A comparison of remote sensing approaches to distinguish unplanned and planned urbanization in Abuja, Nigeria.

by

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List of Acronyms

AGIS	Abuja Geographic Information Systems
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CNN	Convolution Neural Network
DL	Deep Learning
DMSP-OLS	Defence Meteorological Satellite Program-Operational Linescan System
DN	Digital Number
ERTS	Earth Resources Technology Satellite
ETM+	Enhanced Thematic Mapper plus
FCC	Federal Capital City
FCDA	Federal Capital Development Authority
FCN	Fully Convolution Network
FCT	Federal Capital Territory
GCPs	Ground Control Points
GIS	Geographic Information Systems
GLCM	Grey Level Co-Occurrence Matrix
LBP	Local Binary Patterns
ML	Maximum Likelihood
MODIS	Moderate Resolution Imaging Spectroradiometer
MS	Multispectral
MSS	Multispectral Scanning System
NASA	National Aeronautics and Space Administration
NASRDA	Nigeria Space Research and Development Agency
NCEI	National Centre for Environmental Information
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
NTL	Night Time Lights
OBIA	Object-based Image Analysis
OLI	Operational Land Imager
PCA	Principal Component Analysis
RF	Random Forest
RGB	Red Green Blue
RS	Remote Sensing
SLC	Scan Line Corrector
SNAP	Sentinel Application Platform
SNTL	Stable Nighttime Lights
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
TD	Transformed Divergence
TIROS	Television Infrared Observation Satellite
TM	Thematic Mapper
VHR	Very High Resolution
VIIRS	Visible Infrared Imaging Radiometer Suite

WELD	Web Enabled Landsat Data

Abstract

The process of urbanization experienced world-wide has increased rapidly in recent decades, with this trend set to continue. Urbanization is more pronounced in cities in the Global South, and this brings with it significant social and environmental problems such as uncontrolled urban sprawl and uneven resource distribution. While much urbanization in the Global South is unplanned, there have been some rare attempts at strategic, large-scale urban planning. One such example is Abuja, the capital of Nigeria, which is a new planned city with its origins in a Master Plan devised in the 1970's.

This research uses multi-temporal remote sensing to investigate urbanization in Abuja over the last 40 years to critique the original Abuja Master Plan, showing the extent to which urban development has kept with, or diverged from, the original Master Plan. The study also investigated the potential of using remote sensing methods to distinguish unplanned and planned urban settlements in Abuja, Nigeria.

First a time-series of multispectral Landsat images was acquired; cloud-free images from 1975, 1986, 1990, 1999, 2002, 2008 and 2014 were used, with some years specifically selected to correspond with important dates in Nigeria's socio-political development, and to match major milestone targets as prescribed by the Master Plan.

The research also combined Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper plus (ETM+) image classifications of urban built-up land cover with Defence Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) stable nighttime lights imagery to investigate, distinguish and map unplanned and planned urban areas. DMSP-OLS stable nighttime lights imagery from 1999, 2002 and 2008 were selected. Thresholding techniques with ancillary information were successfully applied to distinguish areas of unplanned and planned developments.

Finally, the research focused on developing and applying deep learning and random forest classification techniques on Very High Resolution (VHR) imagery to characterise and map unplanned and planned built-up land at a finer spatial scale. This approach was able to address some of the obvious limitations resulting from using coarse (DSMP-OLS) and medium (Landsat) resolution imagery encountered in the earlier part of the research in attempting to distinguish unplanned and planned built-up settlements. The results of the study have shown deep learning can be successfully adapted to map unplanned and

planned settlements in a city of the Global South, while random forest performed poorly in distinguishing planned and unplanned settlements.

1. Introduction

1.1 Urban areas and urban growth

Urbanization is the process involving an increasing number of people living in urban areas on a permanent basis. Historically, urbanization has been linked to accelerated economic growth and development, but recently the situation is different in developing countries, especially in sub-Saharan Africa, where rapid urbanization continued while economic decline was observed between 1970s and 2000 (United Nations, 2015). As the world continues to urbanize, and with much of the future population growth expected in Africa and Asia, this will no doubt bring enormous environmental, economic, social, and political transformations and challenges (Cohen, 2006). Such growth, especially in Africa, has led to about 62% of the total urban population in the continent to be living in unplanned settlements and slums (UN Habitat, 2015).

Despite the evidence that the world is urbanizing at a faster rate than ever, there is still no unified definition of exactly what constitutes an urban area or urban settlement (Frey & Zimmer, 2001). There is also no single acceptable to all definition of what constitutes an unplanned settlement. The definition of 'urban' differs widely between disciplines, regions and countries, and sometimes what is termed urban changes even within a country over time. Several criteria are used to define urban areas, including administrative boundaries, population density, minimum population threshold, connection to electric grid, infrastructure such as the presence of paved roads, piped water, and sewers, and health and educational services (United Nations, 2015).

In some countries only one criterion (such as population density) is used to define urban areas while in others a combination of different criteria are used (Cohen, 2004). For example, in the United States the criteria outlined by the United States Census Bureau (2010) are that an area will have to meet a minimum population density requirement of 2,500 people before it can be considered urban. In contrast, the UK Office for National Statistics (ONS 2013) defines an urban area in relation to built-up area. Built-up land is defined as any land which is "irreversibly urban in character"; this means the area possesses the characteristics of a village, town or city. Also, areas that are within 200 meters of each other are considered linked as a single built-up area. The Census Bureau links these built-up areas with population using a base referred to as output areas, with urban areas defined as having 10,000 or more residents. The definition of urban is similar between most Global South countries. The term 'Global South' refers to low- and middle-income countries located in Africa, Latin America, Asia and the Caribbean ranked and grouped by the World Bank (Mitlin & Satterthwaite, 2013). Here, urban areas are mostly defined based on a 'threshold' with regards to the number of people that makes up a settlement. The threshold can range from a few hundred up to 50,000 people, but most fall in the range of 1,500 to 5,000 people (Hardoy & Satterthwaite, 1986; De Bonet et al., 2010). In Nigeria, urban has been defined as an agglomeration of over 5,000 people in 1963, and this was raised to over 20,000 in 1991 (Tiffen, 2003).

1.2 Urban sprawl and unplanned settlements

Urban sprawl can be defined as the accelerated expansion of built-up land at the fringe of a city in a disordered and irregular pattern (Bhatta, 2010; Tewolde & Cabral, 2011). A review of literature reveals that there is no unified definition for urban sprawl, which means urban sprawl monitoring is especially challenging. Ewing (1997 pg. 108) defined urban sprawl based on the combination of three different categories, namely: (1) "leapfrog or scattered development; (2) commercial strip development; and (3) large expanses of low-density or single-use development (as in sprawling bedroom communities)." Johnson (2001), on the other hand, went further to state that this definition of sprawl is not comprehensive enough, as sprawl should be seen and recognized as a matter of degree because there is a fine line between what people define as sprawl and multicentred development (a type of compact development). A completely different approach was taking by Angel et al. (2007 pg. 2) when defining urban sprawl, who consider it as both a pattern of urban land use, meaning "a spatial configuration of a metropolitan area at a point in time" and also a process, namely "the change in the spatial structure of cities over time". In this definition, sprawl is used both as a condition (noun) and process (verb), which was also how Galster et al. (2001) defined it. Despite the difficulty in agreeing definition, there is general agreement that urban sprawl occurs at the fringe of cities and is characterised by uncontrolled, rampant and uneven growth. This uneven growth leads to the rise and growth of unplanned settlements, especially in cities of the Global South. This growth is influenced by several factors and processes such as population growth, spatial configuration, land use efficiency etc. (Bhatta et al., 2010), which lead to inefficient utilization of resources.

Unplanned settlements, sometimes also referred to as informal settlements, are areas that generally develop haphazardly, without planning provisions. They are usually associated with poor infrastructure, irregular layout and poor housing quality (UN-Habitat, 2010; Kuffer et al., 2014). It is important to monitor and map unplanned settlements since one third of the urban population in the developing nations live in areas that are unplanned (United Nations 2011). This can only be done effectively by having access to cheap, accurate, reliable and regular data on the urban environment. Doing this will help provide information that will help in better urban management decision making and ultimately reducing the negative impact of urbanization in countries of the Global South, promote more equitable distribution resources, improve environmental sustainability and governance. Because of the varying definitions of what constitutes an urban area, there are limitations in how to assess and monitor rapidly urbanizing cities such as Abuja in a timely manner. Remote sensing provides us with the capacity to observe and manage urban areas effectively through the detection of spatial landscape changes. Satellite remote sensing has shown considerable promise in the past decade in its ability to monitor unplanned settlements and map slums around the world (Patino, 2013; Kuffer et al., 2014; Kuffer et al., 2016).

1.3 Urban planning in the Global South

Urban planning is the process of controlling the development of cities through plan-making, land use design and regulations, with the main objective of improving and enabling cities to function better and be more sustainable (Hall & Tewdwr-Jones, 2010). This is one of the approaches used over the years to regulate and monitor urban growth and urban sprawl in cities of the developing world. This planning involves all the processes that govern the design and use of land in the urban environment. In reality, the theory and practice of urban planning means different things in different part of the world (Watson, 2009). This means that it is important for such plans to be examined periodically to see if in today’s rapidly changing urban environments, they can still play a positive role in the growth and monitoring of cities. The challenge of urbanization in the Global South is exacerbated by lack of relevant spatial information to assist planners, policy makers and other stakeholders address the challenges efficiently. This point was highlighted by De Jong et al. (2000) when they discovered that planning agencies in Ouagadougou, Burkina Faso, lack the necessary spatial information to address issues like provision of infrastructure and social services successfully. The cities of developing countries are structured and planned differently from those of the developed world, and because of this at the World Urban Forum in Vancouver in 2006 stakeholders called for a major shift in thinking with regards the future of cities in the Global South (Watson, 2009). Despite this call, little research in the GIScience community is being conducted to address the impact of urban growth in emerging and developing countries (Akingbade et al., 2009).

Planning in developing countries is performed mainly with the aim of urban modernization. Urban modernization generally involves having new sets of urban layouts and urban forms coupled with a legal mechanism to implement and enforce the new provisions (Watson, 2009). In trying to cope with the challenges of urbanization, some developing countries undertake steps to re-plan their cities in an effort to reduce congestion or handle future urban growth. Some take a bold step by proposing a new planned city or trying to adopt some form of plan in an unplanned city. For example, in Dar es-salaam, Tanzania, the government attempted to tackle the city's uncontrolled growth by adopting an uncommon approach of producing several Master Plans over the years to guide and regulate city's urbanization. In Myanmar the capital was relocated from Yangon to Naypydaw, citing the new location as more strategic geographically to accommodate the economic expansion and urban development in the country (Preechrushh, 2011). Similar reasons of geographical centrality and room for expansion were given in Malawi, where the capital was moved from Zomba to Lilongwe (Kalipeni & Zeleza, 1999). Nigerian cities are no exception when it comes to rapid urbanization; they are among the fastest growing cities in Africa (Braimoh & Onishi, 2007; Merem, 2008) and most of these cities are not planned, meaning that there is no strong mechanism to handle such explosive growth (Oluseyi, 2006). The level of urbanization in and around major cities in Nigeria, and the adverse effect of urban expansion especially in the past 20 years, is making people question how effective government policies are towards urbanization and the relevance of the activities of urban development agencies and related planning authorities in addressing these problems (Arimah & Adeagbo 2000). Some of these reasons led to the creation and relocation of Nigeria's capital city from Lagos to Abuja, initiated in 1976. The relocation was intended among other things, to address the lack of adequate space for future development in Lagos and to foster unity. The country decided that a new capital was needed that is planned, comfortable, secure and centrally accessible, to provide a base for urban development and serve as a symbol of Nigeria's aspiration for unity and greatness (Ikejiofor, 1997).

1.4 Remote sensing of urban areas

Remote sensing is the science of acquiring information about physical objects and the environment using non-contact sensors (Colwell, 1997; Campbell & Wynne, 2011). Urban remote sensing is the field of remote sensing that investigates various phenomena related to urban areas. Having the capability of providing a synoptic view of the urban environment and also the ability to provide data with high spatial detail and temporal frequency, makes remote sensing a useful tool in studying urban environments (Herold et al., 2003; Jensen & Cowen 1999; Xiao et al., 2006; Pham et al., 2011). In the past, aerial photography has been successfully employed as a tool and a major source of information in urban analysis (Jensen, 1982), and it is still in use today, as it continues to provide a means of acquiring the fine spatial resolution data that is critical in urban planning and management (Myint et al., 2011). However, as a result of technological advancement and the availability of ever more detailed very high resolution (VHR) satellite imagery, satellite, as well as aerial, remote sensing systems have increased the potential for urban remote sensing studies. Moreover, these systems can offer additional benefits such as recurrent, comprehensive and consistent coverage of urban areas at (relatively) low costs. Many studies are now using VHR imagery to study different sectors of the urban environment. For example, object-based analysis of VHR satellite imagery has been used to assess urban growth by mapping and quantifying new buildings (Tsai et al., 2011), and urban change detection (Doxani, 2012). Urban remote sensing research over the years has focused more attention to the use of digital, multispectral images from Earth observation satellites (compared to undigitized aerial photographs), a trend which can be attributed to the launch of the second generation sensors like Landsat Thematic Mapper (TM), launched in 1982, and Satellite Pour l'Observation de la Terre (SPOT 1) launched in 1986 (Donnay et al., 2003; Maktav et al., 2005).

The advent of second generation satellites with improved spatial resolution of between 10 m and 30 m in the 1980s gave the field of urban remote sensing an improved prospect (compared to earlier sensors with 80 m resolution and higher) to better manage the challenges of the urban environment. Some of the early urban studies conducted using data from Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+) among others, was to analyse regional urban systems and conduct exploratory investigations of some large cities in North America (Forster 1980; Jensen 1982; Donnay et al., 2003; Jackson et al., 1980). Over the last few years, the spatial resolution of satellite imagery has improved significantly from 10 m to less than 1 m. This was made possible with the advent of the third generation of satellites such as IKONOS, which was the first commercial satellite providing VHR imagery launched in 1999. This heralded a new era of more detailed research in the urban environment. These VHR images have increased the amount of information that can be extracted in complex urban environments (Myint et al., 2011), for example, relatively small features like roads, buildings and intra-urban open areas can be identified, (Puissant et al., 2005), whereas medium resolution satellite sensors struggle to discriminate these (Barnsley, 1997; Franklin & Wulder, 2002; Weng, 2012). Prior to 1999, the main limitation cited for the sporadic research in remote sensing of impervious surfaces was the lack of high (less than 10 m) resolution images (Weng 2012).

Despite the complexities and dynamism of urban areas, remote sensing can be used to extract important attributes of the urban environment. Furthermore, integrating remote sensing data with other ancillary data can help reveal other characteristics of the urban environment like socio-economic conditions (Blaschke et al., 2011; Taubenböck et al., 2008), for example, urban poverty and low-income sites (Thomson 2000; Hall et al., 2001). Other studies have also successfully utilized VHR imagery to estimate population (Wu et al. 2005; Liu et al., 2006). This further shows the significance of remote sensing in providing a unique capacity in the spatial and temporal observation and analysis of the diverse processes and aspects of the urban environment (Herold et al., 2003).

A great deal of research in urban remote sensing has concentrated on general land use and land cover change; more research is needed to target specifically the evolution and change of built-up land (impervious surfaces) over time (Weng 2012). Studying change in built-up land in cities is very important as it can help not just urban planners towards sustainable urban development, but also better and sustainable environmental management.

1.5 Remote sensing data sources

Remote sensing technology has been in existence since the mid-19th century. The first reported aerial photographs were taken with a camera mounted on a balloon in the 1860s by Felix Tournachon in France (Patino & Duque, 2013). Prior to 1946, remote sensing data was only collected in the form of photographs from balloons and aeroplanes. Satellite remote sensing kick-started in earnest only with launch of a satellite called TIROS 1

(Television Infrared Observation Satellite) an experimental system with the aim of monitoring Earth's weather (Fritz & Wexler, 1960). However, the breakthrough for environmental remote sensing came with the launch of ERTS-1 (Earth Resources Technology Satellite 1), later renamed Landsat-1, in 1972 by National Aeronautics and Space Administration (NASA). This launch was so profound in terms of peaceful acquisition and sharing of scientific data that Vincent (1997) stated that there is no event in the history of science that can equal the advent of the Landsat-1 Multispectral Scanning System (MSS). Landsat MSS is part of the first-generation satellites that have a relatively moderate spatial resolution, i.e. imagery with 10-100 metre resolution. Remote sensing images are generally categorised based into three broad groups based on spatial resolution: coarse, moderate and fine resolution imagery (Franklin & Wulder, 2002).

1.5.1 Coarse spatial resolution imagery

Low (or coarse) spatial resolution remote sensing includes images with >100 m resolution, for example, Advanced Very High Resolution Radiometer (AVHRR) imagery, Moderate Resolution Imaging Spectroradiometer (MODIS) and Defence Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) nighttime lights imagery. AVHRR imagery is widely used for environmental studies due to its coverage and its standard in terms of spectral characteristics. On the other hand, Defence Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) nighttime lights (NTL) dataset have a non-standard spectral nature, though it uses the same optical principle with other coarse resolution satellite imagery. DMSP-OLS nighttime stable lights (SNTL) data are part of NTL dataset acquired and made publicly available cost-free by National Centre for Environmental Information (NCEI), which is part of the United States National Oceanic and Atmospheric Administration (NOAA). The nighttime lights data was recorded in 6-bit format, with each pixel recorded as a digital number (DN) ranging from 0 – 63. Each pixel is the average of the OLS visible band recorded DN values of lights from cities, towns and other persistent light in a year. This dataset is becoming very valuable in monitoring urban areas and as a proxy to obtain other complimentary information like land use and socio-economic characteristics of cities around the world (Doll & Pachauri 2010; Small et al., 2011; Gao et al., 2015). Many studies have successfully utilized coarse resolution DMSP-OLS imagery (Letu et al., 2010; Jing et al., 2015; Liu et al., 2015; Ma et al., 2015; Goldblatt et al., 2018) imagery to map land cover and land use. The majority of studies that utilize low-resolution imagery focus on regional and global scale (Lu et al., 2008; Weng, 2012). There are multiple methods that have been used to extract information on urban areas using nighttime lights imagery. These methods include: empirical thresholding technique (Elvidge et al., 1997), thresholding technique using mutation detection (Imhoff et al., 1997), image classification methods (Cao et al., 2009) and thresholding technique with ancillary data (Henderson et al., 2003).

1.5.2 Moderate spatial resolution imagery

The second category of medium (or moderate) spatial resolution remote sensing includes images with 10-100 m resolution, for example, Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) & Operation Land Imager (OLI) imagery. Other medium resolution image sources include Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), SPOT and Sentinel-2 imagery. Studies that have effectively used such data types for an environmental studies include: Song et al. (2001) who indicated when and where to perform atmospheric correction when using Landsat TM data for classification and change detection; Franklin & Wulder (2002) reviewed in detail the different approaches to land cover classification using medium resolution satellite imagery; Liu & Yang (2005) successfully monitored urban land changes in Atlanta using Landsat TM imagery combined with Geographic Information Systems (GIS); Weng & Hu (2008) used medium resolution satellite imagery to estimate and impervious surface successfully; Esch et al., (2009) assessed and analysed impervious surface in a large area using Landsat ETM+ imagery combined with geospatial vector data; Tan et al., (2009) used SPOT multispectral images to successfully map impervious surfaces in an urban area.

Over the past few decades, several other studies have utilized Landsat imagery successfully to extract and map urban land cover and land use. For instance, Yang et al. (2003) presented an approach to map a large area of impervious surfaces using Landsat ETM+ imagery. A similar approach was also suggested by Esch et al. (2009) using Landsat ETM+ images combined with geospatial vector data. Landsat TM imagery was also effectively used to map land cover and perform change analysis in the metropolitan area of Minnesota, USA (Yuan et al., 2005). Several other studies have used Landsat imagery independently or combined with other sensor imagery to successfully detect urban growth, urban socioeconomic attributes, and map land cover and land use in urban areas (Chen

2002; Mundia & Aniya 2005; Xiao et al., 2006; Morton & Yuan, 2009; Dong et al., 2010; Li & Weng, 2010; Ward et al., 2010; Wakode et al., 2014).

Despite the successes of using Landsat for urban studies, some limitations exist. For example, Landsat has a relatively poor temporal resolution. There are also significant time gaps in the Landsat archive between good quality images to conduct intended land cover land use mapping work. Other limitations of Landsat include its basic spatial resolution limitation: 30 m pixels cannot detect small urban features) and its inability to classify/distinguish planned and unplanned urban settlement classes.

1.5.3 Fine spatial resolution imagery

High (or fine) spatial resolution remote sensing includes images with a resolution ranging a from few centimetres to less than 10 m, with imagery of less than 5 m in the group usually referred to as very high resolution (VHR) imagery. Examples of fine resolution sensors includes; IKONOS (3.2 m Multispectral (MS)), QuickBird (2.6 m MS), GeoEye-1 (1.8 m MS), NigeriaSat-2 (5 m MS) and WorldView-4 1.2 m MS) Several studies have employed high resolution imagery such as QuickBird and GeoEye to investigate urban environment in finer spatial detail with great success. For instance, Lu et al. (2011) mapped impervious surfaces using QuickBird imagery, Kuffer et al. (2014) utilized VHR imagery to develop an unplanned settlement morphological index, Wieland & Pittore (2014) investigated the potential of using machine learning techniques on medium and VHR satellite images, and Mboga et al. (2017) used QuickBird imagery to detect and map informal settlements in Dar es Salaam, Tanzania. Aguilar et al. (2013) explored and compared the effect of using GeoEye-1 and WorldView-2 images on classification accuracy in urban areas, and Huang & Zhang (2011) also utilized GeoEye-1 imagery to develop a morphological building index for the automatic extraction of building from VHR imagery in urban areas.

1.6 Urban mapping and image classification

Remote sensing plays a significant role in the area of urban growth detection and mapping. Some of the earliest applications of remote sensing involved urban extent mapping using aerial photography (Wentz et al., 2014). Delineation and mapping of urban areas is usually performed using image classification. Image classification is the process of labelling pixels to information classes in an image. When classifying land cover and land use, there is no single way or standard that is universally accepted as best in terms of accuracy (Stehman, 1997). Land cover is defined as the biophysical attributes of the Earth's surface (Lambin et al., 2001) and land use is described as the purpose or intent applied to these attributes (land cover) by humans (Campbell & Wynne, 2011; Lambin et al., 2001). Land cover is an important variable that links and affects many part of the physical and human environments (Foody, 2002). Tackling various environmental problems like deforestation, flooding, uncontrolled urbanization, loss of agricultural lands, and environmental pollution has made having reliable and frequent information about land cover and land use increasingly important (Nunes & Auge, 1999; Sala et al., 2000).

The classification process is broad and can be approached through different perspectives. The perspective tends to be influenced by the purpose of the study and user preference even though an objective numerical approach is used. This is because the ultimate decision of what classifier or technique to adopt is determined based on the analyst interest. In theory, the method to use in land cover classification should be based on landscape structure (Hubert-Moy et al., 2001), but this is not always the case as each classification is specifically made to satisfy the need of a particular user or target audience (Anderson, 1976). Image classification can be conducted using two major approaches of pixel labelling that are referred to in the remote sensing literature as unsupervised and supervised classification techniques (Duda & Canty, 2002; Wilkinson, 2005; Phyu, 2009).

Supervised classification is a process of using sample pixels whose identity is known to classify pixels of unknown identity. The training pixels are usually well distributed, and representative of their individual classes located in the image to be classified (Zhang & Foody, 2001). Unsupervised classification on the other hand is a semi-automatic process of identifying clusters and natural structures within a multispectral image. It works by organizing data into classes that share similar (spectrally homogenous) characteristics (Duda & Canty, 2002). Image classification are sometimes categorised based on the how a classifier works. For instance, per-pixel algorithms (sometimes referred to as hard classifiers) and fuzzy classification algorithms (sometimes referred to as soft classifiers). Hard classifiers work by assigning each individual pixel to a single land cover (or other class) while soft classifiers work by assigning pixels a class membership of each land cover present instead of a single land cover class (Weng, 2012).

Many image classification methods have been developed over the years to extract information from remotely sensed data, with mapping and extracting impervious surfaces to study urban environments attracting more and more interest (Lu et al., 2011). For instance, Lu & Weng (2009) used IKONOS imagery to extract impervious surfaces, Puissant et al. (2005) explored the usefulness of texture analysis in improving per-pixel classification of VHR imagery, and Sugg et al. (2014) described methods of extracting impervious surface from high resolution imagery using object-based classification technique. Others have also successfully utilized medium spatial resolution data such as Landsat for classification and mapping of impervious surfaces in the urban environment (Esch et al., 2009; Hu & Weng, 2009, 2011; Lu et al., 2011; Xian & Crane, 2005; Yang et al., 2003). Sahoo & Pekkat (2014) attempted to determine the characteristics of impervious surfaces in an urban region using images from Landsat MSS, TM and ETM+, in an effort to assess the role spatial resolution plays in determining the level of urbanization in an area. Weng (2012) gave detailed requirements, methods and trends in classifying and mapping impervious surfaces. Also, maximum likelihood (ML) and support vector machine (SVM) algorithms were combined successfully to classify land cover in Eastern Uganda (Otukei & Blaschke, 2010). Object-based classification approaches are another classification category that works by combining spectral, texture, shape and context of a group of pixels to extract and classify target features (Mathieu et al., 2007; Weng, 2012). Object-based classification approaches have been applied effectively to monitor urban growth by classifying buildings and impervious surfaces (Leinenkugel et al., 2011; Tsai et al., 2011; Doxani et al., 2012). Furthermore, pixel and object-based classification techniques were used to define and classify urban areas with high accuracy in 27 mega cities around the world (Taubenböcket et al., 2012). Machine learning techniques which utilizes ensemble learning capability like random forests (RF) and deep learning (DL) are also becoming popular in the field of urban remote sensing object extraction and classification.

1.6.1 Maximum likelihood

ML is a statistical method that is commonly used in supervised classification of remotely senses data (Kamh et al., 2012). The ML method is among statistical procedures referred to as parametric, as it is based on estimates derived from statistical parameters of the training data chosen by the user. The basic assumption behind the maximum likelihood algorithm is that the frequency distribution of the classes is in multivariate normal form

(Mather & Koch, 2011); i.e. ML operates by using the training data to estimate the means and variances of the classes identified by the user. This is then used to estimate the probabilities of class membership (Campbell & Wynne, 2011). ML is a well-known and well understood technique and has been widely used in the field of remote sensing image classification. The main weakness of this approach is its parametric assumption (normal distribution of data) which can sometimes be problematic and leads to reduced accuracy. The success of parametric classifiers like ML is highly dependent on the size and the quality of the training sets. Also, in situations where different classes overlap each other in feature space, parametric classifiers tend to yield a number of misclassifications (Hubert-Moy et al. 2001).

1.6.2 Random forests

Machine learning approaches are also becoming more widely used in remote sensing image classification in urban areas using both unsupervised and supervised classification techniques (Wieland & Pittore, 2014; Hu et al., 2015; Hu et al., 2015b; Fu et al., 2017; Mboga et al., 2017). Random forest (RF) is a machine learning algorithm that uses an ensemble of classification trees. The RF classifier works by using two parameters to create its prediction model; the parameters are the number of decision trees and the variables utilized to make the tree grow (Ma et al., 2017). The RF classifier is a non-parametric algorithm which makes it suitable for handling unbalanced data (Thanh Noi & Kappas, 2018). It builds binary classification trees (ntree) that draw replacements from the original observations (Eisavi et al., 2015). RF is now being widely utilised for classification in the field of remote sensing due its improved accuracy and performance over other traditional classifiers (Stumpf & Kerle, 2011; Puissant et al., 2014; Me et al., 2017; Thanh Noi & Kappas, 2018). Several studies have successfully utilized RF to analyse and map urban land cover using both medium resolution imagery (Na et al., 2010; Li et al., 2014; Marston et al., 2014) and VHR imagery (Sun et al., 2017; Du et al., 2015).

1.6.3 Deep learning

Deep learning is a neural network technique that uses backpropagation algorithms to make a machine automatically adjust its inbuilt parameters to learn representative and discriminative features in a hierarchical manner from a large dataset (LeCun et al., 2015; Zhang et al., 2016). Due to the limitations of classic remote sensing feature extraction and classification algorithms, (for example, the assumption of normal multivariate distribution of data) a new algorithm is needed that can effectively combine spectral and spatial features within an image (Noguiera et al., 2017). DL algorithm combines spectral and spatial characteristics of an image, and it works without the need for prior knowledge regarding the relationships that exists within the data (Lary et al., 2016). DL is proving to be very successful in solving many advanced remote sensing tasks and improving results (Zhu et al., 2017). A prominent and well-known DL algorithm is convolution neural network (CNN). CNNs have been successfully applied in the field of object detection and segmentation (Girschick et al., 2016), and classification (Zhou et al., 2016; Zhang et al., 2016; Hu et al., 2015; Luus et al., 2015). Its popularity and growing relevance can be linked to its multifaceted application, from image pre-processing to scene recognition, high-level semantic feature extraction and pixel-based classification (Zhang, 2016).

1.7 Remote sensing change detection

Change detection is one of the most important and challenging aspects in the field of environmental remote sensing, due to its multifaceted application and significance. The complexity of impervious surfaces and other distinct features of the urban environment makes digital change detection even more challenging (Lu et al. 2011). A large range of change detection techniques have been developed and applied to monitor environmental change over time (Lu et al., 2004). Example techniques include image differencing, which involves subtracting a transformed image from another image of a different date but registered exactly together with the first image (Coppin & Bauer, 1996); using principal component analysis (PCA) to improve stacked sensor data information and then combining supervised and unsupervised classification to detect and quantify the changes (Deng et al., 2008); neighbourhood correlation image analysis and decision trees based on the logic that images of a geographical location on two dates will be uncorrelated if change has occurred and highly correlated if little or no change is experienced (Im & Jensen 2005); and post-classification comparison (Fichera et al., 2012).

1.7.1 Post classification comparison

Post classification comparison is a widely utilised change detection technique in remote sensing. This technique compares independently-classified images of an area acquired at different times and is widely used in land cover and land use change detection analysis (Ji et al., 2006; Sarvestani et al., 2011; Kamhet al., 2012; Liu 2015). This normally involves two (bi-temporal) or more (multi-temporal) images of the same area with the intention of analysing, uncovering and quantifying any change that has taking place within the area in question. Post-classification comparison works by separate classification and analyses of a combined dataset of two or more alternate dates in order to identify areas of changes in each image and comparing the results afterwards.

1.8 Research Focus

Rapid urbanization has led to the proliferation of unplanned settlements in the cities of the Global South. The effects of rapid urbanization led to the decision of some countries to develop entirely new planned cities to curtail some of the negative effects. Most Nigerian cities are unplanned, containing few, if any, planned neighbourhoods. This leads to many challenges including traffic congestion, pollution and poor infrastructure and inadequate basic social amenities. Some of these challenges led to the decision to create a new planned city – Abuja – to serve as the nation's new capital. Four decades later, the success of this venture has never been comprehensively evaluated.

Planned cities around the world are a relatively new phenomenon and have not been monitored over long timescales in general. In the few instances where monitoring has been conducted, this has not been over the full lifetime of the cities and it has not involved wall-to-wall spatial analysis, e.g. using remote sensing imagery. Thus, using satellite imagery to monitor and analyse urban development in Abuja since the time of its conception in the late 1970s is highly worthwhile and wholly novel. Four decades after the Abuja Master Plan was drawn up, few studies have looked at the city's urban growth and development (Abubakar, 2014; Ujoh, 2010; Zubair et al., 2015). Furthermore, since its publication, there has never been any comprehensive review of Abuja's Master Plan or its success (Abubakar, 2014). This implies that the effects of urbanization in and around Abuja over the past four decades has not been investigated fully, even though Abuja has been growing at an unprecedented rate especially over the past 20 years. Between 2000-2010 alone, according to UN figures, Abuja had a growth rate of 139.7%, making it the fastest growing city in the world in that period (Boumphrey, 2010).

Remote sensing provides us with a unique opportunity to study the city of Abuja from when it came into existence and it also offers us the ability to analyse the pattern of land cover land use change in and around city boundaries. Such information will be significant in understanding how planned cities, especially in the Global South, evolve. The findings of this research will also enable planners to manage the city's fast paced urbanization effectively, including remediating the presence and problems of any future unplanned settlements.

This research project specifically assesses how Abuja, the first planned city in Nigeria, has grown between 1975, when it was first conceived, and 2014. The research focuses in particular on the development and expansion of unplanned settlements in Abuja over the last four decades. The concept of planned cities is principally concerned with the overcoming of all major problems associated with unintended urban growth. As the term implies, planned cities come into existence after rigorous planning, usually captured in a form of a Master Plan. With the help of satellite remote sensing, we can investigate the past, compare it with the present and appraise the successes and failures of a planned Global South city like Abuja.

1.8.1 Research aim and objectives

The aim of this research is to investigate urbanization in the Global South using a range of remote sensing data sources and image processing methods, specifically attempting to identify and map unplanned settlements and distinguish these from planned development in Abuja, Nigeria.

To achieve this aim, three main research objectives are set:

1. To monitor the changing land cover around Abuja over the last four decades using a time-series of Landsat imagery in order to assess the effectiveness of the city's Master Plan in controlling urbanization.

   To fulfil this objective, a series of research questions are set:

   I. How have patterns of land cover in Abuja Federal Capital Territory (FCT) evolved since the 1970s?
   II. Has the Master Plan been effective in dictating the pace and pattern of urbanization in Abuja?
   III. Has unplanned urban development been limited successfully?

IV. Have changes in political governance influenced the nature of urban growth?

2. To monitor urban development and distinguish unplanned and planned urban areas in Abuja using DMSP-OLS nighttime lights imagery.

   To fulfil this objective, two research questions are set:

   I. How effective is DMSP-OLS stable nighttime lights (SNTL) imagery in mapping urban extent at local scale in a Global South environment?

   II. Can DMSP-OLS SNTL imagery successfully distinguish unplanned and planned and urban areas in a Global South environment?

3. To map urban land in detail and distinguish unplanned and planned urban areas in Abuja using VHR GeoEye-1 imagery and deep learning analysis.

   To fulfil this objective, two research questions are set:

   I. Can deep learning offer enhanced classification performance over established machine learning methods such as random forests?

   II. Can planned and unplanned urban settlements be distinguished and mapped successfully using deep learning?

1.9 Thesis outline

1.9.1 Chapter One: Introduction

This chapter provides a general introduction to the research project. Background information is presented on urbanization, urban sprawl and unplanned settlements, and urban planning in the Global South; and on urban remote sensing, data sources, image classification and change detection. Finally, the research focus, aim and objectives are specified in detail.

1.9.2 Chapter Two: Time-series satellite imagery demonstrates the progressive failure of a city Master Plan to control urbanization in Abuja, Nigeria

This first research chapter focuses on investigating temporal change of the city from 1975-2014. An attempt is also made to establish if urban growth has occurred according to the Master Plan, or if there is any diversion. Where any diversion from the Master Plan occurs, this will be investigated to determine the causal factors and the implications of these.

This study focuses on the spatial component of the Abuja Master Plan because it is area that can be effectively analysed and examined using remote sensing. This means, the Master Plan temporal aspect that has not been assessed in the past can be investigated. Taking this into account, the main focus of the chapter is on land cover and land use change, specifically with regards to urban built-up land and the growth and evolution of unplanned settlements. The analysis performed led to the discovery of other data and methodological, for instance the difficulty in using Landsat imagery to distinguish planned and unplanned urban development due to both classes having similar spectral characteristics. There is also the issue of temporal coverage of Landsat and issues of cloud cover and strip lines on ETM+ imagery after 2002.To tackle this problem, a different type of remote sensing imagery is needed, for example, DMSP-OLS nighttime lights. This provides a big advantage over other sensors such as Landsat that have low temporal frequency. Furthermore, the way in which the data is composited together and provided to the user community including the developed methods, means DMSP-OLS NTL could be utilized to assess the development of Abuja at higher temporal frequency.

1.9.3 Chapter Three: Using DMSP-OLS nighttime lights and Landsat TM/ETM+ imagery to map and characterise urbanization in a planned city of the Global South

The second research chapter focuses on investigating, characterising and mapping planned and unplanned built-up land growth in and outside Abuja's planned city compartments using DMSP-OLS stable nighttime lights (SNTL) data combined with Landsat TM/ETM+ imagery. The DMSP-OLS data was chosen to address some of the limitations of independently using Landsat multispectral imagery that is not capable of distinguishing planned and unplanned areas. DMSP-OLS images from 1999, 2002 and 2008 were selected to match available Landsat imagery, also coinciding with the period of change in Abuja after governance returned to democratic rule in 1999 following military dictatorship. In this chapter, a thresholding technique with ancillary data (Landsat image-generated urban built-up land cover) was adopted to extract urban built-up area, and also to map planned and unplanned urban area in Abuja. Thresholding involves determining a certain level of light intensity to map urban areas and reduce over blooming. Blooming is defined as the "spurious indication of light in a location that does not contain a light source" (Small et al., 2005 pg. 278).

This technique was adopted because it is used extensively due to its reliability and relatively higher accuracy than other techniques like thresholding based on mutation detection and thresholding based on empirical technique (Henderson et al., 2003; Milesi et al., 2003; Liu et al. 2012). DMSP-OLS NTL has shown a lot of potential in urban mapping but it also exhibited some limitations. For example, over blooming in dense urban areas is very common and this leads to over estimation of urban extent in cities. Also, the archives of DMSP-OLS NTL extends only to 2010. This is another major limitation to the scope this study intended to cover. Furthermore, the spatial resolution of NTL imagery (approximately 1 km) is another significant limitation that makes it difficult to target smaller settlements. To address these issues, a different technique and imagery with much improved spatial resolution is needed. Using fine resolution GeoEye-1 imagery can address some these limitations observed.

1.9.4 Chapter Four: A simplified approach to mapping complex planned and unplanned settlements in Abuja, Nigeria using deep learning and random forests.

The analysis performed in the earlier chapters have revealed a major limitation with regards to spatial resolution. Coarse and medium resolution imagery are inadequate to successfully distinguish planned and unplanned settlements. GeoEye-1 imagery is utilized to address the problem associated with the limitation posed by coarse and medium resolution images. Still, the two main classes of interest - planned and unplanned settlements - tend to be spectrally confused using traditional classification approaches. Classical remote sensing techniques such as maximum likelihood algorithms, unlike DL, struggle to combine spatial and spectral attributes of an imagery in feature extraction and classification. This is why the third research chapter focuses on developing a novel method of using deep learning approach on VHR imagery to map planned and unplanned settlements in Abuja at a finer scale. This research attempts to utilize VHR GeoEye-1 imagery, plus deep learning analysis, to address the limitations of using moderate (Landsat) and coarse (DMSP-OLS NTL) spatial resolution imagery to distinguish unplanned and planned settlements. Many studies are beginning to use DL in the field of remote sensing as an improvement to other extraction and classification techniques to study urban areas using VHR imagery. For instance, Xu et al., (2018) used a segmentation model combined DL with guided filters to extract buildings in an urban area. Fu et al., on the other hand, proposed an improved Fully Convolution Network (FCN) as an upgrade to CNN in extracting buildings in urban areas. Despite the growing interest in using DL in remote sensing, not much is known on its potential to map and characterise planned and unplanned settlements. DL approach using CNN on a QuickBird imagery was also utilised to detect informal settlements in Dar es Salaam, Tanzania, with the result of the study showing improved accuracy over SVMs (Mboga et al., 2017).

This study utilized an off the shelf CNN architecture that was trained to detect and map planned and unplanned settlements (alongside other land cover) using GeoEye-1 satellite imagery. The methodology proposed here is aimed to study unplanned and planned land characterisation at greater detail. The methodology was designed and simplified in a way to make it easier for urban planners and policy maker to be able to adopt it to monitor and manage unplanned settlements for the future.

1.9.5 Chapter Five: Conclusion

The final chapter provides an overall summary and conclusion on the research project findings. Commentary is provided to set these findings in academic context and to outline the potential societal impact of the research, including its practical significance to urban planners, environmental managers and policy makers in the Global South. Limitations of the present research project, including data sources and image analysis methods, are also outlined, and suggestions made for future avenues of research.

Chapter 2

Time-series satellite imagery demonstrates the progressive failure of city Master Plan to control urbanization

Submitted to *Remote Sensing*

Abstract

Urbanization is a global phenomenon, but its negative effects are most pronounced in developing countries. While much urbanization in the Global South is unplanned, there have been occasional attempts at strategic, large-scale urban planning. One example is Abuja, Nigeria, a new city with origins in a 1970s Master Plan. Here, we use multi-temporal remote sensing to investigate four decades of urbanization in Abuja, showing the extent to which urban development has matched original intentions. Seven Landsat images from 1975 to 2014 were selected to correspond with Master Plan milestones and turning points in Nigeria's socio-political development. Land cover classification and change detection results show built-up land increasing rapidly, from 1,167 ha in 1975 to 18,623 ha in 2014, mostly converted from grassland, often via a pioneer bare soil class. Comparing image analysis against the Master Plan shows that, in the early years, Abuja's development matched broad planning intentions fairly closely. Later, though, unplanned development proliferated, and the city's resemblance to the Master Plan diminished progressively. Level of adherence to the Master Plan varied widely according to the system of government. Notably, after long-term military rule was replaced by democratic government around the turn of the millennium, unplanned development increased sharply.

2.1 Introduction

The current rate of urbanization worldwide is unprecedented, with these rapidly growing urban environments having significant human and environmental consequences. In 1900 only approximately 5% of the world's population lived in cities (Maktav et al., 2005), yet this increased to over 50% by 2008 (Wurm et al., 2009; Pham et al., 2011); and it is forecasted that 70% of global population will be urban dwellers by the middle of the twenty-first century (Maktav et al., 2005).

Much of the world's future urban and population growth will occur in developing countries, with Africa and Asia urbanizing at a faster rate than the rest of the world. By 2050, the global urban population is expected to increase by 2.5 billion, with 90% of this increase in Africa and Asia; China, India and Nigeria alone are forecast to account for 37% of the global urban population increase (United Nations, 2015). Although urbanization is global, its impact is often felt most severely in developing countries poorly equipped to manage the challenges associated with rapid urban growth, such as environmental degradation, high unemployment, poverty and housing shortages (Ji et al., 2001; Karanja & Matara, 2013).

To manage urbanization more effectively, some countries have taken the approach of building new planned cities, often capital cities intended to be emblematic of the country's modern perspective, free of negative legacy and urbanization effects. Motivations for creating these new planned capital cities vary. For example, for Dodoma, Tanzania, the philosophy was to create a city that is a symbol of 'ujamaa' or 'an alternative vision' of human settlement and urbanism (Myers, 2011). In the case of Lilongwe, Malawi, geographical centrality was one of the main reasons cited for relocating the capital from Zomba (the colonial capital) after independence (Kalipeni & Zeleza, 1999; Englund, 2001). More recently, the capital of Myanmar was also relocated from Yangon to Pyinmana (later renamed Naypydaw) as it is "geographically and strategically located" for the development of Myanmar (Preecharushh, 2011, p. 1012). Other examples of planned capital cities include Brasilia (Brazil), Islamabad (Pakistan), Canberra (Australia) and Washington, D.C. (USA). Planned cities are often guided by some form of 'Master Plan', a comprehensive long-term planning document produced to provide a clear framework for city design, land use, growth and development schedule. In developed nations, there has been strong criticism of the use of Master Plans with many countries now moving to more flexible and collaborative initiatives such as strategic spatial plans, strategic urban planning, multifunctional urban projects and smart growth or 'urban villages' (Borja et al., 1997; Healey, 1997; Marshall, 2000; Albrechts, 2001; Steinberg, 2005; Watson, 2009). Some of these criticisms are that Master Planning is less participatory and democratic, and that it does not adequately address environmental concerns such as resource depletion, climate change and environmental sustainability. This led to calls for this approach to be substituted with a more flexible and inclusive approach (Watson, 2009). However, in developing countries, master planning has remained popular, and is still considered a valuable approach for effective urban development and management. One notable example of a planned capital city in the Global South is Abuja, Nigeria.

Given the pace of global urbanization and its negative consequences, monitoring urban area growth is critical to provide essential information for urban management and planning. To monitor urbanization, a regular and reliable source of spatial information is needed, with ground survey labour-intensive and costly. Remote sensing is the only realistic solution. Satellite data has been used widely in mapping urban growth and assessing city morphology, informal settlements, and socio-economic features such as population size and poverty (Jensen & Cowen, 1999; Longley, 2002; Aplin, 2003a; Wurm et al., 2009). Urban remote sensing dates back to the start of the Landsat programme in 1972, when the spatial data requirements needed to delineate broad urban patterns were met with medium (79 by 57 m) spatial resolution Landsat Multispectral Sensor (MSS) imagery (Maktav et al., 2005). Later generations of Landsat and other medium resolution sensors, especially Landsat's Thematic Mapper series (30 m spatial resolution), increased the detail and accuracy of urban mapping to some extent (Gluch, 2002; Blaschke et al., 2011). However, the introduction of very high resolution (VHR) sensors, the first being IKONOS, launched in 1999 with 4 m spatial resolution (multispectral) imagery (Aplin, 2003b; Weng, 2012), improved capabilities dramatically. The greater detail provided by VHR sensors offered improved discrimination of built-up and non-built-up areas and has improved the ability to analyse internal variation within urban settlements (Wania et al., 2014).

While great effort goes into Master Plan development and implementation, there is often little later reflection on the success of this approach. In Abuja, few studies have retrospectively examined the city's urban growth and development (Ujoh et al., 2010; Ujoh et al., 2011; Abubakar, 2014; Zubair et al., 2015), and there has been no comprehensive review of the Master Plan's successes and failures (Abubakar, 2014). Notably, no study has examined how Abuja has developed in relation to the Master Plan document originally designed to guide the city's growth, using satellite remote sensing. This study is one of the first to assess comprehensively the success of a city Master Plan in the Global South using the approach of mapping land cover change using historical remotely sensed imagery.

A few examples where Master Plans have been assessed include six local plans in New Zealand (Laurian et al., 2004); Islamabad, Pakistan (Maria & Imran, 2006); Amman, Jordan (Beauregard & Marpillero-Colomina 2011); the central district plan of Israel (Alfasi et al., 2012; Feitelson et al., 2017); Guangzhou, China (Tian & Shen, 2011); Lucknow, India (Dutta, 2012); Nanjing, China (Qian, 2013); and Lisbon, Portugal (Padeiro, 2016), though these have not generally exploited time-series remotely sensed imagery to aid their assessment. These studies focus mainly on planning policy implementation or the level of conformance of current land use to the Master Plan without interrogating the processes that led to the current situation. Other studies assess Master Plans in relation to architectural design flaws (Maria & Imran, 2006) or focus on variables such as population and economic activity (Qian, 2013). Most studies also fail to analyse the intention of the original Master Plan in relation to the later outcomes observed. Finally, these studies also tend to conduct assessment over a relatively short time-frame rather than considering the full lifetime of a city which can shed light on how, when and why cities deviate from original plans. As such, the findings of this study, which examines long-term change in Abuja, and also comment on the causes of these changes, will have widespread significance for urban planning and management practices in the context of rapid global urbanization.

The aim of this study is to monitor the urbanization of Abuja since its inception in the mid-1970s and assess the extent to which the Master Plan has been realised. To achieve this, a time-series of historical Landsat images is used to generate a series of land cover maps enabling change in land cover types and coverage throughout Abuja's Federal Capital Territory (FCT) between 1975 and 2014 to be quantified. Of particular interest is the distinction between planned (as identified in the Master Plan) and unplanned urban development. The very existence of a Master Plan implies that unplanned development should not have occurred, or at least should be relatively insignificant. There will also be consideration of how prevailing social and political context can influence urban development. For instance, during implementation of Abuja's Master Plan, Nigeria's government switched variously between democratic and military rule, and this may have influenced urban development policies. Ultimately, the study's findings will enable recommendations on how planners and policy makers can better monitor urban growth, thus tackling urbanization and its unwanted consequences more effectively. Four specific research questions are posed here: 1) How have patterns of land cover in Abuja FCT evolved since the 1970s? 2) Has the Master Plan been effective in dictating the pace and pattern of urbanization in Abuja? 3) Has unplanned urban development been limited successfully? 4) Have changes in political governance influenced the nature of urban growth?

2.2 Study Area: The Planned City of Abuja, Nigeria

In 1975 a report was conducted by the Nigerian government's 'Committee on the Location of the Federal Capital of Nigeria' which concluded that Lagos was not capable of continuing as Federal Capital due to inadequate space for future development, lack of cultural diversity, and non-central (within Nigeria) geographical location (Ikejiofor, 1997). The government thus commissioned planning of a new capital city that should be centrally located, ethnically neutral, have sufficient natural land resources for development, and, aspirationally, provide a symbol of Nigeria's ambition to foster unity and portray greatness (Ikejiofor, 1997). In February 1976, the military government of Nigeria issued a federal decree to establish the Federal Capital Development Authority (FCDA) and charged it with the planning and development of the new federal capital of the country, later named Abuja. Therefore, a Master Plan was developed by International Planning Associates (IPA) in 1979 (Abubakar, 2014). This initiated the creation of a new capital city, a policy regarded as one of the most profound decisions taken by Nigeria since independence from Great Britain in 1960 (Vale, 2014). The Master Plan was submitted and adopted for implementation in 1979. Construction began in 1980 with an intended occupancy date of 1986, later moved to 1991 (when Abuja officially replaced Lagos as capital city) due to the slow pace of development. The Master Plan proposed a 20+ year implementation period, with the year 2000 set as the target date by which all phases of the city (as specified in the plan) would be fully developed (IPA, 1979).

The Federal Capital City (FCC) of Abuja covered an area of 256 km^2 (in the original Master Plan), now extended to approximately 450 km^2 (including an extra development phase added in 2005). Located within the Federal Capital Territory (FCT) of Nigeria which covers an area of around 8,000 km^2 (Figure 2.1), the FCT is positioned between latitude 7°25' and 9°20'N, and longitude 5°45' and 7°39' W, with elevation ranging from approximately 100 m (in the southwest) to above 600 m (in the northeast). Abuja has two distinct seasons: the wet season between early April and late October, and the dry season from November to March. The FCT is located within the Guinea-Savanna vegetation zone (Idoko & Bisong, 2010).

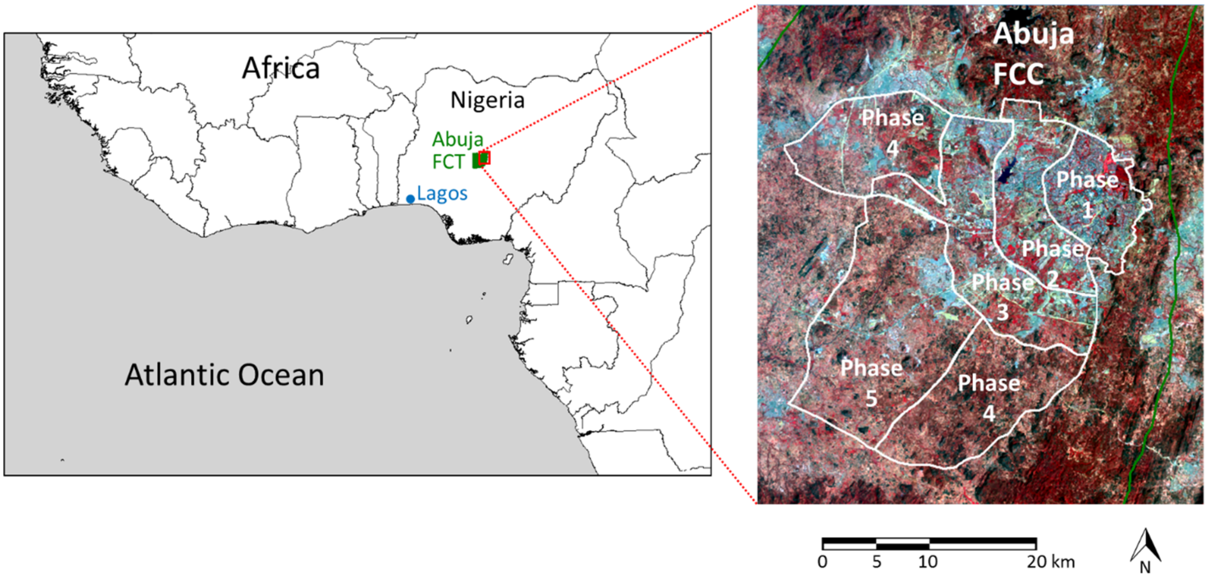


Figure 2.1. Study area showing the extent of Abuja Federal Capital Territory (FCT) on the left, with an inset of Abuja Federal Capital City (FCC) and its phase boundaries on the right. The FCC footprint is overlaid on a false colour composite display of the cropped 2014 Landsat Operational Land Imager (OLI) image area. (FCC map adapted from data supplied by Abuja Geographic Information System agency, Federal Capital Development Authority and Nigeria Space Research and Development Agency; Landsat OLI image supplied by US Geological Survey.)

The Master Plan originally specified four main phases of development (with a fifth phase added in 2005), covering four distinct spatial compartments of the city radiating outwards sequentially from the main urban centre in the northeast of the FCC (Figure 2.1). To the north and east of the urban centre is a large rock outcrop that inhibits urban construction, thus development was intended to be focussed to the west and south. The phased approach of development was adopted to ensure orderly growth of the city, limiting disruption and pollution associated with development, and enabling targeted infrastructural development so the city is habitable, populated and functional at the conclusion of each phase (IPA, 1979). The phases were intended to occur broadly sequentially, though some allowance was made for overlap between phases. While the spatial footprints of these phases were specified precisely in the Master Plan, the timescales for development were less clear. Few specific dates were given, though construction of phase one was scheduled to start in 1980 and end by 1986 (when Abuja was intended to be inaugurated as Nigeria's capital city), and completion of all four phases was scheduled for 2000.

Prior to development, 500-600 small settlements and villages were present in the FCT area, with a total population around 300,000 in 1975. The Master Plan proposed that these settlements and their indigenous residents be relocated from areas earmarked for development within the planned city (IPA, 1979), though there has been little follow-up analysis to investigate the process of relocation or its success.

The Master Plan provides considerable detail on planned land cover and land use distributions (Figure 2.1), organising the city into sectors, and specifying development type (residential, industrial, government facilities etc.) in each sector. Of the FCC's usable land (excluding steep slopes and rock outcrops), 49% was earmarked for residential development, 32.5% for recreational purposes (including green and open space), 16.5% for light industries (including commercial activities) and 2% for government usage (IPA, 1979).

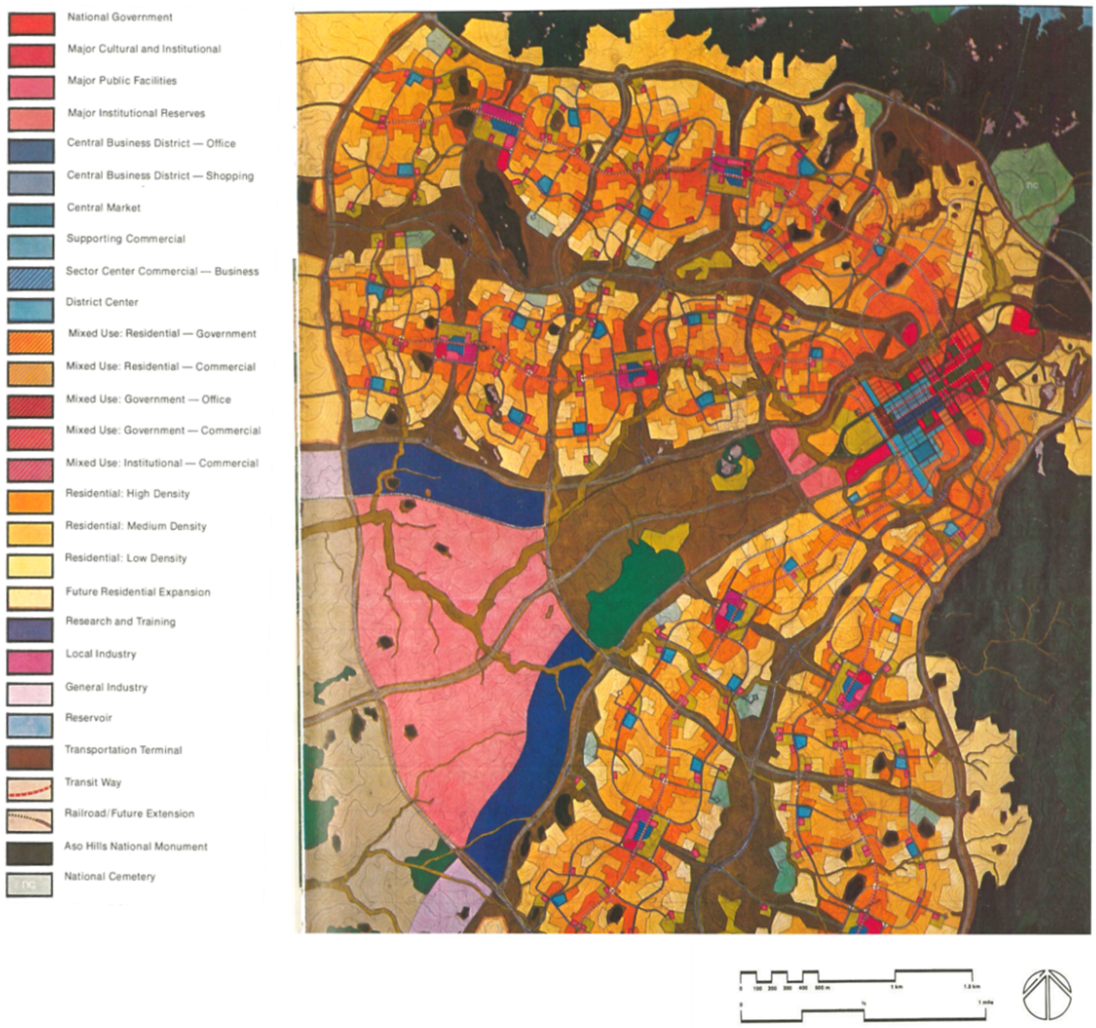


Figure 2.2. Land use plan for Abuja Federal Capital City (source: IPA, 1979).

The main rationale of the Abuja Master Plan was to provide long-term guidance for the systematic implementation and growth of the new Federal Capital City (IPA, 1979). The creators of the Master Plan intended that the plan would “recognize changes and uncertainty by making provisions for both unforeseen growth and transition as well as unforeseen events” (IPA, 1979, p. v). However, the extent to which this has been achieved is questionable.

Since its inception, Abuja has experienced rapid population growth and urbanization. With an urbanization rate of 8.3% per annum, Abuja is the fastest growing city in Africa (Myers, 2011). Such rapid growth has put considerable strain on the city’s urban infrastructure, and has limited overall adherence to the provisions of the Abuja Master Plan (Abubakar, 2014; Iro, 2007). The original population target figure when development was completed in 2000 was 1.6 million people, although it was speculated that this figure may be exceeded (up to a maximum of an additional 1.6 million) whereby the additional population was accommodated in other satellite towns within the FCT (IPA, 1979). In the official 2006 census, population was stated as just under 1.7 million (NPC, 2006), although this figure is highly contentious and other researchers have claimed the true population is far higher. For instance, Iro (2007) estimated unofficial daytime population in Abuja to be close to 7 million, illustrating the problems developers can encounter where plans are based strictly on official figures.

Notwithstanding official census figures, in 2005 the government responded to observations that both urbanization and population growth had far outstripped projections in the Master Plan (United Nations, 2015), by proposing an additional, fifth phase of development. Phase five covers an area of approximately 210 km^2 and extends further southwest from the original development (see Figure 2.1). However, details regarding phase five remain scant in terms of land use distribution, and the proposal has never been ratified by the FCDA.

2.3 Research Data

2.3.1 Remotely Sensed Imagery

The principal form of analytical data used to investigate urbanization in Abuja is a time-series of Landsat remotely sensed images. Seven images were used covering the lifetime of the Master Plan from 1975, 1986, 1990, 1999, 2002, 2008 and 2014 (Table 2.1). These images were downloaded via the online EarthExplorer facility (https://earthexplorer.usgs.gov/). To enable ready comparison, images were acquired from around the same time of year, thus minimizing seasonal effects. Nonetheless, image selection was influenced by availability of cloud-free images. It was not always possible to source images from the same month (January was targeted since this is central in the dry season), however all images selected were within one month of this target window. It was not possible to source images in equal time steps (e.g. every five years), however images were spaced reasonably regularly over the project timescale, with certain years targeted specifically to correspond with political and legislative change in Nigeria. For example, 1975 corresponded with the original (1976) proposal to create Abuja (Moore, 1984), 1986 with intended initial occupation of the city (Ikejiofor, 1998) and 1990 with the proposed relocation of the capital city from Lagos to Abuja (Idoko & Bisong, 2010). 1999 was selected to match Nigeria's switch from military to democratic governance, and 2002, 2008 and 2014 were selected with relatively short intervals to provide some correlation with the four year tenure of elected governments in Nigeria. Matching the imagery to key dates in Nigeria's recent political past is important since civilian rule has seen a marked increase in infrastructural investment in Abuja (Adama, 2007).

Table 2.1. Multitemporal Landsat time-series and NigeriaSat-2 imagery used to analyse urbanization in Abuja (MSS = Multispectral Scanner, TM = Thematic Mapper, ETM+ = Enhanced Thematic Mapper Plus, OLI = Operational Land Imager; B = blue, G = green, R = red, NIR = near infrared, SWIR = shortwave infrared, P = Panchromatic).

Acquisition date	Landsat sensor	Spatial resolution (m)	Spectral bands used (μm)
6 Dec 1975	MSS	60 (resampled from original 79 x 57 resolution)	G (0.5-0.6), R (0.6-0.7), NIR 1 (0.7-0.8), NIR 2 (0.8-1.1)
8 Jan 1986	TM	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
12 Feb 1990	TM	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
28 Jan 1999	TM	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
2 Dec 2002	ETM+	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.77-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.09-2.35)
29 Jan 2008	ETM+	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.77-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.09-2.35)
21 Jan 2014	OLI	30	B (0.45-0.51), G (0.53-0.59), R (0.64-0.67), NIR (0.85-0.88), SWIR 1 (1.57-1.65), SWIR 2 (2.11-2.29)
15 Jan 2014	NigeriaSat-2	5 m and 2.5 m (P)	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), P (0.45-0.90)

Due to the timescale over which urban development is investigated, it was necessary to utilise images acquired from different Landsat sensors: Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI). The spectral and spatial specifications of these instruments vary, but basic multispectral image configurations were used in all cases (see Table 2.1 for details). Thus, the spatial resolution was 30 m for all TM, ETM+ and OLI images, with only the MSS image being at a coarser resolution (originally acquired at 79 x 57 m, subsequently resampled to regular 60 m pixels before data supply). Spectrally, standard visible (blue, green and red), near infrared (NIR) and shortwave infrared (SWIR) bands were used, wherever available. The thermal band (TM, ETM+, OLI), and OLI's coastal and cirrus bands, were omitted since these bands are not optimised for land cover features, and to ensure more direct comparison between images.

2.3.2 Urban Planning Data

The original Abuja Master Plan was used as a source of data on proposed land cover and land use distributions throughout the study area, against which the remote sensing analysis results were compared. The Master Plan data included maps showing proposed development phases including land cover and land use, plus tables, text and figures presenting statistical details of land cover and land use allocations. A map of the original (four) Master Plan FCC phases was obtained from the Abuja Geographic Information Systems (AGIS) Agency, and subsequently digitized. A phase 5 map was obtained from the Federal Capital Development Authority's (FCDA) Department of Urban and Regional Planning, which was also digitised. To enable detailed spatial analysis, vector maps (shapefiles) showing individual districts within the FCC were obtained from AGIS. For six of these districts (Jahi, Katampe, Kaura and Utako located in phase 2; and Kabusa and Saraji in phase 3), detailed land cover and land use budget allocations (i.e. specific planned areal extents of different classes) were available, provided by the FCDA. This data was used to calculate the total expected planned coverage of built-up area in each district.

2.3.3 Reference Data

To enable independent verification of the land cover change analysis, a robust reference data set was compiled from a range of available sources. First, a six-week field campaign was undertaken in 2015. This involved extensive land cover survey throughout the study area and interviews (relating to land cover and land use change over the years and planning policies) with the city's planning officials and residents. Second, land cover maps covering parts of the study area (phases 1-3) were acquired from both AGIS and the FCDA. Third, VHR imagery was accessed, both through Google Earth's historical imagery function (containing imagery dating back to 2001) (O'Regan et al., 2016), and directly from a NigeriaSat-2 image (5 m resolution multispectral imagery (red, green, blue, near infrared bands) and 2.5 m panchromatic band) of Abuja acquired in January 2014 (supplied by the Nigeria Space Research and Development Agency (NASRDA)) (Figure 2.3).

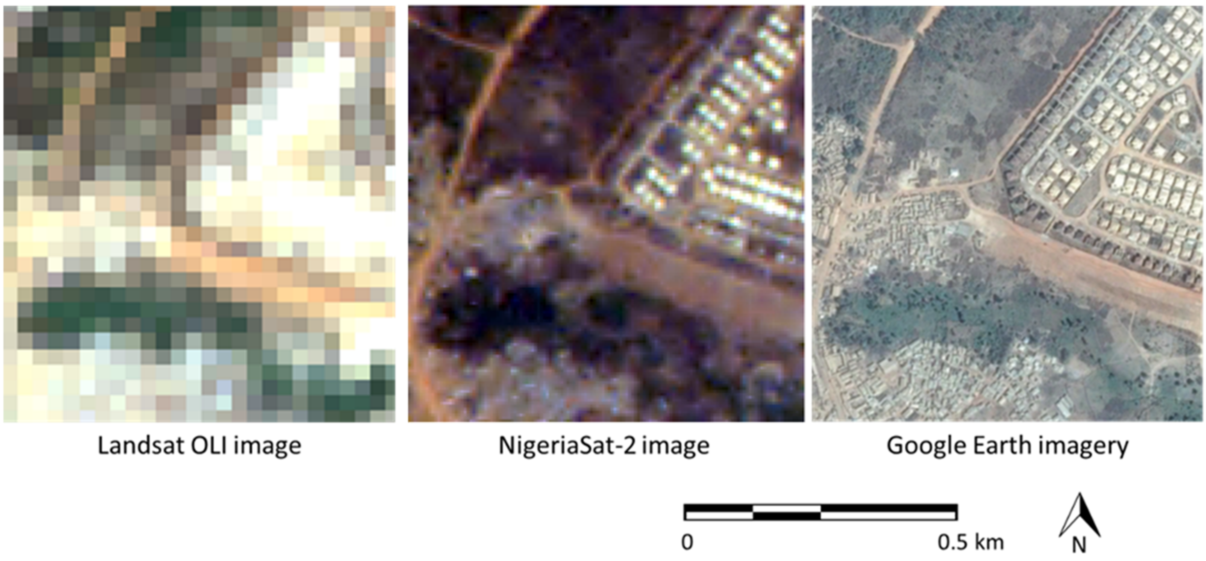


Figure 2.3. Contrast between planned (northeast of image) and unplanned (west and south of image) urban development in Kabusa district, as represented by three different true colour composite images captured in January 2014: Landsat Operational Land Imager, NigeriaSat-2 and Google Earth imagery. (Landsat OLI image supplied by US Geological Survey; NigeriaSat-2 image supplied by Nigeria Space Research and Development Agency; Google Earth imagery © 2018 CNES/Airbus.)

These reference data sources were collated to create a single, comprehensive reference land cover data set for each year of analysis (i.e. each of the Landsat image dates), and were used to train and test land cover classification analysis (Sawaya et al., 2003; Thomas et al., 2003; Yang, et al., 2003). Ensuring close temporal alignment between reference and image data proved challenging, especially for the early image dates. While the 2014 image was very well referenced (fieldwork and NigeriaSat-2 image), and other relatively recent images (1999, 2002, 2009) were covered by historical Google Earth imagery and secondary land cover maps, reference data sources were more limited for earlier image dates (1975, 1986, 1990). In these cases, the fieldwork campaign proved invaluable, eliciting personal observations and oral histories through interviews with long-term planning officials and residents able to provide detailed descriptions of past land cover distributions and changes over time (Jianchu et al., 2005; Weber et al., 2005). This combined composite was especially significant in the accuracy assessment of the older historic images (1975,1986 and 1990).

2.4 Methodology

2.4.1 Land Cover Classification System

Urban land cover classification from remotely sensed data sets can be complex due to the spectral heterogeneity of urban reflectance (Small, 2003; Small et al., 2005; Taubenböck et al., 2012; Momeni et al., 2016), so it is important to define appropriate classes considering the nature of the study area and the technical specifications of the imagery. The classification system used here was developed after careful study of relevant literature and secondary land cover maps and following extensive field observation around the study area. The system was adapted from Anderson's (1976) widely used approach, specifically the level 1 classes.

Six land cover classes were selected: bare exposed rock, bare ground, built-up land, forest, grassland and water (Table 2.2). All six classes were used for all except one of the Landsat images. In the earliest (1975) Landsat MSS image, only four classes were mapped: bare exposed rock, built-up land, forest and grassland. The other two classes, bare ground and water, were omitted because there was no significant presence of these land cover types in 1975. In later images, bare ground appeared as a pioneer class for built-up land. That is, land was converted from (i) an initial class (commonly grassland, but also sometimes forest) in the earliest image, via (ii) the bare ground class in the next image as land was cleared for development, to (iii) the built-up land class in the latest image. Also, no large water bodies were present in the study area in 1975 (water bodies in subsequent years were human-made reservoirs built after this date).

Table 2.2. Abuja land cover classification system.

Land cover class	Description
Bare exposed rock	Bare rock outcrops, including occasional rounded knolls, inselbergs, granitic and other exposed rock outcrops.
Bare ground	Open areas devoid of trees, grass or other vegetation that is not built-up, water or exposed rock. This class often comprises land cleared for development.
Built-up land	Impervious surfaces including building rooftops, asphalt roads and concrete surfaces not necessarily residential.
Forest	Woodlands and thick riverine vegetation. This class generally comprises patches of forest in isolated areas with steep slopes in riverine areas.
Grassland	Areas dominated by grasses, but also including shrubs and isolated trees (i.e. not forest blocks), and any other vegetation.

Water	Water bodies such as reservoirs, rivers and standing water.

2.4.2 Data Pre-processing

The Landsat images were downloaded as level 1 standard products, which are pre-radiometrically and geometrically corrected. To verify the geometric alignment of the images, each Landsat image was cross-checked against a VHR NigeriaSat-2 image (which was within 2-5 m of the ground control points (GCPs) selected) to ensure positional accuracy. Image pre-processing is very important in change detection analysis to minimise errors and have comparable results. All images other than the 1975 Landsat MSS image were geometrically aligned to within approximately 15 m of the NigeriaSat-2 image. The MSS image was geographically displaced by approximately 200 m; this error was consistent throughout the image. Therefore, an image to image co-registration was performed using the 1986 Landsat TM image as a reference. The 1986 image was selected as this was closest in time to the 1975 image, increasing the likelihood of common features (GCPs) being identifiable in both images.

While geometric alignment is essential for accurate change detection analysis, radiometric and atmospheric correction was less important since the results pertained to processed land cover classifications. Although atmospheric correction is advised where spectral pixel (e.g. surface reflectance) values of multi-temporal images are compared, here all images were converted from continuous original pixel values (digital numbers) to classified thematic land cover class labels. These land cover classifications were independently checked using accuracy assessment procedures, and the errors presented. This essentially bypasses any direct requirement for atmospheric correction or radiometric normalization, and is standard practice for post-classification comparison analysis (Singh, 1989; Foody, 2002; Coppin et al., 2004; Aplin, 2006; Chen et al., 2012; Hussain et al, 2013; Tewkesbury et al., 2015).

Prior to classification, all images were cropped to an identical area covering Abuja FCC and its immediate surroundings. The Landsat MSS image contained a data artefact (a diagonal line towards the southern edge of the image – see Figure 2.4) which was masked, and the affected area excluded from all images. The 2008 ETM+ image suffered from striping caused by the scan-line corrector fault which affected all imagery since 2003 (Andrefouet et al., 2003; Zeng et al., 2013). Several methods to overcome this problem have been promoted by the USGS (https://landsat.usgs.gov/landsat-7) including Web Enabled Landsat Data (WELD), Erdas Imagine Mosaicking Method, Historic Techniques (Phase 1 and 2) and Erdas Imagine Focal Analysis. Here, the focal analysis approach was used to gap fill areas of data loss. An iterative approach was employed, with visual assessment used to ensure a satisfactory outcome.

Finally, boundary data of the Master Plan development phases were digitised from maps supplied by AGIS and FCDA to create vector coverages to enable integrated analysis with the classified images.

2.4.3 Class Training and Image Classification

Land cover classification was conducted using the maximum likelihood (ML) approach. ML classification is widely used, well-understood and generally accurate where training data are selected appropriately (Foody et al., 1992; Erbek et al., 2004; Otukei & Blaschke, 2010; Srivastava et al., 2012; Li et al., 2014; Momeni et al., 2016;). Class training samples were chosen carefully from each image to meet the statistical requirements of the parametric ML classifier (Table 2.3). Reference data (described in section 4.4) were scrutinized to select training samples (i.e. image pixels) representing each class; these samples were sufficiently large, distributed throughout the study area and relatively evenly spread between classes to provide robust statistical representation of all classes (Perumal & Bhaskaran, 2010; Fichera et al., 2012; Jia et al., 2014). However, class training for the 1975 Landsat MSS image proved problematic, as the coarse spatial resolution of MSS meant that identifying small features, especially built-up areas (which in 1975 tended to be small, informal settlements), was challenging. As such, the class training samples for this image tended to be relatively small (see Table 2.3).

Table 2.3. Land cover class training and testing details for the 1975-2014 Landsat images of Abuja.

Image year	No. class training samples						Overall classification accuracy (%)
	Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
1975	35	-	21	94	163	-	67.5
1986	192	172	218	205	188	106	90.8
1990	92	268	202	314	546	182	84.6
1999	97	164	257	213	559	264	86.7
2002	153	137	196	147	210	112	86.0
2008	138	184	237	232	325	145	78.8
2014	99	171	225	144	553	358	83.8

Statistical separability testing was then performed on training samples to ensure there was no significant spectral overlap between classes. Specifically, Transformed Divergence (TD) statistics were calculated for all classes and images. TD represents the degree of divergence between pairs of classes as values between 0 and 2000, where a low value suggests poor separability and the 2000 maximum indicates full separability (Chen & Stow, 2002). TD results were generally high for all years of imagery, with many class pairs exhibiting full (TD = 2000) separability. The lowest values were recorded for the 1999 image, with an average TD value of 1972. Having established suitable spectral separability, ML classification was performed (Gong & Howarth 1990, Jensen 1996).

2.4.4 Accuracy Assessment

Quantitative accuracy assessment was conducted for each land cover classification. This involved generating a random sample of points in the study area (a stratified approach was used ensuring all classes were well represented) and, at each point, comparing the classified image pixel with the reference data. The reference data used for accuracy assessment were independent of the reference data used for class training (i.e. the same locations were not used for both training and testing). A relatively large sample of 240 points was used for each image to ensure reliable results. Results were presented and interrogated using the standard error matrix approach (Congalton, 1991; Liu et al., 2015).

2.4.5 Change Detection

Post-classification comparison was conducted on the classified images to identify change over time. This involved overlaying the classifications from the different years and assessing how pixels' class associations change between image dates (Yuan, et al., 2005; Tewkesbury, et al., 2015), and how the area coverage of each class varies. Here, more detailed spatial interrogation was also conducted on the growth of the built-up class, to identify expansion of built-up land for each time period, and to determine which other classes were converted to built-up.

2.4.6 Comparison with Master Plan

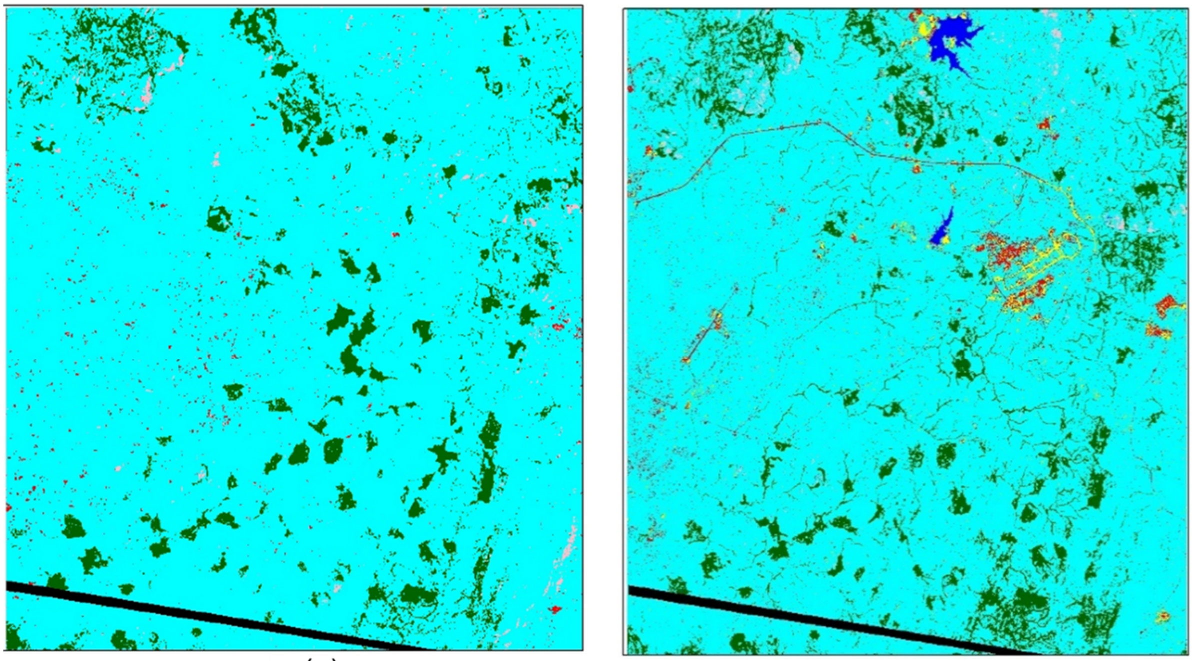
Following image classification and change detection analysis, spatial boundary data drawn from the Master Plan were integrated with the classified images to determine how closely urban development (as determined from the images) matched Master Plan projections. Specifically, vector coverages of the five development phases were overlaid on the land cover classifications, and the area of the built-up class was extracted. This analysis was also conducted beyond the development phase footprints to identify unplanned developments outside the planned area.

As the Master Plan contains a timeline of when and how the city should grow, this enabled comparative analysis of correspondence and deviation between the planned and observed phases of development to be performed. This also identifies evidence of urban sprawl, a common and unwanted phenomenon in many cities around the world (Galster et al., 2001; Wilson et al., 2003; Cohen, 2006; Wakode et al., 2014). Additional local-scale analysis was conducted by comparing Master Plan projections of built-up area for six Abuja districts with the image analysis results.

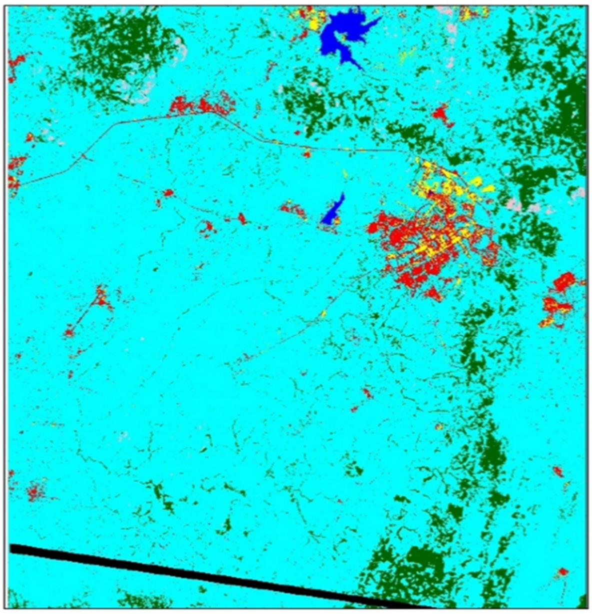
2.5 Results

2.5.1 Land Cover Classification

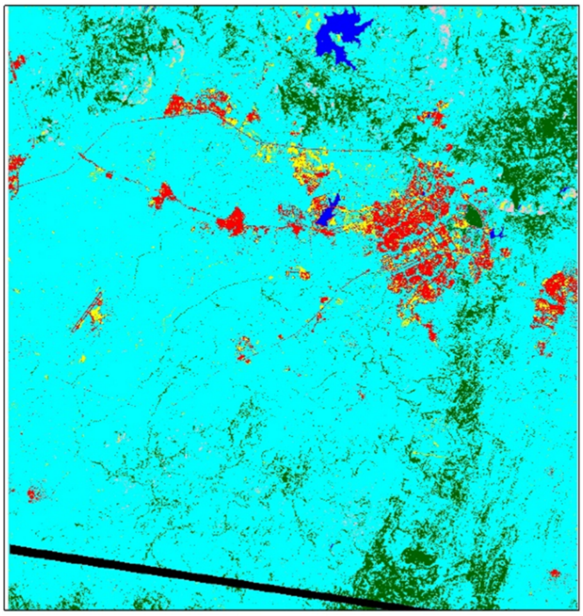
The seven land cover maps (1975, 1986, 1990, 1999, 2002, 2008, 2014) are presented in Figure 2.4. These clearly illustrate the rapid development of Abuja over this period, with built-up land displayed in red. Other notable features include the general dominance of the study area by grassland, and the creation of two water bodies (reservoirs) in the northern part of the study area to supply the population in Abuja, which first became apparent in the 1986 classification). Interestingly, the bare ground class tends to identify land cleared for development – areas shown as bare ground in one image are often converted to built-up land in the subsequent image. Finally, areas of forest in the southern part of the study area were lost rapidly after 1986, replaced by grassland. This surprise finding was investigated during the 2015 field campaign, and although unknown to planning officials at the time, it subsequently became apparent that the two main causes for this forest loss were illegal logging and agricultural clearance (A. Wakili, personal communication, 3 October 2015).



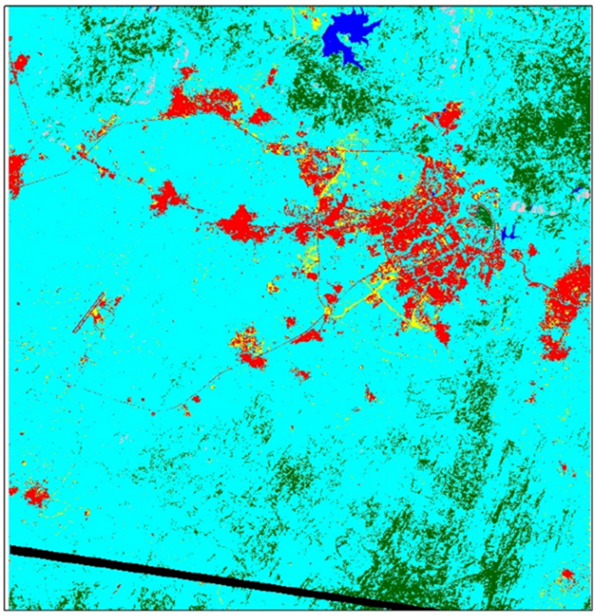
(a) (b)



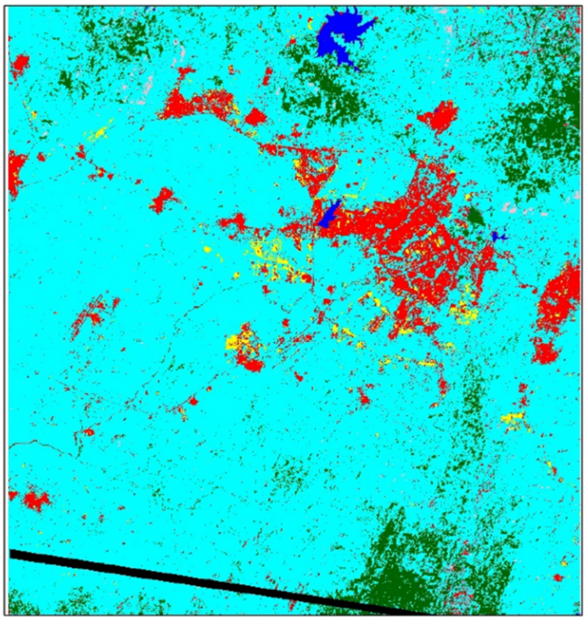
(c)



(d)



(e)



(f)

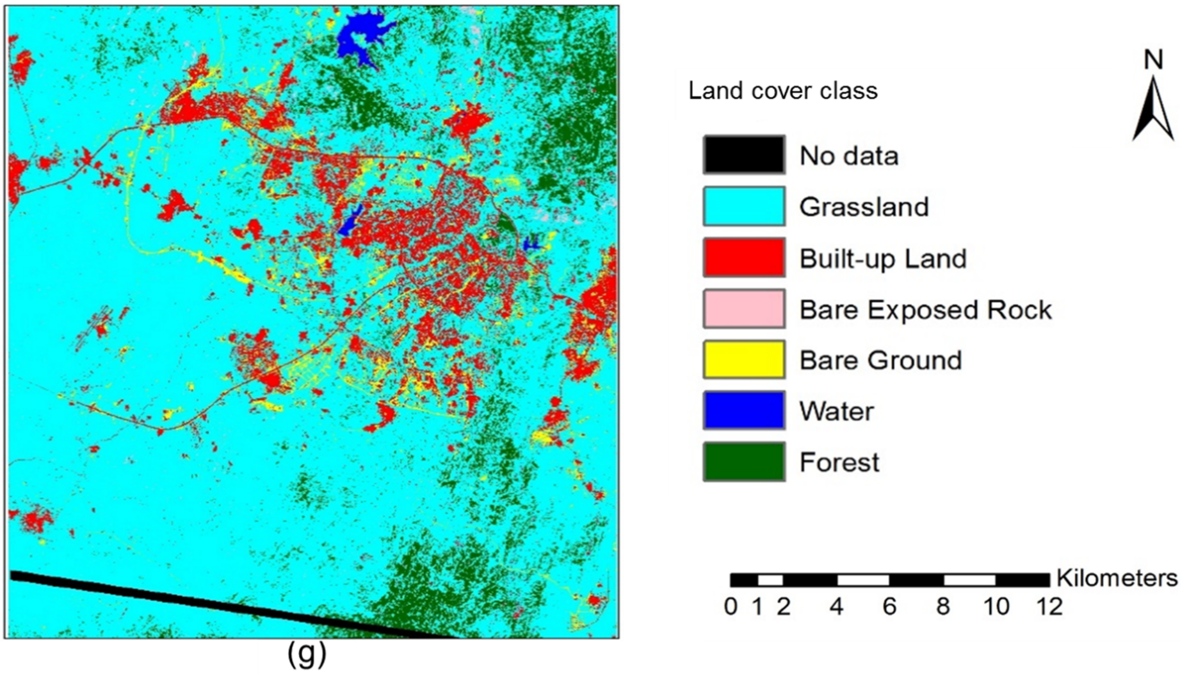


Figure 2.4. Land cover classification of Abuja, Nigeria and its environs in (a) December 1975, (b) January 1986, (c) February 1990, (d) January 1999, (e) January 2002, (f) January 2008, and (g) January 2014. No data corresponds to dropped lines in the 1975 image, with the affected area masked out of all classifications to enable direct comparison.

Quantitative accuracy assessment was performed on all the classified images, with overall classification accuracies shown in Table 2.4a-g. Accuracies were generally high, with all classifications approaching or exceeding 85%, except the 1975 and 2008 images. The 1975 image was likely affected by its coarser spatial resolution and simpler spectral configuration compared to the other images, making class separability more difficult especially for smaller land cover features such as dwellings and informal settlements (i.e. built-up land). The 2008 image may have been affected by the gap filling analysis, though visually it appears relatively accurate, with the representation of built-up land clearly showing urban development progressing between the 2002 and 2014 images. Full error matrices for all classifications are shown in Table 2.4a-g.

Table 2.4a
Error matrix for Abuja land cover classification using 1975 Landsat Multispectral Scanner image.

	Reference class				**Users accuracy (%)**
	Bare exposed rock	Built-up land	Forest	Grassland	
Bare exposed rock	10	0	5	5	50.0

Predicted class	Built-up land	0	8	0	0	100.0
	Forest	0	0	18	1	90.0
	Grassland	0	12	2	18	56.3
Producers accuracy (%)		100.0	40.0	72.0	75.0	
Overall classification accuracy = 67.5%						

Table 2.4b
Error matrix for Abuja land cover classification using 1986 Landsat Thematic Mapper image.

		Reference class						**Users accuracy (%)**
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	40	0	0	0	0	40	100.0
	Bare ground	3	27	8	0	2	0	67.5
	Built-up land	0	0	32	1	4	0	80.0
	Forest	0	0	0	40	0	0	100.0
	Grassland	0	0	0	0	39	0	97.5
	Water	0	0	0	0	0	0	100.0
Producers accuracy (%)		87.0	100.0	80.0	95.2	86.7	100.0	
Overall classification accuracy = 90.8%								

Table 2.4c
Error matrix for Abuja land cover classification using 1990 Landsat Thematic Mapper image.

		Reference class						**Users accuracy (%)**
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	37	0	0	2	1	0	92.5
	Bare ground	0	36	2	0	2	0	90.0
	Built-up land	1	2	23	0	14	0	57.5
	Forest	0	0	0	33	7	0	82.5
	Grassland	2	0	0	3	35	0	87.5
	Water	0	0	1	0	0	39	97.5
Producers accuracy (%)		92.5	94.7	88.5	86.8	59.3	100.0	
Overall classification accuracy = 84.6%								

Table 2.4d
Error matrix for Abuja land cover classification using 1999 Landsat Thematic Mapper image.

		Reference class						**Users accuracy (%)**
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	38	0	0	1	1	0	95.0
	Bare ground	2	24	10	0	4	0	60.0
	Built-up land	0	2	36	1	1	0	90.0
	Forest	0	0	0	40	0	0	100.0
	Grassland	2	0	0	5	33	0	82.5
	Water	1	0	1	1	0	37	92.5
Producers accuracy (%)		88.4	92.3	76.6	83.3	84.6	100.0	

Overall classification accuracy = 86.7%

Table 2.4e
Error matrix for Abuja land cover classification using 2002 Landsat Enhanced Thematic Mapper Plus image.

		Reference class						Users accuracy (%)
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	37	0	0	0	2	1	92.5
	Bare ground	0	21	14	0	5	0	52.5
	Built-up land	0	0	37	0	3	0	92.5
	Forest	0	0	0	38	2	0	95.0
	Grassland	2	0	1	3	36	0	90.0
	Water	1	0	0	0	1	38	95.0
Producers accuracy (%)		93.4	100.0	71.2	91.7	73.5	97.4	
Overall classification accuracy = 86.0%								

Table 2.4f
Error matrix for Abuja land cover classification using 2009 Landsat Enhanced Thematic Mapper Plus image.

		Reference class						Users accuracy (%)
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	33	1	0	0	6	0	82.5
	Bare ground	2	17	14	0	7	0	42.5
	Built-up land	1	1	29	3	6	0	72.5
	Forest	0	0	0	39	1	0	97.5
	Grassland	0	0	1	4	35	0	87.5
	Water	0	0	0	4	0	36	90.0
Producers accuracy (%)		91.7	89.5	65.9	78.0	63.6	100.0	
Overall classification accuracy = 78.8%								

Table 2.4g
Error matrix for Abuja land cover classification using 2014 Landsat Operational Land Imager image.

		Reference class						Users accuracy (%)
		Bare exposed rock	Bare ground	Built-up land	Forest	Grassland	Water	
Predicted class	Bare exposed rock	27	0	0	0	0	0	100.0
	Bare ground	0	21	4	0	0	1	80.8
	Built-up land	0	1	36	0	1	2	90.0
	Forest	0	0	0	26	2	0	92.9
	Grassland	10	6	3	9	53	0	65.4
	Water	0	0	0	0	0	38	100.0
Producers accuracy (%)		92.7	75.0	83.7	74.3	94.6	92.7	
Overall classification accuracy = 83.8%								

2.5.2 Land Cover Change

Extensive land cover conversions have taken place in the study area over the last 40 years, as illustrated by the change detection statistics presented in Table 2.5. The most dramatic class changes involve built-up land, which increased steadily from 1,164 ha (or 0.6% of the study area) in 1975 to 18,623 ha (9.8%) in 2014, and water, which was completely absent at the start of the study but increased to 1,038 (0.5%) ha in 2014 through the reservoir creation. Other notable changes include a slow but steady increase in bare ground during the study period, which can be attributed to the ongoing clearance of land for new urban development. Forest area remained relatively steady throughout the study, averaging approximately 9-9.5% of the study area despite logging and agricultural clearance activities. These losses are offset with gains in human-made forest scattered throughout the study area (e.g. national (government-managed) parks and commercial plantation, as confirmed through fieldwork and interviews in 2015). Similarly, bare exposed rock remained relatively constant (at an average of about 1,000 ha) since this land is unsuitable for urban development or land conversion. Grassland is the only class suffering significant loss of area, with this process being gradual and constant throughout the study period. In 1975, grassland covered 172,082 ha (91.1% of the study area), decreasing to 144,463 ha (76.7%) by 2014. This change occurred as grassland was converted to built-up, often via bare ground as a pioneer urban development class, and also to water.

Table 2.5. Land cover change in Abuja between 1975 and 2014.

Land cover class	1975		1986		1990		1999	
	Area (ha)	Study area %	Area (ha)	Study area %	Area (ha)	Study area %	Area (ha)	Study area %
Bare exposed rock	1327.3	0.7	1357.1	0.7	1167.6	0.6	1208.3	0.6
Bare ground	0.0	0.0	1949.4	1.0	1643.0	0.9	3143.5	1.7
Built-up land	1166.8	0.6	3479.0	1.8	5721.3	3.0	7184.5	3.8
Forest	14501.2	7.6	18421.9	9.7	19272.0	10.1	19926.7	10.5
Grassland	173154.6	91.1	164623.5	86.3	161777.0	84.9	158013.1	82.9
Water	0.0	0.0	822.0	0.4	933.3	0.5	1038.1	0.5

Land cover class	2002		2008		2014	
	Area (ha)	Study area %	Area (ha)	Study area %	Area (ha)	Study area %
Bare exposed rock	880.7	0.5	734.8	0.4	815.5	0.4
Bare ground	3851.5	2.0	2309.2	1.2	6485.8	3.4
Built-up land	12083.8	6.3	15478.4	8.1	18623.3	9.8
Forest	19144.8	10.0	15348.5	8.1	17776.5	9.3
Grassland	153614.5	80.6	155599.2	81.7	145962.9	76.5
Water	938.4	0.5	1044.1	0.5	1038.1	0.5

2.5.3 Master Plan Comparison

The increase in built-up land over the study period is illustrated in Figure 2.5, overlaid with the Master Plan development phase boundaries and with satellite towns and airport development indicated. It is noticeable that the central strategy of the Master Plan, whereby development commenced in the main urban centre in the northeast of the FCC and radiated outwards sequentially during the development phases, was realised to an extent. Figure 2.5 shows early concentration of built-up land in the northeast (the orange and yellow colours representing built-up land in 1986 and 1990 respectively), next adjoined by development extending during the middle period of the study (1999: green, 2002: blue), and finally occurring further out to the west from the urban core (2009: purple, 2014: red).

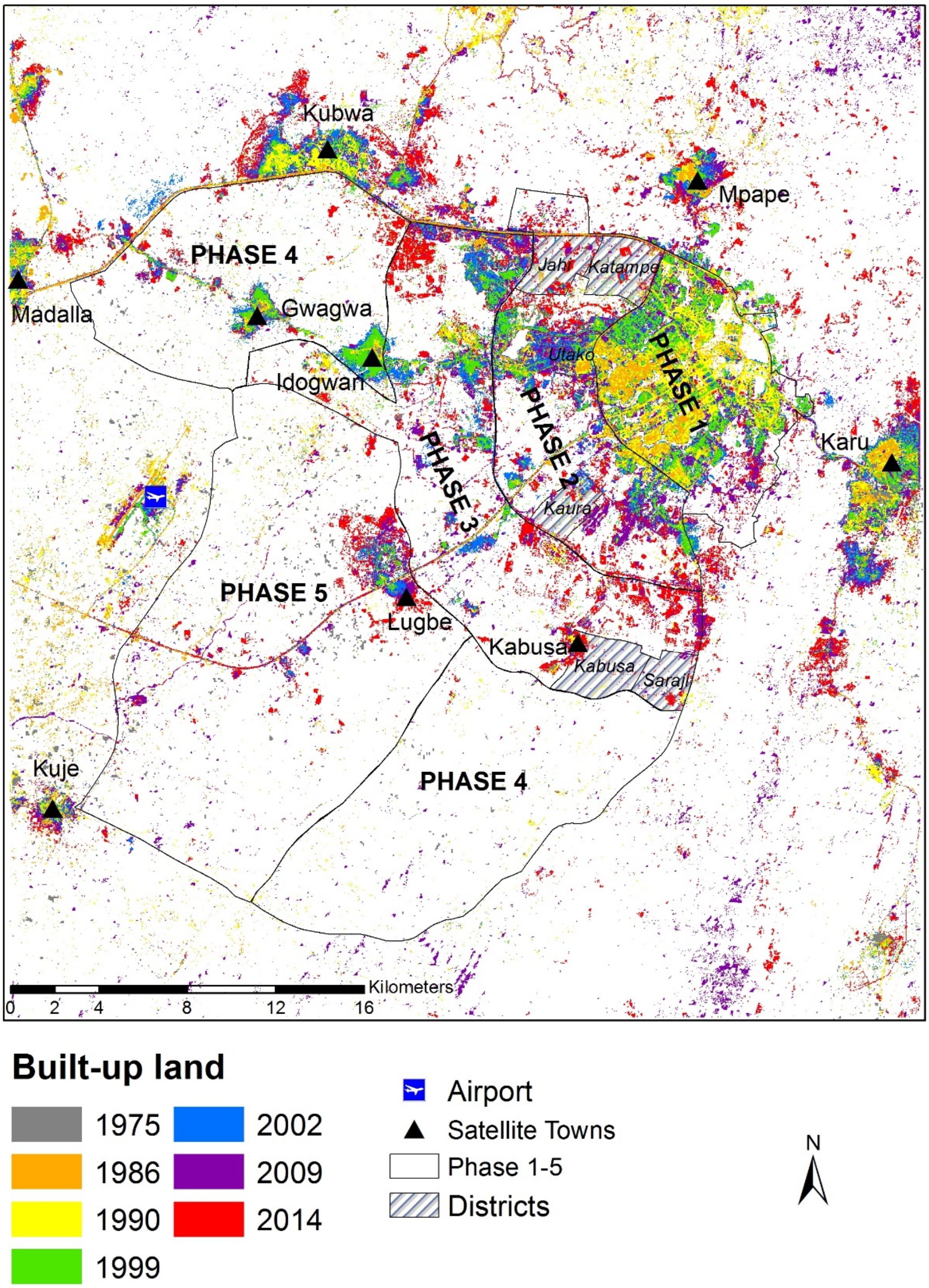


Figure 2.5. Development of built-up land in the Abuja area between 1975 and 2014.

Though the general trend of urban development in Abuja matched the broad Master Plan strategy, it is clear there is significant deviation from the specific objectives outlined in the plan. Figure 2.6 shows the areal extent of built-up land in individual development phase footprints taken from the time-series of land cover maps. It is clear that deviation from original plans occurred early in the development of Abuja. While phase 1 was scheduled for completion in 1986, by this time only 781 ha of built-up land existed, with continued development in this phase footprint continuing right up to at least 2014 when 3,345 ha of built-up land was present. Development in phases 2, 3 and 4 occurred concurrently throughout the 1980s and 1990s, rather than sequentially as intended. In the 2000s, the area of built-up land increased rapidly in phases 2 and 3, while that of phase 4 remained generally static. In contrast to phase 4, phase 5 seems to have been growing fast and steadily since 2005 when it was first proposed. This is perhaps unsurprising as phase 5 was planned relatively recently in light of earlier Master Plan shortcomings.

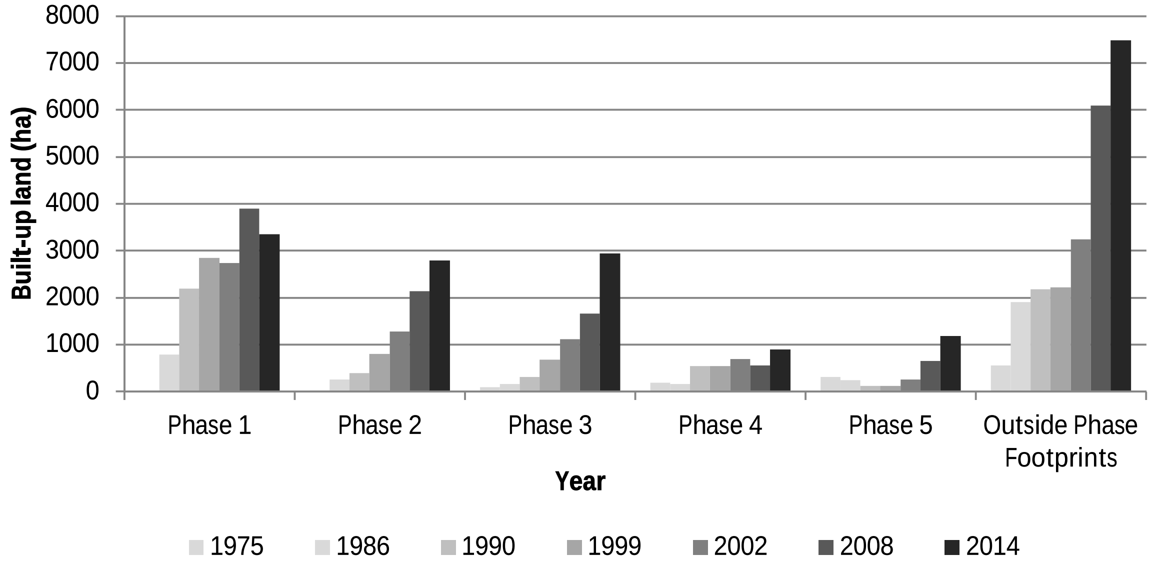


Figure 2.6. Increases in built-up land in Abuja in the Master Plan development phase areas.

Of particular interest is the increase in built-up land outside the phase boundaries (Figures 2.5 and 2.6), showing unplanned urban development. This essentially represents direct failure of the Master Plan. This unplanned development occurred almost immediately after construction commenced on phase 1, and by 1986, when phase 1 was scheduled for completion, unplanned built-up land covered more than twice the area of built-up land within the phase 1 footprint. Unplanned development then remained largely static until 1999, from when a dramatic and sustained increase is observed (see Outside Phase Footprints in Figure 2.6). The unplanned developments are mostly concentrated in the various satellite towns located in and around the outskirts of the FCC, and also around the airport west of Abuja (Figure 2.5).

Figures 2.5 and 2.6 enable broad comparison between Master Plan objectives (development phase footprints/timescales) and image-derived land cover change, but more detailed analysis is conducted for six districts of Abuja where the Master Plan set specific development targets. For Jahi, Katampe, Kaura and Utako (phase 2), and Kabusa and Saraji (phase 3), the Master Plan stated intended areal coverage of built-up land, and these values are compared against built-up land mapped from the time-series of Landsat images (Figure 2.7).

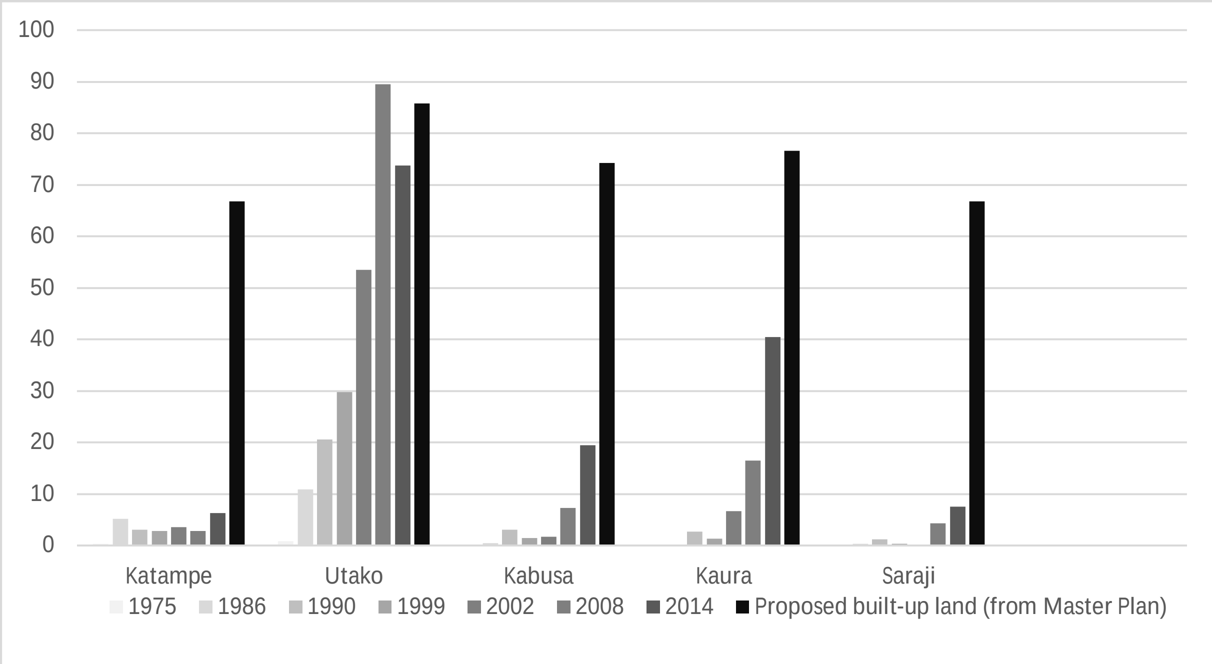


Figure 2.7. Areal coverage of proposed and actual built-up land in individual districts (Jahi, Katampe, Kaura, Utako in Phase 2, and Kabusa and Saraji in Phase 3).

Figure 2.7 shows marked discrepancies between planned and actual built-up land at the scale of individual districts in Abuja. Most of the districts fall well short of projected urban development, with five of the six districts investigated barely registering any built-up land at all before 1999, the date by which the original Master Plan should have been more or less fully implemented. Only Utako can be seen to be urbanizing progressively throughout the original timescale of the Master Plan, with the proportion of built-up land increasing steadily from 1975 (pre-plan), through 1990 (around the time of inaugurating Abuja as Nigeria’s capital), to 1999 (completion of Master Plan). Since 1999, the proportion of built-up land has increased noticeably in all six districts, though only Utako has come close to approaching its original target built-up area. Kaura has developed to about half of its target built-up area, while the other four districts fall far short of their targets. There is no noticeable trend related to development phases. The only real success story, Utako, is in the Master Plan phase 2 footprint. Overall, these district-level results, though only representing a small sample of Abuja's districts, show a general failure to achieve detailed, local-scale Master Plan objectives, with a significant shortfall in built-up land. This does perhaps bring into question why an additional development phase was added in 2005, when so much of the original Master Plan area remained undeveloped.

2.6 Discussion

2.6.1 Evolution of Land Cover in Abuja

The first research question posed in this study was ‘How have patterns of land cover in Abuja FCT evolved since the 1970s?’ Historical remote sensing image analysis clearly shows a picture of rapid and ongoing urbanization, with large areas of grassland being converted to built-up land, plus the creation of two large artificial water bodies to supply the new city (figure 2.4). Interestingly, the bare ground land cover class effectively acts as a pioneer class for urban development, showing where land has been cleared for construction. This offers a potential means of forecasting future urbanization. Though forest cover remained broadly static over the study area as a whole, locally there are interesting, and hitherto unknown, patterns of change. Rural forest patches were lost rapidly after 1986, caused by illegal logging and agricultural clearance (M. Hamza, personal communication, 3 October 2015). Elsewhere, afforestation occurred through parkland developments and commercial plantation.

Historical Landsat imagery has proved effective for land cover classification and change analysis in this urbanizing environment. While recent generations of Landsat (OLI, ETM+ etc.) yielded the most accurate classification analysis, even the earliest MSS instrument, with its coarse spatial resolution and limited spectral band set, enabled effective identification of the major land cover classes. Thus, the Landsat archive provides a valuable resource for retrospective monitoring of urban growth in the Global South and elsewhere. The situation for ongoing and future monitoring is now perhaps even more promising, with the emergence of additional, free sources of moderate spatial resolution imagery from Europe’s Sentinel satellites, plus multiple VHR image sources providing increased local area detail.

2.6.2 Effectiveness of the Master Plan

The second research question posed was ‘Has the Master Plan been effective in dictating the pace and pattern of urbanization in Abuja?’ While some broad intentions of the original Master Plan were followed in the early stages of Abuja’s development, the Master Plan cannot be considered a success overall. Figures 2.5 and 2.6 show that planned development up to 1986 was focused mainly on the phase 1 footprint, as intended. Even so, phase 1 development was slow, and the target date for relocating the capital from Lagos to Abuja was postponed from 1986 to 1991. Thereafter, the general pattern of urban development diverged more and more from Master Plan objectives. Instead of sequential development through phases 2, 3 and 4, urbanization actually occurred more or less concurrently in these phases (Figure 2.6). Local, district-scale analysis (Figure 2.7) reinforces the general discrepancy between Master Plan intentions and actual development, with only one of six sample districts coming close to realising built-up area projections. Ultimately, apparent failure in realizing some of the original Master Plan intentions was confirmed in 2005, when an extra development phase was devised to compensate for lack of success in achieving the original goals. Such failure of master planning can be attributed to slow but consistent disconnect between the planning phase and implementation processes over the years. This seems to be a recurring feature in the Global South, as a similar conclusion was reached by Rizzo (2014), when investigating master planning as a tool for guiding urban development in Qatar. On the contrary, in the Norwegian cities of Sandefjord and Elverum, 96% and 98% of the urban expansion since 1970 was found to be in accordance with their Master Plan (Sagile & Sandberg, 1997).

2.6.3 Unplanned Urban Development

The third research question posed was 'Has unplanned urban development been limited successfully?' Clearly, the principal aim of an urban Master Plan is to control development, thus eliminating, or at least minimising, unplanned urban sprawl. Figures 2.5 and 2.6 show the Master Plan has not been wholly successful in limiting unplanned development, indeed far from it. Substantial parts of the study area outside the Master Plan phase footprints have been developed, including several sizeable satellite towns.

One stated aim within the original Master Plan was to relocate pre-existing settlements within the FCT area, accommodating the population in the newly developed FCC. However, detail was scant on how this relocation would proceed, and it appears now that little action was taken to achieve this goal. To date, the majority of the indigenous population are yet to be provided with compensated land (Amba, 2010). This inaction seems to have played a significant role in the presence, persistence and growth of unplanned urban settlements. Pre-existing settlements close to Abuja such as Karu, Kubwa, Mpape and Kuje have become a magnet for unplanned urbanization (Figure 2.5), offering informal, low-cost development options compared to the relatively high cost of urban construction within the FCC (COHRE, 2008; Jibril, 2009).

Affordability is a key driver of unplanned development. One significant flaw in the original Master Plan was the little regard given to the needs and means of the unskilled/low-income population. Instead, the focus was on high quality infrastructure, including housing, which had the effect of pricing out low-income residents. As Vale (2014) observed, Abuja is a city planned without much regard to Nigeria's poor. Many of the migrants travelling to Abuja in search of better employment opportunities fall under this category, and the inevitable consequence is unplanned urban sprawl. Current residents echo these concerns. For instance, a resident of Ndako village (located in FCC phase 3) interviewed for this study stated, "If informal settlements are not dealt with properly, the city will be a mess in 10-20 years. The planners seem relaxed at the moment. So, if this continues, the city will be in trouble" (C. Akap, personal communication, 9 October 2015).

Though population estimates for Abuja vary, it appears that the Master Plan substantially under-estimated the number of people attracted to the new city. As relocation to Abuja intensified, the development of infrastructure, especially housing, could not match population growth, and this has led to a major expansion of unauthorised housing (Morah, 1992; Mabogunje, 2001). Furthermore, Abuja's rapid and uneven urbanization has resulted in greater pressure on existing service infrastructure such as roads, sanitation and energy supply, affecting the quality of service especially in the suburbs and satellite towns (Ebehikalu et al., 2016; PMNews 2016). The problem of a Master Plan under-estimating population growth is not unique to Abuja. A similar situation was observed in Shenzhen, China where its Master Plan made provision for a population of 4 million, while the 2000 census recorded 7 million inhabitants (Friedmann, 2005; Watson, 2009).

Overall, Abuja's propensity for unplanned urban development is fairly typical of cities in the Global South, exhibiting common problems such as urban sprawl, lack of housing, poor infrastructure and development of slums (Ikejiofor, 1998; Imam et al., 2008; Myers, 2011). Viewing the pattern of urban development across the city as a whole, a striking picture begins to appear – that of a dual city which at its centre is modern, planned, affluent and efficient, while around the periphery is unplanned, under-developed and spontaneous.

2.6.4 Social Context and Political Governance

The fourth research question posed was 'Have changes in political governance influenced the nature of urban growth?' It is clear that the pace of urbanization is not uniform over the study period, and various changes in government have tended to accelerate or slow urban development (Ikoku, 2004). During the early part of Abuja's establishment, up to around the year 2000, urban development is relatively slow (Figure 2.6). Thereafter, the area covered by built-up land increases rapidly. This change can be linked directly to the nature and level of governmental control. In 1999, after 16 years of military rule, Nigeria switched to a democratic government. This had various consequences; in addition to a relaxation of planning legislation and control, Abuja received increased investment (Adama, 2007) leading to more urban development, but also attracting more migrants to the area in search of better employment opportunities, thereby further increasing the demand for housing and urban infrastructure.

Over the study period, the philosophy and approach towards implementing the Master Plan has varied. For example, in the 1980s when construction of Abuja started, the policy on how to tackle indigenous inhabitants was to completely resettle all villages within five kilometres of the new FCC footprint, thereby providing a "blank canvas" (Adama, 2007, p.16) for construction of the new city. However, there was a significant shift in policy in the 1990s, as the military government of the day introduced what it called an 'Integration Policy' (Space for Change, 2013) that sought to upgrade pre-existing villages within the FCC. This policy, though, was short-lived and little action was ever undertaken (COHRE, 2008). In 1999, after the return to civilian rule, the integration policy was abandoned, and a hybrid policy involving both resettlement and village integration was attempted. Overall, none of these initiatives proved particularly successful in solving the problem (Gusah, 2012), thus unplanned settlements remain widespread and continue to expand rapidly.

In 2003, when the government of Obasanjo appointed Mallam Nasir El-Rufai Minister of the FCT, a significant attempt was made to correct and reverse the "bastardization" of the Master Plan pre-1999 (Kalgo & Ayileka, 2001; cited in Olujimi, 2009, p.205). This regime was credited for making determined efforts to realign the physical development of the city with the Master Plan despite political obstacles arising through past regimes' actions and inaction (Olujimi, 2009; Onyedika-Ugoeze, 2016). During this time, many unplanned constructions and even entire settlements were demolished, though this did not solve the problem outright as no sustainable solutions or alternatives were provided for the residents.

Another major shift in land development policy came in 2013 when the FCT minister Bala Muhammed unveiled the “Land Swap Initiative”, a policy which basically provided large tracts of grassland for private developers on the understanding that their construction work would include development of basic infrastructure like roads, water and electricity and also that they would fund the resettlement of any indigenous population living on the allocated land (Premium Times, 2014). A few years later, this policy became marred in controversy with Nigerian Federal Senator and FCT Senate Chairman, Dino Melaye, quoted as saying “despite the good intentions of the Land Swap Initiative, the coordinators of the programme failed to follow the principle of due process. There was flagrant disregard for financial regulations and the extant laws” (Daily Trust, 2016). Considering this, it is perhaps not surprising that most of the districts earmarked for infrastructure development under this initiative are yet to show any visible evidence of construction.

Evidence from Abuja suggests that political inclination and governance play a major role in the growth and management of cities, and this is perhaps especially the case throughout the Global South. Thus, adherence to, or disregard of, a Master Plan may well be influenced by politics, rather than focusing first and foremost on land use need and environmental implications. A similar observation was made by Hameed & Nadeem (2006) in a study to identify the challenges of implementing a Master Plan in Lahore, Pakistan. In that case, weak institutions and lack of coordination between government agencies were identified as major impediments to realizing the city’s Master Plan objectives.

2.7 Conclusions

The rapid pace of urbanization worldwide, and especially in the Global South, has serious social and environmental consequences, including over-population, housing and infrastructure shortages, slum development and urban sprawl. Effective urban planning is essential to control development, yet this study shows that even newly planned cities may have limited success in eliminating unwanted urban sprawl. Here, the 40+ year Landsat image archive enabled assessment of urban development over the whole lifetime of the planned city of Abuja, Nigeria. A series of seven Landsat images from the mid-1970s, when the new city was first proposed, to the modern day show rapid urbanization, with large areas of grassland being converted to built-up land, often via an intermediate bare soil class. Land cover change, as identified from image analysis, was compared against the intentions of the city's original Master Plan, showing that early success in realising plans soon gave way to uncontrolled and unintended development. Of particular concern is the wide-ranging failure to prevent unplanned development in the long-term. Though it is hard to pinpoint very precise reasons for the failure of the planning process, it is clear that the level of adherence to the Master Plan varied according to the system of government in place. For instance, after long-term military rule was replaced by democratic government around the turn of the millennium, unplanned development increased sharply.

It now seems clear that Abuja's original Master Plan included certain significant oversights when anticipating future urban infrastructure requirements. Notably, while uncertainty exists over population estimates, the city's population is almost certainly substantially larger than that originally predicted. Also, insufficient consideration was given to the needs and means of unskilled/low-income residents (Vale, 2014), and it is this large portion of the population that has driven the growth of unplanned development since planned housing is generally unaffordable (COHRE, 2008; Jibril, 2009). Throughout Abuja's development, it appears there was little formal review of progress against the original plans. By design, urban Master Plans are largely static, but this puts them at odds with cities which by their nature are growing and changing in ways not easily predictable (Watson, 2009). Future attempts at large-scale urban planning in the Global South would seem well advised to retain greater flexibility in adapting initial plans according to regular progress reviews. This should increase the likelihood of cities such as Egypt's proposed new capital (CNN, 2016) to develop in a controlled way and reduce the negative consequences of unplanned urbanization.

A first step towards improving urban planning in the Global South and thus reducing unplanned urbanization and its unwanted consequences is simply to gather useful intelligence about the problem. Experience from Abuja shows that planning officials are often wholly under-informed on the reality of urban development. For instance, during this study a senior FDCA planner stated, “A lot of changes have happened to our land use that we don’t even know here in planning” (Abubakar, personal communication, 6 October 2015). One potential and highly effective source of spatial intelligence for monitoring and guiding urban development is remote sensing. Landsat now provides a long-term archive of image data that can enable retrospective monitoring, and new sources of imagery such as Europe’s Sentinel satellites and widely available VHR sensors provide enhanced imaging capabilities for detailed and regular monitoring. We promote the uptake of remote sensing as a key element of urban planning activities, and recommend planners develop monitoring protocols to review land use change regularly using multitemporal imagery. This will enable more effective assessment of urban development activities against stated plans, including Master Plans, mitigating the occurrence and consequences of unplanned urbanization, and leading to better future planning and forecasting.

Chapter 3

Using DMSP-OLS stable nighttime lights and Landsat TM/ETM+ imagery to map and characterise urbanization at a local scale in a planned city of the Global South.

Prepared for submission to *International Journal of Remote Sensing*

Abstract

The world is urbanizing rapidly, and all growth indices indicate that this trend is set to continue. The pace and impact of urbanization is higher in the Global South, with this situation giving rise to myriad of environmental and social issues such as urban sprawl, inadequate infrastructure, growth of slums and crime. To address these problems, planners and policy makers require timely access to accurate spatial information for urban areas to make informed planning decisions and provide future solutions for ongoing urban growth. This information, especially in developing nations in the Global South, is frequently lacking.

Remote sensing offers a rich data source that can be applied to urban studies, but whereby optical remote sensing has traditionally been employed for these purposes, nighttime stable lights data from Defence Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) offers an alternative, novel, effective and robust method of mapping and characterising urban land use. Most previous studies utilizing DMSP-OLS data have been performed at global and regional scale and were focused mostly on developed nations. In this study, DMSP-OLS nighttime stable lights and urban built-up land cover extracted from Landsat TM/ETM+ are analysed for the years 1999, 2002, and 2008 to map urban extent and characterise planned (formal) and unplanned (informal) urban areas in the city of Abuja, Nigeria. Newly developed methods analysing the relationships between the brightness value of DMSP-OLS stable lights pixels and the corresponding proportion of urban built-up land area, derived from classified 30 m Landsat TM/ETM+ imageries are presented. Results suggest that DMSP-OLS nighttime stable lights are appropriate for characterising planned and unplanned urban areas in a fast-growing city in the developing world. The analysis also indicated that areas of planned development are more accurately modelled than areas of unplanned (informal) developments. This study highlights the promising capability of combining nighttime stable lights and Landsat imagery to map urban expansion and characterise complex urban dynamics in rapidly growing cities in the global south.

3.1 Introduction

The world has witnessed urbanization growth at an unprecedented rate over the past 100 years. This trend is set to continue, with most of this growth set to occur in the developing world. Despite occupying only approximately 2% of the total global land surface, cities currently host more than half the world's population (United Nations, 2015). Projections indicate that by 2100, three billion people will be added to the world's population and 70%-90% of these will be living in urban regions (Desa, 2011). Although the world is rapidly urbanizing, urban areas in various regions of the world are experiencing the transformation process and effects in different ways. For instance, in some regions, urban areas grow in a linear form (expanding in one general direction) while in other regions they grow in a dispersed form (expanding in all major directions). Moreover, while many urban areas are growing rapidly, some are actually shrinking (Zhang & Seto, 2013). These different patterns of growth indicate that urban areas need to be studied at the individual level around the world to better understand their functional and growth dynamics. There is growing interest to study and understand urban areas both at global and regional scales (Scott, 2009) in an effort to monitor urbanization and explore its developmental benefits (e.g. better infrastructure and economic opportunity), as well as manage the negative impacts (e.g. pollution and crime).

Despite this interest, very little attention is being given to the study of urbanization in countries of the developing world (Akingbade et al. 2009). Consequently, in many low-income developing countries information on urbanization is scarce, outdated and unreliable (De Jong et al. 2000; Cohen 2006), while sometimes the only up-to-date maps of urban areas in these countries are the maps produced on a global scale (Tatem et al., 2005). Studying and understanding urbanization effectively requires regular monitoring through observation and analysis of reliable data and information (Makhamreha & Almanasyeha, 2011). Remote sensing can provide the data and information needed, at the required spatial and temporal resolution needed to study the urban environment (Jensen & Cowen, 1999). Using satellite remote sensing to study urban areas started in earnest in the 1970s when Landsat MSS data became available (Glutch, 2002), and more recently with the advent of new satellites that provide very high resolution (VHR) imagery, research on urban areas is becoming more widespread (Yang, 2011). The advent of VHR sensors played an important role in the significant transformation of urban studies, with the first being

IKONOS with 4 m resolution in 1999 (Aplin, 2003). The finer spatial resolution (under 5 m) of these sensors provides the capacity to identify and map small features in the urban environment with relatively higher accuracy (Inglada & Michel 2009; Weng, 2012, Momeni et al., 2016). This demonstrates that satellite remote sensing is poised to play a vital role in aiding urban planning (in developing countries) by assisting in the production of urban maps for city, regional, national and global scale analysis and interpretation (Tatem et al., 2005).

Different types of remotely sensed data have previously been used to obtain information about urbanization and urban dynamics. For instance, multispectral Landsat MSS, TM and ETM+ images have been used to study urban expansion and urban growth dynamics in a city in Colombia, Washington D.C, and Shijiazhuang, China (Santana, 2007; Maseket al., 2000; Xiaoet al., 2006). Land cover and land use characterization in urban areas that focus on urban built-up land expansion and change detection analysis are also an area where Landsat data is utilized successfully (Vogelmann et al., 1998; Moller-Jensen & Yankson 1994; Geymen & Baz, 2008). In a study where a meta-analysis was performed on global urban expansion around the world, Seto et al. (2011) found that a total of 326 studies have used remotely sensed images, mostly from Landsat, to map urban land conversion up until the year 2000. The success of using multispectral Landsat imagery and other VHR imagery for urban studies is well established (Yuan et al., 2005; Xiao et al., 2006; Wania et al., 2014; Momeni et al., 2016). Landsat and other VHR satellite imagery are rich data sources for mapping urban areas, however they do also have limitations. For example, while land cover can be mapped directly using Landsat imagery and other optical imagery, the complexity of urban land cannot be mapped directly without additional data/information. Also, using the spectral characteristics of the target features as characterised by the remote sensing sensor alone can struggle to distinguish between different types of impervious surface (in terms of land use) in urban areas, limiting the level of thematic detail in land cover classes that can be discriminated. Compounded by problems with optical data availability resulting from cloud cover and data degradation resulting from the scan line correction error on the Landsat ETM+ sensor during the 2000s, this is a significant challenge that requires new approaches in terms of remote sensing data types utilised and methodological development to address.

An alternative dataset that is receiving prominence and regarded as very promising in the domain of urban research is the nighttime lights (NTL) data, from the Defence Meteorological Satellite Program Operational Line-scan System (DMSP-OLS) (Zhang et al., 2015). The NTL imagery offers global coverage and is available free of charge with different formats updated daily, monthly and annually. Where the DMSP-OLS NTL imagery is unique and differs from the optical sensors historically used for urban studies such as Landsat, is that it can identify and characterise urban areas via light emittance (typically anthropogenically produced light rather than natural fires in this study), and discriminate between built-up and non-built-up land cover classes (which will not emit light) which could be spectrally confused via optical imagery. Thus, this offers a new perspective to minimise confusion and improve discrimination of urban built-up land and other land cover land use classes (Zhang et al., 2015). The potential of DMSP-OLS images in the field of urban mapping were first demonstrated by Croft (1978) after observing nighttime images of some regions around the world from space, with Kramer (1994) providing a detailed breakdown of the feasibility of using DMSP-OLS data to study different environmental facets, including urban areas. The DMSP-OLS sensors have a moderate spatial resolution in two categories, with "fine resolution" at 0.56 km and "smooth resolution" with a nominal resolution of 2.7 km and provide data with a high contrast between lit and un-lit areas (recorded as emittance value ranging from 0-63), offering robust data to identify and map areas where substantial human activity is occurring (Imhoff et al., 1997). The nighttime lights emitted in cities and observed by the DMSP-OLS sensor provides a viable way for delineating and mapping urban areas (Imhoff et al., 1997; Small et al., 2005a; Zhou et al., 2014) and monitoring urban development worldwide (Small et al., 2011), as well as detecting gas flares and wild fires at night (Elvidge et al., 1999).

Several studies have successfully utilized DMSP-OLS NTL data for urbanization studies, including He et al. (2006) which showed how promising DMSP-OLS data was at the regional level in the Bohai Rim region of China, by using it to develop three urban spatial analysis models, namely polygon-urbanization, line-urbanization and point-urbanization and they found that the urbanization process in the region is dominated by polygon-urbanization which happens around big cities. Shao & Liu (2014) combined Moderate Resolution Imaging Spectroradiometer (MODIS) data and DMSP-OLS NTL data to monitor and estimate large scale impervious surface dynamics in China. A similar combination of DMSP-OLS NTL and MODIS Normalized Difference Vegetation Index (NDVI) was also used to extract regional urban extent by Zhang et al. (2015). Additionally, Small et al. (2005b) conducted spatial analysis of global urban extent from DMSP-OLS data and concluded that nighttime lights can be used as a means of creating repeatable consistent maps of human settlements globally. Other studies have also used DMSP-OLS NTL to either map urban built-up land or monitor urbanization dynamics at global level (Sutton et al., 2001; Elvidge et al., 2001; Nghiem et al., 2009; Elvidge et al., 2009, Zhang & Seto, 2013) and also at regional level (Ma et al., 2015; Pares-Ramos et al., 2013; Small & Elvidge, 2013; Small et al., 2011; Gao et al., 2015; Yi et al., 2016; Xu et al., 2015).

Despite the recent increase in the use of DMSP-OLS nighttime lights to investigate urbanization in different regions around the world, very few studies have investigated the effectiveness of using DMSP-OLS nighttime lights to map or monitor urban areas at local scale (Xu et al., 2014), with even fewer studies looking at urban areas of developing countries (Min et al., 2013) despite them experiencing more negative consequences of urbanization, which include shortage of housing, unemployment, environmental degradation and pollution (Ji et al., 2001). This is potentially due to the fact that most of the techniques developed for processing nighttime lights are based on developed nations, remaining untested in developing nations (Imhoff et al., 1997). In one of the few studies focusing on developing countries, Doll & Pachauri (2010) investigated the extent of population access to electricity using DMSP-OLS imagery; the result revealed that there is slow progress in the expansion of energy access in Sub-Saharan Africa. Also in this analysis, it was found that many areas of the world where there is acute shortage of electrification (developing countries) also have large dispersed populations that are not well captured in nighttime light data (Doll & Pachauri, 2010; Small et al., 2011). Min et al. (2013) successfully used DMSP-OLS nighttime imagery to detect rural electrification, with the result consistent when compared with data collected on the ground in Senegal and Mali.

In this research, we attempt to map and distinguish between unplanned and planned urban land use in a planned city of the Global South: Abuja, Nigeria. Combined Landsat TM/ETM imagery and DMSP-OLS stable lights data sets were used to map urban built-up land cover, and also discriminate areas of planned (formal) and unplanned (informal) urban built-up land. Recent analyses (Gumel et al., 2019, submitted to Remote Sensing)) found considerable evidence of unplanned urban growth, not only outside of the Abuja planned city boundaries, but also inside the different city compartments, as prescribed in the 1979

Abuja Master Plan. The objective of this study is to investigate the relationship between DMSP-OLS stable light imagery radiance values and the corresponding proportion of urban built-up land cover. Hence, two specific research questions are posed to achieve the study's objectives: 1) How effective is DMSP-OLS stable nighttime lights (SNTL) imagery in mapping urban extent at local scale in a Global South environment? 2) Can DMSP-OLS SNTL imagery successfully distinguish unplanned and planned urban areas in a Global South environment? To the author's knowledge, this is the first study that has used DMSP-OLS nighttime imagery to discriminate planned and unplanned built-land areas in a developing country.

3.2 Study Area

Abuja is a planned city and the capital of Nigeria. The Federal Capital City (FCC) consists of five concurrent development phases situated within the Federal Capital Territory (FCT), an area of approximately 8,000 km^2 that was apportioned in 1976 in central Nigeria to accommodate the proposed new capital (see Figure 3.1). The FCT is located between latitude 7°25' and 9°20'N and longitude 5°45' and 7°39' W, with a general elevation extending from approximately 100 m in the southwest of the territory, to above 600 m in the northeast. The FCT is also located within the Guinea-Savanna vegetation zone, with two distinct seasons; wet and dry (Idoko and Bisong 2010).

Abuja came into existence after the government adopted a report by a committee in 1975 on the location of the Federal Capital of Nigeria. The report concluded that Lagos (the then Capital) was not ideal for continuing as a Federal Capital due its lack of space to accommodate developmental expansion and its lack of cultural diversity, coupled with its geographical location in the coast which makes access difficult from around the country (IPA, 1979). Construction of Abuja started in 1980, with settlement planned for 1986. However, the official relocation of the capital from Lagos to Abuja occurred in 1992. The city's growth and development are guided by the Abuja Master Plan, produced by the International Planning Associates in 1979.

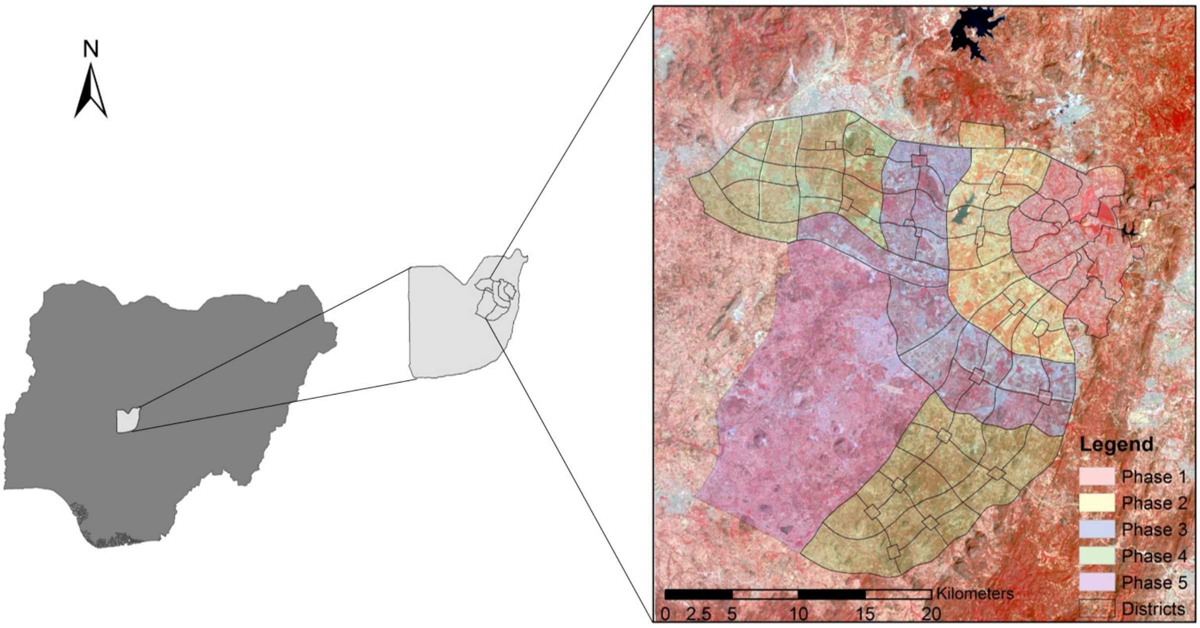


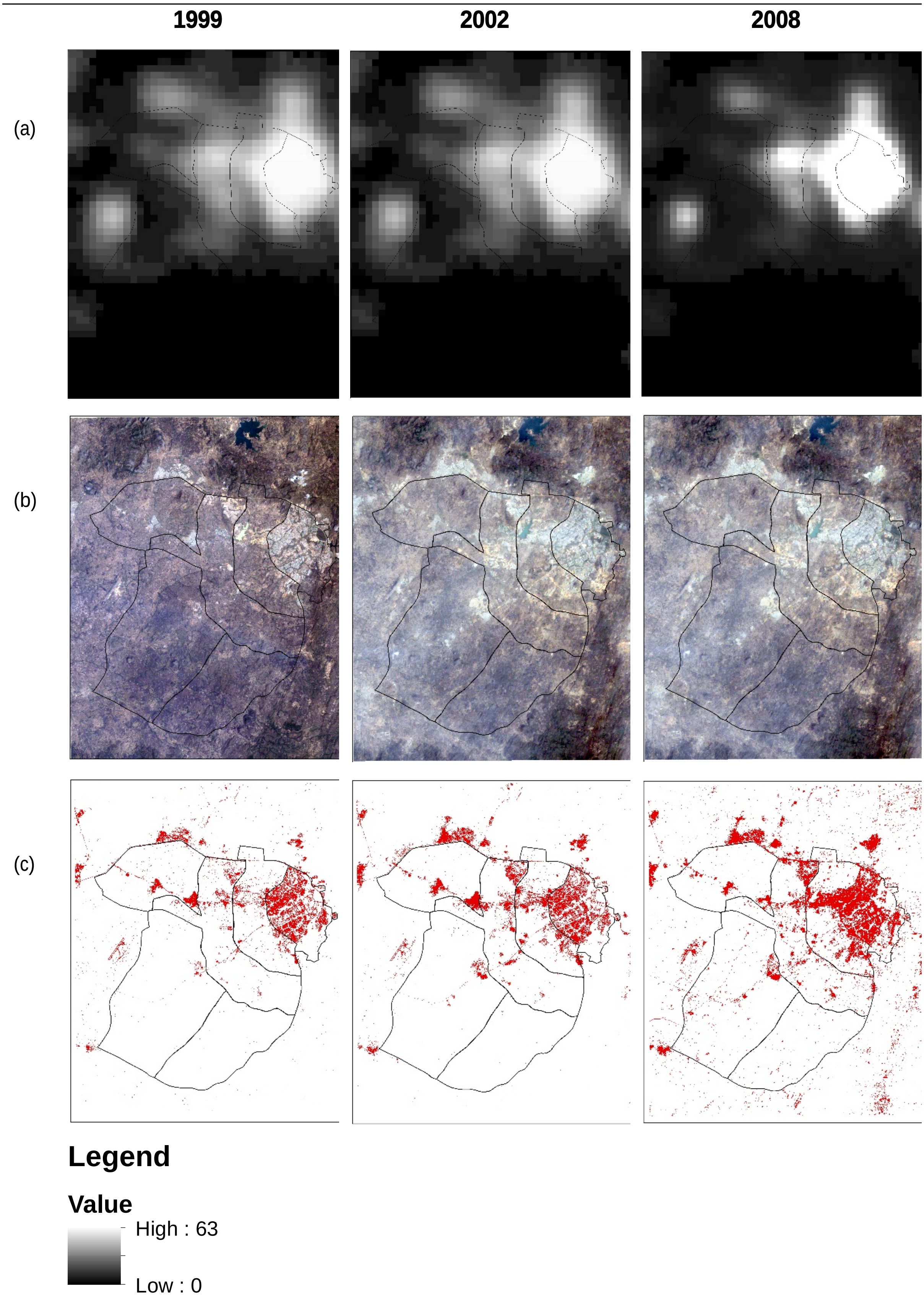
Figure 3.1. Study area comprising Nigeria, Federal Capital Territory and the Federal Capital City Abuja (FCC map adapted from maps supplied by AGIS and FCDA), and Landsat OLI (false colour composite) image of Abuja (2014).

Over the past four decades, Abuja has witnessed fast paced urbanization and rapid population growth. With a high urbanization rate of 8.3% a year, Abuja is the fastest growing city not only Nigeria, but in the African continent as a whole (Myers, 2011). Because of this rapid urbanization, the city's urban infrastructure is under tremendous pressure, making it very difficult to grow adhering to the provisions of the Abuja Master Plan (Iro, 2007; Abubakar, 2014). As result of these and other factors, there is evidence of unplanned settlements emerging alongside the planned developments. Some of the settlements started as small villages housing the local inhabitants of Abuja that were slated for resettlement outside the FCC but were not resettled by the government (Jibril 2009). These settlements are located both outside the planned city boundaries and within some districts in the planned development phases.

3.3 Data

In this study, data from two different sources ware utilised. DMSP-OLS SNTL time series imagery from the version 4 Global annual composite dataset was combined with urban land cover maps created using Landsat TM/ETM+ imagery (Table 3.1). The DMSP-OLS SNTL imagery of 1999, 2002 and 2008 were obtained from the website (https://maps.ngdc.noaa.gov/viewers/dmsp_gcv4/) of National Centre for Environmental Information (NCEI) which is part of the US National Oceanic and Atmospheric Administration (NOAA). Images of three different years were downloaded (1999, 2002, 2008), see Figure 3.2. These years were selected to coincide with the period immediately after a major socio-political event in Nigeria, the return to democracy from military rule which occurred in 1999, that significantly affected the pace and pattern of urban development in Abuja (Gumel et al., 2019, submitted to Remote sensing). The dates were limited by the DMSP-OLS SNTL archives which are available until 2010. The data also coincided with Landsat TM/ETM+ image availability; images from 1999, 2002 and 2008 (Figure 3.2) were used to create urban land cover maps.

The SNTL data were acquired by three different DMSP-OLS satellites: the 1999 image was acquired by the F14 satellite, the 2002 image by the F15 satellite and the 2008 image by the F16 satellite. The different satellites did not have effect on the analysis of the data as each year was analysed independently. Data was recorded in 6-bit format, with each pixel recorded as a digital number (DN) ranging from 0 to 63. Each pixel is the average of the DMSP-OLS visible band recorded DN values of lights from cities, towns and other persistent light over a year. The annual composite data is further screened to exclude factors such as background noise, ephemeral lights, moonlight, sunlight glare, fires and lighting from auroras (Elvidge et al., 2009), making the annual composite data suitable for urban studies.



1999
2002
2008
(a)
(b)
(c)
Legend
Value
High : 63
Low : 0

Figure 3.2. Data: (a) DMSP-OLS nighttime stable lights (b) Landsat TM imagery January 1999, Landsat TM imagery December 2002 and Landsat ETM+ imagery January 2008 (c) Urban area extracted FROM Landsat TM/ETM+ land cover classification. The overlaid planned city boundary data was derived from Abuja city map obtained from Abuja Geographic Information Systems (AGIS) and FCDA. NTL data was obtained from National Centers for Environmental information (NCEI) and Landsat OLI imagery from United State Geological Survey (USGS).

Currently, the Version 4 DMSP-OLS Nighttime Lights Time Series (V4DNLTS) dataset released by NCEI in 2010 is among the most widely-used (Liu et al., 2012b). The dataset consists of cloud-free annual composites combining all available archived DMSP-OLS satellites (approximately 1 km resolution) data from 1992 to 2010. The dataset consists of three types of data: Nighttime Stable Lights (SNTL), cloud free coverage, and raw nighttime lights with no further filtering. Among the three types of data, the SNTL (used here) is the most popular among researchers for its lack of background noise and ephemeral lights such as fires (Huang et al., 2014; Liu et al., 2012b, Elvidge et al., 2009). Limitations of the cloud free coverage and nighttime lights with no further filtering applied include having no cloud free observations at some locations in some years, and data contains ephemeral lights (such as fires) that could be confused with city lights.

The urban built-up land cover of Abuja for 1999, 2002 and 2008 (Figure 3.2) was extracted from a land cover map created using Landsat TM (1999) and ETM+ imagery (2002 and 2008) (Gumel et al. 2019, submitted to Remote Sensing). The images were originally obtained via the United States Geological Survey (USGS) EarthExplorer online facility (https://earthexplorer.usgs.gov/). Detailed information on the imagery used is the study is shown in Table 3.1.

Table 3.1

DMSP-OLS SNTL and Landsat imagery used to characterise urban settlements in Abuja (TM = Thematic Mapper, ETM+ = Enhanced Thematic Mapper Plus, B = blue, G = green, R = red, NIR = near infrared, SWIR = shortwave infrared, VNIR = Visible Near-Infrared, TIR = Thermal Infrared).

Acquisition Date	Sensor	Spatial resolution (m)	Spectral bands used (μm)

28 Jan 1999	Landsat TM	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
2 Dec 2002	Landsat ETM+	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
29 Jan 2008	Landsat ETM+	30	B (0.45-0.52), G (0.52-0.60), R (0.63-0.69), NIR (0.76-0.90), SWIR 1 (1.55-1.75), SWIR 2 (2.08-2.35)
1999	DMSP-OLS (stable lights)	909	VNIR (580-910), TIR (1030-1290)
2002	DMSP-OLS (stable lights)	909	VNIR (580-910), TIR (1030-1290)
2008	DMSP-OLS (stable lights)	909	VNIR (580-910), TIR (1030-1290)

The Landsat imagery was initially used for land cover classification, with six classes selected. For details of the land cover classification system and the classes adopted, see Gumel et al. (2019). For this study we are interested specifically on urban built-up land, with this class selected and its areal coverage extracted for further analysis while the other classes were disregarded.

A map of the planned city boundaries (see Figure 3.1) was also used to identify the relative planned development phases of Abuja and surrounding satellite towns. Finally, reference data were collected through a field campaign in 2015 to help tune the method used to distinguish planned and unplanned settlements (by determining threshold for the DMSP-OLS data; described further below). The field campaign also involved interviews with planning officials and residents to provide valuable information on the history and evolution of existing planned and unplanned settlements.

3.4 Methods

One common difficulty with multitemporal analysis of DMSP-OLS data is that the visible band of the DMSP-OLS sensor does not have on-board radiometric calibration (Elvidge et al., 2014), so when using the multi-temporal DMSP version 4 stable lights dataset, previous studies have first performed inter-calibration, mostly using second order regression techniques developed by Elvidge et al. (2009). An alternative approach to conducting inter-calibration of multi-temporal stable lights data is to classify each year of data independently without directly comparing the radiance value. Since each stable light image (1999, 2002, 2008) is independently integrated and analysed alongside urban built-up land cover generated from Landsat imagery of a corresponding year, inter-calibration was here not deemed necessary. This approach has been successfully applied previously, with Zhuo et al. (2009) using non-radiance calibrated DMSP-OLS NTL to model population density at pixel level in China.

3.4.1 Comparison between SNTL values and Landsat built-up area

Comparison analysis was performed to compare pixel nighttime light brightness (DN) values to total built-up land cover area as extracted from Landsat TM/ETM+ derived land cover classification. A total of 2,346 nighttime lights pixels covered the study area footprint. For each NTL pixel (about 1 km^2 in size, at 923 by 923 m), the proportion of built-up area within that pixel footprint (as identified from the extracted Landsat built-up class data) was calculated using the Geospatial Modelling Environment software package. Correlations between the DMSP-OLS stable lights pixel radiance value and corresponding coverage of urban built-up land were then calculated for the 1999, 2002 and 2008 time periods using regression analysis, and plotted in a series of scatter plots to examine the strength and nature of the relationships present.

3.4.2 Nighttime lights threshold computation

We analysed the SNTL using a thresholding technique combined with additional ancillary data (the Landsat-derived built-up land cover extent), similar to the approach adopted by (Henderson et al., 2003; Liu et al., 2012b). The thresholding approach was first developed by Imhoff et al. (1997). In that study, it was found that using a certain percentage of light intensity, it is possible to successfully classify DMSP-OLS nighttime lights into “Urban cover”. A threshold of ≥89% was determined to be the optimal threshold of mapping cities in the USA (Imhoff et al., 1997). Alternatively, Tatem et al., (2005) found the optimal threshold for mapping urban extent in Kenya to be 20% or 32%, demonstrating that determining a single optimal threshold to classify all cities or regions is difficult and subjective, and remains a major challenge (Zhou et al., 2014). Thresholding can be problematic as there is always a trade-off between using a high or low threshold. A high threshold is more suited to developed nations because it prevents the conurbation of urban clusters while a low threshold generally fits developing nations more because it captures a bigger areal extent and smaller less lit urban clusters (Sutton et al., 2001). In this study, a two-stage thresholding approach was taken. The first stage was to distinguish urban and non-urban land, with the second stage to distinguish between planned and unplanned urban land. Thresholds were applied to generate urban extent maps for each individual year.

To determine the optimal threshold for each year, we overlaid the built-up land cover map with each SNTL image, STNL DN were converted to percentages (%) because it is simpler to understand and easier to perform year to year threshold comparison. Several studies adopted the same format, for example Imhoff et al. (1997) and Tatem et al. (2005). We iteratively tested thresholds from 2% to 100% in multiples of 2% (i.e. 2, 4, 6, 8…100). Finally, the threshold was adopted that gives the closest match after a spatial comparison between the annual stable lights composite and the urban built-up land cover produced from the higher resolution Landsat TM/ETM+ data. An area is ultimately determined to be urban if the majority of an NTL pixel is occupied by urban built-up land cover generated from Landsat (Liu et al., 2012). The significant spatial resolution difference between the DMSP-OLS SNTL and Landsat TM/ETM+ makes this an objective quantifiable approach. This method was first successfully applied by Henderson et al. (2003) to validate an urban boundaries map derived from global night-time satellite imagery for the cities of Lhasa (Tibet), Beijing (China), and San Francisco (USA). Additionally, a similar methodology was applied to extract the dynamics of urban expansion in China from 1992-2008 using DMSP-OLS nighttime lights (Liu et al., 2012a), and Gibson et al. (2014) to update urban expansion estimates and compare relationships between economic growth and nighttime lights expansion in China.

We also sampled nine satellite towns (unplanned settlements) in Abuja to further examine in detail to explore the reasons why they may or may not be correctly identified after applying threshold to the SNTL data. For example, size, age, and proximity of the satellite towns to the planned could play a role in which of the unplanned settlements is captured accurately in each year. The sampled satellite towns that are examined are: Gwagwa, Idogwari, Kabusa, Karu, Kubwa, Kuje, Lugbe, Madalla and Mpape all around the FCC Abuja (see Figure 3.4).

3.4.3 Accuracy assessment

Quantitative accuracy assessment using standard error matrix approach (Congalton, 1991; Li et al., 2014) was performed on all the urban extent maps generated using DMSP-OLS data. As the Landsat imagery used to generate the land cover classifications has much finer spatial resolution than the DMSP-OLS imagery (30 m compared to 1 km), it is appropriate to use it for validation and accuracy assessment (Cao et al., 2009; Henderson et al., 2003; Small et al., 2005a; Liu et al., 2012a). Accuracy assessment was performed using an equalized random approach whereby a fixed number of randomly selected points for each class was used to generate 300 points on each map (100 points each for planned and unplanned urban areas, and 100 points for non-urban area) to ensure an appropriate sample size. This approach makes direct comparison of classification accuracy between classes simple (Aplin et al., 1999). Google Earth's historical image archive was also used to enable independent accuracy assessment of the maps and analysis done using the multitemporal DMSP-OLS SNTL. This was done by first selecting a sample of SNTL random pixel and overlaid on Google Earth imagery to perform a visual interpretation and determine majority class i.e. non-urban, planned urban or unplanned urban. Each point's actual class was then determined and compared alongside the classified thematic class assigned to calculate the accuracy percentages.

3.5 Results and discussion

3.5.1 Comparison Analyses

The results of the comparison analysis (Figure 3.3a-c) illustrate the relationship strength between nightlights brightness values and built-up land coverage for the three years. The R^2 values for the raw stable lights and urban built-up proportion are 0.475, 0.421 and 0.440 for 1999, 2002, and 2008 respectively, with all relationships positive. The R^2 values have shown that there is an observable relationship between SNTL and built-up land coverage. Brighter SNTL pixels having higher coverage of built-up land are seen on the extreme right of the regression plot. While the areas having lower threshold of brightness have little to no built-up land, are seen towards the left of the plots. This further shows that the points with low DN values that are excluded using threshold have little to no urban built-up land, while the SNTL points with high DN values have significant amount of urban built-up land. The comparison also shows that the urban extent maps are relatively accurate despite the over-blooming effect of SNTL that tends to expand the extent of urban areas. Areas of low brightness which show weaker correlation with built-up land from Landsat are likely unplanned settlements, as seen in Figure 3.3 and also displayed visually in the map of unplanned areas (Figure 3.4). This is somewhat expected as unplanned settlements have reduced illumination due to poor electricity supply (Admin, 2015; Ebehikalu et al., 2016), and have less built-up land area coverage per 1 km^2 NTL pixel (see Figure 3.3).

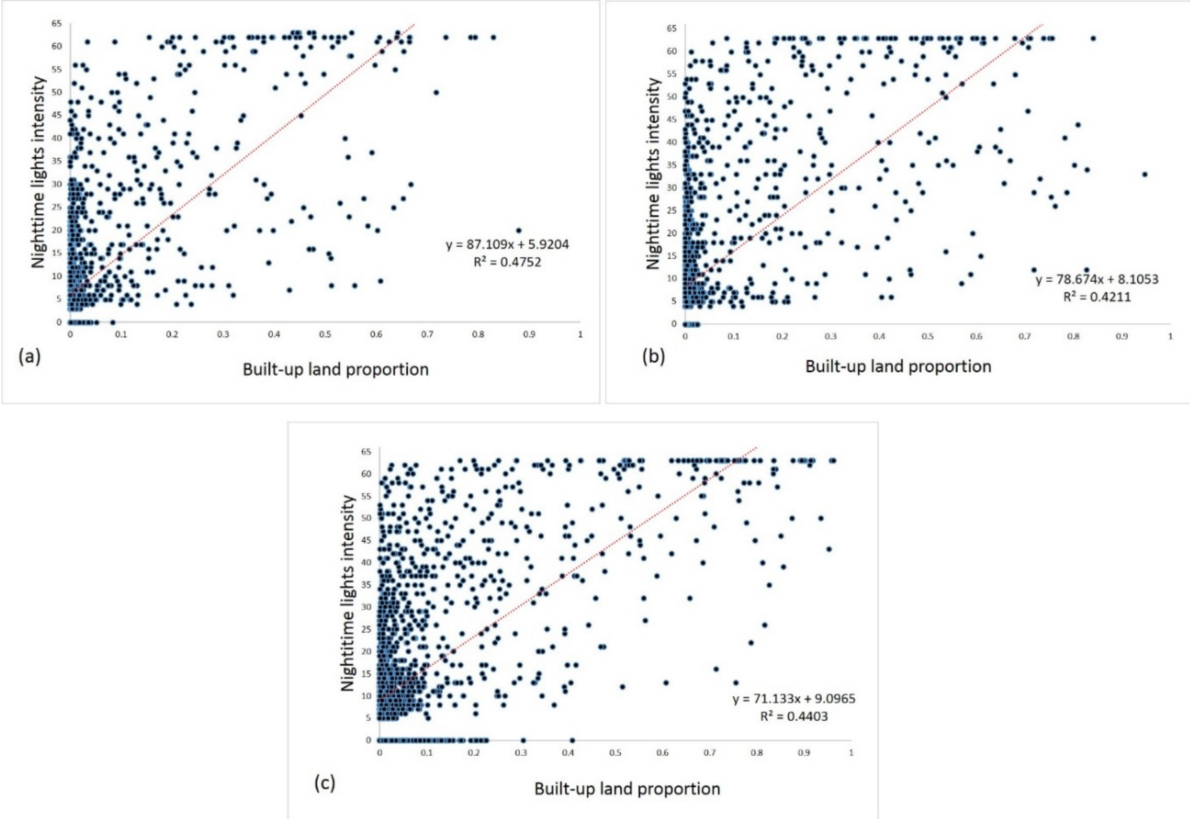


Figure 3.3. Correlations between SNTL and total built-up land coverage from Landsat TM/ETM+ derived land cover classification; (a) Raw stable lights and built-up land proportion 1999; (b) Raw stable lights and built-up land proportion 2002; (c) Raw stable lights and built-up land proportion 2008.

3.5.2 NTL data thresholding

The first stage of creating urban extent map involved determining a threshold for distinguishing urban and non-urban land, with a set of thresholds of ≥ 15% (1999, 2002) and ≥ 21% (2008) adopted to achieve this. The second stage involved further analysing and determining a series of thresholds which were set at ≥ 31% (1999), ≥ 40% (2002), ≥ 42% (2008) respectively to extract the areas of the city that are predominantly populated by planned (formal) settlements. Likewise, the threshold was further lowered to ≤49%, ≤ 53%, and ≤66% for 1999, 2002, 2008 respectively to extract areas the areas that are predominantly occupied by unplanned (informal) settlements. All areas lower than the threshold are regarded as non-urban.

The optimal pixel radiance threshold to identify the urban extents from the DMSP-OLS SNTL data were independently determined for each year (Table 3.2). The optimal threshold values for mapping the urban extent in 1999 and 2002 is ≥ 15% (≥ 9 (DN)) stable light intensity respectively. For 2008 urban extent, the optimal threshold was slightly higher, at 21% (≥ 13 DN) stable lights intensity Therefore, each pixel with the same or higher NTL DN than the threshold level was classified as urban.

Table 3.2.

Showing a breakdown of threshold adopted 1-100% > = Greater than, < = Less than, ≥ = Greater than or equal to, ≤ = Less than or equal to.

DMSP-OLS Image date	Urban extent threshold	Planned area threshold	Unplanned area threshold
1999	≥ 15%	≥ 49%	> 15% ≤ 48%
2002	≥ 15%	≥ 63%	> 15% ≤ 39%
2008	≥ 21%	≥ 66%	> 21% ≤ 65%

The slight increase in the threshold to capture the urban extent in 2008 accurately could possibly be explained by the expansion and densification of the urban agglomeration in the city, increasing the overall nighttime light radiance. A similar discovery was made by (Zhou et al., 2014), which determined the optimal threshold to map large cities such as Beijing and Boston to be as high as 60, while cities with smaller urban clusters have optimal threshold as low as 20.

Figure 3.4 delineates the urban area of Abuja into planned and unplanned settlements using the two-stage thresholding technique for 1999, 2002 and 2008. In the results (Figure 3.4), we can observe that urban areas are expanding a little, mainly to the west. Planned areas to expanded rapidly to the north-west in 2008. On the other hand, unplanned areas were expanding were rapidly from 1999 to 2008 to the south-west and north-west. The accelerated expansion for unplanned areas can be linked to the influx of more people into Abuja and relaxed legislation and land use enforcement under democratic government that returned to Nigeria in 1999. The result shows that the city has been expanding quickly with unplanned urban area growing at a faster rate than planned urban area, with a 27% expansion from 1999 to 2002 alone, while planned areas expanded 16% over the same time frame. It is also possible to observe that planned areas are concentrated mostly in the inner parts of the city, with unplanned areas concentrated mostly on the fringes of the planned city boundary.

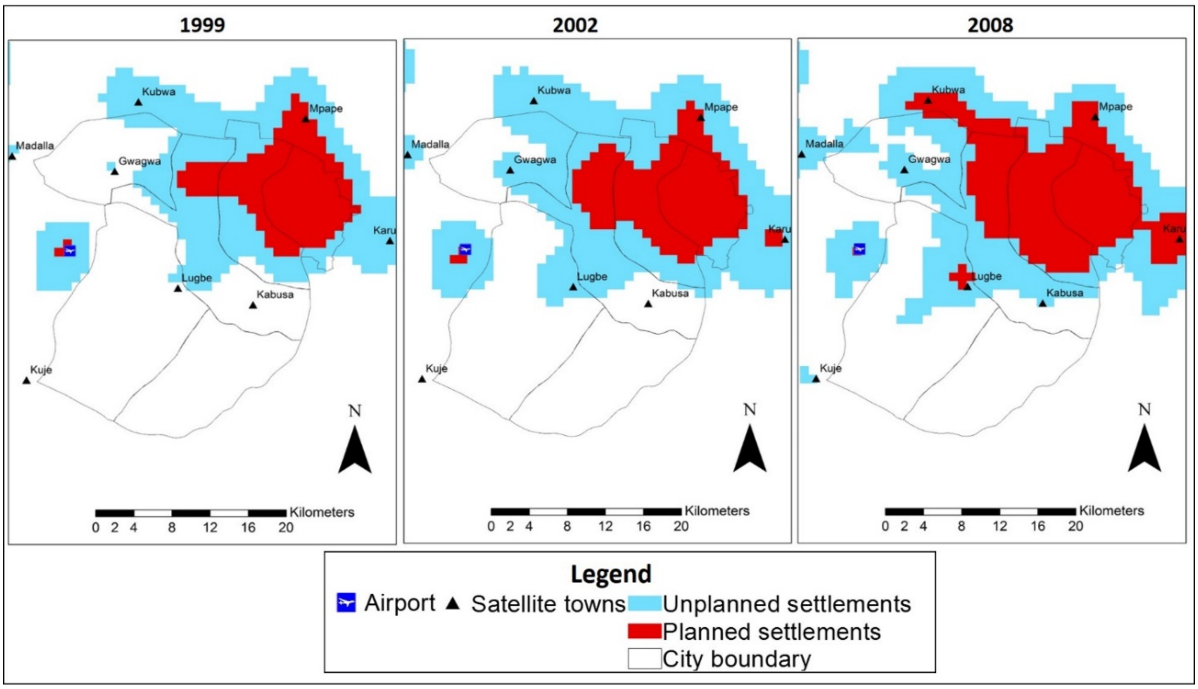


Figure 3.4. DMSP-OLS SNTL thresholded images showing planned and unplanned areas in Abuja for 1999, 2002, and 2008. The overlaid planned city boundary data was derived from Abuja city map obtained from Abuja Geographic Information Systems (AGIS) and FCDA (2015).

The results of the quantitative accuracy assessment for the three years are shown in Table 3.3. The overall accuracies are 73.7% (2008), 79.7% (2002), and 67.0% (1999).

Table 3.3a-c. Accuracy assessment for thresholded DMSP-OLS SNTL images for (a) 1999 (b) 2002, (c) 2008.

(a)

		Reference class			Users accuracy (%)
		Non-urban	Unplanned urban	Planned urban	
Predicted class	Non-urban	100	2	0	98.0
	Unplanned urban	55	36	7	36.7
	Planned urban	20	12	65	67.0
	Producers Accuracy (%)	56.8	69.2	90.2	
	Overall accuracy = 67.0%				

(b)

		Reference class			Users accuracy (%)
		Non-urban	Unplanned urban	Planned urban	

Predicted class	Non-urban	176	5	0	97.2
	Unplanned urban	44	33	2	41.8
	Planned urban	4	6	30	75.0
	Producers Accuracy (%)	78.6	75.0	93.7	
	Overall accuracy = 79.7%				

(c)

		Reference class			**Users accuracy (%)**
		Non-urban	Unplanned urban	Planned urban	
Predicted class	Non-urban	91	8	1	91.0
	Unplanned urban	35	49	15	49.0
	Planned urban	3	15	81	81.0
	Producers Accuracy (%)	70.5	68.0	83.5	
	Overall accuracy = 73.7%				

Looking closely at the accuracy of mapping individual features within the results in Table 3.3, it can observed that characterising planned urban area has the highest accuracy overall (90.28%, 93.75%, and 83.51% producers accuracy and 67.01%, 75.00%, 83.51% users accuracy for 1999, 2002, 2008 respectively) followed by the non-urban class (see Table 3.3). The planned areas are usually better lit and denser, makes it easier for them to be captured more accurately in SNTL. The unplanned area characterisation has the lowest accuracy overall (69.23%, 75.00% and 68.06% producers accuracy, and 36.73%, 41.77%, and 49.00% users accuracy for 1999, 2002, 2008 respectively) which may be partially due to the fact that these areas are usually smaller and less well lit, meaning they may easily be confused with non-urban areas. Despite DMSP-OLS SNTL having coarse spatial resolution, the results have indicated that they can be effectively utilized to map areas of planned and unplanned urban area in cities of the Global South. One of the challenges observed in this study of using SNTL data to map urban extent is the tendency of overestimation of urban areas especially towards the periphery of a city.

The result for the detail examination of nine satellite towns (unplanned settlements) classification using SNTL is shown in Table 3.5. This nine satellite towns were further assessed to verify if the results obtained in figure 4.4 is rather just a reflection of urban density. In the results we can observe that in 1999 four satellite towns are captured as non-urban while only two are captured as non-urban and one as planned by 2002. By 2008 as urban areas continue to expand, seven of the satellite towns are captured correctly as unplanned, while three are misclassified as planned. The overall results show a moderate level of accuracy of capturing and correctly labelling the towns over the three different years in focus.

Table 3.5. Showing Unplanned settlements in Abuja and their classification in different years.

	Towns								
Year	**Gwagwa**	**Idogwari**	**Kabusa**	**Karu**	**Kubwa**	**Kuje**	**Lugbe**	**Madalla**	**Mpape**
1999	Not urban	Unplanned	Not urban	Unplanned	Unplanned	Not urban	Not urban	Unplanned	Planned
2002	Unplanned	Unplanned	Not urban	Unplanned	Unplanned	Not urban	Unplanned	Unplanned	Planned
2008	Unplanned	Unplanned	Unplanned	Planned	Planned	Unplanned	Unplanned	Unplanned	Planned

3.5 Discussion

3.5.1 Urban area mapping

This study looked to answer the research question 'How effective is DMSP-OLS SNTL imagery in mapping urban extent at local scale in a Global South environment?' The results in Figure 3.4 shows that using a threshold value determined using independent land cover data derived from Landsat TM/ETM+ imagery can successfully map urban extent at local level with overall urban area classification accuracy at 73.7% (2008), 79.7% (2002), and 67.0% (1999). This is despite the fact that Nigeria is a developing country, where there is an incessant shortage of electricity, with some areas supplied for only a few hours a day, and others lacking supply completely for days at a stretch in some instances (Muoh, 2016). The lack of constant electricity in Nigerian cities might be expected to pose a challenge on how effective using NTL to map urban areas will be. The use of SNTL version of the DMSP-OLS data minimized this problem. This is possible because, the SNTL are based on the average of annual recorded composite of city night lights rather than a single day observation. The main limitation of the methods applied is the overestimation of the urban extent at the city fringe, which is common with nighttime lights (Elvidge et al., 1997; Small et al., 2011). The reason for this overestimation can be linked to the spatial resolution of the SNTL pixel (1 km) and the nature of how anthropogenic lights operate (it extends to areas beyond the source of illumination). The result has also indicated that urban areas in Abuja have been expanding rapidly from 1999 to 2008.

3.5.2 Distinguishing planned and unplanned settlements

The second research question address in this study is: 'Can DMSP-OLS SNTL imagery successfully distinguish planned and unplanned urban settlements in a Global South environment?'. This study has been successful in using SNTL data, in combination with Landsat-derived built-up land classification, to map urban areas predominantly occupied by planned settlements, and areas predominantly occupied by unplanned settlements (see Figure 3.4). Combining Landsat TM/ETM+ with NTL data helped to improve and further validate the thresholding approach used to classify planned and unplanned areas. Urban built-up areas consist of a collection of features that share similar spectral signatures; this is the reason why using multispectral data such as Landsat imagery alone cannot distinguish planned and unplanned urban land successfully. Using city lights intensity as a proxy to determine the location of planned and unplanned urban areas has proven to be effective.

The reason why SNTL data proved to be an effective proxy linked to the fact that unplanned settlements are not as brightly lit as their planned counterparts. So, their average annual light intensity is low and can be captured successfully.

Despite being a planned city, Abuja has not escaped the proliferation of unplanned settlements, both within the planned city compartments and around the immediate periphery of the city (Gumel et al., 2019). Here, we discriminated planned and unplanned settlements based on light emittance, rather than spectral characteristics. The results in Figure 3.4 demonstrate that applying a threshold combined with ancillary information derived from Landsat TM/ETM+ to DMSP-OLS NTL can aid in the classification of urban areas that are predominantly occupied by planned and unplanned settlements.

Among the nine major satellite towns (which are predominantly unplanned/informal) we sampled in and around Abuja (Table 3.4), only three, namely Kabusa, Lugbe and Kuje, were captured as non-urban and one, Mpape, was misclassified in the DMSP-OLS NTL imagery based unplanned map in 1999. This is most likely due to the small size of these settlements in 1999, resulting in them being more dimly lit, and therefore not captured by the threshold applied. Mpape was misclassified as a planned area most likely due to its close proximity to phase one (where most of the planned development is concentrated). This may have resulted in the area falling into the extended area of phase one over-glow, a feature that is common in areas with high density impervious surfaces (Ma et al., 2012). Mpape was consistently misclassified as a planned area for all the survey years. In 2002, six out of the nine satellite towns (unplanned settlements) – Gwagwa, Idogwari, Karu, Kubwa, Lugbe and Madalla – were correctly captured in the unplanned area classification (see Figure 3.4) and two towns, Kabusa and Kuje, were captured as non-urban while one town (Mpape) was again misclassified as a planned development. However, in 2008, some interesting changes in the area of unplanned settlements start to become obvious. Six satellite towns out of nine were correctly classified – Madalla, Lugbe, Gwagwa, Idogwari, Kabusa and Kuje (a similar number of towns to the 2002 result) – in the unplanned class, but the major difference is that the other three towns, Mpape, Kubwa and Karu, are misclassified as planned area this time around (see Table 3.5). Two of these towns (Kubwa and Karu) were correctly classified as unplanned settlement in 2002 only for them to be converted and misclassified as planned settlements in 2008 while Kuje was finally captured as unplanned. The reason for this conversion/misclassification could be attributed to the fast pace urban sprawl and densification experienced by the two satellite towns within the time frame, as they are among the closest to Abuja city centre. The reason why we have three of the unplanned satellite towns within the planned city boundary could be attributed to the policy of resettlement by the government. The government proposed resettling all the villages found within the proposed planned city location, however this was not achieved, and these villages have continued to grow, now becoming sizable unplanned settlements that are difficult to demolish or resettle.

Analysis on the pattern of mapping unplanned settlements using DMSP-OLS stable lights revealed that, as the unplanned settlements continue to expand, they start to exhibit similar brightness characteristics with planned settlements. This means that as unplanned settlements become bigger, they become more brightly lit on the stable nighttime lights. This is evident in the satellite towns of Kubwa, Karu and Mpape. Furthermore, unplanned settlements that are very close to planned areas are potentially at risk of being affected by the over-glow of the planned area (Elvidge et al., 1997; Ma et al., 2012) making it difficult to be separated using a specific threshold value.

3.6 Conclusions

The majority of urban studies that use DMSP-OLS nighttime lights are based on regional and national scales. This study has shown that DMSP-OLS data can be successfully used to map urban extent at local scale in a city experiencing rapid urbanisation in the Global South. The study has shown how urban extent has been changing overtime, with results revealing how the urban area in Abuja has been expanding rapidly from 1999-2008. The results of this study further illustrate that it is possible to map not only urban extent, but also distinguish areas of planned and unplanned/informal settlements. This was performed by combining Landsat TM/ETM+ derived land cover maps, and the careful application of different thresholds on DMSP-OLS stable lights. Despite the Landsat data having a much higher spatial resolution than the DMSP-OLS stable lights, it is not possible to use it alone to distinguish planned and unplanned areas spectrally. Nightlights, through their differing illumination of planned and unplanned areas, have been demonstrated to offer a solution to this problem.

The results revealed a generally high accuracy, especially with regards to discriminating unplanned and planned urban areas. This is expected considering the coarse size of the DMSP-OLS pixel, and the unplanned areas are relatively small and poorly lit. The accuracy will most likely improve significantly if a similar study is conducted with the newer fully calibrated and higher spatial resolution Visible Infrared Imaging Radiometer Suite (VIIRS) night lights data. The VIIRS data will reduce over-blooming, offer better detection of dim lights, enhance the characterisation of urban typologies and greatly advance the dynamic range of the data (Baugh et al., 2013; Min et al., 2013, Zhang & Seto, 2013).

This study and the methods developed may be very useful to urban planners in developing countries, where ground-based spatial data relevant to mapping planned and unplanned areas is sparse, and the resources required to collect such data on the ground are not available. The remote sensing data utilized for this study method are cost-free and it can be used to complement ground data collection and offer repeatability for monitoring applications.

Chapter 4

A simplified approach to mapping unplanned and planned settlements in Abuja, Nigeria using deep learning and random forests.

Prepared for submission to *Urban Studies Journal*

Abstract

The process of urbanization has increased rapidly in the recent decades. Urbanization is more pronounce in cities of the Global South with the highest predicted urban growth set to occur in this region. Most of the urbanization happening in the Global South is haphazard and unplanned. This leads to significant social and environment problems such as urban sprawl, congestion, pollution, crime and lopsided distribution of resources. While the growth and acceleration of unplanned settlements is clear and unmistakable, not much is done to detect, map and monitor this phenomenon. This research aims to use remote sensing technology through the adoption of machine learning techniques (deep learning and random forests) for a rapid and cost-effective way of mapping and analysing unplanned and planned urban land in a city of the Global South. This will provide useful and critical information to urban planners, policy makers and government officials. The results of the study have shown that deep learning can be successfully utilized to analyse and map unplanned and planned urban areas using VHR imagery. The results have also shown that random forest performed poorly in distinguishing planned and unplanned urban land, and also found a considerable disparity between different methods of accuracy assessment that are utilized alongside deep learning classifications.

4.1 Introduction

Over the past 100 years, the world has experienced unprecedented levels of urbanization. This rapid urbanization has led to a substantial shift in population patterns, with more than half the world's population living in cities (Han et al., 2009; Pham et al. 2011). This growth in urban population is set to continue, with over 70% of global population predicted to be urban residents by 2050 (Maktav et al., 2005; United Nations, 2015). Furthermore, between 1970 and 2000, the total global footprint of urban areas quadrupled (Li et al., 2013), and it is forecast to keep increasing rapidly in the foreseeable future (Seto et al., 2011). Much of this future population and urban growth will occur in the Global South, with African and Asian countries experiencing urbanization at a more rapid rate than the rest of the world. While the urban population is expected to grow by more than two thirds, Africa and Asia will experience most of the growth, with Nigeria, India and China alone expected to accrue one third of the overall urban population growth (United Nations, 2015). The pace and scale of this urbanization presents significant challenges that developing countries struggle to address, such as lack of housing, environmental degradation, high levels of poverty, poor sanitation and over-crowding (Ji et al., 2001; Karanja & Matara 2013; Kuffer et al., 2016).

High population growth experienced in developing countries is one of the prime drivers of urbanization, with this urbanization often uncontrolled and unplanned (Sanli, 2008). In an attempt to better address the negative impacts of urbanization, a number of countries including Brazil, Malawi, Tanzania and Myanmar have built entirely new planned cities. Urbanization in these planned cities is expected to be orderly, organised and predictable; however, in many developing countries, rapid urbanization has led to the spread of informal, unplanned settlements (Mboga et al., 2017). The size and extent of unplanned settlements is substantial in some sub-Saharan African cities, with the area of unplanned urban settlements often exceeding that of planned settlements (Kombe, 2005; Kuffer et al., 2014).

To assess the success of these planned cities in managing urbanization, effective monitoring is required. This is only possible when urban planners and managers have access to regular, affordable and reliable means of obtaining the necessary spatial information (Taubenböck et al., 2012) pertinent to monitoring the development of a city.

This is challenging, if not impossible, in many cases using ground-based surveying alone due to the large areas over which the cities extend, and the spatial complexity of the cities in question. An alternative source of data highly relevant to monitoring city development is provided by satellite remote sensing (Patino & Duque, 2013; Mertes et al., 2015; Joshi et al., 2016; He et al., 2017). This presents an ideal solution to these monitoring requirements as remote sensing can provide a synoptic view of the urban environment at high levels of spatial detail, with high temporal frequency (Franklin & Wulder, 2002) for monitoring the historical (using archived satellite imagery), ongoing and future development of a city. This presents a considerable advantage over *in situ* surveying and monitoring approaches that are time consuming, offer limited spatial coverage and are often expensive (Wentz et al., 2014).

Significant advances in urban remote sensing have been made since the emergence of very high resolution (VHR) satellite sensors (e.g. IKONOS, launched in 1999, providing 4 m spatial resolution multispectral imagery), which provided a great opportunity to analyse complex and detailed urban features (Aplin, 2003; Weng, 2012). In recent years, remote sensing, which has continued to offer more detailed spatial, spectral and temporal resolution data, has been used effectively for mapping urban built-up land and analysing complex socio-economic features (Jensen & Cowen, 1999; Longley 2002; Wurm et al. 2009; Wieland & Pittore 2014). For instance, a range of remote sensing data sets have been used to map impervious surfaces, urban land cover and change in the urban environment (Small et al., 2005; Xiao et al., 2006; Hu et al., 2007; Cao et al., 2009; Sutton et al., 2009; Zhou et al., 2014; Momeni et al., 2016), and to estimate urban population and undertake socio-economic analysis (Doll 2010; Townsend & Bruce, 2010; Veljanovski et al., 2012; Wang et al., 2012; Zhang & Seto, 2013; Canty, 2014; Ma et al., 2015).

Despite considerable activity and success in urban remote sensing analysis, few studies have attempted to distinguish planned and unplanned settlements. Partly this may be due to the spectral similarity of planned and unplanned built-up land, resulting in difficulties discriminating between these two classes through spectral characteristics alone. These limitations are more pronounced in classic remote sensing techniques used in feature extraction and classification of complex urban environments. Deep learning (DL) is well positioned to address some of these limitations as it can effectively combine spatial and spectral characteristics within imagery for improved mapping results (Noguiera et al., 2017). Due to the rapid urbanization experienced in the Global South, it is very important for urban planners and policy makers to be able to monitor and manage the expansion of unplanned settlements using fast and cheap methods to minimise the negative consequences of unplanned urbanization.

Information on the nature and extent of unplanned settlements often exhibits poor consistency (Herold et al., 2003) or is simply unavailable. This, in part, may be due to inconsistent definitions of what constitutes unplanned settlements around the world (Mboga et al., 2017), with no conclusive definition in the literature of formal/informal, planned/unplanned settlements (Owen & Wong 2013). Sometimes referred to as informal settlements, squatter settlements or slums, unplanned settlements are areas that predominantly consist of haphazardly constructed buildings, lack basic infrastructure and social amenities, are overcrowded, and land tenure is insecure or unrecognized by authorities (UN-Habitat, 2016). In one example of a planned city – Abuja, Nigeria – unplanned settlements have proliferated despite the city's development being governed by an over-arching Master Plan (IPA, 1979). Here, these unplanned developments typically comprise small, irregular clustered dwellings, lack paved roads, and have little or no green space (vegetation) within them. Planned settlements by contrast have regular patterns of building locations, generally larger buildings, paved roads and are interspersed with vegetation patches.

Recently, studies have tested VHR satellite imagery as a means of mapping informal settlements. Since it can be challenging to distinguish planned and unplanned urban development purely on the basis of spectral information, alternative approaches that exploit spatial configuration and texture of urban land cover have been adopted (Mboga et al., 2017). Examples include using texture of land cover to map informal settlements include, using the Grey Level Co-Occurrence Matrix (GLCM) to measures contrast, entropy, homogeneity and correlation to extract informal settlements (Stasolla & Gamba, 2007; Pesaresi et al., 2009; Owen & Wong, 2013). A lacunarity based slum detection algorithm was used to derive a slum location map in Hyderabad, India (Kit et al., 2012; Latterly et al., 2013), while Baud et al. (2010) combined visual image interpretation of VHR imagery, spatial indices (shape, clumpiness, and aggregation index) and ground observation to map sub-standard residential areas in New Delhi. Morphological factors such as building density, size and height have also been used to differentiate between slums and formal settlements (Taubenböck & Kraff, 2014). Kuffer et al. (2014) developed an unplanned settlement index by combining spectral information and spatial metrics to help with automatic extraction of unplanned settlements. Limitations to these methods include their high level of technical complexity and challenges in geographical transferability, as they are based on specific features and indices that can be difficult to define and vary considerably between areas (Zhao & Du, 2016).

Recently, object-based image analysis (OBIA) has been used to address some of the challenges attributed to mapping formal and informal settlements, by classifying objects taking into account not just spectral characteristic of features, but also spatial features like size and texture (Aminipouri et al., 2009). Veljanovski et al. (2012) used OBIA to estimate the population of informal settlements in Kibera-Nairobi, Kenya; while favelas in Rio de Janeiro were mapped as objects by Hofmann et al. (2008) and in Sao Paulo, Brazil by Nobrega et al. (2008), the latter by combining a general ontology of informal settlements with a fuzzy-logic classification rule. However, significant concerns have been raised regarding methodological robustness and transferability of OBIA approaches (Hofmann et al., 2011; Kohli et al., 2013; Kuffer et al., 2016). Furthermore, there is considerable uncertainty about how segmentation parameters should be defined (Drăguţ et al., 2010), especially where planned and unplanned settlements are being mapped simultaneously. Typically, segmentation scale optimization is achieved through trial and error (Meinel & Neubert, 2004; Duro et al. 2012). OBIA also presents the new challenge of determining the appropriate scale of analysis. Kuffer et al. (2014) considered urban land cover at the level of object (e.g. roofs) or areas (i.e. the metropolitan scale), while Kohli et al. (2012) constructed a detailed ontology on informal settlements at three different scales: objects, settlements and environs.

Due to the limitations of classic feature extraction algorithms for remote sensing images, there has been a push to develop approaches that effectively combine both spatial and spectral characteristics to discriminate complex features accurately (Nogueira et al., 2017). DL methods, first proposed by Hinton et al. (2006), are becoming a common solution, with their application rapidly growing in the remote sensing field (Wang et al., 2017). DL is a division of machine learning for learning representations (LeCun et al., 2015) that works by attempting to model high level abstraction in data through learning its hierarchical features (Hu et al., 2015; Fu et al., 2017). One of the most popular DL algorithms is convolution neural networks (CNNs). CNNs are artificial neural networks and are generally regarded as the most effective, successful and widely used DL method in both computer vision and remote sensing (Hu et al., 2015; Nogueira et al. 2017; Mboga et al. 2017; Wang et al. 2017;

Zhou et al. 2017). CNNs are being increasingly applied in the remote sensing field for land cover/land use classification using VHR and hyperspectral imagery (Paisitkriangkrai et al., 2016; Längkvist et al., 2016; Liang & Li, 2016; Ma et al., 2016; Alshehhi et al., 2017; Kussul et al., 2017), although very few studies have explored the potential of using CNNs to detect informal or unplanned settlements. In one of the few studies using CNNs to detect informal settlements, Mboga et al. (2017) reported improved classification accuracies when comparing CNNs to support vector machines (SVMs) using GLCM and local binary patterns (LBP), with CNN (5 convolution layers) recording 91.7% accuracy while GLCM+SVM recorded 86.6% and finally SVM+LBP recorded 90.4%. Another study employing DL to identify informal settlements was that of Li et al. (2017) whereby unsupervised deep feature learning was used to map urban villages in China and proved computationally faster and of comparable accuracy to supervised approaches. These studies were mainly looking at informal settlements in isolation which means the CNNs are trained to identify and extract informal settlements only, disregarding other urban land and other land cover classes. The studies also involved designing and optimizing a new CNN architecture which can be complicated and time consuming. No studies have yet explored the potential of DL to detect and distinguish both planned and unplanned settlements, and other urban land cover types, simultaneously.

Here, an investigation on the potential of using DL CNN analysis to detect and map planned and unplanned urban settlements alongside other land cover types using VHR satellite imagery in Abuja, Nigeria in conducted. CNN architecture is trained using three-band (RGB) GeoEye-1 satellite imagery, and classification performance of CNN is then compared to an alternative, established land cover classification machine learning algorithm, random forests (RF), first introduced by Breiman (2001). The RGB image data product provides a valuable test here since its spectral simplicity (lacking any near infrared (NIR) band) may act as a constraint for accurate classification in a complex urban environment. Thus, we might expect that traditional (e.g. RF) classification approaches will struggle to distinguish urban classes accurately, while more sophisticated (e.g. DL) approaches will cope more effectively with spectral overlap between classes. While other VHR image products do include a NIR band, and this might also be likely to increase classification accuracy, RGB images are widely used in Global South countries, crucially because of their low-cost which can be a key criterion for image selection, so it is extremely worthwhile to develop and demonstrate their ability for urban mapping. We present a simple way of detecting and mapping planned and unplanned settlements by allowing the CNN to learn automatically the complex spatial and spectral characteristics of the features that comprise each settlement. We also investigate how different validation procedures influence empirical results, comparing an accuracy assessment procedure (that is more or less automated) commonly used in DL analysis (LeCun et al., 2015) against a standard error matrix approach used in remote sensing classification validation (Congalton 1991). To achieve these objectives, two research questions are posed: 1) Can planned and unplanned urban settlements be distinguished and mapped successfully using DL? 2) Can DL offer enhanced classification performance over established machine learning methods such as random forests?

4.2 Study Area

Abuja, the capital of Nigeria, is a planned city for which construction began in 1980 after the government of Nigeria decided in 1976 that the previous capital, Lagos, was not fit to continue in this role. This was due to having insufficient space in Lagos to accommodate future expansion, lack of cultural diversity, and its non-central geographical location within Nigeria (Ikejiofor, 1997). A comprehensive Master Plan (IPA, 1979) was formulated to guide development of Abuja (Abubakar, 2014) and official relocation of the capital occurred in 1991. The Master Plan was intended to ensure the orderly growth of the city, limiting unplanned or unwanted development. Since construction started, Abuja has experienced rapid urbanization and population growth, and, with an urban area growth rate of 8.3% per year, it is one of the fastest growing cites in the world, and the fastest in Africa (Myers, 2011).

Abuja Federal Capital City (FCC) is located within the Federal Capital Territory (FCT) of Nigeria which covers an overall area of around 8,000 km^2. The FCT lies between latitudes 7°25' and 9°20'N, and 139 longitudes 5°45' and 7°39' W, with elevations ranging from approximately 100 m to above 600 m. The FCT is part of the Guinea-Savanna vegetation zone (Idoko & Bisong, 2010) and has two distinct seasons in a year: the dry season from November to March, and the rainy (wet) season from April to October. The land cover in the FCC is predominantly occupied by grassland vegetation, built-up land (consisting of planned and unplanned settlements), water reservoirs, bare ground and some rock outcrops. Planned settlements are mostly organised, orderly, with paved streets and individual larger houses in comparison to houses located in unplanned settlements.

Unplanned settlements on the other hand are disorganized, with unpaved streets, and with random pattern of buildings.

The study area is an area of 62.5 km^2 located in the northern part of the FCC (see Figure 4.1). This area matches the footprint of the GeoEye-1 image (described below) used for analysis.

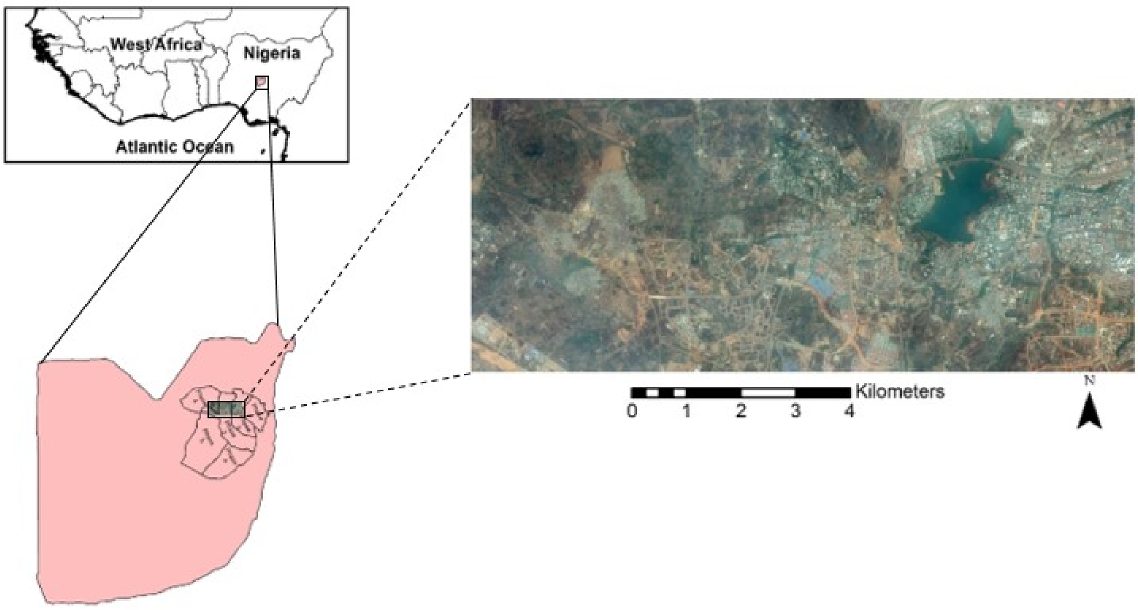


Figure 4.1. Study area, showing the location of the Federal Capital Territory (FCT) within Nigeria (top left), an inset of FCT showing the Abuja Federal Capital City (FCC) footprint in the northeast (bottom left), and the GeoEye-1 image covering the northern part of the FCC (right). (FCT and FCC maps adapted from data supplied by Abuja Geographic Information System (AGIS) Agency and Nigeria Space Research and Development Agency; GeoEye-1 imagery supplied by AGIS.)

4.3 Data

In this study, we utilized a cloud-free February 2014 GeoEye-1 satellite image of Abuja. The image was originally acquired from Digital Globe as a three-band (RGB) pan-sharpened ortho-ready product, and the spatial resolution is 0.5 m. As mentioned above, this image data product, a standard commercial option, has the limitation that it does not include a NIR band, the inclusion of which may ordinarily increase land cover classification accuracy. However, this product has the significant benefit of lower cost which means it may be the only affordable option for users, especially in Global South countries where financial constraints can apply. The spectral limitations of the data set suggest that traditional land cover classification methods may be relatively inaccurate, whereas DL approaches offer the potential for improved land cover feature recognition.

A comprehensive reference data set was constructed to provide training and testing data for the classification analysis. This involved a survey of land cover and land use of the study area, plus interviews with planning officials and residents regarding land cover/land use distributions, conducted during a six-week field campaign in 2015. Though there is a two-year gap between image and field data collection, changes on the ground (e.g. as a result of new urban development) over this time were immediately apparent from the imagery, so any field survey points that were obviously different in the image were omitted from analysis. Additionally, land cover/land use maps of the study area were acquired from the Federal Capital Development Authority (FCDA) and AGIS. These data sources were collated to form an overall reference data set, presented as a vector coverage of the study area, from which various separate training and testing samples were subsequently taken.

4.4 Methods

To address the aims of this study, a five-class classification system was developed, targeting both planned and unplanned settlements, plus bare ground, vegetation and water classes that are also found within the study area. Detailed class descriptions are given in Table 4.1.

Table 4.1. Land cover/land use class descriptions.

Land cover/land use class	Description
Bare ground	Areas of bare earth, devoid of vegetation and not covered by built-up, impervious surfaces.
Planned settlement	Impervious surfaces such as buildings (residential and commercial) with mostly aluminium and ceramic roofing, reasonably regular streets and paved road network, and large concrete surfaces, plus small plots of vegetation (gardens) within planned neighbourhoods.
Unplanned settlement	Impervious surfaces such as small and dense buildings with mostly zinc roofing (with little to no space between houses), roads (usually unpaved) and irregular street network, plus small open areas and occasional trees or other vegetation within unplanned neighbourhoods.
Vegetation	Areas or patches of grasses, shrubs and/or trees not contained within the urban boundary.
Water	Water bodies, such as rivers, reservoirs and ponds.

4.4.1 Deep learning analysis

To classify planned and unplanned settlements using the GeoEye-1 image, a well-known DL architecture, Lenet, was adopted. Lenet is based on the Convolution Neural Networks (CNNs) algorithm pioneered by Lecun et al. (1998), and consists of two convolution layers, two pooling layers, a fully connected layer and one hidden layer (see Figure 4.2). The convolution layers consist of kernels that are used to discover specific local features to improve the classification process. The pooling layers combine semantically related features into single features (Lecun et al., 2015) while the fully connected layer is a softmax layer that assigns a semantic label to each pixel after computing a score for the individual determined class. The convolution layers comprise input feature maps that have assigned weights (filters or kernels) to create new feature maps (Wang et al., 2017). The process works by transforming an input image from original pixel values to a final class score using a softmax layer for individual defined classes (Hu et al., 2015). The parameters of such CNNs are usually trained with classic stochastic gradient descent based on the backpropagation algorithm (Rumelhart et al., 1986; Hu et al., 2015; Wang et al., 2017).

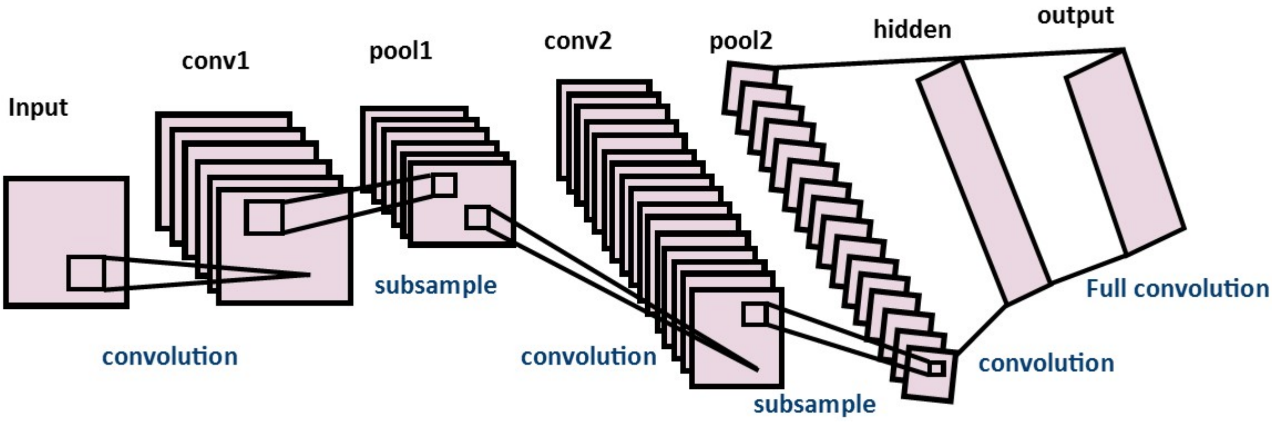


Figure 4.2. Lenet deep learning architecture (adapted from datiaku.com).

The DL architecture adopted is a pixel-based classifier which was trained to combine and recognize both pixel and object-based classification characteristics. The classifier is able to recognize a block of pixels as belonging to a predominant class and ignoring isolated pixels that may belong to minority class if classified in isolation. Prior to performing the DL classification, it is necessary to determine the optimal size of a patch that will be used for classification. The patch size is important because a central pixel of a patch is what DL uses for the training process. To determine the optimal patch, measurements were performed to determine the average coverage of the individual features that comprise the classes we are most interested in, namely planned and unplanned settlements. We measured the area of a range of different features in both planned and unplanned settlements to determine the average size of a feature. Ultimately a patch size of 51 x 51 pixels (25.5 m x 25.5 m) was decided upon, since this covers a typical building in a planned settlement and also encompasses one or more buildings in unplanned settlements which are typically smaller in size.

Once patch size was determined, the Lenet algorithm was trained by selecting a sample of patches automatically from the reference data set. Reference data was provided as a vector coverage of the study area, divided into areas corresponding to the five land cover classes. A sample of 400,000 patches were randomly collected, 80,000 per class. Then, for each patch, the central pixel was selected and input to the CNN for training. The process of selecting a single pixel to represent the patch considers both spatial and spectral information and training is relatively simple and fast compared to traditional remote sensing methods that require prior identification and analysis of certain spatial matrices and tend to be limited by their high level of complexity and limited geographical transferability (Zhao & Du, 2016). Creating a wall to wall land cover map using DL is not common because of the amount of computing power and time needed. Therefore, eight small subset areas were selected from the original GeoEye-1 image (that covers an area in phase 2, 3 and 4 see figure 3.4) for classification, each measuring 506 by 595 pixels or approximately 0.08 km^2. In combination, these eight subsets included a good mixture of the five land cover classes found within the study area, enabling a full and rigorous test of the DL algorithm.

Following DL land cover classification, accuracy assessment was conducted, and two approaches were tested for this. Initially, the standard approach for accuracy assessment provided within the DL software was used. This was easy to deploy and largely automatic, whereby a large number of test patches (i.e. the central pixels of patches, similar to the training process) were selected randomly from the reference data set and, in each case, the classified pixel was compared to the reference class. Here, 10,000 patches were randomly selected, 2,000 per class, and compared to the reference data to create an error matrix. Importantly, test patches were independent of training patches.

The results of this DL software-led accuracy assessment seemed unrealistically high (results presented below), likely due to the restriction of testing samples to only 'pure' reference data. All reference data polygons input for analysis correspond to easily identifiable, pure examples of land cover classes. The implication of this is that no difficult, 'mixed' land cover samples are examined. Clearly there is a higher likelihood of pure samples being classified correctly than mixed samples, and images generally contain a considerable degree of mixed areas or pixels, especially in complex urban environments. This is a well-known issue in land cover classification analysis, with various authors testing the effect of the purity of reference data on classification accuracy (Foody, 2002; Olofsson et al., 2014). We speculate that this may now be a particular concern for DL classification of remotely sensed imagery since many such studies have been published that present very high (often near 100%) accuracies (Liang & Li, 2016; Wang et al., 2017). Are such results reliable? It may well be that authors, some of whom have a computational rather than a remote sensing background, have adopted in-built DL accuracy assessment approaches that, by testing only pure reference samples, do not provide a true reflection of whole image classification accuracy. We will return to this issue in the discussion section below.

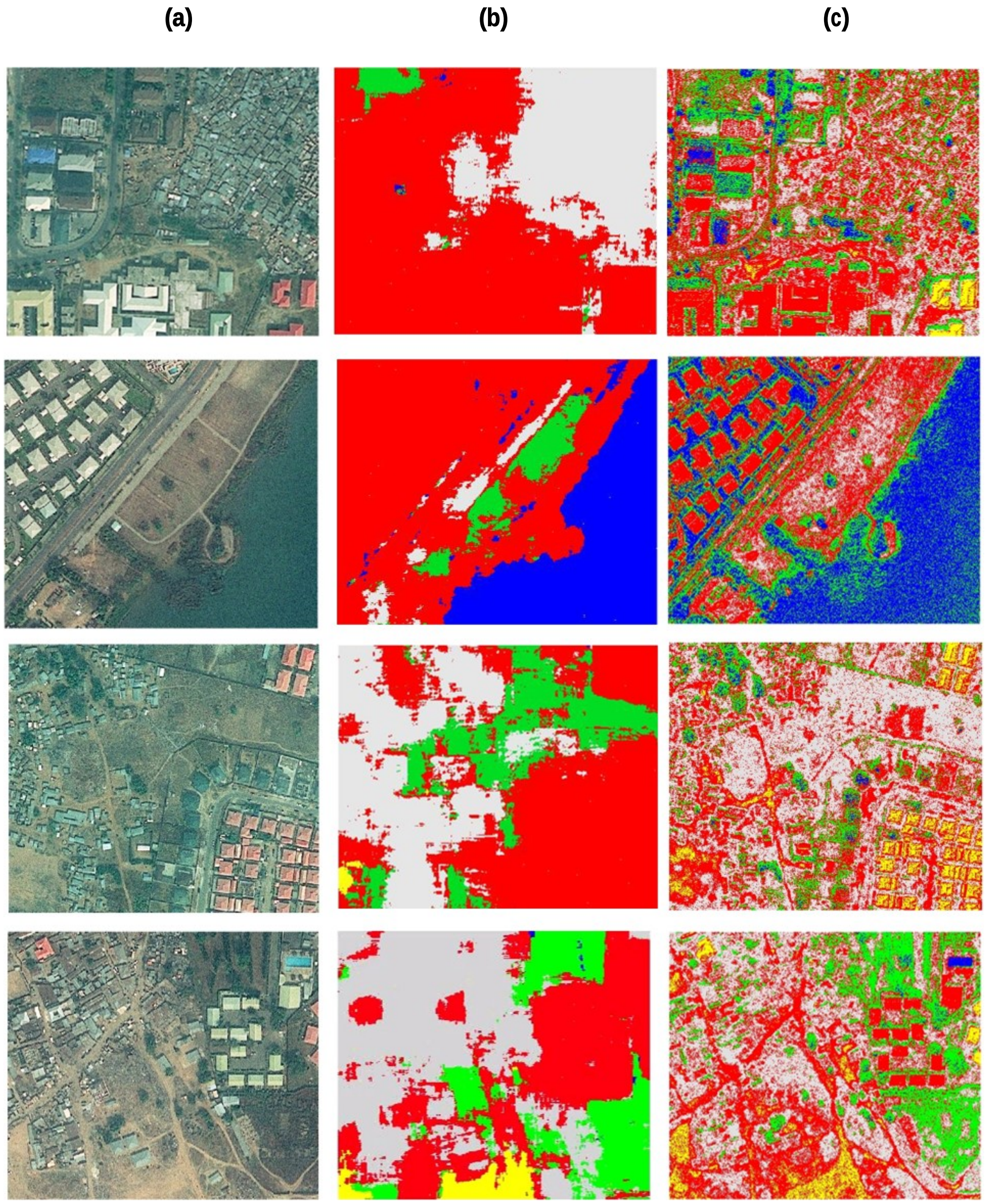
Because of our concerns about the reliability of the DL software-led accuracy assessment approach, we also deployed a separate, objective accuracy assessment approach. A further benefit of this second approach is that the same test can be performed on both DL and random forest classifications enabling clear comparison between the two classification methods. The accuracy assessment approach follows standard land cover classification accuracy assessment methodology, whereby random sample points on classified images are cross-referenced against reference data and results are presented as error matrices (Congalton, 1991; Liu & Yang, 2015). Here, accuracy assessment was performed on the eight classified subset images. As mentioned above, the eight subset areas provide good representation of the five land cover classes present in the study area. Also, though, and importantly, the full subsets present a realistic mixture of land cover, including boundary zones between features (which often exhibit mixed pixels) and more generally the ambiguous, mixed land cover patterns often found in urban areas. Therefore, this second approach to accuracy assessment considers the full range of land cover, from pure to mixed, present in urban areas, providing a fully fair test of classification performance. A random sample of 1,600 points were selected, 200 per subset, and each point's land cover class was compared to the corresponding reference data class. Results were presented as an error matrix.

4.4.2 Random forest analysis

To enable robust comparison of the performance of the DL classification against established machine learning methods, the GeoEye-1 image was also classified using a RF approach. RFs are a machine learning algorithm, first introduced by Breiman (2001) as an ensemble of classification and regression decision trees (Marston et al., 2014). The approach involves using a series of simple decisions that are dependent on the results of sequential tests for assigning labels to different classes (Wieland & Pittore 2014). RFs are non-parametric (Strobl et al., 2008) and can handle diverse types of data (Duro et al., 2012b). Thus, RFs provide valuable comparison for DL analysis since both approaches represent state-of-the-art in machine learning classification (Wieland & Pittore 2014). RF classification was performed using the Sentinel Application Platform (SNAP), based on methods developed by Breiman (2001). The RF classification was performed on the entire GeoEye-1 image, from which the eight subset areas (i.e. matching the subsets analysed in DL analysis) were extracted for observation and analysis. To enable direct comparison, the same training data set used for DL analysis was deployed for RF classification. The RF classifier was set to train on vectors, using ten trees. Then, the same 1,600 test points used for DL accuracy assessment were deployed for RF classification accuracy assessment, with the results presented as a standard error matrix.

4.5 Results

Land cover maps of the eight image subsets generated by DL and RF classification are presented in figure 4.3, and overall class accuracies for the three accuracy assessments (DL automated accuracy assessment approach, DL standard approach, RF standard approach) are presented in Table 4.2.



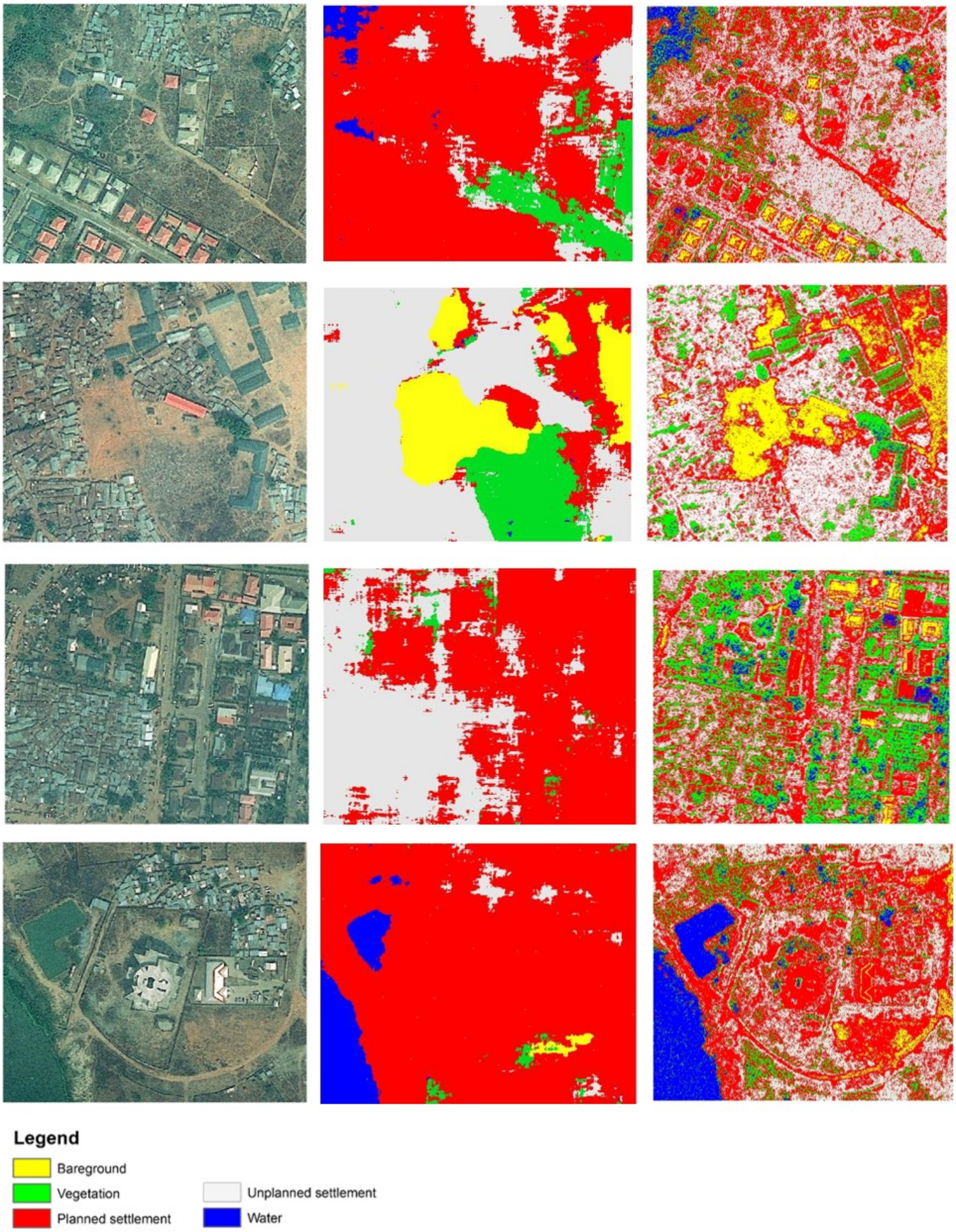


Figure 4.3. Land cover land use classification of a section in Abuja, Nigeria: (a) VHR image subset of mixed land cover areas (b) deep learning classification (c) random forest classification

Table 4.2. Summary land cover classification accuracy assessment results.

Class	Deep learning classification: automated accuracy assessment approach		Deep learning classification: standard accuracy assessment approach		Random forest classification: standard accuracy assessment approach	
	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)	Users accuracy (%)	Producers accuracy (%)
Bare ground	100.0	99.8	67.0	10.0	27.2	80.0
Planned settlement	99.4	99.8	56.2	85.7	12.3	15.0
Unplanned settlement	99.2	99.4	88.0	62.0	37.7	17.7
Vegetation	97.6	100	51.0	36.0	37.1	26.2
Water	99.7	96.7	87.0	88.0	19.1	59.6
Overall accuracy (%)	99.0		66.2		26.8	

4.5.1 Deep learning land cover classification

DL classification, when applied to the image subsets, tended to classify relatively large objects or areas as distinct, homogenous features. There is little evidence of noise or the salt-and-pepper effects common in pixel-based classification of urban study areas. For example, small vegetation features within planned settlements, perhaps corresponding to garden plots, are not classified as separate vegetation objects but are incorporated into the planned settlement class. Homogenous water bodies are also clearly classified. Small patches of bare ground within unplanned settlement are not classified as separate class but recognized as part of the unplanned settlement land use class. The same can be said for small areas of vegetation within planned and unplanned settlements; they are mostly merged with the predominant settlement class in the area.

The overall accuracy of the DL classification using the automated accuracy assessment approach was very high at 99.0%, while that using the remote sensing standard error matrix is a modest 66.0% (Table 4.2). The reason for this clear disparity could be linked to the way the two approaches test classification accuracy. The DL automated accuracy assessment approach uses points fed to it from pure pixels of individual classes. While the remote sensing standard error matrix approach test the classification accuracy using areas consisting of mixed classes (pixels). The performance of the DL classifier is even higher if we look closely into the planned and unplanned individual class accuracies for the two-different accuracy assessment methods. The users and producers accuracy for planned settlement is 56.2% and 85.7% (standard error matrix) and 99.4% and 96.7% (DL automated approach) respectively. While the unplanned settlement class user and producer accuracy is 88.0% and 62.0% respectively (standard error matrix) and 99.7% and 99.4% (DL automated approach) respectively (Table 4.2). The ability of DL to recognize and incorporate small areas of vegetation, bare ground and water within planned and unplanned settlements into the broader settlement class is what contributed to the higher individual accuracy of the two classes. There is a significant difference in the overall classification accuracy between the two approaches, with standard error approach at 66.2% and the DL automated approach at 99.0%. A full confusion matrix for both random forest and DL classification is also shown (Table 4.3).

Table 4.3. Deep learning classification standard error matrix.

Predicted class	Reference class					Users accuracy (%)
	Bare ground	Planned settlement	Unplanned settlement	Vegetation	Water	
Bare ground	6	0	2	1	0	67.0
Planned settlement	51	496	192	135	7	56.2
Unplanned settlement	0	40	380	13	0	88.0
Vegetation	2	43	37	90	5	51.0
Water	0	0	2	11	87	87.0
Producers Accuracy (%)	10.0	85.7	62.0	36.0	88.0	

4.5.2 Random forest land cover classification

The random forest classification overall, and individual class accuracy are low. The overall accuracy is 26.8% (Table 4.2), while the planned settlement producers and users accuracies are 15.0% and 12.3% respectively. The unplanned settlement producers and users accuracy are also low at 37.1% and 17.7% respectively. The RF algorithm been strictly a pixel-based classifier meant it could only classify individual vegetation, bare ground and water pixels within planned and unplanned settlements as independent classes rather than part of the predominant settlement class. This contributed to the low accuracy seen in the planned and unplanned settlement classification. The lack of infrared band in the GeoEye-1 imagery used also contributed in limiting the capacity of RF to distinguish the land cover/land use classes with better accuracy. Table 4.4 shows the RF classification error matrix. It illustrates the misclassification between virtually all the classes.

Table 4.4. Random forest classification standard error matrix.

Predicted class	Reference class					Users accuracy (%)
	Bare ground	Planned settlement	Unplanned settlement	Vegetation	Water	
Bare ground	85	10	168	49	0	27.2
Planned settlement	14	40	130	139	1	12.3
Unplanned settlement	8	93	115	65	24	37.7
Vegetation	0	67	117	119	17	37.1
Water	0	60	120	82	62	19.1
Producers Accuracy (%)	80.0	15.0	17.7	26.2	59.6	

4.6 Discussion

4.6.1 Effectiveness of deep learning for distinguishing planned and unplanned settlements

In this study, the first research question posed was 'Can planned and unplanned urban areas be distinguished and mapped successfully using DL?' The DL approach employed here was relatively effective in mapping planned and unplanned settlements alongside water, vegetation and bare ground in Abuja. Looking at the result in figure 4.3, we can observe that DL is able to map both areas of planned and unplanned settlements to a great extent. Water is also captured well. The areas that DL performed less overall are vegetation and bare ground. Vegetation was sometimes confused as water and occasionally as part of planned area. While bare ground is included as part of planned settlement and vegetation at times.

We adopted a simple DL architecture (Lenet) which consist of two convolution networks and is easy to adapt for the purpose of mapping complex urban features like unplanned settlements. The methods developed in training the CNN is also straightforward and can easily be transferred and tested in other fast-growing cities of developing nations. Having a method that is transferable and able to detect and map features like informal settlements in developing countries that is independent of location is not common but quite desirable (Kuffer et al., 2014; Mboga et al. 2017), with potential for urban planning applications more broadly. However, the DL classification accuracy is also highly dependent on robust and large training dataset and, determining the optimal patch size for training is also crucial for the success of the approach. This means that for remote sensing single scene classification where training data could be limited, DL accuracy could be lower. Also, there is no clear formula on how to determine an optimal patch size for training. This means that there might be some element of subjectivity on this part of the DL process.

Future developments looking to further improve these methods could include applying different CNN that have more than two convolution layers in the architecture as shown by Mboga et al. (2017) or by combining a deep residual network first introduced by (He et al., 2016), with an edge enhancement guided filter applied to a final DL generated map (Xu et al., 2018). However, DL has shown considerable promise in its ability to map unplanned settlements in a planned city. Information like this will be crucial to planners and policy makers to properly monitor and manage a fast-growing city and to identify deprived areas where more resources can be focused to upgrade them (Sliuzas, 2003).

4.6.2 Machine learning classification using spectrally limited imagery

The VHR GeoEye image used for the two classifications is limited in spectral resolution, having only three bands (red, green, blue), however this is the dataset that is readily available to urban planners in developing countries such as Nigeria where mapping unplanned urban areas would be of greatest value. This is mostly due to its lower cost while satisfying the basic requirement of the planners in terms of visualisation. Therefore, whereas the performance of other classification methods such as RF would typically be higher should multispectral VHR imagery be used, for this specific application, random forest classifiers perform poorly, and the DL method developed here perform to a much higher accuracy. This offers a valuable tool to urban planners that is easy to implement by non-experts. Despite the spectral limitation of the VHR image (three visible bands) used, DL algorithm performed well in mapping unplanned and planned settlements. On the other hand, RF algorithm performance was significantly affected by the spectral limitation of the imagery. Hence, DL should be the go-to-approach for urban planners (especially in the Global South) to map and monitor unplanned settlements.

4.6.3 Comparison of deep learning and random forest classification

The second research question posed in this study was 'Can DL offer enhanced classification performance over established machine learning methods such as random forests?'. Most studies that applied DL to remote sensing image processing reported quite a remarkable improvement in accuracy (Mboga et al. 2017; Nogueira et al. 2017; Wang et al. 2017). Here, we attempted to understand if the improvement in accuracy is strictly due to the potential and superiority of DL architecture over other remote sensing classification methods or if it might be due to the differences in accuracy assessment approach in the two fields. The result of the DL automated accuracy assessment was quite remarkable for the two main classes of interest in this study – planned and unplanned settlements, with both having 99% classification accuracy. Considering that DL does not routinely generate wall to wall map, we decided to subset eight areas within the image to see the land cover result visually.

On inspection of the DL generated maps of the eight sampled areas, there is, however, some disparity with our visual comparison and the 99% overall accuracy reported by the DL automated accuracy assessment approach. To perform a more objective assessment, a second accuracy assessment on the eight classified maps was performed using a common RS approach of standard error matrix using an independent set of validation points. The second accuracy assessment showed considerably reduced accuracies (Table 4.2). The overall accuracy of the standard error matrix approach on the DL classification is 66%, with planned and unplanned accuracies being around 70% and 75% respectively. This is considerably lower than the 99% accuracy reported using the two-class linear system. The reason for this difference in accuracy levels is likely attributed to the nature of how the two different approaches investigated handle testing data. The DL automated accuracy assessment approach uses and test pixels that are within an area that is predominantly dominated by a single class. This is because reference data areas are identified as homogenous patches or objects of individual classes. On the other hand, standard error matrix uses and test pixels that are distributed over an area that consist of multiple classes. For example, to test unplanned settlement class, the DL automated approach uses a testing polygon, within the unplanned settlement, to then randomly select test patches (e.g. 500 patches) in an area that is 90% occupied by unplanned settlement. This will most likely result in higher accuracy because of the effect of positive spatial autocorrelation (Woodcock and Strahler, 1987; Congalton & Green, 2008). The disparity shown between the two-different accuracy assessment approach means that care should be taken in interpreting and assessing the quality of a remote sensing classification derived from DL. Overall, DL methods are good at mapping unplanned settlement, and offers a significant improvement in accuracy (see Figure 4.3) over RF (which has a producers and users accuracy of 15.0% and 12.3%) for planned settlement and 37.7% and 17.7% producers and users accuracy for unplanned settlements (see Table 4.4). The accuracy of DL classifiers should be verified with independent data to avoid overestimation of classification accuracy. On the other hand, the RF algorithm does not seem to be sophisticated enough to enable discrimination between planned and unplanned settlements which are quite similar spectrally. The accuracy recorded for RF classification is below acceptable threshold. This also shows that not all machine learning methods are suitable for mapping complex urban features especially using a spectrally limited dataset. The spectral limitation in the VHR imagery used may have played a role in the low accuracy recorded. RF classifier has been revealed to perform better in classifying hyperspectral imagery where dimensionality and excessive data correlation is a big issue (Belgiu & Drăguţ, 2016).

4.7 Conclusion

In this study we investigated the potential of two machine learning approaches in mapping planned and unplanned settlements in Abuja, a rapidly urbanising city of the Global South. This research has shown how a simple CNN can be trained to successfully characterise and map complex land cover and land use using a basic 3-band RGB VHR image. The methodology proposed to map unplanned and planned settlement is simple and can easily be adapted and used by non-experts. This will aid in overcoming the problem of having to develop new methods of capturing detailed information on the morphology of different cities, which is done by adjusting individual spatial metrics of cities based on location (Kuffer et al., 2014). This research also illustrates that the RF classifier is poorly suited to distinguishing and mapping unplanned and planned settlement using 3-band GeoEye VHR imagery.

The results of this study have revealed a marked difference in accuracy assessment result based on the approach adopted when applying DL for remote sensing data. Using an automated accuracy assessment (commonly used in DL classification) for accuracy assessment revealed a very high accuracy result compared to a standard error matrix approach that is widely used in remote sensing. This has clear implication going forward especially in the field of remote sensing. The disparity in accuracy figures for the two approach is linked to the selection of reference data, where the DL automated approach test the classification using reference data from individual homogenous class patches. While the standard error matrix approach for remote sensing uses reference data from areas consisting of mixed classes. More research is needed to better understand the disparity between the two accuracy approaches.

Chapter 5

Conclusion

5.1 Conclusions

This study has successfully utilized remote sensing technology to investigate urbanization in the planned city of Abuja, Nigeria. The research has involved multi-temporal remote sensing to investigate urbanization in Abuja over the last four decades, and multi-source remote sensing to distinguish unplanned and planned urban development at different scales of observation. The study has succeeded in reviewing and analysing urban growth in the city based on the provision of the original Master Plan, showing the extent to which actual urban development has kept pace with, or diverged from, the original plan (Chapter 2). However, limitations in the level of thematic land cover detail achievable using Landsat imagery, and also limitations in the temporal coverage of Landsat, led to an experiment using DMSP-OLS nighttime lights imagery to monitor urbanization in Abuja and specifically to distinguish unplanned and planned urban areas (Chapter 3). Finally, constraints to the level of detail and accuracy achievable using coarse spatial resolution DMSP-OLS imagery meant that further work was conducted using VHR GeoEye-1 imagery to map urban land cover at a high level of detail and distinguish clearly between unplanned and planned urban areas. Here, traditional mapping approaches such as maximum likelihood or random forest classification proved inaccurate because of the high spatial frequency of urban land cover and resulting spectral confusion between classes. Therefore, an alternative, contemporary classification approach based on deep learning analysis was developed which proved successful in distinguishing unplanned and planned urban area (Chapter 4).

5.1 Unplanned urbanization in the Global South

Rapid urban growth is a global affair but in recent years this growth has been experienced most in developing countries. This fast-paced urbanization has led to an explosion of unplanned settlements in cities of the Global South. One of the challenges posed by unplanned settlements is their very complex setting (characterised by disorderly and cluttered features) that is difficult to understand. There is also limited information about the distribution and growth of unplanned settlements, despite housing one third of the urban population of developing countries (United Nations, 2015). This makes mapping and monitoring unplanned settlements challenging. Consequently, unplanned settlements are suffering from neglect and lack of basic infrastructure such as roads, power and social amenities. Urban planners and policy makers need affordable sources of information and reliable analytical approaches to first construct inventories (maps) of unplanned urbanization, and then to monitor these areas. Remote sensing has proven to be an effective technology to provide this information.

5.2 The role of remote sensing

Remote sensing can play a significant role in providing useful information to help in better understanding and monitoring of unplanned urbanization in the Global South. Using diverse types of remote sensing data sources, that range from low through medium to high spatial resolution imagery, unplanned urban development can be successfully detected, mapped and monitored with high temporal frequency. Long-term urban change is difficult to monitor because of a lack of knowledge about built-up land cover and land use change spanning decades. The existence of remote sensing missions such as Landsat, which has acquired imagery around the world for almost half a century, offers the opportunity to analyse the growth and pattern of urban development, including unplanned settlements. Additionally, using DMSP-OLS stable lights imagery has shown to be effective to help further discriminate predominantly planned and unplanned areas of a city. This information will provide a valuable insight into the attributes of unplanned development in cities of the Global South for better monitoring and prediction of, and preparation for, future urban growth. Furthermore, the application and use of VHR imagery provides the opportunity to acquire enhanced information of not just land cover change in Abuja, but also urban land use like unplanned settlements, at greater spatial detail. Such information is highly useful to urban planners as it can help them to plan and allocate resources more effectively to areas in need.

5.3 Urban analysis using medium resolution optical (Landsat) imagery

Reliable, cheap and regular spatial data is the cornerstone of successful urban analysis and management. Remote sensing has shown that it is possible to analyse and monitor urban areas using medium spatial resolution Landsat imagery. Land cover mapping was achieved by classifying a time series of Landsat MSS, TM, ETM+ and OLI imagery of 1975, 1986, 1990, 1999, 2002, 2008 and 2014 using supervised maximum likelihood classification. Post classification comparison was then applied to determine the nature of change taking place in the study area since the city's inception with an emphasis on the growth of urban/built-up land in and around the city (Chapter 2). The historical images of Landsat used to study urban change in Abuja have been successful even though the images have moderate spatial resolution

The Abuja Master Plan proposed different phases of development in specific spatial compartments, dividing the city into four phases. City construction and development was designed to be undertaken gradually. The phases were intended to be undertaken broadly in sequence, though with some overlap between them. That is, phase one should commence first and progress, then phase two will commence while phase one is being completed, and the same process to be repeated for the remaining phases. The results of this study have revealed that urban growth in Abuja in the 1980s honoured the Master Plan's intentions reasonably faithfully (Chapter 2), but as time passed the original plan became less influential and development became more haphazard. This led to rapid increase in development of unplanned settlements and satellite towns on the city's fringes, especially in the last two decades. Overall, there has been significant change in terms of urban land cover in the study area, from relatively vacant grassland with urban settlement of 1,166 ha in 1975, to 18,623 ha of built-up land in 2014. The fastest period of urban growth was from 1999-2014. Within this period, built-up land in Abuja has increased from 7,184 ha to 18,623, an increase of 11,439 ha in 15 years. This rapid urbanization may be attributable to the socio-political situation in Nigeria, as 1999 was the year when Nigeria transitioned back to democracy after 16 years of military rule. This led to more people moving into the capital and more spending on infrastructure by the government to cope with the influx.

The Abuja Master Plan commissioned in 1979 is the principal document that has guided urban growth and land use development in the city. However, since its publication, little attempt has been made to have it fully updated, through a comprehensive review of its shortcomings in comparison with the reality on the ground. The philosophy of the city design was to have a capital city that conforms and achieve three basic goals, namely; Imageability, Flexibility and Efficiency (IPA, 1979), yet this study has found that none of the goals can be confidently considered a full success because of the emergence and growth of unplanned settlements. The Master Plan also stated that development of the city will start by clearing and resettling all the original inhabitants of the city living within the area earmarked for developing FCC (phases 1-4) so that implementation of the master plan will be easy, and chances of unplanned settlements and slums eliminated. This was not the case, based on the findings of this study. Settlements were observed across the entire city as early as 1986 when less than a quarter of the phase 1 area was developed.

Moreover, looking critically into the pattern of urban/built-land area (with the help of GeoEye-1 VHR imagery analysis) in the city, a dual picture begins to appear – one of planned, organized and regulated at its heart, while in mostly haphazard, impoverished and disorganised in its fringe. Part of the problem can be blamed on the Master Plan itself, because it did not anticipate the high influx of people with low income. These people cannot afford to live inside the city but are drawn to the area in search of better opportunities. When they arrive, the best option they have is to stay in the villages and settlements close to the city. This shows that the planners (who overlook reviewing and addressing the shortcomings of the Master Plan) and policy makers have been implementing the plan without demanding for a review. Also, not much significance is given to lower income residents (who are mostly unskilled workers) by the Master Plan. In addition, this class of people are among the first residents of the city, the ones that laid the foundation of building the new city, and the ones that are still helping in the construction and development of the city today. A similar observation was made by Vale (1992), that made him to conclude that Abuja is a city planned without much regard to Nigeria's poor.

Despite the successes of using Landsat imagery to analyse and map urban land cover and land use, some limitations were observed. For example, the spatial and spectral resolution of the Landsat imagery limits the thematic information that can be derived from the imagery. Urban built-up land cover and other urban surface materials are spectrally similar, for example, bare ground and impervious surfaces can have similar spectral signatures, making it very challenging to successfully analyse an urban area (Zhang et al., 2015). As a result, it is not possible to distinguish planned and unplanned urban areas with greater detail and accuracy using Landsat imagery alone without additional ancillary data. Similarly, the 30 m spatial resolution limits the extent to which small urban features can be detected accurately. Other limitations of Landsat include its poor temporal coverage, partly caused by the frequency of cloud cover, and the failed Landsat ETM+ Scan Line Corrector (SLC-off data) after May 2003.

5.4 Monitoring urban development using coarse resolution nighttime lights (DMSP-OLS) imagery

DMSP-OLS nighttime imagery as an alternative remote sensing data source provides a unique advantage that addresses some of the major weaknesses of Landsat imagery. DMSP-OLS NTL has higher temporal frequency (including the annual composites) which can be used to fill in the date gaps in the Landsat historical archives. It can also provide thematic information based on radiance intensity of city lights to highlight urban areas from non-urban. This helps minimize the confusion of classifying spectrally similar land cover and land use in urban areas (Zhang et al., 2015). This capability makes the DMSP-OLS SNTL imagery an effective choice in analysing, characterising and mapping planned and unplanned urban areas in Abuja, Nigeria.

This study successfully utilized DMSP-OLS SNTL to map urban extent and characterise unplanned and planned urban areas in a city of the Global South (Abuja). Most studies that use DMSP-OLS nighttime lights imagery focus on regional or global scales. Of the few studies that use the imagery at city level, most tend to focus on cities in developed nations. This is the first study that applies DMSP-OLS SNTL combined with Landsat derived land cover to map urban extent and to distinguish unplanned and planned urban areas in a city in Nigeria. To do this, urban land cover maps derived from Landsat TM/ETM+ were combined with DMSP-OLS SNTL to map planned and unplanned areas in 1999, 2002 and 2008. The study also sampled nine satellite towns (unplanned settlements) around Abuja to further show the performance of the DMSP-OLS SNTL-based classification technique adopted. The results of the study show a relatively high level of accuracy in classifying planned and unplanned areas in the city (Chapter 3). The method and results of this study can be very valuable to city planners and policy makers that need a rapid and inexpensive way to map and monitor unplanned urban areas in cities of the Global South.

This study also performed a comparative analysis to show the relationship between DMSP-OLS stable lights brightness value with the spatial coverage of urban built-up land cover derived from Landsat images (Chapters 2, 3). The results showed a direct positive relationship between brightness levels of stable lights and the amount of built-up land cover per 1 km^2 area (the size of a SNTL pixel). This is the first study to perform such direct comparison based on the best knowledge available to the author.

The results obtained from the nighttime lights-based classification of the DMS-OLS SNTL has revealed some limitations and areas that can be improved in future research, for example, the issue of inter-satellite calibrations that can affect comparability and consistency between nighttime lights captured by multiple satellites (Huang et al., 2014). There is also the level of accuracy of thematic information derived from the DMSP-OLS imagery classification and limited spatial detail due to the coarse spatial resolution of the sensor.

5.5 Distinguishing planned and unplanned urban development using VHR (GeoEye-1) imagery

The advent of VHR imagery has triggered new interest in the field of urban remote sensing by opening new possibilities in studying urban areas with high spatial detail. Improved spatial resolution (under 5 meters) is the key advantage offered by VHR satellite imagery over Landsat and DMSP-OLS images. High detailed spatial resolution provides an opportunity to utilise newer and improved remote sensing target recognition and scene classification techniques like random forest, deep learning and other machine learning methods. Using GeoEye-1 imagery, this study investigated the potential of using machine learning techniques to distinguish planned and unplanned settlements in Abuja, Nigeria. The study successfully detected and mapped planned and unplanned settlements using a deep learning convolution neural network algorithm (Chapter 4). The detailed information provided by this study is of high significance to urban planners and policy makers. The results of this study have practical impact and offer a high level of accuracy that can be acted upon directly by planners for better city management.

The result of this study has also shown that deep learning performs significantly better in detecting and mapping unplanned and planned areas than random forests using a VHR image with limited spectral composition. The GeoEye-1 image used has only three bands (RGB). The method developed and adopted for this deep learning-based research is clear, uncomplicated and can easily be adapted to map planned and unplanned settlements in other rapidly growing cities of the Global South (Chapter 4). Transferability of methods for mapping unplanned settlements to different cities of the Global South is a subject that is challenging but expedient and desirable to achieve (Mboga et al., 2017). This project has further revealed the capability of deep learning in the area of complex target recognition and intuitive scene understanding, fields that have been highlighted over time to be challenging in the remote sensing community (Zhang et al., 2016).

In addition to mapping planned and unplanned settlements using deep learning, this study investigated and analysed two approaches to accuracy assessment on deep learning classification. DL automated accuracy assessment approach and RS standard error matrix approaches were compared (Chapter 4). The results have shown a significant difference in accuracy figures between the two approaches, with the DL automated approach reporting appreciable increase on all individual classes and overall accuracy. This development has significant ramifications in the field of remote sensing where there is growing adoption of deep learning techniques to solve different problems. The disparity in the accuracy result reported in the DL automated approach is linked to the way testing reference data (for DL automated approach) is collected from relatively pure dataset while the testing is done on a mixed environment. Further research is needed to better understand reasons for such disparity in accuracy assessment between the two approaches. Furthermore, analysing VHR imagery can be challenging, as it could sometimes be noisy because of the level of spectral detail. The level of detail also makes VHR imagery processing and analysis to be slow and time consuming.

5.6 Challenges of mapping unplanned urbanization in cities with no Master Plan

Unplanned urbanization by its nature is difficult to identify and to subsequently map. This problem is more pronounced in cities that grow without any Master Plan or comprehensive land use plans developed over time to guide their growth. Such conditions make it difficult to determine what constitute an unplanned settlement over time. This research has shown that if a section of unplanned settlements can be identified/sampled, remote sensing can easily be utilized in detecting and mapping the rest of the unplanned settlements at the larger city scale. The methods presented in this study (Chapter 3, Chapter 4) can be easily adapted in other cities of the world that are struggling with detecting and monitoring of unplanned settlements.

5.7 Project limitations

The research has highlighted some general problems and limitations, with some of these limitations data related, and others are methods based. The first limitation is the lack of detailed temporal information in the Abuja Master Plan that link urban development to specific targeted years in the Master Plan. This made it difficult to critique the Master Plan comprehensively and to compare and contrast the level of development and diversions, say every 5 years from 1975. There is also a difficulty in obtaining historical reference data corresponding to all the years targeted by the study during a field campaign in Abuja in 2015. As a result, Oral histories obtained through interviews with old-aged residents and long-term urban planners were collected to create a single comprehensive land cover dataset for reference. There are no official land cover and land use maps in the late 1970's and 1980's. If there is, it was not possible to get our hands on them despite several attempts to do so by going and speaking to planning officials in the FCDA. The study also faced some political issues that have to do with unreliability of government information. For example, there is some objection and uncertainty on the official population figures of Abuja (Iro, 2007). There is also a challenge posed by the issue of political corruption in Nigeria. This creates a discrepancy in what is on some official urban planning documents of Abuja, and the reality on the ground.

Another limitation is the type of VHR imagery utilized for the study. The imagery consists of only RGB bands. This type of imagery is limited spectrally, but it is commonly acquired by urban planners in developing countries, as it is cheap and easy to use. Also, DL demands high levels of computational power for processing. This makes it unfeasible to generate wall-to-wall mapping of the entire study area. This was addressed by sub-setting eight areas (with mixed land cover) within the image to perform the classification (Chapter 4). The lack of DMSP-OLS imagery after 2010 is another major limitation faced. This limited the analysis undertaken using the nighttime imagery. Consequently, an unplanned and planned urban area map could not be conducted from DMSP-OLS imagery for 2014. Another limitation of using DMSP-OLS nighttime lights to derive urban extent map is the level of subjectivity involved in determining an optimum threshold for each city. The issue of over-estimation of urban extent due to over-blooming is another well-known limitation when working with DMSP-OLS nighttime lights (Imhoff et al. 1997; Letu et al., 2010).

5.8 Further work

This study has shown how remote sensing can be successfully utilized in analysing and monitoring urbanization in the Global South. The approaches for analysing and monitoring urban areas presented in this study are transferable to other cities around the world and can be easily utilized using other remote sensing data sources. Another area that needs further attention is to have a better synergy globally in an effort to come up with an acceptable worldwide definition and understanding of unplanned developments. Doing this will ease in the establishment of general transferable methods and solutions to analysing, mapping and monitoring urban areas globally.

Despite the successes achieved in this study, there is still opportunity for further development of this research in the future. One aspect that needs to be investigated further is the performance of a new sensor – Visible Infrared Imaging Radiometer Suite (VIIRS) – to map unplanned and planned urban areas in the Global South. This sensor collects nightlights data and was launched in 2011 to address some of the limitations of DMSP-OLS nighttime lights. VIIRS images have improved spatial resolution and the sensor has onboard calibration. This will likely help in reducing issues of over blooming and provide improved accuracy in urban extent mapping and characterising unplanned and planned urban areas (Chapter 3). More studies are also needed to better understand the performance of deep learning and random forest to map unplanned and planned settlements using spatially and spectrally improved VHR satellite imagery.

This study has shown the need for the establishment of effective urban monitoring systems in cities of the Global South to address the challenges of fast paced urbanization like congestion, urban sprawl, infrastructure deficit and emergence of slums. With the advent of new satellite sensors like those of the Sentinel's mission, such monitoring systems could now become a reality. Among the objectives of the Sentinels mission is the global acquisition of high-resolution multispectral images, with high temporal frequency. This dataset provides an opportunity for urban planning and management organisations in developing nations that are financially-constrained to have access to free, high quality remote sensing data to develop and operate effective urban monitoring systems. Additionally, more studies are needed to further understand the effects of politics in the urban growth and management of cities of the Global South.

5.9 Concluding remarks

The problem of delineating urban features and the effectiveness of information on urban changes depends on the availability of useful data, which is more difficult to obtain in developing countries (Weber & Puissant, 2003). This study has provided workable data and information that can be used by policy makers and urban planners to monitor and address the issues around rapid growth of unplanned settlements. This research has successfully utilized time-series satellite imagery to establish the limits of a Master Plan in controlling urbanization in a planned city of the Global South. The study has also demonstrated an approach of combining DMSP-OLS nighttime lights with Landsat derived built-up land cover map to successfully map unplanned and planned areas of Abuja. Finally, this study has also presented a simplified approach of using deep learning on VHR imagery to map unplanned and planned settlements at a finer scale in Abuja, Nigeria. The methods developed and adopted in this study will go a long way in advancing the field of remote sensing literature on cities of the Global South. The study can also have a direct societal impact, as the results presented can be acted upon immediately by the policy makers and urban planners in Abuja, Nigeria.

The accuracy and effectiveness of land cover and land use studies have been influenced by the scarcity of knowledge about such change, especially in the Global South. This study has shown how remote sensing techniques can be successfully applied to detect, distinguish and map unplanned and planned settlement in a fast pace growing city of the Global South.

References

Abubakar, I. R. (2014). Abuja city profile. Cities, 41, 81-91.

Adama, O. (2007). Governing from above: Solid waste management in Nigeria's new capital city of Abuja. Stockholm: Universitetsservice US-AB.

Admin. (2015). Contending with infrastructural deficit in Abuja satellite towns. Housing News

Aguilar, M., Saldaña, M., & Aguilar, F. (2013). GeoEye-1 and WorldView-2 pan-sharpened imagery for object-based classification in urban environments. International Journal of Remote Sensing, 34(7), 2583-2606.

Akingbade, A., Navarra, D. D., & Georgiadou, Y. (2009). A 10 years review and classification of the geographic information systems impact literature (1998-2008). Nordic Journal of Surveying and Real Estate Research, Special series V.4.

Alshehhi, R., Marpu, P.R., Woon, W.L., and Dalla Mura, M., 2017, Simultaneous extraction of roads and buildings in remote sensing imagery with convolutional neural networks. ISPRS Journal of Photogrammetry and Remote Sensing, 130, pp. 139-149.

Amba, K. (2010). The need for popular participation in Abuja: A Nigerian story of informal settlements. Journal of Place Management and Development, 3(2), 149-159.

Aminipouri, M., Sliuzas, R., and Kuffer, M., 2009, Object-oriented analysis of very high resolution orthophotos for estimating the population of slum areas, case of Dar-Es-Salaam, Tanzania. In Proc. ISPRS XXXVIII Conf, pp. 1-6.

Anderson, J.R. (1976). A land use and land cover classification system for use with remote sensor data. US Government Printing Office.

Andrefouet, S., Bindschadler, R., & Colstoun, E. (2003). Preliminary assessment of the value of Landsat-7 ETM data following scan line corrector malfunction. US Geological Survey, EROS Data Center: Sioux Falls, SD, USA.

Angel, S., Parent, J., & Civco, D. (2007). Urban sprawl metrics: An analysis of global urban expansion using GIS. Paper presented at the Proceedings of ASPRS 2007 Annual Conference, Tampa, Florida May,7 (Vol. 7, No. 11). Citeseer.

Aplin, P. (2003). Remote sensing: Base mapping. Progress in Physical Geography, 27(2), 275-283.

Aplin, P. (2003a). Comparison of simulated IKONOS and SPOT HRV imagery for classifying urban areas. In V. Mesev (Ed.), Remotely sensed cities (pp. 23-45). London: Taylor & Francis.

Aplin, P. (2003b). Remote sensing: Base mapping. Progress in Physical Geography, 27(2), 275-283.

Aplin, P. (2006). On scales and dynamics in observing the environment. International Journal of Remote Sensing, 27(11), 2123-2140.

Aplin, P., Atkinson, P. M., & Curran, P. J. (1999). Fine spatial resolution simulated satellite sensor imagery for land cover mapping in the United Kingdom. Remote Sensing of Environment, 68(3), 206-216.

Arimah, B. C., & Adeagbo, D. (2000). Compliance with urban development and planning regulations in Ibadan, Nigeria. Habitat International, 24(3), 279-294.

Barnsley, M. J., & Barr, S. L. (1997). Distinguishing urban land-use categories in fine spatial resolution land-cover data using a graph-based, structural pattern recognition system. Computers, Environment and Urban Systems, 21(3), 209-225.

Baud, I., Kuffer, M., Pfeffer, K., Sliuzas, R., & Karuppannan, S., 2010, Understanding heterogeneity in metropolitan India: The added value of remote sensing data for analyzing sub-standard residential areas. International Journal of Applied Earth Observation and Geoinformation, *12*(5), pp.359-374.

Baugh, K., Hsu, F., Elvidge, C. D., & Zhizhin, M. (2013). Nighttime lights compositing using the VIIRS day-night band: Preliminary results. Proceedings of the Asia-Pacific Advanced Network, 35, 70-86.

Bazi, Y., & Melgani, F. (2006). Toward an optimal SVM classification system for hyperspectral remote sensing images. IEEE Transactions on Geoscience and Remote Sensing, 44(11), 3374-3385.

Beauregard, R. A., & Marpillero-Colomina, A. (2011). More than a master plan: Amman 2025. Cities, 28(1), 62-69.

Belgiu, M., and Drăguţ, L., 2016, Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, pp. 24-31.

Bhatta, B. (2010). Causes and consequences of urban growth and sprawl. Analysis of urban growth and sprawl from remote sensing data (pp. 17-36) Springer Berlin, Heidelberg.

Bhatta, B., Saraswati, S., & Bandyopadhyay, D. (2010). Urban sprawl measurement from remote sensing data. Applied Geography, 30(4), 731-740.

Blaschke, T., Hay, G. J., Weng, Q., & Resch, B. (2011). Collective sensing: Integrating geospatial technologies to understand urban systems—An overview. Remote Sensing, 3(8), 1743-1776.

Boumphrey, S. (2010). World's fastest growing cities are in Africa and Asia. Retrieved from https://web.archive.org/web/20151117022953/http://blog.euromonitor.com/2010/03/special-report-worlds-fastest-growing-cities-are-in-asia-and-africa.html.

Braimoh, A. K., & Onishi, T. (2007). Spatial determinants of urban land use change in Lagos, Nigeria. Land use Policy, 24(2), 502-515. doi:DOI: 10.1016/j.landusepol.2006.09.001.

Breiman, L., 2001, Random forests. Machine Learning, 45 (1), pp. 5-32.

Campbell, J.B., & Wynne, R.H. (2011). Introduction to Remote Sensing, Fifth Edition. Guilford Publications.

Canty, M. J., 2014: Image analysis, classification and change detection in remote sensing: with algorithms for ENVI/IDL and Python. Crc Press.

Cao, X., Chen, J., Imura, H., and Higashi, O., 2009, A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data. Remote Sensing of Environment, 113, pp. 2205-2209.

Cao, X., Chen, J., Imura, H., & Higashi, O. (2009). A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data. Remote Sensing of Environment, 113(10), 2205-2209. 10.1016/j.rse.2009.06.001.

Cao, X., Chen, J., Imura, H., & Higashi, O. (2009). A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data. Remote Sensing of Environment, 113(10), 2205-2209. doi:10.1016/j.rse.2009.06.001.

Chen, D., & Stow, D. (2002). The effect of training strategies on supervised classification at different spatial resolutions. Photogrammetric Engineering and Remote Sensing, *68*(11), pp.1155-1162.

Chen, X., Chen, J., Shi, Y., & Yamaguchi, Y. (2012). An automated approach for updating land cover maps based on integrated change detection and classification methods. ISPRS Journal of Photogrammetry and Remote Sensing, 71, 86-95.

CNN (2016). Egypt is getting a new capital - courtesy of china. Retrieved 19 April 2017 from http://edition.cnn.com/2016/10/09/africa/egypt-new-capital/index.html/

Cohen, B. (2004). Urban growth in developing countries: A review of current trends and a caution regarding existing forecasts. World Development, 32(1), 23-51.

Cohen, B. (2006). Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability. Technology in Society, 28(1), 63-80.

COHRE (2008). The myth of the Abuja master plan: Forced evictions as urban planning in Abuja. Geneva: Centre for Housing Right and Evictions.

Colwell, R.N. (1997). History and place of photographic interpretation. Manual of photographic interpretation, 2, 33-48.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37(1), 35-46.

Congalton, R. G., and Green, K., 2008, Assessing the accuracy of remotely sensed data: Principles and practices CRC press.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Review ArticleDigital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25, 1565-1596.

Croft, T. A. (1978). Nighttime images of the earth from space. Scientific American, 239, 86-98.

Daily Trust (2016). Senate unveils anomalies in FCT land swap. Retrieved 12 February 2017 from https://www.dailytrust.com.ng/news/property/senate-unveils-anomalies-in-fct-land-swap/132559.html.

De Bon, H., Parrot, L., & Moustier, P. (2010). Sustainable urban agriculture in developing countries. A review. Agronomy for Sustainable Development, 30(1), 21-32.

De Jong, S. M., Bagré, A., Van Teeffelen, P. B. M., & Van Deursen, W. P. A. (2000). Monitoring trends in urban growth and surveying city quarters in ouagadougou, burkina faso using spot-XS. Geocarto International, 15(2), 61-67.

Deng, J., Wang, K., Deng, Y., & Qi, G. (2008). PCA-based land-use change detection and analysis using multitemporal and multisensor satellite data. International Journal of Remote Sensing, 29(16), 4823-4838.

Desa, U. (2011). World urbanization prospects, the 2011 revision. United Nations, 505

Doll, C. N. H., & Pachauri, S. (2010). Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery. Energy Policy, 38(10), 5661-5670. doi:10.1016/j.enpol.2010.05.014

Doll, C.N., 2010, Population detection profiles of DMSP-OLS night-time imagery by regions of the world. Proceedings of the Asia-Pacific Advanced Network, 30, pp. 190-206.

Donnay, J. P., Barnsley, M. J., & Longley, P. A. (2003). Remote sensing and urban analysis: GISDATA 9 CRC Press.

Doxani, G., Karantzalos, K., & Tsakiri-Strati, M. (2012). Monitoring urban changes based on scale-space filtering and object-oriented classification. International Journal of Applied Earth Observation and Geoinformation, 15, 38-48.

Du, S., Zhang, F., & Zhang, X. (2015). Semantic classification of urban buildings combining VHR image and GIS data: An improved random forest approach. ISPRS Journal of Photogrammetry and Remote Sensing, 105, 107-119.

Duda, T., & Canty, M. (2002). Unsupervised classification of satellite imagery: Choosing a good algorithm. International Journal of Remote Sensing, 23, 2193-2212.

Duro, D.C., Franklin, S.E., and Dubé, M.G., 2012, Multi-scale object-based image analysis and feature selection of multi-sensor earth observation imagery using random forests. International Journal of Remote Sensing, 33, pp. 4502-4526.

Dutta, V. (2012). Land use dynamics and peri-urban growth characteristics: Reflections on master plan and urban suitability from a sprawling north Indian city. Environment and Urbanization Asia, 3(2), 277-301.

Ebehikalu, N. O., Dawam, P. D., & Kasim, U. (2016). A study of the state of infrastructure in the federal capital territory, abuja. Journal of Resources Development and Management, 18.

Eisavi, V., Homayouni, S., Yazdi, A. M., & Alimohammadi, A. (2015). Land cover mapping based on random forest classification of multitemporal spectral and thermal images. Environmental Monitoring and Assessment, 187(5), 291.

Elvidge, C. D., Baugh, K. E., Dietz, J. B., Bland, T., Sutton, P. C., & Kroehl, H. W. (1999). Radiance calibration of DMSP-OLS low-light imaging data of human settlements. Remote Sensing of Environment, 68(1), 77-88.

Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., & Davis, E. R. (1997). Mapping city lights with nighttime data from the DMSP operational linescan system. Photogrammetric Engineering and Remote Sensing, 63(6), 727-734.

Elvidge, C. D., Erwin, E. H., Baugh, K. E., Ziskin, D., Tuttle, B. T., Ghosh, T., & Sutton, P. C. (2009b). Overview of DMSP nightime lights and future possibilities. Paper presented at the 1-5. 10.1109/URS.2009.5137749.

Elvidge, C. D., Hsu, F., Baugh, K. E., & Ghosh, T. (2014). National trends in satellite-observed lighting. Global Urban Monitoring and Assessment through Earth Observation, , 97-118.

Elvidge, C. D., Imhoff, M. L., Baugh, K. E., Hobson, V. R., Nelson, I., Safran, J., Tuttle, B. T. (2001). Night-time lights of the world: 1994–1995. ISPRS Journal of Photogrammetry and Remote Sensing, 56(2), 81-99. 10.1016/S0924-2716(01)00040-5.

Elvidge, C. D., Sutton, P. C., Ghosh, T., Tuttle, B. T., Baugh, K. E., Bhaduri, B., & Bright, E. (2009). A global poverty map derived from satellite data. Computers & Geosciences, 35(8), 1652-1660. http://dx.doi.org/10.1016/j.cageo.2009.01.009.

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., (2009a). A fifteen-year record of global natural gas flaring derived from satellite data. Energies, 2(3), 595-622.

Englund, H. (2001). The politics of multiple identities: The making of a home villagers' association in Lilongwe, Malawi. In A. Tostensen, I. Tvedten. & M. Vaa (Eds.), Associational

Life in African Cities: Popular Responses to the Urban Crisis (pp. 90-106). Stockholm: Elandas Gotab.

Erbek, F. S., Özkan, C., & Taberner, M. (2004). Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. International Journal of Remote Sensing, 25(9), 1733-1748.

Esch, T., Himmler, V., Schorcht, G., Thiel, M., Wehrmann, T., Bachofer, F., Conrad, C., Schmidt, M., & Dech, S. (2009). Large-area assessment of impervious surface based on integrated analysis of single-date Landsat-7 images and geospatial vector data. Remote Sensing of Environment, 113, 1678-1690.

Ewing, R. (1997). Is Los Angeles-style sprawl desirable? Journal of the American Planning Association, 63(1), 107-126.

Feitelson, E., Felsenstein, D., Razin, E., & Stern, E. (2017). Assessing land use plan implementation: Bridging the performance-conformance divide. Land use Policy, 61, 251-264.

Fichera, C. R., Modica, G., & Pollino, M. (2012). Land cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. European Journal of Remote Sensing, 45(1), 1-18.

Foody, G. M., Campbell, N., Trodd, N., & Wood, T. (1992). Derivation and applications of probabilistic measures of class membership from the maximum-likelihood classification. Photogrammetric Engineering and Remote Sensing, 58(9), 1335-1341.

Foody, G.M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80, 185-201.

Foody, G.M., 2008. Harshness in image classification accuracy assessment. International Journal of Remote Sensing, 29(11), 3137-3158.

Forster, B. (1980). Urban residential ground cover using Landsat digital data. Photogrammetric Engineering and Remote Sensing, 46, 547-558.

Franklin, S., & Wulder, M. (2002). Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. Progress in Physical Geography, 26(2), 173-205.

Franklin, S., and Wulder, M., (2002). Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. Progress in Physical Geography, 26, pp. 173-205.

Frey, W. H., & Zimmer, Z. (2001). Defining the city. Handbook of Urban Studies, 1, 14-35.

Friedmann, J. (2005). Globalization and the emerging culture of planning. Progress in Planning, 64(3), 183-234. 3

Fritz, S., & Wexler, H. (1960). Cloud pictures from satellite TIROS I. Monthly Weather Review, 88, 79-87.

Fu, G., Liu, C., Zhou, R., Sun, T., & Zhang, Q. (2017). Classification for high resolution remote sensing imagery using a fully convolutional network. Remote Sensing, 9(5), 498.

Fu, G., Liu, C., Zhou, R., Sun, T., and Zhang, Q., (2017). Classification for High Resolution Remote Sensing Imagery Using a Fully Convolutional Network. Remote Sensing, 9, pp. 498.

Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: Defining and measuring an elusive concept. Housing Policy Debate, 12(4), 681-717.

Gao, B., Huang, Q., He, C., & Ma, Q. (2015). Dynamics of urbanization levels in china from 1992 to 2012: Perspective from DMSP/OLS nighttime light data. Remote Sensing, 7(2), 1721-1735. 10.3390/rs70201721.

Geymen, A., & Baz, I. (2008). Monitoring urban growth and detecting land-cover changes on the istanbul metropolitan area. Environmental Monitoring and Assessment, 136(1-3), 449-459.

Gibson, J., Li, C., & Boe-Gibson, G. (2014). Economic growth and expansion of china's urban land area: Evidence from administrative data and night lights, 1993-2012. Sustainability, 6(11), 7850-7865. 10.3390/su6117850.

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2016). Region-based convolutional networks for accurate object detection and segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(1), 142-158.

Gluch, R. (2002). Urban growth detection using texture analysis on merged Landsat TM and SPOT-P data. Photogrammetric Engineering and Remote Sensing, 68(12), 1283-1288.

Goldblatt, R., Stuhlmacher, M. F., Tellman, B., Clinton, N., Hanson, G., Georgescu, M., Cheng, W. (2018). Using Landsat and nighttime lights for supervised pixel-based image classification of urban land cover. Remote Sensing of Environment, 205, 253-275.

Gong, P., & Howarth, P. (1990). An assessment of some factors influencing multispectral land-cover classification. Photogrammetric Engineering and Remote Sensing, 56(5), 597-603.

Gusah, S. (2012). Community land trusts: A model for integrating Abuja's urban villages within the city master plan. In L. E. Herzer (Ed.), CHANGING CITIES: Climate, youth, and land market in urban areas (pp. 141-159). Washington, DC: Wilson Center.

Hall, G. B., Malcolm, N. W., & Piwowar, J. M. (2001). Integration of remote sensing and GIS to detect pockets of urban poverty: The case of Rosario, Argentina. Transactions in GIS, 5(3), 235-253.

Hall, P., & Tewdwr-Jones, M. (2010). Urban and regional planning London: Routledge, https://doi.org/10.4324/9780203861424.

Hameed, R., & Nadeem, O. (2006). Challenges of implementing urban master plans: The Lahore experience. Proceedings of World Academy of Science Engineering and Technology, 17, 335-342.

Han, J., Hayashi, Y., Cao, X., and Imura, H., 2009, Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China. Landscape and Urban Planning, 91, 133-141.

Hardoy, J. E., & Satterthwaite, D. (1986). Urban change in the third world: Are recent trends a useful pointer to the urban future? Habitat International, 10(3), 33-52.

He, C., Gao, B., Huang, Q., Ma, Q. and Dou, Y., 2017. Environmental degradation in the urban areas of China: Evidence from multi-source remote sensing data. Remote Sensing of Environment, 193, 65-75.

He, C., Li, J., Chen, J., Shi, P., Chen, J., Pan, Y., Toshiaki, I. (2006). The urbanization process of bohai rim in the 1990s by using DMSP/OLS data. Journal of Geographical Sciences, 16(2), 174-182. 10.1007/s11442-006-0205-0

He, K., Zhang, X., Ren, S., and Sun, J., 2016, Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778.

Henderson, M., Yeh, E. T., Gong, P., Elvidge, C., & Baugh, K. (2003). Validation of urban boundaries derived from global night-time satellite imagery. International Journal of Remote Sensing, 24(3), 595-609. 10.1080/01431160304982.

Herold, M., N.C. Goldstein, and K.C. Clarke, 2003, The spatiotemporal form of urban growth: measurement, analysis and modelling. Remote Sensing of Environment, 86, pp. 286-302.

Hinton, G., Osindero, S. Welling, M., and Teh, Y., 2006, Unsupervised discovery of nonlinear structure using contrastive backpropagation. Cognitive science, 30, pp. 725-731.

Hofmann, P., Blaschke, T., and Strobl, J., 2011, Quantifying the robustness of fuzzy rule sets in object-based image analysis. International Journal of Remote Sensing, 32, pp. 7359-7381.

Hofmann, P., Strobl, J., Blaschke, T., and Kux, H., 2008, Detecting informal settlements from QuickBird data in Rio de Janeiro using an object based approach. In *Object-based image analysis* (pp. 531-553). Springer, Berlin, Heidelberg.

Hu, F., Xia, G., Hu, J., & Zhang, L. (2015). Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. Remote Sensing, 7(11), 14680-14707.

Hu, F., Xia, G., Hu, J., and Zhang, L., 2015, Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. Remote Sensing, 7, pp. 14680-14707.

Hu, F., Xia, G., Wang, Z., Huang, X., Zhang, L., & Sun, H. (2015b). Unsupervised feature learning via spectral clustering of multidimensional patches for remotely sensed scene classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(5), 2015 – 2030.

Hu, X., & Weng, Q. (2009). Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks. Remote Sensing of Environment, 113(10), 2089-2102.

Hu, Z., Du, P. and Guo, D, (2007). Analysis of Urban Expansion and Driving Forces in Xuzhou City Based on Remote Sensing. Journal of China University of Mining and Technology, 17, pp. 267-271.

Huang, Q., Yang, X., Gao, B., Yang, Y., & Zhao, Y. (2014). Application of DMSP/OLS nighttime light images: A meta-analysis and a systematic literature review. Remote Sensing, 6(8), 6844-6866. 10.3390/rs6086844.

Huang, X., & Zhang, L. (2011). A multidirectional and multiscale morphological index for automatic building extraction from multispectral GeoEye-1 imagery. Photogrammetric Engineering & Remote Sensing, 77(7), 721-732.

Hubert-Moy, L., Cotonnec, A., Le Du, L., Chardin, A., & Perez, P. (2001). A Comparison of Parametric Classification Procedures of Remotely Sensed Data Applied on Different Landscape Units. Remote Sensing of Environment, 75, 174-187.

Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of Photogrammetry and Remote Sensing, 80, 91-106.

Idoko, M. A., & Bisong, F. E. (2010). Application of geo-information for evaluation of land use change: A case study of federal capital territory-Abuja. Environmental Research Journal, 4(1), 140-144.

Ikejiofor, U. (1997). Planning and the political process: Sifting some underlying issues in the development of Abuja, Nigeria's new capital. Third World Planning Review, 19(3), 271.

Ikejiofor, U. (1998). Access to land, development control and low-income housing in Abuja, Nigeria: Policy, politics and bureaucracy. Planning Practice & Research, 13(3), 299-309.

Ikoku, G. (2004). The city as public space: Abuja-the capital city of Nigeria. FORUM 6(1), 34-41.

Im, J., & Jensen, J. R. (2005). A change detection model based on neighborhood correlation image analysis and decision tree classification. Remote Sensing of Environment, 99(3), 326-340.

Imam, A., Mohammed, B., Wilson, D. C., & Cheeseman, C. R. (2008). Solid waste management in Abuja, Nigeria. Waste Management, 28(2), 468-472.

Imhoff, M., Lawrence, W. T., Stutzer, D. C., & Elvidge, C. D. (1997). A technique for using composite DMSP/OLS "City lights" satellite data to map urban area. Remote Sensing of Environment, 61(3), 361-370. doi:10.1016/S0034-4257(97)00046-1.

Inglada, J., & Michel, J. (2009). Qualitative spatial reasoning for high-resolution remote sensing image analysis. IEEE Transactions on Geoscience and Remote Sensing, 47(2), 599-612.

IPA (1979). The master plan for Abuja the new federal capital of Nigeria. Nigeria: Federal Capital Development Authority (FCDA).

Iro, I. (2007). Demographic pressure and the application of GIS in land reforms: The case of restoration of Abuja master plan and sanitization of cadastral and land registry. Proceedings of Map Middle East Conference on GIS Development, 9-11 April 2007, Dubai, UAE.

Jackson, M., Carter, P., & Smith, T. (1980). Urban land mapping from remotely sensed data. Photogrammetric Engineering and Remote Sensing 46(8) 1041 – 1050.

Jensen, J. (1996). Introductory digital image processing. Upper Saddle River, N.J.: Prentice Hall.

Jensen, J. R., & Cowen, D. C. (1999). Remote sensing of urban/suburban infrastructure and socio-economic attributes. Photogrammetric Engineering and Remote Sensing, 65, 611-622.

Jensen, J.R. (1982). Detecting residential land-use development at the urban fringe. Photogrammetric Engineering and Remote Sensing, 48(4), 629.

Jensen, J.R., and Cowen, D.C., (1999). Remote sensing of urban/suburban infrastructure and socio-economic attributes. Photogrammetric Engineering and Remote Sensing, 65, 611-622.

Ji, C. Y., Liu, Q., Sun, D., Wang, S., Lin, P., & Li, X. (2001). Monitoring urban expansion with remote sensing in china. International Journal of Remote Sensing, 22(8), 1441-1455.

Ji, C.Y., Liu Q., Sun D., Wang S., Lin P., and Li X., (2001). Monitoring urban expansion with remote sensing in China. International Journal of Remote Sensing, 22, 1441-1455.

Ji, W., Ma, J., Twibell, R. W., & Underhill, K. (2006). Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics. Computers, Environment and Urban Systems, 30(6), 861-879.

Jia, K., Liang, S., Zhang, N., Wei, X., Gu, X., Zhao, X., Yao, Y., & Xie, X. (2014). Land cover classification of finer resolution remote sensing data integrating temporal features from time series coarser resolution data. ISPRS Journal of Photogrammetry and Remote Sensing, 93, 49-55.

Jianchu, X., Fox, J., Vogler, J. B., Yongshou, Z. P. F., Lixin, Y., Jie, Q., & Leisz, S. (2005). Land-use and land-cover change and farmer vulnerability in xishuangbanna prefecture in southwestern china. Environmental Management, 36(3), 404-413.

Jibril, I. (2009). Squatter resettlement/relocation programme in Abuja, Nigeria and the issue of land title security. FIG Conference Paper, 3-8 May 2009, Eilat, Israel.

Jing, W., Yang, Y., Yue, X., & Zhao, X. (2015). Mapping urban areas with integration of DMSP/OLS nighttime light and MODIS data using machine learning techniques. Remote Sensing, 7(9), 12419-12439.

Johnson, M. P. (2001). Environmental impacts of urban sprawl: A survey of the literature and proposed research agenda. Environment and Planning A, 33(4), 717-735.

Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., Jepsen, M.R., Kuemmerle, T., Meyfroidt, P. and Mitchard, E.T., 2016. A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. Remote Sensing, 8(1), pp. 70.

Kalgo, M., & Ayileka, O. (2001). The review of Abuja master plan. Proceedings of the International Workshop for the Review of Abuja Master Plan, 29 November-2 December 2001, Abuja, Nigeria.

Kalipeni, E., & Zeleza, T. (1999). Sacred spaces and public quarrels: African cultural and economic landscapes. Trenton, NJ: Africa World Press.

Kamh, S., Ashmawy, M., Kilias, A., & Christaras, B. (2012). Evaluating urban land cover change in the Hurghada area, Egypt, by using GIS and remote sensing. International Journal of Remote Sensing, 33(1), 41-68.

Karanja, F., and Matara S., 2013, The Transformation from Green to Concrete Cities; A Remote Sensing Perspective. ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, 163-166.

Kit, O., and Lüdeke M., (2013). Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery. ISPRS journal of photogrammetry and remote sensing, 83, pp. 130-137.

Kit, O., Lüdeke M., and Reckien D., (2012). Texture-based identification of urban slums in Hyderabad, India using remote sensing data. Applied Geography, 32, 660-667.

Kohli, D., Sliuzas R., Kerle N., and Stein A., (2012) An ontology of slums for image-based classification. Computers, Environment and Urban Systems, 36, 154-163.

Kohli, D., Warwadekar P., Kerle N., Sliuzas R., and Stein A., (2013) Transferability of object-oriented image analysis methods for slum identification. Remote Sensing, 5, 4209-4228.

Kombe, W.J., (2005) Land use dynamics in peri-urban areas and their implications on the urban growth and form: the case of Dar es Salaam, Tanzania. Habitat International, 29, pp. 113-135.

Kramer, H. J. (1994). Observation of the earth and its environment: Survey of missions and sensors Springer-Verlag.

Kuffer, M., Barros, J., & Sliuzas, R. V. (2014). The development of a morphological unplanned settlement index using very-high-resolution (VHR) imagery. Computers, Environment and Urban Systems, 48, 138-152.

Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from space—15 years of slum mapping using remote sensing. Remote Sensing, 8(6), 455.

Kussul, N., Lavreniuk M., Skakun S., and Shelestov A., (2017). Deep learning classification of land cover and crop types using remote sensing data. IEEE Geoscience and Remote Sensing Letters, 14, pp. 778-782.

Imhoff, M., Lawrence, W. T., Stutzer, D. C., & Elvidge, C. D. (1997). A technique for using composite DMSP/OLS "City lights" satellite data to map urban area. Remote Sensing of Environment, 61(3), 361-370. 10.1016/S0034-4257(97)00046-1.

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., & Folke, C. (2001). The causes of land-use and land-cover change: moving beyond the myths. Global environmental change, 11, 261-269.

Längkvist, M., Kiselev A., Alirezaie M., and Loutfi A., 2016, Classification and segmentation of satellite orthoimagery using convolutional neural networks. Remote Sensing, 8, pp. 329.

Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2016). Machine learning in geosciences and remote sensing. Geoscience Frontiers, 7(1), 3-10.

Laurian, L., Day, M., Backhurst, M., Berke, P., Ericksen, N., Crawford, J., Chapman, S. (2004). What drives plan implementation? plans, planning agencies and developers. Journal of Environmental Planning and Management, 47(4), 555-577.

LeCun, Y., Bengio Y., and Hinton G., (2015). Deep learning. Nature, 521, 436.

Lecun, Y., Bottou, L., Bengio, Y. and Haffner, P., 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), pp. 2278-2324.

Leinenkugel, P., Esch, T., & Kuenzer, C. (2011). Settlement detection and impervious surface estimation in the mekong delta using optical and SAR remote sensing data. Remote Sensing of Environment, 115(12), 3007-3019.

Letu, H., Tana, G., Bagan, H., Hara, M., & Nishio, F. (2010). Assessment of stable light derived from DMSP/OLS night-time imagery. International Journal of Environmental Studies, 67(5), 773-779. 10.1080/00207233.2010.514116.

Li, C., Wang, J., Wang, L., Hu, L., & Gong, P. (2014). Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery. Remote Sensing, 6(2), 964-983.

Li, G., & Weng, Q. (2010). Fine-scale population estimation: How Landsat ETM imagery can improve population distribution mapping. Canadian Journal of Remote Sensing, 36(3), 155-165.

Li, X., Zhou W., and Ouyang Z., 2013, Forty years of urban expansion in Beijing: what is the relative importance of physical, socioeconomic, and neighbourhood factors? Applied Geography, 38, pp. 1-10.

Li, Y., Huang X., and Liu H., 2017, Unsupervised deep feature learning for urban village detection from high-resolution remote sensing images. Photogrammetric Engineering & Remote Sensing, 83, pp. 567-579.

Liang, H., and Li Q., 2016, Hyperspectral imagery classification using sparse representations of convolutional neural network features. Remote Sensing, 8, 99.

Liu, T., & Yang, X. (2015). Monitoring land changes in an urban area using satellite imagery, GIS and landscape metrics. Applied Geography, 56, 42-54.

Liu, X., Clarke, K., & Herold, M. (2006). Population density and image texture. Photogrammetric Engineering & Remote Sensing, 72(2), 187-196.

Liu, Y., Wang, Y., Peng, J., Du, Y., Liu, X., Li, S., & Zhang, D. (2015). Correlations between urbanization and vegetation degradation across the world's metropolises using DMSP/OLS nighttime light data. Remote Sensing, 7(2), 2067-2088. doi:10.3390/rs70202067.

Liu, Z., He, C., Zhang, Q., Huang, Q., & Yang, Y. (2012). Extracting the dynamics of urban expansion in china using DMSP-OLS nighttime light data from 1992 to 2008. Landscape and Urban Planning, 106(1), 62-72. doi:10.1016/j.landurbplan.2012.02.013.

Liu, Z., He, C., Zhang, Q., Huang, Q., & Yang, Y. (2012b). Extracting the dynamics of urban expansion in china using DMSP-OLS nighttime light data from 1992 to 2008. Landscape and Urban Planning, 106(1), 62. 10.1016/j.landurbplan.2012.02.013.

Longley, P. A. (2002). Geographical information systems: Will developments in urban remote sensing and GIS lead to 'better' urban geography? Progress in Human Geography, 26(2), 231-239.

Lu, D., & Weng, Q. (2009). Extraction of urban impervious surfaces from an IKONOS image. International Journal of Remote Sensing, 30(5), 1297-1311.

Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, 25, 2365-2401.

Lu, D., Moran, E., & Hetrick, S. (2011). Detection of impervious surface change with multitemporal Landsat images in an urban–rural frontier. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 298-306.

Luus, F. P., Salmon, B. P., Van den Bergh, F., & Maharaj, B. T. J. (2015). Multiview deep learning for land-use classification. IEEE Geoscience and Remote Sensing Letters, 12(12), 2448-2452.

Ma, L., Fu, T., Blaschke, T., Li, M., Tiede, D., Zhou, Z., Chen, D. (2017). Evaluation of feature selection methods for object-based land cover mapping of unmanned aerial vehicle imagery using random forest and support vector machine classifiers. ISPRS International Journal of Geo-Information, 6(2), 51.

Ma, T., Zhou Y., Zhou C., Haynie S., Pei T., and Xu T., 2015, Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. Remote Sensing of Environment, 158, pp. 453-464.

Ma, T., Zhou, C., Pei, T., Haynie, S., & Fan, J. (2012). Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: A comparative case study from china's cities. Remote Sensing of Environment, 124, 99-107.

Ma, T., Zhou, Y., Zhou, C., Haynie, S., Pei, T., & Xu, T. (2015). Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. Remote Sensing of Environment, 158, 453-464. 10.1016/j.rse.2014.11.022.

Ma, T., Zhou, Y., Zhou, C., Haynie, S., Pei, T., & Xu, T. (2015). Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. Remote Sensing of Environment, 158, 453-464. doi:10.1016/j.rse.2014.11.022.

Ma, X., Wang H., and Wang J., 2016, Semi supervised classification for hyperspectral image based on multi-decision labelling and deep feature learning. ISPRS Journal of Photogrammetry and Remote Sensing, 120, pp. 99-107.

Mabogunje, A. (2001). Abuja; the promise, the performance and the prospects. The Review of Abuja Master Plan. Ibadan: Fountain Publications.

Makhamreha, Z., & Almanasyeha, N. (2011). Analyzing the state and pattern of urban growth and city planning in amman using satellite images and GIS. European Journal of Social Sciences, 24(2), 225-264.

Maktav, D., Erbek, F., & Jürgens, C. (2005). Remote sensing of urban areas. International Journal of Remote Sensing, 26(4), 655-659.

Maria, S. I., & Imran, M. (2006). Planning of Islamabad and Rawalpindi: what went wrong? Proceedings of 42nd ISoCaRP Congress, Istanbul, Turkey, 14-18 September 2006, 4.

Marston, C. G., Danson, F. M., Armitage, R. P., Giraudoux, P., Pleydell, D. R., Wang, Q., Craig, P. S. (2014). A random forest approach for predicting the presence of echinococcus multilocularis intermediate host ochotona spp. presence in relation to landscape characteristics in Western China. Applied Geography, 55, 176-183.

Masek, J. G., Lindsay, F. E., & Goward, S. N. (2000). Dynamics of urban growth in the Washington DC metropolitan area, 1973-1996, from Landsat observations. International Journal of Remote Sensing, 21(18), 3473-3486.

Mather, P., & Koch, M. (2011). Computer Processing of Remotely-Sensed Images: An Introduction. Wiley. West Sussex.

Mathieu, R., Aryal, J., & Chong, A. (2007). Object-based classification of ikonos imagery for mapping large-scale vegetation communities in urban areas. Sensors, 7(11), 2860-2880.

Mboga, N., Persello, C., Bergado, J. R., & Stein, A. (2017). Detection of informal settlements from VHR images using convolutional neural networks. Remote Sensing, 9(11), 1106.

Meinel, G. & Neubert, M., 2004. A comparison of segmentation programs for high resolution remote sensing data. International Archives of Photogrammetry and Remote Sensing, 35(Part B), pp. 1097-1105.

Merem, E.C. & Twumasi, Y.A., (2008). Using geospatial information technology in natural resources management: the case of urban land management in West Africa. Sensors, *8*(2), 607-619.

Mertes, C.M., Schneider, A., Sulla-Menashe, D., Tatem, A. and Tan, B., (2015). Detecting change in urban areas at continental scales with MODIS data. Remote Sensing of Environment, 158, pp. 331-347.

Milesi, C., Elvidge, C. D., Nemani, R. R., & Running, S. W. (2003). Assessing the impact of urban land development on net primary productivity in the South-eastern United States. Remote Sensing of Environment, 86(3), 401-410.

Min, B., Gaba, K. M., Sarr, O. F., & Agalassou, A. (2013). Detection of rural electrification in africa using DMSP-OLS night lights imagery. International Journal of Remote Sensing, 34(22), 8118-8141. 10.1080/01431161.2013.833358.

Moller-Jensen, L., & Yankson, P. (1994). Assessing the land cover change of accra using landsat-TM data. Geografisk Tidsskrift, 94, 21-25.

Momeni, R., Aplin, P., & Boyd, D. S. (2016). Mapping complex urban land cover from spaceborne imagery: The influence of spatial resolution, spectral band set and classification approach. Remote Sensing, 8(2), 88.

Moore, J. (1984). The political history of Nigeria's new capital. The Journal of Modern African Studies, 22(1), 167-175.

Morah, E.U., 1992. Housing Development in Nigeria's New Capital at Abuja. African Development Review, 4(1), 64-86.

Morton, T. A., & Yuan, F. (2009). Analysis of population dynamics using satellite remote sensing and US census data. Geocarto International, 24(2), 143-163.

Mundia, C. N., & Aniya, M. (2005). Analysis of land use/cover changes and urban expansion of Nairobi city using remote sensing and GIS. International Journal of Remote Sensing, 26(13), 2831-2849.

Muoh, O. F. (2016). When 95 million Nigerians are living without electricity something needs to change. Retrieved from Business Insider UK on 15 March 2017, https://www.businessinsider.com/95-million-nigerians-are-living-without-electricity-and-something-needs-to-change-2016-7.

Myers, G. A. (2011). African cities: Alternative visions of urban theory and practice. London: Zed Books Limited.

Myers, G. A., 2011: African cities: alternative visions of urban theory and practice. Zed Books Limited,

Myint, S. W., Gober, P., Brazel, A., Grossman-Clarke, S., & Weng, Q. (2011). Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sensing of Environment, 115(5), 1145-1161.

Na, X., Zhang, S., Li, X., Yu, H., & Liu, C. (2010). Improved land cover mapping using random forests combined with Landsat thematic mapper imagery and ancillary geographic data. Photogrammetric Engineering & Remote Sensing, 76(7), 833-840.

Nghiem, S. V., Balk, D., Rodriguez, E., Neumann, G., Sorichetta, A., Small, C., & Elvidge, C. D. (2009). Observations of urban and suburban environments with global satellite scatterometer data. ISPRS Journal of Photogrammetry and Remote Sensing, 64(4), 367-380. 10.1016/j.isprsjprs.2009.01.004.

Nobrega, R., O'hara C., and Quintanilha J., (2008). An object-based approach to detect road features for informal settlements near Sao Paulo, Brazil. In Object-based image analysis, Anonymous pp. 589-607 Springer, 2008).

Nogueira, K., Penatti O.A., and dos Santos J.A., (2017). Towards better exploiting convolutional neural networks for remote sensing scene classification. Pattern Recognition, 61, pp. 539-556.

NPC (2006). Nigeria population census. Abuja, Nigeria: National Bureau of Statistics.

Nunes, C., & Auge, J. (1999). Land-use and land-cover change (LUCC): Implementation strategy.

O'Regan H.J., Wilkinson D.M., & Marston C. G. (2016). Hominin home ranges and habitat variability: exploring modern African analogues using remote sensing, Journal of Archaeological Science: Reports, 9, 238-248.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E. and Wulder, M.A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment, 148, 42-57.

Oluseyi, O. F. (2006). Urban land use change analysis of a traditional city from remote sensing data: The case of Ibadan metropolitan area, Nigeria. Humanity & Social Sciences Journal, 1(1), 42-64.

ONS (2013). Characteristics of Built-Up Areas. In. UK Office for National Statistics.

Onyedika-Ugoeze, N. (2016). How past leaders distorted Abuja master plan. The Guardian. Retrieved 8 November 2017 from https://guardian.ng/news/how-past-leaders-distorted-abuja-master-plan/.

Otukei, J. R., & Blaschke, T. (2010). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. International Journal of Applied Earth Observation and Geoinformation, 12, S27-S31.

Owen, K.K., and Wong D.W., (2013). An approach to differentiate informal settlements using spectral, texture, geomorphology and road accessibility metrics. Applied Geography, 38, 107-118.

Padeiro, M. (2016). Conformance in land-use planning: The determinants of decision, conversion and transgression. Land use Policy, 55, 285-299.

Paisitkriangkrai, S., Sherrah J., Janney P., and van den Hengel A., (2016). Semantic labeling of aerial and satellite imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9, 2868-2881.

Pares-Ramos, I. K., alvarez-Berríos, N. L., & Aide, T. M. (2013). Mapping urbanization dynamics in major cities of colombia, ecuador, peru, and bolivia using night-time satellite imagery. Land, 2(1), 37-59. 10.3390/land2010037.

Patino, J. E., & Duque, J. C. (2013). A review of regional science applications of satellite remote sensing in urban settings. Computers, Environment and Urban Systems, 37, 1-17.

Perumal, K., & Bhaskaran, R. (2010). Supervised classification performance of multispectral images. Journal of Computing, 2(2), 126-129

Pesaresi, M., Ehrlich D., Gamba P., and Herold M., 2009: A methodology to quantify built-up structures from optical VHR imagery. Boca Raton, FL, USA: CRC Press,

Pham, H. M., Yamaguchi, Y., & Bui, T. Q. (2011). A case study on the relation between city planning and urban growth using remote sensing and spatial metrics. Landscape and Urban Planning, 100(3), 223-230.

Pham, H.M., Y. Yamaguchi, and T.Q. Bui, 2011, A case study on the relation between city planning and urban growth using remote sensing and spatial metrics. Landscape and Urban Planning, 100, pp. 223-230.

Phyu, T.N. (2009). Survey of classification techniques in data mining. In, Proceedings of the International MultiConference of Engineers and Computer Scientists (pp. 18-20).

PM News (2016). Abuja at 40: Residents of satellite towns complain of poor infrastructure. Retrieved 8 November 2017 from https://www.pmnewsnigeria.com/2016/02/04/abuja-at-40-residents-of-satellite-towns-complain-of-poor-infrastructure/

Preecharushh, D. (2011). Myanmar's new capital city of Naypyidaw. In S. Brunn (Ed.), Engineering Earth: The Impacts of Mega engineering Projects (pp. 1021-1044). Springer Netherlands.

Puissant, A., Hirsch, J., & Weber, C. (2005). The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery. International Journal of Remote Sensing, 26(4), 733-745.

Puissant, A., Rougier, S., & Stumpf, A. (2014). Object-oriented mapping of urban trees using random forest classifiers. International Journal of Applied Earth Observation and Geoinformation, 26, 235-245.

Qian, Z. (2013). Master plan, plan adjustment and urban development reality under china's market transition: A case study of Nanjing. Cities, 30, 77-88.

Rizzo, A. (2014). Rapid urban development and national master planning in Arab gulf countries. Qatar as a case study. Cities, 39, 50-57.

Rumelhart, D.E., G.E. Hinton, and R.J. Williams, 1986, Learning representations by back-propagating errors. Nature, 323, 533.

Saglie, I., & Sandberg, S. V. L. (1997). Urban expansion in Norway-development by plan? Scandinavian Housing and Planning Research, 14(2), 51-70.

Sahoo, S. N., & Pekkat, S. (2014). Determination of urbanisation based on imperviousness. Proceedings of the Institution of Civil Engineers-Urban Design and Planning, 167(2), 49-57.

Sala, O.E., Chapin, F.S., Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L.F., Jackson, R.B., & Kinzig, A. (2000). Global biodiversity scenarios for the year 2100. science, 287, 1770-1774.

Sanli, F. B., Balcik, F.B., Goksel, C., (2008). Defining temporal spatial patterns of mega city istanbul to see the impacts of increasing population. Environmental Monitoring and Assessment, 146(1-3), 267.

Santana, L. M. (2007). Landsat ETM+ image applications to extract information for environmental planning in a colombian city. International Journal of Remote Sensing, 28(19), 4225-4242.

Sarvestani, M. S., Ibrahim, A. L., & Kanaroglou, P. (2011). Three decades of urban growth in the city of shiraz, iran: A remote sensing and geographic information systems application. Cities, 28(4), 320-329.

Satterthwaite, D., & Mitlin, D. (2013). Urban poverty in the global south: Scale and nature Routledge. London.

Sawaya, K. E., Olmanson, L. G., Heinert, N. J., Brezonik, P. L., & Bauer, M. E. (2003). Extending satellite remote sensing to local scales: Land and water resource monitoring using high-resolution imagery. Remote Sensing of Environment, 88(1), 144-156.

Scott, A. J. (2009). World development report 2009: Reshaping economic geography. Journal of Economic Geography, 9(4), 583-586. 10.1093/jeg/lbp019.

Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. PloS One, 6(8), e23777. 10.1371/journal.pone.0023777.

Seto, K.C., Fragkias M., Güneralp B., and Reilly M.K., (2011). A meta-analysis of global urban land expansion. PloS one, 6, pp. e23777.

Shao, Z., & Liu, C. (2014). The integrated use of DMSP-OLS nighttime light and MODIS data for monitoring large-scale impervious surface dynamics: A case study in the yangtze river delta. Remote Sensing, 6(10), 9359-9378. 10.3390/rs6109359.

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10(6), 989-1003.

Sliuzas, R., (2003). Opportunities for enhancing communication in settlement upgrading with geographic information technology-based support tools. Habitat International, 27, 613-628.

Small, C. (2003). High spatial resolution spectral mixture analysis of urban reflectance. Remote Sensing of Environment, 88(1), 170-186.

Small, C., & Elvidge, C. D. (2013). Night on earth: Mapping decadal changes of anthropogenic night light in asia. International Journal of Applied Earth Observation and Geoinformation, 22, 40-52. http://dx.doi.org.edgehill.idm.oclc.org/10.1016/j.jag.2012.02.009

Small, C., Elvidge, C. D., Balk, D., & Montgomery, M. (2011). Spatial scaling of stable night lights. Remote Sensing of Environment, 115(2), 269-280.

Small, C., Pozzi, F., & Elvidge, C. D. (2005a). Spatial analysis of global urban extent from DMSP-OLS night lights. Remote Sensing of Environment, 96(3), 277-291.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., & Macomber, S.A. (2001). Classification and change detection using Landsat TM data: when and how to correct atmospheric effects? Remote Sensing of Environment, 75, 230-244.

Space for Change (2013). Abuja land swap initiative: The challenges within. Retrieved 8 November 2017 from http://www.spacesforchange.org/2014/05/abuja-land-swap-initiativethe-challenges-within/.

Srivastava, P. K., Han, D., Rico-Ramirez, M. A., Bray, M., & Islam, T. (2012). Selection of classification techniques for land use/land cover change investigation. Advances in Space Research, 50(9), 1250-1265.

Stark, T., 2018, Using Deep Convolutional Neural Networks for the Identification of Informal Settlements to Improve a Sustainable Development in Urban Environments. (Doctoral dissertation, Technische Universität München).

Stasolla, M., and Gamba, P, 2007, Exploiting spatial patterns for informal settlement detection in arid environments using optical spaceborne Data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36, W49A.

Stehman, S.V. (1997). Selecting and interpreting measures of thematic classification accuracy. Remote Sensing of Environment, 62, 77-89.

Strobl, C., Boulesteix A., Kneib T., Augustin T., and Zeileis A., 2008, Conditional variable importance for random forests. BMC bioinformatics, 9, 307.

Sugg, Z. P., Finke, T., Goodrich, D. C., Moran, M. S., & Yool, S. R. (2014). Mapping impervious surfaces using object-oriented classification in a semiarid urban region. Photogrammetric Engineering & Remote Sensing, 80(4), 343-352.

Sun, X., Lin, X., Shen, S., & Hu, Z. (2017). High-resolution remote sensing data classification over urban areas using random forest ensemble and fully connected conditional random field. ISPRS International Journal of Geo-Information, 6(8), 245.

Sutton, P., Roberts, D., Elvidge, C., & Baugh, K. (2001). Census from heaven: An estimate of the global human population using night-time satellite imagery. International Journal of Remote Sensing, 22(16), 3061-3076. 10.1080/01431160010007015.

Sutton, P.C., Anderson S.J., Elvidge C.D., Tuttle B.T., and Ghosh T., (2009) Paving the planet: impervious surface as proxy measure of the human ecological footprint. Progress in Physical Geography, 33, 510-527.

Tan, Q., Liu, Z., & Li, X. (2009). (2009). Mapping urban surface imperviousness using SPOT multispectral satellite images. Paper presented at the Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009, 3 III-346-III-348.

Tatem, A. J., Noor, A. M., & Hay, S. I. (2005). Assessing the accuracy of satellite derived global and national urban maps in Kenya. Remote Sensing of Environment, 96(1), 87-97. 10.1016/j.rse.2005.02.001.

Taubenböck, H., and Kraff N., (2014). The physical face of slums: a structural comparison of slums in Mumbai, India, based on remotely sensed data. Journal of Housing and the Built Environment, 29, 15-38.

Taubenböck, H., Esch, T., Felbier, A., Wiesner, M., Roth, A., & Dech, S. (2012). Monitoring urbanization in mega cities from space. Remote Sensing of Environment, 117, 162-176.

Taubenböck, H., Post, J., Roth, A., Zosseder, K., Strunz, G., & Dech, S. (2008). A conceptual vulnerability and risk framework as outline to identify capabilities of remote sensing. Natural Hazards and Earth System Science, 8(3), 409-420.

Tewkesbury, A. P., Comber, A. J., Tate, N. J., Lamb, A., & Fisher, P. F. (2015). A critical synthesis of remotely sensed optical image change detection techniques. Remote Sensing of Environment, 160, 1-14.

Tewolde, M. G., & Cabral, P. (2011). Urban sprawl analysis and modelling in Asmara, Eritrea. Remote Sensing, 3(10), 2148-2165.

Thanh Noi, P., & Kappas, M. (2018). Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using sentinel-2 imagery. Sensors, 18(1), 18.

Thomas, N., Hendrix, C., & Congalton, R. G. (2003). A comparison of urban mapping methods using high-resolution digital imagery. Photogrammetric Engineering & Remote Sensing, 69(9), 963-972.

Thomson, C. N., & Hardin, P. (2000). Remote sensing/GIS integration to identify potential low-income housing sites. Cities, 17(2), 97-109.

Tian, L., & Shen, T. (2011). Evaluation of plan implementation in the transitional China: A case of Guangzhou city master plan. Cities, 28(1), 11-27.

Tiffen, M. (2003). Transition in Sub-saharan Africa: Agriculture, urbanization and income growth. World Development, 31(8), 1343-1366.

Townsend, A., and Bruce D., 2010, The use of night-time lights satellite imagery as a measure of Australia's regional electricity consumption and population distribution. International Journal of Remote Sensing, 31, 4459-4480.

Tsai, Y. H., Stow, D., & Weeks, J. (2011). Comparison of object-based image analysis approaches to mapping new buildings in Accra, Ghana using multi-temporal QuickBird satellite imagery. Remote Sensing, 3(12), 2707-2726.

Ujoh, F., & Nigeria Federal Character Commission. (2010). Understanding urban sprawl in the federal capital city, Abuja: Towards sustainable urbanization in Nigeria. Journal of Geography and Regional Planning, 2(5), 106.

Ujoh, F., M., Kwabe, I. D., & Ifatimehin, O. O. (2011). Urban expansion and vegetal cover loss in and around Nigeria's federal capital city. Journal of Ecology and Natural Environment, 3(1), 1-10.

UN-Habitat, 2016, Urbanization and development: Emerging futures. World Cities Report < https://unhabitat.org/wp-content/uploads/2014/03/WCR-%20Full-Report-2016.pdf> last accessed 22nd October 2018.

UN-Habitat. (2010). The state of African cities 2010: Governance, inequality and urban land markets. Nairobi, Kenya: UN-Habitat - United Nations Human Settlement Programme.

United Nations (2015). World Urbanization Prospects: The 2014 Revision, (ST/ESA/SER.A/366). 2014. United Nations Department of Economic and Social Affairs/Population Division.

United Nations. (2011). World urbanization prospects: The 2011 revision. United Nations Department of Economic and Social Affairs (DESA)/Population Division.

Vale, L. (2014). Architecture, power and national identity. Oxford: Routledge.

Veljanovski, T., Kanjir U., Pehani P., Oštir K., and Kovačič P., 2012, Object-based image analysis of VHR satellite imagery for population estimation in informal settlement kibera-nairobi, kenya. In Remote Sensing-Applications, Anonymous InTech, 2012).

Vincent, R.K. (1997). Fundamentals of geological and environmental remote sensing. New Jersey, Prentice Hall.

Vogelmann, J. E., Sohl, T. L., Campbell, P. V., & Shaw, D. M. (1998). Regional land cover characterization using landsat thematic mapper data and ancillary data sources. Environmental Monitoring and Assessment, 51(1), 415-428. 10.1023/A:1005996900217

Wakode, H. B., Baier, K., Jha, R., & Azzam, R. (2014). Analysis of urban growth using Landsat TM/ETM data and GIS—a case study of Hyderabad, India. Arabian Journal of Geosciences, 7(1), 109-121.

Wang, J., Luo C., Huang H., Zhao H., and Wang S., 2017, Transferring Pre-Trained Deep CNNs for Remote Scene Classification with General Features Learned from Linear PCA Network. Remote Sensing, 9, 225.

Wang, W., Cheng H., and Zhang L., 2012, Poverty assessment using DMSP/OLS night-time light satellite imagery at a provincial scale in China. Advances in Space Research, 49, pp. 1253-1264.

Wania, A., Kemper, T., Tiede, D., & Zeil, P. (2014). Mapping recent built-up area changes in the city of Harare with high resolution satellite imagery. Applied Geography, 46, 35-44.

Watson, V. (2009). 'The planned city sweeps the poor away…': Urban planning and 21st century urbanisation. Progress in Planning, 72(3), 151-193.

Weber, C., Petropoulou, C., & Hirsch, J. (2005). Urban development in the Athens metropolitan area using remote sensing data with supervised analysis and GIS. International Journal of Remote Sensing, 26(4), 785-796.

Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment, 117, 34-49.

Weng, Q., & Hu, X. (2008). Medium spatial resolution satellite imagery for estimating and mapping urban impervious surfaces using LSMA and ANN. IEEE Transactions on Geoscience and Remote Sensing, 46(8), 2397-2406.

Weng, Q., (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment, 117, 34-49.

Wentz, E., Anderson, S., Fragkias, M., Netzband, M., Mesev, V., Myint, S., Seto, K. (2014). Supporting global environmental change research: A review of trends and knowledge gaps in urban remote sensing. Remote Sensing, 6(5), 3879-3905. doi:10.3390/rs6053879.

Wieland, M., & Pittore, M. (2014). Performance evaluation of machine learning algorithms for urban pattern recognition from multi-spectral satellite images. Remote Sensing, 6(4), 2912-2939.

Wilkinson, G.G. (2005). Results and implications of a study of fifteen years of satellite image classification experiments. Geoscience and Remote Sensing, IEEE Transactions on, 43, 433-440.

Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, M. P., & Arnold, C. (2003). Development of a geospatial model to quantify, describe and map urban growth. Remote Sensing of Environment, 86(3), 275-285.

Woodcock, C. E., and Strahler, A. H., 1987, The factor of scale in remote sensing. Remote Sensing of Environment, 21(3), 311-332.

Wu, C., & Murray, A. T. (2005). A cokriging method for estimating population density in urban areas. Computers, Environment and Urban Systems, 29(5), 558-579.

Wu, S., Qiu, X., & Wang, L. (2005). Population estimation methods in GIS and remote sensing: A review. GIScience & Remote Sensing, 42(1), 80-96.

Wurm, M., Taubenbock H., Roth A., and Dech S., (2009). Urban structuring using multisensoral remote sensing data: By the example of the German cities Cologne and Dresden. In 2009 Joint Urban Remote Sensing Event, IEEE, 1-8.

Xian, G., & Crane, M. (2005). Assessments of urban growth in the Tampa bay watershed using remote sensing data. Remote Sensing of Environment, 97(2), 203-215. doi:DOI: 10.1016/j.rse.2005.04.017.

Xiao, J., Shen Y., Ge J., Tateishi R., Tang C, Liang Y., and Huang Z. (2006). Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. Landscape and Urban Planning, 75, 69-80.

Xu, H., Yang, H., Li, X., Jin, H., & Li, D. (2015). Multi-scale measurement of regional inequality in mainland china during 2005–2010 using DMSP/OLS night light imagery and population density grid data. Sustainability, 7(10), 13469-13499.

Xu, T., Ma, T., Zhou, C., & Zhou, Y. (2014). Characterizing spatio-temporal dynamics of urbanization in china using time series of DMSP/OLS night light data. Remote Sensing, 6(8), 7708-7731. 10.3390/rs6087708

Xu, Y., Wu L., Xie Z., and Chen Z., (2018). Building Extraction in Very High Resolution Remote Sensing Imagery Using Deep Learning and Guided Filters. Remote Sensing, 10, 144.

Yang, L., Huang C., Homer C.G., Wylie B.K., and Coan M.J., (2003). An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM and high spatial resolution imagery. Canadian Journal of Remote Sensing, 29, 230-240.

Yang, L., Xian, G., Klaver, J.M., & Deal, B. (2003). Urban land-cover change detection through sub-pixel imperviousness mapping using remotely sensed data. Photogrammetric Engineering & Remote Sensing, 69, 1003-1010.

Yi, K., Zeng, Y., & Wu, B. (2016). Mapping and evaluation the process, pattern and potential of urban growth in china. Applied Geography, 71, 44-55. 10.1016/j.apgeog.2016.04.011

Yuan, F., Sawaya, K. E., Loeffelholz, B. C., & Bauer, M. E. (2005). Land cover classification and change analysis of the twin cities (Minnesota) metropolitan area by multitemporal landsat remote sensing. Remote Sensing of Environment, 98(2), 317-328.

Zeng, C., Shen, H., & Zhang, L. (2013). Recovering missing pixels for Landsat ETM SLC-off imagery using multi-temporal regression analysis and a regularization method. Remote Sensing of Environment, 131, 182-194.

Zhang, F., Du, B., & Zhang, L. (2016b). Scene classification via a gradient boosting random convolutional network framework. IEEE Transactions on Geoscience and Remote Sensing, 54(3), 1793-1802.

Zhang, J., & Foody, G. (2001). Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical and artificial neural network approaches. International Journal of Remote Sensing, 22, 615-628.

Zhang, L., Zhang, L., & Du, B. (2016). Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, 4(2), 22-40.

Zhang, Q., & Seto, K. (2013). Can night-time light data identify typologies of urbanization? A global assessment of successes and failures. Remote Sensing, 5(7), 3476-3494. 10.3390/rs5073476.

Zhang, Q., and Seto K., 2013, Can Night-Time Light Data Identify Typologies of Urbanization? A Global Assessment of Successes and Failures. REMOTE SENSING, 5, pp. 3476-3494.

Zhang, Q., Li, B., Thau, D., & Moore, R. (2015). Building a better urban picture: Combining day and night remote sensing imagery. Remote Sensing, 7(9), 11887-11913. 10.3390/rs70911887.

Zhang, X., Li, P., & Cai, C. (2015). Regional urban extent extraction using multi-sensor data and one-class classification. Remote Sensing, 7(6), 7671-7694. 10.3390/rs70607671.

Zhao, W., and Du, 2016 S., Learning multiscale and deep representations for classifying remotely sensed imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 113, 155-165.

Zhou, W., Newsam S., Li C., and Shao Z., (2017). Learning Low Dimensional Convolutional Neural Networks for High-Resolution Remote Sensing Image Retrieval. Remote Sensing, 9, 489.

Zhou, Y., Smith S.J., Elvidge C.D., Zhao K, Thomson A., and Imhoff M., (2014). A cluster-based method to map urban area from DMSP/OLS nightlights. Remote Sensing of Environment, 147, pp. 173.

Zhou, Y., Wang, H., Xu, F., & Jin, Y. (2016). Polarimetric SAR image classification using deep convolutional neural networks. IEEE Geoscience and Remote Sensing Letters, 13(12), 1935-1939.

Zhu, X. X., Tuia, D., Mou, L., Xia, G., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5(4), 8-36.

Zhuo, L., Ichinose, T., Zheng, J., Chen, J., Shi, P. J., & Li, X. (2009). Modelling the population density of china at the pixel level based on DMSP/OLS non-radiance-calibrated night-time light images. International Journal of Remote Sensing, 30(4), 1003-1018. 10.1080/01431160802430693.

Zubair, O. A., Ojigi, L. M., & Mbih, R. A. (2015). Urbanization: A catalyst for the emergence of squatter settlements and squalor in the vicinities of the federal capital city of Nigeria. Journal of Sustainable Development, 8(2), 134.