MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES, NIGERIA

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ABSTRACT

MODELLING LAND COVER IN EDO AND DELTA STATES, NIGERIA

BY

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The land surrounding Edo and Delta states is continuously changing, requiring satellite images and extensive field assessment to monitor and manage. This information is significant in mapping and identifying the temporal and spatial patterns of land use and land cover change, especially with the ongoing conflict regarding oil activities and illegal logging

This study employed the use of Landsat TM and ETM to assess the changes in the land using post-classification comparison change detection technique. Detailed 'from-to' statistical information was generated and put into the model. The combination of the application of remote sensing, modelling and field work, assisted in achieving the objectives of the study, which includes the identification of the key driving forces of land use and land cover change in Edo and Delta states. The post classification of the image showed that 53% of the total area underwent some changes. Results indicate that the forests are being lost at alarming rate of 3.7%, due to a number of socio-economic and political factors driving these changes. The model projections tested various scenarios of land cover change. These models also analysed the relationship between population and land use and land cover changes (agricultural land to be exact).

Acknowledgments

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CHAPTER 1

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: INTRODUCTION

1.1 Introduction

Human activities from time immemorial have caused land cover and land use to change, either intentionally or unintentionally, directly or indirectly. Human beings have shown an incomparable capacity to change or transform the character of the earth's surface at local or even regional scale (Sauer, 1956; Mabogunje, 1997).

Definitions of 'land' (as a term) frequently involve land cover and land use. For example the definition given by FAO is based on both land cover whilst the UN's definition is based on land use only (FAO, 1995/6, UN's Convention to combat desertification, 1994)

Land cover refers to the biophysical state or cover of the earth's surface, which according to Cihlar and Jansen (2001) comprises forest, glaciers, rivers and other open bodies or bare soil or rock. Recent studies include the built environment as part of land cover (e.g. Mannion 2002). Moser (1996) stated 'the term originally referred to the type of vegetation that covered the land surface, but has broadened subsequently, to include human structures, such as buildings or pavement...'

Land use, as defined by Skole (1994), is the human employment of a land cover type, the means by which human activity appropriates the results of Net Primary Production (NPP) as determined by a complex of socio-economic factors. Put simply, land use refers to human use of land for various purposes such as agriculture, logging, urban/industrial development, recreation and so on.

The terms 'Land use' and 'Land cover' are sometimes confused with each other or even used to mean the same thing. Supporting this point, Meyer and Turner (1994, 1995) noted that 'key sources of global data do not distinguish clearly between cover and use'. It is imperative at this point to distinguish between land cover. The distinction between land cover is evident; Meyer and Turner (1994) argue that land cover is the physical, chemical or biological categorization of the terrestrial surface e.g. grassland, forest or concrete while land use refers to the human purposes that are associated with that cover e.g. raising cattle, recreation or urban living. Furthermore Turner and Meyer (1994) stated:

'A single land use may correspond fairly well to a single class of land cover: pastoralism to unimproved grassland, for example. On the other hand, a single class of cover may support multiple uses (forest used for combinations of timbering, slash-and-burn agriculture, hunting/gathering, fuel wood collection, recreation, wildlife preserve, and watershed and soil protection), and a single system of use may involve the maintenance of several distinct covers (as certain farming systems combine cultivated land settlements). Land use change is likely to cause land cover change, but land cover may change even if the land remains altered'.

Vitousek (1994) notes that "three of the well-documented global changes are increasing concentrations of carbon dioxide in the atmosphere; alterations in the biochemistry of the global nitrogen cycle; and on-going land-use/land-cover change." When the users of land *decide* to employ its resources towards different purposes, land use change occurs producing both desirable and undesirable impacts (Briassoulis, 2000).

Land cover change is important to the study of global environmental change, having widespread effects on the natural environment. According to Riebsame *et al.* (1994), Land use patterns result in land cover changes that cumulatively affect the global biosphere and climate. With increasing population and advancing technologies, man has emerged as the major, most powerful and universal agent of environmental change in the biosphere today (Bottomley, 1998). The causes of the earth's major environmental problems – deforestation, loss of biodiversity, pollution, climate change and so forth – are all rooted in human behaviour (Anon, 1992; Russell, 1997).

These changes hold major implications for sustainable development and livelihood systems and also contribute to changes in the biogeochemical cycles of the earth, affecting the atmospheric levels of greenhouse and other trace gases (Turner *et al.*, 1995). At this point, it is crucial and essential to define land cover change.

Briassoulis (2000) stated that at a very elementary level, land cover change means (quantitative) changes in the areal extent (increase or decrease) of a given type of land use or land cover respectively. Land cover change can be further split into two types of change, which are '*conversion*' and '*modification*'. Land cover *conversion* is basically a change from one cover type to another, such as the conversion of forests to pasture. *Modification* involves alterations of structure or function without a wholesale change from one type to another; it could involve changes in biomass, productivity or phenology (Skole, 1994).

Supporting this point, Meyer and Turner (1996) noted that land use (both deliberately and inadvertently) alters land cover in 3 ways: *converting* the land cover, or changing it to a qualitatively different state; *modifying* it or quantitatively changing its condition without full conversion; *maintaining* it in its condition against natural agents of change.

Briassoulis (2000) went on further to explain that land use change may also involve either *conversion* and *modification,* noting that land use *conversion* is a change from one type of use to another i.e. changes in the mix and pattern of land uses in an area. *Modification,* however, involves changes in the intensity of this use as well as alterations of its characteristic attributes, such as changes from low-income to high-income residential areas with the buildings remaining physically and quantitatively unaltered, or changes of suburban forests from their natural state to recreational uses with the area of the land staying unchanged.

1.1.1 Causes/Drivers of Land Cover Changes

In order to understand land cover changes comprehensively, the factors driving these changes must be researched and understood. A plethora of studies now go beyond just looking at a single driver of land cover to study different forces which cut across various disciplines (e.g. Turner *et al.*, 1994, Geist and Lambin 2001). Turner *et al.* (1995) believed that the complexity of the problem deepens with the understanding that three dimensions of drivers – *socioeconomic, biophysical and land management* (proximate) – are relevant to land cover change. These drivers are flows of energy or material of information that arise from identifiable systems or agents.

Socio-economic drivers, which are also known as underlying forces, comprise of economic (e.g. growth of markets, commercialization), political (governance), demographic (population growth), technological (advances in technology), institutional (government subsidies) and cultural factors (beliefs, attitudes). All these factors according to Turner *et al.* (1994) shape the direction and intensity of land use.

Biophysical drivers are forces that often work as catalytic factors leading to sudden shifts in the human-environment condition (Geist and Lambin, 2001). Some examples of these biophysical drivers are geomorphic processes, climate variations/fluctuation and soil variations, which are basically natural processes.

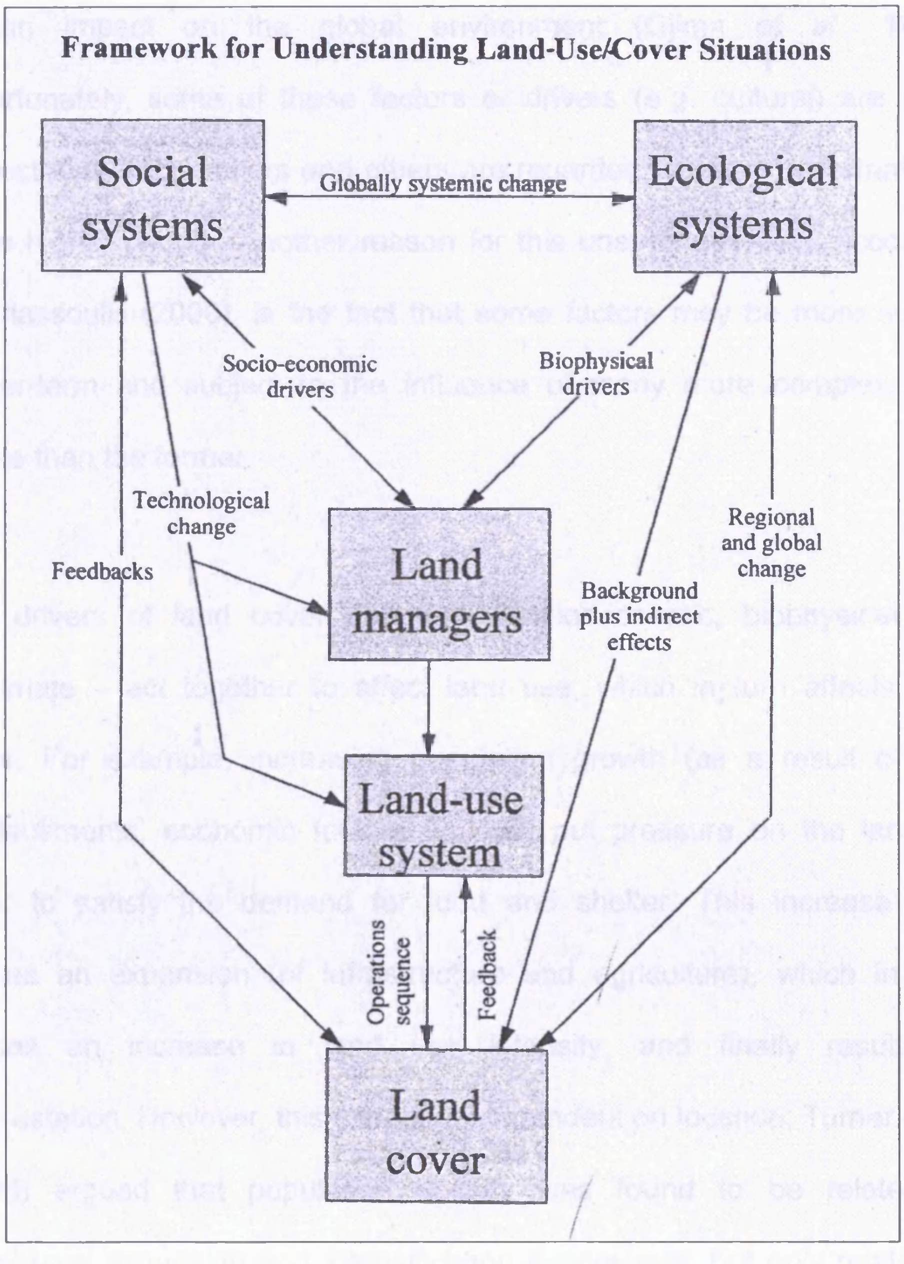
Proximate drivers are the direct causes of land cover change. There are human activities (land uses) that directly affect the environment and thus constitute proximate sources of change (Geist and Lambin, 2001) such as infrastructure expansion, agricultural expansion, pollution, wood extraction (logging) etc. These driving forces vary from place to place depending on human activities, climate or even policies. Certain emphasis is usually laid on specific driving forces (drivers of change) e.g. population growth, wood extraction etc., as according to Stedman-Edwards (2000) 'particular variables play a larger or smaller role, depending on spatial or temporal scales, geographic location and other factors' (Machilis and Forrester 1996, Roque 1997, Stern *et al.* 1992, Stedman-Edwards 2000). In order to understand the dynamics of land cover change, the relationship between proximate causes and underlying (socio-economic) causes as well as biophysical drivers should be taken into consideration (Serneels, 2001).

Geist and Lambin (2001) developed a scheme to illustrate the relationships between these drivers of change (figure 1.1 taken from Turner *et al.*, 1995). The biophysical drivers do not necessarily cause land use change directly but cause land cover change which is fed back to land use decisions, thereby land is altered by the land managers who make these decisions (e.g. human introduction of rinderpest, change in wild herbivore population, advance of woodland with tsetse, leading ultimately to mechanized clearing (Sinclair 1979, Turner *et al.*, 1995). In other words, 'land use change (and the drivers) is the proximate cause of land cover change' (Serbinin, 2002). As Briassoulis (2000) noted, land cover change are connected through the proximate causes of change that translate the human goals of land use into changed physical states of land cover.

1.1.2 Impacts of Land Cover Change

Humans and their activities have caused significant changes in the global system. According to Kates *et al.* (1990), the lands of the Earth bear the most profound imprints of humankind's actions (Briassoulis, 2000).

Figure 1.1 Relationships between socio-economic, biophysical & proximate drivers



Source: Turner et al., 1995

In order to understand fully the causes and the effects of global change, the scientific community must focus greater attention on the social context (i.e. cultural, political, demographic and economic factors) influencing human impact on the global environment (Ojima *et al.*, 1994). Unfortunately, some of these factors or drivers (e.g. cultural) are often neglected by researchers and others are regarded as more important and given higher priority. Another reason for this uneven attention, according to Briassoulis (2000), is the fact that some factors may be more subtle, longer-term and subject to the influence of many more complex, less visible than the former.

The drivers of land cover change – socioeconomic, biophysical and proximate – act together to affect land use, which in turn affects land cover. For example, increasing population growth (as a result of war displacements, economic factors etc) will put pressure on the land, in order to satisfy the demand for food and shelter. This increase then causes an expansion (of infrastructure and agriculture), which in turn causes an increase in land use intensity, and finally results in deforestation. However, this change is dependent on location; Turner *et al.* (1993) argued that population density was found to be related to agricultural expansion and intensification everywhere, but only related to deforestation in some regions. Deforestation can result in the loss of biodiversity, especially in the tropics; biodiversity loss results in declines in ecosystem integrity and also genetic losses that may impede future scientific advances in agriculture and pharmaceutics (Sherbinin, 2002). According to Myers (1991), we are losing between 50 and 100 animal and plant species each day.

Deforestation and the factors that drive deforestation, such as agricultural growth and infrastructure expansion can lead to climate change, by influencing the biogeochemical cycles. For instance, when trees are cut or burned, the carbon stored in the trees is released into the atmosphere as CO_2, which increase the greenhouse effects. This could lead to an increase in global temperature and this in turn would affect sea level and weather patterns.

Land use change may provide greater opportunities for invasion of exotic biological species as natural systems are disrupted. These alterations and invasions may further modify the global environment by changing land surface (cover) properties (Ojima *et al.*, 1994), for example surface albedo and latent and sensible heat flux (Pielke and Avissar, 1990).

Other examples of the impacts of land cover change are changes in atmospheric chemistry due to forest biomass burning after forest clearing (Crutzen and Andrae, 1990; Ojima *et al.*, 1994); increase in concentration of carbon-dioxide (atmospheric) due to fossil fuel demand; rapid run-off of precipitation due to deforestation, causing flooding and soil erosion (Sherbinin, 2002); intensity of exploitation due to technological advances

(Turner *et al.*, 1993); increased hunting of species (caused by poverty), in order to satisfy nutritional needs for sources of protein, which can lead to extinction of indigenous species; saltwater intrusion due to increasing demand for water for tourism developments or urbanization (Briassoulis, 2000) among others. This dual role of humanity in both contributing to the causes and experiencing the effects of global change processes emphasizes the need for better understanding of interaction between humans and the terrestrial environment (Sherbinin, 2002). Understanding the driving forces behind land use changes is essential to predicting the effects of global environment change (Veldkamp *et al.*, 2001).

1.1.3 Modelling Land Cover Change

A descriptive approach to land cover change will identify historic trends and current conditions, but the prediction of future changes in land cover and their effects requires an improved understanding of the cause-and-effect relationships that link human activities with changes in land cover (Sisk, 1998) .The main aim of modelling land cover change is to understand and identify the processes and drivers of these changes. Modelling, especially if done in a spatially explicit, integrated and multiscale manner, is an important technique for predicting, for conducting experiments that test our understanding and describing the latter in quantitative terms (Lambin *et al.*, 2000; Lambin *et al.*, 2001; Veldkamp and Lambin 2001).

CHAPTER 1: INTRODUCTION

The international scientific community has called for research into land-cover change, specifically for research into models that predict spatial patterns of future change (Turner *et al.*, 1995 and Lambin *et al.*, 1999). Verburg *et al.* (2004) noted that models are useful for disentangling the complex suite of socioeconomic and biophysical forces that influence the rate and spatial pattern of land use change and for estimating the impacts of changes in land use. Modelling allows us look at land cover change dynamics and predict what might happen in the future. Currently different types of models are used on specific impacts such as: erosion and sedimentation models (Schoorl and Veldkamp, 2000); land use spatial regression model (Mertens and Lambin, 2000); dynamic simulation modelling – Simile (Muetzelfeldt, 2002); Cellular automata model (Kirtland *et al.*, 1994); IMAGE model (Alcamo *et al.*, 1998) and FEARLUS model (Polhill *et al.*, 2001) among others. Each type of model has advantages and disadvantages depending on the aim of the research. Land use change models can be aimed at predicting the spatial pattern of changes, addressing the question "where are land use changes taking place?" or the rates of change, which addresses the question "at what rate are land cover changes likely to progress?" (Serneels and Lambin, 2001). These two questions have been referred to as the *location* issue versus the *quantity* issue (Pontius and Schneider, 2001; Serneels and Lambin, 2001). Land cover change models attempt to answer vital interrelated questions - Why, when, how, and where do these changes occur.

1.2 Scope of Study

1.2.1 Conceptual Framework

The Land Use and Land Cover Change (LUCC) of IGBP and IHDP foci and '*The Root Causes of Biodiversity Loss Programme*' (Wood *et al.*, 2000) form the theoretical base of this research. There are three LUCC foci – Focus 1 and Focus 2 (which are the main interests in this research) and Focus 3.

Focus 1, land use dynamics, deals with the process (es) of land-use change to increase our knowledge of the driving forces behind land use change. The main aims of Focus 1, according to the LUCC Research/Science Plan (LUCC 1995) are:

a) To undertake comparative studies of land-use/cover dynamics using common protocols and standardized terms and measures of land use and its dynamics;
b) To use the results of these studies to identify and map situations of land-use/cover dynamics, and to improve understanding of these dynamics;
c) To build, from this analysis, local and regional models of land-use/cover change.

Focus 2 involves regional assessment of land cover change as determined from direct observation (e.g. satellite imagery and field studies) and models built from these observations (Turner *et al.*, 1995). The main aims of Focus 2 are:

a) To provide, through direct observations and data, regional and continental patterns of land cover change needed by the global change research community;
b) To provide a basis for analyzing the time-varying spatial dynamics of land cover transitions;
c) To develop an empirical and data-rich framework for diagnostic models of current situations and short-term predictions through models based on direct observation;
d) To establish a foundation of observations and measurements for spatially disaggregating results from macroeconomic analyses.

As Turner *et al.* (1995) also stated, it addresses the following questions:

i) What are the rates and spatial patterns of land cover change, and how will they likely progress?
ii) Where is land cover change presently occurring, and where it will likely occur in the future?
iii) Which natural and cultural landscape attributes contribute the most to the explanation of land cover change?

Based on the above combined aims of LUCC (Foci 1 and 2) and methodologies of the *'Root causes of biodiversity loss programme',* a hybrid conceptual model was constructed by me, in order to investigate the relationship between land cover change and biodiversity (figure 1.2). The conceptual model starts with global factors (socio-economic, biophysical and proximate), which have an effect on the regional and local factors. Based on this model, socio-economic data were collected and a simplistic model of change, based on the statistical data was created.

Using the results to determine the location of land cover changes, remote sensing data were pre-processed and analyzed to identify *'hotspots'* of land cover change and the patterns of the change. This conceptual model (figure 1.2) endeavours to cover all aspects of socio-economic drivers, proximate drivers and biophysical drivers (both qualitative and quantitative) that occur or are present in Edo and Delta States.

1.2.2 Aim

The main aim of this research is to establish, map and model the key driving forces of land cover change in Edo and Delta states in south-western Nigeria and to analyse the impact of these changes.

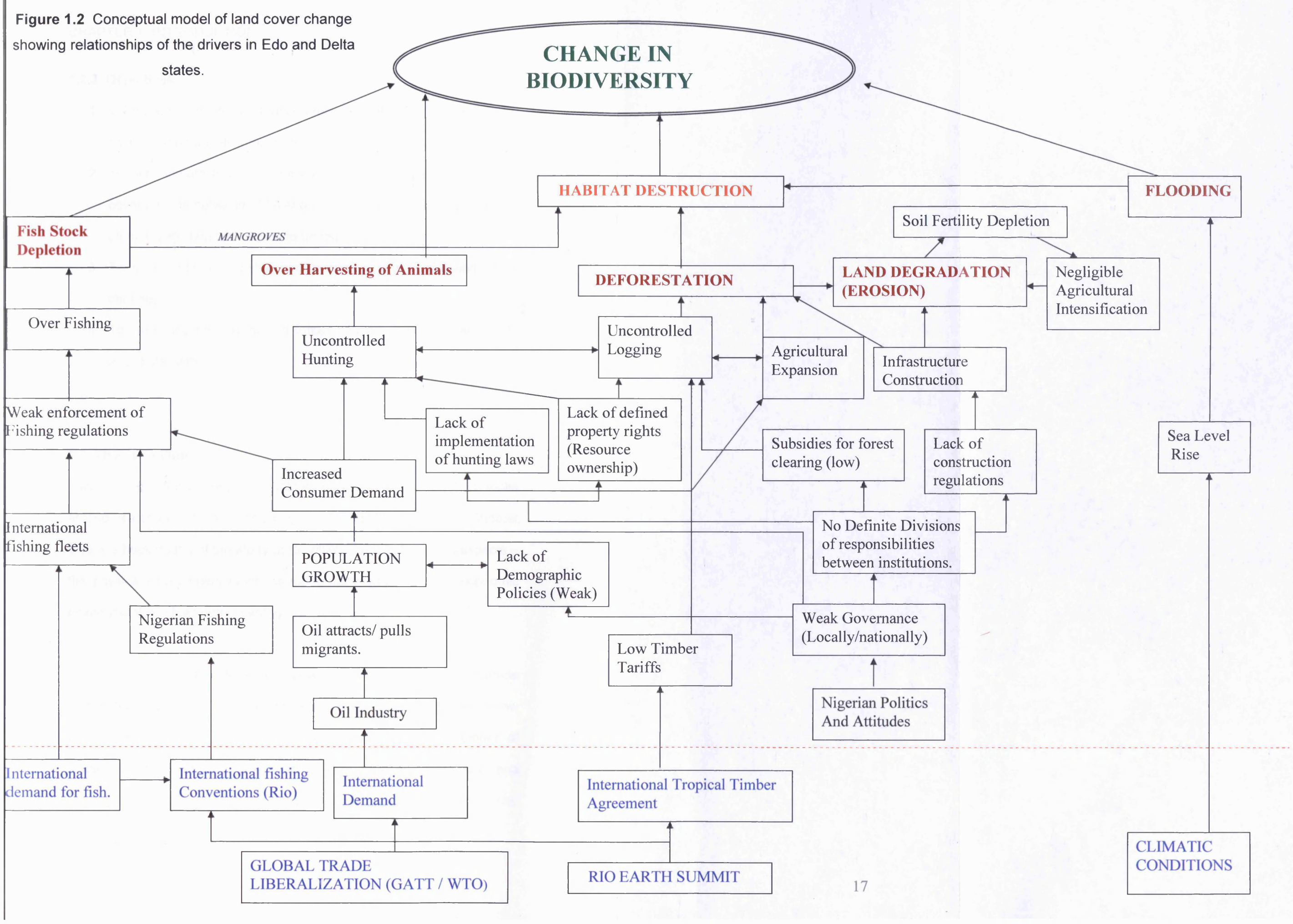


Figure 1.2 Conceptual model of land cover change showing relationships of the drivers in Edo and Delta states.

1.2.3 Objectives

1. To design a model that accurately illustrates and projects land cover change and its impact on biodiversity;
2. To use Remote Sensing data (i.e. satellite images) to map land cover change between 1980 and 2001 and to evaluate the optimum change detection techniques to be used in this research;
3. To investigate the spatial and temporal pattern of land cover change;
4. To determine the key driving forces of land cover change in Edo and Delta States.

1.3 Thesis Outline

This research thesis is organized into eight chapters. Chapter One, looks at land use change, land cover change and modelling in general. Chapter Two is a background of the study area, which is divided into two aspects – the physical environment (such as topography) and the socio-economic environment (such as demography).

The third chapter is the literature review, discusses various points made and methods used by a plethora of researchers. This chapter will review the different research methods used by researchers in a number of studies, Examples include, land cover change, modelling land cover and various applications of Remote Sensing techniques used in land cover change studies.

Chapter Four presents the data that are analysed and utilized in this research. A vast range of data is considered and the processes of selection for the suitable data (i.e. data to be used in modelling) were explained. This research uses statistical data, remote sensing data and field data that were collected by the researcher. Also in this chapter, the acquisition of the satellite images and the image processing techniques are outlined. Chapter Five examines the modelling method used, evaluating the various data and how they are used in this study. It considers the type of modelling technique chosen, and the reason it was chosen. Chapter Six will present the results (modelling and remote sensing) and are compared, tested and validated. These results will also illustrate future land cover change projections in Edo and Delta state.

Chapter Seven will discuss the results. Chapter Eight is the summary or conclusion of the research findings and recommendation of possible future work. It examines what it the land cover change model means to the Nigerian government and how the government can utilize this information.

CHAPTER 2 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: THE STUDY AREA

CHAPTER 2

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: THE STUDY AREA

2.1 Introduction

This research focuses on Edo and Delta States, which are located in south-western Nigeria. Nigeria's tropical forest is diminishing at an alarming rate because of human influence. According to Aweto, the area (i.e. Nigeria) previously characterized by continuous forest cover has been converted into secondary regrowth vegetation, mainly as a result of shifting cultivation and lumbering. (Aweto, 1990). As will be explained later on in this chapter, farming and logging are the two of the most important human activities in Edo and Delta States.

This part of Nigeria was selected for this study, following on from a fact finding investigation carried out by the author. It was discovered that, although, it had been published by previous researchers that there is rapid land use and land cover change occurring in different areas of the region, at varying levels. A study of land use and land cover change of the Mid-Western Nigeria (i.e. Edo and Delta States) as a whole has never been carried out, not to mention modelling these changes. It was also ascertained that this gap was due to a number of factors (e.g. lack of resources, lack of technology and so on), which limited any previous studies from been carried out. There are some other reasons, in addition to why this region was chosen, which are:

a) The region is poorly studied, however land use and land cover changes rapidly in Nigeria (Akinyemi, 2005);
b) It is a diverse region, rich with flora, fauna and natural resources;
c) The region is familiar to the researcher, thereby facilitating communication in gathering data.

2.2 Historical Background of the Study Area

Edo and Delta States were both created from the former Bendel State in 1991. Bendel State started out life as the Mid-Western region (created by referendum, August 9, 1963 and excised from the then Western region), see figures 2.1a and 2.1b; (it then became known as Midwest State), the name derives from a contraction of the phrase BENin DELta.

As time went on, the 'federal character' provision for the sharing of federal revenue among the states in the Federation was hampering the growth and development of the state. As more states were created, increasing from 4 (1963-1967) to 12 (1967-1976) to 19 and then 21, Bendel State, by remaining intact, became disadvantaged in regards to access to federal revenue budget. Although the demand for the creation of Bendel state did not come to fruition in the Second Republic, this demand led the Babangida regime to split the then Bendel State into two parts – one which had an Edo-speaking majority (Edo State) and the other which had a more heterogeneous mix of ethnic groups (Delta State). (Edo state website, 2001)

Edo and Delta States lie roughly between latitudes 5°00`E and 6°43`E and longitudes 5°00`N and 7°34`N. They are bounded in the southeast by Bayelsa State, in the north by Kogi State, in the west by Ondo State and in the east by Kogi and Anambra States. Edo State encompasses a land area of about 17,802 km^2 while Delta State occupies a total land area of about 16,610 km^2.

2.3 Physical Environment of Edo and Delta States

2.3.1 Topography

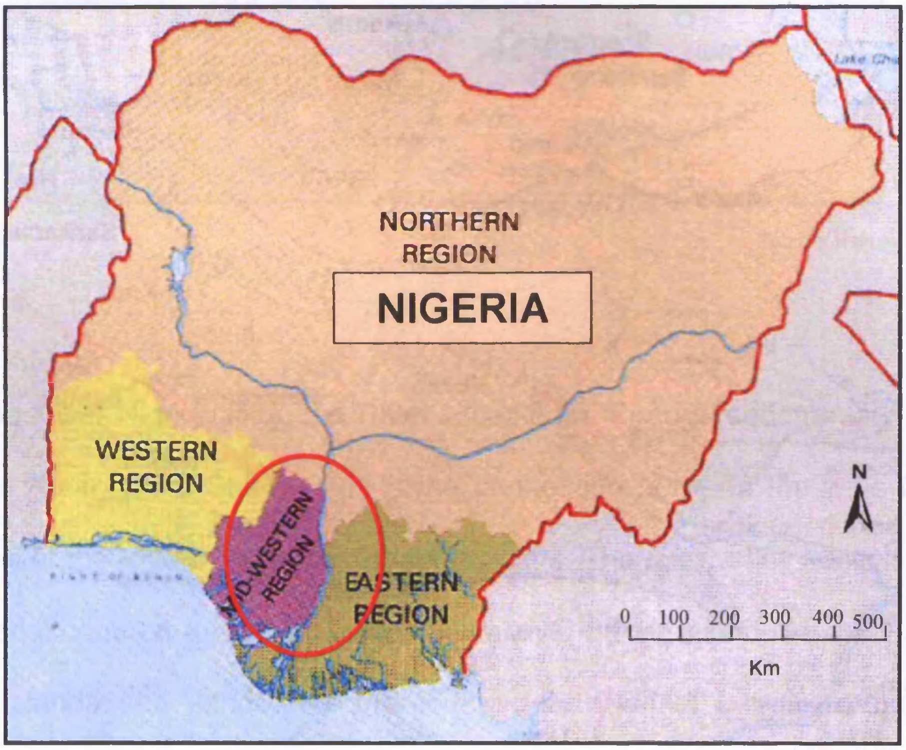
Relief in Edo and Delta States can be classed generally as lowlands, which in Edo State gradually leads to gently undulating relief with elevations increasing northwards from approximately 50m to 300m (figures 2.2a-c). This landscape is interrupted by a sandstone scarp of cuesta that can be found in central Edo State, extending from north of Benin City (capital of Edo State) to Uromi (North east of Edo state).

Elevations at the eastern end of the scarp exceed 300m (FORMECU, 1999). The highest elevation point of the tilted plains of Edo State occurs in the Ishan Plateau (north-east of Edo) and extends to Asaba (north of Delta). The Ishan-Asaba plateau (figure 2.3) rises steeply from the Niger valley and is bordered on the northern edge by a steep slope overlooking the clay vale (Udo, 1970).

Part of the study area, west of Edo State and north of Delta State, lays the Benin lowlands of Nigeria, which have dissected north-facing low scarps. The south-dipping surface has, however, sunk to below 300m and is dissected into blocks by narrow parallel valleys cut by the north-south flowing rivers. These blocks and river valleys can be seen along the road of Asaba to Owo.

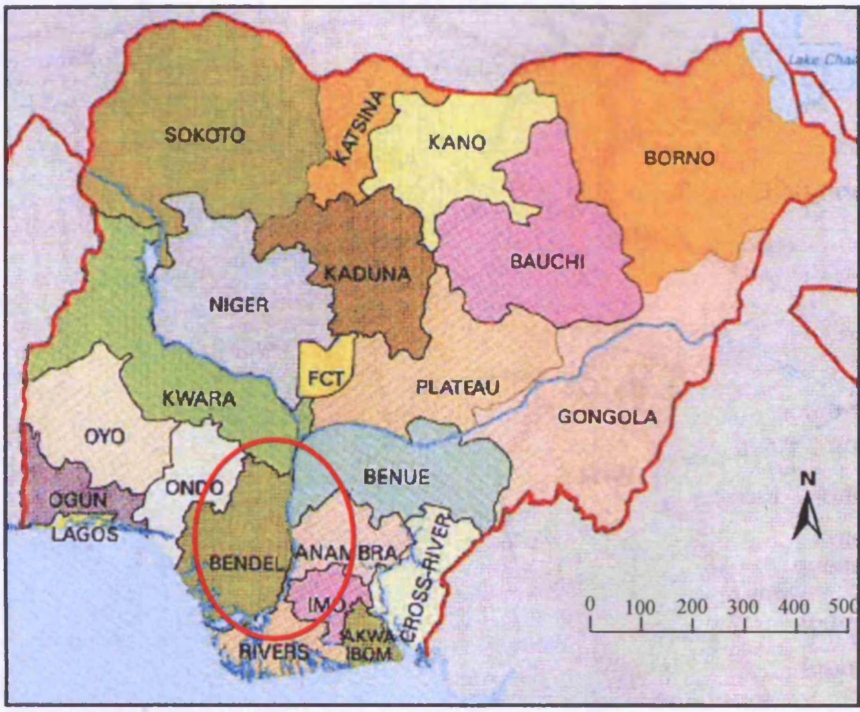
The south of Delta State is part of the Niger Delta, which is vulnerable to flooding (figure 2.3). In these regions flooding is so extensive that the landscape is entirely different in January/February, when the water in the Niger is at its lowest, from September (the high water period), which is also in the flood season (Agabi *et al.*, 1995). In parts of Urhobo division (south of Delta State), there are several lakes, of which a number dry out completely during the dry season. These lakes occur in depressions where there is a presence of clay soil (Udo, 1970). Udo (1970) also noted that the Niger Delta extends from the Benin River in the west to the Bonny River in the east. It is a low region riddled with an intricate system of natural water channels through which the River Niger drains into the sea.

Figure 2.1a Map of Nigeria showing the Mid-Western region (highlighted with the red circle)



Source: Balogun, 2003

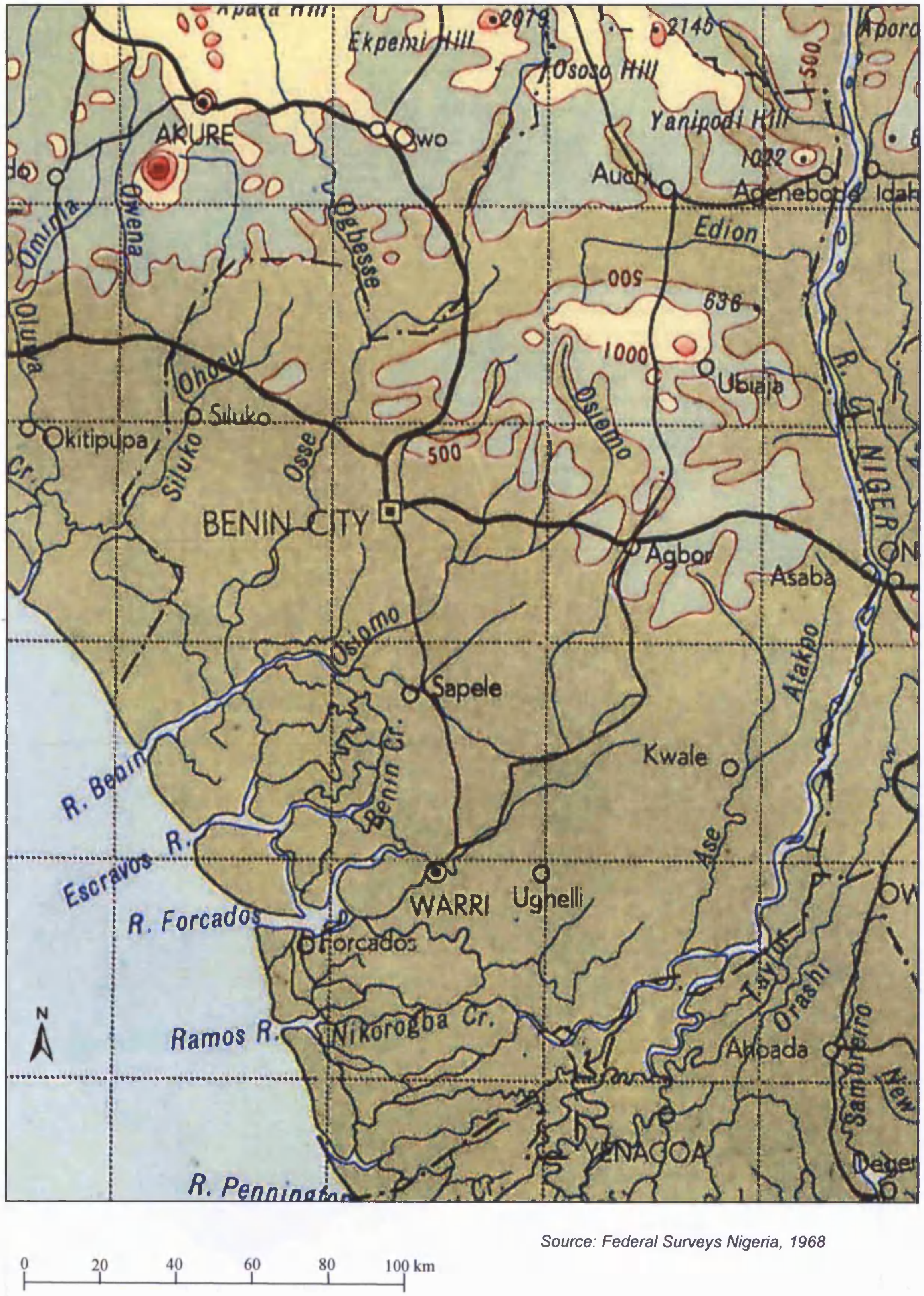
Figure 2.1b Map of Nigeria showing Bendel State (highlighted with the red circle)



Source: Balogun, 2003

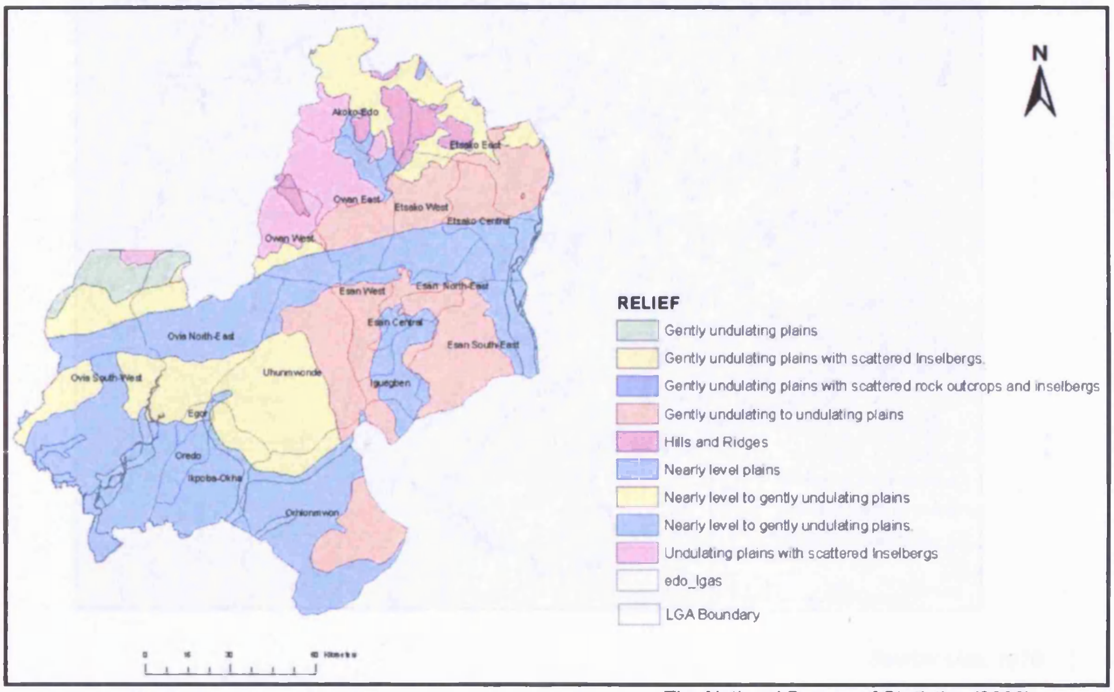
In the lower Niger valley, the River Niger flows through sedimentary rock up to Aboh (Delta State). This is the connection between the wide flood plains of the Rivers Niger and Benue troughs. The river valley section is in material contrast to the wide, mature valleys further inland. At low water, low islands and sandbanks break the river channel but these quickly disappear with the arrival of the flood- water (Agabi *et al.*, 1995).

Figure 2.2a Relief map of Edo and Delta states



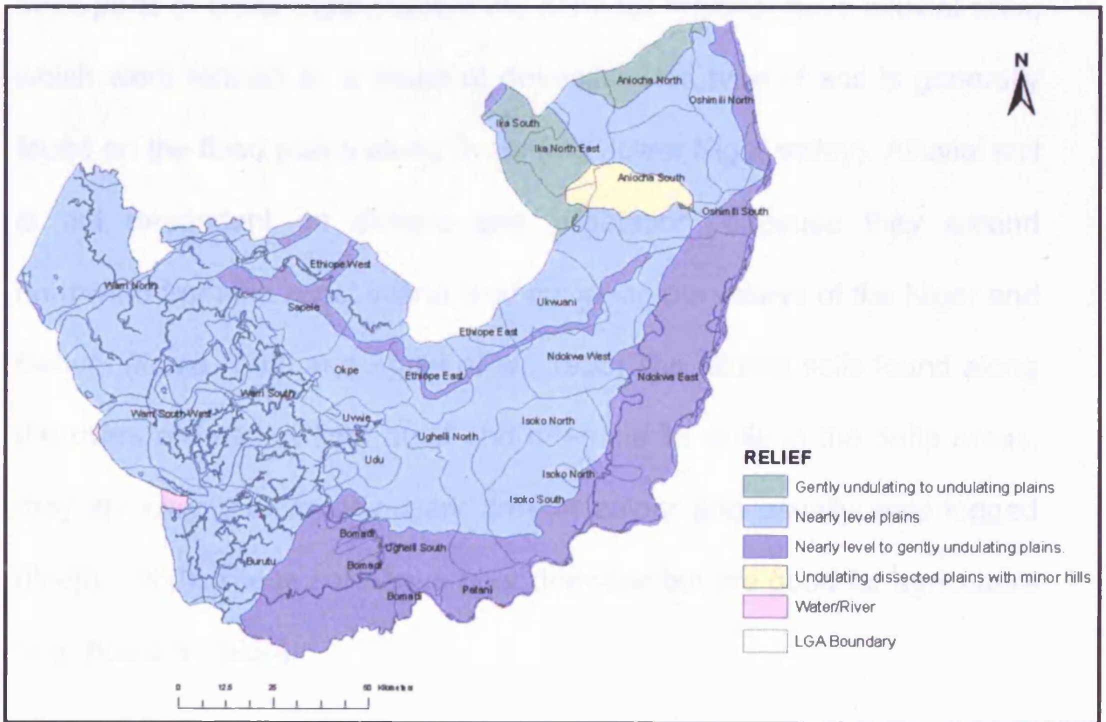
Source: Federal Surveys Nigeria, 1968

Figure 2.2b Relief map of Edo State



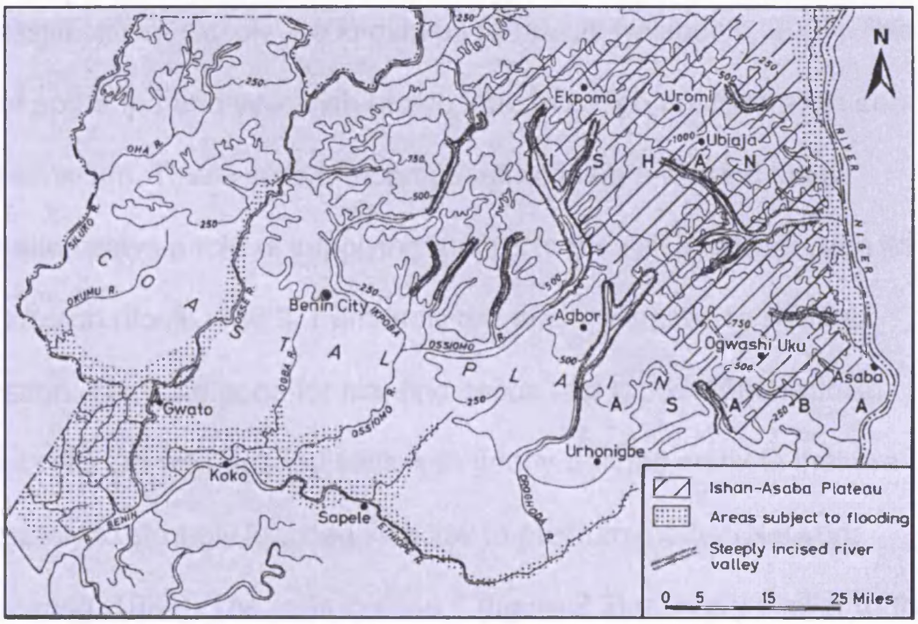
The National Bureau of Statistics (2008)

Figure 2.2c Relief map of Delta State



The National Bureau of Statistics (2008)

Figure 2.3 The Ishan-Asaba Plateau and areas vulnerable to flooding



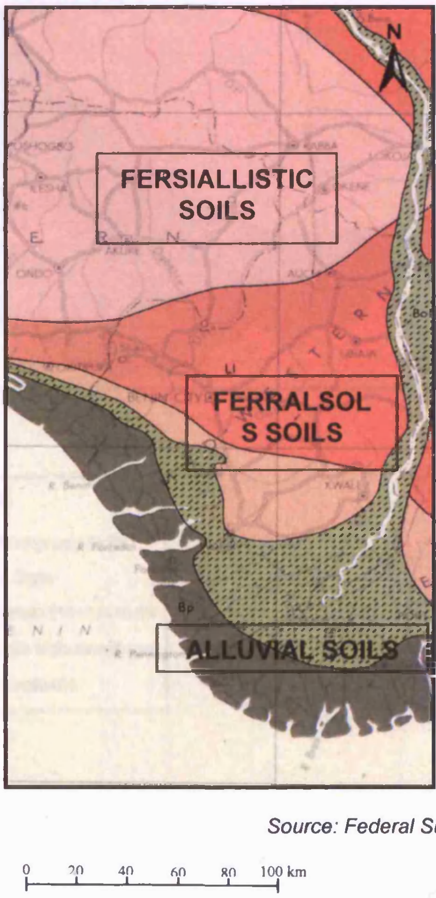
Source: Udo, 1970

2.3.2 Soil Types

Most parts of Delta State (except the northern regions) have alluvial soils, which were formed as a result of deposits. This type of soil is generally found on the flood plains along rivers (e.g. lower Niger valley). Alluvial soil is not dependent on climate and vegetation, because they extend northward from the coast inland, and cut along the valleys of the Niger and Benue. (Iloeje, 1980 and Agabi *et al.*, 1995).The alluvial soils found along the rivers are sandy, light hued and often sterile while in the delta areas, they are clayey or muddy, dark grey in colour and usually waterlogged (Iloeje, 1980). These soils have poor drainage but are good for agriculture (e.g. rice cultivation).

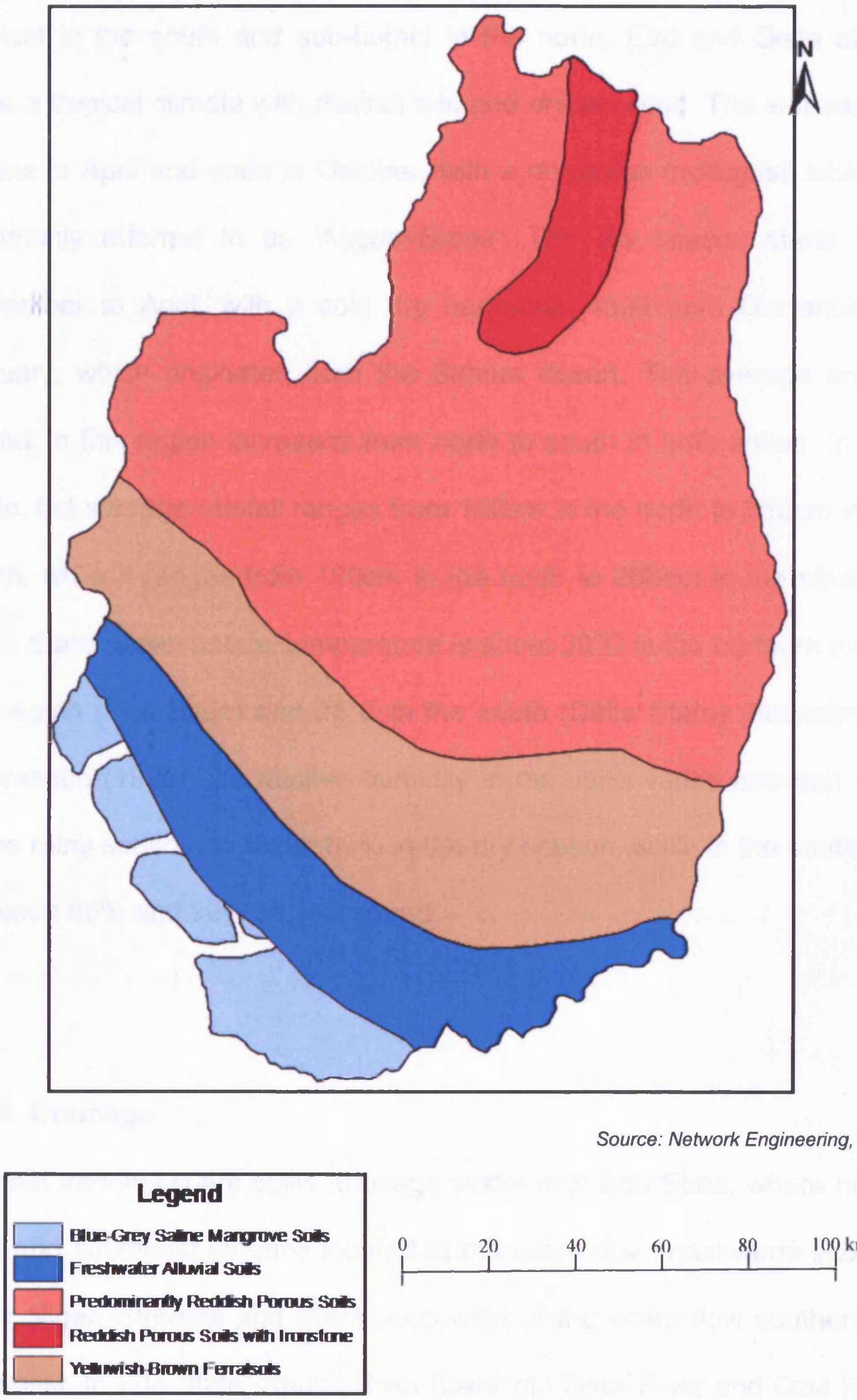
The north of Delta state and Edo state has mostly *ferralsols*. In the FAO soil classification, oxisols are known as ferralsols (wikipedia, 2007).This type of soil is red and yellowish brown, due to a high concentration iron and aluminium. These soils are composed of loam and sand loam. Vegetation plays a role of supplying humus to the soil and protecting it from erosion (Iloeje, 1980). Ferralsols are often restricted to shifting cultivation. They are good for planting cocoa and rubber. The reddish porous soils are well-drained soils with poorly drained pockets that are moderately to strongly leached with low to medium matter (Network engineering, 1981). The soils in zone 5 (figure 2.5) are very similar to the reddish porous soils but contain ironstone.

Figure 2.4 Soil zones



Source: Federal Surveys Nigeria, 1966

Figure 2.5 Soil map of Edo and Delta states



Source: Network Engineering, 1981

2.3.3 Climate

Edo and Delta States are located in the tropics, the climate being humid tropical in the south and sub-humid in the north. Edo and Delta states have a tropical climate with distinct *wet* and *dry seasons.* The *wet season* begins in April and ends in October, with a dry break in August, which is commonly referred to as *'August-Break'*. The *dry season* starts from November to April, with a cold dry harmattan spell from December to January, which originates from the Sahara desert. The average annual rainfall in this region increases from north to south in both states. In Edo State, the average rainfall ranges from 150cm in the north to 250cm in the south, while it ranges from 190cm in the north to 266cm in the south, in Delta State. Mean annual temperature is about 30°C in the northern part of the region (Edo State) and 28°C in the south (Delta State). According to Osemeobo (1998), the relative humidity in the north varies between 75% in the rainy season, to about 65% in the dry season, while in the south it is between 85% and 90% all year round.

2.3.4 Drainage

An east trending scarp splits drainage systems in Edo State, where north, east and southeast streams located at the scarp drain eastwards into the River Niger. Streams and rivers southwest of the scarp flow southerly to the coast. In Edo State, Ikpoba River flows into Osse River and Ozia River flows into Benin River which discharges into the Atlantic Ocean.

Meanwhile in Delta state, the River Niger drains the eastern flank of the state and discharges into the sea through its several distributaries such as the Forcados, Escravos and Warri rivers and creeks such as the Bomadi creeks, amongst others. Rivers Jamieson and Ethiope originate from the north and northeast respectively, and subsequently join and form the Benin River, which eventually discharges into the sea in the West (OnlineNigeria.com, 2006).

2.3.5 Vegetation

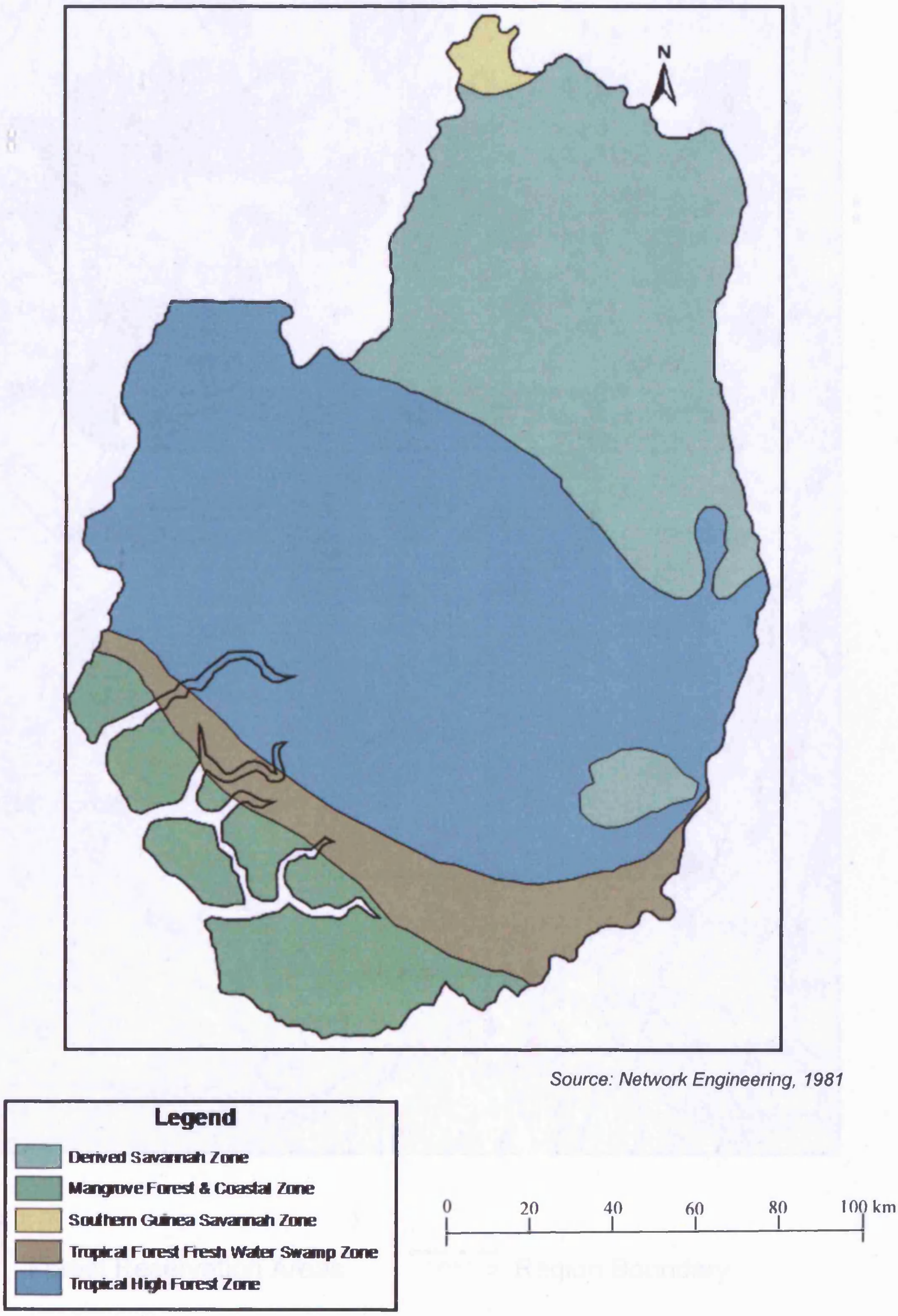
Edo and Delta States have a diverse range of vegetation. The various vegetation zones in this area are: *Lowland rain forest, Mangrove forest, Freshwater swamp forest and Derived savannah forest.* The *Lowland rain forests* extend from the centre of Edo State to the northern tip of Delta State. They encompass a wide variety of different types of plant species such as oil palm, cocoa, rubber, banana, yam, beans and fruits are harvested where accessible, however access to this forest type is limited to the dry season (FORMECU, 1999). The timber industry depends heavily on the resources within this forest. Initially, this region was completely covered by rainforest, but rubber plantations have displaced a lot of the original forests (Edo State website, 2004).

Mangrove forests are found in the southern tip of Edo State and extend to the coastal areas of Delta State (figure 2.6). According to FORMECU

(1999), this area is characterised by swampy ground with fresh or brackish water lagoons and narrow meandering creeks. *Freshwater swamp forests* are located along the River Niger flood plain, where the forest water vegetation replaces the mangrove vegetation. This type of forest is characterised by tall trees with a somewhat open canopy occurring along freshwater creeks and rivers (FORMECU, 1999). One of the most common species found in this vegetation zone is the Raphia (Raffia palm), where palm wine (which is a local drink) is tapped. There are other timber species present in the *freshwater swamp forest*, which tapped. There are other timber species present in the *freshwater swamp forest*, which are harvested where accessible, however access to this forest type is limited to the dry season (FORMECU, 1999).

Derived 'guinea' savannah can be found in the north of Edo State. Areas left to re-grow tend to grow savannah type grasses and shrubs that are susceptible to fire and therefore regeneration of the lowland species is limited, thus creating a '*derived savannah*'. In Edo and Delta States, vegetation is generally thinner and deciduous. FORMECU (1999) carried out a forest resource study of Nigeria and found that this zone of derived savannah has shifted southward as an area of disturbed forest was cleared and is now used for intensive agriculture. According to Beak Consultants (1999), who carried out a Forest Resource Study in Edo and Delta states, "The lowland rain forest is the dominant forest type within forest reserves (figure 2.7), occupying 77% of their forested area, whereas the freshwater swamp forest occupies 22.7%.

Figure 2.6 Vegetation zones in Edo and Delta states



Source: Network Engineering, 1981

Figure 2.7 Forest reserves

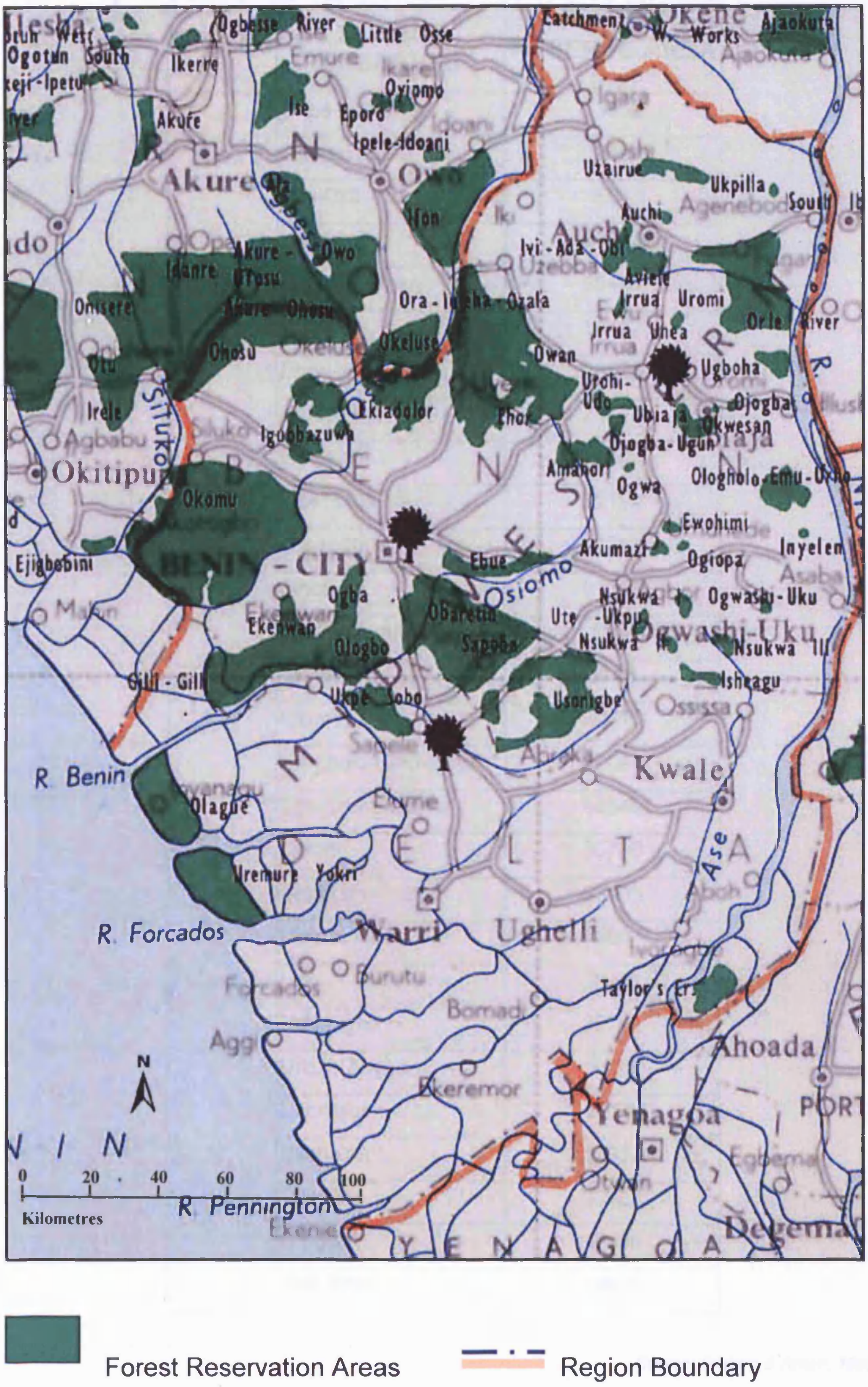


Table 2.1 Forest reserves in the study area

STATES	FOREST RESERVES	FOREST RESERVE AREA (ha)
Delta	Okpe-Urhobo	13962
	Ogwashi-Uku	258
	Gilli-Gilli	554
	Olague	29023
Edo	Uremure Yokri	35401
	Ebue	10422
	Ehor	38578
	Ekiadolor	24720
	Ewohinmi	1235
	Igbuobazuwa	32199
	Obaretin	11352
	Ohosu	51519
	Ojogba-Ugun	1154
	Okhuesan	2718
	Okomu	113766
	Ologholo-Emu-Urho	12044
	Ora-luleha-Ozalla	14540
	Owan	30780
	Sapoba	53406
	Ubiaja	960
	Udo	2137
	Urhonigbe	30791
	Urohi-Ojogba	3195
	Usonigbe	3159
	Ekenwan	20997
	Gilli-Gilli	30927
	Ologbo	17784
	Orle River	42621

Source: Olaleye & Ameh, 1999

2.4 Socio-Economic Environment of Edo and Delta States

2.4.1 Demography

The study area (i.e. Edo and Delta States) has experienced a population growth, with a slightly higher rate in Delta State (due to oil exploration). The 1963/64 national census enumerated the population as 2,535,839, when the region was known as the Mid-Western region. Another census was carried out in 1973 (after the 1967-1970 civil war), but unfortunately the national census was rejected and disputed, because of allegations of over-counting in many areas, especially in Northern Nigeria, for local (state) political reasons. One of the main reasons the census results stir up emotions, is Nigerians' history of arguing over resource allocation. Census numbers in Nigeria guide political redistricting for each of the country's 36 states, the distribution of federal funds, and even civil service hiring (Yin, 2007).

The next attempt to carry out a census was in 1989, which had an estimated population figure of 4,752,000, i.e. an increase of 46.6% within 26 years. Then when Bendel State was divided in 1991, a census was carried out, Edo State had a population of 2,172,005 and Delta State had a population of 2,590,491(provisional). Recently, a census was carried out in Nigeria in 2006 and pre-released provisional figures in December 2006 and the full details or breakdown of the census released in May 2007. The

2006 census put the population of Edo State at 3,218,332 and Delta State at 4,098,391.

2.4.2 Agriculture

Before Nigeria attained independence, agriculture was the most important sector of the economy, and accounted for more than 50% of GDP and more than 75% of export earnings. Consequently, with the rapid expansion of the petroleum industry, agricultural development was neglected, and the sector entered a relative decline (Aregheore, 2005). Oil palm, cocoa and rubber were Nigeria's main export until the oil boom of the 1970's. In the early 1960s, Nigeria's palm oil production accounted for 43% of the world production, nowadays it only accounts for 7% of total global output (World Rainforest Movement, 2001). In the late 1980s, Nigeria controlled farm prices, maintained subsidies on fertiliser and farm exports, and maintained import bans on specific food items in order to encourage agricultural activity. This resulted in a slow agricultural growth but not noteworthy, due to inadequate transportation and electricity networks, lack of technology and the ineffective application of rural credit (Geomatics, 1998).

The oil boom led to an expansion in urban centres, which were in need of some infrastructure construction, thus the government awarded contracts to large foreign construction companies (such as Julius Berger and Cappa

D'alberto). Due to the slow agricultural output, some farmers had to seek other employment in order to feed their families so they headed for the cities where these construction companies (among other multinational companies) were based to seek employment.

Although Edo and Delta are oil-producing states, agriculture still dominates economic activities in Edo state. The form of farming practiced is shifting cultivation, consisting mostly of yams, maize, cocoyams and cassava, combined with oil palm, cocoa, and rubber. The State is very rich in agriculture and is a major food basket for the South-South zone (Edo state, 2005). Farming, logging, fishing and hunting are the major occupations of the people of Edo and Delta States.

Edo and Delta are endowed with abundant natural resources with the main cultivated crops being: rubber (figure 2.9), oil palm (figure 2.10), cocoa (figure 2.8), yam, cassava, maize, plantain and rice as well as a number of fruits and vegetables. Within the rivers and lakes of Delta State there are fish, shrimps, raphia palm (palm wine) and sugar cane, while the forests produce timber and other forest resources (e.g. tree barks used for native medicine).

Human interference has caused the displacement of the forests and made way for oil palm and rubber plantations. In the 1970s, a programme for the development of oil cultivation and production was introduced, with financial aid from the World Bank .The southern part of Edo State extending to north of Delta State is well known for its oil palm and rubber production, with oil plantations and processing mills at Nigerian Institute for Oil Palm Research (NIFOR), Okomu Oil Palm plantation, Presco Oil Palm Plantation, and Obaretin (figures 2.9 and 2.10).

Figure 2.8 Cocoa nursery in Edo State

Figure 2.9 Rubber in its raw form, Michelin rubber estate, Edo State

Figure 2.10 Okomu Oil Processing Mill

The first rubber estate in Nigeria was established in Sakponba (Edo State) in 1903 (Raw Materials Research and Development Council, 2004), other major rubber plantation estates are Michelin estate, Pamol estate, Iyayi estate, Urohonigbe estate and Okomu (which also has a section devoted to rubber plantation).

Cereals (especially maize) are cultivated in the northern part of this region in the hilly areas, while rice is farmed in the swampy zones along the valley of the Niger valley. Generally, livestock production is not really important in this region compared to agriculture. Most people tend to just keep a few goats, pigs and chickens.

2.4.3 Industries

Some of the main (industrial) mineral resources found in Edo and Delta States are quartzite, silica, marble, lignite, gypsum, kaolin, sand, gas and petroleum. Petroleum is the most important resource, with Delta State alone having about 100 oil flow stations. Petroleum (oil) is a sensitive and controversial resource in Nigeria (most especially in the oil producing areas such as Edo and Delta States), causing war, riots and oil spills leading to destruction of other resources and deforestation. As Amnesty International stated in a report, published in 2004;

"Many oil companies have failed to deliver on promises made to communities, or pitted one community against another, in what is understood as a 'divide and rule' policy and, in some cases, interfered with the traditional governance structures of the communities. For communities, oil companies then appear as external players who are taking the wealth from the region, sharing it with the Federal Government, and providing little in return.

Moreover, sometimes the companies are operating on their traditional lands without consulting them, or consulting them inadequately. And when communities object to specific projects, or require better compensation, the companies are deemed to create a division within the communities by supporting one faction, usually the chief and groups associated with the chief, who then, allegedly in some cases, use force to secure compliance of other community factions who may be opposed to the project, in what is understood as a 'divide and rule' policy."

Another major aspect of petroleum exploration is '*gas flaring*' which contributes to global warming, destruction of cropland and forests etc (figure 2.11). In order to reduce gas flaring, the government declared the Associated Gas Re-Injection Decree in 1979, which prevented oil companies from engaging in production of oil after January 1, 1984 flare gas produced in association with oil without permission in writing from the Minister.

Figure 2.11 Gas flaring in Warri, Delta State

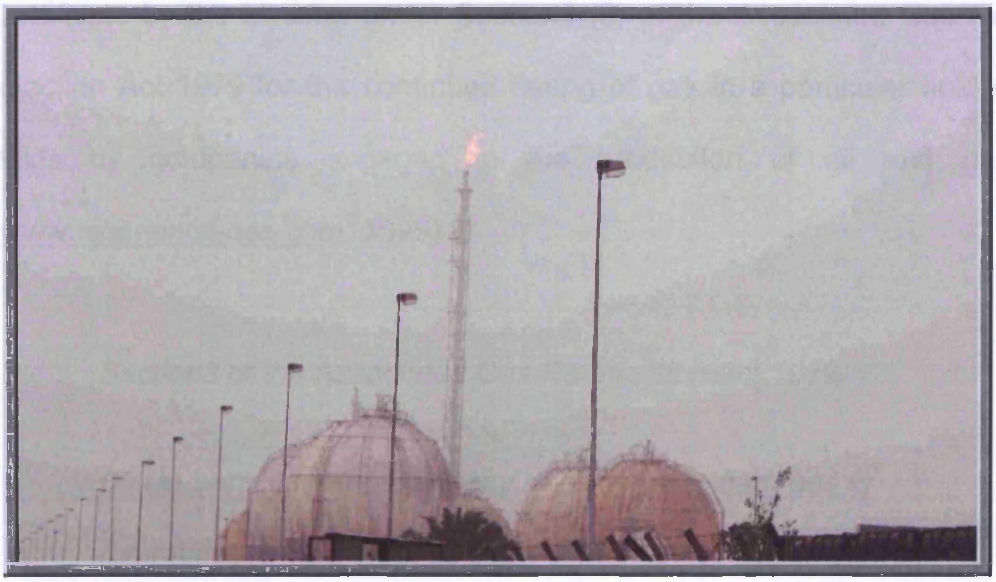
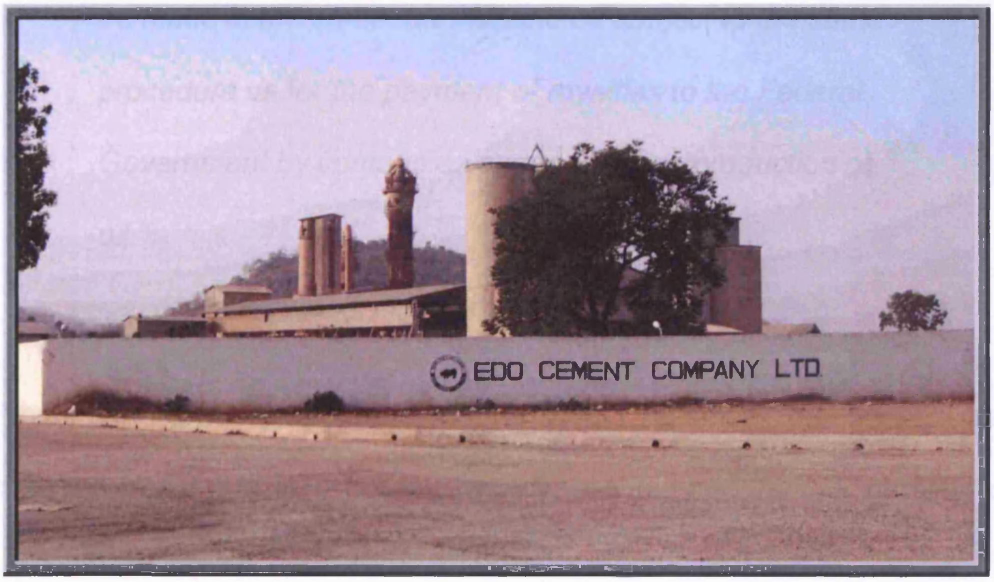


Figure 2.12 Edo Cement Company in Okpilla, Edo State



Then realising that Nigeria depends heavily on the revenue generated from oil production, the 1979 decree was reviewed and another decree was declared - Associated Gas Re-Injection (Continued Flaring of Gas Regulations 1984), which set out the conditions for the issuance of Certificate by the Minister under Section3 (2) of the Associated Gas Re-Injection Act 1979 for the continued flaring of gas in a particular field or fields by companies engaged in the production of oil and gas. (www.nigerianoil-gas.com, 1999)

Section3 of the Associated Gas Re-Injection Act 1979:

(2) (b) permitting the company to continue to flare gas in the particular field or fields if the company pays such sum as the Minister may from time to time prescribe for every 28.317 standard cubic metres (SCM) of gas flared: provided that any payment due under this paragraph shall be made in the same manner and be subject to the same procedure as for the payment of royalties to the Federal Government by companies engaged in the production of oil."

When it became obvious that flaring would continue, the decree was changed to fixing a ₦10 (local currency, pronounced '*naira*'), penalty for each 1000 cubic feet of gas flared; but this unfortunately did not prove to be a deterrent to oil companies (World Bank Report, 1994).

Timber and wood processing industries are found all over Edo and Delta States, making it a major industry, as is evident from the large number of sawmills and furniture making industries. The region's wood industries serve as major suppliers of wood products to various parts of the country (FORMECU, 1999).The timber industry has had an extensive impact on the forests and the rest of the environment, ranging from slash-and-burn, siltation (caused by logs clogging waterways) and over-exploitation of species (both flora and fauna) among others. There are also a number of other industries in Edo and Delta state, such as glass, textiles, rubber, breweries, oil palm, printing and cement (figure 2.12).

CHAPTER 3 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: LITERATURE REVIEW

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CHAPTER 3

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: LITERATURE REVIEW

3.1 Introduction

The natural environment is always in a constant flux and a change in one region can in turn affect the whole earth, which supports Tobler's first law of geography – "everything is related to everything else, but near things are more related than distant things." Early work by pioneers/scholars of the study of the environment such as Mary Somerville, George Perkins Mash and Vladimir Ivanovich Vernadsky, all supported the fact that man has had tremendous effect on the environment, even if they approached the subject from different perspectives and disciplines.

Mary Fairfax Somerville (1848) who was a scientist, mathematician and most importantly a physical geographer, wrote about the influence of man and his activities on earth. In her book *'Physical Geography',* she stated that man dexterously avails himself of the powers of nature to subdue nature.

Furthermore, she went on to say:

> *'Air, fire, water, steam gravitation, electricity, his own strength, and that of animals rendered obedient to his will are the instruments by which he has converted the desert into a garden, drained marshes, cut canals, made roads, turned courses of rivers... By these operations he has altered the climate, changed the course of local winds, increased or diminished the quantity of rain and softened the rigour of the seasons'*

The extent of human influence on the environment was not explored in detail and on the basis of sound data until George Perkins Marsh published '*Man and Nature*' in 1864 (Goudie, 1994), which was and is acclaimed to be a major contribution to the magnitude of human actions on the natural environment. According to him, in a letter to his friend, Spencer F. Baird (1860), "this book is a little volume showing that whereas Rither and Guyot, think that the earth made man, man infact made the earth."

Notwithstanding, G.P. Marsh argued that although not all but most of the destructions are caused by man, but also by biophysical factors. But he also acknowledged the fact that not all changes are bad, by stating, "The physical revolutions thus wrought by man have not all been destructive to human interests. Soils to which no nutritious vegetable was indigenous, countries which once brought forth but the fewest products suited for the sustenance and comfort of man - while the severity of their climates created and stimulated the greatest number and the most imperious urgency of physical wants - surfaces the most rugged and intractable and least blessed with natural facilities of communication, have been made in modern times to yield and distribute all that supplies the material necessities, all that contributes to the sensuous enjoyments and conveniences of civilized life."

It is believed that these impacts (man-induced or biophysical) would lead to global warming which will in turn affect our agriculture, marine life, biodiversity and even our health. Although current studies now state that the world is becoming warmer with changing sea level, changes in precipitation patterns and most importantly climate change.

Barney (1980) stated in his report "Global 2000" to the President of United States, that "if present beliefs and policies continue, the world in the 21st century will be more crowded, more polluted, less stable economically and ecologically and more vulnerable to violent disruption than the poorer in many ways than they are today. Unfortunately for the researchers that were involved in the report, it received a great deal of criticisms from peers and colleagues such as Julian Simon and Herman Kahn who were regarded as "two of the 20th century's greatest futurologists" (Moore, 2001). They wrote a book in response to the Global 2000 report, which was called '*The Resourceful earth- a response to global 2000*', according to Goudie (1194), it took a more optimistic view:

> *'If present trends continue, the world in 2000 will be less crowded (though more populated), less polluted, more stable ecologically*

and less vulnerable to resource supply disruption than the world we live in now. Stresses involving population, resources and environment will be less in the future than now.... The worlds people will be richer in most ways than they are today...The outlook for food and other necessities of life will be less precarious economically than it is now."

Bjørn Lomborg (2000), author of *'The Skeptical Environmentalist'* also supported Simon and Kahn's view. He put forward the point that 'despite all the studies, articles etc about impacts on the environment, majority of indicators show that things have improved and are better although not good enough. Lomborg supported his statement with a few examples, such as that of the UN research – In 1970, 35% of all people in developing countries were starving. In 1996, the figure was 18% and the UN expects that the figure will have fallen to 12% by 2010. However, whatsoever the standpoint of the investigator is, it is unquestionable that our fundamental knowledge is still too far limited on which to build reliable prognoses of the future (Goudie, 1994).

Turner *et al.* (1990) identified two types of global environmental change: Systemic and Cumulative. In the former, global refers to the spatial scale of operation or functioning of a system. A physical system is global in the sense if its attributes at any local level can potentially affect its attributes anywhere else or even alter the global state of the system. An example is the increase of greenhouse gases that will lead to climate change; although these emissions occur locally they affect the global atmosphere. In the latter – Cumulative, "global refers to the areal or substantive accumulation of localized change (Turner *et al.*, 1990). Brookfeld (1989; cited in Turner *et al.*, 1990) stated that these changes 'are local in domain but which are widely replicated and which in summary constitute change in the whole human environment.' It involves both the landscapes or 'faces' of earth and those biogeochemical flows that remain below the globally systemic scale in their movement such as nitrogen oxides, tropospheric ozone and water pollution." An example of this is soil or land degradation and landscape changes.

3.2 Characterising Land Cover Change at Global to Local Scales

Land use and land cover change studies are vastly becoming a global issue due to its significant role in global sustainability and global environmental change. Land-use and land-cover changes are so pervasive that, when aggregated globally, they significantly affect key aspects of Earth System functioning (Lambin *et al.*, 2001).

Land use and land cover change is gaining recognition as a key driver of environmental change (Riebsame *et al.* 1994). As man has been altering the land for his needs and selfish reasons. These changes affect natural habitats and disrupt the ecological system. Globally, land cover today is altered principally by direct human use: by agriculture and livestock raising, forest harvesting and management, and construction. There are also incidental impacts from other human activities such as forests damaged by acid rain from fossil fuel combustion and crops near cities damaged by tropospheric ozone resulting from automobile exhaust (Meyer, 1995). Although, innate events such as climate variations, flooding, fire and ecosystem dynamics may also instigate land use and land cover change. Russell (1997) stated that "human impact on land is ubiquitous although it differs in kind and intensity from one place to another, from one time to another'. Nevertheless, regional or local land use and land cover changes has an effect on the whole earth system, even in places with little or no land cover and land use changes, as the regions of the world are all connected to one another.

Scientists recognize that the magnitude of global land use and land cover change is large. One estimate, for example, holds that the global expansion of croplands since 1850 has converted some 6 million km^2 of forests/woodlands and 4.7 million km^2 of savannas/grasslands/steppes (Lambin *et al.*, 2001).

3.3 Drivers of Land Cover Change in Humid Tropical Forest Regions

Tropical regions are characterised by their high levels of biodiversity. The wide belt of land and water that lies between the tropics of Cancer and Capricorn is home to half of the world's people and some of its most diverse and productive ecosystems. Although, Nair (2007) stated that the term 'tropics' should be used loosely, the major reason for this was the overlap in classification of regions. He explained that the regions lying not only between but also *near* the tropics of

Cancer and Capricorn are usually included under the tropics, but according to the FAO definition if more than 50% of the area of a country falls within the tropics, it is designated as a tropical country, therefore, in this research, the term 'tropics' will be used in a broad sense. Citizens and governments within and beyond the tropics are increasingly aware of this region's unique properties, problems, and potential (Board on Agriculture, 1993). Tropical forests, while occupying only one-tenth of the world's land area, are disproportionately important in terms of global biogeochemical cycles and as home to more than half of the world's species (Thomas and Baltzer, 2002). At the present time, 14 to 16 million hectares of tropical forests are being converted each year to other land uses, mostly agricultural (Roper and Roberts, 1999). Intensive use and depletion of natural resources in the humid tropical region has called for research to study the causes of these changes, as they disrupt biogeochemical cycles, natural habitat and ecosystems. Chowdhury (2006) noted that tropical environments are among the most important locations of global land use and land cover change.

Bridging understanding of local environmental change with regional and global patterns of land-use and land-cover change (LUCC) remains a key goal and challenge for our understanding of global environmental change (Keys and McConnell, 2005). The factors driving land use and land cover changes must be researched and understood, in order to understand and explain past patterns and predicting future patterns. This is also important in understanding the impacts of land use and land cover change. Lambin *et al.* (2003) stated that understanding of the causes of land-use change has moved from simplistic representations of two or three driving forces, to a much more profound understanding that involves situation-specific interactions among a large number of factors at different spatial and temporal scales. Although, some drivers that may be more subtle, in comparison to other drivers of land use and land cover change.

A number of studies that lay emphasis on specific driving forces (drivers of change) e.g. agricultural expansion (Geoghegan *et al.*, 2001), technological innovation (Mannion, 2002), agricultural expansion (Walsh *et al.*, 2006) etc. The drivers of land use and land cover change are numerous and vary in time and space. Some act slowly (and often obscurely) over centuries, while others trigger events quickly and visibly (McNeil *et al.*, 1998). As Lambin *et al.* (2003) puts it, "driving forces could be slow variables, with long turnover times, which determine the boundaries of sustainability and collectively govern the land use trajectory (such as the spread of salinity in irrigation schemes), or fast variables, with short turnover times (such climatic variability associated with El Niño oscillation)."

In the LUCC science/ research programme, which is a combined initiative of the International Geosphere-Biosphere Programme and the International Human Dimensions of Global Environmental Change Programme (IHDP), the drivers of land use and land cover change were divided into *proximate causes/drivers, socio-economic (social/human) drivers* and *biophysical drivers* (Turner *et al.*, 1995; Lambin *et al.*, 1999). In some other studies (Ojima *et al.*, 1994, Lambin *et al.*, 2003, Meyer and Turner, 1992) these drivers are grouped into – *proximate causes and underlying drivers* (which consist of *biophysical* and *socio-economic drivers*). These drivers act together to affect land use, which in turn affects land cover. However human actions rather than natural forces are the source of most contemporary change in the states and flows of the biosphere (Turner and Meyer, 1994).

In most cases, especially in the humid tropical regions, there are underlying forces (socio-economic drivers) that drive proximate causes. For example, Policy/institution factors (socio-economic driver) driving wood extraction (proximate causes), such as government failures, corruption as a form of bureaucratic capitalism and poor, weak or no performance of forestry rules (Geist and Lambin, 2001).

Notwithstanding, Meyer and Turner (1992) stated that three important points must be kept in mind regarding the driving forces – 1) The driving forces of change may vary with the type of change involved; forces that drive some changes may lessen others. 2) The same kind of land cover change can have different areas even within particular world regions and lastly, 3) In the dynamics of underlying "causes," no agreement exists on the level at which adequate explanation is achieved.

3.3.1 Proximate Causes

Proximate causes are activities that directly affect or alter the environment. These results from the interplay of human driving and mitigating forces to directly cause environmental transformations (Moser, 1996). Proximate causes generally operate at the local level (individual farms, households, or communities) (Lambin *et al.*, 2003). Examples of these causes are – pollution, over harvesting, illegal logging, bush burning and infrastructure and agricultural expansion.

The proximate causes of land use and land cover change represent the point of intersection between the core concerns of the natural and the social sciences, between physical processes and human behaviour (Turner and Meyer, 1995). They connect the changes in land cover (Biophysical attributes of the earth's surface) and land use (human purpose or intent applied to human activities that directly alter the physical environment) (Geist and Lambin, 2001). Land use and land cover change are connected through the proximate causes of change that translate the human goals of land use into changed physical states of land cover (Briassoulis, 2000).

One of the most important global economic activities is agriculture, as it provides food and raw materials as needed by humans. It occupies 40 percent of the land surface, consumes 70 percent of global water resources and manages biodiversity at genetic, species and ecosystem levels (FAO, 2007). Unfortunately, as the population increases, demand for food and raw materials increases. The need to increase food supply has aggravated bush burning, because land must be cleared to enable farming to take place (Agabi *et al.*, 1995), or farming intensified (agricultural intensification), which leads to loss of soil nutrients and productivity, deforestation and biodiversity loss. Agricultural intensification and expansion have destroyed biodiversity and habitats, driven wild species to extinction, accelerated the loss of environmental production services and eroded agricultural genetic resources essential for food security in the future (FAO, *ibid*). In the tropics, demand for agricultural land continues to be one of the main driving forces for land cover changes such as deforestation of the tropical rainforests, and cultivation of marginal lands (Dolman and Verhagen, 2003). The IPCC (2000) states that expansion of agriculture through conversion of forests and grassland during the past 140 years has led to a net release of about 121 gigatons of carbon, of which about 60% has been emitted in the tropics, mostly during the last 50 years.

Traditionally in the tropics, subsistence farming has always been the norm, but due to the increased demand for food. Unfortunately, this is not now the case, as these smallholder farmers now cultivate crops for profit (i.e. cash crops), thereby exerting pressure on the land (or soil). In order to supply industry, there has been a rapid expansion of primary production through the introduction of exotic cash crops and intensive extraction of forest products (Osemeobo, 1988). For example, rapid industrialization in the developed world has led to an accelerated demand for raw materials from tropical countries (Osemeobo, *ibid*).

Due to the increased demand for land in the tropical regions, forested lands are cleared to make way for agricultural land. A popular method of clearing the land is *slash and burn*, which is part of shifting cultivation or swidden-fallow agriculture. Slash and burn agriculture is the decimation of rainforests by poor farmers in developing countries who cut and burn native vegetation to clear lands for agriculture (McGrath and Smith, 2006). In Central America, 40% of all the rainforests have been cleared or burned down in the last 40 years, mostly for cattle pasture to feed the export market (often for US beef burgers) (Revington, 1992).

The vast majority of the world's slash-and-burn farmers do not have formal land title - at best they have customary rights, at worst no rights at all. Without some guarantee that the land will remain theirs, farmers have no incentive to invest in making it more productive (Roper and Roberts, 1999). The farmers are not stimulated to apply sustainable techniques or even invest in soil conservation. By burning the vegetation, nutrients are released into the soil (Jones and O'Neill, 1993). After these farmers have utilised the cleared land to farm, it is left to dissipate as it has been made uncultivable. In the past the clearing was left idle for 20 to 100 years, so the forest could recover and again provide fertile land and useful timber. The situation is different today. So many people are practicing slash-and-burn agriculture in a non-rotational manner that fields do not have time to return to secondary forest as they do after natural disturbances (Rhett, 2006). The big commercial farmers also practice this method of farming, only on a much larger scale.

The soils found in the tropical regions are generally low and nutrient deprived. The reason why vegetation in this region is rich and flourishing is because plants decay quickly to provide nutrients for plants that are taken up and stored. Cochrane (2006) pointed out that, the adaptation that tropical rainforests have made to their existence on soils that have been largely leached of their nutrients by millennia of rains is a super efficient recycling system. Farmers tend use chemical fertilizers to increase the fertility and productivity of the soils. The use of fertilizers result in the spread of pollution not just in the streams and rivers, but also (and most seriously) in ground water (Agabi *et al.*, *ibid*).

Another major contributor to pollution is the oil and gas exploration and mining activities. Oil exploration is known worldwide for their negative environmental and social impact at the local level: loss of indigenous peoples' or peasants' lands, health problems, destruction of rainforests, pollution off water resources and air (WRM, 1999). Mining activities produce dust and rain, also where appropriate; heavy metals may cause alteration in land cover; such as substances entering drainage systems will cause changes in aquatic systems and vegetation communities. For example gas flaring can lead to atmospheric pollution by combustion (Agabi *et al.*, *ibid*) or oil spillage, which has adverse effects on biodiversity and an example of land use and land cover change driven by mining activities is gold mining in the Amazon Basin has contributed to deforestation and biodiversity loss in the region.

Land has been cleared and biodiversity displaced or destroyed, in order to make way for roads and other infrastructure have had to be constructed, to service oil, mining and logging companies, thus 'opening the roads' to farmers to induce slash and burn agriculture. For example, agricultural exploitation of the Amazonian eco-region has increased especially since the 1970s, coinciding with the discovery of oil (Southgate and Whitaker, 1994; de Koning *et al.*, 1998). This may have a particularly significant impact in forested regions of the developing world because the infrastructures provided by these companies may be used by other groups to infiltrate the forest and cause widespread land cover change for shifting agriculture and ranching (Mannion, 2002). Cochrane (*ibid*) stated that, in tropical logging operations, forests are rarely clear-cut, since so few of the standing trees have market value so *selective logging* is practiced. Loggers (both legal and illegal) do not only cut trees but they also tend to engage in some illegal hunting either for subsistence or commercial basis, thereby are in danger of over-harvesting the wildlife.

3.3.2 Socio-Economic Drivers

The *socio-economic drivers* accentuate the links across scales from local to international (Stedman-Edwards, 2000). These drivers are also known as underlying causes. Examples of socio-economic drivers are: demographic change, technological change, macroeconomic national or regional policies, markets and industrialization. Globally, population growth is increasing at an alarming rate. According to the United Nations (2007), the world population will reach 6.7 billion by July 2007. In the last 30 years the population has increased from about 4 billion to 6.7billion (table 3.1). Most of the world's population lives in a few countries. In 2007, almost four out of every 10 inhabitants on earth live in China and India. A further 8 countries account for another 2 out of every 10 of the earth's inhabitants, namely, the United States of America, Indonesia, Brazil, Pakistan, Bangladesh, Nigeria, Russian Federation and Japan. Most of the world's most populous countries are located in the tropical regions that contain the tropical forest or what is left of it.

The growing global population has had an effect on demand for food, shelter and services. As the population increases in the tropics, the need for land increases, thereby forcing expansion and encroachment onto forested land. Population growth is associated with the growth of resource consumption and degradation, expansion and intensification of land use, increasing poverty, exploitation of marginal lands and the breakdown of traditional resource management systems (Stedman-Edwards, 2000). Unlike most studies, Lambin and Geist (2007) argued that, both increases and decreases of a given population also have large impacts on land use. The demographic change factor is connected and interrelated to proximate causes (see section 3.3.1).

Table 3.1 Population of the world and major areas

	Population (millions)		
Major area	**1950**	**1975**	**2007**
World	***2 535***	***4 076***	***6 671***
Africa	224	416	965
Asia	1 411	2 394	4 030

Major area	Population (millions)		
	1950	**1975**	**2007**
Latin America and the	168	325	572
Northern America	172	243	339
Oceania	13	21	34

Source: Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (2007)

Existing case studies, according to Lambin *et al.* (2003), highlight that, at the timescale of a couple of decades or less, land use changes mostly as a result from individual and social responses to changing economic conditions. Some of the economic factors that drive land use and land cover change are market growth, urbanisation, commercialisation, industrialisation and policies. Policies, laws and formal and informal institutions have been created due to political, social and economic forces (Steadman-Edwards, *ibid*).

A large body of policies, (such as fiscal policy, agricultural policies or policies imposed by International bodies/agencies), are just a reminder that the use of land is a highly political activity, i.e., determination of land use should not be left to chance, to individual land owners or to the mark*et* alone (Reid *et al.*, 2005). One of such policies is the *Structural Adjustment Program/Policies (SAP).* SAPs have been imposed on developing countries, in order to aid them in solving their economic issues. The World health Organisation (2007) stated that, these policies are economic policies for developing countries that have been promoted by the World Bank and International Monetary Fund (IMF) since the early 1980s by the provision of loans conditional on the adoption of such policies. The SAP policies include currency devaluation, reducing tax on high earners, reducing inflation, privatisation and lower tariffs on imports. One of the primary objectives of SAP was to shift demand for commodities so that fewer commodities are imported and domestic production increases (Braimoh and Onishi, 2007). These policies where employed, have had a negative impact on the society and its environs and drive land use and land cover change. For instance, these policies have had an impact on the disappearing rainforests in Cameroon, where the IMF recommended devaluation of the currency and export tax cuts which played an important role in the increase of timber exports (World Rainforest Movement, 2002) and also has been responsible for most of the economic ills of Nigeria, including the debasement of the naira (local currency), the high rate of inflation, the crippling of domestic industry, high interest rates, high unemployment, and the spread of poverty (Moser *et al.*, 1997).

Although, there a number of developing countries that have clearly benefited from such policies or reforms through promoting rural development, agricultural exports and economic growth. However, many developing regions also suffer from a 'cumulative causation' link between rural poverty, land degradation and deforestation: poor rural households abandoning degraded land for 'frontier' forested lands, deforestation and cropping of poor soils lead to further degradation, which in turn leads to land abandonment and additional forestland conversion, and so on (Barbier, 1997; Barbier 2000).

These negative issues, such as the devaluation of the currency, high unemployment and low tariffs on imports, have brought about increase in population in some areas in the tropical regions. When the market prices of resources (or raw materials) increases, there is a high influx of migrants who need to exploit the specific industry and in so doing, encroach on the marginal lands of the region to turn the resources into cash-producing resources. Supporting this point, Lambin *et al.* (2001) said that large-scale plantation and intensive agricultural projects increase migrant involvement with commercial cultivation, often at the expense of indigenous people living near the forest frontier, where land conflicts follow (Angelsen, 1995; Xu *et al.*, 1999; Ramakrishnan *et al.*, 2000). Migration to the forested regions has been seen as a way been seen as a means of relieving congestion and landlessness in settled agricultural regions (Repetto, 1988). An example of this, was given by Sage (1994), describing the situation in Indonesia, where there was a transmigration program in place to relieve densely populated areas in Java and Bali by clearing tropical forests to resettle the populace on the outer islands.

Recently, there have been a number of researchers, (Shilling, 1992; Adams, 2001; Blaikie, 1985; Kahn and McDonald, 1995) who have looked at the link/relationship *debt* and *poverty* as a driver of environmental degradation. In Africa, this linkage appears to be directly related to the low productivity and input use of African smallholder agriculture generally, which in turn leads to land degradation, stagnant or declining yields and extensive use of land (Reardon *et al.*, 1999, Barbier, 2000). Shah (2007) argues that the reason a number of developing nations are in debt and poverty is partly due to the policies of international institutions such as the International Monetary Fund (IMF) and the World Bank. The poverty situation in developing countries initiated loans from developed nations. Debt, poverty and population growth restrict the capacity of developing countries to adopt environmentally sound policies (Adams, 2001). On the whole, as debt incurred by developing countries mounts up, exploitation of the earth and its resources will be on the increase. The physical environment surrounding the poor is inevitably abused because they are at the margin of existence and cannot therefore afford the luxury of conserving the future (Agabi *et al.*, *ibid*), seeing that there is an abject lack of incentives for them to conserve their physical environments.

Urbanization and industrialization are among drivers of land use and land cover change. Urban areas account for only two percent of the Earth's land surface but over half of the world's population now resides in cities (UN, 2001). This exerts tremendous pressures on land and its resources, especially in developing countries. According to Weir (2002) over the next century, urbanization is predicted to move at a rapid pace. It's estimated that worldwide the migration towards the cities has been moving at three times the rate of population growth. Urbanization often occurs on agricultural land and forests, and is generally accompanied by an increase in energy use, and air, water and noise pollution (Braimoh and Onishi, 2007) and this is similar in the case of industrialization. Some of the effects of these factors (urbanization and industrialization) are - agricultural expansion and intensification in order to meet demands of the urban areas, escalating solid waste disposal, environmental pollution (air, water and noise), and erosion and flooding. Although, with the case of pollution, Mabogunje (1997) argues that as it usually involves naturally occurring compounds such as sulphur or nitrogen, it makes it difficult to establish whether the present state of an ecosystem has been affected by pollution or not. In addition, pollutants tend to travel downstream or downwind from their point of origin to affect other localities, making it difficult in establishing the source and cause of pollution.

Technological progress also fosters growth in individual city sizes, because knowledge accumulation either interacts with and enhances urban scale economies or improves the ability to manage cities through, for example, innovations in commuting technology (Henderson and Wang, 2007). Technology advances in the tropical region (especially in developing countries), have habitually been applied in the agricultural sector to enhance productivity and maximize farm yields and turnover. This includes high yielding crop varieties, fertilizers, pesticides and science-based farming systems such as fish farms, as well as other relevant non-agricultural technologies such as those used for food processing, storage and transport (Grainger *et al.*, 2003). Transport technologies have increased access to land (Grübler, 1994) and greater access to markets.

The *Cultural factor* is an important issue in understanding land use and land cover. This is basically the attitude towards land and development and the land use decisions made. Geist and Lambin (2001) divided this into public attitudes, values, beliefs, individual and household behavior. Attitudes, values and beliefs are prominent variables of this factor, in developing countries there seems to a blasé attitude towards land especially forests. There is a lack of concern for sustaining environment for a longer term or for future generations. In a study carried out by Geist and Lambin (2001), they found out that in all the regions (tropical regions), where the study was carried out, there was an attitude of "Clear before anyone else does' which is a widespread individual and household behavior that reportedly holds true across all regional cases, where there is also 'free for all' society. Most people view the environment and its resources are 'free for all' for quick cash. Nonetheless, with the values and beliefs, the local farmers have developed traditional methods that are productive and well suited for them. A good example of positive impact of cultural factors is given by Rockwell (1994); "In the tropical forest of Northern Australia, an area has been put aside for conservation, that was due to the Aboriginals' beliefs that they consider most of the natural features of the area to be 'permanent manifestations of the actions of legendary ancestors' and they are compelled to protect these 'sacred' sites."

According to Lambin and Geist (2007), many land use and land cover changes are due to ill-defined and weak institutional enforcement that undermine local adaptation strategies, such as subsidies for road construction, agricultural production, and forestry, and widespread illegal logging. Even when laws and strategic policies are agreed, the government (in tropical areas) have limited competency and capacity to implement them.

3.3.3 Bio-Physical Drivers

Biophysical drivers usually work as catastrophic factors that lead to sudden shifts in the human-environment condition (Geist and Lambin, 2001). It comprises of the natural processes of the environment, such as, climatic variations, topography, drainage, soil type and variations and geomorphic processes. Verburg *et al.* (2004) noted that, biophysical factors mostly do not 'drive' land use change directly, they can cause land cover changes (e.g., through climate change) and they influence land use allocation decisions (e.g., soil quality). In addition, land use changes may result in land cover changes which, then, feedback on land use decisions causing perhaps new rounds of land use change (or changes).

Land use is viewed as constrained by biophysical factors such as soil, climate, relief and vegetation (Veldkamp and Fresco, 1997). In the case of a farmer these variables would determine if he is going to carry out any agricultural activity, if the soil is infertile or well drained or even if it's on a hill/slope as the land would be prone to erosion. These biophysical drivers are interlinked with other drivers of land use and land cover change, as Lambin *et al.* (2007) stated that natural variability may also lead to socioeconomic unsustainability, for example when unusually wet conditions alter the perception of drought risks and generate overstocking on rangelands. When drier conditions return, the livestock management practices are ill adapted and cause land degradation.

Veldkamp and Lambin (2001) pointed out how initial efforts aimed at modelling land use change have focused principally on biophysical drivers because of the good availability of data. However incorporating socio-economic drivers of change is required (Turner *et al.*, 1995; Musters *et al.*, 1998; Wilbanks and Kates, 1999). All of the above drivers are interlinked and act together; in one capacity or another to cause land use and land cover change. An approach to further understanding these drivers and how they interact to cause change is by *modelling.* As Verburg *et al.* (2003) understood that models are useful for disentangling the complex suite of socio-economic and biophysical factors that influence the rate and spatial pattern of land use change.

3.4 Modelling Land Cover Change

They are numerous models used in various studies and disciplines, including land use and land cover change studies. Models, according to Wilson (1974), are a formal representation of theory of a system of interest. Models are a simplification of the real world and they can be used to project future scenarios (and present scenarios), to gain a better understanding of the earth system.

Modelling, especially if done in a spatially-explicit, integrated and multi-scale manner, is an important technique for the exploration of alternative pathways into the future, for conducting experiments that test our understanding of key processes, and for describing the latter in quantitative terms (Lambin *et al.*, 2000). Meyer and Turner (1995) emphasized the importance of modeling in global change studies, as they organize a vast array of data for systematic analysis, uncover gaps in the data, expose discrepancies between theoretical expectation and empirical reality, and provide a laboratory for exploring relationships that cannot be experimentally tested in the real world. Researchers studying global environmental change are calling for historical reconstructions of land use and land cover, analysis of the social forces (or drivers) behind land transformations and modeling approaches that can be linked to other types of environmental simulations (Riebsame *et al.*, 1994).

The Land Use and Land Cover Project (LUCC), a core programme of the IGBP and IHDP, has identified the need to develop integrated regional and global models by improving upon existing models and build new one that provide a basis for projecting land-use changes based on changes in the underlying causes or driving forces (Turner *et al.*, 1995). Land use and land cover change models facilitate in recognizing and understanding the drivers of change, how they interact with each other through time and project future scenarios of land use and land cover change. In other words, these models of land use and land cover change illustrate the spatial and temporal relationships between these drivers.

Veldkamp and Lambin (2001) stated that models of land use change could address two separate questions: *where are the land-use changes likely to take place (location of change)* and *what rates are changes likely to progress (quantity of change).* These two questions have been referred to as the *location* issue versus the *quantity* issue (Pontius and Schneider, 2001; Serneels and Lambin, 2001). The *spatial* and *temporal* patterns of land use and land cover change are important modelling issues. Time is just as important as space when researching land changes (Heitel *et al.*, 2007). In addition to these questions, Lambin *et al.* (2000) pointed out that a model should also address: *which environmental and cultural variables contribute most to an explanation of land cover changes.* These questions address the '*where*', '*what* ' and '*why*' of land use and land cover change.

Land use and land change models study the impacts of policies and other factors; this guides policymakers and land use managers towards making sustainable land use decisions and improve policy formulation. King and Kraemer (1993) list three roles a model must play in a policy context: A model should clarify the issues in the debate; it must be able to enforce a discipline of analysis and discourse among stakeholders; and it must provide an interesting form of "advice," primarily in the form of what not to do — since a politician is unlikely to do what a model suggests (Agarwal, 2002).

According to the dictionary, a simulation is the technique of attempting to predict aspects of the behaviour of some system by creating an approximate model of it, which can be done by physical modelling, by writing a special-purpose computer program or using a more general simulation package. *Simulation models* highlight the interactions among all components that form a system, by condensing and aggregating complex ecosystems into a small number of differential equations in a stylized manner. Simulation models are therefore based on an a priori understanding of the forces driving changes in a system

(Lambin, 2000).

Models of land-cover & -use change (LUCC) vary enormously in terms of assumptions concerning: number of possible categories, types of category transitions, spatial dependency, feedbacks, cross-scale linkages, data requirements and so on (Pontius and Jeffrey, 2005). A number of land use and land cover change modelling techniques have been implemented and can be grouped or classed into five categories: *Empirical statistical/ econometric models*, *Optimization models, Stochastic and Simulation models* and *Integrated models*.

3.4.1 Empirical Statistical/Econometric Models

Empirical approaches use regression methods to quantify models from data that describe the spatial and historic distribution of land use changes (Aspinall, 2004). Empirical, statistical models attempt to identify explicitly the causes of land-cover changes using multivariate analyses of possible exogenous contributions to empirically derived rates of changes (Lambin *et al.*, 2000). *Multiple regression analysis* is a widespread statistical technique used in various researches. This is the relationship between a set of independent variables and a dependent variable, whereby these independent variables predict a single dependent variable. Mathematically, the general form of the equation, as given by Briassoulis (*ibid*) is expressed as:

$$LUT_i = a + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots \beta_n X_n + \varepsilon \qquad (3.1)$$

where LUT_i is the area of land occupied by land use type i (in each cell) and X_1, X_2, ... X_n the predictor variables used. The term " ε " is the error term of the statistical model.

Millington *et al.* (2007) suggested that, these techniques could be used for two purposes:

(i) To improve explanation of the mechanisms and processes of change (by examining the statistical significance of the influence of predictor variable upon the dependent variable) and/or

(ii) Predictions of change (derived relationships may be used to *project* future land-use/cover from the current values of the independent variable).

An example of a study where multiple regression technique was applied is one put forth by LaGro and DeGloria (1992), where the proportions of change in each of five classes of land use/land cover (urban, forest, agriculture, vacant and wetland), were used as the dependent variable (*y*) while physiographic and demographic factors (such as slope gradient, farming suitability, distance from urban centers and population density), were used as independent variables (x_i).

Logistic regression as a statistical modeling technique is a *generalized linear model* that is used in describing and predicting a dependent dichotomous variable (i.e. it only contains data coded as 1 (True, success, etc.) or 0 (False, failure, etc.) from a set of independent explanatory variables that may be discrete, dichotomous or continuous. The logistic regression is mathematically expressed as:

$$p = \frac{exp\ (\beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_n X_n)}{1 + exp\ (\beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_n X_n)} \qquad (3.2)$$

where, p is the probability that the dependent variable y equals 1, β_o is the equation constant, and β_i is the coefficient of independent predictor variable X_i. In the study of land use change in Narok district, Kenya carried out by Serneels and Lambin (2001), multiple logistic regression was utilized to estimate the parameters of a multivariate explanatory model in situations where there is a dependent dichotomous variable and independent continuous or categorical variables. From the modeling results, they observed that the explanatory variables of the mechanized agriculture suggest a von Thünen-like model, where conversion to agriculture is controlled by the distance to the market, as a proxy for transportation costs and agro-climatic potential.

Econometric models combine economics theory, land use and statistical data/information to analyze and test economic relationships. A review of these models has been reviewed by Kaimowitz and Angelsen (2000). Econometric models aspire to understand the economic factor or process of land use and land cover change, which is basically the human behavior element, to achieve this, a number of econometric models, according to Verburg *et al.* (2004), rely on statistical techniques, mainly regression, to quantify the defined models based on historic data of land use change (Bockstael, 1996; Chomitz and Gray, 1996; Geoghegan *et al.*, 1997; Pfaff, 1999 cited in Verburg *et al.*, 2004). It uses multiple regressions to simulate response to classic set variables such as crop prices or land productivity (Riebsame *et al.*, 1994). This is based on the supply and demand correlation. In econometric modeling, an increase in the price should lead to a decrease in land or to put it in another way, can lead to an increase in land use and land cover change (or conversion), which utilizes the von Thünen land rent theory. Johann Heinrich von Thünen (1783-1850), who was an economist, developed a model of land use, in 1826, that showed how market processes determines how land in would be used (Hall, 1966). Individuals would be willing to supply or give over their land for a particular use (demand) on the basis of which use enables them to maximize their profits in the form of rent (price) (Mabogunje, 1997). Principally, the land use that would generate the highest potential price (rent) would therefore take up the land area. It is mathematically summarized as:

$$R = Y(p-c) - Yfm \quad (3.3)$$

where R = rent per unit of land; Y = yield per unit of land; p = market price per unit of yield; c = average production costs per unit of yield; m = distance from market; f = transport rate per unit of yield and unit of distance.

An example study where models were developed based on the von Thünen theory was carried out by Nelson (2000). He used the basic von Thünen insights on the role of location and transportation costs to develop a spatial econometric model of land use as a function of geophysical and socio-economic variables, and the results were used to predict spatially explicit effects of road resurfacing on economic activities. A key feature of spatially explicit econometric estimations is that all data elements contain locational attributes, i.e., is georeferenced (Monroe and Müller, 2007).

The Ricardian model is also commonly used in modelling land use and land cover change (e.g. Geoghegan *et al.*, 2001; this modelling approach is based on a theory of land formulated by David Ricardo (1772 – 1823) in 1817, an economist. He argued that only as soil fertility changed, productivity levels would also change, thus ensuring that land of the fertility or quality would provide more output per unit area than land of inferior quality (Mabogunje, 1997). This approach focuses on the inherent profitability of the land, as characterized by physiographic properties such as soil quality, elevation and precipitation (Sills and Pattanayak, 2006). The land with the poorest (or low) fertility utilized for agriculture receives little or no rent at all, because all of its earnings would have to cover capital and labour costs. It relates land use and land cover change to physiographic factors (such as soil fertility, elevation and slope) and distance to markets and roads.

Konagaya *et al.* (1999) developed the Generalized Thünen-Ricardo (GTR) model, which incorporates the two main determinants of land-use changes -Thünen component and Ricardo component. These two components are combined in the GTR model to predict land use changes between urban, agriculture and nature (Konagaya, 1999 cited in Zhou and Skole, 2001).

These modeling approaches have limitations, as Mertens and Lambin (2000) and Serneels and Lambin (2001) stated that it is difficult to distinguish between correlation and causality, for instance it is problematic to determine the direction of the causal relationship between population increase and agricultural expansion. The regression techniques are quite restricted in regards to illustrating the importance of individual predictors or the interactions between them. Irwin and Geoghegan (2001) argued that although empirical models fit the spatial process and land use change reasonably well, they are less successful at explaining the human behavior that leads to the spatial process or outcome of land use change. Nonetheless, they typically consist of variables that capture economic effects. Notwithstanding, Munroe *et al.* (2002) concluded that, more research is needed on explanatory power of econometric models. However, statistical tools and methods are likely to remain an important component of LUCC analyses. If properly used, they remain powerful tools for rigorous hypothesis testing and ranking the relative influence among a set of factors, which can thus be translated into real policy objectives (Munroe and Müller, 2007).

3.4.2 Optimization Models

In general mathematical terms *optimization models* (also known as *mathematical programming)* endeavour to minimize or maximize a real function by controlling one or more parameters. In other words, this can be achieved by systematically choosing the values of real or integer variables from within an allowed set (Wikipedia, 2007). They generate optimal solutions based on certain defined objectives. This modeling approach originates from the land rent theory of von Thünen and Ricardo (Lambin *et al.*, 2000). According to Briassoulis (2000), optimization models are important applications in the analysis of land use – especially land use planning applications – and, recently, they appear to be useful tools in the search for land use solutions which contribute to sustainable development and use of environmental and human resources. *Linear programming* (*LP*) and *Non-linear programming* (*NLP*) are common techniques/ approaches of the optimization model.

The *Linear-programming* (*LP*) model is one of the most common modelling approaches for the reason that it is easier to computationally manage (compared to other modelling approaches). In this model, the objective function and its related variables are linear. An example of an objective function is to maximize profits in a production process. The constraints deal with matters such as the production capacity and the availability of labor (Jongkamp *et al.*, 2004). Gass (1975) stated that linear programming (LP) models have been utilized to make more-informed decisions in nearly all aspects of our society, including industry, government and social services (cited in Arthur and Nalle, 1997). These models optimize the land-use configuration and management under a number of agro-technical, food security, socio-economic and environmental objectives (Veldkamp *et al.*, 2001). Although LP is not properly a spatial technique, because it does not take into account the spatial distribution of the decision variables, it may be used to optimize spatial distributions or to guide the integration of variables (Chuvieco, 1993). This model can be expressed in a standard form:

$$\text{Minimize} \quad Z = cx \qquad \text{OR} \qquad \text{Maximize} \quad Z = c^T x \qquad (3.4)$$

$$\text{Subject to} \quad Ax \leq b$$

$$\text{Where} \quad x \geq 0$$

where x is the vector of variables; A is a matrix of known coefficients; c and b are vectors of known coefficients; cx and c^Tx are the objective functions, with $c = (c_1, c_2, c_3 \ldots, c_n)$; and the equations $Ax \leq b$ are the constraints, and $b = (b_1, b_2, b_2 \ldots, b_n)$. The objective function in the model which is the function $Z = c^Tx$ or cx, maximize or minimize Z, subject to constraints on x. In applications in land use analysis, X represents a vector of production systems with corresponding technical coefficients, and Z represents the variable to be optimized, e.g., economic surplus or use of biocides (Bouman *et al.*, 1999).

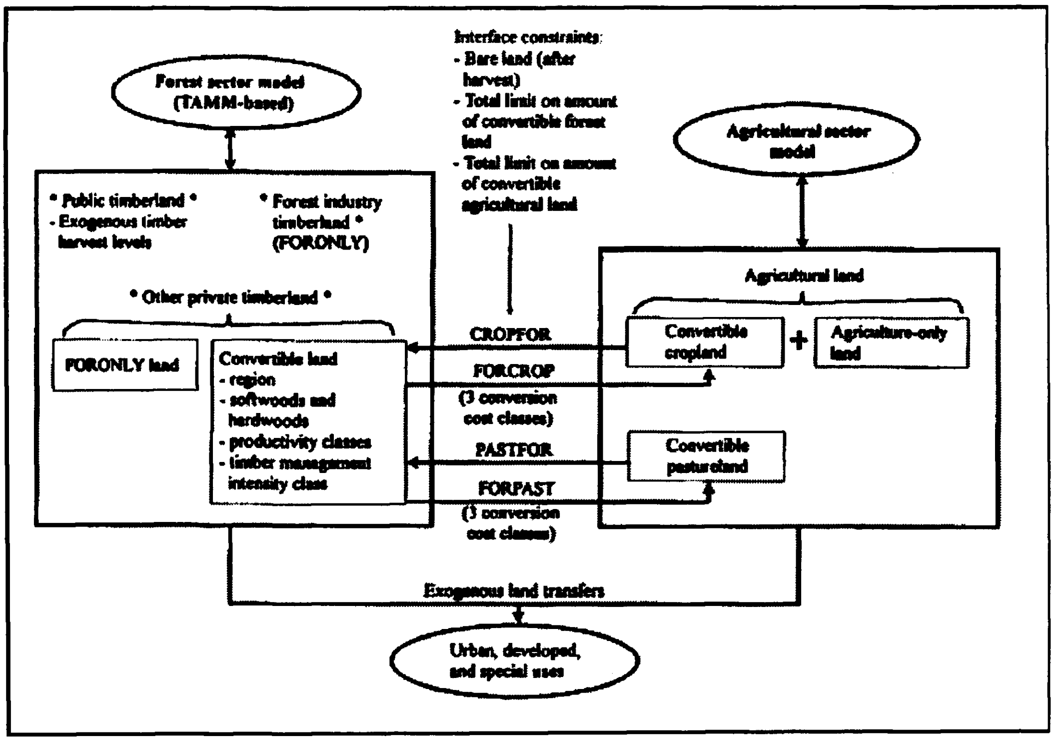
Santé and Crecente (2007) used this modelling approach in a system called *LUSE,* which allows the exploration of rural land use allocations by a variety of multiobjective linear programming methods. The objectives pursued here are the maximization of gross margin, employment in agriculture, natural land use and traditional rural landscape, and minimization of the production costs and the use of agrochemicals. While the decision variables (or constraints) are the areas devoted to the various land uses, what levels must they reach to be considered to satisfy existing demand for those uses or their products, and that the areas devoted to maize and fodder must be sufficient for maintenance of dairy farm production. Santé and Crecente (2007) concluded that, LUSE provides an opportunity for the decision-makers to improve their understanding of the problem, as the system's results show the consequences of prioritising different objectives, the technical feasibility of meeting different sets of objectives, and the trade-offs among objectives.

The *Non-linear programming (NLP)* is the process of solving a system of equalities and inequalities, collectively termed constraints, over a set of unknown real variables, along with an objective function to be maximized or minimized, where some of the constraints or the objective function is nonlinear (Wikipedia, 2007). These models are encountered less frequently in the literature and even less frequently in actual applications given the computational difficulties associated with their solution (Briassoulis, 2000).

A common example of the *non-linear optimization model* is the *Forest and Agricultural Sector Optimization Model (FASOM)* (Adams *et al.*, 1994; 1996a; 1996b). FASOM is a *non-linear optimization model* of the forest and agricultural sectors (see figure 3.1), according to Adams *et al.* (1996a), it was initially developed to evaluate welfare and market impacts of alternative policies for sequestering carbon in trees also can aid in reviewing a wide range of forest and agricultural sector policies. It depicts the allocation of land, over time, to competing activities in agriculture and forestry (Alig *et al.*, 1998) (please see Alig *et al.*, 1998 for mathematical equations and detailed descriptions). FASOM has some limitations, as Agarwal *et al.* (2002) pointed out that, as it works on a broad scale, it means that land capability variations within regions are considered. It also it pays limited attention to land use and land cover change and to the processes of resource degradation (Fischer *et al.* 1996 cited in Briassoulis, 2000).

Optimization models do not explicitly explain the relationships & interactions among the factors and the processes of land use and land cover change, which is a reason why in most cases they are used in conjunction with other models to maximize the analysis and results (e.g. Chuvieco, 1993 and Bouman *et al.*, 1999). By and large, optimization models offer rough guides of desirable land use futures (usually different from the current ones) and they should be used prudently by decision makers when deciding what actions to take to achieve them (Briassoulis, 2000).

Figure 3.1 Links of forest and agriculture sectors in FASOM



Source: Adams et al., 1996a

3.4.3 Stochastic and Dynamic Simulation Models

A *stochastic model* estimates probability distributions of likely outcomes. In the study of land use and land cover change these models look at the transition probabilities of land use and land cover, i.e. changes from one land use or land cover type to another. According to Lambin (2004), the transition probabilities can be statistically estimated from a sample of transitions occurring during some time interval.

Markov chain modeling is a good example of stochastic models. Markov chains was named after and developed by a Russian mathematician – Andrei Andreyevich Markov. It is a process with probabilities for each state that is the probability of moving from one state *i* to another state *j* over time *t*. The markov chain models assume that the immediate past is the best predictor of the near future, under the condition of stationarity, and uses transition probabilities of the past states to estimate future states (Geoghegan *et al.*, 1998). This can be expressed formally as:

$$X_{t+T} = P(T)\, x_t \qquad (3.5)$$

where the matrix of transition probability ***P (T)*** is:

$$P = \begin{pmatrix} p_{11}\ p_{12} \cdots\cdots\cdots p_{1n} \\ p_{21}\ p_{22} \cdots\cdots\cdots p_{2n} \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ P_{n1}\ p_{n2} \cdots\cdots\cdots p_{nn} \end{pmatrix} \qquad (3.6)$$

In the equation, vector ***x*** of the distribution of land covers at time ***t*** and a matrix of transition probabilities ***P (T)*** of changes from each land cover class to the others during a time period ***T*** (CGER, 2000). In the markov chain modelling approach, land use at time *t+1* is based on land use at a previous *t*.

Balzter (2000) used markov chain models to predict vegetation changes using several different data sets and concluded that this modelling approach has the advantage of aggregating very complex information in the transition matrix, so that even ecosystems can be examined for which the underlying processes are not fully understood. In support of this point, Thornton and Jones (1998) stated that, with further development of this model, it would open the way to interpret possible ecological consequences of changes in input conditions on the landscape. This could lead to the derivation of some simple indices or measures of potential ecological impact of technological and economic change on agricultural land use that could be of real value in a range of impact assessment studies. However, these models do not explicitly predict where the changes might occur; neither do they explain the mechanisms underneath the changes (Hsu and Cheng, 1999).

A *dynamic landscape simulation* (DLS) was developed by Wang and Zhang (2001), to study the human induced impacts on landscape change on an area in Chicago Metropolitan region. This model quantifies and integrates socio-economic and demographic factors of landscape change. It consists of two-sub models i.e. urban growth simulation and a land cover simulation sub models that are integrated using utility function of spatial choice. According to Wang and Zhang (2001), the urban growth sub model simulates the urban land expansion driven by socio economic and demographic factors. The land-cover simulation sub model predicts landscape change as the result of urban spatial growth. Three levels of spatial units (section, compartment, and cell) achieve the spatiotemporal interaction between the two sub models. Dynamic transition thresholds and rates, spatial constraints, and socioeconomic/demographic driving factors control the simulation. The model output represents a dynamic series of landscape simulations. Wang and Zhang (2001) concluded that this simulation results are helpful in understanding the current and future landscape patterns and in management planning.

3.4.4 Integrated Models

Integrated models have become increasingly common in studying land use and land cover changes. These models combine two or more modeling techniques to provide insights into the interactions and relationships of complex land use systems (e.g. economic, social, environmental and so on) that cut across disciplines, therefore involve a more multidisciplinary team of researchers rather than individual single discipline researchers. Although all land use models, by definition integrate different disciplines, they are often still too much based on the concepts and methods of a certain discipline. Integrated models are sometimes referred to as *hybrid models*, which according to Lambin *et al.* (2000) they are better described as hybrid models because the level of integration is not always high.

Walz *et al.* (2007) in their study of changes in agriculture concluded that they had too high expectations of the integrated models. Integrated numerical modelling was applied to study changes in agriculture for the Alpine region of Davos in Switzerland. The models integrated in this study were an Input-Output Model, a Resource Model, a Land Use Allocation Model and Ecosystem Service Validation. Walz *et al.* (2007) observed that even though the systematic exchange of data between the models could be realised and the models could be applied for the same scenarios, the explanatory power of their integration was not as high as they initially expected. They went on further to give a probable reason for this, stating that, it might be due to the unclear definition of the end-users of the models and the initially un-realistically high expectations in the integration and operationalisation of the numeric modelling (Walz *et al.*, 2007).

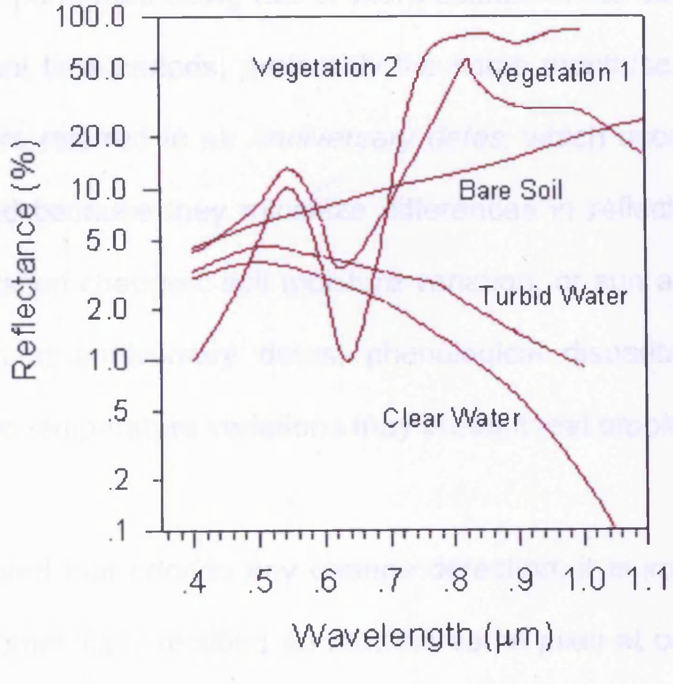
It should be pointed out that the models discussed above do not embody all of the models that have been applied or employed in studying land use and land cover changes. They are merely a representation of some of the more commonly used models. Modeling land use and land cover change study is vibrant, experiencing new model developments. As observed from the above modeling techniques, each model has its own potential and limitations. There is no model that can be regarded as the optimum or the worst, as this is dependent on the purpose of the model, the research question, the spatial scale (or level) and data. Briassoulis (2000) concluded that, it is suggested that a successful model is one that matches satisfactorily purpose, theory, specification, available data and other resources (such as know-how, expertise, money, time, effort). Although, Weng (2002) pointed out that, only a few models have been developed to address how and why the land changes, but remote sensing and GIS based change detection studies have predominantly focused on providing the knowledge of how much, where, what type of land use and land cover change has occurred.

3.5 Application of Remote Sensing to Land Cover Change Study

Globally, over the past centuries, land cover and land use is undergoing rapid changes that need to be monitored. As stated earlier in this chapter, numerous human activities and natural processes are the source of these changes. Even though these changes in some regions may have their advantages to man and their surrounding environment, they create negative impacts on the earth system. These are important to decision and policy makers. According to Anderson (1977), accurate information on land use changes is essential to proper planning management and regulation of the use of land resources at local, regional and administrative levels. It is essential that the decision-makers and planners understand how the processes of land use and land cover change transpire, in order to make better (land use) decisions. Campbell (2002) supporting this stated that, almost all governmental units have a continuing requirement to form and implement laws and policies that directly or indirectly involve existing or future land use.

Remote sensing provides the most efficient and feasible approach to monitor and detect land use and land cover changes. It also provides a viable source of data from which updated land cover information can be extracted efficiently and cheaply in order to inventory and monitor these changes effectively (Mas, 1999), using satellite data (i.e. images). Although, the formal study of land use and land cover dates from the early 1800's, aerial photography and remote sensing were not routinely applied until the 1960's (Campbell, 2002). Rogan and Chen (2003) pointed out that even though coarse-spatial resolution meteorological satellite data have been available since the 1960s, civilian remote sensing at medium spatial resolutions (i.e. <250m) only began in 1972 with the launch of Landsat, the first of a series of Earth Resources Satellite The individual Earth-surface cover types are distinguishable in terms of their spectral reflection characteristics, and changes in the spectral response of objects can also be used as an indication of changes in the properties of the object (Mather, 1999). Figure 3.2 shows the typical reflectance spectra of five materials (or land cover): clear water, turbid water, bare soil and two types of vegetation.

Figure 3.2 Reflectance spectrum of five types of land cover



Source: Crisp, 2001

A major application of remotely sensed data is *change detection* because of repetitive coverage at short intervals and consistent image quality. The basic premise for this, is that changes in land cover result in changes in radiance values and changes in radiance due to land cover change are large with respect to radiance changes caused by other factors such as differences in atmospheric conditions, differences in soils moisture and differences in sun angles (Mas, 1999).

3.5.1 Review of Change Detection Techniques

Singh (1989) defined change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. This process can be performed using two or more scenes of the same geographical areas at different time periods, preferably the same month/season of different years. These are referred to as *Anniversary dates,* which according to Jensen (1986) are used because they minimize differences in reflectance caused by seasonal vegetation changes, soil moisture variation, or sun angle differences. However, even at anniversary dates, phenological disparities due to local precipitation and temperature variations may present real problems.

It should be noted that prior to any change detection, it is imperative that the imagery be geometrically rectified so that the same pixel at one date overlaps the same pixel for the other date (Townshend *et al.*, 1992 cited in Macleod and Congalton, 1998). Lu *et al.* (2004) recommended that before implementing change detection analysis, the following conditions must be satisfied:

1) Precise registration of multi-temporal images;
2) Precise radiometric and atmospheric calibration or normalization between multi-temporal images;
3) Similar phenological states between multi-temporal images; and
4) Selection of the same spatial and spectral resolution images if possible.

The majority of change detection methods depend critically, upon the accuracy of geometric registration (Singh, 1989); because largely spurious results of change detection will be produced if there is misregistration between multi-date images (Lu *et al.*, 2005). *Geometric rectification*, (also known as geometric correction, georeferencing or image rectification) is the process of image adjustment to a pre-established coordinate system (Lillesand and Kiefer 2000); it basically transforms the image coordinate system to a specific map projection. Geometric rectification reassigns coordinates to pixels. Another crucial process to be carried out before change detection is *registration,* which is the process of making an image conform to another image. This is done because, to be able to compare separate images pixel by pixel, the pixel grids of each image must conform to the other images being used (ERDAS, 2003). In most change detection studies, a model called the affine transformation is usually used to co-register two or more images (Verbyla and Boles, 2000).

Change detection has been widely applied in land use and land cover change studies (e.g. Bryne *et al.* 1980, Salem *et al.* 1995, Fung 1992, Dai and Khorram 1999, Zhan *et al.* 2000, Lunetta *et al.* 2002, Lu *et al.* 2005). It has also been used in other nature of studies such as - Urban change (Ward *et al.* 2000, Liu and Lathrop 2002); vegetation change and deforestation (Alwashe and Bokhari 1993, Varjo and Folving 1997, Chavez and Mackinnon 1994); Coastal change (Yang and Liu 2005, Michalek *et al.* 1993); Cultivation monitoring (Dwivedi and Sankar 1991, Manavalan *et al.* 1995) and many other applications. There are numerous change detection techniques that have been employed and developed in various studies (such as the ones outlined above). Only some of these techniques will be reviewed in this chapter and they are – *Image differencing, Principal Components Analysis, Post-Classification Comparison* and *Change Vector Analysis* (please see Singh, 1989, Jensen 1996, Lu *et al.* 2004, for extensive reviews of change detection techniques).

3.5.1.1 Image Differencing

This is one of the quickest, simplest and common change detection techniques, according to Lu *et al.* (2005); it is easy to interpret the resultant image using this method. *Image Differencing* involves the subtraction of one image from another, taken of the same area at different dates. These subtraction results in positive and negative values in area of radiance change and zero values in areas of no change in a new 'change image' (Jensen *et al.*, 1997). This can be expressed mathematically as;

$$\Delta x^k_{ij} = x^k_{ij}(t_2) - x^k_{ij}(t_1) + c \qquad (3.7)$$

where, k is a band (single), i is line number, j is the pixel/column number, x^k_{ij} is the pixel value, t_1 is the first date, t_2 is the second date and c is a constant (Jensen, 1986 and Singh, 1989).

The basic assumption is that these areas of no change should have similar digital values so that they become pixels of zero value after differencing (Fung and Zhang, 1989), as the images are compared on a pixel-by-pixel basis. In image differencing, a threshold level must be selected to separate those pixels that have experienced change from those that have not changed land cover, but may exhibit small spectral variations caused by other factors (Campbell, 1996; 2002). Supporting this statement, Estes *et al.* (1982), Jensen (1986) Singh (1989) pointed out that this is a critical element of image differencing. The threshold level can be selected by experimenting (trial and error), Lu *et al.* (2005) provided two methods that can be used to determine these thresholds – the first method is to select appropriate thresholds in the lower and upper tails of the histogram distribution of the resultant image, representing changed pixel values, based on trial-and-error procedure. The second method is to use the standard deviation from the mean and test if empirically. Macleod and Conglaton (1998) using the latter method; they selected a series of threshold values based on standard deviations from the mean, then to determine the optimum threshold value (i.e. with the highest accuracy), an accuracy assessment was performed on the no-change/change pixels. Conversely, Teng *et al.* (2007) stated that accuracy cannot be evaluated with a level of significance, as the threshold value is determined using numbers of all pixels in the difference image.

Boone *et al.* (2007) used image differencing to detect land cover changes in eight pastoral areas in US, Africa and Mongolia. The images were subtracted from each other band-by-band (i.e. the 2000 green subtracted from 1990 green) and highlighted areas of potential change based upon the standard deviation of the data (threshold values). In this study, they assigned scores 60, 30, and 0 to areas 1.6, 1.96, and 2.3 times the standard deviation below the mean, and 195, 225, and 255 to areas the same deviation above the mean, for instance 128 was assigned to areas that fall within 1.6 standard deviation of the mean.

Volcani *et al.* (2005) used Normalized Difference Vegetation Indices (NDVI) image differencing technique to assess seasonal and inter-annual variations in vegetation in Yatir forest (located on the edge of the Negev Desert in Israel). The NDVI is calculated by

$$NDVI = (NIR - RED) / (NIR + RED) \tag{3.8}$$

where, NIR is the near-infrared band response for a given pixel and *RED* is the red response (Mas, 1999). In this study, a threshold value was derived from the image as one standard deviation (S.D.) from the ΔNDVI mean in cases where the mean was between −0.1 and +0.1. Otherwise, when the mean was either smaller −0.1 or greater than +0.1, ΔNDVI was set to 0 as the reference point. Volcani *et al.* (2005) concluded that this method has proven to be a useful and accurate method for tracing physiological changes in the Yatir forest, which serves as a case study for a manmade forest in the desert fringe.

Image differencing technique has its limitations. Jensen (1982) concluded that it is not effective in detecting all types of change. This technique may not be the most appropriate where the objective is not to classify the specific land covers which change, but rather to quantify the amount and direction of major change (Young and Wang 2001).

3.5.1.2 Post-Classification Comparison

Post-classification comparison identifies change by comparing two or more independently generated classified images, pixel by pixel. Because post-classification comparison permits compilation of a matrix of *'from-to changes'*, it provides more useful results than some other methods (e.g. image differencing that simply identifies pixels that have changed, without specifying the classes involved) (Campbell, 1996; 2002). This technique identifies the nature and quantity of change. According to Singh (1989), post-classification comparison holds promise because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates.

It is imperative that the separate classifications carried out on the images be accurate, because any classification errors will show in the post-classified image and yield incorrect land use and land cover changes in the image. As

Campbell (2002) stated that accurate classification would portray true differences in land use rather than differences in classification accuracy. For instance, Sohl (1999), in a study of change analysis in the United Arab Emirates using post-classification comparison, concluded that due to classification errors in the individually classified images, the generated change image over-represented some types of change. For example, shaded areas were misclassified as agriculture in one of the images because of the similar spectral signatures between the shaded sand areas and agricultural areas without crop cover.

Another example of the use of the post-classification comparison approach is the work of Nichol and Wong (2005) in which SPOT XS images acquired in 1991 and 1995 were used to identify landslides using the above said technique. Post-classification comparison technique was applied using Maximum Likelihood Classifier (MLC) that was able to detect approximately 70% of landslides, with the main omissions being smaller than approximately half a pixel wide. All significant land cover types in the images were classified, including shadow, because it was a significant component of the images due to the steepness of terrain combined with the low Sun angle in winter. Nichol and Wong (2005) including shadow as a class reduced the classification confusion between these areas and forest and water, which had similar spectral characteristics.

In a study of land use and land cover changes of Nairobi, carried out by Mundia and Aniya (2005), post-classification comparison technique was adopted with GIS approaches with demographic and socio-economic data. This technique was chosen based on the available data for the study was acquired in different seasons by different sensors with different spatial resolutions (Landsat MSS, TM and ETM+). Using this technique, they discovered that the urban/built up areas that covered 15km^2 in 1976, increased to 41km^2 in 1988 and increased further by the year 2000 to 62km^2. In addition, they also could quantify the land use and land cover changes in forests, agricultural areas and rangelands.

3.5.1.3 Change Vector Analysis

Change Vector Analysis is a conceptual extension of image differencing (Lu *et al.*, 2004). The vector describing the direction and magnitude of change from the first to the second date is a *spectral change vector* (Singh, 1989). Change vector analysis uses any number of spectral bands from satellite data at different points in time (whether original scaled radiance, calibrated radiance or transformed variables) to produce images that yield information concerning both the magnitude and direction of changes contained in the pixel values (Michalek *et al.*, 1993 cited in Phua *et al.*, in press). The total change magnitude per pixel is computed by determining the Euclidean distance between end points through n-dimensional change space (Lu *et al.*, 2005). A major advantage is its capability to analyze change concurrently in all data layers as opposed to selected bands (Coppin *et al.*, 2004). For a more detailed description of this technique please see Johnson and Kasischke (1998).

A study by Phua *et al.* (in press) examined a spectral change approach to detect deforestation (in Kinabalu Park, Sabah, Malaysia); using pattern decomposition (PD) coefficients from multi-temporal Landsat data by using change vector analysis and image differencing. They calculated the change magnitude between t_1 and t_2 using the soil (C_s) and vegetation (C_v) coefficients of Pattern decomposition method (PDM), as:

$$d_{ij} = \sqrt{[C_s(t2) - C_s(t1)]^2 + [C_v(t2) - C_v(t1)]^2}, \quad (3.9)$$

where, d_{ij} is the Euclidean distance of pixel at row i and column j. They made use of change vector analysis applied over two periods: period 1 (1973–1991) and period 2 (1991–1996), where they focused on deriving the change magnitude by calculating the change angle classes related solely to clearing to explain deforestation in Kinabalu park. Using change vector analysis, they discovered that deforestation had significantly slowed from 1.2% in period 1 to 0.1% in period 2. The results derived showed that the accuracy resulting from the application of this technique (change vector analysis) was significantly higher than that resulting from image differencing with a single PD coefficient.

There are drawbacks of applying this method of change detection, as noted by Johnson and Kasischke (1998), who pointed out that the general limitation of change vector analysis for change labelling is that a change vector contains only dynamic information, and not state (categorical) information (i.e., it does not represent absolute position in spectral space on either date). It is difficult to identify land cover change trajectories (Lu *et al.*, 2004).

3.5.1.4 Principal Components Analysis

Principal component analysis has been extensively used for change detection analysis. Utilization of this change detection technique dates back to 1979 (Lodwick, 1979 cited in Cakir, 2006). Muchoney and Haack (1994) defined *Principal Components Analysis* as a multivariate statistical technique where data axes are rotated into principal axes (or components) that maximize data. Basically, it reduces the dimensionality and volume of the image without reducing or compromising its information content. It is sometimes also known as the *Karhunen- Loève transform.* Mather (1999) suggested that if a data set is compressed, it might prove to be useful. He went on further to say that, relationships between different groups of pixels representing different land cover types might become clearer if they are viewed in the principal axis reference system rather than in terms of the original spectral bands. Principal components analysis identifies the optimum linear combinations of the original channels that can account for variation of pixel values in an image. These linear combinations are expressed as –

$$A = C_1X_1 + C_2X_2 + C_3X_3 + C_4X_4 \qquad (3.10)$$

where, A represents a transformed value for the pixel, X_1, X_2, X_3 and X_4 are pixel values in four spectral channels and C_1, C_2, C_3 and C_4 are coefficients applied individually to the values in the respective channels (Campbell, 2002). The transformed variables (A) are known as *principal components,* which according to Singh (1989) are usually calculated from a variance-covariance matrix, in the form of *eigenvectors* and *eigenvalues*.

Eigenvector is simply multiplied by a constant called the eigenvalue during a transformation. These describe the lengths and directions of the principal axes. The amount of variance that represents each band of an image is provided by the eigenvalue of the corresponding eigenvector. Although Lark (1995 cited in Ceballos and Bottino 1997) noted that an eigenvalue does not necessarily assess the contribution of that PC to the variance of a given variable, but of the *whole system* of variables; therefore, high-eigenvalued components could fail to be retained as proper variables.

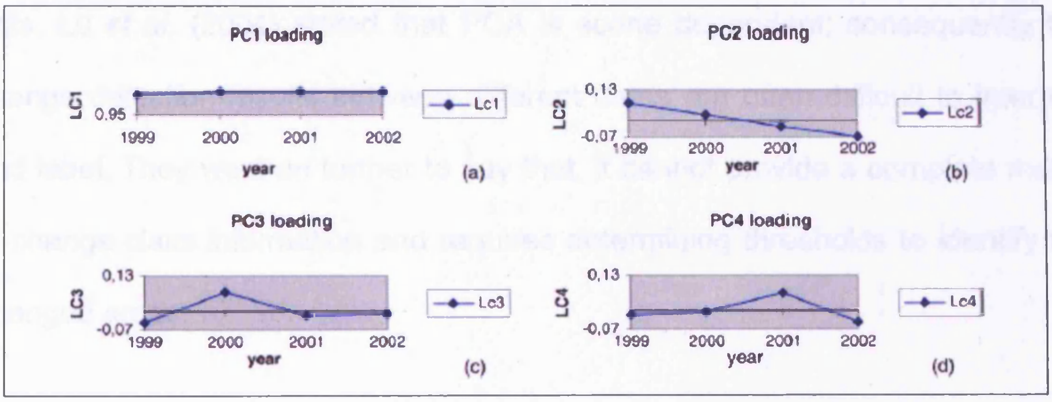
In principal components analysis, the first component (PC1) accounts for majority of the information (i.e. total variance). The first two PCs often contain unchanged information while higher PCs often contain change information (Lu *et al.*, 2005). On the other hand, an earlier study by Lowitz (1978 cited in Mather 1999), shows that high-order components can contain information relating to inter-group differentiation (for example land use and land cover change). Sedano (2005) stated that PCA allows storing most of the change information on the third principal component image (PC3).

In a study by Cifaldi *et al.* (2004) the first five components (PC1 – PC5) together explained approximately 80% of the variation for the Huron and Raisin basins combined and individually. They used PCA to identify major gradients of variation in land cover pattern for three different geographical extents. They reported that out of the five retained components, PC1 and PC2 best separated the sub-catchments by their respective basins and were strong descriptors of land use and land cover patterns for both an agricultural landscape and a suburbanizing landscape. The five principal components captured the principal gradients in land use/cover patterns. PC1 can be summarized as a fragmentation gradient ranging from landscapes dominated by a single land use and land cover type, generally with large patches of agriculture, to more diverse, patchy landscapes. PC2 summarizes patch size variation within a landscape. PC3 summarizes a patch interspersion gradient. The fourth component summarizes spatial patterns in urban land cover and the fifth component summarizes wetland patch size.

Singh (1989) stated that PCA is usually performed using unstandardized variables (variance – covariance matrix, as elucidated above). Although, according to Young and Wang (2001), PCA can use either unstandardized components or variables where the bands with higher variability contribute more to the new principal components images, or standardized components where every original band has equal weight in the creation of the new principal components bands (Singh and Harrison 1985, Eastman and Fulk 1993). Guirguis *et al.* (1996) compared standardized and unstandardized principal components and they concluded that that the standardized PCs are more capable of identifying occurring changes. In a study of land cover changes in the Kitchener-Waterloo-Guleph area, Fung and LeDrew (1987) observed that standardized principal components were more accurate than the unstandardized principal components. Eastman and Fulk (1993) also established that a standardized principal component was more accurate and reliable than the unstandardized principal components.

Lasaponara (2006) also used PCA to evaluate vegetation inter-annual anomalies in the Sicily Island using a temporal series (1999–2002) of the yearly Maximum Value Composite of SPOT/VEGETATION NDVI. In this study, the loading obtained for PC1 (figure 3.3a) accounted for 99.35% of the total variance, which corresponded to areas showing maximum integrated vegetation density levels, PC2 (figure 3.3b) corresponded with areas affected by a decline of vegetation and accounted for 0.30% of the total variance. PC3 and PC4 accounted for 0.19% and 0.16% respectively; both PC loadings show a crossover between negative and positive for 2000 (for PC3) and 2001 (for PC4), these can be related to particular climatic conditions, which Lasaponara (2006) concluded that, this suggests that a widespread climatic anomaly is isolated into a particular component as has been shown by the ability of PC3 and PC4 to capture the contrast between certain years.

Figure 3.3 PC1 – PC4 loadings



Source: Lasaponara (2006)

In He *et al.* (2006) PCA was used to quantitatively study driving forces of landscape changes. The PCA results showed that economic and population factors were the principal driving forces of landscape changes from 1974 to 1995 in the upper Minjiang River basin, and that PCA was a suitable method for investigating driving forces of landscape changes. Mas (1999) used six change detection techniques including *Selective Principal components Analysis (SPCA)*, which uses only two bands of the image instead of all the bands. Selective standardized PCAs were applied to bands 2 and 4 (Landsat MSS). SPCA offered better accuracy than the image differencing procedure that was also applied in this study. Mas (1999) reckon that SPCA removed inter-images variability due to the sensor and to atmospheric conditions that still remained after radiometric normalization.

PCA is a complex change detection technique, as the results are difficult to interpret and most of all it entails the researcher/ user to be familiar with the spectral features of land use and land cover classes. Toll *et al.* (1980) concluded that when they applied this technique to study urban change, it produced poor results in comparison to simple image differencing of band 5 or 7 data. Lu *et al.* (2004) stated that PCA is scene dependent; consequently the change detection results between different dates are often difficult to interpret and label. They went on further to say that, it cannot provide a complete matrix of change class information and requires determining thresholds to identify the changed areas.

As stated earlier, although there are number of change detection techniques, only the main techniques which are widely used have been discussed above. Moreover, new techniques are continually being developed. Each change detection technique has its advantages and disadvantages as made unknown above, but there is no technique that can be regarded as the optimum change detection technique and it dependent on the research and the main objective of the research. As Lu *et al.* (2004) point out that, the technique selected depends on an analyst's knowledge of the change detection methods and the skill in handling remote sensing data, the image data used, and characteristics of the study area. Previous studies have suggested that in order to achieve better results, two or more of the change detection techniques should be used together (Lu *et al.*; Zhang *et al.* 2002) There is a high complementarity between different change detection methods (Coppin *et al.*, 2004). The comparative performance of various techniques in different environments must be evaluated quantitatively; otherwise those interested in monitoring changes in a specific environment may not achieve optimal results because of lack of knowledge about tried and tested procedures of change detection (Singh, 1989).

CHAPTER 4 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: DATA

CHAPTER 4

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: DATA

4.1 Introduction

A broad range of data is required in land cover research projects, which provide means to assess and study the impacts and drivers of change, they also provide model inputs. This includes climate data, demographic data, agricultural data, timber and non-timber product prices, and field data. But regrettably, the study of environmental change is constrained by the poor quantity and quality of available data (Grainger, 2003). Even with technological advances such as computers and GPS, that have made data collection and many kinds of collation easier, Nigeria is still somewhat lacking in its national statistics. Moreover, even where data do exist, the government and its officials limit and restrict its availability to the public due to factors such as corruption.

In this chapter, I am going to describe and discuss the statistical data and satellite images used in this study as well as the generation of land use/cover maps. Section 4.2 discusses demographic data from different sources and critically evaluates them. In section 4.3, the natural resource (primary sector) economic data are outlined with specific reference to forest and agricultural products. Section 4.4 describes the definition of the different types of land use found Edo and Delta states. It also focuses on the remote sensing aspect of this research, outlining the satellite images used and the pre and post processing steps performed. Section 4.5, briefly outlines the ancillary data that were utilized and Section 4.6 discusses the field data and the data collection procedures.

4.2 Demographic Data

Demographic data play an important role in land cover change and a major role in understanding human interactions with the environment. These data indicate the changing location of human occupation of the landscape. This can provide valuable information on land use and land cover, since a variety of functions associated with population distribution can be used to infer certain land uses (Aspinall, 2004).

Globally, where there is an increase in population, there is a decline in natural resources, thereby encouraging people to move on to occupy and utilise new lands. Kok (2004) concluded that 'land use pattern could be described with very simple relationships, with a strong contribution to population density.'

Nigeria has the largest national population on the African continent with an estimated population of about 120 million. Nigeria is now considered to be an overpopulated country. Overpopulated countries have similar characteristics such as high population growth rate due to a wide disparity between two population parameters such as fertility and mortality (Adebile, 2001). Due to the alarming population growth rate, the Nigerian government decided to create a National Population Policy in February 1988, in order to curb the overpopulation. The main objective was to enforce family planning, and limit the female population to giving birth to only 4 children. Unfortunately, this policy was met with a lot of animosity and anger, and people protested that it was discriminatory against women. Furthermore, the Catholic Bishops Conference in Nigeria in late 1988 said that the policy encroaches on the rights of parents, victimizes women, encourages polygamy and could give rise to panic (Osuide, 1988). Odaman (1992) commented that that since the announcement of the policy, the print media did a good job to enlighten the citizens although the electronic media, in turn, highlighted it.'

In a developing country like Nigeria, there has been and still is uncertainty in the demographic data due to the data being over-estimated or even under-estimated as occurred in the 1952-1953 census. According to Cohen and Goldman (1992), this was due to various reasons, such as fear that the census was associated with tax collection, political tension at the time in eastern Nigeria, logistical difficulties and inadequate training of enumerators. An example is the 1973 census that was cancelled due to over-counting. This was due to political reasons and state budget allocation, as the population figures are used to allocate state funds; 'to get more of the usually tiny national cake, ethnic groups or competing regions usually inflate their numbers by including dead people, goats and sheep in the count.' (Onwudiwe, 1994)

Another census was carried out, by the National Population Commission of Nigeria (NPC), in 1991, (which will be referred to as the base census from this point), with a national population of 88.92 million. 'Conversely, the national government removed population as a basis for calculating regional resource distribution and invited demographic experts from the United States, the United Kingdom and the United Nations to assist in the proper recounting of Nigerians' (Onwudiwe, 1994). The passion for doctored figures is stronger now than before because the higher a state is in population, the more revenue allocation it receives from the Federal Government (Mbeke-Ekanem, 2006). In saying this, the 2006 population figure is what most international organizations and even other countries are dependent on, to make population projections and estimates and will also be used in this research as the base population figure.

The results of the most recent census, in 2006, were released by the National Population Commission (NPC) on the 29th of December 2006. The 2006 census put the population of Edo and Delta states at 3,218,332 and 4,098,391 respectively. Unfortunately, as with previous census counts, the 2006 census has been met with a lot of opposition by rejecting the figures. One of those people who contested the census was Bola Tinubu (governor of Lagos state). He called for a recount and stated that the figures were false. "Explaining his objection to the census results, Tinubu claimed that a parallel census conducted by Lagos in collaboration with the National Population Commission put the state's population at more than 17.5 million, not 9.0 million, as the 2006 census suggested" (Yin, 2007). Many believed the census figures were doctored in order to help with the rigging of the 2007 coming elections. Despite all of the disagreement with the census figures, it remains as it is. The 2006 census will be used as a reference to the projected population estimates.

In addition to the Nigerian government data, I also used data from external sources such as International organizations e.g. The International Data Base (IDB), United Nations and 'statistic aficionados' in this research. As Nelson and Geoghegan (2002) pointed out in developing countries, analysis of land use determinants however, is especially constrained by lack of data. One does not typically find detailed crop or forest surveys, government statistical agencies are often under funded and data collection for agricultural and natural resource statistics can be sporadic. Unfortunately, Nigeria is not an exception to this and where these data were available there were issues with the quality.

Whenever population data were missing population estimates were calculated by inter- and extrapolation using growth rates. The calculations of the estimates here and other data sources are based on the simple exponential population growth model by Malthus (1798). This model assumes that the increase in population is proportional to the current population, P, with a growth rate, *r:*

$$dP/dt = r P \qquad (4.1)$$

Obviously, *P*, *r*, and *dP/dt* change with time and one writes *P (t)*, *r (t)*, and *dp/dt (t)* if one wants to stress the time dependence.

Eqn (4.1) Implies that

$$P(t)=P_0 \exp(r(t-t_0)) \qquad t>t_0,\ P(t_0)=P_0 \qquad (4.2)$$

given P_0, the population at some time t_0, and assuming a constant growth rate. (4.1) is approximated by

$$\Delta P/\Delta t = r\,P \qquad (4.3)$$

with a time period Δt and ΔP the change of the population during that time period. Using annual population figures and a time unit of one year this leads to;

$$P_n-P_{n-1} \approx r_n\,P_n$$

Thus $$P_{n-1} \approx (1-r_n)\,P_n \qquad (4.4)$$

And $$P_{n+1}-P_n \approx r_n\,P_n$$

Thus $$P_{n+1} \approx (1+r_n)\,P_n \qquad (4.5)$$

where P_j and r_j are the population and the growth rate in year j respectively. (4.4) and (4.5) can be used to inter- and extrapolate data forward and backward.

The growth rate, r, can be calculated from (4.2) using the change of the population over a period of years:

$$P(t+n)=P(t) \exp(r\,n)$$

Thus $$r = ln\,[P\,(t+n)\,/\,P\,(t)]\,/\,n \qquad (4.6)$$

assuming that, $P\,(t)$ is the population at time t, and the population $P\,(t+n)$, n years later; r is then an average annual growth rate and again units of time as one year.

4.2.1 State/Regional Demographic Data

The State(s) demographic data is an important input for modelling land cover change in Edo and Delta states. Population data indicate how population density has increased or decreased across Edo and Delta states which will have an effect on the surrounding land and its resources. Population growth is used as a driver to model land cover change.

A new set of population figures were acquired, using various national growth rates published by a number of authorities and individuals such as International Data Base population, United Nations, State Statistical Yearbook etc. The National population growth rates have changed over the years and are dependent on various factors such as migration, death & birth rates, as noted by these authorities. A number of population data and their sources were explored in order to obtain consistent and realistic population data and projection. The first set of population data was obtained from '*Edo and Delta States Statistical Yearbook*' (1998), which is a compilation of various statistical data including population and population growth in Edo and Delta states.

The estimated national population growth rate is 3.1% according to the statistical yearbook, both at state and local government level. Using this growth rate, the population estimates were calculated backwards & forwards using the equations 4.1 – 4.6. This simplistic method for deriving population numbers cannot reflect a realistic population growth, as growth rates vary over a period due to the factors stated earlier on and so using a constant growth rate will produce idealistic population figures. Moreover, realistically, growth rates vary from state to state and even between local government areas (LGA).

Edo Agricultural Development Project, a government agricultural organization, stated 4.2% as being the annual population growth rate, which poses the same problem as the 3.1% growth rate. Both growth rates are unrealistic as they repudiated the fact that population will not increase at the same growth rate every year. On the other hand, it cannot be ignored that the figures derived were collated and calculated by the Nigerian National Population Commission itself, who also produced the 1991 census, on which international organizations and individuals base their own estimates.

The *International Data Base* was another source used to obtain growth rates and estimates. According to the Global Population Profile (2002 report), the International Data Base (IDB), is a computerized data bank containing information derived from censuses, surveys, and administrative records (for example, registered births and deaths) for selected years from 1950 to the present and projected population figures. The International Programs Centre (IPC), who collates and investigates the statistical information, derived from all countries and even in some cases international organizations, created the IDB. Some of the major sources of the data include international organizations such as, United Nations, UNESCO & World Health Organization.

Table 4.1 IDB population growth rate estimates

PERIOD	GROWTH RATE (%)
1950 - 1960	2.3
1960-1970	2.5
1970-1980	3.0
1980-1990	2.6
1990-2000	2.6
2000-2010	2.4
2010 – 2020	2.4
2020 – 2030	2.3
2030 – 2040	2.2
2040 – 2050	2.1

Source: http://www.census.gov/cgi-bin/ipc/idbsum?cty=NI

The IDB growth rates were calculated by the IPC using a base population that is based on census data. The IPC assesses the population data for inaccuracies before they are accepted as a base for projection. Patricia Dickerson from the Population Division of the U. S. Census Bureau stated that they use formula in equation 4.6 to derive population growth rates, which was then used to calculate the growth rates for each period starting from 1950 – 2050.

The *United Nations Human Settlements Programme* population growth rate estimates were examined. The UN-Habitat collects population data for different geographic units, collates, analyses and reports at national, rural and urban level, to monitor human settlement conditions and trends. The population growth rate estimates used were taken from the Human Settlements Statistical Database version 4 (HSDB4-99). 'The database contains data from population and housing censuses including the most recent "1990 census round", collected through the Human Settlements Statistics Questionnaire 1992 (HSSQ)'. (http://www.unhabitat.org, 2003). The data provided are based on the member countries, and they commence from the 1970's. The Human Settlements Statistical Database was assembled by gathering statistical data from statistical publications (such as United Nations, World Bank and World Health Organization) and national censuses.

According to the *World Bank the* annual population growth rate dropped from 2.7% in 1980 to 2.1% in 2002. The "World Bank" is the name that has come to be assigned to five associated international organizations that make up the World Bank Group and these are: the International Bank for Reconstruction and Development (IBRD), the International Development Association (IDA), the International Finance Corporation (IFC), the Multilateral Investment Guarantee Agency (MIGA) and the International Centre for Settlement of Investment Disputes (ICSID).

The World Development Indicators database population growth rates, which cover 208 countries and 18 country groups reported on in the World Development Indicators book, were based on either current census data or historical census data extrapolated through certain demographic models. These rates were derived from interpolations and extrapolations based on demographic models. Rates of population change are calculated as proportional changes from the earlier period.

Three principal methods were used to calculate growth rates: least squares, exponential growth rate (equation 4.6), and geometric endpoint. Least-squares growth rates are made use of wherever there is a satisfactorily long time series to permit a reliable calculation (The World Bank Group, 2004). The least-squares growth rate, *r,* is estimated by fitting a linear regression trend line to the logarithmic annual values of the variable in the relevant period. The calculated growth rate is an average rate that is representative of the available observations over the entire period. It does not necessarily match the actual growth rate between any two periods (The World Bank Group, 2004).

The second method, the Exponential growth rate, is based on the exponential growth model. This is the growth rate between two points in time for certain demographic indicators (e.g. Labour force and population), which is given by equation 4.6. The geometric growth rate is applicable to composite growth over distinct periods. It is synonymous with constant proportional growth. The average growth rate over *n* periods is calculated as:

$$r = \exp((\ln(p_n/p_1))/n) - 1 \qquad (4.7)$$

In tables 4.2 and 4.3, the only reliable census figures are based on the 1991 population census (highlighted). As previously pointed out, this was the only census carried out after the 1963 census and unfortunately no other census exercise has been carried out since.

On evaluating the population estimates and growth rates from the diverse data sources; the Statistical Yearbook data was the preferred choice of population estimates to be employed in the model as data input. The main rationale for this is the fact that the data was collated and analysed by Nigeria. Regardless of the questionable reliability of the data, I thought it was a good choice as most international organizations and agencies have previously used census figures collated by the Nigerian National Population Commission. Prof (Dr.) Dennis O. Balogu, a professor of International Agriculture and International Affairs Officer at the University of Arkansas, Pine Bluff, Arkansas, stated that, "If Nigeria would become bold in conducting a census that will provide the desired data; we would have accomplished one of the instruments of Nigerian stability. But if it quivers, then we would have left foreign countries' intelligent agencies to estimate and create destabilizing statistical (population) data for Nigeria." (Orabuchi, 2005)

Comparing the Statistical Yearbook data projected population data, in Edo state the projected population for 2006 in Edo state is 3,433,530 and Delta state is 4,012,058, to the actual 2006 census, which for both states are 3,218,332 and 4,098,391 respectively. In Edo state, there is a colossal gap between the projected and actual unlike in Delta state. This might be due to the reason that, a constant growth rate was used for both states. Looking at the 1991 and 2006 actual census figures, the growth rate from 1991 to 2006 for Edo state is 3.2% and Delta state is 3.9%, which is higher than the national average of 3.2%.

Table 4.2 Edo State population and growth rate estimates

YEAR	STATS STATE YR BOOK	GR (%)	IDB	GR (%)	UN	GR (%)	WORLD BANK	GR (%)
1980	1536110	3.1	1587606	2.6	1581083	2.9	1630589	2.7
1981	1585253	3.1	1633339	2.6	1628303	2.9	1675837	2.7
1982	1635968	3.1	1680390	2.6	1676935	2.9	1722340	2.7
1983	1688306	3.1	1728797	2.6	1727018	2.9	1770133	2.7
1984	1742317	3.1	1778597	2.6	1778597	2.9	1819253	2.5
1985	1798057	3.1	1829833	2.6	1831717	2.8	1865901	2.5
1986	1855580	3.1	1882544	2.6	1884483	2.8	1913744	2.5
1987	1914943	3.1	1936774	2.6	1938768	2.8	1962815	2.5
1988	1976206	3.1	1992565	2.6	1994617	2.8	2013143	2.5
1989	2039428	3.1	2049964	2.6	2052076	2.8	2064762	2.5
1990	2104673	3.1	2109017	2.6	2111189	2.8	2117705	2.5
1991	**2172005**	**3.1**	**2172005**	**2.6**	**2172005**	**2.6**	**2172005**	**2.5**
1992	2239337	3.1	2234993	2.6	2228477	2.6	2226305	2.5
1993	2308757	3.1	2299808	2.6	2286418	2.6	2281963	2.5
1994	2380328	3.1	2366502	2.6	2345864	2.6	2339012	2.5
1995	2454118	3.1	2435131	2.6	2406857	2.6	2397487	2.5
1996	2530196	3.1	2505750	2.6	2464621	2.4	2457424	2.5

YEAR	STATS STATE YR BOOK	GR (%)	IDB	GR (%)	UN	GR (%)	WORLD BANK	GR (%)
1997	2608632	3.1	2578416	2.6	2523772	2.4	2518860	2.5
1998	2689500	3.1	2653191	2.6	2584343	2.4	2581831	2.5
1999	2772874	3.1	2730133	2.6	2646367	2.4	2646377	2.5
2000	2858833	3.1	2795656	2.4	2709880	2.4	2712537	2.5
2001	2947457	3.1	2862752	2.4	2769497	2.2	2780350	2.2
2002	3038828	3.1	2931458	2.4	2830426	2.2	2838737	2.1
2003	3133032	3.1	3001813	2.4	2892696	2.2	2898351	2.1
2004	3230156	3.1	3073857	2.4	2956335	2.2	2959216	2.1
2005	3330291	3.1	3147629	2.4	3021374	2.2	3021360	2.1
2006	3433530	3.1	3223172	2.4	3081802	2.2	3084808	2.1
2007	3539969	3.1	3300528	2.4	3143438	2.2	3149589	2.1
2008	3649708	3.1	3379741	2.4	3206307	2.2	3215731	2.1
2009	3762849	3.1	3460855	2.4	3270433	2.2	3283261	2.1
2010	3879497	3.1	3543915	2.4	3335841	2.2	3352210	2.1

(contd)

Table 4.3 Delta State population and growth rate estimates

YEAR	STATS STATE YR BOOK	GR (%)	IDB	GR (%)	UN	GR (%)	WORLD BANK	GR (%)
1980	1832077	3.1	1938789	2.6	1885714	2.9	1944759	2.7
1981	1890688	3.1	1990543	2.6	1942033	2.9	1998724	2.7
1982	1951174	3.1	2043679	2.6	2000034	2.9	2054187	2.7
1983	2013596	3.1	2098233	2.6	2059767	2.9	2111190	2.7
1984	2078014	3.1	2154243	2.6	2121284	2.9	2169773	2.5
1985	2144494	3.1	2211749	2.6	2184639	2.8	2225409	2.5
1986	2213100	3.1	2270789	2.6	2247571	2.8	2282470	2.5
1987	2283901	3.1	2331406	2.6	2312316	2.8	2340995	2.5
1988	2356967	3.1	2393641	2.6	2378926	2.8	2401021	2.5
1989	2432370	3.1	2457537	2.6	2447454	2.8	2462586	2.5
1990	2510186	3.1	2523138	2.6	2517957	2.8	2525729	2.5
1991	**2590491**	**3.1**	**2590491**	**2.6**	**2590491**	**2.6**	**2590491**	**2.5**
1992	2670796	3.1	2657844	2.6	2657844	2.6	2655253	2.5
1993	2753591	3.1	2726948	2.6	2726948	2.6	2721635	2.5
1994	2838952	3.1	2797848	2.6	2797848	2.6	2789675	2.5
1995	2926960	3.1	2870592	2.6	2870592	2.6	2859417	2.5
1996	3017695	3.1	2945228	2.6	2939487	2.4	2930903	2.5

YEAR	STATS STATE YR BOOK	GR (%)	IDB	GR (%)	UN	GR (%)	WORLD BANK	GR (%)
1997	3111244	3.1	3021804	2.6	3010034	2.4	3004175	2.5
1998	3207693	3.1	3100371	2.6	3082275	2.4	3079280	2.5
1999	3307131	3.1	3180980	2.6	3156250	2.4	3156262	2.5
2000	3409652	3.1	3257324	2.4	3232000	2.4	3235168	2.5
2001	3515351	3.1	3335500	2.4	3303104	2.2	3306342	2.2
2002	3624327	3.1	3415552	2.4	3375772	2.2	3375775	2.1
2003	3736681	3.1	3497525	2.4	3450039	2.2	3446666	2.1
2004	3852519	3.1	3581465	2.4	3525940	2.2	3519046	2.1
2005	3971947	3.1	3667421	2.4	3603511	2.2	3592946	2.1
2006	4012058	3.1	3755439	2.4	3675581	2	3668398	2.1
2007	4131617	3.1	3845569	2.4	3749092	2	3745435	2.1
2008	4254739	3.1	3937863	2.4	3824074	2	3824089	2.1
2009	4381530	3.1	4032372	2.4	3900556	2	3904395	2.1
2010	4512100	3.1	4129148	2.4	3978567	2	3986387	2.1

(contd)

4.2.2 Urban Population Growth Rates

Most of Africa had been largely rural for most of its history, until the communities began experiencing profound and albeit brisk trend of their social and economic survival toward urbanism.

According to a study carried out by the Federal Research division of the Library of Congress (1991), the rise of the Yoruba, Benin and others in the south was stimulated by trade to the coast, and by competition among these growing urban centres for the control of their hinterlands and by the trade from the interior to the Atlantic (including the slave trade). Urban centres certainly play an important role in the economic and population growth of the area and its surrounding districts, such as Warri, Benin, Sapele etc.

In Nigeria, the certified population of an area in order to be classified as an urban center was 20,000 in 1963. But unfortunately with the creation of the new states in Nigeria (between 1967 and 1996), each Local Government Area (LGA) had a headquarter which was then declared to be an urban center by an administrative fiat. Meanwhile some rural settlements were elevated to urban status to fit their new designation, regardless of their population size or level of infrastructure development (Okali *et al.*, 2001).

The rapid growth of urbanization in Nigeria is due to a number of factors such as rapid population growth and the unstable political and economic atmosphere. In 1950, the percentage of the total Nigerian population of more than 20,000 inhabitants living in urban centres was less than 15% and by 1975, this proportion had risen to some 23.4%. By year 2000, the proportion had gone up to more than 43.5% and the projection is that more than 50% of the entire population would be living in urban centres by the year 2010 (UN, 2001). In the 1970's, amid the oil boom, which was the main factor, Nigeria had one of the fastest urbanization growths.

In a study report of the country by the Library of Congress, it was stated that 'among the most important interactions between rural and urban areas through the 1980s in Nigeria and most other parts of Africa were the demographic impacts of urban migration on rural areas. Because the great majority of migrants were men of working age, the rural areas from which they came were left with a demographically unbalanced population of women, younger children, and older people'. This obviously affected the rural economy in Nigeria, as there was now a decrease in smallholder activities in the rural areas. Notwithstanding, the fact still remains, that the majority of Nigerian agricultural population still reside in the rural areas.

Benin City, the capital of Edo state is a major centre of transportation. It provides transportation links to Warri and Sapele (both major seaports and oil towns in the Delta State), to the eastern cities of Onitsha, Enugu, Calabar and Port Harcourt; to the western cities of Ibadan, Abeokuta and also to cities in the northern part of Nigeria such as Abuja and Kaduna. In addition to this, Benin City is also an industrious city with companies such as Guinness, which happens to be one of the largest Guinness breweries outside Ireland. There are also a number of wood and timber processing industries. These industries attract a number of people to the capital in search of 'greener pastures'. In the rural areas in Edo State there is a lot of farming activities present both large and small scale such as the Nigerian Institute for Oil Palm Research (NIFOR) which has a large Palm plantation.

4.2.2.1 National Population Commission

In 1998, the National Population Commission of Nigeria produced an analytical report of the 1991 census. In this report, the urban growth rate was stated to be 4.52% and the rural growth rate was 1.70%. Using these growth rates, the urban and rural population were extrapolated forward and backward based on the base census.

As seen in the tables above, the rural areas still held a higher proportion of population in Edo state, until 1998, when there was a switch and the urban population became slightly higher than the rural population. In 1998, oil revenue dropped to less than $10 billion compared with $25 billion in 1980. This in turn resulted in the devaluation of the Naira (Nigerian official currency), thereby making poverty more severe forcing people to migrate to urban centres or other rural areas in order to better themselves.

Applying the same urban and rural growth as stipulated by the Nigerian National Population Commission, table 4.7, shows that the majority of the Delta state population still resides in the rural areas and the increasing trend of urbanisation is not however experienced in all parts of the state.

The nature of oil exploration in Delta state has led to the creation of squatter settlements for the workers of oil companies and oil services companies along the oil lines/pipes. This might explain the steady increase in rural population. In deriving the urban population growth four major cities were used in this assessment: Benin, Sapele, and Warri and Asaba, which are and have always been classified as major urban centres in both Edo and Delta states. An urban area, in the National Population Commission report, was defined as a settlement of 20,000 persons or more and this was the same criteria used in the 1962, 1963 and 1973 census exercises. Another reason for selecting these four urban centres (cities) was due to the availability of data.

Table 4.4 Edo State urban & rural population estimates.

YEAR	URBAN	RURAL
1980	593445	981265
1981	621539	998235
1982	650962	1015499
1983	681778	1033061
1984	714054	1050927
1985	747857	1069101
1986	783260	1087591
1987	820340	1106399
1988	859174	1125533
1989	899847	1144998
1990	942446	1164800
1991	**987061**	**1184944**
1992	1031676	1205088
1993	1078308	1225575
1994	1127047	1246409
1995	1177990	1267598
1996	1231235	1289147
1997	1286887	1311063
1998	1345054	1333351
1999	1405851	1356018
2000	1469395	1379070
2001	1535812	1402514
2002	1605231	1426357
2003	1677787	1450605
2004	1753623	1475266
2005	1832887	1500345
2006	1915733	1525851
2007	2002324	1551790
2008	2092829	1578171
2009	2187425	1605000
2010	2286297	1632285

Table 4.5 Delta State urban & rural population estimates

YEAR	URBAN	RURAL
1980	516280	1434104
1981	540720	1458905
1982	566318	1484136
1983	593127	1509802
1984	621206	1535913
1985	650613	1562475
1986	681413	1589496
1987	713671	1616985
1988	747456	1644949
1989	782841	1673397
1990	819900	1702337
1991	**858714**	**1731777**
1992	897528	1761217
1993	938096	1791158
1994	980498	1821608
1995	1024817	1852575
1996	1071138	1884069
1997	1119554	1916098
1998	1170158	1948672
1999	1223049	1981799
2000	1278331	2015490
2001	1336111	2049753
2002	1396503	2084599
2003	1459625	2120037
2004	1525600	2156077
2005	1594557	2192731
2006	1666631	2230007
2007	1741963	2267917
2008	1820700	2306472
2009	1902996	2345682
2010	1989011	2385559

4.2.2.2 The World Gazetteer

The *World Gazetteer* was utilized to obtain urban population growth rate. The population 'statistic aficionado' known as Stefan Helders put the database together in 1998. The World Gazetteer contains information about the current population of countries, their administrative divisions, cities and towns as well as some historical data for the countries. Helders had only calculated population figures for 2004, whereas data for preceding years were from official sources e.g. national statistical agencies and international organizations or unofficial sources, such as books, CD-ROMs and even data sent by other population 'statistics aficionados'. Helders (2004) noted that the population figures are far-flung and far from being official but stated that they are calculated carefully (and revised manually if necessary).

The population estimates (which were calculated by me) are based on the base census, and 2004 estimates calculated by Helders. A simple urban growth rate formula was used:

$$UGR = ((p1-p2) / (t_1-t_2)) / p2. \qquad (4.8)$$

Where p1 is latest available population figure;

p2 is the next available population figure;

(t_1-t_2) is time 1 is the latest year which there is available data for and time 2 the next.

For example, taking the population figures from 1991 (762,719) and 2004 (1,113,400) and applying this formula to the population data;

$$= ((1113400 - 762719) / 13) / (762719 * 100)$$

This then gives us an urban growth rate of 3.5 %, which is then used to extrapolate the population for the four main cities (see Table 4.6). This result raises doubt regarding the reliability of the urban population growth. Another questionable matter is the population estimation and the urban growth rate calculated and employed by Helders. As such they cannot be used in this research as a model input.

Table 4.6 World Gazetteer urban population growth

YEAR	BENIN	SAPELE	WARRI	ASABA
1980	515424	74065	245576	33603
1981	534119	76751	254483	34822
1982	553491	79535	263713	36084
1983	573566	82419	273277	37393
1984	594368	85409	283189	38749
1985	615926	88506	293460	40155
1986	638265	91716	304104	41611
1987	661415	95043	315133	43121
1988	685404	98490	326563	44684
1989	710263	102062	338407	46305
1990	736024	105764	350681	47985
1991	**762719**	**109600**	**363400**	**49725**
1992	789414	113436	376119	51465
1993	817044	117406	389283	53267
1994	845640	121515	402908	55131
1995	875238	125769	417010	57061
1996	905871	130170	431605	59058
1997	937576	134726	446711	61125
1998	970392	139442	462346	63264
1999	1004355	144322	478528	65478
2000	1039508	149374	495277	67770
2001	1075890	154602	512612	70142
2002	1113547	160013	530553	72597

YEAR	BENIN	SAPELE	WARRI	ASABA
2003	1152521	165613	549122	75138
2004	1113400	159900	530300	72600
2005	1152369	165497	548861	75141
2006	1192702	171289	568071	77771
2007	1234446	177284	587953	80493
2008	1277652	183489	608531	83310
2009	1322370	189911	629830	86226
2010	1368653	196558	651874	89244

4.2.2.3 Populstat Database

Subsequently, a different urban population growth rate was calculated based on data derived from '*Populstat database*'. Jan Lahmeyer, who is seemingly also a population 'statistic aficionado' and has been collecting data for more than 35 years, initially set it up in April 1999.

'*Populstat*' contains information on the historical, demographical and statistical overview of the population of all the countries in the world, their administrative divisions and their important cities. The population figures were taken from official, such as the international atlas, Statesman's yearbook and so on and unofficial (such as data supplied by colleagues) sources. Population data were available for particular years in all four cities (which are highlighted in table 4.5) and the urban growth rate was calculated using the same formula above.

Looking at the table 4.6 below, it can be seen that there is a decline in urban population in Sapele between 1987 and 1991. Sapele had an inland sea port that was originally designed for the export of timber. It was the centre of the

Nigerian timber industry, with sawmills and a large plywood and veneer factory - Africa Timber and Plywood (AT & P), which employed a number of people including Sapele indigenes. The decline in population from 111200 in 1987 to 109590 in 1991 may possibly be due to the fact of the closure of AT & P and the seaport that in turn led to a decline in economic activities. In a newspaper article, Igbojekwe (2003) stated that in the 50's and 60's, Sapele was second only to Lagos metropolis, arguably in terms of urban development. Sapele today with its scanty dwellers is almost an "endangered specie and a forgotten race" (Igbojekwe, 2003). Another reason for the dip in population may be due to the introduction of the Structural Adjustment Programme (SAP) in 1986, which was aimed at improving the socioeconomic conditions of implementing nations. It was introduced as advised by the World Bank and International Monetary Fund (IMF). This introduction of the SAP led to the devaluation of the naira (as can be seen in table 4.5), causing considerable attrition in the living standards of the majority of Nigerians. Workers were hit by underemployment, unemployment and mass retrenchment (cutting down or back) (Okome, 1994).

Table 4.7 The historical value of one U.S. Dollar in Nigerian naira

Date	Naira per US $	Date	Naira per US $
1972	0.658	1973	0.658
1974	0.63	1975	0.616
1976	0.627	1977	0.647
1978	0.606	1979	0.596
1980	0.550 (0.900 PM)	1981	0.61
1982	0.673	1983	0.724
1984	0.765	1985	0.894 (1.70 PM)
1986	2.02 (3.90 PM)	1987	4.02 (5.90 PM)
1988	4.54 (6.70 PM)	1989	7.39 (10.70 PM)
1990	8.04 (9.30 PM)	1991	9.91
1992	17.30 (21.90 PM)	1993	22.33 (56.80 PM)
1994	21.89 (71.70 PM)	1995	21.89 (84.58 PM)
1996	21.89 (84.58 PM)	1997	21.89 (84.70 PM)
1998	21.89 (88-90 PM)	1999	85.98 (105.00 PM)
2000	99-106 (104-122 PM)	2001	109-113 (122-140 PM)
2002	114-127 (135-137 PM)	2003	127-130 (137-144 PM)
2004	132-136	2005	128.50-131.80

Source: wikipedia

PM = Parallel Market

Table 4.8 Populstat urban population growth

YEAR	BENIN	UGR	SAPELE	UGR	WARRI	UGR	ASABA	UGR
1980	153086		92112		84070		43559	
1981	157334		95059		86402		44088	
1982	161700		98100		88800		44623	
1983	166000	0.027	101100	0.031	91198	0.028	45165	
1984	170482		104234		93660		45714	
1985	175085		107465		96189		46269	
1986	179812		110797		98786		46831	
1987	183200	0.026	111200	0.025	100700	0.027	47400	
1988	187963		113980		103419		47969	
1989	192850		116830		106211		48544	
1990	197864		119750		109079		49127	
1991	202800	0.027	109590	-0.004	111300	0.026	49725	0.012
1992	208276		109152		114194		50322	
1993	213899		108715		117163		50926	
1994	219674		108280		120209		51537	
1995	223900	0.026	135800	0.060	122900	0.026	52155	
1996	229721		143948		126095		52781	
1997	235694		152585		129374		53414	
1998	241822		161740		132738		54055	
1999	248110		171444		136189		54704	
2000	254560		181731		139730		55360	
2001	261179		192635		143363		56025	
2002	267970		204193		147090		56697	
2003	274937		216445		150914		57377	
2004	282085		229431		154838		58066	
2005	289419		243197		158864		58763	

In line with the points made and looking at the population growth rates, the data acquired from Lahmeyer's website can be considered as being relatively reliable and valid, as the growth rates are well-founded in line with political and economic changes in Nigeria as well as in Edo and Delta States. In addition, it comprises urban population data for more cities in Edo and Delta states, with additional time series data than any of the other sources that were obtained. Notwithstanding, this population time-series data obtained from the Populstat database cannot be used as an urban population model input.

The *National Population Commission* growth rates will be utilised in this study. The main rationale behind this decision is based on the fact that although its uses just one growth rate through the time period (1980-2005), the fact still remains that the data was collected and calculated by the Nigerian National Population Commission (NPC). The 1991 census used by other international organisations and agencies were collated, assembled and published by this government organisation. The only difference is the way the projections and growth rates, were calculated by these organisations and agencies.

However, Lahmeyer (1999) made a point regarding the reliability of some of the population data he acquired, when he said he used contemporary sources. 'Therefore, the data possibly will be less reliable when indigenous population (overestimation or under numeration) is counted and this might affect especially figures of the 19th century and the first half of the 20th century of non-European countries.' Yet, there is still some degree of untrustworthiness when it comes to Nigeria's population data (census) due to political and social reasons, as indicated earlier on.

4.3 Natural Resource Economic Data

Nigeria has the potential to develop a thriving economy, especially with her vital dependence on the oil sector that accounts for 25 percent of total GDP, 90 percent of foreign exchange receipts, and 70 percent of budgetary revenues (World Bank, 1994), and being the 10th largest oil producer in the world. But this has always been a near impossible task especially during the military regime, which was rife with corruption. 'The long years of military role in Nigeria had a devastating effect on the Nigerian economy. Economic planning was haphazard, policies distorted, and implementation processes undermined. In addition to corruption, fraud and general mismanagement became the order of the day' (Mudasiru and Adabonyon, 2001)

The economy has been noticeably changing, especially since 1986 when the Structural Adjustment Programme (SAP) was introduced. This programme accentuated removal of the petroleum subsidy, privatisation, trade liberalization, currency devaluation, and slashed government expenditures. The SAP de-industrialised Nigeria by building her to be the importer of finished products and exporter of raw materials, instead of the other way around. With the introduction of SAP, there was a colossal drop in purchasing power that was linked to the collapse of international oil prices and increased rate of inflation. This drop caused a switch in the demand for commodities from department stores (i.e. supermarkets) to open markets (i.e. local markets) because their goods were cheaper. However, the World Bank argued that during the SAP period the real depreciation of the naira improved producer prices especially in raw goods, and liberalization of trading had a very positive impact on a variety of cash crops, particularly cocoa. The espousal of SAP increased the price of goods, especially in the departmental stores.

Economic data are important in modeling land cover change, as they have an effect on one another. For example a change (either positive or negative) in the economy will affect production and prices of goods and services or even policies, which will in turn have an impact on the land cover and vice-versa. With regards the collection and gathering economic data, I experienced immense difficulty as there were either huge gaps in the natural resource (economic) data or they were non-existent. This problem was dealt with by combining the data acquired from Nigerian government sources (e.g. State yearbooks) with data obtained from International organization databases to fill in the gaps.

This next section outlines the natural resource economic data, with specific reference to the production and prices (market prices) of products such as forestry products (timber and non-timber).

4.3.1 Forest Products

The rapidly growing population and population density in Nigeria has an immense pressure on the forests and its products, altering the intricate forest structures and species. Richards (1939) stated that the depleted forest in this area is an irregular patchwork of fragmented forest and it gives a general impression of a chaotic mass of vegetation. All these irregular fragmented forests such as Orle River Game Reserve, Okomu National Park and Gilli-Gilli Game Reserve, were then designated as forest reserves as from 1970, in a bid to conserve the forest or what was left of it (Richards, 1939). Nonetheless, this never stopped individuals from exploiting the forest reserves. In Edo and Delta states, farming and logging are the key occupations. As Richards (1939) stated then that, the destruction to the forests has been caused by farmers practising shifting cultivation on one hand and commercial timber exploitation on the other, and this is still the reoccurring premise in Edo and Delta states. No doubt recently the oil companies have been added to this list of factors contributing to deforestation. Osemeobo (1988) pointed out that rapid industrialization in Europe has led to accelerated demand for raw materials from tropical countries including Nigeria.

Forest products can be divided into Timber forest products and Non-timber forest products (NTFP). The timber forest products include wood products like sawn wood, plywood, pulp board and paper. Non-timber forest products (NTFPs) include all non-wood products such as medicinal plants, resins, gums, latex, leaves (for wrapping kola nuts), rattans, herbs, spices and even bush meat. Acquiring NTFP production and price time series data was impossible as they were hardly documented or collated in Edo and Delta states.

According to FAO Forestry department (2004) 'Nigeria is gradually becoming a wood-deficient country because of urban and rural population pressure, which has greatly increased the demand for wood and wood products.' There is little data available on timber products in Edo & Delta states; and the only available data are on Edo state. These data were acquired from the Edo state yearbook, which is a compilation of statistical data for the state. The other available data sources (such as FAO) unfortunately cover Nigeria as a whole country.

Looking at table 4.7, one can only observe the discrepancy and inconsistency in the market prices, for example in 2001 there is a huge jump in prices as compared with previous years. There is little confidence in the reliability of this data, due to factors such as data collection methods. The published prices were collated by interviewing a small number of people or sawmills in Edo state and so might not be a true representation of the sawn wood market price trend.

Table 4.9 Average market prices (in kobo) for a section of timber products (sawn wood)

YEARS	IROKO (8cmx10cmx4.8m)	MAHOGANY	CEDAR	AFARA
1980	570.75	564.25	666.25	NA
1985	958.5	940.5	934.67	NA
1987	831	728	728	NA
1992	10900	9700	5900	8000
1995	34300	38900	27700	19200
1998	34200	34900	39000	26500
2001*	70000	50000	40000	45000

NA=Not Available

4.3.2 Agricultural Data

FAO (2002) estimated that Nigeria has about 71.2 million hectares of available agricultural land about half of which is currently being utilized. Agriculture (including hunting, forestry and fishing) contributed an estimated 32% of Gross Domestic Product (GDP) in 1998 to the Nigerian economy. An estimated 35.2% of the labour force was employed in the sector in that year. (NigeriaBusinessInfo.com website, 2001). Idumajogwu (2005), states that, "agriculture contributes the largest share of Gross Domestic Product, GDP. It is the largest non-oil export earner, largest employer of labour, and a critical contributor to wealth creation, and poverty alleviation, as about 70% of the population derives its income from agriculture and related activities."

The main crops grown in Edo and Delta states are cocoa, oil palm (used in manufacturing soaps, margarine, grease and candle), yam, rubber, rice, plantain and cassava, of which rubber is the leading export for the region. The combination of soils and climate in this region, allows the farming of a vast number of crops (fruits and vegetables). Cash crops account for the vast majority of the states' revenue, especially cocoa and rubber that were Nigeria's most prominent agricultural exports that was all before the oil boom, but subsequently they suffered declining prices between 1986 and 1987 as can be seen in table 4.7. About half of the work force still engages in farming, as it is their major source of income. Figures 4.1 to 4.6 show pictures of some of the commercial plantations present in the study area.

The data acquired were production and prices of particular crops, but are not consistent with the rest of the data being used. The starting point for these data is 1991/1992 unlike the demographic data, which starts from 1980. The market price dataset was done separately for both states merely due to the fact that after (Bendel state) was split in 1991, Delta state started collating their data in 1992. As can be seen, both tables 4.8 and 4.9 share the same data from 1966 to 1991.

Agricultural products are slightly cheaper in Edo state (as seen in the tables above), due to the fact that there are more farming activities occurring there compared to the Delta state that is predominately riverine in the south-west and south-east parts of the state.

Figure 4.1 Michelin Rubber Plantation in Edo State.

Figure 4.2 Tapping of rubber with the latex dripping into a cup.

Figure 4.3 Okomu Palm Plantation, Edo State

Figure 4.4 Okomu Oil Mill, Edo State

Figure 4.5 Cocoa nurseries

Figure 4.6 Cocoa plantation in Odiguetue, Edo State

Unfortunately, the production and yield statistics available in Edo and Delta are not accurate and their validity still remains questionable, this might be due to the fact that people, especially the small-scale farmers do not report production and yield figures to the government. There has been no particular attention given to collating production and yield data because of the difficulty of gathering this data. The data start from 1992 with no past available data for this area. There were other possible alternatives like using international statistical data, but this only represents the whole of Nigeria

Table 4.10 Market prices (K/KG) for agricultural products in Edo State

YEAR	GARRI (K/KG)	RICE	YAM	PLANTAIN	PALM OIL (Std bottle)	GROUND-NUT OIL (std
1966	8.58	17.82	7.26	3.08	11.22	29.48
1972	12.54	28.16	12.76	5.94	22.22	39.16
1973	12.32	33.88	9.9	10.12	28.82	47.52
1974	16.28	43.12	14.74	9.68	30.36	71.72
1975	25.52	50.6	22	17.6	35.64	81.18
1977	31.7	71.8	20.5	19.3	50.6	92.4
1978	47.2	64	40.7	26.9	98.8	102.4
1979	33.6	75.7	43.8	40.1	90.7	116.1
1980	54.5	130.7	56.3	45.3	91.1	103
1984	140	339	91	102	307	487
1985	84	275	73	79	231	433
1986	76	272	68	92	230	355
1987	105	247	76	96	191	347
1991	201	740	219	NA	714	1111
1992	465	1103	467	NA	1088	1316
1993	1138	1638	1043	NA	1809	2547
1994	1126	3318	1932	NA	2901	3929
1995	1920	3608	1768	NA	6431	7753
1997	2924	3284	1907	NA	4324	6548
1998	2062	4052	2287	NA	5949	8008
1999	1550	3773	2399	NA	5396	7181
2000	2208	3778	3119	NA	5514	9433
2001	**5622**	**6060.5**	**4988**	**5184.5**	**8656.5**	**9026**
2002	5106	6409.5	4599.5	4271	11491.5	11194

NA = Not Available

Table 4.11 Market prices (K/KG) for agricultural products in Delta State

YEARS	GARRI (K/KG)	RICE	YAM	PLANTAIN	PALM OIL (Std bottle)	G/NUT OIL (std bottle)
1966	8.58	17.82	7.26	3.08	11.22	29
1972	12.54	28.16	12.76	5.94	22.22	39
1973	12.32	33.88	9.9	10.12	28.82	48
1974	16.28	43.12	14.74	9.68	30.36	72
1975	25.52	50.6	22	17.6	35.64	81
1977	31.7	71.8	20.5	19.3	50.6	92
1978	47.2	64	40.7	26.9	98.8	102
1979	33.6	75.7	43.8	40.1	90.7	116
1980	54.5	130.7	56.3	45.3	91.1	103
1984	140	339	91	102	307	487
1985	84	275	73	79	231	433
1986	76	272	68	92	230	355
1987	105	247	76	96	191	347
1991	201	740	219	NA	714	1111
1992	524	1337	402	513	1064	1396
1994	1100	2600	NA	NA	2800	4200
1995	1900	4200	1500	2200	5800	8400
1996	2700	5200	NA	NA	5100	8200
1997	2900	5100	NA	NA	5000	7000
1998	2400	5500	2100	2300	6000	8700
2001	**8039**	**5968**	**3618.33**	**3416**	**7794**	**8742**

NA = Not Available

Table 4.12 Main food crops production in Edo State

YEARS	CASSAVA	YAM	RICE	MAIZE
1992	377.347	323.733	4.133	56.703
1993	424.115	338.357	4.2	77.74
1994	456.789	389.223	4.65	57.972
1995	468.752	397.742	7.941	67.086
1996	597.893	358.257	-	65.059
1997	603.475	364	8.181	70.52
1998	602.551	326.462	10.059	68.73
1999	601.309	349.603	9.009	66.463

Source: EDO AGRIC DEVELOPMENT PROJECT

Table 4.13 Industrial crops yield in Edo State. (NA = Not Available)

YEARS	COCOA	PALM KERNEL	RUBBER
1991	707	355.9	110.6
1992	575	381.2	175.6
1993	673.1	386.6	435.5
1994	665.6	359.3	960.4
1995	715.6	450.3	1068.2
1996	584	796.1	722.4
1997	1527	475	801.5
1998	1744	410	262.1
1999	2075	1596	NA
2000	1801.5	1218	NA
2001	16620	11143	NA

Table 4.14 Industrial crops yield in Delta State

YEARS	COCOA	PALM KERNEL	RUBBER
1991	NA	NA	NA
1992	NA	NA	NA
1993	NA	NA	NA
1994	NA	1465.7	993.7
1995	NA	1895	913.2
1996	NA	2433.8	805
1997	NA	2705.8	1196.2
1998	NA	3954.8	1191.4

NA = Not Available

As shown in the tables above, the production and yield data are incomplete with huge gaps in the data (e.g. in 2001), which appears to be the recurring theme with acquiring economic data in Nigeria especially in states where there has not been enough attention given to collating and building socio-economic datasets.

4.4 Remote Sensing

The initial land cover identification and depiction are considered important in order to understand the spatial pattern of the study area. I used Nigerian topographical maps, satellite images and preliminary studies (as in Rilwani and

Ufuah, 1999; Ikhuoria, 1984, 1991 & 1993), to identify the land cover and land use. This method was used improve my perception of the study area. Ideally aerial photographs would have assisted in determining these land uses and cover, but these could not be obtained. There are different types of land cover that are found in Edo and Delta states, these mainly comprises of urban settlements, rural settlements, rivers, swampy areas, farmlands (both plantations and small scale), mountainous regions and forested areas (which also include mosaic forests). It should be noted at this point that a number of farms are often very small and may not be spatially contiguous and some land cover types may not be properly spatially identified from looking at maps.

4.4.1 Remote Sensing Data Acquisition and Satellite Data Pre-Processing

Remote sensing is the dynamic detection and recording of the earth's surface using reflected or emitted electromagnetic energy. It provides an efficient approach to monitor and detect land cover changes. 'Remote sensing data are primary sources extensively used for change detection in recent decades' (Lu *et al.*, 2004). This is due to its effectual and timely manner of gathering data.

The remote sensing data used in this research consist of Landsat TM and Landsat ETM for 1987 & 2001 respectively, minimizing seasonal variability of the land cover and land use as much as possible. All images acquired, fall within eight weeks (tables 4.13 and 4.14). These images were acquired from the ESDI (Earth Science Data Interface) a part of the Global Land Cover Facility (GLCF) web database. A total of 4 scenes each year were obtained, due to the large study area (see figures 4.7 - 4.14). Looking at these images, a visual interpretation of the landscape can be made, including the identification of built-up areas (in cyan); forests or dense vegetation (dark red); and agriculture or sparse vegetation (red). Features were also identified according to their patterns.

Landsat satellites use the Worldwide Reference System (WRS) of scenes divided up into paths and rows. According to NASA (2004), 'The Worldwide Reference System (WRS) is a global notation system for Landsat data. It enables a user to inquire about satellite imagery over any portion of the world by specifying a nominal scene centre designated by PATH and ROW numbers. The WRS has proven valuable for the cataloguing, referencing, and day-to-day use of imagery transmitted from the Landsat sensors.

Table 4.15 Landsat TM scenes acquired for 1986/1987

SCENE	WRS PATH/ROW	IMAGERY DATE
1	189/055	1987-12-21
2	189/056	1987-12-21
3	190/055	1986-12-17
4	190/056	1986-01-15

Table 4.16 Landsat ETM scenes acquired for 2001/2002

SCENE	WRS PATH/ROW	IMAGERY DATE
1	189/055	2001-01-09
2	189/056	2002-01-28
3	190/055	2002-01-03
4	190/056	2001-02-17

The 16-day ground coverage cycle for Landsat 4-7 is accomplished in 233 orbits. Thus, the WRS 2 is made up of 233 paths numbered 001 to 233, east to west, with Path 001 crossing the equator at 64.60 degrees west longitude (Farr, 1999).

The utilization of images acquired during almost or the same season is a fundamental factor of land use/cover change study. This eliminates the effects of seasonal change. According to Singh (1989), 'When investigating year-to-year change, anniversary dates or anniversary windows (annual cycles or multiples thereof) are often used because they minimize discrepancies in reflectance caused by seasonal vegetation fluxes, climatic differences and sun angle differences' (Singh, 1989).

Figure 4.7 Landsat TM - Path 189, Row 055 acquired on 21/12/1987; band combination 4, 3, 2

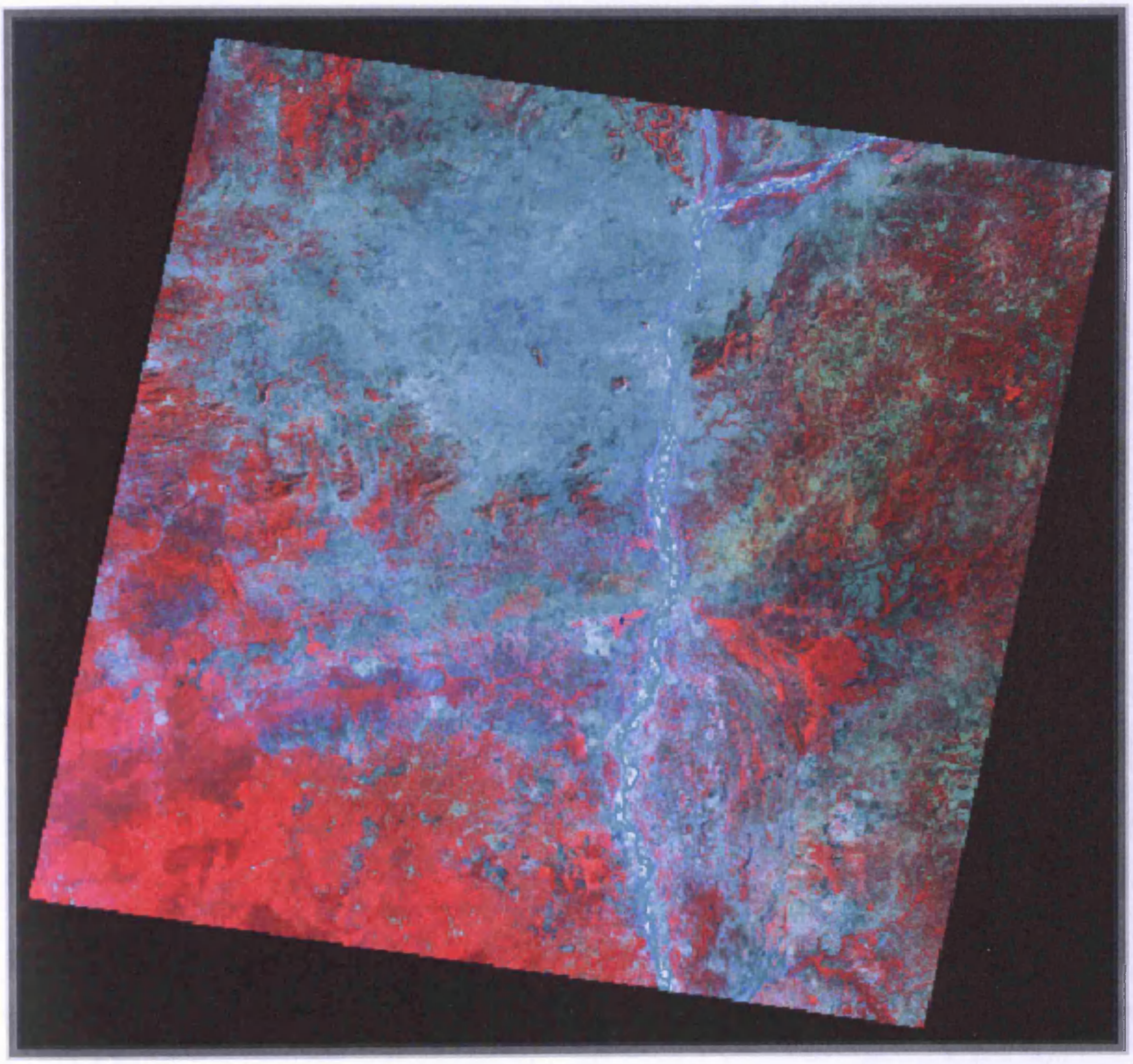


Figure 4.8 Landsat TM - Path 189, Row 056 acquired on 21/12/1987; band combination 4, 3, 2

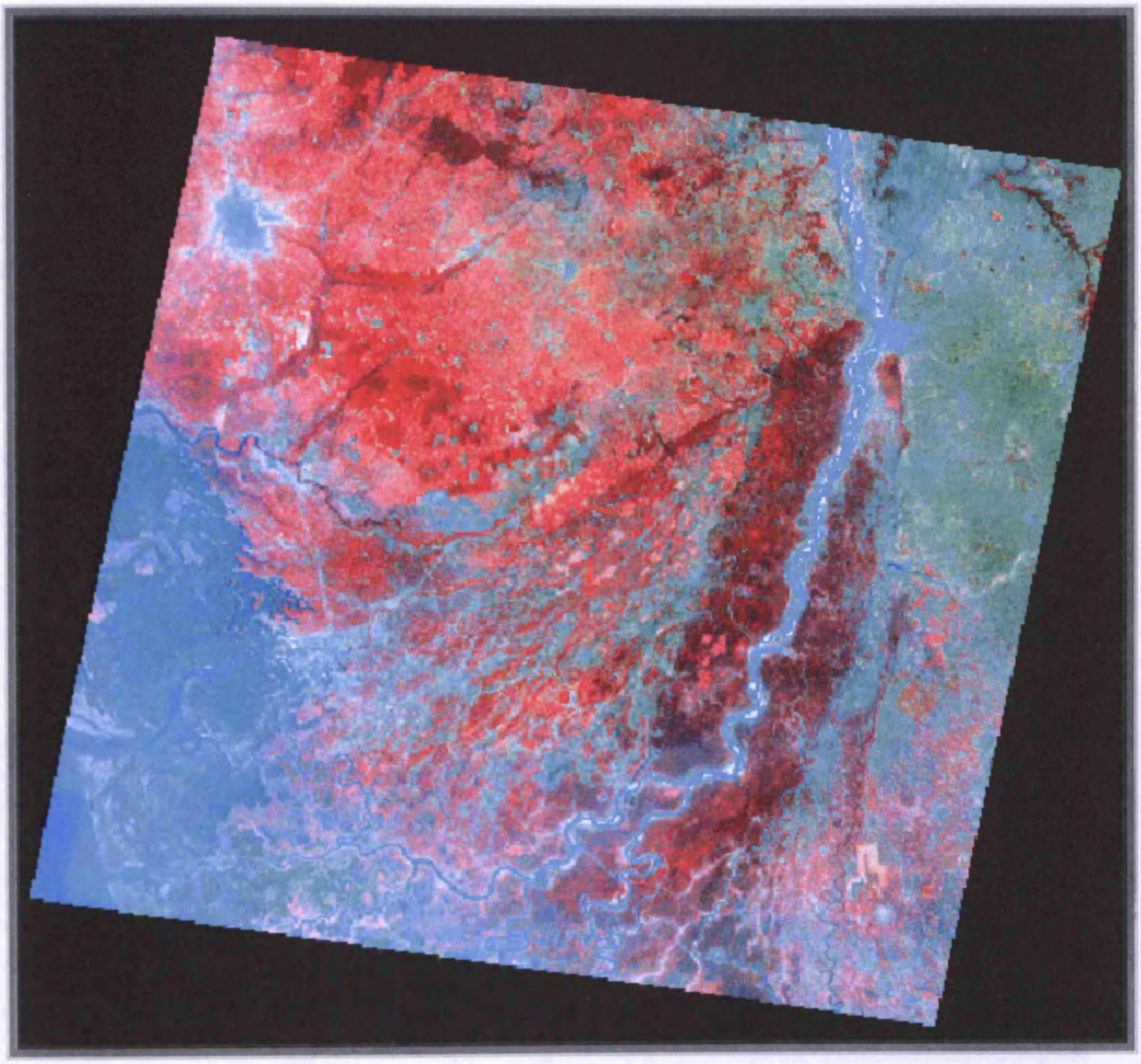


Figure 4.9 Landsat TM - Path 190, Row 055 acquired on 17/12/1986; band combination 4, 3, 2

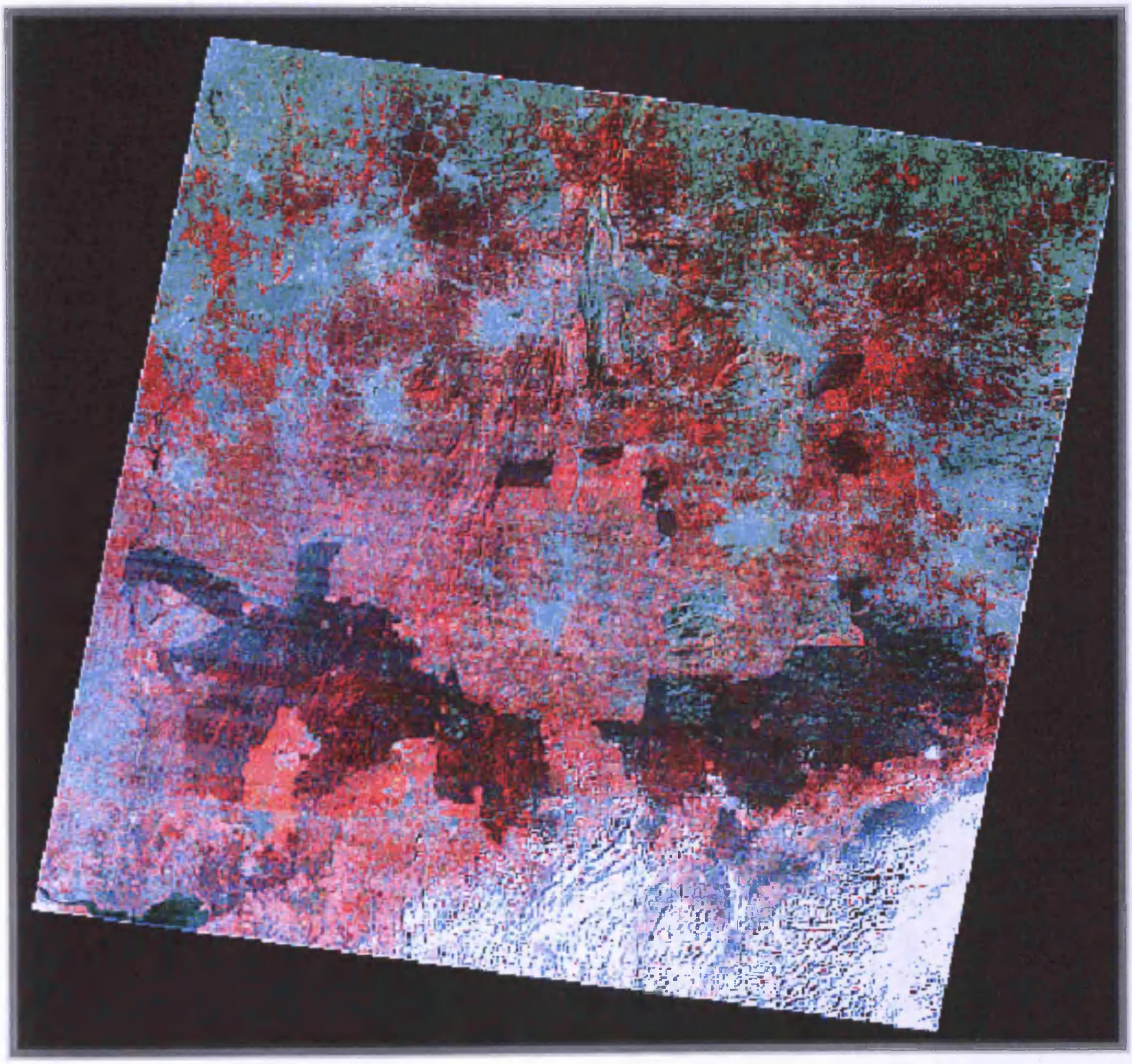


Figure 4.10 Landsat TM - Path 190, Row 056 acquired on 15/01/1986; band combination 4, 3, 2

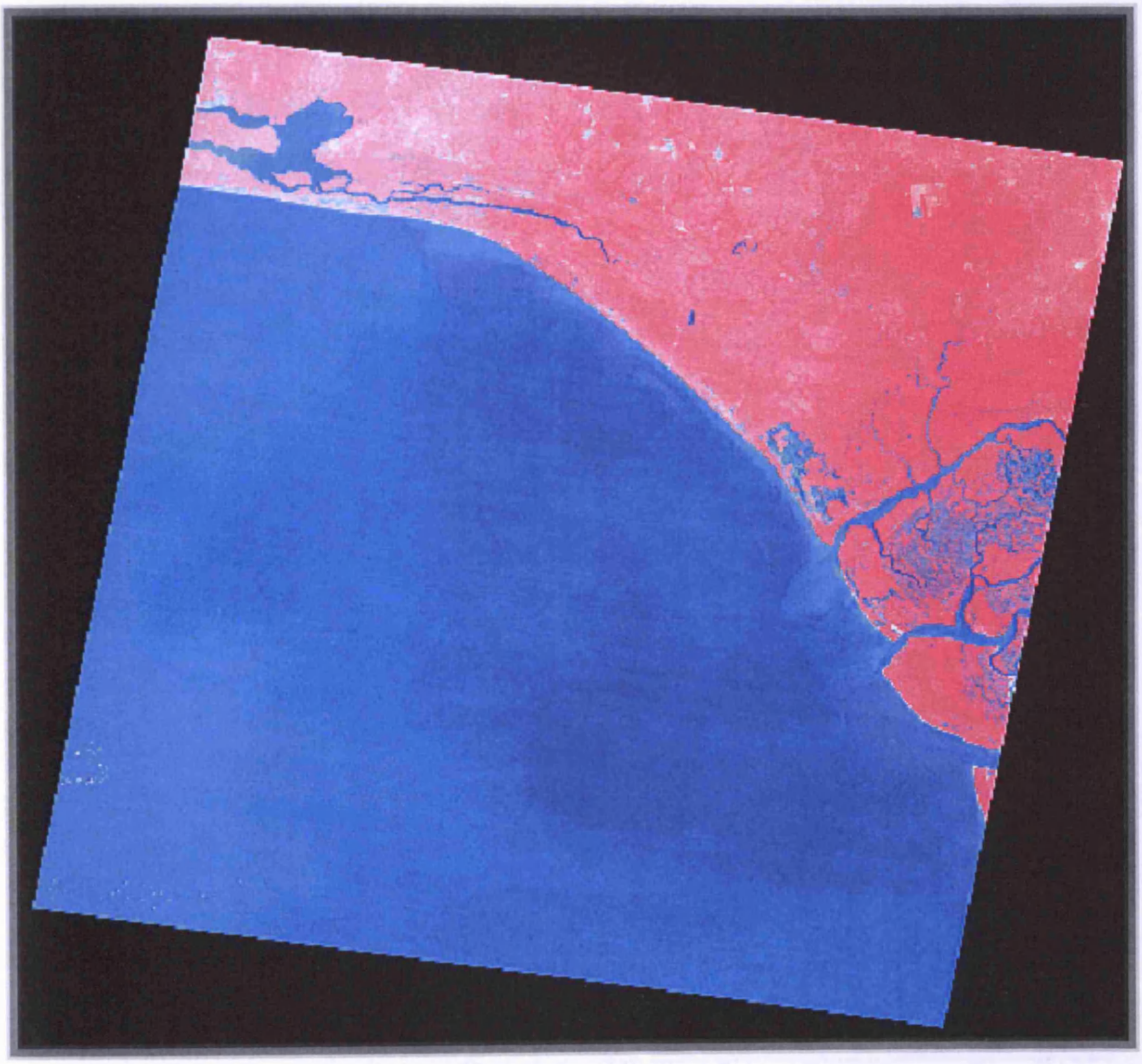


Figure 4.11 Landsat ETM - Path 189, Row 055 acquired on 09/01/2001; band combination 4, 3, 2

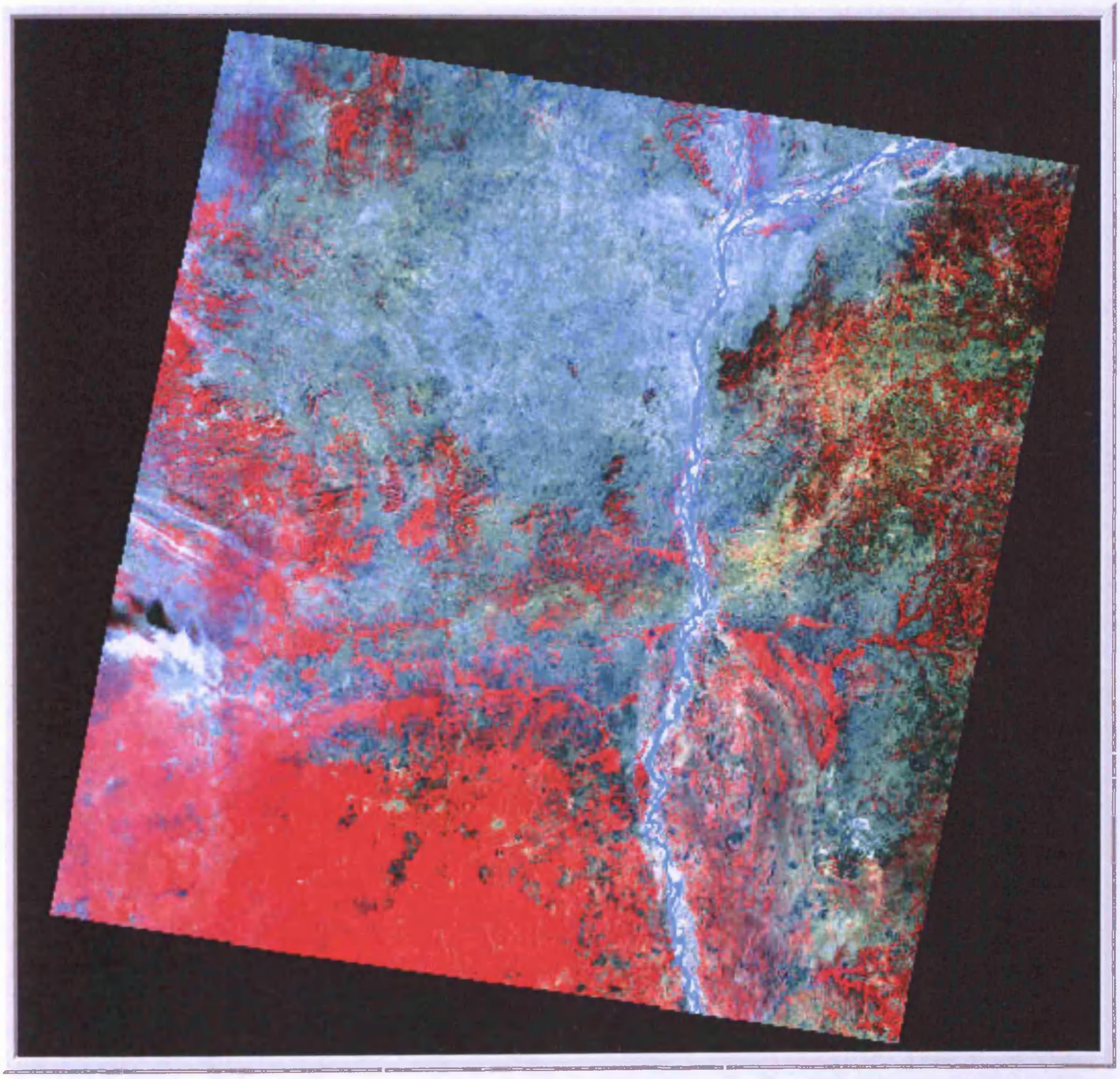


Figure 4.12 Landsat ETM - Path 189, Row 056 acquired on 28/01/2001; band combination 4, 3, 2

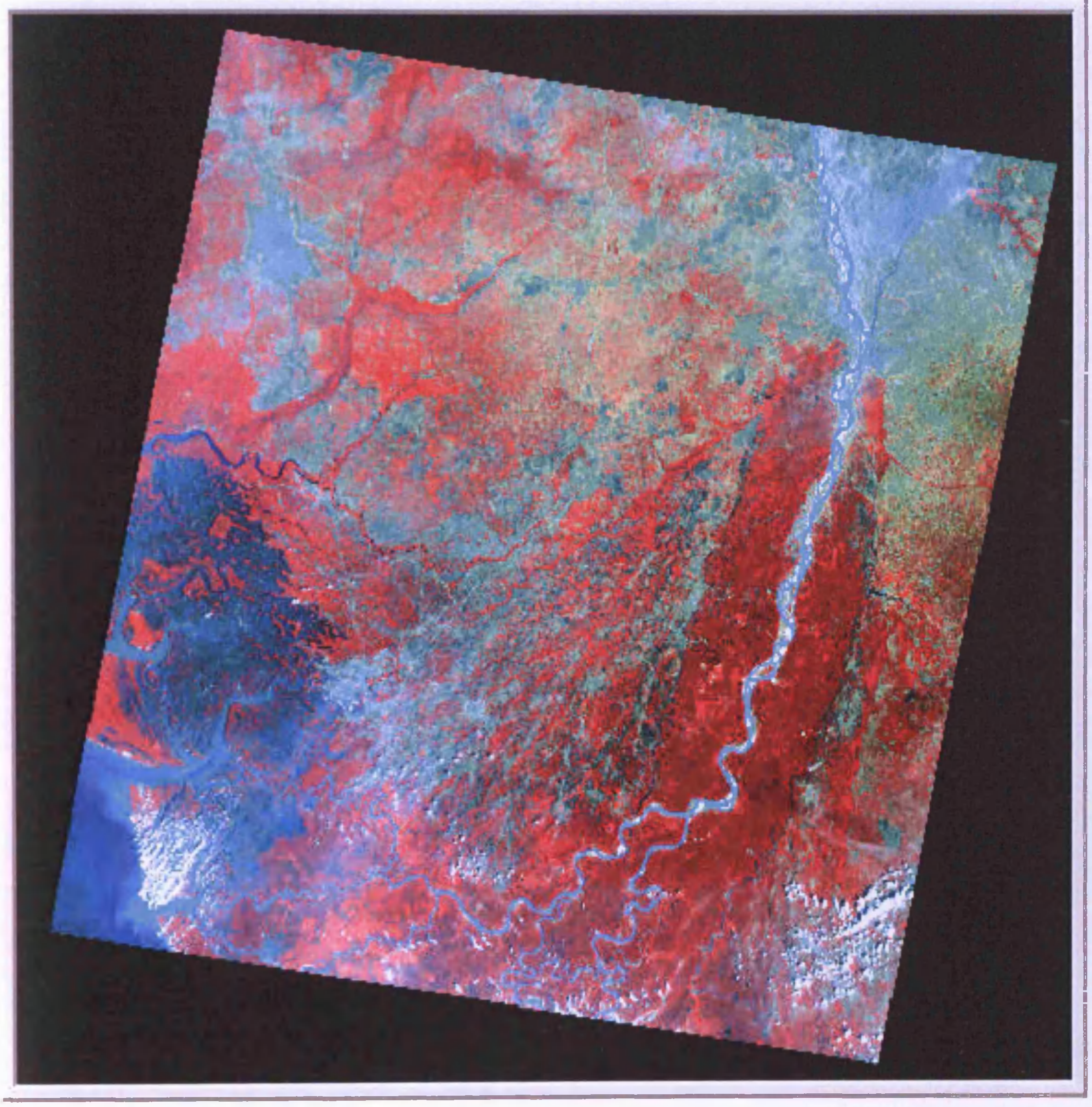


Figure 4.13 Landsat ETM - Path 190, Row 055 acquired on 03/01/2001; band combination 4, 3, 2

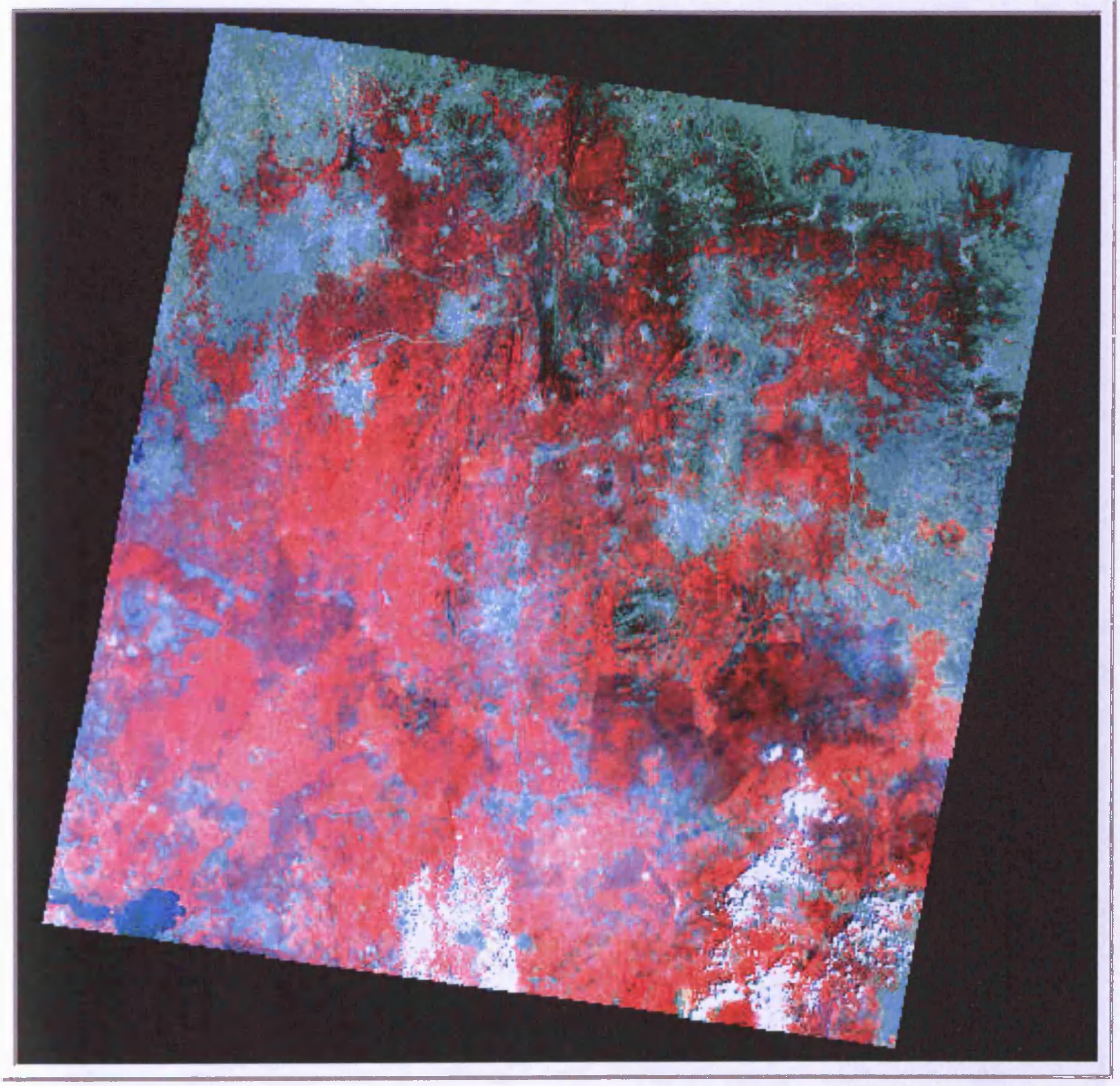
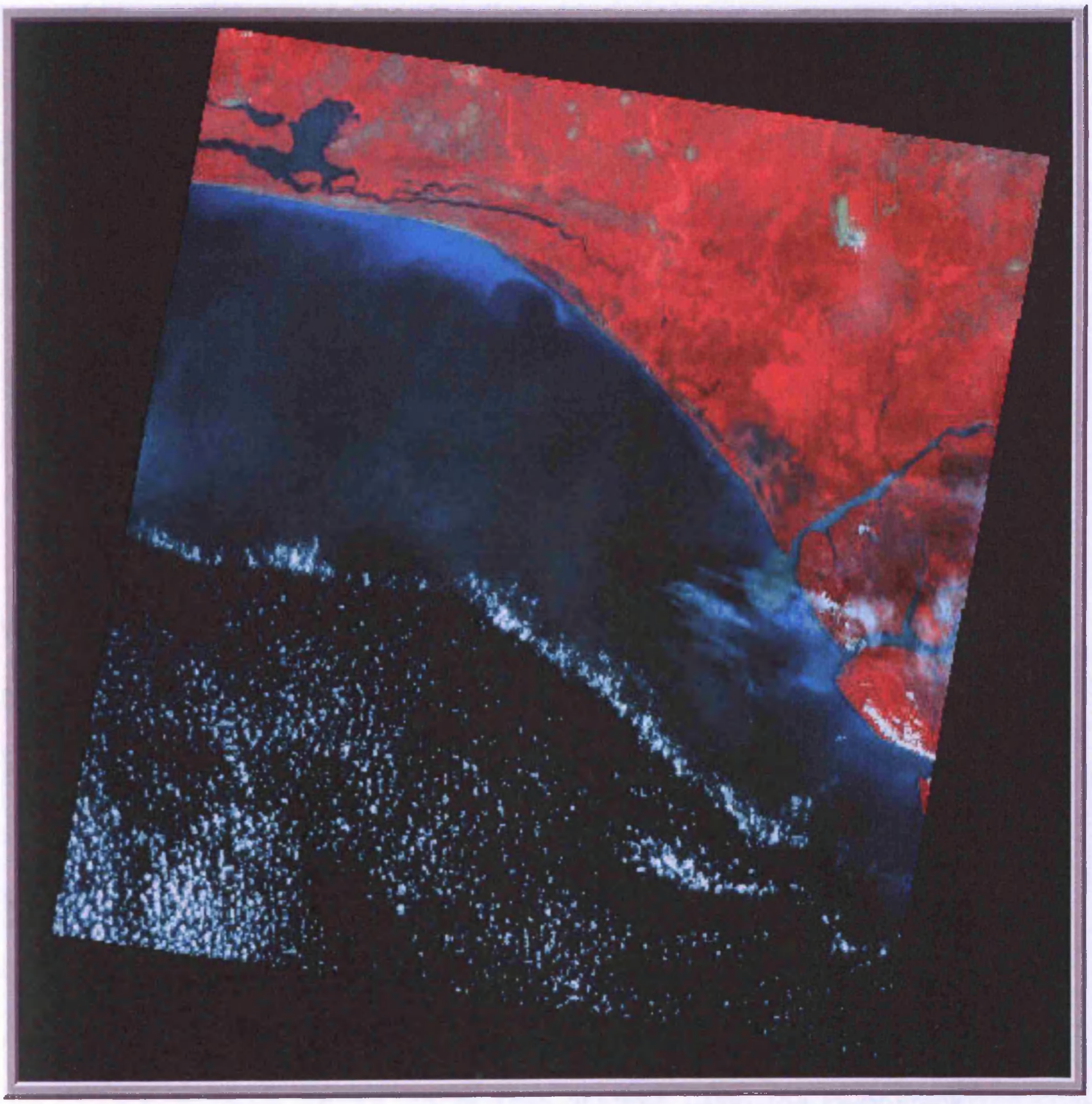


Figure 4.14 Landsat ETM - Path 190, Row 056 acquired on 17/02/2001; band combination 4, 3, 2



Prenzel (2004) stated that remote sensing data collected under the following conditions would aid in providing a systematic analysis for detecting change:

1. Data collected by the same sensor will have similar characteristics (e.g. spatial, spectral and radiometric resolution; geometry, radiometric response).
2. Data acquired under clear atmospheric conditions (i.e. free of cloud and haze) will assist in the identification of real change on the ground surface.
3. Data collected on anniversary dates will have similar surface conditions for the area under study (i.e. consistent plant phenology) as well as consistent sun-terrain-sensor geometry.

Medium-spatial resolution images, such as Landsat TM & ETM, are intended to provide appropriate scales of information for a wide-variety of Earth-resource applications (Rogan & Chen, 2004). The continuity of the Landsat program since 1972 is recognized as a key milestone in the evolution of remote sensing technology (Rogan & Chen, 2004; Franklin, 2001) and is key to land use & land cover change.Each Landsat scene was acquired as separate bands files in a geo-tiff format and imported into ERDAS Imagine. These where then stacked using the *layer-stack* function in order to get complete TM and ETM images (with all the necessary bands). The images were tidied and cleaned up by *pre-processing* methods to remove data (image) distortion or flaws, utilising some of the mosaic features in *ERDAS imagine*.

According to Coppin & Bauer (1996), *pre-processing* commonly involves a series of sequential operations, including calibration to radiance or at-satellite reflectance, atmospheric correction or normalization, image registration, geometric correction, and masking (e.g., for clouds, water, irrelevant features). Notwithstanding, Mather (1999) stated that it is difficult to decide what should be included in the definition of *pre-processing*, because a deficiency in the data depends on the use to which those data are to be employed.

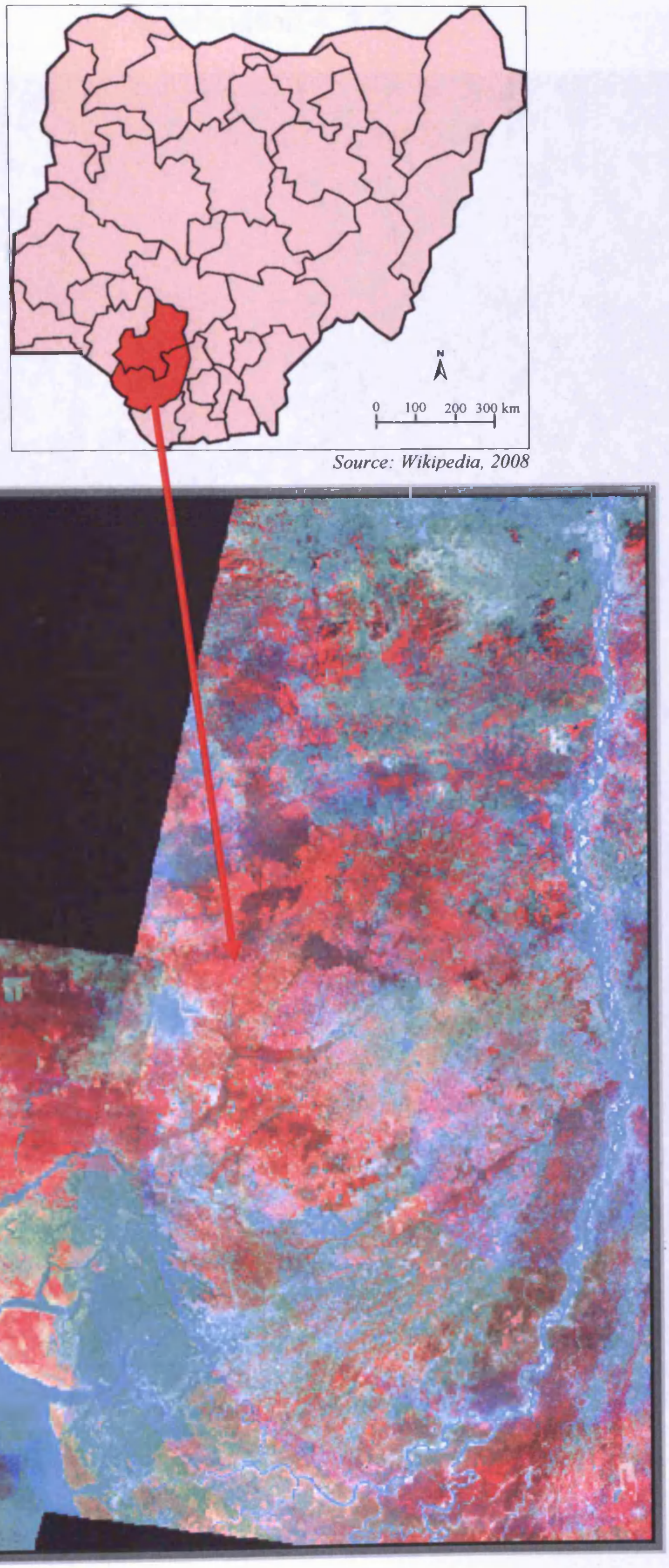
The first pre-processing step performed was *mosaicking*, as the images could consequently go through other pre-processing as 2 whole images, in order to minimise time, effort and storage. The Landsat TM and Landsat ETM scenes were mosaicked (i.e. stitched together) to produce two large images of the study area. This was done by using the *Mosaic Tool* in ERDAS Imagine, by arranging the images the way they were originally captured (figures 4.15 and 4.16). The *Mosaic tool* has a number of features such as *colour balancing*, which smoothens out any colour differences between the image and histogram matching to fine-tune the histogram of the images.

Histogram match function was carried out on all the images (TM and ETM), which is the 'process of determining a lookup table that converts the histogram of one image to resemble the histogram of another' also it works on the supposition that the variation in overall scene brightness and colour are caused by external factors such as atmospheric conditions and sun illumination (ERDAS, 2003). Histogram matching basically modifies the brightness values for one scene to match the other.

Due to the very large size of the mosaicked images and the scenes being larger than the study area, a subset of the area of interest (AOI) was created to reduce processing time and storage (figures 4.17 and 4.18). Subsets are portions of larger images selected to show only the region of interest (Campbell, 2002). Using a map of Edo & Delta States, the study area boundary was defined by producing an AOI polygon. Due to cloud cover present in both Landsat TM and ETM path190 row 055 images, they were not used further in this research as they obscured the land. Since the images had been originally geo-corrected by Global Land Cover Facility (image data source), the subset process was straightforward.

The next pre-processing step was *geometric correction (registration)*. This is done to prevent any errors and to improve the quality of the images. Geometric correction is the transformation of a remotely sensed image so that it has the scale and projection properties of a map, while registration, which is a related technique, is the fitting of the coordinate system of an image to that of another image of the same area (Mather, 1999). The majority of change detection methods depend critically upon the accuracy of geometric registration of the images (Singh, 1989). The mosaicked images were registered to a digitised map of the study area (image to map registration), which had a UTM (Universal Transverse Mercator) coordinate system WGS 84 Zone 32. The map was digitised from a paper map of the study area, which was acquired from the Federal Surveys Department (figure 4.19).

Figure 4.15 Landsat TM mosaicked images of the 4 scenes and a map of Nigeria, highlighting the study area



Source: Wikipedia, 2008

Figure 4.16 Landsat ETM mosaicked images of the 4 scenes; band combination 4, 3, 2

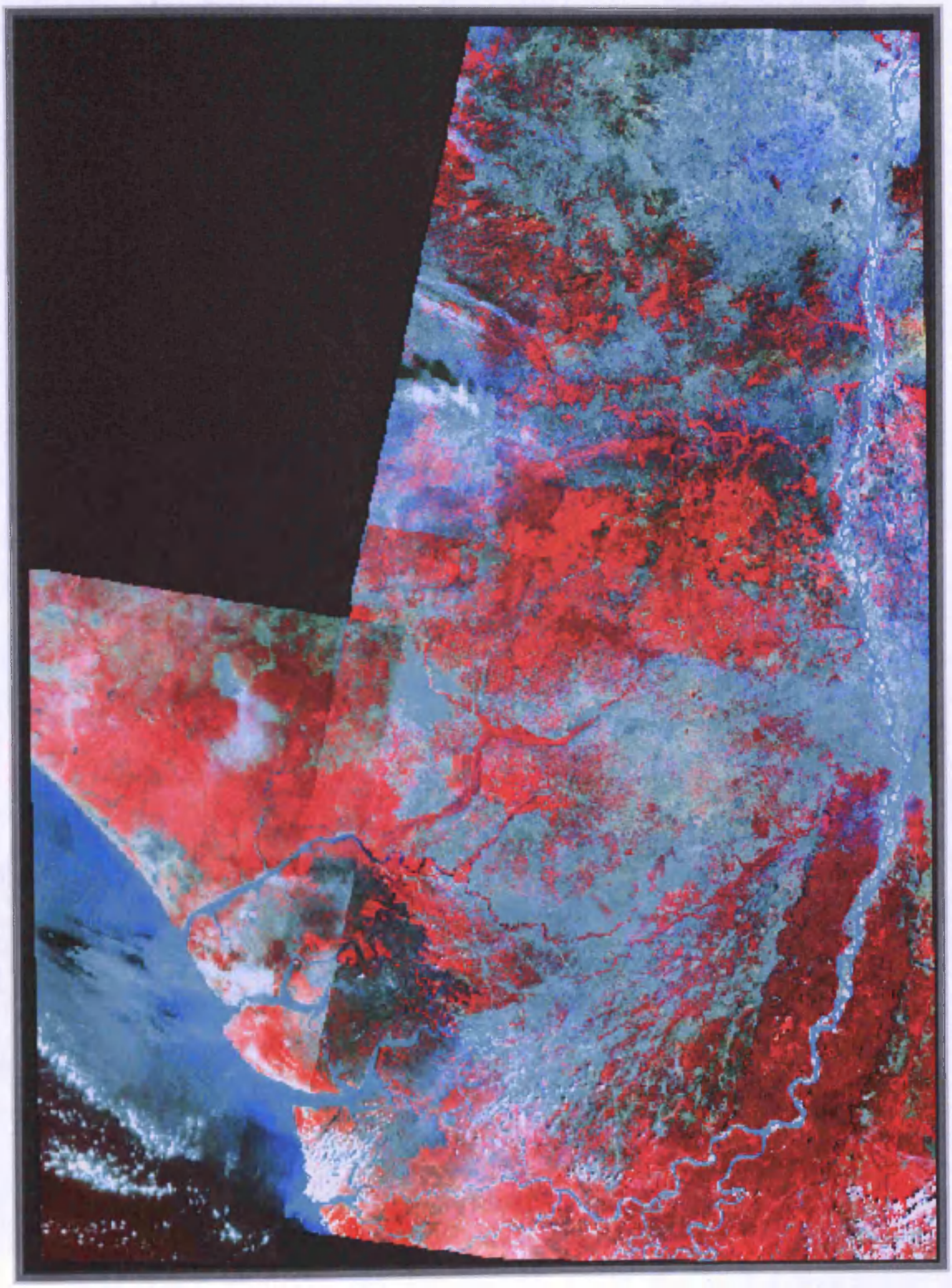


Figure 4.17 Landsat TM subset using AOI; band combination 4, 3, 2

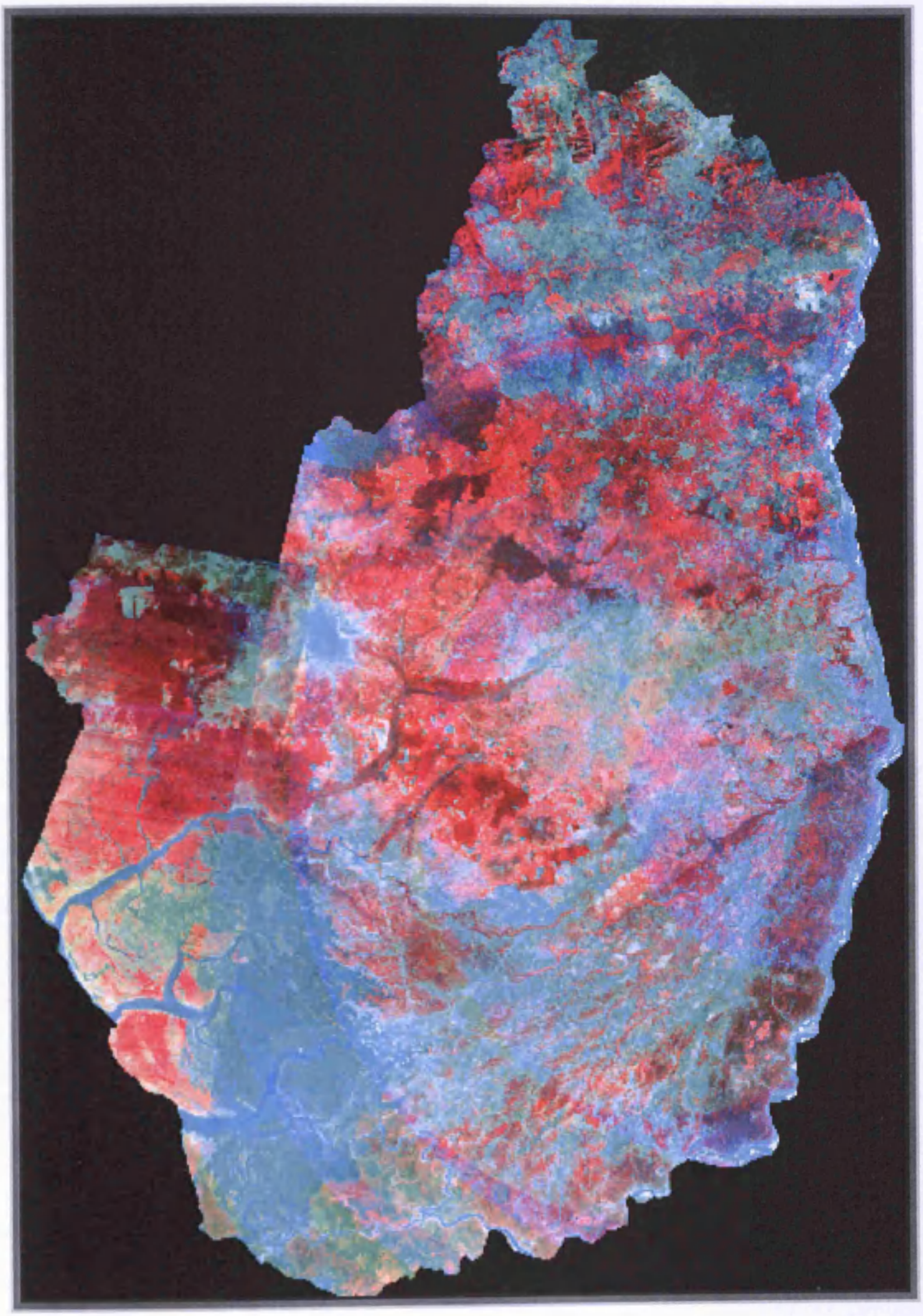
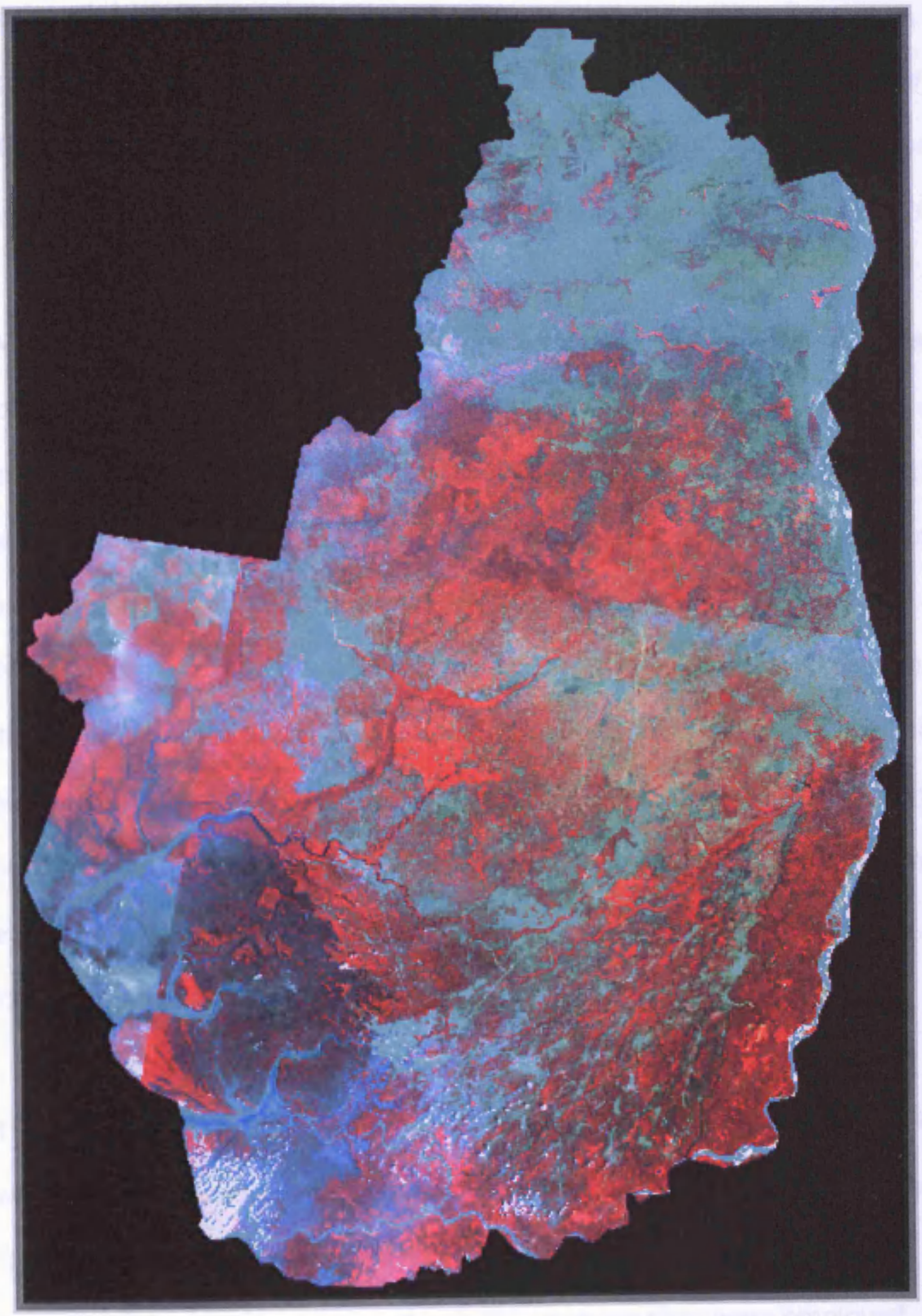


Figure 4.18 Landsat ETM subset using AOI; band combination 4, 3, 2

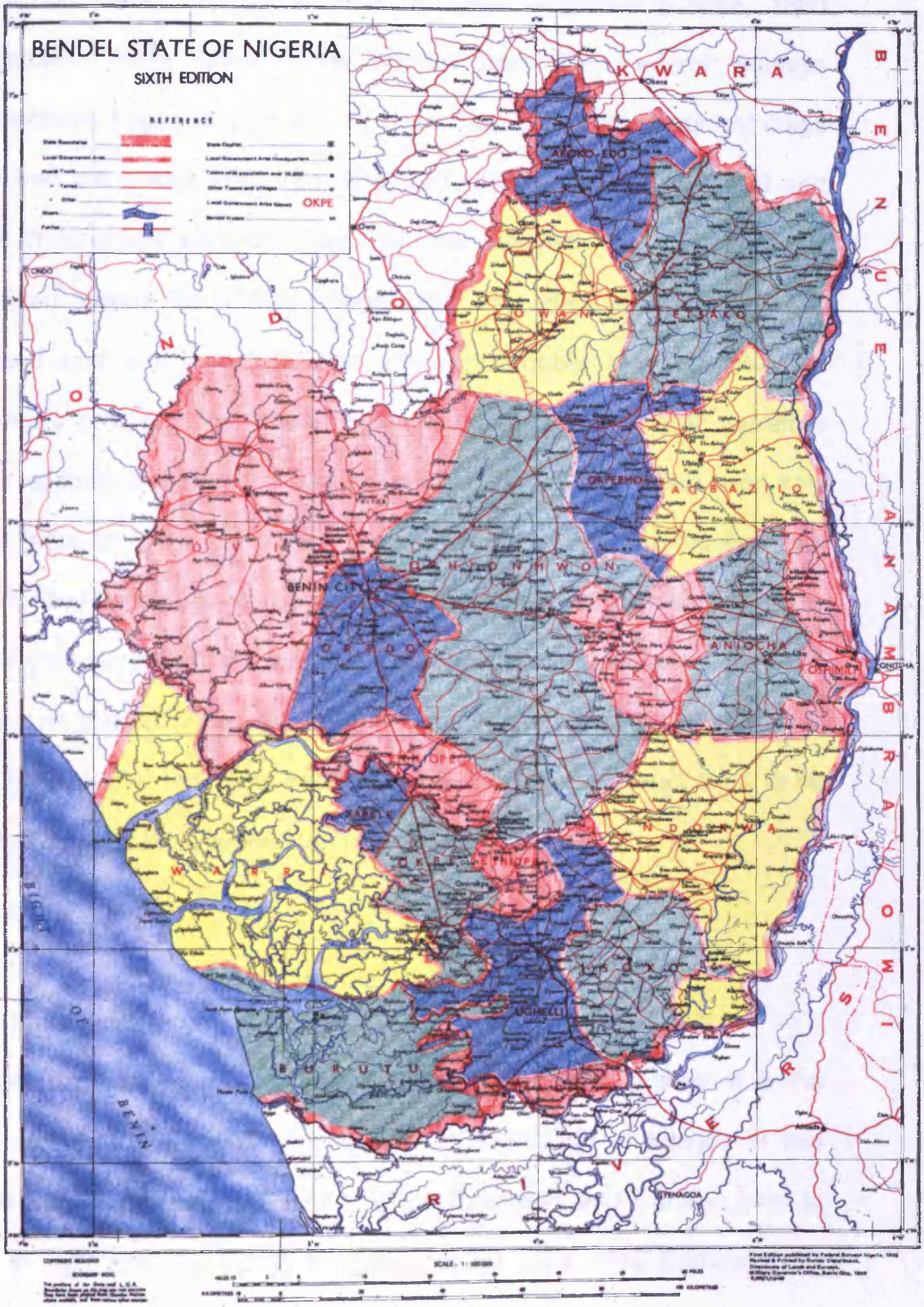


First order polynomial transformation was applied. This transformation is a linear transformation, which relates to the linear equation $y = mx + b$. The registration basically pairs off a point (or pixel) on the digitised map with a point (or pixel) on the image. These points are known as *ground control points* (GCPs). There are features that can be located with precision and accuracy on accurate maps yet are also easily located on digital images (Campbell, 2002).

A total of 20 GCPs were selected in order to cover the entire area. These were locations or features that could be precisely identified on both the image and the map. An overall RMSE (root mean square error) of 0.423 was achieved, according to ERDAS (2003) when rectifying Landsat data, for the rectification to be accurate to within 30 meters; the RMS error should not exceed 1.00. RMSE is the measure of the location error, which is the standard deviation of the difference between actual positions of GCPs and their calculated positions after registration (Campbell, 2002). The image was then resampled using the nearest neighbour resampling method. This simply assigns the value of a corrected pixel to the value from the nearest uncorrected pixel (Campbell, 2002), without losing the original data values.

The second registration was image to image, where the Landsat TM images were geo-registered to the geo-corrected Landsat ETM using the same 20 GCPs evenly dispersed across the images. The same parameters, i.e. first order transformation and nearest neighbour resampling were employed.

Figure 4.19 Map of the study area showing road networks from Benin



4.5 Ancillary data

Topographical maps employed as base maps, with 1:50,000 and 1:100,000 scales and Transverse Mercator projection (Clarke, 1880 Spheroid). These maps were bought from the Federal Surveys Department, Lagos and Benin City (Edo State). The topographical maps obtained are sheets 266, 283, 284, 285, 297, 298, 299, 308, 309 and 318. These maps were compiled from panchromatic aerial photographs acquired around the 1960's. Regrettably, the maps have never been revised and are outdated. The other obtainable map sources are generally compiled from these outdated topographical maps; therefore their reliability and quality are questionable. These maps were used only as a guide for the initial classification scheme and to plan the fieldwork survey and travel routes. The need for a base map of each sub-area (i.e. local government areas) was to assist in the compilation of the land use/cover classes generated from the images. The hard-copy printouts of the Landsat TM and ETM images were also used to select sites to be visited during the fieldwork.

4.6 Fieldwork

Fieldwork is an important stage in change detection studies. It is the verification or confirmation of results (classification of images in this case) attained on the computer or in the laboratory and it is also used to set straight any vagueness by filling in the gaps. This fieldwork was carried out to acquire true information with regards to geographical location and it also facilitated the establishment of training areas for performing supervised classification and to test geo-referencing carried out on the Landsat images. It should be noted that at this point due to security reasons, observations and readings had to be taken in close proximity to the roads.

McCoy (2005) came up with a checklist that can be followed in the preparation of remote sensing fieldwork. They are:

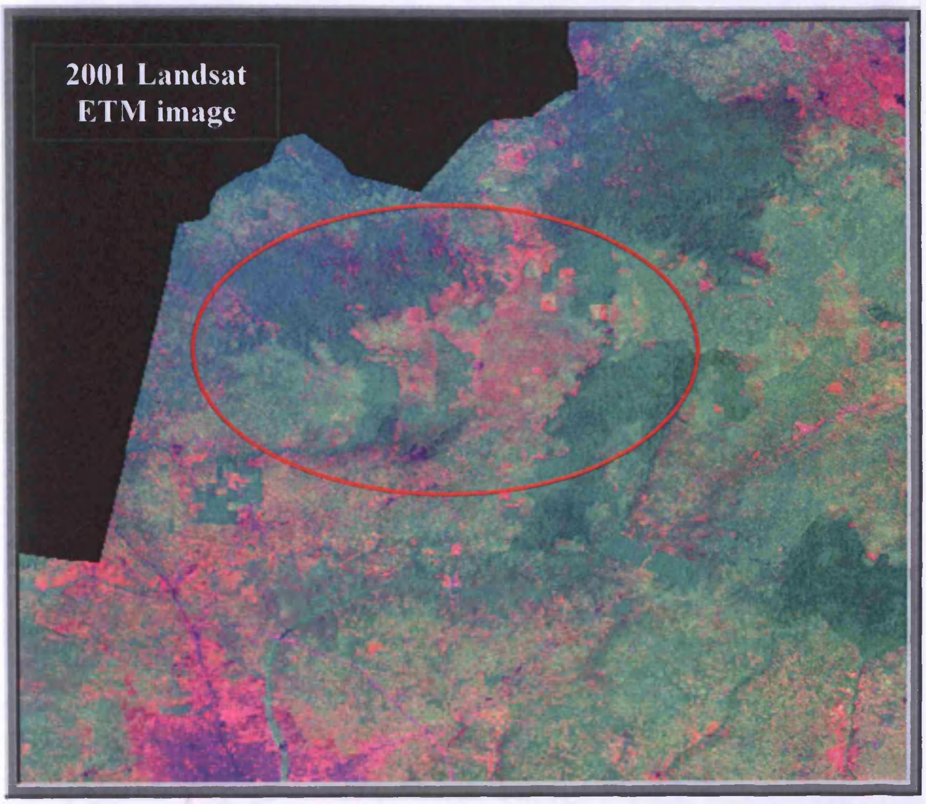
1. Selection of maps.
2. Selection of the coordinate system.
3. Determine the level of accuracy.
4. Investigate satellite visibility for the field trip dates.
5. Determine the location of control points of known coordinates.
6. Create a georeferenced image with an overlay of map features and useful landmarks.
7. Decide on points to visit either for measurement, observation, or accuracy assessment.
8. Identify observations to be made regarding the site characteristics.

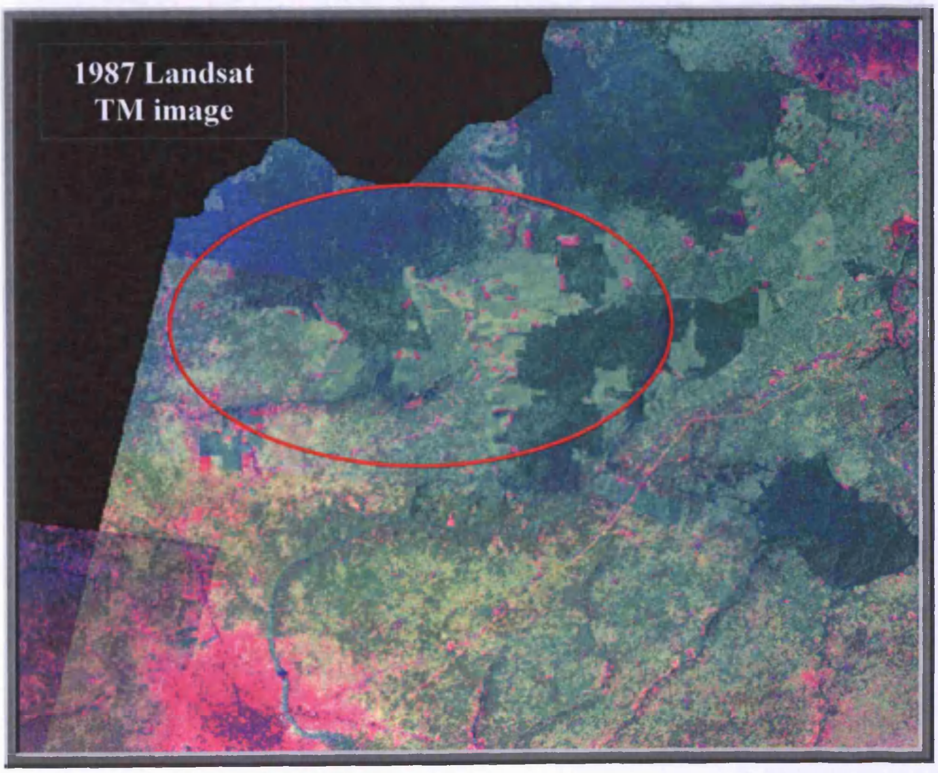
The fieldwork was carried out between December and February, to correspond with the months in which the Landsat satellite images were captured (see tables 4.13 and 4.14), in order to reduce errors in classification of the images (Chapter 5). This time of the year was during the dry season, which made it easy to move around and get more ground covered. Before setting out onto the field, the major sites to be visited had to be selected; this was done by drawing uniform 2cm by 2cm grids across both images, Campbell (2002) referred to this type of sampling as the stratified systematic non-aligned sampling pattern. This assures that sample points will be evenly distributed over the study area and that all classes will be represented (McCoy, 2005). In addition, both images were compared and analysed and large areas of visible land cover change were noticed and were the first sites to be selected (see figure 4.20 a-c). Subsequently, planning the routes by taking one major trunk road out of Benin City (Edo state), sites were selected which covered all land cover classes. The travel routes for fieldwork survey were produced through familiarity with the study area and looking at the map of Benin City. The base image and map were prepared before setting out for the fieldwork. Then, land cover codes were manually used to annotate the map for each major class.

The field survey was carried out throughout Edo and Delta state using the Global Positioning System (GPS) equipment, (GARMIN GPS 12), a digital camera and interview questionnaires. By using "a georeferenced image and a GPS, locational accuracy problems are greatly reduced...However, it is still difficult to be certain that a field location is accurately tied to a single specific image pixel coordinate" (McCoy, 2005). The GPS was used to collect ground control point to verify the accuracy of geo-rectification of images and the supervised classification. A few GPS readings were taken around control sites and compared with satellite images and maps, just to make sure the GPS was in good working condition.

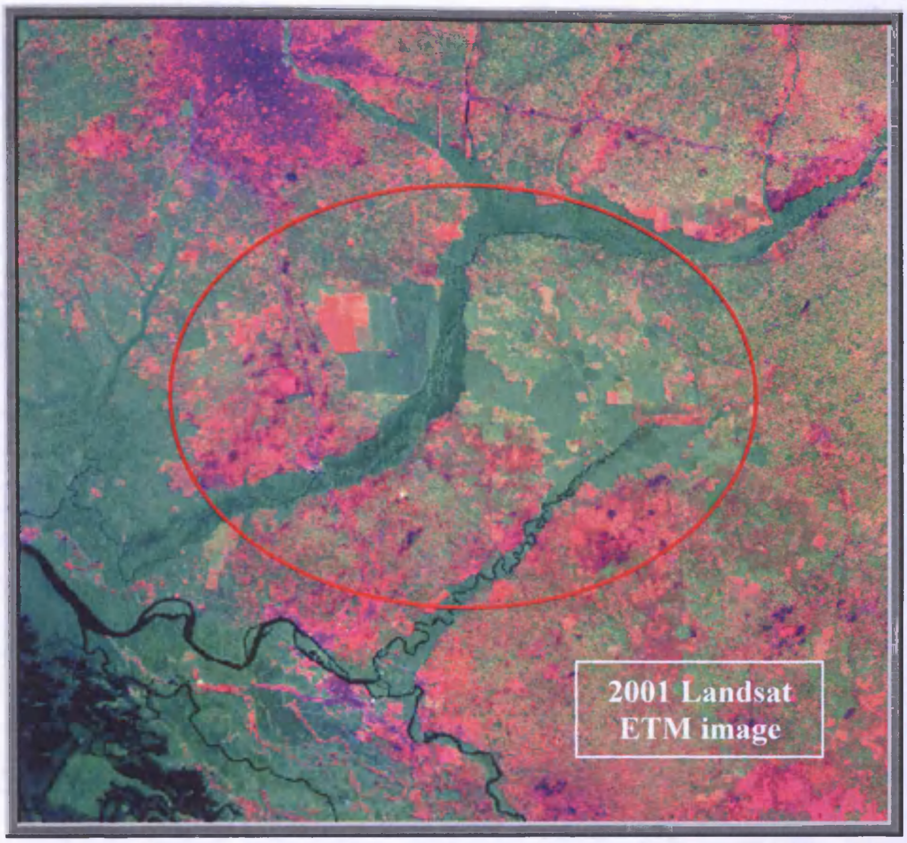
Figure 4.20a-c Cross-sections of the image, showing large areas of land cover change, that were interpreted visually (highlighted in red)

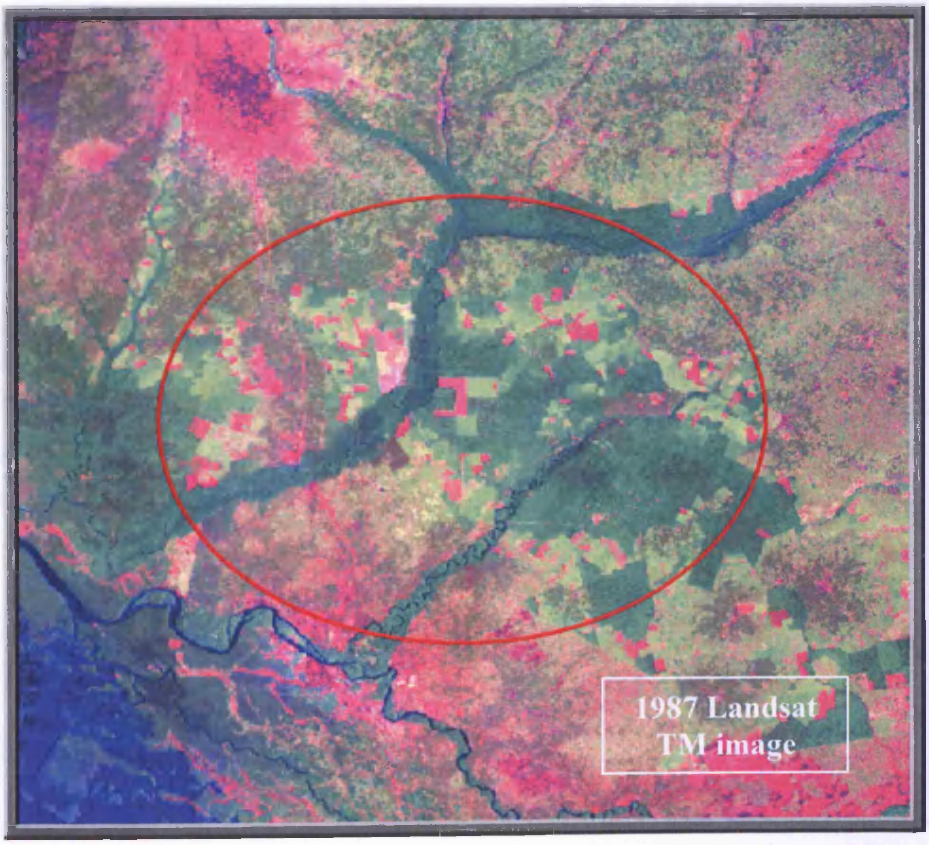
a)



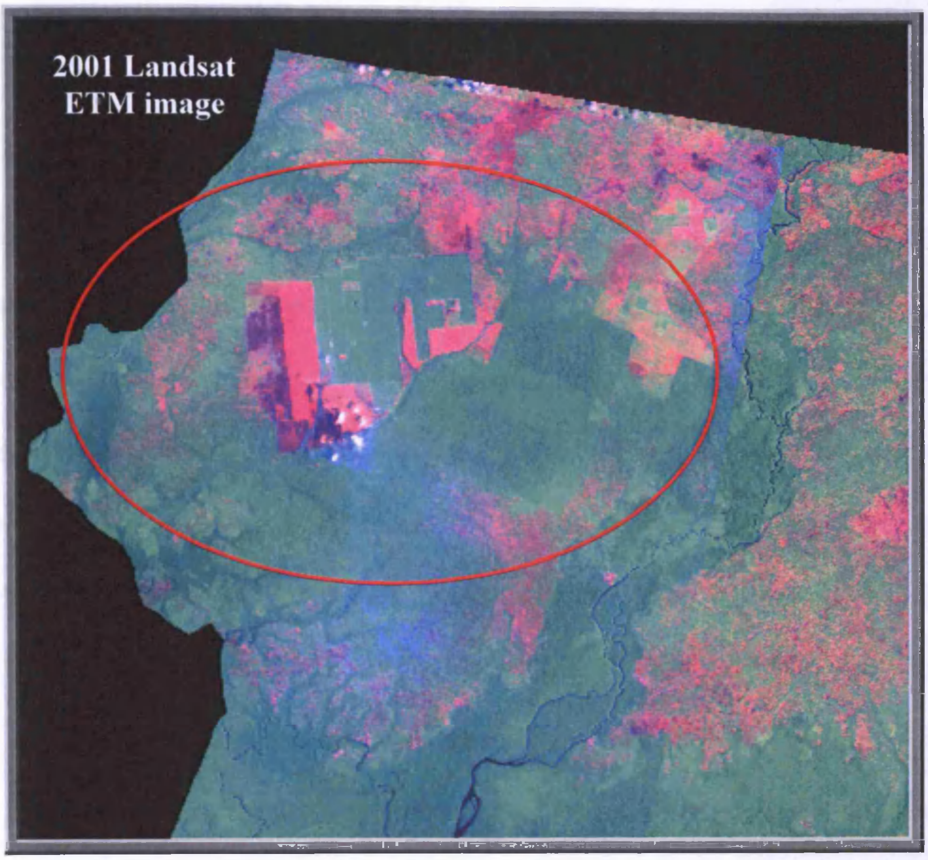


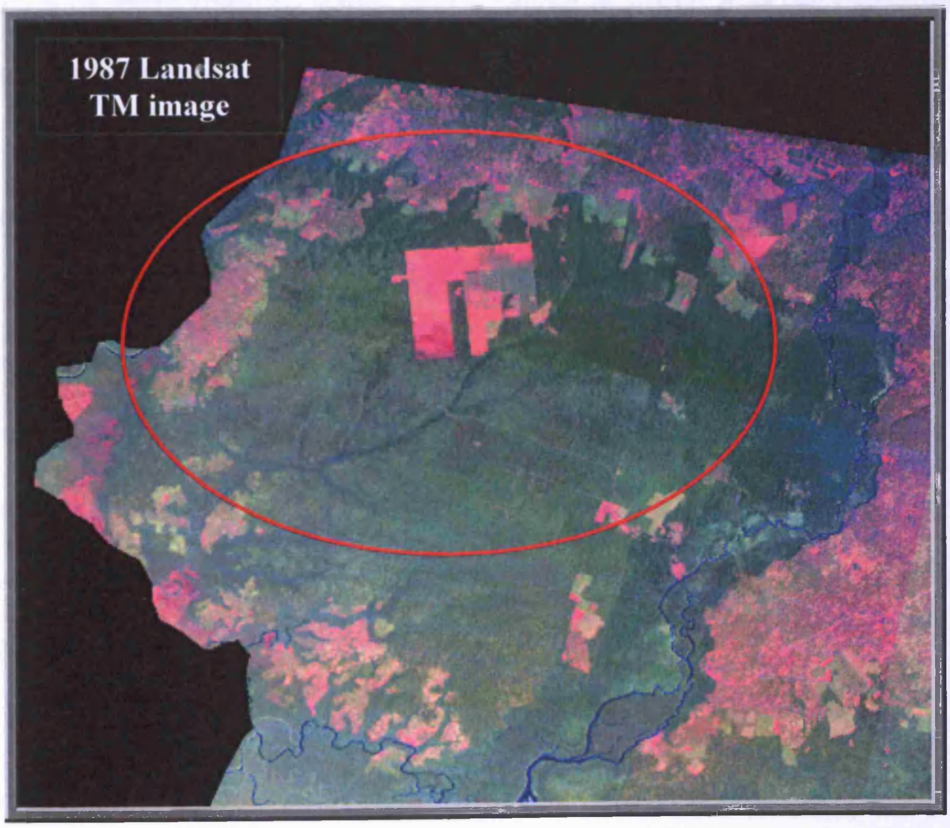
b)





c)





Field notes were taken on a pro-forma sheet (for each site), concerning site location coordinates, rough sketches, date etc (see Appendix I).

The data collected at each site visited comprised of photographs, GPS readings and questionnaires, where possible. As a field site was located, the motor vehicle would stop where it was safe to do so, a GPS reading was taken and photographs taken of the immediate surroundings from where the GPS readings where recorded (see figures 4.21 a-g) and the suitable land cover and land use class names of the surrounding area logged. The data recordings were collected in close proximity to the motor vehicle, due to security reasons. Consequently the collection of field data was restricted to mainly roadside observations. The photographs were used to verify and analyse features and the classified images (see Chapter 5).

Looking at the images in figure 4.20c above, it can be observed that the land, that is Okomu Oil Palm Estate, had changed enormously so the site had to be visited. I had a discussion with Mr Jacques Collignon, who was the manager of the estate. It was discovered that the change was due to plantation growth and development, where palm plantation had increased and in addition, rubber trees had been planted between 1999 and 2000.

Figure 4.21a Field site visited (Okomu plantation), highlighted in red (2001 Landast ETM image). **b-g** Photographs of field site

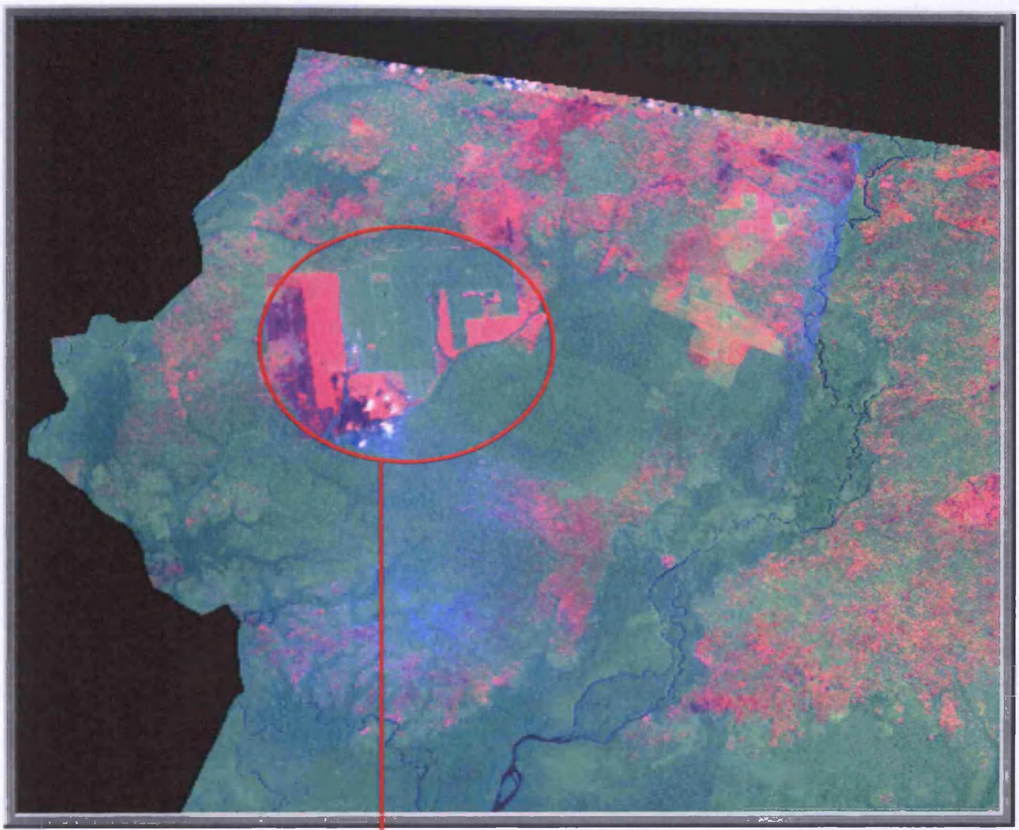


Figure 4.21(b) Okomu Plantation. North of where the GPS readings where taken

Figure 4.21(c) Okomu Plantation. Northeast of where the GPS readings where taken, showing rubber and palm plantation

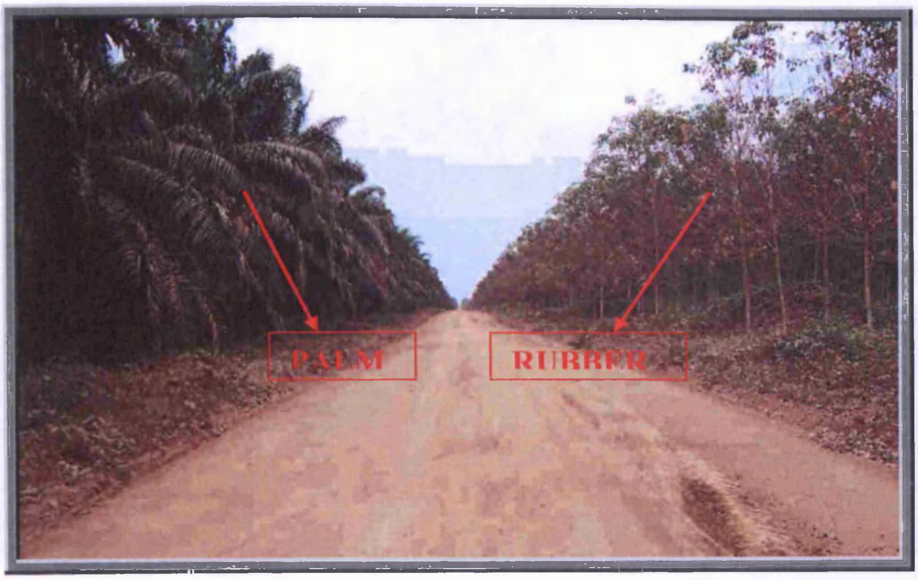


Figure 4.21(d) Okomu Plantation. North-west of where the GPS readings where taken

Figure 4.21(e) Okomu Plantation. South of where the GPS readings where taken, showing the rubber plantation

Figure 4.21(f) Okomu Plantation. Southeast of where the GPS readings where taken, showing the rubber plantation

Figure 4.21(g) Okomu Plantation. South-west of where the GPS readings where taken

The questionnaire conceived was to be distributed, these questionnaire surveys were aimed at corroborating and aiding the results generated from the classification scheme & change detection methods. The questionnaire consisted of open and close ended questions (see Appendix II). It was also to ascertain other factors of land cover change that may not be very apparent unlike acknowledged factors such as socio-economic factors and population growth. The questionnaires were administered to the local indigenes at the sites visited, whom I believed to be a strong driver of land cover change. Unfortunately, due to security reasons, people's mistrust in strangers and fear of the government, especially one asking them questions about their farms and surrounding environment, only a small number of people agreed to fill out a questionnaire and take part in an interview. As this was the case, the questionnaires could not be used as part of the analysis for this research. Notwithstanding, I noticed that the perception of the indigenes was that of all land surrounding their villages or houses belongs to them, so they could farm anywhere they liked, irrespective of government legislation. Most of the people know they are not meant to encroach into the forest and clear it for farming activities, but they still do. This is one of the reasons why most of them refused to be interviewed for fear of what the ramifications will be. I noticed (by observations and speaking to the local indigenes) that the main farming systems carried out in the study area were; shifting cultivation, rotational bush fallow (mainly subsistence) and of course plantation agriculture e.g. Nigerian Institute for Oil Palm Research (NIFOR).

CHAPTER 5 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: METHODOLOGY

CHAPTER 5

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: METHODOLOGY

5.1 Introduction

This chapter describes the methods used here for modelling land cover change. It focuses on the use of the data collected (as discussed in chapter 4), the generation of a land cover classification scheme, and the chosen modelling approach.

5.2 Classification of the Satellite Images

Model calibration will be based on classified RS images. Classification is the process of grouping and assigning analogous pixels into classes. This research is going to use land cover (LC) classes, in order to produce a thematic LUC maps. 'The process of land use classification is not in itself a task of great difficulty; it only requires considerable knowledge and care to prepare a satisfactory land classification scheme' (Campbell, 2002). It is, however, an important stage in image analysis, as Lillesand and Keifer (1994) stated: 'The overall objective of an image classification procedure is to automatically categorize all pixels in an image into land cover themes.'

Before the fieldwork the satellite RS images from 1987 and 2001 were interpreted visually. Transparent acetates were overlaid on the A1 size satellite image plots and the corners marked. I then delineated and outlined land cover features/classes. Unsupervised classification was then carried out on both images; which was done to test the distinctness of classes, It is the process of assigning pixels to classes automatically without previous knowledge of the area typically multispectral images are used. 'Unsupervised training is also called clustering, because it is based on the natural groupings of pixels in image data when they are plotted in feature space. According to the specified parameters, these groups can later be merged, disregarded, otherwise manipulated, or used as the basis of a signature.' (Leica Geosystems GIS & Mapping, 2003)

This unsupervised classification was performed using the ISODATA (Iterative Self-Organizing Data Analysis Technique - Tou and Gonzalez, 1974) algorithm, which is a clustering method, that 'uses spectral distance as in the sequential method, but iteratively classifies the pixels, redefines the criteria for each class, and classifies again, so that the spectral distance patterns in the data gradually emerge' (Leica Geosystems GIS & Mapping 2003) With this method of classification, the original images produce natural classes. Then another unsupervised classification was performed on the images, using 20 iterations maximally and 9 classes for both images (figures 5.1 and 5.2). This decision of selecting these classes was based on my knowledge and familiarity with the area. As stated earlier, a 'visual' land cover classification was carried out, before the fieldwork, using this process, a total of 10 classes were visually identified and a maximum of 20 iterations were applied because I thought that would be enough number of iterations for each image. Also the convergence threshold was left at the default of 0.95, which means that as soon as 95% or more of the pixels stay in the same cluster between one iteration and the next, the iteration is terminated. . (Leica Geosystems GIS & Mapping, 2003). The classified images were compared with the original images and maps of the study area, to establish the characteristics of each class and then class names and colours were assigned to each class. These two images with conjunction with Land use maps obtained by unsupervised classification were used to identify the classes before going out into the field were used to guide the field work.

Photographs and GPS readings were taken during the fieldwork of training sites, to verify and analyse features, to facilitate accurate supervised classification of the satellite images (see Chapter 4 for field work procedures). The collection of training sites for each LUC class was carried out during the field work. McCoy (2005) stated in a supervised classification approach to mapping, one of the primary steps is visiting field sites for the purpose of establishing training sites from which training data are derived. In the case of identifying features, patterns and LUC classes in the 1987 Landsat TM image, individuals (both local and officials) were interviewed to assist in the identification process.

Figure 5.1 1987 TM Unsupervised classified image

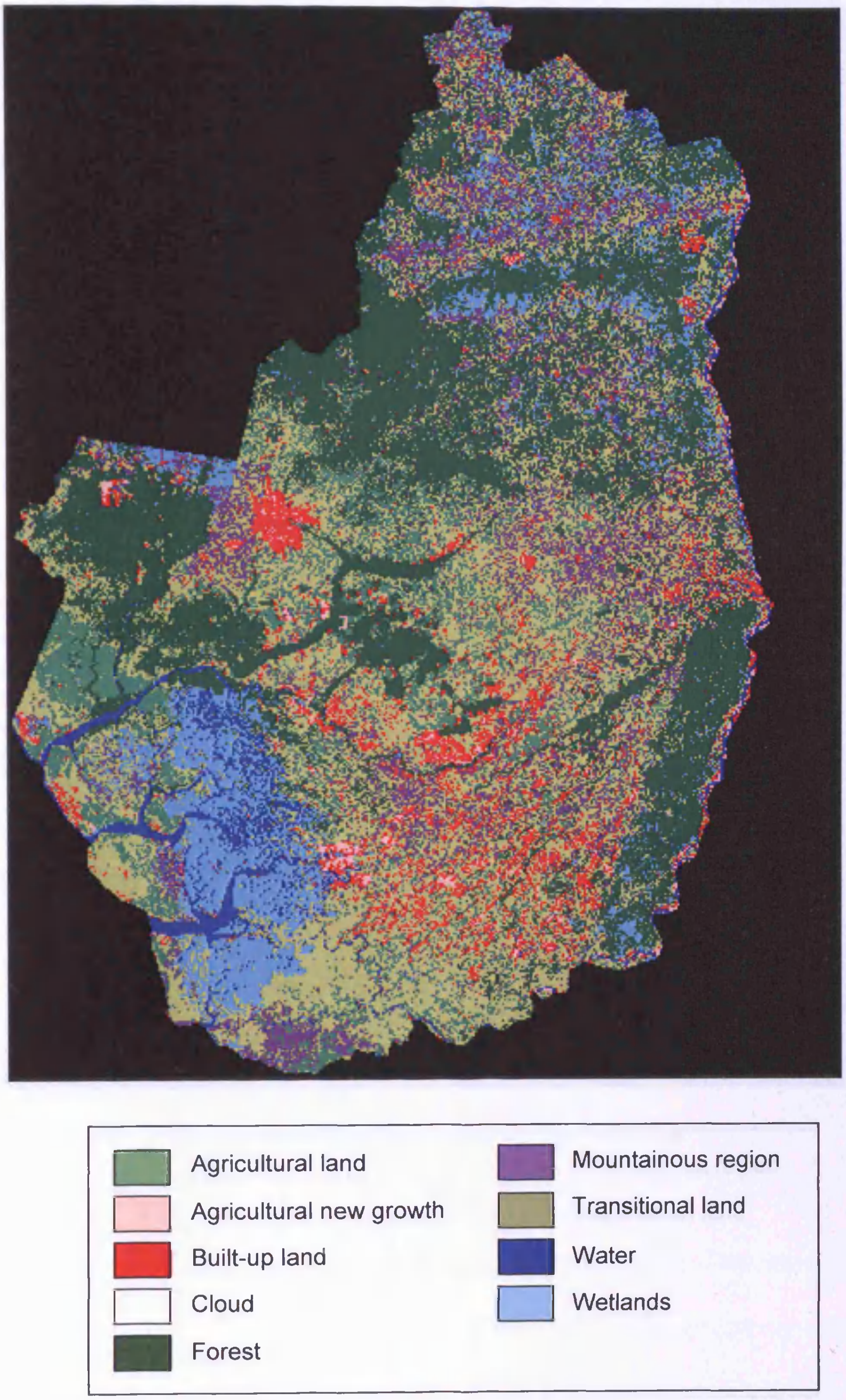
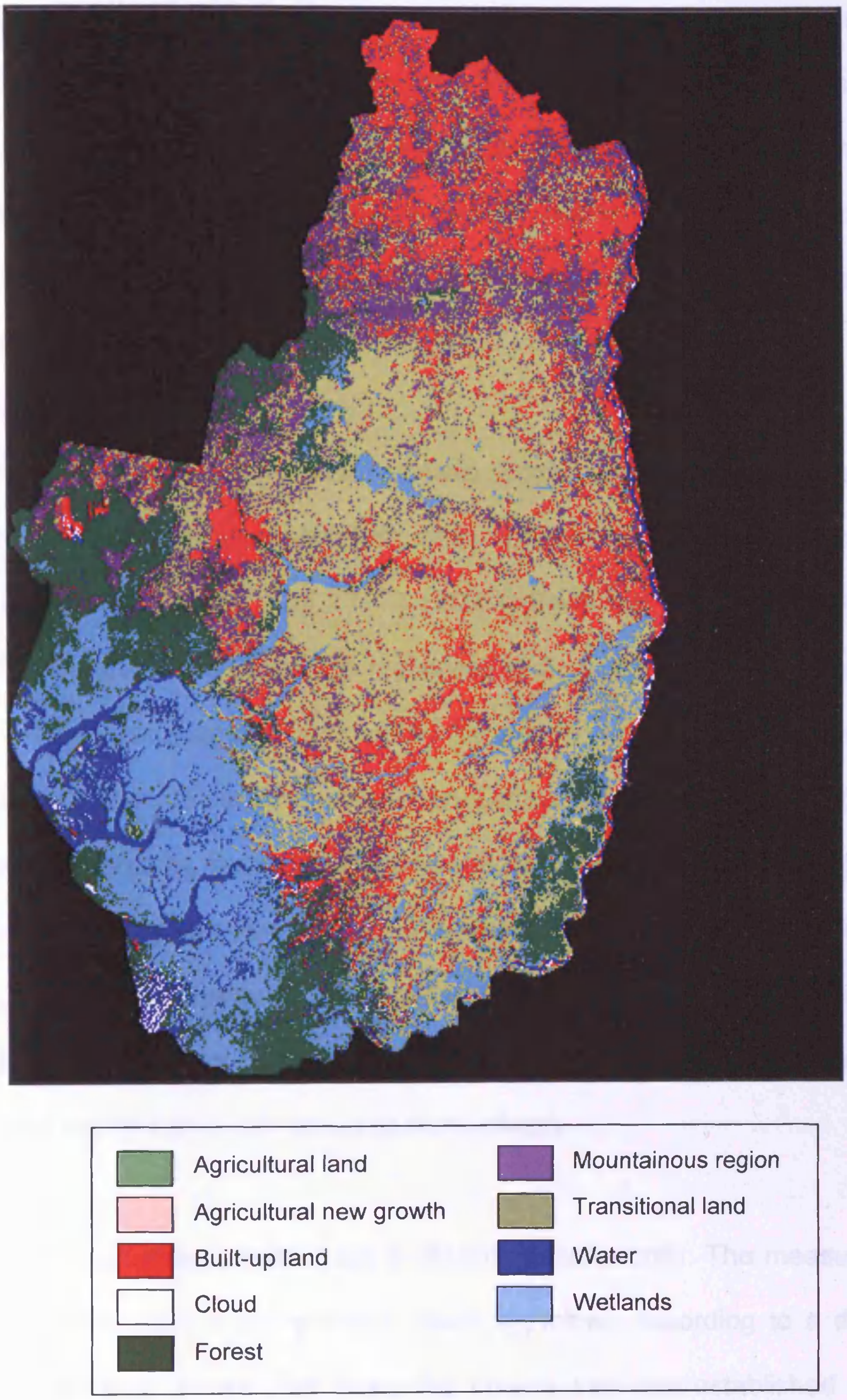


Figure 5.2 2001 ETM Unsupervised classified image



5.2.1 Supervised Classification of Satellite Images

During the field work, ground control points were obtained, which were used to georectify the images. Subsequently, after the field work obtaining ground truth data, supervised classification was performed on both Landsat TM and ETM images. This process uses *training areas/fields* defined by the user to create 9 classes. It serves as a guide as a 'true' representation of the study area as observed or obtained during the course of the field work.

For each of the classes, 50 training sample areas, on average were selected to ensure that there was enough information to generate effectual land use/land cover classes, as Scholz *et al.* (1979 cited in Campbell, 2002) concluded that the most important aspect of training areas is that all land cover types in the scene must be adequately represented by a sufficient number of samples in each class. These training samples where generated by using the AOI (area of interest) polygon tool, where a polygon was drawn around pixels that represent each class, using an average of 30 pixels for each class. This creates signatures that correspond to a class (ERDAS, 2003), which were loaded onto the signature editor (figures 5.5 and 5.6). The training samples areas for each class were merged to create one signature (class).

In classifying an image, each pixel is classified individually. The measurement vector for each pixel is compared to each signature, according to a decision rule, or algorithm. Pixels that pass the criteria that are established by the decision rule are then assigned to the class for that signature (ERDAS, 2003). ERDAS Imagine provides decision rules for parametric and non-parametric signatures, and in this study *Maximum Likelihood Classifier* decision rule was employed. The maximum likelihood classifier 'is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions' (ERDAS, 2003). In other words, it is based on the probability that a pixel belongs to a particular class (ibid, 1987). Maximum classifier was used in this research, as higher accuracies were achieved compared to using any other classifiers, in addition, this classifier has been reported to provide the highest classification accuracies. The maximum likelihood classifier forms a power classification as it's implemented quantitatively to consider several classes and several spectral channels simultaneously (Campbell, 1996).

The supervised employed here comprises of 8 major classes (including cloud in the Landsat ETM image only) – *Built-up land, Agricultural land, Agricultural new growth, Forests, Transitional land, Burnt Areas, Wetlands, Water and Cloud cover*. Please see section 5.2.2 for in-depth description of these classes.

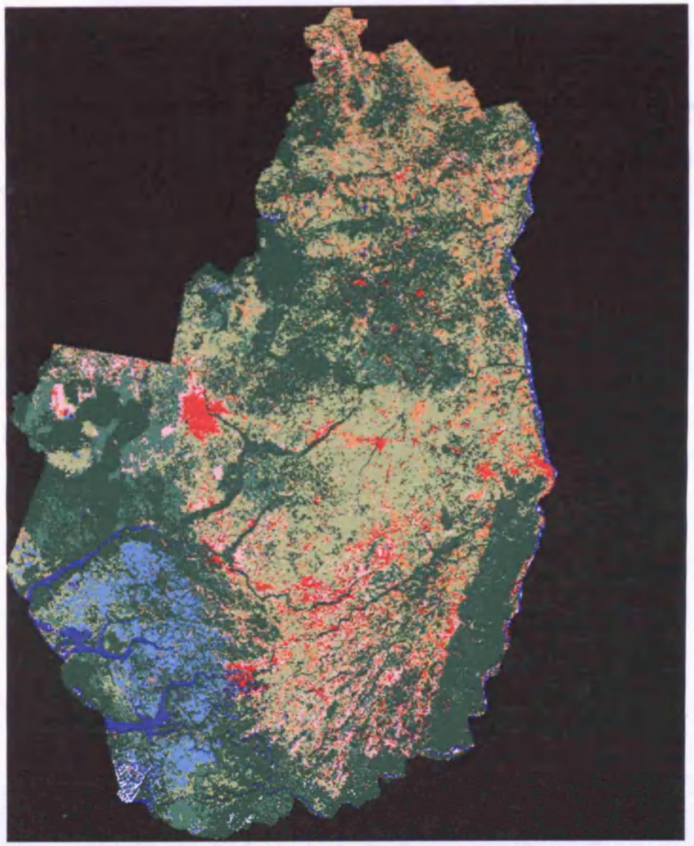
Examining the classifications, it was observed that in the top left corner of the 1987 image there was some cloud cover present, which obscured some land use/land cover information. Since this could give rise to errors in the change detection analysis, the section was cut out to prevent (or reduce) misclassification. In addition, there was also some cloud cover in the 2001 landsat ETM image, but unfortunately this could not be removed, masked or cut out, as it would have impacted on the land cover classification and change analysis. As a result, in order to accommodate this and reduce errors, the *cloud cover* class was added to the classification scheme. It should be noted at this point, that a number of supervised classifications were performed in order to get a classification with little or no errors; this was to reduce the amount of misclassification (or misclassified pixels). The previous supervised classifications performed had a number of misclassifications, and to reduce errors, a reclassification was executed. This decision was based on reviewing the *Signature Separability* and *Error matrix* of each class, this makes it possible to rule out any bands that may not be useful (please see 5.2.4 and 5.2.5 for description). The classifications with the best average signature separabilty and satisfactory overall accuracy were selected to apply in the analysis.

5.2.2 Descriptions of Land Cover Classes

The Federal Department of Forestry's and the USGS classification schemes were both employed with a slight variation to satisfy the objectives of this study (Table 5.2). The classification scheme developed here is also analogous to the FAO Land Cover Classification System (LCCS), primarily the third classification level (table.5.1). The LCCS is an *a priori* classification which enables a comparison of land cover classes regardless of data source, economic sector or country (FAO – Africover, 2003). The LCCS classes are defined by a combination of classifiers, so the single classifiers are detected (and used) and not solely classified, based on the final class name. In other words, emphasis is on a set of classifiers rather than just a name (Gregorio and Jansen, 2000).

Figure 5.3 Landsat TM (1987) Supervised Classification with 8 classes

Figure 5.4 Landsat ETM (2001) Supervised Classification with 9 classes



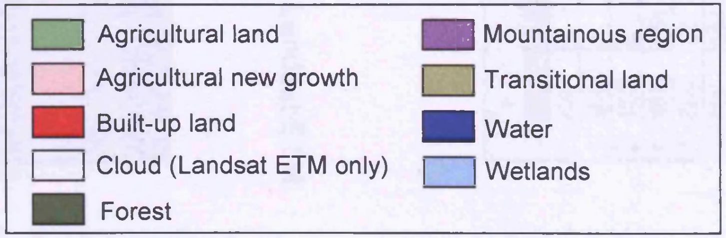
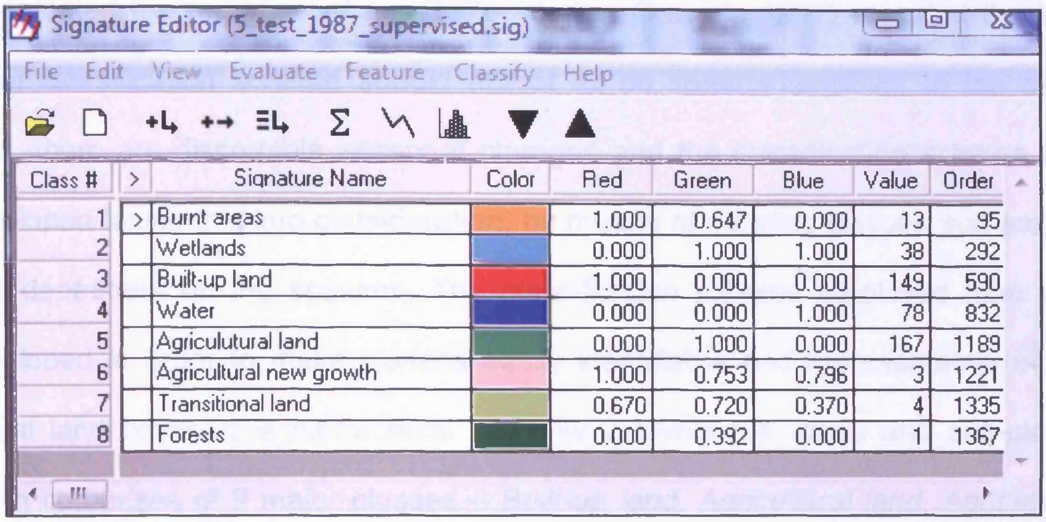
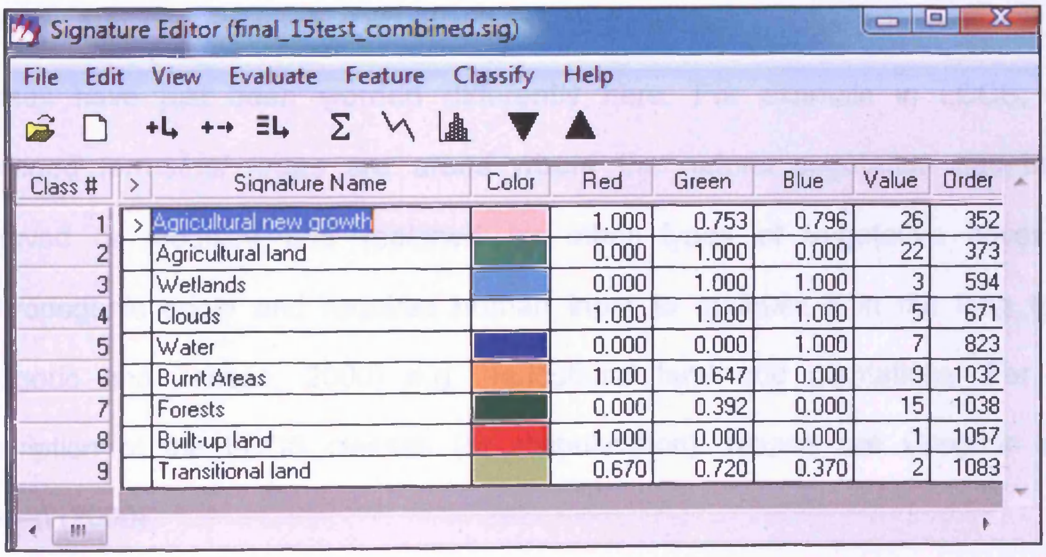


Figure 5.5 Signature editor showing land cover classes for 1987 Landsat TM image



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order
1	>	Burnt areas		1.000	0.647	0.000	13	95
2		Wetlands		0.000	1.000	1.000	38	292
3		Built-up land		1.000	0.000	0.000	149	590
4		Water		0.000	0.000	1.000	78	832
5		Agriculutural land		0.000	1.000	0.000	167	1189
6		Agricultural new growth		1.000	0.753	0.796	3	1221
7		Transitional land		0.670	0.720	0.370	4	1335
8		Forests		0.000	0.392	0.000	1	1367

Figure 5.6 Signature editor showing land cover classes for 2001 Landsat ETM image



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order
1	>	Agricultural new growth		1.000	0.753	0.796	26	352
2		Agricultural land		0.000	1.000	0.000	22	373
3		Wetlands		0.000	1.000	1.000	3	594
4		Clouds		1.000	1.000	1.000	5	671
5		Water		0.000	0.000	1.000	7	823
6		Burnt Areas		1.000	0.647	0.000	9	1032
7		Forests		0.000	0.392	0.000	15	1038
8		Built-up land		1.000	0.000	0.000	1	1057
9		Transitional land		0.670	0.720	0.370	2	1083

They are a number of factors that should be considered in developing a classification scheme (e.g. Anderson 1977 and Scace 1981). One of which was accentuated by Anderson *et al.*, (1976 cited in Omojola 1997) was that the land cover classification scheme should not at all be season-sensitive. In the study area, there are discernible seasonal changes and the classification scheme was developed taking this into consideration, by means of creating classes that are not fully dependent on the seasons. The classification scheme employed here was developed in order to make classes easily identifiable and representative of the actual land cover. It is hierarchical but only 2 levels (i.e. class and sub-class), which comprises of 9 major classes – *Built-up land, Agricultural land, Agricultural new growth, Forests, Transitional land, Burnt Areas, Wetlands, Water and Cloud cover.*

As seen in table 5.1, the third level classification is similar to the classification developed in this research (i.e. comparing the classes) (tables 5.1 and 5.2), the classes have just been worded differently here. For example in LCCS, the *managed terrestrial areas* are areas where the natural vegetation has been removed or modified and replaced by other types of vegetative cover of anthropogenic origin and requires human input to maintain it in the long term (Gregorio and Jansen, 2000) e.g. agricultural land and plantations. For full description of the LCCS classes (or classification), please see Gregorio and Jansen (2000).

Table 5.1 The LCCS dichotomous phase consists of three classification levels

FIRST LEVEL	SECOND LEVEL	THIRD LEVEL
PRIMARILY VEGETATED	TERRESTRIAL	MANAGED TERRESTRIAL AREAS
	AQUATIC or REGULARLY FLOODED	NATURAL and SEMI-NATURAL TERRESTRIAL VEGETATION
PRIMARILY NON-VEGETATED	TERRESTRIAL	CULTIVATED AQUATIC AREAS
		NATURAL and SEMI-NATURAL AQUATIC VEGETATION
	AQUATIC or REGULARLY FLOODED	ARTIFICIAL SURFACES
		BARE LAND
		ARTIFICIAL WATER BODIES
		NATURAL WATER BODIES, SNOW and ICE

Source: http://www.africover.org (2003)

The land cover classes derived in this study are related to the tones and patterns of the images in addition to the fieldwork. This warrants regularity in the classification results and enumeration of land cover change over the time period. Notwithstanding, it was difficult to categorize the classes in the images, especially the 2001 ETM, because the individual scenes were collected at different dates and presence of cloud cover and haze. Figures 5.5 – 5.12 below, are pictures taken during the fieldwork of some of the different land cover and land use classes present in the study area that were used in identifying LUC classes and as supporting evidence (as discussed previously).The attributes of each land cover class are:

a) Built-up land

This class is made up of settlements which have both rural and urban functions, which included industrial areas (e.g. oil rigs and stations). The buildings in this class are predominantly made up of corrugated iron sheet roofing. In most of the settlements, there was a presence of patchy vegetation and farm lands, especially in the outskirts of these areas, bearing in mind that the predominant occupation of local inhabitants (i.e. rural areas) is farming.

b) Agricultural land and Agricultural new growth

These land cover classes are principally lands used for planting and production of crops. It includes cropland, rain fed arable crops, irrigation projects, tree crop plantation, new and immature agricultural crop. This LUC type/class occupies a considerable portion of Edo and Delta states, due to the farming activities carried out (as stated previously) as the soils in the area are nutrient-rich.

The agricultural land vary in sizes and shapes, with smaller farms often found in the surrounding areas of built-up land, where shifting cultivation is the most preferred farming practice. The larger agricultural land are characterised by the more regular shapes and the size of area dedicated to farming, which in most cases nothing more than 2 species are cultivated. For example in Okomu oil palm estate, rubber as well as oil palm are cultivated or in Michelin estate, where only rubber is cultivated. In the course of classification most of these plantations were classified as forests.

c) Forests

This is characterised by areas of disturbed and undisturbed forests. Most of the undisturbed forests are reservation areas such as Ehor forest reserve and Gilli-gilli forest reserves. The disturbed forests are considered to be a mixture of dense and open canopy forests that have been and are continually being encroached on by local indigenes either for farming purposes, fuel wood consumption or even logging purposes.

d) Wetlands

The Ramsar Convention on Wetlands, under the text of the Convention (Article 1.1) defined wetlands as:

"Areas of marsh, fen, peat land 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 can be found along major rivers in the region and along the coast. This is characterised by areas inundated by salt-water (i.e. marshes) and freshwater wetland areas. The soil in this area is water-logged and swampy.

e) Water

This class includes natural water bodies (such as rivers and lakes), canals, dams and man-made water bodies, that are recognized by their pattern and spectral reflectance. The major dams in this area are the Ojirami dam, Okhoro dam and Ikpoba river dam.

f) Transitional land

This constitutes a mixture of grasses, shrubs, bare rock (outcrop), and scattered trees. This class type is related to abandoned agricultural land that has been left to fallow, or recently cleared (forest) land. There is no continuous tree cover; instead there are scattered trees and shrubs. Also included in this class are the bare surfaces (including mountains/rock), since they also comprise of grasses or shrubs. Although the bare rock (or mountains) have a 3-dimensional tone/appearance (unlike the other sub-classes), it was seen as less complicated if it was categorized under this class type. This would reduce classification errors during the supervised classification process.

g) Burnt Areas

These are areas that have been burnt or cleared using fire, to prepare the land for agriculture.

Table 5.2 The Land Cover Classification Scheme employed

CLASS	SUB-CLASS
Built-up land	Settlements (Urban and Rural) Transportation Industrial Commercial
Agricultural land	Cropland and Pasture Rain fed arable crops Irrigation project Agricultural tree crop plantation
Forest	Undisturbed forest Disturbed forest Forest reserves
Wetlands	Forested freshwater swamp Marshes Floodplain Coastal plain
Water	Natural water bodies: Ocean, River, Lake Canal Dams
Transitional or Mosaic land	Immature forest Grassland Shrub land Bare surfaces
Burnt areas	
Agricultural new growth	New agricultural crop Immature agricultural crop
Cloud	

Figure 5.7 Transitional land

Figure 5.8 Rubber plantation

Figure 5.9 Wetland area

Figure 5.10 Burnt area

Figure 5.11 Oil palm plantation

Figure 5.12 Built-up land

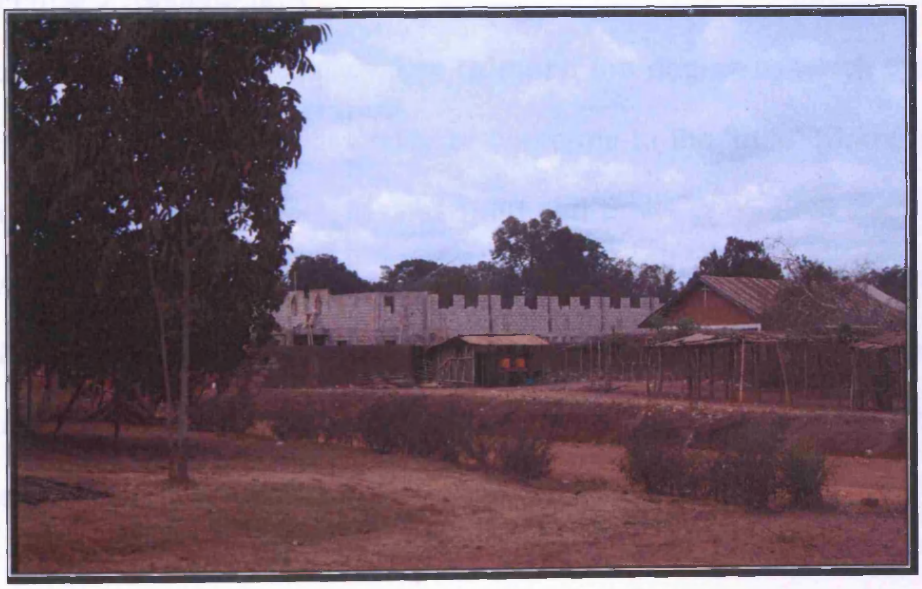


Figure 5.13 Agricultural land

5.2.3 Accuracy Assessment

Classification accuracy is usually taken to mean the degree to which the derived image classification agrees with reality or conforms to the 'truth' (Campbell 1996, Janssen and van der Wel 1994, Maling 1989 and Smits *et al*. 1999 cited in Foody 1992). Accuracy assessment is an important process in remote sensing and especially in classification. Lillesand and Kiefer (2000) expressed "A classification is not complete until its accuracy is assessed". This process examines if each class are correctly representative of the 'true' area on the ground.

An accuracy assessment was carried out on the classified images, using the *error matrix (contingency table)* and *signature separabilty*.

5.2.4 Error Matrix of Classified Images

Error matrix is considered to be a highly effective representation of accuracy of each class, which demonstrates how well classes are grouped properly (Congalton, 1999). The error matrix, which sometimes is also referred to as *confusion matrix,* identifies overall errors for each class and misclassifications (due to confusion between categories) by categories (Campbell, 2002). This compares each class based on a summary of the relationship between the reference data and the classified data.

Table 5.3 Example of error matrix

	Forest	Agriculture	Urban	Water	Total
Forest	562	17	24	5	**608**
Agriculture	35	736	0	20	**791**
Urban	10	0	234	16	**260**
Water	0	0	6	205	**211**
Total	**607**	**753**	**264**	**246**	**1870**

The *reference data*, which is given in the columns (looking at table 5.3 above), are the pixels that were used in the selection of training sites for each class, in other words they are the known pixels or 'true' pixels as verified during the field work (i.e. ground truth). The data along the rows correspond to the *classification results (classified data)* derived from the classification process. The diagonal cells of the matrix (highlighted in yellow) are the numbers of pixels that agree with both datasets, in other words they are the pixels that have been correctly classified. While the non-diagonal cells are the number of misclassified pixels, where these misclassified pixels down the columns are referred to, as *errors of omission* and along the rows are *errors of commission*. The opposite of these errors of commission and omission are known as *user's accuracy* and *producer's accuracy* respectively, which are more widely used. Congalton and Green (1999) defined errors of commission as including an area into a category when it does not belong to that category, and errors of omission excludes that area from the category in which it truly does belong.

The *overall accuracy* was as well calculated. This assesses the total agreement between the reference data and classified data. This is the sum of the correctly classified pixels (i.e. diagonal cells) divided by the total number of pixels in the error matrix (highlighted in blue).

To calculate the percentage of overall accuracy *O*;

$$O = \frac{\sum (D_1, D_2, D_3 \,\ldots\ldots\ldots D_n)}{\sum B} \tag{5.1}$$

where $\sum (D_1, D_2, D_3 \,\ldots\ldots\ldots D_n)$ is the sum of correctly classified pixels and $\sum B$ is the total number of reference pixels.

Another measure of how correctly pixels were classified in accordance with the reference map is known as the *kappa coefficient (κ)*. This is a measure of the difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and a random classifier (Lillesand and Kiefer, 2000). According to Campbell (2002), this measurement of difference between two maps is reported by the diagonal entries in the error matrix and the agreement might be attained solely by chance matching of the two maps. This is also referred to as *KHAT* values and it uses the proportion of chance (or expected) agreement. The kappa coefficient ($\hat{k}$) is given simply as:

$$\hat{k} = \frac{Observed\ accuracy - Chance\ agreement}{1 - Chance\ agreement} \quad (5.2)$$

Bishop *et al.* (1975 cited in Mather 1999) gave a more detailed description of the kappa coefficient as:

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad (5.3)$$

where

x_{ii} = Diagonal cells of the error matrix

x_{i+} = Total number of pixels in row *i*

x_{+i} = Total number of pixels in column *i*

N = Total number of pixels in the error matrix

r = Number of rows in the error matrix

5.2.5 Signature Separability

The *signature separability* of the LUC classes was also assessed; this measures the statistical separation between the classes, determining how distinctive they are from one another. In other words, this process enables the identification LUC classes that are not spectrally separable. This was evaluated using the *Transformed Divergence* as a distance measure (Swain and Davis, 1978; ERDAS, 1997). This is a statistical separation measurement uses a covariance-weighted distance between classes to establish the degree of separabilty. The formula is given as:

$$D_{jk} = \tfrac{1}{2} tr\left((C_j - C_k)\left(C_j^{-1} - C_k^{-1}\right)\right) + \tfrac{1}{2} tr\left(\left(C_j^{-1} - C_k^{-1}\right)(\mu_j - \mu_k)(\mu_j - \mu_k)^T\right) \quad (5.4)$$

$$TD_{ij} = 2000*[1-\exp(-D_{ij}/8)] \quad (5.5)$$

where,

j and *k* = the two classes being compared

C_j = covariance matrix of class *j*

μ_j = mean vector of class *j*

tr = trace of a matrix

T = transpose

The calculated divergence is typically between is between 0 and 2000. A divergence greater than 1900 means that the classes are totally separable, between 1700 and 1900 the separation is fairly good, below 1700 the separation is poor and if it is zero (0) the classes are inseparable (Jensen, 1996).

After this process, the total area (in hectares) for Agricultural land, Forest and Transitional classes were derived, which will be integrated into the model, as these statistical data could not be obtained, due to poor data availability and in most cases lack of data in Nigeria.

5.3 Model Building for Land Cover Change Modelling

Land use change models support the analysis of the causes and consequences of land use changes in order to better understand the land use system and its interactions and to support land use planning and policy. (Verburg *et al.*, 2004). Models are used to predict possible future land cover change projections.

The simple model developed here, consists of three of the major land cover classes outlined above, forest, transitional and agricultural land. The model projections were based principally on the total land area of these classes were collected from the classified 1987 TM image.

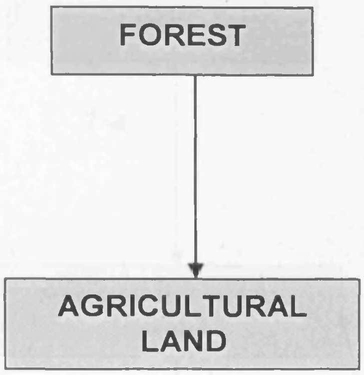
5.3.1 Model Projections of Land Cover Change

The land cover model projections were developed to aid in assessing how the land has been transformed and projecting their future transformations. Three different model projections were implemented using MS Excel, which assume different trajectories for deforested land. These model projections assess probable and possible state of affairs, as future land cover change are tentative.

This model was implemented to provide trajectories for the statistical trends in each land cover type (i.e. agriculture, forests and agriculture) and also present the probabilities of each land use type influencing one another. The model projections were developed using different variables and constants – *deforestation rate (a), abandonment rate (b), rate of agricultural rate of transitional land (c), rate of regrowth of transitional land to forests (d).* Subsequent to establishing these variables, the areas of land cover were extrapolated to 2030 using the past land area estimates.

Model projection I (figure 5.15) is based on the land use conversion from forest to Agricultural land. This model projection assumes that the declines in forests are correlated with an increase in agricultural lands. As the logging companies or even the local farmers obtain what they want (e.g. raw wood) from the forest. The local people then burn the parcel of land to clear it for farming activities. In addition, there are large commercial agricultural corporations in Edo and Delta states that clear large parcels of land for plantations such as oil palm, rubber and cocoa.

Figure 5.14 Model projection I



Using this conceptual model, equations describing the transitions of land cover were formulated, which is expressed as:

$$F_i = (1-a)\,F_0 \qquad (5.6)$$

$$A_i = bA_0 + (1-a)\,F_0 \qquad (5.7)$$

where,

F_i = Forest area at present time

F_0 = Forest area at preceding time

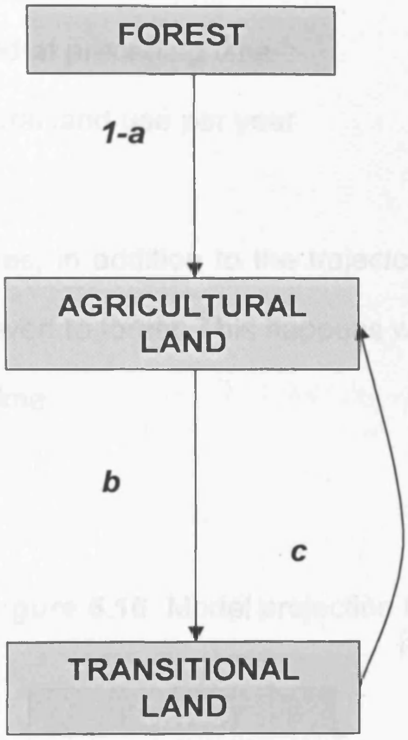
A_i = Agricultural land at present time

A_0 = Agricultural land at preceding time

$1-a$ = deforestation rate per year

b = abandonment rate per year

Figure 5.15 Model projection II



Model projection II, addresses the conversion from forest to agriculture to transitional land and then examines how some of the transitional land is then converted back to transitional land after being left to fallow for a period of time.

This is expressed mathematically as:

$$F_i = (1-a)\,F_0 \tag{5.8}$$

$$A_i = bA_0 + (1-a)\,F_0 + cT_0 \tag{5.9}$$

$$T_i = T_0 + bA_0 - cT_0 \tag{5.10}$$

Where,

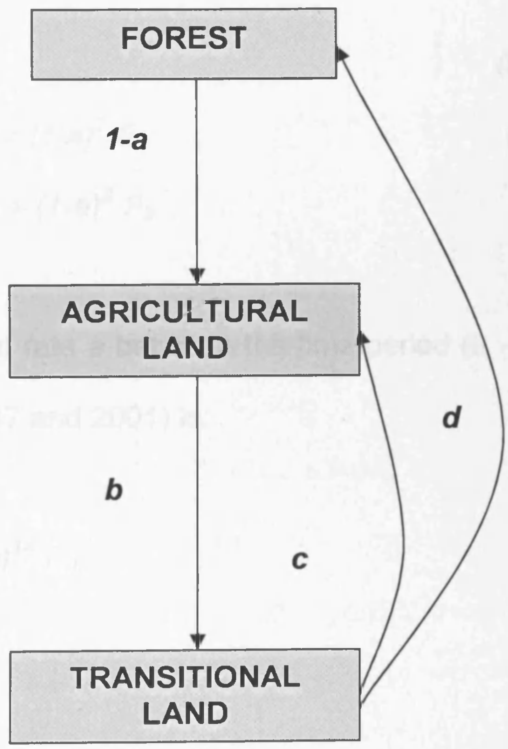
T_i = Transitional land at present time

T_0 = Transitional land at preceding time

c = Rate of agricultural land use per year

Model projection III assumes, in addition to the trajectories of the previous model that transitional land can revert to forest. This happens when the land has been left fallow for a long period of time.

Figure 5.16 Model projection III



This is mathematically expressed as:

$$F_i = F_0 - (1-a)\,F_0 + dT_0 \qquad (5.11)$$

$$A_i = A_0 + (1-a)\,F_0 + cT_0 - bA_0 \qquad (5.12)$$

$$T_i = T_0 + bA_0 - cT_0 - dT_0 \qquad (5.13)$$

Where,

d = Rate of conversion of Transitional land to Forest per year

The deforestation rate per year, *a,* was calculated using the forest areas as derived from the satellite images:

$$F_i = (1-a)\,F_0 \qquad (5.14)$$

$$F_2 = (1-a)\,F_i = (1-a)^2\,F_0 \qquad (5.15)$$

$$F_3 = (1-a)\,F_2 = (1-a)^3\,F_0 \qquad (5.16)$$

Therefore the deforestation rate *a* between the time period (t_1 - t_0) of the available satellite imageries (i.e. 1987 and 2001) is:

$$(1-a)^{14}\,F_0 \qquad (5.17)$$

$$(1\text{-}a) = \sqrt[14]{\frac{F_{14}}{F_0}} \qquad (5.18)$$

So,

$$a = 1 - \sqrt[14]{\frac{F_{14}}{F_0}} \qquad (5.19)$$

$$a = 1 - \left(\frac{F_{14}}{F_0}\right)^{\frac{1}{14}} \qquad (5.20)$$

In the model projections, the rates of change from one land cover to another were assumed to be constant in time, i.e. *a, b, c* and *d* are constant, due to the difficulty faced in getting information based on these, especially the deforestation rate. The other constants (i.e. *b, c* and *d*) and how they were derived are discussed in the next chapter.

5.4 'Socializing the Pixel' and 'Pixelizing the Social' in Edo and Delta States

The process of making remote sensing in general more relevant to the social, political and economic problems and theories pertinent to land cover change, is included in the objectives of the LUCC project (Turner, 1997). This process has been referred to as 'socializing the pixel' and 'pixelizing the social'. In an introduction to the LUCC Open Science Meeting Proceedings, Skole (1996) pointed out that 'the coupling of direct observations with process-level analyses will be an important and necessary endeavour if we are to improve our understanding of cover change'.

In Lambin *et al.* (1999), the term 'socializing the pixel' was given as means to recognize information embedded within a remote sensing imagery that is directly relevant to the core themes of the social sciences (including the LUCC questions) and use it to inform the concepts and theories pertinent to those themes.

Whereas, 'pixelizing the social' a term coined by Geoghegan *et al.* (ibid), is the process of linking the pixel to the people (socio-economic variables). Furthermore, Geoghegan *et al.* (ibid) stated that this as a link is being made of on-the-ground human actions and consequences to remote sensing imagery (i.e. pixels) and putting them in a model. In other words, the terms 'socializing the pixel' and 'pixelizing the social' can be put simply as utilizing remote sensing imagery beyond its bio-geophysical elements and making socio-economic data spatially explicit, respectively.

In this research, the pixels (combined with census and a number socio-economic factors) have been used to model and project land cover change, in Edo and Delta states, by means of using the areas of land cover types as originally obtained from the processed remotely sensed imagery. This method of approach, although having been explored minimally, is largely empirical and atheoritical in nature, but at the same time can be used to model land cover directly from remotely sensed imagery (Geoghegan *et al.*, ibid).

CHAPTER 6 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: RESULTS

CHAPTER 6

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: RESULTS

6.1 Introduction

The results presented in this chapter are derived from the change detection approaches used in this research of the land cover change in Edo and Delta states between 1987 and 2001. In addition to this, results of the land cover model developed will be discussed in this chapter.

6.2 Accuracy Assessment

Accuracy assessment of the land cover classification is by an error matrix. The accuracy of the classification of both images was assessed using signature separabiltiy, overall error matrix, producer's accuracy, user's accuracy, errors of commission, errors of commission and kappa analysis.

6.2.1 Signature Separability

As stated previously (in chapter 5), for a classification to be acceptable, the calculated divergence ideally should be between 0 and 1700, i.e. at 0 - 2000, the classes are totally separable and at 1700 – 1900 the class separation is fairly good (Jensen, 1996).

The signature separabilties for both classifications are very good (tables 6.1 and 6.2) with an overall average of 1929 (1987 image) and 1909 (2001 image). In the 2001 ETM classification the signature separability between Agricultural land: Transitional land (721), Agricultural land: Forests (1457) and Forests: Transitional land (850) are quite poor. This pattern is similar to the 1987 TM classified image - Agricultural land: Transitional land (1382), Agricultural land: Forests (1636) and Forests: Transitional land (1407). This suggests that these class pairs are spectrally close to each other, but to some degree are separable. This might be due to the fact that there is some (pixel) confusion between these classes and their reflectance values.

6.2.2 Assessment and Evaluation of Error Matrices

The error matrix is a common measure for the assessment of the classification, how well the classification has performed, by recognizing the errors and misclassifications in each land cover classes (as previously described in chapter 5). In the error matrices, the total of each column shows the total number of pixels in each class collated during the training sites selection process and it is referred to as the *reference data*. The total of each row shows the number of pixels that have been assigned to each class, which are the classified data results achieved after classification (see tables 6.3 and 6.4). For example, in the error matrix for the 1987 image, there are 3603 pixels of agricultural land and of these 2945 pixels were correctly classified as agricultural land (92.71% accurate). The overall accuracy for the 1987 TM classification is

(49841 / 56074) x 100 = 88.88%

And for the 2001 ETM classification

(74265 / 83251) x 100 = 89.21%

Looking at the Water class in the error matrix for 2001 image, (table 6.3), the percentage of correctly classified pixels is 92.31%, with the rest were misclassified, with cloud cover having the majority number of misclassified pixels (4.92%). This is due to the cloud cover present in the image especially around the coastal regions and the Niger valley. Further examination of the error matrix, it can be observed that there is some confusion between the Forest, Transitional land and Agricultural land classes; this is also shown in the user's accuracy and producer's accuracy for these classes (2001 classified image). This may be due to the conversion of land from forest-agriculture-transitional land, making it sometimes difficult to for the classification to differentiate between these classes as they may have similar spectral or reflectance values (figure 6.2).

Table 6.1 Signature separability for 1987 Landsat TM classification

Class	Burnt areas	Wetlands	Built-up land	Water	Agricultural land	Agric new growth	Trans land	Forests
Burnt areas		2000	2000	2000	2000	2000	2000	2000
Wetlands			2000	2000	2000	2000	1992	1984
Built-up land				1951	2000	1698	2000	2000
Water					2000	1993	2000	2000
Agric land						2000	1382	1636
Agric new growth							1980	2000
Trans land								1407
Forests								

Table 6.2 Signature separability for 2001 Landsat ETM classification

Class	Agric new growth	Agricultural land	Wetlands	Cloud	Water	Burnt Areas	Forest	Built-up land	Trans land
Agric new growth		1996	2000	2000	2000	2000	1999	1933	1932
Agric land			1998	2000	2000	1998	1457	2000	721
Wetlands				2000	2000	1999	1990	2000	1978
Clouds					1999	2000	2000	2000	2000
Water						2000	2000	1997	2000
Burnt Areas							1990	1980	1946
Forest								1998	850
Built-up land									1977
Trans land									

Table 6.3 Error matrix for the 1987 Landsat TM classification (in pixel percentages)

	REFERENCE DATA									
CLASSIFIED DATA	**Class**	**Burnt area**	**Wetlands**	**Built-up land**	**Water**	**Agricultural land**	**Agric New Growth**	**Trans land**	**Forests**	**Total**
	Burnt area	100	0	0	0	0	0	0	0.01	**100**
	Wetlands	0	96.79	0.39	7.01	0.03	0.09	0.15	0.13	**105**
	Built-up land	0	0.58	88.38	2.06	1.14	6.94	1.28	0.09	**100**
	Water	0	0.19	2.43	90.86	0.06	0.43	0.05	0	**94**
	Agric land	0	0	0	0	81.74	0.09	7.57	3.31	**93**
	Agricultural New Growth	0	0.29	8.23	0.01	1.17	90.68	1.72	0	**102**
	Trans land	0	0.87	0.54	0.02	7.05	1.77	81.38	7.84	**99**
	Forests	0	1.26	0.03	0.03	8.83	0	7.86	88.61	**107**
	Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	

Table 6.4 Error matrix for the 2001 Landsat TM classification

CLASSIFIED DATA	REFERENCE DATA									
	Class	**Agric New Growth**	**Wetlands**	**Clouds**	**Water**	**Burnt Areas**	**Built-up land**	**Agric land**	**Forests**	**Trans land**	**Total**
	Agric New Growth	95.30	0	0	0.02	0	1.69	0.06	0.02	4.19	**101**
	Wetlands	0	96.32	0	0.57	0	4.37	0.02	0.97	0.91	**103**
	Clouds	0.36	0	87.78	4.92	0	0.16	0.28	0.05	0.01	**94**
	Water	0.12	0.25	3.95	92.31	1.62	2.73	0.02	0.55	0.17	**102**
	Burnt Areas	0	1.23	7.71	2.04	95.14	6.06	0	0.07	0.79	**113**
	Built-up land	1.45	0.25	0.56	0.08	2.7	83.13	0	0.13	0.95	**89**
	Agric land	0	0	0	0.02	0	0.05	89.58	7.49	4.41	**102**
	Forests	0	1.47	0	0.03	0	0.82	4.95	89.1	2.81	**99**
	Trans land	2.77	0.49	0	0.02	0.54	0.98	5.09	1.63	85.75	**97**
	Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	

Another reason for this can also be put down to the amount of cloud cover (and haze in some areas) present in the 2001 image. Looking at the error matrix for 2001 classification, there is some confusion between the burnt areas and water classes, as seen in figure 6.1, the spectral values of these classes are quite similar, which can explain the misclassification.

The overall accuracy was of the classifications, the 1987 being 88.88% and the 2001 being 89.21%, which are both quite good, according to Anderson et al. (1976) who stated that overall accuracies of 85% and above are satisfactory. Although Congalton and Green (1999) argued that, there is nothing especially significant about this 85% accuracy level, the accuracy of a classification obviously, depends on many factors, including the amount of effort, classification scheme and variability of the classes.

Error matrices are very effective representations of map accuracy, because the individual accuracies of each map category are plainly described along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the map (Congalton and Green, 1999). Tables 6.3 and 6.4 show the comprehensive error matrix for the 1987 classified image and 2001 classified image respectively.

Figure 6.1 Spectral profile for agricultural land, transitional and forests

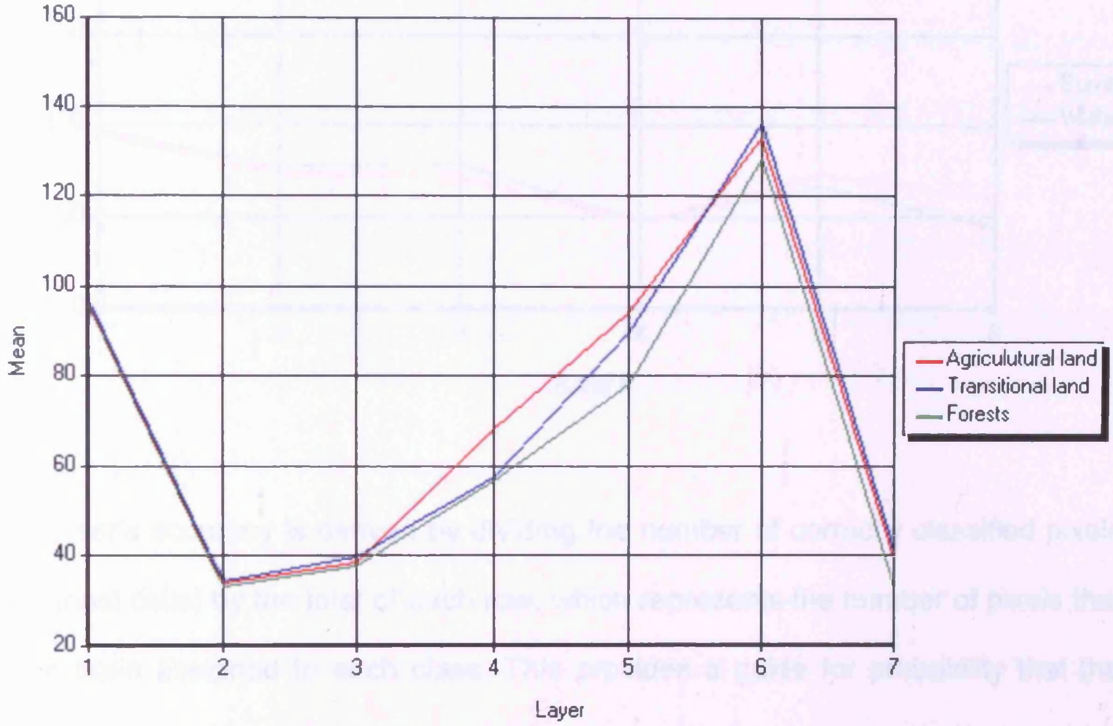
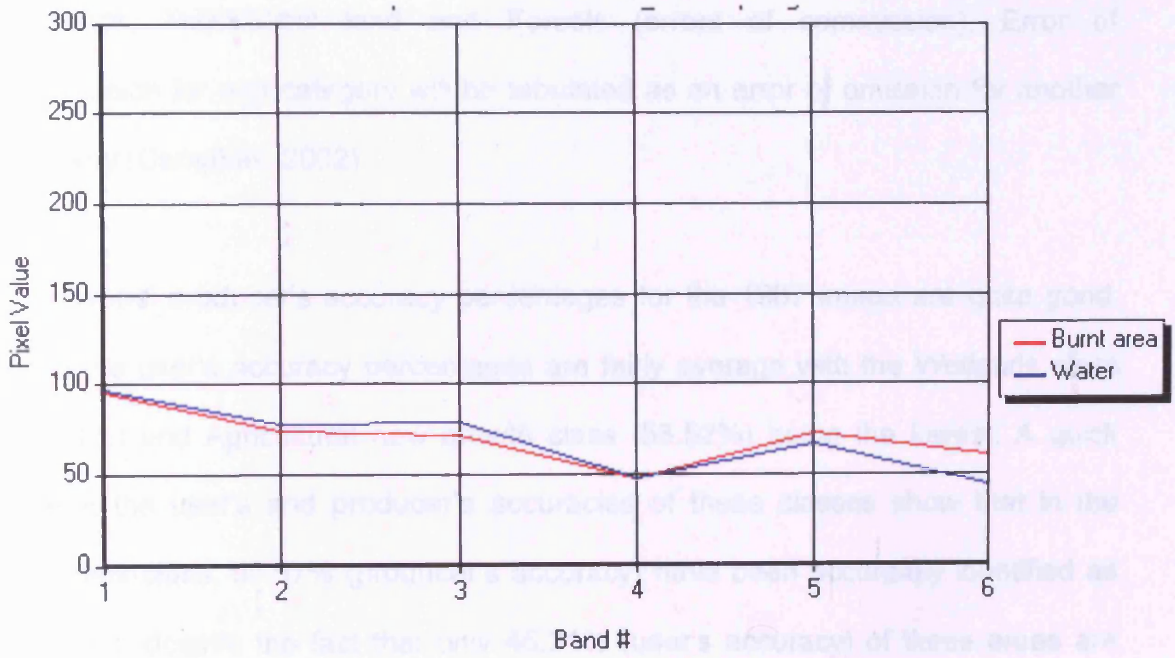


Figure 6.2 Spectral profile comparing the spectral reflectance for burnt areas and water



The user's accuracy is derived by dividing the number of correctly classified pixels (diagonal cells) by the total of each row, which represents the number of pixels that have been assigned to each class. This provides a guide for probability that the pixels on the classified image have been correctly assigned to their respective classes. The producer's accuracy is calculated by dividing the number of correctly classified pixels by the column total for each class, this is a guide of how well the classification was performed in comparison to the reference data (i.e. ground truth).

Using an example in Table 6.3, looking at the Water class, 348 pixels were classified as Built-up land, 1182 pixels as Wetlands, 4 pixels as Transitional land and 5 pixels as Forests but the reference data shows that they are actually categorized in the Water class on the ground. These pixels have been omitted from the Water class (errors of omission) and have been committed to the Built-up land, Wetlands, Transitional land and Forests (errors of commission). Error of commission for one category will be tabulated as an error of omission for another category (Campbell, 2002).

The overall producer's accuracy percentages for the 1987 image are quite good, while the user's accuracy percentages are fairly average with the Wetlands class (45.31%) and Agricultural new growth class (58.52%) being the lowest. A quick look at the user's and producer's accuracies of these classes show that in the Wetlands class, 97.67% (producer's accuracy) have been accurately identified as wetlands, despite the fact that only 45.31% (user's accuracy) of these areas are 'true' wetlands on the ground.

For agricultural land, the errors of omission is 6.79% of the total agricultural land, which form the misclassified pixels and comprise of all but one (i.e. burnt areas) of all the classes (table 6.5). Whilst the error of commission is 10.25% of which transitional land and forests form the majority. With this in mind, it can be concluded that the key sources of error in classifying the agricultural land is the confusion between agricultural land, transitional land and forests. Looking at both transitional land and forests classifications in table 6.3, there is a similar pattern or relationship between these three classes.

Table 6.5 Producer's Accuracy and User's Accuracy for 1987 TM classification

	USER'S ACCURACY	PRODUCER'S ACCURACY	ERRORS OF COMMISION	ERRORS OF OMMISSION
Burnt areas	98.28%	100%	1.75%	0%
Wetlands	45.31%	97.67%	117.88%	2.33%
Built-up land	85.18%	91.40%	15.91%	8.60%
Transitional land	87.71%	83.52%	11.70%	16.48%
Water	99.40%	90.86%	0.55%	9.14%
Forests	96.65%	94.44%	3.28%	5.56%
Agricultural land	90.09%	93.21%	10.25%	6.79%
Agric new growth	58.52%	96.42%	68.34%	3.58%

For the 2000 image classification the overall user's accuracy is less than the 1987 image but the overall producer's accuracy is also quite good (Table 6.6). The user's accuracy for agricultural land is only 55.29% and this shows that this corresponds to actual agricultural land on the ground, while the producer's accuracy for this same land cover type shows that 89.58% of the 'true' agricultural land has been correctly classified. A further explanation, as given by Congalton and Green (1999), is that although the producer of the image can claim that 89.58% of an area that was actual agricultural land on the ground was identified as such on the image, a user of this map will find that only 55.29% of this class states that it would actually be agriculture on the ground. In this aforementioned class, there is some confusion between agricultural land class and transitional land class, as a large proportion of the agricultural land has been incorrectly classified as Transitional land.

Using the same land cover class as above, the errors of omission is 10.42% of the total agricultural land, which form the misclassified pixels and comprise of forests and transitional land (table 6.4). Whereas, the error of commission is 72.43%, with transitional land and forests taking the majority. The key source of error in classifying the agricultural land is the confusion between agricultural land, transitional land and forests, similar to the 1987 image classification.

6.2.3 Kappa Analysis of Classification

Kappa analysis was recognized as a powerful technique used for analysing a single error matrix and comparing the difference between different error matrices (Congalton 1991, Smits et al. 1999, Lu et al. 2005).

Table 6.6 Producer's and User's Accuracies for 2001 ETM classification

	USER'S ACCURACY	PRODUCER'S ACCURACY	ERRORS OF COMMISION	ERRORS OF OMMISSION
Water	98.21%	92.31%	1.57%	2.19%
Agric new growth	53.13%	95.90%	54.76%	84.08%
Agricultural land	55.29%	89.58%	72.43%	10.42%
Built-up land	86.53%	83.13%	12.94%	7.86%
Wetlands	35.37%	96.32%	35.05%	3.68%
Forests	98.02%	89.10%	1.80%	10.90%
Burnt Areas	20.18%	95.14%	376.22%	4.86%
Clouds	32.30%	87.78%	183.46%	12.22%
Transitional land	93.35%	85.75%	6.10%	14.25%

Substituting figures from the error matrices in equation 5.3 (please see chapter 5 for equation):

For the 1987 error matrix,

x_{ii} = 229 + 996 + 3134 + 15316 + 2945 + 2927 + 1656 + 22638 = 49841

$(x_{i+} * x_{+i})$ = (231*229) + (2233*1029) + (3803*3546) + (15421*16856) + (3948*3603) + (3300*3228) + (2035*4003) + (25548*23135)

= 899848599

Therefore,

$$\hat{k} = \frac{56074(49841) - 899848599}{(56074)^2 - 899848599}$$

$$= \frac{1894935635}{2244444877}$$

= 0.8443 *100 = **84.43%**

And for the 2001 error matrix,

x_{ii} = 790 + 393 + 467 + 17592 + 176 + 1523 + 4540 + 35411+ 13373

= 74265

$(x_{i+} * x_{+i})$ = (1487*829) + (1111*408) + (1446*532) + (17913*19057) + (872*185) + (17604*1832) + (8211*5068) + (3616 + 39745)+ (14325+83251)

= 1627716194

Therefore,

$$\hat{k} = \frac{83251(74265) - 1627716194}{(83251)^2 - 1627716194}$$

$$= 0.8589*100 = \mathbf{85.89\%}$$

$\hat{k}$ ranges between 0 and 1. As true agreement (observed) approaches 1 and chance agreement approaches 0, $\hat{k}$ approaches 1 (Lillesand and Kiefer, 2000) indicating the perfect effectiveness (Campbell, 2002). The kappa coefficient ($\hat{k}$) for 1987 TM classification is 0.84, while $\hat{k}$ for 2001 ETM classification is 0.66. Kappa values for 1987 and 2001 of 0.71 and 0.76 respectively represent 84.43% and 65.77% better accuracy than if the classification of pixels resulted by chance. Montserud and Leemans (1992 cited in Mather 1999) suggested that a $\hat{k}$ value of 0.75 or greater shows a 'very good to excellent' classifier performance, while a value of less than 0.4 is poor. Although, Landis and Koch (1977) concluded values greater than 0.80 represent strong agreement, values between 0.40 and 0.80 represent moderate agreement, and values below 0.40 represents poor agreement. Taking these into consideration, it can be concluded that both 1987 and 2001 classifications represent a good strong agreement with the reference data.

6.3 Land Cover Change Detection

Change detection is the identification and evaluation of disparities in land cover on a map, satellite image or aerial photograph. It uses maps or images that have been acquired (or captured) at different times. This process is useful in improving land use decisions. The change detection techniques used in this research are post-classification comparison and image differencing.

6.3.1 Post-Classification Comparison

Post-classification comparison is widely used and is considered as one of the most effective change detection techniques. It is a comparative analysis of two independently classified images by detecting the differences these images and supplying "from-to" land cover information.

After the individual classification of the images, a post-classification was performed to examine the pattern of change and detect the differences between the 1987 image and 2001 image. It provides information on what the land use or land cover initially was in 1987 and what it is in 2001. This also provides the total areas that have changed in each LUC class. Each classified image was recoded, in order for the land cover classes in both classified image are analogous.

Table 6.9 shows the trajectories of change between the land use/cover classes except the Cloud cover class, which has been removed, as this would not be used either in the model or in the change detection process and the Agricultural new growth, which has been merged with Agriculture for ease of interpretation and processing. The table shows the area of land (in hectares) that has changed, giving the pattern of transformation from one land use or land cover to another. In figure 6.3, the land cover and land use where changes have occurred (yellow) and where that has been no change (red), and the 'from-to' land cover information is shown in figure 6.4.

Table 6.10 shows the relative percentage change of the post-classification, this compares the changes among the land cover between 1987 and 2001. Tables 6.7 and 6.8 describe the areal extent of each land cover (in both 1987 and 2001) and the total areas of change for each land cover type (or class). These areas were obtained from the post classification matrix (table 6.8).

Figure 6.3, shows how rapidly the area has undergone changes in less than two decades, the LUCC are quite noticeable and considerable. In Edo and Delta states, during the 14-year period from 1987 to 2001, 52.77% of the area underwent changes, while only 47.23% in the 2001 image are the same cover class as in 1987. Clearly, the total changes might be even larger, as some areas may have been converted after 1987 but reverted back to their previous class in 1987 by 2001. Figure 6.4 is a graphical illustration of the land cover changes that have occurred in the study area. These changes might have been an increase or a decrease for instance, forests have decreased in area by 30.16% (467325 ha), which is the largest negative change, while agricultural land has increased by 27.92% (111445 ha). The large increase of water by111.20% (71461 ha) might be due to the substantial presence of cloud cover and haze that could not be removed.

Table 6.7 Land cover classes and areas they occupy.

Class	1987 Total area (Ha)	% of Total area	2001 Total area (Ha)	% of Total area
Agric	399156	11.76%	510600	15.05%
Built up	96619	2.85%	148846	4.39%
Burnt Areas	26081	0.77%	196855	5.80%
Forests	1549288	45.66%	1081963	31.89%
Trans land	1030149	30.36%	1169732	34.47%
Water	64265	1.89%	135725	4.00%
Wetland	227454	6.70%	149290	4.40%
Total	**3393011**	**100%**	**3393011**	**100%**

Table 6.8 Summary of the land cover changes (in hectares).

Class	1987 Total area	2001 Total area	Total area changed	Percentage change (%)
Agric	399156	510600	111445	27.92%
Built up	96619	148846	52227	54.06%
Burnt Areas	26081	196855	170774	654.78%
Forests	1549288	1081963	-467325	-30.16%
Trans land	1030149	1169732	139582	13.55%
Water	64265	135725	71461	111.20%
Wetland	227454	149290	-78164	-34.36%

Table 6.9 Post-classification matrix showing detailed 'from-to' land cover changes of the study area (in hectares)

		1987								
2001	**Class**	**Agric**	**Agric new growth**	**Built**	**Burnt Areas**	**Forests**	**Trans land**	**Water**	**Wetland**	**Total**
	Agric	35083	2524	1578	31	269898	79321	500	6548	**395482**
	Agric new growth	7469	42093	7877	830	18862	37751	187	48	**115118**
	Built up	4258	43127	39422	442	10734	49317	1170	376	**148846**
	Burnt Areas	12293	25025	10157	10563	60184	74352	1207	3074	**196855**
	Forests	23649	9557	5744	2329	747938	228148	1900	62698	**1081963**
	Trans land	113949	67095	21015	10546	399759	543253	1608	12507	**1169732**
	Water	5228	5768	9849	1235	26731	9375	54747	22792	**135725**
	Wetland	847	1191	978	105	15182	8630	2945	119412	**149290**
	Total	**202775**	**196380**	**96619**	**26081**	**1549288**	**1030149**	**64265**	**227454**	**3393011**

Figure 6.3 Post-classification change image showing areas of change and no-change

Table 6.10 Relative change between 1987 and 2001

	1987							
	Class	**Agric**	**Built**	**Burnt Areas**	**Forests**	**Trans land**	**Water**	**Wetland**
2001	**Agric**	43.70%	9.79%	3.30%	18.64%	11.36%	1.07%	2.90%
	Built up	24.06%	40.80%	1.69%	0.69%	4.79%	1.82%	0.17%
	Burnt Areas	18.81%	10.51%	40.50%	3.88%	7.22%	1.88%	1.35%
	Forests	16.53%	5.94%	8.93%	48.28%	22.15%	2.96%	27.57%
	Trans land	90.36%	21.75%	40.43%	25.80%	52.74%	2.50%	5.50%
	Water	5.52%	10.19%	4.74%	1.73%	0.91%	85.19%	10.02%
	Wetland	1.02%	1.01%	0.40%	0.98%	0.84%	4.58%	52.50%

There is also considerable increase of 654.78% in the burnt areas, as slash and burn is a common occurrence in Africa. In this part of Nigeria, forest burning (or bush burning) usually takes place between November and March, the dates of the satellite images fall within this period (see Chapter 4), hence the high presence of burnt areas. Looking at the a section of the image in figure 6.6, the spectral profile of two areas which are occupied by water but one area is covered by some cloud cover and the other isn't, it is obvious that there is a spectral reflectance variation.

Figure 6.4 Graphical illustration of land cover changes from 1987 to 2001

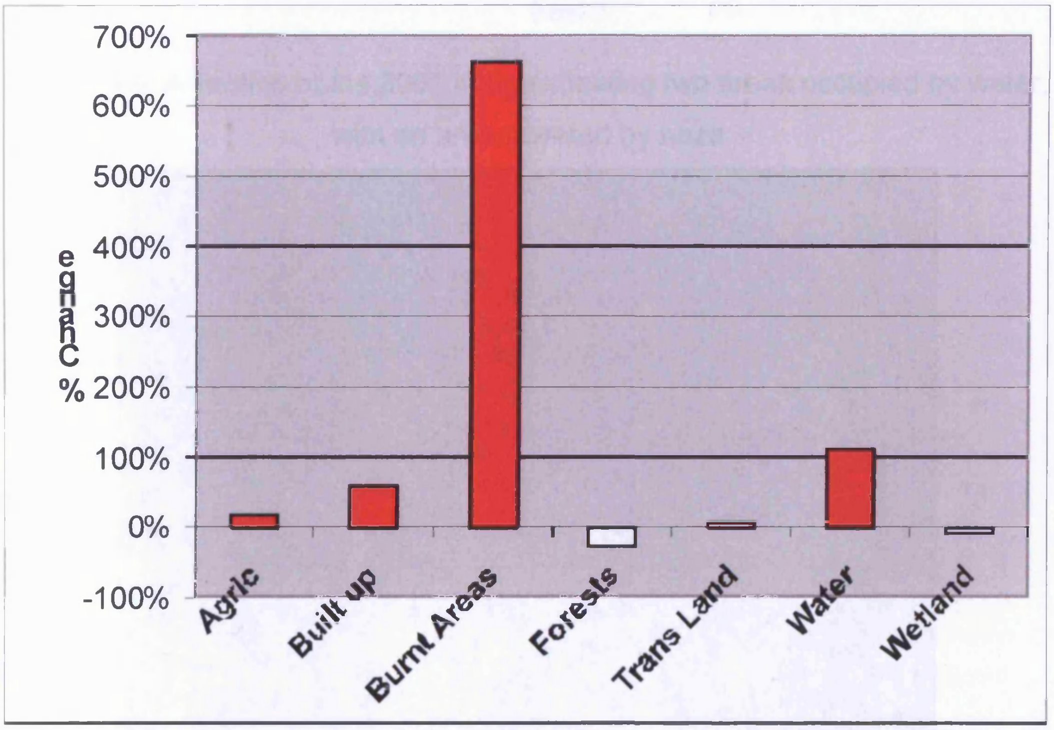


Figure 6.5 Spectral profile of two areas occupied by water

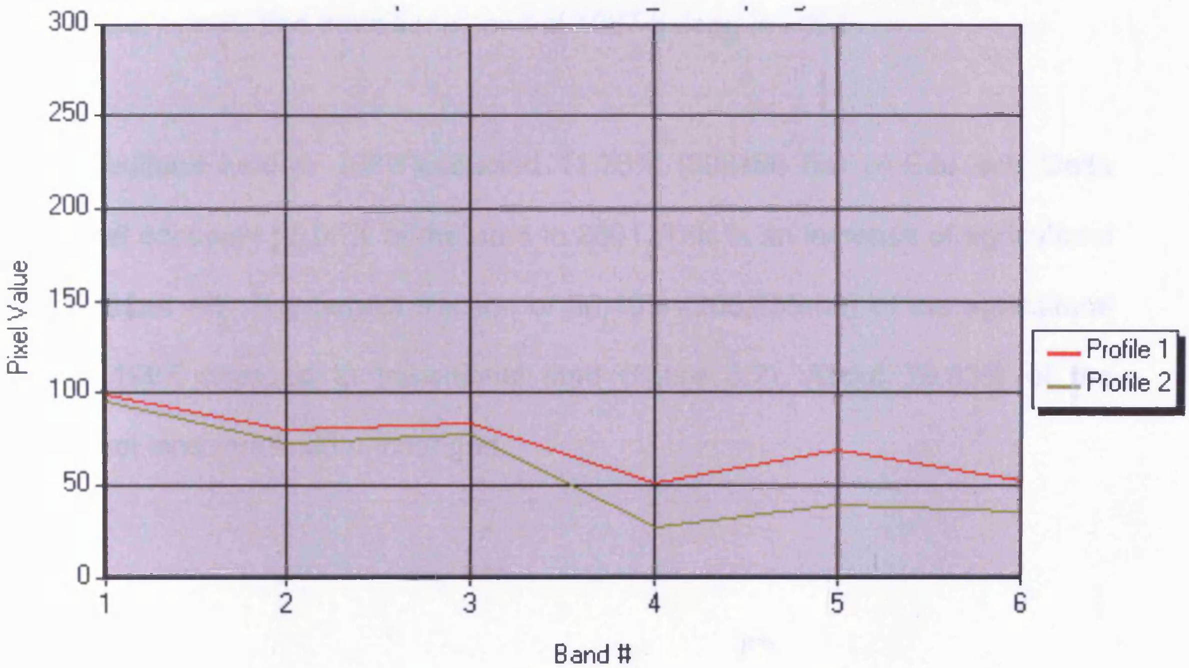


Figure 6.6 A section of the 2001 image showing two areas occupied by water, with an area covered by haze

Figures 6.7 – 6.15 show to which class the areas of agricultural land, built-up land, burnt areas, forests and transitional land in 1987 belong in 2001.

The agricultural land in 1987 occupied 11.76% (399156 ha) of Edo and Delta states and occupied 15.05% of the area in 2001. This is an increase of agricultural land of about 4%. The largest fraction of 36.45% (206,855 ha) of the agricultural area in 1987 changed to transitional land (figure 6.7). About 29.93% of the agricultural land remained unchanged.

Figure 6.7 Changes in agricultural land to other land cover types

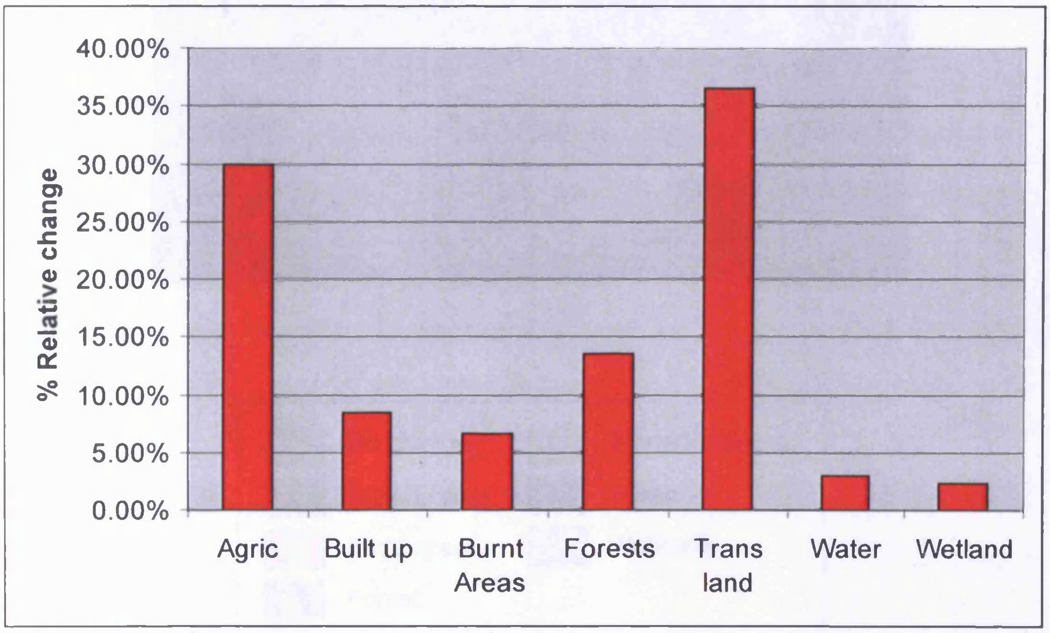
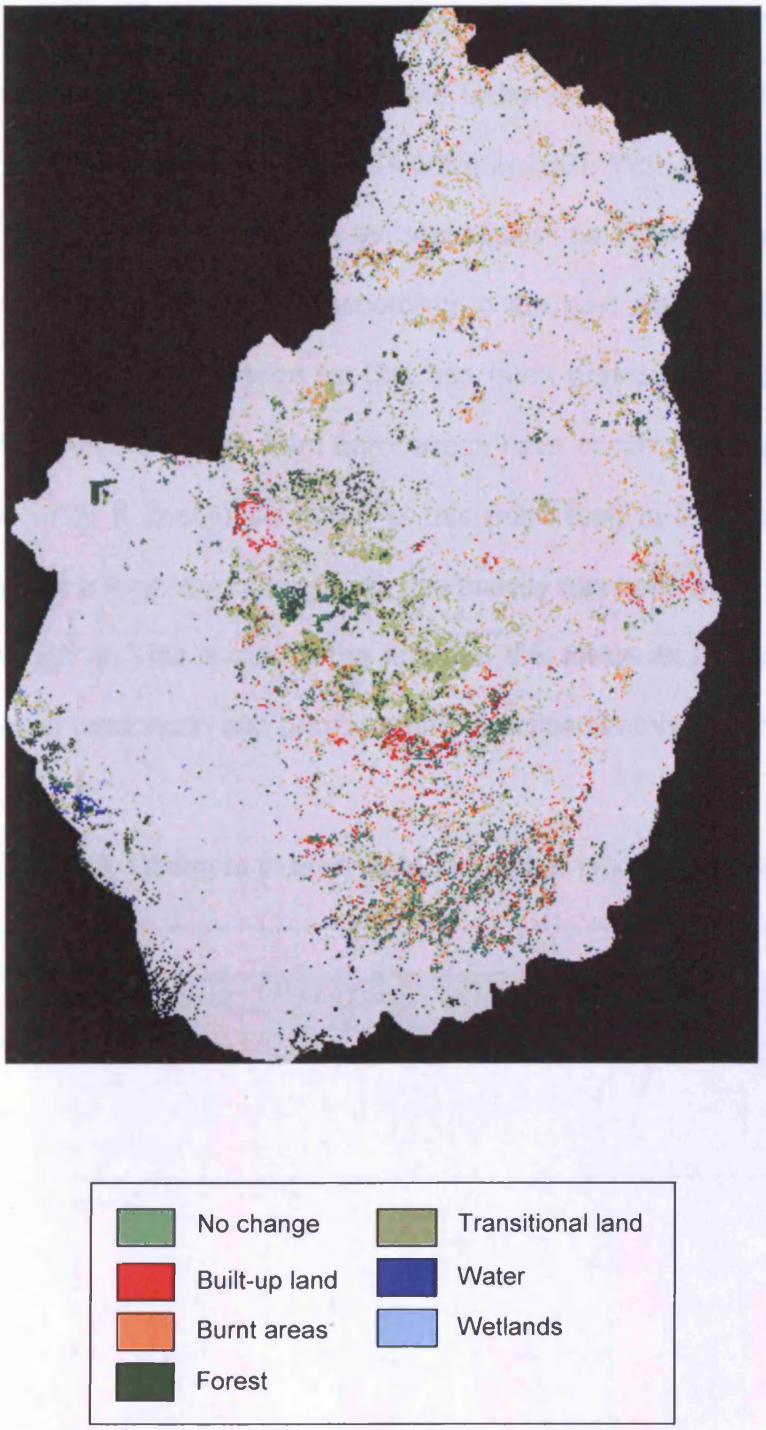


Figure 6.8 Changes from Agricultural land to other land cover types



The built up land changed by 58.65% (54138 ha), which initially, in 1987 this occupied 2.73% (92312ha) of the area, this increased in 2001 to 4.33% (146451 ha). The burnt areas (figure 6.11) in Edo and Delta states increased in area from 20027 ha (0.59%) in 1987 to 152416 ha (4.50%) in 2001. With the large proportion of the initial burnt areas, converted to agricultural land and transitional land. Meanwhile, some of the burnt area according to the post classification has been converted to water, but the reason for this has been previously described in this chapter. Most of these changes from burnt areas have occurred in the north of the region (figure 6.12). It should be noted at this point that, in this research forest burning is seen as a long-term change, as this activity has been seen as escalating in Nigeria, and still is. This is due to the fact that this forms an integral part of the shifting cultivation (and slash and burn) farming practiced in this region.

Figure 6.9 Changes in built-up land to other land cover types

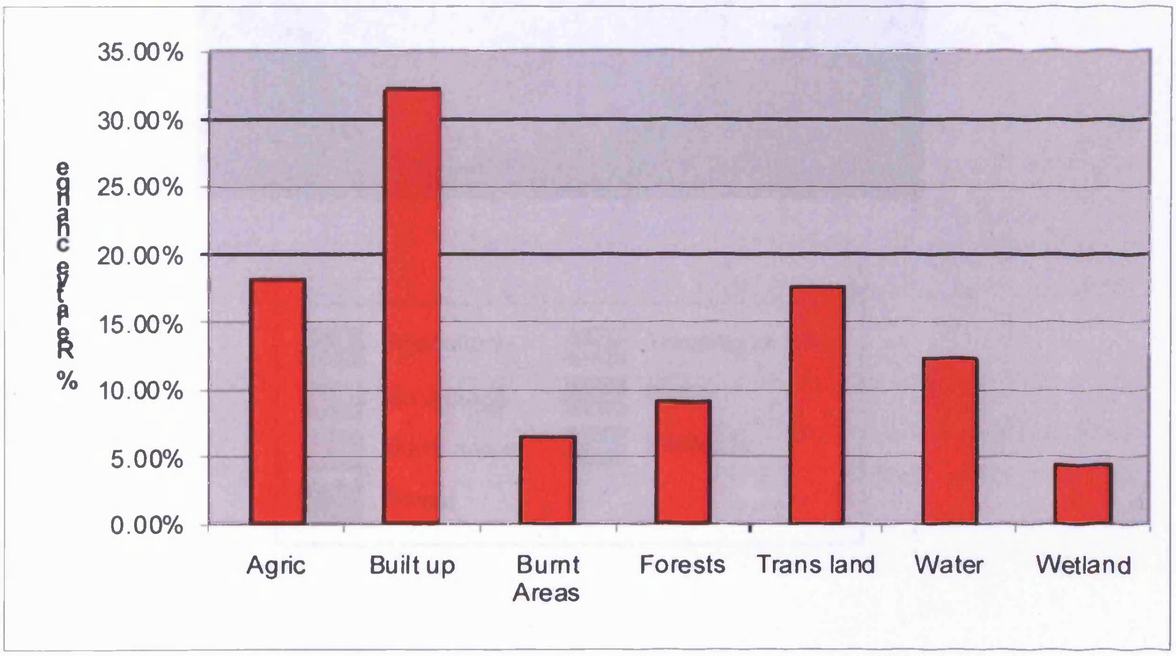
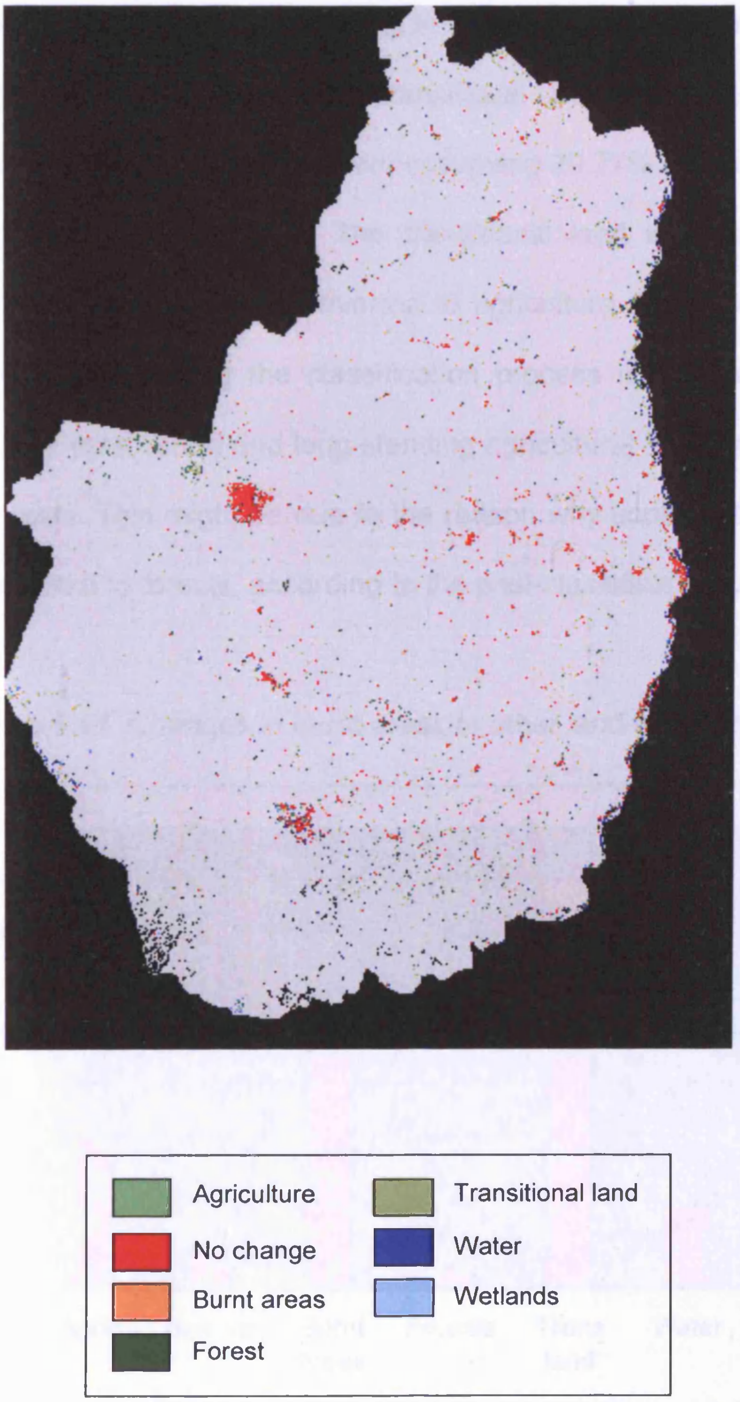


Figure 6.10 Changes from built-up land to other land cover types



Looking at figures 6.13 and 6.15, the conversion of forests to agricultural land and transitional land is evident. The forests in 1987 occupied 41.60% of the total area of the region, and this decreased to 30.14% in 2001. This is a similar pattern in the case of transitional land, with most of the transitional land converted to agricultural land and transitional land. It increased from occupying 29.77% of the total region in 1987 to occupying 30.64%in 2001. The transitional land increased by 4.69% (46501 ha) with large proportions converted to agriculture (24.26 %) and forests (20.05%) (figure 6.14). During the classification process it was detected that a number of the well established and long standing agricultural lands (or farms) were classified as forests. This might be due to the reason why some of the transitional lands were converted to forests, according to the post-classification comparison.

Figure 6.11 Changes in burnt areas to other land cover types

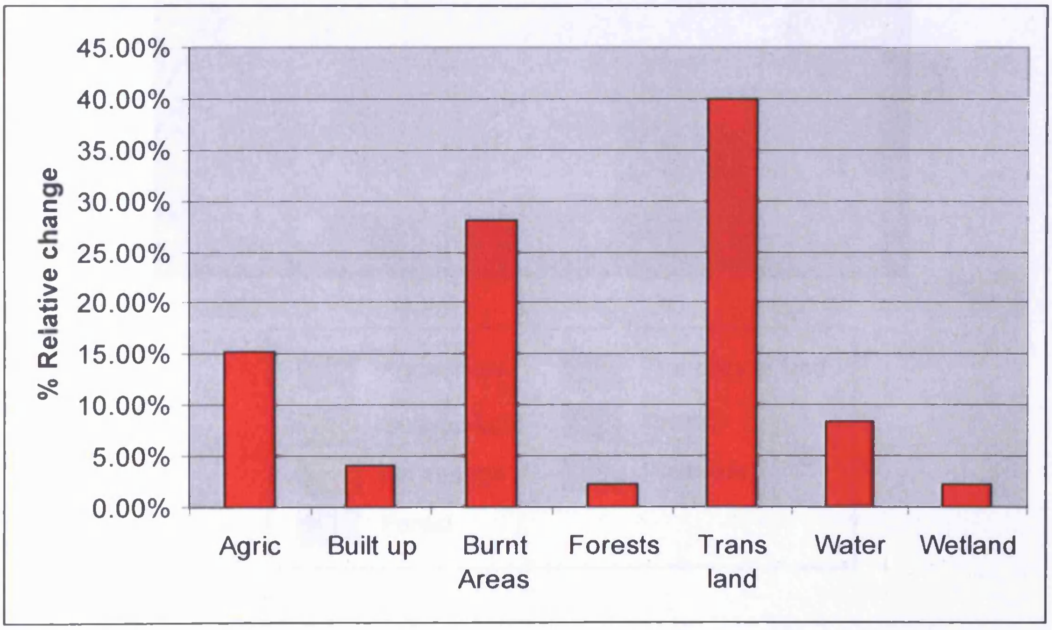


Figure 6.12 Changes from burnt areas to other land cover types

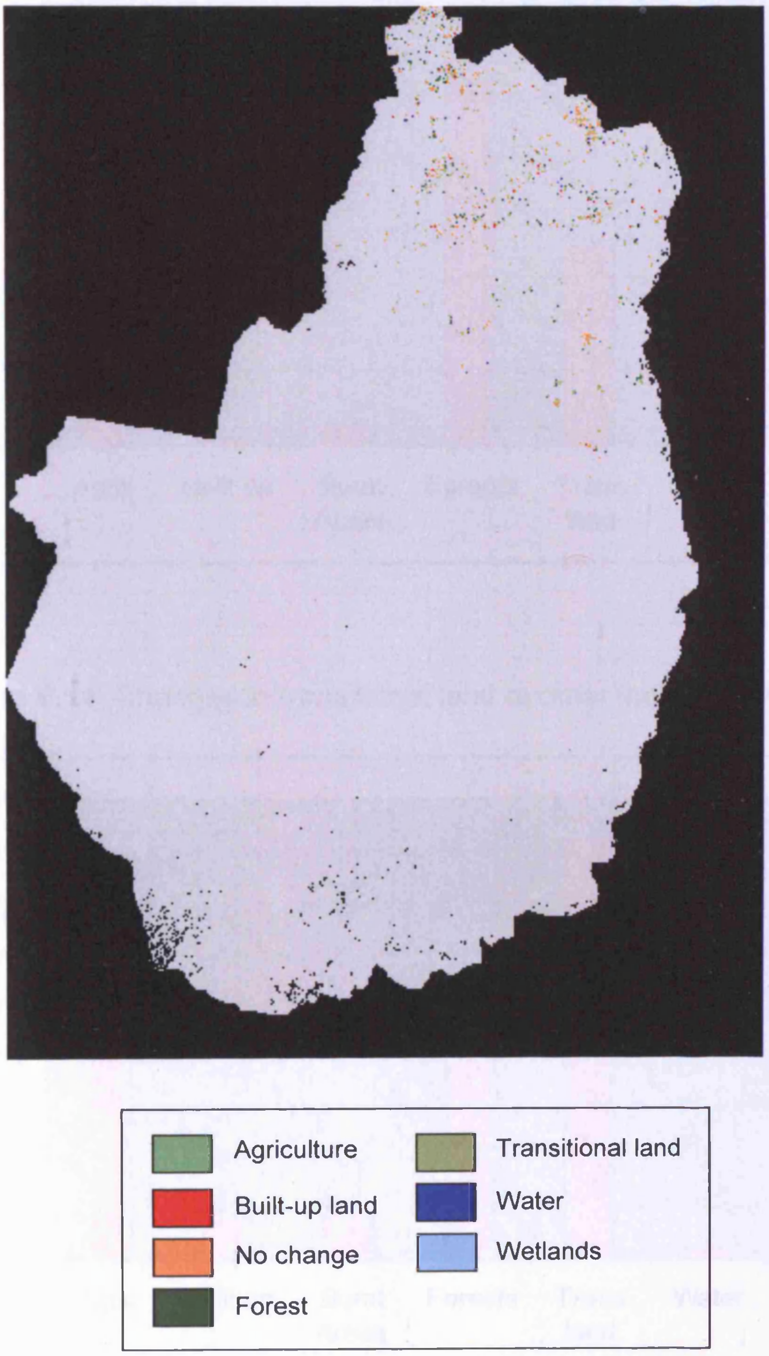


Figure 6.13 Changes in forests to other land cover types

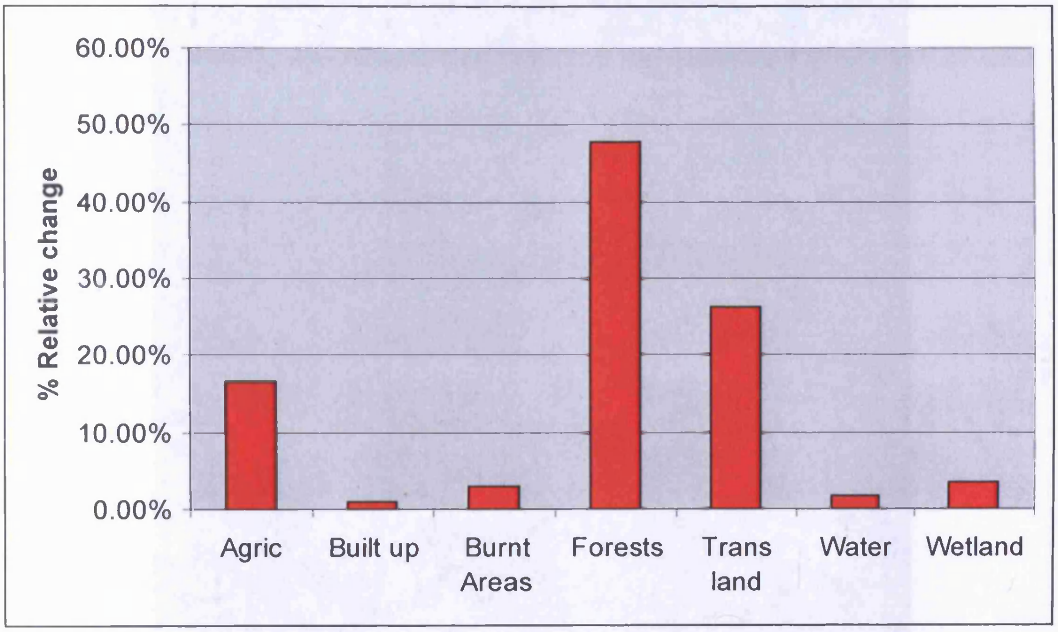


Figure 6.14 Changes in transitional land to other land cover types

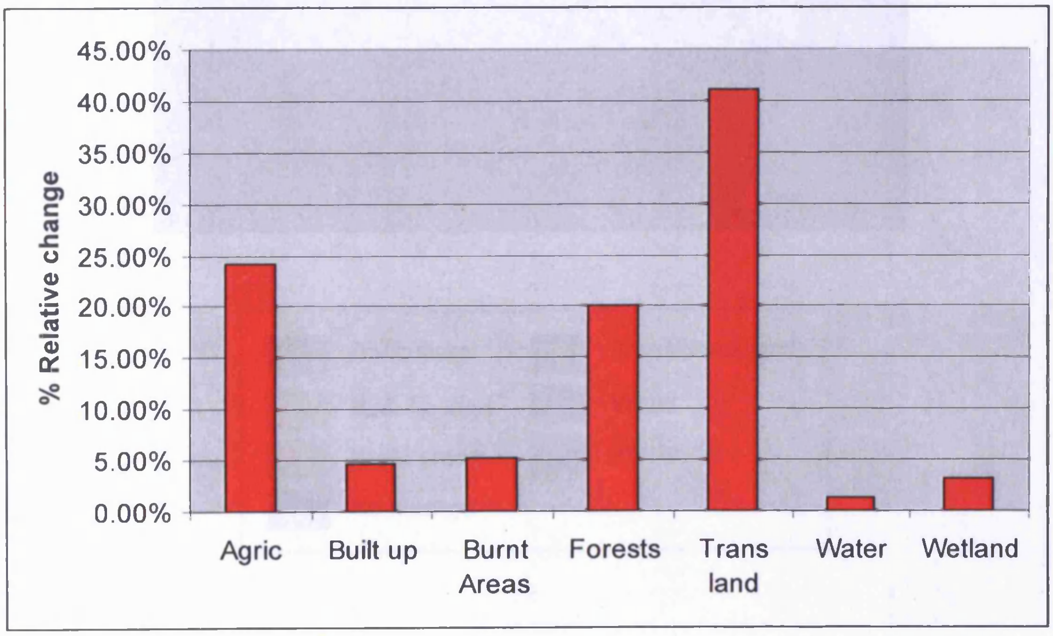


Figure 6.15 Changes from forests to other land cover types

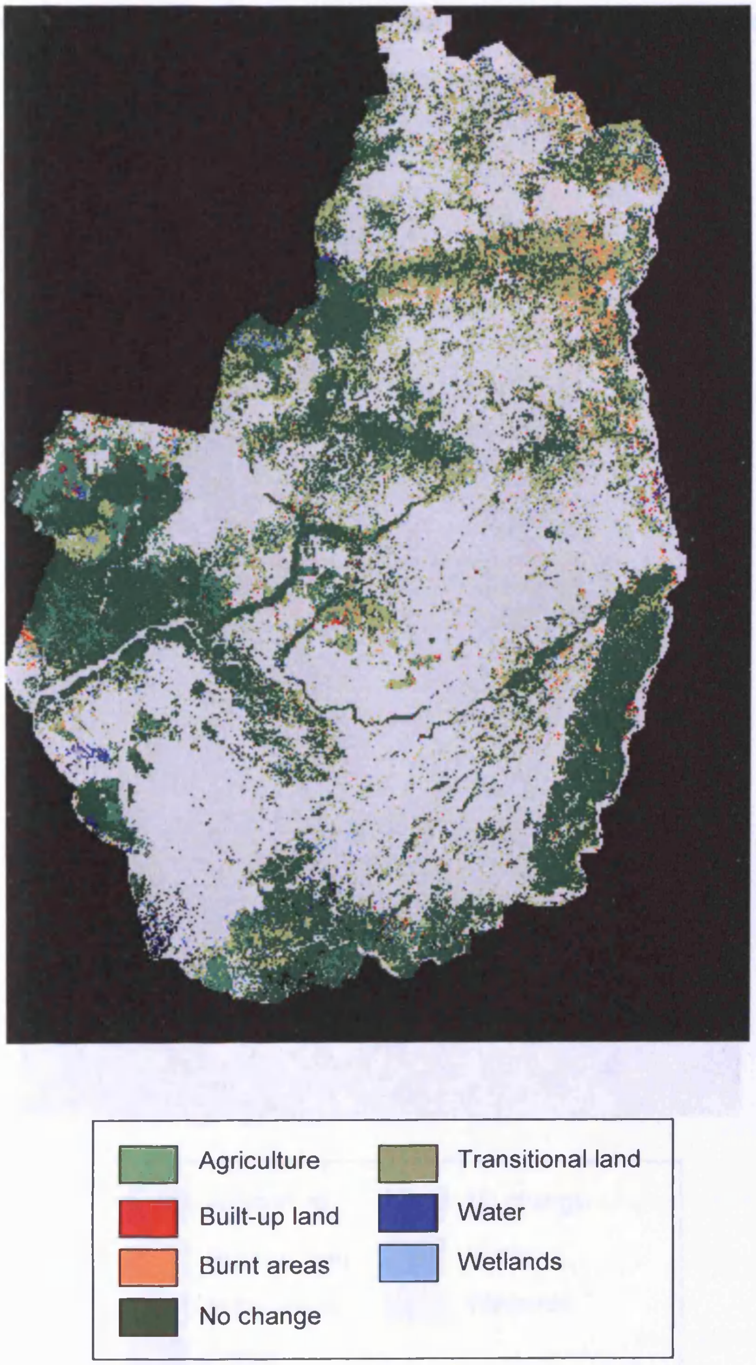
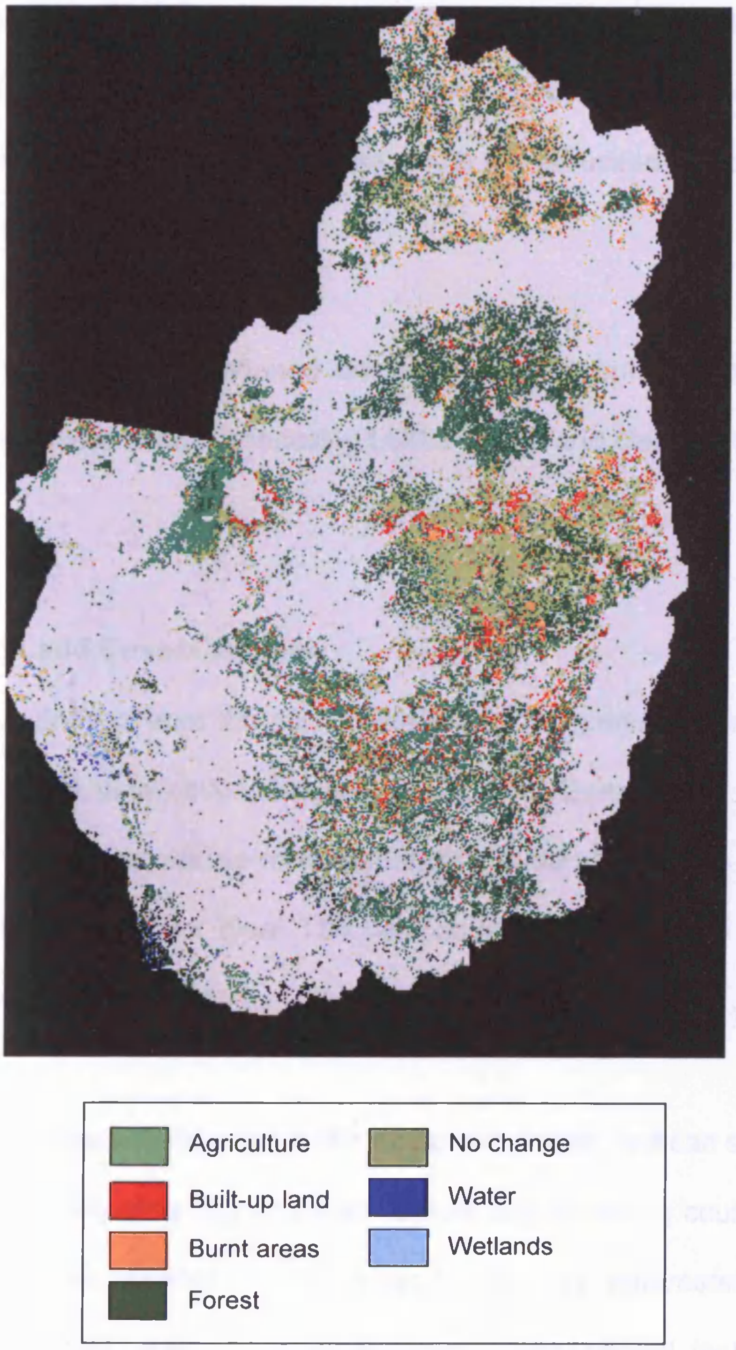


Figure 6.16 Changes from transitional land to other land cover types



On the whole, so far inferring from the post-classification matrix (table 6.1) and the relative percentage change (table 6.4), the focal directions of land cover change is the conversion of forests to transitional land and agricultural land, and the conversion of transitional land to agricultural land also the conversion of agricultural land to transitional land. These would be discussed comprehensively in the next chapter.

These land cover types mentioned above (i.e. agricultural land, forests and transitional land), were used in modelling LUCC in Edo and Delta states.

6.4 Modelling Land Cover Changes

The information derived from the post-classification comparison was incorporated into the model s of land cover changes in Edo and Delta states (presented in chapter 5), as it was impossible to obtain statistical data regarding total areas of each land use or land cover type. The land cover types used are – agricultural land, forests and transitional land.

The variables (or parameters) used in the model are limited, but can still be used to analyse how the study area has changed. Before the modelling could progress, a number of constants needed to be derived, such as *deforestation rate (a), abandonment rate (b), rate of agricultural rate of transitional land (c), rate of regrowth of transitional land to forests (d).*

The deforestation rate was derived from the classified images. The abandonment rate (*b*) is the rate at which agricultural land is abandoned and left to fallow for a period, while rate of agricultural rate of transitional land (*c*) is the rate at which transitional land is re-used for agricultural activities after it has been left to fallow. The rate of regrowth of transitional land to forests (*d*) is basically how long it takes for transitional land to convert back to forests, which may occur as a result of long fallow periods. Originally (in the 1970's) the fallow period ranged between 7- 10 years, but due to population pressure on the land and its resources, this has been reduced to about 3-5 years, after the land has been farmed on for 2- 4 years.

These variables were incorporated into the model projections to simulate the changes in agricultural land, forests and transitional land. The model also shows the conversion these land cover types. This was accomplished by the use of projections. Discussing future land use and land cover by means of projections permits the incorporation of several paths of future development in those sectors relevant to land-use change (Prieler et al., 1998). As discussed in the previous chapter 5, three model projections of land cover change were developed.

6.4.1 Model Projection I

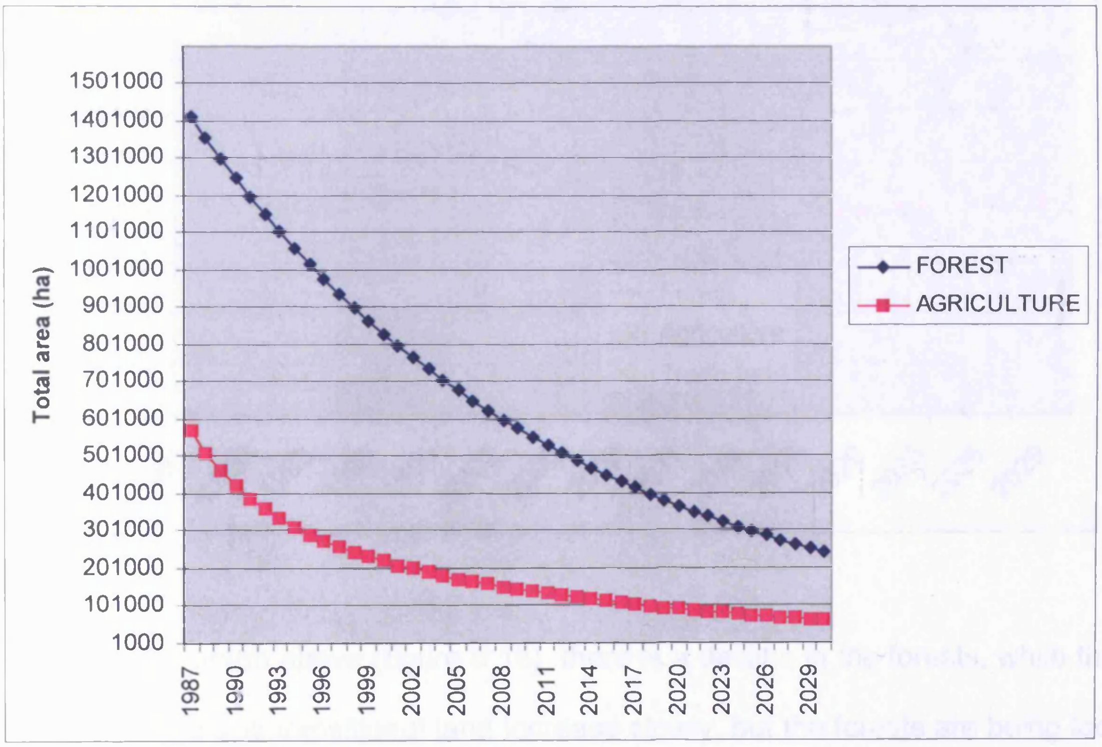
This model projection assumes that the forests are converted to agriculture land (please see appendix II for detailed table). It does not allow land used for agricultural activities to be converted to other land cover type (i.e. forests and transitional land). It presumes that the forested land is being lost with no regrowth whatsoever (i.e. no feedbacks) and there is no agricultural land that is left to fallow for long periods or no natural succession. The result is an increase in the price of land for agricultural purposes and the increase of the use of fertilizers.

As stated previously, the total areas for forest and agricultural land in 1987 and 2001 were derived from the classified images, as the data could not be obtained otherwise. Looking at the graph below (figure 6.17), there is a steady decrease in agricultural land; this is as a result of the increasing rate of deforestation. As the forests are converted to agricultural land, after a period of farming the land will slowly lose its fertility due to intensification and then more forests would need to be converted to these land cover type. When these agricultural land are left to fallow there will be lost to other land cover types and are not being re-used. This model projection predicts, that by 2030 the forests will decrease by 60.85%, i.e. 243345 ha (in comparison to the present area of 648,204 ha).

6.4.2 Model Projection II

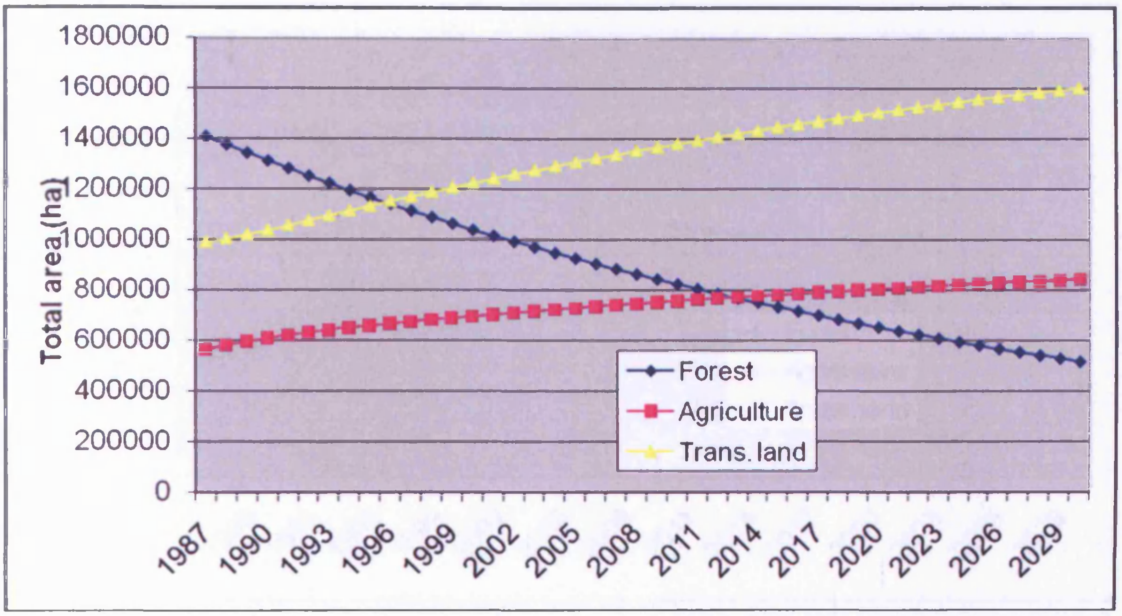
This projection introduces another land cover type – transitional land. It is of the assumption that the forests are cleared to make way for agricultural land, then after a period of farming they are abandoned and left to fallow, which gives rise to the transitional land. After the fallow period, the farmer goes back to this particular parcel of land (i.e. transitional land) to re-plant his crops, as the land will have recovered some of its fertility. In other words, the land is being converted from forests to agricultural land to transitional land and about 10% of this land cover will be converted back to agricultural land.

Figure 6.17 Graphical illustration of model projection I



In this projection, the deforestation rate was calculated as given in equation 5.20 in chapter 5. The deforestation rate obtained was 2.30%, as there is no regrowth of the transitional land back to forests, this calculated rate can be applied to this projection. An abandon rate of 15% was used, which means that 15 % of the agricultural land has been left to fallow every year, leaving 85% of the total agricultural land. In this projection, 10% of the total transitional land has been reused for agricultural activities every year.

Figure 6.18 Graphical illustration of model projection II

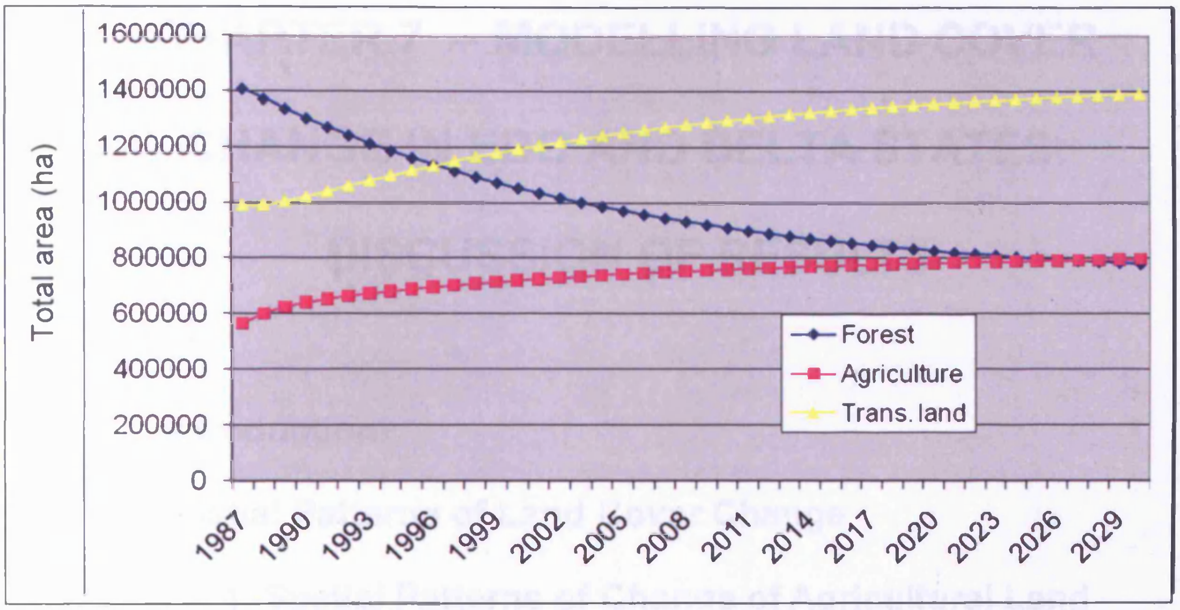


Looking at the graph above (figure 6.18), there is a decline in the forests, while the agricultural land and transitional land increase slowly, but the forests are being lost at a faster rate. This model projection foresees that by the year 2030, the forests will decrease by 36.77%, agricultural land and transitional land would increase by 188.57% and 139.13% respectively.

6.4.3 Model Projection III

This model projection assumes that when forests are being cleared to make way for agricultural land, which in turn are abandoned and left to fallow. These fallow agricultural land are transformed as transitional land, some of these transitional land are then reused after they have been left to fallow for a period. In addition, some of the remaining transitional land is left to fallow for longer periods and revert back to forests.

Figure 6.19 Graphical illustration of model projection III



In this model projection, the deforestation rate was assumed to be 4.0% and the rate at which the agricultural lands are left to fallow is 30% every year. In addition, the rate at which transitional land is reused for agricultural activities is 15% every year and the rate of regrowth of transitional land which reverts back to forest is 2%. In this projection, the loss of forest is slower compared to projection II; there are increases in both the agricultural land (140.25%) and transitional land (140.32%) by the year 2030. Inferring from figure 6.19, this projection foresees all the land cover types gaining a stable state as from 2026.

CHAPTER 7 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: DISCUSSION OF RESULTS

CHAPTER 7

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: DISCUSSION OF RESULTS

7.1 Introduction

The analysis of the results obtained in chapter 6 is discussed in this chapter. It analyses at the impacts of land use and land cover change in Edo and Delta states and also the relationships between thee driving forces. The analysis presented in the previous chapter shows that Edo and Delta states have undergone tremendous transformation between 1987 and 2001.

7.2 Spatial Patterns of Land Cover Change

This study of land use and land cover change in Edo and Delta states has exposed the nature and pattern of change. The spatial pattern was discovered after the post classification process (chapter 6). This provided "from-to" information for the study area between 1987 and 2002. These nature and spatial patterns of change is discussed with respect to each land use and land cover type (or class).

7.2.1 Spatial Patterns of Change of Agricultural Land

There was a 27.92% change in agricultural land between 1987 and 2002. Agricultural land, which covered an area of 399156 ha (11.76%) of the study area in 1987, increased to 510600 ha (15.05%) by 2001, and 87169 ha (21.84%) of the original agricultural land did not undergo any change between 1987 and 2001.

The majority of the original agricultural land has been converted to transitional land (45.36%). The agricultural system employed in Edo and Delta states is shifting cultivation (bush fallow), where farmers move from one place to another after the land loses its fertility and the land is abandoned, left to fallow for a period of 3-5 years. These are situations where agricultural land has been transformed to transitional land. This conversion is mainly concentrated in the south-east of Benin City (figure 7.1), where a lot of the agricultural lands have been abandoned and left to fallow. A vast majority of the original agricultural land in this area has been as a result of the *Taungya system* in Sakpoba Forest reserve area (figure 7.2).

Figure 7.1 Image of study area showing agricultural land that have been converted to transitional land

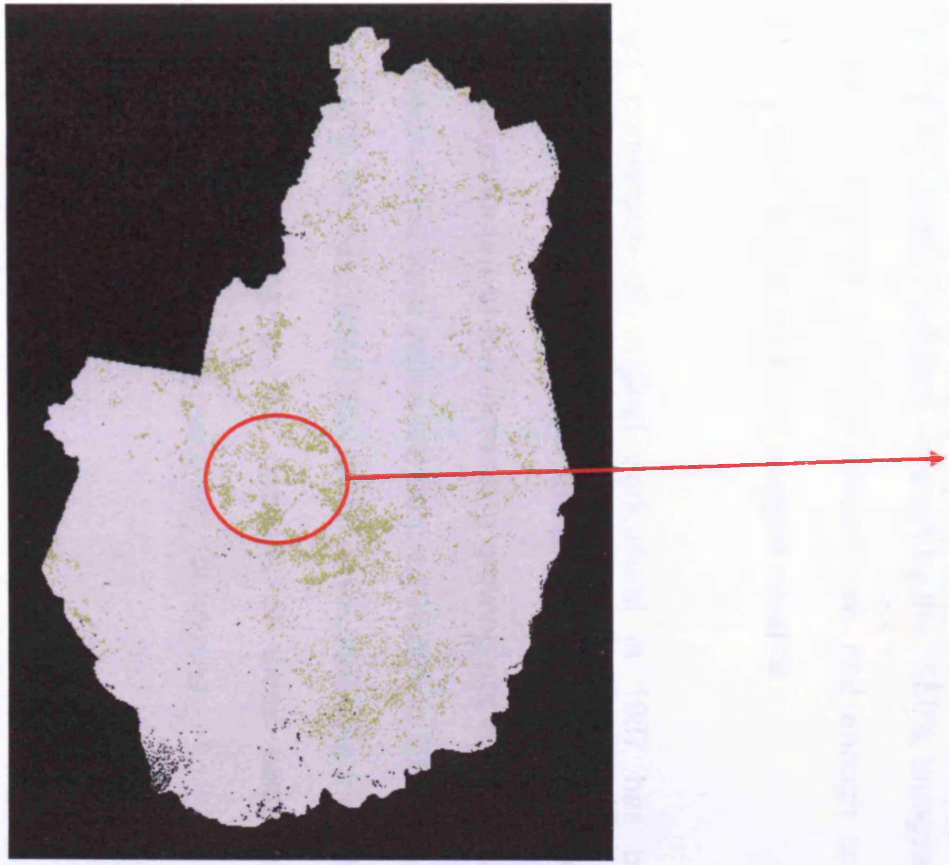
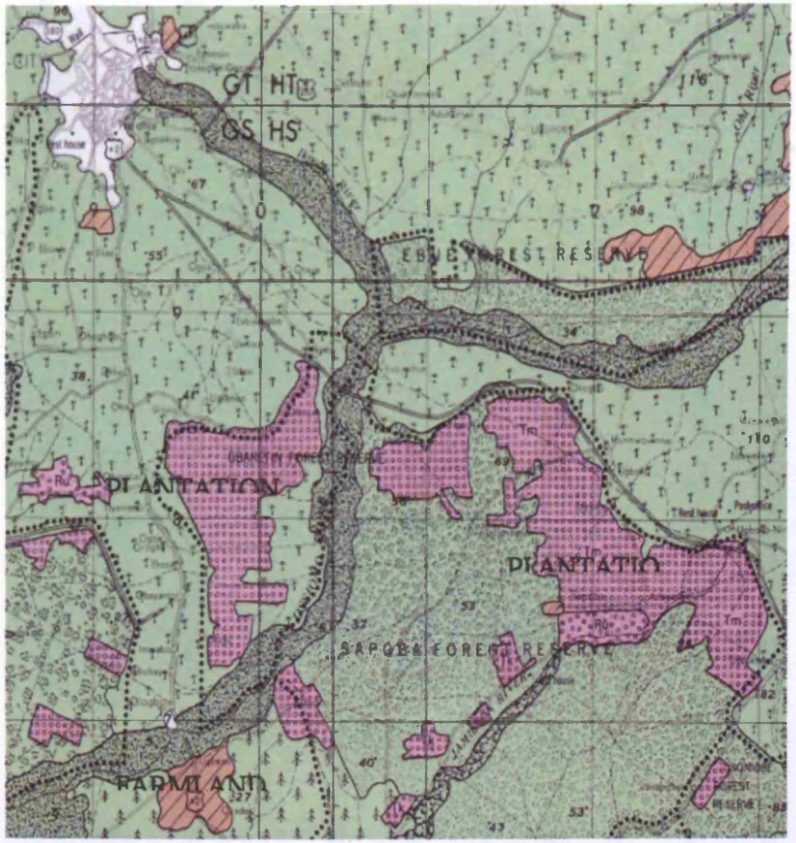


Figure 7.2 Map of study area showing areas of transitional land



Source: Federal Dept of Forestry, 1977

The taungya farming system is an agro-forestry system or method where forest reserves are cleared to make way for farming and these farms are allocated to individual farmers, the food crops are planted alongside trees. In exchange for these farmlands, the Forestry department provided the farmers with tree seedlings to plant and maintain. This system was first introduced in Sakpoba Forest reserve by the Forestry Department in the late 1920's. The main food crops planted on these farmlands were cassava, yam, cocoyam, plantains, rice, maize and various vegetables, while the trees planted were teak (*Tectona grandis*), Sapele wood (*Entandrophragma cylindrica*) and gmelina (*Gmelina arborea*). According to Osemeobo (1988), the taungya farms occupied an area of 68032 ha in Edo and Delta states in the 1980's, but Robson (1955, cited in von Hellermann 2007) pointed out that although by the 1950's, taungya planting continued, it did not expand much as farmers still had enough community farmland and showed little interest in the taungya scheme.

Another major conversion of original agricultural in 1987 has been the transformation to built-up land in 2001 (47386 ha i.e. 11.87%) (figure 7.3). This conversion may be attributed to the increasing growing population in the study area. The population of the area increased from 4,198,884 in 1987 to 6,462,808 in 2001 (according to the calculated population projections). As the settlements increased in size, expanding at the outskirts of these settlements, the agricultural lands were abandoned to make way for houses.

Figure 7.3 Agricultural land that have been converted to built-up land

33206 ha of the original agricultural land in 1987 have been converted to forests in 2001 (figure 7.4). These have occurred where agricultural land has been left to fallow for longer extended periods. An area in Okomu is shown to have converted from agricultural land to forests in 2001 (highlighted in figure 7.4).

Figure 7.4 Agricultural land that have been converted to forests

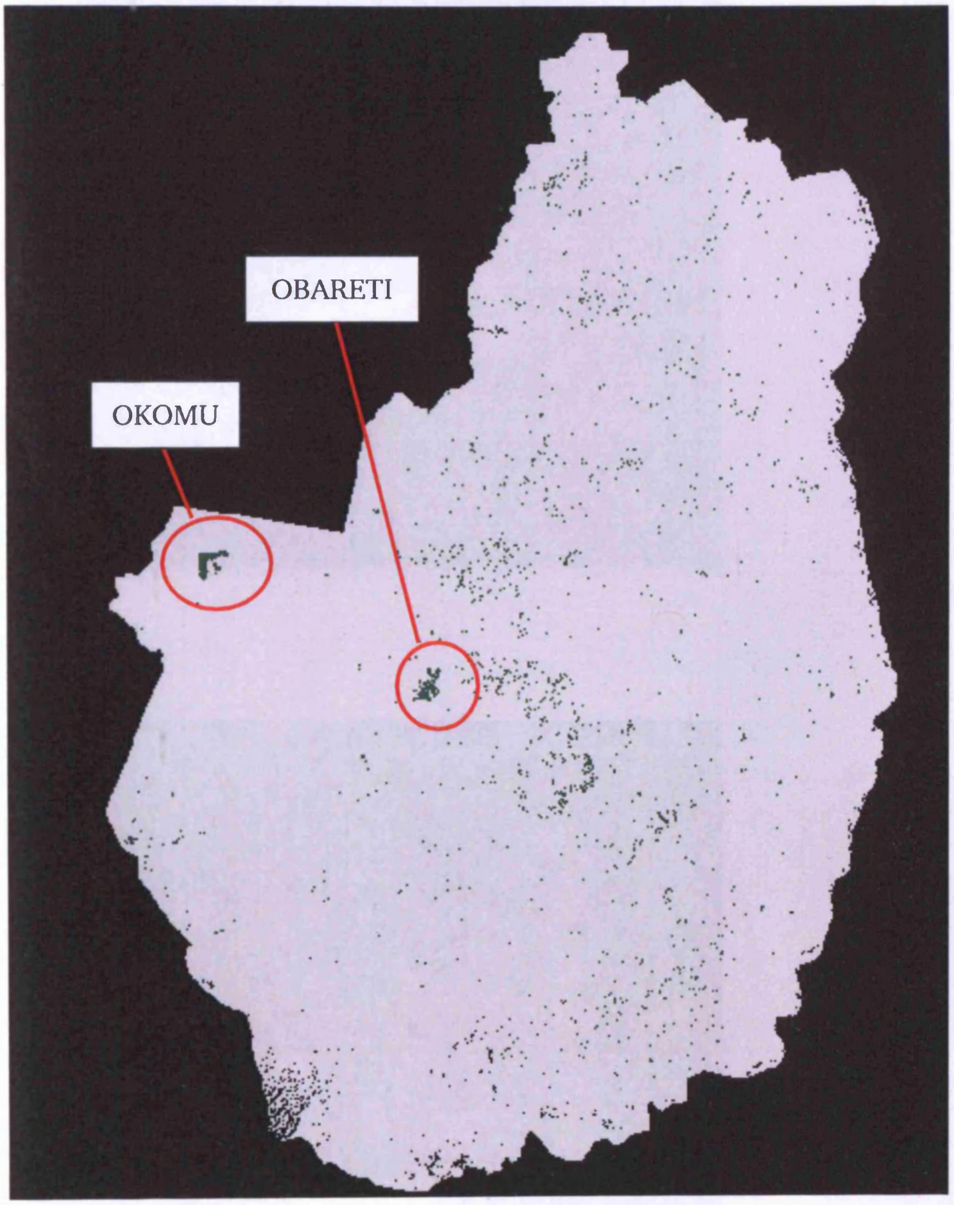


Figure 7.5 Okomu Oil Palm and Forest reserve in 1987

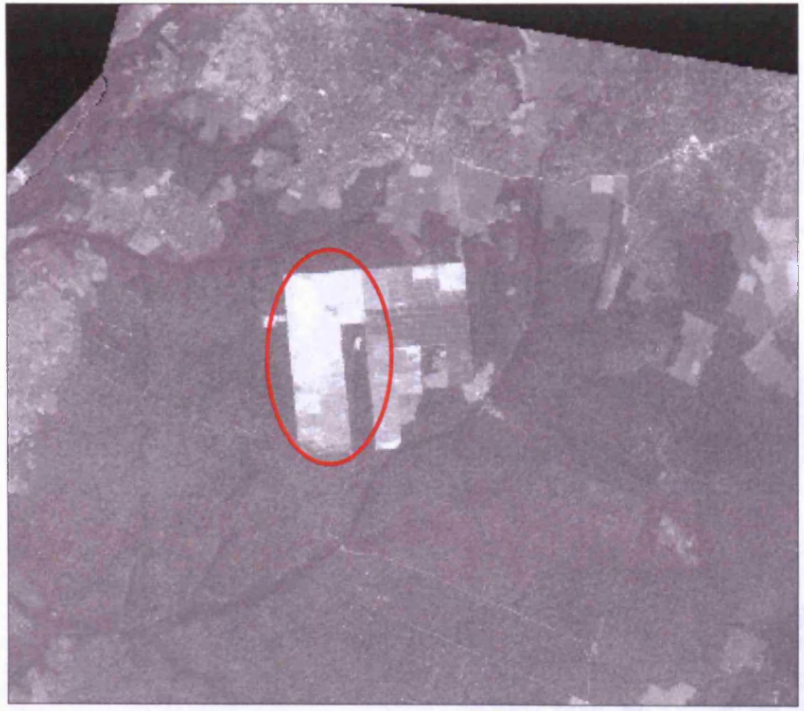
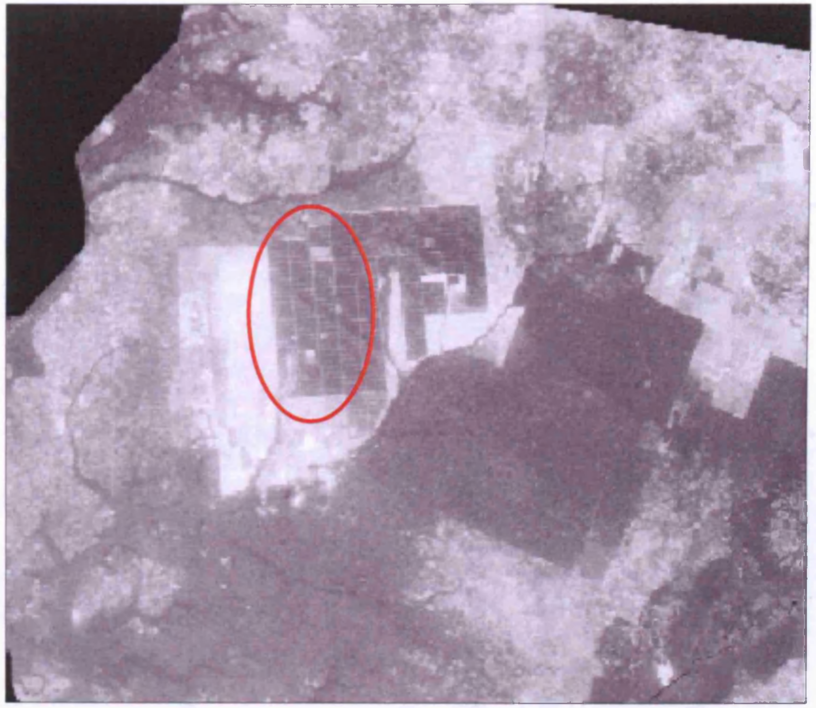


Figure7.6 Okomu Oil Palm and Forest reserve in 2001



This is due to the fact that, in the 1987 image (figure 7.5) during classification this area had been identified as agricultural land but in the 2001 image (figure 7.6) has been identified as forests as the crop had grown and matured. Same also applies to an area south east of Benin City, Obaretin forest reserve (figures 7.7 and 7.8), which has been occupied by agricultural plantations owned and managed by Presco Oil plc. Between 1975 and 1980, a total land area of 1150 ha was cultivated and this increased to 5527 ha in 1993.

Figure 7.7 Presco Plc Oil Palm Estates.

Source: http://www.presco-plc.com/index.cfm/page:plantation

Figure 7.8 Presco oil plantations in 1987

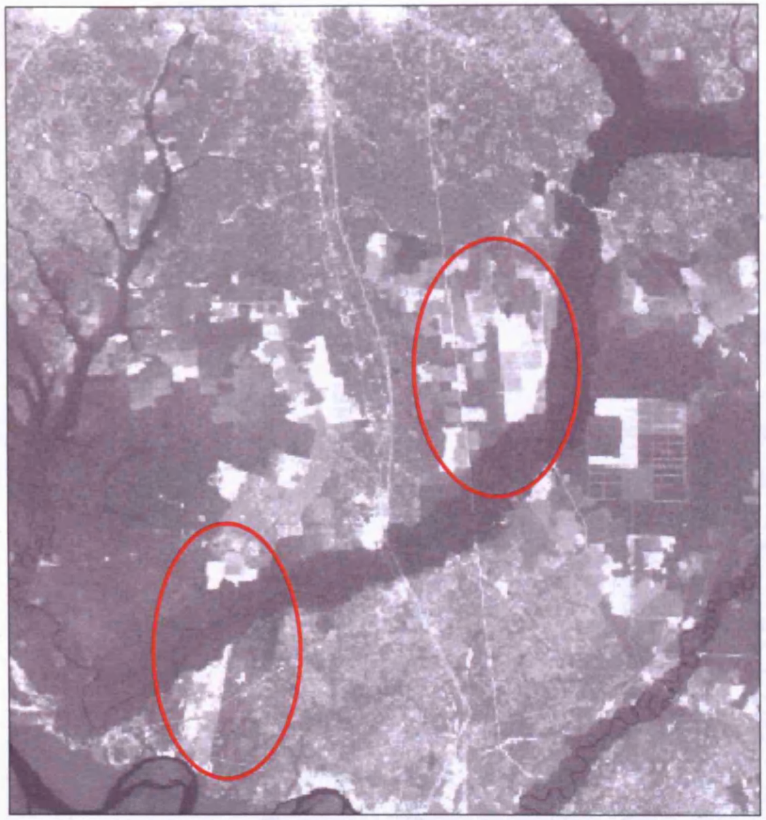


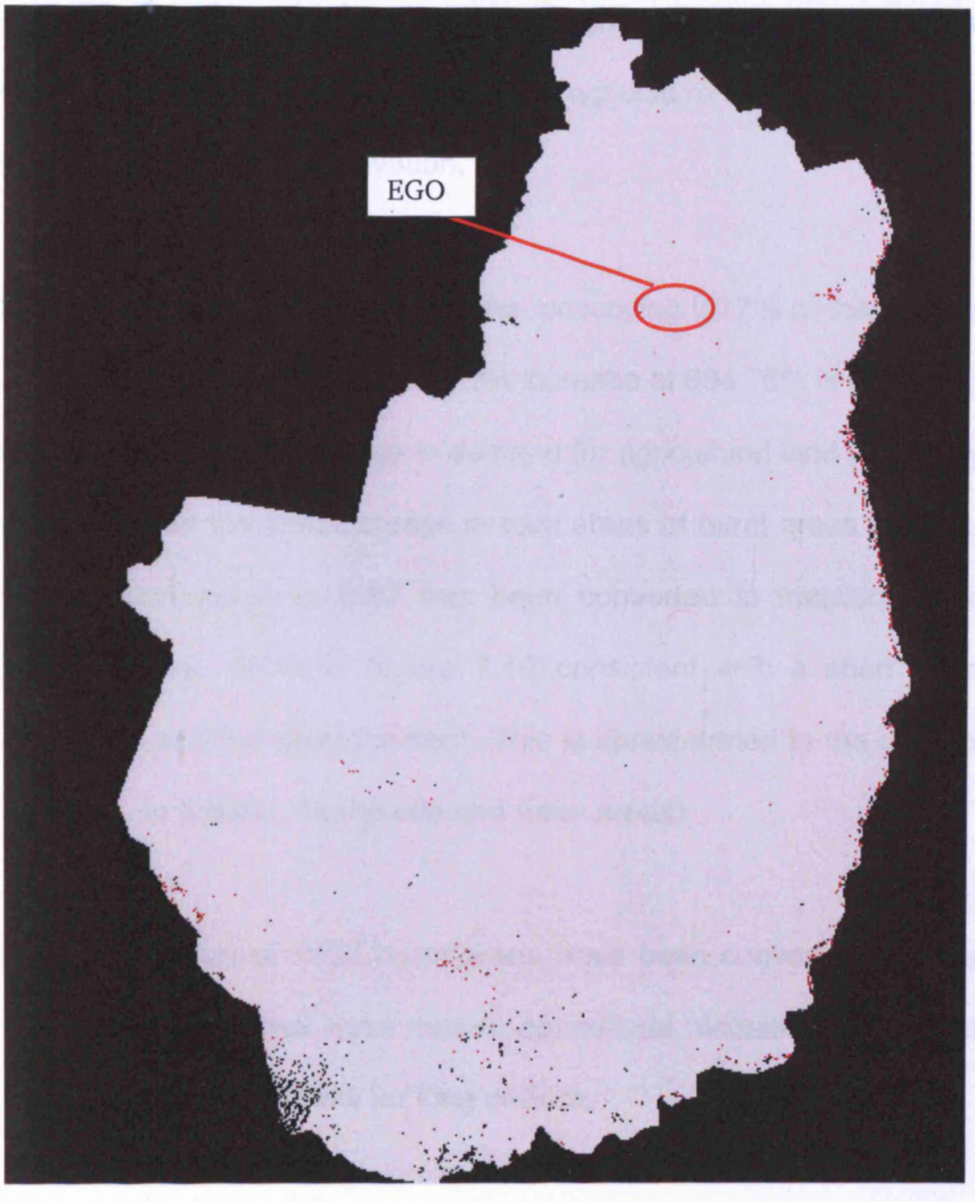
Figure 7.9 Presco oil plantations in 2001

7.2.2 Spatial Patterns of Change of Built-up Land

The built-up land increased from 96619 ha in 1987 to 148846 ha in 2001 which was a change of 54.06% (52227 ha) between the time period. As stated in chapter 6, this land use and land cover type is made of both rural and urban settlements. The increase in built-up land is due to the growing population in the study area, which increased by about 65% between 1987 and 2001. This population explosion has triggered the loss the forests and increase in agricultural lands.

A significant transformation of the original built-up land in 1987 to transitional land in 2001 is shown in figure 7.9. Some of these transformations are down to displacement of communities or settlements due to natural disasters such as floods, ethnic wars or land border disputes. For example according to Uyigue and Ogbeibu (2007) in Egor (highlighted in figure 7.9) and Ogida communities in Edo state, several houses have been abandoned by the owners due to floods and many more areas in the region are vulnerable to floods. With regards to issues such as ethnic wars and land border disputes, there are not usually documented, but speaking to the local population, it was discovered that in some areas in the North of Edo, there has been occurrences. In other areas of these transformations, the main basis for this is put down to misclassification process as some of these areas had similar spectral reflectance with floodplains.

Figure 7.10 Built-up land that have been converted to transitional land



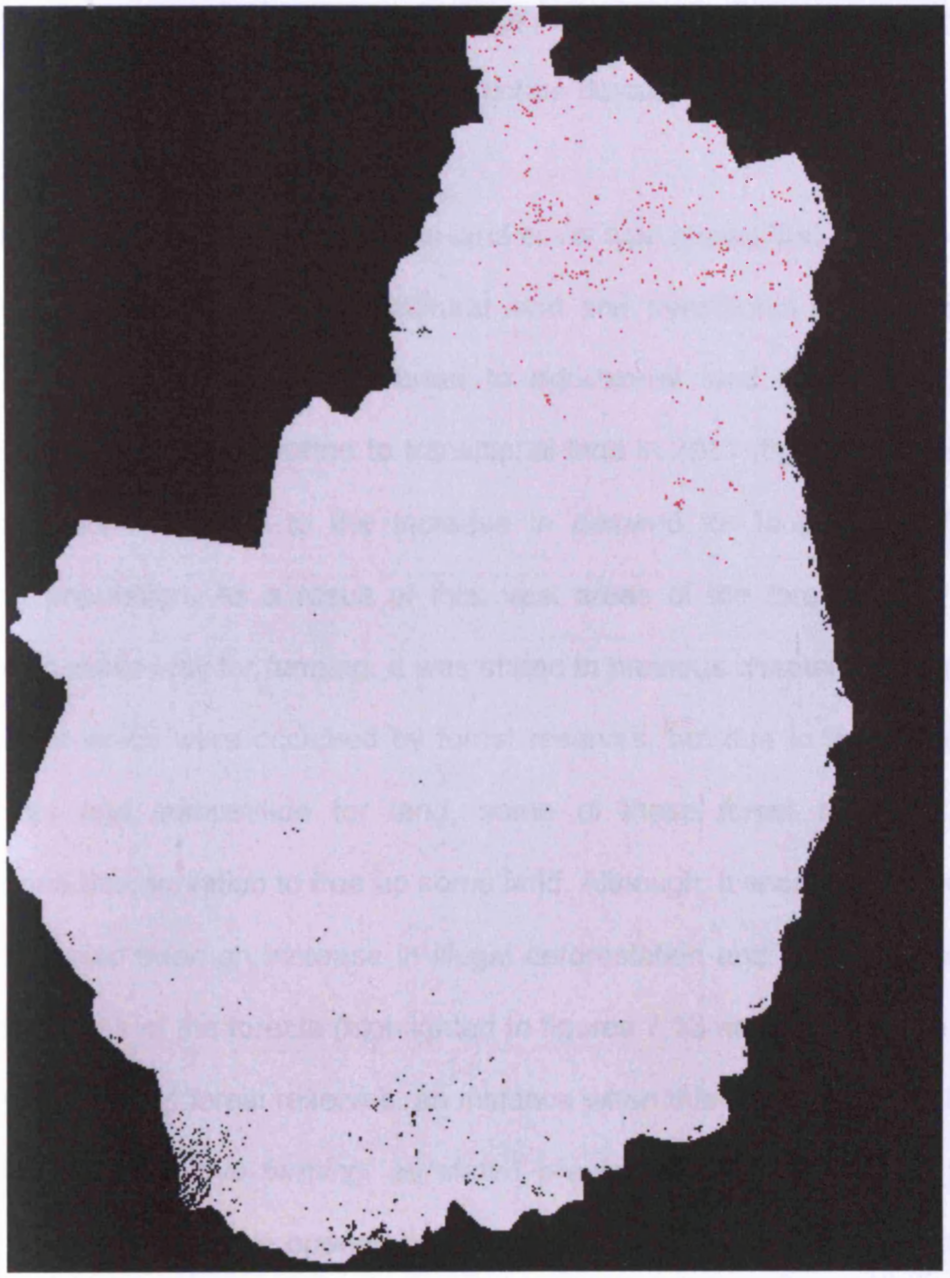
7.2.3 Spatial Patterns of Change of Burnt Areas

Burnt areas mainly result from clearing the land especially forests to make way for farmlands. In Edo and Delta states, the predominant occupation of the local indigenes is farming (as stated n previous chapters). According to some farmers practicing the bush fallow system ('slash and burn') I spoke to, the easiest and quickest method of preparing the ground for agriculture is to burn it down. This is used as a part of shifting cultivation.

The burnt areas increased from 26081 ha, occupying 0.77% of the total area in 1987, to 196855 ha (5.80%) in 2001. This increase of 654.78% is quite colossal. The reason for this is the increase in demand for agricultural land over the years which have caused the vast increase in total areas of burnt areas. The bulk of the original burnt areas in 1987 has been converted to transitional land in 2001(10546 ha i.e. 40.43%) (figure 7.10).consistent with a short period of agricultural use and the abandonment. This is concentrated in the north of the study area (i.e. in Etsako, Akoko-edo and Esan areas).

8.93 % (i.e. 2329 ha) of 1987 burnt areas have been converted to forests in 2001, which are areas that have mature agricultural plantations or agricultural land that has been left to fallow for long periods.

Figure 7.11 Burnt areas that have been converted to transitional land



7.2.4 Spatial Patterns of Change of Forests

Forests in Edo and Delta states have experienced a decline, from 1987 to 2002. It reduced to a total area of 1081963 ha (31.89%) in 2001 from occupying an area of 1549288 ha (45.66%). This huge decline is largely due to farming, logging, fuel wood extraction and infrastructure development.

A breakdown of the conversion of this land cover type shows that majority of the forests in 1987 were lost to agricultural land and transitional land. A total of 288760 ha (18.64%) were converted to agricultural land (figure 7.11) and 399759 ha (25.80%) converted to transitional land in 2001 (figure 7.12). These transformations are due to the increase in demand for food to satisfy the growing population. As a result of this, vast areas of the forests have been cleared to make way for farming. It was stated in previous chapters, the original vast areas which were occupied by forest reserves, but due to the population pressures and competition for land, some of these forest reserves have undergone dereservation to free up some land. Although, it should be noted that there has also been an increase in illegal deforestation and encroachment on the boundaries of the forests (highlighted in figures 7.13 and 7.14). In the case of dereservation of forest reserves, an instance when this has occurred is in the introduction of *taungya farming,* as stated previously in subsection 7.2.1. As these forest reserves are opened up for logging, then the forestry department close the forests to logging companies and open them up to the farmers (i.e. taungya farming). With regards to the conversion of these forests to transitional land, the pattern is similar, as this occurs in forest areas that have been cleared.

Figure 7.12 Forests that have been converted to agricultural land

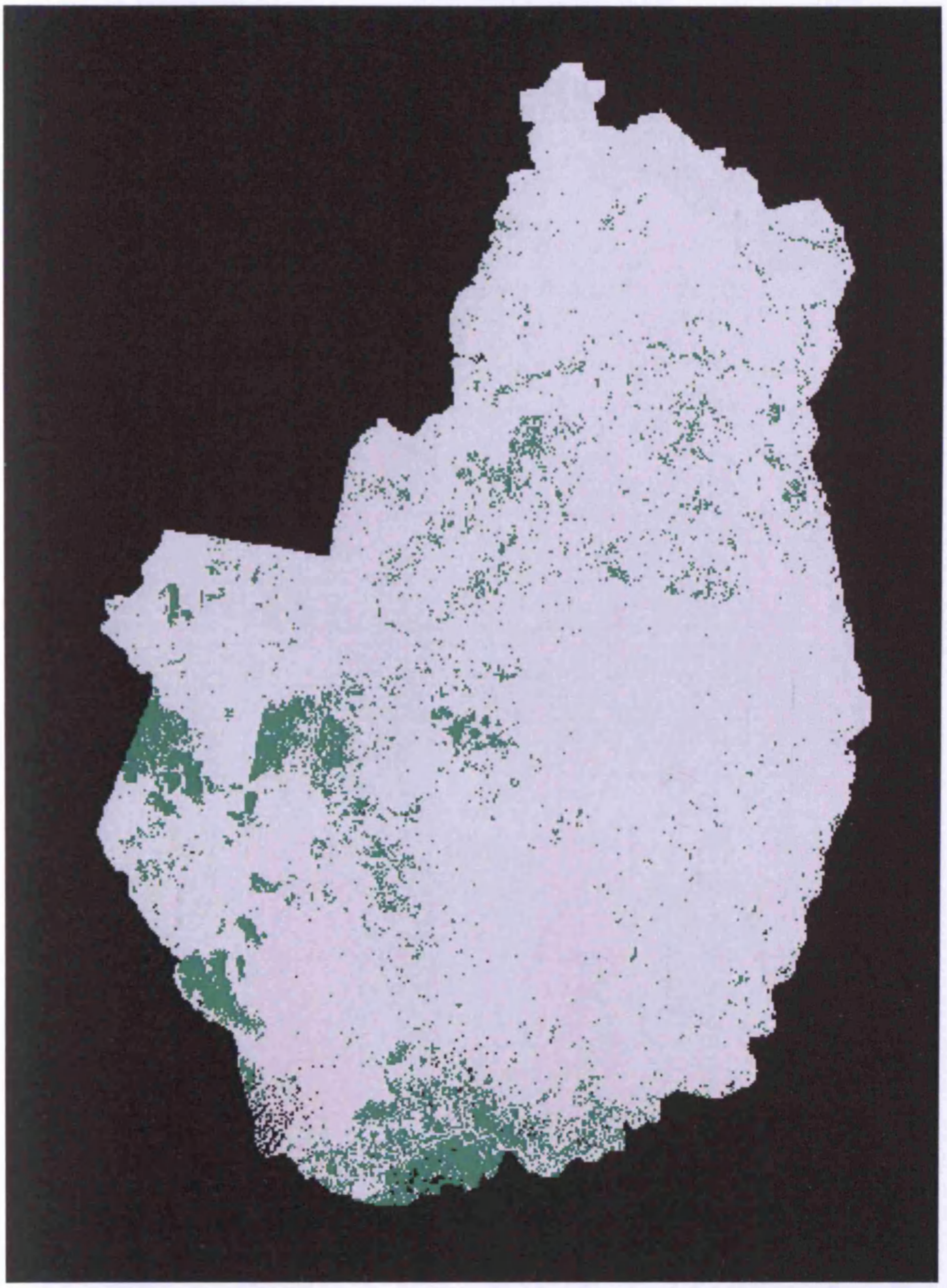


Figure 7.13 Forests that have been converted to transitional land

Figure 7.14 Forest reserves in 1987

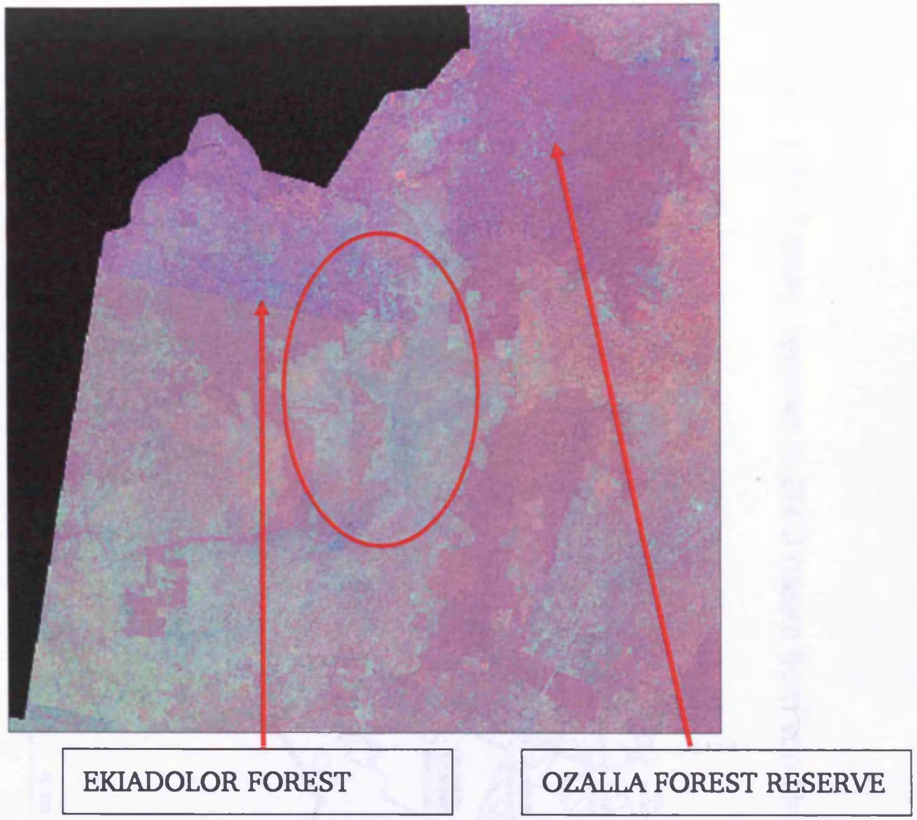


Figure 7.15 Forest reserves in 2001

An apparent change where forests have been lost to transitional land can be seen in figure 7.12; this is distributed around the study area, especially in Okomu forest reserve (south west of study area). In Okomu forest reserves (figures 7.15, 7.16 and 7.17), over the years, large areas of the forest were allocated to individual companies for large plantations (e.g. Okomu Oil Palm estate and Michelin Rubber estate), who have kept on expanding their plantations. At the same time other companies were leaving the area, as according to Oates (1999), the AT & P logging company left Nikrowa (located around the boundary of Okomu forest), leaving behind a large settlement of unemployed people who had few options for supporting themselves other than farming in the forest reserve leading to an overall reduction of forest cover (figures 7.16 and 7.17)

Figure 7.16 Okomu reserve in 2003 (taken from von Hellermann 2007)

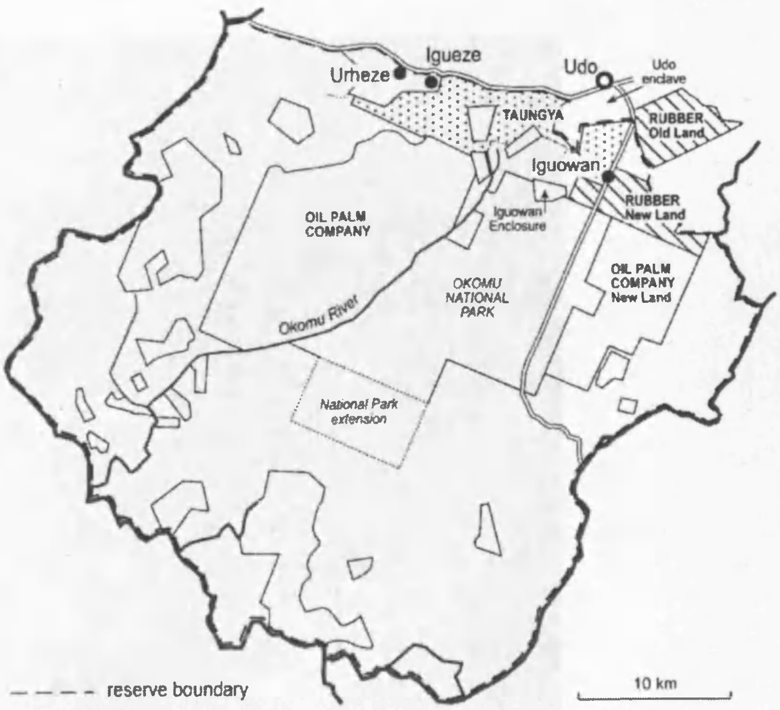


Figure 7.17 Okomu Forest reserves in 1987

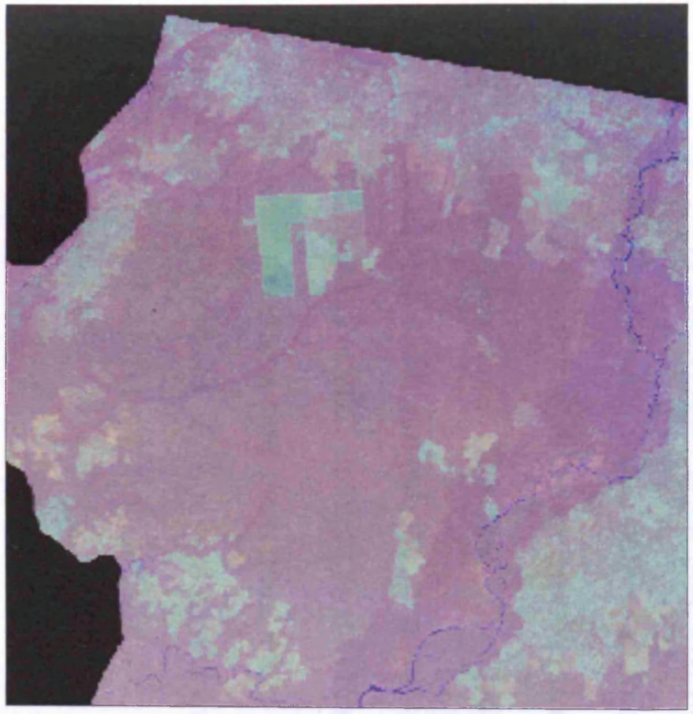
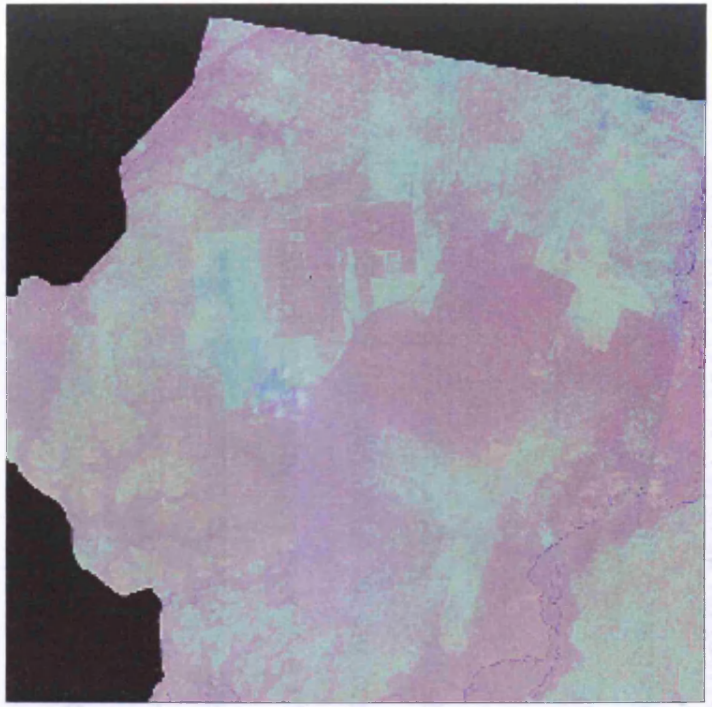


Figure 7.18 Okomu Forest reserves in 2001



7.2.5 Spatial Patterns of Change of Transitional Land

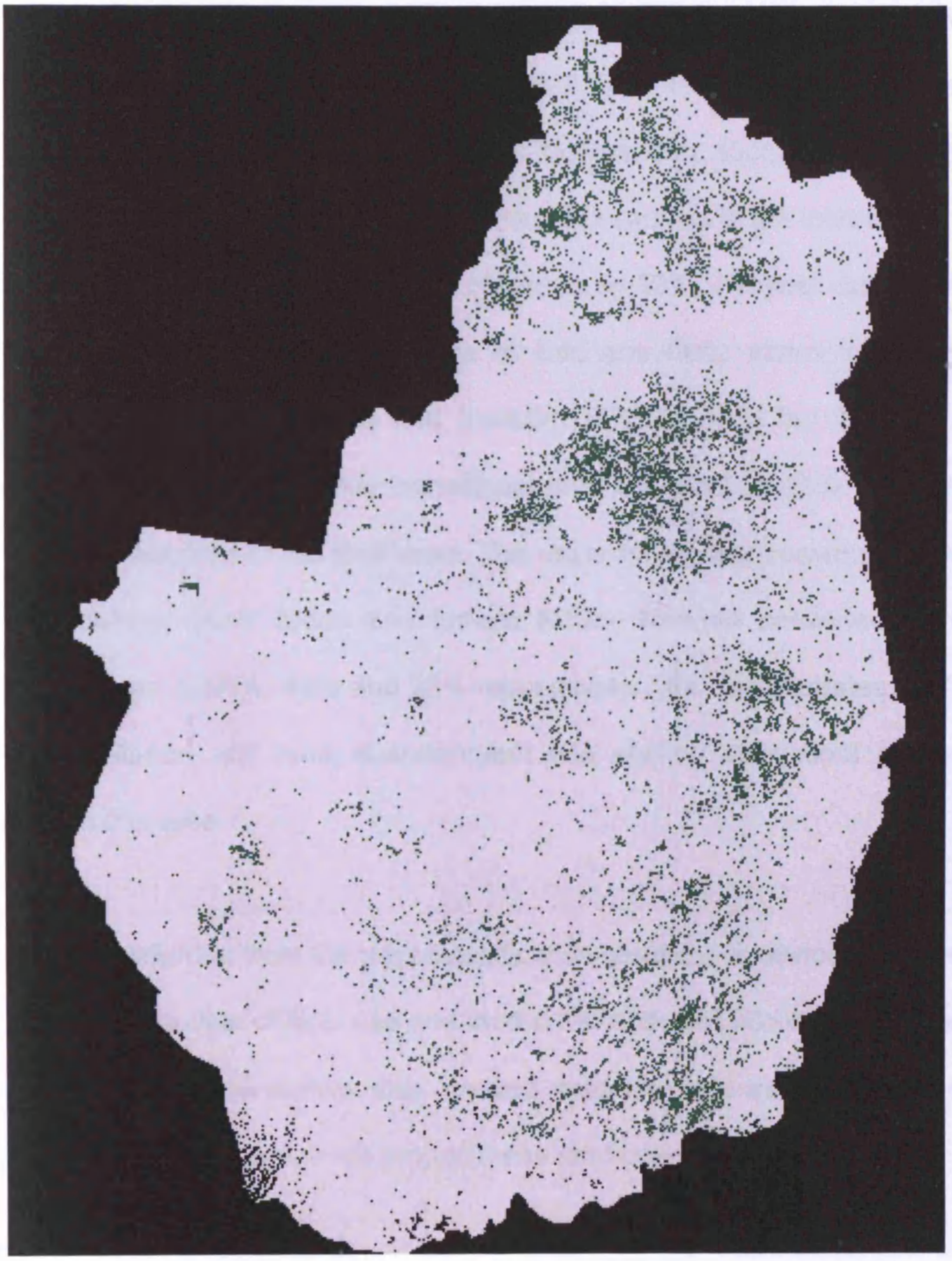
The transitional land between 1987 and 2002 has increased, from occupying 1030149 ha (30.36%) in 1987 to 1169732 ha (34.47%) in 2001 with 543253 ha (52.74%) of this land cover type remaining unchanged (i.e. between 1987 and 2002).

The bulk of the converted transitional land was lost to agricultural land, forests and burnt areas. 117073 ha (11.36%) of the original transitional land was converted to agricultural land, which is expected (figure 7.18), as in the study area, after the land has been cleared for farming, then left to fallow for about 3-5 years, the land will be used again for agriculture . This is concentrated north of the study area (i.e. surrounding areas of Ekpoma, Uromi, Ubiaja and Ekpon).

Another land use and land cover type that the original transitional land converted to was forests at 228148 ha (22.15%) (figure 7.19). With regards to this, as mentioned previously, these converted forests in 2001 are areas that have been either left to fallow for extended periods and trees are left to grow or mature agricultural plantations. This land cover type is distributed all over the study area. 7.22% (74352 ha) of the original transitional land has been converted to burnt areas in 2001. It might be due to the fact that, this transitional land in 1987, over the years, may have been left to grow and a farmer needing the land for farming purposes, will burn the land to make way for agriculture.

Figure 7.19 Transitional land that have been converted to agricultural land

Figure 7.20 Image of study area showing transitional land that has been converted to forests



Analysing the post classification image and statistics, it can be concluded that within the 14 year period (i.e. 1987 to 2001), the land cover has changed tremendously. According to the post classification analysis performed, about 53% of the total land of Edo and Delta states have changed, leaving about 43% of the land cover remaining unchanged. The average annual rate of land cover change between this period, alarmingly, was 3.77%. The main driving force of this change is population growth, which has increased by about 65% during this period. The most significant land cover changes occurred in the increase of the burnt areas at 655% and the decrease of forests by 30%. The post classification analysis shows that in 1987 the area of Edo and Delta states was largely occupied by the forests (45%) and transitional land (30%) but in 2001 the forests only covered 32% while transitional land occupied 34.47%, occupying the largest proportion of the total area. The major land cover conversions were from agriculture, burnt areas and forests (which were all converted) to the transitional land at 90%, 40% and 26% respectively. This demonstrates the fact that deforestation and land abandonment (via shifting cultivation) are very dynamic in this area.

In summary, inferring from the post classification results, it is obvious that there has been a great deal of land use and land cover changes occuring in Edo and Delta states. The quantitative data derived from the post classification were applied in the models, which will project these land cover changes.

7.3 Modelling Land Cover Change

This section analyses the results that were derived from the model projections presented in chapter 6. The quantitative data of the total areas for agricultural land, forests and transitional land were used to calibrate the models to simulate land use and land cover changes in Edo and Delta states. The model projections show simple trajectories of the change and were extrapolated to 2030. These model projections provide a framework for assessing possible future land cover and land cover changes based on past trends.

Model projection I assumes that forests are being lost solely due to conversion agricultural land and these agricultural lands are cultivated for longer periods. This results in decline in the forests and agricultural land, as the calculated annual deforestation rate of 2.5% was used and 20% of the agricultural land is being left to fallow (i.e. converts to transitional land) every year, as observed during the fieldwork. As agricultural areas are lost to other classes and never re-used, an immense forest loss results. This model projection foresees, that by the year 2030 agricultural land area will be reduced to 74525 ha as opposed to the agricultural area of 399156 ha in 1987 that is a loss of about 81%. This projected agricultural area is certainly not sufficient to sustain the increasing population of the study area (chapter 4). This model projection clearly demonstrates that clearing forests is not and cannot be sufficient to support the demand for agricultural lands. Other land classes are also converted to agricultural use, in particular transitional land is brought into agriculture, typically after being left to fallow for 3-5 years.

Model projection II considers this case – converting, or reusing, transitional land for agriculture. It hypotheses the conversion of forests to agricultural land, then from agricultural land to transitional land and then – after a fallow recovery period – back to agricultural.. The same parameter values as in model projection I for deforestation rate *a* and abandonment rate *b*), are used in this projection; in addition to this the rate of at which agricultural land re-uses the transitional land (i.e. *c* = 15%) was employed and a 2% annual conversion of transitional is reverting back to forests. The projections in this projection show that there is a decline in transitional land between 1988 and 1992, but started picking up after 1992 and by 2001 reverted to similar total area as 1987. On the other hand, the total area of forests decreased while agricultural areas increased.

The projected trend of transitional land in model projection III is similar to that of model projection II, except that in this projection, the decline was from 1988 to 1993, which started to increase after 1993, at the same time agricultural land experienced large increase in area, but the annual increases starts to decrease down from 1994 and total agricultural area reaches an almost stable state in 2026. Model projection III foresees that the area of forests will be halved, declining extensively by about 52%, whereas the agricultural land increases by 148% (i.e. 591213 ha) and transitional land also increases by 21% to an area of 216943 ha. This projection seems most realistic of the ones considered here, as considers the conversions on the ground, i.e. 'it models the feedback between the land use and land cover types (agricultural land, forests and transitional land). It takes in account the transitional land reverting to forests, for example in the situation of taungya farming.

The pattern of land use and land cover changes in projections II and III, both demonstrate that the trend between 1987 and 2020 hold different views, for example take projection III, in 1987 out of the combined total areas of the land use and land cover types, forests occupied more than half of the area (52%) and by the end of the projection (i.e. 2030) transitional land will occupy about 42% of the area. This predicts that as more forests are cleared it generates an increase in transitional land, which are not re-used thereby spawning excess abandoned land. All three model projections show that clearing the forests solely will not be adequate to meet the demand for agricultural land and more of the transitional land will need to be recycled in order to satisfy the demand. However, this brings up the question of – how much agricultural land will be required to satisfy the demands? The next section will look to answer this question.

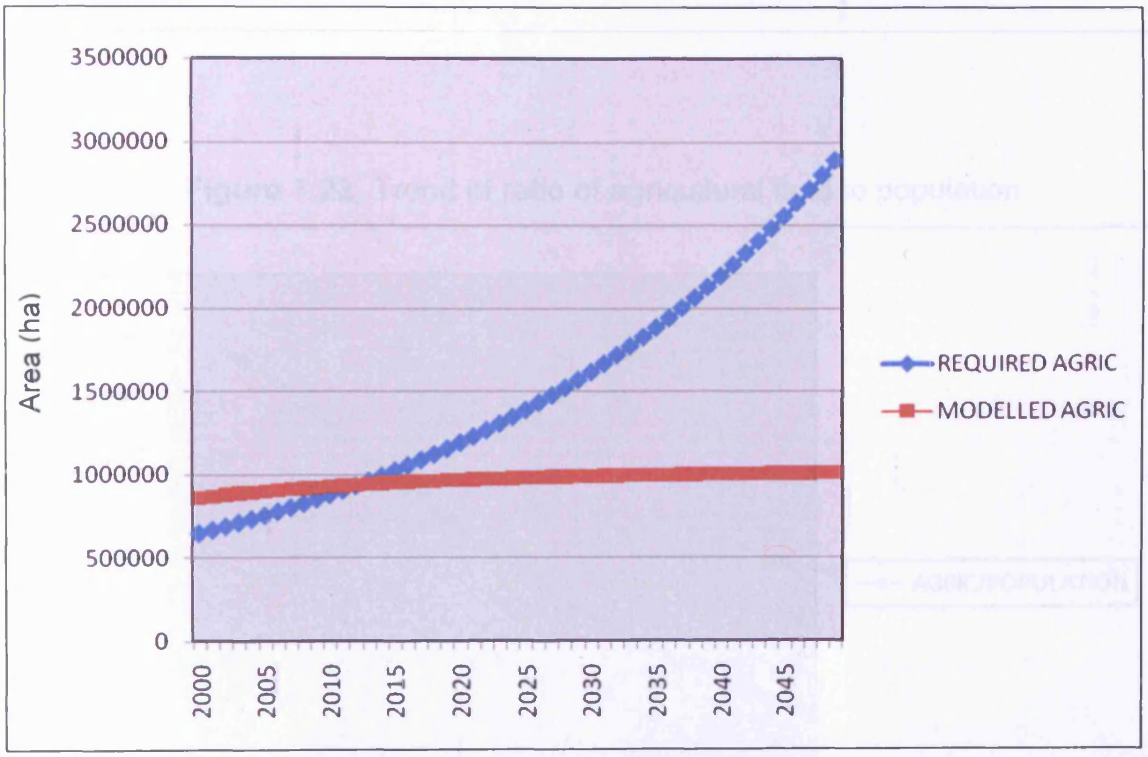
7.4 Relating Population Growth to Modelling Land Cover Change

In Edo and Delta states, there is a correlation between population growth and land use and land cover change. This is demonstrated by the ratios of 0.1 and 0.1 ha agricultural area per person in 1987 and 2001 respectively derived from the classification of the images and population data. As the population increases, the demand for food and land increases. In most circumstances, this involves significant land use change particularly with respect to the loss of forest areas to agricultural land use (Ite, 2001). The expanding population of the study area has driven the rapid loss of forests as large proportions of agricultural land are abandoned every year and the reuse of transitional land does not satisfy the demand. This sub-section analyses and attempts to answer the question – how much agricultural land will be required to sustain the growing population. In order to achieve this, the land area projections attained in model projection III will be employed, extrapolating to 2050.

It seems reasonable and is sufficient for the following arguments to assume for the time period after 2001 a required agricultural area of 0.1 ha/person to sustain the population. Therefore, inferring from the model (please see appendix II) and graph, the agricultural land required to sustain the agricultural land by 2050 is 2884668 ha as opposed to the projected agricultural area from projection III of 1012494 ha (figure 7.21). This implies a ratio of agricultural land and population of 0.0351 compared to the ratio in 1987 of 0.0951 (figure 7.21). This is not adequate to support the growing population using current agricultural practices. This ratio increased rapidly from 1988, then started declining in 1993 as the population was increasing faster than agricultural lands were becoming available. In other words, by 1987 the ratio of agricultural land to population was 2 ha per 21 people, while this went up in 1992 to 2 ha per 13 people, but by 2050 this would have reduced to only 2 ha of agricultural land projected to sustain 57 people, if the current pattern of land use and land cover changes remain the same.

There are various possibilities to increase the agricultural area: increase the amount of transitional land reverted to agriculture, reduce the abandonment rate. These will be exploring in the following partially through the study of extreme case to show possibilities and hard limitations.

Figure 7.21 Projected and required agricultural land extrapolating projection III and assuming a requirement of 0.1 ha/person agricultural area



The first option was to assume that 100% of the transitional land will be converted to agricultural land (figure 7.22). This doubled the agricultural area in 2050 and the ratio resulted in an erratic trend, with a sharp increase in the ratio in 1988, which fell sharply again in the next year before increasing in 1990, then declining in subsequent years. It demonstrates that in 1988, the ratio of the projected agricultural land area to population is 7 ha per 22 people, but in the next year reduced to 11 ha per 43 people and by 2050 the projected ratio will be

1 ha per 14 people.

Another option was to check the trend of this ratio, if deforestation was occurring at a slower rate, whereby forcing the transitional land to be utilized for farming, so a lower deforestation rate of 2% was applied.

Figure 7.22 Trend of ratio of agricultural land to population

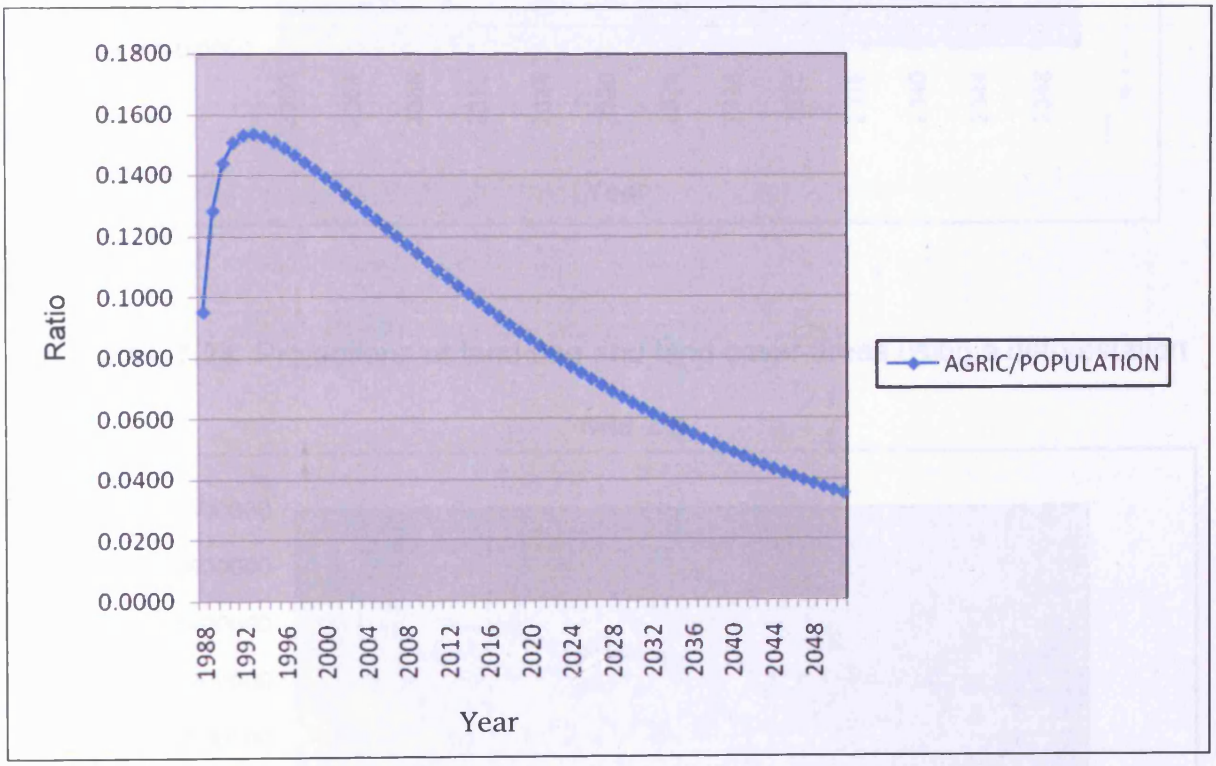


Figure 7.23 Projections of the ratio of agricultural land to population assuming all transitional land is converted to agricultural land

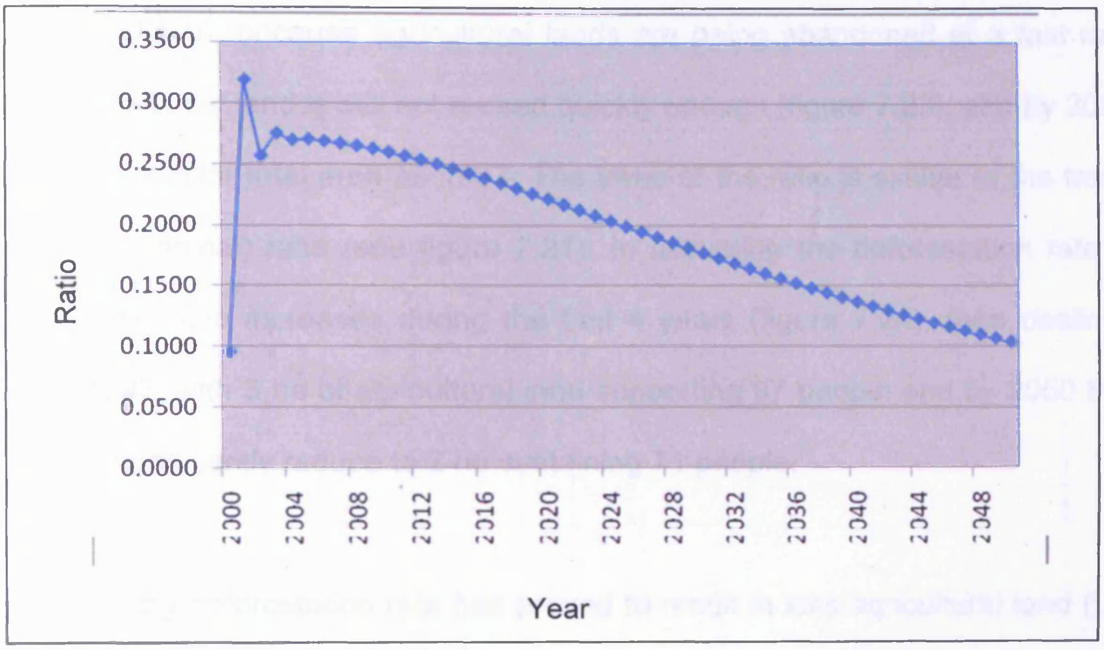
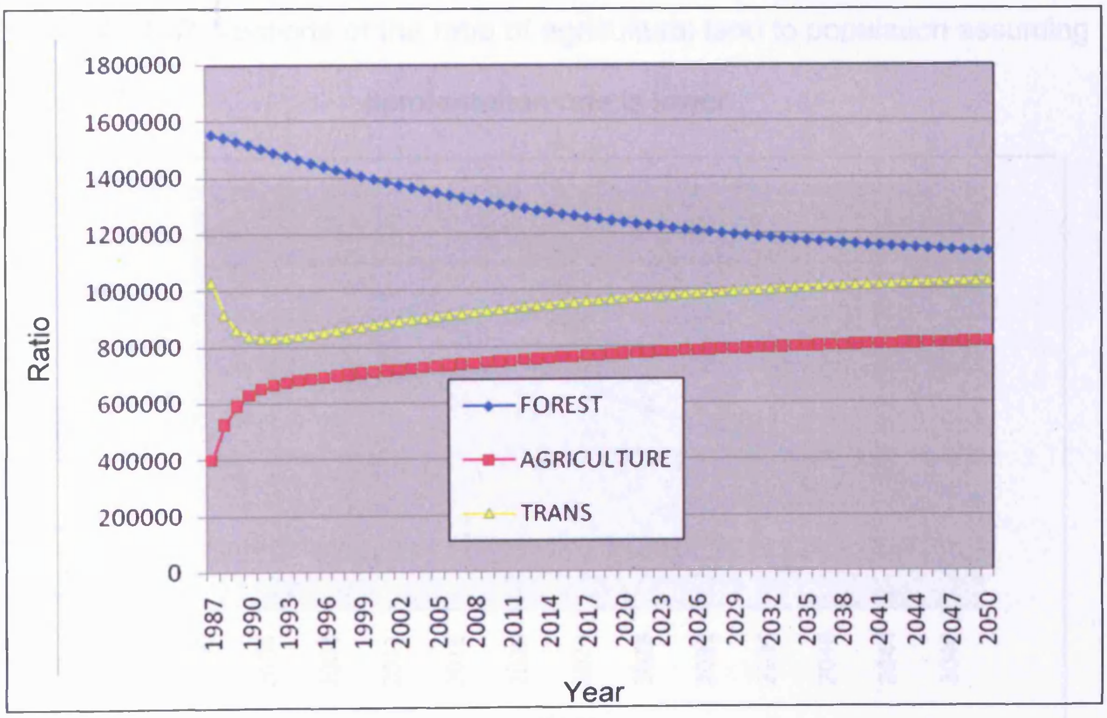


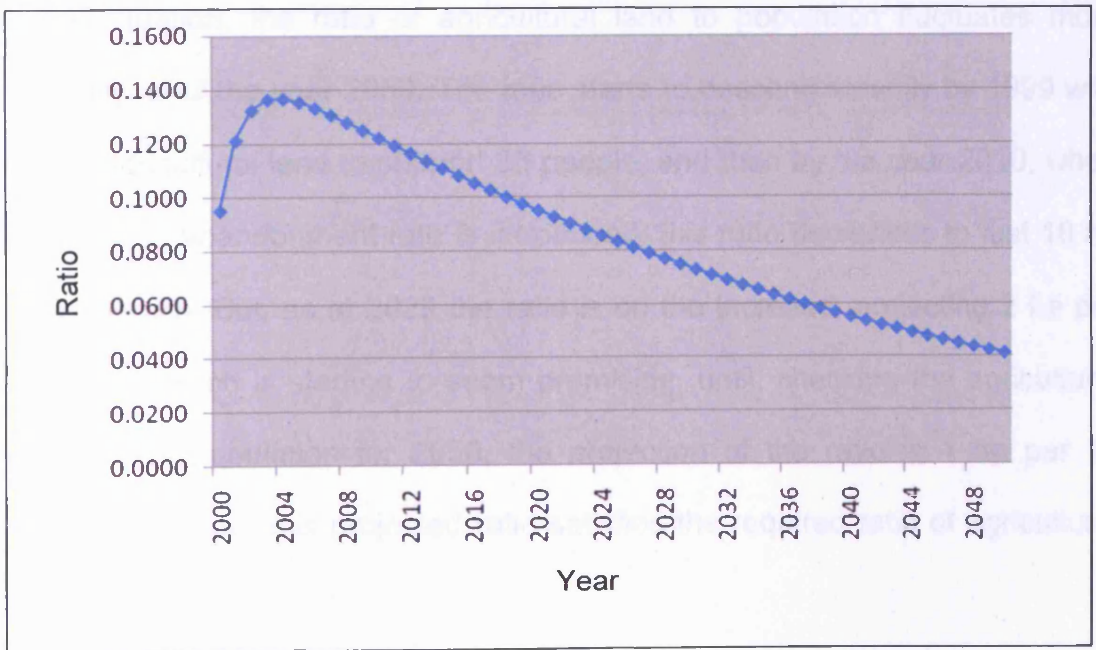
Figure 7.24 Projections of land use and land cover areas using a deforestation rate 2%



In using a lower deforestation, there is not adequate agricultural land to sustain the population, because agricultural lands are being abandoned at a fast rate and transitional land is still not reused quickly enough (figure 7.23), and by 2050 covers a similar total area as 1987. The trend of the ratio is similar to the trend starting (original) ratio (see figure 7.21). In assuming the deforestation rate is lower, the ratio increases during the first 4 years (figure 7.24), then declines from 1992, with 5 ha of agricultural land supporting 37 people and by 2050 this will be significantly reduce to 2 ha sustaining 71 people.

As lowering deforestation rate has proved to result in less agricultural land (i.e. they are abandoned and left to fallow quicker), the rate at which the agricultural land is being abandoned was re-examined.

Figure 7.25 Projections of the ratio of agricultural land to population assuming deforestation rate is lower



It was assumed that the abandonment rate has remained constant for 22 years, from 1987 to 2009 (i.e. 2.8%), allowing for agricultural practice to be transformed as from 2010 due to the realization that the forests are disappearing at an alarming rate. In an interview, Phillip Asiodu, head of Nigerian Conservation Foundation, warned that Nigeria may be left with no forests by 2010 due to ongoing deforestation (Terradaily, 2007). This was also done in line with the Vision 2010 introduced in Nigeria in 1996.

A steady reduction of this rate was used assuming that the rate drops by 0.1% annually, which should result in less agricultural land abandoned every year. In so doing, area of forests declined steadily from1987 to 2050, and. by the year 2050, the forests would reduced by 40.40% (figure 7.24).This is similar to transitional land which also reduce by 34.25% and all of these land has been converted to agriculture increasing in area by 74.65% by the year 2050.

In this situation, the ratio of agricultural land to population fluctuates more erratically, until the year 2050. The ratio starts to descend steadily by 1999 with 5 ha of agricultural land to support 36 people, and then by the year 2010, when the reducing abandonment rate is introduced, this ratio decreases to just 10 ha per 91 people. But, as at 2029 the ratio is on the increase, projecting 2 ha per 19 people, which is starting to seem promising, until, checking the agricultural land ratio to population for 2050, the projection of the ratio is 1 ha per 11 people. Therefore, this projected ratio satisfies the required ratio of agricultural land to population.

Figure 7.26 Trends in land cover change with reducing abandonment rate

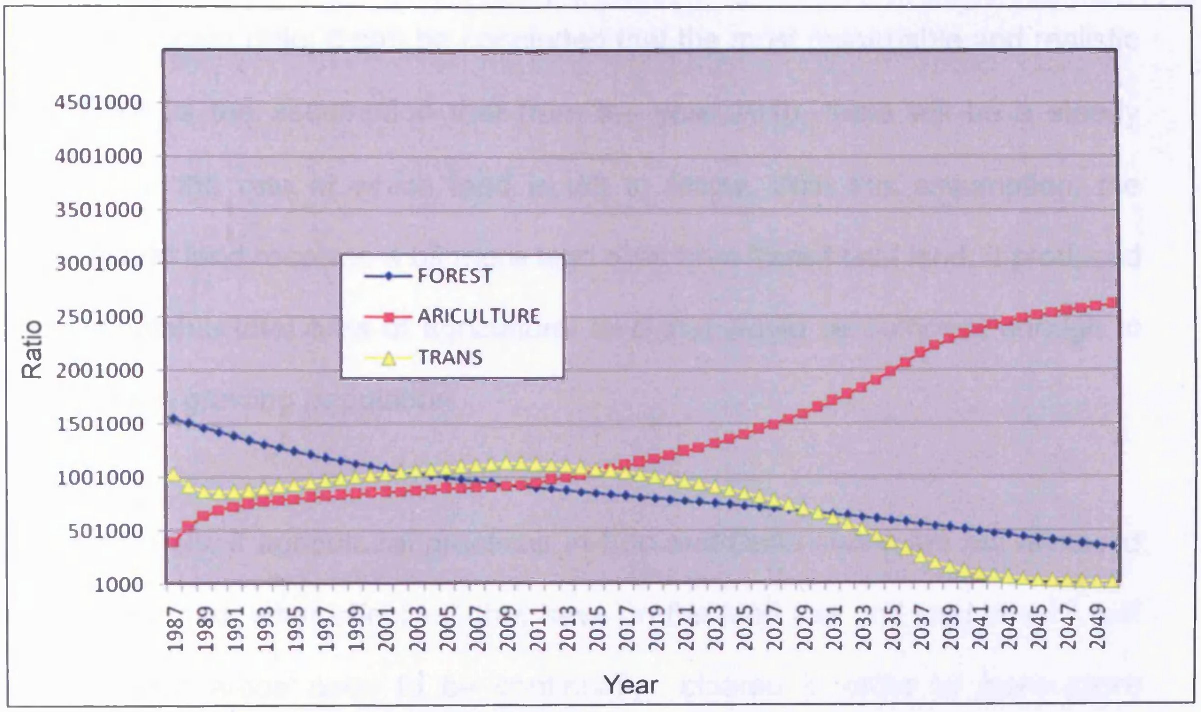
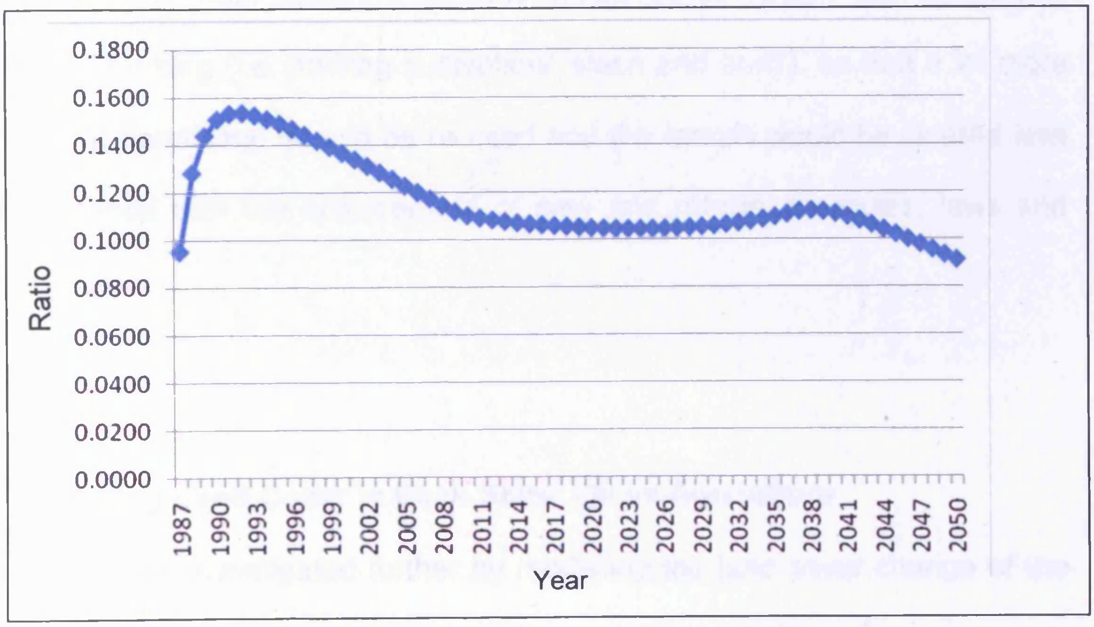


Figure 7.27 Projections of the ratio of agricultural land to population, when the abandonment seizes to be constant



In summary, in looking at the different projections for the agricultural land/population ratio, it can be concluded that the most reasonable and realistic projection is the assumption that from the year 2010, there will be a steady decline in the rate at which land is left to fallow. With this assumption, the agricultural land receives a bit more land area from transitional land. It produced an acceptable total area of agricultural land that would be sufficient enough to sustain the growing population.

Unfortunately, if agricultural practices in Edo and Delta states are not reviewed or transformed, what effect will that have on the land use and land cover?, will more forest areas need to be continually cleared in order to make more agricultural available? Essentially, the available agricultural land will not support the requirement of at least a hectare of agricultural land per 10 people. Deducing, from the above projections of the ratio of agricultural land to population, the most apparent remedy would be to reform the agricultural method of farming (i.e. shifting cultivation/ 'slash and burn'), so that a lot more of the transitional land should be re-used and the forests would be cleared less in accordance with the enforcement of new and reformed policies, laws and regulations.

7.5 Modelling Land Cover in Each State: Oil vs Agriculture

The model was investigated further by modelling the land cover change of the individual states (i.e. Edo state and Delta state). The satellite images were split into their individual states, according to their boundaries and previous processing techniques, as done previously were performed. The end result was the post classification images (figures 7.28 and 7.29). The images were analysed and areas (i.e. forests, transitional land and agriculture) were fed into the model.

Figure 7.28 Post Classification image of Delta State

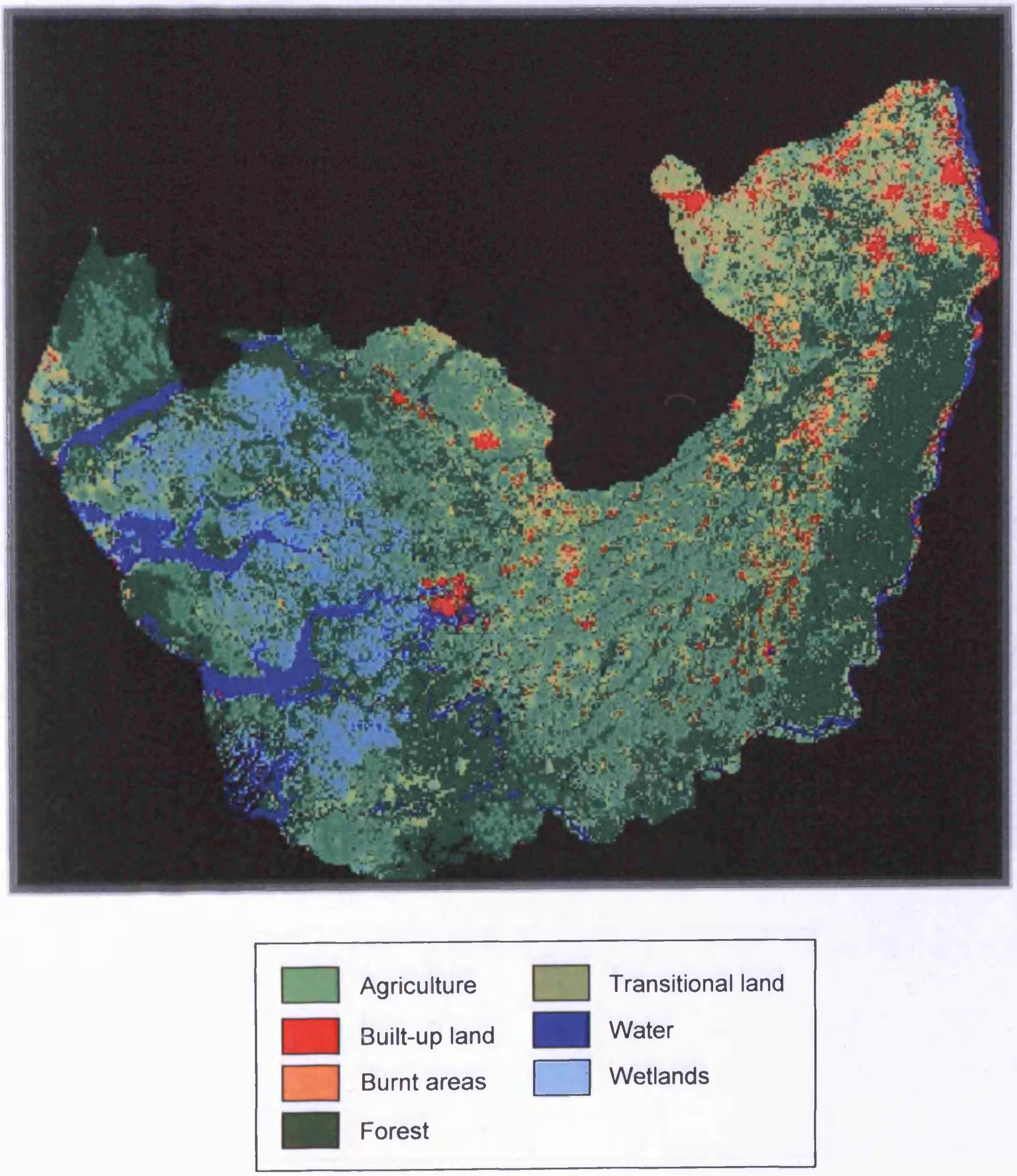
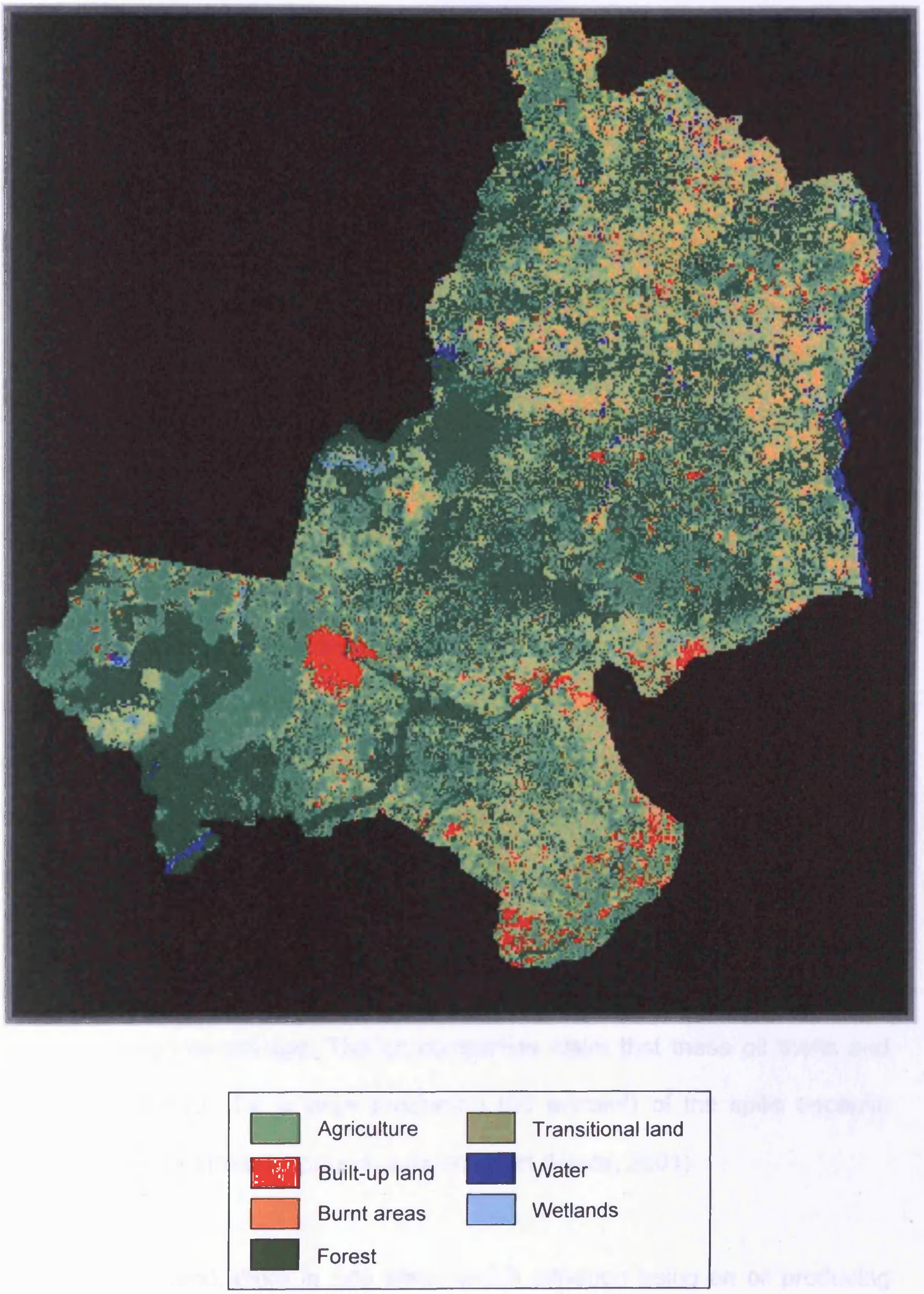


Figure 7.29 Post Classification image of Edo State



These have been done, to look at the model results individually for Edo and Delta states, which have been impacted by agriculture and oil, respectively. As stated earlier, the oil industry is the one of the most important sectors in Nigeria, with Delta state supplying about 35% of Nigeria's oil. The oil companies continue their oil exploration activities in Delta state, they present a constant need for labour, which in turn would increase the settlements (i.e. built up land) and infrastructure and increase demand for land. According to an article by Hinman (1993), only 30% of the Delta is unaffected by heavy flooding, the remaining land has to support a concentrated population. Another environmental peril that the land has and will continue to suffer, will be those caused by oil activities – oil spills and gas flaring. This stresses the reality that the land would need to be monitored and maintained properly. Although as an effect of the politics of oil activities, the locals are filled with frustration with government and the oil companies, coupled with their land and water being polluted via oil exploration and spills (please see chapter 2). They then result in oil theft (also referred to as *bunkering),* which Watts (2005) put it simply as, both small-scale tapping of fuel pipelines for the local market and large-scale theft via barges and flow stations for the international market. Bunkering especially done on a small-scale, have impacted the land and in some cases have caused deaths through oil spillage. The oil companies claim that these oil thefts and sabotage accounts for a large proportion (60 percent) of the spills because communities gain from corporate compensation (Watts, 2001).

On the other hand, there is Edo state, which although being an oil producing state (but on a smaller scale) also seems to be suffering from vast land cover changes, but not as a direct result of oil exploration activities, but agricultural activities (i.e. the predominant occupation) and logging. During a speech given by the governor of the state, he said 'Although Edo state is one of the oil producing states in Nigeria, we are at the bottom of the table' (edo state website, 2008). So Edo is looked at as an agricultural region, with the main farming practice being shifting cultivation (or bush fallow) (please see chapter 2). This practice system persists partly, because there is inadequate access to modern farming inputs (like fertilizers). In Nigeria, fertilizers are very expensive and are therefore beyond the reach of the local farmers (Omofonmwan and Kadiri, 2007). This method of farmng has had its effects on the land; wgich loses it fertility and productivity. Nevertheless, there are a vast number of oil palm, rubber and cocoa plantations present in Edo, which unfortunately have been planted or cultivated as forests were being cleared and cut down. This has been an ongoing problem in this state, even having outsiders encroaching on their lands for various reasons and this has caused communal clashes, land disputes, deforestation and so on. According to Ighile (2006) 'there are Edo indigenes that receive huge sums of money from those who encroached on our land annual homage either in cash or kind are paid to the so called …….. Elders'. This is also common in Delta state. Ighile (ibid) created a table of areas of Edo that have and are been affected by encroachment (table7.1).

The deforestation has always been recognised as an issue, as managing the forest and its resources have been getting increasingly difficult over the years.

Table 7.1 Parts of Edo State where encroachment exists

S/N	AREA OF VISIBLE ENCROACHMENT	NEIGHBORING STATES ENCROACHING ON EDO LAND	PURPOSE FOR ENCROACHMENT
1	Oben: Orhionmwon Local Government Area	Delta State and Oil Companies prospecting for Crude oil	Farm land taken over by the Deltans and oil pipes laid to drain oil to Delta State from Oben in Edo State
2	Iguemokhua – Orhionmwon Local Government Area	Oghara people in Delta State	Illegal exploration of logs in Edo forest reserve and farming in Edo Land
3	Urhonigbe- Orhionmwon Local Government Area	People of Umutu and Urhobo in Delta	Illegal farming on Edo land and exploitation of logs from forest reserve
4	Sakponba – Orhionmwon Local Government Area	Deltans	Illegal exploitation of logs in Sakponba forest reserve
5	Evbonogbon-Ovia South West Local Government Area	Ondo state	Illegal exploitation of logs from forest reserve
6	Safarogbo, Ubayaki, Okomu-Ijaw, Modoti, Agbonokhua (Ikale camp), Gbelebu, Jide inland, Jide upland, Kehinde, Madagbayo, Ofineyege, Okadeye, sule camp, Gbelekanga, Gbolowosho, all in Ovia South Local Government	Indigene of Ondo, Delta and Kogi States	Illegal farming and establishment of plantations in the reserve, illegal exploitation of logs.
7	Gele-Gele, Nikorogha, Iboro, Ikoro, Malagidi, ajakurama, etc. Ovia North East local Government Area	Ijaws	Illegal claim of ownership of the land (Note that the Ijaws came to these places in search of sea foods and local navigation on our waters for economic reasons) Attempts on them to install traditional rulers on the land has been forestalled

S/N	AREA OF VISIBLE ENCROACHMENT	NEIGHBORING STATES ENCROACHING ON EDO LAND	PURPOSE FOR ENCROACHMENT
8	Oja-Akoko Edo Local Government Area	Kogi	Illegal farming on Edo land
9	Ilushi-Esan South –East Local Government Area	Kogi	Illegal farming on Edo land

Source: Ighile (2006)

Recognising this, *taungya* was introduced to the country in Sapoba in the late 1920s, this according to Ball and Umeh (1982) , is a healthy marriage between agriculture and forestry, some of the crops grown were yams, maize, cassava, rice, plantains etc while the trees grown were gmelina arborea, teak, and white afara. Hellermann (2007), described taungya further, where the reserve land is first cleared for farming, then economic timber species are planted in between the plots, growing into forest as the farm is left to fallow in the agreed rotational scheme. Unfortunately, due to the political economy (including the introduction of SAP – chapter 2), this couldn't be carried on, as a forest officer via Hellerman (ibid) regarded it as having failed woefully.

The taungya farming system is still ongoing, but without the tree planting as lack (or scarcity) of the tree seedlings, this has led to more forests being cleared and destroyed with no trees being replaced (and replanted). With these in mind about Edo and Delta states as individual areas, with different causes of land cover change, regardless of being geographically next to each other, the statistics for each state were fed into the model. This is to find out if the model would show the differences in both states.

Looking at the post classification images, in Edo state the largest land cover change between 1987 and 2001 has been in the Wetlands class (table 7.2), followed by the Burnt areas, Water class, the Built up land, Agricultural land and Transitional land in that order. The only decrease in area occurred in the Forest land cover class, which decreased by about 297 384ha between 1987 and 2001. This was not the case in Delta state, which the Burnt areas had increased enormously from 16 ha to 51 966 ha, alongside the Built up areas that had also increased by 89 257 ha (table 7.3). Similar to Edo state, the Agriculture had also increased, but there has been a decrease in the Transitional land by about 29% and as expected a decrease in Forest areas by 19 687 ha.

The next step was to project these changes using the model. In modelling land cover change in the individual states, the same constants, as previous, were used. The model results for Edo state (figure 7.30) were similar to the result for the whole region, in that the projected transitional land there was a decline between 1988 and 1990, but started to increase in area from 1991, which was when the states (Edo and Delta) were split in two separate states. This was the same case in Delta state (figure 7.31).

Table 7.2 Summary of the land cover change in Edo State

Class	1987 (ha)	2001 (ha)	Total change area (ha)
Agriculture	239,286	327,737	88451
Built up	45,445	71,806	26361
Burnt Areas	26,026	109,996	83970
Forests	935,276	637,892	-297384
Transitional land	544,244	599,183	54939
Water	10,182	35,627	25445
Wetland	748	18,966	18218

On the other hand, projected Forest areas in both Edo and Delta states steadily decreases from 935 276 ha in 1987 to 394 902 ha (please see appendix III for detailed table). In both states, forest areas were almost halved by 2030, while the agricultural land areas increased by 330 732 ha (Edo state) and 258 061 ha (Delta state). The ratios of agriculture to population were performed (figures 7.32 and 7.33), and these had the same trend as previous (figure 7.22).

Table 7.3 Summary of the land cover change in Delta State

Class	1987 (ha)	2001 (ha)	Total change area
Agriculture	162652	273762	88451
Built up	51941	89257	26361
Burnt Areas	16	51966	83970
Forests	614489	594802	-297384
Transitional land	483716	342731	54939
Water	53301	92787	25445
Wetland	225912	146723	18218

Figure 7.30 Projection of land cover change in Edo State

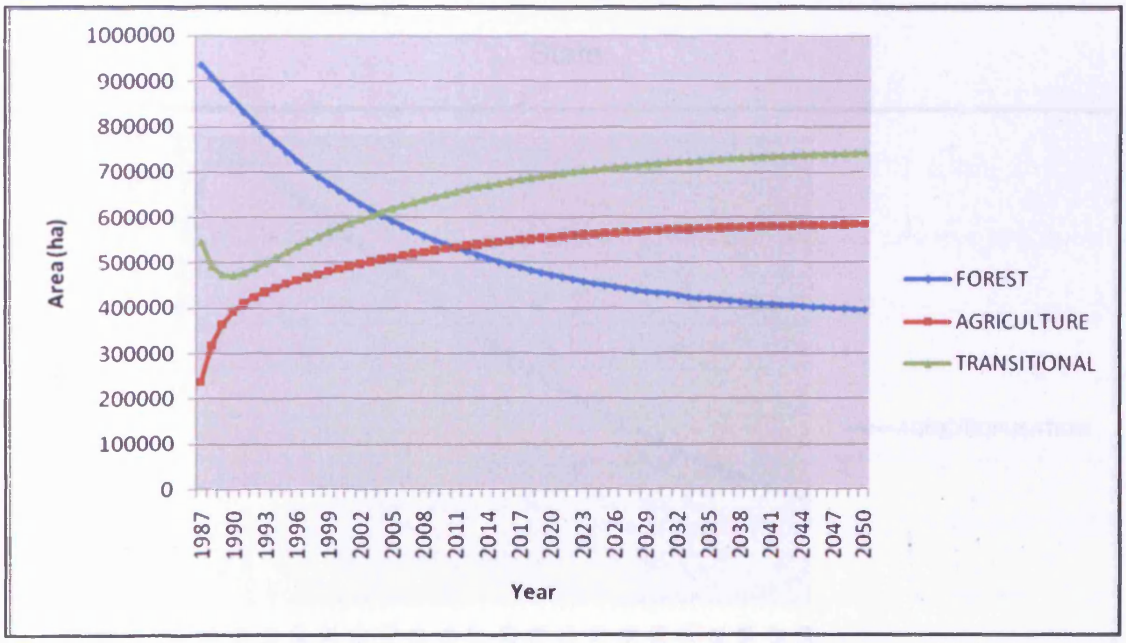


Figure 7.31 Projection of land cover change in Delta State

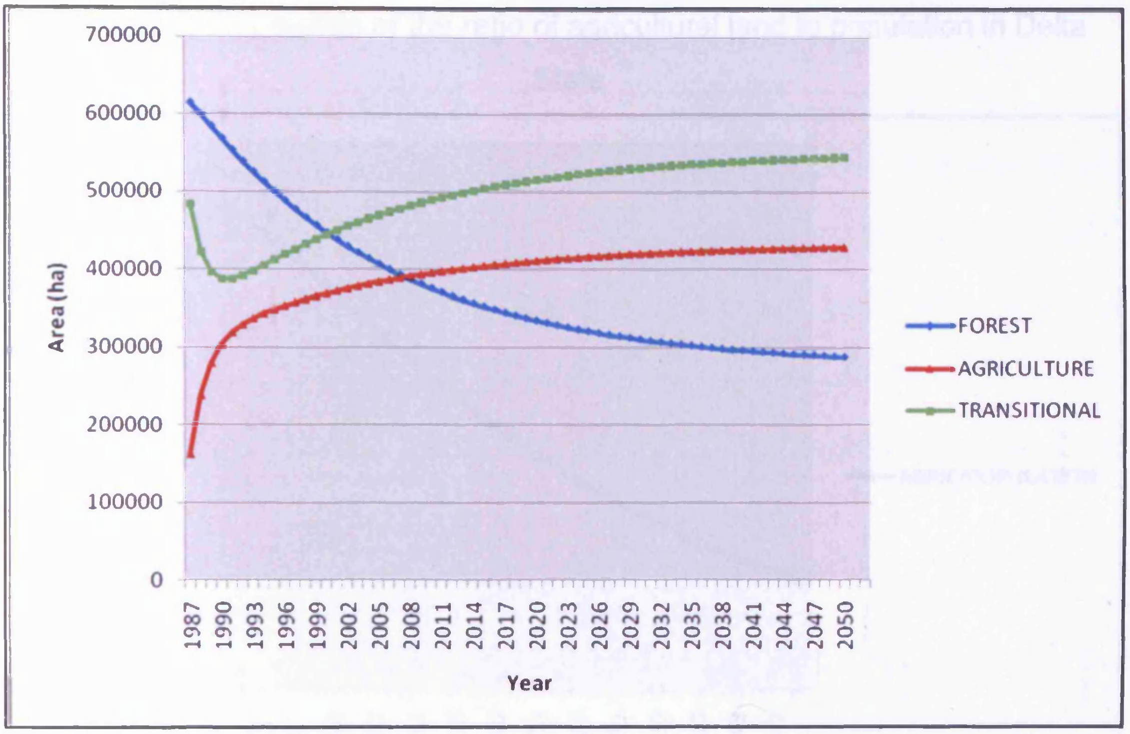


Figure 7.32 Projection of the ratio of agricultural land to population in Edo State

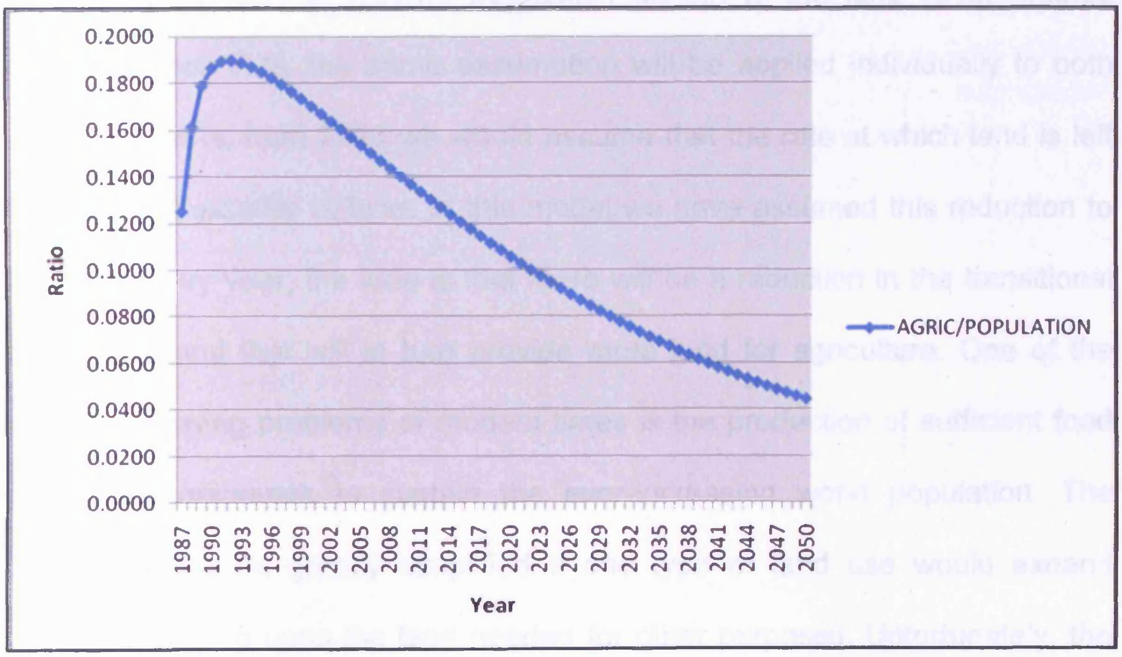
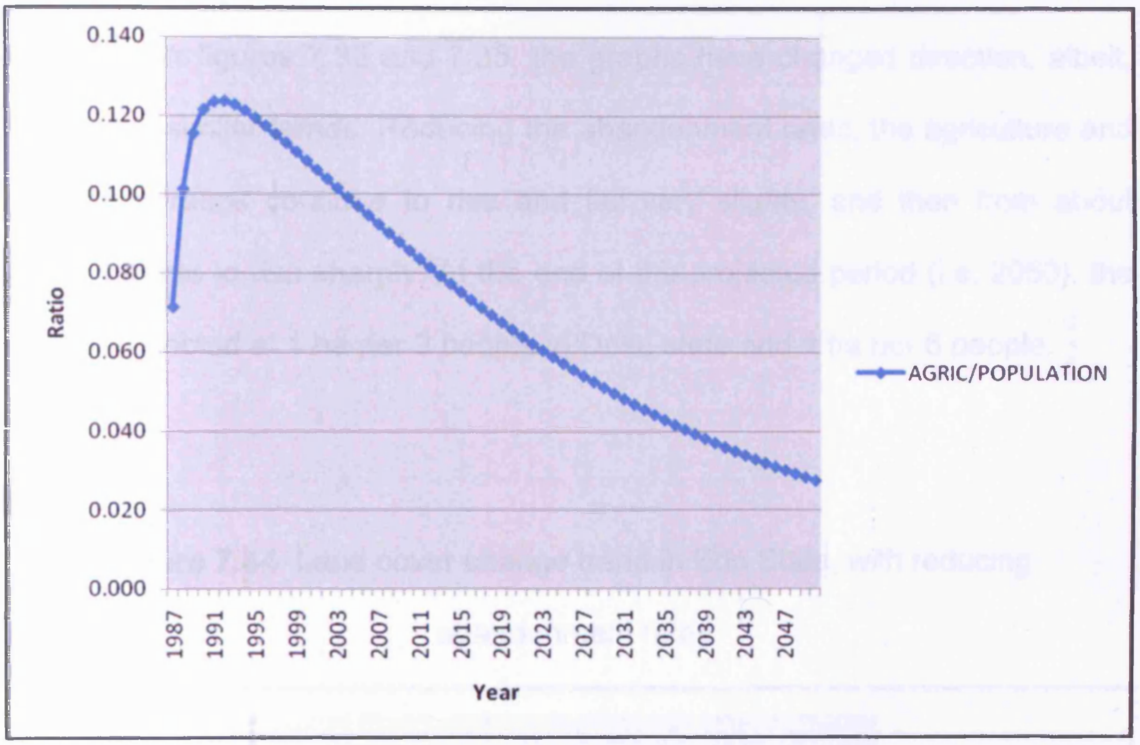


Figure 7.33 Projection of the ratio of agricultural land to population in Delta State



As done previously in relating population growth to the land cover change model (section 7.4), the same assumption will be applied individually to both states, which is, from 2010 we would assume that the rate at which land is left to fallow will steadily reduce. In this model we have assumed this reduction to be 0.1% every year; the idea is that there will be a reduction in the transitional land areas and that will in turn provide more land for agriculture. One of the most challenging problems of modem times is the production of sufficient food and forest resources to sustain the ever-increasing world population. The problem would be greatly simplified if one type of land use would expand without impinging upon the land needed for other purposes. Unfortunately, the fixed nature of the world's land resource base makes the realization of this ideal impossible (Ball and Umeh, 1982).

As shown in figures 7.33 and 7.35, the graphs have changed direction, albeit, still having similar trends. Reducing the abandonment rates, the agriculture and population ratios continue to rise and fall very slighty, and then from about 2033, it starts to rise sharply. At the end of the projected period (i.e. 2050), the ratio is projected at 1 ha per 3 people in Delta state and 1 ha per 6 people.

Figure 7.34 Land cover change trend in Edo State, with reducing abandonment rates

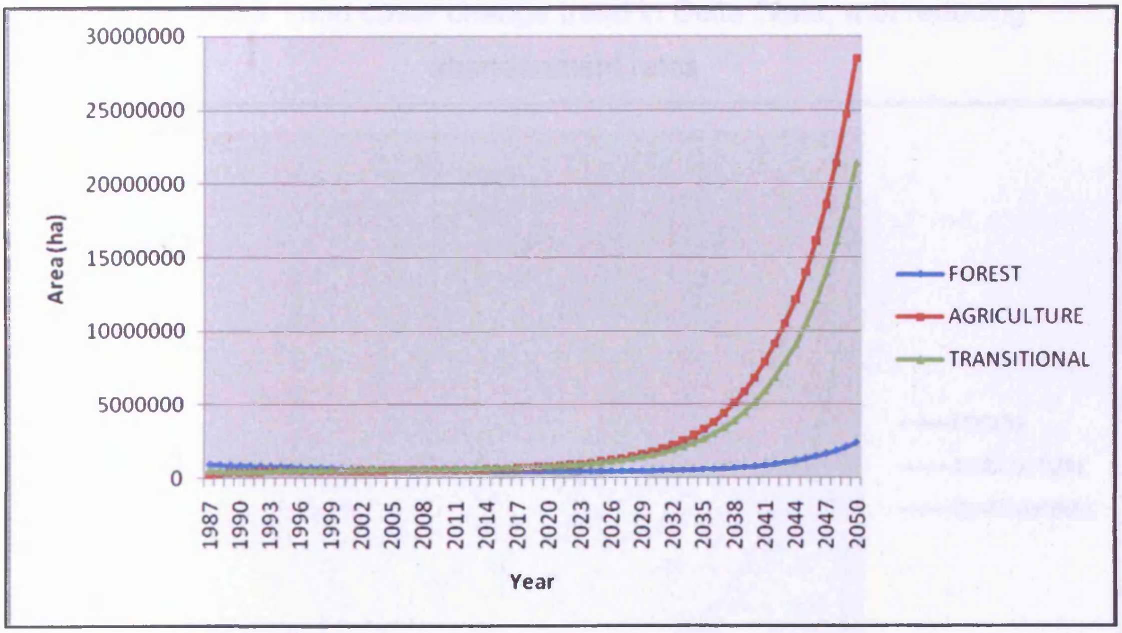


Figure 7.35 Projection of the ratio of agricultural land to population in Edo State, with reducing abandonment rates

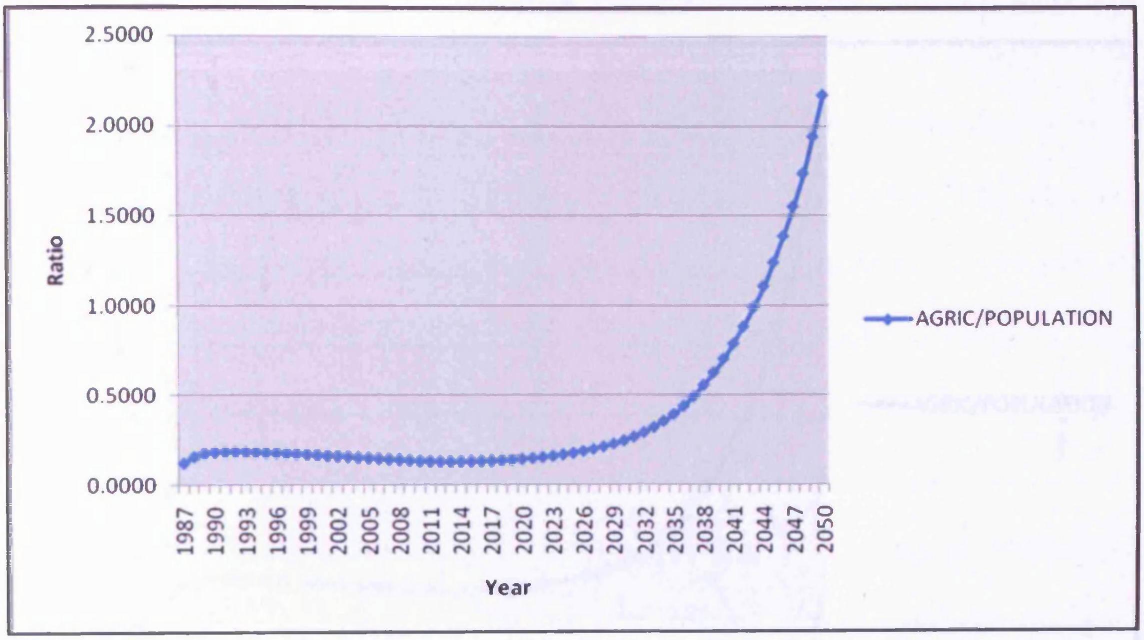


Figure 7.36 Land cover change trend in Delta State, with reducing abandonment rates

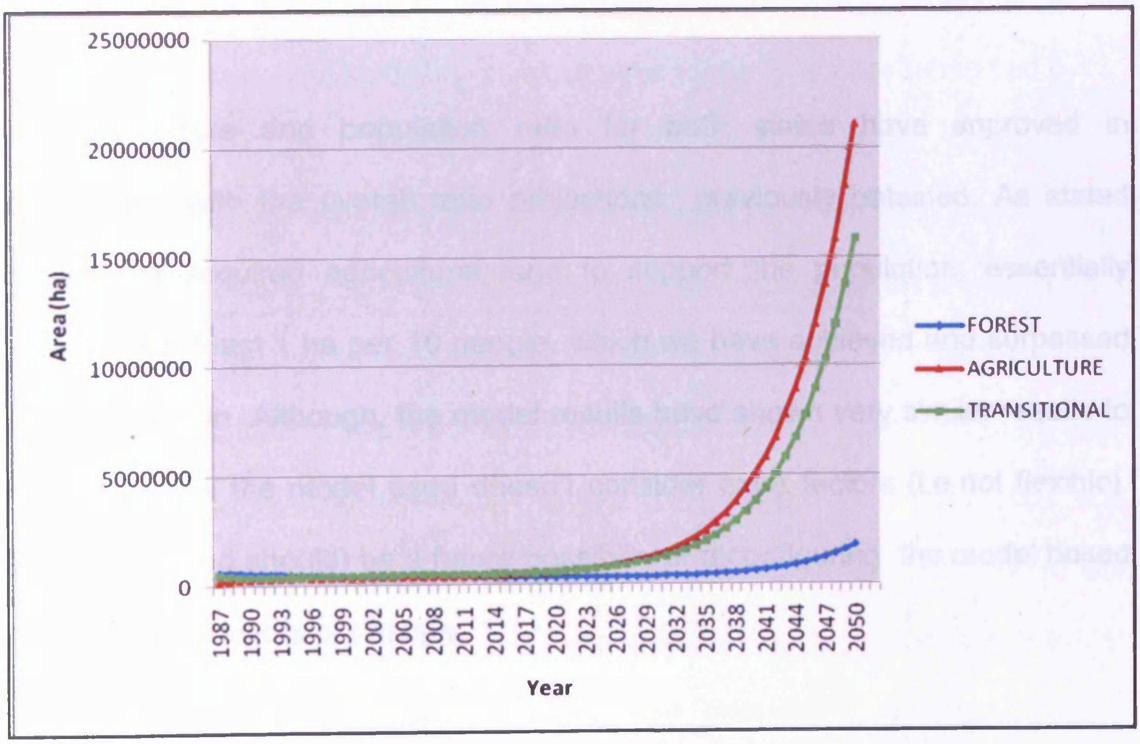
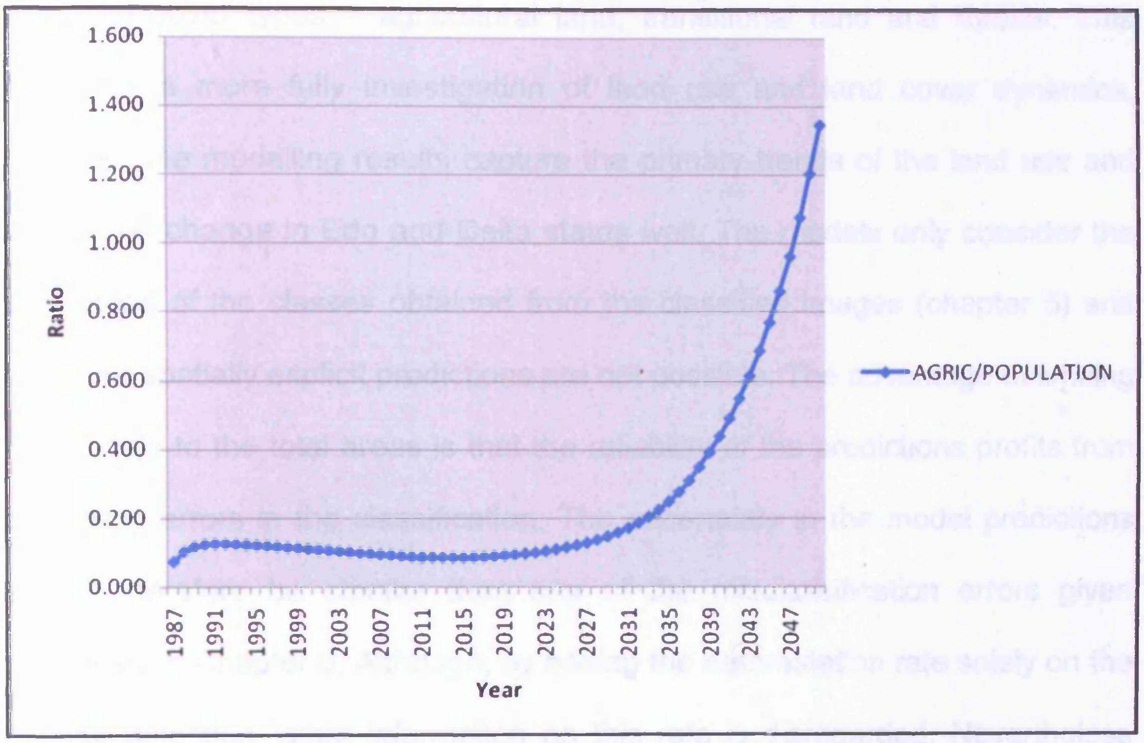


Figure 7.37 Projection of the ratio of agricultural land to population in Delta State, with reducing abandonment rates



The agriculture and population ratio for both states have improved in comparison with the overall ratio projections previously obtained. As stated earlier, the required agricultural land to support the population, essentially should be at least 1 ha per 10 people, which we have achieved and surpassed this expectation. Although, the model results have shown very similar results to each other, as the model used doesn't consider extra factors (i.e.not flexible). There may (and should) be a future possiblity of reconfiguring the model based on the driving factors of change.

7.6 Limitations of Modelling Land Cover Change

The models developed in this research are simple incorporating three land use and land cover types – agricultural land, transitional land and forests. This precludes a more fully investigation of land use and land cover dynamics, however, the modelling results capture the primary trends of the land use and land cover change in Edo and Delta states well. The models only consider the total areas of the classes obtained from the classified images (chapter 5) and therefore spatially explicit predictions are not possible. The advantage of limiting the models to the total areas is that the reliability of the predictions profits from cancelling errors in the classification. The uncertainty in the model predictions should therefore be smaller than any of the misclassification errors given previously in Chapter 6. Although, by basing the deforestation rate solely on the change detection, other information on this rate is disregarded. Nevertheless the deforestation rates used in the models are in line with other research which is an independent corroboration for the change in the forest area detected.

Another point to consider, is the population estimates that were used in the model, as pointed out in previous chapters, due to lack of adequate census figures and growth rates, the population had to be projected. This might also introduce some errors into the model. In order examine these possible errors, the uncertainty of the population estimates as fed into the model, was measured. This was done to evaluate the probability of the 'true' value lies within the best estimate. To do this, two other population estimates – World Bank and UN (chapter 4) were used as other estimates (i.e. measurements) and were incorporated into the model. Figure 2.8 shows the projections of required agricultural land using the Nigerian Statistical Yearbook, World Bank and UN population estimates, still based on the assumption requirement of 0.1 ha /person of agricultural land. The range of values between the *required agricultural land* (which is the estimate to be measured for uncertainty) and the other two estimates seem to be increasing from about 2005, which shows some uncertainty in the population estimates. The only value (e.g. agricultural land) that appeared to have 100% confidence level was that of 1991, but that is expected as this was the only & last census carried out during the period of research (i.e. 1987 – 2001). Notwithstanding, figure 2.9 shows error bars, which represent the confidence level of the population estimates based on calculating the standard errors (and standard deviation). In figure 2.9, from about 2011, the error bars increases, which in other words, the uncertainty increases. This may just be due to the population growth rate used (i.e. 3.1%), which used a constant rate and didn't change with time.

A clear drawback is the assumption of constant rates in the models. This is clearly not realistic. However, in light of the fact that more detailed and time varying information is virtually impossible to obtain, in particular considering the availability of statistical from Nigeria, constant rates are the only reasonable choice. Furthermore, any reasonable combination of values for the four rates in projection III lead qualitatively to the same result, namely a significant reduction in forest area, a limited, small, increase in agriculture and significant increase in transitional land as well as insufficient agricultural area to support the growing population given current agricultural practices. This is a very robust result despite the uncertainties in the rates in the model and the population growth rates.

Figure 7.38 Projection of required agricultural land based on the Nigerian Statistical Yearbook, World Bank and UN population estimates

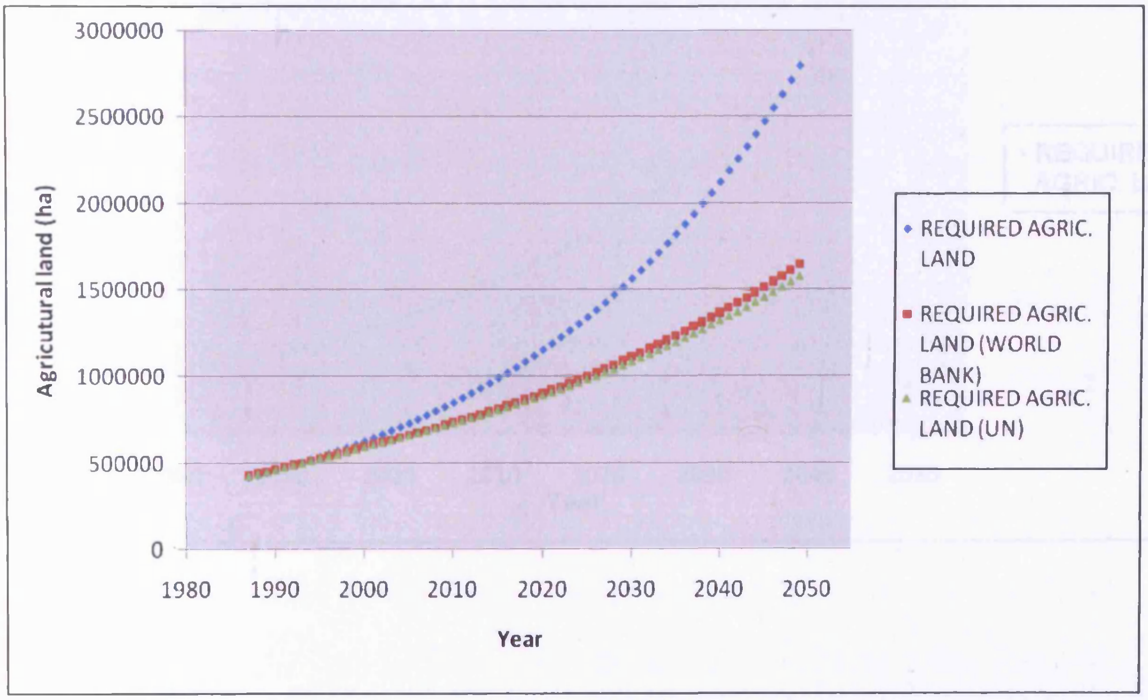
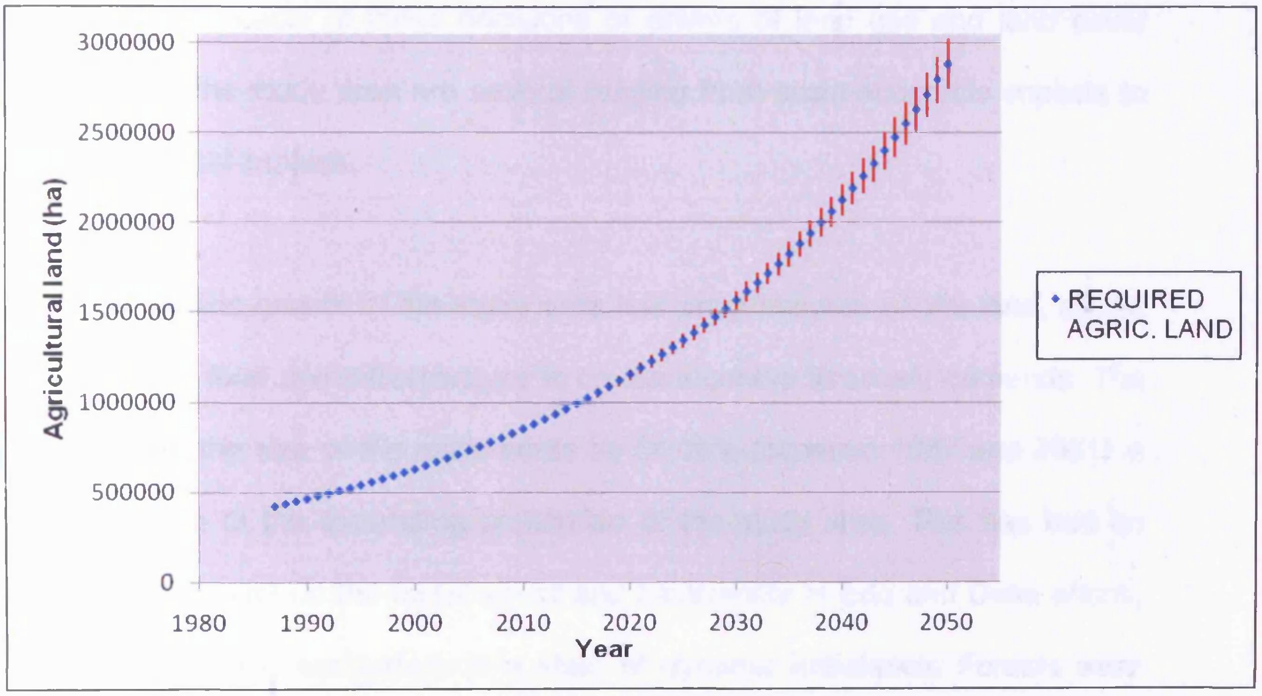


Figure 7.39 Uncertainty of the Nigerian Statistical Yearbook population estimates used in the model to project the required agricultural land



A major limitation of the usefulness of the models is the fact that they do not really consider drivers for land use and land cover change in an explicit way. They are limited to the exploration of the question of what happens if there is no change in agricultural practices or rather general projections such as the one exploring at constant reduction of the abandonment rate. While this provides useful insights, it does not support a more detailed exploration of more focussed cause and effect questions involving multiple drivers of land use and land cover change. Specifically, the important inclusion of the simulation of farmer income seems difficult to achieve in any detailed manner.

7.7 Impacts of Drivers of Land Cover Change in Edo and Delta States

The pattern of land use and land cover change in the study area resulting from the numerous decisions made by land users and land managers, over the years. The impacts of these decisions or drivers of land use and land cover change on the study area are several ranging from socio-economic impacts to environmental impacts.

The population growth in the study area has put pressures on the land, as the demand for food and infrastructure is on the increase to satisfy demands. The increase in the size of the settlements by 54.06% (between 1987 and 2001) is an evidence of the expanding population of the study area. This has had an enormous impact on the forest cover and biodiversity in Edo and Delta states, putting the forest ecosystem in a state of dynamic imbalance. Forests were considerably reduced by 30% within 14 years, while agricultural land and built-up land increased by 27.92% and 54.06% respectively. The rate of deforestation in the study area is immense, as also gathered from the post-classification process and the models, and is a great contributor to reduction in the fallow period, greenhouse emissions and vulnerability of the land to erosion causing disruptions to the ecosystem.

The escalating demand for food to satisfy the ever increasing population has exacerbated the slash and burn farming practice in the study area. The use of fire to clear the forests is the norm in the study areas, which usually occurs between January and February, to clear the land for farming, hunting and also to stimulate the growth of grass for cattle grazing. Forest reservation areas were de-reserved for communities (e.g. taungya) within these areas and also for large plantation projects to meet specific needs (such as increasing demand for timber and demand for land), but this move had several negative consequences, as the system was abused, which initiated illegal farming and illegal logging. As a result of this, in 1994 the State government enforced an edict, which prohibited the de-reservation of these forest reserves for commercial purpose. Nonetheless, these illegal practices continued and their effects are visible in the 2001 image. Speaking to some of the locals during the fieldwork, revealed that their perception of land is that, they and their community own the land around them so they can farm or take products from the forests as they want. In Nigeria, although there are policies and laws, implementational enforcement is limited, due to corruption and lack of resources. In the study area, especially Edo state, the illegal logging has been changed to a criminal offence. Unfortunately, during a visit to the State Forestry department in Edo state, it was discovered that they were lack of vehicles for uniformed patrol officers to monitor the forest areas and the integrity of the staff is questionable, to say the least. In Nigeria, as a whole, the forest and the allocation of land has been immensely influenced by politics.

Apart from clearing the land for farming, speaking to the locals, it was gathered that they tend to go into the forests in search of fuelwood and wildlife. Fuelwood (known locally as *firewood*) is the main source of energy supply especially in rural areas. According to Osemeobo (1992) fuelwood supports about 90% of the domestic energy needs of the rural population and 50% or the urban areas. As 95% of the fuelwood is derived from the natural forests, this high demand poses a threat to the stability of the ecosystem. Similarly threatened by exploitation is the wildlife in the area, due to hunting for personal consumption and bushmeat trade, which is not properly controlled due to inadequate and weak implementation of laws regarding wildlife. Although, in some of the better managed forest reservation areas, such as Okomu forest reservation area, which still provide locals with hunting permits for a nominal fee.

The growing population has also contributed to urbanization, industrialization and infrastructure development. One of the reasons for these increasing developments is due to the split of states of study area in 1991, i.e. the split from Bendel state to Edo and Delta states. This has increased the rate of developments across the region, as the new states were created, the Local Government Areas increased in number from 19 to 43. With the creation of these new LGAs, new headquarters and infrastructure had to be created to support their new status. As stated previously, inferring from the classification of both images, the area of built-up land increased by 54.06% in 14 years (1987 - 2002).

The growth of these areas and the correlating increasing population has contributed to the generation of waste accumulation which is not managed and disposed properly by the state government, and this leads to drainages being blocked up thereby permitting the areas to flood (e.g. Benin City), and also leads to these waste being dumped on abandoned land, in rivers and in some cases by the roadside. In addition, the problem of unemployment is seen in Edo and Delta states, as the population is growing faster than the availability of jobs, thereby driving a proportion of the population into poverty, some indigenes to look for alternative ways to sustain themselves.

In addition to the key drivers of land use and land cover change, revealed during the course of the research, they were a number of impacts of change not covered by this research that were discovered, such as water, land and air pollution. As population and industries grow, so does the need for increased food production, which in turn results in the use of heavier water-borne load of pesticides, and causes water pollution (Agabi *et al.*,1995). The growth of industries in the area has had an effect on the land use and land cover change in Edo and Delta states, they have contributed to pollution of the environment, especially in the case of the oil companies located in the region. For example, in the space of 3 years there were two oil spills in Okpella (Edo state), which affected the agricultural land, forests, water, fish and wildlife. Another example of the effects of the disposal of waste by oil companies, occurred in Igbeku (Delta state), where suspicious waste was discovered buried, that turned out to be toxic waste, which affected the flora and fauna in the area. It was due to an incident in Koko (Delta state) in 1988, that led the Federal Government to set up the Federal Environmental Protection Agency (FEPA), where toxic waste were dumped on a piece of land, which was surprisingly granted to the culprits by a local Chief in the area.

Continuous gas flaring activities is being carried out in the study area, especially in Delta state. According to World Bank, in 2000, Nigeria was reported as flaring the most gas about 46% of Africa's total and accounted for 19.79% of the global total. As a result of this and other contributing factors, as part of the Vision 2010, the Federal Government of Nigeria has ruled that gas flaring should be eliminated by 2008. These activities are major contributors to air pollution and to aggravating greenhouse gas emissions; Marland (1991) reported that Nigeria is one of the 13 major sources, by country, of greenhouse gas emissions.

In summary, this section has looked at the drivers and the impacts of land use and land cover changes. It can be concluded that Edo and Delta states have undergone remarkable changes, which have been substantiated by both the post-classification process and fieldwork. The pattern of change gives an indication of how the forests will be severely depleted and transitional land increasing vastly along with the expansion of built-up land and agricultural area. Nonetheless, the production of food is low and not enough to meet the demands of the growing population. The study area needs drastic measures to be taken by all tiers of the government and land managers, as the region's food security is threatened.

CHAPTER 8 – MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: CONCLUSION

CHAPTER 8

MODELLING LAND COVER CHANGE IN EDO AND DELTA STATES: CONCLUSION

8.1 Summary

The environment around us is continuously changing, triggered by numerous driving forces, of which Edo and Delta states are no exception. This research should contribute to the study of the effects of the rapid land cover changes and how population growth affects the trend and pattern of these changes. The main aim of this research was to map and model land cover changes and to analyse the impacts of these changes in Edo and Delta states. A number of specific objectives were outlined in chapter 1, which are to aid in achieving the main aim. Revisiting these objectives, they are:

1. To design a model that accurately illustrates and projects land cover change and its impact on biodiversity;
2. To use Remote Sensing data (i.e. satellite images) to map land cover change between 1980 and 2001 and to evaluate the optimum change detection techniques to be used in this research;
3. To investigate the spatial and temporal pattern of land cover change;

4. To determine the key driving forces of land cover change in Edo and Delta States.

In order to realize these objectives, classification of remote sensing images and modelling were applied, and in support of the classification process a field assessment was carried out in the course of the research. With the use of satellite images, the past trend of land cover change was mapped and the models predicted the future changes based on the past trends. The images used were Landsat TM 1987 and Landsat ETM 2001, which were the images that were available. These images were classified in accordance to the land cover classification scheme that was created after the field assessment.

A change detection technique –post classification comparison was applied by comparing the individually classified images. Post classification was selected as the optimum change detection technique, because of its ability to provide 'from – to" detailed information for each land cover class. Based on this comparison, there was a 53% overall land cover change between 1987 and 2001, with an alarming average annual rate of 3.77%. The total areas of three specific land cover types – agricultural land, transitional land and forests were obtained from the post-classification results formed the basis for the modelling and projecting changes in these classes.

Inferring from the change detection and modelling results, it is obvious that there are land cover changes in the study area, with forests being reduced by 30% while agricultural land and transitional land have increased significantly by

28% and 14%. The forces driving land cover change were determined, inferring from the field assessment by speaking to the local indigenes, government officials and other researchers in the area. The increasing population growth has had an enormous effect on the area, exerting pressure on the land and its resources, driving competition for land by the land cover types, with the forests being the most affected. The loss of forests in Edo and Delta states has in turn generated a backlash of hazardous effects on flora and fauna, water bodies, soils and the atmosphere. Increasing demands for agricultural land is also one of the key driving forces in the study area, as this is was discovered as being a main contributor to deforestation.

The pattern of change occurs in the majority of the study area, especially around the forest reservation areas, where there is evidence of encroaching by farms, causing fragmentation of these forests. Also, the areas of built-up land increased in size by 54.06%, right across the study area between 1987 and 2001. These increases were inline with the increasing population growth. The models were then applied to project future projections of land cover changes. The projections were then compared with population growth and the results made it clear that if the current agricultural practices in the study area continue, there will not be enough agricultural land to support the population and their demands. In order to resolve these issues, the government will need to reform its policy and laws.

The model was then used to investigate if they were any differences in trends and patterns of land cover change in Edo state and Delta state, by splitting the study area according to their administrative boundary (i.e. state boundary). The thought behind this was to check if they were any differences as Edo state is predominantly an agricultural area while Delta state is an oil producing region, supplying about 35% of Nigeria's oil. This was done by re-doing the post classification for each state and collating the change statistics. In Edo state, about 55% of the agricultural land has been transformed to transitional land, and that was the most significant change in Edo over the 14 year period, this was followed by 33% of the burnt areas converted to transitional land. This, as pointed out earlier, is due to the issue of shifting cultivation (and slash and burn) method of farming practiced here, possibly during the 14 year period, a piece of land may be cleared using fire, then the farmer plants his crop, cultivates then leaves the farm to fallow, which results in the transitional land. In Delta state, agricultural land had the most significant change, which 39% of it changed to transitional land.

The land cover change statistics were fed into the model for both states. It was observed that the agriculture and population ratio for both states had improved in comparison with the overall ratio projections previously obtained, which stated that the required agricultural land to support the population, should be at least 1 ha per 10 people. Although, the model results have shown very similar results and trend, the required agricultural land, according to the model, to support the population for Edo and Delta states were projected at 1 ha per 3 and 1 ha per 6 people respectively.

8.2 Implication of Land Cover Change for State and National Government

This research is fundamental to all tiers of the government (i.e. Federal, State and Local), land use mangers, land use decision makers and the communities, with respect to identifying the nature and pattern (spatial and temporal) of land cover changes and the impacts of these changes. According to Fuller (2006) if such information can influence public opinion, it can exert pressure on policymakers in democratic societies to strengthen enforcement and tighten regulations to improve forest management and protection.

The government is fairly aware of the current state of the environment, but decisions of exactly what needs to be done or implementation of measures is not a strong point for the government. Unfortunately, until recently, the environment has not been seen as an important factor or sector in the development of Nigeria. There is considerable controversy surrounding the reported statistical released by the government, such as census numbers, deforestation rate etc, so to cover up the exact trends.

Regardless of the nature and location of the immense changes in the environment, every person needs to be involved in improving and maintaining a sustainable environment. The main impact of land cover change in Edo and Delta states is deforestation, which in turn has overwhelming effects on the environment and socio-economic sectors of the region and even Nigeria. This substantiates why addressing deforestation should be an important step for the government, industries and communities. The government would need to encourage the use of transitional land, by providing the farmers with an incentive such as fertilizer to improve the land quality, as this would attract the farmers, making the issue of deforestation easier to manage.

It has been concluded in this research study, that the forest is being lost at an alarming rate, which is one of the reasons that, in the development of The National Policy on Conservation in 1988, the Federal Government stipulated, that at least 20% of the State's land area be put under reservation (Dept of Forestry, 2001). Currently, the forests are the responsibilities of both State and Local Governments, but it is of the opinion that the Federal Government needs to be more involved for effective implementation of new and improved policies. It is essential for the government to release more funds to enable the Department of Forestry to function properly. With regards to monitoring the forests, there needs to be more people recruited and the appropriate professional training put in place for the forestry staff especially the forestry patrol officers, seeing that there is a shortfall of honest and dedicated forestry staff. More efforts need to be made towards improving the afforestation projects and deforestation needs to be curbed, not stopped completely, because the demand for forest products is continuous. Emphasis should be placed on afforestation and the dereservation of forest reserves should be stopped if the State government want to meet the requirements of reserving at least 20% of the land area. Furthermore, adequate and efficient laws and policies need to be enforced to protect these forests and wildlife, and more wildlife sanctuaries would need to be created. This would also promote wildlife conservation and protect the endangered species in the area. Adebagbo (1992) suggested protection of the forest ecosystem in this area can only be achieved through purposeful, judicious and deliberate timber exploitation, practiced side by side with vigorously pursued reforestatation programme.

Recently, in Nigeria there has been an influx of non-governmental agencies (such as Nigerian Conservation Foundation, Nigerian Environmental Study Action Team, WWF etc), which educate the communities on environmental issue awareness. It is believed that the government should take a leaf out of their book and work closely with these groups as they also lack the capabilities to do this all on their own, call it a symbiotic relationship. In addition to this, it is imperative, that the government forms a relationship with the communities, seeing that this rapport has been destroyed over the decades. As the government makes land management decisions or enforcing policies, the views of these communities are not considered. This has resulted in the traditional landowners being treated as unwelcome aliens in the utilization of their ancestral lands, and they are often blamed for not cooperating with the government on land matters (Osemeobo, 1990). Speaking to some of the local communities, they have no faith in the government believing that they do not protect the welfare of these communities, even those they had elected into power.

The model projections implemented in this research also highlights a dim future for the availability of agricultural land and agricultural products to satisfy the demands. There is a need for agricultural reform on the current preferred methods of farming – shifting cultivation (slash and burn). This should enable the farmers to maximise their land resourcefully and sustainably. In doing so, these farmers should be encouraged to re-use more of the transitional land and this would result in the farmers curtailing from clearing more forests for agricultural land, as stated previously (section 7.4). In addition the government needs to enforce a law against the use of fire to clear the land, in other words it should be abolished, as it has been said previously the effects the use of fire has on the environment.

8.3 Possible Future Research and Recommendations

This research has analysed the land cover changes and the impacts of these changes using satellite images and simple model projections. The recommendations presented here will be aimed at developing future research.

The images evaluated in this research were used because they were the only available (free) images. This clearly may limit the possible accuracy of the classifications at the quality of these images, may not be optimal. Indeed, the 2001 Landsat ETM image has problems with cloud cover, haze and shadows. Future research using better quality and even higher resolution images such as Quickbird or IKONOS will produce higher accuracy results and therefore fewer errors.

In addition, it is recommended that a nationally accepted land cover classification scheme to be developed, taking the context of Nigeria into account. This would eliminate the time spent creating a new scheme for every research. With regards to the available statistical data, steps need to be taken by the Nigerian Federal government to collate these data, by acquiring higher resolution images which can be used in the future to map the land cover change of the study. This would result in the creation of proper land use and land cover maps, as during a visit to the study area to collate statistical data, the only land use maps available were published in the 1970s. By doing this, and carrying out extensive field assessments, statistical data such as the total areas occupied by a land cover, the deforestation rates, the urban growth rates and the population growth rates can be properly documented. This would improve the accuracies of modelling results and more precise projections can be made.

In conclusion, this research has verified the significance of the combined use of remote sensing and modelling in monitoring and predicting land cover changes in the study area. Although, further research is still needed to investigate these changes and their impacts in detail, as an integral input to the assessment and sustainable management of the land and its resources. Another point would be, in the future, to investigate land cover changes for the individual states, rather than looking at the region.

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APPENDIX I

Pro-Forma at Each Site

Location ....

Sampling Point Code

Date

GPS Point no(s)

GPS Coordinate

x

y

N

Photo #

Serial	ID	Direction
1		
2		
3		
4		
5		
6		
7		
8		

Scale: 1: 250 meters

QUESTIONNAIRES AT SITE #

	1
	2
	3
	4
	5

OBSERVATION/COMENT:

LANDUSE CLASSES COMPARISON

2001/2002 Class (Map)	1986/1987 Class (Map)	Actual Class

COORDINATES & LAND USE CLASSES OF SITES TO BE VISITED

LAND USE	X	Y

APPENDIX II

Model Projections I
Deforestation rate *a* = *0.025* ; Abandonment rate *b* = *0.2*

Year	Forest (Ha)	Agriculture	Year	Forest (Ha)	Agriculture
1987	1549288	399156	**2008**	910393	131696
1988	1510556	358057	**2009**	887634	128117
1989	1472792	324209	**2010**	865443	124684
1990	1435972	296187	**2011**	843807	121384
1991	1400073	272849	**2012**	822711	118202
1992	1365071	253281	**2013**	802144	115129
1993	1330944	236752	**2014**	782090	112157
1994	1297671	222675	**2015**	762538	109278
1995	1265229	210582	**2016**	743474	106486
1996	1233598	200096	**2017**	724888	103776
1997	1202758	190917	**2018**	706765	101143
1998	1172689	182802	**2019**	689096	98583
1999	1143372	175559	**2020**	671869	96094
2000	1114788	169032	**2021**	655072	93672
2001	1086918	163095	**2022**	638695	91314
2002	1059745	157649	**2023**	622728	89019
2003	1033251	152613	**2024**	607160	86783
2004	1007420	147922	**2025**	591981	84606
2005	982235	143523	**2026**	577181	82484
2006	957679	139374	**2027**	562752	80417
2007	933737	135441	**2028**	548683	78402
2008	910393	131696	**2029**	534966	76439

Year	Forest (Ha)	Agriculture	Year	Forest (Ha)	Agriculture
2009	887634	128117	**2030**	521592	74525

Model Projections **II**

Deforestation rate *a = 0.025;* Abandonment rate *b = 0.2;*

Rate of Agric use of transitional land *c = 0.15*

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
1987	1549288	399156	1030149	**2009**	887634	935121	1155839
1988	1510556	512579	955458	**2010**	865443	943663	1169487
1989	1472792	591146	914655	**2011**	843807	951990	1182797
1990	1435972	646935	895686	**2012**	822711	960106	1195775
1991	1400073	687800	890720	**2013**	802144	968019	1208430
1992	1365071	718850	894672	**2014**	782090	975733	1220769
1993	1330944	743408	904241	**2015**	762538	983254	1232801
1994	1297671	763636	917287	**2016**	743474	990587	1244531
1995	1265229	780943	932421	**2017**	724888	997736	1255969
1996	1233598	796249	948746	**2018**	706765	1004707	1267121
1997	1202758	810151	965684	**2019**	689096	1011503	1277994
1998	1172689	823042	982862	**2020**	671869	1018129	1288596
1999	1143372	835180	1000041	**2021**	655072	1024589	1298932
2000	1114788	846735	1017071	**2022**	638695	1030888	1309010
2001	1086918	857818	1033857	**2023**	622728	1037029	1318836
2002	1059745	868506	1050342	**2024**	607160	1043017	1328416
2003	1033251	878850	1066492	**2025**	591981	1048855	1337757
2004	1007420	888885	1082288	**2026**	577181	1054547	1346865
2005	982235	898637	1097722	**2027**	562752	1060097	1355744
2006	957679	908123	1112791	**2028**	548683	1065508	1364402
2007	933737	917359	1127497	**2029**	534966	1070784	1372843

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
2008	910393	926355	1141844	**2030**	521592	1075928	1381074

Model Projections **III**

Deforestation rate *a = 0.040;* Abandonment rate *b = 0.2;*

Rate of Agric use of transitional land *c = 0.15;* Regrowth of Trans Land *d = 0.02*

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
1987	1549288	399156	1030149	**2009**	929612	919824	1129157
1988	1507919	555394	915280	**2010**	915011	925289	1138293
1989	1465908	643256	869429	**2011**	901176	930467	1146950
1990	1424661	695666	858266	**2012**	888068	935373	1155152
1991	1384839	729519	864234	**2013**	875648	940022	1162923
1992	1346731	753494	878368	**2014**	863881	944426	1170286
1993	1310429	772059	896106	**2015**	852731	948599	1177262
1994	1275934	787521	915139	**2016**	842167	952553	1183872
1995	1243199	801080	934314	**2017**	832158	956299	1190135
1996	1212157	813368	953067	**2018**	822674	959849	1196069
1997	1182732	824725	971136	**2019**	813689	963212	1201692
1998	1154846	835338	988409	**2020**	805175	966399	1207019
1999	1128420	845319	1004854	**2021**	797109	969418	1212067
2000	1103380	854737	1020475	**2022**	789466	972279	1216849
2001	1079655	863641	1035297	**2023**	782224	974989	1221380
2002	1057174	872067	1049351	**2024**	775363	977557	1225673
2003	1035875	880046	1062673	**2025**	768862	979990	1229741
2004	1015693	887602	1075298	**2026**	762702	982296	1233595
2005	996571	894761	1087261	**2027**	756866	984480	1237247
2006	978454	901543	1098596	**2028**	751336	986550	1240707
2007	961287	907968	1109337	**2029**	746097	988511	1243986

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
2008	945023	914056	1119514	**2030**	741133	990369	1247092

Relating Population Growth to Modelling Land Use and Land Cover Change.

Projected and required agricultural land (ha) extrapolating projection III and assuming a requirement of 0.1 ha/person agricultural area.

Year	Projected	Required	Year	Projected	Required
1987	399156	419884	**2008**	914056	800262
1988	555394	433317	**2009**	919824	825070
1989	643256	447180	**2010**	925289	850647
1990	695666	461486	**2011**	930467	877017
1991	729519	476250	**2012**	935373	904204
1992	753494	491013	**2013**	940022	932235
1993	772059	506235	**2014**	944426	961134
1994	787521	521928	**2015**	948599	990929
1995	801080	538108	**2016**	952553	1021648
1996	813368	554789	**2017**	956299	1053319
1997	824725	571988	**2018**	959849	1085972
1998	835338	589719	**2019**	963212	1119637
1999	845319	608001	**2020**	966399	1154346
2000	854737	626849	**2021**	969418	1190130
2001	863641	646281	**2022**	972279	1227025
2002	872067	666316	**2023**	974989	1265062
2003	880046	686971	**2024**	977557	1304279
2004	887602	708267	**2025**	979990	1344712
2005	894761	730224	**2026**	982296	1386398
2006	901543	752861	**2027**	984480	1429376
2007	907968	776199	**2028**	986550	1473687

Year	Projected	Required	Year	Projected	Required
2029	988511	1519371			
2030	990369	1566472			
2031	992129	1615032			
2032	993797	1665098			
2033	995377	1716716			
2034	996875	1769935			
2035	998294	1824803			
2036	999638	1881372			
2037	1000912	1939694			
2038	1002118	1999825			
2039	1003262	2061819			
2040	1004345	2125735			
2041	1005371	2191633			
2042	1006344	2259574			
2043	1007266	2329621			
2044	1008139	2401839			
2045	1008966	2476296			
2046	1009750	2553061			
2047	1010492	2632206			
2048	1011196	2713804			
2049	1011863	2797932			
2050	1012494	2884668			

Projections of ratio of agricultural land to population

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.0951	**2011**	0.1061
1988	0.1282	**2012**	0.1034
1989	0.1438	**2013**	0.1008
1990	0.1507	**2014**	0.0983
1991	0.1532	**2015**	0.0957
1992	0.1535	**2016**	0.0932
1993	0.1525	**2017**	0.0908
1994	0.1509	**2018**	0.0884
1995	0.1489	**2019**	0.0860
1996	0.1466	**2020**	0.0837
1997	0.1442	**2021**	0.0815
1998	0.1417	**2022**	0.0792
1999	0.1390	**2023**	0.0771
2000	0.1364	**2024**	0.0749
2001	0.1336	**2025**	0.0729
2002	0.1309	**2026**	0.0709
2003	0.1281	**2027**	0.0689
2004	0.1253	**2028**	0.0669
2005	0.1225	**2029**	0.0651
2006	0.1197	**2030**	0.0632
2007	0.1170	**2031**	0.0614
2008	0.1142	**2032**	0.0597
2009	0.1115	**2033**	0.0580
2010	0.1088	**2034**	0.0563

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2035	0.0547		
2036	0.0531		
2037	0.0516		
2038	0.0501		
2039	0.0487		
2040	0.0472		
2041	0.0459		
2042	0.0445		
2043	0.0432		
2044	0.0420		
2045	0.0407		
2046	0.0396		
2047	0.0384		
2048	0.0373		
2049	0.0362		
2050	0.0351		

Projections of the ratio of agricultural land to population assuming all transitional land is converted to agricultural land.

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.0951	2011	0.2028
1988	0.3184	2012	0.1983
1989	0.2560	2013	0.1938
1990	0.2745	2014	0.1894
1991	0.2689	2015	0.1850
1992	0.2698	2016	0.1807
1993	0.2681	2017	0.1763
1994	0.2666	2018	0.1721
1995	0.2645	2019	0.1679
1996	0.2620	2020	0.1637
1997	0.2593	2021	0.1596
1998	0.2562	2022	0.1556
1999	0.2529	2023	0.1516
2000	0.2493	2024	0.1477
2001	0.2456	2025	0.1439
2002	0.2417	2026	0.1401
2003	0.2377	2027	0.1364
2004	0.2335	2028	0.1328
2005	0.2293	2029	0.1292
2006	0.2249	2030	0.1258
2007	0.2206	2031	0.1224
2008	0.2161	2032	0.1190
2009	0.2117	2033	0.1158

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2034	0.1126		
2035	0.1095		
2036	0.1065		
2037	0.1035		
2038	0.1006		
2039	0.0978		
2040	0.0951		
2041	0.0924		
2042	0.0898		
2043	0.0872		
2044	0.0848		
2045	0.0823		
2046	0.0800		
2047	0.0777		
2048	0.0755		
2049	0.0733		
2050	0.0712		

Projections of the ratio of agricultural land to population assuming deforestation rate is 2%

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.0951	2011	0.0855
1988	0.1210	2012	0.0832
1989	0.1323	2013	0.0810
1990	0.1362	2014	0.0789
1991	0.1365	2015	0.0768
1992	0.1352	2016	0.0747
1993	0.1330	2017	0.0727
1994	0.1304	2018	0.0707
1995	0.1276	2019	0.0688
1996	0.1248	2020	0.0669
1997	0.1219	2021	0.0651
1998	0.1190	2022	0.0633
1999	0.1162	2023	0.0616
2000	0.1134	2024	0.0599
2001	0.1106	2025	0.0582
2002	0.1079	2026	0.0566
2003	0.1052	2027	0.0550
2004	0.1026	2028	0.0535
2005	0.1000	2029	0.0520
2006	0.0975	2030	0.0505
2007	0.0950	2031	0.0491
2008	0.0925	2032	0.0477
2009	0.0901	2033	0.0464

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2010	0.0878	**2034**	0.0450
2035	0.0438		
2036	0.0425		
2037	0.0413		
2038	0.0401		
2039	0.0390		
2040	0.0379		
2041	0.0368		
2042	0.0357		
2043	0.0347		
2044	0.0337		
2045	0.0327		
2046	0.0318		
2047	0.0308		
2048	0.0300		
2049	0.0291		
2050	0.0282		

Projections of the ratio of agricultural land to population, when the abandonment seizes to be constant.

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.0951	**2011**	0.1088
1988	0.1282	**2012**	0.1080
1989	0.1438	**2013**	0.1073
1990	0.1507	**2014**	0.1068
1991	0.1532	**2015**	0.1063
1992	0.1535	**2016**	0.1058
1993	0.1525	**2017**	0.1054
1994	0.1509	**2018**	0.1051
1995	0.1489	**2019**	0.1048
1996	0.1466	**2020**	0.1046
1997	0.1442	**2021**	0.1044
1998	0.1417	**2022**	0.1042
1999	0.1390	**2023**	0.1041
2000	0.1364	**2024**	0.1041
2001	0.1336	**2025**	0.1042
2002	0.1309	**2026**	0.1043
2003	0.1281	**2027**	0.1045
2004	0.1253	**2028**	0.1047
2005	0.1225	**2029**	0.1051
2006	0.1197	**2030**	0.1055
2007	0.1170	**2031**	0.1060
2008	0.1142	**2032**	0.1066
2009	0.1115	**2033**	0.1073

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2010	0.1099	**2034**	0.1082
		2035	0.1091
		2036	0.1102
		2037	0.1115
		2038	0.1118
		2039	0.1114
		2040	0.1105
		2041	0.1092
		2042	0.1076
		2043	0.1058
		2044	0.1039
		2045	0.1018
		2046	0.0997
		2047	0.0975
		2048	0.0953
		2049	0.0931
		2050	0.0909

APPENDIX III

Model Projections III for Edo State

Deforestation rate *a = 0.040;* Abandonment rate *b = 0.2;*

Rate of Agric use of transitional land *c = 0.2;* Regrowth of Trans Land *d = 0.02*

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
1987	935276	239286	544244	**2009**	548684	526203	643919
1988	908750	318546	491510	**2010**	539615	529597	649593
1989	882230	364005	472571	**2011**	531023	532813	654970
1990	856392	391887	470527	**2012**	522881	535860	660064
1991	831547	410520	476739	**2013**	515167	538748	664891
1992	807820	424184	486802	**2014**	507858	541483	669464
1993	785243	435086	498477	**2015**	500933	544075	673798
1994	763803	444367	510636	**2016**	494372	546531	677903
1995	743464	452623	522719	**2017**	488155	548858	681793
1996	724179	460171	534455	**2018**	482265	551062	685479
1997	705901	467182	545723	**2019**	476684	553151	688971
1998	688580	473751	556475	**2020**	471396	555130	692280
1999	672166	479939	566701	**2021**	466386	557006	695415
2000	656614	485783	576410	**2022**	461638	558782	698385
2001	641877	491310	585619	**2023**	457141	560466	701199
2002	627914	496542	594349	**2024**	452879	562061	703866
2003	614685	501497	602624	**2025**	448841	563572	706393
2004	602150	506190	610466	**2026**	445015	565004	708786
2005	590273	510636	617897	**2027**	441390	566361	711055
2006	579020	514848	624938	**2028**	437956	567646	713204

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
2007	568358	518839	631609	**2029**	434702	568864	715240
2008	558256	522620	637930	**2030**	431618	570018	717169

Relating Population Growth to Modelling Land Use and Land Cover Change in Edo State.

Projected and required agricultural land (ha) extrapolating scenario III and assuming a requirement of 0.1 ha/person agricultural area.

Year	Projected	Required	Year	Projected	Required
1987	239286	191494.3	**2008**	526203	364970.8
1988	318546	197620.6	**2009**	529597	376284.9
1989	364005	203942.8	**2010**	532813	387949.7
1990	391887	210467.3	**2011**	535860	399976.2
1991	410520	217200.5	**2012**	538748	412375.4
1992	424184	223933.7	**2013**	541483	425159.1
1993	435086	230875.7	**2014**	544075	438339
1994	444367	238032.8	**2015**	546531	451927.5
1995	452623	245411.8	**2016**	548858	465937.3
1996	460171	253019.6	**2017**	551062	480381.3
1997	467182	260863.2	**2018**	553151	495273.1
1998	473751	268950	**2019**	555130	510626.6
1999	479939	277287.4	**2020**	557006	526456
2000	485783	285883.3	**2021**	558782	542776.2
2001	491310	294745.7	**2022**	560466	559602.2
2002	496542	303882.8	**2023**	562061	576949.9
2003	501497	313303.2	**2024**	563572	594835.4
2004	506190	323015.6	**2025**	565004	613275.3
2005	510636	333029.1	**2026**	566361	632286.8
2006	514848	343353	**2027**	567646	651887.7

Year	Projected	Required			
2029	568864	692931.2			
2030	570018	714412			
2031	571112	736559			
2032	572148	759392			
2033	573129	782933			
2034	574059	807204			
2035	574941	832228			
2036	575776	858027			
2037	576567	884625			
2038	577316	912049			
2039	578026	940322			
2040	578699	969472			
2041	579337	999526			
2042	579941	1030511			
2043	580513	1062457			
2044	581055	1095393			
2045	581569	1129350			
2046	582056	1164360			
2047	582517	1200456			
2048	582954	1237670			
2049	583368	1276037			
2050	583761	1315595			

Projections of ratio of agricultural land to population in Edo State

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.1250	2011	0.1332
1988	0.1612	2012	0.1299
1989	0.1785	2013	0.1267
1990	0.1862	2014	0.1235
1991	0.1890	2015	0.1204
1992	0.1894	2016	0.1173
1993	0.1885	2017	0.1143
1994	0.1867	2018	0.1113
1995	0.1844	2019	0.1083
1996	0.1819	2020	0.1054
1997	0.1791	2021	0.1026
1998	0.1761	2022	0.0999
1999	0.1731	2023	0.0971
2000	0.1699	2024	0.0945
2001	0.1667	2025	0.0919
2002	0.1634	2026	0.0894
2003	0.1601	2027	0.0869
2004	0.1567	2028	0.0845
2005	0.1533	2029	0.0821
2006	0.1499	2030	0.0798
2007	0.1466	2031	0.0775
2008	0.1432	2032	0.0753
2009	0.1398	2033	0.0732
2010	0.1365	2034	0.0711

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2035	0.0691		
2036	0.0671		
2037	0.0652		
2038	0.0633		
2039	0.0615		
2040	0.0597		
2041	0.0580		
2042	0.0563		
2043	0.0546		
2044	0.0530		
2045	0.0515		
2046	0.0500		
2047	0.0485		
2048	0.0471		
2049	0.0457		
2050	0.0444		

Projections of the ratio of agricultural land to population, when the abandonment seizes to be constant (Edo state).

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	**0.1250**	**2011**	0.1345
1988	0.1612	**2012**	0.1335
1989	0.1785	**2013**	0.1331
1990	0.1862	**2014**	0.1334
1991	0.1890	**2015**	0.1343
1992	0.1894	**2016**	0.1357
1993	0.1885	**2017**	0.1378
1994	0.1867	**2018**	0.1404
1995	0.1844	**2019**	0.1438
1996	0.1819	**2020**	0.1478
1997	0.1791	**2021**	0.1526
1998	0.1761	**2022**	0.1583
1999	0.1731	**2023**	0.1650
2000	0.1699	**2024**	0.1727
2001	0.1667	**2025**	0.1817
2002	0.1634	**2026**	0.1920
2003	0.1601	**2027**	0.2039
2004	0.1567	**2028**	0.2177
2005	0.1533	**2029**	0.2335
2006	0.1499	**2030**	0.2518
2007	0.1466	**2031**	0.2729
2008	0.1432	**2032**	0.2974
2009	0.1398	**2033**	0.3257

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2035	0.3974		
2036	0.4426		
2037	0.4957		
2038	0.5583		
2039	0.6271		
2040	0.7033		
2041	0.7880		
2042	0.8823		
2043	0.9877		
2044	1.1054		
2045	1.2369		
2046	1.3839		
2047	1.5483		
2048	1.7322		
2049	1.9378		
2050	2.1678		

Model Projections III for Delta State

Deforestation rate *a = 0.040;* Abandonment rate *b = 0.2;*

Rate of Agric use of transitional land *c = 0.2;* Regrowth of Trans Land *d = 0.02*

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
1987	614489	162652	483716	**2009**	381201	393975	485682
1988	599584	238432	422841	**2010**	375666	396046	489145
1989	584057	280223	396577	**2011**	370423	398009	492426
1990	568626	304438	387792	**2012**	365454	399868	495535
1991	553637	319499	387721	**2013**	360747	401630	498480
1992	539246	329729	391882	**2014**	356286	403300	501271
1993	525514	337351	397992	**2015**	352060	404881	503915
1994	512453	343512	404892	**2016**	348056	406380	506421
1995	500053	348805	411999	**2017**	344262	407800	508795
1996	488291	353542	419025	**2018**	340668	409145	511044
1997	477140	357886	425831	**2019**	337262	410420	513175
1998	466571	361930	432356	**2020**	334035	411628	515194
1999	456555	365724	438578	**2021**	330977	412772	517107
2000	447064	369299	444494	**2022**	328081	413857	518920
2001	438072	372677	450109	**2023**	325336	414884	520637
2002	429551	375872	455434	**2024**	322735	415857	522265
2003	421478	378897	460483	**2025**	320271	416780	523806
2004	413828	381761	465268	**2026**	317936	417653	525267
2005	406580	384475	469802	**2027**	315724	418481	526652
2006	399713	387045	474098	**2028**	313628	419266	527963
2007	393207	389481	478169	**2029**	311642	420009	529206

Year	Forest (Ha)	Agric Land	Trans Land	Year	Forest (Ha)	Agric Land	Trans Land
2008	387042	391788	482027	**2030**	309761	420713	530383

Relating Population Growth to Modelling Land Use and Land Cover Change in Delta State.

Projected and required agricultural land (ha) extrapolating scenario III and assuming a requirement of 0.1 ha/person agricultural area.

Year	Projected	Required	Year	Projected	Required
1987	162652	228390	**2008**	391788	435291
1988	238432	235697	**2009**	393975	448785
1989	280223	243237	**2010**	396046	462697
1990	304438	251019	**2011**	398009	477041
1991	319499	259049	**2012**	399868	491829
1992	329729	267080	**2013**	401630	507076
1993	337351	275359	**2014**	403300	522795
1994	343512	283895	**2015**	404881	539002
1995	348805	292696	**2016**	406380	555711
1996	353542	301770	**2017**	407800	572938
1997	357886	311124	**2018**	409145	590699
1998	361930	320769	**2019**	410420	609010
1999	365724	330713	**2020**	411628	627890
2000	369299	340965	**2021**	412772	647354
2001	372677	351535	**2022**	413857	667422
2002	375872	362433	**2023**	414884	688112
2003	378897	373668	**2024**	415857	709444
2004	381761	385252	**2025**	416780	731437
2005	384475	397195	**2026**	417653	754111
2006	387045	409508	**2027**	418481	777489

Year	Projected	Required			
2029	420009	826440			
2030	420713	852060			
2031	421381	878474			
2032	422013	905706			
2033	422612	933783			
2034	423179	962730			
2035	423717	992575			
2036	424227	1023345			
2037	424709	1055069			
2038	425167	1087776			
2039	425600	1121497			
2040	426011	1156263			
2041	426400	1192107			
2042	426769	1229063			
2043	427118	1267164			
2044	427449	1306446			
2045	427762	1346945			
2046	428059	1388701			
2047	428341	1431751			
2048	428608	1476135			
2049	428860	1521895			
2050	429100	1569074			

Projections of ratio of agricultural land to population in Delta State

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	0.071	2011	0.083
1988	0.101	2012	0.081
1989	0.115	2013	0.079
1990	0.121	2014	0.077
1991	0.123	2015	0.075
1992	0.123	2016	0.073
1993	0.123	2017	0.071
1994	0.121	2018	0.069
1995	0.119	2019	0.067
1996	0.117	2020	0.066
1997	0.115	2021	0.064
1998	0.113	2022	0.062
1999	0.111	2023	0.060
2000	0.108	2024	0.059
2001	0.106	2025	0.057
2002	0.104	2026	0.055
2003	0.101	2027	0.054
2004	0.099	2028	0.052
2005	0.097	2029	0.051
2006	0.095	2030	0.049
2007	0.092	2031	0.048
2008	0.090	2032	0.047
2009	0.088	2033	0.045
2010	0.086	2034	0.044

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2035	0.043		
2036	0.041		
2037	0.040		
2038	0.039		
2039	0.038		
2040	0.037		
2041	0.036		
2042	0.035		
2043	0.034		
2044	0.033		
2045	0.032		
2046	0.031		
2047	0.030		
2048	0.029		
2049	0.028		
2050	0.027		

Projections of the ratio of agricultural land to population, when the abandonment seizes to be constant (Edo state).

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
1987	**0.1250**	**2011**	0.1345
1988	0.1612	**2012**	0.1335
1989	0.1785	**2013**	0.1331
1990	0.1862	**2014**	0.1334
1991	0.1890	**2015**	0.1343
1992	0.1894	**2016**	0.1357
1993	0.1885	**2017**	0.1378
1994	0.1867	**2018**	0.1404
1995	0.1844	**2019**	0.1438
1996	0.1819	**2020**	0.1478
1997	0.1791	**2021**	0.1526
1998	0.1761	**2022**	0.1583
1999	0.1731	**2023**	0.1650
2000	0.1699	**2024**	0.1727
2001	0.1667	**2025**	0.1817
2002	0.1634	**2026**	0.1920
2003	0.1601	**2027**	0.2039
2004	0.1567	**2028**	0.2177
2005	0.1533	**2029**	0.2335
2006	0.1499	**2030**	0.2518
2007	0.1466	**2031**	0.2729
2008	0.1432	**2032**	0.2974
2009	0.1398	**2033**	0.3257

YEAR	AGRIC/POPULATION	YEAR	AGRIC/POPULATION
2035	0.3974		
2036	0.4426		
2037	0.4957		
2038	0.5583		
2039	0.6271		
2040	0.7033		
2041	0.7880		
2042	0.8823		
2043	0.9877		
2044	1.1054		
2045	1.2369		
2046	1.3839		
2047	1.5483		
2048	1.7322		
2049	1.9378		
2050	2.1678		