Remote sensing based assessment of small wetlands in East Africa

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Declaration

I declare that this thesis is my own original work and that it has not been presented and will not be presented to any other University for a similar or any other degree award.

Ich versichere, dass ich diese Arbeit selbständig verfaßt habe, keine anderen Quellen und Hilfsmaterialien als die angegebenen benutzt und die Stellen der Arbeit, die anderen Werken dem Wortlaut oder dem Sinn nach entnommen sind, kenntlich gemacht habe. Die Arbeit hat in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegen.

Emiliana Mwita

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Dedication

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Table of Contents

List of Figures

List of Tables

Abbreviations

ALOS	Advanced Land Observing Satellite
AOI	Area of interest
ASAR	Advanced Synthetic Aperture Radar
AVHRR	Advanced Very High Resolution Radiometer
CVA	Change Vector Analysis
DEM	Digital Elevation Model
DIP	Digital Image Processing
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DPI	Dots Per Inch
ENVISAT	Environmental Satellite
ERS-1	European Remote Sensing Satellite
ESA	European Space Agency
ETM	Enhanced Thematic Mapper
ETM+	Enhanced Thematic Mapper plus
FAO	Food and Agriculture Organization of the United Nations
GIS	Geographic Information System
GLCF	Global Land Cover Facility
GPS	Global Positioning System
IDL	Interactive Data Language
IRS-1B	Indian Remote Sensing satellites
JERS-1,	Japanese Earth Resources Satellite
KWS	Kenya Wild life Service
LANDSAT	Land Sattellite
LCLU	Land Cover and Land Use Change
LCM	Land Cover Change Mapper
LISS-II	Linear Imaging Self-Scanning
MSS	Multi Spectral Scanner
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration

PALSAR	Phased Array type L-band Synthetic Aperture Radar
PCC	Post Classification Comparison
RADAR	Radio Detection and Ranging
RADARSAT	Radio Detection and Ranging Satellite
ROI	Region of Interest
SAR	Synthetic Aperture Radar
SPOT	Satellite Pour l'Observation de la Terre
URT	United Republic of Tanzania

Abstract

Small wetlands in East Africa have in the past few decades become focal points of a broad spectrum of agricultural production and other land-uses. Climate change and population growth are the major factors attributing to increasing use and change of the wetlands. This study aimed at detecting the distribution and extent of small wetlands in Tanzania and Kenya, classifying them into different types, identifying their use patterns and quantifying changes that have taken place from 1976 to 2003.

Field and aerial surveys were conducted; microwave (ALOS-PALSAR, ENVISAT-ASAR, and TerraSAR-X) and optical (LANDSAT and aerial photographs) data, were used to detect spatial distribution of the wetlands using automated and semi automated techniques. Time series LANDSAT images were applied in classification and change detection by post classification comparison (PCC), change vector analysis (CVA) and land use change mapper (LCM). Maps and socio-economic data were also gathered. Driving forces of change were determined qualitatively using group discussions with key informants.

Two types of small wetlands were mainly identified, inland valleys located in the humid highlands and covering 87% of the total surveyed area as well as floodplains in sub-humid lowlands and semi-arid highlands covering the remaining 13%. Eight major land cover and uses were identified with accuracies between 82.76 and 95.17%. Cropland was a dominant land use occupying 57% of the inland valleys and 35% in the flood plains; others included open water, floating vegetation, permanent papyrus swamps, semi-natural vegetation, grazing, shrubs, settlements and bare land. The cover and uses are unevenly distributed between the types and sites.

The major change detected was expansion of cropped land at the expense of natural vegetation. This accounted for 56% of the change in the highland flood plain and 52% in the lowland floodplain. Shrubs proliferated in all wetlands, which is indicated by more than 50% compared to their area coverage in 1976. Climate change, population increase, unemployment, market access, wetland physical access and insufficient knowledge on the use are among the proximate causes of the wetland changes. Underlying factors like poor enforcement of wetland law and policy in Kenya and lack of the same in Tanzania have accelerated these changes.

Combinations of remote sensing data and image processing methods played an important role in achieving the objectives of the study. Optical data proved to be very useful in delineation of small wetlands while microwave data delineated larger areas. The spatial resolution of the images has also proved to be a key factor in studies of small wetlands. To ameliorate the wetlands, it is recommended that a balance is attained between the use and conservation. Policy formulation and law enactment in Tanzania and enforcement of the existing policy and law in Kenya is seen to support wise use. Awareness creation is also important to lessen the over and inappropriate utilization of the wetlands.

1 General Introduction

This chapter introduces the study where a general overview is presented on small wetlands, their status, spatial distribution, potentials, uses and driving forces for their use. The role of remote sensing in detection, characterisation, and monitoring of the wetlands is briefly discussed. The goals, hypothesis, statement of the problem and significance of the study are stated towards the end of this chapter.

1.1 Overview of wetlands

Wetlands are vital and valuable resources both for their rich and unique wildlife habitat, and for the functions they fulfil and services they provide to human society. Wetlands occupy only about 6% of the earth's surface but are among the most productive ecosystems on earth (Turner & Jones, 1990). They are potential areas for agriculture as they possess fertile soils and moisture conditions suitable for crop production (Roggeri, 1995). Wetlands also contain important grasslands for grazing; fishing grounds, recreational resource and macrophytes, which are used for production of handcrafts (Dugan, 1990; Turner & Jones, 1990; Roggeri, 1995).

Wetlands are a common landscape, which features across all continents in different types and sizes (Wood & van Halsema, 2008). Each wetland is unique with respect to its size, shape, hydrology, soils, vegetation and position in the landscape (Kent, 1994; Jensen *et al.*, 1993). By consensus, there are three characteristics (parameters) that distinguish all wetlands:

- Presence of water, typically from a surface or ground water source.
- Presence of unique (hydric) soils, which are a diagnostic of wetland conditions. The soils display properties, which indicate anaerobic conditions in the root zone resulting from prolonged saturation or inundation.
- Presence of wetland vegetation, which possesses morphological adaptations that enable it to tolerate frequent root zone saturation or inundation, and anaerobic conditions (i.e. hydrophytic vegetation).

It is the inter-play between water, soils and vegetation that makes wetlands unique ecosystems, that provide refugia for micro and macro-organisms as well as support to human populations, regulating climate and sustaining the environment (Maltby, 1991).

Due to their high productivity potential, wetlands have attracted human activities since ancient time. However, pressure of use has currently accelerated because of both human pressure and global climatic changes. Wetlands are continuously being converted for different uses. Worldwide wetlands are drained for agricultural use, urban expansion, industrial development and recreation.

In America, for example, from 1780's to 1980's considerable number of wetlands were drained, filled and manipulated to provide unnatural services and commodities, resulting to 53% loss (Dahl, 1990). In Europe, 50% wetland losses have been reported in Netherlands, Germany, Spain, Greece, Italy and France due to conversion into other uses (Commission of the European communities, 1995). In Asia wetlands are largely being drained for rice production and human settlement. Similarly in Africa, being one of the poorest regions of the world and the most arid continent, wetlands are under increasing pressure from industrial and urban use, agriculture expansion, settlement development and other informal activities (Haack, 1996).

In East Africa where wetlands are wide spread, the pressure has been recently increasing due to a growing population, and consequently growing demands for utilizable land, food and water (Roggeri, 1995). Frenken & Mharapara (2002) argue that in Kenya, wetlands have witnessed increased pressure for development due to the need to produce more food, provide employment and settle a rapid growing population. Similarly, in Tanzania, wetland degradation is mainly a result of human activities like farming, livestock keeping, informal settlements, sand mining and natural threats such as drought and rise in sea level (Kamukala & Crafter, 1993).

Growing understanding of wetlands and their vital importance begun in the late 20th century after the Ramsar Convention on wetlands in 1971. The Convention advocated for conservation and wise use of wetlands by national action and international cooperation as a means to achieve sustainable development throughout the world. Signatory nations are obligated to assist the wise use of all wetlands in the nation's territory (not only those that are designated), which means that "their sustainable use/utilization for the benefit of mankind in a way compatible with the maintenance of the natural properties of the ecosystem" must be promoted (Ramsar Convention Secretariat, 2006: 49). The emphasis, however, has tended to be on larger wetlands (>500 ha). Minimal or no attention has been directed to the small wetlands despite their importance (Owor *et al*., 2007, Thenkabail *et al*., 2000).

East African countries have ratified the Convention. Kenya became a member in 1990 and has five wetland sites designated as 'Wetlands of International Importance'. These cover a surface area of 101,849 ha. Tanzania ratified the Convention in the year 2000, and has four sites designated as Ramsar sites, covering a surface area of 4,868,424 ha (Mitsch & Gosselink, 2007).

Numerous initiatives have been in place to inventorise, map and detect change and wetland loss in the advent of the Ramsar Convention. Studying these ecosystems is, however, difficult because of their remote locations and environments, which are associated with dangerous wild animals and flooding conditions (Rebelo *et al.,* 2009a). Advancements in Earth Observation (EO) coupled with ground analyses have provided opportunities for identifying, describing and mapping the distribution of wetlands at a range of scales from local to global (Jones *et al*., 2009).

Remote sensing provides a wide range of methods for digital data capturing and mapping of the wetlands due to its repetitive nature with multi sensors and the resulting multi spectral and multi spatial resolution data. Using digital data provides a standardized data-collection procedure and an opportunity for data integration within a geographical information system (Murphy *et al.,* 2007). It was the intention of this study realised under the Small Wetlands of East Africa project (SWEA) to inventorise, map the distribution and detect changes in the wetlands using remote sensing and GIS techniques, to supplement available information on small wetlands in Kenya and Tanzania.

1.2 Understanding small wetlands

The diverse and dynamic nature and character of wetlands have resulted into difficulties in having a single unifying definition as well as complications in delineating their boundaries. The Ramsar Convention embraced this diversity in a single definition, grouping together a wide variety of landscape units whose ecosystems share the fundamental wetland characteristic of being strongly influenced by water. The Ramsar Convention (2006) considers wetlands to be: “areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water, the depth of which at low tide does not exceed six metres.” This definition reflects a hydrological perspective with water as the key factor. Other authors like Maltby (1991) have stressed the link between hydrology and biology and have proposed “ecohydrological” definitions, while others like Dugan (1990) and FAO (2002,1998) have suggested geomorphological and agricultural (crop) definitions, respectively. Thus, a wide number of wetland definitions that are informed by the perspectives taken and the primary purpose of the interested parties are in circulation.

Small wetlands, depending on where they occur, have acquired different names and definitions suiting perception and needs of the local communities. In the United States of America (USA) they are referred to as isolated wetlands, which means they are not connected by surface water or are surrounded by uplands (Leibowitz, 2003). They are ecologically very important and inhabited by endemic plants and animal species, especially amphibians. In southern Africa small wetlands are known as *dambos* and are defined by Limpitlaw & Gens (2006:1) as “geomorphological features, which are covered by grass and are seasonally inundated’’. The benefits from *dambos* include domestic water supply, grass for thatching, wild plant collection for relish and medicinal use, dry season grazing and small-scale dry season supplementary cultivation.

In West Africa they are commonly known as “bas-fonds” or *Fadamas* (in Hausa local language), meaning a low lying area, which is susceptible to periodic or seasonal flooding

(Okunlola, 2009). In Tanzania they are referred to as *Mbuga* i.e. depressions filled with black clays within the savannah ecotone. In addition these depressions are characterized by periodically saturated soils and a layer of iron concretion in about 50 cm depth. In this work, wetlands are referred to as areas, which are moist, with agronomic potential for field crop and animal production and whose land units are characterized by seasonal freshwater flows and soil flooding. The study focuses on small to medium sized wetlands of between 1 and 500 ha, specifically mountain swamps and inland valleys.

1.2.1 Distribution, extent and types of small wetlands

The exact extent and distribution of wetlands globally is questionable due to the diversity of definitions of wetlands and lack of single homogeneous classification system (Davidson & Finlayson, 2007). Inadequate information for some parts of the world as well as inconsistent mapping policies also contribute to this problem. Rebelo *et al*. (2009a) argue that, based on current information, it is not possible to provide an acceptable figure of the area extent of wetlands at different scales. First, there is little agreement on what constitutes a wetland and second, there are many gaps and inaccuracies in the information.

Most of the available information is generated from estimates. Food and Agriculture Organisation, for instance, gives an estimate of 125 million ha in Africa based on mapping of naturally and marginal naturally flooded areas at a continental scale, using the Soil Map of the World (Spiers, 1999). Because of the scale of mapping, however, only the larger flooded areas are inventoried, and many of the smaller wetlands are ignored. The University of Leiden has estimated that, of the total wetland extent in Africa, approximately 50% is composed of larger floodplains (such as those mapped by FAO) while the other 50% comprises smaller wetlands that may not be captured at this scale (Spiers, 1999). Applying such a general rule and thereby doubling the FAO mapped extent of 125 million ha, would yield an estimate of total wetland extent in Africa of around 250 million ha.

Kiai and Mailu (1998) and Finlayson *et al.* (2001) estimate small wetlands to cover about 12 million ha in Tanzania and Kenya, and make up more than 80% of the total wetlands in East Africa. They are widely distributed in the highlands and lowlands in all climatic types and agro ecological zones. According to Kamukala and Crafter (1993), many wetlands, especially permanent marshes and swamps are found in highlands. There are also many flood plains along river systems and permanent fresh water lakes. In Tanzania wetlands are found on the fringes of lakes like Lake Victoria, Tanganyika, Nyasa and Kivu, and also in large river systems like Rufiji, Ruaha and Pangani and other minor rivers and lakes all over the country. Similarly in Kenya there are many wetlands on the edges of Lake Victoria and in swamps like Lorian, Saiwa, Yala, and Shompole; Lotikipi (Lotagipi) and Kano plains; Kisii valley bottoms and Tana Delta. There are also various seasonal wetlands that occur where internal drainage allows water to collect in some seasons or in some years.

1.2.2 Socio-ecological values and potentials of Small Wetlands

Small wetlands are as important as larger ones though too often they are assumed to be less valuable. They play similar roles as those played by larger wetlands but at a smaller scale, and are extremely valuable for maintaining the biodiversity of a number of plants and animal species. Ecologists describe the value of small wetlands by their aggregate role in protecting wetland dependent species through source sink dynamics (Leibowitz, 2003). Nonetheless, each wetland in an area may fluctuate in the number of individual species it contains. At times wetlands may act as a sink when population of a species dies out locally from that wetland, as it may be a source that produces surplus individuals, which can colonise a nearby sink wetland.

Apart from preservation of ecological functioning, small wetlands are important sources of water for human consumption, crop farming and livestock keeping. They recharge wells and springs that are often the only source of water to some rural communities and for wildlife support systems (Kiai & Mailu, 1998). The recharging of aquifers raises the water table making ground water easily accessible. They provide economic benefits through fisheries and generation of products such as fuel wood, building material (thatch), medicine, honey and various types of natural foods (Haack, 1996). They are important grazing areas and are the only sources of water and pasture/fodder for the pastoral communities during drought. Small wetlands form important recreation sites for game and birds watching, swimming, photography and sailing.

In addition, wetlands have high potential for agriculture especially in sub-Saharan Africa, and East Africa in particular. They are widely used for cultivation of rice both in East and West Africa, horticulture and maize. This contributes to food security and income generation to the local communities in the surrounding areas (Hughes & Hughes, 1992; Windmeijer & Andriesse, 1993; Scoones, 1991). Services such as pollination, harbouring natural predators of agricultural pests, hatching and breeding for fish are also found in wetlands. Moreover, small wetlands stabilize micro climate, mitigate floods, purify water and regulate erosion by sediment trapping. In a nutshell small wetlands possess diverse potential for ecosystem maintenance and well being of human societies. This potential can only be maintained under sustainable uses and management of these fragile resources.

1.2.3 Driving forces for small wetlands utilization

Various factors drive people to use wetlands. The biophysical characteristics of wetlands are in one part a direct driver to their utilization. In the developing world, abundant supply of fresh water, fertile soils and high productivity are of special significance under water scarce conditions coupled with degraded uplands, which are traditionally used for agricultural production (Haack, 1996). Increasing population and demand for food to feed the growing population drag more people to the wetlands. Drought conditions especially in semi arid areas also increase pressure on the wetlands in search for pasture or fodder (Kiai & Mailu, 1998; Thenya, 2001). Individual needs for income generation and desire for sustainable livelihood also force people to invade these resources in an effort to diversify their economy. National and international policies together with improvement of technology and infrastructure all contribute to increased wetlands uses (Wood & van Halsema, 2008).

In the developed world, recognition of wetland values for recreation, conservation and flood protection have driven them to conversion and rehabilitation. The demand for wetlands use is growing and leads to their continued transformation, which impacts negatively on the ecosystem. Monitoring the activities that take place in the wetlands is important to inform the authorities of the status of the resource. Remote sensing offers a unique opportunity for continuous monitoring of the wetlands; information generated can help to check the impact of human pressure and guide on wise use.

1.3 Remote sensing as a tool for detection, characterization and change analysis of small wetlands

Remote sensing offers a cost efficient means for delineating wetlands over a large area at different points in time, and can provide useful information on wetland characteristics. This is facilitated by advancement in earth observation (EO) data, which has provided scientists with information from global to local level on a regular basis. EO technology represents an efficient source of continuous and synoptic information not only of the wetland sites but also of the entire basins that supply water to the wetlands. This provides novel capabilities to wetland managers to inventorise and monitor activities not only on wetlands but also on their catchment areas e.g. to identify and monitor threats upstream in the catchment area that could potentially damage the wetland site (Jones *et al*., 2009)

In situ measurements of wetlands are usually difficult because of remoteness; remote sensing is thus a unique means to overcome such situations (Baker *et al*., 2006). The repetitive nature of remote sensing data capturing in a given spatial and temporal resolution offers opportunity for wetlands change detection. Change detection of the earth's surface can be investigated due to the availability of long-term data (De Roeck *et al*., 2008).

Optical remote sensing techniques have been widely and successfully used to provide land-cover information. Classification of LANDSAT images using semi-automated methods like supervised and unsupervised classifications provide useful information on land use/ cover of a particular area of interest. Time series analysis of satellite images using techniques like image differencing, rationing or change vector analysis (CVA) enables detection of changes in wetlands and other ecosystems (Coppin *et al*., 2004). The optical remote sensing techniques, however, highly depend on sun illumination and therefore, several limiting factors like over clouding in regions of the inner tropics influence data capture and image quality. Microwave remote sensing often compliments these limitations where available because of its ability to penetrate clouds and depending on sensors frequencies, vegetation canopy.

Based on various remote sensing data types, different approaches are used in identifying and classifying wetlands. Wetland delineation involves most often the use of aerial photographs and airborne or satellite remotely sensed data (Baker *et al*., 2006). In the past, visual interpretation of wetlands from maps, aerial photography, and hard copies of satellite images were used extensively (De Roeck *et al*., 2008). Currently, however, digital image processing is highly used. There is, however, no standard method for computer-based wetland classification. LANDSAT, SPOT, Advanced Very High Resolution Radiometer (AVHRR), Indian Remote Sensing satellites (IRS) and radar systems such as European remote sensing satellite (ERS) 1-2, and TerraSAR-X are the most frequently used satellite sensors for wetland detection (Rundquist *et al*., 2001). Change detection has always been done using time series LANDSAT images due to large and reliable archive available. LANDSAT Multi Spectral Scanner (MSS), LANDSAT Thematic Mapper (TM) and SPOT are the major satellite systems that have been used to study wetlands; other systems are NOAA AVHRR, IRS-1B LISS-II and radar systems, including JERS-1, ERS-1 and RADARSAT (Ozesmi & Bauer, 2002).

In different parts of the world many studies have been done on wetlands using remote sensing. Jones *et al*. (2009) evaluated the capacity of earth observation in inventory, assessment and monitoring of wetlands using different techniques and data sets in twenty one countries involving fifty wetlands. In this study very limited field survey, SPOT-5, LANDSAT (TM) /Enhanced Thematic Mapper plus (ETM+), Quick-bird and Synthetic Aperture Radar (SAR) images were used. Despite the limited capacity of stakeholders in using the technology, it was envisaged that the EO would provide the conservation and scientific community with support to review and assess the status of wetlands in many areas of the world. Cowardin & Myers (1974) studied wetlands in Bemidji and Minnesota using field survey and historical aerial photographs. They found out that, the use of multi-spectral aerial photographs and ecological knowledge was essential for wetlands mapping. Baker *et al*. (2006) used multi-season LANDSAT ETM+ imagery from 2001 combined with ancillary topographic and soils data, to map wetland and riparian systems in the Gallatin Valley of Southwest Montana, USA. The technique was very useful in detecting a variety of wetlands and riparian zones present on the landscape.

Hui (2009) used LANDSAT Thematic Mapper (TM) images to classify wetlands employing decision tree technique in Yunchuan plain and it appeared that, a combination of different knowledge and techniques is an effective and promising method of classification. Rebelo *et al*. (2009b) used multi-spectral imageries to capture changes and quantify wetland conditions using several case studies like Bahi swamp in Tanzania, western coastline of Sri Lanka and in other eight countries in Southern Africa. Kashaigili *et al*. (2006) also applied remote sensing and GIS in quantification of Usangu plains dynamics and as a tool for decision support and found it very useful.

The above aforementioned review of literature reveals the usefulness of remote sensing in the study of wetlands. Except for the studies done by Cowardin & Myers (1974) and to some extent Rebelo *et al.* (2009a, b), most of the studies have focused on larger wetlands like RAMSAR sites. In East Africa, only a few papers are found on the use of remote sensing in studying small wetlands. The most featuring studies are Owor *et al.* (2007), Kashaigili *et al.* (2006) and Haack (1996) but none of these studied small wetlands. This study focuses on small wetlands in Kenya and Tanzania. It uses optical and microwave remote sensing data as well as intensive field and aerial survey to detect, map and quantify changes in the small wetlands.

1.4 Statement of the problem

Small wetlands have valuable socio-ecological functions, which fulfil various human needs. Yet they are threatened by agricultural intensification, urban development and human population pressure. Because of the increasing uses and spatial- temporal changes in use, these small wetlands are being lost and there is a danger that they might disappear undocumented. This is because wetland studies in East Africa have tended to focus much on larger wetlands like L. Victoria, Naivasha, large river systems and swamps of international importance (Thenya, 2001; McClanahan & Young, 1996) neglecting small wetlands, which cover about 12million hectares in Tanzania and Kenya (Kiai & Mailu, 1998; Finlayson *et al*., 2001). Lack of documentation of changes in small wetlands implies that there is lack of informed decision making for their sustainable use and management. There is an urgent need therefore to identify, characterise and map them out. Furthermore it is essential to detect and describe the changes taking place in these wetlands, and recommend possible future uses which will not jeopardise their existence. This was the focus of this study.

1.5 Hypothesis and Objectives

This study was realised under the Agricultural Use and Vulnerability of Small Wetlands in East Africa (SWEA) project, in which a multi-disciplinary team of PhD students with background in physical geography, ecology, soil, social science and hydrology worked together to generate a multitude of information on small wetlands in Tanzania and Kenya. Figure 1.1 illustrates SWEA project components and the interaction between the components. The general aim of the project is to provide a quantitative basis for assessing the current and future agricultural potential of small wetlands in East Africa, and to develop tools to guide decision makers and planners on wetland use. The specific research objectives were: (1) to capture the current diversity of wetlands in terms of types and their spatial distribution and to define the driving forces for change and/or use; (2) to determine the potential of wetlands as sites for biodiversity and providers of ecological functions; (3) to determine the dynamics and availability of nutrient and water and link the underlying processes with the production potential to derive site-specific use options; and (4) to quantify factor interactions in view of evaluating future use scenarios and define spatial-temporal extrapolation domains. The geographical aspect of the study aimed at the following specific objectives:-

1. to detect and map out different types of wetlands in terms of size, density, and spatial distribution using optical and microwave remote sensing.
2. to classify LCLU of small wetlands using multi-temporal data
3. to assess the historical land use change over time (1975-2003) and identify their driving forces.

The following hypothesis guided the study:-

1. Small wetlands can be detected using both optical and microwave remote sensing.
2. Differentiation of LCLU of small wetlands can be achieved by classification of multi-sensor and multi-temporal resolution remote sensing data.
3. Detection of land use change in wetlands can be realised by assessment of time series LANDSAT images.

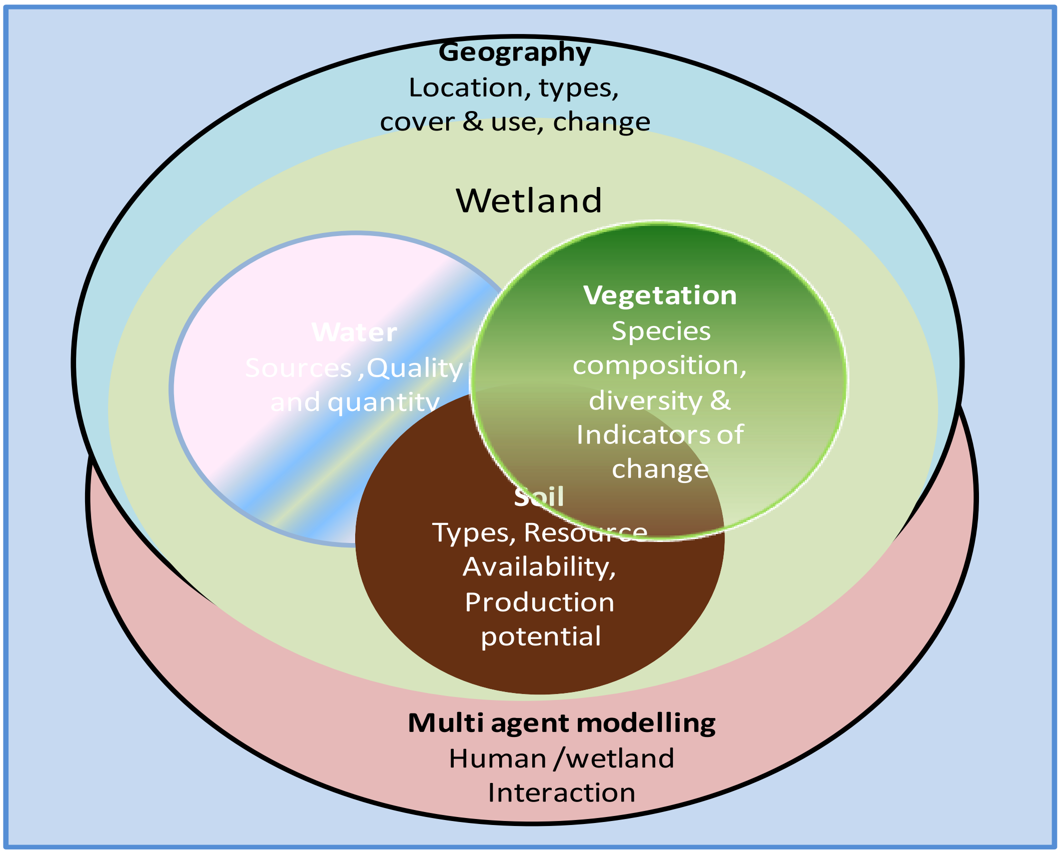


Figure 1.1: SWEA project components
Source: Own illustration

1.6 Significance of the study

The study contributes knowledge on typology of small wetlands in East Africa and social economic activities, which are taking place within the wetlands. Maps are developed to show spatial distribution of wetlands and temporal changes in use patterns, which will enlighten the society on the transformation process of small wetlands and its rate. The main factors, which drive people in transforming these resources, are identified. Spatial data generated by this study will be used as additional input for the data required for development of a decision support model to guide decision makers on how to harmonise uses and conservation for proper management of the wetlands.

1.7 Scope of the thesis

This thesis is structured into seven chapters. This chapter provides the theoretical background and objectives of the study, while chapter two describes in detail the study area. Chapters 3 to 5 form the empirical part of the thesis and address each one of the three objectives, respectively. Thus, chapter three addresses wetlands detection and mapping; chapter four presents the classification of land use and cover using both supervised and unsupervised techniques. Chapter five examines changes in the wetlands using different algorithms and describes the causes or driving forces of the changes. Chapter six discusses the findings of the previous three chapters in relation to the specific objectives. Finally, the summary of key findings, the conclusion and recommendations are presented in chapter seven.

2 Study area

This chapter presents detailed information of the study area. Site selection criteria are introduced followed by general introduction of the two countries. The specific sites chosen for the study are then described in detail in terms of their bio-geophysical and socio-economic characteristics. A general description of geology and soils for the study areas is summarised at the end of the chapter.

2.1 Site selection criteria

Small wetlands of 1-500 ha (inland valleys, mountain swamps and floodplains), located along gradients from humid highlands formed on base rock to sub-humid lowlands formed on sediments were considered for the study. Four representative study sites, two in Kenya and two in Tanzania, were selected in the high wetland density zones to reflect the diversity of physiographic determinants and the differential anthropogenic influence on wetland use. The sites followed gradients from high to low population density and from good to poor market access (Table 2.1). Physical access of the wetlands themselves and availability of infrastructure to reach the sites were an additional criterion for site selection.

Table 2.1: Criteria for selection of study sites

Country	**Tanzania**		**Kenya**	
Sites	Pangani flood plains	Usambara highlands	Laikipia flood plains	Mount Kenya highlands
Geology and parent material	Unconsolidated material, Tectonic valley alluvial	Basic igneous	Tertiary basic igneous rocks and alluvial deposits	Intermediate igneous rocks, Metamorphic
Rainfall	Low	High	Low	High
Population	Sparse	Dense	Sparse	Dense
Market access	Low	High	Low	High

Source: Own illustration

2.2 Location of the study area

The study took place in Kenya and Tanzania, the two being neighbouring countries found on the eastern coast of Africa. Kenya lies across the equator between latitude of 4° North and 4° South and Longitude 34° and 41° East. The country is bordered by Sudan and Ethiopia in the north and Uganda to the west. Somalia lies to the east of the country while Indian Ocean borders the country in the south-eastern part. To the southwest of the country lies Tanzania. Tanzania is situated on the eastern side of Southern and Central Africa between 1° and 11°5' South and 29°5' and 40°5' East. It is bordered to the North by Kenya and Uganda. To the west are Zaire, Rwanda, Burundi and Zambia, and to the south are Malawi and Mozambique.

The two countries experience tropical weather conditions; the coastal areas are hot and humid, the highlands have temperate climate and the northern side of Kenya and central plateau of Tanzania are both dry. Over 70% of Kenya is arid receiving less than 510 mm of annual precipitation while rainfall is highest in the highlands, between 1200-2300mm. In Tanzania the annual precipitation ranges from 600 mm to 1200 mm with the highest rainfall concentrated in the coastal plains and in the highlands (Howard, 1991). The two countries account for 80% of the total small wetlands in the East Africa region, which are scattered all over the countries, with climate influencing their density and diversity (Crafter *et al*., 1992).

Four sites were selected for the study; they included Mt. Kenya highlands (Nyeri and Karatina) and Laikipia flood plains (Rumuruti, Manguo, Pesi and Oljoro Orok) in Kenya, and Usambara highlands (Bumbuli, Lukozi, Magamba and isolated sites in Lushoto town) and Pangani floodplains (Malinda, Magoma, Silabu and isolated sites in Korogwe town) in Tanzania (Figure 2.1).

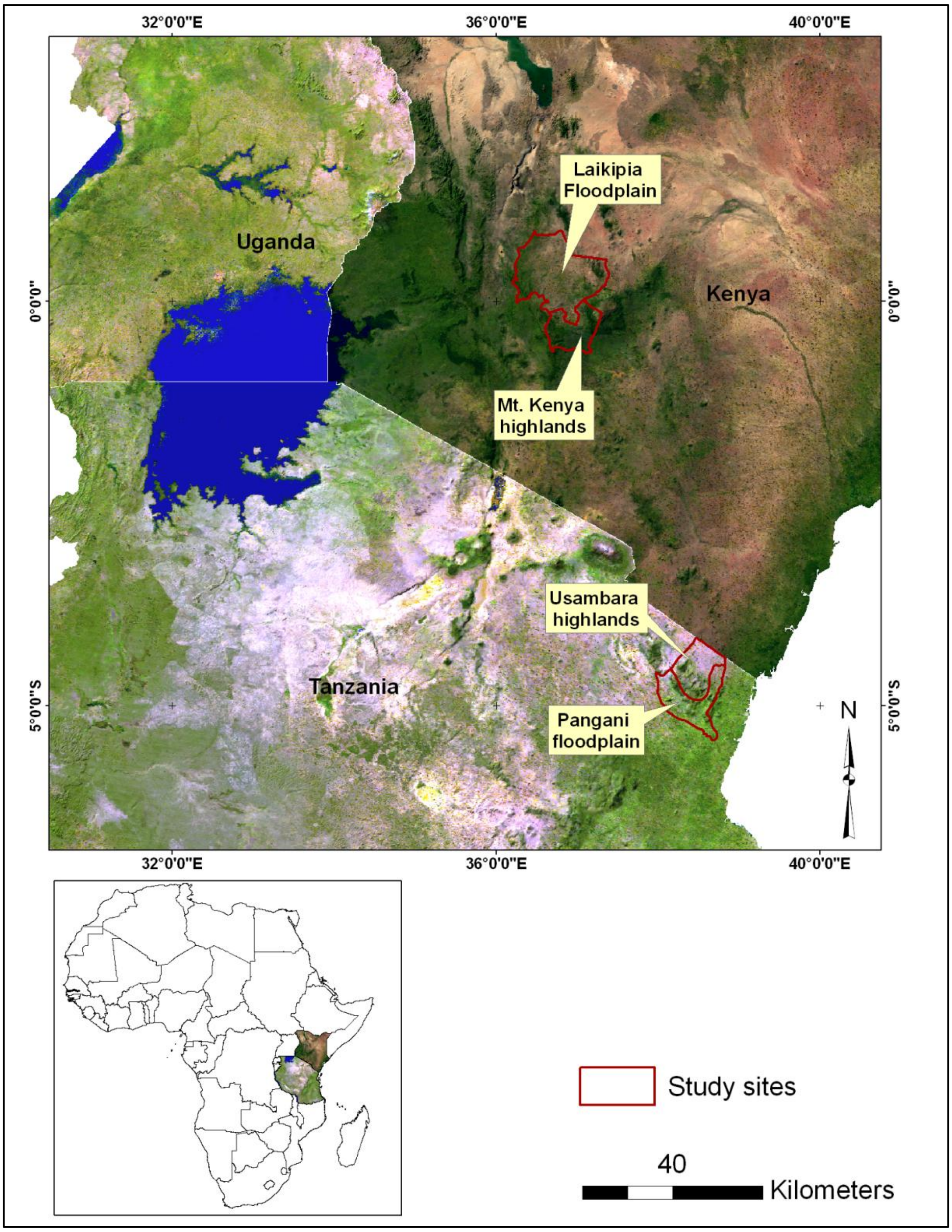


Figure 2.1: Location of the study sites in Kenya and Tanzania with a false colour landsat image at the background
Source: Map library

2.2.1 The Mt. Kenya highland study area

The Mt. Kenya highland study area lies between longitudes 36°53’28’’ and 37°9’55’’E and latitudes 0°23’56’’S to 0°33’5’’S in Nyeri and Karatina towns, rising from 1570 to 1835 m above sea level (Figure 2.1). The main physical features of the district are Mt. Kenya (5199m) to the east and the Aberdare range (3999m) to the west. These mountains are of volcanic origin; they determine relief, climate and soils, and consequently, the agricultural potential of the district. The rainfall is bimodal in pattern. The long rains fall from March to June with peaks in April and short rains commence in late September to November. The annual rainfall ranges between 900-1500 mm per year (Figure 2.2). There is also a short dry season from December to February and a long dry season between May and September.

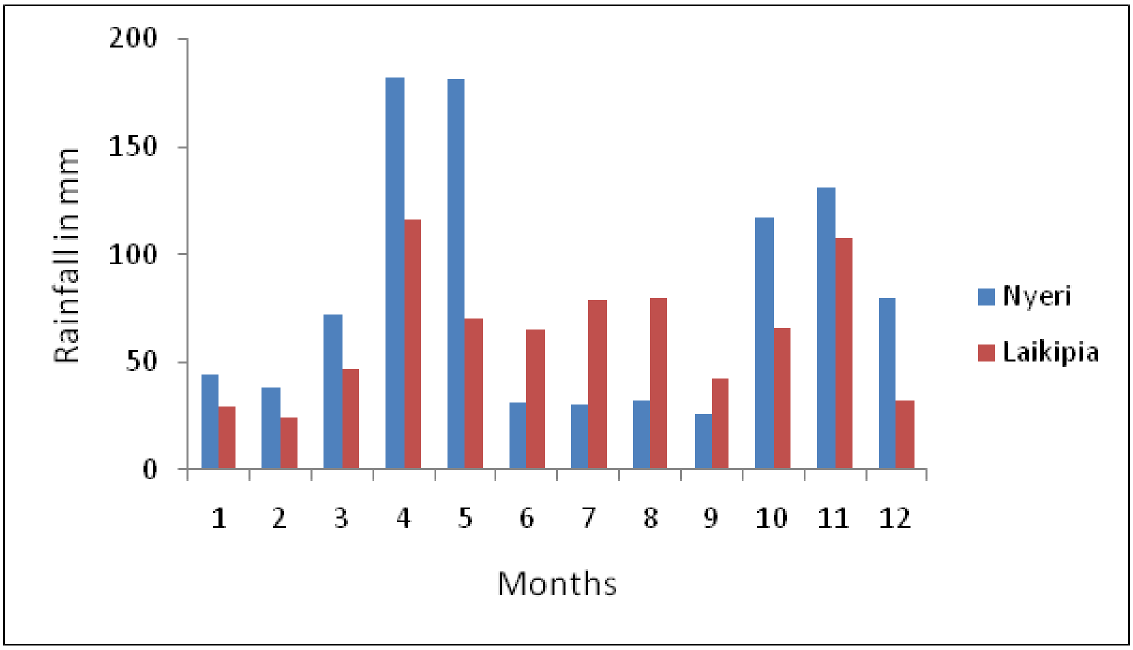


Figure 2.2: Monthly average rainfall at the Kenyan sites (2008)
Source: Nyeri &Rumuruti meteorological stations

The Mt. Kenya highlands are drained by several streams, most of which are permanent with narrow valley bottoms, which are intensively used for cultivation. The dominant vegetation includes *Podocarpus falcatus* forest on the drier northwest and South Western slopes to 1,850m and *Croton sylvaticus – Premna* forest on the north eastern slopes between 1,500m and 1,800m (KWS, 1993). On the dry lower eastern slopes up to 1,800m is the leguminous *Newtonia buchananii* forest. The mid to high-level slopes are dominated by *Juniperus procera–Nuxia congesta–Podocarpus falcatus* forests on the drier eastern parts and the more open (much-logged) cedar with the East African olive (*Juniperus procera–Olea capensis*) forest on the drier west to northeast slopes to about 2,300m. Within the wetlands the most common species are Asteraceae *(Galinsoga parviflora*, *Bidens pilosa*), Poaceae (*Leersis hexandra*), Cyperaceae (*Cyperus javanicus*) Apiaceae (*Hydrocotyle sibthorpioides*) and Commelinaceae (*Commelina benghalensis)*. The total population is 693,664 with annual growth rate of 2.54% (The Administration Police, 2004).

2.2.2 The Laikipia flood plain study site

The Laikipia flood plain study site covers part of Rumuruti and Nyahururu towns in the Rift Valley Province. The overall morphology of Laikipia District is a saucer-shaped plateau formed by extrusive Miocene phonolites (Thenya, 2001). The study site is located between Longitude 36°12’17’’ to 36°45’16’’ E and Latitude 0°28’51’’ N and 0°7’28’’S with altitude ranging from 1780 to 1835 m above sea level (Figure 2.1). It is on the lee ward side of Mount Kenya and Aberdares, which strongly influence the climate of the area. Rainfall ranges between 400 and 1000 mm. High rainfall occurs on the southern and western parts with Nyahururu area receiving 900 mm and Rumuruti less than 500 mm.

A few permanent streams exist and most of them are seasonal; usually they dry up during the dry season. The Ewaso Ngiro is the major permanent river, receiving all the tributaries in the drainage basin. Vegetation distribution is strongly influenced by altitudinal pattern, with dry forest occurring on the highest elevations and a gradient of *Acacia*–*Themeda* bush on the plains (Taiti, 1992). As an exception to the overall regional ecological gradient, however, are edaphic communities of *Acacia drepanolobium* Skpestedt in the central plains, escarpment vegetation and secondary communities induced by historical management factors. The gentle warping in the south has contributed to ponding in valleys leading to the formation of swamps, which are mainly dominated by Poaceae (*Cynodon dactylon*), Cyperaceae (*Cyperus rotundus*, *Cyperus papyrus*, and *Cyperus exaltatus*) and Asteraceae (*Galinsoga parviflora*). The total population is 429,300 and is rising at an annual rate of 2.6% (The Administration Police, 2004). The main economic activities in the area are agriculture, ranching, livestock keeping and small scale business.

2.2.3 The Usambara highlands site

The West Usambara highlands site is located in Lushoto district, which is one of the 8 districts of Tanga region. The district covers the whole of West Usambara Mountain, which is a part of the Eastern Arc Mountains. The sites extend from 38°13'17” to 38°27'59" E and 4°37'38” to 4°51'44.12"S rising from 1320 to 1890 m above sea level (Figure 2.3). Rainfall is bimodal; the long rains fall from March to June with peaks in April and the short rains are in October to December with a dry spell from January to February (Figure 2.3).

The district is drained by three main rivers, namely Umba, Sine and Lwengera but there are numerous small tributaries some of which are permanent and are intensively used for irrigated agriculture. The dominant plant species include *Podocarpus usambarensis, Olea hochleri,* shrubs like *Euclea, Myrsine, Toddalia* and *Maba buxifolia* and *Juniperus procera* (Pitt-Schenkel, 1938, Hamilton, *et al*., 1989). Within the inland valleys, Poaceae (*Cynodon dactylon*), Asteraceae (*Galinsonga parviflora*), Typhaceae (*Typha capensis*), Chenopodiaceae (*Chenopodium opulifolium*) and Cyperaceae (*Cyperus rotundus)* are the most dominant plant species. Lushoto is one of densely populated areas of Tanzania; it has an average population density of 120 persons per square kilometre (Sokoni & Shechambo, 2005). According to the 2002 population census, the total population of Lushoto district was 419,970 (United Republic of Tanzania, 2003). The major economic activities are agriculture, forestry (logging), livestock keeping and horticulture.

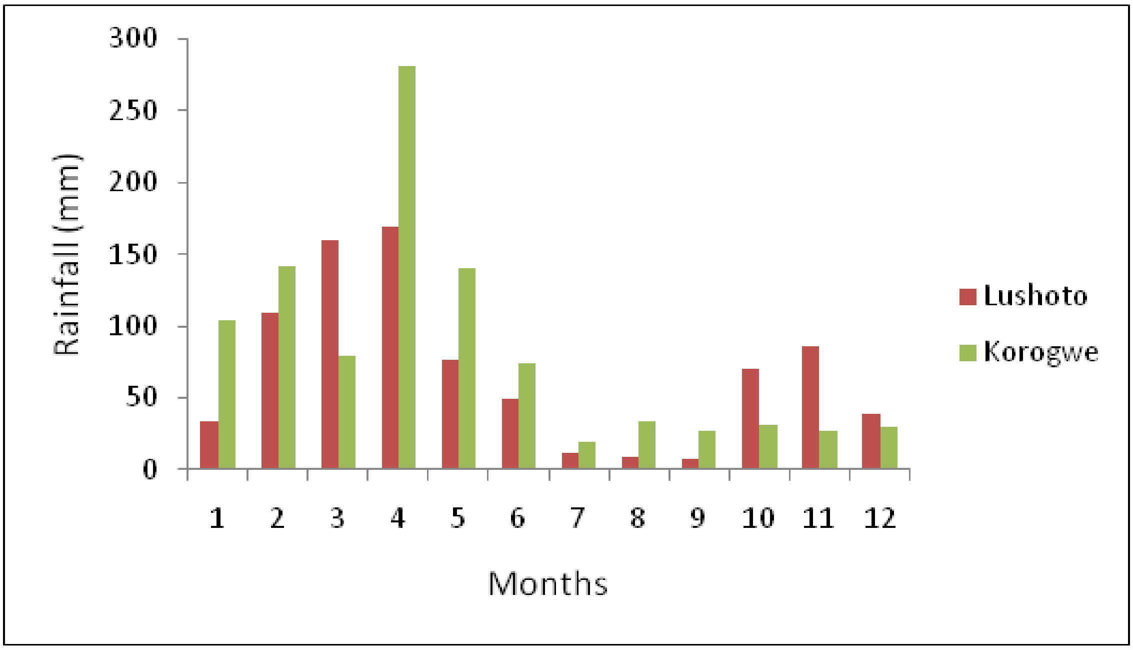


Figure 2.3: Monthly average rainfall at the Tanzanian sites (2008)
Source: Lushoto and Korogwe meteorological stations

2.2.4 The Pangani flood plain

The fourth site is the Pangani flood plain, which is located in Korogwe district also in Tanga region (Figure 2.1). The site is found between Longitudes 38°18'48” and 38°35'49"E and Latitudes 4°51'32” to 5°6'56"S, with altitude ranging between 280 and 380m above sea level. The total area of the district is 3,756 Km^2. The annual rainfall ranges from 500 to1000 mm (Figure 2.3). There are two rainfall seasons; the long rains between March and June, and the short rains between September and November. The study site is on the lee ward side of the Usambara West Mountain and, therefore, receives less rain of between 500 and 800 mm annually, and bears some characteristics of semi arid areas.

The Pangani River and its tributaries Mbeza, Kizara, and Vuluni are the most important drainage system; other rivers include Mkomazi, Soni and Lwengera. Several seasonal streams exist, which dry quickly as the dry season sets. The dominant vegetation includes grasslands dominated by *Penisetum spp, Acacia spp and Cynadon spp*. *Mangifera spp* are also dominant. Within the swamps Cyperaceae (*Cyperus papyrus),* Commelinaceae *(Commelina benghalensis),* Asteraceae *(Pentodon pentandrus, Ageratum conyzoides)* and other various shrub vegetation are the most common. The area is sparsely populated, with a density of 69 persons per square kilometre. The total population in 2002 was 260,791 with an annual growth rate of 1.2%. Agriculture is the main economic activity, but since the district is on the central highway between Arusha and Dar es Salaam commercial activities also prevail (URT, 2007).

2.3 Geology and soils

The soils in the study sites vary with relief and parent material as illustrated in Table 2.2. The Pangani flood plain is dominated by unconsolidated sediment material, forming alluvial Luvisols and Fluvisols in the plain and Vertisols in the fringe areas. In Laikipia, on the other hand, the parent material is granite or tertiary basic igneous rocks, forming Lithosols and Xerosols in the uplands, while alluvial deposits from Fluvisols in the floodplains. The parent material around Mount Kenya is of volcanic origin, forming Andosols and Nitisols, while it is mainly gneiss in the Usambara Mountains, forming mainly Ferralsols. At both sites, the soils in the valley bottom lands are classified as Gleysols.

Table 2.2: Parent material, soil types, landforms, and dominant wetland types in the study areas

Country	Tanzania		Kenya	
	Pangani	Usambaras	Laikipia	Mt. Kenya
Parent rock	Unconsolidated alluvial sediments	Granite and Gneiss	Granite, alluvial deposits	Volcanic and metamorphic rocks
Upland soil	Acrisol,Vertisol	Acrisols,Ferralsol Gleysol,	Lithosol, Xerosol,	Nitisol, Andosol Fluvisol
Lowland soil	Luvisol,Fluvisol	Luvisol	Fluvisol	
Landscape	Flat lowland plain	Undulating mountain highland	Undulating highland slopes and plain	Undulating mountainous highlands
Dominant wetland type	Floodplain	Narrow Inland valleys with steep slopes	Floodplains and wide inland valleys	Narrow to wide inland valleys with gentle slopes

Source: De Puaw, (1984); Jaetzold *et al*., (2006); Sombroek *et al*., (1982); FAO (1988).

3 Detection of small wetlands with optical and microwave remote sensing data

This chapter deals with the first objective of this study. An introduction is initially given on the significance of remote sensing in detection and monitoring of wetland ecosystems. The hypothesis and objective which guides this part of the study are stated. A review of literature on how optical and microwave remote sensing works in wetlands detection is provided as well as data types and techniques used in processing the data. Results are presented and discussed and conclusions are drawn based on the findings. It is important to note that microwave remote sensing data and analysis are part of an input from work done previously for a Masters thesis by Ms. Pamela Nienkemper. Her work on small wetlands detection using microwave data focused in the Pangani flood plain. The study complimented the optical data for one site due to unavailability of data for other sites and time constraint.

3.1 Introduction

Detection and monitoring of wetland ecosystems has assumed increasing importance in light of their social economic benefits and the constant pressures they sustain from land use change and development. The magnitude of this task coupled with the dynamic nature and inaccessibility of wetland ecosystems has limited the use of on-ground methods and encouraged the use of various remote sensing platforms, given their ability to record large areas in comparatively short time periods (Rebelo *et al.,* 2009a). Sensors in the optical range of the electromagnetic spectrum play a very important role in the process but their capability is limited by their inability to penetrate clouds, which is of high relevance in the (sub) humid tropics. As radar operates in the long wave portion of the spectrum, it offers complementary and supplementary data to sensors operating in the optical and thermal bands (Baghdadi *et al.,* 2001). Despite the difficulties of in situ measurements in wetlands, field survey still plays an important role in initial inventory and in ground truthing of the remote sensing data.

3.2 Hypothesis and objectives

In Tanzania and Kenya there exists high diversity of small wetlands. The wetlands are of different sizes and types and are widely distributed over space. It is thus hypothesized that the wetlands can be detected using multi-spatial and multi-spectral resolution data sets from both optical and microwave remote sensing sensors. The detection process leads to the achievement of the following objectives:-

1. To identify and locate where the small wetlands occur
2. To differentiate the small wetlands in terms of type, size, density and spatial distribution
3. To create wetlands' location maps

3.3 Literature review

Based on energy sources there is passive and active remote sensing. Passive remote sensing detects available electromagnetic energy from natural sources, such as sunlight. In contrast, active remote sensing depends on an artificial illumination source, such as radar (Mather, 1987). Depending on the range of electromagnetic spectrum, optical, thermal and microwave types of remote sensing systems are differentiated. The optical remote sensing sensor devices operate in the visible, near infrared, middle infrared and short wave infrared portions of the electromagnetic spectrum. These devices are sensitive to the wavelengths ranging from 300 nm to 3000 nm. Thermal remote sensing records the energy emitted from the earth features in the wavelength range of 3000 nm to 5000 nm and 8000 nm to 14000 nm (Egan, 2003). The previous range is related to high temperature phenomenon like forest fire and the latter to the general earth features having lower temperatures (urban or island heat). In contrast, microwave remote sensing records the back scattered microwaves in the wavelength range of 1 mm to 1 m of the electromagnetic spectrum (Jensen, 1996). Most of the microwave sensors (e.g. Terra SAR-X, ASAR, and PALSAR) are active sensors having their own sources of energy and operate almost regardless of weather. The following paragraphs provide an overview on optical and microwave remote sensing and their role in wetland detection and mapping.

3.3.1 Optical remote sensing

As fore introduced optical remote sensing makes use of visible, near infrared and short-wave infrared sensors to form images of the earth's surface by detecting the solar radiation reflected from targets on the ground. Different materials reflect and absorb solar radiation differently at varied wavelengths. Thus, the targets can be differentiated by their spectral signatures in the remotely sensed images. Depending on the number of spectral bands optical remote sensing systems are classified into four types i.e. panchromatic, multispectral, super spectral and hyper spectral (Liew, 2001). They operate on same principles except that they measure the reflected or emitted energy over different wave lengths of the electromagnetic spectrum and spatial resolution (Asrar, 1989).

Optical remote sensing has been widely used for detection and mapping of wetlands (Rundguist *et al*., 2001). Different types of optical data like aerial photographs and satellite images have been used in wetland studies (Ozesmi & Bauer, 2002). Optical sensors such as LANDSAT Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+), and SPOT High-Resolution Visible (HRV) have shown promise in identifying and monitoring wetland types, hydrologic regimes and landscape changes (Ramsey & Laine, 1997; Kindscher *et al.,* 1997; Haack, 1996). Satellite data have many advantages in mapping wetlands; they are in digital format and relatively easy to integrate into a geographic information system (GIS). Using satellite remotely sensed data for land cover classification is less costly and less time consuming than aerial photography for large geographic areas (Davidson & Finlayson, 2007). Satellite remote sensing can be especially appropriate for wetland inventories and monitoring in developing countries, where funds are limited and little information is available on wetland areas (Ozesmi & Bauer, 2002; Haack, 1996).

Satellite data also cover large areas and therefore wetlands and their surroundings can be mapped. However, because of the spatial resolution of most satellite images (20 – 30 m), it is difficult to identify small or long, narrow wetlands. Also fewer types of wetlands can be identified compared to aerial photography. It is difficult to separate different wetland types from one another because of the overlap in their spectral signatures (Gluck *et al.,* 1996). The overlap in spectral signatures between wetlands and other classes such as agricultural crops and upland forests limits accuracy in mapping with satellite imagery. In order to separate wetlands from uplands, it is usually advantageous to use satellite images from dates when the wetlands are at their highest water levels (Ozesmi & Bauer, 2002). However, many wetlands are only flooded at certain times during the year. Given a satellite's fixed orbit and return interval, it is difficult to capture the optimum water conditions for wetland detection. In addition, lack of cloud free data often prevents the use of optical satellite data. Thus aerial photography is generally preferred for detailed mapping of wetlands, especially if many different vegetation types must be mapped. Synergistic use of both satellite and aerial photography is recommended for better results (Ramsey & Laine, 1997).

3.3.2 Microwave remote sensing

Two main categories of radar systems can be distinguished: Real Aperture Radar (RAR) and Synthetic Aperture Radar (SAR). Since the RAR operating mode is usually airborne (Lewis & Henderson, 1998), it is not further discussed in this study. As the name indicates, SAR systems operate with a short physical antenna, but synthesize the effect of a long antenna through the forward motion of the spacecraft. The obvious advantages of such a system are the possibility to operate even at far ranges with an effectively narrow beam width and the production of highly resolved images (Lewis & Henderson, 1998; Lillesand *et al.,* 2008).

By virtue of day and night observation and cloud penetration capability the active microwave data from Synthetic Aperture Radar (SAR) offers a tremendous potential not only for mapping and monitoring the extent of land submergence but also in identifying the wetland vegetation (Baghdadi *et al.,* 2001). In addition, radar imaging has been found to be extremely useful in delineating flood water boundaries beneath vegetation canopies (Henderson & Lewis, 2008; Baghdadi *et al.,* 2001; Kushwaha, *et al.,* 2000). The term RADAR means Radio Detection and Ranging and is an active microwave sensing system (Campbell, 1996; Lillesand *et al.,* 2008). It is called active since the antenna is both a transmitter and a receiver of electromagnetic radiation in the microwave portion of the spectrum. Hence, data acquisition is independent of solar radiation. Consequently, operations are possible during day and night.

Another characteristic feature of microwave energy is the capability of penetrating clouds, smoke, light rain and haze, which implies that operations are almost irrespective of weather conditions (Lillesand *et al.,* 2008; Kushwaha *et al.,* 2000; Lewis & Henderson, 1998; Campbell, 1996). Normally the antenna fixed to the spacecraft points to the side. Such systems are called side-looking radar (SLR) (Figure 3.1). The basic operation of side-looking radar systems is the production of microwave energy, which is transmitted in short pulses from the antenna. The term for a chain of microwave pulses is pulse repetition frequency (PRF). The system switches between the transmission and receiver mode. It then records the time between the transmission of a signal and the return of the backscatter radiation (Lillesand *et al.,* 2008; Lewis & Henderson, 1998)

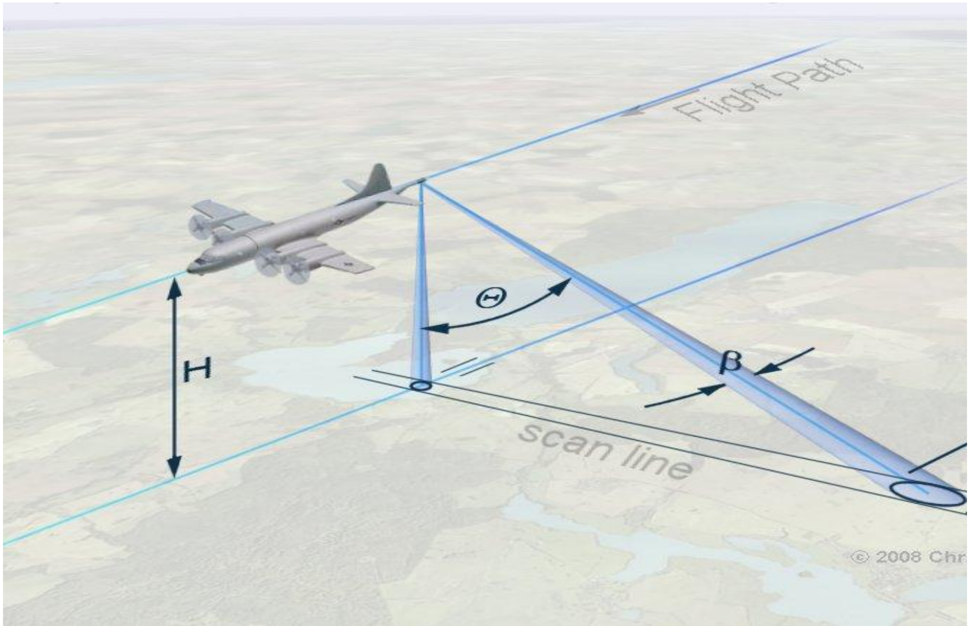


Figure 3.1: Configuration of side-looking airborne radar (SLAR) system
Source: Wolf (2008)

The interaction between the terrain surface and the electromagnetic radiation is influenced by the dielectric constant. Dry natural materials like soils and rocks have low dielectric constant ranging from 3-8 and water has 80, thus intensity of backscatter is influenced by moisture content of the illuminated material (Lewis & Handerson, 1998). The higher the moisture content the higher dielectric constant and the stronger the signal, and the vice versa is true. In addition the dielectric constant controls the penetration depth depending on wavelengths (Figure 3.2). Low moisture content and low dielectric constant result in an increased penetration depth, especially at longer wavelength (Figure 3.2).

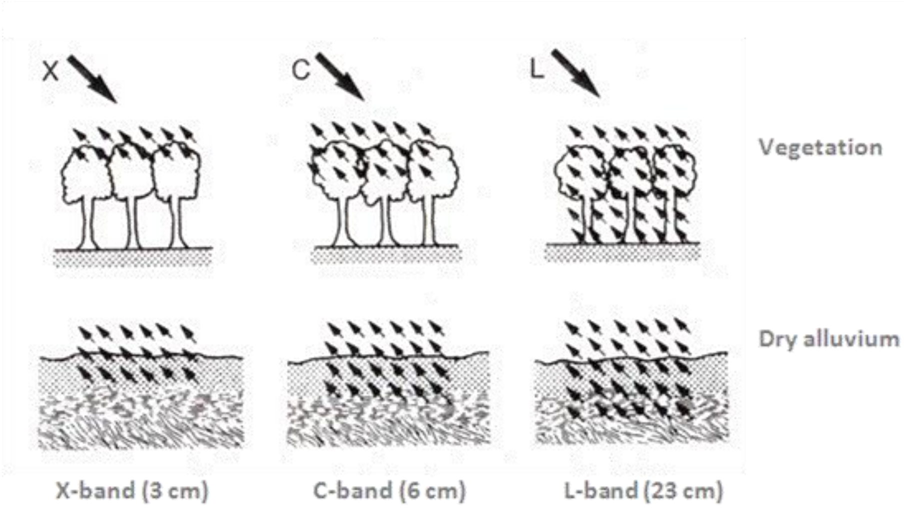


Figure 3.2: Penetration of microwave depths depending on wavelengths and dielectric constant.
Source: modified according to Albertz (2007)

The strengths of Synthetic Aperture Radar (SAR) as an appropriate tool for wetlands detection reside in the sensitivity of radar backscatter to the moisture content of terrain media and the sensitivity of the radar cross-sections to the geometry of the vegetation growing on the terrain surface. The use of SAR in monitoring changes in wetlands moisture increased recently. Hess *et al*. (1995) studied the use of multi frequency (C and L bands) and polarimetric radar backscattering features to map flooding and vegetation in the Amazon floodplain. They suggested from their findings that multi frequency polarimetric SAR can accurately map the extent of inundation on forested floodplains. Kasischke *et al.* (1997, 1995) demonstrated that ERS-1 C-band SAR imagery could be used to discriminate between wetland and non-wetland vegetation.

Analyses of SEASAT synthetic-aperture radar (SAR) data provide evidence that low-frequency systems (L-band) can facilitate the delineation of land-water interfaces beneath a canopy of vegetation (Rundguist *et al*., 2001). With the increasing availability and usage of operational SAR sensors like RADARSAT, Terra SAR-X and PALSAR it has become practical to map wetland ecosystems around the world regardless of cloud or vegetation cover

(Kasischke & Bourgeau- Chavez, 1997). Although the lower microwave frequencies (i.e., longer wavelengths such as P- and L-band) are useful in penetrating canopies of vegetation, higher frequencies (i.e., shorter wavelengths such as X-band) have been used to detect open-surface water (Henderson & Lewis, 2008). The detection of general wetlands can be made in the field or by use of a combination of fieldwork and aerial photographs or other remote sensor technologies (Lyon, 2001). In this study, both optical and microwave data were used in attempting to identify and delineate small wetlands.

3.4 Materials and methods

Four study sites, namely, Mt. Kenya highlands, Laikipia plain, Usambara highlands and Pangani plain were investigated. Within each site, several other test sites were selected as shown in Table 3.1. Some of the test sites were not considered for further studies since they were purposely selected for this particular objective. All the four sites were studied with optical data but for the Pangani plain site microwave data was also used as afore noted. A range of materials and methods, which are summarised in Figure 3.3, were used. The figure shows a series of activities, which were involved from data acquisition to the results. The data collection process begun with acquisition of secondary data, which included satellite images, maps, historical aerial photographs and socio-economic information like population of the study areas. The images were then pre-processed to get baseline information to be used for the next steps of data collection and analysis. In summary the whole process involved three important stages of satellite data acquisition, field campaign and aerial survey.

Table 3.1: Super sites and their specific test sites

Super Site	Test site
Mt. Kenya highland	Nyeri Municipality, Karatina (Tegu) and Aberdares isolated sites
Laikipia flood plain	Rumuruti, Ng'arua, Oljoro orok, Pesi and Manguo
Mt. Usambara highlands	Lukozi, Magamba, Bumbuli and Lushoto town
Pangani plain	Magoma, Silabu, Malinda and Korogwe town Isolated sites

Source: Field survey 2008/2009

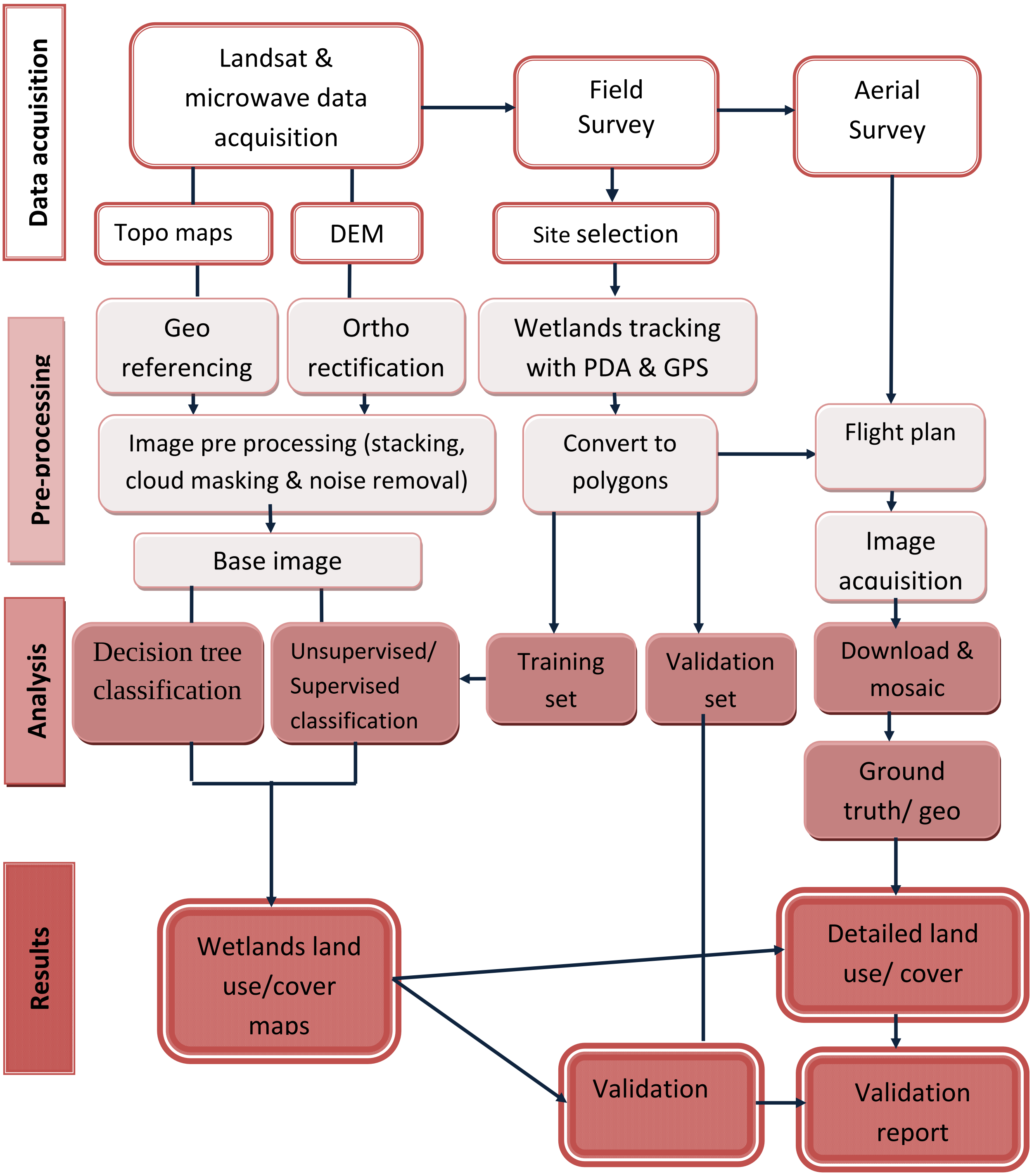


Figure 3.3: Illustration of activities and techniques used in the detection of the wetlands
Source: Own illustration

3.4.1 Data types and pre processing

A number of data sets, which are summarised in Table 3.2 below, were used to achieve the objectives of this part of the study.

Table 3.2: Data types and sources

Type of data	Date of acquisition	Resolution (m)	Source
Aerial photographs	Jan 1961	20	Surveys of Kenya,Surveys
	Feb 1975	30	and Mapping unit Tanzania
	Aug 2008 & Feb 2009	0.25	Aerial survey
Topographical maps	1975	1:50000	Surveys of Kenya & Surveys and Mapping Unit Tanzania
ASTER DEM	2003	30	USGS[1]
ASTER images	2006	15	USGS
Mt. Kenya highlands (169/060)	20-01-2006		
Laikipia (169/060)	21-09-2006		
LANDSAT ETM+		30	USGS
Mt. Kenya highlands (169/060)	12-01-2003		
Laikipia (169/060)	04 -02-2003		
Usambara (167/063)	06-02-2003		
SRTM		90	CGIR[2]
Laikipia 44_12			
Mt. Kenya highlands 44_13			
Usambara 44_14			
PALSAR	Jan, Feb & March 2008		ESA[3]
ASAR	Sept 2006	30	ESA
Terra SAR X	July 2008	1	DLR[4]

[1]United States Geological Survey
[2]Consultative Group on International Agricultural Research
[3] European Space Agency
[4]Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)

3.4.1.1 Topographical maps

Maps are often the starting point in any inventory or analysis; they can be used to collect point location information; topographic contour information; cultural or planimetric details such as roads, waterways, and dwellings; or public land ownership boundaries. The maps can also provide preliminary information to form a variety of land cover themes or layers in a GIS. Topographical maps were obtained from surveys and mapping units of Kenya and Tanzania at a scale of 1:50000. The maps were scanned and geo-referenced in ArcGIS 9.3 using map control points. The digital maps were used to identify potential sites and locate them during the reconnaissance survey. In addition soil and geological maps were obtained from the Institute of Resource Assessment (IRA) Dar es Salaam, Tanzania.

3.4.1.2 Historical aerial photographs

Aerial photographs have traditionally been used for mapping wetlands and especially small wetlands. Historical aerial photographs were obtained from surveys units of the respective countries. The photographs were scanned at 750 dots per inch (DPI) and mosaics were made using Photoshop CS2 software. Topographical maps and LANDSAT images were used for geo-referencing in ERDAS imagine 9.3 software the flood plain sites with root mean square error (RMS) of 0.5m. For the highlands geo-correction wasn't performed because the spatial resolution of the available SRTM-DEM was too course (90).

3.4.1.3 LANDSAT images

The 2003 LANDSAT ETM+ with a 30m resolution scenes were primarily used in the study. It was intended to use the latest available LANDSAT images but the year 2003 was selected due to anomalies in the current LANDSAT 7 sensor, which are produced with gaps in scan lines. Since some of the wetlands were very small they couldn't be located in some of the images because of the gaps. To be able to use these images the gaps must be filled with subsequent closer date images of the same scene or using anniversary images of the same scene, also called Scan Line Corrector (SLC) ON images, which were taken before the fault in the sensor scanner. By filling the gaps original information quality is altered and that may influence the results. Detailed information on gap filling can be found in http://www.geovar.com/data/satellite/LANDSAT/slc.htm.

The images used in the study were acquired between January and February, which is a peak dry season. During this time the difference between upland and lowland wetlands is at the maximum. Since 2009 archived LANDSAT images are available free of charge at USGS website. Images with quality number 9 and less than 10% clouds were selected. These images were nicely geometrically oriented that they didn't require any geo rectification. The images were later subset in ERDAS imagine 9.3 to cover only the selected study sites.

3.4.1.4 Microwave data

ALOS PALSAR, ENVISAT ASAR and TerraSAR-X were the main microwave data used in this study. The images were obtained from ESA and DLR. ASAR dual (hh, hv); PALSAR fine mode and single mode Terra SAR-X were used. These were geocoded using GAMMA remote sensing software and multilooked to enable further analysis. DEM was used to simulate the topographic phase and transformation of data in radar geometry (slant to ground range map) to map coordinate was performed. Geometrical correction of ALOS PALSAR data failed due to displacement, which ranged between 360m and 420m (calculated based on LANDSAT, ENVISAT-ASAR images). The registration was performed again using image to image registration tool in ENVI 4.3 software. The total RMS was between 2.78-2.92 pixels. These values imply certain impreciseness that could not be avoided in the scope of this study.

The output data type was generic binary, which was then converted to type IEEE 32 bit float to be able to use it in ENVI or ERDAS. These images were re-projected to UTM WGS 84. Speckle filter was then applied to improve the image quality. Gamma-map filter, which assumes a gamma distribution for the speckle noise, was chosen. This filter is recently seen to be more valid for regions covered with natural vegetation than assuming a Gaussian distribution like what most other common filters do (Capstick & Harris, 2001, Xiao *et al.,* 2003). Several windows were tested and finally 5x5 was considered appropriate to reduce speckle without over-smoothing the image and hence blurring the edges. Regarding the TerraSAR-X scene, a 7x7 moving window size appeared to be more efficient to reduce speckle properly while preserving precise edges and features.

For the dual polarized ALOS-PALSAR and ENVISAT-ASAR scenes, mean-value images were created by summing-up the two polarization channels (hh and hv) and calculating the mean DN value. Furthermore, a transformation to band ratios was performed resulting in a L-band $\sigma^0_{hh}/\sigma^0_{hv}$ ratio image and a C-band $\sigma^0_{hh}/\sigma^0_{hv}$ ratio image. As indicated by Dubios *et al.* (1995) L-band $\sigma^0_{hv}/\sigma^0_{vv}$ ratio images are good indicators in the context of soil moisture estimation using imaging radars since surface roughness highly influences the feasibility of soil moisture detection. The last preprocessing step was image segmentation, which was performed by Definiens Developer 7 software, which is an updated version of the eCognition software package.

Within the segmentation process pixels are merged to image objects and pixel values are replaced by the mean value of the particular object (Li & Wenjun, 2005). The segmentation was solely applied to the ALOS-PALSAR and ENVISAT-ASAR. TerraSAR-X data were not segmented as this process would degrade the data quality. Five segmentation levels were performed in hierarchical manner using different scale parameters (Table 3.3). One comprehensive example is given in figures 3.4 and 3.5 using the hv-polarized PALSAR scene 2008-05-02 to demonstrate how the segmentation was done. Since the microwave remote sensing data used in this study featured different spatial resolutions, polarizations, wavelengths and backscatter brightness characteristics, the segmentation level was adjusted to the individual scenes.

Table 3.3: Segmentation levels of input image ALOS-PALSAR 2008-05-02, hv-polarized.

Level	**Scale**	**No. of objects**
L1	120	583
L2	80	1349
L3	40	5459
L4	20	23129
L5	10	94089

Source: Nienkemper (2008)

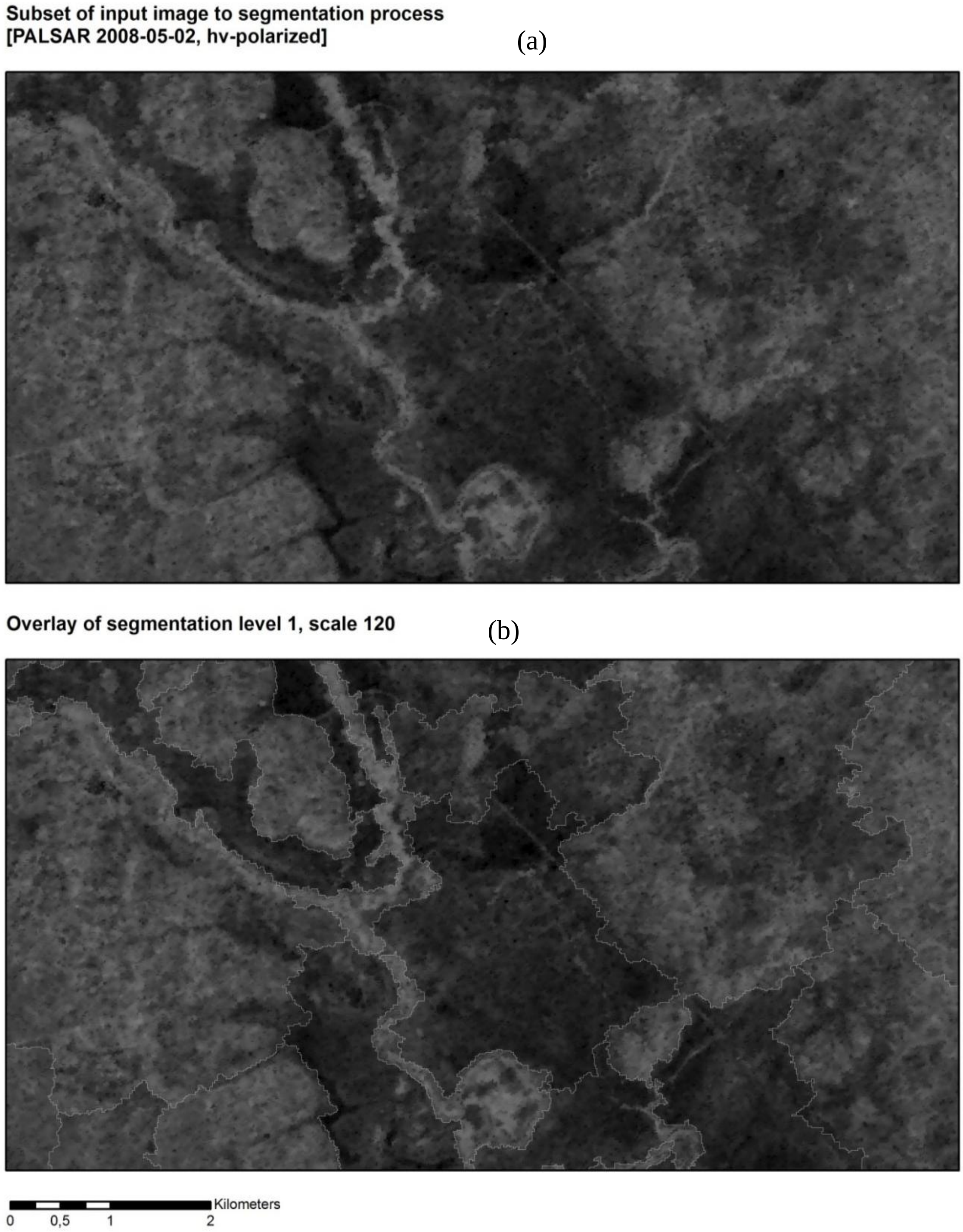


Figure 3.4: An overlay of the filtered ALOS-PALSAR image (2/5/2008) with input image (a) and segmentation level 1 (b)
Source: Nienkemper (2008).

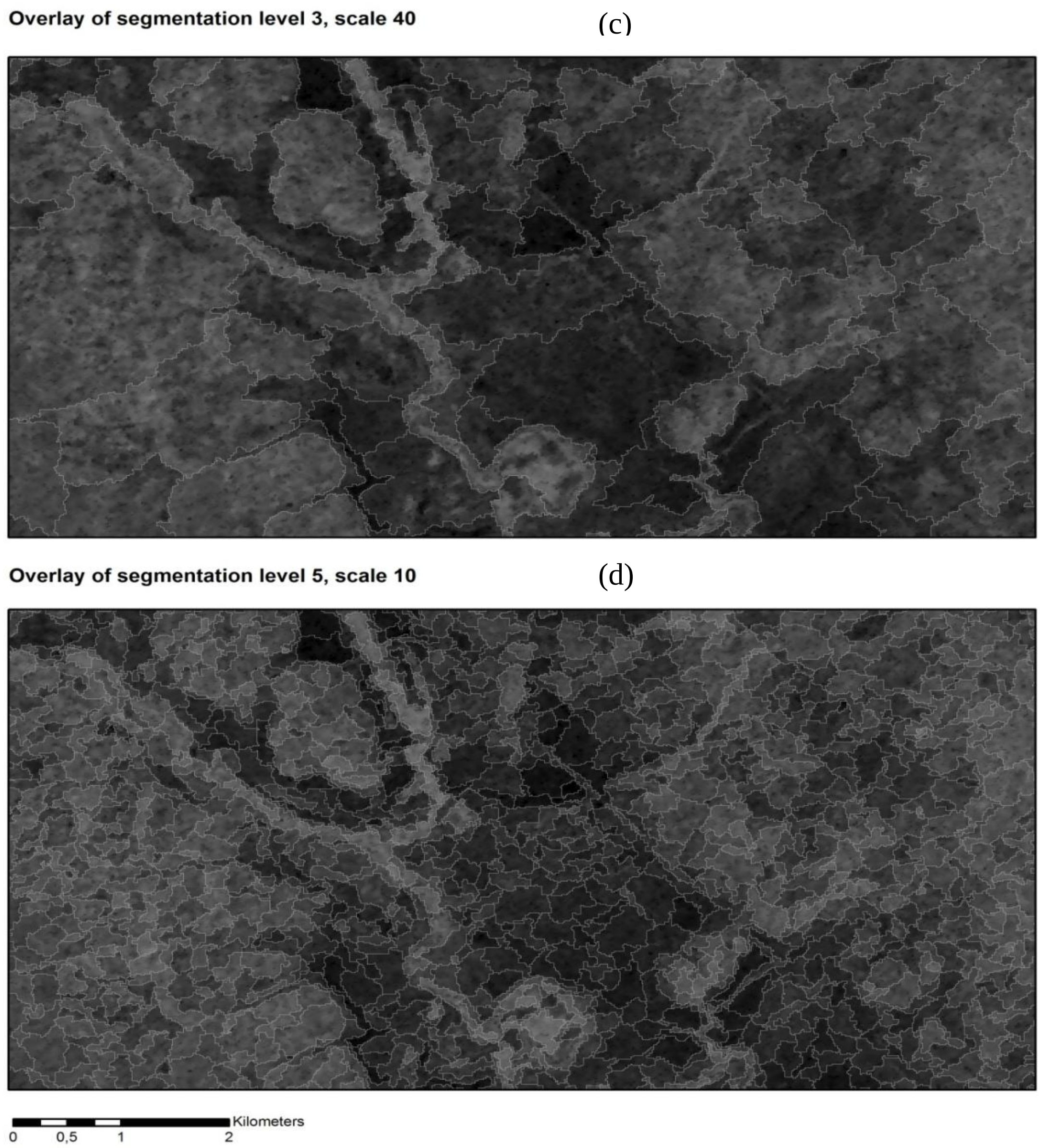


Figure 3.5: The segmentation process part 2: segmentation levels 3 (c) and 5 (d)
Source: Nienkemper (2008).

The upper image of Figure 3.4 (a) displays a subset of the input PALSAR scene. The bottom image (b) shows an overlay of the segment contours of the first segmentation level (L1, scale 120). It is obvious that the objects are still too large since single objects are very heterogeneous exhibiting a wide range of brightness values. The upper image of Figure 3.5 (c) illustrates the overlaid contours of segmentation level 3 (scale 40). The objects are more homogeneous than before, but still too large to sufficiently differentiate the image. The final segmentation level (d), (L5, scale 10) is displayed in the bottom image. The homogeneity of the single segments allows an adequate discrimination of low and high backscatter brightness values.

3.4.1.5 Statistics extraction

Backscatter statistics of pixel and segment based images were examined by extracting different land cover types in optical data, in particular LANDSAT scenes and topographical maps. Samples were selected carefully and were evenly distributed to capture the diversity of land uses and wetlands. The sample data were then saved as shape files in ArcMap then exported to ENVI as 'Region Of Interest' (ROI) to calculate statistics of each 'land cover class', which were exported to Excel and Sigma plot 10.0 for visualization. The outputs are presented in Table 3.4. In general back scatter mean values of water in all images were very low, ranging from -11.47 to -30.98 dB, followed by wetlands, settlements, sparse vegetation and forest. The extracted statistics were used in creating thresholds for decision tree classification for wetlands detection and delineation.

Table 3.4: Overview of backscatter values σ^0 (in dB) of different land cover classes

Data type	Land cover	Min	Max	Mean
PALSAR scene 2008-05-02 hv-polarized	Water	-35,09	-22,88	-30,98
	Settlement	-32,24	-12,032	-20,12
	Short/sparse vegetation	-32,81	-10,1	-19,9
	Forest	-29,60	-4,53	-16,18
	Wetland	**-36,84**	**-14,77**	**-24,14**
PALSAR scene 2008-05-02 hh-polarized	Water	-27,43	-10,80	-22,58
	Settlement	-22,26	10,61	-7,80
	Short/sparse vegetation	-23,10	12,40	-9,89
	Forest	-21,75	7,52	-7,84
	Wetland	**-26,37**	**-0,57**	**-12,20**
PALSAR scene 2008-03-17 hh-polarized	Water	-24,53	-12,38	-21,89
	Settlement	-23,95	11,38	-10,44
	Short/sparse vegetation	-22,44	14,12	-11,61
	Forest	-21,44	8,24	-7,69
	Wetland	**-23,27**	**-4,40**	**-13,75**

PALSAR scene 2008-01-31 hh-polarized	Water	-24,99	-13,61	-20,93
	Settlement	-22,27	11,79	-10,36
	Short/sparse vegetation	-26,11	5,38	-12,29
	Forest	-26,80	7,30	-7,82
	Wetland	**-23,72**	**-2,46**	**-13,83**
ASAR scene 2006-09-21 hv-polarized	Water	-22,90	-11,42	-17,87
	Settlement	-19,95	9,35	-11,33
	Short/sparse vegetation	-22,40	7,354	-10,30
	Forest	-20,88	1,54	-9,89
	Wetland	**-16,83**	**-8,69**	**-12,45**
ASAR scene 2006-09-21 hv-polarized	Water	-14,25	-5,67	-11,47
	Settlement	-16,62	16,47	-5,47
	Short/sparse vegetation	-18,90	10,69	-5,01
	Forest	-19,29	6,31	-5,27
	Wetland	**-10,61**	**-4,80**	**-7,98**

The backscatter values of the Terra SAR-X data were ranging from 30dB to 50dB with a mean value of 41.75. These were extracted from the whole scene since as afore mentioned it was not possible to differentiate land use/cover classes.

3.4.2 Wetlands detection and delineation

Wetlands were detected and delineated using different automated, semi-automated and manual techniques. While automated techniques employed the threshold values of generated DEM/SRTM slopes, Normalized Difference Vegetation Index (NDVI) and classification of optical and microwave data, semi automated involved image enhancement and on screen digitization of the enhanced images and true colour aerial photographs. Finally, manual delineation was done based on field data. Although visual interpretation of the images and maps was involved in the whole process, it was the first and important step. Details of the techniques used are described in the subsequent subsections.

3.4.3 Visual Interpretation

Visual interpretation process involves use of human eyes and a priori knowledge to identify characteristics of features in the images (Lillesand *et al.*, 2008). This was the foremost approach used to identify the study sites in maps, aerial photographs and satellite images. In aerial photographs most fundamental elements of image interpretation include shape, size, pattern, tone, texture, shadows, site, and association (Jensen, 1986). According to Ozesmi & Bauer (2002) early work with satellite imagery used visual interpretation to identify wetlands. Johnson & Barson (1993) in their study of Australian wetlands emphasized on the usefulness of visual analysis of hard copy images in an overview and reconnaissance mapping of wetlands. In this study, black and white aerial photographs, LANDSAT ETM+, ASTER and later colour aerial photographs were visually interpreted for identification and location of the wetlands. Texture, pattern, tone/ colour, association and shape were the most important elements for wetlands interpretation. ASTER images were basically used in the preliminary stages for identification and delineation of wetlands and were not considered for further analysis since only a few scenes were available and some of them especially for Usambara and Pangani plain had cloud over 50%.

3.4.4 Digital Elevation Model (DEM) threshold

ASTER DEMs 30m was used for Mt. Kenya highlands and Laikipia plains while SRTM 90m was used for Pangani plains and Usambara highlands. Though ASTER DEMs could have produced better results due to their spatial resolution, for the Tanzanian sites as afore mentioned they were completely covered by clouds. ASTER DEMs were ordered from Earth Remote Sensing Data Analysis Centre (ERSDAC) ASTER GDS (Japan) and both DEMs and SRTM were downloaded from the United States Geological Survey (USGS) website. The images were then subset to cover areas of interest. Local slope was calculated in degrees using slope function in ArcGIS 9.3. Different slope threshold values were tested for delineation of wetlands and their fringe areas using raster calculator in ArcGIS (Table 3.5). Critical slope values between 6° and 9° were chosen and later used to separate wetlands from non wetlands.

3.4.5 Vegetation indices

Normalised Difference Vegetation Index (NDVI) is among important indices, which are widely employed in wetland studies (Islam *et al.,* 2008; Kulawardhana *et al.,* 2007; Ozesmi & Bauer, 2002). The index derives reflectance values from Red and Near Infrared bands of multispectral remote sensing data. The NDVI from these individuals is calculated as follows:

NDVI=NIR - RED/NIR+ RED

Where, RED and NIR stand for the spectral reflectance measurements acquired in the red and near-infrared regions, respectively. These spectral reflectances are themselves ratios of the reflected over the incoming radiation in each spectral band individually; hence they take on values between 0.0 and 1.0. By design, the NDVI itself thus varies theoretically between -1.0 and +1.0.

To facilitate wetlands identification and delineation NDVI was calculated using LANDSAT ETM+ band 3 (red) and 4 (near infrared) in ERDAS imagine and the thresholds were calculated using raster calculator in ArcGIS. For each site, several empirical thresholds were used in wetlands detection and delineation. The values between 0.10 - 0.712 were responsible for wetlands delineation for the specific sites (Table 3.5).

Table 3.5: Indices and thresholds responsible for wetlands delineation based on LANDSAT-ETM+, ASTER DEM and SRTM.

Site	NDVI (-1.0 to 1.0)	Slope (°)
Laikipia plain	0.27-0.71	<9
Mt. Kenya highlands	0.07-0.15	<6
Pangani plain	0.25-0.6	<8.5
Usambara highlands	0.04-0.37	<5

Source: Own illustration

3.4.6 Unsupervised classification

Unsupervised classification is very often used for wetland studies as it allows natural spectral clusters to be defined with high degree of objectivity (Kindscher *et al.,* 1997). The method involves clustering and cluster labelling. Image clustering was done using Iterative Self Organizing Data analysis (ISODATA) in ERDAS 9.3. No signatures were used in the beginning, the entire images were treated as one cluster and a number of natural clusters were generated after certain times of iteration in a self organizing way. The technique requires large number of clusters, but since only subset images were used and the basic aim was to separate wetlands from other land uses, only 12 clusters were produced. The convergence value was specified as 0.99 for all the data so that the utility would stop processing as soon as 99% is reached and the maximum iteration was specified at 80. Colour scheme option was specified as gray scale to be able to assign new classes in different colours. The resultant clusters were assigned into one of the 12 classes (Figure 3.6 and 3.7), and reference images, maps and historical aerial photographs were used for preliminary cluster labelling.

3.4.7 Supervised classification

Supervised classification was carried out by selecting training sites in ERDAS 9.3 imagine using signature editor and area of interest (aoi) tools. Each training site was defined by a polygon. Area knowledge assisted in the choice of the training sites. Two hundred fifty six random points were also generated for each study site. Some of the points (115) were used in class identification and labelling and the rest (141) were used in accuracy assessment. Minimum distance to mean technique was used in the classification. At first, the twelve classes were verified and but since the aim was to separate wetlands from other land uses/ cover two distinct classes were identified as wetlands and non wetlands.

iop

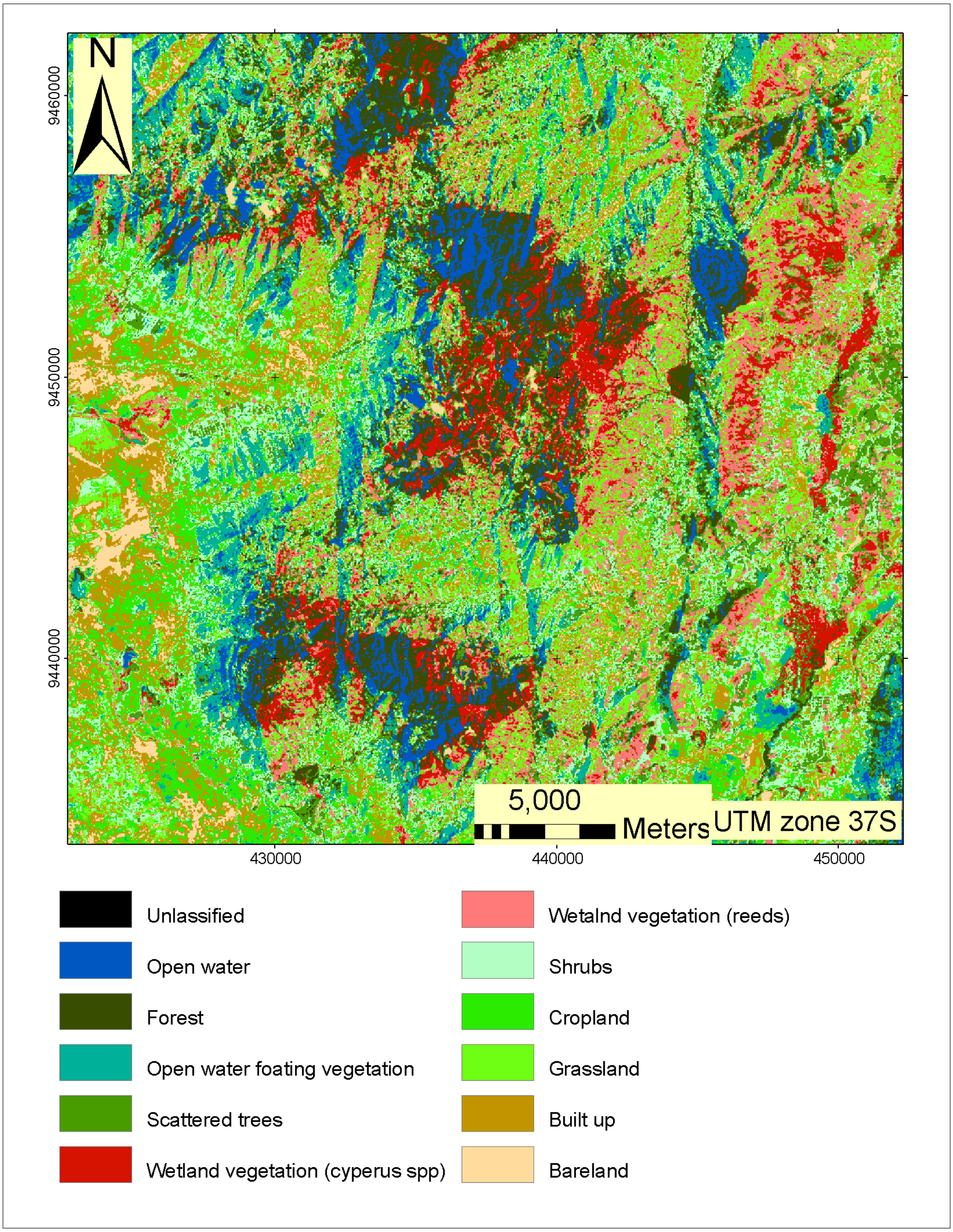


Figure 3.6: Unsupervised classification of the Pangani plain LANDSAT ETM+ image of 06-02- 2003_ Path 167 row 063
Source: Own illustration

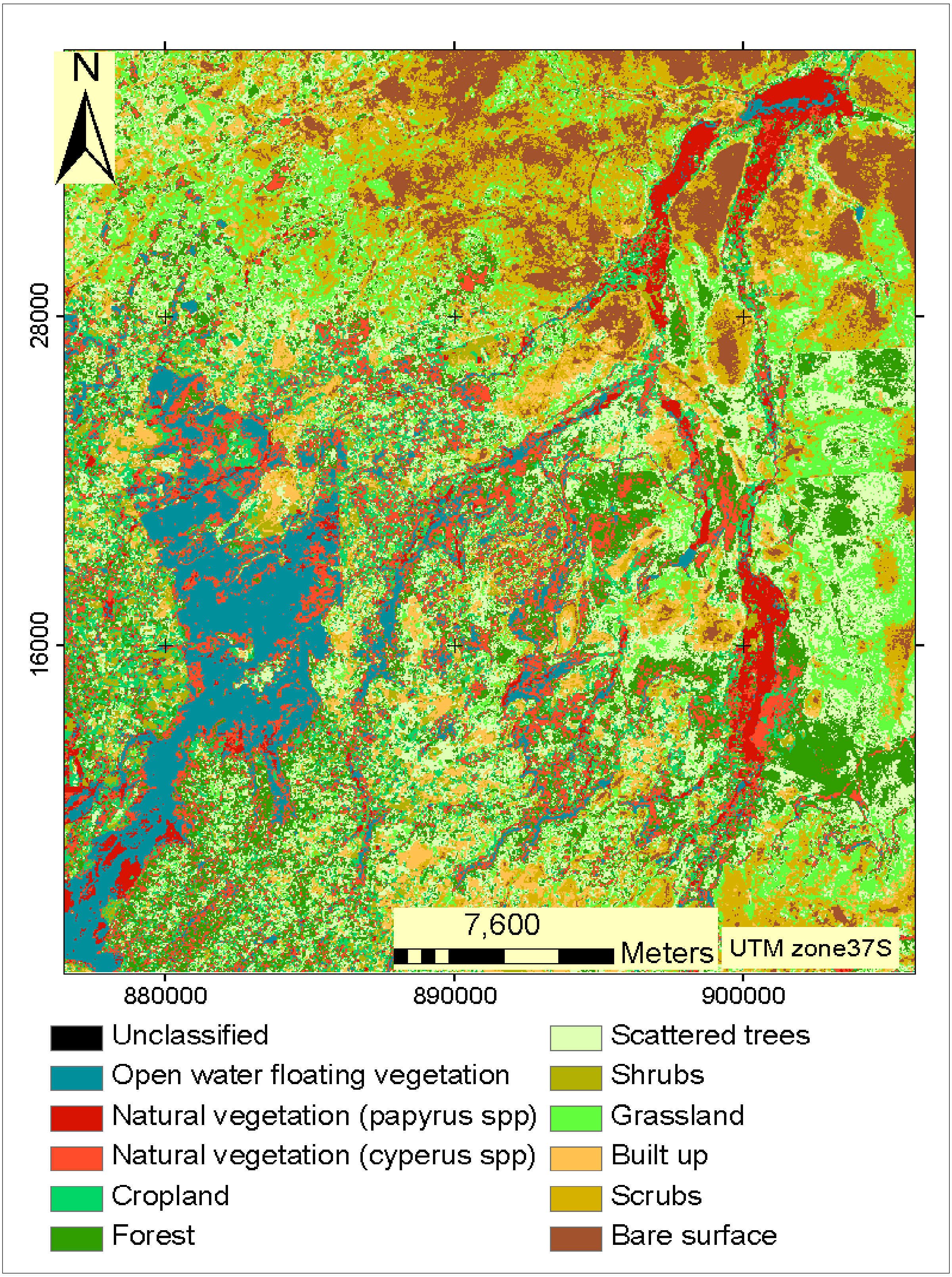


Figure 3.7: Unsupervised classification of the Laikipia plain (b) using LANDSAT ETM+ image of 04 -02-2003_ Path 169/060

Source: Own illustration

3.4.8 Decision tree classification of microwave data

Decision-tree classifiers have been applied in several of the reviewed studies (e.g., Dobson *et al.*, 1995; Hess *et al.,* 2003; Li & Wenjun, 2005 and Ulaby *et al.,* 1996). There are various designs and techniques of building up decision-trees. A detailed overview and discussion of different decision-tree classifiers is given by Safavian & David (1991). Decision-trees applied in the images used in this study are based on a hierarchical concept in a top-down style. At each node a certain threshold or value range is used to separate potential wetland areas from other classes. Therefore, a splitting rule is employed at each node, based on the value of the specific explanatory variable so that the data are divided into increasingly homogeneous subsets based on the particular threshold value (Li & Wenjun, 2005). Referring to C- and L-band data, over one hundred decision-tree setups are built differing with regard to thresholds, polarization and band combination as well as concerning the order of the applied bands. Additionally, segment-based and pixel-based applications of the microwave data is tested since both offer assets and drawbacks. Segmented imagery has the advantage of reduced noise while operating at a pixel-level preserves the sensor resolution (Dobson *et al.,* 1995; Hess *et al.*, 2003). Since all these different decision-tree setups are regarded as part of the empirical derivation of suitable thresholds and efficient rule settings and combinations, only the classifications providing the best results for wetland classes based on the overall accuracy are presented below.

The decision-tree classification of this study was carried out using the software ENVI 4.3. Starting from the root node, that is the first node according to Safavian & Davidson (1991), which no edges enter, the digital elevation model was applied separating the scene in two classes: potential wetland and non wetland. The resulting potential wetland class was featuring slopes lower than 6° and non wetland class slopes above 6°. The underlying assumption was that wetlands generally occurred in level terrain, which was also supported by Li & Wenjun (2005) who applied a slope threshold in their rule-based method for mapping wetlands in Canada. The crucial point, however, was the definition of the site specific slope threshold because if the threshold is too large the application of the DEM is less useful, but if it is too small, wetlands might be excluded from the further classification process (Li & Wenjun, 2005). The threshold applied in this study was derived from the literature (Acres *et al.,* 1985; von der Heyden, 2004). At this node around 48% of the data was excluded from further analysis due to slopes being greater than 6°.

TerraSAR-X was classified in 5 classes using backscatter values on the assumption that a very low backscatter was due to specular reflection, thus representing open water surfaces. Low backscatter values are due to a high degree of moisture, whereas high backscatter returns are representing densely overgrown, dry areas. Hence, it was presumed that dark areas represented water surfaces, whereas bright surfaces delineated dry, overgrown areas. After iteratively applying different threshold values, the final setup of the decision-tree was derived as shown in Figure 3.8. At every node the decision rule with the corresponding thresholds is displayed. Background colors of the derived probability classes were chosen according to the resulting classified image displayed in Figure 3.9**.**

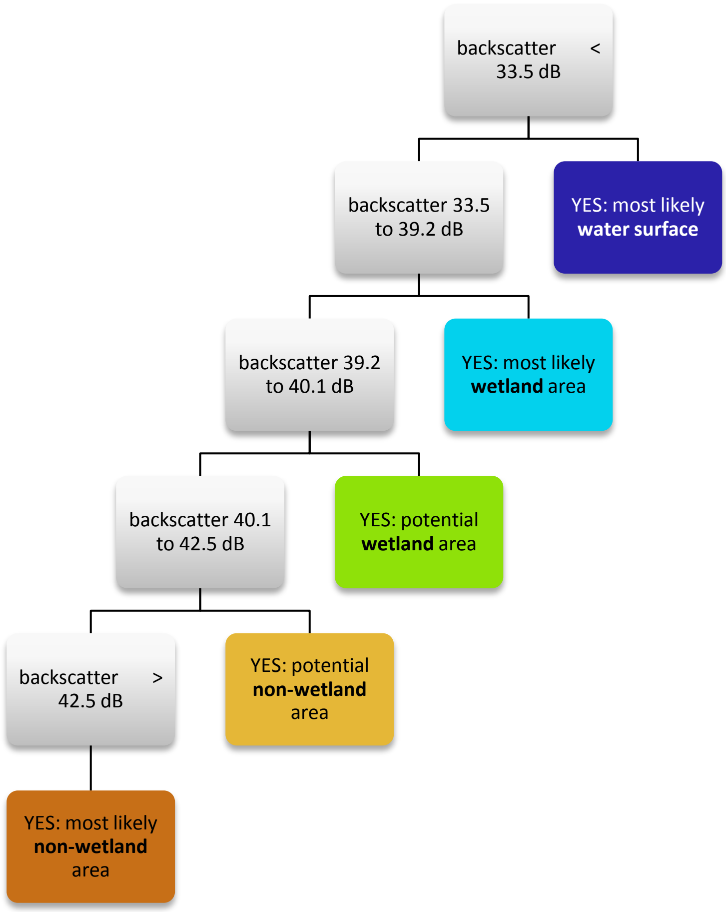


Figure 3.8: Decision tree wetland classification using TerraSAR-X band scene 2008-07-10 (vv)
Source: Nienkemper (2008)

At the root node backscatter values lower than 33.5 dB were excluded from the further classification process and labelled as water surfaces. On this basis, backscatter values in the range of 33.5 to 39.2 dB were regarded to most likely represent wetland areas and backscatter values ranging from 39.2 to 40.1 dB were labelled as potential wetland areas. At the fourth node backscatter values between 40.1 and 42.5 dB were classified as potential non-wetland areas. The final class encompassed values greater than 42.5 dB, which were considered to most likely represent non-wetland areas.

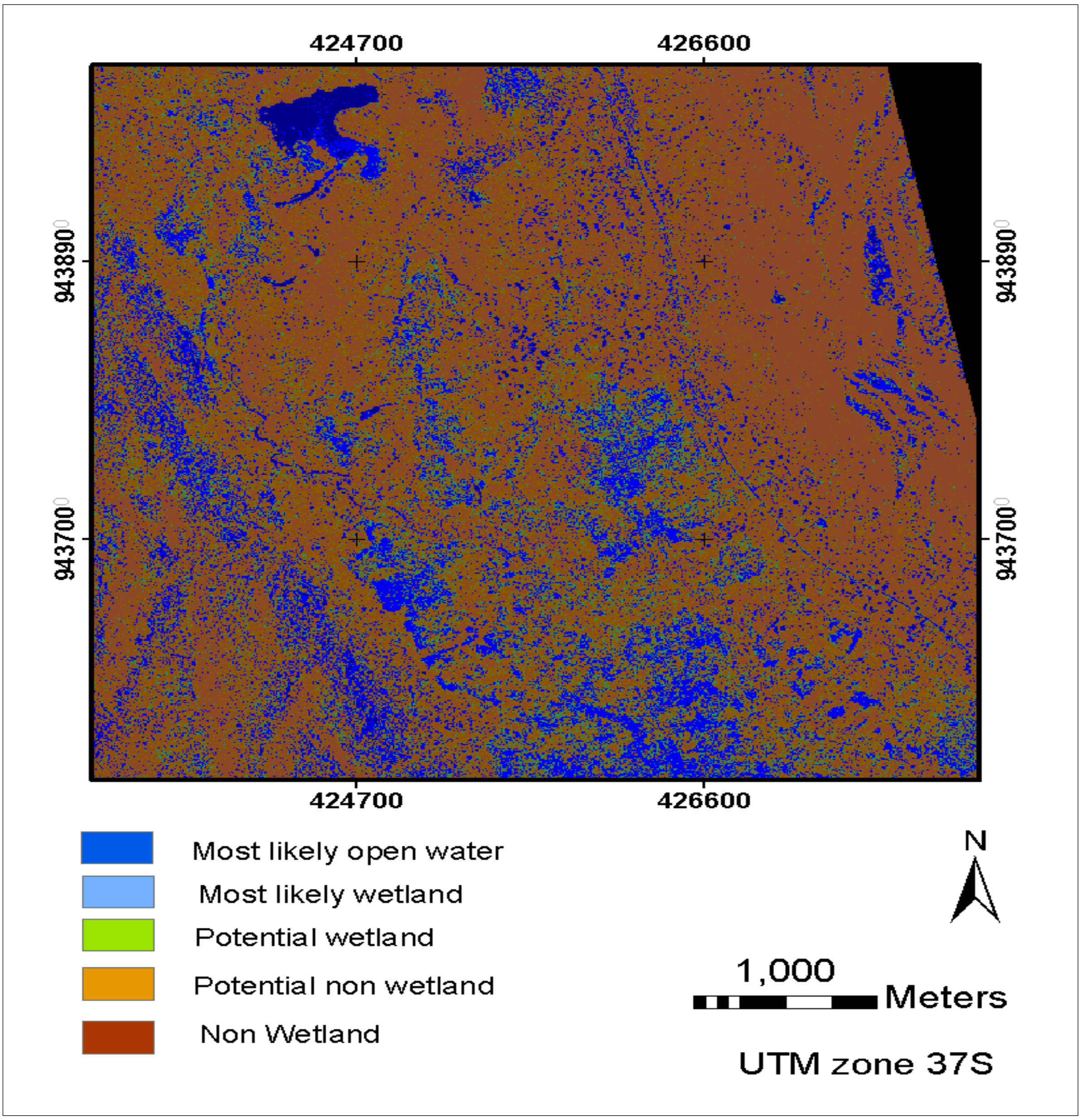


Figure 3.9: Classified X-band image of Pangani plains.
Source: Modified from Nienkemper2008

The classification applied on the C-band data is shown in Figure 3.10, with bands C_{hv+hh}(C-2) data as an example. All areas where the slope exceeds 6° were excluded at the root node. Then the segmented C_{mean}-band was applied with a co-domain ranging from -15.4 to -8.9 dB. Values out of range set up the second non-wetland class. After that the C_{hh}-band (co-domain -14 to -6.8) and the C_{hv}-band (co-domain -17.5 to -11) were applied. Backscatter values from areas that met either one condition were considered to be potential wetland areas. Once more, the non-wetland classes combined to one class resulting in a binary wetland/non-wetland classification of the C-band data. The three non-wetland classes were combined to one non-wetland class to attain a binary classification of non-wetland and wetland areas (Figure 3.11). A similar approach was used for single band C_{hv} (C-1), single band L_{hh} (L-1) and fused band L_{hh+hv} (L-2).

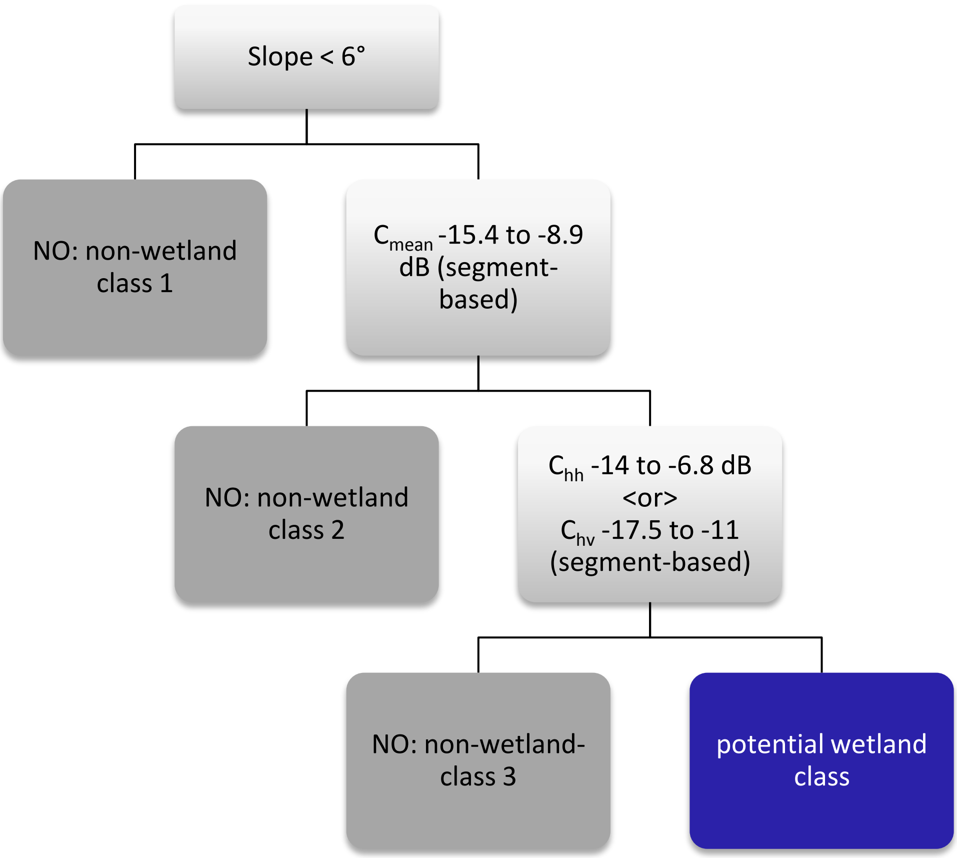


Figure 3.10: Design of the decision-tree classification based on C-band data (C-2).
Source: Nienkemper (2008)

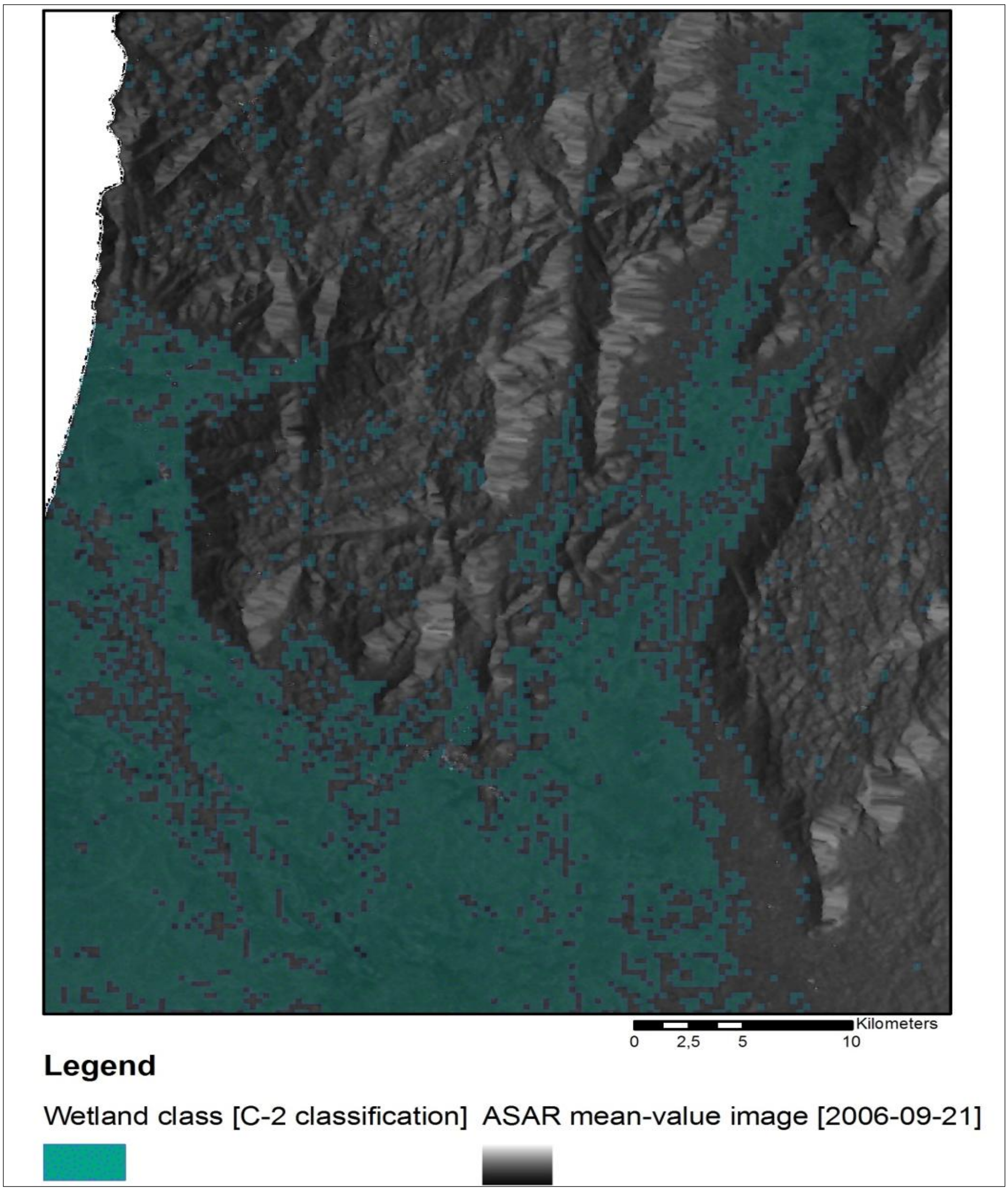


Figure 3.11: Illustration of the C-2 classification result
Source: Modified from Nienkemper (2008)

3.4.9 Image enhancement and display

LANDSAT images were displayed by combining different bands to highlight and identify wetlands from other land uses and cover. According to Islam *et al*. (2008) and Ozesmi and Bauer (2002) combinations of ETM+ band 4,3and 5; band 7, 4 and 2, and 3, 2, 1 displayed in false colour composite (Red, Green and Blue) enhance wetlands depiction, ETM+7 help to distinguish water and locate riparian zone while ETM+2, which is uncorrelated to ETM+7 could provide additional information. ETM+ 4 is the peak reflectance of green vegetation and ETM+ 3 senses in a strong chlorophyll absorption region and strong reflectance region for most soils. ETM+1 provides information on water bodies and is also capable of differentiating soil and rock surfaces from vegetation. ETM+5 is important for discrimination of vegetation and soil.

All afore mentioned bands were sequentially combined and displayed. The combination facilitated the detection and delineation of the wetlands and in checking whether all possible areas were included. Band 3, 4 and 5 gave a better contrast for the detection and delineation of the small wetlands. The rest of the bands were important for providing additional information for precise demarcation.

3.4.10 On screen digitization

On screen digitization was done on the enhanced images and polygons were created. The polygons created were compared with the ones, which were later collected in the field and then edited to correct inclusion and exclusion errors. Some wetlands identified on satellite images didn't exist on the ground as they were either completely transformed into farms or degraded. That was the case in the Laikipia flood plain especially in Pesi and parts of Oljoro Orok. On screen digitization was also done on the newly acquired aerial photographs for proper delineation of wetland boundaries especially for parts, which could not be accessed during the field survey. The boundaries were later used to subset the wetlands in ERDAS imagine for further analysis and use.

3.4.11 Field data collection

Despite the usefulness of remote sensing in wetlands detection, field survey is still crucial for validation of the information gathered in satellite imageries. Field survey was conducted between January 2008 and July 2009 in both the wet and dry seasons for the four sites. Since the wetlands were many even in the selected representative sites, a criterion was developed to focus on specific sites. A circle was drawn on a topographical map and a centre coordinate was located. A radius of 3km was marked and the wetlands falling within the radius were noted and studied in the highlands. In the flood plains a radius of 4km was used.

Before the survey, wetland polygons digitised from topographical maps and LANDSAT images were incorporated in the personal digital assistant (PDA) with Arcpad software 7.0 to enhance tracking of the sites. Signature points produced for accuracy assessment and cluster labelling were also loaded in the PDA. River confluences were marked and traced for location of the wetlands. Most topographical maps, however, were outdated as they were from 1970s and aerial photos were from early 1960s thus some of the information they contained was not reliable. Some wetlands shown on these maps and photographs no longer existed; others were too small to be depicted on the maps or detected in LANDSAT images. Key informants were consulted where difficulties were encountered in accessing the sites. Other wetlands, which were found during the reconnaissance survey, were included in the inventory list. Wetland boundaries were set where the water table was within 60cm of the soil surface. This was determined by soil augering up to 60cm depth.

3.4.12 Aerial survey

The shape files created during the field survey aided in preparation of a flight plan for the aerial survey in three site clusters, namely, Laikipia plains, Mt. Kenya highlands (Nyeri-Karatina) in August 2008 and Usambara highlands and Pangani plains in February 2009. The survey focused on specific wetlands selected in these areas. Flight lines were prepared in ArcGIS with a side lap of 30% and an overlap of 40% (Figure 3.12). The start and end coordinates of defined flight lines were entered into the GPS-unit of the plane. A Nikon D-200 camera with a GPS-link was mounted outside of a plane from which the doors had been removed (Figure 3. 13).

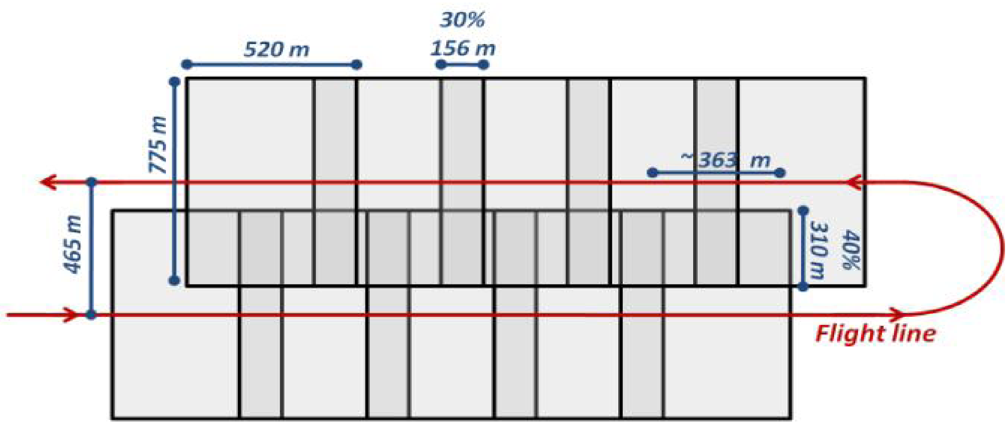


Figure 3.12: Sketch of the flight line configuration with image overlaps
Source: Franke *et al.*, 2009

The image capturing for each flight line was manually controlled. The camera used was equipped with a CCD-sensor with 23.6x15.8mm at 10.9 Mio pixels. The image size of 3872 x 2592 pixels at a flight altitude of 670m resulted in a ground coverage of about 775 x 520m per-picture. A direct link from the camera to a GPS device collected the center coordinates of the images. In addition a GPS track log was recorded to derive the flight path and altitude. The images were mosaiced using Nikon stitching software and geo-referenced using ASTER images, as well as LANDSAT and topographical maps. The aerial photographs produced (Figure 3.14) had a spatial resolution of 0.25m.

Figure 3.13: Camera setting, plane doors removed and a camera mounted outside
Photo by Mwita, February 2009

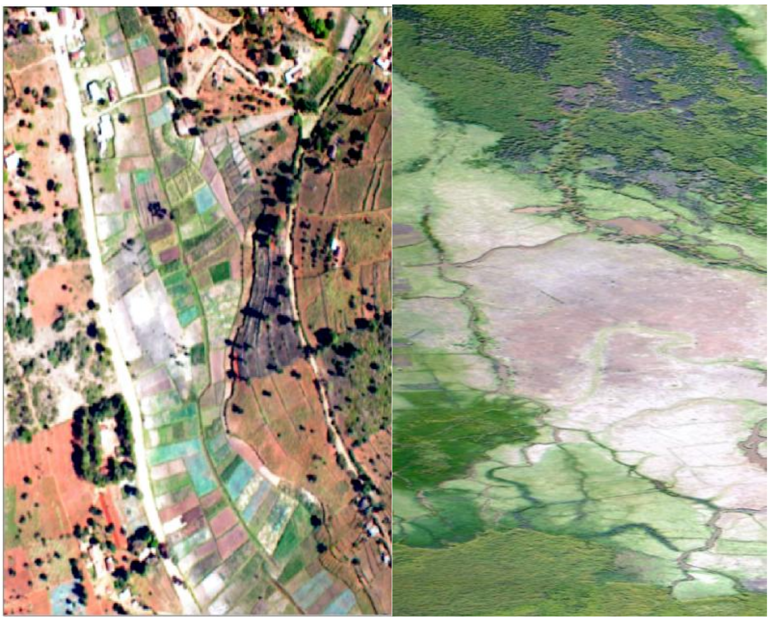


Figure 3.14: Subsections of aerial photographs of Usambara inland valley (left) and Laikipia plains (right) consisting of stitched images along the flight lines. (Flight altitude: 670m above sea level; spatial resolution: 0.25m; date: Sept 2008& Feb 2009).
Source: Aerial survey Sept 2008/ Feb 2009

3.4.13 Ground truth data

A random approach was used to gather ground truth data. The minimum mapping unit was 0.5ha. Global positioning system (GPS) coordinates were taken in the universal transverse Mercator (UTM) zone 37 North for the Laikipia site and South for the rest of the sites using Trimble PDA with Arcpad software 7.0. More than 1020 points were collected for the four sites. Land use/ cover and other objects which couldn't be identified in the aerial photographs were digitized and traced during field survey for their identification.

3.4.14 Accuracy assessment

Accuracy assessment or confusion matrix is normally performed after classification to give an overview of the preciseness of the classification done. The matrix displays producer and user accuracies for each class as well as the overall accuracy of the classification (Campbell, 1996). The producer accuracy is calculated by dividing the number of pixels that are correctly classified in one class by the number of ground truth pixels used for the associated class. Hence, the producer accuracy indicates the probability that a pixel of an image is classified as e.g. wetland given that the ground truth is wetland. The user accuracy is the result of dividing the number of pixels that are correctly classified in one class by the total number of pixels within this class. Consequently, the user accuracy is a measure that indicates the probability that a pixel is e.g. wetland given that it is labelled as wetland.

To calculate the overall accuracy the sum of correctly classified pixels is divided by the total number of ground truth pixels (Lillesand *et al*., 2008). The accuracies can be expressed either in absolute numbers or in percent of pixels (Lillesand *et al*., 2008, Campbell, 1996). The accuracy percentage was determined by overlaying a total of 141 points for each site collected over the delineated wetlands. The calculation was done using ERDAS imagine where the points were imported and their classes identified before the accuracy report was produced. For the microwave data, accuracy assessment was done using ROIs of different wetland classes derived from field work as well as in ENVI. The ROIs of various land covers were combined in one non wetland ROI with several polygons representatively distributed over the image.

3.4.15 Wetlands location maps

After the delineation process wetlands location maps were produced. The study areas were subset from DEMs and SRTMs using shape files from administrative boundaries at division level shape, which were obtained from the respective countries' shape files downloaded from Food and Agriculture Organization of The United Nations Africover data (http://www.africover.org/system/africover_data.php). Shaded reliefs of the study sites were created from DEMs of the specific sites in ArcGIS using spatial analyst tool. The hill shade files were then exported as tiff files. The original elevation models were classified into five classes and colour ramp was used for symbology, false colour images (RGB) were created, which were also exported as tiff files. The two images were later opened in Adobe Photoshop and dragged to align together. A layer palette was used to multiply the shaded relief and the classified images with opacity set at 75%. Painted images were produced and word files were created when the images were exported, renamed and opened again in ArcGIS. Projection was defined and the polygons created during field survey were overlaid in the maps to create the final maps.

3.5 Results and discussion

The following sub sections present the results obtained and the discussion. Comparison is made on the usefulness of the two data sources in the detection and delineation of the wetlands. Types, distribution and density of the wetlands identified are also described.

3.5.1 Wetlands detection and delineation using optical data

Figure 3.15 presents the location maps of the small wetlands identified. A total of 51 wetlands were identified by applying both automated, semi automated and manual techniques. They were either flood plains or inland valleys. On LANDSAT ETM+ images flood plains were much easier to detect and delineate than inland valleys because they were larger in size as compared to inland valleys, which were long, narrow and fragmented. In the Laikipia plain, for example, Rumuruti site was much easier to delineate. This could be explained by its location in a semi arid area where it is surrounded by drier uplands, which reduce signature confusion with the riparian areas. In the Pangani plain some sites like Magoma and Malinda were very distinct compared to Silabu since they were wetter and covered with natural wetland vegetation like papyrus and reeds. Silabu, on the contrary, was drier and was covered with short grass and herbs, hence difficult to distinguish from bare surface.

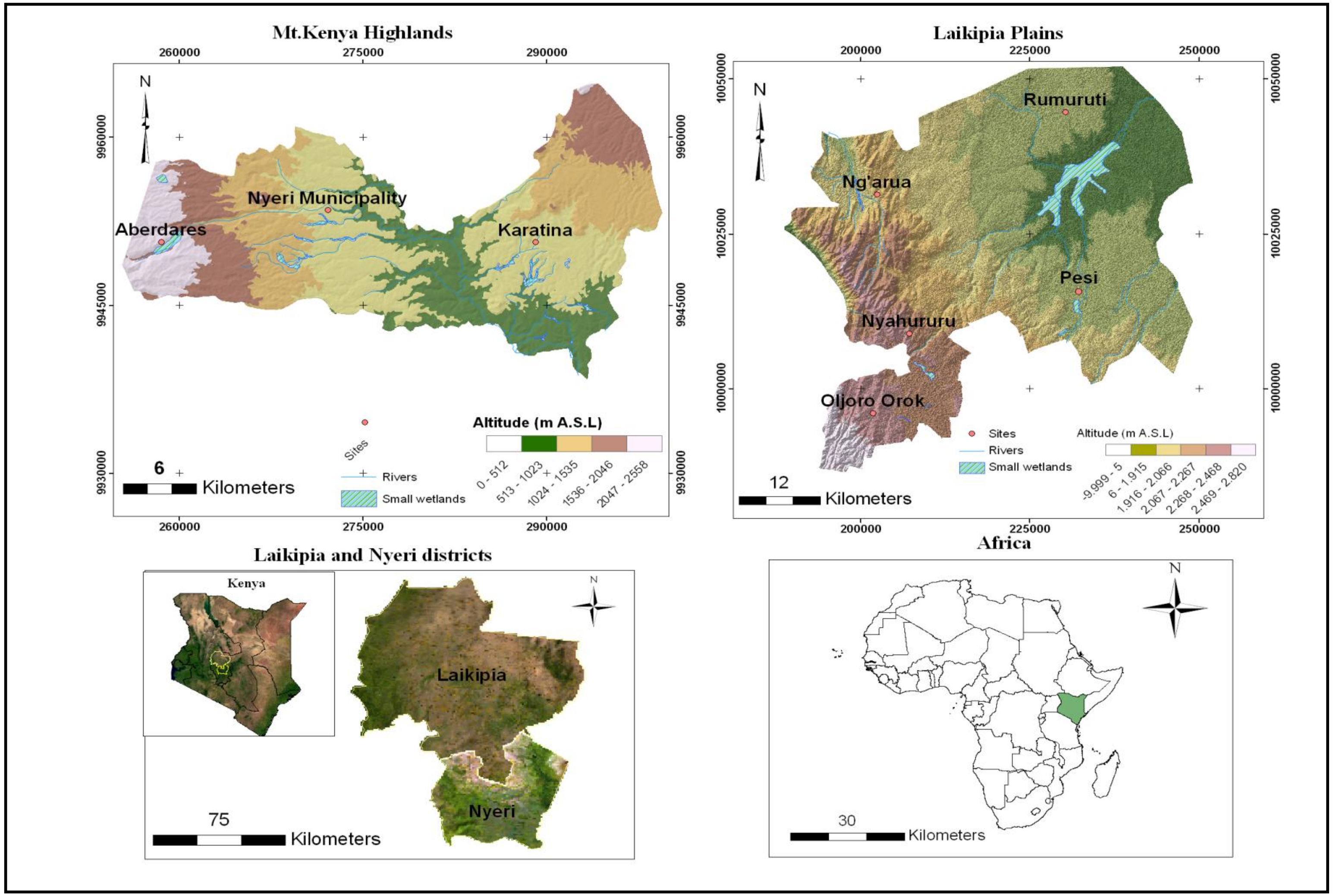


Figure 3.15: Wetland maps for Kenyan sites
Source: Map library and field survey, 2008

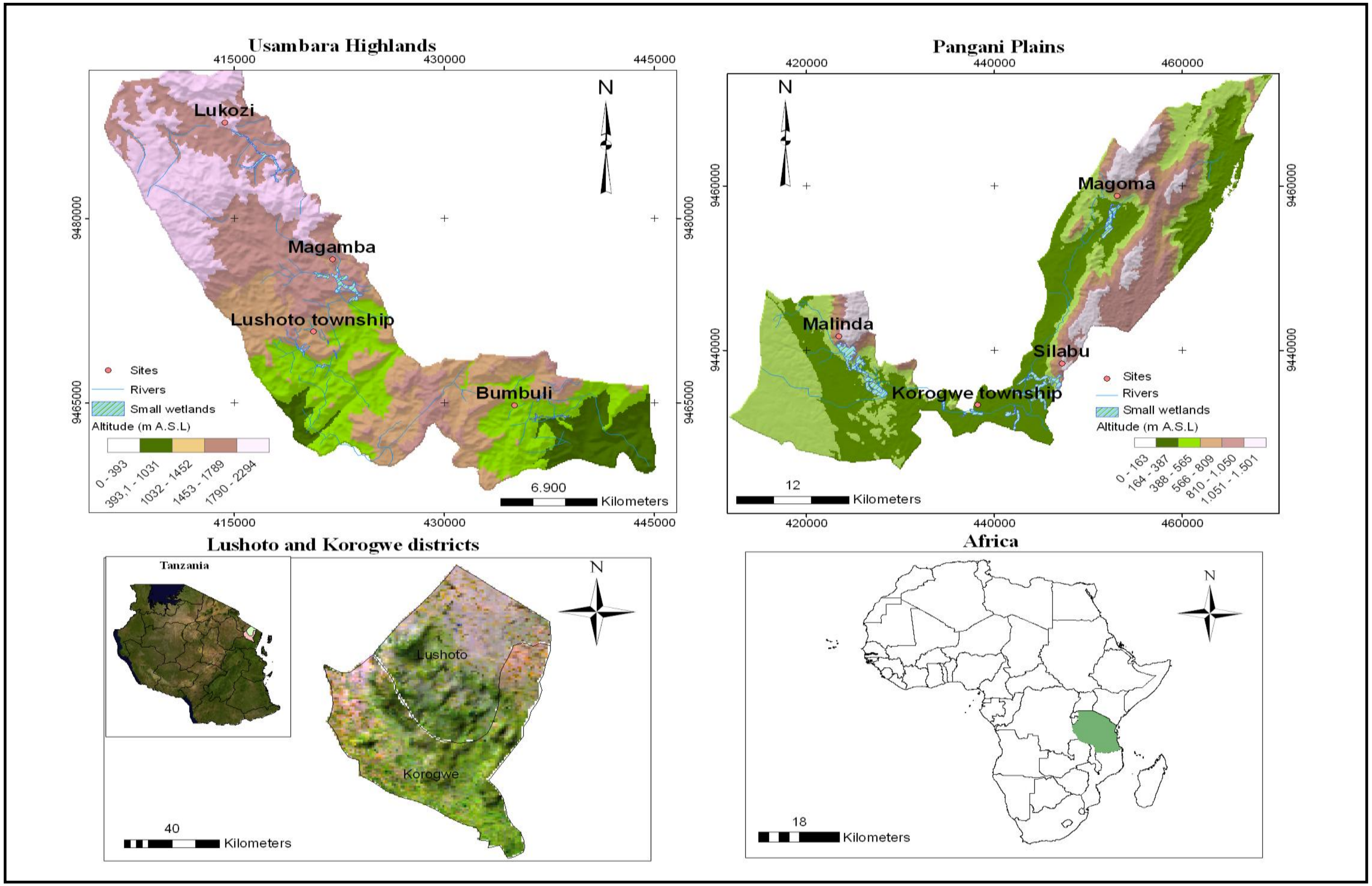


Figure 3.16: Wetland map for Tanzanian sites
Source: Map library and field survey, 2008

Inland valleys were first delineated with LANDSAT images then they were adjusted by high resolution aerial photographs. NDVI thresholds were very effective in wetlands detection. The values between 0.27 - 0.71 clearly separated the Laikipia plain wetlands from other land uses or cover (Figure 3.16). For the Pangani plain NDVI threshold of between 0.25-0.6 were responsible for delineation of wetlands. NDVI was, however, not very effective for the highland sites (Figure 3.16) since the images were from dry season and most of the inland valleys had been drained for agricultural activities. It could be possible that most of the crops were already harvested and the fields were bare and dry thus resembling the highlands or that the valleys were covered with herbaceous weeds, which were also on the uplands. Some valleys, which were covered by natural wetland vegetation like *cyperus* and *typha spp* had slightly higher NDVI values. In general, however, this index was not very effective for both upland sites as the threshold values ranged between 0.04-0.32, which is close to bare soil (Madra, 2005).

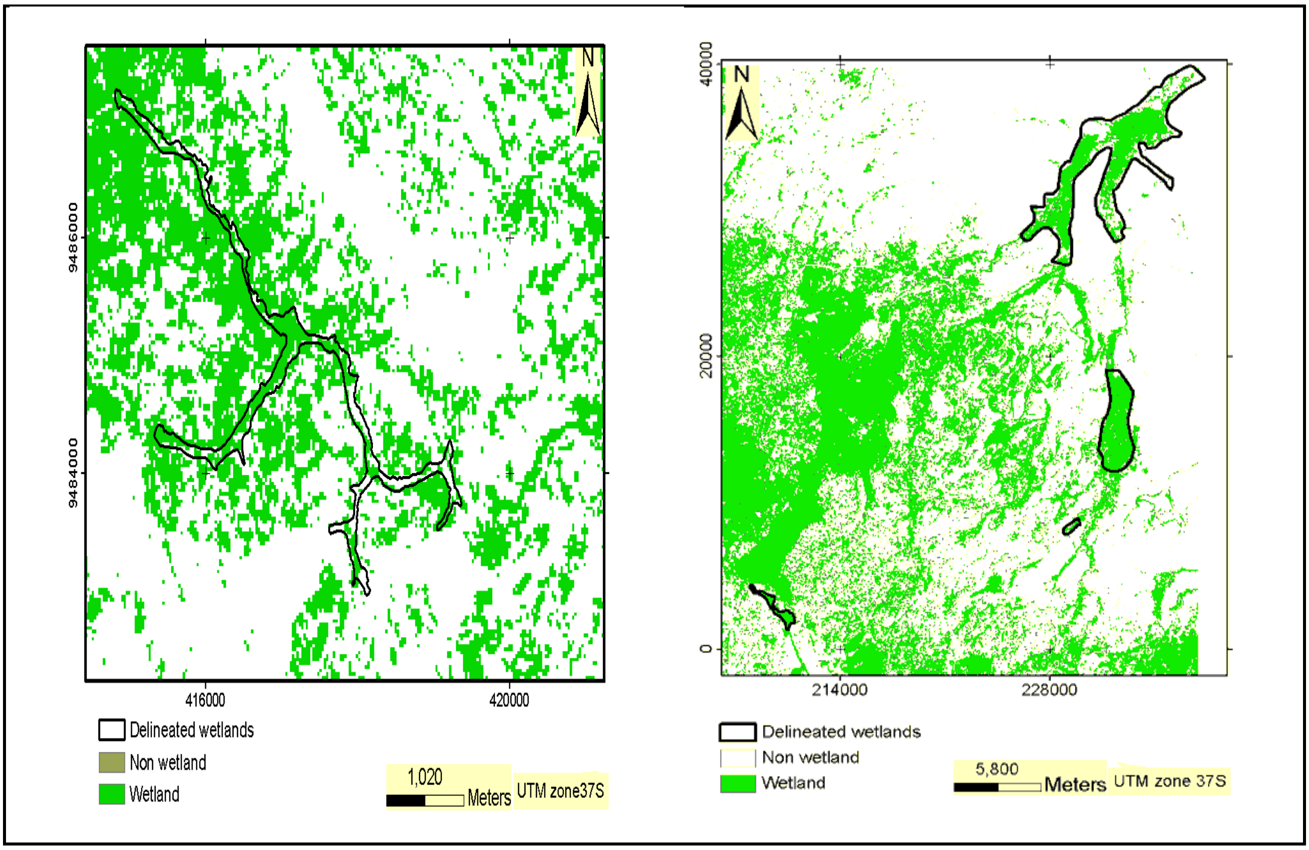


Figure 3.17: Wetland detection using NDVI threshold method for Usambara highlands (left) and Laikipia plain (right)
Source: Own illustration

According to Islam *et al.* (2008) wetlands with barren lands and\or sparse vegetation have lower NDVI as a result of soil moisture that is relatively higher than the surrounding uplands. When wetlands have natural vegetation or crops the NDVI will vary depending on vegetation density and vigour. Kulawardhana *et al.* (2007) used NDVI threshold in their study and observed that NDVI is very useful in differentiation of wetland vegetation and also for distinguishing the wetland boundaries from the surroundings. They further add on that even though in some cases the accuracies may be lower due to spectral confusion between the wetland and upland vegetation or sometimes crops cultivated, spectral data coming from red and near infrared region of the spectrum clearly distinguish between wetlands and non wetlands.

Thresholds of DEMs and SRTMs worked better in inland valleys. The inland valleys were clearly depicted (Figure 3.17) at between 5˚- 6˚. Flood plains were not easily marked out. A threshold of 6˚ was tested but many areas, which for this study were still considered as parts of the wetlands, were omitted. The omitted areas were included when a threshold of 9˚ was used. Similar observations are made by Thenkabail *et al.* (2006), Kulawardhana *et al.* (2007) and Islam *et al.* (2008) who noted that slope threshold does not work well in plain areas due to incorrect stream alignments. Nevertheless they recommend that slope remains an effective indication of the low lying areas.

The importance of aerial photographs in detection and delineation of small wetlands is emphasised in the literature (Everitt *et al.*, 2004; Ozesmi & Bauer, 2002; Lyon, 2001; Niedzwiedz & Batie, 1984). In addition to their usefulness in detailed mapping of the wetlands, they are indeed effective in boundary delineation. In this study, both historical and current aerial photographs were very practical in marking the boundaries of both inland valleys and flood plains. Since the resolution of the current images was very high the boundaries were clearly visualized and demarcated by digitization. Despite the fact that manual tracking of the boundaries assisted much in confirmation of wetlands existence, not all areas were accessible. Thus the aerial images complimented the missing information.

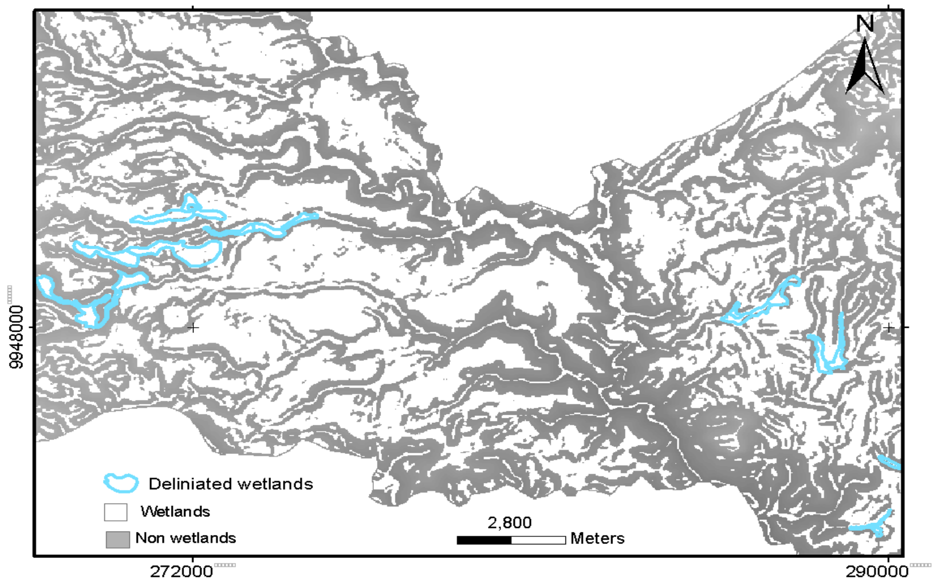


Figure 3.18: Slope threshold of Mt. Kenya highland (Authors own illustration)

Delineation of the wetlands is, however, very challenging due to the fact that they are very dynamic and diverse. Their spatial extent and biophysical characteristics change with season or hydrological regime (Whitcomb *et al.,* 2009). Time series data over a given wetland are in principle very desirable when delineating or monitoring the state and extent of a given wetland.

3.5.2 Wetlands delineation using microwave data

With microwave data, wetlands were detected by observation of backscatter signals of different land uses and the results of decision tree classification (see Table 3.4, Figure 3.8-3.11). In all six scenes the backscatter values of water and wetland were clearly separable from other land uses. This is because areas with high soil moisture content have inherently lower backscatter values. In the dual polarised PALSAR scene acquired on 2^{nd} of May 2008, the water values ranged between -27.4 to -10.8dB. Wetland values ranged between -26 to -0.6 dB and when plotted they produced a bi-modal distribution, which can be explained by moisture variation within a given wetland. Within the wetland there were parts, which were very wet (permanently flooded) and others, which were drier (seasonally flooded). Van de Giesen (2001) had similar observations of the L_{hh} backscatter of flood plains in West Africa and concluded that one peak was for wetter and another for drier parts of the flood plains.

In L_{hv} of the same date the values for wetland ranged between -38.8 to 14.8 dB. In the January scene backscatter values for water and for the wetlands were lower and there was an overlap in backscatter values with other land uses. January is a drier month and wetlands are possibly similar to other vegetated and non overgrown areas. The longer rains begin in March thus the values also slightly change but it is gradual since the soils are not completely saturated.

The backscatter values for C band were lower than those of L band. For example the mean from water surfaces is -17.9 dB for C_{hv} and -11.5 dB for C_{hh} and the mean from wetland areas is -12.5 dB for C_{hv} and -8 dB for $C_{hh.}$ This scene was acquired towards the end of the dry season but the capability of C band in detecting inundation is limited. Whitcomb *et al.* (2009) noted that C-band SAR is primarily useful in sensing the characteristics of relatively sparse and short layers of vegetation and it is very useful in distinguishing herbaceous wetlands from clearing. Generally L-band SAR is seen to perform better in detection and differentiation of wetland types as also noted by Slatton *et al.* (1996), Yamagata and Yasuoka (1993), Whitcomb *et al.* (2009) than C-band due to its ability to penetrate much into vegetation canopy. Terra SAR-X, for example, detected values of 42.5 to < 33.5 dB for open water and between 40.1 and 33.5 dB for wetlands.

3.5.3 Accuracy assessment

Accuracy assessment was performed for both optical and microwave data as described in section 3.5.12. The percentages of accuracy obtained from the classification of the images are presented in Table 3.6. In general producer accuracies are lower than user accuracies in microwave data for the non wetlands class (43.10-49.04%). This indicates that there was some confusion in the classification, i.e. some ground truth points were misclassified (Non wetlands) with other land use classes (Wetlands). User accuracies are higher, that is to say the percentages of correctly classified wetlands within their given classes were higher. Overall classification accuracy was lower in microwave data than in optical data.

LANDSAT image classification produced higher accuracies in Laikipia site for wetland class (97.35%) and non wetland class (86.36%). Overall classification using both supervised and

NDVI classification was high (96% & 91.49%, respectively) in Laikipia site. As already mentioned, this site, particularly Rumuruti test site, is located in the semi arid area and the surroundings are mostly bare. Thus the few wetlands existing in the area are identifiable without much spectral confusion. The situation is, however, different as you move towards Manguo and Oljoro Orok sites as the rains are higher and thus the wetlands are not as distinct; there is much overlap with other land uses. For the Pangani plain site the overall accuracies for NDVI and supervised classification are 82.26 and 80.85%, respectively. User accuracy is very low (50%) as compared to producer accuracy. This is caused by its location close to the Usambara highlands. The confusions are even higher with other land uses. This is a common problem with small wetlands classification using LANDSAT images as observed by Ozesmi & Bauer (2002) and Kulawardhana *et al.* (2007).

C-band 1 and C-band2 classification produced overall classification of 45.2 and 55.59, respectively. The number of correctly classified wetland pixels was almost equal in C1 & C2 (78.57% and 78.86%, respectively). The number of correctly classified wetland ground truth points was higher than in non wetlands (Table 3.6). Similarly in L band 1 and 2 wetlands were classified better than non wetlands, the user accuracy being 88.73 & 88.35%, respectively. The overall accuracy was also higher by almost 9% in L band 1 and 4% in L band 2. A combination of the two sensors C and L produced almost similar overall accuracies to L band 1&2 (54.13 & 57.10, respectively) but increased user accuracies by more than 10% as compared to C band 1. Although this combination of the bands doesn't improve classification, it increases the user accuracy. L band is seen to work better in wetlands classification as compared to other microwave data.

It is ascertained that combining data sets and methods is of significant importance in the detection of wetlands. Dependency on a single data set may not produce satisfactory results as each data set has its limitations especially when dealing with small wetlands.

Table 3.6: Accuracies of classification of wetlands using radar and optical data sets

	NDVI threshold		**Minimum distance to mean**	
Pangani plain	Wetland	Non wetland	Wetland	Non wetland
Producer Accuracy [%]	81.63	80	94.85	80.7
User Accuracy [%]	98.53	83.75	50	81.48
Overall Accuracy [%]	**82.26**		**80.85**	
Laikipia plain				
Producer Accuracy [%]	89	98	97.35	67.86
User Accuracy [%]	98	100	92.44	86.36
Overall Accuracy [%]	**96**		**91.49**	
Decision-tree Pangani plain				
	Wetland	Non wetland	Wetland	Non wetland
Fusion C- and L-band	CL-1		CL-2	
Producer Accuracy [%]	61.97	49.04	78.34	43.1
User Accuracy [%]	95.45	79.86	78.91	85.78
Overall Accuracy [%]	**54.13**		**57.1**	
L-band	L-1		L-2	
Producer Accuracy [%]	63.77	47.31	80.29	46.77
User Accuracy [%]	88.73	79.74	88.35	88.61
Overall Accuracy [%]	**53.88**		**59.47**	
C-band	C-1		C-2	
Producer Accuracy [%]	45.4	45.04	73.48	43.16
User Accuracy [%]	78.57	67.3	78.86	82.41
Overall Accuracy [%]	**45.2**		**55.59**	

Source: Own illustration

3.5.4 Wetland types, density and distribution

Among the 51 wetlands identified and surveyed, the main wetland types were inland valleys and floodplains. A morphological approach of inland valley classification by Windmeijer & Andriesse (1993) was used for wetlands differentiation. The results were valley heads (15.9%), mid stream sections (64.3%) and flood plains (19.8%). Valley heads had either concave shape with side slopes between 3 and 6% or convex shapes, with side slopes of up to 20%. Wetland sizes ranged between 0.5 and 5 ha, with valley heads and mid stream inland valleys occupying areas between 0.5 and 35 ha and flood plains from 10 to 747.54 ha. The highlands were dominated by valley heads and mid stream inland valleys.

Even though the area covered by flood plains is larger, they are not as dense as the narrow inland valleys in the highlands. Inland valley swamps dominated the humid highlands and they were densely distributed, whereas floodplains were the dominant wetland type in the semi-arid and sub-humid zones and are sparsely distributed. Even though some of the inland valleys are drained for agricultural activities they remain wet for the most part of the year. Their location in humid areas makes them more resistant to drought. Large parts of the flood plains are seasonally flooded thus in dry seasons they are completely dry except for some parts, which are covered by open water or where the water table is high and thus are moist throughout the dry season.

3.5.5 Comparison between optical and microwave data in wetland detection and delineation

Even though the sensor characteristics, processing, classification techniques, as well as spatial and temporal resolution are completely different between the optical and microwave data, some comparison can be made on the results obtained. Compared to all other data sets, aerial photographs were very effective in both identification and discrimination of the wetland boundaries. This is attributed to their higher resolution of 0.25m. The detailed information contained was very useful in the classification process and differentiation of the land uses as detailed in the next chapter. However, as observed by different authors like Niedzwiedz and Batie (1984), Ramsey and Laine (1997), Ozesmi and Bauer (2002), aerial photographs are only suitable for a limited geographical area because they are relatively expensive. For this study, the aerial survey included only the areas of interest to minimise cost. In addition it is rarely possible to obtain time series aerial photographs of a given area, which are potentially necessary for wetlands detection. In the study sites in both countries, the only available aerial data were from early 1960s and 1970s; no current information was found in the archives.

The final classification on TerraSAR-X was very comparable to the LANDSAT image, especially for Malinda site. Despite the temporal differences, the differentiation between permanent, seasonal and non wetlands was very similar to the classified LANDSAT images. C-band as afore mentioned is very effective in detection of short and sparse vegetation. This was also true for Silabu site. In LANDSAT and NDVI images, for instance, the delineation wasn’t very clear as some parts of the site were classified under non wetland, but in C-band it was very clear. The omission error in the NDVI image was because the site was drier and sparsely vegetated or some parts were covered by open water.

L-band data from both dry and wet season could not distinguish the small wetlands of interest to this study; the delineation was too general, which included the whole flood plain. Within the flood plain there were variations; some areas didn’t qualify to be considered wetlands under the scope of this study. These were quiet visible in optical data and Terra X-SAR. De Roeck *et al.* (2008) in their study of remote sensing and wetland ecology in South Africa used both LANDSAT and ENVISAT ASAR images and found out that the LANDSAT images were efficient in delineation of both small and large wetlands but ASAR data detected only larger wetlands. They assumed that probably the wetlands were lost during the pre processing stage of the Radar images. The generalization could also be a result of the slope threshold used for separation of wetlands from non wetland areas. As already noted in section 3.13 slope thresholds do not work efficiently on plains. In addition to that, the SRTM (90m) resolution was too course and this could also have contributed to the non-detection of the small wetlands.

3.6 Conclusion

The use of multi-spatial and multi-spectral resolution data for detection and delineation of small wetlands has proved to be of special significance in this study. While optical data are capable of depicting smaller wetlands, which cannot be delineated by microwave data, their capacity is limited by clouds, haze and vegetation canopy. On the other hand microwave data operates regardless of weather and are able to detect larger wetlands. A slight change in soil moisture content reduces or increases the wetland sizes. Due to the diverse nature of the small wetlands and environment in which they occur, single data types and methodology are insufficient for mapping them correctly. The detected inland valleys are smaller in size and dense while flood plains are larger and scattered. The study forms a stepping stone in identification and documentation of small wetlands in East Africa so as to improve the understanding of their existence and spatial extents. The maps produced will aid in further classification of the wetland uses and cover. The information generated from the classification will create awareness on the processes taking place in the small wetlands and implications on their future existence.

4 Classification of wetlands use and cover using multi temporal data sets

In this chapter digital classification and characterisation of small wetlands using traditional unsupervised and supervised techniques is done with multi-temporal data. The classification is preceded by an introduction, a review of different classification approaches and digital methods employed in mapping wetlands. Materials and methods are described, followed by results and discussion, and a conclusion.

4.1 Introduction

Wetlands vary greatly in their genesis, geographical location, water regime, chemistry, and plant communities. The diverse nature of the wetlands has made it difficult for scientists to come up with a single classification system. As a result, different classification systems have been developed depending on the demands of the scientific, management or regulatory authorities. Wetlands have thus been classified using environmental, geographical, hydrological or ecological factors.

Some of the classification systems include Anderson *et al.* (1976); Cowardin *et al.* (1979); Scott, (1989); Windmijer & Andriesse, (1993); Brinson, (1993). These types and classification systems have something to do with the hydrological, soil or edaphic and vegetation characteristics of wetlands. Other systems that characterize wetlands use their functions and uses (Adamus *et al.,* 1991; Brinson, 1993). Still, other description systems are based on the scale of the identification or inventory of wetlands (Lyon, 2001).

Remote sensing has been used to classify and map wetlands cover and uses with different techniques and data sets (Ozesmi & Bauer, 2002). Aerial photographs, in particular, have traditionally been used for small wetlands classification (Baker *et al.,* 2007) while LANDSAT images have served a great deal in the classification of wetlands at a larger scale (Lyon, 2001; Ozesmi & Bauer, 2002). Unsupervised classification or clustering, supervised classification, principal component analysis, hybrid classification and fuzzy classification are among the most common applied techniques in wetlands classification (Rundquist, *et al.,* 2001; Zhang, *et al.,* 2000). Classification of wetlands is very important for their better understanding, proper monitoring and management. The ultimate goal of classification is to reduce variations within classes to enable detection of differences between them.

4.2 Hypothesis and objectives

Small wetlands in East Africa are covered by a variety of vegetation and are used diversely. It is hypothesized that the diversity of cover and use can be identified and differentiated by detailed classification of multi-temporal and multi-spatial resolution remote sensing data. The area covered by each LCLU class can be quantified to determine their proportion through statistics extracted from the thematic maps produced.

The specific objectives are:-

1. To capture the diverse land cover and use in the detected small wetlands
2. To quantify the proportion of each LCLU class within the specific sites

4.3 Literature review

Although the focus of this chapter is on classification of LCLU types, it is necessary to have an overview of wetlands classification approaches as they form a basis for wetlands use and cover mapping.

4.3.1 Wetlands classification approaches: An overview

Wetlands have been classified, globally, nationally and locally. At the global level, wetland classification has value if it provides readily understood terms, a framework for international legal instruments for wetland conservation, and assists in the dissemination of information (Scott & Jones, 1995). Under the auspices of the Ramsar Convention on wetlands (2006), an international classification system was developed by Scott (1989). The Ramsar Convention provides a very broad framework to aid the rapid identification of the main wetland types represented at each site. This classification system is largely based on form and relationships rather than intrinsic content or wetland processes (Finlayson & Valk, 1995). The classification recognizes some 30 natural wetland types (Scott, 1989), which include:

- marine and coastal wetlands
- inland wetlands
- "Man-made" wetlands.

The system was designed to provide a very general framework to classify the diverse range of wetlands globally and to be applied in situations where little information exists. There is, however, often great confusion and sometimes controversy locally over whether a given type of habitat is or is not a wetland. Generally it is a departure point for wetland classification at local levels.

The United States of America has done a lot of effort to study and classify wetlands at national level. The hierarchical classification of Cowardin *et al.* (1979) is one of the most comprehensive and widely applauded wetland classification systems (Figure 4.1). This system is described in depth by Cowardin & Golet (1995). Basically, it divides wetlands into systems, sub-systems, classes and sub-classes, along with a series of water regimes, chemistry and soil modifiers. The basic units of the hierarchical system are marine, estuarine, riverine, lacustrine and palustrine. The US classification is also accompanied by a list of plants known to occur in wetlands, and a list of hydric soils. The system has been widely adopted with modifications to suit the needs of the users.

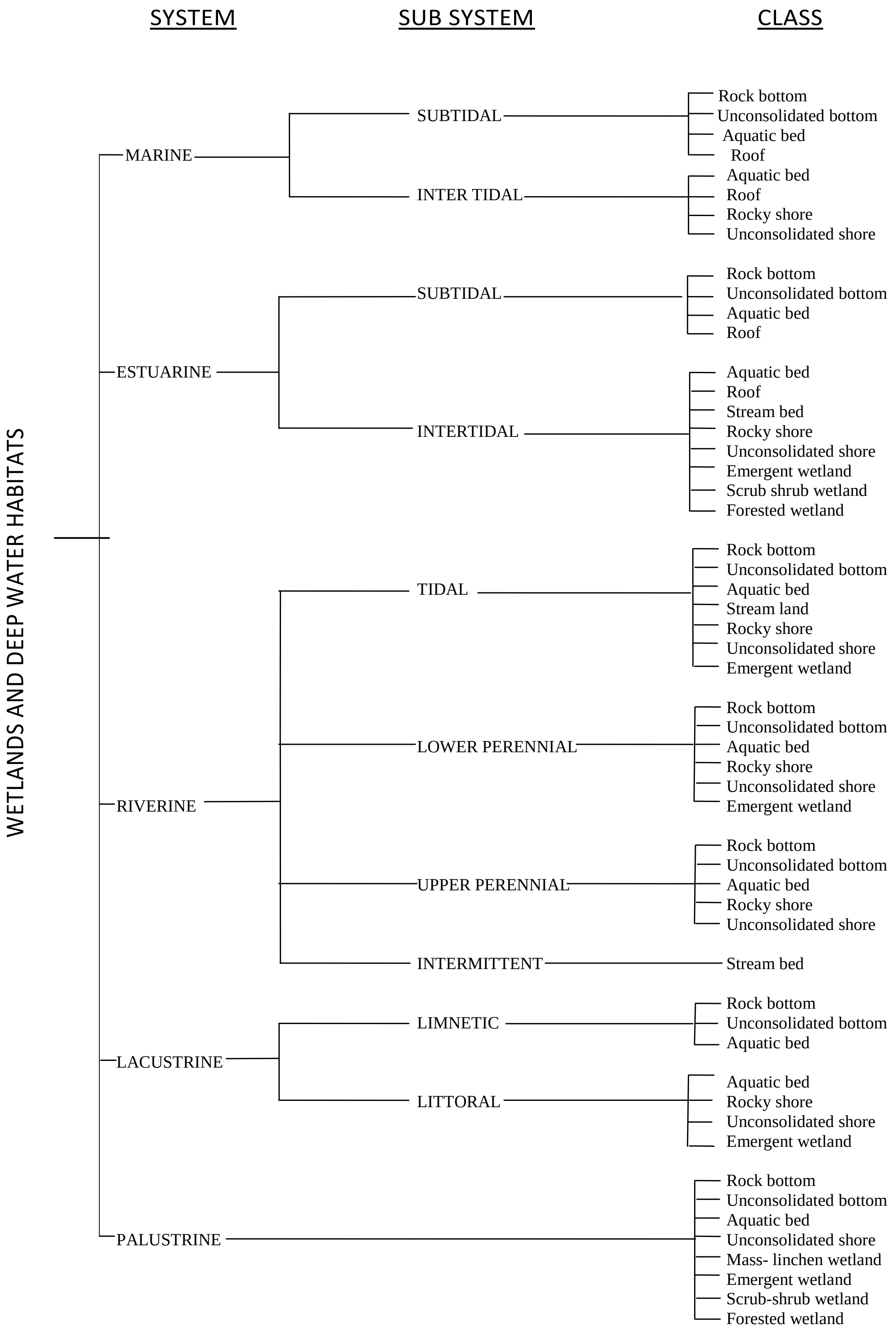


Figure 4.1: Cowardin's wetlands classification system
Source: Cowardin *et al.* (1979)

Another well known classification system is the Canadian Wetland Classification System (National Wetlands Working Group, 1997). The system is also based on a hierarchical system, which includes (1) physiognomy and hydrology (classes) (2) surface morphology (forms); and (3) vegetation physiognomy (types). The five wetland "classes" are differentiated by their developmental characteristics and the environment in which they exist. The five classes are: bog, fen, marsh, swamp, and shallow water (Figure 4.2). Some wetlands accumulate peat (partially-decomposed organic matter) and are called peatlands.

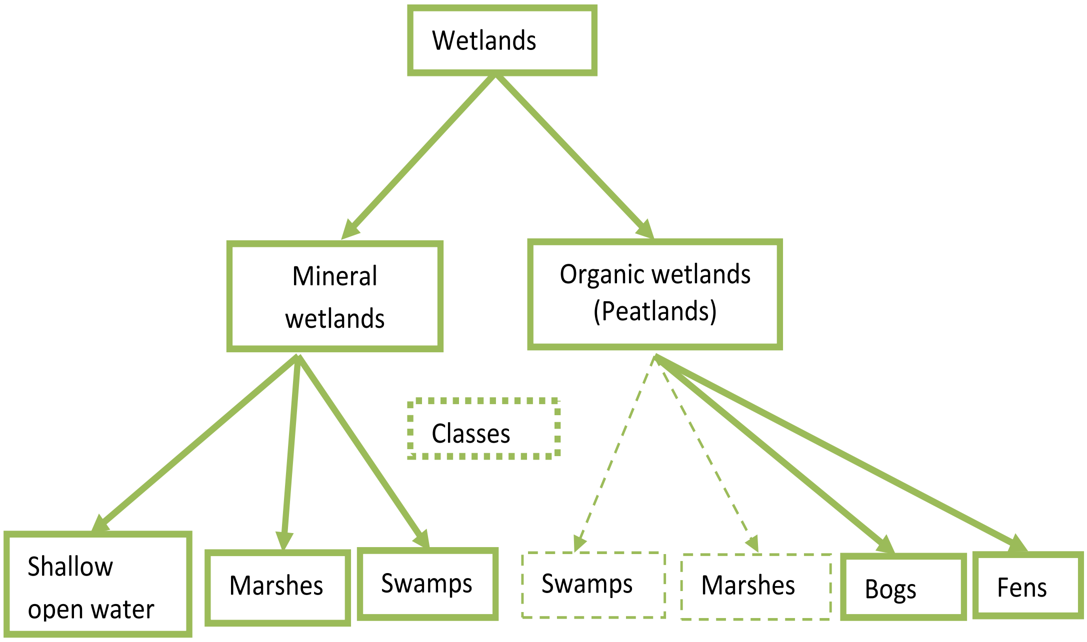


Figure 4.2: The Canadian Wetland Classification System
Source: National Wetlands Working Group (1997)

South Africa also proposed a classification system. According to Dini *et al.* (1998), the classification is based on the Cowardin system used by the United States National Wetland Inventory, but has been adapted to accommodate the full range of South African wetland diversity. A significant departure from the original Cowardin system is the separation of endorheic (pan or playa) ecosystems from other lacustrine and palustrine habitats. Palustrine wetlands have also been distinguished into four subsystems, based on position in the landscape.

The riverine system has been divided into five subsystems, whereas the Cowardin system makes use of four. The addition is the result of Cowardin's intermittent subsystem being divided into lower and upper intermittent. These subsystems accommodate wetlands in channels containing flowing water for only part of the year. This allows the distinction made between the upper and lower perennial subsystems, on the basis of gradient and water velocity, to be extended to the intermittent subsystem. The Palustrine system is divided into four subsystem, flat, slope, valley and flood plain bottom (Figure 4.3).

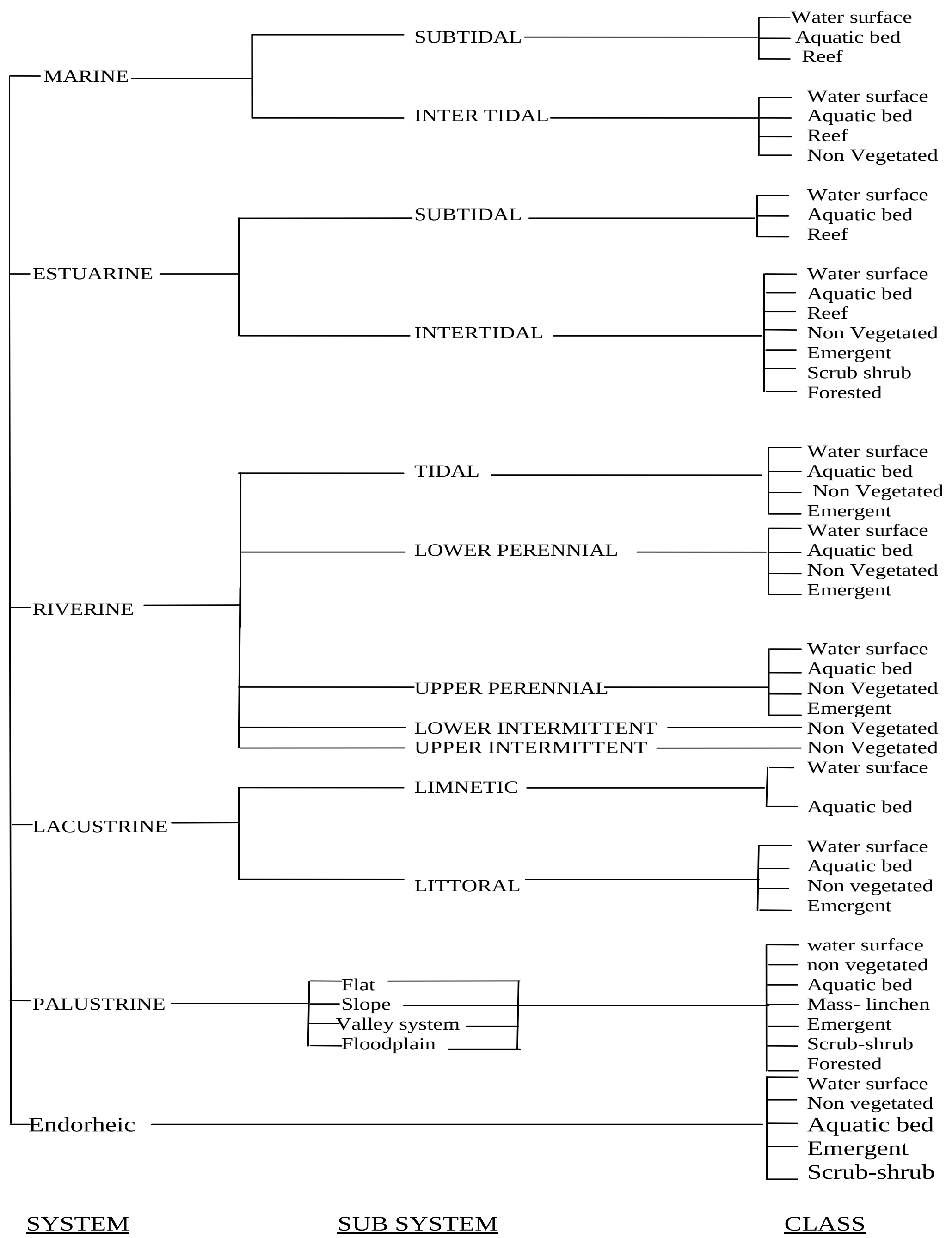


Figure 4.3: South African proposed wetland classification system
Source: Dini *et al.*(1998)

Windmeijer & Andriesse (1993) also made a classification of inland valley systems in West Africa using a geomorphological and hydrological approach. Their classification is preceded by Raunet (1985) who divides the inland valleys longitudinally into three parts: the valley head, the midstream part, and the downstream part, each with its own hydro geo morphological characteristics. The valley head forms the most upstream part of the valley. It has a concave profile, there is no stream channel, and the morphology and the soils are dominated by colluvial processes. The midstream part of the valley is wider, with the central part of the concave valley bottom being almost flat, and a shallow stream channel being present in the central part of the valley. Although some river flooding and associated sedimentation may occur, colluvial processes still dominate the morphology and the soils. The downstream part of the valley shows limited development of levee systems, and alluvial soils occur.

River flooding and subsequent sedimentation are more important downstream than in the upstream part, but colluviation remains significant at the fringes of the valley bottom. The downstream part changes gradually into a floodplain proper. Windmijer's classification combines the first two classes of Raunet into a stream inland valley with an imminent centrally located stream channel. The channel is shallow and only up to a few meters wide with bottoms varying in width from 10 to 100m in their lower reaches dominated by colluviums. They extend over distances of up to 25km or more. The second class is river inland valleys, which include downstream part of Raunet with a wider, larger and more distinct water course. A flood plain develops, which may be up to 200m wide.

The review of literature doesn't show a specific wetlands' classification system in the East African region. The existing classification systems are adopted either from Ramsar (Kalinga & Shayo, 1998) or from Cowardin *et al.* (1979) (Kiai & Mailu, 1998). Thus the Windmijer's approach was adopted for typifying the wetlands detected in this study as described in chapter 3. Detailed classification of the wetlands' use and cover employs varied techniques ranging from basic field and literature surveys (Hughes, 1995; Taylor *et al.,* 1995; Pressey & Adam, 1995) to highly sophisticated technological approaches using aerial photography (Taylor *et al.,* 1995; Wilen & Bates, 1995; Zoltai & Vitt, 1995) and satellite imagery

(Nakayama, 1993; Hess *et al.,* 1990). This chapter describes the digital techniques that were applied for the detailed classification of wetlands using both aerial photographs and satellite images.

4.3.2 Digital classification of wetlands

Over the past few decades, geospatial technology (multi-spectral, hyper-spectral, optical and microwave sensors) and tools (digital image processing [DIP] and Geographic Information Systems [GIS]), opened new vistas for wetland inventory and classification at multiple scales. Application of remotely-sensed data for wetland mapping, classification and characterization gained momentum in the recent past due to increased availability and access to data from different sources (Jones *et al*., 2009). The digital classification involves data collection from the field and remote sensing archives, pre-processing and classification using different available algorithms. Support tools of geospatial analysis, namely Global Positioning Systems (GPS), meta-database and internet GIS, have added further dimension to the overall approach of wetland inventory and management (Nagabhatla & Galal, 2007). The raster/vector data sets having information on area, boundary, location, geomorphology, soil characteristics, water regime, water quality, and vegetation pattern are prepared using both spatial and non-spatial domains and linked with the meta-database.

Digital classification has been done using various remote sensing data sets ranging from optical to microwave to capture the broad diversity of types and land use and land cover (LCLU) of wetlands. LANDSAT data, aerial photographs, SPOT, Advanced Very High Resolution Radiometer (AVHRR) and Synthetic Aperture Radar (SAR) and many others have been successfully used in classification of wetlands (Ozesmi & Bauer, 2002). Since satellite data are in digital format they can easily be integrated in GIS. Using remotely sensed data for classification is less costly and less time consuming than field data collection (Nagabhatla & Galal, 2007). The nature of the location of wetlands in the remote areas associated with thick forests and wild animals or water logged conditions makes it difficult for their field survey (Rebelo, *et al.,* 2009a; Rundquist *et al.,* 2001). Nevertheless a combination of both field and remote sensing techniques improves the results as they complement each other and are necessary for accuracy assessment.

Each type of data set has its spectral, temporal and spatial resolution. Thus their application for wetland mapping depends on the scale and level of details required. In most cases a combination of different data sets is often recommended for higher accuracy. Satellite image classification, for example, can be limited by fluctuating water levels, which change the spectral reflectance of the vegetation (Rundquist *et al.,* 2001). In the event of fire in the wetlands, visible scars are normally left for a long period and the scars are normally misclassified as open water on satellite imagery. The growth pattern of wetland vegetation is a challenging task in the classification. According to Ozesmi & Bauer (2002), these difficulties can be solved by using high resolution aerial photographs. On the other hand, the use of aerial photographs is not suitable for large areas classification as they are time consuming (Rundquist *et al*., 2001). Optical data as already discussed in the previous chapter are limited by clouds. Microwave data, however, can collect data regardless of time and weather, although they require relatively complex processing procedures. The processing at times degrades the quality of data. The images are also expensive and not readily accessible compared to some optical data, such as LANDSAT images (Rundquist *et al.,* 2001; Limpitlaw & Gens, 2006).

In a nutshell, digital classification is very important for understanding the status of wetlands for their proper monitoring and management. Once the data are acquired they have to be processed to extract the information required. The processing employs varied techniques. These techniques, their usefulness and limitations are discussed in the following subsection.

4.3.3 Digital image processing techniques for LCLU classification

There exist a number of techniques, which are used in classification of images for LCLU mapping. Some of the widely used techniques include, unsupervised classification or clustering, supervised classification, principal component analysis, hybrid classification, regression analysis mostly applied to aerial photographs, procedures based on vegetation indices, fuzzy classification, image segmentation, decision tree and many others, to mention just a few. Each of these techniques has a number of benefits and limitations depending on the data types, specific LCLU characteristics and objectives of the classification.

According to Ozesmi & Bauer (2002) and (Jensen, 1996), unsupervised classification has been widely applied for wetlands classification. Standard procedures for this traditional method of classification groups pixels with similar spectral values. Using ancillary information like aerial photographs and maps the analyst labels the clusters. The advantage here is that the clusters are grouped based on image statistics and some uses and the analysts do not need to invest time in obtaining training data. The clusters, however, may not necessarily correspond to the desired information classes. On the contrary, supervised classification needs training statistics to recognise the various classes. The benefit is that the desired classes are attained but much time is required in obtaining the training data (Lillesand *et al.,* 2008; Ozesmi & Bauer, 2002; Jensen, 1996).

Principal component analysis is another approach applied when using multi-temporal data sets. The method aims to re organise image information to reduce the number of bands and then apply clustering to the first few principal components to classify the wetlands. The results obtained from the first three components may highlight vegetation patterns and differences in wetness as well as to distinguish wetlands from uplands (Gluck *et al*., 1996). Hybrid classification has also been used for wetlands classification. In this approach unsupervised classification is done in only a portion of the study area. The clusters produced are assigned classes, statistics generated are in put in a second step and a supervised classification (maximum likelihood) is applied to the entire area (Deng, *et al*., 2008; Pope *et al.,* 1994).

Other methods based on NDVI of SPOT vegetation and of LANDSAT images band 4 and 3 have also proved to be very useful in wetlands classification (Islam *et al.,* 2008). Decision tree classification is as well commonly used (Wright & Gallant, 2007; Baker *et al.,* 2006; Hui *et al.,* 2009). Image segmentation features a lot in the current literature, one of its advantages being the ease of using the results directly in GIS (Jones *et al*., 2009).

This study used a combination of aerial photographs and time series LANDSAT images based on unsupervised and supervised image classification techniques and quantify the area share of each use in the four preselected study sites. The combination of these data sets is seen to yield sophisticated results given the small size of the wetlands studied.

4.4 Materials and methods

In this section materials and methods used in data collection and analysis are described. Since acquisition of aerial photographs has already been explained in the previous chapter, it won't be repeated. The metainformation on LANDSAT images are described followed by pre processing procedures and data analysis.

4.4.1 Data types

Table 4.1 shows the remote sensing data types used in this study, their coverage for each site and their dates of acquisition. Basically LANDSAT Multi Spectral Scanner (MSS), TM and ETM+, aerial photographs and topographical maps were used. All LANDSAT images were downloaded from the global Land Cover Facility (GLCF) (http://glcf.umiacs.umd.edu/data/LANDSAT/) of the USGS and the National Aeronautics and Space Administration (NASA). The data are free of charge and are put at disposal in a standardised and orthorectified format. In addition to these data sets, rainfall data was collected to assist in selection of the images since they were obtained from a dry season. Ground truth data used (256 points per site) were collected during field survey carried out from January 2008 to June 2009.

Table 4.1: Data sets used

Data type	Laikipia plain			Mt. Kenya Highlands			Usambara highlands &Pangani plain		
LANDSAT	Path/row	Year	Date	Path/row	Year	Date	Path/row	Year	Date
MSS	181/060	1976	25/01	180/060	1976	10/02	179/063	1976	10-Feb
TM	169/060	1986	28/01	168/060	1987	01/01	167/063	1987	01-Jan
ETM	169/060	1995	06/02	168/060	1995	30/01	167/063	1995	07-Jan
ETM+	169/060	2003	04/02	168/060	2003	12/01	167/063	2003	06-Jan
Aerial Photographs		1961 2008	25/01 07/09		1961 2008	25/01 07/09		1975 2009	10/03 04/02
Topographical maps		1978			1988			1985	

Source: Own illustration

4.4.1.1 LANDSAT Images

Time series LANDSAT data, which included LANDSAT Multispectral Scanner (MSS), TM, and ETM+, were used. A description of each is given in below. In addition a summary of the basic characteristic features of each sensor are summarised in Table 4.2.

Table 4.2: Satellite data characteristics

Satellite	Sensor	Spectral range µm	Bands	Scene Size km	Pixel Res (m)
LI-4	MSS multi-spectral	0.5 - 1.1	1,2,3,4	185x185	60
L4-5	TM multi-spectral	0.45 - 2.35	1,2,3,4,5,7		30
L4-5	TM Thermal	10.40 - 12.50	6		120
L7	ETM+ multi-spectral	0.45 - 2.35	1,2,3,4,5,7		30
L7	ETM+ Thermal	10.40 – 12.50	6.1,6.2		60
L7	Panchromatic	0.52-0.90	8		15

Source: Own illustration

LANDSAT MSS started to operate in 1972 (Satellite Imaging Cooperation (SIC), (2010). The MSS sensor images a swath of 185 km (115 miles) wide. Each pixel (picture element) in an MSS scene represents a 68m x 82m ground area. This sensor has 4 bands that simultaneously record reflected radiation from the earth's surface in the green (band 1), red (band 2), and near-infrared (bands 3 and 4) portions of the electromagnetic spectrum. The characteristics of the MSS bands are selected to maximize their capabilities for detecting and monitoring different types of earth's resources. For example, MSS band 1 can be used to detect green reflectance from healthy vegetation, and band 2 is designed for detecting chlorophyll absorption in vegetation. MSS bands 3 and 4 are ideal for recording near-infrared reflectance peaks in healthy green vegetation and for detecting water-land interfaces.

The TM is an advanced, multispectral scanning earth resources sensor designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity, and greater radiometric accuracy and resolution than the MSS sensor (NASA, 2003). This sensor also images a swath of 185 km (115 miles) wide but each pixel in a TM scene represents a 30 m x 30 m ground area (except in the case of the far-infrared band 6, which uses a larger foot print of 120 m x 120 m pixel). The TM opto-mechanical sensor has 7 bands that simultaneously record reflected or emitted radiation from the earth's surface in the blue-green (band 1), green (band 2), red (band 3), near-infrared (band 4), mid-infrared (bands 5 and 7), and the far-infrared (band 6) portions of the electromagnetic spectrum. TM band 2 can detect green reflectance from healthy vegetation, and band 3 is designed for detecting chlorophyll absorption in vegetation. TM band 4 is ideal for near-infrared reflectance peaks in healthy green vegetation and for detecting water-land interfaces. TM band 1 can detect water for bathymetric (water depth) mapping along coastal areas, and is useful for soil-vegetation differentiation and for distinguishing forest types. The two mid-infrared bands on TM are useful for vegetation and soil moisture studies, and discriminating between rock and mineral types. The far-infrared band on TM is designed to assist in thermal mapping, and for soil moisture and vegetation studies.

The LANDSAT-7 satellite was successfully launched on April 15, 1999. It is designed for a 705 km, sun-synchronous, earth mapping orbit with a 16-day repeat cycle (NASA 2003, SCI, 2010). LANDSAT-7 is equipped with the ETM+ sensor, the successor of TM. The observation bands are essentially the same seven bands as TM, and the newly added panchromatic band 8, with a high resolution of 15 m. An instrument malfunction occurred on May 31, 2003; as a result, all LANDSAT 7 scenes acquired since July 14, 2003 have been collected in "SLC-off" mode.

Generally the main difference among the LANDSAT data is the resolution, e.g. MSS (60 m), TM (30 m) and the additional band in ETM+ (15m) and the number of bands. The later sensors however, produce better quality images than the MSS sensor due to technological advances in data capturing and processing.

4.4.1.2 Rainfall data

In order to evaluate image quality (impact of air moisture), rainfall data were obtained from Nyeri, Rumuruti, Lushoto and Maji Korogwe meteorological Stations. The data were very important to provide an overview of rainfall trend in the study sites before image acquisition to enable proper selection of the images to be used for this study. In addition to the daily rainfall data, a ten year average was calculated and the results are presented in Figure 4.4. Two dry seasons are observed from the figures, from December to March, and June to September for all the sites except for Laikipia site, which continues to receive high rainfall even after June. January and February images were selected as they had low cloud cover and coincided with the field survey.

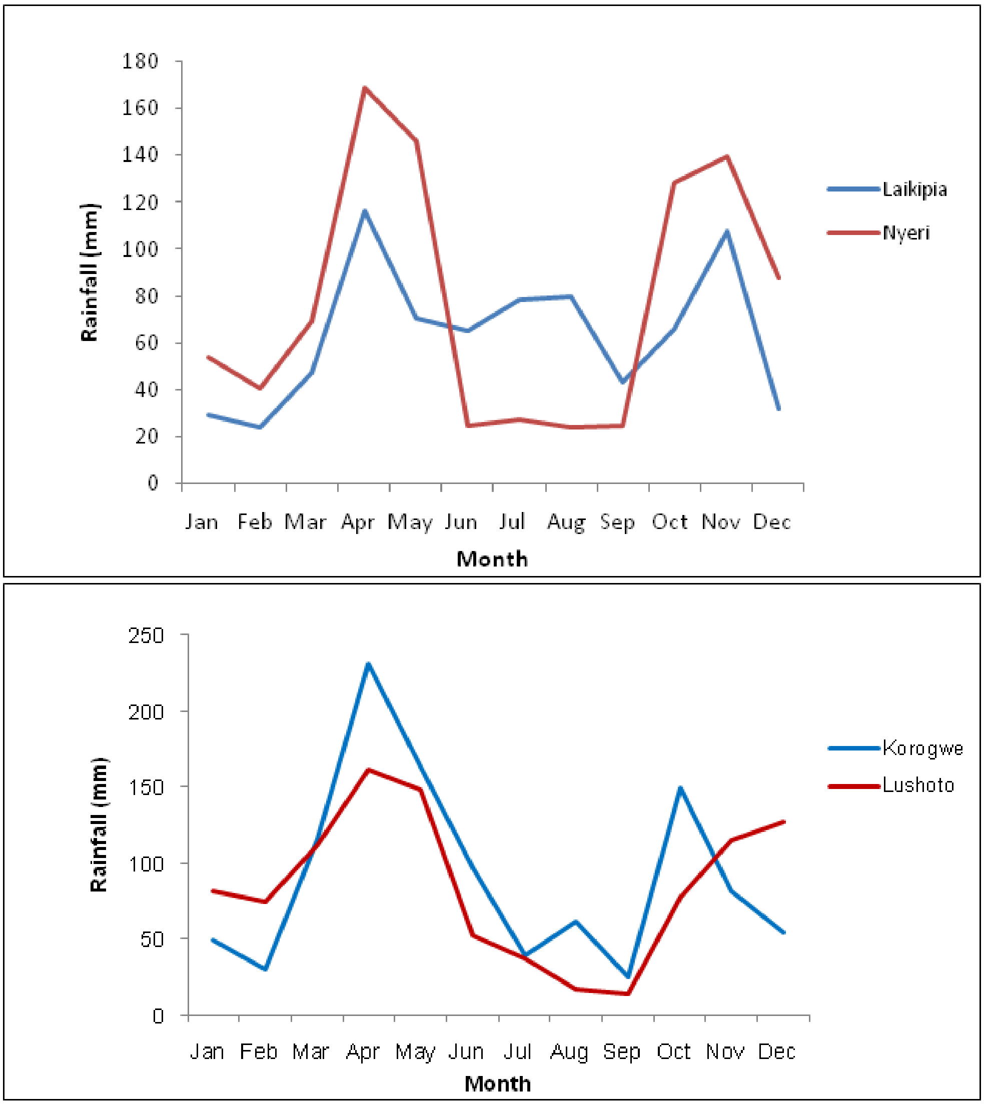


Figure 4.4: Monthly average rainfall in the Kenya sites (top) and Tanzanian sites (down) (n=10 yrs) 1999-2008.
Source: Meteorological stations of Nyeri, Rumuruti, Lushoto and Maji Korogwe

4.4.2 Data pre-processing

The LANDSAT images were downloaded from GLFC, unzipped and afterwards layer stacked to create composite images. Co-registration was not important because the images fitted together but they were all re-projected to UTM zone 36N for the Laikipia site and 37S for all other sites. Only six bands (1-5, 7) were used for analysis, without the thermal band. Quick statistics were generated in ENVI 4.3 and converted to percentage from digital numbers and plotted for spectral reflectances (Figure 4.5 and 4.6). The mean values were lower in the 1985 Laikipia plain scene and higher in the 1995 and 2003 scenes. In Pangani plain the mean values were almost similar in 1987 and 1995 but higher in 2003. According to Haack *et al.* (1987) and Yang & Lo (2002), it is important to normalize the data when dealing with multi sensor and multi temporal images to reduce the noise resulting from sensor differences, sun angle and phenological effects. However, care should be taken to ensure that the data quality is not degraded.

Several radiance to reflectance transformations are proposed or designed to remove the unwanted effect of the solar and atmosphere noise, e.g. path irradiance in order to estimate the reflectance of the surface like Dark Object Subtraction (DOS) and Multivariate Alteration Detection. For this study, Multivariate Alteration Detection (MAD) was chosen. MAD identifies no-change pixels in bi-temporal images automatically, which are used for radiometric normalization (Canty, 2008). For the implementation of MAD analysis spatial subsets were chosen, which were used for the identification of no-change pixels. The statistics of these pixels were then applied to normalize the whole image with an orthogonal regression. In this case the subsets have to be chosen carefully so that they encompass a great variance of different land covers. The 2003 scenes from both sites were used for normalization.

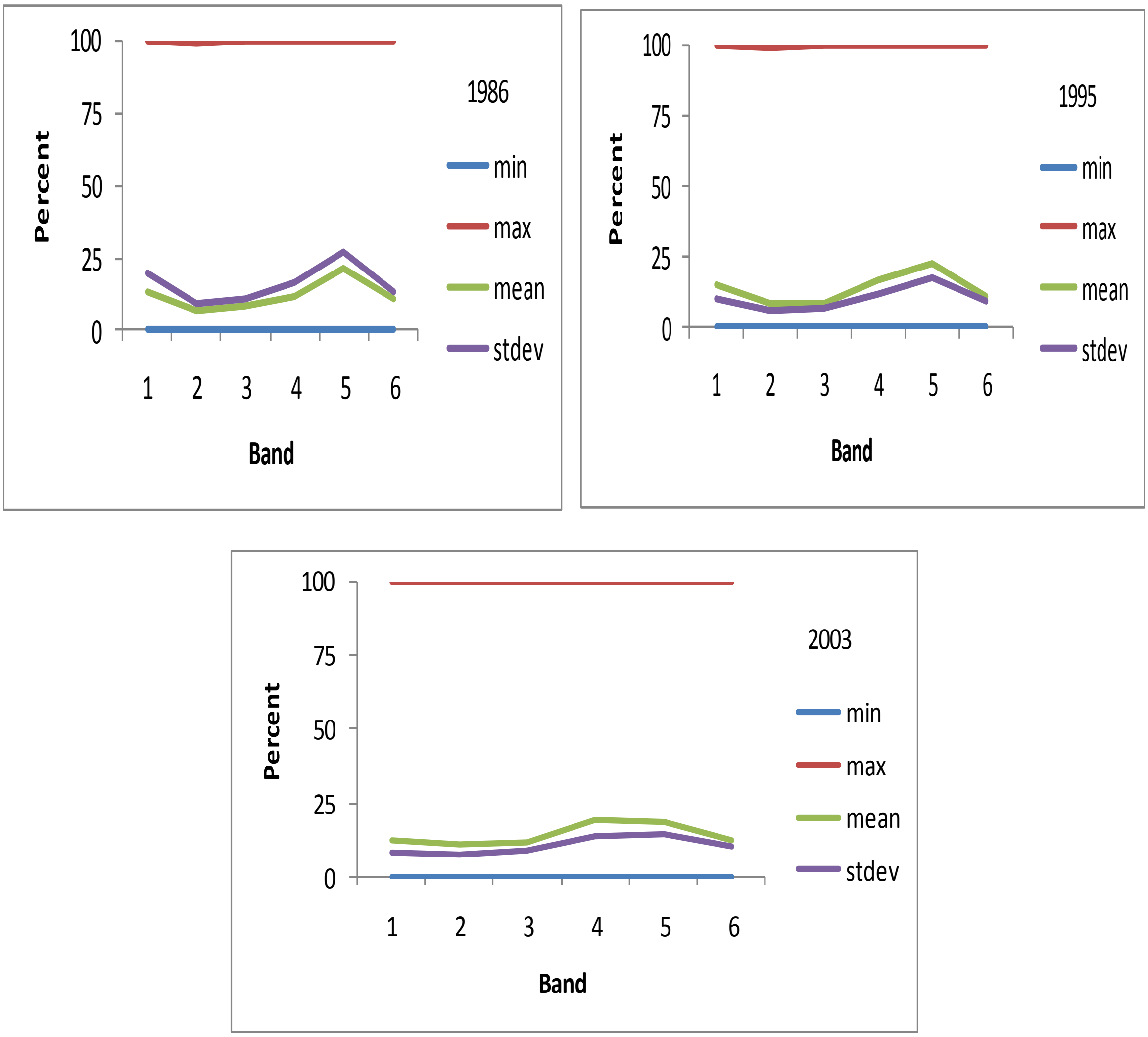


Figure 4.5: Spectral reflectance plots of the Laikipia floodplain scene 169_060 of 1985, 1995 and 2003, respectively.
Source: Own illustration

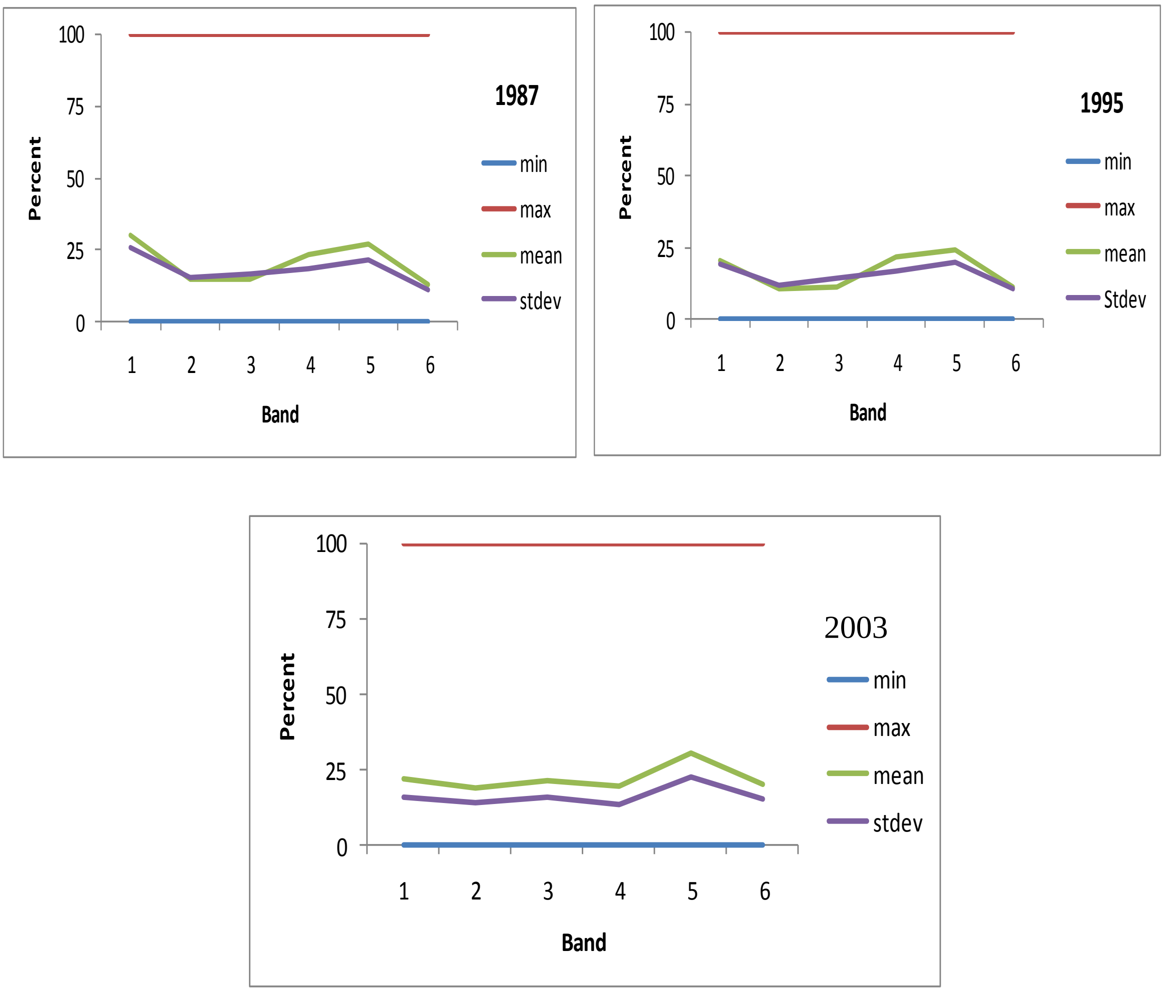


Figure 4.6: Spectral reflectance plots of the Pangani floodplain scene 167_063 of 1987, 1995 and 2003, respectively.
Source: Own illustration

After the normalization the images were subset and the polygons created during the delineation process were used for cutting the subset images. A classification scheme was then prepared (Table 4.3). According to Lyon (2001), preparation of a scheme is a prerequisite in the classification process. Even though the wetland types may be adopted from known systems of classification, the detailed land use classification lies in the interest of the scientists. Thus the scheme for this study was prepared after observation of land uses and cover in the study areas. Details of the classes and their description are provided in Table 4.3. Classification was conducted in ERDAS imagine. The MSS images were re-sampled to 30m for presentation purpose.

Table 4.3: LCLU classification scheme

Use type	**Code**	**Description**
Open water	OP	Areas permanently flooded with standing water for 12months.
Open water floating vegetation	OP/FV	Permanently flooded areas for more than 6 months with floating vegetation like Nile cabbage, which normally dry up during drought.
Permanent papyrus swamp	PS	Areas dominated with *Papyrus* other wetland vegetation like *Typha domingesis* exists, may be permanently flooded or with high soil moisture content throughout the year.
Natural vegetation	NV	Areas covered with other wetland vegetation like *Cyperus* species which survives in flooded conditions for 3months and less moisture condition for the rest of the months.
Cropland	CL	Cultivated areas with field crops rice, maize, beans etc or vegetables. Could be seasonally flooded with high moisture content for most part of the year.
Forest	FO	Areas covered with either exotic or natural tree stands which are seasonally flooded.
Shrubs	SH	Shrub dominated areas mostly seasonally flooded.
Grassland/ grazing	GG	Seasonally flooded areas covered with *Pennisetum* or *Cynodon* which are used for animal grazing.
Burnt	BN	Seasonally flooded areas usually burnt in dry season.
Bare land	BL	Areas without vegetation cover due to prolonged drought or degradation.
Built up	BU	Settlements, roads or any other kind of infrastructure.

Source: Own illustration

4.4.3 Data Analysis

Both unsupervised and supervised classifications were applied for the floodplain test sites i.e. Rumuruti, Manguo, Magoma and Malinda using time series LANDSAT images. For the inland valleys (Lukozi, Nyeri, and Karatina) unsupervised classification was done on true colour aerial photographs. An automated classification of the aerial photographs for the inland valleys was preferred to on screen digitization due to diverse use cover and land fragmentation of these wetlands that wouldn’t have been distinguished manually.

Unsupervised classification was done for all test sites using the ISODATA clustering algorithm in ERDAS imagine 9.3. The convergence value was specified as 0.99 and the maximum iteration was specified at 80. Colour scheme option was specified as gray scale to be able to assign new classes in different colours. Since the study areas were subset into their specific size, 9 clusters were produced per site (Figure 4.7/9). The clusters were identified and labelled using maps, aerial photographs and NDVI values. Signatures were generated for field identification of the classes and as training the supervised classification. In the field the 256 points were collected using Trimble PDA in UTM coordinate system for cluster labelling (111) and accuracy assessment (145). Minimum distance to mean algorithm was used for classification and between 6 and 9 classes were identified out of the 11 classes since the wetlands were not uniform in terms of LCLU in each time sequence and sites as shown in some selected sites in Figure 4.7-4.9.

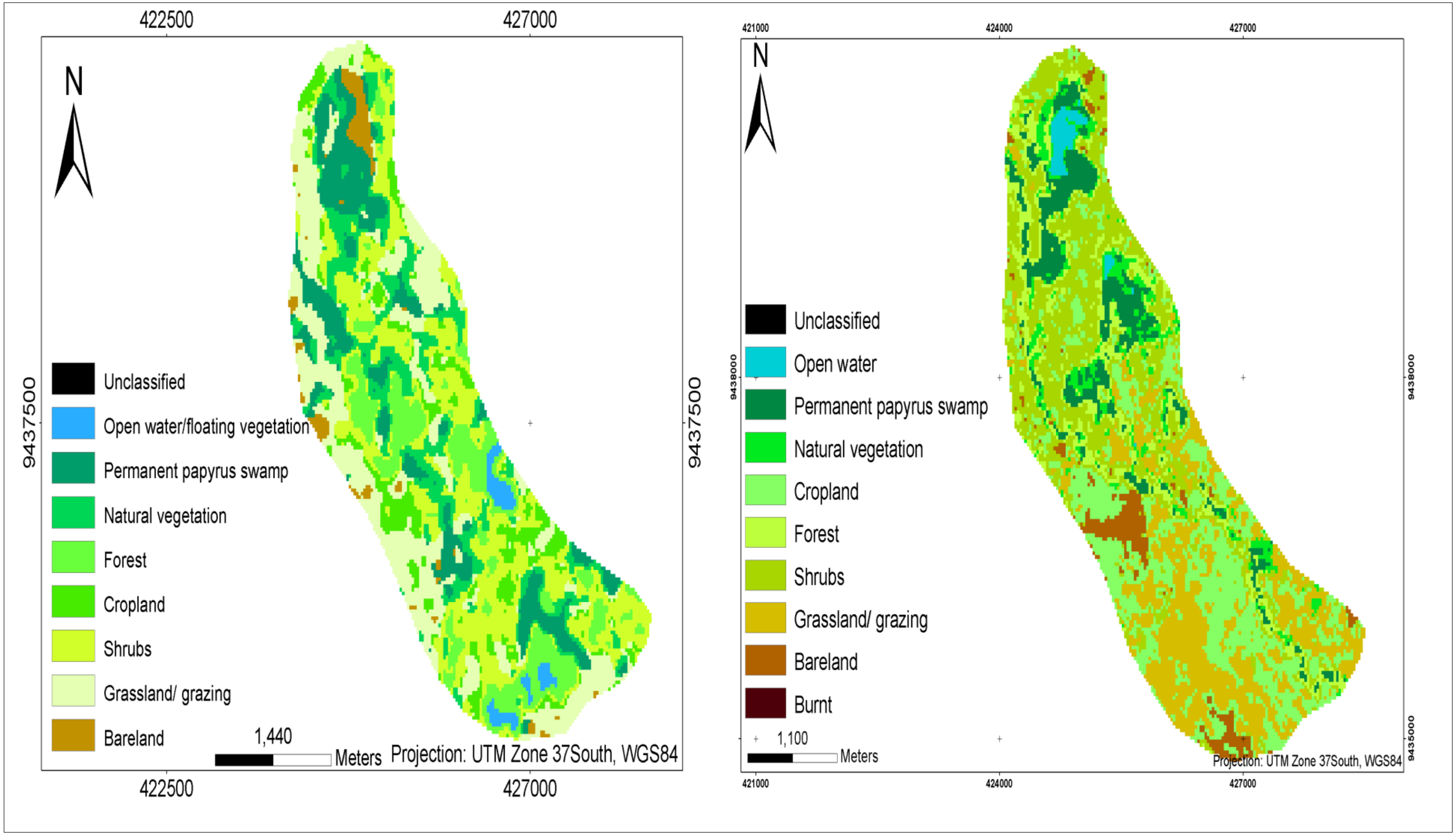


Figure 4.7: MSS unsupervised (left) and ETM+ supervised (Right) LCLU maps of Malinda test site 1976 & 2003.
Source: Own illustration

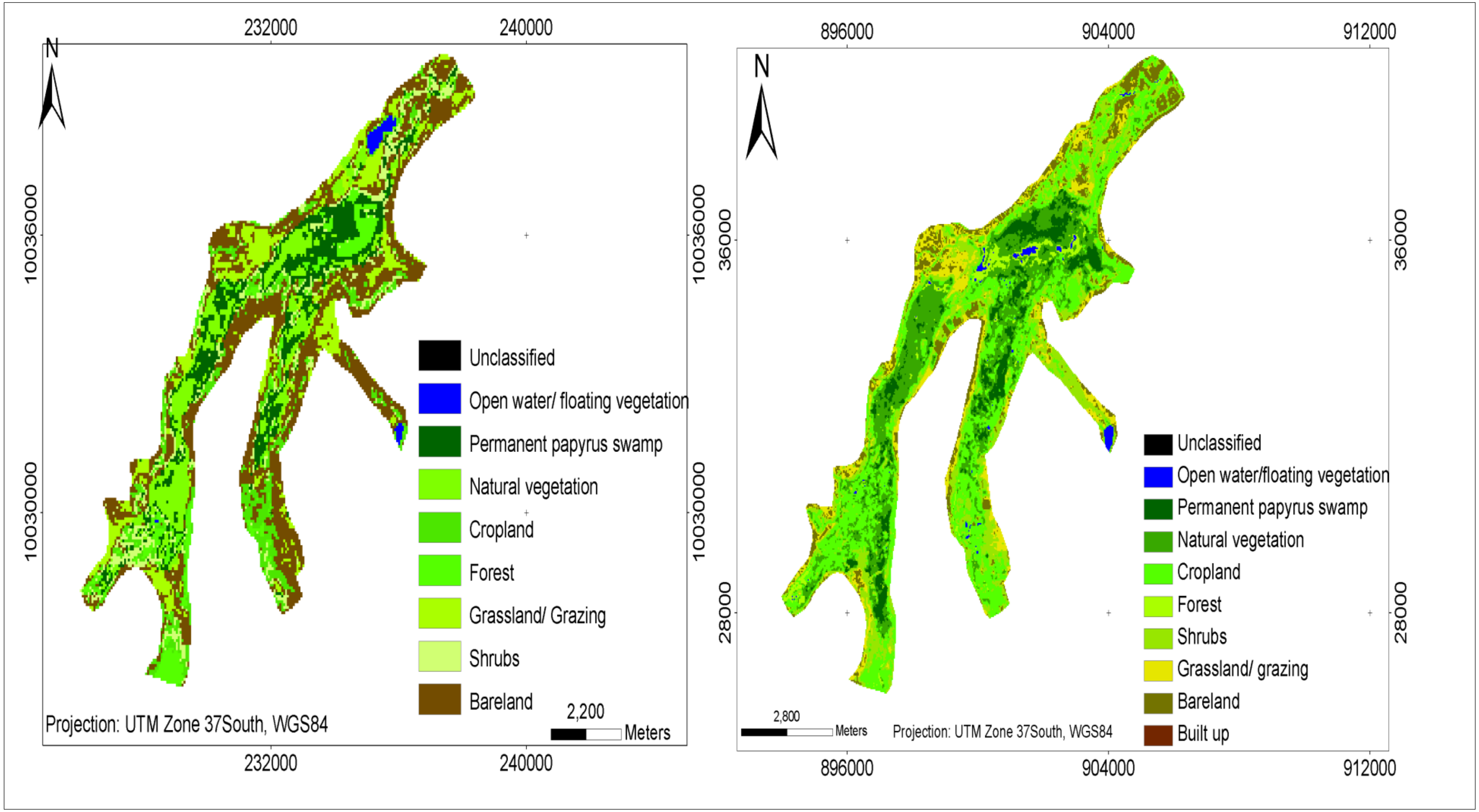


Figure 4.8: MSS unsupervised (left) and ETM+ supervised (Right) LCLU maps of Rumuruti test site, 1976 & 2003.
Source: Own illustration

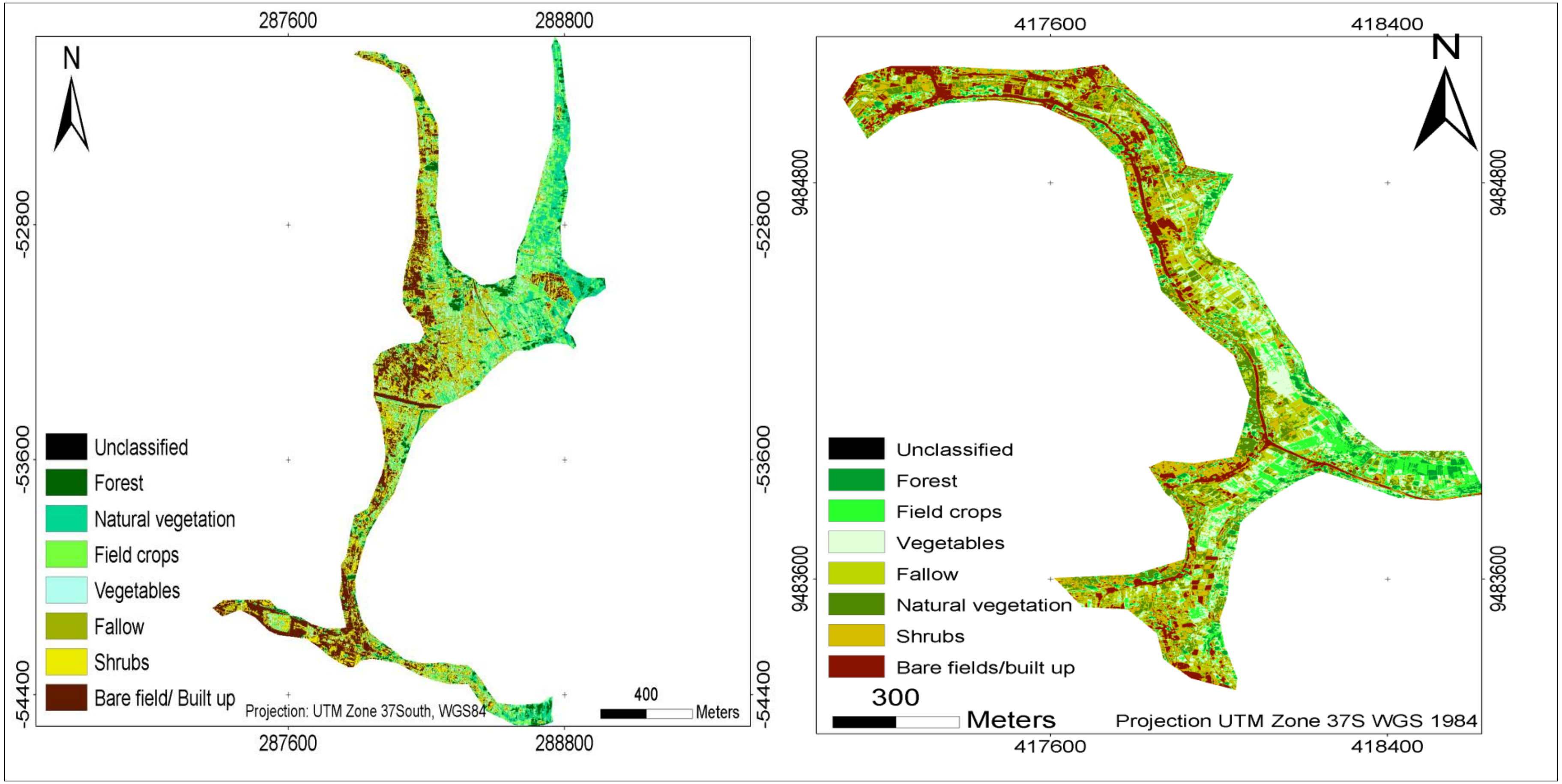


Figure 4.9: LCLU maps of inland valleys created from unsupervised classification of aerial photos of Tegu test site, 2008 (Left) and Lukozi test site, 2009 (Right).
Source: Own illustration

4.4.4 Accuracy assessment

Accuracy assessment was performed for all supervised classified wetlands. Even though it wasn't possible to obtain an excellent coverage of data for all the three time slots for ground truthing the LANDSAT images, historical aerial photographs for the Tanzanian sites were useful for MSS data truthing as they were taken in 1975, a year before the MSS data were taken. Maps, field survey and interviews with the indigenous people facilitated the exercise. Yang & Lo (2002) comment that an assessment of a LANDSAT MSS-based and a LANDSAT TM-based land use and cover map should be sufficient to shed light on the overall accuracy of the land use/cover mapping where not enough spatial coverage data is available. This was adopted for this study. A random approach was adopted for accuracy assessment with 145 points for each site collected in the field.

4.5 Results and discussion

Wetlands LCLU classification results and discussion are presented in the following subsections. The classification accuracies are examined and the area share of each class is computed.

4.5.1 Wetlands LCLU classification

Eleven main types of land use and cover were identified and classified. These include open water, floating vegetation, permanent papyrus swamps, natural wetland vegetation (mixed vegetation), cropland, forest (natural and exotic), shrubs, grassland or grazing, burnt areas, bare land and built up/ settlements. Examples of the cover/uses are displayed in Figure 4.10 and 4.11. The uses were not uniform in all wetlands. Floodplains in Rumuruti and Malinda had up to nine classes while in Manguo and Magoma mainly 6-7 classes were found. Open water, floating vegetation, papyrus swamps, grazing and burnt areas were common in the flood plains. Instead of grassland in the inland valleys fallows were dominant and the grasses are harvested as livestock feeds for zero grazing. Large parts of the inland valleys were intensively cultivated both for horticulture and subsistence crops like maize, beans and potatoes while floodplains were extensively used.

Figure 4.10: Permanent papyrus swamp in Rumuruti
Photo: by Mwita, June 2009

Figure 4.11: Wetland cultivation in Usambara highlands (Lukozi)
Photo: by Mwita, February 2009

Most of the classes were detectable in the LANDSAT images. However, the separability for some of the classes was very poor. Clusters generated by unsupervised classification were mixed. For instance, in Pangani plain it was not possible to distinguish rice from *Cyperus* species because they were showing similar reflectivity in all bands. Similarly in Laikipia plain different vegetation types in the swamp could not be separated by classification and field crops like maize were mixed with other wetland vegetation. Supervised classification split the classes but still some classes like settlements in Rumuruti were not possible to separate from bare land because they are made of mud, which reflects in the same way as bare land. Floating vegetation and other aquatic vegetation were mixed. This problem is common in the classification of wetlands using medium or low resolution images. Islam *et al.* (2008) observed similar difficulties in classifying wetlands in Ruhuna River Basin in Sri Lanka. For example, irrigated grownup rice was mixed up with riparian vegetation, mangrove and water bodies with densely populated aquatic plants (which also has a high NDVI), irrigated fields under preparation with marshy land or shallow water and seasonal wetlands (which were dry for that date) with harvested agricultural fields. Yang & Lo (2002) had similar experience where forest (clear cuts, sparse forest, and wetlands) were mixed with cropland or grassland.

Though inland valleys were detected by LANDSAT images it was not possible to classify them using the same images because they were narrow. Some were covered by 3pixels in width. According to FGDC (1992), in order to consistently identify an object in a LANDSAT image of 30m, it takes a window of nine pixels or approximately 0.9 ha and if the object is not square or adjacent areas have similar spectral reflectance up to 25 pixels are needed for confident classification. Since the resolution of the images was higher inland valley classes were easier to identify and to label. On screen digitization applied for detailed land use maps of the flood plains was achieved successfully.

4.5.2 Classification accuracies of the mapped wetlands

The overall accuracies were very high as observed in Table 4.4; they ranged from 82.76 to 95.17% with a Kappa index of 0.7 to 0.94. The MSS data had lower accuracies as compared to other LANDSAT data largely due to the resolution of the images. The masking out of the wetlands from other uses is seen to have increased accuracies since the spectral mixture with upland LCLU was restricted. Producer accuracies for OP/FV in Malinda and Magoma sites for MSS and TM data were the lowest (33.33%), which means many pixels were confused with other LCLU types. This could be a result of spectral mixture between OP/FV and PS or other vegetation. In 1995 much vegetation was observed over the open water area, which didn't appear in the following images. User accuracies were higher, which means many LCLU were labelled correctly. The results imply that the identified and labelled LCLU was properly done.

Table 4.4: Results of accuracy assessment of LANDSAT MSS, TM and ETM+ LCLU maps of floodplain sites

Manguo test site

Year	Accuracy %	OP/FV	PS	NV	CL	GG	BU	BL	Overall %	Kappa
1976	Producer	100	83.33	97.14	82.22	100			91.03	0.88
	User	86.67	100	82.93	97.37	93.75				
1986	Producer	100	80	93.02	100	92.86	83.33		91.72	0.90
	User	90	92.31	93.02	91.67	96.3	71.43			
1995	Producer	100	83.33	93.88	93.55	100	40	100	93.1	0.91
	User	100	90.91	92	93.55	96.15	100	88.89		
2003	Producer	95.65	66.67	100	0	100	100	85.71	93.79	0.91
	User	95.65	100	93.51	0	95.45	75	100		

Rumuruti test site

Year	Accuracy %	OP/FV	PS	NV	CL	FO	SH	GG	BU	BL	Overall %	Kappa
1976	Producer	33.33	94.12	76.19	92.31	72.73	88.89	81.25	100		88.28	0.86
	User	100	76.19	94.12	80	80	88.89	92.86	93.88			
1986	Producer	50	100	60	100	66.67	97.22	93.33	66.67	75	92.41	0.91
	User	100	93.33	100	96.55	100	87.5	96.55	66.67	75		
1995	Producer	50	90.91	93.75	96.97	100	97.5	87.5	80	90.91	93.1	0.92
	User	100	90.91	88.24	96.97	100	95.12	93.33	88.89	83.33		
2003	Producer	100	100	93.55	100	100	100	100	71.43	25	95.17	0.94
	User	100	90	100	97.96	100	100	100	62.5	33.33		

Magoma test site

Year	Accuracy %	OP/FV	NV	CL	SH	GG	BL	Overall %	Kappa
1976	Producer	50	94.44	76.19	87.1	84.21	100	82.76	0.79
	User	100	91.89	94.12	87.1	80	86.67		
1987	Producer	40	100	87.88	100	100	90	86.21	0.83
	User	100	92.16	100	92.5	92.86	100		
1995	Producer	33.33	95.83	92.86	95	92.86	100	90.34	0.88
	User	100	90.2	89.66	95	92.86	100		
2003	Producer	40	82.61	100	95.83	100	100	91.72	0.90
	User	100	100	92.54	100	100	100		

Malinda test site

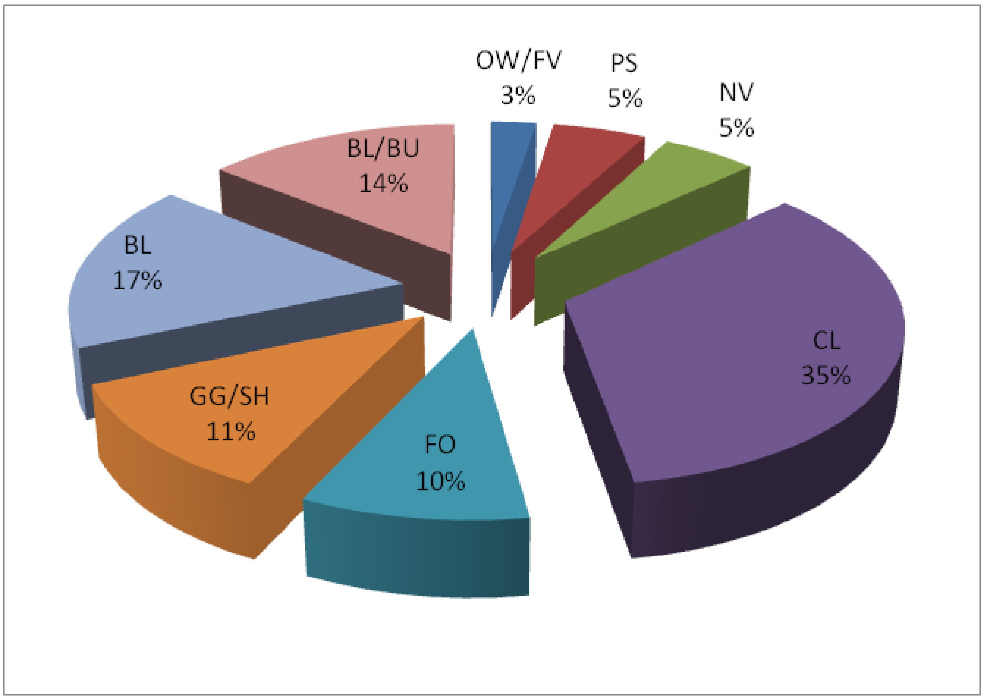
Year	Accuracy %	OP/FV	PS	NV	FO	CL	SH	GG	BL	BN	Overall %	Kappa
1976	Producer	33.33	95	50	100	71.43	82.93	87.1	80		88.32	0.85
	User	100	79.17	80	84.62	83.33	91.89	75	80			
1987	Producer	100	84.21	89.47	76.19	93.75	73.33	100	76.92		94.48	0.93
	User	100	84.21	80.95	100	78.95	100	81.48	100			
1995	Producer	66.67	87.5	92.45	84.62	100	81.48	100	100		92.41	0.9
	User	100	82.35	92.45	84.62	86.36	100	71.43	100			
2003	Producer	100	97.92	70	87.1	90.91	93.75	90.91	91.67	100	94.48	0.94
	User	100	97.92	63.64	90	90.91	93.75	90.91	91.67	100		

Source: Own illustration

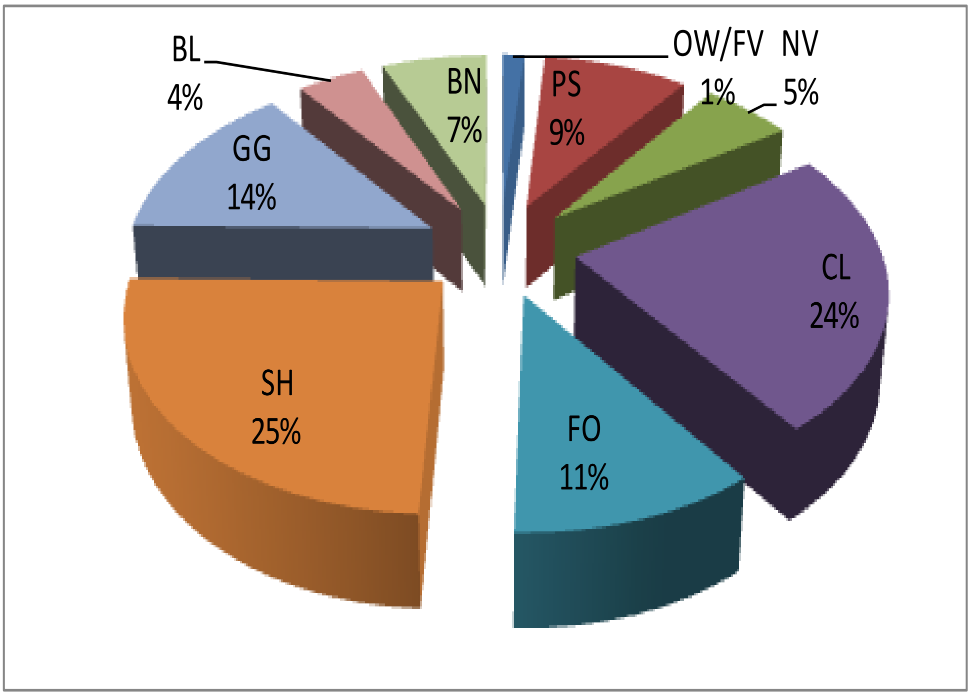
4.5.3 Computation of wetlands' LCLU areas

One of the objectives of this study was to determine the percentage coverage of each LCLU. This was done after the classification process. The maps were opened in ArcGIS and using field calculator, the areas for each LCLU were calculated in ha and then exported as dbf-files to excel. The percentage of each cover was finally calculated per site and results presented in figures.

The results show that floodplains in Laikipia site covered 919.35 ha, 171.81 ha in Manguo and 747.54 ha in Rumuruti. In the Pangani site they covered 1109.1 ha in Malinda 567.1 ha and in Magoma 542 ha. The percentage of each LCLU is shown in the Figures 4.12. The largest share (35 and 24%) was covered by cropland in Laikipia and Pangani, respectively, followed by grassland/ grazing combined with shrubs (11 and 39%) and bare land (17 and 4%). Natural vegetation covers the same percentage of 5% in both sites and open water covers 3% in Laikipia and 1% in Pangani. Laikipia is settled and the built up area covers 14%. No settlements were found in the Pangani plains but seasonal burning was very common and covered 7%. Although all sites exceeded the required 500 ha, they were considered because it was impossible to find the sites with the specified size. Rumuruti site was an exception because of the scarcity of wetlands in that arid area.



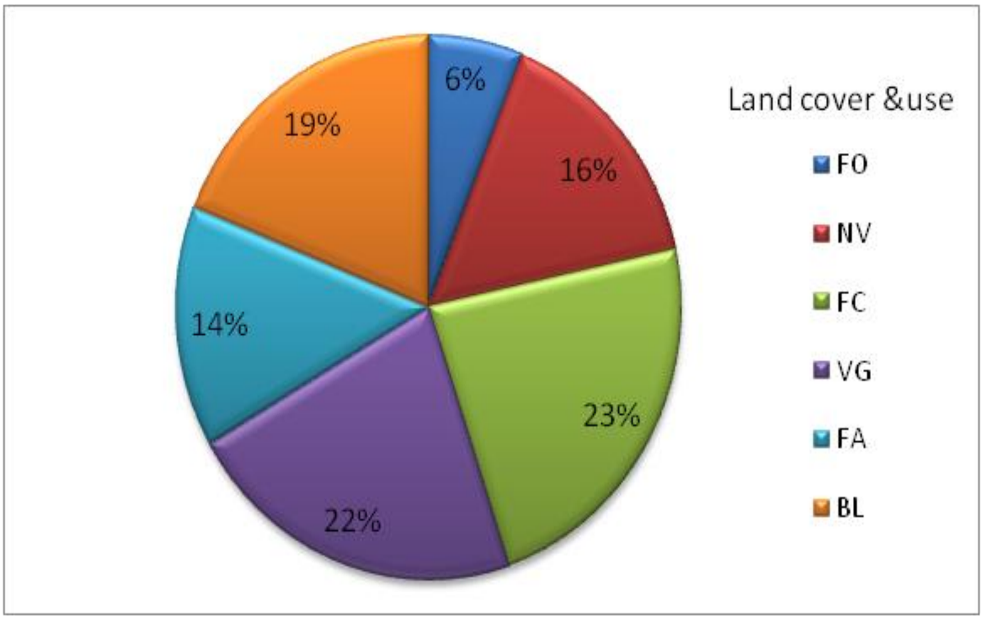
LCLU in Laikipia floodplain



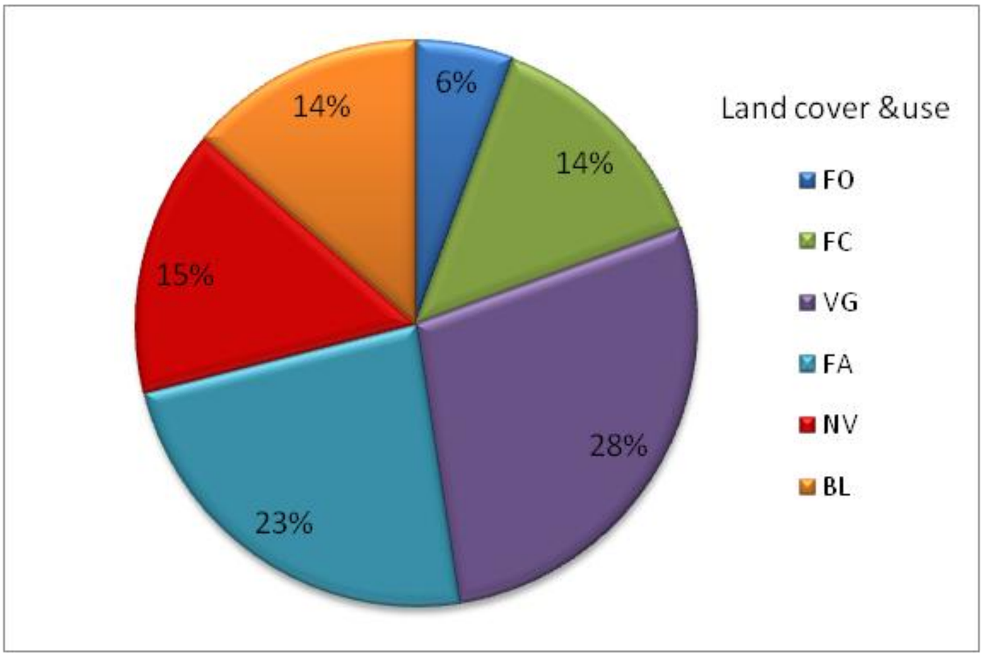
LULC in Pangani floodplain

Figure 4.12: Area Coverage of different LCLU types in Laikipia and Pangani sites. BL-bare land; BU-built up; CL-crop land; FO-forest; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation; OW-open water; PS-papyrus swamp; SH-shrubs
Source: Own illustration

The inland valleys covered 60.65 ha in Mt. Kenya and 32.75 ha in the Usambaras. Figure 4.13 shows that the vegetables covered 22.84% in Mt. Kenya and 28% in the Usambaras. Field crops were 23% in Mt. Kenya 14% in Usambara, and fallow 23 and 14% respectively. Natural vegetation, which were largely various *Cyperus* species, covered 16 and 15% in Mt. Kenya and the Usambaras. Bare land and built-up areas accounted for 19% in Mt. kenya and 14% in Usambara, and forests 6% in both sites. The covers and uses are very dynamic i.e. they change a lot with seasons. In wet season more field crops are like maize and beans and arrow roots are produced and in dry season more vegetables are cultivated in rotation.



LCLU in Mt. Kenya highlands



LCLU in Usambara highlands

Figure 4.13: Area Coverage of the LCLU Types in Mt. Kenya and Usambara highlands. BL- bare land; FA- fallow; FC-field crops; FO-forest; NV- natural vegetation; VG-vegetables
Source: Own illustration

The uses have been increasing over time. In 1976 there were no settlements in the wetlands; they only emerged in the subsequent years. In the Rumuruti site, for instance, there was an increase in cropland, bare land and built up areas between 1976 and 2003 (Figure 4.14). Covers were, however, decreasing in permanent *Papyrus* swamps and shrubs increased in 2003. This implies that the wetlands are continuously being transformed and the transformation may have negative implications on the resource and the surrounding communities, which directly depend on them.

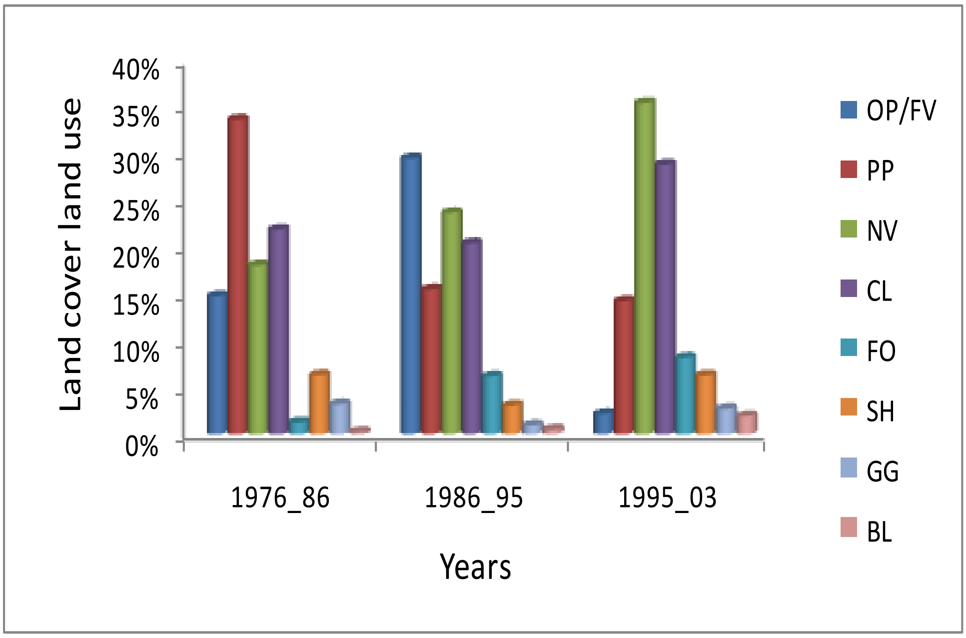


Figure 4.14: Time series LCLU of the Rumuruti test site. BL-bare land; BU-built up; CL-crop land; FO-forest; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation; OW-open water; PS-papyrus swamp; SH-shrubs
Source: Own illustration

4.6 Conclusion

The results have revealed that, digital classification of wetlands is significantly useful in identification and labelling of the LCLU classes. Time series data are essential in determination of the classes. The resolution of the images matters a lot for appropriate classification of the wetland uses and cover. The thematic maps produced portray the diverse ways in which small wetlands are utilised. Among the uses, agriculture covers the largest part of the wetlands. This together with other uses is on the increase and may have negative impacts on the resource. The increasing uses call for continued monitoring of the wetlands to understand the ongoing transformation processes and their driving forces. The next chapter focuses on factors for wetlands transformation and the resulting impacts.

5 Assessment of land cover and use changes in small wetlands of East Africa

As observed in the previous chapters, a multitude of human activities, which are on increase, are undertaken in the small wetlands in East Africa. These activities alter the natural status and functioning of the wetlands. This chapter focuses on detection of cover and use changes in small wetlands, and the driving forces behind these changes. It presents the hypothesis and objectives, literature review as well as material and methods used to achieve the goals of this study. The results are also presented and discussed and a conclusion is drawn from the observation made on the results and the discussion.

5.1 Introduction

Since ancient time, wetlands have been used for different human activities, due to their diverse ecological richness. Activities such as farming, grazing, fishing and settlement development are common in wetlands particularly in sub-Saharan Africa, and have caused significant loss of wetlands and their riparian areas (Rebelo *et al.*, 2009b; Haack, 1996). The majority of wetlands lost historically (more than 80% of all wetland conversions since 1980) were drained or filled to create agricultural land (Baker *et al.*, 2007). Hydrological disturbance through drainage and vegetation clearance alters wetlands functionality leading to their loss and degradation.

Over the years, remote sensing has been used as a tool to map wetlands. With regular passage of sensors over a locality, land information in the form of multi-date and multi-spectral images can be obtained within a constant period of time (Rundquist *et al.*, 2001). Changes in surface environmental conditions can therefore be monitored using space-borne digital imageries. With the launch of remote sensing, satellites like the LANDSAT series with MSS and later TM, and ETM+, it has become cost effective and convenient to acquire multi-date digital images over a greater array of spatial and temporal scales (Lu *et al.*, 2004). The multi-date images facilitate detection of changes in wetlands and other environmental resources.

In the recent past, small wetlands in East Africa have received high pressure of use, and especially for agriculture intensification. The increasing pressure is mainly attributed to population growth, emerging upland shortages, and increasingly variable climatic conditions in parts of East Africa (Mwita *et al.*, 2010; Franke *et al.*, 2009). The increasing pressure and uncoordinated wetlands use in Kenya and Tanzania are a consequence of unclear policies on wetlands management (Rebelo, *et al.*, 2009b; Thenya, 2001). As a result the wetlands are continuously being lost and degraded, and this may eventually lead to their depletion. Monitoring of these fragile ecosystems therefore, helps to determine their resilience to human interference, and guide decision makers on the best way to manage them without compromising their future existence.

5.2 Hypothesis and objectives

It is hypothesized that land use changes in the small wetlands can be detected by multi temporal LANDSAT images using different techniques. Furthermore it is assumed that anthropogenic factors have greater influence on wetland changes. The following objectives are to be achieved:-

1. To assess the historical land use change between 1976 and 2003
2. To identify driving forces of the changes

5.3 Literature review

This review provides a theoretical background of land cover and land use change, driving forces of LCLU change, the role of remote sensing in change detection and techniques used.

5.3.1 Theoretical background of land cover and use change

Land cover refers to the biophysical state of the Earth's surface and immediate subsurface. It includes biota, surface water, ground water, soil and human made structures (Braimoh, 2004). Land use on the other hand is the human exploitation of land cover, for instance, land may be used for agricultural production and water extraction for industrial production. Thus land use leads to land cover change. There are a number of theories by for example Malthus (1967), Boserup (1965) and Von Thunen (1826) among others, which have been formulated in an attempt to explain the underlying factors of land cover and use change (LCLU). These theories are discussed in this section.

Malthus' theory stated that, "the populations of the world would increase in geometric proportions and that of the food resources available for them would increase only in arithmetic proportions" (Malthus, 1967:8). In other words, if human population was allowed to increase in an uncontrolled way, then the number of people would increase at a faster rate than the food supply. A point would come when human population would reach a limit that food resources could support it. Any further increase would lead to population crash caused by natural phenomena like famine or disease.

The important element in Malthusian theory, which is directly related to LCLU, is population density. The increase in population exerts pressure on land such that frequency of cultivation increases thereby shortening fallow periods needed to rejuvenate the soil fertility (Braimoh, 2004). Soil fertility is reduced by shortened fallow length and thus productivity drops, which leads to food scarcity. Since food demand is high due to increased population, more arable areas are invaded for cultivation. With the decline of arable areas marginal areas are encroached for cultivation leading to their degradation.

Applicability of this theory in the developed world may be insignificant due to increased technology, population control measures and financial means for farmers' compensation. Despite population control measures in the developing world, particularly in Africa, the growth rate is still high. This coupled with global climatic changes and dependency on environmental resources for production has resulted into land shortage and degradation of upland areas. In turn, wetland ecosystems have become focal points of production by commercial and traditional users, entailing rapid change in wetland use and degradation.

While Malthus perceived population growth as a threat to resources, Boserup (1965) believed that population density was an incentive to development i.e. incentive for agricultural intensification. An increase in population leads to an increase in demand for food thus labour input per unit of land is increased to meet demand for intensive cultivation and farm management. It follows therefore, that adaptation of conservation techniques and high yielding species is a necessity for maintenance of soil fertility and yield increase.

According to Lambin & Geist (2006) and Braimoh (2004), this theory suits better to perfect market conditions.

The situation is very different in most of the African countries. Lack of efficient markets for crops and capital to invest in agriculture has led to failure in agriculture (Ponte, 1998). In the highlands of East Africa, coffee for instance, was the main cash crop which people relied on for income generation. Price failure in the world market has caused people to turn their focus to horticultural crops, since they take shorter time to mature and are on high demand, (Ponte, 1998) thus increasing pressure on wetlands.

Von Thunen (1826) set a basic analytical model of the relationships between markets, production and distance. For this purpose he looked upon the agricultural landscape. According to the model, the relative costs of transporting different agricultural commodities to the central market, determines the agricultural land use around a city. The most productive activities will thus compete for the closest land to the market and activities not productive enough will be located further away.

Von Thunen's ideas are still relevant to date, within the cities; land is more expensive than in the peripheries. Thus investment in land will go to the highest returning activities. Nonetheless, development in transport and infrastructure has facilitated movement of goods and services. Thus at times, transport cost has no relation to where the products are located. Markets are everywhere and sometimes farmers have access to road-side markets where they can easily sell their produce. Consumers can also pick the products from where they are produced. That is the case with wetland products in the study sites, where farmers sale their crops before they are ready to harvest as brokers normally travel to the villages to reserve them. As a consequence agriculture is intensified and more wetlands are encroached.

These theories provide a basis for understanding interactions of different factors and their implications to LCLU change. They also offer an insight into the drivers of LCLU change, which are discussed in detail in the following section.

5.3.2 Driving forces of LCLU change in wetlands

Assessing the driving forces behind LCLU is necessary if past patterns are to be explained and used in forecasting future patterns. Driving forces on LCLU change can include almost any factor that influences human activity (Braimoh, 2004). Geist & Lambin (2002) divides driving forces of LCLU change into proximate and underlying causes, which are adopted and modified here, (Figure 5.1) to describe the situation in small wetlands in East Africa. Proximate causes are human activities or immediate actions at the local level, such as agricultural expansion and macrophyte extraction that originate from intended land use and directly impact on land cover. The biophysical factors are also included here, for it is their presence that stimulates people to think of accessing and utilizing them to satisfy their needs.

Underlying driving forces are categorized into five broad clusters: demographic, economic, technological, policy and institutional and cultural factors. These are further subdivided into specific factors; for example, cultural or socio-political factors are partitioned into public attitudes, values and beliefs, as well as individual or household behaviour. Underlying driving forces are fundamental social processes, such as human population dynamics or agricultural policies that underpin the proximate causes and either operate at the local level or have an indirect impact from the national or global level. There are also contributing factors, including fires, drought, floods and other environmental and social calamities, which may lead to LCLU change. The interaction between these factors leads to LCLU change in the wetlands.

In East Africa, wetlands have been widely used in different ways to satisfy human needs. The use of wetlands has been largely necessitated by increased population, which is a result of either natural increase, in migration or resettlement. The population has increased pressure on upland areas that have been traditionally used for agriculture. In addition climate changes (high rainfall variations) have led to poor harvests. These dominant drivers have led to the search for supplementary food production and income generating opportunities by the poor as a survival strategy, especially by using wetlands to produce crops in the dry season for food security.

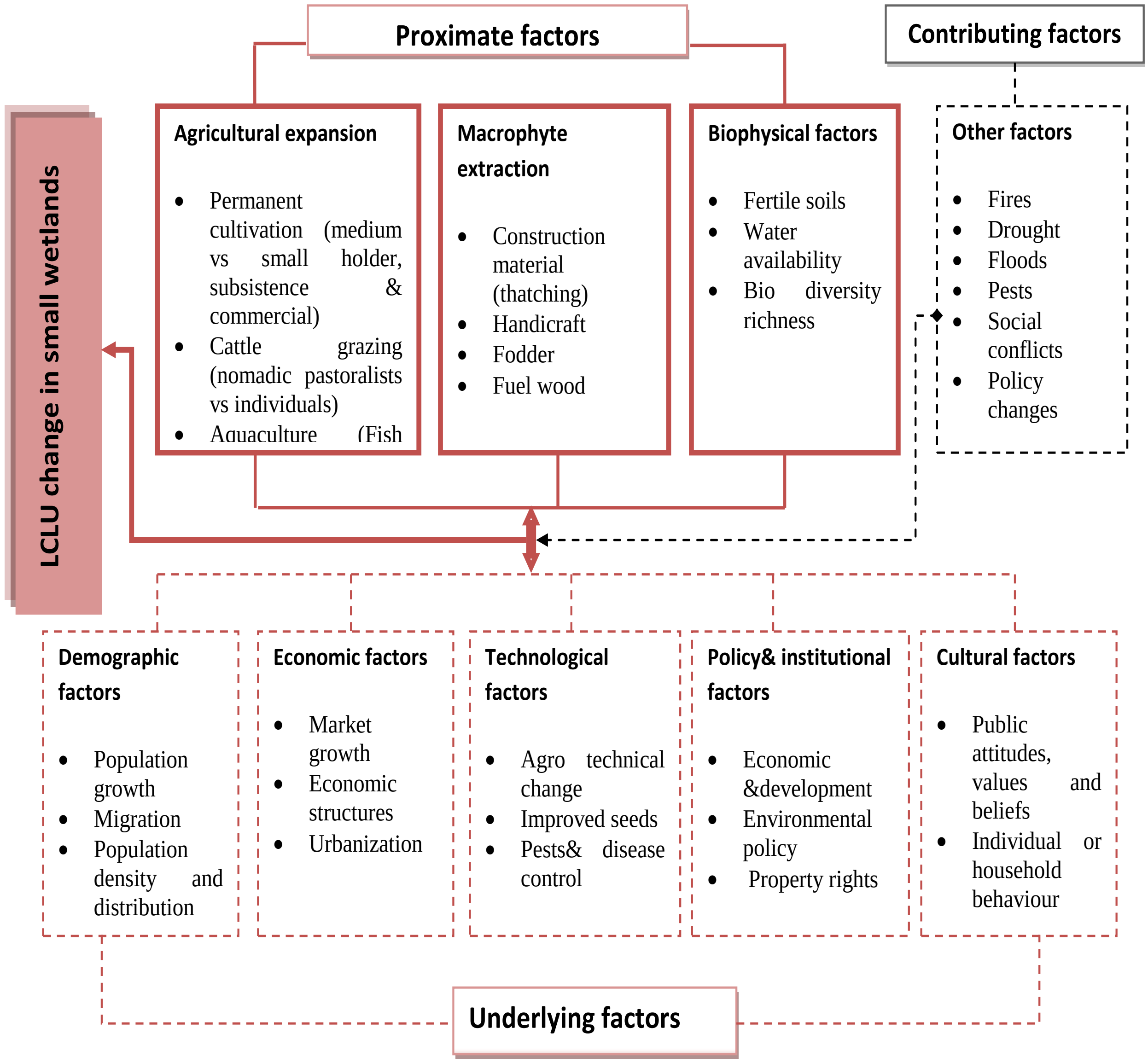


Figure 5.1: Conceptual model of LCLU change

Source: Modified from Geist & Lambin (2002)

For the better-off households, cultivation of wetlands is more in response to market opportunities, which may reflect not only rural food shortages, but also urban demands. Government food security policies also act as drivers through local pressures that encourage, or require, communities to expand wetlands cultivation. The opening up of new markets like the East African Cooperation common market also have implications on wetlands utilization pattern, i.e. people have to produce more to meet the market demand. Moreover, modernization in the form of an increased need for cash for purchases, school fees, taxes, etc. is often reported as part of the combination of drivers operating in this area (Wood & van Halsema, 2008).

Development policies (which have failed to reduce rural poverty) and the macro development situation (which has led to rapid population growth) further contribute to changes in wetlands. In addition lack of tenure security like in Rumuruti site where most of the people are squatters, is perhaps one of the factors contributing to long term land degradation. Improvements in wetland use technology like introduction of small electrical pumps, which can be used to draw water for irrigation when the water level is lowered in wetlands, encourage people to continue utilizing the wetlands and their riparian areas. Cultural attitudes towards certain kinds of food like rice in the Pangani plains attract more farmers in the wetlands. The implication of these activities on wetlands if not controlled, is ultimately degradation and loss of ecosystem functions.

5.3.3 Change detection in wetlands with remote sensing

Wetlands like many other ecosystems are changing. The changes may be induced by anthropogenic factors or natural phenomena. Change is defined as "an alteration in the surface components of the vegetation cover" (Milne, 1988 in Coppin *et al*., 2004:1566) or as ''a spectral/spatial movement of a vegetation entity over time'' (Lund 1983 in Coppin *et al*., 2004:1566). The rate of change can either be dramatic and/or abrupt, as exemplified by fire; or subtle and/or gradual, such as biomass accumulation. Change can therefore be seen as a categorical variable (class) or in a continuum.

Two main ecosystem changes can be distinguished; land-cover conversion, i.e. the complete replacement of one cover type by another, and land-cover modification, i.e. more subtle changes that affect the character of the land cover without changing its overall classification (Coppin *et al.*, 2004). Land-cover modifications are generally more prevalent than land-cover conversions. Some ecosystem modifications are human-induced, for example tree removal for agricultural expansion. Others have natural origins resulting from, for example, flooding and disease epidemics. In the spatial context, four types of change can be observed whereby spatial entities either (1) become a different category, (2) expand, shrink or alter shape, (3) shift position, or (4) fragment or coalesce (Khorram *et al*., 1999).

Change detection and monitoring involve the use of multi-date images to evaluate differences in land cover due to environmental conditions and human actions between the acquisition dates of images (Singh, 1989). Successful use of satellite remote sensing for LCLU change detection depends upon an adequate understanding of landscape features, imaging systems, and information extraction methodology employed in relation to the aims of analysis. The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values. The changes in radiance due to land cover change must be large (signal) with respect to radiance changes resulting from other factors like differences in atmospheric conditions, differences in Sun angle and differences in soil moisture (noise) (Lu *et al*., 2004).

Studies on wetlands change have involved the use of satellite images and statistical sampling to estimate the changes over time (Dahl, 1990). Although aerial photograph interpretation has traditionally been used to monitor changes in wetland resources, identifying wetland sites on multiple years of photos can require a significant time investment (Ramsey & Laine, 1997). The spatial resolution of aerial photographs can enable more precise change detection, but replicating these interpretations is difficult and can be inconsistent (Coppin *et al*., 2004). The accuracy of change detection through photo interpretation is also vulnerable to human error and variability between photographs.

Satellite images, in particular those with high temporal resolution, precise spectral bandwidths, repetitive flight paths, and accurate georeferencing procedures are preferred for change detection (Coppin *et al*., 2004; Jensen, 1996). LANDSAT-based classification procedures can provide equal or greater overall accuracies than other comparable space-borne sensors, such as Satellite Probatoire d'Observation de la Terra (SPOT) or Indian Remote Sensing Satellite (IRS), because of LANDSAT's greater spectral resolution. Many studies have used LANDSAT images for change detection (Hui *et al*., 2009; Baker *et al*., 2007; Kashaigili *et al.,* 2006; Munyati, 2004; Ramsey & Laine, 1997). With application of different techniques, changes can be identified and quantified. In East Africa, change detection has been done in larger wetlands and swamps like the Usangu plain (Kashaigili *et al.*, 2006) and Bahi swamp in Tanzania (Rebelo *et al.*, 2009b) as well as Omo river delta

(Haack, 1996) in Ethiopia. This particular study detects change in small wetlands using different techniques.

5.3.4 Change detection techniques

Change detection involves three major steps: (1) image pre-processing including geometrical rectification and image co-registration, radiometric and atmospheric correction, and topographic correction if the study area is in mountainous region; (2) selection of suitable techniques to implement change detection analyses; and (3) accuracy assessment. A good change detection research should provide the following information:- area change and change rate, spatial distribution of change types, change trajectories of land-cover types, and accuracy assessment of change detection results (Coppin *et al*., 2004, Lu *et al*., 2004). Furthermore, the accuracies of change detection results depend on many factors, including: precise geometric registration between multi-temporal images, calibration or normalization between multi-temporal images, quality ground truth data and classification, and change detection methods or algorithms used. In addition, classification and change detection schemes, analyst’s skills and experience, knowledge and familiarity of the study area ensure detection of changes.

A number of techniques exist for accomplishing change detection. These can be grouped into two general classes, those based on thematic categorization (classification) of the input data and those based on spectral change between acquisition dates (Johnson & Kasischke, 1998). The categorization-based approaches are procedures, which assess change based on classification and comparison of the results from each date; or assess change based on direct two-date categorization. The spectral approaches involve procedures like band differencing, transformed band differencing (e.g. vegetation indices), rationing, regression, principal components, and change vector analysis (CVA) and of recent, land cover change mapper (LCM) by Castilla *et al*. (2009).

Any change detection technique possesses its own set of advantages and disadvantages, and no single approach can be considered optimal or applicable in all cases (Coppin *et al*., 2004). Among the many factors governing selection of a change detection strategy are information requirements, spectral coverage, data availability and quality, image processing resources, analyst skill and experience, phenomenological knowledge, time and cost constraints, and the importance of labelling the changes that are detected (Coppin *et al.*, 2004; Lu *et al.*, 2004; Johnson & Kasischke, 1998). The methods used in this study are post-classification comparison (PCC), CVA, and LCM.

5.3.4.1 Post-classification comparison change detection (PCC) method

Post-classification change detection involves the comparison of two images from different dates that are independently classified and labelled (Figure 5.2). The area of change is normally extracted through the direct comparison of the two different independent classification results (Coppin *et al.*, 2004). An algorithm simply compares the two classification maps utilizing class pairs specified by the analyst and generates a map indicating the areas of change. The "from-to" change class information can be detected by comparing to another change detection method, which is not able to detect "from-to" information (Jensen, 1996). The advantage of this method is that, it bypasses the difficulties in change detection labelling associated with the analysis of images acquired at different times of year or by different sensors. The major disadvantage of this approach is high sensitivity to the individual classification accuracies.

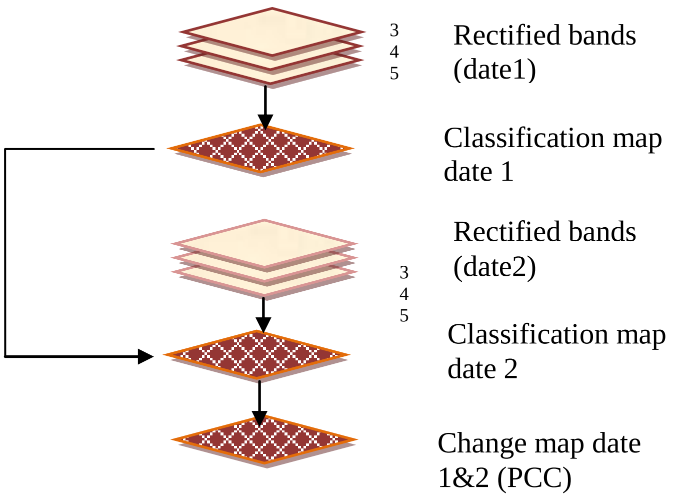


Figure 5.2: Work flow of post classification change detection
Source: Own illustration

5.3.4.2 Change vector analysis (CVA) method

CVA is a multivariate change detection technique that processes the full dimensionality (spectral and temporal) of the image data and produces two outputs, change magnitude and change direction (Figure 5.3). Any number of input bands may be employed from each acquisition date (Figure 5.4). Once the corresponding input bands from each acquisition are geometrically registered and radiometrically normalized, CVA may be implemented. Changed areas may then be described in terms of magnitude and direction, as well as by other attributes such as geographic location and area. A major advantage is its capability to analyse change concurrently in all data layers as opposed to selected bands (Deng *et al.*, 2008). The change magnitude is calculated by determining the Euclidean distance between end points through n-dimensional change space:

$$CM = \sqrt{\sum_{i=0}^{n}(DN_{2i} - DN_{1i})^2}$$

Where n= number of spectral bands, i=spectral band number from 1 to n, DN2i=pixel value at T2 in band i, and DN1i=pixel value at T1 in band i (Warner, 2005).
The change direction depends on whether the change is positive or negative in each band; thus 2^n possible types of change can be determined per pixel. Normally an empirical change magnitude threshold is determined to prove if a pixel represents change or not.

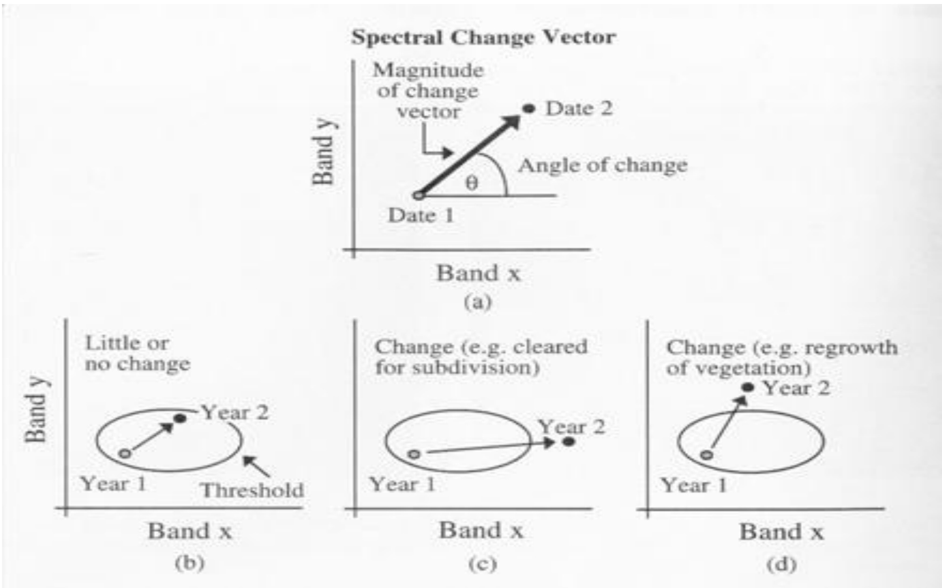


Figure 5.3: Schematic diagram of CVA.
Source: Jensen, (1996): 276.

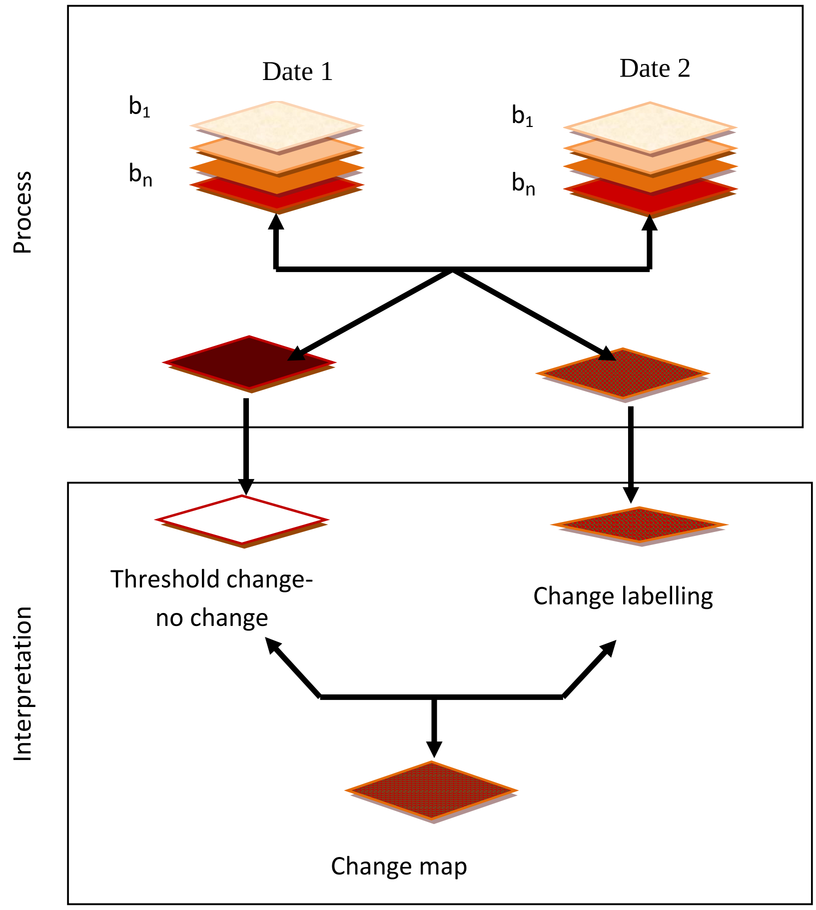


Figure 5.4: Flow diagram of CVA
Source: Modified from Johnson and Kasischke, (1997): 413

5.3.4.3 Land cover change mapper (LCM) method

Another method used is LCM, created by Castilla *et al*., (2009); they devised the method and implemented the tool in the IDL programming language (ITTVIS, 2008). To be able to use LCM, the user needs two images the initial state and final-state images (which must have the same dimensions and be co-registered), and indicate the Minimum size Mapping Unit (MMU) required for change regions and for holes within change regions (if different from the former). A difference image is generated from the two co-registered images. A histogram of this difference image is used to automatically select a set of three change thresholds, lower, medium and upper.

Initial change regions are created using the upper change threshold, and then grown subject to the other two thresholds and to adjacency and similarity constraints (areas that are similar to and near the change areas are merged). Then all regions of change smaller than the MMU are either removed or aggregated to a neighbouring change region depending on proximity, and the resulting change mask is converted into a polygon vector layer. Figure 5.5 shows the work flow of LCM, the process is briefly illustrated within the figure. This method is very robust in detecting changes and produces results in a few seconds. The limitation is in the size of the images, which can be used (4000 columns x 10000 rows). Additionally, unless the analyst does a specific change, (like in this case it was first used for timber harvest), the type of change in the area have to be identified by the analyst.

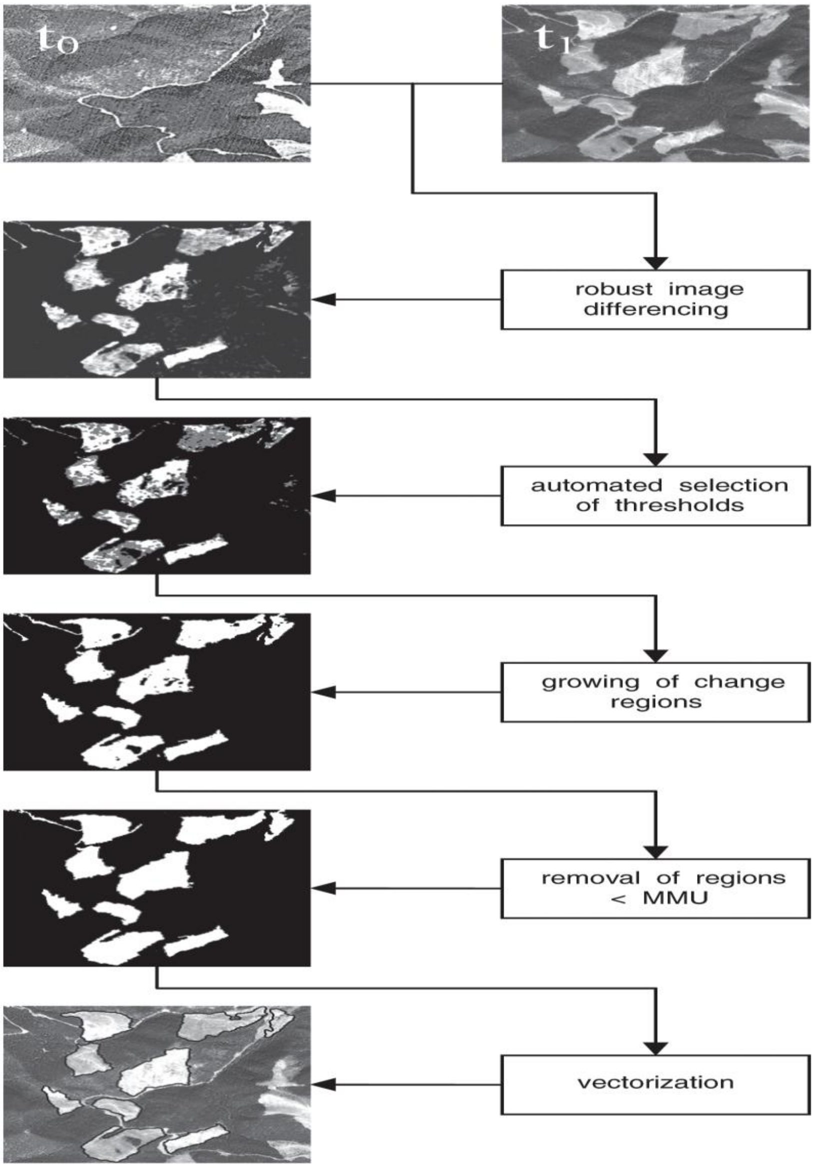


Figure 5.5: LCM workflow
Source: Castilla *et al.* (2009): 942

These methods have been chosen because of their diverse abilities to detect specific changes in LCLU, PCC for example specifies changes from a specific class to another, CVA shows magnitude and the direction of change and LCM works better with small areas and is very effective also in identifying areas with significant changes. All the three methods allow the user to choose a threshold of change and thus can only show changes of interest according to the subject matter.

5.4 Data analysis for change detection

Data analyses involved pre-processing of the data sets, followed by change detection using three different techniques, which are described in detail in the following subsections.

5.4.1 Data types

LANDSAT images were mainly used for change detection with ten year interval data for 30 years from 1976 being selected. It was, however, not possible to acquire images sequentially for all the sites due to either poor data quality like high cloud coverage (>10%) or missing information (as was the case of all images collected after July 2003) due to sensor failure already explained chapter 3.4.4. Table 5.1 shows a list of all images used. Aerial photographs were also used.

Table 5.1: Data types

Data type	**Laikipia plain**			**Usambara highlands &Pangani plain**		
LANDSAT	**Path/row**	**Year**	**Date**	**Path/row**	**Year**	**Date**
MSS	181_060	1976	25/01	179_063	1976	10/02
TM	169_060	1986	28/01	167-063	1987	01/01
ETM	169_060	1995	06/02	167-063	1995	07/01
ETM+	169_060	2003	04/02	167-063	2003	06/01
Aerial photos		1961	25/01		1975	10/02
		2008	07/09		2009	04/02

Source: Own illustration

5.4.2 Data pre-processing

As already mentioned in the literature review, before attempting change detection there is need to pre-process the data to rectify the images, and co-register them before removing atmospheric and sensor noise, and to sub-set the scenes where necessary to cover the areas of interest. In this study, the co-registration of the images was not necessary because they fitted together, but the 1976 images were resampled to 30m with root mean square error of 5. Radiometric correction was done using MAD as afore described in chapter 4 section 4.4.2. Subsets were then created and used for further analysis. Change detection was basically done for the flood plain test sites i.e. Rumuruti, Manguo, Magoma and Malinda.

5.4.3 Change detection

Detection of changes in the wetlands was done by using LCM, CVA and PCC. The techniques use different approaches and procedures as elaborated further in this section.

5.4.3.1 Change detection using PCC

PCC requires two thematic classified maps of two different time sequence. Since image classification for all sites was done as described in chapter 3, a few changes were done to create equal number of classes for most of the images. The main land use classes ranged between six and eight. These classes included:-

1. Open water/ floating vegetation (OP/FV)
2. Permanent *papyrus* swamp (PS)
3. Natural wetland vegetation (NV)
4. Cropland (CL),
5. Forest (FO)
6. Shrubs (SH)
7. Grassland or grazing (GG)
8. Bare land/ built up (BL/ BU)

Some classes like bare land and built up were merged and renamed bare land to ensure equal number of classes in all data sets. A matrix was calculated in ERDAS 9.3 Imagine using GIS analysis tool. Wetlands with six land use categories produced 36 possible combinations and those with eight classes produced 64. These values were re-coded and labelled to indicate change and non change areas as binary images. Green colour was assigned for changed classes, with non-change classes being assigned white colour.

Changes from natural vegetation and grazing land to agriculture, and conversion of natural vegetation to shrubs were further analysed to observe how much land is converted into such uses as they were seen to be among the major changed areas. Table 5.2 shows the total area converted to cropland and shrubs from natural vegetation and from grazing to cropland. All resulting binary images of change images and change of interest are shown in sequence Figures 5.6 to 5.13.

Area coverage (hectares) of each class was calculated in ERDAS by adding area column in the attribute files. These statistics were then extracted and exported to excel file where summary tables were created showing size of each class and classes in which they changed into. Table 5.3 is presented as an example, the rest of the tables are found in appendix 3. Accuracies were then calculated where change and no change error matrix was produced from the tables.

Table 5.2: LCLU conversion from natural vegetation cropland and shrubs, from grazing to cropland area in hectares

	1976-1986/7			1986/7-1995			1995-2003		
	NV to CL	GG to CL	NV to SH	NV to CL	GG to CL	NV to SH	NV to CL	GG to CL	NV to SH
Magoma	97.0	29.8		10.5	22.0		108.9	32.0	
Malinda	32.0	12.2	27.3	19.6	0.54	14.49	35.0	17.9	48.7
Rumuruti	111.4	51.2	82.5	60.0	29.2	62.0	92.4	25.0	33.3
Manguo				33.3					

Source: Own illustration

Table 5.3: Matrix table of Rumuruti 1995/2003 size in hectares

	OP/FV03	PS03	NV03	CL03	FO03	SH03	GG03	BL03	Total
OP/FV95	3.78	8.1	0.9	0.27	3.24	0	0	0	16.3
PP95	46.08	43.02	20.34	3.24	3.33	0.54	0	0	116.5
NV95	60.48	138.87	119.97	26.1	16.2	3.87	0	0	365.5
CL95	0.09	10.35	36.9	39.78	8.82	19.35	0.54	0.27	116.1
FO95	19.26	26.01	5.13	0.45	10.26	0	0	0	61.1
SH95	0	1.17	7.29	11.61	3.78	15.48	6.57	1.17	47.1
GG95	0	0	1.26	4.05	0.72	8.19	5.4	0.81	20.4
BL95	0	0	0	0.09	0	1.35	1.71	1.35	4.5
Total	129.69	227.52	191.79	85.59	46.35	48.78	14.22	3.6	747.5

Source: Own illustration

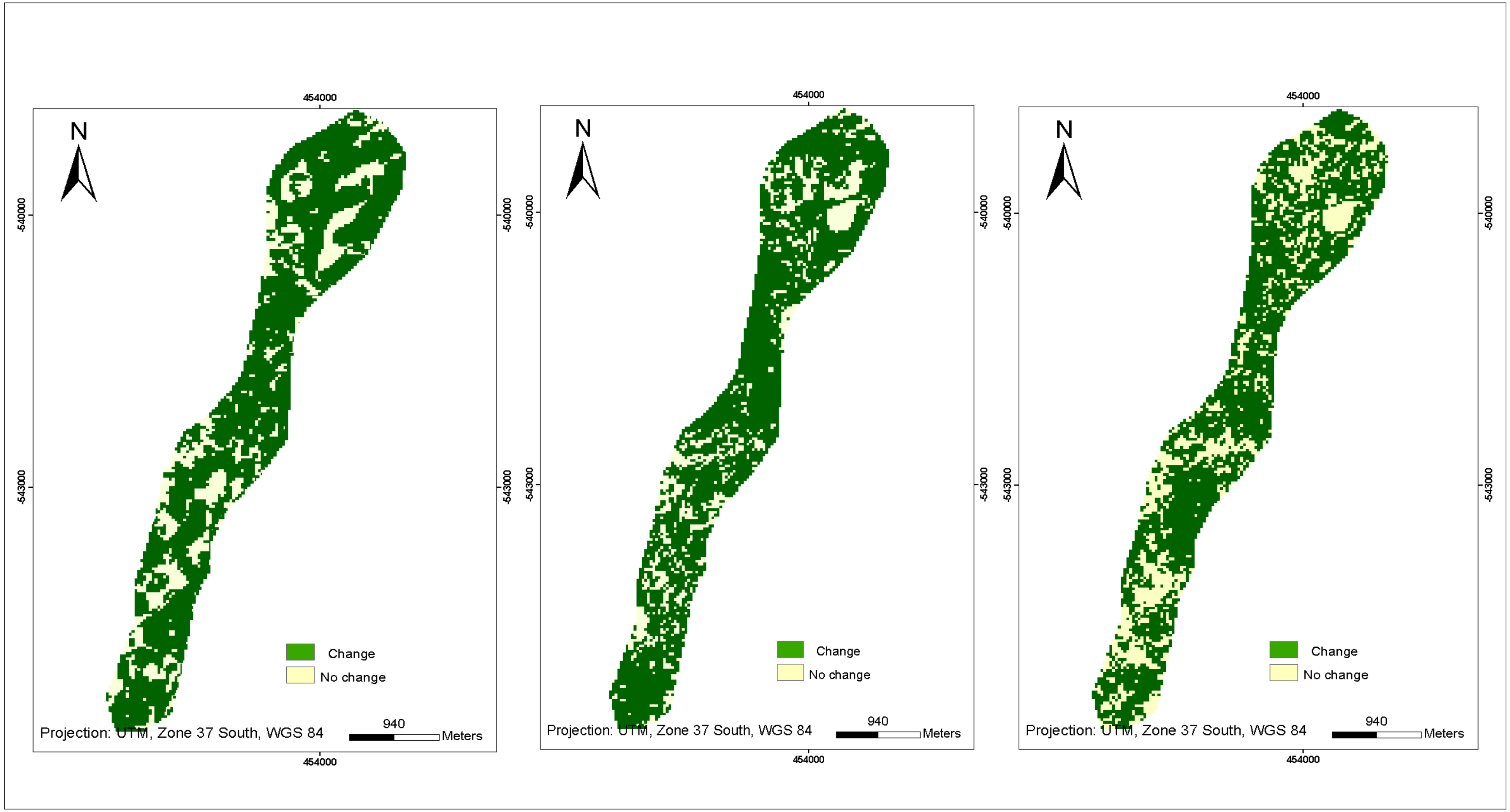


Figure 5.6: Binary images of the PCC change analysis for Magoma site between 1976 and 1987, 1987 and 1995 and from 1995 to 2003 in sequence

Source: Own illustration

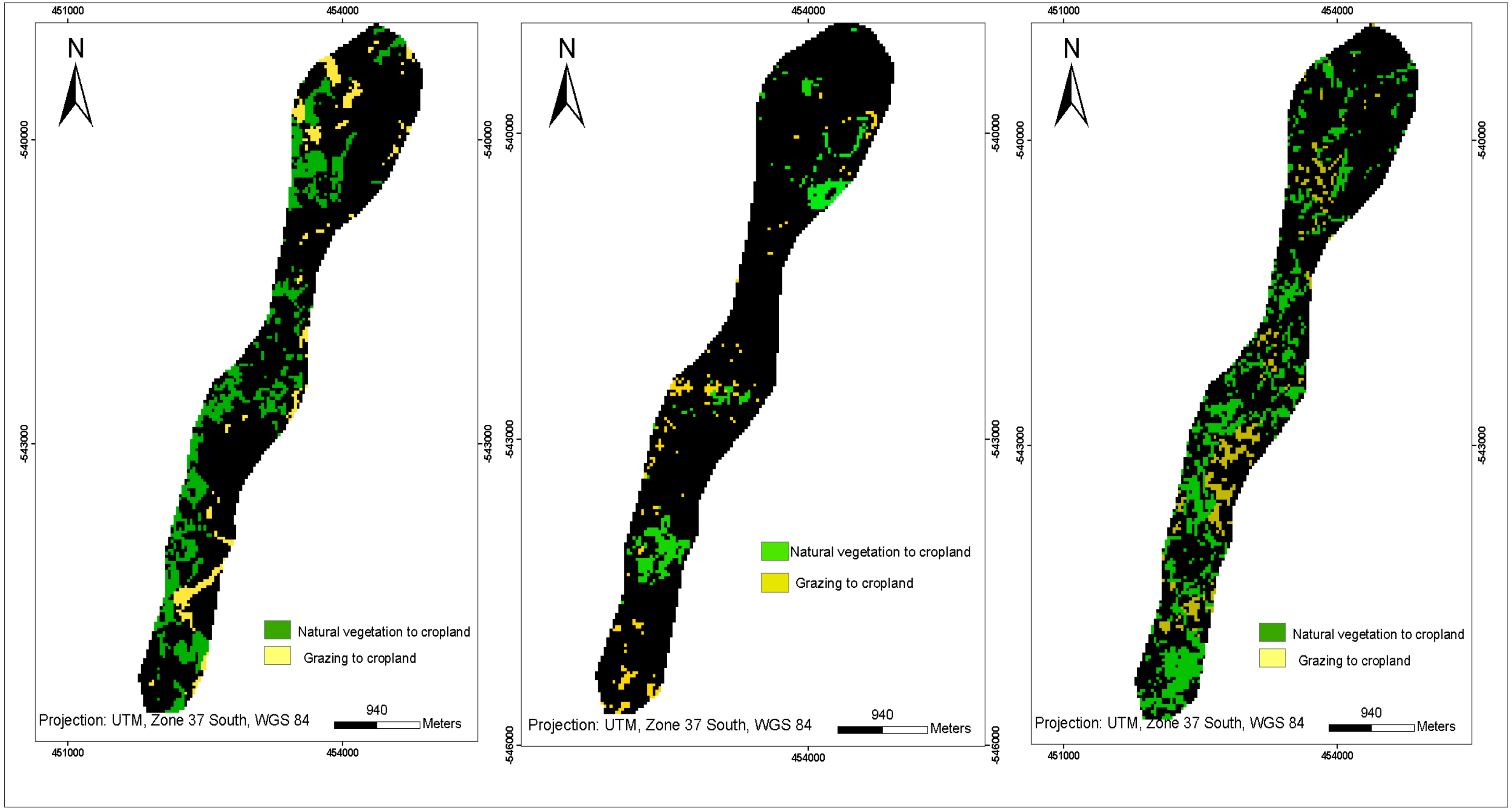


Figure 5.7: Spatial distribution of converted natural vegetation and grazing areas into cropland for Magoma site for the time period 1976 to 1987, 1987 to 1995 and 1995 to 2003

Source: Own illustration

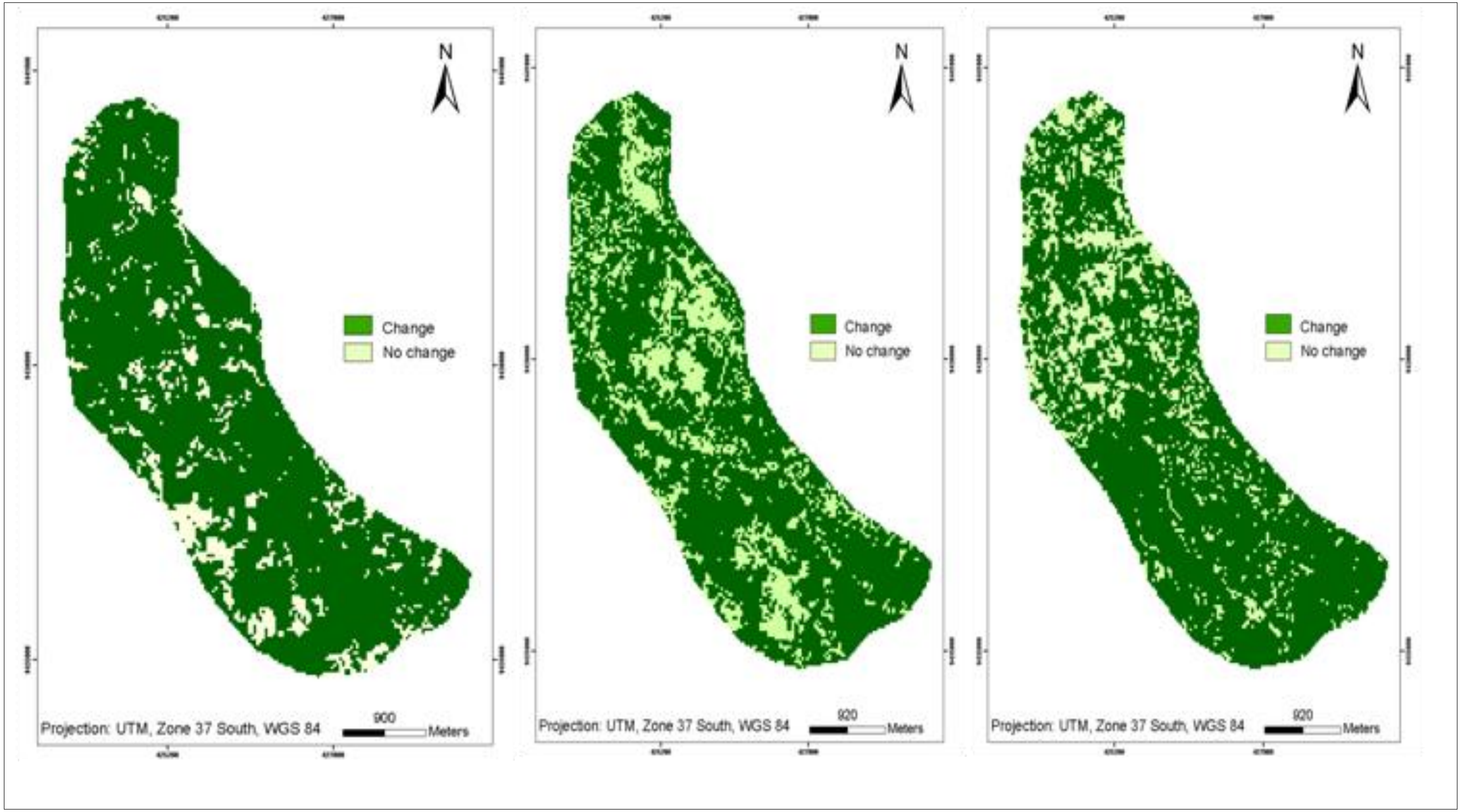


Figure 5.8: Binary images of the PCC change analysis for Malinda site between 1976 and 1987, 1987 and 1995 and from 1995 to 2003 in sequence
Source: Own illustration

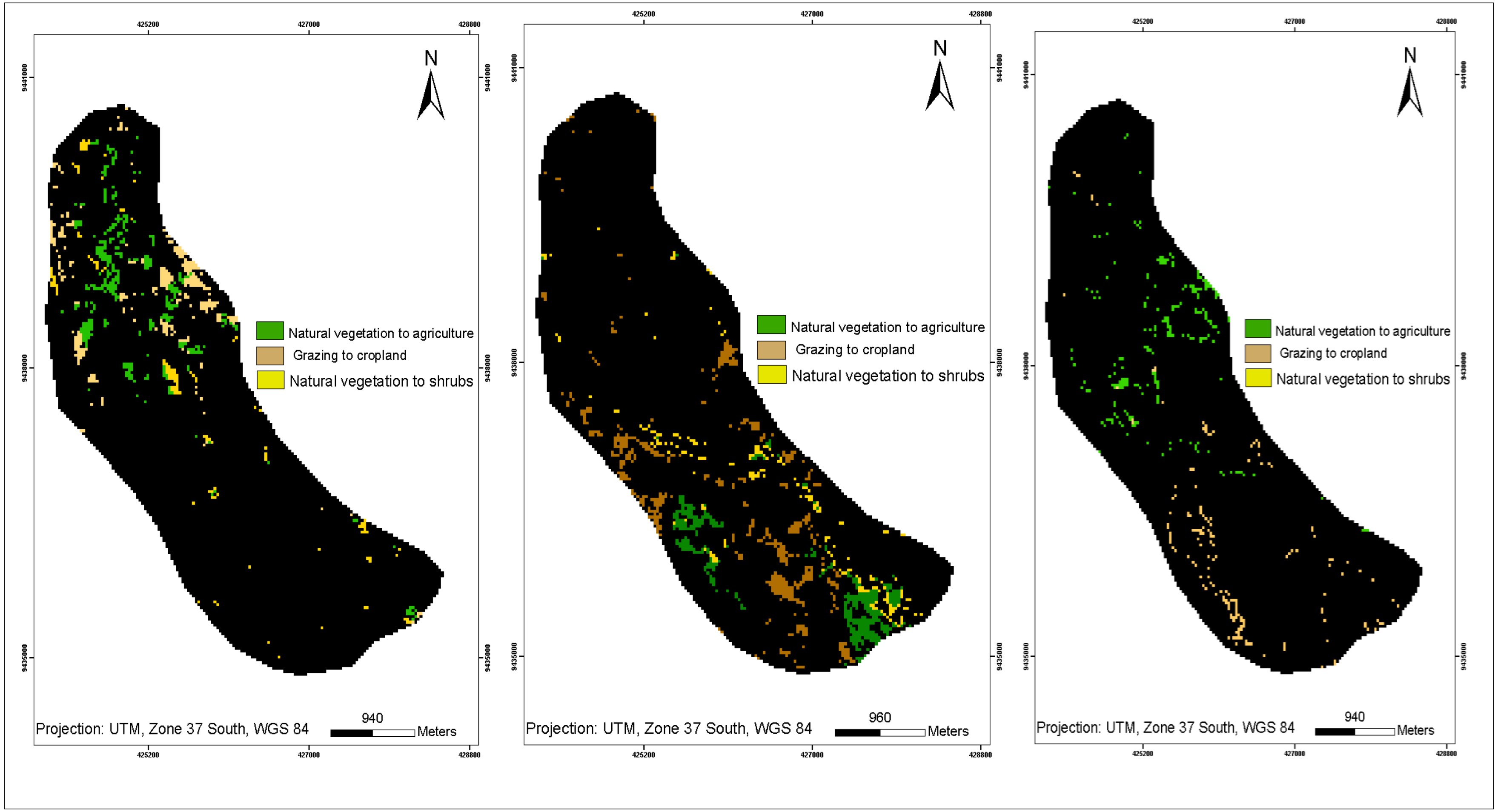


Figure 5.9: Spatial distribution of converted natural vegetation and grazing areas into cropland for Malinda site for the time period 1976 to 1987, 1987 to 1995 and 1995 to 2003

Source: Own illustration

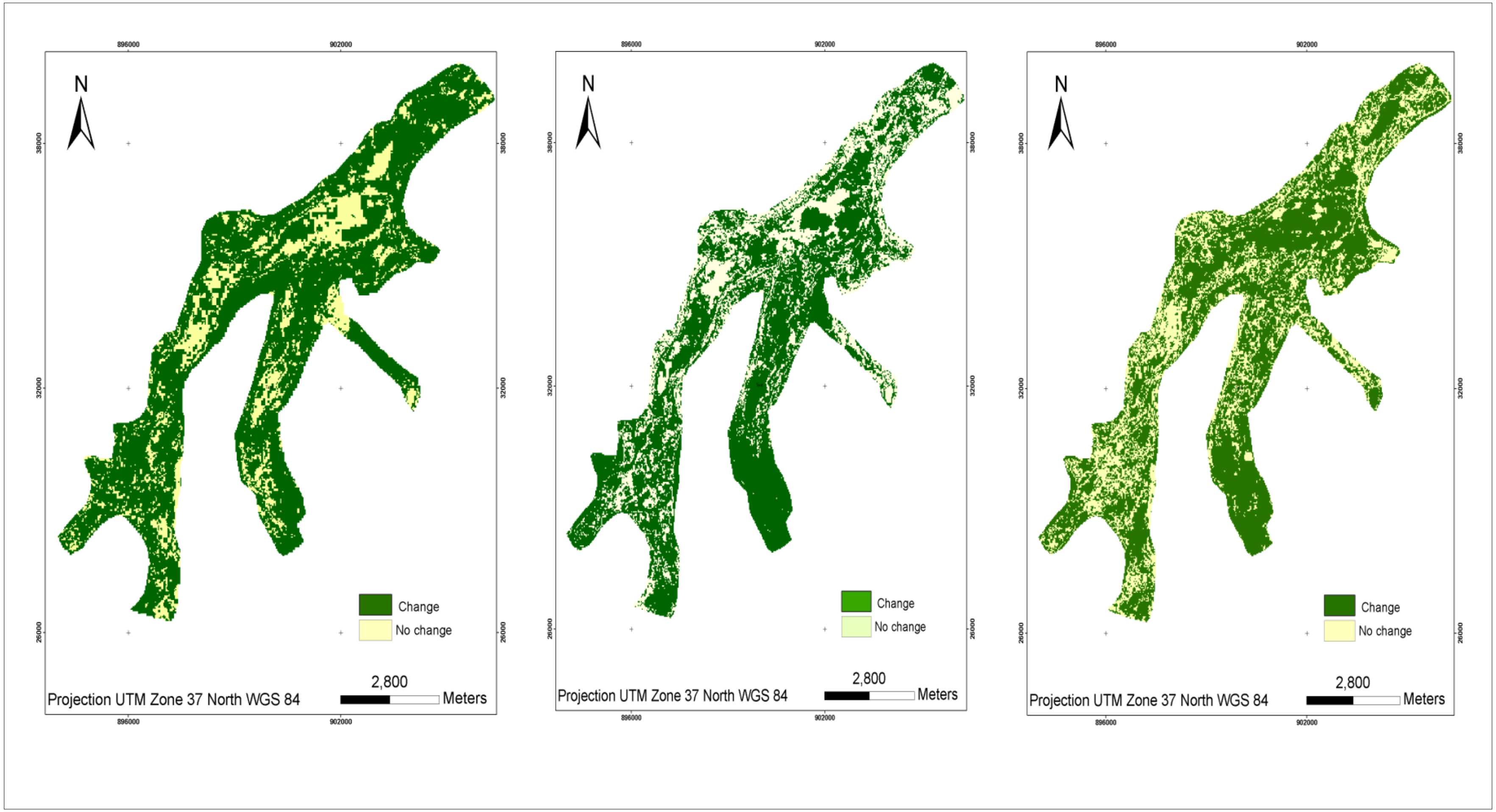


Figure 5.10: Binary images of the PCC change analysis for Rumuruti site between 1976 and 1986, 1986 and 1995 and from 1995 to 2003 in sequence

Source: Own illustration

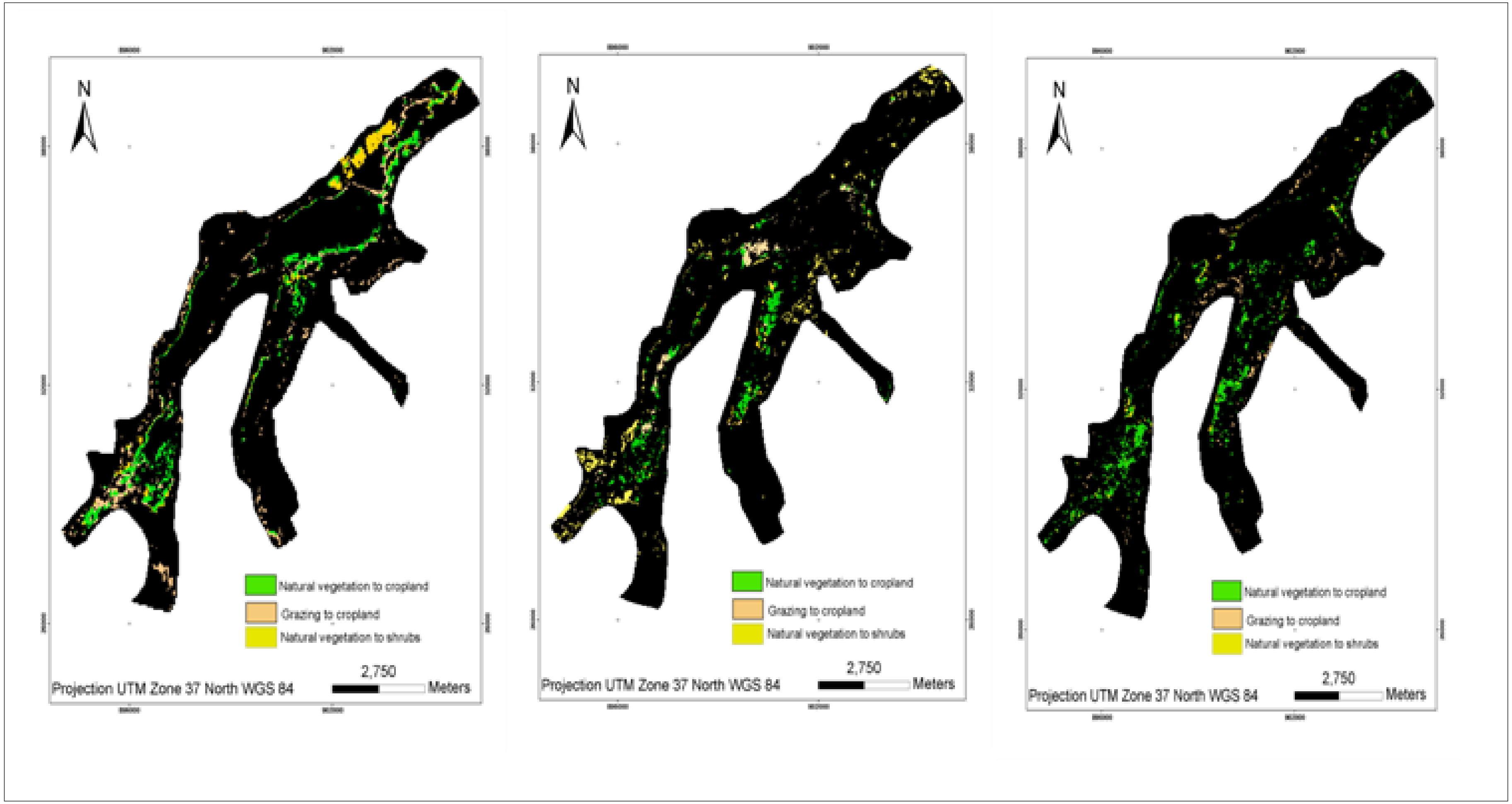


Figure 5.11: Spatial distribution of converted natural vegetation and grazing areas into cropland for Rumuruti site for the time period 1976 to 1986, 1986 to 1995 and 1995 to 2003

Source: Own illustration

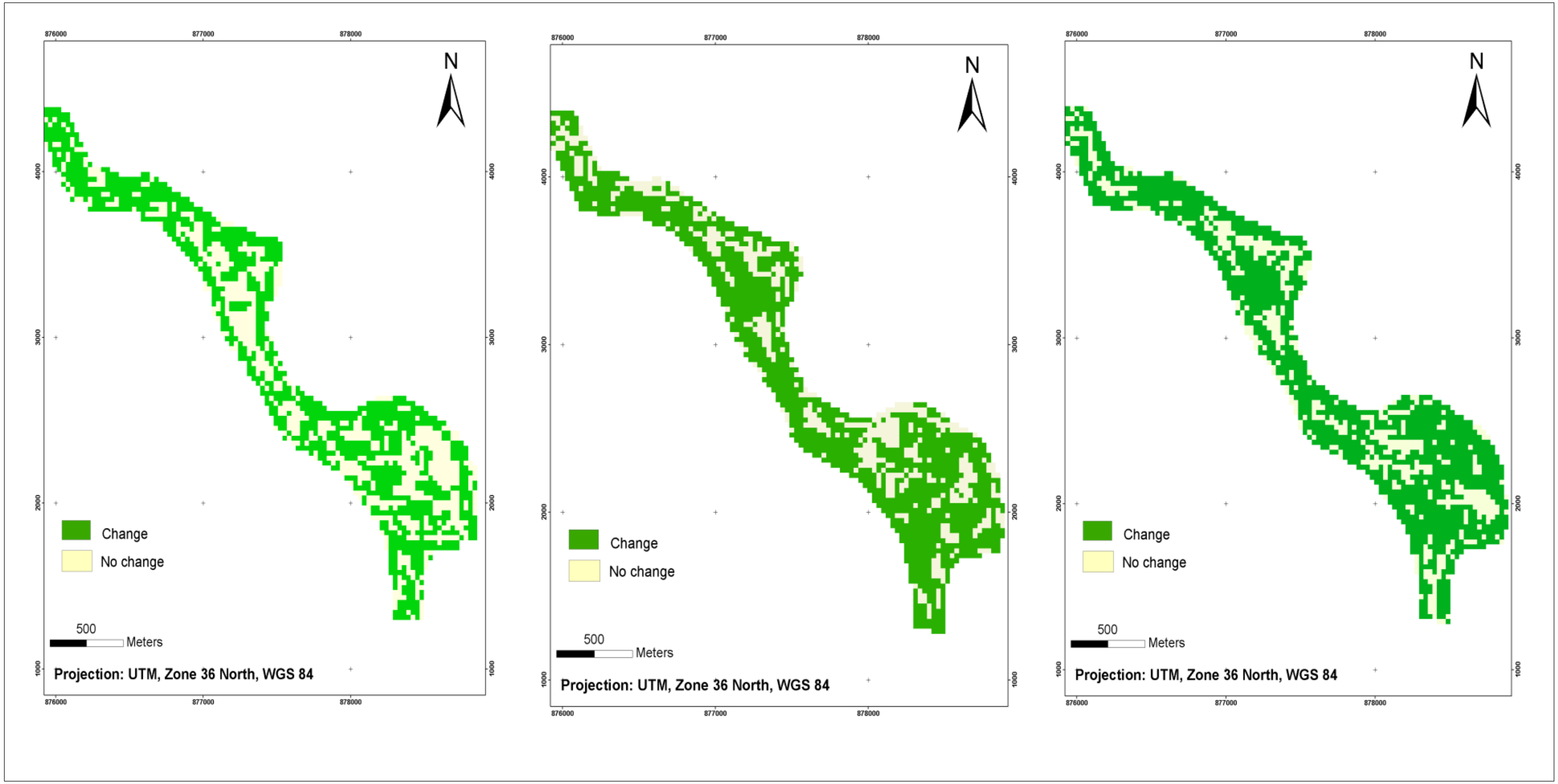


Figure 5.12: Binary images of the PCC change analysis for Manguo site between 1976 and 1986, 1986 and 1995 and from 1995 to 2003 in sequence

Source: Own illustration

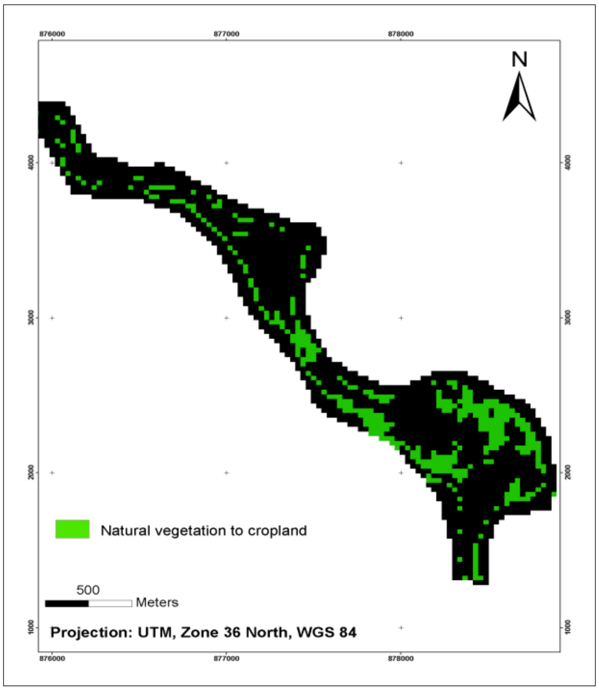


Figure 5.13: **Spatial distribution of converted natural vegetation areas into cropland for Magoma site for the time period 1976 to 1987, 1987 to 1995 and 1995 to 2003**
Source: Own illustration

5.4.3.2 Change detection using CVA

CVA also requires two images radiometrically corrected co-registered and same size. Interactive Data Language (IDL) program by Klein (2001) was used for analysis in ENVI software 4.3. Data sets of between 1986/7-1995, and 1995-2003 were used for each site as inputs for analysis. Initially 1986/7 images were used as initial state images and 1995 images as final state, later 1995 images served as initial state and 2003 as final state in the second sequence of change detection. Two output images namely change magnitude and change direction, were generated per single analysis for each site.

Change thresholds were established in an iterative process using analysts' expert knowledge of the study areas. The thresholds of above 25 and 30 digital number values were used to identify areas with significant changes. This means that change areas constituted between 75 and 79.2% of the wetlands and between 20.8 and 25% remained unchanged in the two time sequence. Figure 5.14 (a,b,c,d) shows thresholds applied to the four study sites for images of between 1986/7 and 1995.

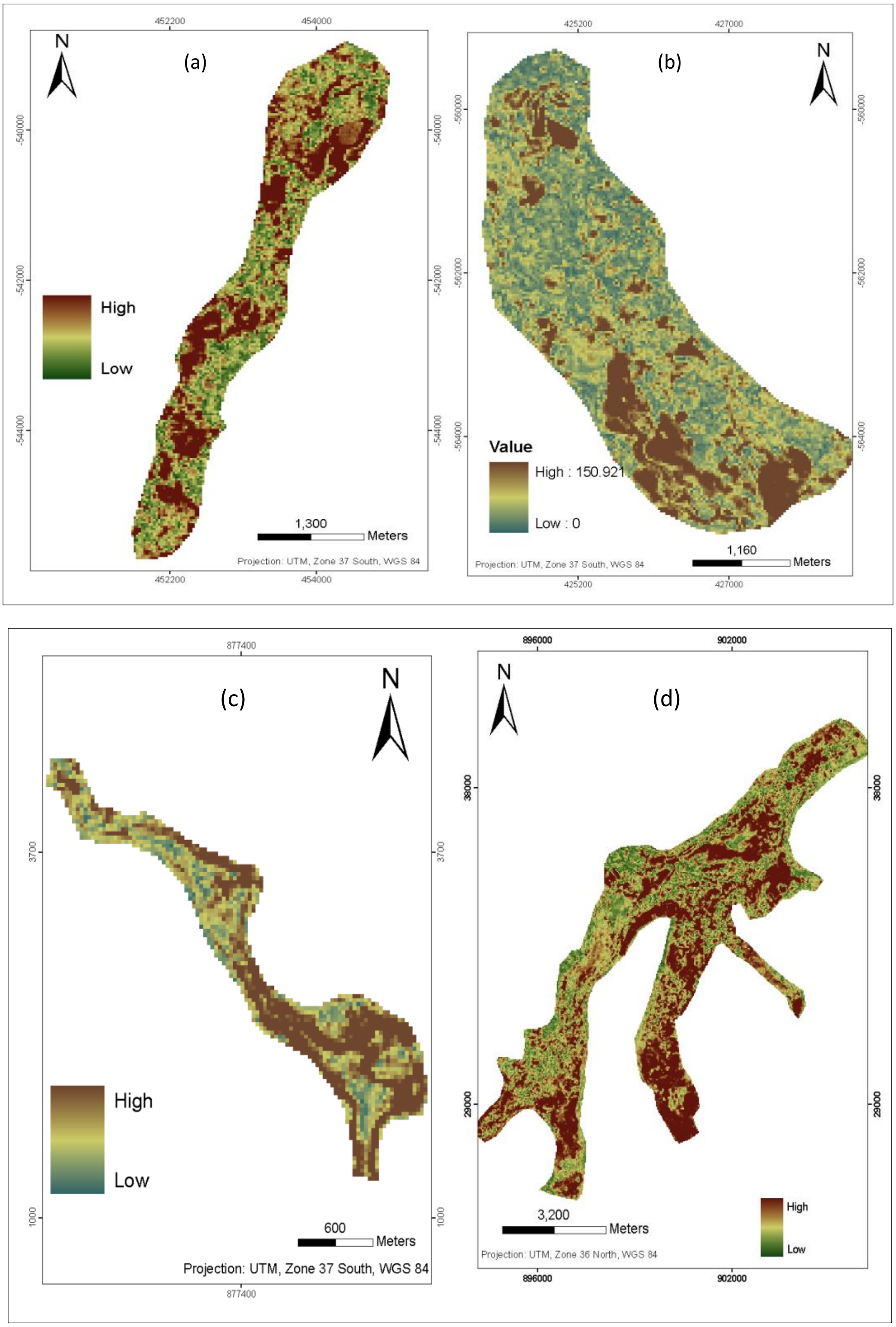


Figure 5.14: **CVA magnitude threshold images for site a) Magoma b) Malinda c) Manguo and d) Rumuruti presented with colour intensity, the brown colour represents high magnitude i.e. high LCLU, green colour represents low magnitude hence low LULC change**
Source: Own illustration

More information on the changes was obtained in change direction images. There were 2^3 output directions that equated eight different change types (Table 5.4). The change directions were the combinations of increase and decrease of reflectance in the three bands used in this study. Johnson & Kasischke (1998) suggest that, given the potentially large number of possible change vector directions, it is often desirable to implement some type of simplification in the characterization of change direction. This has been accomplished in a number of ways that vary in complexity and ease of implementation (Colwell *et al*. 1980).

Table 5.4: CVA codes for LANDSAT- TM and ETM+

		Code							
		1	2	3	4	5	6	7	8
Band	1	-	+	-	+	-	+	-	+
	2	-	-	+	+	-	-	+	+
	3	-	-	-	-	+	+	+	+

1- band 3, 2 - band 4, 3 - band 5

Source: Own illustration

In some CVA applications, general characterization of change directions by virtue of the change space `sectors' in which they occur can be useful and sufficient. An arbitrary `sector code' may be assigned and used to distinguish these sectors, which represent general change directions. All codes with increase in all bands were selected, followed by decrease in all bands, codes with increase in vegetation (band -3&+4) and decrease in vegetation (band +3&-4), then the remaining codes which represent complex changes were combined. Percentages of change direction were calculated and, density slices were created for change directions with decreasing intensities, and decreasing values of magnitude. They were then displayed with bands of LANDSAT ETM+ as gray scale background (Figure 5.15). For change labelling previous supervised classified images in chapter three were used.

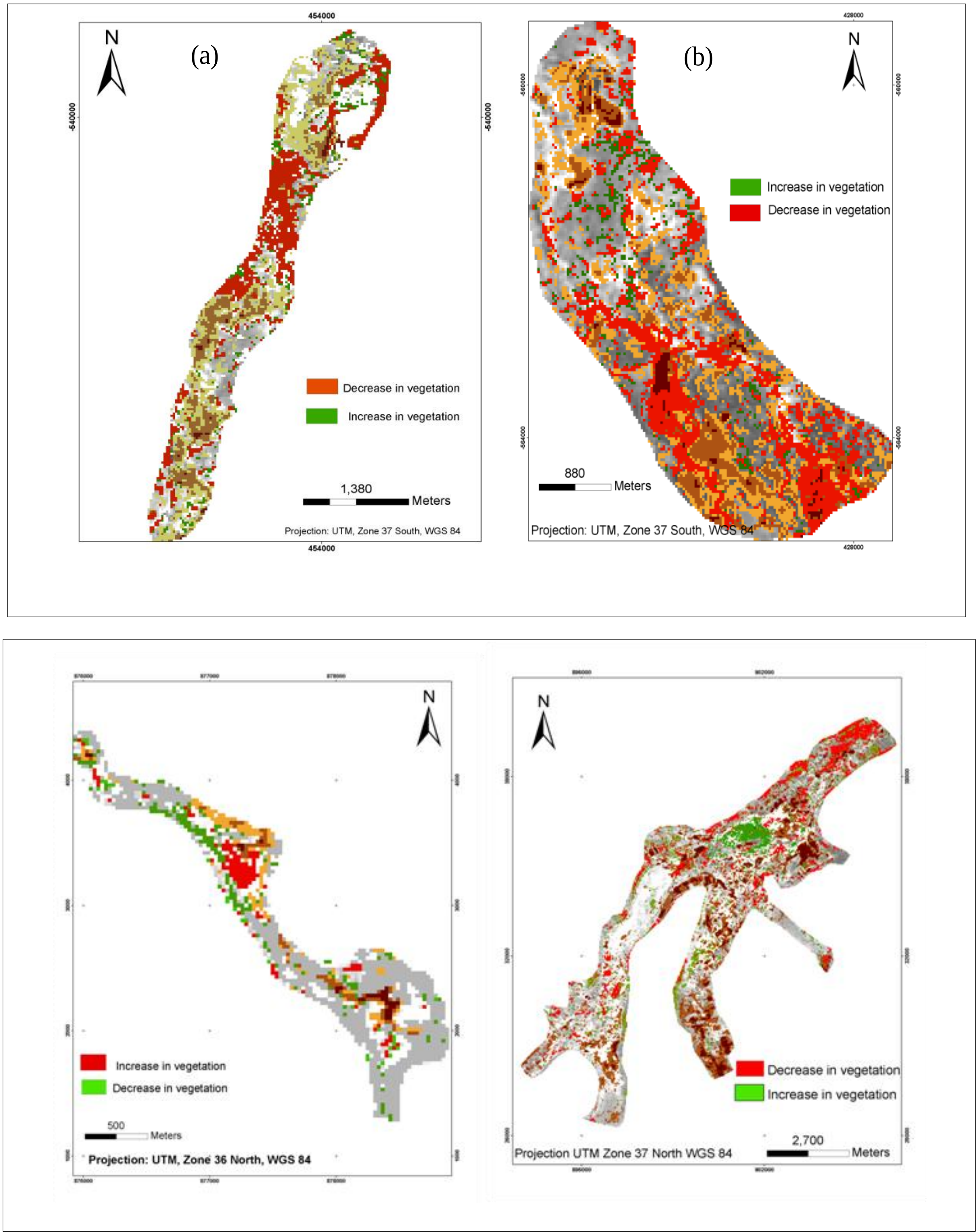


Figure 5.15: Change direction of interest overlaid on a grey scale LANDSAT image channel 4 and magnitude image for the four sites a) Magoma b) Malinda c) Manguo and d) Rumuruti

Source: Own illustration

5.4.3.3 Change detection using LCM

Use of LCM requires two images, one for initial state and the other for the final state. The analysis was done using LCM software evaluation version (Castilla, 2009). The evaluation software handles only single channels thus band 4 was selected for analysis. As for the case of CVA same image in the same sequence were used as inputs for earlier and later images, two times sequence detection was done, between 1986/7 and 1995, and between 1995 and 2003. Minimum Mapping Unit (MMU) was specified as 0.5ha for change regions.

A difference image was generated first, and then histograms of change of the difference image were used to select a set of three change thresholds, lower, medium and upper automatically. The initial change regions were created using the upper change threshold, and then grown subject to the other thresholds and to adjacency and similarity constraints. All regions of change smaller than the MMU were either removed or aggregated to a neighbouring change region depending on proximity, and the resulting change masks were converted into vector polygon layers. Figure 5.16 (a,b,c,d) shows changes detected in the four sites, change difference images created by a composite difference image (b4_1986-1995), in the *Red* channel; final state image (b4_1995), in *Green*; and initial-state image (b4_1986), in *Blue,* and vector polygons overlaid.

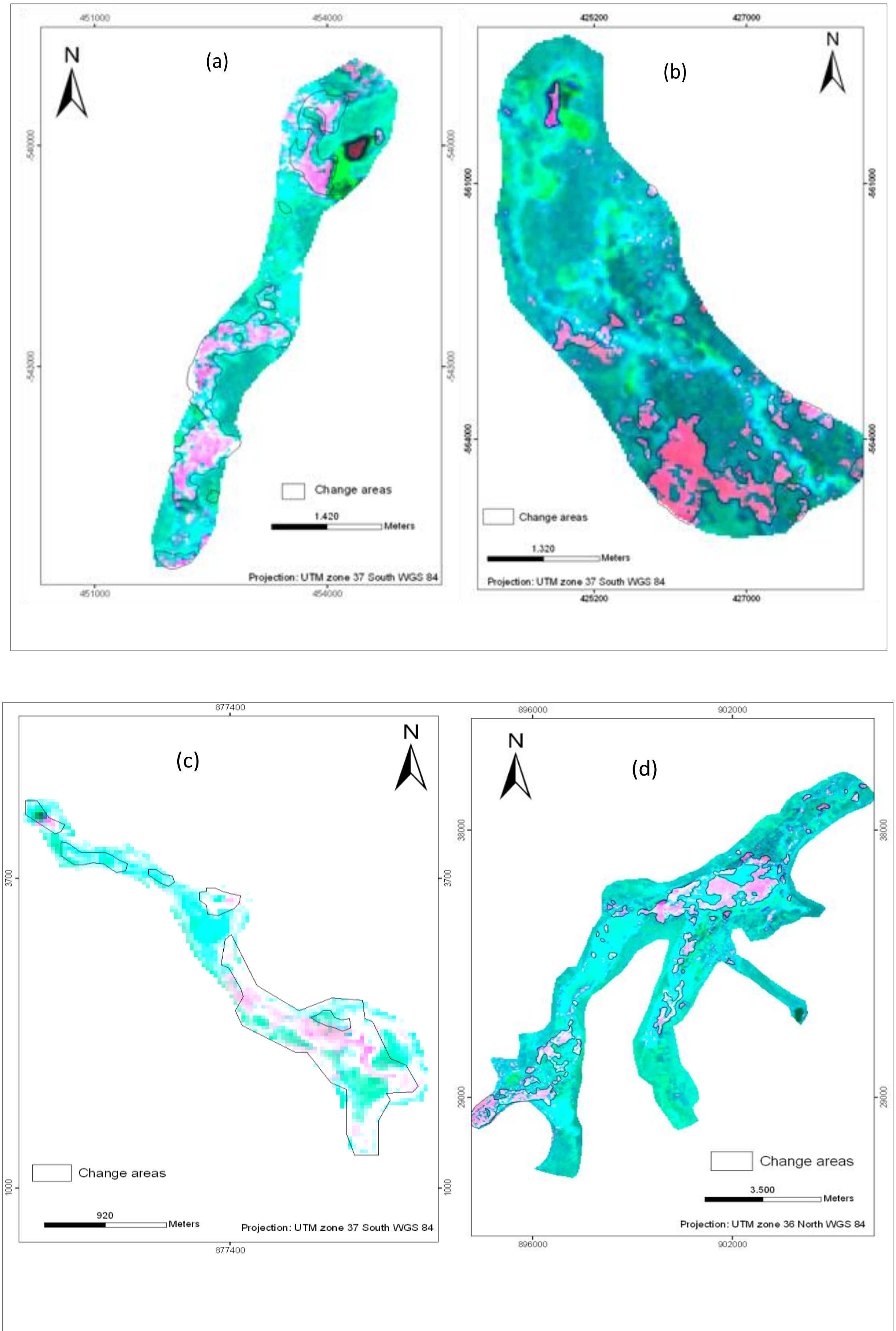


Figure 5.16: LCM change results for site a) Magoma b) Malinda c) Manguo and d) Rumuruti from 1986 to 1995. RGB composite of difference image, initial state and final images overlaid with vector polygons.

Source: Own illustration

5.4.4 Accuracy assessment

In post classification change detection, accuracies were obtained by calculating the percentage of change pixels i.e. the pixels in the major diagonal of the matrix from the total number of all classes. Change and no change error matrix were also estimated by adding the change and no change diagonal values. Accuracies for CVA were done by comparing the LANDSAT scenes, which were used for analysis with relevant change direction codes, that were more significant for wetland change i.e. code 3 and 4 though the codes were representing more than one class. The results where overlaid in ArcGIS with classified images. LCM accuracies were obtained by identifying the polygons which succeeded to map the changes correctly. The polygons were adjusted using the images and field data. A confusion matrix was used to determine the change detection accuracy.

5.5 Results and discussion

In the following paragraphs, details of detected changes for each site are presented and the findings are discussed in detail in comparison with findings from other related studies.

5.5.1 Detected changes

A number of changes were detected in the wetlands. These mainly entailed land-cover modification i.e. more subtle changes that affect the character of the land cover without changing its overall classification (Coppin *et al.*, 2004). The results show that at one point in time, each category of the land uses in the wetland has changed from one class to another. In Rumuruti site for instance, the area covered by open water/ floating vegetation was 10.62 ha in 1986, it increased abruptly in 1995 to 127.69 ha and declined tremendously to 16.29 in 2003 (Figure 5.17). The abrupt increase could be attributed to increase in rainfall and the resulting floods in the plain. It can be remembered that in the 1990s', East Africa and other parts of the world experienced *El nino* rains which flooded rivers and swamps. During the same years (1995), the areas covered by cropland and grazing were also reduced (Figure 5.17).

According to the village leaders, Rumuruti wetland was put into use since 1960s but only a few people were allowed to use it. A large part was used as ranches and there were a lot of wild animals some of which exist to date but their number has decreased. More people were allowed in the wetland in 1980s and since then cultivation has increased. The permanent swamp has also been shrinking due to increased interference from both cultivation and grazing. During drier years more people invade the wetland for both cultivation and animal grazing.

Increase in natural vegetation in between 1995 and 2003 is a result continued disturbance in the permanent swamp area. Since *Papyrus* species are hard for browsers and grazers, livestock keepers normally burns the area for re-growth of species, which can be easily consumed by livestock. Once *Papyrus* is severely burnt, it is succeeded by different *Cyperus* species like *Excaltatus* and *Diverse*, other grass and shrubs species like *Asteraceae* and *Polygonum* also covers the area. Thenya (2001) also noted increase in agriculture and macrophyte harvest in the Ewaso Narok wetland in the recent years but also suggests that the wetland has high capability of restoring itself in wet season.

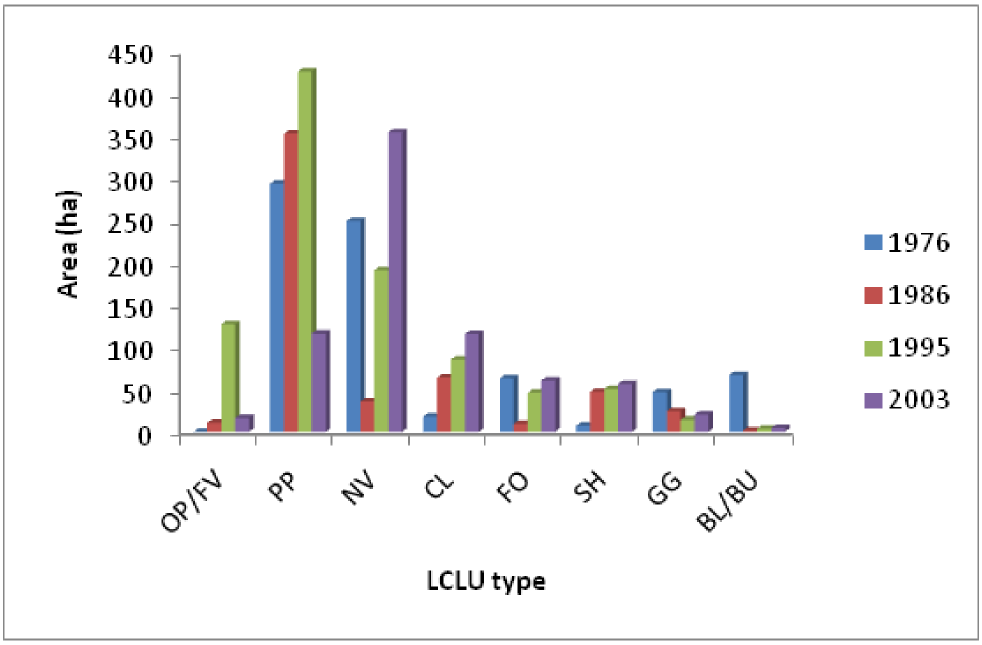


Figure 5.17: LCLU change of Rumuruti 1976-2003. BL-bare land; BU-built up; CL-crop land; FO-forest; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation; OP-open water; PS-papyrus swamp; SH-shrubs
Source: Own illustration

In Manguo, changes are also taking place. The area covered by open water/ floating vegetation decreased from 42.93 ha in 1976 and 11.97 ha in 2003 (Figure 5.18). Papyrus swamp changed from 30.78 ha to 11.07 ha between 1976 and 2003; in the same period the area covered by natural vegetation has been increasing steadily from 50.94 to 81.63. One plausible explanation for this is perhaps the inhabitation by hippopotamus, which limits accessibility by humans. The fringes have been increasingly cultivated as observed in the figure but dropped rapidly in 2003 due to increase in natural vegetation and water which impeded the physical accessibility. Built-up areas close to the wetlands emerged from 1990s' and gradually increase.

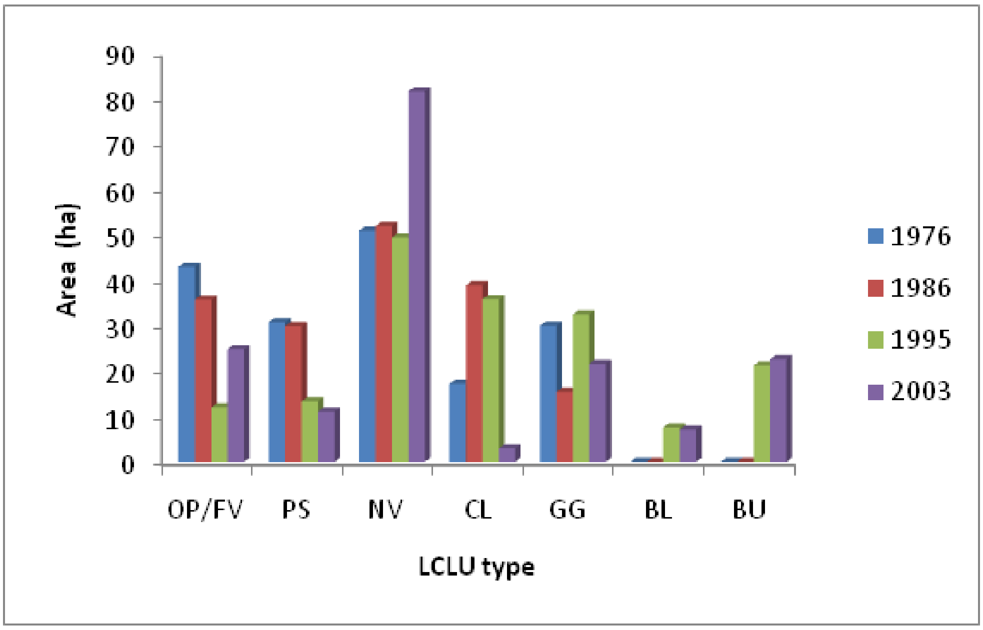


Figure 5.18: LCLU change of Manguo1976-2003. BL-bare land; BU-built up; CL-crop land; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation; OP-open water; PS-papyrus swamp.
Source: Own illustration

In Malinda the situation is the same as in other wetlands but significant change can be observed on the permanent *Papyrus* swamp which covered 153.28 ha in 1976 shrunk to 91.07 ha in 2003 (Figure 5.19). This change can be explained by increased agricultural activities in the wetland, which replaced the natural vegetation. The area under cultivation was 81.36 in 1976 and rose up to 109.65 in 2003. Open water/ floating vegetation declined by 32% from 47.61 to 15.48 ha. Large part of the lost area was covered by other wetland vegetation like *Papyrus* and *Typha domigensis* due to increased nutrients brought by increased agricultural activities in the wetland. Shrubs proliferated by more than 75% between 1976 and 2003. This can be attributed to dynamic moisture condition in this wetland in particular because it has two distinct characteristics. One part of the wetland is permanently flooded and the other part is seasonally flooded i.e. completely dry in dry season and flooded during wet season.

The shrubs are common in seasonally flooded areas; these areas are used for grazing in dry season and rice cultivation in wet season. Thus in dry season most of the wetland species, which can't survive in moisture stress conditions are replaced by different kinds of shrubs. Increase in siltation due to flooding and manure from the livestock grazed in the area could also contribute to the increase in shrubs. A similar observation was made by Dewidar (2004) who found out that shrubs increased at a higher rate in Lake Burulus of due to increased siltation processes. According to the village leaders, Malinda wetland began being used for agricultural production in 1980s. Since then, the area under agriculture has increased (from 81.36 ha in 1987 to 139 ha 2003) depending on availability of rains in the drier parts and throughout the year in moist parts.

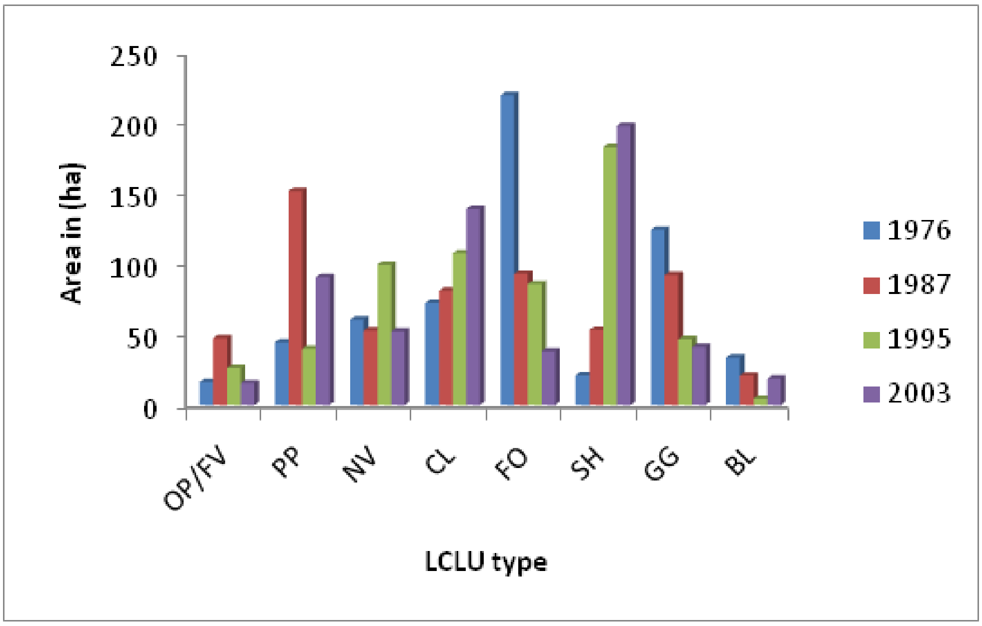


Figure 5.19: LCLU change of Malinda 1976-2003. BL-bare land; BU-built up; CL-crop land; FO-forest; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation, OW-open water; PS-papyrus swamp; SH-shrubs.
Source: Own illustration

Magoma wetland on its part shows a decline in areas covered by open water/ floating vegetation from 29.97 ha in 1976 to 21.6 ha in 2003 , fluctuation in natural vegetation and increase in agricultural area (186.22 to 291.78 ha) (Figure 5.20). Large parts of open water were replaced by other wetland vegetation and like in Malinda shrubs also increased. Zedler & Kercher (2004) observed increase in invasive species in wetlands and argue that, wetlands are vulnerable to invasion in part because they are landscape "sinks" that accumulate materials resulting from both terrestrial and wetland disturbances (excess water, nutrients, sediments, salts, heavy metals, other contaminants, and debris). Nearly every disturbance to an upland watershed causes some change downstream.

In addition grazing areas and bare land are decreasing; most of these declining areas have been converted to farmlands. The increase in agricultural area is attributed to increased efforts by the government to establish irrigation schemes for rice production in Magoma site. According to the District Agricultural Officer, the government established two schemes in this area. One in the 1990s and the other one in 2005. This has increased the area under agriculture in the wetland and cultivation is done throughout the year.

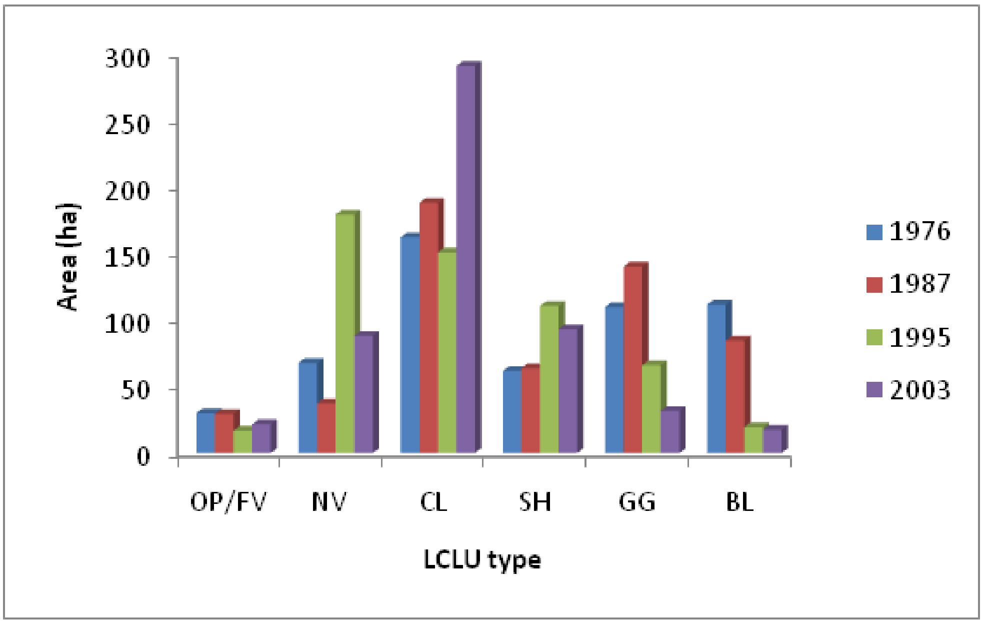


Figure 5.20: LCLU change of Magoma 1976-2003. BL-bare land; CL-crop land; FV-floating vegetation; GG- grassland/grazing; NV- natural vegetation; OP-open water; SH-shrubs
Source: Own illustration

With CVA analysis two different changes of interest, which were related to decrease in vegetation and increase in vegetation were selected. A comparison was done using earlier and later images. The results indicate that areas with decrease in vegetation are related to areas that have been converted from either natural vegetation or permanent swamps to cropland. Such areas were related to code 3 (see table 5.2:20) in the change direction and accounted for 47.76% in Malinda, 34.23% in Magoma, 70.72% in Manguo and 72.60% in Rumuruti.

Increase in vegetation was largely related to areas covered by permanent swamps and other natural wetland vegetation classes. Some areas covered by shrubs were also included. In most cases a great contribution to this class was conversion from open water areas to permanent swamps or natural vegetation. These accounted for 30.85% in Malinda, 58.26% in Magoma, 23.19% in Manguo and in Rumuruti 22.72% of the total wetland. The changes were related to code 4 of change direction.

CVA analysis indicates that changes in the wetlands studied are non directional; they are scattered all over the wetlands. Some specific changes, like decrease in vegetation, are more prominent in the areas covered by natural vegetation are also sparsely distributed throughout the sites. Decrease in wetland vegetation accounts for majority of land cover change in the areas and thus decrease in wetland area. Baker *et al*. (2007) used CVA to map changes in Gallatin valley of south west Montana and also found that decrease in wetland cover accounted for major change in the wetland.

Using the LCM technique most of the significant changed areas indicated were related to decrease in spectral reflectance (brightness) which also means decrease in vegetation in the given sites. In Rumuruti site 28 polygons were detected (19 in the earlier images 1987-95 and nine in the later images 1995-2003) which covered 177 ha. Only 12 ha were detected in Manguo by six polygons (three earlier and three later) in the same period. In Malinda 7 polygons were identified between 1987 and 1995, which indicated a change area of 52.83 ha. Another 15 polygons were identified between 1995 and 2003 that indicated change area of 168.29 ha. Significant change in Magoma site was 47.182 ha (8 polygons) from 1987 to 1995 and 83.77 ha in 12 polygons from 1995 to 2003. Most of the polygons were located in the cultivated areas and burnt or where vegetation was harvested.

In general, the results show shrinking of the areas covered by natural vegetation while other land uses are increasing. The main factor contributing towards the loss is agriculture. Wood

& van Halsema (2008) comment that agriculture in wetlands has double impact; clearing and tillage that lead to both physical and in situ loss. Many studies like Liu *et al.* (2004), World Resources Institute (2000), and USGCRP (1997), which deal with changes in wetlands report loss of wetland due to agricultural activities worldwide. Most of them rank it as the first and most significant cause of loss natural vegetation.

Liu *et al.,* (2004) report 73.6% wetlands loss due to agricultural development in Small Sanjiang Plain, China from 1950 to 2000. In Europe, conversion to agriculture alone has reduced wetlands by some 60 percent (World Resources Institute, 2000). In United States for instance, the National Wetlands Inventory (NWI) found that 9.2 million acres of wetlands had been lost nationwide between the 1950s and 1970s due to agriculture (USGCRP, 1997). No proper estimates are given for African wetlands but greater losses are suggested due to poverty and high dependency on agriculture as the main primary source of income (Finlayson & Spiers, 1999).

5.5.2 Change detection accuracies

The accuracies for each site are presented in the table 5.4 below. For PCC accuracies of Malinda, Manguo and Rumuruti were higher; meaning the classification of the images was done appropriately. Magoma had lower accuracies, this was also the case with the classified images and it suggests that there were some minor errors in the classified images. Macleod & Congalton (1998) note that, lower accuracy in PCC change detection is one of the common problems. It is contributed by combining the errors from both classifications. It is thus suggested that the classification should be very carefully done to reduce the errors for better change detection results.

Table 5.5: Accuracy assessment of post classification change detection (%)

Year	Magoma	Malinda	Manguo	Rumuruti
1976-86/7	71.61	83.79	74.12	78.03
1986/7-95	65.29	88.92	72.97	82.14
1995-2003	57.17	60.77	82.3	82.61

Source: Own illustration

CVA images when overlaid in ArcGIS matched well with their respective change classes. This means that CVA was able to distinguish the change areas appropriately. All classified images which were used for change labelling had accuracies above 86% and Kappa indices above 0.83. With LCM overall change accuracies were, for Malinda 88% (0.86 Kappa), Magoma 90% (0.87), Manguo 95% (0.94) and Rumuruti 85% (0.83).

5.5.3 Methods comparison

Despite its limitation i.e. high dependence on accurate classification, PCC detection was the most straight forward technique as it indicated changed classes and change from a specific class to another. With CVA, despite the long processing steps and several empirical tests for proper change thresholds, its strength in depicting change magnitude and direction makes it an effective method for mapping LCLU change. LCM mapped only significantly changed areas and all newly opened areas for agriculture or areas where macrophytes were harvested were identified and mapped accurately. Macleod and Congalton (1998) had similar observation using PCC also Johnson and Kasischke (1998) appreciate the strength of CVA in depicting change magnitude and direction. Castilla *et al.* (2009) recognise not only the efficiency of LCM in mapping changes but also its robustness.

5.5.4 Driving forces of LCLU changes

It was another aim of the study to identify relevant driving forces of wetland change using spatial parameters. However, lack of sufficient ecological, socio-economic and demoghraphic data made it impossible to attain this objective. Since it was still in the interest of this research to identify factors, which led to wetlands change, group discussion was organised with several key informants, who included: village leaders, elders and selected farmers who have farms in the wetlands. The key informants had different views on wetland uses and resulting changes as discussed below.

Climate change was noted as one of the factors which lead to increased wetlands utilization and the resulting changes. The respondents argued that in the recent years, seasons have changed dramatically, rainfall has become so variable and unreliable that cultivation on upland areas, which has over the years been used for crop production, is very uncertain. Wetlands offer production security to farmers because of availability of water or moisture content to support crop production. Mitsch & Gosselink (2007) comment that the on-going climate change may have implications on wetlands status and use while Thenya (2001), Kiai & Mailu (1998) and Haack (1996) confirm that drought conditions especially in semi arid areas have increased pressure on the wetlands for cultivation or search for pasture or fodder.

Rural impoverishment was another reason related to wetland use change. In rural areas poverty, unemployment and underemployment are very high, and rural population is growing faster than rural employment creation. As other economic options disappear, increasing numbers of rural residents engage in wetland resource utilization to support their livelihood. Wood *et al*., (2008) and Schuyt (2005) argue on both population increase and poverty to be among the major driving force of wetland use and consequent degradation.

Regional infrastructure improvement in terms of transport, market access and communication has facilitated increased wetland uses in rural areas since the linkage between rural and urban areas has also improved a lot. Farmers are able to communicate with their customers in urban areas and are assured of disposing their products to markets timely. At times farmers do sale their produce while still in the farms to the brokers who pick the harvest when ready. Famers are also able to sell their crops at road side markets. This is the case in Malinda and Magoma for rice and in Lukozi, Rumuruti and Karatina for horticultural crops.

Increased demand for wetland products in urban areas and neighbouring countries encourage more farmers to acquire plots in the wetlands. Technology expansion i.e. production of high yielding seeds and availability of pesticides motivate people to continue intensifying their activities in the wetlands. Availability of diesel pumps, which are used for water abstraction from wetlands to the uplands, has made cultivation possible in the riparian areas. This finding is also supported by Wood *et al*., (2008) who argue that market forces are the major driver of wetland cultivation in Africa. The growing urban centres are a major stimulus for vegetable and some cereal cultivation. This also affirms Boserup (1965) who argued that population increase is an incentive for agricultural intensification.

Economic liberalisation in Tanzania (late 1980s'), in particular, has opened more markets within and outside the country for agricultural crops. In the past food crops were only sold in the domestic markets. Market failure for traditional cash crops like coffee, tea and cotton has constrained farmers so much that and they can't continue depending on these crops as a source of income. Thus in both Kenya and Tanzania such farmers have turned their attention to either horticulture or other means of diversifying their economy. This finding is supported by Ponte (1998) who noted that economic reforms carried out under structural adjustment programs in Tanzania since 1984 have brought a wave of changes in farming practices and rural livelihoods. Agricultural market liberalization and increased commercialization of rural life made farmers to switch from slow to fast growing cash crops. Farmers also switched from cash crops requiring high input use to those requiring low input.

All the above mentioned factors have led to intensification of human activities in the wetlands leading to changes in the wetlands status, which could be ameliorated or irreversible. Thus care should be taken when extending activities in the wetlands to minimise negative impacts on the wetlands.

5.6 Conclusion

In this chapter spatially explicit changes that have taken place in the wetlands were detected. Three different methods i.e. PCC using change matrix, CVA and LCM were used in assessing the changes. The results have revealed that different changes are taking place in the four study sites. The major changes detected were (semi) natural vegetation decrease, shrinking of permanent swamps and increase of shrubs and herbs due to increased cultivation activities. Driving forces of these changes have also been qualitatively identified as mainly climate change, impoverishment, population growth, increased market forces and infrastructure improvement. It is important that the activities taking place in the wetlands are checked to ensure sustainability and their continued support to the population. A general discussion of the study and overall status of wetlands in Kenya and Tanzania is done in the next chapter.

6 General discussion

This study commenced by hypothesizing that small wetlands can be detected by using both optical and microwave remote sensing. It was also assumed that differentiation of small wetlands can be achieved by classification of multi spatial resolution remote sensing data. Finally it was postulated that detection of land use change in the small wetlands can be achieved by assessment of time series LANDSAT images. The information generated from this study would help in a better understanding of the status of the small wetlands, which would contribute to their proper management through making informed decisions.

The results of the study presented and discussed from chapter 3 to 5 confirmed the hypotheses and goals of the study. These findings are revisited in this chapter. Status and management of wetlands in Kenya and Tanzania is reviewed to give an insight of its relation to current situation of the small wetlands.

6.1 Small wetlands detection and mapping

The first objective dealt with detection and mapping of small wetlands using both optical and microwave remote sensing. Different kinds of data and methods were employed to achieve this objective. Data sets ranging from aerial photographs, digital elevation models (DEM), LANDSAT, ASTER, ALOS PALSAR, ENVISAT ASAR, TerraSAR-X and topographical maps were used. The methods included visual interpretation of the images, making DEM threshold, calculation of vegetation indices, and classification using unsupervised and supervised techniques. In addition decision tree classification, image enhancement, and on screen digitization were used for data analysis while aerial survey and ground truthing data were collected in the field.

Fifty one wetlands were identified; these were mainly of two types, flood plains and inland valleys. Windmiejer & Andriesse (1993) inland valley classification approach was used for wetlands differentiation into valley heads covering 15.9%, mid-stream section accounted for 64.3% and flood plains were 19.8%. Wetland sizes ranged between 0.5 and 747.54 ha. Inland valleys were smaller in size (0.5-35 ha) and were densely distributed in the highlands, and while flood plains were large (10-747.54 ha) and sparsely distributed.

Despite their limitation in spatial coverage, aerial photographs were more effective in delineation of wetlands because of their high spatial resolution. However the data capture was influenced by weather and processing was tedious given the fact that it was difficult to get high resolution data for georectification. LANDSAT images detected both small and large wetlands and microwave data were best in detecting larger areas in the flood plain. Lyon (2001), Tiner (1999), and Lillesand *et al*. (2008) ascertain that detection of wetlands is very challenging due to their dynamic nature. They occur along a soil moisture continuum between permanently flooded and drier habitats which makes them difficult to identify on the ground and on the images. Also the size of wetlands changes rapidly with occurrence of increased moisture content in the soil. Hence determination of their actual size is a great challenge. A combination of different data types and techniques was necessary because of varied capabilities of both optical and microwave data in capturing and detecting wetlands diversity.

6.2 Classification of wetlands' cover and use

It was important to understand the status of the detected wetlands in terms of cover and use. The wetlands were digitally classified using unsupervised and supervised methods with time series LANDSAT images and aerial photographs. Ten main LCLU types were identified which were open water, floating vegetation, permanent papyrus swamps, natural vegetation, cropland, forest, shrubs, grassland or grazing, bare land, built up areas and burnt areas. Burning was also common in flood plains particularly in dry season. It was considered in the classification though it is normally temporary in some areas but in other areas the scars lasted long.

The study revealed that inland valleys were intensively used for agriculture and land fragmentation was a common phenomenon due to limited plots in the wetlands. Vegetable production was a predominant activity in those areas and field crops were also produced. Floodplains were extensively used for farming and grazing. The accuracies of classification were relatively high ranging from 82.76 to 95.17% with a Kappa index of 0.79 to 0.94, possibly because the areas of interest were masked and separated from the uplands thus minimizing the spectral confusion with LCLU of the uplands. In unsupervised classification classes were mixed due to similar reflectivity among different LCLU classes. Signature confusion is a common problem in wetlands classification as observed by Islam *et al*. (2008) and Ozesmi and Bauer (2002).

Agriculture occupies the largest share of LCLU i.e. between 24-35% in floodplains and 43.7-47.24% in the inland valleys. Grazing covered 11-39%, and built up areas 14% in Laikipia and up to 19% in the highlands. Other uses covered less than 8%. The results showed that modification and conversion of wetlands were ongoing. Thus their monitoring is important for better understanding of the transformation processes. Many studies have shown that among the many wetland uses, agriculture is an overriding land use (Verhoeven & Setter 2010; Wood & van Halsema 2008). According to the Millennium Ecosystem Assessment (2005), economic and population pressures have been the major driving forces in wetland transformation and the pressures are envisaged to increase. Some measures need to be taken to create a balance between the uses and services that wetlands can provide to the ecosystem.

6.3 Assessment of changes in the wetlands

The last objective of this study was to assess the changes, which have taken place in the wetlands, from 1976 to 2003 and identify the driving forces behind the changes. The temporal coverage was limited by availability of relevant data. To accomplish the objectives it was hypothesized that; change detection in the wetlands could be achieved by assessment of time series LANDSAT images. Three different time sequences were assessed 1976-1986/7, 1986/7-1995 and 1995-2003 were assessed using PCC. LCM and CVA were used to detect changes between 1986/7 and 1995 and 1995 and 2003. The results reveal that many changes mainly modification of the wetlands, have taken place. The PCC approach shows that at least each land use in the wetlands had changed from one class to another between 1976 and 2003.

Significant changes are seen in the general reduction of natural vegetation, which is revealed by all the three methods. The PCC method for instance detected shrinking of the permanent swamps, invasion of vegetation in open water areas, increase of shrubs and increase in croplands in all sites. Grazing areas and bare lands are overtaken by other uses like agriculture and in Laikipia plains by built up areas. In general conversion to agriculture accounts for more than 50% in all wetlands and it is increasing. CVA magnitude image confirms vegetation loss by indicating higher intensity in areas where vegetation has been completely lost. Changes in the wetlands are non directional as they are scattered all over and very little increase in vegetation is evident.

Mwakaje (2009), Kashaigili *et al.* (2006) and Thenya (2001) observed high increase of agriculture and other uses in the wetlands in Kenya and Tanzania. The Millennium Ecosystem Assessment (MA) identified agriculture as the major cause of wetland degradation and loss (Wood & van Halsema, 2008). In different parts of the World wetland uses are increasing and the general implication is their loss through conversion and filling. Changes in wetlands are dynamic, during dry seasons more land is converted into farms and in wet seasons most of the farms are abandoned because of floods.

Field experience and change detection analysis show an increase in vegetation during wet years and decrease in drier years. A similar observation is made by Thenya (2001) who notes that, in Ewaso Narok wetland vegetation re-generates fast in wet season. Field experience further proved that wetlands are heavily impacted by anthropogenic factors especially in dry season. Burning frequency is very high in search for pasture, thatch materials and hunting, intensive grazing takes place and animal trampling destroys the vegetation tremendously. Some famers are over using water for irrigating their crops which may imply lack of knowledge on how much water can be used or is required for proper plant growth (Figure 6.1). The implication of these activities is wetlands' destruction and loss. In addition a lot of changes happen, which are seasonal, that can't be monitored by LANDSAT images due to cloud cover penetration limitation in wet season. These changes could be captured by aerial survey in dry season and towards the end wet season. Only dry season aerial survey was conducted thus the seasonal changes were not appropriately mapped.

Figure 6.1: Water abstraction for upland irrigation in Rumuruti site. Poor timing and over irrigation leads to water loss
Photo: by Mwita, June, 2009

6.4 Driving forces of change in small wetlands

Since there were limited spatial data for identification of the driving forces, the information on driving forces was qualitatively collected through group discussion. Results show that the main driving forces of change are climate change, poverty or rural impoverishment as well as communication and infrastructure improvement. In addition increased demand for wetland products, economic liberalization and regional integration has exerted more pressure on wetlands uses. Rebelo *et al*. (2009a) add on that increasing population in conjunction with efforts to increase food security is escalating pressure to expand agriculture within wetlands. Wood & van Halsema (2008) also comment that the drive to increase economic output (especially food production) has led to excessive emphasis on provisioning services, frequently crop-specific, at the expense of regulating and supporting services and involving excessive water use. This is also true for the wetlands within this study where larger parts have been transformed into horticultural fields for food and income generation. In general wetlands are very hard to work on but they are invaded because of lack of alternatives and also as a result of efforts to diversify farmers' economies.

6.5 Status of wetlands in Kenya and Tanzania and management challenges

The results have shown that small wetlands are on high demand for use and in some areas the uses are increasing. Field experience unveils uncontrolled use of wetlands in all sites. Wetland vegetation are burnt haphazardly, a lot of water is abstracted for upland agriculture and drier parts of the wetland and farms are established anywhere in the wetland provided there is access particularly in floodplains. That is the reason why the changes show non directional pattern. This is a common problem with many wetland resources but the small ones are more vulnerable due to lack of attention.

These problems are partly a result of unclear wetland management authority, policy or legal base. Schuijit (2002) argues that despite their importance, wetlands throughout Africa are being modified and reclaimed. A major factor contributing to these activities is that, decision-makers often have insufficient understanding of the economic values of wetlands, so the protection of wetlands is not a serious alternative. Other authors like Schuyt (2005) attributes the problem to information failures to relate or understand the consequences of land use, water management, pollution and infrastructure on wetlands and the fact that many wetland functions do not have a market price and as such are not recognized as having an economic value by different stake holders. Rebelo *et al.* (2009b) add that knowledge of the African wetland resource is far from complete and is inadequate to support management needs. Mwakaje (2009) argues that lack of wetland policies and law to enforce policy contributes to these problems. Generally each of the concerns of these authors in one way or another has a role to play in the current status of small wetlands though at a varied extent in the two countries.

Kenya and Tanzania are signatories of the Ramsar convention and have designated Ramsar sites, which means, much is known about the wetlands at least at the government level. Management of all environmental resources in the two countries is under environmental management law and other sectoral legislations. Kenya has a Wetland Policy and Wetland Act enacted in 2009 within the environmental management law but Tanzania doesn’t. In Tanzania, wetlands are under the custody of the Wildlife Department. The wildlife policy of

1997 in section 3.2.1 **on wildlife protection** one of the objectives is to enhance the conservation of biological diversity by administering wetlands. However in section 3.3.1 on **strategies for protecting biological diversity,** the second strategy is to identify, create and upgrade a series of protected area networks and "important" wetlands in order to safeguard the biological diversity of Tanzania and the fourth strategy is to incorporate important wetlands into the wildlife protected area network. The Policy recognises only 'important wetlands' and in protected areas.

The Agriculture and Livestock Policy (1997) points out that, the government will implement measures, which will minimize encroachment in public lands including forests, woodlands, wetlands and pasture. The Water Policy on the other hand, is concerned with improving the management and conservation of ecosystems and wetlands (Ministry of Water and Livestock, development, 2002). Under the water policy the government of Tanzania banned all agricultural activities in water sources on 1st of April 2006, but this included mainly the larger wetlands especially rivers Ruaha, Rufiji and Pangani, small wetlands are unclearly covered by any of the policies.

Kenya has a Wetland Policy (Government of Kenya, 2008), which prohibits wetlands reclamation unless there is a great public interest. The policy also requires strict regulation on water abstraction and exploitation of goods and services. The policy statements, however, are not enforced on small wetlands in particular. Great challenge on the Kenyan side is on property rights as noted by Odete *et al.* (2002). Some of the wetlands are privately owned thus in some cases it may be difficult to implement government interests. The Wetland act enacted last year will probably help in enforcing the policy.

In summary efforts are there to manage wetlands but small ones are not seen to have received required attention despite their usefulness. Lack of appreciation of wetland potentials, lack of wetlands policy and law in Tanzania, and poor enforcement of the available policy in Kenya are among the challenges in small wetlands management.

6.6 Conclusion

The discussion above has shown how remote sensing facilitated detection of small wetlands detection, their classification and assessment of the changes that have taken place between 1976 and 2003. The use of microwave and optical remote sensing and various methods have proved that remote sensing plays a significant role in the assessment and monitoring of small wetlands. Wetlands play a crucial role in supporting livelihoods of local communities and therefore, are modified to fit their needs for food production and income generation, in the process they are degraded and lost. Climate change, increased population and infrastructure improvement are among the drivers of change in the use of wetlands. Challenges arising from their great diversity, extent and use as well as absence or poor enforcement of policies fosters their transformation and degradation. Recommendations are made in the subsequent final chapter on possible ways of mitigation of negative impacts and creation of a balance between the use and conservation of the resource.

7 Conclusions, recommendations and outlook

In this final chapter general recommendations are given following the finding of the study, discussions and on site observation of the situation of small wetlands. The recommendations are preceded by conclusions.

7.1 Conclusions

Following the preceding discussion, it is concluded that, remote sensing facilitates small wetlands detection, classification and assessment. Both optical and microwave data have high potential in assessment and monitoring small wetlands but their resolutions should be highly considered for excellent results. Application of different techniques improves and confirms the results.

Changes are taking place in the wetlands that are inevitable due to increasing population, demand for food and diversification of livelihoods for the local communities. This calls for proper planning and management of wetlands to ensure wise use and maintenance of their values and potentials.

Small wetlands potentials are not properly appreciated and their management is unclear. In some cases over exploitation or misuse of wetland resources suggests lack of adequate knowledge particularly of the users. Lack of policy/ law or unsatisfactory enforcement of the policies/ law, and lack of guidance contributes to this problem. Thus there is a need for more aggressive policy work.

7.2 Recommendations

The following are recommended to improve the situation

1. For appropriate mapping, higher resolution images like Quickbird are suggested to reduce labour intensive processing of aerial photographs.
2. It would be of great interest to monitor seasonal change of wetlands by capturing remote sensing data before and immediately after the end of wet season.

3. Agriculture department in conjunction with other stakeholders should look for better ways in which the agriculture wetland interaction may be maintained to create a kind of balance between utilization and conservation.
4. Farmers and other wetland users should be sensitized and educated by wetland experts or extension officers on the best ways of extracting wetland resources without jeopardising their existence.
5. Tanzanian government should facilitate wetland policy formulation and law to back up the policy. The policy should state clearly the foreseers of small wetlands and stipulate their responsibilities.
6. Kenyan government should enforce the law to minimise the negative impacts on the wetlands. The land ownership challenge especially when it comes to enforcement of government regulations on wetland use and management should be addressed by the concerned authorities.

7.3 Outlook

Since this study did not achieve spatial extrapolation, it is suggested that this is done in the second phase by acquiring all necessary data sets such as infrastructure, land use and population maps to facilitate the exercise. This study also covered small areas; it can be extended to larger spatial coverage to be able to extrapolate the results in other areas with similar circumstances.

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Landsat imagery
http://glcf.umiacs.umd.edu/data/LANDSAT/ (Accessed on 12th Oct 2007)

Appendix 1: Matrix tables

Manguo

		1986						
		OP/FV	PS	NV	CL	GG	BL	Total
1976	OP/FV	11.88	6.48	10.62	2.7	3.69	0.36	35.73
	PS	3.6	11.88	9	4.77	0.63	0	29.88
	NV	11.16	8.64	27	2.52	2.52	0.09	51.93
	CL	6.39	3.24	3.78	6.48	16.2	2.79	38.88
	GG	2.34	0.54	0.54	0.72	6.93	4.32	15.39
	Total	35.37	30.78	50.94	17.19	29.97	7.56	171.81

		1995						
		OP/FV	PS	NV	CL	GG	BL	Total
1986	OP/FV	2.88	0.18	8.82	13.59	9.45	0.9	35.82
	PS	1.8	8.82	14.31	5.76	0.27	0	30.96
	NV	6.84	4.32	25.02	13.95	0.81	0	50.94
	CL	0	0	0	0.36	6.48	7.02	13.86
	GG	0.45	0	1.26	2.16	14.31	13.23	31.41
	BL	0	0	0	0	1.17	7.65	8.82
	Total	11.97	13.32	49.41	35.82	32.49	28.8	171.81

		2003							
		OP/FV	PS	NV	CL	GG	BL	BU	Total
1995	OP/FV	5.22	0.9	5.76	0	0	0	0.09	11.97
	PS	0.81	0.63	11.79	0	0	0	0.09	13.32
	NV	12.6	7.11	29.07	0	0	0	0.63	49.41
	CL	5.67	1.71	24.3	0	0.36	0	3.78	35.82
	GG	0.54	0.72	9.45	0.09	6.75	1.71	13.23	32.49
	BL	0	0	0.36	0.27	2.16	2.61	2.16	7.56
	BU	0	0	0.9	2.61	12.33	2.79	2.61	21.24
	Total	24.84	11.07	81.63	2.97	21.6	7.11	22.59	171.81

Rumuruti

		1986								
		OP/FV	PP	NV	CL	FO	SH	GG	BL	Total
1976	OP/FV	0	0	0	0	0	0	0	0	0
	PP	2.7	266.94	12.69	9.9	0.72	0.99	0.45	0	294.39
	NV	6.57	201.16	17.46	18.45	4.77	0.9	1.8	0	251.11
	CL	0	1.98	0	5.4	0	9.9	0.63	0	17.91
	FO	0	54.9	2.07	3.78	1.17	1.08	0.36	0	63.36
	SH	0	1.08	1.53	1.08	0	0.81	0.54	0	5.04
	GG	0.18	22.95	1.1	14.03	1.71	5.04	2.16	0.09	47.26
	BL	1.17	4.32	0.79	11.8	0.81	28.98	18.54	1.53	67.94
	Total	10.62	553.33	35.64	64.44	9.18	47.7	24.48	1.62	747.01

1995

1986	OP/FV	PP	NV	CL	FO	SH	GG	BL/BU	Total
OP/FV	0	2.25	5.85	1.89	0.63	0	0	0	10.62
PP	126	211.68	146.88	27.09	40.05	2.16	0	0	553.86
NV	3.51	10.89	14.31	3.42	3.33	0.18	0	0	35.64
CL	0.09	0.81	18.27	32.49	1.8	10.71	0	0.27	64.44
FO	0.09	0.27	2.97	5.04	0	0.81	0	0	9.18
SH	0	0.45	1.53	12.24	0.36	25.65	6.93	0.54	47.7
GG	0	0.72	1.26	3.33	0.18	8.91	7.29	2.79	24.48
BL	0	0.45	0.72	0.09	0	0.36	0	0	1.62
Total	129.69	227.52	191.79	85.59	46.35	48.78	14.22	3.6	747.54

Malinda

1987

1976	OP/FV	PP	NV	CL	FO	SH	GG	BL/BU	Total
OP/FV	4.14	1.44	3.6	34.83	2.61	0.99	0	0	47.61
PP	6.57	11.07	20.34	3.69	64.08	4.86	31.86	9.81	152.28
NV	0.36	12.15	10.98	9.54	16.11	0	1.71	2.07	52.92
CL	0.36	4.23	7.2	14.58	35.64	5.76	10.98	2.61	81.36
FO	4.05	11.7	13.14	1.26	47.97	3.24	7.65	4.41	93.42
SH	0.09	0.9	1.35	8.55	17.91	2.88	18.09	3.69	53.46
GG	0.81	2.25	3.51	0.27	26.37	3.24	47.52	8.64	92.61
BL/BU	0	0.9	0.63		9.81	0.27	6.84	2.52	20.97
Total	16.38	44.64	60.75	72.72	220.5	21.24	124.65	33.75	594.63

1995

1987	OP/FV	PP	NV	CL	FO	SH	GG	BL/BU	Total
OP/FV	16.2	0	0.09	0	0.09	0	0	0	16.38
PP	0	36.54	4.32	3.69	0	0.18	0	0	44.73
NV	0.36	1.26	43.29	14.13	1.35	0.36	0	0	60.75
CL	4.05	0	16.47	18.09	20.79	12.06	0.09	0	71.55
FO	0	2.16	26.37	64.35	40.41	71.91	15.57	0.63	221.4
SH	1.35	0	0.27	0.27	4.41	14.49	0.36	0.09	21.24
GG	3.69	0	3.42	4.41	14.85	72.36	23.4	2.61	124.74
BL/BU	0.54	0	5.58	2.97	4.14	11.97	7.47	1.17	33.84
Total	26.19	39.96	99.81	107.91	86.04	183.33	46.89	4.5	594.63

2003

1995	OP/FV	PP	NV	CL	FO	SH	GG	BL/BU	Total
OP/FV	5.13	13.86	2.16	1.08	0.72	0.9	0.18	2.16	26.19
PP	0.63	16.56	5.22	0.18	12.69	4.32	0	0.36	39.96
NV	9.63	39.51	22.5	3.42	14.4	5.22	0.81	4.32	99.81
CL	0.09	13.68	14.31	6.57	34.2	30.24	3.96	4.86	107.91
FO	0	3.69	6.3	11.79	17.28	36.81	9.27	0.9	86.04
SH	0	4.5	2.34	62.91	8.19	62.55	40.23	2.61	183.33

GG	0	0.27	0.45	19.53	0.81	8.64	14.13	3.06	46.89
BL/BU	0	0	0	1.17	0	0	2.79	0.54	4.5
Total	15.48	92.07	53.28	106.65	88.29	148.68	71.37	18.81	594.63

Magoma

1987

1976		OP/FV	NV	CL	SH	GG	BL	Total
	OP/FV	12.06	0.72	6.12	3.6	4.5	2.97	29.97
	NV	0	14.49	26.46	3.69	20.25	2.97	67.86
	CL	2.25	10.35	64.44	18.54	53.55	13.4	162.53
	SH	6.21	3.87	24.31	7.47	15.66	4.33	61.85
	GG	6.93	4.86	29.69	17.82	22.32	28.35	109.97
	BL	1.98	2.97	37.35	12.78	24.12	32.67	111.87
	Total	29.43	37.26	188.37	63.9	140.4	84.69	544.05

1995

1987		OP/FV	NV	CL	SH	GG	BL	Total
	OP/FV	11.34	6.3	10.53	1.17	0.09	0	29.43
	NV	0.27	8.46	21.96	3.51	2.97	0.09	37.26
	CL	2.34	81.09	64.62	27.72	12.06	0.54	188.37
	SH	2.61	15.75	33.93	5.04	6.57	0	63.9
	GG	0.27	61.29	16.38	44.19	16.2	2.07	140.4
	BL	0	6.84	3.6	29.25	28.26	16.74	84.69
	Total	16.83	179.73	151.02	110.88	66.15	19.44	544.05

2003

1995		OP/FV	NV	CL	SH	GG	BL	Total
	OP/FV	10.17	2.52	4.05	0.09	0	0	16.83
	NV	3.51	33.39	104.85	22.86	9.63	5.49	179.73
	CL	6.93	38.43	93.51	7.74	4.14	0.27	151.02
	SH	0.99	5.67	54.63	27	14.31	8.28	110.88
	GG	0	8.19	32.04	22.77	1.62	1.53	66.15
	BL	0	0	2.7	12.78	1.98	1.98	19.44
	Total	21.6	88.2	291.78	93.24	31.68	17.55	544.05

Appendix 2: Selected ground truth data

Location	X.coord	Y.coord	Altitude	LCLU
Rumuruti	227311	10029189	1808	Natural vegetation
Sosian	230336	10035020	1792	Fallow
Rumuruti	227337	10029514	1809	Fallow
Salama	230940	10034494	1794	Fallow
Salama	230891	10034256	1802	Grazing
Salama	231198	10034633	1782	Grazing
Rumuruti	226723	10028465	1812	Cropland
Tegu	288754	9948240	1724	Cropland

Tegu	288768	9947756	1729	Cropland
Sosian	230221	10034836	1794	Grazing
Sosian	229740	10033751	1793	Grazing
Sosian	228708	10031136	1804	Fallow
Sosian	228522	10030823	1803	Shrubs
Sosian	228204	10030220	1797	Grazing
Rumuruti	227527	10029664	1814	Forest
Rumuruti	227349	10029563	1811	Fallow
Rumuruti	227343	10029150	1805	Shrubs
Sosian	230525	10035161	1797	Shrubs
Salama	230671	10033882	1784	Papyrus swamp
Salama	229332	10031332	1798	Grazing
Sosian	228868	10031880	1797	Natural vegetation
Rumuruti	229424	10031418	1807	Grazing
Sosian	228713	10031046	1794	Cropland
Rumuruti	227275	10029631	1794	Cropland
Rumuruti	227599	10029970	1665	Natural vegetation
Rumuruti	227051	10029266	1808	Grazing
Rumuruti	226753	10028415	1820	Papyrus swamp
Sosian	230363	10035167	1795	Cropland
Sosian	227700	10029874	1805	Papyrus swamp
Sosian	227739	10029824	1817	Papyrus swamp
Rumuruti	226882	10028512	1810	Papyrus swamp
Rumuruti	226720	10028532	1825	Shrubs
Sosian	230323	10035021	1791	Cropland
Sosian	229961	10034537	1787	Cropland
Sosian	228750	10031229	1806	Bare land
Salama	228672	10029791	1794	Bare land
Rumuruti	227615	10029707	1807	Cropland
Rumuruti	226885	10028669	1810	Cropland
Rumuruti	226763	10028558	1801	Cropland
Rumuruti	228151	10030229	1798	Open water
Rumuruti	228176	10030396	1807	Papyrus swamp
Rumuruti	227853	10029689	1805	Shrubs
Kinamba	231282	10034665	1783	Vegetables
Salama	229308	10031097	1787	Bare land
Salama	228922	10030431	1801	Grazing
Rumuruti	227746	10029656	1804	Built up
Salama	229321	10031105	1795	Grazing
Rumuruti	227368	10029463	1811	Cropland
Kinamba	231418	10034719	1789	Fallow
Rumuruti	227152	10029029	1811	Shrubs
Salama	227921	10029262	1807	Cropland
Rumuruti	227016	10028927	1808	Fallow
Sosian	230395	10035039	1790	natural vegetation
Salama	230723	10034298	1766	natural vegetation
Sosian	228916	10032301	1791	natural vegetation
Rumuruti	227194	10029459	1814	natural vegetation
Rumuruti	227178	10029475	1816	Papyrus swamp
Rumuruti	227180	10029463	1856	Papyrus swamp
Salama	230944	10034524	1781	Burnt
Rumuruti	226888	10028570	1811	Bare land
Sosian	229621	10033564	1797	Cropland
Sosian	229157	10032961	1799	Vegetables
Sosian	228809	10031462	1805	Vegetables
Sosian	228341	10030677	1801	Vegetables

Sosian	228390	10030700	1803	Vegetables
Rumuruti	227519	10029699	1808	Vegetables
Rumuruti	227037	10028640	1807	Papyrus swamp
Salama	227795	10029203	1808	Burnt
Kinamba	231833	10034911	1785	Bare land
Tegu	288674	9947057	1713	Cropland
Tegu	288699	9947082	1703	Vegetables
Tegu	228822	10030174	1800	Vegetables
Mkundi	424788	9437843	334	Open water
Sangei	424796	9437830	339	Burnt
Lukozi	416658	9485511	1747	Bare land
Lukozi	416671	9485509	1761	Built up
Lukozi	416721	9485423	1740	Vegetables
Lukozi	417172	9485040	1737	Vegetables
Tegu	288686	9947203	1701	Vegetables
Kinamba	231148	10034345	1805	Cropland
Low-Hambalawey	417936	9484641	1757	Fallow
Mavumo	415834	9484182	1752	Shrubs
Hemboye	416094	9486237	1741	Vegetables
Mavumo-Viti	416960	9484787	1738	Vegetables
Viti	416557	9485805	1707	Vegetables
Viti	417971	9484455	1740	Cropland
Hemboye	416875	9484702	1744	Fallow
Mavumo	416014	9484201	1748	Shrubs
Low-Hambalawey	417990	9484474	1732	Vegetables
Viti	417624	9485071	1750	Cropland
Mavumo	416986	9484801	1758	Fallow
Hambalawey	417764	9485005	1730	Shrubs
Hambalawey	418156	9484247	1729	Cropland
Viti	416527	9485851	1759	Fallow
Viti	416520	9484410	1732	Shrubs
Viti	416167	9484223	1753	Vegetables
Mavumo	416040	9484233	1771	Cropland
Hemboye	415037	9487068	1750	Fallow
Low-Hambalawey	418051	9484420	1739	Shrubs
Viti-mid	416367	9486047	1734	Shrubs
Hemboye	417065	9484940	1725	Vegetables
Mavumo	416378	9484263	1731	Cropland
Hambalawey	418127	9484348	1746	Fallow
Hemboye	415107	9487036	1750	Shrubs
Mavumo	416515	9484355	1759	Cropland
Hambalawey	418152	9484229	1722	Fallow
Viti	417580	9485063	1748	Shrubs
Mavumo	415285	9486876	1754	Vegetables
Mavumo	416765	9484671	1748	Cropland
Mavumo-Viti	417074	9484950	1754	Fallow
Mavumo-Viti	417134	9485002	1746	Shrubs
Viti	415938	9486497	1754	Vegetables
Hambalawey	417845	9485002	1743	Cropland
Hemboye	415255	9486859	1738	Fallow
Low-Hambalawey	417900	9484827	1720	Vegetables
Viti	416520	9485851	1742	Vegetables
Mavumo-Viti	417039	9484927	1724	Vegetables
Low-Hambalawey	417950	9484574	1743	Vegetables
Hemboye	415008	9487094	1762	Fallow
Low-Hambalawey	417989	9484496	1746	Cropland

Hemboye	415145	9486996	1761	Cropland
Mavumo	415616	9484218	1754	Vegetables
Hambalawey	418140	9484295	1739	Vegetables
Mavumo	415786	9484189	1749	Vegetables
Mavumo	415579	9484179	1756	Fallow
Mavumo	415460	9484313	1765	Cropland
Mavumo	416097	9484138	1758	Cropland
Mavumo	416066	9484135	1750	Vegetables
Mavumo	416328	9484256	1750	Vegetables
Mavumo-Viti	416964	9484765	1751	Vegetables
Mkundi	425464	9438761	336	Fallow
Mkundi	425442	9438763	332	Bare land
Mkundi	425392	9438481	335	Fallow
Sangei	425344	9438160	349	Natural vegetation
Sangei	424937	9437802	358	Burnt
Malinda	425792	9438366	342	Fallow
Sangei	425440	9438230	347	Burnt
Sangei	425792	9438366	342	grazing
Sangei	424908	9438067	340	Bare land
Mkundi	425346	9438695	336	Open water
Mkundi	425605	9438779	351	Open water
Mkundi	425421	9438683	343	Floating vegetation
Mkundi	425787	9438487	343	Fallow
Mkundi	425743	9438431	348	Natural vegetation
Mkundi	425470	9438991	327	Cropland
Mkundi	425647	9438502	339	Fallow
Kiloza	427297	9436348	344	Grazing
Kiloza	427258	9436372	321	Cropland
Kiloza	427240	9436365	348	Fallow
Kiloza	427267	9436399	353	Burnt
Kiloza	427200	9436358	333	Grazing
Kwasunga	426430	9436942	328	Fallow
Mafuleta	425163	9436749	340	Burnt
Kwasunga	425513	9436805	340	Grazing
Mafuleta	426647	9437099	274	Grazing
Mkundi	425561	9438011	338	Cropland
Mkundi	425287	9438947	341	Natural vegetation
Mkundi	425414	9438711	342	Natural vegetation
Mkundi	425627	9438571	339	Bare land
Mkundi	425499	9438760	353	Bare land
Sangei	425298	9438097	326	Papyrus swamp
Sangei	424789	9437952	333	Open water
Mkundi	425327	9438657	342	Floating vegetation
Mkundi	425427	9439024	337	Fallow
Mkundi	425451	9438619	337	Burnt
Kiloza	427299	9436393	335	Grazing
Sangei	425069	9437890	340	Fallow
Sangei	425077	9438059	329	Burnt
Sangei	425121	9437990	333	Grazing
Sangei	425172	9437980	337	Grazing
Mkundi	425754	9438522	347	Cropland
Mkundi	425673	9438541	343	Vegetables
Mkundi	425717	9438329	348	Cropland
Malinda	425707	9438365	333	Cropland
Mkundi	425713	9436775	342	Fallow
Mkundi	425737	9436584	340	Cropland

Kiloza	427220	9436325	328	Cropland
Kiloza	426360	9436927	323	Vegetables
Mkundi	425706	9438262	351	Open water
Tegu	288768	9947291	1705	Vegetables
Tegu	288788	9948421	1757	Cropland
Tegu	288762	9948327	1722	Vegetables
Tegu	288762	9948147	1680	Vegetables
Tegu	288761	9947649	1706	Cropland
Tegu	288789	9947564	1711	Cropland
Tegu	288766	9947502	1698	Natural vegetation
Tegu	288760	9947333	1701	Fallow
Tegu	288750	9947216	1733	Cropland
Tegu	288790	9947018	1711	Cropland
Tegu	288664	9947033	1692	Shrubs
Tegu	288776	9948060	1710	Fallow
Tegu	288782	9947408	1705	Forest
Tegu	288699	9947204	1700	Natural vegetation
Tegu	288665	9947055	1700	Natural vegetation
Tegu	288658	9947008	1694	Fallow
Tegu	288751	9947768	1713	Grazing area
Tegu	288750	9947765	1712	Cropland
Tegu	288753	9947709	1722	Grazing area
Tegu	288781	9947885	1684	Cropland
Tegu	288784	9947573	1713	Cropland
Tegu	288773	9948069	1697	Natural vegetation
Tegu	288778	9947899	1678	Vegetables
Tegu	288771	9947870	1212	Vegetables
Tegu	288763	9947647	1708	Cropland
Tegu	288685	9947101	1715	Cropland
Tegu	288803	9947964	1695	Natural vegetation
Tegu	288778	9947762	1719	Vegetables
Tegu	288774	9947958	1711	Natural vegetation
Tegu	288757	9947692	1712	Vegetables
Tegu	288755	9947245	1716	Cropland
Tegu	288730	9947056	1699	Cropland
Tegu	288777	9948329	1719	Natural vegetation
Tegu	288771	9948243	1707	Fallow
Tegu	288758	9948179	1711	Natural vegetation
Tegu	288750	9947682	1702	Natural vegetation
Tegu	288762	9947632	1697	Bare field
Tegu	288755	9947564	1705	Natural vegetation
Tegu	288758	9947750	1711	Vegetables
Tegu	288761	9947707	1713	Cropland
Tegu	288791	9947186	1712	Natural vegetation
Tegu	288759	9947420	1714	Fallow
Tegu	288777	9947299	1699	Vegetables
Tegu	288704	9947136	1700	Vegetables
Tegu	288735	9947105	1699	Cropland