EVALUATION OFDEVELOPMENT DYNAMICS OF AWKA CAPITAL TERRITORY, ANAMBRA STATE,USING REMOTE SENSING AND PRESCOTT SPATIAL GROWTH MODEL.

D017

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JUNE, 2019

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BEING APh.D. DISSERTATION SUBMITTED TO THE DEPARTMENT OF SURVEYING AND GEOINFORMATICS, FACULTY OF ENVIRONMENTAL SCIENCES, NNAMDI AZIKIWE UNIVERSITY AWKA

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF A DOCTOR OF PHILOSOPHY (Ph.D.) IN SURVEYING AND GEOINFORMATICS.

SUPERVISOR:

DR. E.J. EMENGINI

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JUNE, 2019

CERTIFICATION

I ESOMCHUKWU C. IGBOKWE, hereby certify that I am responsible for the work submitted in this dissertation and that this is an original work which has not been submitted to this University or any other institution for the award of a degree or a diploma.

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Signature of Candidate   Date

APPROVAL PAGE

This is to certify that this Dissertation has been read and approved as meeting part of the requirements for the award of Doctor of Philosophy (Ph.D.) in Surveying and Geoinformatics, Faculty of Environmental Sciences, Nnamdi Azikiwe University Awka, Anambra State.

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DEDICATION

This work is dedicated to the Almighty God for his mercies.

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My profound gratitude goes to God Almighty for his grace and enablement to successfully complete this program. I wish to express my sincere appreciation to Dr. E.J. Emengini and Dr. J.C Ojiako, my supervisors, for their support, constructive criticisms and for edging me towards the completion of this Dissertation, I'm forever grateful. I am particularly indebted to Prof. J.I. Igbokwe, the former Head of Department, Surveying and Geoinformatics, for his help, motivation and advice. I will ever remain grateful to Prof. M.N. Ono for his untiring efforts and constructive criticisms done on this work and throughout the course of this program. I also wish to thank Dr. Shalom Onwuka for his efforts and guidance throughout the program duration. I would like to express my gratitude to Dr. J.O. Ejikeme and Surv. C. Onwuzuluigbo for always being there as pillar of support since the start of this program.

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ABSTRACT

Monitoring development is an essential part of assessing current development trends with a view of improving urban quality of life in the future as growth affects man and his environment adversely.Urban development prediction has acquired an important consideration in urban sustainability; an effective approach of urban prediction can be a valuable tool in urban planning and decision making. This study therefore investigated the development dynamics of Awka Capital Territory in Anambra State using Remote Sensing and Prescott Spatial Growth Model. The objectives were to: examine the spatial extent of landcover and landuse in Awka Capital Territory for the last 27 years (1990 – 2017); ascertain the trend of change and transition of the landcover/landuse classes during this period; validate Prescott spatial growth model using landcover/landuse reference data for 2018 and image correlation; and predict the future urban development dynamics for the next 30 years (2018 – 2048). The methodology involved acquisition of medium resolution Landsat and Sentinel Satellite images for 1990, 1999, 2008 and 2017, image pre-processing, development of classification scheme, landcover/landuse classification, trend analysis, landcover/landuse transition and impact analysis, Prescott Spatial Growth Model calibration, validation and future urban projection to 2048.The results revealed that urban area grew from 27.92% to 31.19%, to an of area of 14437.68 hectares between 1990 and 1999, 31.19% to 33.67%, to an area of 15586.73 hectares between 1999 and 2008, and 33.67% to 37.24%, to an area of 17237.45 hectares between 2008 and 2017. Trend of change analysis indicated that urban area had an annual rate of change of 0.62% between 1990 and 1999, 0.43% between 1999 and 2008 and 0.56% between 2008 and 2017. Transition results showed that between 1990 and 1999, urban area gained 1272.73 hectares from vegetation and 242.5 hectares from open space, also between 1999 and 2008 urban area gained 1000 hectares from vegetation and 149.05 hectares from open space, in the last epoch between 2008 and 2017 urban area gained 1068.27 hectares from vegetation, 582.45 hectares from open space. The study revealed two patterns inherent in the study area: edge-expansion and infilling, with edge-expansion being the most dominant growth pattern in the study area between 1990 and 2017, there was no evidence of spontaneous pattern of growth within the study area, while also revealing a consistent increase in high surface temperature in urban areas, a diminishing open space and a growing trend of deforestation in the study area. Hypothesis testing also validated the claim that vegetation and open space lost part of their area mass to urban area. Validation of Prescott Spatial growth model gave an overall accuracy of 93.36%, kappa of 0.9083, model error of 6.64% and an image correlation of 0.9585. Prediction of the future urban development dynamics of Awka Capital Territory in 2048 revealed that urban areas is expected to increase from 35.45% to 49.41% i.e. from area coverage of 17798.44 hectares to 22871.51 hectares. It was recommended that the approach be used as tool for planning and decision making in urban development.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Studies have shown that there remain only few landscapes on the Earth that is still in their natural state(Opeyemi*et al*, 2015; Kumar *et al*, 2007). Due to anthropogenic activities, the Earth surface is being significantly altered in some manner and man's presence on the Earth and his use of land has had a profound effect upon the natural environment thus resulting into an accelerated growth in settlement expansion (Zubair, 2008).

Settlements are products of human activities. They are dynamic and constantly changing with man's changing social and economic needs. Settlements whether informal or formal, require constant monitoring. This is especially true in most developing countries including Nigeria where proper and periodic monitoring of formal settlements is not carried out; there is a very high tendency for informal settlements to develop (Opeyemi*et al*, 2015).

Urbanization is among the most significant process that has shaped landuse activities and has drawn a great deal of attention throughout the world (United Nations, 2017). It is estimated that urban population will rise from 3.57 billion in 2010 to 6.34 billion in 2050 where almost 70 percent of the world's population is expected to live in the cities (United Nations, 2017). This immense figure is mainly due to migration from rural to city in search of better quality of life generated by urban activities and services (Deng *et al*, 2018).

However, an increase of urban population has forced cities to expand vertically or horizontally, encroaching into agricultural land and natural boundaries, and changing landuse and landcover without us realizing it (Su*et al*, 2017). Awka Capital Territory is no exception; Awka Capital Territory is rapidly developing into a mass of urban areas growing to merge with each other which has caused spatial landuse and landcover changes. There has been a migration from rural to urban areas, resulting in the territory becoming a highly urbanized with 62% of its population living in urban areas(UN-HABITAT, 2009). The shift in urban migration has posed problems for Awka Capital Territory, infrastructure improvements, both physical and social, has lagged behind the growth in population. There are problems in erosion control, flooding due to unregulated building patterns, poor sanitation, uncontrolled street trading, mountains of garbage, and chaotic transport systems, creating congestion, noise pollution, and overcrowding.

Deeper understanding of the concepts or mechanisms underlying the urban growth can assist toward formulating appropriate policies of urban growth management, and thus, lessening the negative impacts of urbanization while maximizing the positive impacts (Aguayo*et al*, 2018).

Thus, in order to understand the dynamic process of urban spatial growth, researchers throughout the world have implemented diverse approaches, where spatial models have been developed to study, predict and simulate future urban growth (Batty, 1994).

To understand the phenomenon of urban growth in Awka Capital Territory, a broad analysis of the spatial trends of urban growth would help in addressing the needs of the present and future needs of the region. This plays a key role in planning for infrastructure and becomes crucial in planning especially when resources are scarce. Remote Sensing (RS) and Geographic Information System (GIS) are effective tools for analyzing urban development in Awka Capital Territory. The collection of remotely sensed data facilitates the synoptic analyses of Awka Capital Territory over time; such data also provide an important link between intensive, localized ecological research and regional, national and international conservation and management of biological diversity (Wilkie and Finn, 1996).

With the collection of these spatial and statistical data for a different time period, it is then possible to monitor, manageurban growth and also predict what future urban growth would look like. For the latter, Prescott Spatial Growth Model is introduced. Prescott Spatial Growth Model was developed at Prescott College (AZ) in collaboration with National Aeronautics and Space Administration (NASA) and is a dynamic process model with a raster-based structure, so it is suitable to work with remotely sensed data. The model allows users to build different future growth scenarios based on socio-economic predictions such as population, employment and other controlling factors.

The model allows easy integration of remotely sensed data, it is also compatible with ESRI ArcGIS software, this is an advantage compared to cellular automata and other agent-based models which require UNIX environment, long run time and high number of simulations. It also allows users to build different future growth scenarios with landcover/landuse maps based on different influencing factors such as population, distance to infrastructural facilities, transportation data, migration and developable land space, so in any case where data is inaccessible, growth scenarios can be made by either using any of the available factors e.g. population, transportation data, migration and developable land data, it can accommodate a wide range of user inputs. This model has also been successfully demonstrated and validated in Atlanta and in Mobile bay by (Estes *et al*, 2010) and (Estes *et al*, 2009) respectively, and the overall the model prediction in these studies provided exceptional flexibility and good performance in predicting landcover/landuse.

The combination of remotely sensed data and Prescott Spatial Growth Model in this research can provide a detailed insight into the spatial extents of landcover/landuse with emphasis on urban growth of Awka Capital Territory, in the past, present and also the future.

Therefore, this research investigated and analyzed the status of urban development of Awka capital territory between 1990 and 2017 with a view to detecting the change dynamics that has taken place particularly in the urban area and also to ascertain the trend and characteristics of the growth dynamics in the last 27 years so as to predict possible changes that might take place in this status in the next 30 years using both Remote Sensing data and Prescott Spatial Growth Model.

1.2 Statement of the Problem

Awka Capital Territory of Anambra State has witnessed very remarkable expansion, growth and developmental activities such as building, road construction and many other anthropogenic activities since its inception. Hence Awka Capital Territory is rapidly developing into a mass of urban areas growing to merge with each other. This is seen in places like Awka, Ifite, Okpuno,Nwafia,Amawbia, Enugwu-Ukwu,Abagana, Nibo, Nise, and Agulu. This has, therefore, resulted to increased land consumption, modification and alterations in the status of landcover/landuse over time.

Theavailableinformation on the growth dynamics in the Awka Capital City isinsufficient.Thismakesdecisionmakingprocesscomplexandlesstransparent, the studies of Musa *et al*, (2017), Agada et al, 2014 and Nzomiwu *et al*, (2017), failed to detail the growing urban trends and growth dynamics in Awka Capital Territory.

There are no landcover/landuse maps currently available to correctly evaluate the status in landcover/landuse change of Awka Capital Territory. Again,there is not enough data to effectively and efficiently plan and manage urban growth and also prepare for future development. The lack of sufficient spatial and non-spatial data on landcover/landuse within the study areamay lead to improper management i.e.deforestation, developments along or on flood plains and encroachment into prime agricultural land.

Urban prediction models have been studied extensively by Aniekan*et al*, (2012), Ramachandra *et al*, (2012), Youjia and Lijun (2014), Eric and Jamal (2015), Wubishet*et al*, (2015), Dimitrios and Giorgos (2012), in different localities with different results obtained, the choice of applying Prescott Spatial Growth Model sterns from the studies of Martin *et al*, (2015), and Estes *et al*, (2009, 2010), these studies demonstratedthe model's applicability in predicting future urban developments with conventional remote sensing data, which is readily available, hence can be applied in any locality.The studies also noted the model's good validation capacity and model performance.

It is to this effect that this study investigatedthe urbandevelopmentdynamics between 1990 and 2017, and also predict the possible changes that may occur in the next 30 years (2018-2048) using Prescott spatial growth model, so that planners can have the necessary data for planning and management of urban growth in the study area

1.3 Aim and Objectives

1.3.1 Aim

The aim of this study is to evaluatedevelopment dynamics of Awka Capital Territory in Anambra State using Remote Sensingand Prescott Spatial Growth Model with a view to predicting future development dynamics for the next 30 years.

1.3.2 Objectives

The following specific objectives were pursued in order to achieve the aim above.

i. To ascertainthe spatial extent of landcover and landuse in Awka Capital Territory for the last 27 years (1990 – 2017)
ii. To ascertain the trend of changes andtransition of the landcover/landuse classes during this period.

iii. To validate Prescott spatial growth model using landcover/landuse reference data for 2018 and Pearson's product movement correlation coefficient.

iv. To predictthe future urban development dynamics for the next 30 years (2018 – 2048)

1.4 Research Questions

The following Research questions guided the study:

i. What are the spatial extents of landcover/landuse in Awka Capital Territory for the past 27 years?

ii. What is the trend of change and transitions of the landcover/landuse classes for the last 27 years (1990 – 2017)?

iii. Is Prescottspatial growth model validationwithin acceptable accuracy?

iv. What will be the future urban development dynamicsfor Awka Capital Territory for the next 30 years (2018 – 2048)?

1.5 Hypothesis

The study tested the following hypotheses.

H_o: Urban growth did not lead tosignificant declinein vegetation.

H_o: Urban growth did not lead to significant decline in open space.

1.6 Justification of the Research

Thereare manyreasonswhyurbanizationprocesseshavebeenahotresearchareafor severaldecades.Oneofthemostimportant reasonsforsuchaninterestisthat,thesizeandspatial configuration ofanurbanareadirectlyimpactsenergyandmaterialflowssuchascarbonemissionsand infrastructuredemands,andthushasdirectorindirectconsequences ontheproperfunctioningofEarth asasystemandonthequalityoflifeofurbaninhabitants (Abebe, 2013).

Althoughurbangrowthisaninescapableprocess,effortscan bemadeto protectnaturalresources,reduce natural hazards suchasflooding andimprovethelivelihoodsofurbandwellersthroughproperwayof urbanplanningandmanagement(Soffianian et al,2010).Todosocityplanners, policymakersandresource managersneedmoreadvancedandquicktechniques toacquirequantitativeinformationonurbangrowth processesand development trends.Itcanfacilitatetheurgentestablishmentofmanagementmechanismsandrelevant policyinterventionsforproperallocationofresourcesandurbaninfrastructures basedonempirical evidences (Abebe, 2013).

This study is justified because it canprovidetimeserieslandcover mapsexplicitlyexhibitingthedynamicsofdevelopment trends;andcan also showunderlyingpatternsandcharacteristicsvisualizedclearly in a GIS environment. This study canprovideanimproveddescriptionandunderstandingofthetransition of landcover/landuse into urbanareas and valuabledata toanalyzeurbanizationprocessesandpatternsempirically.

Therefore,assumingthaturbanizationwillcontinuetobeoneofthemajorglobalenvironmental and socialchallengesintheforeseeablefuture,understanding andquantifyingthechangingpatternsofurban growthis critical, so astoputforwardappropriatepoliciesandmonitoringmechanismson development trends.

1.7 Scope of the Research

The scope of this studyis limited toevaluating thedevelopment dynamics of Awka Capital Territory in Anambra State Nigeria using remote sensing and Prescott Spatial Growth Model and is defined by the objectives outlined. The study’s area coverage is limited to the boundary of Awka Capital Territory, which covers 400 square kilometers, the methodology used is limited to data acquisition of medium resolution satellite imageries; Landsat 5TM of 1990, Landsat 7ETM+ of 1999 and 2008, Landsat 8OLI of 2017 and Sentinel-2 of 2018, image preprocessing, development of classification scheme, image classification, trend analysis, land cover/land use transition,hypothesis testing, Prescott Spatial Growth Model calibration and validation and urban development prediction to 2048.

The study investigatedthe spatial extents of landcover/landuse in Awka Capital Territory between 1990 and 2017, analyzed the trend of change, transition and impact of the landcover/landuse classes during the said period,validated Prescott spatial growth model using landcover/landuse reference data for 2018 and image correlation; andpredicted future urban development for the next 30 years (2018 – 2048).

The investigation provided insights on the spatial spread, trend of change and land gain of urban area between 1990 and 2018, and also predicted urban area extent in 2048, using Prescott Spatial Growth Model.

1.8 Study Area

This section discusses the study area of the study. The discussion is done under the following: location, topography, climate, and geology.

1.8.1 Location

Awka capital territory was the chosen area for the study; Awka Capital Territory is located in Anambra State, South Eastern Nigeria (See fig. 1a and 1b). It is located between latitude 6^0 5’ N and 6^0 15’ N and longitudes 7^0 0’ E and 7^o 5’ E (see fig 1c). Awka capital territory covers a land mass of 400 square kilometres and comprises of six local government areas namely Anaocha. Awka North, Awka South, Dunukofia, Njikoka and Orumba North, in part or full(UN-HABITAT, 2009).

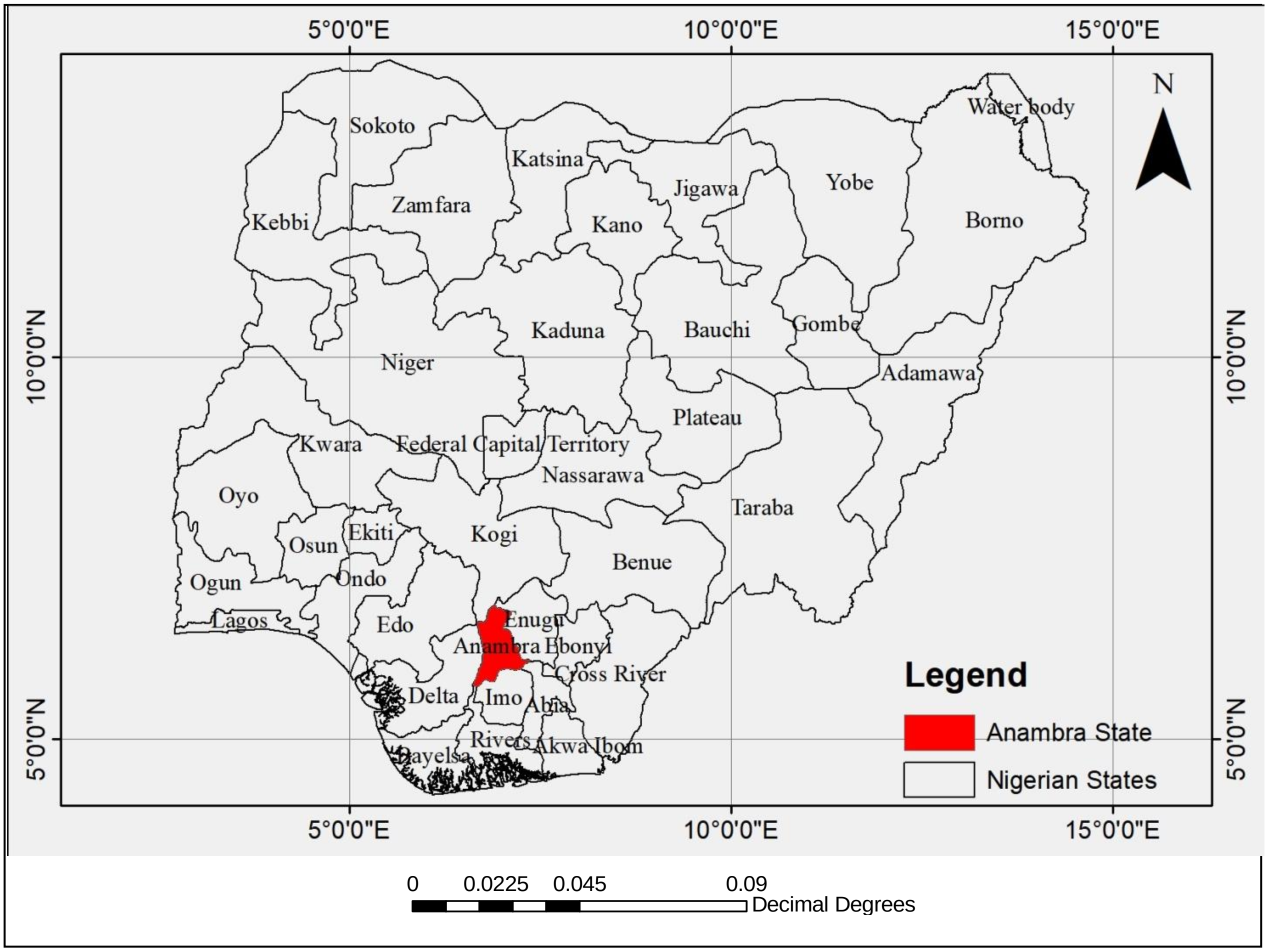

Figure 1a: Map of Nigeria

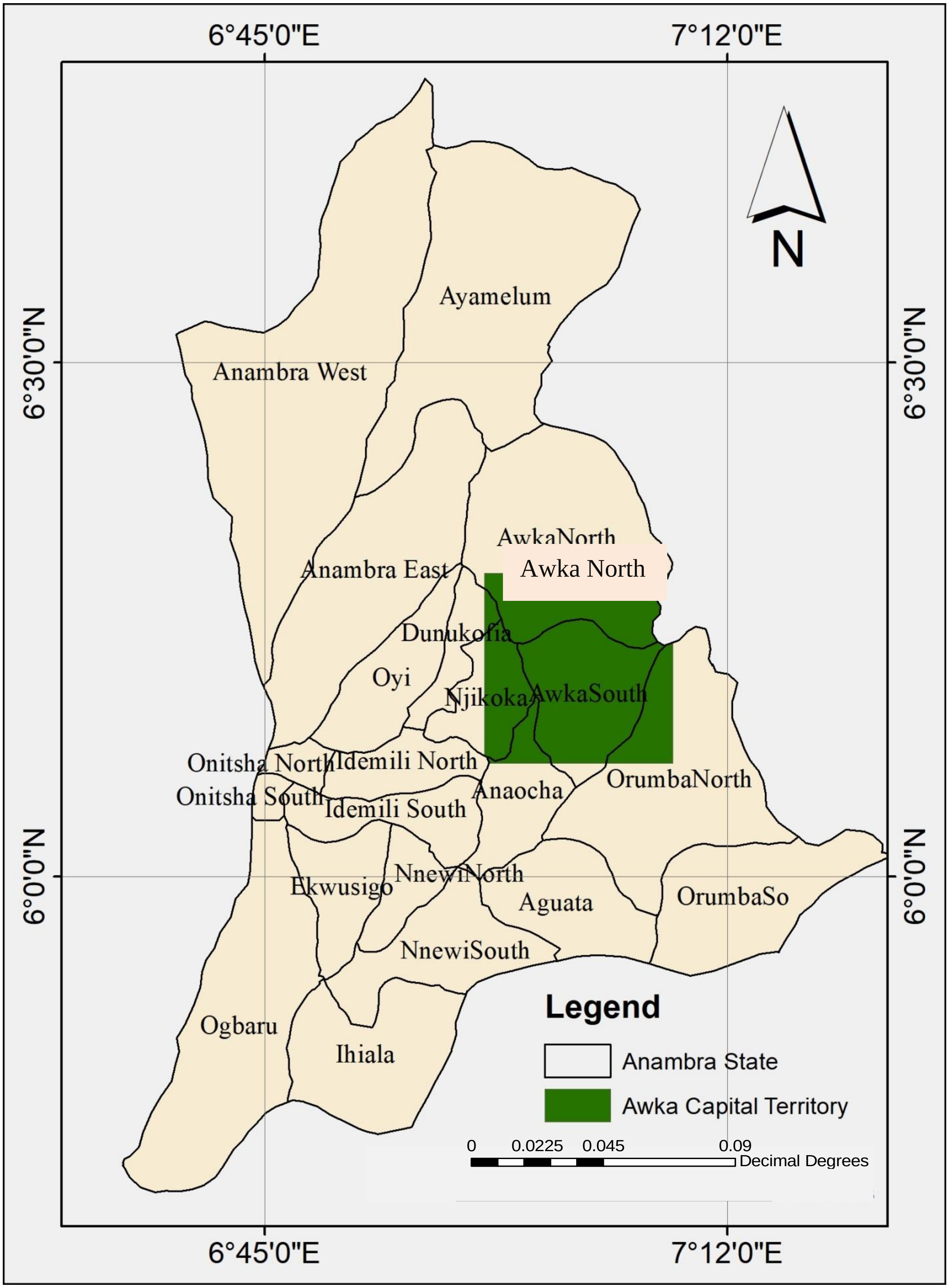

Figure 1b: Anambra State showing Awka Capital Territory

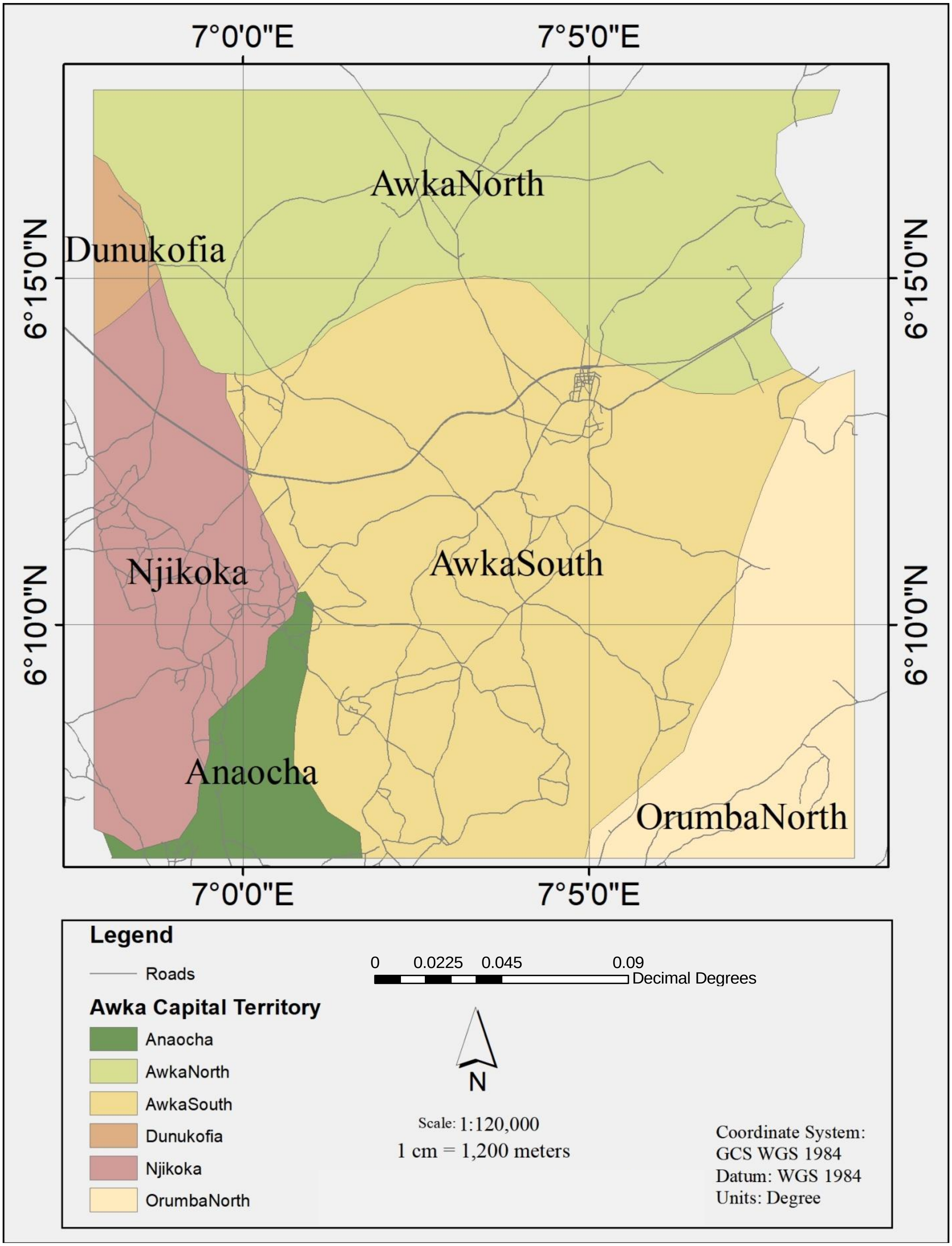

Figure 1c: Awka Capital Territory

1.8.2 Topography

The study area is predominantly a low-lying region on the western plain of the Mamu River with almost all parts at 333 meters above sea level. The major topographic feature in the region is two celestas (asymmetric ridges) with east facing escarpments each trending southward outside Awka urban to form part of Awka-Orlu upland.In a section of Agulu, the land rises above 333 meters or (1000ft) above mean sea level outside Awka urban but within the study area (Adeboboye et *al*, 2012).

1.8.3 Population

Awka Territory has witnessed one of the fastest population growths in the state. The annual growth rates witnessed in the area for the past sixteen years vary from 2.20% per annum for Orumba North to 6.47% per annum for Njikoka. The average rate of growth per annum for the area is 2.63% per annum. Both Awka North with its figure of 5.34% and Njikoka recording 6.47% are experiencing faster population growth rates when compared to the other LGAs in Anambra State (UN-HABITAT, 2009).

According to the 2006 census, the population of the six local Government Areas that make up the Awka Capital Territory is 1,003, 911, with an average annual growth of 3.17% per annum recorded during the past sixteen years (UN-HABITAT, 2009).

1.8.4 Climate

The study area has rainforest vegetation with two seasonal climatic conditions. They are the rainy season and the dry season. The dry season also has a period called harmattan. The dryness of the climate tends to be discomforting during the hot period of February to May, while the wet period between June and September is very cold.

The harmattan which falls within December and February is a period of very cold weather when the atmosphere is generally dry with mist (Agada et al, 2014). Awka Capital Territory is characterized by the annual double maxima of rainfall with a slight drop in either July or August known as dry spell or (August break). The annual total rainfall is above 1.450mm concentrated mainly in eight months of the year with few months of relative drought. Climatologically records since 1978, show that ACT has a mean annual rainfall of about 1,524mm (UN-HABITAT, 2009). ACT has mean daily temperature of 27^0C, with daily minimum temperature of 18^0C. Annual minimum and maximum temperature ranges ace about 22^0C and 34^0C respectively. It has a relative humidity of 80% at dawn (Ada et *al*, 2014).

1.8.5 Geology

The two geologic formations underlying Awka Capital Territory are the Imo Shale and Ameki Formation(Nzomiwu *et al*, 2017). In the riverine and low-lying area particularly the plain west of Mamu River as far as to the land beyond the permanent site of Nnamdi Azikiwe University, the underlying impervious clay shales cause water logging of the soil during rainy season.

The soil sustaining forest vegetation on the low plains farther away from the river maintains a good vegetation cover. The soil is rich and good for root tuber crops like yam, cassava and maize. The two main types of soil found in the area are ferruginous and hydromorphic soil. Ferruginous soil is rich in iron and is derived from marine complexes of sandstone, clay and shales. They therefore vary from the deep red and brown porous soil derived from sandstones and shales to deep porous brown soil derived from sandstone and clay (UN-HABITAT, 2013).

CHAPTER TWO

LITERATURE REVIEW

Understanding the phenomenon of development and analyses of development trends would help in addressing the present and future needs of a region. This plays a key role in planning for infrastructure and becomes crucial in regional planning especially when resources are scarce (Sudhira et. al., 2003).

This chapter borders on the basic principles and theories that serve as a backbone for this study; some of which are urban remote sensing, urban growth development and urban prediction models. together with review of related literatures.

2.1Theoretical Framework

2.1.1Urban Remote Sensing

According to (Zubair, 2006), urban remote sensing is a powerful tool that can assess and compare how urban forms evolve and how solutions to urban problems are developed within a large area. Urban remote sensing analyses involves in-depth cross-comparisons of cities across geographic areas, nation-wide or globally. Each remote sensing "measurement" is a synoptic point in time and space that can have high temporal resolution, and allows for the acquisition of data that may be too costly to collect in-situ.

The data is also not constrained by political boundaries or hindered by different collection methods. Quantitative as well as qualitative comparisons can be made for past, present, or future temporal and spatial patterns of urban development trajectories. By incorporating social and economic data with remote sensing analysis such as public health, population, industrial data, or patterns of vulnerability issues of sustainability can be analyzed and studied.

2.1.2 Features of Urban Remote Sensing

According to (Zubair, 2006) the features of a typical urban remote sensing includes:

a. Each measurement covers a complete spatial area at a point in time
b. Measurements occur at specific times and multiple scenes can allow for quantification of change over time
c. Capacity for description, classification, measurement of physical properties impossible to get in-situ
d. Capacity for routine periodic updating and comparison of measurements
e. Regional / Global Comparison of Measurements over time
f. Measurements are not bounded by political boundaries and are collected in the same manner globally

2.1.3 Remote Sensing Platform

To understand the application of remote sensing in urban growth, there is a need to understand remote sensing platforms and how they operate, this is to understand the platform better suited to the needs of the study at hand. Remote sensing platforms refers to the device used to house/transport the remote sensing hardware (sensor). There are three types of remote sensing platform

Ground-based platforms: - this may be a man standing on the ground, tower or hydraulic mast which carries the special photographic systems or scanners. The main limitations of Ground-based platforms are that it is confined to areas which are accessible, prone to instability of the mast or man and small area coverage.Air-borne platforms: refers to those that carry sensors in flight. They include helicopters (average altitude of 5km), low altitude aircrafts (10km), medium altitude aircrafts (15km), high altitude aircrafts (15-100km) and sounding rockets (over 100km). Their advantages include easy maintenance, low operating cost and accessibility. Their major limitation is the instability due to air turbulence hence difficult to maintain line of sight.

Space-borne platforms: In spaceborne platforms, sensors are mounted on-board a spacecraft (space shuttle or satellite) orbiting the earth, there are several remote sensing satellites providing imagery for research and operational applications. This study employed the use of spaceborne remote sensing because it provides the following advantages over ground based and airborne platforms:

i. Large area coverage
ii. Frequent and repetitive coverage of an area of interest
iii. Quantitative measurement of ground features using radiometrically calibrated sensors
iv. Semiautomated computerized processing and analysis
v. Relatively lower cost per unit area of coverage

2.1.4 Remote Sensing Imaging Systems

This refers to the device used to acquire remote sensing data. It is also known as sensors. Several ways exist for classifying sensors, these includes:

a. Classification based on the radiation source: this includes passive and active systems (sensors). Passive systems do not generate their own electromagnetic energy but they depend on external sources of illumination or thermal radiation from targets themselves. While active systems incorporate their own energy sources.

b. Classification based on the bandwidth used: Earth features can be observed by using different or combinations of bandwidths such as

Broad waveband sensing: involves gathering information from many wavelengths to form a composite image e.g. panchromatic film

Narrow waveband sensing: in this method, radiation from an object is recorded only in a single selected waveband of the spectrum.

Bi-spectral sensing: involves simultaneous recording of radiation from the target in two non-adjacent wavebands. This often enhances the location and identification of environmental phenomena

Multispectral sensing: involves the arrangement of series of sensors to operate at several very narrow bandwidths across a selected waveband of radiation spectrum. This permits the recording of 3 or more images of a scene or target areas simultaneously.

Spectral signatures or response is a unique characteristic known to be associated with particular objects or environmental phenomena. If the spectral response of an object is known, it can be used to identify and interpret the object from a remotely sensed image.

2.1.5 Image Interpretation

Image interpretation sometimes also called Photo interpretation, is a systematic process of extracting useful information from remote sensing imageries. It involves inspecting, identifying, and recognizing image features and arriving at logical conclusions. The principles of image interpretation are based on the following four basic premises

A remote sensor image is a pictorial representation of the terrain

The image is composed of patterns; indicators of things and event, which reflect (emit) the physical, biological and cultural components of the terrain

Similar patterns in similar environment reflect similar conditions and unlike patterns reflect unlike patterns;

The type and amount of information, which can be obtained from an image, is proportional to the knowledge, experience, skill and motivation of the analyst or interpreter. Also efficiency of the methods used and awareness of the limitations imposed on the analyst by the sensor system and data format are important factors to the wealth of information that can be obtained.

2.1.6 Approaches to Image Interpretation

There are two main Approaches to photo interpretation, namely:

Manual photo interpretation or visual photo interpretation: involves a human interpreter to extract information from the image data by visual inspection. Visual aids or image enhancement tools are employed to facilitate photo interpretation.

Computer-assisted photo interpretation or digital image processing; involves the use of computer to perform feature identification, recognition and classification based on the image in digital form both these approaches were used in this study.

2.1.7 Phases of Manual Photo Interpretation

Effective photo interpretation involves the following stages:

1. Examination and detection
2. Recognition, identification and classification
3. Ground truthing
4. Examination and detection; here a general examination of the images is made to establish the general characteristics of the area covered which acquaints the analyst with the area in general terms. Knowledge of the local environment and any information gained through examination will improve his reference level

Detection involves selection of significant features from a varied spectrum of features. General patterns of relief vegetation, water body etc. is established and the most significant feature noted. The following elements in the image data aid in detection:

Spatial resolution: It is a measure of the smallest angular or linear separation between two objects that can be resolved by the sensor. It is the ability of the sensor to distinguish closely spaced objects of the terrain. The higher the sensor's resolution, the greater the data volume and smaller the area covered. In fact, the area coverage and resolution are interdependent and these factors determine the scale of the imagery.

Spectral resolution: It refers to the dimension and number of specific wavelength intervals in the electromagnetic spectrum to which a sensor is sensitive i.e. the recording of the same scene in different spectral interval. Narrow bandwidths in certain regions of the electromagnetic spectrum allow the discrimination of various features more easily.

Temporal resolution: It refers to how often a given sensor obtains imagery of a particular area. Ideally, the sensor obtains data repetitively to capture unique discriminating characteristics of the phenomena of interest.

Radiometric sensitivity/resolution: It is the capability of the sensor to differentiate the spectral reflectance/ emittance from various targets. The greater the ability to discriminate two targets with small radiance differences the higher the resolution.

Recognition, identification and classification: here the interpreter exercises personal judgment to allocate objects into known categories based on the knowledge and understanding of the phenomena. He concentrates on features of interest and extracts information of interest about them. Visual photo interpretation is based on seven non-geometric image characteristics, which usually aids in identification and recognition. They are tone, pattern, shape, shadow, size, texture and location

Ground truthing: this is the final stage and involves a field survey to check the interpretation.

2.1.8 Digital Image Processing

Computer-assisted photo interpretation or digital image processing; involves the use of computer to perform feature identification, recognition and classification based on the image in digital form. The stages in digital image processing include image acquisition, image pre-processing, image enhancement, pattern recognition and image classification and finally thematic mapping.

Mapping Problem

Here the need for mapping using remote sensing method is established

a. Acquisition of Suitable Data

Based on the mapping requirements and features of interest, suitable satellite imageries are acquired either from commercial data providers or from government agencies.

b. Analysis of the Image Statistics

This involves identify the image characteristics like spatial resolution, radiometric resolution, spectral resolution etc.

c. Image Pre-Processing

This is involves image restoration and image rectification. Image restoration and rectification refer to the operations performed on the image to remove systematic errors and noise introduced during scanning and transmission process. Main pre-processing operations are correction or elimination of radiometric distortions, geometric distortions, noise removal, and image resampling and image registration. Image resampling technique of assigning appropriate brightness values to pixels in the output matrix based on the pixel values which, surround their transformed positions in the original input matrix of the image is performed. Image registration implies the super-imposition of an image onto a map or another image so as to orient the image to a map/image coordinate system

d. Image Enhancement

This involves the operations performed on the image to modify it in a useful way or improve the pictorial quality. The radiometric and geometric properties of the image are usually enhanced.

e. Pattern Recognition and Image Classification

Image classification is a way of categorizing image features into image landcover types or regions based on the reflectance characteristics of the image. It is a process of converting the image scene into thematic map in which regions with similar properties are indicated in the same way. There are two main types of classification namely Supervised and unsupervised classification.

f. Thematic Mapping

This is the final stage, different thematic information generated from the image are presented as maps, graphics or tabular data. It involves the use of suitable data format (vector or raster) to represent the result of the classification.

2.1.9 Geographic Information System (GIS)

According to (Wu, 2004), GISis defined as a computer-based system for capturing, storing, querying, analyzing, managing and displaying geographically referenced data.

A spatial component makes it geographical,data from different sources, different suppliers from different hardware platforms, combined, analyzed together and interpreted makes it information.

The ability to integrate with different software and make it available online makes it a system

The power of GIS is the ability to combine geospatial information from different sources in unique ways by layers or themes and extract something new. GIS consists of a series of overlays for a specific geographic region. These overlays may depict thematic information such as landcover and landuse, geology, topography, utility, hydrography, soils etc but must share common geographic coordinate framework. For instance, a GIS analysis might include the location of a highway intersection and the average number of vehicles that flow through the intersection throughout the day, and extract information useful for locating a business. GIS might include both the location of a river and the water depth along its course by season, and enable an analysis of the effects of development on runoff within the watershed. Overlaying the path of a severe thunderstorm with geospatial data on the types of structures encountered homes, stores, schools, post offices could inform an analysis of what types of building construction can survive high winds and hail.

2.1.10 Landuse/LandcoverChange

Humaninterventionandnaturalprocessesareresponsible fortheconstantchangeinlandcoverallover theworld.Landcover changeisdeterminedbytheinteractionin spaceandtimebetween biophysicaland humaninfluences. Urbanization isarapidlandcoverchangeprocessthatproduces different patterns depending ontheproximitytolargeurbancentersacrossthelandscape(Wu,2004).Manylandcover changemodelshavebeenused toidentify thedrivers assumedto affectconversionsoflandbetweenbuilt upandnon-builtuplandcovercategories.

Informationabout urbanization,obtainedfrommultiplemulti-temporalimages,canprovidevaluableknowledge aboutthepatternsofurbangrowthandtheprobable factorsdrivingthechanges.Thisinformationisimportant forplanners,policymakersandresource managerstomakeinformeddecisions.

Nowadaysdecisionmakersarebecomingmoreandmore dependentonmodelsoflanduse/coverchange(Veldkamp&Verburg,2004).Descriptionandmodelingo flandsystemsishighly dependent ontheavailability andqualitydata(Tayyebi*et al*,2010).Thespatial dependencyof landcoverchangescanbeanalyzedbytheintegrationofremotesensingandGIS techniques. Thesetechniqueshaveanefficientspatialcapabilitytomonitorurbanexpansioninurban areas.

2.1.11 UrbanGrowth Dynamics

Development or Physical development in urban growth studies can be defined as the process of changing and becoming larger, stronger, or more impressive, successful, or advanced. It is a shift of population from rural areas to cities, and the resulting growth of urban areas.

Urban development the past decades has mainly focused on structuring urban growth: more inhabitants, more mobility, more welfare etc. In year 2000 only 37 percent of Africans live in urban areas, making Africa the least urbanized continent (Microsoft, 2009). At the same time, however, it is also the most rapidly urbanizing continent. Africa's major cities, often national capitals, are the primary destinations for the vast majority of migrants, and some experience population growth rates of 8 to 10 percent per year (Microsoft, 2009).

Dozens of African cities now have populations of more than 1 million. The largest cities in Africa include Cairo, Giza, and Alexandria in Egypt; Kinshasa, DRC; Casablanca, Morocco; Cape Town and Johannesburg, South Africa; Addis Ababa, Ethiopia; Lagos, Nigeria; and Luanda, Angola. Two of the world's largest metropolitan areas are located in Africa: The combined Cairo-Giza metropolitan area has about 12 million inhabitants, and Lagos and its surrounding suburbs are home to close to 17 million people. By 2015 the population of the Lagos metropolitan area is expected to be more than 23 million (Microsoft, 2009).

Urban housing also tends to be in short supply and thus relatively expensive. Workers often reside on the outskirts of cities in what are politely called unscheduled settlements (more commonly known as shantytowns) where rents are cheaper. While usually lively places to live, they are also overcrowded and lack basic services such as sewage systems and clean water supplies. This raises the risk, especially for children, of contracting infectious and parasitic diseases. Cholera is a particularly dangerous threat in urban areas.

As cities grow, so too does their ethnic diversity. Although mixing of ethnic groups occurs more than in the past, different groups tend to segregate themselves in different neighborhoods. This is especially true when groups have a history of political conflict. For example, in Nairobi, Kenya, the Luo and Kikuyu seldom mix; the same holds for the Igbo and Hausa in Nigeria's largest cities. Immigrants, such as Mozambicans in South Africa, often cluster in particular districts. Many older West African cities feature so-called "stranger quarters" for immigrant.

Rapidlygrowing regions that have major metropolitanareas inbothdevelopedand lesser developedcountriesfaceparticularissues inwhichthespatialnature ofthedistribution of landcovertypeshasenvironmental(e.g., transport pollution andenergyuse)andsocial (e.g.,provisionofservices)implications.Models oflandscapetransformation processesthat characterize thegrowthandinternalcomposition ofurban environmentsinterms ofeconomicandbiophysicalinformation canbe valuabletoolstoplannersandmanagers.

These typesof modelscanbemodifiedtoutilizeremotelysenseddataas inputsandmayprovide effectivewaysforunderstandingtheprocessof landscape transformation (Ward et.al, 2000).

2.1.12 Urban Growth Models

The socioeconomic, natural, technological and social processes both drive and are profoundly affected by the evolving urban spatial structure within which they operate. Research into the understanding, representation and modeling of this complex system has a long tradition in geography and planning (Batty 1994, Alberti and Waddell 2000). However, during the last years, models of landuse change and urban growth have been expanded and have become important and innovative tools for city planners, economists, ecologists and resource managers to support intelligent decisions so they can take timely and effective action for a sustainable development of urban regions.

This development was mainly driven by increased resources and usability of multiple spatial datasets and tools for their processing (e.g. Geographic Information Systems). Community-based collaborative planning and consensus-building efforts in urban development have also been incorporated into urban planning at the local level (Klostermann 1999). The models have shown potential to support planning and management decisions in:

1. Providing knowledge and understanding of the dynamics of the urban system (intuition structuring)
2. Anticipating and forecasting future changes or trends of development
3. Describing and assessing impacts of future development
4. Exploration of different policies and optimization of urban planning and management.

The application, performance, and modeling results respectively strongly depend on the quality and scope of the data for parameterization, calibration and validation (Longley and Mesev 2000, Batty and Howes 2001). As landuse change models simulate both the human and biological system, the requirements placed on the data are fairly complex and range from natural and ecological parameters to socioeconomic information and detailed landuse/cover data with defined spatial and temporal accuracy. Concerning this, (Longley and Mesev, 2000) state that the understanding of physical and socioeconomic distributions through urban modeling still remains limited by the data available.

Remote sensing methods have been widely applied in mapping land surface features in urban areas (Haack *et al*. 1997, Jenson and Cowen 1999). In general, remote sensing techniques can provide spatially consistent datasets that cover large areas with both high detail and high temporal frequency, including historical time series. Despite such advantages, there are only a few studies that focus on integration of remote sensing data products in landuse change model applications for urban environments

2.1.13 Review of Urban Landuse Change/Growth Models

Models of many kinds have been used by a host of diverse professionals, (Taha, 1976). Transportation engineers use models to predict the number of commuters that will travel by car versus those who will make their trips by transit; economists use models to represent the flow of dollars within a regional economy; and biologists use models to describe the impact of water pollutants will have on living organisms. In essence, a model is a simplified representation of a real-life system, (Taha, 1976). By representing reality with only those variables that truly affect the behavior of the system, and by clarifying the relationships between those variables, the assumed "real world" is broken down into a form amenable to analysis (Taha, 1976).

Models can range from simple spreadsheets that provide order-of-magnitude estimates to highly complex simulations that require the use of a super-computer. Simple models provide rapid estimates with minimal effort and required data input. Technically-complex models provide the greatest level of accuracy, but they are usually much more costly in terms of data needs, hardware and software demands, and required professional expertise.

The four main types of planning models (land-use, transportation, economic, and environmental impact) are briefly described below. These models are considered land-use models but many have elements of the other three model types, as well as geographic information system (GIS) components.

a. Land-Use Models

Land-use models often incorporate a variety of landuse categories as inputs and, thereby, can account for different sub-classifications of urban and nonurban landuse such as commercial, industrial, and agricultural, and even more detailed sub-classifications such as density of residential use and type of commercial/industrial development

Some models offer an environmental approach and predict, for example, the impact of transportation and land-use choices on air and water quality. Many of the more user-friendly models are integrated with GISs to become spatially explicit decision-support systems with relational database technology.

The common denominator of the models is that each predicts changes in landuse. Understanding these models comprehensively, however, requires a basic understanding of the components of transportation and urban economic models–the foundations of many of the land-use models. Two major federal actions in the early 1990s added momentum to the integration of transportation and economic models and to the development of land-use models. In 1990, US Congress passed the Clean Air Act amendments, which mandated that metropolitan areas look at the relationships between transportation and air quality. One year later, Congress passed the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991, TEA-21's precursor surface transportation law. ISTEA required transportation planners to consider the likely effect of transportation policy decisions on landuse and development, and the consistency of transportation plans and programs with provisions of all applicable short- and long-term land-use development plans (Deakin, 1995).

b. Transportation Models

In the United States, both urban transportation and economic modeling began in earnest in the mid1950s. Today, modern transportation models use some variant of the Urban Transportation Planning System (UTPS) models, which are characterized by a four-step, single-destination, separable-purpose, and daily trip-based approach. Using the following four steps, transportation models answer questions about future travel patterns:

Trip Generation: How many trips will be made? Trip Distribution: Where will the trips be? Mode Split: Which modes (automobile, transit, cycle, or on foot) will be used? Traffic Assignment: What routes will be used and at what time of day will the trips be taken? (Beimborn*et al*, 1996)

c. Economic Models

Urban economic models predict employment, population, wage rates, rents, incomes, and prices, among other variables, for different geographic areas. Until recently, these models tended to be used in for predicting economic growth rather than estimating the impacts of transportation policies on landuse markets.

d. Environmental Impact Models

Many different types of models have been developed to assess the impacts that both natural and anthropogenic changes can have on the environment. These models range from predicting the long-range transport of pesticides to evaluating the impacts of vehicular emissions on air quality.

More recently, models have been developed to address the effects that human induced landuse changes can have on different aspects of the environment including surface water quality, groundwater recharge and pollution, habitat fragmentation, wildlife loss, floral and faunal community composition, and impaired ecosystem function. A great many of these models are watershed models, or models that examine the relationship between landuse in the watershed and water quality including nutrient loading, fecal coli form loadings and urban storm water runoff.

2.1.14California Urban Futures (CUF) Model: CUF-1

The California Urban Futures Model is known as the CUF Model or CUF-1. The purpose of the CUF-1 model is to provide a framework for simulating how growth and development policies might alter the location, pattern, and intensity of urban development. The model is designed to consider growth and development policies at various levels of government (e.g., state government, local government, and special districts). The model was originally developed to simulate the impacts of alternative regulatory and investment policy initiatives on urban development in the Northern California Bay Region.

The CUF-1 model allows the user to:

Predict population growth at a sub-area level (e.g., a city) and then aggregate predicted growth to larger units (e.g., a county),

Allocate growth to individual sites based on development profitability,

Incorporate several variables, including spatial accessibility, to determine the location and density of new development

Assemble, organize, manage, and display data describing land development options with geographic information systems (GIS)

Incorporate development policies into the growth forecasting process

Simulate new policy scenarios quickly and display results in easy to understand map forms with various levels of detail.

The CUF-1 model uses two primary units of analysis, political jurisdictions (incorporated cities or counties) and developable land units (i.e., undeveloped or underdeveloped areas that may be developed or redeveloped -DLU). First, the model predicts population growth based on city population growth trends and development potential by DLU. The CUF-1 model then simulates growth of an area by determining how much new development to allocate to each DLU per model period based on population growth of each city or county, the profitability potential of each DLU if developed, and user-specified development regulations and/or incentives. This is accomplished using four related sub-models: the bottom-up population growth sub-model, a spatial database, the spatial allocation sub-model, and the annexation incorporation sub-model (Landis, 1995).

2.1.15 California Urban Futures (CUF) Model Second Generation: CUF-2

The purpose of the California Urban Futures Model Second Generation (CUF-2) model, like the CUF-1 model, is to provide a framework for simulating how growth and development policies might alter the location, pattern, and intensity of urban development. The second generation was developed to address some of the theoretical holes of the first model.

The CUF-2 model performs many of the functions as the CUF-1 model (see the evaluation of the CUF-1 model). Several changes were made to the first generation, however. The following provides a brief description of each of the four main components of the CUF-2 model:

The activity prediction component uses a series of econometric models to predict future population, households, and employment by jurisdiction at 10-year intervals. Although the future population and households are predicted as they are in the CUF-1 model, the employment prediction is a new component of CUF-2.

The GIS based spatial database generates and updates the location and attributes of each developable land unit (DLU) and allows the user to visually display the spatial pattern of growth. In CUF-2, DLUs are one-hectare grid-cells, not (as in CUF-1) irregularly-shaped polygons.

The landuse change sub-model is calibrated against historical urban landuse changes Independent variables include: local population and employment growth; proximity to regional job centers; site slope; whether the site is within or beyond city boundaries or spheres of influence; the uses of surrounding sites; the availability of vacant land; site proximity to freeway interchanges and transit stations; and site proximity to major commercial, industrial, and public landuse.

The model allows for spatial bidding for sites between four types of new development landuse and three types of redevelopment and use change sub-model is calibrated against historical urban landuse changes.

2.1.16 California Urban and Biodiversity Analysis Model (CURBA)

The CURBA model was developed as a tool to help urban planners to evaluate the possible effects of alternative urban growth patterns and policies on biodiversity and natural habitat quality. CURBA can help direct urban growth while promoting environmental and ecological quality.

The CURBA model consists of two major components, an Urban Growth Model and a Policy Simulation and Evaluation Model. The Urban Growth Model assists the user in calibrating equations that describe past urbanization patterns and applying the equations to predict future development patterns. The Policy Simulation and Evaluation Model predicts how alternative development policies will affect future urbanization patterns and the associated impacts on habitat integrity. For example, CURBA can help users investigate the effects of urban growth on vegetation landcover by type, habitat for various species (e.g., different mammals, reptiles, and birds), changes in the level of fragmentation, etc. The CURBA model is used in conjunction with ArcView and various Avenue scripts.

2.1.17 DELTA

The DELTA model predicts changes in urban areas, including changes in the location of households, population, employment and the amount of real estate development.

Typically, DELTA is set up to interact with a transport model. With a transport model, DELTA predicts changes in landuse that affect the demand for transportation and the impact of changes in accessibility on a variety of factors, including the location of different activities (e.g., households, employment) and the value of buildings. An optional regional level can be added within DELTA to model the regional economy and migration between urban areas.

2.1.18The Disaggregated Residential Allocation Model (Dram) and The Employment Allocation Model (EMPAL) RAM/EMPAL

DRAM/EMPAL predicts the interactions and distribution of employment and housing in a specified geographic area. DRAM/EMPAL combines two spatial interaction models: the Disaggregated Residential Allocation Model (DRAM) and the Employment Allocation Model (EMPAL) to quantify the interactions between the metropolitan patterns of employment and population location and the networks of transportation facilities that connect them. DRAM/EMPAL provides a tool that relates future estimates of the location and type of employment in an area to their prior distributions, regional growth or decline, and the region's transportation system.

DRAM/EMPAL formed the two major components of an integrated set of computer models known as the Integrated Transportation and Landuse Package (ITLUP). Output from DRAM/EMPAL (i.e., employment and household location and landuse, trips generated for home-to-work, home-to-shop, and work-to-shop) were used with the third component of ITLUP to perform standard travel demand modeling (including sub-models to estimate trip distribution, modal choice, and traffic assignment). DRAM/EMPAL currently is the most widely used employment, population, and landuse forecasting application; it has been used internationally in more than 4 dozen metropolitan areas.

DRAM/EMPAL has been incorporated into a new system called METROPILUS, which combines employment and residence location and land consumption into a single, comprehensive package operating within an ArcView GIS environment.

2.1.19 Growth Simulation Model (GSM)

The GSM was developed by the Maryland Office of Planning beginning in 1992 to predict population growth and new development effects on landuse/landcover nutrient pollution loads, and small streams under alternative land management strategies to develop these estimates, the GSM uses population, household, and employment predictions to estimate demand for residential and commercial development. Demand is then distributed to developable land, based on capacity under existing or alternative zoning, development regulations, and resource conservation mechanisms; and on information about development patterns and trends. Landuse change to accommodate predicted growth is then estimated as a function of management tools.

The GSM can address many different user-defined land-use types. Under current implementation, the Maryland Office of Planning is using three categories of residential density, four types of non-residential developed land, four types of natural vegetation cover, and four categories of agricultural land. These landuse can be modified by the user.

The model is capable of addressing the effects on land-use patterns from changes in transportation, local zoning, city/country master plans, and local fiscal policies e.g. fees, taxes and incentives. The model is also capable of addressing the effects of changing land-use patterns in travel demands, local government fiscal condition, and availability of open space, school quality, crime and landuse.

GSM generates landuse and landuse change information in a dataset that can then be tied to the original landuse GIS dataset. There is a great deal of flexibility regarding the data needed to run GSM. At a minimum, landuse/landcover data and geo-referenced management areas are necessary to operate the model

2.1.20 INDEX

INDEX was developed in 1994 to measure the characteristics and performance of land-use plans and urban designs with "indicators" derived from community goals and policies (e.g., measures the degree of transit orientation in a proposed residential subdivision).
The number of land-use categories addressed by INDEX® is determined by the number of landuse categories in each community's unique land-use planning system. Therefore, the actual land-use categories are defined by the community and can be as detailed or general as needed.
Outputs are determined by community customization. Selected results are mapped in ArcView shape files and some are stored in an Access database.

2.1.21 SLEUTH

The SLEUTH (Slope, Landuse, Exclusion, Urban, Transportation, Hill shade) model, commonly known as the Clarke Cellular Automata Urban Growth Model or as the Clarke Urban

Growth Model, is intended to simulate urban growth in order to aid in understanding how expanding urban areas consume their surrounding land, and the environmental impact this has on the local environment. SLEUTH derives its name from the six types of data inputs: slope, landuse, urban, exclusion, transportation, and hill shade. This model simulates the transition from non-urban to urban land-use using a grid of cells (cellular automaton) each of whose landuse state is dependent upon local factors (e.g., roads, existing urban areas, topography), temporal factors, and random factors.

The SLEUTH model assumes two landuse maps and a set of predefined landuse categories with names assigned by the user (e.g., a numeric value, such as 6, in the landcover file to represent forest nonurban landuse).

The model provides outputs as a set of GIF image files that can be merged into an animation or brought into a GIS as data layers. Resolution of output images depends on the resolution of the input data.

2.1.22 Prescott Spatial Growth Model (PSGM)

The PSGM was developed at Prescott College (AZ) in collaboration with National Aeronautics and Space Administration (NASA) and is a dynamic process model with a raster-based structure. The PSGM is an ArcGIS 9. × Compatible application that assigns future growth into available land based on user-defined parameters. The model allows users to build different future growth scenarios based on socio-economic predictions such as population, employment and other controlling factors. The PSGM is a grid-based model that is predictive;several inputs are needed for the model to run, including developable land, population and employee growth prediction and suitability rules. A network of primary and secondary roads is needed as input into the model to show areas of existing transportation networks. One of the input parameters, developable land, is in the form of a binary grid indicating land grid cells suitable for accepting future growth. Growth prediction is specified in terms of acres consumed, for each predicted year for each developed landuse type. The PSGM allocates predicted population and employment growth for specific prediction years to user-specified landuse categories.

The PSGM was employed in this research and the choice of applying this model in this research work was due to its unique raster based structure that simply allows easy integration of data, it is also compatible with ESRI ArcGIS software, this is an advantage compared to cellular automata and other agent based models which require UNIX environment, long run time and high number of simulations. It also allows users to build different future growth scenarios with landcover/landuse maps based on different influencing factors such as population, employment, transportation data, migration and developable land space, so in any case where data is inaccessible, growth scenarios can be made by either using any of, or combine population, distance to infrastructural facilities, transportation data, or migration and developable land data, it can accommodate a wide range of user inputs. This model has also been successfully demonstrated and validated in Atlantaand also used for evaluating impact of landuse change on submerged aquatic vegetation and sea grasses in Mobile bay by (Estes *et al*, 2010) and (Estes *et al*, 2009) respectively, they tested its error in the quality of landuse classes predicted and the spatial arrangement of the classes, the overall the model prediction in these studies provided exceptional flexibility and good performance in predicting landcover/landuse growth.

2.2Literature Review

Urban growth can be explained as the expansion of human settlements to accommodate a growing population while depleting natural resources. Pathan *et al*, (1989, 1991) and Kumar *et al*, (2007) described urbanization as the process through which the productive agricultural lands, forests, surface water body and groundwater prospects are being irretrievably lost. Urban growth is often uncoordinated and extends along the fringes of metropolitan areas with incredible speed. Commonly, urban growth invades upon prime agricultural and resource land in the process. Land is often developed in a fragmented and piecemeal fashion, with much of the intervening space left vacant or in uses with little functionality (Torrens and Alberti, 2002).

Jat*et al*, (2008) noted the importance of remote sensing and geographic information system (GIS) as tools for monitoring and planning purposes. Unlike conventional surveying and mapping techniques, remote sensing has proven to be a cost effective and technologically sound method of analyzing urban growth. Danson *et al*, (1995) noted effectiveness of environmental remote sensing as a tool in obtaining information on the nature and properties of objects on the earth surface and in the atmosphere through the use of data from sensors which record electromagnetic radiation reflected or emitted from those objects. Remote sensing data are especially important in the areas of rapid landuse changes where the updating of information is tedious and time-consuming.

The monitoring of urban development is mainly to find out the type, amount, and location of land conversion that has occurred (Yeh and Li, 1999b). Lin *et al*, (2007) noted that monitoring and simulating urban growth and its effects on land-use patterns and hydrological processes in urbanized watersheds are essential in land-use and water resource planning and management.

Research works were reviewed and effort was made to identify methods and procedures used by researchers and identify gaps in literature.

The reviewed literatures cover aspects of landcover / landuse change, monitoring and prediction of urban growth, application of growth models in monitoring and forecasting urban growth and development.

2.3.1Monitoring Urban Growth

Onojeghuo and Onojeghuo (2013), monitored urban growth as a vital part of assessing current trends with a view of improving urban quality of life in the future as growth affects man and his environment adversely. They indicated that despite the researches carried out on growth in Lagos state, very few have focused on mapping and predicting urban growth in Eti-Osa local government area (LGA) using remote sensing and GIS techniques. Their paper focused on mapping urban growth in Eti-Osa LGA from 1984 – 2000 and 2000 – 2006 respectively using remote sensing and GIS techniques.

The results were used to perform future prediction analysis of likely urban growth scenario in the study area. The remotely sensed data used for the study were Landsat Thematic Mapper satellite scenes for 1984, Landsat Enhanced Thematic Mapper scenes for 2000 and 2006, and 1 meter high resolution IKONOS imagery of the study area dated 2005 for ground truthing.

The results of the study indicated the spatial extent of urban growth was larger from 2000 – 2006 (net increase 1250 hectares) in comparison with that of 1984 – 2000 (net increase 929 hectares). The key findings of the study showed that urban growth in the study area occurred at a fast leapfrog pattern in the eastern area of Eti-Osa LGA and a slower polynucleated pattern in the former Maroko town, an area that was evacuated and demolished in 1990.

The future prediction analysis was performed using Idrisi Land Change Modeler algorithm which runs on the multi-layer perception neural network and Markov chain modeling. The results of 10 years future prediction for the study area, based on urban growth trends between 2000 and 2006 indicated that the spatial extend of urban growth was 2,220 hectares. Given the current trends of urban growth and results of the future simulation, it was recommended that the Lagos State government take urgent measures to mitigate the occurrence of this trend in the study area.

Adebayo (2007) in their study, noted that the recent upsurge in urban growth and decentralization of economic activities has made urban fringe a topical issues in both local and international debates, however, the problem once visible in the city center has moved to the suburbs due to globalization forces that culminated into mega city development.

There were lots of transformations in the urban fringe landscape in the last two decades making it highly vulnerable to risks, as much as expected of the city itself owing to large agglomeration of people and economic activities in this area. Lack of dependable institutions and absence of government has caused problems on jurisdictional administration of these urban hinterlands. The border line between urban and rural landscape is called the urban fringe.

Often times, a conflict zone with neither rural nor urban features, lying outside the corporate existence of the city. Because of proximity to the city, it experiences much of urbanization processes and serves as buffer for urban development. One-prominent force that shape urban fringe landscape in the developing countries is the informal sector activities, and these constitute about 65% of the urban economy. Informal sector response to the failure of urban governance has various dimensions. Notable among them, are the uncoordinated residential development, emergent transition in demographic re-agglomeration different form the hitherto initial population and restructuring of economic activities at the fringe areas.

This research workwas a part of a larger ongoing study on urban fringe structural characteristic in developing countries and indeed, Ibadan-Nigeria in particular. It therefore, exposed ways toward mainstreaming risk reduction and vulnerability in the area.

It also examined the attendant role of informal sector activities in shaping the urban fringe environment and impact of globalization forces on the urban fringe local landscape with a view to fill the gaps in the areas of urban policy development, governance and planning in developing countries.

Adewale, *et al*., (2014) examined the growth pattern of settlements in Oke-Ogun area of Oyo State, Nigeria between 1984 and 2011; and predicted the future growth pattern of settlements in the study area. Both primary and secondary data were used for this study.

Primary sources of data included Global Positioning System (GPS), Landsat TM and ETM+ imageries of 1984, 1990, 2000, and 2011. Secondary data included administrative map and population data of the study area. Descriptive statistics and geospatial technique were used to analyze the data collected.

Their results showed a random pattern of settlement distribution in the study area. Results revealed that settlements covered about 0.52% of the total land area in 1984; 1.32% in 2000; and 3.78% in 2011. Whereas linear pattern of growth characterized the periods between 1984 and 1990; clustering, infilling, and fringes were the patterns of growth that characterized the periods between 1990 and 2011.

They predicted that, at an average 1.2% of annual growth rate, settlements will occupy about 44.37% of the total land area by 2031. The study concluded that settlements in the study area varied in the patterns of distribution; the area was dominated by indigenous settlements type with overconcentration of social and economic infrastructures in few centers.

Aniekan, *et al*, (2012) explored the implementation of a loosely coupled logistic regression model and geographic information systems in modeling and predicting future urban expansion of Lagos from historical remote sensing data (Landsat TM images of Lagos acquired on 1984, 2000 and 2005). ArcGIS and MATLAB software were used for the modeling.

Three Landsat images were classified using the k-means unsupervised algorithm in MATLAB. Ten salient explanatory landuse variables were extracted for the calibration of the model. The model was calibrated by running a simulation for period 1984 to 2000. The computed logistic coefficients of the 10 explanatory variables showed that all the 10 explanatory variables are significant at 95% confidence level based on a two-tailed test, since all the 10 variables yields p-values <0.05.

The simulated map in 2000 was compared with the reference data in 2000; and evaluated using the Kappa statistic. The computed Kappa statistic was 0.7640; which implied a substantial agreement between the predicted and the reference data. The calibration model for 1984-2000 was used to predict 2005 map. A comparison of the predicted and reference data in 2005 yielded Kappa statistics estimate of 0.6998; which indicated a substantial agreement between the predicted and the reference data. A prediction of 2030 was derived upon satisfactory result obtained for the 2005 prediction based on the 1984 2000 calibrated models. An urban expansion of 129.49% was predicted between 1984 and the forecasted 2030.

Ezeomedo (2012) through his study aimed to identify, model and analyze urban growth in Onitsha Metropolis using Remote Sensing and GIS Techniques. The study area is Onitsha North and South area and its environs (Obosi, Nkpor and IyiowaOdekpe). The data used for this study includes: Topographic map of the study area, NigeriaSat-1 image, LandSat ETM+ image, SPOT 5 image and IKONOS image

The digitized topographical map and SPOT 5 were co-registered at a sub-pixel level to the coordinate system of IKONOS. The digitized map and NigeriaSat-1 were also co-registered at a sub-pixel level to the coordinate system of the LandSat ETM+. Sub-map was created in ILWIS 3.3 to define the area of interest from the full scene of the images (IKONOS, SPOT 5 and LandSat ETM+. The image was re-sampled with reference to the multispectral band using nearest neighbor interpolation to preserve the original values of the pixels. The supervised classification method was adopted.

The nature of urban change structure was studied and quantified using the Shannon entropy. The results of the growth measurement indicated that there has been high rate of growth and dispersed nature of urban development between 1964 and 2008; using the computed average annual rate 0.876% and yearly rate of change of 1.56%, the result shows increase of 38.54% and 68.64% respectively.

2.3.2Landcover / Landuse Change

Using Abuja asacase study,Christopher, (2015) investigated the nature of landuse/landcover change (LULCC).Specific objectiveswere: designofanobjectbasedclassificationmethodto extracturban LULC;validateamethodtoextractLULC indeveloping countriesfrommultiple sourcesof remotely senseddata; apply themethodtoextractLULCdata;usetheoutputs tovalidateanUrbanGrowth Model(UGM);optimizean UGM to representpatternsandtrendsand through this iterativeprocess identify andpriorities the driving forces ofurbanchange;and finally use the outputsof the landusemaps to determine ifplanninghascontrolled landusedevelopment.

Landsat7ETM(2001),Nigeriasat-1SLIM(2003)andSPOT5HRG (2006)sensordataweremerged withlandusecadastreinOBIA,toproducelandusemaps.Overallclassificationaccuracieswere 92%,89%and96%respectively.PostclassificationanalysisofLULCCindicated4.43%annual urbanspread.Shannon's Entropyindexforthestudyperiodwere0.804(2001),0.898(2003)and 0.930(2006). CellularAutomata/Markovanalysisiswasalsousedtopredicturbangrowthtrendof 0.89%perannum.

Study by Yadav et.al, (2012) aimed at findingout thestatusofecological corridorsbetween NagziraWildlife SanctuaryandNavegaonNational Parkusing temporalremotesensingdata. TheNagzira-Navegaoncorridorliesbetweenthenorthlatitudeof20.39ºand21.38ºandeastlongitudesof89.27ºto 82.42º.Thisareaisoneofthemostbiodiversity richzonesof centralIndia.Ithastwoprotectedareas;NagziraWildlifeSanctuary andNavegaonNationalParkhaveconnectivitythroughaforestpatch.Gondiadistrictprovides suitableandhealthycorridorsfortransferofenergyresources,wildlifemovementsandgeneticexchange ofwildlife betweendifferentprotectedareasofcentralIndia.

In thisstudy, the following dataandsoftware'swereused forvectorlayercreation:GoogleEarth Imagery andSurveyofIndiatoposheetsno.55o/15,55o/16,64c/3,64c/4,64c/8,64d/1and64d/5with scaleof1:50.00.Software used includes ArcGIS10, ERDASImagine11 and QuantumGIS1.6. Resultoflanduse/coveranalysisofmulti-temporalsatelliteimagesofNagzira-Navegaoncorridorrepresentstheareaofeachlanduse/covercategoryofthethreedifferent years (1990,2001&2009)andfourdifferentclasses(Denseforest,Openforest,nonforest&waterbody).Densef

orest ischaracterizedbymore than40%canopydensity,whiletheforestwithcanopydensitybetween10%and40%isdefinedas Openforestandlessthe10%canopydefinedasNonforest(FSI2005).Forestcoverwaslargelyconfinedtot he protectedareawhile relativelynonprotectedareaswereoccupiedbyagricultureland(nonforest).Nagzira-Navegaoncorridorhasanumberofwetlands andotherpocketsofwater bodydistributedinthewholestudyarea.

Changeanalysisofwholetimeperiodinstudyarea,givesinformationaboutchangesofthreediffer enttimeperiods. Water bodies havebeendecreasingcontinuouslyinbothdecades.Forestlossanddegradationoccur due tohumaninterferences,urbanization,cattlegrazing,noisepollution, airpollutionetc. Lookingatthe resultofthisstudy,thepositionofthecorridorisnotsatisfactory.Theoverallforestcoverand water bodyaredecreasingcontinuously inthecorridor.

Sunday *et al*, (2013) explained that the rapid growth and expansion of the population of Suleja Local Government Area (LGA) is caused by the large influx of people into the WA its location near the Federal Capital City of Abuja has had the most profound effect on its population expansion. The increase in population over the years has brought about rapid development in physical structures and its micro economy at large. The official population figure for Suleja WA in the last census 2006 is estimated at 216,578 people (NPC, 2006).

The materials used in this study were satellite images of three different epochs (Table 1), sourced from the National Space Research and Development Agency (NASRDA) and Global Landcover Facility {GLCF) website the administrative map of Suleja Local {Area was a valuable material.

The study utilized ILWIS 3.3 software for the processing and classification of the satellite images. The method involved scanning and digitization of map of Suleja WA, Georeferencing, sub setting the map boundary on satellite images, application of supervised maximum likelihood classification logic (Maximum Likelihood Classifier) for the classification of the images and conduct post classification comparison technique for change detection.

The outputs were; generation of change map products and LULC change statistics used for analyses. The following landuse/land categories were used in this study: Bare surface, Built-up land, Farm land and vegetation.

Landuse Landcover change data obtained from each epoch is presented in color composite maps and tables. The method for the analyses of the LULC Change is the Post-classification Comparison Method (PCM). Post classification comparison analyses reveal the change between two epochs. Change data is generated and from the change statistics the rate of change is derived. The spatial and temporal changes were examined.

Classification Accuracy Assessment average score of 96% was achieved using the error matrices method. Field verification was carried out in order to generate additional data to test the quality or accuracy of the classification. It is done by creating a confusion matrix, in which classification results arc compared to the additional .ground verification information in order to test the quality or accuracy of the satellite images classification.

This study provided data on the type, pattern and rate of landuse and landcover change in Suleja WA. The study reveals that urbanization is largely responsible for the significant change and modifications in landuse and landcover in Suleja WA. The results obtained showed that the proportion of area covered by built up land, farm land and bare soil is on the increase, whilst there is decline in vegetation.

Since 1991 when the seat of Nigeria federal government was officially relocated to Abuja, the neighboring towns in Suleja WA witnessed a large influx or immigration of people into them because of proximity to the federal capital city and low cost of living.

In general, anthropogenic activities have been identified to cause the changes in landuse/landcover and these are driven by synergetic factors of rapid growth of population and urbanization. These factors give rise to the expansions that have greatly influenced the changes leading to an increase in the pressure on land, loss of adaptive capacity, and means of production which will ultimately lead to changes in social organization and attitudes.

Thus, the effects of changes brought about in landuse/landcover on physical environment calls for concern by speeding up measures for sustainable development to preserve the natural environment because, if mitigating measures are not put in place now or those put in place are not seriously implemented, the trend could lead to serious environmental degradation.

Zubair (2006) examined the use of GIS and Remote Sensing in mapping Landuse Landcover in Ilorin between 1972 and 2001 so as to detect the changes that has taken place in this status between these periods. Subsequently, an attempt was made at predicting the observed landuse landcover in the next 14 years.

In achieving this, Land Consumption Rate and Land Absorption Coefficient were introduced to aid in the quantitative assessment of the change. The result of the work shows a rapid growth in built-up land between 1972 and 1986 while the periods between 1986 and 2001 witnessed a reduction in this class. It was also observed that change by 2015 may likely follow the trend in 1986/2001.

The study carried by Ojigi (2006), aimed to carry out the spatial variation analysis of Abuja landuse and cover types from different classification algorithms in order to establish which method produces the most probable result. The Objectives of the study include: to carry out detailed fieldwork and ground truthing of the site for confirmation and effective validation of the prevailing landuse(s) and cover types, to be used for the development of the training sites and spectral signatures; to adopt four (4) supervised classification algorithms namely; maximum likelihood, parrallepiped, minimum distance and fisher's classifiers for the landuse and cover types; to carry out a comparative spatial analysis of the four classification algorithms and display findings and lastly to assess the accuracy of the classifications.

Theeffectiveareaunderstudywasthenorthernpartof theFederal Capital City (FCC), Abuja. It is located between longitudes6^0 20'Eand$7^0$33'EoftheGreenwichmeridian,and with latitudes $8^0$30'N and $9^0$20'N of the equator and occupies an areaofabout8,000 squarekilometers. Thedatacollectedforthestudyincluded,2001Landsat-7ETM 345imageofthestudyarea and thebase map(scale1:10,000)of the area. Thetrainingsiteforsixlanduseandcovertypeswascreated basedonthein-situassessmentofthesite carriedoutduring the fieldworkandgroundtruthing exercise.

Therepresentative landuseand cover typesintheimagewhichincluded,closed canopy vegetation, water, open vegetation, urban built-up, rock outcrops andbaregroundwereassigned unitinteger identifier1-6 and digitizedlogically to formthetrainingsite. Atthis pointthe softwareisnot yetawareofthelanduseclassesorlegend,butthe identifierinteger. Thesignaturefileswhichcontain thestatistical informationabout thereflectancevaluesofthepixelswithinthetrainingsitefor eachofthesixlanduseandcovertypesorclasseshastobe developed. In doingthis, the MAKESIG sub-module of the Image Processing/Signature development module of Idrisi-32 wasused.Each integeridentifier(1-6)wasthenreplacedbythe respectivelanduseandcovertypes,enablingthesoftwareto assignandcreatethem astheclassificationlegendinthenext procedure.

Havingcreatedthesignaturefile,eachpixelinthestudyarea nowhavea landuseandlandcovervaluein eachofthethree(3) bandsofthe Landsat-7ETMImagery,hencethedataisreadyfor supervisedclassification. Four (4)image classificationalgorithmsnamely; Maximum Likelihood(MLC), Parrallepiped(PC), Minimum Distance (MDC)andFisher'sClassifier(FC)werecarriedoutonthe2001 Landsat-7 ETM 345imageryof northernpartof theFCC,Abuja, NigeriausingtheImageClassification/HardClassifiermoduleof Idrisi-32GIS.

TheresultfromPCvariedgreatlyfromthoseofMLC,MDC,and FC.Thecoveragearea classifiedbythePCis less than that of MLC, MDC and FC, explaining that some pixels were left unclassified in the process. The PC for bare ground and closed canopyvegetation is not realistic.

Thisstudy showed thatmaximum likelihoodclassification (MLC) algorithmsproduces best result for urban LU/LC classificationof theFCC,AbujaNigeriausing Landsat-7ETM data.Differentsatelliteimagedatafrom othersensorscouldbe experimented insimilar way for the same area for a more conclusiveanalysisonthebestalgorithmsuitableforthemost probableLU/LCresults.

2.3.3PredictingUrban Growth and Development.

Gabriele *et al*, (2013) aimed at analyzing urban expansion over time in several southern Italian towns, using satellite images. Sample towns are located in south of Ban, one of the most important cities in southern Italy, Analyses were carried out using Landsat images acquired 2 August 1999 and 2 July 2009. The obtained results showed a significant urban expansion and an increase of irregularity degree in city fabric. In order to carry out such analyses, Landsat TM data have been adopted to compute Normalized Difference of Vegetation Index (NDVI). Results have been adopted as input data to test autocorrelation indexes in remote sensing.

In the paper, each step of the process were carried out using free tools and data. Operating system (Linux Ubunto), QGIS software (GRASS GIS and Quantum GIS) and software for statistical analysis of data (R) are open source type, while Landsat data are dowaloadable and ready to use. This aspect is very important, since it puts no limits and allows everybody to carry spatial analyses on remote sensing data.

Concerning autocorrelation analysis, it was considered as a method for examining transformations taking place in urbanized areas located in southern Italy. The main objectives of the study were: (i) assessing if variation in urban structure over time can be quantitatively determined using TM images, (ii) investigating and describing modification of urban shape and morphotology over time.

Analyzing and comparing different years, the process of urban intensification has been observed, and the increase of urbanized area has been revealed. This change shows the transformation that took place in the area under investigation and the transformation from quite regular to more fragmented peripheral settlements. The relevance of the technique herein used is that it provides a reliable way of analyzing urban structure and its transformation over lime.

The methodology implemented allowed obtaining synthesis maps useful to analyze landuse change and to interpret urbanized areas, or more precisely complementary areas to vegetated surfaces.

In the first phase, detection based on NDVI index focusing attention on complementary pixels to vegetation allowed us to identify where a loss of green areas occurred over time.

In the second step, always based on NDVI index, autocorrelation allowed us to identify the clustering of not vegetated pixels and, comparing the results at different dates, to understand if a small settlement has become an important center after ten years. The planner can get support by reading such developments and trying to rectify trends and organizing new actions for the future development of the area.

In order to produce landuse dynamics, data more connected to built up areas and to new waterproofing, due to urbanization, should be included in methodology of also supervised classification. In this way it could be possible to define appropriate landuse classes as buildings, roads, etc. and assess how they are changed over time.

However, this study is a preliminary one and quite suggestive and its main objective is to present a way of applying autocorrelation analysis to the forecasting of urban areas evolution. The need of analyzing more time periods and a comparative analysis among many urban areas would be fruitful, and the application of geostatistical analysis applied to satellite time series represents a major challenge for further investigation.

The aim of the study by Selçuk, (2008) was to analyze Landuse /Landcover (LULC) changes using satellite imagery and GIS in Rize Province (North East Turkey). The Data used includes Landsat MSS and Landsat ETM images, aerial photos and topographic maps. Remote sensing image processing was performed using ERDAS Imagine 9.1. The training sites and test sites maps, generated from aerial photo interpretation in 1973 and 2002, were digitized for the goal of creating a spatial database.

Digital Elevation Model (DEM) was produced from the standard topographic maps with the scale of 1/25.000. DEM was created by using ArcGIS 9.2 GIS software. Slope and elevation maps were generated by using DEM. The images were geo-referenced to (Universal Transverse

Mercator-UTM, WGS84. The radiometric corrections and systematic errors were removed from the data set. Supervised classification technique was done using training areas and test data for accuracy assessment. Landuse\landcover classification was performed to produce the Landuse\landcover map of the periods, accuracy assessed, errors were corrected.

The findings identified Landuse\landcover changes in Rize over the years, forests areas were converted to agricultural uses, bare ground areas were converted to residential areas while the forest in the coastal areas had become denser as the area is rugged and can neither be used for agricultural or residential purposes. It also shows that agricultural and residential areas are located at altitudes 100m above m.s.l.

It is worthy to note that the study reported some problems that stemmed from using different sensor technologies (spatial resolution and spectral resolution) in comparing Landsat MSS and ETM data, and in determination of landcover. These problems were eliminated by independently applying supervised classification.

The study by Bayes (2013) aimed to map, detect, quantify and analyse the landcover changes of Dhaka City over time. This research's broad objective was to quantify and investigate the characteristics of urban landcover changes (1989-2009) within the study area using satellite images.

The study area for this research is Dhaka City Corporation (DCC) and its surrounding impact areas. This selected study area almost covers the biggest urban agglomeration and is the central part of Bangladesh in terms of social and economic aspects. Therefore, this area has huge potentiality to face massive urban growth in near future based on the current trend of rapid urbanization.

This research depended on secondary data. To prepare the base maps for analysis purpose and applying the different methods to achieve the research objectives, Landsat satellite images for (1989, 1999 and 2009) were collected from the official website of U.S. Geological Survey (USGS). Table 4 shows the details of the Landsat satellite images used for analysis.

For the purpose of ground-truthing/ referencing, several base maps of Dhaka City (for the year of 1987, 1995 and 2001) were collected from the Survey of Bangladesh (Sob). Again, for comparing the images some other reference satellite images (IRS image of 1996 and Landsat satellite image of 2003) were also collected from the Department of Urban and Regional Planning, Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh.

Composite generation technique was performed for this particular research, for visual purpose any 3 bands are combined that are acting a False Color Composite (FCC). The FCC of RGB= bands 4, 3 and 2 has been chosen for this research. Also the Supervised classification method was used. For this research, a hard classifier called ‘Fisher Classifier’ has been chosen. A 3×3 mode filter was applied to generalize the fisher classified landcover images. This post-processing operation replaces the isolated pixels to the most common neighboring class. Finally the generalized image is reclassified to produce the final version of landcover maps for different years.

It is not typical to ground truth each and every pixel of the classified image. Therefore some reference pixels are generated. These are points on the classified image. Each point of reference pixels represents specific geographic coordinate of the image. The randomly selected points within the classified image list two sets of class. The first set of class values represents the actual landcover type. The second set of class values are known as reference values.

The result obtained from the research shows that over the years (1989 to 2009) built-up area has increased in huge percentage (from 8.4% to 46%). It is also noteworthy that fallow has decreased in good rate (from 38% to 17%). Other landcover types have decreased in a very small amount. Gains in built-up area are evident in all three combinations. Again fallow landcover type is decreasing in large percentage in all the years. The changes (in terms of gains and losses) in other landcover types are almost the same or not influencing. Therefore an abrupt increase in built-up area and decrease in fallow landcover type is quite clear from this kind of analysis

In case of built-up area, the core southern part of Dhaka city has remained the same. While the north-east and south-west parts have converted to built-up areas. The northern part of Dhaka city has gained water body followed by a massive decrease in the south-east and south-west parts. No particular pattern on gains or losses is found for vegetation. In cases of low land the changes are evident in eastern and western parts. Fallow land has decreased markedly and the losses are clear in north-western and mid parts. In summary, it can be stated that fallow land and water body types are basically converting into built-up areas over the years. This is the general trend of landcover change pattern for Dhaka city from 1989-2009.

Carmelo *et al*, (2012) aimed to use RemoteSensing(RS)techniques,incombinationwithGISandlandscapemetrics, toanalyzeandcharacterizethedynamicsofchangesduringafifty yearperiod(1954-2004). Thestudyareais theProvinceofAvellino,intheCampaniaregion(Italy).Thisareaischaracterizedbymany smalltownsandsettlementsscatteredacrosstheProvince.ItscapitalcityAvellino(40°5’55”N14°47’23”

E,348ma.s.l.,42kmNEofNaples,Totalpopulation:52,700)issituatedinaplain called“Concadi Avellino”andsurroundedbymountains.

Thedatasetincludedaerialphotosfor 1954,1974and 1990, LandsatimagesMSS 1975,TM1985and1993,ETM+2004)anddigitalaerial orthophotosfor 1994and2006. Digitalimage-processingsoftwareERDASImagine(v.9.3andv.200)hasbeenusedto process,analyzeandintegratethespatialdataandgeographicinformation.

The approach, which was followed,isbased onthe following processing procedure. First of all the multi-temporal dataset underwent a geometricregistration,inordertodecreasethedistortionseffectsandtoreducepixelerrors that could be interpreted as LC changes. Subsequently,Landsatimages were atmosphericallycorrectedbymeans ofthespecific softwaretoolembeddedinERDASImagine.Nexttaskwasimageclassification. Usingthe supervisedapproaches,fourclasseshavebeendefined: Urban,Woodland,Croplandand Grassland/Pasture. Then, to each image, the supervisedMaximumLikelihood Classification (MLC)algorithm was applied.Finally,a3×3majorityfilterhasbeenappliedtotheclassified LC data, to reduce the “salt&pepper” effect. Jointlywith “Post-classification comparison”,aGISapproachwas combined,to efficiently integrateLCmapsandtoquantitativelyrevealthechangedynamics ineachcategory. Inaddition, ERDASImagine,ESRI ArcGISDesktop(v.9.3)was used to analyze and integrate LC maps and extract the GIS layers describing changes and dynamics of landcover.

Threefundamental dates waschosen for performing landscape metrics analysis: 1954, 1985 and 2004. Logically,1954and2004havebeenchosenbecause theseareplacedatthestartandattheendof theoverallperiodofanalysis,whiletheintermediatestephasbeenfixed at1985.

ThesoftwarepackageFRAGSTATSrasterversion3.3 was usedtocalculatetheselectedlandscapemetricswiththepatchneighbor8-cellrule optionbothatlandscapeandatclasslevel.

Theresultsindicatedthaturbanizationhasconsiderably modified theLCofthestudyarea,withsignificantlandconversions. Inparticular,duringthefive decadesanalyzed,theUrbanLCtypehasalmostquintupled passing from 893.45 hectares to 5,104.44 (from the 1.6% to the 9.1% of the total area of study), mostly at the expense of the cultivated areas, which have most suffered the effects oftheexpansionofthebuilt-upareas. WoodlandandGrassland/PastureLCtypeshave, instead,shownarelativelylowerchangerate,althoughthefirstonecategoryhasrecorded a valuable 16% increment between 1954 and 2004.

The study by Prakasam (2010) aimed to detect landuse and landcover changes through the application of RemoteSensing technologyandGIS whichprovidesefficientmethodsforanalysisoflanduseissuesandtoolsfor landuseplanningandmodeling. KodaikanalTaluk geographically located in west part of Dindigul district,lies between $10^0$6’38”Nto $10^0$26’57”NLatitudesand $77^0$16’00”Eto $77^0$44’56”Elongitudes, itscovering 1081.33sq.km(108133Hectares). Thetotal populationofthestudyareaisabout58203personsconsistingof9752males and28451females accordingto2001census.

Multi-temporalsatellitedatasetobservedbyLANDSAT5,ThematicMapper(TM), LANDSAT4,andMultiSpectralScanner(MSS)andSurveyofIndiaTalukmapdrawnon scale 1:63360wereusedfortheanalysis.Theresolutionis30meters/pixel.Digitallanduse/landcoverclassificat ion through supervised classificationmethod,basedonthefieldknowledgeisemployedtoperformtheclassification. ArcGIS9.2andErdasImagine9.2 whicharepowerfultoolsforextractingthelanduse andlandcoverlayer were used for this study. Thelanduselandcoverclassesinclude agricultureland,harvestedland,wasteland,forest,built-up(settlement,road),water body and cloudcoverareas. Tosumup,itcouldbestatedthatKodaikanalTalukoneofthemajorbio-diversityzones ofthecountryisunderthethreat ofenvironmental andecological problemsduetoimproper managementof land, thefreegiftof nature.Hence there is need for effectivemeasures to be takentoprotect thelandunderforestandagricultureinKodaikanalTaluk.

The main objective of this study by Dirim*et al*, (2009) was to investigate multi-temporal changes of the natural resources using remote sensing and geographic information system techniques. This was achieved by using topographic maps of Bursa Province (Scale: 1/100.000, 1984), Soil Maps of Bursa Province (Scale 1/25.000 and 1/100.000, 1995), Landsat5 TM (16 June 1984 and 06 August1998 full frame) and Integrated Land and Water Information System (lLWIS, 1997)

The satellite data from Landsat5 TM was converted to ILWIS format. The individual spectral band information was geo-referenced and processed using the ILWIS software. The maps of urbanized areas for the city of Bursa and the maps of shoreline changes of the U1uabat Lake were derived from visually interpreted Landsat5 TM images using digitizing and rasterizing procedures. Soil-map was digitized and rasterized. Consequently the Land Capability Classes (LCC) maps of the urbanized areas of the city of Bursa for 1984 and 1998 were produced from rasterized soil map with reclassification procedure.

Various databases like thematic, topographic, soils, landcover and landuse maps as well as attribute databases were prepared using data structures (raster and vector) in ILWIS package.

Results gathered from statistical analysis of urbanized areas maps, show the area extent and direction of the urbanization in the fourteen years period. The Urbanization was due to good roads which proved very attractive areas for building, housing and factories that are geared towards the Yalova-Istanbul, Izmir and Ankara. As a result of population increase and industrial development, 6373ha good-quality agricultural lands have been converted to urban land at a rate of 148.9%.

The results also showed that 26292ha vegetative cover mainly forested areas have been degraded in fourteen years period and 13152 ha dense–very dense forested land have become bare or less dense forest cover. Shoreline changes maps for the years of 1974, 1984 and 1998 showed that decrease of the coverage of the lake is in continuing at a rate of about 12 % from 133.1 to 116.8 km2 due to sediments transported by the surface water of surrounding irrigated agricultural land, tributary streams and mainly Mustafakemalpaşa river in a fourteen years period.

From the results of the study, the authors asserted that there is an urgently need to produce more detailed and recent information on our natural resources using new technologies and to establish local, regional and national landuse plan and law in sustainable bases to prevent degradation. The research also showed that GIS and remote sensing technologies have an important place in studying urbanization processes and natural resources.

Sudhira*et al*, (2003) focusedon urbangrowthpatternanalysesfortheradialandlineargrowth along Bangalore – Mysore highway. This is to be achieved by generating various GIS layers such as built-up theme alongthehighway,roadnetwork,cityboundaryetc, using collateral data such as the Survey of India toposheets, in other to determine the spatial changes in built-up area and the pattern ofgrowthusingGIS.

ThisstudywascarriedoutintheBangalore-Mysorehighway,between$12^0$19'30"Nto $13^0$01'15"N,latitudesand$76^0$45'30"Eto$77^0$31'44"Elongitudes.See figure 3.7 for map of the study area. The data collection was carried out in two phases. This involved primary data collection and secondary data collection. The data used includes Satelliteimage–IRS-LISSdatascenescoveringPath99–Row65andPath100–Row 64 and Satelliteimagery–liss3; path:100row:64& Path:99row:65 whichwasprocuredfromNationalRemoteSensingAgency(NRSA),Hyderabadforthe year 1998.

Urban growth over the period of three decades (1972-98) was determined by computing theareaofallthesettlementsfrom thedigitizedtoposheetsof1971-72andcomparingit withtheareaobtainedfrom theclassifiedsatelliteimageryforthebuilt-uptheme.The toposheetsindigitalformatwere firstgeo-registered.Theareaunderbuilt-up (for 1972) was added to this attribute database after digitization of the toposheets for the built-up feature for the study area.

The standard processes for the analyses of LISS data such as band extraction, restoration, classification, and enhancement were carried out. Band extraction was done initially through a programme written in C++ and subsequently IDRISI 32 was used for image analyses. Supervised classification approach was adopted as it was found more accurate comparedtounsupervisedclassification.TheMaximum LikelihoodClassifier(MLC)or Gaussianclassifierwasemployedfortheimageclassification.Theoriginalclassification of land-use of 16 categories was aggregated to vegetation, built-up (residential & commercial), agricultural and open lands, and water body.

Area under built-upthemeafter classificationwasextracted fromclassifiedimages, whichgavetheurbanareaof1998.Further,byapplyingvectoranalyses,thebuilt-uparea under villages selected for the region between Bangalore – Mysore was computed. TheShannon'sentropyapproachwascomputed todetectand quantify the urban growth phenomenon. Thebuilt-up areacomputedfortemporaldataindicatedthattherewas194%increasein thebuilt-upareafromtheseventiestolatenineties.Amoredetailedinvestigationof the distributionofthebuilt-up revealed that the change is higher as the proximity to Bangaloreincreases.TheBangaloreNorth– Southsegmenthadthehighestincreasein built-up area while it was least in Srirangapatna – Mysore segment with 128%. It can also beobservedthatthereisadecliningtrendinthechangeinbuilt-upareaasonemove fromBangalore towards Mysore.

In conclusion it can be seen thattheBangalorecitywasgrowinginradialdirection(from thecitycentre)aswellas linearlyalongthemajorroads.ThestudydemonstratesGIS andremotesensingcoupled withstatisticalanalyses,suchasarrivingatShannon'sentropyhelped immenselyinspatial andtemporalanalysesforstudyingthegrowth andfordelineatingtheregionswithhigher growth.

Nina and Kumar (2012)attempted toexaminetheurban growthandtrend of developmentofRohtakcityanditsimpactonlandusechangebetween 1983and 2010. They analyzedtherelationshipbetween urbangrowthandlandusechangesandtheirimpactonRohtakcity. Rohtak city islocated at theintersection of 28˚41'1" North latitude and 76˚12'42" Eastlongitude in the NCRregion of Haryana on NationalHighway No. 10. Spread over 100.57 km^2,itlies70kmnorth-westfrom Delhiand240kmsouthofChandigarh,thestatecapital.

The study was based ontheremotesensingspatialas wellasthenon-spatialdataavailablefrom the various sourcesfordifferent periods.ThesourcesareCensusof India,StatisticalAbstract of

Haryana,TownandCountry Planning,DistrictGazetteerofRohtakdistrictand Town directoryofHaryana. Landusemapofthestudy area for 1983 wasacquiredfrom theSurvey ofIndia GuideMapwhereasCartosat-1andLISS-IVimage with2.5 meterand5.8meterresolutionof2010was accessedfrom NationalRemoteSensingCentre,Hyderabadanddigitizedintothe GISenvironment usingon-screen digitization.Topographic sheetno H43W9 atscale of 1:50,000was usedforthegeoreferencingofGuideMapandCartosat-1andLISS-IV image.

Thestudy was based onsupervised classificationand visual interpretation of the Guide map andsatelliteimagery.Fieldsurvey was performedthroughout the study area using Global PositioningSystem (GPS)and obtainedaccurate location point data for eachlanduse class included inthe classificationscheme.The1983landusemapdepictsasituation thatexisted27years before theCartosat-1andLISS-IV image of 2010.Hence,the1983mapcouldnot be checkedagainstthegroundtruth but,theavailablehistorical dataforthestudyarea wereusedto validate theinterpretationmade. However,Cartosat-1and LISS-IV images digitizeddataof2010wasdirectly checkedagainst ground truththroughoutthestudyarea.Canalandmajorroads aredigitizedinlinearaswellaspolygonfeatures.The changeinrespectofpublicutilitiesandfacilitiescould notbeseenforlackofinformationin1983guidemap.

ERDAS 9.0software was usedforthe geo-referencingofspatial data.ArcGIS 9.3 softwarehas been usedforthedigitization,integration,overlayand presentationofthespatialandnon-spatialdataoflandusechangeinthecity. GuideMap,Cartosat-1,LISS-IVimages andCensusdataareusedtoidentify differentpatternsof landuse/landcoverchangesandgrowthofthecity.A databaseis builttoidentifying betweenlandscapechangesand urban growth. Thetechnique is possibleto verify thepressureexercised bytheurban growthonthe agriculturalareas andistoidentifytherecent spatialconfigurations. Thiscomparativeapproach has demonstrated howlandscapechangescanbederivedfrom satelliteimagery andguidemapinthe urbanspatial structure.

As at 1983 thecityaddednearly11.00km^{2}areatoitsexisting boundaryin1981census. Thechangeisobservedforaperiodof27yearsbetween 1983to 2010in percentage andareashowninkm^{2}within eachlanduseclass.

Douglas *et al.*, (2000) aimed todevelopapproachesfor utilizing remotelysenseddatasourcesandspatial modeling techniques for regional planning.Theobjective ofthispaperistopresent asimpleandrobust methodfordelimitingtheextentofurbanareas andtheirinternal composition intermsofurban (e.g.,CBD, residential),rural(grassland, crops),andnatural(e.g.,forest)landuse mixes, usingremotelysensed information. Thesoutheastregion ofQueensland, Australia is the study area of this research.

Remotely sensedimagesofthestudyareafor October 1988andJune 1995wereobtained fromafullygeo-referencedLandsat5ThematicMapper (TM)imagedatabase. Asupervised classificationapproachwasappliedinitially,butfailedto provide adequateseparationbetweenthe target classes.Thefirststageofthe modified unsupervisedclassification processinvolvedsegmenting theimageintovegetation, water,and soil-impervious surface classes.

ForLandsat TMimagerynormalized differencevegetation index(NDVI),band 5,andband 3arecommonlyusedforvegetationclassification. Unsupervisedclassificationusingtheisocluster algorithm was appliedtoacompositeofNDVI, band5,andband3toproduce20classes.This allows separationofthegreenphotosynthesizingcomponentoftheimages.Afurtherunsupervised classificationwasperformed onthe greenvegetation segmentoftheNDVI,band

5,andband3compositetoallow separationof thewoodyandnon-woody vegetation components. This wasrelativelyeasy becausethewoodycomponentofthevegetationinthestudy areacomprises primarily sclerophyllous eucalyptspecieswhichhavedistinctlydifferent spectral characteristics from non-woody vegetation suchasgreencropsandgrassland.

Followingextractionof thewoodyandnon- woodyvegetationcomponentsofthe images, theremainderof theunclassifiedareasof the imagesconsistsof exposedsoil andimpervious surfacesandareasofestablished urban cover typescomprising aspectralmixofimpervious andvegetated surfacesresulting fromresidentiallandscaping.

A post-classification comparisonmethodology wasusedwhereeachpixelintheimagewas assignedtoanewclassbasedonits1988and 1995 landcover types.The urbanclass issplitintoanestablishedresidential(highlevelsof landscaping)classandaclass thatincludesexposedsoil andimpervioussurfacessuchasindustrialbuildings.Bothofthese urbanclassesarecombinedintooneclassinthe accuracy assessment,butare separatedhereto demonstratethe potential ofthismethod for contributing totheclassificationofurbanlandcovertypestomatchtheVIS modelandprovidevalidationfortheCAmodel.

Themajorityoftheconfusionbetween urbanandcleared classesoccurredindistinguishing landscapedresidential areasfromsparselyvegetatedsoil.Furtherconfusionbetween the cleared andurban classes occurredbecauseof thedifficultyindistinguishing exposed and/or sparsely vegetatedsoil.Confusion alsooccurred betweencleared andforestclasses.Thisresultedincommission andomissionerrorsfortheforestclassof13% and5%respectively. The resultsobtained fromthisapplication of Landsat ThematicMapper (TM) imagedata indicatethatthelandcovertypecomposition ofanurban areaandurbanizing areascanbe successfullyclassified usingacarefullydesignedimageprocessingmethodology. This methodology shouldbegloballyapplicable givenitsrelianceonmoderate spatialresolutionimagedataanda combinationofstandard imageprocessing operations.

Dimitrios (2012) indicated that urban growth prediction has acquired an important consideration in urban sustainability. He observed that an effective approach of urban prediction can be a valuable tool in urban decision making and planning. He studied a large urban development that had occurred during last decade in the touristic village of Pogonia Etoloakarnanias, Greece, where an urban growth of 57.5% has been recorded from 2003 to 2011.

The studypredicted new urban settlements using fractals and theory of chaos. More specifically, the study found that the urban growth is taking place within a Sierpinski carpet. Several shapes of Sierpinski carpets were tested in order to find the most appropriate, which produced an accuracy percentage of 70.6% for training set and 81.8% for validation set. He stated that this prediction method can be effectively applied in urban growth modeling, once cities are fractals and urban complexity can be successfully described through a Sierpinski tessellation.

Oka, (2009) indicated that biodiversity is an important part of a complex urban ecosystem and provides significant ecosystem services. It benefits urban communities environmentally, esthetically, recreationally and economically. Variations in landuse and development have generated green spaces of different distribution and composition. While the development has continued, the infrastructure and urban areas being developed have substantial impact on biodiversity.

The paper examined the types of urban green space and the level of sustainability that has been achieved within its setting in terms of biodiversity conservation in the midst of developing infrastructure in Calabar, Cross River State.

The aim is to determine the type and spatial context of urban green space in the study area, the number of developmental activities and managing strategies in sustaining biodiversity. To achieve these objectives, observations, data collection and analysis were carried out; orthophotographs were used to determine the spatial attributes of the green spaces. The result showed that infrastructure predicts have a dramatic impact on biodiversity. If the contribution of urban green spaces to future generation is to be justified, then urban environmental asset will always be deemed to be poor substitutes. Landuse planning, environmental impact assessment and contracting supervisory role to credible companies or individuals with good asset base are the principal tools for avoiding or minimizing the adverse impacts of infrastructure development on biodiversity.

The ability to maintain and make the most beneficial use of biodiversity depends on using and managing biodiversity sustainably in other activities where the production of goods and services for human consumption is the principal objective.

Hussein and Muhsi (2014) stated that GIS, Remote Sensing Techniques and Information Technology are today been used extensively for managing, controlling and predicting the rapidly growing urbanization of large cities, towns and villages. They stated that urban growth is the expansion of towns and cities with respect to the increase of the size of a built-up area and urban growth mainly depends upon the city requirement, facilities available and industrialization. They indicated that these causes migration of people from rural to the urban areas, putting immense pressure on infrastructure, natural resources and lead to formation of slums or uncontrolled urban expansions. Urban growth areas increasingly encroach on the surrounding rural areas causing enormous pressure and dense on the limited scale of infrastructure, very often leading to the unplanned and unsustainable development. Urban growth is a recent phenomenon in Kurdistan Region of Iraq, as result of regional development plans that started during the end of 90th of the 20th century.

They stated that the urban growth made in the study area has been occurred as a result of the stability of the security situation and the growth of the economic situation in the region. The growth of urban cities have been take uncontrolled policies, which lead the engineers, planners and decision makers to use information technologies such as GIS and Remote Sensing to monitor this type of growth and to study the future expectation or prediction .Their study aimed to observe and predict the urban growth of Dohuk City using the twin techniques of GIS and Satellite images.

Data were derived from high resolution satellite imagery and filed survey. The outcome of their work showed that the area of Dohuk has been expanding through the period from 2003-2012 with a rapid growth. The main purpose of their study was to use high resolution imagery for detecting urban growth changes occurred in residential areas of Dohuk city during the last ten years. Their database were designed and developed to support application modules namely built up area, green and recreational areas. Finally, change process of Dohuk city residential areas over the last ten years was determined using GIS overlay analysis and its relation with population growth was studied.

In this period, they indicated that urban growth of residential areas have been expanded rapidly because of many reasons such as; the demographic migration from the villages and rural areas adjacent to the city center as well as migration from areas of central and southern Iraq, because of the stable security situation and moderation climate in addition to providing business and investment opportunities in addition to the fact that the city is considered as trade free zone with neighboring countries.

Ramachandra *et al* (2012) analyzed spatial pattern involving temporal remote sensing data, geographic information system with spatial metrics. This involved (i) temporal analysis of landuse pattern, (ii) exploring interconnection and effectiveness of population indices, Shannon's entropy for quantifying and understanding urbanization and (iii) understanding the spatial patterns of urbanization at landscape level through metrics.

The study was carried out for a rapidly urbanizing region in India; Greater Bangalore is the administrative, cultural, commercialindustrial and knowledge capital of the state of Karnataka. India with an area of 741 sq km and lies between the latitude 12° 39'N and longitude 77°22 7E.

Urban dynamics was analyzed using temporal remote sensing data of the period 1973—2010. The time series spatial data acquired from Landsat Series Multispectral sensor thematic mapper and enhanced thematic mapper plus sensors for the period 1973-2010 were downloaded from the public domain (http:glcf.umiacs.umd.edu/data}. Survey of India (SO1) toposheets of 1:50,000 and 1:250.000 scales were used to generate base layers of city boundary. City map with ward boundaries were digitized from the BBMP (Bruhat Bangalore MahanagaraPalike) map.

Population data was collected from the Director of Census Operations, Bangalore region (http:censuskarntaka.gov.in). Ground control points to register and geocorrect remote sensing data were collected using handheld pre-calibrated GPS (Global Positioning System). Urban dynamics of rapidly urbanizing landscape - Bangalore has been analyzed to understand historical perspective of landuse changes, spatial patterns and impacts of the changes. The analysis of changes in the vegetation cover shows a decline from 72% (488 sq. km in 1973) to 21% (145sq. km in 2010) during the last four decades in Bangalore.

Landuse analyses show that there has been a :584% growth in built- up area during the last four decades with the decline of vegetation by 66% and water body by 74%. Temporal analyses of greater Bangalore reveals an increase in urban built up area by 342.83% (during 1973-1992), 129.56% (during 1992-1999), 106.7% (1999- 2002), 114.51% (2002-2006) and 126.19% from 2006 to 2010. Urban growth pattern of Greater Bangalore has been done in four directions through landscape metrics and gradient analysis across six time periods. The urban density gradient illustrates radial pattern of urbanization during 1973-2010 indicating of intense urbanization at central core and growth at outskirts, which conform to Shannon's entropy, alpha and beta population densities. Landscape metrics further highlight of compact growth in the region.

Gradients of alphaand beta densities illustrate urban intensification in the center and growth in NW and SW regions. Landscape metrics point towards compact growth in the region, due to intense urbanization in 2000. The analysis confirms that the nature of landuse depended on the activities while the level of spatial accumulation depended on the intensity and concentration of urban built-up. Central areas have a high level of spatial accumulation and corresponding landuse, such as in the CBD, while peripheral areas have lower levels of accumulation, unplanned concentrated growth or and water body), traffic congestion, enhanced pollution levels and also changes in the local climate.

Youjia and Lijun (2014) stated that the middle basin of Heihe River has witnessed rapid urban growth and excessive agricultural activities during the last two decades, mainly because of its economic development and increasing population pressure. In this study, they aimed at understanding the growth dynamics of the region, to forecast its future expansion, and to provide a basis for regional management. They calibrated and validated a SLEUTH model with historical data derived from different sources, which comprised remotely sensed and strategic planning data records from 1995, 2000, 2005, and 2009.

Three scenarios based on local regional ecological planning were designed to simulate the spatial pattern of urban growth in different conditions. The first scenario allowed urban expansion without any additional managed growth limitations and the continuation of the actual historical trend. The second scenario was limited based on environmental considerations and managed growth was assumed with moderate protection.

The third scenario simulated managed growth with strict protection on wetland reserves and productive agricultural areas in the study area. They indicated that the results of these models of growth in the study area obtained under different scenarios are of great potential use to city managers and stakeholders. They also suggested that scale sensitivity and spatial accuracy are among the factors that must be considered in practical applications. They urged future researchers to build on the present study to produce models for similar regions in northwest China.

Eric and Jamal (2015) indicated that Toronto's Census Metropolitan Area (CMA) has faced on-going challenges concerning its demographic shifts in the urban and rural fringe tending to become a megacity over the coming decades, due to rapid population increase and urban amalgamation. For this research they examined past urban landuse transitions in Toronto's CMA based on collected remote sensing data between 1973 and 2010.

A Markov Cellular Automata approach was used deriving the CMA urban future based on the existing and planned strategies for Ontario. This is done by a combination of multi-criteria evaluation processes originating transition probabilities that allow a better understanding of the regions urban future by 2030. While the transition probabilities are incorporated from the traditional Markov Chain process, the variables for suitability are measured through a text mining approach, by incorporating several planning documents. The result offered a more integrative vision of policymaker's preference of future planning instruments, allowing for the creation of a better integration of propensity of future growth indicators.

They indicated that the northern part of Toronto is expected to register continuous growth in the coming decades, while agricultural land will continue to decrease. Urban areas after 2020 tend to become more clustered suggesting an importance of planning of green spaces within the Toronto.

In the study of Praveen *et al* (2013), they used mainly two types of data. These are topographic map and data of georeferenced and merged data of LISS III and PAN of IRS ID of 2003 in the digital mode a Sensing Agency (NRSA), Government of India, Hyderabad, and used. The spatial resolutions centimeters, and spectral resolutions are 4 and 1 meters, respectively.
The topographic map 57 0/6 (1:50,000 scale) is obtained from the Survey of India, Hyderabad, 1976; it is converted to digital mode using scanning. The topographic map is georeferenced Arc GIS software and spatial analyst tools and demarcated the boundary of study area.

A supervised signature extraction with the maximum likelihood algorithm was employed to georeferenced and merged LISS III and PAN for landuse/landcover mapping for the year classification of satellite imagery began, an extensive field survey was performed throughout the System (GPS) equipment. This survey was performed in order to obtain accurate locational point class included in the classification scheme as well as for the creation of training sites and for signature.

The satellite data was enhanced before classification using histogram equalization in ERDAS lmagine and to achieve better classification accuracy. In supervised classification, spectral signatures are the image. These specified locations are given the generic name “training sites” arid are defined by digitized over the raster scene. The vector layer consists of various polygons overlaying different help to develop spectral signatures for the outlined areas.

The landuse maps pertaining of two different periods were used for post classification comprises changes in the landuse category and dynamism with the changes. Post classification comparison is method of change detection with fairly good results. It involves independently produced spectral classification results from different or segment-by-segment comparison to detect changes in the classes.

Knowledge about landuse/landcover has become important to overcome the problem of biog ecosystems, biodiversity; deterioration of environmental quality; loss of agricultural lands, destructive wildlife habitat. The main reason behind the LU/LC changes includes rapid population growth, rural of rural areas as urban areas, lack of valuation of ecological services, poverty; ignorance of biophysical incompatible technologies. Present study area Tirupati is a rapid developing town and is a world famous pilgrim centre. During the past few decades, the study area has witnessed substantial increase in population industrialization, and transportation activities have negative impact on the environmental.

Due to involvement of multiple data sets, they used latest technologies like remote sensing and interpretation of remote sensing imagery field surveys, and existing study area conditions, we have categories, that is, agriculture, built-up area, dense forest, mining, open forest, other land, plantal and the study area covers 125 km and LU/LC changes were estimated 1mm 1976 to 2003.

It was evident from that the LU/LC (agriculture built-up area, plantation, other land, and dense forest from 1976 to 2003. Comparison from toposheets and satellite imagery interpretation indicates that the built-up comprise nonagricultural uses like building, transport, and communications is largely broadened from 5.911 net addition of 12.44km^2 This is due to urban expansion and population increase in this study are; The agricultural lands which are used for paddy and production of food, vegetables, and other mix other homestead trees are largely decreased from 68.23km (1976) to 21.45 km (2003), with net.

The study area witnessed large amount of agriculture land converted into settlements and other spread area, both man-made and natural water features such as rivers/streams, tanks, and reservoir 1976 to 9.91 km in 2003, with net decline of 2.18 km Water spread area decrease is occurred spread area into built-up area or human developmental area as the population increased significance forest comprising all land with tree cover of canopy density of 70% and above is significantly (4.25km^2) with a net decrease of 18.10 km This is attributed to conversion of forest lands into activities. Open forest land comprising all lands with tree cover of canopy density between 10% and 40% is significant addition of 10.90 km of land in 2003 which is due to implementation of afforestation the period of 2001-2003 under Haritha predict includes agricultural tree crops and other horticulture nurseries also increased from 0.79 km (increase of 21.01 kin The other land consisting of roads, mostly link roads, joining the village without scrub and sandy area is largely broadened from 15.64 km (1976) to 38.22 km (2003) with no mining activities were found in the study area, but a small addition of 0.13km mining land was

This paper focuses on LU/LC changes in an urban area, Tirupati, India, using remote sensing clearly show that LU/LC changes were significant during the period from 1976 to 2003. There is noticed. On the other hand there is decrease in agricultural area; water spread area, and forest significant impact of population and its development activities on LC/LC change. This study proves remote sensing technologies is effective tool for urban planning and management.

Atef *et al*, (2012) stated that the spatial, temporal and spectral characteristics of the remote sensing data are effectively used in landuse and landcover change mapping, hence helping in decision making for sustainable land resource management. The aim of their study was to map urbanization growth using satellite imagery, Google imagery and GIS in Mafraq city/North Jordan. Landsat imageries of 1987, 2005 and Google Earth (GeoEye-1) imagery of 2010 were used in GIS environment to map the change in the urbanization at Mafraq city. Maximum likelihood algorithm of supervised classification was used to delineate two landuse and landcover classes for the study area, namely: populated areas and non-populated areas from 1987 and 2005 imageries. On-Screen digitizing was adopted on Google Earth (GeoEye-1) imagery of 2010 to map the populated areas.

The main change observed for the time period of 1987-2010 was that the urbanized areas have in- creased approximately by 7.14 km2 (approximately 23% of the study area). The population density within the study area has increased from approximately 965 inhabitants per sq. km in 1987 to 1808 inhabitants per sq. km in 2005 and reached 2146 inhabitants per sq. km in 2010. The increase in the populated area within Mafraq city has impacted the surface hydrology runoff which leads to diverting some Wadis to avoid passing through the city centre. Also, the increase in urbanization in Mafraq city has put more pressures on the waste water treatment plant and solid waste dumpsite that serve Mafraq city.

Dimitrios*et al* (2011) stated that urbanization changes have been widely examined and numerous urban growth models have been proposed. They introduced an alternative urban growth model specifically designed to incorporate spatial heterogeneity in urban growth models.

Instead of applying a single method to the entire study area, they segment the study area into different regions and applied targeted algorithms in each sub region. The working hypothesis is that the integration of appropriately selected region-specific models will outperform a globally applied model as it will incorporate further spatial heterogeneity. They examined urban landuse changes in Denver, Colorado. Two landuse maps from different time snapshots (1977 and 1997) were used to detect the urban landuse changes, and 23 explanatory factors were produced to model urbanization. The proposed Spatially Heterogeneous Expert Based (SHEB) model tested decision trees as the underlying modeling algorithm, applying them in different sub regions. In their study, the segmentation tested is the division of the entire area into interior and exterior urban areas. Interior urban areas are those situated within dense urbanized structures, while exterior urban areas are outside of these structures. Obtained results on this model regionalization technique indicated that targeted local models produce improved results in terms of Kappa, accuracy percentage and multi-scale performance. The model superiority is also confirmed by model pair wise comparisons using t-tests.

The segmentation criterion of interior/exterior selection may not only capture specific characteristics on spatial and morphological properties, but also socioeconomic factors which may implicitly be present in these spatial representations. The usage of interior and exterior sub regions in the present study acts as a proof of concept. Other spatial heterogeneity indicators, for example landscape, socioeconomic and political boundaries could act as the basis for improved local segmentations.

Wubishet*et al* (2015) stated that a changing mosaic of natural vegetation and human landuse has evolved within and around the Flint River Watershed (FRW) in Alabama and

Tennessee over the past several decades. To determine the cause of change and linkage between human activities and environmental change can prove problematic.

Subsequently, there is a need to produce predictions of future environments based on planning instruments and socio-economic parameters. Scenarios of potential future landuse landcover (LULC) change are required in order to better manage potential impacts on many environmental issues. Their study created future scenarios for the year 2030 from baseline landuse of 2001, relative to three predicted landuse scenarios which include differences related to conservation, planning, and development.

The future growth scenarios were created using the ArcGIS tool, Prescott Spatial Growth Model (PSGM). The model allows users to build different future growth scenarios based on socio-economic predictions such as population, employment and other controlling factors. The simulation results indicate that LULC changes associated with future urbanization can increase by ~23% - 43% within the FRW, which will lead to significant environmental issues if not managed properly. Their overall analysis and model results demonstrated the ability of future growth scenarios to explore and evaluate options for a future environment. Spatial modeling and analysis tools, such as PSGM, provide a powerful approach to evaluate potential impacts of LULC change in the future and should be used to manage urbanization in areas with more intense development.

Dimitrios and Giorgos (2012) stated that human population continues to aggregate in urban centers. This inevitably increases the urban footprint with significant consequences for biodiversity, climate, and environmental resources. Urban growth prediction models have been extensively studied with the overarching goal to assist in sustainable management of urban centers. Despite the extensive body of research, these models are not frequently included in the decision making process. Their review aimed at bringing this gap by analyzing results from a survey investigating developer and user perceptions from the modeling and planning communities, respectively.

They studied and cited overviews of existing models, including advantages and limitations, are also provided. A total of 156 manuscripts were identified. Analysis of aggregated statistics indicates that cellular automata are the prevailing modeling technique, present in the majority of published works. There is also a strong preference for local or regional studies, a choice possibly related to data availability.

The survey found a strong recognition of the models' potential in decision making, but also limited agreement that these models actually reach that potential in practice. Collaboration between planning and modeling communities is deemed essential for transitioning models into practice. Data availability was considered a stronger restraining factor by respondents with limited algorithmic experience, which may indicate that model input data are becoming more specialized, thus significantly limiting wide-spread applicability.

Their review assessed developer and user perceptions and critically discusses existing urban growth prediction models, acting as a reference for future model development. Specific guidelines were provided to facilitate transition of this relatively mature science into decision making activities.

Manju *et al* (2011) stated that rapid expansion of urban areas due to rise in population and economic growth is an increasing additional demand on natural resources thereby causing land-use changes especially in megacities. Therefore, serious problems associated with rapid development such as additional infrastructure, informal settlements, environmental pollution, destruction of ecological structure and scarcity of natural resources has been studied carefully using remote sensing and GIS technologies for a rapidly grown megacity namely, Delhi.

Their research work evaluated the landuse/landcover (LULC) changes and urban expansion in Mega city Delhi and highlights the major impact of rapid urbanization and population growth on the landcover changes which needs immediate attention. The results indicated that the city is expanding towards its peripheral region with the conversion of rural regions in to urban expansions. Built-up area of Delhi witnessed an overall increment from 540.7 km^2 to 791.96 km^2 or 16.86% of the total city area (1490 km^2) during the study period 1997 to 2008 which mainly came from agriculture land, waste land, scrub-land, sandy areas and water body. The increment in forest cover of 0.5 % is very small when considering the increment in built up category to 17%. Total area of water body has reduced by 52.9% in a ten year period (58.26 km^2 in 1997 to 27.43 km^2 in 2008) with shallow water body now having a dismal presence. LULC changes are studied with the urban growth parameters such as population, vehicles, gross state domestic product etc.

The results laid emphasis on the concepts of urban planning to be applied such that more consideration is towards the preservation and management of natural landuse classes which will increase the quality of life in an urban environment.

Pardeep *et al* (2016) stated that urban growth refers to the extent of urbanization, which is a global phenomenon mainly drawn by the population growth and large scale migration in the developing, urban growth is taking its toll on natural resources at an alarming rate .Their study of urban growth of the Hisar city (Situated in Haryana, India) had been studied at mid scale level over the period of 1989 to 2013, extracting the information related to the growth in pervious surface, their growth and temporal variability.

Statistical Classification approach was used for the classification, remotely sensed images obtain from Google earth were also used. The resulted indicated that Hisar today, is one of the fast growing cities in Haryana, the city showed tremendous rise in the built-up area. There was continuous increase in the amount of urban built-up area from 1989 to 2013. The total built-up area in 1989 was just 18 km2, in 2013, the urban built up reached to 313 km2. The urban changes and flow direction or urban growth. It has grown along the NH 10. Besides NH 10 it has also growth along other transport routs in North and South directions. The city is connected with its surroundings by many roads and a few railway lines.

The road pattern of the city has played most important role in the changing pattern of the city. It has considerable interaction with smaller urban places. They indicated that this study can be used for predicting the future urban growth. This is useful for the urban planning authorities in developing countries where data is not available regularly

Martin *et al* (2015) indicated that urban growth and landuse change models are an important and innovative tool that support planning and development of sustainable urban areas. They stated that the data requirements for parameterization, calibration and validation of urban models are intense due to the complexity of the models and their objectives. In study several urban landuse change models are evaluated and their demands on spatial data sets were compared. These needs were discussed and evaluated based on the use of remotely-sensed high spatial and temporal resolution data. The results showed especially the need for accurate urban landuse information due to the Level II and III of the USGS/Anderson landcover/use classification scheme. An appropriate methodology for urban landuse differentiation using high resolution remotely sensed data is presented and evaluated in test sites in the southern California city of Santa Barbara, USA. The approach was based on irregularly-shaped regions of homogenous urban landuse as the defined mapping units.

Within these regions, spatial and fractal metrics were applied to describe the landcover structure, to acquire urban landuse information and to describe socioeconomic features. The application of one of the evaluated urban growth models is presented, based on a seventy-year time series of air photos. The urban growth process, as well as future predictions of landuse change are well represented in the model based upon the concept of cellular automata and demonstrate the potential of a combined remote sensing and modeling approach.

Kenneth and Gunter (2014) stated that during the last decades, cities in sub-Saharan Africa have undergone rapid urban growth due to increased population growth and high economic activities. Their research paper explored the impacts of varying modeling settings including spatial extend and its location for the city of Nairobi using a cellular automata (CA) urban growth model (UGM). Their UGM used multi-temporal satellite-based data for classification of urban land-use of 1986, 2000 and 2010, road data, slope data and exclusion layer. Monte-Carlo technique was used for model calibration and Multi Resolution Validation (MRV) technique for validation. Simulation of urban land-use was done up to the year 2030 when Kenya plans to attain Vision 2030. Three spatial grid sizes varying in extent and location were applied in the UGM calibration and validation. Thus, their research explored the impacts of varying spatial extent (grid) and location on urban growth modeling and hence can contribute to an improved sustainable planning and development. This is useful for future planning as the Nairobi grows and expands into the peri urban areas.

Estes *et al*, (2010)'s study provided results on the performance of the Prescott Spatial Growth Model in predicting landuse in the Atlanta metropolitan area. The Prescott Spatial Growth Model was used to perform blind simulations and guided simulations for the Atlanta region for the 1980–2000 periods to evaluate the performance of the model in the quantity and spatial distribution of urban growth. Quantitative comparisons of both the blind and guided simulations with actual land use were used to assess the model's performance.

The error in the quantity of land-use classes predicted and the spatial arrangement of the classes was assessed. The model provides exceptional flexibility and good overall performance in predicting land use in this study.

Courage *et al* (2013) using Harare metropolitan province in Zimbabwe as an example, classified Landsat imagery (1984, 2002, 2008 and 2013) by using support vector machines (SVMs) and analyzed built-up and non-built-up changes. The overall classification accuracy for the four dates ranged from 89% to 95%, while the overall kappa varied from 86% to 93%. The results demonstrated that SVMs provide a cost-effective technique for mapping urban landuse/cover by using medium- resolution satellite images such as Landsat. Based on landuse/cover maps for 1984, 2002, 2008 and 2013, along with change analyses, built-up areas increased from 12.6% to 36.3% of the total land area, while non-built-up cover de- creased from 87.3% to 63.4% between 1984 and 2013.

The results revealed an urban growth process characterized by infill, extension and leapfrog developments. Given the dearth of spatial urban growth information in Harare metropolitan province, the landuse/cover maps are valuable products that provide a synoptic view of built-up and non-built-up areas. Therefore, the landuse/cover change maps could potentially assist decision-makers with up-to-date built-up and non-built-up information in order to guide strategic implementation of sustainable urban landuse planning in Harare metropolitan province.

Prakasam (2010) studied the changes in landuse and landcover in Kodaikanal Taluk over 40 years period (1969-2008). The study was done through remote sensing approach using SOI Taluk map of Kodaikanal (1969), and Land Sat imageries of May 2003 and April 2008.

The landuse landcover classification was performed based on the Survey of India Kodaikanal Taluk map and Satellite imageries. GIS software is used to prepare the thematic maps. Ground truth observations were also performed to check the accuracy of the classification.

The study brought to light that forest area that occupied about 70 per cent of the Taluk's area in 1969 has decreased to 33 per cent in 2008. Agricultural land, Built up area, Harvested land and Wasteland also have experienced change. Builtup lands (Settlement) have increased from 3 per cent to 21 per cent of the total area. Kodaikanal area is identified as one of the biodiversity area in India. Proper landuse planning is essential for a sustainable development of Kodaikanal Taluk.

Yadav *et al* (2012) attempted to find out the status of ecological corridors between Nagzira Wildlife Sanctuary and Navegaon National Park using temporal remote sensing data. It is found that 6.22 percent dense forest is converted to open forest and 6.66 percent open forest to non forest between 1990 and 1999. After observation of change analysis, it is found that maximum deforestation occurred in the corridors. In the following decade (1999 to 2009), 1.81 percent dense forest is converted to open forest and 2.21 percent of the open forest to non forest. Water bodies have been decreasing continuously in both decades. Forest loss and degradation occur due to human interference, urbanization, cattle grazing, noise pollution, and air pollution and so on. As per the details obtained from field survey regarding the conflict analysis in the corridor,

it can be inferred that most of the sites along the NH-6, state highways and railway tracks show presence of human encroachment in terms of agriculture land and build-up area. Due to high frequency of traffic on roads/railway, wild animals often divert from their original dispersal route and enter these hamlets leading to conflict situations.

Estes *et al*, (2009) stated that there is a continued need to understand how human activities along the northern Gulf of Mexico coast are impacting the natural ecosystems. The gulf coast is experiencing rapid population growth and associated land cover/land use change. Mobile Bay, AL is a designated pilot region of the Gulf of Mexico Alliance (GOMA) and is the focus area of many current NASA and NOAA studies, for example. This is a critical region, both ecologically and economically to the entire United States because it has the fourth largest freshwater inflow in the continental USA, is a vital nursery habitat for commercially and recreational important fisheries, and houses a working waterfront and port that is expanding.

The study performed Watershed and hydrodynamic modeling for Mobile Bay to evaluate the impact of land use change in Mobile and Baldwin counties on the aquatic ecosystem. Watershed modeling was done using the Loading Simulation Package in C++ (LSPC) for all watersheds contiguous to Mobile Bay for land use Scenarios in 1948, 1992, 2001, and 2030. The Prescott Spatial Growth Model was used to predict the 2030 land use scenario based on observed trends. All land use scenarios were developed to a common land classification system developed by merging the 1992 and 2001 National Land Cover Data (NLCD). The LSPC model output provides changes in flow, temperature, sediments and general water quality for 22 discharge points into the Bay.

These results were inputted in the Environmental Fluid Dynamics Computer Code (EFDC) hydrodynamic model to generate data on changes in temperature, salinity, and sediment concentrations on a grid with four vertical profiles throughout the Bay's aquatic ecosystems.

The models were calibrated using in-situ data collected at sampling stations in and around Mobile bay. This phase of the predict focused on sediment modeling because of its significant influence on light attenuation which is a critical factor in the health of submerged aquatic vegetation. The impact of land use change on sediment concentrations was evaluated by analyzing the LSPC and EFDC sediment simulations for the four land use scenarios. Such analysis was also performed for storm and non-storm periods. In- situ data of total suspended sediments (TSS) and light attenuation were used to develop a regression model to estimate light attenuation from TSS.

This regression model was used to derive marine light attenuation estimates throughout Mobile bay using the EFDC TSS outputs. The changes in sediment concentrations and associated impact on light attenuation in the aquatic ecosystem were used to perform an ecological analysis to evaluate the impact on seagreasses and Submerged Aquatic Vegetation (SAV) habitat. This is the key product benefiting the Mobile Bay coastal environmental managers that integrates the influences of sediments due to land use driven flow changes with the restoration potential of SAVs.

Mas (1999) tested six change detection procedures using Landsat Multi-Spectral Scanner (MSS) images for detecting areas of changes in the region of the TeÂrminos Lagoon, a coastal zone of the State of Campeche, Mexico. The change detection techniques considered were image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison.

The accuracy of the results obtained by each technique was evaluated by comparison with aerial photographs through Kappa coeffcient calculation. Post-classification comparison was found to be the most accurate procedure and presented the advantage of indicating the nature of the changes. Poor performances obtained by image enhancement procedures were attributed to the spectral variation due to differences in soil moisture and in vegetation phenology between both scenes. Methods based on classification were found to be less sensitive at these spectral variations and more robust when dealing with data captured at different times of the year

Xiaojun, (2014) presented a research that integrated remote sensing, GIS, and dynamic spatial modeling for predicting urban spatial growth with different development conditions considered. The study area is a fast growing American metropolis. The prediction was based on a cellular automate urban growth model governed by a set of complex transition rules combining both socio-economic and biophysical conditions. Historical urban extent data derived with remotely sensed imagery are used to calibrate the model. Two possible future growth scenarios were assessed.

The first scenario assumes that the current development conditions do not change and therefore, can be termed as 'continuation. The second is a hybrid growth strategy in which both conventional urban development and alternative growth efforts are addressed. It was found that many small-size urban patches would emerge and smaller ones would merge to form larger urban clusters. If current conditions do not alter, the process of urbanization would deplete vegetation and open space. A restrictive growth plan should be adopted in order to promote the livability and sustainable development in the study area. Overall, this study demonstrated the usefulness of remote sensing, GIS, and dynamic modeling in urban and landscape planning and management. The methodology developed in this research can be easily adapted to other urban areas with similar growth patterns.

Hemanandhini*et al* (2016) stated that distribution network for conveying water, power and sewage are essential for urban development. Because of rapid growth on urbanization and industrialization, there is an exponential growth in population which results in a greater surge in community development program and urban growth.

As a prelude to the mapping of the area under such growth help us to device the appropriate town/city planning. Now-a-days, rural areas are changed into urban (i.e.) metropolitan area. In the study remote sensing and Geographical information system techniques were used for detecting landuse and landcover changes for the year 1995, 2005 and 2015 in Thiruvannamalai by using satellite image and secondary data of this area. With the help of these data, urban growth for the forthcoming year 2025 and 2035 was estimated by using trend line analysis and Marcov chain analysis. Their study mainly highlights the time to time changes of urban growth using remote sensing and GIS techniques.

2.3Research gaps

After the critical review and evaluation of previous related studies, the following gaps were identified:

All the studies carried out in the area of urban growth mapping and analysis i.e. Mas (1999), Yadav *et al* (2012),Prakasam (2010), Atef *et al*, (2012) and Praveen *et al* (2013), were only concerned with mapping landcover/landuse, none of these studies tried to analyze the trend and annual rate of change of landcover/landuse.

In the field of urban planning, one of the important subjects of concern is the analyzing the trend of landuse transition. So, there is the needto carry out a research work that will move further in analyzing the trend and annual rate of change of landcover/landuse in Awka Capital Territory between 1990 and 2017.

The works of Courage *et al* (2013), Pardeep *et al* (2016) and Eric and Jamal (2015)did not take into consideration, the influencing factors of growth when modeling landuse and landcover change. This study intends to model future urban growth in Awka Capital Territory between 1990 and 2017, using population density, developable land and road network data as influencing factors of growth in the study area.

The works of Hussein and Muhsi (2014), Douglas *et al*, (2000)and Nina and Kumar (2012),the spatial extent changes in the study areas before or after the urban modeling was not attempted, this is necessary especially when studying urban growth and development. Its imperativeness is viewed from the perspective of understanding the spatial extent urban growth.

Since the parameters and datasets are sometimes hugely dependent on the growth models, most of which are commercially expensive, there were no indications of the calibration and validation process of used urban growth models in the works of Hemanandhini*et al* (2016), Xiaojun (2014), Dimitrios*et al* (2012), Dimitrios (2012), and Youjia and Lijun (2014).

This research work part adopted the methodology of the following: Wubishet*et al* (2015), Estes *et al*, (2009) and Estes *et al*, (2010), in addition it used Prescott Spatial Growth Model for predicting future urban development dynamics in Awka Capital Territory due to its unique raster based structure that simply allows easy integration of data, it is also compatible with ESRI ArcGIS software, this is an advantage compared to other models which require UNIX environment. The data needed for the model can be accessed, calibration process is a straight forward procedure with no complications and with several validation techniques.

CHAPTER THREE

METHODOLOGY

Thischapterpresentstheoverallmethods,techniques,approachesandmaterialsadopted in achieving the aim and objectives of the study. Itmainly explainedthedatasourcesandtypes,methodsoffielddata collection,that was used,identification,imageclassification technique that wasemployed,andmodeling methods that were used,accuracyassessment,statistical analysesandlistofsoftwarepackages that wereused to achieve the research objectives. The flowchart for the methodology that was adopted in this study is shown in figure 3.0

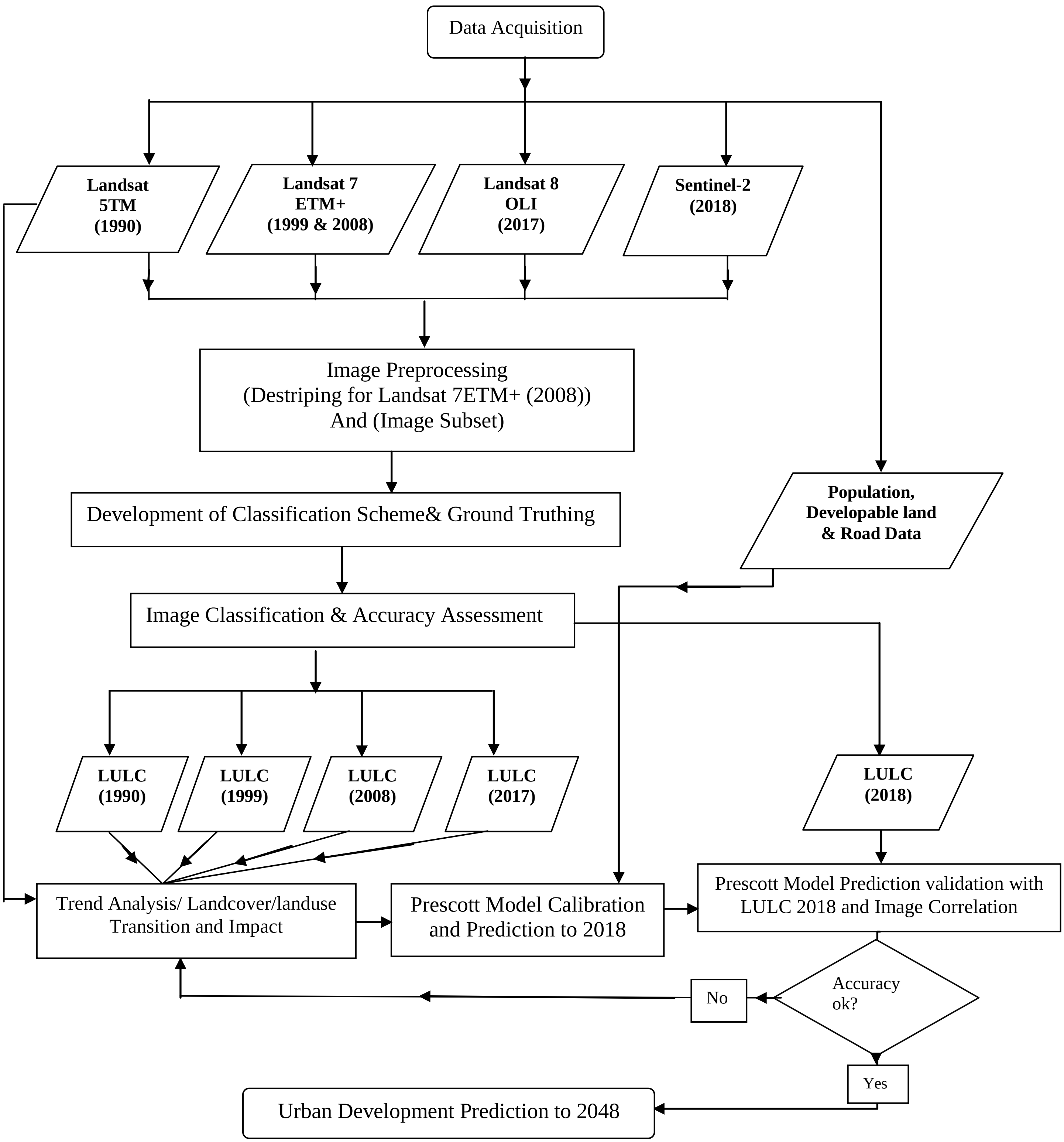

Fig 3.0 Flowchart of Methodology

3.1 Data Requirement:

The images and data that was used in this research includes:

i. Landsat 5 Thematic Mapper
ii. Landsat 7 Enhanced Thematic Mapper
iii. Landsat 8 Operational Land Imager
iv. Sentinel-2
v. Boundary map of Awka Capital Territory
vi. Transportation data ofAwka Capital Territory
vii. Population data of Awka Capital Territory

3.2 Data Acquisition

3.2.1 Acquisition of Primary Datasets

These data were obtained through field visits peculiar to this research. They include the coordinates of randomly selected points of features used for accuracy assessment which was obtained using handheld GPS and non-spatial (attribute) data describing the characteristics of landcover/landuse features on ground.

3.2.2 Acquisition of Secondary Datasets

The secondary datasets needed were obtained from already existing medium. They include:

i. Map of the administrative boundary, published and unpublished records and relevant information about of Awka Capital Territory which was obtained from the Awka Capital Territory Development Authority (ACTDA) Awka.
ii. Landsat and Sentinel imagery were obtained from www.earthexplorer.usgs.gov.

iii. Transportation data was obtained from Anambra state ministry of works, housing and transport.

iv. Estimated population data was obtained from National bureau of statistics Nigeria (NBS), of 1990, 1999, 2008, and 2017.

3.3 Hardware and Software Requirements

3.3.1 Hardware requirements

The hardware components include the equipment that were used for the execution of the research and they include:

i. Garmin 76 handheld GPS, used for collection of co-ordinates of landcover/landuse features during ground truthing.

ii. A computer system to aid processing and analysis.

iii. A scanner, used for scanning analogue maps.

iv. A printer used for presentation of the result in hardcopy format.

v. Digital camera used for taking pictures of the landcover/landuse features in study area.

3.3.2 Software requirements

The following software packages were used for this study:

i. ArcGIS Software version 10.5: This was used to display, process, enhance, process, calibrate, apply and validate Prescott spatial growth model.

ii. Erdas Imagine: This was used for radiometric correction, the development of landcover/landuse classes, transition probability and Accuracy assessment

iii. Microsoft suite (Microsoft Excel and Word): This was used for performing statistical analysis and also the task of editing and production of text report.

3.4 Image preprocessing

Image preprocessing was done in this study to correct scan line dropout in LandSat 7 ETM+ 2008 imagery, the correction filter used was focal statistics in Erdas imagine. The focal statistics tool performs a neighborhood operation that computes an output raster where the value for each output cell is a function of the values of all the input cells that are in a specified neighborhood around that location. The function performed on the input is a statistic, such as the maximum, average, or sum of all values encountered in that neighborhood.

Conceptually, on execution, the algorithm visits each cell in the raster and calculates the specified statistic with the identified neighborhood. The cell for which the statistic is being calculated is referred to as the processing cell. The value of the processing cell, as well as all the cell values in the identified neighborhood, is included in the neighborhood statistics calculation.

The neighborhoods can overlap so that cells in one neighborhood may also be included in the neighborhood of another processing cell.

This was achieved through the following steps:

1. Select Image Interpreter > Spatial > Focal Analysis....
2. Input File: Enter the name of the input file, or click on the File Selector button. The default file extension was .img.
3. Output File: Enter the name of the output file, or click on the File Selector button. The software automatically adds the *.img extension.

4. Coordinate Type: Click the appropriate button to select the type of coordinates to use. If the input file does not have map coordinates, the coordinate type automatically defaults to File.
5. Focal Definition: The checkboxes in this kernel let you define the area of the moving window to use for processing. Turn on a checkbox to include the data value in the computation. Turn off any checkboxes representing values you want to exclude from the computation.

By turning selected checkboxes off, you can create circular and doughnut-shaped kernels. By default, all values are initially turned on (dark).

6. Select Size: Click the dropdown list button to select the kernel size. The choices are:

   3 x 3 (this was used)

   5 x 5

   7 x 7
7. Function Definition: This group lets you select options for the output file.

Function: Click the dropdown arrow to select the type of computation to use for this function.

[Use dropdown list] Click the dropdown arrow to select which values of the input file to use in computing the focal function.

Use all values in computation all values in the input file will be used in the computations.

Ignore specified value(s): Ignore the value specified below. This option is often used to ignore zero.

Use only specified value(s): Use only the values specified below when computing the function.

[Apply dropdown list] Click the dropdown arrow to select which values of the input file you would like to apply the focal function.

Apply function at all values Apply the function to all values.

Don't apply at specified value(s): Apply the function to all values except one. This option is often used to ignore zero.

Apply only at specified value(s): Apply the function to only the values specified below. For example, you may want to apply a focal function to only certain classes of a thematic file. Using this option, you can enter those classes.

[value] If you want to ignore a certain value, or apply the function to only selected values, enter the value(s) here. Enter multiple values as a comma separated list. Enter a range of values using a colon. For example, entering 1:5 would apply the function only to the values 1, 2, 3, 4, and 5.

Ignore Zero in Stats. Whenthis checkbox is on, pixels with zero file values are ignored when statistics are calculated for the output file.

8. OK Click to run this program with the options selected

This is also shown in figure 3.1

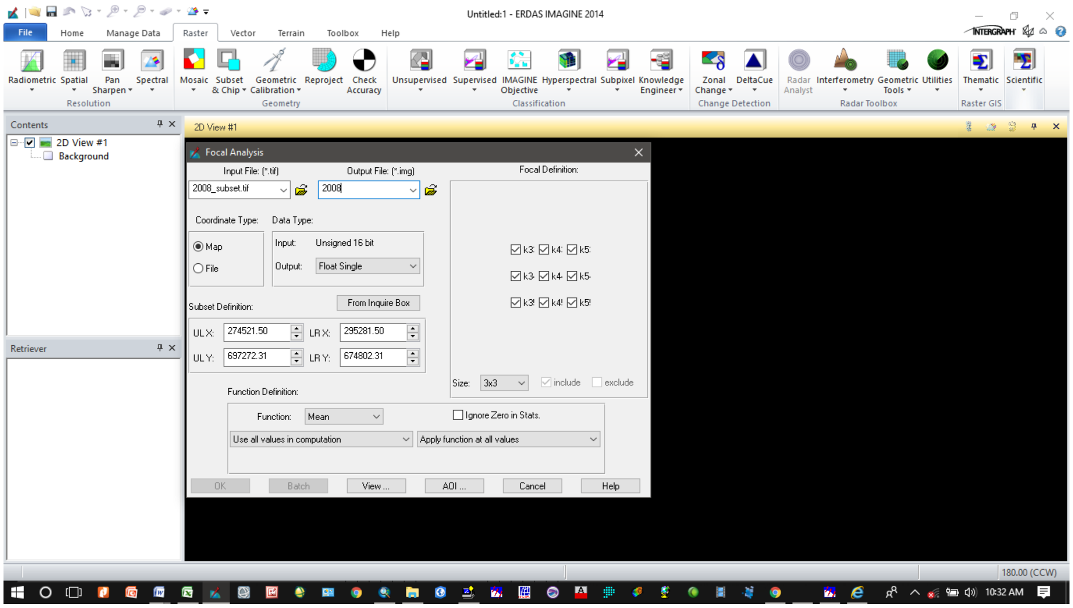

Figure 3.1: Focal statistics process

3.5 Image Subset

This process was carried out in order to cut out the area of interest from the images using the bounding coordinates of Awka Capital Territory gotten from ACTDA (table 3.1). This was achieved using the ArcGIS 10.5 software

Table 3.1: Bounding coordinates of Awka Capital Territory. (ACTDA, 2017)

Points	Easting	Northing
1	274607.529	697272.315
2	295287.410	697195.241
3	295209.287	674817.063
4	274521.502	674891.702

*These coordinates are referenced in the Universal Transverse Mercator Zone 32N.

Then image subset was done in ArcGIS by:

1. Open ArcToolbox
2. Select Data Management Tools

3. Select Raster

4. Select Raster processing

5. Then Select clip.

The clip tool dialogue box opens...

6. Select the input Raster (Image for subset)

7. Leave output extent as blank

8. Enter the bounding coordinated to be used for the subset in the Xmin and Xmax, Ymin and Ymax column

*Xmin and Xmax being the lowest and highest values of the Easting coordinate, this also applies to Ymin and Ymax.

9. Specify output raster (where to save the subset image)

10. Click ok for the process to run.

This process was repeated until a subset had been done for all the images. The software process is also shown in figure 3.2

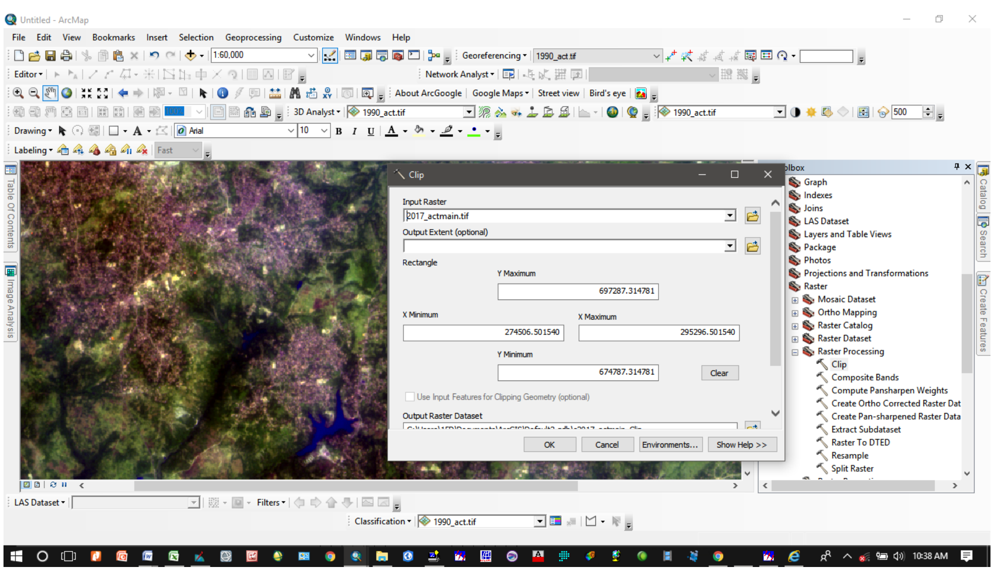

Figure 3.2: Subset Process in ArcGIS

3.6 Development of a Classification Scheme

A classification scheme was developed for the study area after Anderson *et al* (1967). This says that a landuse and landcover classification system which can effectively employ orbital and high-altitude remote sensor data should meet the following criteria (Anderson, 1967):

1. The minimum level of interpretation accuracy in the identification of landuse and landcover categories from remote sensor data should be at least 85 percent.
2. The accuracy of interpretation for the several categories should be about equal.
3. Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.
4. The classification system should be applicable over extensive areas.
5. The categorization should permit vegetation and other types of landcover to be used as surrogates for activity.
6. The classification system should be suitable for use with remote sensor data obtained at different times of the year.
7. Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensor data should be possible.
8. Aggregation of categories must be possible.
9. Comparison with future landuse data should be possible.
10. Multiple uses of land should be recognized when possible.

Some of these criteria should apply to landuse and landcover classification in general, but some of the criteria apply primarily to landuse and landcover data interpreted from remote sensor data.

It is hoped that, at the more generalized first and second levels, an accuracy in interpretation can be attained that will make the landuse and landcover data comparable in quality to those obtained in other ways.

For landuse and landcover data needed for planning and management purposes, the accuracy of interpretation at the generalized first and second levels is satisfactory when the interpreter makes the correct interpretation 85 to 90 percent of the time. For regulation of landuse activities or for tax assessment purposes, for example, greater accuracy usually will be required. Greater accuracy generally will be attained only at much higher cost. The accuracy of landuse data obtained from remote sensor sources is comparable to that acquired by using enumeration techniques.

In addition to perfecting new interpretation techniques and procedures for analysis, such as the various types of image enhancement and signature identification, we can assume that the resolution capability of the various remote sensing systems will also improve resolution, or resolving power, of an imaging system refers to its ability to separate two objects some distance apart. In most landuse applications, we are most interested in the minimum size of an area which can be recognized as having an interpretable landuse or landcover type.

Obviously, such a minimum area depends not only on the type and characteristics of the imaging system involved, but pragmatically also on the order of "generation" of the imagery, that is, how far the study image is removed in number of reproduction stages from the original record. The user should refer to the most recent information available in determining the resolution parameters of the system.

The kind and amount of landuse and landcover information that may be obtained from different sensors depend on the altitude and the resolution of each sensor. There is little likelihood that any one sensor or system will produce good data at all altitudes. It would be desirable to evaluate each source of remote sensing data and its application solely on the basis of the qualities and characteristics of the source.

However, it is common practice to transfer the data to a base map, and no matter what the guidelines are it is difficult to use a base map without extracting some additional data from such maps. Topographic maps, road maps, and detailed city maps will generally contribute detail beyond the capabilities of the remote sensor data.

The multilevel landuse and landcover classification system described has been developed because different sensors will provide data at a range of resolutions dependent upon altitude and scale. In general, the following relations pertain, assuming a 6inch focal length camera is used in obtaining aircraft imagery. The classification level and characteristics is shown in table 3.2.

Table 3.2 Classification levels and data characteristics (Anderson, 1967)

Classification Level	Typical Data Characteristics
I	LANDSAT (formerly ERTS) type of data
II	High-altitude data at 40,000 ft (12,400 m) or above (less than l:8O,OOO scale)
III	Medium-altitude data taken between 10,000 and 40,000 ft (3,100 and 12,400 m) (1:20,000 to 1:80,000 scale)
V	Low-altitude data taken below 10,000 ft (3,100 m) (more than 1:20,000 scale)

Based on these classifications by Anderson *et al* (1967), level one classification scheme was adopted for this study.

3.7 Identification and definition of feature class on the images

This was done to identify and define various class features on the scene before following a familiarization visit to the site. Thus the following class features in Awka Capital Territory were identified and defined according to level I classification scheme, this scheme was adopted because of the resolution of the image sets and to ensure that the features are discriminated adequately following the field visits to the study area as shown in figure 3.3

1. Urban Area
2. Water Body
3. Vegetation
4. Open space

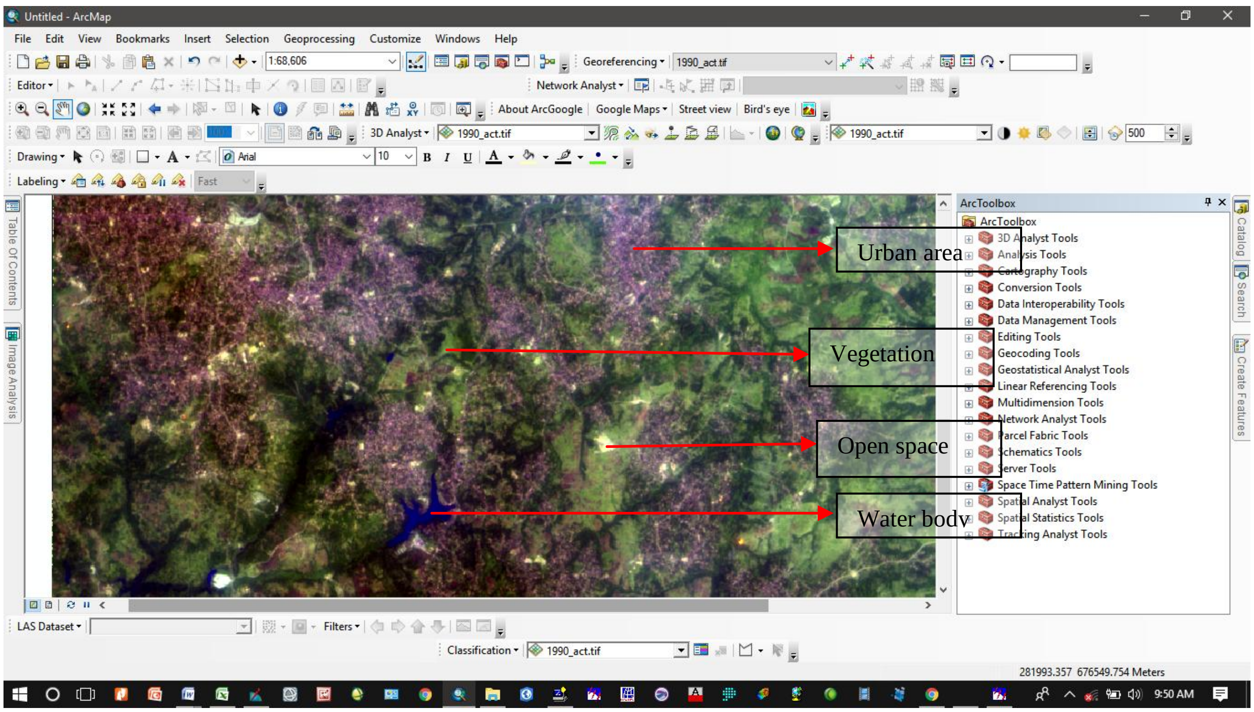

Figure 3.3: Feature class identification process

3.8 Ground Truthing

Groundtruthwas carried out to assesstheaccuracy of the landcover/landuse classification and also collect sample data for accuracy assessment.Forthispurpose,thecoordinates of 256 selected ground controlpointswascollected and used toassesstheaccuracy ofclassification of images. Randomsamplingtechnique wasusedtodeterminethelocationofthepoints.

HandheldGPSGarmin 76 wasused tocollect thefield data.Digitalcamerawas also be used to capturethelandcover types and tying the pictures with the ground coordinates for easy identificationofvisitedsites.

3.9 Accuracy Assessment

Inthisstudy, accuracy assessment was carried out in order to identify the features on satellite image and also for accuracy assessment of data extraction. This was achieved by the following the following steps

1. First Launching into the classifier function
2. Then clicking on the accuracy assessment tool
3. Open the true image and the classified image in separate viewers then link the viewers together
4. Then import points collected from the field on the true image from the accuracy assessment dialog box
5. Fill out the reference by marching the pixel color of the random points on the true image to the classified class types they march
6. Then click on report, then accuracy to perform the accuracy assessment task

These steps were repeated for all classified images as well as the post classification change detection images. This is shown in figure 3.4.

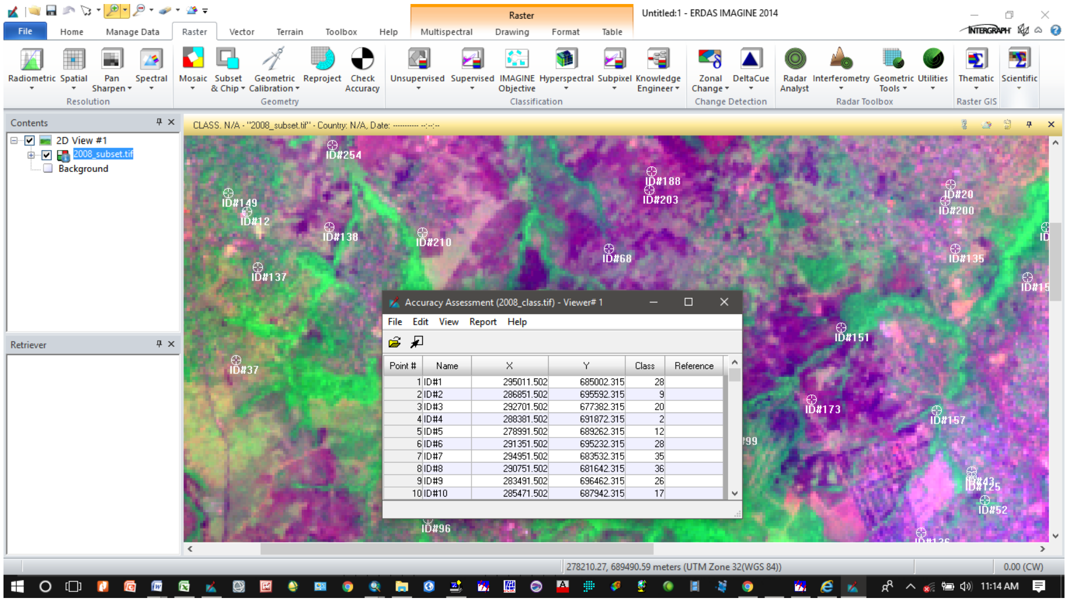

Figure 3.4: Accuracy Assessment process

3.10 Procedures adopted in achieving objective no. 1

Objective no.1: "To examinethe spatial extent of landcover/landuse in Awka Capital Territory for the last 27 years (1990 – 2017)".

To achieve this objective, the subset images of 1990, 1999, 2008, 2017 and 2018 (2018 was used a reference data for model validation) were classified using maximum likelihood supervised classification method in Erdas Imagine. The first stage of this process is the training stage, in the training stage, a training sample was prepared for each of the subset images, where the signature samples of the landcover landuse classes identified on the images were collected, this process was repeated for the five subset images.

To create, manage, evaluate, edit, and classify signatures using the Signature Editor. Signatures are specific areas to which you assign a name to perform supervised classification. Signature files use the. sig extension and since they are hierarchical file architecture (HFA) format

The following types of signatures can be defined:

i. Parametric (statistical) (this was used in this research)

ii. Nonparametric (feature space)

Procedure to create signatures

Signatures were created from AOI (Area of Interest) objects. Signatures can also be collected from feature space images as well as from objects in shapefile data sets that are displayed in a View.

To Create Signature from AOI Object

1. In order to create signatures, you must have the image you are classifying opened in a View.
2. Create an AOI layer.
3. Then, using theDrawing tools, you can create point, line, polygon, and "seed" areas of interest.
4. To enter an AOI into the Signature Editor, first select the object, then select Edit > Add from the Signature Editor menu bar or click the icon on the Signature Editor tool bar.

When all of the signatures are entered, Edit, View, and Evaluate menu options was used to evaluate and edit the signatures. When the signatures have been edited properly, the Classify menu is then used to perform the image classification. The training stage procedure is shown in figure 3.5.

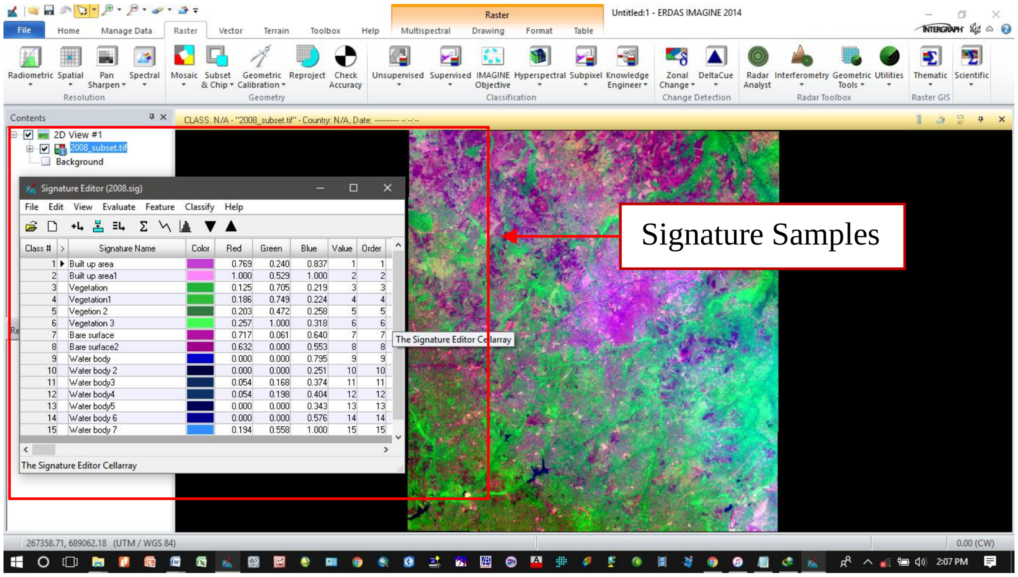

Figure 3.5: Signature sample training stage

After the training stage, the signature samples collected were used to classify the subset images using maximum likelihood supervised classification algorithm in Erdas imagine. This process produced five landcover/landuse maps i.e. 1990, 1999, 2008, 2017 and 2018. The procedure used is shown in figure 4.6 and classified images in fig 3.7.

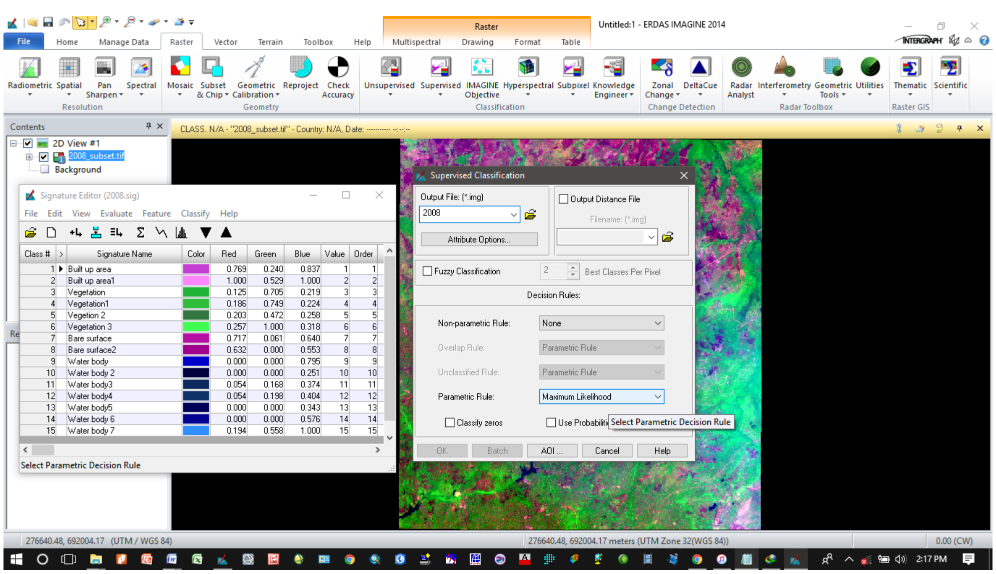

Figure 3.6: Maximum Likelihood Supervised classification process

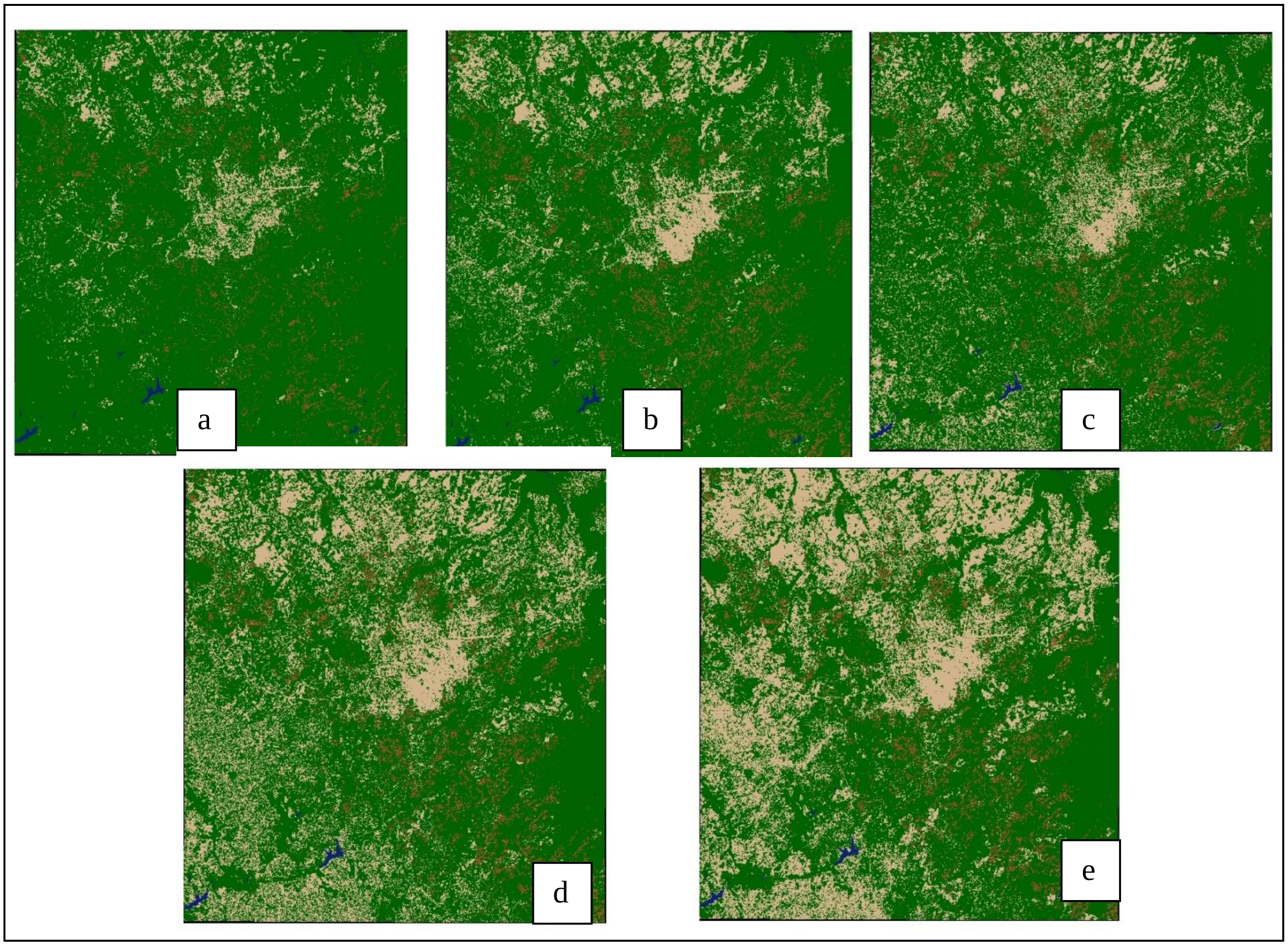

Figure 3.7: Landcover/landuse images of (a) 1990, (b) 1999, (c) 2008 (d) 2017 and (e) 2018

3.11 Procedures adopted in achieving objective no. 2

Objective no 2: “To ascertain the trend of change and transition of the landcover/landuse classes in the last 27 years”.

To achieve this objective, the results obtained from the landcover/landuse classification statistics table was used to compute trend analysis adopted from long *et al* (2007).

A method of calculating and comparing the area of the resulting land cover/land use types of each year was adopted for data analysis. The comparison of the landcover/landuse statistics will assist in identifying the percentage change, trend and annual rate of change between 1990 and 2017. In achieving this, table was prepared showing the areas and percentage change for each year measured against each other. To determine the rate of change of landcover/landuse, the year period 1990-2017 was divided into three sub-periods 1990 – 1999, 1999 – 2008 and 2008 - 2017 and compared against each other.

The comparative analysis in landcover/landuse change focuses on the three sub-periods and the spatial distribution of the average (annual) rate of landcover/landuse change between the three periods as proposed by Long *et al*. (2007).

Percentage change to determine the trend of change can be calculated by dividing the observed change by the sum of the area of the particular landcover/landuse type in that period multiplied by 100

$$\text{(Trend) \% change} = \frac{\text{Observed change x 100}}{\text{Total Area}} \qquad \text{... (3.1)}$$

Where Observed change = (Area of before year – Area of after year)

Total Area = sum of total area of both years

The annual percentage rate = Trend divided by N (number of years).

A trend percentage with a value greater than zero means that the landcover/landuse type has increased over the period of years while a value less than zero shows a decrease in the landcover/landuse type over a period of time.

The transition of the landcover/landuse classes in the last 27 years was also calculated using matrix union and discriminant function change detection in Erdas imagine.

Matrix union and discriminant function change detection was used to compute the probability of change per pixel from two images that depict the same area at different points in time. The process performs an unsupervised classification on the input before image and uses that and discriminant function analysis to compute a probability of change between the input after image to generate any of the output files.

The output images generated are grayscale images composed of single band continuous data with pixel values in the range from 0.0 to 1.0. These values represent the probability that the pixel has changed in a significant way.

I. Values near 0.0 indicate a low probability of change.

II. Values near 1.0 indicate a high probability of change.

This process was done by:

1. Input before Image: This image is the earlier of the two images (before). Enter the name, or click the dropdown arrow to open the Recent Files list.

Click to open a File Selector to navigate to the desired file, or right-click to open the Recent Files list.

2. Input after Image: This image is the more recent of your two images and reflects change over time (after). Enter the name, or click the dropdown arrow to open the Recent Files list.

Click to open a File Selector to navigate to the desired file, or right-click to open the Recent Files list.

3. Specify process Area: Specify the area of the input files to be processed.

4. Select Intersection   Click to automatically use the intersection of the two input files.
5. Select Coordinate Type: Click the appropriate radio button to select the type of coordinates to use. If the input file does not have map coordinates, the coordinate type will automatically default to File.
6. Specify Output Options: Specify the output files to be generated.
7. Select Positive Change Image: Click to check the checkbox to generate an output image based on Input before Image.
8. Select output [file name]: Enter the output file name.

Click to open a File Selector to navigate to the desired directory, or right-click to open the Recent Files list.

9. Select Negative Change Image: Click to check the checkbox to generate an output image based on Input after Image.
10. Select output [file name]: Enter the output file name.

Click to open a File Selector to navigate to the desired directory, or right-click to open the Recent Files list.

11. Select Combined Change Image: Click to check the checkbox to generate an output image based on a combination of Input before image and Input after image, by using the maximum (highest) file values.
12. Click to open a File Selector to navigate to the desired directory, or right-click to open the Recent Files list.

13. Select Low Values: Remove values that are less than the specified number of standard deviations (Sigma) from the mean of the calculated values. Click to check the checkbox to apply this option, and enter a number of standard deviations.
14. Select - [3.00] Sigma^ Enter a value to represent the number of negative standard deviations. The default is 3.00.

High Values: Remove values that are more than the specified number of standard deviations (Sigma) from the mean of the calculated values. Click to check the checkbox to apply this option, and enter a number of standard deviations.

+ [3.00] Sigma^: Enter a value to represent the number of positive standard deviations. The default is 3.00.

15. Unsupervised Options: An unsupervised classification approach measures a multivariate statistical distance of the pixel DN vectors in one image with spectral signatures derived from the other image. These are then converted into probabilities using a proprietary algorithm.
16. Select number of Classes: Specify the number of classes (categories of data) to be created.
17. Maximum Iterations: Enter the number of maximum times that the ISODATA clustering utility should recluster the data. This parameter prevents this utility from running too long, or from potentially getting "stuck" in a cycle without reaching the convergence threshold.
18. Convergence Threshold: Specify the convergence threshold. The convergence threshold is the maximum percentage of pixels whose cluster assignments can go unchanged

between iterations. This threshold prevents the ISODATA utility from running indefinitely.

By selecting a convergence threshold of .95, you specify that as soon as 95% or more of the pixels stay in the same cluster between one iteration and the next, the utility should stop processing. In other words, as soon as 5% or fewer of the pixels change clusters between iterations, the utility stops processing.

19. Skip Factors: For faster (although less accurate) processing, you can enter an X and Y skip factor.

X: Enter the X skip factors to use when processing. Entering a 1 processes all pixels, 2 processes every other pixel, 3 every third pixel, and so forth.

Y: Enter the Y skip factors to use when processing. Entering a 1 processes all pixels, 2 processes every other pixel, 3 every third pixel, and so forth.

20. Click OK: Click to run this program with the options selected and close this dialog.

This process was done as shown in figure 3.8.

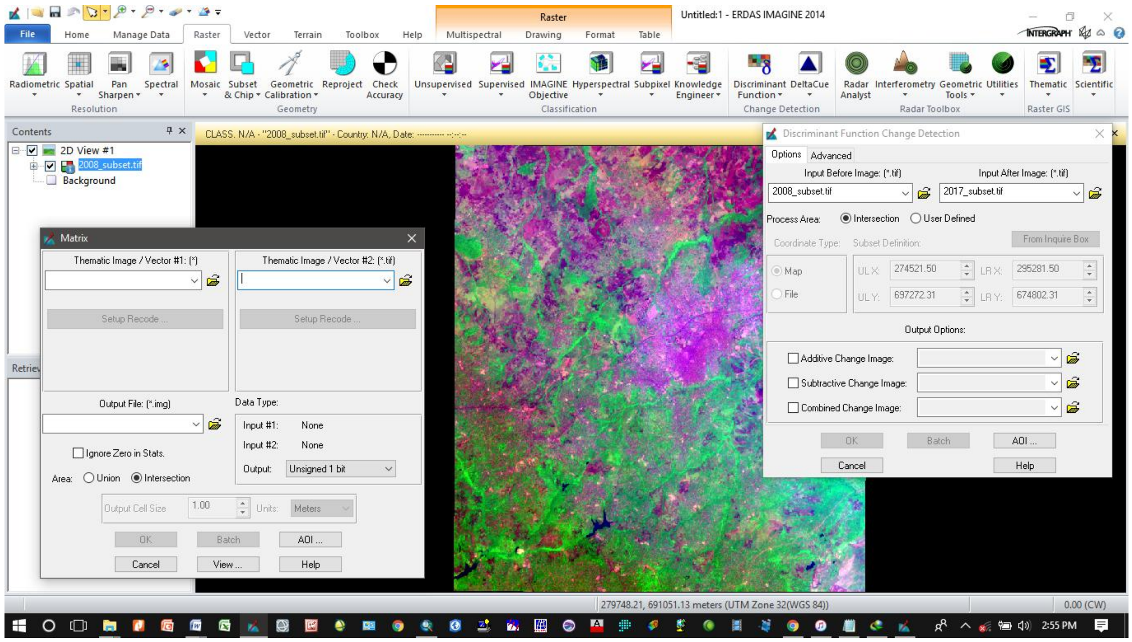

Figure 3.8: Matrix union and discriminant function change detection process

The classes i.e. vegetation and open space within the study area were also significantly tested to determine which class contributed to urban area at a probability level of 0.05. The significance level is the probability value that forms the boundary between rejecting and not rejecting the null hypothesis. This was represented as $P<0.05$ in which P stands for the probability of the null hypothesis. The 0.05 thus represents the probability value that separates a decision to reject null hypothesis from the decision not to reject it.

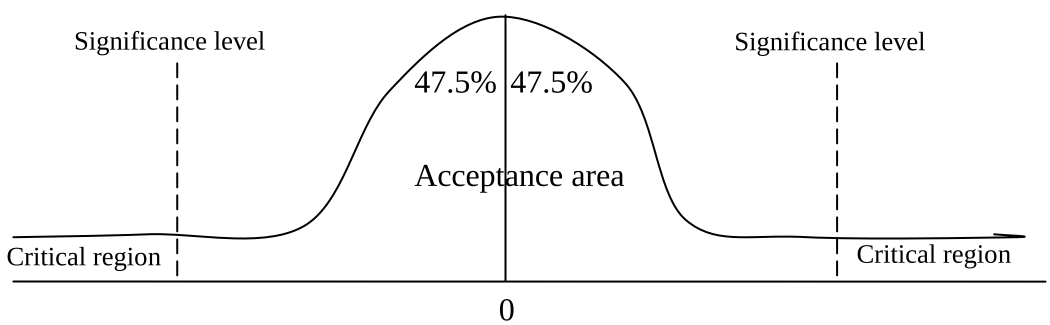

Figure 3.9: Normal curve showing critical region and significance level at 95% (0.05).

The t- test was used to determine whether two classes are significantly different. The formula used is given in equation 3.2 by Pradhan *et al*, (2013). Figure 4.9 shows significance level at 95%.

$$t = \frac{\overline{X1} - \overline{X2}}{\sqrt{\frac{S_1^2 + S_2^2}{n_1 + n_2}}} \quad \text{... (3.2)}$$

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

S - Standard deviation

n - Number of subjects in each class

3.12 Procedures adopted in achieving objective no. 3

Objective no 3: "tovalidate Prescott spatial growth model using landcover/landuse reference data for 2018 and Image Correlation (Pearson's product movement correlation coefficient)'"

To achieve this objective, landcover/landuse maps of 1990, 1999, 2008 and 2017, estimatedpopulation data for 1990, 1999, 2008 and 2017, road network data for 1990, 1999, 2008 and 2017 were used a model inputs and calibrated. For the model to work effectively, these data have to be calibrated, in doing this the population data was used to create a kernel density raster layer, then the raster layer was resampled so that they have the same pixels i.e. column and rows with the landcover/landuse maps, thereby giving them the same geometry.

This was done for road network data and developable land as well by converting themto Euclidean distance raster. After which during the input, the software removes no data backgrounds for data conformity.

The input in the model was done by:

1. Input initial image (select 1990 LULC image from the software interface)
2. Input after image (select 2017 LULC image from software interface)
3. Add spatial variables (select road network data, developable land and population data from software interface)
4. Click on check geometry (checks geometry for conformity between input datasets)

This procedure is shown in figure 3.10.

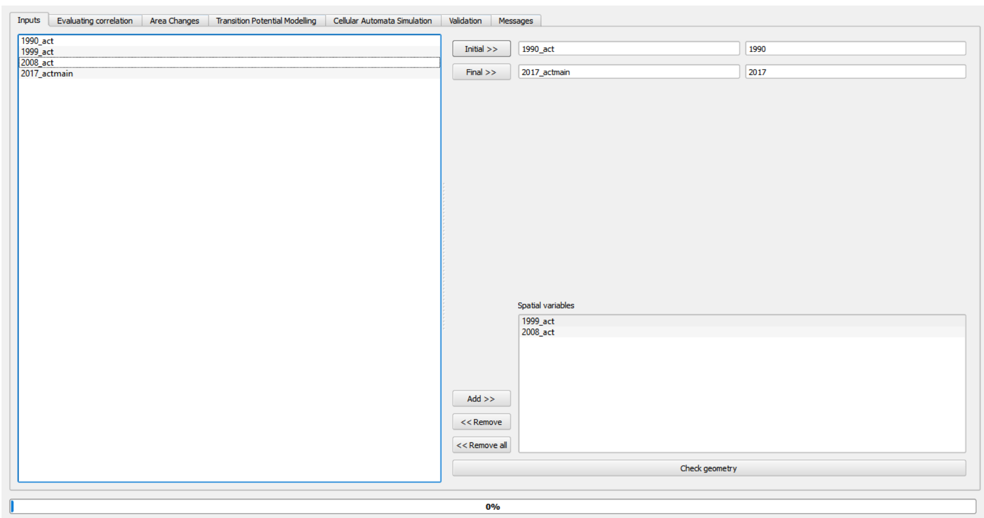

Figure 3.10: Model input process

After this process, the model was trained using artificial neural network, the training works by using classic realization of multilayer perceptron. The input data is a collection of pixels of initial state raster and factor rasters. The target output data is the change map.

So, the model performs the following actions:

1. Initial preprocessing of the data (dummy coding and normalization).
2. Sampling.
3. Training.

The model uses multilayer perceptron with numpy.tanh sigmoid function. Therefore, target variables (the change map categories) was scaled to (-1, 1) interval during dummy coding instead of (0, 1). A user can set arbitrary number of hidden layers (one or more) and arbitrary number (one or more) of neurons in the layers.

Training set is divided in two parts: learning set (80% of samples by default) and validation set (20% of samples).

The module uses on-line learning with stochastic: a random sample is selected from the learning set; the weights of the net are updated during forward/backward propagation.

A error of fitting (for a sample) is the average square error of partial outputs of the net:

$$E = \frac{t_i - o_i}{d} \qquad \text{… 3.3}$$

Where E is a sample error, t_i is the target value of a output neuron for given sample, o_i is the real output value of the neuron, d is the count of output neurons.

The module then returns this information about learning:

i. Graph of the average square errors. The errors (mean of all E on learning set and validation set) are calculated on learning and validation sets after every epoch and plotted on the graph.

ii. Min validation overall error. This is average square error E that is achieved on all validation set (mean of all E on validation set). This is the best currently achieved result. The weights of the net are stored and after training the best weights will be returned as the best net.

iii. Delta overall accuracy. It is the difference between min validation error and current validation error.

iv. Current validation kappa. It is the kappa statistic achieved on the validation set

The software procedure to model the transition potential was done by:

1. Click and define number of samples (1000 random samples were used)
2. Select method for training transition potential (Artificial neural network was used)
3. Select neighborhood sampling point (1px was used)
4. Select learning rate (0.100 was used)
5. Select maximum number of iterations (1000 was used)
6. Then click on train for the process to run

This process is shown in figure 3.11

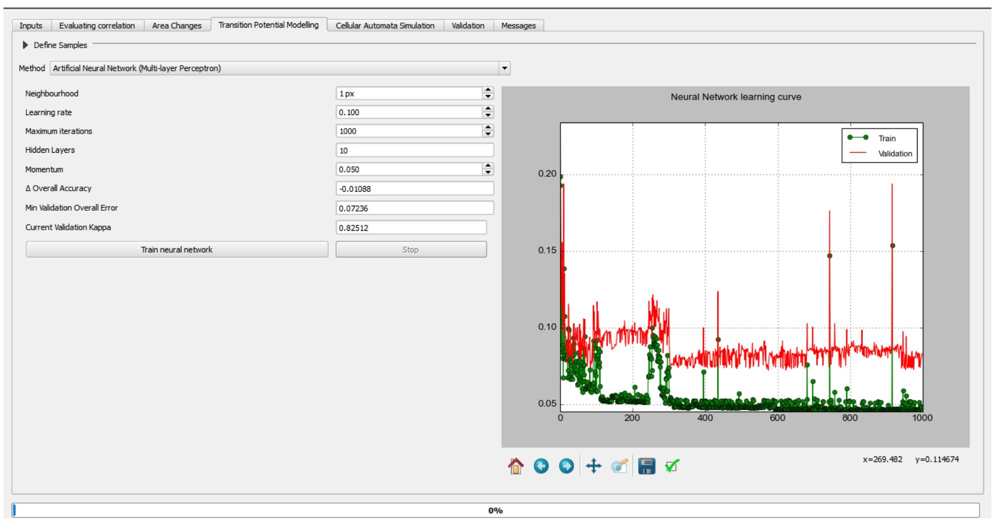

Figure 3.11: ANN training process

After this ANN training, the model was then used to predict urban development in 2018. The result of the prediction was then validated by comparing it with the reference data i.e. the landcover/landuse map of 2018, by cross tabulation, kappa statistics and image correlation (Pearson's product-moment correlation coefficient). This was done by

1. Selecting the reference map (LULC map of 2018 was used)
2. Selecting the simulated map (the results from the 2018 prediction was used)

3. Then click on validate for the process to run

This is shown in fig 3.12

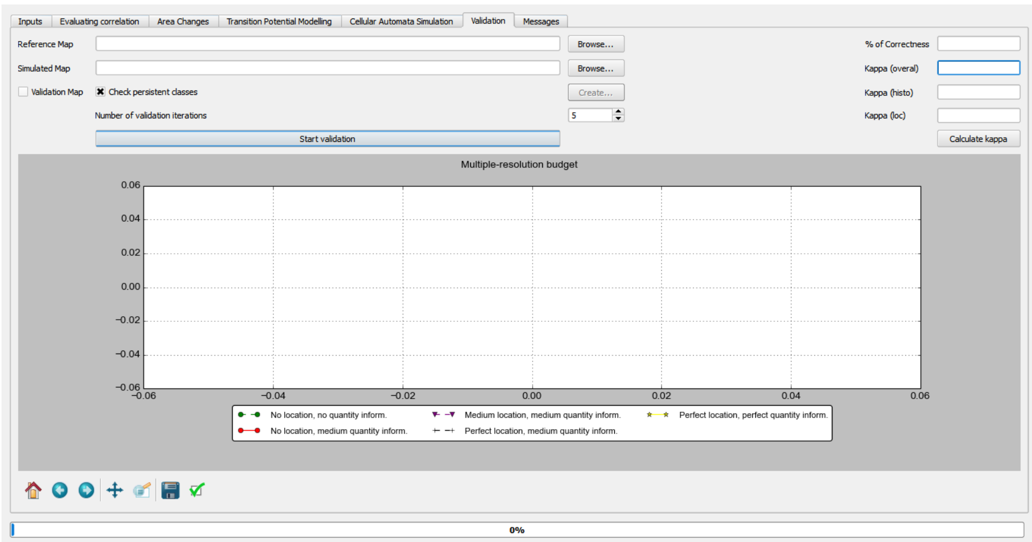

Figure 3.12: Model Validation process

4.13 Procedures adopted in achieving objective no. 4

Objective no.4: "To predict future urban development for the next 30 years (2018 – 2048)"

After the validation, and ascertaining that the model results were within acceptable range (kappa statistics of 0.9083), the objective no.4 was then achieved by predicting future urban development for the next 30years (2018 - 2048) using the transition potentials modeled and trained by artificial neural network. The module works as follow scheme:

1. Simulator takes transition probabilities from the transition matrix and calculates count of pixels that has to be changed (for every transition class);
2. Simulator calls a model, pass to its initial state raster and factor rasters

3. The model scans pixels of the rasters (and its neighbors if the model uses neighborhood) and calculates transition potentials of every transition class;
4. Simulator constructs a 'certancy' raster i.e. the pixel of the raster are the difference between two most large potentials of correspondent pixels of transition potential rasters. As result the raster contains the model confidence: the bigger is difference, the bigger is confidence;
5. Simulator constructs a raster of the most probable transitions i.e. the pixels of the raster are the transition class with the biggest potential of transition. This raster is an auxiliary raster used during the next stage.
6. For every transition class, the simulator searches in the raster of the most probable transitions, a needed count of pixels with the greatest confidence and changes the category of the pixels. If confidence of two or more pixels is close, then random choice of the pixel is used.

The module gives the following outputs:

i. Rasters of transition potential (scaled to percents) that are output from the models
ii. Raster of the difference between the two most large potentials or 'certancy';
iii. Result of simulation.

The described scheme is used if a user specified only on1.e iteration of simulation. If several iterations have to be performed, in general the scheme is the same, but initial state rasters are changed on the next iterations: the first simulated map is the initial state map for the second iteration, the result of the second iteration is the initial states of the third iteration and so on.

This procedure was done by:

1. Clicking on the simulation tab
2. Check the box for “prefix of transition potential maps” and select a location to save
3. Check the box for “certancy function” and select a location to save
4. Check the box for “simulation result” and select a location to save
5. Select number of iterations
6. Then click on start for the simulation process to run

3.14: Estimating Land Surface Temperature

In order to analyze the effect of Urban growth on urban heat islands, land surface temperature of Awka capital territory was estimated from Landsat 5 TM, Landsat 7 ETM+ and Landsat 8OLI. The calculation was done by:

1. Converting top of atmosphere (TOA) radiance:

Using the radiance rescaling factor, Thermal Infra-Red Digital Numbers was converted to TOA spectral radiance using the formula:

$$L\lambda = ML * Qcal + AL \qquad \ldots 3.4$$

Where:

$L\lambda$ = TOA spectral radiance (Watts/ (m2 * sr * µm))

ML = Radiance multiplicative Band (No.)

AL= Radiance Add Band (No.)

Qcal= Quantized and calibrated standard product pixel values (DN)

2. Converting Top of Atmosphere (TOA) Brightness Temperature:

Spectral radiance data was converted to top of atmosphere brightness temperature using the thermal constant Values in Meta data file.

$$BT = K2 / \ln (k1 / L\lambda + 1) - 272.15 \quad \text{… 3.5}$$

Where:

BT = Top of atmosphere brightness temperature (°C)

$L\lambda$ = TOA spectral radiance (Watts/(m2 * sr * µm))

K1 = K1 Constant Band (No.)

K2 = K2 Constant Band (No.)

3. Calculating Normalized Differential Vegetation Index (NDVI):

The Normalized Differential Vegetation Index (NDVI) is a standardized vegetation index which was calculated using Near Infra-red and Red bands.

$$NDVI = (NIR - RED) / (NIR + RED) \quad \text{… 3.6}$$

Where:

RED= DN values from the RED band

NIR= DN values from Near-Infrared band

4. Calculating Land Surface Emissivity (LSE):

Land surface emissivity (LSE) is the average emissivity of an element of the surface of the Earth, this wasfirstly calculated from NDVI values to get Proportion of vegetation value.

$PV = [(NDVI – NDVI\ min) / (NDVI\ max + NDVI\ min)]^2$ … 3.7

Where:

PV = Proportion of Vegetation

NDVI = DN values from NDVI Image

NDVI min = Minimum DN values from NDVI Image

NDVI max = Maximum DN values from NDVI Image

Then Land Surface Emissivity is calculated by

$E = 0.004 * PV + 0.986$ … 3.8

Where:

E = Land Surface Emissivity

PV = Proportion of vegetation

5. Calculating Land Surface Temperature (LST):

The Land Surface Temperature (LST) is the radiative temperature which was calculated using Top of atmosphere brightness temperature, Wavelength of emitted radiance, Land Surface Emissivity.

$LST = (BT / 1) + W * (BT / 14380) * \ln(E)$ … 3.9

Where:

BT = Top of atmosphere brightness temperature (°C)

W = Wavelength of emitted radiance

E = Land Surface Emissivity

CHAPTER FOUR

PRESENTATION AND DISCUSSION OF RESULTS

This chapter presents the overall results as obtained from the analysis done to achieve the set objectives. The results of the landcover/landuse mapping between 1990 and 2018, trend analysis and landcover/landuse transition, hypothesis testing, calibration and validation of Prescott Spatial Growth Model and future urban development prediction are subsequently discussed.

4.2 Landcover/landuse mapping

4.2.1 Landcover/landuse mapping of Awka Capital Territory in 1990

The landcover/landuse distribution of Awka Capital Territory in 1990 as shown in figure 4.1 and table 4.1 indicate that vegetation, accounted for the largest land cover/use of about 50% and anarea of about 23144.9 hectares. Urban area had 27.92 % and a coverage area of 12922.45 hectares.Open space and water body had the lowest turnout with 12.82% and 9.26% with an area of 5936.22 and 4286.22 hectares respectively.

Table 4.1: Landcover/Landuse distribution for 1990

Class Name	Area (Hectares)	Percentage (%)
Urban area	12922.45	27.92
Vegetation	23144.9	50.00
Open space	5936.22	12.82
Water body	4286.22	9.26
Total	46289.79	100

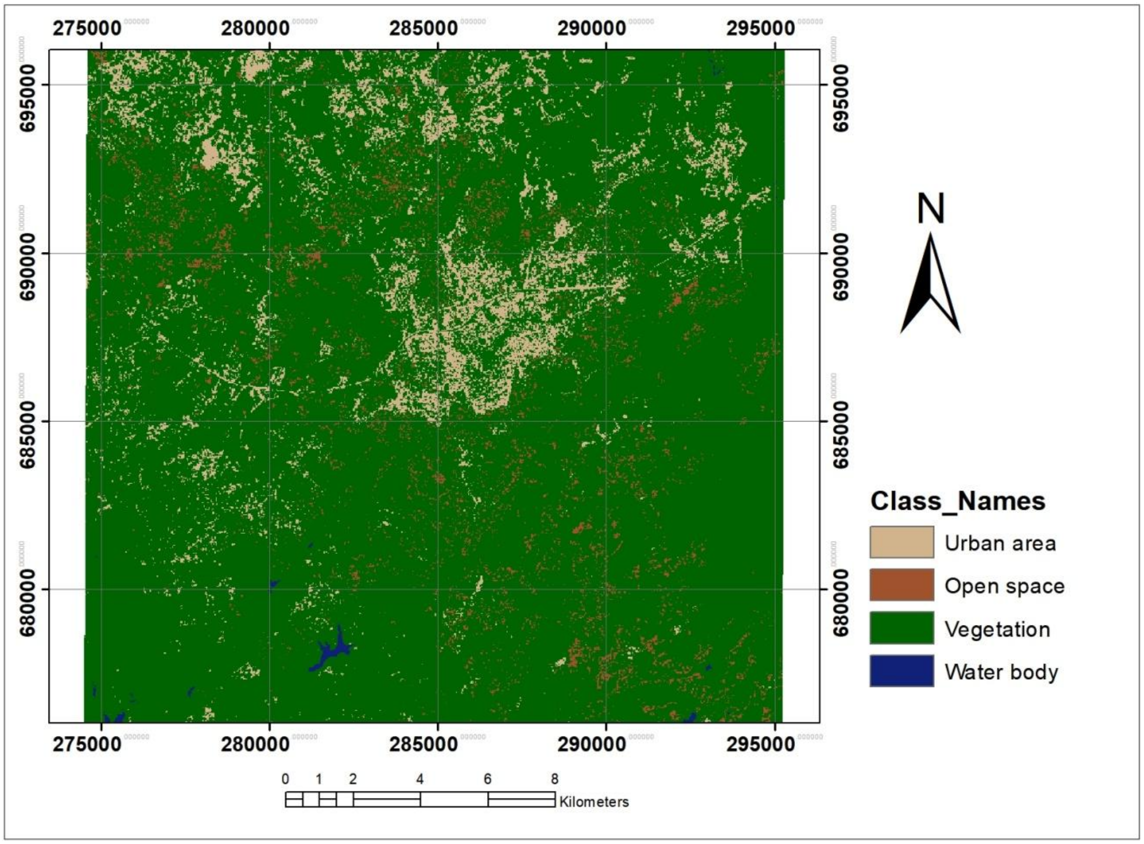

Figure 4.1: Landcover/landuse map of Awka Capital Territory 1990

A confusion matrix was calculated to determine the accuracy of the landcover/landuse classification, the confusion matrix is an indication of major problems in situation where spectral responses of scene features overlap, where categories shares identical spectral signatures (Ndukwe, 1997).

The precision of the classified images was ascertained and accuracy assessment was carried out by comparing the classified landsat image with known reference pixels. Table foraccuracy assessment was prepared as shown in tables 4.2

Table 4.2: Accuracy assessment for 1990 Landsat 5 TM (supervised classification)

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	ReferenceTotals	ClassifiedTotals	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	80	81	78	97.50%	96.30%	0.9461
Vegetation	73	69	67	91.78%	97.10%	0.9595
Open space	99	102	99	100.00%	97.06%	0.952
Water body	4	4	4	100.00%	100.00%	1
Totals	256	256	248			Overall K^ =
Overall Classification Accuracy = 96.88%						0.9534

Intable 4.2,the total reference points used was 256 and total number of points classified was 256, the total number of correctly classified points was 248.

Urban area had a total reference of 80 points, total classified of 81 points and number of correctly classified points as 78. This gives the producer's accuracy for urban area as 97.50% and user's accuracy as 96.30%. The kappa for urban area was at an agreeable value of 0.9461.

Vegetation had a total reference of 73 points, total classified of 69 points and number of correctly classified points as 67. This gives the producer's accuracy for vegetation as 91.78% and user's accuracy as 97.10%. The kappa for vegetation was at an agreeable value of 0.9595.

Open space had a total reference of 99 points, total classified of 102 points and number of correctly classified points as 99. This gives the producer's accuracy for open space as 100.00% and user's accuracy as 97.06%. The kappa for open space was at an agreeable value of 0.952.

Water body had a total reference of 4 points, total classified of 4 points and number of correctly classified points as 4. This gives the producer's accuracy for water body as 100.00% and user's accuracy as 100.00%. The kappa for water body was at an extremely agreeable value of 1. The overall classification accuracy gotten was 96.88% and the overall kappa was 0.9534.

4.2.3 Landcover/landuse mapping of Awka Capital Territory in 1999

The landcover/landuse distribution of Awka Capital Territory in 1999 as shown in figure 4.2 and table 4.3, indicated that vegetation, accounted for the largest land cover/use of about 46.73% and an area of about 21629.79hectare. Urban area had 31.19 % and a coverage area of 14437.68hectares.Open space and water body had the lowest turnout with 12.30% and 9.78% with an area of 5693.72and 4528.6hectares respectively.

Table 4.3: Landcover/Landuse distribution for 1999

Class Name	Area (Hectares)	Percentage (%)
Urban area	14437.68	31.19
Vegetation	21629.79	46.73
Open space	5693.72	12.30
Water body	4528.6	9.78
Total	46289.79	100

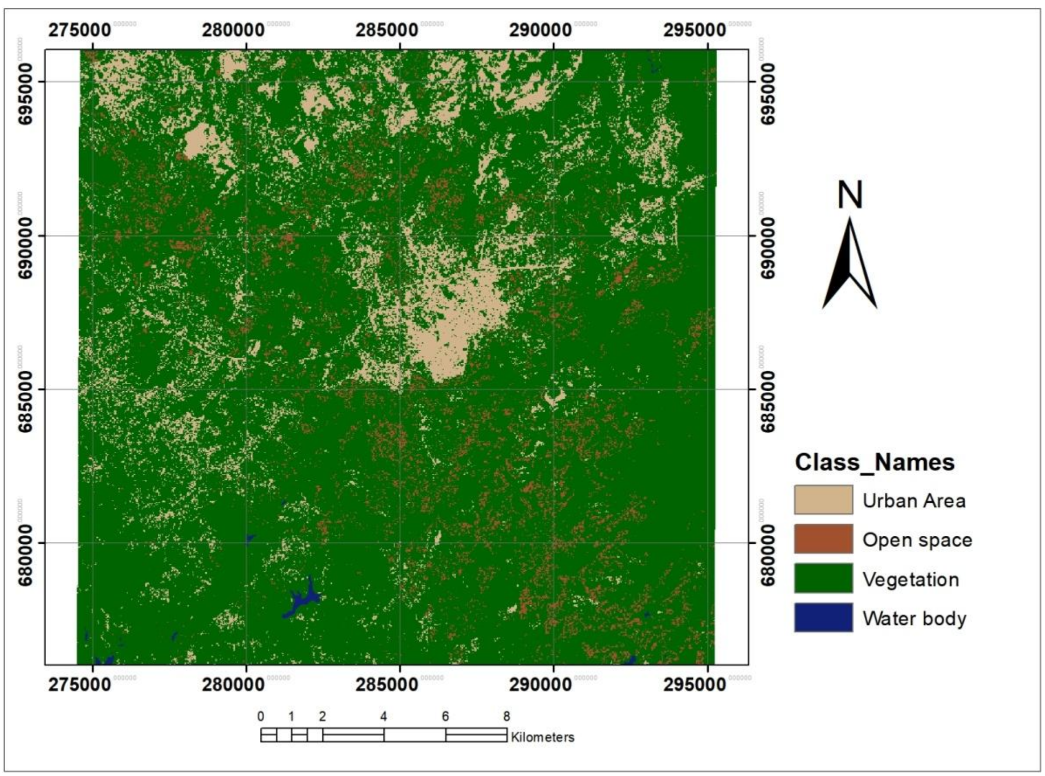

Figure 4.2: Landcover/landuse map of Awka Capital Territory 1999

Table 4.4: Accuracy assessment for 1999 Landsat 7 ETM+ (supervised classification)

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	ReferenceTotals	ClassifiedTotals	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	187	184	181	96.79%	98.37%	0.9395
Vegetation	57	61	57	100.00%	93.44%	0.9156
Open space	9	7	6	66.67%	85.71%	0.8519
Water body	3	4	3	100.00%	75.00%	0.747
Totals	256	256	247			Overall K^ =
Overall Classification Accuracy = 96.48%						0.9164

Intable 4.4,the total reference points used was 256 and total number of points classified was 256, the total number of correctly classified points was 247.

Urban area had a total reference of 187 points, total classified of 184 points and number of correctly classified points as 181. This gives the producer's accuracy for urban area as 96.79% and user's accuracy as 98.37%. The kappa for urban area was at an agreeable value of 0.9395.

Vegetation had a total reference of 57 points, total classified of 61 points and number of correctly classified points as 57. This gives the producer's accuracy for vegetation as 100% and user's accuracy as 93.44%. The kappa for vegetation was at an agreeable value of 0.9156.

Open space had a total reference of 9 points, total classified of 7 points and number of correctly classified points as 6. This gives the producer's accuracy for open space as 66.67% and user's accuracy as 85.71%. The kappa for open space was at an agreeable value of 0.8519.

Water body had a total reference of 3 points, total classified of 4 points and number of correctly classified points as 3. This gives the producer's accuracy for water body as 100.00% and user's accuracy as 75.00%. The kappa for water body was at an agreeable value of 0.747. The overall classification accuracy gotten was 96.48% and the overall kappa was 0.9164.

4.2.4 Landcover/landuse mapping of Awka Capital Territory in 2008

The land cover/land use distribution of Awka Capital Territory in 2008 as shown in figure 4.3 and table 4.5 indicated that vegetation accounted for the largest landcover/landuse of about 44.47% with an area of about 20583.59 hectares. Urban area with 33.67% and an area of 15586.73 hectares, water bodyand open space had the lowest outcome with 9.78% and 12.07% with an area of 4529.8 and 5589.67hectares respectively.

Table 4.5: Landcover/Landuse distribution for 2008

Class Name	Area (Hectares)	Percentage (%)
Urban area	15586.73	33.67
Vegetation	20583.59	44.46
Open space	5589.67	12.07
Water body	4529.8	9.78
Total	46289.79	100

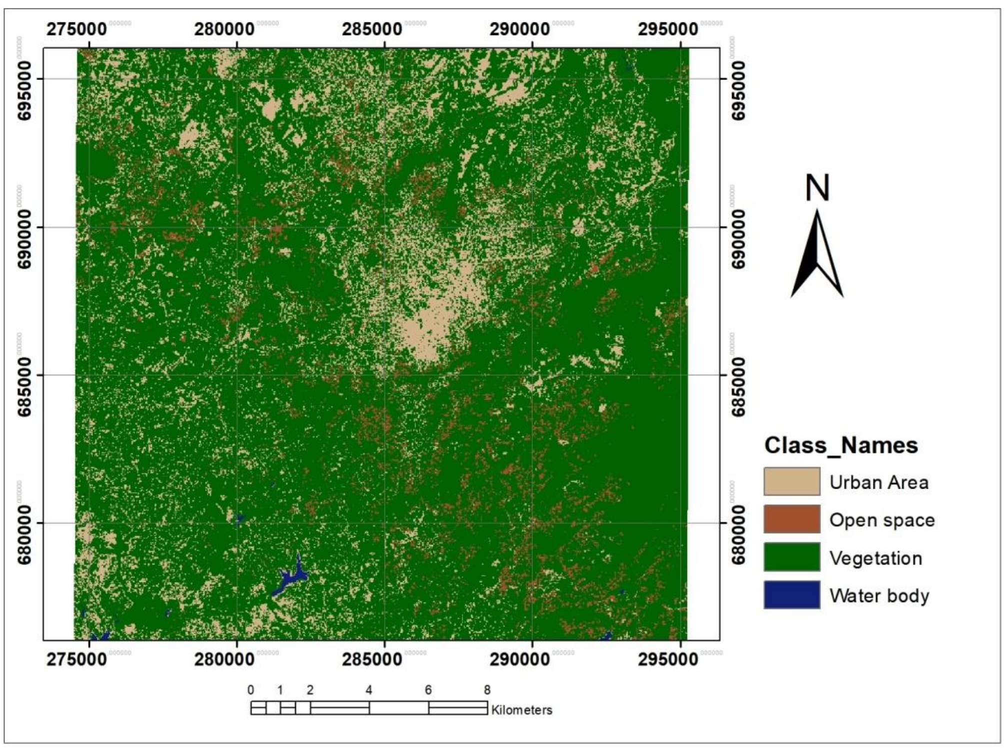

Figure 4.3: Landcover/landuse map of Awka Capital Territory 2008

Table 4.6: Accuracy assessment for 2008 Landsat 7 ETM+ (supervised classification)

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	ReferenceTotals	ClassifiedTotals	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	87	85	82	94.25%	96.47%	0.9465
Vegetation	85	83	80	94.12%	96.39%	0.9459
Open space	72	76	72	100.00%	94.74%	0.9268
Water body	10	10	10	100.00%	100.00%	1
Totals	256	256	246			Overall K^ =
Overall Classification Accuracy = 96.09%						0.9437

Intable 4.6,the total reference points used was 256 and total number of points classified was 256, the total number of correctly classified points was 246.

Urban area had a total reference of 87 points, total classified of 85 points and number of correctly classified points as 82. This gives the producer's accuracy for urban area as 94.25% and user's accuracy as 96.47%. The kappa for urban area was at an agreeable value of 0.9465.

Vegetation had a total reference of 85 points, total classified of 83 points and number of correctly classified points as 80. This gives the producer's accuracy for vegetation as 94.12% and user's accuracy as 96.39%. The kappa for vegetation was at an agreeable value of 0.9459.

Open space had a total reference of 72 points, total classified of 76 points and number of correctly classified points as 72. This gives the producer's accuracy for open space as 100% and user's accuracy as 94.74%. The kappa for open space was at an agreeable value of 0.9268.

Water body had a total reference of 10 points, total classified of 10 points and number of correctly classified points as 10. This gives the producer's accuracy for water body as 100.00% and user's accuracy as 100.00%. The kappa for water body was at an agreeable value of 1. The overall classification accuracy gotten was 96.09% and the overall kappa was 0.9437.

4.2.5 Landcover/landuse mapping of Awka Capital Territory in 2017

The land cover/land use distribution of Awka Capital Territory in 2017 as shown in figure 4.4 and table 4.7 indicated that vegetation also accounted for the largest land cover/use of about 41.29%, and an area of about 19115.32 hectares. Urban area accounted for 37.24% and an area of 17237.45 hectares, water bodyand open space had 9.94% and 11.54% and area coverages of 4601.35 and 5334.67hectares respectively.

Table 4.7: Landcover/Landuse distribution for 2017

Class Name	Area (Hectares)	Percentage (%)
Urban area	17237.45	37.24
Vegetation	19115.32	41.29
Open space	5334.67	11.52
Water body	4602.35	9.94
Total	46289.79	100

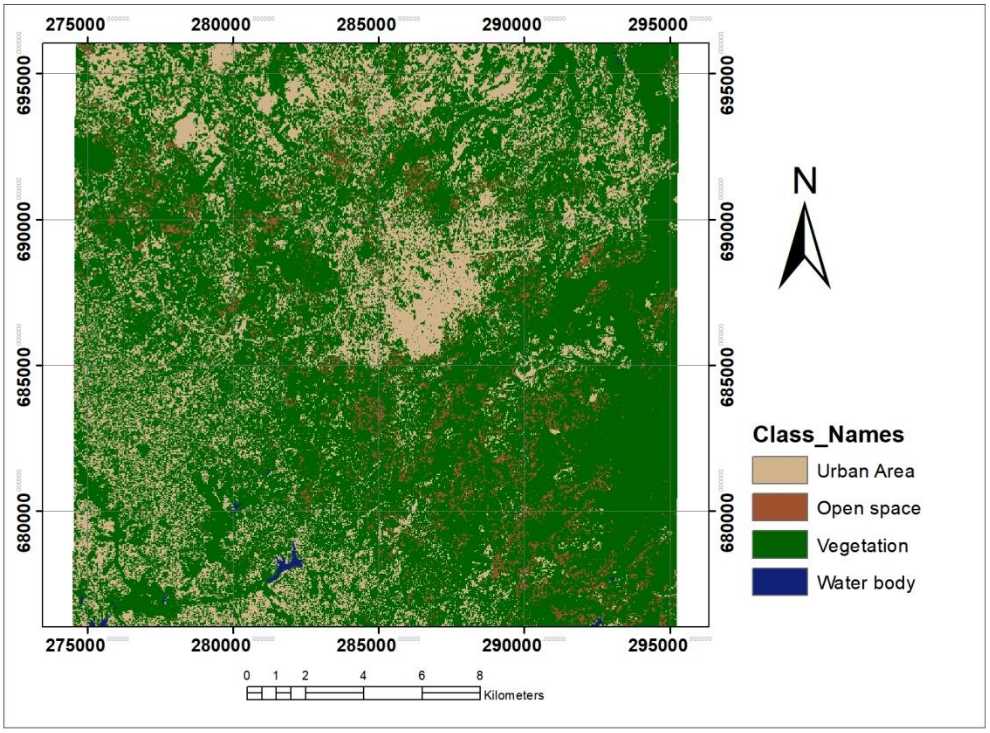

Figure 4.4: Landcover/landuse map of Awka Capital Territory 2017

Table 4.8: Accuracy assessment for 2017 Landsat 8 OLI (supervised classification)

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	ReferenceTotals	ClassifiedTotals	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	189	189	189	100.00%	100.00%	1
Vegetation	22	22	21	95.45%	95.45%	0.9534
Open space	28	28	28	100.00%	100.00%	1
Water body	17	17	16	94.11%	94.11%	0.9601
Totals	256	256	254			Overall K^ =
Overall Classification Accuracy = 99.22%						0.9710

From Table 4.8,the total reference points used was 256 and total number of points classified was 256, the total number of correctly classified points was 254.

Urban area had a total reference of 189 points, total classified of 189 points and number of correctly classified points as 189. This gives the producer’s accuracy for urban area as 100% and user’s accuracy as 100%. The kappa for urban area was at an agreeable value of 1.

Vegetation had a total reference of 22 points, total classified of 22 points and number of correctly classified points as 21. This gives the producer’s accuracy for vegetation as 95.45% and user’s accuracy as 95.45%. The kappa for vegetation was at an agreeable value of 0.9534.

Open space had a total reference of 28 points, total classified of 28 points and number of correctly classified points as 28. This gives the producer’s accuracy for open space as 100% and user’s accuracy as 100%. The kappa for open space was at an agreeable value of 1.

Water body had a total reference of 17 points, total classified of 17 points and number of correctly classified points as 16. This gives the producer’s accuracy for water body as 94.11% and user’s accuracy as 94.11%. The kappa for water body was at an agreeable value of 0.9601. The overall classification accuracy gotten was 99.22% and the overall kappa was 0.9710.

4.2.6 Landcover/landuse mapping of Awka Capital Territory in 2018

The land cover/land use distribution of Awka Capital Territory in 2018 as shown in figure 4.5 and table 4.9 indicated that vegetation also accounted for the largest landcover/landuse of about 40.08%, and an area of about 18555.33 hectares. Urban area accounted for 38.45% and an area of 17798.44 hectares while water body and open space had 9.96% and 11.50% and an area of 4611.35 and 5324.67hectares respectively.

Table 4.9: Landcover/Landuse distribution for 2018

Class Name	Area (Hectares)	Percentage (%)
Urban area	17798.44	38.450034
Vegetation	18555.33	40.085146
Open space	5324.67	11.502904
Water body	4611.35	9.961916
Total	46289.79	100

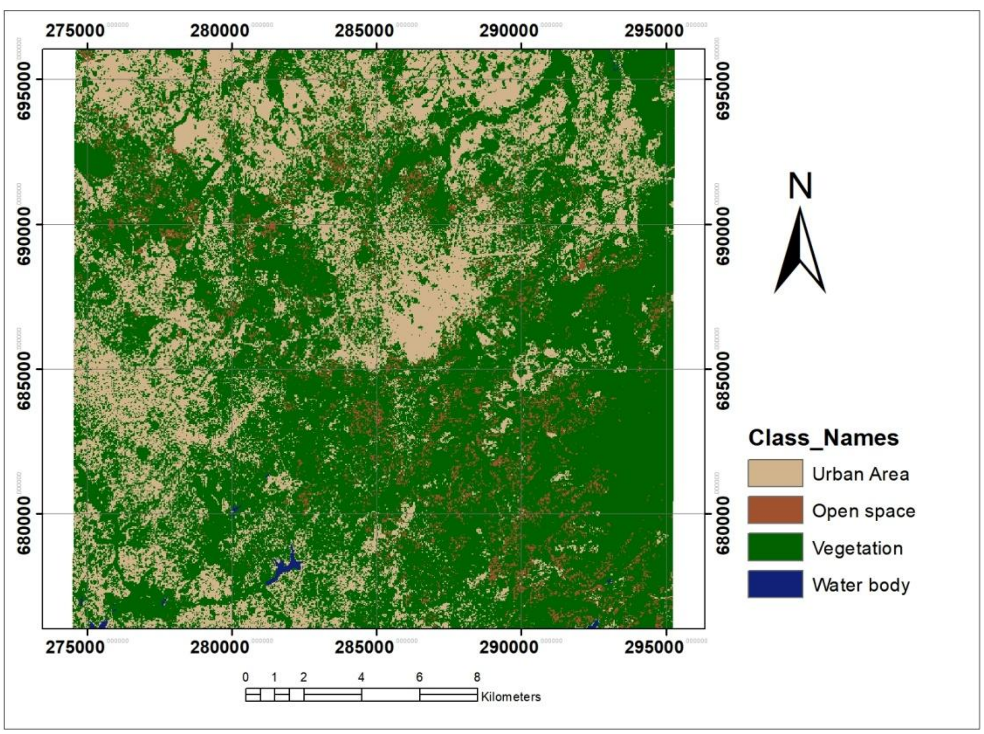

Figure 4.5: Landcover/landuse map of Awka Capital Territory 2018

Table 4.10: Accuracy assessment for 2018 Sentinel-2 (supervised classification)

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	ReferenceTotals	ClassifiedTotals	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	111	111	110	99.10%	99.10%	0.9906
Vegetation	73	73	73	100.00%	100.00%	1
Open space	42	42	41	97.62%	97.62%	0.9789
Water body	30	30	30	100.00%	100.00%	1
Totals	256	256	254			Overall K^ =
Overall Classification Accuracy = 99.22%						0.9924

From table 4.10,the total reference points used was 256 and total number of points classified was 256, the total number of correctly classified points was 254.

Urban area had a total reference of 111 points, total classified of 111 points and number of correctly classified points as 110. This gives the producer's accuracy for urban area as 99.10% and user's accuracy as 99.10%. The kappa for urban area was at an agreeable value of 0.9906.

Vegetation had a total reference of 73 points, total classified of 73 points and number of correctly classified points as 73. This gives the producer's accuracy for vegetation as 100% and user's accuracy as 100%. The kappa for vegetation was at an agreeable value of 1.

Open space had a total reference of 42 points, total classified of 42 points and number of correctly classified points as 41. This gives the producer's accuracy for open space as 97.62% and user's accuracy as 97.62%. The kappa for open space was at an agreeable value of 0.9789.

Water body had a total reference of 30 points, total classified of 30 points and number of correctly classified points as 30. This gives the producer's accuracy for water body as 100% and user's accuracy as 100%. The kappa for water body was at an agreeable value of 1. The overall classification accuracy gotten was 99.22% and the overall kappa was 0.9924.

4.2.7 Summary of landcover/landuse analysis of Awka Capital Territory from 1990 to 2018

The summary of landcover/landuse analysis of Awka Capital Territory is displayed in table 4.11 and figure 4.6 and summarily discussed below.

Table 4.11: Landcover/landuse distribution of Awka Capital Territory from 1990 to 2018

Class Name	1990		1999		2008		2017		2018	
	Area	%	Area	%	Area	%	Area	%	Area	%
Urban area	12922.45	27.92	14437.68	31.19	15586.73	33.67	17237.45	37.24	17798.44	38.45
Vegetation	23144.9	50.00	21629.79	46.73	20583.59	44.46	19115.32	41.29	18555.33	40.08
Open space	5936.22	12.82	5693.72	12.30	5589.67	12.07	5334.67	11.52	5324.67	11.50
Water body	4286.22	9.26	4528.6	9.78	4529.8	9.78	4602.35	9.94	4611.35	9.96
Total	46289.79	100	46289.79	100	46289.79	100	46289.79	100	46289.79	100

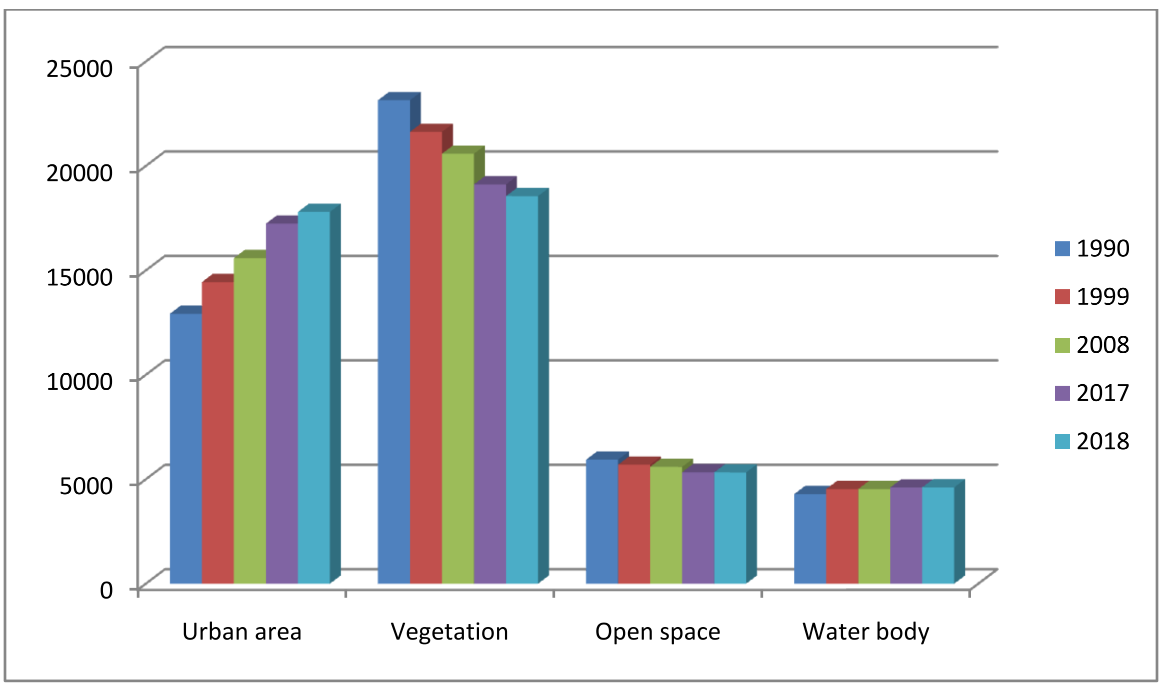

Figure 4.6: Histogram of landcover/landuse distribution of Awka Capital Territory from 1990 to 2018

From table 4.11 and figure 4.6, the landcover/landuse distribution of Awka Capital Territory in 1990 indicate that Vegetation, accounted for the largest land cover/use of about 50% and with area of about 23144.9 hectare. Urban area had 27.92 % and a coverage area of 12922.45 hectares.Open space and water body had the lowest turnout with 12.82% and 9.26% with an area of 5936.22 and 4286.22 hectares respectively.

In 1999, vegetation, decreased from 50% to 46.73% to an area of about 21629.79hectares. Urban area increased from 27.92% to 31.19 %, to area of 14437.68hectares.Open space decreased from 12.82% to 12.30 to an area of 5693.72 hectares while water body increased from 9.26% to 9.78% to an area of 4528.6hectares.

In 2008, vegetation decreased further from 46.73% to 44.46%, to an area of 20583.59 hectares. Urban area increased further from 31.19% to 33.67%, to an area of 15586.73 hectares while open space decreased from 12.30% to 12.07%, to an area of 5589.67 hectares. Water bodyincreased slightly from 9.78% to 9.78% to an area of 4529.8 hectares.

In 2017, vegetation continued its gradual decrease from 44.46% to 41.29%, to an area of 19115.32 hectares, while urban area also increased from 33.67% to 37.24%, to an area of 17237.45 hectares. Open space continued decreasing from 12.07% to 11.52%, to an area of 5334.6 hectares while water body increased from 9.78% to 9.94%, to area coverage of 4601.35.

The land cover/land use distribution of Awka Capital Territory in 2018 also indicate gradual decrease of vegetation from 44.46% to 40.08%, to an area of 18555.33 hectares, while Urban area increased from 33.67% to 38.45%, to an area of 17798.44 hectares. Open space also decreased from 11.52% 11.50%, to an area of 5324.67 hectares, while water body increased from 9.94% to 9.96, to an area of 4611.35 hectares.

4.3 Trend Analysis and Landcover/landuse Transition

4.3.1 Trend Analysis

A method of calculating and comparing the area of the resulting landcover/landuse types of each year by Long *et al* (2007) was adopted for data analysis. The comparison of the land cover/land use statistics will assist in identifying the percentage change, trend and rate of change between 1990 and 2017. In achieving this table was prepared showing the areas and percentage change for each year measured against each other. To determine the rate of change of landcover/landuse change, the year period 1990-2017 was divided into three sub-periods 1990 - 1999, 1999 - 2008 and 2008 – 2017, and then compared against each other.

The comparative analysis in landcover/landuse change focuses on the three sub-periods and the spatial distribution of the average (annual) rate of land cover/land use change between the three periods, (Long *et al*, 2007).

Percentage change to determine the trend of change was calculated by dividing the observed change by the sum of the area of the particular landcover/landuse type in that period multiplied by 100

$$\text{(Trend) \% change} = \frac{\text{Observed change x 100}}{\text{Total Area}} \quad \text{... (5.1)}$$

Where Observed change = (Area of before year – Area of after year)

Total Area = Sum of the total area of both years

The annual percentage rate = Trend divided by N. where N= (number of years).

A trend percentage with a positive value means that the landcover/landuse type has increased over the period of years while a negative value shows a decrease in the landcover/landuse type over a period of time.

In this study, between 1990 and 2017, the difference in area for urban area was 1515.23 hectares between 1990 and 1999, 1149.05 hectares between 1999 and 2008, then 1650.72 hectares between 2008 and 2017. Between 1990 and 2017 for vegetation, the difference area was -151511 hectares between 1990 and 1999, -1046.2 hectares between 1990 and 2008 and -1468.27 hectares. Between 1990 and 2017 for open space, the difference area was -242.5 hectares between 1990 and 1999, -104.05 hectares between 1990 and 2008 and -225 hectares. Between 1990 and 2017 for water body, the difference area was 242.38 hectares between 1990 and 1999, 1.2 hectares between 1990 and 2008 and 72.55 hectares. As shown in table 4.12.

Table 4.12: Difference in area between 1990 and 2017

Class Name	Difference 1990-1999	Difference 1999-2008	Difference 2008-2017
Urban area	1515.23	1149.05	1650.72
Vegetation	-1515.11	-1046.2	-1468.27
Open space	-242.5	-104.05	-255
Water body	242.38	1.2	72.55

Between 1990 and 2017, the total area for urban area was 27360.13 hectares between 1990 and 1999, 30024.41 hectares between 1999 and 2008, then 32824.18 hectares between 2008 and 2017 this indicates gradual growth in Urban area between 1990 and 2017. Between 1990 and 2017 for vegetation, the total area was 44774.69 hectares between 1990 and 1999, 11283.39 hectares between 1990 and 2008 and 10924.34 hectares; this indicates a decline between 1990 and 2017. Between 1990 and 2017 for open space, the total area was 11629.94 hectares between 1990 and 1999, 11283.39 hectares between 1990 and 2008 and 10924.34 hectares; this also indicates a decline in open space between 1990 and 2017. Then between 1990 and 2017 for water body, the total area was 8814.82 hectares between 1990 and 1999, 9058.4 hectares between 1990 and 2008 and 9132.15 hectares; this also indicates an increase in water body between 1990 and 2017. As shown in table 4.13.

Table 4.13: Total area between 1990 and 2017

Class Name	Total Area 1990 – 1999	Total Area 1999 - 2008	Total Area 2008 – 2017
Urban area	27360.13	30024.41	32824.18
Vegetation	44774.69	42213.38	39698.91
Open space	11629.94	11283.39	10924.34
Water body	8814.82	9058.4	9132.15

The trend of change for the class features between 1990 and 2017 was given as 5.53% for urban area between 1990 and 1999, 3.83% between 1999 and 2008 and 5.03% between 2008 and 2017. The trend of change for vegetation between 1990 and 2017 was given as -3.38% between 1990 and 1999, -2.48% between 1999 and 2008, then -3.69 between 2008 and 2017. The trend of change for open space between 1990 and 2017 was given as -2.085% between 1990 and 1999, -0.92% between 1999 and 2008 and -2.33% between 2008 and 2017. Then lastly, the trend of change of water body was given as 2.75% between 1990 and 1999, 0.01% between 1999 and 2008 and 0.79% between 2008 and 2017, as shown in table 4.14 and figure4.7.

Table 4.14: Trend of change between 1990 and 2017

Class Name	Trend of Change 1990 – 1999	Trend of Change 1999 – 2008	Trend of Change 2008 – 2017
Urban area	5.53	3.82	5.02
Vegetation	-3.38	-2.47	-3.69
Open space	-2.08	-0.92	-2.33
Water body	2.74	0.01	0.79

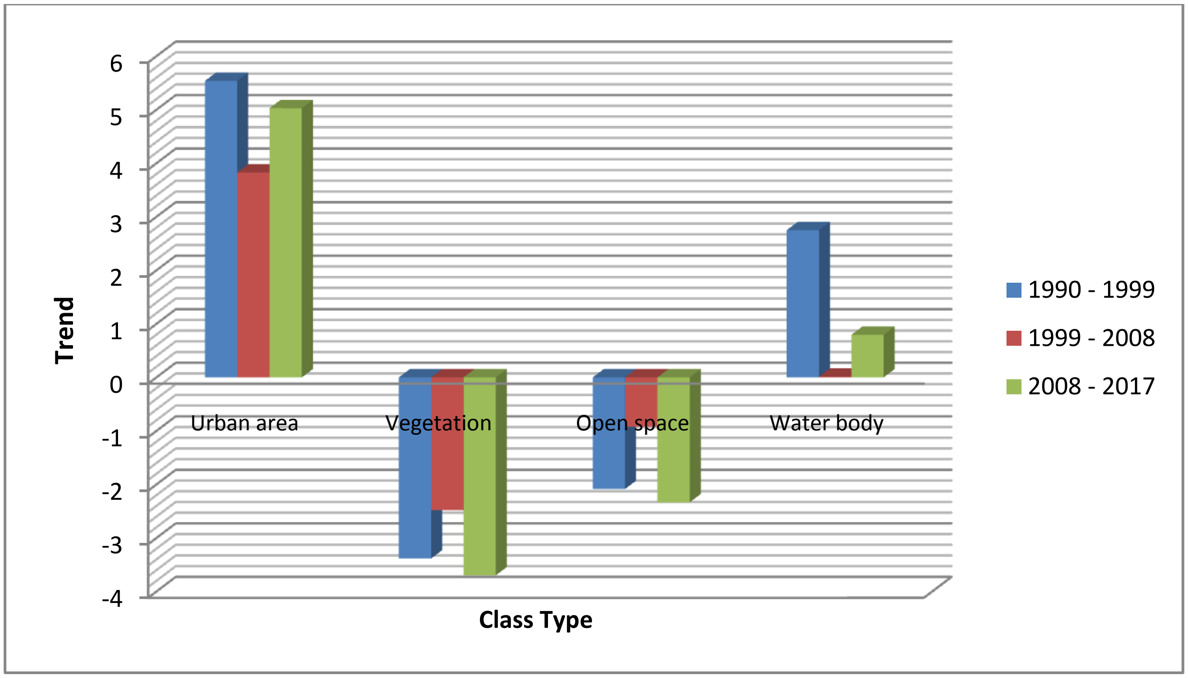

Figure 4.7: Trend of change between 1990 and 2017

The annual rate of change between 1990 and 2017, for urban area was given as 0.62% between 1990 and 1999, 0.43% between 1999 and 2008 and 0.56% between 2008 and 2017. For vegetation, the annual growth rate was given as -0.37% between 1990 and 1999, -0.27% between 1999 and 2008, and -0.41% between 2008 and 2017. For open space, the annual rate of change was give as -0.23% between 1990 and 1999, -0.10% between 1990 and 2008 and -0.25% between 2008 and 2017. For water body the annual rate of change was given as 0.30% between 1990 and 1999, 0.001% between 1999 and 2008 and 0.08% between 2008 and 2017, as shown in table 4.15 and figure 4.8.

Table 4.15: Annual rate of change between 1990 and 2017

Class Name	Annual Rate of change 1990 – 1999	Annual Rate of change 1999 – 2008	Annual Rate of change 2008 – 2017
Urban area	0.61	0.42	0.55
Vegetation	-0.37	-0.27	-0.41
Open space	-0.23	-0.10	-0.25
Water body	0.30	0.001	0.08

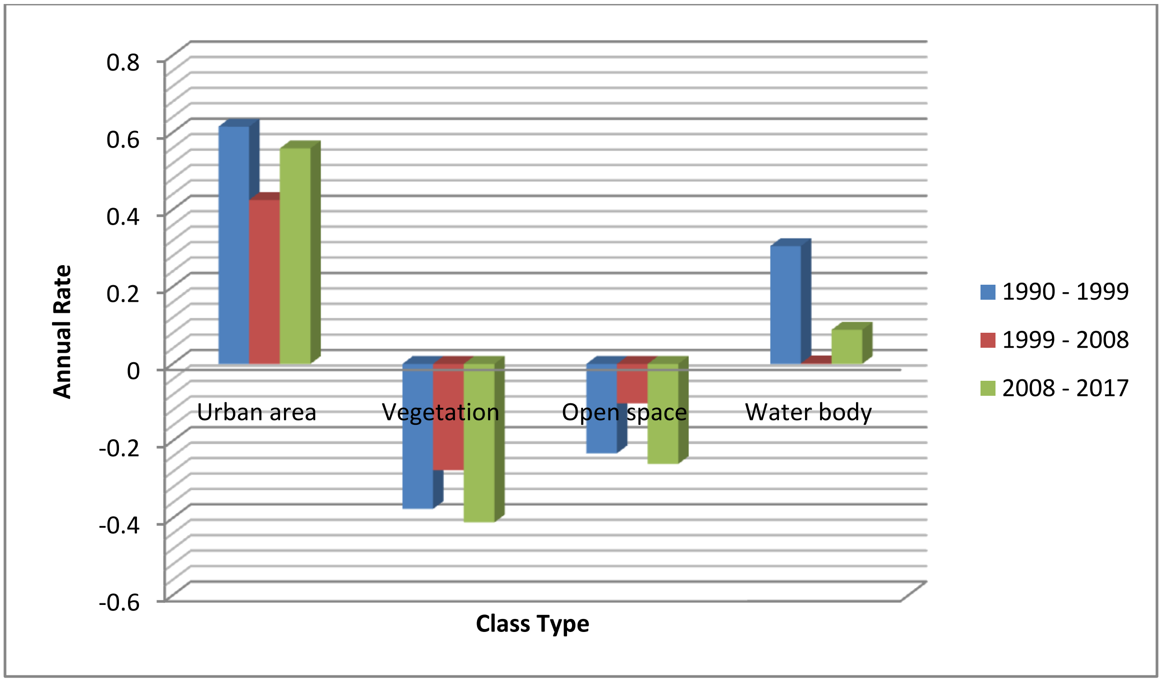

Figure 4.8: Annual rate of change between 1990 and 2017

This indicates that both urban area and water body had a positive growth between 1990 and 2017, while vegetation and open space declined between 1990 and 2017.

4.3.2 Landcover/Landuse Transition

Land change is non-linear. It is associated with other societal and biophysical system changes as human societies constantly co-evolve with their environment through change, instability, and mutual adaptation, (Takenori, 2010). A transition is a process of system change in which the structural character of the system transforms.

The concept of landcover/landuse transition refers to any change in landcover/landuse systems from one state to another one — e.g., from a system dominated by annual crops for local consumption to a system with large tree plantations in response to market demand or new institutions, (Takenori, 2010). Forest transitions are shifts from decreasing to expanding national forest areas i.e., from net deforestation to net reforestation - that has taken place in several European countries, in North America and, more recently, in China, India, Vietnam, Costa Rica, among others (Takenori, 2010).

Discriminant function matrix was used to calculate the landcover/landuse transition in the study area between 1990 and 2017. The results in table 4.16 showed that between 1990 and 1999, urban area had an unchanged area of 12922.45 hectares while gaining 1272.73 hectares from vegetation, 242.5 hectares from open space. Vegetation had an unchanged area of 21629.79 hectares, while 1273.73 hectares transitioned to urban area, 152.27 transitioned to open space and 90.11 transitioned to water body. Open space had an unchanged area of 5541 hectares, while 242.5 hectares transitioned to urban area and 152.27 hectares to water body. Water body had an unchanged area of 4286.22 while gaining 90.11hectares from vegetation and 152.27 hectares from open space.

Table 4.16: Landcover/landuse transition between 1990 and 1999

Class Name	1990	Urban area	Vegetation	Open space	Water body
Urban area	12922.45	12922.45	0	0	0
Vegetation	23144.9	1272.73	21629.79	152.27	90.11
Open space	5936.22	242.5	0	5541.45	152.27
Water body	4286.22	0	0	0	4286.22
1999	46289.79	14437.68	21629.79	5693.72	4528.6

Similarly, in table 4.17 the transition results between 1999 and 2008 showed that, urban area had an unchanged area of 14437.68 hectares while gaining 1000 hectares from vegetation, 149.05 hectares from open space. Vegetation had an unchanged area of 20583.59 hectares, while1000 hectares transitioned to urban area, 45 transitioned to open space and 1.2 hectares transitioned to water body. Open space had an unchanged area of 5544.67 hectares, while 149.05 hectares transitioned to urban area. Water body had an unchanged area of 4529.6 while gaining 1.2 hectares from vegetation.

Table 4.17: Landcover/landuse transition between 1999 and 2008

Class Name	1999	Urban area	Vegetation	Open space	Water body
Urban area	14437.68	14437.68	0	0	0
Vegetation	21629.79	1000	20583.59	45	1.2
Open space	5693.72	149.05	0	5544.67	0
Water body	4528.6	0	0	0	4528.6
2008	46289.79	15586.73	20583.59	5589.67	4529.8

Then in the last epoch between 2008 and 2017 in table 4.18, the landcover/landuse transition results indicated that urban area had an unchanged area of 15586.73 hectares while gaining 1068.27 hectares from vegetation, 582.45 hectares from open space. Vegetation had an unchanged area of 19115.32 hectares, while1068.27 hectares transitioned to urban area, 327.45 transitioned to open space and 72.55 hectares transitioned to water body. Open space had an unchanged area of 5007.22 hectares, while 582.45 hectares transitioned to urban area. Water body had an unchanged area of 4529.8 while gaining 72.55 hectares from vegetation.

Table 4.18: Landcover/landuse transition between 2008 and 2017

Class Name	2017	Urban area	Vegetation	Open space	Water body
Urban area	15586.73	15586.73	0	0	0
Vegetation	20583.59	1068.27	19115.32	327.45	72.55
Open space	5589.67	582.45	0	5007.22	0
Water body	4529.8	0	0	0	4529.8
2017	46289.79	17237.45	19115.32	5334.67	4602.35

4.3.3 Urban Growth Pattern within Awka Capital Territory

In order to measure the spatial dimension of urban growth pattern in Awka Capital Territory, this study employed the use of spatial metrics to analyze urban growth patches in Awka Capital Territory. This metrics are numerical indicators that quantify the spatial pattern of urban patches within the study area. The metrics used were: size and urban expansion index.

a. Size

The size of an urban area has often been used as a simple index of growth. The idea of using the urban area size for growth, causes more land consumption than compact development. Because growth is characterized by an increase in the built-up area, this attribute gives considerable information for understanding the behavior of such growth. Larger urban area size values indicate a greater degree of growth. This study was able to identify the sizes of urban area patches within the study area. The urban area patches and sizes occupied between 1990 and 2017 area is displayed in table 4.19.

Table 4.19: Urban patches and area occupied between 2008 and 2017

Urban Patch	Area (Hectares)						Area (Hectares)			
	1990	1999	% Change 1990-1999	Annual Rate 1990-1999	% Change 1999-2008	Annual Rate 1999-2008	2008	2017	% Change 2008-2017	Annual Rate 2008-2017
Abagana	1235.30	1380.15	0.53	0.06	0.37	0.04	1489.99	1647.79	0.48	0.05
Agulu	1167.22	1304.08	0.50	0.06	0.35	0.04	1407.87	1556.97	0.45	0.05
Amawbia	1788.17	1997.84	0.77	0.09	0.53	0.06	2156.85	2385.27	0.70	0.08
Awka	2693.04	3008.81	1.15	0.13	0.80	0.09	3248.28	3592.29	1.05	0.12
Enugwu-Ukwu	1198.12	1338.61	0.51	0.06	0.35	0.04	1445.14	1598.19	0.47	0.05
Ifite	900.21	1005.76	0.39	0.04	0.27	0.03	1085.81	1200.80	0.35	0.04
Okpuno	700.10	782.19	0.30	0.03	0.21	0.02	844.44	933.87	0.27	0.03
Nibo	979.08	1093.88	0.42	0.05	0.29	0.03	1180.94	1306.01	0.38	0.04
Nise	936.20	1045.97	0.40	0.04	0.28	0.03	1129.22	1248.81	0.36	0.04
Nwafia	1325.01	1480.37	0.57	0.06	0.39	0.04	1598.19	1767.45	0.52	0.06
Total	12922.45	14437.66	5.54	0.62	3.83	0.43	15586.73	17237.45	5.03	0.56

From table 4.19, Abagana occupied an area of 1235.30 hectares in 1990, 1380.15 hectares in 1999, 1489.99 hectares in 2008 and 1647.79 hectares in 2017, with an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Similarly, Agulu occupied an area of 1167.22 hectares in 1990, 1304.08 hectares in 1999, 1407.87 hectares in 2008 and 1556.97 hectares in 2017, with an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Enugwu-Ukwu occupied an area of 1198.12 hectares in 1990, 1338.81 hectares in 1999, 1445.14hectares in 2008 and 1598.19 hectares in 2017, with an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively. Thus, indicating a similar growth rate between Abagana, Agulu and Enugu-Ukwu.

Amawbia occupied an area of 1788.17 hectares in 1990, 1997.84 hectares in 1999, 2156.85 hectares in 2008 and 2385.27 hectares in 2017, with an annual growth of 0.09%, 0.06% and 0.08% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Awka occupied an area of 2693.04 hectares in 1990, 3008.81 hectares in 1999, 3248.28 hectares in 2008 and 3592.29 hectares in 2017, with an annual growth of 0.13%, 0.09% and 0.12% between 1990-1999, 1999-2008 and 2008-2017 respectively. This indicated that Awka and Amawbia had the highest growth rate amongst other urban patches between 1990 and 2017.

Ifite occupied an area of 900.21 hectares in 1990, 1005.76 hectares in 1999, 1085.81 hectares in 2008 and 1200.80 hectares in 2017, with an annual growth of 0.04%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Similarly, Nise with the same growth rate as Ifite, occupied an area of 936.20 hectares in 1990, 1045.97 hectares in 1999, 1129.22 hectares in 2008 and 1248.81 hectares in 2017, with an annual growth of 0.04%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Okpuno occupied an area of 700.10 hectares in 1990, 782.19 hectares in 1999, 844.44 hectares in 2008 and 933.87 hectares in 2017, with an annual growth of 0.03%, 0.02% and 0.03% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Nibo occupied an area of 979.08 hectares in 1990, 1093.88 hectares in 1999, 1180.94 hectares in 2008 and 1306.01 hectares in 2017, with an annual growth of 0.05%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Lastly, Nawfia occupied an area of 1325.01 hectares in 1990, 1480.37 hectares in 1999, 1598.19 hectares in 2008 and 1767.45 hectares in 2017, with an annual growth of 0.06%, 0.04% and

0.06% between 1990-1999, 1999-2008 and 2008-2017 respectively.The urban patches growth rate is summarized in Figure 4.9.

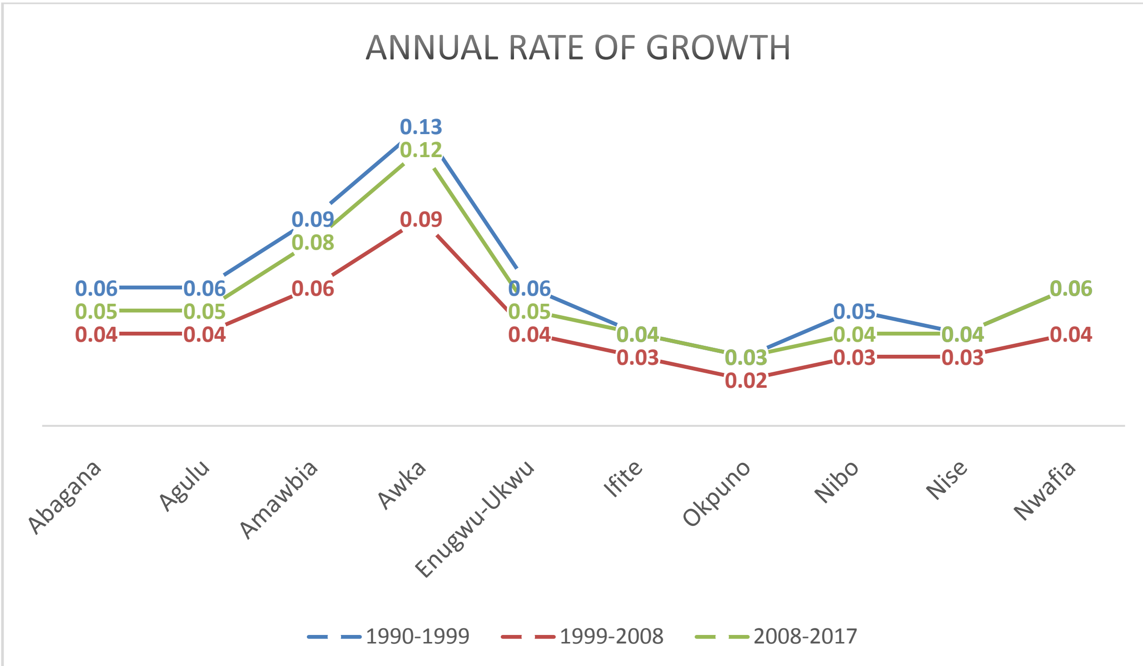

Figure 4.9: Urban patch growth rate

b. Landscape Expansion Index

A quantitative method by Xu *et al*, (2010) was used to distinguish three urban growth types: infilling, edge expansion, and spontaneous growth. The dominance of each growth types is meaningful to describe the process of landscape pattern changes between two or more time points. Whether a growth patch is called infilling, edge expansion, or spontaneous growth is determined by LEI value which is calculated as follows:

$$LEI = \frac{L_C}{P} \qquad \ldots (4.2)$$

where *LEI* is Landscape Expansion Index, L_C is the length of the common boundary of a newly grown urban patch and the pre-growth urban patches, and *P* is the perimeter of this newly grown patch. Urban growth type is identified as

(a) infilling when LEI > 0.5,

(b) edge-expansion when $0 < \text{LEI} \leq 0.5$,

(c) spontaneous growth when LEI = 0, which indicates no shared-boundary

The results show two types of growth within the study area. Between 1990 and 1999, 68.2% of overall growth in the study area was attributed to edge-expansion, while 31.8% was attributed to infilling growth with Awka and Amawbia having a high percentage of edge-expansion in the said period.

Similarly, between 1999 and 2008, there was an almost even growth pattern in the study area, with 55.7% of the growth attributed to edge-expansion, while 44.3% was attributed to infilling growth.

In the last epoch between 2008 and 2017, edge-expansion was the dominant growth pattern in the study area with 75.61% of growthwhile 24.39% was attributed to infilling. There was no indication of spontaneous growth in the study area. The summary of the results is displayed in figures 4.10 - 4.13.

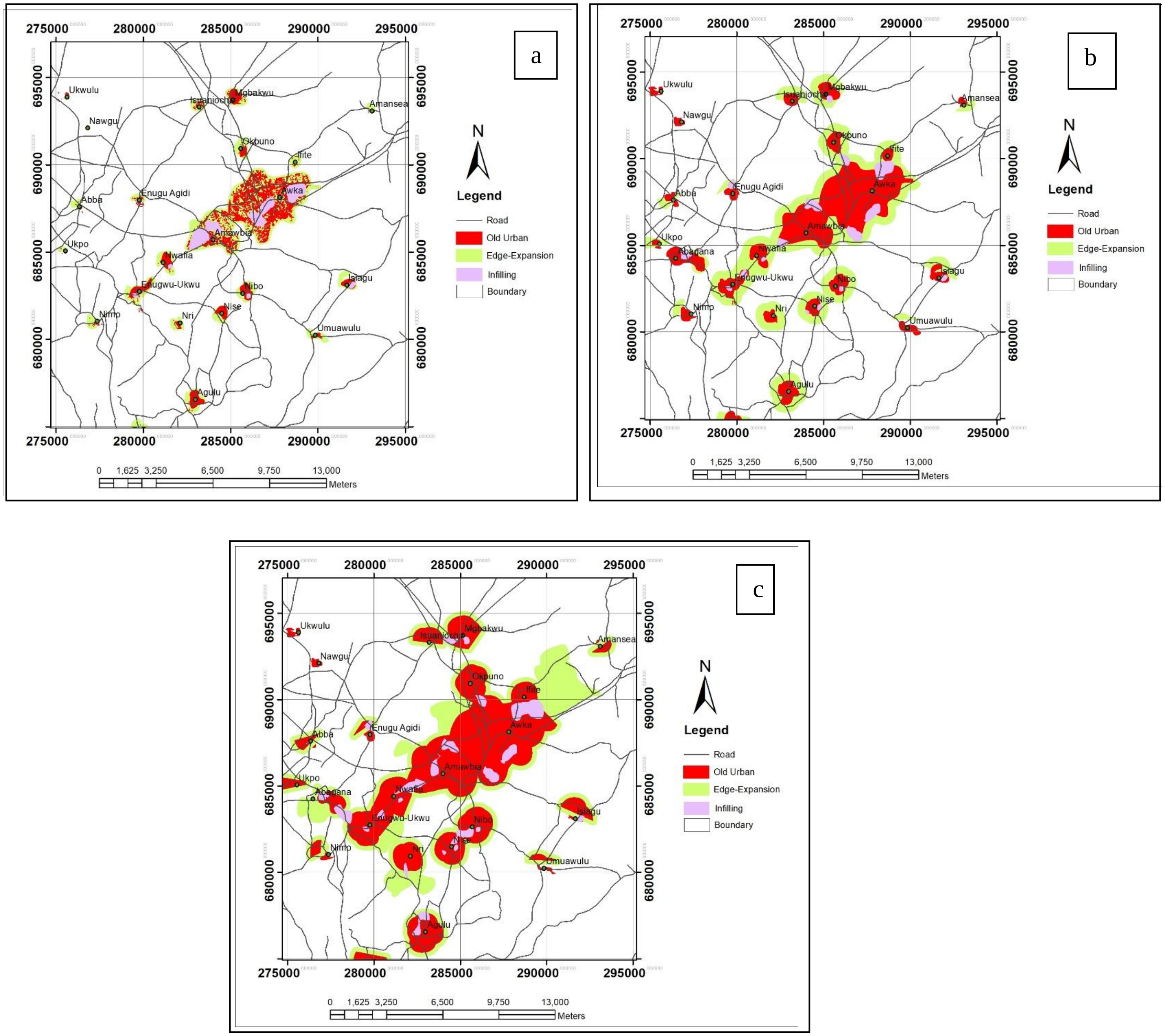

Figure 5.10: Growth pattern between (a) 1990 and 1999, (b) 1999 and 2008, (c) 2008 and 2017

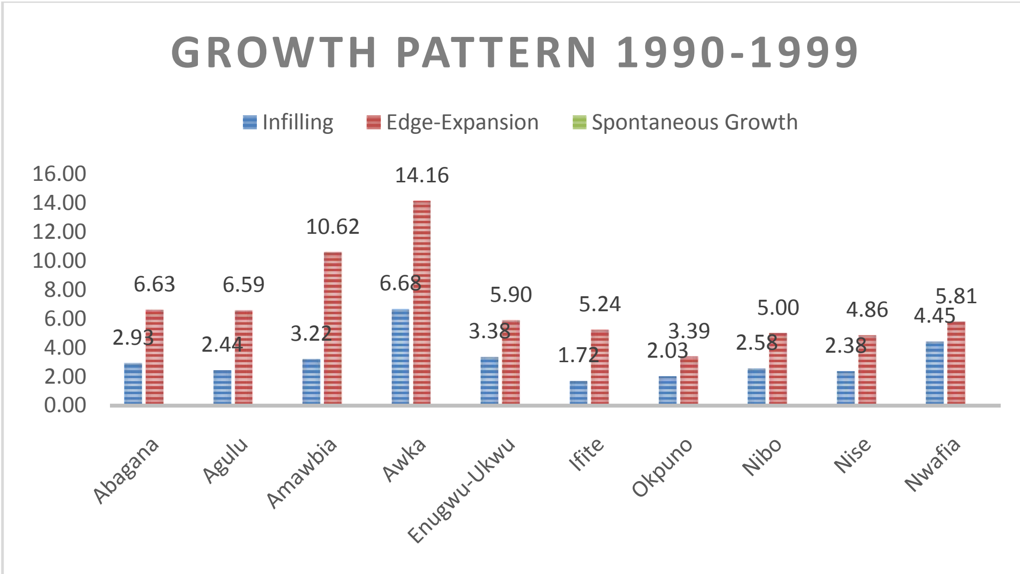

Figure 4.11: Growth percentage between 1990 and 1999

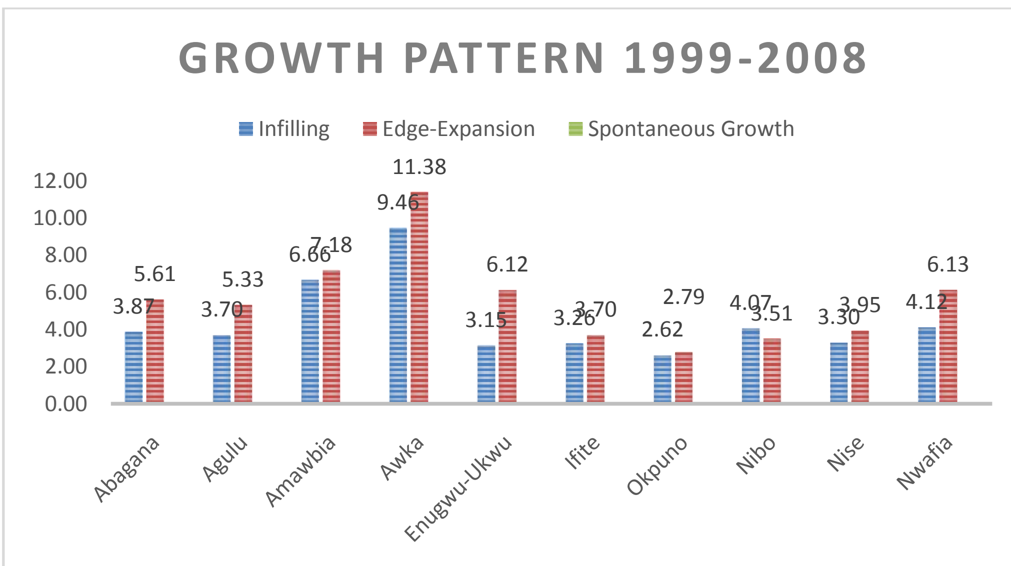

Figure 4.12: Growth percentage between 1999 and 2008

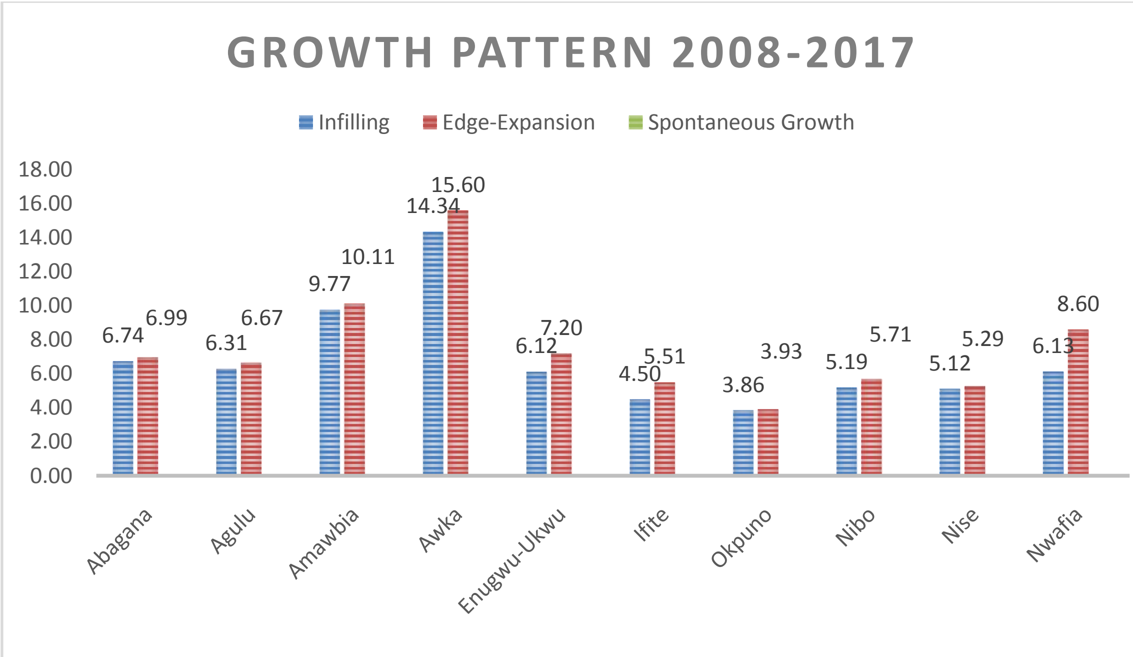

Figure 4.13: Growth percentage between 2008 and 2017

4.4 Influence of Urban growth onLULC Land Surface Temperature, Vegetation and Open Surface spatial extentsin Awka Capital Territory

4.4.1 Land Surface Temperature of Awka Capital Territory in 1990

The land surface temperature of Awka Capital Territory in 1990 as shown in figure 4.14 and table 4.20, revealed that the mean temperature in 1990 was 30.2°C while themin and max temperature was 24.23°C and 36.17°C respectively.The mean temperature for areas covered by vegetation was 25.31°C with a min and max temperature of 24.23°C and 26.39°C respectively. The mean temperature for areas covered by waterbody was given as 25.16°C with a min and max temperature of 24.44°C and 25.89°C respectively. The mean temperature of areas covered by open space was given as 28.36°C with a min and max temperature of 26.39°C and 30.33°C respectively while the mean temperature of areas covered by urban area is given as 33.25°C with a min and max temperature of 30.33°C and 36.17°C respectively. The areas covered by urban area had the highest temperature reading in the study area, followed by areas covered by open spacewith a moderate temperature reading, then areas covered by waterbody and vegetation had the lowest temperature readings in the study area.

Table 4.20: Land surface temperature distribution for 1990

Class Name	Min. Temp (°C)	Max. Temp (°C)	Mean Temp (°C)
Urban area	30.33	36.17	33.25
Vegetation	24.23	26.39	25.31
Open space	26.39	30.33	28.36
Water body	24.44	25.89	25.16
Awka 1990	24.23	36.17	30.2

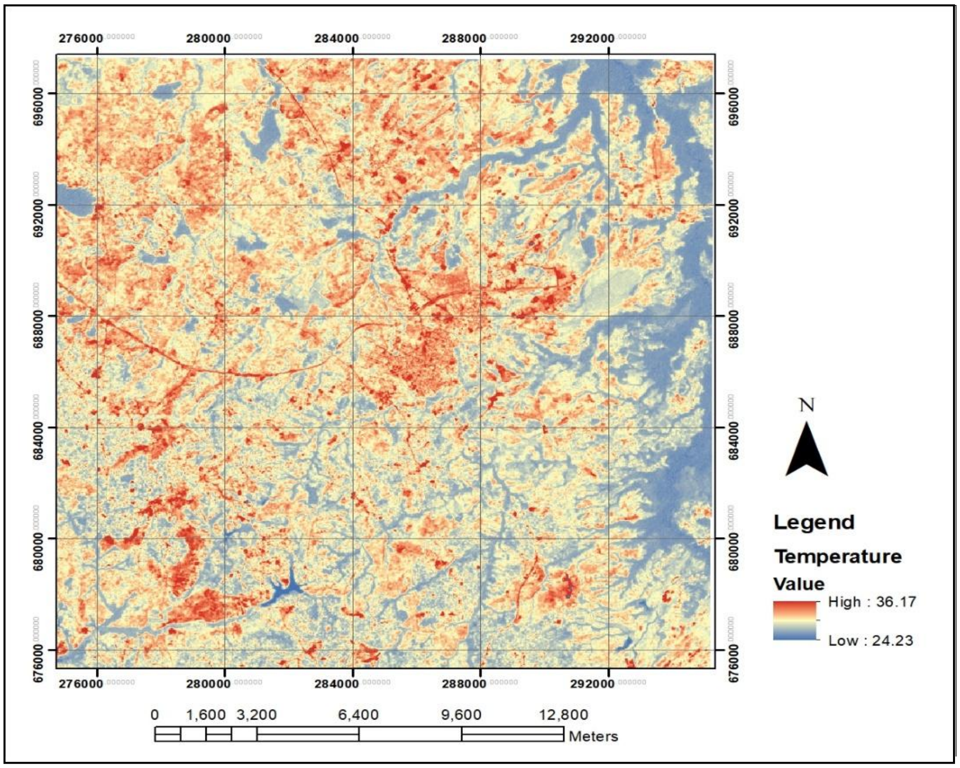

Figure 4.14: Land surface temperature of Awka Capital Territory 1990

4.4.2 Land Surface Temperature of Awka Capital Territory in 1999

The land surface temperature of Awka Capital Territory in 1999 as shown in figure 4.15 and table 4.21, revealed that the mean temperature in 1999 was 31.01°C while themin and max temperature was 24.02°C and 37.99°C respectively. The mean temperature for areas covered by vegetation was 24.68°C with a min and max temperature of 24.02°C and 25.24°C respectively. The mean temperature for areas covered by waterbody was given as 25.06°C with a min and max temperature of 24.30°C and 25.83°C respectively. The mean temperature of areas covered by open space was given as 29.97 with a min and max temperature of 27.59°C and 32.35°C respectively while the mean temperature of areas covered by urban area is given as 34.11°C with a min and max temperature of 30.23°C and 37.99°C respectively.In the same case as the temperature in 1990, the areas covered by urban area have the highest temperature reading in the study area, followed by areas covered by open space having a moderate temperature reading, then areas covered by waterbody and vegetation having the lowest temperature reading in the study area.

Table 4.21: Land surface temperature distribution for 1999

Class Name	Min. Temp (°C)	Max. Temp (°C)	Mean Temp (°C)
Urban area	30.23	37.99	34.11
Vegetation	24.02	25.24	24.68
Open space	27.59	29.35	28.47
Water body	24.30	25.83	25.06
Awka 1999	24.02	37.99	31.01

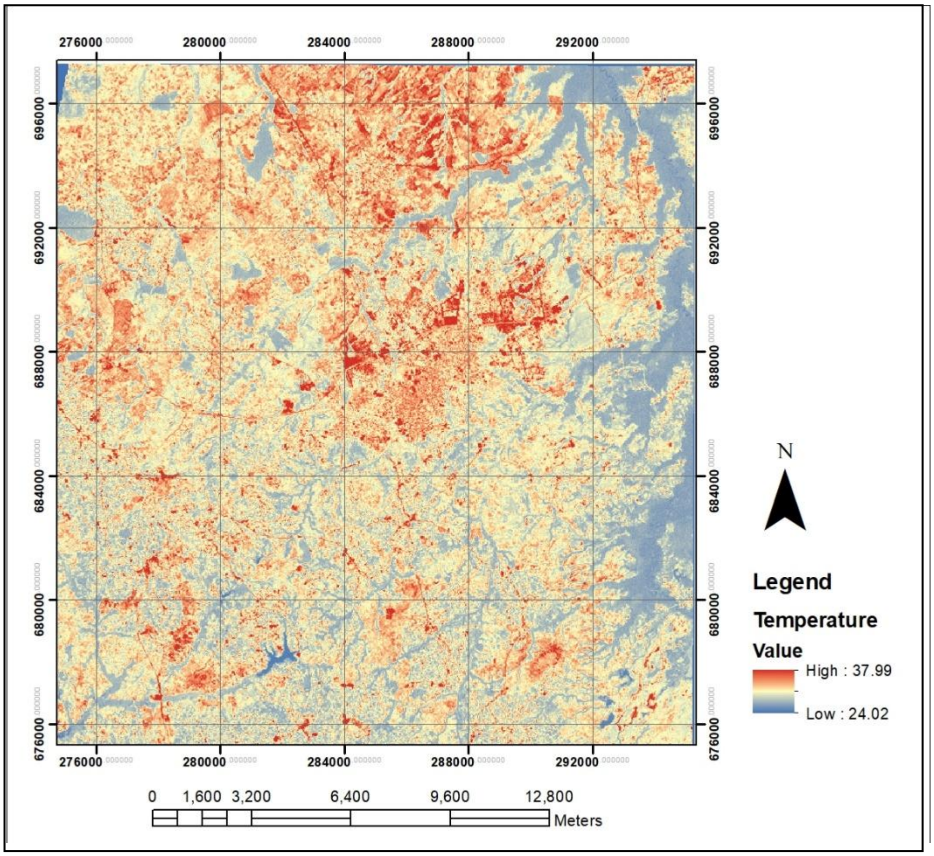

Figure 4.15: Land surface temperature of Awka Capital Territory 1999

Table 4.22: Change in land surface temperature between 1990 and 1999

Class Name	Mean Temp (°C) (1990)	Mean Temp (°C) (1999)	Change (°C)
Urban area	33.25	34.11	0.86
Vegetation	25.31	24.68	0.63
Open space	28.36	28.47	0.11
Water body	25.16	25.06	0.1
Mean Temp for the year	30.2	31.01	0.81

From Table 4.22,it can be deduced that the mean surface temperature for areas cover by urban area increased from 33.25°C to 34.11°C between 1990 and 1999, while the mean temperature for areas covered by vegetation decreased from 25.31°C to 24.68°C. similarly areas covered by open space increased from 28.36°C to 28.47°C while areas covers by water body decreased from 25.16°C to 25.06°C, bringing the overall mean surface temperature between 1990 and 1999 from 30.2°C to 31.01°C. this indicates an increase in the surface temperature in Awka Capital Territory between 1990 and 1999 with urban area having the most change with an increase of 1.08°C.

4.4.3Land surface temperature of Awka Capital Territory in 2008

The land surface temperature of Awka Capital Territory in 2008 as shown in figure 4.16 and table 4.23, revealed that the mean temperature in 2008 was 31.21°C while themin and max temperature was 24.18°C and 38.24°C respectively. The mean temperature for areas covered by vegetation was 24.76°C with a min and max temperature of 24.18°C and 25.35°C respectively. The mean temperature for areas covered by waterbody was given as 24.99°C with a min and max temperature of 24.26°C and 25.72°C respectively. The mean temperature of areas covered by open space was given as 27.85°C with a min and max temperature of 27.34°C and 28.37°C respectively while the mean temperature of areas covered by urban area is given as 34.31°C with a min and max temperature of 30.39°C and 38.24°C respectively. Similarly, in 1990 and 1999 the areas covered by urban area also had the highest temperature reading in the study area, followed by areas covered by open space with a moderate temperature reading, then areas covered by waterbody and vegetation had the lowest temperature reading in the study area.

Table 4.23: Land surface temperature distribution for 2008

Class Name	Min. Temp (°C)	Max. Temp (°C)	Mean Temp (°C)
Urban area	30.39	38.24	34.31
Vegetation	24.18	25.35	24.76
Open space	27.34	28.37	27.85
Water body	24.26	25.72	24.99
Awka 2008	24.18	38.24	31.21

Table 4.24: Change in land surface temperature between 1999 and 2008

Class Name	Mean Temp (°C) (1999)	Mean Temp (°C) 2008	Change (°C)
Urban area	34.11	34.31	0.2
Vegetation	24.68	24.76	0.08
Open space	28.47	27.85	0.3
Water body	25.06	24.99	0.07
Mean Temp for the year	31.01	31.21	0.2

From Table 4.24,it can also be deduced that the mean surface temperature for areas cover by urban area increased further from 34.11°C to 34.31°C between 1999 and 2008, while the mean temperature for areas covered by vegetation increased from 24.68°C to 24.76°C. Areas covered by open space decreased from 28.47°C to 27.85°C while areas covers by water body decreased from 25.06°C to 24.99°C, bringing the overall mean surface temperature between 1999 and 2008 from 31.01°C to 31.21°C. this indicates an increase in the surface temperature in Awka Capital Territory between 1999 and 2008 with a steady increase of urban area temperature as was in 1990, 1999 with a temperature change of 0.2°C in 2008.

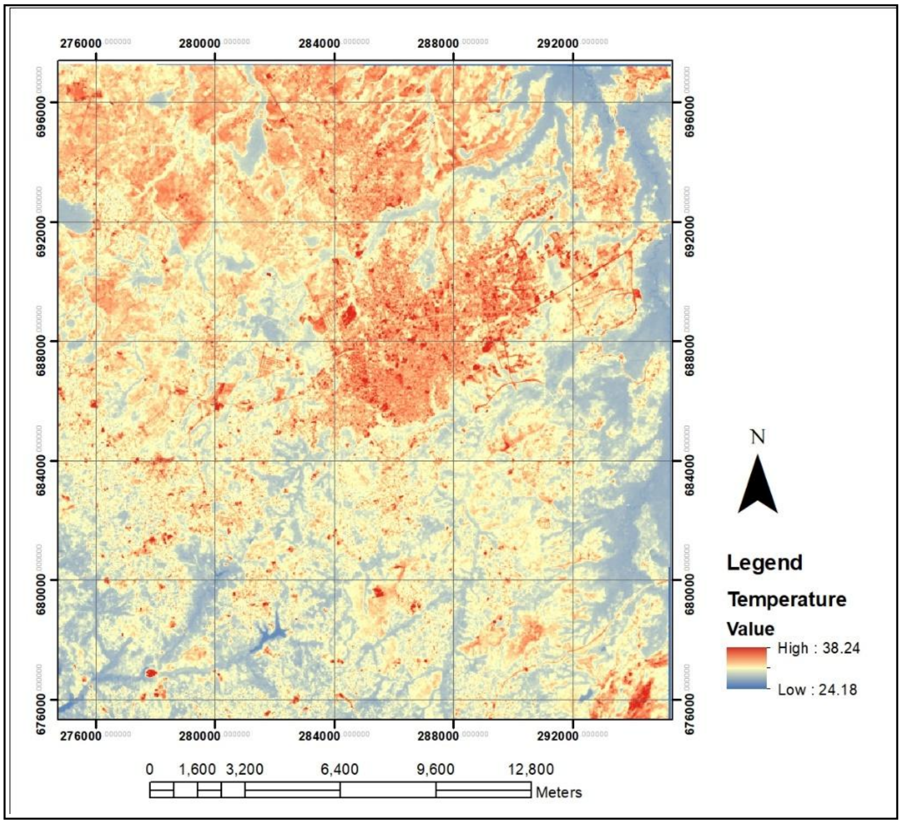

Figure 4.16: Land surface temperature of Awka Capital Territory 2008

4.4.4 Land surface temperature of Awka Capital Territory in 2017

The land surface temperature of Awka Capital Territory in 2017 as shown in figure 4.17 and table 4.25, revealed that the mean temperature in 2017 was 31.82°C while themin and max temperature was 24.29°C and 39.35°C respectively. The mean temperature for areas covered by vegetation was 25.50°C with a min and max temperature of 24.22°C and 26.77°C respectively. The mean temperature for areas covered by waterbody was given as 24.74°C with a min and max temperature of 24.26°C and 25.23°C respectively. The mean temperature of areas covered by open space was given as 30.08°C with a min and max temperature of 28.59°C and 31.57°C respectively while the mean temperature of areas covered by urban area is given as 35.96°C with a min and max temperature of 32.58°C and 39.35°C respectively. Similarly, in 1990, 1999 and 2008, the areas covered by urban area also had the highest temperature reading in the study area, followed by areas covered by open space with a moderate temperature reading, then areas covered by waterbody and vegetation had the lowest temperature reading in the study area.

Table 4.25: Land surface temperature for 2017

Class Name	Min. Temp (°C)	Max. Temp (°C)	Mean Temp (°C)
Urban area	32.58	39.35	35.96
Vegetation	24.22	26.77	25.50
Open space	28.59	31.57	30.08
Water body	24.26	25.23	24.74
Awka 2017	24.29	39.35	31.82

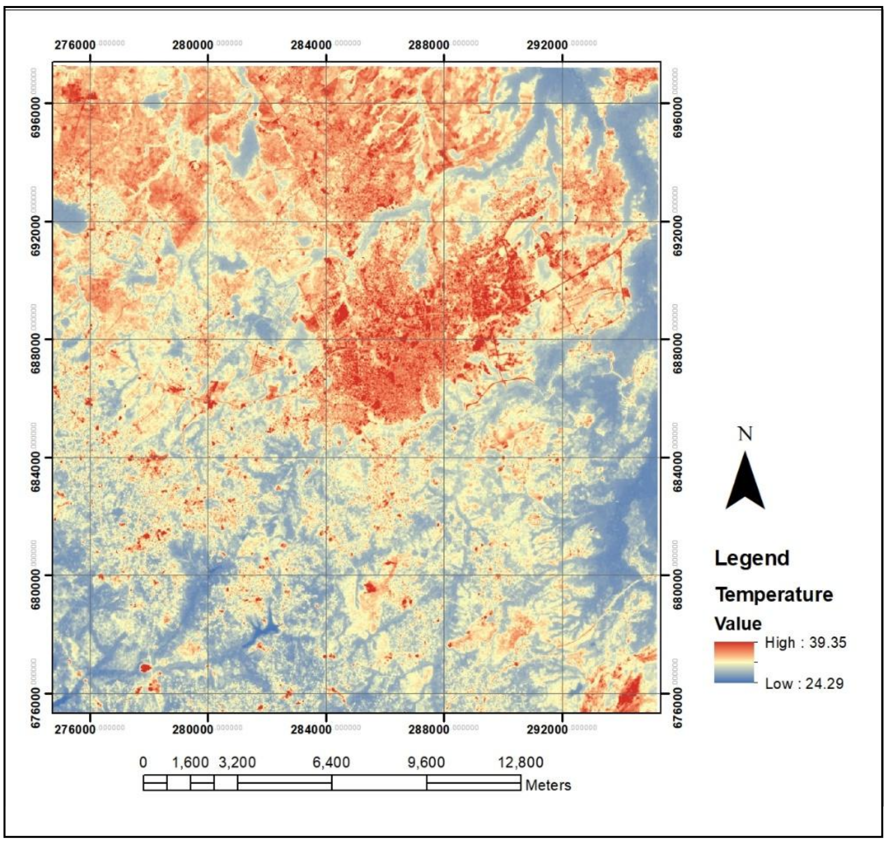

Figure 5.17: Land surface temperature of Awka Capital Territory 2017

Table 4.26: Change in land surface temperature between 2008 and 2017

Class Name	Mean Temp (°C) 2008	Mean Temp (°C) 2017	Change (°C)
Urban area	34.52	35.96	1.44
Vegetation	24.76	25.50	0.74
Open space	28.77	30.08	1.31
Water body	24.99	24.74	0.25
Mean Temp for the year	31.21	31.82	0.6

From Table 4.26,it can also be deduced that the mean surface temperature for areas cover by urban area increased further from 34.52°C to 35.96°C between 2008 and 2017, while the mean temperature for areas covered by vegetation increased from 24.76°C to 25.50°C. Areas covered by open space increased from 28.77°C to 30.08°C while areas covers by water body increased from 24.99°C to 24.74°C, bringing the overall mean surface temperature between 2008 and 2017 from 31.21°C to 31.82°C. this indicates an increase in the surface temperature in Awka Capital Territory between 2008 and 2017 with a steady increase in urban area temperature as was in 1990, 1999 and 2008 with a temperature change of 0.6°C in 2017.

In order to ascertain if there was a relationship between land surface temperature and each of the landcover class in the study area, a Pearson's correlation coefficient was conducted to test for the relationship between landcover/landuse and their mean surface temperatures in the study area between 1990 and 2017, the resulting scatter plots are shown in table 4.28 and subsequently discussed.

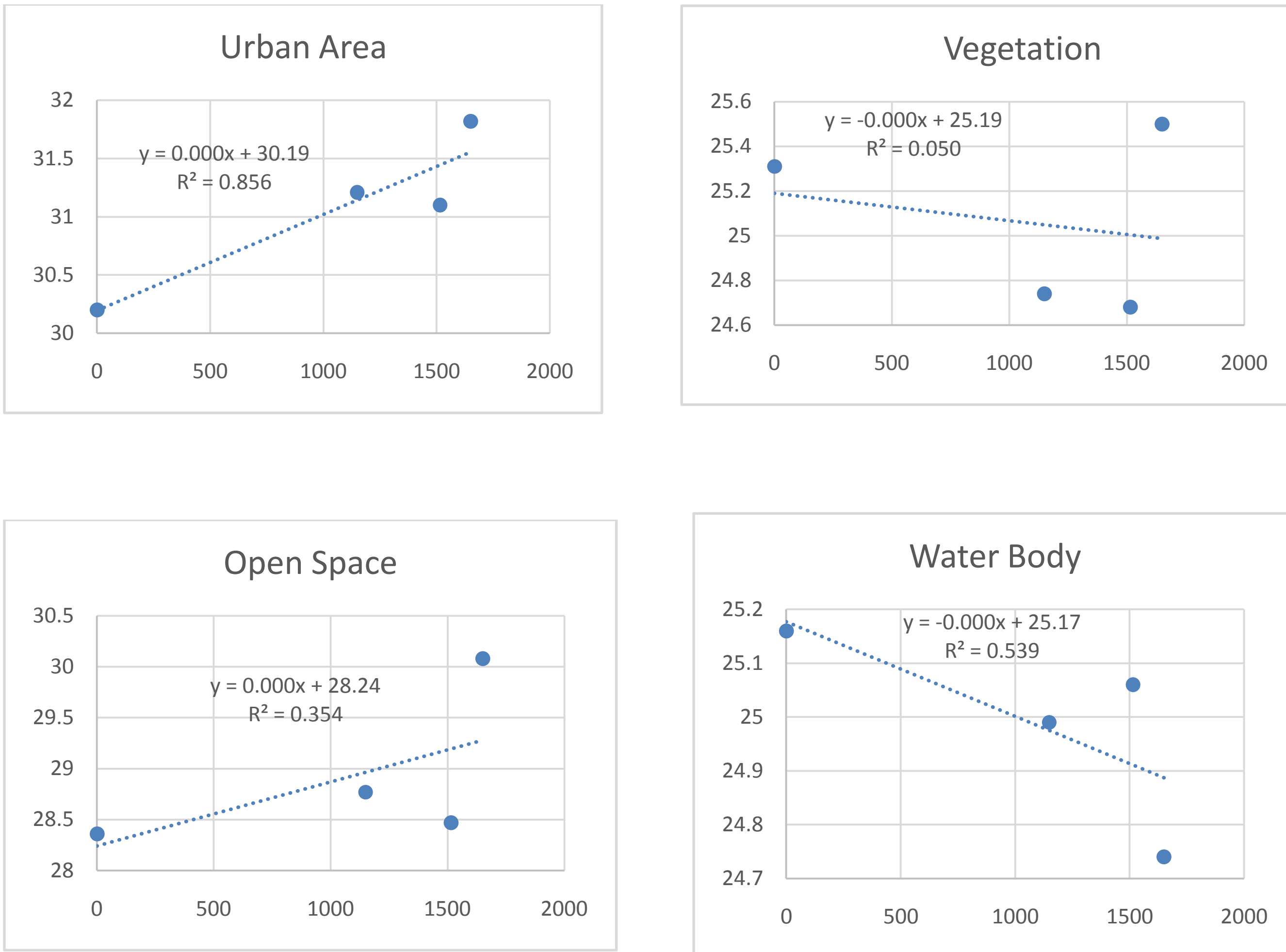

Figure 4.18: Scatter plot of the correlation between (a) LST and urban area, (b) LST and vegetation, (c) LST and open space, (d) LST and waterbody

From fig 4.18 (a), the test gave a correlation coefficient of 0.925 which indicated a strong consistent relationship between LST and urban area in the study area, this indicates that as urban areaincreasesfrom 1990 to 2017, its land surface temperature was increasing as well and because urban development in Awka Capital Territory is going up, its urban surface temperatureis increasing as a resultant effect of expansion into other landuse classes and the subsequent replacement of natural vegetation canopies that would have reduced surface temperature by surfaces such as bare land (soils), metal, tar, cemented buildings and concrete among others.

The dry nature of these non-evapotranspirative materials in the urban environment is responsible for high variation of land surface temperature.More so, the removal of vegetation cover often leads to the adjustment in local water balance because the interception role of the canopy is lost, evapotranspiration is changed or reduced and surface runoff is increased. This is observations were also reported by Nzomiwu *et al*, (2017) and Zaharaddeen*et al*, (2016).

The result in figure 4.18 (c), with a correlation coefficient of 0.730 indicated that open spaces had high surface temperature as a result of the conversions of vegetation to open space, its openness with no natural vegetation to help reduce evaporation and transpiration in its surface lead to a high surface temperature.

From figure 4.18 (b) and (d), vegetation and waterbody had a correlation coefficient of -0.22 and -0.73 respectively, this indicated a negative relationship between LST against vegetation and LST against waterbody, because unlike urban area and open space, vegetation canopies reduce surface temperature through transpiration and evaporationwhile water body surface temperature changes much less rapidly than on land, so it will have relatively lower surface temperature. From the results, it is certain that there is indeed a consistent relationshipbetween LSTand urban area in Awka Capital Territory.

In order to investigate the effect of urban growth on the spatial extents of vegetation and open space in the study area, recall the land cover/ land use results,the results indicated an increase in urban area from 1990 through to 2017, results also show a decrease in vegetation and open space classes from 1990 through to 2017.

Investigating further using the landcover/land use transition results, it can be seen that between 1990 and 2017, vegetation lost a total area of 3342 hectares to urban area, that's 17.4% of its overall area mass from 1990 to 2017 lost to urban area. Similarly, open space lost a total of 974 hectares to urban area, that's 18.25% of its overall area mass from 1990 to 2017 lost to urban area. this indicates that urban area gained 35.66% of growth from vegetation and open space. This corresponds to the pattern indicated by the landcover/landuse results, that as urban area grew from 1990 to 2017, vegetation and open space classes declined in the said period.

This result indicates a growing trend of deforestation and diminishing open spaces. This a trend that needs to be tackled because vegetation offsets the effects of air pollution, reduces surface temperature while open spaces are essential for leisure activities, organized sports or cultural endeavors, so if left to diminish, it will affect the health and social lives of inhabitants in Awka Capital Territory. To buttress this assertion further, t-test was usedto statistically confirmif indeed urban growth lead to vegetation and open space decline between 1990 and 2017.

4.4.6 Hypothesis Testing

T-test was used toascertain if there was any evidence of significant lossof vegetation and open space classes due to urban growth in the study area.

To test the claim;

Step 1: State the hypothesis and identify the claim

H_o= Urban growth did not lead to significant decline in vegetation.

H_i= Urban growth lead to significant decline in vegetation.

Step 2: Compute the t-test

Table 4.27: Area for vegetation and urban area

Year	Vegetation	Urban area
1990	23144.9	12922.45
1999	21629.79	14437.68
2008	20583.59	15586.73
2017	19115.32	17237.45
	21118.4	15046.0775

Therefore X_1= 21118.8 X_2 = 15046.0775

The formula for t-test

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2 + S_2^2}{n_1 + n_2}}} \qquad \text{… (4.3)}$$

Where $\bar{X}_1$& $\bar{X}_2$= the meansofvegetationand urban area

S- Standard deviation

n - Number of subjects in each group

$$S = \frac{\sqrt{\Sigma(X - X)}^2}{n} \qquad \text{… (4.4)}$$

Table 4.28: Standard deviation for vegetation

X_1	X_1-X	$(X_1\text{-}X)^2$
23144.9	23655.89	559601131.7
21629.79	-9488.86	90038464.1
20583.59	-12303.98	151387923.8
19115.32	-21118.8	446003713.4

Standard deviation for vegetation s_1 = 1699.664

Table 4.20: Standard deviation for urban area

X_1	X_1-X	$(X_1\text{-}X)^2$
12922.45	-2123.65	4509889.323
14437.68	-608.42	370174.8964
15586.73	540.63	292280.7969
17237.45	2191.35	4802014.823

Standard deviation for Urban area s_2 = 1823.39974

$$t = \frac{6072.7225}{881.308}$$

t = 6.89

Degree of freedom

$=P_1 + P_2 - 2$

= 4+4-2= 6

At 0.05 level of significance

df = 6

Step 3: Declaration of result

Critical or table value of t is 2.447 (see appendix 1)

Since the calculated t is more than the table value, we reject the null hypothesis and accept the alternative hypothesis i.e. urban growth lead to significant decline in vegetation.

To test the claim no.2

Step 1: State the hypothesis and identify the claim

H_o= Urban growth did not lead to significant decline in open space.

H_i= Urban growth lead to significant decline in open space.

Step 2: Compute the t - test

Table 4.30: Area for open space and urban area

Year	Open space	Urban area
1990	5936.22	12922.45
1999	5693.72	14437.68
2008	5589.67	15586.73
2017	5334.67	17237.45
	5638.57	15046.0775

Table 4.31: Standard deviation for open space

X_1	X_1-X	$(X_1\text{-}X)^2$
5936.22	23655.89	559601131.7
5693.72	-9488.86	90038464.1
5589.67	-12303.98	151387923.8
5334.67	-21118.8	446003713.4

Standard deviation for open space s_1 = 249.2545

Table 4.32: Standard deviation for urban area

X_1	X_1-X	$(X_1\text{-}X)^2$
12922.45	-2123.65	4509889.323
14437.68	-608.42	370174.8964
15586.73	540.63	292280.7969
17237.45	2191.35	4802014.823

Standard deviation for Urban area s_2 = 1823.39974

$$t = \frac{9407.53}{751.322}$$

t = 12.52

Degree of freedom

$=P_1 + P_2 -2$

= 4+4-2= 6

At 0.05 level of significance

df = 6

Step 3: Declaration of result

Critical or table value of t is 2.447 (see appendix 1)

Since the calculated t is more than the table value, we reject the null hypothesis and accept the alternative hypothesis i.e. that urban growth lead tosignificant decline in open space.

4.5 Calibration and Validation of Prescott Spatial Growth Model

4.5.1 Calibration of Prescott Spatial Growth Model

In order for the model to run smoothly, its data inputs had to be prepared to achieve data conformity. For the data input to conform, it has to strictly follow the following rules:

ii. Input data must have the same area

iii. Input data must have the same pixel count (same row by column)

iv. Input data should be 8bit unsigned integer and 32bit float point

v. Input data can either be single band or multiple band

vi. Class categories must follow the same sequence

Following this, the input data i.e. landcover/landuse maps of 1990, 1999, 2008, and 2017 were prepared for input, using the rules as guideline. Alongside the landcover/landuse maps, the road network of Awka Capital Territory from 1990 to 2017 and estimated population data from 1990 to 2017 were also used as influencing variables. Influencing variables are layers that may influence growth, following this; raster was created for the road network using Euclidean distance, which was then used as an input. Population data was also interpolated to create a kernel density raster which was also used an influencing variable input. After which a prediction to 2018 was made using the input datasets.

4.5.2 Validation of Prescott Spatial Growth Model

Traditionally, model validation refers to comparing the simulated and reference maps (Vliet *et al*, 2011). Sometimes the simulated maps can give misleading results. In that case, it is necessary to validate the predicted/simulated map with the base/reference map.

The main objective of model validation is to find out whether the simulation is giving any abrupt result or not. This justifies the modeling output in terms of reality. In order to validate the model's prediction of landcover/landuse of 2018, the predicted landcover/landuse of 2018 was compared to the actual landcover/landuse of 2018 using kappa statistics, cross tabulation and image correlation (Pearson's product-movement correlation coefficient).

According to Pontius (2000), kappa is a member of family of indices that have the following desirable properties:

If classification is perfect, then Kappa = 1

If observed proportion correct is greater than expected proportion correct due to chance, then Kappa > 0

If observed proportion correct is equal to expected proportion correct due to chance, then Kappa = 0

If observed proportion correct is less than expected proportion correct due to chance, then Kappa < 0

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

Table 4.26: Interpretation of kappa statistic

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

Source: Fung and Ledrew, 1988.

Thepredicted landcover/landuse of Awka Capital Territory in 2018 as shown in figure 4.14 and table 4.33 indicate that vegetation had 40.04 %, with area of about 18534.38 hectares. Urban area had 38.67% with an area of 17901.32 hectares while water body and open space had 9.95% and 11.33% with an area of 4609.22 and 5244.87 hectares respectively.

In comparison with the actual landcover/landuse of Awka Capital Territory in 2018, it read that vegetation had 40.08 %, with area of about 18555.33hectares. Urban area had 38.45% with an area of 17798.44 hectares while water body and open space had 9.96% and 11.50% with an area of 4611.35 and 5324.67hectares respectively. This gives a difference of 102.88 hectares between actual and predicted urban area, 20.99 hectares between actual and predicted vegetation, 79.8 hectares between actual and predicted open space and 2.13 hectares between actual and predicted water body.

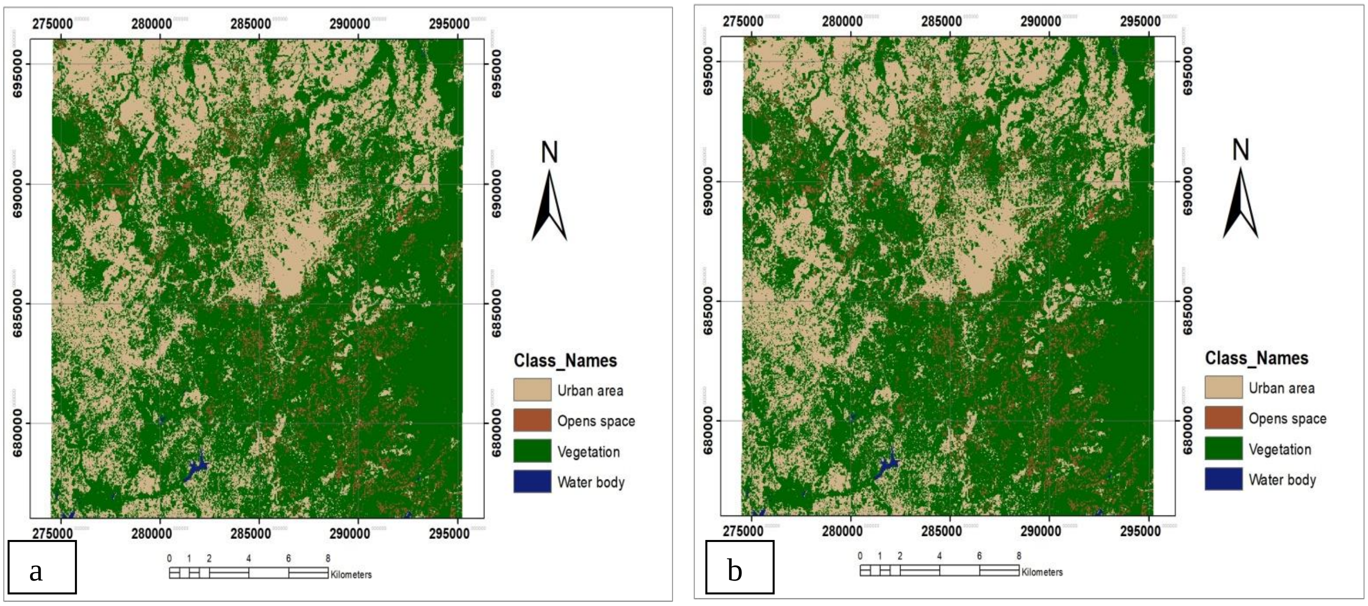

Figure: 4.18: (a) 2018 landcover/landuse map, (b) predicted 2018 landcover/landuse map

Table 4.33: Comparison between 2018 predicted landcover/landuse and actual 2018 landcover/landuse

Class Name	2018 Landcover/landuse		2018 Predicted Landcover/landuse		Difference	
Urban area	17798.44	38.45%	17901.32	38.67%	102.88	0.22
Vegetation	18555.33	40.08%	18534.38	40.04%	20.99	0.04
Open space	5324.67	11.50%	5244.87	11.33%	79.8	0.17
Water body	4611.35	9.96%	4609.22	9.95%	2.13	0.01
Totals	46289.79	100%	46289.79	100%		

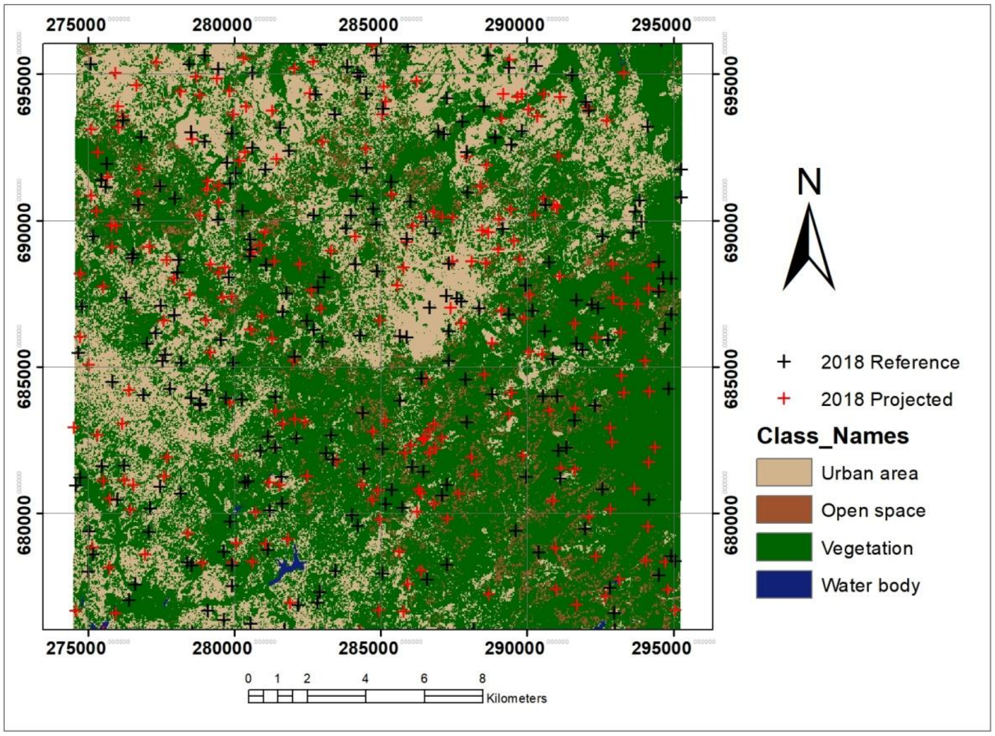

Figure: 4.19: Accuracy assessment points for model validation

Table: 4.34: Model Validation Accuracy

ACCURACY TOTALS						KAPPA (K^) STATISTICS
Class	2018 Reference	2018 Predicted	Number Correct	ProducersAccuracy	UsersAccuracy	Kappa
Urban area	198	198	189	95.45%	95.45%	0.9214
Vegetation	39	39	34	87.17%	87.17%	0.8956
Open space	15	15	12	80.00%	80.00%	0.8165
Water body	4	4	4	100.00%	100.00%	1
Totals	256	256	239			Overall K^ =
Overall Classification Accuracy = 93.36%						0.9083

From Table 4.34,the total 2018 reference points used was 256 and total number injected into 2018 predicted map was 256, the total number of correct points was 189.

Urban area had a total 2018 reference of 198 points, total classified of 198 points and number of correct points in 2018 predicted map as 189. This gives the producer's accuracy for urban area as 95.45% and user's accuracy as 95.45%. The kappa for urban area was at an agreeable value of 0.9214.

Vegetation had a total 2018 reference of 39 points, total classified of 39 points and number of correct 2018 predicted map points as 34. This gives the producer's accuracy for vegetation as 87.17% and user's accuracy as 87.17%. The kappa for vegetation was at an agreeable value of 0.8956.

Open space had a total 2018 reference of 15 points, total classified of 15 points and number of correct 2018 predicted points as 12. This gives the producer's accuracy for open space as 80% and user's accuracy as 80%. The kappa for open space was at an agreeable value of 0.8165.

Water body had a total 2018 reference of 4 points, total classified of 4 points and number of correct 2018 predicted points as 4. This gives the producer's accuracy for water body as 100% and user's accuracy as 100%. The kappa for water body was at an agreeable value of 1.

The overall accuracy gotten was as 93.36%; overall kappa was given as 0.9083 and the model error was given as 6.64%. Hence the model result is adjudged to be acceptable.

Pearson product-moment correlation coefficient (r) between two images was also calculated to determine the similarities between the two images. The r-value is a measure of the linear association in the variation of the input variables (images, in this case). The coefficient ranges from -1, indicated a perfect negative linear association, to 1, indicated a perfect positive linear association. An r-value of 0 indicates no correlation between the test variables. The results of the correlation coeffcient gave a value of 0.9585, which indicates a good positive relationship between the two images as shown in table 4.35

Table 4.35: Image correlation matrix

	2018 Reference LULC	2018 Predicted LULC
2018 Reference LULC	1.000	0.9585
2018 Predicted LULC	0.9585	1.000

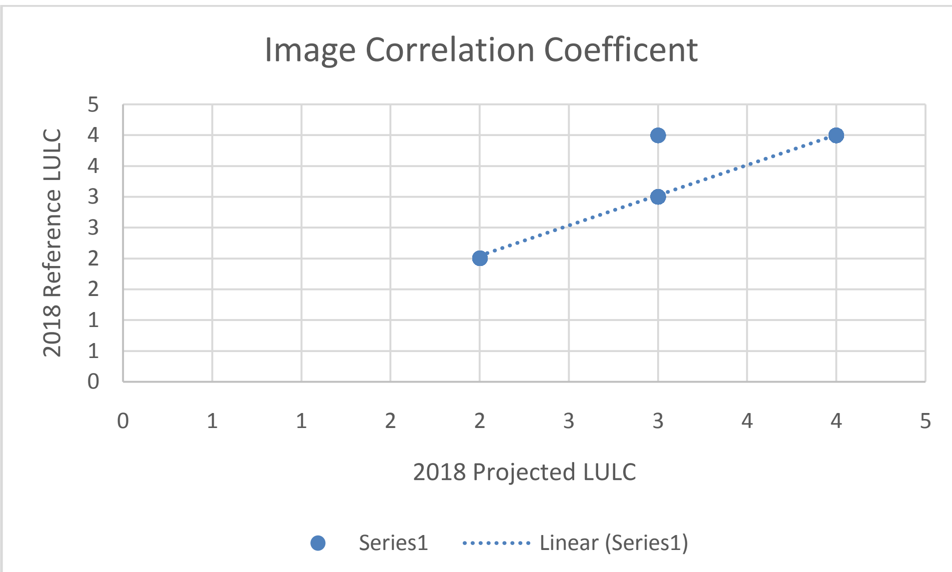

Figure 4.20: Correlation graph between 2018 reference LULC and 2018 predicted LULC

From figure 4.20 and table 4.35, the correlation coefficient of 0.9585 between the two images indicate a close similarity between them, so in all the results of the model prediction is adjudged to be acceptable.

4.6 Future Urban Development Prediction

Land change prediction in Prescott spatial growth modeler is an empirically given process that moves in a step wise fashion from change analysis; to transition Potential Modeling; to change prediction. It is based on the historical change from 1990 to 2018. The change assessed between 1990 and 2017 are identified and modeled as transitions from one landcover/landuse state to another. Prescott spatial growth model was used to predict the change for (30 years) from the 2018 to 2048 and the result is shown in fig 4.21.

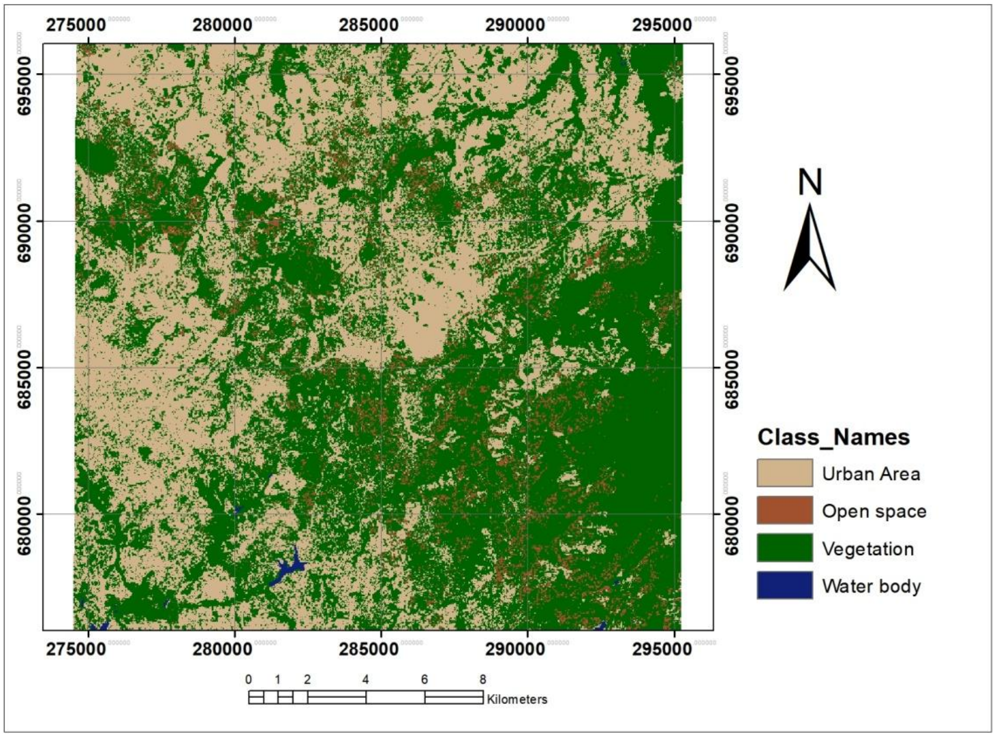

Figure 4.21: 2048 predicted future urban development

Table: 4.36: Landcover/landuse distribution of Awka capital territory 2048

Class Name	2048 Landcover/landuse Prediction	
	Hectares	Percentage (%)
Urban area	22871.51	49.41%
Vegetation	13853.39	29.93%
Open space	4852.99	10.48%
Water body	4711.9	10.18%
Totals	46289.79	100%

The prediction results tabulated in table 4.36, indicated that by 2048 urban area is expected to grow to 49.41% covering an area of 22871.51 hectares (figure 4.22), vegetation is expected to decrease to 29.93% covering an area of 13853.39 hectares, open space is expected to decrease to 10.48% covering an area of 4852.99 hectares while water body is expected to increase to 10.18% covering an area of 4711.9 hectares.

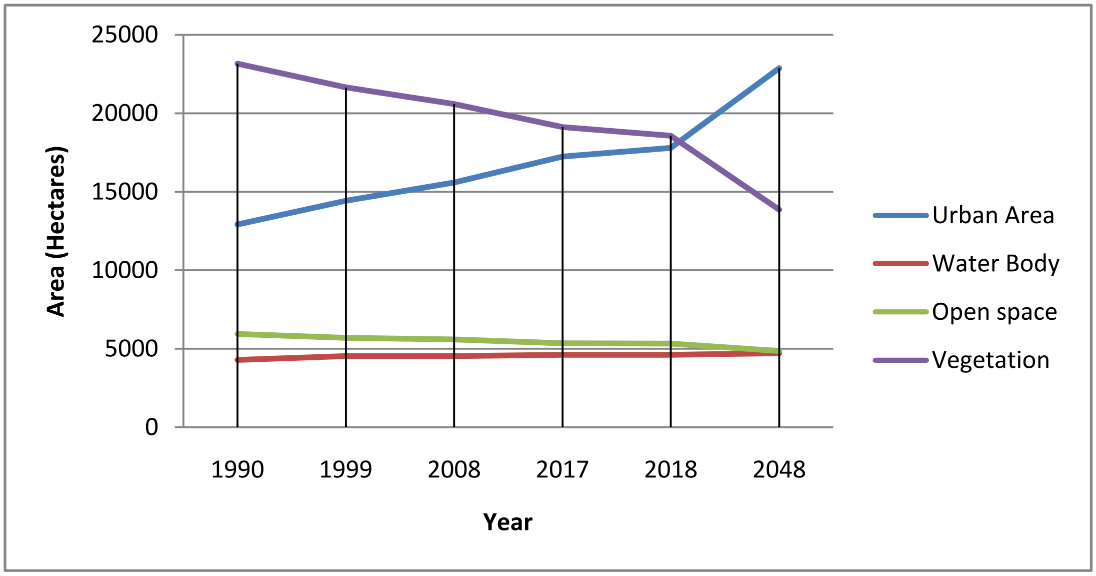

Figure4.22: Graph of urban development from 1990 to 2048

Thirty years from 2018, the vegetation and open space classes are expected loss part of its area urban area based on their distance to roads and as population increases. Water body is expected to increase from 9.96% to 10.18% with area coverage of 4711.9 hectares. Urban area is expected to increase from 35.45% to 49.41% i.e. from area coverage of 17798.44 hectares to 22871.51 hectares while open space and vegetation is expected to decrease from 11.50% to 10.48% i.e. from 5324.67 hectares to 4852.99 hectares and 40.08% to 29.93% i.e. from 18555.33 hectares to 13853.39 hectares respectively.Following, the same trend as noted while examining the landcover/landuse changes in Awka Capital Territory, if urban area is expected to increase from 18555.33 hectares to 13853.39 hectares in 2048, then one would expect more alterations to the natural environment and more problems associated with that in Awka Capital Territory. To prevent these estimates from becoming a reality and to mitigate the negative effects, critical landuse areas should be identified and protected from development to reduce per capita land consumption, and proper developments encouraged with critical landuse planning.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATION

5.1 Summary of Findings

The landcover/landuse distribution of Awka Capital Territory in 1990 indicated that vegetation, accounted for the largest land cover/use of about 50% and an area of about 23144.9 hectare. Urban area had 27.92 % and a coverage area of 12922.45 hectares.Open space and water body had the lowest turnout with 12.82% and 9.26% and an area of 5936.22 and 4286.22 hectares respectively.

In 1999, vegetation, decreased from 50% to 46.73% to an area of about 21629.79hectares. Urban area increased from 27.92% to 31.19 %, to an area of 14437.68hectares.Open space decreased from 12.82% to 12.30 to an area of 5693.72 hectares while water body increased from 9.26% to 9.78% to an area of 4528.6hectares.

In 2008, vegetation decreased further from 46.73% to 44.46%, to an area of 20583.59 hectares. Urban area increased further from 31.19% to 33.67%, to an area of 15586.73 hectares while open space decreased from 12.30% to 12.07%, to an area of 5589.67 hectares. Water bodyincreased slightly from 9.78% to 9.78% to an area of 4529.8 hectares.

In 2017, vegetation continued its gradual decrease from 44.46% to 41.29%, to an area of 19115.32 hectares, while urban area also increased from 33.67% to 37.24%, to an area of 17237.45 hectares. Open space continued decreasing from 12.07% to 11.52%, to an area of 5334.6 hectares while water body increased from 9.78% to 9.94%, to area coverage of 4601.35.

The land cover/land use distribution of Awka Capital Territory in 2018 also indicate gradual decrease of vegetation from 44.46% to 40.08%, to an area of 18555.33 hectares, while Urban area increased from 33.67% to 38.45%, to an area of 17798.44 hectares. Open space also decreased from 11.52% 11.50%, to an area of 5324.67 hectares, while water body increased from 9.94% to 9.96, to an area of 4611.35 hectares.

The trend of change for the class features between 1990 and 2017 was given as 5.53% for urban area between 1990 and 1999, 3.83% between 1999 and 2008 and 5.03% between 2008 and 2017. The trend of change for vegetation between 1990 and 2017 was given as -3.38% between 1990 and 1999, -2.48% between 1999 and 2008, then -3.69 between 2008 and 2017. The trend of change for open space between 1990 and 2017 was given as -2.085% between 1990 and 1999, -0.92% between 1999 and 2008 and -2.33% between 2008 and 2017. Then lastly, the trend of change of water body was given as 2.75% between 1990 and 1999, 0.01% between 1999 and 2008 and 0.79% between 2008 and 201, as shown in table 5.14 and figure5.8.

The annual rate of change between 1990 and 2017, for urban area was given as 0.62% between 1990 and 1999, 0.43% between 1999 and 2008 and 0.56% between 2008 and 2017. For vegetation, the annual growth rate was given as -0.37% between 1990 and 1999, -0.27% between 1999 and 2008, and -0.41% between 2008 and 2017. For open space, the annual rate of change was given as -0.23% between 1990 and 1999, -0.10% between 1990 and 2008 and -0.25% between 2008 and 2017. For water body the annual rate of change was given as 0.30% between 1990 and 1999, 0.001% between 1999 and 2008 and 0.08% between 2008 and 2017. This means that both urban area and water body had a positive growth between 1990 and 2017, while vegetation and open space declined between 1990 and 2017.

Discriminant function matrix was used to calculate the landcover/landuse transition in the study area between 1990 and 2017. The resultsshowed that between 1990 and 1999, urban area had an unchanged area of 12922.45 hectares while gaining 1272.73 hectares from vegetation, 242.5 hectares from open space. Vegetation had an unchanged area of 21629.79

hectares, while 1273.73 hectares transitioned to urban area, 152.27 transitioned to open space and 90.11 transitioned to water body. Open space had an unchanged area of 5541 hectares, while 242.5 hectares transitioned to urban area and 152.27 hectares to water body. Water body had an unchanged area of 4286.22 while gaining 90.11hectares from vegetation and 152.27 hectares from open space.

The transition results between 1999 and 2008 showed that, urban area had an unchanged area of 14437.68 hectares while gaining 1000 hectares from vegetation, 149.05 hectares from open space. Vegetation had an unchanged area of 20583.59 hectares, while1000 hectares transitioned to urban area, 45 transitioned to open space and 1.2 hectares transitioned to water body. Open space had an unchanged area of 5544.67 hectares, while 149.05 hectares transitioned to urban area. Water body had an unchanged area of 4529.6 while gaining 1.2 hectares from vegetation.

Then in the last epoch between 2008 and 2017 in table 5.18, the landcover/landuse transition results indicated that urban area had an unchanged area of 15586.73 hectares while gaining 1068.27 hectares from vegetation, 582.45 hectares from open space. Vegetation had an unchanged area of 19115.32 hectares, while1068.27 hectares transitioned to urban area, 327.45 hectares transitioned to open space and 72.55 hectares transitioned to water body. Open space had an unchanged area of 5007.22 hectares, while 582.45 hectares transitioned to urban area. Water body had an unchanged area of 4529.8 while gaining 72.55 hectares from vegetation.

The results of analyzing the growth pattern also revealed two patterns inherent in the study area: edge-expansion and infilling, with edge-expansion being the most dominant growth pattern in the study area between 1990 and 2017, there was also no evidence of spontaneous growth within the study area. The results achieved from investigating the effects of urban growth in the study area revealed a consistent increase in surface temperature in urban areas, a diminishing open space and a growing trend of deforestation in the study area.

The t-test was used to test the hypothesis, to ascertain which of the classes lost significantly to the growth of urban area. The t-test for the null hypothesis; H_o= urban area did not lead to significant decline in vegetationand alternate hypothesis; H_i= urban area lead to significant decline in vegetation resulted to a t test value of 6.89 at df of 6, the null hypothesis was therefore rejected and the alternative hypothesis i.e. urban area lead to significant decline in vegetation was accepted since the calculated t is more than the table value. The t-test was also conducted for the null hypothesis; H_o= urban area did not lead to significant decline in open space and alternative hypothesis; H_i= urban area lead to significant decline in open space, the results gave a t value of 12.52 at df of 6, therefore the null hypothesis was rejected and the alternative hypothesis i.e. urban area lead to significant decline in open space was accepted since the calculated t is more than the table value. The results of the hypothesis testing supported the claim that urban area lead to significant decline in vegetation and open space in the study area.

The results of the validation gave an overall accuracy as 93.36%; overall kappa as 0.9083, the model error as 6.64% and image correlation as 0.9585. Hence the model result is adjudged to be moderately accurate.

5.2 Conclusion

This study has demonstrated the ability of predicting future urban development in Awka Capital Territory using Prescott spatial growth model. The research work captured as accurate as possible four landcover/landuse classes as they change through time. The four classes were distinctly produced in contrast to urban development for 1990, 1999, 2008, 2017 and 2018.

The study also generated the trend of change and annual rate of change between 1990 and 2017. A modeled prediction was made into 2018and validated using 2018 reference landcover/landuse by determining their kappa and image correlation. A final prediction was then made into 2048 for future urban development dynamics. This prediction can be used a decision support tool and will guide the relevant authorities on how to manage and monitor development to ensure a habitable environment in the near future.

5.3 Contribution to Knowledge

Contributions to knowledge in this work are hereby articulated.

1. Generation of current landcover and landuse map

The study carried out was able to generate landcover/landuse maps of Awka Capital Territoryfor past years (1990, 1999, 2008 and 2017) and current year (2018). This is an addition to the spatial data availability for the study area. The study was also able to identify the spatial extents of landcover/landuse in the study area this can be used for informed decisions on landuse planning.

2. Determination of the Pattern and Trend of Changes within the Study Area

The study was able to determine the pattern of growth, trend of change, annual rate of change of Awka, Ifite, Okpuno, Nwafia, Amawbia, Enugwu-Ukwu, Abagana, Nibo, Nise, and Agulu in the study area. The study revealed that Abagana had an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively and Agulu had an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively while Enugwu-Ukwu had an annual growth of 0.06%, 0.04% and 0.05% between 1990-1999, 1999-2008 and 2008-2017 respectively. Thus, indicating a similar growth rate between Abagana, Agulu and Enugu-Ukwu.

Amawbia grew with an annual rate of 0.09%, 0.06% and 0.08% between 1990-1999, 1999-2008 and 2008-2017 respectively, Awka's annual growth rate was 0.13%, 0.09% and 0.12% between 1990-1999, 1999-2008 and 2008-2017 respectively. This indicated that Awka and Amawbia had the highest growth rate amongst other urban patches in Awka Capital Territory between 1990 and 2017.

Ifite also had an annual growth of 0.04%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively. Similarly, Nise with the same growth rate as Ifite, had an annual growth of 0.04%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively.

Okpuno had an annual growth of 0.03%, 0.02% and 0.03% between 1990-1999, 1999-2008 and 2008-2017 respectively. Nibo had an annual growth of 0.05%, 0.03% and 0.04% between 1990-1999, 1999-2008 and 2008-2017 respectively. Nawfia had an annual growth of 0.06%, 0.04% and 0.06% between 1990-1999, 1999-2008 and 2008-2017 respectively. This provides data on how the towns are changing, their rate of change and pattern of change.

3. Influence of urban growth on Land surface temperature, vegetation and open surface

The study was also able to test the influence of urban growth on landcover/landuse surface temperature by calculation the spatio-temporal surface temperature viability between 1990 and 2017, thereby confirming a strong influence of urban growth on urban area surface temperature.

The study also identified a case of deforestation and open space diminishing in Awka Capital Territory, as 17.4 % of vegetation cover and 18.25% of open space has been lost to urban growth from 1990 to 2017, rapid depletion of vegetation cover will have a wide range of impacts such as in the reduction of the natural cooling effects of shading and evapotranspiration of plants and shrubs as already seen in the high surface temperature of urban areas in Awka Capital Territory.

Hypothesis testing was also carried out to buttress the claim that urban growth lead to vegetation and open space decline. this supported the claim that vegetation and open space have lost part of its area to urban area. The results here will add to data collection that will provide insights on how to manage deforestation and enable proper landuse planning and management of any problems that may arise as a result of expansion of urban heat islands in the study area.

4. Prediction of future urban dynamics of Awka Capital Territoryin 2048

Future urban development of Awka Capital territory was modeled with Prescott spatial growth model, the model validation gave an overall accuracy of 93.83%, kappa of 0.9083, model error of 6.64% and image correlation of 0.9585.

This indicates that the model produces acceptable results and can be integrated for future urban planning. The prediction into 2048 using Prescott spatial growth model, indicates the likelihood of growth as population increases and access/number of roads increases. This will guide the relevant authorities on how to manage and monitor development to ensure a habitable environment for the growing populace.

5.4 Recommendation

This study has successfully investigated the urban development dynamics of Awka Capital Territory, and based on the experience and results obtained, the following recommendations are hereby proffered:

1. Thisresearch work was able to generate landcover and landuse maps of Awka Capital Territoryfor the years 1990, 1999, 2008, 2017 and 2018. It is recommended that the data obtained here be used as an addition to the spatial data availability for the study area. This will take care of the lack of landcover/landuse maps of Awka Capital Territory between 1990 and 2018.

2. The study was able to determine the trend of change, annual rate of change, transitions of landcover/landuse classes and the pattern of growthwithin the study area. The result obtained from the trend and annual rate of change, the transitions of landcover/landuse and pattern of growth in the study area is recommended as it provides data on what landcover/landuse class are changing, what they are changing into, their rate of change and the pattern at which the urban patches in the study area are growing. This will enable relevant authorities plan and manage landcover/landuse changes in the study area.
3. The study was able to analyze the relationship between LST and Landcover/landuse classes in Awka Capital Territory, this indicateda consistent increase in surface temperature in urban areas between 1990 and 2017, it also identified a growing trend of deforestation during said period, the results obtained here is recommended as it provides relevant data that will help with the effortstowardsa planned reforestation, advocating tree planting as part of landscaping activities and development of parks and botanical gardens on open spaces within the Awka Capital Territory to reduce thedeforestation and hence lower the expansion of urban heat islands in the study area.
4. The study has successfully demonstrated and predicted the future urban development dynamics of Awka Capital Territory using Prescott spatial growth model, so therefore the approach, is hereby recommended to be used as tool for planning and decision making in urban development in the study area. This will guide relevant authorities on how to manage and monitor urban development to ensure a habitable environment in the near future

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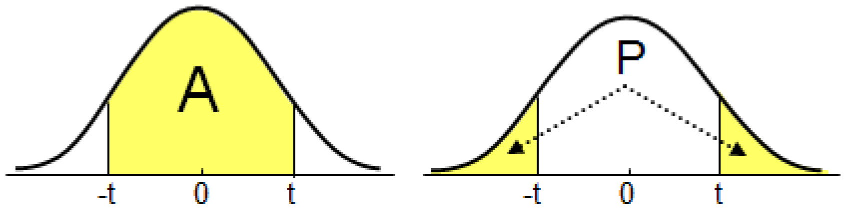
Appendix 1: Values of the t-distribution

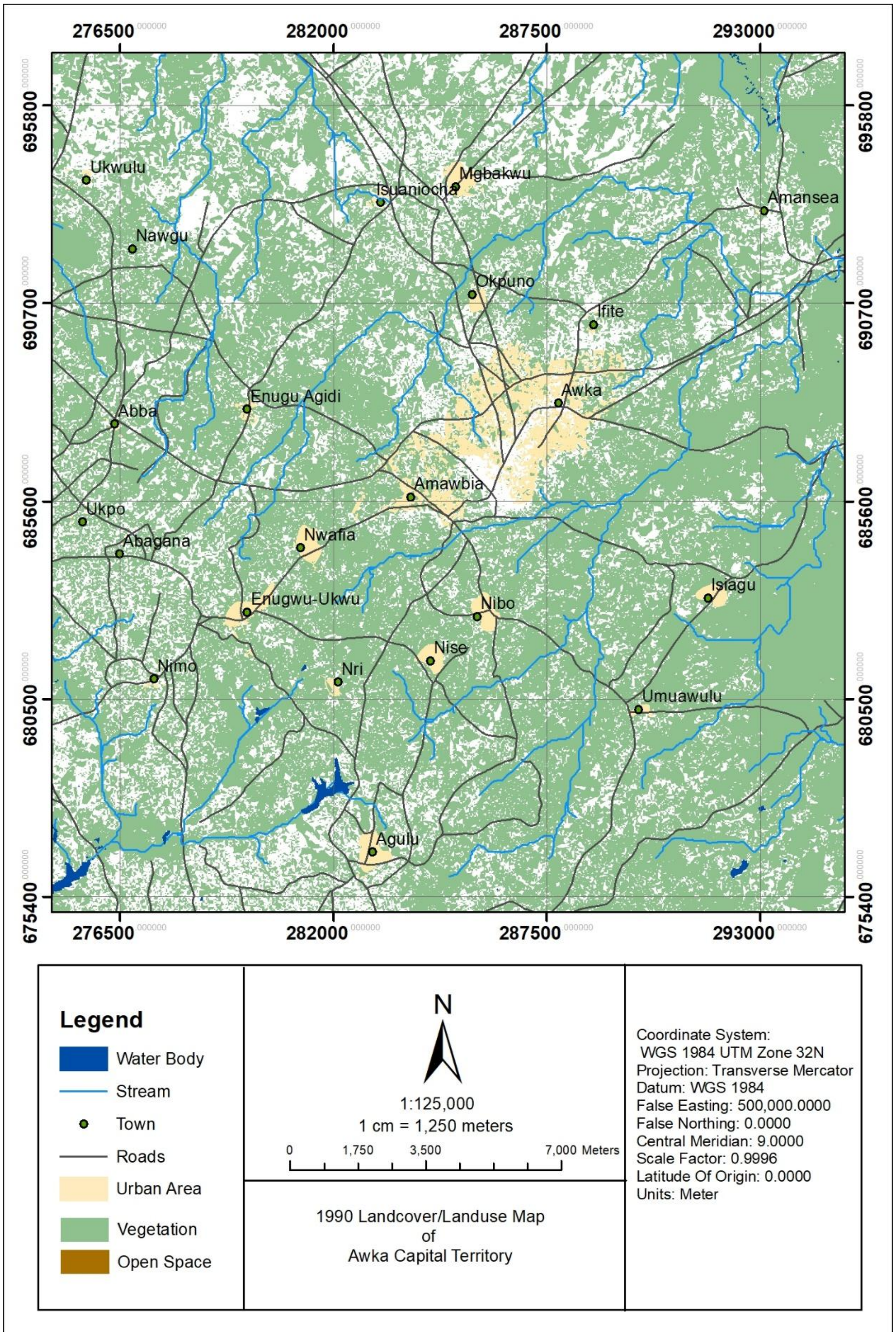
Values of the t-distribution



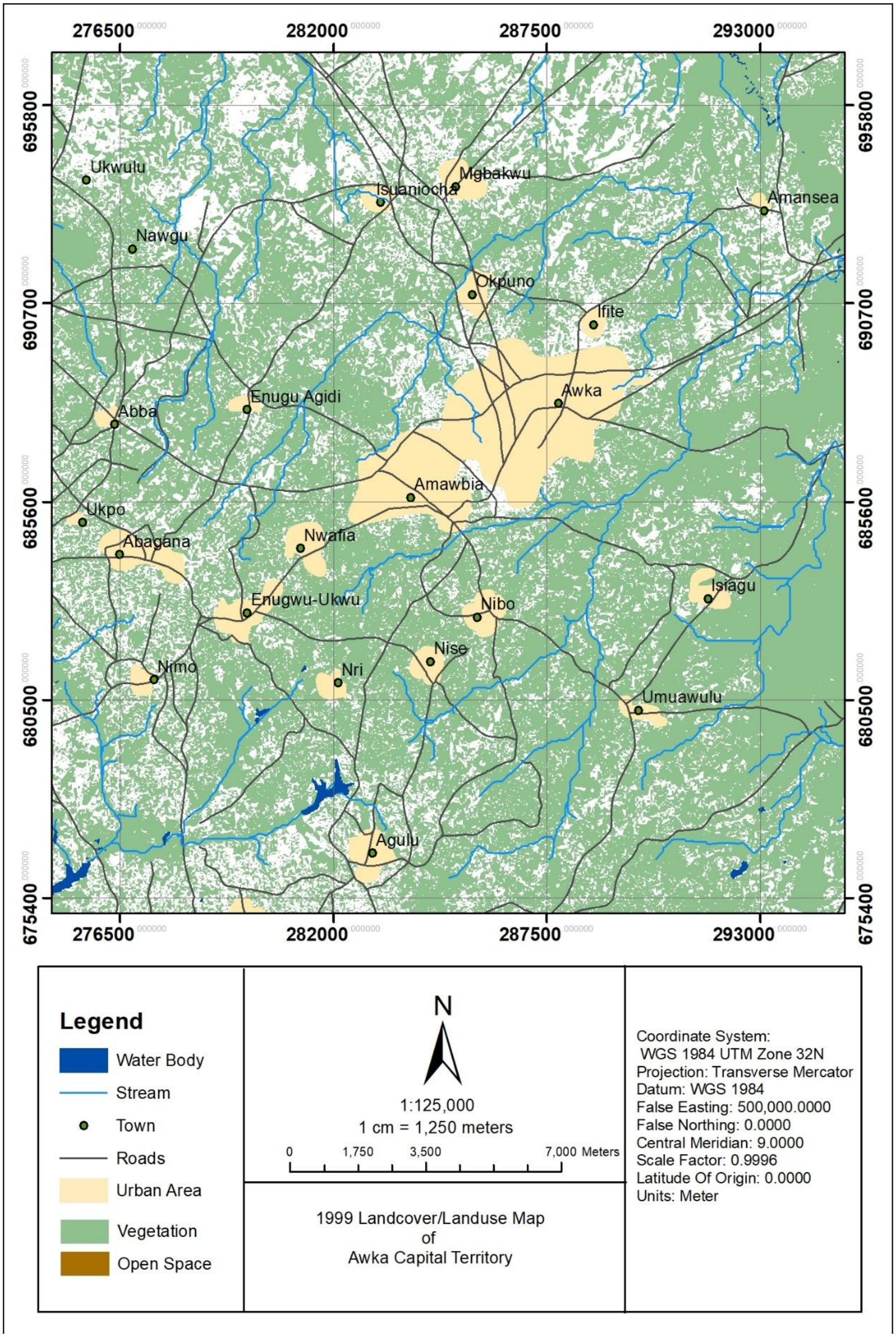
DF	A P	0.80 0.20	0.90 0.10	0.95 0.05	0.98 0.02	0.99 0.01	0.995 0.005	0.998 0.002	0.999 0.001
1		3.078	6.314	12.706	31.820	63.657	127.321	318.309	636.619
2		1.886	2.920	4.303	6.965	9.925	14.089	22.327	31.599
3		1.638	2.353	3.182	4.541	5.841	7.453	10.215	12.924
4		1.533	2.132	2.776	3.747	4.604	5.598	7.173	8.610
5		1.476	2.015	2.571	3.365	4.032	4.773	5.893	6.869
6		1.440	1.943	2.447	3.143	3.707	4.317	5.208	5.959
7		1.415	1.895	2.365	2.998	3.499	4.029	4.785	5.408
8		1.397	1.860	2.306	2.897	3.355	3.833	4.501	5.041
9		1.383	1.833	2.262	2.821	3.250	3.690	4.297	4.781
10		1.372	1.812	2.228	2.764	3.169	3.581	4.144	4.587
11		1.363	1.796	2.201	2.718	3.106	3.497	4.025	4.437
12		1.356	1.782	2.179	2.681	3.055	3.428	3.930	4.318
13		1.350	1.771	2.160	2.650	3.012	3.372	3.852	4.221
14		1.345	1.761	2.145	2.625	2.977	3.326	3.787	4.140
15		1.341	1.753	2.131	2.602	2.947	3.286	3.733	4.073
16		1.337	1.746	2.120	2.584	2.921	3.252	3.686	4.015
17		1.333	1.740	2.110	2.567	2.898	3.222	3.646	3.965
18		1.330	1.734	2.101	2.552	2.878	3.197	3.610	3.922
19		1.328	1.729	2.093	2.539	2.861	3.174	3.579	3.883
20		1.325	1.725	2.086	2.528	2.845	3.153	3.552	3.850
21		1.323	1.721	2.080	2.518	2.831	3.135	3.527	3.819
22		1.321	1.717	2.074	2.508	2.819	3.119	3.505	3.792
23		1.319	1.714	2.069	2.500	2.807	3.104	3.485	3.768
24		1.318	1.711	2.064	2.492	2.797	3.090	3.467	3.745

25		1.316	1.708	2.060	2.485	2.787	3.078	3.450	3.725
26		1.315	1.706	2.056	2.479	2.779	3.067	3.435	3.707
27		1.314	1.703	2.052	2.473	2.771	3.057	3.421	3.690
28		1.313	1.701	2.048	2.467	2.763	3.047	3.408	3.674
29		1.311	1.699	2.045	2.462	2.756	3.038	3.396	3.659
30		1.310	1.697	2.042	2.457	2.750	3.030	3.385	3.646
31		1.309	1.695	2.040	2.453	2.744	3.022	3.375	3.633
32		1.309	1.694	2.037	2.449	2.738	3.015	3.365	3.622
33		1.308	1.692	2.035	2.445	2.733	3.008	3.356	3.611
34		1.307	1.691	2.032	2.441	2.728	3.002	3.348	3.601
35		1.306	1.690	2.030	2.438	2.724	2.996	3.340	3.591
36		1.306	1.688	2.028	2.434	2.719	2.991	3.333	3.582
37		1.305	1.687	2.026	2.431	2.715	2.985	3.326	3.574
38		1.304	1.686	2.024	2.429	2.712	2.980	3.319	3.566
39		1.304	1.685	2.023	2.426	2.708	2.976	3.313	3.558
40		1.303	1.684	2.021	2.423	2.704	2.971	3.307	3.551
42		1.302	1.682	2.018	2.418	2.698	2.963	3.296	3.538
44		1.301	1.680	2.015	2.414	2.692	2.956	3.286	3.526
46		1.300	1.679	2.013	2.410	2.687	2.949	3.277	3.515
48		1.299	1.677	2.011	2.407	2.682	2.943	3.269	3.505
50		1.299	1.676	2.009	2.403	2.678	2.937	3.261	3.496
60		1.296	1.671	2.000	2.390	2.660	2.915	3.232	3.460
70		1.294	1.667	1.994	2.381	2.648	2.899	3.211	3.435
80		1.292	1.664	1.990	2.374	2.639	2.887	3.195	3.416
90		1.291	1.662	1.987	2.369	2.632	2.878	3.183	3.402
100		1.290	1.660	1.984	2.364	2.626	2.871	3.174	3.391
120		1.289	1.658	1.980	2.358	2.617	2.860	3.160	3.373
150		1.287	1.655	1.976	2.351	2.609	2.849	3.145	3.357
200		1.286	1.652	1.972	2.345	2.601	2.839	3.131	3.340
300		1.284	1.650	1.968	2.339	2.592	2.828	3.118	3.323
500		1.283	1.648	1.965	2.334	2.586	2.820	3.107	3.310
∞		1.282	1.645	1.960	2.326	2.576	2.807	3.090	3.291

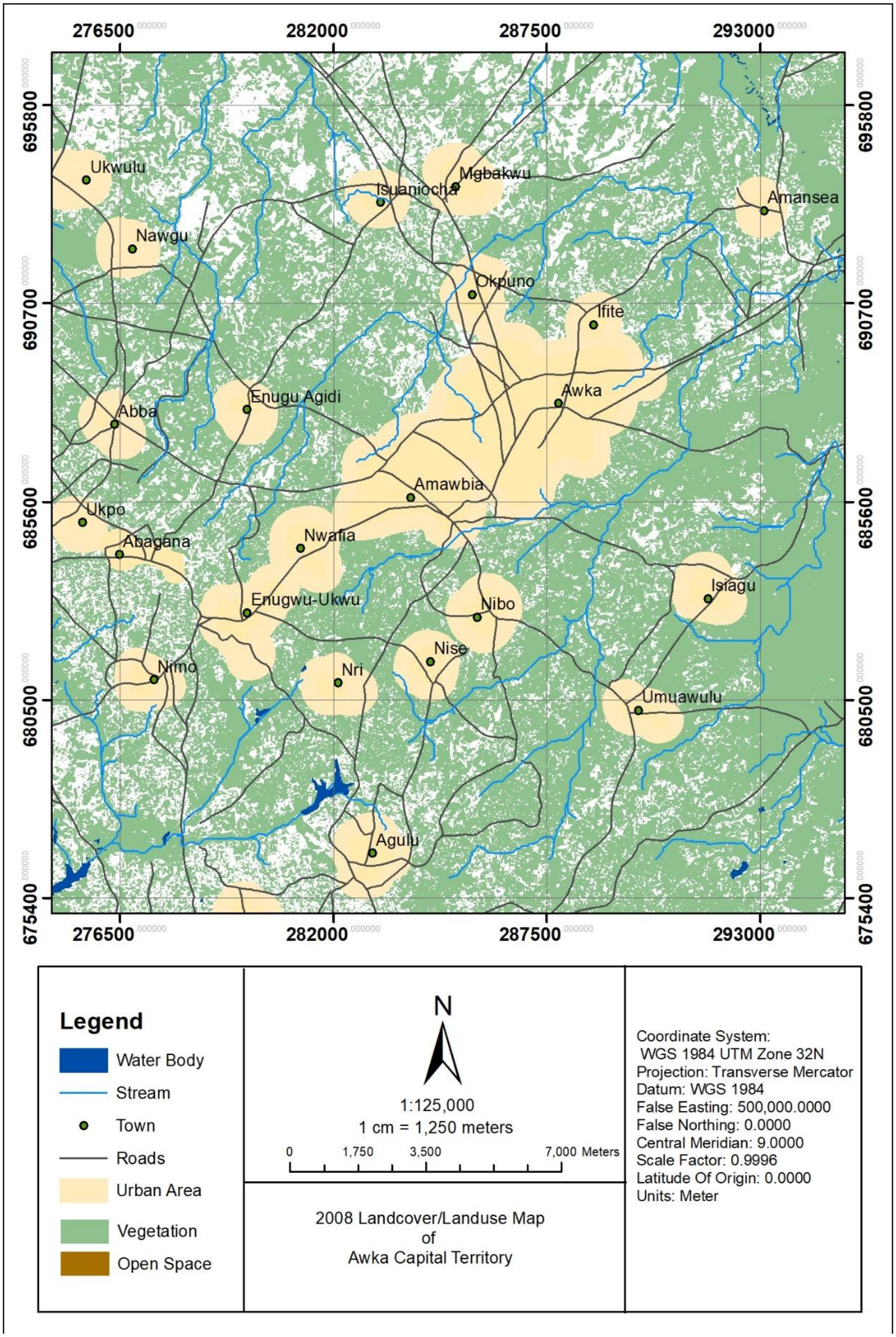
Appendix 2: Landcover/landuse map of 1990



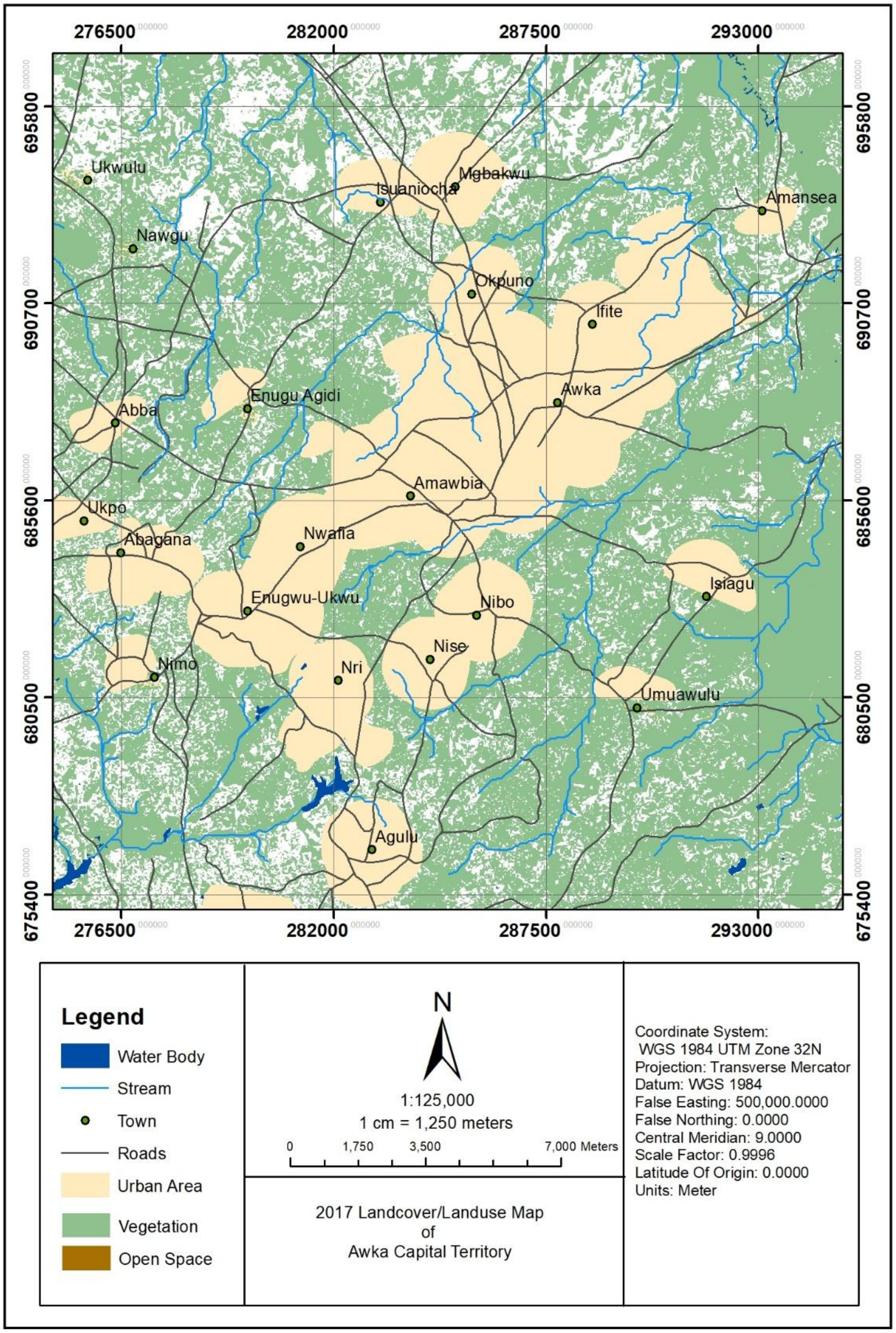
Appendix 3: Landcover/landuse map of 1999



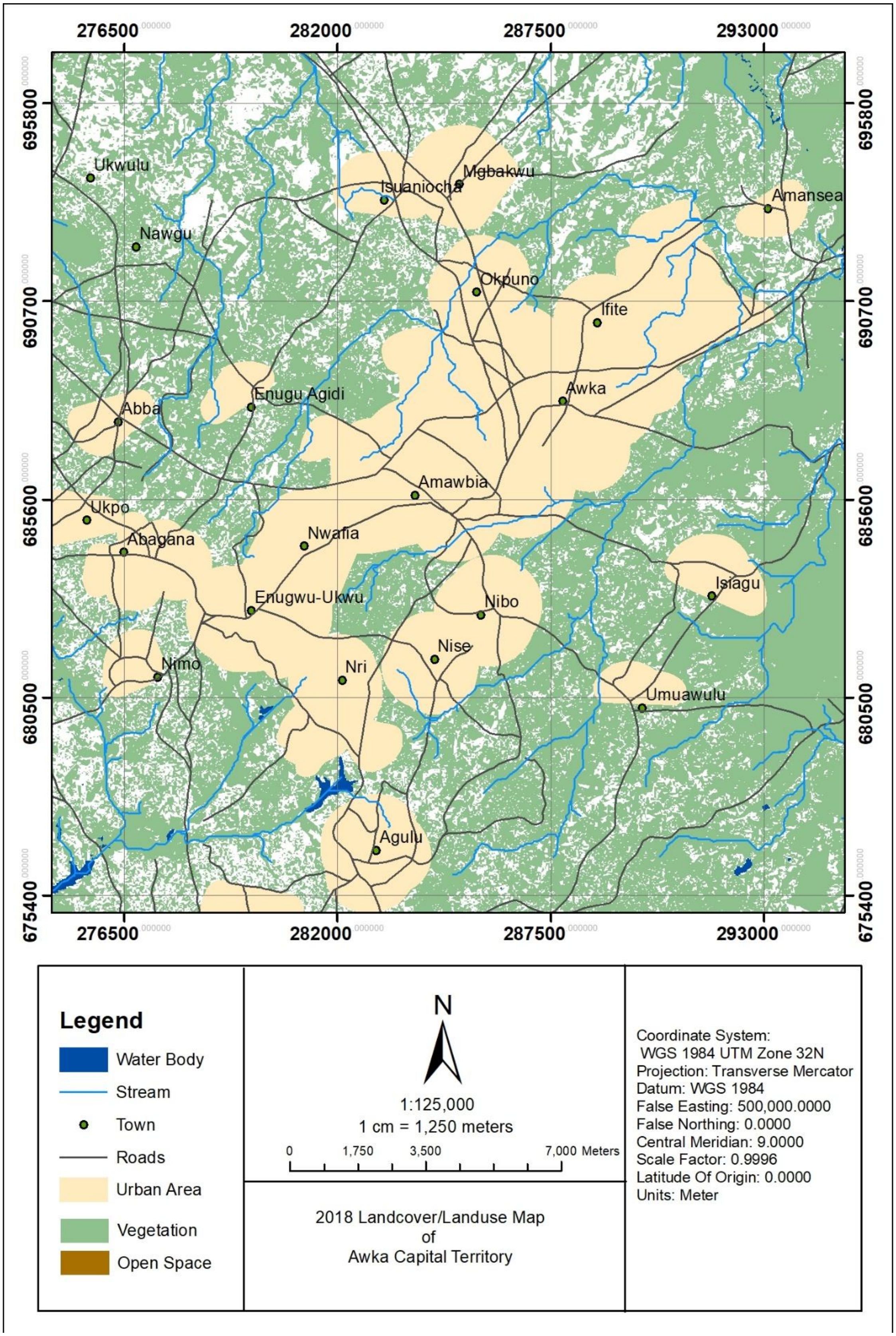
Appendix 4: Landcover/landuse map of 2008



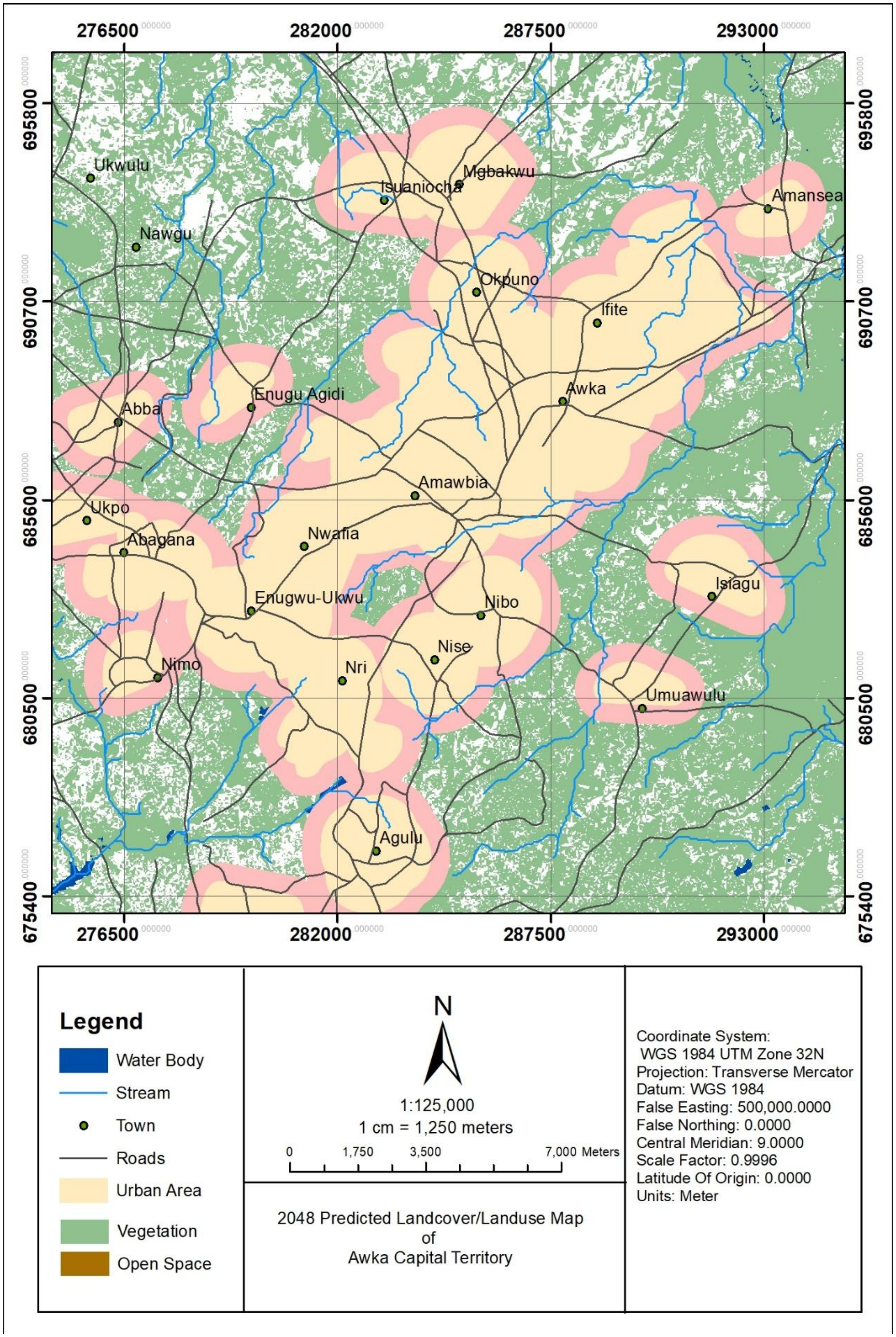
Appendix 4: Landcover/landuse map of 2017



Appendix 5: Landcover/landuse map of 2018



Appendix 6: Landcover/landuse map of 2048



Appendix 7: Validation Accuracy Assessment cell listing

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Imagine - Class Accuracy (Validation Accuracy Assessment)
------------------------------------------------------

Random Points Cell Listing
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Options Used in this run:
-------------------------

Number of Points     : 256
Window Size          : 3
Window Majority Rule: Clear Majority
No Majority Action   : Discard Window
Distribution         : Stratified Random


CELL 1 (4) CELL 2 (4) CELL 3 (4) CELL 4 (4)
4   3   4        4   3   3        4   4   4        4   4   4
4   4   3        4   4   4        3   4   4        4   4   4
4   4   3        3   4   3        4   3   3        4   4   4

CELL 5 (3) CELL 6 (3) CELL 7 (3) CELL 8 (3)
3   3   3        3   3   3        3   3   3        3   3   3
3   3   2        3   3   3        3   3   3        3   3   3
3   3   4        3   3   3        3   3   3        3   3   3

CELL 9 (3) CELL 10 (3)     CELL 11 (3)     CELL 12 (3)
3   3   3        3   3   3        3   3   3        3   2   3
3   3   3        3   3   3        3   3   3        4   2   3
2   3   3        3   2   3        2   2   3        3   3   3

CELL 13 (3)      CELL 14 (3)      CELL 15 (3)      CELL 16 (3)
3   3   4        3   3   3        3   3   3        3   3   3
3   4   4        3   3   3        3   3   2        3   3   3
4   3   3        3   3   3        3   3   3        4   4   3

CELL 17 (3)      CELL 18 (4)      CELL 19 (3)      CELL 20 (3)
3   3   3        4   4   4        2   3   3        3   3   3
3   3   3        4   4   4        2   3   2        3   3   3
3   3   3        4   4   4        3   3   3        3   3   3

CELL 21 (4)      CELL 22 (3)      CELL 23 (3)      CELL 24 (3)
4   4   4        3   4   3        2   3   3        4   3   3
4   4   4        4   3   4        2   3   3        4   3   3
4   4   3        3   3   3        3   2   2        3   3   4

CELL 25 (3)      CELL 26 (3)      CELL 27 (3)      CELL 28 (3)
3   3   3        3   3   3        3   3   3        3   4   3
```

3 3 3	3 3 3	3 3 3	3 3 3
3 3 3	3 3 3	3 3 3	3 3 3
CELL 29 (4)	CELL 30 (4)	CELL 31 (4)	CELL 32 (3)
4 4 4	4 4 4	4 4 4	4 3 3
4 4 3	4 4 4	4 4 3	4 3 3
4 4 3	4 4 4	4 3 4	4 3 3
CELL 33 (3)	CELL 34 (3)	CELL 35 (3)	CELL 36 (4)
4 3 3	3 3 3	3 3 3	4 4 4
4 3 4	3 3 3	3 3 3	4 3 4
3 3 4	3 3 3	3 3 3	4 4 4
CELL 37 (3)	CELL 38 (4)	CELL 39 (3)	CELL 40 (3)
4 3 3	4 4 4	3 3 3	4 3 3
3 3 4	3 4 4	3 3 3	3 3 3
3 3 3	4 4 4	3 3 3	3 3 2
CELL 41 (3)	CELL 42 (4)	CELL 43 (3)	CELL 44 (3)
3 3 3	4 4 4	3 3 3	3 3 3
3 3 3	4 4 4	3 3 3	3 3 3
3 3 3	3 4 4	3 3 3	3 3 3
CELL 45 (3)	CELL 46 (4)	CELL 47 (4)	CELL 48 (3)
3 3 3	4 4 4	4 4 4	3 3 3
3 3 3	4 4 4	4 4 4	3 3 3
3 3 3	4 4 4	4 3 4	3 3 3
CELL 49 (3)	CELL 50 (4)	CELL 51 (3)	CELL 52 (3)
4 3 4	4 4 4	3 3 3	3 4 4
3 3 4	4 4 4	3 3 3	3 3 3
3 4 3	4 4 4	3 3 3	3 3 4
CELL 53 (4)	CELL 54 (4)	CELL 55 (3)	CELL 56 (3)
4 4 4	4 4 3	3 3 3	3 3 3
3 4 4	4 4 3	3 3 3	3 2 3
4 4 4	4 4 3	3 3 3	2 3 3
CELL 57 (3)	CELL 58 (4)	CELL 59 (3)	CELL 60 (3)
3 3 3	4 4 4	3 3 3	3 3 3
4 3 3	4 4 4	3 3 3	3 3 3
3 3 4	4 4 4	3 3 3	3 3 3
CELL 61 (4)	CELL 62 (3)	CELL 63 (3)	CELL 64 (4)
4 3 3	3 3 2	3 3 3	4 4 4
4 4 4	3 3 3	3 3 3	4 4 4
3 4 3	3 3 3	3 3 3	4 4 4
CELL 65 (3)	CELL 66 (3)	CELL 67 (3)	CELL 68 (4)
3 3 3	3 3 4	3 3 3	4 4 4
3 3 3	3 3 4	3 3 3	4 4 4
3 3 3	3 4 3	3 3 4	4 4 4

CELL 69 (3)			CELL 70 (4)			CELL 71 (3)			CELL 72 (4)		
3	3	3	4	4	4	3	3	3	4	4	4
3	3	3	3	4	4	3	3	3	3	3	4
3	3	3	4	4	4	3	3	3	2	2	3
CELL 73 (3)			CELL 74 (3)			CELL 75 (3)			CELL 76 (4)		
3	3	3	3	4	4	3	3	4	4	4	4
3	3	3	3	3	4	3	3	4	4	3	4
3	3	3	3	3	4	3	4	4	3	4	4
CELL 77 (3)			CELL 78 (4)			CELL 79 (3)			CELL 80 (3)		
3	3	3	4	3	3	3	3	3	3	3	3
3	3	3	4	3	4	4	3	3	3	3	3
3	3	3	4	4	4	3	3	3	3	3	3
CELL 81 (4)			CELL 82 (4)			CELL 83 (3)			CELL 84 (4)		
4	4	4	4	3	3	3	4	2	4	4	4
4	4	3	4	4	4	3	3	3	2	4	4
4	4	4	4	3	3	4	4	4	4	4	4
CELL 85 (3)			CELL 86 (3)			CELL 87 (3)			CELL 88 (4)		
3	3	3	3	3	3	3	2	3	4	4	4
3	3	3	3	3	4	2	3	3	4	4	3
4	3	3	3	3	4	2	3	3	4	4	4
CELL 89 (3)			CELL 90 (4)			CELL 91 (3)			CELL 92 (3)		
3	3	3	4	3	4	3	3	3	3	3	3
3	4	3	4	3	3	3	3	3	3	3	3
4	3	3	4	4	4	3	3	3	3	3	3
CELL 93 (3)			CELL 94 (3)			CELL 95 (3)			CELL 96 (3)		
3	3	3	3	3	3	3	3	3	3	2	3
3	3	3	3	3	3	3	3	3	3	3	2
3	3	3	3	3	3	3	3	3	3	2	2
CELL 97 (2)			CELL 98 (3)			CELL 99 (3)			CELL 100 (3)		
2	3	3	3	3	3	3	3	3	3	3	3
4	3	2	3	3	2	3	3	3	4	3	3
3	2	2	3	2	2	3	3	3	3	3	3
CELL 101 (4)			CELL 102 (3)			CELL 103 (4)			CELL 104 (4)		
4	4	4	3	4	3	4	4	4	4	4	4
4	4	4	3	4	4	4	4	4	4	4	4
4	4	4	3	3	3	4	4	4	3	3	3
CELL 105 (3)			CELL 106 (3)			CELL 107 (4)			CELL 108 (3)		
3	3	3	4	3	3	4	4	4	2	2	3
3	3	3	4	3	3	3	4	4	3	3	3
3	3	3	3	3	3	3	4	4	4	3	3
CELL 109 (3)			CELL 110 (4)			CELL 111 (3)			CELL 112 (3)		

```
2   3   3         4   4   4         3   3   3         3   3   3
3   3   3         4   4   4         3   3   3         3   3   3
3   3   3         4   4   4         3   3   3         3   3   3

CELL 113 (0)      CELL 114 (3)      CELL 115 (3)      CELL 116 (4)
0   0   0         3   3   4         3   3   3         4   4   4
0   0   0         3   3   3         3   3   3         4   4   3
3   3   3         3   3   4         3   3   3         4   4   4

CELL 117 (3)      CELL 118 (3)      CELL 119 (3)      CELL 120 (4)
3   3   3         3   3   3         3   2   3         4   4   4
3   3   3         3   3   3         3   3   3         4   4   4
4   4   4         3   3   3         2   3   3         4   4   4

CELL 121 (3)      CELL 122 (3)      CELL 123 (3)      CELL 124 (3)
3   4   3         3   3   3         3   3   3         4   3   3
3   4   3         3   3   3         3   3   3         3   3   4
4   3   3         3   4   3         3   3   3         3   4   4

CELL 125 (3)      CELL 126 (3)      CELL 127 (3)      CELL 128 (2)
3   3   3         3   3   3         2   3   2         3   3   2
2   2   3         3   3   3         3   3   3         3   2   2
2   3   3         3   3   3         3   3   3         2   2   2

CELL 129 (4)      CELL 130 (3)      CELL 131 (3)      CELL 132 (4)
3   2   3         3   4   3         3   3   3         4   4   4
4   4   4         4   4   3         3   3   3         4   4   4
4   4   4         3   4   3         3   3   3         4   4   4

CELL 133 (3)      CELL 134 (4)      CELL 135 (3)      CELL 136 (3)
3   3   3         4   4   4         3   3   3         3   3   3
2   3   3         4   4   4         4   4   3         3   3   3
3   3   3         4   4   4         4   4   3         4   4   4

CELL 137 (4)      CELL 138 (0)      CELL 139 (3)      CELL 140 (4)
3   4   4         0   0   3         3   4   3         4   4   4
3   4   3         0   0   3         3   4   3         4   4   4
4   4   3         0   0   3         3   4   3         3   4   4

CELL 141 (4)      CELL 142 (4)      CELL 143 (4)      CELL 144 (3)
4   4   4         3   4   3         4   4   4         3   3   3
4   4   4         3   4   4         4   4   4         2   4   3
4   3   2         4   4   4         4   4   4         3   2   3

CELL 145 (4)      CELL 146 (3)      CELL 147 (3)      CELL 148 (3)
4   4   4         3   3   4         3   3   3         3   2   2
4   3   4         3   3   3         3   3   3         2   2   3
3   4   3         3   3   3         3   3   3         3   3   3

CELL 149 (3)      CELL 150 (3)      CELL 151 (4)      CELL 152 (4)
2   4   3         4   3   3         4   4   3         4   4   4
3   3   3         3   3   3         4   4   3         4   4   4
```

3 3 3	3 3 3	3 4 4	4 4 4
CELL 153 (4)	CELL 154 (4)	CELL 155 (3)	CELL 156 (4)
3 3 4	4 4 4	3 3 3	4 4 3
4 4 4	4 4 4	3 3 3	4 4 3
4 4 4	4 4 4	3 3 3	4 4 3
CELL 157 (4)	CELL 158 (4)	CELL 159 (4)	CELL 160 (3)
3 4 4	4 4 4	4 4 4	3 3 3
3 4 4	4 4 4	4 4 4	3 3 3
3 4 4	4 4 4	4 4 4	3 3 3
CELL 161 (3)	CELL 162 (4)	CELL 163 (3)	CELL 164 (4)
3 3 3	4 4 4	3 3 2	4 4 4
3 3 3	4 4 4	3 3 3	3 3 4
3 3 3	4 4 4	3 2 2	3 3 4
CELL 165 (4)	CELL 166 (4)	CELL 167 (3)	CELL 168 (3)
4 4 4	4 4 4	3 3 3	3 3 3
4 4 4	4 4 4	4 4 4	3 3 3
4 3 3	4 4 4	3 3 3	3 3 3
CELL 169 (3)	CELL 170 (3)	CELL 171 (3)	CELL 172 (4)
4 4 3	4 3 3	3 3 3	4 3 3
4 4 3	3 3 3	3 3 3	4 4 4
3 3 3	3 3 3	3 3 3	4 3 3
CELL 173 (4)	CELL 174 (4)	CELL 175 (3)	CELL 176 (3)
3 4 4	3 4 4	3 3 3	3 3 3
4 4 4	4 4 3	3 3 3	3 3 3
4 4 4	4 4 4	3 3 3	3 3 3
CELL 177 (3)	CELL 178 (3)	CELL 179 (3)	CELL 180 (3)
4 3 3	3 3 3	3 3 3	4 4 3
3 3 3	4 3 3	3 3 3	4 4 3
3 3 4	3 3 2	3 3 3	3 3 3
CELL 181 (3)	CELL 182 (3)	CELL 183 (3)	CELL 184 (3)
3 3 3	3 3 4	3 3 3	2 3 3
3 3 3	3 4 4	2 3 3	3 3 2
3 3 3	3 3 4	2 3 3	2 3 2
CELL 185 (1)	CELL 186 (4)	CELL 187 (3)	CELL 188 (4)
1 1 1	2 3 3	4 3 3	3 3 3
1 1 1	3 4 4	4 3 3	4 4 3
4 4 4	4 4 4	3 3 3	4 4 4
CELL 189 (3)	CELL 190 (3)	CELL 191 (3)	CELL 192 (2)
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3 3 3	2 3 2	3 3 4	2 2 2
3 4 3	3 3 3	3 2 3	2 3 2

CELL 193 (4)
4 4 3
4 4 4
3 3 4

CELL 194 (3)
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3 3 3
3 3 4

CELL 195 (3)
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4 4 3
3 3 3

CELL 196 (3)
3 3 3
3 3 3
3 3 3

CELL 197 (4)
4 4 4
4 4 4
4 4 4

CELL 198 (3)
3 3 3
3 3 3
3 3 3

CELL 199 (3)
3 3 3
3 3 3
4 4 4

CELL 200 (3)
3 3 3
3 3 3
3 3 3

CELL 201 (3)
3 3 3
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CELL 230 (3)
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CELL 231 (4)
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CELL 232 (3)
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CELL 233 (2)
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CELL 234 (3)
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CELL 235 (4)
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CELL 236 (3)
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2	4	3	3	3	3	4	4	4	3	3	3
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CELL 237 (4)			CELL 238 (4)			CELL 239 (4)			CELL 240 (3)		
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4	4	4	3	4	4	4	4	4	3	3	3
4	4	4	3	3	3	4	4	4	4	4	4
CELL 241 (4)			CELL 242 (4)			CELL 243 (4)			CELL 244 (4)		
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4	4	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	4	4	4	4	4	4	4
CELL 245 (4)			CELL 246 (4)			CELL 247 (4)			CELL 248 (4)		
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3	4	4	3	4	4	3	4	4	4	4	3
4	3	4	4	4	4	3	4	4	4	4	4
CELL 249 (4)			CELL 250 (2)			CELL 251 (2)			CELL 252 (2)		
4	4	3	2	2	3	3	2	2	3	2	2
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3	4	4	3	2	3	2	2	3	3	4	3
CELL 253 (2)			CELL 254 (2)			CELL 255 (2)			CELL 256 (2)		
2	2	2	4	2	2	2	3	2	2	3	3
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2	3	3	3	4	4	4	2	2	3	2	3

Appendix 8: Validation Accuracy Assessment Points

Validation Accuracy Assessment Points

ID	Easting	Northing	Class Tag
ID#1	290931.5	690522.3	4
ID#2	286491.5	682572.3	4
ID#3	275781.5	675282.3	4
ID#4	285051.5	693612.3	4
ID#5	289431.5	690372.3	3
ID#6	282411.5	683112.3	3
ID#7	280941.5	686712.3	3
ID#8	293301.5	695022.3	3
ID#9	290991.5	677412.3	3
ID#10	293151.5	677742.3	3
ID#11	291621.5	686472.3	3
ID#12	286041.5	682302.3	3
ID#13	280731.5	675012.3	3
ID#14	294141.5	687672.3	3
ID#15	282231.5	688482.3	3
ID#16	280731.5	680022.3	3
ID#17	295101.5	696402.3	3
ID#18	288681.5	689592.3	4
ID#19	285171.5	683142.3	3
ID#20	292941.5	687342.3	3
ID#21	286251.5	680052.3	4
ID#22	290571.5	690762.3	3
ID#23	276711.5	690912.3	3
ID#24	286221.5	694752.3	3
ID#25	293301.5	684102.3	3
ID#26	293211.5	687132.3	3
ID#27	288081.5	681912.3	3
ID#28	290271.5	690192.3	3

ID#29	280401.5	693882.3	4
ID#30	275931.5	695022.3	4
ID#31	283011.5	692682.3	4
ID#32	286431.5	682512.3	3
ID#33	287451.5	688602.3	3
ID#34	294351.5	682242.3	3
ID#35	287271.5	679812.3	3
ID#36	276141.5	675342.3	4
ID#37	275721.5	680502.3	3
ID#38	282921.5	696972.3	4
ID#39	281361.5	688602.3	3
ID#40	291081.5	692202.3	3
ID#41	289851.5	681972.3	3
ID#42	279951.5	693612.3	4
ID#43	279081.5	691332.3	3
ID#44	292341.5	678522.3	3
ID#45	294171.5	684162.3	3
ID#46	281781.5	696342.3	4
ID#47	280311.5	695532.3	4
ID#48	292101.5	679872.3	3
ID#49	279921.5	687402.3	3
ID#50	277701.5	688632.3	4
ID#51	275271.5	690312.3	3
ID#52	285891.5	689262.3	3
ID#53	281331.5	675582.3	4
ID#54	281301.5	693732.3	4
ID#55	290571.5	694302.3	3
ID#56	280551.5	686262.3	3
ID#57	284301.5	675972.3	3
ID#58	277941.5	688002.3	4
ID#59	293661.5	680832.3	3
ID#60	292881.5	682422.3	3
ID#61	286551.5	684582.3	4

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ID#63	291621.5	683562.3	3
ID#64	282591.5	694332.3	4
ID#65	293421.5	688032.3	3
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ID#67	279861.5	683772.3	3
ID#68	279411.5	694842.3	4
ID#69	292821.5	680142.3	3
ID#70	291141.5	694212.3	4
ID#71	281391.5	683472.3	3
ID#72	285921.5	677562.3	4
ID#73	294021.5	685182.3	3
ID#74	281901.5	676932.3	3
ID#75	286101.5	689802.3	3
ID#76	290061.5	693792.3	4
ID#77	293181.5	686172.3	3
ID#78	286371.5	690102.3	4
ID#79	286641.5	682842.3	3
ID#80	274581.5	676662.3	3
ID#81	288111.5	688602.3	4
ID#82	276441.5	680112.3	4
ID#83	290061.5	685512.3	3
ID#84	275121.5	693102.3	4
ID#85	280611.5	678342.3	3
ID#86	289131.5	693462.3	3
ID#87	286851.5	682212.3	3
ID#88	275031.5	685062.3	4
ID#89	290301.5	675642.3	3
ID#90	292071.5	693852.3	4
ID#91	288531.5	684732.3	3
ID#92	280881.5	689142.3	3
ID#93	281661.5	683052.3	3
ID#94	278901.5	678282.3	3

ID#95	293271.5	697122.3	3
ID#96	290871.5	680412.3	3
ID#97	286791.5	690282.3	2
ID#98	291141.5	681522.3	3
ID#99	283491.5	681792.3	3
ID#100	275511.5	681102.3	3
ID#101	279051.5	691062.3	4
ID#102	290511.5	685422.3	3
ID#103	279831.5	694422.3	4
ID#104	289041.5	690042.3	4
ID#105	286371.5	678042.3	3
ID#106	284961.5	686592.3	3
ID#107	279171.5	688482.3	4
ID#108	286821.5	680322.3	3
ID#109	290751.5	683502.3	3
ID#110	275661.5	691482.3	4
ID#111	276981.5	696672.3	3
ID#112	294531.5	687612.3	3
ID#113	293031.5	697212.3	0
ID#114	289401.5	695472.3	3
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ID#116	280731.5	696762.3	4
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ID#136	291621.5	681492.3	3
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ID#140	289761.5	688662.3	4
ID#141	291861.5	675882.3	4
ID#142	279021.5	686592.3	4
ID#143	288771.5	696102.3	4
ID#144	285831.5	682062.3	3
ID#145	275991.5	696522.3	4
ID#146	280071.5	678972.3	3
ID#147	292821.5	682902.3	3
ID#148	294051.5	678372.3	3
ID#149	280071.5	681942.3	3
ID#150	275721.5	678132.3	3
ID#151	276411.5	684192.3	4
ID#152	283311.5	688962.3	4
ID#153	276051.5	693162.3	4
ID#154	289671.5	694212.3	4
ID#155	292371.5	685992.3	3
ID#156	292011.5	675582.3	4
ID#157	291111.5	688092.3	4
ID#158	276021.5	693882.3	4
ID#159	290361.5	693552.3	4
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ID#164	278151.5	694392.3	4
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ID#166	282681.5	695412.3	4
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ID#168	285381.5	690882.3	3
ID#169	280641.5	688902.3	3
ID#170	284151.5	696702.3	3
ID#171	294141.5	681732.3	3
ID#172	285771.5	676632.3	4
ID#173	275331.5	682662.3	4
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ID#194	277101.5	689082.3	3
ID#195	291021.5	690432.3	3
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ID#198	275931.5	676572.3	3
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ID#204	275811.5	689082.3	3
ID#205	280371.5	692322.3	4
ID#206	294711.5	678342.3	3
ID#207	295041.5	676692.3	3
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ID#209	282471.5	681252.3	3
ID#210	287451.5	690102.3	3
ID#211	279681.5	688392.3	4
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ID#214	279141.5	696462.3	4
ID#215	293211.5	684672.3	3
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ID#218	281181.5	681042.3	4
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ID#225	284481.5	692442.3	3
ID#226	275121.5	690852.3	4

ID#227	282051.5	695172.3	3
ID#228	289371.5	675582.3	3
ID#229	281061.5	678942.3	3
ID#230	282051.5	683202.3	3
ID#231	276171.5	683052.3	4
ID#232	284721.5	680442.3	3
ID#233	282951.5	686982.3	2
ID#234	278811.5	694272.3	3
ID#235	289461.5	684102.3	4
ID#236	281031.5	689592.3	3
ID#237	278421.5	679302.3	4
ID#238	289551.5	689292.3	4
ID#239	289251.5	696972.3	4
ID#240	284601.5	696312.3	3
ID#241	281451.5	692082.3	4
ID#242	285561.5	687762.3	4
ID#243	279591.5	687372.3	4
ID#244	287391.5	687012.3	4
ID#245	284361.5	680952.3	4
ID#246	285111.5	694572.3	4
ID#247	285621.5	678702.3	4
ID#248	278571.5	692772.3	4
ID#249	289821.5	694302.3	4
ID#250	284721.5	682782.3	2
ID#251	274731.5	688182.3	2
ID#252	288591.5	688542.3	2
ID#253	290961.5	678792.3	2
ID#254	289131.5	686922.3	2
ID#255	292821.5	675582.3	2
ID#256	286281.5	680802.3	2

Appendix 9: Image Correlation Table Report

```
#               STATISTICS of INDIVIDUAL LAYERS

#   Layer           MIN          MAX         MEAN          STD
#  ---------------------------------------------------------------
       1            0.0000       4.0000       3.2318       0.6169
       2            0.0000       4.0000       3.2653       0.6304
#  ===============================================================


#                    COVARIANCE MATRIX

#   Layer             1             2
#  ---------------------------------------------------------------------------
       1            0.38054       0.37276
       2            0.37276       0.39743
#  ===========================================================================


#                    CORRELATION MATRIX

#   Layer             1             2
#  ---------------------------------------------------------------------------
       1            1.00000       0.95852
       2            0.95852       1.00000
#  ===========================================================================
```

Appendix 10: Population data for Awka Capital Territory

LG	% Annual growth	Annual Growth	1990	1999	2008	2017
Awka South	2.79	0.0279	130,664	163,339.22	209,963	269,893.96
Awka North	5.34	0.0534	60,728	93,093.548	150,536	243,424.02
Dunukofia	1.95	0.0195	73,473	85,877.168	102,352	121,987.43
Njikoka	6.47	0.0647	72,945	122,401.39	219,117	392,252.49
Orumba North	2.2	0.022	127,476	152,007.23	185,291	225,862.88
Anaocha	2.63	0.0263	200,609	247,585.94	313,706	397,485.22
Total	3.17	0.0317	665,895	858,109.75	1,141,424	1,518,277.9