INTEGRATING GEOINFORMATION AND SOCIOECONOMIC DATA FOR ASSESSING URBAN LAND-USE VULNERABILITY TO POTENTIAL CLIMATE-CHANGE IMPACTS OF ABUJA

BY

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Declaration

I hereby declare that this submission is my own work towards the PhD and that, to the best of my knowledge, it contains no material previously published by another person, nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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Dedication

To my parents Professor Ibrahim S. Mahmoud and Mallama Maimuna Isah Ibrahim (late)

&

My wife, son, brothers and sisters for their love

Abstract

This dissertation is framed as a retrospective research concept that analysed and monitored land use change to assess the impacts of urbanization on climate in cities. Multi-source datasets such as remote sensing images, vector layers, topographical maps, historical climatic variables and socioeconomic information were used for the retrospective landscape studies. Land-use Land-cover (LULC) maps were produced from historical Landsat series data using support vector machine information extraction algorithm. Subsequently, spatio-temporal settlement expansion analysis, change detection and urban growth modelling into the future was implemented to assess potential climate impacts due to urbanization. Thermodynamics of the urban landscape was investigated using relevant discrete historic climatic data and continuous thermal spatial datasets. Climate indices calculation and multiple spatial statistical approaches were used to analyse changes in air and land surface temperature and to detect urban warming and heat island impacts. Urban flood-risk assessment was investigated by integrating multisource geoinformation and morphometric analysis approach. Using object-based image analysis, the generated urban density information and urban structural types were useful in demonstrating the relevance of integrated geospatial datasets analysis for land use and climate change studies. Two silent urbanization impacts identified in this study were, increased imperviousness which result in land surface temperature modification and urban flood-risk propagation. LULC was observed to have moderated urban micro climate in different urban landscapes of Abuja. The proposed disaggregation concept used in the morphometric analysis in this study also revealed the hydrological processes such as flood-risk can be perennial and imminent due to inadequate natural drainage densities and low bifurcation ratio status of the landscape. The output of synergizing multi-source geospatial datasets facilitated fine-scale human wellbeing and security vulnerability assessment for improved disaster risk reduction in the context of climate impacts in cities. The main findings of this dissertation is a proof of concept of how integrated datasets and methodical research approach can be used for empirical climate and land use change science at local scale. Therefore, relevant institutions such the Federal Capital Development Authority and policy makers in other regions of Nigeria can adopt the concept demonstrated in this research for rapid assessment of urban landscapes to potential climate change impacts.

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Acronyms

AGIS	:	Abuja Geographic Information System
AMAC	:	Abuja Municipal Area Council
Br	:	Bifurcation Ratio
CAR	:	Conditional Autoregressive Model
Dd	:	Drainage Density
DEM	:	Digital Elevation Model
DRR	:	Disaster Risk Reduction
EAAA	:	Error Adjusted Area Accuracy
FCC	:	Federal Capital City
FCDA	:	Federal Capital Development Authority
FCT	:	Federal Capital Territory
FLAASH	:	Flash Line-of-sight Atmospheric Analysis of Spectral Hypercubes
GEC	:	Global Environmental Change
GIS	:	Geographic Information Systems
GIT	:	Geospatial Information Technologies
GTP	:	Ground Truth Point
GCM	:	Global Circulation Models
GIMMS	:	Global Inventory Modelling and Mapping Studies
GUF	:	Global Urban Footprint
GRUMP	:	Global Rural Urban Mapping Project
IPCC	:	Intergovernmental Panel on Climate Change
LCM	:	Land Change Modeller
LCC	:	Land Cover Change
LULC	:	Land-Use Land-Cover
LULCC	:	Land-Use Land-Cover Change
LST	:	Land Surface Temperature
MDG	:	Millennium Development Goals
OSGOF	:	Office of the Surveyor General of the Federation
OBIA	:	Object Based Image Analysis
RAI	:	Rainfall Anomaly Index
RS	:	Remote Sensing
RCM	:	Regional Circulation Models
SDG	:	Sustainable Development Goals
SRTM	:	Shuttle Radar Topographic Mission
SVM	:	Support Vector Machines
TRMM	:	Tropical Rainfall Measuring Mission
UBL	:	Urban Boundary Layer

UHI	:	Urban Heat Island
UCI	:	Urban Cold Island
UST	:	Urban Structural Types
UMT	:	Urban Morphological Types
VHR	:	Very High Resolution

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Acronyms

AGIS	:	Abuja Geographic Information System
AMAC	:	Abuja Municipal Area Council
Br	:	Bifurcation Ratio
CAR	:	Conditional Autoregressive Model
Dd	:	Drainage Density
DEM	:	Digital Elevation Model
DRR	:	Disaster Risk Reduction
EAAA	:	Error Adjusted Area Accuracy
FCC	:	Federal Capital City
FCDA	:	Federal Capital Development Authority
FCT	:	Federal Capital Territory
FLAASH	:	Flash Line-of-sight Atmospheric Analysis of Spectral Hypercubes
GEC	:	Global Environmental Change
GIS	:	Geographic Information Systems
GIT	:	Geospatial Information Technologies
GTP	:	Ground Truth Point
GCM	:	Global Circulation Models
GIMMS	:	Global Inventory Modelling and Mapping Studies
GUF	:	Global Urban Footprint
GRUMP	:	Global Rural Urban Mapping Project
IPCC	:	Intergovernmental Panel on Climate Change
LCM	:	Land Change Modeller
LCC	:	Land Cover Change
LULC	:	Land-Use Land-Cover
LULCC	:	Land-Use Land-Cover Change
LST	:	Land Surface Temperature
MDG	:	Millennium Development Goals
OSGOF	:	Office of the Surveyor General of the Federation
OBIA	:	Object Based Image Analysis
RAI	:	Rainfall Anomaly Index
RS	:	Remote Sensing
RCM	:	Regional Circulation Models
SDG	:	Sustainable Development Goals
SRTM	:	Shuttle Radar Topographic Mission
SVM	:	Support Vector Machines
TRMM	:	Tropical Rainfall Measuring Mission
UBL	:	Urban Boundary Layer

UHI	:	Urban Heat Island
UCI	:	Urban Cold Island
UST	:	Urban Structural Types
UMT	:	Urban Morphological Types
VHR	:	Very High Resolution

CHAPTER 1 : INTRODUCTION

1.1 Background Information

Lately, climate change phenomena has emerged as the topmost global public problem with increasing complexity and manifestations that will impede sustainable development agenda, environmental management plans, and human well-being and security programs. According to Vitousek (1992), land use change may evolve to become the most crucial factor driving climate change in the coming decades. Hence, the United States (U.S.), National Research Council (NRC's) (2005) report suggested the inclusion of Land-Use/Land-Cover Change (LULCC) processes in the broadening of climate change science being a significant factor forcing climate change. Population growth has also been identified as a major driver of LULCC. The global population projection documented by Cohen (2003), the Intergovernmental Panel on Climate Change (IPCC) fifth Assessment Report (AR5) and the 2012 United Nations (UN's) population figures was totalled to reach 9.1 billion by 2050 with most of the growth in developing countries (UN, 2012). The combined effect of LULCC and population growth has amplified the need for climate scientists and government agencies, to make concerted effort across administrative boundaries to prepare for and co-manage projected problems. Therefore, there is urgent need for studies aimed towards better understanding of the linkages between LULCC and climate change impacts.

By far, Africa is projected to be at the receiving end of the most severe and disproportionate consequences of Global Environmental Change (GEC) such as climate change impacts (Desanker & Magadza, 2001; Greschke & Tischler, 2015; Hope, 2009; Mirza, 2003; Wentz *et al.*, 2014). The exacerbation of climate change impacts is expected because of lower adaptive capacity in developing countries, especially the West African sub-region (Cooper *et al.*, 2008; Mutanga *et al.*, 2013). This is due to the heavy dependence of West African countries especially

Nigeria, on natural resources such as land and rain-fed agriculture for food production (James *et al.*, 2015).

Nigeria's susceptibility to rapid LULCC including urbanization, fluctuations in rainfall, rise in temperature, sensitivity of hydroelectric power generation to rainfall variation, rapid population growth increases vulnerability to climate change impacts. Unfortunately, most documentation on climate change impacts in Nigeria focused on coastal regions such as sea level rise and flooding consequences (Adelekan, 2010; Adesina, 2009), land degradation and desertification in the north-eastern region (Obioha, 2008), as well as shortages in food production in the agro ecological zones (Amosu *et al.*, 2012; Oyekale, 2009). Herein, LULCC, especially due to urbanization occurring in the hinterland is used as nexus for assessing the effects of urban development on climate change. Major urbanization dimensions include the demographic, spatial, economic and social and can be directly or indirectly vulnerable to climate change impacts. Urban development, devoid of sustainable spatial planning and efficient implementation can induce vulnerability issues that can be linked to urban climate science. Key urban climate factors worthy of consideration in investigating urban climate change includes location, land cover, landforms, water bodies, population, urban structure, artificial heating and pollution. At local scale, all these factors contribute to the development of a city specific climate.

Nigeria is listed among countries expected to experience the greatest urban population growth worldwide, coupled with the facts that is the most populous African country. Therefore, the country is expected to experience LULCC due to population growth which will drive the LULCC processes and by extension serve as a climate change forcing factor. Thus, the need to assess urbanization-based LULCC in the context of climate change impacts on the hinterland such as Abuja is urgently needed. The goal of this study is to attempt linking urban LULCC to climate change and potential impacts. This research effort is done as a proactive approach to enhance development efforts in West Africa particularly Abuja in Nigeria. This will help to identify drivers of rapid urbanisation, its link to climate forcing and associated vulnerabilities and their impact on people and places. This can be achieved through exploring the integration of land use change assessment and modelling with historic climatic variables, relevant ancillary information and socioeconomic datasets.

In order to achieve this goal, (i) multi-sensor and multi-temporal remote sensing (RS) image analysis and Geographic Information Systems (GIS) approach is considered to derive reliable land cover maps and project future settlement expansions; (ii) in-situ meteorological variables were also acquired for this study; (iii) RS indices such as Normalized Difference Vegetation Indices (NDVI) and Normalized Difference Built-Up Indices (NDBI) were derived for assessing landscape indices relations with the retrieved Land Surface Temperature (LST) for Urban Heat Island (UHI) detection. Spatial statistical approaches were applied to better understand the urban thermodynamics of Abuja for temperature development studies and imminent climate change impacts assessment; (iv) furthermore, the weighted overlay analysis socioeconomic field survey concept was used to determine physical and social vulnerability to flood-risk in the study area; (v) For improved vulnerability assessment, fine-scale information such as urban density and Urban Structural Types (UST) was derived using Object-based Image Analysis (OBIA).

1.2 Research Motivation

Vulnerability and impacts of climate change in Nigeria have been identified at the national level within a broad framework (FME-SCCU, 2011; FME, 2003, 2013, 2014). Major national resources identified to be vulnerable to climate change impacts in the physical environment includes (i) natural ecosystems, (ii) agricultural ecosystems, (iii) water resources, (iv) coastal resources, (v) LULCC and forestry, (vi) energy and health and human well-being and security.

Vulnerabilities includes temperature and precipitation shifts, shortage in food production due to overdependence in rain-fed agriculture, land degradation and desertification, sea-level rise coastal flooding and rapid landscape disturbance. To be able to provide adaptive and mitigative solutions, these themes need to be further investigated and properly understood with empirical evidence towards sustainable management strategies at the local scale (Koblowsky & Speranza, 2012; Sayne, 2011). In response to the local scale research call, most researches aiming at better understand of climate change impact have focused on rainfall patterns and agricultural ecosystems (Ajetomobi & Abiodun, 2010; Apata *et al.*, 2009; Hassan *et al.*, 2012; Odekunle *et al.*, 2007; Oyekale, 2009). Very few studies investigated urbanization-based LULCC and its implication on climate change and mostly focused on coastal areas (e.g. (Adesina, 2009; Amosu *et al.*, 2012; Chiadikobi *et al.*, 2011). The observed lack of research and limited knowledge the implication LULCC and urbanization has on climate change serves as the impetus for this current study. Considering Nigeria's high population, the country has been noted to be a potential contributor global warming and consequently climate change (FME, 2003). In the case of Abuja, few studies on LULCC have been carried out. However, these studies have only focused on demonstrating the use of RS and GIS landscape change detection. Thus, there is need to go beyond LULCC to analyse settlement expansion and project future urban expansion in the context of urban climate change impact assessment. Furthermore, fundamental urban climate change phenomenon such as change in surface temperature patterns, heat island formations and change in drainage geography due to imperviousness need to be known about Abuja.

1.3 Prior Works

Earlier landscape researches conducted in Abuja have focused on land cover mapping and algorithm comparison, Master Plan implementation evaluation and LULCC analysis. An attempt is made to review some relevant research:

Ojigi, (2006) investigated the *variations of Abuja land use land cover from image classification algorithms* which compared three different image classifiers (maximum likelihood, parallepiped minimum distance and fisher's methods) to analyse Landsat-7 ETM image. The author documented that maximum likelihood performed best over the two other algorithms. Ibrahim Mahmoud (2007), investigated *evaluation of the restoration of Abuja master plan in 2007 for sustainable development* the study combined field work with master plan and a 2007 VHR image from Ikonos sensor. The author used paper-based master plan map and VHR-RS image and GIS approach to develop a geodatabase of illegal structures and demolished buildings for sustainable city management. LULCC related studies that have used various RS datasets includes the works that analysed urban sprawl monitoring (Ade & Afolabi, 2013; Chima, 2012; Fanan *et al.*, 2011; Ogidiolu *et al.*, 2013; Usman, 2013); agricultural land loss (Alagbe *et al.*, 2013; Ishaya & Ifatimehin, 2009).

Most of these researches only assessed LULCC using traditional image classifiers such as maximum likelihood with the exception of Chima (2012) who applied the OBIA. Apparently, earlier researches did not consider analysing the expansion settlement patterns in a systematic way which significantly differentiates them from this study. The observed settlement expansion served as a basis for assessing the imminent impacts urbanization has on climate change such as the UHI and flood-risk due to change in drainage geography. As a follow-up this research subsequently coupled historical climate variable (temperature) with thermal remote sensing layers of retrieved LST to detect UHI in the context urban climate science and its impact on human well-being. Multiple spatial statistical approaches were further used to analyse the relationships between LST, vegetation indices and built-up indices in time steps and cumulative effect at Abuja. From an urban flood-risk perspective, multi-data sources and weighted overlay approach was used to determine vulnerability of Abuja to flood-risk. The flood-risk zone map was subsequently used to identify high risk locations. This informed the identification of a suitable location to demonstrate the Social Vulnerability Assessment (SVA) concept in Kubwa settlement which the most developed satellite town in Abuja. As added value, the fine-scale vulnerability assessment demonstrated in this thesis further demonstrated the relevance of extracted information from VHR for climate risk assessment which is more efficient than field survey approach.

1.4 Problem Definition

LULCC is the most evident anthropogenic driver of GEC such as the climate change phenomena which is currently the biggest environmental change facing the world over. Several decades of research focused on mapping and monitoring of anthropogenic LULCC have revealed that Africa as a continent will suffer severest consequences of anticipated impacts (Laurance *et al.*, 2014; Willcock *et al.*, 2016). West Africa will experience most of the consequences of anthropogenic LULCC such as vegetation loss and climate change (Aleman *et al.*, 2016), due to the size of human population and their overdependence on natural resources. Major LULCC to be witnessed in sub-Saharan Africa is in the urban sector (UN, 2014), and serious social and environmental problems and risks associated to large-scale settlement expansion should be expected (Turok, 2016). Unfortunately, very little research have been conducted in West Africa including Nigeria on the impacts urbanization has on climate change. Nigeria is a major hotspot of rapid urbanization, being the most populous African nation, and this also implies that the country will experience most of the expected impacts due to either non-existent or weak, ambivalent and piecemeal urban policies.

Furthermore, the fastest growing city in Nigeria is Abuja (Aliyu & Bashiru, 2013). Abuja, the study area for this research is located in the hinterland of Nigeria and has undergone rapid LULCC in the recent past decades. It is not surprising that Abuja faces numerous environmental and ecological problems associated with rapid urbanization-based LULCC and population growth. From well-established sources of published works, urbanization-based LULCC has direct and indirect impacts on biodiversity and ecosystems services (Laurance *et al.*, 2012; Seto *et al.*, 2012), and climate change and impacts (Meller *et al.*, 2015; Seto & Shepherd, 2009). Therefore, the current urbanization taking place in Abuja is diminishing the vegetation, biodiversity and ecosystems functioning, and has negative impacts on provisioning of ecosystems services which is also accelerating climate change impacts. With climate change manifestation, impacts will threaten human well-being and security, and also impede attainment of Sustainable Development Goals (SDGs) such as sustainable cities and communities. For instance, Fanan *et al.* (2011) assessed how urban expansion led to vegetation cover loss around Abuja, while studies on the loss of agricultural land in Abuja was also assessed by Alagbe *et al.* (2013).

Considering the roles vegetation cover and agricultural lands play in ecosystem services, carbon sequestration, climate change mitigation, evaporative cooling and biogeochemical cycles, there is the need to design a research theme that will systematically assess potential climate change impacts in Abuja due to anthropogenic activities. One of the most evident anthropogenic process is settlement expansion, it therefore makes sense to engage in scientific research that can support policy interest on the urbanization phenomenon in Abuja. Assessing urban landscapes to identify specific vulnerabilities to urban population with potential exposure to climate change impacts. Thus, understanding on the static patterns and dynamic processes on urbanization in Abuja need to be better understood from a retrospective perspective. It is therefore worthwhile to generate data suitable for analysing the urbanization phenomenon for improved understanding on how urban growth can serves as forcing factor thereby influencing local urban climate to change. Output from such foundation studies need to be further investigated to ascertain the effect of settlement expansion in Abuja has on the urban thermodynamics in the immediate, mid and long term such as amplified temperatures leading to heat waves/stress. Also, change in drainage geography due to imperviousness coupled with increasing precipitation can cause urban flood-risks especially in extreme scenarios and changing LULC. An added value worth investigating is the potential usability of combining derived information from moderate and VHR satellite images for fine-scale vulnerability assessment in the context of potential climate change impacts mitigation.

1.5 Research Objectives

The theme of this study is to integrate geoinformation, socioeconomic and climate datasets to evaluate the impacts of LULCC and urbanization on potential climate change impacts in Abuja. This will be useful for assessing the vulnerability of people and places in Abuja. To achieve this, the theme is decomposed into the following goal and specific objectives.

i. **Goal:** The aim current study is to assess the influence of urban land-use change on urban climate change by assessing vulnerability of places and people to potential climate change impacts in Abuja.

ii. **Objectives:** The specific objectives of this study are (see Table 1.1)

1. To assess land cover changes from 1986 to 2014 and predict future urban land change into 2050;
2. To assess temperature variability in Abuja from 1982 to 2014 for potential climate change impact assessment;
3. To determine the flood-risk zones of Abuja and evaluate the exposure/susceptibility of Kubwa settlement in Abuja to flood-risk;
4. To assess the application of moderate and very high resolution remote sensing datasets for fine-scale city vulnerability to potential climate change impacts.

Justification for investigating objective one is established on the fact that rapid LULCC has occurred in the landscape of Abuja and the need to reliable datasets to evaluate the retrospective change is vital. Updated LULCC assessment is lacking, hence LULCC mapping and monitoring is needed urgently. This will pave way for the analysis of settlement expansion patterns and projecting the urban footprint into the future. The outcome of this objective can be used to infer logical and potential climate change impacts due to settlement expansion evidence in Abuja. This study can serve as a basis for identifying emerging mega cities in Nigeria as well as validate Global Urban Footprint (GUF) datasets for Abuja (e.g. Global Rural-Urban Mapping Project (GRUMP)).

For the second objective, the essence is justified based on the fact that settlement expansion was evident in Abuja, and therefore the need to investigate if rapid urban footprint expansion can be linked to air temperature and surface temeprature changes. The study area has only one meteorological ground station. The remote sensing based LST can be used to have a spatially continous understaning of the urban thermodynamics of Abuja for urban heat island detection which has impact on human well-being. The remote sensing indicies such as the NDVI and the NDBI are inputs explanatory to LST in a spatial statistic environment. This investigation, will serve as a scientifc contribution to fill the knowledge gap of settlement expansion implication to climate change impacts in Nigeria and mitigation strategies to climate proof such cities.

Justification for investigating objective three is established on the fact that LULCC and urbanization are connected to climate change impacts with varying degree of vulnerabilities. Therefore, it makes sense to spatially determine Abuja's physically vulnerability to flood-risk and assess the exposure/susceptibility of Kubwa settlement to flood-risk. Kubwa is one of Abuja's most developed sattelite towns, and is used to demonstrate SVA approach which combines both geospatial and socioeconomic analysis for vulnerability assessment.

Justification of objective four is centred on demonstrating the applications of combining information from moderate and very high resolution images for fine-scale vulnerabiliry assessment in the study area. The retrieved LST from moderate resolution image is integrated with extracted urban density and UST for improved vulnerability assessment at district level. Based on the understanding UHI effects which has implication on human well-being and health related chnallenges, a geospatial approach is plausible to spatially analyse vulnerable places and build useful databases for element at risk with the UST layer.

1.6 Key Issues Addressed by Research

Based on the specific objectives, key issues addressed by research includes:

1. To what extent is urbanization manifesting in Abuja?
2. How can multi-sensor and temporal remotely sensed and socioeconomic datasets be used to assess and analyze (urban and peri-urban landscapes) changes?
3. Can settlement expansion analysis be used assess potential climate change effects?
4. Can multi scale temperature datasets be used to assess and analyze urban climate change risk?
5. What variations or changes are occurring in Abuja's air temperature and rainfall pattern in the past decades (1982 to 2014)?
6. Is rapid LULCC and urbanization increasing urban land surface temperature (ULST) in Abuja?
7. Is there evidence of UHI formation in Abuja?
8. Is Abuja susceptible to flood-risk due to settlement expansion into floodplains?
9. Can places and people exposed to flood-risk be identified for improved disaster risk management?
10. Can VHR satellite images be used to assess vulnerability of people and places in Abuja?
11. What information extraction techniques can be applied to extract information from VHR images?
12. What are the salient urban forms in Abuja and how can they be used as indicators for extracting fine scale information usable for assessing vulnerability assessment?

1.7 Research Approach

Based on the research objectives and key issues outlined, the study involves an integrated assessment that incorporates geoinformation, historic climate variable, socioeconomic and ancillary datasets for urban landscape climate change impacts assessment. The overall work flow to achieve the various research components is presented in Figure 1.1.

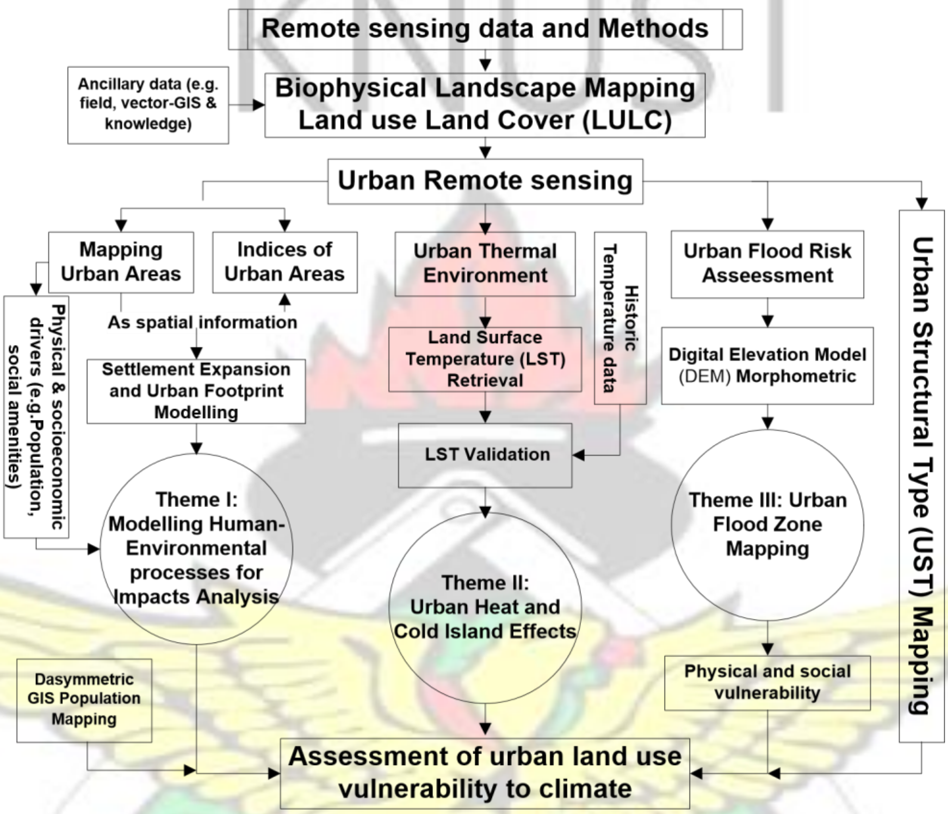

Figure 1.1: Overall flow of work.

The integrated assessment research approach is a multi/interdisciplinary concept which combines understanding of different scientific disciplines to add value to broad contextual topics such as climate and land use change towards providing vital and interlinked information to interested decision making organizations (Rotmans, 1998; van der Sluijs, 2002). Basically, the integrated assessment research procedure involves an iterative order which gives researchers the opportunity to communicate their scientific output across to decision making authorities that revert their feedback to researchers for improvement and further assessment (Rotmans, 1998). Methodically, integrated assessment-based research concept gives room to combine quantitative and qualitative procedures to answer complex human-environment system problems. The thesis is organized into eight chapters, four of the chapters are tied to the specific objectives and are stand-alone papers. The methods and techniques used in answering the formulated questions are illustrated in Table 1.1 and it links the formulated research objectives, questions and methodology.

Table 1.1: Overview of chapters, research question and issues addressed in this thesis

Research Objectives	Research Questions	Research Methodology
1. To assess land cover changes from 1986 to 2014 and predict future urban land change into 2050;	1. How can multi-sensor and temporal remotely sensed and socioeconomic datasets be used to assess and analyze (urban and peri-urban landscapes) changes? 2. To what extent is urbanization manifesting in Abuja? 3. Can settlement expansion analysis be used assess potential climate change effects?	• Literature review • Develop a work flow that will address LULC mapping and monitoring urban landscape • Methodical steps to integrate RS population and ancillary data for modelling urban growth and assessing its potential impact on Abuja's climate
2. To assess temperature variability in Abuja from 1982 to 2014 for potential climate change impact assessment;	4. How can multi scale temperature dataset and indices be used to assess and analyze urban climate change risk? 5. What variations or changes are occurring in Abuja's air temperature pattern in the past decades (1982 to 2014)? 6. Is rapid LULCC and urbanization increasing urban land surface temperature (ULST) in Abuja? 7. Is there evidence of UHI formation in Abuja?	• Literature review • Generating and analysing relevant climate indices for assessing changes in urban air temperature (Trend analysis) • Calculation of relevant RS-based landscape indices and retrieval of LST • Spatial statistic for UHI detection and modelling of dependent and explanatory variables to spatial patterns
3. To determine the flood-risk zones of Abuja and evaluate the exposure/susceptibility of Kubwa settlement in Abuja to flood-risk;	8. Is Abuja susceptible to floodrisk due to LULCC and settlement expansion into floodplains? 9. Can places and people exposed to flood-risk be identified for improved disaster risk management?	• Literature review • Multi-source data preparation • Integrated geoinformation, morphometric and meteorological datasets for flood-risk and human security

4. To assess the application of moderate and very high resolution remote sensing datasets for fine-scale city vulnerability to potential climate change impacts.	10. Can VHR satellite images be used to assess vulnerability of people and places in Abuja? 11. What are the salient urban forms in Abuja and how can they be used as indicators for extracting fine scale information usable for assessing vulnerability assessment? 12. Can VHR image product be integrated with moderate resolution information?	• Literature review • Multi-source and scale data preparation • OBIA urban density and UST extraction for fine scale city vulnerability assessment

1.8 Thesis Structure

To achieve the goal of the research, the content of the research structured under the following chapters:

- **Chapter One: Introduction**

  This chapter presents the general idea of the research problem, objectives, questions, and overview of the methodology used for the study. Also, prior work in relation to the research theme is presented.

- **Chapter Two: Theoretical background climate and land use change science**

  In this chapter, theoretical background from published literature and recurrent issues in framing up an integrated climate and land use change research was done, to put relevant issues in perspective of the research philosophy.

- **Chapter Three: Study area, Data and General Methodology**

  This chapter presents a study area, data and general methodological framework to help the reader follow the various methods used in different chapters.

 Chapter Four: Land Use Land Cover and Settlement Expansion Analysis

Chapter 4 makes an attempt to retrospectively assess historical land use change in Abuja using hind cast remote sensing Landsat series data. Subsequently, this chapter analysed settlement development using the land cover maps. Furthermore, urban growth modelling of Abuja into year 2050 was implemented in the context of possible climate change impacts if rapid LULCC continues to identify potential impacts.

- **Chapter Five: Temperature Variability for climate Impacts Assessment**

Chapter 5 coupled historical climatic station temperature data with spatially continuous RS data of Abuja to study the urban thermal environment. Results of this hind cast analysis are to observe the variability in air and surface temperature in the context of urbanization induced warming and climate change impacts.

- **Chapter Six: Urban Flood-risk Assessment of Physical and Social Vulnerability**

Assessment of urban flood risk is presented in this chapter using integrated geoinformation and morphometric approaches. The method generated flood-risk zonation map that can be used by city and municipality managers for human security in the context of potential climate impact. Here relevant dataset suitable for assessing the vulnerability of people and places were generated, weighted and overlaid.

- **Chapter Seven: Fine-scale vulnerability assessment using urban density and urban structural types**

Chapter 7 extracted urban density and urban structural types of Abuja from VHR WV-2 imagery to conceptualize a fine-scale vulnerability assessment of urban risk to potential climate change impacts.

- **Chapter Eight: Synthesis of assessment of urban land use vulnerability to potential climate change impacts in Abuja**

Chapter 8 provides a synthesis of the research findings, knowledge contributed, research conclusions, recommendation and further research outlooks.

CHAPTER 2 : THEORETICAL BACKGROUND AND KEY ISSUES

2.1 Climate Change Science and Spatial Analysis Approach

Climate change science have evolved with new research ideas about climate variability and change concepts, vulnerability to its impacts, mitigation and or adaptation, especially those studies focusing on global climate change (Dore, 2005; Greschke & Tischler, 2015; McCarthy *et al.*, 2001; Metz, 2007; Parmesan & Yohe, 2003; Schroter *et al.*, 2005). One prominent approach used lately by scientist, advocacy groups, and non-governmental organizations (NGOs) to depict evidence of climate change is the spatial analysis approach using hotspot mapping methods (Preston *et al.*, 2011). The spatial analysis concept has been used to identify potential impacts of climate change, convey result in map form with apparent visual rendition of elements that communicate visually explicit hotspots which is usually more informative compared text(Eakin, 2005). Hotspot maps are produced with specific objectives at mind.

Concerted effort has been made by scientists to explore data and methods to enable them develop robust approaches to guide designated authorities and NGOs clearly communicate impacts of climate on places and people. According to Myers (1990) hotspot mapping can be routed to production of biodiversity hotspot maps aimed at conservation efforts. Hence, hotspot maps explicitly serves as decision making tools in priority areas to help organization develop strategies to resolve environmental challenges linked to climate change (Kok *et al.*, 2010; Midgley *et al.*, 2011; Yusuf & Francisco, 2009).

To make this subsection complete some global hotspot mapping attempts are reviewed. Generally, mapping of hotspots can be categorized into three broad types: those focused on climate parameters, those analysing societal vulnerability patterns to impacts of climate change and those focused on how system such as water or agriculture are likely to be impacted by climate change. Lately, the exposure component of the IPCC formulation on SpatialVulnerability Assessment (SVA), a concept that will be discussed subsequently (i.e hotspot mapping) have been used to project perturbation in specific parameters on precipitation and temperature using the hotspot mapping concept. One of the earliest climate model output to depict hotspot of climate vulnerability is the Regional Climate Change Index (RCCI) (Giorgi, 2006). This index measures the variation in regional mean surface air temperature and Interannual precipitation variability between a 1960 -1979, baseline and projection of 20802099. This was achieved with the application of ensemble multi-models based on scenarios (A1B, B1 and A2) of IPCC for comparison toward the identification of global regional changes defined as hotspots and region expected to experience paramount relative changes. According to Giorgi (2006) the predicted warmest hotspots were located in northern latitudes (the Mediterranean and North Eastern Europe) (Figure 2.1). It should be noted that small RCCI means that compared to other region, small response climate change occurred in such places.

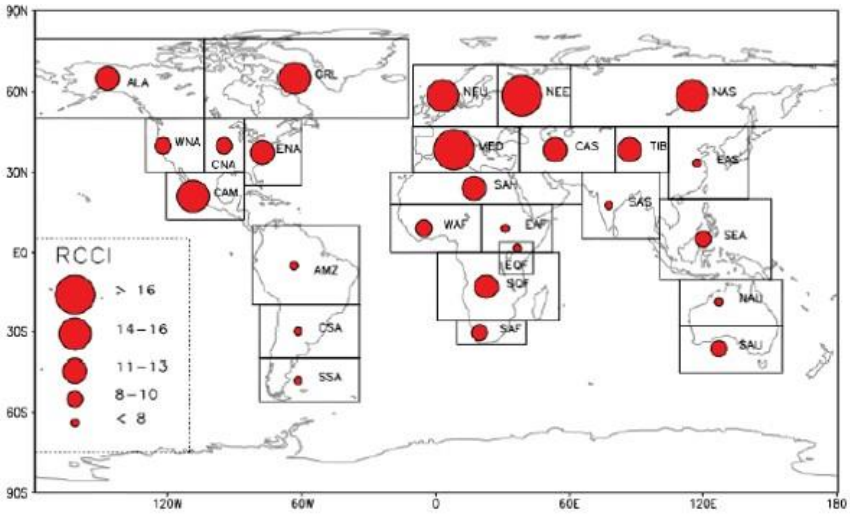

Figure 2.1: The Regional Climate Change Index (adopted from Giorgi 2006, p. L08707).

Similarly, the Climate Change Index (CCI) was introduced by Baettig *et al.* (2007) specifically to analyse the magnitude of future climate change compared to current natural climate variations.

The increasing probabilities of the future changes is tracked in relation to a return cycle from 1 out of 20 for similar event in the present climatology. The computation of the index is based on Global Climate Models (GCM) that run the IPCC's special report on emission scenarios (SRES) A2 and B2 scenarios generating indicators of driest and hottest years, extremely wet/dry/warm seasons of the winter and summer months and may others. The CCI suggested that globally the tropics and high latitude will experience huge frequency perturbation in climate systems and depicted hotspots of hot regions comparable to the RCCI with the exception of the Amazon and northern southern Africa having high climate risk exposure in future compared to present (Figure 2.2).

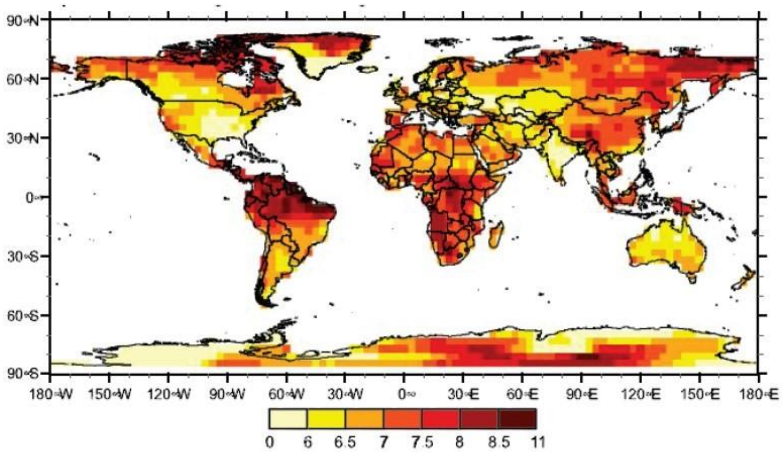

Figure 2.2: The climate change index (CCI) (adopted from Baettig 2007, p. L01705).

In general, both RCCI and CCI have added to the plethora of literature because they expanded the horizon of scientist about climate parameters useful for assessing vulnerability in a broader context. On the contrary, the Met office of UK produced a map of regional temperature variations with a rise of 4°C in mean global temperature (Figure 2.3). The map had both interactive web and poster versions targeted at policy and decision makers with circles in varying colors indicative of potential impacts. The Amazon, West and southern Africa, Central Asia, Arctic and northern latitudes including western USA were regions highlighted to have highest temperature changes.

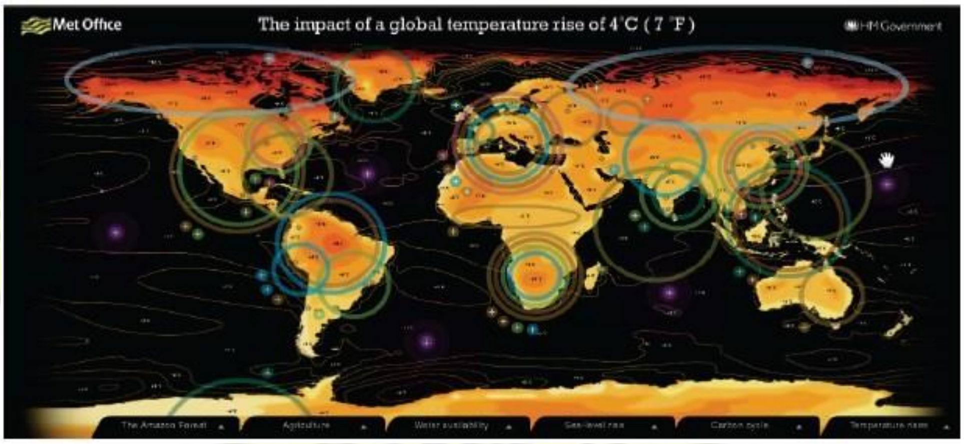

Figure 2.3: A 4°C in mean global temperature and possible impacts (Source: UK Met office).

Another hybrid hotspot map produced lately aimed at highlighting multisector climate impact using climate parameters linked to agriculture, ecosystems, health and water (Piontek *et al.*, 2013). Outputs from three GCM to depict Representative Concentration Pathway (RCP8.5) to serves as input for a multiple Global Impact Models (GIM) is sought by this model to identify thresholds in temperature based on sectors and associated impacts is classified as severe mild or low.

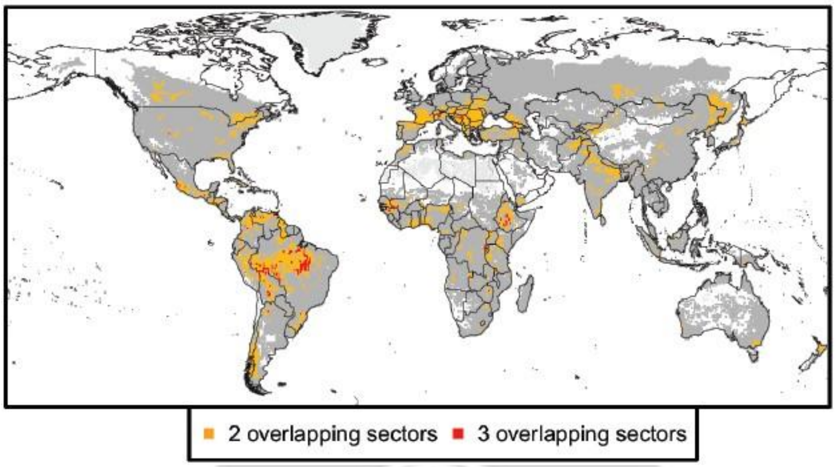

Figure 2.4: Multi-sector impact hotspots for overlapping sectors (two sectors-orange) and (three sectors-red) (adopted from Piontek et al 2013. Copy right proceedings of the National Academy of Science).

According to Figure 2.4 the Amazon, Andes, African Highlands and parts ow West Africa, Ganges basin, East and South Europe, Central USA and southern Mexico were all found to portray high climate impacts.

Another area that received considerable hotspot mapping effort is the migration driven population dynamics aimed for policy making (Adamo & de Sherbinin, 2011; Black *et al.*, 2011; de Sherbinin *et al.*, 2011). On this topic, the Climate Vulnerability Index (CVI) was developed to predict the climate change impacts of on human population through the interrelation that exist between climate human population density distributions (Samson *et al.*, 2011). Subsequently, the Climate-Demography Vulnerability Index (CDVI) was developed by Samson *et al*. (2011) which served as population dimension to identify areas of potential climate impact having densely human population. The CVI showed that the Amazon basin, eastern Australia, northern and southern Africa, Sudan, central China and Mongolia are hotspot of climate vulnerability, while for the CDVI increased warming was projected for the similar region identified (Figure 2.5).

For accountability and transparency regarding responsible and sustainable use of scarce public resources, further, pressure exerted by international donor on development agencies increased the effort to develop spatial indicators through hotspot maps in a scientifically acceptable manner (Barnett *et al.*, 2008). While hotspot mapping approach present great opportunities and benefit for communicating apt and informed strategies suited for policy and decision-making process inherent are two fundamental information communication challenges (de Sherbinin, 2014b). Such challenges stems from: i) data availability and mapping scale issues for certain relevant variables; and ii) uncertainty related to scale and indicators which are proxies explored in vulnerability measurement. This subsection, is therefore timely for reviewing expected challenges present in available hotspot mapping methodologies which can help in its application for climate change mapping efforts and thus fit into the overall SVA concept.

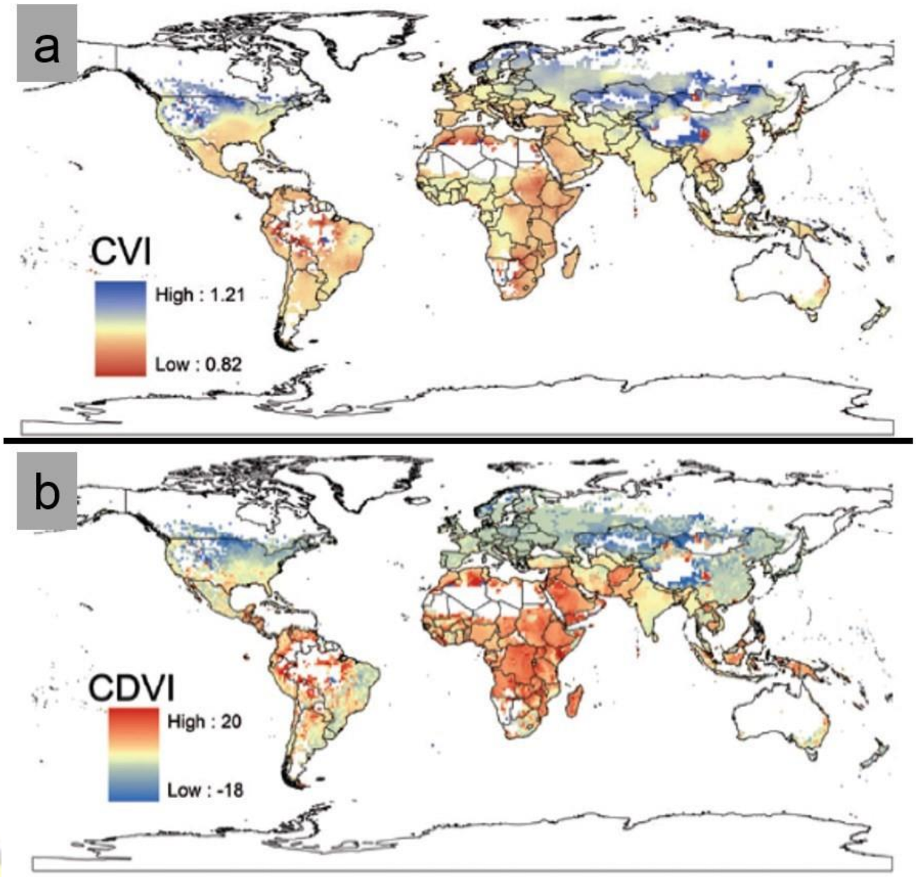

Figure 2.5: (a) Climate vulnerabilities index (CVI) and (b) Climate demography vulnerability index (CDVI). (Adopted from Samson et al. 2011 Figure 4 and 5).

The integration of spatial data and method emerged as one of the plausible standard tool for assessment of climate change vulnerability (BMZ, 2014; UNDP, 2010). Thus, an initiative aimed at research Priorities On Vulnerability, Impacts and Adaptation (PROVIA) identified the measurement and mapping of vulnerability as the foremost step needed to support adaptation decision making process (PROVIA, 2013b). Therefore, assessment of vulnerability can be often used interchangeably with SVA, because the holistic vulnerability concept is inherent of high amount of spatiotemporal heterogeneity (Preston *et al.*, 2011). Different studies have their unique goals, but SVAs in general are targeted towards the identification of potential areas at high risk of experiencing the impacts of climate (i.e. hotspots of potential climate change impact). This review is to gain better understanding of factors that determine vulnerability which can support the identification of requisite planning and capacity development need. Until now, consensus on best practice in SVA is yet to be reached, however, some popular approaches exist and are classified into the following:

1. Indices-based SVA: This procedure normalises constituents of vulnerability into indicators and are subsequently combined to arrive at a spatial index. The structure of the approach is based on the vulnerability framework of IPCC, using indicators categorized into three components namely: exposure, susceptibility and adaptive capacity (BMZ, 2014; de Sherbinin, 2014b; Midgley *et al.*, 2011; Preston *et al.*, 2007). Another common method is the principal component analysis approach which is based on a data reduction architecture (Abson *et al.*, 2012; Cutter *et al.*, 2003).
2. Participatory Vulnerability Mapping (PVM): This approach is a combination of both Community-Based Vulnerability (CBV) and Stakeholder-Driven Vulnerability (SDV) mapping concept that occurs at the local level in relatively small extent. Basically, the CBV approach is traditional and promote the participatory rural appraisal (PRA) (Kienberger, 2012). On the other hand, SDV mapping approach incorporates local governments including members of the community (UNHABITAT, 2013).
3. Story Maps Vulnerability Assessment (SMVA): This approach allow users employ the overlay of spatial series of spatial data or maps to demonstrate impacts of climate change using a story telling paradigm. It is not formally endorsed, hence it may include qualitative hotspot maps for illustration of reports of journal publications (Warner, Afifi, *et al.*, 2012; Warner, van der Geest, *et al.*, 2012). For visualization purposes spatial data are often overlaid to discern aspect such as stressor spatial extent and direct or indirect impacts areas (UNEP, 2011).
4. Impacts Assessment, Mapping and Monitoring (IAMM): Theoretically, vulnerability and impact assessment differ from each other, however, for climate risk mapping and

monitoring, impacts assessment approach have been explored (Preston *et al.*, 2007; UNHABITAT, 2013). The IAMM belongs to the comprehensive toolbox useful for

spatially explicit climate impact assessment. In this thesis, direct and integrated scenario based approaches are applied. In the case of the direct approach, it is useful for describing climate extremes such as flood hazard mapping. While the integrated approach can be feed into process based modelling studies to produce maps of potential climate impact zones (Ericksen *et al.*, 2011). A simplistic use of this approach can be achieved through overlay operation (e.g. identified climate risk areas on stressor maps. More so, impacts assessment outputs can be integrated as input for a comprehensive vulnerability assessment.

Due to inherent unresolved issues in vulnerability concept, de Sherbinin (2014a) concludes that the vulnerability assessment method are neither superior nor mutually-exclusive to each other. Hence, selecting a method should take into consideration the study goal, data integrity and availability, scale, assessment timeframe and funding availability.

Issues relating to data availability and mapping scale is a measurement and conceptual challenge that can affect the fundamental concept of the process to be mapped. However, Abson *et al* (2012) highlighted the relevance of indicators in reducing the quantity and complication of information worthy of presentation and at the same time indicative of interactions of several, spatially identical pointers through a singular vulnerability measure. Although, this approach is inherent of trade-off between the fullness of information and representation of the real world complexity, including presentation and usefulness of the information for policy direction (Abson *et al.*, 2012). Furthermore, Hinkel (2011) documented that since, vulnerability is somewhat not directly measurable because of its emergent behaviour, indicators are involved and are related to constructs of vulnerability and their aggregation. Based on IPCC framework, measures such as sensitivity and factors are also used as indicator variables. In the case of sensitivity, commonly used variables include level of poverty and infant mortality rates. In the case of factors which are related to coping strategy/adaptive capacity, institutional capacity, education, availability of funding for disaster risk reduction and preparedness, including insurance, are considered as vulnerability measures. Despite the availability of dataset, these indicators only serves as surrogates for inherent vulnerability measures (de Sherbinin, 2014a). However, numerous studies have been done on indicators for measuring vulnerability. Kasperson *et al.* (2005) highlighted the complexity involved to incorporate vulnerability in global mapping effort including climate change. Fekete (2012) further established the challenges involved when differentiating indicators aimed at measuring susceptibility from those targeted at adaptive capacity. However, major determinants include preparedness, institutional capacity and actions such as insurance arrangements (Lucas & Hilderink, 2004). Specific study by Chen *et al.* (2011) focused on climate stressor indicators which indicated the difficulty involved coping/resilience process from such as a stressor is influenced by preparedness (e.g. emergency management, institutional capacity and good governance) and actions such as insurance arrangements. An example of climate vulnerability assessment is the study by Midgley *et al.* (2011) which utilized a detailed list of indicator developed by IPCC comprising 16 indicators on exposure, 23 on sensitivity and 12 related to adaptive capacity. Considering these numerous indicators, effective selection of the relevant indicators should be based on theoretical relationships, coupled with fair knowledge of contribution from exposure, susceptibility and adaptive capacity in determining the overall vulnerability (Adger & Vincent, 2005; Preston *et al.*, 2011). Nevertheless, the quantification of precise contribution from the measurement components is difficult due to underlying uncertainties linked to the data as well as knowledge gaps about the relationships amongst them which further introduces complication into SVA, particularly for coarse scale over larger extents. Generally, there is no singular universal way of depiction of vulnerability. According to Fussel (2007), quantitative assessment of vulnerability needs a system analysis approach and can be done by asking relevant questions such as: what is vulnerable?; is the value attributed to the vulnerable system important?; is the system vulnerable to an external hazard and when is the vulnerability going to occur? The following subsection present the attempt in this study to review global efforts on hotspot mapping with regards to climate change.

In SVA, the exposed element needs to be mapped. However, two paradigm exist about data. The first relies on already available datasets while the second generate its own data through participatory mapping approach. Mapping exposed element consist of organizing data needed and contextual evaluation of such data based on proximity to the measured component, how recent they are and spatial resolution and correctness and reliability. A scoring system may be included in this approach such that confidence of each underlying datasets is assessed (YCELP. *et al.*, 2005). Accordingly, the need for strong consideration for appropriate spatial data resolution in SVA has been emphasised, especially in mapping climate indicators (de Sherbinin, 2014a). Generally, scale has impact on the detail mapped (e.g. global land cover maps which range from 300m to 1 km) which is also dependent on the mechanism used for data collection. Due to data limitation which is linked to how up-to-date data is, numerous vulnerability maps have input variable older than 10 years. This has influence on validity of indicators mapped especially when site situation have change for instance phenomenal event such as rapid urbanization, change in economic situation and including impacts from major disaster. Therefore, it is important that detailed metadata of all layers accompanied with such maps (de Sherbinin, 2014a). In SVA, one reliable and accurate data source is satellite images and by extension allows scientist generate reliable land cover maps through semi-automated approaches such as decision tree. Although, confidence in the land cover maps differ according regions of the world. On the other hand some parameters may entail accurate in-situ measurements (e.g. censuses of human population and agricultural practices as well as hydrological gauges are difficult to gather and are inherent of data gaps). Data streams of theses nature extremely sparse in developing counties that are climate sensitive.

Ascertaining the accuracy and reliability of numerous layers of data used can be difficult, time consuming and multi-disciplinary in nature, all these makes SVA task herculean and limit the realization of assessing and documenting uncertainties associated to datasets used in SVA. But best practice suggest inclusion of uncertainty information in SVA mapping. Some model output provide these ideal maps however, their interpretation can be subjective due to absence of data layers. This can somewhat be handled through descriptive statistical approaches such looking at the wide array of measures outliers, skewness, mean, and standard deviation. The use of spatial statistics and packages such as Geoda or ArcGIS may allow scientist compute Moran's *I*, ordinary least square regression to identify patterns in data usually un easy to identify visually (aspect of this were taken up in chapter 5).

With the exception of investigation carried out by Preston (2013) and Giannini *et al.* (2011) to the poplar practice considering that the projection of economic and population was included in their work most SVA have included future scenarios with including expected changes in spatial distribution exposed elements at risk (Preston, 2012). Lately, efforts have been made to develop spatially framed scenarios on socioeconomic pathways on population distribution in climate science (Jones, 2013). Other relevant issues include climate stressor measurement which is the mapping of exposure and is not any trivial especially in the case of climate datasets (PROVIA, 2013a). For instance, challenges have been associated with the use of General Circulation Models (GCM) generated scenario-based climate dataset (e.g. World Bank Hazard Hotspot collection (CHRR, 2005; Dilley *et al.*, 2005) including the Global Assessment Reports of United Nations Environment Programme (UN-ISDR, 2009)) for SVA in the context of flood, drought and possible losses linked to these events as a proxy for future change scenarios. The GCM dataset are associated with methodical faults and are not suited to pics like flooding which is a localized event and is problematic to map with global mapping efforts (de Sherbinin, 2014a). This is also indicative of the fact that data is critical for localized phenomena and when the required data is lacking studies on these topics is hampered especially with inadequate data of local climatology. Because SVA needs accurate information the use of GCM outputs is limited (Brown & Wilby, 2012), despite downscaling efforts GCM comparison with observed stream flow yield in underestimation of standard deviation and temporal autocorrelation (Brown & Wilby, 2012). The GCM are also known for their coarseness and usually require resampling from its original rectangular grid to equal latitude and longitude additions grids accustomed to GIS packages. Although, climate model downscale could be used coupled with SVA's but laptops and desktop computing are not capable of handling the process considering the data volume required for the pre-calculation (Kitoh, 2012), and such data output is overwhelming to the SVA expert who is not a climate expert. The coarseness of GCM also make them unable to correctly characterise critical local climate systems such as orographic rainfall (Oettli *et al.*, 2011). The most common and relevant proxies used in climate science are precipitation and temperature including their broad fluctuations and these changes are already manifesting (Warner, Afifi, *et al.*, 2012; Warner, van der Geest, *et al.*, 2012). These variables need to be explored to extract relevant parameters such as tipping points inherent the climate system however, substantial processing are necessary (Duarte *et al.*, 2012). A plausible approach to handle abrupt changes too could be through scenario based SVA for future abnormal climatic events as well as the stress test proposed (Brown & Wilby, 2012; Storch *et al.*, 2011). Reflecting on all of the data issues reviewed above certainly result in a compounded uncertainty topic which has influence on SVA targeted as climate action. Therefore, a realistic option is to use the best data available since gathering data of the past is unrealistic. But uncertainty and communicating the risk is a major challenge scientist producing maps indicating vulnerability or hotspot should make transparent highlighting either at the map level or accompanying report.

In SVA, spatial resolution and spatiotemporal scale influences plays an important role in the choice of geographic extent and unit of analysis to be considered. In a GEC research context an exhaustive review about scale is documented in Gibson *et al.* (2000), and Kienberger *et al.* (2013). In SVA, scalar dynamics need to be avoided in order not to fall into the "ecological fallacy" pitfall. This concept refers to a situation of performing analysis at one level and applying it for another level (e.g. making inference for a group based on individual characteristics) (Mayhew, 1997). In a spatial context, this situation may also be termed as spuriousness associated with regression analysis which is peculiar with shared spatial location instead of causal connection. Therefore, spatial location alone is not sufficient to infer household vulnerability notwithstanding its location on a high pixel characterized in a high exposure or sensitivity area. In a local context single living elderly resident is likely to be vulnerable heat or flood impact in a different way compared to an elderly occupant with support which implies that variable intervention will be required for the different resident scenario.

Numerous challenges linked to data related to uncertainties generally used for SVA have been reviewed above. Uncertainties from primary data sources are usually transferred to secondary datasets (Fekete *et al.*, 2012) and may consist of data gaps or missing values usually replaced with averages which can result in incorrect calculation errors. Furthermore, Preston *et al.*, (2011) highlighted the challenge faced by SVA with questions on accuracy or exactness of vulnerability maps due to poor handling of uncertainty sources. Other aspects related to uncertainties are researches on climate change modelling and projection from single model and multiple collections model referred to as model ensembles to robustly provide more climate data which tend to reduce modelling uncertainty (Dosio & Paruolo, 2011; Easterling *et al.*, 2000; Murphy *et al.*, 2004; van der Linden & Mitchell, 2009). Additionally, Dosio & Paruolo (2011) worked on bias-corrected projections of Regional Climate Models (RCMs), and are hence found to be potentially useful for the assessment of impacts of climate change sequel to the release of the first probabilistic climate change projection in 2009 for the United Kingdom (UKCP09) (Murphy *et al.*, 2009). Further insights to recent development in climate change science in past decade was a gradual shift from the widely applied emission scenarios as demonstrated by Nakicenovic *et al.*, (2000) in the SRES to RCP clarified in Moss *et al.*, (2010). The RCP-based approach utilizes radiative forcing which has been used, for example, in the latest IPCC Fifth Assessment Report (AR5) for climate modelling (IPCC, 2013). Interestingly, no completely new knowledge of facts was revealed as evidences from climate change science in the AR5 report compared to the IPCC's Fourth Assessment report. However, more confidence and better understanding of climate change was offered from detailed studies which contributed to human influence as being the dominant causative of climate change and also provided better climate change models. The AR5 report was a major inspiration for this research. One of the overarching relevance this research brings to bear includes improved understanding of how urban land uses are vulnerable to climate change impacts in Africa. To conclude this subsection on global climate science, numerous researches have been carried out from a regional perspective all aiming at revealing the potential impacts and vulnerability to various continent that forms the globe (Füssel *et al.*, 2012).

2.1.1 Climate Change Science in Africa and regional concerns in West Africa

In Africa, significant works have also been published aiming at revealing the potential impacts and vulnerability of the continent to climate change (Giannini *et al.*, 2008; Hendrix & Glaser, 2007; Hulme *et al.*, 2001). The AR5 report of the IPCC focused on regional impacts of climate change, highlighted Africa as one of the highly vulnerable continent. This is true of natural and managed environments such as ecosystems, hydrology, some coastal zones, transport and communication. However, net climate change impacts to human settlements, health, fire danger and fisheries are poorly understood. In substantiating this claim further, human knowledge about climate change and its impacts is rapidly increasing through advanced climate modelling to give a better understanding of the natural system. Generally, model predictions shows changes in climate patterns with regional differences, such as changes in surface temperature or average precipitation (IPCC, 2013). The major projected trends of climate change using decadal analysis over land across Africa are evidence of definite increased temperature, due to anthropogenic activities over the last 50-100 years (Raffaello *et al.*, 2013; Seneviratne *et al.*, 2012). But Rowell, (2012) found that precipitation projections were observed to be more uncertain than temperature projections and again precipitation exhibit higher spatial and seasonal dependence than temperature projections (Orlowsky & Seneviratne, 2012). For instance under all emission scenarios, climate projection for Africa indicated an overall increase in temperature ranging from +0.20^{o} C to +0.40^{o} C by the end of 2065 in A2 and B1 scenarios. Thereafter, an increase of +0.80^{o} C per decade is projected till the end of the century 2100. An import from historical climate record for Africa shows that the continent is highly vulnerable to the various manifestations of climate change. Remarks gathered from previous synthesis and assessment (Collier *et al.*, 2008; Hulme & Arntzen, 1996) concluded that the African continent especially West Africa (WA) is particularly vulnerable to the impacts of climate change. Due to factors such as widespread poverty, recurrent droughts, overdependence on rain fed agriculture, inequitable landmass distribution, which makes climatic effects very different according to location within the sub-continent, hence there is somewhat no WA-wide climate effect.

2.1.2 Climate Change Science and climate impacts in Nigeria

This subsection reviewed climate impact studies in Nigeria, specifically those that have suggested significant climate change consequences. The review was based on two notable sources mainly official document and academic works. This review is important because it syntheses documented facts about climate change impact from both sources. Attempting to fully understand the effects of climate change on Nigeria is fraught with difficulties. Some issues are known and relatively well understood, there is still great uncertainty about the key climatic processes and impacts. Nigeria is likely to experience significant climatic shifts in the near future. However, much of such assertions are from coarse global models which suggest the inherency of uncertainties in such declaration (Houghton *et al.*, 2001). Compared to other regions of the world, climate science in Nigeria is faced with constraints. A likely reason for this is that Nigerian climate science and associated infrastructure are relatively poorly developed. This challenge may be explained by many constraints, some are outlined below:

Data Constraints: Irrespective of the duration analysed, climate science is established on data availability. Trusted, spatially distributed and long-time series climate data is vital to designing any development centric policy targeted at solving or abating consequences of climate variability or change. Unfortunately, climate report on Africa suggests that systems observing climate in Africa are in a poor state compared to other continents, and are still deteriorating lately (Washington *et al.*, 2004). Insights gathered from findings show that climate station in Nigeria is not well covered by the World Meteorological Organization (WMO) and World Weather Watch (WWW) stations in Africa. Similarly, data collected by the Nigerian Meteorological Agency (NIMET) is seldom sufficient to capture reliable data to model local climate in Nigeria. The shortage in data-capturing stations such as (synoptic stations, upper air stations, automatic stations, radiosonde for vertical cross section and lower tropospheric information and high technology integrated systems for climate data monitoring) are exacerbated by spatially unbalanced distribution. Also consistent failures in routine data transmission resulting to significant area in Africa left unmonitored particularly Nigeria. Apparently, Figure 2.6 reveals that Africa especially Nigeria is the most poorly reported compared to other regions of the world. In fact according to (WMO., 2003), observations of the upper-air density of Nigeria is somewhat below the WMO recommended values. Although, satellite based observation is an option, this may not be a lasting solution for Africa including

Nigeria, considering technical challenges such as algorithms used for interpretation which also need in-situ-based data for calibration and validation, which Nigeria lacks.

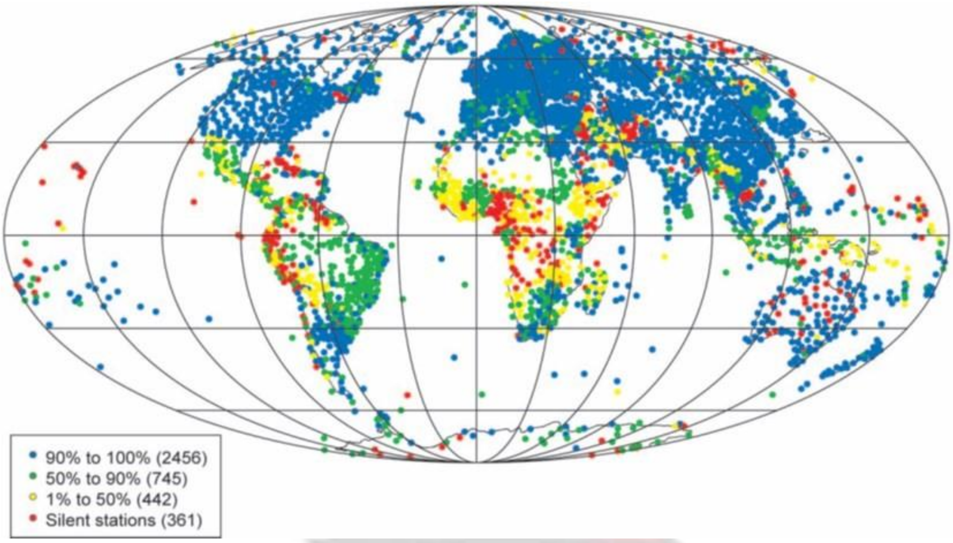

Figure 2.6: The global network of World Weather Watch (WWW) stations are color coded to show reporting rates. Data-sparse areas and low reporting rates for Africa are clearly visible (WMO 2003).

Also, considering the high cost involved in sampling the atmosphere, but immediate development demands in sectors such as defence, health, education are priority areas on Nigeria's national budget. Thus, for climate science to accomplish its potential by providing evidence input toward developing dependable policies in Nigeria, adequate and consistent investment in essential climate and weather observing systems will also be included in the priority list as other issues and their management will be vigorously pursued. Over the years, climate change and its related time scales have often been perceived by the Nigerian government as a distant and least pressing need. For instance, inter-annual circles and variability in climate have been mostly linked to agriculture which is a significant chunk of Nigeria's economy and has been made available through climate information service basically as onset of rain dates, length of dry spell during rainy season, while other tested and tried parameters are associated to seasonal accumulations. Another area of application of meteorological data is the aviation industry which has also suffered from poor data collection suited to serve the industry appropriately except for recent developments provision of Doppler radar in the airports which is also suffering operational, infrastructural and management setbacks.

Science Constraints: Nigeria's second foremost climate science constraint is the scarcity of climate specialist. For instance, journal publication on climate science in Nigeria is characterised by low peer-reviewed articles. This is same in the entire African continent compared to other parts of the world (Washington *et al.*, 2006). Although, scanty outstanding documented science of climate are present in numerous universities across Nigeria, (however, existing skills is weak in several climate science applications such as ocean and atmospheric interactions, time scale downscaling of climate predictions, utility of climate information for disaster management, urban climate monitoring and analysis considering recent development in cities and other areas of need). Also linked to the shortage of climate scientist in Nigeria and a network of data observation and monitoring systems is the poor understanding of the fundamental circulation status above crucial and sensitive parts of the country. Importantly, improved understanding of circulations over Nigeria, and accuracy of their modelling is vital for better management of climate-linked and affected activities, including and beyond Nigeria which can be regional or global in scale. Therefore, if concerted new and successful research efforts are not initiated and undertaken, the current status quo is likely to deteriorate. How did climate science and system in Nigeria find its self in the current status quo? Foremost is the poor science-based investment in Nigeria in general, incorrect presumption on investment in development and education sector. However, advances seen in technological growth in certain sectors are exception inadequate investment highlighted. For example Coyle (2005) revealed that the use of mobile technology across Africa between 1998-2003 grew to 5000%, a rate faster than was experienced in any part of the world and Nigeria was the largest market. Obviously, a number of reasons attest to the fact that the use of mobile phones in Africa is timely which experienced a remarkable acceptance. For example, in the context of climate science, such kind of acceptance never occurred. In many institutions in Nigeria, climate scientist earn low salaries compared to administrators. Apparently, remuneration regime can be scaled up should climate scientists deliver the required information needed and demonstrate user applications closely linked to return on economic investment and productivity, this will promote the need for investment in climate science and infrastructure.

From government documents at national level, Nigeria's vulnerability to climate change has been documented in the Nigeria's First and Second National Communication (FSNC) submitted to the United Nations Framework Convention on Climate Change (UNFCCC, 2003) and the Building Nigeria's Response to Climate Change (BNRCC) Project (FME-SCCU, 2011). In these reports projections corroborate wetter climate over the entire country in B1 scenario than in A2 scenario, except in the northeast, where they predict a drier climate. This has spurred concerted effort to develop legal instrument such as the nation's climate change policy and secure the final approval. The FME (2013) in the policy document highlighted a number of areas in Nigeria vulnerable to climate change impacts. They include areas such as increase in occurrence of extreme weather events, change in temperature and rainfall, increasing pressure on ecology and ecosystems, increased soil erosion and flooding, negative impacts on agriculture, water resources, forest, coastal/marine environment and including socioeconomic and sociocultural sectors.

The academia is the second pathway to reviewing reported impacts of climate change in Nigeria. This is a reliable and robust information pool through research publishing. However, for a variety of reasons, relatively little work has been found reporting climate change impacts in Nigeria. One of the earliest evidence of climate change in Nigeria was outlined by Olaniran (1991) using time series of different amount of daily rainfall data from 1919–1985. Similarly, Bello (1998) reported evidence of climate change based on rainfall records in Nigeria. The study concluded that there has been a change in rainfall seasonality and replicability of rainfall regime in the different ecoclimatic zones of Nigeria. A couple of earlier studies have corroborated similar findings from different studies. For example, evidence provided by Ayoade (1983) were based on biological, lithogenetic and morphological indicators. Olaniran and Sumner (1989) studied the variability of climate over Nigeria using onset, retreat and length of rainfall season. Street-Perrott *et al.*, (2000) described climate change as a continuous change in climate, which could be described based on significant rainfall reduction, amplified dryness and heat rates, that rapidly modify the environment to become arid in nature which depletes the water reserve other ecological resource base. Obioha (2008) investigated the chain of interactions between climate change, population drift, pressure, and conflict over land resources. Likewise, Odjugo (2009) identified the need also to investigate wind related hazards as an environmental problem like flooding and gully erosion that needs to be properly addressed. Results of the research showed evidence of climate change with increasing temperature and rainfall patterns. Adejuwon (2006) assessed possible climate change effects on production of food crops in Nigeria and discovered that farmers are faced with low yields. Also, Ajetomobi & Abiodun (2010) established facts on climate change impacts on cowpea productivity in Nigeria and increasing poor farm output. Other impacts reported in academic journals include the works of Awosika, (1994) who remarked on threat global climate change impacts due to sea level rise imposes on coastal resources and energy production in Nigeria (e.g hydroelectric power generation). Adesina (2009) reported how Nigerian coastal cities are already living with climate change and Adelekan (2010) studied the vulnerable urban poor population located in coastal urban communities to flood impacts in Lagos, Nigeria. Risk communication in climate change and adaptation remains an issue in Nigeria. However, Felix (2009) researched on communication of climate change risks especially on research gaps and policy related challenges in Nigeria, that needs to be addressed for improved climate risk communication. Fasona & Omojola (2005) highlighted climate change perspective to human security and communal clashes in Nigeria. Although this topic requires clear evidences to determine plausible link of conflicts to climate change especially in certain regions in Nigeria (Sayne, 2011).

Lately, researches on climate change impacts have been intensified. One of such studies is the work of Odjugo (2010a). In a broad context, he documented potential areas climate is imminent in Nigeria with key negative highlights especially to poorer tropical regions of the world. Furthermore, Odjugo (2010b) narrowed the scope of climate change investigation and documented regional evidence of climate change in Nigeria. He reported that temperature was steadily increasing from 1970s. The temperature anomalies indicated a strong climate change signal and the increasing temperature in the semi-arid region was higher than the coastal area of Nigeria. Regarding agriculture and food security, Hassan *et al.* (2012) carried an in-depth analysis, which revealed that about half of the working population in Nigeria is engaged in agriculture and this group is highly vulnerable to impacts of changing climate considering their dependence on subsistence agriculture.

It is noteworthy to document that international observers contributed to the pool of record on how climate change impact is manifesting in Nigeria. Of this contribution is a special report from the United State Institute of Peace (UNIP) in 2011. The report by Sayne (2011) highlighted that Nigeria will see increasing climate shift in critical parameters such as temperature, rainfall, storms and sea level rise I the coast for the entire twenty-first century. More so, that adaptive capacity in Nigeria to the critical shift areas can engineer violent conflict in peculiar regions of the country. There is the urgent need to establish evidence-based research program towards effective policy creation with an all-inclusive stakeholder engagement prior to taking critical sustainable and adaptive steps. Despite remarkable achievement made to develop and approve a National Policy for climate change matters by the highest government body in 2013, a major bottle-neck to the final success of this effort is the series of political patronage traps that have confronted Nigeria with competing institutional arrangements for climate policy implementation. Similarly, Koblowsky & Speranza (2012) in their briefing paper understudied the uncertainty surrounding the operationalization of the institutional arrangement to oversee the recently approved legal framework on climate change in Nigeria. In it, climate policy process in Nigeria was acknowledged a novelty for the country, because rarely has such a wide group of stakeholders from the key sectors of society together elaborated a wide-ranging policy. Nigeria illustrates the complex case of multiple stakeholders in a developing and oil-exporting country that is emitting greenhouse gases with climate change impact vulnerability potential. This policy processes involving various stakeholders pursuing this common goal have resulted in two competing proposals for new institutional arrangements: the creation of (i) a National Climate Change Commission reporting directly to the presidency and (ii) a National Agency directly affiliated to the Federal Ministry of Environment (FMEnv).

2.1.3 Knowledge Gaps

Knowledge gaps have been identified in the literature about climate change impacts in Nigeria. Gaps here refer to knowledge deficit. For instance, (i) to what extent climate change is manifesting in Nigeria at (sub-national) level, (ii) what are the expected climatic shifts and associated risks expected at different spatial scales (local changes) in Nigeria, (iii) what are the climate change driving forces in Nigeria, (iv) what are the uncertainties and limitations in our current understanding and our modelling abilities in Nigeria, (v) can the effect of future climate change scenarios due to rapid urbanization be assessed, (vi) how will climate drivers affect (sustainable) development objectives like livelihood and human security, and (vii) to what extent can integrated geoinformation and socioeconomic data-based approach be applied to urban land use vulnerability assessment procedure for Abuja. Evidences are needed about how rapid urbanization can be linked to climate change, including feedback loops.

The pre-existing limitations in climate change related risk and vulnerability assessment includes the absence of probabilistic dataset coupled with low spatiotemporal resolution, poor understanding of uncertainty related to results obtained about variability and change in climate analysis, and the non-inclusion of biophysical and socioeconomic factors in modelling climate. For a comprehensive and contemporary assessment of vulnerability and climate impacts, the inclusion of land use in climate change science is crucial. Objectively, outputs of multi-source data vulnerability assessment are useful and easily implicit for decision-making. But result of this approach is lacking developing and makes climate and land use change domain to be faced with knowledge gaps. This makes assessment of climate change impacts at both regional and sub-national scales deficient of detailed answers to local questions needed in the IPCC global mega-assessment (GMA). The GMA has a five year or more cycle for publishing newer editions, but needed regional and local information are outdated within this timeframe. Also, fine-scale thematic studies such as urbanization topics required are lacking and if available not properly communicated. In the case of Nigeria, numerous remarks have been made on the potential climate change impacts with regards to coastal regions (Adesina, 2009; Awosika, 1994), food security (Adejuwon, 2006), drought impacts (Street-Perrott *et al.*, 2000), security issues (Brown *et al.*, 2007; Fasona & Omojola, 2005), but knowledge and information is lacking with regards to urban land use (urbanisation), which is being projected to be a major phenomenon in the future. To successfully and robustly generate appropriate local climate change vulnerability data, information is needed about actual risks, vulnerability and impacts, but presently, impending impacts on these relevant themes are only literature based. Thus, in this current study, a multidisciplinary and integrated approach is explored on the role of land use especially urbanization in climate change debate. This study focuses on urban land use of Abuja in Nigeria's FCC and peri-urban areas which cover about 785 Km^2.

2.2 Climate and Land Cover Change related studies

Land Cover Change (LCC), chiefly driven by urbanization, have significantly influenced regional climate specifically temperature changes (Qian & Ding, 2005; Zhao *et al.*, 2001). As one land cover is replaced with another (e.g. removal of forest and natural grass land for crops or grazing etc.) so also is change in albedo, latent heat flux, and energy forcing/redistribution accompanied; thus affecting regional climate (Timbal & Arblaster, 2006). For instance, vegetation clearance leads to reduction in evaporation in soil as well as cloud formation (Herrmann *et al.*, 2005). This further establishes temperature amplification and a regional scale precipitation decrease. Despite the observed increasing temperature trends shown by most weather stations following the dramatic LCC, negligible significance in temperature trends was recorded prior to the LCC. Hale *et al.* (2006) demonstrated how LCC contributes to regional climate change and as a feedback loop, modified climate somewhat regulate LCC through land use (Gao *et al.*, 2006; Liu *et al.*, 2005). A typical example is the drought which prompts rapid LCC within shorter time period (Pitman *et al.*, 2004; Reid *et al.*, 2000). Hence, in a geographic context, climate change can determine permissible LCC due to the influence it exert on the Earth surface energy flux and balances (Gao & Liu, 2011). Apparently, climate and land-use change (CLUC) is a reality and its varying impact on all sectors and level of societies has made it one of the world's biggest public policy issues. Hence the need to understand the link between these two has been recognized due to recent phenomenal changes in climate. For the past three centuries, significant effects of humans on the global environment including its atmosphere, hydrosphere, lithosphere and biosphere have escalated (Crutzen, 2002; Ellis, 2011; Ellis & Ramankutty, 2008; Gradstein & Ogg, 2004; Vince, 2011). Crutzen & Stoermer (2000) and Steffen *et al.* (2007) documented that, the earth may have already transitioned from the Holocene to the unambiguously human-dominated era of the Anthropocene. The word "Anthropocene" (the geological age since the industrial revolution) popularized by the Nobel Prize winner Paul Crutzen is apt for the change that is occurring globally, regionally and locally. This concept was further expanded with emphasis on human impact on the landscape

(Goudie & Viles, 2010). Weight of evidence from retrospective understanding of the recent past on scientific discovery on the earth and life sciences reveals that the human footprint on critical life-supporting services of the system earth has grown exponentially since the time of Charles Darwin.

Substantial amount of researches on changes and dynamics in the landscape have increased in the recent past decades. Basic themes are landscape LULCC reconstruction from different viewpoints, such as mapping or monitoring (Pontius Jr & Petrova, 2010; Reid *et al.*, 2000), landscape studies and management (Cissel *et al.*, 1999; Leyk, 2005), temperature (Qian & Ding, 2005; Zhao *et al.*, 2001), ecology (Bolliger *et al.*, 2004; Schindler, 2009), forestry (Manies *et al.*, 2001), food security (Wheeler & von Braun, 2013), or population dynamics (Guzman *et al.*, 2009; Parish *et al.*, 2012). Insights from past situations of the landscape and the comparison of multi-date data supports better understanding of landscape dynamics and helps to better manage our environment in a sustainable manner (Swetnam *et al.*, 1999). A body of studies on this theme are mostly based on remotely sensed data from satellite imagery such as Landsat data (Leyk & Zimmermann, 2006; Xiubin, 2012), aerial photos (Alard, 2001; Mast *et al.*, 1997) or paper maps (Ibrahim Mahmoud, 2012; McChesney & McSweeney, 2005). Many studies have also used historical inventory or survey data (Axelsson, 2001; Bolliger *et al.*, 2004; Comer *et al.*, 1995; Mladenoff *et al.*, 2002). But a major determinant is the scale and thematic focus of the research, hence either topographic maps (Hodgson & Alexander, 1990; Kienast, 1993), or cadastral maps (Domaas, 2007; Skanes, 1996) were presented to be appropriate legacy data sources. Apparently, land cover and land use (LCLU) information from such research outcomes are vital to the policy development process vis-à-vis Millennium Development Goals (MDGs) 1 and 7 targeting food security and environmental sustainability respectively (Chilar, 2000; Dai & Khorram, 1998; Defries & Belward, 2000). Hence, accurate and recent land cover information at global, regional and local scale is urgently needed to adequately monitor and understand Earth events such as climate variability/change which aligns with the MDGs and Sustainable Development Goals (SDGs). Objectively, the aim of MDG-1 is to eliminate hunger and poverty, while sustainability in the use of natural resources including land is the targeted of MDG-7. With the recently developed SDG more target focused on specific issues around climate actions have also been set. According to Chilar (2000), data on land cover is essential in taking action about conservation of biodiversity in the context of proper land resource management and Jones *et al.* (2009) opined that data on land cover is a baseline for specialized land resource database creation. Similarly, emphasis of the need for up-to-date data on land cover was stressed by Helmer *et al.* (2000) for improved understanding of the impacts rainfall has on flood propagation, run-off, soil erosion and crop production. Due to the recurrent emphasis on the need for reliable land cover information for key societal benefits including climate studies, and numerous programs have been initiated such as the international Geosphere-Biosphere Program (IGBP), the framework convention for climate change, the Kyoto protocol, biodiversity convention, NASA's Land Cover-Land Use Change (LCLUC) program, Food and Agricultural Organization (FAO) LULC information program and Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2001).

It can also be argued also that due to altering future temperature and precipitation patterns, climate change will impact water supply and demand significantly throughout the world (IPCC, 2007). This will manifest with varying spatiotemporal impacts and are likely to have considerable implications for water resource planning, thus promoting water stress, adding to the risks to water infrastructure systems and effecting return on investments in these systems. In the subsequent sub-headings works corroborating the importance of land cover change studies are put in perspective of this research, hence appropriate logical overview will be provided.

2.3 Remote sensing derived information for landscape assessment and climate change context

Substantial amount of RS datasets from earth observation satellites exist. Due to their overwhelming availability in the recent past it has emerged an important source to obtain regular, accurate and valuable LULC information (Chilar, 2000; Lillesand *et al.*, 2004). Such output is becoming quite popular and can be applied to study and understand processes (Xie *et al.*, 2008), such as earlier explained in the MDG 1 and MDG 7 in (section 2.2) with links to climate change and the recently set SDGs having goal 11 aiming at sustainable cities and communities, 13 dedicated to climate action and goal 15 for life and water. Through RS, LULC information can be obtained at different spatio-temporal scales. Owing to its multi-scale information extraction capabilities, available socioeconomic datasets, especially population census data could be integrated with RS satellite data to better understand social and economic processes in the environment. In the past socioeconomic data has been quite inaccessible, and where available it was found to be not up to date and unreliable. But lately, guaranteed linkages to some of the data sources pool through agencies of government data archives (e.g. meteorological and census data, Earth observing systems such as remote sensing of the environment-Landsat series, ASTER and Rapideye, WorldView 2 etc.). Topographic maps are reliable historic sources of spatial information and could be integrated with medium and high resolution satellite data such as the Landsat satellite series and ASTER data that allow insights into the historic location and possible climate conditions, footprint of built environment, element-at-risk, hazards processes that permit explicit visualization through LULCC monitoring. Therefore, there is urgent need for regional science research output of this sort that focuses on Africa especially the West African sub-region. In this thesis, regional science is described as a discipline focused on the study of geopolitical and socioeconomic understanding, behavioural patterns having regional and spatial scopes through integrated analytical and empirical investigative approach (Isard, 1975; Isserman, 2003; Patino & Duque, 2012). Hence, the spatiotemporal dimension included in regional science research makes RS useful for biophysical, Urban Structural Types (UST), geospatial and socioeconomic data extraction, which can be linked to the array of phenomena under analysis.

Lately, the motivation to link LULCC information to climate change and its impacts have been more stressed. This include the need to understand the proportions of the Earths atmospheric gas composition and surface energy balances through anthropogenic activities such as enhanced Greenhouse Gasses (GHGs) emission and LULCC (Pielke, 2005; Wu & Yang, 2013). According to Mahmood *et al.*, (2010), if not more than at a regional scale, the contribution of LULCC induced climate forcing can be compared to that of GHGs at the global scale. This has made LCC to be gazetted as the chief CO_2 emission source globally with a contribution of (20%) (Chilar, 2000; Ray *et al.*, 2009; Rodriguez-Yi *et al.*, 2000). For instance, intensified surface modification particularly due to urban cluster development (Davin *et al.*, 2007). Therefore, mapping and monitoring LULCC is important to understand the changing climate because its intensification triggers disasters, including extreme events, storm surges, heat waves, flood and drought. Such phenomenon adversely affects the expected progression on the set targets towards achieving MDGs 1 and 7 as well as SDGs 11, 13 and 15; hence generating reliable LULCC information is of essence especially for better understand climate change issues in West Africa. Both targets can be associated with frameworks on Natural Hazards Risk Management (NHRM) as well as the concurrent climate change discussions which requires research attention.

In the last few decades, concerned public and scientific community's interest in CLUC has significantly increased. This focus evolved from the understanding that human activities have modified the environment through significant population increase, deforestation, urbanization, rural-urban migration, and accelerated socioeconomic activities which have intensified these environmental changes over the last several centuries (Mahmood *et al.*, 2010). It is also apparent that there has been an increasing commitment to climate change initiatives, such as the UNFCCC, subsequent Kyoto protocol, IPCC and post-2015 sustainable development agenda. Therefore, it becomes essential that accurate sensing of LULCC, at appropriate scales, and in a timely manner so as to better understand their impacts on climate and provide improved prediction of future climate. Dale (1997) observed that there exist a complex and mutually interactive relationship between climate change and land cover change. Many studies from both modelled and observed data have also documented LCC as a chief anthropogenic factor in climate modification (Feddema *et al.*, 2005; Mahmood *et al.*, 2006; Nuñez *et al.*, 2008). Accordingly, the report by NRC (2005) argued that though LCLUC represents a foremost human climate forcing factor, hence, LULCC effects must be assessed in detail as part of all future climate change assessments, including the forthcoming IPCC assessment, in order for the report to be scientifically complete (NRC, 2005). This includes not only climate effects in the regions where LULCC occurs through anthropogenic activities such as rapid urbanization, but also their role in altering hemispheric and global atmospheric and ocean circulations at large distances from the location of LULCC (Cinar, 2015).

2.4 Remote sensing of urban environment

RS technology has been widely applied in urban LULC classification and change detection (Richards & Jia, 2006). RS data contain valuable information suitable for geoinformation-based analysis of urban land-use, which is a dynamic process characterized with rapid changes in land cover resulting in urbanization coupled with incremental trends of human population. Its utility for urban studies (e.g. settlement expansion analysis, slum detection and urban growth modelling etc.) has captivated ample research interest using manual, pixel and automatic information extraction procedures. Notably, subject of interest for regional scientists which includes some socioeconomic variables are not directly measured from the air, but remote sensing delivers relevant measurement for studying contextual social phenomena and their effects on the land surface (Rindfuss & Stern, 1998b). This suggests that there is a likelihood of nexus between emerging trends in urban land-uses and the changing climate especially in local context. Hence, uniqueness of remotely-sensed data such as synoptic, coverage, repeat cycle, allow for spatial data exploration for testing hypotheses and models of urban areas and for constructing new theories that can help policy makers to analyze and respond to emerging problems in urbanization processes (Rashed *et al.*, 2005).

Objectively, questions related to pattern description apparent in the urban fabric is fundamental in urban analysis (Rashed *et al.*, 2001). This topic has been investigated through mapping of land-cover-land-use, where constellations of landscape is viewed as discrete, organized and homogeneous pieces of landscape fabric, each one with a dissimilar type of landcover and function. The applications of these data source serves as input for urban settlement analysis in regional science and have captivated ample research interest. With the availability of fine and spatiotemporal details from RS, extracting relevant information pertaining to urban settlement from such resolutions is further supported by the hypothesis of urban surface appearance. Maps generated from land-cover-land-use studies through the thematic classification of satellite images can be considered the starting point for further analyses in most urban applications (Donnay *et al.*, 2001; Maantay & Ziegler, 2008). Existing relationships inherent amongst urban land-cover and other environmental factors as well as variables describing socioeconomic conditions were explored in the late 1950s using aerial photography (Green, 1956, 1957). To characterize these relationships in a cost effective approach the use of satellite remote sensing has been explored in research focus of the last three decades. Especially in urban environment where these relationships are built on the concept of physical appearance of urban settlement which is a reflection of the society that created it. Here the assumption is that urban dwellers with similar physical housing conditions will have similar social and demographic characteristics (Jain, 2008; Taubenböck, Wurm, *et al.*, 2009). However, Jensen and Cowen (1999a) earlier highlighted the role of spatial resolution as the most important requirement for properly identifying urban socioeconomic attributes using satellite RS.

Accordingly, several works have used satellite remote sensing at a medium resolution, such as Landsat Multi Spectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery, to explore the relationships between land-cover and socio-economic data (Bagan & Yamagata, 2012; Blaschke *et al.*, 2011; Emmanuel, 1997; Forster, 1983; Jenerette *et al.*, 2007; Mennis, 2006). Apparently, the increased availability of remotely-sensed data has significantly decreased its cost in the last two decades.

Recurrent concerns in applications of remotely sensed data and procedures applied to urban environments according to Phinn *et al.* (2002) are (i) land-use/land-cover mapping; (ii) assessment of the usefulness of texture measures to aid in separating urban land-cover and land-use types; (iii) impervious surface mapping for input to energy and moisture flux models; (iv) land-use/land-cover change mapping; and (v) application of empirical models to estimate biophysical, demographic and socioeconomic variables. The last theme is of special interest for regional scientists, urban planners, policy makers and it aligns closely with the focus of this study. An array of topical applications of satellite remote sensing to the specific field of regional science in urban settings exist, however, this research explored in part aspects of the four listed areas of application in order to link urban land-use and climate change as described in the next subsection.

2.4.1 Settlement expansion analysis and growth modelling

The concepts of settlement expansion analysis and urban growth monitoring suggests observation and measurement of transformations within cities using multi-temporal approach. An urbanized space is inherently a complex phenomenon, due to its containment of large number of people living in close proximity and conditions relatively diverse but dense with emerging organized processes. These evolving circumstances and processes are connected to space. Therefore, measuring, analysing and understanding the urban context, its emergent interconnections and constant changes in geospatial information perspectives are crucial. Many datasets such as the historic topographic, thematic maps, aerial photos and remote sensing allow insight into urban land-cover characteristics and their changes in use over time, at various spatiotemporal scales. Historic topographic, thematic maps, aerial photos mostly allow visual information analysis such as multi-temporal land-cover changes (Ibrahim Mahmoud, 2012; McChesney & McSweeney, 2005). Remotely sensed images are one primary data source, inherently suited for delivering information on urban land-cover/land-use characteristics, their changes in use at different scales in space and time. Ample research interests in urban growth monitoring have been demonstrated with geoinformation-based capabilities. However, limitations have also been highlighted accordingly (Gong *et al.*, 2015b; Musakwa & Niekerk, 2013; Shafizadeh Moghadam & Helbich, 2013; Sharma *et al.*, 2013; Sturm-Hentschel *et al.*, 2013).

2.4.2 Assessment of urban thermal environment

Land covers, as the biophysical state of the earth's surface and immediate subsurface, are sources for most of the material and energy movements and interactions between the geosphere and biosphere. Changes in land cover include changes in biotic diversity, actual and potential primary productivity, soil quality, runoff, and sedimentation rates (Stefanov *et al.*, 1992). However, understanding these changes require the knowledge of land use change that drives this processes. Consequently, LULCC have environmental implications at local and regional levels, and can be linked to the global environmental change processes. The inherent dependencies of the natural environment elements have direct effects on one another and may cause indirect effects on other element. Urbanization, is the conversion of other types of land to built environment and is linkable to socioeconomic growth. This type of LULCC currently being witnessed globally has impacts on climate. Certainly, covering land with buildings, roads and other impervious surfaces, generally promote higher solar radiation absorption, and a greater thermal capacity and conductivity, thus storing the heat during the day and releasing it by night. This makes urban area to experience a relatively higher temperature compared with the surrounding peri–urban and rural areas. This thermal difference, in conjunction with waste heat released from urban houses, transportation and industry, contribute to the development of UHI. UHI refers to the phenomenon of higher atmospheric and surface temperatures occurring in urban areas than in the surrounding rural (highly vegetated or forested) areas due to urbanization (Voogt & Oke, 2003). Although Landsberg (1981) earlier documented that urban climate studies have long been concerned about the magnitude of the difference in observed ambient air temperature between cities and their surrounding rural regions, which collectively describe the UHI effect. Oke (1979) reported two types of UHI which can be distinguished using pertinent temperature measurement methods such as the Urban Canopy Layer (UCL) heat island, and the Urban Boundary Layer (UBL) heat island. UCL heat island refers to the air between the roughness elements, e.g., buildings and tree canopies, with an upper boundary just below roof level. In UBL heat island air situates above the former, with a lower boundary subject to the influence of urban surface. Studies concerning UHI have traditionally been conducted for isolated locations and with in-situ measurements of air temperatures. The advent of satellite remote sensing technology has made it possible to study UHI both remotely and on continental or global scales (Streutker, 2002b). Consequently, the 1.1-km spatial resolution of NOAA AVHRR satellite data has been used to study UHI phenomenon from derived LST measurements (Gallo & Owen, 1998; Streutker, 2002b). Similarly, 120-m spatial resolution Landsat TM Thermal Infrared (TIR) has been explored to derive surface temperatures (Aban *et al.*, 2011; Yuan & Bauer, 2007). Weng *et al.* (2004); Saleh (2011) and Srivanit *et al.* (2012) used Landsat ETM+ image of Indianapolis City, in USA to investigate the applicability of vegetation fraction derived from a spectral mixture model as an alternative indicator of vegetation abundance to land surface temperature LST.

2.4.3 Urbanization induced change in drainage geography impacts

Drainage systems include landscape element that ensures movement of water. This element comprises of soil and vegetation thriving on the soils, the geologic materials beneath the soil, the stream channels that carry water on the surface, and the zones where water is held in the soil and moves underneath the surface (Beechie *et al.*, 2006). In addition to these are many constructed elements, including pipes, sewer lines, culvert and compacted land surfaces, and pavements and other impervious surfaces that are not able to absorb water.

A landscape can be subdivided into distinct drainage basins, each comprising all the elements of a drainage system that contribute water to specific stream channel (Horton, 1932). Conversely, each channel collects the rainfall from its own individual drainage basin, and consequently leads to the runoff process into the basin (Strahler, 1964). The collection, movement, and storage of water through drainage basin characterize the hydrology of a region. The ever-changing shape of stream channels and the viability of plants and animals living in those channels, can be sensitive to the hydrologic processes occurring over these basins (Gregory, 2006).

These systems have evolved over hundreds of decades under the prevailing hydrologic conditions; in turn, their stability depends on the continued stability of those hydrologic conditions (Kleinhans, 2010). Alteration of natural drainage basins, either by the impacts of forestry, agriculture, or urbanization, which is the case of Abuja can impose dramatic changes in the movement and storage of water. Some of these changes are planned to make the land more useful for the intended purpose of landscape alteration. However, some changes are unintended and can have significant consequences (Booth, 1991). Flooding, channel erosion, landsliding, and destruction of aquatic habitat are some of the unanticipated changes that can also results from these alterations (Nicholas, 2013). Alterations of drainage geography accompanying urbanization are among the most severe and potentially damaging. Their impacts have been inventoried by numerous studies (Dewan & Yamagunchi, 2009; Gregory *et al.*, 1992; Kondoh & Nishiyama, 2000; Vietz *et al.*, 2016). Gregory *et al.* (1992) identified river channel change due to urbanization and potential flood locations for the Monks Brook drainage basin in Southern England. Dewan & Yamaguchi (2009) evaluated land use/cover changes and urban expansion in Greater Dhaka, Bangladesh, between 1975 and 2003 using satellite images and socio-economic data to highlight vulnerable people. To gain insight on what may constitute sufficient minimal drainage requirement to reduce potential impacts of change in drainage geography, Vietz *et al*. (2016) highlighted uncertainties that should be accounted for by future research. With urbanization, drainage geography changes is likely to impacts areas that never before have known either flooding or erosion consequences (Das & Saraf, 2007). Therefore, combining land cover information with morphometric outputs in a GIS environment is valuable for assessing urban flood-risk and useful for municipality managers in a climate change preparedness context.

2.4.4 Urban Structural Types (UST) assessment

UST refers to Urban Morphological Types (UMT). But its definition varies across multitude of application. Previously, mapping UST's have been done by visual interpretation of aerial photographs (Banzhaf & Hofer, 2008). The use of Multi-sensor remote sensing data from the Landsat, TerraSAR-X, Quickbird and Shuttle Radar Topography Mission (SRTM) sensors have been demonstrated by Taubenböck, *et al.* (2008b) for experimenting urban structure analysis of a mega city in Mexico. Netzband *et al.* (2009) used geospatial technology to identify vulnerable groups and their physical environment and concluded that it could enhance the search for equity in megacities. They combined spatial, physical and sociodemographic information. This contribution shows potential benefits of bridging the gap between spatial analysis and remote sensing in social science. Similarly, knowing that beyond land-use and land-cover information, it is the urban composition that explains social disparities, Hofer *et al.* (2009) assessed the vulnerability in urban area to natural hazards based on regional planning deficits. Imageries from Quickbird sensor and TerraSAR-X device, Spotlight mode, were taken to delineate UST. Hofer *et al.* (2009) proposed that LULC and their changes have significant influence on heat balance, especially in the urban area. UST for areas under investigation were delineated in which the urban morphology is rather characteristic for the social strata. The UST was compared with climate parameters to find out if significant correlations exist between UST and climate measurements. Lately, Bochow *et al.* (2010) proposed to develop a universal UST classification system which is adaptable to user-definable USTs and automatic in its application. Other notable contributions include that of Huck *et al.* (2011) who suggested delineating parameters for object-based urban structure mapping in Santiago de Chile using QuickBird data. Heiden *et al.* (2012) demonstrated characterization of UST using hyperspectral remote sensing and height information. Delineation of central business districts in mega city regions using remotely sensed data was again established (Taubenböck *et al.*, 2013). Heldens *et al.* (2013) analyzed surface thermal patterns in relation to urban structure types using the city of Munich as a test site.

2.5 Remote sensing-based risk and vulnerability assessment under LULCC and climate change conditions

This research is conducted with the belief that integrated RS, historic climatic and limited socioeconomic data can support the development of robust and reliable procedure to synergise relevant information from a variety of spatial and non-spatial sources for modelling vulnerability in urban landscapes. Esch *et al.* (2010) demonstrated the use of remote sensing for sustainable urban development. While Taubenböck *et al.* (2009) worked on risk and vulnerability assessment to tsunami hazard using very high resolution satellite data. Similarly, Cutter (2010) researched on social science perspectives on hazards and vulnerability science.

Therefore, integrating RS, historic climatic and socioeconomic data can lead to developing formalism for assessing the vulnerability of urban and peri-urban landscapes to climate change. In this respect relevant biophysical, UST, socioeconomic and geospatial information encoded on satellite data are systematically unlocked, which could be utilized to answer questions of significant societal or environmental concerns, such as variety of environmental management needs, climate change mitigation and adaptation, multi-temporal hazard, risk and vulnerability assessment of urban landscapes.

Substantial amount of definitions and frameworks to assess risk and vulnerability in a rich multidisciplinary tradition exist from scientific literatures (Adams, 1995; Adger, 2006; Alwang *et al.*, 2001; Birkmann *et al.*, 2013; O'Brien *et al.*, 2007; Thornton *et al.*, 2006; Turner *et al.*, 2003). However, these numerous approaches have their specific weaknesses, strengths and fields of application. Of these definitions none is superior or widely accepted than the other. Overall, vulnerability assessment and risk modelling are important components for an effective end-to-end hazard early warning system and therefore contribute significantly to disaster risk reduction such as climate impacts. A pre-condition for arrangement of human security preparedness structures, detailed evacuation and recovery planning is the knowledge about elements at risk, susceptibility, coping and adaptation mechanisms. Mapping of hazards and vulnerability indexes are effective tools to project impacts of different climate change scenarios (Füssel & Klein, 2006), and to facilitate adequate adaptation strategies (FAO, 2007). To this end, the assessment and mapping of climate change vulnerability is a popular analysis approach that enables the representation of local context within vulnerability assessment through the spatial rendering of geographically heterogeneous determinants of vulnerability and their interactions (Preston *et al.*, 2011). Every decision making process involves risk and two diverse understanding exist about risk. The first definition established by Blaike (1994) describes risk quantitatively, which can be attributed to a traditional approach. While the second defines risk in a non-quantitative perception (Slovic, 1987). According to Blaike (1994), risk can be traditionally defined as both the function of hazard on one hand and vulnerability on another end. This suggest that the occurrence of hazard is accompanied with proportional probability as well as vulnerability to impacts associated to a specific hazard type. However, probability in the context of hazard can be understood to be the occurrence of a natural hazard likelihood based on previous records, that such hazard had in the past occurred which can be described statistically in a frequentist probability (Petr, 2014). Although, there still remain incomplete knowledge about the causalities despite a quantity probability is attained, hence uncertainty remains regarding the phenomena which makes vulnerability a nexus for measuring coping strategy to resist and or recover after a catastrophic event (Blaike, 1994). Some definitions on risk in the context of climate change by Willows & Connell (2003) is "a combination of chance or probability of an event occurring, and the impact or consequence associated with the event" and by IPCC as combining the magnitude of the impact with the probability of its occurrence (Schneider, 2007). The aforementioned definitions suggest a sense of 'certainty' once risk is quantified. But critically this understanding of risk is faulty, because whilst risk is quantified, uncertainty still exist about a system and its processes. Objectively, such shortcomings of risk and vulnerability need to be communicated to the end-users of risk assessment. Additionally, Slovic (1987) documented that investigation from other literature includes the non-quantitative risk which is a non-technical view related to risk perception or "intuitive judgements". Thus risk perception refers to the understanding or feeling of people about hazard. Recently, Etkin & Ho (2007) explored risk perception in the context of climate change, climate change adaptation (Adger, 2009) and also forestry (Blennow, 2013). However, a major consequence of the risk perception is that it may result in delay or insensitivity to a potential risk, or in the policy domain specific risks might be excluded from policies if perceived too low. Hence, risk perception is a crucial factor that influences decision making.

To illustrate understanding of both quantified and non-quantified risk, this study puts settlement expansion in the context of climate change impacts due urbanization phenomena. Here information about risk from surface temperature, urban flood risk and human security alongside with expert knowledge accrued from urbanization-induced climate impacts in Abuja from the past years is integrated. The question arises which risk understanding is more dominant and will impact human security. However, while large documentation about diverse perspective of risk and vulnerability exist, there is still a lack of understanding of how risk and vulnerability is dealt with in the context of uncertainty. Fundamentally, risk is a quantified representation of uncertainty (van Asselt, 2005), or a "controllable island in the sea of uncertainty" as a metaphor (Nowtony *et al.*, 2001), while vulnerability relates to the impacts of a hazard. Thus to manage risk issues, this study explores a remote sensing perspectives which aims at offering insights into thinking and understanding of vulnerability issues with regards to uncertainty, appears in climate and land use change domain, which is yet to be investigated.

Earth Observation (EO) has been appealing to considerable amount of researchers who have expressed interest in the concept of assessing vulnerability and risk of systems before an expected event regarding the development of strategies of preparedness (Schneiderbauer, 2007). Many authors such as Miura & Midorikawa (2006) and Sarabandi *et al.* (2008) have shown that EO data are widely used for mapping or up-dating building inventory data. Rashed & Weeks (2003a) reported its utility as input for multi-criteria GIS-based vulnerability studies. Similarly, Rashed & Weeks (2003b) also demonstrated the use of RS data to assess the vulnerability of urban places (urban vulnerability) using pixel-based spatial metrics and a spectral unmixing approach. Taubenböck (2011) further documented the capabilities of remote sensing for diagnosing the multi-faceted and complex vulnerability of a city. Even when direct measurement of vulnerability had proven difficult, Tapiador *et al.* (2011) used VHR RS data to derive very fine socioeconomic sensing which can be used to indirectly measure vulnerability from indicators. Gallopin (1997) defined an indicator as a variable, which is a representation of an attribute, such as quality and/or characteristics of a system. The reliability of an indicator is determined by its ability to indicate the characteristics of a system which are relevant to the underlying interest determined by the goal or guiding vision (Birkmann, 2006). Thus, indicator systems are usually used to resolve the abstract term ‘vulnerability’ into measurable parameter (Bollin & Hidajat, 2006).

This study considered relevant indicators of an “urban system prone to climate change impact”. Here two generic determinants of vulnerability recognized by Adger *et al.* (2004) and Taubenböck *et al.* (2008) and recently reported as a suitable approach by Preston & StaffordSmith (2009) was adopted for assessing vulnerability. Under these two generic determinants five key indicators considered here are: housing condition and transportation (physical vulnerability indicators), population (social vulnerability indicator), production (economic vulnerability indicator) and protected areas (environmental vulnerability indicator). Specifically, Taubenböck *et al.* (2008) documented that components specifying vulnerability include the physical, demographic, social, economic, ecological and political aspects contributing and adding up to the holistic conceptual idea (Figure 2.7).

Meta-Framework

Itemization based on the considered hazard type, system, time and scale

Conceptual Framework	Components	Causes	Indicators / Variables	Index
RISK — HAZARD	Natural Hazard, Human-induced threats, phenomenon	Urbanization-based Land use Land cover change, increased precipitation, Floods, gully, erosion and Insurgency attacks etc.	Magnitude, intensity, spatial exposure, probability of occurrence, duration and time	Indexing of indicators
	Secondary threats, after effects	Temperature development, Urban Heat Island effects, Destruction of life and property and Health challenges etc.	Topography (Height, slope), orientation, soil types, wetness index, spatial exposure etc.	
RISK — Vulnerability (Exposure × Susceptibility / Coping Capacity)	Physical Vulnerability	Location	Accessibility, distance etc.	
		Structural exposure	Number of structure, built-up density, building height, building material and construction types, roof type, building age, urban rate, sealed areas, open spaces etc.	
		Critical Infrastructure	Street and infrastructure network, public transport, communication lines, pipelines, sewer lines, supply, lifeline etc.	
	Demographic Vulnerability	Population structure	Total population, population density distribution, day and night time distribution, age pattern etc.	
		Population development	Population growth rate, migration rate etc.	
	Social Vulnerability	Social Status	Education, public awareness, health, social network, gender etc.	
		Accessibility to and supply of local facilities	Hospital, school, fire service, emergency response shelter etc.	
	Economic Vulnerability	Individual financial potential	Per-capita income, insurance, property, unemployment rate etc.	
		Government potential	Local relief budget, gross national product, help programmes and organization, inflation, Human Poverty Index (HPI) etc.	
	Political Vulnerability	Decision structure	Political systems, willingness, early warning systems, crises and information management etc.	
	Ecological Vulnerability	Natural resource	Water supply and balance, land, agriculture, forest etc.	

Figure 2.7: A structured hierarchy of conceptualizing hazards and vulnerability indicators and selection based on system (adapted from Taubenböck *et al.* (2008) and slightly modified).

The conceptual idea adapted for this study uses a meta-framework developed by Taubenböck *et al*. (2008), which is applicable to various systems (e.g., urban areas), various elements or attributes within a system (buildings, people, environmental services, etc.), various scales (local, regional, national, global), and various hazards (climate change, etc.). But considering that the result of holistic conceptual framework in Figure 2.7 is an arbitrary number of measurable indicators, the overall conceptual framework serves as the basic outline to identify capabilities and limitations of remote sensing data and methods to contribute to the holistic concept. Hence this study measured vulnerability using indicator-based conceptual model of vulnerability that incorporate both biophysical and socioeconomic indicators to provide a multi-hazard assessment of vulnerability at intra urban level.

CHAPTER 3 : METHODOLOGY

3.1 Relevant geographical characteristics of the study area

Abuja Figure 3.1 is the Federal Capital City (FCC) of Nigeria; it was originally estimated to have a population 2.5 Million. The planned city is located in the center of Nigeria and within the Federal Capital Territory (FCT) and covers a land mass of approximately 8000 Km^2. FCT is bounded on the North by Kaduna State, the West by Niger State, the East and southeast by Nasarawa State and the southwest by Kogi State. FCT falls within latitudes 8^o 25' and 9^o25 North of the Equator and longitudes 6^o 45’ and 7^o 39' East. The FCT’s natural endowments such as its rolling hills, isolated highlands and other endearing features make it a delight. The savannah grassland of the North and the Middle Belt, the richness of the tropical rain forests of the south and an equable climate all combined to make the FCT a soil-rich agricultural haven which has been used for numerous farming purposes.

As in the tropics, the FCT experiences two major weather conditions annually. These are the rainy season and the dry season. The rainy season begins from April and ends in October. Within this period, there is a brief interlude of harmattan occasioned by the North East Trade Wind, laden with dust haze, intensified coldness and dryness. Fortunately, the high altitudes and undulating terrain of the FCT act as moderating influence on the weather of the territory. Rainfall in the FCT reflects the territory's location on the windward side of the Jos Plateau and the zone of rising air masses. The annual total rainfall is in the range of 1100mm to 1600mm.

3.1.1 Anthropogenic situation of Abuja

The rationale for choosing Abuja as a test site for this study is based on the fact that Abuja is an excellent area to provide a synoptic view of minimal, medium and extreme view of situation of urbanization in a Nigerian environment. The city is currently experiencing rapid urban land-use change, population growth, which is rapidly influencing LCLUC’s (e.g. the increase in land demand for housing, deforestation and conversion of farmlands into built-up environment to also meet housing demands, increased automobile usage leading to congestion, pollution etc) (Akingbade *et al.*, 2012). Land use conversion have significant effects on people and places especially in urban and peri-urban settlements of Abuja and these impacts have varying vulnerabilities to be assessed for improved understanding and informed decision towards adaptation. Since geophysical and remote sensing techniques have proved to be timeand cost-effective, as well as non-destructive and non-invasive; integrating and correlating results from historic climatic, socioeconomic and remote sensing data is explored in the test area for this study. The study focuses on exploring the links between urbanization and its potential impacts on climate in Abuja at local scale, which could be up- scaled for the West African region.

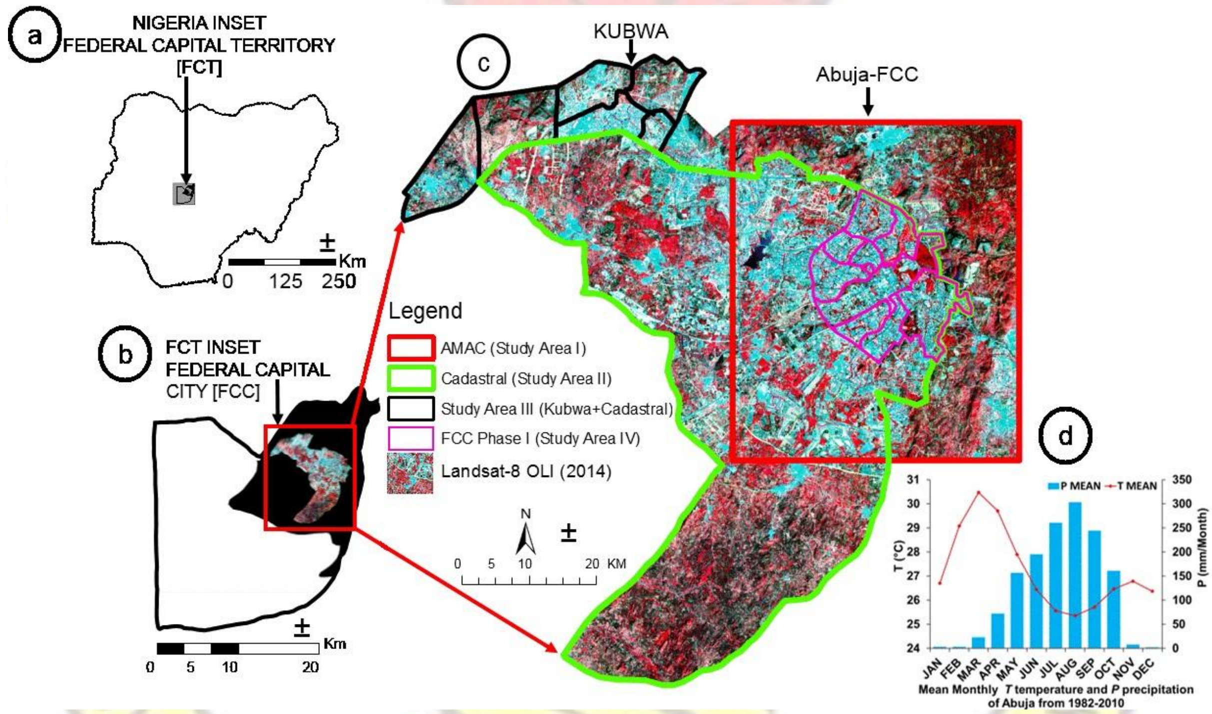

Figure 3.1: Location map and climate of the study area. (a) Map of Nigeria inset Federal Capital Territory [FCT], (b) FCT inset Federal Capital City of Nigeria (FCC) and Kubwa satellite town, (c) Zoom of FCC rendered from false color composite of Landsat 8 imagery of 2014 with vector of study sites and, (d) the variation in mean monthly temperature in (°C) and precipitation in (mm) measured from Abuja airport (24 km from the study area) are shown in the climograph.

3.1.2 Physiography

The FCC and surrounding can be divided into three general physiographic provinces which are differentiated by unique assemblages of landforms, underlying geology and elevation (Figure 3.2).

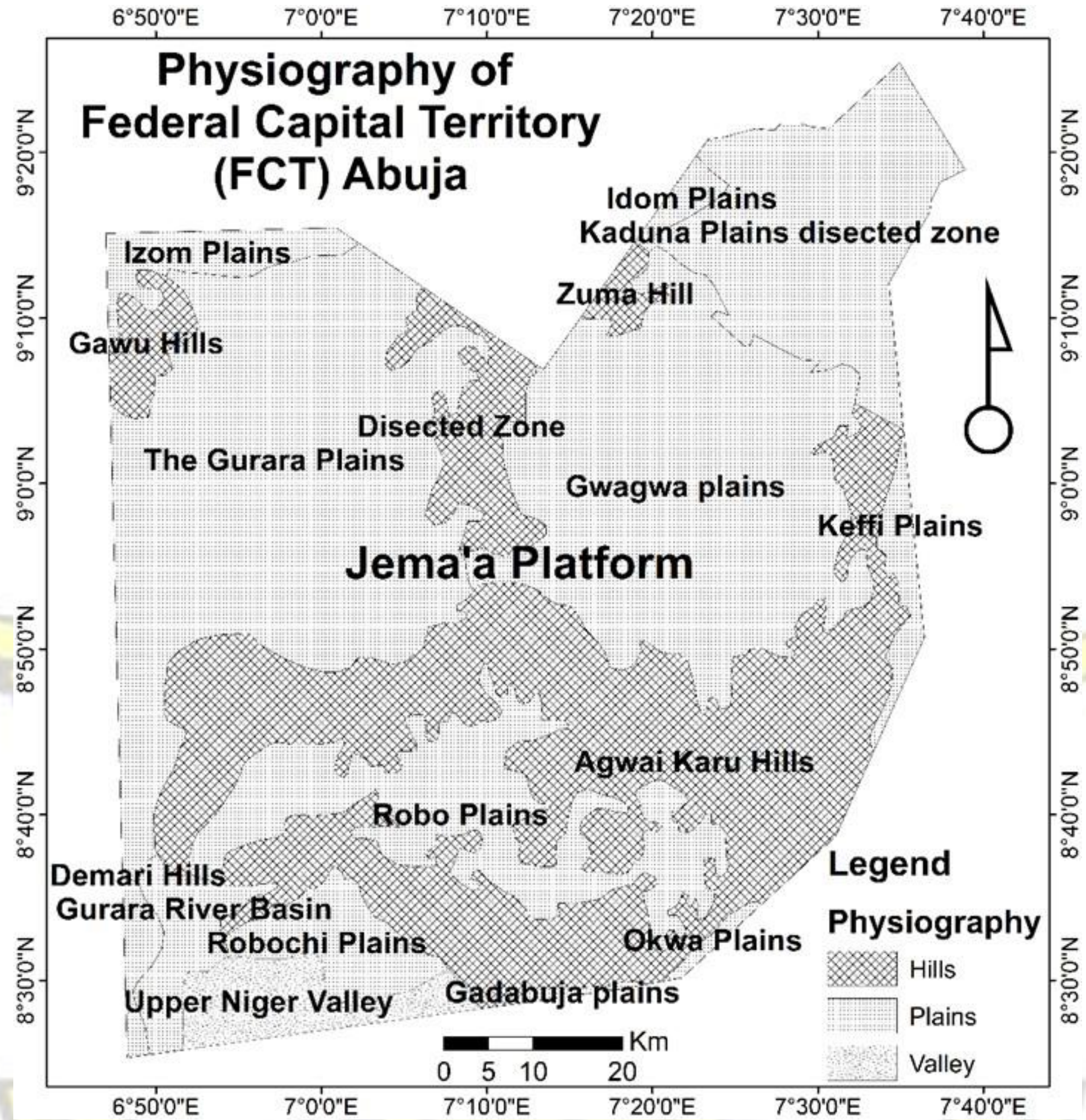

Figure 3.2: Physiographic provinces of FCT, Nigeria (produced by researcher)

These three provinces are the upper Niger valley along the Western and South-eastern boundaries of the FCT study area, the Jema'a platform which occupies the central and eastern two-thirds of the study area and the Kaduna plains in the extreme northeast of the FCT. The upper Niger Valley is located in the western and South-Western portions of the FCT study area.

It contains the lowest elevations within the FCT, less than 60 meters (200 Feet) at the territory's southwest corner. The Gurara River is the major tributary of the Niger River passing through the physiographic province. The Gurara River enters the FCT to the north at an elevation of 240 meters (800) within the Jema'a platform. With the exception of the fact that some tributaries in the eastern portion of the FCT and adjacent study areas, all drainages within FCT enter the Niger River through the Gurara River system. The Upper Niger Valley is bordered on the east and north by Jema'a platform, which gradually grades into the basin, changing from the escarpments of the platform to the relatively level terrain of the river basin and floodplain. A broad flat plain occurs where the river cuts through sedimentary rock (Nupe Sandstone) with formation of expensive back swamps. A narrower floodplain occurs where the river crosses basement complex rock. Five sub-provinces are grouped within the Upper Niger Valley. These include the Rubochi Plains, Gadabuke Plains, Abaji-Zokutu Hills, Demari Hills, and the Gurara River Basin.

3.1.3 Hydrology

Abuja is underlain by mostly basement complex bedrock. Groundwater is stored in the weathered mantle overlying the rock, or in systems of joints depth of weathered and limited extent of fracturing, although the basement complex is considered to be a poor source of groundwater. The depth of the weathered mantle is usually insufficient to retain an adequate supply of water. Further, the system of joints and fracture is too poorly developed to compensate for the lack of a deep, permeable recharge and storage area. The common occurrence of seeps and springs indicates the likelihood that much of the water contained within the soils and weathered mantle occurs as perched water tables perhaps laying on an impermeable layer of soil, (Mabogunje, 1977). No quantification of available supply was performed as part of prior wall investigations in the FCT. although, it was concluded that current information indicates groundwater is not a reliable source of water in FCT (Mabogunje, 1977). Two areas within the basement complex zone of the FCT are identified as potential sources of groundwater, although further study to determine actual resources is required. These areas are the Gwagwa Plains and the northern most extension of the Agwai-Karu Hills. The less rugged topography of the Gwagwa plains indicates that the infiltration into the underlying saprolite deposits may be greater than occurs in other basement complex rocks of FCT. The Northernmost Agwai-Karu Hills are considered a potential groundwater source because of the extent of faulting within the underlying metamorphic geologic structure (FCDA, 1979b). Due to its porosity and permeability, the Nupe Sandstone, found in the southwest portion of the FCT, contains sizeable quantities of groundwater. The Southwest flowing stream emptying into the Gurara River supplies large quantities of water to the sandstone (du Preez & Barber, 1965). Groundwater reserves within the sandstone have not been quantified. A further source of groundwater is the unconsolidated alluvium of floodplains and stream channels, particularly the Gurara River Plain. The quantity of water retained in these materials depends on the porosity, permeability, depth of alluvium, hydraulic gradient and, to lesser extent, ground cover. The amounts are therefore highly variable throughout the FCT. Chemical constituents of the groundwater throughout the FCT include calcium and/or sodium bicarbonate with low concentrations of dissolved solids, sulphates and iron. An indication of possible pollution is the presence of nitrates from some sample wells. Apart from the nitrate levels, the quality of the water is adequate for drinking, agriculture and industry (du Preez & Barber, 1965).

3.1.4 Vegetation

The area now designated the FCT falls within the Savannah Zone vegetation of the West African sub-region. Patches of rain forest, however, occur in the Gwagwa plains, especially in the gullied train to the south and the rugged south-eastern parts of the territory. These areas of the FCT form one of the surviving occurrences of the mature forest vegetation in Nigeria. The dominant vegetation of the Territory is, however, classified into three savannah types.

The Park or Grassy Savannah: This is about 53 percent (i.e. 4,231 square km) of the total area of the FCT (FCDA, 1979b). Vegetation occurs annually and tree species found include *Albizia, zygia, Butyrospernum paradoxam, Anniellia oliveri and Parkia clappertoniana.*

The Savannah Woodland: This region covers 12.8 percent of 1,026 square km of the territory (FCDA, 1979b). It occurs mostly on the Gurara, Robo and Rubochi plains and surrounding hills. Common trees found in this region include *Afzelia Africana, Anogeissus leiocarpus, Butyroscarpus paradoxim, Daniella oliveri, Khaya senegalensis, Prosopis africana, Uapaca togoensis, Albizia, zygia, vitex doniant, Bombox costatum and Ptrecarpus erinaceus*.

The Shrub Savannah: This class of vegetation occurs extensively in rough terrain close to hills and ridges in all parts of the territory. It covers about 12.9 percent or 1,031 square km of the land area (FCDA, 1979b). Tree species found in it include *Antiaris africana, Anthocleista nobils, Ceiba pentandra, Cola gigantean, Celtis spp, Chlorophora excelsa (iroko) Khaya grandifolia (Benin Mahogany) Terminalia superba (afara), Triplochiton scleroxylon* and *Dracacna arborea*. Certain tree species normally associated with other parts of the rain forest in the south of Nigeria are also found in some of the forest patches, e.g. *Piptadeniatrum africanum (agboin) Lophira alata (ekki)* and *terminalia ivorensis (idigbo)*. Apart from the rain forest elements, some dominant tree species of the savannah wood lands yield high quality timber, e.g. *Anogeissus leiocarpus, Daneilla oliveri, Khaya senegalensis* and *Pterocarpus arenaceous.*

3.2 Material

Relevant spatial and non-spatial (ancillary) dataset of Abuja were, acquired, downloaded, gathered and assembled for carrying out this study. A complete list of the sensor names, acquisition day and spatial resolution can be found in Table 3.1.

Table 3.1: Spatial /Non-spatial datasets and software used

Sensor/Data Name	Acquisition day	Spatial resolution (m)
Landsat Series (Raster)	1986-12-26	30/120 m
	2001-12-27	28.5/15/60 m
Thematic Mapper (TM)-5	2014-12-23	30/15/100 m
Enhanced Thematic Mapper (ETM+)-7		
	2010-12-11	0.5/2 m
Operational Land Imager (OLI/TIRS)-8	2013-12-20	0.5 m
WorldView (WV-2) Image (Raster)	2013 update	20 m
WV-2 (8-Bands)		
WV-2 Picture mode	Updated 2008 Update	-
Digital Elevation Model (DEM)		
SPOT		
Administrative Boundary (Vector)		
State and Municipality Boundary		
Road and infrastructure layers		
Software/Packages		
GIS/Digital Image processing (ILWIS 3.3, ENVI 5.1, ArcGIS 10.2, R package eCognition)		
Ancillary Official Data		
Meteorological Data	1982-2014	
Population Data	2006 (UN	
Field Work	2013/2014 & 2015	Local scale
Landscan population data	2014	90 m

3.2.1 Spatial Datasets

Four major satellite images from different sensors were downloaded and acquired for this study. The downloaded images are the medium resolution ones from the official website of United States Geological Survey (USGS) – (http://earthexplorer.usgs.gov/). The images were from 1986, 2001 and 2014 belonging to Landsat TM, ETM+ and OLI-TIRS sensors respectively. Landsat TM is a multispectral sensor with 7 bands including a Thermal Infrared (TIR) band. Bands 1, 2 and 3 are in visible range, bands 4 and 5 are in the near-infrared (NIR) wavelength, band 6 is TIR band and band 7 is in the Mid-Infrared (MIR) range. The ETM+ sensor is also multispectral with 8 bands, bands 1-3 are in the visible range, band 4 is in the NIR, bands 5 and 7 are Short-Wave Infrared (SWIR), band 6 is a TIR band and band 8 is the panchromatic band with a 15 m spatial resolution. The OLI-TIRs sensor has 11 bands, here, the first is a coastal aerosol band, bands 2-4 are the visible bands, while band is the NIR, bands 6 and 7 are SWIR. Band 8 is panchromatic, band 9 is Cirrus while bands 10 and 11 are the TIR. The Very High Resolution (VHR) image was from World View-2 satellite operated by Digital Globe for 2010 and 2013 and was acquired from the Nigeria Office of the Surveyor General of Federation (OSGOF). It has 8 bands, its comprises of 1 panchromatic band at 0.5 m while other are 2 m spread into coastal, blue green, yellow, red, red edge and NIR 1 and 2 bands. The Digital Elevation Model (DEM) is a 20 m DEM from SPOT satellite and was acquired from OSGOF. Other spatial data set used in this study were vector layer such as the administrative boundaries of the FCT, the comprehensive Abuja Master Plan (AMP), the infrastructure layer, Orthophoto and cadastral map of the FCC as well as the reference point used for the 1986 image classification. These dataset were all acquired from the survey and mapping department of the Federal Capital Development Authority (FCDA) and the Abuja Geographic Information System (AGIS).

3.2.2 In-situ climate station meteorological data and field data collection

The major climate variables used in this thesis included the long-term historic temperature and precipitation data of Abuja from 1982 to 2014. Field survey of LULC, vulnerable population to flood-risk and UST were also collected.

3.2.3 Socioeconomic data

The socioeconomic data acquired from official source for this research is the 2006 population census data from NPC. However, to have a long term population pattern perspective of Abuja, the UNFPA projections were acquired.

3.3 General Methodology for Image processing and spatial analysis

3.3.1 Image pre-processing

To generate Land-Use/Land-Cover (LULC) maps and subsequent spatial analysis and change detection, geometric correction is a requirement to be met to ensure registration between the AMP map, TM, ETM+ and OLI-TIRS scenes, while radiometric rectification is another rule of thumb to correct viewing geometry issues, unwanted atmospheric conditions, sensor noise and response (Chander *et al.*, 2009; Jensen, 2005a). All images downloaded had geometrically correction done from the provider. Although, the ETM+ image had 28.5m spatial resolution, it was resampled to 30 m using the cubic convolution algorithm and was subsequently projected to the Universal Transverse Mercator (UTM) system zone 32, Minna Datum. As a quality control measure all other images were thoroughly inspected to ensure they all have same spatial resolution. It should be noted too that the thermal infrared bands other the Landsat TM and ETM+ sensor were resampled to 30 m in order to make them comparable as well as prepare them for later use in (Chapter 5), except for the OLI-TIRS that was already at 30 m resolution from source. Radiometric correction is a vital pre-processing step, it is the conversion of digital numbers to reflectance unit (Chander *et al.*, 2009), which aims to minimize differences in solar zenith angles and incident solar radiation effects. In this thesis, all the Landsat images in DN values were radiometrically corrected to radiance (L) by extracting calibration coefficients from the header file to implement the provided formula shown in Equation (3.1):

$$L_\lambda = (gain \times DN) + bias \qquad (3.1)$$

here L_λ represents the satellite radiance while the DN signifies the satellite image digital number values.

After calculating the radiance values, the calculation of reflectance (ρ) as proposed by Vermote *et al.* (1997) for the number of image bands. Equation (3.2) show the formula for converting radiance to reflectance. This formula is applied on the entire scene using information from header file except for the $E_{Sun\lambda}$ values which were extracted from the Landsat 8 science data user handbook (NASA, 2015).

$$P\rho = \frac{\pi L\lambda d2}{E_{Sun\lambda cos\theta 2}} \quad (3.2)$$

The dimensionless planatery reflectance was dipited as $P\rho$, the at sensor aperture spectral radiance is L_{λ}, while d represents the Earth-Sun distance in astronomical units, $E_{Sun\lambda}$ stands for the solar exo-atmospheric irradiance and the solar zenith angle is denoted as θ_2.

Another vital step is the atmospheric correction, this aims to remove phase angle and atmospheric effects. Although this process normally requires information on aerosol and gaseous compositions present in the atmosphere as well as the bi-directional reflectance characteristics of element contained in the scene (Eckhardt *et al.*, 1990). According to Prakash & Gupta (1998), in multi-temporal Landsat data for relatively flat areas, though solar elevation angle is variant but not significant especially when images are from same season (such as dry season images of December and January), here factors such as atmospheric, phonological and seasonal are considered comparable which was the case of dataset used in this study. Given that the image fall in the same phenological season, radiometric nomalization was not applied for the images of Abuja and were suited for urban application as vegetation is slighly suppressed in December period. The Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) module embedded in ENVI 5.1 digital image processing software was used for the atmospheric correction in this study.

3.3.2 Reference data and field campaign

The two major digital image classification procedure are the supervised and unsupervised. In this study the supervised approach was considered. However, before doing a supervised reference data is required developing the classification scheme and subsequent comparison purposes such as validation/accuracy assessment. For the 1986 TM image reference data obtained from FCDA was used to categorize the land cover types, while the "Historical Google earth image view" was used for the ETM+2001 and actual field work was done for the OLI 2014 image. The field-based verification was done with the study area between 6th November and 10th December 2014. A five-day initial field campaign carried out first and subsequently the detailed reference data (Figure 3.3). The data collection period also falls in the dry season period which is suitable for correlating satellite image and ground features. The stratified random sample approach was used considering the proportional variance in target feature. Five major classification scheme included, water, built-up, vegetation, bare/arable-land complex landscape (Table 3.2). Sampling locations were selected within the study area, however, where accessibility was impossible due to security challenges at the time the field work was done VHR image from Google Earth and 2013 world view were used to collect more reference points. Samples were collected based on pre-fieldwork determined polygons with 100 m × 100 m, 200 m × 200 m and 300 m × 300 m in some instances. With the field work 281 samples were gotten and in combination with the VHR image, a total of 433 samples were collected with water having the least while built up have the highest sample points.

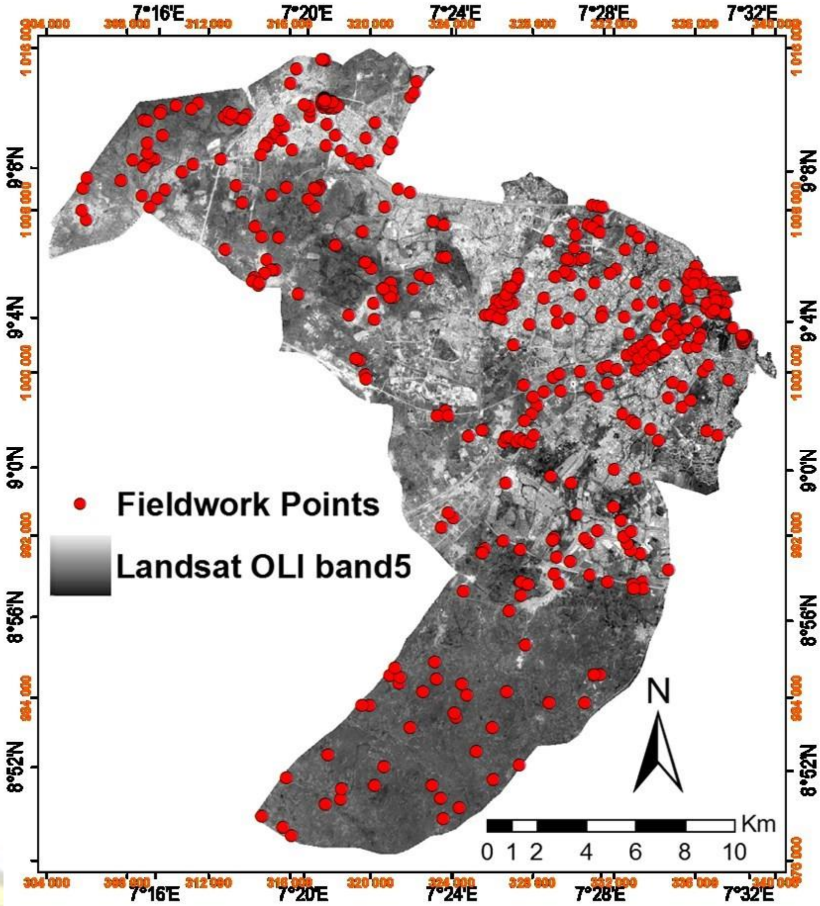

Figure 3.3: Locations of reference data collection.

Table 3.2: Reference data and classification scheme

Land Use/Cover	Types Description
Water	River, permanent open water, lakes, ponds and reservoirs
Built-Up	Residential, commercial and services, industrial, transportation, roads, mixed and other urban features
Vegetation	Coniferous and deciduous forest, mixed forest lands, shrubs and grassland (green areas)
Bare/Arable-land	Exposed soils, area of active excavation, Agricultural areas crop fields and fallow land
Complex Landscapes	Rock-outcrops metamorphosed rock dark soils, wetland and mucky water

3.3.3 Accuracy assessment

In principle, accuracy assessment of classified images is good practice and a vital step in the field of RS applications. Information about possible errors that gives room for improvement is one of the gains. Various method of accuracy assessment are available, one of such is the

Kappa coefficient (Rosenfield & Fitzpatirck-Lins, 1986; Singh, 1989a), which was carried out in this study. This approach is one of the most popular measures of addressing the difference between actual agreement and chance agreement. For instance overall accuracy of image classification is informative of the performance of specific classifier, the user's and producer's accuracies helps determine the correctness of assigned pixels to reality on ground (Jensen, 2005a). Specifically, overall accuracy in image classification is the ratio of the correctly classified pixels to the total sample counts evaluated (Congalton, 1999; Corves & Place, 1994). Inherent in overall accuracy is the percent of correctly classified categories arranged in a diagonal pattern and was computed in here using the following Equation (3.3):

$$OA = \frac{\sum(diagonally\ arranged\ correctly\ classified\ classes)}{\sum(coulmntotal\ or\ rowtotal)} \qquad (3.3)$$

The measure of analyst image classification precision based on category is determined through Procucer's Accuracy and it is informative of errors associated with omission. The error of omission is when pixel belonging to a different class is classified into another category.

Considering the relevance of absolute precision with regards to the mapped spatial data, the error of omission is important to both producers and users. The Procucer's Accuracy can be computed using the number of correctly classifies pixel per category (diagonally) by column total of number of reference point per category. The equation below was used to compute the Procucer's Accuracy Equation (3.4).

$$PA = \frac{count\ of\ correctly\ labelled\ features\ in\ a\ coulmn}{Row\ total\ items\ verified} \qquad (3.4)$$

The chance that a training site mapped image truly represents the same class on ground is referred to as User's Accuracy and is informative of error of commission. It is indicative of the probable pixels assigned into a class truly belongs to the ground feature. It is also an important measure to the user as it gives insight on the agreement between the classified result and ground situation (Congalton, 1991; Lillesand *et al.*, 2004). The User's Accuracy is derived by dividing the count of the correctly mapped samples of a given class against the sum of validated samples owned by the category and is determined by the following formula Equation (3.5):

$$UA = \frac{count\ of\ correctly\ mapped\ features\ in\ a\ row}{Row\ total\ items\ verified} \tag{3.5}$$

Contrary to the common practice of reporting the error matrix in terms of sample counts. A more informative way of presentation of the error matrix is in terms of the unbiased estimator of the proportion of area of the error matrix proposed by Olofsson *et al.* (2013) was also explored for computing accuracy assessment in Olofsson *et al.* (2014). This is because there are uncertainties associated with area of land use or land cover change obtained directly from a map may differ greatly from the true area of change due map classification error and such errors should be adjusted.

Since an accuracy assessment was performed from the constructed error matrix, the erroradjusted and confidence intervals approach of expressing LULC area was applied. This approach is based on the "good practices for assessing accuracy and estimating area of land change document" (Olofsson *et al.*, 2014). In this thesis, accuracy assessment was performed using hybrid approach comprising of secondary reference data, field campaign and VHR image. Details of the two accuracy assessment procedures are explained in Chapters four and five.

3.3.4 Biophysical information extraction

1. Band selection

Additive color composite is the typical way of displaying satellite images which comprises of a minimum of three bands, by assigning each to the primary colors namely Red, Green and Blue (RGB) (Jensen, 2005a; Lillesand *et al.*, 2004). In the fields of digital image processing and remote sensing, RGB have been extensively applied to visualize images in true, false and arbitrary colors (Jensen, 2005a; Lillesand *et al.*, 2004). The two prominent color composite namely the natural color composite and false color composite. The best choice of band composite is dependent on the aim of the study. In this study, the false color composite was adopted owing to its good visual discrimination advantage. For Abuja, (bands 4, 3 and 2) was used in visualizing the TM and ETM+ images of 1986 and 2001, while (bands 5,4 and 3) were used in the case of OLI-TIRS for 2014 in the RGB arrangement. However, for image classification all the visible bands were utilized since the Support Vector Machine (SVM) algorithm can handle more than three multiple image bands.

2. Training sample selection

Typically, training samples are generated through filed work also known as ground truth or its extraction from air photo image and historical map. But non availability of trusted ground control samples makes this stage of remote sensing application subjective. For Abuja ancillary data for 1986 image gotten from FCDA was used, while for 2001 the training was extracted using the "Google Earth Historical view" and field work was done for 2014.

3. Image classification and LULC generation

Advances recorded in the field of geospatial information science (GI-Science) and method makes it possible for researchers to effectively extract relevant biophysical parameter such as LULC maps and to subsequently extract urban and model urban growth as was achieved in this study. Known methods that have been developed over the years to categorize land cover includes the manual classification approach (Kara *et al.*, 2013), fuzzy and hard classifiers (Lizarazo & Barros, 2010), expert systems (Hermosilla *et al.*, 2012), object-based image analysis (Blaschke, 2010), machine learning (Cristianini & Scholkopf, 2002; Tuia & CampsValls, 2011), subpixel (Song, 2005), and urban spectrometry (Herold *et al.*, 2004).

Due to the heterogeneous nature of tropical landscapes, this study adopted the SVM classifier to generate land cover information of Abuja. The choice of SVM is based on the ability of the classifier to robustly handle images of heterogeneous landscapes (Bruzzone & Serpico, 2000; Longepe *et al.*, 2011). The three satellite epochs sought for this study from 1986, 2001 and 2014 were subjected to the SVM classifier. The SVM-based supervised classification approach is a non-parametric machine learning algorithm that used the hyperplane to separate feature of different category with a maximum distance margin located close to it (Sáez *et al.*, 2013). The best generalization is achieved when the margin distance is farthest from vectors from both classes. An illustration of the SVM concept and theoretical basis is presented in Chapter 4 and more details can be found in Cortes & Vapnik (1995) and lately (Mountrakis *et al.*, 2011).

4. Remote sensing landscape indices

Relevant RS indices generated included the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Built-up Index (NDBI) and Land Surface Temperature (LST). The equations for computing these indices is provided in Chapter 5 of this thesis.

5. Morphometric analysis

Globally, drainage characteristics have been studied at basin or sub-basin through traditional geomorphologic methods (Jain *et al.*, 2000; Longepe *et al.*, 2011; Salami, 1999). Although these researches focused on geometric characteristics of drainage basins (Richards, 1993). Furthermore, Gardiner (2002) reported how other works used the morphometric characteristics of basins to predict and or describe geomorphic processes.

The assessment of stream by measurement of its different aspects of the network is also considered part of morphometric studies. Kumar *et al.* (2000) highlighted the evaluation of drainage/stream network ordering, basin area, length and perimeter of drainage channels, stream frequency, drainage density, texture, bifurcation ratio, basin relief, concentration time and ruggedness numbers as part of morphometric parameters analysis. In this study, the application of morphometric analyses for urban flood risk assessment was demonstrated for Abuja to assess how settlement expansion affects change in drainage geography thereby leading to urban flooding. Figure 3.4 presents a logical overview of the numerous morphometric computation performed included standardization of the Digital Elevation Model (DEM), computation of first derivatives and relevant hydrological parameters.

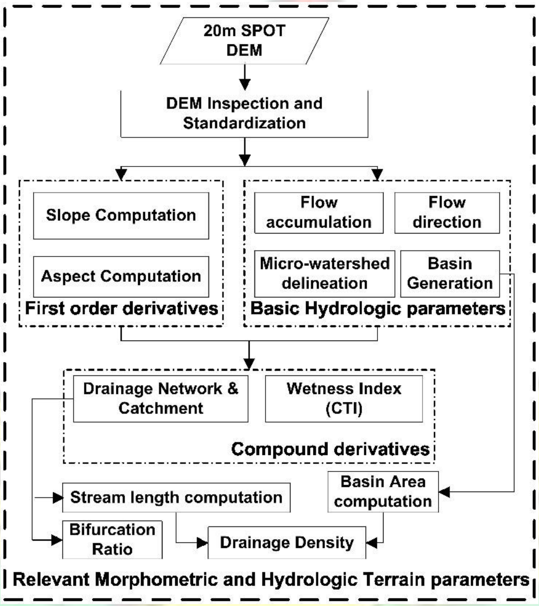

Figure 3.4: Morphometric Analysis

Followed by generation of compound derivatives such as Drainage Network Ordering (DNO) and Compound Topographic-wetness Index (CTI). Other parameters produced included stream length, bifurcation ratio, basin and drainage density. To produce the final flood risk map, the GIS weighted overlay approach was explored and the method performed well in achieving a flood-risk zonation map. To avoid redundancy, details of the study including explicit methodology is presented in Chapter six.

3.3.5 Urban flood-risk and vulnerability assessment

Based on the morphometric information extracted, the weighted GIS overlay approach was used assess the physical vulnerably of to flood-risk. Subsequently, social vulnerability concept was used in Kubwa settlement which was identified as a high flood-risk zone in the physical vulnerability map. The social vulnerability assessment is an explorative approach adopted to measure indicators such as exposure, susceptibility and to determine the overall vulnerability of people along Kubwa drainage.

3.3.6 Object Based Image Analysis (OBIA)

The subsection is brief overview of the object based image analysis performed in this study for deriving urban density information and UST using VHR WV-2 imagery. The WV-2 image was pan-sharpened using the Gram-Schmidt spatial resolution merge algorithm (Aiazzi *et al.*, 2007). Subsequently, the WV-2 data resized to the desired region of interest. The two core steps of OBIA approach segmentation and classification were implemented to achieve the purpose of the study.

3.3.7 Other method relevant to specific objectives

To minimize repetition and redundancy, other specific method peculiar to a chapter used are explicitly explained in the method sections of the relevant chapters. This allows the chapter to be readable and understandable as standalone (e.g. chapters 4 to 7).

CHAPTER 4 : ANALYSIS OF SETTLEMENT EXPANSION AND URBAN GROWTH MODELLING USING GEOINFORMATION FOR ASSESSING POTENTIAL IMPACTS OF URBANIZATION ON CLIMATE IN ABUJA CITY, NIGERIA[1]

Abstract

This study analyzed the spatiotemporal pattern of settlement expansion in Abuja, Nigeria, one of West Africa's fastest developing cities, using geoinformation and ancillary datasets. Three epochs of Land-use Land-cover (LULC) maps for 1986, 2001 and 2014 were derived from Landsat images using support vector machines (SVM). Accuracy assessment (AA) of the LULC maps based on the pixel count resulted in overall accuracy of 82%, 92% and 92%, while the AA derived from the error adjusted area (EAA) method stood at 69%, 91% and 91% for 1986, 2001 and 2014 respectively. Two major techniques applied for detecting changes in the LULC epochs involved the use of binary maps as well as a post-classification comparison approach. Quantitative spatiotemporal analysis were conducted to detect LULC changes with specific focus on the settlement development pattern of Abuja, the federal capital city (FCC) of Nigeria. Logical transitions to the urban category were modelled towards predicting future scenarios for the year 2050 using the embedded land change modeller (LCM) in the IDRISI package. Based on the EAA, the result showed that urban areas increased by more than 11% between 1986 and 2001. In contrast, the changes rose to 17% between 2001 and 2014. The LCM model projected LULC changes that showed a growing trend in settlement expansion, which might take over allotted spaces for green areas and agricultural lands if stringent development policies and enforcement measures are not operationalized. In conclusion, integrating geospatial technologies with ancillary datasets offered improved understanding of how the urbanization processes such as increased imperviousness of such a magnitude could influence urban microclimate through the alteration of natural land surface temperature. Urban expansion could also lead to increased surface runoff as well as change in drainage geography leading to urban floods.

Keywords: land-cover change; settlement expansion; support vector machines; urban growth modelling; climate impact

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4.1 Introduction

Some of the most dynamic places on planet Earth are urbanized locations in several ways and across multiple dimensions. Globally, the expansion of urban forms is documented to be a principal front in habitat destruction which begins with habitat loss and later results in species extinction (Hahs *et al.*, 2009). Notwithstanding their importance, their growth is associated with huge impacts on contiguous ecosystems (Yuan *et al.*, 2005). For instance the loss of arable agricultural land to urbanization, especially in developing nations, is tagged to be a result of prevalent anthropogenic activities (Lopez *et al.*, 2001; Seto *et al.*, 2000). Similarly, the unprecedented transformation of natural landscapes into urban settings significantly affects the natural functioning of ecosystems (Turner, 1994). Hence, urbanization has been the foremost human led land-use anthropogenic activity with huge and irreversible impacts. It is a major force that drives changes such as Land-Use Land-Cover Change (LULCC), biodiversity loss, the biogeochemical cycle, hydrological systems and climate (Grimm *et al.*, 2008). Another prominent agent that can be linked to the unprecedented growth witnessed in urban expansion is population increase (Holdgate, 1993). One hundred years ago, of every ten persons, two resided in urban areas, by 2030 the number of people living in urban areas is likely to hit six, and by 2050 seven out of every ten (World Health Organization, 2014). From the 1950s, the number of global urban inhabitants have increased and by 2050 a two fold increase is anticipated from an approximate value of 3.4 thousands of million as at 2009 to 6.4 thousand of million by 2050 (World Health Organization, 2014). The year 2020 is projected to be when a majority of mega cities in the world will be in developing countries due to differential population growth and anthropogenic activities such as change in LULC (Taubenböck *et al.*, 2010; UN Habitat, 2011). Therefore, governments in West African countries and Nigeria in particular must act fast to better understand spatial and urban growth patterns for improved municipal planning.

The pathway to understanding the process of urbanization can be established by deliberate monitoring of biophysical and socioeconomic conditions of the existing and transformed urban areas (Wentz *et al.*, 2014). However, reliable information on the biophysical dimensions of urban landscapes, especially the urban LULC of the built environment can be difficult to obtain. Hence, remotely sensed data and its applications can provide critical information about urbanization in order to advance urban science for improved policy and decision making. But having access to requisite biophysical, socio-economic characteristics of the urban areas becomes more difficult because gaps exist between these data streams. Moreover, linkages between data collection time lags, administrative and landscape units and spatio-temporal scales pose great challenges.

The paucity of reliable information coincides with the time when substantial growth in urban areas has been witnessed worldwide and hopes are high from policy makers and research groups. These groups hope that fine-scale information to comprehend the impacts of urbanization on local environment and human security such as temperature variability linked to urban heat and cold islands, local environmental and climate change/variability will become more available. This has paved the way lately for more attention directed towards urbanization science with new directions in data collection and analysis (Solecki *et al.*, 2013), as well as monitoring changes in urban LULC considering its strong influence on ecosystems (Stow & Chen, 2002). Remarkably, remote sensing scientists are motivated by this call to meet the needs for linked environmental and socio-economic information through the advancement of remotely sensed data application and methods (Patino & Duque, 2012; Rindfuss & Stern, 1998a; Weng, 2014; Wentz *et al.*, 2012).

Support Vector Machine (SVM) method is one of the latest additions to the existing catalogue of superior and robust image classification techniques for handling multispectral satellite images that support LULC analysis considering their non-linearity and multidimensionality (Hsu & Lin, 2002; Mountrakis *et al.*, 2011; Tuia *et al.*, 2009). The SVMbased approach is a non-parametric machine learning algorithm that uses hyperplanes to separate features of different categories with a maximum distance margin located close to it (Sáez *et al.*, 2013). The best generalization is achieved when the margin distance is farthest from vectors from both classes despite minimal training samples which previously limited numerous remote sensing applications (Mountrakis *et al.*, 2011).

One of the standard ways of simplifying reality is the use of models and in spatial analysis, LULCC mapping, monitoring and modelling can be regarded as models used for decision support to assess the root causes and implications. Modelling LULCC leads to improved understanding of human-environmental systems interaction toward sustainable and spatially framed land-use policy development and planning (Verburg *et al.*, 2005; Verburg *et al.*, 2006). Hence, such spatial models are suitable for assessing arrays of complex biophysical and socioeconomic drivers of spatiotemporal patterns of LULCC and measuring the change consequences (Verburg *et al.*, 2004). Lately, different models such as the cellular automatabased, agent-based, machine learning, and spatially explicit approaches has been applied to study changes in LULC (Brown *et al.*, 2004; Gong *et al.*, 2015a; Tayyebi & Pijanowski, 2014). Similarly, the Land Change Modeller (LCM) have been used to model urban sprawl and growth (Khoi & Murayama, 2010; Megahed *et al.*, 2015). Hua *et al* (2014) ran the SELUTH model which derives its name from input data requirement to run the model slope, land use, exclusion, urban extent, transportation and hill shade over Jimei in Fujian Province, China. Other approaches such as artificial neural networks have also been applied for urban modeling studies (Alsharif & Pradhan, 2014; Grekousis *et al.*, 2013; Sibanda & Pretorius, 2011). The LCM approach is embedded in the IDRISI package which is an integrated environment suitable for analysis, prediction and validation of LULCC (Eastman, 2014). LCM uses categorical gridded images with the same land-cover types sequentially similar in order of arrangement as input for modelling LULCC (Roy *et al.*, 2014). Land-cover changes are evaluated between multiple time lines and change results are calculated and presented in the form of graphs and maps. The proceeding step is predicting the future by generating LULC maps based on the transition potential maps (Roy *et al.*, 2014), trusting the Multi-Layer

Perception (MLP) neural networks output (Vega *et al.*, 2012). For short time frames, the LCM performed better with good prediction accuracies particularly with stable land-covers types against rapid conversion (Roy *et al.*, 2014). Also, comparing LCM outputs to other LULCC models that predict change based on supervised classifiers such as the Weights of Evidence (WoE) approach that uses user defined weighting, more accurate change maps are generated. This is because, the final change map uses the overall change potential maps which are based on neural networks outputs that are capable of expressing changes in various land-cover types robustly better than single probabilities derived from the WoE approach (Vega *et al.*, 2012).

The FCT of Nigeria, was established in 1976 but physical development only began in 1980 (FCDA, 2001) and has been characterized as one of the fastest growing cities in West Africa (Aliyu & Bashiru, 2013). The territory has experienced rapid LULC changes, urban spatial expansion and transportation infrastructure expansion over the last 30 years and is the major focus of urban spatial analysis in this study. Over time, urban growth significantly changed in Abuja which gave way to complex urban dynamics such as conversion of agricultural land to settlement, road and infrastructure (FCDA, 2001), population growth with an estimated annual growth rate of 9.4% (UNFPA, 2015). Table 4.1 presents an overview of how significant population in the FCC differs from other parts of the FCT which indicate rapid population growth as a major driver to consider in this study. For instance, the decrease in agricultural activities and concomitant loss of cultivated land is likely to contribute to landlessness, food shortages and put the livelihood of inhabitants in jeopardy. To date, the environmental and socio-economic sustainability of Abuja, which is essential for development planning, has received relatively little attention. So far, no available systematic study on Abuja's spatiotemporal dynamic of urban growth changes in the context of climate impacts has been made. In the short, medium and long-term development, this current study is appropriate to bridge the knowledge lacuna between these urban events. One of the few studies that have previously been done was to detect LULCC in Abuja and that was based on the maximum likelihood classifier (Fanan *et al.*, 2011).

Table 4.1: Population statistics of the municipalities in FCT for the year 2006.

Municipality Name	No of Inhabitants Population	No of Households Units
Abuja Municipal (AMAC)	776,298	188,093
Abaji	58,642	10,572
Bwari	229,274	51,797
Gwagwalada	158,618	33,196
Kuje	97,233	17,696
Kwali	86,174	15,206
Total	1,406,239	316,560
Mean	234,373.2	52760

This study aims to integrate remotely sensed and ancillary data such as a master plan, digital elevation model and population to detect LULCC from 1984 to 2014, spatiotemporally analyze the settlement expansion pattern and model changes to project the LULC in 2050 using LCM in the context of climate impact. Major themes considered to achieve the goal of this study included biophysical information extracted from remotely sensed data as a baseline for subsequent applications such as analyzing settlement expansion which is the focus of this work. Other aspects investigated is the development of a land use change index and modelling urban growth (from past into the future using LCM which can be contextualized for potential climate change impacts). The subsequent subsection presents and describes the study area as a motivation considering the anthropogenic land-use situation and potential climate change impacts.

4.2 Materials and Method

4.2.1 Datasets

In this current study, three epochs of cloud free Landsat series images were downloaded through the EarthExplorer web portal (EarthExplorer., 2014) for 1986, 2001 and 2014 at no cost (Table 4.2). Other ancillary datasets used comprised of a hard copy of the Abuja Master Plan (AMP) obtained from the survey and mapping department of the Federal Capital Development Authority (FCDA) (FCDA, 1979a), a 20 m Digital Elevation Model (DEM) purchased from the Office of the Surveyor General of the Federation (OSGOF) (OSGOF., 2014), used for slope generation and GoogleEarth Maps (Google Earth Maps, 2014). The municipality administrative vector data was acquired from the National Space Research and Development Agency (NASRDA). Socioeconomic data such as census population was collected from the National Population Commission. Major road networks derived from a global position system field campaign in 2008 and a 2010 WorldView-2 Very High Resolution (VHR) satellite image were obtained from OSGOF.

Table 4.2: Satellite Image description

Acquisition Date	Sensor	Spatial Resolution	Landsat Series	Number of Bands	Radiometric Resolution
26 December 1986	TM	30 m	Landsat 5	7	8 bits
27 December 2001	ETM+	30 m	Landsat 7	8	9 bits
7 December 2014	OLI-TIRS	30 m	Landsat 8	11	16 bits

TM: Thematic Mapper; ETM+ Enhanced Thematic Mapper Plus; OLI-TIRS Operational Land Imager-Thermal Infrared Sensor

4.2.2 Overview of Methodology

The downloaded satellite images for this study were ortho-rectified/georeferenced L1T (terrain corrected) product from source. However, the geometric accuracy was verified by overlaying and comparing with existing maps. Here coordinate system verification and projection to UTM zone 32, WGS1984, Minna Datum was ascertained. Radiometric correction was performed by converting the Digital Numbers (DN) to at-sensor radiance using the radiometric calibration module in ENVI-5 in conjunction with the provided metadata in the header file. The Flash Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) atmospheric correction in ENVI-5 was applied to the at-sensor radiance corrected images of 1986, 2001 and 2014 with the appropriate atmospheric and aerosol models (e.g., Kaufman Tenre aerosol retrieval, tropical setting and urban aerosol model) to produce atmospherically corrected at sensor reflectance images.

Figure 4.1 presents the schema of the methodology used to analyze settlement expansion and future urban growth of Abuja. Basically, the SVM classifier was applied to the preprocessed multi-temporal epochs of Abuja for 1986, 2001 and 2014 to produce retrospective and recent LULC maps of the study area. The classified images were validated using the accuracy assessment measure based on reference points from multiple sources (e.g., preexisting points, historical GoogleEarth maps and field campaigns. Subsequently, to determine and quantify LULCC amounts for the three time stamps considered in this study, a robust change detection approach for time t1 to detect what has been converted to another category in time t2 was explored. The transitions between t1 and t2 are presented as a change matrix which serves as the input to the proceeding step; mainly the calibration and transition modelling of target LULC types. To derive relevant LULC information for city or municipality managers that could be used for settlement expansion analysis, qualitative and quantitative settlement expansion footprints and annual land-use change rate (ALUCR) were computed. In addition driving forces analysis was set for modelling the transition between 1986 and 2001 and was subsequently used to test the predictive power of the LCM by producing a predicted LULC map for 2014. The real LULC map of 2014 was compared to the modelled LULC map predicted from the t1 and t2 categorical maps as a way of validating the LCM-LULCC model.

After validating the modelling step between 2001 and 2014, the model was considered fit for using similar prediction timeframe (approximately 15 years) to predict the LULC scenario for 2050.

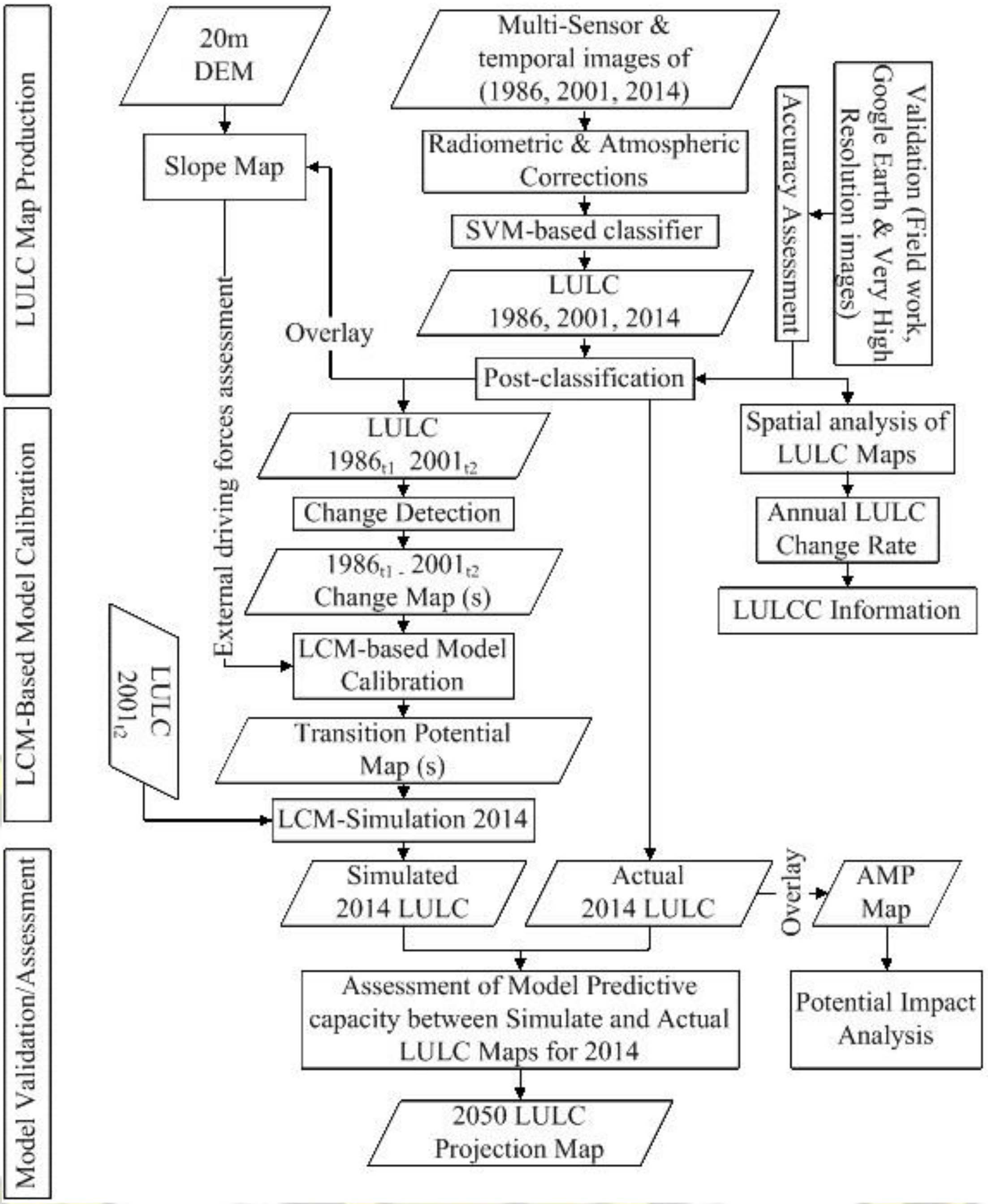

Figure 4.1: Methodology for settlement expansion analyses and future urban growth modelling

4.2.3 Production of LULC Maps and LULCC Detection

The LULC maps of 1986, 2001 and 2014 produced in this study were generated using the SVM-based classifier and five major LULC classes were extracted (see table 3.2). To avoid the 'salt and pepper or speckle effect' often associated with pixel based image classification, a post-classification step based on the majority/minority analysis approach was applied. The option of the 3 by 3 filtering kernel tool was chosen which is suitable for enhancing the quality of the produced maps as well as retaining the Minimum Map Unit (MMU) in urban studies such as the smaller features representative of the urban landscapes.

The LULCC detection was based on two main approaches: the first is the binary method that relays areas/information of change and no change. The output of this technique has only two options, it shows whether changes in pixels have occurred or not between two epochs (Weng, 2011). A more detailed change detection technique explored is the post-classification comparison approach. This second method yields a "from-to" trajectory with an accompanying complete matrix containing records of exact count of transformed pixels from an initial class to another category (Weng, 2011). However, the change or no-change detection method is often associated with a problem of precise threshold identification. The thresholding methods usually have external influences on the resulting differences and can been linked to atmospheric conditions (e.g. sun angle, variable soil moisture, phonological differences) coupled with the threshold which is subjective to the image scene and somewhat dependent on the understanding of analyst of the study area (Weng, 2011). In the case of the post-classification method, autonomous image classification output is proceeded by applying a thematic overlay concept. This results in a complete "from-to" change matrix informative of transformations between categories of the multi-date maps (Singh, 1989b). This technique can be associated with high error propagation effects emanating from independent LULC maps. For instance, images of two dates with a classification accuracy of 80% is likely to have $0.80 \times 0.80 \times 100 = 64\%$ combined classification accuracy measure (Singh, 1989b). The combination of the binary and post-classification change detection techniques yield a binary mask containing the extent of changed and unchanged areas at two time stamps (Mas, 1999). The resultant change mask was subsequently overlaid on the second classified map which facilitates the identification of changed pixels at the t2 classified imagery (Mas, 1999). In this current study, a hybrid approach which combines the change and no-change area binary maps of 1986-2001 and 2001-2014 derived from the NDVI was considered. Applying the NDVI thresholding approach directly for change detection underperformed in detecting many settlement and urban features, however, a direct image differencing approach by combining the near infrared difference with red difference performed better for urban change detection studies (Veettil, 2012). Consequently, an overlay of the areas of change was implemented to construct a change matrix of the study periods; 1986-2001 and 2001-2014.

4.2.4 Accuracy Assessment and Error Adjusted Area Assessment

Accuracy assessment was based on field reference data and an Orthophoto image from the survey and mapping department of FCDA for the 1986 image. The "Historical View" tool in GoogleEarth engine was used to validate the image of 2001. Field data, 2013 VHR and GoogleEarth images were used for the 2014 classification as reference. Given that the stratified random sampling approach employs the probability sampling design techniques which is key in demonstrating statistically rigorous assessment, for each of the produced LULC map, a set stratified random points (200, 250 and 250 for 1986, 2001 and 2014 respectively) were generated using the random point tool in ArcGIS 10.1 toolbox (Table 4.3).

Table 4.3: Sample sizes allotted to the targeted LULC classes in 1986, 2001 and 2014.

LULC Category (Strata)	**Sample Sizes**			**Actual/Verified LULC Category**		
	1986	2001	2014	*1986*	*2001*	*2014*
Water	40	50	50	*40*	*50*	*50*
Built-Up	40	50	50	*38*	*50*	*45*
Vegetation	40	50	50	*55*	*52*	*55*
Bare/Arable-land	40	50	50	*41*	*59*	*56*
Complex Landscapes	40	50	50	*26*	*39*	*44*
Total column	200	250	250	*200*	*250*	*250*

The smoothed LULC maps were converted to polygons using the data conversion tool in ArcGIS 10.1. Subsequently, a column/field titled 'Actual' was created for validating the classified map against the actual LULC. The randomly created points were used to verify the smoothed classified maps based on the reference data and actual LULC visualized from the reference data/VHR images (see italics row and columns in Table 4.3). The output matrices were further used to calculate overall, user's and producer's accuracies. The Kappa statistic, one of the commonly applied measure of difference between actual and change agreement, was computed (Rosenfield & Fitzpatirck-Lins, 1986).

In order to derive an error free area of LULCC information, the adjusted error matrix was computed. This involves three basic steps namely: i) sampling design, ii) response design and Error Adjusted Area Assessment (EAAA) analysis. The first step in EAAA is the sampling design stage. This is a practice used for determining the spatial unit subset that is subsequently used at the final EAAA step (Olofsson *et al.*, 2014; Stehman & Czaplewski, 1998). For this EAAA approaches, collection of reference points were also based on the stratified random points to facilitate the computation of error adjusted change area detail as well as validate the SVM-based LULCC maps which requires a probability sampling approach (Olofsson *et al.*, 2013). This procedure allows the scientist to compute confidence interval estimates with statistical inferences and uncertainty measures. Methodically, the five major LULC categories were used as sample strata. The LULC categories were suitable for stratification since they are the region of interest for communicating accuracy assessment results as well as the error adjusted class area estimates (Olofsson *et al.*, 2014). The stratified sampling is achievable by either equalizing the sample size of each class or making sample size proportional to the target category spatial extent on the map. Equalizing the samples is more advantageous to the user's accuracy than the producer's and overall accuracies (Stehman, 2012), whereas, using the proportional sample size approach, makes the standard errors of the estimated overall accuracies and producer's appear smaller in comparison with the equal sampling (Olofsson *et al.*, 2014). To robustly compute the EAAA, both sampling approach were adopted such as increasing the sample size of the target and rear category such as built-up in 1986 which conforms to Olofsson *et al.* (2014) recommendation for obtaining good EAAA results.

The response design stage is the proceeding step used to compute the EAAA. It is a technique suitable for determining the sampling unit of reference data for LULC classification (Stehman, 2012). Accordingly, Table 4.3 was used for collecting the reference data showing the sample sizes and strata of LULC maps of 1986, 2001 and 2014. The final accuracy assessment analysis involves using the classified map containing *m* classes for constructing an error matrix (Congalton & Green, 2009). Adopting the recommendation proposed by Olofsson *et al.* (2014) for computing LULCC maps accuracies using stratified random sampling techniques in pixel-based classification maps, the area error inherent in the confusion matrices of the produced LULC classification and LULCC maps were adjusted for each category on the maps, while their area of proportions ($\hat{P}_{ij}$) were computed using Equation (4.1):

$$\hat{P}_{ij} = W_i \frac{n_{ij}}{n_{i+}} \tag{4.1}$$

here the area of proportion belonging to a category i in the map is W_i, while n_{ij} refers to the sample count labelled as i which belongs to class j contained in the reference dataset, the sample count mapped in category i is known as n_{i+} on the map. The adjusted error matrix of each cell element $\hat{P}_{ij}$ indicating the probability of a randomly determined area is classified to category i on the image data to class j in the reference data (Mas *et al.*, 2014).

Using the newly computed error matrix, overall, user's and producer's accuracies were computed. The overall accuracy ($\hat{O}$) relays information on the overall proportion of correctly classified areas based on the sum of the diagonal adjusted error matrix represented as $\hat{P}_{ii}$

Equation (4.2):

$$\hat{O} = \sum^{m} \hat{P}_{ii} \tag{4. 2}$$

$i=1$

The user's and producers accuracies were computed based on Equations (4.3) and (4.4) respectively.

$$\hat{U}_i = \frac{\hat{P}_{ii}}{\hat{P}_{i+}} \qquad (4.3)$$

$$\hat{P}_j = \frac{\hat{P}_{jj}}{\hat{P}_{+j}} \qquad (4.4)$$

The user's accuracy for class i expressed as $(\hat{U}_i)$ which is the proportion of area labelled as i having a class reference i, while producer's accuracy denoted as $(\hat{P}_j)$ of category j is proportional to the area of reference labelled j mapped as category j.

The area estimate and uncertainty were systematically computed using the approach proposed by Olofsson *et al*. (2014), the constructed adjusted error matrix facilitated the computation of the area estimator using the area of proportion for category j. Here, the area of category j denoted as $(\hat{A}_j)$ was derived from Equation (4.5):

$$\hat{A}_j = A_{tot} \times \hat{P}_{+j} \qquad (4.5)$$

A_{tot} refers to the total area, while Equation (4.6) serves as the area estimator embedded in an error adjusted estimator.

$$\hat{P}_{+j} = \sum_{i=1}^{m} W_i \frac{n_{ij}}{n_{i+}} \qquad (4.6)$$

The area error adjusted estimator takes into account the area containing the error of omission present in the map category j and it eliminates the area of the map containing the error of commission (Olofsson *et al.*, 2014). The computed standard error $S(\hat{A}_j)$ was achieved based on Equation (4.7).

$$S(\hat{A}_j) = A_{tot} \times S(\hat{P}_{+j}) \tag{4.7}$$

Accordingly, the standard error computed for the stratified estimator based on the proportional area $S(\hat{P}_{+j})$ was derived from Equation (4.8).

$$S(\hat{P}_{+j}) = \sqrt{\sum_{i=1}^{m} \frac{W_i \hat{P}_{ik} - \hat{P}_{ik}^2}{n_{i+} - 1}} \tag{4.8}$$

In order to assess uncertainty of the area estimates with sampling variability for computing confidence interval, the use of $\hat{P}_{+j}$ derived from the reference samples was considered rather than the $\hat{P}_{i+}$ from the map areas. Hence, $\hat{A}_j$ which is the approximate of 95% confidence interval (CI) was computed based on Equation (4.9).

$$CI = \hat{A}_j \pm z \times S(\hat{A}_j) \tag{4.9}$$

where z denotes the percentile of the standard normal distribution curve and 95% confidence correspond to z score of 1.96.

4.2.5 Land use change analysis and urban growth indicators

Information on land use change is vital, not only in spatio-temporal urban growth and transport analysis, but also in different global, regional, local and urban context analysis. The dynamics of urban areas such as driving forces of urban development is reflected by land use change (Aljoufie *et al.*, 2013; Xie *et al.*, 2005; Zhang & Guindon, 2006). Hence, relevant indicators can be used as an effective means of quantifying and analyzing the spatio-temporal relationships between land use change and urban growth. In this study, one indicator was implemented to annualize the quantification of the spatio-temporal LULC change and urban expansion in Abuja. First, the so-called Annual Land Use Change Rate (ALUCR), which was previously defined by Tian *et al*. (2005) Equation (4.10) as follows:

$$ALUCR_{a,t} = \frac{(LU_{a,t} - LU_{a,t-1})/LU_{a,t-1}}{(N_t - N_{t-1})} \times 100 \qquad (4.10)$$

where $ALUCR_t$ [%] is the land use change rate; $LU_{a,t}$ and $LU_{a,t-1}$ are the total land area of land use class a in hectares at the time t (current year) and time $t - 1$ (former year); N is the total number of years from time t (current year to time $t - 1$ (former year)). In this way, ALUCR enables class-wise change analysis.

4.2.6 LULCC model implementation and validation

The LCM analysis was implemented using the IDRISI Selva software. The modelling procedure involves change analysis, modelling transition potential and determination of driving forces, predicting change and validation of the model. The generated LULC maps of Abuja city for 1986, 2001 and 2014 met the minimum requirement for implementing the LCM change analysis and prediction into 2050. The LCM is a rigid model structure which is based on a fixed flow of procedure with a minimum requirement of two LULC maps and the initial map serves as t1 and later serves as t2. The 1986 and 2001 LULC maps were used for the change analysis step to assess changes between the two time stamps. The two dates had the same specification (matching backgrounds, legends and spatial characteristics) and were used as the basis of understanding the nature of change in Abuja. These maps were used to generate transition potential maps and the probability matrix which were suited for identifying prevalent transitions to the urban category and this in turn was used as an input for the modelling of land cover changes. In LCM analysis, the modelling transition potential is vital for change location determination (Eastman, 2014). Output of this step generates a series of transition potential maps that corresponds to significant land-cover transition into urban based on the change analysis phase implemented (Eastman, 2014). The transition maps are considered as suitability of image pixels that have transformed into urban pixels considering a number of driving forces or factors useful for modelling processes of historical change. In this study, elevation, slope and distance to existing urban forms in 1986 were used as predictive variables. The distance to urban areas was used in the modelling phase, while elevation and slope were used independently as have been considered in similar recent studies (de Noronha Vaz *et al.*, 2011; Megahed *et al.*, 2015) which were documented to have influence on settlement expansion, urban growth or sprawl and were evident in the LULCC between 1986 and 2001. In 1986, the distance to urban areas was set as a dynamic factor for recalculating the prediction period of (14 years), from 2001 to 2014. As settlements expands, so does the distance to the extent of urban forms change in time from 1986. To assess the influence of topography as a driving force, a spatial overlay of the urban footprint was performed on the slope layer. Likewise, randomly generated elevation points corresponding to settlement were extracted from the DEM and superimposed on the computed hill-shade as a backdrop layer.

The LCM also allows users to have a quick optional test of potential exploratory model power for driving force which is presented in the Cramer's V. This depicts the correlation coefficient indicating either no correlation (meaning a redundant variable) or perfect correlation referring to significant potential variable ranging from 0.0 to 1.0 respectively (Eastman, 2014). Notably, the Cramer's V does not assure good model performance due to its lack of consideration of mathematical variables and a complex relationship (Khoi & Murayama, 2010), but it helps to determine the usefulness of a driving force (Eastman, 2014). In LCM, the MLP neural network is a feedforward neural one direction network that flows from an input to output with hidden layer (s) in between (Nazzal *et al.*, 2008). The computation of nodes can be grouped as layers where each node receives an input signal to the destination node (Sibanda & Pretorius, 2011). For every input signal into another node, the subsequent layer contains the original input multiplied by a weighting and combined with a threshold which is channeled through the activation function in a hidden linear or non-linear units

(Sibanda & Pretorius, 2011). The weights are defined in the training stage preceding the network prediction stage which uses a proportion of the data to change the weight in order to minimize errors in the observed and predicted outputs (Sibanda & Pretorius, 2011). Generally, the MLP neural network is suitable for modelling multiple transitions at once (Eastman, 2014), and was applied in this study.

The LCM prediction steps, calculates the change rate from both the initial step and the transition potential maps generated from the second step in order to predict the future scenario of 2014. Based on the Markov-Chain analysis, implementing this step helps to ascertain the quantity of transformation of other land-cover to urbanized areas in every transition that occurred in 2014 (Eastman, 2014). From this step, the hard and soft predictions are the two basic types of prediction derived as output (Eastman, 2014). The hard prediction result is the projected 2014 map showing pixels of the specific land-cover category which is the most likely class to be converted into. The soft prediction is somewhat of a vulnerability map depicting pixels assigned to values ranging from 0.0 to 1.0 which is indicative of a pixel's probability to transform into an urban pixel in 2014 (Eastman, 2014).

Model validation is an important step. In this study validation was used to ascertain the quality of the predicted map of 2014 in comparison to actual 2014 LULC maps which is reality. Two notable approaches used in validating such models are the visual and statistical procedure (Pontius & Chen, 2006). Using the visual approach yields a crisscrossed tabulation between the 2001 LULC map, the predicted 2014 map and the 2014 actual map used for assessing the accuracy of the map model. The result of this process is a map containing four main categories (Pontius & Chen, 2006), namely: i) Hits which signifies model prediction of change and the situation actually occurred; ii) False alarms that refers to the predicted change from one category to urban area with persistence in urban class; iii) Misses suggest persistent model prediction that eventually changed to urban class in actual sense and iv) Null success depicts areas where the model predicted no-change and no change occurred. The hits and null success are indicative of model correctness, while the false alarms and misses signify errors due to disagreement between the model simulation map and the reference map (Pontius & Chen, 2006). The Figure of Merit (FOM) is a ratio between hits, simulation hits, misses and false alarms and was computed to ascertain the overall agreement between the observed and predicted maps. FOM ranges from 0% signifying absence of overlap between the predicted and observed change, to 100% suggesting a perfect agreement between the predicted and observed change (Rodríguez *et al.*, 2013). The statistical procedure measures the agreement between paired maps showing variable numbers of LULC categories (Eastman, 2014). The actual LULC map of the 2014 is used as the reference map while the model simulation map was utilized for comparison. The kappa variation techniques were applied as the statistical validation procedure in this study. Here, the Kappa for no information (K_{no}) signifies overall accuracy obtained in the simulation run, while Kappa for location ($K_{location}$) means agreement level in a location (Nadoushan *et al.*, 2012). Considering the difficulty in interpretation encountered with the Kappa for correctly assigned proportion against the proportion of incorrectly assigned by change ($K_{standard}$) (Kim *et al.*, 2011), the $K_{standard}$ was not used in this study. However, $K_{location}$ was somewhat useful for the validation in the absence of $K_{standard}$ (Pontius & Millones, 2011). After assessing the model's predictive power, the model was applied to predict the LULC map of 2050 scenario with the assumption of similar driving forces based on the changes between 1986 and 2014 LULC maps. Driving forces are not static, especially since the world is a dynamic system, so different triggers in variable rate and velocity are likely to evolve and may influence the urban evolution process as well as model results.

4.3 Results

4.3.1 Production of LULC Maps and Accuracy Assessment

Figure 4.2 presents the SVM-based LULC Maps of Abuja city for 1986, 2001 and 2014. Five major classes, namely water, built-up, vegetation, bare/arable land and complexlandscapes were derived from the multi-date satellite images. It is apparent from Figure 4.2 that changes in area of proportions covered the retrospective LULC map categories occurred, especially in the built-up land which is the major focus of this study, and analyzing these pattern is useful for gaining insights about composition of map total area and changes in the pattern during the considered years of analysis.

Table 4.4 presents the accuracy assessment obtained based on the pixel count error matrices from the LULC maps. The overall accuracies derived from the pixel count matrices of the generated retrospective LULC maps for 1986, 2001 and 2014 were 83%, 92% and 94% respectively, while kappa accuracies were 81%, 93% and 94% in 1986, 2001 and 2014 respectively (Table 4.4).

To derive accurate proportions of the targeted LULC categories, the error adjusted area matrix (EAAM) computed based on the pixel count matrix was produced (Table 4.5). The EAAM gives more informative and accurate detail in terms of omission and commission errors leading to confusion and misclassification in the three LULC maps (Table 4.5). The robustness of the EAAM can be confirmed by comparing the overall accuracies derived from the pixel count with the one recorded from the EAAM.

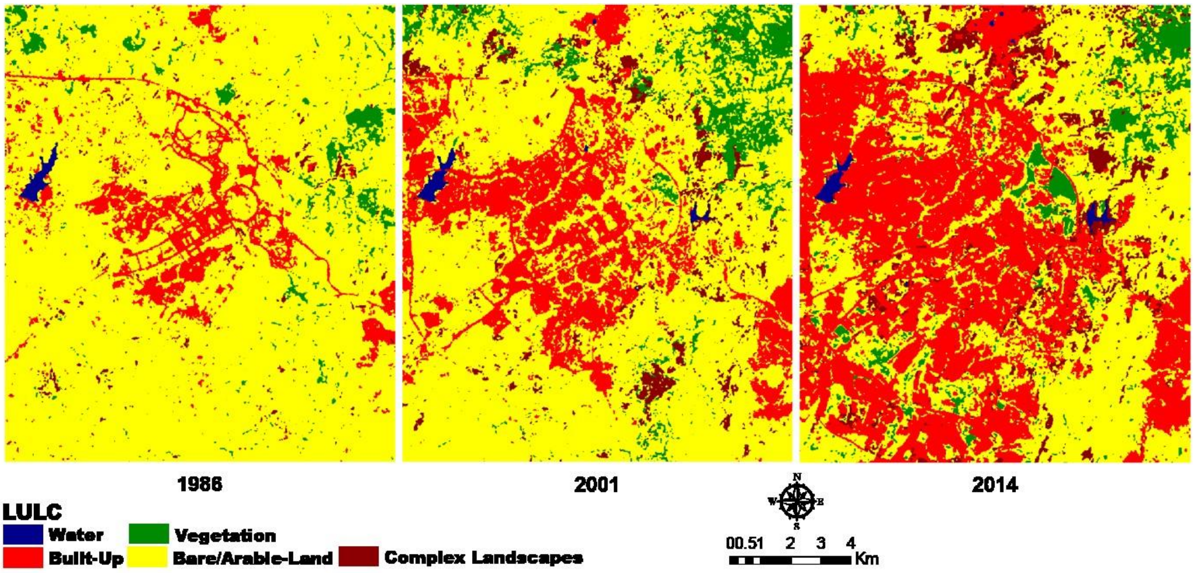

Figure 4.2: Classified images of Abuja for 1986 (left), 2001 (middle) and 2014 (right).

Table 4.4: Summary of LULC map accuracies (%) for 1986, 2001, and 2014 based on the pixel count matrices.

Land Cover Class	1986		2001		2014	
	Producer's	User's	Producer's	User's	Producer's	User's
Water	100	100	100	100	100	100
Built-Up	94.7	92.3	96.0	96.0	100	88.2
Vegetation	72.7	100	94.2	96.1	90.9	100
Bare/Arable-land	65.9	65.9	78.0	92.0	82.1	92.0
Complex-Landscapes	84.6	55.0	94.9	75.5	100	89.8
Overall accuracy	83		92		94	
Kappa statistic	81		91		93	

Table 4.5: Error adjusted matrix of LULC Maps of 1986, 2001 and 2014. WAT: Water; BUP: Built-Up; VEG: Vegetation; BAL: Bare/Arable Land; CL: Complex Landscapes.

Year	Class Name	WAT	BUP	VEG	BAL	CL	Total	User's(%)
	Water	0.390	0.000	0.000	0.000	0.000	0.390	100 92
	Built-Up	0.000	4.885	0.000	0.405	0.000	5.260	100
	Vegetation	0.000	0.000	5.060	0.000	0.000	5.060	66
1986	Bare/Arable-land	0.000	4.270	17.079	57.624	8.540	87.530	
	Complex-Landscapes	0.000	0.000	0.308	0.484	0.968	1.760	55
	Total	0.39	9.13	22.45	58.53	9.51	100.00	
	Producer's(%)	100	53	23	98	10		69
	Water	0.520	0.000	0.000	0.000	0.000	0.520	100

	Built-Up	0.000	19.210	0.000	0.800	0.000	20.010	96
	Vegetation	0.000	0.000	22.463	0.458	0.458	23.380	96
	Bare/Arable-land	0.000	1.564	0.782	35.963	0.782	39.090	92
2001	Complex-Landscapes	0.000	0.000	0.694	3.471	12.844	17.010	76
	Total	0.52	20.77	23.94	40.69	14.08	100.00	
	Producer's(%)	100	92	94	88	91		91
	Water	0.640	0.000	0.000	0.000	0.000	0.640	100
	Built-Up	0.000	37.809	0.000	5.041	0.000	42.850	88
	Vegetation	0.000	0.000	5.550	0.000	0.000	5.550	100
	Bare/Arable-land	0.000	0.000	3.518	40.462	0.000	43.980	92
2014	Complex-Landscapes	0.000	0.000	0.142	0.570	6.268	6.980	90
	Total	0.64	37.81	9.21	46.07	6.27	100.00	
	Producer's(%)	100	100	60	88	100		91

The drop in the 1986 LULC map overall accuracy threshold of 83% based on pixel count to 69% using the EAAM is due to the inclusion of error of commission in estimating the area of proportion. Similarly, a decline in the resultant pixel count overall accuracies was observed in the 2001 and 2014 LULC maps from 92% and 94% to 91% each respectively achieved based on the EAAM (Table 4.5). Some confusion was observed between categories (e.g. BUP, VEG, BAL and CL). Major confusion occurred in the form of errors of commission given that incorrectly classified pixels are prominent in the rows especially between BAL and CL in 1986 and 2001 (Table 4.5). Similarly, errors of omission are evident between VEG, BAL and CL in 1986 and 2001 (Table 4.5).

4.3.2 LULCC detection and Spatio-temporal analysis of LULC distribution

The area distribution of the various LULC is reported in Table 4.6 (1986, 2001 and 2014) respectively. Comparing the pixel count matrices and the error adjusted matrix revealed a slight difference between the mapped and estimated area for the LULC categories. For all the categories, the produced maps fell within a 95% confidence interval of the estimated area which is indicative of the robustness and reliability of the produced maps (Olofsson *et al.*, 2014).

Table 4.6: Proportion of LULC for 1986, 2001 and 2014.

Year	Class Name	Mapped Area (%)	Estimated Area (%)	Confidence Interval
	Water	0.39 5.26	0.39	± 0
	Built-Up	5.06	9.13	± 2.9
	Vegetation 1986	87.53	22.45	± 5.4
	Bare/Arable-land		58.53	± 6.5
	Complex-Landscapes	1.76	9.51	± 4.1
	Total	100	100	
	Water	0.52	0.52	± 0
	Built-Up	20.01 23.38	22.77 23.94	± 1.2
	Vegetation	39.09	40.69	± 1.1
2001	Bare/Arable-land			± 1.9
	Complex-Landscapes	17.01	14.08	± 1.3
	Total	100	100	
	Water	0.64	0.64	± 0
	Built-Up	42.85 5.55	37.81 9.21	± 1.9
	Vegetation	43.98	46.07	± 1.7
2014	Bare/Arable-land			± 2.6
	Complex-Landscapes	6.98	6.27	± 0.3
	Total	100	100	

The spatial arrangement of physiographic features was obtained by subjecting the classified images to spatial analysis, the information about changes in land cover proportion was derived. Subsequently, changes in the spatial composition of geographic features was obtained by comparing the classified images of 1986, 2001 and 2014 against each other (Table 4.7).

Table [1].7: Spatial analysis result of error adjusted matrices of the 1986, 2001 and 2014 LULC maps from showing map category, class area in hectares and percentage and area changed in hectares.

[1] .3.3 Analysis of settlement expansion, floodplain encroachment and driving force

Land use cover types	1986 Area (Ha)	%	2001 Area (Ha)	%	1986-2001 Area Changed (ha)	2014 Area (Ha)	%	2001-2014 Area Changed (ha)	1986-2014 Area Changed (ha)
WAT	13513.3	0.4	18017.7	0.5	4504.4	22175.6	0.6	4157.9	8662.4
BUP	316180.7	9.1	719778.9	20.8	403598.3	1310053.1	37.8	590274.1	993872.4
VEG	77775.9	10.4	829479.7	23.9	751703.8	719150.4	19.2	-110329.3	-641374.5
BAL	2028040.6	70.5	1409643.6	40.7	-618396.9	1596387.0	36.1	186743.4	-431653.6
CL	329429.6	9.5	488020.1	14.1	158590.5	217174.0	6.3	-270846.1	-112255.6
Total	3464940	100	3464940	100	3464940	100			

As displayed in Table 4.8, noticeable LULC changes appeared during the 28-year study timesteps. In this study, significant transitions from other classes into the water category were from vegetation and bare/arable land. During the 28 year time step, 0.03% of the vegetation transformed into water, while 0.2% of bare/arable land transformed into water similarly. Approximately, 24.9% of bare/arable-land had been converted to built-up while 4.8% of area mapped as bare/arable-land 1986 is now vegetation. Generally, persistence in all the classes stood at 4.3%.

Table 4.8: Main LULC conversions from 1986 to 2014.

From Class	To Class	1986-2014 Area (ha)	1986-2014 Area (%)
Vegetation	Water	12.20	0.03
Bare/Arable-land	Water	65.80	0.20
	Built-Up	11937.00	31.20
	Vegetation	1978.00	5.20
Persistence	(All classes)	18137.10	47.40

approximately 48% which is indicative of unprecedented urban growth and conformed to the quantitative measures in Table 4.7.

The evolution of the built-up land category in Abuja city can also be seen in the LULC maps presented in Figure 4.2. From the time stamps it was apparent built-up land increased by more than 50% from 1986 to 2001 and between 2001 and 2014 the expansion was

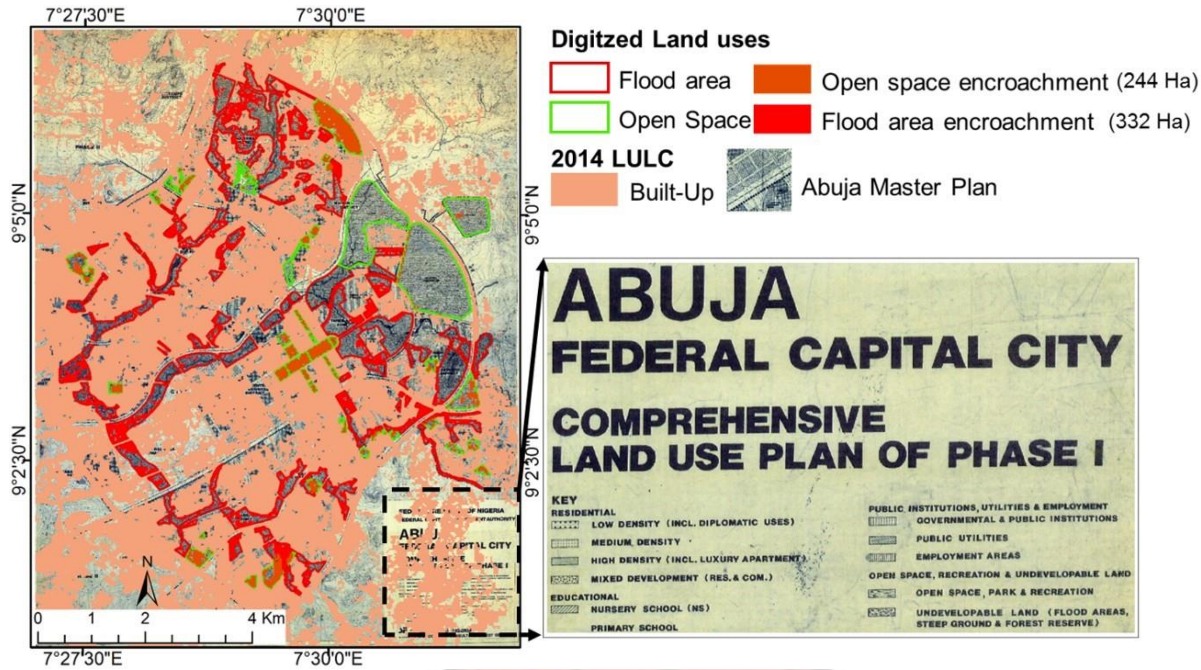

Figure 4.3: Overlay of digitized open space and undevelopable area from the Abuja Master Plan (AMP) on extracted 2014 built-up layer and AMP, (b) zoom-out of the overlay of digitized open space and undevelopable area from the AMP of Abuja for better visualization and (c) zoom of the AMP legend.

For further spatio-temporal analysis, the overlay analysis of the extracted 2014 built-up time stamp on the AMP map facilitated the evaluation of how settlement development did not conform to the plan. The AMP is a comprehensive document prepared to guide development in Abuja city to avoid chaotic urban development. From the overlay, lateral settlement development situation was observed in Figure 4.3 and the uncontrolled lateral settlement expansion in Abuja is suggesting possible environmental challenges such as floods due to floodplain encroachment as highlighted with black boxes (Figure 4.3).

The computed annual land use change rate (ALUCR) analysis further established the LULC transformation rate in Abuja between 1986 and 2014 (Table 4.9). Built-up land being the core interest for Abuja city dramatically increased by 8.51% rate between 1986 and 2001 and 6.31% rate from 2001 to 2014 (Table 4.9). Hence, for integrated spatial and socioeconomic analyses, the ALUCR can be compared with population growth rate and other relevant indices for data driven decision making.

Table 4.9: Annual Land Use Change Rate (ALUCR) and use change in Abuja from 1986 to 2014.

Year	Water Area (ha)	LUCR %	Built-Up Area (ha)	LUCR %	Vegetation Area (ha)	LUCR %	Bare/Arable-land Area (ha)	LUCR %	ComplexLandscape Area (ha)	LUCR %
1986.00	13513.30	-	316180.70	-	77775.90	-	2028040.60	-	329429.60	-
2001.00	18017.70	2.22	719778.90	8.51	829479.70	0.44	1409643.60	−2.03	488020.10	3.21
2014.00	22175.60	1.78	1310053.10	6.31	719150.40	−4.73	1596387.00	1.02	217174.00	−4.27

The rapid growth in Abuja can be tied to population growth, construction of transportation infrastructure, business development and the government's development policies, such as massive estate housing development projects.

The assessment of driving forces such as transportation infrastructure and suitable topography are presented in Figure 4.4 and 4.5 but later discussed in the subsection 4.2.

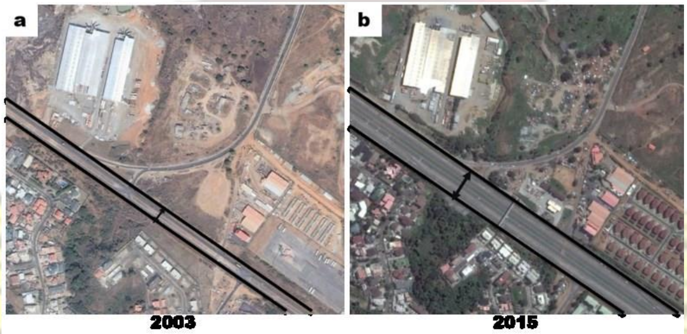

Figure 4.4: Example of the road expansion between 2003 and 2015 in the outer Northern Express Way of Abuja (image source Google Earth).

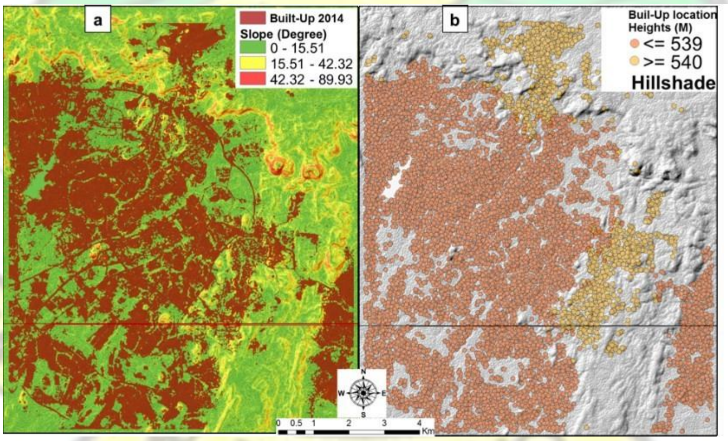

Figure 4.5: Assessment of the influence of topography on urban expansion. (a) Shows the GIS overlay of built-up on DEM derived slope. While (b) presents a constraint analysis showing built-up dependency on suitable heights as overlaid onto hillshade.

4.3.4 Land Use Change Model Implementation and Validation

Based on the LULCC maps, the most significant transitions occurred from all four categories: water, vegetation, bare/arable-land and complex-landscape to built-up, hence all were used as the major transition in the model. The transitions had varying urban spatial trend indicating a divergent predictor variable will affect them. Table 4.10 presents the Cramer's V of relevant and considered factors, it is a representation of the potential explanatory power of major LULC category as driving force in the settlement expansion process. The Cramer's V of 0.15 and above for any variable is useful, while values ≥0.4 is good (Eastman, 2014). The proceeding step was to run the sub-model of relevant transitions and produce transition maps. Based on the transition model modelling step, a simulation of 2014 built-up situation was modelled which yielded a somewhat satisfactory 2014 built-up prediction. Figure 4.6 (A and B) is a comparison of the predicted 2014 built-up and the real 2014 urban foot print. Overall the prediction consist of both under and over prediction.

Table 4.10: Cramer's V driving force threshold for potential LULCC to built-up.

Driving Force	**Cramer's V**
Distance to Built-up in 1986	0.51
Bare/Arable Land	0.73
Vegetation	0.21

Figure 4.6 (C) is a map illustration of the ocular validation of the projected urban LULCC of 2014 showing the precision achieved by the LCM model. The map consists of hits, misses, false alarms and null success, 1.08% hits was achieved, 6.04%, misses was recorded, false alarms marked 5.89 and null successes was 86.99%.

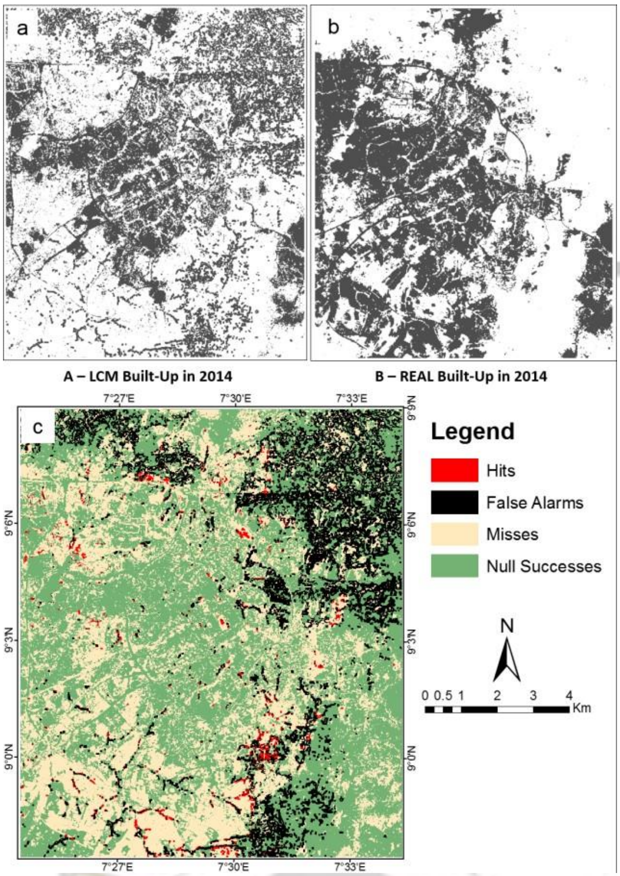

Figure 4.6: (a) LCM built-up, (b) Real built-up and, (c) Ocular Map validation of correctness using 2001 and 2014 as reference and projected LULC map of 2014.

Figure 4.7 presents the LULC projection into the year 2050 that was performed, similar to the model testing implemented between the 2001 and 2014 time stamps, the actual 2014 LULC map and overlay of built-up area expansion footprint from 1986 to 2050.

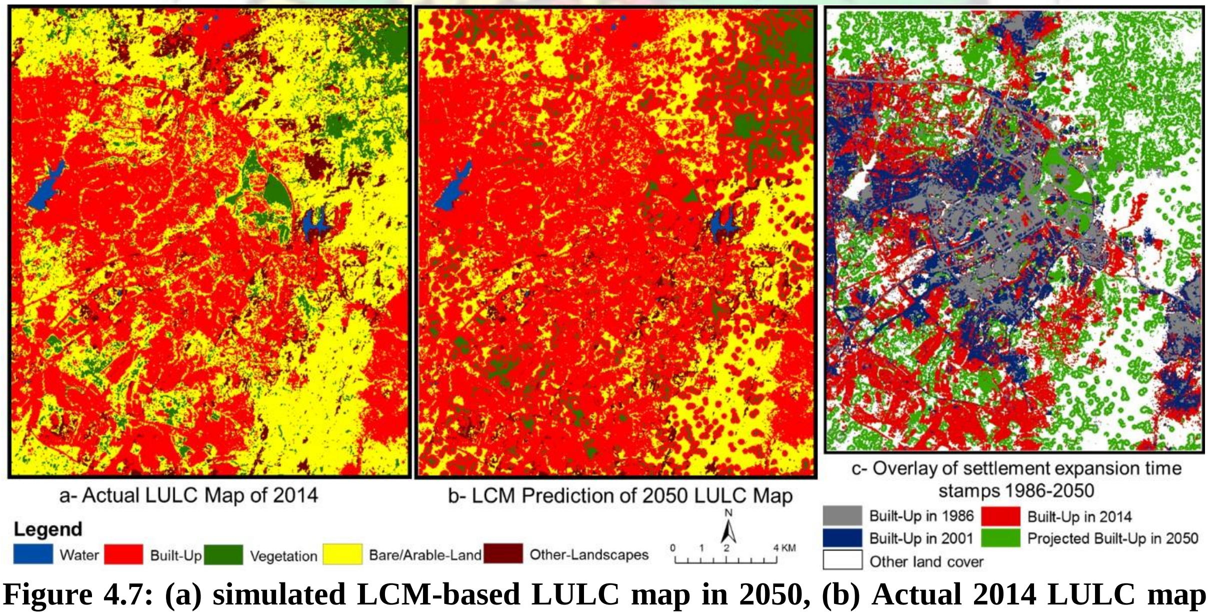

Figure 4.7: (a) simulated LCM-based LULC map in 2050, (b) Actual 2014 LULC map and (c) overlaid time stamps of built-up from 1986 to 2050 projection scenario.

4.4 Discussions

4.4.1 Relevance of Data Adequacy for LULCC Mapping and Spatio-Temporal Analysis

Depending on the overall goal and context, target parameters could either be mapped or monitored such as LULCC, which is mostly dynamic and is best studied within a continuity framework. Given that LULCC can be linked to urbanization and global warming trends, adequate image time series are needed to identify changes and track trends from an historical perspective which is the basis for modelling the future. However, in tropical regions such as West Africa, especially Nigeria, cloud cover hampers the opportunity presented by the Landsat image archives to select the desired image time series from a particular Landsat sensor and thus leads to image scarcity. This challenge hindered the dense LULCC analysis such as the settlement expansion and urbanization phenomena this study investigated. However, mapping and monitoring urbanization for analyzing imminent problems with limited data is still valuable for apt policy and decision-making rather than missing studies which denies city managers the comparison of empirical findings of urban development processes with other socio-economic indicators. Hence, due to the scarce availability of sufficient cloud free Landsat image for the same season over the study area, the authors adopted the Multi-Sensor and Multi-Temporal (MSMT) concept demonstrated in this study. But this approach is associated with challenges that require thorough image pre-processing steps that must be fulfilled (see method section 4.2.4) since the direct application of Digital Number (DN's) will not suffice anymore in a MSMT context (Chander *et al.*, 2009; Vicente-Serrano *et al.*, 2008). Therefore, conversion of DN to at-surface reflectance was performed to create high quality scientific data to produce reliable downstream products such as the LULC maps. This procedure yields data that is illumination and atmospheric artefact independent and therefore plausible for comparison such as the change analysis performed in this study.

From the LULC change analysis of Abuja, water increased by 0.1% between 1986 and 2001 and by 2014 another 0.1% increase was recorded. Generally, it is apparent that water surfaces have doubled and expanded by 2% between 1986 and 2014 (Table 4.7). Substantial increase in the built-up class occurred between 1986 and 2001 by 403,598.3 ha (20.8%), which is an average of more than 26,906 ha/year for the timeframe. Built-up significantly expanded in size by 590,274.1 ha (37.8%) from 2001 to 2014, which is more than 42,162.4 ha/year, with a net growth of approximately 993,872.4 ha in urban area in the study period (Table 4.7). A vegetation increase of 51,703.8 ha could be measured in 1986-2001 which is also apparent in Figure 4.2. But between 2001 and 2014 vegetation declined drastically by 510,329.3 ha which can be linked to rapid deforestation, urban growth and a lack of policy on parks and gardens. The increase in vegetation in 1986-2001 can be attributed to annual variation (in 2001 comparatively high precipitation values were recorded) and increasing precipitation trends after the 1980 drought period. In addition to variability of natural condition, policy on protected areas received more enforcement such as the millennium park establishment and developments of parks and gardens in the city center of Abuja.

Visually, of the total change in built-up area, most of the areas were previously bare/arable land which formed the newly urbanized areas in the study period. Apparently, the dominant land use types in 1986 were natural vegetation cover and bare/arable land for cultivation, and urban area (referred to as built-up category herein) was in the city center (Figure 4.2). The increment in the built-up category reveals that rapid urban development was as a result of the demand for residential, public offices, academic and business/commercial purposes. This conforms to the substantial growth witnessed in Abuja between 1986 and 2001 as highlighted in Table 4.7. From the classification results, urban expansion started to evolve in all directions (Figure 4.2). Noticeably, between 1986 and 2001 the observed decline in bare/arable land category by 17.8% is a significant change which can be attributed to dryness of the drought period in the 1980's. The vegetation and complex landscape occupied 23.9% and 14.1% respectively over the study area in 2001, but declined to 9.2% and 6.3% by 2014 respectively due to both human and natural processes occurring on them as well as misclassification errors. For instance, the complex landscape is a complicated category because in this class several activities are taking place on them such as farming as well as quarrying in some locations. Similarly, landscapes such as Murky water, dark soil and wetland have identical spectral signatures and remain a source of misclassification in this study. Remarkably, the built-up category grew to 17% in the 2001 to 2014 study period. An explanation of the slight increase of (5.4%) observed in bare/arable land can be linked to farmland expansion while the decline in vegetation was at the expense of intensified urban expansion in Abuja city.

4.4.2 Settlement expansion, floodplain encroachment and driving force analysis

With climate change impacts such as increased rainfall and decreased flood return period, encroached areas make buildings and people in such locations susceptible to flood impacts. Uncontrolled lateral expansion in Abuja also poses a direct and indirect threat to essential ecosystems from a future settlement development perspective. According to Seto *et al* (2012) in the coming decade, rapid land conversion rates are likely to occur that might be in biodiversity hotspots that in year 2000 were undisturbed and relatively urban. In the case of Abuja, urban growth was expected as there was provision for expansion in the master plan. However, according to FCDA (FCDA, 2001), the actual land budgeted for specific purposes had been exceeded, and proximity to existing buildings or infrastructure is a factor that increases pressure on the available land irrespective of the land use specified for such parcels. Hence, for integrated spatial and socioeconomic analysis, the ALUCR can be compared with the population growth rate and other relevant indices for data driven decision making. The rapid growth in Abuja can be tied to population growth, construction of transportation infrastructure, business development and the government's development policies, such as massive estate housing development projects. Similarly, other possible social problems in Abuja due to rapid urban growth are the accelerated loss of highly productive farmlands, alteration of energy budgets with joint modifications of climatic, hydrologic, and biogeochemical cycles, habitat fragmentation or reduction in biodiversity (Seto *et al.*, 2011). Looking at the negative ALUCR of -4.73 between 2001 and 2014 for vegetation and positive ALUCR of 1.02 between 2001 and 2014 this situation can be linked to micro-climate modification such as urban heat island development in Abuja.

The observed LULC changes and settlement expansion in Abuja is driven by intertwined socioeconomic and environmental factors. Socioeconomically, some of the growth pace in Abuja can be associated with the period of economic oil boom and relocation of government department headquarters to the center. During this period a dramatic settlement expansion pattern was noticed which can be linked with the upward changing pattern of both the economy and the population. This was a period of drastic provision of transportation infrastructure in both the city and satellite towns (Figure 4.4). Two notable patterns of the expansion exhibited are outward growth of the city based on the master plan and sprawl development towards the satellite towns with a pattern discerned along the outer Northern and Southern expressways of the city.

Geographically, the spatial overlay of extracted built-up land for 2014 on the slope map generated from a 20m DEM proved that the built-up development pattern of Abuja city is supported by the suitable topography and slope of the converted landscape (Figure 4.5a). Results obtained from the overlaid 2014 LULC built-up footprint on DEM-derived hill-shade as backdrop of Abuja city is presented in Figure 4.5b. The constrained analysis performed on built-up samples generated shows that urban expansion significantly occurred in topographically flat and suitable landscape of ≤ 539 meters height (Figure 4.5b).

4.4.3 Land Use Change Model Implementation and Validation

The visual comparison presented in Figure 4.6 showed that the simulated 2014 built-up footprint performed satisfactorily, however over prediction is apparent in the upper right corner of Figure 4.6(a) when compared to the actual in Figure 4.6(b) which could be due to inadequacy of driving force restriction and model uncertainty. A 37.1% built-up extent in 2014 was achieved by the model prediction for the 2014 urban landscape, while the actual built-up extent in 2014 was 40.4%. A difference of 3.3% was observed and this can be a source of the observed error in the model. In this study, a FOM of 12.6% was achieved which can be regarded as a low performance, however it is still comparable with some recent studies such as Olmedo *et al.* (2013) and Megahed *et al.* (2015) where FOM was 10.4% and 12.76% respectively. This also suggests that in modelling large areas such as Abuja, consideration for more complex predictive variables as driving forces will be needed to achieve better results. While visual assessment remains the swiftest approach to analyze spatial patterns, which is usually a weakness associated with the statistical technique, ocular examination still remains subjective and somewhat misleading, hence the statistical technique is still vital in model validation (Pontius & Chen, 2006). The Kappa variation was used to compare the projected 2014 LULC map to the real LULC map of 2014 and realized a K_{no} of 85% and $K_{location}$ of 95%. These high accuracy measures suggest that changes in the categorical maps are systematic for the 28 years (1986 to 2014) epoch assessed. It is also critical to carry out visual assessment all through the FOM analysis because it helps the analyst identify localized areas of change rather than regions of no change (Megahed *et al.*, 2015).

Figure 4.7(a) is the actual LULC situation in Abuja. In comparison to Figure 4.7(b) in the middle which is the 2050 LCM prediction, built-up will significantly grow and take over adjacent land categories in the absence of policies on strict adherence to the master plan or sustainable spatial planning. This is indicative of continuous removal of natural cover and ecosystem destruction. Modification of natural cover such as vegetation will certainly reconfigure energy balance (temperature development) such as the formation of an UHI due to impervious surfaces which has been established and well documented based on building configuration including shape, size, and geometry (Wentz *et al.*, 2014). Therefore, the model result provides an insight on the need for a carbon mitigation strategy and green urban design in Abuja due to potential disappearance of the vegetation cover. The settlement footprint of Abuja can be used to validate GUF datasets such as the GRUMP and dasymetric Landscan population map. Also Figure 4.7(c) illustrates the spatial pattern of built-up land in Abuja suggesting numerous environmental challenges (e.g. UHI potential, distortion of urban hydrology). Complementary to the UHI, urbanization can also influence precipitation patterns. In literature, two factors noted are: (i) the influence of urbanization in altering convective forces driving precipitation and, (ii) the variability of aerosol abundance in urbanized spaces (Rosenfeld & Lensky, 1998). Also an output from dedicated urban climate studies noticed the occurrence of locational shift and regional increase in convective precipitation linked to urbanization which thus results in an increase in surface temperature (Ashley *et al.*, 2012). Thus, with the dozens of studies pointing to the impact of urbanization on precipitation, Abuja is most likely not going to be an exception even though research output might differ if explored.

4.4.4 Framework for future research

The absence of previous research for a city such as Abuja hampers opportunities for comparison of findings this study revealed regarding data selection, methodology used and results obtained. This study is just the tips of the iceberg, however, the research provide a sufficient basis for further studies and therefore, can be classified as foundation research that urgently needs to be followed-up with more integrated approaches that will address other aspects this study did not consider. For instance, in concordance to numerous projections, rapid settlement expansion is unavoidable and considering the total world urban population currently at approximately 7.4 billion which by 2050 is anticipated to range from 8.3 to 10.9 billion especially in developing countries with nearly 70 to 80% urban dwellers. As a result of this reason, urban planners proposed two coping strategies to address the ever-increasing population pressure exerted on urban areas. The first is through population control while the second suggests efficient urban management agenda. The initial proposal has proven to be very challenging especially in developing regions like West Africa including Nigeria. Sustainable urban management is founded on two major planning procedures namely strategic and operational planning. In the case of urban planning, one of the principal datasets needed is land use. Fundamentally, land use data is useful for strategic and operational planning particularly for detecting and monitoring changes, trends analysis and for future prediction based on scenarios/consequences and review of master plans. Therefore, a relevant aspect to be further investigated related on the generated dataset includes the assessment of influence of settlement expansion of land surface temperature and UHI formation, flood risk zonation of the city and its integration with urban density information/urban structural types for risk and vulnerability assessment to impending phenomena such as climate change. It will also be worthwhile to compare the SVM based approached used in this study with other similar methods that have integrated GIS approach with artificial neural network and fuzzy logic by incorporating more driving force constraints based on additional data (Grekousis *et al.*, 2013; Riccioli *et al.*, 2016; Triantakonstantis & Stathakis, 2015) and other integrated urban RS and GIS approaches tested (Mahboob *et al.*, 2015).

4.5 Conclusions

The FCC of Nigeria, Abuja, was used as the test site for this study using integrated remote sensing datasets and GIS modelling approaches. It was established that significant LULC change and settlement expansion occurred in the recent past epochs. Due to the study timeframe and limited cloud free datasets available from a single Landsat sensor, the multi-sensor and multi-temporal images of Landsat (TM, ETM+ and OLI for 1986, 2001 and 2014 were used for this study. The utility of these datasets was realized because a rigorous image preprocessing rule of thumb was met to ensure that real change over time was recognized and results obtained are reliable and fit for further use (e.g. informed policy and decision-making). Also, the application of a robust information extraction algorithm such as SVM required limited trainings samples and yielded good image classification in the results obtained. In future the SVM and other advanced methods such as object oriented image analysis and random forest can either be integrated or compared to assess their performance in problematic or heterogeneous areas.

The core objective was to spatio-temporally analyze LULC for 1986, 2001 and 2014. Based on the pixel counts error matrix, overall accuracies of the three LULC maps ranged from 82% to 94%. Contrary to these statistics, the adjusted area error gave a somewhat different accuracy measure that ranged from 69% to 91%. The study found out that computing area information directly from pixel count for accuracy assessment can be misleading. Hence in producing local maps that can be useful for evaluating the correctness of global maps, climate modelling and other relevant applications, assessing error propagation in regional maps by applying the error adjusted area estimator yields a more reliable and informative result including confidence intervals and uncertainty measures. The different components of LULC change analysis allowed better understanding of the transformation processes especially from the bare/arable land and vegetation categories to the built-up class. The computed indices provided empirical insight into a realistic spatio-temporal situation and detailed annual land use and urban spatial expansion change rates in the study timeframe and major impacts on the landscape with potential influence on the local climate of Abuja. The forces governing such a momentous expansion might be numerous, however, apparent drivers in the case of Abuja included suitable topography, availability of public infrastructure such as social amenities and population growth particularly in the recent past two decades.

Two salient aspects ascertained by this research are that massive impervious surface development is going on due to urbanization, which may lead to elevated urban temperatures known as the UHI phenomenon which is one of the likely climate control factors at a local scale highlighted by the Fifth Assessment Report of the IPCC (2013), and COP 21 (2015). Complimentary to the UHI is the change in drainage geography that may also increase surface runoff which translates to flash flood events in cities. With rapid urban expansion in Abuja, when rainfall increases, surface runoff is expected to increase and can trigger flash flood events in area deficient of adequate drainage densities or sewer lines especially looking at the 2050 built-up projection in the context of climate change. From this study further research is needed to empirically verify present and future impacts of urbanization on Abuja city.

CHAPTER 5 : COUPLING THE EFFECTS OF SETTLEMENT EXPANSION ANALYSIS WITH URBAN TEMPERATURE DATA FOR ASSESSMENT OF LOCAL WARMING IN ABUJA

Abstract[*2]

The objective of this study is to couple settlement expansion analysis with Land Surface Temperature (LST) of urban thermal configuration as a climate forcing indicator with potential impacts on human health in Abuja city. The spatiotemporal pattern of LST and Urban Heat Island (UHI) formation and variations in Abuja were analyzed and discussed using remote sensing (RS) data. RS data of 1986, 2001 and 2014 were used to derive relevant biophysical indices such as the Land use Land cover (LULC) maps, LST, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built Index (NDBI) for improved understanding of interplay amongst each other. Result showed that urbanization have dramatically occurred in Abuja which have resulted in imperviousness and thus modified the thermal setting of the region through land atmosphere interactions thereby leading to the formation of UHI. The quality of the mono-window derived LST was assessed by plotting it against the air temperature data and it conformed to the maximum air temperature which is indicative of urban heating which exacerbate heat waves phenomenon in summer as well as amplifies water and energy consumption rates. The relationship between LST, NDVI and NDBI showed negative correlation between LST and NDVI which is indicative of how green cover can weaken UHI effects with decreasing R^2 that suggest the continuous decline in vegetal cover. However, the positive correlation observed between LST and NDBI meant UHI formation can be strengthened with increasing built-up in the study area. Therefore, within the context of climate change, urban greening effort is an efficient approach to dampen formation of large UHI. This study demonstrated an integrated research scheme for urban ecosystem modelling and can be used in the context of urban land use and climate studies.

Keywords: Landsat TM , ETM+ and OLI; land surface temperature; urban heat island

5.1 Introduction

The urbanization phenomenon is backed-up with substantial documentation proving it to be a major climate forcing factor on local weather and climate (Angel *et al.*, 2011; Bornstein *et al.*, 2012; Hu *et al.*, 2015; Seto & Christensen, 2013; Seto *et al.*, 2011). Urbanization is mostly triggered by population growth especially that the vast world populace currently reside in urban locations (Seto *et al.*, 2012; United Nations, 2012), and may be considered the most drastic

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Land Use/Land Cover (LULC) transformation from an ecosystem perspective (Fu & Jones, 2013; Güneralp *et al.*, 2013; Mondal & Southworth, 2010). The process of urban evolution imposes noticeable impacts on adjacent environments such as agricultural lands or abandoned lands (Jiang *et al.*, 2013; Pandey & Seto, 2015; Zhang *et al.*, 2004). Pertinent to rapid urbanization are a plethora of aspects that fall within the intensified land transformation topics relevant to modification in Land Surface Temperatures (LST) and urban climate studies, e.g. land cover change and temporal climate change (Cinar, 2015; Myint *et al.*, 2015; Sun *et al.*, 2010; Zheng *et al.*, 2014), hydrological cycles disruption, water contamination and air pollution (Carlson & Traci, 2000; Shao *et al.*, 2006; Sheppard, 2005; Weng, 2001) and human health such as morbidity and mortality (Baker *et al.*, 2004; Fischer *et al.*, 2012; Gong *et al.*, 2012; Harlan *et al.*, 2013; O'Loughlin *et al.*, 2012; Patz *et al.*, 2005).

Numerous studies have highlighted urban expansion and its negative impact on urban eco-environment (Aban *et al.*, 2011; Carlson & Traci, 2000; Cui & Shi, 2012; Di Ruocco *et al.*, 2015; Srivanit *et al.*, 2012) especially in the developed world. However, such studies are lacking and still nascent in developing regions of the world such as West Africa (WA) though urgently needed as the region is currently experiencing rapid urbanization. One prominent negative impact of urbanization is the formation of Urban Heat Islands (UHI) (Nie & Xu, 2014; Rinner & Hussain, 2011; Streutker, 2002a). Kalnay and Cai (2003) documented that UHI effect can also be seen as one of the consequences of human driven LULC conversion, and a direct representation of environmental degradation (Lu *et al.*, 2009). The formation of UHI was first described by Luke Howard in 1818 (Howard, 1833). Since then it has received increasing attention (Camilloni & Barros, 1997; Parnell & Walawege, 2011; Peng *et al.*, 2011). According to Zhang *et al* (2009), the UHI phenomenon can be categorized into three namely; canopy, boundary and surface heat island levels. Based on the availability of the remote sensing-based spatially continuous temperature data, this study focused on the surface UHI which denotes relative amplification of Urban LST (ULST) in contrast to surrounding natural areas (Yuan & Bauer, 2007). Complimentary to the benefit spatiotemporal analysis of LULC offers, mapping and monitoring relevant variables that portray information on critical environmental conditions can be gained. Thus, investigating ULST using RS, is a plausible idea for improved understanding of vulnerable places due to LULC change (LULCC) (Lo & Quattrochi, 2003), which is currently intense in WA. Output from this kind of study will contribute to the knowledge about the mutual relationship between temperature and vegetation at local scale. Also, insight about the most optimal spatial extent needed to ensure maximum mutual relationship between temperature-vegetation to be maintained can be gained using approaches such as RS (Myint *et al.*, 2010), and climate modelling (Kormann & Meixner, 2001). From previous studies it is known that numerous LULCC indices, such as NDVI, NDBI, NDBal and NDWI, are correlated to LST and as these indices change the LST of such location is significantly affected (Rinner & Hussain, 2011; Xiong *et al.*, 2012).

There exist a relationship between air temperature (T_{air}) and LST, but the interplay is not obvious and well understood. However, investigating the comparing T_{air} and LST can be relevant for assessing the reliability of remotely-sensed LST measurement. This can improve the understanding of the inherent variability of urban thermal environment in data poor environments like WA. Zhou *et al.* (2011), documented that higher and spatially scattered variations can be observed within air temperature during night time, while the ULST is prominent during the daytime. Furthermore, Kawashima *et al*. (2000) described that a range of variation exist in LST which is always larger than the range of variation in the air temperatures, the LST alone can explain approximately 80% of the observed variation in air temperature. Similarly, Gallo *et al.* (2011) evaluated the relationship between T_{air} and LST under clear- and cloudy-sky conditions and found that generally, LST was higher than T_{air} for both the clear and cloudy conditions.

Contrary to the advantage of checking the reliability of LST with T_{air}, urbanization can affect in-situ meteorological data by introducing uncertainty in T_{air} around urban areas (Yan *et al.*, 2010). More so, in regions like WA, there is a significant dearth of ground-based meteorological stations which further creates a huge lacuna of in-situ data availability that is suited for temperature development and local warming studies (He *et al.*, 2013). Furthermore, the modification of signal around the available ground-based meteorological stations can influence these in-situ data with more uncertainties considering that the in-situ records lack homogeneity (Yan *et al.*, 2010). Therefore, remotely sensed LST is a vital data source and index commentary to scarcely available long-term T_{air} and can form a basis for area-wide assessment of regional and local climate change (Jin & Dickinson, 2010). Thus, a systematic coupling of T_{air} and LST can serve as a strong impetus for improved understanding of local temperature developments studies for regions such as WA.

Lately, numerous UHI studies and application have been carried out (Balogun *et al.*, 2012; Connors *et al.*, 2013; Gallo *et al.*, 1993; Gallo & Owen, 1999; Liu *et al.*, 2014; Weng *et al.*, 2004; Yang *et al.*, 2011). But to date, most UHI studies have focused on assessing the intensity of UHI and using simple linear regression (lm) models to understand the relationships between LST and LULC indices in an episodic mode with little or no consideration for its extent (i.e. UHI footprint) (Bowler *et al.*, 2010; Dontree, 2010; Tan & Li, 2015). However, most RS data are non-normal and the relationship are also not non-linear which makes the simple lm approach not robust in explaining the relationship between spatial variables such as LST, vegetation and built-up indices. Yet, this kind of studies are also lacking in WA which has now become necessary especially with imminent climate impacts. Therefore, the lack of systematic appraisal of settlement development in the region, makes it urgent to advance on the impetus for regional and local urban climate science in WA by generating a relevant spatially explicit dataset of urban areas. This dataset were used to assess the changes in LULC and settlement expansion. Objectively, this research will systematically link urban land use to changes in LST which is needed for forcing sustainable urban environment planning towards improved understanding of UHI in fast growing African cities.

In this study, settlement expansion was examined in Abuja the Federal Capital City (FCC) of Nigeria. Abuja was ideal for this study at a regional/local level because the phenomenal urbanization is ongoing which will modify the land surface properties (Ibrahim Mahmoud *et al.*, 2016). The increasing rate of settlement expansion is very likely to amplify UHI and influence local climate change (Li *et al.*, 2012; Parker, 2010; Qin & Jianhua, 2015; Wu & Yang, 2013; Xie *et al.*, 2013). More so, to the knowledge of the authors, no previous studies have generated spatially explicit LULC maps for monitoring of the urban footprint of the FCC with the goal of implementing an integrated spatiotemporal analysis of LULC with LST, vegetation abundance as well as built-up indices in the study area. In addition no study have statistically assessed the relationship between biophysical landscape parameters of the study area. In this study, a novel statistical approach is demonstrated to analyze spatially explicit data with both linear regression model (lm; R package 'lm'; (Chambers, 1992; Wilkinson & Rogers, 1973)) in an episodic time step and the Generalized Linear Mixed-Effect Model (GLMM; R package 'lme'; (Pinheiro *et al.*, 2014)) for incorporating data multilevel hierarchy, random and cumulative mixed effects, based on lme function using *'lme4'* package (Bolker *et al.*, 2009). Hence, a comparative approach such as this current study is needed to consolidate on aspects of previous methods, and conceptualize better spatial data exploratory approach. Therefore, this research is conducted in no better time than now because it contributes to research on RS of urban thermal environment over Abuja from 1986 to 2014. The specific objectives of this study are: (1) to generate core air temperature core climate indices from 1982 to 2014; (2) to generate reliable LULC maps and extract vegetation and built-up indices of Abuja from Landsat data for integrated and mutual urban landscape analysis;

(3) to retrieve continuous LST and analyze spatio-temporal variations and patterns of UHI from RS data of Abuja to track the altering effect of urban land use change in urban landscapes; and (4) to explore zonal statistics, univariate and multivariate statistics and both linear spatial regression and spatial autoregression statistical approaches to assess the interplay between LST and other biophysical parameter derived from 30 m resolution Landsat series datasets.

5.2 Materials and Methods

5.2.1 Data

The test site used for this current study is phase I to IV of FCC (see section 3.1) for description of study area. Temperature data can be derived from multiple sources which includes in-situ meteorological climatic stations and the satellite-based sensing approach. Both data sources were considered in this study. The type of study to be conducted underlines the necessity to consider multiple climatic data sources if it borders on different thematic dimensions when assessing urban temperature in the context of climate change. Climate data used for this study were monthly and yearly values of minimum and maximum temperatures sorted by decades for the whole time series. These data were acquired from the Nigeria Meteorological Agency (NIMET) Abuja airport climate station and covers the time period 1982 to 2010. Similarly, satellite images are the important source of data to obtain information about the Earth's surface without direct contact. Detailed characteristics of the data and sources for the study are presented in Table 4.2.

5.2.2 Core Climate Indices

In climate science, monthly averages of daily climate parameter such as temperature, precipitation and others smooth over a lot of important information such as that which characterizes the behaviour of extremes that are usually responsible for impacts (Zhang *et al.*, 2011). Major differences in indices of extreme can be categorized into two: the first looks at how the distribution was defined, and the second considers how far into the tails of the distribution the index threshold is located (Folland *et al.*, 1995; Peterson *et al.*, 2008). According to Zhang (2011), indices that characterize aspects of the far tails of the distribution tend to be more relevant to society and natural systems than indices that characterize aspects of the distribution that occur more frequently. This is because the more extreme an event, the more likely it is to cause societal or environmental damage. Based on datasets collected from the meteorological station for climate variability and change assessment, this study generated six core climate indices of temperature patterns of Abuja (Table 5.1) in relation to climate variability and change assessment. The computed indices were based on those defined by Frich *et al.* (2002) presently known as the Expert Team on Climate Change Detection, Monitoring Indices 'ETCCDI' which were established by the European Climate Assessment (ECA) indices (Klein Tank *et al.*, 2002) and proposed by Trewin (2009).

Table 5.1: Selected extreme temperature Indices of Abuja recommended by the ETCCDI

ID	Indicators Name	Indicators Definition	Unit
TXx	Max T_{max}	Monthly maximum value of daily max temperature	°C
TNx	Max T_{min}	Monthly maximum value of daily min temperature	°C
TXn	Min T_{max}	Monthly minimum value of daily max temperature	°C
TNn	Min T_{min}	Monthly minimum value of daily min temperature	°C
TX90p	Warm Days	Percentage of time when daily max temperature > 90^{th} Percentile	%
TN90p	Warm Nights	Percentage of time when daily min temperature > 90^{th} Percentile	%

5.2.3 LULC Mapping and Calculation of Relevant Remote Sensing Indices

The downloaded cloud-free Landsat image series were used to produce LULC maps of 1986, 2001 and 2014 based on the Support Vector Machine (SVM) algorithm (Mountrakis *et al.*, 2011). Five LULC categories in the classification scheme for this study to generate the desired LULC information for the three epochs (see Table 3.2). Necessary image preprocessing steps such as radiometric and atmospheric corrections were applied on the images. Subsequently, suitable spectral reference information were used in the classification stage.

The produced LULC maps were subjected to the Error Adjusted Area Estimator (EAAE) proposed by Olofsson *et al.* (2014) for accuracy assessment. The EAAE accuracy evaluation methodology consists of three major steps, sample design, response design and accuracy assessment analysis. The sample design step involved the generation of stratified random points from reference point acquired from survey and mapping department of the Federal Capital Development Authority (FCDA), Orthophoto image of 1986, for the 1986 satellite image. For the 2001 and 2014 images, GoogleEarth was used in selecting samples for the LULC map evaluation. In the case of the 2014 image field information was also gathered for the accuracy assessment. The response design was achieved using the overlay analyses which was used to compare the reference point with the LULC categories for the three maps and to construct error matrices. In 1986, 576 sample point were used while 878 points were considered for the 2001 image and 577 points were extracted from the field campaign in 2014. For areas where accessibility was a challenge, the high resolution image of 2013 and GoogleEarth were utilized for validation. The EAAE of each category according to the map, and descriptive accuracy measures such as user's, producer's and overall accuracy based on the EAAE were calculated.

The Normalized Difference Vegetation Index (NDVI) is one of the widely applied vegetation indices to strengthen the vegetation information (Lu *et al.*, 2009). The NIR refers to the Near Infrared bands of the satellite image and R is the Red band of the image. The NDVI is calculated as follows Equation (5.1):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{5.1}$$

Comparably, the Normalized Difference Build-up Index (NDBI) is an approach used to strengthen the robust extraction of build-up land cover from urban areas as well as built-up information. Given that the NDBI is a good indicator of built-up feature in urban areas due to its high reflectivity in the mid-infrared (MIR) band than the NIR band, it was calculated by using Equation (5.2) as follows:

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \tag{5.2}$$

5.2.4 Retrieval of Land Surface Temperature for Urban Heat Island Detection

The thermal bands belonging to the satellite images of the 1986, 2001 and 2014 epochs were used for retrieving LST over Abuja city. Accordingly, radiometric correction were performed on these thermal bands to ensure the LST information derived is reliable. The conversion from the thermal DN's into spectral radiance was achieved by applying the Equation (5.3) based on Chander *et al.* (2009).

$$L_\lambda = \frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN}(DN - QCALMIN) + LMIN_\lambda \tag{5.3}$$

where $\boldsymbol{L_\lambda}$ is the at-sensor spectral radiance, $\boldsymbol{LMAX_\lambda}$ is the maximum at-sensor spectral radiance; $\boldsymbol{LMIN_\lambda}$ is the minimum at-sensor spectral radiance; $\boldsymbol{QCALMAX}$ and $\boldsymbol{QCALMIN}$ represents the maximum and minimum numerical value of the image, and can be retrieved from the header file. The spectral radiance can be converted into a more useful physical variable such as the brightness temperature corresponding to the apparent temperature of a surface measured at the sensor in Equation (5.4). The formula for conversion is as follows: (Weng & Lu, 2008)

$$T_{sat} = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda}+1\right)} \tag{5.4}$$

with T_{sat} the brightness temperature, L_λ. is the at-sensor spectral radiance, K_1 and K_2 are the constants of calibration given by the manufacturer of the sensor. For TM sensors K_1 and K_2 are respectively equal to 607.76 watts/ (meter squared * ster * m) and 1260.56 Kelvin. In Landsat

ETM+ K_1 and K_2 are respectively equal to 666.09 watts and 1282.71 Kelvin. While K_1 and K_2 in OLI band 10 and 11 respectively are equal to 774.89; 480.89 watts and 1321.08; 1201.14 Kelvin.

Similar to prior works on intensity of UHI (Tan & Li, 2015; Zhou *et al.*, 2013), this current study assessed the spatial variation of LST by applying comparable approach. The mono-window algorithm for retrieving LST from Landsat data was adopted. However, implementing this procedure requires knowledge of the emissivity (**ε**) based on the nature of LULC. The emissivity can be calculated from NDVI (Van de Griend & Owe, 2003; Zhang *et al.*, 2006). When NDVI values ranges from 0.157 to 0.727 Equation (5.5) as follows can be applied:

$$\varepsilon = 1.0094 + 0.047 Ln\ (NDVI) \qquad (5.5)$$

Similarly, Zhang (2006) proposed a complete land surface emissivity estimation method using NDVI (Table 5.2). In this study the complete approach proposed by Zhang was adopted. **Table 5.2: NDVI-based emissivity estimation**

NDVI	Land Surface Emissivity (ε)
NDVI < −0.185	**0.995**
−0.185 ≤ NDVI < 0.157	**0.970**
0.157 ≤ NDVI ≤ 0.727	**1.0094 + 0.047ln(NDVI)**
NDVI > 0.727	**0.990**

Therefore, emissivity corrected LST based on object reflectance was computed as follows: Equation (5.6)

$$T_s = \frac{T(k)}{1 + (\lambda * \rho\ )\ ln\varepsilon} \underline{T}(\underline{k}) - 272.15 \qquad (5.6)$$

let $T(k)$ be the computed brightness temperature, the raw wavelength of emitted radiance be λ, ρ = h*c/σ (1.4038*10^{-2} mk), σ is the Stefan Bolzmann's constant, the Plank's constant is h, the light velocity is c and -272.15 stands for conversion of Kelvin to Centigrade.

5.2.5 Statistical analysis

The fluxes inherent in LST have created a strong impetus for a multidimensional application of exploratory spatial statistical approaches for improved understanding of LST and the predators that causes the inconsistencies. Hence, this study applied several exploratory statistical tools to evaluate the different aspects of derived LST in conjunction with explanatory variables and are listed below:

1. Zonal Statistics As Table (ZSAT): The ZSAT was used to understand the spatiotemporal dynamics of LST across the various LULC in the study area. This was implemented in ArcGIS 10.2 based on the vectorized LULC which is categorical and LST is a continuous. With ZSAT a set of statistics were calculated such as the minimum, mean and maximum statistics of LST derived based on LULC and were subsequently used to compute a boxplot to visualize the thermodynamics in R (R Development Core Team, 2014). In the case of NDVI corresponding mean and standard deviation thresholds were computed to identify spatial patterns of vegetation abundance against LST per LULC over the 2014 time step.
2. The univariate regression statistical approach using the clustering analysis tool in Geoda spatial statistical package was employed to determine clustering and statistically significant LST locations based on the Getis-Ord Gi* statistic (see Equations 5.7-5.9), while the continuous index of measure of spatial heterogeneity in the 2014 derived LST was explored to determine the hot and cold spots using the local Moran's *I* which is a Local Indicator for Spatial Association (LISA) and was computed based on Equations (5.7 to 5.9) (Anselin, 1995).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \qquad (5.7)$$

Let x_j be the attribute value feature j. $w_{i,j}$ serves as the special weight between feature i and j. n equals the total number of feature and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \qquad (5.8)$$

$$S = \sqrt{\frac{\sum_{j=0}^{n} x_j^2}{n} - (\bar{X})^2} \qquad (5.9)$$

No further computation are needed and the z-score represent the G_i^* statistic in Equation (5.10)

$$I_i(d) = \frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})^2} \sum_j w_{ij}(d)(x_i - \bar{x}) \qquad (5.10)$$

3. Furthermore, the multivariate simple state linear regression (SSLR) which is a traditional additive linear regression model 'lm' written in Equation (5.11) was used to detect the influence of vegetation on LST thermodynamics. This approach evaluate two parameters at a time (lm: $y = a + b_x + E$), (5.11), where $a + b_x$ represent the linear predators and E is the error. The SSLR modelling approach was used to establish the relationship between LST, NDVI and NDBI. The LST is the dependent variable and the NDVI and NDBI serves as the predator/explanatory variables. The R statistical package was used to implement the SSLR modelling for the study duration (R Development Core Team, 2014).

4. Given that the SSLR has limitation in modelling non-stationary phenomena, the multivariate statistical approach based on the band collection statistics was implemented to explore how best to model LST in order to determine the correlation coefficient of LST, NDVI and NDBI at the same time. This approach was used compute the covariance and correlation matrices which depicts how much variance exist from the mean and the variances are read along the diagonal of the covariance. The below formula Equation (5.12) is used in computing the correlation coefficient:

$$Cov_{i.j} = \frac{\sum_{k=1}^{N}(Z_{ik} - \mu_i)(Z_{jk} - \mu_i)}{N - 1} \tag{5.12}$$

let Z is the value of the cell, i, j refers to the layers of the stack, μ stands for the mean of a layer, N is the number of cells and k denote a specific cell.

5. To better understand the cumulative relationships between LST, NDVI and NDBI, a novel approach was developed based on the generalized linear mixed-effects models (GLMM; R package using ‘lme’ function; (Pinheiro *et al.*, 2014) that incorporate the random factor in modelling the effects of predators on the LST (Bolker *et al.*, 2009). In the GLMM model constructed for this study, the statistical data exploration protocol concept proposed by Zuur *et al.* (2010) was considered. The protocol is useful and helps scientists and environmental managers avoid violation and type I or type II errors (i.e. the incorrect rejection of a truce null hypothesis which is false positive and the failure to reject a false null hypothesis which is a false negative) that potentially result in wrong environmental conclusions. However, a series of steps are involved in this approach. The first was to perform a random sampling and tabulation of data to organize the dataset for subsequent analysis including data normality check and detection of outliers. Followed by check for correlation amongst the predators (NDVI and NDBI), to assess if the

Variance Inflation Factor (VIF) exceeds the acceptable threshold which is 5. The heterogeneity of variance, was evaluated from the series of global models fitted using different weighting functions. The nested global models included the null model which has no weighting applied. The other models were applied with different weighting combinations of fixed variables such as the 'lme' with optimized control, the 'lme-Indent' which uses constant variances to allow different variances according to the level of the factor classification, 'lme-Fixed' which is based fixed weights determined by variance covariate, 'lmeexponential' that uses the exponential of the variance covariate and 'lme-power' that considers the power of variance covariate. For each of the fitted global models, the corrected Akiake Information Criterion (AIC_C) was computed. The best model is determined based on the lowest AIC_C ranked values which signifies better agreement for the modelling (Burnham & Anderson, 2004; Johnson & Omland, 2004), and the dredge function of the *'MuMIn'* package in R was used for the calculation (Barton, 2014). To generate residuals and temporal auto-correlation function plots, as well as over-dispersion aimed at determining goodness of fit, the diagnostics plot was explored using the CAR function in R (Burnham & Anderson, 2002; Zuur *et al.*, 2010). To determine the overall effects of the predators on LST using the best model compared to the null model, the Wald Z tests was applied: $y \sim 1 + (1 \mid lmeID)$, here y serves as the response, while the evaluation of significant differences were done with maximum likelihood ratio tests (X^2, P< 0.0001) and ANOVA. Though, it is uncommon to compute R^2 in GLMM, however, the R^2 was computed alongside the GLMM confidence interval to compare with the SSLR modelling approach.

5.3 Results

5.3.1 Core Climate Indices and Observed Changes in Air Temperature

In total six climate indices were computed. Figure 5.1 (a-f) presents the generated indices and they include the monthly maximum value of daily maximum temp (TXx), monthly minimum value of daily maximum temperature (TXn), monthly maximum value of daily minimum temperature (TNx), monthly minimum value of daily minimum temperature ((TNn), warm days (TX90p) with percentage of days when TX>90th percentile and warm nights (TN90p) with percentage of days when TN>90th percentile.

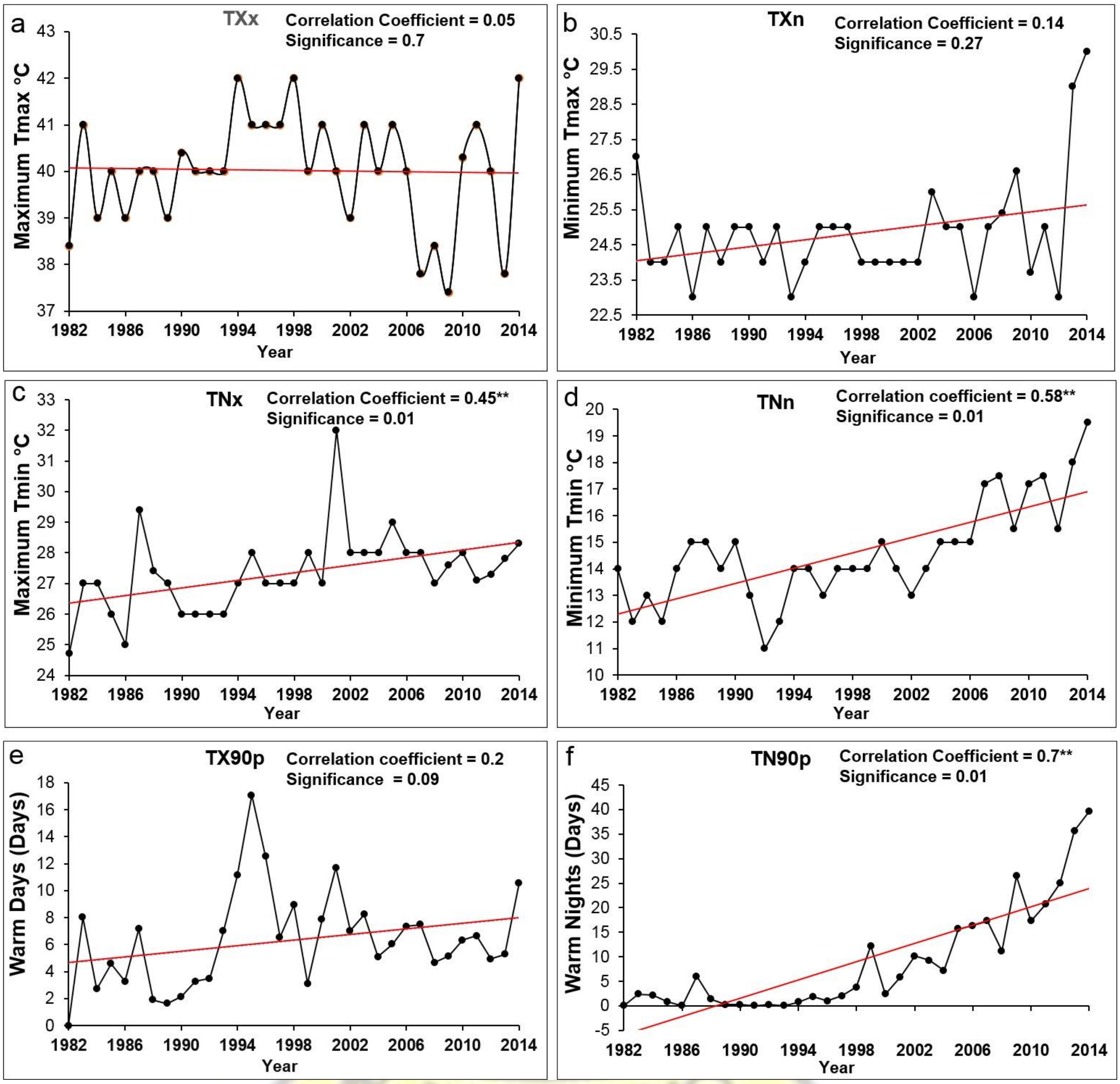

Figure 5.1: ETCCDMI core climate indices of Abuja based on climate station air temperature data. (a) Monthly maximum value of daily maximum temperature (b) Monthly maximum value of daily minimum temperature (c) Monthly minimum value of daily maximum temperature, (d) Monthly minimum value of daily minimum temperature, (e) Warm days (TX90p) with percentage of days when TX>90th percentile, and (f) Warm nights (TN90p) with percentage of days when TN>90th percentile.

5.3.2 Analysis of LULC Change and Accuracy Assessment

The change in LULC of the recent past three decades was studied using Landsat-TM, ETM+ and OLI 8 datasets of 1986, 2001 and 2014 respectively. The produced LULC maps provided evidence of LULC changes in Abuja's landscape as shown in Figure 5.2, and the most apparent change is the dramatic settlement expansion pattern. The LULC maps were used to generate area statistics during these past 28 years, which reveal substantial conversion in the various land-cover types. In accordance with the computed error adjusted area accuracy assessment (EAAA), the overall accuracies yielded 91.6%, 92.3% and 92.9% respectively (Table 5.3).

Table 5.4 presents the proportions of the LULC classes in the study area. The estimated area slightly differed from the mapped area in some of the LULC classes. This is expected because the EAAA excludes error of commission and incorporates omission error in determining the area of proportion and computation of the accuracy assessment. For all of the classes, the estimated area fell within 95% Confidence Interval (CI) which is also indicative of reliability of the maps produced (Olofsson *et al.*, 2013). For instance, the result showed that water almost doubled from 0.25% of the total map area to 0.31% from 1986 to 2014 with CI ranging from ±0.01 to ±0 with very low uncertainty (Table 5.4).

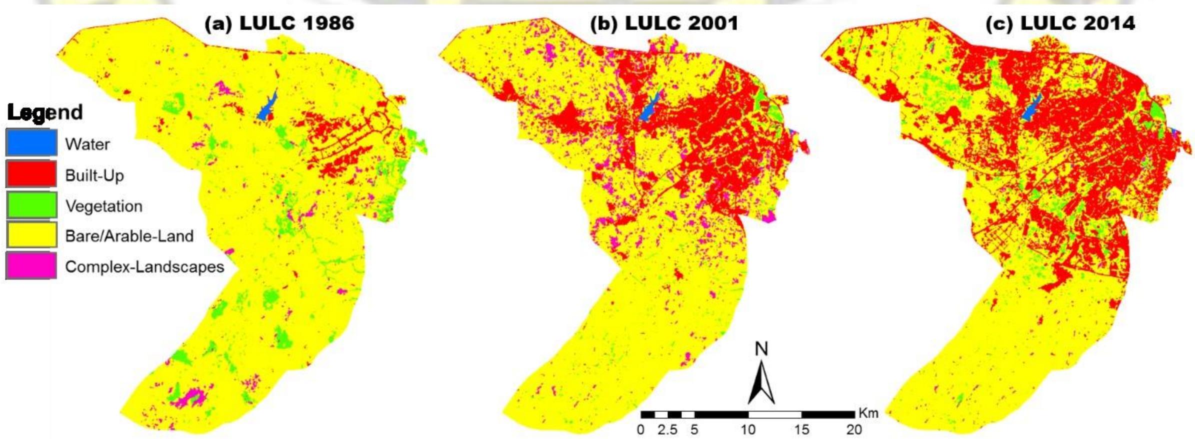

Figure 5.2: Generated LULC maps from Landsat TM, ETM+ and OLI 1986, 2001 and 2014 satellite images.

Table [3].3: Error adjusted matrix of LULC Maps of 1986, 2001 and 2014. WAT: Water; BUP: Built-Up; VEG: Vegetation; BAL: Bare/Arable Land; CL: Complex Landscapes.

Year	Class Name	WAT	BUP	VEG	BAL	CL	Total	User's(%)
	Water	0.250	0.000	0.000	0.000	0.000	0.250 3.820	100
	Built-Up	0.000	3.261	0.000	0.466	0.093	5.570	85
	Vegetation	0.000	0.000	5.060	0.136	0.340	88.120	91
1986	Bare/Arable-land	0.000	1.325	1.988	80.832	3.975		92
	Complex-Landscapes	0.000	0.000	0.000	0.097	2.153	2.250	96
	Total	0.250	4.586	7.028	81.531	6.561	100.00	
	Producer's (%)	100	71	72	99	33		91.6
	Water	0.280	0.000	0.000	0.000	0.000	0.280	100
	Built-Up	0.000	17.749	0.212	0.159	0.000	18.120	98
	Vegetation	0.000	0.034	1.565	0.011	0.000	1.610	97
2001	Bare/Arable-land	0.000	1.752	3.505	65.963	1.402	71.850	91
	Complex-Landscapes	0.000	0.000	0.238	0.356	7.546	8.140	93
	Total	0.280	19.535	5.520	65.717	8.948	100.00	
	Producer's (%)	100	92	94	88	84		92.3
	Water	0.310	0.000	0.000	0.000	0.000	0.000	100 99
	Built-Up	0.000	31.988	0.000	0.262	0.000	32.250	100
	Vegetation	0.000	0.000	4.470	0.000	0.000	4.470	89
2014	Bare/Arable-land	0.000	1.713	2.569	54.800	2.569	61.650	
	Complex-Landscapes	0.000	0.000	0.000	0.000	1.330	1.330	100
	Total	0.310	33.700	7.039	55.062	3.899	100.00	
	Producer's (%)	100	91	28	99	34		92.9

[3] .3.3 Analysis of Land Surface Temperature (LST)

Figure 5.3 shows the LST maps for Abuja derived from the Landsat thermal bands. The LST maps display varying intensity of surface temperature over the study period which will in the following be linked to LULC changes.

Table 5.4: Output of spatial analysis of the proportion of the generated 1986, 2001 and 2014 LULC maps based on the computed error-adjusted area (E-Area) matrices in percentage and the 95% confidence interval (CI). WAT: Water; BUP: Built-Up; VEG: Vegetation; BAL: Bare/Arable Land; CL: Complex Landscapes.

	1986		2001		1986-2001	2014		2001-2014	1986-2014
LULC	E-Area	CI	E-Area	CI	E-Area Change	E-Area	CI	E-Area Change	E-Area Change
WAT	0.25	± 0	0.28	± 0.01	0.03	0.31	± 0	0.03	0.06
BUP	**4.59**	**± 0.1**	**19.54**	**± 0.5**	**14.95**	**33.7**	**± 0.2**	**14.16**	**29.11**
VEG	7.08	± 0.2	5.52	± 0.03	-1.56	7.0	± 3.5	1.52	-0.04
BAL	81.52	± 1.8	65.72	± 0.6	-15.81	55.1	± 3.9	-10.66	-26.47
CL	6.56	± 1.8	8.95	± 0.3	2.39	3.9	± 2.2	-5.05	-2.66
Total	100		100			100			

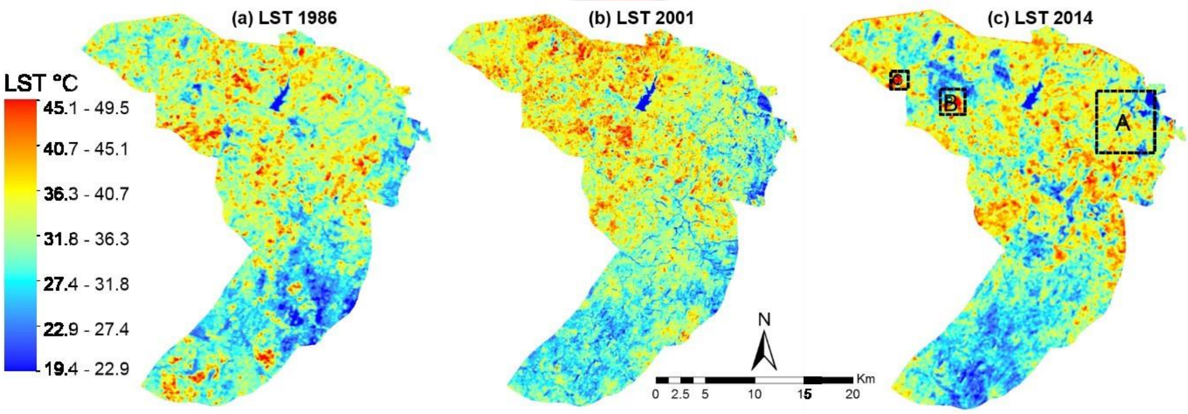

Figure 5.3: Landsat-derived LST maps for 1986 (a), 2001 (b) and 2014 (c). For further detailed illustration, test site are highlighted on the 2014 with square boxes indicating formal (A) and informal built-up areas (B and C).

Evidently, a progressing and variable LST dynamics can be observed visually and in the descriptive statistics presented in Figure 5.4. From the boxplot, it is apparent that amplified LST is majorly driven by urbanization-based LULCC, as mean temperature in builtenvironment have increased from 26 to 35°C. Also, traces of seasonal variations and farm lands which are sometimes left as bare area in fallow periods which make such locations have high temperature (Figure 5.4).

For clarity, and to highlight the influence of LULC in LST patterns for formal and informal built-up areas, Figure 5.5 shows a zoom into the study area as indicated by the squares in Figure 5.3(c). Figure 5.5(a - i) is the zoom-in of the formal and informal built-up area (test site A, B and C) presenting a more detailed portion of the Landsat OLI 2014 image (first column), retrieved LST (second column) and LULC characteristics (third column) respectively. It is apparent that vegetated areas tend to form a cold hotspot with temperature ranging from 2533°C, while a mixture of bare/arable areas and built environment had (high to very high hotspots) with temperatures ranging from 33-37°C.

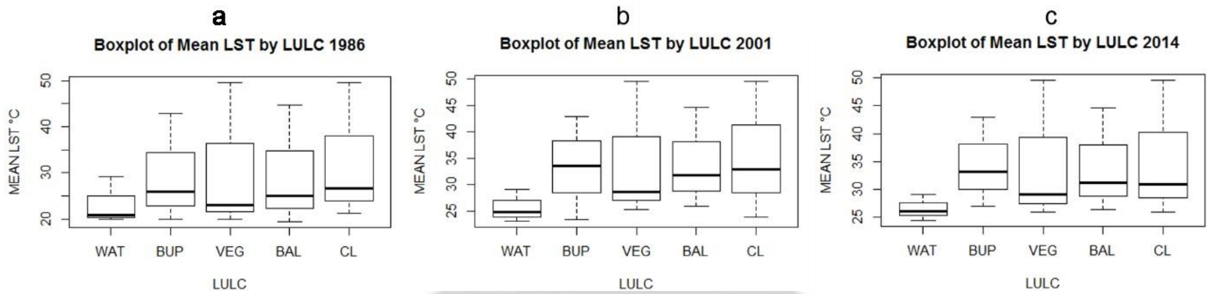

Figure 5.4: Descriptive statistic characterizing LST pattern according to LULC types 1986, 2001 and 2014, (a, b and c) respectively. (WAT-water; BUP-built-up; VEGvegetation; BAL-bare/arable land; CL-complex landscapes).

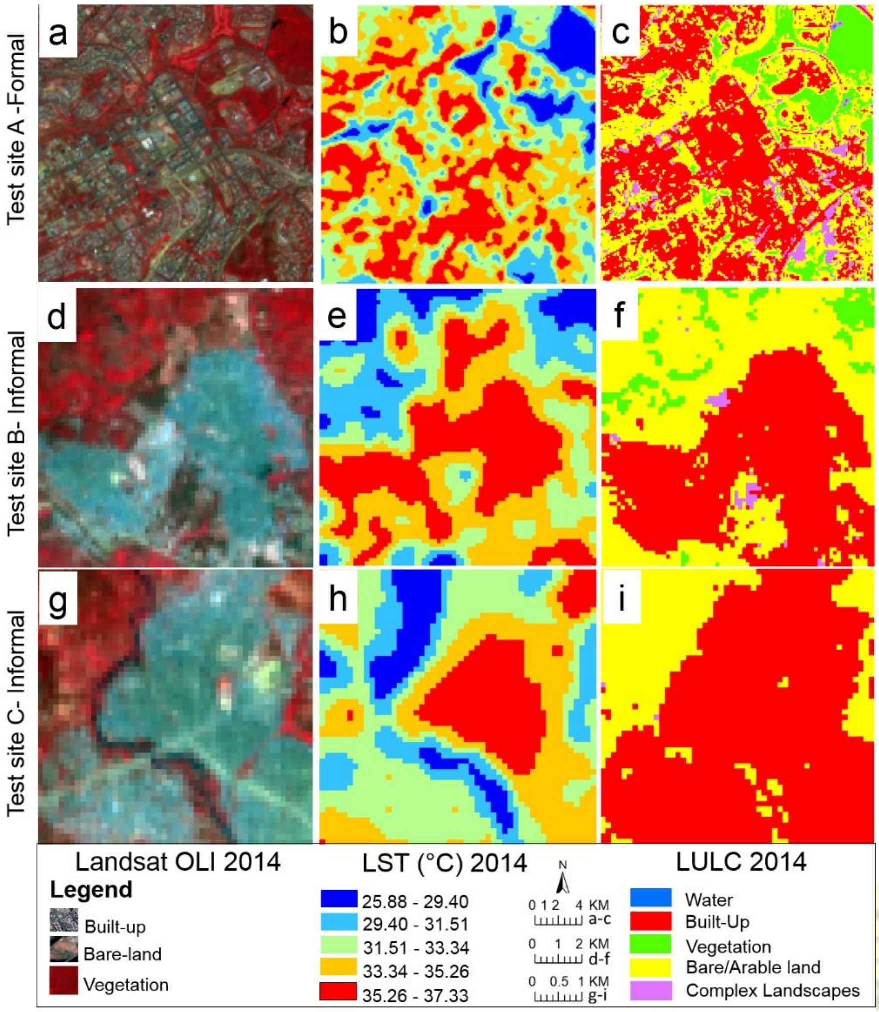

Figure 5.5: Zoom of the geographical distribution of LST in test site A, B and C for comparison. Subset of a 2014 Landsat image in false colour composite showing portions of formal and informal settlements in Abuja (a, d, g) is arranged in the first column, (b, e, h) showing the zoom of the retrieved LST °C and (c, f, i) showing the LULC map. First row is the formal settlement while the second and third rows belongs to the informal settlements.

5.3.4 Characteristic of LST by Landsat derived vegetation and built-up indices

The NDVI is a widely used index to determine vegetative greenness of a given area. In the study area the NDVI ranges from -0.13 to 0.90 at the given dates. Similarly, the NDBI is sensitive to the built environment. In this study, the NDBI maps produced for the same time steps varied in values from -0.26 to 0.26, -0.54 to 0.53 and -0.75 to 0.98 respectively. In order to spatially characterize the quantitative relationship between LST and NDVI, the mean thermal values were investigated using zonal statistics. The result of the descriptive statistic of the

LULC-based LST and NDVI correlation analysis for the 2014 time step being the most recent situation is shown in Table 5.5. It can be seen that built-up area shows the highest LST over all other LULC types with 33.2°C, followed by bare/arable land and complex landscapes with 31.3°C and 30.9°C respectively. The lowest LST was observed on water bodies (26.1°C) which is expected, followed by vegetation (29°C). For the timeframe studied (1986 to 2014) and comparing the mean LST for built-up in 1986, 2001 and 2014 as presented in Figure 5.5, this implies that urban development brought up LST by an average of 8°C linked to alteration of the natural environment such as removal of vegetation cover in place of non-evaporating and transiting surfaces (e.g. concrete, metal and asphalts) Figure 5.5 and Table 5.5. Apparently, values of standard deviation between the LST and NDVI were indicative of heterogeneity and propositional differences in the abundance of vegetation in all the surface materials.

Table 5.5: Descriptive statistic of landscape indices of the 2014 land cover types.

Landsat year	2014	
Land use/cover types	Mean LST (°C) (SD)	Mean NDVI (SD)
Water	26.1 (1.35)	-0.25 (0.32)
Built-Up	33.2 (1.21)	0.23 (0.12)
Vegetation	29.1 (1.28)	0.76 (0.05)
Bare/arable land	31.3 (1.48)	0.52 (0.12)
Complex Landscapes	30.9 (2.01)	0.51 (0.14)

5.3.5 UHI detection and correlation analysis of remotely sensed indices

Figure 5.6 presents univariate and bivariate statistical approaches applied to detect clustering of high LST values with statistical significance as well as the hot and cold UHI/UCI hotspots for the 2014 time step. Figure 5.6(a) shows that out of the 10,000 samples generated, over 3497 points clustered have high LST, 2580 low LST and non-significant points amounted to 3923 points. Figure 5.6(b) showed that the high and low LST points were significant at $P< 0.05$ and 0.01 which is indicative of potential candidates for UHI and UCI as further shown in Figure 5.6(c and d) based on NDVI and NDBI. The univariate local Moran's *I* of LST was positive with 0.099, while the bivariate LISA between LST and NDVI yielded negative Moran's *I* of -0.119 and that of LST and NDBI resulted in a positive Moran's *I* of 0.092.

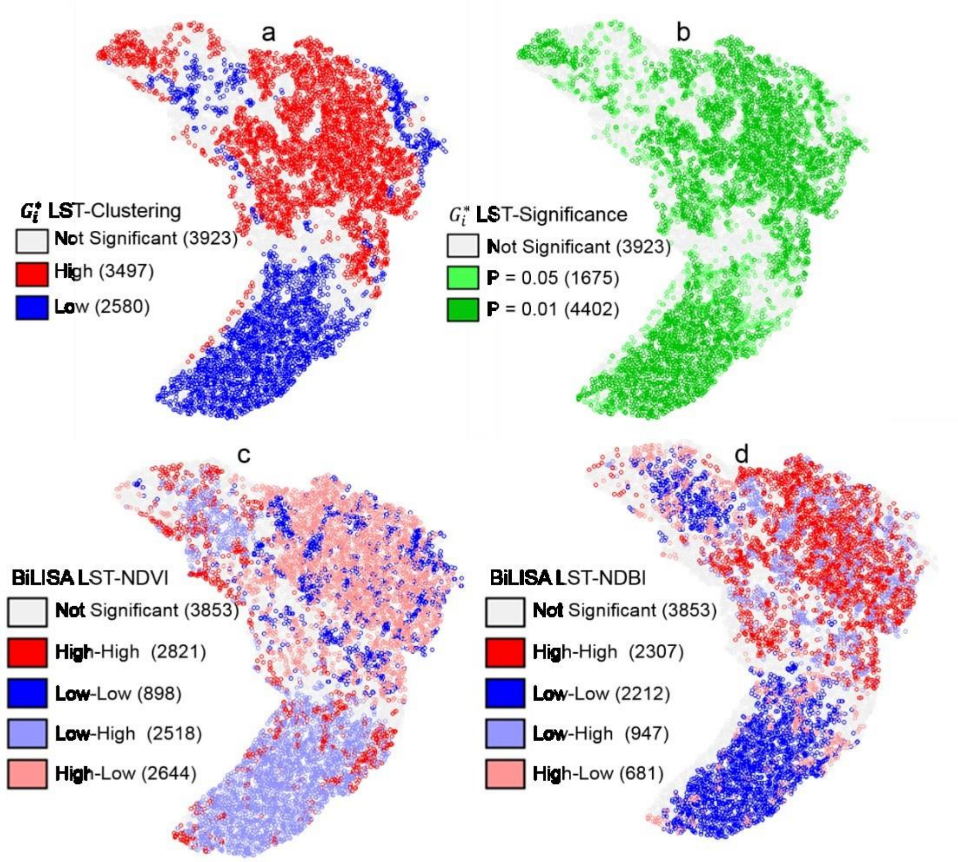

Figure 5.6: Statistical detection of UHI based on clustering, significance and hotspot analysis. (a) clustering detection, (b) statistically significant LST locations, (c) bivariate local indicator of spatial association analysis between LST and NDVI and (d) bivariate local indicator of spatial association analysis between LST and NDBI

Figure 5.7 present the systematic SSLR correlation analysis of the relationship between LST and NDVI as well as NDBI. Results indicated that the coefficients of determination of LST to NDVI at the given dates were fairly low with maximum R-square values less than 0.5. Similar situation was recorded in the case of exploring the relationship of LST to the NDBI with slightly higher R^2 values of NDBI in 2001 and 2014 than it was in 1986. Additional multivariate correlation coefficient analysis based on the band collection statistics in a GIS environment was sought to examine if LST modelling could be improved. The result further indicated that LSTs were dimensionless though with better results, weak negative correlation with vegetation abundance and fairly strong positive correlation with imperviousness at pixel scale (Table 5.6).

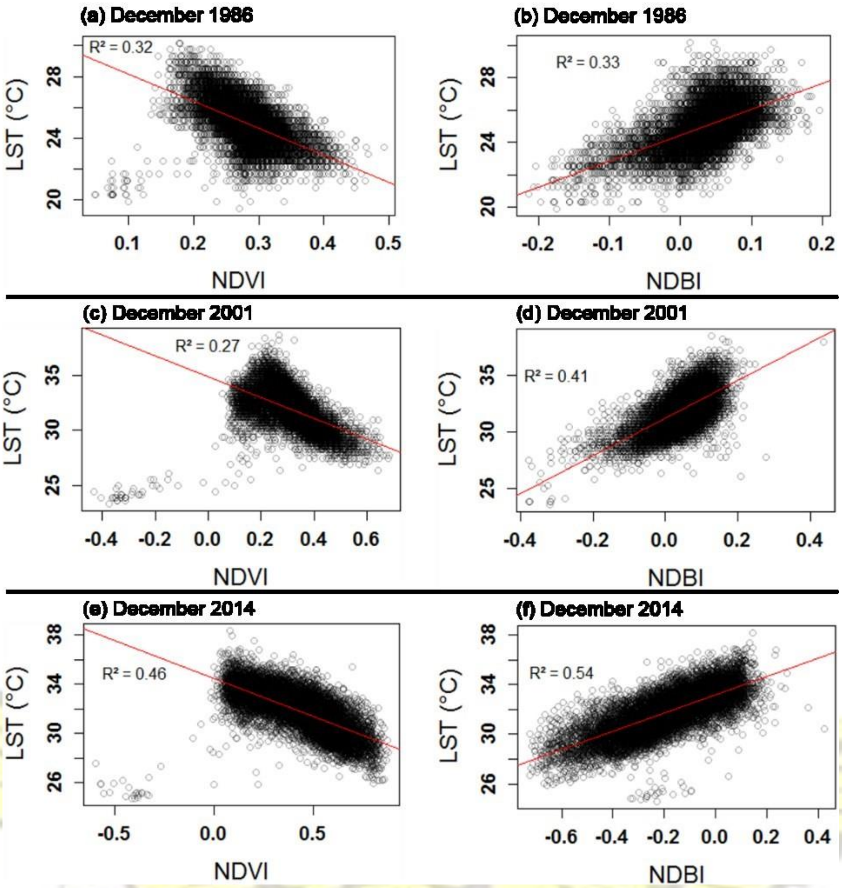

Figure 5.7: Scatterplots of LST with NDVI and NDBI, respectively: (a) 1986 LST and NDVI, (b) 1986 LST and NDBI, (c) 2001 LST and NDVI, (d) 2001 LST and NDBI, (e) 2014 LST and NDVI, and (f) 2014 LST and NDBI.

Table 5.6: The correlation coefficient of LST, NDVI and NDBI

Parameters	**LST**			**NDVI**			**NDBI**		
Years	**1986**	**2001**	**2014**	**1986**	**2001**	**2014**	**1986**	**2001**	**2014**
LST	1	1	1						
NDVI	**-0.56**	**-0.51**	**-0.67**	1	1	1			
NDBI	**0.57**	**0.64**	**0.73**	**-0.63**	**-0.53**	**-0.91**	1	1	1

Complimentary to the SSLR model used to explore the relationships between independent variables (NDVI and NDBI) with dependent variable (LST) for individual years, a more advanced approach was applied to better understand the interplay amongst the variables which is the mixed effect model (GLMM; R package 'lme'). It was used for enhanced data exploration based on protocol for avoiding statistical problems (e.g. data normality and outlier presence, collinearity, heterogeneity variance, dependences and interaction). The presence/absence of data normality and outliers yielded a satisfactory data standardization result (Figure 5.8).

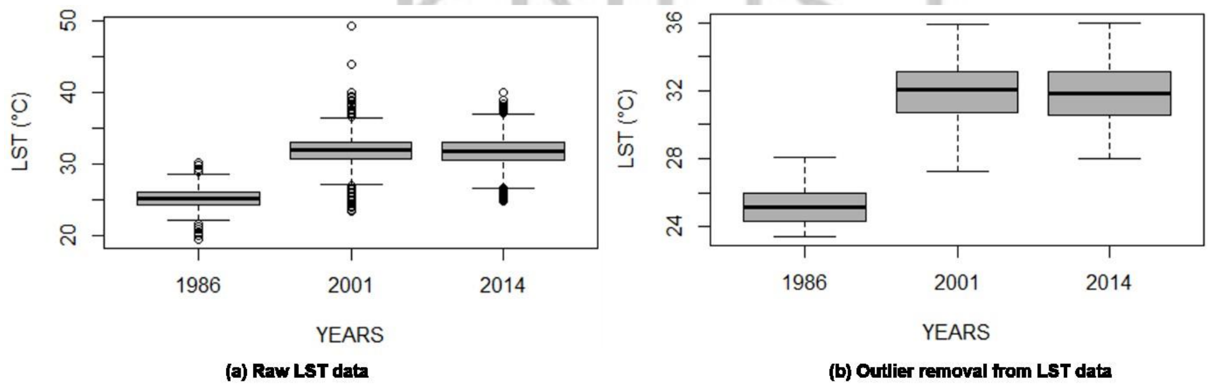

Figure 5.8: Normality check and outlier removal

No collinearity was found from the assessment between the independent variables using the Pearson correlation coefficient and variance inflation factors (VIF; R package 'car'; (Fox & Weisberg, 2011)) which yielded a VIF of 1.2. This threshold is less than a VIF value of >3 which is indicative of presence of collinearity between the dependent and independent variables. To further investigate the effects of NDVI and NDBI on LST the mixed effect models was developed. This began by first determining the homogeneity of variance using the null model which yielded an AIC_c value of 1051129 (first row Table 5.7).

Table 5.7: Model comparison for best model selection. Best model is indicated in bold.

Models	Degree of Freedom	AIC_c
Nullmodel		1051129
LST-lme	5	900787
LST-lmeID	**7**	**891609**
LST-lmeFIX	5	904640
LST-lmeExp	6	898303
LST-lmePow	6	896790

Of all the global models constructed, the four binary nested models significantly outperformed the null model. However, the best model was the model that had AIC_c value of 891609 in the third row of Table 5.7. Ideally, the model with ($\Delta AIC_c < 2$) or more (i.e. lower than the null model) is regarded as the best model. In this case the best model differed with $\Delta AIC_c < 16$ and was used to assess the relationship between the variables.

The result of the CAR model showed that there is no interaction going on between the variables. From the constructed series of diagnostic plots the over-dispersion test yielded a value of 1 which is indicative of a good data dispersion. When data produces a dispersion value > 3 is indicative of over-dispersion. The performed residual check yielded a good residual fit. The result of the spatial autocorrelation test was 0, meaning no spatial autocorrelation between variables (Figure 5.9).

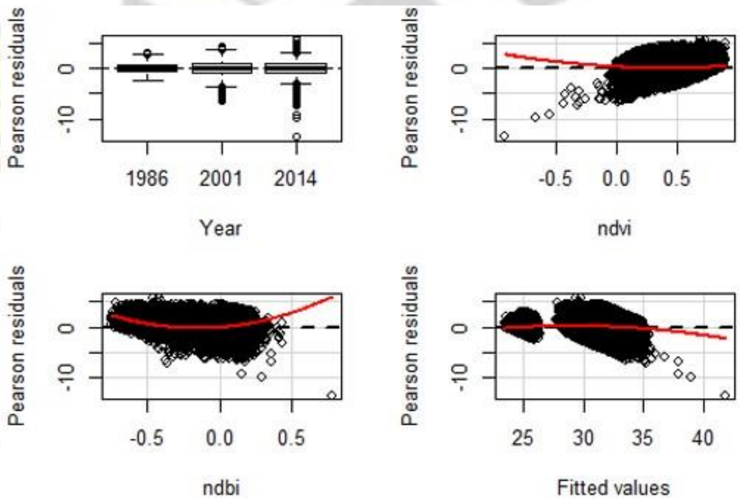

Figure 5.9: Data interaction plot

The overall effect of NDVI and NDBI was determined using the Wald Z test compared to the null model. The best model was significantly better than the null model at ($P < .0001$) indicating that NDVI and NDBI had strong negative and positive effect on the LST which is indicative of the presence of UHI apparent in Figure 5.10 considering the R^2 of 0.91.

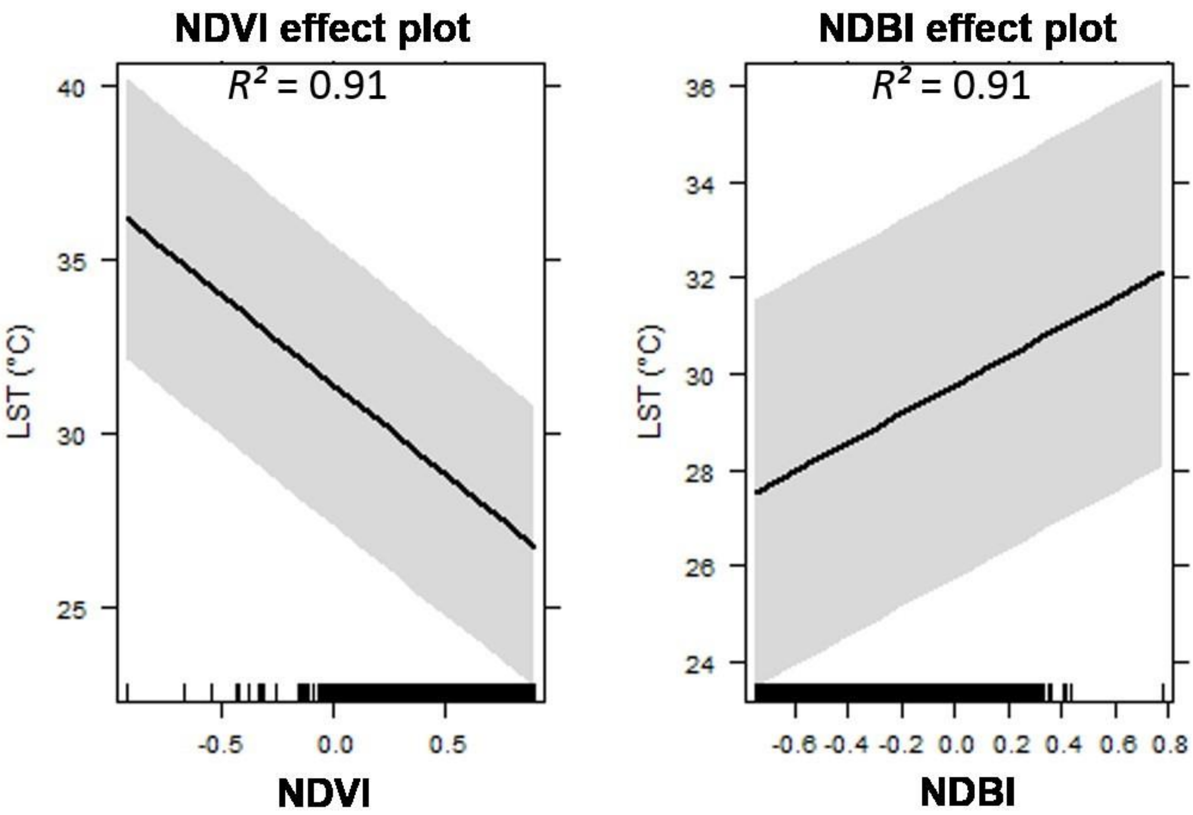

Figure 5.10: Cumulative effects of independent variables on urban warming. Result of the mixed-effect models showing effects of NDVI (left) and NDBI (right). The line indicates the mean presence while the grey shading represents 95% confidence interval with R^2 of 0.91 (i.e. 91% of variability is accounted for).

5.4 Discussions

5.4.1 Air Temperature Indices

Apparently, Figure 5.1(a) confirms that daily maximum temperature rose from 1980 to 1996 and decreased from 1997 to 2009. By 2010 daily maximum temperature increased with a nonsignificant positive trend as at 2014. Figure 5.1 (b) reveals an increase in minimum maximum temperatures which used to be 23.5°C in 1980 and rose to 24.5°C 1997 and subsequently dropped to 24°C from 1998 to 2002. After 2002, a consistent increase in the minimum maximum temperature was observed from 24°C to 30.5°C. Here a significant positive trend was recorded which is indicative of a significant increase in minimum maximum temperature with varying pattern. Figure 5.1 (c) shows significant positive trend in the daily maximum minimum temperature values. In Figure 5.1 (d) an increase can be observed in monthly minimum value of minimum temperature in Abuja, which is indicative of increasing minimum temperature. The trend observed in Figure 5.1 (c and d) is indicative of increasing minimum temperatures, which matches the realities in Abuja as demand for cold drinks is on the increase as well as proliferation of cold rooms for massive ice block production in Abuja. Additional relevant climate change indices generated for analyzing changes in heat fluxes in Abuja were those on warm days (TX90p) with percentage of days when TX>90th percentile and warm nights (TN90p) with percentage of days when TN>90th percentile. Observed trends of warm days is apparent in Figure 5.1 (e). This further buttresses the impacts of temperature changes and how increasing warm days lead to human discomfort, increases the demand for air conditioning in homes, offices and cars as is currently being experienced in Abuja. Figure 5.1 (f) shows that warmer nights in Abuja have significantly increased with significant positive trends which agrees with current temperature situation making people sleep outside in the absence of active cooling appliances at night such as fans and air conditioning especially when there is power outage. In terms of health, continuous warm days and night usually affect more of elderly people, which especially leads to respiratory ailments (Chan *et al.*, 2012). While for children, especially infants heat rashes is experienced and makes such babies cry often (Basagaña *et al.*, 2011; Xu *et al.*, 2012). Also, the warm days can be associated with the increasing demand for chilled drinks including local products such as "Zobo" and "kunu" often hawked on streets, and in traffic jams, which is another obvious impact of heat flux on people in Abuja.

5.4.2 Multi-source Landsat data for retrospective LULCC mapping, monitoring and settlement expansion analysis

Based on the spatial analysis of the LULC derived from EAAA provided in Table 5.4. It is apparent that a remarkable increase occurred in the BUP category of the study area at the expense of BAL. For instance, the fraction of BUP area increases from 4.6% ± 0.1% in 1986 to 19.5% ± 0.5 in 2001 and further to 33.7% in 2014. In contrast, a decrease in VEG and BAL areas was observed between 1986 and 2001. While a slight increase in VEG was observed in 2014, probably due to environmental greening policy and seasonal variation, a noticeable decline in BAL further occurred in 2014 and can be associated to settlement expansion (Table 5.4). For the CLs category, an increasing and decreasing trend between 1986 to 2001 and 2014 was observed which can be mainly linked to either seasonal variation, fire, quarry and farming. Spatio-temporal image analysis enable city managers, environmental and climate scientist gain better understanding of LULC changes which is an added information source towards local climate studies. Generally, LULC maps and spatial analysis presented in this study is valuable for training and validation of global and regional dataset such as the urban footprints for regional assessment (e.g. synergizing urban science with population growth and climate impacts) (Di Ruocco *et al.*, 2015). Also in regions like West Africa, currently facing rapid LULC change but with outdated and inaccurate regional and global maps, local maps of cities such as Abuja are invaluable. Such maps can be used to validate Global Urban Footprint (GUF) datasets (e.g. GRUMP). Similarly, assessing map accuracies using error adjusted approaches with focus on error propagation is essential for ascertaining accurate area estimates. Such maps could be relevant for the quantification of available urban land stock that should be vegetated for mitigating the effect of UHI or estimates of carbon released to the atmosphere arising from vegetation clearing and other factors. Similarly, the results of this study could be compared to other findings. In this study, the generated maps are of good quality despite using historical images of 1986 and 2001 where validation was based on reference data from secondary source and GoogleEarth respectively. During the validation of LULC maps, integrating field surveys, local knowledge and robust image classifiers with very high resolution (VHR) satellite images sources (e.g. GoogleEarth, World-View etc.) can be worthwhile considering their availability. However, for field work questions of spatial distribution can arise and that is where VHR images (here: GoogleEarth) can be helpful, considering that partly validated LULC maps are more reliable than the non-validated ones.

5.4.3 Effect of LULCC and settlement expansion on LST

It is apparent from Table 5.4 that LULCC have occurred in Abuja during the analyzed periods and has influenced the modulation of the LST of Abuja as was proved by Figure 5.4 and 5.5. Specifically, comparing the LST of built-up land in 1986 to 2001 and 2014, Figure 5.4 shows that the intensity of built-up land LST have been amplified by approximately 8.0°C due to LULCC with settlement expansion being the major cause. This has also resulted to the very high potential of UHI formation which is visible in Figure 5.5. Figure 5.6 depicts a statistical perspective of large UHI potential in Abuja if measures are not put in place especially in the informal settlements with more conspicuous UHI formations.

5.4.4 Relevance of multiple remote sensing indices and spatial statistics for improved LST modelling

Lately, the relevance of RS-based LST datasets have been promoted for numerous potential applications such as GEC, particularly for urban climate science. However, it has also been realized that the utilization of single remote sensing variables such as LST for in-depth urban thermodynamics has proven to be elusive to reveal combined effects of built-up, vegetation, LULC and hydrology aspects of LST (Buyantuyev & Wu, 2010; Zhou & Wang, 2011). Therefore, it is regarded as insufficient for urban thermal environment studies, especially studies with a focus on climate change requires other relevant indices such as NDVI, NDBI and LULC maps which were considered in this study.

Complimentary to the need for multiple remote sensing indices for robust LST modelling, multi-statistical approaches are critical for compressive modelling of the various dimensions inherent of LST-based analysis as demonstrated in this study. The ZSAT applied to assess the relationship between LST with LULC and NDVI was only able to provide static measures of spatial variation which is important for quick assessment of variables interplay. The univariate LISA statistics based on Getis-Ord Gi* was only useful for the identification of clustering patterns in LST, while the bivariate LISA statistics proved to be relevant for identifying UHI and UCI hotspots and the relationships with neighboring points. Based on the rapid urbanization rate in Abuja, it was expected that Abuja city would have formed a conglomerated largeregional scale UHI but this is not the case due to its interconnectivity with other pieces of settlement. Similarly, because Abuja is planned with varying densities, Urban Structural Types and some vegetation landscape in the city center, the morphology of UHI was dispersed coupled with the presence of scattered satellite-towns.

The multivariate SSLR approach which is a global model was only able to show the linear relationship between two variables at a time (e.g. LST-NDVI and LST-NDBI), yet R^2 were low. Furthermore, the multivariate cell band statistics proved relevant for assessing the more than two variables at a time (e.g. LST as dependent variables while NDVI and NDBI were independent variables). This model is similar to geographically weighted regression which provides a cell by cell information and accounts for local spatial variability with local coefficients useful for comparison purposes however unable to capture cumulative effects.

In contrast, the GLMM was useful for exploring the dataset and providing standardized steps to avoid type I and II errors. This can lead to making erroneous ecological or environmental conclusions. The exploration of nested/multiple global models also suggest the effectiveness of GLMM over SSLR model in LST modelling because the measure AIC_c was helpful for best model selection. It also provided a cumulative effect of the two LST predators considered in this study in regulating the spatiotemporal thermodynamics of the study area with a very high R^2 measure and confidence interval that reduces uncertainty result interpretation and conclusions (Figure 5.10).

5.5 Conclusion and future outlook

In this study, the use of historic air temperature data and multi-temporal Landsat TM/ETM+ and OLI-TIRS images of 1986, 2001, and 2014 was employed to produce relevant climate indices (TXx TNx TXn and TNn) and landscape indices such as LULC, NDBI and NDVI. This facilitated a better understanding of trends air temperature and spatially explicit urban thermodynamics of Abuja. An improved understanding of the influences urbanization has on urban thermal environment was gained. However there is the need to further develop the method with more in-situ dataset in future.

The use of multiple landscape indices and a variety of statistical approaches proved to be useful to assess the spatiotemporal distribution of UHI effects in the city of Abuja. However, there is the need to further develop the method with more in-situ dataset in further research. Interestingly, the univariate and bivariate LISA, SSLR correlation analysis and mixed effect modelling performed satisfactory in modelling the relationships between LST with NDVI and NDBI. The regression analysis proved that green area can weaken urban heat island effect. In contrast the built-up areas and bare/arable land can accelerate UHI formation due increasing building aspect with potential effects. Thus, while urban environment in Abuja continues to develop, more scientific urban planning attention should be given to future city planning and development in Abuja and environ through urban greening for urban climate management especially for regions without green areas.

It should be noted that the results of this study reflect particular sites and times, and the relationship between LST with NDVI and NDBI would vary with differences in climate zone, land use types, vegetation species, seasons, and the timing of LST acquisition. Future research outlooks should acquire in situ LST data measured with the same overpass of satellites for the calibration and validation of the LST distribution. This will refine the utility of satellite derived

LST for Abuja city and other similar urban areas in order to address topics on urban climate. Also, more landscape remote sensing based indices should be considered for exploring LST sensitivity to landscape processes (e.g. wetness index computes from digital elevation models and the Normalized Difference Water Index) which could be useful for accounting for water balance and LST relationship. The findings of this study can aid in understanding the roles and importance of vegetation cover and can support, providing practical guidelines for planning urban vegetation structure with stronger cooling effects to counteract adverse UHI effects in cities peri-urban areas with conditions similar to regions with normal temperatures.

CHAPTER 6 : FLOOD-RISK MAPPING OF ABUJA – AN INTEGRATED DATA APPROACH FOR VULNERABILITY ASSESSMENT

Abstract*[4]

Natural landscapes have profoundly been changed due human activities in Abuja. This study is about coupling dataset from various sources for assessing physical and Social Vulnerability (SV) to flood risk being vital components in disaster risk assessment. Abuja was used as a study

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area to provide evidence that human security can be threatened with settlement expansion devoid of adequate spatial planning. To do this, precipitation data of Abuja was used to analyze rainfall anomaly and its change/variability indices. Subsequently, Land-Use/Land-Cover (LULC) maps were used to extract settlement expansion to understand built-up morphology and assess their flood vulnerability. Furthermore, SPOT 20 m Digital Elevation Model (DEM) was used to extract relevant linear hydrologic features such as first order derivatives, basins, Drainage Network Order (DNO) and Compound Topographic-wetness Index (CTI). The weighted overlay approach in GIS was used to produce the flood risk zonation map which fits into the physical vulnerability assessment. While the Method for the Improvement of Vulnerability Assessment in Europe (MOVE) framework was used in overall assessment of SV which also takes into account the physical component. The computed rainfall anomaly showed that precipitation history in Abuja experienced variability and change. The computed indices also showed proved that total annual precipitation amount and days exceeding 10mm have significantly increased which is a vital variable of climate that can be used to asses human security. The LULC and settlement assessment revealed that urban foot print have remarkably increased by more than 50% and settlement expansion have developed into floodplains as was proved using the Kubwa area. The morphometric analysis such as bifurcation and drainage density computation were useful indicators to identify parts of Abuja vulnerable to flood risk. The weighted overlay-based flood risk zonation map was useful in the spatial identification of vulnerable places to flood risk in Abuja. The SV component of the MOVE framework was explored for Kubwa that was highlighted a high flood risk area in flood zonation map. The characterization Kubwa's SV using three factors 1) exposure and susceptibility proved that households in the upper, middle and lower part of Kubwa drainage are vulnerable to flood risk during rainy season. In conclusion this study proved that integrated geoinformation and ancillary data and methods is cost effective and efficient in assessing human security to climate and LULC changes. Therefore, its output can be used for municipality emergency management purposes such as education and improved disaster risk reduction campaigns.

Keywords: Landsat TM , ETM+ and OLI; DEM, Morphometric, Flood hazard

6.1 Introduction

Lately enormous societal demands for reliable spatio-temporal information on natural hazard phenomenon such as floods and droughts, and their characteristics have increased. The occurrence of these hazards have become a common experience in many parts of the world due to environmental degradation, such as deforestation, intensified land use, and the increasing population (Chadchan & Shankar, 2009; Dawson *et al.*, 2007; Jensen & Cowen, 1999b; Petit *et al.*, 2001). Obviously, the need for such information is aimed at ensuring good governance and development planning such as improved environmental monitoring and disaster risk management (DRM) programs. Unarguably, geospatial information technologies have become integral to any of these comprehensive environmental monitoring and DRM plans especially for land use change analysis, flood risk and vulnerability analysis being the focus for this current research. For instance with improved information updates, flooding has emerged to be the most frequent singular natural disaster worldwide with greatest damage potential that affects the highest number of people to the sum of over 200 million (Camps-Valls & Bruzzone, 2009; Volpia *et al.*, 2011). Aside from being a natural process, flood-driven impacts is partly caused by the tendency that more people start to live in hazard prone regions as a result of rapid growth in population and extension of infrastructure into floodplains, which consequently makes more societies exposed to flood damages. Verstappen (2006) reported that the consequence is that the magnitude of the impact of a disaster increases since it is dependent on the susceptibility of the land and the vulnerability of the society. Comfort *et al.* (1999b) further documented that the vulnerability is compounded with the increasing complexity of interdependent systems. Thus investigating the trends of these consequences are important for developing countries (West Africa), land locked countries and Small Island Developing States (SIDS), which are often affected disproportionately by such disasters (Camps-Valls & Bruzzone, 2009).

Numerous definition of flood and its classification exist. Rozalis *et al.* (1998) considered flood as an exposure to a natural hazard whose extent of damage is immeasurable. While Kron (2002) described a flood event to be the outcome of heavy rainfall and melting snow, it triggers temporary overland water flow in rivers systems. Overflow of water around river systems is classified to be a river flood. The two other existing types are flash and coastal flood. However, it is possible to predict river flood through proper methods (Shawe-Taylor & Cristianini, 2004). In natural hazard management, especially in assessing flood hazard, risks and vulnerability for management purposes, identification and mapping flood susceptible zones and delineation of risk areas is required to better understand historical and potential hazardous events. This will allow reliable identification of flood risk zones and further develop it into a "State of Art" forecasting tools. Such tools will not only help to map potential flood hazards but also assist to develop and design flood-mitigating measures. However, in order to achieve this, knowledge on LULC, morphometric and hydrologic characteristics of landscapes and certain flood event is a pre-requisite that must become available through flood risk and vulnerability assessment.

Historical LULCC is one of the less well understood anthropogenic influences on climate which is the focus of this study from a regional and local context. To date only vague understanding exists about the linkage between climate change and land use change in Africa especially the West African sub-region. Interestingly, LULCC in Africa is the only spatially oriented indicator with historic changing representation, which is currently going on at a large scale in West Africa (WA) (Eastman *et al.*, 2005). Thus it represents a unique and valuable data source to complement model simulation used to study climate and can be used for comparison with information on the present climate state for natural hazards assessment. In WA, rainfall intensification and variability is one major cause of extreme events such as flood and drought (Washington *et al.*, 2006). The consequences of such event have impact on the people and places since they are part of the natural process. Therefore, it is essential to pay close attention to these natural processes in order to understand them for improved human and environmental security. Globally, drainage characteristics have been studied at basin or subbasin level through traditional geomorphologic methods (Jain *et al.*, 2000; Longepe *et al.*, 2011; Salami, 1999). These researches focused on geometric characteristics of drainage basins (Richards, 1993). Furthermore, Gardiner (2002) reported how other works used the morphometric characteristics of basins to predict and or describe geomorphic processes.

The assessment of stream by measurement of its different aspects of the network is also considered part of morphometric studies. Kumar *et al.*(2000) also highlighted the evaluation of drainage/stream network ordering, basin area, length and perimeter of drainage channels, stream frequency, drainage density, texture, bifurcation ratio, basin relief, concentration time and ruggedness numbers as part of morphometric parameters analysis. This prompted the use of geomorphic thinking for analysis of flood potential and risk and has motivated numerous researches, to investigate the relationships between basin morphometry and flooding impact (1995). An alternative method to traditional approach in identification of drainage networks at basin or sub-basin level is by using remote sensing and Digital Elevation Model (DEM) (Nooni *et al.*, 2014; Zuo & Carranza, 2011). Meanwhile, examination of drainage network using fieldbased approach have been viewed to be difficult considering their vast existence in rough terrains, which poses accessibility challenges. Notwithstanding, advantages of collecting and transporting flows, numerous valleys exist and are cartographically marked as fluvial channels (Cristianini & Scholkopf, 2002; Guo *et al.*, 2005; Joachims, 1998; Kavzoglu & Colkesen, 2009; Longepe *et al.*, 2011). Hence drainage networks and basin extents can be extracted from DEMs (Pike *et al.*, 2009). DEM extraction is achieved through gravity as water flows from upper to lower elevation with the assumption that there is no obstruction, loss to ground water and evapotranspiration. The most robust means of information extraction in DEM is the automatic method with significantly smaller cell size of DEM than the watershed dimensions. Also, in recent years, RS and GIS have been embedded in the evaluation of the geo-environmental multi-temporal hazards. The purposes of using remote sensing are to investigate the susceptibility of the land and the vulnerability of the society, to construct hazard zoning maps and potential damage maps, to monitor potential hazards, and to deal with emergency situations after a disaster (Bruzzone & Serpico, 2000; Kecman, 2001; Verburg *et al.*, 2006).

Many studies that employ remote sensing as the principal information source for assessment of hazards or disasters have been published (Krishnamurthy & Jayaprakash, 2013; Nedelea *et al.*, 2013). By extension, flood hazard and risk mapping have also been studied with the application of remote sensing and GIS tools and lately radar remote sensing have globally been extensively explored for flood monitoring (Cohen & Goward, 2004; Lambin, 1997; Mayaux & Lambin, 1995). Some researchers have applied probabilistic methods (ITC., 1970; Jensen, 2005b; Qiang & Lam, 2015; Veldkamp & Lambin, 2001; Wulder *et al.*, 2008). In some areas, some have employed hydrological and stochastic rainfall method for flood susceptibility mapping (Bruzzone *et al.*, 1995; Müller & Munroe, 2014). Integrated GIS and neural network methods for flood susceptibility mapping have also been applied in various cases (Bruzzone & Serpico, 2000; Foody & Mathur, 2004; Kusimi, 2008). Similarly, bivariate and multivariate statistical models in GIS have been used for flood susceptibility (Huang *et al.*, 2002). Recently, Tehrany *et al*. (2001) applied support vector machine and frequency ratio method for flood susceptibility analysis and its verification, while Tehrany *et al*. (2015) assessed flood susceptibility using GIS-based support vector machine model with different kernel types.

To approach flood studies from a land use perspective, this study considers urban landscape changes that consequently results into flooding occurrence and impacts. Flood events in urban landscapes are a topical global phenomenon and have caused varying devastation and economic losses. Recently the Centre for Research on the Epidemiology of Disasters (CRED), reported that flooding in 2010 affected 178 million people and that amongst all natural disasters the occurrence of floods is the most frequent. Last century alone Abhas *et al.*(2007) reported in the International Strategy for Disaster Reduction (ISDR) statistical analysis a total numbers of 7,486 hydro-meteorological events were recorded. No doubt flood hazards are natural phenomena occurring on different landscapes, but damage and losses from floods are the consequence of human action like urbanization processes. For instance constraining flood water passages, rapid sealing of large parts of the earth surface with roofs, roads and pavements - (imperviousness), altering drainage geography by obstructing sections of natural will aggravate flooding impacts. Apparently, many natural disasters, including anticipated flood hazards can, however, be averted with objective synergies between relevant government departments, Non- Governmental Organisations (NGOs) and other concerned stakeholders to address the risks of natural disasters through development centric research, effective preparedness, forecasting, early warning, and prompt response.

Over the years, experience has shown that flood disasters trigger immediate responses from emergency management institutions saddled with response tasks. However, the memory of such devastating event is short-lived as time passes by, leaving communities unprepared for possible return periods. This model suggests a weak post-disaster response. Thus to develop safer, sustainable communities it is necessary for communities to become more knowledgeable about dealing with disasters, floods and documenting accumulated knowledge (Bruzzone & Carlin, 2006). Consequently, societies must move from the current paradigm of relief-based post-disaster response towards the preparedness paradigm. Hence ISDR (2009) proposed the need for decision makers to adopt holistic approaches for flood disaster management. Unfortunately, the inefficiency in Disaster Risk Reduction (DRR) in WA can be linked to weak knowledge management due to inadequate attention to Information Management and Communications (ICT) training and research. DRR is a partnership and shared responsibility between government and people since the ultimate aim is to guarantee human security, protection of livelihood and ecosystems against catastrophes (Li *et al.*, 2003).

In WA, exceptionally large amounts of rainfall in Sub-Saharan Africa from July to September 2007 led to catastrophic flooding event that took lives, displaced families across the region and destroyed properties worth billions of US dollars (OCHA., 2012). The consequences of such event have impact on the people and places since they are part of the natural process. Nigeria alone accounts for nine states most affected by flood such as Bauchi, Borno, Kebbi, Lagos, Nasarrawa, Ogun, Plateau, Sokoto and Yobe. In August 2007, death toll reached 46 persons and over 2,500 families were displaced (IFRC, 2012). Also, cases of farmland and crop contamination as well as livestock depletion was recorded. According to Kolawole *et al.* (2014)

flooding effects exacerbated due to bad drainage conditions, ill-timed discharge of dam water and chaotic settlement development on floodplains.

Apparently, Nigeria has had her fair share of flood disasters lately. This is evident with the recent past widespread devastating flood disaster that occurred traversing major Nigeria cities up to 31 states in the country from June to September 2012. The most impacted states were those with close proximity to the Niger-Benue River and in the downstream are those around the Niger Delta area; these are; Adamawa, Taraba, Benue, Niger, Kogi, Anambra, Bayelsa, Delta, Edo, Rivers, Cross River and Akwa Ibom. This flood incident has been characterized to be most overwhelming in the past four decades. Impacts sustained from the flood even included destruction of properties such as submerged houses, damaged transportation routes in all the affected areas. According to Missionary International Service News Agency (2012) overall estimate of displaced people was put at 1.3 million and death toll was about 431 persons. Also, farmland of about 1525 square-kilometre was destroyed. Conversely, the Nigerian National Emergency Management Agency (NEMA) forecasted occurrence of flood event and issued relocation advice to residents within the floodplain to upland areas without synthesized and spatially explicit information. This information should have included delineation of spatial extent of areas exposed, susceptible and vulnerable to flood risk along Niger and Benue Rivers (Martin *et al.*, 2015).

The inception of Abuja was in 1984 by the Federal Capital Development Authority (FCDA). There, was in existence a master plan with rapidly growing populations, but not without master plan implantation challenges such as illegal structures and haphazard developments and floodplain encroachment. Over the years, inhabitant have recorded losses such as partial or full house damages, businesses and personal belongings to flooding that accompany consistent heavy rainfall for several days. Record of hard numbers was not found but the degrees of losses were always estimated in the millions of naira. The flood most often submerged, access roads, houses and vehicles and swept debris along the channel.

Complex problems due to numerous factors embedded in natural hazards and anthropogenic hazards (land use change by humans) challenges require the use of integrated approaches that can incorporate knowledge from a broad range of scientific disciplines. Thus, in land use change science, flood vulnerability studies, and climate change impact analysis, the importance of the application of geo-information technologies make sense. Remarkably, GIS technology with other technologies have contributed in flood intelligence. The result is the product of a process of gathering and assessing flood-related data to enable emergency managers to determine the extent of actual or likely effects of flooding on a community (Mathur & Foody, 2008). RS data is a primary and reliable source of information for disasters management cycle. Acquiring near real time data about a disaster can also be delivered by remote sensing. Such dataset can allow authorities to generate timely and detailed situation reports during floods to locate and identify the affected areas and to implement corresponding damage mitigation. This is because accurate and timely information is essential in order to address emergency situations. Thus, mapping flood zone is crucial to effective and efficient land use planning in regions prone to flood risks. It easily generates readable and rapidly accessible maps and charts that helps the administrators and planners to identify areas of risk so as to prioritize their mitigation/ response efforts (Cortes & Vapnik, 1995; Pal & Mather, 2003). Some previous studies have applied remote sensing and GIS for flood vulnerability mapping and risk assessment in Nigeria (Chiadikobi *et al.*, 2011; Ejenma *et al.*, 2014). However, it is not just enough to create maps showing the flood prone areas and how low or highly susceptible an area is to flooding. There is the need to advance such studies by reducing the risks of such places through vulnerability assessment for preparedness.

Vulnerability assessment concept is a wide and multidisciplinary field of study. It could be approached using generic indicators from either a physical and social points of view (Taubenböck, Post, *et al.*, 2008). To physically assess multi-faceted and complex vulnerability, remote sensing approach can serve as a diagnostic tool for such endeavour. Social vulnerability assessment can be analysed using socioeconomic status, composition of household, disability and also climatic condition. The Method for the Improvement of Vulnerability Assessment in Europe (MOVE) framework was adopted for this study given that it integrates both physical and socioeconomic interaction in its concept of vulnerability assessment. The framework considers major factors that make a system or society exposed to a hazard, the society or systems susceptibility to a stressor and the resilience and adaptive capacity (Figure 6.1). The approach emphasizes the consideration of several thematic perspectives to assessing natural and socioeconomic hazards and associated vulnerability (Birkmann *et al.*, 2013). The MOVE framework highlights possible links between diverse DRM and climate change adaptation concepts and looks valuable for communicating complex problems to address attitudinal change in societies for improved DRR and adaptation strategies. Thus, the framework clearly distinguishes risk and vulnerability as well as presents a possible hybrid approach in natural hazard and vulnerability assessment (Birkmann *et al.*, 2013).

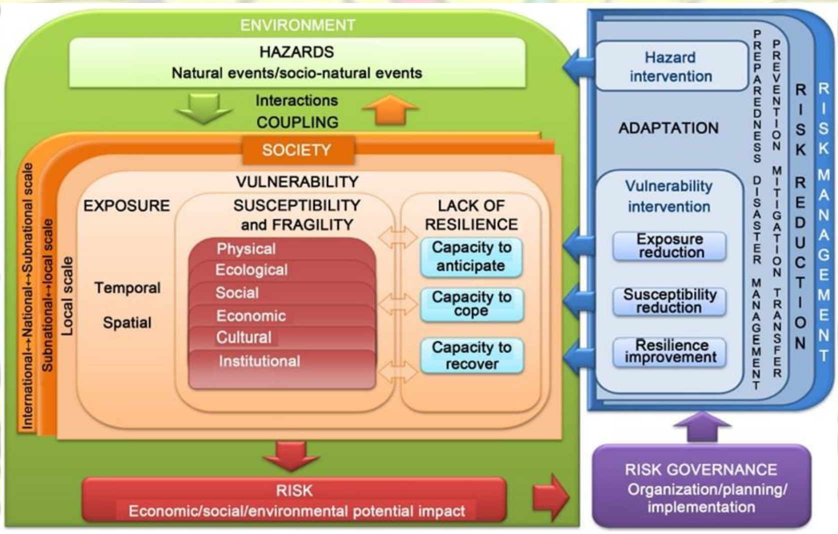

Figure 6.1: The MOVE framework for natural hazards: Framing vulnerability risks and societal response (Source Birkmann et al (2013))

Hence, in the case of Abuja while overall physical vulnerability is initially assessed using the weighted overlay approach to zone flood risk zones of Abuja. By definition, exposure is described as the proximity of the assessed unit to the geographic location of hazard occurrence and susceptibility refers to the tendency of element at risk (physical and social) to experience damage. Resilience refers to the ability of the society to respond and can be measured based on access to public support, resources and infrastructure in relation to the hazard in question. The adaptive capability of a society or system is judged based on the ability of such a system or society to learn from past experience to change present unsustainable practices as a key to preparing for future occurrences of hazard and vulnerabilities. The framework characterized vulnerability using three major factors such as i) exposure (E) denoting proximity of the assessed unit to geographic location of a risk; 2) susceptibility (SUS) signifying the tendency of element at risk to experience distress; and 3) lack of resilience (LoR) is defined based on limitation of a system or community that is, lack of accessibility to, availability and mobilization of resources, effectively responding to a known hazard. In this study, only exposure and susceptibility was assessed.

The goal of conducting this study was focused on integrating GIS and RS techniques with morphometric analysis to generate a flood-risk maps of Abuja. Combining information from historic climatic data with land use and morphometric analysis will improve understanding of the exposure of various places and people to flood risks in the context of climate change. Such maps would not only provide detailed lists of threatened locations, forming a firm basis for the creation of a flood mitigation policy, but would also serve as a valuable educational and public relation tools for DRR and emergency response. Relevant hydrologic parameters such as basin flow accumulation and pour point are computed to assess

Abuja. Furthermore, characteristics such as slope, drainage network, drainage watershed (basin), and wetness index are extracted from a DEM. Each characteristic is inherent in the basin and network parameters relevant to the flood risk. Also the entire basin was analysed to identify areas prone to flood risk. The varying susceptibility of Abuja settlements is assessed by evaluating its flood risk, and using Kubwa one of Abuja's regional settlement experiencing rapid urbanization. Through this assessment, causative factors can be unlocked and logical recommendation that will help reduce flood risk can be proffered to the relevant stakeholders.

6.2 Materials and Methods

6.2.1 Study Area and Data

The details of the study area used for this research have been presented in section 3.1. Similarly, other relevant datasets such as the historical precipitation records, OLI 2014, 20 m DEM and geolocation-based socioeconomic data have also been earlier presented (see section 3.2).

6.2.2 Precipitation data analysis and climate indices

The acquired 32 years precipitation data of Abuja was analysed to specifically visualize the precipitation pattern of Abuja in past decades. Subsequently, the rainfall anomaly index proposed by Lamb index determination was applied on the precipitation data to analyze rainfall pattern using the formula below Equation (6.1):

$$X_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{r_{ij} + m_i}{\sigma_i} \qquad 6.1$$

the measured rainfall is r_{ij} and j signifies the year within the station i, m_i and σ_i correspond to the average and standard deviation of recorded rainfall at station i, where N_j connotes the numbers of station with rainfall record in the year j. Abuja the study site has only one meteorological station located at the Nnamdi Azikwe International Airport, hence the provided formula is modified in Equation (6.2) as:

$$X_i = \frac{r_i + mi}{\sigma} \qquad 6.2$$

where the rainfall anomaly index is X_i for year i, the total annual rainfall for year i is r_i , while m_i and σ_i correspond to the average and standard deviation of recorded rainfall for the study period (Sané *et al.*, 2015).

However, monthly averages of daily climate parameter such as precipitation can smoothen vital information in data. According to Zhang (2011), some of the smoothened effect describes the behaviour of extreme event which usually result in flood impacts. An extreme event can be considered far into the tails of the distribution where the index threshold is located (Folland *et al.*, 1995; Peterson *et al.*, 2008). Figure 6.2 illustrates the distribution of extreme event where occurrence is more likely to cause environmental and societal destruction. Relevant precipitation indices defined by Frich *et al.* (2002) presently known as the Expert Team on Climate Change Detection, Monitoring Indices 'ETCCDMI' indices were generated from the precipitation data. Theses indices were established by the European Climate Assessment (ECA) indices (Klein Tank *et al.*, 2002) and proposed by Trewin (2009) were computed. The freely downloadable RClimdex package from the provided website at: http://cccma.seos.uvic.ca/ETCCDMI/index.shtml developed by Zhang and Yang (2011), was used to compute the ETCCDMI indices based on the available precipitation data over the study area.

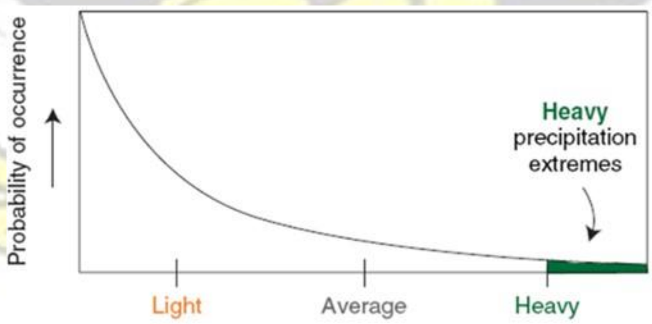

Figure 6.2: Probability distribution of daily precipitation. The high black line indicates the often occurrence of characteristic weather event. The shaded area denote extreme event. (Source: IPCC report 2005).

6.2.3 Landsat-based detection of settlement expansion and flood area encroachment

The downloaded cloud-free Landsat data for 1986, 2001 and 2014 were considered for generating LULC types using the SVM classifier (Sáez *et al.*, 2013). Five major LULC types were extracted, including water, built-up, vegetation, bare/arable-land and complex landscapes. The SVM being a supervised classifier helped in producing land use information of the study area for 1986, 2001 and 2014. Assessment of accuracy was done by using a stratified random sampling design approach due to its obvious advantage allowing representative and manageable sample population. For the various years, different sample sizes were used considering the varying proportion of target category. For 1986 (574) sample point were used while (891) points were considered for the 2001 image and (500) points were extracted from the field campaign in 2013. For areas where accessibility was a challenge the high resolution image of 2013 was utilized as ground control. The error matrix, area of each category according to the map, and descriptive accuracy measures such as user's, producer's and overall accuracy were calculated. Post classification technique, which allows comparison of independently classified images were used to extract settlement expansion extent for the three image epochs. This was followed by an overlay of the built-up layers for 1986, 2001 and 2014, which resulted in the detection of settlement expansion in Abuja for three time stamp 1986, 2001 and 2014.

To detect flood plain encroachment, this study extracted drainage layer of water bodies in Abuja using a 2013 WV-2 VHR image in combination with and GoogleEarth image to determine how close settlement are to the drainage pattern, using manual on-screen digitization method (Goodchild, 1991; Okada *et al.*, 2014). Subsequently, proximity analyses using the multiple buffering technique was applied to finally determine flood plain encroachment by expansion settlement (Steinfeld *et al.*, 2013). Based on local knowledge of the area the multiple range of 100 and 150 m was constructed to assess the closeness of settlement to the water ways.

6.2.4 DEM processing and morphometric analysis

The field of geomorphometry involves quantitative physiographic means of depicting the characteristics of drainage network (Rosgen, 1994). However, over the years, geomorphometry have developed with mathematical analysis of the earth surface configuration, dimension, shape, and landforms (Singh *et al.*, 2013). DEM processing is a rule of thumb specifically required to inspect and standardize continuous height data. The fill tool embedded in the spatial analysis and hydrology geoprocessing module of ArcGIS 10.2 and fill-sink tool in the DEM Hydro-processing module of ILWIS 3.3 were intermittently used to inspect and standardize the DEM dataset. This procedure reduces the spurious sinks that might not perform in all areas thus to stimulate the flow of water on the surface of the ground (Hardin *et al.*, 2007; Howarth & Wickware, 1981; Lindley, 2013). The standardized DEM was further inspected for visual artefacts through hillshade map generation. The following step was to derive various morphometric terrain parameters such as the first order derivative (e.g. slope and aspect). Furthermore, the DEM was exploited to generate hydrologic terrain parameters such as basin, flow direction, flow accumulation, watershed, Drainage Networks Orders (DNO), Catchment and Topographic-wetness Index (CTI). The CTI specifically belongs to the compound derivatives family, which takes slope and flow accumulation maps as input to generate intermediary maps before arriving at the wetness index. In computing the CTI, the cell size and other relevant mathematical coefficients were taken into account.

6.2.5 Linear network extraction method

Linear hydrologic networks such as DNO also referred to as stream orders. In this study, the Strahler (1952) approach was considered for the extraction of DNO. It is a modified Horton's system that allows the scientist to determine stream order, which considers the fingertip channel designated as first order, and where two first order joins is considered second order and the joining of two second order forms the third order segment and so on. Other valueadded information extracted included the stream length and basin area, Drainage Density

(Dd) and Bifurcation Ratio (Br). This stream order was computed using the spatial analysis tool in ArcGIS 10. Stream length discloses characteristics of an area’s surface runoff having gentle slopes. The generated stream order served as an input for computing the stream length for the various stream orders and calculation was implemented using the SQL query builder tool embedded in ArcGIS10. The amount of stream channel length per unit area is regarded as the Dd. Dd in urban areas comprises of underground water and is a good index to measure network texture, and can be indicative of balance between resistance surface rock and soil with the overland flow erosive power. To the calculate Dd of Abuja basins, the length of the entire channels within the basin was determined by computing the drainage geometry in meters and was divided by the basin area using the field calculator tool with the formula below Equation (6.3):

$$Drainage\ density\ (m^{-1}) = \frac{total\ channel\ length\ (m)}{basin\ area\ (m^2)} = m^{-1} \qquad 6.3$$

According to Chankao (1982) adequately drained watershed should have Dd ≥5 while moderate to poorly drained regions possess Dd in the range of 1-5 or lesser Dd value. Areas with poor drainage density attracted higher weights whilst regions adequately drained were assigned lower weight values and was implemented in the spatial analyst tool of ArcGIS. Br establishes the relationship between streams of different orders. Hence, the lower stream orders are interlinked to the higher ones until the end (Schumaker, 2004), depending on the number of streams. Br was computed using Equation (6.4) below:

$$B_r = \sum_{i=1} \frac{n_i}{n_j} \qquad 6.4$$

where B_r is the bifurcation ratio, n_i refers to the total number of the initial order and n_j represents the total number of the later order.

6.2.6 Weighted overlay-based flood hazard mapping

In flood hazard mapping, numerous contributing factors are essential to be considered. Previous studies such as that of Rachna and Joisy (2009) used factors such as annual rainfall, watershed size, watershed slope and river/stream gradient, Dd, land use and soil, infrastructure and communication trunks to rate flood hazard using a weighted approach. Similarly, Surjit and Kaushik (2012) proposed a Flood Risk Index (FRI) using GIS to assess risk and vulnerability of flood hazard in Ghaggar basin, India, with hydrology, soil, slope type, Dd and LULC. Other authors have assessed flood risk or zonation using numerous criteria concept (Krishnamurthy & Jayaprakash, 2013; Nedelea *et al.*, 2013). To successfully assess flood risk in Abuja and based on available dataset, various relevant factors such as LULC map, DEM and other morphometric derivatives such as wetness index, slope, Dd and watershed maps were integrated using weighted overlay approach (Figure 6.3). The weighted GIS overlay and remote sensing approach used here is an efficient method to delineate flood hazard risk zones for Abuja and can be used for preparedness and emergency response planning.

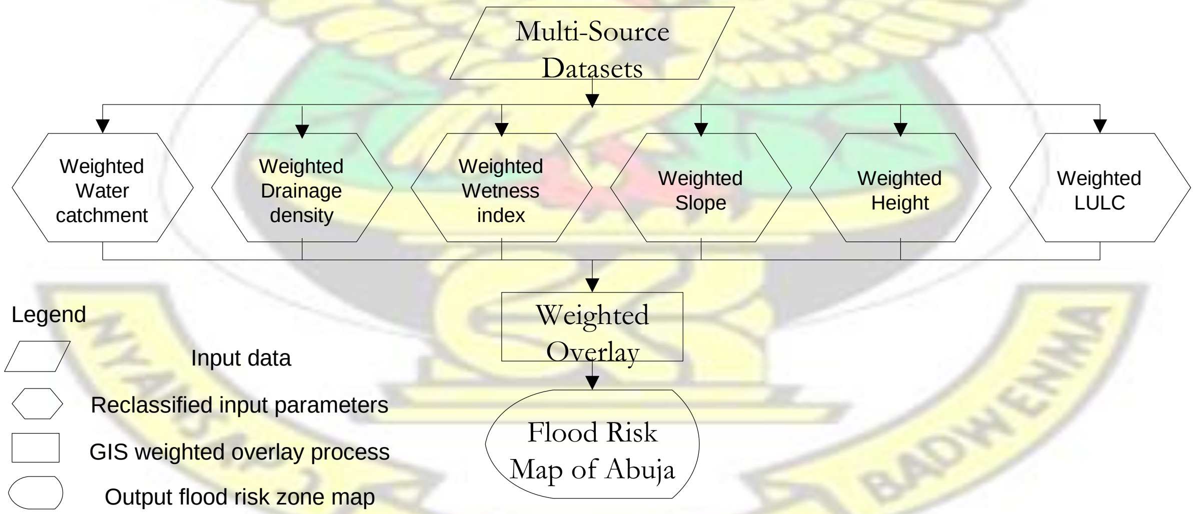

Figure 6.3: Weighted overlay for flood risk zone mapping

6.2.7 Social vulnerability assessment

To assess Social Vulnerability (SV) being a critical component of disaster risk assessment. In this study, only Kubwa was used as a case study due to data availability constraints. Table

6.1 presents the two indicators chosen for each vulnerability component considering previous work and expert knowledge. A purposive/random sampling approach was used to gather 107 samples by means of structured questioning and geolocation mapping (available on request). Vulnerability assessment was implemented based on the MOVE framework and further characterized in a GIS using two crucial factors such as exposure and susceptibility described in the introduction section of this chapter.

Table 6.1: Vulnerability components, number of indicators and functional association

Component	Number	Indicators	Functional Association
Exposure (E)	1	Household size	Positive
Susceptibility (SUS)	1	Number of children under four years	Positive

The table describes the functional association between indicators and vulnerability. Standardization was applied to all the survey data using the linear min-max normalization proposed by Iyengar and Sudarshan (1982) and subsequently demonstrated (Kumar *et al.*, 2014; Sané *et al.*, 2015). The normalization formulae can be implemented using Equation (6.5) when indication relate positively with vulnerability values.

$$X_{ij} = \frac{X_{ij} - min\ (X_{ij})}{max(X_{ij}) - min\ (X_{ij})} \qquad 6.5$$

In situation when there is negative relation between indicators and vulnerability, the normalization of such scenario can be computed using Equation (6.6) below:

$$X_{ij} = \frac{max(X_{ij}) - X_{ij}}{max(X_{ij}) - min(\ X_{ij})} \qquad 6.6$$

In this case, X_{ij} refers to the normalized value of the indicator i of the factor j; X_{ij}, the value of the indicator i; max(X_{ij}) and min(X_{ij}) respectively are the maximum and minimum values of the indicators i of the factor j. The assumption is that regions M exist, where K indicators of vulnerability and $x_{ij}(i = 1,2, . . . , M; j = 1,2, . . . , K)$ represent the normalized scores. The development level of the i^{th} zone, here assumption is that $\bar{y}_i$ is the linear sum of x_{ij} represented as Equation (6.7):

$$\bar{y}_i = \sum_{j=1}^{K} w_j x_{ij} \qquad 6.7$$

$w's$ $(0 < w < 1$ $and \sum_{j=1}^{K} w_j = 1)$ signify weights. According to Iyengar and Sudarshan's procedure, the assumption is that the weights inversely vary as the location variances which is indicative of the difference in vulnerability. Thus w_j being the weight can be determined using Equation (6.8) and the normalizing constant here is c Equation (6.9)

$$w_j = \frac{c}{\sqrt{var(x_{ij})_i}} \qquad 6.8$$

$$c = \left[\sum_{j=1}^{j=k} \frac{1}{\sqrt{var(x_{ij})_i}}\right]^{-1} \qquad 6.9$$

To ensure that undue domination of large variation in any of the indicators is avoided especially in terms of contribution from other indicators, the weighted approach was applied. In the context of this study, the two components (E and SUS) were aggregated into a composite indicator of socio-economic vulnerability using Equation (6.10) which took into account specific weight for the two components as provided below:

$$VU = \frac{\sum_{j=1}^{n} w_j x_j}{m} \qquad 6.10$$

VU in this equation is the vulnerability index for a given neighbourhood, while m refers to the number of components, the weights of domain j is represented as w_j and component j is contained in x_j which are E and SUS. The two components in this study had same number of indicators. Hence, weight *w* equals 1 for the two indicators and m represents 2. Computation of vulnerability index is between 0 and 1, where 1 indicates maximum vulnerability and 0 suggest no vulnerability.

6.3 Results and Discussions

6.3.1 Climograph of Abuja and rainfall anomaly index analysis

The most crucial variable that influences climate and people's lives is rainfall. For instance the regional climate in Sudano-Sahelian WA has remained unpredictable till date (Traore *et al.*, 2013). This further corroborates the significant influence rainfall has in determining environmental changes. Hence, rainfall parameter is suitable for characterizing and analysing climate variability or change in the three WA ecological zones, (i.e. Sundanian, Sahelian and Sahelo-saharan) and Abuja fall within the Sudano-Sahelian zone. Livelihoods in this region is not dependent on rainfall, but the occurrence of extremes such as flood risk is a threat to human security in settlement and crops on farmlands.

Figure 6.4 displays the computed climograph of Abuja using the monthly mean of both rainfall and temperature data from 1986 to 2014 and the Rainfall Anomaly Index (RAI) for the same period. Figure 6.4 (a) of the climograph illustrates May to October as wet and cool months in Abuja. In these months, varying flood events in Abuja suburb such as Kubwa settlement have been recorded in the past (i.e. 27th August 2008 and 31st August 2009) due to heavy rainfall (Musa, 2009; Solomon, 2010). Figure 6.4 (b) displays the computed rainfall anomaly index of Abuja from 1986 to 2014. The computed annual rainfall index depicted the historical precipitation pattern of Abuja and it showed that Abuja experienced much dry years. This conforms to the period when the entire WA experienced widespread drought in the 1970s and 1980s (Nicholson, 2013), as the drought event is apparent in the 1982.

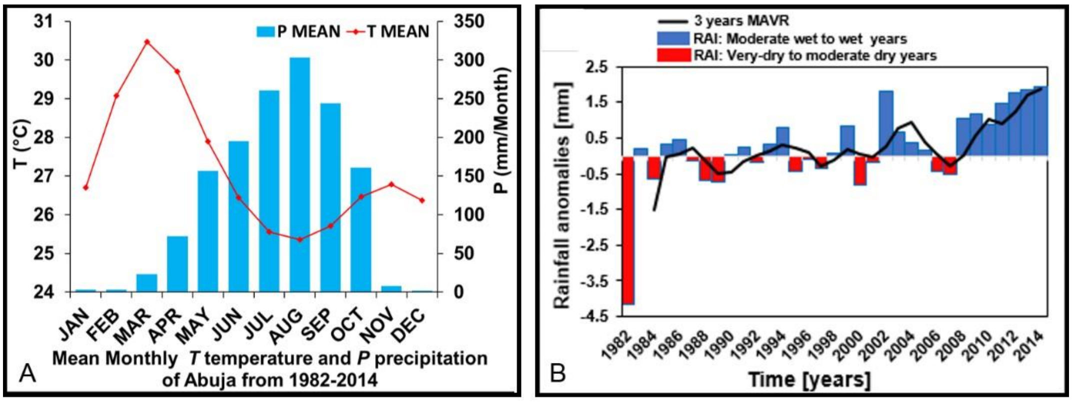

Figure 6.4: Climograph of Abuja metrological station. (a) showing long-term monthly mean (1982-2014) temperature and rainfall and (b) is a display of annual rainfall anomaly index

However, in 2000, Abuja experienced more stable wet years from 2007 which corresponds to the historical flood event dates in Kubwa settlement of Abuja. When the negative values fall below -0.5 such periods are defined as dry years and above 0.5 positive values are categorized wet years. Although, this index was applied to determine flood and drought years, in this study the usefulness of the index is justified for flood risk vulnerability assessment.

6.3.2 Precipitation-based climate indices

Figure 6.5 presents the computed annual precipitation days and annual count of days when precipitation exceeded 10mm. In accordance to Figure 6.5 (a), the total precipitation in Abuja show significant positive trends in p-value less than 0.05 threshold and a correlation coefficient of 0.48, which is indicative of increasing rainfall trend in Abuja. Figure 6.5 (b) presents how the number of days having precipitation exceeding 10mm have increased from 45 days to approximately 80 days with a correlation coefficient of 0.51 based on p-value less than 0.05. Such increase might be due to climate variability. In the context of flood event increasing rainfall days coupled with other factors including soil properties and soil sealing tendencies, LULC change, settlement expansion and floodplain encroachment, urban density, infrastructural injustice and solid waste challenges are factors that exacerbate flood risk threat on human security; and Abuja is currently undergoing all these processes in varying proportion and locations especially in Kubwa.

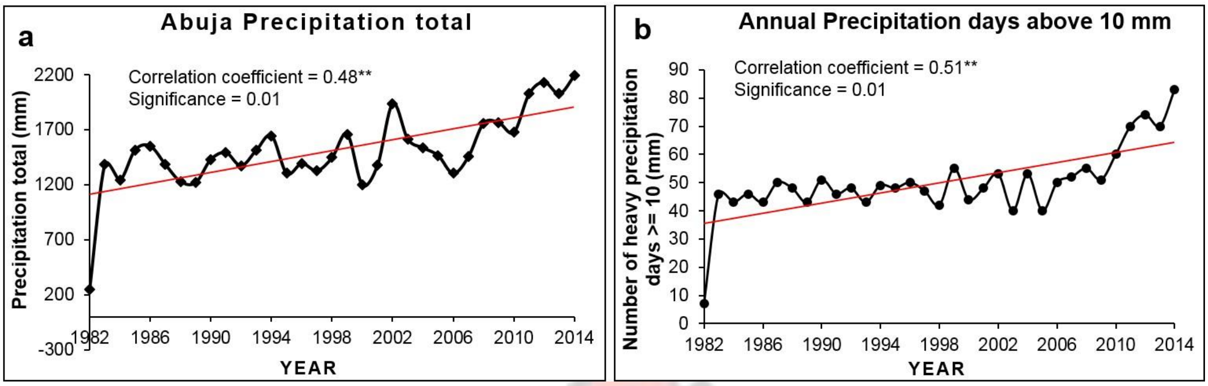

Figure 6.5: Precipitation indices, (a) depicts the total annual precipitation days and (b) the annual count of days when precipitation exceeds 10mm

6.3.3 Settlement expansion and floodplain encroachment analysis

Using the downloaded Landsat image series, LULC maps for 1986, 2001 and 2014 with major LULC categories (Water, Built-Up, Vegetation, Bare/Arable-land and Complex Landscapes). The overall accuracies of the produced maps yielded 91.6%, 92.3% and 92.9% respectively. Built-up in 1986 was 3.65% of the total area classified, by 2001 built-up grew to 18.32% and in 2014 33.02%. Significant changes in built-up were observed in the 1986-2001, 2001-2014 and 1986-2014 time-steps with 14.67%, 14.70% and 29.37% respectively. Since the focus of this study is on urban areas, settlement for the three years referred to as built-up in the LULC maps were extracted and overlaid to produce the overall settlement expansion map (Figure 6.6a). Apparently, settlement in Abuja has grown with strong potential of triggering more flood events especially in regions of infrastructural injustice as well as encroachment into floodplains.

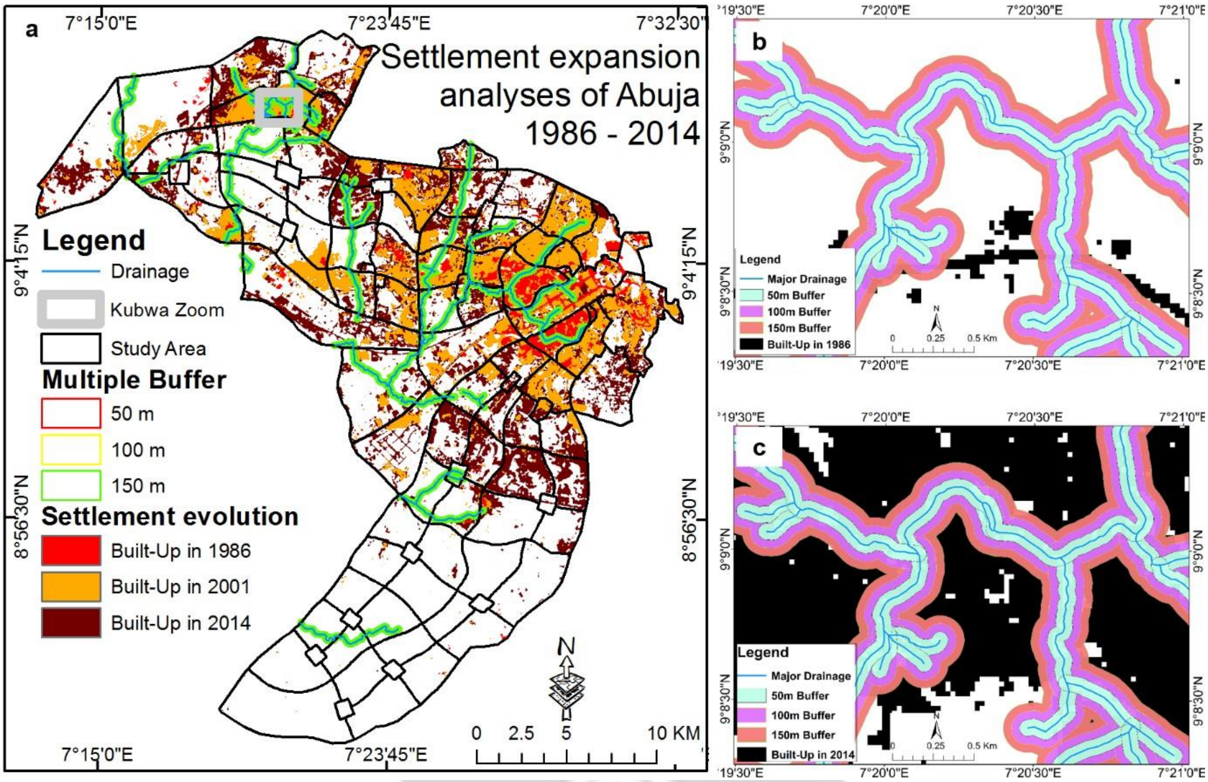

Figure 6.6: Settlement expansion in Abuja. (a) Settlement development of Abuja from 1986 to 2014, (b) 1986 settlement footprint of Kubwa and overlay of multiple buffer around the drainage (c) 2014 settlement footprint of Kubwa and overlay of multiple buffer around the drainage.

For instance the Kubwa settlement as at 1986 was an open area used for farming. By 2014 it had been built with evidence of encroachment into the drainage area floodplain. Other factors such as change in drainage geography, solid waste menace are inherent in the builtenvironment and Abuja is not an exception. Figure 6.6 (b and c) presents the zoom-in of the central part of Kubwa area highlighted in grey color in Figure 6.6 (a) for a detailed visualization of settlement encroachment in the study area. The visual interpretation showed that built-up expanded dramatically over the period assessed. In Figure 6.6 (b and c), the proximity analysis layer depicting 50, 100 and 150 m distance buffer generated from the drainage in conjunction low lands to detect floodplain encroachment was superimposed. Based on proximity analysis, it is apparent that built-up have encroached into floodplain and the buffer zone also indicate varying degree of potential exposure to flood impact.

6.3.4 Morphometric properties of linear drainage networks

The study revealed that Abuja is endowed with numerous streams in relation to its size. The entire study area has over 300,000 streams which were within the entire basin area of about 600 km^2. Considering the importance of linear morphometric parameters in the study of hydrology of an area and usefulness for analysis of flood risk potential, four major linear drainage parameters were computed and analysed namely; stream order (Nu), Stream length (Lu), Area in percentage and Br for Abuja basin. Stream order also known as DNO, which refers to the hierarchy of streams of the study area and also depicts the morphology of Abuja streams in their order. Based on the aggregation method adopted, four major drainage basins were identified to understand the various orders in various basins, which is indicative of hydrological processes going on in the three basin selected for comparison (Table 6.2).

The Kubwa basin had 6 stream orders, AMAC North possessed 8 stream orders while AMAC South contain 7 stream orders. From Table 6.2 it is apparent that the three selected basins had varying numbers of streams from different orders. Hence the drainage basin morphometric parameters can be used to describe and assess their flood risk potentials. No segment of the basins to the best knowledge of the researcher is gauged and only piecemeal information on the basin is available as no research has been carried in this direction. Thus, the usefulness of generating information on stream order in this study is invaluable. Typically, hydrologic and geomorphic problems like flooding and erosion cannot be excluded in some parts of Abuja considering result of the morphometric analysis presented in Table 6.2 making it a useful information for flood risk assessment. This analysis in Table 6.2 further indicate dominance of first order streams having over 50% of the streams area. This implies that run off depends on the area, rains may fall and overland water flow may occur, yet there can be no danger of floods.

Table 6.2: Linear Aspect of the Drainage Network of Kubwa, AMAC Basins

River Basins	Stream Order (U)	Number of Streams (NU)	Stream Length in m (Lu)	Stream length extent in (%)
	1	38196	135, 904	55.58
	2	17054	300, 060	25.17
	3	6312	764, 506	9.88
Kubwa	4	2923	1,597.000	4.73
	5	2083	2,685.000	2.81
	6	1333	5,965.000	1.26
	Sub-Total	67901	11, 447, 467.8	-
	1	48234	135,903.2	55.90 24.69
	2	21302	300,059.3	10.21
	3	8818	764,505.3	4.60 2.27
	4	3987	1,597.000	1.13
AMAC	5	1954	2,685.000	
North	6	969	5,965.000	
	7	718	17,040.000	0.83
	8	313	74,350.000	0.36
	Sub-Total	86295	102, 837, 467.8	-
	1	43617	135903.1	54.78
	2	20668	300059.3	25.95
	3	7612	764505.3	9.56 4.94
AMAC	4	3940	1597000	3.20
South	5	2542	2685000	
	6	878	5965000	1.10
	7	376	17040000	0.47
	Sub-Total	79633	28, 487, 467.8	

However, floods may occur in situation when run off exceeds the capacity of the catchment area or river bank, the likelihood of flood will be high in distal areas of the basin due to presence of gentle slope gradient and low surface run-off (Singh & Awasthi, 2011). Based on the settlement development pattern observed in Figure 6.6 and DNO in Table 6.2, variable threat of perennial flood events may increase in some segments of Abuja basin. If not addressed the situation will get worse as climate change manifest.

6.3.5 Bifurcation Ratio in Flood-Risk Assessment

Higher bifurcation ratios are indicative of shorter lag time, which also may result in greater peak discharge. Br is relevant to humans because as it reduces, flood risk potential in human environment increases (Waugh, 1996). Br is useful in detecting how basins are prone to flood risk when disaggregated than as a whole. The overall bifurcation ratio of the entire Abuja basin ranged from 1.70 to 4.36 with a mean bifurcation ratio of 2.57 (see row one) (Table 6.3). However, for Kubwa and AMAC (North and South) basins, the Br varied due to different environmental conditions that dominate and the mean Br were 2.01, 2.08 and 2.26 respectively as shown in Table [5].3 and implies varying flood risk potentials in Abuja. The Kubwa basin had the lowest Br which indicates that Kubwa is vulnerable to flood events.

Table 6.3: Bifurcation Ratio of Abuja Basins

Basins	1st order/ 2nd Order	2nd Order/ 3rd Order	3rd Order/ 4th Order	4th Order/ 5th Order	5th Order/ 6th Order	6th Order/ 7th Order	7th Order/ 8th Order	Mean Bifurcation Ratio
Abuja	2.01	2.55	2.06	1.70	2.22	2.86	4.36	2.57
Kubwa	2.24	2.70	2.16	1.40	1.56	-	-	**2.01**
AMAC North	2.26	2.42	2.21	1.04	2.02	1.35	2.29	2.08

[5] .3.6 Computation of Drainage density (Dd)

The computed Dd of Abuja is presented in Figure 6.7. Theoretically, the inverse function of infiltration process can be signified as Dd. Thus, areas with less rain water infiltration experience surface runoff due to high concentration of Dd (Dunne & Black, 1970; Gregory & Walling, 1968). Hence, high values of Dd is favourable for runoff and indicative of minimal occurrence of flood event.

AMAC South	2.11	2.72	1.93	1.55	2.90	2.34	-	2.26

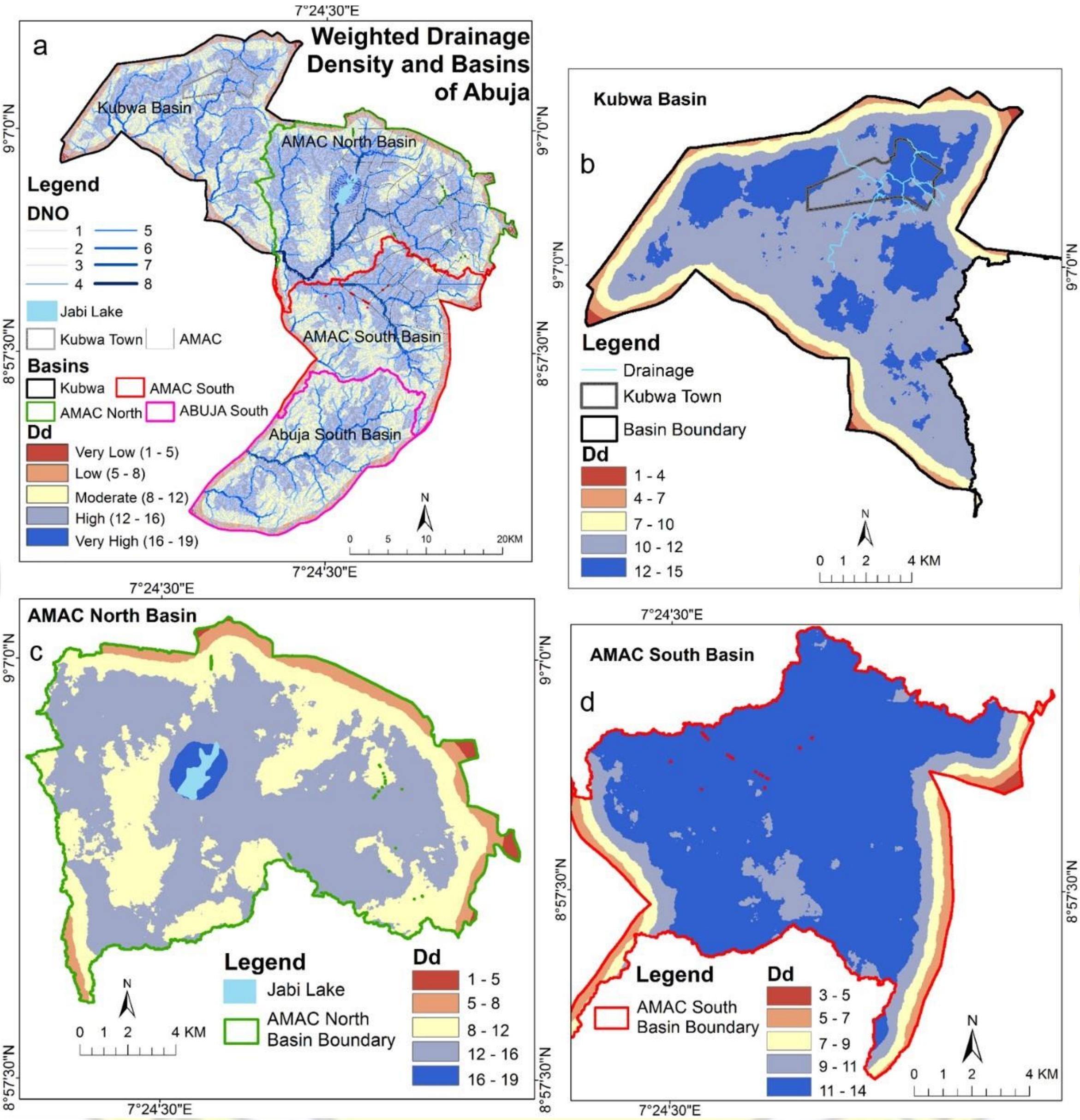

Figure 6.7: Map showing the weighted drainage density of Abuja

To fit the computed Dd for our flood hazard assessment, the weighted approach was applied (Wang *et al.*, 2011). From the computed Dd map it is apparent that the three stratified basins have varying drainage densities which is also indicative of varying flood occurrence probability and subsequent impact. Figure 6.8 presents the six weighted maps of slope (in degrees), CTI, micro watershed, DEM and overlaid stream orders, 2014 LULC Map and drainage density maps labelled (a-f) respectively.

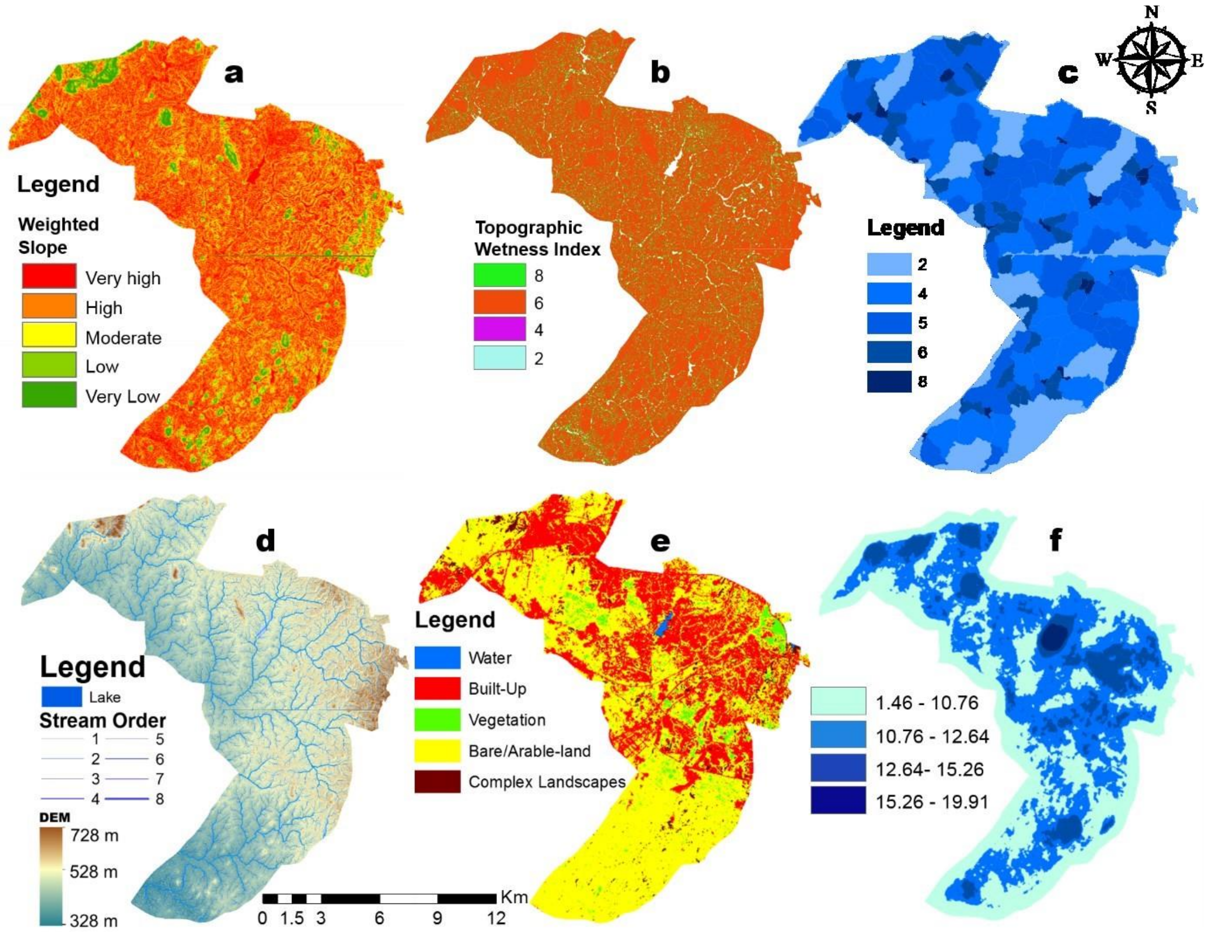

Figure 6.8: Weighted factor maps (a) slope, (b) Compound Topographic Wetness Index, (c) Micro-watershed Maps, (d) DEM/stream order, (e) LULC 2014 and (f) Drainage density map

The slope map contains useful information such as gentle and steep slopes Figure 6.8(a). In the context of this study, areas with steep slopes have low flood risk as runoff is high, conversely in regions of gentle slopes, low runoff is the norm, which makes such location susceptible to flood occurrence. A close detail of the DEM depicting height shows that substantial part of Abuja is a moderately low and flat area and potentially flood prone, considering LULC change and settlement development pattern along floodplains. The CTI is a good indicator for locating areas with tendency of accumulating water and are likely to be wet for a period of time. These areas are usually low, which may be related to the angle of slope, thus lower slopes implies higher wetness index value. It has been found to be highly correlated with soil attribute such as horizon and depth (Moore *et al.*, 1993). The generated CTI map presented in Figure 6.8(b) clearly indicate that many areas have high wetness values, which is informative for deducing how Abuja landscape is flood prone considering soil saturation potential. Figure 6.8(c) is the optimised micro watersheds generated for Abuja, which was based on size of DEM derived basin.

Run off durations and amount of water level that result in flood event depend on the size of the watershed. Hence, areas critically affected by flood are small areas having microwatersheds. In the case of Abuja, the micro-watershed sizes ranged between <1 and 47 sq. km. Figure 6.8(d) is a display of DEM with an overlaid stream order for better visualization. Height information deduced from DEM gives an impression of the relief and in the case of Abuja it can be seen that Abuja can be distinguished rest with generally low altitude. Thus, the DEM was utilized to identify lower locations such as like Kubwa settlement which is more susceptible to flood event. Figure 6.8(e) shows the 2014 LULC maps of Abuja with some builtup areas located in areas of (i) gentle slope (ii) low height, (ii) high wetness index location, (iv) within small watersheds and (v) and in low drainage densities. Integrating all these factor maps of Abuja with other relevant parameters such as soil and rainfall data using GIS-based approach can help to produce decision support maps for detecting climate related risks including floods (Giupponi *et al.*, 2013). All these factors map generated for Abuja were subsequently assigned to logical weights based on their perceived contribution to the flood process. Details of the weighting assigned to six maps used in the overlay are tabulated and presented (Table 6.4). In this study, rainfall analysis was done separately and result showed increasing trends in annual wet days as well as the total amount of annual precipitation. Thus the upward trend of rainfall as presented further confirms the vulnerability of different location to flood threat in Abuja.

Table 6.4: Table showing weighting details of various factors

a

Class	Drainage density (Dd)	Weight
1	< 1 – 11	8 (Very High)
2	11 - 13	6 (High)
3	13 - 15	4 (Moderate
4	> 15	2 (Low)

b

Class	Topographic Wetness Index	Weight
1	> 7	8
2	3 – 7	7
3	-3 – 3	5
4	< -3	2

c

Class	LULC Map	Weight
1	Water	8
2	Built-Up	7
3	Vegetation	5
4	Bare/Arable-land	4
5	Complex Landscapes	2

d

Class	Slope (Degree)	Weight
1	< 3	8
2	3 - 9	7
3	9 - 21	5
4	21 - 50	4
5	> 50	2

e

Class	Micro-Watershed (Sq. Km)	Weight
1	< 1 - 5	8
2	5 - 10	7
3	10 - 25	5
4	25 - 35	4
5	> 35	2

f

Class	Height (m)	Weight
1	< 390	8
2	390 - 428	7
3	428 - 528	5
4	528 - 628	4
5	> 628	2

6.3.7 Flood hazard mapping

The ultimate goal of producing the flood hazard zone for Abuja and environ is to determine the probability of flood risk occurrence for each zone and was estimated from the combined total of the weight assigned to the selected contributing factors. The overall weighted sum of all causative factor maps were overlaid. The multi-criteria analysis functionality in a GIS can be leveraged on to the sum of relevant weighted layers (Heywood *et al.*, 1995; Mokarram & Aminzadeh, 2010). The contributing factors are displayed in a logical raking from the highest to the lowest (i.e. 6 to 1) and resulted in the flood risk hazard map (Table 6.5).

Table 6.5: Relevant factors contributing to urban flood risk zone map

Class	Contributing Factor	Weighting
1	Topographic Wetness Index	6
2	Micro-Watershed size	5
3	Drainage density	4
4	LULC type	3
5	Slope	2
6	Height	1

The ranking is based on expert judgement of the factor maps. CTI was ranked 6th because it is indicative of water collection intensity, the micro-watershed size is a strong determinant of run off durations and amount of water level that result in flood event and was ranked 5th, Dd was ranked 4th because its shortfall increases runoff chances in a given area which can result to flood event. LULC was ranked 4th because it is a chief determining factor of runoff especially when the land use hinders infiltration and facilitate overland flow. Slope and Height were ranked 2nd and 1st meaning least contributing factors in this case because they have also been considered in computation of CTI. However, individually slope is useful in identification of flat, gentle and steep locations of an area. High locations also releases water quickly, while low areas with adequate drainage and porous soil might not lead to flooding but when combined with other factors can trigger flood event. Using the spatial analyst geoprocessing toolbox embedded in ArcGIS 10.2 enabled the successful generation of the flood hazard zonation map of Abuja was achieved by implementing the weighted overlay analysis.

Figure 6.9 presents the flood risk zone map of Abuja which illustrates how various parts of Abuja and its inhabitants are exposed to flood risk. Generally, flood risk in Abuja can be characterized as low to moderate. However, in the Northern and North-Western parts noticeable patches of high flood risk zones can be seen. Kubwa basin which had the lowest bifurcation ratio in the morphometric analysis (Table 6.3). In terms of drainage density (see Figure 6.7), substantial parts of Kubwa settlement is also poorly drained, and is a factor in the flood propagation process coupled with built-up within the floodplains as depicted in the settlement expansion encroachment into the floodplain in Figure 6.6. For the AMAC regions, apparent flood risk ranges from low to moderate flood risk potential and this can be attributed to factors such as high Br, Dd and height of 400m and above as well as adequate sewer line infrastructure.

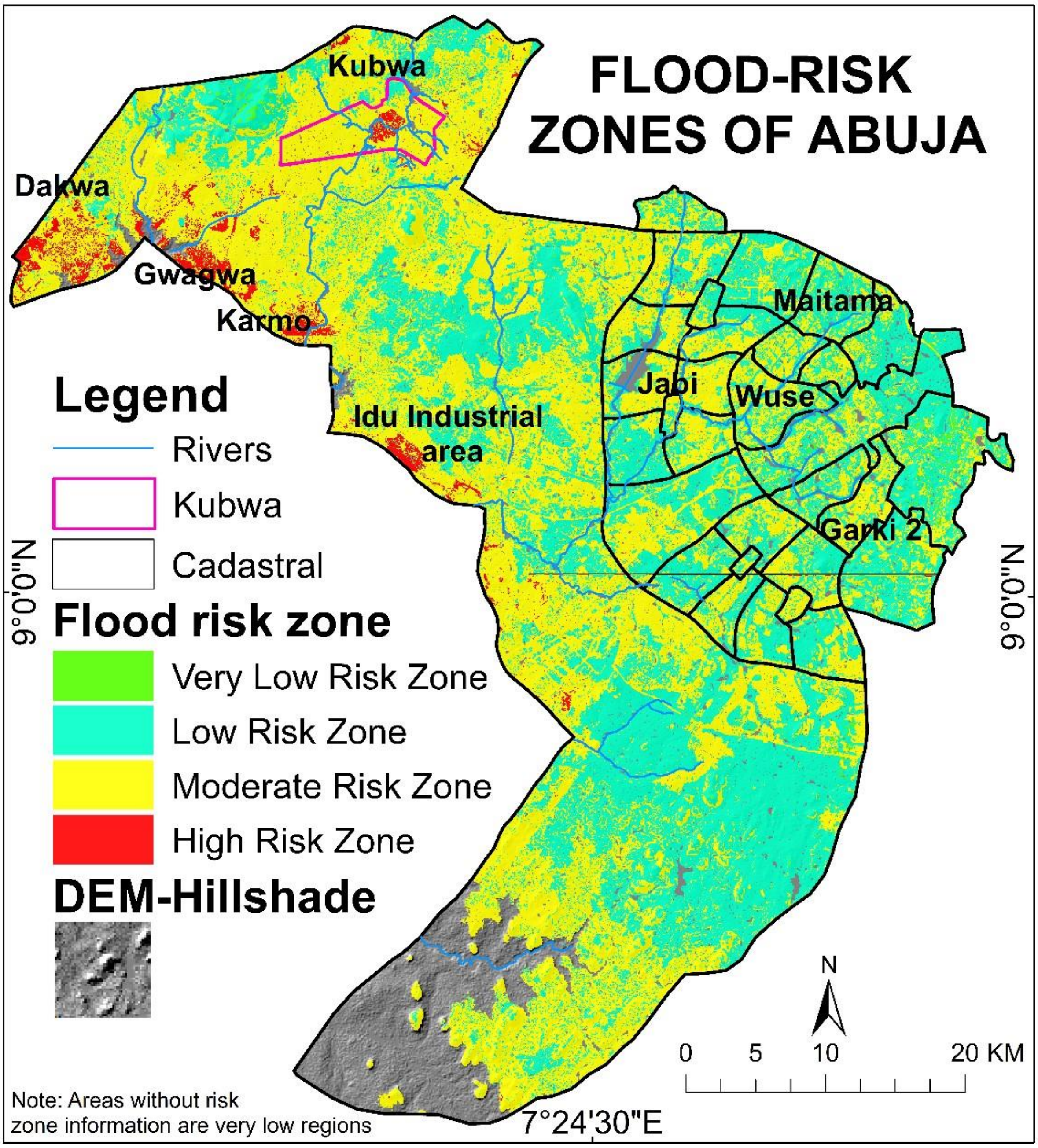

Figure 6.9: Flood risk hazard zone map of Abuja

6.3.8 Analysis of social vulnerability

Figure 6.10 provides a descriptive statistic of the social survey conducted with the aim of assessing and analysing social vulnerability of inhabitants in the central part of Kubwa to flood risk. For instance the level of education can be somewhat indicative of how quick household or communities would resist and respond in emergency situations such as flood risk hazard.

Figure 6.10 (a) displays that 46% percent of respondents were university graduate, 25% were professional, 20% attended primary school and 5% are semi-illiterate. Figure 6.10 (b) indicated that 51% of respondent in the area were job wage earners. From Figure 6.10 (c) it was apparent that 77% of inhabitants along this area were tenants. While Figure 6.10 (d) showed that flood impact was usually wall/fence-humification, road overflow and occasional inundation at 52%, 46% and 2% respectively.

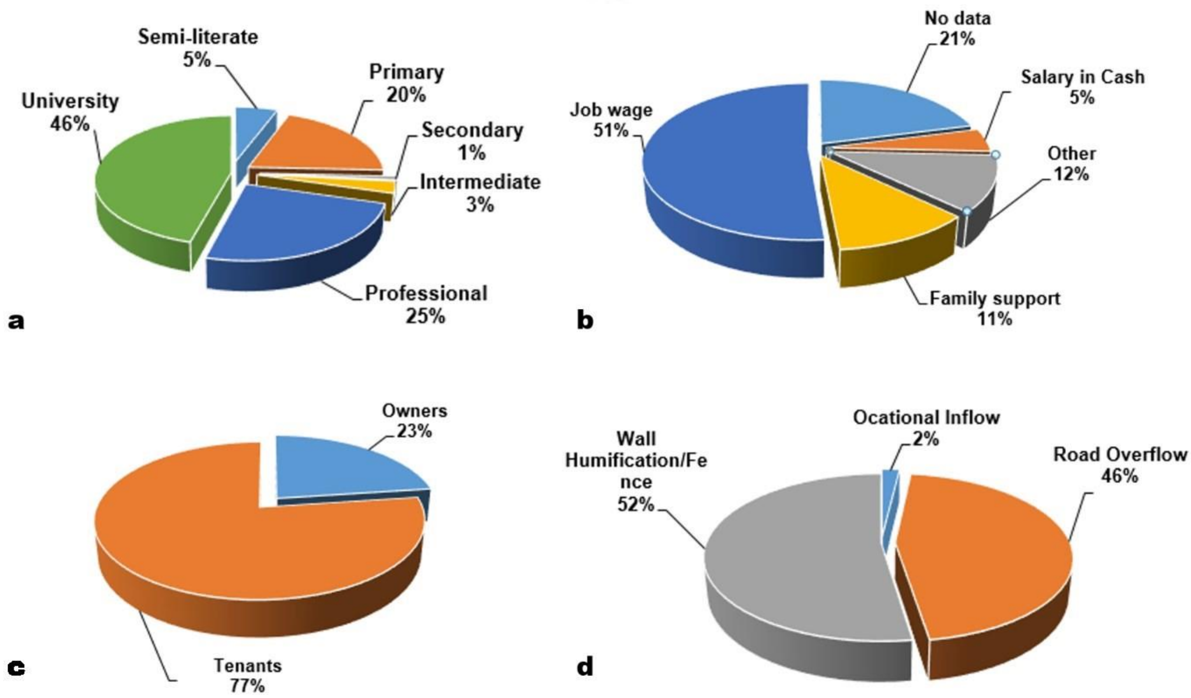

Figure 6.10: Descriptive statistic of social survey conducted in central part of Kubwa. (a) describes the educational level of respondents in the survey, (b) shows the economic status of respondents, (c) highlights the social status of respondents and (4) gives an idea of impacts based of existential questions asked.

From a separate findings about Kubwa master plan, parcels close to the river were designated as green areas, but became built-up due to housing demand because it is expensive to live in the city. Workers prefer to settle in a satellite town such as Kubwa which is somewhat affordable. In addition, despite policy and enforcement effort settlement expansion is going on with poor spatial planning standard and without reflection of environmental risk tied to development in such locations as can be seen in settlement along natural water drainage in

Kubwa. Another important issue on house ownership is the unequal distribution of wealth and development imbalance and infrastructural injustice between the main city and Kubwa. There are other driving forces governing settlement expansion toward floodplain including socioeconomic status of persons and land use policy challenges. Specifically, poor spatial planning of nearby settlement to the city, master plan implementation/development control issues, access to land are big problems that encourage settlement in floodplains without thinking of flood occurrence or reoccurrence. Thus with vagaries of the weather, more serious impacts can be expected in Kubwa area due to climate and LULC change.

The foremost element analysed to further assess the social vulnerability of Kubwa settlement in study was exposure, which was also determined based on household size. In terms of exposure, Figure 6.11 displays most of the exposed population to flood impact from the sampled families that are located in the upper middle and lower part of the floodplain of Kubwa drainage. Exposure is represented in graduated dot and as the dot enlarged so is the increase in vulnerability to flood. Considering the spatial distribution of exposure in Kubwa, adverse consequence is dependent on household population. Hence households with more number of persons are likely to be affected in case flood disaster occurs in prone areas. Susceptibility was determined using the number of children below the age of 4 years in a particular household. Here, these household have the tendency to suffer most impact from flood events in the rainy season.

Susceptibility is depicted in Figure 6.12 with scattered distribution pattern in the upper, middle and lower parts of Kubwa floodplain and ranking was from very low to very high. Household with fragile target age (below 4) in the sampled population were depicted to be susceptible to flood event in Kubwa. This is because children within such age bracket are affected by water borne diseases and are humidity sensitive. Considering the settlement location, steady state wetness of the highlighted households can affect health of children.

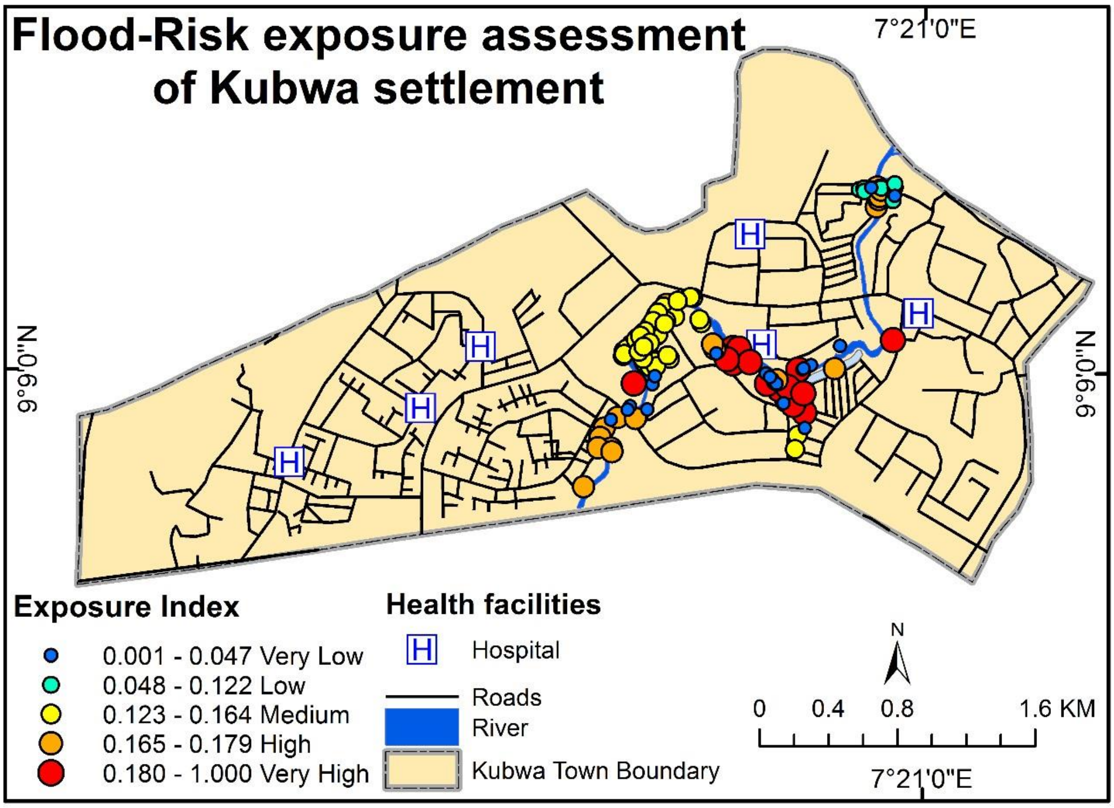

Figure 6.11: Exposure of Kubwa to flood-risk based on household size

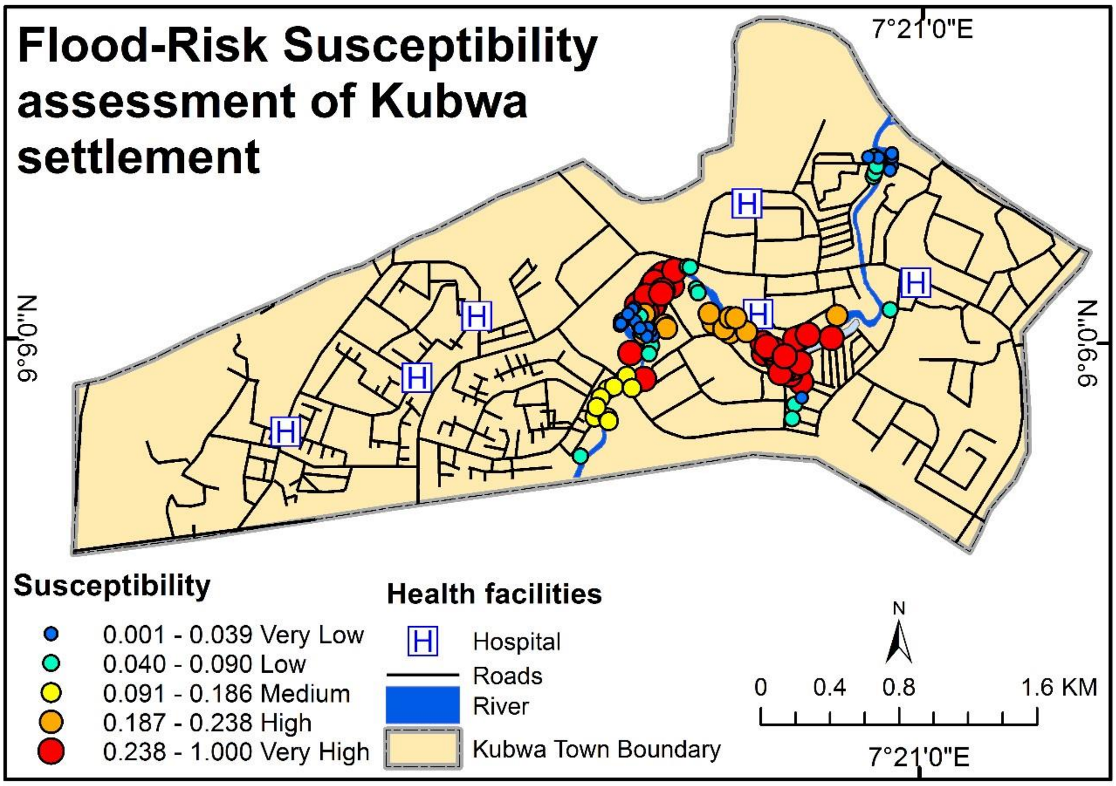

Figure 6.12: Household susceptibility in Kubwa

However, vulnerability to flood risk is not exclusively tied to climatic conditions but rather a combination of numerous contributing factors such as socioeconomic status, poor drainage infrastructure and obstruction of drainage due to solid waste dumping in the water ways. In this study, due to limited indicators and sampling carried out, the final vulnerability assessment was computed based on exposure and susceptibility of house hold size and population of children less than age 4 (Figure 6.13).

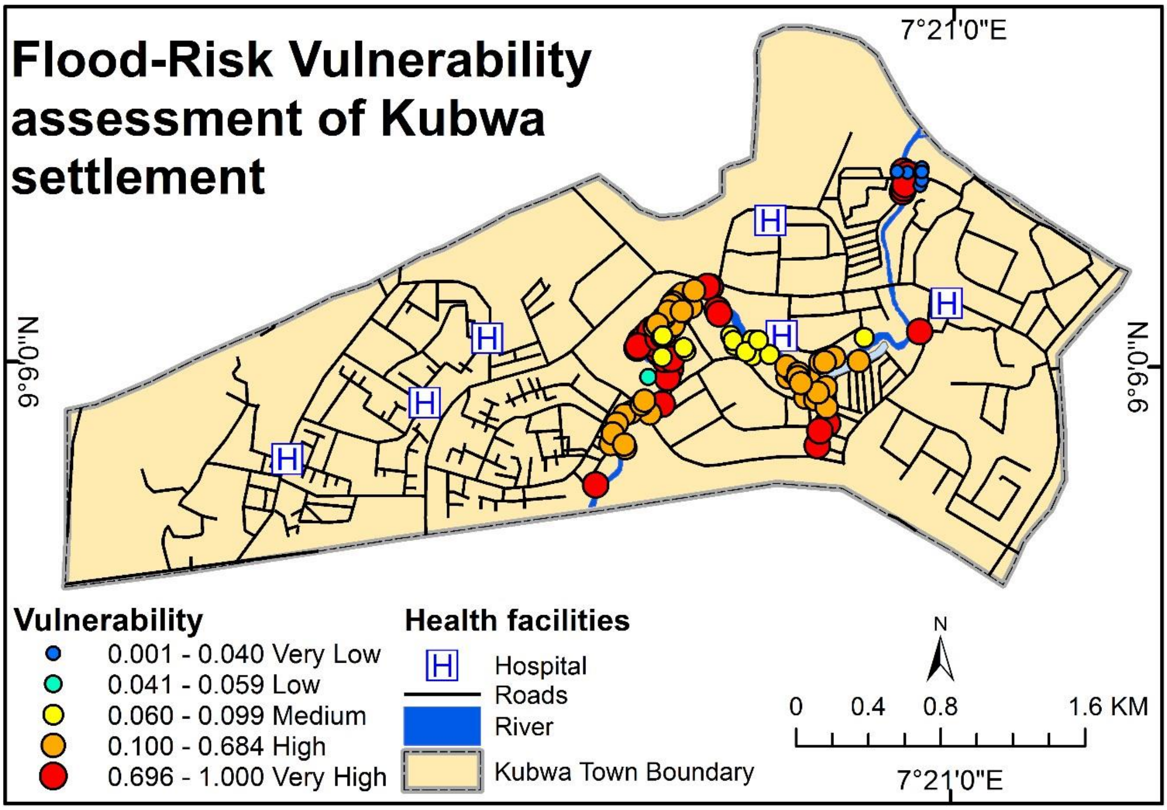

Figure 6.13: Flood-risk vulnerability map of Kubwa

6.4 Conclusions

Considering that rainfall is a vital variable of climate that can be used to assess human security, precipitation analysis was performed. Result showed increasing trend in rainfall pattern, total annual precipitation amount and number of days with precipitation above 10mm, which are likely threat to human security depending on the location characteristics. The rainfall anomaly index computed show at one point dry years possibly indicative of drought and lately wet years coupled with land use related factors may have induced the recorded flooding events.

This can be considered to be the manifestation of climate variability/change linked to LULC change in Abuja.

Additionally, the morphometric analysis such as computation of drainage density, bifurcation ration and the weighted overlay for flood risk zone identification of Abuja showed that various parts of Abuja such as Dakwa, Gwagwa, Karmo, Kubwa, Kagini, Karsana, and Idu industrial area are highly susceptible to flood risk. Similarly, the flood risk zone, exposure and susceptibility map generated, further confirms that various parts of Abuja are exposed, susceptible and vulnerable to flood risk in varying degrees.

In the case of social vulnerability assessed for Kubwa, the exposure and susceptibility indicators were found to be important for assessing settlement vulnerability to flooding in the central part of Kubwa which is a human security challenge. The approach demonstrated proved to be a simple and cost effective means of conceptualizing and assessing human security threats due to natural and human-induced hazards. The created flood hazard map can be used by responsible government department, municipality administration for disaster risk reduction through risk city awareness initiatives.

CHAPTER 7 : VERY HIGH RESOLUTION REMOTE SENSING OF URBAN DENSITY AND URBAN STRUCTURAL TYPES OF ABUJA CITY FOR FINESCALE VULNERABILITY ASSESSMENT

Abstract

This study used the WorlView-2 Very High Resolution (VHR) image of Abuja to extract fine scale urban density information and Urban Structural Types (UST) of Abuja to support urban dynamics monitoring and effective management. Advanced digital image analysis such as the Object-Based Image Analysis (OBIA) by segmentation and subsequent classification was applied for UST extraction using spectral and contextual image properties. The UST classification was characterised by identification of building density and interpretation of various building types (e.g. type of settlement, building status, land use and development types) vegetal cover, structure, proportion, homogeneity and composition at local aggregation scale. Results of this study contribute to integrated assessment of human security using UST concept with output from coarse image resolution dataset such as Landsat for identifying vulnerable urban landscapes and exposed people to potential climate and land use change impacts at a finer scale. New insight to assessing urban spatial vulnerability assessment was provided in this study using urban characteristics such as urban density, UHI, flood zone maps and UST suggest their consideration in investing how local cities climates and human wellbeing can be spatially assessed.

Keywords: Abuja, Urban density information, Urban Structural Types (UST), Object-Based Image Analysis (OBIA)

7.1 Introduction

The most apparent footprint of development in urban driving forces such as the socioeconomic, cultural and environmental characteristics is the settlement shape. Hence, the spatial structure of an urban area is the physical representation of numerous processes of city evolution and the characterization of the city form is a vital information source (Anas *et al.*, 1989), and can be utilized for numerous contemporary applications (e.g. urban spatial vulnerability assessment). The world have witnessed urbanization-induced rapid development and currently, over half of the global human population reside in cities (UN, 2012). Therefore, synoptic and recent spatiotemporal information of urban areas is of essence.

RS data qualifies to provide critical urban information needs for urban planners (De Paul, 2007), and other urban applications (Patino & Duque, 2012). The advancement in the development of Very High Resolution (VHR) optical space-based sensors such as Ikonos, Quickbird, GeoEye series, SPOT and WorldView series has paved way for fine scale house or block level data (Maktav *et al.*, 2005), and information extraction capabilities. Notwithstanding this advances, image with VHR have their own challenges they pose in their analysis (Donnay *et al.*, 2001), while statistical analysis by conventional approach have been overtaken by contemporary object oriented image analysis concept (Blaschke & Strobl, 2001). Numerous concepts of about image segmentation methods and tools have been proposed (Dragut *et al.*, 2010; Esch *et al.*, 2008; Neubert *et al.*, 2006; Reinhold *et al.*, 2008). Many works have been documented on the use of object-based image classification in urban area (Aguilar *et al.*, 2012; Bahr, 2004; Myint *et al.*, 2011; Stow *et al.*, 2007; Taubenböck & Kraff, 2013; Thiel *et al.*, 2008). Taubenböck *et al.*(2007) proposed an approach for the detection of urban structure with building estimate using VHR dataset, which yielded improved result and high accuracy. The application of LiDAR data have been demonstrated (Haithcoat *et al.*, 2001; Weidner, 1995) and combined analysis using multispectral image have been implemented (Kressler & Steinnocher, 2008; Rottensteiner *et al.*, 2004).

RS-based structuring extraction is image data dependent (Taubenböck, Esch, *et al.*, 2008a), and purpose dependent. A somewhat straight forward approach of structuring for ecological applications such as urban biotopes have been presented (Bochow *et al.*, 2007). In the case of UST extraction in built landscape, similar to the procedure applied by Bochow *et al.* (2007) was demonstrated (Banzhaf & Hofer, 2008; Wurm *et al.*, 2009). Here spatial unit at block level characterization was applied based on LULC and urban material. Using the urban fabric concept, homogeneous urban morphological areas are aggregated based on their physical representation and use. Classification is based on contextual building parameters such as size, shape, height (floor), density and proportion of vegetation as well as impervious surfaces. The mapping of area-wide UST using remote sensing approaches has been done through visual analysis of Color Infrared (CIR) aerial photo images or field campaign (Socher, 1999), which is known to be a laborous approach especially in large cities (Wurm *et al.*, 2009). However, the said approach guarantees quality UST information generation but with irregular updating disadvantage. Recently, Banzhaf and Hofer (2008) proposed a contemporary approach using segmentation concept on CIR aerial photo images, while Meinel (2008) demonstrated automatic labelling method on topographic maps describing the potentials and challenges in mapping at area-wide scale.

UST can be used as a monitoring system for analysing urban dynamics, ecosystem services and regulatory functions using specific land use information (Banzhaf & Hofer, 2008). Urban density being a measure for determining urban dimensions such as form, social and functional (Jenks *et al.*, 2005) and is relevant in measuring environmental quality, mobility systems, urban forms and physical infrastructure, socio-economic factors which can be linked to distance, diversity, population as well as maximum and efficient use of a potential city. By extension, urban density information and UST can be used for assessing city vulnerability to potential climate impacts due to urban land-use changes. Specifically, its usefulness for fine scale vulnerable hot spot analysis is proposed in this study by integrating UST with UHI and Flood zone data and information generated from chapters 5 and 6 of this dissertation. Measuring urban density information here refers to intensified use of a space divided by the total urban area. Classification of urban structure can be described to be the identification of buildings such as housing types, industrial buildings, infrastructure, open spaces, parks and garden, structural composition that reveals their amount, pattern of imperviousness, connectivity of the various landscape, open and other green spaces and their homogeneity at neighbourhood scale. The characteristic of aggregation facilitates the extraction of UST. However for any substantial spatial context impact to be noticed, UST changes has to occur in large scale. With respect to dynamics in urban structure in a city such as Abuja, the added value of urban density and UST in urban science for climate impact and vulnerability analysis is assessed. Such analysis is informative of the contribution of building structure and composition in identifying vulnerable inhabitant based on the variability in urban density and structure. Data models (i.e. the extracted UST, UHI, urban density, road density and NDVI) are combined to assess vulnerability of people and places in the study site. The description of how the various vulnerability pieces are combined to further identify vulnerable places or hotspots is presented in the method chapter This is based on the location of urban structure inference of people likely to be impacted. In this study, measuring urban density information and extraction of UST is explored for assessing the vulnerability of Abuja city to potential climate impacts due to climate and urban land use changes. Here, VHR WorldView-2 image data is used to extract urban density information and UST by rule-based segmentation and classification concept.

7.2 Materials and Methods

7.2.1 Data

The WorldView-2 imagery comprises of six row and five column with scene size covering a spatial extent of 16 x 14 km^2 approximately 17km to the West and 20km East-ward. The scene was in a WGS84 Universal Transverse Mercator (UTM), zone 32N projection. The image was generated in a nadir look angle position at a scale of 1:12,000 and with a dynamic range of 11bit per pixel (1024 level). The image was collected on 11th December, 2010 with cloud cover of just 1%. The imagery had nine bands, one panchromatic band with 0.5 m spatial resolution and eight multispectral bands (coastal, blue, green, yellow, red, red edge, nearinfrared 1 and 2) with 2 m spatial resolution. Other dataset used in this study included thematic vector layer derived from the Abuja Master Plan (AMP) (Ibrahim Mahmoud, 2007), administrative boundary and road vector, subset of landscape indices map information (e.g. Landsat derived 2014 LCLU map, Landsat-based LST of 2014 and flood zonation map).

Cities have their unique characteristic in terms of shape during the evolution phase, however, similar cultural areas are bound to have identical urban fabric. In this study, urban density and UST extraction model is demonstrated using Abuja as a case study. Details about the study area is described in chapter three. However, this study adopts a multi-site approach and two distinct sites were defined to demonstrate urban density and UST extraction and usability for fine-scale vulnerability assessment.

7.2.2 Methods

The objective of this study was to explore the extraction of urban density information and UST of Abuja using VHR optical satellite data. The rule-based OBIA information extraction approach was applied. Transferability of the ruleset developed for the UST was tested in a small portion of Abuja WV-2 image with slightly different morphology. Using advance image analysis techniques, the WV-2 image was pan-sharpened using the Gram-Schmidt sharpening method (Aiazzi *et al.*, 2006). Subsequently, a subset of the image was used to reduce redundancy and computational processing time.

7.2.3 Conceptualization of information extraction order

In this study, physical image properties were used to conceptualize information extraction order similar to the approach developed by Ibrahim Mahmoud (2012). This approach is based on saliency and semantics of apparent image features to support relevant information extraction procedure (Leyk *et al.*, 2006), which aids the definition of object simplicity for information extraction. The first focus of this study was to extract the built-up density information in the FCC. The second was the extraction of UST. The urban density based on the 2D land development concept, while for UST, the visual image interpretation and expert knowledge. was useful in extracting water body being the most trivial object to be extracted. This concept was subsequently applied for other targeted objects such as vegetation using the NDVI method. Similar to the deconstruction approach proposed by Ibrahim Mahmoud, (2012), information extraction was done by sequential procedure.

7.2.4 Multi-step-based OBIA information extraction approach

Based on the interpretation derived from human cognition of image features, the step-wise strategy demonstrated by Ibrahim Mahmoud (2012) was adopted, which facilitates effective translation of salient image objects to OBIA rule set. Logically, simpler object were extracted first, then followed by more complex features. Sequential aspects were solved by using sequential and iterative procedure (Figure 7.1).

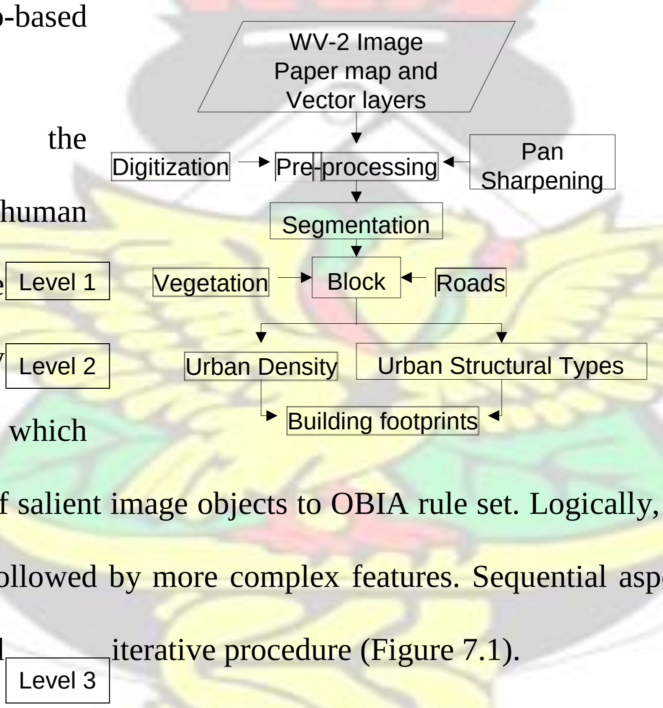

Figure 7.1: OBIA urban density and UST extraction workflow

7.2.5 OBIA implementation

In OBIA, two fundamental workflow are (i) segmentation and (ii) classification, hence these two steps were implemented in this study. Unlike the trial and error approach commonly used, this current study, applied the automated approach for Estimation of Multi-Scale

Parameter (ESP-2) which is a generic tool developed by Dragut *et al.* (2014) for eCognition software. The algorithm leverages on the local variance potential to detect scale transitions in geospatial data such as the satellite image used in this study. The tool produced a series of optimal scale options that could be applied depending on the target objects.

7.2.6 Segmentation and Classification

Segmentation, which is the process of breaking down image into smaller units (Blaschke *et al.*, 2008), was applied using optimal parameters derived from the ESP-2 tool to efficiently break the image into meaningful objects. Here, scale parameter of 96 with shape of 0.2 and compactness of 0.8 were used. Due to spectral and contextual confusion among objects, the use of thematic layer map developed for complex features was considered in the initial segmentation of the image. This approach proved useful in generating meaningful object boundaries. For the transferability test site, scale parameter of 49 with shape of 0.8 and compactness of 0.9 was used.

Assigning the identified and interpreted object to a relevant category is known as classification (Blaschke *et al.*, 2011). In the case of urban density information generation, the segmentation result was exported as vector file for subsequent analysis in R statistical package. To classify the image segmentation result, relevant container in the class hierarchy section was first created. The spectral information utilized in the classification process was the NDVI. This was useful in discriminating the variation in vegetation cover. Six block level and twelve building level USTs were extracted; details of the UST extracted are tabulated and described in Table 7.1 and 7.2.

Table 7.1: Description Block Level UST extraction scheme

S/No	Urban Structural Types
1	Commercial and Industrial
2	Educational
3	Public
4	Residential

5	Green Areas
6	Major and Minor Roads

Table 7.2: Description Building Level UST extraction scheme

S/No	Urban Structural Types	S/No	Urban Structural Types
1	Building footprint	7	Garki Village (informal)
2	Access road	8	Mixed and Commercial buildings
3	Express way	9	Tall Buildings
4	Major roads	10	Garki Modern Market
5	Vegetation Areas	11	Residential Block of Flat
6	Un Tared Road	12	Building footprint

7.2.7 Ruleset Transferability

To test the transferability of the OBIA based ruleset developed to extract UST in Abuja, a 2 km extent was defined around Jabi Lake. The site condition of this location was different from the city core. Hence, the ruleset was slightly modified. Subsequent to the image segmentation, this was followed by assigning the segmented and merged water object to the created container. The merge region operation was achieved using the spectral information based on mean NIR ≤ 399 threshold. Subsequent to the merge region rule applied, the contextual information using area ≥ 830584 pixels was used to further classify the water object into the created water class in the class hierarchy. The second spectral information utilized in the classification process was the NDVI. This was useful in discriminating the variation in vegetation cover. Here, seven USTs were extracted; details of the UST extracted are tabulated and described in Table 7.3 towards vulnerability assessment.

Table 7.3: Description UST extraction scheme in transferability test site

S/No	Urban Structural Types	Description
1	Major roads	Roads (tared/untarred)
2	Informal settlement	No planning No vegetation
3	Formal settlement	Planned with tarred roads & green
4	Commercial Lots	Business areas large buildings/Plaza
5	Mixed development	Residential, offices and business
6	Public School	Government school
7	Uncompleted Buildings	Buildings under construction

7.2.8 Accuracies of segmentation, classification and GIS modelling for city density generation

According to Congalton (1999), the quality of a thematic map can be determined using accuracy assessment measures. Thus, accuracy assessment has to be done in an objective way to ascertain the value of classification map for use. Hence, result of the OBIA-derive layers were compared to the Ground Truth Point (GTP) extracted from the image, based on previous field work and local knowledge. Basically, the accuracy assessment focused on classification accuracy and building segmentation. Semantically, the extracted polygons implied sizes and shape of buildings and further processed in a GIS environment for fine tuning such as attribute data creation. A round figure of 150 random samples were generated using ArcGIS 10 toolbox over the AMP designated residential areas. Subsequently, points manually labelled into two category of GTP as built and non-built. The accuracy assessment was eventually implemented in *R* statistical package with a script specifically designed to an overlap between the OBIA derived features and generated random points. After the script assigns the points to either built or non-built, a table of two columns is subsequently created belonging to the OBIA class and GTP. Furthermore, the bivariate table is used to construct a confusion matrix based on a function embedded in the *caret* package. According to Kuhn (2008) the aim of the package is to compute a statistical cross tabulation between the observed and predicted data class.

Similarly, Esch, *et al.* (2008) proposed an approach for accuracy assessment evaluation of image segmentation result. The accuracy assessment was implemented for three shape aspect attributes (*Area, BorderIndex and rectangular Fit*) and two for locational precision (*X-and-Y position*). Subsequently, a randomised sampling technique was employed as point initially and later manually upgraded to polygon. Although not all point were built, but nearest building were supplemented using manual intervention approach. A total of 125 built polygon were digitized and further inputted in eCognition for computation of their attribute. The GTP and

OBIA were combined also into a multivariate table and each row describing an observed feature with five columns. The upper five belongs to the GTP while the lower five columns belong to the OBIA features.

Built-Up density was computed based on the AMP vector layer sectors. Considering built-up in-homogeneity, a moving window concept was employed (Taubenböck *et al.*, 2006). Subsequently, the built environment density was computed based on percentage of built-up area. This was followed by using a script in R to add up the entire OBIA features and divide it by the AMP vector layer sectors. The mean object size per sector was also computed which can useful for socioeconomic analysis. Also two attribute tables are generated from this step. The road density analysis was not considered here. Also, the non-built-up area was not validated in this study. Since remote sensing is not able to detect land-use, discriminating apartment and office is not realistic. However, a statistical evaluation was implemented by performing a spatial joint between the density map to assess the relationship between the urban density information and LST by zonal statistics.

7.2.9 Conceptualization of fine scale vulnerability assessment

Different data models are combined in the modelling approach. Using the multi-temporal hazard assessment concept, the LST and flood risk zonation was tied to the exposure piece. The extracted urban density and UST was linked to identifying places and people either susceptible, sensitive or vulnerable to potential heat stress or flood impacts. Given that population exposure mapping form an important part in the assessment of social dimensions of vulnerability (Aubrecht *et al.*, 2011), the dasymetric population map was used for gaining insight of population estimate potentially vulnerable to the stressor. Also, the UST is useful in discerning environmental quality and infrastructural justice, which can lead to the understanding of people's adaptive capacity such as road access in the case of flood. The combination of these vulnerability pieces is informative of vulnerable population to heat stress or flood impacts by applying the simple overlay and comparison procedure (Figure 7.2). For the transferability test site the weighted overlay approach was applied to determine the overall vulnerability (Figure 7.3). Datasets used included the NDVI, UST, Road density and LST maps. These maps were reclassified and were combined using the weighted overlay approach.

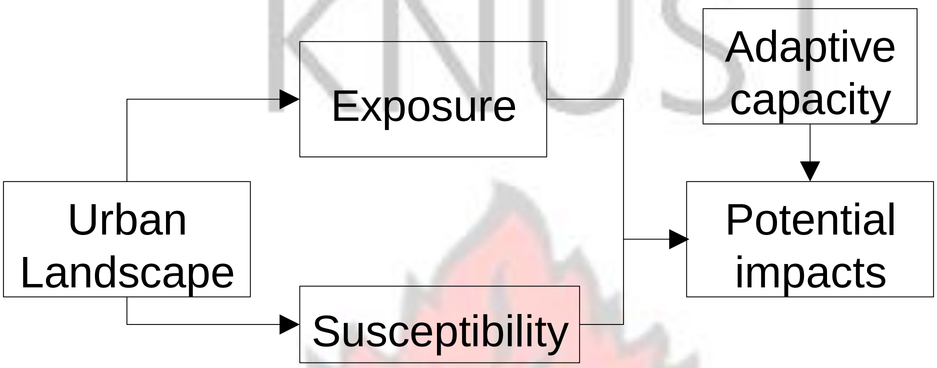

Figure 7.2: Vulnerability assessment modelling concept

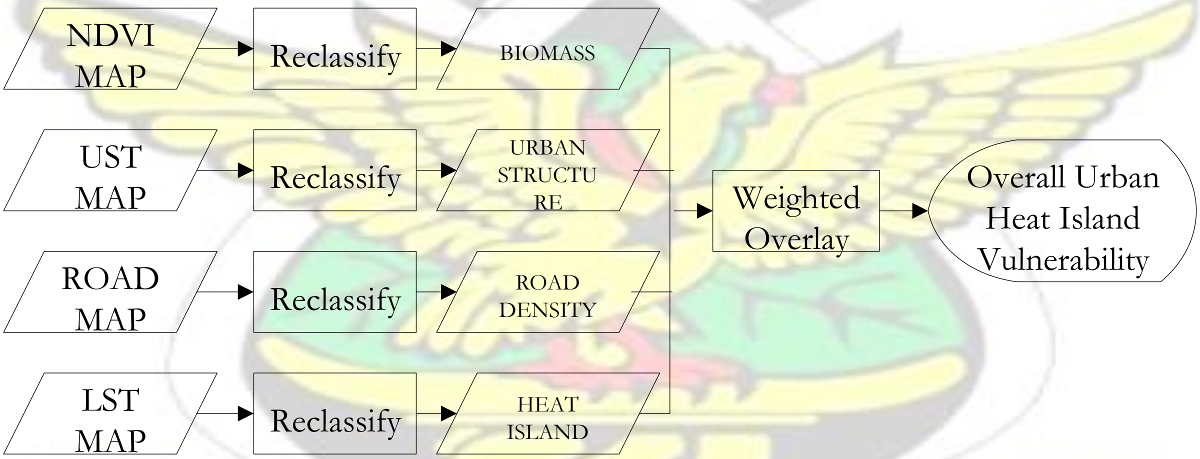

Figure 7.3: Weighted overlay modelling approach for identifying place and population vulnerable to potential impacts of UHI

7.3 Result and discussion

The generation of fine scale information such as urban density information and UST from VHR dataset using OBIA information extraction is worthwhile and help towards improved city management including climate impacts assessment. The proceeding section proves the utility of VHR data for fine scale information on urban landscapes such as urban density information and socioeconomic linkages through interpretation.

7.3.1 Urban footprint accuracies and built-up density extraction of Abuja

Figure 7.4 presents the computed urban density information from WV-2 VHR data of Abuja. However, cautious interpretation of the result obtained is required because the analysis is 2D based (i.e. foot prints), hence building height was not considered. Also, high rise dwelling units can lead to high residential density which this study did not consider. Therefore, a contextual interpretation of obtained result is sought to semantically provide some logical and realistic expiations. Based on the spatial evaluation it is apparent that Garki 2 district had the highest percentage of built-up area, followed by the central business district in limited small sectors. Percentage of built-up area in Wuse 2 district ranged between medium to high. While Asokoro, Maitama and Wuse districts were heterogeneous, hence dispersed high densities occurred within large low density sectors.

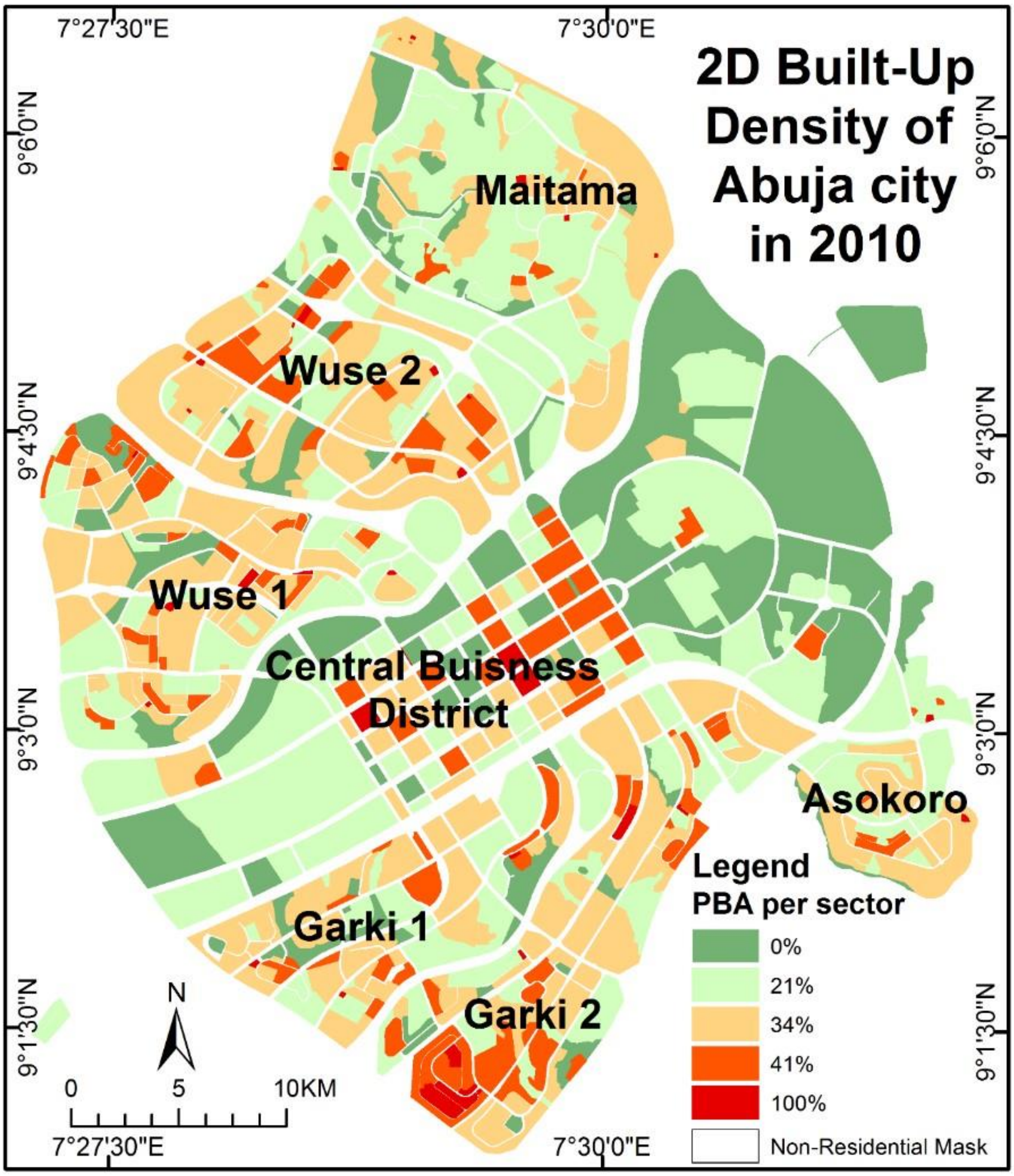

Figure 7.4: Percent of Built-Up Area (PBA) based on 2010 WV-2 Image

7.3.2 Block Level Urban Structural Types of Abuja city

Based on Figure 7.5 the UST classification was at block level showing classes such as the major and minor roads, commercial and industrial buildings, residential buildings, public buildings, educational and green areas.

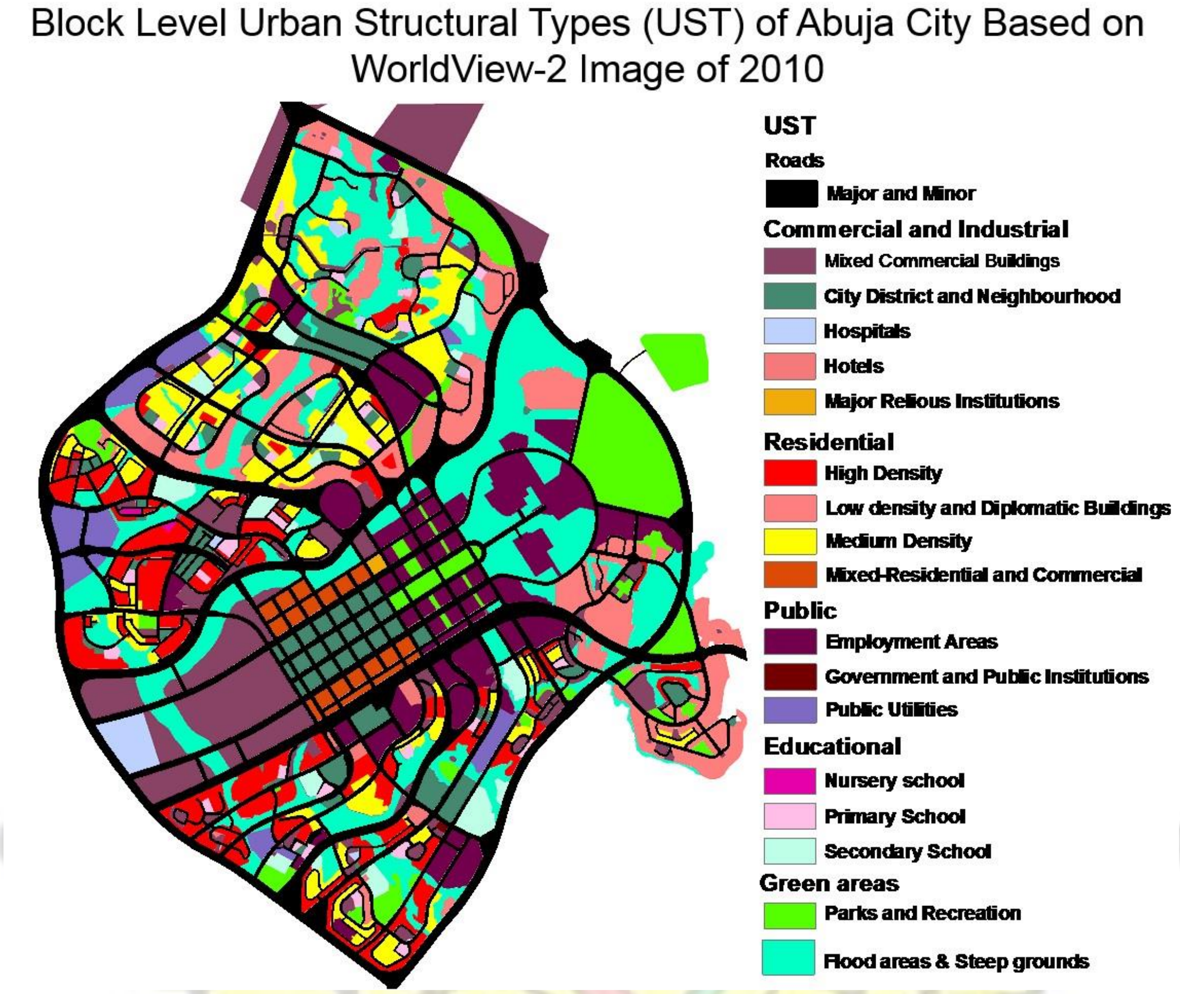

Figure 7.5: Block Level Urban Structural Types of Abuja

These major UST have sub-classes in terms of land use which is depicted in the UST map legend. Most of the public, commercial and industrial and high density residential buildings are tall buildings. Other USTs comprise of the roads rendered in black and educational structures. At block level, the two vegetation types were delineated as parks and recreation and steep grounds in green and cyan respectively.

7.3.3 Potential utility of extracted urban density information and UST for rapid vulnerability assessment of urban landscape to potential climate impacts

Figure 7.6 presents transparent overlay of the 2010 WV-2 urban density information on LST of 2014 Landsat image.

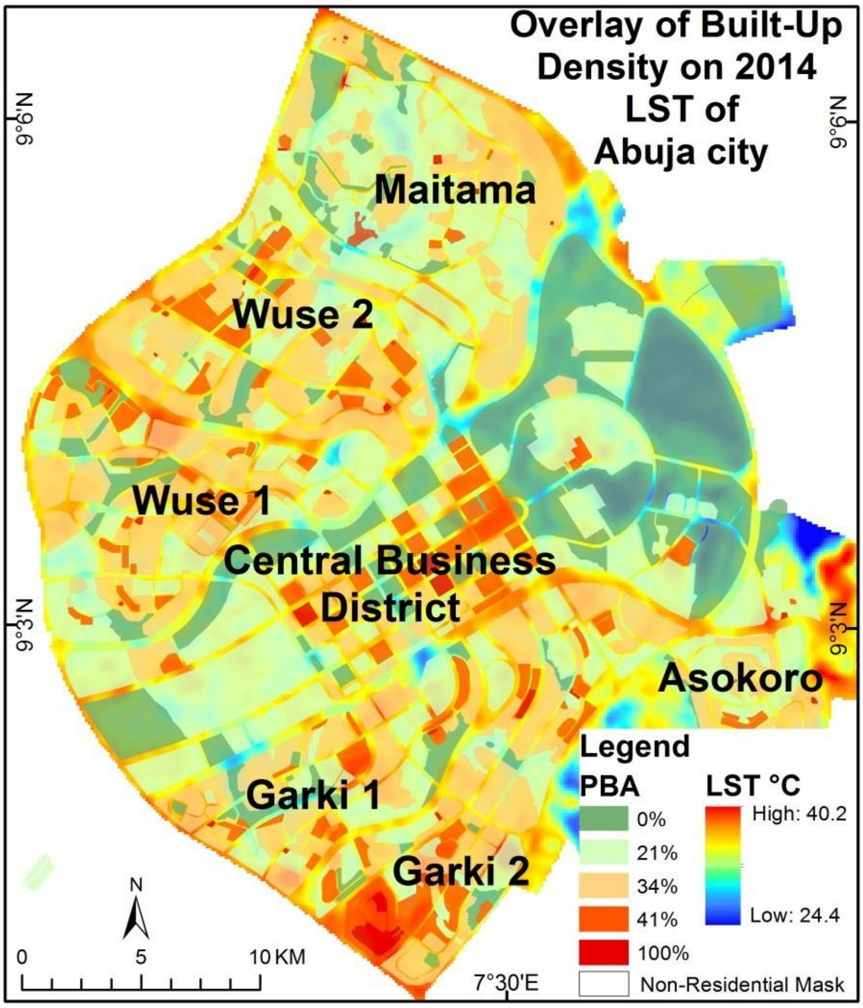

Figure 7.6: Overlay analysis of 2010 built-up density on 2014 LST

The visual assessment gives an overview of partial agreement between LST and urban density information. The urban density information corroborate its usefulness for fine scale urban landscape environmental monitoring and provides city managers with spatially explicit variation of LST patterns at district level. In the context of sustainable city management and local climate change mitigation action, this maps is useful for rapid assessment UHI potential at district level.

7.3.4 Statistical evaluation between LST, UDI in Abuja

Figure 7.7 presents the statistical relationship between the LST and urban density information in the six major district of Abuja city. The graph shows that Garki 2 had the highest maximum and mean LST (36°C, 33.51°C) which somewhat agrees with the urban density information of Abuja compared to other districts. It is also apparent that the CBD had lowest maximum and mean LST (34°C, 32°C) which can be associated to the presence of vegetation especially in north-eastern part of the CBD.

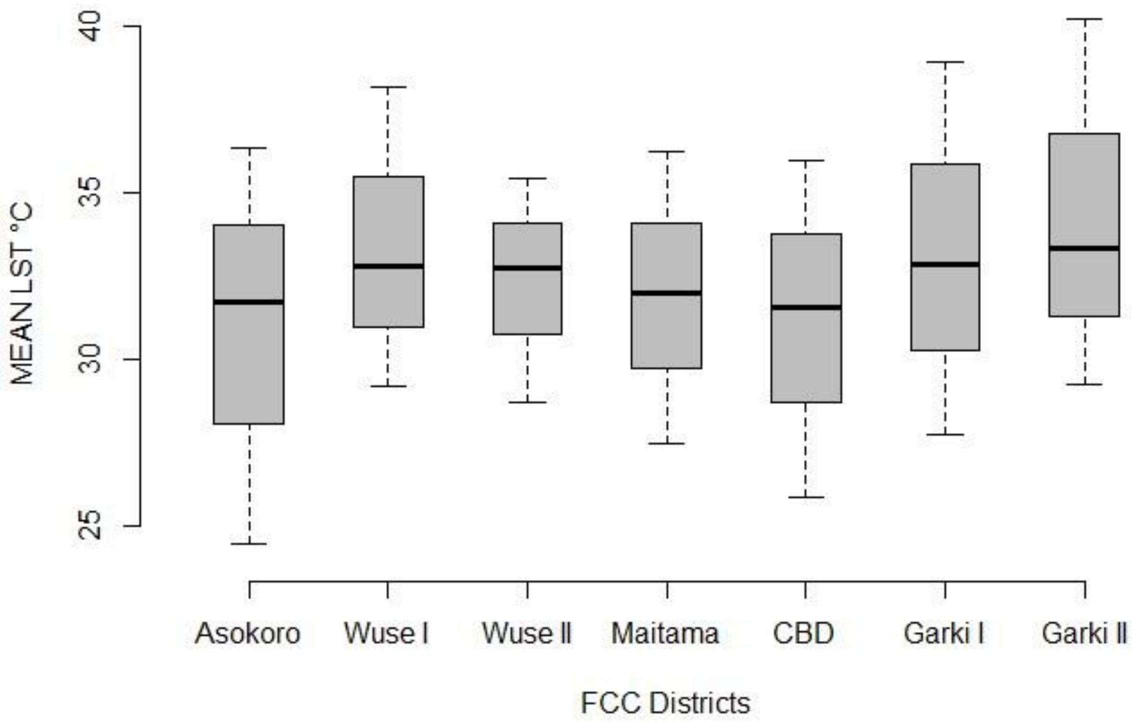

Figure 7.7: Zonal statistic of LST in Abuja districts based on urban density

7.3.5 Towards an integrated location-based physical and social vulnerability assessment of Abuja to potential climate impacts

Figure 7.8 presents maps of depicting urban indicators relevant for urban multi-temporal hazards and risk assessment including potential climate change impacts. Figure 7.8 (a) presents the 2014 LST pattern of Abuja. As can be seen, this map depicts the spatial pattern and footprint of surface temperature and the test site for UST in demarcated with black rectangle confirms UHI potential in Garki 2 district of Abuja. Based on Figure 7.8 (b), which is the flood zone map of Abuja, Garki 2 district falls within the moderate flood risk zone.

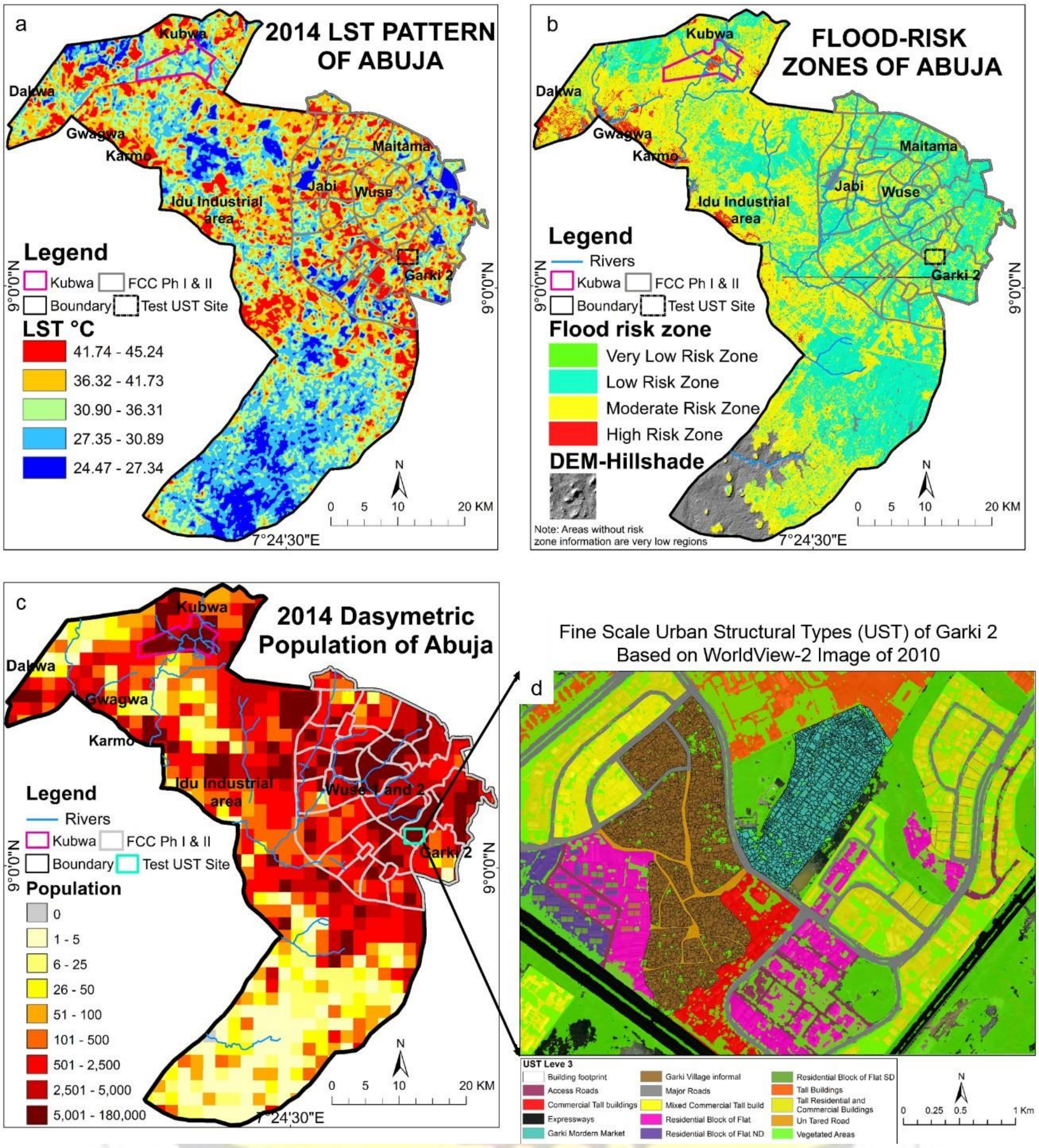

Figure 7.8: Example of visual comparison of Physical and Social Urban Risk Indicators towards Fine-scale Vulnerability Assessment of Abuja

Apparently, Garki 2 district can be inferred to have multi-temporal hazard potential in terms of UHI and flood risk from a physical point of view. With Figure 7.8 (c) depicting the 2014 dasymetric population distribution of Abuja. The estimate of human population exposed to potential risks can be contextualized within a social vulnerability assessment framework as have been demonstrated by Patel *et al.* (2015) and Aubrecht *et al.* (2013). Comparing the dasymetric population map also is form of validation of the global dataset. Area such as Kubwa, Wuse 1 and 2 and Garki 1 and 2 depicted high population density per kilometre square. Figure 7.8 (d) the UST of Garki 2 further provides fine scale detail of the landscape. The UST is also a good indicator for understanding the urban fabric and well suited for analysing the sociospatial differentiation of the urban form. The visual analysis of these urban indicator maps serves as a basis for integrated disaster risk management including assessment of potential urban climate change impacts and mitigation pathways.

Figure 7.9 presents the extracted UST of the transferability test site together with the 2014 LST of the same location. By comparing the UST and LST maps, it is apparent that the lake area has lower temperature which is expected as lakes are meant to provide cooling in cities. Similarly, green urban landscape plays a vital role in the wellbeing of urban agglomeration, thus the extracting vegetation structure at the UST scale is a valuable information in managing urban ecological systems. It is clear in Figure 7.9 (a and b) that the presence of vegetation in the formal settlements is serving as a medium for evaporative cooling while areas without vegetation such as the informal settlements are having higher surface temperature thus leading to the formation of UHI effect.

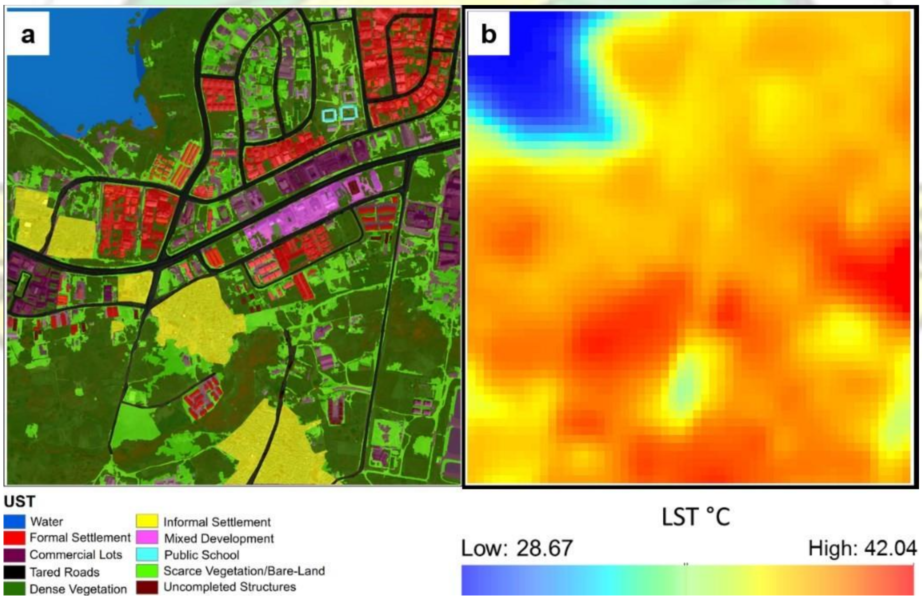

Figure 7.9: (a) UST of transferability test area and (b) LST of transferability test area As a result, more of latent heat flux is experienced in the densely vegetated areas, while the

informal settlements are seeing more of sensible heat flux. It is un arguable that urbanization is largely a climate forcing factor as presence and absence of vegetation is depicting the shifts in surface latent and sensible heat situation depending on the urban morphology. Similarly, in the case of flood risk, inference can be drawn from presence and absence of access road that the informal settlements are more vulnerable to flood impacts compared to the formal settlement where access roads exist.

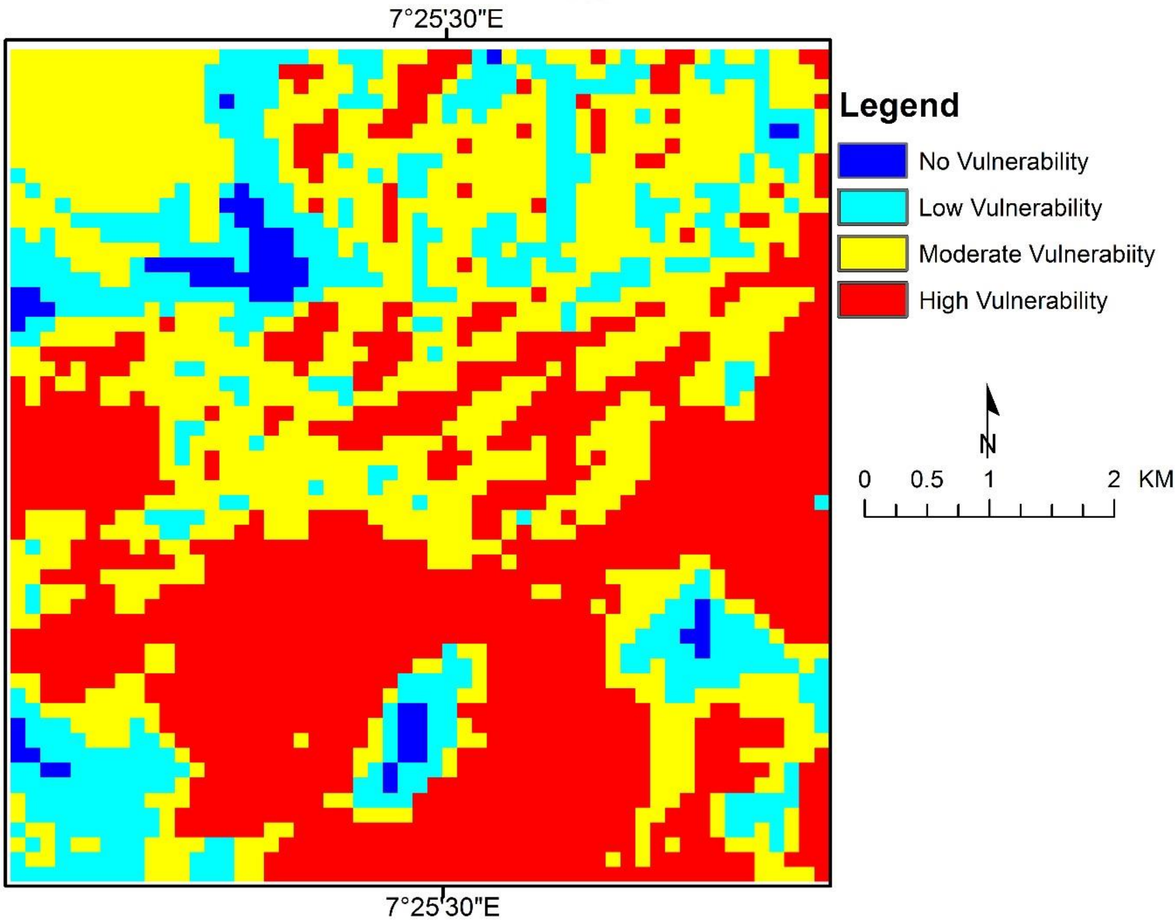

Figure 7.10: Standardized Urban Heat Island Vulnerability

Figure 7.10 present a weighted overlay UHI vulnerability assessment map of the transferability test site of this study. It can also be inferred that generally, potential UHI effects in the transferability site of this study area may include (i) energy demand (i.e. higher temperature in summer) (Zhang & Li, 2015), (ii) Air pollution and greenhouse gas emission (Hong *et al.*, 2015), especially in the formal and commercial areas, (iii) Heat-related illness and mortality (Chan *et al.*, 2012; Cyril *et al.*, 2013; Tong *et al.*, 2015), general discomfort, heat stress, respiratory difficulties, heat cramps and exhaustion particularly in the informal settlement; and (iv) impairment of water quality (which affects metabolism and reproduction of many aquatic species) in the lake area as water temperature rises (Othman *et al.*, 2016; Yu *et al.*, 2012).

7.4 Conclusion

A number of conclusions can be drawn from this study. VHR images are well suited for urban density information and UST extraction. Hence, relevant urban indicator such as urban density can be derived which is somewhat linked to human activity. For instance, the derived urban density information and UST are vital foundation investigation for fine scale studies about socio-spatial differentiation in representing socio-environmental and socio-ecological settlement impacts due to environmental change. Impacts such as the UHI effects and flood can be contextualized all within the big picture of climate and land use change context. In this study, the utility of UST further proved that there is a higher temperature in urban areas of Abuja. From a socioeconomic point of view, there are populations vulnerable and sensitive to UHI within the test site. Informal settlement are also susceptible to flooding effect due to infrastructural and environmental injustice such as lack of roads and sewer line.

CHAPTER 8 : SYNTHESIS OF RESEARCH FINDINGS

8.1 Summary of Research, Main Results and Research Conclusions

Many forecast have documented that urban growth is inevitable due to population growth and will dramatically drive the Global Environmental Change such as LULCC and climate change. Lately, the increasing variability of the climate has also been observed and repeatedly recognized as one of the most severe threats to the environment. Unfortunately, causes and effect of the changing climate are not entirely understood, not only at the global scale but including regional and local scales. Africa, especially West Africa has been identified as one of the severely threatened regions of the world. The knowledge about the impacts of the changing climate regime in also poorly understood in West Africa. Thus, avoiding the negative impacts and anticipating potential positive gains for sustainable human living conditions is challenged. Significant population growth trends aggravates the challenge further, especially in regions experiencing rapid urbanization. By far in West Africa, Nigeria has the highest population and has also one of the highest growing rate. This will continuously serve as a driver for land conversion from natural state to built-environment. In Nigeria, land conversion effects have been observed, and lately increasing significantly at the expense of natural cover. It is unclear how these interacting changes in land use will force climate to change especially in the urban environment of Nigeria and thus the living conditions of city inhabitants.

Geospatial Information Technologies (GIT) such as RS and GIS more and more enable interested scientists to gain better insights on spatiotemporal patterns occurring in urban environments and its surroundings. The combination of these GIT allows scientist to derive relevant geoinformation products from climate and socioeconomic data inputs for improved spatiotemporal discrimination of socio-spatial dimensions of LULCC on local climate change impacts and possible feedback loops. But so far, these kinds of analysis that support better understanding of the climate-urban interactions and the vulnerability of cities and their inhabitants to climate change in West Africa are rare, which is mainly due to limited availability to base data. However, where such studies exist, they seldom implement rigorous data standardization and validation strategies. This in turn raises question on reliability of existing investigations. Based on these gaps, especially at local scale, inventories of urban environments remains challenging and relevant to researcher, policy and decision-makers for improved understanding of human well-being and security in urban areas will respond to climate variability. This dissertation addresses relevant research question that empirically close the knowledge gap about data issues, methodologies and scientific explanations about climate change within the urban climate science framework and the core analysis are structured into four components.

The analysis of settlement expansion and urban growth modelling for assessing potential impacts of urbanization on climate in Abuja city was the first analysis investigated in hind-cast mode using LULCC inventories of 1986, 2001 and 2014. While the study demonstrated the relevance of Multi-sensor/Multi-temporal RS images to assess retrospective changes in LULC, the urbanization processes and drivers were tracked and was subsequently used to project settlement expansion for the year 2050. In the result it was apparent that urban areas increased by about 11% between 1986 and 2001. By the second time step between 2001 and 2014 the change rose to about 17%. These show that in the past three decades (1986-2014), population growth in Abuja was phenomenal. Furthermore, the computed urban growth indices was characterized by a significant annual land use change rate. From 1986 to 2001 the change rate was above 8.5%, and between 2001 and 2014 the change rate exceeded 6.3% which is indicative of swift LULCC. The land change model projected a future growing trend in urban land use. This could take over allotted spaces for green areas and agricultural lands if stringent development policies and enforcement measures were not operationalized. Hence two salient aspects inferred from this study are that: massive impervious surface development occurred, which may lead to elevated urban temperature known as the UHI phenomenon, which have been proven by Coutts *et al*. (2007) and (Sun *et al.*, 2010). Complimentary to the UHI is the change in drainage geography and may also increase surface runoff, which may translate to flooding event in urban cities. When rainfall increases, surface runoff is expected to trigger flooding in Abuja especially looking at the 2050 built-up projection in the context of climate change.

Pertinent issues regarding multi-scale temperature datasets, whether or not changes in air and surface temperature and the effects urbanization-based LULCC is having on ULST and UHI formation were addressed. This was achieved by coupling settlement expansion analysis with discrete and continuous temperature data for assessing the potential impacts of urbanization on Abuja's climate. Based on the relevant climate indices analysed, it was discovered that minimum air temperature in Abuja had changed significantly with positive trends. This was further confirmed in the number of warm and cold days analysed. Similarly, the urban surface thermodynamics and analysis revealed that from 1986 to 2014, Abuja has witnessed an increase surface temperature intensity by about 8°C. The increasing air and surface temperature is as a result of the rapidly changing land cover with impervious surfaces particularly the built-environment. The use of multiple landscape indices and statistical approaches proved to be useful for assessing the spatiotemporal distribution of urban heat island and effects in the city of Abuja. The regression analysis proved that green area can weaken urban heat island effect. In contrast the built-up areas and bare/arable land can accelerate UHI formation due increasing building aspect with potential effects.

In order to gain better understanding of Abuja's susceptibility to flood risk due to LULCC and settlement expansion trajectories into floodplain as well as spatially map places and people vulnerable to flood risk, an integrated dataset approach for vulnerability assessment to floodrisk mapping of Abuja was demonstrated. From the Abuja flood zone map produced, various parts of the city are exposed in varying degree to flood risk which ranged from very low risk zones to high risk zones. The area extent of high risk zone is about 1.8%, the moderate risk zone occupies 56.1%, low risk zone covers 41.3% and very low risk areas is about 0.6%. In Abuja main city, flood risk ranged from low to moderate, while in the peri-urban areas such as Kubwa, Gwagwa, Karmo, Dakwa and idu industrial area, low, moderate and high risk zones were found. In view of Kubwa having representative characteristic of flood risk, the social vulnerability conducted revealed that resident along the Kubwa drainage were exposed and susceptible flood risk in the up, middle and downstream. Although, Lack of Resilience was not measured, logical inference suggest that inhabitant living along Kubwa River are vulnerable to flood impacts during rainy season at varying degrees, and may also have varying resilience.

The relevance and added value VHR images offer in the risk and vulnerability assessment process of places and people was explored for Abuja which is novelty. Furthermore, the aspect of data scale which is a challenging theme in RS was explored which is another novel concept in the West African region. The integration of moderate and VHR image products procedure was demonstrated for Abuja towards fine-scale vulnerability assessment of urban land use to potential climate change impacts using integrated geoinformation datasets. Specifically, fine scale urban indicators such as urban density and UST information can be derived from VHR satellite images. When extracted, such information can offer better understanding of socioeconomic, socio-environmental and socio-ecological insights. In this study, the World View-2 VHR image of Abuja was used to explore urban density information and UST extraction based on the object oriented image analysis. This information was subsequently combined with other medium scale landscape indices to assess urban vulnerability in the context of potential climate impacts due to urbanization. An areas such as Garki-2 was identified to vulnerable to local warming and flood impact especially Garki village. Hence, proactive climate action is needed in Garki 2 district of Abuja. The output of relevant information can significantly support research and relevant authorities in data poor regions such as West Africa.

This dissertation demonstrated how integrated geoinformation and socioeconomic datasets of Abuja can be used to assess potential vulnerabilities of nascent West African cities to climate and land use change impacts. Chapter 4 revealed that LULCC mapping, monitoring and modelling for assessing the impact settlement expansion is a useful approach for investigating the impacts urbanization has in forcing urban climate change. One of the achievement of the concept was that two emerging principal urban climate vulnerability indicators were identified such as: 1) the modification of land surface temperature which propagate urban heat island formation and 2) increased run off which may trigger flood events in cities.

As a follow up to the assertion made in chapter 4 on the modification of LST and the UHI formation consequence, chapter 5 coupled discrete and continuous temperature datasets with relevant landscape indices of Abuja. This investigation proved to be useful for detecting the effects of rapid settlement expansion on local warming development in nascent cities. The combination of multiple statistical approaches employed further revealed fundamental relationship enigmas that exist between landscapes indices. This helped in empirically unlocking the role LULCC especially settlement expansion plays in forcing urban climate which has attendant impacts on human-wellbeing.

Chapter 6 also demonstrated the proof of concept and usability of multi-source data approach in measuring spatially explicit flood-risk exposure, susceptibility and physical/social vulnerability of people and places toward human security preparedness in Abuja. Specifically, the morphometric analysis and flood-risk zonation map was useful in identifying very high flood risk zones such as Kubwa with poor drainage density and low bifurcation ratio which is indicative of flood-risks.

Based on the datasets generated in chapters 4-6 using moderate resolution satellite images, the usefulness of these datasets were explored in combination with information extracted from VHR image for improved human-wellbeing vulnerability assessment in settlement with scarce in-situ socioeconomic information such as urban density information and UST.

8.2 Innovations and scientific contributions

The main innovation of this research is that the study demonstrates how to overcome the challenge of data scarcity due to cloud cover by using use of multi-sensor and multi-temporal remote sensing images through rigorous digital image processing. Also, the analysis of settlement expansion and modelling of urban growth for the year 2050 based on the scarce remote sensing images of 1986, 2001 and 2014 to draw inference on potential climate change impacts for the study area. Another innovation by this research is the coupling of discrete and continuous temperature datasets with settlement expansion analysis for urban heat island detection using multiple spatial statistics approaches. This concept will contribute to improved and rapid settlement expansion monitoring and land management capabilities municipality managers require potential local warming analysis with the climate change impacts assessment framework. Also, the combination of knowledge based morphometric and land use change concept for an integrated of physical and social vulnerability assessment of settlements to flood risk in dry urban region such as Abuja within the climate change context. The synergy of moderate and very high resolution satellite image product for fine scale vulnerability assessment for improved mitigation/adaptation to potential climate change impacts.

8.3 Limitation of research

The limitations of this research are summarized below:

i. Dense satellite images is required for detailed land cover change assessment to robustly model change and predict future patterns. However, Landsat images of Abuja was scarce due to cloud cover and research timeframe.
ii. Access to sufficient secondary datasets such as historic climatic data and socioeconomic datasets was a challenge. In addition, Abuja had only one climate station situated in the airport which hampered spatial reliability assessment of the land surface temperature retrieved. Also, population data was not at district level which could have supported detailed estimate of vulnerable population to potential climate change impacts. Other socioeconomic data were not readily usable for detailed integrated analysis.
iii. Recent very high resolution image and sufficiently detailed field work is required to derive urban structural types. However, due to the size of study area and age of the WV2 image field verification was based on unchanged image characteristics.
iv. Global datasets from CRU, TRMM, GRUMP, MLOST and GIMMS were not considered in this study. It will be promising if future works consider using these datasets for urban climate change and impact analysis.
v. The generated urban footprint could not be used to validate global urban footprint datasets such as the GRUMP and GUF data of Abuja.

8.4 Recommendations

This research encountered scarcity of suitable RS images for mapping, monitoring and modelling land use land cover changes especially settlement expansion analysis. Yet the research does provide a basis for further urban RS towards urban climate science. The main areas for future work directly relevant to this research are as follows:

- Further investigation of land use land cover, settlement expansion analysis and urban growth modelling using dense satellite dataset to capture decadal and seasonal timeframes is needed. Since more RS datasets such as ASTER, Sentinel 1 and 2 are now freely available.
- Although, this research used Support Vector Machine (SVM), a machine learning algorithm in the classification of satellite images, also the land change modeller is based on Artificial Neural Networks (ANN), there is the need to consider comparing SVM with Random forest algorithm to liken the capabilities of both algorithms in heterogeneous urban landscapes of West African countries.
- Other flexible land change modelling approaches such as Clue-S interface should be considered for projecting and analysing land cover change within scenario frameworks.
- Considering the challenge of limited climate datasets, the TRMM and CRU dataset of Abuja should be acquired, validated and used for detailed near medium and long term climate analysis.
- To gain better understanding of landscape performance on Abuja, global NDVI datasets from GIMMS should be considered in future research. This can also be used other global temperature and rainfall analysis within the context of urbanization and climate change impacts.
- The synergies between moderate and VHR RS datasets such as WV-2 & 3, Radar and Lidar should be further explored in West Africa with the goal of to overcome scarcity of spatially explicit socioeconomic base data in the sub-region for development-centric urban science and imminent climate change impacts. This data fusion approach will also enable researchers and urban managers to create reliable inventories and geodatabases of various urban dimensions for climate change impacts analysis.

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