CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Information on landuse and landcover is the basis which the past, present human interactions and the impacts of such interactions with the natural resources and the environment can be understood. Such knowledge is also required for rational and sustainable allocation of land resources for future development. In Nigeria, all land development programmes and projects have evolved without an appreciation of the value of landuse and landcover information (Adamatzky,1994).

Economic development and population growth have triggered rapid changes to earth's landcover over the last two centuries; and there is every indication that the pace of these changes will accelerate in the future. Landcover change can affect ability of the land to sustain human activities through the provision of multiple ecosystem services and the resultant economic activities can affect climate and other facets of global change(Ayodeji,2006). Accordingly, systematic assessments of earth landcover must be repeated, at a frequency that permits monitoring of both long-term trends as well as inter annual variability and at a level of spatial detail to allow the study of human-induced change(Hathout,2002).

Mirbagheri (2006) states that although the terms landcover and landuse are sometimes used interchangeably, they are actually different. Simply put, landcover is what covers the surface of the earth and landuse describes how the land is used. Examples of landcover classes include: water, snow, grassland, deciduous forest and bare soil. Landuse examples include wildlife management area, agricultural land, urban, recreation area etc. Two land parcels may have similar landcover, but different landuse for instance, a golf course and an office building are both commercial landuse. The former would have a landcover of grass, while the later would be considered built-up.

An increasingly common application of remotely sensed data is for change detection which is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 2003). Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the population of interest. Change detection is useful in such diverse applications as landuse change analysis, monitoring shifting cultivation, assessment of deforestation, damage assessment and disaster monitoring (Nashat,2002).

Ayodeji (2006), listed four aspects of change detection which are important when monitoring natural resources:

i. detecting that changes have occurred;
ii. identifying the nature of the change;
iii. measuring the area extent of the change; and
iv. assessing the spatial pattern of the change.

The basic premise in using remote sensing data for change detection is that changes in landcover result in changes in radiance values which can be remotely sensed. Techniques to perform change detection with satellite imagery have become numerous as a result of increasing versatility in manipulating digital data with modern computers (Herold *et al.*, 2003).

Human activities have significantly transformed the earth's environment. Population growth and intense economic activities in the urban areas entail an increased demand for resources and pressure on the land. The expected population and economic growth in the future decades will lead to an increased pressure on the available space which shall lead to conflicts between various landuses such as residential areas, agricultural land e.t.c. Sustainable spatial planning involves exploring the effects of landuse and landcover change, which is a key issue in securing a better environment. The impact of urban expansion can result in environmental and socio-economic effects. Varlyguin (2008) gives an overview of the environmental impact induced by urban sprawl characterized by loss of open space, reduced biodiversity and land fragmentation. Socio-economic impacts are often a direct consequence of the environmental impact (Ojigi, 2006).

Mapping is the graphical representation of a portion of the earth surface to scale on paper. The main methods of mapping an area are ground survey method, photogrammetric method, integrated method and remote sensing techniques (Wells, 1987).

Ground techniques includes the conventional land surveying methods and satellite methods of position fixing. These methods involve the determination of co-ordinates of point on the earth's surface from which a graphic representation in form of maps, plans and charts can be produced. Two basic methods are commonly used in the photogrammetric approach. The analogue method used the stereo plotters for producing maps and the analytical method relies on derivation of digital information through the analysis of image or photo co-ordinates measured using either a mono comparator or stereo comparator (Wilson, 1977).

The integrated method involves the use of information from various sources, this leads to optimal use of available resources and versatility in acquiring data from sources such as field measurement, maps etc. Remote sensing is a technology that employs electromagnetic energy as a means of detecting and measuring characteristics of targets or terrain features. Satellite images are often used as data source, the trends in image processing makes this method applicable in many areas especially in landcover and landuse mapping (Wu,2002).

The advent of air and space borne remote sensing has made it possible to acquire pre and post project landuse and landcover data in a consistent manner. In addition, Geographic Information Systems (GIS) has made it possible to integrate multisource and multidate data for the generation of landuse and landcover changes involving such information as the trend, rate, nature, location and magnitude of changes. Airborne remote sensing refers to those that carry sensors in flight. They include helicopters (average altitude of 5km), low altitude aircrafts (10km), medium altitude aircrafts (15km), high altitude aircrafts (15km-100km) and sounding rockets (over 100km); on the other hand space borne platforms includes all remote sensing spacecrafts which can be manned and unmanned satellites (Ndukwe, 2001).

Landcover refers to the biophysical state of the land surface and can be directly observed on the terrain or from remote sensing images. Landuse on the other hand refers to the purpose for which humans employ the land. In other words it is the human activities that are directly related to land, making use of it's resources or having an impact on them. Landuse is described by specifying the mix and particular pattern of landuse types, the extent as well as natural and physical characteristics. Landuse involves the management and modification of natural environment or wilderness into built environment such as settlements and semi-natural habitats such as arable fields, pastures and managed woods, it is also the arrangements, activities and inputs people undertake in a certain landcover to produce change or maintain it (Dietzel and Clarke, 2007). Cellular automata are composed of five basic elements i.e. cells, states, neighbourhood, probability and transition rules (these elements are discussed in detail in the theoretical framework). The cells are adjacent objects and can take different shapes and dimensions. The states are the discrete attribute of each cell and the surrounding conditions. The transition rules are uniform and applied in all cells or neighboring states. In other words, cellular automata consist of a simulation environment represented by a raster image (gridded space), in which a set of transition rules determine the attribute of each given cell taking into account the attributes of cells in it's neighbourhood (Rimal, 2011).

A model is an abstraction of reality that is used to understand complex relationships. A model is usually the result of the examination of a relationship between two or (more) sets of data. It can be used to explain how and even why these data interact together or how does that relationship help to understand more about reality and it's systems (Chatterjee and Price, 1991).

Landuse depends on three types of factors, the inherent qualities of land itself, the effects of neighbouring landuse activities and the aggregate demand of land for particular activity. Every model is only an abstraction of reality. It has to go through some simplifications. In general, we can define change in landuse landcover as a function of various factors. Mathematically, according to(Engelen *et al.*,1995) it can be defined as:

$$\Delta L = \Delta L_1 + \Delta L_2 + \Delta L_3 \qquad \text{...(1.1)}$$

Where ΔL is total change in landuse types, ΔL_1, ΔL_2, ΔL_3, e.t.c. are changes in different landuse types. e.g ΔL_1 may represent change in settlement area, ΔL_2 may represent change in agriculture area, ΔL_3 may represent change in forest area and so on. If only two kinds of changes are to be studied then only two components of the series should be considered. The change is not scalar only, but has positional value also. Theoretically, when transition from one landuse class occurred e.g when farm land transit to built-up area, it might not necessarily change the magnitude (area). Here lies the importance of spatial analysis in geographic information system (GIS).

Each landuse type change can be a function of different factors e.g

$$\Delta L_1 = F\ (X_1, X_2, X_3 \ldots) \qquad \text{...(1.2)}$$

Where ΔL_1 is change in landuse type (say) settlement X_1, X_2, X_3, X_4 … are factors (like population growth, economic growth, policy, e.t.c) responsible for change. F is a function of various factors X_1, X_2, X_3, X_4, e.t.c. For an example, population growth can force settlement area to increase and it can increase the demand for agricultural land. Also these factors can influence each other again due to population growth, state policy may change e.t.c not only this, the factor itself may be representing the process of population growth which can have their own drivers. Due to these reasons landuse landcover change becomes more complex and challenging phenomenon

(Engelen *et al.*,1995) Assuming factors to be independent the function $F(X_1, X_2, X_3, \ldots)$ can be decomposed further into additive series as below:

$$F(X_1, X_2, X_3, \ldots) = f(X_1) + f(X_2) + f(X_3) + \ldots \qquad \ldots(1.3)$$

Where $f(X_1)$ is a function of only factor X_1

$F(X_2)$ is a function of factor X_2 only and

$F(X_3)$ is a function of factor X_3 only

This could be decomposed into multiplicative series and if there is no change the resultant is zero.

Landuse/landcover data refers to data which can be classified from raw satellite data into landuse and landcover categories based on the return value of the satellite image. There are few landuse and landcover data sets because (a) satellite data acquisition is usually very expensive and (b) the classification process is very labour intensive (see Table 1.1). Most landuse and landcover data products are released several years after the satellite images were taken, and thus out of date to a certain extent when they are released. Nonetheless, landuse and landcover provides a very valuable method for determining the extents of various landuses and cover types, such as urban, forested, shrubland, agriculture, etc.(Engelen *et al.*,1995).

Landuse/landcover data are mostly available in a raster or grid data structure, with each cell having a value that corresponds to a certain classification. Sometimes landuse and landcover data are converted to a vector format, but file sizes become very large by doing so (Rimal, 2011).

Table 1.1: Summary of landuse /landcover collections

Collection Name	Usage notes
National landcover dataset	i. 30m resolution ii. Available from the national map iii. 21 landcover classes iv. 1992, 2001, 2006 imagery dates
US coastal landcover data	i. 30m resolution ii. Available from google earth iii. 21 landcover classes iv. I992, 1996, 2001 and 2005
North Carolina statewide landuse /landcover	i. 30 m resolution ii. An unfiltered version of the 1996 data exists iii. Vectorized versions of the 1990 data are in Basic pro 8
USGS landuse and landcover	i. Historical data based on manual interpretation of 1970's and 1980's data ii. Data are available in geographic information retrieval and analysis system

Source: (Adamatzky, 1994).

1.2 Statement of the Problem

The establishment of many industries especially the oil refinery in Kaduna attracted many people to the area from different parts of the country. Moreover, the ethno-religious crises in the northern part of the study area made many people to migrate to the southern part of the area. All these resulted to over consumption of natural resources in which other landuse classes were converted to built-up area.

Influx of people to Kaduna resulted in over exploitation of the natural resources especially land, vegetation and open space in the area. These brought about over urbanization and misuse of land meant for other uses. The crisis in the study area also affected other landcovers which were converted to built-up area by inhabitants moving from the northern part of the study area to the southern part of the area

The location of refinery, textile factories and manufacturing companies attracted people from different parts of the country to Kaduna which resulted in tremendous development of the area, invariably other land spaces initially used for other things became built-up. This resulted to many environmental problems such as flooding, deformation of structure and erosion.

The Government agencies, whose mandate it is to map the area, have not been keeping pace with developments on ground. There is therefore no up to date maps that detail current states of various Landuse types. The fringes of the study area especially the western bye–pass and eastern express way will witness rapid physical development. The transition from one landcover class to the other will assist in the change detection. Furthermore new modeling techniques need to be explored to map and model landuse developments in the study area and predict future patterns. Hence, this research study is exploring these new techniques to map and model landcover and landuse in Kaduna and Environs.

1.3 Aim and objectives

1.3.1 Aim

The aim of this study is to model and map the landcover and landuse changes in Kaduna with a view to ascertaining landuse changes in the area.

1.3.2 Objectives

The aim of the study will be achieved through the following objectives:

i. To classify the multi-temporal satellite imageries of landsat ETM+ (Spatial resolution 30m) of Kaduna and Environs into Built up areas, open space, farmlands, vegetation and water bodies (The Images of 2004, 2009 and 2014 were used).

ii. To model the landcover and landuse changes of Kaduna and Environs using cellular Automata

iii. To determine the landcover and landuse changes within the Study Area.

iv. To predict the pattern of changes (25 years) with multiple logistic regression.

v. To produce the landcover and landuse maps of Kaduna and Environs for the years 2004, 2009 and 2014 in softcopy and hardcopy.

1.3.3 Research Questions

In Order to achieve the above stated objectives, the following Research questions will be answered:

i) Is it possible to classify multi-temporal imageries into built- up area, open space, farmland, vegetation and water bodies?

ii) Is it possible to model landcover and landuse using cellular Automata?

iii) What are the landcover and landuse changes in the study area?

iv) Is it possible to predict pattern of changes using multiple logistic regression?

v) Is it possible to produce landcover and landuse maps of the study area?

1.4 Hypothesis

The study tested the following hypotheses.

H_o: Farmland did not transit to built - up area

H_1: Farmland transited to built - up area.

H_o: Vegetation did not transit to built – up area

H_1: Vegetation transited to built – up area

H_o: Open space did not transit to built – up area

H_1: Open space transited to built – up area.

Decision rules are statements phrased in terms of the statistics to be calculated, that dictate precisely when the null hypothesis will be rejected and when it will not. The level of significance selected is used to formulate the decision rule. At 0.05 level of significance, it implies that only 5% or less will be attributable for the null hypothesis to be retained; of the 5%, 2½% will be extremely low and 2½% extremely high (Anigbogu, 2000). The table for t-values will normally be consulted to obtain the percentile (P 0.975) that corresponds to a t-value such that 0.025 of the distribution falls to its right (above it) and 0.025 falls to the left (below it). The outcome of testing to accept or reject the null hypothesis (Ho) will statistically determine which landuse class will transit to built – up area.

1.5 Justification of the Study

Landcover and landuse change process can be identified and recognized using satellite imageries. Remotely sensed data in conjunction with Geographic Information System can provide significant results of changes of the earth surface. Landuse has changed the ecosystem rapidly and extensively due to consequences of rapidly growing demand on natural resources (Watson and Zakri, 2003). It has resulted in degradation of the natural ecosystem functioning.

It is imperative to develop a sustainable landuse plan by understanding landcover and landuse change process and it's impact on the environment. The development of suitable and reliable indicators which can provide all essential information about the viability of a system, it's rate of change and how it contributes to sustainable development is essential. Nowadays, this kind of assessment is made possible by data provided by modern earth observing systems to analyze the environment using quantitative (hard number), qualitative (subjective valuation) and spatial form. Change in the use of land occurring at various spatial and temporal levels are sometimes beneficial, but when it is detrimental; the impacts are better analyzed using remotely sensed data which provide planners and decision makers with adequate information necessary for the current state of development and the nature of changes that have occurred. Various techniques exist for modeling and mapping landuse and landcover. These techniques have been studied by various researchers. However, the use of multiple logistic regression analysis and cellular automata in characterizing patterns and rates of landcover and landuse changes is still being investigated globally. Hence, this study is investigating the use of this approach in modeling and mapping of landcover and landuse patterns of Kaduna and Environs. Multiple regression analysis and cellular automata helps in creating models designed to test what if scenarios and predict the nature and patterns of change. The local Government Areas within the study area, the State Government, non- governmental organization and policy makers will benefit from this research work, since it will help them in effective planning. This justify the study of mapping and modeling of landcover and landuse using cellular automata and multiple logistic regression.

1.6 Scope of the study

The study concentrates on the modeling and mapping of landcover and landuse changes using cellular automata and multiple logistic regression of Kaduna and environs. The study entails supervised classification for the year 2004, 2009 and 2014 of Kaduna and environs into built-up area, farmland, vegetation, open space and water bodies.

Confusion matrices were prepared to ascertain the precision of the classified landsat imageries. Statistical analyses were carried out to show how landcover and landuse transits. Various analysis were performed to show the landcover and landuse changes in the study area and subsequently the prediction for the next 25 years.

1.7 Limitation of the study

Landcover and Landuse changes for 2004, 2009 and 2014 were determined. However, what took place yearly within these epochs cannot be determined which is the flaw of this research work.

1.8 Study Area

The Gbagyis were initial settler in the study area. However, when the area became the capital of Northern Nigeria, other tribes from other parts of Nigeria started settling down in the area which resulted in rapid development of Kaduna and environs.

1.8.1 Location

Kaduna is the Capital of Kaduna State. It was the Administrative Capital of former northern region of Nigeria. It is a cosmopolitan town.

The study area selected for this study is Kaduna and environs which is located within Kaduna State in North-Western part of Nigeria. It lies between latitudes 10^0 $23^{'}27$”N and $10^0 40^{'}36$”N and longitudes $7^0 20$’ 18”E and 7^0 $31^{'}35$”E. It is bounded in the North and South by Igabi and Kachia Local Government Areas respectively. It is also bounded in the East and West by Kajuru and Chikun Local Government Areas (See Figs. 1a,1b and 1c).

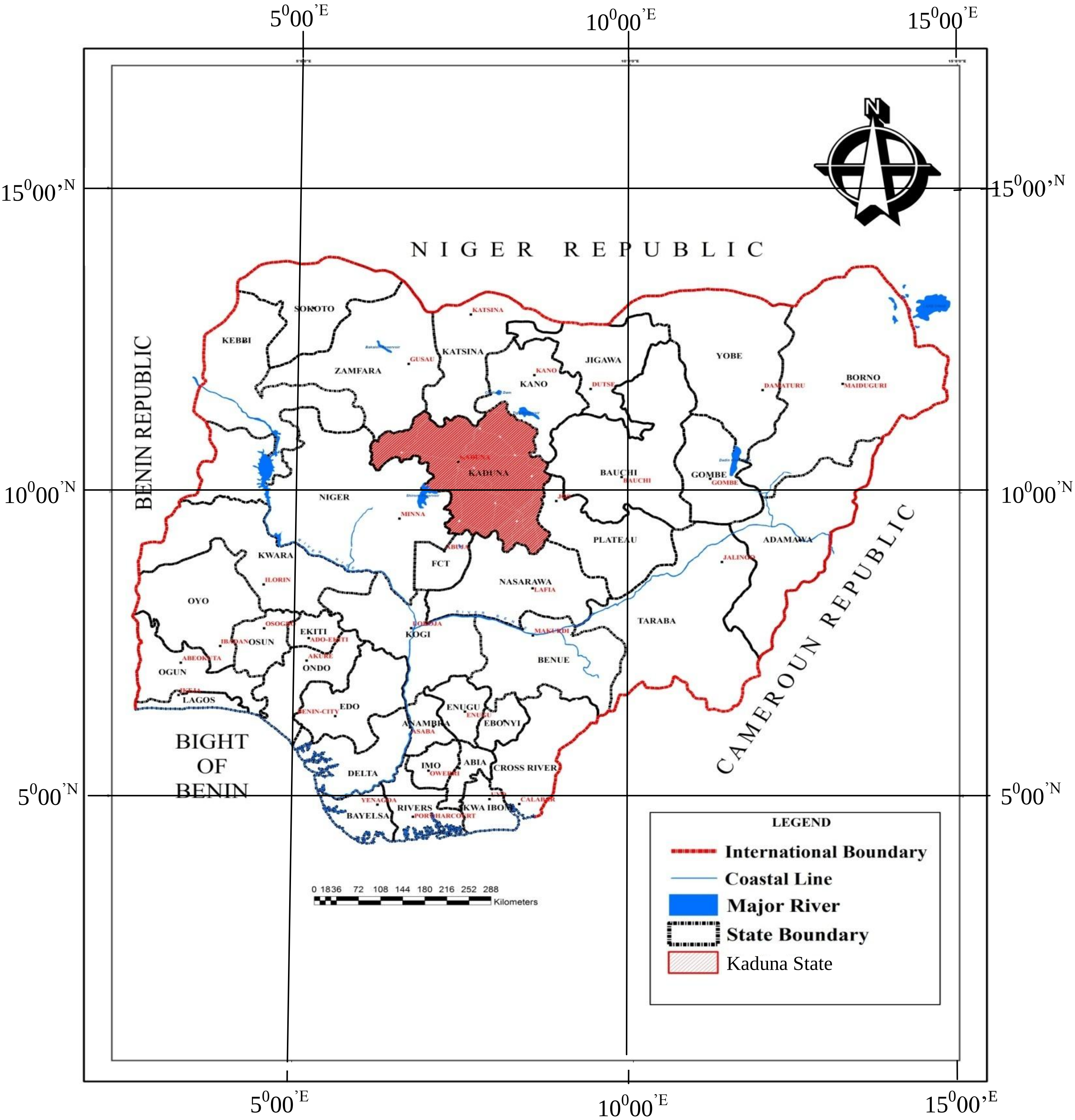


Fig.1a: Map of Nigeria Showing the Location of Kaduna State

(Source: Extracted from Administrative Map of Nigeria, 2000)

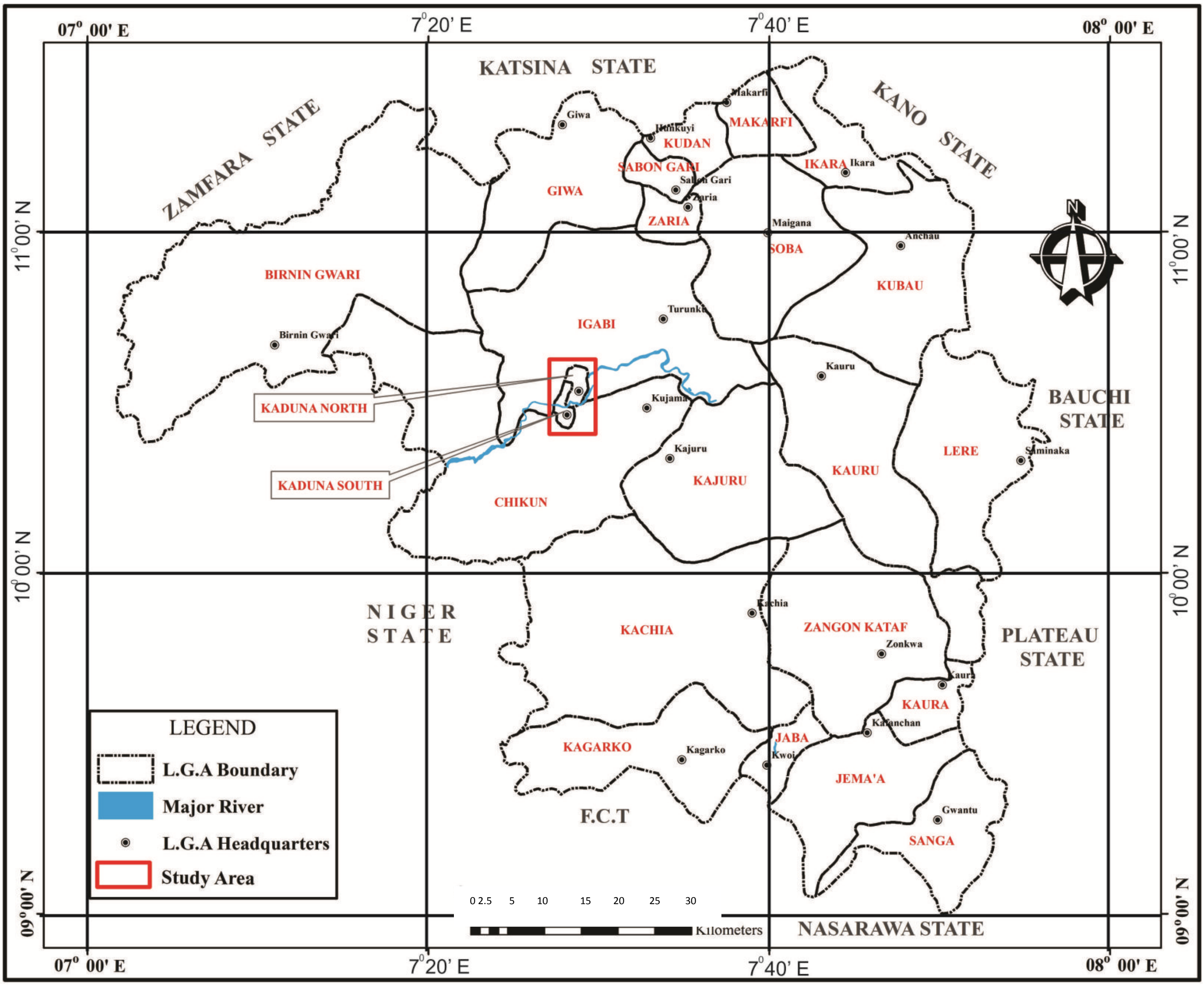


Fig.1b: Map of Kaduna state showing the Location of the Study Area (Kaduna North and South Local Government Areas)

(Source: Extracted from Administrative Map of Kaduna state, 2000)

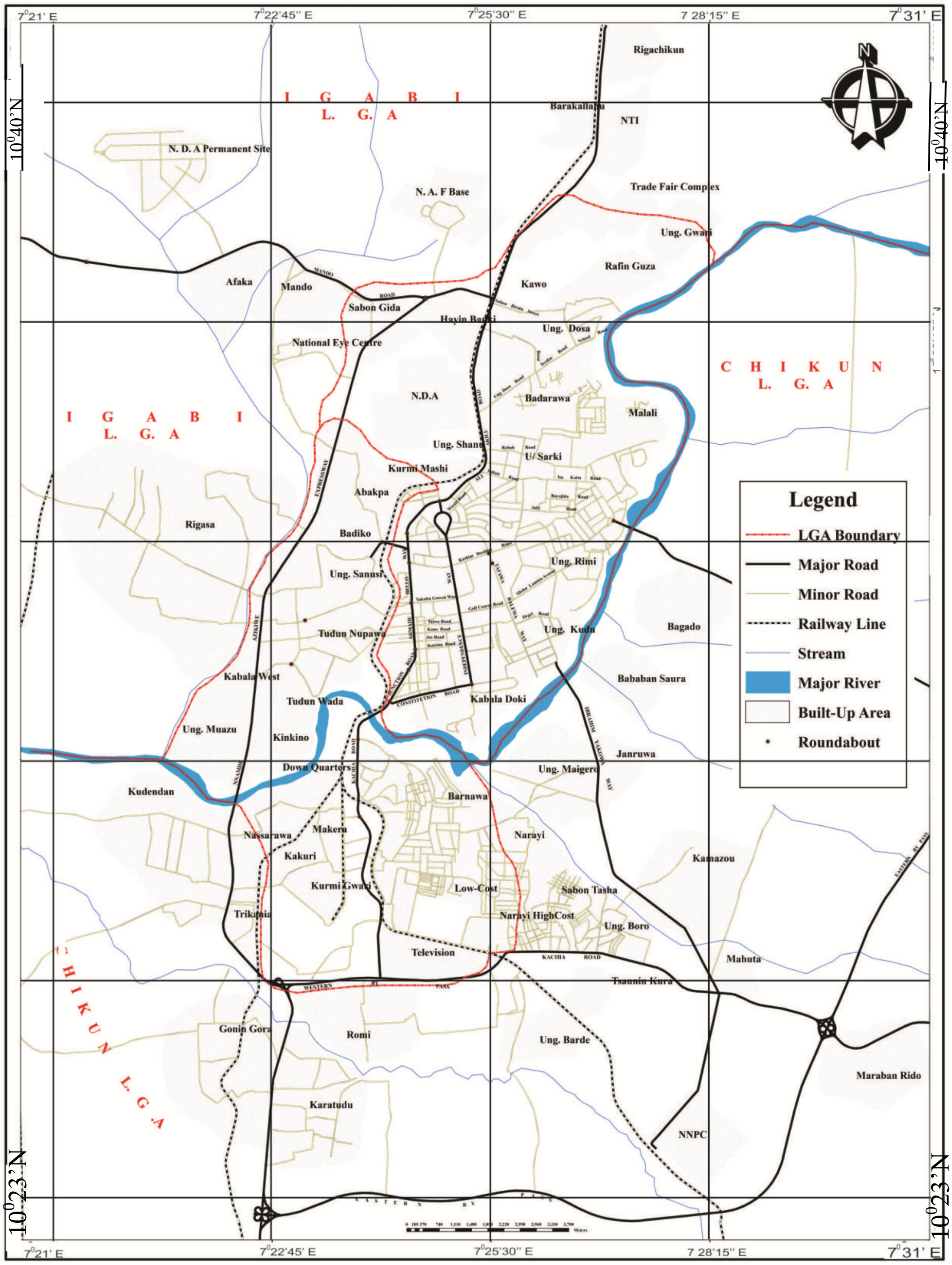


Fig.1c: Map of Kaduna (Study Area)

(Source: Kaduna State Geographic Information Service, 2016).

1.8.2 Vegetation

The vegetation of the area lies on the Guinea Savannah Vegetation belt of Northern Nigeria which is characterized by shrubby vegetation and scattered trees. Although, most significant part of the study area has been altered by cultivation and settlement activities. The vegetation is affected by anthropogenic activities through cutting down of trees for cooking, cultivation and construction works; also animal grazing coupled with seasonal bush burning have affected the vegetation of the area. Parkland trees are found in the open cultivated land with shrubs found almost every where except areas where cultivation is being practiced. Common trees found in the area includes isoberlina joka, acacia albida, khaya senegalensis, magni fera indica and several others. There is also large area of green grasses especially during the wet season. The common grasses found in the study area are albazia zygia, tridax precumbense among others. During the rainy season the grasses are green but turned brownish during the dry season (Kaduna State Water Board, 2014).

1.8.3 Climate

The climate of the study area is characterized by two main seasons, namely rainy and dry seasons. The average rainfall is about 1192.74mm, the mean annual relative humidity is 83.6% and the temperature varies from 15^{0c} to 27^{0c} (Kaduna State Water Board, 2014). The study area experiences high temperature all year round which is a characteristic of the tropics. The mean daily temperature in the area can be as high as 34^{0c} between month of March and May. Temperature could be as low as 20^{0c} during December to January. This temperature is intensified by humidity due to the dry harmattan wind. The study area has two seasons. These two seasons are determined by two prevailing air masses blowing over the area at different periods during the year.

1.8.4 Population

Kaduna metropolis attracts people from all over the country. It was the administrative headquarters of the former Northern Region of Nigeria. The population of the town is 1,128,334 and the breakdown is as follows 357, 694 for Kaduna North, 402,390 for Kaduna South and 368, 250 for Chikun (National Population Commission, 2006).The major ethnic groups in the study area are the Adara, Hausa, Fulani, Gbagyi, Jaba and Kaje.

1.8.5 Agricultural and Soil Pattern

The agricultural and soil pattern of the area is fairly plain with isolated rock outcrops of inselbergs found in the area thus creating undulations in the area. The inselbergs are granitic in origin formed from underlayed basement complex rocks. The area is part of the extension plains of the Northern Nigeria. Depressions are found along the water courses where streams occur. The area under study is found on crystalline basement complex of the Northern Nigeria, the basement complex rocks are intrusive igneous rocks which have been in existence since the Precambrian time. The soils are generally well drained and mostly sandy-loam in the plains while in the valleys there are deposits of hydromorphic soils which occupy the flood plains of the rivers. The soils in the area are rich in mineral content and therefore support the high agricultural productivity in the area. Long duration crops such as cocoyam, ginger are grown, also maize, guinea corn and sugar cane are grown during rainy season and the dry season by irrigation. The soil pattern of the area varies from clay to Chad sand to younger granite. The colouration of the overburden soil which are laterites vary from depth to depth and from location to location due to weathering and geomorphologic effects (Kaduna State Water Board, 2014).

1.8.6 Water Resources and Culture of the Area

There are many streams mostly seasonal scattered within the study area. River Kaduna is the major river within the metropolis. River Kaduna flows north-west towards Kaduna metropolis and thereafter takes the south west direction turn at Mureji, Kaduna River covers a total distance of 540km. There are several seasonal streams within the study area used for irrigation. The people living within the area are mostly farmers and the modern religion as transformed the native culture of the people to Christianity and Islam (Kaduna State Water Board, 2014).

1.8.7 Economic Activities

Kaduna is a cosmopolitan town and is regarded as an administrative town. The influx of people from different parts of the country has resulted in the rapid socio-economic development of the area. The city of Kaduna is a major commercial center in Northern Nigeria and largely due to its commercial importance, it is the site of location of many banks that have branches in the city. Also within the area are various industries such as the ideal flour mills, a Federal superphosphate fertilizer company, electric meter company, Kaduna refinery, Peugeot Automobile, Defense industries, Berger paints and the Northern Nigeria publishing company. Trading activities also form another vital occupation for the inhabitants of the study area (Kaduna State Water Board, 2014).

1.9 Assumptions Adopted

The Secondary data used were obtained from statutory organizations, hence they are assumed to be correct. Satellite imageries acquired are also assumed to be correct.

CHAPTER TWO

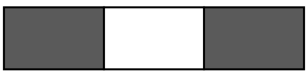
THEORETICAL AND CONCEPTUAL FRAMEWORK

In order to understand the modeling and mapping of landcover and landuse changes using multiple logistic regression and cellular automata, we need to understand the theoretical foundation of this study. Such theories includes concept of cellular automata, classification scheme, multiple logistic regression, methods of mapping, modeling e.t.c

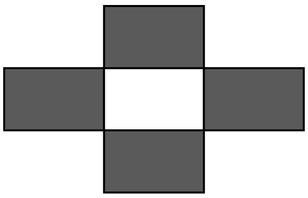
2.1 Cellular Automata

Cellular Automata are discrete dynamical systems whose behaviour is specified by the interaction of local cells. Cellular automata have been used for simulating various complex systems in the real world and also modeling (Batty *et al*., 2004).

A Cellular Automaton (CA) has a n-dimensional cellular space and consists of a regular grid of cells. Neighbourhood of a cell consists of the surrounding adjacent cells, including the cell itself. For 1-dimensional CAs, a cell is connected to r local neighbor in each side, including itself, where r is called a radius (see Fig. 2.1a)



(a) Neighborhood (1-dim, r =1)



(b) Von Neumann Neighborhood 2-dim, r =1

(c) Moore neighborhood 2-dim, r =1

Fig 2.1 : Neighborhoods

For two (2) dimensional cellular automata (CA), two different types of neighbourhood of the radius r exist. The von Neumann neighborhood has the size 5 (see Fig. 2.1b) consisting of a central cell, cells adjacent to above and below and to right and left. The Moore neighborhood has the size 9, consisting of the central cell and the surrounding 8 adjacent cells (Eyitayo and Akeju, 1999).

Each cell in CA has a finite number of possible states. For instance, in 2-state Cellular Automata a cell has either 0 or 1, white or black and so on (see Fig. 2.1c). The state of a cell in the next time step is determined by it's current state and the states of it's surrounding cells. Such transitions of cellular states are represented by cell – state transition rules (called Cellular Automata rules). The state of each cell changes synchronously in discrete time steps according to local and identical Cellular Automata-rules. The collection of finite number of cells in the grid at some time step is called a configuration. $S_t(0 \leq t \leq n)$ represents a configuration of Cellular Automata at a time step. A configuration S_t consist of cells $C_{xy,}$ where x and y represent co-ordinates of cells in the configuration (Baker, 1989).

Cellular Automata are dynamic models that are discrete in time, space and state. A hybrid model consisting of logistic regression model and cellular Automata was designed to improve the performance of the standard logistic regression model to simulate urban expansion (Farouq, 2014).

Cellular Automata belongs to a family of discrete connectionist technique that are currently being used to investigate fundamental principles of dynamics, evolution and self-organisation. Essentially a cellular automaton model is composed of a finite set of grid cells, the current state of each cell, a set of transition rules for the cells and the neighbourhood of a cell. In a strict cellular automaton the rules must be uniform and must apply to every cell, state and neighbourhood. Cellular automata are composed of five elements (Araya, 2009).

i. **Cell space**- The cell space is composed of individual cell. Theoretically, these cells may be in any geometric shape, yet most Cellular Automata adopt regular grids to represent such a space, which make Cellular Automata very similar to a raster GIS.
ii. **Cell states**: The states of each cell may represent any spatial variable e.g the various types of landuse.
iii. **Time step**: A Cellular automata will evolve at a sequence of discrete time steps. At each step, the cells will be updated simultaneously based on transition rules.
iv. **Transition rules:** These rules are the heart of a Cellular Automata that guides it's dynamic evolution. A transition rule normally specifies the states of cell before and after updating based on its neighbourhood condition.
v. **Neighborhood**: Each cell has two neighbors in one dimensional cellular automata, whereas in two dimensional cellular automata there are two ways to define it. (see fig. 2.1b and fig. 2.1c).

The processes involved in Cellular Automata model are as follows:

i. For every cell the model reads the state of the cells located within an extended neighborhood composed of thirteen cells.
ii. Model select what would the new state of the cell be at the next time step (for example five to ten years later), according to the predefined transition rules

The rules are based on an intuitive understanding of the processes as there is no obvious way of finding which parameter should or should not be included in the model. The Cellular Automata models are useful because cell space is composed of individual regular cell, the state of each cell represents the various types of landuse and the state of each cell before and after updating is based on neighbourhood condition. However, the calibration of Cellular Automata model is very difficult when there is a large set of parameters (Farouq, 2014). Using cellular automata (CA) for simulation of landuse changes is difficult, because there are numerous spatial variables and parameters that must be utilized. Most of the parameter values for Cellular Automata simulation can be automatically determined by the training of an Artificial Neural Network (ANN).

Advantages of applying the Cellular Automata models to landuse are:

i. Cellular Automata are explicitly spatial

ii. Cell state is typically a landuse

iii. Cellular Automata models are often designed to test what if scenarios and policies

iv. Cellular Automata is of a limited set of equations and transitions rules.

v. Model input /output are in most cases raster images (used/created in GIS/ remote sensing software)

Cellular Automata can be seen as an extension of GIS, in which dynamics are applied on the data. Cellular Automata models are good for capturing pattern of landuse changes.

In a Cellular Automata model, a stochastic factor such as if the probability of a landuse change of a cell is greater than a random value, may be included.

Depending upon their transition rules and calibration methods Cellular Automata may be classified as follows:

2.2.1 Macro and Micro integrated Cellular Automata

These models are defined with larger neighbourhoods and more cell states representing socio-economic landuses and natural landcover. Their overall dynamics are constrained by the models at the macro level. At the macro level, the modeling framework integrates several components, sub-models representing the natural, social and economic sub-systems which are linked to each other in a network of mutual reciprocal influence (Couclelis, 1997).

The micro cellular automata model determines the fate of individual parcels of land based on their individual institutional and environmental characteristics as well as on the type of activities in their neighbourhoods. Their overall dynamics are constrained by the models at the macro level. The macro cellular automata describes long-range spatial interactions and the micro level describes the short-range interactions and location choices (Engelen *et al*., 1995).

At the macro level, a town is modeled as a single region as one centroid interacting with the external world. A single set of linked dynamic equations generated is integrated in the socio-economic and environmental systems. The growth co-efficients are fed into a cellular model operating on the micro level which allocates the socio-economic growth to cells. The cellular model will return the results of the allocation to the macro-level, to inform it about the amount of open space left and its suitability for specific landuses. Thus the full coupling of the macro and micro scales is guaranteed (Geertman and Stillwell, 2003).

The model is given by

$N(t) = N(o)_e^{(\beta - \delta)t}$ ...(2.1)

Where

N(t) is the size of the area at time t

N(o) is the initial size of the area at t = 0

$^{\beta}$ is initial rate per time unit.

$^{\delta}$ is the later rate per time unit.

e is a constant 2.7

2.2.2. Sleuth model

Sleuth is a model for the computation of simulation of urban growth and the landuse changes that are caused by urbanization. Sleuth is a highly successful urban and landuse change model. Five parameters control sleuth's behavior entirely, each with a possible integer value between 0 and 100. The system allows self modification i.e as the entire system grows faster or slower, control parameters are changed as a consequence. The net effect is to amplify rapid growth and retard stagnation, in what are termed boom and bust stages (Dietzel and Clarke, 2007).

This model is based on influence factors which are slope, landuse map and urban area. Five factors control the behaviour of this system. These are DIFFUSION factor which determines the overall depressiveness of the distribution both of single grid cell and in the movement of new settlements outward through the road system, a BREED coefficient which determines how likely a newly generated detached settlement is to begin it's own growth cycle, a SPREAD coefficient which controls how much normal outward organic expansion takes place within the system, a SLOPE-RESISTANCE factor which influences the likelihood of settlement extending up steeper slopes and road gravity factor which has the effort of attracting new settlement on to the existing roads if they fall within the given distance from the road (John *et al.,* 2011).

2.2.3 Cellular Fuzzy automata model

Urban development is a process of physical concentration of people and buildings. This is a continuous process in space and over time which is a fuzzy process. Zone of transition is a place where both urban and non-urban features occur, which has been broadly termed as fringe. Temporally, if an area has been developed from one state (non-urban) to another (urban) at a certain period of time, then development has taken place (Clarke and Gaydos, 1998).

The transition rule is heuristically defined to simulate rural-urban land conversion in a fast growing metropolis. The concept of fuzzy logic control is used to mimic land conversion process. Preconditions of an action are described by fuzzy sets and state changes are simulated according to these fuzzy sets. A fuzzy set can be expressed as follows.

Let x be a collection of objects, whose generic element is denoted as x. A fuzzy set A in x is a set of ordered pairs.

$$A = ((x, \mu_A(x)) \mid X \in X) \qquad \ldots(2.2)$$

Where $\mu_{A(x)}$ represents the grade of membership of x in A, which associate with each X a real number in (0, 1).

For the development of an area in space and over time, a fuzzy concept of urban or non-urban can be defined according to cui *et al.,* 2014 as follows.

Let x be a collection of cells representing an area in a regional context.

Xij is a generic form of a cell in X. An urban fuzzy set S_{urban} can be defined as a set of ordered pairs.

$$S_{urban} = ((x_{ij}, \mu_{Surban}(x_{ij}) \mid X_{ij} \in X)) \qquad \ldots(2.3)$$

Where $\mu_{Surban}(xij)$ is a membership function of cell xij in the fuzzy set S_{urban}, the value of which represents the state a cell undergoing an urban development process.

The membership function determines how and to what degree a cell belongs to in the set. The closer the grade of membership is to l, the higher the degree of membership of the cell in that fuzzy set (Li and Yeh, 2000).

2.2.4 Artificial neural network cellular automata model

Artificial neural networks are used for simulation. It is capable of using noisy and fuzzy information to handle urban growth simulation. Neural networks consist of processing units referred to as neurons or nodes, which are organized in couple of layers (Li and Yeh, 2002).

A neural network has a threefold design, one input layer, one output layer and hidden layer in between whose nodes report to those of contiguous layers. All the neurons, except those in the input layer perform two simple processing functions, collecting the activation of the neurons in the previous layer and generating an activation as the input to the next layer. The neurons in the input layer only send signals to the next layer (Li and Yeh, 2001).

Simple functions establish the interactions between neurons; the collection signal for receiver neuron q is given by

$$net_q = \sum_{p=1}^{n} W_{pq} I_p \qquad ...(2.4)$$

Where P equals a sender neuron in the input layer.

q is a receiver neuron in the next layer

Ip is the signal from neuron P of the sender layer

W_{pq} is the parameter or weight to sum the signals from different input nodes.

The activation will become the input for its next layer and such activation is usually expressed as:

$$\frac{1}{1+ net_q} \qquad ...(2.5)$$

The activation will be passed to the next layer as the input signal and equations (2.4) and (2.5) will be used to process the signal, these routines remain until the final signals are obtained. Parameters (weights) are decisive to define the final signals. The algorithm involves an iterative procedure for minimizing error in which the weights continuously undergo adjustments by means of comparison between the calculated and desired outputs. This process of adjusting weights according to the errors will be repeated as many iterations as necessary in order to render the errors compatible with acceptable thresholds (Yeh and Li, 2003).

The output error is defined in equation (2.6) by

$$E_k = 0.5 \sum_{q=1}^{m} (O_{Kq} - D_{Kq}) \qquad \ldots (2.6)$$

Where

O_{kq} is the calculated network output

D_{kq} is the desired output from neuron q.

M is the number of neurons in the output layer of the network.

2.2.5 Multi-cellular automata model

In single cellular automata, all cells update their states simultaneously. It can enhance saliency consistency among similar regions; influenced by similar neighbors, a clear boundary will naturally emerge between the object and the background. However, in multi-cellular automata, each cell represents a pixel and the number of all pixels in an image is denoted by H. The saliency value consist of the set of cell's states, different from that obtainable in single cellular Automata. The concept of multi cellular automata evolved where two cellular automata are linked with each other. It can be implemented manually or carried out automatically (Aniekan *et al*., 2012).

A multi-cellular Automata consists of a number of cells, the next state q_1 (t+1) of a cell is assumed to be dependent only on itself and on it's two neighbours which is denoted in equation 2.7 as:

$$q_1(t+1) = f\,(1 - 1(t), q(t), q_{i+1}\ (t)) \qquad \ldots (2.7)$$

where $q_1(t)$ represents the state of the i^{th} cell at t^{th} instant of time.

f is the next state function or rule of the automata.

2.2.6 Statistic based cellular automata

Configurations in cellular automata consists of an initial state which can never be generated in the course of cellular automaton evolution, a second class which cannot arise except within the time steps and the third class of configuration which appears in cycles and may be visited repeatedly. The cellular automaton configuration is defined by 2^N, repeated applications of the mapping yield successive time steps in the evolution of the cellular automaton (Fates, 2013). Successive time steps in cellular automata can be compared with iteration of a random mapping with equal probability. The probability (p) between possible images (k) is given by

$$P = \left(1 - \frac{1}{k}\right)^k \qquad ...(2.8)$$

The changed pixels will be extracted by overlaying the temporal data and the converted cells in each window used as transition probabilities for the cells. A statistical ensemble of states for a finite cellular automaton with half probability when properly accomplished is useful in modeling and mapping of an area (Favier, 2004).

2.2.7 Stochastic Cellular Automata Model

Cellular automata are models that assume space, state and time discrete. A square lattice represents the space and each element that constitutes the lattice is called a cell. Each cell has a neighbourhood, set of internal states variables and a local rule that describes the transition between the states (Schiff, 2007).

In Stochastic cellular automata, the rules for cell states transition are performed by means of probabilities. The model is based on spatially explicit representation. Each cell is defined by:

i. It's discrete position $(i,j) \in Z^2$ in the lattice where i = l, . . ., n is the column and j = 1, …, n is the row;
ii. The finite set of internal states that describe the possible behavior of the cells in a given time step (t) which is given by

$$\int_{(i,j)}^{t} \in (E,V,F,O) \qquad ...(2.9)$$

Where E is an empty cell which denotes unburnable cells.

V is a cell with potential to burn

F is burning cell

O is a burnt cell

iii. The local rule that determines the future cell state as a function of the present cell state and present neighbourhood cell states (Chopard and Droz, 1998).

The cellular automata model is stochastic because the state transition function is performed according to probabilities values. Thus for each cell in t = o, there is a probability D for its state to be occupied and the probability 1 – D for it to be empty.

2.3 Theory of Remote sensing

Remote sensing is the science (and to some extent art) of acquiring information about the earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy, processing and analyzing it (Wu, 2002).

The principle of remote sensing can be briefly summarized as follows:

The earth's surface is illuminated by a wide spectrum of electromagnetic radiation coming from the sun. Table 2.1 shows different parts of the electromagnetic spectrum ranging from the ultraviolet part up to the infrared region.

Table 2.1: The electromagnetic spectra

Spectral range	Colour	Wave length in μM (10^{-6})
Ultra violet		<0.3
Visible part of the spectrum	Violet Blue Green Yellow Orange Red	0.4 -0.446 0.446 -0.5 0.5 -0.578 0.578 -0.592 0.592 -0.62 0.62 -0.7
Reflected IR Thermal IR		0.7 - 3.0 3.0 -100

Source:Wu,2002

The radiation coming from the sun is interacting with the atmosphere and does not reach the earth’s surface completely uninfluenced, passing through the atmosphere, a large part of the energy is absorbed. The stratospheric ozone for example absorbs major parts of the ultraviolet radiation. The water content in the atmosphere is responsible for the absorption of specific parts of infrared radiation. Only for some wavelengths the atmosphere is to a large extent transparent, particularly in the visible proportion of the electromagnetic spectrum. These atmosphere windows where the energy transmission is effectively undisturbed are used in remote sensing(Baker,1989).

All objects on the earth’s surface (targets) interfere with the radiation. Targets reflect, transmit or absorb the incoming electromagnetic waves. The process taking place depends on the physical and chemical structures of the targets and the wavelength involved. The reflected part of the spectrum is the most important for remote sensing application dealing with land. Over the different wavelengths, targets reflect in a specific manner (Lillesand and Kiefer, 1987).

Remote sensors acquire data using scanning systems, which employ a sensor with a narrow field of view that sweeps over the terrain to build up and produce a two-dimensional image of the surface (see fig 2.2)

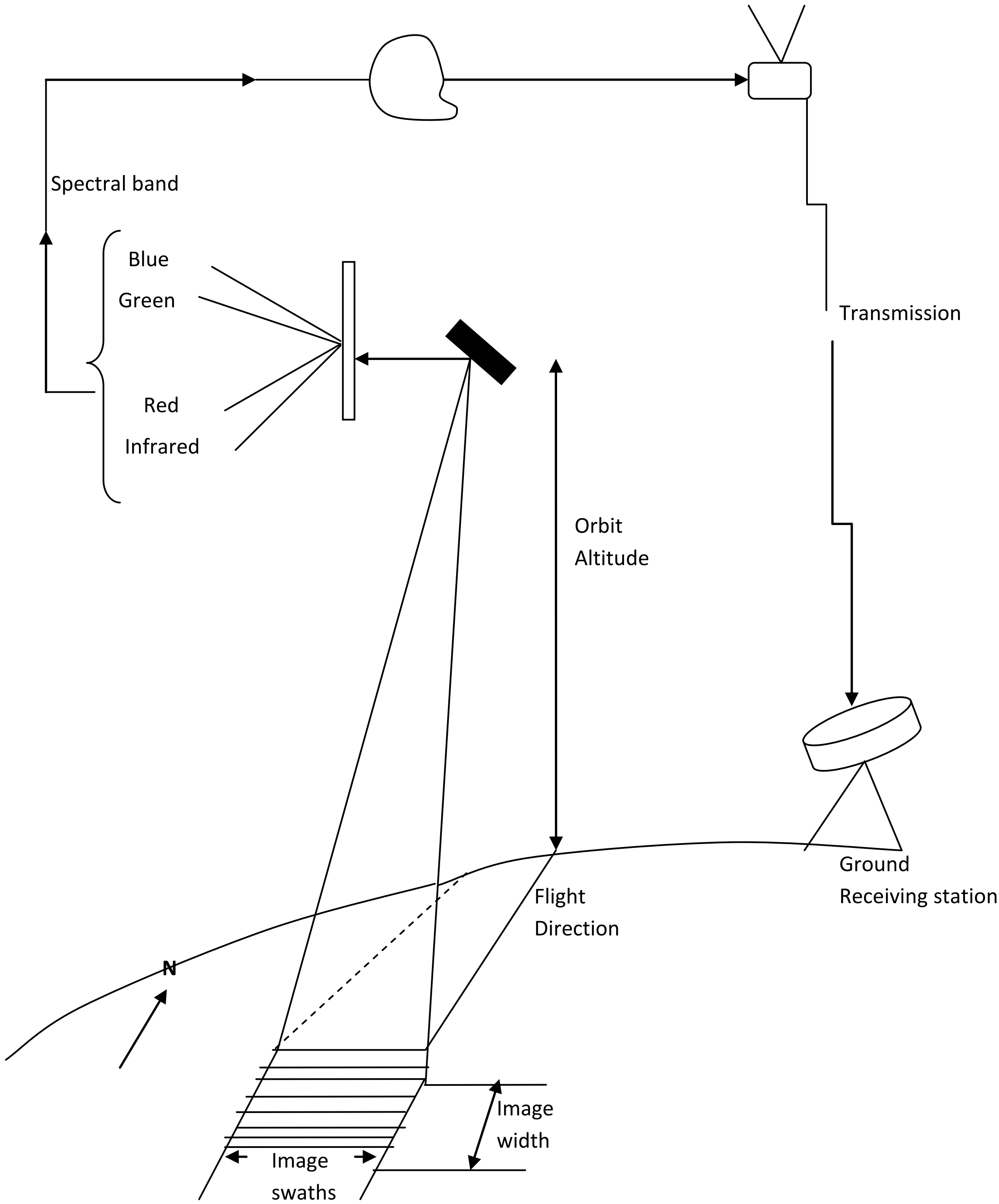


Fig. 2.2: Principle of data recording

Source: Wu, 2002

In 1972, the American satellite landsat delivered multispectral imagery of earth's surface. Landsat satellites 1-3, operational until 1983, were equipped with the multispectral scanner (MSS) with four(4) bands, image size 185km x 185km and pixel size 80m x 80m. Landsat 4 (launched in 1982) and landsat 5 (launched in 1984) Carried in addition to the multispectral scanner, the Thematic Mapper sensor (TM), characterized by seven spectral bands, image size of 185km x 185km and pixel size 30m x 30m. The pay load of landsat 7, operational since April 1999, consists of an Enhanced Thematic Mapper sensor (ETM). In addition to the multispectral bands, similar to those of landsat5, the ETM sensor scans Earth in a panchromatic band with a pixel size of 15m x 15m. During the operational phase of the landsat satellite program an extensive archive of satellite images were created, which offers a retrospective view and the analysis of changes (Maurya *et al*.,2013).

2.4. Classification Scheme

There is no one ideal classification of landcover and landuse, and it is unlikely that one could ever be developed. There are different perspectives in the classification process, and the process itself tends to be subjective, even when an objective numerical approach is used. There is, in fact, no logical reason to expect that one detailed inventory should be adequate for more than a short time, since landuse and landcover patterns keep on changing. In order to address the issues associated with classification and to standardize the landcover and landuse information that could be generated using remote sensing data; Yildrim *et al.*,(2002) developed some criteria for classification systems.

i. The minimum level of interpretation accuracy in the identification of landcover and landuse categories from remote sensor data should not less than 85 percent.

ii. The accuracy of interpretation for the several categories should be equal.

iii. Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.

iv. The classification system should be applicable over extensive area.

v. The categorization should permit vegetation and other types of landcover to be used as surrogates for activity.

vi. The classification system should be suitable for use with remote sensor data obtained at different time of the year.

vii. Effective use of subcategories that can be obtained for ground surveys or from the use of larger scale or enhanced remote sensor data should be possible.

viii. Aggregation of categories must be possible.

ix. Comparison with future landuse data should be possible.

x. Multiple uses of land should be recognized when possible.

Accordingly,(Msoffe, 2011) proposed a multi level landuse and landcover classification system, where in landuse and landcover information at levels I and II would generally be of interest to users who desire data on a nationwide, interstate or statewide basis. More detailed landcover and landuse data such as those categorized at levels III and IV usually will be used more frequently by those who need and generate local information at the intra-state, regional or municipal level. It was intended that these later levels of categorization would be developed by the user groups themselves, so that their specific needs might be satisfied by the categories they introduced into the structure. The system satisfied the three major attributes of the classification process (1) it gave names to categories by simply using accepted terminology (2) It was amenable to further refinement on the basis of more extended and varied use and (3) it allowed inductive generalizations to be made at the more generalized levels to ascertain principal objective of providing a landuse planning and management activities. Later on, many refinements and customizations were effected in the landcover and landuse classification systems, commensuration with the needs of users (Farrow and Winogard, 2001).

There is no clear guideline in our current mapping laws on landcover and landuse mapping. No generally accepted classification scheme has been adopted for the country. Classification scheme is an essential part of landcover and landuse mapping. Non availability of such a scheme in the country means that analysts are left to devise a scheme to be used in a given situation. United States Geological Survey released a classification scheme, consisting of IV levels of classification (Janssen, 2003). Levels I and II of the scheme are provided in Table 2.2.

Table 2.2: Classification Scheme for use

S/No	**Level 1**	**Level II**
1	Urban or built-up Areas	1.1 Residential 1.2 Commercial and services 1.3 Industrial 1.4 Transportation, communication and utilities 1.5 Industrial 1.6 Mixed urban or built-up 1.7 Urban or built-up land

Table 2.2: Classification Scheme for use (continued)

2.	Agricultural land	2.1 Cropland and pasture 2.2 Orchards, groves, vineyards, ornamental, horticulture 2.3 Confined feeding operations 2.4 Other agricultural land
3.	Rangeland	3.1 Herbaceous rangeland 3.2 Shrub-bush land rangeland 3.3 Mixed rangeland
4.	Forest land	4.1 Deciduous forest land 4.2 Evergreen forest 4.3 Mixed forest land
5.	Water	5.1 Streams and canals 5.2 Lakes 5.3 Reservoirs 5.4 Bays and estuaries
6.	Wetland	6.1 Forested wetland 6.2 Non-forested wetland
7.	Barren land	7.1 Dry salt flats 7.2 Beaches 7.3 Sandy areas other than beach 7.4 Bare Exposed rock 7.5 Strip mines, quarries and gravel 7.6 Transitional area 7.7 Mixed barren land

Table 2.2: Classification Scheme for use (continued)

8	Tundra	8.1 Shrub and bush Tundra 8.2 Herbaceous Tundra 8.3 Base ground Tundra 8.4 Wet Tundra 8.5 Mixed Tundra
9	Perennial snow or ice	9.1 Perennial snowfields 9.2 Glaciers

Source: (Li,2007).

Detail classification can extend up to level II or more depending on the nature of the area being modeled and the available image resolution (See Table 2.3). However, the aim should be to ensure that the classification scheme adopted and the classes labeled should be able to convey meaning as to the landcover and landuse patterns in the area and satisfy the need for which it was carried out.

Table 2.3: Image data characteristics for the four level classification scheme

Classification level	**Image data characteristics and mapping scale**
i.	Low resolution satellite images. Example landsat MSS (80m ground resolution) mapping scale 1:120,000 to 1:240,000
ii.	Medium resolution satellite images e.g. landsat T.M 4, Nigeriasat-1 etc (30-35m ground resolution) mapping scale between 1:60,000 to 1:120,000
iii.	High resolution satellite images e.g. SPOT XS (10-20m ground resolution). Mapping scale between 1:25,000 to 1:50,000
iv.	Very high resolution satellite images e.g. IKONOS (1-5m ground resolution). Mapping scale 1:5,000 to 1:25,000

Source: (Li,2007).

2.4.1. Image Classification

Image classification is the process of categorizing image features into image landcover types based on their reflectance characteristics or emittance properties. It can also be described as the process of converting an image scene into a thematic map in which regions with similar properties are indicated in the same way. Digital image classification is a pattern recognition operation where picture elements are identified and regions with similar properties digital numbers (DNs) are indicated in the same way. This is analogous to the visual interpretation where areas of identical reflectance characteristics are recognized as similar features and symbolized in the same way (Ndukwe, 1997).

Spectral patterns of pixels are used as numerical bases for categorization of scene features. Grouping is based on the fact that identical features have similar inherent spectral reflectance and emittance properties (spectral signatures) or exhibit same combinations of DNs. Classification computer programs utilize spectral pattern recognition algorithm based on pixel by pixel spectral information. The use of multispectral image data is justified by the fact that radiance measurements obtained in various wave-length bands enhance pattern recognition. Feature identification using remote sensing imagery is quite effective for landcover studies. There are two main types of classification procedure used in digital image interpretation which are (i) supervised classification and (ii) un-supervised classification (Marvin, 2000).

2.4.1.1. Supervised Classification

The interpreter literarily supervises the pixel categorization process by specifying to the computer numerical descriptors or parameters of various landcover types present in a scene. Hakan,(2005) asserted that supervised classification can be carried out through a combination of field work, map analysis and personal experience for the selection of training sites, the spectral characteristics of these sites were used to train the classification algorithm for eventual landcover mapping. Every pixel both within and outside the training sites are then evaluated and assigned to the class which has the highest likelihood of being a member. On screen selection of polygonal training data (ROI) and screening the seeding of training data were then carried out. The seed program begins at a single $x_,$ y location and evaluates neighboring pixel value in all bands of interest. Using criteria specified by the analyst, the seed algorithm expands outward with spectral characteristics similar to the original seed pixel. This is a very effective way of collecting homogeneous training information.

A supervised classification involves the following operations (Igbokwe, 2005), as presented in Fig. 2.3.

Adoption of suitable object categories depends on the area being mapped. A suitable object category will be adopted and the area would be grouped into classes using high spectral and spatial resolution image data of the landcover.

Training over representative area involves the interpreter or analyst to train the computer to recognize the portions he has visited by ground truthing, thus defining the training area in the image.

Once the training areas have been defined, the statistics characteristics of these areas have to be extracted and used for classifying pixels in the image into various classes such as water bodies, settlements and bare surface.

Feature selection entails reduction of image bands i.e extracted class statistics are used to select the suitable band for classification. If bands are recorded in the same visible band, one band is selected.

Selection of suitable classification algorithms entails the choice of a particular algorithm which depends on the nature of the input image and expected accuracy. The classification algorithm computes the average spectral pattern for each training class and then assigns the remaining image cells to the most similar class.

To ensure that classification is within permissible accuracy, it is usually necessary to compare the classified image with an assumed true map. Hence when classified image is overlaid with trained image, it will generate a confusion matrix (error matrix) the diagonal elements of the matrix show percentage of correctly classified pixels in every feature class. The non-diagonal elements contain information on error of classification.

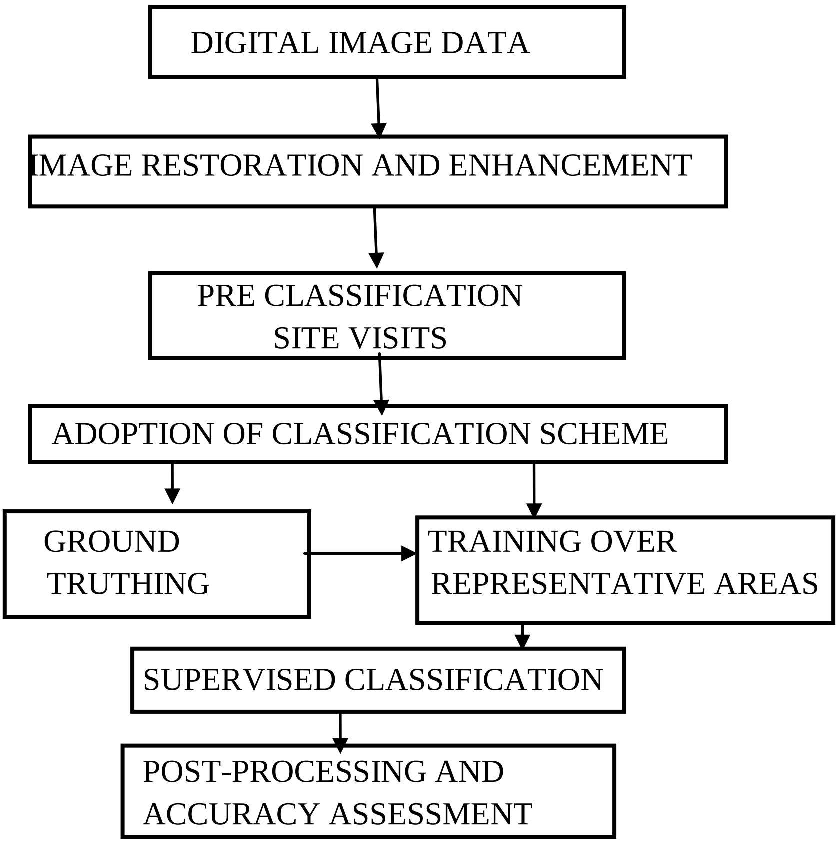


Fig. 2.3: Procedure for supervised classification (Igbokwe, 2005)

2.4.1.2. Unsupervised Classification

In the unsupervised classification approach, no training sets are used,instead partitioning of features is performed by method of cluster analysis which can identify natural grouping of patterns. Image data are first classified by aggregating them into their natural spectral groupings or clusters present in the scene. Then the interpreter ascertains the landcover identity of the spectral grouping by field checks or by comparing with reference data such as large scale imagery or maps. The computer or algorithm automatically group pixels with similar spectral characteristics (means, standard deviations, covariance matrices, correlation matrices etc) into unique clusters according to some statistically determined criteria. The analyst then re-labels and combines the spectral cluster into information classes (Zhou *et al.*, 2010).

Classification algorithm includes

(i) Parallelepiped classification algorithm

The parallelepiped algorithm is a computationally efficient method of classifying remote sensor data. Unfortunately, because some parallelepipeds overlay, it is possible that an unknown candidate pixel might satisfy the criteria of more than one class. In such cases it is usually assigned to the first class for which it meets all criteria. A more elegant solution is to take the pixel that can be assigned to more than one class and use a minimum distance to mean decision rule to assign it to just one class (Khatibi, 2015).

The parallelepiped classifier uses the class limits stored in each class signature to determine if a given pixel falls within the class or not; the class limits specify the dimension (in standard deviation units) of each side of a parallelepiped surrounding the mean of the class in feature space. If the pixel falls inside the parallelepiped, it is assigned to the class. However, if the pixel falls within more than one class, it is placed in the overlap class (code 255). If the pixel does not fall inside any class, it is assigned to the null class (code 0).

The parallelepiped classifier is typically used when speed is required. The drawback is (in many cases) poor accuracy and a large number of pixels classified as ties (or overlap, i.e class 255).

(ii) Minimum Distance to mean classification Algorithm

The decision rule is computationally simple and commonly used. When used properly it can result in classification accuracy comparable to other more computationally intensive algorithms, such as the maximum likelihood algorithm. Like the parallelepiped algorithm, it requires that the user provide the mean vectors for each class. To perform a minimum distance classification, a program must calculate the distance to each mean vector. From each unknown pixel, it is possible to calculate this distance using Euclidean distance based on the Pythagorean Theorem. The computation of the Euclidean distance from point to the mean of class measured in band relies on the equation (2.10) according to (Khatibi, 2015).

$$Dist = SQRT\ ((BV_{ijk} - \mu_{ck}) + (BV_{ijl} - \mu_{cl})) \qquad ...(2.10)$$

Where μ_{ck} and μ_{ci} represent the mean vectors for class c measured in bands K and L.

BV_{ijk} – Matrix in Band K

BV_{ijl} – Matrix in Band L

Minimum distance classifies image data on a database file using a set of 256 possible class signature segments as specified by signature parameter. Each segment specified in signature for example, stores signature data pertaining to a particular class. Only the mean vector in each class signature segment is used (Khatibi, 2015).

(iii) Fisher classification

Is one of the simplest classification algorithms. The method finds a direction W in the N dimensional space. The Fisher classifier calculates the projection of the sample onto W, the idea is to find a direction which after projecting will maximize interclass variability and minimize intraclass variability. It can be achieved by maximizing the following function in equation (2.11).

$$J_{(w)=} \left| \frac{m_1 - m_2}{S_1^2 + S_2^2} \right|^2 \qquad ...(2.11)$$

Where m_1 and m_2 are the mean value of the projected positive and negative samples respectively. s_1 and s_2 are the standard deviations of the projected samples.

In the simple two-dimensional case, after the points are projected onto the line, the two classes are transformed into two sets of points upon the line. The interclass variability in this case is the distance between the class centers and the intraclass variability is the distance of class members from their class centers. Different criteria can be employed to determine the class for a new sample, by Calculating the distance from the point to the means of the projected training classes and adding a weighing scheme in order to minimize the bias caused by the relative sizes of the training classes. The advantage of fisher's classification is that the vector w can be found swiftly using a simple procedure (Pereira *et al.*, 2012).

(iv) Maximum likelihood classifier

Is one of the most popular methods of classifications in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood is defined as the posterior probability of a pixel belonging to class K (Pereira *et al*., 2012)

$L_k = P(k/x) = P(k) * P(x/k)/EP_{(i)} * P(x/i)$ … (2.12)

Where P(k) - prior probability of class K

$EP_{(i)}$ – Exponential of (i)

P(x/k) --- conditional probability to observe X from class k or probability density functions.

P(x/i) – Conditional Probability to observe x from class i

Usually P(k) are assumed to be equal to each other and EP(i) * P(x/i) is also common to all classes. Therefore L_K depends on P(x/k) or the probability density function.

For mathematical reasons, a multivariable normal distribution is applied as the probability density function. In the case of normal distributions, the likelihood can be expressed as follows:

$L_k(x) = \frac{1}{2\pi\frac{n}{2}/\varepsilon_k/\frac{1}{2}}$ exp $/{}^1/_2(x-\mu_k)\ \Sigma_k^{-1}\ (x-\mu_c)^t$ ...(2.13)

Where n-number of bands

X image data of n bands

$L_k(x)$ likelihood of x belonging to class K

μ_k - mean vector of class K

μ_c – mean vector of another class

Σ_k variance - covariance matrix of class K

$/\Sigma_k/$ determinant of Σ_k

The maximum likelihood has an advantage from the view point of probability theory, but care must be taken with respect to the following items

(i) Sufficient ground truth data should be sampled to allow estimation of the mean vector and the variance covariance matrix of population

(ii) The inverse matrix of the variance covariance matrix becomes unreliable when very high correlation exists between two bands. In such cases, the number of bands should be reduced by a principal component analysis.

(iii) When the distribution of the population does not follow the normal distribution, the maximum likelihood method cannot be applied.

2.4.1.3 Object – based classification

Is a process of classifying image with respect to semantic information that is not present within an individual pixel. In this process we recognize objects as well as relations between them (Dutta, 2006). It is a way of organizing image processing that enables sorting and merging segments into objects and/or objects classes/types (based on their common characteristic and defined semantic model)

Semantic modeling – reflects conceptual (notional) modeling i.e. processes of recognition, interpretation and simplification of reality into a corresponding semantic model for particular use. Lo and Yeung, 2007 suggested that Object – based classification consists of the following steps:

(i) Segmentation and computation of spectral, geometric, textural, conceptual and temporal attributes.

(ii) Object (semantic) classification

(iii) Post classification (verification, error elimination) and result validation.

The basic input data is represented by multispectral satellite images. However, depending on the aim of the particular object – based analysis, other auxiliary data layers can be added and this helps to fine –tune the process of sorting segments into object classes.

The merits of this classification includes:-

(i) It uses a vast variety of remote sensing data characteristics (spectral, spatial, temporal) and combines them with GIS functionalities in the various processing phases.

(ii) Object – based classification uses all available and usable segment characteristics for their classification e.g., shape, texture, relations with other segments.

(iii) Results (identified objects) are vectors which demand easier post-processing than pixel-based classification results. To a certain degree the generalization can also be performed during the main processing phases e.g. elimination of small objects based on their shape or size.

(iv) It classifies the images contents into objects in a way that is close to the human understanding of the environment. The results are already generalized, since the classification uses clear semantic rules that can also be used to enhance or omit certain typical object characteristics e.g. linearity, length, width, rectangularity of buildings to enhance their key differences.

(v) The fact that the basic computation entities are objects (and not pixels) reduces the demand on computer algorithms and at the same time enables the users to utilize more complex computation techniques and a wider set of data characteristics.

The limitations of the object based classification are:

(i) When processing extensive databases (large area of interest, high spatial resolution, or both) powerful processing hardware is needed, since numerous pixels are processed simultaneously during the multispectral image segmentation.

(ii) Segmentation has no uniform solution. Even a minimal change in the radiometric resolution, the segmentation parameters, or the pre-processing procedures yields different results.

(iii) Object-based classification is a relatively new method of remote sensing, therefore there is no general consensus (nor enough studies) that would deal with the relation between the object obtained within the segmentation process and the geographical object (Dutta, 2006).

2.4.1.4 Pixel-Based Classification

Pixel-based classification is a method that uses multispectral techniques, which compare the similarity of each pixel in the image with assigned classes. In this case, each pixel is assigned to a class according to a selected mathematical algorithm

Pixel-based classification methods are divided into two groups: supervised and unsupervised classification. Unsupervised classification is used if there is no or insufficient information about the landcover and landuse of the area to be classified. In the supervised classification method samples are collected through the image for the specified classes, and each pixel is compared with these samples(Halder,2013).

Pixel-based image classification algorithms analyze the numerical properties of image features and objects and then classify data into categories. More importantly, the classification algorithms typically employ the process of training and testing first and foremost, the description of training classes is an extremely important component of the classification process. In supervised classification, statistical processes or distribution-free processes can be used to extract class descriptors, while unsupervised classification relies on clustering algorithms to automatically segment the training data into prototype classes (Alphan, 2003).

2.5. Multiple Logistic Regression Analysis

Logistic regression analysis is a popular and widely used analysis that is similar to linear regression analysis except that the outcome is dichotomous (e.g. success/failure or yes/no). The epidemiology module on regression analysis provides a brief explanation of the rationale for logistic regression and how it is an extension of multiple linear regression. The outcome in logistic regression analysis is often coded as 0 or 1 where 1 indicates that the outcome of interest is present and 0 indicates that the outcome of interest is absent. If we define p as the probability that the outcome is 1, the multiple logistic regression model can be written as follows

$$\hat{P} = \frac{\exp(b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p)}{1 + \exp(b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p)} \qquad \ldots(2.14)$$

$\hat{p}$ is the expected probability that the outcome is present

X_1 through X_P are distinct independent variables, andb_0 through b_p are the regression Coefficients. The multiple logistic regression model is sometimes written differently in the following form the outcome is the expected log of the odds that the outcome is present

$$\ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p \qquad \ldots(2.15)$$

Regression analysis is a statistical methodology that utilized the relationship between two or more quantitative variables so that one variable can be predicted from the other variable or variables (Field, 1997). It attempts to establish a relationship between a numerical variable which is the dependent variable and one or more explanatory numerical variables (referred to as independent or predictor variables).

Simple regression seeks to predict an outcome from a single predictor, whereas multiple regression seeks to predict an outcome from several variables. Multiple regression is a logical extension of simple regression; each predictor variable has its own coefficient and the outcome variable is predicted from a combination of all the variables multiplied by their respective coefficient and a residual term (see equation (2.16).

$$Y=ß_0 + ß_1X_1 + ß_2X_2 + \ldots + ß_nX_n + E_i \qquad \ldots(2.16)$$

Y is the outcome variable, $ß_1$is the coefficient of the first predictor (X_1), $ß_2$is the coefficient of the second predictor (X_2), $ß_n$is the coefficient of the n^{th} predictor (X_n) and E_i is the difference between the predicted and the observed value of Y for the i^{th} subject.

In logistic regression, instead of predicting the value of a predictor variable Y from a predictor variable X_1 or several predictor variables (Xs) the probability of Y occurring given known values of X_1 (or X_2) can be predicted. In it's simplest form, when there is only one predictor variable X_1 the logistic regression equation from which the probability of Y is predicted is given by equation (2.17).

$$P(Y) = \frac{1}{1 + e^{-(ß_0 + ß_1X_1 + Ei)}} \qquad \ldots(2.17)$$

P(Y) is the probability of Y occurring, e is the base of natural logarithms, $ß_0$ is a constant, X_1 is a predictor variable and $ß_1$ is the coefficient. When there are several predictors, equation (2.17.) becomes (see equations (2.18) and (2.19)).

$$P(Y) = \frac{1}{1 + e^{-Z}} \quad \ldots(2.18)$$

$$Z = ß_0 + ß_1X_1 + ß_2X_2 + \ldots + ß_nX_n + E_i \quad \ldots (2.19)$$

The outcome in logistic regression analysis is often coded as 0 or 1. A value close to zero means that Y is very unlikely to have occurred and a value close to 1 means that Y is very likely to have occurred (Chatterjee, 1991).

There are various processes under which the transition from one state (landuse type) to another takes place. Major processes are organic growths, breeding, slope resistance growths, road gravity growth and diffusion, when the urban area grows around its perimeter it is called an organic growth. Major urban areas have their influence on the nearby areas and influence them to convert them into urban area. When the area between the two urban areas start growing into urban area and soon starts to influence other adjoining cells then it is called a Breeding. It has been observed that better transport network also influences the urban growth, when the roads influence the cells near the settlements, this is referred to as road gravity growth. When the area is not near to an urban area in a flat terrain and it starts growing into urban area, this is referred to as diffusion. The higher slope is found to resist the growth of urban area which is called slope resistance.

Beside these processes the cells have the geo-physical attributes also which influence the landuse landcover change e.g. altitude, DEM, aspect etc. Therefore ideally transition rule should address all these processes and it should consider all the influencing factors (Houet and Lawrence, 2007).

Cellular automata can be represented in quadruple as follows: (U, S, N, T)

Where U is universe (cell space or lattice) S is set of all possible states which a cell can attain, N is neighborhood of a cell and T is a set of transition rules. We can represent a state of a cell at time t + 1 as a function of its state at time t, it's neighborhood and transition rule becomes.

$S_{t+1} = f(S_t, N, T)$

Where S_{t+1} is state of a cell at time (t +1), S_t is a state of a cell at time t, N is neighborhood and T is a set of transition rules followed by cells.

2.6 Satellite Imaging Systems for Mapping

There are several remote sensing satellites currently available which provide various imageries suitable for landcover and landuse mapping. These satellite sensor platforms are characterized by the wavelength bands employed in image acquisition, spatial resolution of the sensor, the coverage area and the temporal resolution (Jensen, 2004).

Spatial resolution refers to the ability of an entire remote sensing system to render a sharply defined image i.e the smallest object that can be detected by the sensor. Paul (2002) defined spatial resolution as the qualitative measure of the amount of details that can be observed on an image.

Remote sensing images are composed of a matrix of picture elements or pixel which are the smallest units where spectral response is measured. The size of the pixel varies according to the technical design of the sensors. Images where only large features are visible are said to have coarse or low resolution. In fine or high resolution images, small objects can be detected. Commercial satellite provide imagery with resolution varying from a centimeter to few metres. (Verburg *et al.,* 2004).

The spatial resolution has relevance in the identification of objects on the earth's surface, the scale of the analysis and the locational precision of the object. For a homogenous feature to be detected generally its size has to be equal to or larger than the pixel. If the feature is smaller, it may not be detectable because the average brightness of all features in that pixel will be integrated over the pixel area and then recorded. However, smaller features may sometimes be detectable within a particular pixel thus allowing sub-pixel detection. The spatial resolution of the data must be compatible to the project objectives. New developments in remote sensing are, directed towards high spatial resolution images of about 1 to 2m, enabling the identification of small features (Wu, 2008).

Distortions due to lens defects can degrade a recorded image and subsequently affects the spatial resolution. Remotely sensed imageries are classified as follows:

i. Low resolution image

   60m – 85m

ii. Medium resolution image

   30m – 60m

iii. High resolution image

   10m – 25m

iv. Very High resolution image

   0.5m – 10m

Spectral resolution is the recording of the same scene in different spectral interval. The narrower the spectral interval, the better the spectral resolution. Higher spectral resolution permits discrimination between different terrain features that have only small differences in spectral reflectivity. Factors that determine the spectral quality of images includes sun’s elevation, atmospheric conditions, relief, terrain slope and environment (Herold *et al.,* 2003)

Features or targets of the earth’s surface can be characterized and distinguished by the spectral reflectance over a variety of wavelength. Satellite sensors measure the reflected radiation of the surface in different spectral intervals, in spectral band or channels, in order to capture these differences. The capability of a satellite sensor to identify targets on the earth’s surface depends to a great extent on the number of spectral bands, which is the spectral resolution (Li and Yeh, 2002).

The spectral resolution describes the ability of a sensor to distinguish between fine wavelength intervals. Remote sensing systems record the reflected proportion of radiation in several separate wavelength ranges (so called spectral bands or channels) at various spectral resolution. The finer the spectral resolution, the narrower the wavelength range for a particular channel or band and different objects can be detected and distinguished. Advanced multi-spectral sensors called hyper spectral sensors, detect hundreds of very narrow spectral bands throughout the visible, near infrared and mid-infrared portions of the electromagnetic spectrum. The high spectral resolution facilities fine discrimination between different targets based on their spectral response in each of the narrow bands (Brown *et al.,* 2000).

Radiometric resolution is the sensitivity of a sensor to the level of the signal received. Radiometric resolution is determined by the number of discrete levels into which a signal strength may be divided. The maximum number of practically possible quantizing levels for a sensor system depends on the signal-to-noise ratio and the confidence level that can be assigned when discriminating between the levels.

Radiometric resolution refers to the dynamic range, or the number of different output levels used to record the radiant energy for a single measurement. The dynamic range of the most common satellite data is 7 bits or 128 different levels (landsat MSS, IRS) or 256 levels (8 bits) for landsat TM and ETM.The greater the radiometric resolution, the more accurately the remotely sensed data can represent variations in surface leaving radiance. Many images processing software tools are designed to process 8-bit data, and other byte sizes might require special handling (Chen *et al.,* 2007).

Temporal resolution is the time lag between two possible image acquisitions on the same area. It describes how frequently a system senses an area or how frequently we are able to look at a given scene. The quality of satellite sensor image depends on the combination of spatial and spectral resolutions (Jensen, 2004).

In addition to spatial and spectral resolution the concept of the temporal resolution is also important to be considered in a remote sensing system. The temporal resolution depends on the revisit period which refers to the time it takes for a satellite to observe and image the same area on the ground at the same viewing angle a second time after completion of one entire orbit cycle (Wu, 2008). The revisit period of a satellite sensor is usually several days (see Table 2.4). Therefore the absolute temporal resolution of a remote sensing system to image the exact same area at the same viewing angle a second time is equal to this period.

Table2.4: Temporal resolution of some common satellite platforms

Remote sensing platforms	**Temporal Resolution**
IKONOS	4 days
Landsat 1,2 and 3	18 days
Landsat 4,5 and 7	16 days
SPOT	26 days
NOAA-AVHRR	1 day

Source: (Chen *et al., 2007).*

Gajbhiye and Sharma, (2012) citing Wu, (2008) that actual temporal resolution of a sensor depends on a variety of factors, including the satellite/sensor capabilities, the swath overlap, the orbit altitude and the geographic latitude of the area of interest. The most prominent factor influencing the temporal resolution is that cloud free conditions are required during the image acquisition. The possibility to obtain cloud free images for a certain region in successive orbits is limited. However, the ability to collect imagery of the same area of the earth's surface at different periods in time is one of the most important elements for applying remote sensing data. By imaging on a continuous basis at different times it is possible to monitor the changes that take place on the earth's surface.

The use of digital space remote sensing images involves digital image processing; only in a few cases data can be used directly. The obligatory steps in image processing prior to the data analysis are the following.

(i) Radiometric correction

(ii) Geometric correction

(iii) Image enhancement

Radiometric correction is necessary due to sensor irregularities over time and the unwanted atmospheric influences. Processing is also required when physical units (like reflected or emitted radiation) are to be calculated. In particular, when remote sensing data are used for monitoring purpose, great care has to be taken on the radiometry.Geometric correction deals with the conversion of the image matrix to real world co-ordinates. Image enhancement involves the improvement of the appearance of the imagery to assist in visual interpretation and analysis (Gajbhiye and Sharma, 2012).

Nashat, (2002) submits that interpretation and analysis of remote sensing imagery involves the identification and/or measurement of various targets in an image in order to extract useful information. Targets in remote sensing images may be any feature or object that can be observed in an image. The target must be spatially and spectrally distinguishable i.e. it must contrast with other feature around it in the image. Ayodeji, (2006) further states that Image analysis is performed manually (Analogue image analysis, e.g. Visual interpretation) and/or digitally. Digital processing and analysis is common now with the advent of digital recording of remote sensing data and the development of computers. Digital image analysis is performed when the full spectral information (multi-channel datasets) is to be used. In the collection of landcover information, digital image classification procedures are performed. Based on the spectral signature of required classes or categories (forests, grassland), the pixel's spectral information is statistically assigned to one of them. The output of such a classification is a thematic map.

Image analysis does not rely solely on the digital image information but includes also auxiliary information like topographic maps, thematic maps and digital terrain models. Above all, it should not be forgotten that ground truthing is essential for validating the results. The use of satellite images does not make ground surveys superfluous. Digital processing and analysis needs at least a standard personal computer and special software e.g. Erdas imagine and ER mapper (Jensen, 2004) .

There is no doubt that remote sensing data represent a data source which contributes to a deeper understanding of processes on the earth's surface. Remote sensing data provides a synoptic overview of large areas. The position, distribution and spatial relationships of features on the earth's surface are clearly evident; thus spatial relationship can be examined. Remote sensors view a broader portion of the spectrum than the human eye, enabling the detection and identification of various environmental features of the earth's surface or the atmosphere, particularly when sensors focuses on a very specific bandwidth (Dutta, 2006). Through repetitive looks at the same area, the data represents a unique data source for monitoring purpose and change detection. The uses of remote sensing data for monitoring requires some input of methodological work and pre-processing capabilities such as geometric and radiometric corrections which are time and cost intensive. The use of satellite data and the ability for detection and identification of e.g. landcover classes depends on the spectral and spatial resolution of satellite sensors. The spatial resolution determines the scale of work. Common satellite imagery enables mapping at a scale of 1:50,000 or 1:100,000. With new high resolution satellite systems like IKONOS, this limit can drastically be reduced, enabling map production at scale of 1:5,000 (Maurga *et al.*, 2013)

2.6.1 Usefulness of Satellite Data in Landuse and Landcover Mapping

Landuse and landcover data are essential for planners and decision makers and also useful for land resource management. There are three classes of data included in landcover.

i. Physical structures built by human being

ii. Biotic phenomena such as natural vegetation, agricultural crops etc.

iii. Any type of development

Most of these phenomena are directly visible from remote sensing imageries, hence remote sensing techniques are particularly suitable for production of landuse and landcover maps. Satellite images provide an up-to-date means of producing landcover and landuse maps of cities when imageries are available at different spatial resolutions (Nashat, 2002).

2.6.2 Formats used to Present Landcover Mapping

The interpretation of landcover and landuse data must be portrayed in a user compatible form. There are three principal formats used to portray interpreted results which are as follows.

i. Maps or graphic displays: Maps remain the most effective and commonly-used method of presenting the final output. Landcover and landuse data can also be presented in graphic form such as histograms.

ii. Statistical table: Another common form of presenting landcover and landuse maps is in tabular form.

iii. Data files: Classification results can be recorded in computer storage media such as disc. Interpreted data in this format can be incorporated into an existing Geographic Information System (GIS) especially when the image data have been geometrically rectified (Paul, 2002).

2.7 Landcover and Landuse Data from Remotely Sensed Data

Remote sensed data provides the capability to monitor a wide range of landscape and biophysical phenomena which is needed by managers and policy makers. Remote sensing techniques need to be combined and complemented with in-situ measurements. Satellite-based remotely sensed data is commonly recorded in digital form as a grid of cells or pixels. The data file value assigned to each pixel is the record of reflected radiation or emitted heat from the earth's surface at that location. Pixel value of commercially available imagery representing the radiance of the surface in the form of digital numbers (DN), which are calibrated to fit a certain range of value e.g from 0 to 255 in an image of 8 bits can be used in landcover studies (Jensen, 2004).

In remotely sensed data four distinct types of resolution must be considered: spectral (the specific wavelength intervals that a sensor can record), spatial (the area on the ground represented by each pixel), radiometric (the number of digital levels into which the radiance of the surface recorded by the sensor is divided and expressed; this is commonly expressed as the number of bits) and temporal (how often a sensor obtains imagery of a particular area). Conversion of DN back into absolute radiance is a necessary procedure for comparative analysis of several images acquired at different times which allows for more accurate comparison of images across rows, paths and dates.

There exist several imageries with very different imaging characteristics e.g Landsat series, SPOT, ASTER, IKONOS, Quick bird, Geo-eye etc. Landsat series is a primary environmental data source. It has provided a continuous coverage since 1972 to date through it's multi-spectral scanner (MSS), Thematic Mapper (TM) and enhanced TM sensor (ETM). Remotely sensed data is not free of errors. Error or noise is introduced into the remotely sensed data by the environment (e.g. atmospheric scattering), or random or systematic malfunction of the remote sensing system (e.g. an uncalibrated detector creates striping). Therefore, the quality and statistical characteristics of digital remote sensor data should first be assessed (Jensen, 2004).

Satellite image processing and analysis refers to the act of examining images for the purpose of detecting, identifying, classifying, measuring and evaluating the significance of physical and cultural objects, their patterns and spatial relationship. The image processing, image classification or segmentation, post processing and evaluation. There are several methods for the image classification and choosing the most appropriate method will always depend on the characteristics of the image and the type of analysis being performed. Satellite image classification into landcover categories is based on the fact that landcover types have unique spectral response patterns; hence spectral pattern recognition can be more important. The classification process is usually in two parts: training and classifying. Training is the process of defining the criteria by which these patterns are recognized. Training can be performed with either an unsupervised or supervised method. However, both methods have some drawbacks; unsupervised training doesn't guarantee that the classification makes sense for the interpreter and supervised training results in many cases is subjective because the interpreter has previously established the categories without taking into account the full spectral characteristics in the image. Using a combination of supervised and unsupervised classification may yield optimal results (Ndukwe, 1997).

Classified images require post-processing to evaluate classification accuracy, reduce isolated pixels and improve map representation. A very common post processing operation is to generalize the image through a low pass filter over the classified result and fuzzy convolution using the distance error image file generated during the parametric classification. Landcover maps derived from remotely sensed data inevitably contain errors of various types and degrees. It is therefore very important that the nature of these errors are determined, in order for both users and producers of the maps to be able to evaluate their appropriateness for specific uses (Alphan, 2003).

The error matrix is commonly used for determining the accuracy of maps derived from remotely sensed data. More recent research into classification accuracy assessment is focused on factors influencing the accuracy of spatial data, such as classification scheme, ground verification e.t.c. An error matrix compares the classification to ground truth or other data (existing maps). Error matrix technique is appropriate for remotely sensed data which is discrete rather than continuous data. Although the most efficient and widely-used technique is the error matrix; such methods like field survey with the assistance of historical GIS data, use of high resolution imageries etc can also be used (Hong *et al.*, 2000).

Landcover and landuse mapping should provide area change, change rate and spatial distribution of changed types. The accuracy depends on the performance of the image processing, classification approach, availability of good quality data, complexity of landscape and the environment of the study area. Landuse changes can be identified by using two geo-referenced images of the same area, taken at different dates. Remotely sensed data when used in conjunction with the techniques of Geographic Information System will produce the desired results in landcover and landuse studies (John *et al*., 2011).

2.8 Modeling

Modeling is the process of producing a model; a model is a representation of the construction and working of some system of interest. A model is similar to but simpler than the system it represents. The purpose of a model is to enable the analyst to predict the effect of changes to the system. On the one hand, a model should be a close approximation to the real system and incorporate most of it's salient features. A good model is judicious trade off between realism and simplicity. An important issue in modeling is model validity. Model validation techniques involves simulating the model under known input conditions (Araya, 2009).

Generally, a model intended for a simulation study is a mathematical model developed with the help of simulation software. Mathematical model classifications include deterministic (input and output variables are fixed values) or stochastic (at least one of the input or output variables is probabilistic); Static (time is not taken into account) or dynamic (time varying interactions among variables are taken into account). Typically simulation models are stochastic and dynamic. Modeling is arguably the most important part of a simulation study. Simulation modeling involves identifying the problem, formulate the problem, collection and processing real system data, formulate and develop a model, validate the model, document model for future use, select appropriate experimental design and perform simulation runs (Lei *et al*., 2006).

Fischer and Sun, (2011) noted that land is a dynamic canvas through which human and natural systems interact. Understanding the many factors influencing landcover and landuse change has been the focus of scientific study across multiple disciplines, location and scale. But direct measurements alone are not sufficient to provide an understanding of the forces driving change. Linking observations at a range of spatial and temporal scales to empirical models provide a comprehensive approach to understanding landuse change (Ahmadzadeh, 2003).

The primary utility of models is to provide a systematic approach to understanding a research problem. An important aspect is the link between direct observations, case studies and models in an effort to test or identify dominant features of landcover change. Development of diagnostic models can lead to an improved understanding of the current and recent situation and at the same time provide credible, geographically – referenced predictions. The length of time over which a prediction is valid is a function of the persistence of the observed phenomena. There is evidence to suggest that much, if not most landuse changes is spatially and temporally persistent over 5 to 10 years intervals. It should be noted, however, that certain events can alter trends significantly and rapidly. Changes in political, institutional and economic conditions can cause rapid changes in the rate or direction of landcover change. Therefore, an effort to understand the primary kinds of influences which cause landuse change is necessary (zang *et al.*, 2012).

Veldkamp and Lambin, (2001) asserted that several different approaches are used to project future landcover and landuse. These can be divided into broad categories (a) models that predict total landuse change for a region and (b) models that predict landuse for specific parcels or grid cells.

Most models are in some way mathematical, which relied on equations that seek a static or equilibrium solution. The most common mathematical models are sets of equations based on theories of population growth and diffusion that specify cumulative landcover and landuse change over time (Eastman,2006). A variant of this model is based on linear programming, potentially linked to GIS information on land parcels. A major drawback of such models is that a numerical or analytical solution to the system of equation must be obtained, limiting the level of complexity that may practically be built into such models.

System models represent stocks and flows of information, material or energy as set of differential equations linked through intermediary functions and data structures. Time is broken into discrete steps to allow feedback. Human and ecological interactions can be represented within these models, but they are dependent on explicit enumeration of causes and functional representation and they accommodate spatial relationships with difficulty (Wu and Webster, 2000).

Statistical techniques are a common approach to modeling landcover and landuse change, given their power, wide acceptance and relative ease of use. They include a variety of regression techniques applied to space and more tailored spatial statistical methods. Unless they are tied to a theoretical framework, statistical techniques may downplay decision making and social phenomena such as institutions. Successful examples of combining theory and statistics are provided by spatial econometrics (White *et al.,*1979).

Expert models combine experts judgment with probability techniques such as Bayesian probability or symbolic artificial intelligence approach such as expert systems and rule based knowledge systems (Lei *et al.,*2006). These methods express qualitative knowledge in a quantitative fashion that enables the modeler to determine where given landuse are likely to occur. It can be difficult to include all aspects of the problem domain, which leaves room for gaps and inconsistencies.

Within the field of artificial intelligence, symbolic approaches such as expert systems are complemented by a biologically inspired evolutionary paradigm. Examples of this field such as artificial neural networks and evolutionary programming, are finding their way into landcover and landuse change models (Kocabas and Dragicevic, 2007).

Fung and Ledrew, (1988) opines that, neural networks are silicon analogs of neural structure that are trained to associate outcomes with stimuli. Cellular models include cellular automata (CA) and Markov models. Each of these models operates over a lattice of congruent cells. In CA each cell exist in one of a finite set of states and future states depend on transition rules based on a local spatiotemporal neighborhood. The system is homogenous in the sense that the set of possible states is the same for each cell and the same transition rule applied to each cell. Time advances in discrete steps and updates may be synchronous or asynchronous.

Simulation modeling is necessary in landcover and landuse changes study when it is impossible to observe certain process in the real world. Data model backed up by the view of reality as basis, consists of conceptual modeling, Reality refers to the phenomenon as it actually exists, including all aspects which may or may not be perceived by individuals. The view of reality is the mental abstraction of the reality for a particular application (Fung and Ledrew, 1988).

Conceptual data modeling is an arrangement of a human conceptualization of reality. Tessellation, vector and object oriented are the different forms in which data can be conceptualized. Logical data modeling is the representation of data model designed to reflect the recording of data in the computer. Physical data modeling is the representation of the data structure in the format of the implementation software. In other words it involves populating the database (Mohan *et al*., 2014).

2.9 Landcover and landuse change analysis with cellular Automata and Multiple Logistic Regression

Landsat TM images of the area acquired in three (3) different epochs are necessary. Image restoration and rectification are necessary to be performed on the satellite imageries. Pre processing precedes image enhancement and classification. Pre processing operation will involve corrections or elimination of radiometric, geometric distortions and noise removal. Image enhancement will be performed on the image data to modify it in a useful way or improve it's pictorial quality. This ensures image features to be easily discriminated which is a necessary step in image processing (Lo and Yeung, 2007).

The next step is image classification which involves categorizing image features into image landcover types. Spectral patterns of pixel are used as numerical bases for categorization of scene features. Representative training areas from where training sets are established. Literarily the pixel categorization is supervised by specifying to the computer numerical descriptors or parameters of various landcover types present in the scene (Kocabas and Dragicevic, 2007).

The model evolves in discrete time steps, changing the state of all its cells according to a transition rule. For cellular automata developed on a homogeneous cell space, a vector of transition potentials is calculated for each cell from the neighbourhood effect using equation (2.20)

$$Pj = VNj \qquad \ldots(2.20)$$

Where Pj – Potential of the cell for landuse

V – a scalable random perturbation term

Nj – the neighbourhood effect on the cell for landuse.

The selection of the forces driving landuse helps in understanding the processes of landuse transition. Landuse drivers are usually chosen on a case-to-case basis. Explanatory variables are usually extracted using ArcGIS and Visualised in MATLAB. The extracted variables used for modeling are proximity variables from satellite imageries such as distances to river, major roads, built-up area,notable institutions, industrial and commercial areas (Verburg *et al.*, 2004).

The logistic regression model is the most commonly used parametric model for modeling landuse change. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more metric (interval or ratio scale) independent variables; usually it is expressed in equation (2.21) as:

$$q_1 = \beta_o + \sum_{l=1}^{n} \beta_i x_i + \epsilon_i \qquad \ldots(2.21)$$

Where q is a binary dependent variable

$\beta_o, \ldots \beta 1$ are logistic regression coefficients

x_i are independent variables

ϵ_i is the residual error.

The next step is the calibration of the model by running a simulation for two epochs after which validation is carried out. The statistical results of each explanatory variable are obtained based on a two-tailed test at 95% confidence level; to obtain the least and most significant distance in the model. Landcover and landuse changes are obtained by overlaying maps of different epochs; the future prediction of urban expansion can be carried out using the parameters of the already calibrated model. Finally urban expansion can be calculated by noting the number of urban cells for each epoch and determining the urban expansion as shown in Table 2.5

Table 2.5: Urban expansion from 1984 to the predicted 2030.

Year	No of urban cells	Urban expansion
1984	57,882	
2000	90,814	32,932 cells (56.9%) 1984 – 2000
2005	94,948	37,066 cells (64.04%) 1984 – 2005
2030	132,836	74,954 cells (129.49%) 1984 – 2030

Source: Aniekan *et al.*, (2012).

Cellular automata will be used in modeling in this research work and multiple logistic regression will be used in the prediction using Terrset land change modeler

CHAPTER THREE
LITERATURE REVIEW

Several works were reviewed under this section. The procedures, methods used, successes and short comings by the researchers were identified. The reviewed works centered on the modeling and mapping of landcover and landuse changes using multiple logistic regression and cellular automata. It covered works accomplished around the world.

3.1 Landcover and Landuse change analysis using Cellular Automata and multiple Logistic Regression

Deep, (2014) carried out landcover landuse changes in Dehra dun city in India. Geographically the city is located in between $29^{0}57'$ and $31^{0}27'50''$ north latitudes and $77^{0}34'27''$ and $78^{0}18'30''$ east longitude. The temporal data of IRS (Indian remote sensing satellite) which operates in three spectral bands in the visible and near infrared region with 5.8m spatial resolution and has revisit of 5 days were used in this study. The acquired data of the Dehradun area were processed and analyzed using remote sensing and GIS techniques to detect changes. In order to detect changes, post classification change analyses were carried out using ERDAS imagine, Arc map and Idrisi. Pre-processing was done to remove radio metric and geometric errors from the dataset. The figure 3.1 shows the method used for the study.

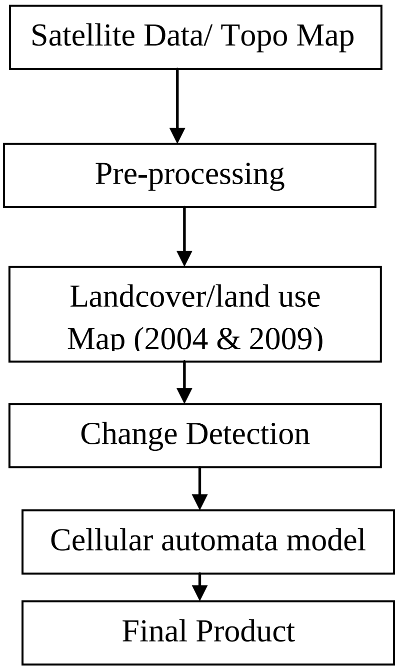


Fig 3.1: Schematic presentation of methodology adopted for the study

Source: (Deep, 2014)

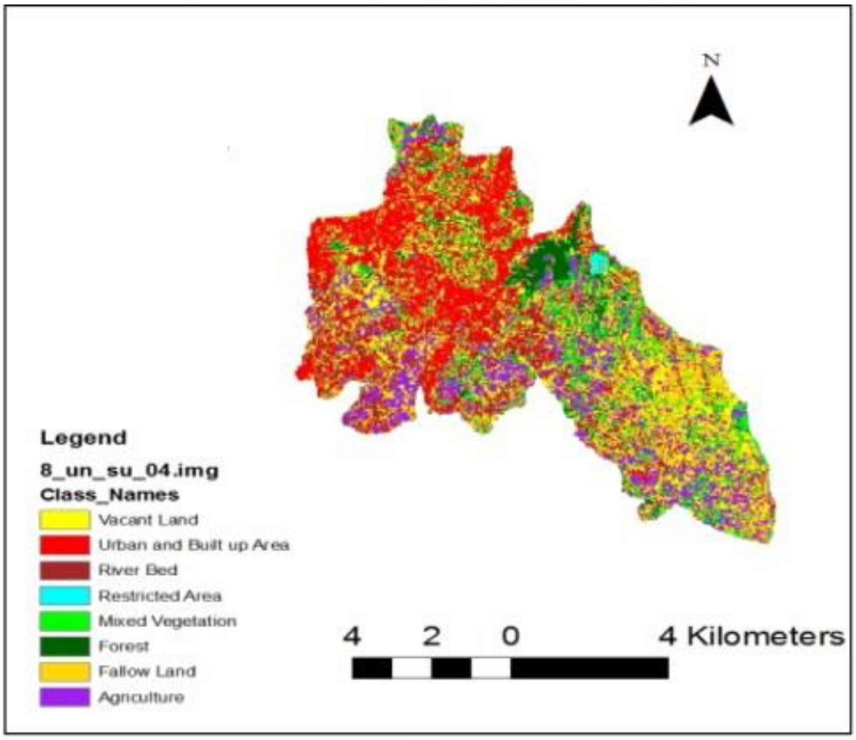
It is clear from the visual interpretation that urban and built-up area has increased significantly during the period 2004-2009. The accuracy assessment was used to validate the classification and to check the similarity of the classification with the actual classification. The cellular automata consists of four elements i.e. cells, states, neighourhood and rules, cells are the smallest spatial unit. The Table 3.1 shows the conversion matrix of landuse and landcover change from 2004 to 2009. Some aspects of Table 3.1 was adopted in this study.

Table 3.1: The conversion matrix

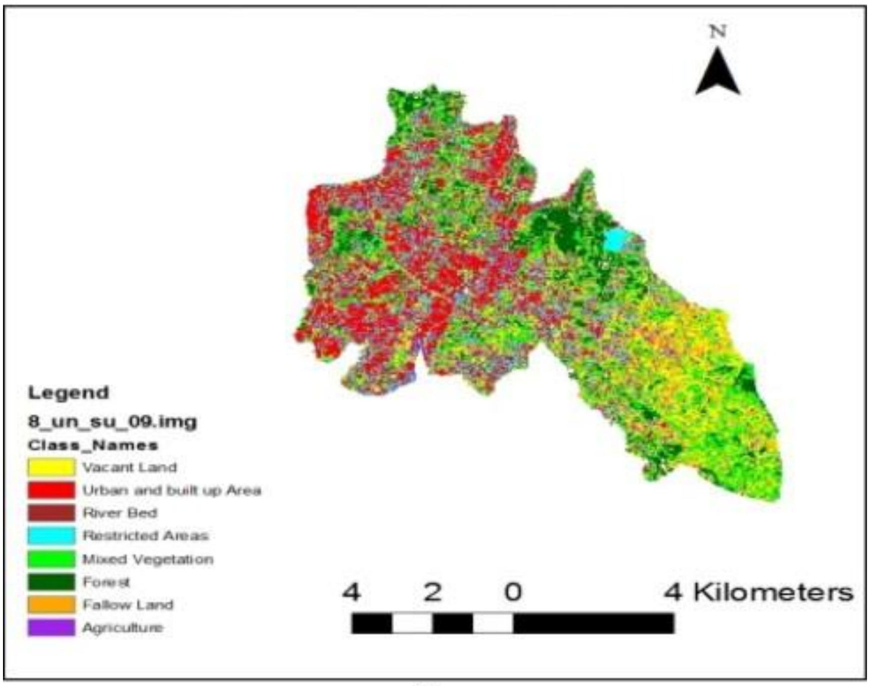
Classification	Built-up	Agriculture	Forest	Fallow land	River bed	Vacant land
Built-up	27.16	0	0	0	0	0
Agriculture	3.15	17.73	0	3.89	0	0.45
Forest	0.006	0	2.13	1.15	0	0.01
Fallow land	1.18	1.9	0	10.2	0	0.48
River bed	0.02	0	0	0	0.88	0
Vacant land	0	0	0	0	0	4.31

Source: (Deep, 2014)

The study demonstrated the application of remote sensing and GIS in landcover landuse changes using cellular automata. Fig. 3.2 shows the generated landuse map of the area for years 2004 and 2009. Built-up area has increased significantly. Fig. 3.1 was adopted in this research, also Fig. 3.2 was referred to while assessing the visual and qualitative characteristics of products generated from this research. The conversion matrix in Table 3.1 was also referred to while preparing the confusion matrix in this research.



A



B

Fig. 3.2: Generated landuse map of the area
Source: (Deep, 2014)

Khalilnia *et al*., (2013) made use of two images of Tehran the capital city of Iran, which were taken by TM and ETM for years 1988 and 2010 as base information layers to study patterns of urban growth for the city of Tehran using cellular automata and the logistic regression functions as transition functions. The main elements of the cellular automata include cellular networks, cell status, neighbourhoods, time and transition rules. A new model was built to predict the urban growth of the city of Tehran. To achieve this aim, a homogenous cellular network with two states, as urban and non-urban over two classified satellite images with a period of 10-years difference was used. The logistic regression was used as the transition function to assess the urban growth. This function has the ability to model the external effects and non-linear interactions between the relevant variables for it's non linear nature. Four factors were considered during modeling i.e urban, main road, agriculture and neighborhood as shown in the Table 3.2.

Table 3.2: Factors affecting the urban growth in Tehran.

Variables	Types of variables	Definition of variables	Ranges of variable
Urban	Spatial	Distance of each cell from urban cells	$0 \leq D$ norm ≤ 1
Main road	Spatial	Distance of each cell from road cells	$0 \leq D$ norm ≤ 1
Agriculture	Spatial	Distance of each cell from agriculture cells	$0 \leq D$ norm ≤ 1
Neighborhood	Spatial	The number of urban cells in the neighborhood of each cell	Depends on the neighborhood definition

Source: (Khalilnia *et al.*, (2013)

The city of Tehran is located in the Southern part of Albor mountains between east longitude from $51^{0}02^{'}$ to $51^{0}36^{'}$ with a length of approximately 50km, and north latitude from $35^{0}34^{'}$ to $35^{0}50^{'}$ with a length of approximately 30km. The landsat imageries were classified using supervised method in the ENVI software by the introduction of 10 learning areas for each landuse. The Table 3.3 shows the characteristics of the obtained images.

Table 3.3: Characteristics of the obtained images

Projection system	Base level	Satellite	Spatial resolution M	Radiometric resolution (m)	Sensor	Data of acquisition
UTM Zone 39	WGS 84	Land Sat 5	28.5	8	TM	27/9/88
UTM Zone 39	WGS 84	Land Sat	28.5	8	ETM^{+}	17/10/10

Source: Khalilnla *et al.*, 2013

A threshold was used to define the probability and the simulated image of the urban growth was generated. The pattern of urban growth were extracted using cellular automata and furthermore, the weighting co-efficient of parameters were selected. Urban growth pattern can be predicted with accuracy of up to 76% (See Fig. 3.3 for real land growth and simulated land growth for 2010). Fig. 3.3 and fig. 3.4 were referred to while assessing the visual and qualitative characteristics of products generated from this research. The variables in Table 3.2 shall be adopted with minor moderation.

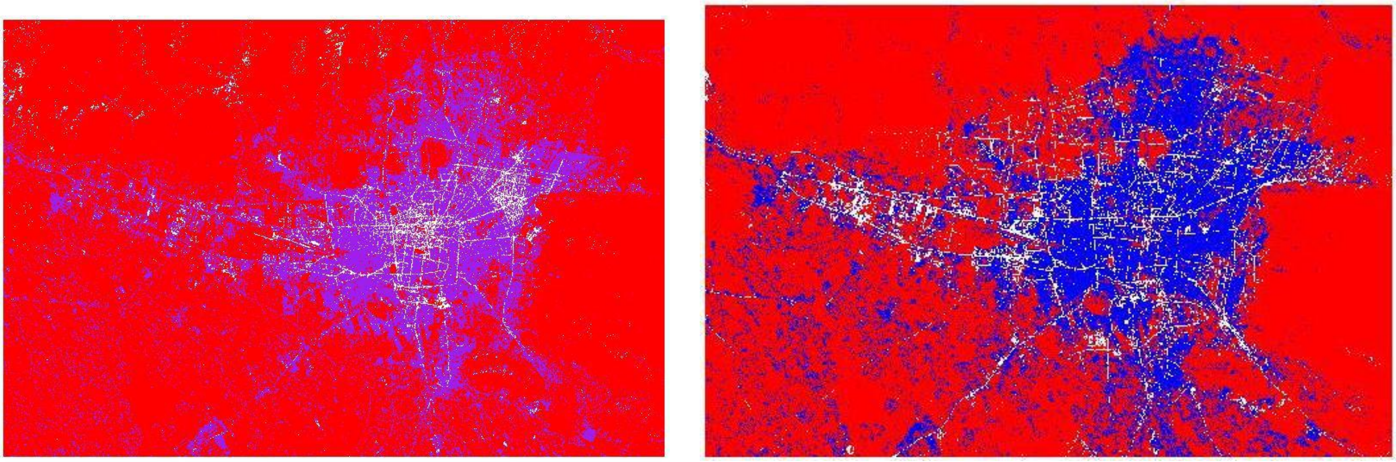
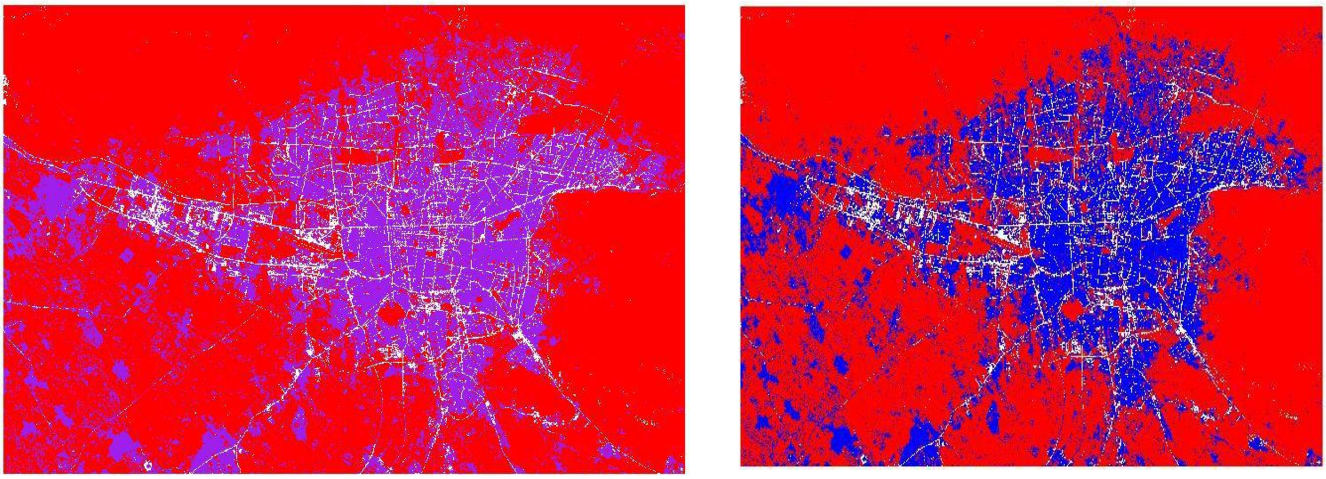


Fig. 3.3: Real land growth of Tehran in 2010 (a) and Simulated land growth of Tehran for 2010 (b)
Source: (Khalilnia *et al.*, 2013)



Urban Non-urban Pathway

Fig. 3.4: Two classified images used in the study, image obtained in 1998 (a) and in 2010 (b)

Source: (Khalilnia *et al.*, 2013)

Wu *et al*., (2011) carried out landcover and landuse at the phoenix metropolitan region in the United States of America. The phoenix metropolitan area is the fifth most populous and the fastest-growing city in the United States. It is located in the Northern Sonoran Desert, with a warm and arid climate. The metropolitan area is characterized by a decentralized pattern of dispersed new towns connected by a regional network of highways. The landuse map of 1995 and 2000 were used. The area was classified into urban land, agricultural land, desert and recreational land. A regular grid with cells of 100m x 100m was adopted. Logistic regression was used to help determine the probability of a cell to be converted to each of the four landuse types. Specifically, the regression equation is given by $\text{Log}\left(\frac{P_{ij}^{t}}{1-P_{ij}^{t}}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$. Where P^t_{ij} is the probability of the cell ($_{ij}$) for the occurrence of a landuse type at time t; X_1, X_2, … X_n are the driving factors and $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are corresponding co-efficients. The researchers used a regular grid with cells of 100m x 100m based on the appropriateness of most processes of interest and the available data. At each step, decisions of various agents affect land conversion on a cell-by-cell basis. The location of each cell was represented by the co-ordinates of it's center ($_{ij}$). A regression model was established for estimating the population growth, based on the population data of 1960-2000. $P_{(t)} = 1.7343 \times 10^{-30}\ e^{0.0383t}$. Where $P_{(tj)}$ is the population in year t . The square correlation coefficient of population at year t is 0.9986. Hence, there is a strong correlation between them. The standard error of the projection was 70.666mm. Table 3.4 depicted the projection for the area.

Table 3.4: Projections of phoenix metropolitan area (ha)

Landuse type	**1995**	**2000**	**2010**	**2020**
Urban land	54,290	73,012	101,452	105,591
Agricultural land	30,827	18,536	6,252	3,814
Desert	187,691	180,451	163,638	161,258
Recreational land	12,865	13,674	14,331	150,101

Source: (Wu *et al.*, 2011).

Several factors including topography, distance to railway, major roads, rivers, opens spaces and public facilities were considered as the determinants of the probability of landuse types. The proximity to major roads has a positive impact on the urban growth.

The researchers defined the probability of landuse conversion of a cell as, $\frac{P_{ij}^t}{1-P_{ij}^t} = f(S_{ij}^t, C_{ij}^t, n_{ij}^t)$. Where P_{ij}^t is the probability of the cell (I, j) for the occurrence of a landuse type at time t; S_{ij}^t includes the biophysical state of the cell ij at time t; C_{ij}^t is a constraint factor and n_{ij}^t is the neighborhood of the cell (i, j) at time t. The bio-physical factors that impact the landuse conversion includes elevation, slope, aspect and soil texture. The result shows that urban patches would increasingly expand and merge during the urbanization process. Urban landuse will increase faster from 2000 to 2010 and slow down a little between 2010 and 2020. Fig. 3.5 shall be adopted in this research work to depict maps for different epochs.

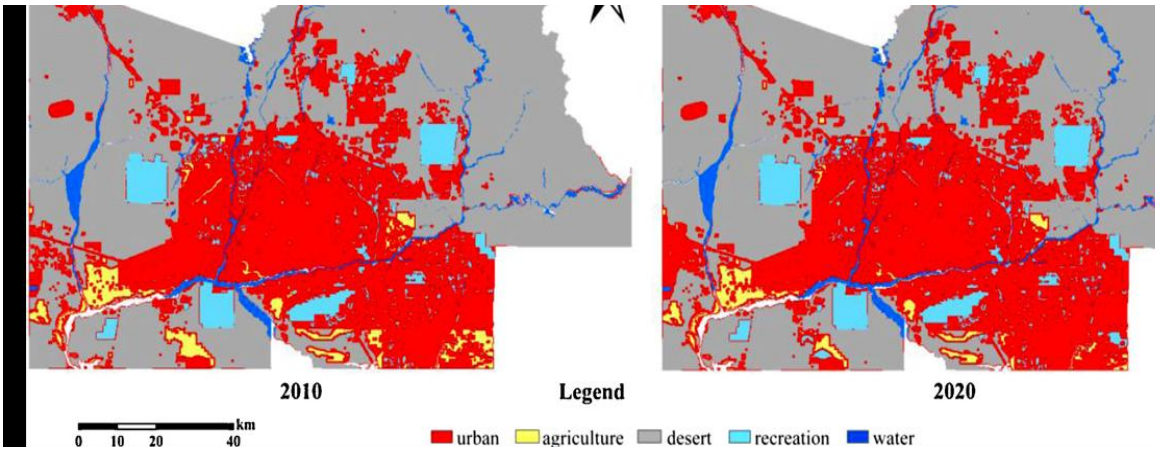


Fig 3.5:Generated map for 2010 & 2020

Source: (Wu *et al*., 2011).

Yaakup and Shamsuddin, (2007) predicted and simulated landuse pattern of Kuala Lumpur in Malaysia using logistic regression analysis and Geographic Information System technology. The landuse datasets for years 1990, 1997 and 2000 were obtained from the landuse/ cover obtained from the Department of Agriculture, Kuala Lumpur. The landuse categories were re-classified into agriculture, cleared land, forest, mining, open space/ recreation urban and water bodies. Additional data were obtained and digitized from hardcopy maps from the Department of town and country planning, Negeri. All data were converted into Arcinfo format for analysis. The tools under the Grid and spatial Analyst modules was used to prepare the necessary spatial variables. All data were prepared and stored in ArcGIS version 9 software and the logistic regression model was calibrated for the year 1997 using the statistical package SPSS version 13. All variables were converted into 100m by 100m cell format for analysis. The size of future urban area demanded by 2010 was derived by applying the urban area growth ratio calculated from 1990 to 2000. The ratio is assumed to be constant until the year 2010. The projected population growth for the year 2010 was adopted from the Draft state structure plan of Negeri. Before executing the logistic regression analysis the variables were first checked for spatial autocorrelation (spatial dependency) using the Moran's 1 Index computed using the Grid module of Arc info 9.0. It was found that the Moran's 1 index for all variables exceeded 0.8, indicating high autocorrelation. A spatial random sampling procedure was carried out using the Grid module, Arc GIS 9 was used to reduce the spatial autocorrelation detected to ensure that the logistic regression analysis produces more reliable parameters. The overall prediction success rate for the model was very good i.e 95.8% with 0.5% cut off value. The success rate for non- urban use was very high i.e 99.8%. However, the prediction success rate for urban use was quite low i.e 63.9%. This is understandable as the study area is predominantly rural in nature. The spatial information based on the prediction of urban extent can help planners and urban mangers to focus on the probable areas that are highly susceptible to change to urban use and appropriate policy measures could then be formulated to direct infrastructure to the relevant areas. Fig. 3.6 was referred to while assessing the visual and quantitative characteristics of products generated from this research.

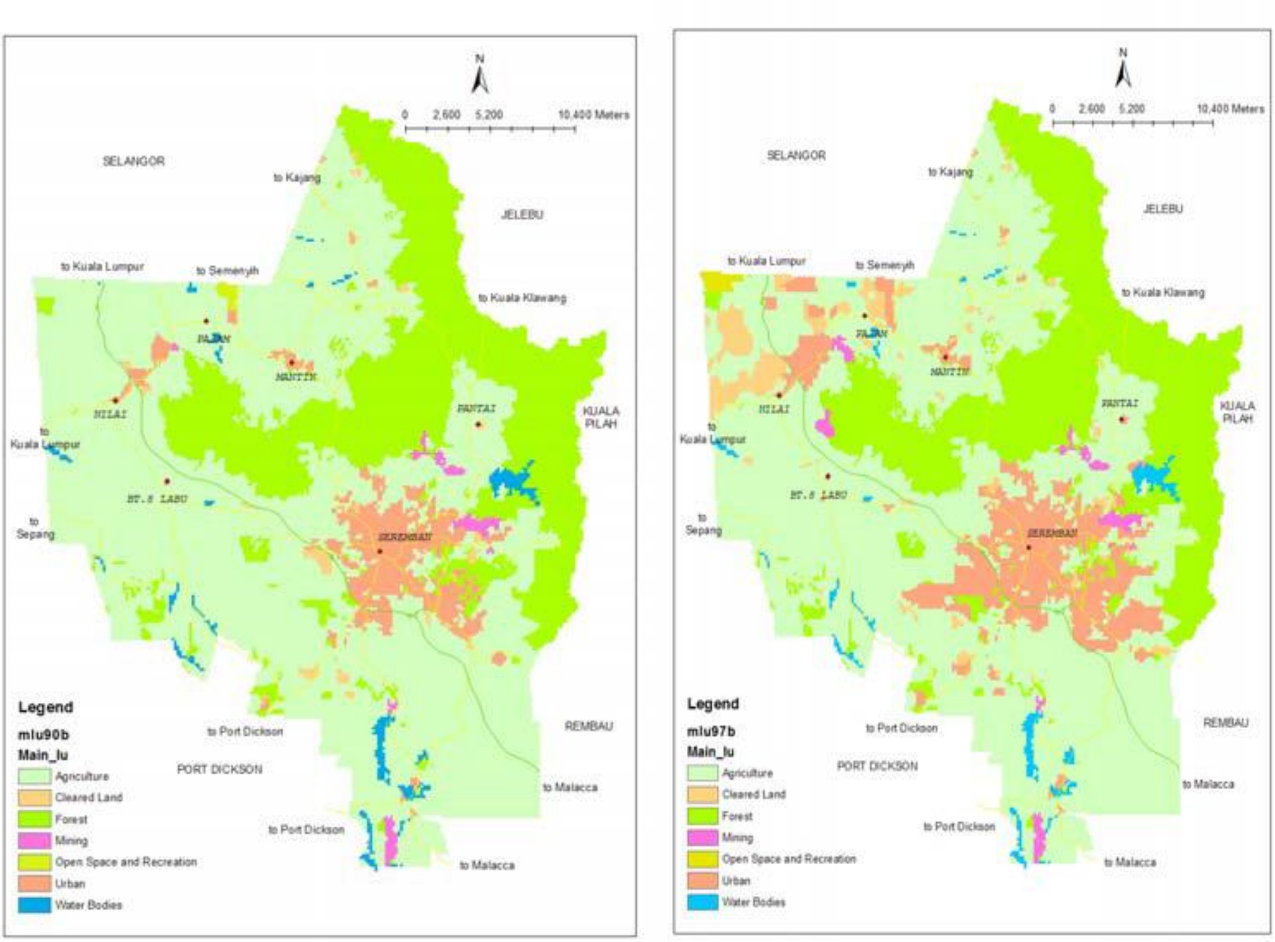


Fig. 3.6: Product generated for the area
Source: (Yaakup *et al.*, 2007).

Hong *et al*., (2000) carried out landuse changes at Paochiao watershed in Taiwan which is an urbanized watershed in the Tamsui river basin. The watershed is bordered to the south by the Taipei metropolitan area. The Paochiao watershed is approximately 98.61km^2 with a mean elevation of 214.82m. Due to the expansion of the Taipei metropolitan area, landuse and it's patterns in the Paochiao watershed have changed over the last decade. The total population of the area in 2000 was 237,861. Four historical SPOT images for 1990, 1993, 1998 and 2000 were used. The area was classified using supervised classification. The classified landuse data for all year were inputted into the landscape pattern analysis package using Geographic Information System (GIS) Software Arcview 3.0. The urban growth and the landcover change model were combined to form a probabilistic model to generate multiple simulations of growth. As a cellular automata model, space is represented as a regular grid of cells that change states as the model iterates. State changes are controlled by a set of conceptually simple rules that specify neighborhood conditions, such as slope suitability, that must be met before a change can occur. For this model, transition rules between time periods are uniform across space, and are applied in a nested set of loops. The outermost of the loops executes each growth period, whereas an inner loop executes growth rules for a single year. The transition rules implemented involve randomly choosing a cell and investigating the spatial properties of that cell's neighborhood and then urbanizing the cell based on probabilities influenced by other local characteristics.

The researchers used the logistic model given in equation (3.1)

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad \ldots(3.1)$$

Where p_i is the probability of a grid cell in the occurrence of a considered landuse type, the Xs are driving factors, β_1 is the coefficient of each driving factor in the logistic model. After fitting the logistic regression models to all landuses, the restricted area and landuse transition rules were specified for the watershed. The first step in the iterative procedure generates a preliminary allocation for which the iteration variable has an equal value for all landuse types by allocating the land-use type with the highest total probability of landuse occurrence for the considered grid cell. Conversions not permitted in the conversion matric are not allocated. Total allocated area is smaller than the demand area, the value of the iterative variable is decreased. These procedures are repeated as long as demands are incorrectly allocated, when allocation and demand are equal, the final landuse at this time step is saved and the allocation procedure continues for the next year until the target year is reached. The area of the water body was assumed constant during the simulation period. An area with a slope >21% was defined as restricted areas. Landuse transition rules indicated that forested, cultivated land, grassland and bare land can be converted between any of these land-use classes and built-up land, while the water body remains unchanged. Built-up land can be converted into other landuses with the highest conversion costs. The driving factors of landuse transition in this study are distance to major roads, altitude, slope, the distance to river, the distance to built-up land, distance to urban planning areas, soil drainage, soil erosion co-efficient and population density. Results show that increase ratio for built-up area is 82.58%. Other areas of land-use classes all decreased by 49.31%, 47.92%, 42.40% and 11.5% for cultivated land, bare land, grass land and forest respectively, the water body remained unchanged (See fig. 3.7). Fig. 3.7 was referred to while assessing the visual and qualitative characteristics of products generated from this research.

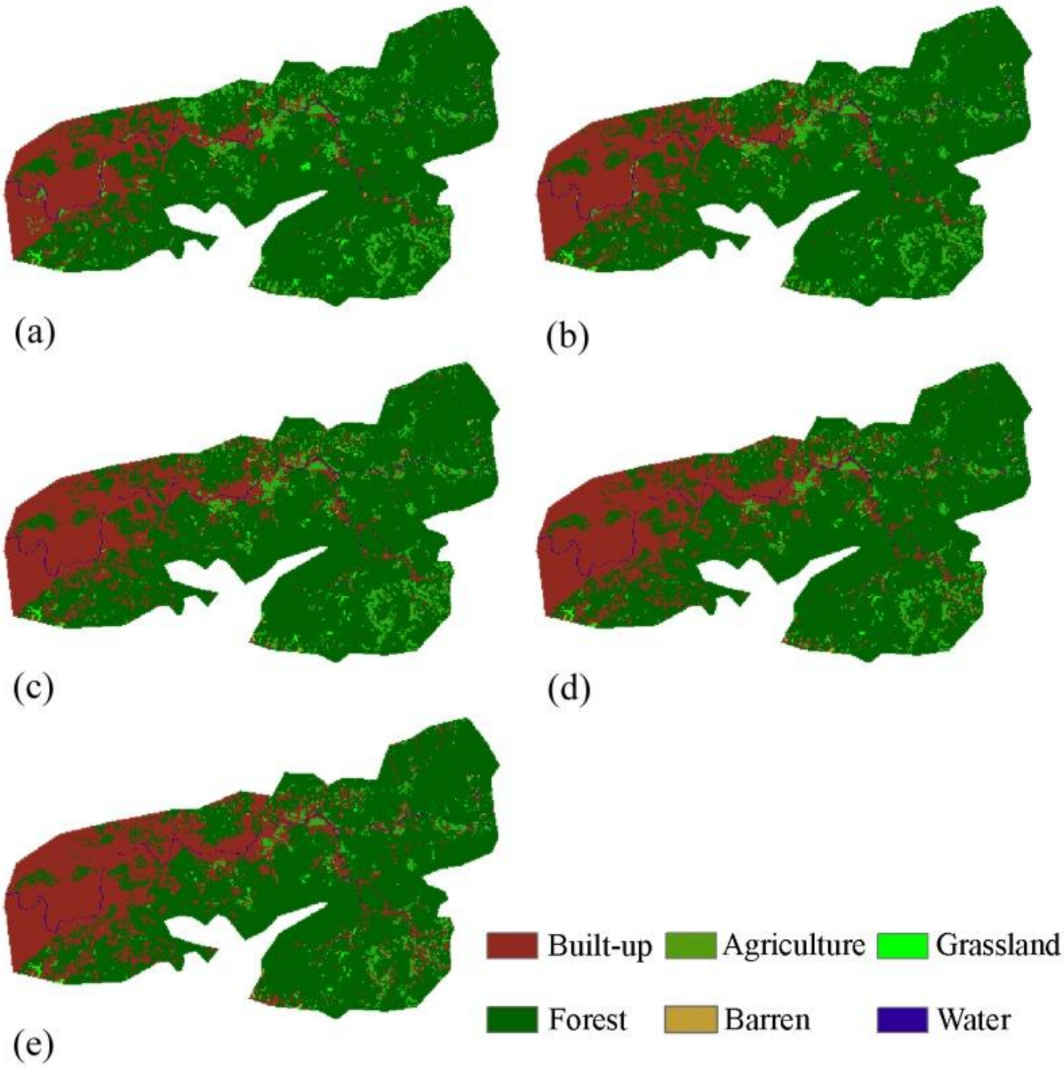


Fig. 3.7:The land-use distribution in Paochiao watershed in (a) 2005, (b) 2010, (c) 2015, (d) 2020, and (e) 2025.
Source: (Hong *et al*., 2000)

Almeida *et al*., (2000) carried out landcover and landuse change using cellular automata and multiple logistic regression at Bauru, Brazil using satellite imageries of 1979 and 1988. Urban landuse change based on the estimation of landuse transition probabilities using logistic regression were carried out. Different simulation outputs for the period were carried out and statistical validation tests were then conducted for the best results, employing a multiple resolution fitting procedure. From the period 1979 to 1988, five types of transition were observed: non-urban to residential use, non-urban to industrial use, non-urban to services, residential to services and residential to mixed use. To explain each of the five existent landuse transitions, twelve variables were selected from an initial bunch of over forty variables regarding infrastructural and socio-economic aspects of Bauru. Empirical procedures were used for variables selection, like the visualization of distinct variables superimposed on the final landuse map to ascertain the different types of landuse change. A preliminary selection of independent variables were then carried out, it then becomes necessary to check for their spatial dependence or association. This was carried out for all possible pairwise combination of variables existent in each of the five landuse transitions separately. The correlation indices for values less than 0.5 suggested less association, since none of the values surpassed this threshold simultaneously for the three indices considered, no variable initially selected for modeling have been discarded from the analysis. Probabilities of landuse transition were initially calculated for the whole study area in absolute terms i.e. without the influence of socio-economic or infrastructural factors. This was accomplished through a cross-tabulation operation between the initial 1979 data and final 1988 satellite data. A customized reckoning of transition probabilities was then conducted at the cellular level, taking into account the local socio-economic and infrastructural variables (See Fig. 3.8). Each landuse transition was separately modeled. Each transition is coded as 1 and permanence in the original state as well as changes to uses other than the one considered in the transition were coded as 0. A change in the cell landuse during the simulation period is dependent on its initial state as well as on its P_{ij} (x,y), which is the probability that a cell at position (x, y) will change from state i to state j. The dependence of the local transition probabilities $P_{ij}(x,y)$ on each independent variable Vn(x, y) was estimated by the logistic model (See Fig. 3.9). A statistical package MINITAB release 13.0 was used. The simulation output was accomplished using ER – mapper employed by the

DINAMICA model. The simulation result was validated according to a multiple resolution fitting method and the value for goodness of fit obtained for window sizes of 3 x 3, 5 x 5 and 9 x 9 cells was 0.907868. It is observable that the landuse transitions comply with economic theories of urban growth and change, where there is a continuous search for optimal location. Fig. 3.8 and Fig. 3.9 were referred to while preparing the visual and qualitative characteristics of products generated from this research.

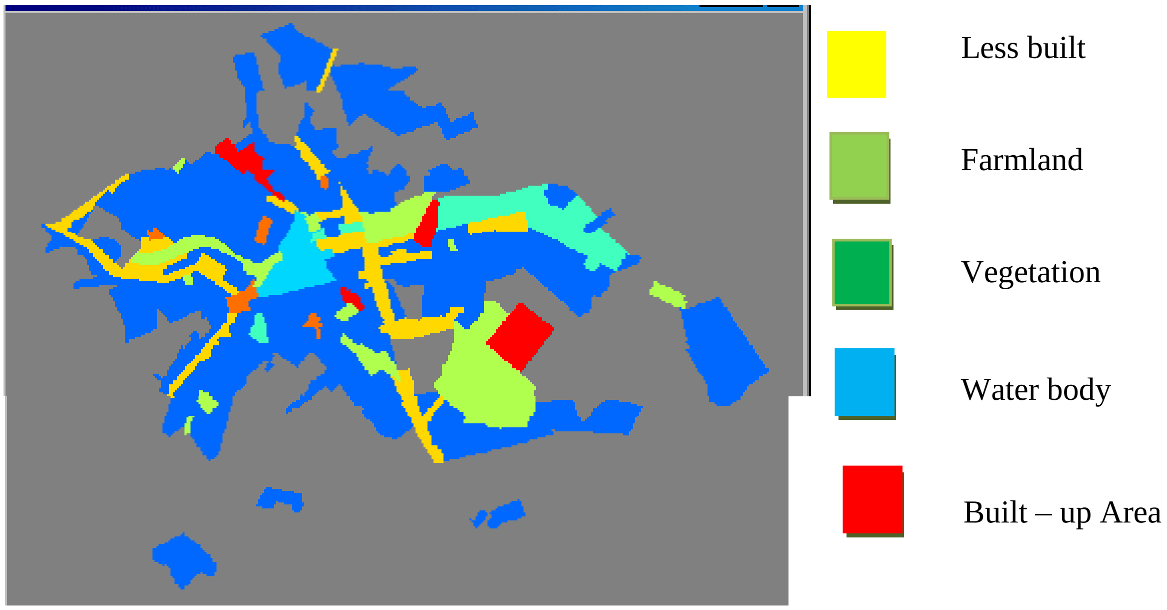


Fig. 3.8: Example of a map of probabilities for the transition “res_serv”. High probabilities are in mid gray.

Source: **(Almeida *et al.*, 2000)**

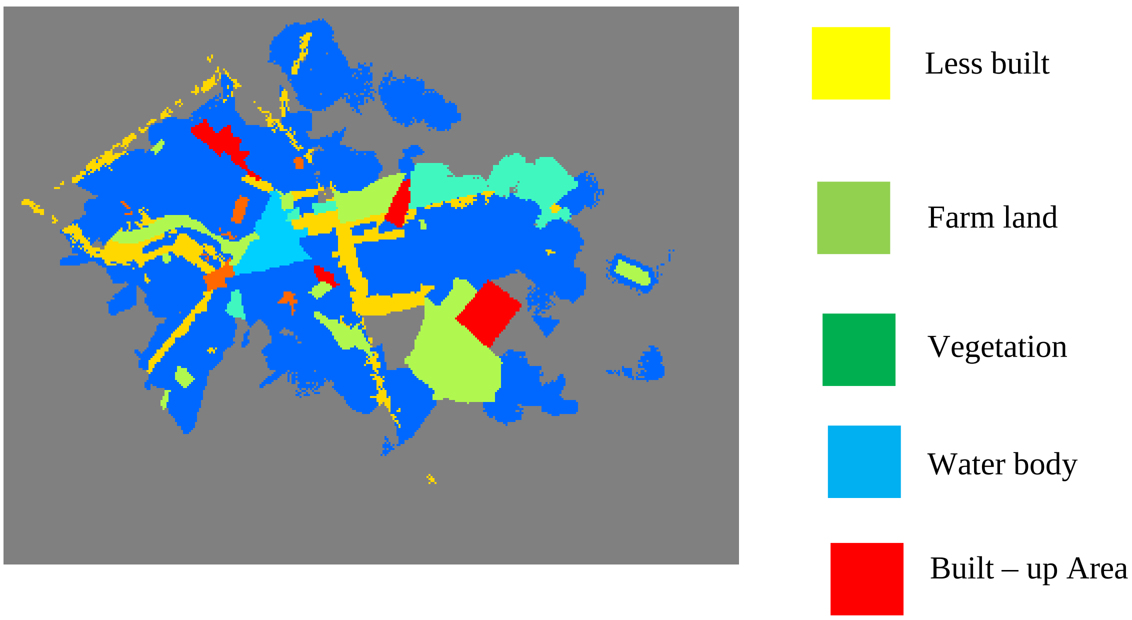


Fig. 3.9 : Example of a landuse transition map: “res_serv”. Areas of transition are in light gray.

Source: **(Almeida *et al.*, 2000)**

3.2 Landcover and Landuse change analysis using cellular Automata

Khatibi, (2015) The researcher carried out application of genetic algorithm for simulation of landuse and landcover changes in Karaj city, Iran. This study, present a new method to simulate urban landuse changes based on developing a python program for optimizing the results and investigating the efficiency of Genetic Algorithm tool in DINAMICA EGO and investigating it's effectiveness. Karaj city located 35 kilometers west of Tehran province and south of Alborz mountains was considered as the study area. This area is located between latitudes of 35^0 42' N and 35^0 53'N and longitudes of 30^0 50' E and 31^0 03'E. In this study landuse cover map of Karaj was produced from satellite images of TM and ETM+ of landsat from 1985 to 2000. These images were pre-processed, processed and post-processed and different landuse cover classes were derived. For mode implementation of landuse cover using cellular Automata, there are different platforms such as SLEUTH, LEAM and MOLAND which have only the ability to model binary changes. Many models such as SLEUTH are implemented in a distinctive framework using predefined parameters. In this study, DINAMICA EGO, a raster based software was used. This software not only is it able to model unlimited changes of a class, but also the user could enter any amount of changes to the model. Also several tools are implemented in the software in order to facilitate the users with limited knowledge of computer programming to perform spatial analysis. There is a tool in DINAMICA EGO for comparison which determine minimum and maximum similarity according to reciprocal similarity based on fuzzy analysis. The tool was used to determine moving window size on the maps. These dimensions are numbered between 1 and n and used to compare patterns and structures of the map changes in the dimension of moving windows used to investigate border and area of cells of a class and to model and perform analysis. After determination of the original matrix of coefficients in preparing the model, modified matrix of co-efficient was computed by the developed genetic algorithm program. In the next step, the new DINAMICA EGO model was run by using original and modified matrix separately and maps of landuse landcover changes were stimulated. Finally the result of model implementation were validated for two produced maps and a comparison among original and genetic algorithm co-efficients were accomplished in order to clarify that genetic algorithm is useful or not for improvement of simulation results. Accordingly a performance and structuring of genetic algorithm, were implemented using python 2.7 programming language and the primary matrix of coefficients was used as input and optimized matrix of coefficients as output. Algorithm of implementation of the program was carried out by using primary matrix of the coefficients as first parent chromosome in the program. Collection of amounts in the matrix was considered as gene. Then possible up and bottom limits for the purpose of jump were directed to the program. Some parts of chromosomes were released in the original manner and some were randomly selected. Then, the previous process was repeated using parent chromosome with respect to population size and therefore a new population is formed from the parent gene. Genetic algorithm considers evolutionary approach and addresses gene diversity, natural selection and simulates a population in genetic algorithm which was entered to the model and then new simulation results were compared with the outputs of the main model. Also, reciprocal similarity method was used in this research for comparison which is a combination of Kappa accuracy coefficient and fuzzy analysis. In this method, sore areas with same size on both maps were compared in the way that their similarity index amounts to the difference with the base map. In this research, model assessment using genetic algorithm demonstrated that there is no significant difference between the result of main model and genetic algorithm application. It seems that genetic algorithm approach will lead to optimal result but this does not guaranteed that it has better outputs compared to original status.

Cui *et al.*, (2014) carried out urban landuse changes in the city of Wuhan, China using cellular automata. To simulate the urban landuse change, the transition rules of the model were set by globally restrained conditions, locally restrained conditions and a random variable. Then landuse patterns and changes were obtained from classified landsat TM images. A spatial temporal transition matric was constructed from the classified images and was applied to the proposed model for simulating landuse changes in the city of Wuhan. To define the spatial objects, the simulation objects were first divided into regular grids. Each grid was considered as a cell. For urban land, the cellular space consists of all the grids within the study area. Each cell may appear in one of the following states; vegetated land, agriculture land, developed land, water or undeveloped land. The state changes of cells from one cell state to another one are restricted by two major restriction conditions: the spatial value of cells and change threshold of cell state. Spatial value influences urban landuse change, but threshold values control the type change of landuse. Not only is urban development influenced by spatial factors such as traffic, hydrology and terrain, but also is influenced by local environment. The two images were captured at different times, the researchers obtained a state change probability pattern for landuse. The thresholds for transition rules can be set based on the probability image and the real landuse information. Once the transition rules are ready, the landuse change pattern can be simulated. The total probability was then normalized to a value within (0,1) and compared with the threshold. When $P_t < P_{threshold}$, the landuse has changed to other land including vegetated land, agriculture land and undeveloped land. Table 3.5 was used in this research work since the various classes transited to built-up area; also Fig. 3.10 was used while preparing the landcover and landuse maps.

$P_t \geq P_{\text{threshold, i – developed land}}$

P_t , P_{threshod}, i – other land

Table 3.5: Transition probability patterns of landuse from 1999 to 2002

Year	1999	2000	2001	2002
	Agricultural land	Undeveloped land	Developed land	Vegetated land
Agricultural land	0.6585	0.0287	0.3111	0.2016
Undeveloped land	0.127	0.5097	0.2507	0.0926
Developed land	0.0934	0.0796	0.7594	0.0676
Vegetated land	0.1316	0.0378	0.1904	0.6807

Source: (Cui *et al.*, 2014)

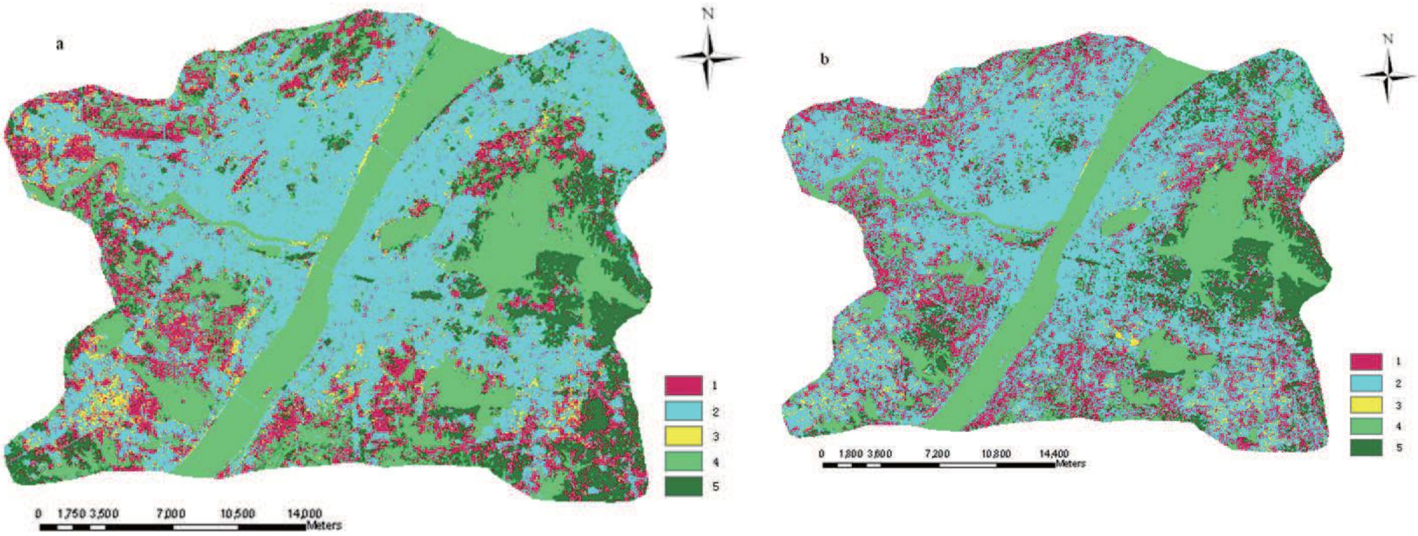


Fig. 3.10: Comparison between the simulation result and the actual image of 2005 (1 represents agriculture land, 2 represents developed land, 3 represents undeveloped land, 4 represents water and 5 represents vegetated land)

Source: (Cui *et al.*, 2014)

Pradhan *et al.*, (2013) carried out landuse change using cellular automata, statistical and empirical model using multiple logistic in Tripoli, Libya. Tripoli is located between latitudes N32^0 33’ and N32^0 53’ and longitudes 12^0 50’E and 13^0 3’E along the Mediterranean coast in North Africa. It covers an area of 1,143.73km^2 with population of about 1.3 million. In this study, four satellite images were classified to extract the landuse maps of metropolitan Tripoli. Landsat-TM for 1984 and 1996 including SPOT 5 for 2002 and 2010 were used. The maximum likelihood classification technique which is a supervised classification method was used. The images were classified by selecting accurate polygons as training areas based on field survey of the study area. Three classes were used namely built-up, agriculture and excluded areas. The classified images were re-sampled to the same spatial resolution (30m x 30m). The selection of the pixel size was intended to avoid the decrease in spatial details of the images. Therefore, the re-sampling step was conducted after image classification. Consequently, the analysis, simulation and future landuse change prediction were carried out using Idrisi software. The transition probability matrices provide the transformation rules and demonstrated the change probability of different landuse classes into other classes, while the transition area matrix reflect the quantity of landuse change to other landuse classes in the predicted future. The contiguity filter 5 x 5 was selected i.e. each cell centre is surrounded by matrix space 5 x 5 cellular to reflect the cellular changes significantly. The result of landuse changes were presented in the (Table 3.6). The results illustrate landuse change history and quantity of change in each landuse class. However, this remarkable rate of landuse change (agriculture area to built up areas) raises many questions about urban growth patterns, driving forces of urban growth process, urban policies and sustainable environmental regulation implemented in the studied area. The amount of annual landuse changes are shown in Table 3.6 from 1984 to 2010 for Agriculture and built-up areas. The method of presentation in Table 3.6 was referred to while determining the landuse changes in this research work.

Table 3.6: Amount of landuse changes observed in square kilometers

	Agriculture area	**Built-up area**	**Restricted area**
1984	1,018.47	86.40	38.89
1996	972.10	132.77	38.89
2002	941.05	163.82	38.89
2010	829.26	275.61	38.89
Annual change 1984-1996	-3.86	3.86	0
Annual change 1996-2002	-5.18	5.18	0
Annual change 2002-2010	-13.97	13.97	0
Total change	-189.21	189.21	0

Source: (Pradhan *et al.*, 2013)

Zang *et al.*, (2012) carried out modeling of urban landuse of Daqing city in China. The city experienced unprecedented urban expansion due to rapid development of Petroleum industry. Daqing is situated between the latitudes of $45^0$46’N to 46^0 55’N and longitudes of 124^0 19’ to 125^0 12’E. It covers an area of 5,144 sq kilometers and comprised of five sub-districts including Ranghulu, Saertu, Longfeng, Honggang and Datong. The population of Daqing is about 1.31million. The modeling was carried out using landsat Thematic Mapper (TM) images acquired in 2000 and 2005 and spot images taken in 2010 which were acquired from the China remote sensing satellite ground station and the landuse survey office of China. These images were geo-rectified and mosaiced with high resolution images. Six landuse classes, agricultural land, forest, grassland, built up area, water and barren landuse were derived using the unsupervised classification function provided by the ERDAS Imagine 9.3 software. Classification accuracy was improved by manual interpretation. The cellular automata model was developed using the expression $U_i = f(P_i, N_i, C_i, R_i)$

where U_i is the probability of cell I being converted to urban landuses, P_i is the global urban expansion probability, N_i is the neighborhood effect, C_i is the constraint factor and R_i is the random factor.Logistic regression analysis was used to determine the global urban expansion probability. The neighborhood effect was calculated by dividing the number of urban cells within the neighborhood by the total number of cells in a neighborhood (e.g 3 x 3 cells). The resultant Ni, therefore represents the impact of neighboring land and uses on the land conversion probability of a particular cell. Furthermore, two constraint factors (l, i) slope and water body were incorporated in the cellular automata model. In particular, a cell with a slope $22^0.5$ and higher or identified water body cannot develop into urban lands. Results shows that the city experienced a rapid urban expansion with a significant increase of built-up lands from agricultural land, grassland and water body. Specially, the geographic area of the built-up land has increased from 32,380 ha in 2005 to 50,224 ha in 2010 with an increment of 55.11%. Simultaneously, rural lands including agricultural land, grassland, and water body decreased to 2.16%, 14.07% and 27.84% respectively.

Qui and Ballestores, (2012) carried out landuse change at Hunterdon county in New Jersery in the United States. It encompasses $1,094km^2$ of the western portion of the state and has 26 municipalities. The population of the area is approximately 129,000 people. The landsat data for 1986, 1995 and 2004 were used in the modeling and editing carried out within the ArcGIS environment using agent analyst. The transition rules embedded in the cellular automata model was modified to include government regulatory policies on landuse changes. Three sets of landuse/cover were used to ascertain the landuse change. The landcover/use was classified into 6 categories i.e. agriculture, barren lands,forest, urban, wetlands and water based on a modified Anderson classification system. The usual neighborhood configurations used in cellular automata models include the Von Neumann pattern that assume a lattice composed of regularly shaped cells or grids. The neighborhood in this study was defined by an external buffer with a thickness of 145m around the edge of a cell. Driving factors that were considered includes landuse type of cell, distribution of landuses in a parcel's neighborhood in terms of percentages, parcel size, amount of wetlands within a parcel, distance from the center of a parcel to its nearest stream, major roads and urban centers. The distances from the center of a parcel to it's nearest streams, roads and urban centers were calculated by conducting NEAR analysis in ArcGIS between the point layer and the respective line layers. The average slope for each parcel was calculated using the spatial analyst in ArcGIS by overlaying the slope raster with the parcel layer. When applying the landuse change prediction model, the transition rules were derived using 1986 and 1995 re-classified parcel-based landuses in Hunterdon county. The derived transition rules were then used in the cellular automata module to predict future landuse pattern using the parcel-based landuses in 1995. Since the transition rules were based on cumulative landuse changes in a 9-year period from 1986 to 1996, the future landuse changes predicted by the model should reflect the landuse pattern in 2004, the 9th year from 1995. Since no landuse data for 2004 was available, the landuse data in 2002 was used as a reference to evaluate the model performance using an array of accuracy measurements.

Pereira *et al*., (2012) aimed to model the dynamic use and landcover of the sub-basin of Arroiro Grande in Brazil.Summer data for 1991, 2002 and 2011 of Land sat 5 TM sensor and land sat 7 ETM + were used. The geo referencing and image classification were carried out using SPRING software developed by the National Institute for space research. Supervised classification was carried out. Shuttle Radar Topography Mission (SRTM) was used to prepare the slope map. The Dinamica EGO uses the cellular Automata method as a model of spatial simulation, the input parameters were thematic maps of the landscape (usually derived from remote sensing data) represented by a matrix. Spatial variables were classified as dynamic and static. The structure of the Dinamica EGO is based on Functor. It uses two complementary processes, the functor Expander which is a function responsible for expansion and contraction of the thematic classes of patches and patcher responsible for the formation of new patches, the variance and the isometry of the patches. Similarity measures for fuzzy logic was applied in the context of the local neighborhood on the actual maps and simulated maps. The functions of exponential decay and decay constant are applied when comparing the two maps in two ways i.e they have a map of similarity of the first map that is related to the second among the values chosen as the lower value. This method presents only cell that have not changed in comparison as can be seen in the equation. If (i1 = i 2) then null else i2. Where i1 and i2 were map 1 and map 2 respectively. There is significant increase of forest areas and the class of agricultural use which resulted in the decrease of the field areas (see Table3.7). Between 1991 and 2002 forest areas increased by 4.49% , the areas of agricultural use 37.21% and 18.08% decrease in fields. Between 2002 and 2011 the tendency remains and the forests have increased at a rate similar to the previous period 4.98%, as agricultural areas had a less significant increase being 17.8% and a reduction in the field presents a slight decrease compared to the previous index of 17.3% (See Table 3.7). Table 3.7 was referred to in this research work while determining the changes of the landuse and landcover; also Fig.3.11 served as a guide in the preparation of the products generated in this research work.

Table 3.7: Evolution of landuse and landcover in the sub- basin

Thematic class	1991(ha)	2002(ha)	2011(ha)
Forest	15,078.15	15,735.625	16,,517.07
Field	14,812.65	12,103.625	9,959.85
Agricultural use	5,376.78	7,339.3125	8,652.15
Water Shed	89.64	173.3125	231.3

Source: (Pereira *et al.,* 2012)

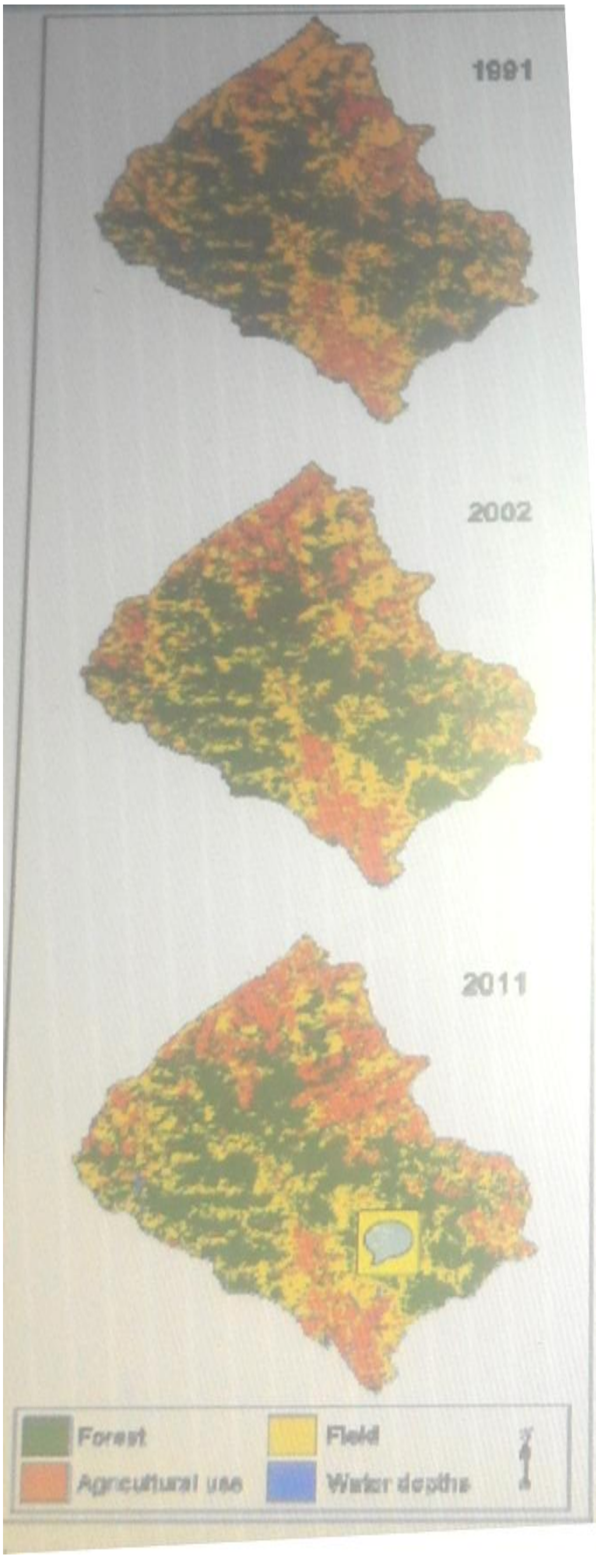


Fig.3.11: Thematic maps of landuse and landcover in micro-basin of Arroio Grande in 1991, 2002 and 2011.
Source: (Pereira *et al.*, 2012)

Araya, 2009 carried out urban landuse change analysis and modeling of the concelhos of Setubal and sesimbra in Portugal using multi temporal and multi spectral satellite images acquired in the years 2000 and 2006. The total area is about 2,957.4km^2 and the population of the area is around 2.6million. The specific objective of this study is to quantify and investigate the characteristics of urban landuse over the study area using satellite images. Classification was carried out, then change detection was carried out. Various softwares were used to process, quantify, analyse and model the spatial dataset. For the preliminary data processing, the study area was extracted, Arc GIS 9.2 – Arc info version was used. Cellular automata was accomplished using base landcover image for 2000, the transition area matrix and transition suitability maps. A contiguity filter was used in which a pixel that is near one landuse category e.g. urban area is more likely to become an urban pixel than pixel that is farther. The definition of nearby is determined by a spatial filter that the user specifies. In this study the default contiguity filter in idrisi 5*5 was applied. The 5*5 contiguity filter considers the predicted landuse change to be within two pixels of the edge including the diagonal. Based on these inputs, the module determines the location of change, the number of pixels that must undergo each transition and the pixels were selected according to the largest suitability for a particular transition. The initial analysis used the 1990 and 2000 landcover maps to predict for the year 2006. Due to their unsuitable nature for urban development, three landcover classes; water bodies and marsh area, developed areas and protected area were considered as a constraint. These were created from the landuse map of the year 2000, which was used as a base for simulation. Fig.3.12 presents the actual and simulated landuse maps for the year 2006 based on the minimum mapping unit (MMU) of 1ha and 25ha. Fig. 3.12 was referred to in this research work.

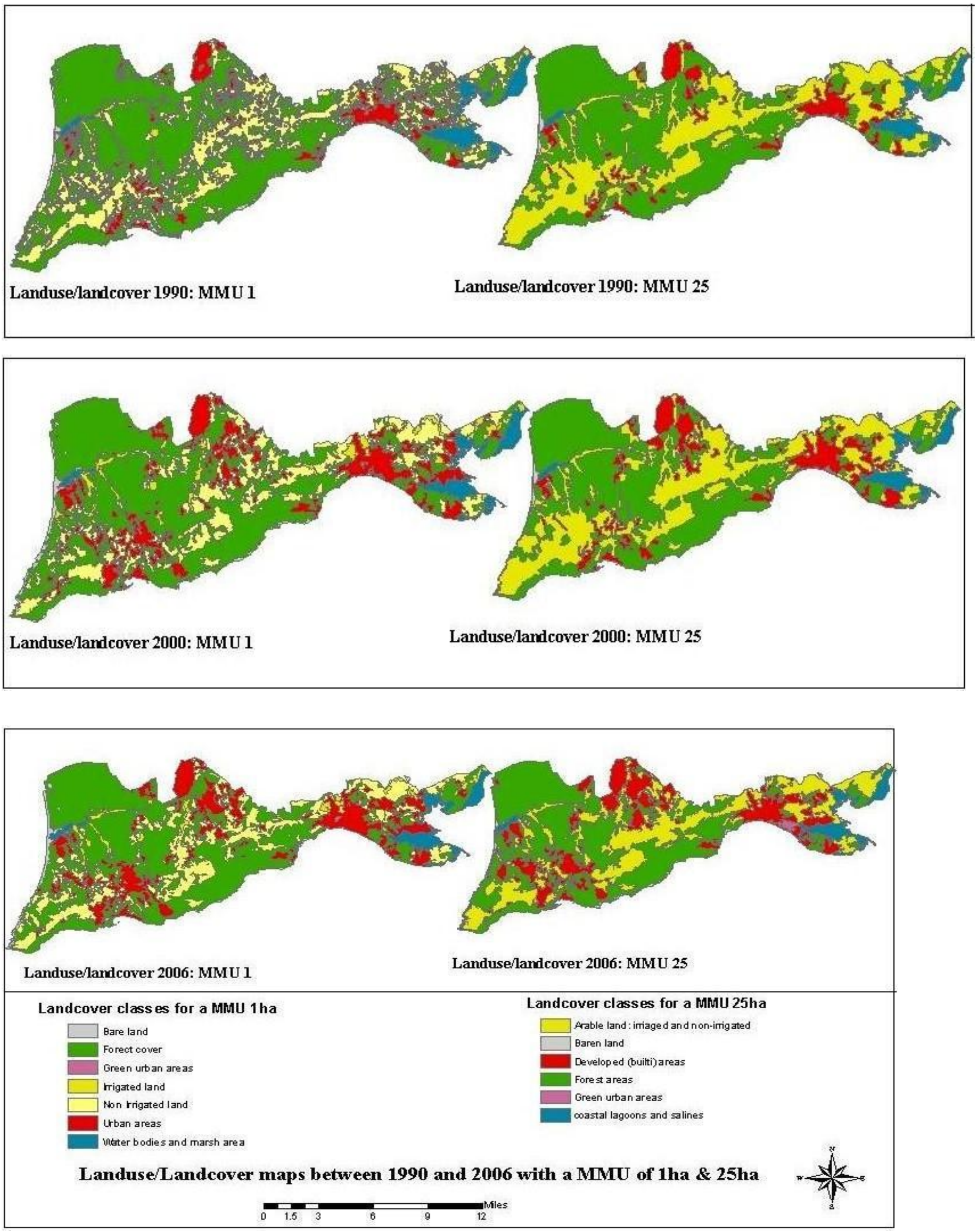
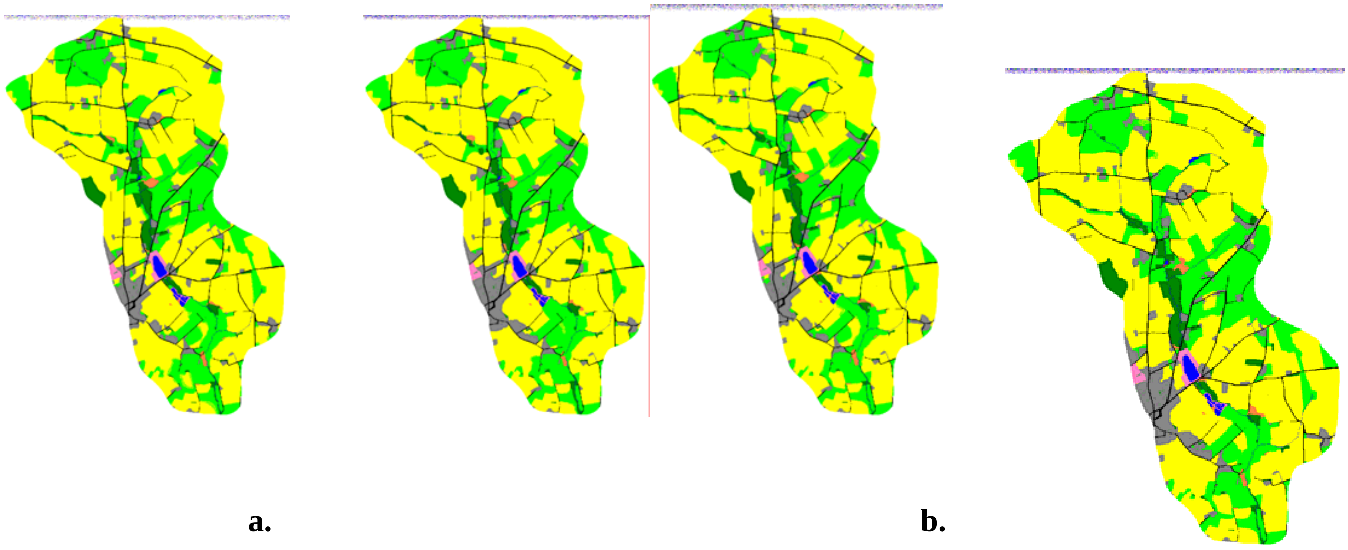


Fig. 3.12: Landuse/landcover maps between 1990 and 2006 with a MMU of 1ha & 25ha Source: (Araya, 2009).

Houet and Lawrence, (2007) carried out landcover and landuse changes using cellular automata in the central Brittany in western part of France. The watershed of the Coet-Dan River which covers 1200 ha is characterized by intensive agricultural activities. A time series of multi-scale and multi-temporal satellite imageries were used. Different landcover classes were identified from remote sensing data used which includes built-up areas, woodland, Grassland crop and plantation. Cellular automata function available in Idrisi Kilimanjaro software was used. A transition probabilities matrix which determines the likelihood that a cell or pixel will move from a land-use category or class to every other category from date1 to date 2 was adopted. This matrix is the result of cross tabulation for the two images adjusted by the proportional error and is translated in a set of probability images, one of each landuse class. A transition area matrix which records the number of cells or pixels that are expected to change from each landuse class to other landuse class over the next time period was also adopted. This matrix was produced by multiplication of each column in the transition probability matrix by the number of cells corresponding to landuse in the later image. Transitions rules were produced for each landcover class using a suitability map built from spatial dependencies and driving forces of change. Suitability maps represent the probability (range from 0 to 255) of a pixel or a cell to belong to the corresponding landuse type. Each suitability map highlights where changes are plausible for one landuse category if the future changes could not occur in some specific areas e.g. urban areas cannot become crops. The set of all the suitability maps used to project and model a foresight scenario integrates transition rules. The researchers opined that suitability maps correspond to Boolean images where landcover types will not change woodland, fallow land, built-up areas, crops and grassland. The projection in the next future phase is processed by considering specific spatial rules (driven factors of changes and their respective weight) except for some areas where constraints are set. The approach adopted by the researchers shows the influence of spatial relationship between landscape features and landuse/landcover changes, which have to be taken into account to improve urban planning. It was discovered that using cellular automata to model landuse and landcover plausible state there is the possibility of integrating multi-scaled factors of landscape evolution. The two scales used by them were field scale and farm scale. (See Fig. 3.13). The format of presentation in Fig. 3.13 served as a guide in the preparation of products generated in this research work.



a. **b.**

■Roads ■Built-up areas ■ Woodland □ Fallow land □ Crops ■Grassland ■Leisure space ■ Water

Fig. 3.13: The projected landuse and landcover for 2015 and 2030 with a long time trajectory –1981-1999– (a) without considering (b) or in considering the landscape features (riparian wetlands and hedgerows network)
Source: (Houet and Lawrence, 2007).

Lei *et al*., (2006) adapted METRONAMICA an established cellular automata (CA) modeling system in Jinhu ,China which is located along the coast line with a total area of approximately 7849 Square kilometers. Jinhu a city is located in Western liaoni corridor near the liadong bay. Jinhu coastal area belongs to temperate mon soon climate, it’s topography is rolling. The main data sources are 1990, 2000, and 2010 three phase remote sensing datum (120-31, 120-32, 121-31, 121-32) and administrative map of the area, related plan and datum of four cities, landscape classification was based on the characteristics of natural geography of the area. The landuse status issued in 2007 was used as reference material and the whole area was classified into farmland, garden, forest, grassland, built-up area, water body and unused land. The researchers used Auto sync module of Erdas 2011, the landsat TM images in 1987 was used for the calibration and served as the base to adjust the images in 1990, 2000 and 2010. Band selection for false color synthesis and remote sensing image interpretation were carried out. ArcGIS 9.3 was used to prepare the landuse map, field investigation data and google earth high resolution images were used to support image interpretation and analysis. An integrated model was carried out using Logistic regression model and Cellular Automata model. This model uses a dynamic multi-period conversion rules that are based on multiple time-based data to predict the landuse quantity. This model was used. $X_{t+1} = M_{ij}x_t$ (i-j = 1, 2, …, n). Where X_{t+1} and x_t are the status of landuse in t+1 and t time, M_{ij} is the different time interval condition transition probability matrix. In this study the cross tab function in GIS analysis module of IDRISI 15.0 was used to calculate the transition probability matrix. Cellular Automata was used effectively to model the dynamic of change in events due to promixity. A cellular automata is a cellular entity that independently varies it's state based on its previous state and that of it's immediate neighbor according to a Transition rule and a neighbourhood function defined by transition rules that involves immediate neighboring cells and a number of contributing factors such as topography, proximity to urban centre and transporting network. The unit problem in standard Cellular automata simulation was operated on a cell by cell basis. A cell which is the basic unit of cellular automata has only a binary value 1 for successful development and O for non-change. There are no intermediate values for these black or white cells. This raises a problem when there is a need to differentiate growth rates between cells or for a cell between different periods. The grey state of the cell was used to overcome this problem by assigning a value that ranges from O to 1 for each cell in the Cellular automata model, so there is the need to determine the values of cell status which is the basic idea of logistic – Cellular automata model. The parameters of logistic – Cellular automata model are, total amount of simulation conversion 777, the iterative number of times is 2, the diffusion parameters is 3. A comparison of the three epochs shows changes in landcover due to landuse. It was discovered that changes occur around farm land, forest, built up area and water body. Landuse models are useful tools to understand the landuse process and spatially explicit urban expansion models to trace urban development and predict the possible expansion in the future. (see Fig.3.14). A prediction map was produced in this research work similar to Fig. 3.14

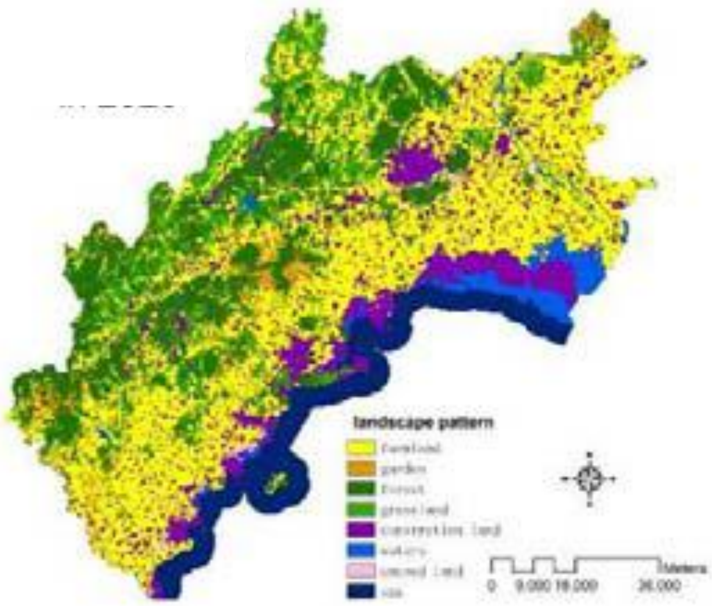


Fig.3.14: Simulation map for 2020

Source: (Lei *et al*., 2006).

Batty *et al*., (2004) carried out landcover and landuse changes at Delaware State. The state is partitioned into three counties from north to south, New Castle County, Sussex County and Kent County. The population of the area is about 796,000. Satellite imageries for 1984, 1992 and 2000 were used. Seven different types of landuse classifications were employed; residential, commercial, industrial, agricultural, forest, water and barren. Residential, commercial and industrial areas were categorized as urban regions, while agricultural land was considered as a rural area with considerable potential for urbanization. A post-classification comparison method is used to detect the landuse change. Bi-temporal change maps can be generated by overlaying individual classifications using the Arcinfo software. The researchers modeled the urban growth using a spatial logistic regression model. A post-classification assessment is used to analyze the landuse change between two periods of time. The researchers used a 50m x 50m cell size, seven predictor variables were compiled using Arcinfo. A summary of these predictors are shown in Table 3.8. Three categories of predictors were employed; site specific characteristics, proximity and neighborhood characteristics. Since population is a leading force propelling global landuse change, the site specific, population density were considered as chief predictor. Proximity is a prime cause of urban expansion. The proximity variables measure the minimum Euclidean distances to the nearest commercial site, residential area, industrial site and transportation network respectively. The distance decaying mechanism of various factor was signified by the type and size of the selected neighborhood.In this study, a circular neighborhood with a 200m radius was selected after considering the effect of neighboring impacts in current landuse distribution. The logistic regression result was estimated using the maximum likelihood algorithm. The models can be regarded as effective descriptions of the rural-urban land conversion (see Fig. 3.15).

Table 3.8 summary of predictor variables for the rural-urban land conversion

Variable name	Description
Dens-Pop	Population density of the cell
Dist-com	Distance from the cell to the nearest commercial site
Dist – Res	Distance from the cell to the nearest residential area
Dis- ind	Distance from the cell to the nearest industries site
Dis- road	Distance from the cell to the nearest road
Per-Urb	Percentage of urban landuse in the surrounding area
Per –Agr	Percentage of rural landuse in the surrounding area

Source: (Batty *et al*., 2004).

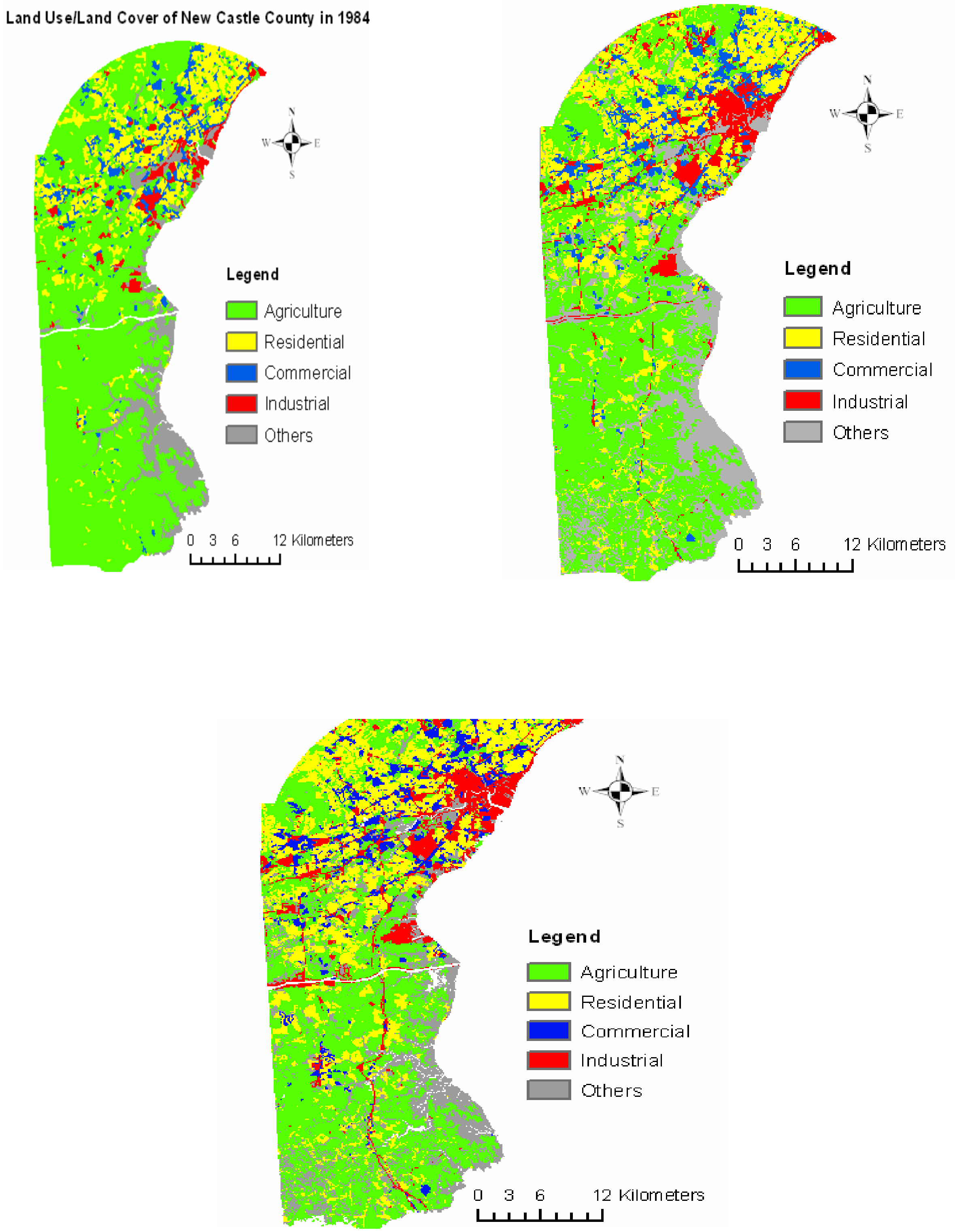


Fig.3.15: Landuse and landcover of New Castle county in 1984, 1992 and 2002

Source: (Batty *et al.*, 2004)

Singh, (2003) carried out modeling of landuse landcover changes using cellular automata in a Geo-spatial environment at shimla, the state capital of Himachal Pradesh in India. It is bordered by Jammu and Kashmir in the north, Punjab on west and southwest, Haryana in the south, Uttar Pradesh in the southeast and China in the east. The hilly town is surrounded by green pastures and snow-capped peaks. It lies between latitudes 30^0 $45^{'}$ $50^{''}.54^N$ to 31^0 $43^{'}$ $11^{''}.93^N$ and longitudes 76^0 $59^{'}$ $33^{''}.92^E$ to 78^0 18' $53''.84^E$. The landsat TM data for 1987 and IRS ID for 1999 were acquired from Geoinformatics Division, Indian Institute of Remote Sensing. The satellite data were georeferenced in lambert conical conformal (LCC) projection system. Due to cloud, snow and shadow in the 1987 satellite data, only 53% of the total area was classified. Visual interpretation and unsupervised classification technique were carried out; also ground truthing was carried out due to difficulty in classification, barren land and grass land were merged, and horticulture and agriculture were also merged. The final classes were settlement, agriculture, Barren, scrub, forest. ERDAS imagine 8.5 was used to geo-reference the satellite data and subsequently the classified data was used to prepare the landuse maps. Arcview 3.2 was used to digitized the factors maps required such as road map, city centers, tourist centers etc. Arc GIS 8.3 was used for analysis. landsat image had a resolution of 30m therefore IRS image was resampled to bring the image on 30m, the following maps were generated in grid format of 30m cell size i.e classified maps for 1987 and 1999, Altitude, slope, aspect, major city centers, major tourist centers, major industries, national and state highways. Distance map (from city centers, tourists, industries and highways). The model was run for different neighborhood size, in the first attempt the Moore's neighborhood was taken into account. The weight assigned to them according to their distance with respect to the center cell. The display was not cleared therefore the areas of maximum changes in the settlement classes were marked in different colored rectangles. The simulated result was compared with the actual landuse map of 1999 and results were compared visually. Cells were allocated to different classes according to their scores. The situation was arrived when required cells were less than the total number of cells of equally suitable scores.

Pennachin *et al*., (2002) carried out cellular automata modeling at Amazonian. The study area is located in an Amazonian colonization frontier in the north of Mato Gross State, Brazil. The model was run for two sub-areas of colonization projects using an 8-year time span from 1986 to 1994. The simulated maps were compared with land-use and land-cover maps obtained from digital classification of remote sensing images. The results from the validation methods for the two areas indicated a good performance of the model, indicating that it be used for replicating the spatial patterns created by landscape dynamics in Amazonian colonization regions occupied by small farms. The cellular automata model consists of a regular n-dimensional array of cells that interacts within a certain vicinity, according to a set of transition rule. Thus in a cellular automata model, the state of each cell in an array depends on it’s previous state and the state of cells within a defined Cartographic neighborhood, all cells being updated simultaneously at discrete time steps. The algorithm used to make the cells interact locally is known as the cellular automata local rule. For running the simulations, the model works in phases, each one having it’s own parameters, the number of time steps, the transition matrix, being the rates fixed within the phase, an eventual saturation value for each type of landuse and landcover class; the minimum sojourn time for each type of transition before a cell changes it's state; the co-efficients of the logistic model applied to calculate each spatial pij, the percentage of transitions executed by each transitional function together with the parameters mean patch size and patch size variance of each type of landuse and landcover class. Each phase has fixed parameters; consequently the model can be run using multiple phases, each one consisting of several time steps. The results obtained were impressive. The simulations were performed by using spatial data that were obtained mainly from satellite imagery. In view of this fact, it can be said that the achieved results are encouraging, especially considering the fallible character of environmental prediction (See Fig.3.16 for products generated). In this research work the study area was classified with minor alteration as shown in Fig. 3.16.

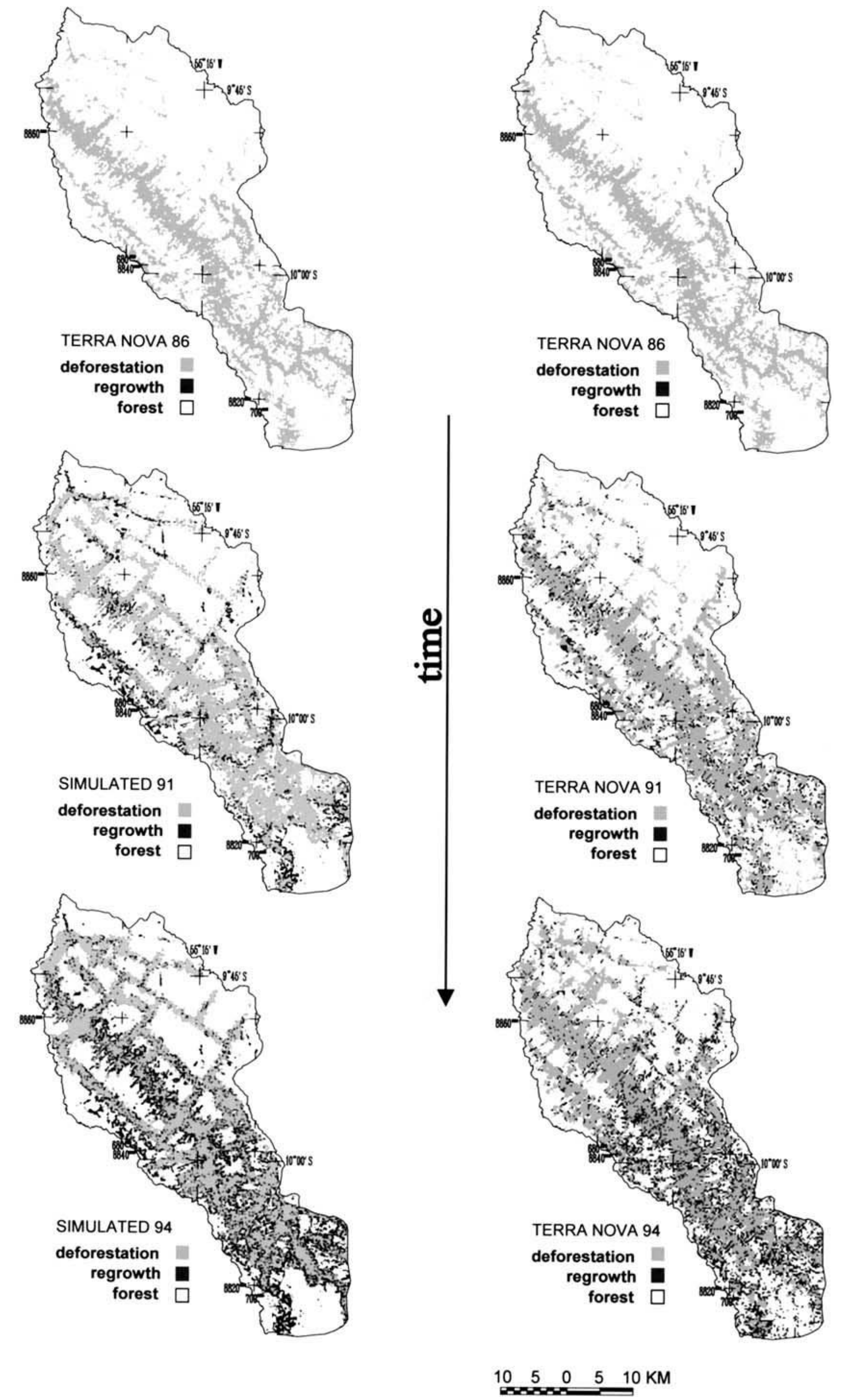


Fig.3.16: products generated for the area

Source: (Pennachin *et al.,* 2002)

3.3 Landcover and Landuse change Modeling (General)

Chibuike *et al.,* (2016) carried out spatio temporal analysis of landuse and landcover changes in Owerri municipal and its environs, Imo State Nigeria. The study area lies in the humid tropical region. The annual rainfall is about 2500mm and the mean temperature is 27^{oc}. The landsat ETM imageries for years 1991, 2001 and 2014 were used. The images were classified as built-up area, open space, forest, farmland, vegetation and water bodies. Accuracy assessment was performed to ascertain the acceptability of the classified images. Landuse and landcover maps were produced. The analysis shows that Built-up area is increasing. The researchers recommended that the current growth pattern needs to be managed through effective landuse planning and management in order to protect the fertile agricultural land in Owerri Municipal area.

Etok *et al.,* (2016) carried out mapping of landcover and landuse changes in the Cross river basin in Nigeria using Geographic Information System approach. The Cross River basin lies between latitudes $4^0$51'N and 6^0 34' 30''N of the equator and longitudes 7^0 45' E and 8^0 46' 19'' East of Greenwich meridian. The study area is under lain by a wide range of diverse geological formations ranging from the ancient metamorphic rocks, the Precambrian Basement complex from Ogoja to Obudu and Akamkpa to the Sedimentary rock of the Asu River Formation. The satellite imagery landsat thematic mapper (TM) and Enhanced Thematic Mapper (ETM+) of year 2003 and 2013 covering the study area were used. All the data used in this study area were projected to the Universal Transverse Mercator (UTM) Projection system. ArcGIS 10.1 was used for the image analysis and processing prior to the classification, image enhancement (radiometric/Spatial and spectral enhancements) were carried out. Supervised classification was adopted for the study using maximum likelihood. Training Samples that displays the typical spectral pattern of landcover classes were defined. The corresponding pixels in the images were compared numerically to the defined training samples and labeled to corresponding landcover classes based on their characteristics. The annual rate of decrease in forest cover and water body area were 3.5% and 0.25% respectively. The researchers asserted that the loss of the landcover was driven by the human activities. The results of accuracy assessment indicated that the derived maps achieved a relatively low accuracy due to scan line failure defect on the landsat 7 Enhanced Thematic mapper (ETM) sensor which resulted in the image having gaps and consequently yielding an approximately 22% data loss.

Santosh,(2015) carried out landcover mapping analysis and Urban Growth modeling using remote sensing techniques in greater cairo region Egypt. This study modeled the urban growth in the Greater Cairo Region one of fastest growing mega cities in the world using remote sensing data and ancillary data. The selected area for the study is the metropolitan area of Cairo, the political capital in addition to parts of Giza city that belong to the Greater Cairo Region. The study area is located at 30^0 02'N and 31^0 21'E in the middle of the Delta Region and covers an area of 8942km^2. Three cloud free landsat images for the year1984,2003 and 2014 were used. In addition to these datasets, ancillary data such as Google Earth maps and road networks were used. Multiple satellite scenes for the study area, obtained at different times (1984, 2003 and 2014) were classified to produce landuse/landcover maps. This classification was validated through an accuracy assessment process, which was performed with the aid of validation data or reference maps. The validation was followed by landuse/landcover detection analysis to determine the amount of each class at time $t_1$and another class of time t_2. These transitions were recorded in a change matrix that represented the input to the subsequent steps, calibrating and modeling the transitions of interest. After the driving forces had been set, the transitions between 1984 and 2003 were modeled to produce a predicted map of 2014. Four landuse/landcover classes were considered, Urban, vegetation, water and Desert. In the post- classification step, each raster map was converted to a vector format, and then generalized to a minimum map unit (MMU) of one hectare, by selecting all polygons of an area less than one hectare and eliminating them.For accuracy assessment, 100 random points per class were generated over the study area and visually compared to Google Earth images to validate the maps. The accuracy assessment resulted in an overall accuracy of 96%, 97.3% and 96.3% for 1984, 2003, and 2014 landcover/landuse maps respectively. The most significant changes in both periods (1984-2003 and 2003-2014) are the transitions from vegetation and desert to urban areas. Over 19 years, from 1984 to 2003, vegetation lost 13% to urban, representing 19,179 hectares and almost the same percentage (12%) within only 11years from 2003 to 2014, representing an amount of 16,486 hectares. These results shows that the Egyptian cultural heritage will be surrounded by Urban areas, especially around the pyramids area indicating a gradual loss of value and of it's unique appearances. If this trend continues, protection policies have to be undertaken to preserve the cultural heritage and the agricultural fields that will be negatively affected.

Mohan *et al.,* (2014) carried out landcover and landuse change of Bihar, India. The study area, a part of Muzaffarpur district (Bihar) India lies between $26^0$14'55''N to $26^0$59'41''N latitudes and $85^0$11'15''E to $85^0$33'22''E longitudes and the total area is about 492.32 sq. km. It is situated on the banks of the Burhi Gandak river which flows from the Someshwar Hills of Himalayas. This saucer shaped, low centered town lies on the great indo-Gangetic plains of Bihar, over Himalayan silt and sand brought by the glacier-fed and rain-fed meandering rivers of the Himalayas. The soil of the town is highly fertile, well drained and sandy, white coloured and very soft. The landscape is green all year round. The town is surrounded by the flood plain dotted with ponds and oxbow lakes, with sparkling sandy river banks and clean air and water. Landsat TM images of year 1988 and 2010 were employed as the source in this study to provide landuse/cover categories respectively. The images are projected to WGS-1984 and UTM Zone-45N coordinate system. Erdas imagine version 9.3 was used to perform landuse/cover classification in a multi-temporal approach. Twelve(12) landcover/ landuse categories were identified in the study area. Each image was separately classified using the supervised classification maximum likelihood algorithm in ERDAS Imagine. Eight separable landuse/cover categories have been identified i.e. agriculture land, vegetation, scrubs, fallow land, waste land, built-up area, water bodies and river bed. From the classified images of 1988 and 2010, the area of each landuse categories were computed and compared statistically. It is obvious that there are significant changes in landuse/cover categories especially for agriculture land and built up areas.The study demonstrated the efficiency of remote sensing data in the study of landuse and landcover changes. It gives a fairly good understanding of landuse/landcover changes for a period of two decades which in turn will be very helpful for local administrative bodies for decision making in the district. Table 3.9 was referred to in the research work during the determination of the landcover and landuse changes; also Fig. 3.17 and Fig. 3.18 guided me in the preparation of landuse and landcover maps for the study area.

Table 3.9: Landuse and landcover classification statistics between 1988 and 2010

LUCC Class	Year 1988 in (sq.km)		Year 2010 area in sq.km		Changed area	Changed area (%)
Agriculture land	137.485	27.85%	154.229	31.33%	16.743	12.178
Vegetation	159.707	32.35%	166.723	33.86%	7.015	4.393
Scrubs	34.570	7.0%	35.360	07.9%	0.89	2.283
Fallow land	110.440	22.38%	52.317	10.63%	-58.123	-52.629
Waste land	3.9357	0.80%	30.5067	6.2%	26.571	675.143
Built up area	12.278	2.49%	38.209	7.76%	25.930	211.185
Water bodies	25.498	5.17%	9.909	2.02%	-15.588	-61.138
River bed	9.750	1.98%	5.069	1.03%	-4.680	-48.006

Source: (Mohan *et al.*, 2014)

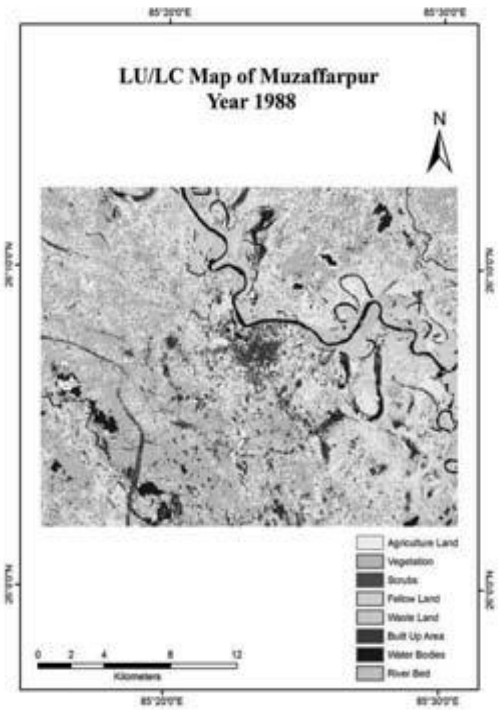


Fig. 3.17: Landuse/cover map of study area for 1988

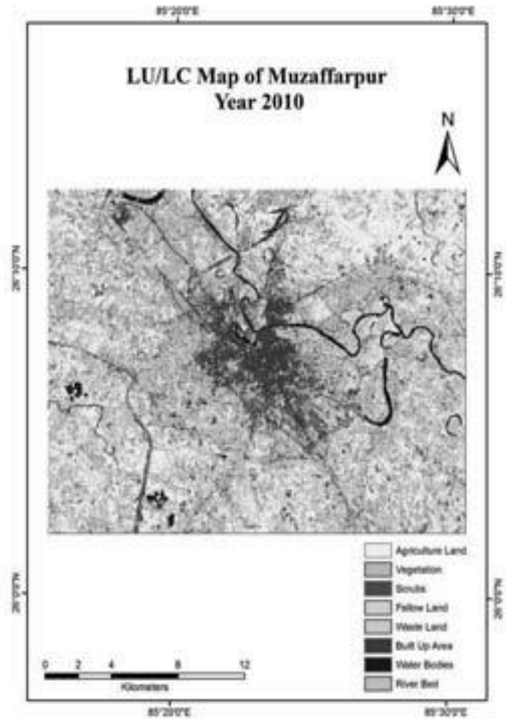


Fig. 3.18:. Landuse/cover map of study area for 2010

Source: (Mohan et *al*., 2014)

Olatunde, (2013) carried out application of remote sensing and geographic information system (GIS) in landcover/landuse change in Auchi, Edo State. The aim of the study is to produce landuse and landcover map of Auchi with a view to presenting the existing pattern and analysis of the various identified landuse and landcover using remotely sensed data and Geographic Information System techniques. The area lies between latitudes $7^{0}14^{'}$ North and $7^{0}34^{'}$ North of the equator and longitudes $6^{0}14^{'}$ East and $6^{0}41^{'}$ East of the Greenwich meridian. Auchi is located on a slightly undulating terrain of about 300m above sea level. The area is characterized by two distinct seasons, the wet and dry seasons. The author used ArcGIS 9.3 as the implementation software. The satellite imagery of the study area was downloaded from Google earth and thereafter exported to ArcGIS 9.3 environment. Geo-referencing of each image scene was carried out, after which all the geo-referenced imageries were matched together. The classification scheme was developed based on the researcher’s prior knowledge of the study area and the spatial resolution. Layers were created based on the classification scheme. On-screen digitizing was carried out using ArcGIS 9.3 and the vectorized map of the study area was produced. The landuse and landcover maps were then derived. From the analysis, it was observed that Auchi has built-up area (36.83%), less dense forest (10.48%), barren land caused by erosion (3.65%), vacant land (1.6%), scrub land (37.96%) and grass land (9.49%).

Jadab, (2013) carried out landcover landuse change detection in Paschim. The study area is located between latitudes 22^{0} $32^{'}$ 42”N to 22^{0} $48^{'}$ 49”N and longitudes 86^{0} $33^{'}$ 50” E to 86^{0} $59^{'}$ 23” E and covers an area of 583.50 sq km. This area is extremely rugged in nature and sometimes is capped by laterites. The relevant 1: 50,000 topographic sheets published by survey of India served as one of the data source. Besides digital data of IRS P6 (November 2010) with 23.5mm resolution was used. The researcher carried out image processing using remote sensing software ERDAS IMAGINE 9.2, landcover/landuse classification using supervised classification method and change detection analysis by overlay operation in Arc GIS 9.3 software was also carried out. The comparative study of maps for two study years revealed the geographical distribution and changing nature of different landcover and landuse categories in the study area. In conclusion, the study revealed that landcover/landuse has changed over the years, to ensure planned development and monitoring the land utilization patterns, preparation of landuse and landcover is very necessary. This research demonstrates the ability of GIS and remote sensing in capturing spatio-temporal data. Between 1970-1971 and 2010-2011, the percentage of forest land has decreased by 4.08%, also between 1970-1971 and 2010-2011, the percentage of other uncultivated excluding fallow land has increased by 4.13%.

Igbokwe and Ezeomedo, (2013) Carried out mapping and analysis of landuse and landcover for sustainable development using high resolution satellite images. Onitsha and it's environs lies in the north-western part of Anambra state, in south-eastern Nigeria. It is located between latitudes 6^0 $02^,$ $56^{,,}$N and 6^0 $38^,$34"N and longitudes 6^0 37' 30" E and 6^0 59' 30"E. The area is about 3,063 km^2. Field visits to the study area was carried out to obtain ground control points for georeference and ground truth sampling. The object-oriented approaches was used for mapping detailed landuses. This approach considers group of pixels and the geometric properties of image objects. It segments the imageries into homogenous regions based on neighboring pixels, spectral and spatial properties. It is based on a supervised maximum likelihood classification. The pre-processing post image processing and analysis were carried out to enhance the quality of the images and the readability of the features using the spatial analysis tool of Integrated Land and Water Information System (ILWIS 3.3). The scanned and digitized old topographical map of 1964 and satellite images of SPOT-5, 2005 and IKONOS, 2008 were geometrically corrected and the projection was set to Universal Transverse Mercator (UTM) projection system, zone 32. The spheroid and datum were referenced to WGS 84. All the images were geometrically co-registered to each other using ground control points into UTM projection with geometric errors of less than one pixel, so that all the images have the same co-ordinate system. The nearest neighbourhood resampling technique was used to resample the topographic map and SPOT-5 into a pixel size of IKONOS during the image-to-image registration. The ground control points (GCPs) are known ground points whose positions can be accurately located on the digital imagery. Such features include road intersections, corners of open field or lawns. Coordinates of GCPs were obtained using Global Positioning System(GPS). A sufficient number of such points is used to solve the transformation co-efficient. A geometric transformation of map-to-map were used for the scanned/digitized topographic map of the study area, in the other hand an image-to-map transformation were applied to the remotely sensed data of spot and IKONOS using Affine transformation, the result of the exercise was checked using Root Mean Square (RMS) error which is the process of measuring the deviation between the actual location and the estimated location of the control points in geometric transformation and was found to be 0.7 pixel. Classification and post- classification overlay was carried out and thematic landcover maps for the year 1964, 2005 and 2008 were produced for the study area by supervised classifications using a maximum likelihood classifier. Four major landcover classes were mapped, built-up areas, open/bare lands, vegetations including the cultivated and uncultivated land and water body; to be able to detect possible details, change trajectory of post classification comparison was used to map the patterns and extents of landuse and landcover in the study area as well as determine the magnitude of changes between the years of interest 1964, 2005 and 2008 respectively. The error matrix based accuracy assessment method is the most common and valuable method for the evaluation of change detection results. Thus, an error matrix and Kappa analyses were used to assess change accuracy. Kappa analysis is a discrete multivariate techniques used in accuracy assessments. Image differencing is one of the widely used change detection approaches and is based on the subtraction of images acquired in two different times. This is performed on a pixel by pixel or band by band level to create the different image. In the process, the digital number(DN) value of one date for a given band is subtract from, the DN value of the same band of another date. Since the analysis is pixel by pixel raw (unprocessed) input images might not present a good result. In image rationing method, geo-corrected images of different date are rationed pixel by pixel (band by band). It also looks at the relative difference between images Ratio Value greater or less than one reflects cover changes. Regression method is based on the assumption that pixels from time 1 are in a linear function of time 2. The regression technique accounts for differences in the mean and variance between pixel values for different dates. The method is applied to analyze the amount of change in vegetation versus non vegetation by computing normalized difference vegetation index (NDVI). The result of the study shows a positive change in the built-up areas, base surface were decreased. The proportion of the study area recorded negative change although very minimal in nature. This may be due to sand deposit, land reclamation and other development activity along the coast. In conclusion the study demonstrates the usefulness of satellite data for the preparation of accurate and up-to-date landcover/landuse maps.

Ahmed and Raquib, (2012) modeled urban landcover and landuse change using the landsat satellite images of 1989, 1999 and 2009. Dhaka is located in central Bangladesh at $23^{0}43^{'}00^{''N}$, $90^{0}24^{'}00^{''E}$ on the eastern bank of the Buriganga river. The landsat satellite images were collected from the official website of US Geological Survey (USGS). Landsat path 137 Row 44 covers the whole study area. The pixel size is 30m. Five landcover types i.e Built-up area, water body, vegetation, lowland and fallow land were identified. A supervised classification was carried out. Training sites are the areas defined for each landcover type within the image. The chosen color composite was used to digitize polygons around each training site for similar landcover. Then a unique identifier is assigned to each known landcover type. At beginning, the training sites have been developed based on the collected reference data and ancillary information. Spectral signature for each type of landcover were accomplished by analyzing the pixels of the training sites. Fisher classifier was used because most areas for the classes are known. After image classification some isolated pixels were found, it became necessary to generalize the image and remove the isolated pixels. A 3 x 3 model filter has been applied to generalize the fisher classified landcover images. This post-processing operation replaces the isolated pixels to the most common neighboring class. The generalized images are reclassified to produce the final version of landcover maps for different years. The supervised classification in every year is independent of the classification of the other years because this method can lead to substantial overestimates of land change in the post classification change analysis. The researchers did not carry out ground truthing of each and every pixel of the classified image, some reference pixels were generated. 250 reference pixels have been generated for each classification image to perform accuracy assessment. The amount of land change ranges from approximately 2% to 20% for 1989-1999, while the figure is approximately 1% to 17% for 1999-2009. The errors in the maps are not much larger than the amount of land change between the two points in time 1989- 1999 and 1999 – 2009. Fig 3.19 was referred to while preparing the landcover and landuse maps in this research work.

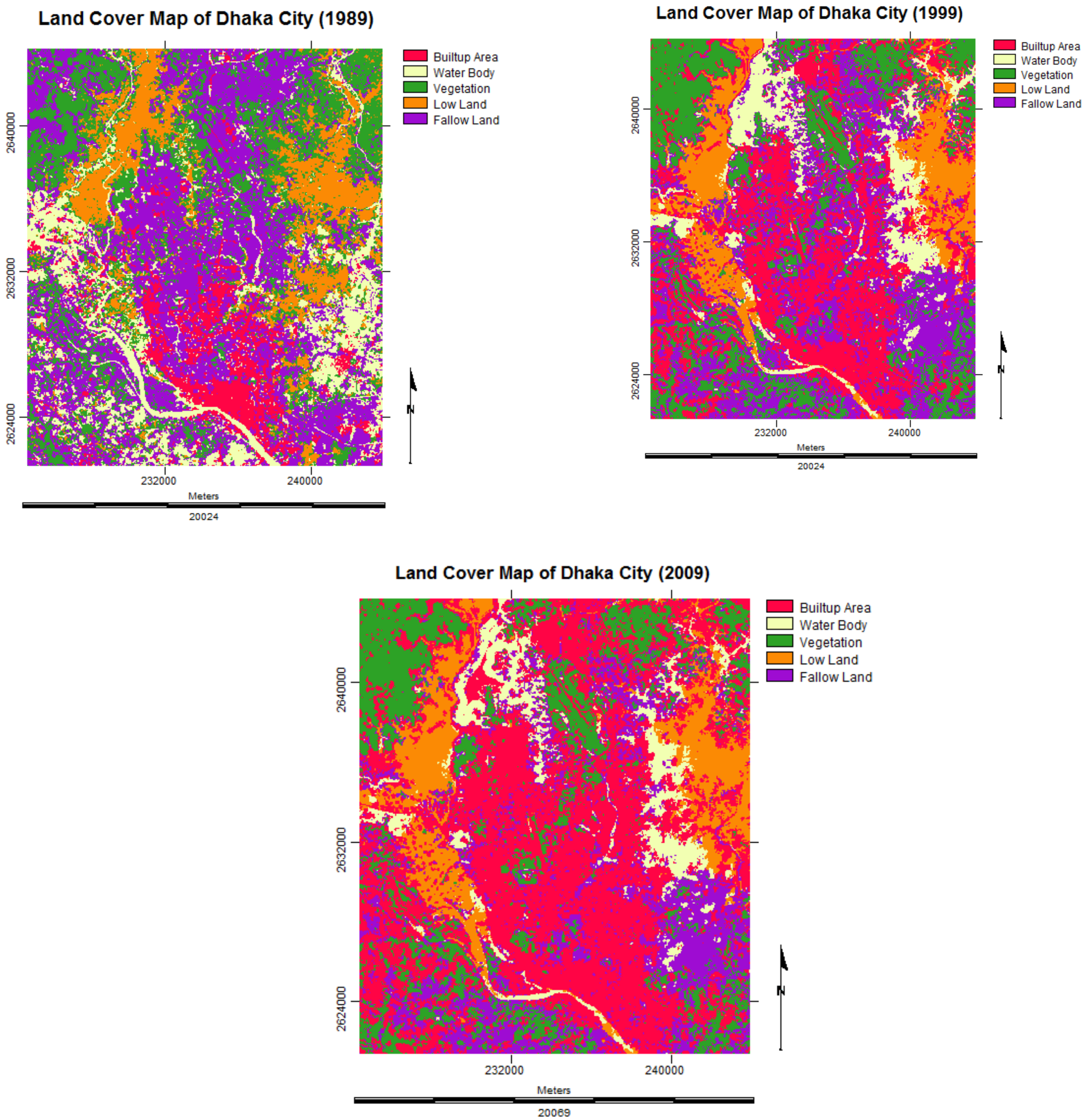


Fig.3.19 : Generated maps for 1989, 1999 & 2009

Source: (Ahmed and Raquib, 2012)

Sateesh, (2011) Carried out landcover and landuse using digital classification techniques in Madhya India. The study area is located in the northern part of Madhya Pradesh. It forms the northwestern part of Sagar commissioner's Division. It lies on the Bundhekhard plateau between the Jamni, a tributary of the Betwa and the Dhasan river. It extends between the latitudes $24^{0}26^{'}$ N and $25^{0}\ 34^{'}$ N and between longitudes $78^{0}\ 26^{'}$ E and $79^{0}\ 21^{'}$ E, the total geographical area is 5048 sq km. The researcher prepared various thematic data i.e. landcover and landuse using LISS – 3 + Pan data and created a landcover landuse map from satellite imagery using unsupervised classification. Preprocessing of satellite image prior to image classification and change detection is essential. Preprocessing commonly comprises a sense of sequential operations, including atmospheric correction or normalization, image registration, geometric correct and masking e.g. for clouds, water, and irrelevant features. Image enhancement will be applied to the image in order to increase the amount of information that can be displayed interactively. Contrast enhancement is applied primarily to improve visual analysis. It is a deterministic grey level transformation and involves a pixel – by-pixel radiometric transformation that is designed to enhance visual discrimination of low contrast image features. Field surveys was carried out to determine the major types of landuse and landcover, such data would be used in the mapping of landuse and landcover. Firstly it will aid in landuse landcover classification, by associating the ground features of a specific type of landuse and landcover with the relevant imaging and spectral characteristics. Secondly, ground data will be used for accuracy assessment of the developed landuse and landcover maps. The classification accuracy is most important to assessing the reliability of maps, especially when comparing different classification techniques. During this study the accuracy assessment, method was used. This method shows above 90% accuracy in the map produced. In conclusion the landuse and landcover map clearly shows that area of cropland is higher than others.

Rimal, (2011) carried out the application of remote sensing and geographic information system in landcover/landuse change at Kathmandu metropolitan city, Nepal. The aim of the study is to ascertain the landcover and landuse changes of Kathmandu metropolitan area from 1976 to 2009. The specific objectives are to analyze the changing landcover and landuse pattern from 1976 to 2009; also to predict landcover/landuse in the year 2017 using Markov model. A Markov chain is the behavior of the system over time as described by the transition probabilities. Four pairs of cloud free landsat images was used to classify the study area. The imageries for October 28, 1976, October 31 1989, December 27, 2001 and January 15, 2009 were projected to the universal Transverse Mercator (UTM) Projection System (zone 45). Supervised approach using maximum likelihood parameter system was applied to improve the accuracy of the landuse classification of the images for years 1976, 1989, 2001 and 2009. There is no doubt that human activities have profoundly changed landcover in the city as shown in Table 3.10 The IDRISI GIS Taiga version was used for the analysis of images. Markov chain model was used to determine the future change of landcover and landuse changes for the study area. The urban/built-up areas in Kathmandu had a noticeable increase (see Table 3.10). The urban development change is very high from 16.85% ($10.9km^2$) in 1976 to 66.61 ($43.1km^2$) in 2009; population migration in the city area is the cause of noticeable increase in the built-up area. Open field has been largely decreased from 1976 to 2009.

Table 3.10 was referred to while determining the percentage of landcover and landuse changes in this research work.

Table3.10: Landuse statistic of Kathmandu City 1976-2009

Years	**1976**		**1989**		**2001**		**2009**	
Landuse type	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Urban/Built up	10.9	16.85	17.7	27.35	27.6	42.66	43.1	66.61
Water body	1.9	2.90	0.7	1.1	2.8	4.33	2.4	3.71
Forest cover	9	13.9	5.7	8.8	1.9	2.93	1.5	2.32
Open field	4.5	7	1.5	2.32	0.5	0.78	0.4	0.62
Cultivated land	38.40	59.35	39.1	60.43	31.9	49.3	17.3	26.74
Total	64.7	100.00	64.7	100	64.7	100	64.7	100

Source: (Rimal, 2011)

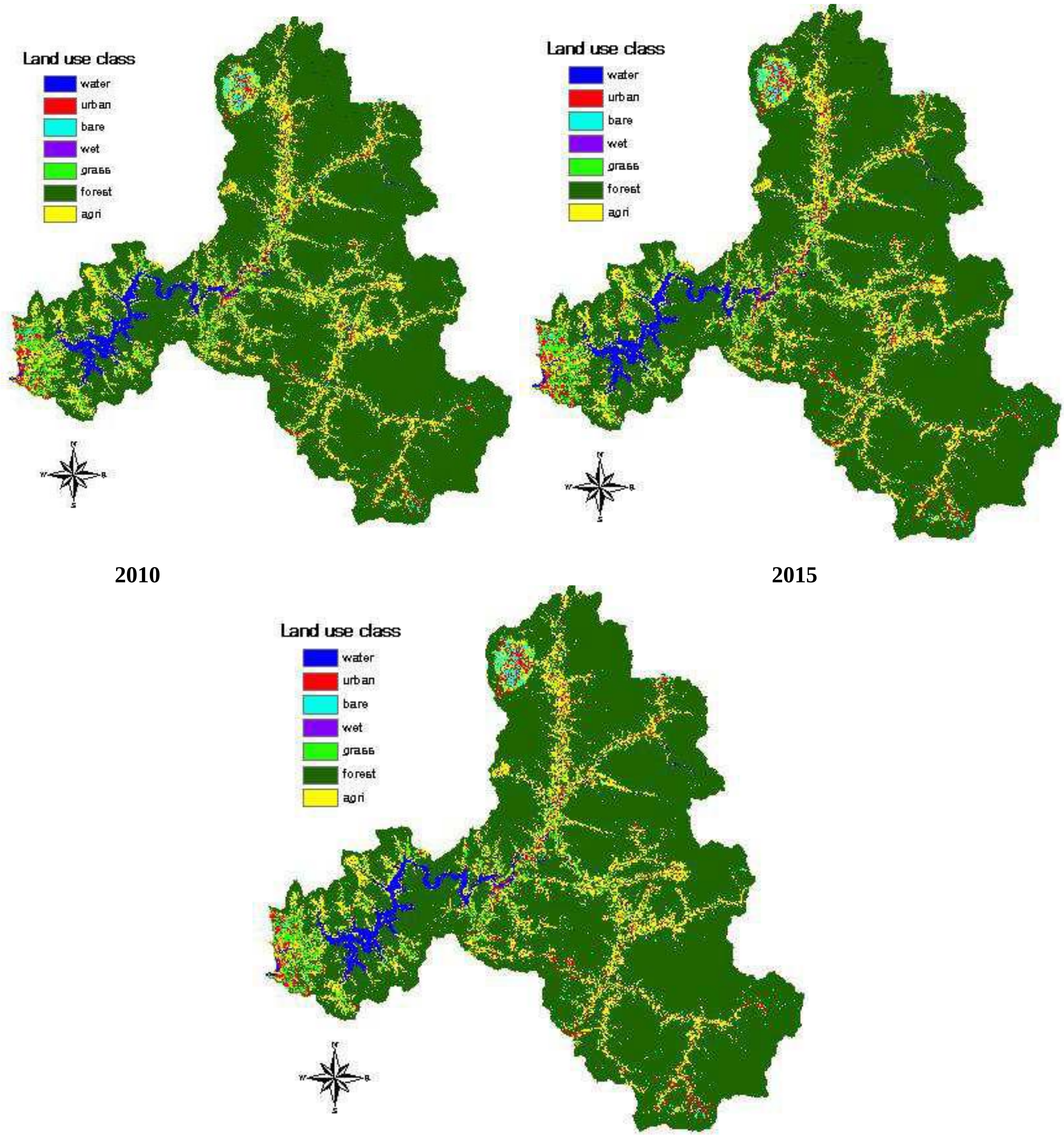
John *et al.,*(2011) predicted landuse change in the Soyang River basin in South Korea. The study aims at extracting variables which influence landuse change and predicted future landuse changes in the Soyang river basin using 1995 and 2000 landuse maps. The prediction map is validated with the map of actual landuse for 2006 to test the applicability of the landuse prediction model using relative operating characteristic and variations of the kappa index of agreements for major landuse classes (urban, forest and agriculture). The Soyang River basin is located in the north eastern part of south Korea and contains the largest branch area of the North Han river. The landuse maps consists of seven landcover classes (water, urban, bare land, wetland, grassland, forest and agriculture) obtained from the Ministry of Environment. The altitude, slope, aspect, relief and culture were derived from the DEM. Socio-economic data e.g. distance to road, river, stream, urban area, administrative centers, zoning of reserve forest were obtained. The model output is compared to a map of landuse prediction with actual landuse map of 2006. The relative operating characteristic (ROC) is an index of discrimination accuracy that can validate landuse prediction map. Independently of any specified quantity of landuse change. ROC equals to 1 when a prediction map has perfect suitability, while ROC equals to 0.5 when a prediction map has random suitability values. The researchers used the kappa index of agreement that has several variations, each of which measures different characteristics of agreement. Kappa equals 1 when agreement is perfect, while kappa equals 0 when agreement is as expected by chance. The researchers used three kappa index of agreement (K_{no}, $K_{location}$,$K_{standard}$). Using the combination of K_{no}, $K_{location}$,$K_{standard}$ for the evaluation allows for a determination of an overall success rate while providng an understanding of the factors that contribute to the strength or weakness of the results. Kappa statistics was carried out in this research work and Table 3.11 was utilized. Fig. 3.20 was referred to while assessing the visual and qualitative characteristics of products generated from this research.

Table 3.11: Definitions of the Kappa index of agreement

K_{no}	Measure of the overall proportion correctly classified versus the expected proportion correctly classified.
$K_{location}$	Measure of the spatial accuracy due to correct assignment of values
$K_{standard}$	The proportion assigned correctly versus the proportion that is correct by chance

Source: (John *et al.*, 2011).

The result shows that temporal and spatial landuse change pattern 1970-2000 of the Soyang river basin have different patterns for each landuse class. The Fig. 3.20 shows a temporal landuse for major landuse classes. Urban landuses have increased steadily and urban growth has been occurring at the center of the city near the river. Forest covers have increased under the influence of zoning of national protection areas.



2020

Fig. 3.20: Landuse map for 2010, 2015 and 2020

Source: (John *et al.*, 2011).

Njoku *et al.,* (2010) The researchers discussed the relevance of remote sensing and GIS techniques for periodic landcover and landuse mapping and change detection. Owerri and environs are characterized by natural and man-made problems and rapid landuse and cover changes such as induced soil infertility and degradation. This study examines the application of multi-temporal remotely sensed data in changes between 1986 and 2000. The study provides temporal empirical comparative assessment of TM 86 and ETM + 2000, while identifying the primary drivers of the intra-class dynamics during the periods in order to predict what types will dominate the area in the future. The study area, Owerri metropolis is a closely-settled built-up area and the administrative capital of Imo state of Nigeria. The pre - 1976 owerri comprised largely pockets of rural settlements of predominantly subsistence farmers. It lies between latitudes 5^0 25' N and 5^0 34' N and longitudes 6^0 07' E and 7^0 06' E covering an area of approximately 5,792.72km^2. The population of the study area in 2006 was 401,873. The study was undertaken with corrected Landsat Thematic Mapper 1986(TM86) and Enhanced Thematic Mapper plus 2000 (ETM+ 2000)Satellite imageries. These were used for landcover and landuse classification and statistical change analysis. The 1: 100,000 administrative map of Imo state covering the study area was obtained from the Ministry of lands and urban Development, Owerri, Nigeria. The map was used for the enhancement of the classification, orientation and geometric registration of the imageries during interpretation. The imageries were preprocessed, corrected for system errors, terrain distortion and were geographically registered before being used for the change analysis using the ILWIS ACADEMIC 3.0 GIS software. The major landcover and landuse classes identified in the study were built-up area, poorly dispersed forest vegetation, cultivation, bare/eroded surfaces and water body. Land areas and features were assigned different spectral signatures to represent changes from one class to the other. The largest inter-class change occurred between the cultivation and the forest vegetation classes. The study revealed that the change from forest vegetation class to other classes were relatively small. In conclusion, the imageries proved very useful and effective in the accurate mapping of ground features.

Orisakwe, (2008) carried out Geographic Information System predictive model for Owerri Urban landuse Development. The area lies between latitudes 5^0 27’31’’ North and 5^0 29’ 58” North of the equator and longitudes 7^0 00’ 23’’ East and $7^0$03’38’’ East of the Greenwich meridian. Owerri lies within the humid tropical region of Nigeria. There are two major seasons in Owerri i.e dry and rainy seasons. The dry season lasts from the month of November to March while the rainy season starts from March and ends in October. The researcher used landsat TM satellite imageries for 1977, 1987, 1997 and SPOT 5 Satellite imagery for 2005. The SPOT 5 Satellite imagery was resampled using ILWIS 3.3 to attain the same resolution with the Landsat TM imageries. Auto cad 2007 software was used for geo referencing and was exported to ILWIS 3.3. Areas that have potential for development in each of the landuse types were determined and the multi data were used to build a landuse predictive model. Analysis carried out shows that vegetation and green zones were decreasing as a result of these areas been converted to built-up area. This research demonstrates the ability of Geographic Information system and remote sensing in capturing spatio-temporal data for landuse changes analysis.

Ojigi, (2006) carried out the study of comparative analysis of four(4) image classification methods (maximum likelihood, parallepiped, minimum distance and fisher's method) to experiment which method best classifies the 2001 landsat-7 ETM 345 imagery for part of Abuja, Nigeria. The area is located in the centre of the country in the guinea savanna of the middle belt between longitudes $6^{0}20^{'}$E and $7^{0}33^{'}$E of the Greenwich meridian and latitudes $8^{0}30^{'}$N and $9^{0}20^{'}$N of the equator and occupies an area of about 8,000 square kilometers. The study area is typified by gentle undulating terrain interlaced with riverine depressions. The land rises irregularly from 305m to 610m above mean sea level. The soil structure of the area is thin with texture generally stony with smaller occurrences of loam. The image data was splitted in the three bands (red, green and blue) and re-saved as 24-color bit image in TIF format in order to retain the original values. Each of the bands was geo referenced using the rectangular co-ordinates of the edges and other verified terrain features (e.g road junctions and hill tops) in the image using Idrisi software. The linear stretched images of the three bands formed the working image data for the processing of the supervised classification in this study. The training site for six landuse and cover types was created based on the in-situ assessment of the site carried out during the fieldwork and ground truthing exercise. The signature files which contain the statistical information about the reflectance values of the pixels within the training site for each of the six landuse and cover types i.e closed canopy vegetation, water, open vegetation, urban built-up, rock outcrops and bare ground were developed, using MAKESIG Sub-model of the Idrisi. Four (4) image classification algorithms i.e maximum likelihood, parallepiped, minimum distance and Fisher's classifier were carried out on the 2001 landsat-7 ETM 345 imagery of the area using the image classification/

Hard classified module of Idrisi-32. A categorical map image (raster) was created for the true (field verified) classes and compared with the four classification maps using ERRMAT model. The result of the study shows that based on the adequate prior knowledge of the area, the maximum likelihood gives a better representation of the area (see Table 3.12). The author recommended that this experimental approach be used for different datasets from various sensor platforms. The research was basically on existing landuse/landcover of the study area which is impossible in Kaduna due to lack of existing updated maps. Table 3.12 was used in adopting maximum likelihood classification as an accurate classifier in this research work.

Table 3.12: Classification Accuracy index of Agreement

Landuse/Landcover types	**Classification Algorithms/kappa index of Agreement (%)**			
	MLC	**MDC**	**PC**	**FC**
Closed canopy vegetation	46.03	46.26	49.8	47.52
Water	74.87	69.52	65.42	72.27
Open vegetation	68.62	21.80	25.6	14.19
Urban Built-up	47.88	58.56	28.04	65.65
Rock outcrops	53.7	47.86	79.22	66.03
Bare Ground	79.31	59.39	89.18	52.22

Source: (Ojigi, 2006).

Hadi, (2005) The researcher carried out mapping of landcover and landuse in Perlis which is situated in the northern peninsular Malaysia with neighboring borders of Thailand in the north and Kedah in the south. It covered an area of 7959sq.km and has a tropical Monsoon with winter wind. The temperature is between 21-23^{0C} having dry season from January to April and rainy season from May to December. A Landsat digital spectral data taken on 13th March 1997 was used and analysis carried out using IDRISI, a raster-based GIS software. The image was atmospherically corrected using the darkest pixel approach and geo- corrected with a residual mean square error of less than half a pixel. IDRISI with a composite image of bands TM3, TM4 and TM5 was used for the classification of the landcover and landuse on the basis of spectral signature for nine clustering areas. The 1:5,000 topographic map produced in 1987 and a landuse map at scale 1:5000 were used to support this study. The area was classified into urban areas, grassland, reserved forest and water bodies. A minimum of 30 pixels were selected in the training areas for each class. The training areas were selected on the bases of unsupervised classified images, primary field data and the secondary data using IDRISI the polygons around each training area were digitized and assigned a unique identifier for each cover type, a spectral signature file for each class was subsequently created. These signature files were used to categorize spectral data in the entire image by maximum likelihood classifier. Most of the classes were easily separated and mapped based on their distinctive spectral reflectance signature within the TM bands used. The researcher concluded that conventional data collection in the past mainly by ground surveys for landcover and landuse mapping is accurate but it is time-consuming and costly; it is also subjected to site accessibility and reliability on human capabilities. Satellite remote sensing can be used to generate the necessary dynamic information for modeling and mapping landcover and landuse changes.

Santosh, (2003) Carried out modeling of landcover change in Himachal Pradesh state. The study area is located in the Southern part of Himachal Pradesh, which is on the border of the middle Himalayas simla district with a geographical extent of 30^{0}45’50”.54N to 31^{0}43’ 11”.93N and 76^{0} 59’33”.92E to78^{0}18’53”.84E Two scenes of the LANDSAT-5 TM satellite acquired in 1999 were used for the study. Both images were geo-referenced in Lambert conformal conic projection system and Everest spheroid using ERDAS IMGINE image processing software. First the IRS-D satellite image is geo-referenced with the help of 63 well distributed points from Geo-coded hard copy of the satellite images along with GPS observations. Image to image registration was carried out to geo-reference the LANDSAT- TM satellite images. During pixel by pixel change detection process, it is important that both the images should have same spatial resolution. The IRS–ID LISS-III images was re-sampled to 30m from its original resolution of 23m. The purpose of the step is to match the spatial resolution of the two images. Only three bands in each satellite image are taken for the case study. The LANDSAT-TM image and the IRS-ID LISS III images were used as image 1 and image 2. Three bands of LANDSAT-TM (5,4,3) and three bands of IRS-ID LISS-III (3,2,1) images were taken into consideration for classification purpose. After obtaining the satellite in digital format, images are geo-referenced and mosaiced using ERDAS IMAGINE image processing software. Geo-referencing attaches real world co-ordinate to the image so that it can be co-registered with any other imagery or spatial data that overlies the same area. Real world ground control point (GCP), Obtained were used for geo-referencing along with well distributed point from geo-coded hand copy of the image. Mosaicing is the method by which individual images are joined together to form a single layer. The result is shown in Table 3.13 which was utilized while determining percentages of changes in this research work. The study revealed the importance of fuzzy sets and fuzzy logic in image classification and change detection process. Satellite image acquired in 1987 has more snow covered area than the satellite image of 1999.

Table 3.13: Landcover/landuse classes

Class	Area (Ha)	% Area
Forest	263636.1	52.51
Agriculture	127282.59	25.35
Water	40792.32	8.13
Barren land	46139.76	9.19
Snow cover	6265.98	1.25
Settlement	7471.98	1.49
Undefined	10433.25	2.08

Source: Santosh, (2003).

Marvin, (2000) carried out mapping of landcover change with satellite remote sensing in Minnesota. The researcher used six landsat TM/ETM+ images containing the TCMA which helps in studying how landcover in the metropolis changed between 1986, 1991 and 1998. The satellite data were geometrically corrected to match the UTM map projection. Landuse data from field observations were collected for a random sample of areas. With the landuse data as reference material, training statistics, which described the spectral radiometric temporal response of a subset of known areas, were generated and used to classify each pixel of the entire area into one of the five landcover classes agriculture, urban, forest, wetland and water. Following image classification, the researcher mapped and quantified the landcover changes between 1986 and 1998. A map of the major landcover types and the changes from rural to urban was prepared. The majority of the changes were at the periphery of the major cities of Minneapolis and St. Paul from 1986 to 1998, urban areas increased to 52,019 ha or 28.4%. Agriculture decreased 49,091 ha or 13.4%. forest decreased 5,089 ha or 4.5%.In conclusion landcover information provides important inputs to local, regional and state landuse planning; also accurate and timely information is necessary for providing essential services in urban area.

3.4 Gaps Identified

Several related studies on modeling and mapping landcover and landuse changes using multiple logistic regression and cellular automata have been reviewed. Most of these studies adopted similar approaches in their methodologies. Indeed, some gaps were identified in the methodologies, which can be improved upon. Generally, in all the works reviewed, they did not mention the season in which the satellite imageries used were acquired. Also, few of the works used imageries for only two epochs instead of three epochs. Three epochs will ensure detailed analysis.

Santosh, (2015) carried out landcover mapping analysis and urban growth modeling using remote sensing techniques. The accuracy assessment for years 1984, 2003 and 2014 were given, but what was responsible for the increase in 2003 and decrease to 96.3% in 2014 were not stated.

Deep, (2014) illustrated landcover and landuse changes using cellular Automata and Multiple logistic regression. Landcover and landuse maps for the year 2004 and 2009 were produced. The generation of maps for 2014 will have assisted in determining changes within the area.

Mohan *et al*., (2014) carried out landcover and landuse change of Bihar, India using land sat TM images of year 1988 and 2010. Twenty-two (22) years is too long to carry out such a research work; it would have been better to use satellite imageries of 5-10 years for this study. At 5 – 10 years interval, changes are better detected which will give reasonable results than twenty- two (22) years span. In the works of Khalilnia *et al*., (2013), classified satellite images of 10years difference was used which resulted in accurate prediction of Urban growth.

Jadab, (2013) carried out landcover and landuse change detection mapping in Paschim. The dates of two epochs used were not mentioned which makes it difficult to ascertain whether the results obtained can be used for planning and development. The scale of the maps generated would have assisted decision makers if it was clearly stated

Pradhan *et al*., (2013) carried out landuse change using landsat TM and spot 5. A better approach would have been the use of satellite imageries acquired from the same platform. The number of classes used i.e built-up area, agriculture and excluded areas are probably too few which could affect the result of landuse change prediction. A 3 x 3 cellular matrix space, will reflect changes significantly compared to the matrix space of 5 x 5 used by the researchers.

Ahmed and Raquib, (2012) presented a detailed approach for mapping and modeling of landcover and landuse change. However, the researchers did not carry out ground truthing of every pixel of the classified image, some reference pixels were generated which lead to substantial overestimates of land change.

John *et al*., (2011) predicted landuse change in the soyang River Basin. The values of Kappa index of agreement obtained were not given making it difficult to rely on the predicted maps of 2010, 2015 and 2020.

Sateesh, (2011) presented a detailed approach of landcover and landuse mapping of northern part of Madhya Pradesh. Ground data was used for accuracy assessment and the accuracy achieved was above 90%. It was not clear how the accuracy assessment was achieved.

Njoku *et al*., (2010) carried out detection and mapping of landcover and landuse classes of the city of Owerri and environs. The date of production of the 1:100,000 administrative map covering the study area used for enhancement was not indicated. The work of the researchers would have been appreciated if the transition of the various classes were clearly shown.

Araya, (2009) presented a detailed approach to urban landuse change in Setubal Sesimbra in Portugal. Water bodies and marsh area were classified as a class which will make interpretation confusing, also the protected area was not specified.

The works of Batty *et al*., (2004) was adopted for 8 years interval due to available data. Seven different types of landuse classifications were employed i.e Agriculture, residential, commercial, industrial, forest, water and barren land, but in the final maps presented, forest, water and barren land were grouped together. Their works would have been better appreciated if barren land, water and forest were separately shown. In the works of Ojigi (2006), if available landcover and landuse datasets were available the methodology will have been re-enforced by the use of classification algorithms.

Singh, (2003) carried out comprehensive mapping and modeling of landcover and landuse changes. However, due to cloud, snow and shadow in the 1987 satellite data only 53% of the total area was classified; also due to difficulty in classification, barren land and grass land were merged. Obviously for landcover and landuse changes, image data should be free from cloud and snow in order to carry out proper classification which will enhance the quality of results to be obtained.

The work of Pennachin *et al*., (2002) is quite elaborate. However, the researchers did not indicate the sensor of the satellite imagery used, making it difficult to rely on the maps produced. The maps produced should have been placed within a frame to enable the simulated maps to be easily read.

Hong *et al*., (2000) presented a detailed approach to modeling and mapping of landcover and landuse changes using multiple logistic regression and cellular automata, but unfortunately the four spot images used were not taken at regular intervals. The transition rules were implemented randomly. The area of the water body was assumed constant during the simulation period which obviously affected the final results. Results shows that all landuse have changed, but the water body remained constant which is not true. Better results could have been obtained if the water body was not assumed constant.

In the research work of Almeida *et al*., (2000) the interval between the two satellites imageries used was not exactly 10 years; also the season of the year in which the imageries were acquired was not indicated. Probabilities of landuse transition were calculated in absolute terms without the influence of socio-economic or infrastructural factors which obviously will affect the exact area of the computed landcover and landuse changes in the study area. The works of Batty *et al.*, (2004) took care of these anomalies in their work. Though the satellite imageries used were at eight (8) years interval. Summary of some of the works reviewed and the gaps identified are presented in table 3.14.

Table 3.14: Summary of some works reviewed

S/No	Title	Methodology	Results	Gaps Identified
1.	Landcover mapping analysis and urban growth modeling using remote sensing techniques in greater Cairo region by Santosh, (2015)	The urban growth in the greater Cairo region was modeled using remote sensing and ancillary data. Classification was validated using a reference map.	The most significant changes were the transition from vegetation and desert to urban areas.	The accuracy assessment for 1984, 2003 and 2014 were given, but what was responsible for the increase in 2003 and decrease to 96.3% in 2014 were not stated.
2.	Landcover landuse changes using cellular Automata and multiple logistic regression, Deep, (2014)	The acquired data of the Dehradun area were processed and analyzed using remote sensing and GIS techniques.	It is clear from the visual interpretation that built-up area has increased significantly during the period 2004 – 2009	Landcover/landuse map for 2004 & 2009 were used. Additional data for 2014 would have assisted the study.

Table 3.14: Summary of some works reviewed (continued).

3.	Prediction of landuse changes based on land change modeler using remote sensing. By Mohan *et al.*, (2014).	Erdas Imagine was used to perform landcover and landuse classification in a multi-temporal approach. Eight (8) separable landuse cover categories were identified. The area of each landuse were computed and compared statistically.	Landuse and landcover classification statistics between 1988 and 2010 were presented in tabular form showing changes in percentages.	The time interval of twenty-two years is too long; it would have been better to use satellite imageries at regular intervals within a shorter period in order to appreciate the changes.
4.	Landcover/landuse and change detection mapping in Binpur II block Paschim medinipur district west Bengal: A remote sensing and GIS perspective Jadab, (2013).	Erdas imagine 9.2 was used in the image processing. Arc GIS 9.3 was used in the image classification which was successful.	The study revealed that landcover/landuse has changed over the years.	The dates of the data used were not mentioned which makes it difficult to rely on the results obtained.

Table 3.14: Summary of some works reviewed (continued).

5.	Monitoring and predicting landuse change in Tripoli metropolitan city using cellular automata models in geographic information system by Pradhan *et al.*, (2013).	The maximum likelihood classification technique was used. Softwares were used to accomplish landcover landuse changes using multiple logistic regression and cellular automata.	The results of landuse change were presented in tables which indicates the quantity of change in each landuse class.	A 3 x 3 cellular matrix space will reflect changes better than the 5 x 5 used by the researchers.
6.	Modeling urban landcover growth dynamics using multi-temporal satellite images: A case study of Dhaka Bangladesh by Ahmed and Raquib, (2012)	A supervised classification was carried out. Spectral signature for each type of landcover were accomplished by analyzing the pixels of the training sites. The generalized images are reclassified to produce the final version of the landcover maps.	Landcover maps for 1989, 1999 and 2009 for the study area were produced showing changes in landuse.	Ground truthing of every pixel of the classified image was not carried out which led to overestimation of land changes

Table 3.14: Summary of some works reviewed (continued).

7.	Predicted landuse change in the Soyang River Basin South Korea by John *et al.*, (2011)	The project was carried out by classifying the area into landcover classes such as water, wetland, and forest etc. prediction was carried out for 2010, 2015 and 2020.	The result shows both temporal and spatial landuse change pattern from 1970 to 2000 of the Soyang river basin. Urban landuses have increased steadily especially at the centre of the city.	The researchers used the Kappa index of agreement but did not give the value obtained in their work, making it difficult to rely on the predicted maps of 2010, 2015 and 2020.
8.	Landcover and landuse mapping using digital classification technique in Madhya India using remote sensing by Sateesh, (2011)	Unsupervised classification was used. Field surveys was carried out to determine the major types of landcover and landuse 90% accuracy assessment was achieved	The study area was classified into major landcover and landuse types	Although 90% accuracy was achieved. However, how the accuracy assessment was carried out was not clearly shown.

Table 3.14: Summary of some works reviewed (continued).

9.	Detection and mapping of landuse and landcover classes of a developing city in south eastern region of Nigeria using multi-band digital remotely sensed data by Njoku *et al.*, (2010)	Corrected landsat TM of 1986 and enhanced thematic mapper plus 2000 were used. ILWIS ACADEMIC 3.0 was used in the change analysis	The study revealed that the change from forest vegetation class to other classes were relatively small.	The date of production of the 1:100,000 administrative map used for enhancement was not indicated.
10.	Urban landuse change analysis and modeling: A case study of Setubal and sesimbra. Portugal by Araya, (2009)	The specific objective of this study was to investigate the characteristics of urban landuse using satellite images.	Landcover/landuse maps for 1990, 2000 and 2006 were produced based on minimum mapping unit of 1ha and 25 ha	Water bodies and marsh area were classified as a class which will make the interpretation confusing, also the protected area was not specified.
11.	Modeling urban dynamics through GIS-Based cellular automata by Batty *et al.*, (2004)	A post classification comparison method was used to detect the landuse change. The researchers modeled the urban growth using logistic regression	Landuse map of New Castle County in 1984, 1992 and 2002 were produced indicating changes	In the final presentation, forest, water and barren land classes were grouped together making it difficult to identify changes in these classes

Table 3.14: Summary of some works reviewed (continued).

12.	Modeling landuse landcover changes using cellular automata in a geo-spatial environment by Singh, (2003)	Visual interpretation and unsupervised classification technique were carried out. Erdas Imagine 8.5 was used to geo-reference the satellite data and then classified to prepare landuse maps	Classified maps for 1987 and 1999 were produced showing landuse changes	Image data used for landcover and landuse changes should be free from cloud, snow and shadow
13.	A stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian by Pennachin *et al*., (2002)	The model was developed using spatial data that were obtained from satellite imagery and the landcover and landuse maps were prepared after classification.	The validation methods indicated good performance of the model.	The researchers did not indicate the sensor of the satellite imagery used, hence it is difficult to rely on the maps produced.
14	Monitoring and predicting landuse changes of urbanized Paochiao watershed in Taiwan using remote sensing data by Hong *et al*., (2000)	The classified landuse data were inputted into the landscape pattern analysis. The urban growth and the landcover change model were	Landuse maps for year 2005, 2010, 2015, 2020 and 2025 were produced showing Built-up,	The four (4) spot images used were not taken at regular intervals. The transition rules were implemented randomly.

Table 3.14: Summary of some works reviewed (continued).

		combined to form a probabilistic model to generate simulation growth for the study area	Agriculture, Grassland, Forest, Barren and Water Classes	
15	Modeling the urban evolution of landuse transitions using cellular automata and logistic regression at Baura, Brazil by Almeida *et al.*, (2000)	Probabilities of landuse transition were initially calculated for the whole study area in absolute terms i.e. without the influence of socio-economic or infrastructural factors	A probability and landuse transition maps were produced. Also logistic regression analysis was presented	Probabilities of landuse transition were obtained without the influence of socio-economic or infrastructural factors which will affect the landcover and landuse changes in the study area.

The studies reviewed have facilitated in understanding how landcover and landuse changes were be carried out using cellular automata and multiple logistic regression. The review has shown clearly the works of other researchers world wide, their successes and gaps identified. In this research work accuracy assessment of classified images were carried out, also landcover and landuse changes were determined at regular intervals. The works of Almedia *et al.,* (2000) is similar to the works of Pennachin *et al.,* (2002) except that validation methods used were slightly different.

CHAPTER FOUR

METHODOLOGY

The chapter deals with the methodology adopted in the execution of this research. The flowchart of the methodology is shown in Fig.4.1.

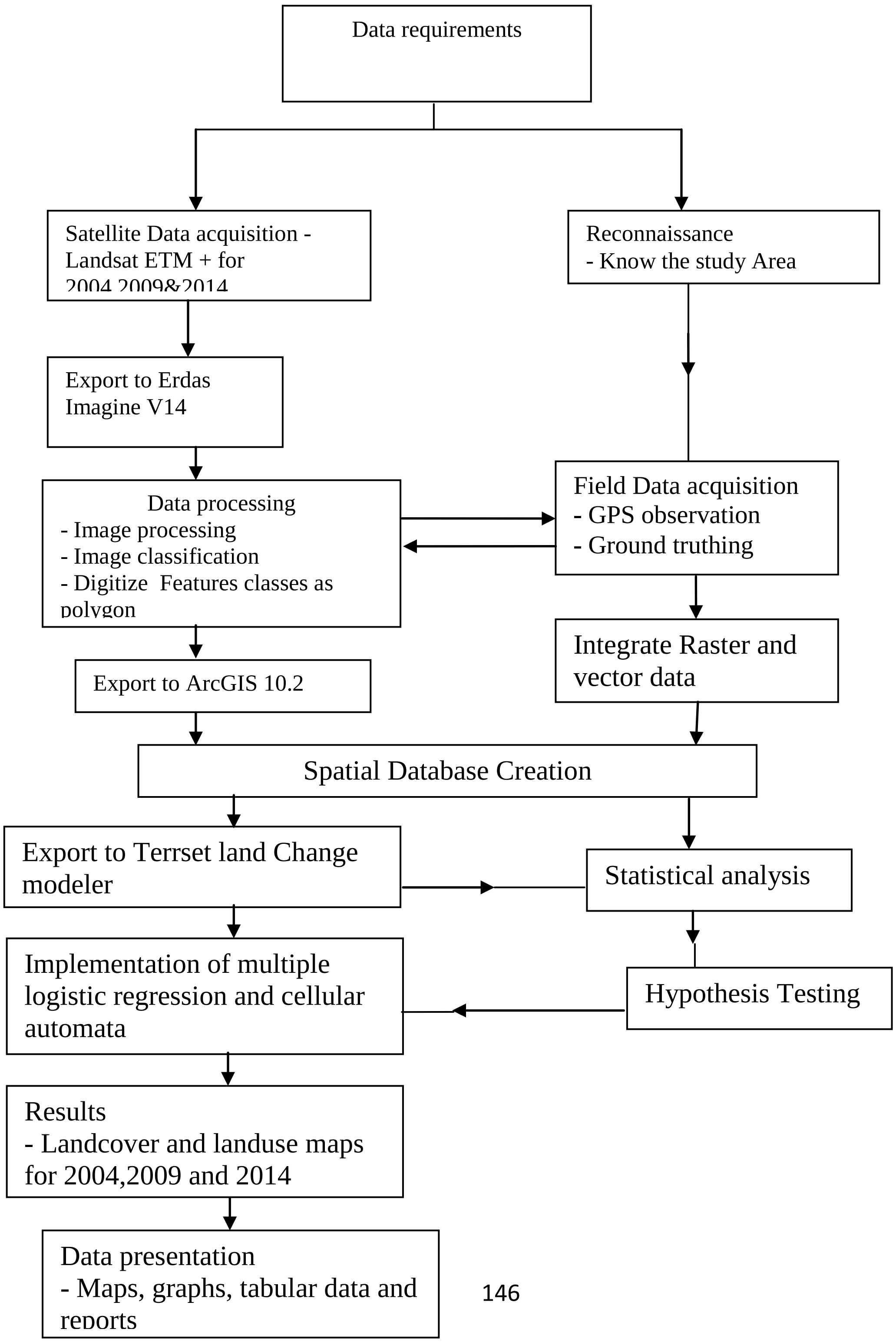


Fig. 4.1: Flowchart of the methodology adopted

The steps in fig 4.1 were followed in order to achieve the desired result

4.1 Data Requirements

The data that were used in this research included (i) primary and (ii) secondary data.

The primary data includes the following:

(i) Global positioning system (GPS) co-ordinates of the corners of the study area and prominent features in the study area.

The secondary data includes the following:

(i) 30m resolution, landsat-7 ETM + image of the area for years 2004, 2009 and 2014.

(ii) Administrative map covering the area.

(iii) Topographic map 1:50,000 covering the study area.

4.2 Hardware and Software Requirements

The following hardware and software were used.

The hardware requirements includes the following:

(i) An acer laptop with minimum configuration of 1GB RAM, 250GB Hard disk, 3.00GHZ microprocessor speed.

(ii) A0 Hewlett Packard scanner

(iii) A3 Hewlett Packard colour printer

(iv) Magellan promark XC-M

(v) 2GB USB flash disk

The following softwares were used

(i) Erdas Imagine V14: Used in classification of the images.

(ii) ArcGIS 10.2 GIS software: Used in the preparation of the landcover and landuse map.

(iii) Terrset land change modeler: Used in the modeling and prediction of the study area.

(iv) Microsoft word 2007: It was used for typesetting of this research work

(v) Microsoft power point 2007: It was used for the presentation of this research.

4.3 Data Sources

The data that were used in this study were obtained from the following sources.

(i) The landsat-7 ETM + for the years 2004, 2009 and 2014 were obtained from the National centre for Remote sensing, Jos, Plateau state; for December 2004, 2009 and 2014 in Joint Photographic Expert Group (JPEG) format.

(ii) The Administrative map covering the study area from the Kaduna State Geographic Information Service (KADGIS), Kaduna; in the year 2016 in Joint Photographic Expert Group (JPEG) format.

(iii) The 1:50,000 123SE,144NE,124SW and 145NW topographic map was obtained from the office of the Surveyor-General of the Federation, Kaduna zonal office, Kaduna; in hardcopy in the year 2016.

(iv) Field data needed for Georeferencing and accuracy assessment were obtained through Global Positioning System (GPS) observations; in the year 2016.

(v) Ancillary data such as Kaduna street guide map which assisted in feature identification was obtained from Kaduna State Geographic Information Service (KADGIS), Kaduna; in hardcopy at scale 1:1000.

4.4 Data Processing

The data processing involves the following stages:

(i) Radiometric and geometric corrections of all satellite imageries were already carried out by the National Remote Sensing Centre in Jos.

(ii) Landcover and landuse classifications

(iii) Accuracy assessments

(iv) Statistical analysis

Also the global positioning system coordinates of some prominent points in the study area were plotted as shown (See Appendix iv). Each of these steps were described in the methodology

4.5 Procedures adopted in achieving objective No. i

Objective No. i “To classify the multi-temporal satellite imageries of landsat ETM + of Kaduna and Environs into built-up areas, farmland, vegetation, open space and water bodies” was achieved as follows:

The four bounding geographic co-ordinates of the study area were converted into UTM grid co-ordinates using the Geographic Calculator Software (see plates 4.1a to 4.1d). The software when used in zones 31, 32 and 33 will yield good results. The results were compared with manual computation (see Table 4.1 and Appendix 1).

The four bounding coordinates which are the common points in all the datasets were transformed to Minna UTM Zone 32N coordinate system. In order to ensure that accurate results were obtained, the transformation was carried out using the Geographic Calculator Software (See plates 4.1a to 4.1d)

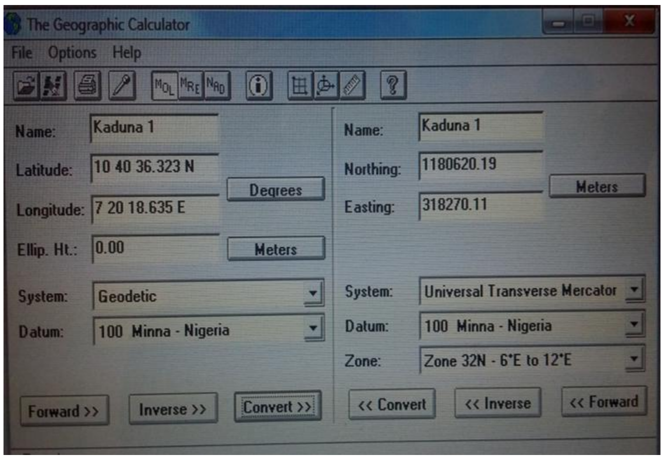


Plate 4.1 a: Geographic Calculator Software Coordinate Conversion of (Lat 10^{O} 40' 36''.323N and Long. 7^{0}20' 18". 635E)

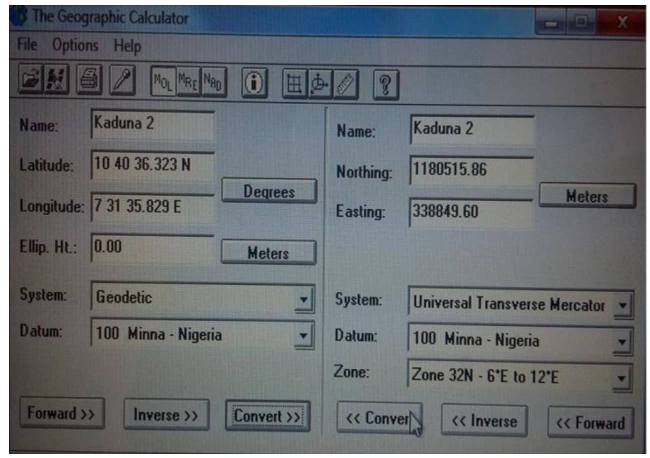


Plate. 4.1b: Geographic Calculator Software Coordinate Conversion of (Lat 10^{O} 40' 36''.323N and Long. 7^{0}31' 35". 829E)

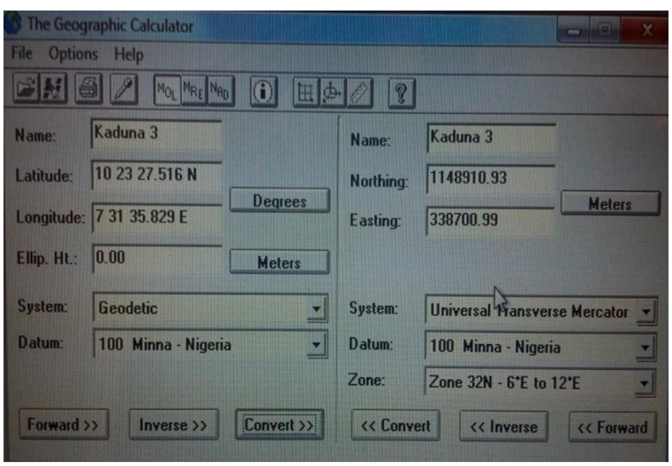


Plate 4.1c: Geographic Calculator Software Coordinate Conversion of (Lat 10^{O} 23' 27''.516N and Long. 7^{0}31' 35". 829E)

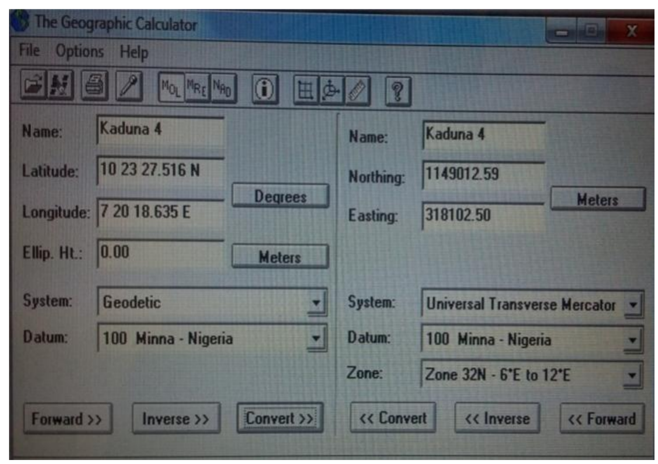


Plate 4.1d: Geographic Calculator Software Coordinate Conversion of (Lat 10^{O} 23' 27''.516N and Long. 7^{0}20' 18". 635E)

Table 4.1: Comparison of Co-ordinate Conversion using Manual Method and Geographic Calculator Version 3.09 Software.

S/N	Geographic Co-ordinate System	Minna UTM Zone 32 (manual method)	Minna UTM zone 32 Geographic Calculator Software
1	10^0 40'36"323N 07^0 20' 18". 635E	1180620.188mN 318270.129mE	1180620. 190mN 318270. 110mE
2.	$10^0$40' 36". 323N 07^0 31' 35" 829E	1180515.857mN 338849.620mE	1180515.860mN 338849.600mE
3.	10^0 23' 27". 516N 07^0 31' 35".829E	1148910.935mN 338701.024mE	1148910.930mN 338700.990mE
4.	10^0 23' 27". 516N 07^0 20' 18".635E	1149012.598mN 318102.537mE	1149012.590mN 318102.500mE

The universal Transverse Mercator (UTM) Projection was introduced in Nigeria by Federal Surveys Department around 1975 for mapping and surveying (Uzodinma *et al.*, 2013). The projection has been modified for universal application. The world is divided into 60 zones each 6^0 wide in longitude. Nigeria is covered by three UTM zones namely zones 31,32 and 33. Salient features includes conformal. A rectangular metric grid is superimposed on each zone-one system for northern hemisphere and another for southern hemisphere. Each zone has it's own independent co-ordinate system with x-axis 500,000m west of the central meridian and y-axis lying along the equator (Uzodinma and Ezenwere, 1993).

These formulae are required to convert Geographical Co-ordinates to Universal Transverse Mercator (UTM) Co-ordinates

$$\left.\begin{aligned} &N = M + W^2K + W^4B \\ &\Delta E = WR + W^3C + W^5 111 \\ &E = E_0 \pm \Delta E \end{aligned}\right\} \qquad \text{...(4.1)}$$

Where $W'' = 10^{-4}\Delta\lambda''$

$\Delta\lambda''$ – longitude difference (in seconds of arc) between point and central meridian

M – distance on the meridian from parallel of origin (Equator) to the parallel

ϕ- latitude of the point

N – Northings of the point

E – Eastings of point

E_0 – False Easting of the central meridian.

K, B, R,C, 111 are tabulated in UTM Table 11 for each 5' of latitude

ΔE are positive or negative depending on whether point is East or West of the central meridian.

The co-ordinates obtained from the manual computation were adopted for geo-referencing since there was no significant difference between the co-ordinates obtained using the manual computation and the software. The geo-referencing of the study area for the year 2004, 2009 and 2014 were carried out using ArcGIS 10.2 as described below.

The ArcGIS 10.2 was launched by clicking on Arcmap. The dataset was imported using the add data tool and the map was located by browsing. The + sign on the geo-referencing tool bar was clicked and the corner of the study area was zoomed to identify the intersection. The + Tool on the corner was clicked and right clicked to input X and Y co-ordinates. A dialogue box appeared in which the Eastings and Northings co-ordinates were entered and OK was clicked. The same process was repeated on the other corner points of the study area, update geo-referencing was clicked in order to complete the geo-referencing.

Erdas imagine V14 was used for the classification as follows, the study area was fitted to frame and displayed in the working area. The signature editor tool was used in picking the training sites. Raster menu (supervised) and the signature editor were clicked. A polygon was drawn on area of interest using the polygon tool. New signature from area of interest, repeatedly on the entire study area was created for the built –up area class. All the added training sites were merged by clicking on selected signatures tool (See plates 4.2 and 4.3). Another training site for farmland was selected and the process repeated same for the other classes i.e vegetation, open space and water bodies. The images were saved in the destination drive and the classification accomplished after a pre-classification visits to the site. In plate 4.2, the pixel with the maximum likelihood was classified into the corresponding class and the probability of the pixel well defined as shown in the dialogue box of Erdas Imagine. In plate 4.3, the dialogue box of Erdas Imagine shows the built-up area which is the major class from which other classes transited to with probability of 1.00. The classified images were exported to Terrset land change modeler. The various classes were symbolized according to their natural colours based on the description in Table 4.2.

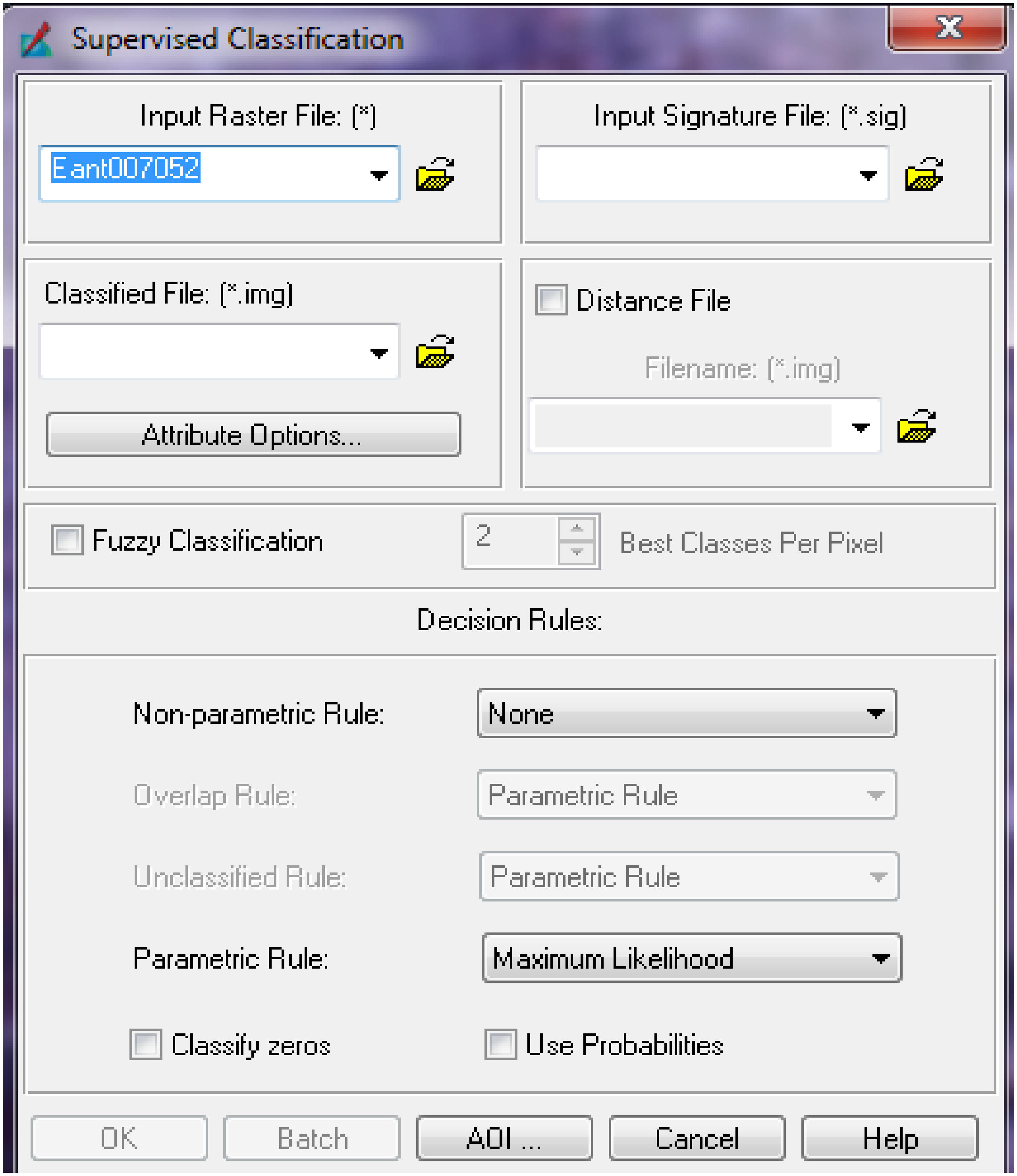


Plate 4.2: Supervised classification (Dialogue Box of Erdas Imagine)

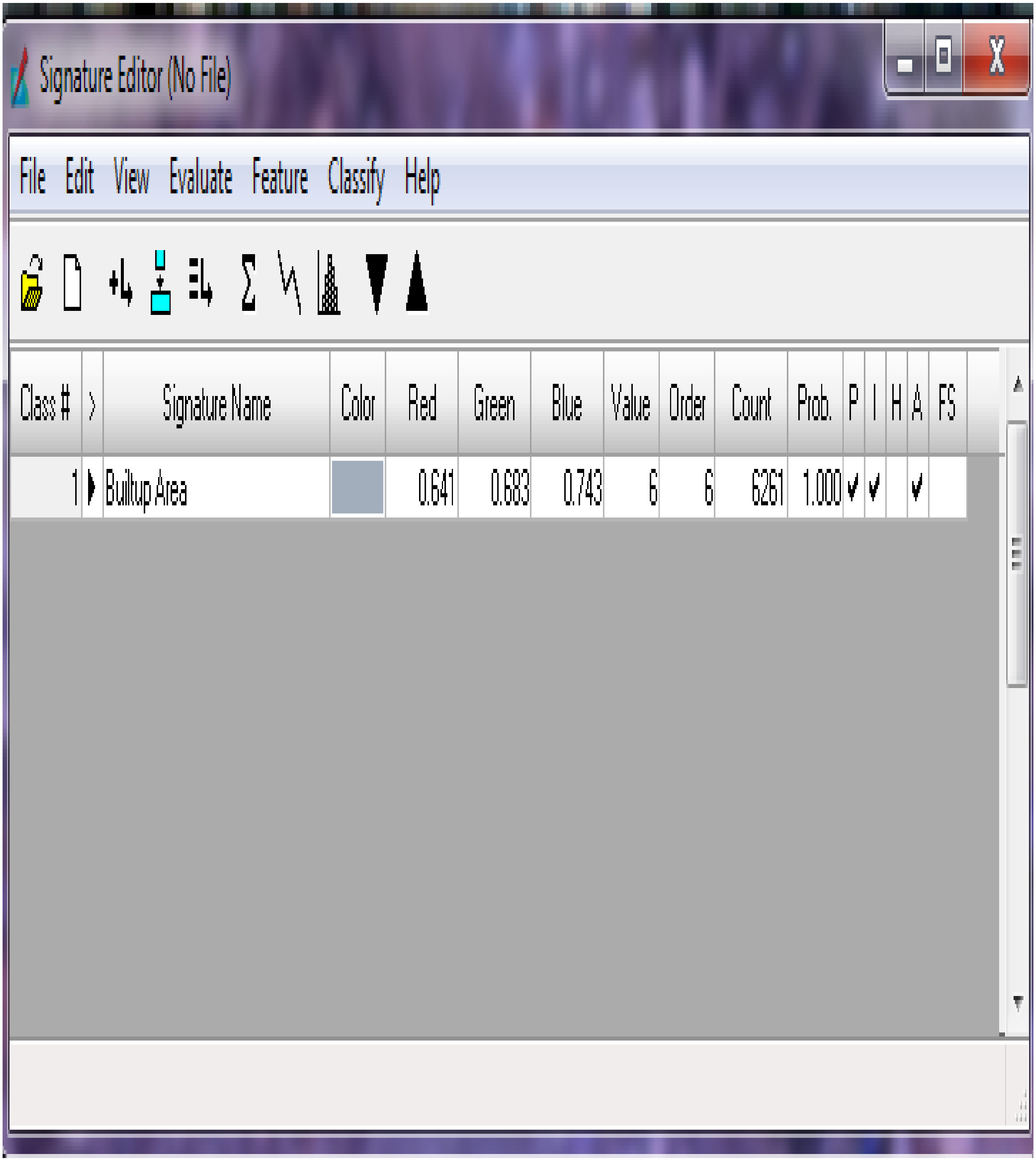


Plate 4.3: Signature Editor (Dialogue Box of Erdas Imagine)

The Classified images for 2004, 2009 and 2014 using Terrset land change modeler clearly shows Built-up areas, farmland, vegetation, open space and water bodies for the study area. The earlier landcover images and later land cover images were prepared to enable landuse changes for Kaduna and Environs to be detected (See plates 4.4, 4.5 and 4.6).

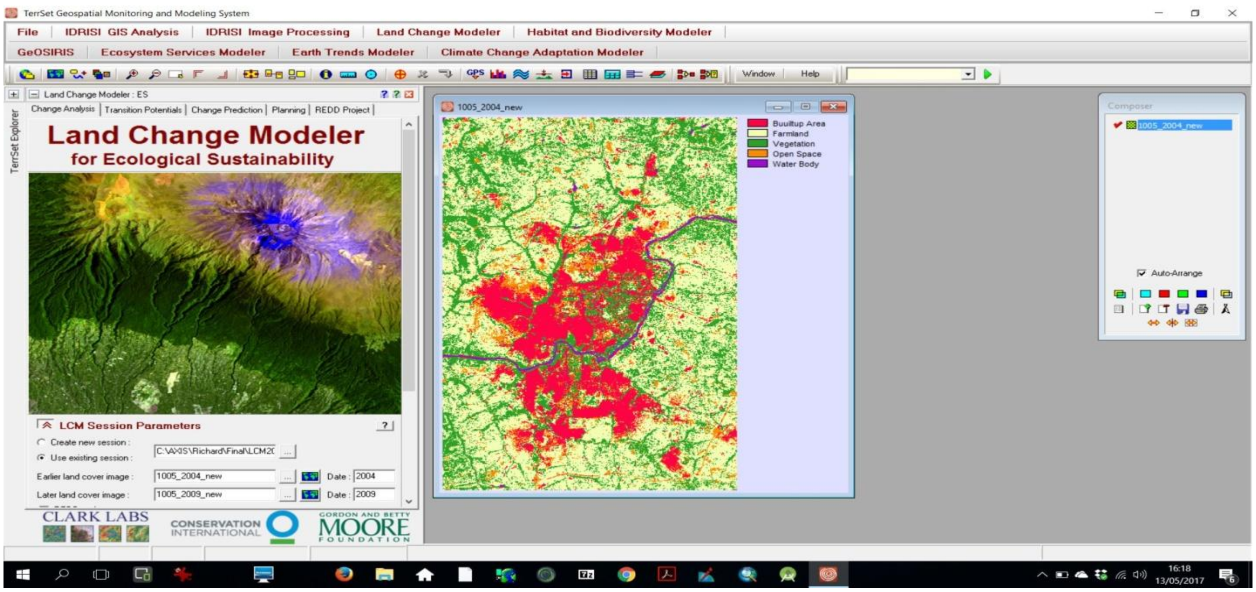


Plate 4.4: Classified Image for 2004

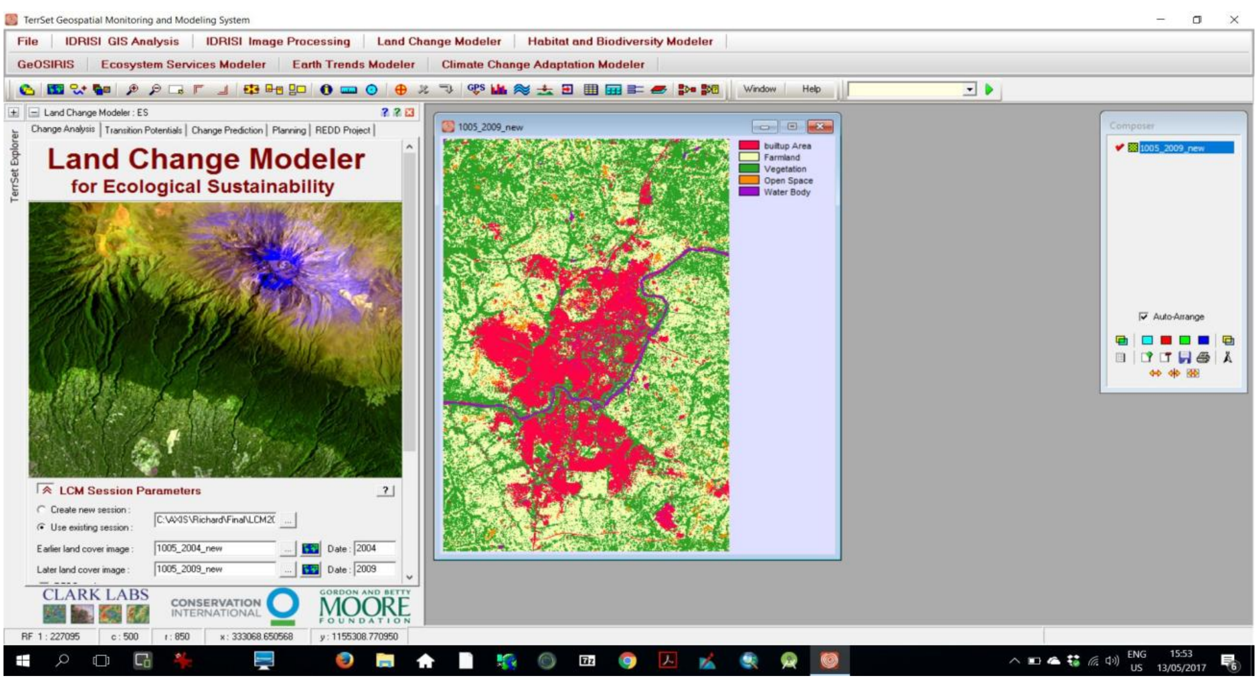


Plate 4.5: Classified Image for 2009

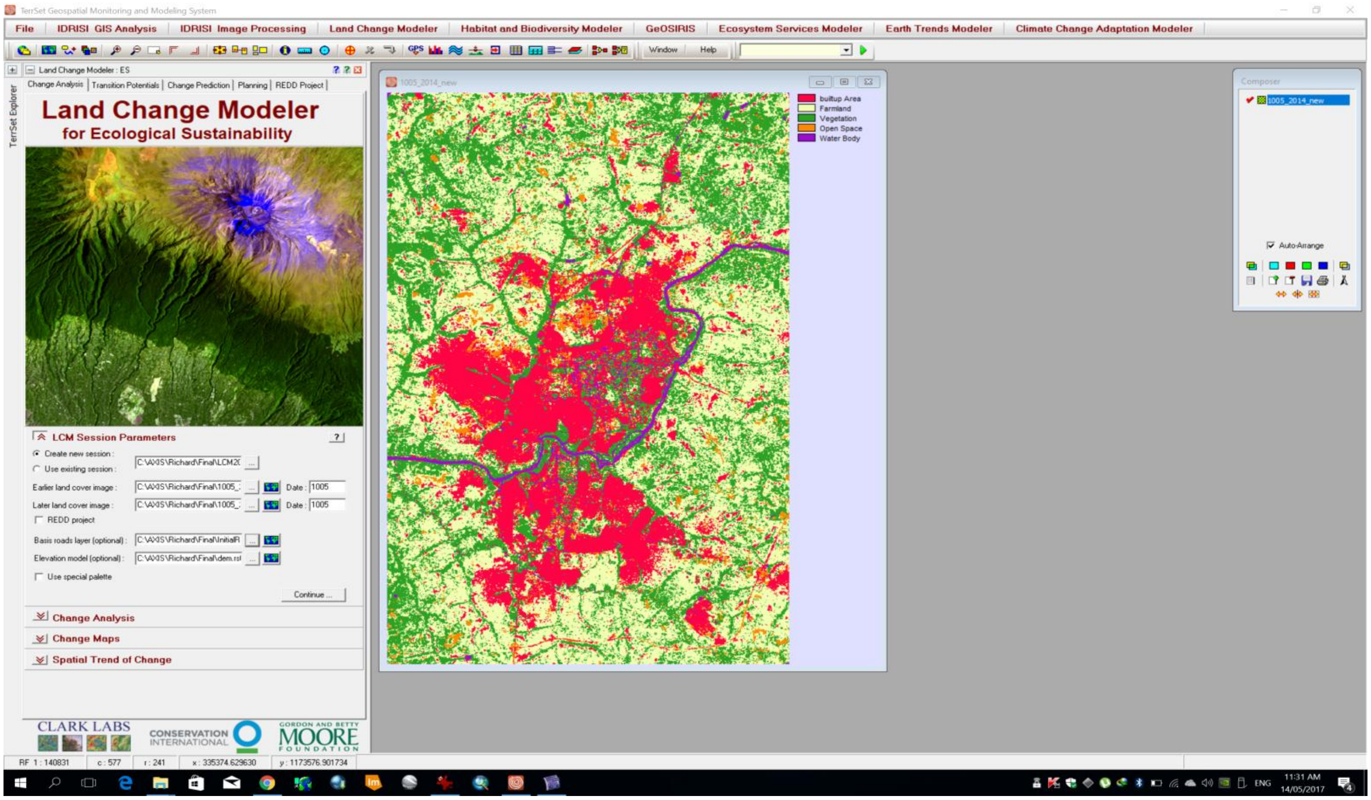


Plate 4.6: Classified Image for 2014

Table 4.2 : Description of Classes Adopted

S/No	Class	Description	Colour assigned
1	Built-up	Includes all residential, commercial and industrial development	Pink
2.	Farm land	Includes field crops, Horticulture, orchards, improve pasture, ploughed fields and fallow land.	Light green
3.	Vegetation	Includes all vegetation features such as evergreen, deciduous, scrub and forest.	Dark green
4.	Open space	Includes bare earth or soil, unpaved roads and excavation sites.	White
5.	Water bodies	Water related features such as freshwater, lakes, rivers and streams.	Blue

4.6 Procedures adopted in achieving Objective No. ii

Objective No. ii "To Model the landcover and landuse changes of Kaduna and Environs using cellular automata " was achieved as follows:

In a cellular automaton, spatial variation is represented as a raster of fixed resolution with each cell being assigned to one of a number of defined states. Such models were used in studying processes of urban growth in which possible states will likely be limited to undeveloped and developed. At each time step, the next state of each cell is determined by a number of rules based on the properties of the cell and it's neighbors.

The file name was displayed in the Terrset land change modeler after opening it from the menu. It was minimized to make room for the land change modeler. A new project was created in the project parameters panel. The earlier landcover image was entered LANDCOVER 2004 CMA and later landcover image was also entered LANDCOVER 2009 CMA. The default palette was filled and the continue button was clicked. A graph is now presented with gains and losses by category. In the change map panel, the map transition option was clicked to show vegetation areas that have transited to built-up area. Each transition was modeled using logistic regression. The transitions were modeled by clicking on the second tab.

In Terrset, cellular automata varies its state based on its previous state and that of its immediate neighbor according to a transition rule that involves immediate neighbouring cells and the road network. The cellular automata simulation was operated on a cell by cell basis. A cell which is the basic unit of cellular automata has a binary value 1 for successful development and O for non-change. The transition area helps in showing a class expected to change to other class over the period of five (5) years.

Artificial neural networks were used for simulation. It is capable of using noisy and fuzzy information to handle urban growth simulation. Transition rules helps in dynamic evolution. A transition rule normally specifies the states of cell before and after updating based on its neighborhood condition. Simple regression seeks to predict an outcome from a single predictor, where multiple regression seek to predict an outcome from several predictors. The results generated from these procedures are presented in the next chapter.

Transition from farmland to Built-up area is shown in red, from vegetation to Built-up is shown in yellow. Farmland persistence and vegetation persistence are shown in green and brown colours for all classes (see plate4.7)

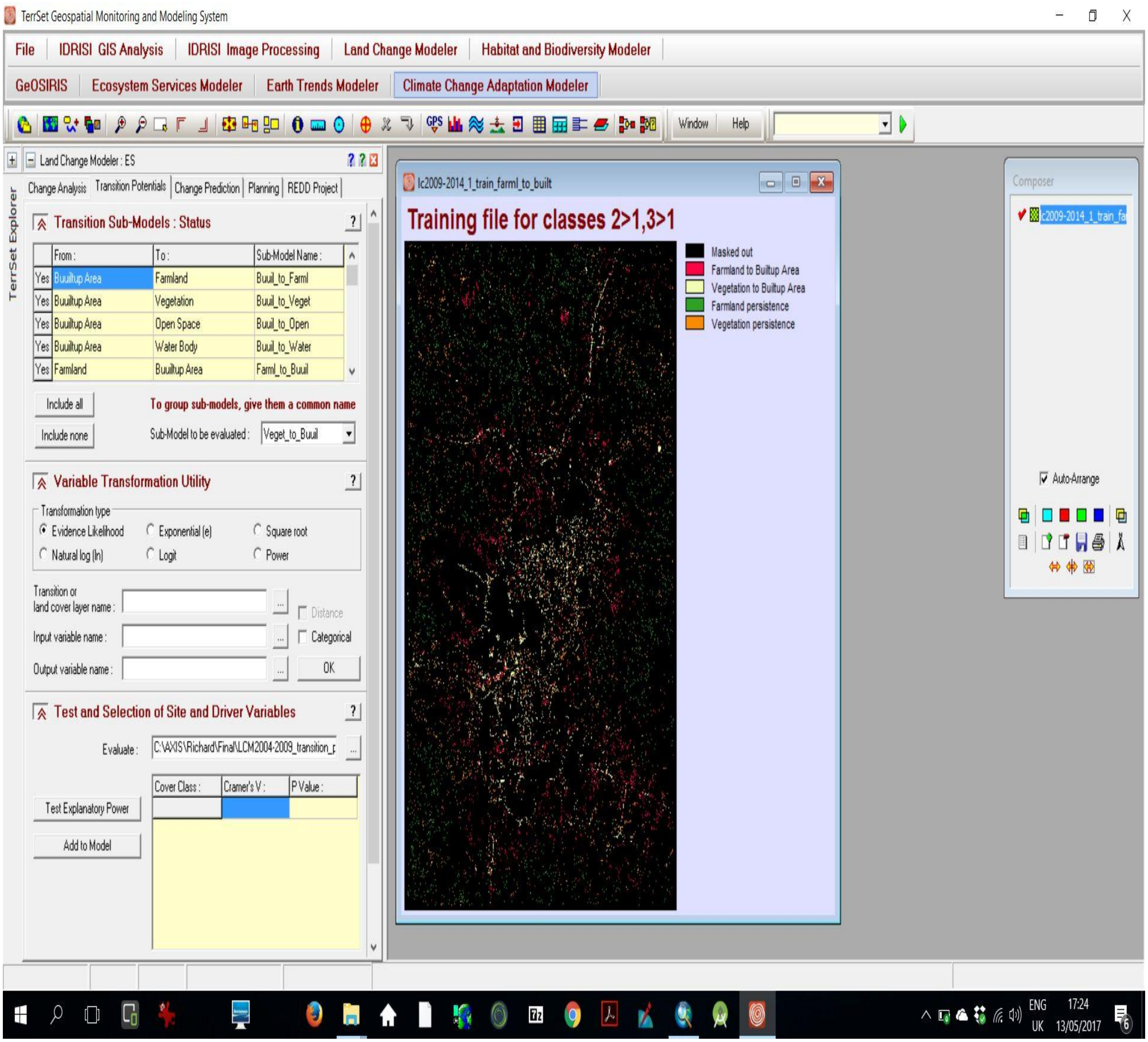


Plate 4.7: Transition from the various classes

4.7 Procedures adopted in achieving Objective No. iii

Objective No. iii. "To determine the landcover and landuse change within the study area" was achieved as follows:

A statistical hypothesis is an assertion about the distribution of one or more random variables. It is frequently denoted by symbols such as H_0 or H_1. A test of statistical hypothesis is a procedure based on the observed values of the variables, that may lead to the acceptance or rejection of the null hypothesis (Batty *et al.***,** 1986).

The various classes i.e Built-up area, farmland, vegetation, open space and water bodies within the metropolis were significantly tested to determine which class transit to built-up area at a probability level of 0.05. The significance level is the probability value that forms the boundary between rejecting and not rejecting the null hypothesis. This was represented as $P<0.05$ in which P stands for the probability of the null hypothesis. The 0.05 thus represents the probability value that separates a decision to reject null hypothesis from the decision not to reject it.

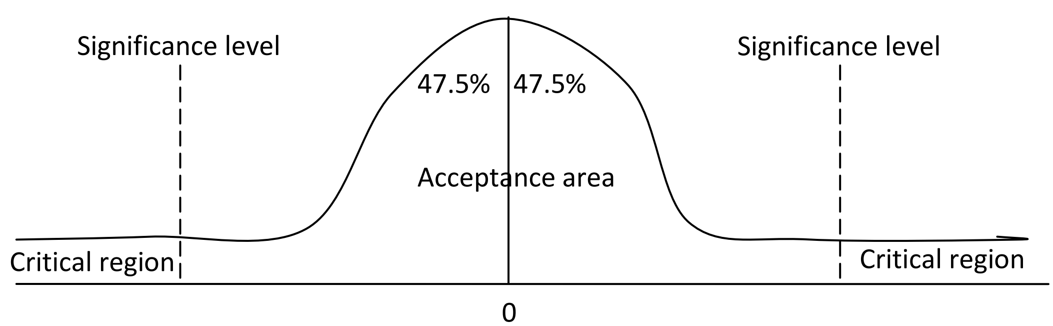


Fig. 4.2 : Normal curve showing critical region and significance level at 95% (0.05).

The t- test was used to determine whether two classes are significantly different. The formula used is given in equation 4.2 by Pradhan *et al.*, (2013). Fig. 4.2 shows significance level at 95%.

$$t = \frac{\overline{X}1 - \overline{X}2}{\sqrt{\frac{S_1^2 + S_2^2}{n_1 + n_2}}} \qquad \text{.. .(4.2)}$$

Where $\overline{X}_1$ & $\overline{X}_2$ -Mean of classes

S - Standard deviation

n- Number of subjects in each class

Analysis of Variance (ANOVA) was also used to determine whether there was a significant difference between the classes. Analysis of variance focuses on variability. It involves the calculation of several measure of variability. A ratio was formed with class differences as the number for (variance between classes) and an error term as the denominator (variance within classes). The following operations were performed.

(i) The variance of the three epochs i.e 2004, 2009, and 2014 were combined into one composite group known as the total groups variance V_t

(ii) The mean value of the variances of each of the three epochs i.e 2004, 2009, and 2014, computed separately, known as the within groups variance V_w

(iii) The difference between the total group variance and the within groups variance known as the between groups variance ($V_b = V_t - V_w$) was determined.

(iv) The F ratio was then computed as ${Vb}/{Vw}$.The degree of freedom was determined using the number of groups minus 1.

Bar and pie chart were then constructed using the number of pixels for each class after the level of significance was tested.

4.8 Procedures adopted in achieving Objective No. iv

Objective No. iv "To predict the pattern of changes (25 years) with multiple logistic regression" was achieved as follows:

The landcover and landuse map for 2014 was used to predict for the changes (25 years) later by using the prediction tab in Terrset software to produce the map for 2039. The transition potentials were used to create the prediction. The change prediction tab in the land change modeler provides dynamic landcover change. At the change prediction tab, the change Demand modeling panel was opened, where the end year of the prediction was specified i.e. 2039. There are several explanatory variables which helps in prediction. In multiple logistic regression, the dependent variable is discrete such as landcover types (e.g. vegetation, open space and water bodies), by default the prediction was created.

4.9 Procedures adopted in achieving Objective No. v

Objective No. v "To produce the landcover and landuse maps of Kaduna and environs for the year 2004, 2009 and 2014 in softcopy and hardcopy" was achieved as follows.

In Terrset, the map window was launched by using display launcher. The software will automatically keep track of the models. Display launcher provides a quick composition facility with automatic placement of both the title and the legend. The add layer button of composer was clicked and the vector layer road was added. Add layer again was clicked to include the railway lines with a special symbols: also prominent features such as Nigerian Defence Academy, central market, railway station, Kaduna polytechnic, Kaduna State University (KASU) and Ahmadu Bello stadium were included.

Legends were constructed like all map components, the software allows it to be displayed and was automatically constructed. The scale bar was displayed and it's length, text, number of divisions and colour were controlled. The standard north arrow provided by Terrset can be varied and it was varied in such a way that it was readable. The roads were annotated using the text frame a sizeable and place able rectangular box that contains text. The map grid was incorporated, the position of the origin and increment in X – axis and Y – axis were carried out. The softcopy was saved in a flash drive and the hard copies printed for the years 2004, 2009 and 2014. The results generated from these procedures are presented in the next chapter.

CHAPTER FIVE

PRESENTATION AND DISCUSSION OF RESULTS

The results of this research were presented and discussed in accordance with the objectives of the study.

5.1 Objective No.1 "To classify the Multi-temporal satellite imageries of landsat ETM + of Kaduna and Environs into built-up areas, farmland, vegetation, open space and water bodies "was analyzed as follows:

Image classification involves categorizing image features with the aim of converting them into a thematic map. The supervised classification was used where sample areas depicting faithfully the features to be classified were selected from the image data. Representative samples of cover types (training sets) were picked, which constitute sub-samples of images whose identity were verified through ground-truthing.

The confusion matrix is an indication of major problems in situation where spectral responses of scene features overlap, where categories shares identical spectral signatures (Ndukwe, 1997). The precision of the classified images were ascertained and accuracy assessment was carried out by comparing the classified landsat image with known reference pixels. Tables of confusion matrices were prepared as shown in tables 5.1 to 5.3

Table 5.1: Confusion matrix for 2004 landsat ETM+ (supervised classification)

Classified image	**Reference map**							
	Built-up Area	**Farmland**	**Vegetation**	**Open space**	**Water bodies**	**Total**	**Error of Commission**	**User's accuracy**
Built-up Area	118574	40	50	0	0	118664	0.1	99.9
Farmland	40	356303	50	0	0	356393	0.1	99.9
Vegetation	50	40	208988	0	0	209078	0.1	99.9
Open space	30	40	20	62666	0	62756	0.1	99.9
Water bodies	0	0	0	0	7788	7788	0	100
Total	118694	356423	209108	62666	7788	754679		
Error of Omission	0.1	0.1	0.1	0	0			
Producer's accuracy	99.9	99.9	99.9	100	100			

From Table 5.1 the values at the diagonal represents the correctly classified pixels for each class i.e 118574 pixels for Built-up area for the year 2004. However, the values off the diagonal represent incorrectly classified pixels. The first row shows that farmland had 40 incorrectly classified pixels while vegetation had 50 incorrectly classified pixels. Accordingly, other information were revealed in the confusion matrix.

Error of omission occurs as a result of omitted area during classification, while the producer's accuracy is the probability that a classified image belongs to that particular class. The producer's accuracy was obtained by dividing the classified images by the total pixels recorded. As an example for vegetation, the producer's accuracy is 208988/209108 or 99.9% therefore the error of omission is 0.1%.

Error of commission occurs if a particular class on the ground is assigned to another class on the reference map. The user's accuracy is the probability that the pixels in the classified image represents that class on the ground. The user's accuracy was obtained by dividing the classified images by the total pixels recorded. As an example for Built-up area, the user's accuracy is 118574/118664 or 99.9% therefore the error of commission is 0.1%. This is an indication that the Built-up area in the study area was correctly classified by this amount (99.9%).

The overall accuracy was computed by dividing the total corrected number of pixels i.e summation of the diagonal to the total number of pixels in the matrix. The overall accuracy is 754319/754679 or 99.9%. Yaakup and Shamsuddin., (2007) succinctly submitted that the overall accuracy (%) required for a reliable landcover change analysis and modeling is a function of the scale of the map and imagery employed in the classification. The researchers stated that for scale 1:50,000-1:250,000, an overall accuracy of 50% -70% is acceptable. Indeed, the classification carried out can be said to be reliable as shown in (fig. 5.1)

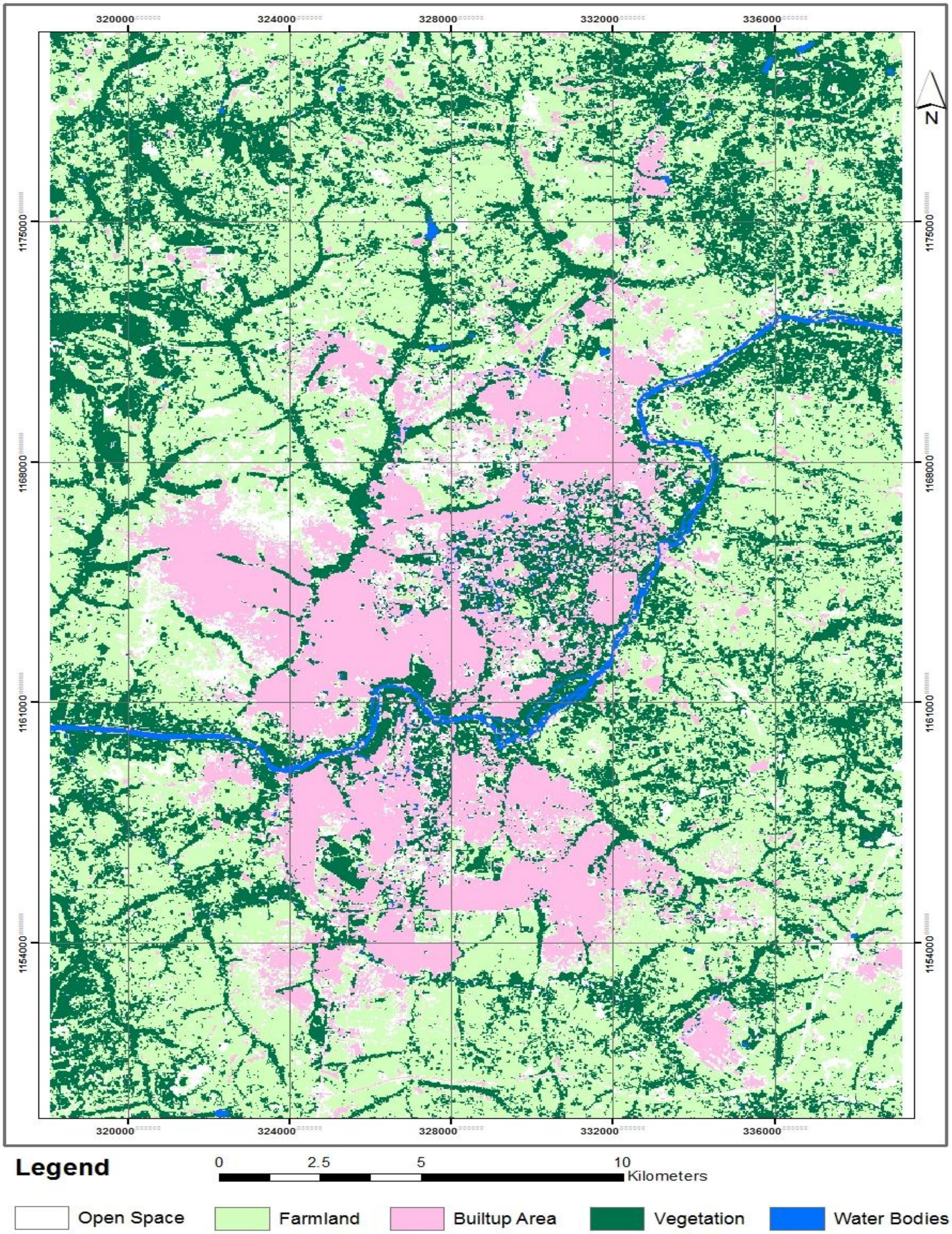


Fig. 5.1: classified image of Kaduna and Environs for 2004

The kappa coefficient determines the difference between the observed agreement between two maps and the agreement that might be attained by change matching of the two maps. It gives a measure of agreement.

The Kappa coefficient is given in Pradhan *et al.,* (2013) as:

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ij} - \sum_{i=1}^{r}(X_{1+} \,.\, X_{+1})}{N^2 - \sum_{i=1}^{r}(X_{1+} \,.\, X_{+1})} \qquad \ldots 5.1$$

Where

r- Number of rows in the confusion matrix

N- Total number of observations included in matrix

Σx_{ij} - Number of observations along the major diagonal

(X_{1+})- Total observations in row i shown as marginal total to the right of the matrix

(X_{+1})- Total observations in column i shown as marginal total at bottom of the matrix

$\sum_{i=1}^{r} x_{ij}$ = 118574+356303+208988+62666+7788= 754319

N = 118694+356423+209108+62666+7788= 754679

$\sum_{i=1}^{r}(X_{1+}X_{+1})$ = 118664 x 118694 + 356393 x 356423 + 209078 x 209108 + 62756 x 62666 + 7788 x 7788 = 188834566440

$$K = \frac{754679 \times 754319 - 188834566440}{(754679)^2 - 188834566440}$$

= 0.99 = 99%

0.99 is an indication of the correctness of the classification

The kappa statistic is more reliable than other validation techniques because it has the ability to evaluate the actual agreement and chance agreement (Fung and Ledrew, 1988).

Table 5.2 Interpretation of kappa statistic

Kappa	**Interpretation**
< 0	No agreement
0.0-0.20	Slight agreement
0.21-0.40	Fair agreement
0.41-0.60	Moderate agreement
0.61-0.80	Substantial agreement
0.81-1.00	Almost perfect agreement

Source: Fung and Ledrew, 1988.

The computed value was 0.99 and from Table5.2, the result was satisfactory, the classification can be said to be reliable.

Similarly the confusion matrix for the years 2009 and 2014 were prepared as shown in Tables 5.3 and 5.4 respectively.

Table 5.3:Confusion matrix for 2009 landsat 7 ETM+ (supervised classification)

Classified Images	Reference map							
	Built up Area	**Farmland**	**Vegetation**	**Open space**	**Water bodies**	**Total**	**Error of Commission**	**User's Accuracy**
Built up Area	141765	44	53	0	0	141862	0.1	99.9
Farmland	44	280914	53	0	0	281011	0.1	99.9
Vegetation	53	44	297945	0	0	298042	0.1	99.9
Open space	36	44	22	20755	0	20857	0.5	99.5
Water bodies	0	0	0	0	12940	12940	0	100
Total	141898	281046	298073	20755	12940	754712		
Error of Omission	0.1	0.1	0.1	0	0			
Producer's Accuracy	99.9	99.9	99.9	100	100			

Table 5.4: Confusion matrix for 2014 landsat ETM+ (supervised classification)

Classified Images	**Reference map**							
	Built up Area	**Farm Land**	**Vegetation**	**Open space**	**Water bodies**	**Total**	**Error of Commission**	**User's Accuracy**
Built up Area	156119	47	53	0	0	156219	0.1	99.9
Farmland	47	319446	53	0	0	319546	0.1	99.9
Vegetation	57	46	228337	0	0	228440	0.1	99.9
Open space	38	46	23	35347	0	35454	0.3	99.7
Water bodies	0	0	0	0	15070	15070	0	100
Total	156261	319585	228466	35347	15070	754729		
Error of Omission	0.1	0.1	0.1	0	0			
Producer's Accuracy	99.9	99.9	99.9	100	100			

The overall accuracies computed for the years 2009 and 2014 which were 99.9% are acceptable, therefore the classifications carried out are reliable as shown in fig. 5.2 and

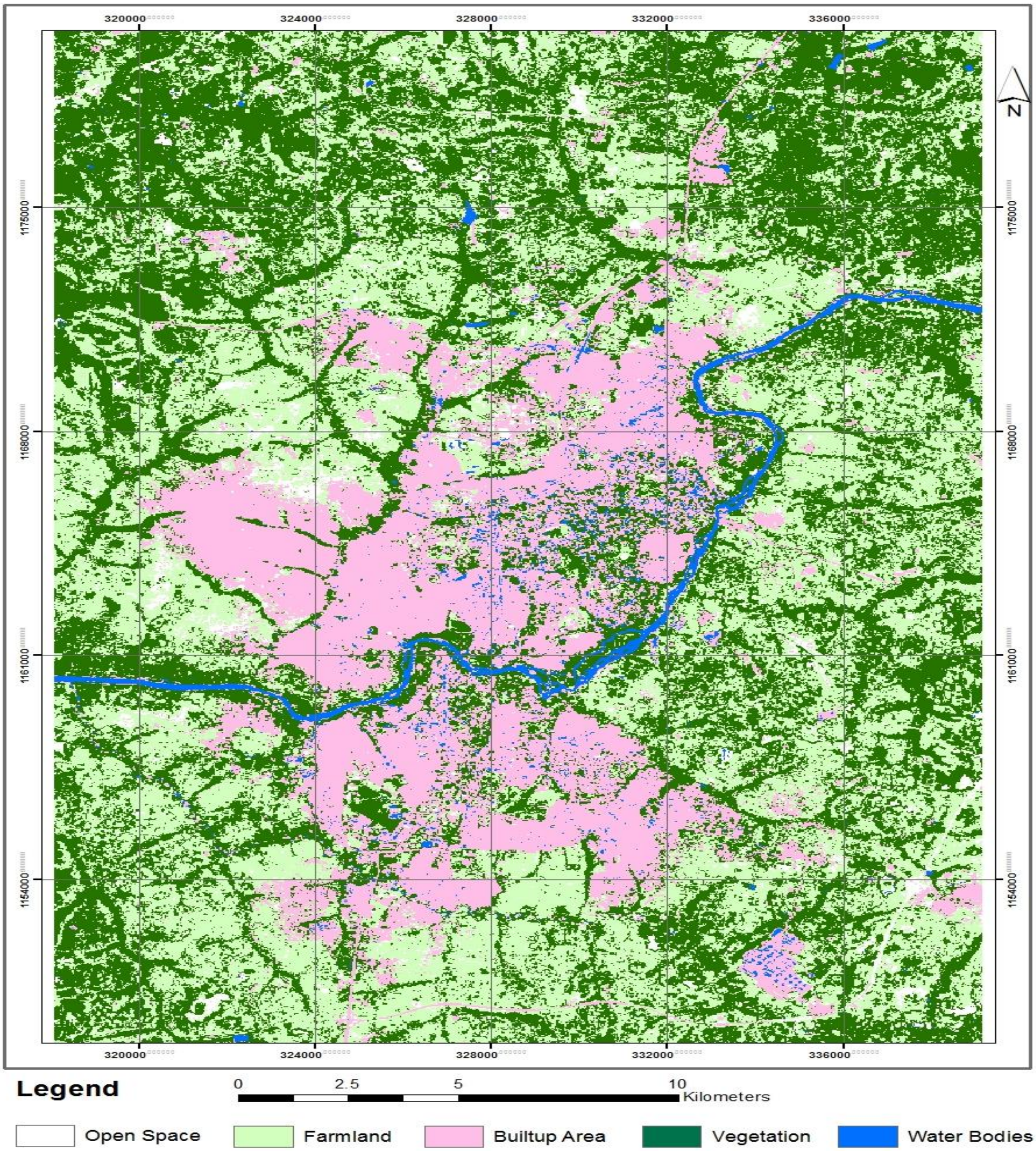


Fig. 5.2: Classified image of Kaduna and Environs for 2009

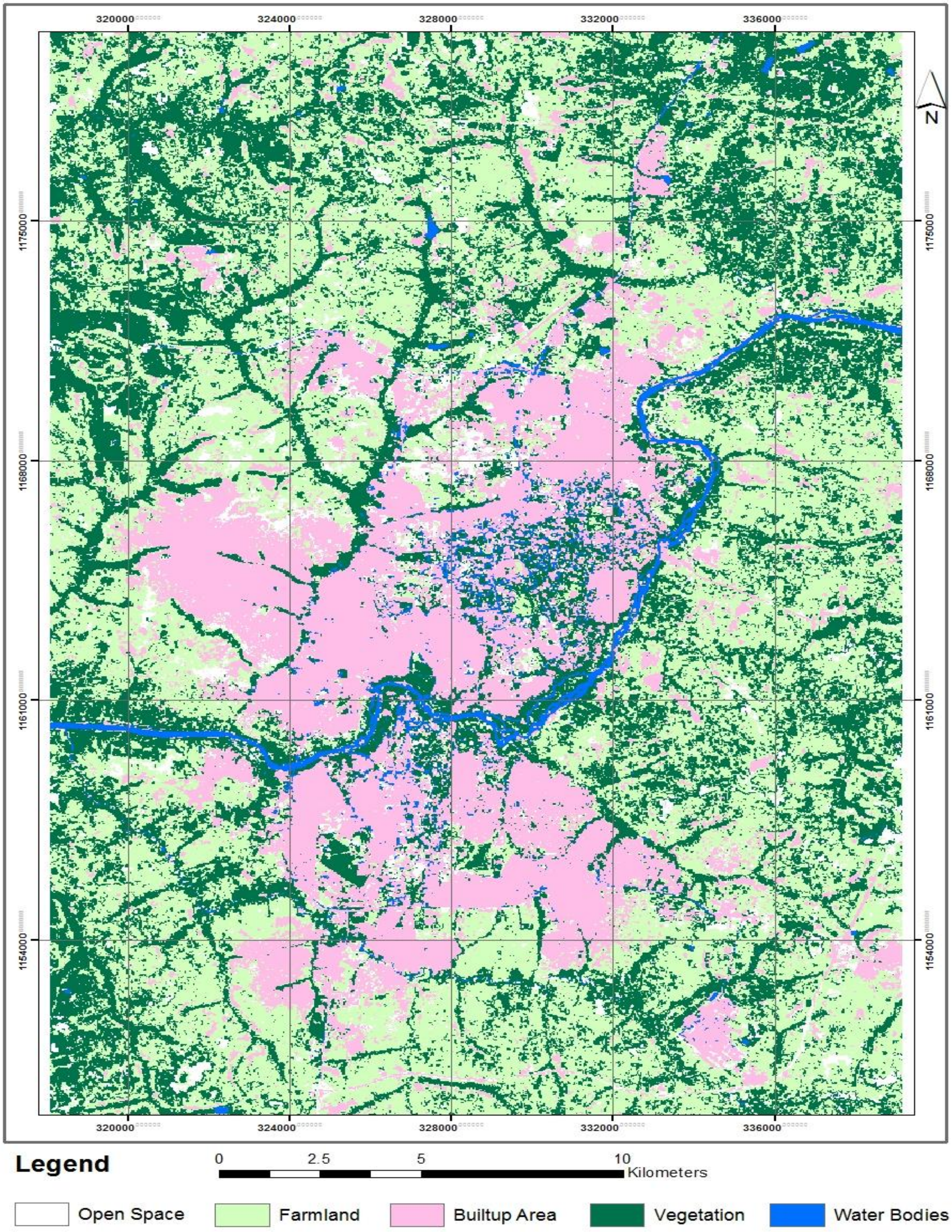


Fig. 5.3: Classified image of Kaduna and Environs for 2014

5.2 Objective No. ii To model the landcover and landuse changes of Kaduna and environs using cellular Automata was analyzed as follows:

The growth of urban areas universally has gained considerable momentum due to ever increasing population. Since the turn of the century, urban growth has increased tremendously, the current rate is unprecedented. In Nigeria, the growth is likely to continue at the rate of 5 percent (Okeke, 2002).

The urban spatial structure is identified by space-activity relationship; this relationship explains urban spaces and the activities they accommodate. The diversity and intensity of the relationship explains the texture of the urban structure. The apparent maze of space-activity relationships in urban areas exhibit distinct characteristics. The Study Area was classified into built-up area, farmland, vegetation, open space and water bodies. A model for year 2004 was developed based on time-based data. Cellular automata was used to model the change in the study area on a cell by cell basis to determine the landuse process and develop spatially explicit models to detect urban development. For land change modeler using Terrset, new session was created using the classified image of year 2004 and year 2009. The transitions that were considered were farmland to built-up area, vegetation to built-up area and open space to built-up area. Using the transition potential tab the Boolean images were generated (see fig 5.4 to fig 5.8). The Boolean image (true or false) i.e 0 and 1 for built-up area, vegetation, farmland were generated. In Fig. 5.4, the areas that are transiting are represented by red dots. Cellation provides for cellular Automata in the Terrset system. This is typically used in dynamic modeling where the future state of a pixel depends upon its current state and that of its neighbours.

The image files that represent the first state were inserted in the cellation operation. The prefix for the output image was entered to produce maps for 2004, 2009 and 2014 where changes were noted (see plates 5.1 to 5.3).

The red dot represents areas that are transiting from farmland to built-up from 2004 – 2009 (see fig. 5.4). The dotted red portions represent areas transiting from farmland to built-up area from 2009 – 2014 (see fig. 5.5). The dotted red portions represent areas transiting from vegetation to built-up area from 2004 – 2009. The coded black portions are not transiting (See fig. 5.6). The dotted red portions represent areas transiting from vegetations to built-up area from 2009 – 2014 (see fig. 5.7). The potential for transition from open space to built-up area is not noticeable, which shows that open space do not transit to built-up for the year 2004 – 2014 (see fig. 5.8).

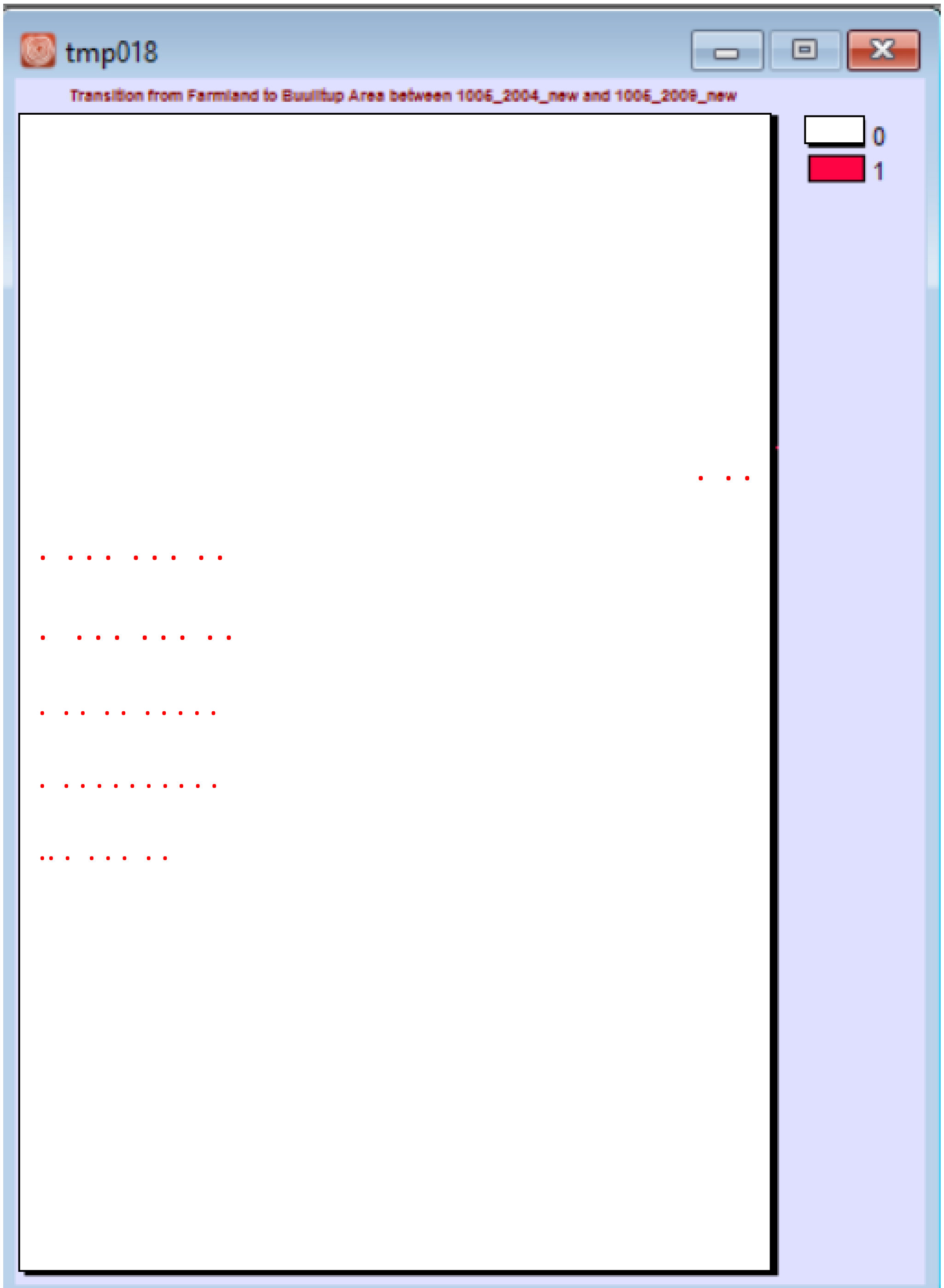


Fig 5.4: Transition from farmland to built-up area for 2004-2009

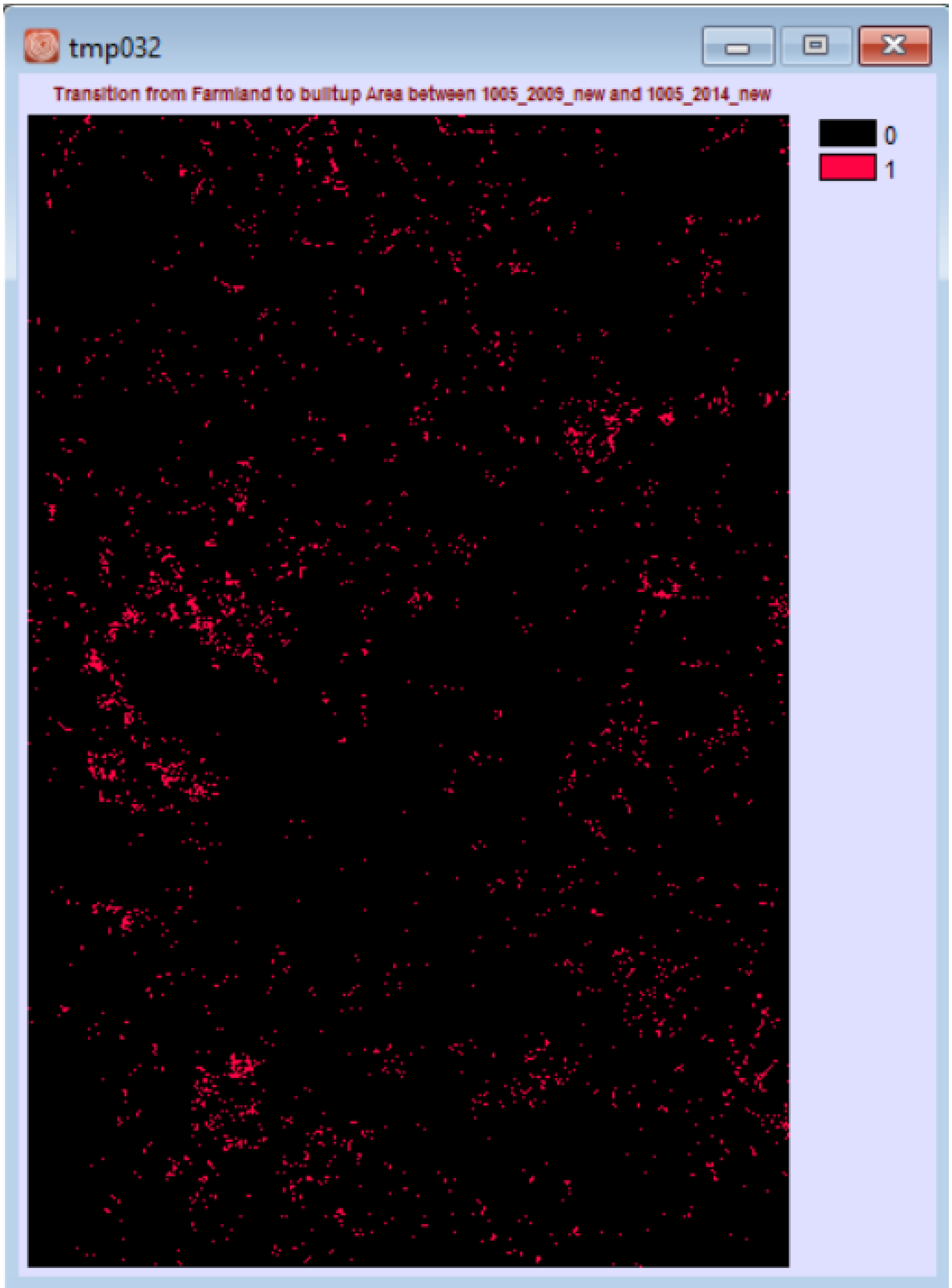


Fig.5.5: Transition from farmland to built-up area for 2009- 2014

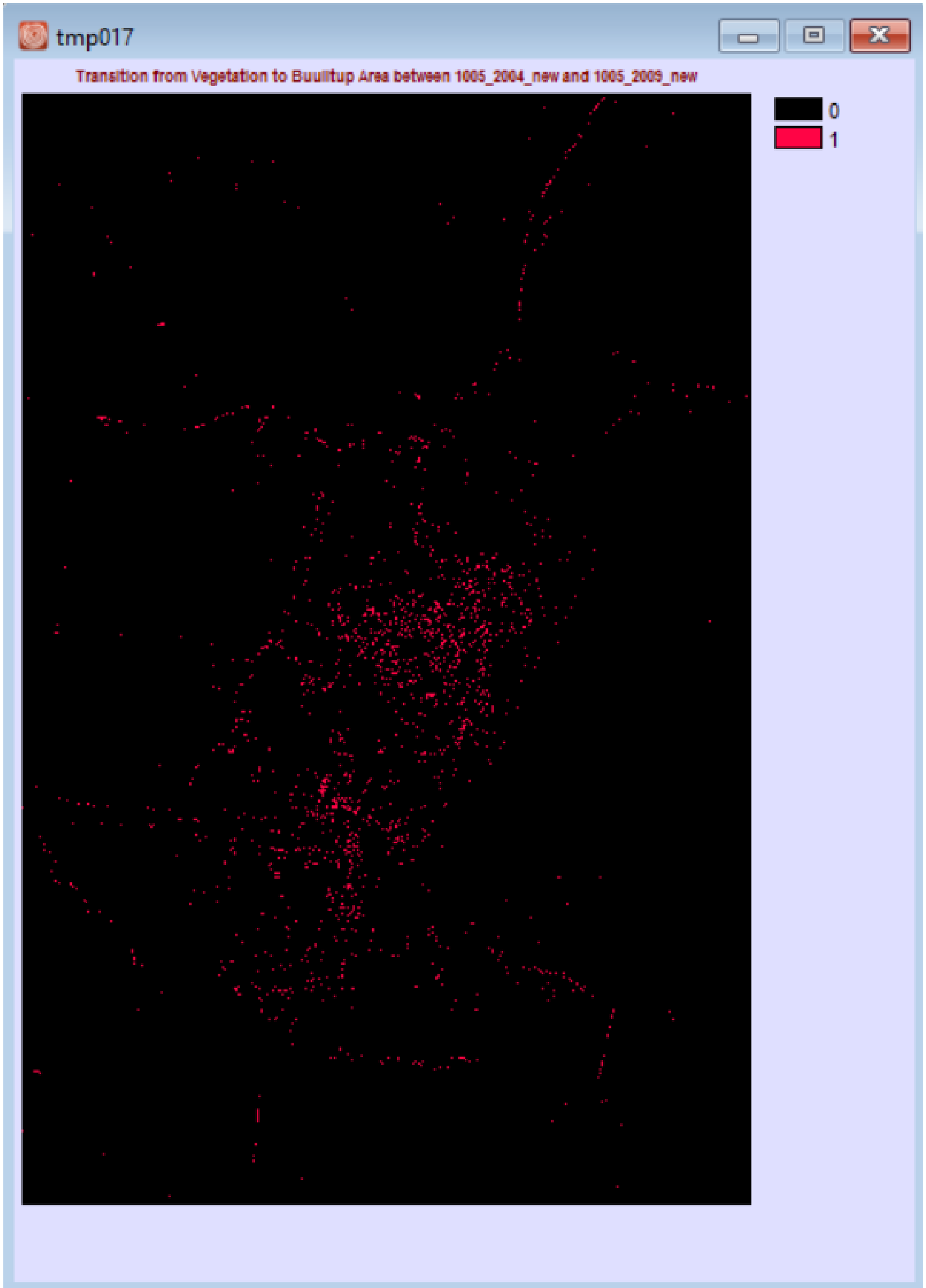


Fig. 5.6: Transition from vegetation to built-up area for 2004-2009

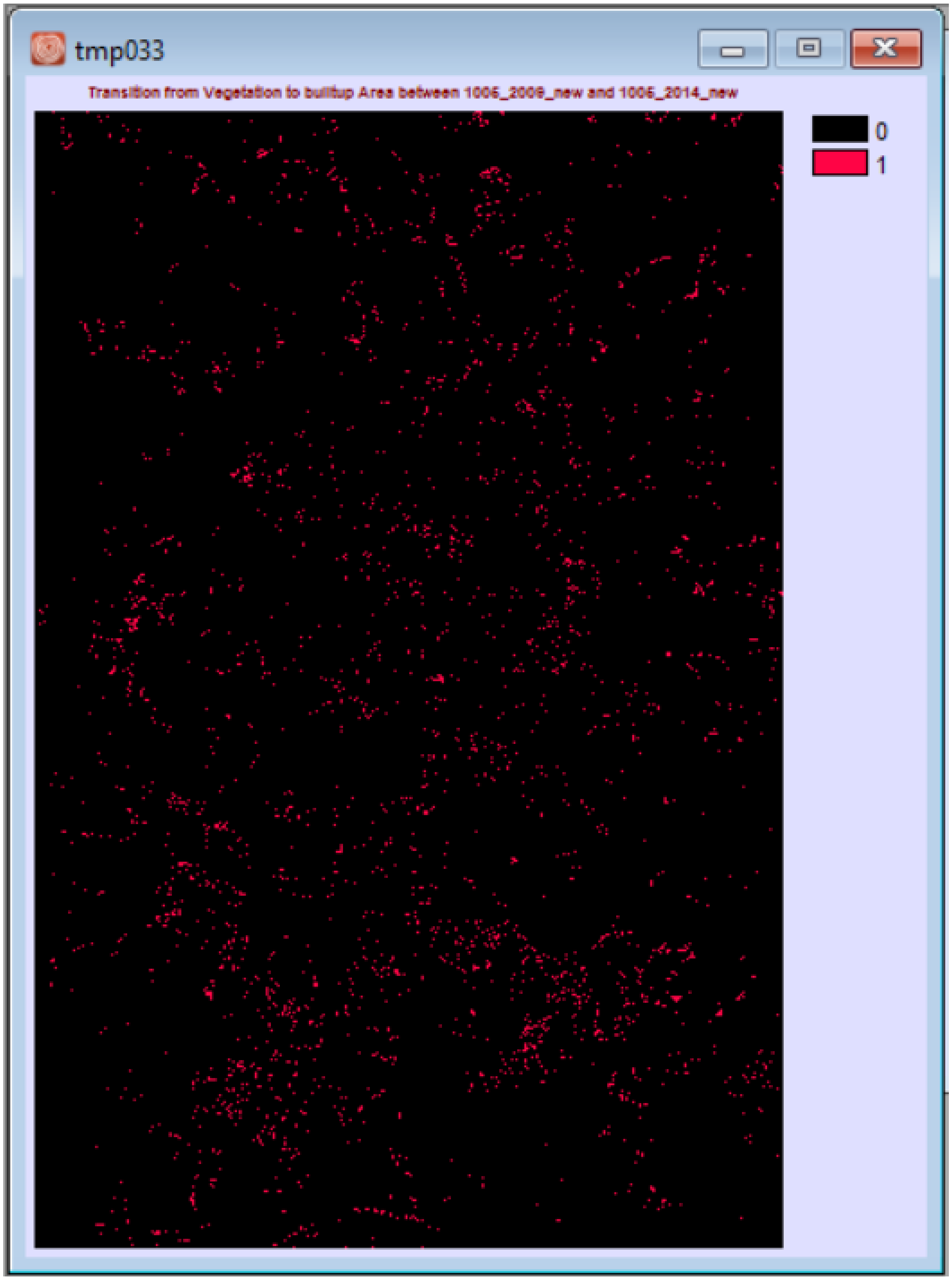


Fig.5.7: Transition from vegetation to built-up area for 2009-2014

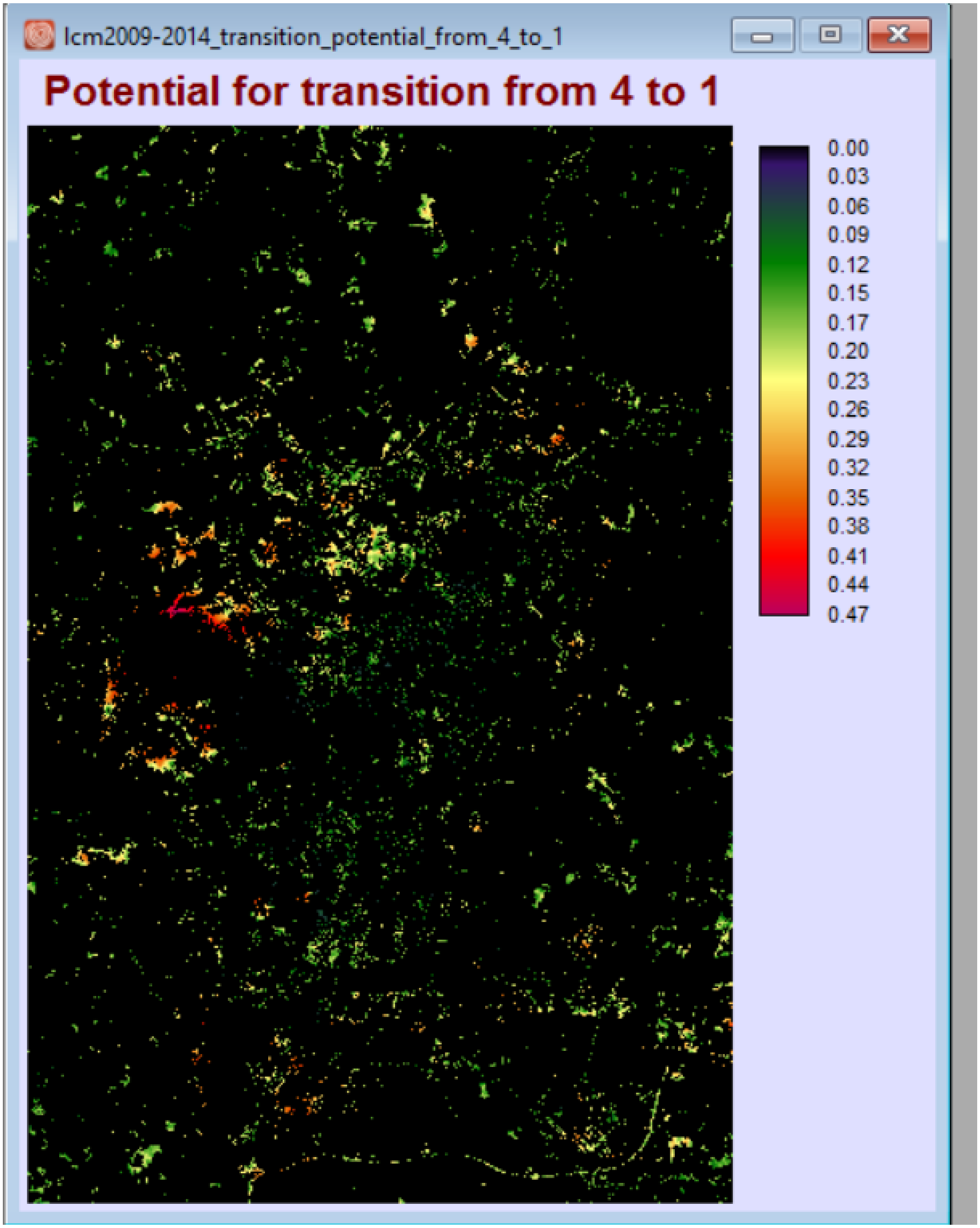


Fig.5.8: Transition from open space to built-up area for the study area (2004-2014)

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5.3 Objective No. iii To determine the landcover and landuse changes within Kaduna and Environs was analyzed as follows:

The study area was classified into built-up area, farmland, vegetation, open space and water bodies. The t-test was used to ascertained which of the classes transited to the develop area i.e. built-up area. When the landcover classes are more than 30, then the z-test is used to determine if there were significant changes, but in this research work there are five classes. Hence, the t-test was used.

5.3.1 To test the claim that farmland will transit to built-up area

Step 1: State the hypothesis and identify the claim

H_o= Farmland did not transit to built-up area

H_i= Farmland transited to built-up area

Step 2: Compute the t-test

Table 5.5: Pixels for built- up area and farmland

Year	Farmland (pixels)	Built-up area (pixels)
2004	356303	118574
2009	280914	141765
2014	319446	156119
	$\overline{X}_1$ = 318887.667	$\overline{X}_2$ = 138819.333

The formula is given by Mirbagheri, 2006.

$$t=\left(\frac{\overline{X}_1-\overline{X}_2}{\frac{\sqrt{S_1^2+S_2^2}}{n_1+n_2}}\right) \qquad \text{... 5.2}$$

Where $\overline{X}_1$& $\overline{X}_2$ – the means of farmland and built-up area

S - Standard deviation

n - Number of subjects in each group

$$S = \frac{\sqrt{\Sigma(X - \overline{X})^2}}{n} \qquad \text{...5.3}$$

Table 5.6: Standard deviation for built-up area

X_1	$X_1-\overline{X}$	$(X_1-\overline{X})^2$
118574	-20245.333	409873508.3
141765	2945.667	8676954.075
156119	17299.667	299278478.3

S_1= 15468.558

Table 5.7: Standard deviation for farmland

X_2	$X_2-\overline{X}$	$(X_2-\overline{X})^2$
356303	37415.333	1399907144
280914	-37973.667	1441999385
319446	558.333	311735.739
318887.667		

S_2= 30779.962

$$t = \frac{318887.667 - 138819.333}{14063.442}$$

t = +12.804

Degree of freedom

$=P_1 + P_2 - 2$

= 3+3-2= 4

At 0.05 level of significance

df=4

Step 3: Declaration of result

Critical or table value of t is 2.776 (see appendix 2)

Since the calculated t is more than the table value, we reject the null hypothesis and accept the alternative hypothesis i.e farmland will transit into built-up area.

5.3.2 To test the claim that vegetation will transit to built-up area

Step 1: State the hypothesis and identify the claim

H_o= Vegetation did not transit to built-up area

H_i= Vegetation transited to built-up area

Step 2: Compute the t - test

Table 5.8: Pixels for built-up area and vegetation

Year	Vegetation (pixels)	Built-up area (pixels)
2004	208988	118574
2009	297945	141765
2014	228337	156119
	245090	138819.333

Table 5.9: Standard deviation for built-up area

X_1	$X_1-\overline{X}$	$(X_1-\overline{X})^2$
118574	-20245.333	409873508.3
141765	2945.667	8676954.075
156119	17299.667	299278478.3

S_1= 15468.558

Table 5.10: Standard deviation for vegetation

X_2	$X_2-\overline{X}$	$(X_2-\overline{X})^2$
208988	-36102	1303354404
297945	+52855	2793651025
228337	-16753	280663009
	0	

S_2= 66163.951

$$t = \frac{245090 - 138819.333}{27739.697}$$

$$= \frac{106270.667}{27739.697}$$

$$= +3.8$$

Step 3: Declaration of result

Critical value t= 2.776 (see appendix 2)

We reject the null hypothesis since the calculated value is more than the table value and accept the alternative hypothesis i.e. vegetation will transit into built-up area.

5.3.3 Test the claim that open space will transit to built-up area

Step 1: State the hypothesis and identify the claim

H_o= Open space did not transit to built-up area

H_i= Open space transited to built-up area

Step 2: Compute the t-test

Table 5.11: Pixels for built-up area and open space

Year	Open space (pixels)	Built-up area (pixels)
2004	62666	118574
2009	20755	141765
2014	35347	156119

Table 5.12: Standard deviation for built-up area

X_1	$X_1-\overline{X}$	$(X_1-\overline{X})^2$
118574	-20245.333	409873508.3
141765	2945.667	8676954.075
156119	17299.667	299278478.3
138819.333		

S_1= 15468.558

Table 5.13: Standard deviation for open space

X_2	$X_2-\overline{X}$	$(X_2-\overline{X})^2$
62666	23076.667	532532559.8
20755	-18834.333	354732099.6
35347	-4242.333	17997389.28
39589.333		

S_2= 17371.068

$$t = \frac{39589.333 - 138819.333}{\frac{\sqrt{15468.558^2 + 17371.068^2}}{6}}$$

$$= \frac{-99230}{9495.8788}$$

= - 10.4497

Degree of freedom

$=P_1 + P_2 - 2$

= 3+3-2

= 4

At 0.05 level of significance

df=4

Step 3: Declaration of result

Critical or table value of t is 2.776 (see Appendix2)

Since the calculated t is less than the table value we accept the null hypothesis i.e open space do not transit into built-up area.

The results of the hypothesis testings are shown in Table 5.14.

Table 5.14: Results of hypothesis testing

S/N	Hypothesis testing	Result
1.	Farmland will transit to built -up area	In the study area farmland will transit to built-up area
2.	Vegetation will transit to built-up area	It is obvious that vegetation will transit to built-up area.
3.	Open space will transit to built-up area	Open space do not transit to built-up area

5.3.4 Analysis of variance (ANOVA)

Step 1: Add the pixel for each class

Table 5.15: Pixels for the various classes

Built-up area	X^2	Farmland	X^2	Vegetation	X^2	Open space	X^2	Water bodies	X^2
11.8574	140.5979	35.6303	1269.5289	20.8988	436.7598	6.2666	39.2703	0.7788	0.6065
14.1765	200.9732	28.0914	789.127	29.7945	887.7122	2.0755	4.3077	1.2940	1.6744
15.6119	243.7314	31.9446	1020.4575	22.8337	521.3779	3.5347	12.4941	1.5070	2.2710
41.6458	585.3025	95.6663	3079.1028	73.5270	1845.8499	11.8768	56.0721	3.5798	4.5519

Step 2: Sum the pixels for all the classes

$\Sigma x = 41.6458 + 95.6663 + 73.5270 + 11.8768 + 3.5798 = 226.2957$

Step 3: Sum the squares of the pixels

$\Sigma x^2 = 585.3025 + 3079.1028 + 1845.8499 + 56.0721 + 4.5519$

$= 5570.8792$

Step 4: Sum all the classes for the three epochs

$N = n_1 + n_2 + n_3 + \ldots + n_n$

$= 3 + 3 + 3 + 3 + 3$

$= 15$

Step 5: Determine the total sum of square

$$ss_{Total} = \Sigma x^2 - \frac{(\Sigma x)^2}{N}$$

$$= 5570.8792 - \frac{(226.2957)^2}{15}$$

5570.8792 -51209.7438/15

= 5570.8792-3413.9829

= + 2156.8963

Step 6: Determine the between sum of squares

$$ss_{between} = \frac{(\Sigma x_1)^2}{n_1} + \frac{(\Sigma x_2)^2}{n_2} + \frac{(\Sigma x_3)^2}{n_3} + \ldots + \frac{(\Sigma x)^2}{N}$$

$$= \frac{(41.6458)^2}{3} + \frac{(95.6663)^2}{3} + \frac{(73.527)^2}{3} + \frac{(11.8768)^2}{3} + \frac{(3.5798)^2}{3} - \frac{(226.2957)^2}{15}$$

$$= \frac{1734.3727}{3} + \frac{9152.04095}{3} + \frac{5406.2197}{3} + \frac{141.0726}{3} + \frac{12.81496}{3}$$

- 3413.9829

$$\frac{16446.5209}{3} - 3413.9829$$

5482.1732 – 3413.9829

2068.1903

Step 7: Determine within sum of square

$ss_{within} = ss_{Total} - ss_{between}$

2156.8963- 2068.1903

= 88.706

Step 8: Determine the degrees of freedom $df_{between} = K - 1$

Where K is the number of groups =5-1 = 4

df_{within}= N-K where N is the total size

15-5 = 10

df_{Total} = N – 1

= 15 – 1

= 14

Step 9: Determine the mean square (MS)

$$\text{Mean square} = \frac{\text{sum of degrees K}}{\text{degrees of freedom}}$$

$$\text{for between } MS_{between} = \frac{SS_{between}}{df}$$

$$= \frac{2068.190}{4}$$

= 517.0475

$$\text{For within } Ms_{within} = \frac{SS_{within}}{df}$$

$$= \frac{88.7054}{10}$$

= 8.87054

Step 10: Determine the F_{ratio}

$$F_{ratio} = \frac{MS_{between}}{MS_{within}}$$

$$= \frac{517.0475}{8.87054}$$

= 58.2882

Step 11: Declaration of result

Referring to F-table (Appendix3) with 4 and 10 df and at 0.05 level of significance. The table is entered now where these two values intersect is 3.48. The calculated value is greater. Then, we reject the null hypothesis and conclude that there are significant differences among the groups classified i.e built-up area, vegetation, farmland, open space and water body.

Table 5.16: Summary of ANOVA

Item	SS	df	Ms	F	P
Between groups	2068.19	4	517.05	58.288	0.05
Within groups	88.706	10	8.87		
Total	2156.896	14			

5.3.5 Landcover and landuse changes from 2004 to 2014

Table 5.17: Pixel values for the three(3) epochs

Class code	**Year 2004**	**Year 2009**	**Year 2014**	**Class**
22	118574	141765	156119	Built-up area
33	356303	280914	319446	farmland
44	208988	297945	228337	vegetation
55	62666	20755	35347	open space
66	7788	12940	15070	water bodies

Built-up area from table 5.17 was 16% of the entire study area in 2004 and increased to 19% and 21% in the 2009 and 2014 respectively. It is obvious that farming activities decreased from 47% in 2004 to 37% in 2009 and increased to 42% in 2014. The vegetation class which was 28% in 2004 increased to 39% in 2009 and decreased to 30% in 2014. The open space which was 8% in 2004 decreased to 3% in 2009 and increased to 5% in 2014. The water bodies remains relatively constant between 1% to 2%. All of these were depicted in the bar graph and pie chart in fig.5.9 to fig 5.11 and plate.5.1 to plate 5.5. In the year 2004 the built-up area increased from 118.574km^2 to 141.765km^2 in the year 2009 and 156.119km^2 in the year 2014. The other classes also increased and decreased as shown in Table 5.17.

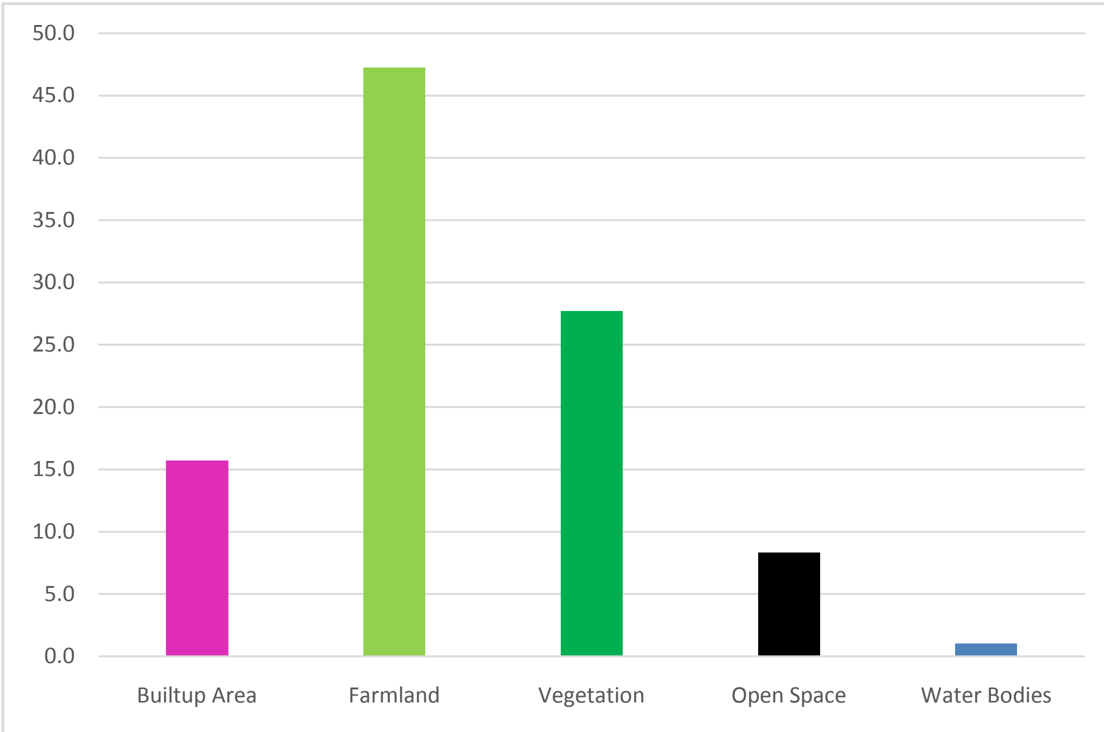

Fig. 5.9: Bar chart for year 2004

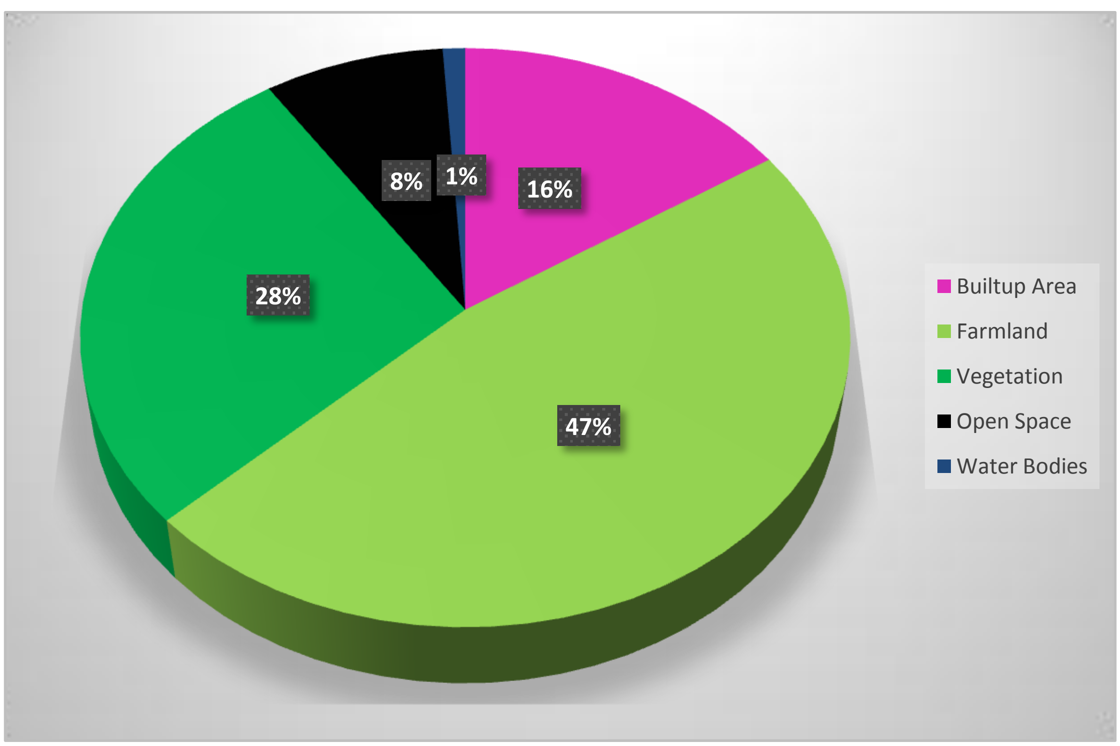

Plate 5.1: Pie chart for year 2004

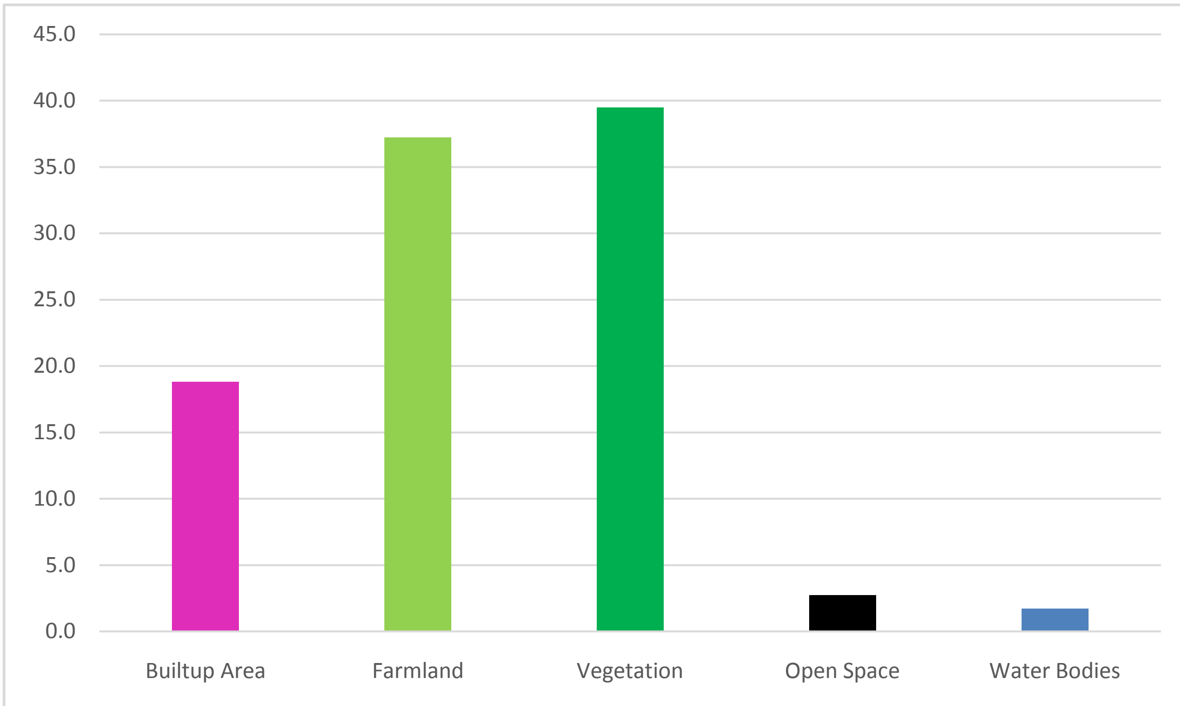

Fig.5.10: Bar chart for year 2009

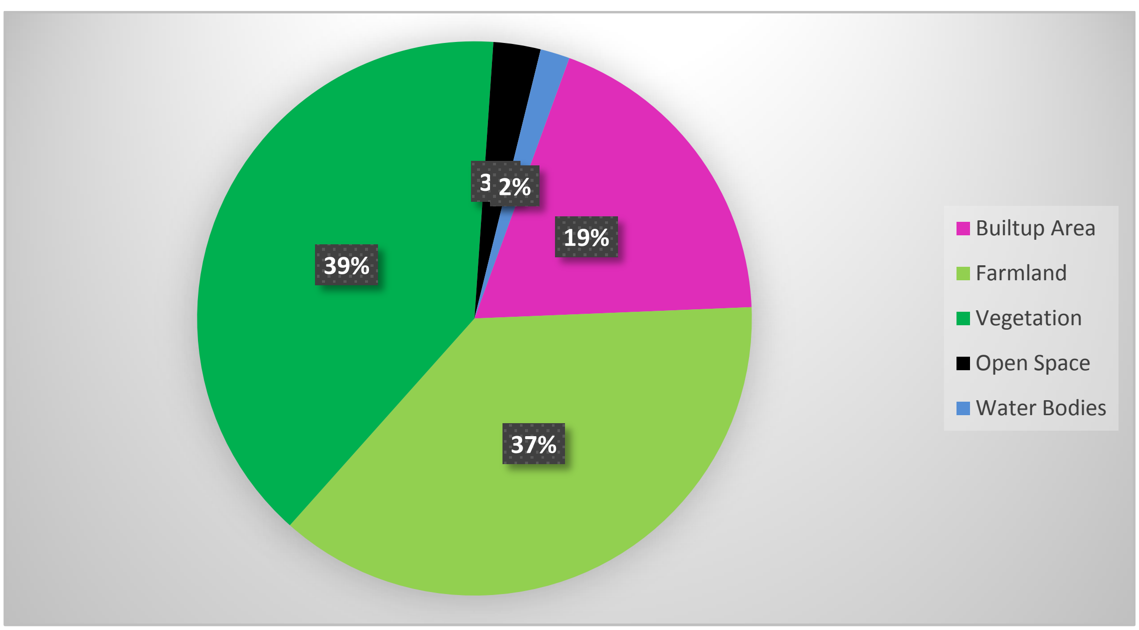

Plate 5.2: Pie chart for year 2009

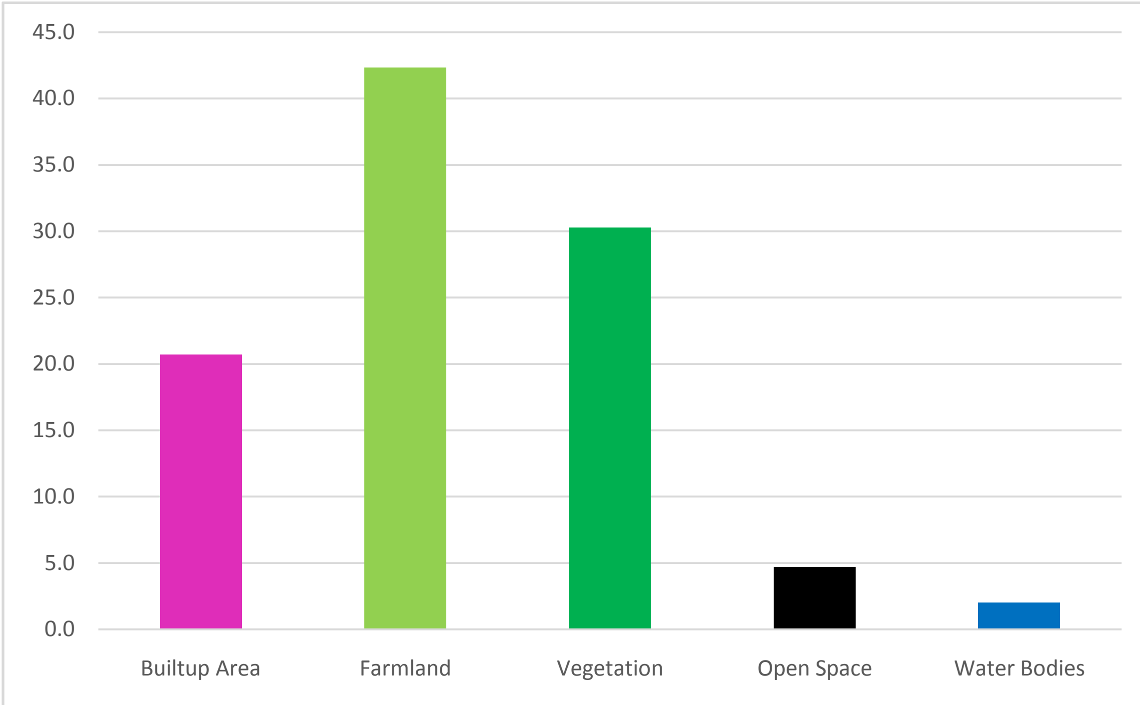

Fig.5.11: Bar chart for year 2014

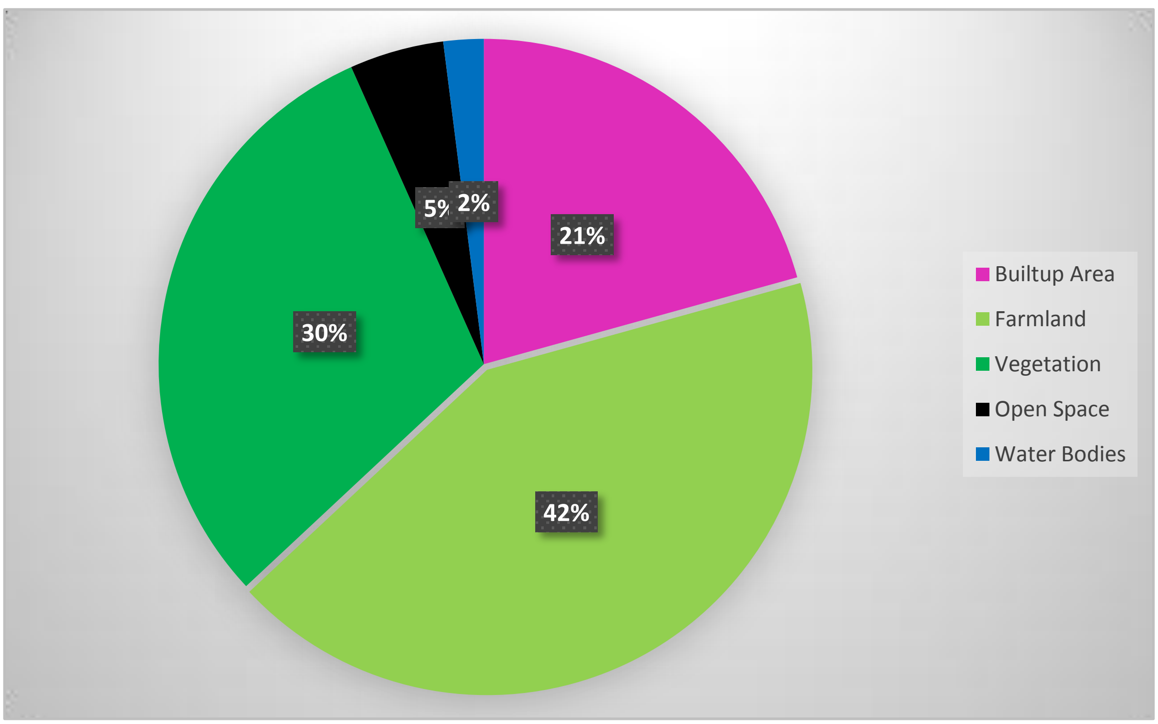

Plate 5.3: Pie chart for year 2014

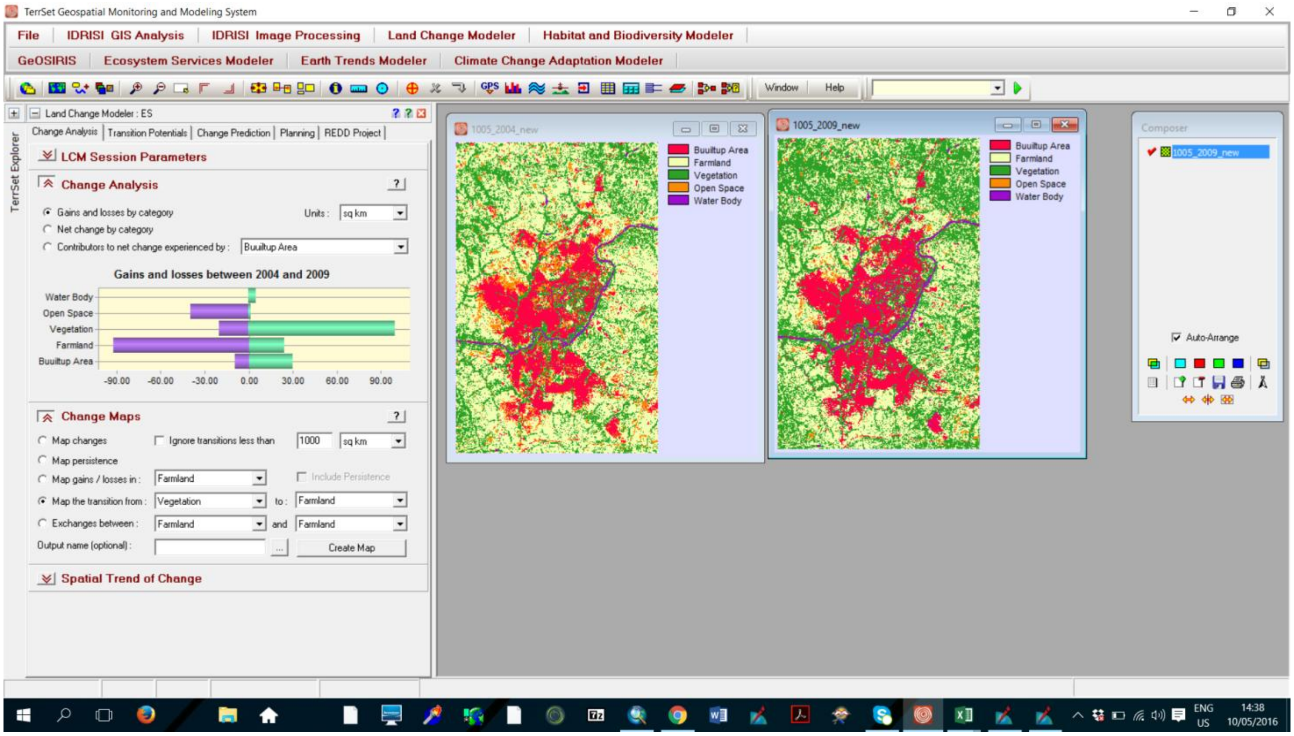

Plate 5.4: Gains and losses between 2004 and 2009

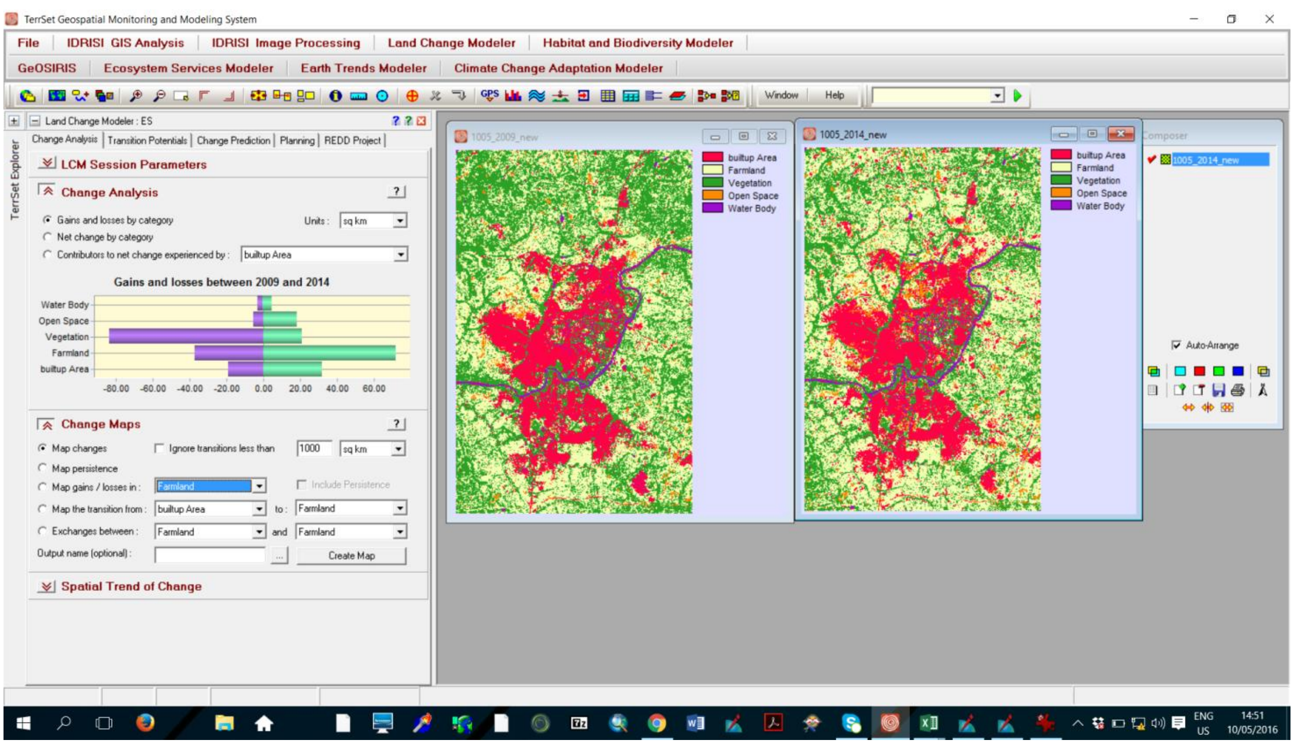

Plate 5.5: Gains and losses between 2009 and 2014

5.4 Objective No iv "To predict the pattern of changes (25 years) with multiple logistic regression" was analyzed as follows:

Prediction is a statement that says what you think will happen, the act of making such a statement. Land change prediction in land change modeler is an empirically given process that moves in a step wise fashion from i) Change analysis ii) Transition Potential Modeling to iii) Change prediction. It is based on the historical change from 2014 to 2039. In change analysis, change is assessed between 2014 and 2039 between the two landcover maps. The changes that are identified are transitions from one landcover state to another. Terrset land modeler software was used to predict the pattern of changes for (25 years) from the 2014 and the result is shown in fig 5.12. Twenty five years from 2014 the vegetation and farmland classes are expected to have transited to built-up areas especially on the fringes of the study area. The water bodies is not expected to increase and this is same for the open space. The Built-up area is expected to increase from 156.119 Km^2 to 227.889 Km^2 and farmland and vegetation will decrease to 126.786Km^2 and 89.12Km^2 respectively.

The study revealed that areas potentially suitable for development are nearer to the roads and built-up areas. Proximity to built-up areas and roads are the independent variables that influenced the prediction . The built-up areas will increase by 2.87Km^2 yearly and 71.77km^2 in 25years which is 31.5% of the developed area.

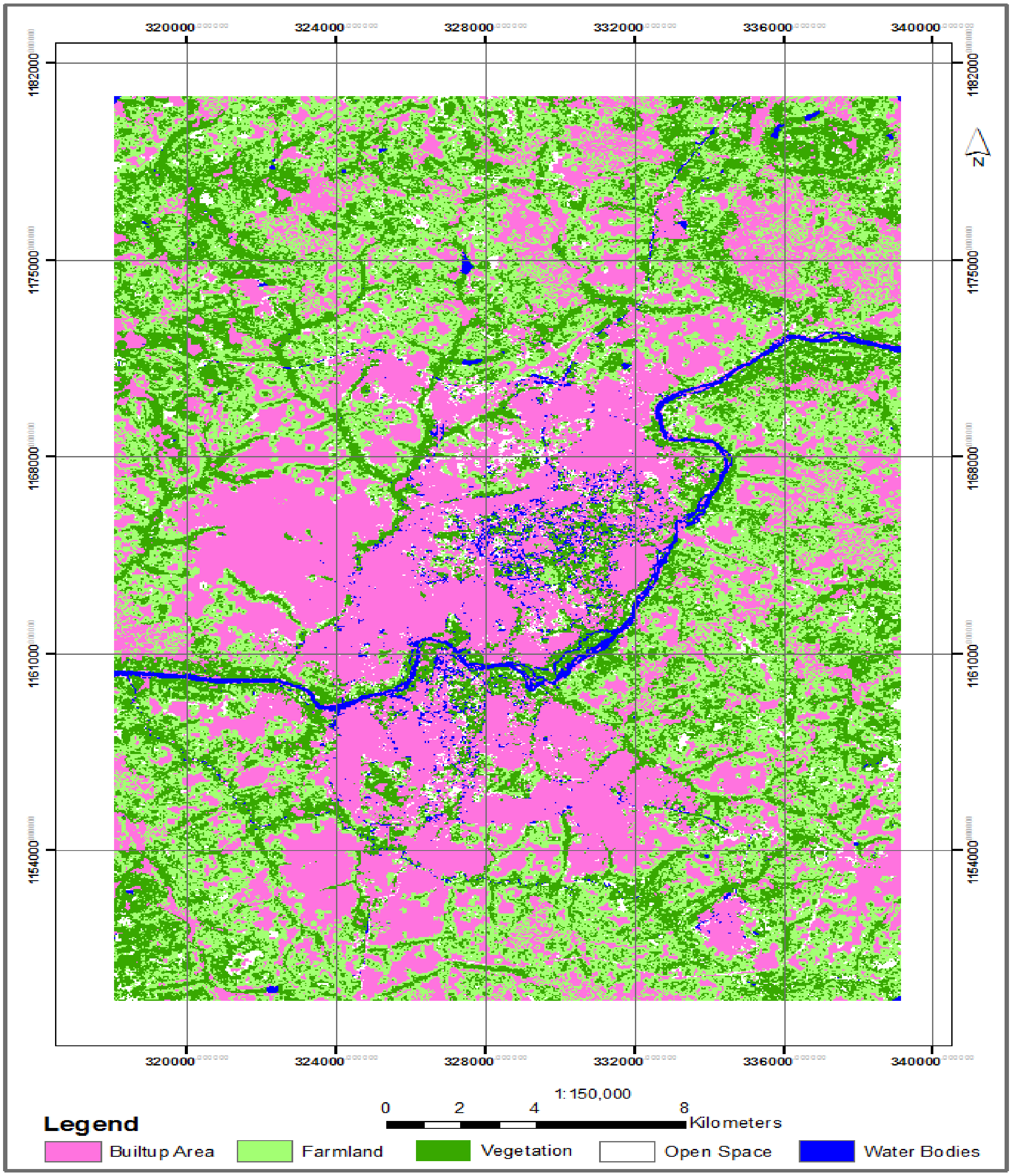

Fig. 5.12: Prediction of Landcover and Landuse patterns of Kaduna and Environs for 25 years ending 2039.

5.5 Objective No v "To produce the landcover and landuse maps of Kaduna and Environs for the year 2004, 2009 and 2014" was analyzed as follows:

From fig.5.13 to fig 5.15 it is obvious that due to the partitioning of the study area as result of crisis, rapid development is taking place at the Southern part of the study area due to the movement of people from the Northern part of the area to the Southern part. Areas around institutions such as Kaduna Polytechnic and the Kaduna State University are also witnessing rapid development due to provision of accommodation for the students and staff.

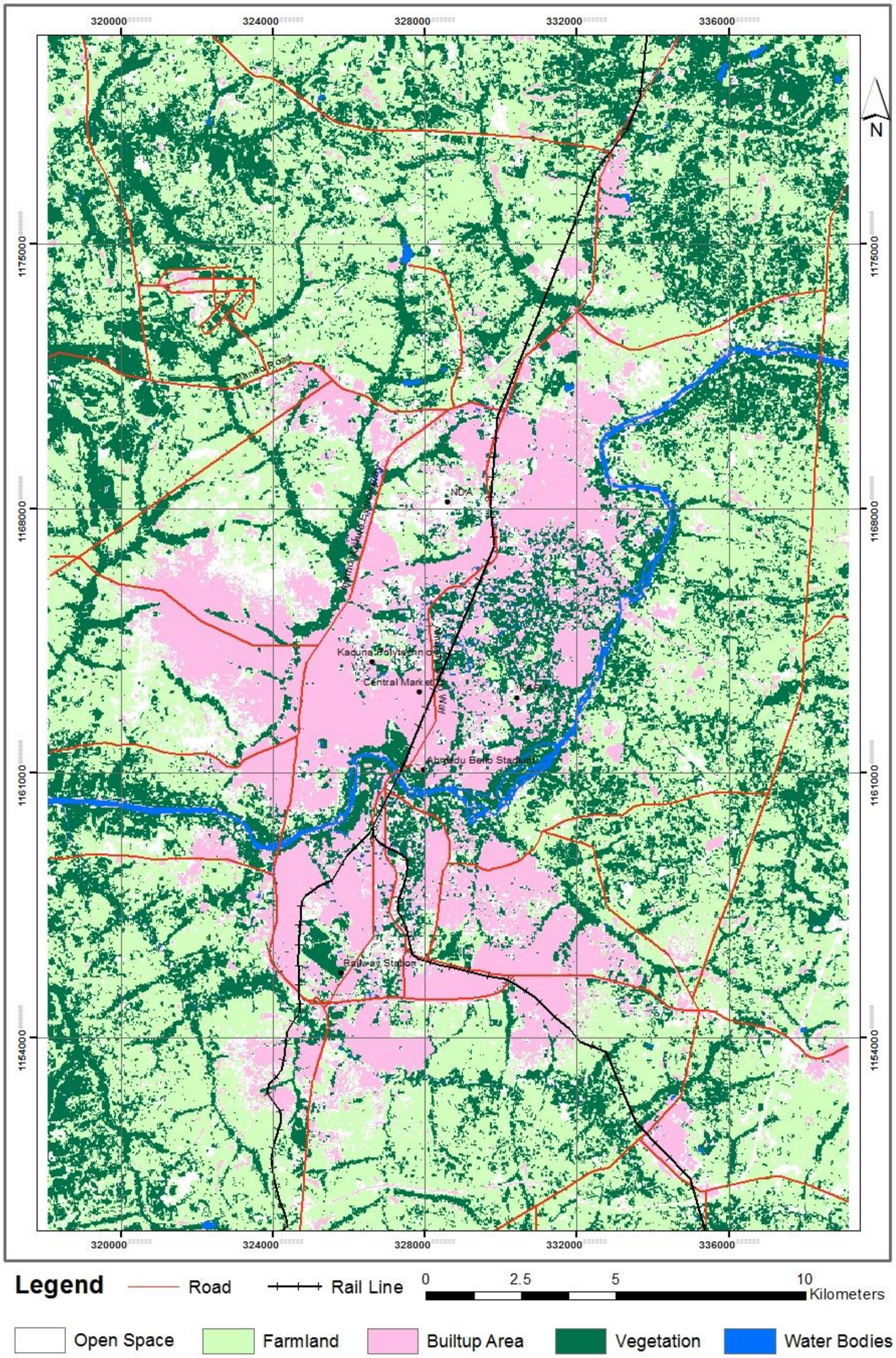

Fig.5.13: Landcover and landuse map of Kaduna and Environs for 2004

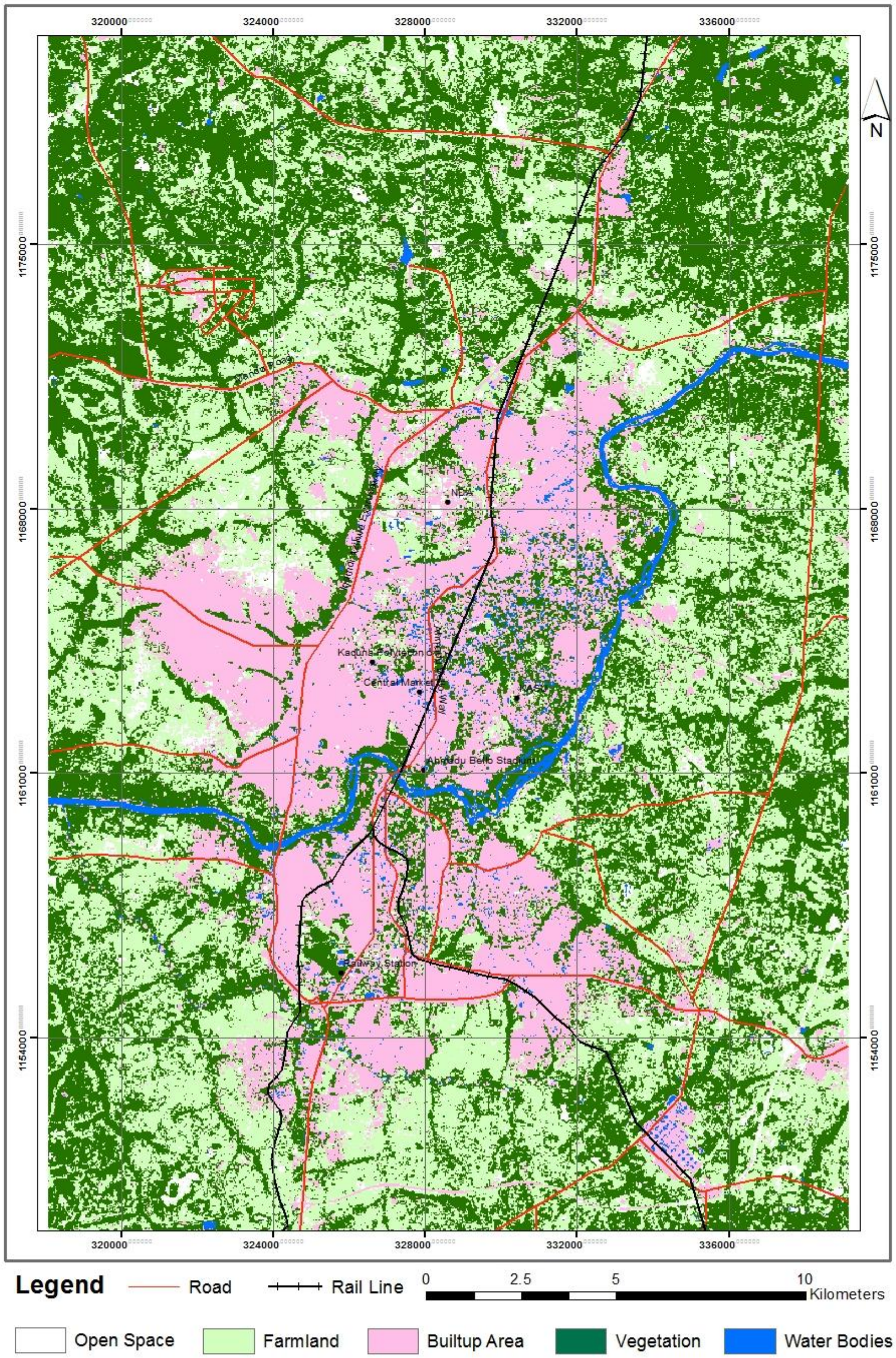

Fig.5.14: Landcover and landuse map of Kaduna and Environs for 2009

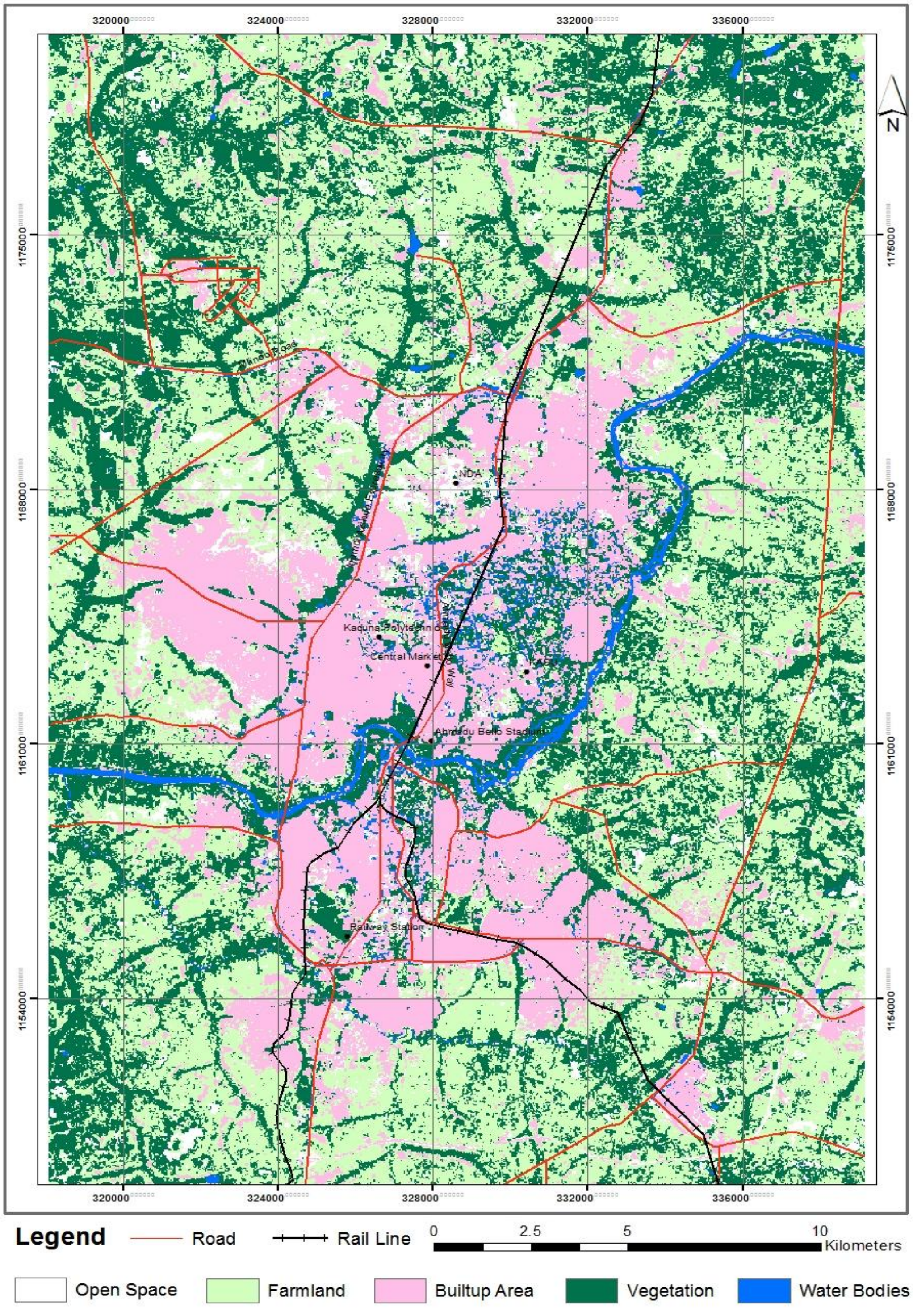

Fig.5.15: Landcover and landuse map of Kaduna and Environs for 2014

5.6 Summary of Research Results and Findings

Kaduna and Environs due to socio-economic activities is experiencing changes as summarized below.

5.6.1 Built- up Areas

Kaduna is rapidly undergoing physical development and expansion with remarkable changes in 2004 at 16% to 19% in year 2009 and 21% in the year 2014. These changes were largely adduced to it's proximity to the Federal Capital Territory, Abuja because many people working in Abuja have their houses in Kaduna where they returned to. The physical development of Kaduna and environs extends from the city centre to the undeveloped areas. The study area is a combination of traditional and modern buildings with compact built-up, even though it is surrounded with medium development along it's ribbon-like transportation routes including the Kaduna – Kachia road, Kaduna – Abuja road to the South, Kaduna – Birnin Gwari Road and Kaduna – Zaria road to the north. Also along the western – bye pass and the recently Eastern – Bye pass which has just been constructed.

The study area also witnessed increase in built-up area due to the constant ethno-Religious Conflicts in the area. Inhabitants moved from the northern part of the study area in places like Badarawa, Kawo, Rigasa to resettle in the Southern part of the study area like Barnawa, Sabo, Kakuri, and Gonin-Gora. Government initiative for inhabitants to own property around Igabi also resulted in the increase in built-up area.

5.6.2 Farmland

The economy of Kaduna and environs, especially during the pre-British period depended almost entirely on agriculture, but socio-political changes has resulted in a shift to modern economy. In the year 2004, farmland was 47%, the inhabitants in Year 2009 took to trading which resulted to decrease to 39%. The economic hardship where commercial activities were reduced made the inhabitants to return to farming which resulted in increase to 42% in 2014. The fluctuation in farmland is also as a result of Government taking over large areas used for farming in some areas especially at Igabi and Ungwar Muasu, Urban encroachment has also led to decrease in farmland in the study area.

5.6.3 Vegetation

The vegetation of the area was 28% in the year 2004 and increased to 39% in the year 2009, this is attributable to areas meant for open space not well Kept. However, due to Governemnt intervention in the year 2014, the vegetation of the area decreased to 30%. The government forest reserve at Afaka witnessed illegal deforestation which also resulted in the decrease from the year 2009 to year 2014.

5.6.4 Open Space

The open space in Kaduna and environs especially the parks and recreation areas in Kabala West and Tudun Wada witnessed decrease of 8% in the year 2004 to 3% in the year 2009 due to Government negligence. Grasses overgrown the parks and recreation areas including the green belts in the study area.

However, in 2014 Government intervention resulted to near normalcy which led to increase to 5% in the year 2014.

5.6.5 Water Bodies

Increase in water bodies from 1% in 2004 to 2% in 2009 and 2014 was attributed to construction of water reservoirs in the study area. Some streams in the study areas are now wider thereby containing more volume of water including the main river i.e River Kaduna which flows across the city.

CHAPTER SIX

CONTRIBUTION TO KNOWLEDGE

Landcover and landuse changes studies within Kaduna and Environs will assist decision makers and other professionals especially urban planners in managing the study area. It is evident that the studies revealed changes at every five (5) years. Furthermore, remarkable contributions to knowledge in this work are hereby articulated.

6.1 Generation of current landcover and landuse map

The work carried out was able to generate landcover and landuse map of Kaduna and Environs for the years 2004, 2009 and 2014. This is an addition to the spatial data availability for the study area.

6.2 Determination of the Landcover and Landuse Changes within the Study Area

Hypothesis testing was carried out and it was evident that farmland and vegetation areas in the study area will transit to built-up areas. The study revealed that it is true that built- up areas continued to increase in 2004, 2009 and 2014. This will guide urban planners on how to effectively plan for the study area in the future.

6.3 Prediction of future Landcover and Landuse Changes of Kaduna and Environs

Kaduna and environs was modeled using cellular Automata and prediction for the pattern of changes from 2014 to 2039 with multiple logistic regression was carried out. The fringes of the study area and especially the western by-pass and eastern express way are expected to witness massive transition to Built-up area. This will guide the state government on how to control and monitor development to ensure a habitable environment. This prediction is covered in section 5.4.

6.4 Statistical Analysis of Geo-spatial data

In this study statistical analysis was used to determine how seamless data can be manipulated to detect landcover and landuse changes

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

Landuse change conceptualize the relationship between different classes of landcover and their uses. Different disciplinary concepts can assist in the analysis of landuse change in specific situation. The paradigms and theories applied by different disciplines are often difficult to integrate and research results can be used to test theories in specific case studies. The conventional surveying technique is time consuming, the use of landsat ETM+ imageries in modeling and mapping of landcover and landuse changes is an important approach; it structures the model around the human environment relationship which can be improved using cellular Automata. Landcover and landuse maps when prepared at regular intervals will assist relevant Government agencies in the planning of the study area.

7.2 Recommendations

It might be argued whether results obtained from modeling and mapping of landcover and landuse changes and the prediction could be used for development and policy making. However, due to dearth of adequate and current landcover and landuse maps, based on findings of this study, the following recommendations are made:

1. Landcover and landuse maps when prepared on regular basis can be used for planning purpose. It is therefore recommended that there should be regular and timely preparation of Landcover and Landuse maps

2. Modeling and mapping of landcover and landuse changes using multiple logistic regression and cellular Automata should be intuitive with predefined rules. The rules should be properly articulated to ensure successful implementation.
3. The use of ancillary data for ground truthing is inevitable in image classification.
4. Multi-temporal landsat satellite imageries are needed for modeling and landuse changes.
5. Further studies should be carried out on modeling and mapping of landcover and landuse for sustainable development.

7.3 Further Research Topics

In the execution of this research work, it is obvious that other related researchable areas could not be covered. Therefore, the topics below are posited for future research works.

i. An appraisal of capabilities of imaging system for landcover modeling of Kaduna and Environs.

ii. Spatial audit of the physical developments of Kaduna and Environs.

iii. An integrated approach for detecting changes in Kaduna in Northern Nigeria.

iv. Landcover and landuse mapping using 30 m spatial resolution imageries.

v. Mapping and modeling of urban environmental problems of Kaduna

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APPENDIX 1

Conversion of Geographical Co-ordinates to universal transverse Mercator projection (UTM).

These formulae are required to convert geographical co-ordinates to universal transverse Mercator (UTM) co-ordinates.

$N=M + w^2k + w^4B$

$\Delta E = WR + W^3C + w^5III$

$E = E_0 \pm \Delta E$

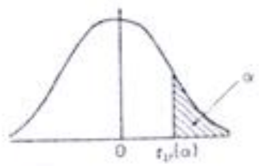
	North westerly point	North easterly point	South easterly point	South westerly point
ϕ	10^0 40’ 36”.323	10^0 40’ 36”.323	10^0 23’ 27”.516	10^0 23’ 27”.516
Λ	07^0 20’ 18”.635	07^0 31’ 35”.829	07^0 31’ 35”.829	07^0 20’ 18”.635
M_1	1179016.4080	1179016.4080	1142163.9693	1142163.9693
ΔM	+1115.5075	+1115.5075	+6372.8415	+6372.8415
M	1180131.9155	1180131.9155	1148536.8108	1148536.8108
K_1	1363.084	1363.084	1322.374	1322.374
ΔK	+1.229	+1.229	+7.051	+7.051
K	1364.313	1364.313	1329.425	1329.425
B_1	1.295	1.295	1.260	1.260
ΔB	+0.0001	+0.001	+0.006	+0.006
B	1.296	1.296	1.266	1.266
R_1	303796.8699	303796.8699	304122.4618	304122.4618
ΔR	- 10.0488	-10.0488	-55.6413	-55.6413

APPENDIX 1 CONTINUED

R	303786.8211	303786.8211	304066.8205	304066.8205
C_1	111.615	111.615	112.235	112.235
∆C	-0.019	-0.019	-0.016	-0.016
C	111.596	111.596	112.129	112.129
III	0.058	0.058	0.059	0.059
W”	-0.5981365	-0.5304171	-0.5304171	-0.5981365
M	1180131.9155	1180131.9155	1148536.8108	1148536.8108
W^2K	488.1065	383.8390	374.0235	475.6248
W^4B	0.1659	0.1026	0.1002	0.1620
N	1,180,620.1879	1,180,515.8571	1,148,910.9345	1,148,910.9345
WR	-181705.9859	-161133.7247	-161282.2411	-181873.4638
W^3C	- 23.8808	-16.6533	-16.7329	-23.9949
W^5III	- 0.0044	- 0.0024	-0.0025	-0.0045
∆E	-181729.8711	-161150.3804	-161298.9765	181897.4632
E	318270.1289	338849.6196	338701.0233	318102.5368

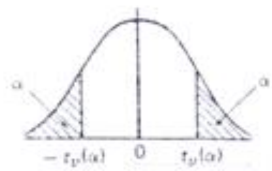
Appendix II: PERCENTAGE POINTS OF THE t DISTRIBUTION

ONE-SIDED TEST



$\Pr(T_\nu > t_\nu(\alpha)) = \alpha$,
for ν degrees of freedom.

TWO-SIDED TEST



$\Pr(T_\nu > t_\nu(\alpha) \text{ or } T_\nu < -t_\nu(\alpha)) = 2\alpha$,
for ν degrees of freedom.

ν	$\alpha = 0.4$ $2\alpha = 0.8$	0.25 0.5	0.1 0.2	0.05 0.1	0.025 0.05	0.01 0.02	0.005 0.01	0.0025 0.005	0.001 0.002	0.0005 0.001
1	0.325	1.000	3.078	6.314	12.706	31.821	63.657	127.320	318.310	636.620
2	0.289	0.816	1.886	2.920	4.303	6.965	9.925	14.089	22.327	31.598
3	0.277	0.765	1.638	2.353	3.182	4.541	5.841	7.453	10.214	12.924
4	0.271	0.741	1.533	2.132	2.776	3.747	4.604	5.598	7.173	8.610
5	0.267	0.727	1.476	2.015	2.571	3.365	4.032	4.773	5.893	6.869
6	0.265	0.718	1.440	1.943	2.447	3.143	3.707	4.317	5.208	5.959
7	0.263	0.711	1.415	1.895	2.365	2.998	3.499	4.029	4.785	5.408
8	0.262	0.706	1.397	1.860	2.306	2.896	3.355	3.833	4.501	5.041
9	0.261	0.703	1.383	1.833	2.262	2.821	3.250	3.690	4.297	4.781
10	0.260	0.700	1.372	1.812	2.228	2.764	3.169	3.581	4.144	4.587
11	0.260	0.697	1.363	1.796	2.201	2.718	3.106	3.497	4.025	4.437
12	0.259	0.695	1.356	1.782	2.179	2.681	3.055	3.428	3.930	4.318
13	0.259	0.694	1.350	1.771	2.160	2.650	3.012	3.372	3.852	4.221
14	0.258	0.692	1.345	1.761	2.145	2.624	2.977	3.326	3.787	4.140
15	0.258	0.691	1.341	1.753	2.131	2.602	2.947	3.286	3.733	4.073
16	0.258	0.690	1.337	1.746	2.120	2.583	2.921	3.252	3.686	4.015
17	0.257	0.689	1.333	1.740	2.110	2.567	2.898	3.222	3.646	3.965
18	0.257	0.688	1.330	1.734	2.101	2.552	2.878	3.197	3.610	3.922
19	0.257	0.688	1.328	1.729	2.093	2.539	2.861	3.174	3.579	3.883
20	0.257	0.687	1.325	1.725	2.086	2.528	2.845	3.153	3.552	3.850
21	0.257	0.686	1.323	1.721	2.080	2.518	2.831	3.135	3.527	3.819
22	0.256	0.686	1.321	1.717	2.074	2.508	2.819	3.119	3.505	3.792
23	0.256	0.685	1.319	1.714	2.069	2.500	2.807	3.104	3.485	3.767
24	0.256	0.685	1.318	1.711	2.064	2.492	2.797	3.091	3.467	3.745
25	0.256	0.684	1.316	1.708	2.060	2.485	2.787	3.078	3.450	3.725
26	0.256	0.684	1.315	1.706	2.056	2.479	2.779	3.067	3.435	3.707
27	0.256	0.684	1.314	1.703	2.052	2.473	2.771	3.057	3.421	3.690
28	0.256	0.683	1.313	1.701	2.048	2.467	2.763	3.047	3.408	3.674
29	0.256	0.683	1.311	1.699	2.045	2.462	2.756	3.038	3.396	3.659
30	0.256	0.683	1.310	1.697	2.042	2.457	2.750	3.030	3.385	3.646
40	0.255	0.681	1.303	1.684	2.021	2.423	2.704	2.971	3.307	3.551
60	0.254	0.679	1.296	1.671	2.000	2.390	2.660	2.915	3.232	3.460
120	0.254	0.677	1.289	1.658	1.980	2.358	2.617	2.860	3.160	3.373
∞	0.253	0.674	1.282	1.645	1.960	2.326	2.576	2.807	3.090	3.291

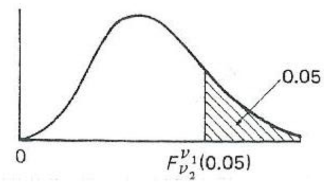
Appendix III: Percentage points of the F-Distribution

UPPER 5 PER CENT POINTS

The values tabulated are $F_{\nu_2}^{\nu_1}(0.05)$ such that $\Pr(F_{\nu_2}^{\nu_1} > F_{\nu_2}^{\nu_1}(0.05)) = 0.05$, where ν_1 is the degrees of freedom in the numerator and ν_2 is the degrees of freedom in the denominator.

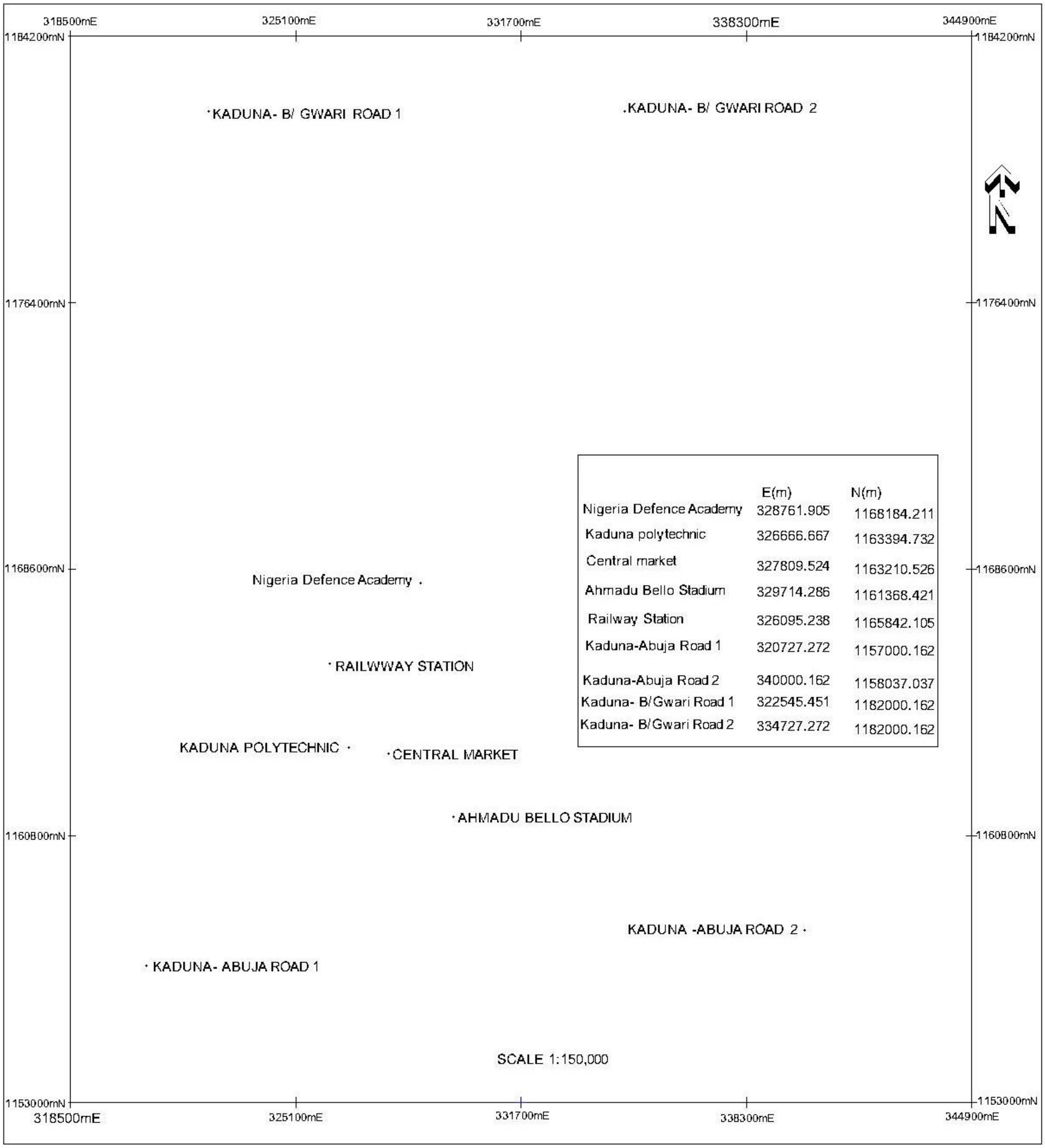
The lower percentage points of the distribution are obtained using the relationship

$$F_{\nu_2}^{\nu_1}(0.95) = 1/F_{\nu_1}^{\nu_2}(0.05)$$



ν_2 \ ν_1	1	2	3	4	5	6	7	8	9	10	15	20	40	60	120	∞
1	161.4	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	245.9	248.0	251.1	252.2	253.3	254.3
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.43	19.45	19.47	19.48	19.49	19.50
3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.79	8.70	8.66	8.59	8.57	8.55	8.53
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.86	5.80	5.72	5.69	5.66	5.63
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.62	4.56	4.46	4.43	4.40	4.36
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	3.94	3.87	3.77	3.74	3.70	3.67
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.51	3.44	3.34	3.30	3.27	3.23
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.22	3.15	3.04	3.01	2.97	2.93
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.01	2.94	2.83	2.79	2.75	2.71
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.85	2.77	2.66	2.62	2.58	2.54
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.85	2.72	2.65	2.53	2.49	2.45	2.40
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.62	2.54	2.43	2.38	2.34	2.30
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.67	2.53	2.46	2.34	2.30	2.25	2.21
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.60	2.46	2.39	2.27	2.22	2.18	2.13
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.40	2.33	2.20	2.16	2.11	2.07
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.49	2.35	2.28	2.15	2.11	2.06	2.01
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	2.45	2.31	2.23	2.10	2.06	2.01	1.96
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	2.41	2.27	2.19	2.06	2.02	1.97	1.92
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	2.38	2.23	2.16	2.03	1.98	1.93	1.88
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.20	2.12	1.99	1.95	1.90	1.84
21	4.32	3.47	3.07	2.84	2.68	2.57	2.49	2.42	2.37	2.32	2.18	2.10	1.96	1.92	1.87	1.81
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34	2.30	2.15	2.07	1.94	1.89	1.84	1.78
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32	2.27	2.13	2.05	1.91	1.86	1.81	1.76
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30	2.25	2.11	2.03	1.89	1.84	1.79	1.73
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.09	2.01	1.87	1.82	1.77	1.71
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.27	2.22	2.07	1.99	1.85	1.80	1.75	1.69
27	4.21	3.35	2.96	2.73	2.57	2.46	2.37	2.31	2.25	2.20	2.06	1.97	1.84	1.79	1.73	1.67
28	4.20	3.34	2.95	2.71	2.56	2.45	2.36	2.29	2.24	2.19	2.04	1.96	1.82	1.77	1.71	1.65
29	4.18	3.33	2.93	2.70	2.55	2.43	2.35	2.28	2.22	2.18	2.03	1.94	1.81	1.75	1.70	1.64
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	2.16	2.01	1.93	1.79	1.74	1.68	1.62
40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	1.92	1.84	1.69	1.64	1.58	1.51
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04	1.99	1.84	1.75	1.59	1.53	1.47	1.39
120	3.92	3.07	2.68	2.45	2.29	2.17	2.09	2.02	1.96	1.91	1.75	1.66	1.50	1.43	1.35	1.25
∞	3.84	3.00	2.60	2.37	2.21	2.10	2.01	1.94	1.88	1.83	1.67	1.57	1.39	1.32	1.22	1.00

Appendix IV: Global Positioning System (GPS) Co-ordinates of some prominent points in the study area



	E(m)	N(m)
Nigeria Defence Academy	328761.905	1168184.211
Kaduna polytechnic	326666.667	1163394.732
Central market	327809.524	1163210.526
Ahmadu Bello Stadium	329714.286	1161368.421
Railway Station	326095.238	1165842.105
Kaduna-Abuja Road 1	320727.272	1157000.162
Kaduna-Abuja Road 2	340000.162	1158037.037
Kaduna- B/Gwari Road 1	322545.451	1182000.162
Kaduna- B/Gwari Road 2	334727.272	1182000.162

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