COMPARATIVE ANALYSIS OF TWO PREDICTIVE MODELS FOR FORECASTING FOREST DEPLETION IN AFAKA FOREST RESERVE, KADUNA STATE, NIGERIA

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BY

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DEPARTMENT OF GEOGRAPHY,
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AUGUST, 2015

DECLARATION

I declare that the work in this thesis entitled "Comparative Analysis of two Predictive Models for Forecasting forest Depletion in Afaka Forest Reserve, Kaduna State" has been carried out by me in the Department of Geography. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this thesis was previously presented for another degree or diploma at this or any other Institution.

Olushola Michael OLANIYI	_____	_____
Name of Student	Signature	Date

CERTIFICATION

This thesis titled "**Comparative Analysis of two Predictive Models in Forecasting forest Depletion in Afaka forest reserve, Kaduna State, Nigeria**" by Olushola Michael OLANIYI, meets the regulations governing the award of the degree of Master of Science in Remote sensing and GIS of Ahmadu Bello University, and is approved for its contribution to knowledge and literary presentation.

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DEDICATION

This thesis is dedicated to GOD who has been my source of inspiration, in Him I live, in Him I have my being and to everyone striving to add value to their lives through quality education.

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Bless the Lord oh my soul and forget not all His benefits. I want to express my appreciation to God almighty for He is the fountain of knowledge. For His mercies, provision and protection over my life. May His name be praised.

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ABSTRACT

This study seeks to forecast forest depletion in Afaka Forest Reserve in Kaduna State and to compare results of Markov Chain Model and CA- Markov model with a view to determine a better model in forecasting forest depletion. The extent of forest covers in 1973, 1990 and 2009 were examined. Forecast of forest depletion for 2028 was done using Markov chain model and CA- Markov model. The year 2028 was used based on the fact that markov chain model can forecast based on the year interval of the input satellite imageries (1990-2009 an interval of nineteen years). Both primary and secondary sources of data were used. The primary source included use of Landsat images of the study area for 1973, 1990 and 2009. Idrisi Selva was used for analysis of these data and for forecasting forest depletion. Student T- test was used to test for significant differences between results of the two predictive models. The result revealed that the forest was declining at the rate of 0.09% per year. Forest forecast for 2028 using markov chain model reduced from 3724.25ha in 1973 to 3168.75ha in 2028. Using CA- markov to forecast for 2028, the result revealed that forest cover will decrease to 3019.54ha. The result was tested using T-test statistics. There was no statistically significant difference between results of the two models used in forecasting forest depletion. However, CA- Markov was better between the two models because it gave the spatial distribution of these changes. New land use/land covers that were likely to emerge were also indicated in the result of CA-Markov model which were lacking in Markov chain model. On the basis of the finding this study therefore recommend CA- Markov model in forecasting forest depletion.

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CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Nature endowed man; since ages, with many natural resources for the sustenance of his socio-economic needs. Since these needs are ever changing and ever on the increase, the resources are often at the risk of depletion (Nwadialor, 2001). Nwadialor (2001) stated that one of the most affected of these resources appear to be "natural forest", which has been continuously under threats of over-exploitation by man, leading to negative changes in its status and productivity. Accordingly, changes occur as human beings attempt to adjust their seemingly endless wants and desires for food, shelter, recreation, infrastructural facilities and so on to the forest resources available to them.

Forest depletion is akin to deforestation; which broadly speaking, refers to the gradual or rapid process of temporary or permanent removal of trees, resulting in the partial or complete eradication of tree cover in a locality (Jones, 2000). It can occur due to natural or human factors. In recent times, the rapid rate of deforestation and forest degradation in developing countries have resulted in annual loss of about 17-20 million hectares of forest (Flazzel & Magrath, 1992). According to Flazzel and Magrath, deforestation in simple terms is the reduction of the stocking vegetation cover resulting from human activities. Forest degradation is the reduction or loss of biological, economic productivity, complexity of forests and woodlands as a result of land use /land cover changes or combination of processes arising from human activities, fire, erosion *etc.*

Human activities are globally recognized as the foremost cause of deforestation, with agricultural and urban-industrial activity complex being the most important factors (Geist & Lambin, 2003; Odihi, 2003; Vince & Iovanna, 2006). According to Odihi (2003), poverty and other socio-economic woes which force people in the third world to exploit or pillage forest resources for the purpose of energy and commercial gains are increasingly recognized as important deforestation factors. The author noted that population growth among communities around forests impose a lot of pressure on the forest for subsistence farming. Salami and Balogun (2004) noted that the mode of incursion is through agro-forestry.

According to Food and Agriculture Organization of United Nations (FAO, 2010) forest can be referred to as land spanning more than 0.5 hectares with trees higher than 5 meters and canopy cover of more than 10 percent or trees able to reach these thresholds *in situ*. However, it does not include land that is predominantly under agricultural or urban land use.

Nearly one thousand (1000) forest reserves are included in the International Union for Conservation of Nature (IUCN) world database on protected areas. Many of these have no forest left and most are highly degraded due to unsustainable extraction of timber, fuel wood, economically important plants, bush meat and other resources (USAID, 2008).

Forestry development began in Nigeria in 1889 with emphasis on forest reservation and regulated timber exploitation (Geometics Nigeria Limited, 1997). Significant portions of forest reserves in Nigeria that remained relatively undisturbed until the 1980s have been lost in the last two decades. As these natural forest ecosystems disappear, so do many of

the animal life, timber pharmaceuticals, fruits and food which they provide (Akpu, Tanko & Yahaya, 2012). In 1980, demand for forest products, especially timber became insatiably high as a result of increasing human population pressure and economic growth. This led to unregulated forest exploitation, resulting in degradation of forest resources in the country (Geomatics Nigeria Limited, 1997). In an attempt to preclude total depletion of forest resources, the Federal Government of Nigeria has geared effort towards increasing 10 percent (91,000 km^2) of the total land area under forest reserve to 20 percent towards meeting the FAO specification of 25 percent in the future (Ezebilo, 2004).

Afaka forest reserve was established in 1954 as an experimental plantation site to increase productivity, arrest deterioration and desertification of the semi- arid zone of the Northern Guinea savannah of Nigeria. However, human influence has been identified as a critical factor militating against realization of these noble objectives (Nwadialor, 2001). Due to rapid urban growth coupled with inadequate planning, as well as poor monitoring strategy, this forest reserve is now greatly threatened; which could be devastating, if no control measure is adopted. The areas under forest cover at Afaka forest reserve decreased by 48 percent in 1995; which led to opening of forest canopy and exposure of bare forest floor that were subsequently subject to erosion (Fuwape, Akindele & Adekunle, 2006); hence, the need to forecast the future state of this forest reserve using predictive models.

A model is a representation of reality used to simulate a process, understand a situation, predict an outcome, or analyse a problem (GIS Glossary, 1996). Detecting past changes and predicting these kinds of changes in the future play a key role in decision making and long term planning. Modelling is the main tool for studying land use and land cover

change (Schneider & Pontius, 2001). Predictive models of land use change are important tools for managing ecological issues. Forecast modelling can be used to evaluate land use systems and identify important factors that affect land use decisions (Rounsevell, Annetts, Audsley, Mayr & Reginster, 2002).

Carmel, Kadmon and Nirel (2001) attested that both mechanistic and empirical approaches are widely used in modelling vegetation dynamics. The mechanistic approach assumes that factors underlying the process are known, and explicit functions are used to connect these independent factors with modelled variable (Levin, 1997). In empirical models, future changes in vegetation are extrapolations of past changes. In a pure empirical model, no ecological assumptions are built into the modelling processes, which are based on observations only. Transition models (also called Markov models) are the most common empirical models of vegetation dynamics, and are often used to predict expected future vegetation (Callaway & Davis, 1993).

The most popular methods in recent land use/ land cover literature are the cellular and agent- based models or a hybrid of the two (An, Linderman, Qi, Shortridge & Liu, 2005; Breuer, Huisman & Frede, 2006; Le Ber, Benoit, Schott, Mari & Mignolet, 2006). Cellular models include both Cellular Autom ata (CA) and Markov Chain (MC) models. For CA, each field's future state depends on the transitions calculated from spatio-temporal neighbourhoods, whereas in MC models, the field's future state depends on transitions calculated from lagged state value probabilities (Sengupta *et al.,* 2005).

Markov process models are a class of probability used to study the evolution of system overtime. Transition probabilities are used to identify how a system evolves from one time

period to the next. A markov chain is the behaviour of the system overtime, as described by the transition probabilities and probability of the system in various states (Bhagawat, 2011). Markov chain model analyses two qualitative land cover images from different dates and produces a transition matrix, transition area matrix and a set of conditional probability images. However, Cellular Automata_ Markov is a combined cellular automata/ Markov Chain land cover prediction procedure that adds an element of spatial contiguity, as well as knowledge of likely spatial distribution of transitions to Markov change analysis (Eastman, 2009).

Importantly, Remote Sensing provides an efficient means of obtaining information on temporal trends and spatial distribution needed for understanding, modelling and projecting land use change (Elvidge, Suttton & Wagnar, 2004). According to Weng (2002), integrating Remote Sensing and Geographic Information System provides a comprehensive source of accurate, objective, up-to-date, and timely information that is peculiar to the site of forest operations. The monitoring tool has been essential, facilitating sound decision making and consequently better management and governance of the forest sector.

Venema, Calamai and Fieguth (2005) noted that proper forest monitoring and management can only be achieved by using Remote sensing techniques and creating spatial representations such as maps to know the exact locations and extent of deforestation. Hence, the need to use satellite imageries in modelling forest depletion.

1.2 STATEMENT OF THE RESEARCH PROBLEM

The uncontrolled conversion of forest into other land cover types and uses is an internationally recognized problem (Wiestske, 1998). Wiestske noted that trees are seen as obstacles to progress and their removal viewed as the first stage of development; hence deforestation has prominently become one of the most important environmental issues since the last century. Khadka (1997) observed that forests are socially, economically and environmentally important; especially tropical forests, which are home to at least two-thirds of the world's living organism (some three million species). He noted that tropical forests play important roles in the economy of many countries, but forest resources are at great risk because of severe exploitation.

Deforestation and forest degradation are critical issues, threatening biodiversity, ecosystem stability and long-time availability of forest product as well as depleting the natural resource base underpinning many natural economies (UNESCAP & ADB 2000). If the world's net forest area continues to decline by 5.2 million hectares per year (the average of net annual loss between 2000 & 2010), it will take 775 years to lose all of the world's forest (FAO, 2012). About 80% of the world's original cover of forest has been cleared, fragmented, degraded or converted to plantation, of which about 50% has been totally cleared. Almost 80% of mammals and about 60% of birds listed by International Union for the conservation of nature have declined primarily as a result of habitat loss (IUCN, 2003).

The annual rate of change in total forest area (land with at least 10 percent tree cover and 0.5 ha area) from 1990 to 2000 for the whole of Africa was estimated to be -0.74 percent, equivalent to losing more than 5 million hectares of forest a year, an area roughly the size

of Togo and the highest rate of any region (FAO, 2001). The depletion of forest-based wildlife as a result of commercial harvesting and trade of bush meat is of growing concern. This has reached crisis dimensions in parts of tropical Africa, where many species of primates and antelopes, among others are threatened (FAO, 2001).

Reasonable numbers of medicinal species are threatened by habitat loss following heightened deforestation (Agbogidi & Ofuoku, 2006). Anthropogenic activities including farming, hunting, tree felling, bush burning, mining operation, petroleum exploitation, civil engineering construction and water exploration have been shown to impact forests negatively (Adeyemo & Jegede, 2002). Adelusi, Agboola and Oni (2002) noted that urban forest reserves and enclaves have suffered more and undue depletion and degradation with loss of biodiversity and renewable resources as a result of urbanisation and encroachment on areas originally perceived as forest reserves and estate. In the same vein, Okonkwo, Umar and Nwafor (2002) reported that serious anthropogenic activities of man constitute great environmental hazards. Impacts of certain projects on vegetation of ecosystems in the tropics; including Nigeria, are widespread. This includes; establishment of modern markets, television stations, amusement parks, housing estate, company sites, stadia in Nigeria and other parts of the tropics has led to the removal and destruction of various economic vegetation, the use of some are yet to be discovered.

Growing urbanization in Kaduna metropolis has led to encroachment of settlements into areas of forest reserve, thereby leading to clearing of natural forest cover which may result to loss of soil nutrient through erosion, compaction and water logging; which are caused mainly by stripping forests for fire woods (Ndabula, 2006). The implication of this

includes loss of biodiversity, land degradation, climate change and a host of others. This led to the curiosity about the future of Afaka forest reserve.

Akingbogun, Kosoko and Aborisade (2012) studied urban growth effect on the Eleyele Forest reserve in Ibadan, Oyo state, using Remote Sensing and Geographic Information System (GIS). The results showed that there was a large decrease in forest plantation between 1984 and 2000 from 0.88 hectares (12.5%) to 0.01 hectares (0.13%).

Ati, Sheyin, Abbas and Mohammed (2010) assessed changes in Kagoro forest using Remote Sensing and GIS. Result of the study revealed significant depletion of the forest as a consequence of human activities; particularly cultivation, for agricultural purposes. Undisturbed forest decreased from 231.52 km^2 in 1987 to 175.82km^2 in 2005 with a percentage change of 24.06%. The forest is therefore, in danger of being destroyed and laid bare in the nearest future.

Nwadialor (2001) monitored the trend of depletion of natural forest in Afaka forest reserve. The findings revealed that natural forest has decreased from its original status of 95.98% in 1962 to 61.96% in 1994. Yahaya (2011) corroborated this in his assessment of change in vegetation of the same forest reserve using Remote sensing and Geographic Information System, stating that the forest plantation decreased from 41.6% in 1973 to about 14.1% in 2009.

Akpu, Tanko and Yahaya (2012) in their assessment of the implication of urban growth on vegetation cover in Afaka forest reserve revealed that natural forest/plantation decreased

from 20.94% in 1990 to about 11.6% in 2009. They observed that natural forest/plantation was declining at the rate of 2.23%.

It has been established by Nwadialor (2001) that the natural forest of Afaka decreased to 61.96% in 1994 and Tanko (2011) confirmed that this vegetative cover decreased to 46.8% in 2009. It revealed that 15.16% of the forest has been lost between 1994 and 2009, which implies that the forest cover is fast depleting. This informed the researcher's decision to compare the Cellular Automata-markov and Markov Chain models in forecasting rate of depletion. In spite of the importance of such study, there is no study that has attempted a prediction of forest depletion in Afaka forest Reserve using Cellular_ Automata markov and Markov Chain models. A comparison of their individual performance will guide future researchers on which model to adopt.

It is against this background that the study intends to answer the following questions:

1. What was the extent of the forest in 1973?
2. What was the extent in 2009?
3. What will be the extent in 2028, Using Markov chain model?
4. What will be the extent in 2028, Using Cellular Automata markov chain model?
5. Is there a significant difference between the results of Markov Chain model and the Cellular Automata markov chain model?

1.3 AIM AND OBJECTIVES OF THE STUDY

The aim of this research was to undertake a comparative analysis of Cellular automata-markov and Markov chain models in forecasting forest depletion of Afaka Forest Reserve, Kaduna State, Nigeria. The specific objectives were to:

i. determine the land cover of the forest in 1973, 1990 and 2009.
ii. forecast possible forest loss for 2028 using Markov Chain model and Cellular Automata- markov model.
iii. determine the significant differences between results of the two models.

1.4 RESEARCH HYPOTHESIS

H_o-There is no significant difference between results of the Markov chain model and the Cellular Automata- markov model in forecasting forest depletion.

1.5 SCOPE OF THE STUDY

This study focuses on comparing Markov chain model and Cellular Automata-Markov model in forecasting forest depletion in Afaka Forest Reserve. The emphasis will be to determine the better model for forecasting forest depletion. Also, use the better model to forecast forest depletion in Afaka forest reserve from 2009 to 2028. This is because the year interval between the input data (1990 and 2009) is nineteen years and markov model has the capability to forecast based on the year interval. This made the researcher to project to forecast for the next nineteen years from 2009 which is 2028.

1.6 JUSTIFICATION OF THE STUDY

A key sector of both economic and environmental concern is the forest sector. Forest provides many social, economic and environmental benefits. In addition to timber and paper product, forests provide wildlife habitat and recreational opportunities, prevent soil erosion and flooding, helps provide clean air, water and contain certain tremendous biodiversity; ecotourism value of the forest is a formidable tool for sustainable economic development in Nigeria (Adeyemo & Okosodo, 2005; Akachukwu, 2005). Forests are also an important defence against the global climate change. Through the process of photosynthesis, forests produce life-giving oxygen and consume huge amount of carbon dioxide, the atmospheric chemical most responsible for global warming. By decreasing the amount of carbon dioxide; in the atmosphere, forest can reduce the effects of global warming (Manstrendrea & Schneider, 2009).

A major consideration for choice of location is the occurrence of heterogeneity of abundant, valuable and native tree species that inhabit the Afaka environment. Also observed by Barrera and Amujo (1971), the Reserve has been known in the past for its high potentials in biodiversity of flora and fauna. A GIS based forest monitoring system will make it easy for the country to embark on forest certification programme, which is the new international initiative for combating unsustainable exploitation of the world's forest. The imprecision of land use/land cover changes has brought about constraints in land resource management. The application of remote sensing and Geographic Information System to acquire relevant data and a model to forecast future use of this forest will provide planners with basic tools for future planning.

CHAPTER TWO

CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

2.1 INTRODUCTION

This chapter reviews related works that have been done and documented by researchers. The first part of this chapter considered conceptual framework. The basic concepts includes: Forest reserves, Change detection, Models, Remote sensing and Geographic Information System. Relevant literature was reviewed under the following themes: application of Markov Chain Models and Cellular Automata Models.

2.2 CONCEPTUAL FRAMEWORK

2.2.1 Forest Reserves:

Forest reserves are areas designated by state governments for the protection of timber and other forest resources. Harvesting of timber may be allowed under permit and under special concession to people in surrounding communities. Harvested timbers are mostly replaced with exotic tree species. Most of these forest reserves are also poorly managed by the various State Ministries of Agriculture and Natural Resources (Usman & Adefalu, 2010).

The first forest reserve in Nigeria is the Olokemeji reserve established near Ibadan around 1900 (Onokerhoraye, 1985). This was followed by the establishment of other forest reserves in various parts of what forms the present day Nigeria. In these reserves, lumbering activities where made illegal. By 1908, a Forest Ordinance promulgated by the colonial government gave protection to all commercial timber outside the reserves.

In 1917, the first definitive government policy on forestry came into existence. In that year, the then Governor General; Lord Lugard, stated that each province of the country must reserve a minimum of 25% of its forests. This policy statement later faced a lot of opposition in the eastern part of the country. This was because of the high population density and resultant higher pressure on land (Egboh, 1979). Felling of timber therefore required a government permit.

At the time of independence in 1960, many forest reserves were already in place in the country. Many of these forest reserves were to later become game reserves. For instance, the Yankari game reserve which was opened in 1962 was a forest reserve for some time (Onokerhoraye, 1985). From about 800 forest reserves and about 30 game reserves in the 1980s, the number of forest reserves in the country has now increased to 966. There are also 8 national parks, 12 strict nature reserves and 28 game reserves in the country today (Areola 1982; Federal Government of Nigeria, 2001).

The indiscriminate felling of trees has continued in virtually every part of the country. For instance, the Federal Department of Forestry (2001) estimated that Nigerian forests are being depleted at an annual rate of 3.5%. Nigeria used to have about 20% of its area covered with natural forests but, this has been reduced to about 10%. It lost about 60% of its natural forests to agricultural encroachment, excessive logging and urbanization between the 1960s and the year 2000 (FAO, 2001). In some areas, natural forest has been totally replaced with monocultures of exotic trees. Indiscriminate felling of trees has continued in both the high forest and savannah areas.

The result has been serious reduction in timber resources. There is the fear that what is left of forests and wildlife may be completely lost within the next few years if care is not taken. Today we continue to find evidences of serious soil erosion in many parts of the country. On the other hand, the rate of afforestation continues to be far slower than the rate of exploitation.

According to FAO Global Forest Resources Assessment (2005) deforestation is a result of the combination and interaction of complex factors acting on a given forest. Causes of deforestation are very complex. A competitive global economy drives the need for money in economically challenged tropical countries (Urquhart, 2007). The three main causes of deforestation in the world (FOA, 2005) are;

1) Agriculture – conversion of forests into crops and pasture. It was implicated as a factor in 96% of forests assessed (Geist & Lambin 2002). Deforestation by poor farmers of most tropical countries is driven by need for basic human need like food. Most farmers in tropical countries are poor by American standards. In Bolivia, a country holding some of the Amazon forest, per capita income is $800. Farmers must raise crops for food and to sell (World Bank, 1998).

2) Infrastructural expansion. These include roads development and encroachment of human settlements. It is of particular concern in Latin American countries and urban sprawling in United State and accounted for 72% of cases studied.

3) Wood extraction accounted for 67% of the cases studied. Industrial logging is the primary issue in Asian countries while domestic fuel wood gathering is main driver in

Africa. Forest fires are often purposefully set by people. On the average 104 million hectares of forests were significantly affected each year by forest fire, pests (including insects and diseases) or climatic events such as drought, wind, snow, ice and floods (FAO, 2005). However, most of the information from developing countries regarding forests affected by disturbances is severely under reported, with information missing from many countries, especially for forest fires in Africa (FAO, 2005). Governments sell logging concessions so that they service their international debt, for industrial development or for other projects (Urquhart, 2007). Other drivers of deforestation are population growth, poverty, landlessness and consumer demand (UNEP, 2007; FAO, 2005).

2.2.2 Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Change detection is useful in a variety of subjects; for example, monitoring deforestation, coastal dynamics, shoreline change and river transportation on multi-temporal digital images (Muttitanon & Tripathi, 2005). It involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel by pixel or segment to segment comparison to detect changes in cover type (Falahtkar, Soffianian, Khajeddin, Ziaee & Nadoushan, 2011).

Many change detection methods have been developed and used for various applications. For example, there are post classification comparison, image differencing, image ratioing and principal component analysis (Chen, 2000).

2.2.2.1 Post Classification Comparison

The Post Classification Comparison (PCC) method performs a multispectral classification on each source image, and then compares the resulting classified images for differences (Howarth & Wickware, 1981). Classifications require human expertise to generate a classified image. One advantage of the post-classification comparison is that this method minimizes the search space and effects of seasonal and atmospheric differences between scenes.

The process of classification itself can be either supervised or unsupervised. The comparison of classified images can be carried out visually, or by computer. A computer is better in quantitative analysis, but human operators are much better in discriminating patterns and shapes (Phalke, 2005). The principal advantage of post classification comparison lies in the fact that the two dates of imagery are separately classified; thereby minimizing the problem of radiometric calibration between dates (Copping, 2004). The main disadvantage of PCC method is that errors depend upon the accuracy of training data sets used. Furthermore classification errors introduce spurious change detection (Phalke & Couloigner, 2004).

2.2.2.2 Image Differencing

Image differencing is one of the simplest digital algorithms for change detection. Image differencing means taking an image at one time and subtracting it from another image from a later time (Deer, 1995). The resultant image represents changes between the two dates. For example, each 8-bit band has digital values ranging from 0 to 255; the total potential range of the different image is -255 to +255. Usually, a constant is added to the resulting

value so that all differences are positive. Pixels exhibiting a significant radiance change are expected to lie in the tails of the distributions of the difference image, whereas the unchanged pixels should be grouped about the mean (Trisirisatayawong & Samchimchom, 2002).

Potential errors can be introduced by radiometric differences and poor registration of temporal images (Radke, Srinivas, Omar & Badrinath, 2005). This method does not discriminate between differences due to scene changes and viewing effects. The bias and variance of errors are unknown and might be substantial. In that case simple image differencing techniques do not give an accurate detection of changes. Some form of radiometric standardization is normally applied to reduce the effect of illumination angle and intensity (including path effects) and viewing angle. Image Differencing has been used in coastal studies, in temperate forests, desertification and in the analysis of irrigated crops (Ha, Ahn & Park, 2002).

2.2.2.3 Image Ratioing

Image ratioing is based on ratio of the first image with respect to second. Final values can range from 0 to 255. To achieve equal possibility of getting a ratio between 1/255 to 1, and 1 to 255, the input temporal images must be normalized. The ratio values from 1/255 to 1 have reassigned values from 1 to 128 whereas the values from 1 to 255 have reassigned values from 128 to 255. In the areas where there is no change it is expected to obtain a normalized value of 128, while areas with large deviation from this normalized value represents the changes A threshold is often used to filter out source variations (Deer & Eklund, 2002).

The main limitation of this method is that its performance depends on statistical distributions of input images (Todd, 1979). This method requires determination of a threshold that will indicate when a change is significant. This method does not discriminate between differences due to scene changes and viewing effects. As this method works on a pixel level, neighbourhood viewing effects will appear as potential changes (Deer & Eklund, 2002).

2.2.2.4 Principal Component Analysis (PCA)

The Principal Component Analysis technique uses Principal Components Transformation (PCT) to detect changes. PCT is a linear transformation which defines a new, orthogonal coordinate system such that the data can be represented without correlation (Wiemker, Speck, Kulbach, Spitzer & Bienlein, 1997). The axes of new coordinate system are defined by eigen vectors of the covariance matrices. Each individual pixel is transformed by vector multiplication of its original vector (i.e. pixel intensity value) and the eigen vectors, resulting in coordinates of a new data set of pixel vectors. In summary PCT transforms original intensity values of temporal data into a new parameter space. The orthogonal Principle Component one (PC1) and two (PC2), represent axes of the new space. The PC1 axis represents unchanged component while PC2 axis represents the changes (Singh, 1989). Thus, PCA method is based on the idea that multi-temporal data are highly correlated, especially unchanged regions. So, the change can be highlighted by rotating data axes into principal components maximizing the data variance. The PCA method gives information of the overall changed portions of temporal images but does not give information about type of

change that has occurred in the object of interest. Selection of appropriate threshold for change detection is crucial and largely influences detection process (Phalke, 2005).

2.2.3 Land Use /Cover Change (LUCC) Models

Hundreds of models of LUCC have been described in literature on landscape ecology, geography, urban planning, economics, regional science, computer science, statistics, geographic information science, and other fields. Because of differing disciplinary perspectives, as well as differing methodological approaches, data availabilities, and modelling goals, attempts to categorize models are complicated by a relatively large number of dimensions on which the models vary (Munthali & Murayama, 2011). A number of reviews of LUCC models have been produced in recent years, each from their own perspective and producing a number of different typologies.

Perhaps the first of these reviews was published by Baker (1989) in the context of landscape ecology, so its focus was on land-cover change. Models were grouped according to the goals of the models. Whole landscape models seek to model change in some aggregate attribute or state of the landscape over time. Distributional models describe changes in the proportion of landscape in each of a number of land-cover classes. Spatial landscape models describe the location and configuration of changes in land cover (Baker, 1989).

A pair of publications in late 1990s reviewed significant amount of work that had gone into modelling tropical deforestation (Lambin, 1997) availabilities and modelling goals. Attempts to categorize models are complicated by a relatively large number of dimensions on which the models vary.

Agarwal, Green, Grove, Evans and Schweik (2002) described nineteen (19) models that were arrayed on dimensions of space, time, and human decision-making. Models were characterized on these three dimensions according to both the scale at which they operated and degree of complexity in the representation. Parker, Manson, Janssen, Hoffmann & Deadman (2003) focused on agent-based models as tools for representing human decision-making and simulating the aggregate outcomes that result from decisions made by many individuals. Agent-based models represent a qualitatively different approach to the mathematical and statistical approaches that pervaded earlier reviews, and offer potential for new LUCC models, similar to the approach of ecological modelling offered by individual-based models (DeAngelis & Gross 1992). Parker *et al.,* (2003) argued that combining agent-based models, to represent human level decision-making, with cellular models, to represent biophysical landscape change, offers a promising approach for future model development in LUCC.

The review by Parker *et al.,* (2003) appears to be the first to address both land-use and land-cover change, though it has a specific focus on agent-based models. The distinction is important because it affects both the data requirements for calibration and validation and the process representations required. There is not always a one-to-one relationship between the two and while human activity defines land-use, land-cover change can proceed with or without a proximal human driver (e.g., through climate change). If we are to bridge human activity and ecological structure and function, representations of both processes are required, adding greater dimensionality to considerations of models in this field (Cihlar & Jansen, 2001).

According to whether the modelling approach is oriented primarily toward (a) fitting data or (b) simulating processes. The first category of models includes a broad range of models that employ social science theory and represent decision-making and biophysical processes to varying degrees.

2.2.3.1 Empirically Fitted Models

They are based on statistically matching the temporal trends (in the case of longitudinal data) and/or spatial patterns (in the case of cross-sectional data) with some set of predictor variables. The variables to be predicted may represent land use, land cover, change in either of these or some combination and may be measured over pixels, derived from remotely sensed data, parcels (i.e., irregularly shaped spatial units defining legal ownership) or aggregated over some jurisdictional unit. Predictor variables are factors thought to influence land-use, including proximity to roads, proximity to cities and towns, mix of economic activity, demography, income and wealth, and biophysical factors like slope and soils (Cihlar & Jansen, 2001).

Some of the earliest empirically fitted models represented LUCC as Markov random processes, in which the state of land at some time in the future was a function only of its present state, represented by a transition probability (Burnham, 1973; Bell, 1974; Muller & Middleton, 1994). Though these simple models have appeal for their minimal data requirements and analytical properties, their assumptions are restrictive and they have little utility for analysing policy. To address some of the restrictions, later models have used Markov framework, but added a dependence on neighbouring states (Turner, 1987) and

introduced spatial and temporal non-stationarity to the transition probabilities (Sklar & Costanza, 1991; Brown *et al.*, 2000).

Statistical estimation methods are more commonly used to fit LUCC models. Some of these models have been constructed with only loose connection to theory, while others are constructed in a more rigorous, usually economic, theoretical context. Given the discrete nature of land-use and -cover categories and changes, the most common approach is to estimate a logistic regression function that describes either the probability of a particular land category occurring or of the location transitioning from one land category to another. This approach has been used for modelling development in urban areas (Landis, 1994; Landis & Zhang, 1998a; 1998b), along urban-rural gradients (Wear & Bolstad, 1998) and in tropical forests (Chomitz & Gray, 1996; Mertens & Lambin, 1997).

2.2.3.2 Dynamic Process Models

In contrast to empirically fitted models, dynamic process models of LUCC seek to represent the most important interactions between agents, organisms, and their environment as computer code. Though fitted models can be used to generate simulations (Brown, Goovaerts, Burnicki & Li, 2002), simulation is clearly more central to the use of process models. Although these models need to be calibrated and validated, they de-emphasize the fitting of data and emphasize the fidelity of model elements and processes to what is known about the processes. Three types of dynamic process models that have been used for LUCC: process flow models, cellular automata (CA), and agent-based models.

Models that track material and energy flows through a landscape and how they are transformed and/or transmitted at each location work well for some natural processes and to represent stable, stylized socioeconomic systems (Fitz, *et al.*, 1996).

Models of this sort have been used in a variety of settings, including the Everglades (Wu *et al.*, 1996) and the Patuxent Watershed (Voinov, *et al.*, 1999). These modelling approaches often include enough stochasticity that they become simple simulation platforms to evaluate empirical models as described above. Their primary limitation for modelling LUCC, however, is an inability to represent complex ecological or social interactions, including competition and cooperation, the role of institutions, interest groups, and limits to rational behaviour, that give rise to behaviours and decisions that affect land-use and cover (Fitz, *et al.*, 1996).

Gaps and inconsistencies left by mathematical modelling approaches saw the proliferation of cellular automata (CA) in combination with Markov Chain models as an alternative (Munthali & Murayama, 2012). In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatio-temporal neighbourhood (Kamusoko, Aniya, Bongo & Munyaradzi, 2009), while in Markov models, cell states depend probabilistically on temporally lagged cell state values (Munthali, 2012). These cellular models (CMs) underlie many LUCC studies in which Markov–CA combinations are common (Li & Reynolds, 1997; Kamusoko, *et al.*, 2009). Cellular Models assume that the actions of human agents are important, and others assume a set of agents coincident with lattice cells and use transition rules as proxies to decision-making, and as such they both fail to simulate decisions expressly and explicitly (Parker *et al.*, 2003).

Cellular automata (CA) and other cellular models are fairly common in land-use modelling literature (Batty & Xie 1994; Batty, Couclelis & Eichen, 1997; Clarke & Gaydos, 1998). In some CA models, the cells are considered simple actors with fixed neighbourhood relations and update rules. In other models, CA represents the state and dynamics of the environment. The cells can represent parcels of land, each with their own characteristics and each changing as a result of some fixed rules based on the cell's state and the state of its neighbours. CA models, coupled with data on heterogeneity of the environment, can capture important dynamics of LUCC, including diffusive, road-driven, and spatially random changes (Clarke & Gaydos, 1998).

Further, because they are dynamic and iterative, CA models can represent endogenous interactions and feedbacks. An important challenge in the development of CA models is how to establish the rules that govern system behaviour, and incorporation of heterogeneity and dynamism into these rules. Also, the simplified decision rules of CA models make policy interventions difficult to explore at the level of individual decision makers, social groups, or institutions (Clarke & Gaydos, 1998).

Agent-based models (ABMs) are defined in terms of entities and dynamics at a micro level, i.e., at the level of individual actors and their interactions with each other and with their environment (Epstein & Axtell 1996; Kohler, Kresl, Van West, Carr, & Wilshusen, 2000; Gimblett, 2002; Janssen, 2003a; Parker *et al.,* 2003). ABMs consist of one or more types of agents, as well as an environment in which the agents are embedded. Agents in ABMs may be individuals (e.g., householders, farmers, developers) or institutions (e.g., townships, NGOs, firms; Janssen 2003b). Therefore, systems can be studied at many scales

and parts (specified at different scales) can be integrated into a coherent whole. Agent specification requires defining their state (e.g. preferences, memory of events, and social connections) and their decision-making rules, heuristics and other mechanisms to perform particular behaviours. The agents generate their individual behaviours in response to inputs from other agents and from the environment (Clarke & Gaydos, 1998).

Agents may also adapt, or change their behaviour, through learning or evolution based on their experience. Adaptive behaviours are usually represented in the models using some learning algorithm, such genetic algorithms. As the model is run, agent behaviour is generated as agents use their rules to determine which other agents to interact with, what to do when they interact, and how to interact with the environment. Representing human decision-making in ABMs remains an active area of research (Balmann & Happe, 2002; Hoffmann, Kelley & Evans, 2003; Lynam, 2003).

Environment of an ABM typically represents the physical environment, e.g., land, water, roads or other infrastructure. The environment at any location has associated states, e.g., land-cover type, soil quality, and aesthetic quality. The environmental entities in a model may have their own dynamics, describing how they change in time both independent of and as a result of agent behaviour, e.g., to represent soil erosion processes, forest growth and other aspects of environmental change. These dynamics are often represented by coupling with CA-based models (Jansen, Anderies, Stafford-Smith & Walker, 2003; Lynam, 2003).

The agents' behaviours affect each other and the environment. The environment changes in response to agent behaviours, but also by following its own dynamics. Thus ABMs

embody complex interlaced feedback relationships, leading to nonlinear and path dependent dynamics often observed in complex systems. Note that the model's output is the micro-behaviour of agents and the environment, as well as the emergent macro level structures, relationships and dynamics which result from the micro-level activity (Clarke & Gaydos, 1998).

Spatial relationships can be incorporated into agent behaviour in order to create more realistic interaction with neighbouring agents, such as when a farmer is more likely to learn from a nearby neighbour than from a farmer located far away (Polhill, Gotts & Law, 2001). However, the models also can include social networks of various kinds; each defining an interaction topology based on; for example membership in groups, business contacts, and common information sources. These characteristics facilitate the investigation of three particularly important properties that define complex systems: emergence, scaling, and feedbacks. Parker *et al.,* (2001) argued that spatial landscape metrics can be used as measurable map properties that "emerge" from individual-level decision-making and interaction. These measures can serve as scaled outputs from an agent-based model, which has inputs at the level of individual decision-making.

Recently developed agent-based models have been used to examine feedbacks between land-use change and transportation networks (Batty & Torrens 2001; Waddell, 2002) and environmental characteristics (Rand *et al.,* 2002).

2.2.4 Remote Sensing

Remote sensing is the science of acquiring, processing and interpreting images that record the interaction between electromagnetic energy and matter (Sabins, 1996). Remote Sensing

is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation (Lillesand, Kiefer & Chipmam, 2008). Remote Sensing is the instrumentation, techniques and methods to observe the Earth's surface at a distance and to interpret the image, the images or numerical values obtained in order to acquire meaningful information of particular objects on the Earth (Buiten & Clevers, 1993). Remote Sensing of the earth's environment comprises measuring and recording of electromagnetic energy reflected from or emitted by the planet's surface and atmosphere from a vantage point above the surface and relating such measurements to nature and distribution of surface materials and atmospheric conditions (Reddy, 2008). The remote sensing sensor measures the energy that is reflected or backscattered by the earth's surface. The measured energy is converted and stored as a digital number (DN) value, which ranges from 0-255. Each pixel (picture element or unit area or ground cell) has a single DN value. Most sensors measure reflected sunlight passive remote sensing; however, some sensors detect energy emitted by the earth itself or provide their own source of energy (active remote sensing) (Lillesand & Kiefer, 2000).

There is a wide range of remote sensing sensors which, linked to a certain platform, can be classified according to their distance from the Earth's surface, airborne, space borne or even ground based sensors (Bakker *et al.*, 2004). Satellite remote sensing is used with great success in monitoring and detection of vegetation and land cover changes. Satellite image data can be used to efficiently monitor the status of existing clear cuts or emergence of new ones, and even assess regeneration condition. In countries where cutting is controlled and regulated, remote sensing serves as a monitoring tool to ensure companies are following

cut guidelines and specifications (Meseret, 2009). Another unique quality of Remote Sensing (RS) data is that it provides a means of quickly identifying and delineating various forest types, a task that would be difficult and time consuming using traditional ground surveys (Canada Centre for Remote Sensing Tutorials, 2008). Remote sensing technique for forest cover change detection and monitoring has been used to assess dissimilarities in forest cover over two or more time periods caused by environmental conditions and human actions (Kreuter, Harris, Matlock & Lacey, 2001; Zhongmin, Guodong, Zhiqiang, Zhiyong & Loomis, 2003). In addition, it is an important tool for vegetation description and classification on a large scale (Chen & Tian, 2007). Effective analysis and monitoring of land cover changes require a substantial amount of data about the Earth's surface. This is most widely achieved by using remote sensing tools (Araya & Cabral, 2010).

2.2.5 Geographic Information System

Geographic Information System can be defined as a system for capturing, storing, checking, integrating, manipulating, analysis and displaying of data which are spatially referenced to the Earth. This is normally considered to involve a spatially referenced computer database and appropriate application software (Burrough & McDonnell, 1998). Geographic Information System (GIS) is an information system that is designed to work with data referenced by spatial or geographic coordinates. In order words, a GIS is both a database system with specific capabilities for spatially – referenced data as well as a set of operations for working with data (Star & Estes, 1990). Geographic Information System can be defined as a computerized system that facilitates the phases of data entry, data analysis and data presentation, especially in cases when we are dealing with georeferenced data.

GIS and remotely sensed data are used to define initial conditions, to parameterize CA-Markov model, to calculate transition probabilities and to determine the neighbourhood rules (Wang & Zhang, 2001).

Using GIS, customized maps may be created to answer specific resource questions, such as a map that displays locations of only stressed or diseased species. Creating maps that show the spatial relationships between harvestable tree species and other features such as mills, steep slopes, or even ecologically sensitive riparian areas are possible and useful to managers (Sheffield & Royer, 1989).

Vegetation is sensitive to stress factors associated with changes in moisture, temperature, as well as anthropogenic factors, such as air pollution, forest pests and disease. GIS together with remote sensing offers the means to monitor magnitudes and rates of decline (Rock & Vogelmann, 1989). Defoliation also can be related to factors such as climate, forest types, ecozones, slope, and aspect and this analysis can be accomplished with a GIS (Van Sickle, 1989). GIS has now made it possible to incorporate spatial components into harvest planning and simulation models. In some cases, the modelling capabilities of a particular GIS may be used directly to aid decisions about timber harvesting; in other cases, an external model is linked to a GIS database. Forest fire managers have used GIS for fuel mapping, weather condition mapping and fire danger rating (Holder, Van, Wyngaarden, Pala & Taylor, 1990).

2.3 LITERATURE REVIEW

2.3.1 Transition Probability Matrix

Markov chain model was used to forecast forest loss of Afaka. Markov model is one of the most widely used models for predicting forest depletion as confirmed by the literature. Its outputs include, transition probability matrix, transition area and condition probability images.

Transition area matrix gives the probability that a particular land use class will change to every other land use in the predicted map. Transition area matrix records the total number of pixels that are expected to change to every other one. The 5 * 5 matrix rows represented the older land cover and the column represents newer categories.

2.3.2 Application of Markov Chain Model

Mubea, Ngigi and Mudia (2010) applied Markov chain analysis in predicting land cover change in Nakuru Municipality, Kenya. The projected land use/land cover for 2015 showed a substantial increase in urban and agricultural land use. Islam and Ahmed (2011) predicted land use change in Dhaka city, Bangladesh, using GIS aided Cellular Automata-markov. They modelled the land use change based on the past trend (1991-2008) to generate the future land use map of Dhaka city for the year 2020 and 2050. The result showed that urban built-up areas will increase significantly.

Rimal (2011), studied urban growth and land use/land cover change in Birantnagar Sub-Metropolitan city of Nepal. The study focused on historical urban growth phenomenon and prediction of land use and land cover change of Birantnagar over four decades by utilizing remote sensing and markov chain model. The result revealed a growing tendency in urban

land use, which might threaten the areas that are currently reserved for forest and agricultural purpose. In 1976, urban land cover was 4.8% but increased to 38% in 2009, while cultivated land decreased from 79% in 1976 to 55.8% in 2009.

Xia, Zeephongsekul and Arrowsmith (2008), utilized Markov chains to analyse outcome and trend of events associated with spatio-temporal movement pattern in Phillip Island. They tested whether stationery discrete absorbing Markov chain could be effectively used to model spatio-temporal movement of tourists. The result obtained showed that markov chain can indeed be effectively used to provide information on tourist movement patterns. Penguin parade is the most significant pattern for a one attraction visit to the Island with the conditional probability of 0.903.

Ahmed (2011) analysed and predicted future urban growth of Khulna city for 2019 using Multi-layer Perception Markov (MLP-Markov) model. Satellite images of 1989, 1999 and 2009 were used. The result revealed that 33.33% of total study area will be converted into built up area in 2019.

Jeganathan, Roy and Jha (2010), studied change dynamics of forest cover (between 1972 and 1999) in Shimla district, India, using remote sensing and GIS based techniques. Based on their findings, a non spatio-temporal Markov prediction was made for the year 2009. The predicted forest area in 2009 increased from 52.32% in 1999 to 55.49% with 55 errors under Markovian assumption of stationarity. Markov chain analysis can project future change in land use based on the changes from one period to another and spatial characters can be modelled using Cellular Automata (Eastman, 2003).

Datong (2011) carried out a study to determine the market share of mobile communications industry in Yola, North Eastern Nigeria Using first order Markov chain to find out the equilibrium market share of products in 2011 as a basis for predicting future market shares. The result revealed that optimum market mix among the various service providers were as follows: MTN 52.5%, Globacom 27.5%, Zain 15.4% and Etisalat 4.7%.

Abubakar, Lawal and Mohammed (2014) used Markov chain to formulate a four state model for annual rainfall distribution in Minna with respect to crop production. The result shows that in the long run 14% of annual rainfall shall be low rainfall, 34% annual rainfall shall be moderate rainfall and well spread, 47% of annual rainfall shall be high rainfall and 5% of annual rainfall shall be moderate rainfall not well spread.

2.3.2 Application of Cellular Automata Model

Currently, CA-based models are among the most popular ways to simulate land-use changes (Clarke & Gaydos, 1998; Caruso, Peters, Cavailhes & Rounsevell, 2007; Long, Shen, & Mao, 2012). A key advantage of CA is their simplicity; they can generate spatial-temporal patterns of great complexity through a limited set of relatively simple rules (White, Uljee & Engelen, 2012). The models' outcomes were typically a set of simulated land-use maps, which can easily be visualized, quantified and analysed by users (Jantz, Goetz & Shelley, 2004).

Moreover, information from other models, such as population growth models, can easily be integrated into a CA model to constrain land-use changes. This makes CA models suitable for testing various "what-if" scenarios and policies (White, Engelen & Uljee, 1997; Hasbani, Wijesekara, & Marceau, 2011).

In addition, these models can be linked to Geographic Information Systems (GIS) to utilize their functionality and directly use raster-based spatial data derived from remote sensing platforms, revealing CA-markov model as the optimum predictive model for urban growth in 2010 and 2018, using CA-Markov model based on land use types of 1994 and 2002, it was revealed that the urban and built-up area in 2010 was about 226.98sqkm. While for 2018, based on 2002 and predicted urban and built- up area in 2018 was about 261.53sqkm

Revestity (2011) assessed and predicted human impacts on land use changes of urban area of Zanjan (Iran), using Multi- temporal satellite imageries and GIS for 2020. A combined cellular automata with markov was employed. The result indicated that built up areas will increase from 4662 hectares in 2011 to 5550.4 hectares in 2020 which may endanger other land uses. Ongsomwang and Saravisutra (2011) modelled urban growth in Nakhon Ratchasma province of Thailand. They compared results of CA- markov and logistic regression model 2002 using overall accuracy and kappa *hat* coefficient of agreement for urban and built-up areas basis. Results revealed that CA-markov model had overall accuracy of 93.41% and kappa hat coefficient of Agreement of 0.84; while logistic the regression had 89.41% and 0.71%.

Kushwaha, Nandy, Ahmad and Agarwal, (undated) assessed forest ecosystem dynamics, predictive modelling and forest cover prediction in part of north-eastern India, using temporal satellite imagery of 1975, 1990 and 2009. The result predicted forest cover for the period of 2028 using cellular automata markov model, that by 2028 a forest area of 4,563.34 Km^2 will be lost.

Olayiwola, Ajala and Sangodipe (2014) examined growth pattern of settlements in Oke-Ogun area of Oyo state, Nigeria between 1984 and 2011 using CA-markov to predict future growth pattern. The result revealed that at an annual growth rate of 1.2%, settlements will occupy about 44.37% of total area by 2031.

Most documented literature focused on use of Markov chain model and Cellular Automata- Markov Model in forecasting urban growth. None compared use of Markov chain model and Cellular Automata- Markov model with a view to determine the better model to forecast forest loss, which makes this research relevant.

CHAPTER THREE

STUDY AREA AND METHODOLOGY

3.1 INTRODUCTION

This chapter focused on description of the study area and methods, adopted to achieve set objectives.

3.2 THE STUDY AREA

This section describes the study area. The location, climate, soils, vegetation, geology, relief and hydrology were considered.

3.2.1 Location, Position and Size of the Study Area

It is geographically located between latitudes 10° $33'$ N – 10° $42'$ N of the equator; longitudes 7° $13'$ E – 7° $24'$ E of the Greenwich meridian in figure 1 (Nwadialor, 2001). Afaka forest reserve is situated some thirty (30) kilometres Northwest of Kaduna Township, along Kaduna-Lagos express highway and is about 12,243.760 hectares in areal extent.

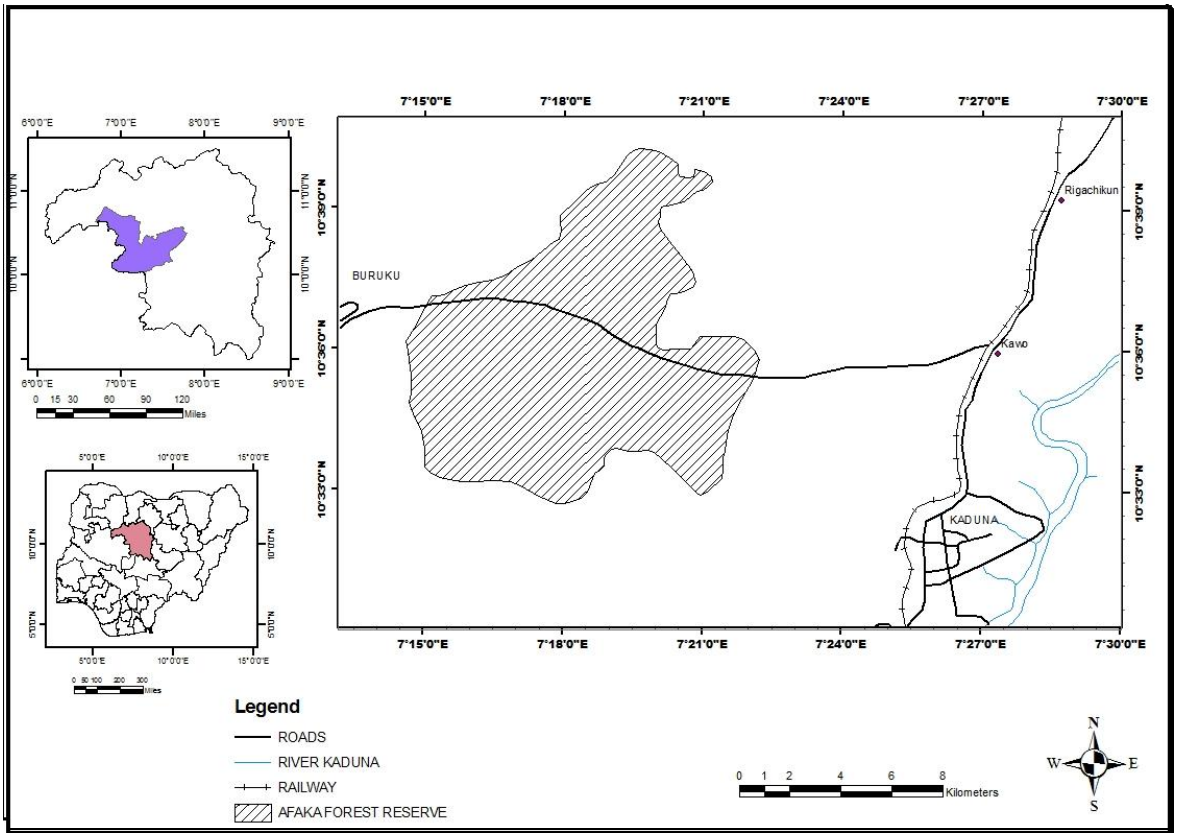


Figure 3.1: Afaka Forest Reserve and Environs

Source: Adapted and modified from Afaka Forest Map (2013)

3.2.2 Geology

The soils and weathered rock mantle of Afaka Forest Reserve; considerable part of the Nigerian savannah are underlain by Pre-Cambrian Basement Complex; the oldest rock in Nigeria. Principal rocks of the complex are gneisses, migmatites and granites. Schist, phylites, quarzites, and pegmatites are also common and in limited areas, amphibolites, diorites and gabbros occur. The older granites are frequently exposed on land surface either in the form of domed hills (inselbergs) or as low outcrops. There is great variation in thickness of soil and weathered rock over the Basement Complex. Younger rocks (laterites

and ironstones) of Tertiary Period, alluvial and colluvial deposits of Quaternary Period also occur at Afaka (Barrera & Amujo, 1971).

Lateritic material known as plinthite (Gk. Plinthite-brick) characteristically occurs as the C horizon or part of it. It is normally a sesquioxide rich, humus poor, highly weathered mixture of clay, quartz and other diluents; soft when wet, but may become hard (rock like) when dry. Its appearance depends upon its content of iron and aluminium; it may be a continuous mass if this content is high vascular or with coarse tubular pores if intermediate in iron pebbles in a matrix of softer materials (Barrera & Amujo, 1971). .

3.2.3 Relief

The relief of Afaka Reserve is part of the large area of peneplain characteristic of much of northern Nigeria, which forms the so-called "African erosion surface". The highest elevation along the main Kaduna- Lagos road is 2,108 ft, and the lowest elevation along the Resa stream to the west is about 1,950 ft. Erosion along streams has resulted in a gentle convex relief. Numerous low, flat- topped, ironstone hills and a few low outcrops of granite dot the landscape (Barrera & Amujo, 1971).

3.2.4 Climate

The climate of Afaka, like that of most parts of Africa that share the same latitude, has marked wet and dry seasons caused by movement of Inter Tropical Convergence Zone. Wet season lasts about 6 months or roughly from early April to early October. The rainfall amount and distribution at Afaka forest reserve is similar to that of Kaduna which has a mean annual precipitation of about 1099.3mm. The hottest months are March and April,

and the coolest are December and January. The lowest mean relative humidities occur in months of December through March; which are characterized by the dominance of Tropical Continental air mass and harmattan winds. The highest relative humidity occurs in July and August (Barrera & Amujo, 1971).

3.2.5 Soils and Vegetation

The soils are Ferric Luvisol (FAO, 1974), derived from Precambrian Basement Complex formations. The surface horizons are greyish brown, sandy loam or loamy sandy with a moderate medium sub angular, blocky structure. The underlying horizons are light yellowish-brown or yellowish-white with few faint or distinct mottles, sandy clay loam to clay loam and strong medium sub angular, blocky structure (Jaiyeoba, 1998).

Natural vegetation of the area is Northern Guinea Savannah with *isoberlina doka* as dominant species on deeper soils, changing to almost pure *Montes Kerstingii* on eroded areas bordering gully formations, *Uapaca togoensis* and *Parinari curatellifolia* are locally common (Keay, 1953).

The woodland is open with an average of 172 stems of all species. The herb layer is completely dominated by grasses which grow to a height of 5 to 8 feet by the end of rains. The principal species are *Andropogon pseudapricus*, *Hyparrhenia notolosia* and *Loudetia simplex* (Forestry Research Institute of Nigeria, 1964).

Trees occurring in the forest include: *Antiaris Africana, Khaya Senegalensis, Millettia thonningii, Diospyros mespiliformia, Afzelia Africana, Chlorophora excels, Anthocleista spp., phoenix reclinata, Vitex doniana, V. diversifolia, Lannea spp., Afromosia laxiflora* and *Uapaca togoensis.* Characteristic shrubs are *Terminalia glaucescens, Gardenia spp.,*

and *Philiostigma thonningii;* the grasses are *Hyparrhezia spp.,* and *Andropogon spp* (Barrera & Amujo, 1971).

The most common trees are; *Isoberlina doka, Monotes kerstingii, Uapaca togoensis* and *Parinari curatellifolia;* others include *Afrormosia laxiflora, Lanea kerstingii, Swartzia madagascariensis, Cussonia barteri* and *Daniellia oliveri.* Shrubs include *Gardenia spp.,nTerminalia avicennioides, Philostigma thonningii* and *Annona senegalensis.* Common grasses are: *Andropogon schirensis, Loudetia Simplax, Trachypogon spicatus, Schizachyrium sanguineum, Monocymbium cerasiiforme, Andropogen ascinodis, Backeropsis uniseta and Andropogen gayanus* (Barrera & Amujo, 1971).

The vegetative cover has relatively more grass and fewer trees than savanna Woodland. The principal trees are: *Terminalia glaucescens, Annona senegalensis, Afrormosia laxiflora, Detarium microcarpum, Gardenia spp., Combretum spp., Parkia clappertoniana, Ficus spp., Vitex doniana, Sysygium guineansc* and *Anogeissus leiocarpus.* The associated grasses are: *Ctenium newtonii, Hyparrhenia cyaneseens, H.rufa, Beckeropsis uniseta, Monocymbium cerasiiforme, Andropogon pseudaprius, A. scirensis* and *Trachypogon Plumosus* (Barrera & Amujo, 1971).

The grass savanna is dominated by several species of Graminea with a scattering of low trees. It covers valley bottoms, and some uplands in the Northern part of the Reserve. Grasses in the fadamas include thick and tall growth of Hyparrhenia and Andropogen. In the upland areas are species of *Ctenium newtonni, Laudetia simplex* and *Trachypogon plumosus.* Palms *(Raphia sudanica* and some *Elaeis guineensis*) are also common along

stream and water sheds. In some of the better drained parts along the water sheds there are numerous bamboos (*oxytenarth abyssinica*).

3.2.6 Hydrology

The Afaka Reserves contains headwaters of a number of small intermittent streams which radiates from all directions. Chidawaki in the northern part of the reserve is bordered by fadamas and the channel is not deeply incised. The Resa (largest stream of the Reserve), is located in the south and is bordered by steeper slopes and strips of fadamas. A two-year record from stream gauging station established on the 8,300 acre. Resa watershed shows that the streams' discharge starts after the first heavy rains and continues after the last rain to late November or early December due to ground water sustained flow. Most of the Reserve has good surface drainage, but there are some narrow bottomlands (fadama) where it is impeded. Internal soil drainage varies with location (Barrera & Amujo, 1971).

Little is known of ground water resources at Afaka. The Basement Complex is generally considered to be poor source of ground water because of the shallowness of weathered aquifers above the igneous rocks and the lack of deep, substantial cracks and fissures. This water source however, appears to be sufficient for local civic uses under present conditions. Along the fadamas, subsurface water is more abundant and there is probably a limited underground flow along the Chidawaki, and perhaps Resa, throughout dry season (Barrera & Amujo, 1971).

Water-table levels fluctuate widely depending on the amount of rain fall, the length of dry season, and position with reference to streams. In parts of the upland areas water-table may

rise to within 6 ft of the surface during an especially wet year and only to about 24ft in a drier year (Barrera & Amujo, 1971).

3.3 METHODOLOGY

This section mainly concerns the method used in this research work for attainment of the set objectives. A reconnaissance survey of the study area was carried out to acquaint the researcher with information about the present state of Afaka forest reserve.

3.3.1 Types and Sources of Data

The types of data used for this research were satellite imageries of 1973, 1990 and 2009. The imageries were obtained from the National Centre for Remote Sensing, Jos and via satellite protocol and downloading links of earth explorer, since Afaka forest reserve lies on Row 189 Path 53 on World Referencing System. The Primary data include:

I. Landsat (MSS) of 27th November, 1973 with spatial resolution of 79m and Land Sat (TM) of 29th September 1990 with a spatial resolution of 30m were used to forecast forest depletion for 2007.

II. Nigeriasat – 1 of 26th December, 2009 with spatial resolution of 32m was used to forecast forest depletion in 2028.

III. Ground Control Points (GCPs) were obtained using Global Positioning System (GPS) to validate coordinates of the classified imageries. While

existing literature from journals, textbooks, conference proceedings, seminar papers, theses and reports and web references form the Secondary data.

3.3.2 Image Processing

Satellite imageries for the study area were imported into Erdas imagine 9.2 environments. A subset covering Afaka forest reserve was extracted from the full scene of Land sat (MSS) of 1973, Land sat Thematic mapper (1990) and Nigeriasat -1 of 2009. The image bands were layer stacked to produce a colour composite.

Geometric correction was carried out to correct distortions in the imageries which may be as a result of the satellite platform for acquisition, angle of acquisition, earth rotation *etc*. Land Sat MSS with spatial resolution of 79m and Nigeria Sat- 1 with spatial resolution 32m were resampled to 30m. This was done to bring all the satellite imageries to a common spatial resolution of 30m. The satellite imageries were projected to Universal Transverse Mercator (UTM) zone 32. Georeferencing was done to bring all the satellite images to the same coordinate referencing system to allow overlay analysis to be carried out.

Image enhancement was carried out to improve visual interpretation of imageries by increasing the apparent distinctions between false colour composites of the sub scene images. Supervised classification of images into land use/land cover classes was done, using Idrisi selva. Supervised classification is much more accurate for mapping of classes; however, it depends heavily on the cognition and skills of the image specialist (Short, 2013).

3.3.3 Classification

Image classification is a procedure to automatically categorize all pixels in an image of a terrain into land cover classes (Reddy, 2008). Image classification was carried out using

the supervised image classification. Training samples were identified and delineated on the digital image of 1973, 1990, and 2009. The objective was to identify the set of pixels that accurately represents spectral variation present within each information region. The data sets were classified into the following classes: Grassland, Farmland, Natural forest/Plantation, Water body and Bare surfaces (See Table 1). Ground truthing was used to verify accuracy of the image classification.

Table 3.1: Land use land cover classification scheme

CODE	**LAND USE/LAND COVER CATEGORIES**	**DESCRIPTION**
1	Grassland	Lands on which grasses or low green plants are the main vegetation
2	Farmland	Cultivated lands
3	Natural forest/Plantation	Any species of plants (flora)
4	Water body	Rivers, lakes and reservoirs
5	Bare surfaces	Exposed Soils

Source; Modified from Jensen, (2005)

The classifier employed was the maximum likelihood method. The kappa coefficient expresses proportionate reduction in error generated by a classification process compared with the error of a completely random classification (Congalton, 1991). The kappa coefficient value represents how well remotely sensed classification agrees or is accurate to the referenced data (Jensen, 2005).

3.3.4 Data Analysis

Image bands 4, 3, 2 were selected from each of the layer stacked satellite imageries of 1973, 1990 and 2009. It was used to create a false colour composite. Training data sets were selected based on the land cover classes under investigation using the Editor tool in Erdas Imagine 9.2. These data were collected from relatively homogeneous areas consisting of land use/ land cover classes. Signature file was supplied to the Erdas 9.2 software to perform a supervised classification. The ground control points acquired during ground truthing was used to carry out accuracy assessment for the classified imageries. According to Jensen (1986) the ideal number of check points required to be tested in the land use classification map is determined from the binomial probability given by:

$$N = 4 (p) (q\sim) / e^2 \quad \text{……..1.1}$$

Where N= number of points required

P=expected percent accuracy

q~=difference between 100 and p

e= maximum allowable error

Classified satellite imageries of 1973, 1990 and 2009 were imported from Erdas 9.2 into Idrisi selva environment. The classified satellite imageries of 1990 and 2009 were the input for forecasting using Cellular_Automata Markov model, while the output was classified image of 2028. Also Markov chain model used the same input and the output were transition matrix, transition area matrix and a set of conditional probability images of 2028.

The overall accuracy and kappa co-efficient of agreement were used as basis. Results obtained from the two models were compared. Student T-test was used to test for significant difference between the two models.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter focused on results and discussion. Discussion of results obtained from the extent of forest cover in 1973, 1990 and 2009. Forest projection for 2028 was done, using markov chain model and Cellular Automata_ markov model. Results of Markov chain model and Cellular Automata_ Markov model were compared. These are represented using tables, maps and charts.

TABLE 4.1: Land use/land cover Distribution of Afaka Forest Reserve

LAND USE/LAND COVER	**1973**		**1990**		**2009**	
	AREA (Ha)	**%**	**AREA (Ha)**	**%**	**AREA (Ha)**	**%**
Bare Surface	874.23	8.2	982.14	9.2	1154.60	10.8
Forest	3724.25	34.9	2858.95	26.8	2488.02	23.3
Water body	851.24	8.0	844.92	7.9	822.88	7.7
Farmland	5093.86	47.8	5583.03	52.4	5757.19	54.0
Grassland	119.32	1.1	393.86	3.7	440.21	4.1
TOTAL	**10662.90**	**100**	**10662.90**	**100**	**10662.90**	**100**

Source: Author's Analysis, 2015

4.2 Extent of forest cover in 1973, 1990 and 2009

The analysis shows that farmland had the largest area coverage of 5093.86 ha (47.8%) in 1973. This may not be unconnected with encroachment into the forest reserve by the neighbouring communities whose major occupation was farming. However forest has the second highest area coverage of 3724.25ha (34.9%) while the least coverage was grassland with coverage of 119.32 ha (1.1%).

In 1990, farmland had the highest areal extent of 5583.03 ha (52.4%). Forest decreased from 3724.25 ha to 2858.95 ha, losing 865.3 ha in seventeen (17) years. This equally led to increase in the bare surfaces and grassland (see figure 4.1), indicating the influence of population pressure on the forest reserve.

In 2009; in response to population growth around the forest and the need to earn a living, there was more encroachment through farming from 5583.03 ha in 1990 to 5757.19 ha gaining 174.16 ha. Bare surface increased from 982.14 ha in 1990 to 1154.60 ha in 2009. This is most likely as a result of urbanisation around the forest reserve. However, forest cover dropped from 2858.95ha in 1990 to 2488.02 ha in 2009. This resulted from human influence on the forest reserve. This corroborates the work of Ndabula (2006) which noted that urbanization in Kaduna metropolis led to encroachment of settlements into areas of forest reserve. This was supported by the study of Adelusi, Agboola and Oni (2002) that urban forest reserves and enclaves have suffered more and undue depletion and degradation as a result of urbanisation and encroachment on areas originally perceived as forest reserves and estates.

Fig 4.1 indicates that the dominant land use class in 1973 was farmland (agriculture). This was concentrated in the south western part of the study area. This confirms Salami and Balogun (2004) study that the major source of intrusion into forest land is through agroforestry.

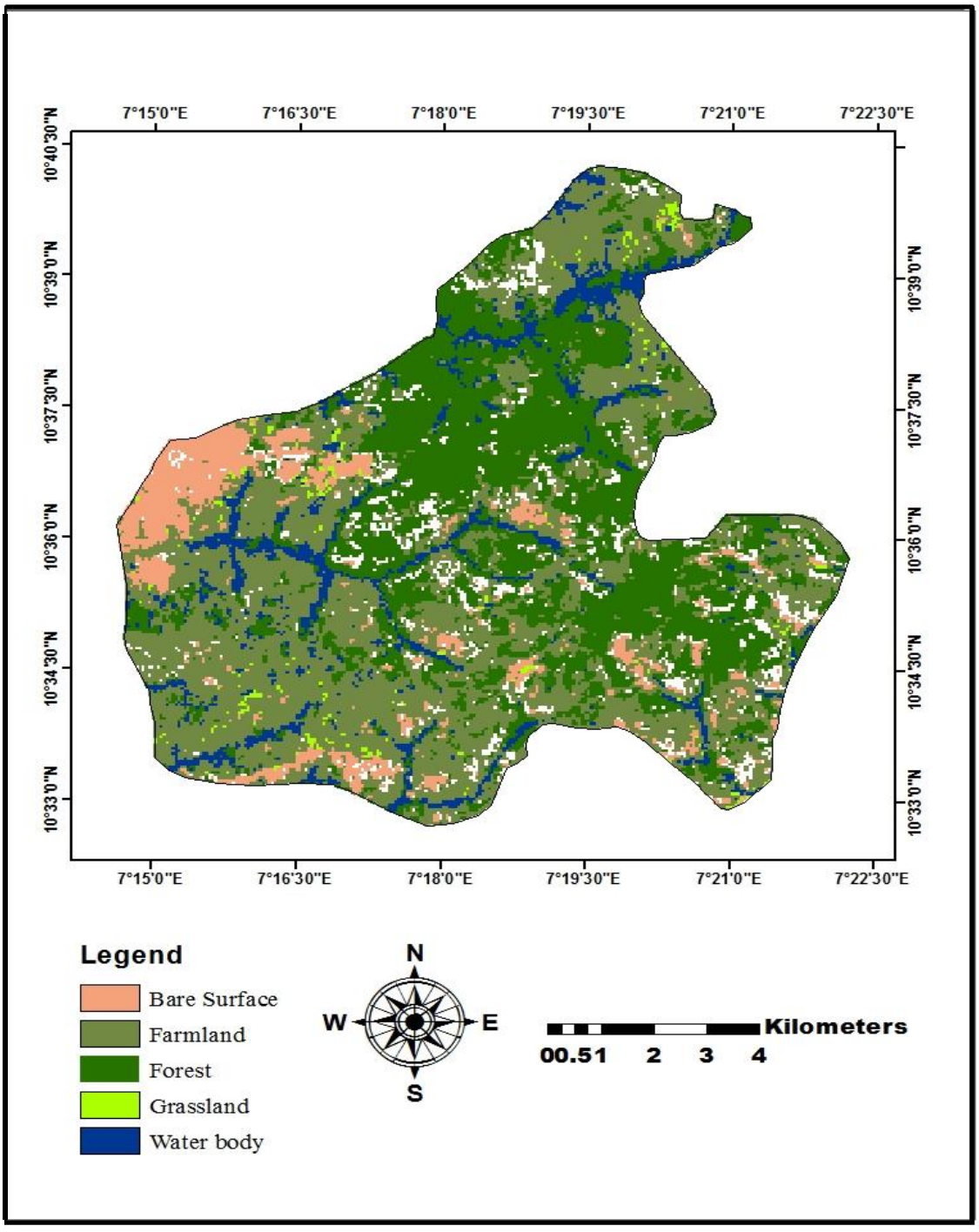


Figure 4.1: Land cover of Afaka forest reserve in 1973

Source: Author's Analysis, 2015

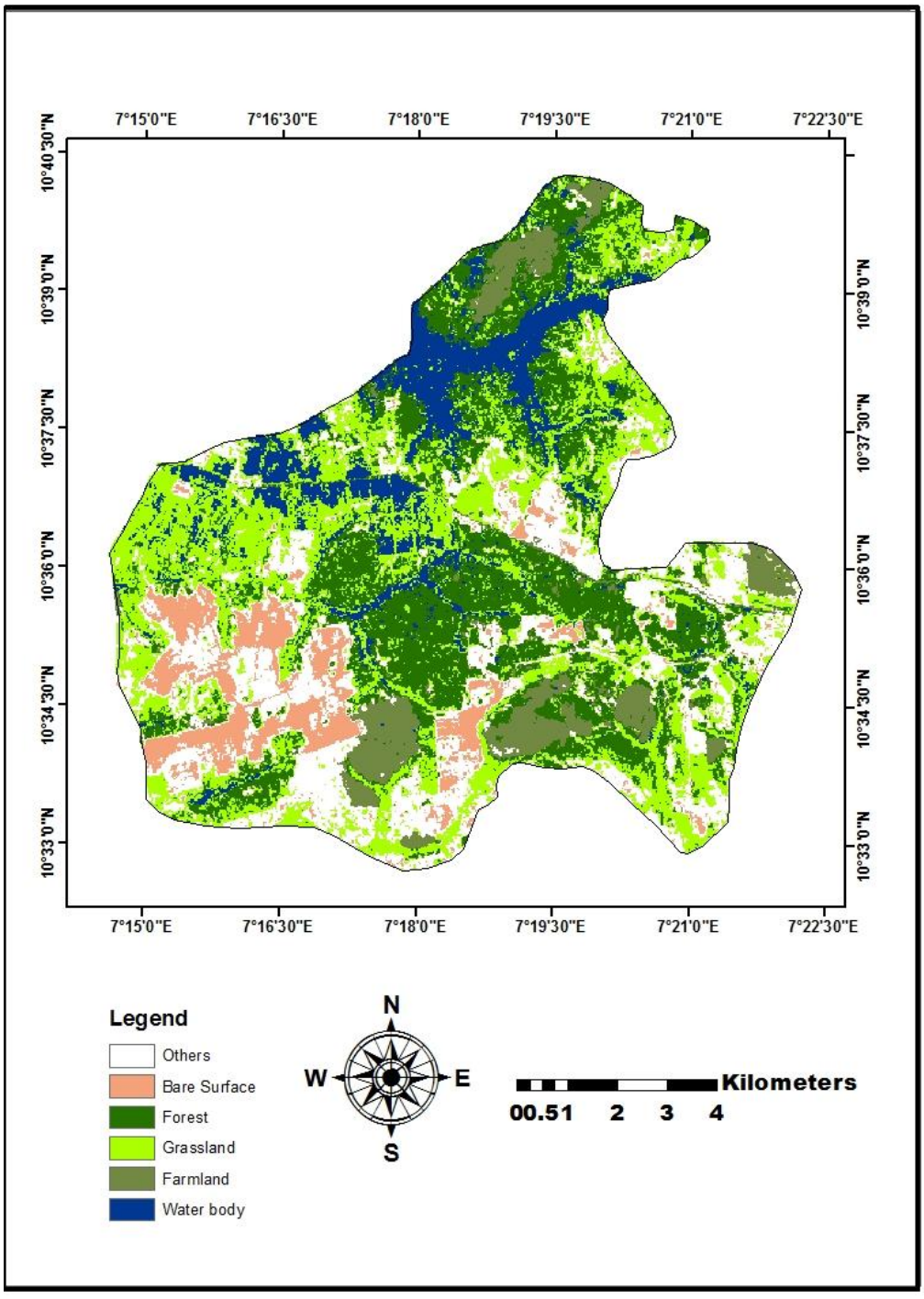


Figure 4.2: Land use/ cover of Afaka forest reserve in 1990

Source: Author's Analysis, 2015

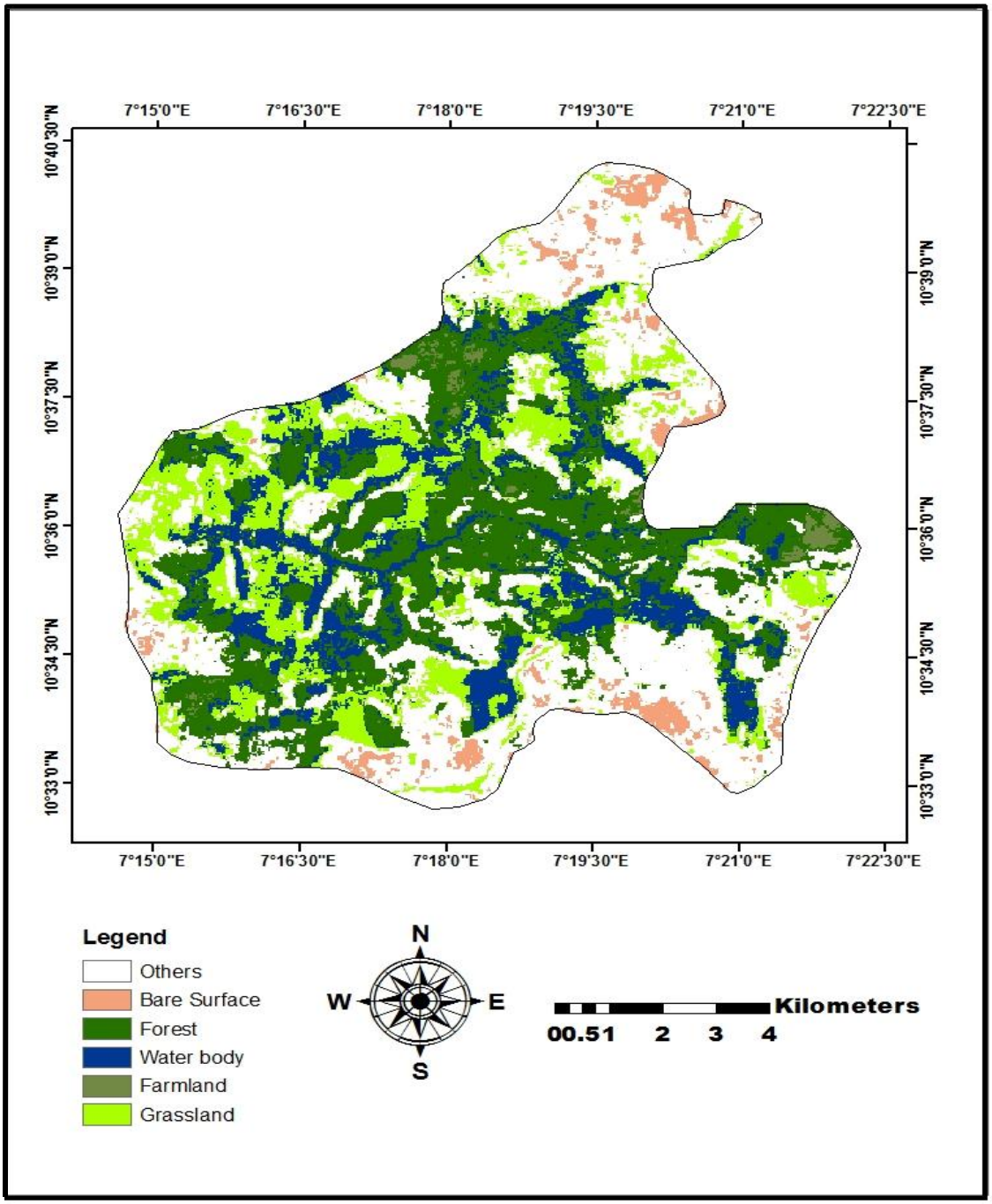


Figure 4.3: Land use/ cover of Afaka forest reserve in 2009

Source: Author's Analysis, 2015

4.3 Land use/cover changes in Afaka Forest Reserve

Table 4.2: Land use/cover change

Landuse/cover Category	1973- 1990		1990- 2009		1973- 2009	
	Area (Ha)	Percentage Change (%)	Area (Ha)	Percentage Change (%)	Area (Ha)	Percentage Change (%)
Bare Surface	107.91	0.12	172.46	17.56	280.37	32.07
Forest	-865.30	-23.23	-370.93	-12.97	-1236.23	-33.19
Water body	-6.32	-0.74	-22.04	-2.61	-28.36	-3.33
Farmland	489.17	9.60	174.16	3.12	174.16	3.42
Grassland	274.54	230.09	46.35	11.77	320.89	268.93

Source: Author's Analysis, 2015

Table 4.2 shows the extent of change in land use/land cover of the area. Bare surface, farm land and grassland increased by 0.12%, 9.60% and 230.09% respectively. Grassland has the highest percentage increase. Indiscriminate felling of trees could be responsible for high conversion of forest into grassland between 1973 and1990. This explains the decrease in forest land by 23.23% under the same period.

Between 1990 and 2009, bare surface, farmland and grassland increased by 17.56%, 3.12% and 11.77% respectively. There was a reduction in the rate at which forest was being converted into grassland when compared with the years between 1973 and 1990. This may not be unconnected with legislation against indiscriminate felling of trees and natural regrowth, while forest and water body decreased by 12.97% and 2.61% respectively.

The results show an increase in bare surface, farmland and grassland by 32.07%, 3.42% and 268.93% respectively between 1973 and 2009. This reveals human interference either through deforestation, thereby exposing the soil to erosion or/both clearing of land for development. On the other hand, there was a decrease in forest and farmland by 33.19%.

4.3.1 Rate of change

Table 4.3: Rate of Change

Landuse/ land cover classes	**1973-1990 Rate(Ha)**	**%**	**1990-2009 Rate (Ha)**	**%**	**1973-2009** Rate (Ha)	%
Bare Surface	6.00	0.01	8.62	0.88	7.58	0.87
Forest	-48.07	-1.29	-18.55	-0.65	-33.41	-0.90
Water body	-0.35	-0.04	-1.10	-0.13	-0.77	-0.09
Farmland	27.18	0.53	8.71	0.16	4.71	0.09
Grassland	15.25	12.78	2.32	0.59	8.67	7.27

Source: Authors Analysis, 2015

Between 1973 and 1990, bare surface, farmland and grassland increased by 0.1%, 0.53% and 12.78% respectively while forest and water body decreased by 1.29% and 0.04% respectively. Grassland gained more than any other land use/ land cover. However, between 1990 and 2009, bare surface had the highest increase of 0.88% per annum while forest remained the worst hit, losing 0.65% per annum.

In general, between 1973 and 2009 grassland increased by 7.27% annually, while forest reserve decreased by 0.90% per annum. Therefore, more of the forest reserve was fast becoming grasslands. Urgent steps are needed to arrest the situation.

This negates the study of Akpu, Tanko and Yahaya (2012) on the assessment of implication of urban growth on vegetation cover in Afaka forest reserve. They observed that natural forest between 1990 and 2009 was declining at the rate of 2.23%, while this

study revealed that the forest was declining by 0.65 per annum under the same period. This was because the study covered Afaka forest reserve and its environs.

4.4 FORECAST OF FOREST LOSS USING MARKOV CHAIN MODEL

TABLE 4.4: Transition Probability derived from Land use/Land cover map of 2028

LAND USE/LAND COVER 2009	**Bare Surface**	**Forest**	**Water Body**	**Farm land**	**Grassland**
Bare Surface	**0.0286**	0.4589	0.2398	0.0041	0.2686
Forest	0.0521	**0.5073**	0.1645	0.0141	0.2621
Water body	0.0451	0.3679	**0.2335**	0.0088	0.3446
Farmland	0.1355	0.5033	0.0531	**0.0946**	0.2135
Grassland	0.0035	0.3893	0.3023	0.0387	**0.2661**

Source: Author's Analysis, 2015

The row categories represent land use/ land cover classes in 2009 whilst column categories represents 2028 classes. From Table 4.4, bare surface has a 0.0286 probability of remaining bare surface in 2028, meaning that bare surface has a high tendency of changing to another land use/land cover classes and probability of changing to forest given to be 0.4589. This was a desirable change because there was high tendency for bare surface to be transformed into forest which may be through afforestation.

Forest has a probability of 0.5073 of remaining forest and a probability of changing to grassland 0.2621. This result contradicts Zubair (2006)'s which shows that forest land has 0.3203 probability of remaining forest in 2015 and the probability of changing to

wasteland was 0.4050. Though markov chain model was used, he was considering Ilorin and its environs not a forest reserve. This, again, runs contrary to the work of Wieske (1998) which showed that trees were obstacle to progress and their removal as the first stage of development.

The probability of farmland remaining farmland is 0.0946 and 0.5033 probability of being changed to a forest. This is a positive development because there will be more conversion from farmland to forest land cover.

Probability of grassland surviving is 0.2661 and probability of being converted to forest is 0.3893, provided every other factor is held constant in 2028. Based on the transition probability table, forest will be the most stable land cover category and bare surface least stable.

4.4.2 Projected land use/land cover

Table 4.5: Projected land use/Land cover for 2028, Using Markov Model

Land use/land cover Classes	2028	
	Areas in hectares (ha)	Areas in Percentage (%)
Bare surface	12558.85	64.4
Forest	3168.75	16.2
Water body	1618.98	8.3
Farmland	139.14	0.7
Grassland	2016.33	10.3

Source: Author's Analysis, 2015

Table 4.5 shows land use/land cover projection for 2028, using markov chain model. It raises an alarm that 12558.85ha of the forest may be converted to bare surface, if nothing is done to salvage the forest reserve, however this large area coverage by bare surface is because new land use/cover were included. It suggests that tree felling will have a great impact on the future of the forest. The area covered by forest is 3168.75ha as against 3724.25ha in 1973. By implication 555.5ha; representing 17.5% of the forest will be lost to other land use/land cover in 2028. Apart from the other land use/land cover that were initially forest reserve. This confirms the results of Akingbogun *et al.,* (2012), which reveal that forest plantation in Eleyele forest Reserve will decrease greatly from 12.5% in 1984 to 0.13% in 2000.

This was in conformity with Rimal (2011) that a growth in urban land use might threaten the areas that are currently reserved for forest reserve and agricultural purposes in 1976.

The distribution of land use/cover change for 2028 revealed that bare surfaces were more at the boundaries of the study area, with major concentration at the northern and south-western part of the study area.

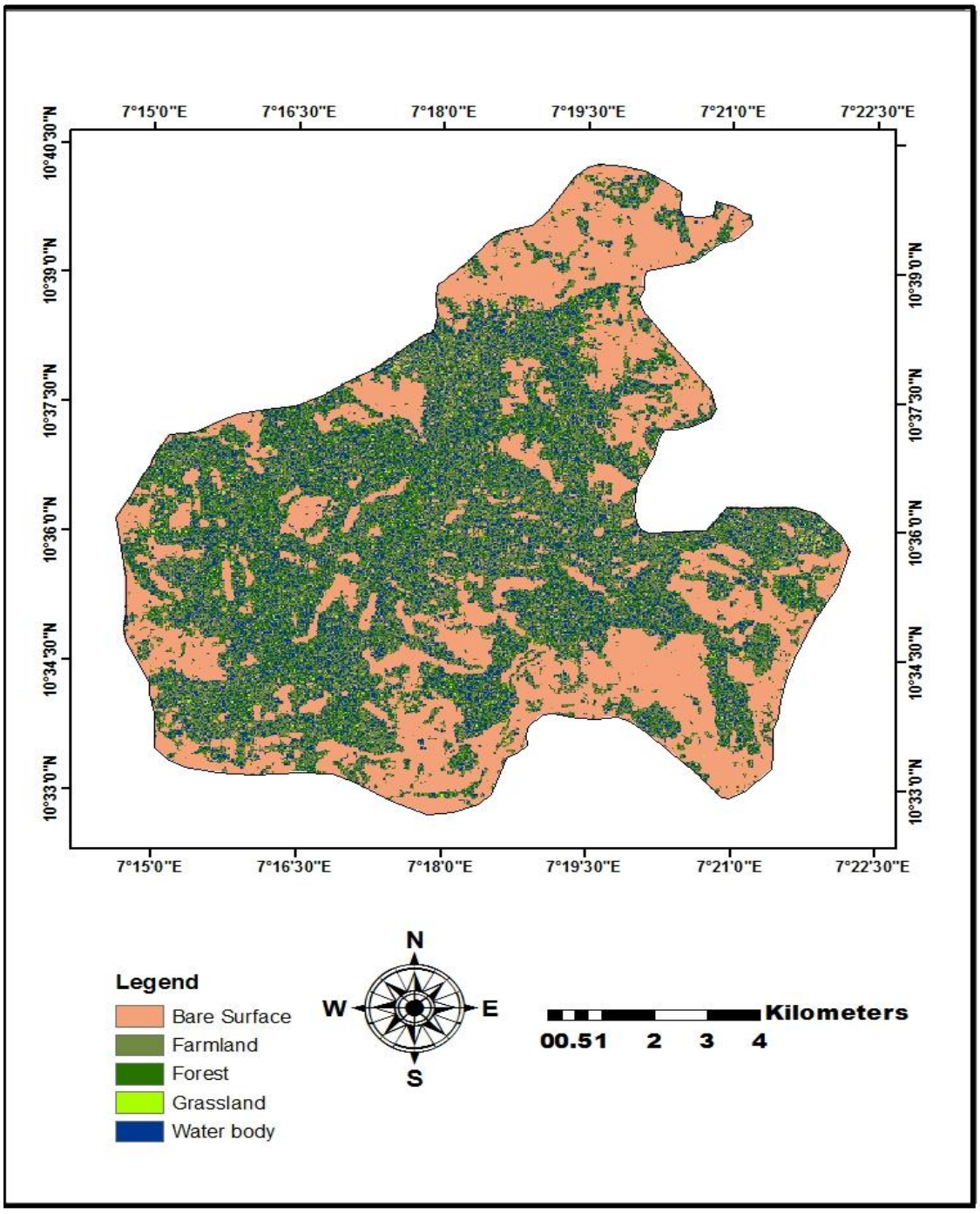


Figure 4.4: Forecast of Afaka for 2028, using Markov Chain

Source: Author's Analysis, 2015

4.5 FORECAST OF FOREST LOSS USING CA- MARKOV MODEL

In Table 4.6 it can be observed that forest could decrease from 3724.25ha in 1973 to 3019.54ha in 2028. This signifies that 18.9% of the forest area would be lost to other land use/land cover in 2028, while grassland will increase from119.32ha in 1973 to 2041.18ha in 2028, gaining 1894.86ha, when forest forecast is done using Cellular Automated-Markov model. This was attributed to indiscriminate felling of trees and conforms with the forest loss predicted by Kushwaha, *et al.*, (undated) when they assessed forest ecosystem dynamics in part of north- east India, by 2028 forest area of 4,563.34km^2 will be lost.

TABLE 4.6: Land use/land cover Projection 2028, using CA_Markov

Land use/land cover Classes	1973		2028	
	Areas in hectares (ha)	Areas in Percentage (%)	Areas in hectares (ha)	Areas in Percentage (%)
Bare surface	874.23	8.2	442.82	6.1
Forest	3724.25	34.9	3019.54	41.6
Water body	851.24	8.0	1647.32	22.6
Farmland	5093.86	47.8	116.07	1.6
Grassland	119.32	1.1	2041.18	28.1

Source: Author's Analysis, 2015

The projected map indicates that grassland is more prominent in the western part of Afaka. This may be as a result of intrusion from neighbouring communities. More bare surfaces tend to be in the northern part of the study area. It was also observed that other land use/land cover classes, other than the ones mentioned, are likely to emerge. These new classes are represented by others in figure 4.5

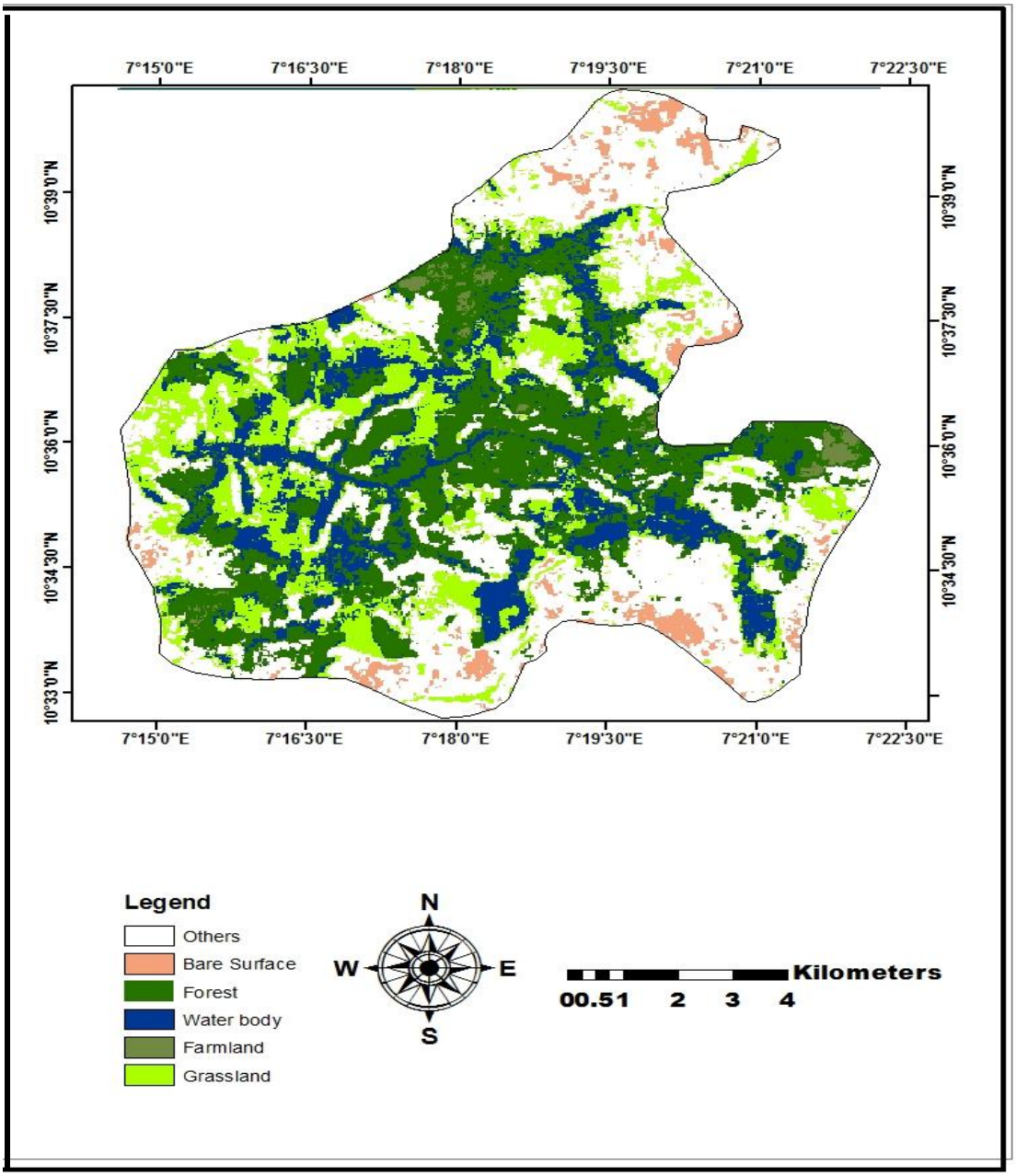


Figure 4.5: Forecast using CA_Markov model

Source: Author's Analysis, 2015

4.6 Differences between Markov chain and Cellular Automata markov chain model

From figure 4.6, the total area that will be covered by bare surface using markov model is 12558.35ha. There was a sharp contrast when compared with that of CA_ Markov that has 442.82 ha. This was because in markov chain model new land use/ land cover classes that emerged were grouped under bare surface. The area covered by forest using Markov was 3168.75 ha while that of CA_ Markov was 3019.54 ha. There exists a difference of 149.21 ha. Water body also has a difference of 28.34 ha. Farmland results revealed a difference of 23.07 ha. Grassland results differ by 24.85 ha.

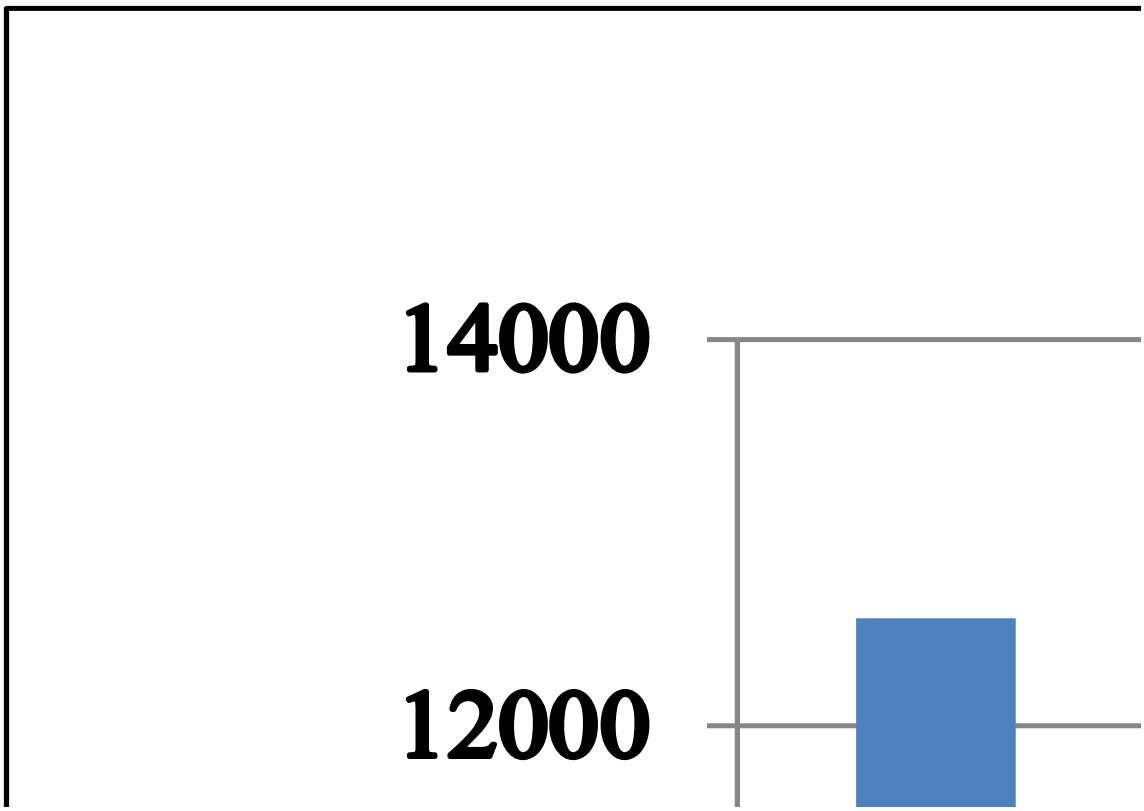


FIGURE 4.6: Land use/Land cover Forecast, 2028

SOURCE: Author's Analysis, 2015

The rates of change from 1973- 2009 was observed to be -45.77 ha per annum (-1.28%). By implication 45.77 ha of the forest cover was lost annually. There was a sharp contrast in the results of the two models under consideration. The Markov model revealed Bare Surface in 2028 to be 12568.85 ha while CA_Markov gave a result of 44.2 ha. This was because Markov did not separate new land use/land cover that will emerge from that of bare surfaces.

Based on land use/cover map for 2028 produced by both models, it is observed that CA-markov indicate new land use/cover classes that are likely to emerge apart from the classified classes indicated as 'others' while these new classes were grouped under bare surface in markov chain which was responsible for the wide gap between the results under bare surfaces.

4.6.1 Hypothesis Testing

H_o : There was no significant difference between the results of markov model and CA_Markov

Table 4.7: Test Statistics

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	Markov Chain Model - CA_Markov Model	2452.42400	5402.54267	2416.09053	-4255.71873	9160.56673	1.015	4	.367

Source: Author's Analysis (2015

Sig (2-Tailed) value is 0.367 which is greater than 0.05. We do not reject the null hypothesis. There is no statistically significant difference between the results of Markov chain model and Cellular Automata Markov model. The differences between condition means are likely due to chance. Lopeza *et al*. (2001) used goodness of fit test to quantitatively assess capabilities of Markov models in predicting different land use classes, and reported a value of 6677 for χ 2. They showed that land use areas predicted by Markov models have a statistically significant difference at α=0.05, when compared with land use areas of maps from aerial photo interpretation. Therefore CA-markov model is a better model because it shows the spatial distribution of land use/ cover and new land use/cover that are likely to emerge in 2028.

Table 4.8 Shows that the kappa co-efficient is 0.0728 and indicates that the level of agreement between the variables is due to chance.

Table 4.8 Proportional Cross tabulation

	0	1	2	3	4	5	Total
1	0.6274	0.0006	0.0095	0.0051	0.0009	0.0004	0.6440
2	0.0000	0.0106	0.0774	0.0304	0.0028	0.0413	0.1625
3	0.0000	0.0055	0.0255	0.0201	0.0003	0.0316	0.0830
4	0.0000	0.0001	0.0020	0.0006	0.0005	0.0038	0.0071
5	0.0000	0.0059	0.0404	0.0283	0.0014	0.0275	0.1034
Total	0.6274	0.0227	0.1548	0.0845	0.0060	0.1047	1.0000

Overall Kappa 0.0728

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 INTRODUCTION

At the beginning of this research, the aim was a comparative analysis of two predictive models in forecasting forest depletion of Afaka forest reserve and objectives were outlined which centred on comparative analysis of two predictive models in forecasting forest depletion of Afaka forest reserve. The forest was said to be depleting according to Nwadialor (2001) and Tanko (2011). This raises the question of what will be the state of this forest in the nearest future and which predictive model best predicts forest depletion, hence the relevance of this study. This chapter presents the concluding part of the study with summary of findings, conclusion and recommendations.

5.2 SUMMARY OF FINDINGS

This research made use of satellite images of 1973, 1990 and 2009 which were processed using Erdas Imagine 9.3 and Idrisi Selva. Most widely used models for forecasting forest depletion, Markov Model and CA_Markov were used to forecast forest depletion. The results were subsequently compared. The results reveal that there occurred a steady increase in the area occupied by grassland over time as a result of anthropogenic factors.

As at the first available Landsat image of the study area in 1973, farmland was a dominant land use class and was concentrated on the south-western part. The areal extent of forest cover in 1973, 1990 and 2009, were 3724.25 ha (34.9%), 2858.95 ha (26.8%) and 2488.02 ha (23.3%) respectively.

Projecting forest depletion for 2028 using Markov chain model, the results revealed that, forest cover will decrease from 3724.25 ha in 1973 to 3168.75% (16.2%). CA_Markov was also used to forecast forest loss for 2028. The result revealed that forest land cover would decrease from 3724.25 ha in 1973 to 3019.54 ha in 2028.

Comparing results of the two predictive models using student T- test statistical analytical technique, it would be inferred that there is no statistically significant difference between results of the two predictive models. However, CA-Markov model performs better than markov chain model because it indicated spatial distribution of the change.

5.3 CONCLUSION

Spatial distributions of these changes were not considered in markov model; the locations of these changes were not indicated. For instance, areas of dense forest cover cannot easily be identified, while this was considered in CA_Markov model. The differences between the two models in forecasting forest depletion is not quite significant, the differences between condition means are likely due to chance with an indication that other Land use/land cover classes are likely to emerge in future in the case of CA- Markov model.

Using either of the predictive models in forecasting future state of Afaka forest reserve, the study revealed a decrease in forest land cover. This is majorly due to anthropogenic factors. Based on the results obtained, CA_Markov gives a better result in forecasting because it gives the spatial distribution of these changes; where it is more concentrated and where the changes are sparse, which is lacking in markov chain model. Also, new classes apart from the ones mentioned are grouped into a new class and it is labelled ‘no class’ for easy identification while Markov grouped these new classes under bare surface make it

difficult for users to identify new classes that are likely to emerge. Therefore, CA- Markov is the better model for forecasting forest depletion.

5.4 RECOMMENDATIONS

Afaka forest reserve was established to arrest deterioration and desertification in the semi-arid zone of the Northern Guinea Savannah. This study looked at models for forecasting future state of the reserve. Based on results obtained, the following recommendations were put forward to preserve the forest reserve:

- ✓ Geospatial techniques should be employed in monitoring forest resources because they give timely and more accurate results.
- ✓ CA_Markov models should be used to forecast forest depletion because it adds to the spatial distribution of the forest change.
- ✓ Farming activities in the forest reserve should be controlled for natural regrowth because the years under review revealed that farmland increased more than any other land use/ cover.
- ✓ Enforcement of legislation concerning indiscriminate felling of trees, since the major source of intrusion into the forest is through the neighbouring communities.

REFERENCES

Abubakar, U. Y., Lawal, A., & Mohammed, A. (2014). Markov Chain Model and Its Implication to Annual Rainfall Distribution for Crop Production. *American Journal of Theoretical and Applied Statistics.*Volume 3. No 2 pp 39-43

Adelusi, H. M., Agboola, O.D., & Oni, P. I. (2002). Urbanization: Implication Forest Resources Depletion and Environmental Management in Nigeria. In: Abu, J. E., Oni, P. L and Popoola, L (eds). Proceedings of FAN held in Akure, Ondo State, Nigeria between 4th and 8th November, pp 69-79

Adeyemo, A. I., & Jegede, G. (2002). Effects of Anthropogenic Activities on Nigerian Environment. In Abu, J. E, Oni, P. L and Popoola, L (eds). Proceedings of FAN held in Akure, Ondo State, Nigeria between 4th and 8th November. pp 89-93

Adeyemo, A. I., & Okosodo, F. (2005). Ecotourism for Economic Empowerment in Nigeria.Proceedings of the 31st Annual Conference of the Forestry Association of Nigeria held at University of Agriculture Makurdi. November 20-25, 228-239

Agarwal, C., Green, G. M., Grove, J. M., Evans, T. P., & Schweik, C. M. (2002). *A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice.* GTR NE-297. Newton Square, PA: U.S.D.A. Forest Service, North-eastern Research Station. Pp 61.

Agbogidi, O. M., & Ofuoku, A. U. (2006). Biodiversity Conservation and Poverty Alleviation in the Niger Delta Area of Nigeria. *Agriculturea Conspectus Scientifiucs* 71(3): 103-110

Ahmed, B. (2011). Modelling Spatio-temporal Urban land Cover Pattern Dynamics using Remote sensing and GIS Techniques. A Case Study of Khulna City. *Journal of Bangladesh Institute of Planners.* Vol. 4. Page 15-32

Akachukwu, A. E. (2005). Disappearing Forests, the Consequences and Challenges of Sustainable Development in Nigeria. Proceedings of the 31st Annual Conference of the Forestry Association of Nigeria held at University of Agriculture Makurdi. November 20-25, 49-57.

Akingbogun, A. A., Kosoko, O. S., & Aborisade, D. O. (2012). Remote Sensing and GIS Application for Forest Reserve Degradation, Prediction and Monitoring. In: FIG Young Surveyors Conference, Knowing to Create the Future, Rome, Italy, 4-5 May

Akpu, B., Tanko, A. I., & Yahaya, T. Y (2012). Assessing the Implication of Urban Growth Vegetation Cover in Afaka Forest Reserve Area, Kaduna, Nigeria using Remote Sensing and Geographic Information System. A Paper Presented at International Conference on the Future of Energy Use in Nigeria's Dry lands held at Bayero University Kano, Nigeria. 12th-15th November.

An, L., Linderman, M., Qi, J., Shortridge., A., & Liu, J. (2005). Exploring Complexity in a Human- Environment System: An Agent Based Spatial Model for Multidisciplinary and Multiscale Integration. *Annals of the Association of American Geographers* 95 (1): 54-79.

Araya, Y. H & Cabral, P. (2010). Analysis and Modelling of Urban Land cover Change in Setubal and Sesimbra, Portugal. *Remote Sensing* 2: 1549-1563

Areola, O. (1982). "Forest Resources". *In* Barbour, M. *et al.* (Eds.) *Nigeria in Maps.* Hodder and Stoughton. Hong Kong.

Ati, O. F., Sheyin, T., Abbas, I., & Mohammed, S. O. (2010). Assessing Changes in Kagoro Forest, Kaduna State Nigeria, Using Remote Sensing and GIS. *Research Journal of Applied Sciences, Engineering and Technology* 2 (2): 121-132, 2010

Baker, W. (1989). A Review of Models of Landscape Change. *Landscape Ecology*, 2 (2): 111-133.

Bakker, W. H., Grabmaier, K. A., Huurnemen, G. C., Van der Meer, F. D., Prakesh, A., Tempfli, K., Gieske, A. S. M…, & Woldai, T. (2004). Introduction to Remote Sensing. In Kerle, N., Jensen, L. F & Huurnemen, G. C (eds.). *Principles of Remote Sensing* 3rd edition, ITC, Enschede, The Netherlands

Balmann, A., Happe, K., Kellermann, K., & Kleingarn, A. (2002). Adjustment Costs of Agro-environment Policy Switching: An Agent-based Analysis of the German Region Hohenlohe. In *Complexity and ecosystem management: the theory and practice of multi-agent systems*, M., Janssen, (ed.), pp 127–157, Cheltenham: Edward Elgar.

Barrera, A. V., & Amujo, S .J. (1971). The Soil Survey of Afaka Forest Reserve Station Series, Samaru, Zaria. *FAO/UNDP joint publication.*

Batty, M., Couclelis, H., & Eichen, M. (1997). Urban Systems as Cellular Automata. *Environment and Planning B*, 24 (2): 159-164

Batty, M., & Torrens, P. (2001). Sprawl SIM project pages http://www.geosimulation.org/sprawl/ Last accessed Jan 12, 2014.

Batty, M. & Xie, Y. (1994). From Cells to Cities. *Environment and Planning B*, 21: S31-S38.

Bell, E. J. (1974). Markov Analysis of Land-use Change: Application of Stochastic Processes to Remotely Sensed Data. *Socioeconomic Planning Sciences*, 8 (60), 311-316.

Berger, T. (2002). Agent- Based Spatial Models Applied to Agriculture: A Simulation Tool for Technology Diffusion, Resource Use Changes and Policy Analysis. *Agricultural Economics* 25: 2245- 2260

Bhagawat, R. (2011). Application of Remote Sensing and GIS, Land use/ Land cover Change in Kathmandu Metropolitan City, Nepal. *Journal of Theoretical and Applied Information Technology.* 2005- 2011 JATIT and LLS

Breuer, J. A., Huisman, A., & Frede, H. G. (2006). Monte Carlo Assessment of Uncertainty in the Simulated Hydrological Response to Land Use Change. *Journal of Environmental Model Assessment* 11: 209-218.

Brown, D.G., Goovaerts, P., Burnicki, A., & Li, M.Y. (2002). Stochastic Simulation of Land covers Change using Geostatistics and Generalized Additive Models. *Photogrammetric Engineering and Remote Sensing*, 68 (10):1051-1061.

Brown, D.G., Pijanowski, B.C., & Duh, J. D. (2000). Modeling the Relationships between Land-use and Land-cover on Private Lands in the Upper Midwest, USA. *Journal of Environmental Management*, 59, 247-263.

Buiten, H. J., & Clevers, J. G. P. W. (eds) (1993). Land Observation by Remote Sensing, Gordon & Breach. Campbell, J. B. 2002 *Introduction to Remote Sensing* 3rd edition ISBN: 1572306408;

Burnham, B. O. (1973). Markov Inter temporal Land-use Simulation Model. *Southern Journal of Agricultural Economics*, July, 253-258.

Burrough, P. A., & McDonnell, R. A. (1998). *Principles of Geographical Information Systems.* New York: Oxford University Press. Baker, W. L. 1989. A Review of Models in Landscape Change. *Landscape Ecology* 2 (2):111–133

Callaway, R. M., & Davis, F. W. (1993). Vegetation Dynamics, Fire and Physical Environment in Coastal Central California. *Ecology* 74: 1567 – 1578.

Canada Centre for Remote Sensing Tutorials (2008). *Fundamentals of Remote Sensing Introduction* Date Modified: 2008-01-29. www.ccrs.nrcan.gc.ca/resource/tutor/fundam

Carmel, Y., Kadmon, R., & Nirel, R. (2001). Spatio-Temporal Prediction Models of Mediterranean Vegetation Dynamics. In *Ecology Applications* 11 (1), pp. 268 – 280

Caruso, G., Peters, D., Cavailhes, J., & Rounsevell, M. (2007). Spatial Configurations in a Periurban City. A Cellular Automata-based Microeconomic Model. *Regional Science and Urban Economics*, 37 (5): 542-567.

Chen, J. Y., & Tian, Q. J. (2007). Vegetation Classification Based on High Resolution Satellite Image. *Journal of Remote Sensing*, 2: 221- 227

Cho, S. H. (2000). Digital Change Detection by Post-classification Comparison of Multitemporal Remotely-Sensed Data. *Journal of the Korean Society of Remote Sensing*, vol. 16, No. 4, 2000, pp.367-373.

Chomitz, K. M., & Gray, D. A. (1996). Roads, Land-use and Deforestation: A Spatial Model Applied to Belize. *The World Bank Economic Review* 10 (3): 487-512.

Cihlar, J., & Jansen, L. J. M. (2001). From Land Cover to Land-use: A Methodology for Efficient Land-use Mapping over Large Areas. *Professional Geographer*, 53 (2), 275-289.

Clarke, K. C., & Gaydos, L. J. (1998). Loose-coupling a Cellular Automation Model and GIS: Long-term Urban Growth Prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*. 12 (7), 699-714.

Congalton, R. (1991). "A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data." *Remote Sensing of Environment*, Vol. 37: 35-46.

Copping P., Jonckheere I., Nackaerts K., & Muys, B. (2004). Digital Change Detection Methods in Ecosystem Monitoring: A Review, *International Journal Remote Sensing*, 25, pp 1565-1596

Dantong, G. M. (2011). A Markov Chain Model Analysis of GSM Network Service Providers Market Mix. *International Journal of Engineering and Technology*. IJET-IJEN vol 11 No. 04

DeAngelis, D. L. & Gross, L. J. (Eds.) (1992). *Individual Based Models and Approaches in Ecology*. New York, Chapman and Hall.

Deer, P. J. (1995). Digital Change Detection Techniques: Civilian and Military Applications. Available at: http://ltpwww.gsfc.nasa.gov/ISSSR- 95/digitalc.htm [Accessed: January 10, 2014].

Deer, P. J., & Eklund, P. (2002). Values for the Fuzzy C-Means Classifier in Change Detection for Remote Sensing, Proceedings of the 9th Int. Conf. on Information Processing and Management of Uncertainty (IPMU 2002), IPMU, ESIA - Universite Savoie, 2002, pp.187-194.

Eastman, J. R. (2003). *Idrisi for Windows, Users' Guide* version 32. Clarke Lab for Cartography, Technology and Geographic Analysis. (Worcester: Clarke University)

Eastman, J. R. (2009). *IDRISI Taiga Guide to GIS and Image Processing Manual*, Version 16: Clark Labs: Worcester, MA. USA

Egboh, E. O. (1979). Establishment of Government Controlled Reserves in Nigeria, 1897-1940. *Savanna* (8) 2.

Elvidge, C. D., Suttton, P. C., & Wagnar, T. W. (2004). Urbanization. In Gutman, G., Janetos, A and Justice, C. (Eds). *Land Change Science: Observing, Monitoring and Understanding Trajectories of Change on Earth Surface.* Dordrecht, Netherlands, Kluwer Academic Publishers, pp.315-328

Epstein, J. M., & Axtell, R. (1996). *Growing Artificial Societies: Social Science from the Bottom Up*. Washington, D.C.: Brookings Institution Press.

Ezebilo, E. E. (2004). Threats to Sustainable Forestry Development in Oyo State, Nigeria. Unpublish M.Sc thesis, Swedish University of Agricultural Science.

Falahatkar, S., Soffianian, A. R., Khajeddin, S. J., Ziaee, H. R & Nadoushan, M. A. (2011). Integration of Remote sensing Data and GIS for Prediction of Land cover Map *International Journal of Geomatics and Geosciences*, Volume 1, No. 4: 847-864

FAO (1974). *Soil Map of the World* (1:5,000,000) Vol. 1. Legend, UNESCO, Paris

FAO (2001). State of the World's Forests. Rome, Food & Agriculture Organization.

FAO (2010). Global Forest Resources Assessment, Terms and Definition. Forest Department. Freeman and Co., New York, NY.

FAO. (2005)**.** Global Forest Reserves Assessment, 2005. FAO Forestry Paper, 140. FAO, Rome.

FAO (2012). Food and Agriculture Organization of the United Nations. State of the World's Forests, *Vialle delle terme di Caracalla*, Rome, Italy.

Federal Department of Forestry (2001). Forestry Outlook Study for Africa: Nigeria. Federal Department of Forestry/ FAO. Rome.

Federal Government of Nigeria. (2001)**.** First National Biodiversity Report.

Fitz, H.C., DeBellevue, E.B., Costanza, R., Boumans, R., Maxwell, T., Wainger, L., & Sklar, F.H. (1996). Development of a General Ecosystem Model for a Range of Scales and Ecosystems. *Ecological Modelling* 88:263-295.

Flazzel, J. C., & Magrath, V. (1992). A Supervised Thematic Mapper Classification with a Purification of Training samples. *International Journal of Remote Sensing*, 13 (11):2039-2049

Forest Research Institute of Nigeria (1964). Afaka Investigation Area. Prepared for the Nigerian Forestry Conference, Kaduna.

Fuwape, J. A., Akindele, S. O. & Adekunle, V. A. (2006). Forest Management and Forest Landscapes in Nigeria. In: *Patterns and Processes in Forest Landscape. Consequences of human management.* Lafortezza, R and Sanesi,G (eds,) 2006 Accademia Italian di scienze forestali

Geist, H., & Lambin, E. (2003). Is Poverty the Cause of Deforestation? *The International Forestry Review* 5 (1) PP.64-67

Geomatics Nigeria Limited (1997). Forestry Development in Nigeria. Paper presented at Forest Resource Study Workshop, held at FDF, Abuja, 14 November

Gimblett, H. R., ed. (2002). *Integrating Geographic Information Systems and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes*. New York: Oxford University Press.

GIS Glossary (1996). Environmental Systems Research Institute Inc. January, 2.

Ha, S., Ahn, B., & Park, Y. (2002). Change Detection of Land-cover from Multi-temporal KOMPSAT-1 EOC Imageries. *Korean Journal of Remote Sensing*, vol. 18, No.1, 2002, pp.13-23.

Hasbani J. G., Wijesekara, N., & Marceau, D. J. (2011). An Interactive Method to Dynamically Create Transition Rules in a Land-use Cellular Automata Model, Cellular Automata - Simplicity Behind Complexity, Alejandro Salcido (Ed.), ISBN:978-953-307-230-2,InTech, Available from: http://www.intechopen.com/articles/show/title/an- interactive-method-to-dynamically- create-transition-rules-in-a-land-use-cellular-automata.

Hoffmann, M., Kelley, H., & Evans, T. (2003). Simulating Land-cover Change in South-Central Indiana: An Agent-based Model of Deforestation and Afforestation. In *Complexity and Ecosystem Management: The Theory and Practice of Multi-agent Systems* M. Janssen (ed.), pp 218–247, Cheltenham: Edward Elgar.

Holder, G., Van, R., Wyngaarden, S., Pala, & Taylor, D. (1990). "Flexible Analysis through the Integration of a Fire Growth Model using an Analytical GIS", Proceedings, GIS '90 Symposium, Vancouver, BC: Forestry Canada, 153-157. http://rst.gsfc.nasa.gov/sect1/ 9/06/2013

Howarth, P. J. & Wickware, G. M. (1981). Procedures for Change Detection Using Landsat Digital Data. *International Journal of Remote Sensing*, vol. 2, pp. 277-291.

Islam, M. S., & Ahmed, R. (2011). Land Use Change Prediction in Dhaka City using GIS Aided Markov Chain Modelling. *Journal of Life Earth Science*, Volume 6: 81- 89

IUCN (2003). The World Conservation Union, Gland, Switzerland. www.iucn.org

Jaiyeoba, I. A. (1998). Changes in Soil Properties Related to Conversion of Savannah Woodland into Pine and Eucalyptus Plantations, Northern Nigeria. *Land Degradation and Development*, 9. Pp 207-215

Jansen, M. (Ed.) (2003a). *Complexity and Ecosystem Management: The Theory and Practice of Multi-Agent Approaches*. Northampton, Massachusetts, Edward Elgar Publishers.

Jansen, M. A., Anderies, J. M., Stafford-Smith, M. & Walker, B. H. (2003). Implications of Spatial Heterogeneity of Grazing Pressure on the Resilience of Rangelands. *Complexity and Ecosystem Management: The Theory and Practice of Multi- Agent Approaches*. M. Janssen. Northampton, Massachusetts, Edward Elgar Publishers: 103-126.

Jantz, C.A., Goetz, S. J., & Shelley, M. K. (2004). Using the SLEUTH Urban Growth Model to Simulate the Impacts of Future Policy Scenarios on Urban Land use in the Baltimore-Washington Metropolitan Area. *Environment and Planning B,* 31 (2): 251-272.

Jeganathan, C., Roy, P. S., & Jha, M. N. (2010). Markov Model for Predicting Land cover Changes in Shimla District. *Indian Foresters*, Volume 136, Issue 5

Jensen, J.R. (1986). *Introductory Digital Image Processing- A Remote Sensing Perspective*, Prentice – Hall, N. J. Pp 379

Jensen, J.R. (2005). *Introductory Digital Image Processing: A Remote Sensing Perspective* 3rd edition. New Jersey: Prentice-Hall. pp. 467-494

Jones, R.L. (2000). Deforestation. In: D.S.G Thomas and A. Goudie, (eds), *The Dictionary of Physical Geography*. pp 7 Oxford; Blackwell.

Kamusoko, C., Aniya, M., Bongo, A., & Munyaradzi, M. (2009). Rural Sustainability under Threat in Zimbabwe: Simulation of Future Land use/cover Changes in the Bindura District Based on the Markov-cellular Automata Model. *Applied Geography* 29, 435–447.

Keay, R. M. S. (1959). *An Outline of Nigerian Vegetation*, Government Printer, Lagos

Khadka, M. B. (1997). Spatial Assessment of Human Disturbance on Middle Hills Forest of Napal; A Case Study of Shivapuri Watershed and Wildlife Reserve; *ITC Journal* 2 (1), 170-171

Kohler, T., Kresl, J., Van West, C., Carr, E., & Wilshusen, R. H. (2000). Be there then: A Modelling Approach to Settlement Determinants and Spatial Efficiency among late ancestral Pueblo Populations of the Mesa Verde Region, U.S. Southwest. In

Dynamics in Human and Primate Societies, Edited by T.A. Kohler and G. J. Gumerman, pp 145-178.

Kreuter, U. P., Harris, H. G., Matlock, M. D., & Lacey, R. E. (2001). Change in Ecosystem Service Values in the San Antonio Area, Texas. *Ecological Economics*, 39, 333-346.

Kushwaha, S. P. S., Nandy, S., Ahmad, M., & Agarwal, R. (Not dated). Forest Ecosystem Dynamics Assessment and Predictive Modelling in Eastern Himalaya. ISPRS Archives XXXVIII- 8/W 20, Workshop Proceedings, Earth Observation for Terrestrial Ecosystem.

Lambin, E. F. (1997). Modelling and Monitoring Land-cover Change Processes in Tropical Regions. *Progress in Physical Geography*, 21(3): 375-393.

Landis, J.D. (1994). The California Urban Futures Model: A New-Generation of Metropolitan Simulation-Models. *Environment and Planning* B, 21(4), 399-420.

Landis, J.D. & Zhang, M. (1998a). The Second Generation of the California Urban Futures Model. Part 1: Model Logic and Theory. *Environment and Planning A*, 25: 657-666.

Landis, J.D. & Zhang, M. (1998b). The Second Generation of the California Urban Futures Model. Part 2: Specification and Calibration Results of the Land-use Change Submodel. *Environment and Planning A*, 25: 795-824.

Le Ber, F., Benoit, M., Schott, C., Mari, J. F., & Mignolet, (2006). Studying Crop Sequences with Carrot age, an hmm- based Data Mining Software**.** *Ecological Modelling* 191: 170-185.

Levin, S.A. (1997). Mathematical and Computational Challenges in Population Biology and Ecosystems Science. *Science* 275: 334 – 343.

Li, H., & Reynolds, J.F. (1997). Modelling Effects of Spatial Pattern, Drought, and Grazing on Rates of Rangeland Degradation: A Combined Markov and Cellular Automaton Approach. In *Scale in Remote Sensing and GIS.* D.A. Quattrochi, M.F. Goodchild (eds.), pp 211–230, New York: Lewis Publishers.

Lillesand, T. M. & Kiefer, R.W. (2000). *Remote Sensing and Image Interpretation.* John Wiley and Sons, Inc.

Lillesand, T. M., Kiefer, R.W., & Chipman, J. W. (2008). *Remote Sensing and Image Interpretation*. New York: John Wiley & Sons, Inc.

Long, Y., Shen, Z. & Mao, Q. (2012). Retrieving Spatial Policy Parameters from an Alternative Plan using Constrained Cellular Automata and Regionalized Sensitivity Analysis. *Environment and Planning B,* 39 (3): 586.

Lo´peza E., Bocco G., Mendoza M., & Duhau, E. (2001). Predicting Land cover and Land use Change in the Urban Fringe: A case in Morelia city, Mexico, *Landscape and Urban Planning*, 55,pp 271285

Lynam, T. (2003). A Multi-agent Agro-system Models from the Semi-arid Areas of Zimbabwe. *Complexity and Ecosystem Management: The Theory and Practice of Multi-Agent Approaches*. M. Janssen. Northampton, Massachusetts, Edward Elgar Publishers: 188-217.

Mastrendrea, M., & Schneider, S. H. (2009).“Global Warming” *Microsoft Encarta 2009[DVD]***.** Redmond, W.A: Microsoft Corporation.

Mertens, B., & Lambin, E. F. (1997). Spatial Modelling of Deforestation in Southern Cameroon: Spatial Disaggregation of Diverse Deforestation Processes. *Applied Geography*, 17: 143-168.

Meseret. M. (2009). Assessment of Forest Cover Change using Remote sensing and GIS Techniques: Case Study in Adaba- Dodola Forest Priority Area, Ethiopia. Unpublished M..Sc thesis, School of Graduate Studies, Addis Ababa, Ethiopia.

Mubea, K. W., Ngigi, T. G., & Mudia, C. N. (2010). Assessing Application of Markov Chain Analysis in Predicting Land cover Change: A Case Study of Nakuru Municipality. *JAGST* Volume 12 (2)

Muller, M. R. & Middleton, J. (1994). A Markov Model of Land-use Change Dynamics in the Niagara Region, Ontario, Canada. *Landscape Ecology*, **9**, 151-157.

Munthali, K.G. (2012). Agent Based Simulation in Geospatial Analysis. In *Progress in Geospatial Analysis*, Y. Murayama, (ed.), Tokyo: Springer Science +Business Media B.V.

Munthali, K. G., & Murayama, Y. (2012) Extending Agent-based Land use/cover Change Models to Tropical Deforestation: A Focus on Farm-based Decision-making in Tropical Small Holder Farming. *International Journal of Geographical Information Science*. doi:10.1080/13658816.2012.661057 (First published online 1 March 2012).

Muttitanon, W., & Tripathi, N. K. (2005). Land use/land cover Changes in the Coastal Zone of Ban Don Bay, Thailand using Landsat 5 TM data. *International Journal of Remote Sensing* 26(11-10): 2311-2323.

National Centre for Remote Sensing, Jos (2013), *Landsat MSS 1973* of Afaka Forest Reserve on Row 189 Path 53 on World Referencing System.

National Centre for Remote Sensing, Jos (2013), *Landsat TM 1990* of Afaka Forest Reserve on Row 189 Path 53 on World Referencing System.

National Centre for Remote Sensing, Jos (2013), *NigeriaSat 1 2009* of Afaka Forest Reserve on Row 189 Path 53 on World Referencing System.

Ndabula, C. (2006). Assessment of Land Use/ Land Cover Changes in Kaduna Metropolitan Area using Remote Sensing and Geographic Information System.. Unpublished Msc Thesis, Department of Geography, Ahmadu Bello University, Zaria.

Nwadialor, I. J. (2001). An Assessment of Spatio-temporal Variabilities of Deforestation for Sustainable Forestry Development; A Case Study of Afaka Forest Reserve. International Conference of Spatial Information for Sustainable Development, Nairobi, Kenya. October 2-5, 2001.

Odihi, J. (2003). Deforestation in Afforestation Priority Zone in Sudano-Sahelian Nigeria. *Applied Geography*, 23, p. 227-259

Okonkwo, M. C., Umar, G., & Nwafor, O. E. (2002). Forest Resources Depletion and the National Economy, In: Abu, J.E., Oni, P.L and Popoola, L (eds). Proceedings of FAN held in Akure, Ondo State, Nigeria between 4th and 8th November, p 94-100

Olayiwola, A. M., Ajala, O. A., & Sangodipe, J. A. (2014). Physical Growth Pattern of Settlements in Traditional Region, Southwest Nigeria. *International Journal of Geosciences*, Vol, 5, 1345-1360

Ongomwang, S., & Saravisutra, A. (2011). Optimum Predictive Model for Urban Growth Prediction, Suranarce, *Journal of Science and Technology*, 18 (12); 141-152

Onokarhoraye, A. (1985). An Outline of Human Geography. The Geography and Planning Study Notes. Department of Geography and planning, University of Benin.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M., & Deadman, P. (2001). Multi-Agent Systems for the Simulation of Land-use and Land-cover Change: A Review. *Annals of Association of American Geographers* 93, 314–337.

Phalke, S., & Couloigner, I. (2004). *Change Detection of Manmade Objects using High Resolution Imagery and GIS Data.* Submitted to ERSeL Symposium Proceedings, Prague, Czech Republic

Phalke, S. (2005). Change Detection of Man- Made Objects using very High Resolution Images, Geomatics Engineering, *UCGE Reports* No. 20220, University of Calgary

Polhill, J. G., Gotts, N. M., & Law, A. N. R. (2001). Imitative and Non-imitative Strategies in a Land Use Simulation. *Cybernetics & Systems* 32(1-2):285–307.

Radke, J. R., Srinivas, A., Omar, A., K., & Badrinath R., (2005). Image Change Detection Algorithms: A Systematic Survey. *IEEE Transactions on Image Processing*, vol. 14, No. 3. 2005, pp. 294-307.

Rand, W., Zellner, M., Page, S.E., Riolo, R., Brown, D.G. & Fernandez, L.E. (2002). The Complex Interaction of Agents and Environments: An Example in Urban Sprawl. *Proceedings of Agent 2002, Social Agents: Ecology, Exchange, and Evolution*, October 2002, Chicago, IL.

Reddy, M. A. (2008). Remote Sensing and Geographical Information Systems. Third Edition. BS Publication, Hyderabad, India. p 196.

Revestity, M. A. (2011). The Assessment and Predicting of Land use Changes to Urban Area Using Multi-temporal Satellite Imagery and GIS: A case study on Zanjan, Iran (1984-2011). *Journal of Geographic Information System* 3, 298-305

Rimal, B. (2011). Urban Growth and Land use/Land cover Change of Biratnagar Sub-Metroplitan City, Nepal. *Applied Remote Sensing Journal* 2 (1): 6-15

Rock, B. N. & Vogelmann, J. E. (1989). "The Use of Remote Sensing for the Study of Forest Damage", In Proceedings of the Global Natural Resource Monitoring Assessments: *Preparing for the 21st Century*, Vol.1. Bethesda, MD: American Society for Photogrammetry and Remote Sensing, 453-467.

Rounsevell, M. D. A., Annetts, J. E., Audsley, E., Mayr, T., & Reginster, I. (2003). Modeling the Spatial Distribution of Agricultural Land Use at the Regional Scale. *Agriculture, Ecosystems and Environment* 95: 465- 479.

Sabins, Jr. F. F. (1996). *Remote sensing: Principles and Interpretation*. Third edition.

Salami, A. T., & Balogun, E. E. (2004). "Validation of NigeriaSat-1 for Forest Monitoring in South Western Nigeria" *A Technical Report* submitted to National Space Research and Development Agency (NASRDA), Federal Ministry of Science and Technology, Abuja.

Schneider, L. C. & Pontius, Jr, R. G. (2001). Modelling Land-use Change in the Ipswich Watershed, Massachusetts, USA. *Agriculture, Ecosystem and Environment* 85, 83-94.

Savannah Forestry Research Institute (2013). *Location Map of Afaka Forest Reserve and Environs.*

Sengupta, R., Lant, C., Kreft, S., Beaulieu, J., Peterson, W., & Loftus (2005). Modelling Enrolment in the Conservation Reserve Program by Using Agents within Spatial Decision Support Systems: an example from Images Southern Illinois. *Environmental and Planning B: Planning and Design* 32 (6): 821-834

Sheffield, R. M. & Royer, L. A. (1989). "GIS: A Broad-scale Inventory Perspective", In Proceedings, Society of American Foresters National Convention, Spokane, Washington, September 24-27, 1989. 38-42.

Short, Sr, M. N. (2013). *Image Processing and Interpretation*. Moro Bay, Califonia.

Singh, A. (1989). Digital Change Detection Techniques, Using Remotely sensed Date. *International Journal of remote sensing,* 10. Pp 989-1003

Sklar, F. H. & Costanza, R. (1991). The Development of Dynamic Spatial Models for Landscape Ecology: A Review and Prognosis. In Turner, M.G., and Gardner, R.H., Eds. *Quantitative Methods in Landscape Ecology*. *Ecological Studies* Vol. 82. New York: Springer Verlag, pp. 239-288.

Star, J. & Estes, J. (1990). *Geographic Information Systems An Introduction*, Prentice-Hall, New Jersey, pp. 147-148.

Tanko, Y. Y. (2011). An Assessment of Spatio-temporal Changes in Vegetation Cover in Afaka Forest Reserve using Remote Sensing and GIS, Unpublished B.Sc dissertation of Geography Department, Ahmadu Bello University, Zaria.

Todd, W. J. (1979). Urban and Regional Land Use Change Detected by Using Landsat Data. *Journal of Research by the United States Geological Survey,* vol. 5, pp. 527-534.

Trisirisatayawong, I., & Samchimchom, W. (2002). Large Area Change Detection by Differencing Radiometrically-normalized Images. 23rd Asian Conference on Remote Sensing, 2002, Kathmandu, Nepal, Data processing, Algorithm and Modelling session.

Turner, M.G. (1987). Spatial simulation of landscape changes in Georgia: A Comparison of Three Transition Models. *Landscape Ecology*, **1**, 29-36.

UNEP (2007). Billion Tree Campaign website. http://www.unep.org/billiontreecampaign/FactsFigures/QandA/index.asp

UNESCAP & ADB (2000). State of the Environment in Asia and Pacific. Economic and Social Commission for Asia and the Pacific and Asian Development Bank, New York, United Nations. In State of the Environment and Policy Retrospective 1972-2002

United States Agency International Development (USAID, 2008). Nigerian Biodiversity and Tropical Forestry Assessment. Maximizing Agricultural Revenue in Key Enterprises for Targeted Sites (Markets).

Urquhart, G., Walter, C., David, S. & Chris, B. (2007). Tropical Deforestation. NASA Earth Observatory Library: Tropical Deforestation Fact Sheet. http://earthobservatory.nasa.gov/Library/Deforestation/, last accessed February, 2014

Usman, B. A., & Adefalu, L. L. (2010). Nigerian Forestry, Wildlife and Protected Areas: Status Report. *Tropical Conservation* pp 44-50

Van Sickle, G. A. (1989). "GIS – A Tool in the Forest Pest Management", In A Wider Perspective, GIS '89 Symposium Proceedings, Vancouver, Canada, March 7-10, 1989. Vancouver, BC: Forestry Canada, 213-219.

Venema, H. D., Calamai, P., & Fieguth, P. (2005). "Forest Structure Optimization Using Evolutionary Programming and Landscape Ecology Metrics," *European Journal of Operational Research,* 164 (2): 423-439.

Vince, C., & Iovanna, R. (2006). Analyzing Spatial Hierarchies in Remotely Sensed Data: Insights from a Multilevel Model of Tropical Deforestation. *Land use Policy* 23(3), p. 223-238

Voinov, A., Costanza, R., Wainger, L., Boumans, R., Villa, F., Maxwell, T., & Voinov, H. (1999). Patuxent Landscape Model: Integrated Ecological Economic Modelling of a Watershed. *Environmental Modelling & Software*, 14 (5): 473-491.

Waddell, P. (2002). UrbanSim: Modelling Urban Development for Land-use, Transportation and Environmental Planning. *Journal of the American Planning Association*, 68(3): 297-314.

Wang, X., & Zhang, C. (2001). A Dynamic Modelling Approach to Simulating Socio-economic Effects on Landscape Changes. *Ecological model*, 140: 141-162

Wear, D. N. & Bolstad, P. (1998). Land-use Changes in Southern Appalachian Landscapes: Spatial Analysis and Forecast Evaluation. *Ecosystems* 1:575-594.

Weng, Q. (2002). Land Use Change Analysis in the Zhujiang Delta of China Using Remote Sensing, GIS and Stochastic Modelling. *Journal of Environmental Management* 64, 273-284.

White, R., Engelen G., & Uljee, I. (1997). The Use of Constrained Cellular Automata for High Resolution Modelling of Urban Land-use Dynamics. Environment and Planning B: *Planning and Design*, 24 (3), 323-343.

White, R., Uljee, I., & Engelen, G. (2012). Integrated Modelling of Population, Employment and land-use Change with a Multiple Activity-based Variable Grid Cellular Automaton. *International Journal of Geographical Information Science,* 26 (7):1251-1280.

Wiemker, R., Speck, A., Kulbach, D., Spitzer, H., & Bienlein, J. (1997). Unsupervised Robust Change Detection on Multispectral Imagery using Spectral and Spatial Features. Third International Airborne Remote Sensing Conference and Exhibition, 7–10 July 1997, Copenhagen, Denmark, vol. I, pp.640-647.

Wietske, B. (1998). Rader for Rain Forest; Monitoring Systems for Land Cover Change in the Colombian Amazon. *ITC Journal* 1 (1*),* 65.

World Bank (1998). Knowledge for Development. World Development Report. World Bank. Washington, D.C. USA. http://www.worldbank.org/wdr/wdr98/overview.pdf, last accessed February, 2014.

Wu, Y., Sklar, F.H., Gopu, K., & Rutchey, K. (1996). Fire Simulations in the Everglades Landscape using Parallel Programming. *Ecological Modelling* 93: 113-124.

Xia, J., Zeephongsekul, P., & Arrowsmith, C. (2008). Modelling Spatio-temporal Movement of Tourist Using Finite Markov Chains, *Mathematics and Computers in Simulation* 3065

Zhongmin, X., Guodong, C., Zhiqiang, Z., Zhiyong, S. & Loomis, J. (2003). Applying Contingent Valuation in China to Measure the Total Economic Value of Restoring Ecosystem Services in Ejina Region. *Ecological Economics* 44, 345-358.

Zubair, A. O. (2006). Change Detection in Land use and Land cover using Remote Sensing Data and GIS, (A Case Study of Ilorin and its Environs in Kwara state). Unpublished M.sc. dissertation, Universsity of Ibadan.