1.0 INTRODUCTION

1.1 Background to the Study

Human activities have continued to significantly shape the surface of the earth and the existence of man on the surface of the Planet Earth. His activities on it has affected the environment in its natural setting greatly thereby leading to a noticeable change in the land use and land cover (LULC) over time. Increase in human population will hence have a greater influence on the surface of the Planet Earth.

Over the past few years, urban areas have been expanding and increase in population is one of the key reasons accountable for this. Since the 1950s,the world's urban population started to increase appreciably and it is projected to nearly double to 6.4 billion in 2050 from 3.4 billion in 2009 (WHO, 2018). Urban lands over the past years have been changing rapidly by way of responding to rapid increase in the number of people and the conversion of rural lands to urban lands (Vaz and Nijkamp, 2015). The United Nations projected that the population of urban areas will rise by 1.35 billion at a rate of 2.2 percent per annum by 2030. It has been predicted that urban areas are going to appreciate by 1.2 million km^2 by 2030 the world over, which is thrice its size in the year 2000 (Jiao, 2015). Nigeria, India and China are together expected to contribute 37% of the anticipated growth of the global urban population from 2014 to 2050, (UN, 2014).

The increasing urban population causes increasing demand for urban land use. However, the expansion of urban areas is creating lot of challenges in numerous countries, particularly in terms of forest loss and environmental degradation. Population increase is considered to be among the most significant drivers of change in any urban system. If the urban area increases in population, the urban area must grow upward or outward in order to accommodate the increasing population. Together with technological improvement and economic growth, rapid growth of urban population can be identified by the expansion of the urban fringes and redevelopment in the centre of the city (Rui, 2013).

Urban growth is usually accompanied by changes in LULC in numerous areas around the globe, particularly in emerging economies (Belal and Moghanm, 2011). Moreover, urban areas grow in different directions, occasionally growth may even expand to regions that are highly susceptible to some hazards. As a result, administrators and policy-makers should look for ways of overcoming this challenge through risk reduction and provision of alternative measures. Urban growth if not well managed can lead to urban sprawl, which is a serious challenge for many developing countries including Nigeria (Noor and Rosni, 2013).

By the 21st century, urban population had reached landmark point with over half of the world's population living in urban centres (Jiao, 2015). As cities continue to grow, such accelerated urban growth processes generally give rise to deforestation, loss of fertile farmlands, environmental degradation, disappearance of open green spaces, an increase in the vehicular movement; air, water, and noise pollution; high consumption rates of energy; disappearance of surface waters and depletion of groundwater, soaring rent, increased cost of transportation, congestion, unemployment and damage to the ecosystem biological diversity (Chima, 2012), These negative consequences on the environment have drawn much interest by researchers and policy-makers, who view the growth process not only as a sign of the strength of the local economy, which rarely has been well planned, but also as a sign for concern over the destruction of environmental and ecosystem well-being (Sharaf, 2006).

Due to rapid upsurge in the population of urban areas, policymakers, and planners are faced with the problem of resource planning and redistribution to deal with the envisaged hitches that may crop up in the future in trying to achieve sustainability in the growth of urban centres. The growth of the population of Nigeria is not very different from the global picture. By 2020, Nigeria's population was projected to be more than 206 million (Worldometer, 2020) and there is the general desire for urban migration which will increase the burden on the natural resources available. The continued growth of urban population has led to modification in the LULC at the urban fringes causing deforestation in the process. This is because; the urban population has to be supported by a boost in food production and urban infrastructure and this is more often than not achieved through an increase in urban housing and the expansion of areas under cultivation.

Most of the African countries have rural economies and depend heavily upon their natural resources and as a result, land use changes lead to degradation of these resources which can lead to rapid declines in standards of living. This degradation creates an imbalance in the ecosystem leading to the extinction of biodiversity, increased depletion of ozone layer and global warming (Dang and Kawasaki, 2014).

The International Geosphere-Biosphere Programme (IGBP) and the Human Dimensions of Global Environmental Change Programme (HDP) established the Core Project Planning Committee (CPPC) to develop a multi-disciplinary research programme involving scholars from diverse fields to forecast the LULC pattern in the upcoming years. The committee concluded among others that: To model land cover demands information on land use and it is impossible to predict upcoming scenarios of land cover in the dearth of information on the drivers of the change in land use. The main reasons for land use changes are population related. There is need for increased research to appreciate how these drivers interrelate with change in land cover or how predictions about these drivers can be employed to predict upcoming patterns of land use, rates of change in land cover and status of land cover (Lambin and Geist, 2006).

The conclusions of the working group are very central to this study. As can be seen, human population plays a vital role in determining urban expansion. The rising human population is, therefore, an indication of the increase of human activities on the land use. This population has in recent years concentrated in urban centres giving rise to the growth of these areas to the detriment of other contending land uses. The concentration of population in urban areas also brings with it associated problems such as the development of slums, housing problems, and general environmental degradation.

Nigeria has been witnessing a rapid migration from the hinterland to urban cities. This increased rate of urbanisation has undoubtedly stimulated numerous problems. Ojo *et al.* (2017) identified some of the problems facing urban areas and their inhabitants in Nigeria to include poverty, unemployment, widespread destitution and expansion of slums, growing insecurity and increasing crime wave, poor housing, services and amenities. Additional problems consist of inferior and insufficient housing, transport problems, increased traffic congestion, low output, insufficient health and educational facilities, insufficient water supply and sanitation, unsuitable land use, insecure land tenure, increased pollution, absence of green spaces, haphazard urban development and increased susceptibility to disaster. To facilitate the critical assessment of the current and future needs of urban expansion and to promote inclusive and unbiased urban and rural development, accurate, reliable and timely data on trends in urbanisation are needed (UN, 2014).

In Nigeria, also, efforts have been made in creating environmental awareness and on how best to utilize our land resources sustainably. The establishment of the Ministry of Environment with the Federal Environmental Protection Agency (FEPA),as its major parastatal, and which has metamorphosed into the National Environmental and Standards Regulatory and Enforcement Agency (NESREA) was to achieve this goal. The pattern, trend and characteristics of urbanisation in Nigeria demand for steps designed at curbing the growth of urban centres, regulating the rate of movement of people from rural to urban centres and enhancing the quality of life. The picture in Nigeria is not entirely different from the picture on micro-level in Benue State.

The urban areas in the three zones A, B and C represented by Makurdi, Gboko, Otukpo and Katsina-Ala have been experiencing influx of migrants from the adjoining rural areas leading to the growth of these cities with attendant challenges of inadequate infrastructure and deforestation. The key concern of this study is the astronomical growth in these urban areas. This infers that the growth in these urban areas will have a great effect on the landscape on the outskirts of these urban areas by changing them. As a result, there is need for special care and constant evaluation of our decision-making to examine and plan the growth of these areas. With the growing significance of urban areas in driving changes in the environment, there is burning desire to know how these urban areas have evolved, and how and where they may grow to in the future. Over the years, studies on change detection employing remote sensing and GIS have mostly focused on unraveling data on the quantity, location, type of LULC changes that have occurred but only a few have ventured into addressing how and why these variations have arisen (Friehat *et al*., 2015).

In recent times, a lot of models have been developed so as to model land use dynamics, urban growth and deforestation. This research concentrates only on modelling of urban growth and its implication on the physical environment with specific emphasis on deforestation in Benue State which will facilitate the determination of the major driving factors.

It is against this background that this research modelled urban growth and its implications on the physical environment with specific emphasis on vegetation loss in Benue State which further led to the determination of the major driving factors. The driving forces responsible for urban growth and how they impact on vegetation in Benue State were examined to aid future planning. In the end, trend of urban growth and vegetation change and their driving factors were established and the model was used to predict future urban growth scenarios. This was intended to assist urban planners in their decision-making processes on land use.

1.2 Statement of the Research Problem

The world population is increasingly becoming urban day by day and this has been causing a lot of concerns in the last few decades. Studies have shown that rapid urban growth can lead to social, physical and environmental problems (Mundhe and Jaybhaye, 2014; Ohwo and Abotutu, 2015). Under such urbanisation conditions, farmland and forests at urban suburbs may be transformed to built-up and industrialized areas which degrades the environment. Certainly, increase in population may give rise to the expansion of urban areas which causes alteration in LULC in many urban cities (Triantakonstantis and Mountrakis, 2012; Hashem and Balakrishnan, 2015; Mundhe and Jaybhaye, 2014; Opatoyinbo *et al*., 2015). The rate of such changes is apparent in less developed countries where the percentage of population increase is high like Nigeria and

Benue State in particular. These irrepressible urban changes in Nigerian cities have created a lot of physical and social challenges, including the destruction of vegetation. This discrete development around the city leads to unplanned development if not well planned (Sankhala and Singh, 2014).Of particular concern is how earth's resources will match the concentration of human populations in urban areas especially in developing countries. A lot of problems are connected with the transformation of forests to farmland and then into urban use. Urban growth leads to more decrease and alteration of vegetation as more ecosystems are disturbed and habitats are destroyed (Skwirk, 2014).

Before the 1980s, a large number of forest resources in Nigeria that remained relatively intact have disappeared in the last few decades due to greater demand thereby threatening the forest cover especially as there is no proper management and planning (Danburi, 2015).Disappearance of open spaces is but one of the challenges of urban expansion.

However, despite predictions that the urban populations globally will rise considerably by 2030, not so much is known about future locations, extents, and rates of urban growth. While this population is increasing in Nigeria, the resources to manage the cities are dwindling. The increased movement of persons into the urban areas from the rural communities to benefit from the apparent opportunities provided by these urban areas, creates a lot of problems on both the socio-economic infrastructure and the resources of the environment (Ohwo and Abotutu, 2015). For example, growth of urban areas has been identified as being responsible for a lot of environmental problems, which include air, water, land and noise pollution, deforestation, local climate modification, and traffic congestions (Lanrewaju, 2012) .

Despite the unceasing rapid urbanisation and urban growth going on in Nigeria, many towns in Nigerian cities do not have suitable development plans and precise information on the percentage and pattern of urban expansion that is vital for future development planning. Responding to these issues has been problematic as we do not know exactly what the future scenarios will be.

Benue State has four major urban areas comprising Makurdi, Gboko, Otukpo and Katsina-Ala. These urban areas are fast-growing and during the past thirty years have experienced high rate of population increase as a result of rural-urban migration but there exists a gap in modelling the future pattern of their growth and the impact on vegetation change. The key challenges posed by urban growth in Benue State are shortage of infrastructure and rapid deforestation (Adewumi, 2013; Ohwo and Abotutu, 2015). The new areas of growth are faced with shortages or complete absence of good roads, water, electricity, health care facilities, schools and security. The growth of urban areas also gave rise to the clearance of vegetation thereby depriving the new areas benefits of ecosystem services such as provision of shade, wind control, pollution control through removal of carbon-dioxide and oxygen production, reduction of run-off and increase in water quality. The need to monitor the growth of these urban areas and be able to predict future scenarios for proper planning is, therefore, very pertinent. These processes of urban growth are not static but dynamic with time with their attendant consequences. Information on the future effects of these changes, their trends and future states is however lacking or scarce in Benue State. This research was aimed at filling this gap.

1.3 Research Questions

The focus of this research was to find answers to these questions:

i. What are the types and extent of LULC in Benue State?
ii. What have been the trend and rate of these LULC changes from 1987 to 2017?
iii. Which factors are the drivers of LULC changes in Benue State?

iv. How may the trend and rate of LULC change from 1987 to 2017 be used to predict and model change scenarios into the year 2030?
v. How has urban growth affected vegetation in Benue State?

1.4 Aim and Objectives

The study was aimed at modelling LULC dynamics on the physical environment of Benue State, Nigeria with a view to providing the much needed information to guide urban planning into the 2030s. The specific objectives were to:

i. Identify and map the types and extent of LULC classes in Benue State.
ii. Determine the trend and rate of LULC changes from 1987 to 2017 in the State.
iii. Identify the drivers of LULC changes and their contributions to urban growth in Benue State.
iv. Model and predict the pattern of urban growth in Benue State into year 2030
v. Evaluate the impact of urban growth on vegetation.

1.5 Justification for the Study

In assessing how urban growth impacts the physical environment, it is pertinent to appreciate the development process of urban areas and the impact of their growth on the physical environment particularly with regards to biodiversity and the degradation of the land (Musa, Hashim, & Reba, 2017). Although, several studies have been carried out on assessing urban expansion in recent years (Arsanjani *et al*., 2013 and Xie and Fan, 2014) and its impact on the environment (Wei and Ye, 2014 and Grawe *et al*., 2012), but assessing the effect of urban growth on the environment with specific focus on deforestation has not been on the front burner of works by researchers. In places where deforestation has taken place as a result of urban development, so as to plan properly for the management of the environment would require information on the level of the deforestation as well as the location but this has remained a difficult matter.

Nigeria is one among the nine countries that are anticipated to contribute over half of the world's projected population increase from 2015 to 2050 (UN, 2015). The country's large population of over 206 million in 2020 (Worldometer, 2020) and its high growth rate (about 3 percent) (projected from 2006 census) are contributing to environmental deterioration. The continuous increase in population comes with its attendant consequences on land use through expansion of agricultural land and conversion of land for residential and other human activities. Benue State has experienced and is still experiencing a high level of physical development especially in its urban centres of Makurdi, Gboko, Otukpo and Katsina-Ala. This development has culminated into substantial changes in land use owing to the construction of new settlements, roads, industries, expansion of agricultural lands. Being aware of the drivers of urban growth and how they interact is required to improve land use planning and help the government in meeting her development plans. This understanding will provide a way to specify and predict the driving forces that are shaping urban growth.

Models of land use change are extremely vital in explaining the drivers and quantifying their contributions towards land use change, and thus assist in making informed decisions. Models that are capable of capturing aspects of the complex changes involved in land use change can support understanding of these changes. Land use change models can be employed to predict demand for land for specific uses and where resulting land use changes will occur given different environmental, economic and social conditions. They can, therefore, aid in understanding the drivers of urban expansion and which areas are likely to be under greatest pressure, and can thus offer support to land use policy decisions. Models of land use can as well be employed to investigate alternative future scenarios (Soesbergen, 2015).

Technological developments in GIS, remote sensing and urban growth modelling have broadened our ability to link information across a broad spectrum of disciplines. Recent developments in these fields have enabled researchers to model urban expansion with ease. Since urban growth is not a static process, the combination of GIS with modelling techniques provides an avenue to assess their spatial and temporal characteristics and detect the driving forces contributing to urban growth. The usefulness and information content of GIS and Remote Sensing data depends, significantly, on our understanding of the socio-political, economic and ecosystem structure and function. Consequently, a way to increase the utility of remote sensing data and GIS for understanding land use ecosystem process has been the fusion of RS and GIS with socio-economic and ecosystem modelling technologies.

It is necessary, therefore, to investigate the changes in urban growth pattern to have a better knowledge of the processes. This can be done through modelling to assess and predict future changes in urban growth pattern. This will take the form of the magnitude of change and their directions to enable planners to formulate policies of land use considering the predicted changes. Using modelling can reduce ambiguity and increase our knowledge of the changes in urban growth pattern. Spatial planning is a future-based task, that is highly influenced by past and present activities, and policy makers have to improve their skills in analysis, problem solving and decision-making to be able to predict with certainty. With the aid of models of land use, it can aid scenario building and offer a significant aid in decision making process. Understanding these changes can assist in devising sustainable management strategies and therefore reducing environmental problems (Korir, 2014).

1.6 Scope of the Study

The focus of this study is on modelling LULC dynamics on the physical environment of Benue State, Nigeria. The study was specifically set to model, simulate and forecast urban growth and its implication on the physical environment with specific emphasis on deforestation in Benue State which further led to the determination of the major driving factors. The study covered the entire Benue State which comprises 23 local government areas for general LULC changes. The major urban areas of Makurdi, Gboko, Otukpo and Katsina-Ala, as shown in Figure 1.2 were selected for urban growth assessment vis-à-vis its implication on vegetation loss in Benue State.

The justification for the selection of these urban areas is that Makurdi is the state capital and is the most urbanised town in the state. Gboko and Otukpo are the traditional homes of the Tiv and Idoma nations and the second and third largest towns in the state. Katsina-Ala is the headquarters of Zone A senatorial District and the largest in the zone. Data from Landsat TM, Landsat ETM+ and OLI for 1987, 2007 and 2017 were utilised and the processing was purely remote sensing and GIS-based, integrated with Global Positioning System (GPS) and topographic map data, and detailed ground truthing of the study area. Other ancillary data employed were Google Earth images and ASTER GDEM data. This study, therefore, employed remote sensing and GIS methods to appraise urban LULC changes and their impact on vegetation in Benue State.

1.7 The Study Area

The study area is discussed under various sub-headings which are listed here.

1.7.1 Location of Benue State

Benue State which came into being on 3rd of February 1976 is situated within the lower River Benue valley in Central Nigeria. Its lies within longitude 7° 47′ and 10° 0′ East of the Greenwich and Latitude 6° 25′ and 8° 8′ North of the Equator (Figures 1.1 and 1.2). It has common boundary with five other states namely: Cross-River in the south, Nasarawa occupies the northern part, Enugu and Ebonyi lies in the south-western part, Taraba in the east, and Kogi in the western part. Benue state also shares boundary with Cameroun in the south-east. The State has a population of 6,671,338 (2021estimates) with an area of 33,955 km^2. Benue state has 23 local government areas and 275 council wards (See Figure 1.2).

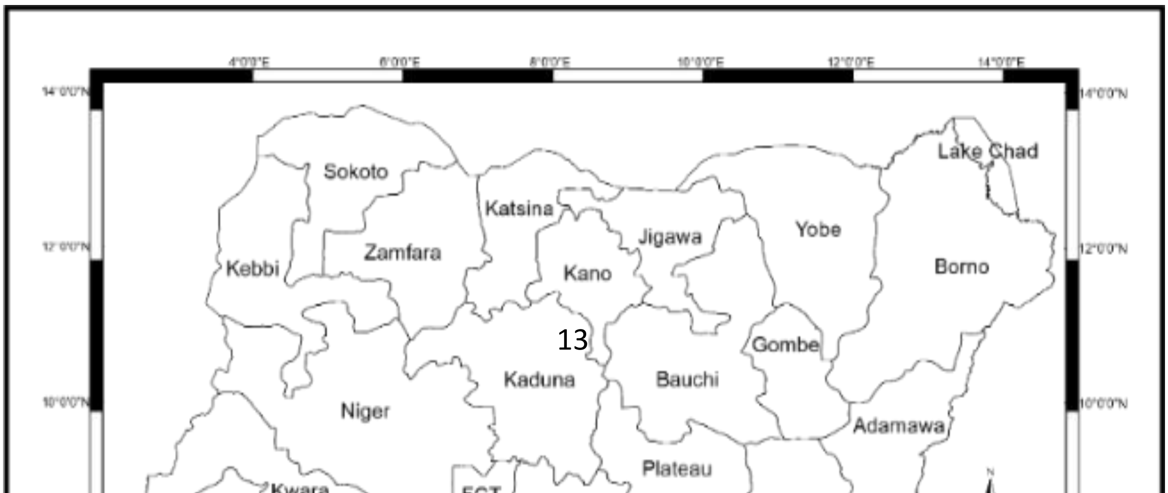

Figure 1.1: The Study Area Within Nigeria

Source Produced from GADM Shapefile

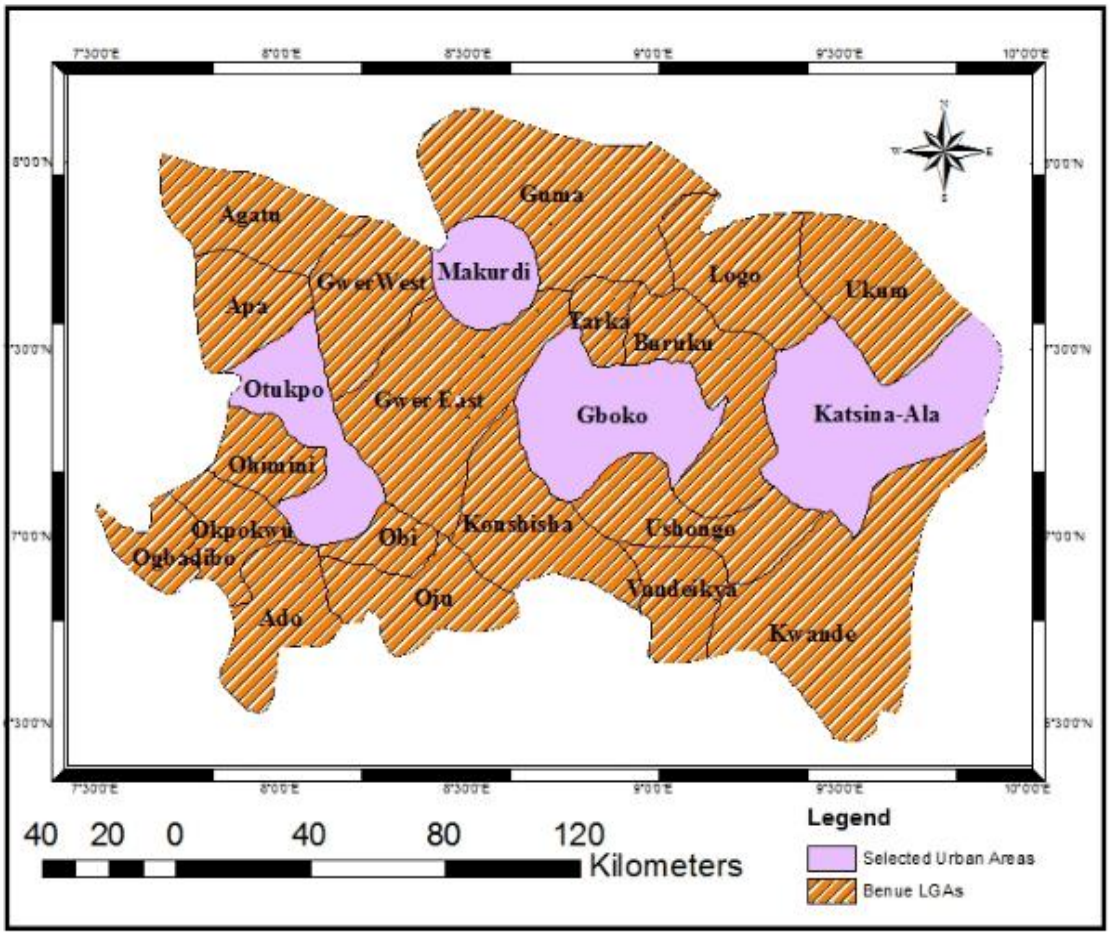

Figure 1 2: Benue State: The Study Area

Source: Produced from GADM Shapefile

1.7.2 The Geology of Benue State

According to Kogbe (1989), Benue is situated within the Benue Valley. In the past, the waters of the Atlantic Ocean overflew the Niger and Benue channels, also called the Niger/Benue Trough. Due to this, several deposits of marine origin constitute the core surface geology of the greater part of the state. These deposits have experienced fluctuating levels of change and have basement complex rocks under them at variable depths. Meta-sediments of over 20m thickness occur in the southern parts in areas like Okpokwu, Ogbadibo and Ado. The geology of Benue State has Meta-sediments occurring in greater portions of the state. Basement Complex rocks made up of early igneous and metamorphic rocks are found mostly in Kwande and the parts of Oju. These basement complex rocks are also widely scattered in various sites as upland residuals, like inselbergs, knolls and ravines and are below most of the meta-sediments (Uchua, 2011).

The basement rocks consist more of Migmatites, porphyritic granites, diorites, gneisses and pegmatites. In the greater part of Benue State, basement complex rocks and sedimentary rocks have both been greatly affected by weathering to give rise to other landforms of greater depth and height. Several solid minerals like salt, limestone, shales, silica, sand, baryte, coal, gypsum and kaolin are found in these rocks and are presently being mined. Within the meta-sediments, the sandstone are the dominant minerals with some limestone, quartzite, siltstone and shale. There exist alluvial deposits like sand, gravel, pebbles and clay on the floodplains of major rivers that are deposited on top of these meta-sediments. These rocks contain lots of minerals, for example, gypsum, shales, coal, limestone, salt, silica, sand, baryte and kaolin which are presently being extracted (Tse, 2012).

1.7.3 The Relief, drainage and hydrology of Benue State

The land of Benue State is generally low-lying with an average height of 1000m to 2500m and moderately undulating with some laterite capped mesas, inselbergs, knolls and buttes. In areas such as Wannune, Adikpo, Mkar, and Igbor, the major features of the relief include presence of deep valleys, steep slopes and generally rugged relief. In other places, the landscape is characterised by broad open valleys and floodplains. The *fadama* areas are widely utilised for irrigation during the dry season.

Several factors including relief, anthropogenic activities, climate and the structure of the rocks. The major drainage feature in the area is the River Benue which is the major tributary of the River Niger. It takes its source from the Cameroonian Mountains, and flows through central Nigeria, and meets the River Niger at Lokoja in Kogi State about 483000m from the coast. During the rainy season between May and September, the river is navigable and is used for transportation purposes, as well as for tourism, fishing and irrigated farming (BNSG, 2017). Two major rivers in Benue State are River Benue and River Katsina-Ala, and they have many smaller tributaries such as Konshisha, Kpa, Mkomon, Loko, Okpokwu, Apa, Amile, Dura, Ogede, Mu, Be, Aya and Ombi. These rivers and streams provide extensive alluvial floodplains that are utilised extensively for irrigation farming.

Even with the high network of streams, many of them are seasonal. The major characteristic feature of these areas is that runoff occurs both on the land surface and the channels of the river during the wet season where the waters overflow the banks at the peak of the wet season thereby resulting in severe floods. These waters are utilised for a wide range of purposes including fishing, irrigation, domestic consumption, industrial uses, drinking water for livestock and recreational purposes (Uchua, 2011).

1.7.4 The climate of Benue State

Benue State is located in the tropical climate with two different seasons, the dry season and the rainy (wet) season (Abah, 2014).The rainy season begins in April and stops in October with an August break, whereas the dry season commences from November and stops in March. The yearly rainfall is between 15cm and 18cm. Temperatures varies between 23^0C-38^0C for most of the year. According to the classification by Thornthwaite, the area is represented as *B3*. The average monthly values of rainfall range from 0.77cm to 22.75cm. This has brought about three distinct rainfall periods in the area: the wet period, the moderate period and the dry period. The harmattan winds usually brings a cooling effect particularly between November and February and it is linked with seasonal harmattan dry winds coming from the NE from the Sahara Desert (BNSG, 2017).

1.7.5 The vegetation of Benue State

The vegetation of Benue State are of two types: the rainforest region which has lofty trees and grassland and oil palm plants lie in the western part and borders to the south of the state while the Guinea savannah is located in the east and northern fringes with trees and grasses mixed together having average height. The natural vegetation of Benue State consists of woodland and tall grasses. The guinea savannah has isolated forests, patches of woodland, scrubs and shrubs in addition to tall grasses(Abah, 2014). Halima and Edoja, (2016) and Hula, (2014) observed that the vegetal cover of the state was hitherto covered by forest but due to uncontrolled and continuous clearing of the vegetation for agricultural activities together with other anthropogenic activities such as burning of the bushes, grazing and hunting among others, have to a large extent, impacted on the original forests. The original forest vegetation is now reduced to secondary forest and savannah vegetation.

Continuous clearance of the forest vegetation has given rise to the emergence of secondary vegetation at various stages of growth. The grasses grow very tall and are coarse when matured. There are pockets of scattered trees that are of economic benefits and they include mango, shea butter, locust bean, African iron, Isoberlinia, cashew, *Daniellia oliveri*, *Gmelina arborea*, oil palm, etc. These trees produce products that serve as raw material for some small-scale industries.

The south comprising Oju, Ado, Obi, Ogbadibo and Okpokwu LGAs, have a forested vegetation with various tree species including oil palm. The oil palm is used for producing palm wine, broomsticks, palm oil, palm kernel and numerous other products. Thick forests are found in isolated localities such as Vandeikya, Kwande and Okpokwu. On a general note, forest in the area may be classified as gallery forests, village forest and forest reserves. The major tree species found here are usually used for timber. Other trees of economic importance include bamboo, raffia palm, *ogbono*, African pear, oil palm, orange and coconut.

The appearance of the vegetation cover of the State varies according to the season. During rainy season, the vegetation becomes very fresh and greenish but wither and die away in the dry season. Some trees are deciduous shading their leaves during the dry season but regain their leaves with the onset of the next rainy season. The plants have adaptive features to enable them overcome the drought conditions by developing long taproots, leathery leaves and succulent stems (Hula, 2014).

1.7.6 The soils of Benue State

The soils in Benue are derived from the breakdown of cretaceous sediments comprising siltstones, sandstones, shales, and mudstones. They vary so much in texture with mostly medium textures (Ade, 2014). One can find alluvial soils close to the floodplains and attract rigorous farming activities. Benue State is covered mostly by alluvial soils which are deposited on floodplains by different streams and rivers during intermittent overflowing (Nyagba, 1995). Alluvial soils have been found to be very fertile and are, therefore, capable of supporting the cultivation of different crops such as lowland rice, vegetables and irrigated crops.

The material from which the soils are derived vary considerably, ranging from loams to clays, gravels, sand or mixture of these according to the pattern of deposition. The basins of most of these rivers and streams have large areas of floodplains where hydromorphic soils are found, (Nyagba 1995).

1.7.7 Population characteristics of Benue State

Benue state with an estimated population of 6,671,338 (2021 population estimates*)* is placed ninth in Nigeria as the most populated state. Population distribution in the state based on Local government areas (LGAs), however, reveals clear dichotomy. Some LGAs are less populated such as Apa, Agatu, Guma, Ohimini, Gwer East and Logo, with below 70 persons per km2 while Gboko, Obi, Okpokwu, Ogbadibo, Vandeikya and Katsina-Ala have densities that range between 140 and 200 persons per km2. The state capital, Makurdi, has a density of more than 380 persons per km2. A closer examination of the figures reveal that females are more with 50.2percent of the total population while males are less constituting 49.8 percent (NBS, 2012). Benue State is mostly rural, where settlements are dispersed in small homesteads with a population of about 630 people who are mostly farmers. Benue State urbanisation process started long before the colonial era but was slow and they persisted very low up to the time the state was created in 1976. The rate of urbanisation now is, however, on the increase (BNSPC, 2016).

Benue towns can be grouped into three. The first category is made up of towns with a population ranging between 80,000 and 500,000 persons. They include Makurdi, Gboko and Otukpo the traditional seat of power of Tiv and Idoma respectively. The second category is made up of urban areas with a population ranging from 20,000 to 49,999 people and comprises Katsina-Ala, Adikpo and Zaki-Biam which are all administrative headquarters of local governments areas. The last group includes urban areas with a population ranging from 10,000 to 19,000 people and comprises Wannune, Ugbokpo, Otukpa, Vandeikya, Okpoga, lgumale, Oju, Utonkon, Ugbokolo, Lessel, lhugh, Ugba, Naka, Korinya, Adoka, and Aliade towns. Most of these urban areas are administrative headquarters of LGAs that were last created (BNSG, 2017).

The people of the state are mainly farmers. Over 80% of the total population is dependent on farming for their living taking advantage of the rich alluvial soils of the Benue valley. The state has a vast area of land and produces part of the food that feeds the whole nation. This has earned Benue State the slogan of “The Food Basket of the Nation”. The state is blessed with agricultural products such as yam, cassava, rice, soya beans, millet, potatoes, guinea corn, groundnuts, maize and benniseed. The state produces over 70% of the country’s soya beans yield, (Benue State Government, 2017).

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Conceptual Framework

Studies of land use change adopt diverse definitions of the major terms lands, land use, land use change, and cover and land cover change. Definitions and the descriptions of these terms differ with the objective of the use and the setting of their use. Here attempt is made to define these terms as applied in this research work.

2.1.1 Concept of land

Land denotes space. Land is a specific area of the surface of the earth, a fixed resource which is made up of soils, water, minerals and biota. Land is an area of the surface of the earth, comprising both land and water, and the natural resources in their original states (Adewumi, 2013).

2.1.2 Concept of land cover

Land cover is the observable state of the surface of the earth and its immediate underlying surface. Soesbergen, (2015) defined land cover as the observable surface features of land such as the vegetation or the presence of built structures. Therefore, land cover is directly observable, either in the field or through remote sensing. In other words, it refers to the observable features of the surface of the earth, manifested in the spread of vegetal cover, desert, ice, water and other observable characteristics of the land, as well as those created mainly by the activities of man.

2.1.3 Concept of land use

Land use connotes the purpose of land, both social and economic or the different ways for which man engage land cover (Soesbergen, 2015). Lambin and Geist (2006) on their part defined land use as including the ways where the different aspects of the land surface are employed and the intention behind their use – the use for which the land is put to. Land use is the envisioned use of land and cover types by human agents, or land managers and the use to which land is put that places emphasis upon social, economic and aesthetic functions. It is in itself abstract and manifested in the cover on the land. In summary, land use connotes human use of land.

2.1.4 Land use change

Land use change is the transformation of both land uses and cover over a period of time. Land use change denotes modification in the primary uses to which a piece of land is exposed to which results in urban expansion (Owoeye and Ogunleye, 2015). Land use change denotes measurable rise or decline in the extent of a particular type of land use, the observable modification in land cover caused by man's activities on the land (Rui, 2013). It is a usual occurrence connected with increase in population, growth in market and strategy action.

However, the connotation and conceptualization of land use change is much wider. As regards land cover change, two kinds of change have been recognized: conversion and modification (Turner *et al*., 1993). Land cover conversion according to Turner *et al*. (1993), refers to the total conversion of a particular land cover type to the other. They usually have great effect on biogeochemistry, hydrology and energy balance. Land cover modification alternatively refers to smaller land cover modifications which affect the nature of the cover without altering its general categorization Modification leads to degradation of the ecosystems such as by overgrazing of the grassland or impoverishment of the forest.

2.1.5 Driving factors of land use and land cover change

Driving factors refer to processes and forces leading to modifications in LULC or ecosystem changes. They are those factors whose interaction results in the exhibition of diverse land use classes.

2.1.6 Definition of a model

Models can be defined in various ways. They can be considered as an abridged symbolisation of reality that emphasises on the main agents and cause-and-effect relationships of an event. Models define the relationship among these factors, and the strengths of such relationships (Anastasiadis *et al*., 2013). On a broader perspective, models are defined as constructs, approximations of reality which is achieved through interpretation of composite real-world relations to the point that they are comprehensible and rationally manageable through the use of symbols (Briassoulis, 2000). Mathematical methods are applied for the management of the relationships among the entities embodied by these symbols.

2.2 Theoretical Framework

The purpose of a theory is to elucidate, forecast, and appreciate a phenomena and, in several cases, to test and widen pre-existing facts, based on giving assumptions. Theoretical framework is the arrangement that is capable of supporting a theory of a research in a study. A theoretical framework consists of concepts which includes definitions and making reference to literatures that are relevant and pre- existing body of theories which are employed for a given research. The theoretical framework tries to introduce and describe the theory which tries to explain the reason for the existence of the research problem being studied. The theoretical framework should be able to show an appreciable understanding of concepts and theories that are applicable to the topic of the research and that relate to the wider areas of knowledge being considered. In theoretical framework, pertinent research works are reviewed including the theories and analytical models that are related to the problem of the research being investigated. The adoption of a theory is dependent on how appropriate it is, simplicity of application, and its explanatory ability.

2.2.1 Theories of urban form

Several theories and models have been put forward to give explanation to the expansion and growth of urban areas. A few of such are discussed here.

2.2.1.1 Concentric zone theory

Burgess propounded the concentric zone theory in the year 1925 to describe city patterns. This theory views the functional zonation of city patterns as a sequence of concentric rings of land use that are centred on the Central Business District, (CBD). This theory seeks to describe the pattern of urban change (Candau, 2002). The theory suggests that land use in a city can be grouped into a series of concentric rings and that the city expands by increasing these zones outward. According to it a city consists of five concentric rings each performing a specific urban function. Zone I is at the centre and houses financial, trading, government and leisure facilities. Zone II is a transitional zone where the downtrodden and old residential houses and light industries are situated. The CBD expands into this zone as the CBD expands. Zone III consist of homes of the working class. Along with these industries are immigrants who occupy old residents with little facilities. Zone IV is a residential area meant for middle-class individuals. Zone V is for the elitist class with good quality residential homes and best of facilities compared to others. It is devoted to suburban and satellite development. Burgess was too simplistic in his assumptions. The theory is defective in that the vital effect of relief and transport linkages are not taken into account and the cities with single CBD cannot be observed in real life situation (Abd-Allah, 2007; Briassoulis, 2000). This theory does not fit our study area as most of the selected urban areas do not have these concentric zones as defined by this theory.

2.2.1.2 Radial sector theory

Hoyt in 1939 propounded the radial sector theory in which it was contended that residential land use types that are alike occupy wedge-shaped sectors spreading from the CBD following road networks. Hoyt opined that competition for space is not the only source through which a city can grow; other factors are also involved such as relief social kinship also contribute. As a result, cities expand in sectors, rather than in concentric rings. Low-income earners do co-habit areas with the high income earners and may not live in isolation as portrayed.

The sector theory stems from the idea that high cost residential areas are located in wedge shapes and spread out in sectors along radial lines from the CBD to the urban fringe. Residential areas that command high rent are situated in some sectors and the cost of securing houses decrease gradually decrease in all directions as one move away from those sectors into the hinterland. According to this theory, the demands of high-income groups is a key factor driving the patterns of urban growth and residential relocation. The model seeks out to elucidate the predisposition for different social and economic groups to separate on the basis of their choice of residential homes.

The model predict that, with time, there is tendency for good quality houses to grow outward over time, along network of roads. (Briassoulis, 2000). Hoyt theory is an improvement over the concentric theory as it has more semblances to reality. The sector model takes direction in conjunction with distance as drivers controlling the allotment of houses. It also recognises that there exist other points where rigorous urban activities are carried out apart from the CBD. This theory does not fit our study area as most of the selected urban areas do not have these radial sectors as defined by this theory, however, the routes along which growth is experienced have some semblance to this theory.

2.2.1.3 Multiple nuclei theory

The multiple nuclei theory was initially propounded by McKenzie (1933) and was elaborated on later by Harris and Ullman (1945) in order to surmount some of the limitations of the concentric and radial sector theories. The multiple nuclei theory sees urban centres as areas made of numerous centres, or nuclei, together with centres that are serving various purposes. The basis of the multiple nuclei theory is that a lot of urban areas and cities have numerous nuclei that serve as growth centres rather than just having a single urban are from which all urban activities revolve (Candau, 2002). Most of these other centres are settlements that existed a long time before; others arise from urban. These nuclei differ in their number and functions from city to city.

While the concentric zone model projected that towns grow out in zones from the center nucleus outward, the Multiple Nuclei on the other hand suggest that related activities are occurring simultaneously in other adjoining urban areas. Unique land use zones emerge due to the fact that some activities tend to fend off each others; residential hoses do not normally grow close to manufacturing areas, and some other activities cannot pay for the high costs of the areas they desired. As a result, there exist several districts. The distribution of these districts in space is more multifaceted than what obtains in the concentric zone theory.

This theory appears to explain more the spatial pattern of urban activity by recognising vital impacts such as relief, historical trends and accessibility. Most importantly multiple nuclei theory attempts to explain closer the 'why' structure of urban spatial patterns rather than the ‘how’ (Abd-Allah, 2007). This theory has a lot of semblances with the structure of urban areas in our study area and is adopted in combination with the radial sector theory for this study.

2.2.2 Urban growth models

Urban growth models are used to clarify dynamic forces and drivers of LULC change and to bring up to date strategies that drive such change. Models of urban growth are essential apparatus that aid planning and growth of urban areas sustainably (Herold *et al*., 2001; Chima, 2012). In the 21st century, urban growth is regarded as the most vital social and economic event that is capable of influencing urban planning (UN, 2015).

The problem of urban growth monitoring is to acquire timely and accurate data on LULC of different epochs using techniques of GIS and remote sensing (Zhang & Murayama, 2016). Modelling urban growth started since the sixties when theoretical and descriptive approaches were adopted to explain Urban Growth Models. It was during this era that efforts were made to develop Large Scale Urban Models (LSUMs) which seek to explain urban areas according to their functions including their spatial land use, demographic and economic attributes (Chima, 2012). These were mostly mathematical models, which flourished during the beginning of computer usage in planning (Leao *et al*., 2004; Osman *et al*.,2016). These models employed a top-down method which was in tune with thoughts at the time. These models were criticised for their inability to correctly elucidate urban structure. Chima, (2012) identified seven limitations of the LSUMs. These are:

i) absence of theoretical structure

ii) complexity of the models, which give rise to huge internal errors

iii) Expensiveness - refers to exorbitant cost of running the models.

iv) Hyper comprehensiveness - since they were trying to duplicate too much.

v) Grossness - the models provided information that was too generalised and not helpful to policy makers.

vi) Mechanicalness - refers to the intricate computer models that can make huge errors as a result of rounding errors and the need to get results through numerous iterations.

vii) Hungriness – this refers to the model's requisition for large volume of data.

Despite these limitations, there were greater use of these during the 1990s mainly due to advancements in computer technology and data accessibility supported by improvements in GIS (Chima, 2012). Later on, new models were introduced with a view to overcoming the limitations of the previous model. One of these is cellular automata proposed for geographical modelling by Tobler in 1979 (Chima, 2012).

2.2.2.1 Driving forces of urban growth

Access to information on the driving factors of urban growth is essential so as to advance the procedure of land use planning and assess the impact of future growth (Hashem and Balakrishnan, 2015). These driving factors have an effect on the future situation of urban areas. To detect key drivers accountable for LULC changes, appropriate methods are needed. Various studies have been conducted on analysing drivers that shape urban growth using different approaches. Nduwayezu *et al*.(2016) posited that within a statistical approach, LULC change which is the dependent variable and is defined as a function of a set of drivers which are independent. Hu and Lo, (2007) identified neighbourhood characteristics and distance to economic centres as the major drivers of urban growth. On the other hand, Huang *et al*.(2009)identified zoning, population concentration, distance to roads, commercial centres, residential, and neighbourhood features as major driving factors of New Castle city growth. Shamsuddin and Yaakup, (2007) and Ogunbodede and Balogun, (2013) also recognised accessibility to infrastructure/facilities and major centres, physical characteristics, initial conditions, growth pressure, market factors, socioeconomic factors as some of the major drivers of urban growth in Seremban District in Malaysia and Benin City in Nigeria..

2.2.3 Urban growth modelling

Urban expansion is among the numerous approaches in which man alters land cover. Even though the trend of urban growth is universal in nature, the effects are more pronounced in developing countries where many people migrate from rural settlements to urban cities to look for better opportunities (UN, 2014). It further noted that the enduring urbanisation and total expansion of the world's population is predicted to increase by 2500 million people in urban area by 2050, with almost 90 per cent of the increase situated in Asia and Africa. Simultaneously, the ratio of the population in urban centres the world over is estimated to rise up to 66 per cent by 2050(UN, 2014). This will likely raise the rates of urbanisation in Africa when compared with other parts of the world (Nduwayezu *et al*., 2016).

Urban growth, especially the conversion to settlements from rural land use at the fringes of urban centres, has been seen as a pointer to economic growth and development (Sahalu, 2014; Yuan, *et al*., 2005). Though, urban growth relevance became unstable with impact on ecological system, greater economic imbalances and social disintegration. Urban growth refers to the rate at which urban population is increasing. (Arsanjani, 2011; Sahalu, 2014).

Rapid growth of urban centres together with change in land cover, has turn out to be a worldwide occurrence. Abebe (2013) noted that there are two basic groups of land change models. These are statistical estimation models and dynamic simulation-based models. Simulation-based models attempt to capture the pattern of urban change in space and time by integrating spatial interaction effect into the model. These models are deficient because of their poor explanatory capacity and incapability in integrating socio-economic factors (Hu and Lo, 2007). Empirical models make use of statistical analysis to make known the relations between land cover and independent variables and have much improved interpretability compared to simulation models.

Linard *et al*. (2013) observed that the quality and nature of data that is accessible determines to a large extent the results of urban growth models. Remote sensing data have been mostly valuable in modelling urban growth due to their spatial detail, accuracy and consistent urban mapping capabilities at different scales both spatial and temporal. Urban features are easily visible on satellite imagery of varying spatial resolutions thus making them to be easily monitored and modelled.

2.2.4 Approaches to LULC change modelling

There exist various models formulated to achieve specific objectives. In general, it is very difficult to adopt a classification scheme that will consider the different models of LULC changes. The same event can be modelled at different levels of spatial detail using corresponding theories as well as within either a static or a dynamic framework. Again, the same problem that a model deals with can also be tackled by adopting other modelling methods and/or model designs. Model specification for solving a particular problem under study may range from very simple to highly sophisticated.

Today, there exist a lot of models that deal with urban growth. Moreover, many drivers have been identified as being accountable for that urban growth. These drivers can be grouped into four: biophysical, socio-economic, cultural and institutional. Even though all these drivers are important, it is not possible to take into account all the drivers in a single model. With the exception of data availability, the key reason for not including all the drivers is that it makes the model less complex, faster and easily understandable than the most complex models (Triantakonstantis and Stathakis, 2015).

Enaruvbe and Atafo (2016), pointed out that Irwin and Geoghegan in 2001 classified models based on their extent of spatial explicitness and economic rationale. Briassoulis, (2000) and Izah *et al.*(2018) gave a comprehensive outline of the different features of land use models including purpose, theoretical grounding, role of space, spatial extent, sectoral focus, problem focus and the implementation of time, (See Table 2.1). Due to the number of qualities, Briassoulis, (2000), suggests differentiating between only four “modelling traditions’’ namely statistical/econometric models, spatial interaction models, optimisation models and integrated models. Walz (2006), noted that this classification scheme features mainly the model design and solution techniques; that specific modelling purposes, underlying theories, differentiation of land use classes as well as spatial and temporal level of analysis are not explained in this classification scheme

Table 2 1: Aspects to Differentiate Land Use Models

Characteristic	Types of specification

Purpose	Descriptive, explanatory, predictive, prescriptive and impact assessment models
Theoretical grounding	micro-/macro-economic, spatial interaction theory, integrated, a-theoretical models
Implementation of space	Spatially explicit, aspatial models
Spatial extent	Global, national, interregional, regional and local level
Sectoral focus	Urban, agricultural, forest sector models
Problem focus	Deforestation, urbanisation, land abandonment , etc.
Implementation of time	Static, quasi-dynamic and dynamic models
Modelling tradition	Statistical, programming, gravity type, simulation and integrated models

(Adapted from Briassoulis, 2000 and Walz 2006).

Walz (2006), observed that the different model properties are usually combined in similar ways. The purpose of the modelling exercise implies a particularly strong characterisation of the modelling process and the final model. Table 2.2 shows some of these typical combinations of modelling techniques with reference to modelling purposes and gives some application examples from the literature. Still, it has to be noted that the boundaries between these application examples are blurred, because some of them are strongly imprinted by the methodological approach (e.g. linear programming), whereas others are more strongly characterised by their overarching idea (e.g. integrated modelling).

Table 2 2: Classification of Modelling Approaches

Purpose	Typical Techniques	Typical model applications and examples
Description	Qualitative, Quantitative and statistical techniques	Qualitative complex system models (Vester and von Hesler, 1980) Multiple logistic regression models (Schneider and Pontius, 2001; Wear and Bolstad, 1998)
Explanation	Theoretical economic and sociological approaches	Conceptual models (e.g. Thünen, 1966) Human ecology models (e.g. Machlis *et al.*, 1997)
Simulation	Multi-criteria, pattern-based, statistical, agent-based, and econometric techniques	Integrated allocation simulation models Urban/metropolitan level (e.g. Salvini and Miller, 2003; Wegener, 1999) Regional level (e.g. Engelen *et al.*, 1995; Veldkamp and Fresco, 1996) - Global level (e.g. Alcamo *et al.*, 1994) Integrated models to derive quantity of change (e.g. Fischer and Sun, 2001; Isard, 1972; Leontief *et al.*. 1977)
Impact assessment	Process based, statistical, multi-criteria and indicator based techniques	Ecosystem-impact models (e.g. Turner *et al.*, 1995b; Veldkamp and Verburg, 2004) Deforestation on carbon flux (e.g. Hirsch *et al.*, 2004) Soil degradation (e.g. Donohue *et al.*, 2003) Biodiversity (e.g. Zebisch *et al.*, 2004) Social system impact models (Brouwer and van Ek, 2004; Sairinen, 2004)
Prescription	Optimisation techniques	Linear programming models (Campbell *et al.*, 1992) Utility maximization models (Nijkamp, 1980) Multi-criteria decision making models (Janssen, 1992)

(Adapted from Briassoulis, 2000 and Walz, 2006).

This approach by Briassoulis (2000), is similar to that adopted by Lambin *et al*. (2000) and Veldkamp and Lambin, (2001) who evaluated models based on their capability of reproduction and predicting growth processes. They classified models as empirical–statistical, stochastic, optimization, dynamic/process based and, again, integrated approaches which refers to the use of more than one approach at a time.

Agarwal *et al*. (2002) in their approach adopted different methods in dealing with scale and complication of time, space and the manner human decisions are made. Guan *et al*. (2011) on the other hand classified models into three groups: dynamic models, empirical and statistical models and system dynamic or integrated models; they posited that dynamic models are more appropriate in predicting changes in LULC in the future compared to empirical/statistical models. Integrated model on their part cut across disciplines and involves elements of different modelling approaches which are considered to be the best for the improvement and understanding of changes in land cover processes (Guan *et al*., 2011).

More recently, Heistermann *et al*. (2006) and Mchetti (2012), reviewed land use models at continental to global scales and categorised them into a) geographic land use models, including empirical-statistical and rule- or process-based models b) economic land use models and c) integrated models. Geographic models according to Heistermann *et al.*(2006) are those that allocate area to a given land use based on suitability of locations local characteristics. According to Michetti (2012), geographic models focus more on biophysical features. Economic models make use of demand and supply of land by diverse types of land uses as a base for allocation of land, while integrated models combine these two approaches with an economic analysis of global markets.

The National Research Council (NRC, 2014), proposed a classification of the approaches for LULC modelling, founded on the methods employed, theoretical and empirical considerations, and the type of application. The NRC proposed five groups, including the models that are pattern based to those that are based on the agents of change. Those that are based on agents of change are more often than not concerned with finding explanations to the processes that brings about the change. A sixth group comprises the hybrid groups. Framing models of LULC modelling in the context of conceptual approaches permit for a better appreciation of their merits and shortcomings and for improving their use as tools for making predictions and knowing the change processes. These groups are: Machine-Learning and Statistical approach, Cellular approach, Sector-Based Economic approach, Spatially Disaggregate Economic approach, Agent-Based approach and Hybrid approaches.

1. Machine-Learning and Statistical approach utilises classifications of previous LULC to standardize parametric or non-parametric associations amongst those changes and spatially and temporarily specific predictors, generally automated, software programs ratify and reproduce the change patterns. Based on thorough statistical methods, these models use interpretation of changes so as to create the relationship between changes in space and time and the drivers.

2. Cellular approach joins in maps of suitability for LULC with neighbourhood effects and facts about the quantity of change anticipated to be able to predict changes in the future,

3. Sector-Based Economic approach make use of partial and general equilibrium structural models to depict supply and demand for land by other sectors of the economy within areas based on general trading activities. This approach assesses the econometric models in a basic and reduced manner to detect the underlying relationship which have an effect on the spatial balance of land systems.

4. Spatially Disaggregate Economic approach approximates basic or reduced form econometric models to detect the underlying relationships affecting the spatial balance in land systems.

5. Agent-Based approach predicts the findings and actions of diverse land-change players that relate with each other and the surface of the land to effect changes in the land system.

6. Hybrid approaches include programmes that usually combine more than one approach into a single model or modelling frame.

Several researches have been carried out on LULC change modelling and these researches have been grouped into pattern-based and agent based models. Agent based models are based on drivers which are most important in the prediction process while pattern-based models are largely based on the analysis and classification of remotely sensed data over space and the changes that occur over time (Agarwal *et al*., 2002).

This study adopted a classification scheme put forward by NRC (2014), because of its simplicity of approach and ease of understanding. Within this classification approach, the hybrid approach fits the model type adopted. This is because the models approach consists of machine learning (Multilayer perceptron) and cellular approach (Markov chain analysis). A brief review of these two models and some related models is presented in Appendix A.

2.3 Land Use and Land Cover Change Studies

Global interest in the analysis of LULC started long ago but was popularised by the conference on Human Environment held in Stockholm in 1972. By 1992, at the United Nations Conference on Environment and Development (UNCED), the scientific research community re-echoed their call for research into land use change. This was when the International Geo-sphere and Biosphere Programme (IGBP) in conjunction with

International Human Dimension Programme (IHDP) jointly set up a committee to initiate an agenda for research and encourage studies in LULC changes. They came up with three core subjects for LULC change research which is similar to the Global Land Project (GLP) research efforts of seeking to galvanize a range of research questions that will enhance our knowledge of land change dynamics, the causes and effects of land change, and evaluation of system outcomes and modelling, especially susceptibility and flexibility of land systems (Braimoh and Osaki, 2010). Since then, a lot of researchers have been researching on themes that are core to understanding LULC change as a key driving factor of environmental change. These researchers dwelt within the multidisciplinary field of land-change science (LCS) - a scientific field that seeks to appreciate the changing aspects of the land system as a combined human-environment system (Braimoh and, 2010).

In pursuance to these goals, several researches were carried out. Garrard `*et al*. (2016) investigated LULC change in Sagarmatha National Park, in the Himalayas of Eastern Nepal. LULC changes that arose during 1992– 2011 in the region were assessed through the use of satellite imageries of varying dates in conjunction with land use data and sociological information assembled from semi-structured interviews and satellite imageries. It was revealed that there has been a decrease in snow and ice area at points above 6000m while lakes that are ice-capped and rocks and soil increased. It was also reveals that forest and farmlands in the region of 3000 and 6000m, are decreasing, while grazing lands, urban areas and shrub land are on the increase. These LULC changes occurring in the protected area is a pointer to the prevailing danger of land deterioration. The study concluded that human activities in conjunction with changes in climate may be responsible for the changes at higher altitudes, whereas anthropogenic activities are the main cause in lower altitudes.

Cheruto *et al.*(2016) assessed LULC change by using of GIS and RS methods in Makueni County, Kenya to evaluate quantitatively LULC changes in the area from 2000-2016. Supervised classification approach was used with maximum likelihood classifier in ERDAS imagine to detect LULC changes. Landsat multispectral satellite data of 2000, 2005 and 2016 were used as the main data. Seven major LULC classes were identified during classification. The study carried out change detection to relate the extent of changes between time intervals among the land cover classes. The end results showed that there were increase and decline in area of the many LULC classes between 2000 and 2016. There were observed considerable changes from some land cover classes to others. Rainfall, drought and some socio-economic factors were observed to be responsible for the changes.

The use of GIS and remote sensing has been extensively used in detecting LULC dynamics particularly urban growth (Aithal and Ramachandra, 2016; Al-shalabi *et al*, 2012; Dami *et al.*, 2014; Debnath and Amin, 2015; Hamdy *et al*., 2017; Jafari *et al.*, 2016; Mishra *et al*., 2014; Oyinloye and Fasakin, 2014), urban planning (Aburas *et al*., 2017; Jain *et al.*, 2017; Kumar *et al.*, 2015; Megahed *et al*., 2015; Mohammady *et al.*, 2014; Mohammed *et al.*, 2016; Owoeye and Akinluyi, 2018; Rahimi, 2016) and cropland loss (Fertner *et al*., 2016; Friehat *et al*., 2015; Gupta, 2014).

There exist numerous ways of using remote sensing images for assessing change in land use in urban areas. Even though there are several methods of detecting change in remote sensing during image classification, researchers have recently grouped them into image regression, image ratio, image differencing and post classification method(Sahalu, 2014). The classification approaches mostly depend on the methodology for data transformation and techniques for analysis used. These methods include image differencing, image ratio, normalised difference vegetation indices (NDVI) and principal components. These techniques identify the changes but are unable to offer information on the pattern of change. The post classification method involves classifying the images individually and then overlaying the classified maps. The result is in form of “from-to” change matrix of the conversions among different classes on the two dates. It has to be noted that the classifications have to be consistent for each of the independent classification (Almutairi and Warner, 2010; Makuti *et al*., 2018). Change detection is the procedure of categorizing variances detected in the state of a land cover at different time intervals. Detection of change is a very important procedure in the day-to-day monitoring and management of our God-given resources and urban growth as it gives us the prospect of measuring the distribution of features in both space and time.

Due to growing flexibility in digital and computer technology, approaches of handling change detection using satellite imageries have also increased. Change detection studies using GIS in conjunction with remote sensing have mostly centred on offering the information of where, how much, what type of LULC change has taken place.

2.4 Drivers of Land Use and Cover Changes

For one to appreciate LULC changes in detail, the driving factors for these changes must be investigated and understood. According to Soesbergen (2015), a driver of land use change is defined as that which causes a variation in the overall total extent assigned to a particular type of LULC or a variation in extent of area coverage of a given type of land use. He further observed that drivers are scale-dependent, as changes in areal extent of land use may not be detected if the study is carried out at a low resolution or for a small extent. In addition, different drivers may exert an overriding control on the land use structure at different scales of analysis.

Many studies now seek to explain LULC using multiplicity of drivers that cut across many disciplines rather than from a single driver. The manner in which man uses land give rise to the type of LULC. The choice to use land for particular use is based on numerous factors that are interrelated. According to Chima (2012), these factors can be political or socioeconomic and may be at local or global scale. Soesbergen (2015), while quoting Geist and Lambin (2002), noted that there exists immediate and underlying (root) causes of land use change.

The direct causes of change in land use are attributable to actions of man that emanate from the rationale for which land use is intended, this tend to affect land cover directly (Robson and Berkes, 2011). These underlying factors carry on at the local and individual levels. This comprises the observable action of man on pre-existing land cover. The origin of change in land use depict a mixture of political, socio-economic, population, cultural, technological and biophysical factors. All these factors are interlinked with each other. The origin of change in land use are started outside the immediate environments and cannot always be guided from within.

Understanding the drivers of land use change from global to local level demands diverse study techniques. Change in land cover can be appreciated by comparing land cover maps of successive years. Conversely, understanding small alterations in the nature of land cover changes will need very close examination, which might need remotely sensed data from satellites with shorter revisit periods (Osunmadewa and Enokela, 2011). The overall picture of reasons of LULC change can best be appreciated through the use of place-based study and relative studies of land use changes (Sahalu, 2014).

Arsanjani (2011), noted that examining the drivers behind LULC change is vital if earlier forms can be elucidated and be utilised in predicting forthcoming scenarios. LULC change can result from varied drivers that regulate some variables. These drivers may involve any issue which influences the activities of man, as well as local culture, economic and financial matters, environmental conditions among other factors. Consequently, these driving factors must be seen to affect these governing variables. LULC change is often explained by several selected biophysical and socioeconomic variables. The relations between driving factors and LULC change could be done qualitatively and quantitatively through the use of appropriate methods.

Soesbergen, (2015) and Arowolo and Deng, (2017) classified drivers as proximate and underlying (biophysical) drivers. Proximate drivers are local or direct human modifications that cause changes in the landscape. Proximate drivers are anthropogenic actions or instantaneous actions at the local level, such as growth of farmlands, that directly influence land cover. Proximate drivers refers to the immediate causes of LULC change. There exist land uses that have direct effect on the environment and therefore constitute proximate sources of change such as expansion of infrastructures, expansion of farmlands, contamination, wood harvesting (logging) etc. These drivers differ from one place to another depending on man's activities, the climate or even policies in place.

Eguavoen (2007), noted that strong importance is usually placed on some definite driving factors such as wood extraction and population growth, as some drivers play a greater or lesser role, taking into cognizance the extent or time, specific location and other factors. Underlying or indirect factors are the main factors that elucidate the more proximate drivers of land cover change and include the political, social, population, economic, biophysical, technological and cultural factors.

Soesbergen, (2015) further asserted that biophysical drivers in most cases never directly cause change in land use but rather cause land cover changes. Biophysical causes are factors that often work to speed up the drivers that can lead to abrupt shifts in the human-environment condition. Key biophysical drivers for modification in land use include climate, water accessibility and soil conditions.

2.5 Drivers of LULC Change in the Developing World

Chima, (2012) observed that several factors operate in time and space to explain change in land use. These factors may vary from location to location, but some of these factors may be common in all locations, for instance, population/earnings, political, socio-economic, technology and cultural factors. These factors collectively or singly have environmental effects with eventual impact on LULC (Anifowose *et al*., 2011).The rate of urban growth is governed by the level of interface between the drivers. While the drivers of change in land use in developed countries are a compound mix up of all factors with technical know-how being at the centre , the situation in developing countries seems to be different with population being the dominant factor (Ujoh *et al.*, 2010).

2.6 Impact of LULC Change

Significant changes in the global system leaving significant imprints on the surface of the earth have been caused by man's activities. Studies reveal that LULC change has a lot of impact on the environment in various ways. These include deforestation and biodiversity loss, land degradation, socio-economic impact, pollution, hydrological impact and effect on surface temperature including urban heat island. Melliger *et al*. (2018) noted that urban growth directly and indirectly caused major shifts in species composition decreasing its biodiversity and richness. Another study by Tesfaw *et al*., (2018) showed that change in land use has considerable effect on deforestation by way of reducing protected areas and making them more vulnerable. Deforestation brings about decline in biodiversity, especially in the tropics. Decline in biodiversity leads to degenerations in the quality of the ecosystem and also hereditary losses that may hamper future scientific innovation. Deforestation and the drivers of deforestation, such as expansion of farmlands and expansion of facilities can result to change in climate, by affecting the biogeochemical cycles. For example, the cutting and burning of trees releases the carbon deposited in trees into the atmosphere as carbon dioxide, which increases the greenhouse effect. This can cause rise in global temperature which will sequentially impact sea level and weather patterns (Nzoiwu. *et al*., 2017).

Another impact of LULC change is land degradation. Wang *et al*. (2015) in their study concluded that great LULC changes had created a lot of harm to the ecosystem such as degradation of the land and ecosystem service decline in the Nenjiang River Basin. This has a serious consequence on the environment and therefore needed to be monitored and regulated.

Other areas of impacts such as pollution (Wu *et al*., 2012), hydrological processes (Gumindoga *et al.*, 2018; Mukherjee *et al*., 2018) and socio-economic impact (Toh *et al*., 2018) have been studied.

2.7 Urban Growth

Urban growth refers to the conversion of the empty land or virgin lands to construction of built-up together with industrial, infrastructural and residential development. Urban growth occurs mostly in the peripheral city settlements. The human activities here are more industrial based than agriculturally based (Aithal and Ramachandra, 2016; Friehat *et al*., 2015; Mohammady, 2014; Owoeye and Ibitoye, 2016; Zhai *et al*.,2016; Abd-Allah, 2007). Two categories of urban growth are recognised. These are: spontaneous and self-organization method. Spontaneous growth results in a regular and thin spatial pattern, which comprises additional chance components, whereas self–organizational growth result in spatial cluster pattern, which is joined with more socio-economic activities (Aithal and Ramachandra, 2016; Cheng, 2003). Urban growth culminates into LULC changes in many urban areas the world over, particularly in developing countries. In view of this, urban growth cannot be exhaustively discussed without reference to changes in LULC. Modern urban growth comprises three interconnected obstacles spatial change: the waning of city nucleus, the appearance of border cities which both contend with and balance the service of the core city centre, and the rapid urban growth in the fringe of towns which denote the spatially most extensive indicator of such growth (Jitendrudu, 2006; Röder *et al*., 2015).

2.8 Land Use and Land Cover Modelling

Anastasiadis *et al*. (2013) defined a model as a basic depiction of realism that emphasises the important factors and interaction of a given event. Models explain the relationship among these factors, and state how strong such relationships of the different factors are. In building models, scientists are required to clearly state their assumptions, state the issues that are of interest, and vividly explain their procedure. This is of importance to the scientist through exerting on them a high standard of scientific rigour. The beneficiaries of the research also derive some benefits by appreciating how research questions have been framed, the setting in which a research has been conducted, and its strong points and weaknesses.

Anastasiadis *et al*. (2013) noted that there are two major categories of models; theoretical or conceptual models and numerical or computer models. Theoretical models are those that stress the manner of interaction among the diverse parts of a system without aiming at quantifying the extent of any connections. Numerical and computer models give the description of the process through which the different components of a system interrelate and also quantify the extent of the diverse interactions. Numerical models are usually built inside the setting of a more general numerical computer models. These model types are in most instances triggered by other researches where data have been gathered and analysed.

Models that treat LULC change plainly are essentially those in which the aim of model construction is land use change. Models of land use can broadly be understood as basics that help us in understanding and evaluating the complex linkages and feedbacks between different factors that shape land use change. Agarwal *et al.*(2002) and Mas *et al*. (2014) noted that within change in land use researches, models can be identified as important instruments used for explaining, predicting and evaluating impact and providing explanations for changes in land use. However, lot of definitions of land use models exist (Soesbergen, 2015). Heistermann *et al.*(2006) defined land use model as 'an instrument to estimate the transformation of regions assigned to a particular land use type. Verburg *et al*. (2004) defined it as an instrument to aid the appraisal of the reasons and cost of change in land use.

Change in land use is the product of a composite web of interaction involving biophysical and socio-economic forces over spatial and temporal sphere. In order to cope with this intricacy for practical purposes at least is not possible without some simplification of the complex associations to a controllable and reasonable dimension. As a result, it is essential for some symbolic models which will explain the relationships of interest. Considering the demand for land use change models, the uses of these models are not different to define. At first, general use is to provide decision support in various decision and policy making contents. More specially, as noted by Briassoulis (2000), models can be used to explain the relationships between the driving factors in space and time and the resulting patterns of land use and their changes. Models of change in land use can be used also as a means of explaining the observed relationship.

Very often, models are employed in predicting future configuration of land use patterns under various circumstances of biophysical and socio-economic change. Credible and successful predictions of future patterns is dependent on the assumptions, specifications and theoretical basis of the models themselves including the settings of changes from which they derive the levels of the variables during the prediction (Briassoulis, 2000). The model to be developed is expected to meet these needs

The main aim in modelling LULC change is to know and identify the processes and drivers shaping these changes. Modelling is a vital technique for predicting and carrying out experiments that test our knowledge and explains our understanding in quantitative terms (Lambin *et al.*, 2000). Calls have been made to the international scientific community to carry out studies into LULC, especially for studies into models that can forecast spatial patterns of future change (Adewumi, 2013). Verburg *et al.* (2004) noted that models are suitable for separating the multifaceted set of social,economic and biophysical factors that affect the rates and spatial pattern of change in land use and for assessing the effect of changes in land use. Modelling enables us to examine land cover change dynamics and predict future pattern. Each specific model has its benefits and shortcomings depending on what the research hopes to achieve. Land use change models may be targeted at forecasting the nature of changes in space, tackling the issue of "where are land use changes occurring?" or the rates of change, which address the issue of "at what rate is land cover changes expected to occur?" (Aithal and Ramachandra, 2016). These questions have been tagged the *location* issue versus the *quantity* issue Land cover change models seek to answer important questions that are interrelated - Why, when, how, and where do these changes occur?

2.8.1 History of LULC change modelling

Modelling change in land use essentially started about seven decades ago. During this time, there was not much interest but by 1980s and 1990s, the tempo of activities in the field expanded greatly owing to advancement in geospatial technology (Wegener 1994; Kim, 2012). Due to developments in computing and availability of spatially explicit digital data, computer based modelling and associated simulations have become common tools in land use research. These models according to Walz, (2006) and Chang, (2013) are designed for a variety of purposes, and are based on various methodologies and operate at different scales. Despite exceptions, they are often criticised for their bias towards inductive analysis of vast digital data sources and for their lack of theory. The two types of models of land use change identified by Theobald and Hobbs in 1998 were: regression-type models with spatial transition-based models (Mas *et al*., 2014).

2.8.2 Why are models used to understand LULC?

Anastasiadis *et al*. (2013) suggested that models are employed to comprehend land use because the drivers and decisions that shape LULC change are intricate. This intricacy comes from the method of taking decision by the owners of land when deciding on land use, amount and organizational practices, and from geographic unpredictability, economic uncertainty and communications between owners of land . Those that own the land usually combine economic, social, geographic and personal information together in traditions that are not completely known. Moreso, the attitudes, ethics and actions that regulate how they take decisions on how their land is to be used vary among individuals. This embraces the intention for using the land, the information considered relevant, the emphasis placed on diverse types of information, and their perception of the future.

Faced with such intricacy, a researcher must show his sense of judgment as to the process of modelling the decisions of land owners. Scientists are also expected to exert their sense of judgment in their choice of methods to be employed. For instance, should they try to overtly model the decisions of land owners individually? Is it possible for their model to be able to unravel the 'best' result? Will they employ a statistical method and presume that upcoming pattern will be like the pattern noticed in the past? Should they model the decision of representative land owners or cumulative view of land owners?

The LULC project, a core programme of IGBP and IHDP, have lent their support to the development of combined local and large-scale models by improving on the pre-existing models and building new models that are capable of predicting future land use patterns using changes in the drivers (Turner *et al.*, 1995; Monks *et al*.,(2015). LULC change models enable the recognition and understanding of the drivers of change, the manner they interact with each other through time and project future pattern of LULC change. Put differently, these models of LULC change show the spatial and temporal relationships between these drivers.

Models of land use change could deal with two separate issues: in which areas are the land use changes probably expected to happen (location of change) and at what rates are changes probably expected to progress (quantity of change) (Veldkamp and Lambin 2001; Aithal and Ramachandra, 2016)These two questions seek to answer the location and the quantity questions. The extent of change in LULC over space and time are equally important modelling issues as location and quantity issues. Models of land use are required to examine the intricate pattern of links and feedbacks and to find out the significance of driving factors and identify which driving factors contribute most to explaining land cover changes (Heistermann *et al*., 2006; Lambin *et al*., 2000; Soesbergen, 2015). Models are employed in predicting the quantity of land taken, its location and the intended purpose under varying circumstances. These questions address the *'where', 'what'* and *'why'* of LULC change.

Models are employed due to the fact that they entail the researchers writing down and making formal their findings. The application of models assists in clarifying the scope of the study; the manner it will be handled, and also that which is beyond the scope of the study; that which is presumed or overlooked. Consequently, their research is made accessible to other scientists, and is open to criticisms by other scholars. This openness make it possible for the worth of the model to be verified and assist in ensuring that the results from it stand the test of time and are interpreted in the perspective of the decisions, judgments' and assumptions made in the course of model development. Land use models are employed in reaction to issues that are hard to find solutions to. These issues often come up in a policy perspective where it is necessary to measure the would-be impact of a given action, to search alternative ways, or to predict future scenario.

2.8.3 Urban growth modelling methods

The use of models in land change studies creates an avenue to know the drivers and interactions influencing land cover change and can be used in simulating future ecological and monetary effect of change in land use (Hunt, 2012). Different researchers have attempted developing models to simulate urban change in land cover and deforestation. These include cellular automata model, agent-based models, Markov model, logistic regression, artificial neural networks, Land change modeler and Multilayer perceptron. The common subject matter with the different types of model is the selection of 'predictor variables' – which are the constituents which are acting together with each other to force the change. With the intricacies of urban growth and deforestation, a lot of independent variables will be used. A few of these models are briefly reviewed below.

2.8.3.1 Artificial neural networks

An Artificial Neural Network (ANN) is a model which tries to predict the pattern and functionalities of biological neural networks (Krenker *et al*., 2011). Triantakonstantis and Stathakis (2015), viewed ANNs as potent tools that employ a machine learning algorithm so as to model intricate relationship. Distinct from most multivariate modeling approaches, ANNs has nothing to do with input data relationships and as such it is needless making presumptions about spatial autocorrelation and multi-collinearity of the data. Such set of rules produce results to a number of specific problems. ANN is a model whose inspiration stems from the nervous system of human which interconnects the neurons to fulfill the complex jobs in a short period. The ANN model was modelled after the biological nervous system. The ANN model is used by computers in order to solve systems that are not linear. The ANN comprise of three layers: input, hidden and output layers. An ANN comprise of a set of processing nodes called neurons that are linked to each other. ANN is made up of simple neuron-like processing elements as can be seen in Figure 2.1. The “intelligence” of a neural network develops from the combined actions of neurons, with each performing only a restricted number of operations.

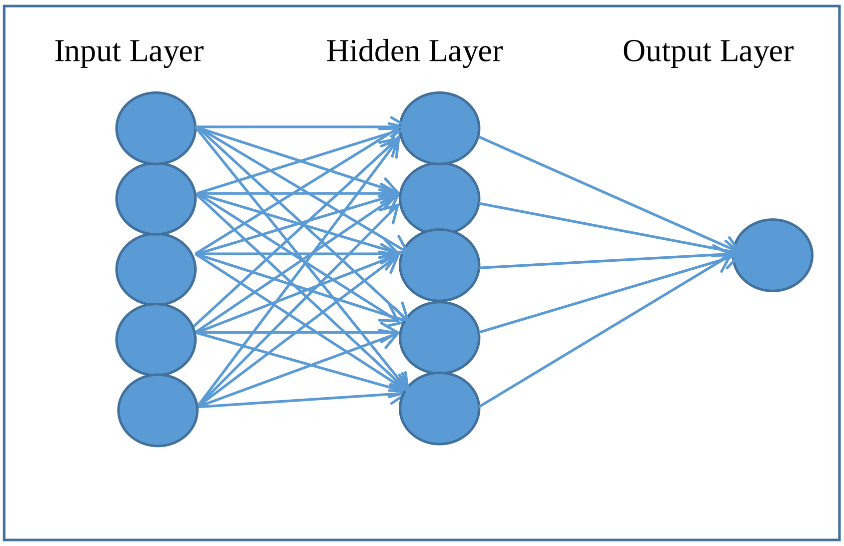

Figure 2. 1:ANN structure

(Source: Adopted from Mohammady *et al.*, 2014)

The ANN is an example of a Non-Linear Prediction (NLP) method that has been extensively used in a variety of areas, in addition to LULC change modelling (Baysal, 2013; Okwuashi, 2011; Triantakonstantis and Stathakis, 2015; Wang and Maduako, 2018; Zhai *et al.*, 2016).

ANNs are great tools that make use of machine learning technique to measure and model intricate behaviours and patterns. ANNs are usually employed for investigation based on the following reasons:

i. They are capable of dealing with incomplete, noisy and ambiguous data

ii. The relationships of input data do not affect ANN.(Nkoana, 2011).

The way the elements are linked and the power of those linkages define the behaviour of ANN. During training of the network, the weighted connections are automatically regulated.

The Input layer gets input data from the outside world through the input unit. These units code the data structure offered to the network for processing (Nkoana, 2011; Wang and Maduako, 2018). The layer next to the input layer is the hidden layer, and the nodes in this layer are known as Hidden units. The Hidden layer receives information from the input layer in a feed-forward architecture. The Output layer is the last layer of the network, and the units represent coded values for the training application being considered.

With the improvement in computer technology and software engineering, the use of ANNs in modelling land use has considerably improved in recent years and is likely to boost more in the coming years.

2.8.3.2 Multilayer perceptron

A Multilayer Perceptron (MLP) is a feed forward ANN model that seeks to map group of input data onto a group of relevant outputs. It is made up of numerous layers of nodes with each layer completely linked to the other. MLP is a system made up of a numerous solitary processing elements, called neurons or perceptron with a nonlinear activation function (Abuelaish, 2018; Mishra *et al.*, 2014). MLP uses a supervised learning method known as back-propagation used to train the network. MLP is an adjustment of the standard linear perceptron and is capable of differentiating data that cannot be linearly separated. It consist of an input layer, hidden layer and output layer. It is a feed forward technique which implies that data normally flows in one direction starting from input to output. The MLP is a self iterating learning process which learns by the input and output data (e.g. back-propagation algorithm).

The MLP attempts to determine the linear output from nonlinear inputs based on the weights through the use of a nonlinear activation function. Mathematical notation as given by Baysal (2013) is:

$$Y = \varphi(\sum_{i=1}^{n} \varphi ixi + b) = \varphi\ (w^{T}\ x + b) \quad \textbf{(2.1)}$$

where φ represents the vector of weights, x is the vector of inputs; b is the bias and φ is the activation function.

The back-propagation algorithm is utilised in training the MLP. Back-propagation algorithm is made up of two parts which are forward and backward Activation is transmitted from input to output layer in the first step. In the second part errors are moved from output to hidden layer and the system is trained (Baysal, 2013). Since their emergence, they have been quite successfully used for a variety of purposes such as LULC change modelling. The advantages are then obvious: the solution is obtained clearly in terms of the training data, whereas the back propagation generally used for the training of MLP proceeds iteratively and may well miss the optimum since it relies on a gradient method and thus can get trapped in local minima. The MLP is capable of modelling multiple transitions at a time. MLP assist in calibrating the drivers and their association with land use changes.

2.8.3.3 Land change modeler

The Land Change Modeler (LCM) is an application in IDRISI to help in solving problems of rapid land transformation and the demand for the protection of biodiversity (Eastman, 2012). It is a model made by Clark Labs for users concerned with land change and conservation as this application presents a robust set of instruments for the analysis of change and the formation of viable plans and scenarios for the future. Tools for land change modelling are sequentially organized around major tasks by tabs in the Land Change Modeler interface:

Land change prediction using Land Change Modeler is a step-by-step process starting with 1) Change Analysis, 2) Transition Potential Modelling, and ending with 3) Change Prediction. It is anchored on changes in the past from earlier time to later time land cover maps to predict upcoming states. The first step in this modelling process is Change Analysis.

Change Analysis: In Change Analysis changes are assessed between LULC maps of earlier time and those of later time. The changes that are noticed are transformations from one LULC status to the other. It is probable that with several LULC classes the likely grouping of transitions can be very bulky. The most essential duty is to spot the main transitions that can be assembled together and modelled, known as a sub-model. Each sub-model of transitions is capable of being modelled distinctly, but in the end each sub-model will be pooled with all sub-models in the last process of change prediction.

Transition Potential Modelling: This is the next step in the change prediction procedure It is the point of identifying the potential of land cover to transit to other forms of land cover. Here, maps of transition potential are created which in real meaning are maps of suitability for each of the transitions. In LCM, a group of maps of transition potential are organised in an empirically assessed transition sub-model with the same causal drivers. A transition sub-model may comprise of a single LULC transition or a set of transitions that are believed to be affected by similar underlying drivers. These drivers are then employed to model the past change process. Transitions are modelled using either logistic regression, a multi-layer perceptron (MLP) neural network, or a SimWeight. Once adjusted, the model is used to forecast future pattern.

Change Prediction: This is the last step in Change Prediction. Based on the past rates of change and the transition potential maps generated, the LCM is capable of predicting future states for a specific date in the future. The model is also capable of determining the effect of the variables on future change, the amount of change that has occurred from the earlier time to the later time, and to determine the relative amount of transition to the future date. So as to build a model that is stronger LCM makes provision for inclusion of restrictions and incentives, which may include road development, zoning maps. Driving variables may be dynamic or static. he dynamic drivers are always recalculated at interval.

2.8.3.4 Markov chain analysis

The Markov Chain model was developed by Andrei Andreyevich Markov in 1906. It is a Markov process in which space is distinct and it is a stochastic process that is based on probabilities. It is a chance process in which the current state of the sequence is the only determinant of the next state.

It assumes that the future state (t+1) is dependent on the present state (t). The expected upcoming change is only dependent on the present change, so the transition involving these two epochs can be modelled mathematically (Iacono *et al*., 2015). In equation form, it can be represented as;

$$X_{t+1} = f(X_t) \qquad \textbf{(2.2)}$$

where X_{t+1} is the LULC at time t + 1 and X_t is LULC at time t.

The arrangement of the Markov chain model as used in LULC change involves a vector n_t with measurement $m\times 1$ (where m is the number of states, in this case LULC classes) illustrating the distribution of LULC among current states and an $m\times m$ matrix of transition probabilities (P) that govern the probability of transition involving each pair of LULC i and j. The model can then be rewritten as a different equation.

$$n_{t+1} = pn_t \tag{2.3}$$

where n_{t+1} is another $m\times 1$ column vector explaining the distribution of LULC at time $t+1$. Since the transitions are probabilities, it follows that:

$$\sum_{j=1}^{m} pij = 1 \qquad i = 1,2,\ldots m \tag{2.4}$$

meaning that the rows of the transition matrix should add up to 1. Maximum likelihood estimates of the transition probabilities can be attained as :

$$p_{ij} = n_{ij}/\sum_{j=1}^{n} n_{ij} \tag{2.5}$$

where p_{ij} is the probability of transition involving i and j and n_{ij} represents the number of transitions from i to j. It is possible to obtain these values empirically. In order to check how valid the Markov model is, the initial step is to test the null hypothesis that LULC at one point in time, $t + 1$, is statistically not dependent on LULC at the earlier time period, t. Under the hypothesis of independence, the number of expected transitions in each cell of the transition matrix can be derived by:

$$m_{ij} = n_{i+} n_j \tag{2.6}$$

where n_{i+} is the marginal total of transitions for the ith row of the transition matrix and n_{+j} is the marginal total for the jth column of the transition matrix.

An additional vital property of Markov chains is the property of stationarity, mostly as it relates to the transition probability matrix. This feature is important for uses in which a Markov model is to be utilized for prediction. The transition probability matrix *(P)* is presumed to remain stable in succeeding times, implying that at any future time $t + k$. the matrix of cell transitions can be accomplished by multiplying the vector of present LULC, *ntnt* by the transition probability matrix P_t raised to the kth power (P^k). In most predicting applications, the transition probability matrix is presumed to remain constant throughout consecutive periods, and is rarely tested empirically.

Baysal (2013) reported that the model was used first by socio-economic studies in 1950s, thereafter it found its way into urban research too, and specifically for LULC modelling it was in the 1970s. Koomen and Beurden (2011) reported that Burnham (1973) was among the pioneers to suggest usage of Markov model for modelling LULC change. When used in LULC and several other areas of uses, Markov model often stipulate both periods and a fixed set of states as distinct values. Transitions involving the states of the system are presented in the structure of a transition matrix that records the probability of moving from one state to the other. A Markovian analysis uses matrices; which can be employed to determine the probability of LULC change of one LULC class to the other.

Markov chain analysis has a lot of merits over other modelling approaches. Mubea *et al*.(2010) while enumerating its merits stated that they are methodically compact and simple to execute with empirical data such as LULC. Additionally, the LULC transition probability outcome can then serve as a pointer to the trend and magnitude of LULC process. They are comparatively simple to get from successional data. The major disadvantage of Markov model is that the authentication of Markov models is dependent on predictions of system behaviour over time, and is as a result frequently hard, and may not even be attainable, for a very long period of time. Also, in certain instances, the data that is available may not be enough to approximate probability rates particularly for exceptional transitions (Mubea *et al*., 2010). Another setback of Markov model is that it is non-spatial, implying that further assumptions are needed for distribution. One must make a distinction involving first and second-order Markov matrix. First order matrix utilizes a matrix with present LULC and a change matrix on the basis of skilled knowledge, while the second order determines transitions from one land use to the other by evaluating two maps of LULC over time, that is, the change matrix is derived from past changes in land use. (Koomen and Beurden, 2011).

2.8.3.5 Cellular automata

The concept of Cellular Automata (CA) are methods of processing data based on neighbourhoods and inputs. In this method, neighbourhoods and features of automata are altered overtime based on the rules that guide their reaction. Since the last four decades, numerous models have been developed for simulating LULC changes particularly in urban growth, using CA (Santé *et al*., 2010). The study further stressed that CA models are capable of simulating urban expansion on the basis of the assumption that historical urban growth influences the pattern of urban growth in the future through neighboring interactions between land uses.

An automata processes data in a logical manner, relentlessly carrying out its subsequent action following application of data collected from outside its system base on in light of instructions that have already been programmed within the system (Roy, 2016).Cellular Automata (CA) are algorithms that describe the state of the cell according to the past state of the surrounding cells, using some transition rules. CA have a capability of simulating intricate spatial and temporal processes like urban development.

A finite automaton (A) is represented by a finite set of states $S=\{S_1,S_2,S_3,........., S_N\}$ together with a set of transition rules T.

$$A \sim (S, T) \tag{2.7}$$

A Cellular Automaton (CA) is aspatially situated and is linked to a limited system. The space in is CA separated into regular spatial cells with each cell representing a specific border of position of an automaton (Liu, 2009). The general behaviour of a CA system is controlled by the collective result of all the transition rules. Transition rules characterize an automaton's state, S_{t+1}, at the time step (t+1) based on its state, $S_t(S_{t+1} \epsilon S)$, and input, I_t, at time step t:

$$T: (S_t, I_t) \rightarrow S_{t+1} \tag{2.8}$$

An automaton may be defined by A, belonging to a CA lattice as given by Roy(2016) follows:

$$A \sim (S, T, R) \tag{2.9}$$

where, R represents automata neighbouring A

A cellular automaton comprises five fundamental elements namely "cells", "states", ''time'' and neighbourhood" and" transition rules" (Liu, 2009).

i) *The cell(C)*:The CA is made up of cells which are the building blocks of the system. The cell is the fundamental spatial unit of two-dimensional raster forms of CA employed in urban expansion and LULC change modelling (Liu, 2009). Nevertheless, there are instances where one- and three-dimensional CA have also been employed in explaining other linear objects

*ii) The states(S)*This represents the value in each pixel. It represents the features of pixels, such as type of LULC and define spatial changes of the surface of the land. States may be qualitative values that stand for varied types of LULC, social and economic status, binary values for instance urban or non-urban (Roy, 2016).

iii) The time (t) denotes the period involving changes in the states of all cells.

iv)The transition rule (T): These rules are produced on the basis of the surroundings of the cells. Transition rules govern the value a cell may haves at any given point in time and regulate the process of automata adapting over time; and it decides the likelihood of change of cells based on to the highest probability of change to another value (state). It offers the definition of the process of change of the state of one cell as a response to its present state and the neighbouring cells. Transition potentials of individual cells are derived from the suitability, accessibility, zoning, and neighbourhood effects

v)The neighborhood (R) This explains how each cell is linked to other cells. The neighbourhood of a cell gives the cluster of cells closet to it defined by their remoteness from an individual CA. The main objective of the Cellular Automata is to determine the subsequent state from the present state.

CA is referred to as a distinct active system which implies that the nature of each cell at time $t+1$ is governed by the nature of its neighbouring cells at the time t which determines the transition rules (Baysal, 2013). Generally, the nature of each cell is dependent on the features of the cell in the past together with its neighbouring cells based on some transition rules. In a linear CA for a single cell, there exist three neighbouring cells, so the subsequent state of the cell depends on these three neighbouring cells. The subsequent state qi (t+1) of a cell is presumed to be reliant only on itself and on its two neighbours (Baysal, 2013; Maji *et al*., 2003).This relationship is given as:

$q_i(t+1) = f(q_{i-1}(t).\ q_i(t).\ q_{i+1}(t)$ **(2.10)**

Where $q_i(t)$ is the state of the i^{th} cell at t^{th} instant of time. 'f' is the subsequent state function and known as the rule of the CA (Maji *et al*., 2003).

CA methods have several shortcomings in urban land simulations. As a result of spatial diversity, different parts of cities must be handled by varying transition rules. So, using a single transition rule by CA perhaps might be unsuitable for modelling in space. (Triantakonstantis and Mountrakis, 2012).

2.9 Review of Literature on Urban Growth Modelling

Various attempts have been made by different authors to identify factors that are responsible for urbanisation and also model urban growth to highlight the most important factors and predict future urbanisation trends in various cities. Diogo and Koomen (2010) in their work investigated process of LULC change in Portugal from 1990 to 2000. The authors created a matrix with cross tabulation tools in the ARCGIS 9 x package and regular spreadsheet software. Using that they determined the amount of expected LULC changes from the pre-existing category to that of the other categories over the period of time which permits identifying the transitions between land use classes. Other changes, including inner changes in national land involving forests and semi-national vegetation were omitted in their research. They concluded that urban growth and farmland abandonment were noted to be the most common change in land use processes observed in Portugal from 1990 to 2000. Both urban growth and agricultural land abandonment processes were affected by the distance to the major urban centres. Whereas new urban centres are located close to the cities in coastal areas, agricultural abandonment occurs in marginal areas. They stated further that agricultural intensification will likely manifest in regions close to water bodies in the southern part of the country, possibly as a reaction to the increasing demand for goods. They summed up that natural areas tend to be situated in regions where the slope is very high where urban centres and farming activities are unlikely to occur. One feature of interest in their result is the fact that soil attribute was not significant in driving the process in the area.

Araya and Cabral (2010) showed that urban expansion in Setúbal and Sesimbra, Portugal have increased significantly from 1990 to 2000 by as high as 91.11%. A greater proportion of this expansion was, however, at the fringes of urban centres as a result of the merger of other minor villages and through the conversion of farmland. They predicted that the cities will continue to grow and would exert a greater impacts on the resources. They observed that increase in population was among the key drivers for the observed growth in the area.

Arsanjani *et al*. (2013) in their study analysed the suburban growth in Tehran, Iran. A hybrid model comprising logistic regression model, Markov model, and CA were considered to enhance the working of the model. Both environmental, social and economic variables involved in urban slumps were used in creating a probability matrix of spatio-temporal states of urban areas for 2006, 2016, and 2026. Relative operating characteristic (ROC) was used in validating the model. The calibration was done by comparing the classified and predicted LULC maps. The result showed a match of 89% between the predicted and the classified maps of 2006, which proved to be acceptable. Subsequently, it was used for simulating future LULC. In the end, future LULC maps for 2016 and 2026 were simulated using this hybrid approach. The predicted maps show a new kind of suburban growth in the neighborhood of Tehran towards the border to the west during the period. The model could not account for the major factors driving the urban growth.

Ozturk (2015), in his study on urban expansion of Atakum District in Samsun, Turkey, predicted its growth using CA-MC and MLP-MC models. Landsat TM, ETM+ and OLI images for 1989, 2000 and 2013 were utilized for extracting historical LULC data. Based on the LULC data for 1989 and 2000, the city expansion for 2013 was predicted through CA-MC and MLP-MC models. Results of the prediction were then evaluated side by side with the classified 2013 LULC data for validation. The results reveal that the MLP-MC approach offered the best results based on the validation using the kappa statistics. On the basis of the result, the nature of urban expansion for 2025 was predicted with MLP-MC. The model predicted that between 2013 and 2025, urban expansion rate of 35.2% will be experienced and there will be an expansion in the area covered by artificial surfaces and the destruction of agricultural land and forest land. This results reveal that the urban expansion models offer a superior explanation of the present patterns and changes over time and are capable of predicting future changes using previous and present changes in LULC. The study, however, did not detect the driving factors responsible for the expansion of the urban area.

Al-sharif *et al*. (2013) carried out a study to analyse urban sprawl in the city of Tripoli, Libya. In their study, logistic regression model was employed in modelling urban growth and examining the correlation between urban sprawl and diverse drivers. The study identified 11 factors that influence urban growth which include among others, distance, slope; reserved area; and population density. These factors were derived from pre-existing maps and remote sensing data of 1984 to 2002. In addition, validation was achieved through relative operating characteristic (ROC) method using data from 2002 to 2010 in which 0.86 rate of accuracy was achieved. In the end, probability maps of urban sprawl were created to determine six scenarios of urban growth patterns for 2020 and 2025. The outcome of the results revealed the effectiveness of logistic regression model in determining the drivers of urban expansion, their behaviour, and urban pattern development.

Relatedly, Forkuor and Cofie (2011) mapped LULC change in Freetown, Sierra Leone. Landsat data of 1974, 1986 and 2000 were utilised in the study and nine LULC classes were mapped. Special emphasis was attached to the expansion or decline of farmlands *vis-a-vis* other LULC classes. The results show that key changes were observed between farmlands, urban cities, grasslands, evergreen forest and barren land. Built-up areas recorded a monumental increase of 140% between 1974 and 2000, signifying a high rate of urban growth. It was also revealed that (27%) of farmlands in 1986 were replaced by built-up areas in 2000, particularly at the urban suburbs, in reaction to an increament in human population. Over 14% of evergreen forests were replaced by farmlands. These key changes imply a strong connection involving urban growth, agriculture and deforestation. Their study, however, failed predict future scenarios and identify the drivers of urban growth.

Hamdy *et al.* (2017) set to analyse the drivers of urban growth in Aswan area of Ghana using google earth historical imagery of 2001 and 2013. Logistic regression was used to analyse and classify the drivers for urban growth. The Cellular automata were used in predicting future scenarios using ArcGIS software and Land Change Modeler in Idrisi

Selva. The result revealed that the most important driving factor in Aswan was proximity to religious sites. The result reveal that there is high probability of other areas becoming urban expansion when such areas are close to religious sites. The results also showed urban growth in risk areas to be 59.79 % in 2001, then increasing to 65.45 % in 2013.

A study by Islam and Sarker (2016) focused on the pattern of land use in Rangpur City, Bangladesh using GIS and RS. The main data utilised were Landsat TM and Landsat ETM+ images acquired in 1989, 2000 and 2014. After the images were corrected, change detection was carried out. They performed supervised classification using the maximum likelihood algorithm and to identify areas that have of changed. Six categories of classes were derived after the classification based on field verification, condition of the area, and data from remote sensing. The result indicated that Rangpur is gradually changing with other LULC types have been transformed into urban areas. The study concluded that there is a substantial change of land use practices in the area in the past 26 years. The study also did not to make predictions into the future and identify the driving forces behind the observed pattern.

Jafari *et al*. (2016) attempted a dynamic prediction of urban growth using CA-Markov in Hyrcanian region, Gilan, Iran. The study used Landsat series such as TM, ETM+ and OLI for 1989, 2001 and 2013 respectively. The land use maps of 1989 to 2013 were obtained by GIS technology and remote sensing. The transition matrices were introduced by running Markov chain analysis, where the expected pixels to change from a given land use land cover class to another class for a specific time interval (1989-2001, 2001-2013) was revealed. The study detected that there is a major modificationy in land use from 1989 to 2013. The results of the study predicted a frightening increase in urban development for the target years of 2025 and 2037, with a growth prediction to 11510 and 18320 ha, respectively. The study concluded that the CA-Markov model is a competent tool for supporting urban planning decisions and facilitating the process of sustainable urban growth. The study was able to predict future scenarios for the Hyrcanian region, Gilan. The study did not identify the driving factors that are shaping the predicted pattern.

Makboul *et al*. (2015) studied of urbanisation trends in Lâayoune City, Morocco, through GIS and remote sensing techniques. Plan of Laayoune 1975, Landsat TM 1984 and 2010, ETM+ 1999 and 2003 and OLI 2015 were used. The study relied on both unsupervised and supervised classification methods to provide an accurate distinction involving urban land use and other LULC types. The research explored the spatial features, temporal and the rate of urban growth in a year from 1975 to 2015. Over time, urban growth indicated rapid and slow growth stages, towards the eastern side of the city. They recognized four spatial patterns of urban expansion: security, socioeconomic, demographic migration and normal urban expansion type. The key drivers of urban growth were identified to include population, commerce, industrialization, and security. Even though the study was able to identify the driving factors of urban growth, future scenarios upon which planning are based was not presented.

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Mohammady *et al*. (2014) used Artificial Neural Network (ANN) to simulate urban growth patterns in Sanandaj city. The study used Landsat series of TM and ETM+ satellite imageries obtained in 2000 and 2006. The images were classified based on Anderson level 1 with ENVI software. The study used Maximum Likelihood for classification and an overall accuracy and kappa value of 92.57% and 89.17% for 2000 and 94.71% and 92.68% for 2006, respectively were derived. Dataset used for the model included distance to principal roads, distance to region centres, altitude, slope, distance from spaces and distance from residential areas. Percent Correct Match (PCM) and Figure of Merit (FoM) were used to evaluate ANN results. PCM and FoM are forms of accuracy assessment and gave values of 90.10% and 43.75%, respectively which proves the accuracy of modelling process.

Roshanbakhsh *et al*. (2017) evaluated LULC changes in Hamedan. Landsat TM images of 2002 and 2009 were used. MLP was adopted in classifying the imageries. This resulted in five LULC classes namely: i) plant cover, ii) water, iii) type 1 soil, iv) type 2 soil, and v) urban areas. Next, the changes in the classified images (2002-2009) were assessed using LCM and LULC change maps and figures prepared. The results revealed the largest increases in type 2 soil and then urban areas. Changes in the other LULC classes were largely restricted. It was also revealed that nearly 800 hectares of Hamedan's farmlands and vegetation were destroyed between 2002 and 2009.

Sivakumar (2014) mapped the urban city of Pune region from 1991 to 2010, with a view to simulating its future expansion with RS and GIS approach. Landsat series of TM and ETM+ for 1991, 2001 and 2010 were utilised as data sources. Supervised classification approach was employed with maximum likelihood algorithm in mapping urban centres. The accuracy assessment performed on the classified maps showed an overall accuracy and Kappa statistics of 86.33% and 0.76 respectively. Based on the different classified images, transition probability matrix and area change were determined. The adopted the Markov model in QGIS software, to simulate the probable urban expansion for the year 2021. The result showed that built-up area is predicted to expand greater in the year 2021 when related to 2010. This research provides a perception into appreciating urban expansion and assists in the development of successive infrastructure planning, management and decision-making. Even though the study was able to simulate the urban expansion, factors shaping the predicted pattern were not accounted for.

Triantakonstantis and Stathakis (2015) set to analyse and model the urban change in Athens, Greece between 1990 and 2000 using CORINE land cover maps. The ANN modelling approach was used. The model was developed using drivers such as elevation, slope, distance from roads and proximity to urban areas. The model was validated using the prediction map for 2006 which was compared with a reference map of 2006. The accuracy assessment produced a Kappa index of agreement of 0,639 and a Cramer's V value of 0,648. These inspiring results point to the value of the developed urban expansion simulation model.

Zhang (2016) analysed urban growth simulation in Dongguan City, China using Neural Network. The study was based on data from remote sensing of preceding years and the interrelated physica, social and economic factors aimed at predicting urban expansion in 2024. Landsat TM and ETM+ imageries of 2004, 2009 and 2014 were classified and the LULC changes over time were compared using results of maps of 2004, 2009, and 2014. The outcome of the study revealed declining water and forest areas while urban centres expanded between 2004 and 2014, and this rising trend was reported to persist in the years to come. ANN-CA was then utilised to predict urban expansion for the year 2024. The Figure of Merit (FoM) of the predicted map of 2014 was 8.86%, which is acceptable in the prediction process. The result of the simulation revealed decreases in water body and forest. The author suggested that the finding can assist in identifying which areas should be used for future planning by stakeholders.

2.10 Review of Literature on Urban Growth Modelling: Nigerian Perspective

Closer home in Nigeria, several works have been carried out on urban land use changes. While some focused on assessment of mere urban changes over time, others sought to model urban growth in different urban areas. Eyoh *et al*., (2012)attempted to model urban growth in Lagos from historical remote sensing data employing logistic regression and GIS. The dataset used were Landsat TM images of 1984, 2000 and 2005. ArcGIS and MATLAB software were utilized for the modelling. The classification system adopted was the k-means unsupervised algorithm in MATLAB. Ten drivers were extracted for calibration. The result of logistic coefficients of the ten drivers show that all the ten drivers were significant at 95% confidence level, since all the ten drivers yielded p-values <0.05.

The predicted map for 2000 when compared with the classified reference map of 2000 yielded a Kappa statistic of 0.7640; which means there was substantial agreement involving the predicted and the classified map. Again, the predicted map of 2005 was also put side by sided with the reference map of 2005. The result showed a Kappa coefficient of 0.6998 signifying a substantial agreement between predicted and reference map. The prediction for 2030 scenario was based on the 1984-2000 calibrated model. A 129.49% urban growth from 1984 to 2030 was predicted by the model. The study did not, however, specify the most influential variable accounting for the predicted urban growth.

Ismail *et al*. (2013) adopted a post-classification change detection approach in analysing urban growth pattern of Kazaure Local Government Area of Jigawa State in Nigeria. The study used Landsat TM, for 1988, ETM for 1999 and 2007. These were integrated into a GIS environment for analysis. The study also utilised structured questionnaires in stratified and systematic random sampling to acquire information on LULC change in the area. The result showed that increases in population and expansion of economic activities have led to the growth of the urban area from 12.2% in 1988 to 13.5% in 1999 and 29.7% in 2007. Again, bare surfaces declined greatly over the years from 34.2% in the year 1988 down to 18.4% in the year 1999 and lastly to 4.1% in the year 2007. The study only showed a descriptive analysis of the pattern but the model did not predict future scenarios of urban growth in the area.

Ayila *et al*. (2014) in their study examined the expansion of Kano City in Nigeria from 1986 to 2005 using remote sensing. The study adopted Markov model to simulate future LULC in the area. Images used were Landsat TM of 1986, Landsat ETM of 2000 and 2005 which were classified into four LULC classes. The results reveal a sharp expansion in urban area from 13.2% in 1986 to 19.3% in 2005 and a change rate of 1.51% per year (1986-2000) and 1.24% (2000-2005). Also, vegetation cover reduced to 13.6% in 2005 from 33.9% in 1986. The study also noted that changes by 2015 are going to exhibit more or less the same trend in the time covered with urban area predicted to cover 21.70% of the entire area. The study is deficient in that there was no prediction of future patterns of urban growth

Relatedly, Isma *et al*. (2014) analysed satellite images of Damaturu in order to observe urban growth of the area and to simulate future urban expansion of the town to 2030 using linear regression statistics. The results showed that the urban area of Damaturu will grow to 99 Km^2 by 2030 from about 54.37Km^2 in 2009. The built-up area was projected to increase by 82% in urban land area, with 102% expansion in built up area. The study concluded that if the current growth rate is maintained, by 2030 urban expansion will consume most of the adjoining villages in the fringes in Damaturu.

Likewise, Oyinloye and Fasakin (2014) analysed the urban growth of Akure using Landsat MSS images of 1972, TM of 1986 and ETM+ 2002. Post-classification comparison analysis was done to map and identify the urban growth process in Akure. The results of the analysis showed a speedy expansion in the built-up area from 9.972 km^2 in 1972 to about 38.527 km^2 in 2002. The increase was attributed to growth in population of Akure within the study period. The study predicted that the urban area of Akure will expand in size of up to 500% from 9.772 km^2 in 1972 to 58.637 km^2 in 2022 at the rate of 13.1% per annum. The study suggests regular monitoring of urban area to take care of the ever-increasing urban growth in the town. The study though could predict future patterns of urban growth in Akure, the factors shaping the observed pattern were not revealed by the study.

Wakirwa (2015), investigated the growth of urban sprawl in Gombe metropolis between 1991 and 2014. Landsat TM of 1991, ETM+ of 2005 and 2014 were utilised. After the classifying the images, the extent of urban land use was determined for the three epochs by using statistical data generated and used for post-classification comparison among the years. The results revealed that that urban land use was high between 2005 to 2014 occupying about 51.43% of the total land mass. The spatial extent of urban sprawl occupied about 12.78% between 1991 and 2014 and high annual rate of 12.78% were also witnessed in 2014.The result also revealed that there was a progressive increase of urban sprawl both in terms of extent and annual rate throughout the study period, especially between the period of 2005 and 2014. The study did not, however, predict future scenarios of urban growth in Gombe metropolis to guide future planning.

Another study by Mahmoud *et al*. (2016),attempted analysing the spatio-temporal patterns of settlement expansion in Abuja, Nigeria using geoinformation and ancillary datasets. Using Support Vector Machines (SVM) from Landsat images, LULC maps for 1986, 2001 and 2014 were produced. The overall accuracy was 82%, 92% and 92% respectively. the analysis was done to determine LULC changes on the growth pattern of Abuja, Nigeria. Transitions of other LULC types to the urban areas were modelled in order to predict future states for year 2050 using the LCM in IDRISI Selva. The end result revealed an increase in excess of 11% from 1986 to 2001 and 17% from 2001 to 2014 in urban areas. The LCM model predicted LULC changes reveal a rising trend in the growth of urban areas, which is likely to replace the green areas and farmlands if strict measures are not taken. The study concluded that combining geospatial techniques with other datasets enhanced our understanding of the process of how urban growth could affect the microclimate of urban areas by alteration of natural land surface temperature.

Musa *et al*. (2017) investigated urban growth and its effect on deforestation in Bauchi urban area, Nigeria in between 1986 and 2016 through the use of remote sensing data and GIS approaches. Landsat TM images of 1986 and 1996, ETM of 2006 and OLI of 2016 were used. Maximum likelihood algorithm was employed in the classifying the images after they were geometrically and radiometrically corrected. Accuracy assessment was done by cross validation via confusion matrix. The kappa statistics were 1986 (0.83%) and 1996 (0.87%), 2006 (0.90%) and 2016 (0.92%). Post-classification assessments and analyses were done and the end results revealed that urban land expanded by 565.24%, farmlands by 66.42% while forest decreased by 91.8% from 1986 to 2016. The LULC features of the area were further classified again into forest area and non-forest area for cross-tabulation assessment and the result indicates a change-over of 149.66km^2 (39.68%) due to deforestation and that of 4.68km^2 (1.24%) due to afforestation between 1986 and 2016. This result reveals speedy urban growth and rapid deforestation.

2.11 Empirical Studies on Land Use Change and Deforestation

Deforestation is defined as the total clearance of forest land for farming, logging, urban development, cattle rearing, pasture and associated uses. Various attempts have been made by different authors to model deforestation and identify factors that are responsible for it and highlight the most important factors and predict future deforestation. Alba (2011), set to simulate land cover pattern in 2020 in the Kayabi region in the Brazilian Amazon through GIS and RS techniques. The study adopted the IDRISI LCM in the modelling process in which CLASlite's fractional cover images of 2000, 2006 and 2009 were used. The procedure adopted were in five stages: (i) Development of forest land cover maps for the three set of years; (ii) Change cover analysis through cross-tabulation of forest cover maps; (iii) Determination of transition potentials from forest to disturbance by anthropogenic activities using MLP neural network. Following this, the Markov chain was used to simulate future landscape scenario; (iv Validation of the model performance and (v) Simulating a LULC map for 2020. The result showed that the model was capable of predicting increase in deforestation in the area successfully and identifying the key drivers responsible for anthropogenic disturbance expansion in the region. They found that distance from existing disturbance and distance from roads were the key drivers shaping deforestation in the Kayabi region.

Furthermore, Arekhi (2011) set to forecast the distribution of deforestation in space to detect the driving factors inducing forest degradation of Ilam province. Six drivers including forest fragmentation index, elevation, slope, proximity to road and settlements and remoteness from the forest fringe were considered. Landsat TM for 1988,ETM+ for 2001 and 2007 were used. The classification was done for two classes of forest and non-forest. The study used logistic regression method to model and estimate the spatial distribution of deforestation. The outcome of the study revealed that 192.94km^{2}of forest land were cleared in the 19 years. The result of the modelling showed that there was more forest clearance in the fragmented forest cover and in the regions close to forest/non-forest fringe. Other results reveal that proximity to road, settlement areas and slope had negative relationships with rate of forest loss. Meanwhile, the rate of deforestation declined with increasing elevation. In the end a spatial model was produced to forecast the location of deforestation through logistic regression. The model was validated through ROC method which was 0.96.

Fisseha *et al*. (2011) also analysed changes in LULC at the Debre-Mewi Watershed of northwest Ethiopia between 1957 and 2008. Aerial photographs of 1957 and 1982 with Landsat images of 2008 were analysed. The study employed focused group discussions and field visits to compliment the aerial photos and Landsat images. Four LULC classes of shrub, grazing, forest and cultivated land were identified after image classification of 1957 and 1982 air photos. The analysis of 2008 image reveals the occurrence of Eucalyptus plantation forest and rock outcrop. The results revealed a decline in forest cover from 4.8% to 0.37% while cultivated area increased from 71.04% to 81.51% of the total area. The rock outcrops and Eucalyptus plantation were responsible for 3.30 and, 1.28% respectively, of the entire area of the waters0hed in 2008. The study did not however model future scenarios.

Pérez-Vega *et al*. (2012) in their study compared two spatially explicit models, DINAMICA EGO and LCM in assessing LULC change modelling and their impacts on biodiversity loss in Western Mexico. The DINAMICA EGO model employed the weights of evidence technique which creates a change potential map according to a set of drivers and previous trends while the LCM model was based upon neural networks. Relative Operating Characteristic (ROC) and Difference in Potential were used for assessment.

The result showed that maps of LCM were more accurate compared to the method of DINAMICA EGO.

In another case, Adedeji *et al*. (2015) studied Gambari Forest Reserve with a view to assessing and predicting dynamics in its LULC. The study investigated the extent and change rate in the area coverage of the forest reserve from 1984 to 2014. The study used Landsat TM of 1984 and 2000 and OLI/TIRS of 2014. They used ArcGIS 10.0 for classification of the images in addition to ground truth data. The nature and trend of change were analysed through the use of LCM and Markov chain model. They used neural networks in IDRISI to predict 2044 scenario. The result of the study showed great decline in the forest reserve extent. They also reported that urban growth in form of settlements contributed a lot to the deforestation process in the area.

Ibrahim *et al*. (2015) evaluated the root causes and consequence of forest clearance on farming activities in Nigeria. Data about the variables in the area between 1975 and 2013 were employed. The study used block recursive and ordinary least square regressions techniques for analysis. The results indicated that fuel wood use was the major direct cause of forest loss while Gross Domestic Product (GDP) and population were the indirect causes that affect fuel wood consumption at 5% and 1% levels respectively. The study recommended the sourcing of alternative energy sources and legislation against indiscriminate forest clearance should be enacted to reduce the direct and indirect causes of forest clearance. Though they did not attempt to predict pattern of deforestation, the major causes of deforestation were highlighted to enable better planning.

Koranteng and Zawila-Niedzwiecki (2015), investigated LULC change in the lower half of the Ashanti Region of Ghana spanning 40 years. The study relied on Landsat images of 1990, 2000 and 2010 to evaluate changes in LULC. CA-Markov was utilized in forecasting ULC changes for year 2020 and 2030. The predicted results revealed that there will be an expansion in urban area while farmlands were expected to decline between 2020 and 2030. Farming is expected to be the leading land use type. Forest lands are expected to decrease from 50% to 10% between 1990 and 2030.

Reddy *et al*. (2017) also carried out a study to predict changes in forest cover in India with LCM. Classified forest cover data of varying dates were used to create the forest covers of 1880 and 2025. Drivers such as nearness to settlements, water bodies and roads; elevation and slope were overlaid with spatial data to establish the correlation involving change in forest cover and these drivers. The study postdicted to 1880 using the Multilayer Perceptron Neural Network revealed that forests occupied 1,042,008 km^2.representing 31.7% of India. It also revealed that between 1880 and 2013, 40% of the forest cover was lost. It was identified that large scale farming and rights of most of forest lands by individuals and non-governmental agencies were the major factors causing deforestation in the area. Six states of the Northeast and one union territory were used for forecasting of upcoming forest cover in 2025 because of the high deforestation rate in the region. The predicted results showed massive deforestation in the Northeastern part and hereafter is expected to affect the other forests greatly before the year 2025.

Areendran *et al*. (2017) investigated temporal and spatial patterns of LULC changes in Northern India to identify deforestation rate, and to predict future scenarios for Kosi River wildlife corridor through the use of geospatial technologies. Satellite imageries of 2009 and 2014 were used in mapping the changes. They used LCM to simulate LULC change distribution for year 2020 and 2030 using present situations. The results revealed that dense forest would decrease by 8.5 km^2 in area, while plantation area would cover 4.31% (27.9 km2) of the area by 2030 if the present condition is maintained. The study shows that human activities such as construction of resorts, residential houses and buildings were the main drivers of deforestation in the area.

2.12 Empirical studies using the different models

2.12.1 Review of empirical works that used Markov chain analysis

Markov chain analysis has long been applied in LULC change modelling by different authors. Iacono *et al*. (2015), stated that the use of Markov chain analysis to study urban environment came to the fore in the 1970s as a substitute to replace large-scale models of urban studies for urban land use prediction. Huang *et al. (*2008) investigated the detection and forecasting of changes in land use in Beijing using geospatial techniques. The authors studied the expansion of Beijing city, its spatial and temporal variability covering a period from 1984–2005 through statistical classification techniques using remote sensing images from Landsat TM and SPOT4 for seven years. The methodology adopted involved three stages: First, using images different dates, LULC changes were detected using remote sensing. On the basis of the result of classification of the images, the process of LULC change with the model of urban growth were analysed by GIS techniques. The authors used Markov, transitional probabilities matrix and the spatial distribution rules of urban land and urban growth intensity. In the end, the association of population, urban land area and GDP were incorporated in a linear regression analysis. The result showed that LULC change detection through images of multi-dates by means of remote sensing is a good way of researching into urban growth. As plausible as the work seems, it did not identify the major drivers of urban expansion by ranking them according to their contribution to the model.

Ayana and Kositsakulchai (2012), also used Markov modelling and remote sensing technologies in a study to assess LULC in the Fincha watershed in Oromiya Regional State, Ethiopia, from 1985 to 2005. Landsat TM of 1985, Landsat ETM+ of 1995 and 2005 were utilised as the base data layers from which the maps of LULC of the area were derived. The LULC maps of Fincha watershed was produced for 1985, 1995, and 2005 from the Landsat images. The general overall accuracy of the respective maps was well over 86%, with KAPPA indices of over 0.83 for the three sets of years.. Generally, both the user's and producer's accuracies were very high. The results revealed that farmland and water bodies expanded in area by 53.59% and 93.10%, respectively. Forest, swamp area, shrub lands and grazing lands declined in landmass significantly. The study observed that the LULC change process were very much unstable. The study found that satellite remote sensing and Markov modelling proved useful in illustrating and evaluating the spatial pattern, direction and rate of LULC change.

In another study, Berakhi *et al*. (2015) investigated changes in LULC and its repercussions in Kagera river basin, East Africa. The study set out to measure LULC changes that occurred from 1984 to 2011, and forecast future scenarios. The study also examined the spatial connection between population expansion/density and LULC changes, and their socioeconomic impacts. To analyse the past and future LULC dynamics, the study used a post classification analysis and Markov model of LULC change. The study measured the past LULC changes between 1984 and 2011 and forecasted potential changes employing multi-level data-sets. The authors also studied how population expansion and policies of government influence LULC change. Data-sets from diverse sources made up of multi-dates images, population, DEM and other supporting data were used. Historical LULC changes were analysed and evaluated to predict future change scenarios. The results showed a substantial expansion in agricultural land area at the detriment of woodland savannah. Generally, changes were more noticeable and fast during the period 1984–1994 phase but were comparatively slow between 1994 and 2011 phase. The phase 1984–1994 witnessed more categories and transition intensities than 1994–2011. The study identified increase in population, expansion in settlement, and local policies as important driving factors of LULC change. The study predicted that future scenarios will indicate expansion in agricultural land use, decrease in woodland savannah and forest vegetation, and considerable loss of wetland to agricultural use. The study did not categorically state which factor contributed more to the model building.

Relatedly, Kumar *et al*. (2014) attempted modelling LULC change using a Markov chain analysis with remote sensing data. In order to appreciate LULC change, the authors studied different LULC classes and their variability in space and time in Tiruchirappalli city from 1998 to 2006, using Satellite images from Indian Remote Sensing (IRS). The Markov model was used for acquisition and understanding LULC dynamics. Model performance was appraised using the classified LULC map taken out from CARTOSAT-1 PAN image and the predicted LULC map from the Markov model. Their result indicates that Markov chain analysis in conjunction with geospatial techniques are competent in successfully depicting the spatial and temporal trend of urbanisation in the area.

Khawaldah (2016) carried out a study on the prediction of future LULC in Amman area with Remote Sensing and GIS-based Markov model. The study was aimed at analysing LULC dynamics in western populated part of Amman and to detect the process of urbanisation and urban growth between 1984 and 2014 so as to simulate future scenarios of LULC in 2030 through the use Markov model. The study relied on Landsat TM images of 1984, 1999 and Landsat 8-OLI images for 2014. The future pattern of LULC map were predicted based on 1999 and 2014 LULC maps using the Markov chain analysis. The results showed that urban area increased by 147% between 1984 and 2014 and was projected to increase by 43.9% between 2014 and 2030 using Markov chain analysis. The revealed areas that will experience significant urban expansion by 2030 will assist urban city planners and decision makers in planning of Amman. The urban growth was traced to the high of population growth and high immigration rate and other social and economic changes.

2.12.2 Review of empirical works that used Multilayer Perceptron

Few works have been done on the use of Multilayer Perceptron (MLP) alone in modelling LULC changes. Most authors prefer combining it with other modelling approaches. Dzieszko (2014) attempted LULC modelling using CORINE land cover data and MLP. The aim was to bring to the fore and explain the key changes in LULC in Poznań Lakeland Mesoregion using database from CORINE Land Cover. The main thrust for identifying the key driving factors in LULC changes in the area was change analysis. The main transitions were grouped together for modelling. In all, eight transitions were recognized were grouped into 5 sub-models with the same driving variables. Every single sub-model was taken together with all sub-models in the last process of change prediction. Driving variables were utilised in modelling the past change process. MLP method was used in modelling the transitions. By means of the past rates of change in conjunction with the transition potential, model pattern for year 2006 was simulated. Model validation was done using CORINE Land Cover 2006 database. The author concluded that past transitions are crucial to predict future transitions.

In another study by Kakkar (2013) the usage of remote sensing and GIS in developing a regional perception on 'Greater Chandigarh Region' (GCR) was carried out. Different sources of database were considered as inputs for carrying out the research. In order to be able to identify built up areas and other land-covers, satellite images of different dates were digitally processed. A classification was done for the three periods of 2000, 2006 and 2012. The vector products were employed in identifying areas of urban expansion among the three epochs. All these LULC features were arranged in Arc GIS, were later taken to *IDRISI Taiga* software. The study was set to categorise the drivers of urban expansion and their precise mathematical relation with this growth. CA-Markov and MLP were tested on 2000 and 2006 data using these drivers, and the 2012 predicted results were authenticated against actual data of LULC of 2012. Of the two models, MLP was the best suited prediction model, and was used in prediction of built-up maps of 2024 and 2048.

2.12.3 Review of empirical works on Artificial Neural Networks (ANN)

Various works have been done on modelling of LULC changes using ANN. Jitendrudu (2006) used artificial neural networks and geographical information systems to model urban growth and forecast future development in Dehradun City. The model considered the physical factors of urban expansion in Dehradun like road network, current development and topographic features. The ANNs were then used in learning the patterns of expansion in the area. The study used GIS in developing the driving variables and remotely sensed data to provide the calibrated data for the model in the form of temporal datasets that permit LULC mapping and change detection. The model testing was done using percentage match metric and urban expansion dispersion metric. The study reveals that urban expansion at the city edges, is the most dynamic zone where the other LULC types are always converted to built-up area. The drivers and the best performing model upon prediction were used to predict the future urban expansion. The study concluded that (1The use of ANN is suitable in modelling non-linear features of urban systems, (3) The model was able to effectively combine the use of GIS and ANN.

Thekkudan (2008) performed a study to evaluate how effective ANN are in predicting locations of urban change in Montgomery county, Virginia. The study attempted the testing of the Land Transformation Model (LTM) using the Stuttgart Neural Network Simulator (SNNS). This research explored the changes of socio-economic and biophysical variables and how they influence model development for Montgomery County, Virginia. The results of the study show a Kappa value of 0.319 and a percent correct metric (PCM) of 32.843%. A ROC value of 0.660 indicated that the model was used to forecast areas of change better than chance. The study concluded that simulation maps from LTM provided an acceptable means for predicting change in urban centres and suburbs for urban planning.

In another study, Ahmadizadeh *et al*. (2014) conducted a study on detecting LULC change through remote sensing and ANN in Birjand, Iran. This study examined the dynamics in LULC in Birjand of Iran using Landsat TM of 1986 and 2010.ANN was used for classification and it resulted into five LULC classes that were delineated which include irrigation farming, pasture, barren land, dry farmlands and urban area. Cross-tabulation was performed to monitor LULC change. The result revealed overall accuracy of 89.67% in 2010 and 88.78% in 1986 image classification and a Kappa statistics of 0.8539 and 0.8424 respectively. The outcome revealed substantial changes in land use for the area. Barren land recorded the highest increase of about 378 percent. The dry farmlands decreased by about 48 % in the period under review. Urban area has expanded considerably by almost 219 %. Irrigation farming increased by almost 17.16 % principally due to population increase. The result revealed how appropriate the application of the ANN technique can be for LULC change detection. The study concluded that ANN was very efficient classifying Landsat images in the area. The study was limited to mere classification of LULC without attempting to model the future scenarios of these changes.

Triantakonstantis and Stathakis (2015) researched on urban growth prediction in Athens, Greece, using ANN. They set out to analyse and model the urban change, between 1990 and 2000 using CORINE LULC maps. The model used driving factors of urban changes (like proximity to roads, slope, etc.) under the ANN modelling approach. The model validation was through comparison of the predicted map of 2006 with the classified map of 2006 for the area. The result shows a high accuracy from Kappa statistics of 0.639 and a Cramer's V coefficient value of 0.648. The study only used a few variables in modelling future land use patterns and it is possible that other variables excluded could have explained better the observed pattern of land use.

Rahimi (2016) in his research on urban land use modelling focused on the smart-growth infill approach. The objective was to use the infill development pattern modelling approach to simulate future urban development through the use of potentials within the city. The method used was the Land Transformation Model (LTM) of urban land use change built on ANN and a GIS. In this method, future growth patterns of Tabriz city were based on trend of historical growth and infill growth pattern. The result reveals a decline of 31.26 % in green spaces and 60.93 % of farmland and wasteland between 2005 and 2021. During the same period, built area was projected to increase by 89.75 %. The study concluded that the use of infill development pattern model is effective in regularizing urban expansion in the years to come. The result of infill growth pattern, reveals the expansion of built area by 40.32% while farmland and wasteland area were projected to decrease by 32.67% until 2021. The approach. not only preserves the green spaces and farmland areas but also recovers and rehabilitates old and worn-out surfaces.

2.12.4 Review of empirical works that used Land Change Modeler

Many researchers have adopted IDRISI-Land Change Modeler (LCM) in studying land use change modelling since its launch by Clark Labs. A few of such studies are reviewed here. Oñate-Valdivieso and Sendra (2010) investigated LULC changes in Catamayo-Chira Basin, Spain. The focus of the study was to categorize explanatory driving factors, and to clarify the connection among these drivers using the Land Change Modeler in IDRISI. Changes in LULC were analysed using the procedure put forward by Pontius *et al.* (2004) to determine within-changes among the class of persistence, gain and loss. The driving factors were assessed using the Cramer's V test. In the end six driving factors were identified which include DEM, total annual precipitation, slope, proximity to watercourse, the type of land and proximity to the early land cover location. After the drivers were selected, maps of transition potential were produced using logistic regression and MLPNN in Idrisi Selva LCM using LULC maps of 1986 and 1996. The study then predicted LULC map of 2001 through Markov chain. The accuracy of the model was validated using confusion matrix, Kappa index, and ROC. Their result indicates that logistic regression performed a little better than MLPNN.

Pérez-Vega *et al*. (2012) compared two models DINAMICA and LCM in order to assess the transition potential maps from these two LULC models considering the same driving factors using the weights of evidence approach and ANN. In order to contrast maps resulting from the models, three techniques of visual interpretation, ROC and difference in change potential index were used. The result showed that DINAMICA had better results as per the transition level while LCM resulted in more correct transition potential maps.

Aithal *et al*. (2013) used Land Change Modeler in predicting changes in land use in a rapidly urbanising landscape of Bangalore. The study was aimed at modelling changes in LULC in a fast growing urban area with 10 km buffer taking into account all agents. The methodology adopted was the LCM in conjunction with CA-Markov to predict the likely land use pattern in 2020 with the information of land use changes between 2006 and 2012. The results revealed an urban growth of 108% with the decrease of green space to 7%. They concluded that the picture of urban growth provided critical information for better planning of Bangalore city.

Mishra *et al*. (2014) employed the LCM in forecasting LULC changes using remote sensing in Muzaffarpur (bihar), India. They recognised LULC change as a significant factor contributing to changes in the environment on all spatial and temporal scales. Their main focus was to analyse the current status and predict the upcoming expansion pattern of Muzaffarpur city, Bihar (India) through the use of images of Landsat satellite of 1988 and 2010. These 1988 and 2010 data sets were used for simulation of change and for preparing simulation map of year 2025 and 2035. The LCM, a module in IDRISI Selva was used in analysing the changes in LULC among the various classes from 1988 to 2008. They also used ERDAS Imagine in preparing LULC classification using supervised classification approach. The neural network module in IDRISI Selva was used in predicting LULC change. The result obtained an accuracy of 72.28% for all the land conversion types.

Friehat *et al*. (2015) investigated urban sprawl in northeastern Illinois, in order to assess its effect on farmland and nature over time. Base maps were prepared from satellite images and change detection was performed to analyse changes overtime. The prediction of future urban growth for year 2020 and 2030 was performed using the LCM in IDRISI Selva. The results showed that from 1989 to 2010, the urban area increased by 82.2%, while farmland and urban open spaces decreased by 25.8% and 32.5% respectively. The simulated maps indicated an expansion of urban land, which will likely result in further decline in farmlands especially in the fringes.

Kumar *et al*. (2015) investigated the use of LCM in predicting future LULC in Vijayawada city. The focus of the research was to analyse the status of the city so as to simulate its future growth using Landsat images of 1973, 2001 and 2014. After classification, LULC images were prepared and used for predicting future pattern of LULC for 2030 and 2040 using the LCM from TerrSet software in IDRISI. Neural network and CA-Markov in LCM of IDRISI was employed in predicting LULC changes. Ancillary data used include dynamic road network from topographic sheets of Survey of India and elevation map from SRTM image. The result showed an accuracy of over 80% obtained in all stages. The study did not identify the driving factors responsible for the predicted changes.

In another study, Megahed *et al*. (2015) conducted a study to model urban expansion in the Greater Cairo Region (GCR), using remotely sensed data and other supplementary data. Three LULC maps of 1984, 2003 and 2014 derived from images of satellite through

Support Vector Machines (SVM) were used. Thereafter, LULC changes were identified using change/no-change maps and comparing already classified maps. Through the use of some selected statistical metrics from FRAGSTATS software, urban expansion pattern in space and time were analysed. The main transitions to urban areas were modelled so as to simulate future patterns for the year 2025 using LCM. The results of the model after validation, showed that 14% of the vegetal cover and 4% of the desert in 2014 will become urban areas by year 2025.

Roy (2016) investigated long term prediction of soil erosion between 1950 and 2025 in a Mediterranean area where rapid urban expansion and LULC changes have been observed. LCM and cross tabulation in IDRISI were used in analysing land cover change. Cramer V coefficient was used in identifying and selecting the significant explanatory variables. The prediction of LULC maps for 2011 were based on three time periods: 1950-1982, 1982-2003, and 2003-2008. These simulations were thereafter compared with the classified map of 2011 to assess the accuracy of the model. Slope, altitude, proximity to urban area in early year, proximity to roads, and proximity to streams were the main topographic and distance variables identified. Additionally, three constraints and incentives were included during the simulation process. The evaluation of the model accuracy was based on Kappa index and confusion matrix. LCM from IDRISI was then used to simulate LULC pattern in 2011. The study however, did not state the explanatory variables that accounted for the predicted pattern.

A study by Mahmoud *et al*. (2016) investigated the spatio-temporal patterns of settlement expansion in Abuja, Nigeria using geoinformation and ancillary datasets. Using Support Vector Machines (SVM) from Landsat images, LULC maps for 1986, 2001 and 2014 were obtained. The overall accuracy was 82%. 92% and 92%

respectively. Quantitative spatio-temporal investigation was performed to identify LULC changes with special attention on the settlement growth pattern of the area. Conversions to the urban class were modelled so as to simulate future patterns for the year 2050 through the use of LCM in the IDRISI. The end result revealed that the urban area expanded by over 11% from 1986 to 2001, 17% from 2001 to 2014. The LCM model predicted LULC changes which indicates a rising trend in the growth of urban areas, which may possibly consume areas allocated for green areas and farmland if care is not taken. The study concluded that combining geospatial technologies with ancillary datasets has greatly enhanced our understanding of how urban growth processes could modify the microclimate of urban areas. Urban growth is also capable of increasing runoff as well as altering the drainage configuration that can lead to floods in urban areas.

Hamdy *et al*. (2017) employed logistic regressions to analyse and classify the drivers of urban sprawl. This study was situated at Aswan area covering the period between 2001 and 2013. Data used in logistic regression was prepared from ArcGIS and IDRISI Selva. The historical images of the area were studied through the use of Google Earth to study urban growth changes between 2001 and 2013. In this study, the authors used a change analyses in post classification with ArcMap and LCM in Idrisi Selva to identify, measure and examine the changes. The LCM is capable of quantitatively assessing different land use changes regarding the gains and losses associated with each LULC category. Detecting the driving forces is the major significant step to simulation of urban expansion in the future and Cramer V coefficient was used in identifying those drivers. A Cramer's V coefficient in the range of about 0.15 or higher is considered useful. The study identified four groups of drivers: Accessibility, Planning and Policies, Services Buildings and Natural eco-environment. The results revealed that urban growth in risk areas to be 59.79 % in 2001, then increasing to 65.45 % in 2013.

Furthermore a study conducted by Saifullah *et al*. (2017), attempted to spatially model LULC change in South Tangerang City, Banten. The study aimed at measuring the LULC change and explaining its dynamics; identifying the spatial structure of LULC change and urban growth rate; modelling the spatial relationship between LULC change and its drivers and predicting the future LULC change sensitivity. Change analysis using post-classification comparison approach was done as a prerequisite to modelling LULC change in LCM in IDRISI. During analysis of change, each date of rectified image was classified separately into given classes. Three sets of Landsat images, Landsat TM (1990), Landsat ETM (2002) and Landsat OLI (2014) were used. A number of techniques were employed classifying the images. Four land classes were obtained after the classification procedure. These include vegetal cover area, open/bare area, urban area and water body. Change analysis was applied to the LULC maps that resulted from the classification. The LULC change analysis were divided into two epochs:: 1990-2002 and 2002- 2014. Multilayer perceptron was used in modelling LULC change sensitivity prediction. The model validation was done with Relative Operating Characteristic reaching 0.804 for 2014, which is good enough to predict LULC change in 2032.

2.12.5 Review of empirical works that used Markov Chain –MLP

Dadhich and Hanaoka (2010) undertook a study to predict urban expansion using multiple land use data of 1989, 2000 and 2002 by combination of MLP and Markov model in Jaipur city of India. The study used MLP to create transition potential areas for each land use class by including spatial variables or factors that affect and influence the urban growth in the area. They also used Multi-layer perceptron neural network approach to calculate conversion probabilities for urban growth which were later used in Markov model for urban growth simulation. Model assessment was done through cross tabulation of the simulated map with the actual map of 2002. The results revealed good matching between actual and simulated urban with difference of only 3% in total urban area and 94% accuracy in 1*1 pixel matching in both data sets.

In a similar vein, Baysal (2013) conducted a study to analyse LULC changes and predict the changes for Malatya, Turkey. Data inputs were Landsat images for 1990, 2000 and 2010 which were classified using the object-based image classification. Classification accuracy was assessed through the Kappa index whose overall results had the value to be 75%. Suitability analysis was performed for the urban category to be used in the modelling process using Multi Criteria Evaluation. The key modifications in the area were the conversion of farmlands and orchards to urban land. Simulation for the future was performed after detecting the changes using Cellular Automata and Markov Chain approach on one hand and MLP and Markov model approach on the other hand with the support of the suitability analysis. For model validation, both models were used to simulate scenario for 2010 using the 1990-2000 change data. The maps were validated through comparison of predicted maps with classified maps for the corresponding years, different kappa statistics were calculated. The results revealed that the approach of using MLP-Markov Chain yielded a higher overall accuracy, and was subsequently employed in predicting the pattern of LULC for the year 2020. The end result of prediction reveals that; the urban centres would expand to 1575ha and -936ha of farmlands and orchards will be converted to urban centres if the current trend is maintained.

Furthermore, Razavi (2014) studied the dynamics in LULC in Kermanshah City, Iran in order to predict the trend of LULC changes using ANN and Markov Model. Landsat images of 1987, 2000 and 2006 were used. The results showed declining trend in garden and green space area, range land and forest. Conversely, there was expansion of urban area, farmland and water signifying that degradation in the area is on the increase due to the growth in the urban area and farmland. Lastly, the predicted LULC classes for 2025 were done with Markov Model. Results from change prediction matrix on the basis of the maps of years 1987 and 2006 showed that most of land cover classes will remain unchanged between 2006 and 2025. The explanatory variables were however not identified.

Masud *et al*. (2016) carried a study to monitor and predict LULC change with Markov model and Multilayer Perceptron in Sahiwal Tehsil. The study employed tools of RS and GIS. Three Landsat TM 1999, 2009 and 2014 were used as data sources and a supervised classification approach using maximum likelihood classifier was adopted. In the end five LULC classes including vegetation, urban area, water, barren land and cultivated area were extracted. In addition, CA-MARKOV and MLP _MARKOV models were used for projecting LULC changes in the area. The projected images of 2014 from both models were then compared with a base map of 2014 and MLP_MARKOV was selected for projecting 2019 LULC changes. The projected LULC classes for 2019 showed similar trends with an increasing trend in cultivated land.

Zhai *et al*. (2016) worked on prediction of change in LULC in Long Island Sound Watersheds (LISW) using nighttime light data. The focus of the study was to model the LULC changes from 1996 to 2001 and 2006 in the LISW in the area, which has undergone urban expansion and deforestation. The low-density development pattern was a major factor in deforestation and the growth of urban areas. The study reported that the main driving factors were proximity to roads, proximity to developed areas, and economic and social drivers, such as population density and nighttime light intensity. The study also evaluated and compared the results of logistic regression–Markov model to that of MLP–MC model to determine which one would give a better result. The results revealed that both models were able to guarantee high accuracies in their simulation, but the MLP–MC model produced superior performance. In the end, MLP–MC model was used in predicting land use map for 2026 which indicated continued deforestation and increase in urban growth.

2.13 Research Gaps

The literature has revealed that so far, not much has been done on LULC change modelling to address land use transformation processes in Benue State. Previous attempts were made to characterise or model land use change in Abuja, Akure, Bauchi, Damaturu, Gombe, Ibadan, Kano, Kazaure and Lagos but not much has addressed the peculiarities of Benue State. Another gap is the impact of LULC transition processes with particular priority on urban expansion and changes in forest cover. Many authors have only focused attention on either one or the other.

2.14 An Appraisal of the Reviewed Literature

Attempt has been made here to review different modelling methods stating their merits and drawbacks and related researches on modelling of urban growth and deforestation. It is pertinent to note that various factors play leading roles in determining various land use patterns in different localities as shown in the reviewed works. It is also clear that different methodologies exist in achieving particular set objectives in urban growth modelling.

Different model approaches have been adopted in modelling changes in LULC in general and urban growth and deforestation in particular. The choice of a particular model or a combination of models is greatly influenced by different factors. The creation of a module like LCM in IDRISI which the MLP and MC combined is of great value in land use modelling.

This study used driving factors to predict LULC changes without considering spatial attributes like socioeconomic data. It used LCM in IDRISI, to predict urban expansion and its implication on deforestation. In several of the studies reviewed, Land Change Modeler demonstrated to be a powerful modelling tool to predict urban growth including land cover changes. The modelling methods embedded in the LCM include MLPNN, Markov chain, and regression models. Studies have shown that results generated through LCM in neural networks are more accurate than the results from other models (Fuller *et al*., 2011; Khoi, 2011; Pérez-Vega *et al*., 2012). It is against this background that this study used the LCM in IDRISI as used by Saifullah *et al*., (2017) and Zhai *et al*., (2016) by combing Multilayer perceptron with Markov chain (MLP – MC) in modelling and predicting urban growth in Benue State.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Research Design

Spatial information technology is defined as the information technology system of space observation, acquisition, storing, processing, retrieval, displaying, managing, manipulating, and analysing the spatial information on the surface of the earth with a view to studying and supporting the sustainable development of society, and making decision for economic development (Li *et al*., 2011). It is a combination of remote sensing, GIS, Digital Cartography, GPS and Database Management Systems. Spatial information technology involves the use of satellites and computers in capturing, checking, integrating, storing, analysing, manipulating and managing of image (vector and raster) data of the earth and its environment. Then, computer literacy is a very strong requirement in this technology for every user and researcher.

3.2 Data Types and Sources

The data utilised for this study was from primary and secondary sources. The primary data source collection is first-hand information and comprises personal observation, taking of pictures; and taking of locational points using handheld Global Positioning System (GPS). The GPS was in addition utilised for ground truthing during image classification. The secondary data used consists of Satellite Remote Sensing imageries, Digital Elevation Model (DEM), Population data, Road network, Rail network and drainage network characteristics.

3.2.1 Satellite remote sensing imageries

Satellite imageries used included Landsat TM (1987); Landsat ETM+ (2007); and Operational Land Imager (OLI) (2017). The Landsat imagery dataset was sourced from the *Earthexplorer* platform from United States Geological Surveys (USGS), Global Land Cover Facility (GLCF) and GloVis. Changes in LULC were assessed using data from Landsat satellites series such as (Landsat TM, ETM and OLI). Table 3.1 gives a summary of the image characteristics for the dataset used. Dry season images of the three data sets were acquired from January to March so as to minimise the impacts of clouds that are prevalent during the rainy season. Because the images are from the same season and comparable climatic conditions, it enhanced the classification as the spectral reflection of most features are easily comparable across the different images. In addition, high resolution Google earth images were used to aid in classification.

Table3. 1: Specifications of Satellite Imageries Used

Satellite	Path/Row	Sensor	No of Bands	Bands used	Date Acquired	Spatial Resolution
Landsat	188/54,55 187/55,56	TM	7	NIR, R, G (4,3,2)	29/01/1987	30m
Landsat	188/54,55 187/55,56	ETM+	8	NIR, R, G (4,3,2)	21/12/2007	30m
Landsat	188/54,55 187/55,56	OLI	11	NIR, R, G (5,4,3)	16/02/2017	30m
ASTER GDEM*	-	Radiometer	1	-	2011	30m

TM= Thematic Mapper, ETM+= Enhanced Thematic Mapper Plus, OLI = Operational Land Imager: ASTER= *Advanced Spaceborne Thermal Emission and Reflection* Radiometer
Source: Modified from, (2015)* http://www.gisat.ez/content/en/products/digital-elevation-model/aster-gdem

3.2.2 Other ancillary data used

The Digital Elevation Model (DEM) data used was the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) DEM for the year 2011, (Table 3.1). The data is a raster data format, with a 30m resolution and a scene coverage of 1^{o} x 1^{o} (approximately 111 km x 111 km). The data were downloaded using the *Earthexplorer* online platform from United States Geological Surveys (USGS).The DEM was clipped to the area of study. The DEM was used for the determination of slope and elevations of points which affect the cost of construction and were used as drivers in the model. Higher slopes and marshy areas attract higher cost of construction as opposed to plain and gentle slopes.

Population data- Population data were sourced from the National Population Commission. The population of the 23 local government areas was mapped to produce the population density of the state.

Transportation network- Major roads and rail network were mapped from Google Earth in order to have an up-to-date database of the transportation network in the state.

Drainage network characteristics- The major water bodies in the state (rivers and lakes) were mapped from Google Earth to ensure higher accuracy.

All these ancillary data were used as drivers during modelling and were targeted at modelling and predicting the pattern of urban growth in Benue State.

3.3 Tools and Materials Used

The tools used for carrying out the research were;

i. ArcGIS 10.2 used for pre-processing of images and vector data.

ii. ERDAS Imagine 2014, used for classification and accuracy assessment of classification

iii. Idrisi Selva, used for change detection and modelling.

iv. Google Earth Image, used for delineation and updating of transportation and drainage maps. It was also used in preparing point data files for modelling.

v. Global Positioning System-This was used for classification and data validation

3.4 Data Analysis: Specific Approaches to Achieving the Objectives of the Study

3.4.1 Mapping the types and extent of LULC classes in Benue State

This objective one was achieved through the examination of Landsat TM of 1987, ETM+ of 2007 and OLI of 2017 images acquired and their subsequent classification. In order to map the types and extent of LULC classes in Benue State, the data were subjected to some processing and analytical procedures which are outlined here.

3.4.1.1 Data pre-processing

Landsat TM, ETM and OLI were pre-processed, so that inherent errors and formatting that are required for further direct processing of the data were taken care of. The downloaded Landsat images were in separate bands and need to be layer stacked. This is a process whereby different bands of an image are joined together to form a single multispectral image and was done using ERDAS Imagine 2014. The produced multispectral image from the scenes was then mosaicked. Specifically, the three (3) satellite imageries, Landsat TM (1987); Landsat ETM+ (2007); and Landsat OLI (2017) were corrected radiometrically through haze removal operations, so that radiometric errors added to data, due to atmospheric scattering were corrected, using the ERDAS Imagine 2014 image processing software.

Radiometric correction refers to the elimination of alterations in the amount of electromagnetic energy received by each detector. A diversity of agents are capable of causing distortion in the image. Radiometric correction involves the procedure of histogram matching of the satellite images from different time periods. Focal analysis module in ERDAS 2014 was used in removing scan lines on images especially the 2007 Landsat image. Geometric correction refers to the process of co-registration of the satellite images, so as to enhance a better overlap of the images in the best possible way. This function was achieved in IDRISI through the RESAMPLE module. This is very essential due to the fact that some of the essential methods are based on the comparison of the two images from different time periods, e.g. supervised classification Although most of Landsat images have been already georeferenced, images with a lot of cloud cover normally reduce the geometric accuracy, and hence required to be geo-referenced.

In order to obtain images that are cloud free, mosaicking of two or more images of the area was performed so as to replace pixels affected by clouds with cloud free pixels from another image. In order to do this, accurate geometric registration among images was done. It is imperative that mosaic is done using in the same season to ensure that the images are compatible. In effect, the appearance of vegetation fluctuate greatly throughout the year; hence, all the images need to be obtained in the same month to avoid variability (Congedo and Munafò, 2012). The area of study covers more than a single scene of Landsat. As a result, several scenes were acquired as shown in Table 3.1. The DEM data were used to derive elevation and slope characteristics of the area.

3.4.1.2 Image Rectification

This operation was carried out by clipping Benue State using the already mosaicked scenes. The shapefile of Benue State was used to clip from the larger scenes that were earlier mosaicked. The technique used was the subset method in ERDAS 2014 and the desired shapefile of Benue State was used as the Area of Interest (AOI). The preference of this technique was based on its simplicity of use and its higher accuracy. This is because the mosaicked area is larger than the Area of interest (AOI) and it helps in defining precisely the study area.

3.4.1.3 Image Enhancement

Image enhancement is the alteration of images so as to make them better suited for human viewing In order to get better visual quality and outlook of an image to ease classification and interpretation, image enhancement is necessary. It increases the contrast among different features thereby enhancing easy identification of features and subsequent classification. After image enhancement, band combination processes were performed to select the different bands which will enable the classification of a given earth surface feature. The key motive of colour composite is to identify certain brightness values which are connected with some surface features. A combination of band 4,3,2 (for RGB) was done for the Landsat TM and ETM images and 5,4,3 for OLI images as this produced superior results. The choice of these band combination is based on the fact that it is appropriate for studies in urban application and defining water, land and vegetation boundaries. In this study ERDAS Imagine 2014 image processing software was used in enhancing the images using histogram equalization and linear contrast stretching. The rationale behind this is to enhance the amount of information on the image.

3.4.1.4 Image Classification

Image classification was done through a per-pixel image classification approach using supervised classification algorithm. This is an approach for classifying areas on the image that are spectrally alike through identification of “training” sites of features that are known and then generalizing their spectral signatures to other features that are unknown (Mather and Koch, 2011). It is a process of using samples whose identity is known to categorize samples whose identity is unknown. A Maximum Likelihood algorithm of supervised classification was adopted because of the author's familiarity with the terrain. This method was chosen because it is easier to accomplish and more so, the large volume of images to be interpreted could not warrant the use of visual on-screen interpretations. The visual method depends largely on the skill and familiarity of the interpreter and is therefore prone to much error if the interpreter is not well experienced.

The identification of training sites used was based on spontaneous recognition and logical inference both of which are products of visual interpretation. Spontaneous recognition refers to the capability of the interpreter to recognize objects at a glance such as agricultural plots. In logical inference, the interpreter draws conclusion based on ground control points, his professional knowledge and field experience over the years(Congedo and Munafò, 2012).

The Maximum Likelihood classifier is among the most frequently used classification algorithms (Huang *et al*., 2009). Maximum Likelihood classification presumes that the probability distributions for a particular class follow the normal distribution model (Richards and Jia, 2006). This is denoted by this equation as described by Richards and Jia, (2006), is:

$$g_i(x) = \ln p(\omega_i) - \tfrac{1}{2} \ln |\Sigma_i| - \tfrac{1}{2} (x - m_i)^t \Sigma_i^{-1} (x - m_i) \qquad \textbf{(3.1)}$$

where: ω_i = class (where i = 1, . . . M and M represent the total number of classes)

x = pixel vector in n-dimension where n represent the number of bands $p(\omega_i)$ is the probability that the correct class is ω_i occurs in the image and is assumed the same for all classes

$|\Sigma_i|$ = determinant of the covariance matrix of the data in class ω_i

Σ_i^{-1} = inverse of the covariance matrix and m_i = mean vector

The Maximum Likelihood classifier assigns pixels to the categories that have the biggest probability to decide class membership of a given pixel. In choosing training sites, colour composite images which bring to light certain surfaces, and aid photo-interpretation were viewed. Each band was allocated to a particular colour: Red, Green and Blue (RGB)(NASA, 2011). A Supervised classification of Landsat image data for the three periods (1987, 2007 and 2017) was done with the Maximum Likelihood Classifier to identify and map LULC classes. The first stage entails the classification of Benue State while in the second stage, four major cities in four Local Government Areas (Makurdi, Gboko, Otukpo and Katsina-Ala) were classified. In order to ascertain the areal coverage and change rate in the LULC of Benue State, these variables were determined: Total area (T_a), Changed area (C_a), Change extent (C_e) and Annual rate of change (C_r) These termss can be illustrated by these formulae as given by: Yesserie (2009)

$$C_a = T_a(t_2) - T_a(t_1); \quad \textbf{(3.2)}$$

$$C_e = C_a / T_a(t_1); \quad \textbf{(3.3)}$$

Where t_1 and t_2 are the earlier and later dates of the LULC.

Table 3. 2: Classification Scheme Adopted

S/N	Class	Description
1	Water bodies	Open water features including lakes, rivers, streams, ponds and reservoirs.
2	Urban Areas	Urban and rural areas as well as homestead area such as residential, commercial, and man-made features.

3	Grassland	Areas mostly occupied by grasses with vegetated sandbars and grazing lands
4	Bare surface	bare land and exposed river sand building sites, mine sites, open spaces, bare soils.
5	Forest	Forest vegetal cover, mixed forest, plantations, parks and vegetated lands.
6	Agricultural/Farm lands	Areas consisting of cultivated lands used for the production of annual crops, perennial woody crops. agricultural lands, and crop fields.

Source: Modified from Anderson *et al*., (1976)

`3.4.1.5 Fieldwork and ground-truthing

Fieldwork was done so as to collect geographical data to map land cover and for determining accuracy of the classification. Ground-truth data were also acquired on spatial features from the study area, such as spatial location, LULC, road network using GPS. A total of 235 sample coordinate points were taken for the whole of Benue State. This was made up of 67 in Makurdi, 62 in Gboko, 56 in Otukpo and 50 in Katsina-Ala. This can be seen from Appendix B1 and B2.

Ground truthing enabled the collection of inference data and to increase ones' knowledge of land cover conditions. It also enables familiarity of features as they appear on the satellite image on the computer screen, for verification and validation of the interpreted results. The process of identifying and transferring ground points onto the screen was done using the GPS. Each LULC class was physically identified in the field and the position of the area recorded using GPS which was later transferred to the image whereby it was easier to identify the appearance of such land uses and land cover on the screen. Inaccessible areas were complimented with the use of Google earth images. In summary, both visual interpretation and digital image classification methods were employed in data interpretation.

3.4.1.6 Sampling technique

The sampling technique adopted in selecting control points for accuracy assessment was the stratified random sampling. There are two primary purposes to implement stratification in the accuracy assessment: 1) when the layers are of importance for reporting results and 2) when there is the need to increase the precision of the accuracy and area estimates (Olofsson *et al*., 2014). It avails one the opportunity of selecting control points within the different LULC classes (strata) to be used for determining accuracy. Each of the LULC classes had control points proportional to the size of the area covered.

3.4.1.7 Accuracy assessment

Classification accuracy could be inhibited by the sharpness of images used and dearth of small details with inescapable oversimplification impact and as a result, errors are always expected. This is the reason why the errors in every classification should be stated and explained (Siddhartho, 2013). Accuracy assessment is a procedure whereby the final classified map is compared with ground truth or reliable sources so as to assess the extent of agreement or disagreement. This study adopted the Error Matrix approach as used by Friehat *et al.* (2015) in determining classification accuracy.

Accuracy assessments of the classified maps (1987, 2007 and 2017) were done by means of the error matrix (ERRMAT in Idrisi Selva). The error matrix assesses accuracy via four parameters which include Kappa Index of agreement (KIA), overall, user's and producer's accuracies. The overall accuracy spell out the total pixels accurately classified and is derived by dividing the total number of pixels accurately classified by the overall number of pixels contained in the error matrix. The producer's accuracy defines the probability of a reference pixel being accurately classified. It represents the error of omission. It defines the number of samples accurately classified for a particular column divided by the total for that column (Sarmento, 2015) . The omission errors arise when an area is excluded on the map from the land cover class it should belong to. The user's accuracy conversely defines the probability that a classified pixel on a map really represents the same class on the surface. User's accuracy represents the error of commission. The error of commission defines the inclusion of an area on the map in a land cover class in which that area should not be included. It is determined by dividing the number of samples accurately classified for a particular row by the sum of the row, (Sarmento, 2015). The Kappa index determines the agreement between a classified map and a reference map (Congalton and Green, 2008). All accuracy parameters have index values that ranges from 0 to 1, where 0 symbolizes poor and 1, excellent classification accuracy.

The Kappa statistics formula put forward by Cohen Kappa in 1960 and modified by Jenness and Wynne (2007) was used for calculating Kappa statistic. It has the advantage of correcting for chance agreements between the observed and simulated values.

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \qquad \textbf{(3.4)}$$

Where :*i* is the class number

N is the sum of classified pixels that is to be compared with ground truth

mi,i is the number of pixels belonging to the ground truth class i,that have also been classified with a class i (that is, values along the diagonal of the confusion matrix)

Ci is the total number of classified pixels belonging to class *i*

Gi is the over all number of ground truth pixels belonging to *i*

Kappa value changes from -1 to +1 and the meaning of these values are:

< 0: Less than chance agreement

0.01–0.20: Slight agreement

0.21– 0.40: Fair agreement

0.41–0.60: Moderate agreement

0.61–0.80: Substantial agreement

0.81–0.99: Almost perfect agreement. (Borana and Yadav, 2017).

A simpler method of determining Kappa in an error matrix with number of rows and columns is given by Siddhartho (2013):

$$K = \frac{(NA-B)}{(N2-B)} \qquad \textbf{(3.5)}$$

Where, N = sum number of observations in the error matrix

A = the sum of correct classifications contained in the diagonal elements

B = the sum of the products of row total and column total for each LULC type in the error matrix

Simply put:

$$\check{K} = \frac{\text{Observed Accuracy} - \text{Chance Agreement}}{1 - \text{Chance Agreement}} \qquad \textbf{(3.6)}$$

Under ideal conditions, the accuracy of the classification ought to be assessed by overlaying an already existing LULC map. Due to absence of already existing LULC classification for Benue State, handheld Garmin GPS receiver was used to take coordinates points of selected LULC to serve as ground control points from the field complimented with Google Earth images. These points were established through stratified random sampling by taking coordinate at ±3m accuracy as was used by Appiah (2016).

3.4.2 Analysis of the trend of LULC changes from 1987- 2017

The methodology for achieving this objective two was through the use of Change Analysis Tab in IDRISI. Here, the focus was on the spatial trend of change to directly detect the definite spatial nature of every major land change that has occurred in Benue State from 1987-2007, 2007-2017 and1987-2017. The principle under which this pane works is the polynomial order in which the spatial outline and trend of LULC between two epochs is generalized. It computes trend surface polynomial equations up to the 9th order for spatial data sets, and then interpolates the surfaces based on those equations. The common equation for the polynomials fitted by TREND as given by(Saifullah, Barus, & Rustiadi, 2017b) is:

$$Z = \sum_{i=0}^{k} \sum_{j=0}^{i} b\text{ij } X^{i-j} y^{j} \qquad \textbf{(3.7)}$$

Where k = is the maximum order to be fitted;

b = coefficient of the polynomial equation;

both *i* and *j* are iteration variables related with *k*, in which *i = 0,…k* and *j = 0,…i*. (Saifullah et al., 2017b)

3.4.2.1 Determining the rate of rural-urban land conversion in Benue State

This section is also part of objective two of the study. After a successful classification, the LULC classes for 1987, 2007 and 2017 were compared to establish the change extent. The extent of changes were divided by the time interval between the initial and the later date to arrive at the rate of rural- urban conversion. This operation is represented by the following equation as given by Yesserie, (2009):

$$C_r = C_e/(t_2-t_1); \qquad \textbf{(3.8)}$$

Where C_e = Change extent

t_1 and t_2 = the initial and later times respectively of the LULC classified.

3.4.3 Modelling the growth of the urban areas of Benue State

The modelling approach adopted was the LCM in Idrisi Selva software. For LCM to be used, certain conditions have to be satisfied:

i) The land cover maps must have a common legend.

ii) That the classes in both maps must be the same and in a particular order.

iii) That the background in both maps must be the same and should have a zero value.

iv) That area extent as well as resolution and coordinates of both maps are the same (Eastman, 2012). In executing modelling of urban growth, the following procedure was adopted.

3.4.3.1 Change detection procedure

Many change detection algorithms exist. They include post classification comparison, image differencing, image ratioing, multi-date composite image. While image differencing, can only offer change or non-change information, post classification approach can offer "from-to" change matrix. Besides, it is the commonest change detection technique, and has effectively been used in detecting and monitoring urban growth and urban dynamics (Rawat, *et al.,* 2013 and Sahalu, 2014). As a result, the study adopted post classification technique LCM in IDRISI to find out changes in LULC between 1987and 2007, 2007 and 2017, and 1987 and 2017. The Land Change Analysis panel has the capability to create a diversity of change graphs and maps, which aid in understanding current land cover gains, losses and change "from-to" map. It offers a quick assessment of changes quantitatively, letting the investigator to make assessments of gains and losses, persistence, net change and specific transitions displayed as maps and graphs (Eastman, 2012). The spatio-temporal changes of urban growth were also assessed by producing the land use and land cover maps for the three epochs (1987, 2007, and 2017) on maps were again classified to show areas that are urban and areas that are non-urban. In this study, LULC maps of Benue State derived from classification of image for 1987and 2007 were used for the analysis.

3.4.3.2 Transition potential modelling with LCM

The transition potential was used to generate transition potential maps of allowable accuracy so as to run the actual modelling. Here, a group of transitions were set into sub-model and investigate the potential power of explanatory variables. It has provisions for adding variables in static or dynamic form based on their impact on urban growth (Eastman, 2012). Static variables never vary with time. Dynamic variables are those that change with time like distance to urban centres, distance to existing infrastructure and such distances are recomputed at intervals during the prediction process.

3.4.3.3 Development of model variables for Benue urban areas

Procedurally, modelling of the selected transitions using selected variables followed the analysis of the LULC changes between 1987 and 2007 and identifying the major transitions. The model was run twice; the first was done to produce transition potential map after the chosen drivers were included while the second was done to produce a map of prediction using the transition potential map produced earlier. These variables exist in two forms: constraints and factors. Constraints are those variables that inhibit the growth of urban areas while factors are those that favour the growth of urban areas. (Eastman, 2012).

The list of constraints used were roads, existing urban centres, water bodies while the factors include proximity to urban areas, proximity to roads, proximity to rivers, slope, elevation, population density and likelihood image. The empirical likelihood transformation is a valuable way of including categorical variables into the analysis. It was created by finding out the relative frequency with which the different types of land cover come about within the transition areas (1987 to 2007).

3.4.3.4 Transition sub-models development

The main thrust of this research was the modelling of urban growth. Consequently, all the changes (transition) from other land cover classes to urban area were utilised as a transition sub model. All the sub-models that relate to urban area were grouped into urban area sub-model as the emphasis is on modelling urban growth and most of the sub-models share the same variables for prediction. These variables are proximity to urban area, roads, rivers, railways with elevation, slope, population density and the evidence likelihood of transformation to the urban area. The likelihood image was prepared by using a Boolean map derived from the changes from all land cover classes to urban area that was created during the change analysis stage using the 1987 land cover. Through the combination of both maps with a variable transformation method, the likelihood image was produced. The evidence likelihood image is a technique of including categorical variables into the model. MLP as one of the options has the capability of modelling multiple transitions as one sub-model and all transitions to urban area were assigned a common sub-model name. This generated a series of transition potential maps -- one for each transition.

3.4.3.5 Test and selection of driver variables

This option offers a fast method of testing the extent to which a particular variable can explain the observed pattern. It shows the extent to which the variables are related with the distribution of land cover classes. The instrument of measure of association commonly employed is Cramer’s V coefficient. Cramer’s V is a measure of association between a land cover change driver and a category. The Cramer’s V, has a array of values varying from 0 to 1. A variable with a high Cramer’s V is an indication that it has a good potential explanatory value. It must, however, be noted that this is not an indication of a strong performance since other complexity of the relationship have to be taken into account.

The MLP feedback on variable power is a post-training procedure that is particularly powerful. It can be used to evaluate the value of the model and make adjustments by removing variables with no predictive capability (Eastman, 2012). A value as low as 0.15 or greater is considered to be good and worth being included in the model.. All the variables used in the modelling process were subjected to the Cramer’s V to ascertain their power of explaining urban growth in Benue State.

3.4.3.6 Transition sub-models structure

In the Transition Sub-model, all the transitions that occurred involving the two land cover maps 1987 and 2007 were listed. Here, it is required that specification should be made of which transitions is to be employed in creating the transition potentials (Eastman, 2012). For this study, all significant transitions from all land cover categories to urban areas between 1987 and 2007 were included as this is the main focus of the research. In addition, key transitions between other land cover categories were also included as they have a substantial function in the changes in the area.

After all the model variables have been chosen here, each transition was then modelled in the Run Transition Sub-Model. In order to enhance improved end results on the accuracy of MLP, key transitions were included in the transition sub model (Eastman, 2006). On the basis of this, transitions such as from all land cover classes to urban centres, forest to farmland, forest to grassland and forest to bare surfaces were considered. In the end, the transitions so chosen were set into sub-model status. Both dynamic and static variables were considered.

3.4.3.7 Run transition sub-model

This is the stage at which the modelling of transition sub-models was carried out. This phase runs the specified transition sub-model for the five locations. MLP was employed in modelling the selected transitions in LCM. The choice is based on its capability to model many transitions at a time as opposed to the other methods which can only model a solitary transition at a time.

3.4.3.8 Change demand modelling

This is the stage at which the amount of change that will occur in 2030 using the Markov chain prediction process occurred. Here, the Markov chain was utilised in determining the quantity of change using the 1987 and 2007 LULC maps along with 2017 and 2030. The Markov Chain enabled the determination of precisely the quantity of land that would be anticipated to transition from 2017 to 2030 on the basis of prediction of the transition potentials into the future and generates a transition probabilities file. The resultant file consists of a matrix that notes the probability that every one LULC class will change to every other class. The transition potential modelling for all included transitions was completed before performing change prediction.

3.4.3.9 Validation test of the model

The capability of the model to correctly predict is tested by using the model to predict to a future date of already known land condition, this is known as the validation test (Eastman, 2012). The validate module in Idrisi was used for the validation process. It offers a relative analysis based on the Kappa Index of Agreement (KIA), which is a statement of relative accuracy, attuned for chance agreement. Validate process offers numerous measures of agreement with each having a special type of Kappa (Pontius, 2000). These measures are Kstandard – the standard KIA and Klocation-Kappa for location (of correctly predicted cells). After the validation, the model was employed to simulate the LULC patterns for the year 2030. The Validation panel offers an opportunity to assess the quality of the prediction of land use map relative to a reality map. This was done by running a 3-way cross-tabulation between the prediction map of 2017 and a map of reality 2017..The result of the validation is shown in this format where:

A | B | B = Hits (green) – Model predicted that there will be change and it occurred

A | A | B = Misses (red) – Model predicted absence of change but it changed

A | B | A = False Alarms (yellow) –Model predicted change but there was no change

3.4.4 Predicting future LULC pattern by 2030

3.4.4.1 Change allocation

The prediction of urban scenarios for 2030 was achieved through the use of Change Allocation panel in the LCM Module of IDRISI. In order to accommodate some changes in the form of the variables, some dynamic variables were selected and included in the prediction process. Constraints and incentives were also added to the model in the prediction. In the prediction, both hard and soft change prediction maps from the Change Allocation panel were produced. A hard prediction is an assurance to a particular state. The output is a land cover map with the same classes as the inputs. On the other hand, the soft prediction is a continuous mapping of susceptibility to change for the chosen set of transitions. It does not predict the exact change but rather, the extent to which those areas have the correct setting to change. The hard prediction produces only a sole result while the soft prediction is a complete assessment of potential to change.

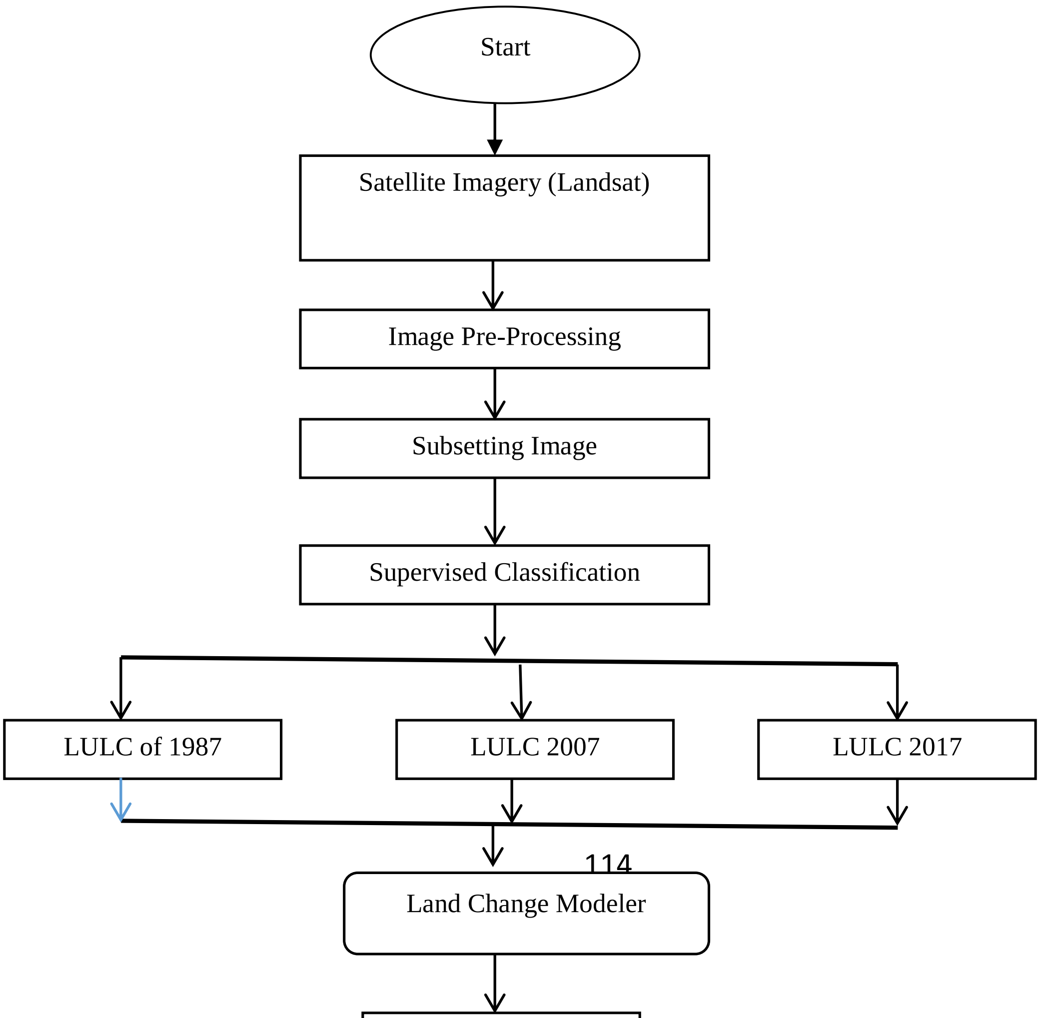


Figure 3. 1: Flow chart showing the Methodology

Source: Modified from Jain *et al*. (2017) and Roy (2016)

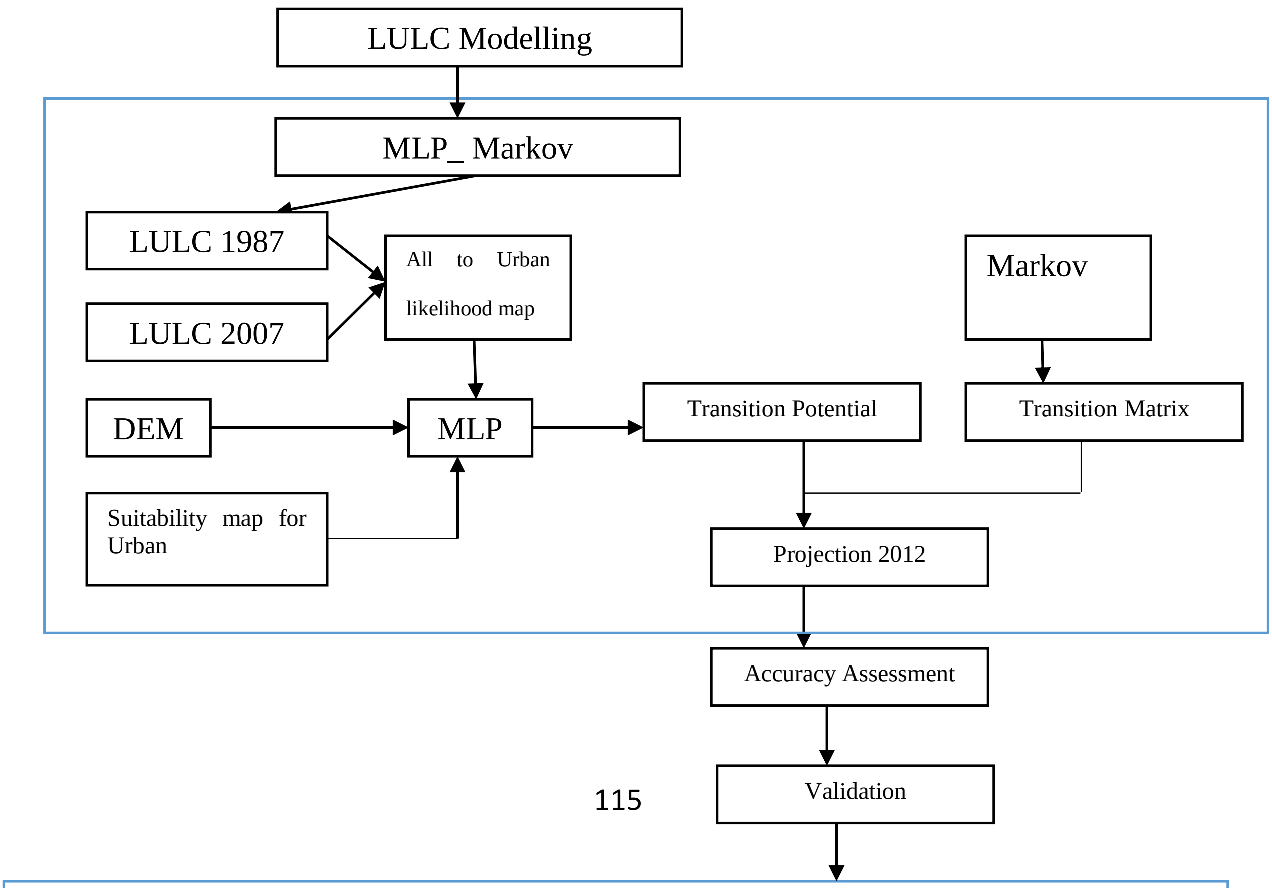


Figure 3 2: The Schematic Flow Chart of the model

Source: Modified from Jain *et al*. (2017) and Roy (2016)

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Classification of LULC for 1987, 2007 and 2017

The results of classification for the LULC changes in 1987, 2007 and 2017 are presented using tables, figures and charts to illustrate and interpret all LULC classes in the three periods. The results are discussed immediately as they are presented for the state and the four cities Makurdi, Gboko, Otukpo and Katsina-Ala+ in the Local Government Areas (LGAs).

4.2: Extent of LULC Types in Benue State

The LULC distributions for the three periods for Benue State are shown in Figures 4.1, 4.2, 4.3 and Table 4.1. so as to achieve objective I

Table 4.1 shows that Urban Area increased from 40106 ha (1.28%) to 75711ha (2.42%) between 1987 - 2007 and further increased to 99187 ha (3.17%) in 2017. The urban area concentrated around Makurdi, Gboko, Otukpo and Katsina-Ala townships. Forest land decreased from 1031389 ha (32.95%) to 712679 ha (22.77%) and u566203 ha (18.09%) during the same periods under consideration. This result agrees with the works of Oyinloye and Kufoniyi (2011) where they showed that Akure Between 1987 and 2007, Grassland appreciated from 1312974 ha (41.94%) to 14536.41 ha (46.43%). It further increased to 1707891 ha (54.55%) by 2017. Farmland increased from 68831 ha (21.99%) to 853283 ha (27.26%) from 1987 -2007 but declined to 679232 ha (21.7%) in 2007. Bare surface and Water body recorded minimal changes during the period.

urban area has been on the increase while the forested area has been on the decline.

Table 4. 1: Area Statistics of LULC in Benue State for 1987, 2007 and 2017

Land cover Class	1987		2007		2017	
	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)
Water Body	23642	0.76	21108	0.67	12422	0.40
Urban Area	40106	1.28	75711	2.42	99187	3.17
Grassland	1312974	41.94	1453641	46.43	1707891	54.55
Bare Surface	33963	1.08	13964	0.45	65466	2.09
Forest	1031389	32.95	712679	22.77	566203	18.09
Farmland	688309	21.99	853283	27.26	679232	21.70
Total Area	**3130400**	**100**	**3130400**	**100**	**3130400**	**100**

LULC maps were also created for the period to show spatial pattern as shown in Figures 4.1- 4.3. It is clear from the results that Urban area is consistently on the increase while forest lands are consistently on the decline. This result is in agreement with the studies conducted by Ayila *et al*. (2014) in Kano and Wang and Maduako (2018) in Lagos that urban areas have continued to increase while the forest areas are on the decline.

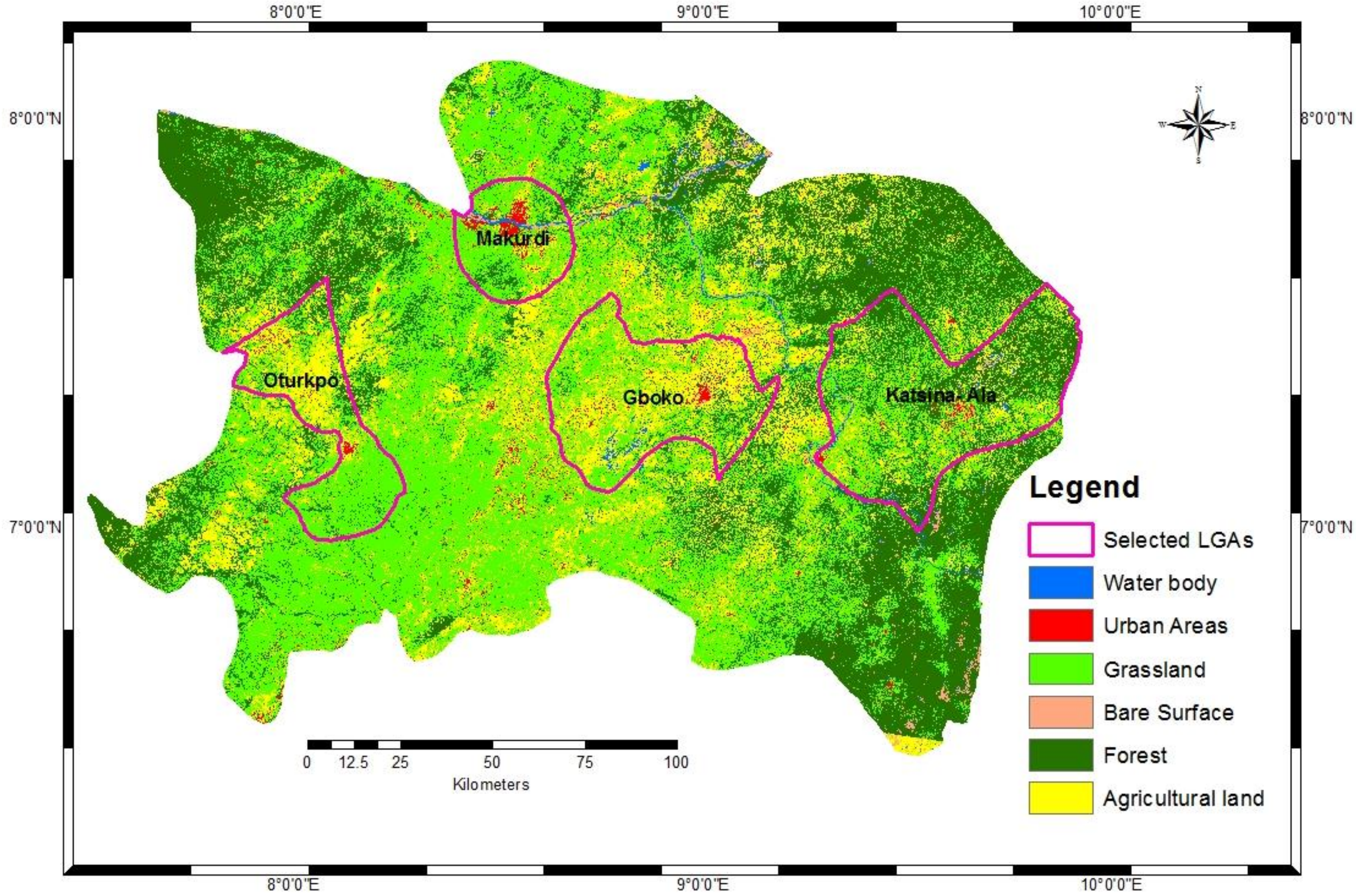


Figure 4. 1: LULC Map of Benue State for 1987

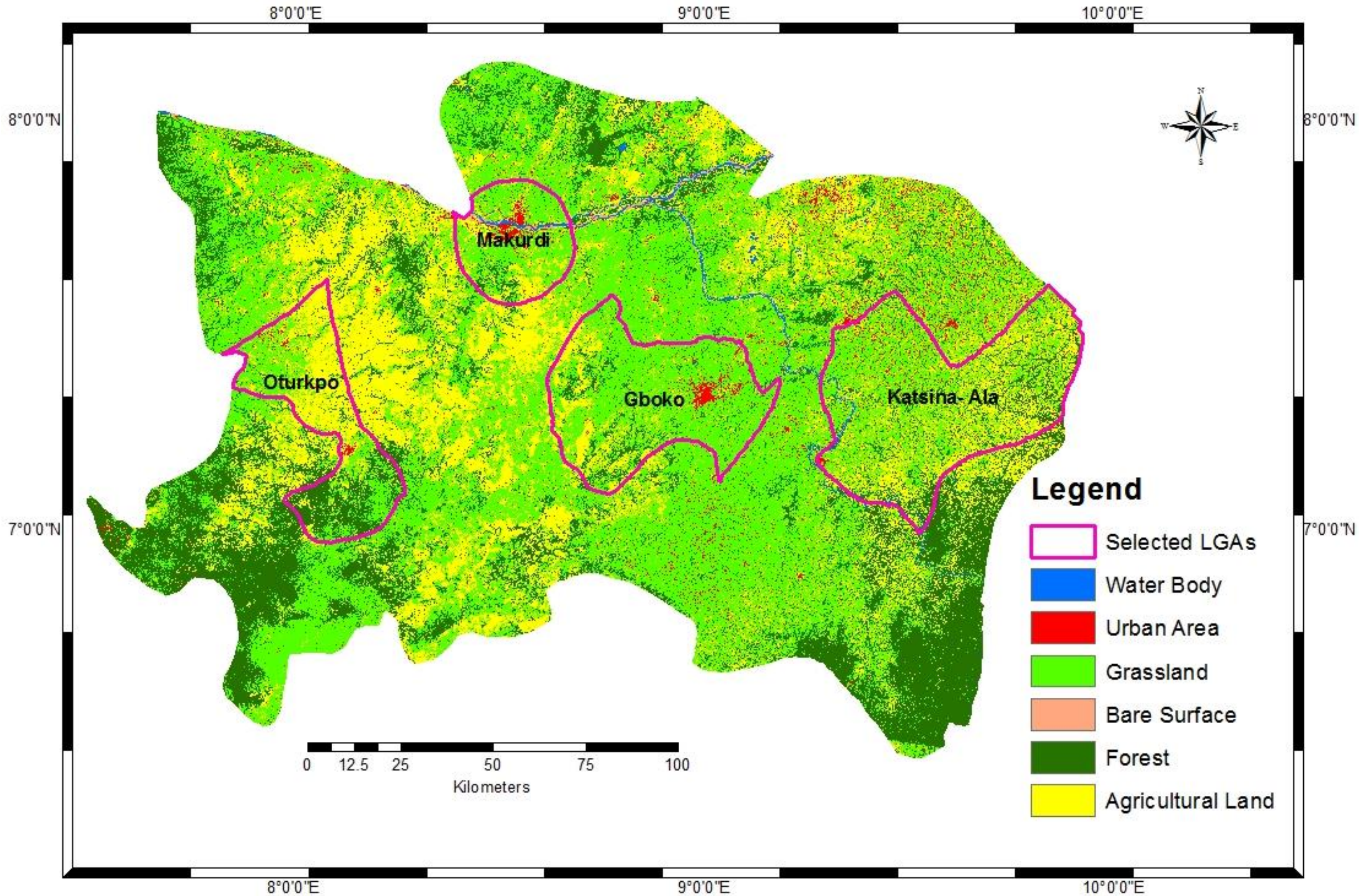
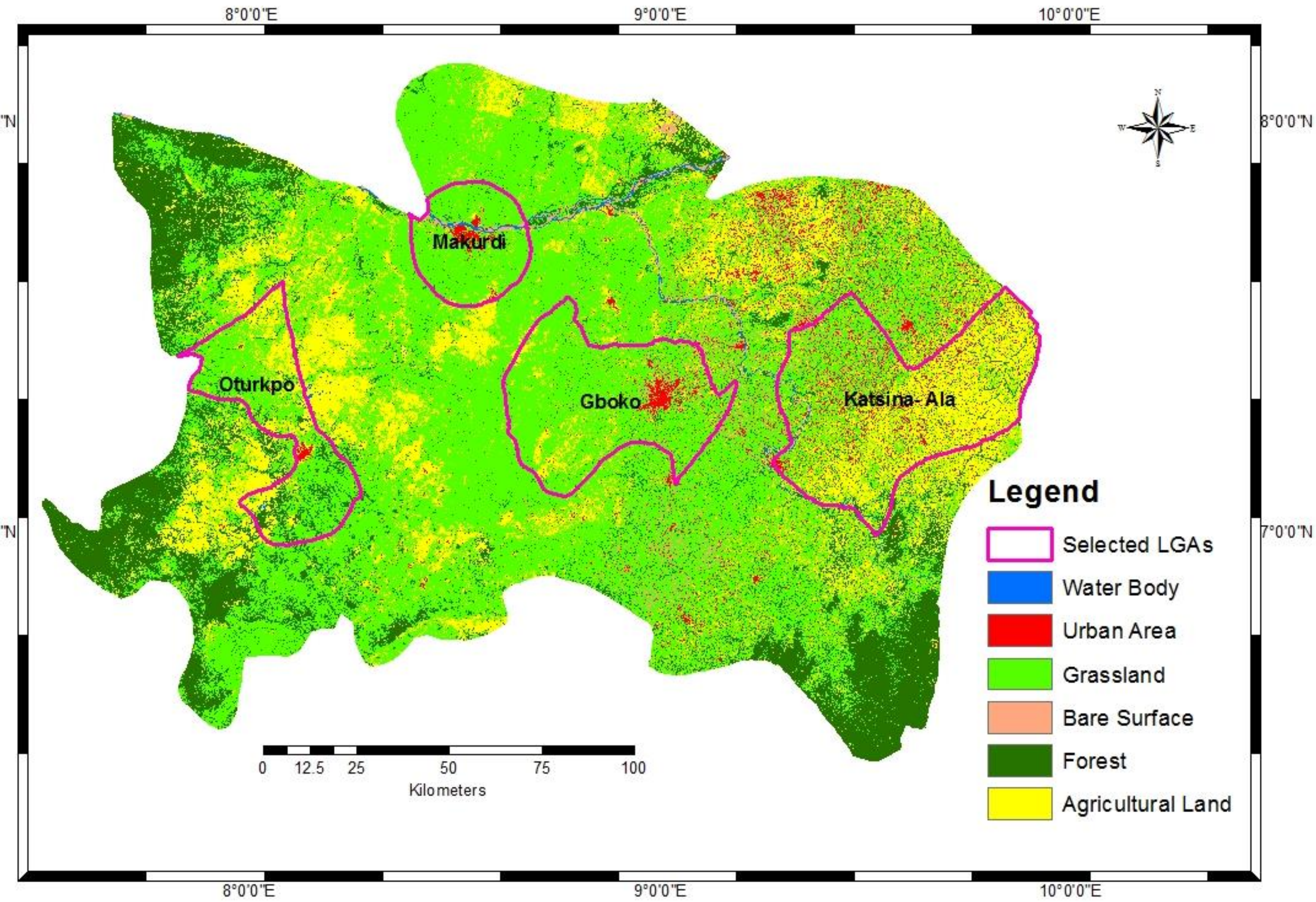


Figure 4. 2: **LULC Map of Benue State for 2007**



8°0'0"E
9°0'0"E
10°0'0"E
8°0'0"N
7°0'0"N
Makurdi
Oturkpo
Gboko
Katsina- Ala
Legend
Selected LGAs
Water Body
Urban Area
Grassland
Bare Surface
Forest
Agricultural Land
0
12.5
25
50
75
100
Kilometers

Figure 4. 3: LULC Map of Benue State for 2017

4.2.1: Extent of LULC Types in Makurdi

A closer look at the classified images of Makurdi (Figures.4.4, 4.5, 4.6 and Table 4.2) shows that urban area represented 3.44% (2871ha) in 1987 and rose to 10.9% (9102ha) in 2007. It continued to expand in 2017 to 17.95% (14996ha). Although urban area has grown in all parts, the major areas of growth were the North-east of the area. Forest cover stood as the second largest cover type in 1987 being represented by 26.93% (22492ha). By 2007, the forest cover decreased to 18.55% (15494ha) and further decreased to 12.87% (1075ha) in 2017. The forest in the Southwest and Northeast have gradually given way to agricultural activities. Grassland which was the leading land cover in 1987 accounted for 40.07% (33474ha) of the entire area and rose to 46.99% (39250ha) by 2007. There was, however, a decline to 29.5% (24635ha) in 2017.The decline could be due to expansion in agricultural activities during the period. Farmland covered 21062ha (25.22%) in 1987 and declined in 2007 to 15762ha (18.87%) but again rose to 29415ha (35.22%) in 2017. This fluctuation could be due to decline in prices of farm produce in 2007 and the rise in prices of same in 2017. Bare surface and Water body represent less than 3% for each of the three periods.

Table 4. 2: Area Statistics of LULC in Makurdi for 1987, 2007 and 2017

Land cover Class	1987		2007		2017	
	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)
Water Body	2046	2.45	1820	2.18	1817	2.18
Urban Area	2871	3.44	9102	10.9	14996	17.95
Grassland	33474	40.07	39250	46.99	24635	29.5
Bare Surface	1576	1.89	2093	2.51	1908	2.28
Forest	22492	26.93	15494	18.55	10750	12.87
Farmland	21062	25.22	15762	18.87	29415	35.22
Total Area	**83521**	**100**	**83521**	**100**	**83521**	**100**

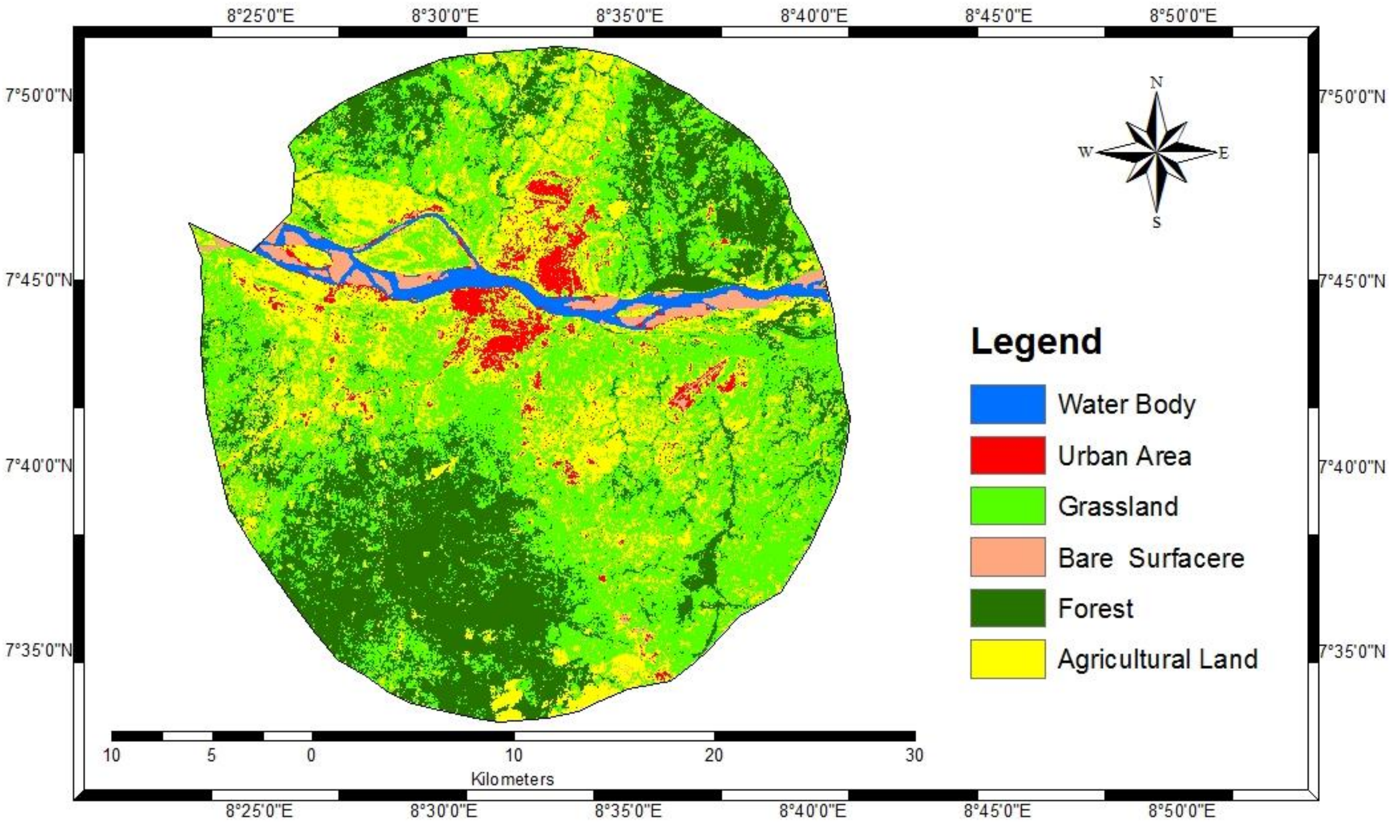


Figure 4. 4: LULC Map of Makurdi for 1987

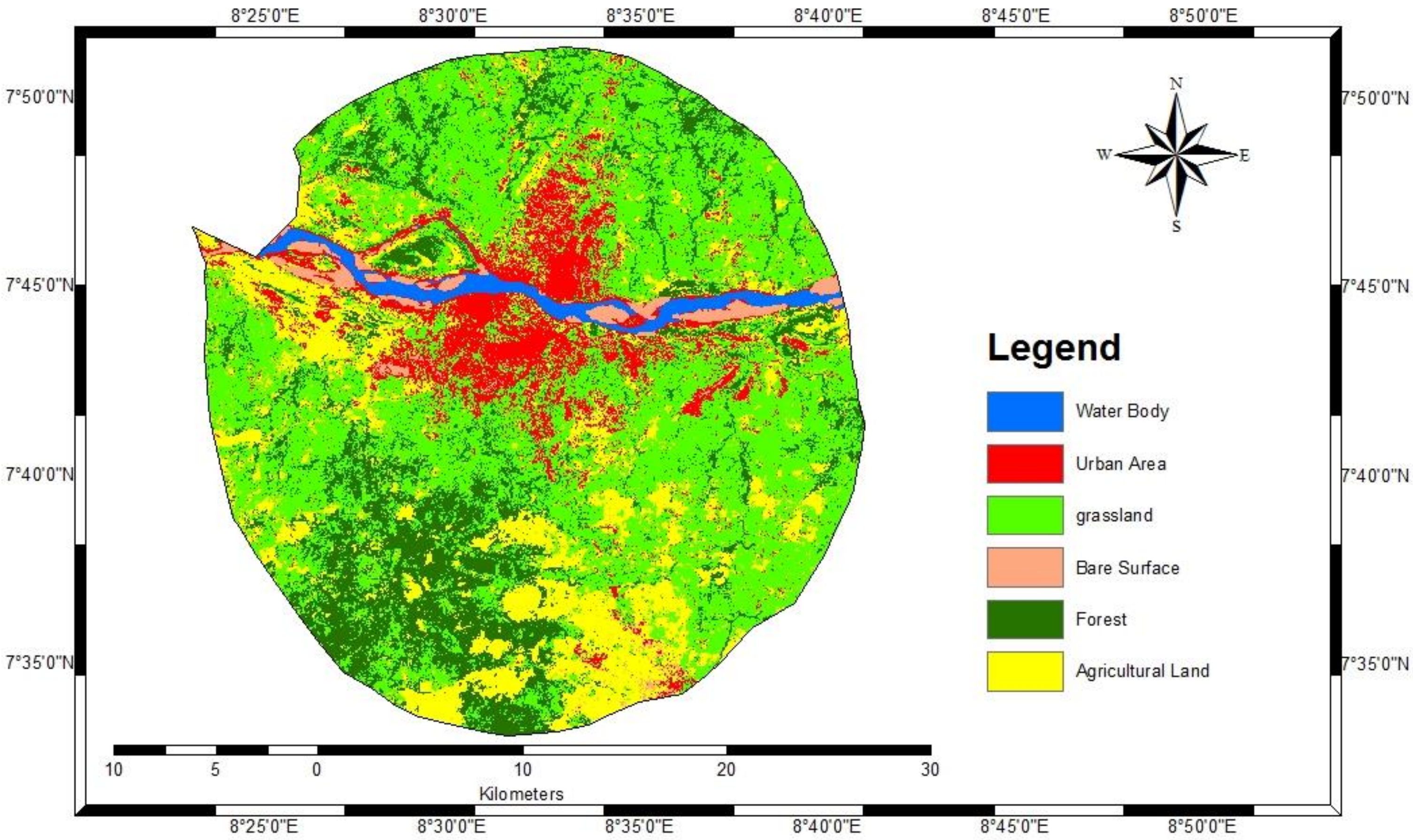


Figure 4. 5: LULC Map of Makurdi for 2007

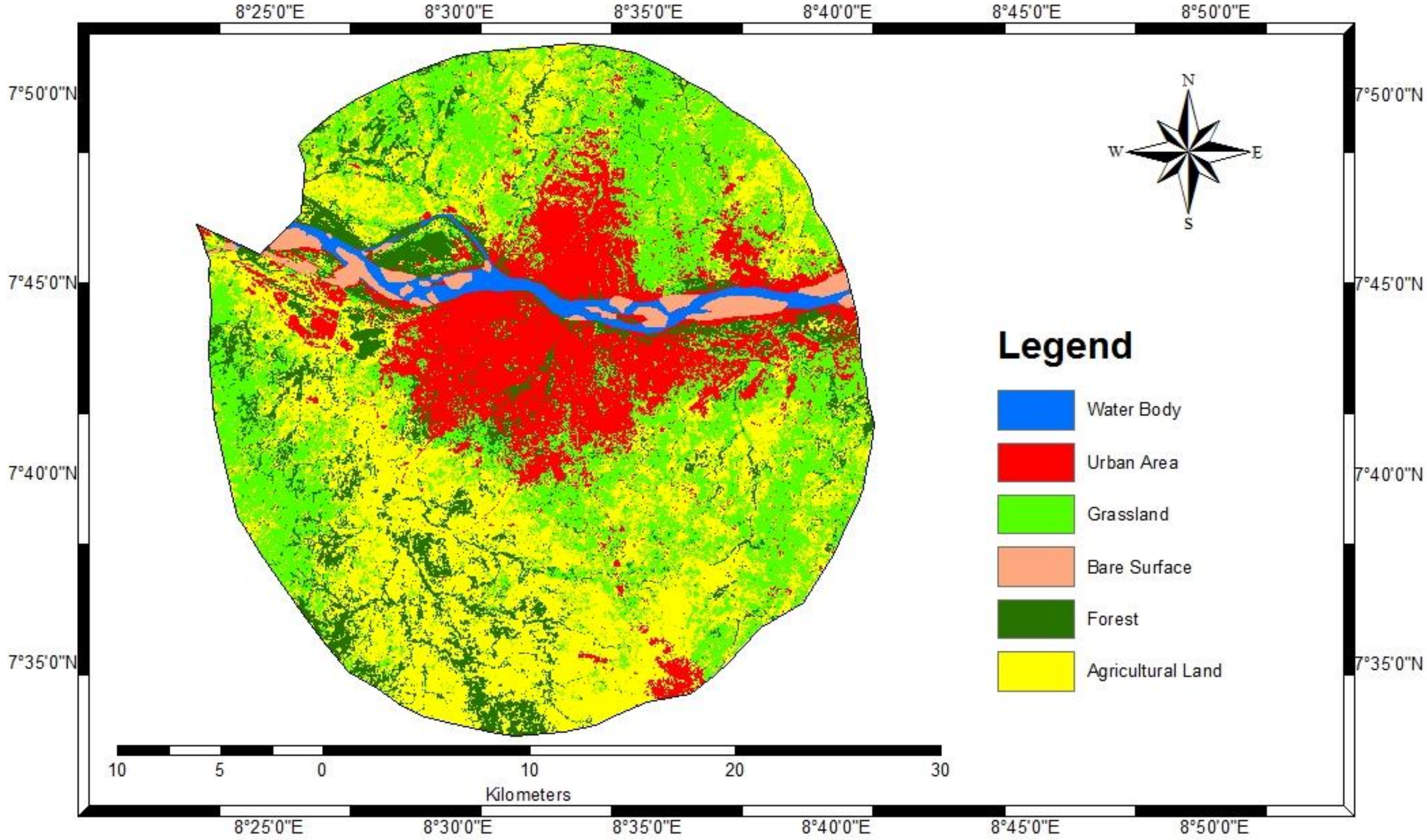


Figure 4. 6: LULC Map of Makurdi for 2017

4.2.2 Extent of LULC Types in Gboko

The LULC distributions for Gboko for the 3 Periods are shown in Table 4.2 and Figures 4.7, 4.8, 4.9. The classification reveals a steady expansion in urban area from 3232ha (1.68%) in 1987 to 8542ha (4.45%) in 2007 and rising up to 16614ha (8.65%) in 2017. The growth of the urban area has been directed towards the northeast area of the map as can be seen from Figures 4.8 and 4.9. Forest land on the other hand declined from 52108ha (27.13%) to 46523ha (24.23%) and down to 16723ha (8.71%) in the same period. Grassland was the dominant land cover occupying 69074ha (35.97%) in 1987 increasing to 79874ha (41.59%) and 129715ha (67.54%) in 2007 and 2017 respectively. Water body and Bare surface experienced slight variations during the same period.

Table 4. 3: Area Statistics of LULC in Gboko for 1987, 2007 and 2017

	1987		**2007**		**2017**	
Land cover Class	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**
Water Body	840	0.44	220	0.11	277	0.15
Urban Area	3232	1.68	8542	4.45	16614	8.65
Grassland	69074	35.97	79874	41.59	129715	67.54
Bare Surface	2252	1.17	8353	4.35	2500	1.30
Forest	52108	27.13	46523	24.23	16723	8.71
Farmland	64542	33.61	48536	25.27	26219	13.65
Total Area	**192048**	**100**	**192048**	**100**	**192048**	**100**

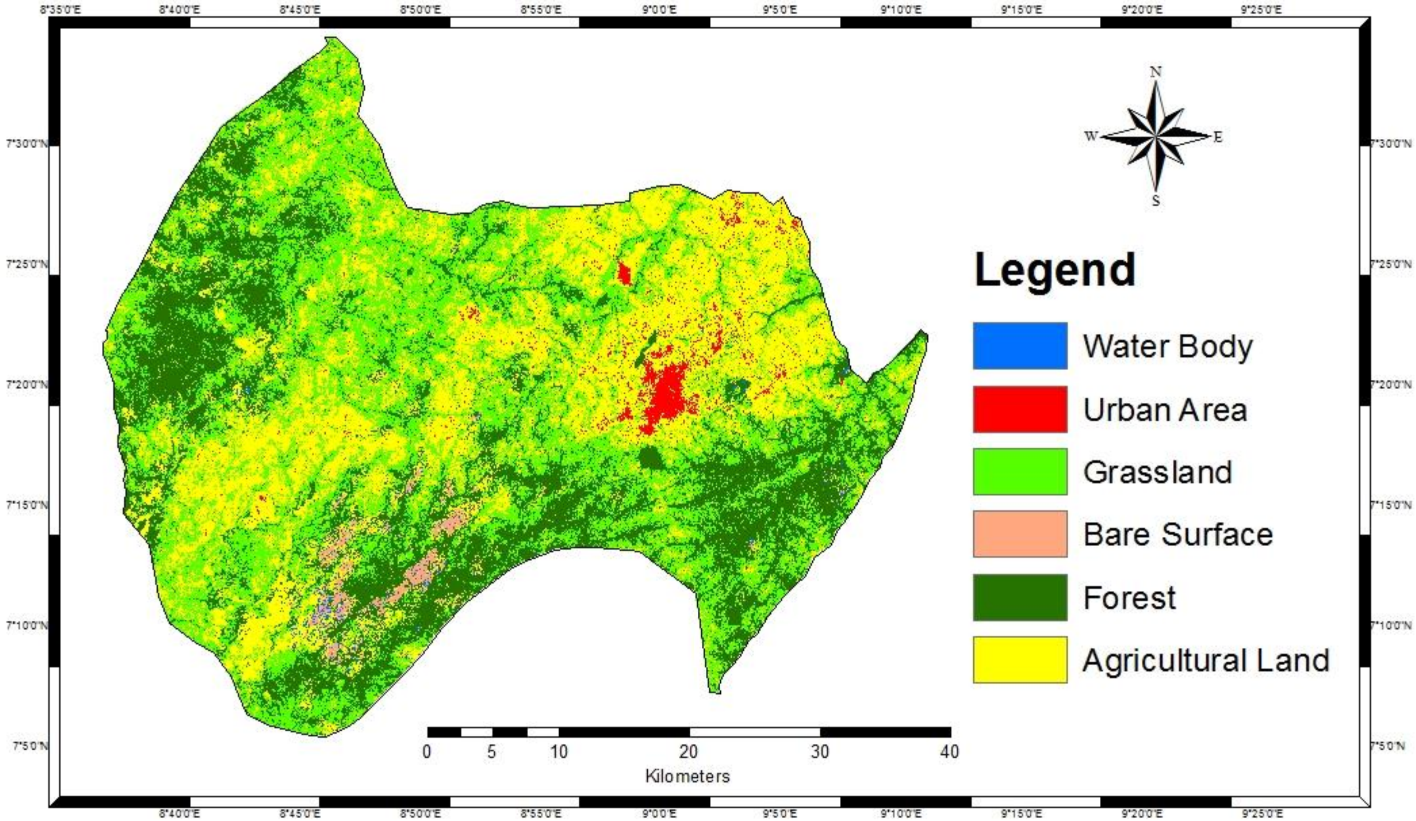


Figure 4. 7: LULC Map of Gboko for 1987

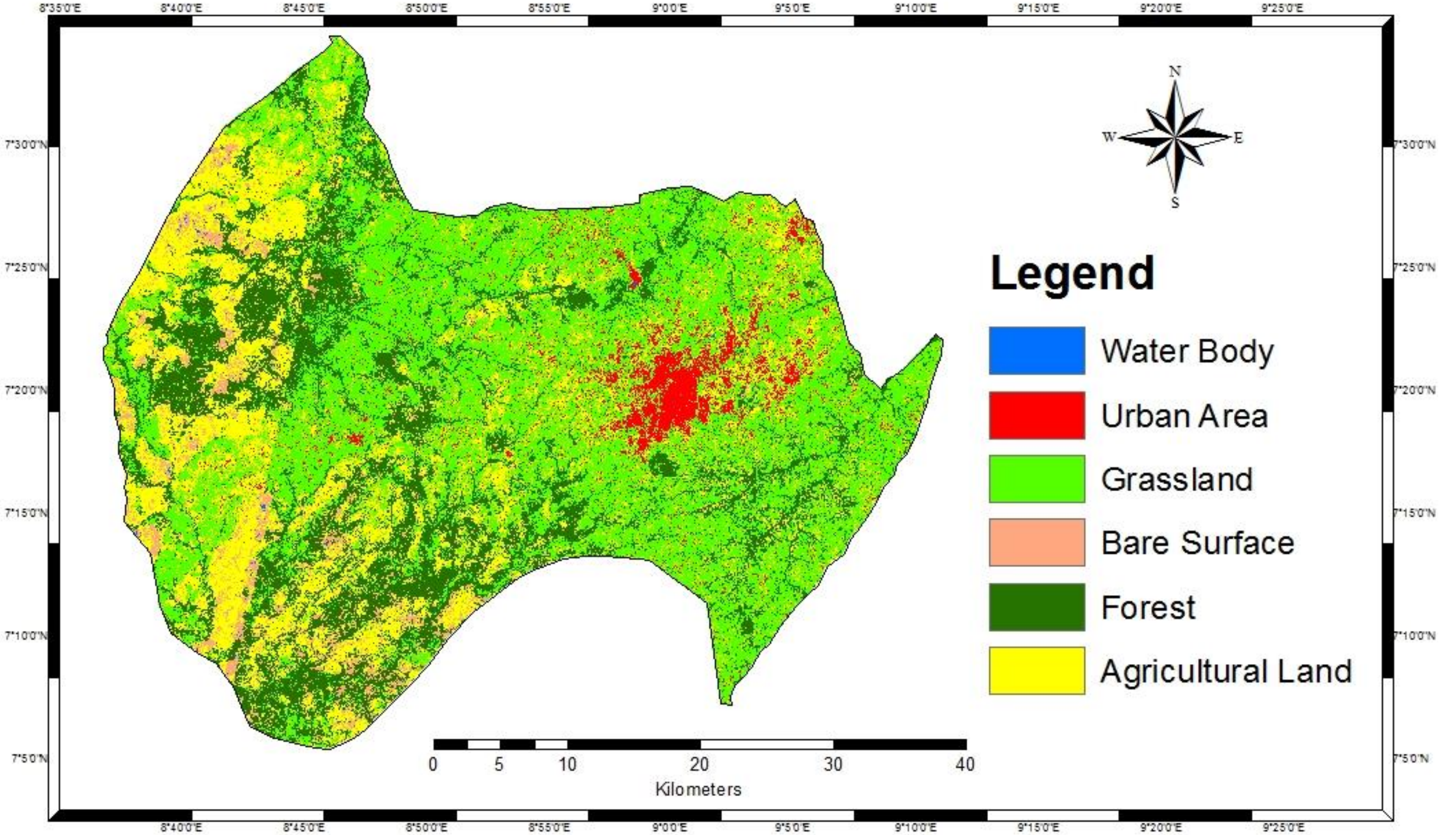


Figure 4. 8: LULC Map of Gboko for 2007

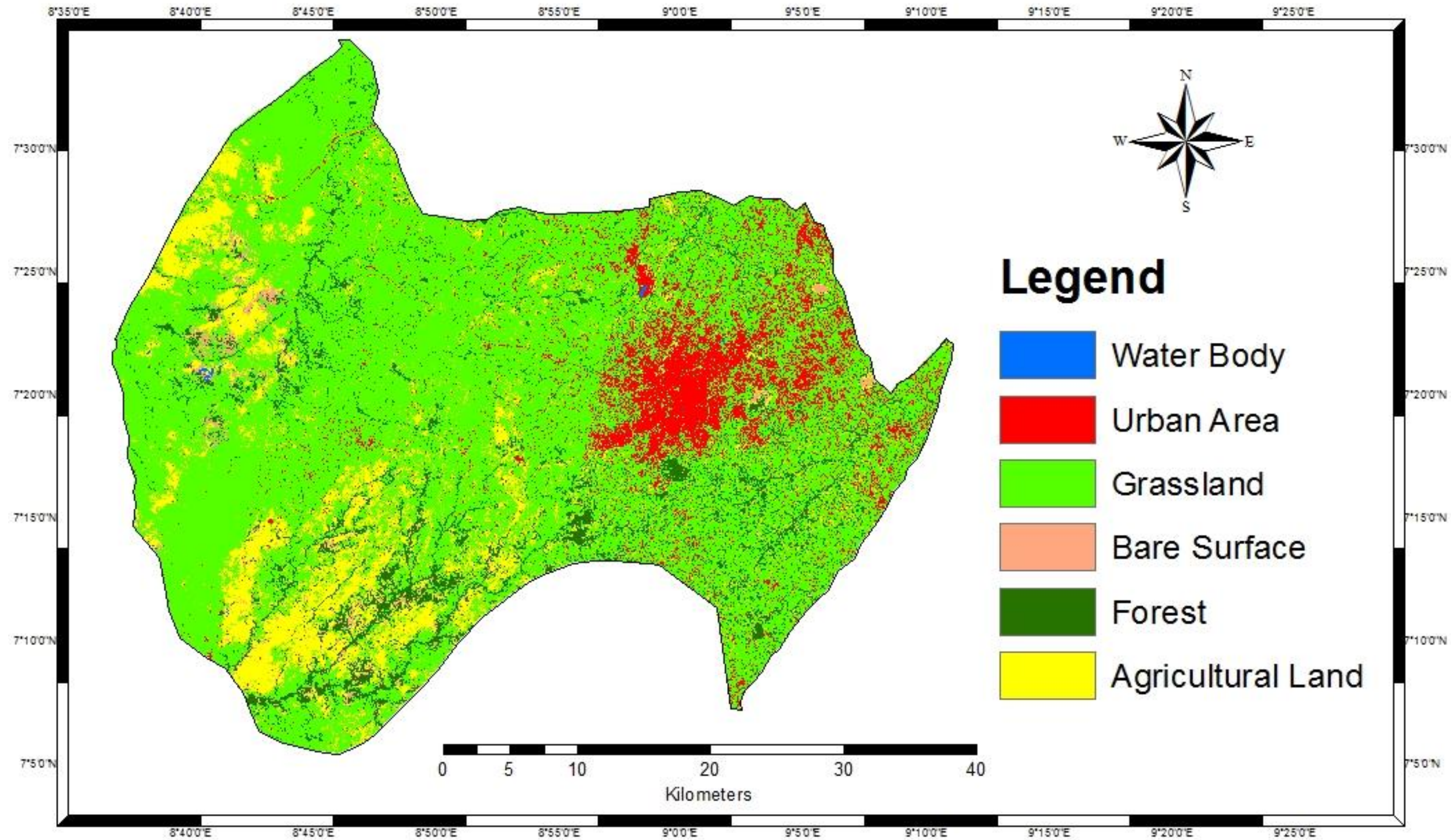


Figure 4. 9: LULC Map of Gboko for 2017

4.2.3: Extent of LULC Types in Otukpo

The distribution of LULC classes in Otukpo as shown in Table 4.4 and Figures 4.10, 4.11 and 4.12 reveal that Urban area occupied 3251ha (2,43%) in 1987, appreciating to 8348ha (6.25%) in 2007 and climaxing to 15475ha (11.59%) in 2017. Forest land decreased from 33234ha (34.88%) in 1987 to 27289ha (20.44%) in 2007 and further declined to 16741ha (12.54%) in 2017. Grassland was the major land cover in Otukpo spanning an area of 42559ha (31.86%) in 1987, expanding to 57071ha (42.75%) and 58623ha (43.92%) in 2007 and 2017 respectively. Farmland, the second largest land cover occupied 21821ha (16.33%) in 1987 and rose to 29778ha (22.31%) in 2007. In 2017, however, the area devoted to agricultural activities declined to 28346ha (21.24%). This may be likely due to rural-urban migration by youths and the adoption of more intensive farming practices aimed at increasing output as opposed to the extensive method of expanding the area under cultivation (Bloch *et al.*, 2015)

Table 4. 4: Area Statistics of LULC in Otukpo for 1987, 2007 and 2017

	1987		**2007**		**2017**	
Land cover Class	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**
Water Body	5692	4.26	3418	2.56	6226	4.66
Urban Area	3251	2.43	8348	6.25	15475	11.59
Grassland	42559	31.86	57071	42.75	58623	43.92
Bare Surface	27034	20.24	7587	5.69	8080	6.05
Forest	33234	24.88	27289	20.44	16741	12.54
Farmland	21821	16.33	29778	22.31	28346	21.24
Total Area	**133491**	**100**	**133491**	**100**	**133491**	**100**

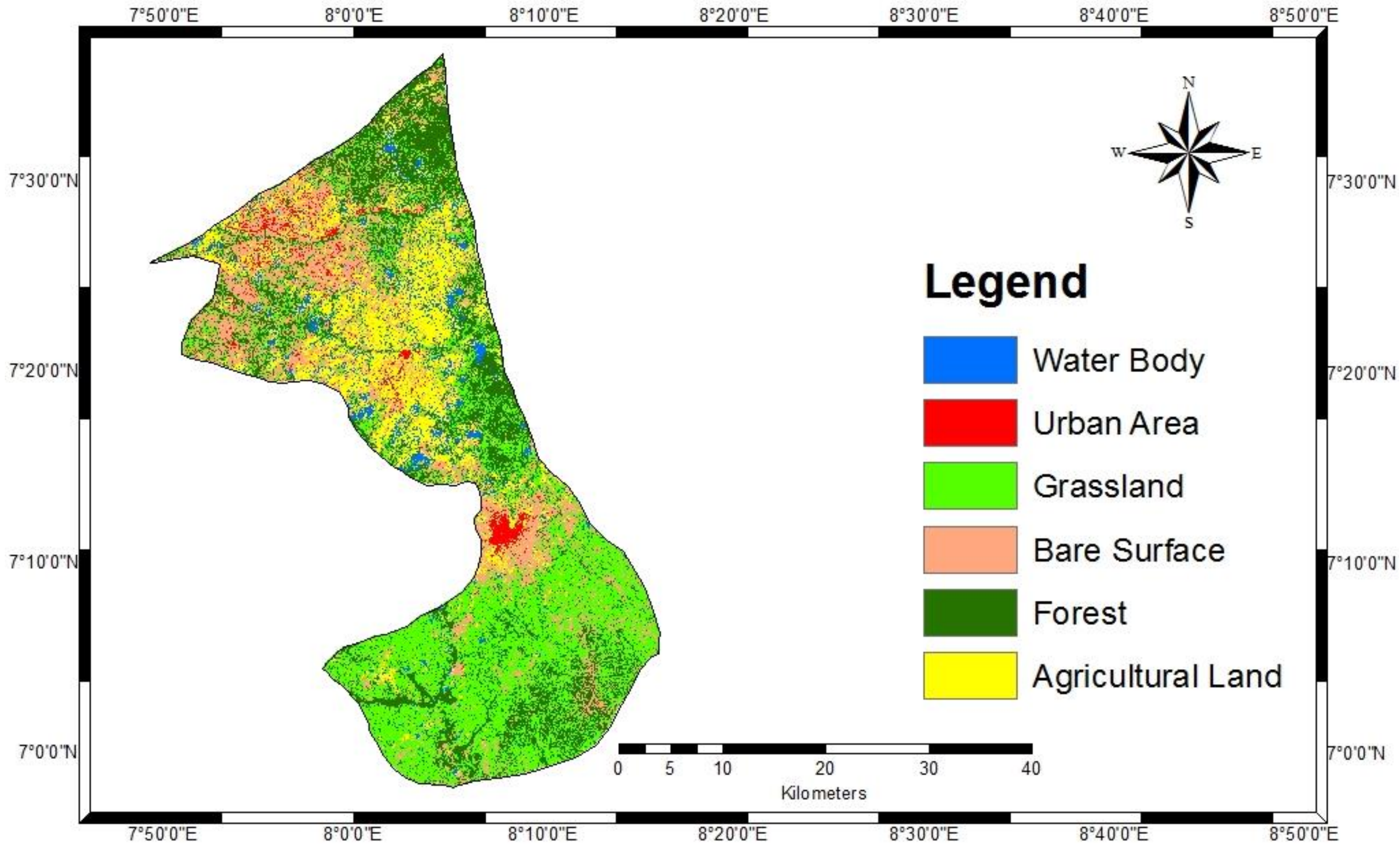


Figure 4. 10: LULC Map of Otukpo for 1987

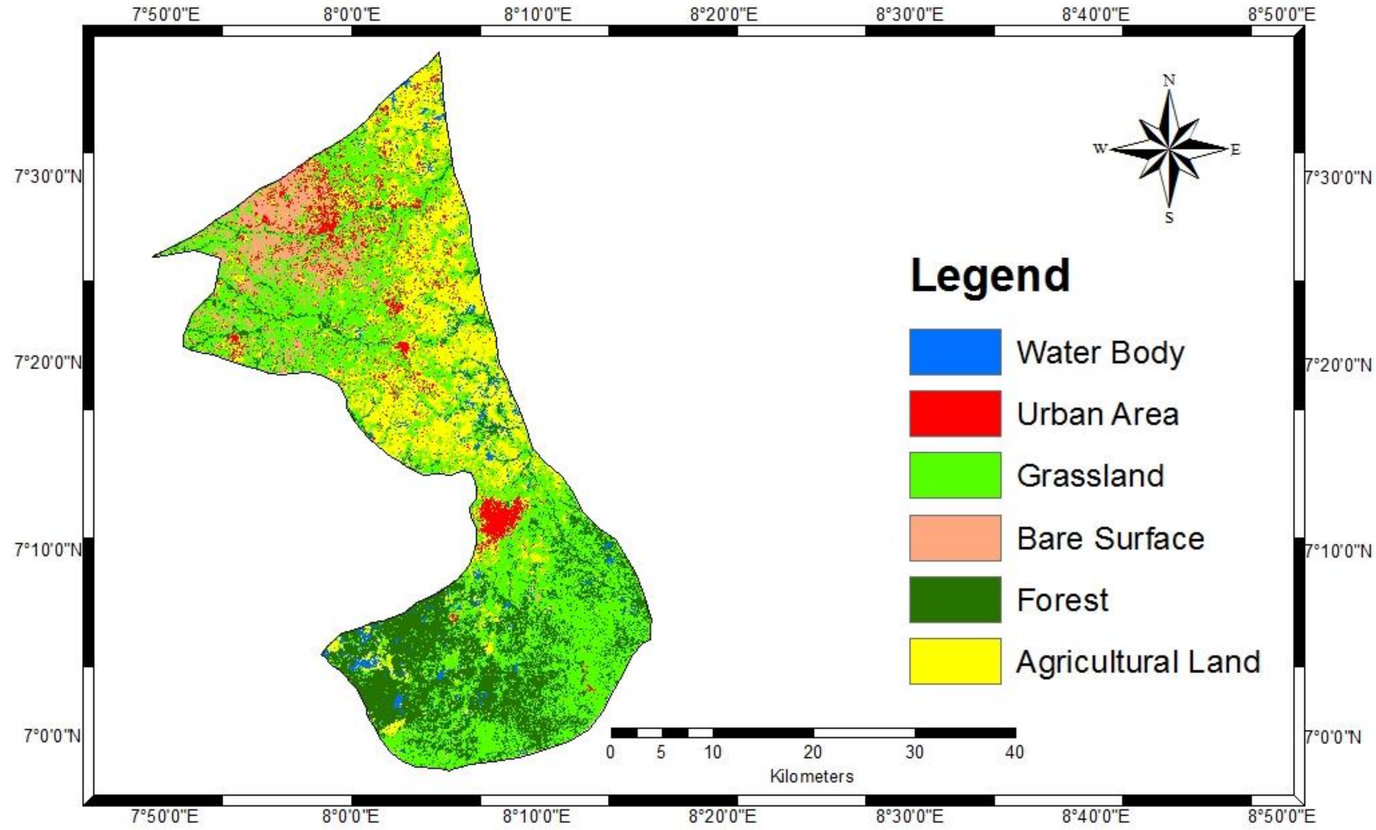


Figure 4. 11: LULC map of Otukpo for 2007

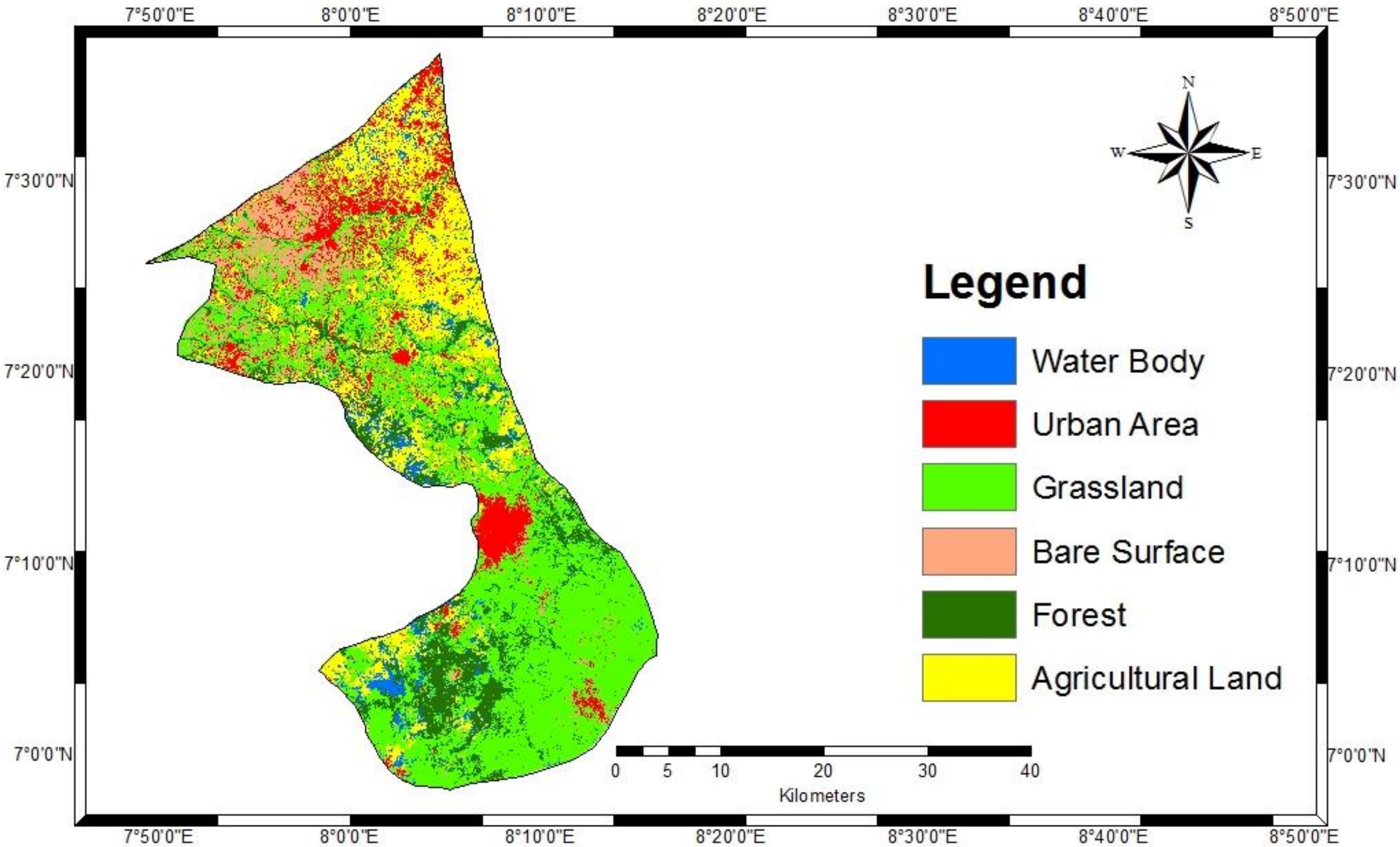


Figure 4. 12: LULC Map of Otukpo for 2017

4.2.4: Extent of LULC Types in Katsina-Ala

An analysis of the classification of LULC classes showed that urban area has been on a steady increase from 7867ha (2.93%) in 1987 to 10381ha (3.86%) in 2007 and rising sharply to 15905ha (5.92%) in 2017. This large increase in urban area may be due to rural-urban migration in search of better working conditions and better standard of living which has increased demand for urban residential settlements. The incessant farmers - herders conflicts may have contributed a lot in this regard. Forest land on the other hand has been on the decline during the same period from71200ha (26.40%) to 66401ha and then decreasing sharply to 29026ha (10.8%) in the three periods. The decrease in forest land is due to the pressure from farming activities and increase in urbanisation as evidenced by their increase in the same period under review. Farmland too has been increasing from 66226ha (24.63%) to 106926ha (39.77%) and sharply to 154679ha (57.58) in 2017. Bare surface and water body each accounted for less than 1% of the land cover and showed no significant changes. This can be seen in Table 4.5 and Figures 4.13, 4.14, 4.15.The absence of much change in bare surface may be due to te fact that they are made up of rock outcrops and exposed sand from the river bed.

Table 4. 5: Area Statistics of LULC in Katsina-Ala (1987, 2007 and 2017)

	1987		2007		2017	
Land cover Class	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**
Water Body	2402	0.89	3256	1.21	1323	0.49
Urban Area	7867	2.93	10381	3.86	15905	5.92
Grassland	120480	44.81	81295	30.24	66824	24.87
Bare Surface	673	0.25	605	0.22	896	0.34
Forest	71216	26.49	66401	24.70	29026	10.80
Farmland	66226	24.63	106926	39.77	154679	57.58
Total Area	**268864**	**100**	**268864**	**100**	**268864**	**100**

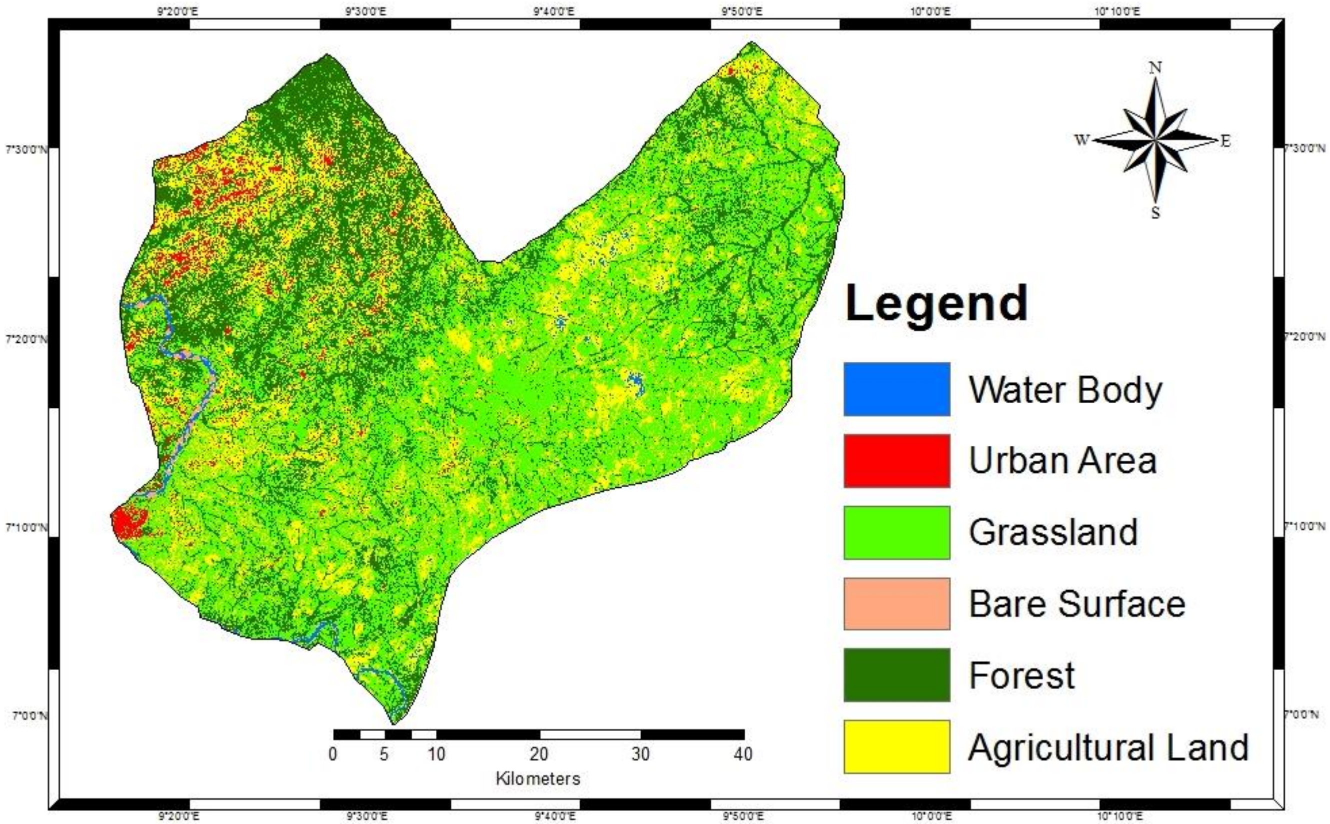


Figure 4. 13: LULC Map of Katsina-Ala for 1987

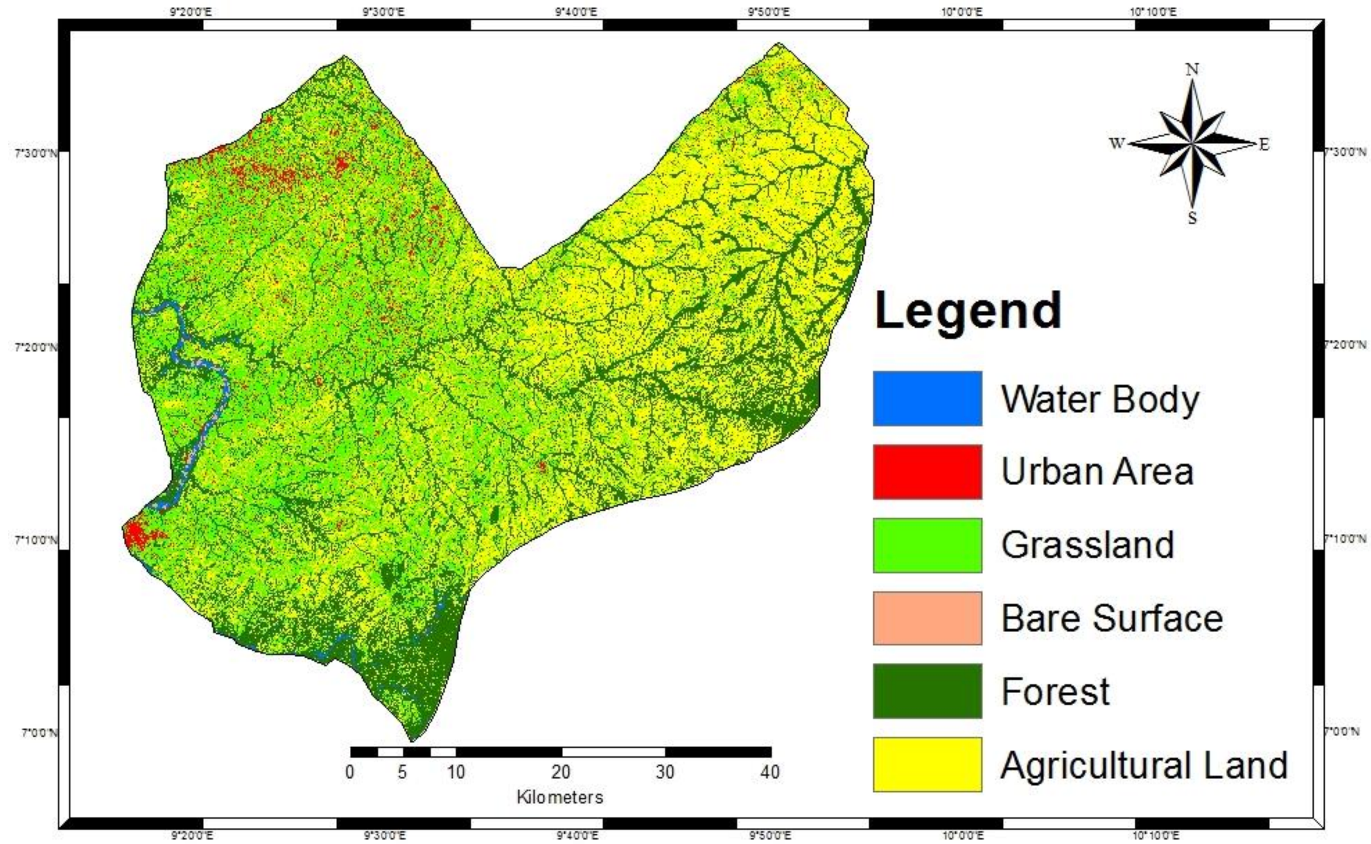


Figure 4. 14: LULC Map of Katsina-Ala for 2007

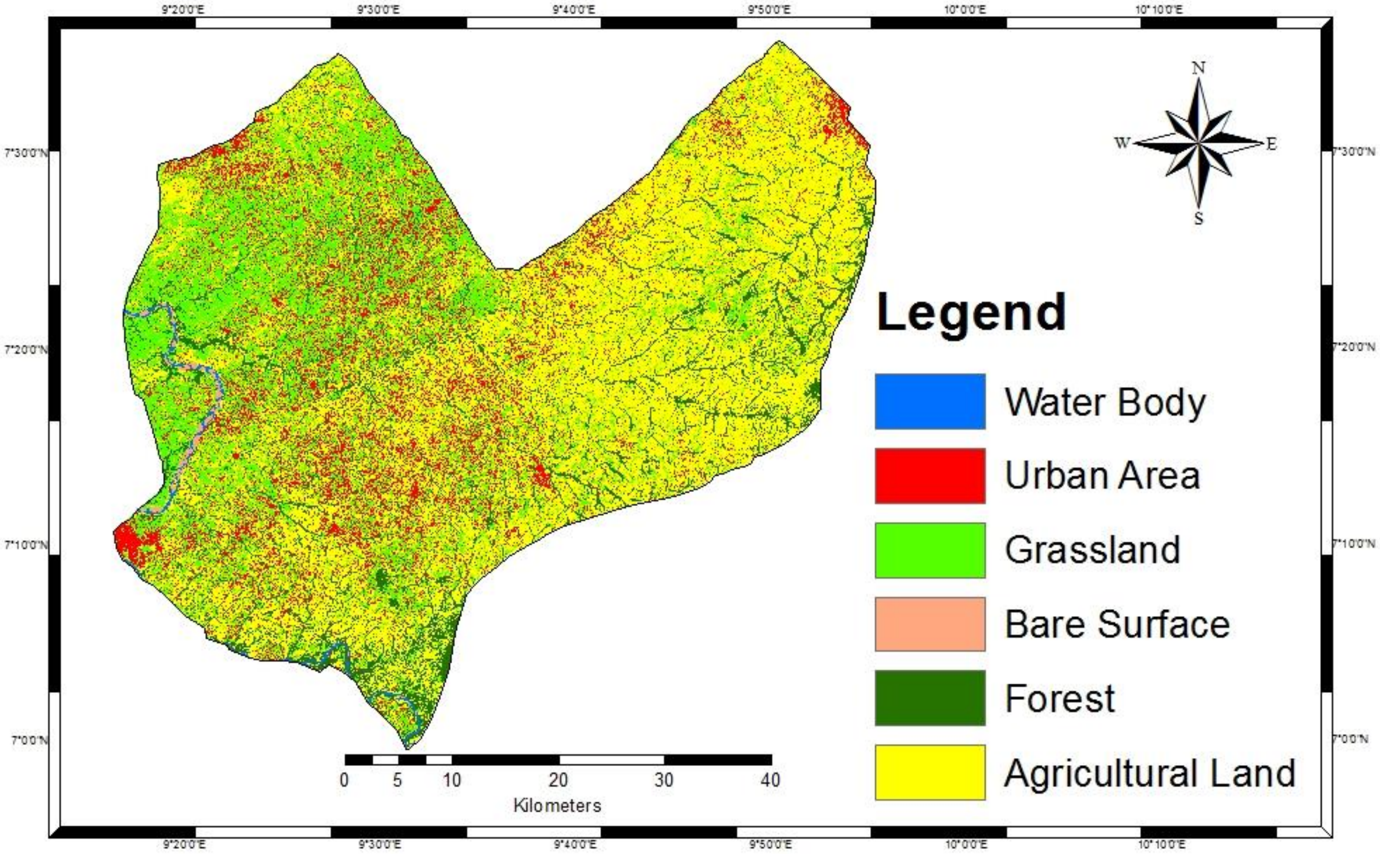


Figure 4. 15: LULC Map of Katsina-Ala for 2017

4.3: Accuracy Assessment of Classified Maps

It is difficult to attain a 100% accuracy in any classification and as such there exist some standards which each classification must attain for it to be acceptable.

4.3.1 Assessment of classification accuracy of LULC in Benue State

The individual classification accuracy for the three epochs of 1987, 2007 and 2017 showed an overall accuracy of 82.92%, 86.7% and 89.82% respectively (See Table 4.6). This overall accuracy was substantially good and is acceptable for the successive and detection of changes. User's accuracy of different LULC categories ranged between 63.46% and 97.78%; and producer's accuracy ranged between 51.56 % and 100%. The overall Kappa was also calculated for each of the maps that was classified to determine their accuracy. The classification results of LULC maps of the three periods of 1987, 2007 and 2017 had Kappa statistics of 0.79, 0.87 and 0.89 respectively.

Table 4. 6: Accuracy Assessment Result of LULC Classification in Benue State

LULC Class	1987 classification		2007 classification		2017 classification	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Water Body	90.91	93.75	92	85.19	84.62	97.78
Urban Area	80.52	96.87	78.79	91.23	86.3	88.89
Grassland	51.56	63.46	75.76	72.46	91.53	76.06
Bare Surface	90.2	92	92.73	92.73	84.91	88.24
Forest	97.46	83.94	100	92.91	97.01	94.2
Farmland	81.37	75.45	73.49	82.43	75.31	92.42
Overall Accuracy	**82.92%**		**86.7%**		**89.82%**	

Overall Kappa	0.79	0.84	0.87

The Kappa coefficient for the three periods ranges from substantial agreement to almost perfect agreement on the kappa scale used by Baysal (2013), an indication that it can be used. Kappa takes care of all components of the confusion matrix and eliminates the conformity that happens by chance. Accordingly, it offers a much thorough accuracy assessment of the classification.

4.3.2: Assessment of classification accuracy of LULC in Makurdi

The accuracy of classification for the three periods of 1987, 2007 and 2017 for Makurdi showed an overall accuracy of 88.78%, 82.7% and 80.52% respectively (See Table 4.7). This was considered a decent overall accuracy and, therefore acceptable for the succeeding detection of change and analysis. The user's accuracy for different land cover categories ranged between 60.38% and 100% and the producer's accuracy ranged between76 % and97.14%.

Table 4. 7: Accuracy Assessment Result of LULC Classification in Makurdi

LULC Class	1987 classification		2007 classification		2017 classification	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Water Body	95	100	85.71	78.26	80.95	94.44
Urban Area	97.14	100	86.11	96.87	88.24	85.71
Grassland	83.78	83.78	85	70.83	82.05	60.38
Bare Surface	83.33	78.95	79.17	79.17	85.71	85.71
Forest	80.56	85.29	83.87	78.79	76	97.44
Farmland	91.53	87.1	75.76	100	77.27	78.46

Overall Accuracy	**88.78%**	**82.7%**	**80.52%**
Overall Kappa	**0.86**	**0.79**	**0.76**

The overall Kappa was also calculated for each of the maps that was classified to determine their accuracy. The results of the three periods 1987, 2007 and 2017 revealed Kappa statistics of 0.86, 0.79 and 0.76 respectively. The Kappa coefficient for the three periods ranges from substantial agreement to almost perfect agreement on the kappa scale, an indication that it can be used.

4.3.3: Assessment of classification accuracy of LULC in Gboko

The classification accuracy for the three periods of 1987, 2007 and 2017for Gboko showed an overall accuracy of 80.77%, 85.84% and 86.24% respectively (see Table 4.8). This was also considered a decent overall accuracy and, therefore, usable for the later change detection and analysis. The user's accuracy for different LULC categories ranged between 74.07% and 100% and producer's accuracy ranged between 64 % and 94.44%.

Table 4. 8: Accuracy Assessment Result of LULC Classification in Gboko

LULC Class	1987 classification		2007 classification		2017 classification	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Water Body	80.95	89.47	80	84.21	94.44	77.27
Urban Area	86.49	91.43	88.89	100	74.19	85.19
Grassland	80.56	76.32	82.98	81.25	86.89	82.81
Bare Surface	64	84.21	71.43	83.33	86.36	82.61
Forest	82.93	79.07	91.67	86.84	82.05	100
Farmland	83.33	74.07	90	80.36	93.62	88

Overall Accuracy	**80.77%**	**85.84%**	**86.24%**
Overall Kappa	**0.76**	**0.83**	**0.83**

The overall Kappa was also calculated for all the classified maps to determine their accuracy. The results of the three periods 1987, 2007 and 2017 revealed Kappa statistics of 0.76, 0.83 and 0.83 respectively. The Kappa coefficient for the three periods ranges from substantial agreement to almost perfect agreement on the kappa scale, an indication that it can be used.

4.3.4: Assessment of classification accuracy of LULC in Otukpo

The result of classification accuracy for 1987, 2007 and 2017 for Otukpo showed an overall accuracy of 84.85%, 85.59% and 86.44% respectively (See Table 4.9).Based on the scale of assessment, it was also considered a decent overall accuracy and, therefore, usable for analysis of change detection.

Table 4. 9: Accuracy Assessment Result of LULC Classification in Otukpo

LULC Class	**1987 classification**		**2007 classification**		**2017 classification**	
	Producer's Accuracy (%)	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**
Water Body	86.96	100	81.48	91.67	85.71	94.74
Urban Area	76.47	100	85.29	85.29	79.49	88.57
Grassland	91.07	86.44	87.5	81.67	89.66	86.67
Bare Surface	84.21	50	88	81.48	88.46	69.7
Forest	86.11	93.94	81.58	88.57	85.71	88.24
Farmland	86.21	89.29	87.5	87.5	87.72	90.91

Overall Accuracy	**84.85%**	**85.59%**	**86.44%**
Overall Kappa	**0.83**	**0.82**	**0.83**

The user's accuracy for different classes ranged between 50% and 100% and the producer's accuracy ranged between 76.47 % and 91.07%. The results of overall kappa for the three periods 1987, 2007 and 2017 revealed Kappa statistics of 0.83, 0.82 and 0.83 respectively. The Kappa coefficient for the three periods show that the kappa agreement was virtually in perfect agreement level implying that it can be used.

4.3.5: Assessment of classification accuracy of LULC in Katsina-Ala

The result of classification accuracy for 1987, 2007 and 2017 for Katsina-Ala showed an overall accuracy of 87.18%, 89.32% and 91.6% respectively (see Table 4.10). Based on the scale of assessment, the overall accuracy was considered a good one and, therefore, usable for change detection study. The user's accuracy for the different land cover categories ranged between 73.08% and 96.61% and the producer's accuracy ranged between 81.82 % and 95.16%. The results of overall kappa for the three periods revealed that for 1987 it was 0.84, 2007 was 0.87 and 2017 was 0.90.

Table 4. 10: Accuracy Assessment Result of LULC Classification in Katsina-Ala

LULC Class	1987 classification		2007 classification		2017 classification	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Water Body	81.82	75	83.33	95.24	87.5	95.45
Urban Area	86.11	88.57	90.62	87.88	91.67	94.29
Grassland	87.93	91.07	90.48	96.61	91.23	96.3

Bare Surface	86.36	73.08	86.96	76.92	88.89	80
Forest	90	92.31	89.13	87.23	90.57	94.12
Farmland	87.5	90.74	91.21	87.5	95.16	86.76
Overall Accuracy	**87.18%**		**89.32%**		**91.6%**	
Overall Kappa	**0.84**		**0.87**		**0.90**	

The Kappa coefficient for the three periods showed that the kappa agreement was virtually in perfect agreement implying that it can be used.

4.4: Trend and Rate of Change in LULC in Benue State for 1987,2007 and 2017

This section presents results for objective two. In order to examine the trend in LULC changes between the years, total land cover changes for each LULC type were tabulated. During the period under review, major changes were observed to have taken place on the major LULC types. From 1987 to 2007, urban area increased by 36505ha (88.77%) at rate of 4.44% per year while forest land decreased to 31871ha (-3.09%), with an annual rate of 0.15%.The comparative trends of the observed changes are shown in Figure 4.16.

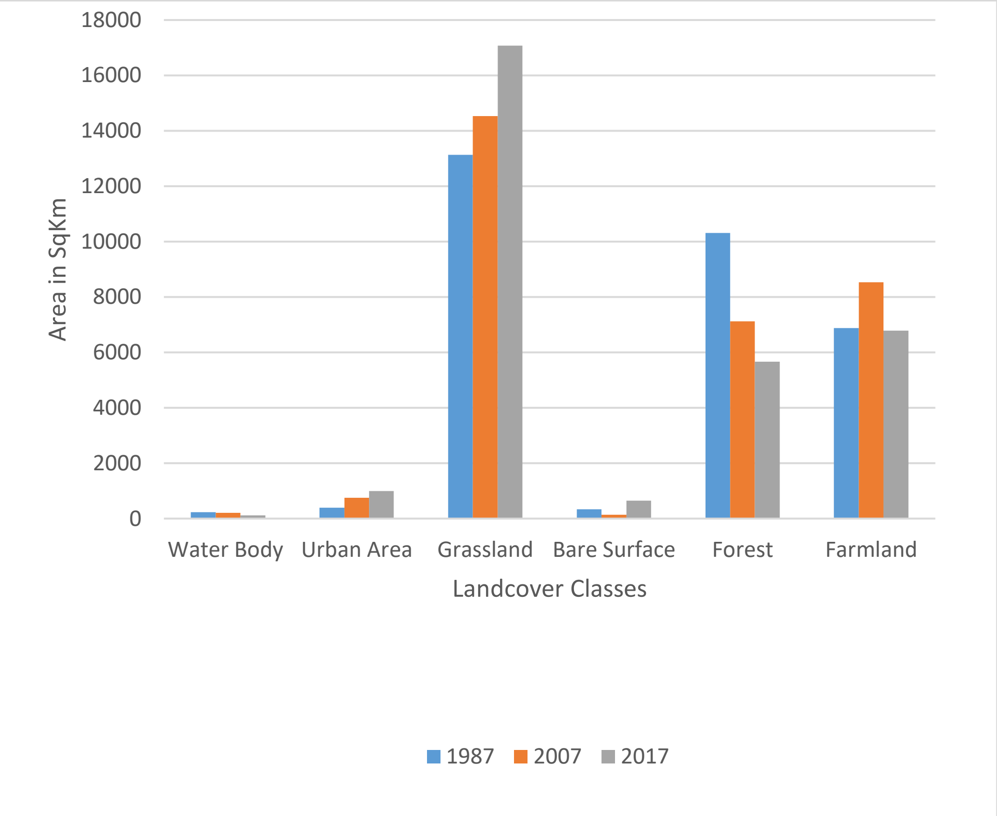


Figure 4. 16: Trend of Land Cover Changes in Benue State (1987-2017)

The decrease in forest resources might not be unconnected with increased anthropogenic activities such as logging, fuel wood collection for domestic uses and farming activities evidenced by increased area of farming during the period under reference. The effects of this might not be immediate but could lead to increased soil erosion, destruction of watershed and increased warming due to concentration of carbon-dioxide as reported by Nzeh (2012). Farmland increased to 164974ha (23.97%) at rate of 1.2% per year, grassland increased to 140667ha (10.71%) at the rate of 0.54% per year. This could be as a result of the resolve of the government and the populace to increase food production and enhance food security and the encouragement by the government to the people to embrace agriculture. The decrease in the second period might probably be because of low return from agriculture occasioned by low food prices. Bare surface decreased to 19999ha (-58.88%) with an annual rate of change of -2.94%.

Table 4. 11: Annual Rate of LULC Change for Benue State (1987, 2007 and 2017)

LULC Class	1987-2007 Area (ha) Change	Percentage of Change	2007-2017 Area (ha) Change	Percentage of Change	1987-2017 Area (ha) Change	Percentage of Change	ANNUAL RATE OF CHANGE		
							1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	-2534	-10.72	-8686	-41.15	-11220	-47.46	-0.54	-4.12	-1.58
Urban Area	35605	88.77	23476	31.01	59081	147.31	4.44	3.1	4.91
Grassland	140667	10.71	254250	17.49	394917	30.08	0.54	1.75	1
Bare Surface	-19999	-58.88	51502	368.82	31503	92.76	-2.94	36.88	3.09
Forest	-31871	-3.09	-146476	-20.55	-465186	-45.1	-0.15	-2.06	-1.5
Farmland	164974	23.97	-174051	-20.39	-90775	13.19	1.2	-2.04	0.44

The total area for water body has not changed significantly and it accounted for a -10.72% change. In the second period between 2007 and 2017, the urban area increased by 23476ha (31.01%) at the rate of 3.1% per year, while forest land was continuously converted and lost 146476ha (-20.55%) at the rate of -2.06% per year. Grassland showed a drastic increase amounting to 25425ha (17.49%) at the rate of 1.75% in a year, farmland decreased by 174051ha (-20.39%) at the rate of -2.04% in a year. This period witnessed a substantial change in bare surface amounting to 51502ha (368.82%) at the rate of 36.88% in a year, while water body recorded a negative change of 8686ha (41.15%) with the lowest annual rate of change of -4.12% as shown in Table 4.11. The decrease in water body could be due to land reclamation of the water bodies, siltation and natural shrinkage in the volume of lakes and rivers, the potential effects are ecosystems and habitat loss, loss of livelihood, economic losses and increased poverty among the inhabitants. The general trend of LULC changes from1987 to 2017 was not significantly different from the pattern observed in the previous periods.

Although significant growths in agricultural land and urban centres could be seen as the most vital changes caused by urban growth in Benue State over the years, farming activities have eaten into the forest areas more than the other LULC categories. This means that the area is now being utilised with greater intensity relative to what obtained in the past. With the present rate of LULC change, a large amount of the forest left in the state will be completely converted to other LULC classes in the near future if steps are not put in place to control the menace of vegetation loss in the state. Similarly, if the present rate of deforestation is not controlled considerably, it is going to be a key source of increased emissions of carbon in the state.

4.4.1: Trend and Rate of Change in LULC in Makurdi for 1987,2007 and 2017

The trend in the LULC changes in Makurdi from the first period (1987-2007) reveals that urban area increased by 6231ha (24.88%) where the rate of change pr annum was 4.98%. In the second period (2007-2017), urban areas increased by 5894ha (15.08%) with the rate of change per annum of 1.51% (see Figure 4.18).

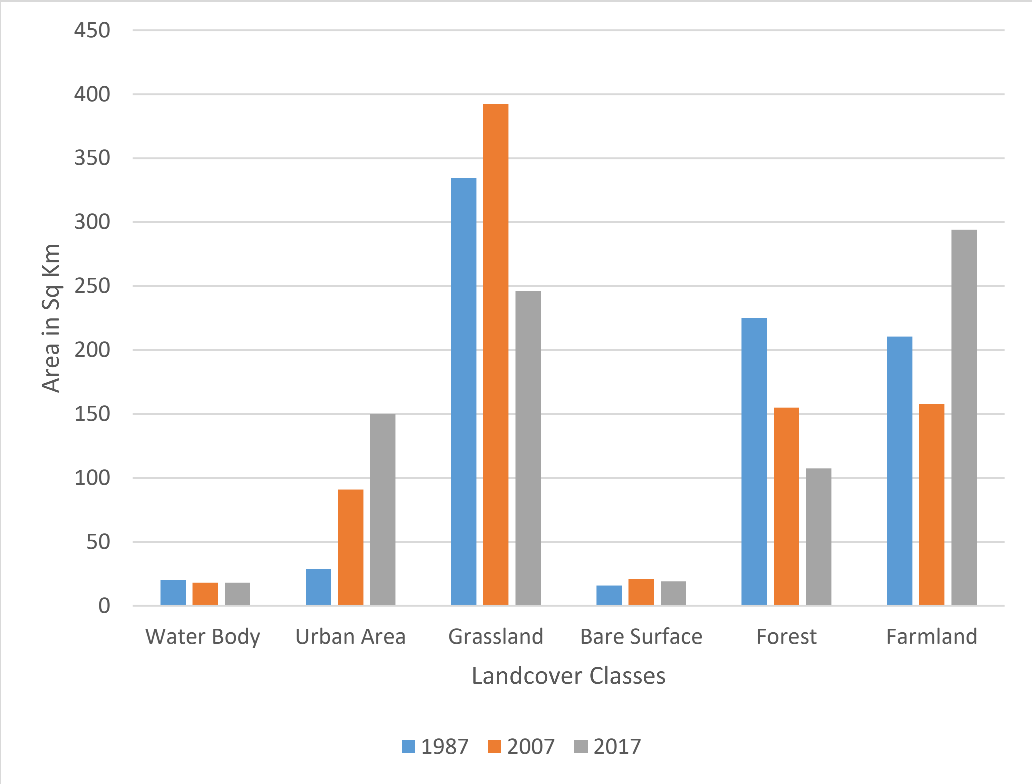


Figure 4. 17: Trend of Land Cover Changes in Makurdi (1987-2017)

The overall trend (1987-2017) showed that urban areas increased by12125ha (422.33%) with an annual rate of change of 14.07% (see Table 4.12). The continuous increase in urban area may probably be due the influx of population to the state capital in search of white-collar jobs. The establishment of Federal University of Agriculture Makurdi and Benue State University in the city has also attracted a lot of student population. Forest land has diminished by 6998ha (31.11%) with the annual rate of change of -1.56% between 1987 and 2007. Between 2007 and 2017, 4744ha (-30.62%) of forest was lost at the rate of 3.06% per annum. The overall trend showed that 11742ha (-52.21%) of forest was lost at the rate of 1.74% per annum.

Table 4. 12: Annual Rate of LULC Change for Makurdi (1987, 2007 and 2017)

LULC Class	1987-2007 Area (ha) Change	Percentage of Change	2007-2017 Area (ha) Change	Percentage of Change	1987-2017 Area (ha) Change	Percentage of Change	ANNUAL RATE OF CHANGE 1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	-226	-11.05	-3	-0.16	-229	-11.19	-0.55	-0.02	-0.37
Urban Area	6231	217.03	5894	64.75	12125	422.33	10.85	6.48	14.07
Grassland	5776	17.26	-14615	-37.23	-8839	-26.41	0.86	-3.72	-0.88
Bare Surface	517	32.81	-185	-8.83	332	21.07	1.64	-0.88	0.7
Forest	-6998	-31.11	-4744	-30.62	-11742	-52.21	-1.56	-3.06	-1.74
Farmland	-5300	-25.16	13653	86.62	8353	39.66	-1.26	8.66	1.32

This high rate of forest loss is very worrisome considering the dangers posed by deforestation. Grassland appreciated by 5776ha (17.26%) at the rate of 0.86% per annum in the first period. By the second period, however, there was a sudden decrease in the area of grassland by -14615ha (37.23%) at an annual rate of-3.72%. The decline was also noticed in the overall trend depreciating by 8839ha (26.41%) at an annual rate of -0.88%. Farmland witnessed a decrease in the first period declining by 5300ha (25.16%) but rising sharply in the second period by13653ha (86.62%) at an annual rate of 8.66%. The fluctuation in the pattern of change may be due to a reluctance to engage in farming at the initial time but a sudden change in attitude owing to government desire to enhance food security. Figure 4.17 depicts the trend in LULC changes in Makurdi during the period.

4.4.2: Trend and Rate of LULC Change in Gboko for 1987,2007 and 2017

The trend in LULC changes in Gboko (Table 4.13 and Figure 4.18) shows that urban area increased by 5310ha (164.29%) in the first period at rate of 8.21% per year while in the second period the change was 8072ha (94.5%) at the rate of 9.45% per year. As there was an increase in urban area, the rate also increased to 9.45% which signifies a rise in the rate of urban expansion between 2007 to 2017. The overall trend (1987-2017) revealed that urban area has increased up to 13382ha (414.05%) with an annual rate of change as high as 13.8% higher than the rate in the first period.

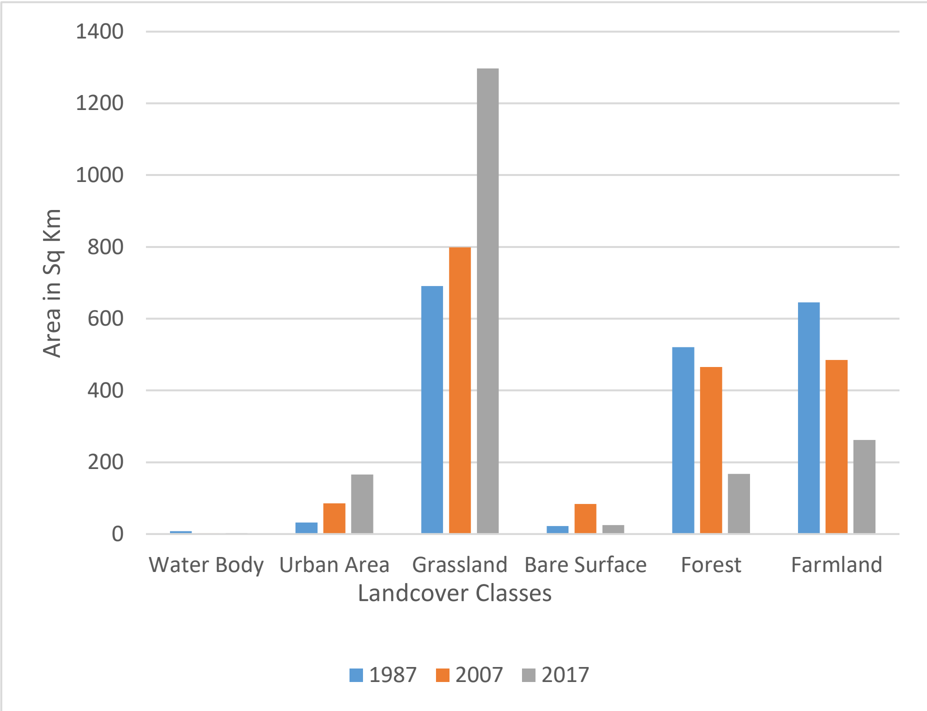


Figure 4. 18: Trend of Land Cover Changes in Gboko (1987-2017)

Forest land in Gboko has been on the decline throughout the period with a loss of 5585ha (-10.72%) in the first period with an annual rate of -0.54% and 29800ha (-64.05%) in the second period with an annual rate of -6.41%. The overall trend shows that forest lost was 35385ha (67.91%) at the rate of -2.26% per year. This high rate is an indication that in no distant future the area may be completely devoid of forest vegetation. Farmland also decreased during the period losing 16006ha (-24.8%) in the first period at the rate of -

1.24% per year and 22317ha (45.98%) in the second at the rate of change of -4.6% per year.

Table 4. 13: Annual Rate of LULC Change for Gboko (1987, 2007 and 2017)

LULC Class	1987-2007 Area (ha) Change	Percentage of Change	2007-2017 Area (ha) Change	Percentage of Change	1987-2017 Area (ha) Change	Percentage of Change	ANNUAL RATE OF CHANGE 1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	-620	-73.81	57	25.91	563	67.02	-3.69	2.59	2.23
Urban Area	5310	164.29	8072	94.5	13382	414.05	8.21	9.45	13.8
Grassland	10800	15.64	49841	62.4	60641	87.79	0.78	6.24	2.93
Bare Surface	6101	270.91	-5853	-70.07	248	11.01	13.54	-7.01	0.37
Forest	-5585	-10.72	-29800	-64.05	-35385	-67.91	-0.54	-6.41	-2.26
Farmland	-16006	-24.8	-22317	-45.98	-38323	-59.38	-1.24	-4.6	-1.98

The overall trend indicates that 38323ha (-59.38%) was lost between 1987 and 2017 at the rate of -1.98% per annum. The decline in farmland could be due to involvement of the aged and absence of the youth who have migrated to the cities. Grassland increased throughout the period, 10800ha (15.64%) by the first period with a 0.78%change rate. By the second period, it increased to 49841ha (62.4%) with the annual rate of change rising to 6.24%. The overall trend shows that it increased by 60641ha (87.79%) at an annual rate of change of 2.93%. This might be due to clearance of forested areas for agriculture and later abandoning it for grassland to take over. Water body and bare surface recorded minimal changes.

4.4.3: Trend and Rate of LULC Change in Otukpo for 1987,2007 and 2017

The trend in LULC change in Otukpo (Table 4.14 and Figure 4.19) revealed that urban area has been on the increase recording an increase of 5097ha (156.78%) in the first period with a 7.84% annual rate. The second period witnessed dramatic increase to

7127ha (85.37%) at the rate of 8.54% per year. The overall trend shows an increase of 12224ha (376.01%) with an annual rate of change of 12.53%. The area of forest declined to the tune of 5945ha (-17.89%) in the first period. It further declined by 10548ha (-38.65%) at the rate of -3.87% per annum. The overall trend was also negative losing 16493ha (-49.63%) at the rate of -1.65%. This massive loss of forest land may be partly due to increase in urban area which has taken over areas hitherto occupied by forest and increase in farming area. Farmland showed an increase in the first period by 7957ha (36.46%) at the rate of 1.82%. There was, however, a decrease in the second period by -1432ha (-4.81%) at the rate of -0.48%. The fluctuation may be due to declining food prices which may have discouraged farmers to continue the expansion of land area under cultivation. The overall trend, however showed an increase to 6525ha (29.9%) at the rate of 1%. Grassland witnessed a continuous increase throughout the period, increasing to 14512ha (34.1%) in the first period at the rate of 1.71% and 1552ha (2.72%) at 0.27% per annum in the second period.

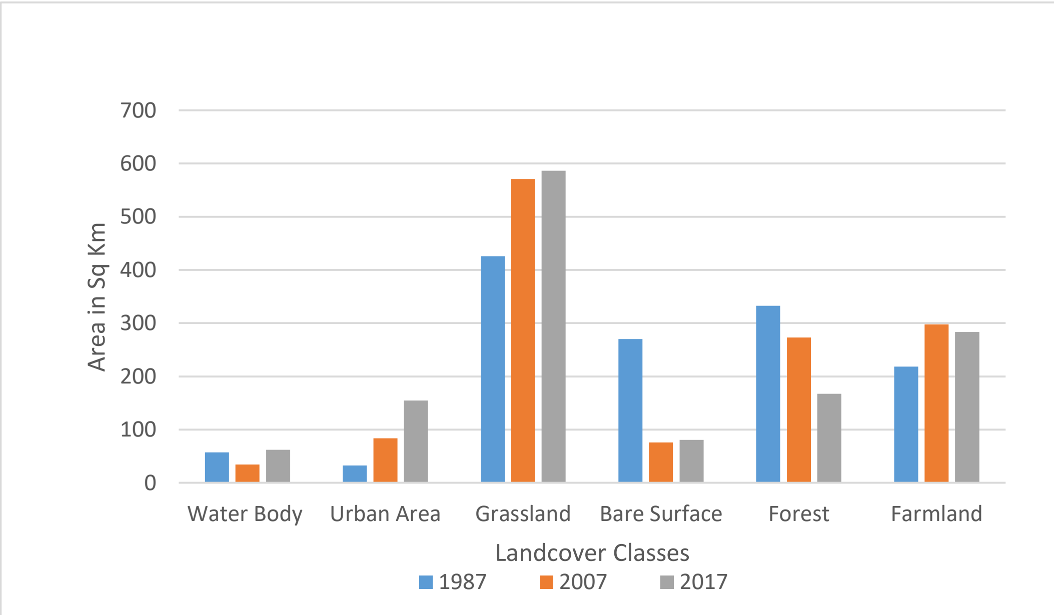


Figure 4. 19: Trend of Land Cover Changes in Otukpo (1987-2017)

The overall trend shows that 16064ha (37.75%) was gained at the rate of 1.26%. Bare surface and water body showed insignificant fluctuating trend during the period.

Table 4. 14: Annual Rate of LULC Change for Otukpo (1987, 2007 and 2017)

LULC Class	1987-2007 Area (ha) Change	Percentage of Change	2007-2017 Area (ha) Change	Percentage of Change	1987-2017 Area (ha) Change	Percentage of Change	ANNUAL RATE OF CHANGE		
							1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	-2274	39.95	2808	82.15	534	9.38	2	8.22	0.31
Urban Area	5097	156.78	7127	85.37	12224	376.01	7.84	8.54	12.53
Grassland	14512	34.1	1552	2.72	16064	37.75	1.71	0.27	1.26
Bare Surface	-19447	-71.94	493	6.5	-18954	-70.11	-3.6	0.65	-2.34
Forest	-5945	-17.89	-10548	-38.65	-16493	-49.63	-0.89	-3.87	-1.65
Farmland	7957	36.46	-1432	-4.81	6525	29.9	-1.82	-0.48	1

4.4.4: Trend and Rate of LULC Change in Katsina-Ala for 1987, 2007 and 2017

The trend in LULC change in Katsina-Ala is shown in Table 4.15 and Figure 4.20. Urban area continued to expand throughout the period. In the first period, it increased by 2514ha (31.96%) at the rate of 1.6%. By the second period, it increased by 5524ha (53.21%) at the rate of 5.32%. The overall trend shows that urban area increased by 80.38ha (102.17%) at the rate of 3.41%. This indicates that the urban area in Katsina-Ala is not expanding at a very fast rate compared to the other urban areas of Makurdi, Gboko and Otukpo.

As with other areas, forest in Katsina-Ala has been on the decline over the years. In the first period, -4815ha (-6.76%) was lost at the rate of -0.34% per year while 37375ha (-56.29%) was lost in the second period at the rate of -5.63% per year. The overall trend shows that forest declined by -4219ha (-5.92%) at the rate of -0.2%. The decline in forest area was mostly due to expansion in farmlands. Farmland has been on the increase over the entire period. It increased by 407ha (61.46%) at the rate of 3.07% during the first period and 47753ha (44.66%) at 4.47% rate per year during the second period.

The trend over the entire period shows an increase of 88453ha (133.56%) at the rate of 4.45% per year. The rate of expansion of farmland is very high in this region owing to the fact that the inhabitants are largely agrarian and the area forms one of the core areas agricultural base in Benue State. As farmland increases, grassland decreases. In the first period, grassland lost -39185ha (-32.52%) at the rate of -1.63% increasing to -14471ha (-17.8%) at the rate of -1.78% in the second period. The overall trend shows that 53656ha (-44.54%) was lost at the rate of -1.48%. This massive loss was largely due to expansion of agricultural land.

Figure 4. 20: Trend of Land Cover Changes in Katsina-Ala (1987-2017)

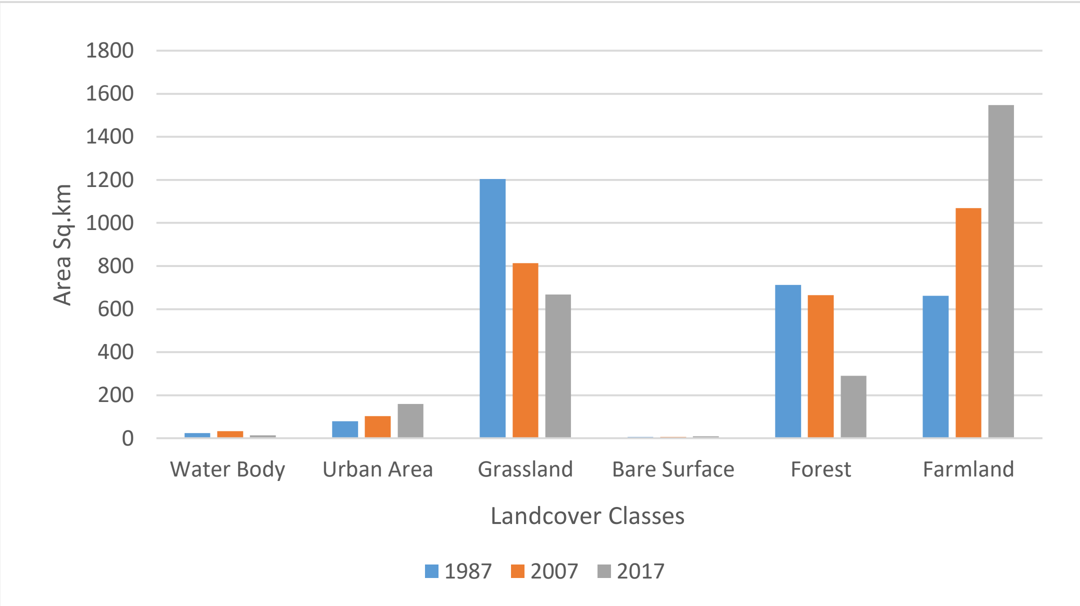


Table 4. 15: Annual Rate of LULC Change for Katsina-Ala (1987, 2007 and 2017)

LULC Cl	1987 -	Percen	2007 -	Percen	1987 -	Percen	ANNUAL RATE OF CHANGE

							1987-2007 (%)	2007-2017 (%)	1987-2017 (%)
Water Body	854	35.55	-1933	-59.37	-1079	-44.92	1.78	-5.94	-1.5
Urban Area	2514	31.96	5524	53.21	8038	102.17	1.6	5.32	3.41
Grassland	-39185	-32.52	-14471	-17.8	-53656	-44.54	-1.63	-1.78	-1.48
Bare Surface	-68	-10.1	291	48.1	223	33.14	-0.51	4.81	1.1
Forest	-4815	-6.76	-37375	-56.29	-4219	-5.92	-0.34	-5.63	-0.2
Farmland	40700	61.46	47753	44.66	88453	133.56	3.07	4.47	4.45

4.5 Comparison of LULC Changes Within Benue State

The LULC changes in the selected Local Government Areas housing the urban areas was compared to identify the pattern of changes in the various urban areas from 1987-2007, 2007-2017 and 1987-2017.

4.5.1 Comparison of LULC changes within Benue State from 1987-2007

Figure 4.21 and Table 4.16 show the LULC changes in the four urban areas and the whole state. From these, it can be seen that farmlands had the highest positive change in Katsina-Ala while forest had the highest negative change in the whole state It is also clear that urban area, grassland and farmland had positive change in all locations except for grassland in Katsina-Ala and farmland in Gboko. Although all the urban areas experienced positive urban growth between 1987 and 2007, Makurdi had the highest growth in urban areas (24.88%) followed by Gboko (11.95%), Otukpo (9,23%) and Katsina-Ala with the least (2.85%).

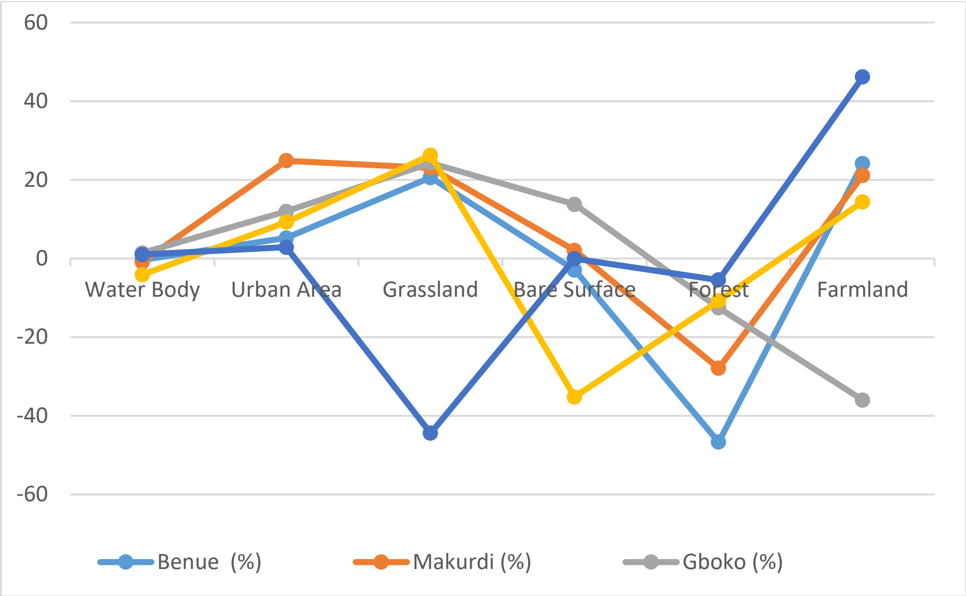


Figure 4. 21: Comparison of LULC Changes within Benue State from 1987-2007

The loss of forest land is highest in Makurdi (-27.94%) followed by Gboko (-12.57%), Otukpo (-10.76%) and Katsina-Ala (-5.46%). This pattern of change is not surprising as the highest percentage of growth in Makurdi is due to its status as the state capital which have led to a corresponding decline in forest land.

Table 4. 16: Comparison of LULC Changes within the State from 1987-2007

Land Cover Class	Benue		Makurdi		Gboko		Otukpo		Katsina-Ala	
	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)
Water Body	-2534	-0.37	-226	-0.90	-62	1.40	-2274	-4.12	854	0.97
Urban Area	35605	5.22	6231	24.88	5310	11.95	5097	9.23	2514	2.85
Grass land	140670	20.61	5776	23.06	10800	24.31	14512	26.27	-39185	-44.46
Bare Surface	-19999	-2.93	517	2.06	6101	13.74	-19747	-35.21	-68	-0.08
Forest	-318710	-46.7	-6998	-27.94	-5585	-12.57	-5945	-10.76	-4815	-5.46
Farm land	164970	24.17	-5300	21.16	-16010	-36.03	7957	14.41	40700	46.18

4.5.2 Comparison of LULC changes within Benue State from 2007-2017

A comparison of LULC changes between 2007 and 2017 reveal that Otukpo had the highest percentage of urban growth (29.74%) followed by Makurdi (15.08%), Gboko (6.96%) and Katsina-Ala (5.15%) (See Table 4.17 and Figure 4.22).

Table 4. 17: Comparison of LULC Changes within Benue State from 2007-2017

Land Cover Class	Benue		Makurdi		Gboko		Otukpo		Katsina-Ala	
	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)
Water Body	-8686	-1.32	-3	-0.01	57	0.05	2808	11.72	-1933	-1.8
Urban Area	23476	3.57	5894	15.08	8072	6.96	7127	29.74	5524	5.15
Grass land	254250	38.61	-14615	-37.38	49841	42.99	1552	6.48	-14471	-13.48
Bare Surface	51502	7.82	-185	-0.47	-5853	-5.05	493	2.06	291	0.27
Forest	-146480	-22.25	-4744	-12.14	-29800	-25.7	-10548	-44.02	-37375	-34.82
Farm land	-174050	-26.43	13653	34.92	-22317	-19.25	-1432	-5.98	47753	44.48

During the period, Otukpo lost the highest percentage of forest land (-44.02%) followed by Katsina-Ala (-34.82%), Gboko (-25.7%) and Makurdi (-12.14%). The highest positive growth was recorded by farmland in Katsina-Ala while the highest negative change was forest in Otukpo (-44.02%). The increase in farmland is not a surprise as the area is regarded as the "Food Basket of the State".

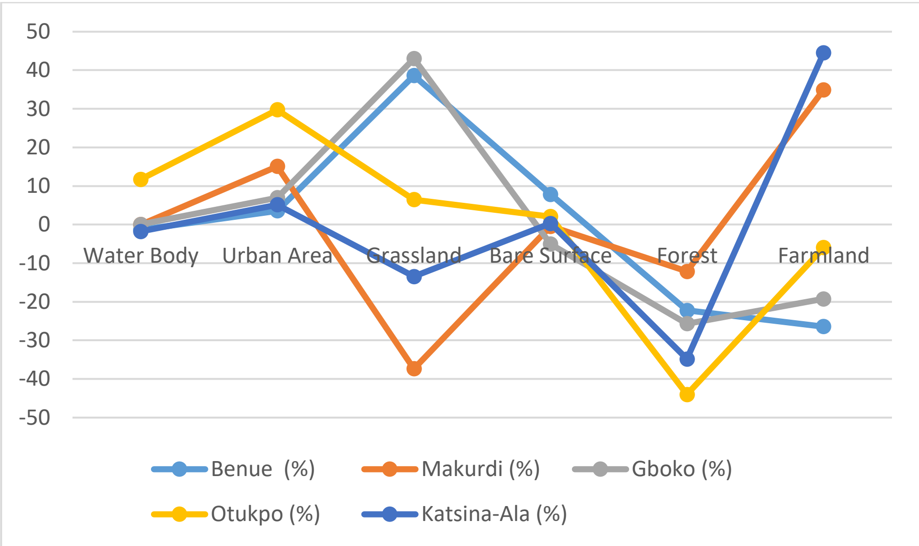


Figure 4. 22: Comparison of LULC Changes Within Benue State from 2007-2017

4.5.3 Comparison of LULC Changes within the State from 1987-2017

A comparative analysis of the LULC changes over the period 1987 - 2017 revealed that Makurdi, the state capital, had the highest percentage positive change (29.13%). This was closely followed by Otukpo (17.27%), Gboko (9.01%) and Katsina-Ala (4.15%). Forest loss also maintained a similar pattern with Gboko placing second to Makurdi (See Table 4.18 and Figure 4.23).

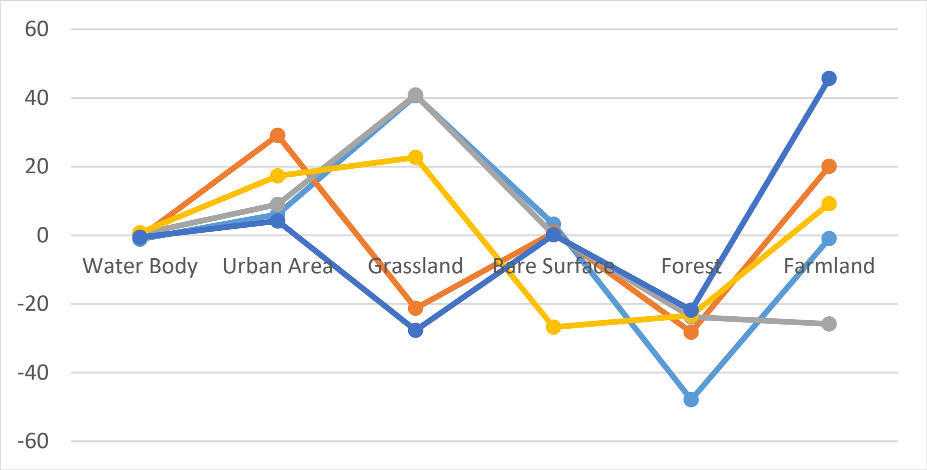


Figure 4. 23: Comparison of LULC Changes Within Benue State from 1987-2017

Table 4. 18: Comparison of LULC Changes within Benue State from 1987-2017

Land Cover Class	Benue		Makurdi		Gboko		Otukpo		Katsina-Ala	
	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)	Ha	(%)
Water Body	-11220	-1.16	-229	-0.55	563	0.38	534	0.75	-1079	-0.56
Urban Area	59081	6.08	12125	29.13	13382	9.01	12224	17.27	8038	4.15
Grass land	394920	40.67	-8839	-21.24	60641	40.82	16064	22.69	-53656	-27.71
Bare Surface	31503	3.24	332	0.8	248	0.17	-18954	-26.77	223	0.12
Forest	-46519	-47.91	-11742	-28.21	-35385	-23.82	-16493	-23.3	-42190	-21.79
Farm land	-9078	-0.94	8353	20.07	-38323	-25.8	6525	9.22	88453	45.68

4.6: Land Change Analysis Using Land Change Modeler (LCM)

The results of LULC analysis for Benue State for the first period (1987 -2007) show that almost all the land cover classes lost and gained some grounds. Farmland, grassland and urban area witnessed a net gain while forest and bare surface witnessed a net loss. As can be seen from Figure (4.24a), forest contributed the highest area to the growth in urban area followed by farmland and bare surface while grassland contributed negatively to urban growth. The contributors to net loss in forest came from farmlands, grassland and forests in that order as is depicted in Figure (4.24c). Grassland, mostly from farmland, grassland and urban area in that order. Bare surface, farmland and urban area were the major contributors to decreasing forest land.

Figure 4. 24: Gains/Losses of LULC, Contribution to Net Change in Urban Area and Forest (Ha) in Benue State from (A):1987 – 2007, (B): 2007 -2017 and (C): 1987- 2017

Makurdi, the state capital, witnessed a distinct land cover transition during the period. In the first period, grassland experienced the highest transition losing over 100ha but gaining over 150ha. Farmland and forest had more negative changes than positive changes resulting in the loss of these LULC categories. As can be seen from Figure (4.25a) urban area and bare surface increased. Farmland was the largest contributor to urban area expansion followed by grassland, forest and bare surface. This implies that the urban area is expanding at the expense of these land covers. The decrease in forest land was as a result of expansion in grassland and farmland. Areas hitherto occupied by forest have now been cleared and taken over by farms or abandoned as grassland. The second period (Figure 4.25b) showed a similar pattern. The transition among the land cover classes as grassland experienced the highest change followed by farmland, forest and urban area. The overall transition (Figure 4.25c), however, illustrated a marked difference in the pattern. Farmland showed a positive change while grassland had a negative change along with forest land. Urban area continued its positive change during the period. Farmland was the largest contributor to urban growth followed by grassland and forest. The largest contributor to loss in forest land was farmland, grassland and urban area.

Figure 4. 25: Gains/Losses of LULC, Contribution to Net Change in Urban Area and Forest (Ha) in Makurdi from (a):1987 – 2007, (b): 2007 -2017 and (c): 1987- 2017

Gboko, the traditional headquarters of the Tiv people show marked trend in land cover transitions. All the classes experienced transitions but farmland had the highest positive transition followed by urban area. Grassland had the highest negative transition closely followed by forest land (Figure 4.26a). Farmland, grassland and forest were the major contributors to urban area expansion. Farmland, grassland and urban area were responsible for the decline in the forest land. In a similar vein, land cover transition pattern in the second period had a lot of resemblance to that of the first period. as can be seen in Figure in (4.26b). The period between 1987-2017 saw grassland having the dominant positive transition closely followed by urban area. Farmland and forest witnessed a negative transition (Figure 4.26c).

Again, farmland, grassland and forest were the major contributors to urban growth while grassland, farmland, bare surface and urban area accounted for the decline in forest land.

Figure 4. 26: Gains/Losses of LULC, Contribution to Net Change in Urban Area and Forest (Ha) in Gboko from (a):1987 – 2007, (b): 2007 -2017 and (c): 1987- 2017

The gain and losses graphics in Otukpo (Figure 4.27a, b and c) show that grassland witnessed the major positive transition followed by urban area. Farmland had a negative transition in the first and second periods but was positive in the overall trend while forest declined throughout during the periods. Contributors to urban expansion came mainly from farmland, grassland and forest during the first two periods but bare surface took over leadership in the overall trend. This was followed by farmland, forest and grassland.

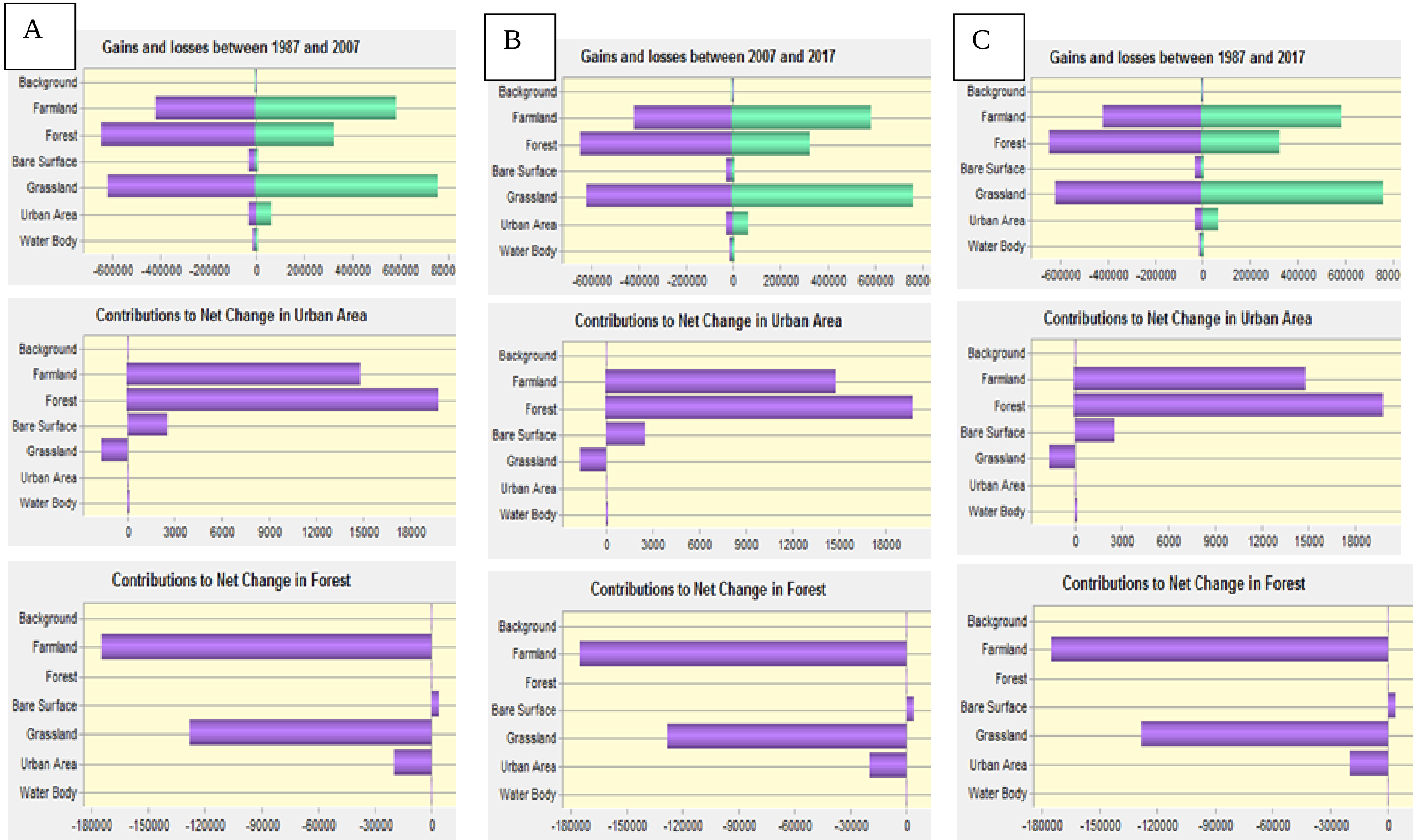


Figure 4. 27: Gains/Losses of LULC, Contribution to Net Change in Urban Area and Forest (Ha) in Otukpo from (A):1987 – 2007, (B): 2007 -2017 and (C): 1987- 2017

The land cover transition in Katsina-Ala (Figure 4.28a, b and c) show that all the land cover classes underwent changes. Farmland and urban area maintained a positive change throughout the period. Grassland was positive only during the first period but was negative in the second and overall periods. Forest land declined throughout the period but was highest in the first period. Urban area gained more from bare surface in the first period but was overtaken by grassland in the other periods. Farmland and forest were the other major contributors. Farmland, grassland and forest were accountable for decreasing forest in the area. From the analysis of the pattern, trend and rate of LULC transition in Benue State and the selected urban areas, it is clear that these land cover classes are not static in nature. Urban areas are continually on the increase in size by taking up lands previously occupied by farmland, grassland and forest. Forest land had been lost as a result of anthropogenic activities such as farming and urban settlement. In other areas, the forests were cleared giving way for takeover by grassland. This is clearly evident in the contribution to net change in urban areas and forest.

Figure 4. 28: Gains/Losses of LULC, Contribution to Net Change in Urban Area and Forest (Ha) in Katsina-Ala from (a):1987 – 2007, (b): 2007 -2017 and (c): 1987- 2017

4.7 Identification of Drivers and their Contribution to Urban Growth

The LCM's Test and selection of site and driver variable module was employed in an attempt to test the potential power of the drivers (explanatory variables). These set of drivers were chosen on the basis of pilot surveys as well as reviews from relevant academic literatures. Table 4.19 illustrates the Cramer's V coefficient for each of the drivers, As can be seen from Table 4.19, all the variables namely, likelihood of transition, distance from urban areas, roads, rivers, railways, digital elevation model (DEM), slope and population density chosen had Cramer's V value greater than 0.15 and were used in the process as was shown by Wang and Maduako (2018). It is also evident that likelihood of transition, DEM and population density had values greater than 0.4, implying that these three drivers are strongly associated with transition and hence retained in the sub-model structure. Also, the LCM MLP model results shown in Appendices B to F reveal that likelihood of transition, distance from urban areas and railways were most important drivers in shaping urban growth as revealed by the influence order.

Table 4. 19: Cramer's V Test Values for Explanatory Variables

Variable	Benue State	Makurdi	Gboko	Otukpo	Katsina-Ala
Likelihood	0.4261	0.4894	0.4244	0.4495	0.4048
Dist_Urban	0.3756	0.3155	0.3513	0.3763	0.3623
Dist_Roads	0.3200	0.2367	0.2425	0.2904	0.2418
Dist_Rivers	0.3375	0.2622	0.3051	0.3200	0.2563
DEM	0.4274	0.4509	0.4644	0.5030	0.4375
Slope	0.3964	0.3946	0.3931	0.4039	0.3846
Pop density	0.4252	0.4282	0.4610	0.4828	0.4140
Dist_Rails	0.1829	0.2755	-	0.2349	-

4.8 Sensitivity Analysis

Upon conclusion of the process, the MLP produces a wide range of statistics that give information pertaining the power of the drivers in explaining the LULC pattern as well as the accuracy of the models in predicting class change or no change. A vital part of the statistics generated is known as “Forcing Independent Variables to be Constant”. After the system has trained on all of the explanatory drivers, the system tests the power of explanatory variables relatively by selectively keeping the inputs from selected variables constant. Holding the input values for a selected variable constant successfully eliminates the variability associated with that variable. Using the modified model, the MLP procedure repeats the skill test using the validation data. The difference in skill thus provides information on the power of that variable. This process is replicated for all the driver variables to find out their power on the skill measure and model accuracy.

Three different sensitivity analyses were run. In the first section, a single variable is held constant. This is repeated for all variables. Appendix C shows the sensitivity of holding one variable constant for each of the five selected areas. In the second sensitivity, all variables are held constant (at their mean values) except one.

The final test in section 3 is entitled Backwards Stepwise Constant Forcing. Starting with the model developed with all variables, it then holds constant every variable in turn to determine which one has the least effect on model skill. Step 1 thus shows the skill after keeping constant the driver with the lowest negative result on the skill. If a variable is held constant and the skill does not decrease much, then it suggests that that variable has little value and can be removed (See Appendix D).

It then tests every possible pair of variables that include that determined in step 1 to figure out which pair, when held constant, have the least effect on the skill. It continues in this manner progressively holding another variable constant until only one variable is left. Details of these are provided in Appendices E to I. The backward stepwise analysis is very useful for model development. The backward stepwise MLP result was used in assessing the best model combination of driver variables on the basis of percentage accuracy and skill measure by successively removing the weakest driver variable one after the other.

The results of the backwards stepwise constant forcing in Appendix C shows that for Benue State all the eight independent variable combination had an accuracy rate of 75.60% and 0.6746 of skill measure. MLP repeating test with the removal of variable 6 (population density) had a higher accuracy rate of 75.64% and a 0.6751 of skill measure compared to the use of all the eight variables. In Makurdi, the removal of variables 6 and 5 (population density and slope) yielded the highest accuracy of 76.27% and a 0.7152 of skill measure compared to 75.97% accuracy and 0.7119 of skill measure when all the variables were used. In Gboko, the elimination of variable 5 (slope) produced the same result of accuracy of 78.72% and a 0.7447 skill measure with all the variables used.

In Otukpo, the elimination of slope (variable 5) had a higher accuracy of 78.15% and a 0.7503 skill measure in contrast to 78.05% accuracy and a 0.7492 skill measure when all the variables were used. The situation in Katsina-Ala was quite distinct. Here , the exclusion of variable 2 and 5 (distance from roads and slope) yielded the best combination of variables with an accuracy of 72.69% and a 0.6723 skill measure compared with the 71.43% accuracy and a 0.6571skill measure obtained from the inclusion of all the variables. These best combinations were then utilised to predict sensitivity of growth of urban areas.

Table 4.20 presents list of all independent variables used in the modelling process with their corresponding numbers. Distance from urban area was assigned number 1, distance from roads, number 2, through to the last variable distance from railways with number 8 as is shown in Table 4.20.

Table 4. 20: List of Independent Variables

Variable Code	Name of Variable
Independent variable 1	Distance from urban area in 1987
Independent variable 2	Distance from roads
Independent variable 3	Distance from rivers
Independent variable 4	Digital elevation model
Independent variable 5	Slope
Independent variable 6	Population density
Independent variable 7	Evidence likelihood of transition
Independent variable 8	Distance from railways

4.9 Transition Potential Modelling using MLP

After selecting the predictor variables, all the transitions were then modeled in a single transition sub-model called urban area, as they had common drivers, with the intent of creating the transition maps for Benue State, Makurdi, Gboko, Otukpo and Katsina-Ala . As earlier stated, MLP was used in modelling the transitions and it generated maps of transition potential for each of the evaluated transition sub-models. . The results of the MLP transition modelling is presented in Appendix J^1 and J^2. It shows two maps of transition potential from forest to urban area and farmland to urban area for Benue State. In Makurdi, three transition maps were created which include transition from grassland to urban area, forest to urban area and farmland to urban area. The situation was similar in Gboko where the three transitions were from grassland to urban area, bare surface to urban area and forest to urban area. In Otukpo, there were four transitions to urban area.

These were transitions from grassland, bare surface, forest and farmland to urban area. Appendix J[2] reveals the nature of transition in Katsina-Ala where there were transitions from grassland, bare surface and forest to urban area. These maps of transition potential produced from MLP modelling were then used in Markov model for determining the extent of change to be anticipated for each transition and for predicting of future patterns.

At this stage, the models were ready to predict the urban expansion scenarios for 2017 on the basis of the changes that occurred between 1987 and 2007, and the location of the possible future changes simulated from the transition potential maps. The simulated maps of LULC were then generated from the five transition models, each for the identified location. These were Benproject model, MKD model, GBK model, TKP model and KAL models.

4.10 Model Predictions and Validations

Results from Markov chain model predictions are on the basis of a transition probability matrix of LULC changes from 1987 to 2007 and changes in the past. This formed the basis for projection to 2017. Figures 4.29 showed the classified and predicted LULC maps of Benue State for 2017 which revealed noticeable differences. This has been the expectation as the past change processes between 1987 and 2007 cannot be alike as between 2007 and 2017 in Markov model. Again, the driving variables are bound to vary during the period thereby affecting the prediction results .

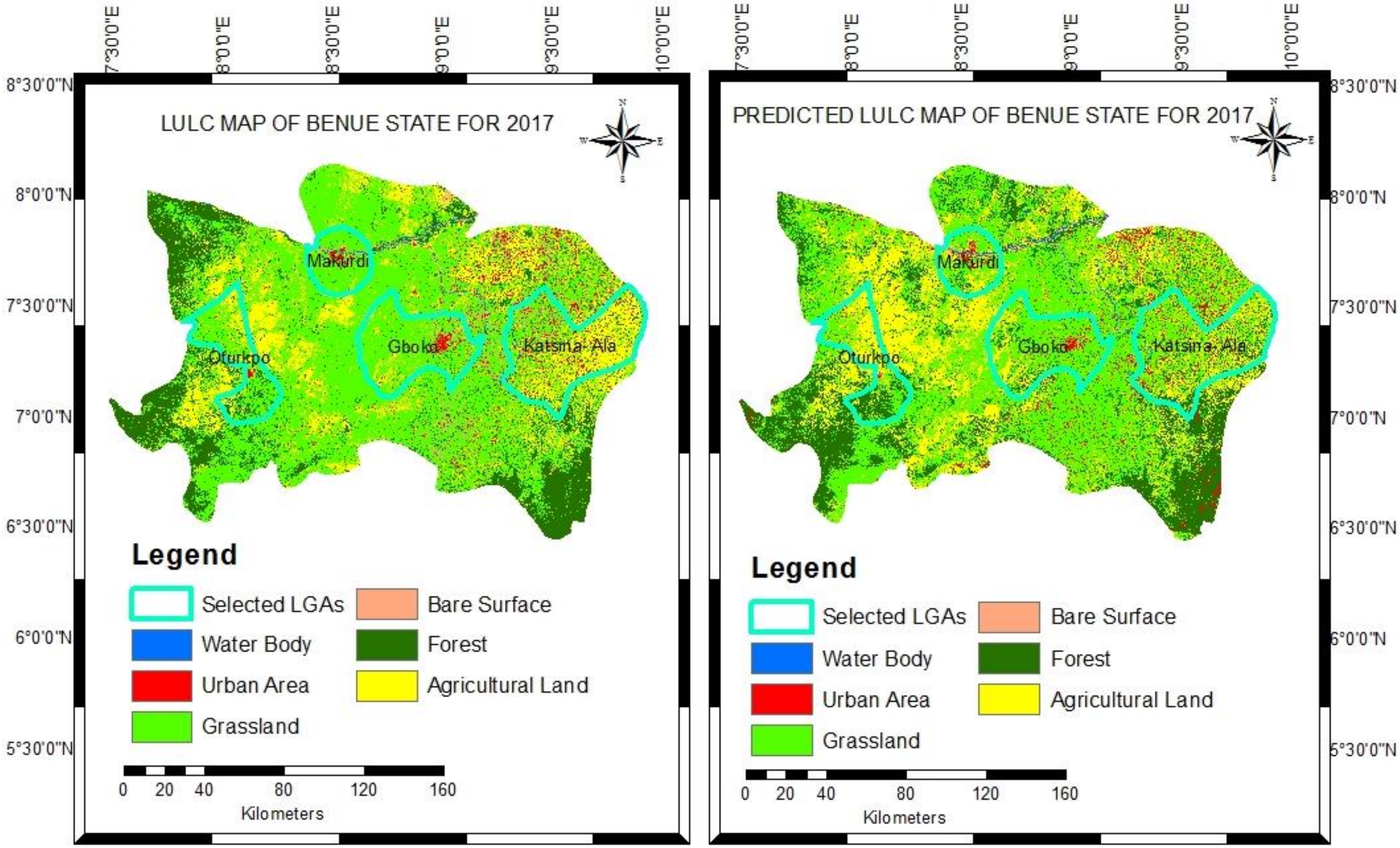


Figure 4. 29: Classified and Predicted LULC Maps of Benue State for 2017

Figures 4.30 showed the classified and predicted LULC maps of Makurdi for 2017. It is noticeable from it that the model under-predicted urban area extent while it over-predicted grassland.

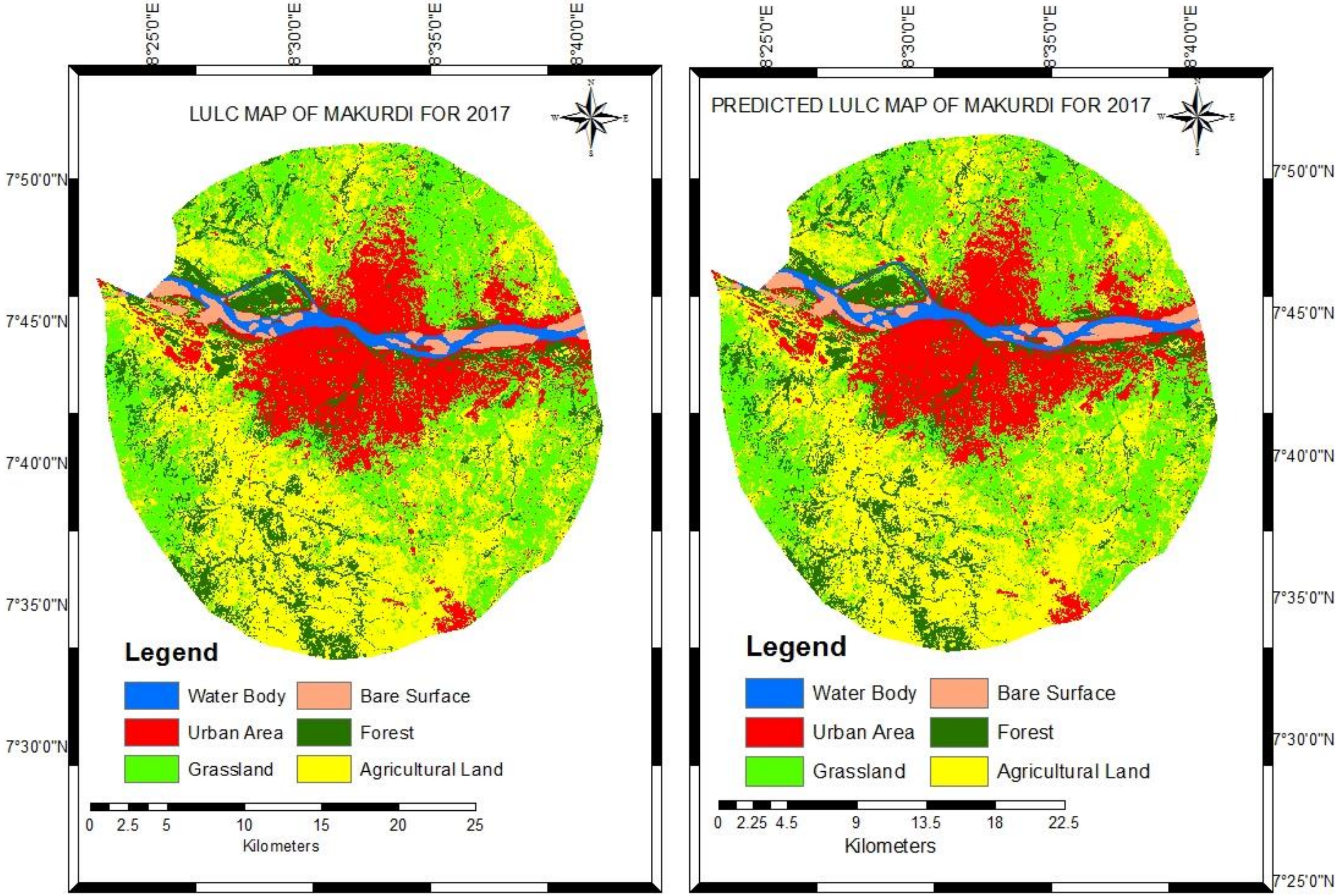


Figure 4. 30: Classified and Predicted LULC maps of Makurdi for 2017

In Gboko (Figure 4.31), the model predicted less of urban area and grassland but predicted more of farmland compared to the classified map for the same year. The model also overestimated forest area as compared to the actual map. While there had been much growth of urban areas, nevertheless, the change from other land cover categories was restricted. This is due to the power of the drivers included in the transition sub model on which the MLP accuracy and Markov model greatly depend on.

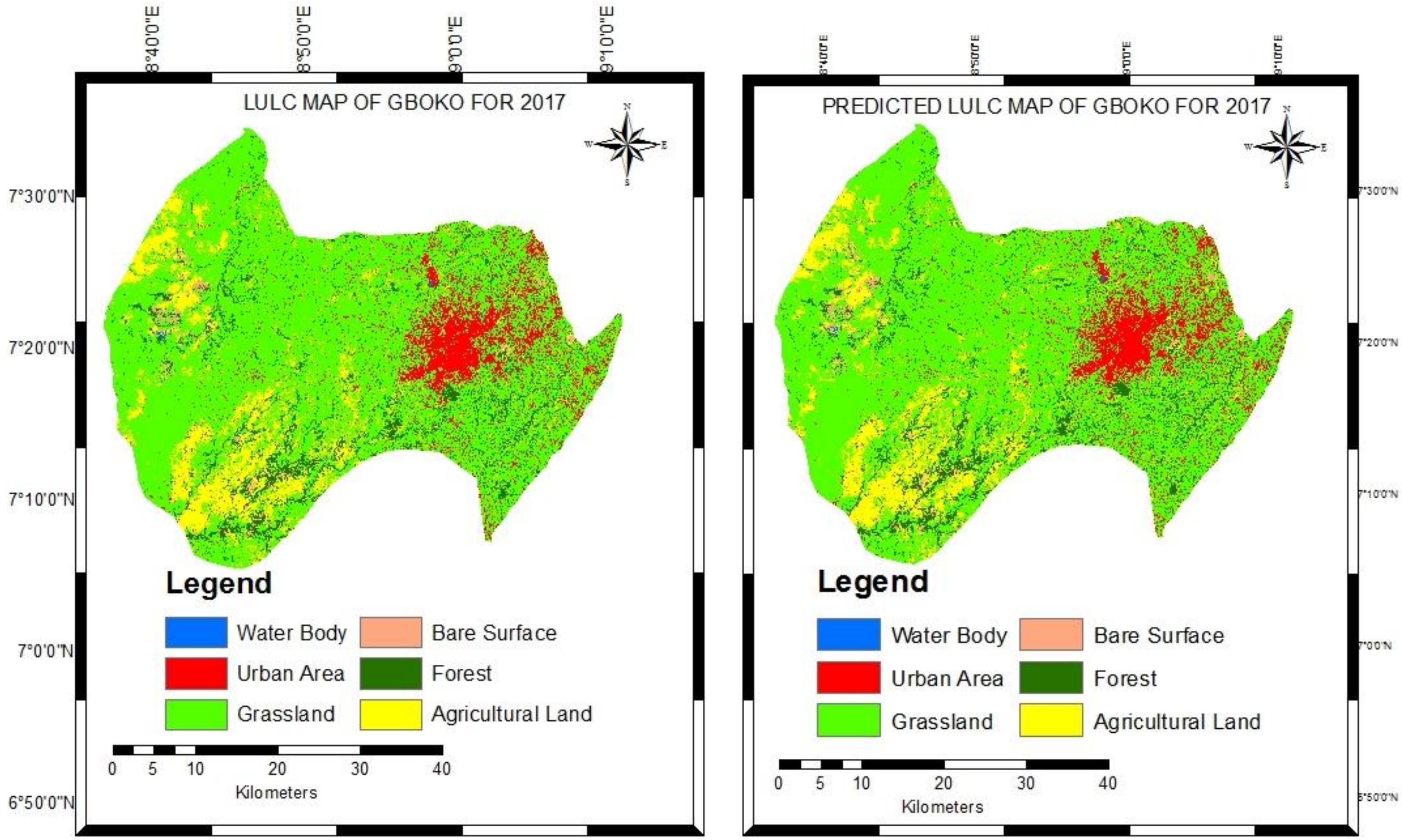


Figure 4. 31: Classified and Predicted LULC maps of Gboko for 2017

The situation in Otukpo (Figure 4.32) shows that the predicted urban area was slightly less than that in the actual map while forest were overestimated.

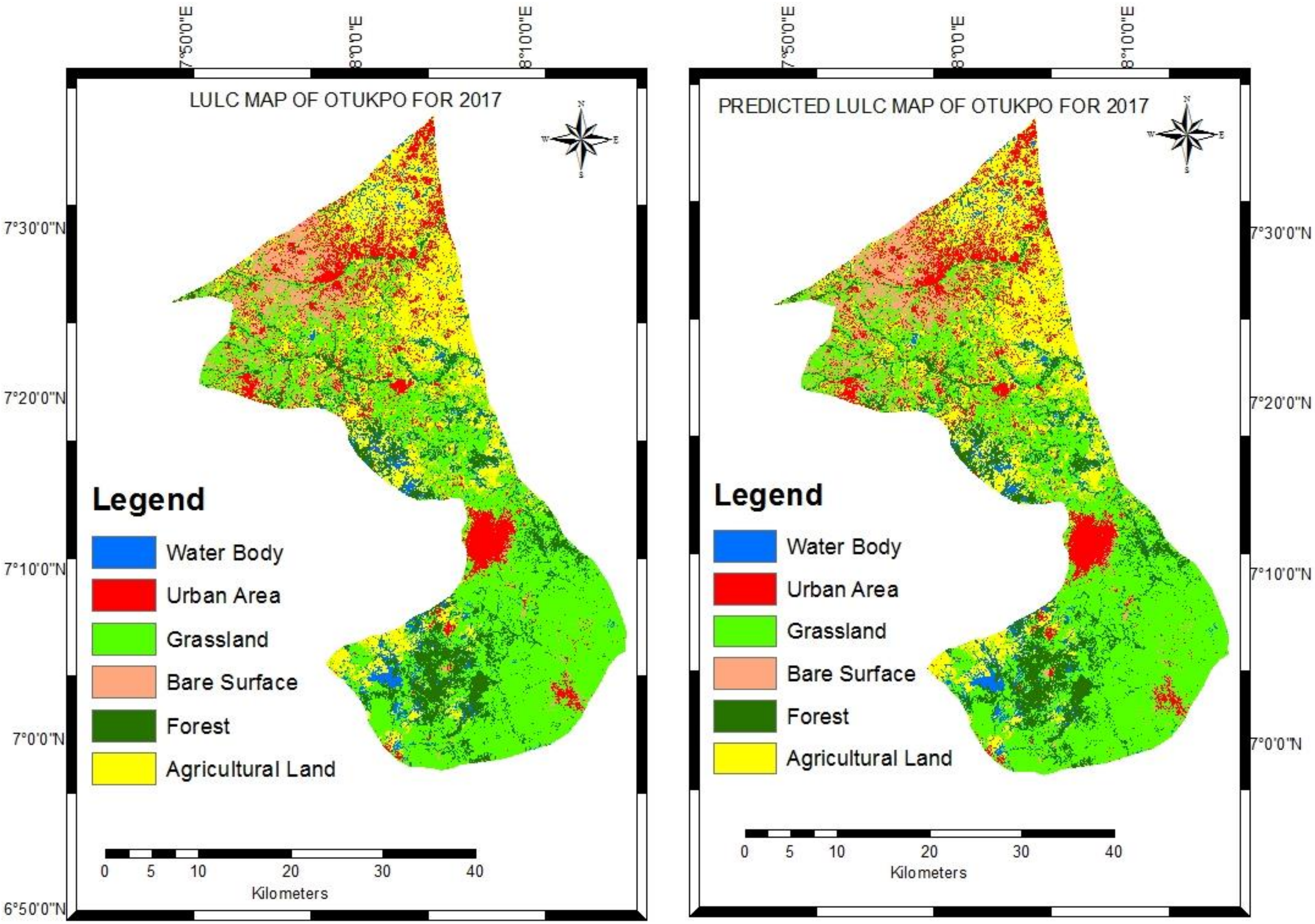


Figure 4. 32: Classified and Predicted LULC maps of Otukpo for 2017

The same scenario plays in Katsina-Ala (Figure 4.33) where urban areas were underestimated while forest area was slightly overestimated. On the whole, these models were able to correctly predict future scenario to some degree.

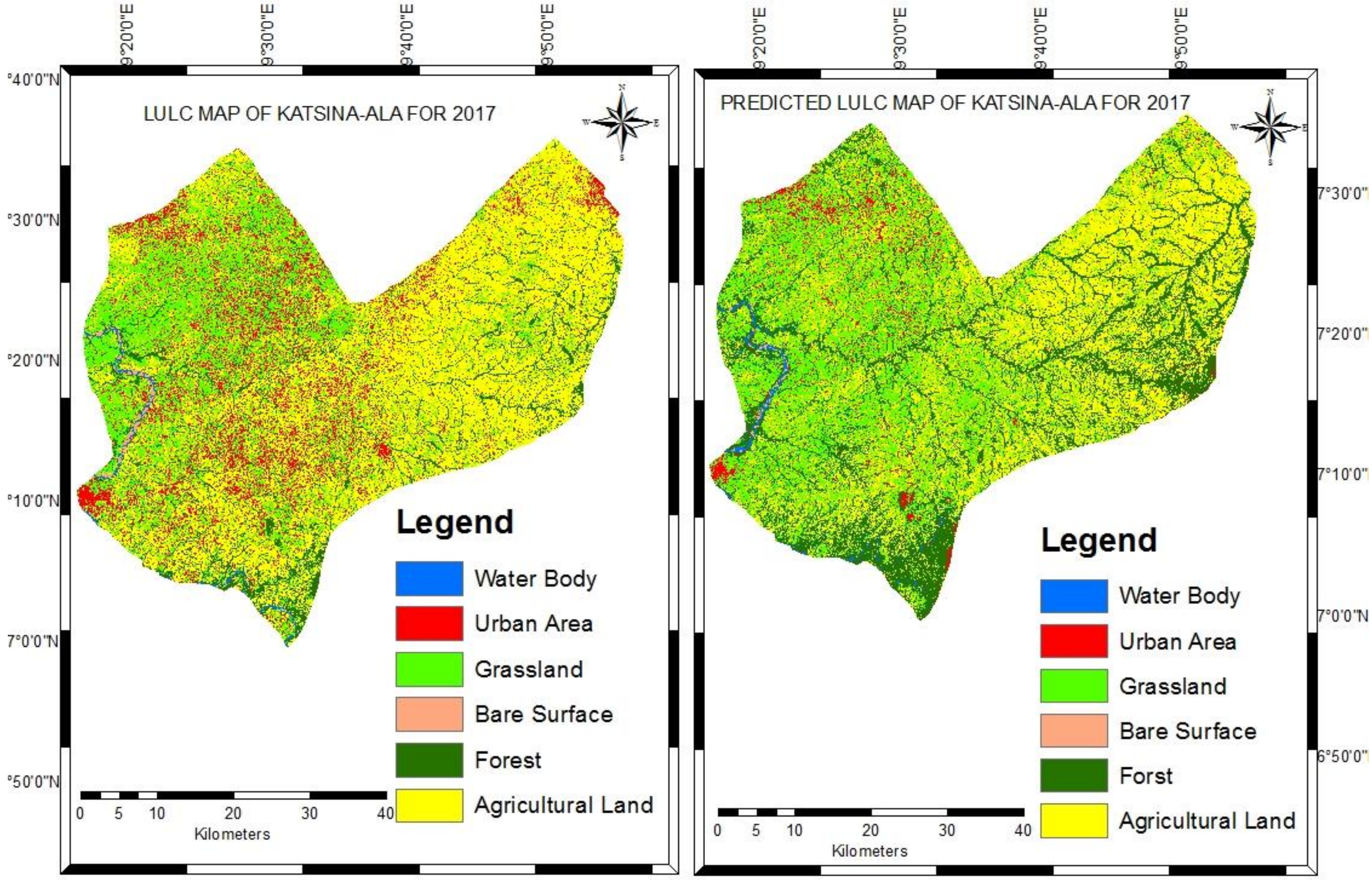


Figure 4. 33: Classified and Predicted LULC Maps of Katsina-Ala for 2017

In difference to the hard prediction, in the map of soft prediction, a large amount of the areas that actually changed in 2017 are deemed to be susceptible. In order to appraise the extent to which these models were able to forecast future LULC through soft prediction, the Relative Operating Characteristic (ROC) in Idrisi Selva was applied. The ROC statistic reveals how accurate a continuous surface predicts the points given a distribution of a Boolean variable. In this study, the soft prediction was used to assess against the real change from 2007 to 2017. The results of ROC is presented in Appendices K, L, M, N and I. The result of the ROC statistic reveal that Benue State had an Area Under the Curve (AUC) value of 0.785, Makurdi 0.814, Gboko 0.830, Otukpo 0.817 and Katsina-Ala 0.858, which indicate high value, showing the soft prediction were great . Spatial modelling and prediction are not meant for developing models that will be able to predict correctly future pattern but to predict as close as possible to that future state. In this perspective, a developed model can be regarded as being successful.

4.11 Modelling and Prediction of the Pattern of Urban Growth for 2030

After model validation, hard and soft predictions were both performed for the year 2030 so as to map likely transitions from other LULC categories to urban area. The prediction was restricted to short-term as they are more precise compared to long term predictions (Alba, 2011; Araya, 2009). Figures 4.34 to 4.38 shows the comparison of classified map of 2017 and predicted land cover maps in 2030 complemented by Table 4.21. The resulting 2030 prediction shows that considerable changes will occur in the future. In Benue State, the dominant land cover category will be grassland occupying 1627370ha (51.99%), followed by farmland with 822515ha (26.28%). Forest land will occupy 52300009ha (16.7%), urban area 122436ha (3.91%), water body 21106ha (0.67%) and bare surface will occupy 13963ha (0.45%).

In Makurdi, the dominant land cover category will also be grassland occupying 41689ha (49.91%), followed by urban area with 17384ha (20.81%). Farmland is projected to occupy 12290ha (14.72%), forest area 8557ha (10.25%), bare surface 1781ha (2.13%) and water body will occupy 1820ha (2.18%). Grassland continued its dominance in Gboko. Otukpo and Katsina-Ala. It is evident from Table 4.21 that Makurdi the State capital had the highest percentage of urban area relative to other locations. This is basically because of the city being the centre of government and the small size of Makurdi relative to other areas. The percentage area of forest in Benue State is higher compared to the percentage area in other locations with Otukpo having the least percentage area occupied by forest.

Table 4. 21: Projected Land Cover Statistics for 2030

Land Cover Class	**Benue**		**Makurdi**		**Gboko**		**Otukpo**		**Katsina-Ala**	
	Area (Ha)	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**
Water Body	21106	0.67	1820	2.18	217	0.11	3409	2.55	3247	1.21
Urban Area	122436	3.91	17384	20.81	18157	9.46	16819	12.60	17083	6.35
Grass land	1627370	51.99	41689	49.91	104756	54.55	65986	49.43	115669	43.02
Bare Surface	13964	0.45	1781	2.13	8217	4.28	6830	5.12	605	0.23
Forest	523009	16.70	8557	10.25	14277	7.43	14660	10.98	25431	9.46
Farm land	822515	26.28	12290	14.72	46424	24.17	25787	19.32	106829	39.73
Total	**3130386400**	**100**	**83521**	**100**	**192048**	**100**	**133491**	**100**	**268864**	**100**

A closer comparative look at the statistics for 2030 projection and the 2017 land cover for Benue State reveals that farmland, urban area and water body classes are estimated to increase by 143282ha, 23249ha and 8684ha (4.58%, 0.74 and 0.27%) but grassland, forest and bare surface classes are estimated to decrease -80521ha, -43194ha and 51502ha (-2.56%, -1.39% and -164%) as is shown in Table 4.22.

Table 4. 22: LULC Changes Between 2017 and 2030 for Benue State

Land Cover Classes	LULC in 2017 Area (Ha)	LULC in 2017 Area (%)	LULC in 2030 Area (Ha)	LULC in 2030 Area (%)	Change Area (Ha)	Change Rate %
Water Body	12422	0.40	21106	0.67	8684	+0.27
Urban Area	99187	3.17	122436	3.91	23249	+0.74
Grassland	1707891	54.55	1627370	51.99	-80521	-2.56
Bare Surface	65466	2-09	13964	0.45	-51502	-1.64
Forest	566203	18.09	523009	16.70	-43194	-1.39
Farmland	679232	21.70	822515	26.28	143283	+4.58
Total	**3130400**	**100**	**3130400**	**100**		

When 2017 maps are compared with the 2030 maps, some differences will be noticed. The urban areas present a pronounced change as can be noticeably seen in Figure 4.34. The urban areas are concentrated in Makurdi, Gboko, Otukpo and Katsina-Ala which expand inside and around the existing urban areas and road network, which mean that the expansion was mostly affected by these spatial variables such as distance from roads, town and the population density. Findings also showed that farmland will increase 4.58% from 21.70% to 26.28% in 2030. This is attributed to increase in farming activities by the population in order to generate enough food for the increasing population. This result is at variance with the work of Ismail and Abubakar (2015) who found out that in Wudil farmlands were to decrease due to shift from agricultural activities to other activities in the area. The increase in urban area class agrees with the results of Addae and Oppelt, (2019) that the Greater Accra Metropolitan Area (GAMA), in Ghana was increasing alarmingly from 1991 to 2025. The continuous increase in urban area can be attributed to quest for white-collar jobs and the pull factor of amenities present in urban areas coupled with the overall increase in total population.

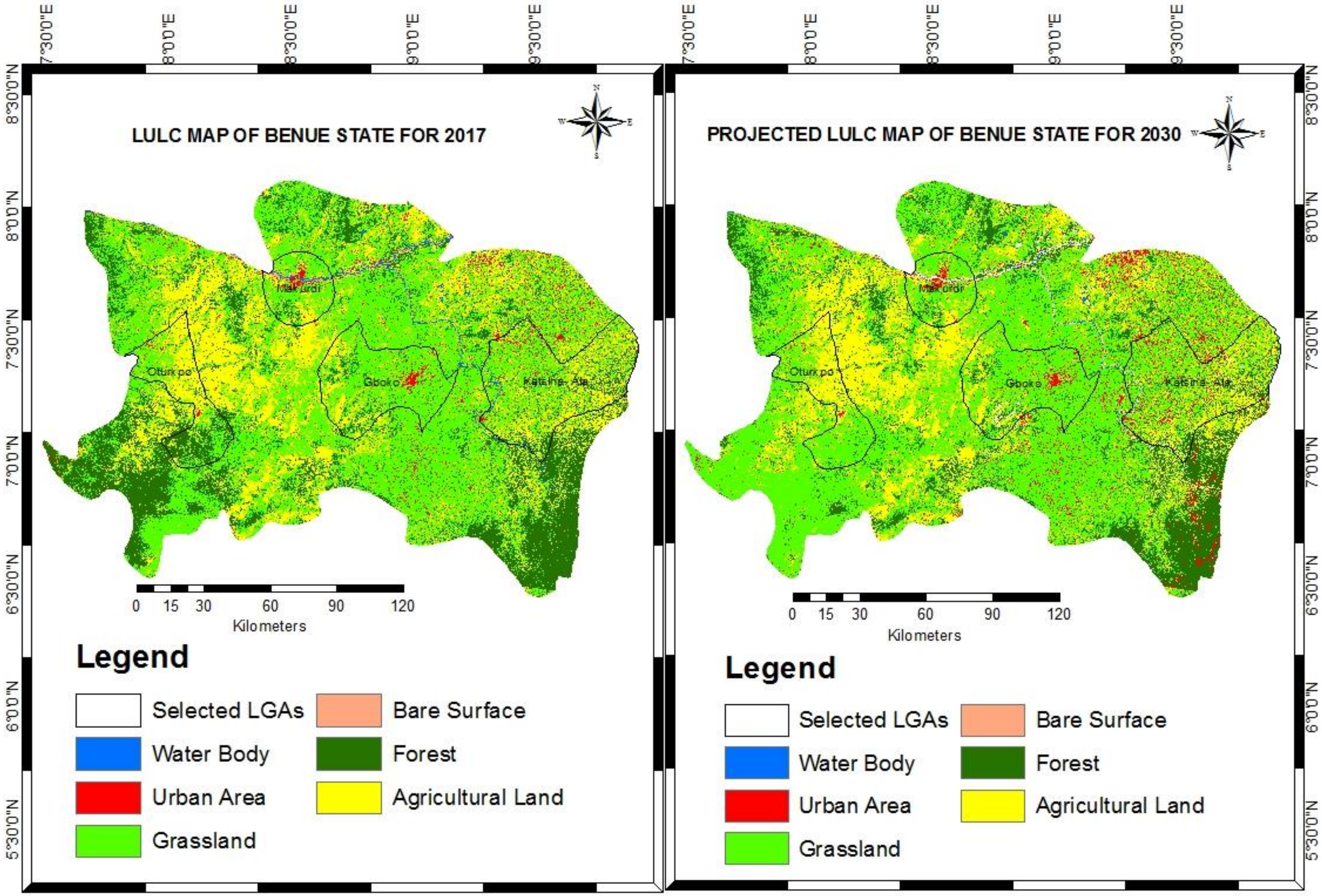


Figure 4. 34: Classified and Projected LULC Maps of Benue State for 2017 and 2030

The results of the year 2030 prediction for Makurdi shows that grassland will be the dominant class as it will increase by 20.41% to 49.91% from 29.5% between 2017 and 2030 (see Table 4.23). Urban area is estimated to increase by 2.86% to 20.81% from 17.95% between the period under reference to become the second largest class after grassland. It is predicted to extend to the north west and south eastern parts of Makurdi. In contrast, farmland. forest and bare surfaces are estimated to decline by 20.5%, 2.6% and 0.15%respectively yielding 12290ha, 8557ha and 1781ha (14.72%, 10.25% and 2.13%) respectively. The decline in area of the predicted farmland is similar to the results obtained by Attaallah (2018), who predicted that agricultural land in the Gaza Strip will decline by 5.6% by 2036 to the advantage of urban areas. Similar results were obtained by Ozturk (2015); Raziq, *et al.*, (2016); Rimal, *et al.*, (2017); Padmanaban *et al*., (2017). This result, however, is at variance with that predicted by Ansari and Golabi (2019) in which agricultural area was estimated to grow by 4.17% between 2015 and 2030 in Meighan Wetland, Iran. The variation is due to the fact that Meighan is an agricultural area while Makurdi is an urban area.

Table 4. 23: LULC Changes Between 2017 and 2030 for Makurdi

Land cover	**LULC in 2017**		**LULC in 2030**		**Change**	
Classes	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Rate %**
Water Body	1817	2.18	1820	2.18	3	0
Urban Area	14996	17.95	17384	20.81	2388	+2.86
Grassland	24635	29.5	41689	49.91	17054	+20.41
Bare Surface	1908	2.28	1781	2.13	-127	-0.15
Forest	10750	12.85	8557	10.25	-2193	-2.6
Farmland	29415	35.22	12290	14.72	-17125	-20.5
Total	**83521**	**100**	**83521**	**100**		

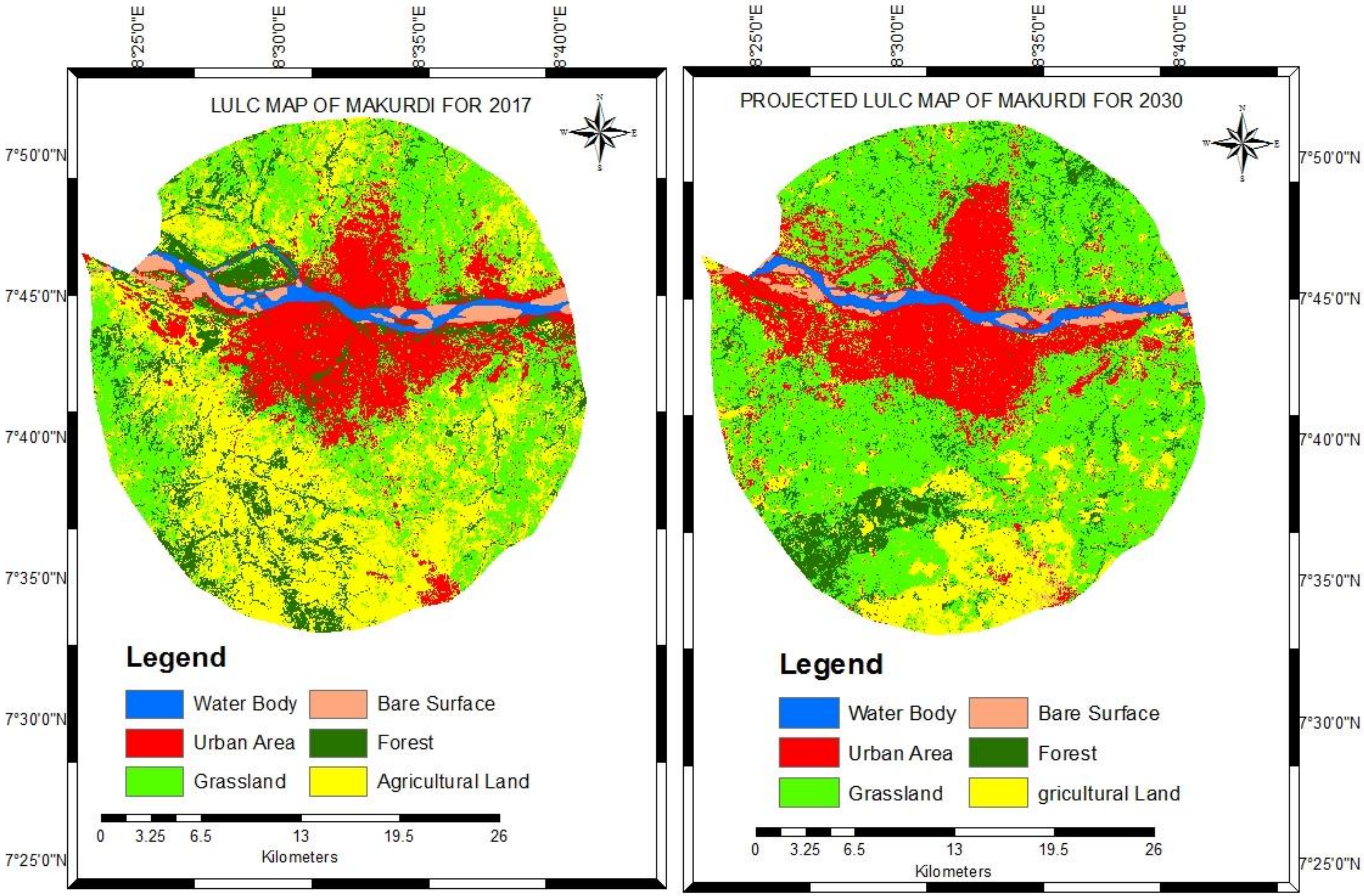


Figure 4.35: Classified and Projected LULC Maps of Makurdi for 2017 and 2030

The result of the 2030 projection for Gboko shows that farmland, urban area and bare surface will increase by 10.52%, 0.81% and 2.98% respectively between 2017 and 2030 to occupy 46424ha (24.17%), 18157ha (9.46%) and 8217ha (4.28%) respectively as shown in Table 4.24. Grassland , forest and water body are estimated to decline by -12.99%, -1.28% and -0.04% respectively. The expansion of the urban area is due to increment in the migration of youth to urban areas, migration of youth in search of good jobs and the increasing desire to enjoy social and infrastructural amenities in the urban centre.

Table 4. 24: LULC Changes Between 2017 and 2030 for Gboko

Land cover	LULC in 2017		LULC in 2030		Change	
Classes	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Rate %
Water Body	277	0.15	217	0.11	-60	-0.04
Urban Area	16614	8.65	18157	9.46	1543	+0.81
Grassland	129715	67.54	104756	54.55	-24959	-12.99
Bare Surface	2500	1.30	8217	4.28	5717	+2.98
Forest	16723	8.71	14277	7.43	-2446	-1.28
Farmland	26219	13.65	46424	24.17	20205	+10.52
Total	**192048**	**100**	**192048**	**100**		

The increase in urban population necessitates the expansion of urban areas to accommodate the increase. This study is in concurrence with that of Friehat *et al*., (2015) in Northeastern Illinois. Grassland and forest lost their land mainly to farmland and urban area expansion. Figure 4.36 shows the spatial extent of the predicted land cover categories. The striking feature of the prediction is the development of urban settlement along the north eastern part of Gboko. This is incidentally the area where the major high institution, Akperan Orshi College of Agriculture is situated and is expected to expand into an urban area by 2030.

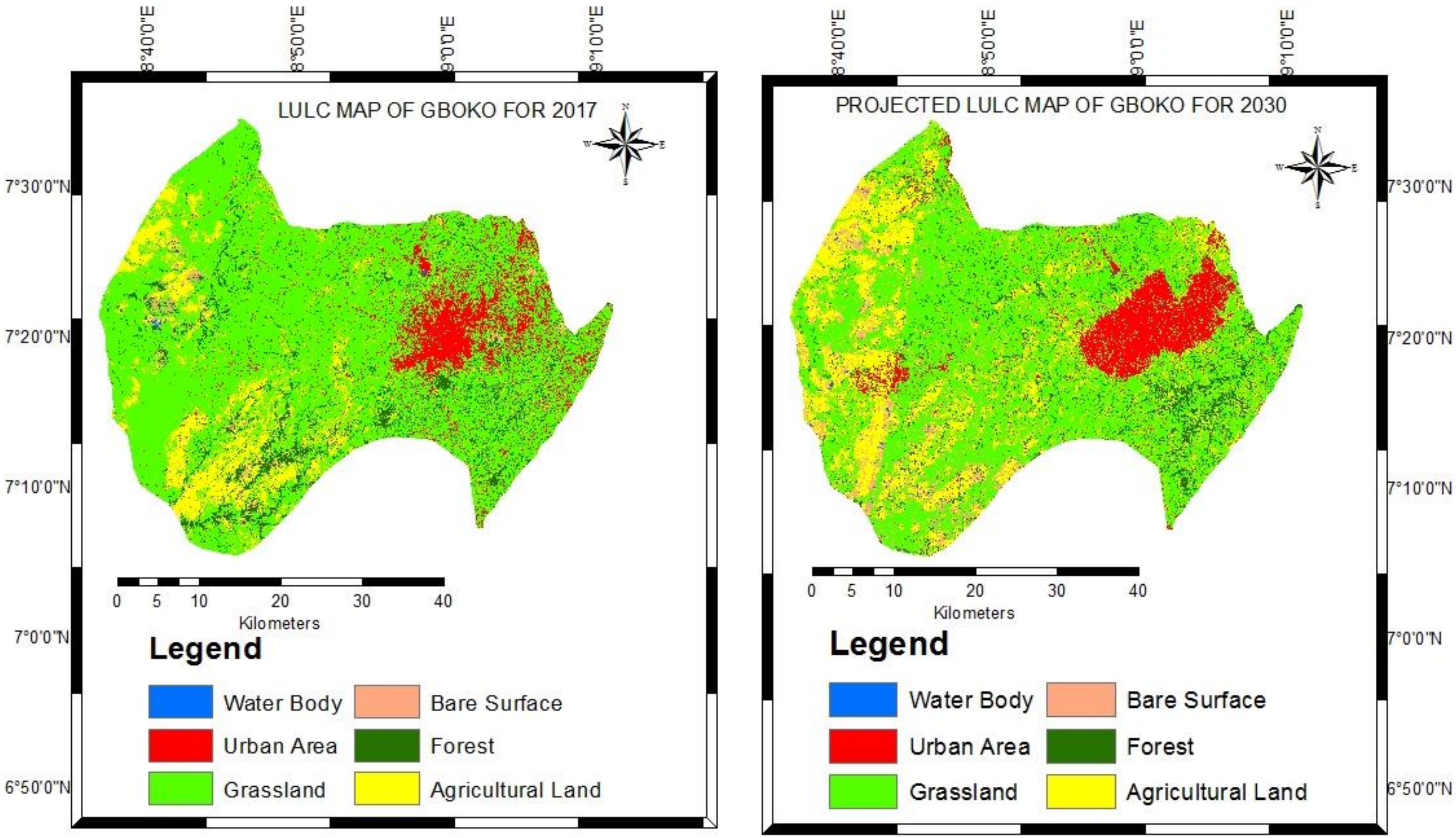


Figure **4. 36: Classified and Projected LULC Maps of Gboko for2017 and 2030**

The result of land cover prediction for Otukpo (Table 4.25 and Figure 4.37) shows that between 2017 and 2030, only grassland and urban area were estimated to increase by 5.51% and 1.01% from 43.92% and 11.59% in 2017 to 49.93% and 12.60% in 2030. The urban area is predicted to stretch from the centre of the region eastward. This pattern of growth is at variance with the prediction in many urban areas like Makurdi and Gboko where urban growth is accompanied by a corresponding growth in farmland.

Table 4. 25: LULC Changes Between 2017 and 2030 for Otukpo

Land cover	**LULC in 2017**		**LULC in 2030**		**Change**	
Classes	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Rate %**
Water Body	6226	4.66	3409	2.55	-2817	-2.11
Urban Area	15475	11.59	16819	12.60	1344	1.01
Grassland	58623	43.92	65986	49.43	7363	5.51
Bare Surface	8080	6.05	6830	5.12	-1250	-0.93
Forest	16741	12.54	14660	10.98	-2081	-1.56
Farmland	28346	21.24	25787	19.32	-2559	-1.92
Total	**133491**	**100**	**133491**	**100**		

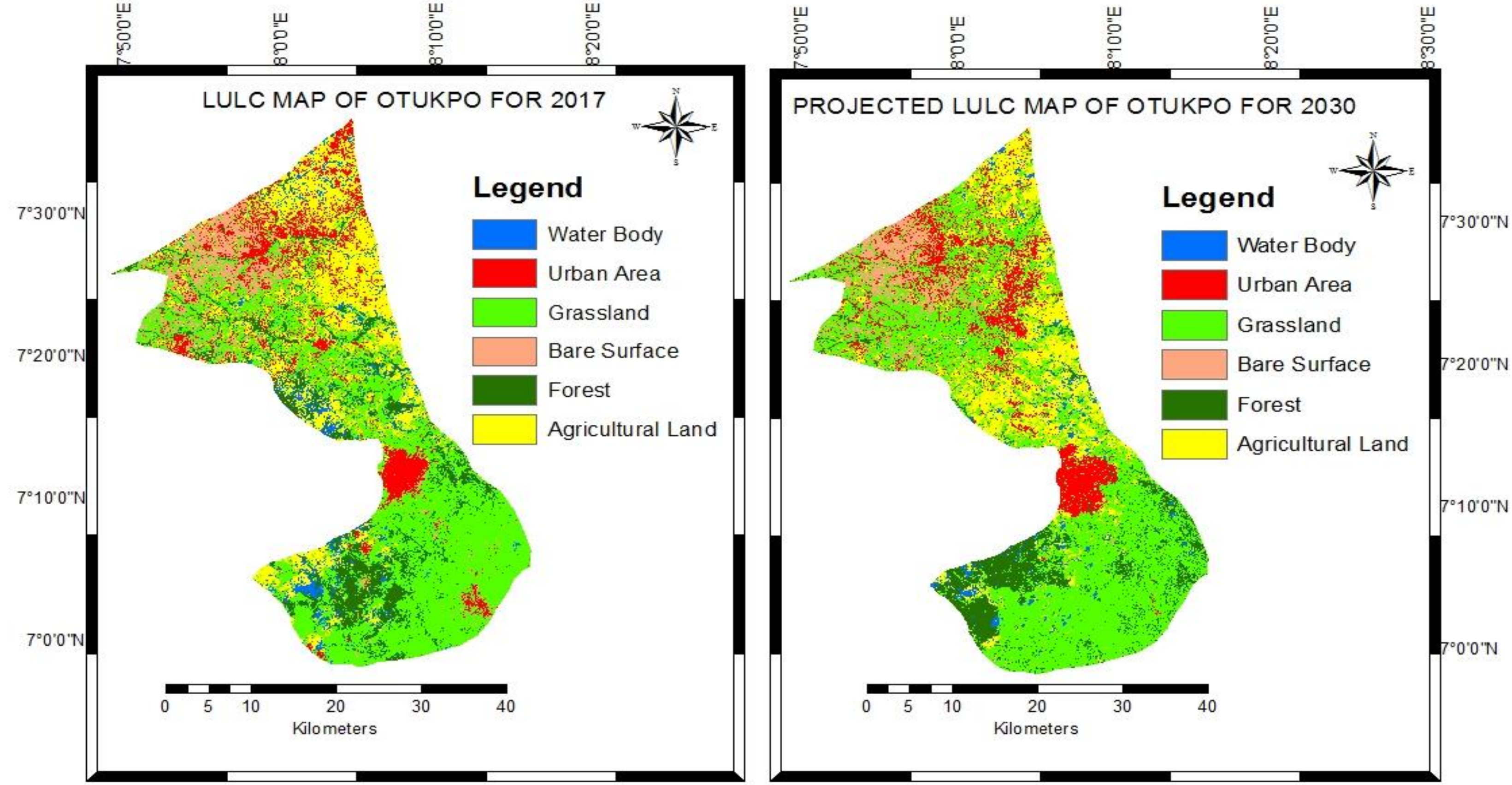


Figure 4. 37: Classified and Projected LULC Maps of Otukpo for2017 and 2030

This prediction agrees with work in Semarang City in Java, Indonesia by Hadi *et al.* (2016). The result also revealed that the farmland will decline from about 28346ha in 2017 to 25787ha by 2030. This can be explained by the shifting nature of activities from largely agriculture to other activities in the area. This trend in LULC change is similar to that of Wudil town in Kano city in Nigeria, where the agricultural land is projected to decline by about 2.38% over a period of 14 years as revealed by Ismail and Abubakar (2015). The prediction also reveals that farmland, forest and bare surface will decline during the period by -1.92%, -1.56% and -0.93% respectively resulting in 25787ha, 14660ha and 6830ha in 2030. The major reason for the conversion is due to increased demand for land and it would be easy to convert these land cover types due to fewer or no restrictions. These land use types facilitate urbanization as these classes have more potential to change to urban areas.

Based on the predicted results for Katsina-Ala for 2030 grassland will dominate the LULC classes in the area accounting for 43.02% of the area followed by farmland (39.73%), forest (9.46%), urban area (6.35%), water body (1.21%) and bare surfaces (0.23%). The trend shows that grassland, urban area and water body will increase by 18.15%, 0.43% and 0.73% respectively as depicted in Figure 4.38 and Table 4.26. Urban area is predicted to cover the south western, north western parts of the area and grassland will cover the south east and the west. Farmland, forest and bare surface will decrease during the period by 18.21%, 1.34% and 0.11%. The trend in farmland transition between 2017 and 2030 is similar to that of Otukpo area where farmlands are decreasing with time.

Table 4. 26: LULC Changes Between 2017 and 2030 for Katsina-Ala

Land cover	LULC in 2017		LULC in 2030		Change	
Classes	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Area (%)**	**Area (Ha)**	**Rate %**
Water Body	1323	0.49	3247	1.21	1924	+0.72
Urban Area	15905	5.92	17083	6.35	1178	+0.43
Grassland	66824	24.87	115669	43.02	48845	+18.15
Bare Surface	896	0.34	605	0.23	-291	-0.11
Forest	29026	10.80	25431	9.46	-3595	-1.34
Farmland	154679	57.58	106829	39.73	-47850	-18.21
Total	**268864**	**100**	**268864**	**100**		

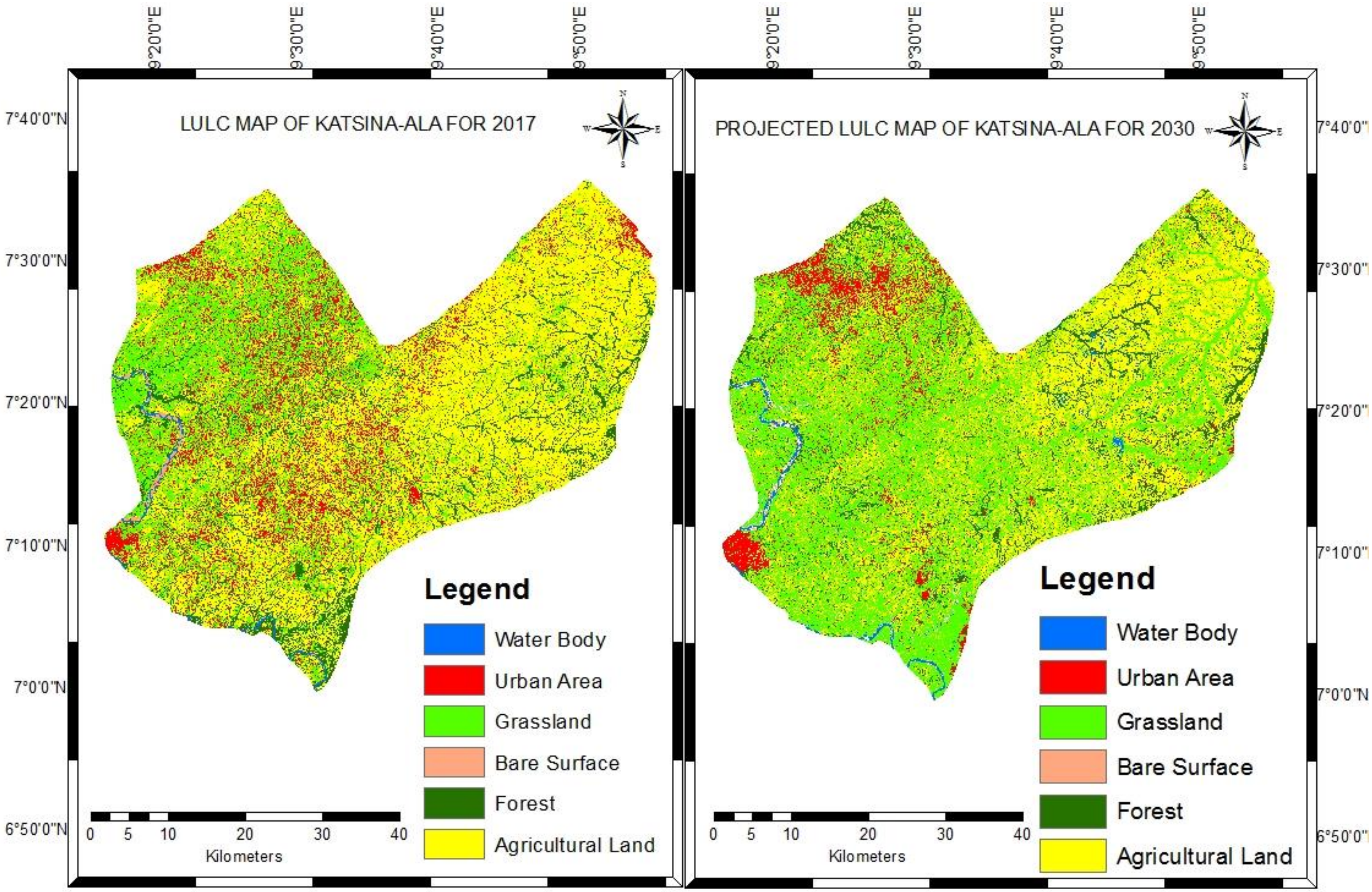


Figure 4. 38: Classified and Projected LULC Maps of Katsina-Ala for2017 and 2030

4.12 Soft Prediction

The soft prediction output is made up of maps that show the likelihood of change for a particular set of transitions. The result of the soft prediction for the five models for 2030 is presented in Appendix P. The soft prediction represents an uninterrupted mapping of susceptibility to change for chosen set of transitions. The soft prediction identifies the degree to which the land cover class has the susceptibility to be altered. The soft prediction outcome detects the areas with contrasting degrees of susceptibility as opposes to identifying what and the quantity of land cover categories that would be changed. From the modelled result for Benue State, it is clear that the majority of the south eastern parts of the state is extremely susceptible to transition with this group of driving variables. For Makurdi, the north west and south west have higher degree of vulnerability than the other areas. In Gboko, the north east has higher degree of vulnerability of transition to other land cover categories. The modelled result for Otukpo shows that the north has higher vulnerability values compared to the other areas. In Katsina-Ala, the north west has higher degree of vulnerability of transition to other land cover categories

4.13 Impact of Urban Growth on Deforestation

The impact of urban growth on vegetation loss was assessed after the 2030 projection. A closer look at the contributions to net change in forest and urban area between 1987 and the projected 2030 reveals the salient details. In Benue State (see Figure 4.39) urban area was the third largest contributor (20913ha) to deforestation. In other words, by 2030, forest lands will give up over 20913ha of land to the expansion of urban areas during the period. The contribution to net change in urban area shows that forest ranked second in contributing to urban expansion.

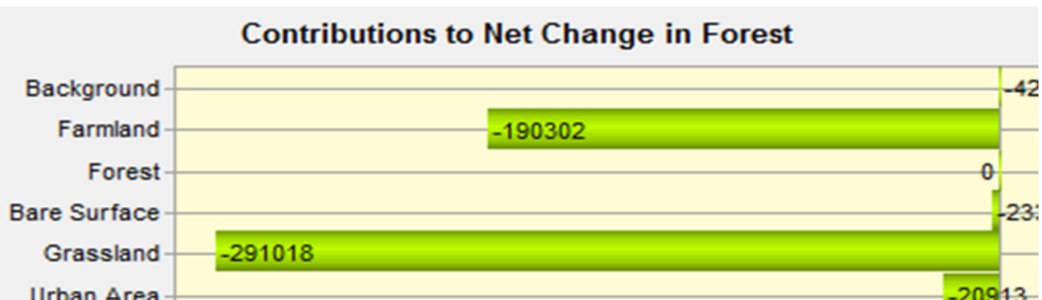


Figure 4. 39: Contributions to Net Change in Forest and Urban Area from 1987-2030 in Benue State (in Ha)

The situation in Makurdi is not different from that of the state. Here too, urban area is ranked third in contributing to deforestation taking up 422ha of land during the period. Farmland and grassland were the largest contributors to urban expansion in the area as is shown in Figure 4.40.

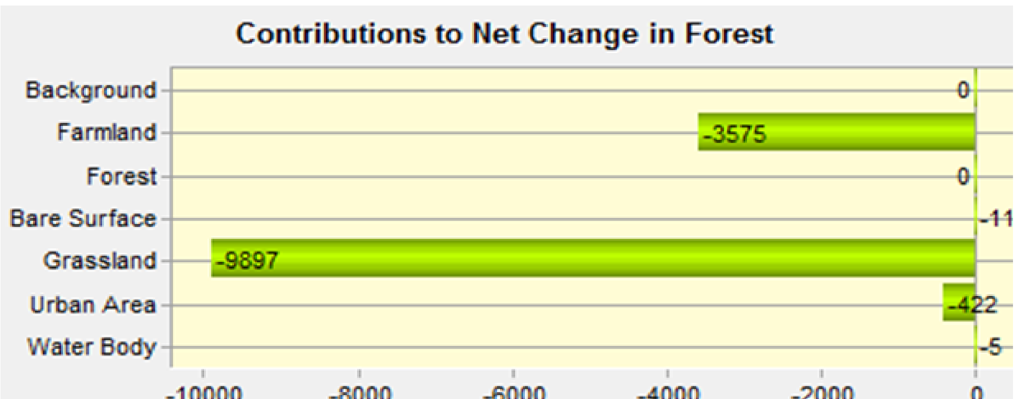


Figure 4. 40: Contributions to Net Change in Forest and Urban Area from 1987-2030 in Makurdi (in Ha)

Figure 4.41 reveals the net contribution to change in forest and urban area in Gboko. Urban area is the fourth largest contributor to deforestation gaining over 907ha from forest areas. The net contribution to urban growth shows that forest is ranked third after farmland and grassland giving up lands for urban expansion.

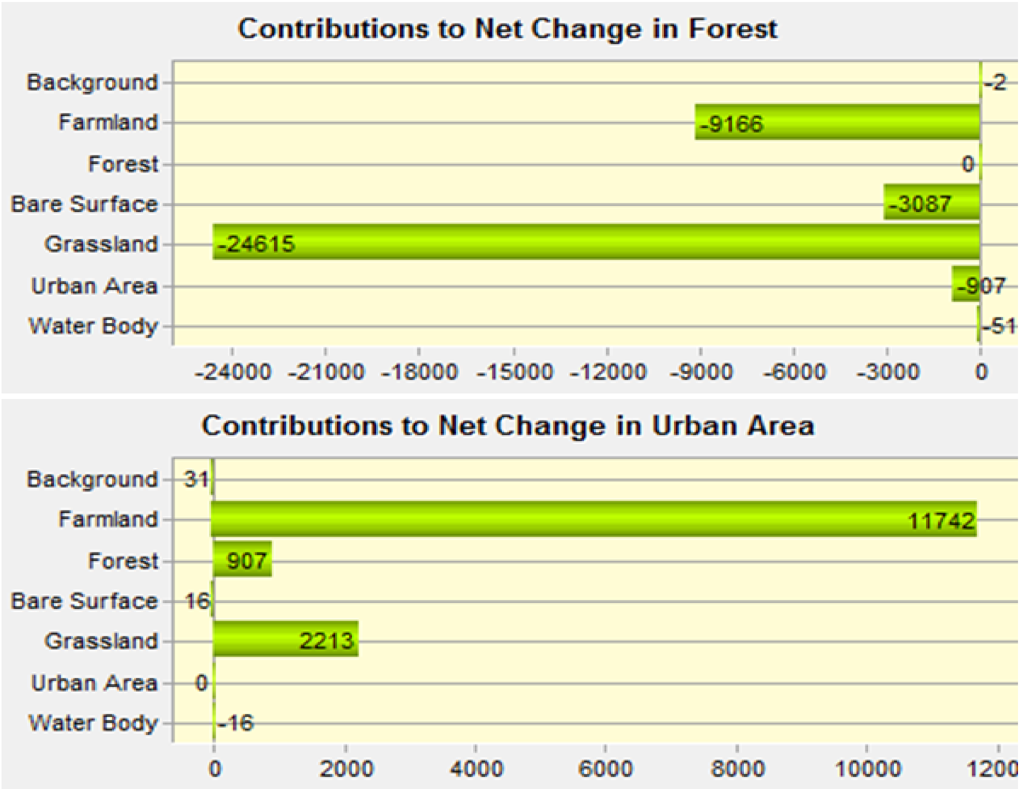


Figure 4. 41: Contributions to Net Change in Forest and Urban Area from 1987-2030 in Gboko (in Ha)

In Otukpo (see Figure 4.42) urban area is predicted to be the third largest contributor (2226ha) to deforestation. In other words, forest lands is projected to lose over 2226ha of land to the expansion of urban areas during the period. The contribution to net change in urban area shows that forest is ranked third in contributing to urban expansion after farmland and bare surfaces. Unlike in the other locations, forest are projected to gain more area (507ha) from bare surfaces. This can be due to afforestation programme being embarked upon by the State Government especially in exposed areas.

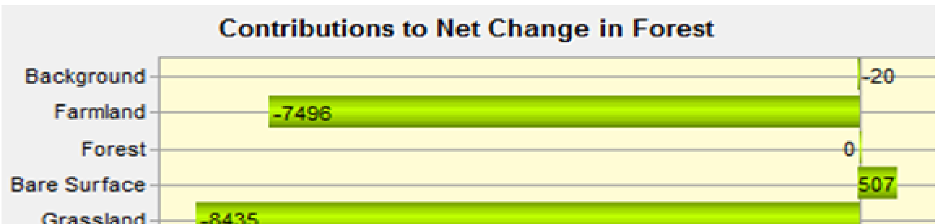


Figure 4. 42: Contributions to Net Change in Forest and Urban Area from 1987-2030 in Otukpo (in Ha)

In Katsina-Ala, urban area is the third largest contributor to deforestation with forest losing over 4052ha of land to urban expansion during the period. Forests are ranked second in contribution to urban expansion, second only to farmlands.(see Figure 4.43)

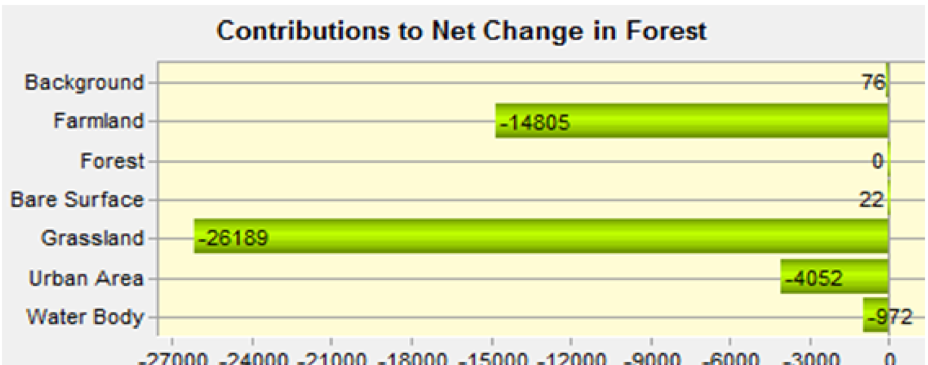


Figure 4. 43: Contributions to Net Change in Forest and Urban Area from 1987-2030 in Katsina-Ala (in Ha)

4.13.1 Implications of the observed impacts

Urban growth has continued to be a threat to the existence of forest for a long time due to deforestation. The depleting forest resources is a threat to biodiversity as rightly stressed by Ohwo and Abotutu (2015). The results indicated that urban expansion is among the major drivers of deforestation in all the five locations. This finding agrees with that of Zhou, *et al.*, (2017) where the effect of urban expansion of six mega-regions of China on forest loss was examined. The total area of deforestation due to growth of urban centres, however, varied greatly in the five locations. The total area of deforestation in Benue State is greater as it includes all the other four locations of Makurdi, Gboko, Otukpo and Katsina-Ala. Deforestation due to urban expansion leads to habitat alteration which leads to the endangering and extermination of species and habitat loss. Aside from decreasing the richness of indigenous species, urban growth increases the domineering effect of imported species in the area (Kharel, 2010). These issues represent serious challenge to the sustainable management of our environment. The diverse species of plants and animals that are necessary to set up and maintain the various food webs and chains in addition to natural cycles are thoroughly being exhausted and thereby causing ecological imbalance and threatening man's survival in the environment as observed by Ohwo and Abotutu (2015).

Agricultural expansion is also affected by urban expansion as areas previously under cultivation are converted to urban areas. This has the effect of reducing areas under cultivation especially at the fringes where there exist barriers to prevent further expansion of these agricultural areas. This has a tendency of reducing farm output if intensive practices are not adopted. Where there are no barriers, there is the tendency for cultivated areas to expand further to accommodate the loss to urban areas thereby causing more deforestation.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Major Findings

This chapter provides the key findings of this research work, the conclusions derived from the findings and the recommendations that emanate from the conclusion and the implications and contributions of the findings to present knowledge and to suggest areas of research in the future.

The summary of the findings as they relate to the objectives are briefly stated in this section. The first objective was to map the types and extent of LULC classes in Benue State. The study found out that six major LULC classes exist in Benue State. They comprise of water body, urban area, grassland, bare surfaces, forest and farmland. The extent of these land cover classes vary according to location. In Benue State, grassland occupied the largest area 41.94% in 1987, followed by forest with 32.95%, farmland (21.99%), urban area (1.28%), bare surface (1.08%) and water body occupied the least area of 0.76%. Similar scenarios occurred in 2007, 2017 and other locations of Gboko, Makurdi, Otukpo and Katsina-Ala with farmland expanding to occupy more land than forest which was declining. Urban area which ranked fourth in extent continued to expand during the period.

The result of the trend and rate of LULC changes from 1987 to 2017 show that in Benue State and the selected urban areas, urban areas continued to increase in extent owing to expansion of the built-up areas while forest decreased continuously over the period in all the locations. Urban areas in Benue State increased by 59081ha representing 147.31% at an annual change rate of 4.91%. Forest on the other hand was on the decrease in all the locations. Between 1987 and 2017, there was a -45.1% loss of forest at the rate of -1.5% per annum.

The results also revealed that farmland increased in area between 1987 and 2017 in Benue State, Makurdi, Otukpo and Katsina-Ala. The situation was different in Gboko where farmland declined during the period. The expansion in urban areas was due to rising infrastructure demands generated by population growth and the presence of employment opportunities in these urban areas.

The study identified eight drivers that are responsible for urban growth in the state. These variables include population density, evidence likelihood of transition, elevation, slope, proximity to urban areas, roads, rivers, and railway. The contributions of these variables, however, vary in importance in each location even though it was noticed that evidence likelihood of transition was ranked the highest in determining urban growth in all the selected locations. In Benue State, the variables, in order of importance, are evidence likelihood of transition, proximity to railways, proximity to urban area, elevation, proximity to roads, proximity to rivers, slope and population density. In Makurdi, distance to urban area was the second most important variable after likelihood of transition, followed by distance to railways, elevation, proximity to rivers, proximity roads, slope and population density. The order in Gboko in rank was evidence likelihood of transition, proximity to urban areas, population density, proximity to roads, proximity to rivers, elevation and slope. The scenario in Otukpo saw likelihood of transition ranking first, followed by population density, distance from railways, altitude, proximity to roads, proximity to rivers, proximity to urban areas and slope. In Katsina-Ala, distance from rivers followed likelihood of transition, then elevation, proximity to urban area, population density, slope and proximity to roads.

The findings of the modelling and prediction of urban growth in Benue State show that urban area will occupy 122436.09ha (3.91%) of the total area by 2030 which represents the fourth largest class. The urban areas are concentrated in Makurdi, Gboko, Otukpo and Katsina-Ala which are the major urban centres in the state. Forest lands are projected to occupy 52300008.72ha (16.7%) occupying the third largest class and is concentrated mostly in the south eastern part of the state.

The urban area projection in Makurdi revealed that it will cover 16942.13ha (20.28%). representing the second largest land cover class. It will grow towards the north along Lafia road, east along Gboko road and the west along the Benue River. Forest area will cover 9721.08ha (11.64%), and will be concentrated on the south western part of the area. Urban area in Gboko will cover 18157ha (9.46%) and will stretch along the north east and south west axis. The forest in Gboko will cover 14277ha (7.43%) and will dominate the eastern part of the area. Otukpo will have urban area covering 16819ha (12.6%) stretching eastward with some patches of isolated urban areas in the northern part of the area. The forest will cover 14660ha (10.98%) to be found in the south western part. In Katsina-Ala urban area will cover 17083ha (6.35%) spreading to the south east and with some patches in the north west of the area. The forests are projected to be concentrated mainly along the river and stream channels scattered in the area covering 25431ha (9.46%).

Another finding of the research relates to the rate of urban growth and deforestation. Makurdi has a higher growth rate of 2.86%annually followed by Otukpo with 1.01%, Gboko with 0.81% with Katsina-Ala having the least growth rate of 0.46% between 2017 and 2030. The rate of deforestation was highest in Makurdi (-2.6%), Otukpo (-1.56%), Katsina-Ala (-1.34%) and Gboko (-1.28%).

The impact of urban growth on deforestation in Benue State, according to the projection, will experience a rapid urban expansion into areas formally occupied by the forest land. In Benue State urban area will be the third largest contributor (20913ha) to deforestation. In other words, by 2030, forest lands will give up over 20913ha of land to the growth of urban areas. This scenario is a replica of what happens in other urban areas in Benue State.

5.2 Implications of the Findings

The study has filled the gap in the inadequacy of information about the existing LULC types in Benue State, which can assist in formulating policies for the growth of urban areas in Benue State. The research reveals that proximity to urban areas, roads and railways were the most important drivers of urban growth. This is consistent with previous studies that found that areas nearer urban centres are prone to be converted to urban areas in the same manner as areas close to roads and railways. Currently, there is common consensus that LULC change processes are causing major environmental impacts at local and global scales. In this perspective, this research has made inputs of two kinds: First, it provides proof that MLP-Markov model can aid develop our understanding of the changes of LULC change processes and that it is a very important tool in simulating and predicting future urban growth patterns. Secondly, it offers an important instrument for monitoring past and future changes in Benue State thus, helping to provide future pattern of urban growth for effective management. The research has also revealed the extent of urban interference on the forest resources of Benue State so that measures can be taken to avoid total deforestation of the state due to urban growth.

5.3 Conclusion

It is well known that the future is uncertain. But having the ability to factor in specific areas within the uncertainty grants key insights that can prove to be very important in taking vital decisions when considering the future. As the urban areas of Benue State continue to expand, understanding the current patterns of urban growth and land use and their impact and predicting the possible future patterns of growth of these urban centres will empower the government of Benue State, other stakeholders and policy makers by providing them with information and support that will prove to be essential for future planning and development decisions.

This study reveals that the combination of GIS, remote sensing, and modelling offers a potent tool for observing spatio-temporal LULC change, plus modelling intricate interactions between man and nature. The outcome of the LULC change study showed the main change paths in Benue State, particularly the expansion of urban areas is at the detriment of farmland, grassland and forest. The results of modelling urban expansion and its impact on the physical environment of Benue State, indicated that, if the nature of change remains the same 122436.09ha, (3.91%) of the total area will be taken over by urban area by the year 2030 while forest will depreciate to 523009ha (16.7%).

This research revealed that the expansion of urban areas in the state and the selected urban areas occurred at the expense of farmlands, grassland and forest land which implies that the state will experience serious crises of managing the urban growth if adequate planning measures are not put in place. Also, the state stands the risk of experiencing hazards associated with deforestation if appropriate measures are not taken. According to the results of the MLP-Markov model, urban areas will expand in the future. The combination of satellite remote sensing, GIS and MLP-Markov model provides useful information on LULC dynamics and change trends into the future which could help policy makers to make better decisions for the future of the area. The provided future projections could be effectively used for planning and decision making in the management of land.

The study revealed how invaluable RS data and GIS integration can be for evaluating urban expansion and its effects on deforestation and simulation of future LULC scenarios. The predicted LULC scenarios into 2030 show a frightening rapid loss of farmland, grassland and forest and high rate of urban growth which requires huge attention from our town planners and policy makers in the management of these urban areas. The increased urban growth will increase the demands on forest tree leading to increase in carbon dioxide concentration and ultimately global warming and climate change.

Many parts of urban areas in Benue State are not planned. This study will contribute to shaping the urban structure of these urban areas in a planned manner. Decision makers and city planners can set off proper plans on the basis of the outcome of this study.

Overall, the study provided a very valuable insight not only on the extent of future growth of urban areas but most importantly on its spatial pattern. This is very important in maintaining sustainable urban growth by balancing between population increase and urban expansions.

Lastly, since the agreement between the classified and predicted land cover maps for the year 2017 were high as depicted by the AUC value (Benue 0.785, Makurdi 0.814, Gboko

0.830, Otukpo 0.817 and Katsina-Ala 0.858) it can be concluded with some level of accuracy that the data from Landsat and the MLP-Markov model integrated with GIS techniques are invaluable in modelling of urban growth and assessing the impact on deforestation in Benue State.

5.4 Recommendations

Based on the nature and rate of change of various LULC types identified in the area especially from 1987 to 2017 and the modelled results for 2030, the following recommendations are made:

i. Focus on urban planning is essential to control the expansion of urban areas and make provision for infrastructural facilities in areas that are predicted to be transformed to urban centres thereby minimizing the negative impacts of urban expansion in the state.
ii. Due to the increasing urban growth at the cost of farmland and the likelihood of its continuation in the future, food shortages and environmental imbalance are most likely.
iii. Developing and putting into action appropriate urban plans for the protection of farmlands is immediately needed. Proper urban planning to ensure the protection of farmlands is crucial to create robust urban environment and sustainable development.
iv. Government should evolve a policy that will prioritise the provision of infrastructural facilities and social amenities to cater for the envisaged urban growth especially in areas with high urban growth rate. These are Makurdi, Otukpo, Gboko and Katsina-Ala in that order.

v. Tree planting should be encouraged by all concerned to cushion the effect of the deforestation occasioned by rapid urban growth in Makurdi, Otukpo, Gboko and Katsina-Ala .

vi. A comprehensive approach needs to be implemented in expanding the vegetal cover in the urban and rural areas. This can be accomplished through diverse means like planting of new trees, particularly on sidewalks, residential areas and on public and private lands. This also calls for community consciousness on the adverse effects of present inefficient urban form and the import of creating environment friendly cities.

vii. The findings of this study can be used as a guideline for the environmentalist to investigate impacts of land use dynamics and urban expansion to natural resources and ecological service systems, as well as an effect to people's livelihood for natural and land resources management in the year 2050.

In addition to recommendations based on the outcome of the research, the study further made some suggestions into areas of further research. These include:

i. The use of high resolution satellites like IKONOS and QuickBird are vital in creating good quality land cover maps. For the reason that urban areas have intricate and mixed features, very high resolution imageries will offer improved information by mapping of these areas. In addition, the use of supplementary data as ground truth assists in improved accuracy of the image classification. These can be investigated further for similar studies.

ii. integrating social and economic data, land policy, biophysical and anthropogenic factors could improve the performance of the model for future predictions. Consequently, it is essential to all the stakeholders for efficient utilization of land. This can also be investigated further for LULC dynamics

iii. The impact of LULC changes on other constituents of the environment such as hydrology, soil and temperature can also be investigated in the area to complement this study.

iv. Similar studies can be carried out to model and predict future urban scenarios in 2050 to expand the scope so as to cover a longer period of time.

5.5 Contribution to Knowledge

This research has filled the gap in the inadequacy of information about the current LULC types in Benue State, which can assist the planners, stakeholders and experts in devising policies for the growth of urban areas in the state.

Currently, there is a common consensus that LULC change processes are causing considerable environmental impacts worldwide. In this perspective, this research has made contributions of three kinds: First, it provides proof that MLP-Markov model can help to develop our understanding of the changes of LULC processes and that it is a very vital tool to predict future urban growth patterns. Secondly, it offers an important instrument for monitoring past and future changes in Benue State thus, helping to provide future pattern of urban growth for effective management. Thirdly, the research has also revealed the extent of urban interference on the forest resources of Benue State to be 20913ha between 1987 and 2030 so measures should be taken to avoid total deforestation of the state due to urban growth.

Many parts of urban areas in Benue State are not planned. This study will contribute to shaping the urban structure of these urban areas in a planned manner. Stakeholder, experts and city planners can set off proper plans on the basis of the findings of this study.

Overall, this study offered a very valuable insight not only on the extent of future growth of urban areas but most importantly on its spatial pattern. It reveals that Makurdi, Gboko, Otukpo and Katsina-Ala will grow at the rate of 2.86%, 0.81%,1.01%, and 0.46% respectively. This insight is very important in maintaining sustainable urban growth by balancing between population increases and urban expansions.

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Appendices

Appendix A1 Review of Land Use Land Cover Change Models

Name of Author(s)	Model Name	Builder	Model Type	What it Explains	Variables	Strengths	Weakness
(Agarwal *et al.* 2002)	Markov Model	Wood *et al.*. 1997	Spatial Markov model	Landuse change	Multi Temporal Land Use/ cover maps	Considers both spatial and temporal change	No sense of Geography
(Agarwal *et al.* 2002)	CA	Clarke *et al.*. 1998; Kirtland *et al.*. 2000	Cellular Automata model	Change in urban areas over time	Extent of urban areas, Elevation, Slope, Roads	Allows each cell to act independently according to rules	Doesn't include human and biological factors
(Adhikari & Southworth, 2012)	Combination of CA and MARKOV Methods	Clark Labs	Spatio-Temporal dynamic modelling	Predicts land use/cover in the future	Multi-Temporal Land Use/ cover maps, Suitability maps	Creating the Data is easy, CA add spatial dimension to the model, can simulate change among several categories	Socioeconomic factors are not Considered,Calibrating the model with MCE is too much timeconsuming compared to other methods
(Agarwal *et al.* 2002)	UrbanSim	Paul Waddell (University of California, Berkeley)	Cellular Automata and individual-based model	Spatial maps of housing units by pixel, nonresidential square footage per cell and other economic and demographic characteristics	Parcel files, business establishment files census microdata, Environmental, political,and planning boundaries, location grid control totals from economic regional forecasts, travel access indicators, scenario policy assumptions	Structure allows multiple types of policies to be explored High degree of precision,Employment locations modelled, Designed to provide inputs to the transportation demand model	High data demands, designed for urban areas hard to understand the model, It has rigid model structure, Output must be imported into GIS for viewing
(Li & Yeh, 2002)	Combination of ANN and CA methods	Antony Gar-On Yeh, XiaLi	ANN & Cellular Automata Model	Predicts land selected land class in the future	Multi-Temporal Land Use/ cover maps	Calibrating the model with ANN	It can simulate change only in two category
(Pontius & Chen, 2008)	GEOMOD	Clark Labs	Cellular Automata	Predicts land selected land class in the future	Land use/cover map	Need only one-time land use map for calibration	It can simulate change only in two category

(Source: Adopted from Agarwal, Green, Grove, Evans &Schweik, 2002 Baysal, 2013)

Appendix A^2 Review of Land use Land cover Change Models

Name of Author(s)	Model Name	Builder	Model Type	What it Explains	Variables	Strengths	Weakness
(Torrens, 2000) (Agarwal *et al.* 2002)	SLEUTH	Dr Keith C. Clarke at UC Santa Barbara	Spatially explicit Cellular Automata model	GIS maps of probability (continuous) of urbanisation in a specified pixel	Multi-Temporal Land Use Map, Impervious surface cover, Road networks (for each time period), Slope (%), Undevelopable land	Relatively easy to transfer among regions, incorporate many different land use classifications systems, it generates continuous measure of density of development, take into consideration the future developments (such as road)	Designed for urban settings, Data demands are high, Un-calibrated model would produce more Error, Difficult to use
Eastman, J.R.	Land Change Modeler	Clark Labs	Markov Chain, MLP, Logistic Regression , SimWeight	Change Analysis, Predicts land use/cover in the future	Land Use Land Cover data, Road, DEM, Other Infrastructure	Environmental modelling platform, taking into consideration the future projects, Using the ANN for development of transition potentials, calculating the changes in two time periods	Consideration of one sub model
(Agarwal *et al.* 2002)	CLUE (Conversion of Land Use and Its Effects)	(Veldkamp and Fresco 1996a)	Discrete, finite state model	Predicts land use/cover in the future	Land suitability for crops, Temperature/Precipitation, Effects of past land use, Impact of pests, weeds, diseases, Human Drivers, Population size and density, Technology level, Level of affluence, Political Structures, Economic conditions, Attitudes and values	Covers a wide range of biophysical and human drivers at differing temporal and spatial scales	Limited consideration of institutional and economic variables
(Agarwal *et al.* 2002)	LUCAS (Landuse Change Analysis System)	Michael Berry, Richard Flamm, Brett Hazen, Rhonda MacIntyre, and Karen Minser; University of Tennessee	Spatial stochastic model	Transition probability matrix, landscape change. Assesses the, impact on species habitat.	Land cover type, Slope, Aspect, Elevation, Land ownership, Population Density, Distance to nearest road, Distance to nearest economic market, centre, Age of trees	Model shows process, output (new land use map), and impact (on species habitat)	LUCAS tended to fragment the landscape for low proportion land uses, due to the pixel-based independent grid method. Patch based simulation would cause less fragmentation, but patch definition requirements often lead to their degeneration into one cell patches

Source: Adopted from Agarwal *et al.*,2002 and Baysal, 2013

Appendix B[1] Coordinates of Sample Points for Makurdi and Gboko (in UTM)

	Makurdi				Gboko		
	Eastings	Northings	Land cover		Eastings	Northings	Land cover
1	438752.46	858545.8	Water Body	1	497342.07	818724.65	Wate body
2	440807.51	857414.81	Water Body	2	497256.32	819295.68	Wate body
3	445769.64	857072.09	Water Body	3	497013.36	818153.62	Wate body
4	450432	855529.84	Water Body	4	475677.99	825029.48	Wate body
5	453069.32	855015.76	Water Body	5	475636.78	824831.51	Wate body
6	463139.07	856386.85	Water Body	6	513996.7	811698.55	Wate body
7	449370.23	861253.3	Urban Area	7	500611.5	811515.82	Urban
8	450808.76	860910.58	Urban Area	8	502623.76	809725.07	Urban
9	450329.25	857826.08	Urban Area	9	501597.87	808222.57	Urban
10	448479.7	857791.81	Urban Area	10	499852.32	810410.31	Urban
11	449849.74	856866.46	Urban Area	11	499596.22	809542.34	Urban
12	451391.03	856523.14	Urban Area	12	499177.3	808380.19	Urban
13	446116.39	856112.47	Urban Area	13	498820.58	811102.85	Urban
14	446561.66	855187.12	Urban Area	14	502609.3	809823.75	Urban
15	449507.23	851725.62	Urban Area	15	500302.34	808239.01	Urban
16	438957.93	861750.53	Urban Area	16	499543.17	807778.08	Urban
17	445431.38	867586.81	Grassland	17	498875.46	807412.64	Urban
18	445123.12	864228.14	Grassland	18	473572.31	830209.78	Grassland
19	443410.58	861760.53	Grassland	19	471803.71	830530.98	Grassland
20	455537.52	859825.36	Grassland	20	472071.68	827979.2	Grassland
21	457421.32	858146.42	Grassland	21	475433.79	827961.35	Grassland
22	453722.23	857495.25	Grassland	22	477398.89	827390.32	Grassland
23	458962.61	853622.48	Grassland	23	475969.73	826373.18	Grassland
24	460606.65	853382.58	Grassland	24	476059.05	815843.06	Grassland
25	450228.64	850736.76	Grassland	25	476809.36	814540.41	Grassland
26	453687.97	846864	Grassland	26	472557.6	814326.27	Grassland
27	447043.31	849742.87	Grassland	27	477488.21	808369.73	Grassland
28	444954.01	851940.56	Grassland	28	471289.22	807852.24	Grassland
29	446255.54	850188.41	Grassland	29	461238.62	807691.64	Grassland
30	447077.56	847446.63	Grassland	30	474319.04	786071.08	Grassland
31	442522.2	857865.39	Grassland	31	487406.61	807630.96	Grassland
32	442830.45	854198.26	Grassland	32	485602.29	808023.55	Bare Surface
33	433873.85	855089.34	Grassland	33	481457.72	803937.13	Bare Surface
34	440278.76	852141.92	Grassland	34	480671.68	802919.98	Bare Surface
35	437196.19	858516.56	Bare Surface	35	483833.7	803223.34	Bare Surface
36	440587.02	856700.13	Bare Surface	36	483887.3	802331.11	Bare Surface
37	443001.71	856597.31	Bare Surface	37	483655.06	800055.92	Bare Surface

38	459219.49	855802.05	Bare Surface	38	475044.34	790610.76	Bare Surface
39	455280.64	856528.77	Forest	39	474776.38	796838.53	Forest
40	456821.93	856597.31	Forest	40	475937.57	795089.76	Forest
41	458945.48	856425.95	Forest	41	475508.82	792074.02	Forest
42	459870.25	857831.11	Forest	42	468005.71	795286.05	Forest
43	456680.92	858687.92	Forest	43	468130.76	793537.28	Forest
44	458979.73	859983.41	Forest	44	473579.45	789895.19	Forest
45	454766.88	861765.57	Forest	45	470345.97	787843.05	Forest
46	454208.86	863856.17	Forest	46	475758.93	785648.16	Forest
47	454801.13	865912.51	Forest	47	468080.74	795261.07	Forest
48	449183.99	866563.68	Forest	48	467651.99	792316.7	Forest
49	443601.1	866118.14	Forest	49	473922.45	795528.74	Forest
50	440587.02	863616.27	Forest	50	470635.37	794119.01	Agricultural Land
51	443241.46	844183.91	Forest	51	470851.79	793440.91	Agricultural Land
52	445091.01	840074.67	Forest	52	468420.17	792245.32	Agricultural Land
53	450554.02	837949.79	Agricultural land	53	466294.29	792673.6	Agricultural Land
54	454150.36	837572.79	Agricultural land	54	466222.83	792659.32	Agricultural Land
55	457130.19	842268.09	Agricultural land	55	468580.95	790357.36	Agricultural Land
56	452026.81	847443.2	Agricultural land	56	468866.78	788216.01	Agricultural Land
57	453533.85	848505.64	Agricultural land	57	475601.72	808664.17	Agricultural Land
58	449903.25	848539.91	Agricultural land	58	477584.68	807290.13	Agricultural Land
59	452574.82	850418.03	Agricultural land	59	474994.32	804506.37	Agricultural Land
60	447265.94	851857.46	Agricultural land	60	482658.22	806326.57	Agricultural Land
61	445005.38	854016.61	Agricultural land	61	483158.42	810002.52	Agricultural Land
62	449115.43	857032.57	Agricultural land	62	485748.78	816031.83	Agricultural Land
63	447300.19	857820.83	Agricultural land				
64	438377.84	854688.35	Agricultural land				
65	435398.02	857018.86	Agricultural land				
66	441537.42	859829.19	Agricultural land				
67	451547.3	864017.25	Agricultural land				

Appendix B2 Coordinates of Sample Points for Otukpo and Kastina-Ala (in UTM)

	Otukpo				Katsina-Ala		
	Eastings	Northings	Land cover		Eastings	Northings	Land cover
1	400170.15	822726.96	Water Body	1	533483.76	795316.85	Water Body
2	399903.7	818365.01	Water Body	2	535333.17	795842.37	Water Body
3	398926.71	817029.72	Water Body	3	535558.78	796335.02	Water Body
4	401798.47	813172.23	Water Body	4	535976.38	797118.53	Water Body
5	393035.15	819967.36	Water Body	5	536384.24	799268.9	Water Body
6	394397.02	812400.71	Urban Area	6	540151.49	805481.86	Water Body
7	404166.93	796252.59	Urban Area	7	531751.3	793159.28	Water Body
8	403249.15	795748.14	Urban Area	8	532220.3	793120.62	Water Body
9	403189.94	794768.93	Urban Area	9	531378.6	792599.6	Water Body
10	404107.72	794056.78	Urban Area	10	530948.18	793551.44	Water Body
11	406150.52	793225.93	Urban Area	11	530917.76	791780.48	Water Body
12	408844.65	797083.44	Urban Area	12	533443.22	792755.09	Water Body
13	394633.87	812210.8	Urban Area	13	532393.15	793820.85	Water Body
14	393479.24	808946.76	Urban Area	14	548841.04	802274.4	Grassland
15	395847.7	812626.22	Urban Area	15	548941.04	801441.49	Grassland
16	403152.77	787884.32	Grassland	16	547813.98	802024.52	Grassland
17	403670.87	785695.92	Grassland	17	548841.04	800525.29	Grassland
18	407371.6	785844.29	Grassland	18	547092.29	797388.01	Grassland
19	404077.95	778834.01	Grassland	19	543528.16	865855.96	Grassland
20	401524.45	776868.17	Grassland	20	535089.74	799664.62	Grassland
21	411220.35	784100.99	Grassland	21	563235.31	806436.99	Grassland
22	415241.15	790295.26	Grassland	22	573206.11	818086.96	Grassland
23	410443.2	792528.16	Grassland	23	583927.3	823514.84	Grassland
24	400414.23	788856.11	Grassland	24	533498.03	789789.22	Grassland
25	373695	813551.58	Grassland	25	540116.04	806999.54	Bare Surface
26	391902.57	820198.36	Grassland	26	537634.29	801704.06	Bare Surface
27	400562.26	824092.96	Grassland	27	537655.14	809261.12	Bare Surface
28	400599.27	808514.56	Grassland	28	540222.75	805790.69	Bare Surface
29	400562.26	817156.87	Grassland	29	538869.55	803881.92	Bare Surface
30	398822.92	819530.72	Grassland	30	533668.41	792186.51	Forest
31	391384.47	808751.95	Grassland	31	535056.3	796906.32	Forest
32	386647.54	811385.44	Grassland	32	551340.14	837657.55	Forest
33	406261.38	794256.62	Grassland	33	551812.03	836852.41	Forest
34	402116.57	795480.64	Grassland	34	548980.72	836186.08	Forest
35	400492.34	815658.37	Forest	35	547315.24	834964.48	Forest

36	402116.57	814434.36	Forest	36	545372.18	833048.8	Forest
37	402449.63	812060.5	Forest	37	546538.02	831743.91	Forest
38	403374.81	809167.37	Forest	38	556170.03	830133.61	Forest
39	403041.75	805903.33	Forest	39	548508.83	814830.38	Forest
40	403818.9	801993.89	Forest	40	572703.76	814698.82	Agricultural land
41	404892.11	796986.55	Forest	41	573432.4	813275.94	Agricultural land
42	398415.84	787357.62	Forest	42	572981.33	811835.06	Agricultural land
43	400115.76	785836.87	Forest	43	568435.97	809701.38	Agricultural land
44	399304.02	783500.11	Forest	44	567360.35	808104.98	Agricultural land
45	398304.82	826311.03	Agricultural land	45	570066.75	802656.37	Agricultural land
46	397638.69	821192.41	Agricultural land	46	577214.42	803315.76	Agricultural land
47	395381.25	816778.53	Agricultural land	47	575965.32	809111.41	Agricultural land
48	391717.53	815072.33	Agricultural land	48	580371.39	805293.91	Agricultural land
49	390385.27	811370.6	Agricultural land	49	575687.74	809423.75	Agricultural land
50	394937.16	807550.19	Agricultural land	50	581447.51	809666.68	Agricultural land
51	393086.8	806214.9	Agricultural land				
52	394271.03	802246.11	Agricultural land				
53	398304.82	796133.45	Agricultural land				
54	404818.1	796133.45	Agricultural land				
55	402782.7	792698.78	Agricultural land				
56	399748.1	787951.08	Agricultural land				

Appendix C Forcing a Single Independent Variable to be Constant

Model	Benue State			Makurdi			Gboko			Otukpo			Katsina-Ala		
	Acc(%)	SM	IO	Acc(%)	SM	IO	Acc(%)	SM	IO	Acc(%)	SM	IO	Acc(%)	SM	IO
With all variables	75.60	0.6746	N/A	75.97	0.7117	N/A	78.72	0.7447	N/A	78.05	0.7492	N/A	71.43	0.6571	N/A
Var. 1 constant	73.29	0.6438	3	64.76	0.5772	2	69.15	0.6298	2	78.02	0.7488	7	68.91	0.6269	4
Var. 2 constant	75.04	0.6672	5	75.36	0.7043	6	73.40	0.6809	4	75.81	0.7235	5	72.69	0.6723	7*
Var. 3 constant	75.37	0.6717	6	75.07	0.7008	5	76.60	0.7191	5	77.76	0.7458	6	64.71	0.5765	2
Var. 4 constant	74.94	0.6658	4	74.04	0.6884	4	77.66	0.7319	6	71.40	0.6732	4	65.97	0.5916	3
Var. 5 constant	75.50	0.6733	7	76.03	0.7123	7	78.72	0.7447	7 *	78.15	0.7503	8*	72.27	0.6672	6
Var. 6 constant	75.64	0.6751	8 *	76.18	0.7142	8*	73.40	0.6809	3	63.21	0.5796	2	70.17	0.6420	5
Var. 7 constant	51.37	0.3516	1**	25.28	0.1034	1**	29.79	0.1574	1**	19.91	0.0847	1 **	29.41	0.1529	1 **
Var. 8 constant	62.70	0.5026	2	73.34	0.6800	3	–	–	–	67.65	0.6303	3	–	–	–

Key: Acc= Accuracy, SM= Skill measure, IO= Influence order, ** = Most Influential, * = Least Influential

Appendix D The Result of MLP with Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
Benue			
With all variables	All variables	75.60	0.6746
Step 1: var.[6] constant	[1,2,3,4,5,7,8]	75.64	0.6751
Step 2: var.[6,5] constant	[1,2,3,4,7,8]	75.37	0.6717
Step 3: var.[6,5,3] constant	[1,2,4,7,8]	75.10	0.6681
Step 4: var.[6,5,3,2] constant	[1,4,7,8]	74.50	0.6600
Step 5: var.[6,5,3,2,4] constant	[1,7,8]	73.71	0.6495
Step 6: var.[6,5,3,2,4,1] constant	[7,8]	70.03	0.6004
Step 7: var.[6,5,3,2,4,1,8] constant	[7]	49.88	0.3317
Makurdi			
With all variables	All variables	75.97	0.7117
Step 1: var.[6] constant	[1,2,3,4,5,7,8]	76.18	0.7142
Step 2: var.[6,5] constant	[1,2,3,4,7,8]	76.27	0.7152
Step 3: var.[6,5,2] constant	[1,3,4,7,8]	75.43	0.7052
Step 4: var.[6,5,2,3] constant	[1,4,7,8]	74.91	0.6989
Step 5: var.[6,5,2,3,4] constant	[1,7,8]	73.04	0.6765
Step 6: var.[6,5,2,3,4,8] constant	[1,7]	70.42	0.6450
Step 7: var.[6,5,2,3,4,8,1] constant	[7]	50.06	0.4007
Gboko			
With all variables	All variables	78.72	0.7447
Step 1: var.[5] constant	[1,2,3,4,6,7]	78.72	0.7447
Step 2: var.[5,4] constant	[1,2,3,6,7]	77.66	0.7319
Step 3: var.[5,4,3] constant	[1,2,6,7]	72.34	0.6681
Step 4: var.[5,4,3,6] constant	[1,2,7]	64.89	0.5787
Step 5: var.[5,4,3,6,1] constant	[2,7]	48.94	0.3872
Step 6: var.[5,4,3,6,1,2] constant	[7]	32.98	0.1957
Otukpo			
With all variables	All variables	78.05	0.7492
Step 1: var.[5] constant	[1,2,3,4,6,7,8]	78.15	0.7503
Step 2: var.[5,1] constant	[2,3,4,6,7,8]	77.98	0.7483
Step 3: var.[5,1,3] constant	[2,4,6,7,8]	77.34	0.7411
Step 4: var.[5,1,3,2] constant	[4,6,7,8]	73.07	0.6922
Step 5: var.[5,1,3,2,4] constant	[6,7,8]	65.95	0.6108
Step 6: var.[5,1,3,2,4,6] constant	[7,8]	63.95	0.5880
Step 7: var.[5,1,3,2,4,6,8] constant	[7]	49.97	0.4283
Katsina-Ala			
With all variables	All variables	71.43	0.6571
Step 1: var.[2] constant	[1,3,4,5,6,7]	72.69	0.6723
Step 2: var.[2,5] constant	[1,3,4,6,7]	72.69	0.6723
Step 3: var.[2,5,6] constant	[1,3,4,7]	71.43	0.6571
Step 4: var.[2,5,6,3] constant	[1,4,7]	65.97	0.5916
Step 5: var.[2,5,6,3,1] constant	[4,7]	60.92	0.5311
Step 6: var.[2,5,6,3,1,4] constant	[7]	57.14	0.4857

Appendix E Land Change Modeler MLP Model Results for Benue State

1. General Model Information

1) Input Files

Independent variable 1	Dist_urban87
Independent variable 2	Dist_Roads
Independent variable 3	Dist_Rivers
Independent variable 4	Ben_DEM4
Independent variable 5	Ben_slope
Independent variable 6	Ben_pop
Independent variable 7	Ben_Evilikelihood
Independent variable 8	Dist_Rails
Training site file	Benproject_Train_Urban Area

2) Parameters and Performance

Input layer neurons	8
Hidden layer neurons	7
Output layer neurons	4
Requested samples per class	10000
Final learning rate	0.0000
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3043
Testing RMS	0.3064
Accuracy rate	75.60%
Skill measure	0.6746

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Forest to Urban Area	0.7312
Transition : Farmland to Urban Area	0.6027
Persistence : Forest	0.6856
Persistence : Farmland	0.6796

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6	h-Neuron 7
i-Neuron 1	-3.0261	-2.2495	0.3159	-4.1061	-2.0528	9.8523	6.5702
i-Neuron 2	-0.0699	-0.8114	-0.3382	1.0547	-0.3636	-0.5653	4.7911
i-Neuron 3	-0.1351	0.1805	0.1906	0.0208	0.1678	-0.3966	-1.8006
i-Neuron 4	1.3213	0.8600	0.6941	-1.6690	-1.5379	1.8013	-3.7943
i-Neuron 5	0.2746	-0.1233	0.0168	-0.8502	-1.0370	1.9247	-0.5396
i-Neuron 6	-0.0239	-0.4524	0.9967	0.0133	0.7305	0.2300	-1.5842
i-Neuron 7	4.7674	-2.9020	-5.3159	-3.0813	3.7322	-7.1368	10.6840
i-Neuron 8	-1.4530	-0.5362	-0.7285	0.0246	0.5829	2.3699	-9.0017

2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4
h-Neuron 1	-3.4588	9.6349	-8.3096	1.4954
h-Neuron 2	11.6184	-3.7168	6.6662	-8.3061
h-Neuron 3	12.5238	-11.3036	13.5913	-15.0371
h-Neuron 4	19.3162	-10.4752	8.2764	-8.4749
h-Neuron 5	-4.9526	3.7922	-9.3020	3.6419
h-Neuron 6	-3.6439	-15.9328	13.7687	-2.9915
h-Neuron 7	-5.0846	-6.5715	6.4317	3.1700

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	75.60	0.6746	N/A
Var. 1 constant	73.29	0.6438	3
Var. 2 constant	75.04	0.6672	5
Var. 3 constant	75.37	0.6717	6
Var. 4 constant	74.94	0.6658	4
Var. 5 constant	75.50	0.6733	7
Var. 6 constant	75.64	0.6751	8 (least influential)
Var. 7 constant	51.37	0.3516	1 (most influential)
Var. 8 constant	62.70	0.5026	2

2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	75.60	0.6746
All constant but var. 1	33.52	0.1136
All constant but var. 2	25.94	0.0125
All constant but var. 3	25.08	0.0010
All constant but var. 4	25.60	0.0080
All constant but var. 5	25.88	0.0117
All constant but var. 6	22.13	-0.0383
All constant but var. 7	49.88	0.3317
All constant but var. 8	41.26	0.2168

3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	75.60	0.6746
Step 1: var.[6] constant	[1,2,3,4,5,7,8]	75.64	0.6751
Step 2: var.[6,5] constant	[1,2,3,4,7,8]	75.37	0.6717
Step 3: var.[6,5,3] constant	[1,2,4,7,8]	75.10	0.6681
Step 4: var.[6,5,3,2] constant	[1,4,7,8]	74.50	0.6600
Step 5: var.[6,5,3,2,4] constant	[1,7,8]	73.71	0.6495
Step 6: var.[6,5,3,2,4,1] constant	[7,8]	70.03	0.6004
Step 7: var.[6,5,3,2,4,1,8] constant	[7]	49.88	0.3317

Appendix F Land Change Modeler MLP Model Results For Makurdi

1. General Model Information

1) Input Files

Independent variable 1	Mkd_Dist_urban_87
Independent variable 2	Mkd_Dist_Roads
Independent variable 3	Mkd_Dist_Rivers
Independent variable 4	Mkd_DEM
Independent variable 5	Mkd_slope
Independent variable 6	Mkd_Pop
Independent variable 7	Mkd_Evilikelihood
Independent variable 8	Mkd_Dist_Rail
Training site file	MKD_Train_Urban Area

2) Parameters and Performance

Input layer neurons	8
Hidden layer neurons	7
Output layer neurons	6
Requested samples per class	1922
Final learning rate	0.0003
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.2298
Testing RMS	0.2380
Accuracy rate	75.97%
Skill measure	0.7117

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Grassland to Urban Area	0.7247
Transition : Forest to Urban Area	0.7540
Transition : Farmland to Urban Area	0.5953
Persistence : Grassland	0.6625
Persistence : Forest	0.7626
Persistence : Farmland	0.7716

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6	h-Neuron 7
i-Neuron 1	1.0392	-4.6102	0.3090	14.2795	-3.3411	5.1908	-0.7529
i-Neuron 2	1.6122	-2.0673	2.3669	-0.8926	-3.3460	2.2382	-0.0384
i-Neuron 3	-0.1182	1.7166	-5.7173	-2.6984	-1.3999	0.5811	0.1867
i-Neuron 4	-0.5132	-2.8909	-4.1387	-3.7687	0.6857	6.4227	-0.3204
i-Neuron 5	-0.7714	-1.5569	0.1180	-1.4836	0.1680	-0.4551	0.5417
i-Neuron 6	8.4965	-0.1391	-0.4492	1.0418	-0.4128	-2.1347	4.8803
i-Neuron 7	-19.5379	5.4851	9.9790	1.5915	1.9092	2.5548	-18.1781
i-Neuron 8	3.8416	1.5092	-1.5570	6.1678	0.3765	-2.1465	2.1893

2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5	o-Neuron 6
h-Neuron 1	10.7957	3.6401	-4.0097	7.7166	-3.0263	-9.2154
h-Neuron 2	2.9334	0.7592	-0.4776	-6.7295	-9.4794	3.5107
h-Neuron 3	1.8189	-2.8126	5.8921	-5.0673	-5.5624	-5.6568
h-Neuron 4	-7.0916	-1.1417	-6.8694	4.9387	0.3644	5.8583
h-Neuron 5	0.3474	0.4555	3.4632	1.9884	-3.5714	-5.6637
h-Neuron 6	-5.7276	-8.9150	-1.3974	-1.5035	1.6842	1.4925
h-Neuron 7	-9.2942	4.4571	-4.7595	-14.7817	4.7113	-8.0497

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	75.97	0.7117	N/A
Var. 1 constant	64.76	0.5772	2
Var. 2 constant	75.36	0.7043	6
Var. 3 constant	75.07	0.7008	5
Var. 4 constant	74.04	0.6884	4
Var. 5 constant	76.03	0.7123	7
Var. 6 constant	76.18	0.7142	8 (least influential)
Var. 7 constant	25.28	0.1034	1 (most influential)
Var. 8 constant	73.34	0.6800	3

2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	75.97	0.7117
All constant but var. 1	22.61	0.0713
All constant but var. 2	17.20	0.0064
All constant but var. 3	17.36	0.0083
All constant but var. 4	17.50	0.0100
All constant but var. 5	17.20	0.0064
All constant but var. 6	17.29	0.0074
All constant but var. 7	50.06	0.4007
All constant but var. 8	17.20	0.0064

3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	75.97	0.7117
Step 1: var.[6] constant	[1,2,3,4,5,7,8]	76.18	0.7142
Step 2: var.[6,5] constant	[1,2,3,4,7,8]	76.27	0.7152
Step 3: var.[6,5,2] constant	[1,3,4,7,8]	75.43	0.7052
Step 4: var.[6,5,2,3] constant	[1,4,7,8]	74.91	0.6989
Step 5: var.[6,5,2,3,4] constant	[1,7,8]	73.04	0.6765
Step 6: var.[6,5,2,3,4,8] constant	[1,7]	70.42	0.6450
Step 7: var.[6,5,2,3,4,8,1] constant	[7]	50.06	0.4007

Appendix G Land Change Modeler MLP Model Results for Gboko

1. General Model Information

1) Input Files

Independent variable 1	Gbk_Dist_urban_87
Independent variable 2	Gbk_Dist_Roads
Independent variable 3	Gbk_Dist_Rivers
Independent variable 4	Gbk_DEM
Independent variable 5	Gbk_Slope
Independent variable 6	Gbk_pop
Independent variable 7	Gbk_Evilikelihood
Training site file	GBK_Train_Urban Area

2) Parameters and Performance

Input layer neurons	7
Hidden layer neurons	6
Output layer neurons	6
Requested samples per class	32
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3017
Testing RMS	0.3032
Accuracy rate	78.72%
Skill measure	0.7447

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Grassland to Urban Area	0.7600
Transition : Bare Surface to Urban Area	0.7000
Transition : Forest to Urban Area	0.8286
Persistence : Grassland	0.4400
Persistence : Bare Surface	1.0000
Persistence : Forest	0.7474

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6
i-Neuron 1	-0.9000	1.1659	-1.3883	2.3257	1.9060	2.9810
i-Neuron 2	-1.4654	-0.5888	-2.1427	1.0876	3.1797	2.3654
i-Neuron 3	0.8612	-0.2483	0.7324	-0.7459	0.2078	-1.2698
i-Neuron 4	0.4821	-0.9153	2.4770	-0.9041	-1.9883	-2.9490
i-Neuron 5	0.1164	0.4422	0.0139	0.3763	0.1069	0.0532
i-Neuron 6	-0.4364	0.2907	0.8509	0.6867	-1.1662	-0.7411
i-Neuron 7	8.3376	3.6003	-3.1203	-9.3015	5.5508	-2.2187

2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5	o-Neuron 6
h-Neuron 1	3.8167	-3.9829	-1.8059	2.8117	-5.4926	-1.8352
h-Neuron 2	0.7526	-2.2253	-2.2618	0.2494	-2.0777	-0.6619
h-Neuron 3	-0.0950	1.8777	3.5531	-4.3681	-1.6355	-2.6221
h-Neuron 4	-6.8902	3.3515	1.3499	-5.7378	4.6689	0.7375
h-Neuron 5	-1.8362	-2.9653	-3.6414	4.4484	-1.7923	1.5102
h-Neuron 6	-4.6930	-0.5939	-3.4599	-0.5444	2.7928	1.2450

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.72	0.7447	N/A
Var. 1 constant	69.15	0.6298	2
Var. 2 constant	73.40	0.6809	4
Var. 3 constant	76.60	0.7191	5
Var. 4 constant	77.66	0.7319	6
Var. 5 constant	78.72	0.7447	7 (least influential)
Var. 6 constant	73.40	0.6809	3
Var. 7 constant	29.79	0.1574	1 (most influential)

2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	78.72	0.7447
All constant but var. 1	27.66	0.1319
All constant but var. 2	26.60	0.1191
All constant but var. 3	20.21	0.0426
All constant but var. 4	30.85	0.1702
All constant but var. 5	20.21	0.0426
All constant but var. 6	30.85	0.1702
All constant but var. 7	32.98	0.1957

3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.72	0.7447
Step 1: var.[5] constant	[1,2,3,4,6,7]	78.72	0.7447
Step 2: var.[5,4] constant	[1,2,3,6,7]	77.66	0.7319
Step 3: var.[5,4,3] constant	[1,2,6,7]	72.34	0.6681
Step 4: var.[5,4,3,6] constant	[1,2,7]	64.89	0.5787
Step 5: var.[5,4,3,6,1] constant	[2,7]	48.94	0.3872
Step 6: var.[5,4,3,6,1,2] constant	[7]	32.98	0.1957

Appendix H Land Change Modeler MLP Model Results for Otukpo

1. General Model Information

1) Input Files

Independent variable 1	Tkp_Dist_urban_87
Independent variable 2	Tkp_dist_roads
Independent variable 3	Tkp_Dist_Rivers
Independent variable 4	Tkp_DEM
Independent variable 5	Tkp_slope
Independent variable 6	Tkp_Pop
Independent variable 7	Tkp_Evilikelihood
Independent variable 8	Tkp_Dist_Rail
Training site file	TKP_Train_Urban Area

2) Parameters and Performance

Input layer neurons	8
Hidden layer neurons	8
Output layer neurons	8
Requested samples per class	5008
Final learning rate	0.0001
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.1986
Testing RMS	0.2020
Accuracy rate	78.05%
Skill measure	0.7492

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Grassland to Urban Area	0.8745
Transition : Bare Surface to Urban Area	0.5537
Transition : Forest to Urban Area	0.9410
Transition : Farmland to Urban Area	0.5725
Persistence : Grassland	0.7536
Persistence : Bare Surface	0.8223
Persistence : Forest	0.8243
Persistence : Farmland	0.6551

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6	h-Neuron 7	h-Neuron 8
i-Neuron 1	3.7731	-6.7136	-3.5277	7.5610	-3.9422	2.9169	7.1136	7.8933
i-Neuron 2	-0.1175	-3.0398	-2.6924	2.9528	-6.6940	-0.3257	5.1204	-0.6173
i-Neuron 3	-1.2441	4.2065	0.1575	0.3152	-5.7063	-0.0538	0.9181	-1.9114
i-Neuron 4	2.5185	-1.9478	6.0886	-8.2281	-5.8309	1.2405	-4.8619	7.5721
i-Neuron 5	-0.3096	0.1928	0.2758	1.0577	-0.5335	0.3700	0.4357	0.2247
i-Neuron 6	4.9312	-22.5933	-1.8141	3.1209	5.7217	3.9778	-5.1581	-3.2276
i-Neuron 7	-22.6381	29.0709	9.3565	2.0301	-2.0291	-35.3652	22.0784	-7.6348
i-Neuron 8	3.0640	3.2977	-0.4807	0.0832	-0.9074	2.2408	-5.5369	-4.0431

2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5	o-Neuron 6	o-Neuron 7	o-Neuron 8
h-Neuron 1	-0.1570	-14.9407	4.5967	-6.6459	1.1199	-12.5342	9.6474	-7.4490
h-Neuron 2	-6.1660	3.6288	-10.0034	-9.4348	-2.7405	5.2672	-0.2132	-5.4319
h-Neuron 3	-5.4279	-4.3411	3.4133	9.7338	-12.8448	0.6449	-7.3423	0.2527
h-Neuron 4	-7.4227	-8.7110	-0.7342	-2.3002	3.2309	-13.0400	5.1466	5.8625
h-Neuron 5	-2.3965	6.6796	-7.0596	-0.2805	2.6499	-13.0019	3.2936	-5.4045
h-Neuron 6	10.7033	-4.7779	-9.2836	-16.6913	6.3734	-6.3161	-21.0622	-9.2852
h-Neuron 7	-9.8057	8.1033	-17.2893	-11.3040	-6.0167	-1.3564	-3.1065	-0.4088
h-Neuron 8	-2.7040	-13.7091	-5.8087	-5.2877	6.2869	-8.0847	4.1711	4.7715

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.05	0.7492	N/A
Var. 1 constant	78.02	0.7488	7
Var. 2 constant	75.81	0.7235	5
Var. 3 constant	77.76	0.7458	6
Var. 4 constant	71.40	0.6732	4
Var. 5 constant	78.15	0.7503	8 (least influential)
Var. 6 constant	63.21	0.5796	2
Var. 7 constant	19.91	0.0847	1 (most influential)
Var. 8 constant	67.65	0.6303	3

2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	78.05	0.7492
All constant but var. 1	15.56	0.0349
All constant but var. 2	12.46	-0.0005
All constant but var. 3	12.44	-0.0007
All constant but var. 4	15.89	0.0388
All constant but var. 5	12.44	-0.0007
All constant but var. 6	11.80	-0.0080
All constant but var. 7	49.97	0.4283
All constant but var. 8	17.62	0.0585

3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	78.05	0.7492
Step 1: var.[5] constant	[1,2,3,4,6,7,8]	78.15	0.7503
Step 2: var.[5,1] constant	[2,3,4,6,7,8]	77.98	0.7483
Step 3: var.[5,1,3] constant	[2,4,6,7,8]	77.34	0.7411
Step 4: var.[5,1,3,2] constant	[4,6,7,8]	73.07	0.6922
Step 5: var.[5,1,3,2,4] constant	[6,7,8]	65.95	0.6108
Step 6: var.[5,1,3,2,4,6] constant	[7,8]	63.95	0.5880
Step 7: var.[5,1,3,2,4,6,8] constant	[7]	49.97	0.4283

Appendix I Land Change Modeler MLP Model Results for Katsina-Ala

1. General Model Information

1) Input Files

Independent variable 1	Kal_Dist_urban_87
Independent variable 2	Kal_dist_roads
Independent variable 3	Kal_Dist_Rivers
Independent variable 4	Kal_DEM
Independent variable 5	Kal_Slope
Independent variable 6	Kal_Pop
Independent variable 7	Kal_Evilikelihood
Training site file	KAL_Train_Urban Area

2) Parameters and Performance

Input layer neurons	7
Hidden layer neurons	7
Output layer neurons	6
Requested samples per class	98
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.2646
Testing RMS	0.2767
Accuracy rate	71.43%
Skill measure	0.6571

3) Model Skill Breakdown by Transition & Persistence

Class	Skill measure
Transition : Grassland to Urban Area	0.6286
Transition : Bare Surface to Urban Area	-0.2000
Transition : Forest to Urban Area	0.7767
Persistence : Grassland	0.3268
Persistence : Bare Surface	0.9538
Persistence : Forest	0.8605

2. Weights Information of Neurons across Layers

1) Weights between Input Layer Neurons and Hidden Layer Neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5	h-Neuron 6	h-Neuron 7
i-Neuron 1	-6.6809	5.0903	-1.1694	2.4638	2.8225	1.2709	-2.6510
i-Neuron 2	-1.0912	1.9658	-0.1010	-0.5334	-0.4177	-0.0872	-4.6951
i-Neuron 3	-1.8674	3.3248	-0.4709	1.1869	1.7842	-0.3218	-3.4233
i-Neuron 4	4.8969	-0.3547	0.6167	-2.4847	-1.7500	0.4349	-1.1842
i-Neuron 5	0.4778	-2.2288	0.6416	0.8286	-1.3500	0.5820	1.1091
i-Neuron 6	-2.5474	1.3551	0.8395	1.1409	-4.8745	4.3844	2.0805
i-Neuron 7	4.6504	-6.0321	0.6731	0.7168	17.1197	-14.3629	-14.5352

2) Weights between Hidden Layer Neurons and Output Layer Neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5	o-Neuron 6
h-Neuron 1	6.3086	-0.9086	6.2094	-0.6790	-5.4492	-4.8432
h-Neuron 2	-8.6264	-2.2799	-2.0183	-0.4795	1.5649	1.4575
h-Neuron 3	1.4128	-1.4986	-0.0787	-1.2497	-2.4499	-1.1151
h-Neuron 4	0.0366	-1.5186	-3.4044	0.7973	-1.5959	1.6595
h-Neuron 5	7.3700	-3.5627	-8.7647	8.8278	-4.9755	-5.3315
h-Neuron 6	-8.8499	-0.0130	4.5265	-6.7277	1.9923	5.6554
h-Neuron 7	-4.3674	3.5986	-5.5892	-10.4658	2.1124	-11.1137

3. Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	71.43	0.6571	N/A
Var. 1 constant	68.91	0.6269	4
Var. 2 constant	72.69	0.6723	7 (least influential)
Var. 3 constant	64.71	0.5765	2
Var. 4 constant	65.97	0.5916	3
Var. 5 constant	72.27	0.6672	6
Var. 6 constant	70.17	0.6420	5
Var. 7 constant	29.41	0.1529	1 (most influential)

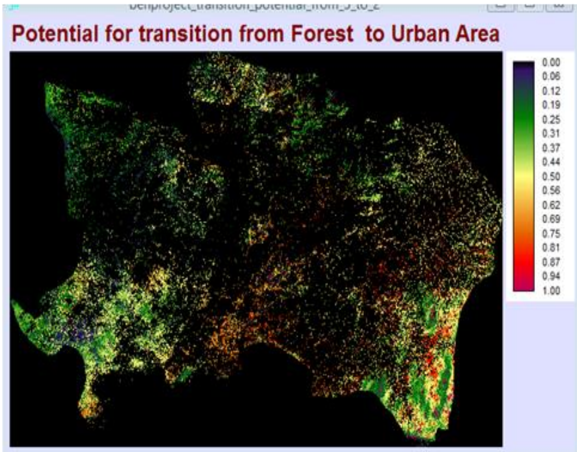
2) Forcing All Independent Variables Except One to be Constant

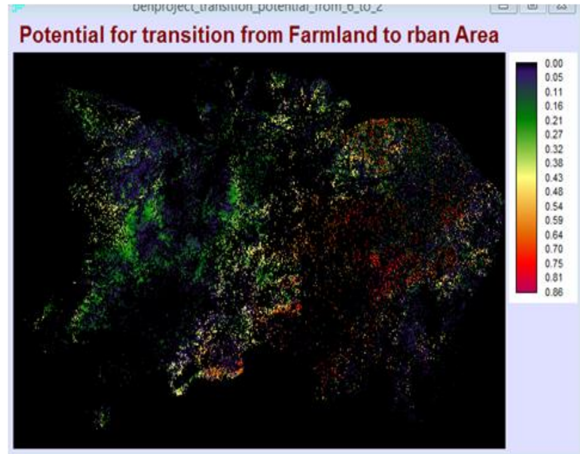
Model	Accuracy (%)	Skill measure
With all variables	71.43	0.6571
All constant but var. 1	18.07	0.0168
All constant but var. 2	18.07	0.0168
All constant but var. 3	18.07	0.0168
All constant but var. 4	20.17	0.0420
All constant but var. 5	18.07	0.0168
All constant but var. 6	18.07	0.0168
All constant but var. 7	57.14	0.4857

3) Backwards Stepwise Constant Forcing

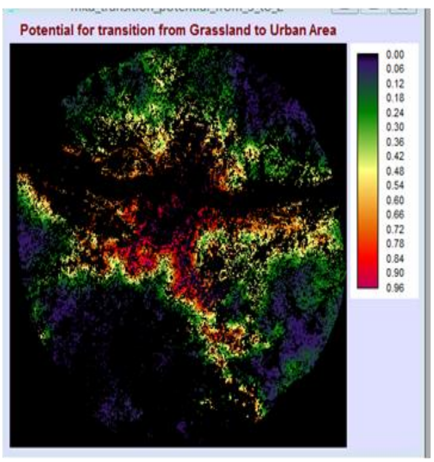
Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	71.43	0.6571
Step 1: var.[2] constant	[1,3,4,5,6,7]	72.69	0.6723
Step 2: var.[2,5] constant	[1,3,4,6,7]	72.69	0.6723
Step 3: var.[2,5,6] constant	[1,3,4,7]	71.43	0.6571
Step 4: var.[2,5,6,3] constant	[1,4,7]	65.97	0.5916
Step 5: var.[2,5,6,3,1] constant	[4,7]	60.92	0.5311
Step 6: var.[2,5,6,3,1,4] constant	[7]	57.14	0.4857

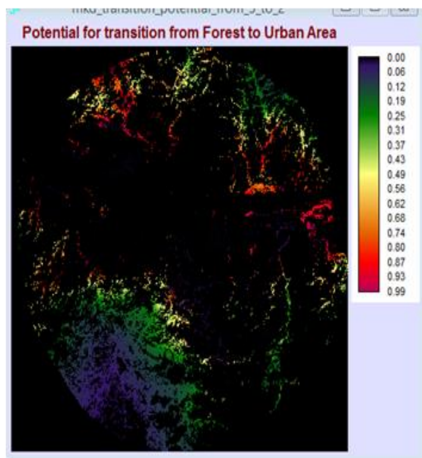
Appendix J[1] Transition Potential Maps

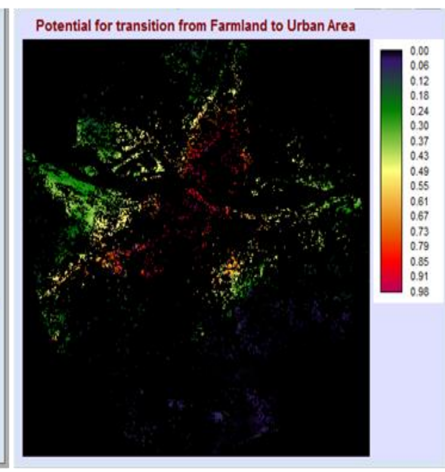




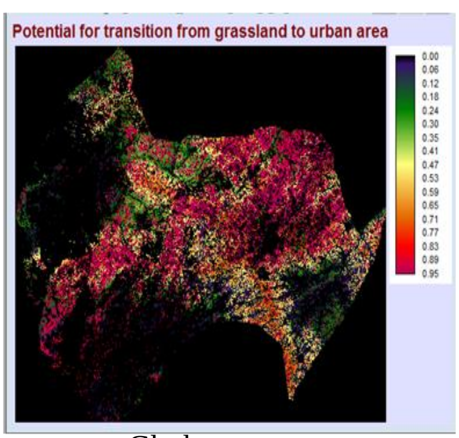
Benue

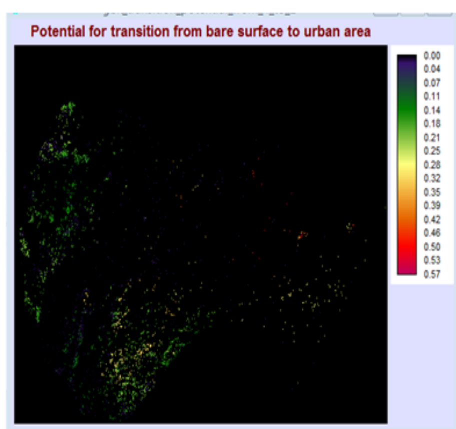


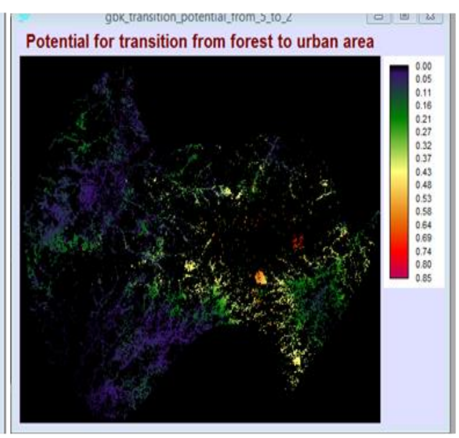




Makurdi

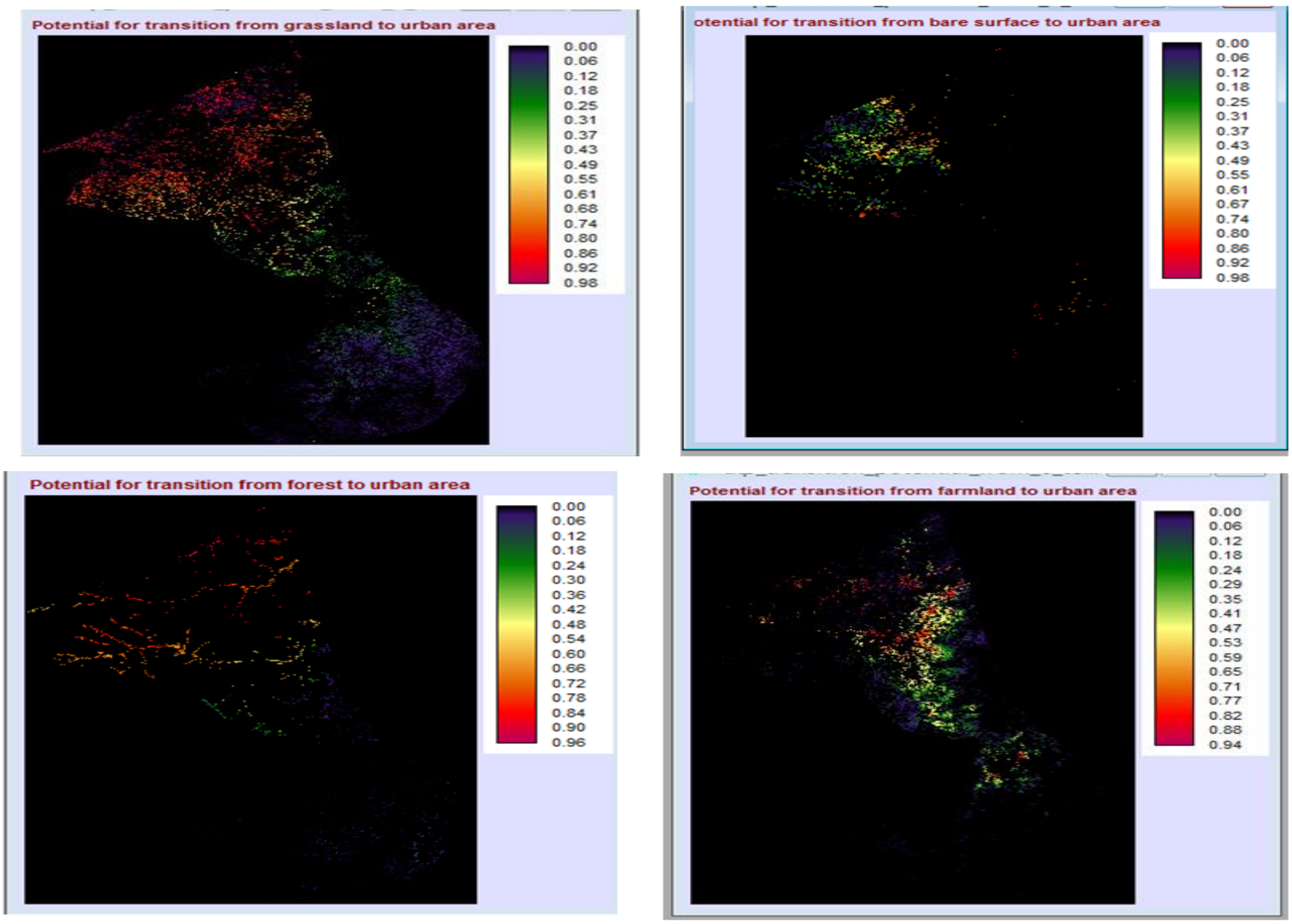




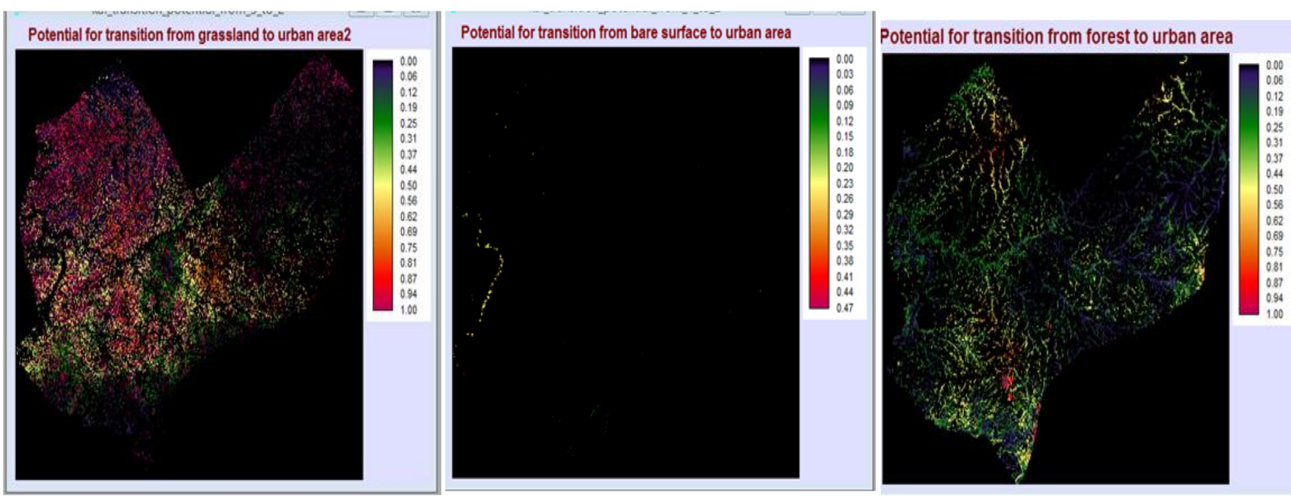


Gboko

Appendix J^2 Transition Potential Maps



Otukpo



Katsina-Ala

Appendix K Result of ROC Statistic for 2017 Soft Prediction Map for Benue State

```
                    Result of ROC**
                    ===============

                    AUC =  0.785

*****************************************************************
The following section list detailed statistics for each threshold.
*****************************************************************

With each threshold, the following 2x2 contingency table is calculated
_________________________________________________________________________
                                   Reality (reference image)
                         ------------------------------------------------
Simulated by threshold          1                     0
-------------------------------------------------------------------------
         1                      A(number of cells)    B(number of cells)
         0                      C                     D
For the given reference image:  A+C=1102020           B+D=33680062
_________________________________________________________________________
```

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	5.0000	4.8480	0.5986	86199	7.8219	1600033	4.7507
3	10.0000	9.8421	0.4764	113873	10.3331	3309416	9.8260
4	15.0000	14.8025	0.3730	128619	11.6712	5019993	14.9049
5	20.0000	20.0232	0.2942	139798	12.6856	6824681	20.2633
6	25.0000	24.9242	0.2211	167949	15.2401	8501218	25.2411
7	30.0000	29.9376	0.1596	210592	19.1096	10202316	30.2919
8	35.0000	34.9954	0.0962	251740	22.8435	11920404	35.3931
9	40.0000	39.9908	0.0263	285188	25.8787	13624458	40.4526
10	45.0000	45.1139	0.0123	338941	30.7563	15352603	45.5837
11	50.0000	50.0246	0.0000	377515	100.0000	17022067	100.0000
12	55.0000	55.0000	0.0000	384620	34.9014	18745526	55.6576
13	60.0000	60.0000	0.0000	494841	44.9031	20374409	60.4940
14	65.0000	65.0000	0.0000	584573	53.0456	22023781	65.3912
15	70.0000	70.0000	0.0000	678492	61.5680	23668966	70.2759
16	75.0000	75.0000	0.0000	777752	70.5751	25308811	75.1448
17	80.0000	80.0000	0.0000	910514	82.6223	26915153	79.9142
18	85.0000	85.0000	0.0000	995236	90.3102	28569535	84.8263
19	90.0000	90.0000	0.0000	1025186	93.0279	30278689	89.9009
20	95.0000	95.0000	0.0000	1068988	97.0026	31973991	94.9345
21	100.0000	100.0000	0.0000	1102020	100.0000	33680062	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

No info of location and no info of quantity:	N(n) =	0.5000
Perfect info of location and perfect info of quantity:	P(p) =	1.0000
Perfect info of location and no info of quantity:	P(n) =	0.5317
No info of location and perfect info of quantity:	N(p) =	0.9386
No info of location and no info of quantity:	PerfectChance =	0.5000
No info of location and perfect info of quantity:	PerfectQuantity =	0.4386
Perfect info of location given no info of quantity:	PerfectLocation =	0.0614

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.9683	0.9683	0.9683	0.9386	0.5000
2	0.9248	0.9229	0.9832	0.9406	0.5010
3	0.8764	0.8761	0.9333	0.9390	0.5002
4	0.8277	0.8297	0.8837	0.9386	0.5000
5	0.7761	0.7808	0.8315	0.9386	0.5000
6	0.7287	0.7349	0.7824	0.9386	0.5000
7	0.6811	0.6879	0.7323	0.9386	0.5000
8	0.6328	0.6405	0.6817	0.9386	0.5000
9	0.5848	0.5937	0.6318	0.9386	0.5000
10	0.5367	0.5458	0.5805	0.9386	0.5000
11	0.0109	0.0054	0.0109	1.0000	0.5317
12	0.4404	0.4532	0.4817	0.9386	0.5000
13	0.3968	0.4063	0.4317	0.9386	0.5000
14	0.3519	0.3595	0.3817	0.9386	0.5000
15	0.3073	0.3127	0.3317	0.9386	0.5000
16	0.2630	0.2658	0.2817	0.9386	0.5000
17	0.2207	0.2190	0.2317	0.9467	0.5042
18	0.1755	0.1722	0.1817	0.9604	0.5112
19	0.1273	0.1253	0.1317	0.9572	0.5096
20	0.0798	0.0785	0.0817	0.9632	0.5127
21	0.0317	0.0317	0.0317	0.9386	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.937	0.000	1.068	0.000
2	0.850	0.031	0.964	0.024
3	0.753	0.005	0.857	0.003
4	0.655	-0.037	0.747	-0.012
5	0.552	-0.092	0.629	-0.021
6	0.457	-0.129	0.521	-0.023

7	0.362	-0.155	0.413	-0.022
8	0.266	-0.187	0.303	-0.021
9	0.170	-0.235	0.193	-0.022
10	0.073	-0.262	0.084	-0.020
11	-0.978	1.000	-1.112	0.005
12	-0.119	-0.447	-0.136	-0.023
13	-0.206	-0.377	-0.235	-0.016
14	-0.296	-0.342	-0.338	-0.012
15	-0.385	-0.281	-0.439	-0.008
16	-0.474	-0.177	-0.540	-0.004
17	-0.559	0.131	-0.641	0.002
18	-0.649	0.354	-0.747	0.004
19	-0.745	0.303	-0.854	0.002
20	-0.840	0.401	-0.961	0.001
21	-0.937	0.000	-1.068	0.000

No.	CorrectChance	CorrectQuantity	CorrectLocation	ErrorLocation	ErrorQuantity
1	0.500	0.468	0.000	0.000	0.032
2	0.500	0.423	0.002	0.058	0.017
3	0.500	0.376	0.000	0.057	0.067
4	0.500	0.330	0.000	0.054	0.116
5	0.500	0.281	0.000	0.051	0.169
6	0.500	0.235	0.000	0.048	0.218
7	0.500	0.188	0.000	0.044	0.268
8	0.500	0.141	0.000	0.041	0.318
9	0.500	0.094	0.000	0.038	0.368
10	0.500	0.046	0.000	0.035	0.419
11	0.005	0.000	0.005	0.000	0.989
12	0.453	0.000	0.000	0.029	0.518
13	0.406	0.000	0.000	0.025	0.568
14	0.360	0.000	0.000	0.022	0.618
15	0.313	0.000	0.000	0.019	0.668
16	0.266	0.000	0.000	0.016	0.718
17	0.219	0.000	0.002	0.011	0.768
18	0.172	0.000	0.003	0.006	0.818
19	0.125	0.000	0.002	0.004	0.868
20	0.079	0.000	0.001	0.002	0.918
21	0.032	0.000	0.000	0.000	0.968

** : A ranked image (Tmp$Rank_Ben_landcov_predict_2017b_soft) based on the input image was created in the working directory.
In addition, a percentile map(Tmp$percentile_Ben_landcov_predict_2017b_soft) based on the threshold bands user specified was also created in the working directory.

Appendix L Result of ROC Statistic for 2017 Soft Prediction Map for Makurdi

```
Result of ROC**
===============

AUC =  0.814

******************************************************************
The following section list detailed statistics for each threshold.
******************************************************************

With each threshold, the following 2x2 contingency table is calculated
_________________________________________________________________________
                                    Reality (reference image)
                         ------------------------------------------------
Simulated by threshold          1                      0
-------------------------------------------------------------------------
          1                     A(number of cells)     B(number of cells)
          0                     C                      D
For the given reference image:  A+C=166451            B+D=759871
_________________________________________________________________________
```

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	5.0000	5.9343	0.6010	6982	4.1947	47989	6.3154
3	10.0000	10.6154	0.3889	11487	6.9011	86846	11.4291
4	15.0000	16.0927	0.2192	16617	9.9831	132453	17.4310
5	20.0000	20.6763	0.0142	20521	12.3286	171008	22.5049
6	25.0000	25.5335	0.0020	25188	15.1324	211334	27.8119
7	30.0000	31.3864	0.0000	28975	17.4075	261764	34.4485
8	35.0000	36.2479	0.0000	31665	19.0236	304107	40.0209
9	40.0000	40.0001	0.0000	32658	19.6202	337872	44.4644
10	45.0000	45.0001	0.0000	34416	20.6764	382430	50.3283
11	50.0000	50.0001	0.0000	40790	24.5057	422372	55.5847
12	55.0000	55.0001	0.0000	53868	32.3627	455610	59.9589
13	60.0000	60.0001	0.0000	70969	42.6366	484825	63.8036
14	65.0000	65.0001	0.0000	85778	51.5335	516332	67.9500
15	70.0000	70.0001	0.0000	114315	68.6779	534111	70.2897
16	75.0000	75.0002	0.0000	137972	82.8905	556771	73.2718
17	80.0000	80.0002	0.0000	153621	92.2920	587438	77.3076
18	85.0000	85.0001	0.0000	160035	96.1454	627340	82.5587
19	90.0000	90.0001	0.0000	162342	97.5314	671349	88.3504
20	95.0000	95.0001	0.0000	163409	98.1724	716598	94.3052
21	100.0000	100.0000	0.0000	166451	100.0000	759871	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

No info of location and no info of quantity: N(n) =	0.5000
Perfect info of location and perfect info of quantity: P(p) =	1.0000
Perfect info of location and no info of quantity: P(n) =	0.6797
No info of location and perfect info of quantity: N(p) =	0.7052
No info of location and no info of quantity: PerfectChance =	0.5000
No info of location and perfect info of quantity: PerfectQuantity =	0.2052
Perfect info of location given no info of quantity:PerfectLocation =	0.2948

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.8203	0.8203	0.8203	0.7052	0.5000
2	0.7760	0.7823	0.8797	0.7052	0.5000
3	0.7390	0.7523	0.9265	0.7052	0.5000
4	0.6953	0.7172	0.9812	0.7052	0.5000
5	0.6579	0.6879	0.9729	0.7052	0.5000
6	0.6194	0.6567	0.9244	0.7052	0.5000
7	0.5690	0.6192	0.8658	0.7052	0.5000
8	0.5262	0.5881	0.8172	0.7052	0.5000
9	0.4908	0.5641	0.7797	0.7052	0.5000
10	0.4446	0.5320	0.7297	0.7052	0.5000
11	0.4084	0.5000	0.6797	0.7052	0.5000
12	0.3866	0.4680	0.6297	0.7052	0.5000
13	0.3735	0.4359	0.5797	0.7052	0.5000
14	0.3555	0.4039	0.5297	0.7052	0.5000
15	0.3671	0.3719	0.4797	0.7052	0.5000
16	0.3682	0.3398	0.4297	0.7982	0.5567
17	0.3520	0.3078	0.3797	0.8864	0.6104
18	0.3158	0.2758	0.3297	0.9242	0.6335
19	0.2708	0.2438	0.2797	0.9272	0.6353
20	0.2231	0.2117	0.2297	0.8922	0.6140
21	0.1797	0.1797	0.1797	0.7052	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.641	0.000	1.561	0.000
2	0.552	-0.064	1.345	-0.029
3	0.478	-0.077	1.165	-0.054
4	0.391	-0.083	0.952	-0.078
5	0.316	-0.105	0.769	-0.096
6	0.239	-0.140	0.582	-0.109
7	0.138	-0.204	0.336	-0.132
8	0.052	-0.270	0.128	-0.150

```
   9      -0.018      -0.340      -0.045      -0.168
  10      -0.111      -0.442      -0.270      -0.187
  11      -0.183      -0.510      -0.447      -0.183
  12      -0.227      -0.503      -0.553      -0.153
  13      -0.253      -0.434      -0.616      -0.111
  14      -0.289      -0.385      -0.704      -0.081
  15      -0.266      -0.044      -0.648      -0.008
  16      -0.264       0.316      -0.780       0.043
  17      -0.296       0.615      -0.937       0.064
  18      -0.368       0.743      -1.093       0.055
  19      -0.458       0.753      -1.249       0.036
  20      -0.554       0.634      -1.405       0.014
  21      -0.641       0.000      -1.561       0.000
------------------------------------------------------
   1           0.500           0.320           0.000           0.000           0.180

  No.   CorrectChance CorrectQuantity CorrectLocation   ErrorLocation   ErrorQuantity
-------------------------------------------------------------------------------------
   2           0.500           0.282           0.000           0.097           0.120
   3           0.500           0.252           0.000           0.174           0.074
   4           0.500           0.217           0.000           0.264           0.019
   5           0.500           0.188           0.000           0.285           0.027
   6           0.500           0.157           0.000           0.268           0.076
   7           0.500           0.119           0.000           0.247           0.134
   8           0.500           0.088           0.000           0.229           0.183
   9           0.500           0.064           0.000           0.216           0.220
  10           0.500           0.032           0.000           0.198           0.270
  11           0.500           0.000           0.000           0.180           0.320
  12           0.468           0.000           0.000           0.162           0.370
  13           0.436           0.000           0.000           0.144           0.420
  14           0.404           0.000           0.000           0.126           0.470
  15           0.372           0.000           0.000           0.108           0.520
  16           0.340           0.000           0.028           0.061           0.570
  17           0.308           0.000           0.044           0.028           0.620
  18           0.276           0.000           0.040           0.014           0.670
  19           0.244           0.000           0.027           0.009           0.720
  20           0.212           0.000           0.011           0.007           0.770
  21           0.180           0.000           0.000           0.000           0.820

--------------
** : A ranked image (Tmp$Rank_Mkd_landcov_predict_2017b_soft) based on the input image was created
    in the working directory.
    In addition, a percentile map(Tmp$percentile_Mkd_landcov_predict_2017b_soft) based on the
    threshold bands user specified was also created in the working directory.
```

Appendix M Result of ROC Statistic for 2017 Soft Prediction Map for Gboko

```
                         Result of ROC**
                         ===============

                         AUC =  0.830

******************************************************************
The following section list detailed statistics for each threshold.
******************************************************************

With each threshold, the following 2x2 contingency table is calculated
_________________________________________________________________________
                                    Reality (reference image)
                         ------------------------------------------------
Simulated by threshold           1                      0
-------------------------------------------------------------------------
          1                      A(number of cells)     B(number of cells)
          0                      C                      D
For the given reference image:   A+C=184492            B+D=1947275
_________________________________________________________________________
```

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	5.0000	4.0959	0.9703	4065	2.2033	83249	4.2752
3	10.0000	8.1254	0.9689	11532	6.2507	161682	8.3030
4	15.0000	11.5892	0.9673	22092	11.9745	224962	11.5527
5	20.0000	16.8440	0.7022	44364	24.0466	314711	16.1616
6	25.0000	22.8843	0.5004	55512	30.0891	432327	22.2016
7	30.0000	27.0883	0.4088	60185	32.6220	517274	26.5640
8	35.0000	32.4976	0.3020	64133	34.7619	628640	32.2831
9	40.0000	36.4580	0.2146	65748	35.6373	711451	36.5357
10	45.0000	42.0318	0.1057	68095	36.9095	827924	42.5171
11	50.0000	47.2841	0.0599	71347	38.6721	936640	48.1000
12	55.0000	52.0432	0.0353	73835	40.0207	1035605	53.1823
13	60.0000	58.4564	0.0174	76447	41.4365	1169707	60.0689
14	65.0000	63.8697	0.0085	78555	42.5791	1282999	65.8869
15	70.0000	68.7435	0.0012	79253	42.9574	1386198	71.1866
16	75.0000	75.0000	0.0000	87434	47.3918	1511392	77.6157
17	80.0000	80.0001	0.0000	105883	57.3916	1599532	82.1421
18	85.0000	85.0000	0.0000	148772	80.6387	1663231	85.4133
19	90.0000	90.0000	0.0000	177043	95.9624	1741548	89.4351
20	95.0000	95.0001	0.0000	181622	98.4444	1843558	94.6737
21	100.0000	100.0000	0.0000	184492	100.0000	1947275	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

No info of location and no info of quantity:	N(n) =	0.5000
Perfect info of location and perfect info of quantity:	P(p) =	1.0000
Perfect info of location and no info of quantity:	P(n) =	0.5865
No info of location and perfect info of quantity:	N(p) =	0.8419
No info of location and no info of quantity:	PerfectChance =	0.5000
No info of location and perfect info of quantity:	PerfectQuantity =	0.3419
Perfect info of location given no info of quantity:	PerfectLocation =	0.1581

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.9135	0.9135	0.9135	0.8419	0.5000
2	0.8763	0.8796	0.9544	0.8419	0.5000
3	0.8430	0.8463	0.9947	0.8419	0.5000
4	0.8183	0.8176	0.9707	0.8426	0.5004
5	0.7866	0.7742	0.9181	0.8556	0.5075
6	0.7367	0.7242	0.8577	0.8567	0.5081
7	0.6990	0.6895	0.8157	0.8539	0.5066
8	0.6486	0.6447	0.7616	0.8472	0.5029
9	0.6106	0.6120	0.7220	0.8419	0.5000
10	0.5570	0.5659	0.6662	0.8419	0.5000
11	0.5076	0.5225	0.6137	0.8419	0.5000
12	0.4623	0.4831	0.5661	0.8419	0.5000
13	0.4006	0.4301	0.5020	0.8419	0.5000
14	0.3485	0.3853	0.4478	0.8419	0.5000
15	0.3004	0.3450	0.3991	0.8419	0.5000
16	0.2455	0.2933	0.3365	0.8419	0.5000
17	0.2128	0.2519	0.2865	0.8419	0.5000
18	0.2030	0.2106	0.2365	0.8419	0.5000
19	0.1796	0.1692	0.1865	0.9362	0.5516
20	0.1339	0.1279	0.1365	0.9508	0.5596
21	0.0865	0.0865	0.0865	0.8419	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.827	0.000	1.209	0.000
2	0.753	-0.044	1.101	-0.027
3	0.686	-0.022	1.003	-0.021
4	0.637	0.004	0.929	0.004
5	0.573	0.087	0.802	0.055
6	0.473	0.093	0.656	0.045
7	0.398	0.076	0.554	0.031
8	0.297	0.034	0.423	0.011

9	0.221	-0.013	0.323	-0.004
10	0.114	-0.088	0.167	-0.020
11	0.015	-0.163	0.022	-0.031
12	-0.075	-0.251	-0.110	-0.040
13	-0.199	-0.410	-0.291	-0.052
14	-0.303	-0.589	-0.443	-0.060
15	-0.399	-0.825	-0.584	-0.068
16	-0.509	-1.104	-0.744	-0.068
17	-0.574	-1.130	-0.840	-0.052
18	-0.594	-0.291	-0.869	-0.010
19	-0.641	0.596	-0.967	0.012
20	-0.732	0.689	-1.088	0.007
21	-0.827	0.000	-1.209	0.000

No.	CorrectChance	CorrectQuantity	CorrectLocation	ErrorLocation	ErrorQuantity
1	0.500	0.413	0.000	0.000	0.087
2	0.500	0.380	0.000	0.075	0.046
3	0.500	0.346	0.000	0.148	0.005
4	0.500	0.318	0.001	0.152	0.029
5	0.500	0.274	0.012	0.131	0.082
6	0.500	0.224	0.012	0.121	0.142
7	0.500	0.189	0.010	0.117	0.184
8	0.500	0.145	0.004	0.113	0.238
9	0.500	0.112	0.000	0.110	0.278
10	0.500	0.066	0.000	0.100	0.334
11	0.500	0.022	0.000	0.091	0.386
12	0.483	0.000	0.000	0.083	0.434
13	0.430	0.000	0.000	0.072	0.498
14	0.385	0.000	0.000	0.063	0.552
15	0.345	0.000	0.000	0.054	0.601
16	0.293	0.000	0.000	0.043	0.663
17	0.252	0.000	0.000	0.035	0.713
18	0.211	0.000	0.000	0.026	0.763
19	0.169	0.000	0.010	0.007	0.813
20	0.128	0.000	0.006	0.003	0.863
21	0.087	0.000	0.000	0.000	0.913

** : A ranked image (Tmp$Rank_Gbk_landcov_predict_2017b_soft) based on the input image was created in the working directory.
In addition, a percentile map(Tmp$percentile_Gbk_landcov_predict_2017b_soft) based on the threshold bands user specified was also created in the working directory.

Appendix N Result of ROC Statistic for 2017 Soft Prediction Map for Otukpo

```
                         Result of ROC**
                         ===============

                         AUC =  0.817

*****************************************************************
The following section list detailed statistics for each threshold.
*****************************************************************

With each threshold, the following 2x2 contingency table is calculated
_________________________________________________________________________
                                    Reality (reference image)
                         ------------------------------------------------
Simulated by threshold           1                      0
-------------------------------------------------------------------------
          1                      A(number of cells)     B(number of cells)
          0                      C                      D
For the given reference image:   A+C=171586            B+D=1308177
_________________________________________________________________________
```

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	5.0000	5.1889	0.7185	11393	6.6398	65391	4.9986
3	10.0000	10.4664	0.3986	21794	12.7015	133084	10.1732
4	15.0000	15.3254	0.1517	28939	16.8656	197841	15.1234
5	20.0000	19.6368	0.0783	32472	18.9246	258106	19.7302
6	25.0000	24.6747	0.0428	38552	22.4680	326575	24.9641
7	30.0000	32.2217	0.0210	50730	29.5655	426075	32.5701
8	35.0000	36.0621	0.0144	56476	32.9141	477157	36.4750
9	40.0000	42.1121	0.0063	64538	37.6128	558622	42.7023
10	45.0000	45.5169	0.0030	68248	39.7748	605294	46.2701
11	50.0000	49.6049	0.0009	70957	41.3536	663078	50.6872
12	55.0000	54.1095	0.0003	72556	42.2855	728136	55.6604
13	60.0000	60.3183	0.0001	73895	43.0659	818673	62.5813
14	65.0000	64.5533	0.0000	76761	44.7362	878475	67.1526
15	70.0000	70.2625	0.0000	85910	50.0682	953809	72.9114
16	75.0000	74.5763	0.0000	93048	54.2282	1010505	77.2453
17	80.0000	80.0813	0.0000	102320	59.6319	1082694	82.7636
18	85.0000	84.7874	0.0000	111288	64.8584	1143365	87.4014
19	90.0000	89.8814	0.0000	118898	69.2935	1211133	92.5817
20	95.0000	95.0001	0.0000	146759	85.5309	1259017	96.2421
21	100.0000	100.0000	0.0000	171586	100.0000	1308177	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

No info of location and no info of quantity:	N(n) =	0.5000
Perfect info of location and perfect info of quantity:	P(p) =	1.0000
Perfect info of location and no info of quantity:	P(n) =	0.6160
No info of location and perfect info of quantity:	N(p) =	0.7950
No info of location and no info of quantity:	PerfectChance =	0.5000
No info of location and perfect info of quantity:	PerfectQuantity =	0.2950
Perfect info of location given no info of quantity:	PerfectLocation =	0.2050

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.8840	0.8840	0.8840	0.7950	0.5000
2	0.8476	0.8442	0.9359	0.8025	0.5043
3	0.8088	0.8037	0.9887	0.8007	0.5032
4	0.7699	0.7663	0.9627	0.7987	0.5021
5	0.7316	0.7332	0.9196	0.7950	0.5000
6	0.6894	0.6945	0.8692	0.7950	0.5000
7	0.6304	0.6366	0.7937	0.7950	0.5000
8	0.5998	0.6071	0.7553	0.7950	0.5000
9	0.5502	0.5606	0.6948	0.7950	0.5000
10	0.5211	0.5344	0.6608	0.7950	0.5000
11	0.4839	0.5030	0.6199	0.7950	0.5000
12	0.4410	0.4684	0.5749	0.7950	0.5000
13	0.3807	0.4207	0.5128	0.7950	0.5000
14	0.3423	0.3882	0.4704	0.7950	0.5000
15	0.2975	0.3444	0.4133	0.7950	0.5000
16	0.2640	0.3112	0.3702	0.7950	0.5000
17	0.2215	0.2689	0.3151	0.7950	0.5000
18	0.1866	0.2328	0.2681	0.7950	0.5000
19	0.1459	0.1937	0.2171	0.7950	0.5000
20	0.1324	0.1544	0.1660	0.7950	0.5000
21	0.1160	0.1160	0.1160	0.7950	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.768	0.000	1.302	0.000
2	0.695	0.037	1.151	0.022
3	0.618	0.028	1.027	0.026
4	0.540	0.018	0.903	0.015
5	0.463	-0.009	0.785	-0.006
6	0.379	-0.029	0.642	-0.017
7	0.261	-0.039	0.442	-0.017
8	0.200	-0.049	0.338	-0.019

9	0.100	-0.078	0.170	-0.024
10	0.042	-0.105	0.072	-0.029
11	-0.032	-0.164	-0.055	-0.039
12	-0.118	-0.258	-0.200	-0.052
13	-0.239	-0.435	-0.404	-0.069
14	-0.315	-0.559	-0.535	-0.075
15	-0.405	-0.679	-0.686	-0.071
16	-0.472	-0.800	-0.800	-0.069
17	-0.557	-1.027	-0.944	-0.065
18	-0.627	-1.310	-1.062	-0.060
19	-0.708	-2.035	-1.200	-0.059
20	-0.735	-1.894	-1.246	-0.026
21	-0.768	0.000	-1.302	0.000

No.	CorrectChance	CorrectQuantity	CorrectLocation	ErrorLocation	ErrorQuantity
1	0.500	0.384	0.000	0.000	0.116
2	0.500	0.344	0.003	0.088	0.064
3	0.500	0.304	0.005	0.180	0.011
4	0.500	0.266	0.004	0.193	0.037
5	0.500	0.233	0.000	0.186	0.080
6	0.500	0.195	0.000	0.175	0.131
7	0.500	0.137	0.000	0.157	0.206
8	0.500	0.107	0.000	0.148	0.245
9	0.500	0.061	0.000	0.134	0.305
10	0.500	0.034	0.000	0.126	0.339
11	0.500	0.003	0.000	0.117	0.380
12	0.468	0.000	0.000	0.106	0.425
13	0.421	0.000	0.000	0.092	0.487
14	0.388	0.000	0.000	0.082	0.530
15	0.344	0.000	0.000	0.069	0.587
16	0.311	0.000	0.000	0.059	0.630
17	0.269	0.000	0.000	0.046	0.685
18	0.233	0.000	0.000	0.035	0.732
19	0.194	0.000	0.000	0.023	0.783
20	0.154	0.000	0.000	0.012	0.834
21	0.116	0.000	0.000	0.000	0.884

** : A ranked image (Tmp$Rank_Tkp_landcov_predict_2017b_soft) based on the input image was created in the working directory.
In addition, a percentile map(Tmp$percentile_Tkp_landcov_predict_2017b_soft) based on the threshold bands user specified was also created in the working directory.

Appendix O Result of ROC Statistic for 2017 Soft Prediction Map for Katsina-Ala

```
Result of ROC**
===============

AUC =  0.858

******************************************************************
The following section list detailed statistics for each threshold.
******************************************************************

With each threshold, the following 2x2 contingency table is calculated
_________________________________________________________________________
                                   Reality (reference image)
                         ------------------------------------------------
Simulated by threshold          1                      0
-------------------------------------------------------------------------
          1                     A(number of cells)     B(number of cells)
          0                     C                      D
For the given reference image:  A+C=176596           B+D=2809370
_________________________________________________________________________
```

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	5.0000	4.6811	0.9999	14825	8.3949	124951	4.4477
3	10.0000	10.5637	0.7147	31085	17.6023	284344	10.1213
4	15.0000	15.8117	0.5453	42522	24.0787	429610	15.2921
5	20.0000	20.7031	0.4382	52881	29.9446	565306	20.1222
6	25.0000	25.8150	0.3245	62402	35.3360	708424	25.2165
7	30.0000	30.5313	0.2230	67240	38.0756	844415	30.0571
8	35.0000	35.7791	0.1368	71883	40.7048	996468	35.4695
9	40.0000	40.1486	0.0795	76254	43.1799	1122569	39.9580
10	45.0000	45.8732	0.0349	85200	48.2457	1284558	45.7241
11	50.0000	50.9416	0.0039	92982	52.6524	1428118	50.8341
12	55.0000	55.1527	0.0000	102001	100.0000	1544841	100.0000
13	60.0000	60.0000	0.0000	111695	63.2489	1679886	59.7958
14	65.0000	65.0000	0.0000	117233	66.3849	1823646	64.9130
15	70.0000	70.0000	0.0000	122612	69.4308	1967565	70.0358
16	75.0000	75.0000	0.0000	128395	72.7055	2111080	75.1442
17	80.0000	80.0000	0.0000	134419	76.1167	2254355	80.2441
18	85.0000	85.0000	0.0000	140835	79.7498	2397237	85.3301
19	90.0000	90.0000	0.0000	148070	83.8467	2539300	90.3868
20	95.0000	95.0000	0.0000	161509	91.4568	2675160	95.2228
21	100.0000	100.0000	0.0000	176596	100.0000	2809370	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

```
----------------------------------------------------------------------------
No info of location and no info of quantity:                 N(n) =  0.5000
Perfect info of location and perfect info of quantity:       P(p) =  1.0000
Perfect info of location and no info of quantity:            P(n) =  0.5591
No info of location and perfect info of quantity:            N(p) =  0.8887

No info of location and no info of quantity:        PerfectChance =  0.5000
No info of location and perfect info of quantity:  PerfectQuantity =  0.3887
Perfect info of location given no info of quantity:PerfectLocation =  0.1113
----------------------------------------------------------------------------
```

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.9409	0.9409	0.9409	0.8887	0.5000
2	0.9040	0.8996	0.9877	0.8943	0.5029
3	0.8560	0.8477	0.9535	0.8975	0.5047
4	0.8112	0.8014	0.9010	0.8996	0.5058
5	0.7692	0.7583	0.8521	0.9017	0.5069
6	0.7245	0.7132	0.8010	0.9030	0.5076
7	0.6806	0.6717	0.7538	0.9008	0.5064
8	0.6312	0.6254	0.7014	0.8972	0.5045
9	0.5904	0.5869	0.6577	0.8943	0.5030
10	0.5392	0.5364	0.6004	0.8936	0.5026
11	0.4937	0.4917	0.5497	0.8926	0.5021
12	0.0342	0.0188	0.0342	1.0000	0.5591
13	0.4157	0.4118	0.4591	0.8978	0.5048
14	0.3694	0.3677	0.4091	0.8931	0.5023
15	0.3230	0.3237	0.3591	0.8887	0.5000
16	0.2769	0.2796	0.3091	0.8887	0.5000
17	0.2309	0.2355	0.2591	0.8887	0.5000
18	0.1852	0.1914	0.2091	0.8887	0.5000
19	0.1400	0.1473	0.1591	0.8887	0.5000
20	0.0990	0.1032	0.1091	0.8887	0.5000
21	0.0591	0.0591	0.0591	0.8887	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.882	0.000	1.134	0.000
2	0.808	0.050	1.025	0.044
3	0.712	0.079	0.895	0.055
4	0.622	0.098	0.775	0.049
5	0.538	0.117	0.665	0.045
6	0.449	0.128	0.549	0.039
7	0.361	0.109	0.442	0.027
8	0.262	0.077	0.323	0.016
9	0.181	0.051	0.223	0.009

10	0.078	0.044	0.094	0.006
11	-0.013	0.035	-0.021	0.004
12	-0.932	1.000	-1.191	0.016
13	-0.169	0.081	-0.227	0.007
14	-0.261	0.040	-0.340	0.003
15	-0.354	-0.019	-0.455	-0.001
16	-0.446	-0.092	-0.574	-0.004
17	-0.538	-0.194	-0.692	-0.006
18	-0.630	-0.350	-0.810	-0.008
19	-0.720	-0.615	-0.926	-0.009
20	-0.802	-0.709	-1.032	-0.005
21	-0.882	0.000	-1.134	0.000

No.	CorrectChance	CorrectQuantity	CorrectLocation	ErrorLocation	ErrorQuantity
1	0.500	0.441	0.000	0.000	0.059
2	0.500	0.400	0.004	0.084	0.012
3	0.500	0.348	0.008	0.097	0.046
4	0.500	0.301	0.010	0.090	0.099
5	0.500	0.258	0.011	0.083	0.148
6	0.500	0.213	0.011	0.076	0.199
7	0.500	0.172	0.009	0.073	0.246
8	0.500	0.125	0.006	0.070	0.299
9	0.500	0.087	0.004	0.067	0.342
10	0.500	0.036	0.003	0.061	0.400
11	0.492	0.000	0.002	0.056	0.450
12	0.019	0.000	0.015	0.000	0.966
13	0.412	0.000	0.004	0.043	0.541
14	0.368	0.000	0.002	0.040	0.591
15	0.324	0.000	0.000	0.035	0.641
16	0.280	0.000	0.000	0.030	0.691
17	0.235	0.000	0.000	0.024	0.741
18	0.191	0.000	0.000	0.018	0.791
19	0.147	0.000	0.000	0.012	0.841
20	0.103	0.000	0.000	0.006	0.891
21	0.059	0.000	0.000	0.000	0.941

** : A ranked image (Tmp$Rank_Kal_landcov_predict_2017_soft) based on the input image was created in the working directory.
In addition, a percentile map(Tmp$percentile_Kal_landcov_predict_2017_soft) based on the threshold bands user specified was also created in the working directory.

Appendix P Results of Soft Prediction