenges in the district (GOK, 2002). To ensure effective management of these problems in the district and alleviation of poverty, LULC change data is poised to play a key role in policy formulation and implementation.

Hydro-electricity is the main source of energy in Kenya, accounting for over 70% of total energy supply for both industrial and domestic use (KPLC, 2004). Mbeere District has four of Seven Forks dams, which accounts for over 73% of Kenya's total power production (KenGen, 2003). Reports have indicated that there has been increased siltation leading to the lowering of water levels in the reservoirs (Nthiga, 2005; Gakii, 2005). The siltation has been attributed to both loss of vegetation within the catchment area as well as within and around the dams. The original buffer zones between the dams and surrounding communities have been cultivated illegally. Poor cultivation and soil conservation methods around the dams have therefore resulted into soil erosion, increasing the rate of siltation.

On the other hand, no digital change detection has been done on Mbeere district so far. The only study focusing on land cover change covered both Embu and Mbeere districts and used a political ecology among other approaches to understand how human decisions have contributed to the observable land use land cover patterns in the area. The research used aerial photographs, satellite images and group interviews. The images and photographs were interpreted using visual interpretation and corrections made during the ground observations (Olson, 2004).

## Research Goal and Objectives

The goal of this research was to map LULC change in Mbeere district using satellite data from 1987 to 2000.

The specific objectives were:

1. To create LULC maps of Mbeere district for the years 1987 and 2000.
2. Detect and quantify spatial pattern of LULC change in the district in the period 1987-2000.
3. Analyze factors that have contributed to the observable LULC change patterns.

# CHAPTER II

## LITERATURE REVIEW

### Land Use Land Cover Change Mapping

The pace, magnitude and spatial reach of human alterations of the earths land surface are unprecedented (Lambin *et al*, 2001). Several regions around the world are currently undergoing rapid, wide-raging changes in land cover (Mas, 1999; Coppin *et al*, 2004). Land cover change on the other hand has been recognized as an important driver of global environmental change (Petit *et al*, 2001). According to Foody (2001), land cover change is a major component of global change with grater impact than that of climate change. Causes of these fluxes are anthropogenic as well as natural or combination of the two.

Due to increasing recognition of the impacts of the changing global land cover; the availability of timely, reliable LULC information is becoming more important than ever in supporting decision making processes at various levels, both within a country and between countries (Ramankatty & Foley, 1999). In addition, with increasing global environmental change and more emphasis on sustainable development (Bradley & Mustard, 2005; Leitao & Ahren, 2002), spatial data are poised to play a leading role in altering current environmental trends through sound policy formulation and implementations. According to Jansen & Gregorio (2002), land cover data may form a reference base for various applications; including forest and rangeland monitoring, statistics for planning and investment, biodiversity conservation, climate change, and desertification monitoring.

Spatial data are important in the process of resource management decision making, yet there is still no substantial land cover information existing both at local and global scales (Chandra *et al.*, 2005). In developing countries land cover data are inadequate or unavailable, of inconsistent quality, and out of date; while generating it is time consuming and expensive (Haack & Richard, 1996). This has been attributed to difficulties in accessing some regions as a result of limited infrastructures, civil and military disturbances; lack of trained personnel, equipment or funds to collect information properly; or rapid changes in the resource base not detectable by traditional data collection methods (Defries & Townshend, 1999). However, with wide application of land cover data, its need has increased and its availability is being aided by advancing technologies in remote sensing and geographic information systems.

Land use and land cover are often used interchangeably in many remote sensing change detection studies (Seto, *et al*, 2002). Land use is a term used to refer to the human uses of the land, or the immediate actions modifying or converting land cover (Bradley & Mustard, 2005; Meyer &Turner, 1992). Land use can consist of varied land covers; and it is an abstract concept constituting a mix of social, cultural, economic and policy factors which have little physical importance with the respect to reflectance properties, and hence has limited relationship to remote sensing (Treitz & Rogan, 2004). On the other hand, land cover refers to the vegetation type that characterizes a particular place, or the actual distribution of vegetation, water, deserts, ice and other physical features of the land, including those created by human activities (Estreguil & Lambin, 1996; Meyer & Turner, 1992). According to Cihlar & Jansen (2001), land cover is characterized by the biophysical features of the terrestrial environment, typically based on a classification system consisting of discrete classes and formulated for a specific purpose. Land use however refers to the manner in which these biophysical assets are used; or the intent with which a particular land cover was formed.

Ecosystems are continuously changing; where change is defined as "an alteration in the surface component of vegetation cover" or as "a spectral /spatial movement of a vegetation entity over time" (Coppin *et al.*, 2004). In addition, land cover changes are often conceived as simple and irreversible conversion from one type to another (Mertens & Lambin, 2000). Distinction has however been made between land cover conversion and land cover modification; with the former referring to the complete replacement of land cover with another and the latter implying the more subtle changes that affect the character of land cover without changing its overall classification (Coppin *et al.,* 2004; Meyer & Turner, 1992; Jansen & Gregorio, 2002). Land cover modification is more prevalent than land cover conversion and both can be human induced or of natural origin. The rate of change can either be dramatic as exemplified by fire; or gradual, such as biomass accumulation (Coppin *et al*., 2004). Similarly, land cover changes are most often viewed as non continuous in space, leading to complex landscape mosaics and mixtures of cover types (Mertens & lambin, 2000).

Land cover changes are so pervasive that, when aggregated globally, they significantly affect key aspects of Earth system functioning (Lambin *et al*, 2001, Lambin *et al*, 2003). Land cover exerts large influence on many basic environmental processes and consequently any transformation in it can have marked impact on the environment at local to global scales. Concerns about LULC change emerged on research agenda on global environmental change several decades ago with the realization that land processes influences climate. In the 1970s it was widely recognized that land cover change modifies surface albedo and thus affecting surface-atmosphere energy exchange; while in the 1980s, terrestrial ecosystems as a sources and sinks of carbon were highlighted (Lambin, *et al*, 2001).

It is widely recognized today that land cover change causes soil erosion, increased surface run off and flooding, carbon dioxide concentration, and climate change (Lambin, *et al*, 2003). Land cover change contributes significantly to earth-atmosphere interactions and biodiversity loss, it's a major factor in sustainable development and human responses to global change, and it is important in integrated modeling and assessment of environmental issues in general (Turner, *et al*, 2004). The temporal and spatial dynamics of land cover have, for instance, important influences on hydrological and climatic systems that impact significantly on global biogeochemical cycling (Boyd, 2002); and biodiversity loss (Mas, 1999). LULC changes also determine, in part the vulnerability of places and people to climate, economic, or sociopolitical perturbations (Lambin, *et al*, 2003).

As a result of increasing emphasis on sustainable development today, it is important to monitor and quantify the process of land cover change. Current data play an important role at regional and global level in formulation and implementation of policies. These policies on the other hand are aimed at achieving sustainable resource use, reverting negative environmental conditions, preserving biodiversity and endangered species and ensuring biological continuity threatened by increasing human population and intensification of human activities. However, land cover change is still poorly documented today. Since it was recognized by the international Geosphere-biosphere program (IGBP) as a core field of study, it has received a wide attention from different scholars worldwide (Xu *et al*, 2002).

To understand and predict the change process, one needs to monitor and characterize spatial patterns of LULC change (Petit *et al*, 2001). While the study of land cover change includes description and classification of LULC, monitoring of change, and mechanism of driving forces, the ultimate goal of scientists is to build models that can be used to forecast changes and predict their impacts (Xu, *et al*, 2002).

A variety of methods and techniques of LULC change study have been developed and applied, including remote sensing, GIS, and statistical methods (Xu *et al,* 2000). Historically LULC change analysis has been based on aerial photographs and ground surveys (Haack & Richard 1996; Mas, 2004), making it difficult to have large scale data, and the process being time consuming and expensive. However, due to their high resolution, and accessibility, aerial photographs still remain an important tool in surveying and mapping of natural resources today (Sebego & Arnberg, 2002). Field based studies on the other hand allow the observation and description of process of land cover though they are not sufficient in quantifying and analyzing spatial-temporal patterns of LULC at an aggregated level (Petit *et al*, 2001). According to Defries and Townshend (1999), a comparison of land cover data sets from ground cover based sources have showed substantial disagreements. This is a situation where different datasets of the same area reflect different geographical phenomena at the same point in space. The discrepancies result from differing definitions and classification of cover types, inconsistent interpretation of land cover definitions, confusion between natural and human modified vegetation, and the actual disagreement about the geographical coverage of land cover types (Defries & Townsend, 1999). Moreover, field studies alone cannot provide predictions of future patterns of change.

Remote sensing has emerged as an important method in LCLU change monitoring (Collins & Woodcock, 1996; Cobly & Keating, 1998; Treitz & Rogan, 2004; Petit *et al,* 2001). Since the launch of the first satellite in 1972 (Haack & Richard, 1996; Defries & Townshend, 1999), space borne remote sensing has been providing vital data for the analysis of regional and global land cover (Petit *et al*, 2001). Remote sensing has provided an alternative method of land cover change detection with the advantage of capabilities of large regional to global coverage, high temporal and spatial resolution and easy accessibility (Mayuax *et al*., 2004; Jansen & Gregoria, 2003). According to Defries and Townshend (1999), satellite data provide the basis for geographically referenced global land cover characterization that is consistent, repeatable over time, and potentially more reliable than ground based sources. The application of satellite data for mapping land cover at a large scale started with regional studies in Africa (Turker *et al*., 1985) and South America (Townshend *et al*., 1987). These laid the basis for land cover classification, and satellite data are now a primary source for both static depictions of land cover and identification of land cover change.

## Digital Change Detection

Landscapes both natural and human made are dynamic and in state of flux, and it is important that these changes are documented and understood (Coppin *et al*, 2004).Both remote sensing and field based methods have been used in the study of LULC change, and in grater sense, for inventories of both biophysical and human made features. Remote sensing has become more important due to ability to cover large areas, high temporal and spatial resolution and cheap accessibility of remote sensing data (Collins & Woodcock, 1996; Colby & Keating, 1998).

Digital change detection involves systematic steps from image acquisition to preprocessing, classification and actual change detection. Historically, this form of remote sensing started in the 1960s with limited analysis of mutispectral scanner data and digitized aerial photographs (Lillesand, *et al* 2004), and since the launching of landsat-1 in 1972, digital image processing has seen tremendous growth to date. The whole process from data acquisition to the final extraction of the intended information involves various steps and every stage is important as it can have significant impacts on the final results.

Successful implementation of change detection analysis using remote sensed data requires careful consideration of the sensor, environmental characteristics and image processing methods (Lu, *et al*, 2003); and failure to understand the impacts of these various parameters can lead to inaccurate results.

### Data Acquisition and Preprocessing

Data should be obtained from a sensor that acquires data at approximately the same time of day and on anniversary dates. Same date images eliminate diurnal sun angle effects while anniversary dates images minimizes the influence of seasonal sun-angle and plant phonological differences (Jensen, 2005).

Raw digital images usually have some geometric distortions as a result of variations in the altitude, attitude, Earth curvature, atmospheric refraction, relief displacement, and nonlinearities in the sweep of a sensor's IFOV (Lillesand, *et al* 2004). These errors should be corrected to ensure accuracy of the final results. According to Lu *et al* (2003), the importance of accurate spatial registration of multi-temporal imagery is obvious because largely spurious results of change detection will result if there is misregistration.

Atmosphere affects the radiance received by the sensor by scattering, absorbing, and refracting light; and correction for these effects, as well as for sensor gains and offsets, solar irradiance, and solar zenith angles are necessary. These must be included in the in radiometric corrections procedure that are used to convert satellite recorded digital counts to ground reflectances (Chavez, 1996).

Dealing with multi-date image datasets requires that images obtained by sensors at different times are comparable in terms of radiometric characteristics (Mas, 1999). Conversion of digital numbers to radiance or surface reflectance is a requirement for any quantitative analysis of multi-temporal images; and several methods such as dark object subtraction (DOS), relative calibration and second simulation of the satellite signal in the solar spectrum have been developed for atmospheric normalization (Lillesand *et al.*, 2004). The COST model (Chavez, 1996) is an improved DOS technique and includes the use of the cosine of the solar zenith angle to achieve results similar to those of physical models.

## Image Enhancement

The main goal of image enhancement is improving visual interpretability of an image by increasing the apparent distinction between features in the scene (Lillesand, *et al* 2004). This ensures that features appears clear and increases the ability to distinguish different features. Different techniques are used in image enhancement including principal components analysis, Kauth-Thomas transformations and vegetation indices. (Jensen, 2005; Lillesand, *et al* 2004).

**Principal Components Analysis**

Principal components analysis is a technique that transforms the original remotely sensed data into substantially small and easier to interpret set of uncorrelated variables that represent most of the information present in the original data sets (Jensen, 2005). Principal components analysis is therefore a data compression method which allows redundant data to be compacted into fewer bands. It is a linear transformation which decorrelates multivariate data by translating and /or rotating the axes of the original feature space, so that the data can be represented without correlation in a new components space (Lasaponara, 2006).

**Spectral Vegetation Indices (SVIs)**

These are dimensionless, radiometric measures that indicate relative abundance and activity of green vegetation (Jensen, 2005). SVIs are used to create output images by mathematically combining digital numbers (DN) values of different bands; and usually use the inverse relationship between the red and the near-infrared reflectance associated with the healthy green vegetation. SVIs use the well known characteristic shape of the green vegetation spectrum by combining the low reflectance in the visible part of the spectrum with the high reflectance in the near infrared (Rendeaux, *et al,* 1996). These vegetation indices therefore operate by contrasting intense chlorophyll pigment absorption in the red against the high reflectivity of plant materials in the NIR (Elvide & Chen, 1995).

Vegetation indices have been grouped into two categories; ratio based and orthogonal indices (Lawrence & Ripple, 1998). Ratio based vegetation indices include normalized difference vegetation index (NDVI), Simple Ratio (SR) and several modified versions of NDVI designed to address its sensitivity to factors such as soil variability and atmospheric conditions (Lawrence & Ripple, 1998). Soil based or orthogonal vegetation indices on the other hand are based on there being a line in the spectral space along which bare soils of differing brightness will lie, with the Kauth-Thomas being the most common.

**Kauth-Thomas or Tasseled Cap Transformations**

The KT or tasseled cap was originally developed using Landsat multipsectral scanner data for agricultural application (Kuath & Thomas, 1976). KT is an orthogonal transformation of the original Landsat MSS data space to new four-dimensional feature space (Jensen, 2005). The KT is sensor specific; and different sets of coefficients are invoked depending on which Landsat data are used (Patterson & Yool, 1998). KT transforms develops orthogonal indices based on library of soil spectra and assumes no interaction between sub pixel components; and therefore producing three spectral features representing changes in brightness, greenness and wetness (Rogan *et al*, 2002).

## Image Classification

Multispectral image classification is the process of sorting out pixels to finite numbers or class themes based on the data file values. The overall objective of image classification procedures is automatically categorizing all the pixel values in an image into land cover classes or themes (Lillesand, *et al* 2004). The basis of image pixel categorization is based on the fact that different features have different reflectance. The classification process involves pattern recognition inherent in the image, with spectral pattern considered the most scientific, though temporal and spatial pattern recognitions can be used too.

Supervised and unsupervised classification schemes are the most widely used classification methods. Both supervised and unsupervised classification algorithms typically use hard classification logic to produce a classification map that consists of hard discrete classes (Jensen, 2005). Before classification is carried out, the specific target classes should be identified. This requires the use of a classification scheme containing taxonomically correct definitions of classes of information that are organized according to logical criteria (Jensen, 2005). Standardized classification schemes have been developed and applied by various researchers to aid in specifying land cover classes. The main purpose of standardization of classification schemes is to ensure uniformity, and comparitability of various research works with high degree of accuracy.

Supervised classification always requires *a priori* knowledge of the study area to ensure selection of the training sites. According to Jensen (2005), in a supervised classification, the identity and location of some of the land cover types are known a priori through a combination of field work, interpretation of aerial photographs, map analysis and personal experience. Training sites spectral characteristics are used in training the algorithms for the land cover mapping in the image. Petit *et al* (2001) used supervised classification to map land cover changes in South-eastern Zambia and discriminated ten land cover classes.

Unsupervised classification involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values (Lillesand, *et al* 2004). The spectral classes from the unsupervised classification are then identified and their information utility defined through comparing the classified image with reference data available. The advantage of unsupervised classification is that it is automated and does not require *a priori* knowledge of the study area. This makes it easy and needing less skills and experience. There are various clustering algorithms used in determining the natural spectral groupings present in a data set; and Iterative Self-Organizing Data Analysis (ISODATA) is the widely used. This algorithm permits the number of clusters to change from iteration to the next, by merging, splitting, and deleting clusters (Lillesand, *et al* 2004).

## Accuracy Assessment

The need for accessing accuracy of spatial data derived from remote sensing techniques and used in Geographic Information System (GIS) analysis has been recognized as a critical component of many projects (Congalton & Green, 1993). According to Congalton & Green (1991), if information derived from remote sensing data is to be used in some decision-making process, then it is critical that some measure of its quality be known. The most common accuracy assessment elements include overall accuracy, producer's accuracy, user's accuracy and kappa coefficient (Lu, *et al* 2003). One of the most common methods of expressing classification accuracy is the preparation of a classification error matrix (Lillesand, *et al* 2004). An error matrix is an array of numbers set in rows and columns that express the number of sample units assigned to a particular category in one classification relative to the number of sample units assigned to a particular category in another classification (Congalton & Green, 1991). The error matrices compare, on a category by category basis, the relationship between known reference data and the corresponding results of the automated classification. The matrix is able to identify both omission and commission errors in the classification as well as the overall, producer's and user's accuracy.

## Change Detection Methods

Digital change detection encompasses the quantification of temporal phenomena from multi-date imagery that is most commonly acquired by satellite-based multi-spectral sensors (Coppin *et al*, 2004). In general, change detection involves the application of multi-temporal datasets to quantitatively analyze the temporal effects of the phenomena (Lu *et al*, 2003).

Good change detection research should provide the following information: (1) area of change and change rate; (2) spatial distribution of changed types; (3) change trajectories of land cover types; and (4) accuracy assessment of change detection results. A large variety of change detection methods have been developed and applied (Collins & Woodcock, 1995), and the choice of an appropriate system and technique will depend on the objectives of the study and the size of the budget but few, if any, guidelines exist to facilitate this selection process (Green *et al,* 1998). Different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases. Previous literature has shown that image differencing, principal component analysis and post classification comparison are the most common methods used for change detection. Change detection methods have been grouped generally into image algebra, transformation and classification.

The algebra category includes image differencing, image regression, image ratioing, vegetation index differencing, change vector analysis and background subtraction. These techniques involve subtraction of two or more images of almost identical radiometric characteristics; where subtraction results in positive and negative values in areas of radiance change and zero values in areas of no change (Green *et al*, 1998)

Transformation category on the other hand includes PCA, KT, Gramm-Schmidit (GS), and Chi-square transformations. Transformation change detection methods usually results in change/no change information and do not show from/to information. Classification category includes post-classification comparison, spectral-temporal combined analysis, expectation-maximization algorithm change detection, unsupervised change detection, and hybrid change detection and ANN (Lu, *et al*, 2003). This category has the advantage of showing both change no change as well as 'from to' information.

**Image Differencing**

In this method, spatially registered images acquired at different times are subtracted to produce a residual image which represents the change between the two dates (Mas, 1999). This would result in datasets with positive and negative values representing areas of change and zero values representing no change (Coppin *et al*, 2004).Using an image with 8-bit image, the potential range of differences range between -255 to 255. In the algebra based change detection category, image differencing is the most often practiced. Visible red band image differencing has shown to be suitable for change detection in arid and semi-arid environments, but it is not clear this is true in other environments such as moist tropical regions.

**Vegetation Index Differencing**

This method involves subtracting images which have been converted to the various vegetation indices for both dates in the study. The main advantage of vegetation index differencing is that it emphasizes differences in the spectral response and reduces impacts of topographic effects and illumination (Lu *et al*, 2003).

**Principal Components Analysis**

It involves two registered images to form a new multiband image containing bands from each date (Lillesand, *et al* 2004). The main advantage of these transformations is reducing data redundancy and emphasizing different information in the derived components. Then a PCA based on variance-covariance matrices or a standardized PCA based on analysis of correlation matrices is then performed. Fung & LeDrew (1987) used PCA in examining land cover change in the Kitchener-Waterloo-Guelph area Canada and concluded that minor components can detect land cover changes and standardized principal components computed from the eigenvectors of the correlation matrix provide more accurate information for change detection than do non-standardized principal components derived from the covariance matrix.

**Post Classification Comparison**

Post classification analysis is the most common of these methods and it involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel by pixel or segment by segment comparison to detect changes in cover type (Coppin *et al*, 2004). In addition to the algorithms which are applied on the classified images to determine those pixels with a change between the two dates, statistics can be compiled to express the specific nature of changes between the two images (Lillesand, *et al* 2004). The main advantage of these methods lies in the fact that the two images are separately classified thereby minimizing the problem of radiometric calibration between the dates. However, the accuracy of post classification comparison depends on the accuracy of initial image classification of each date. Misclassification and misregistration errors that may be present in the original images are compounded and the results obtained using post classification comparisons are therefore frequently judged as unsatisfactory (Coppin, *et al*, 2004).

# CHAPTER III

## METHODS

### Study Area

Mbeere District lies in latitude 0° 20' and 0° 50' south and longitude 37°16' and 37°56' east, and covering a total area of 2097 square kilometers. It slopes from the northwest to southwest direction; with altitude around 500 meters above see level on the Tana River basin to 1,200 meters above sea level.

Rainfall is bimodal with annual averages of 610-892mm. The 'long rains' fall between April and June, while the 'short rains' are experienced from October to December. It is interesting to note that the people in the district who are predominantly agriculturalists rely mostly on the short rains from October to December. Although rainfall is erratic and unreliable, the long rains are the most unreliable. Analysis of rainfall from the district since 1959 to the present has revealed that there has been a significant decline in the amount of rainfall recorded throughout the years to date. Droughts are common in the area and prolonged droughts cause significant reduction in vegetation which takes a long time to recover. Surface runoff and poor farming methods have increased soil erosion which is clearly evident by the deep gullies which are common and have contributed to transportation problems in the district.

Temperatures range from 20°C to 28°C with annual average of about 24°C. July is usually the coldest month with an average monthly temperature of 15°C; while September is the warmest month with temperature maximums raising up to 30°C. Humidity is generally low throughout the district, though there is climate variation around Kiambere, Kindaruma, Masinga and Kamburu dams on the southern region. High temperatures cause high evaporation throughout the year.

Vegetation is generally of savanna type. There is one game reserve within the district plus several forest reserves including Kianjiru and Kiambere forests (Mbugua, 2002; Kamau, 2004). According to Olson (2004), in 1950s and 1960s, Mbeere District was covered mostly by bush or grassland; and vegetation was basically of derived savanna created by many years of grazing animals and use of fire.

Human population in Mbeere District has been increasing (Chira, 2003; Gicimbi, 2002). Based on the 1999 population and housing census, the total population of the district was 170, 593, and was growing at a rate of 2.3% annually. The population density based on the 1999 census was estimated to around 82 persons per square kilometer compared to 65 persons per square kilometer in the 1989 census. High population density in the neighboring high potentials districts has pushed the landless people to the more marginal areas in Mbeere District. This migration has increased agricultural practices that are incompatible with the unstable and fragile arid environment (Southgate & Hulme, 1996).

Agriculture and livestock keeping are the most common land use activities. In Mbeere District, small-scale agriculture is widely practiced with most production being for subsistence use, while small-scale horticulture is practiced in some parts of Gachoka Division (Mbugua, 2002). Increasing human population has led to loss of vegetation through cultivation, overgrazing, fuel wood and charcoal production (Mbugua, 2002; Sindiga, 1984).

Pastoralism is practiced across the district, and land under this practice is in patches and surrounded largely by cultivated farms. Overall, some tracts of land have been left intact, particularly on the lower eastern zone of the district due to its marginal nature (Mbugua, 2002).

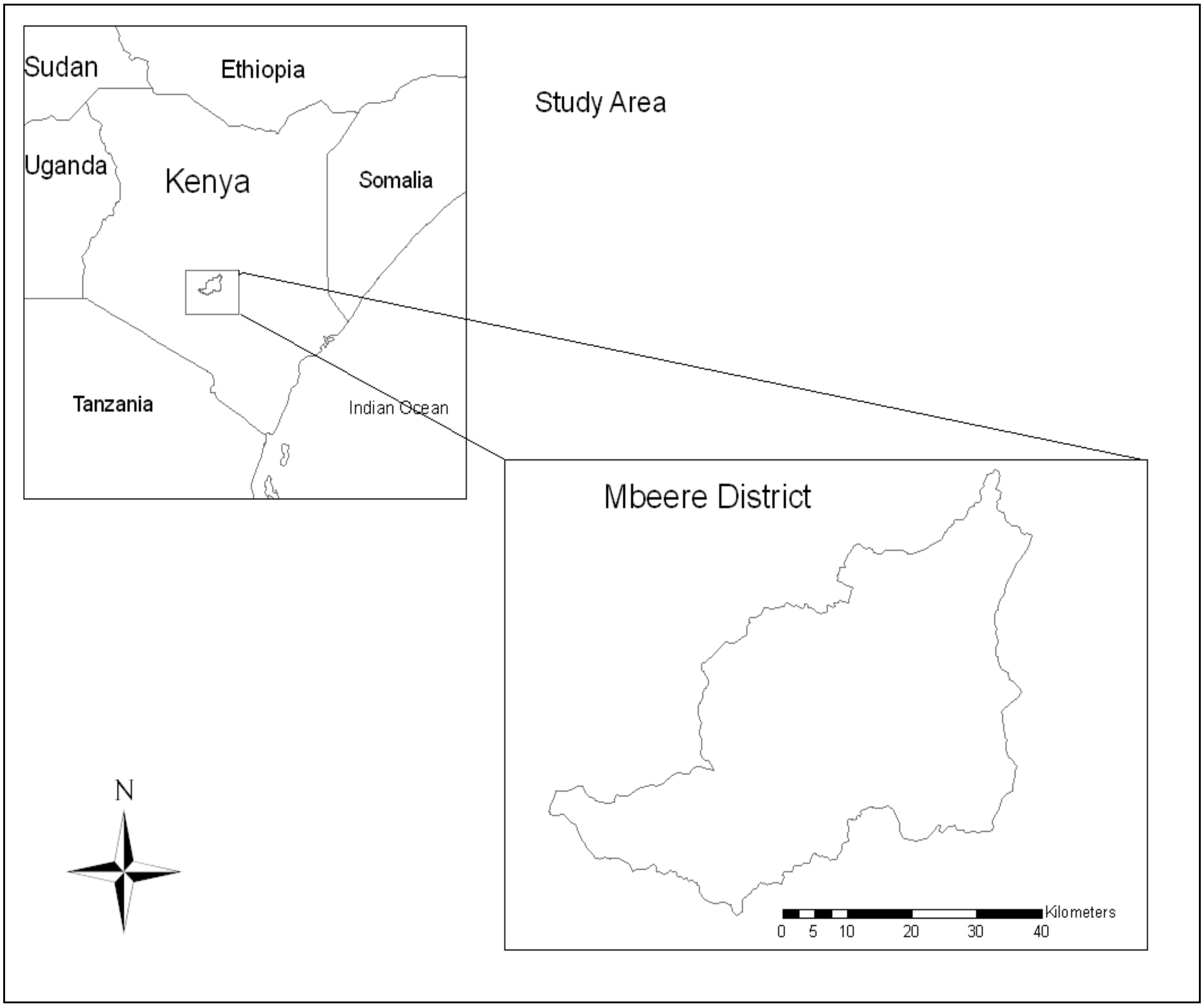
Land adjudication in Mbeere District effected by the government starting in 1970s and 1980s caused rapid settlement and increased cultivation and grazing. This has had enormous impact in land cover between this period since land was cleared for agriculture and grazing was secluded to private lands as opposed to the traditional communal grazing lands.

**Table: 1** Climate ecological zones of Mbeere.

| Agro-Ecological zone | Altitude in M | Annual mean temp in degree Celsius | Annual Mean rainfall in mm |
|---|---|---|---|
| UM 4 Sunflower-maize | 1,280-1,400 | 20.7-20.0 | 960-1,100 |
| LM 3 Cotton | 1,070-1,280 | 22.0-20.7 | 900-1,100 |
| LM 5 Lower midland Livestock-millet | 830-1,130 | 23.5-21.7 | 700-900 |
| IL 5 Lowland Livestock-millet | 760-830 | 23.9-23.5 | 640-780 |

Source: Olson, 2004.

**Figure 1: Study area map**



## Data Sets.

### Landsat Data

Landsat images used in this research included February 25th 1987 Thematic Mapper (TM) and 21st February 2000 Enhanced Thematic Mapper plus (ETM+). Both images were obtained from University of Maryland's Global land cover facility. The dates chosen were significant because documented significant changes in land cover occurred in the late 1970s and 1980s in Mbeere District. Land adjudication program effected by the government within this period abolished the traditional communal land ownership in favor of private ownership which resulted in significant fragmentation of the environment.

These images were also chosen because they were cloud free and near anniversary in their acquisition dates. February is usually dry period and was ideal for differentiating evergreen woodland from Comiphori-dominated deciduous woodlands common in the study area.

**Table 2**: Landsat images

| Image | Path/row | Acquisition date |
|---|---|---|
| Landsat TM | 168/60 | Feb 25th 1987 |
| Landsat ETM+ | 168/60 | Feb 21st 2000 |
| Landsat TM | 168/61 | Feb 25th 1987 |
| Landsat ETM+ | 168/61 | Feb 21st 2000 |

### MODIS Data

Moderate Resolution Imaging Spectroradiometer (MODIS) images were also used in the study. The images included 13 MODIS 32 days' composites at 1km resolution for the period November 16$^{th}$ 2000 to February 1$^{st}$ 2002. This period was important as it captured the full year growing period with both dry and wet seasons which is characteristic of the study area. The images were obtained from University of Maryland's Global Land cover Facility. The images were subset to the study area and projected to UTM zone 37 South. NDVI was calculated for each image and the 13 images were combined into a single 13 bands image. The data was finally used to generate a time series for all the land cover classes indicating change in NDVI as affected by the phenological changes throughout the different seasons.

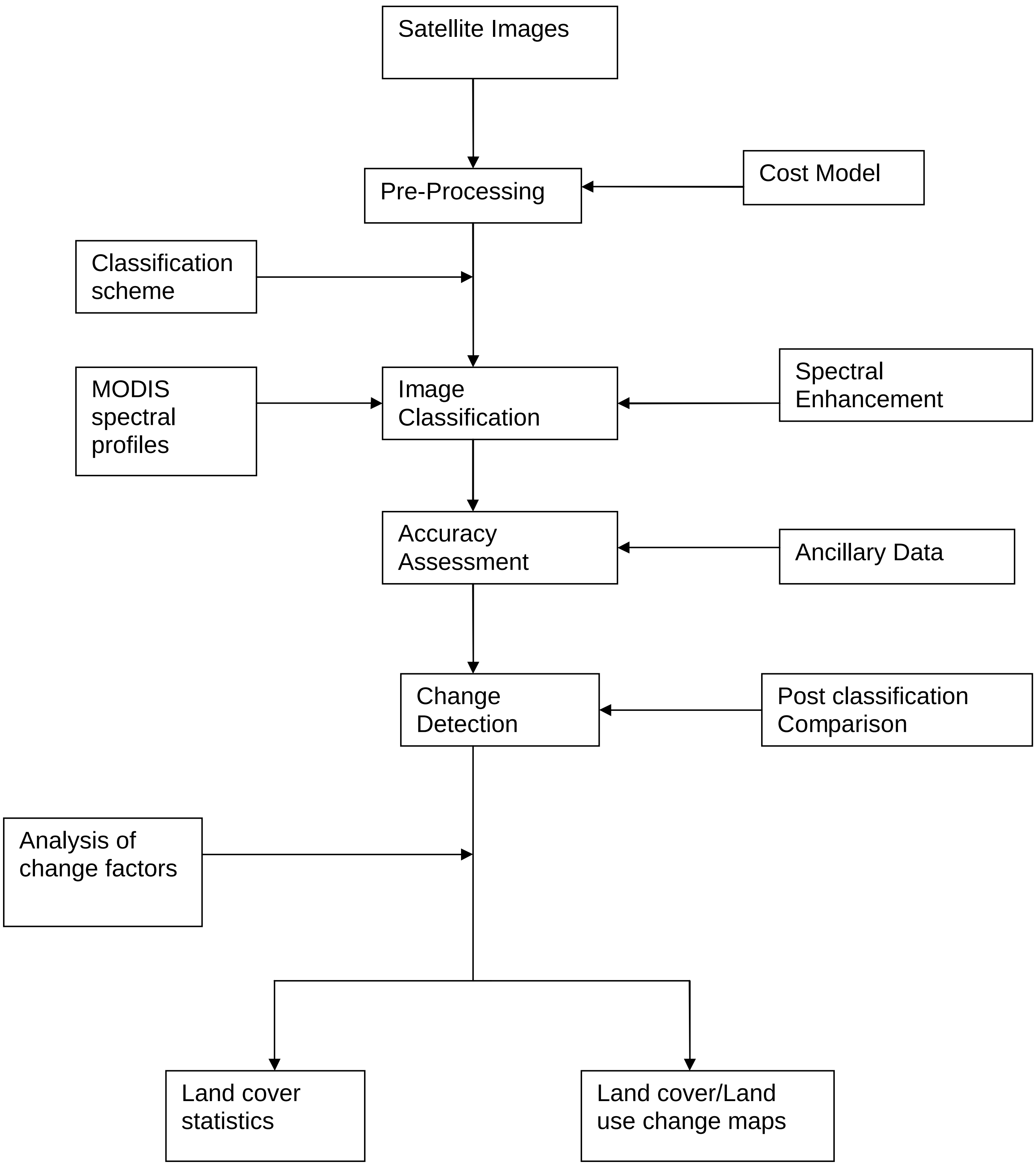
### Ancillary Data

Ancillary data in this research included aerial photographs, topographic maps, and GPS points which were used in class separation and accuracy assessment. Aerial photographs were full area coverage of the study area in 1988 at the scale of 1:50, 000.Topographic maps at the scale of 1:50,000 were also used. Both aerial photographs and topographic maps were acquired from Kenya Department of Surveying and Mapping. Aerial photographs and topographic maps were both scanned to digital form, and the maps were projected to UTM zone 37 south.

**Field Data**

Field data included GPS points, and digital photos which were used in accuracy assessment of 2000 land cover map. During field work, GPS points were collected and accompanied by detailed description of the location and land cover types. Due to high in-accessibility in most parts of the district, most of the points were collected off the main roads. Digital photos of different land cover types were taken and their GPS spatial location recorded. Digital photos and their accompanying GPS points were used in identifying different land cover classes during land cover classification and in accuracy assessment.

**Figure 2:** Study Methodology



## Image Preprocessing

### Geometric Correction.

The two Landsat images were already georectified and no image registration was necessary. The images were re-projected to UTM zone 37 south and subset to the study area using Mbeere District boundary shapefile. MODIS images were subset to Mbeere district and then re-projected to UTM zone 37 South. Topographic maps were georectified to their actual latitude and longitudes in the map using keyboard registration.

### Radiometric Correction

In change detection, radiometric correction is important to ensure that the changes recorded are not as a result of changes in radiometric performances of the sensors, changes in solar illumination angle, atmospheric scattering and absorption as well as the general conditions of the atmosphere. The 1987 TM image was converted to ETM+ digital numbers (DN) equivalent (USGS, 2005). The two images were then converted to reflectance using COST model which reduces haze effects (Chavez, 1996).

## Thematic Extraction

### Classification Scheme

The classification of the two Landsat images was geared towards separating six classes as indicated in the classification scheme below. The classes were based on field work experience and a modification of AfriCover classification scheme (FAO, 1997) and a hierarchical class system was adopted.

**Table 3**: Land cover classification scheme.

| Class | Description |
|---|---|
| Dense Woodland | This class includes dense woody vegetation with less undergrowth. Predominantly evergreen throughout the year and particularly found on the higher zones of protected Kiambere, Kiang'ombe and Kianjiru hills. |
| Sparse Woodland | This class includes the evergreen less dense woody vegetation, and mostly surrounding the dense woodland. It is also characterized by open canopy with substantial under growth. |
| Bushland | The class is characterized by scattered deciduous comiphori species. Most of the undergrowth is perennial consisting mostly of grass which dries up with dry season. The canopy is open during the dry season but closes up during wet seasons. |
| Wooded Grasslands | Consists of open grasslands with scattered shrubs and scrubs. Most of the wooded grassland has changed from bushland through complex interaction of natural and human factors for a long period of time. |
| Open Grasslands/Abandoned Settlements | Includes abandoned farm lands and other fields which had been cleared. Characterized by bare soils and scattered regrowing vegetation. |
| Settlement/Agriculture/ Developed Areas/Bare Ground | This class includes farmlands, urban centers, homes, and bare ground. |
| Water | This includes all water bodies in the district. |

**Image Classification**

Unsupervised Iterative Self-Organizing Data Analysis (ISODATA) classification algorithm was used in the image classification. This is because unsupervised classification is automated and requires little *a priori* knowledge of the area. During field work, the study area was found to be highly heterogeneous, with land cover changing within a small area. This made it difficult to locate homogenous areas for training site selection.

Classification of the two Landsat images was carried out within ERDAS IMAGINE. The maximum iterations were set to 36 and number of classes set to 20 for the two images to ensure consistency in the results. The targeted classes as per the classification scheme were all coded with particular numbers and each of the spectral classes in the output raster assigned a code corresponding to the class it falls in. Class labeling was achieved through comparison of the classified image with the original images, use of topographic maps, aerial photographs, digital photos and field study knowledge to identify the various classes.

Most of the classes were confused from the first classification. Cloud shadow and wet soil were classified as water while few cloud shadow pixels were classified as sparse woodland. Sparse woodland was highly mixed up with other types of active vegetation including active crops and agro forestry fields. Bushland, wooded grassland, and settlement were on the other hand highly mixed up, while Clouds were grouped in the same class with built up areas. However, dense woodland was well separated from other classes in both images.

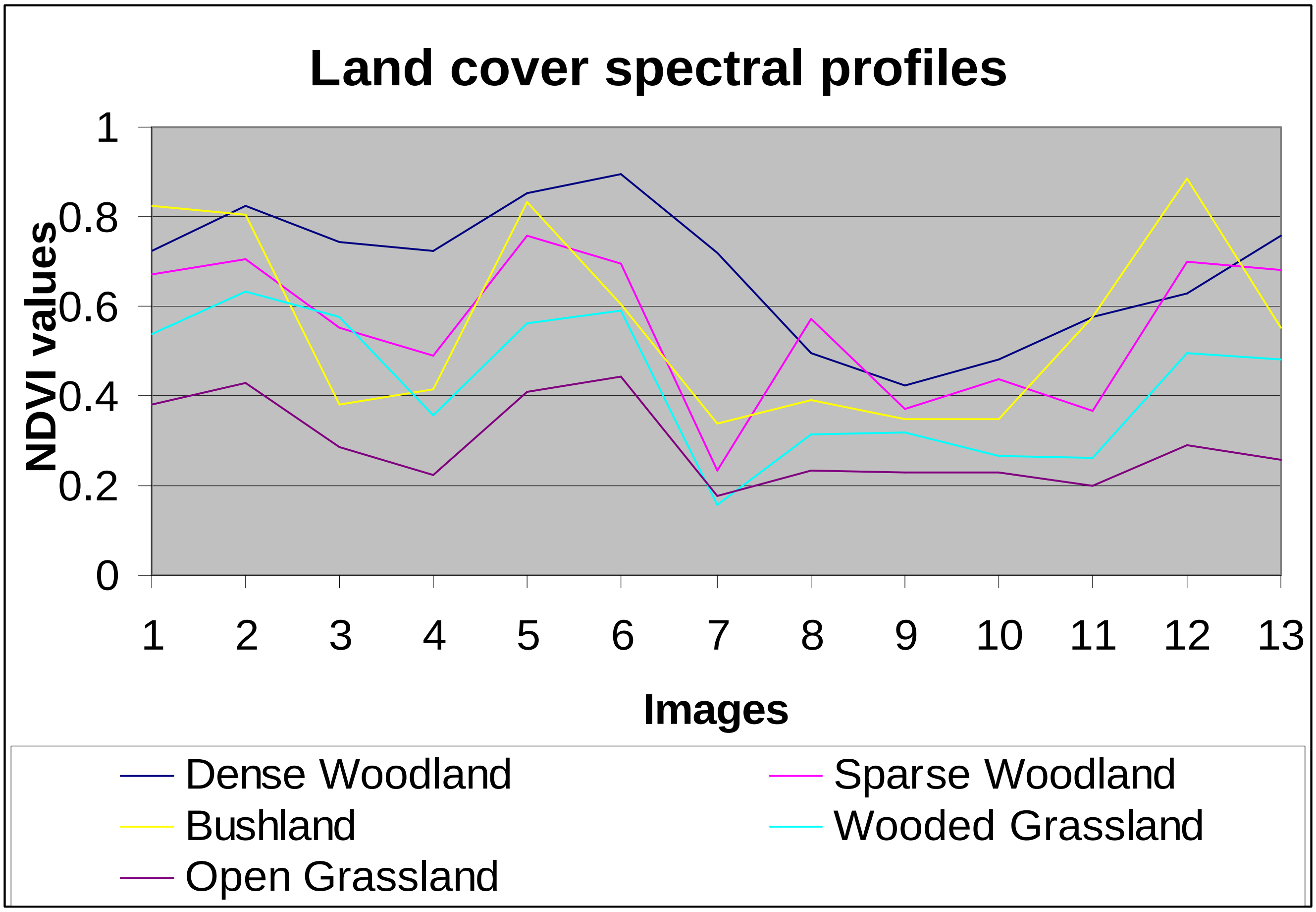
Several spectral vegetation indices were used to enhance the images in order to extract the mixed pixels. This was also aimed at evaluating the performance of different spectral enhancement methods in separating different land cover classes. The indices used included Normalized Difference Vegetation Index (NDVI), Principal Component Analysis (PCA), Soil and Atmospherically Resistant Vegetation Index Two (SARVI2), and Kauth-Thomas (KT). NDVI was capable of extracting vegetation from non vegetation and the extracted pixels were reclassified separately. Though NDVI was capable of distinguishing the vegetation, its biggest shortcoming was inability to separate water and wet soil. The study area has several rice paddies which are sometimes wet and flooded. These wet agricultural fields were being clustered spectrally in the same classes as water bodies.

Spectral profiles of the mixed classes from the Landsat images were used to identify the bands which were capable of separating them. Through the profile, bands which could separate the mixed class were extracted from the full image, and then the mixed pixels extracted from the bands and reclassified.

Time series profiles of the MODIS NDVI image composite were used to aid in separation of different land cover classes based on their phenological characteristics. Vegetated and non vegetated pixels were separated by their phenological characteristics as vegetated areas were found to have high NDVI values throughout the period for evergreen vegetation and high NDVI values during rainy seasons for deciduous vegetation.

Apart from separating vegetated with non vegetated pixels, the MODIS data were used to distinguish between various vegetation types. Evergreen vegetation had high NDVI values throughout the season though the peak fluctuated during the dry season. Deciduous vegetation had low NDVI values during the dry season and high values in the wet season, with almost the same values as the evergreen vegetation at the peak of the growing season.  Deciduous vegetation was differentiated with grass by the time it took to build to peak NDVI values during the growing season. Both classes started at low levels during the dry season, but grass peaked up faster than deciduous vegetation. The same trend was observable as NDVI values dropped with dry season, with the grass values dropping to the minimum faster than the bushland.

**Figure 3**: MODIS land cover classes spectral profiles.



## Accuracy Assessment

Points used in accuracy assessment were based on the GPS points acquired during the field work and interpretation of 1988 aerial photographs and 1974 topographic maps. The accuracy assessment points were independent from those used in land cover classes labeling. A confusion matrix was generated for both 1987 and 2000 land cover maps with both producers and users accuracies. Kappa statistics were also calculated for the two land cover maps.

## Change Detection

Several change detection techniques were used in this research and their applicability in mapping land cover change in arid lands evaluated. The techniques included post classification comparison, vegetation index differencing and multiple principle component analysis.

### Multitemporal PCA

The two images were combined into one 12 band image and PCA was run resulting in 12 principal components. The components were then interpreted separately to identify which captured land cover change between the two dates. Each component was compared to an image displaying two bands representing 1987 and 2000 SARVI2. There was no component showing consistency with the change observable from the 1987 and 2000 SARVI2.

### SARVI2

The 2000 SARVI2 image was subtracted from 1987 SARVI2 image. Different color codes were used to show areas that changed and areas that had not changed between the two dates. Different colors were also used to show areas where land cover increased and degreased between the dates. The change difference images was then threshold to identify change pixels, and it was found that SARVI2 did not capture changes consisted with the two images.

**Post Classification Comparison**

Post classification comparison change detection method was applied on the final 1987 and 2000 Mbeere land cover maps. The two land cover maps were compared pixel by pixel with the final results showing both change-no-change information as well as ‘from to’ land cover change information. The results were used to generate different maps including change-no change map, change in settlement class map, and a general land cover change map.

# CHAPTER IV

## RESULTS ANALYSIS AND DISCUSSIONS

Two land cover maps of Mbeere District based on 1987 Landsat TM and 2000 ETM+ were produced using unsupervised classification. Clouds and shadows in the 1987 image were masked out using unsupervised classification. There were no clouds in the 2000 images and the few shadows were masked out using unsupervised classification. Initial maps had seven classes corresponding to the classification scheme. However, after accuracy assessment, dense woodland and sparse woodland were combined to woodland, while open grassland and wooded grassland were combined to grassland. These classes had low initial accuracy and their pixels were highly mixed. The final two land cover maps therefore had five land cover classes.

**Classification of the 1987 Landsat TM Image.**

Initial unsupervised classification of the 1987 Landsat TM image yielded results with most of the classes mixed. Dense woodland was however separated from most of the other classes but was mixed with sparse woodland. Sparse woodland was on the other hand mixed with other types of active green vegetation including crops. The upper zone of the district covering Siakago, Evurori and parts of Gachoka Divisions had high concentration of agro-forestry which was classified as sparse woodland.

Bushland was mixed with dry crops especially dry rice fields. Some of abandoned farmlands in the more marginal areas were also picked out as bushlands in the initial classification. Wooded grassland was on the other hand clumped in the same class as abandoned farmlands, open grasslands and some dry crop fields. Water was mixed with wet soils, flooded rice paddies and shadows. Settlement had the poorest differentiation of all the classes, and was mixed with virtually all the other classes except with dense woodland.

Mixed classes were then masked out and enhanced with several spectral enhancement including NDVI, SARVI2, KT, PCA and SR. The main aim was to evaluate the applicability of different spectral enhancement methods in separating different land cover classes. Simple ratio (SR) was used to separate water and cloud shadows which could not be achieved through initial unsupervised classification. NDVI on the other hand was capable of separating sparse woodland with active crops, while SARVI2 was capable of separating water with wet soil.

The classification resulted in a 1987 land cover map with seven classes. Settlement was the dominant class covering 37.2%, followed by sparse woodland at 13.8% while dense woodland covered 3.9 % and water 2.8% (Table 4).

**Table 4:** Area covered by each land cover class in 1987 land cover map, in hectares and percentage.

| Land cover class | Area in Ha | Percentage % |
|---|---:|---:|
| Dense Woodland | 8505.45 | 3.86 |
| Sparse Woodland | 27404.47 | 13.78 |
| Bushland | 30553.47 | 12.43 |
| Wooded Grassland | 40849.11 | 18.53 |
| Grassland | 24874.56 | 2.84 |
| Settlement | 81972.36 | 37.19 |
| Water | 6260.22 | 2.79 |

**Classification of the 2000 ETM+ Image**

Unsupervised ISODATA classification was run on the 2000 image and the resulting spectral clusters were mostly mixed. Dense woodland was well separated with most of the other classes but was mixed with sparse woodland. Sparse woodland was in addition mixed with agro-forestry and active green crops, while some dry irrigated crops were classified as bushland. Settlement was the most confused class and was mixed with all other classes except with dense woodland.

The 2000 image had high spectral similarities between classes than the 1987 image. The image was enhanced using PCA and subset to the first four components. The remaining two components had little or no information and were considered noise. The PCA subset was reclassifified again using unsupervised classification and then recoded. Mixed classes were masked out and reclassified for several times until they were clearly separated.

The classification resulted into a land cover map with seven classes. Settlement was the most dominant class covering 51.1%, while dense woodland covered only 2.2 % of the total area (Table 5).

**Table 5:** Area covered by each land cover class in 2000 land cover map, in hectares and percentage.

| Land cover class | Area in Ha | Percentage % |
|---|---:|---:|
| Dense Woodland | 5179.32 | 2.23 |
| Sparse Woodland | 21768.21 | 3.39 |
| Bushland | 24370.11 | 10.51 |
| Wooded Grassland | 29650.32 | 12.79 |
| Grassland | 27330.75 | 2.23 |
| Settlement | 118367.20 | 51.06 |
| Water | 5168.79 | 2.25 |

**Accuracy Assessment Results**

The 1987 land cover map had an overall accuracy of 73.3% and kappa statistics of 0.6791. Water had the highest accuracy with 100% producer's and 95% user's accuracy. Dense woodland had high producer's accuracy but the lowest user's accuracy. The commission errors in the dense woodland class were attributed to high agro-forestry in the upper wet areas in the district. The results also indicated a high level of class confusion between the sparse woodland and settlement. The overall low accuracy in the land cover map was attributed to the high heterogeneity in land cover classes which caused high spectral similarities.

**Table 6:** 1987 land cover map accuracy assessment error matrix

| Reference data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Classified data | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Classified total | Producer's Accuracy % | User's Accuracy % |
| Dense Woodland | **26** | 21 | 0 | 0 | 0 | 3 | 0 | **50** | **100** | **52.00** |
| Sparse Woodland | 0 | **66** | 4 | 1 | 0 | 17 | 2 | **90** | **65.33** | **71.74** |
| Bushland | 0 | 2 | **40** | 6 | 0 | 8 | 3 | **59** | **81.63** | **67.80** |
| Wooded Grassland | 0 | 2 | 3 | **38** | 0 | 6 | 6 | **54** | **74.51** | **70.37** |
| Water | 0 | 0 | 0 | 0 | **20** | 1 | 0 | **21** | **100** | **95.24** |
| Settlement/Built up Areas | 0 | 9 | 0 | 2 | 0 | **73** | 6 | **90** | **66.97** | **81.11** |
| Grassland | 0 | 2 | 2 | 4 | 0 | 1 | **45** | **54** | **72.58** | **83.33** |
| Totals | **26** | **101** | **49** | **51** | **20** | **109** | **62** | **418** | | |
| Overall classification accuracy= **73.33** <br> Overall kappa statistics = **0.6197** | | | | | | | | | | |

The 2000 land cover map had an overall classification accuracy of 73.6% and a kappa statistics of 0.6852. Wooded grassland and sparse woodland had the lowest producer's accuracy of 59.5% and 60.8% respectively. The high omission errors in sparse woodland were attributed to high confusion with dense woodland and agro-forestry. On the other hand, the high omission errors in wooded grassland were due to high spectral confusion between the wooded grasslands and the open grasslands.

**Table 7**: 2000 land cover map accuracy assessment error matrix

| Reference data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Classified data | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Classified total | Producer's Accuracy % | User's Accuracy % |
| Dense Woodland | **19** | 10 | 0 | 1 | 0 | 0 | 0 | **30** | **100** | **63.3** |
| Sparse Woodland | 0 | **65** | 1 | 1 | 0 | 10 | 1 | **78** | **60.8** | **83.3** |
| Bushland | 0 | 5 | **54** | 3 | 0 | 3 | 0 | **65** | **81.8** | **83.1** |
| Wooded Grassland | 0 | 8 | 4 | **44** | 0 | 7 | 2 | **65** | **59.5** | **67.7** |
| Water | 0 | 0 | 0 | 0 | **41** | 0 | 0 | **41** | **100.00** | **100.00** |
| Settlement/Built up Areas | 0 | 15 | 4 | 11 | 0 | **64** | 3 | **97** | **68.8** | **66.00** |
| Grassland | 0 | 4 | 3 | 14 | 0 | 9 | **44** | **74** | **88.00** | **59.5** |
| Totals | **19** | **107** | **66** | **74** | **42** | **93** | **50** | **450** | | |
| Overall classification accuracy= **73.6%**<br>Overall kappa statistics = **0.6852** | | | | | | | | | | |

Overall, the low accuracy in both maps was attributed to high spectral similarities between classes, and high heterogeneity in land cover classes. Overgrazing and irregular settlement in the district has resulted into complicated vegetation pattern leading to high spectral confusion.

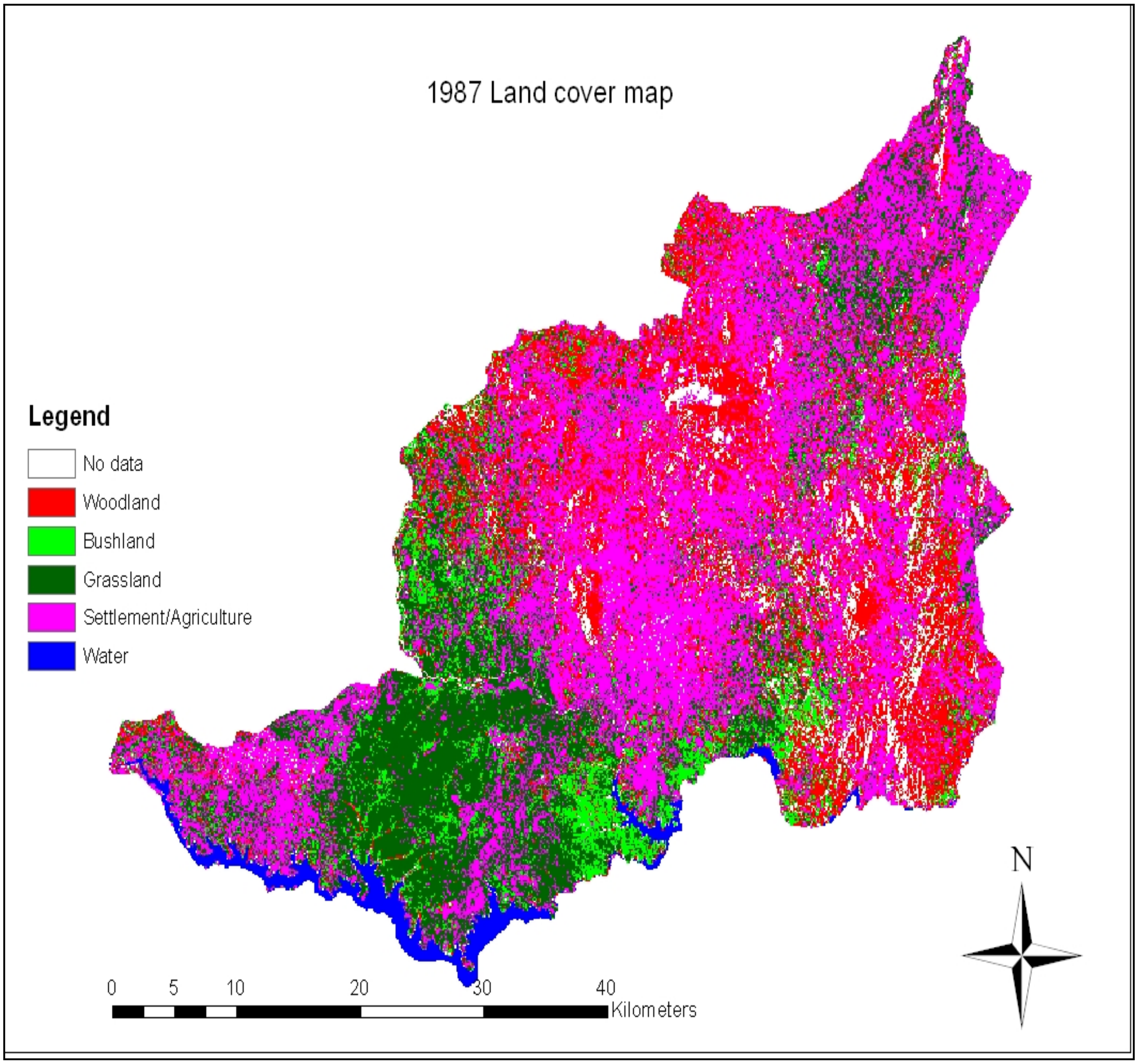
Post classification comparison requires high level of accuracy in the land cover maps. Due to low accuracy in the two land cover mps, some classes which had highest level of confusion were combined into single class.  Dense woodland and sparse woodland were combined into woodland, while wooded grassland and grassland were combined into grasslands. In the end, the final maps had five classes; Woodland, Bushland, Grassland, Settlement/Agriculture/Bare soil, and Water. Woodland covered all the evergreen woody vegetation, mostly concentrated in the higher zones of protected areas of Kiambere, Kiang'ombe, and Kianjiru hills. Grassland on the other hand included all open areas covered with grass, scrub and shrubs. It also included abandoned farmland with grass and shrub regrowth.

The final1987 map had an overall accuracy of 85.5% and a kappa statistics of 0.8268 (Table 8). All the five classes had a producer's and user's accuracy of above 80%, with water having the highest accuracy.

**Table 8**: Final 1987 land cover map accuracy assessment error matrix.

| | Reference data | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Classified data | 1 | 2 | 3 | 4 | 5 | Classified total | Producer's Accuracy | User's Accuracy |
| Woodland | **71** | 3 | 4 | 6 | 0 | **84** | **85.5** | **83.5** |
| Bushland | 0 | **52** | 4 | 4 | 0 | **60** | **91.2** | **86.7** |
| Grassland | 0 | 1 | **70** | 13 | 0 | **84** | **86.4** | **83.3** |
| Settlement/Built up Areas | 12 | 1 | 3 | **104** | 1 | **121** | **81.3** | **86.00** |
| Water | 0 | 0 | 0 | 1 | **49** | **50** | **98.00** | **98.00** |
| Totals | 83 | 57 | 81 | 128 | 50 | **399** | | |
| Overall Accuracy=**86.50**<br>Overall kappa statistics=**0.8268** | | | | | | | | |

**Figure 4:** 1987 Land cover Map



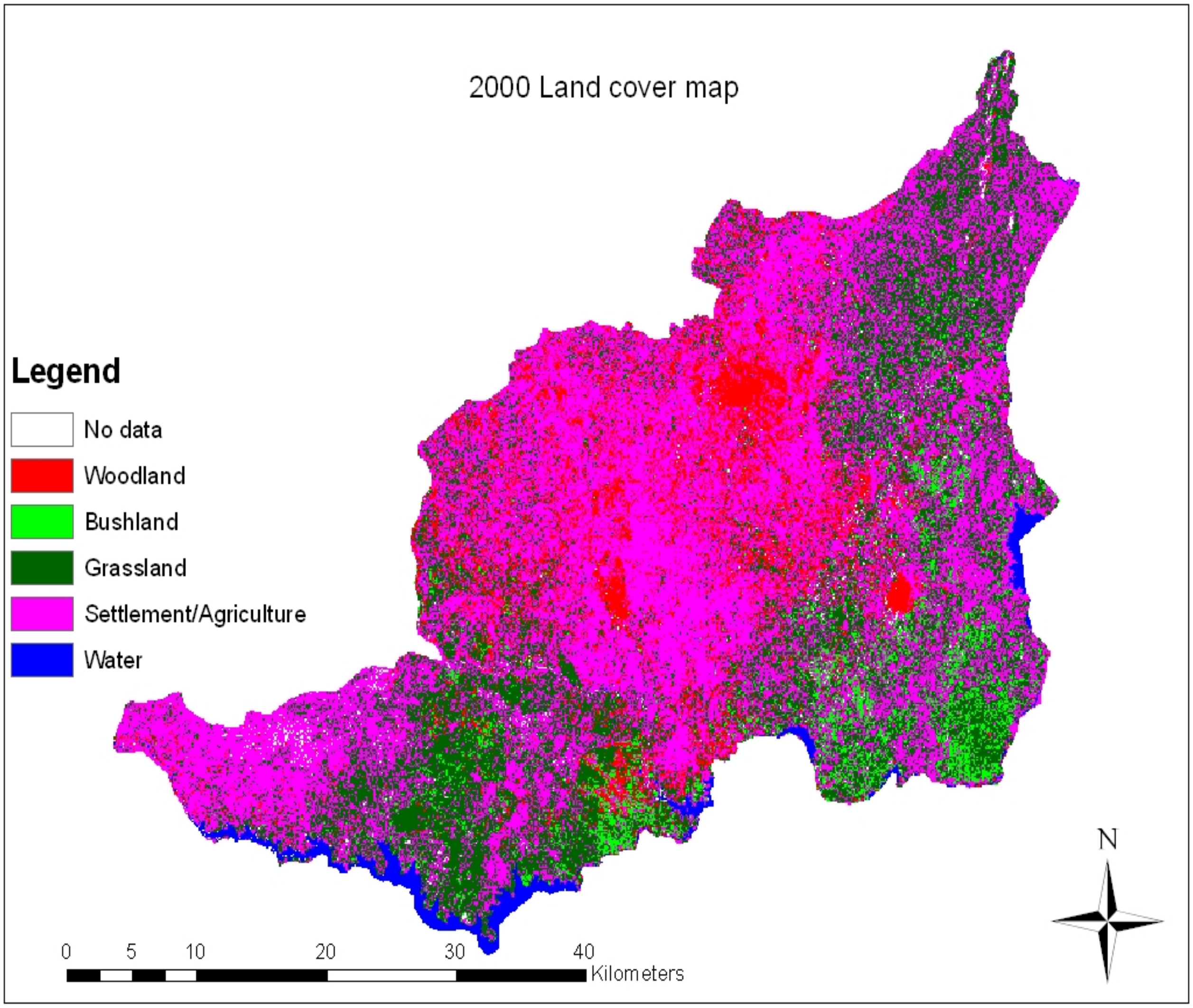

The 2000 map had an overall accuracy of 85% and an overall kappa statistics of 0.8107 (Table 9). Water had the highest accuracy with producer's and user's accuracy standing at 97% and 96% respectively. The other four classes had relatively high values of user's and producer's accuracy ranging from 77% to 88%. Woodland had low producer's accuracy of 77.5% indicating high omission errors. This means that there was a 77.5% probability of correctly mapping out woodland pixel in the image. Settlement on the other hand had low user's accuracy of 77.8%; an indication of relatively high commission errors.

**Table 9**: The final 2000 land cover map accuracy assessment error matrix

| Reference data | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Classified data | 1 | 2 | 3 | 4 | 5 | Classified total | Producer's Accuracy | User's Accuracy |
| Woodland | **79** | 5 | 2 | 4 | 0 | **90** | **77.5** | **87.9** |
| Bushland | 6 | **67** | 4 | 3 | 0 | **80** | **83.8** | **83.8** |
| Grassland | 1 | 6 | **76** | 6 | 1 | **90** | **88.4** | **84.4** |
| Settlement/Built up Areas | 16 | 0 | 4 | **70** | 0 | **90** | **84.3** | **77.8** |
| Water | 0 | 2 | 0 | 0 | **48** | **50** | **98.00** | **96.00** |
| Totals | 102 | 80 | 86 | 83 | 49 | **400** | | |
| Overall Accuracy=**85**<br>Overall kappa statistics=**0.8107** | | | | | | | | |

The final accuracy achieved after merging some previous classes was therefore considerably high given the fact that there was high spectral confusion between land cover classes. Given the high complex nature of arid and semi-arid environments, the level of accuracy achieved could be considered high enough for post classification comparison change detection.

**Figure 5:** 2000 Land cover Map



## Change Detection Results and Discussion

### Multitemporal PCA Change Detection.

Multi-temporal PCA results indicated that the first three components accounted for 92.6 % of variation between the two dates. However, PCA was unable to capture meaningful changes consisted with the observable pattern in the two images. No component was consistent with the land cover change between the two dates.

### SARVI2 Change Detection

The SARVI2 change map was evaluated at different thresholds for changes consisted with two land cover map dates. The different thresholds did not yield changes consistent with the visual changes in the two dates. Therefore SARVI2 was unable to capture any substantial land cover changes between the two dates.

### Post Classification Comparison

The two land cover maps were compared pixel by pixel through post classification comparison. Post classification comparison was the only method which was capable of capturing land cover changes between the two dates. Apart from change no change information, post classification comparison also resulted in a change matrix that provided “from-to” change information. The results indicated that both land cover conversion and land cover modifications were significant between 1987 and 2000.

Woodland reduced by 41.3%, while bushland reduced by 29.5% (Table10). Land cover change matrix between the two maps indicates that settlement and agriculture accounted for the highest percentage loss in vegetation. The only woodland covered area that remained relatively unchanged between the two dates was restricted to the highest points in the three protected hills; Kiambere, Kianjiru and Kiang’ombe. The results indicated loss of woodland in the lower zones on these protected areas, an indication of increasing human encroachment on protected areas.

Vegetation modification was also high between the two dates. Woodland changed significantly to bushland and grassland. Woodland modification could be attributed to selective cutting of trees in the protected areas for fuel wood, charcoal making, building materials and overgrazing. Similarly, there was a huge conversion of woodland to bushland around Kiambere dam. This may be attributed to the change in land tenure which made a huge part of the woodland a public property leading to increased overgrazing, charcoal making, fuel wood harvesting and vegetation clearing for agriculture and settlement.

The results however indicated that grassland increased between the two dates. This could be attributed to high rates of abandonment of once agricultural farms which were no longer productive. After privatization of land was initiated by the government in the early 1970s, there was rapid in migration since people were free to sell their private lands. Most of the migrating population was from surrounding high potential districts like Embu which were already experiencing high population pressure. The migrating population introduced farming skills which were incompatible with the arid environment and most abandoned their farms after a few seasons since they were unproductive. On the other hand, overgrazing was converting woodland and bushland to grassland as the grazing land continued to shrink. Change matrix however indicated that there was very high loss of grasslands to settlements between the two dates. The highest loss was around Mwea and attributed to increased irrigation agriculture.

Water level in the reservoirs receded between 1987 and 2000. Some areas which were mapped as water in the 1987 image were mapped either as vegetation or bare soil in the 2000 image. Although the rainfall patterns in the area were found to be decreasing with time, the receding water level could be partly attributed to land cover loss which has contributed to more soil erosion and therefore dam siltation.

**Table 10:** Land cover change between 1987 and 2000.

| Land cover classes | 1987 | 2000 | Land cover change in sq. km | % land cover change |
|---|---|---|---|---|
| Woodland | 50062.5 | 29409.57 | -20652.93 | -41.3 |
| Bushland | 18818.01 | 11800.35 | -7017.66 | -29.5 |
| Grassland | 49750.38 | 63952.56 | +14202.20 | +28.5 |
| Settlement | 95528.52 | 121503.4 | +29974.90 | +31.4 |
| Water | 6260.22 | 5168.79 | -1091.43 | -17.4 |

**Figure 6:** Land cover change between 1987 and 2000.

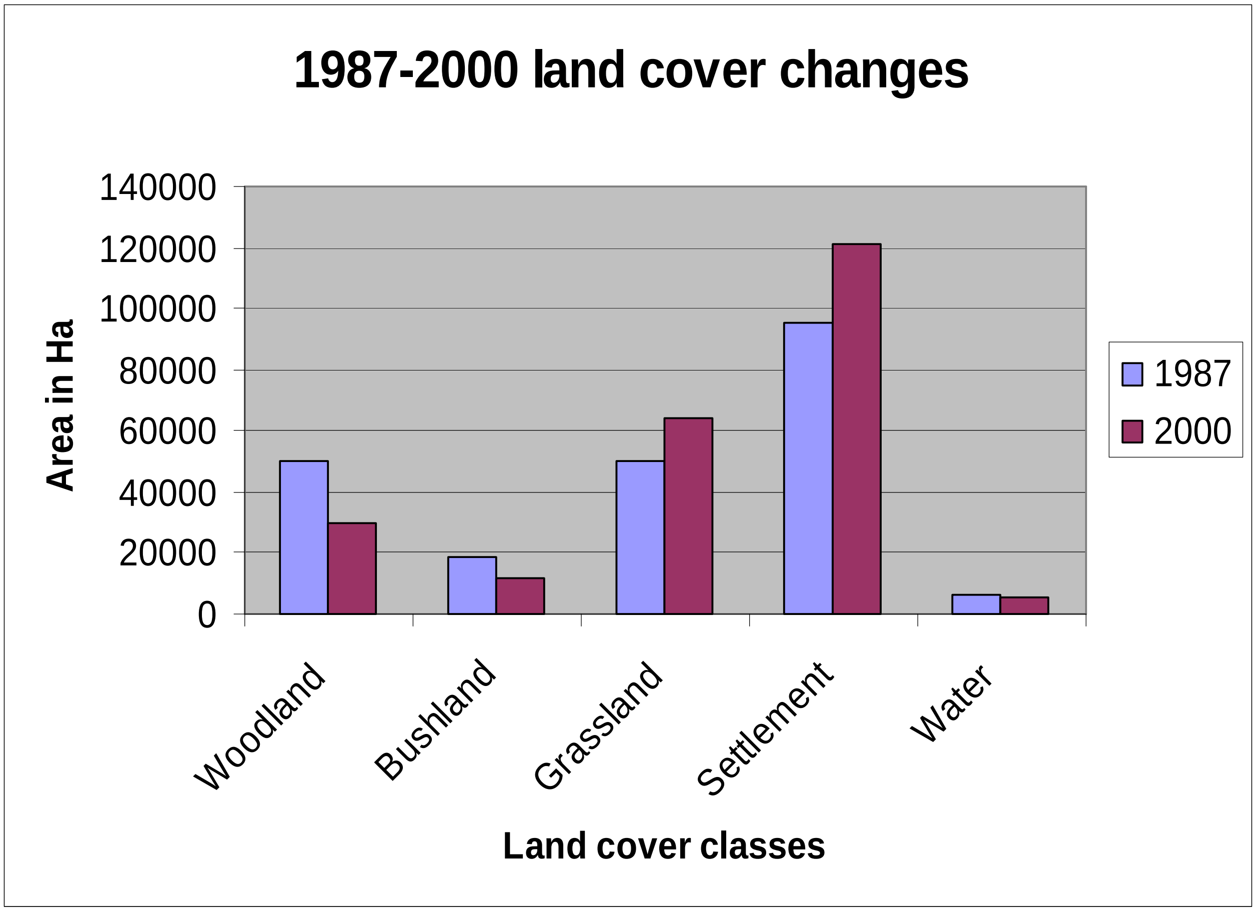
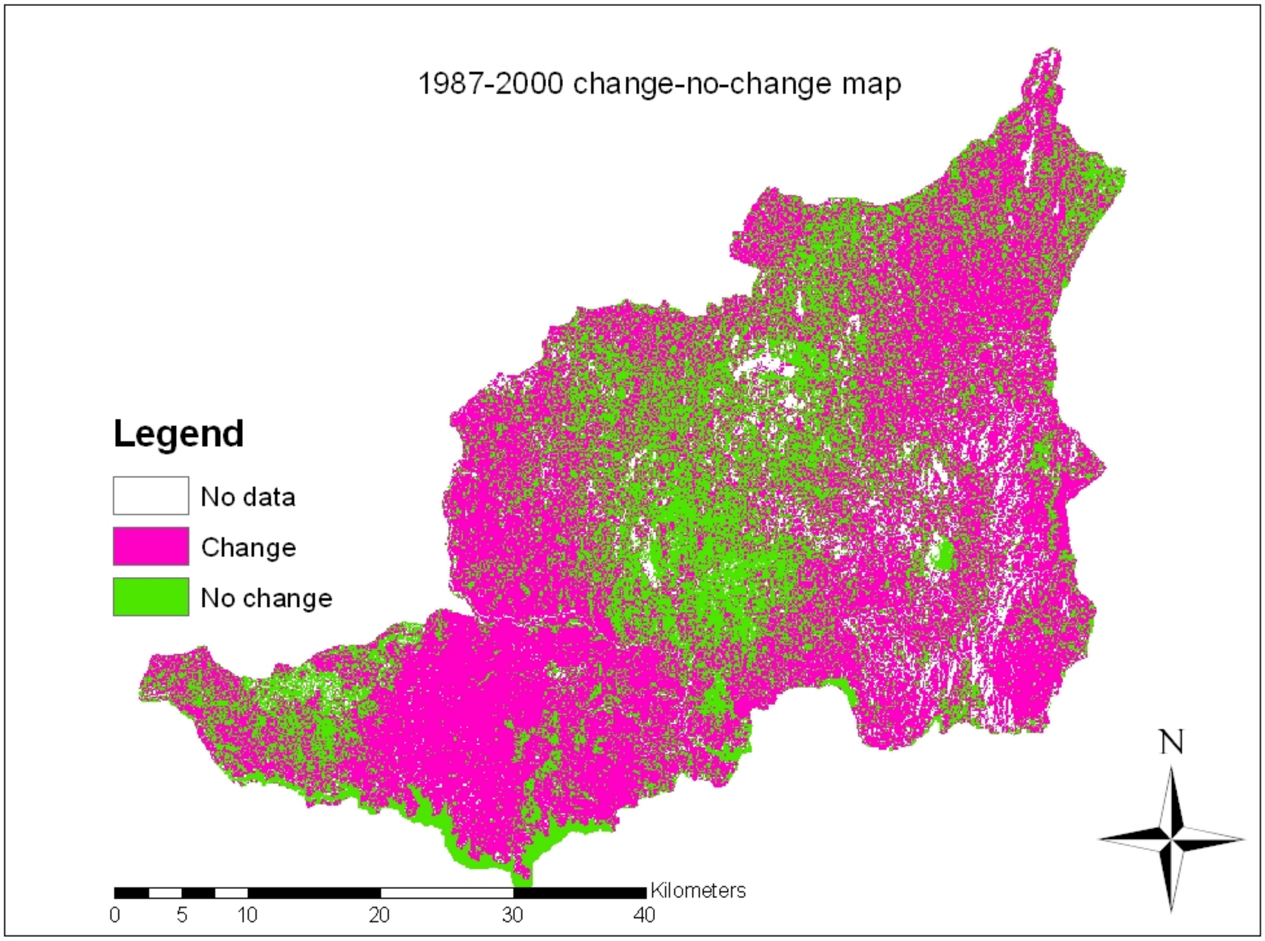


**Table 11:** 1987-2000 land cover change matrix

| | 2000 land cover classes | | | | | |
|---|---|---|---|---|---|---|
| 1987 land cover classes | Woodland | Bushland | Grassland | Settlement/Built up Areas | water | Total(Ha) |
| 1.Woodland | **11146.14** | 2491.92 | 2936.7 | 9256.14 | 133.65 | 25964.55 |
| 2. Bushland | 3830.22 | **2620.17** | 2187.18 | 1781.91 | 60.66 | 10480.14 |
| 3.Grassland | 10379.43 | 5852.34 | **24729.3** | 20375.28 | 665.28 | 62001.63 |
| 4.Settlement/Built up Areas | 24467.22 | 7647.3 | 19570.14 | **63040.68** | 972.72 | 115698.06 |
| 5. Water | 37.44 | 35.65 | 187.11 | 349.0 | **4282.38** | 4282.38 |
| Total(Ha) | 49860.45 | 18647.37 | 49610.43 | 95003.46 | 6114.69 | |

**Figure 7:** Change-no-change 1987-2000 Mbeere land cover map



## Causes of Land Cover Change

The current land cover change pattern in Mbeere District could be attributed to a complex interaction of environmental, socio-economical and demographic factors. Some of the factors that may have influenced rapid change in land cover in the district are as follows.

**Land Tenure System**

The land tenure system before 1980s in most parts of Mbeere District was communal. Shifting cultivation and pastrolisim were the main economic activities as there was plenty of the land. Communal grazing land was also readily available and therefore less overgrazing. Land adjudication in the district was effected by the government which led to rapid change in land cover. Subdivision and privatization of land meant no communal grazing land and this led to overgrazing. Land adjudication also meant the end to shifting cultivation, causing increased overcultivation and degradation of the fragile environment. Privatization of land resulted into increased further subdivision of the land and subsequent selling of the land to people outside the district, contributing to population increase in the district through immigration.

Kiambere Dam had a two-kilometer buffer zone of free land at completion. Increasing population in the areas surrounding the dam and beyond led to the landless people encroaching on the buffer area for settlement, agriculture and grazing. Extensive overgrazing on this buffer zone coupled with other human activities including charcoal making and selective cutting of trees for building materials became significant. Destruction of this buffer zone has caused increased soil erosion which partly may be responsible for siltation of the reservoir.

**Rapid Population Growth**

Kenya as a country has been experiencing high population growth. Mbeere District population density was 65 persons per kilometer squared according to 1989 population census, and during the 1999 population census, the population density had increased to 82 persons per square kilometer. Based on 1999 population census, Mbeere District population was growing at a rate of 2.3%, with average family size of around six persons per family. Agriculture is the main economic activity with over 80% of the population depended on farming (GOK, 2005). Rapid population growth has therefore translated to increased clearance of vegetation for agriculture and overgrazing.

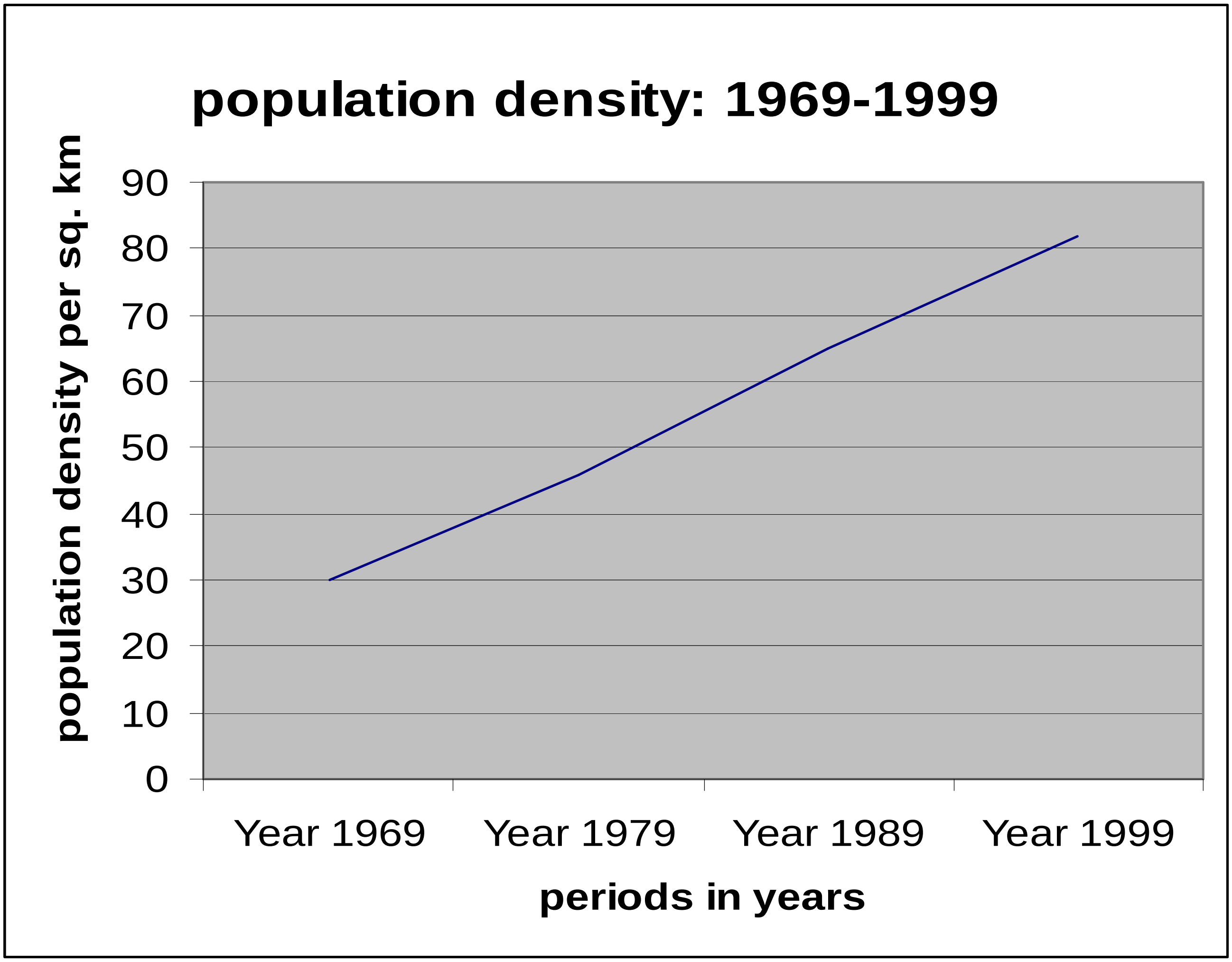
Fuel wood is the main source of energy in the district. Rapidly growing population has increased the rate of trees cutting for fuel wood. This selective cutting has had adverse effect on land cover and is responsible for a big percentage of land cover conversion in the district. Harvesting of posts and poles as building materials also has been a major cause of land cover conversion in the district. The increasing population has meant increased demand for building materials further stretching the already overstretched environment.

**Table 12:** Mbeere population growth from 1969 to 1999.

| | **Population** | | | | **Density km2** | | | | **Growth rate** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1969 | 1979 | 1989 | 1999 | 1969 | 1979 | 1989 | 1999 | 1969-79 | 1979-89 | 1989-99 |
| **Mbeere** | 62,407 | 92,037 | 135,403 | 170,953 | 30 | 46 | 65 | 82 | 4.0 | 3.9 | 2.4 |
| **Siakago** | 11,207 | 16,522 | 25,982 | 34,330 | 30 | 46 | 71 | 93 | 4.0 | 4.6 | 2.8 |
| **Gachoka** | 21,809 | 31,165 | 45,560 | 59,102 | 27 | 39 | 57 | 74 | 3.6 | 3.9 | 2.6 |
| **Mwea** | 12,915 | 22,642 | 32,911 | 40,680 | 25 | 53 | 65 | 79 | 5.8 | 3.8 | 2.1 |
| **Evurori** | 16,476 | 21,708 | 30,950 | 36,841 | 40 | 53 | 74 | 90 | 2.8 | 3.6 | 1.8 |

Source: Olson, 2004.

**Figure 8**: Mbeere population density from 1969 to 1999.



**Poverty and High Dependency Ratio**

Poverty level in the district stands at above 60%, while dependency ratio is 100: 97.8 (GOK, 2005). High poverty levels can be attributed to over reliance on agriculture, persistent drought, poor soils and erratic rainfall. High dependency levels are as result of large household size with majority of the population consisting of the young and nonworking. Charcoal making has been a very common way of survival during the harsh conditions among the poor. Charcoal making has on the other hand been one of the main causes of vegetation conversion due to selective cutting of the big trees.

Poverty has led to subdivisions of the already small pieces of land for reselling. This has increased the population further and reduced considerably the available grazing land, causing more overgrazing and land degradation. New agricultural techniques that are incompatible with arid lands have been introduced through in-migration from high agricultural potential areas, and these methods have adversely affected the environment causing increased degradation.

**Infrastructures**

Mbeere district population pattern is greatly influenced by physical amenities like road network. Population density is high in urban areas and along the main roads in the district. Market centers like Siakago, Ishiara, Kiritiri, Karaba and Gachoka have influenced high population settlement around them. On the other hand, there is linear settlement pattern along Kiritiri-Embu road, Embu-Siakago-Kiritiri road and Embu-Ishiara road.

**Natural Factors**

Based on the observable land cover change pattern in this research, land cover change in Mbeere District can be attributed to several natural factors. An analysis of rainfall data from the district dating back to the 1950s revealed a downward trend in the annual averages over time. The decreasing rainfall has meant prolonged drought which causes adverse land cover conversion through vegetation loss.

The more agricultural potential areas of Siakago, Evurori and Gachoka have had high population density than the more marginal areas. On the other hand, water bodies in the district have influenced settlement pattern, with people preferring to settle close to water bodies like dams and permanent rivers.

# CHAPTER V

## CONCLUSION AND RECOMMEDATIONS

### Results Summary

Two land cover maps corresponding to 1987 and 2000 Landsat images were produced. The overall accuracy of the two maps was above 85% and the overall kappa statistics was above 0.81. Different land cover classes had differing producer's and user's accuracy levels indicating different levels of omission and commission errors. Woodland in 2000 had the lowest producer's accuracy of 74.4%, while settlement in 2000 user's accuracy of 77.8 % was the lowest.

Post classification comparison change detection was the only method which was able to capture changes between the two dates. Apart from capturing the changes between the two land cover maps, it provided important "from-to" change information. Results revealed that Mbeere District had undergone significant land cover change between 1987 and 2000. A total of 29,409.6 hectares of woodland and 7,017.7 hectares of bushland were lost between the 1987 and 2000 period. Grassland on the other hand increased by 14,202.2 hectares. Settlement/ agriculture increased by 29,974.9 hectares and accounted for the highest type of change between the two dates.

Land cover modification was by far the most common type of land cover change in the district between the two dates. There was high conversion of woodland and bushland to grassland. Most dense woodland in the district is found in protected areas, and conversion to bushland and grassland is an indication of selective cutting of trees as well as overgrazing in the protected areas.

The research confirmed that vegetation phenology can be used to aid in land cover change detection especially in arid and semi-arid areas which are characterized by high spectral similarities between classes. MODIS NDVI data was used to aid in class separation by following phenological characteristics of various land cover classes.

The research had several limitations. Choosing satellite images was the most significant limitation of the research. Cloud free images were hard to get, a typical problem in the tropics. Mbeere District experiences erratic rainfall, with rainfall differences within very small areas causing high intra seasonal variability. This was a big shortcoming since even anniversary date images exhibited very high variability on different spots within a small area.

Ancillary data to support satellite images were limited. The ancillary data used was 1988 aerial photographs, topographic maps based on 1974 aerial photographs and GPS points. Topographic maps used were too general and failed to capture finer details. More ancillary data like aerial photographs corresponding to the same period as the satellite images could have been of more use.

Field work in this research was also inadequate. Time available for the field work was limited. Mbeere district on the other hand has a poor road network and this limited the accessibility of some regions. The study area however exhibited high variability in land cover classes within very small distance, and therefore accurate classification in this area requires extensive field work.

Image classification was highly inhibited by high spectral similarities between several land cover classes. Woodland for example had high spectral similarities with agro-forestry agriculture. This spectral similarities affected the classification accuracy of both woodland and settlement/agriculture classes. Some grassland pixels had similar spectral characteristics with some dry crops especially dry rice fields. The high heterogeneity coupled with high spectral similarities was therefore a significant drawback in this research.

## Conclusion

There are several important inferences that can be drawn from this research. It can be inferred that despite the difficulties associated with digital land cover change detection in arid lands, it is still an important method in understanding the changing fragile arid environments globally. It can also be inferred that anniversary dates is not an adequate solution in choosing satellite images for land cover change detection in arid environments. Stochastic events like erratic rainfall in arid lands can lead to high spectral differences within a small area. This makes availability of images one of the most important factors that determine results of any digital land cover change detection in arid and semi-arid environments.

Land cover change pattern as demonstrated by the change matrix revealed a complex land cover change pattern with no clear cut direction. Based on this research therefore, it can be inferred that there was no specific direction in land cover change in, as change occurred in both positive and negative directions.

Post classification comparison is an important method for land cover change detection in arid and semi-arid lands. Apart from its ability to show change from no change, the ‘from-to’ information is important in indicating the trends in environment. This information is useful in environmental policies formulation and planning. However, caution should be taken right from choosing satellites images through image classification to ensure high accuracy. Images with phenological differences should be avoided to ensure mapping of actual changes between the images as opposed to phenological differences. On the other hand, MODIS data can be of significant use in both choosing ideal data for change detection as well as aiding in image classifications. MODIS data can be used to distinguish actual changes and phenological differences between images.

Extensive field work is necessary in order to ensure high accuracy in land cover change detection in arid and semi-arid regions. Extensive field work will aid in image classification in areas characterized by high heterogeneity and spectral similarities.

## Recommendations and Future Research

Based on the findings of this research, several recommendations can be made. To begin with, Mbeere district is undergoing rapid land cover change and therefore there is need for increased application of digital land cover change detection to ensure clear understanding of the trends and impacts of the changes. In addition, more satellite based land cover change research should be carried out in the other arid areas of Kenya to establish the current environmental conditions.

Arid and semi-arid lands in Kenya are characterized by persistent drought and famine. This research established that there are likely alarming land cover changes in these environments too. Sound policies which are aimed at achieving long term balance between the population and the physical environment should therefore be formulated based on the current environmental changes pattern. Up to date land cover, rainfall, and other types of data should be used to predict impacts of the observable trend, and set up necessary mitigation measures.

Further research in arid and semi-arid land should try to integrate both field based and digital based land cover change methods to ensure high accuracy. On the other hand, digital change detection should make use of more ancillary data as well as extensive field work. Future research also should focus on application of higher temporal and spatial resolution data to achieve higher accuracy.

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