Studies on urban growth in Conakry, Guinea, using geo-spatial data

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Abstract

Conakry, capital of Guinea, is believed to have experienced a rapid urban growth over the last recent years. However, studies on the detailed information related to the nature of the growth and its drivers are lacking. Land-use and land-cover (LULC) change studies, especially related to urban growth are essential for the planning and management for sustainable urban development. This study examines the dynamics of LULC changes in Conakry in 1986, 2000 and 2016. LULC changes were observed through Landsat sensors, Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI). Supervised classification method was applied to generate the LULC maps for these three years. Furthermore, the Logistic Regression Model (LRM) was used to examine the relationship between urban growth with two categories of driving forces (i.e., socioeconomic and physical). Subsequently, the hybrid Cellular Automata and Markov (CA-Markov) model in IDRISI Software was used to predict the future LULC change in Conakry based on the current growth probabilities. Finally, data of the Defense Meteorological Satellite Program's Operational Line-scan System (DMSP/OLS) were used to discuss in more detailed the nighttime lights in each of the five communes of Conakry from 1992 to 2013 as proxy of urban growth.

The most intense LULC change in Conakry was the conversion of vegetation cover to urban land-use. The area of urban class (i.e., residential, commercial, industrial, transportation, utilities and communication) has experienced continuous growth over the study period from 15% (60.73 km^2) in 1986 to 49% (206.58 km^2) in 2016. The area of vegetation class (i.e., mangrove forests, reserved forest and non-reserved forest), which appeared to be the most dominant land-cover type, had sharply decreased from 52% (217.48 km^2) in 1986 to 35% (147.32 km^2) in 2016. Bare ground (i.e., fallow land, bare exposed, parks, shrubs, area and transition) decreased from 27% (114.76 km^2) in 1986 to 9% (39.88 km^2) in 2016. To validate the LULC classification, the overall accuracy assessment was conducted with corresponding reference images. The resulting overall accuracy coefficients were 0.81, 0.79 and 0.88 for 1986, 2000 and 2016 respectively.

LRM has revealed that the variables of elevation, population density, distance to major roads,

distance to existing urbanized areas and slope have resulted in the model with the best fit and high statistical significance, suggesting that these variables influence urban growth in Conakry. The LRM model was validated by the Relative Operating Characteristic (ROC), method which showed a high agreement (0.89) between the simulated urban growth probability map and the actual one.

The integrated CA-Markov chain revealed that based on the current growth probabilities, urban area will continue to increase at the expense of vegetation and bare ground cover. The proportion of the urban area was 49% in 2016, and it is expected to increase to 52% by 2025, while vegetation will decrease from 35% in 2016 to 32% in 2025. The Vegetation Adjusted Nighttime Urban Index (VANUI) indicator of urban growth showed increasing pattern in each commune of Conakry. However, there was a difference in the spatial and temporal VANUI distribution at the commune level. The urban core communes (Dixinn and Matam) showed rapid increase and large VANUI values (0.81-0.83). The active economic and administrative center, the Kaloum commune showed values (0.31-0.42), while the sub-urban communes (Ratoma and Matoto) exhibited values (0.09-0.27). This difference in VANUI is explained by the difference of the historical development of the city, which is strongly related to the topography (horizontal distance to the port), the altitude.

This study discussed that the rapid urban growth has been led by both rapid population growth and extreme poverty in rural areas, which have resulted in migration into Conakry. This study provides useful information on further urban development in Conakry. Given that urban growth has occurred mainly due to population growth and migration from rural areas, population growth in Conakry is expected to continue at an accelerated rate. Therefore, better management plans are needed not only for Conakry but also for the entire country. The results of this study will provide bases for assessing the sustainability and the management of the urban area and for taking actions to mitigate the degradation of the urban environment.

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1. Introduction

1.1 Research background

The most extreme anthropogenic land-use and land-cover (LULC) transformation caused by urbanization has been universal and important socioeconomic and environmental issues around the world (Li.; 2014, Verburg et al.; 2004). The percentage of the world's population living in urban areas was 30 % in 1950, 54 % in 2014, and is projected to be 66 % by 2050 of which 90% will be living in urban areas of Asia and Africa (United Nations.; 2014). This unprecedented growth will pose many challenges to planners and policy makers (Yuan et al., 2005, Pacione., 2007). Urbanization can be defined by various indices depending on the field of study. In geography for instance, land-use and land-cover (LULC) change, population, and economic data are often used as indices for explaining urbanization (Murayama et al., 2017, Thapa et al., 2010).

Though urbanization promotes socioeconomic development and improves the quality of life in both urban and rural areas (United Nations.; 2014), nevertheless, in developing countries, rapid urbanization and uncontrolled urban growth have exceeded the capabilities of most cities for appropriate management (Linard et al., 2013, Zhang et al., 2016). Urban growth is regarded as the most powerful and visible anthropogenic force that has caused the fundamental conversion from natural to artificial land-use in the cities around the world (Wu., 2002, Hung et al., 2010). Despite urban areas cover a very small percentage of the world's land surface in comparison with other land-cover types, their rapid expansion has marked effects on environment and socioeconomics, via impacts in natural vegetation and biodiversity (Tan et al.; 2016, Cui et al.; 2016), local and regional climate change (Onishi et al.; 2010, Stewart et al.; 2012, Patz et al.; 2005), change in hydrological cycle (Pradhan.; 2009, Singh et al.; 2013), huge demand for available resources, and driving up rents and cost of land (Ifechukwude.; 2015) etc. Without effective planning, there is no doubt that the goals for sustainable development will be achieved (Dewan et al.; 2009, Lambin et al.; 2003).

Conakry, capital of Guinea, is an urban area that was characterized by rapid growth in the second half of the 20th century, which had implications for the city's infrastructure and the sustainable development. From the outset, Conakry's development was the product of several superimposed historical strata: firstly, the planning and creation of facilities for the benefit of Europeans during the colonization phase (1880-1958), secondly, the minimal state intervention associated with limitations on private initiatives during the first regime (1958-1984); and thirdly, the central role of private investment (local and foreign) accompanied by the beginning of a development policy for the metropolitan city (1984-2008) (Odile., 2011, World Bank., 1984). After the country's independence in 1958, the population of Conakry boomed from 50.000 inhabitants in 1958 to 600.000 in 1980, to nearly 2 million today (National Bureau of Planning., 2013). This growth is essentially the result of high natural increase, and the migration from rural area (National Urban Planning.; 2016). The distribution of cities throughout the country's territory is balanced in terms of size, but the distribution of the population among cities is unbalanced, with Conakry showing a notably greater population than any other cities. In particular, more than half of the Guinea's urban population resides in Conakry, which has 15 times the population of Kankan, the second-largest city (Aly et al.; 2012). Conakry's rapid urbanization can be explained by the accumulation of economic, administrative and cultural functions. As the country's capital and only sizeable international harbor (an outlet for bauxite exports), the city remains the location of rare industries, and has the country's main educational institutions, despite long-standing efforts at decentralization (Odile.; 2011).

Today, urban conditions in Conakry largely reflect the problems and shortcomings of Guinea's overall economic development processing. Conakry's growth since independence has taken place with only little urban development planning (Odile., 2011, Aly et al., 2012, World Bank., 1984). Authorities in charge of urban planning and management have met increasing difficulties to plan for spatial expansion and to identify, coordinate and carry out the most critically needed investments in basic infrastructure and service (World Bank.; 1984), hence, Conakry has become overcrowded, exerting considerable pressure on basic urban services and resulting in drastic degradation of the environment. Additionally, Conakry has faced unprecedented urbanization issues caused by unplanned urbanization pressure such as landscape fragmentation, informal settlement on the coastal banks, poverty and unemployment, rural-urban migration, deterioration of the road surfaces, air and water pollution, deficient solid waste collection and disposal, recurrent flooding during the rainy seasons in many parts of the city (Traore et al.; 2017), and the degradation of the mangrove forests (Balde et al.; 2014)

However, while rapid urbanization is expected to exacerbate these problems, experiences from the developed countries showed that urbanization has the potential to boost national economy and improve the quality of life and social well-being (Collier.; 2017, Murayama et al.; 2017). This requires accurate, consistent, and timely geospatial information on urban growth patterns in order to assess current and future urban growth process (Yasmine et al.; 2015). Geospatial information will be important for setting policies that promote inclusive and equitable urban, environmental, and socioeconomic development (Murayama et al.; 2017). Studying the spatial and temporal urban growth in Conakry is urgently needed for promoting sustainable urban planning and to improve the overall environmental and socioeconomic development. The Geographic Information System (GIS) and Remote Sensing (RS) are powerful tools to analyze the spatial and temporal urban growth patterns (Bhatta et al., 2010, Weng et al., 2001), to model and predict future urban growth pattern (Yusuf et al., 2014, Triantakonstantis., 2012).

1.2 Objectives of the study

1. To examine the spatial and temporal land-use and land-cover (LULC) change, especially an urban growth in Conakry in 1986, 2000 and 2016 using GIS and RS technique

2. To investigate the relationship between urban growth with two categories of drivers: (socioeconomic and physical) using Logistic Regression Model (LRM)

3. To predict future land-use and land-cover (LULC) change in Conakry by 2025 using the integrated Cellular Automata (CA) and Markov model.

4. To discuss in detailed the urban growth pattern in each of the five communes of Conakry by analyzing nighttime light data of the Defense Meteorological Satellite Program's Operational Lines-Scan System (DMSP/OLS) in 1992, 2000, 2005 and 2013.

1.3 Study area

1.3.1 Baseline information

The republic of Guinea is a West Africa country and shares border with Senegal, Mali and Guinea-Bissau in the North, Serra Leone, Liberia and Ivory Coast in the South. It covers a total area of 245.857 km^2. The decentralization process started in 1986, in a country that inherited a highly centralized administration from the colonial period (Odile.; 2011). After the publication of the fundamental law of 1991, later modified by the 2001 constitution, the Guinea territorial divisions are the regions, prefectures, sub-prefectures, neighborhoods, and districts. Local governments consist of urban municipalities and rural development communities. Guinea accounts 341 municipalities divided into 38 urban municipalities, of which five are located within the capital city of Conakry (National Bureau of Planning.; 2016).

The study area consists Conakry, the capital and the largest city, which is in the coastal region of Guinea. This city covers area extending from 9° 34′30″N to 9° 45′00″N latitude and 13° 34′30″W to 13° 45′0″W longitude. The geographical area is approximately 420 km^2. The current spatial structure of Conakry is largely based on French colonial era development model. The city is administratively divided into five communes: three downtown communes (1) Kaloum in the southeast, which includes the major islands, the active economic and administrative center, (2) Dixinn, which includes the main university and many embassies, and (3) Matam, and two suburban communes, (4) Ratoma, and (5) Matoto, the location of Conakry's international airport (Figure 1.1). This city was originally settled on the small Tombo Island and later spread to the neighboring Kaloum Penisula.

In Guinea, urban population has been increasing very rapidly in the last recent decades (Figure 1.2). However, this growth was not in parallel with the infrastructure and basic services needed. Table 1.1 shows the percentage of the urban population with access to urban service (National Urban Planning.; 2016). Per the United Nations Department of Social Affairs (UNDESA., 2014), 35% of the Guinea's population resided in urban area in 2014, but the near future prediction has indicated that urban population will soon overtake rural one (Figure 1.3). Thus, sustainable urban planning and management is urgently needed for the economic and environmental development.

Guinea has an abundance of untapped natural resources, including a variety of large mineral deposits, specially bauxite and iron ore, and enormous agricultural land, rich fisheries and hydro-electrical potential. Yet, poverty in the country is deep and widespread and per capita income slightly increased from $ 330 in 2007 to $ 450 in 2012 (World Bank.; 2016). Over half of the population currently lives below the poverty line 55.2% in 2015 (World Bank.; 2016). Recent estimations of the population of Conakry was approximately at 1.7 million in 2014 (National Institute of Statistics of Guinea.; 2014), while population estimates vary according to sources.

The relief is characterized by estuaries and the littoral plain with an altitude varying from 0 to 160 m above sea level (Figure 1.1). The soil types include saline, hydromorphic, and ferrous. The Vegetation consists of palm trees, mangrove in the marshy zones, coconuts trees, gasoline forest, small islands of primary forest formation, forest gallery along the river, mango trees and plantations in some places (Figures 1.4,1.5). Conakry was originally covered by a dense vegetation and thick mangrove forests, but compared with the rest of the Guinean territories, the landscape pattern has changed considerably in recent years with substantial reduction in vegetation cover due primarily to the expansion of residential area, the cutting of trees to produce charcoal, the use of forests as pastures by livestock owners during the dry season, and general deforestation (Sylla et al.; 2012).

The climate is the sub-tropical maritime type, hot and humid characterized by two alternating seasons (dry and wet). The wet season lasts from June to October and the dry season from December to April (Sylla et al.; 2012). The rainfall season is largely controlled by the movement of the tropical rain belt also known as the Inter-Tropical Conversion Zone (ITCZ). This season sees an extraordinary amount of precipitation, averaging between 1500 mm and 4000 mm both in July and August (Balde et al.; 2014). The dry season is influenced by the harmattan wind between December and April. The highest temperature is recorded between March and April, while the temperature reached 38˚C and the lowest temperature between November and December with the temperature around 25˚C (Sylla et al.; 2012). Figures 1.6, 1.7 illustrate some typical unplanned urbanization issues in Conakry.

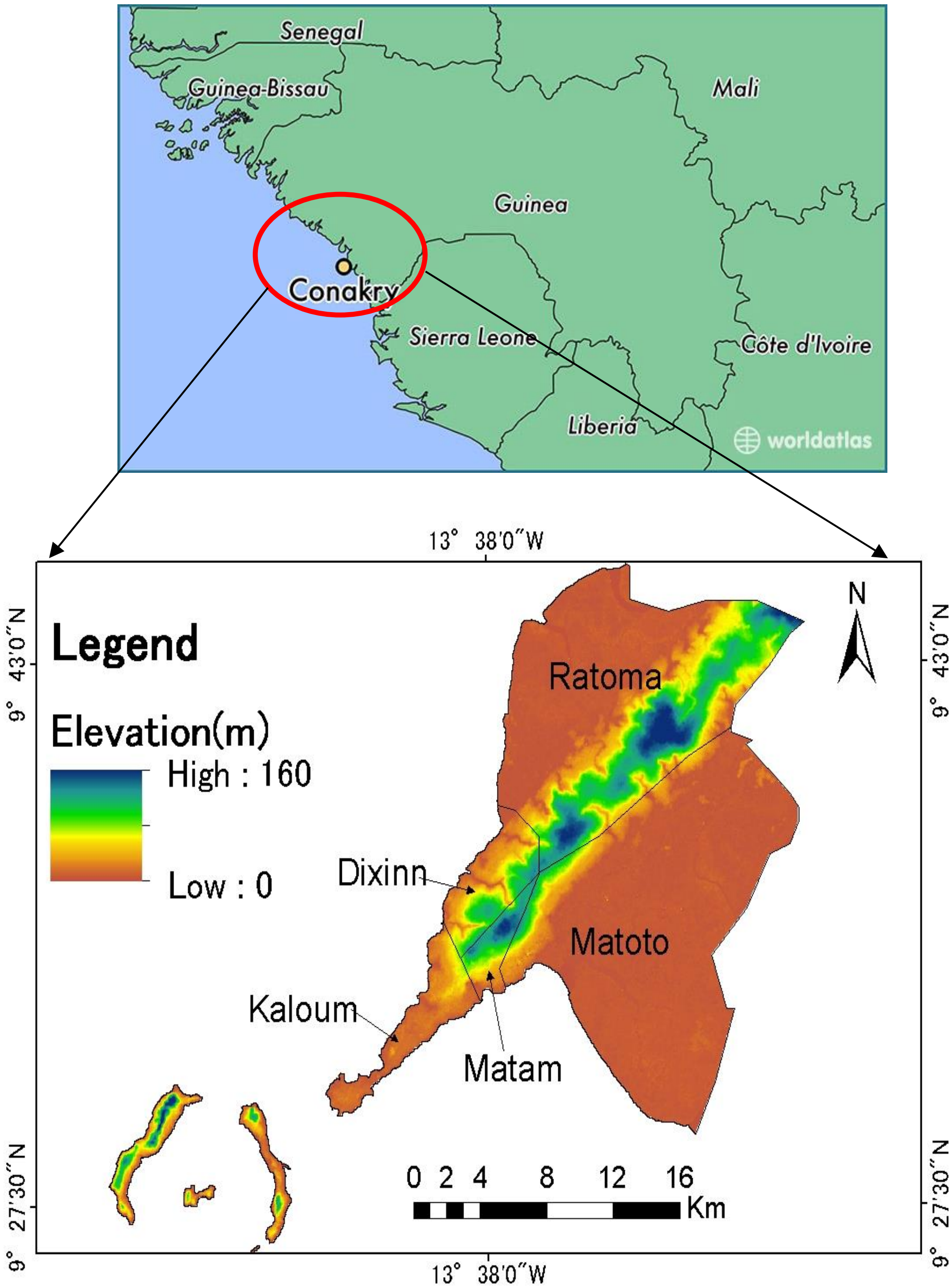


Figure 1.1 Geographical location of Conakry in Guinea

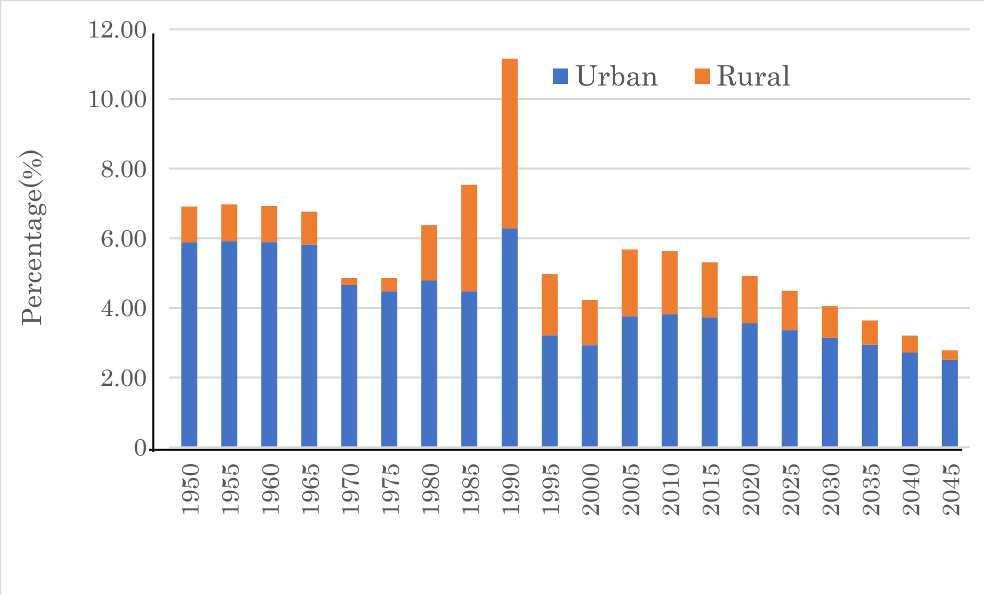


Figure 1.2 Urban and Rural population growth in Guinea from 1950 to 2045
Source: United Nations Department of Economic and Social Affairs (UNDESA, 2014)

Table 1.1 Percentage population with access to urban services in Guinea

Indicators	1996	2013
Urban population living in slums	43%	59%
Urban population with access to adequate decent housing	10%	21.7%
Urban population with access to clean water	48%	61.5%
Urban population with access to adequate sanitation	8%	27%
Urban population with access to regular waste management	9%	11%
Urban population with access to clean energy	1.5%	5.9%
Urban population with access to transportation common	11.4%	27.6%

Source:(National report on Habitat Guinea, 2016).

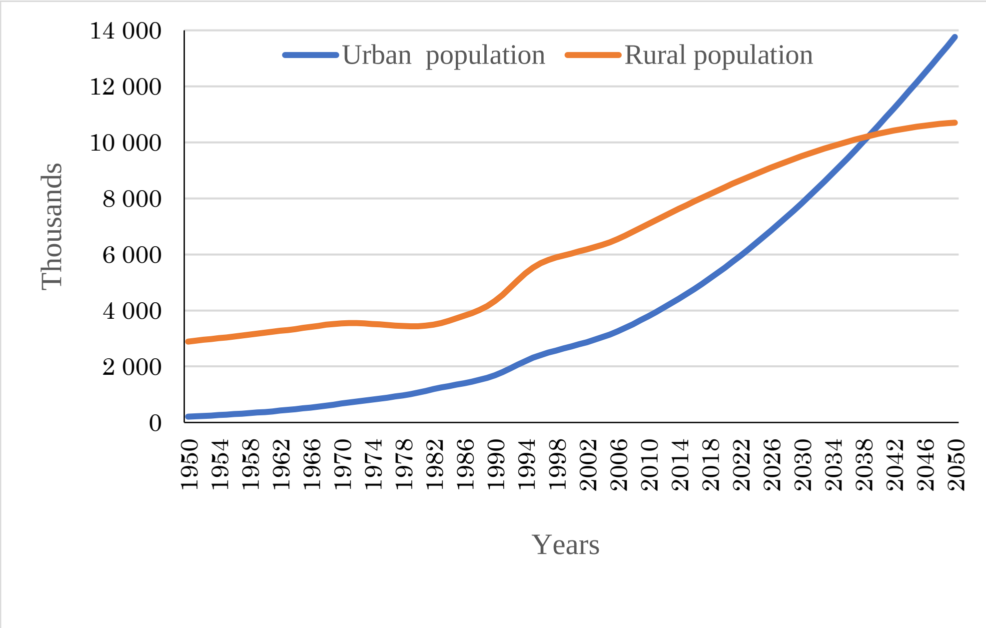


Figure 1.3 Future urban and rural population trend in Guinea from 1950 to 2050
Source: United Nations Department of Economic and Social Affairs (UNDESA, 2014)

Figure 1.4 Palm trees along the coast of Conakry

Figure 1.5 Mangrove in the marshy zones in Matoto

Figure 1.6 Roads flooded in Conakry in 2016

Figure 1.7 Slums in the commune of Kaloum

1.4 Justification and relevance of the study

Conakry has emerged to become the premier economic, commercial, and administrative center of Guinea, and the most urbanizing city in the country. Concomitant with high rate of population growth, there has been an unprecedented growth in the urban extent. This has resulted in tremendous LULC changes in the metropolitan city, whereby urban expansion has consumed vast extent of vegetation cover, and has pushed the rural/urban fringe farther and farther away from the original Conakry's urban core. Current urban development and planning in Conakry is in a critical stage. Like in many developing cities, Conakry faced severe socioeconomic and environmental issues including the landscape fragmentation, informal settlement on the coastal banks, poverty and unemployment, deterioration of the road surfaces, air and water pollution, deficient solid waste collection and disposal, recurrent flooding during the rainy seasons in many parts of the city (Traore et al.; 2017), and the degradation of the mangrove forests (Balde et al.; 2014).

However, detailed information related to the nature of the urban growth and its drivers are lacking. Land-use and land-cover (LULC) change studies, especially related to urban growth are essential for the planning and management for sustainable urban development. To ensure that urbanization produces optimal environmental and socioeconomic development level, authorities need to formulate smart and sustainable urban development strategies. This requires accurate, consistent, and timely geospatial information on urban growth pattern to assess current and future growth trends (Murayama et al.; 2017).

Satellite remote sensing data are suitable for poorly researched area such as Conakry, with less data availability, and can provide detailed information on urban LULC changes. This study aims to contribute to the understanding of the spatial and temporal LULC changes, the drivers of LULC changes as well as potential future urban growth in Conakry. The results of this study can provide a broad spatial overview, which can be used to understand current and future urban expansion as well as to support sustainable urban planning and improve the overall environmental and socioeconomic development.

1.5 Structure of the Dissertation

This thesis dissertation consists of six chapters. The outline of each chapter is presented as follow. Chapter1 describes the research background, objectives of the study, study area, justification and relevance of the study, and the structure of the dissertation.

Since the main objective of this study is to examine the spatial and temporal land-use and land-cover (LULC) change, especially the urban growth pattern, chapter 2 provides the conceptual background related to LULC change, urbanization and urban growth, importance of Remote Sensing (RS) and the Geographic Information System (GIS) in studying and monitoring urban growth, as well as an overview of the urbanization issues in Conakry city.

Chapter 3 states the methodological framework used to achieve these objectives. It includes data for LULC classification and for Logistic Regression Model (LRM); method of LULC classification using the Supervised Maximum Likelihood Classification (MLC) algorithm, Logistic Regression Method (LRM) to examine the drivers of urban growth, and the integrated Cellular Automata (CA) and Markov method (CA-Markov) to simulate the future LULC change in Conakry.

Chapter 4 presents the results. It includes the post-classification result on LULC changes, the accuracy assessment of the LULC classification, the result of the LRM, accuracy assessment of the LRM using the Relative Operating Characteristic (ROC), the result of the (CA-Markov) analysis, accuracy assessment of the (CA-Markov) model, and the results of the Vegetation Adjusted Nighttime Urban Lights Index (VANUI).

Chapter 5 makes a brief discussion of the results obtained in Chapter 4. It discusses about the urban growth and the demographic dynamic in Conakry, urban growth in commune level

Chapter 6 makes a summary of the main findings; contributions to knowledge, based on the study findings, limitations and suggestions for sustainable urban development.

2. Literature review

2.1 Land-use and land-cover (LULC) change

The term land-use and land-cover (LULC) is often used interchangeably in the literature although each term has its own unique meaning. Thus, it is important to draw attention to their unique characteristics to differentiate between them. In general, the term LULC change identifies all kinds of human modification of the Earth's surface (Cheng.; 2014). It is a central component of global environmental change with direct impact on climate, environment, and human society (Tunner et al., 1991, Singh et al., 2013). Changes in LULC are among the most important drivers of global change (Vitousek et al.; 1997). Land-cover refers to the physical and biological cover over the surface of land, including water, vegetation, bare soil, and/or artificial structures (Ellis et al.; 2007). Land-use, on the other hand, has a complicated expression with different views compared with the term land-cover. In fact, social scientists and land managers characterize this term more generally to involve the social and economic purposes (Thapa.; 2009). According to Sherbinin et al, (2002), land-use refers to the purposes for which humans exploit, modify or convert the land-cover.

"Land-use concerns the function or purpose for which the land is used for the local human population and can be defined as the human activities, which are directly related to land, making use of its resources or having an impact on them" (Vitousek et al.; 1997). In fact, it emerges from all the above definitions that LULC are not equivalent although they are interchangeably used. The above definitions show that land-use and land-cover (LULC) are highly linked, such that change in one leads to change in the other. Land-cover is a more significant factor in human life/environment land-use. This is because of the various impacts that LULC change may have on the environment and thereby human well-being (Deilami.; 2017). Two types of land-cover change can be identified: conversion and modification. Land-cover conversion means the change from one cover type to another, while land-cover modification refers to the alterations of structure or function without a total change from one type to another (Vitousek et al.; 1997). These conversions and their consequences are obvious around the world and it has been becoming a disaster around the metropolitan areas in developing countries.

Since the Neolithic revolution in the early Holocene, humans have colonized land by channeling terrestrial ecosystem process to maximize their utilities for social purposes, that is to produce as much as biomass as possible for food, feed and energy; as well as to convert land-cover itself to create living and working spaces (Souza et al.; 2017). Urbanization and agricultural land-uses are the two most commonly recognized high level classes of land-use (Souza et al., 2017 , Melese et al., 2016). Human beings continuously change the environment (Land-cover) to provide their essentials (e.g. food and accommodation). However, the pace, extension and intensification of the LULC changes have increased dramatically in the 20th century. For example, more deforestation has occurred between 1950 and 1980 than in the 18th and 19th centuries combined (Lambin et al.; 2001a). This has mostly occurred as an effect of the expansion of cities and farmlands (Ellis et al.; 2007).

In the last 50 to 100 years, population growth and economic development have increased human demands on the Earth's land surface and land system change has been recognized as a driver of global environmental change at all scale from the local, to the global (Souza et al.; 2017). More recently, industrialization has encouraged the concentration of human populations within urban areas (urbanization) and the depopulation of rural areas, accompanied by the intensification of agriculture in the most productive lands and the abandonment of marginal lands (Ellis et al.; 2007). Furthermore, current global environmental change is unique, the human reshaping of the earth has reached a truly global scale, is unprecedented in its magnitude and rate, and increasingly involves significant impacts on the biochemical systems that sustain the biosphere (Meyer et al.; 1992). Concerns about LULC change emerged in the research agenda on global environmental change several decades ago, with the realization that land surface processes influence climate, terrestrial ecosystems and the central aspects of earth system functioning (Lambin et al., 2003, Lambin et al., 2001). It directly impacts biotic diversity worldwide (Sala et al.; 2000), contribute to local climate change (Chase et al.; 2000), as well as to the global climate warming (Huang et al., 2009). On the other hand, it is also important to recognize that all impacts are not negative though, as many forms of LULC changes are associated with continuing increases in food and fiber production, in resource use efficiency, and in wealth and well-being (Lambin et al., 2001).

Monitoring LULC changes is considered as an essential step to assist the identification of drivers (Zimmerman et al.; 2017). Landscape dynamics studies integrating human-environment interactions and related to environmental issues have become increasingly important. Over the recent years, these studies moved away from a focus on detecting and identifying LULC changes (Lambin et al., 2001, Loveland et al., 2011) to an understanding of the driving of landscape changes (Houet et al. 2011). Such studies are still largely supported by national and international global environmental change programs such as the LULC change (Lambin et al.; 2001a).

In developing countries, lack of statistical and Geo-spatial data constitutes the main constraint in assessing the effects of LULC change. In Guinea, only few studies have been conducted to analyze the LULC change patterns. For instance (Balde et al.; 2014) studied the role of LULC change in improving the livelihood of local mangrove rice farmers in the Guinean coastal zone. Based on both satellite and field survey, their results showed a substantial LULC change with 41.7% of the total area (5.099 ha) converted from non-agricultural to agricultural land. Furthermore, Sylla et al., (2012) investigated the LULC change surrounding Conakry and its two neighboring cities (Coyah and Dubreka). Using map interpretation with integration of RS and GIS, their results showed that these three cities were on the verge of being unified, because of the expansion of residential areas and the changing of the economic realities, such as the improvement of transportation and communication infrastructure, rural to urban migration and population growth causing considerable influence on LULC change patterns.

Studying LULC can significantly contribute to improve our understanding of natural-human interactions and for promoting sustainable urban planning and to improve the overall environmental and socioeconomic development. Mapping and monitoring land-cover have been widely recognized as an important step to better understanding and provide solutions for social, economic, and environmental problems (Ayalew et al., 2005, Fan et al., 2007, Richard., 2015).

2.2 Urbanization and Urban growth

Urbanization and urban growth are two different concepts often found in the literature of urban studies. The distinction should be cleared that urbanization refers to the proportion of the national population living in urban areas, and urban growth refers to an increase in urban population size, independent of rural population (United Nations.; 2005). Urbanization can be viewed and perceived to mean a lot of things depending on how it is used. It can be perceived as a characteristic of the population, as a kind of LULC, as well as characteristic of social and economic processes and interaction affecting both population and land (Thapa.; 2009). In geography, LULC, population, and economic data are often used as indices for explaining urbanization (Li.; 2014). Murayama et al, (2017) used LULC change and economic indices to describe urbanization in Asia and Africa. Per the United Nations, (2005), urbanization is simply defined as "the movement of people from rural to urban areas with population growth equating to urban migration. Essentially, it involves the complex change of life styles, which result from the impact of cities on society. Per the Pravitasari, (2015) urbanization is a process of relative growth in a country's population accompanied by an even faster increase in the economic, political, and cultural importance of city relative to rural areas. Nowadays, urbanization is commonly used for more broad sense and it refers to much more than simple urban population growth; it involves the physical growth of urban areas as well as the changes in the socioeconomic and political structure of a region as a result of population migration to an urban area (Tan et al., 2016, Richard., 2015, Deng et al., 2010). The broader concept of urban development implies changes, growth or decline. The term includes the physical, socio-economic and environmental dimension. Physically and functionally, urban development includes both new development and urban redevelopment. The physical aspects of urban growth are related to land-cover and the functional to land-use. Hence, temporal and spatial urban growth indicates the spatial and temporal dimensions of land-use and land-cover (LULC) change at the level of the urban landscape (Cheng.; 2003)

Urban growth has two contradictory facets. On the one hand, mega-cities act as engines of economic and social growth, on the other hand, most of this growth is being accompanied by both poverty and environmental degradation (e.g. encroachment on valuable agricultural land, increasing energy consumption, inner-city decline). The impacts of land-use changes on environmental sustainability will become globally significant through their cumulative effect. This is one of the major global change issues (Vitousek et al.; 1997). Urban growth can occur in a several ways such as sprawling or compact, scattered or clustered, continuous or leapfrog, planned or organic(Cheng.; 2014). Sprawling is generally defined as development of rural land in outskirt of the city into urban land in a dispersed manner (Li.; 2014), whereas compact growth within the city in infilling and densification manner. Scattered or leapfrog growth means the formation of new urban patches that are isolated from the existing city, while clustered or continuous growth is defined as new growth that are grouped together to form a urban cluster.(Nong et al.; 2011).

Urbanization has been a dynamic complex phenomenon taking place all around the world. This process without any sign of slowing down has led to the significant changes in the land-cover and landscape pattern (Deng et al., 2010, Sefidi et al., 2016). Previous literature characterized urbanization alternatively as an increase in the share of the population living in cities, the level of non-agricultural employment or production, the pace of resource consumption, or the presence of traffic congestion (Narumasa.; 2014). Drastic urbanization, especially in developing countries, will continue to be one of the important issues of global change influencing the human dimensions (Deng et al.; 2010). Though urbanization promotes socioeconomic development and improved quality of life, it is the most powerful and visible anthropogenic force that has caused the fundamental conversion from natural to artificial land-use in the cities around the world (Wu.; 2002). The contemporary world has become an urban world; this is apparent in the expansion of urban areas and the extension of urban influences across much of the habitable surface of the planet. Although urban land-cover occupies less than 2% of the Earth's land surface (Lambin et al.; 2001b), urban areas are expanding due to the inability of existing urban infrastructure to sustain the population and its activities (Seto et al., 2010, Tan et al., 2016). The twentieth century witnessed the rapid urbanization of the world's population. The global proportion of urban population increased from a mere 13 per cent in 1900 to 29 per cent in 1950 and 54 per-cent of the world's population residing in urban areas in 2014 (United Nations.; 2005).

Moreover, since the world is projected to continue to urbanize, 60 per cent of the global population is expected to live in cities by 2030. The fastest growing urban agglomerations, which are medium-sized cities with less than 1 million inhabitants will be located in Asia and Africa (United Nations.; 2014). This rapid increase in urban population and urbanization will pose many challenges to planners and policy makers (Murayama et al.; 2017). It will lead to significant changes in land-cover and landscape pattern (Sefidi et al., 2016, Deng et al., 2010). Drastic urbanization, especially in the developing countries, will continue to be one of the important issues of global change influencing human dimensions (Deng et al.; 2010). Rapid urbanization and urban growth in the developing world require a scientific understanding of complex urban growth patterns and process. This knowledge is highly crucial to sustainable land management and urban development planning. Progress in modern remote sensing and GIS technique has opened great opportunities, and significant success already been achieved in monitoring and managing fast urban growth. However, these techniques are still poor when it comes to supporting decision making on sustainable development, as reasonable theories and methods have not been sufficiently and systematically developed to understand the complexity inherent in urban growth. Understanding the urban growth system is a prerequisite for modeling and forecasting future trends on urban LULC change and its ecological impacts (Cheng.; 2003).

Theoretical analysis can provide a guideline for selecting modeling methods currently available in complexity modeling and in remote sensing and GIS environment. Modeling urban growth aims to support urban development planning and sustainable growth management. Scientific planning and management must be based on the proper understanding of the dynamic process of urban growth, i.e., from past to present and future. Such understanding enables planners to experimentally simulate decision-making based on various scenarios. However, the dynamic process involves various socioeconomic and physical and ecological components at varied spatial and temporal scales, which result in such a complex dynamic system (Li.; 2014).

Sustainable development refers to "development that meets the needs of the present without compromising the ability of the future generations to meet their own need"(Alcamo et al. 2013). The existing of all the above-mentioned problems caused by urbanization indicates that our cities are not sustainable due to the problems caused by the rapid urbanization and urban growth. The current changing urban spatial pattern is a great challenge for sustainable development (Gao et al.; 2015). Therefore, a sustainable city must "achieve a balance among environmental protection, economic development, and social wellbeing (Braimoh and Vlek 2004).

2.3 Importance of Remote Sensing and GIS in urban growth study

The International Federation of Surveyor (IFS,2010) stated that almost 70% of urban growth in developing countries is not planned. Efforts to produce or update existing urban geospatial information for planning purposes have been hampered by prohibitive cost of acquiring geospatial data. Although most of the developed countries are well equipped with detailed land-cover information (Murayama et al., 2017, Tan et al., 2016), our current understanding of the LULC change and its effects are largely limited by the lack of accurate and timely land-cover data in the developing countries. Land-cover data are inadequate or unavailable, of inconsistent quality, and out of date; while generating it is time consuming and expensive (Murayama et al.; 2017). Understanding the urban patterns dynamic process, and their relationships is a primary objective in the urban research agenda with a wide consensus among scientists, resource managers, and planners, because future development and management of urban areas require detailed information about ongoing process and patterns (Bhatta.; 2010). Satellite remote sensing and the geographic information system (GIS) provide valuable insights into urban LULC changes and monitoring the growth processes at multiple spatial and temporal scale. Since the launch of the Earth resource satellite Landsat-1 in 1972, satellite remote sensing has become an increasingly powerful and effective tool for monitoring and management of land-cover information (Jalan et al. 2014). Compared with the traditional mapping methods such as field survey, and basic aerial photointerpretation, satellite remote sensing has the advantages of low cost, large area coverage, repetitive data, digital format, and accurate geo-referencing procedures (Weng et al., 2008, Yuan et al., 2005). Remote sensing data, although challenged by the spatial and spectral heterogeneity of urban environment (Herold et al. 2005), seems to be an appropriate source of urban data to support such studies (Al.; 2012). Analysis of urban growth from remote sensing data, as pattern and process, helps us to understand how an urban landscape is changing through time. This understanding includes: (1) the rate of urban growth, (2) the spatial configuration of growth, (3) whether there is any spatial or temporal disparity in growth, and (5) whether the growth is sprawling or not. Therefore, land-use information generated from satellite images have become an essential data for land-cover management and urban land planning. Especially in developing countries, remote sensing can provide fundamental and cost effective land-cover information that is not available from other sources (Fan et al., 2007, Souza et al., 2017). Urban growth remains a major topic concerning remote sensing (RS) and geographic information system(GIS). These applications have proved to be effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Masser. 2001). GIS has gradually shifted its emphasis from system-oriented to science-oriented. In addition, GIS needs to incorporate broader and more fundamental scientific concepts to better understand geographical phenomena such as process, pattern, heterogeneity and scale (Cheng.; 2003). Urban growth is the projection of political, social and economic activities into a land system at the level of the urban area. The spatial and temporal dimensions are major concerns of GIS and remote sensing. Modeling spatial and temporal urban growth enriches the spatial science of GIS. Methodological research into urban growth can contribute to improving current GIS, its spatial analysis and modeling functions such as exploratory spatial data analysis and spatial econometric.

Remote sensing-based techniques have provided an efficient approach for mapping urban areas at multiple scales. Urban areas or human settlements can be mapped at different scales using remote sensing data with different spatial resolution. High (<10m) (e.g., SPOT, IKONOS, Quick Bird) and medium (10-100m) (e.g., Landsat TM/ETM+, ASTER). Spatial resolution remote sensing imagery have been applied worldwide in mapping urban areas or built up areas for individual cities or city-regions (Li et al.; 2014). The spatial resolution or ground cell size of one pixel as finite image element is the most characterizing of remote sensing image. As higher the spatial resolution as better, the interpretability by human observer will be. However, a very high resolution led to a high object diversity which could end up in problems when an automated classification algorithm is applied to the data.(Moeller, 1950). The temporal resolution is another crucial factor especially when studying urban areas. An ideal solution would be a sensor recording permanent the entire earth and delivering this data in real time. But due to technical restrictions such a system cannot be realized. As better the temporal resolution becomes as coarser will the spatial resolution. Polar orbiting systems like Landsat and Aster typically offer repetition cycles of 16 days. In the recent years, remote sensing data and geographic information system(GIS) techniques are widely being used for mapping (to understand the urban pattern), monitoring (to understand the urban process), measuring (to analyze), and modeling (to simulate) the urban growth, land-use and land-cover change, and sprawl. The physical expressions and patterns of urban growth and sprawl on landscapes can be detected, mapped, and analyzed by using remote sensing data and GIS technique (Bhatta et al., 2010, Chen et al., 2006).

2.4 Overview of the urbanization trends in Conakry.

Founded in the colonial periods, Conakry is an urban area that was characterized by rapidly accelerating growth in the second half of the 20th century, which had implications for the city's infrastructure and the socioeconomic and environmental development (Aly et al.; 2012). From the outset, Conakry's development was the product of several superimposed historical strata: firstly, the planning and creation of facilities for the benefit of Europeans during the colonial phase (1880-1958); secondly, the minimal state intervention associated with limitations on private initiatives during the first regime (1958-1984), and thirdly, the central role of private investment (both local and foreign) accompanied by the beginning of the development policy for the metropolitan area under the second regime (1984-2008) (Odile.;2011). The Guinea's overall economic performance since independence in 1958 has been poor. The economic policies have been governed by the socialist development philosophy of the ruling party (Party Democracies of Guinea). This has led to replacing a market-oriented rural economy with a centrally planned economy promoting state ownership of land and means of production, collectivized labor, and allocation of resources through central decision making. Though agriculture is the most important sector in Guinea's economy, employing about 80% of the total population, agricultural production has, in per capita terms, has fallen far below (World Bank.; 1984). Regarding the mining production, the country is one of the world's largest bauxite and alumina producers. The mining sector has almost become the country's exclusive source of foreign exchange earnings. However, due to the depressed external markets and leveling in production capacity, revenues from mining has stagnated over the last few years (Diallo et al.; 2011). Nevertheless, while agricultural production has fallen and economic and living conditions in rural areas have deteriorated, there has been a steady increase in the importance of the urban sector. More than 50% of the country's GDP is now generated in urban areas (World Bank.; 1984). Urban population has been growing at an alarming rate over the last recent years (Figure 2.1). However, the geographical distribution of the population is uneven and is influenced by the urbanization progressing strongly toward the major cities. Conakry, the capital city and the main economic, administrative and cultural center of Guinea concentrates almost 50% of the urban population, making up to 18.1 % of the total country's population (Table 2.1); while, Conakry's area is representing only 1% of the country's territory.

Moreover, it appeared that the important disparities in terms of economic opportunities, access to employment, and public services demonstrate the attractiveness of Conakry to other cities. For instance, in a report on urban development in Conakry, the World Bank stated that over 60% of all industrial enterprises were in the Conakry area, that these businesses accounted for about 50% of employment in the secondary sector, and that the proportions were similar for trade and public administration (World Bank.; 1984). Today's urban conditions in Conakry largely reflect the problems and shortcomings of Guinea's overall economic development process since independence. Weakness of key institutions arising from the dearth of adequately trained staff, shortfall of investments in basic infrastructure and utilizes and lack of maintenance of existing assets due to chronic unavailability of foreign exchange for recurrent cost financing. The lack of systematic maintenance and the erratic functioning of urban services have caused a steady deterioration of environmental conditions in both the city's older districts and the recent extension. Despite its important urbanization and urban expansion in Conakry, there are very little information on the spatial and temporal urban growth process. Thus, it is important to conduct research on the LULC changes in Conakry to promote sustainable land-use planning.

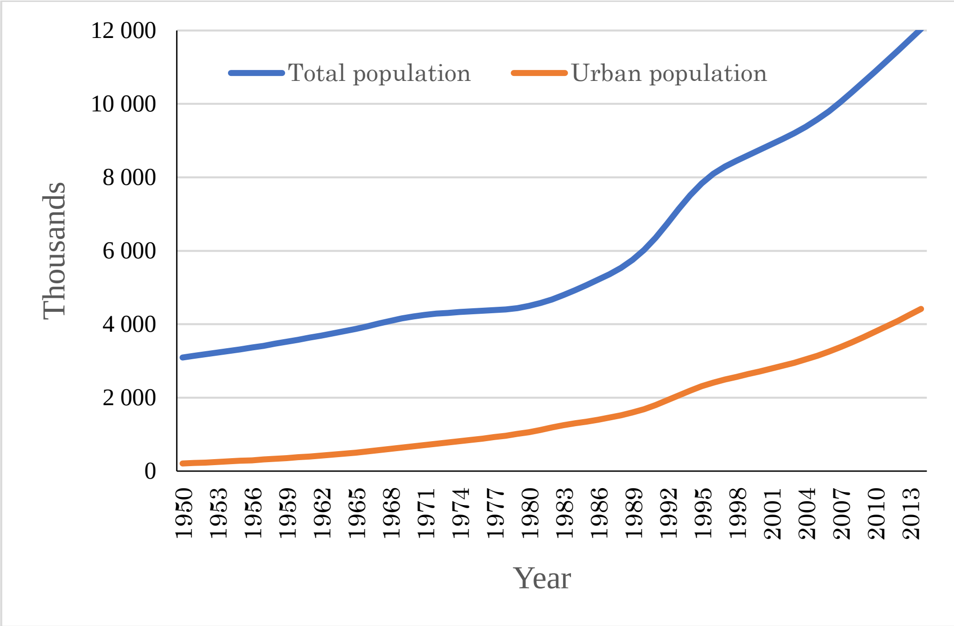


Figure 2.1 Urban and Rural population growth in Guinea during the period 1955-2015. Source: United Nations Department of Economic and Social Affairs (UNDESA, 2014)

Table 2.1 Urban population distribution in Guinea in 2015

Natural regions and Conakry	Population (%)	Area (%)
Conakry	18.5	1
Lower Guinea	20	18
Middle Guinea	21	22
Upper Guinea	19.8	42
Forest Guinea	20.7	17

3. Research methodology

3.1 Data and methods

3.1.1 Landsat data

Remote sensing data has emerged as the most useful data source for quantitatively, spatially and temporally measuring LULC change. The dynamics of changes processes can be investigated using a temporal series of remote sensing data. While census data provide a statistical view of demographics and economics (Hu., 2004, Loveland et al., 2011). The actual spatial patterns of urban landscape can only be effectively observed trough remote sensing due to the frequent revisiting, observations of the sensors, update our view of urban landscape, manifesting time series of urban growth, recording the variability of urban development in space and time, thus permitting a rigorous comparison with economic and demographic data (Bhatta, 2012, Zimmerman et al., 2017).

Among the remote sensing data, Landsat satellite has been operating since 1972, providing a continuous global record of the Earth's land surface. Perhaps the most successful satellite remote sensing program dedicated to land observations has been the Landsat program (Lauer et al., 1997). The Landsat family of satellites has provided humanity with standardized, moderate spatial resolution, multispectral images of the world (Green., 2006). It offers a unique combination of three important characteristics. First, the archive of imagery extents back to 1972, allowing for broad-area analyses over several decades. Second, the imagery has been collected globally on a regular basic, providing consistent repeat coverage. And third, the imagery is currently available at no cost and with no user restrictions (Miller et al. 2013).

Landsat data have been widely used in various environmental studies such as urban landscape changes (Ma et al., 2010, Kaimaris et al., 2016 , Kamusoko et al., 2013), urban heat island assessment (Grover et al., 2015, Xiong et al., 2012, Tan et al., 2016), and deforestation monitoring (Arekhi et al., 2012, Linkie et al., 2004) etc. Satellite remote sensing has offered considerable promise for characterizing landscape patterns at different spatial scales and monitoring landscape dynamics by detecting changes in landscape patterns (Li et al. 2014). The historical LULC change data obtained from remote sensing integrated with socioeconomic data are often used as inputs to land LULC models (Hu., 2004, Liu et al., 2001, Masser., 2001). The reliability of the results of LULC change modeling is not affected by the selected modeling method, but it is also highly dependent on the accuracy of LULC change mapping from remote sensing and the quality of socioeconomic data.

Computer-assisted production of spatially-detailed and thematically accurate LULC maps from satellite images is still a challenge for the remote sensing and photogrammetry research community (Ma et al., 2010, Loveland et al., 2011). Therefore, many change detection techniques, which are the process of identifying the difference in the state of an object or phenomenon by observing it at different times have developed including image differencing, vegetation index differencing, selecting principal components analysis and post-classification and so on (Fan et al., 2007, Li et al., 2014).

In this study, Landsat images from different sensors, Landsat (TM) acquired on January 3, 1986, Landsat (ETM+) on December 19, 2000, and Landsat (OLI) on January 20, 2016, were downloaded from the United States Geological Survey (USGS) Earth Explorer (https//earthexplorer.usgs.gov/) and were used as primary data for the LULC classification and LULC prediction. Figure 3.1 shows the red, green and blue (RGB) false color combination of these Landsat images. This false color combination 5- 4-3 provides the user with a great amount of information and color contrast for identifying and discriminating unique feature on the ground. Furthermore, the selection of these Landsat data was based on the availability of high-quality satellite imagery (clear and nearly free of cloud). Table 3.1 provides detailed information related to these Landsat data.

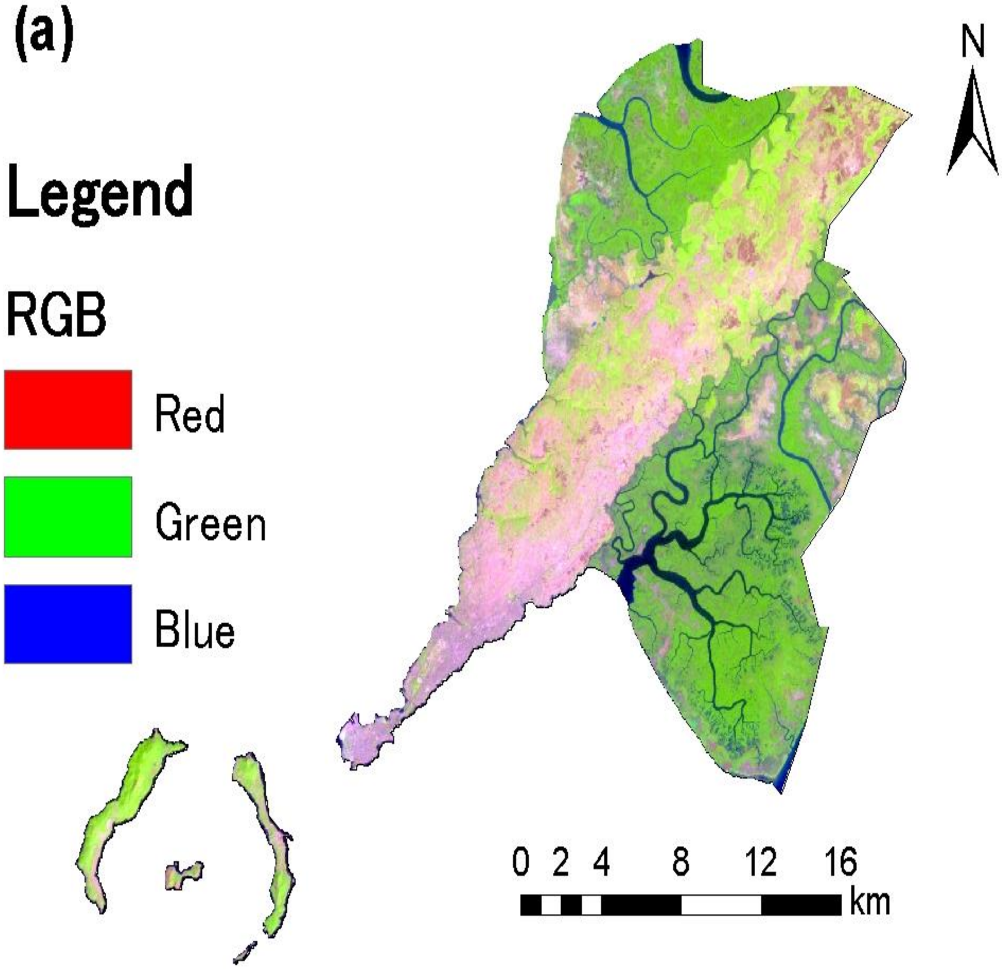


Figure 3.1 Temporal image of Conakry: a) Landsat Thematic Mapper (TM) of 1986

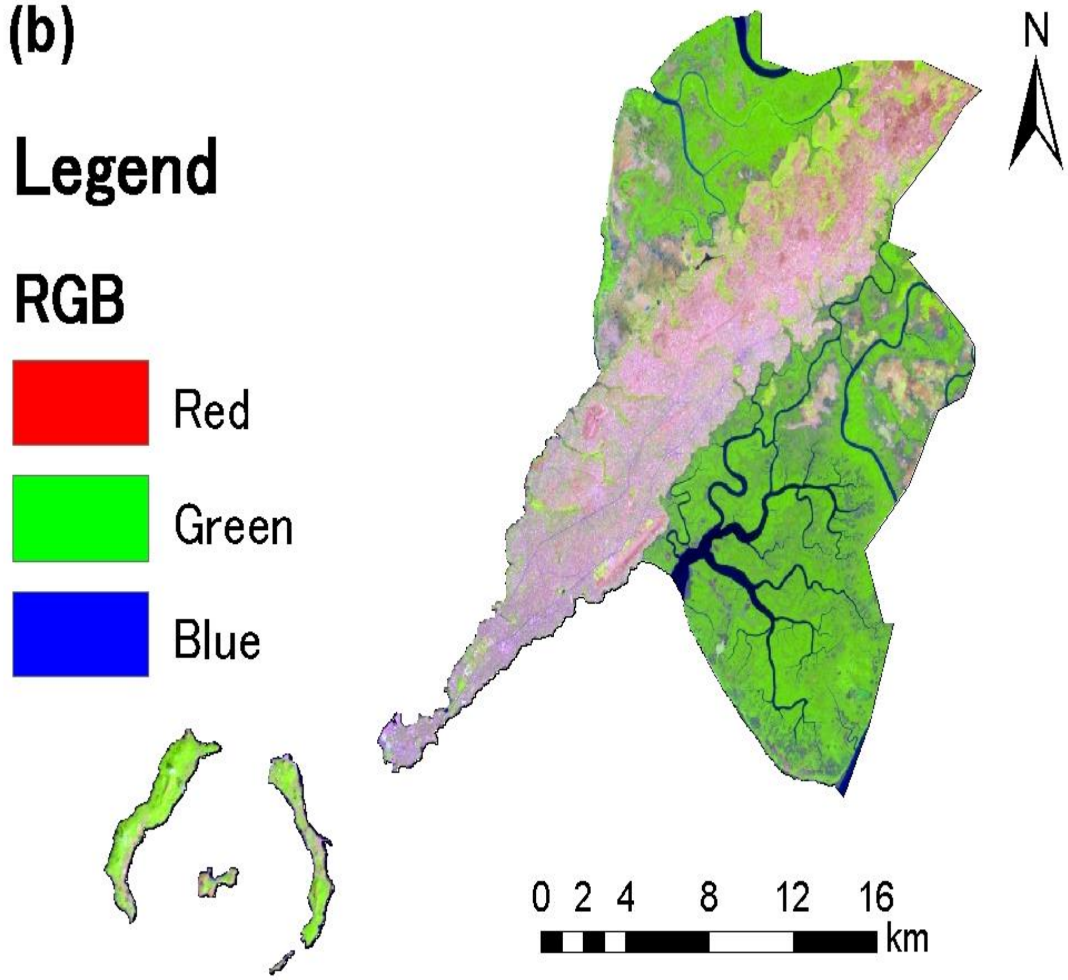


Figure 3.1 (continued) Temporal image of Conakry: b) Landsat Enhanced Thematic Mapper Plus (ETM+) of 2000

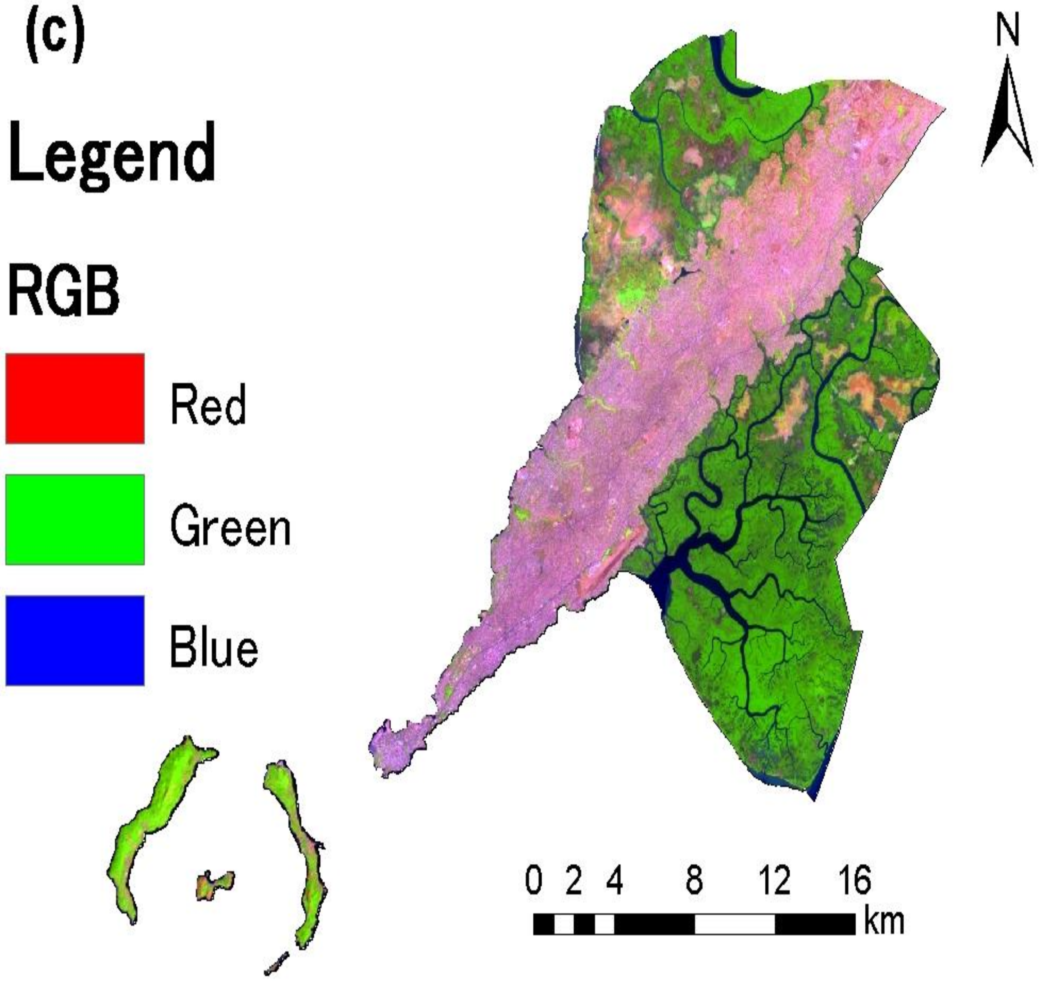


Figure 3.1 (continued) Temporal image of Conakry: c) Landsat Operational Land Imager (OLI) of 2016

Table 3.1 Details information of the Landsat data used in this study

Satellite	Sensor	Path/row	Spatial resolution (meters)	Date of acquisition	Sources
Landsat 5	TM	202/53	30	01/03/1986	USGS
Landsat 7	ETM+	202/53	30	12/19/2000	USGS
Landsat 8	OLI	202/53	30	01/20/2016	USGS

3.2 Data for Logistic Regression Model (LRM)

3.2.1 Explanatory variables

Landscape change is often seen as a function of socioeconomic and biophysical factors that are referred to as the driving forces of land-use change (Thapa et al.; 2010). A prerequisite to the development of realistic models of LULC change is the identification of the most important driving forces. Case studies of the determinants of LULC change can help to analyze which theory is appropriate in a particular region or city and stimulate the development of new theoretic understandings (Verburg et al.; 2004). Urban growth is typically driven by a variety of forces that relate to one another based on different spatial and temporal settings. Understanding the causes and consequences of urbanization processes to explore the extent and location of future landscape change is very important (Thapa et al.; 2010). Land-use policies are often determinant of the land-use conversion. However, incorporation of social, political, and economic factors is often hampered by a lack of spatially explicit data and by methodological difficulties in linking social and biophysical data. Biophysical data are often extracted from remote sensing data in raster format. Socioeconomic data are often collected by censuses or surveys. For land-use modeling, two aspects regarding drivers of land-use change are of importance and should be considered in the modeling. One is the selection of drivers (explanatory variables); the other is how to quantify the relations between land-use and driving forces (Hu et al.; 2010). Many of the previous studies have identified the driving forces or determinants of urban growth to be mainly socioeconomic, physical and neighboring factors (Tan et al., 2016, Li., 2014 , Abubakr et al., 2014). Some studies have reported that population growth, economic growth and industrialization have positive and significant effects on urban growth (Deng et al., 2010, Tan et al., 2016). In practice, many processes that influence urban LULC changes interact and lead to complex patterns, depending on the local cultural, socioeconomic, and biophysical context at different spatial scales (Lambin et al., 2001).

The selection of the urban growth drivers is a crucial aspect of urban growth modeling, because urban growth drivers are the main characteristics that can help to understand the processes of land-use transition from non-urban to urban (Eyoh et al.; 2012). Nevertheless, there is no hard and fast rule or known global formula for selecting urban growth drivers. Therefore, the list of urban growth drivers can be endless. Based on a literature review, field survey and personal communications with members of the urban planning bureau (UPB) in Conakry, the drivers of the urban growth in the study area were selected and summarized into two categories. Socioeconomic and physical drivers. In addition, the choice of these variables conforms to most dynamic simulation modeling practices, which usually consider the determining factors of SLEUTH (slope, land-use, exclusion, urban extent, transportation, hill shade) (Eyoh et al., 2012, Abubakr et al., 2014, Yu et al., 2011, Lin et al., 2011).

3.2.2 Socioeconomic proximity drivers

The socioeconomic driving forces considered in this study include distances to active economic center (X1 = DAEC), to the urbanized area (X2 = DUA), to major roads (X3 = and population density (X4=PD). The active economic center was digitized from Google Earth, urbanized areas were extracted from the 1986 LULC map. Layer of the major roads was obtained from the Open-Street-Map (https://www.openstreetmap.org/) a free Geospatial data source, and the population density data was obtained from the socioeconomic data and applications center (SEDAC), NASA. The distance in this study refers to the Euclidean distance in the raster image between each cell and the nearest cell of the target features.

The influence of the socioeconomic conditions in the city can be best characterized by the access that a location has to socioeconomic center, which as a significant effect on urban growth pattern (He et al., 2007 ,Verburg et al., 2017), transportation plays a critical role in urban growth because a good transportation increases the accessibility of land and decreases the cost of construction (Cheng.; 2014). Transportation systems also provide mobility for people and goods, and they influence patterns of growth as well as the level of economic activity through the accessibility that they provide to the land (Meyer et al.; 1992). However, diverse types of roads have varied strengths of impact or potential to attract new development. Several studies have indicated that transportation infrastructure is one of the main driving forces of urban growth (Bhatta et al., 2010, Eyoh et al., 2012, Abubakr et al., 2014). In this study, based on the literature review on growth studies and the discussion with some experts of the urban planning in Conakry, these variables were considered including distance to major roads, population density as population growth creates rapid urban land demand, therefore leads to urban growth because much land will be required to satisfy further growth of urban population. All the distance variables were computed in ArcMap10.2 using a distance operator. These spatial data were registered to the same Universal Transversal Mercator (UTM) Zone 28 coordinate system with the cell size of 30 meters. R statistical package was used for the LRM, Arc Map 10.2 and IDRISI software were using for computing spatial variables and producing maps. Table 3.2 shows the list of the socioeconomic variables included in the model.

Table 3. 2 Socioeconomic variables included in the model

Variable	**Description**	**Nature**
Explanatory variable	Socio-economic factors	
DAEC(X1)	Distance to active economic center	Continuous
DUA(X2)	Distance to urbanized areas	Continuous
DMR(X3)	Distance to major roads	Continuous
PP(X4)	Population density	Continuous

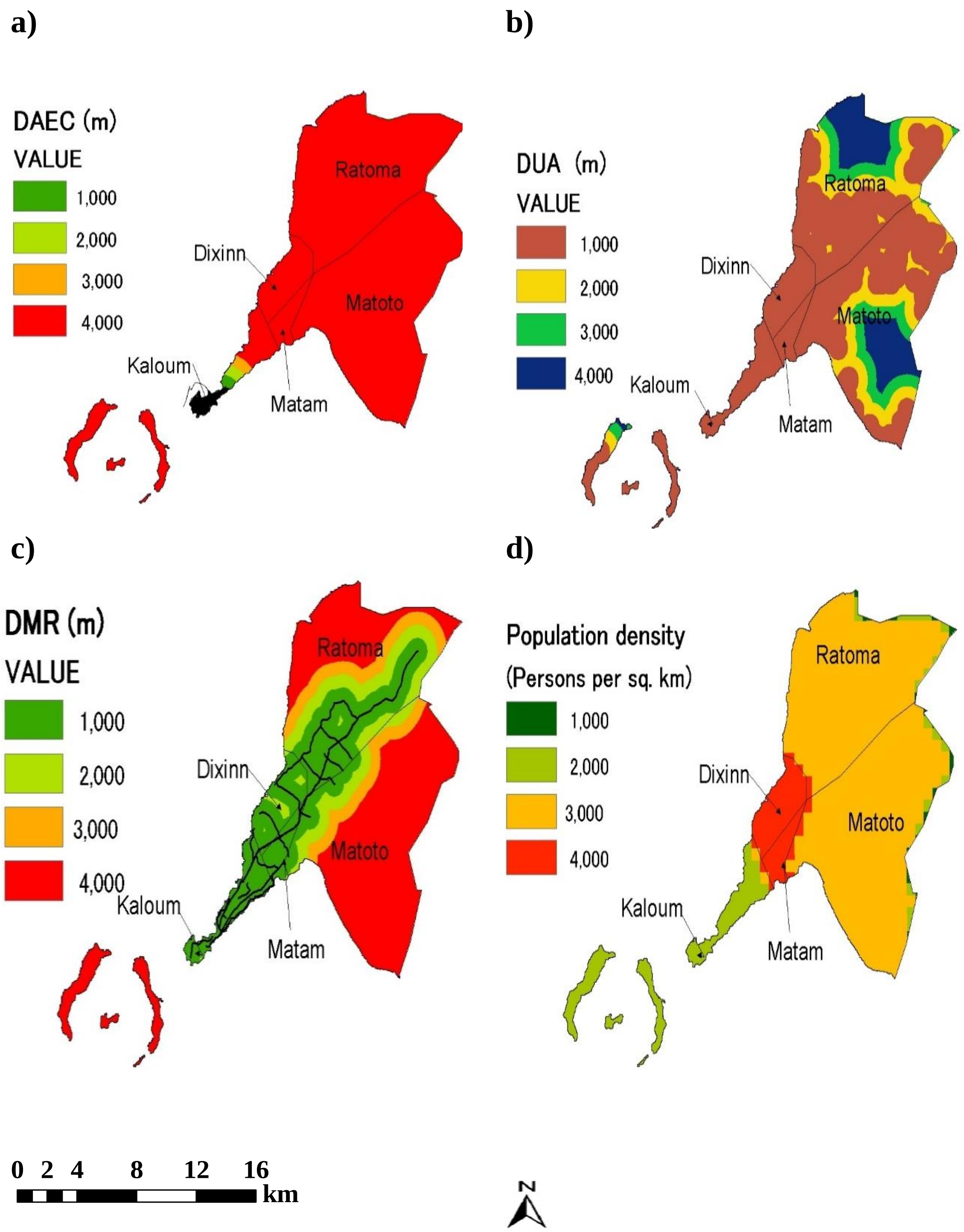


Figure 3.2 Socioeconomic variables included in the LRM: a) Distance to Active Economic Center (DAEC), b) Distance to Urbanized Areas (DUA), c) Distance Major Roads (DMR), d) Population density

3.2.3 Physical urban growth drivers

The physical drivers include characteristics and process of the natural environment such as weather and climate variations, landforms, topography, geomorphology process, volcanic eruptions, soil types and processes, drainage patterns, and the availability of the natural resources (Nong et al.; 2011, Verburg et al.; 2004). Topography factors such as elevation and slope are among the most important physical factors of urban growth (Dewan et al.; 2009). The elevated areas were usually developed in the early stage of urban development as they cannot be invaded by flood (Ma et al.; 2010). Conakry as a coastal city, slope and elevation were selected as physical drivers to check their influences on urban growth process. Slope and elevation information were extracted from the digital elevation model (DEM-ASTER), which was freely acquired from the USGS Earth Explorer (https://earthexplorer.usgs.gov/). The slope variable was generated in percentage rise, then reclassified into four categories based on the topographic characteristics of the study area: 0–6: low slope, 6–17: gentle slope, 17–73: high slope, 73 greater: steep slope, while the elevation was classified as: 0–6: low elevation,6–34: moderate, 34–78: high elevation, 78–160: very high elevation. Table 3.3 shows the list of the topographic drivers included in this study.

Table 3.3 Physical Topographic drivers

Variable	Description	Nature
Slope (X7)	Percentage rise	Continuous
Elevation (X8)	Elevation	Continuous

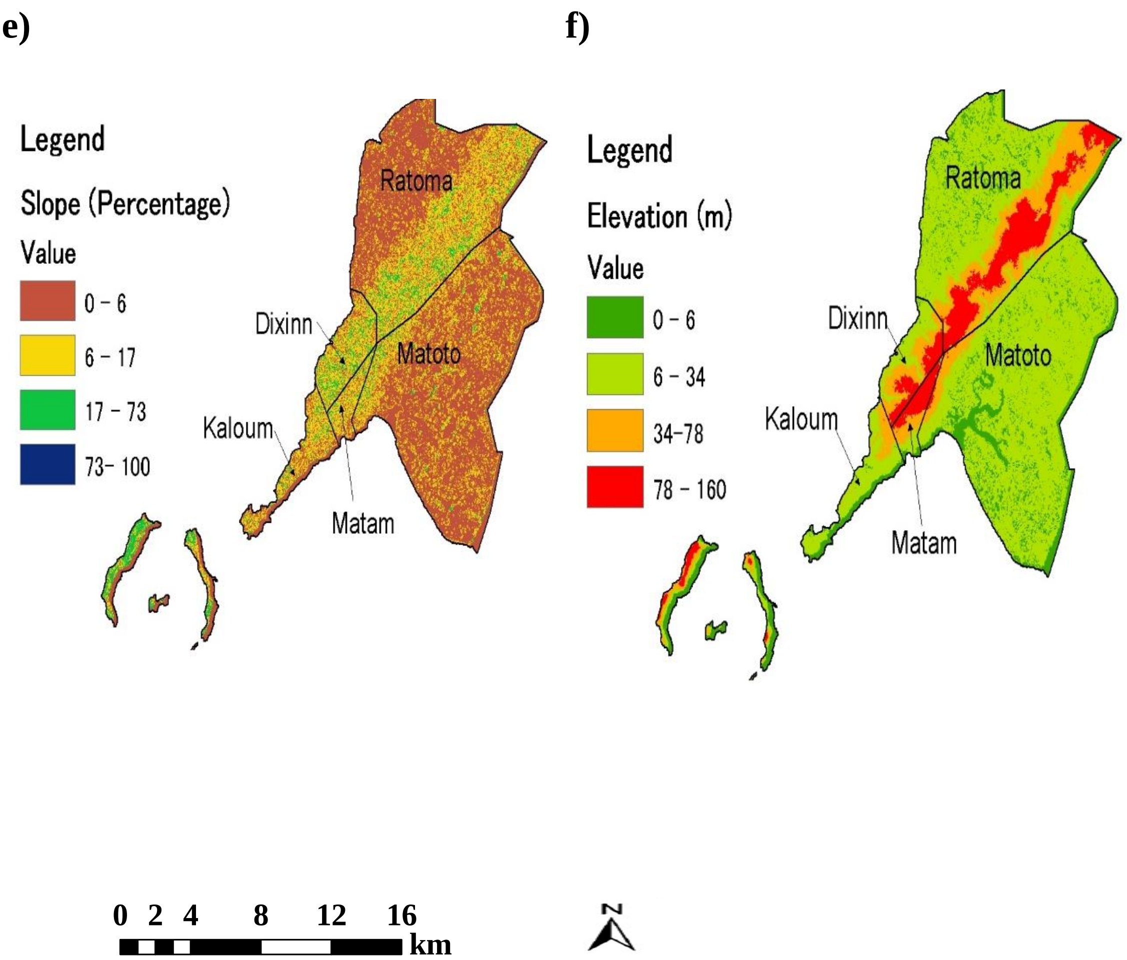


Figure 3.2 continued Physical drivers included in the LRM) e) Slope in percent, f) Elevation in meters

3.2.4 Normalization of the explanatory variables

A high discrepancy in term of the data range existed between the socioeconomic distance variables and physical topographic variables. Therefore, prior to the model calibration, data normalization was conducted. The distance variables were normalized to a range of 0 to 10. This process is particularly critical when the LRM is applied; since it requires that the variables are linearly related to the dependent variable. A natural log transformation was performed for the continuous distance variables; because the natural log transformation is commonly effective in linearizing distance decay variable. The Variable Transformation Utility (VTU) in IDRISI software from the Clark Labs was used and applied to all distance variables.

3.2.5 Dependent variables

The LULC maps allow the analysis of urban growth patterns and preparation of binary maps (urban growth/ non-urban growth) as basic input for urban growth modeling. For creating the dependent variable, the binary variable urban and non-urban data needs to be extracted from the LULC maps. The dependent variable is dummy variable with values of 0 representing no change and 1 representing change respectively. The urban growth that occurred from 1986 to 2000 was considered as dependent variables (Figures 3.3). Hence, binary image with the categories non-urban growth (cells remained unchanged) to urban growth (cells changed) was created. To generate this spatial transition map, the raster calculator function in Arc Map10.2 was used to generate the growth between 1986 and 2000. This binary map was used in the calibration phase of the LRM to examine the relationship between urban growth and different drivers. The generated urban growth map from the calibration is used to assess the accuracy of the model. Figure 3.4. illustrates the analytical framework of the overall study.

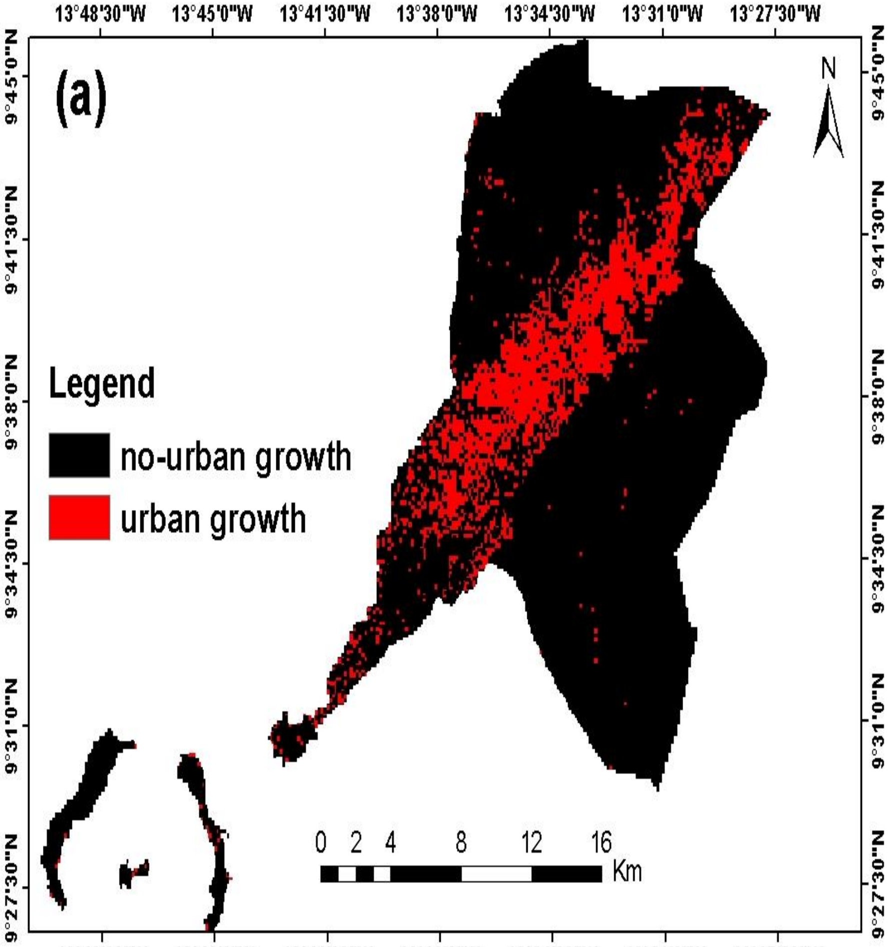


Figure 3.3 Dependent variable (Y) a) binary urban growth between 1986 and 2000

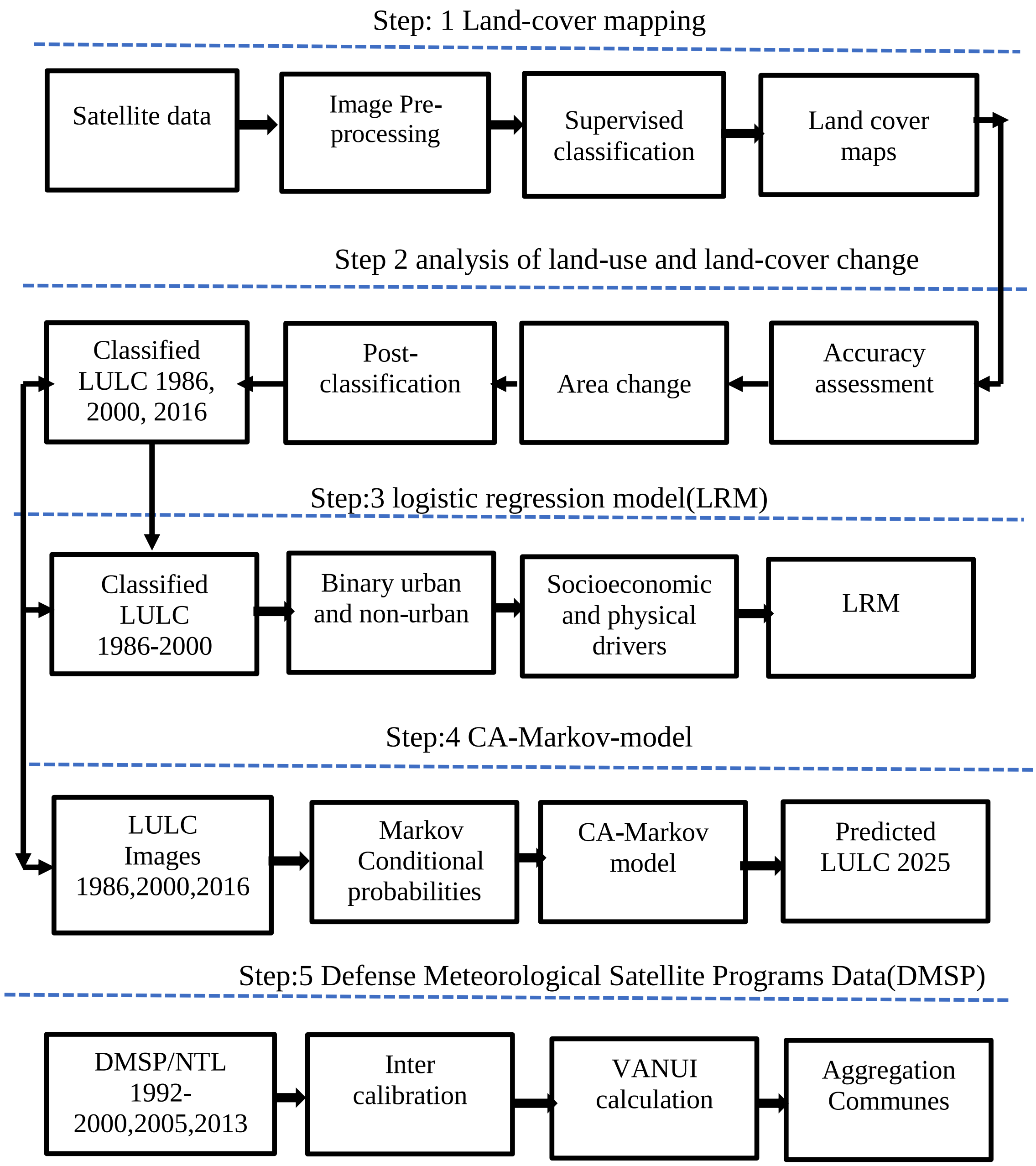


Figure 3.4 Analytical framework of the study.

3.3 Land-use and land-cover(LULC) classification

Change detection by GIS is a process that measures how the attributes of an area have changed between two or more time periods (Mwape.; 2010).The classification of land-cover types from satellite image is probably the most important objective of digital image analysis. It is a process of categorizing pixels in an image to one of land-cover classes (Cheng.; 2014). However, classification of remote sensing image to obtain reliable and accurate LULC information remains a challenge that depends on many factors such as complexity of landscape, the remote sensing data selected, image processing and classification methods (Manandhar et al.; 2009). The land-cover information can be gained from RS data by applying a variety of techniques such as visual interpretation, land-cover classification, and change detection. Different approaches and algorithms have been developed to improve the accuracy of LULC classification such as neural networks (Yuan et al., 2009, Kynova et al., 2015), fuzzy expert system (Laha et al., 2006, Sarath et al., 2014), object-oriented classification (Kressler et al.; 2003), random forest classification (Murayama et al.; 2017). There are various detection techniques, such as spectral transformation, image classification on combined datasets and comparison of LULC maps. In this study, the maximum likelihood classifier (MLC) was selected to extract land-cover information from Landsat data as well as to produce land-cover images.

MLC is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest (Ahmad et al.; 2013). An equal prior probability among the classes is also assumed. This classifier is based on the probability that a pixel belongs to a specific class. It takes the variability of classes into accounts by using the covariance matrix. Therefore, MLC requires sufficient number of representative training samples for each class to accurately estimate the mean vector and covariance matrix needed by the classification algorithm (Ahmad et al.; 2013). When the training samples are limited or non-representative, inaccurate estimation of the mean vector and covariance matrix often results in poor classification results. In this study, the choice of the LULC change detection methods depends on whether the output information from the detection meets the data requirements of the two modeling approaches of this dissertation, the logistic regression model and the CA-Markov chain model, in terms of content accuracy. The requirements are accurate LULC classification maps, a change/no change matrix, and an accurate historical urban growth. Satellite remote sensing has offered considerable promise for characterizing landscape patterns at different spatial scales and for monitoring landscape dynamics by detecting changes of landscape patterns (Hu.; 2004). Remote sensing has the advantages of large area coverage, repeated viewing capability and ease to integrate with GIS. When the environment in a large metropolitan area experiencing rapid suburbanization needs to be monitored constantly, the use of remote sensing has demonstrated more advantages than the traditional field surveying. Mapping from time series of satellite data has successfully revealed the dynamics of urban land characteristics for large metropolitan areas (Eyoh et al., 2012, Deng et al., 2010)

3.3.1 Image Pre-processing

Due to the complex land-cover homogeneity in the study area, pre-processing and enhancement of the satellite images was fundamental to reduce or eliminate confusion between different spectral signatures and improve the overall images classification. First-Line of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) model was applied to improve radiometric and atmospheric correction using the ENVI 5.3 software. For the geometric correction, the common Universal Transversal Mercator (UTM) 28N zone projection was applied to all the images. Next, the three images were then imported into ERDAS to match, by means of an image-to image matching method, then resampled using the nearest neighbor algorithm with a root mean square error of less than ± 0.5 pixel per image to a 30-m spatial resolution. The study area was then extracted from the temporal imagery by overlaying the boundary of the city on visible and infrared bands of Landsat data in ArcMap10.2. Prior to the image classification using supervised classification algorithm, unsupervised classification and the normalized difference vegetation index (NDVI) were used to help in selecting appropriate polygons as training sites and improving the overall classification accuracy. The NDVI was computed by subtracting the near infrared band from the red band over the near infrared band plus the red band of each Landsat image. Figure 3.4 shows the NDVI images for 1986, 2000 and 2016 respectively. These images clearly show the degradation of the vegetation cover in the study area, it also illustrates some features found in the study area based on their spectral reflectance.

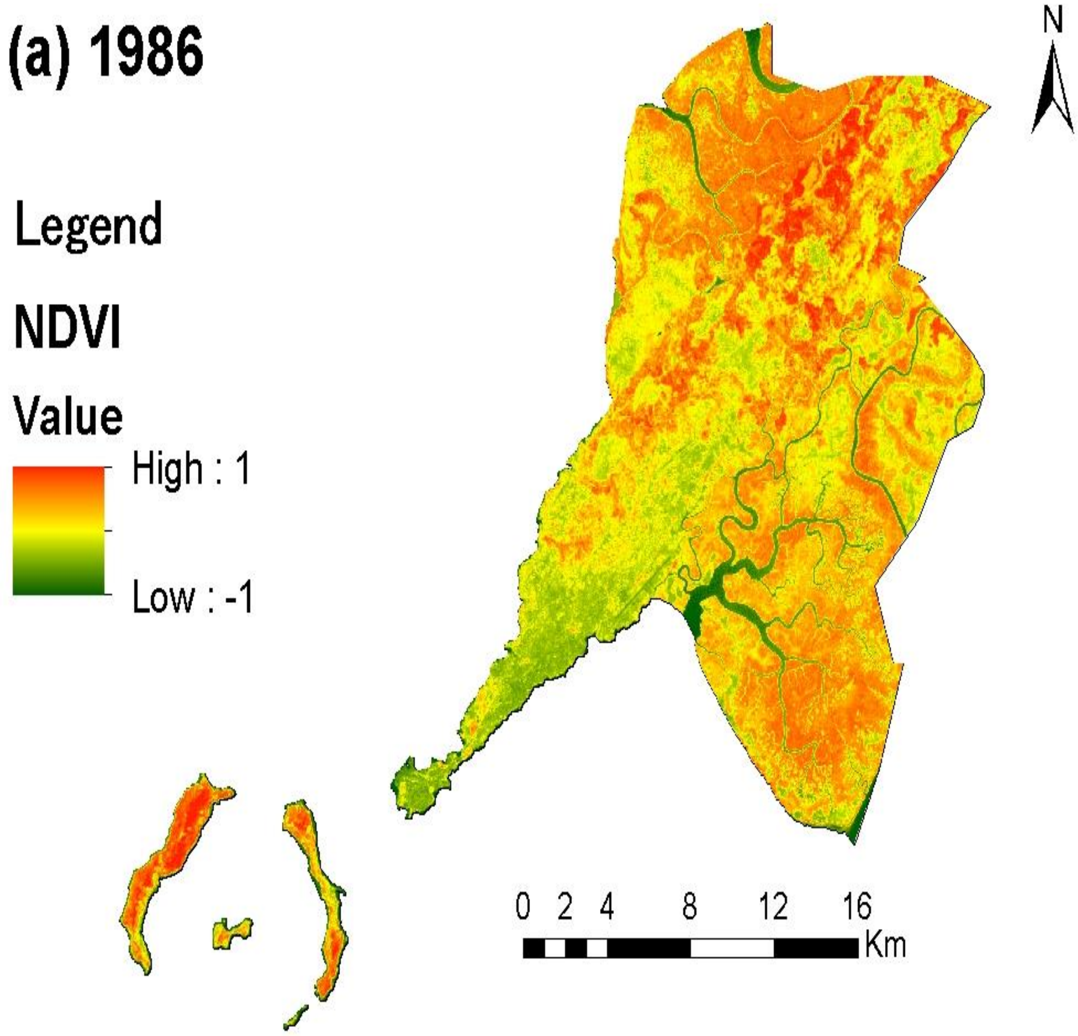


Figure 3.5 a) Normalized Difference Vegetation Index(NDVI) of the TM in 1986

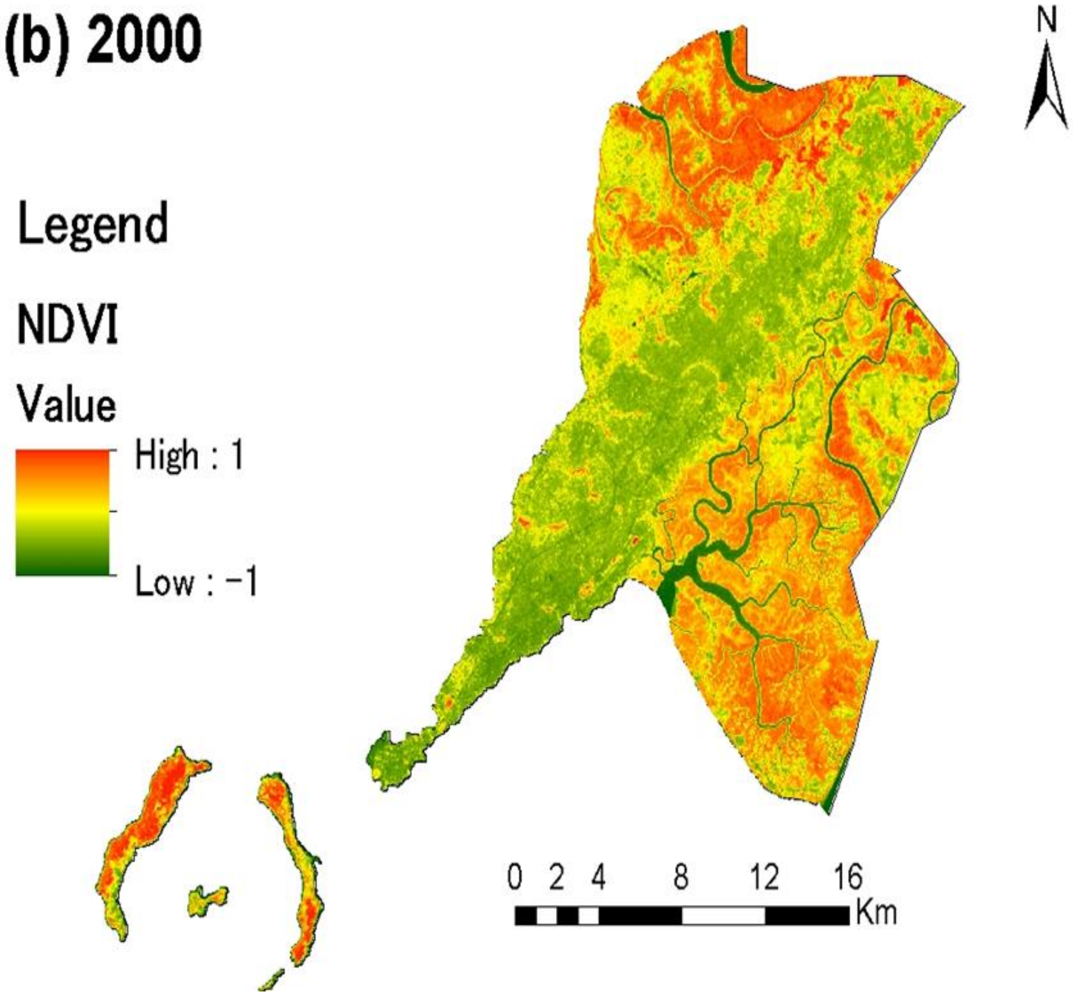


Figure 3.5 b) Normalized Difference Vegetation Index(NDVI) of t the (ETM+) in 2000

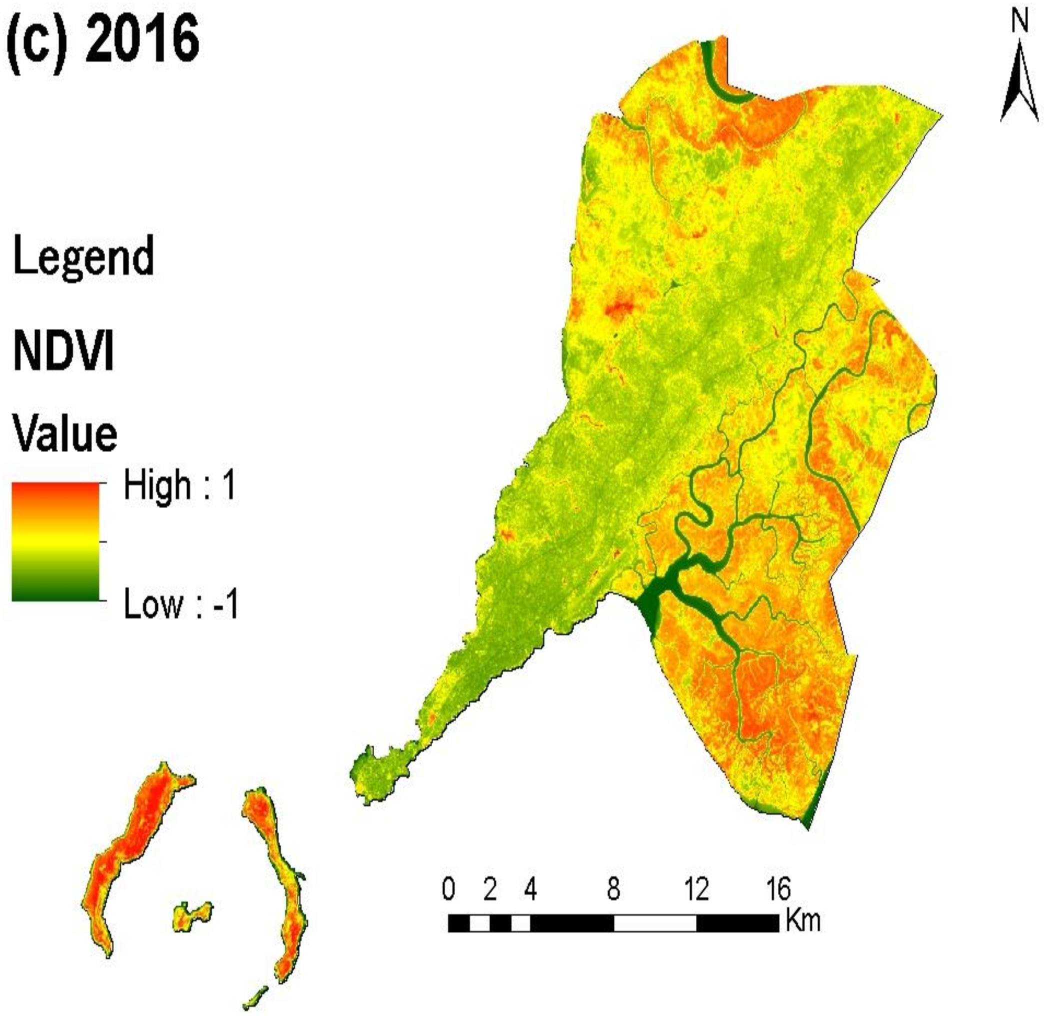


Figure 3.5 c) Normalized Difference Vegetation Index(NDVI) of t the (OLI) in 2016

3.3.2 Image classification

The spatial databases derived from remote sensing provide a strong visual portrayal of urban growth patterns, and convey how the progress of modern urbanization has caused profound changes to the landscape, which in turn have affected the environment, the microclimate patterns and the quality of human life (Xiong et al., 2012, Yuan et al., 2005). Remotely sensed data used for urban applications in urban environments characterized by highly heterogenous surface must meet certain conditions in terms of temporal, spatial, spectral and radiometric characteristics. The ideal conditions for change detection are the use of the data acquired by the same or similar sensor and recorded using the spatial resolution, viewing geometry, spectral bands, radiometric resolution, season and time of day (Dewan et al.; 2009).

In this study, the Landsat data of 1986, 2000 and 2016 were classified independently. A classification scheme was established based on ancillary information of field survey, local knowledge and visual image interpretation. Then, the images classification was conducted using the maximum likelihood classification (MLC) algorithm which is a supervised classification, and the most widely adopted parametric classification algorithm (Yuan et al., 2005, Xavier et al., 1997). A supervised classification per (Eastman.; 2012) is where the user develops the spectral signatures of known categories, such as urban or non-urban, and then the software assigns each pixel in the image to the cover type to which its signature is most comparable. For each class, 50 ground-truth polygons were digitized based on the visual interpretation of locations on Google Earth and on the image, itself. The pixels in the polygons that were selected as representative of each class was plotted in spectral space and a visual check was made that all classes could be separated in at least one combination of bands. The choice of classification method depends on the data available, knowledge about the area under investigation, and if the land-cover composition of the study area is known from field work or from other sources. Nevertheless, when there is no enough knowledge of land-cover classes, unsupervised classification may be essential (Nduwayezu, Sliuzas, and Kuffer 2017). Considering the spectral characteristics of the satellite images, and existing knowledge of land-use of the study area, four LULC categories namely: (1) Urban, (2) Water, (3) Vegetation, and (4) Bare ground were respectively identified and classified for 1986, 2000 and 2016. Table 3.4 shows the description of each LULC class considered in this study.

Table 3. 4 Land-use and land-cover classes

Class	Description
Urban	Residential, commercial, industrial, transportation, utilities, communication etc.
Water	Rivers, lakes, ponds, reservoirs, and other water bodies
Vegetation	Mangrove forests, high vegetation, reserved forest, non-reserved forest
Bare ground	Fallow land, bare exposed, parks, shrubs, area and transition

3.3.3 Accuracy assessment of the classified images

Accuracy assessment is essential for individual classification if the classification data is to be used in change detection and modeling (Hassan et al. 2016). It is the procedure used to compare the classification results to geographical reference data that are assumed to be true (Richard.; 2015). In this study, both ground control points and Google Earth images were used for the accuracy assessment of the classified images. Around 200 ground control points were collected using a handled Garmin Global Positioning System (GPS)during the field survey. In addition, a random generator in Arc Map was used to randomly generated 200 pixels (50 pixels from each class), following the recommended minimum sample size of 50 random points for each land-cover class. The comparison of classification results and reference data was carried out statistically using error matrices, the most widely used technique to assess the accuracy for classification results. In addition, a non-parametric Kappa test was also performed to measure the extent of classification accuracy as it doesn't only accounts for diagonal elements but for all the elements in the confusion matrix (Jokar Arsanjani 2012). Equally guidelines characterize Kappa coefficient over 0.75 as excellent, 0.40 to 0.75 as fair to good, and below 0.40 as poor. Finally, the classified data derived from the MLC method and reference data were compared and statistically represented in the form of error matrices. The following equation is used to compute the kappa coefficient

$$\boldsymbol{k} = \frac{N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r}(Xi + X_{x+1})}{N^2 - \sum_{i=1}^{r}(XiX_{x+1})} \tag{1}$$

Where; N is the total number of observations (pixels), r is the number of rows and columns in the error matrix, X_{ii} is the observation in row i and column i, X_{i+} is the marginal total row i, and $X_{+\,i}$ is the marginal total of column i, a kappa coefficient equal to 1 means perfect agreement where as a value close to zero means that the agreement is not better than would be expected by chance.

3.3.4 Land-use and land-cover(LULC) change detection: determining the area of change from satellite data

Digital change detection based on satellite images is a process of identifying differences in the state of an object or phenomena by observing it at various times. Basically, it involves the ability to quantify temporal effects using multi-temporal data set (Kavanagh et al. 2004). Timely and accurate change detection of land-use or land-cover is necessary to understand human interactions with the earth's features and can inform better policy decisions (Singh et al., 2013 , Li., 2014). Change detection methods from digital imagery can be broadly divided into spectral (change vector analysis, image differencing, image rationing, change vs no change binary mask) and post classification change detections. The basic premise in using remote sensing data for change detection is that changes in LULC must result in changes in radiance values, and changes in radiance due to LULC change must be large with respect to radiance changes caused by other factors, such as difference in atmospheric conditions, sun angle, and soil moisture(Singh et al.; 2013). In post-classification comparison, change detection method, two dates of images are classified independently and registered. The corresponding pixels are compared. A frequency matrix is generated to cross-tabulate the specific from-to nature of the changes between the two dates (Hu.; 2004).

3.4 Logistic Regression Model (LRM)

Spatial modeling are popular in the last two decades due to increased computing power, improved availability of spatial data, and the need for innovative planning tools to help decision making (Nong et al.; 2011). Modeling is an important tool for studying land-use change due to its ability to integrate measurements of changes in land-cover and the associated drivers (Lambin et al.; 2001a). There are mainly two groups according to the key mechanisms to simulate the process of land-use change (Hu et al.; 2010). These are rule-based process and empirical-statistic models.

Rule-based process imitate processes and often addresses the interaction of components forming a system, of which there are Cellular Automata (CA) with the great capability to handle temporal dynamic (Triantakonstantis et al.; 2012). CA focuses on micro spatial pattern, but it is difficult to reflect macro-changes affected by social and economic factors (Nong et al.; 2011). In contrast, empirical statistical models locate land-cover changes by applying multivariate regression techniques to relate historical land-use changes to spatial characteristics and other potential drivers. LRM is one of the most popular empirical-statistical approaches to modeling, and can be used for explaining the relationship of several x_i explanatory variables to a dichotomous single dependent variable y, which represents the occurrence or non-occurrence of an event (Nong et al.; 2011). This method has been widely used in land-use and land-cover change (Pontius., 2003, Eyoh et al., 2012), deforestation analysis (Arekhi et al., 2012, Linkie et al., 2004), in agriculture area changes (Balde et al., 2014, Ullah et al., 2015) etc. In the context of urban growth modeling, LRM was used to study the relationship between urban growth and socioeconomic and physical drivers (Triantakonstantis., 2012, Traore et al., 2017, Judex et al., 2003, Verburg et al., 2017). One of the advantages of this model is its ability to estimate the weights of various spatial factors by developing statistical relationships between historical urban growth and spatial factors (Abubakr et al., 2014,Kleinbaum et al., 2010).

The LRM also describes the effects of several factors (Kleinbaum et al., 2010). The use of this model can determine the coefficients of the explanatory variables (both continuous and categorical), whereas the dependent variable is a binary categorical variable (Huang et al., 2009). The value of the binary dependent variable is either 1 or 0; and can be computed by using the well-known logistic regression equation (Mahiny et al.; 2003). The model gives the probability of the existence or the nonexistence of each type of LULC change at every location based on the driving factors and quantifies the interaction between the different land-use, where x_i is the explanatory variable and logit (Y) is a linear combination function of the explanatory variables, the parameter β_i represents the regression coefficient to be estimated. The logit (Y) can be transformed back to the probability that (Y = 1)

$$\text{logit (Y)} = \beta_0 + \sum_{i=1}^{n} \beta_i \, x_i \tag{2}$$

$$P(Y = 1) = \frac{\exp(\beta_0 \ + \sum_{i=1}^{n} \beta_0 \, x_i \ )}{1 + \exp(\beta_0 + \sum_{i=1}^{n} \beta_i \, x_i)} \tag{3}$$

The typical logistic model can effectively explain the determinants of urban land conversion. This stepwise logistic regression was used to estimate the coefficients of the defined model. The dependent variable is a binary presence or absence event, where 1 = presence (occurrence of urban growth) and 0 = other. All analysis was made using pixels of 30 × 30 meters as unit of observation. Dependent and independent variables were therefore converted to a raster-based format. However, spatial autocorrelation can be expected in models in which relative location matters (Verburg et al., 2017). Regression based on dependent variable that exhibits spatial autocorrelation is influenced by the spatial structure (Triantakonstantis et al.; 2012). In this study, spatial autocorrelation or multicollinearity analysis was conducted prior to the logistic regression calibration.

3.4.1 Multicollinearity Analysis of the Explanatory variables

A correlation test was conducted among the explanatory variables to check for multicollinearity. Multicollinearity describes a situation in which two or more explanatory variables are highly; linearly correlated. Perfect multicollinearity exists if the correlation between two or more explanatory variables is equal to 1 or – 1 (Verburg et al.; 2004). One consequence of multicollinearity is that the standard errors of the affected coefficients tend to be large. In that case, the test of the null hypothesis that the coefficient is different from zero may lead to a failure to reject a false null hypothesis of no effect of the explanatory variable. In this study, using a Pearson's correlation coefficient and the variance inflation factors (VIF) assessed the multicollinearity test among the explanatory variables. Generally, a little bit of multicollinearity is not necessarily a huge problem, but severe multicollinearity is a major problem, because it basically shoots up the variance of the regression coefficients, making them unstable (Verburg et al.; 2004). Additionally, the VIF is another statistical approach to check for the presence of the multicollinearity in the regression analysis; and it has been used in many studies (Midi et al., 2010, Menard., 2004). For determining the presence of multicollinearity using the VIF technique, the general rules of thumb are that values of VIF should not exceed 10 (Abubakr et al.; 2014).

3.4.2 Statistical Test for Association between Dependent and Explanatory Variables: Cramer's V Test

The Cramer's V test measures the association between two nominal variables, giving a value between 0 and +1. The explanatory test procedure is based on a Cramer's V contingency test analysis, which can test the strength of the association between the dependent variable in this case, urban growth for the period of (1986–2000) and the explanatory variables. The test was performed using the explanatory variable test procedure in IDRISI software from the Clark Labs. Variables with a Cramer's V value of about 0.15 or higher are good, while those with values of 0.4 or higher are very good (Eastman.; 2012). Based on Cramer's test, we found a high-strength association between the dependent and some explanatory variables (Table 3.6). The variable elevation shows the highest coefficient, followed by the distance to major roads. However, the LRM can explain more explicitly the association between these variables and the dependent variable. Thus, logistic regression was implemented between the explanatory and the dependent variable to find out the weight of each explanatory variable in explaining the urban growth process in Conakry.

Table 3.6 Cramer's V test for association between dependent and explanatory variables

Explanatory variables	Cramer's V	p- value
DAEC	0.15	0.079
DUA	0.22	0.074
DIZ	0.32	0.042
DMR	0.39	0.032
DIA	0.22	0.074
PD	0.37	0.036
Slope	0.32	0.042
Elevation	0.42	0.0001

3.5 Urban growth prediction based on Cellular Automata(CA) and Markov Chain.

Models are simplifications of reality; LULC change models are tools to support the analysis of the causes and consequences of LULC change for a better understanding of the system functionality, and support land-use planning and policy (Yasmine et al.; 2015). The hybrid Cellular Automata (CA) and Markov Chain are considered as one of the best options for the analysis of LULC on different spatial scales (Hamdy et al.; 2016). By using models, the behavior and future evolution of the systems can be simulated (Zhao et al., 2016, Al-Ahmadi et al., 2011). Therefore, they can be used as interpretative tools for analyzing system dynamics, and providing hints for data collection and design of experiments (Araya et al. 2010). Cellular Automata (CA) and Markov Chain based models are dynamic model for simulating the evolution of a system using local transition rules. They are able to handle large amounts of data and in many fields of studies such as population, land-use, socioeconomic activities (Al-Ahmadi et al., 2011). CA and Markov Chain models are of special interest in modeling urban systems because of several advantages. Firstly, CA-Markov chain is a discrete dynamical system, and its structure offers a capacity for modeling dynamic and complex spatial system (Wolfram.; 2010). Secondly, they can be easily incorporated with GIS and RS because they operate on lattice, raster-format geographic data (Deep. 2014) and consequently, they can work at high spatial resolution with computational efficiency. Thirdly, the model's results are a set of land-use maps, which are easily be visualized, quantify, and analyzed (Hamdy et al. 2016). These models have two distinct types of important tasks: simulation and optimization. Simulation aims to develop realistic scenarios under specific conditions, whereas optimization is to provide an optimal solution for planning problem. By combining simulation with optimization, these models can assist planners in predicting the consequences of changes occurring under different conditions (Liu et al.; 2011) simulation of future LULC change based on CA-Markov Chain

In this study, we develop a LULC change analysis scenario to project LULC of 2016. This is accomplished by analyzing a pair of LULC maps of 1986 and 2000 using Markov module in Idrisi software, which will then output a transition probability matrix, a transition areas matrix and a set of conditional probability images. The transition probabilities matrix records the probability that each LULC category will change to every other category. This matrix is the result of cross-tabulation of the two images adjusted by the proportional error. The transition areas matrix records the number of pixels that are expected to change from one LULC class to another LULC class over the next time (Jönsson et al.; 2002). This matrix is produced by multiplication of each column in the transition probability matrix by the number of cells of corresponding LULC in the later image. In both files, the rows represent the older LULC categories and the columns represent the newer categories. Markov chain is developed into an essential predictive approach in geographic research and simulations due to its features of descriptive power, simple trend projection of LULC transition (Liu and Phinn 2001). Let C_t be a vector of LULC distribution at time t. The LULC distribution at time $\mathrm{t}+1$, C_{t+1} is given by

$$C_{t+1} = M.C_t \tag{4}$$

Where: M is an $\mathrm{m \times m}$ transition matrix whose elements p_{ij} is the probability of transition from one land-cover i to j within the interval t to $\mathrm{t}+1$. The p_{ij} is usually derived by diving each element x_{ij} in the change/no change matrix by its marginal row total.

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^{q} x_{ij}} \tag{5}$$

The distribution of land-cover after n time periods is made powering matrix M:

$$C_{t+1}^{n} = M^{n} C_{t} \tag{6}$$

A major advantage of the Markov modeling technique is its operational simplicity and the ability to provide projection of LULC change with minimum data requirement (Braimoh and Vlek 2004). This is particularly relevant for the study area, because historical data on land-use is virtually nonexistent. Once a transition matrix has been created, it only requires the current LULC information to project the future LULC distribution. However, one inherent problem with the Markov analysis is that it provides no sense of geography. The transition probability may be accurate on a per category basis, but there is no knowledge of the spatial distribution of occurrences within each LULC category, in other word, there is no spatial component in the modeling outcome (Jönsson et al.; 2002). The combination of Markov chain and Cellular Automata (CA-Markov) allows simulating the evolution of the geographical area represented by pixels. Each pixel can take a value from finite set of states. All pixels are affected by a transition function that takes an argument the measured values and values of the neighboring pixels as a function of time. In this study, the transition function was determined based on the difference between 2000 and 2016. CA-Markov then used this transition function to predict the urban growth for 2025. In order words, the transition probability matrix, created from the changes observed between 2000 and 2016, the transition probability maps of 2016 and each scenario were used to produce maps of the urban growth of 2025. In an iterative process, CA-Markov uses the transition probability maps of each land-cover type to establish the inherent suitability of each pixel to change from one land-cover to another. To assign a weight of suitability to the pixels that are away from the pixel analyzed, a 5 x 5 filter was used (Figure 3.5). Since it is considered that the probability of changes during the years analysis stays constant, any year after 2016 can be projected (Jönsson et al.; 2002). However, projections in the short term are more realistic than projections in the long term, so we run the simulation until 2025. CA-Markov model, as rule based simulation model is one the most widely used simulation model that consists of a lattice of discrete cells. Based on the transition rules and neighborhood cell state, the cell determines whether or not to change from one state to another (Nong et al.; 2011). One of the advantages of CA-Markov model is that it is inherently spatial and dynamic(Carvalho et al.; 2015). In addition, it is simple and highly acceptable. However, CA-Markov model focuses on the simulation of spatial pattern rather than interpretation of the spatial and temporal processes of the land-use change. Its output gives a map showing land-cover pattern.

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Figure 3.6 5×5 filter used in the CA-Markov prediction.

4. Results

4.1 Post classification of the LULC change

To assess the spatial and temporal LULC change in Conakry, a post-classification analysis through pixel by pixel comparison was conducted in Arc Map10.2 using classified LULC maps of 1986, 2000 and 2016 respectively. The quantitative result of this analysis is shown in Table 4.1 including the area and proportion changes of each class. From the overall trends, the intense LULC occurred in Conakry over the period of study, was mainly characterized by a significant increase in urban area and a substantial decrease in vegetation and bare ground cover respectively. The vegetation class (i.e., mangrove forests, high vegetation, reserved forest, non-reserved forest) was the most dominant land-cover type in 1986 representing up to 51% of the total area; followed by bare ground (27%) (i.e., fallow land, bare exposed, parks, shrubs, area and transition), urban (i.e., residential, commercial, industrial, transportation, utilities, communication) (15%), and water 5% (i.e., rivers, lakes, ponds, reservoirs, and other water bodies) respectively.

The area under vegetation decreased from 52% (217.48 km^2) in 1986 to 35% (147.32km^2) in 2016, with an annual decrease rate of 0.57% in the first period (1986-2000) and 0.50% in the second period (2000-2016) respectively. The area under bare ground area decreased from 27% (114.76 km^2) in 1986 to 9% (39.88km^2) in 2016, with an annual decrease rate of 0.35%, in the first period (1986-2000) and 0.81% in the second period (2000-2016). The area under urban has increased from15% (63.03 km^2) in 1986 to 49% (206.58 km^2) in 2016 with an annual increase rate of 1% in the first period (1986-2000) and 1.25% in the second period (2000-2016) respectively.

The area under water showed a slight increase 5% (24.63 km^2) from 1986 to 6% (26.10 km^2) in 2016 due to seasonal variation and the geographical location of the study area, as a coastal city. Figure 4.1 shows the area in percentage change, while Figure 4.2 shows the LULC change maps for the three years study period 1986, 2000 and 2016 respectively. To further illustrate the results of land changing in each LULC class, Figure 4.3 shows the changing patterns in each LULC class over the 30 years study period.

Table 4.1 Observed LULC area change in Conakry between 1986, 2000 and 2016

Year	**1986**		**2000**		**2016**	
LULC	Area (km2)	Area (%)	Area (km2)	Area (%)	Area (km2)	Area (%)
Urban	63.03	0.15	123.76	0.29	206.58	0.49
Water	24.63	0.05	21.80	0.05	26.10	0.06
Vegetation	217.48	0.52	181.86	0.43	147.32	0.35
Bare ground	114.76	0.27	92.49	0.22	39.88	0.09
Total	419.90	1.00	419.90	1.00	419.90	1.00

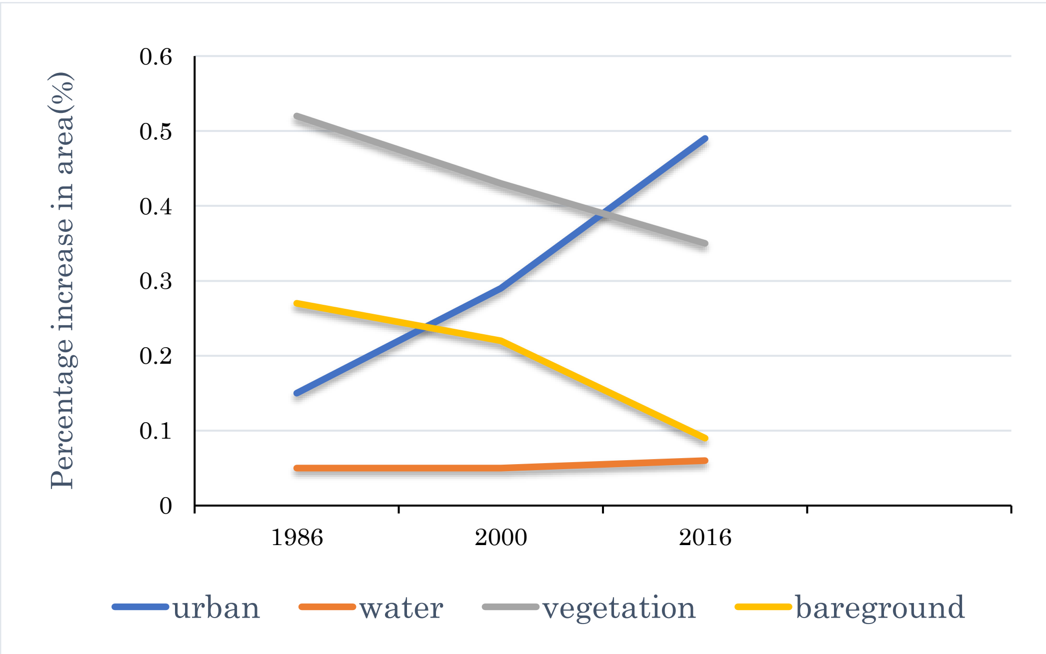


Figure 4.1 Percentage area changes in Conakry in 1986, 2000 and 2016.

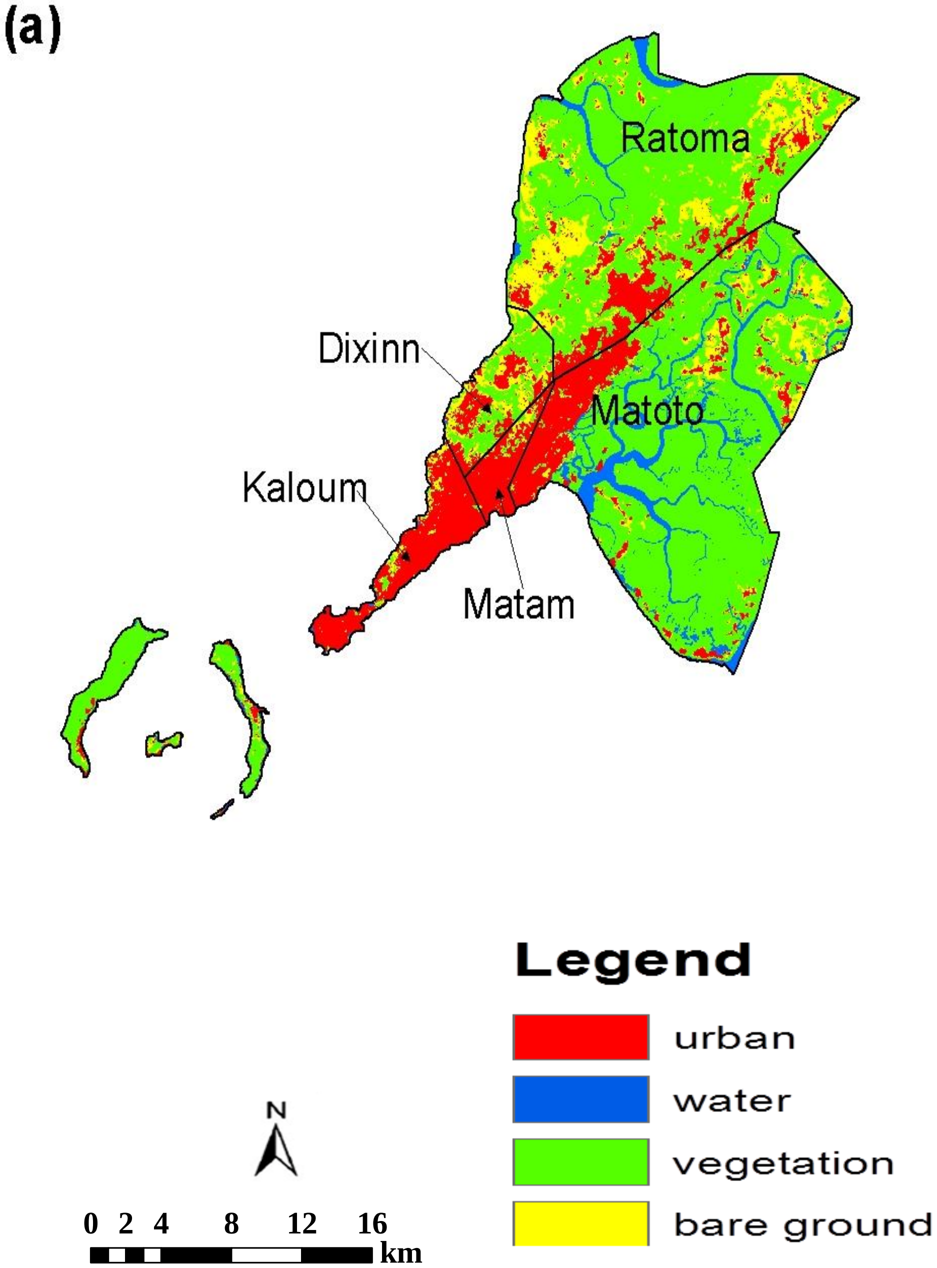


Figure 4.2 a) Land-use-land-cover map for the year 1986

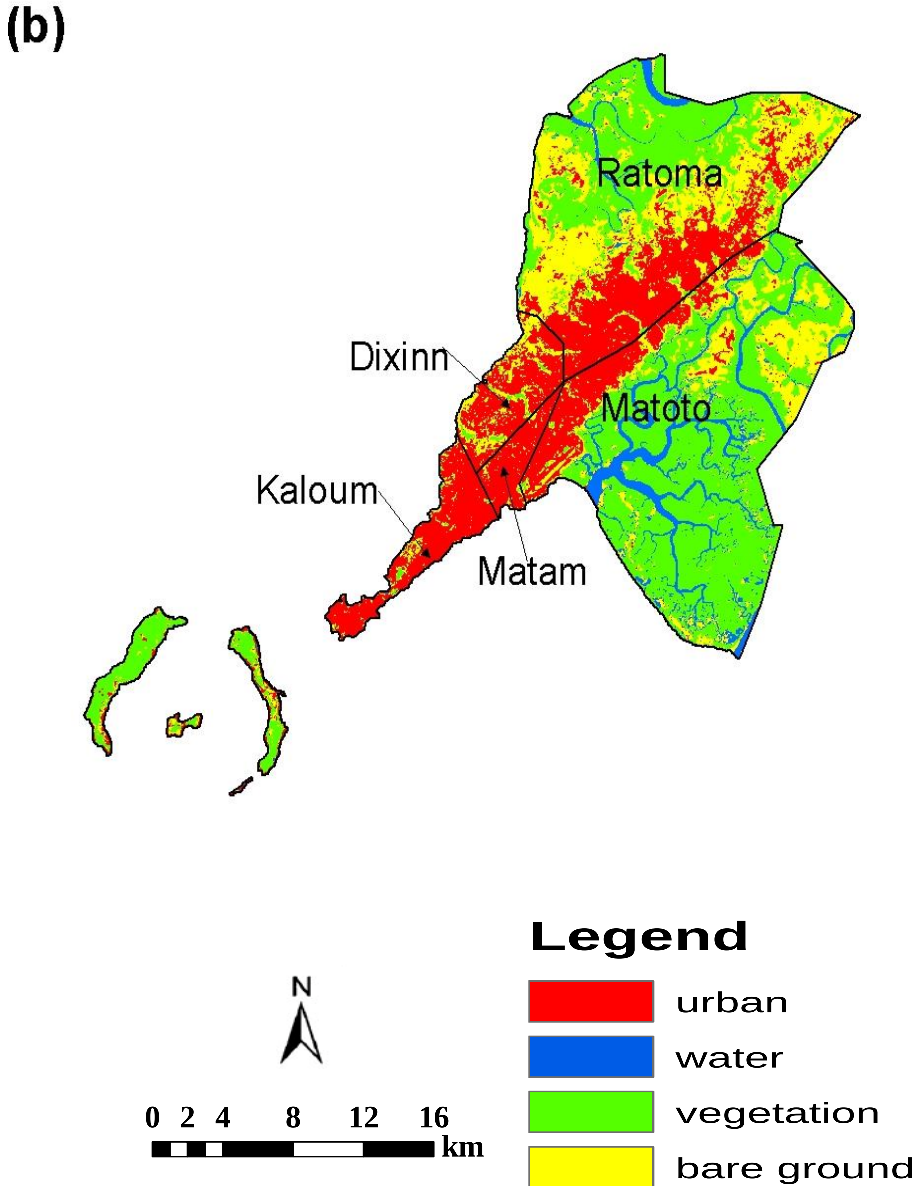


Figure 4.2 b) Land-use-land-cover map for the year 2000

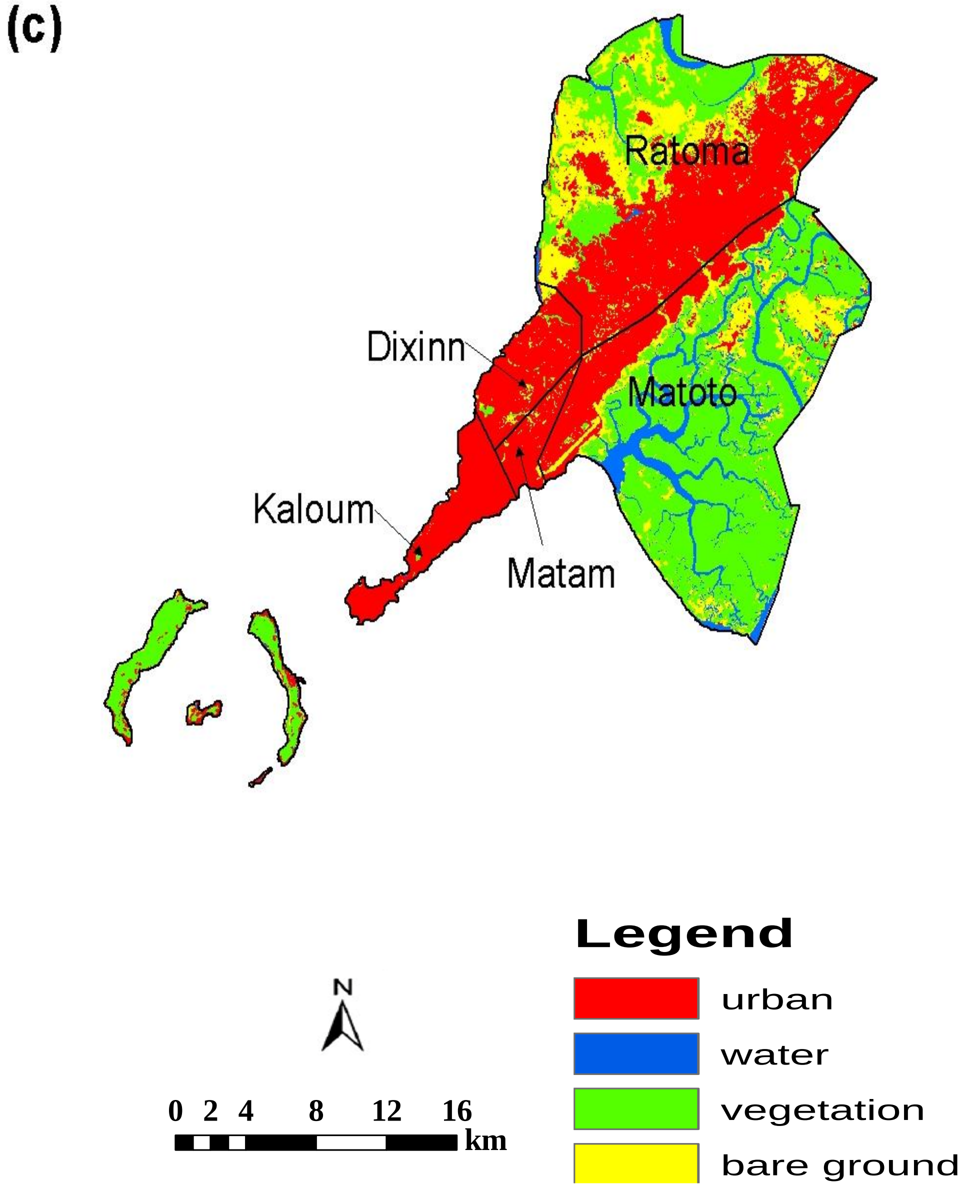


Figure 4.2c) Land-use-land-cover map for the year 2016

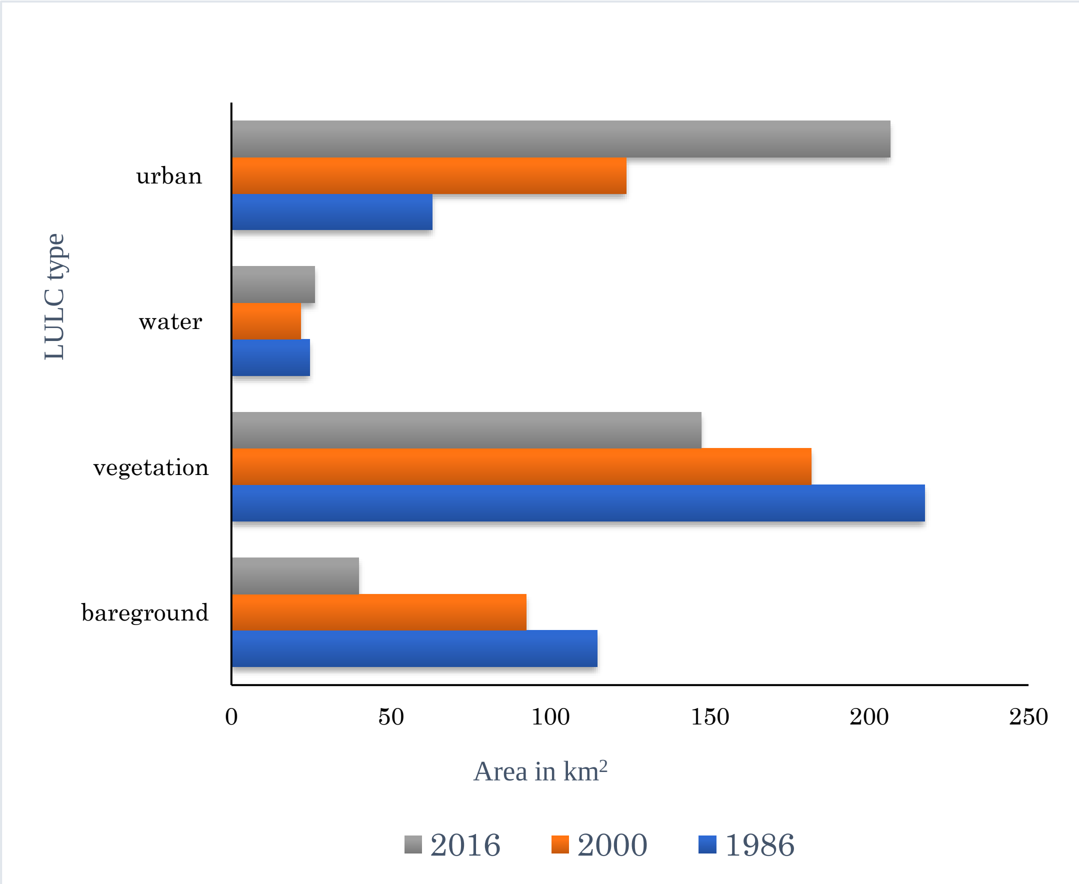


Figure 4.3. Changing pattern in LULC over in the study area.

4.1.1 Accuracy assessment of the LULC classification

Accuracy assessment is an important part of any classification project. It compares the classified image to another source that is assumed to be correct (Mcgee, Campbell, and Parece 2014). This task is accomplished by compiling an error matrix. An error matrix is a table of values that compares the value assigned during the classification process to the actual value from an image that is assumed to be correct. A vital component of accuracy assessment, Cohen's kappa coefficient is calculated from error matrix. As mentioned in section 3.3.4, Kappa tells us how well the classification process was performed as compared to just randomly assigned values. Tables 4.2, 4.3, and 4.4 show the results of the accuracy assessment of the three classified LULC maps 1986, 2000 and 2016 respectively. The overall accuracy varies from 0.79 to 0.88 and the kappa coefficients vary from 0.72 to 0.83. These accuracies meet the minimum USGS total accuracy set out by Anderson et al. (1976), hence the classified results can be used as data source for post classification comparison and further analysis.

Table 4.2. Error matrix of the 1986 classified land-cover map of Conakry

	Reference image					
Classified image	Urban	Water	Vegetation	Bare ground	Total Row	User's accuracy (%)
Urban	48	3	3	4	58	83
Water	2	39	4	3	48	81
Vegetation	4	3	45	2	54	83
Bare ground	6	3	1	30	40	75
Total column	60	48	53	39	200	
Producer's accuracy(%)	80	81	85	77		
Overall accuracy:				0.81		
Kappa coefficient				0.75		

Table 4.3 Error matrix of the 2000 classified land-cover map of Conakry

	Reference image					
Classified image	Urban	Water	Vegetation	Bare ground	Total Row	User's accuracy (%)
Urban	46	3	5	5	59	78
Water	3	38	2	3	46	83
Vegetation	3	2	39	7	51	76
Bare ground	1	3	5	35	44	80
Total column	53	46	51	50	200	
Producer's accuracy (%)	87	83	76	70		
Overall accuracy				0.79		
Kappa coefficient				0.72		

Table 4.4 Error matrix of the 2016 classified land-cover map of Conakry

	Reference image					User's accuracy(%)
Classified image	Urban	Water	Vegetation	Bare ground	Row Total	
Urban	49	2	1	2	54	91
Water	2	42	2	1	47	89
Vegetation	3	2	45	2	52	87
Bare ground	2	3	2	40	47	85
Total column	56	49	50	45	200	
Producer's accuracy(%)	88	86	90	89		
Overall accuracy				0.88		
Kappa coefficient				0.83		

4.2 Logistic Regression Model (LRM)

A logistic regression model was used to associate the urban growth with socioeconomic and physical driving forces and to generate the urban growth probability map. This regression model is useful for situation that predicts the presence or absence of a characteristic or outcome based on values of a set of predictor variables (Eyoh et al.; 2012). Prior to running LRM, the multicollinearity test was checked by using the hierarchical cluster analysis with a Pearson correlation coefficient (Table 4.5). This analysis showed any multicollinearity problem, suggesting that the variables are independent from each other. Table 4.6 shows the result of LRM including the estimated coefficient, standard error, odds ratio, z value, and p-value of the 6 explanatory variables. The negative sign of the distance variables indicates that decreasing the distance, increase the probability of urban growth occurrence inversely (Abubakr et al.; 2014,Hu.; 2004). From the model result, it seems that the urban growth tends to occur near existing urbanized areas. Distance to urbanized areas (X_2) has a coefficient of -0.001 and a p value less than 5 percent. Suggesting that decreasing the distance to an urbanized area, increase the probability of urban growth. This would be expected due to the Conakry's limited urban services, proximity to an existing urbanized area increase the benefit like ease of access to urban services.

Distance to major roads (X_3) exhibits a coefficient of -0.380 and a p value less than 1%, suggesting high probability of urban growth in areas near major roads. This result demonstrates that access to roads has high influence on urban growth in Conakry. As transportation roads open the access of city to the countryside and responsible for linear branch development (Thapa et al.; 2010), increase the accessibility of land and decreases the cost of construction (Cheng.; 2014). Transportation systems also provide mobility for people and goods, and they influence patterns of growth as well as the level of economic activity through the accessibility that they provide to the land (Meyer et al.; 1992).This result is also supported by the study conducted by the World Bank in accessing urban services and poverty in Conakry. The World Bank found that living far away from major roads greatly reduce the chance in accessing urban services including paved roads, pipeline water, electricity (World Bank.; 1984). Several other studies have revealed that accessing in transportation infrastructure as one of the main urban growth driving forces (Bhatta et al., 2010, Eyoh et al., 2012, Abubakr et al., 2014). Proximity factors are widely mentioned in most of the literature. The area which is in the proximity to infrastructure, major roads, and public services tend to growth in future due to potential benefits like ease of access, economic opportunities, social services etc.

Population density (X_6) has a coefficient of 0.048 and a p value less than 1 % suggesting that increase in population density, will increase urban growth development in Conakry. As population growth creates rapid urban land demand, therefore leads to urban growth as most land will be required to satisfy further growth of urban population. Population density is often established as land-use determinants to indicate labor availability, accessibility, or presence of local markets (Nong et al.; 2011)

Slope (X_5) and Elevation (X_6) have coefficients 0.017 and 0.106 and p values less than 5% and 1% respectively, illustrating that slope and elevation influence urban growth in Conakry. This result illustrates the physical condition of the study area as a coastal city, surrounded with several rivers and wetland zones, therefore urban development maybe not be suitable for low slope and low elevation areas. Figure 4.4 shows the urban growth probability map generated from the LRM. As it can be observed from this figure that the dark green color shows very low probability area, the green color indicates low probability areas, the yellow color shows moderate areas, and the red color shows a very high probability area. However, as it is also important to notice that although LRM based analysis is one of the most applied models in modeling and predicting, LULC but it is not temporally explicit. Its output probability map can only answer where urban development can occur, but cannot answer when and how much will changed. On the other hand, the hybrid Cellular Automata and Markov chain models can predict the quantity of LULC change (Hu.; 2004).

Table 4.5 Correlation Coefficients and the Variance Inflation Factors (VIF) of the explanatory variables.

Variable	DAEC	DUA	DMR	PD	Slope	Elevation
DAEC	1	-0.16	0.38	-0.04	-0.06	0.01
DUA		1	-0.32	0.22	0.03	0.22
DMR			1	-0.48	0.12	-0.32
PD				1	-0.00	0.49
Slope					1	0.39
6Elevation						1

Table 4.6 Statistics coefficients of the 8 explanatory variables included in the LRM model

Variable		Coefficient	Std.Error	Odds ratio	z value	p-value
Intercept		-4.611	0.529	0.009	-8.701	<2e-16***
(DAEC)	X_1	0.540	0.059	1.716	9.092	<2e-16***
(DUA)	X_2	-0.001	0.000	0.999	6.631	0.03679*
(DMR)	X_3	-0.380	0.026	0.681	-14.643	<2e-16
(PD)	X_4	0.048	0.008	0.952	-5.736	4.8e-09
(Slope)	X_5	0.017	0.005	1.018	3.123	0.00179**
(Elevation)	X_6	0.106	0.009	1.112	11.056	<2e-16***

Significance Codes: 0 “*** “0.001, “**” 0.01, “*” 0.05, “. “0.1, ““1

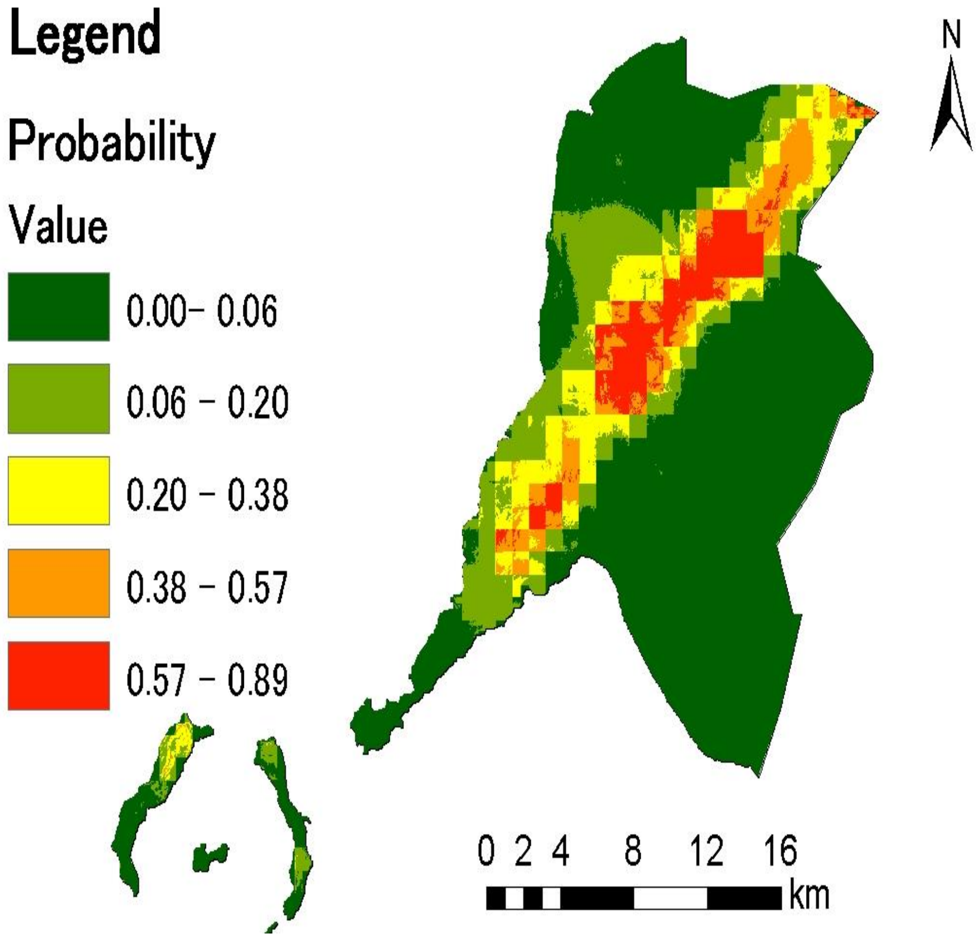


Figure 4.4 urban growth probability map of Conakry for 2000.

4.2.1 Validation of the LRM based on the Relative Operating Characteristic (ROC)

The ROC method is an excellent technique for assessing the validity of a model that predicts the location of the occurrence of a class by comparing a suitability image depicting the likelihood of that class occurring. This method has been applied in LULC modeling studies and is considered as reliable method to validate models (Pontius et al.; 2001). It calculates the percentages of false-positives and true positives for a range of thresholds or cut-off values, relating them in a chart. The ROC computes the area under the curve, which varies between

0.5 and 1.0. A value of 0.5 indicates a random assignment of the probabilities, indicating that the expected agreement is due to chance, while a value of 1.0 indicates a perfect assignment of probability. It has been shown that an ideal spatial agreement can exist between the actual urban growth and the predicted urban growth probability map (Pontius and Schneider 2001). In this study, the model validation was conducted by comparing the simulated map of 2000 from the logistic regression with the actual urban growth of 2000 using random samples of 5000 cells in both maps. The ROC curve is based on several two-by-two contingency table. The contingency table is based on the comparison between the actual and the predicted probability image. Table 4.7 shows the contingency table. 'A' is the number of true positive cells; which are predicted as urban growth and agree with the actual image. 'B' is the number of false positive cells; predicted as urban growth but disagreeing with the actual image. 'C' is the amount of false negative cells; which are predicted as non-urban growth but disagree with the actual map. 'D' is the number of true negative; cells, which are predicted as non-urban growth and agree with the actual image. From every contingency table, a single data point (x, y) is created, where x and y are the rate of false positives and the rate of true positives, respectively.

(True positive %) = A/ (A + C)
(False positive %) = B/ (B + D)

Those data points are joined to form the ROC curve, from which the ROC value is computed. The ROC curve is illustrated in Figure 4.5, the ROC value shows 0.89% of the area under the curve (AUC), indicating high agreement between the predicted and the actual urban growth map

Table 4.7 Two by two contingency table showing the number of grid cells in actual map versus a predicted map.

		Actual map		Total
		Urban growth (1)	No-urban growth (0)	
Predicted map	Urban growth (1)	A	B	A+B
	No-urban growth (0)	C	D	C+D
	Total	A + C = 103639	B + D = 1619591	A + B + C + D = 1,723,230

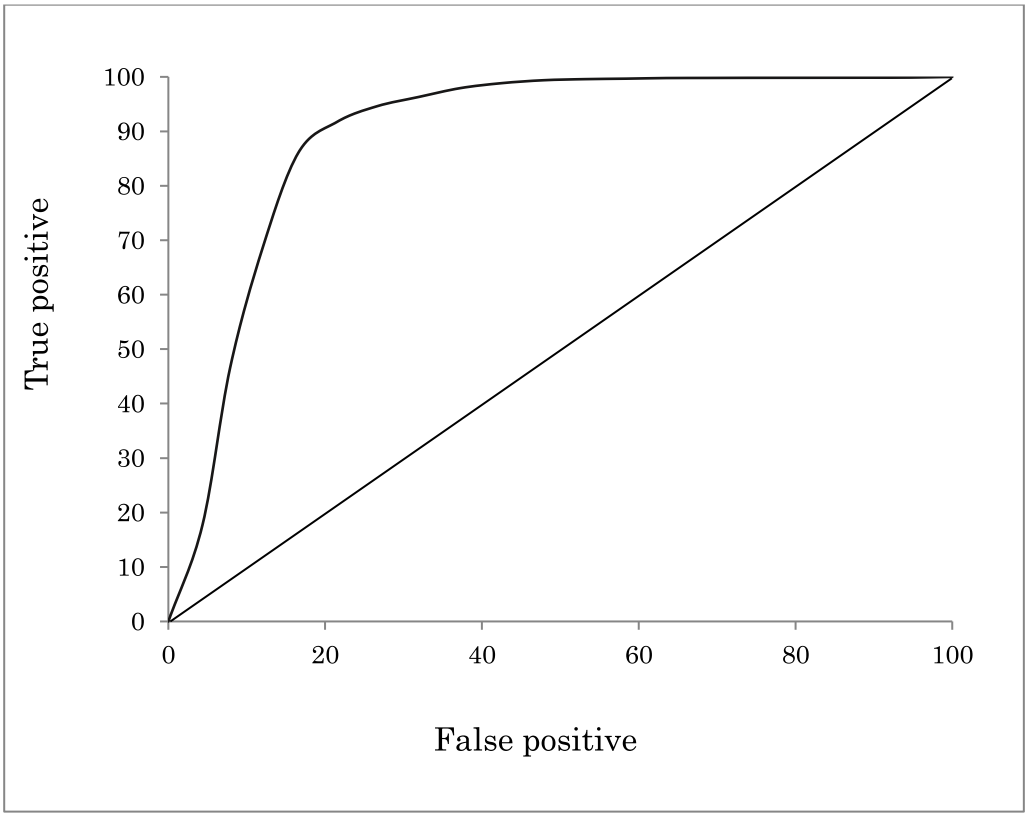


Figure 4.5 Relative operating characteristic (ROC)

4.3 Markov models and the transition probability matrices

The two techniques used in this study to predict future LULC in Conakry are based on Markov and Cellular Automata (CA) model. Markov model was firstly applied by using the LULC maps of 1986 and 2000 to generate the transition probability matrix (Table 4.8) and conditional probabilities maps of 2016 (Figure 4.6). The transition probability matrix records the number of pixels anticipated to change from one land-use category to another. From Table 4.8, the diagonal elements represent the no-change probability of transition. Probability of transition from water to urban is 0.016, probability of transition from vegetation to urban is 0.326 and the probability of transition from bare ground to urban is 0.127 respectively. This result shows that vegetation class has the highest probability of transition to urban. However, one inherent problem with the Markov model is that it provides no sense of geography. The transition probabilities may be accurate on a per category basis, but there is no knowledge of the spatial distribution of the occurrence within each land-use category, i.e., there is no spatial component in the modeling outcome (Jönsson et al.; 2002). Therefore, we used Cellular Automata (CA) to add a spatial character to the model, and predict urban growth by 2025 using the transition probability matrix (Table 4.8) and the conditional probabilities of change maps (4.6).

Table 4.8 Transition probability matrix 2000-2016

	Probability of transition				
From/ To	Urban	Water	Vegetation	bare ground	Total
urban	0.936	0.000	0.000	0.063	1.000
water	0.016	0.862	0.108	0.011	1.000
vegetation	0.326	0.096	0.459	0.117	1.000
bare ground	0.127	0.051	0.000	0.821	1.000

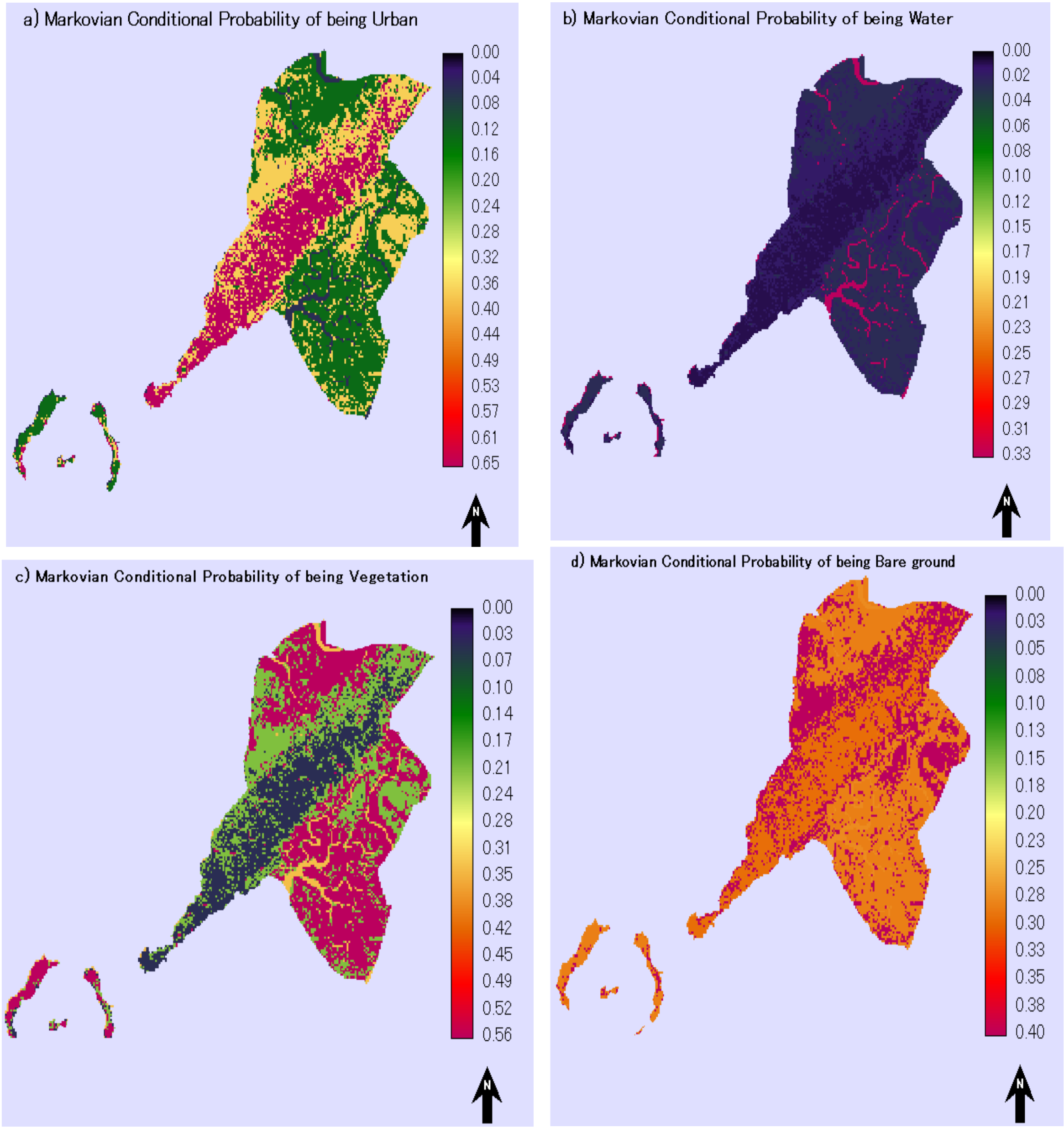


Figure 4.6 Markovian conditional probability of changes in 2016

4.3.1 Accuracy assessment of the Predicted Markov model based on ROC

The ROC (relative operating characteristic) is an excellent method to compare a Boolean map of “reality” versus a suitability map. Thus, the ROC is included here as an excellent statistic for measuring the goodness of fit of the predicted Markov model map in this case the Markovian probability of being urban (Figure 4.6 a), and the binary urban growth map from 2000 to 2016 (Figure 4.7). The ROC value ranges from 0 to 1, where 1 indicates a perfect fit and 0.5 indicate a random fit(Pontius et al.; 2001). The result of ROC was 0.92, which is a very strong value and indicates that the soft prediction was very accurate. The ROC curve is shown in Figure 4.8.

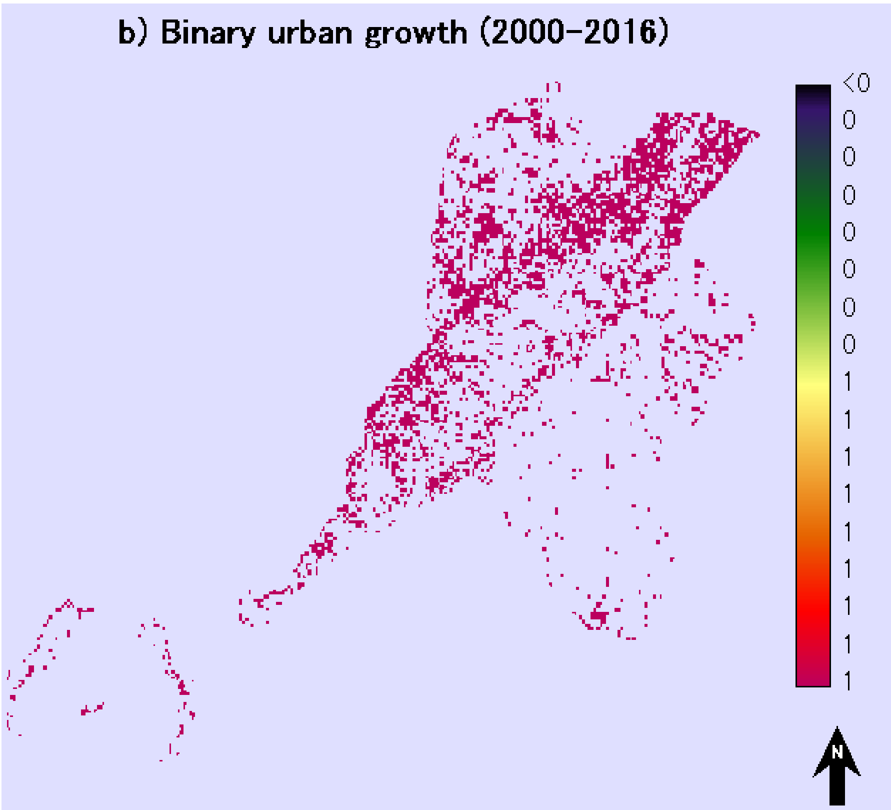


Figure 4.7 binary urban growth from 2000 to 2016

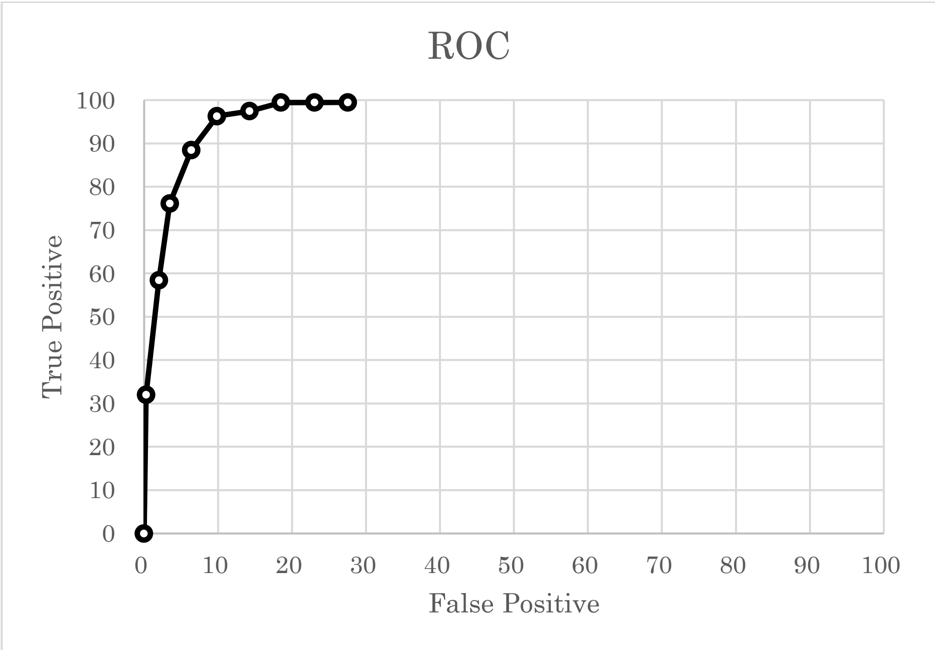


Figure 4.8 Relative Operating Characteristic(ROC) showing agreement between the two maps

4.3.2 Future LULC patterns in Conakry based on CA-Markov model

A cellular automaton is an agent or object that can change upon the application of rule that relates the new state to its previous state and those of its neighbors (Jönsson et al.; 2002). Cellular automata analysis was carried out by the module of CA-Markov in the Idrisi software. The LULC projection for the year 2025 was conducted based on the transition probability matrix between 2000 and 2016 (Table 4.8) and Markovian conditional probability maps (Figure 4.6). The predicted LULC for 2025 is shown in Figure 4.9 and the spatial and temporal distribution of the 2025 LULC is presented in Table 4.9. From Table 4.9, it seems that urban area will continue to increase at the expense of vegetation. The area under urban represented 49% (206.58km^2) of the total area in 2016, and it is predicted to reach 52% (218.32km^2) in 2025. Vegetation will decrease from 35% (147.32km^2) in 2016 to 32% (134.68km^2) in 2025 respectively. Bare ground shows almost no change in its area. In contrast water will slightly increase (Table 4.9).

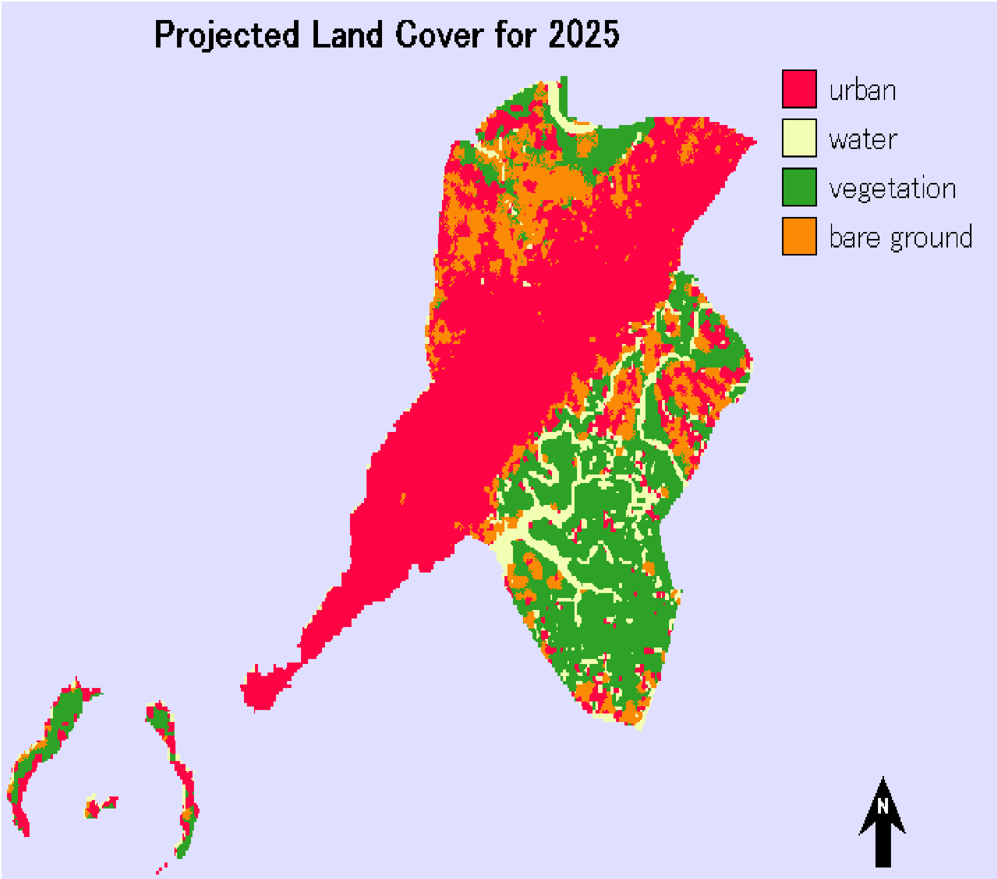


Figure 4.9 CA-Markov Chain predicted LULC map for Conakry 2025

Table 4.9 Spatial and temporal areas change based on CA-Markov from 2016-2020.

Year	2016		2025	
LULC	Area (km2)	Area (%)	Area (km2)	Area (%)
Urban	206.58	49	218.32	52
Water	26.10	6	29.04	7
Vegetation	147.32	35	134.68	32
bare ground	39.88	9.49	37.80	9
Total	419.90	100	419.90	100

4.4 DMSP/OLS Nighttime Light (NTL) Data

Recently, there has been an increased interest of using nighttime images of Earth that show visible light emissions, providing a picture of urbanization in cities (Small et al.; 2011). Mapping urban areas at global and regional scales is an urgent and crucial task for detecting urbanization and human activities throughout the world and is useful for discerning the influence of urban expansion upon the ecosystem and the surrounding environment (Jing et al. 2015). The operational Line scan System (OLS) sensor carried by the Defense Meteorological Satellite Program (DMSP) has provided a new data approach for the study of urbanization at a large scale (Ma et al., 2016, Sutton et al., 2001). The scanning in DMSP/OLS is different from that of Landsat TM, SPOT, HRV and NOAA AVHRR sensors, which use the reflection and radiation of surface features against the sunlight (Yi et al. 2014). Due to the unique capability of DMSP-OLS to detect low levels of visible and near-infrared nighttime radiance signal, the composed stable nighttime light data have been used for mapping urban areas (Jing et al., 2015, Ma et al., 2016), estimates the spatial sprawl trends of cities by measuring socioeconomic activities and dynamics (Elvidge et al., 2012), and used to map aggregated measures of urban areas such as total area extent (Yi et al. 2014). Furthermore, previous studies have commonly suggested that DMSP/OLS night radiance data could be indicative of urbanization-related socioeconomic activities, especially in the absence of census data (Jing et al., 2015, Sutton et al., 2001, Ma et al., 2016).

Highly urbanized areas are associated with larger populations and more intense socioeconomic activities than less-developed regions. It can be inferred that cities with similar populations and economic parameters should present homogenous intensity of human activity, which could be observed using the nighttime light data. Although the urbanization evaluation methods based on statistical data increase the scientific studies on urbanization, the statistical data lacks spatial characteristics, which confine this method to the field of demography and regional economic (Yi et al.; 2014). Thus, the crucial spatial characteristic of urbanization cannot be expounded and proved effectively. Given its easy access, low cost and integrity of spatial cover, the long-term DMPS/OLS night light data, therefore offer immense potential as a supplement to census, and statistical socioeconomic datasets for estimating spatial and temporal equality of cities at multiple scale. Moreover, although nighttime light (NTL) data do not measure land-cover directly, and many non-urban places are light at night, including agricultural fields and fishing vessels, it has been shown to be strongly correlated with population density (Xin et al., 2017,Yi et al., 2014).

To further illustrate the effectiveness of the urban expansion in Conakry, the DMSP/OLS Nighttime Lights time series Version 4 data between 1992 and 2013 were freely downloaded from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NOAA/NGDC). Which were acquired by four DMSP satellites including F10, F14, F15, and F18. These images are grid-based annual data compositions with a 0-63 digital number (DN) and a 30 arc-second (approximately 1 km at the equator) spatial resolution for pixels.

The nighttime light data provide a consistent and timely measure to characterize distinct categories of urbanization processes. This satellite derived observations of anthropogenic brightness at night have been universally regarded as effective proxy measures of urban dynamics to significant quantitative relationships between nighttime lighting signals and demographic and socioeconomic variables in relation to urbanization process at local scales (Ma et al. 2016). In comparison with statistical data and land-use maps, continuous surveys of nighttime lights can provide consistent and spatially explicit information regarding human activities and urban development (Elvidge et al., 2015, Sutton et al., 2001).

Figure 4.10 shows the nighttime light data (NTL) of Conakry from 1992 to 2013. The range of Digital Number (DN) values of each pixel is 0-63. The DN value directly indicates the intensity of the area's light (Ma et al. 2016). The DN value of the pixels in non-light areas is zero. A pixel with a DN value of 63 is a saturation pixel and most of saturation is found in the core urban area (Letu et al. 2012). The nighttime light grid data images record the light intensity (indicated by DN value) and spatial extent information of cities (indicated by the light pixel counts)(Xin et al. 2017).

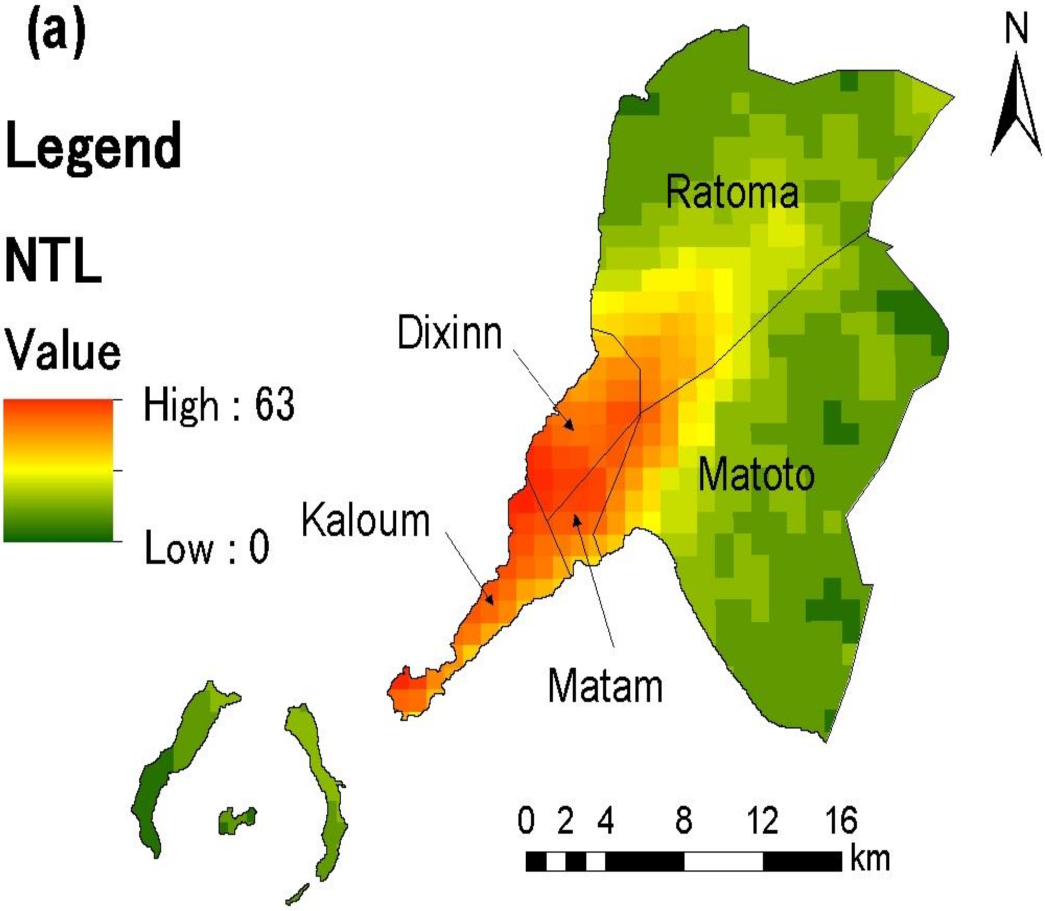


Figure 4.10 a) Nighttime light image of Conakry in 1992

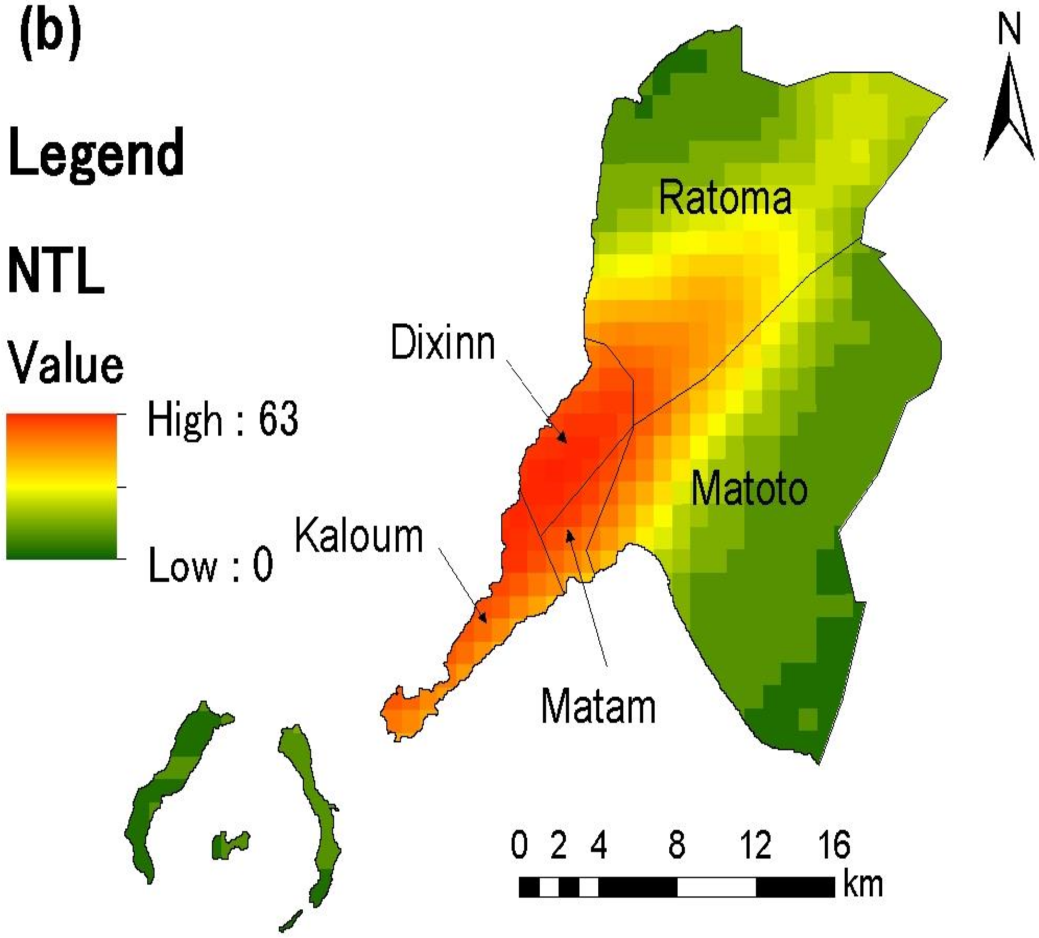


Figure 4.10 b) Nighttime light image of Conakry in 2000

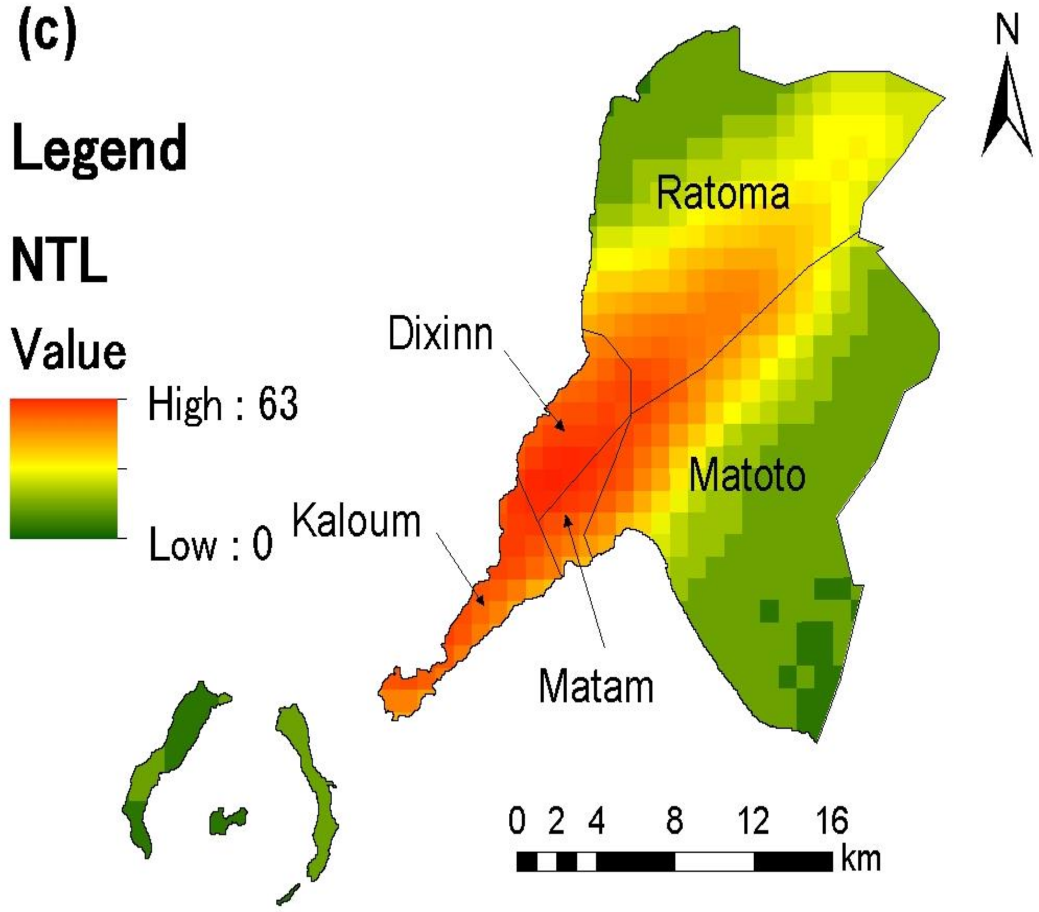


Figure 4.10 c) Nighttime light data of Conakry in 2005

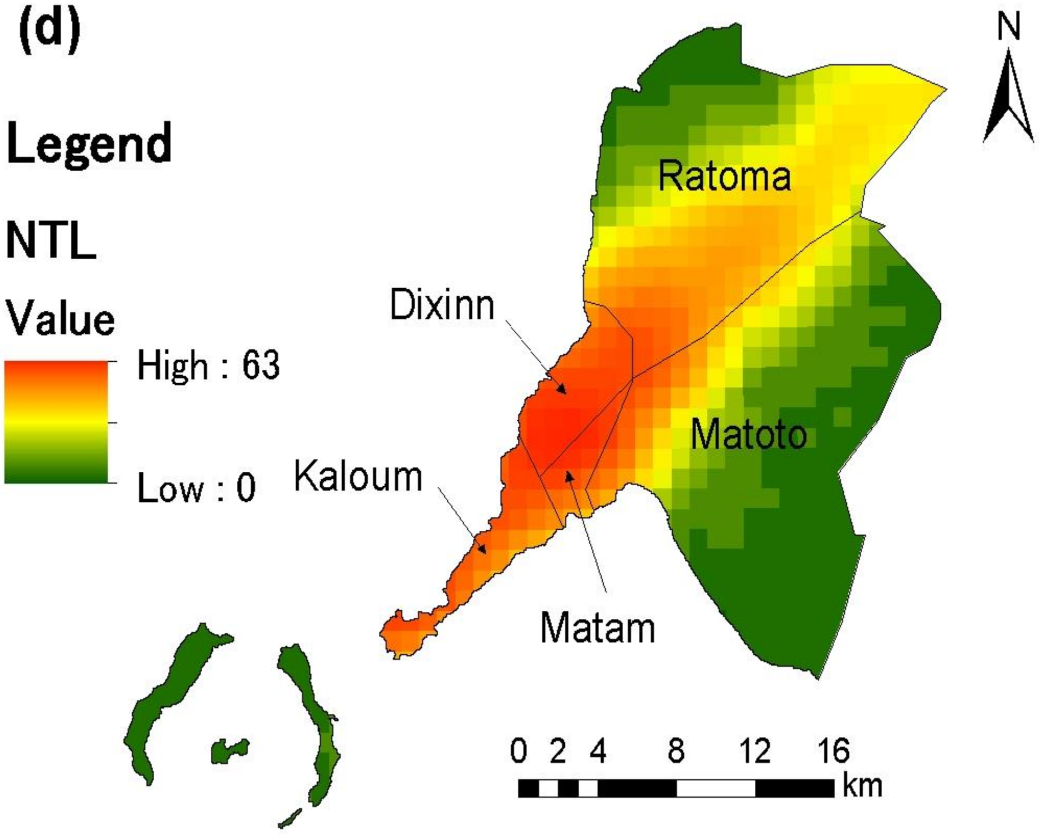


Figure 4.10 d) Nighttime light data of Conakry in 2013

4.4.1 Data inter-calibration

In order to reduce inter-annual variations and response variations among sensors, an inter-calibration of the night light data (NTL) was performed according to the method developed by Elvidge et al, (1999). The NTL from satellite F15 in 2005 was chosen as the reference dataset, as it has the highest cumulative DN value. A second-order regression model was developed for each satellite image using the Equation (8) for the period 1992, 2000, 2005 and 2013.

$$DN_{calibrated} = a \times DN^2 + DN + c \qquad (7)$$

Where: $DN_{calibrated}$ is the calibrated DN, DN is the original DN value, a, b, and c are coefficients.

4.4.2 Vegetation Adjusted Nighttime Urban Index(VANUI)

Several approaches have been proposed in extracting urban and non-urban areas from the nighttime lights data, such as Urban Lights Index (ULI), (Gao et al., 2015), the Compounded Night Lights Index (CNLI) (Yi et al., 2014), Vegetation Adjusted Night Light Index (Jing et al. 2015) etc. In this study, the Vegetation Adjusted Nighttime Urban Index (VANUI) was used for the extraction of the urban and non-urban areas in the study area, because VANUI offers a relatively good approach in reducing the saturation and blooming effects and also, it reflects the dynamics of urban population size, economic scale, and urban expansion simultaneously(Gao et al.; 2015).

Prior to computing VANUI, the MODIS (Moderate Resolution Imaging Spectro radiometer) derived annual average normalized difference vegetation index (NDVI) for 2014 was downloaded from NASA. All the NTL were geo-referenced using the UTM 84 projection and overlay with the study area boundary shapefile. Using the raster calculator in Arc Map 10.2, the Equation 9 was used to compute VANUI.

$$\text{VANUI} = (1 - NDVI) x\ NTL_N \quad (8)$$

Where, NDVI is the annual average NDVI derived from MODIS datasets. The NDVI values were constrained from 0 to 1. The NLD_N is the normalized value of the preprocessed NLD (Equation 10).

$$NLD_N = \frac{NLD - NTL_{min}}{NTL_{max} - NTL_{min}} \quad (9)$$

Where: NLD is the normalized nighttime data, NTL_{min} and NTL_{max} are the minimum and maximum values in the NTL (0 and 63, respectively)

The VANUI values range from 0 to 1. Urban cores and central business districts with sparse vegetation and a high lighting intensity have high VANUI values close to 1 while, peri-urban areas with lush vegetation and diffuse lighting show low VANUI values close to 0 (Qingting et al. 2016). The rationale behind using VANUI for urban extraction is that VANUI is positively correlated with impervious surface, and inversely correlated with abundant vegetation surface (Jing et al.; 2015). Thus, the synergy use of these two types of data can improve the accuracy of estimating the spatial distribution of urban areas (Xin et al.; 2017). Figure 4.11, clearly pictures a fluctuating increase in VANUI over the study period.

Table 4.10 Vegetation Adjusted Nighttime Urban Index(VANUI) from 1992 to 2013 in each commune of Conakry.

Communes	1992	2000	2005	2013
Dixinn	0.51	0.58	0.82	0.83
Matam	0.54	0.58	0.76	0.81
Kaloum	0.31	0.30	0.39	0.42
Ratoma	0.09	0.17	0.18	0.27
Matoto	0.09	0.12	0.13	0.17

5. Discussion

5.1 Urban growth and demographic dynamics

Chapter 4 has examined the notable LULC change occurred in Conakry in 1986, 2000 and 2016. The LULC change was observed through Landsat sensors TM, ETM+ and OLI respectively. The classification of the multi-temporal images into urban, water, vegetation, and bare ground has resulted in a highly simplified and abstracted representation of the study area. The post-classification comparison of the classified maps has revealed a continuous increase in the urban area and a substantial decrease in vegetation and bare ground area. The total urban area has increased from 15% (63.03 km^2) in 1986 to 49% (206.58 km^2) in 2016; vegetation decreased from 52% (217.48 km^2) in 1986 to 35% (147.32 km^2). Bare ground decreased from 27% (114.76 km^2) in 1986 to 9% (39.88 km^2) in 2016.

This sharp increase in the urban area can largely be explained by the rapid urbanization process in Conakry as result of the rural-urban migration, natural population growth and the primacy functions of the city. For instance, the population of Conakry increased from 0.8 million in 1986, to 1.3 million in 2000 and 2.2 million in 2014 (Figure 5.1) (SNSG.; 2014). Moreover, Guinea is one of those African countries characterized by moderate urbanization of 30-40% (Odile.; 2011).

Meanwhile, the population growth in Conakry was three times high than the national average 3.1% (National Institute of Statistics of Guinea.; 2014). Furthermore, there has been a steady increase in the importance of rural-urban migration, since the agricultural productivity has fallen, and the economic and living conditions in rural areas has deteriorated. The geographical distribution of the population is uneven and is influenced by the urbanization progressing strongly toward major cities (World Bank.; 1984). The urban population in Guinea reached a threshold of 30% in 2010, Conakry, the capital city and the main economic, administrative and industrial center, concentrates more than half of this population (Aly et al.; 2012). It also emerges that the important disparities in terms of access in economic opportunities, employment, education, health and public services demonstrate the attractiveness of Conakry. For instance, it was found that almost 50% of all industrial enterprises were in the Conakry area, these enterprises accounted for about 50% of employment in the secondary sector, and that proportions were similar for trade and public administration (World Bank.; 1984). The poverty map shows the poverty incident in all the 8 administrative regions in Guinea (Figure 5.2). This figure clearly indicates low poverty incidence in Conakry and its surrounding cities (24.4%). This once demonstrates the attractiveness of Conakry for important migration despite its pronounced congestion.

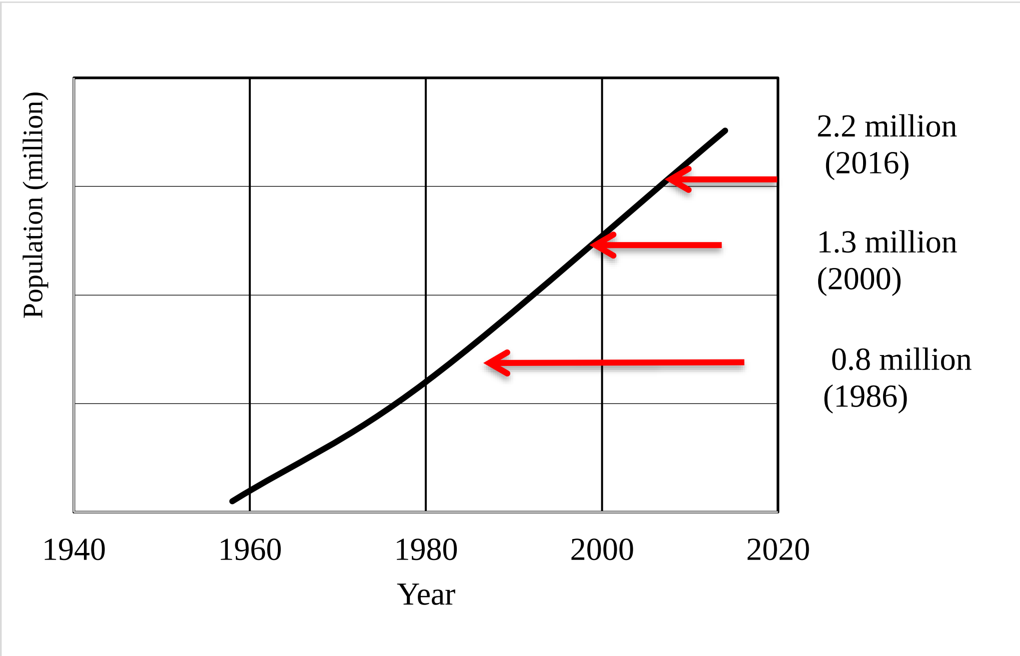


Figure 5.1 Population trend in Conakry 1986, 2000, and 2016.
Source (National Service of Statistic of Guinea 2014)

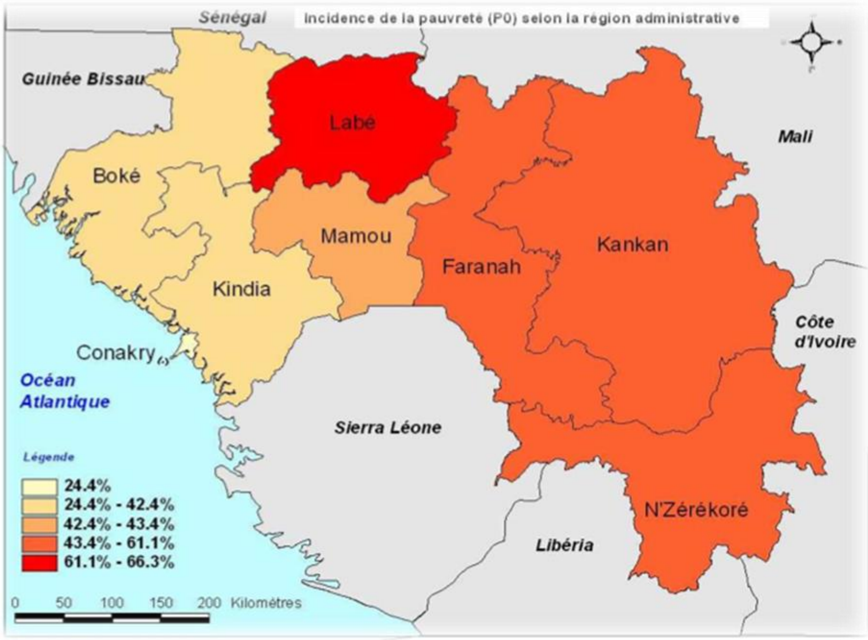


Figure 5.2 Poverty incidence map of Guinea's regions in 2010. Source: (World Bank, 2010)

On the other hand, virtually in all over Africa, as in many developing countries, rural poverty rates exceed urban ones. This is expected given that urban areas provide a wider and deeper labor market, permitting higher capacity to pay for services, and access to urban facilities at lower per capita cost. This difference between the urban and rural areas means that urban areas will continue to grow to the detriment of rural zones (Ifechukwude.; 2015). In Guinea, net regional migration has shown important association between poverty and migration (Figure 5.3). The two poorest regions (i.e., Mid and Upper Guinea) are excellent emigration zones and these regions are characterized with extreme poverty, low access to basic urban services and infrastructure. In contrast, Conakry and its surrounding cities are excellent migration zones due to their economic, administrative and cultural functions (National Urban Planning.; 2016). In addition to the internal migration, Conakry had also registered international migrations, mostly from neighboring countries such as Mali, Sierra Leone and Liberia (Figure 5.3), particularly after the civil wars that triggered in 2002 and 2003 in Sierra Leone and Liberia respectively leading many people to flee their countries.

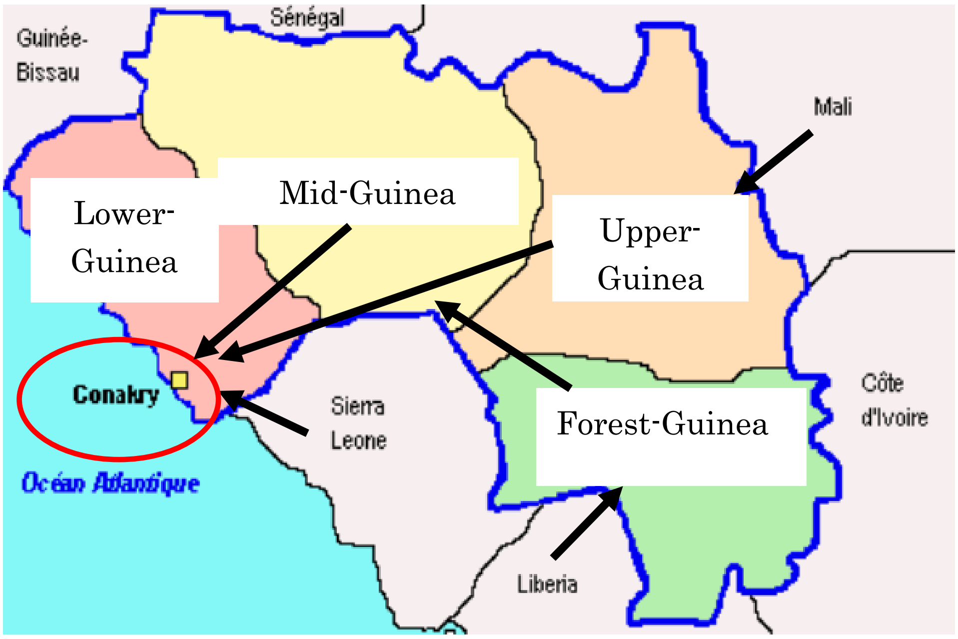


Figure 5.3 Population dynamics and regional and international migration
Source (National urban planning, 2016).

Gugler et al, (1978), the urban primacy has reached extremes in countries including Guinea, Senegal, Liberia, and Togo. In Guinea for instance, the capital is apparently nearly nine times, in each of the other three countries, it is nearly seven times bigger than the next-largest city. An expression once used to highlight the pernicious consequences of the dominant position of Paris in relation to the rest of France is now echoed in West Africa.

The growth of the national capital and its ever more impressive skyline area a source of pride to some. But the disparity between the concentration of resources in the capital cities and the neglect that is the fate of much of their hinterlands. The hubris of captial cities in West Africa is rooted in the political and social structure of these countries, which tends to appropriate to the capital. This study, like another case studies in the same region (West Africa); for example, studies have shown that urban development in Bamako Metropolitan city (Mali) and Dakar (Senegal) was mainly driven by the rapid population growth and the primacy of these cities leading to an unprecedented urbanization processes. As result, the demand for land for housing in these metropolitan cities have increased sharply resulting to various socioeconomic and environmental problems (Murayama et al., 2017).

Future LULC prediction in 2025 based on the current LULC change patterns has revealed that if the current trend prevails, the urban area will further increase to the detriment of the non-urban areas (i.e., vegetation and bare ground). The change areas of the 2025 LULC predicted is presented with that of 2016 in (Figure 5.4). The result showed that urban area would increase from 206.58 km^2 in 2016 to 218.32 km^2 in 2025, while vegetation would decrease from 147.32 km^2 in 2016 to 134.68 km^2 in 2025. Bare ground would slightly decrease from 39.88 km^2 in 2016 to 37.80 km^2 in 2025 respectively.

The observed and simulated LULC changes provide a panoramic view of urban expansion as well as simulated growth scenario for Conakry. This result conveys important insight about the potential urban dynamic in Conakry. Moreover, future urban and rural population trend in Guinea has revealed that by 2040, the urban population will overtake the rural one (Figure 5.5). Given that urban growth has occurred mainly due to population growth and migration from rural areas, population growth in Conakry is expected to continue at an accelerated rate. Therefore, better management plans are needed not only for Conakry but also for the entire country.

Urbanization can be regarded as both an opportunity and a challenge. Apart from the improvement of the living conditions of residents by providing better socio-economic infrastructure, urbanization provides businesses access to a wide range of high-quality infrastructure and services and to larger markets for goods and services. Some good urbanization policies can attract foreign direct investment and offer production factors and desired opportunities to the private sector. Nevertheless, to examine the development of Conakry, which remained quite a small town for extended period, has offered an opportunity to analyze how historically recent urban expansion has changed the natural landscape and has contributed to the degradation of various ecosystems.

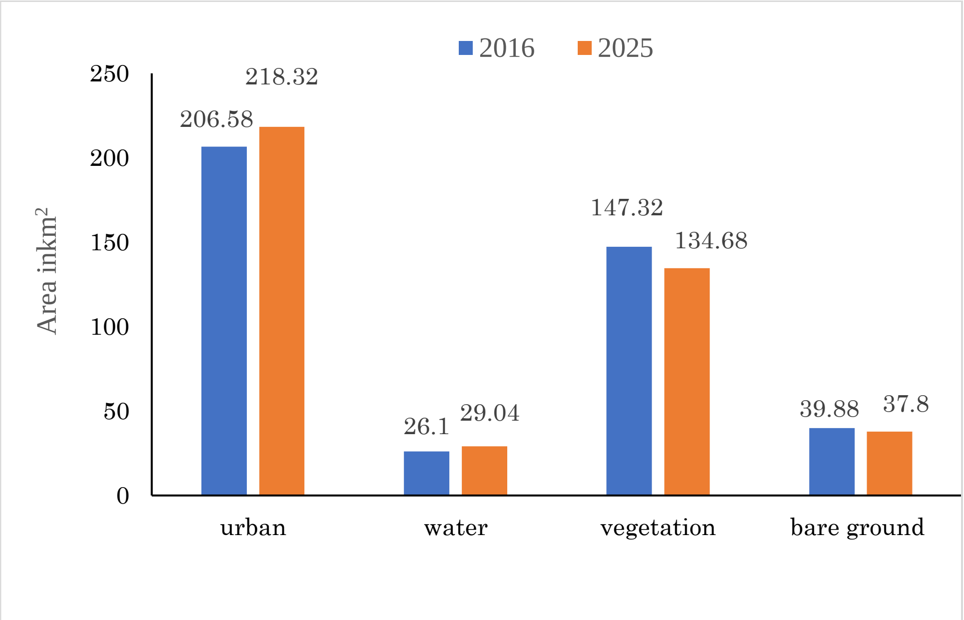


Figure 5.4 LULC change area in Conakry from 2016 to 2025

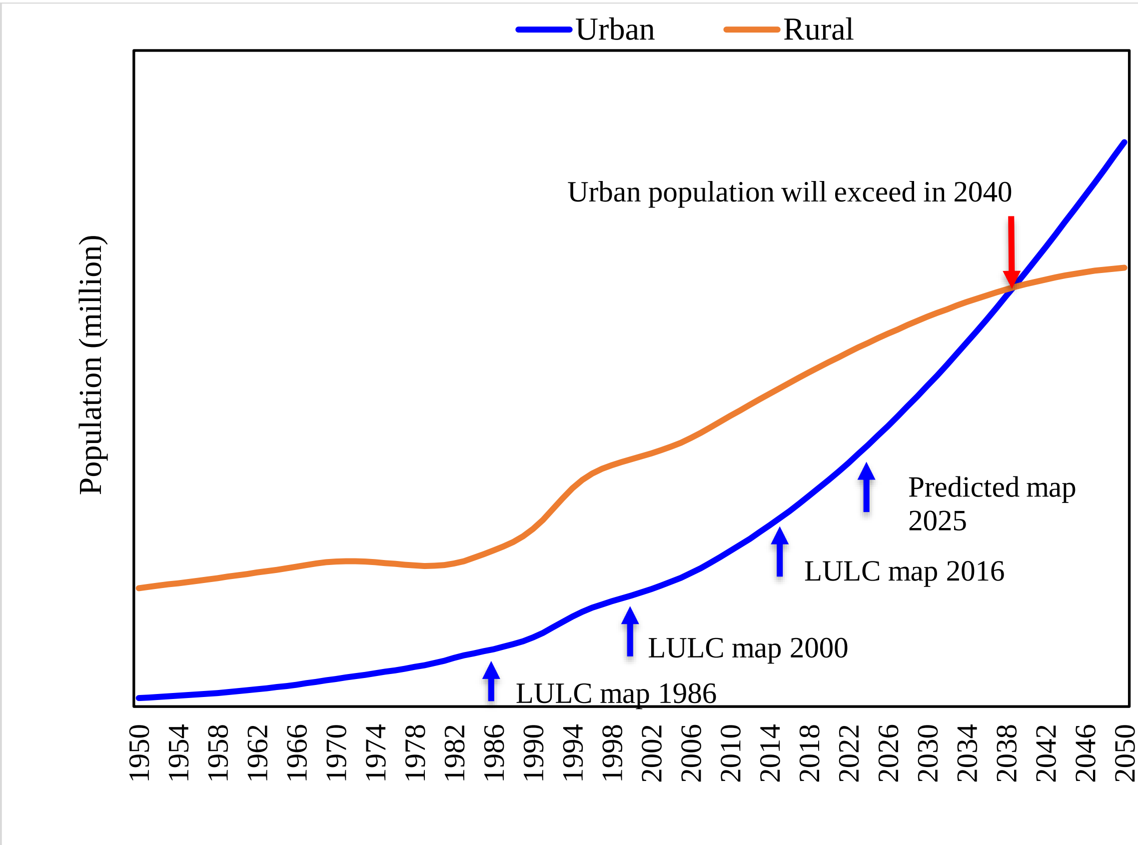


Figure 5.5 Urban and rural population trend in Guinea from 1950 to 2050. Source:(UNDESA, 2014)

5.2 Urban growth in commune level

Logistic regression model (LRM) was used to examine the relationship between urban growth with two categories of driving forces (socioeconomic and physical). LRM is an excellent method to examine the link between urban growth and its driving forces. The result of LRM has indicated that the variables of elevation, slope, population density, distance to major roads, and distance to existing urbanized areas have resulted in the model with the best fit and the highest statistical significance. Suggesting that these variables influence urban growth process in Conakry. However, comparison of the LULC map and the urban growth probability map showed a difference between the urban growth and the probability map in the commune of Kaloum (Figure 5.6). As the Kaloum commune was built in a defensive geographic setting, which has allowed for the construction of the harbor, whereby bauxite and agricultural products where exported (Odile.; 2011), the initial site was the Tombo Peninsula (about 5 by 3 km), stretching into the interior. The urban development of the site was restricted, as it could only go in one direction. The current urban planning in Conakry combined both colonial dominance and Western urban conceptions. The period of colonial conquest and the implementation of the first town-planning project were decisive for Conakry. The frequent legacy of French colonization, a trend that was not corrected after independence (Odile.; 2011). Planning decisions made at the time of its foundation remain visible in the old city center (Kaloum) and have influenced subsequent developments (Odile.; 2011). This site flourished first as a port of export, especially after the constructions of the railroad Conakry-Kankan, it is also the location of all administrative and institutional activities.

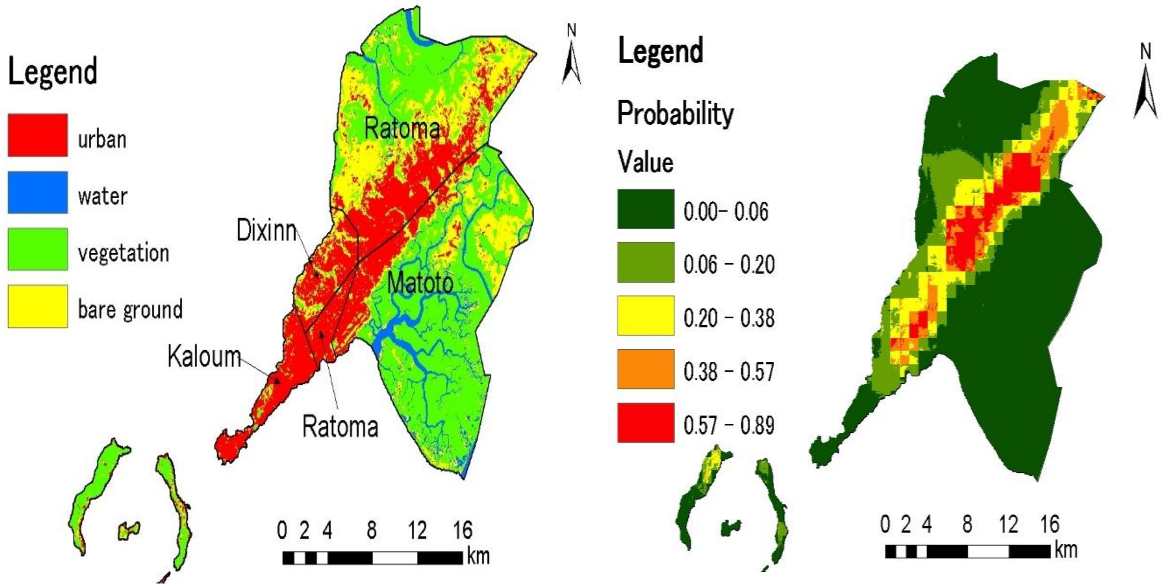


Figure 5.6 Comparison LULC map of 2000 and the urban growth probability map in 2000

Furthermore, the Nighttime Light (NTL) data of the following years 1992, 2000, 2005 and 2013 were analyzed to discuss in detail the spatial and temporal variation in the NTL pattern at commune level as proxy of urbanization and urban expansion in Conakry. The Vegetation Adjusted Nighttime Urban Index (VANUI) was computed to reflect the comprehensive nighttime light pattern in each commune of Conakry. The VANUI ranges between 0 and 1. Urban core districts with sparse vegetation and high lighting intensity have higher VANUI close to 1, while Peri-urban areas with lush vegetation and diffuse lighting show low VANUI values close to 0 (Qingting et al.; 2016). The result of the VANUI analysis revealed increasing NTL in each of the five communes (Figure 5.5).

However, there was a difference in spatial and temporal NTL distribution at the commune level. The urban core communes (Dixinn and Matam) showed rapid increase and large VANU values (0.81-0.83). The active economic center, the Kaloum commune has shown values (0.31-0.42), while the sub-urban communes (Ratoma and Matoto) exhibited values (0.09-0.27). This VANUI difference is largely explained by the difference of the historical development, which is strongly related to the topography (horizontal distance to the port) and the elevation of the city. As illustrated in (Figure 5.9). The core urban communes (Dixinn and Matam), located inland of Conakry, were developed later after the post-colonial period (1958-1984), largely as residential areas, commercial, factories and cultural centers. These communes are densely populated communes, with density varying between 6.1 and 14.6 persons/m^2. The active economic and administrative center (Kaloum), which is in cape-head and lowland area was developed earlier during the colonial period (1880-1958) as port, administrative, offices, industrial and residential areas. This commune has less residential buildings and low density 4.6 persons/m^2; therefore, less night-population. The sub-urban communes (Ratoma and Matoto) newly developing residential (1984-2000) were mainly agricultural lands and dense mangrove forests. These communes showed very low VANUI values (0.09-0.27) and population density varying between 3.5 and 4.1 persons/m^2 (Figure 5.9).

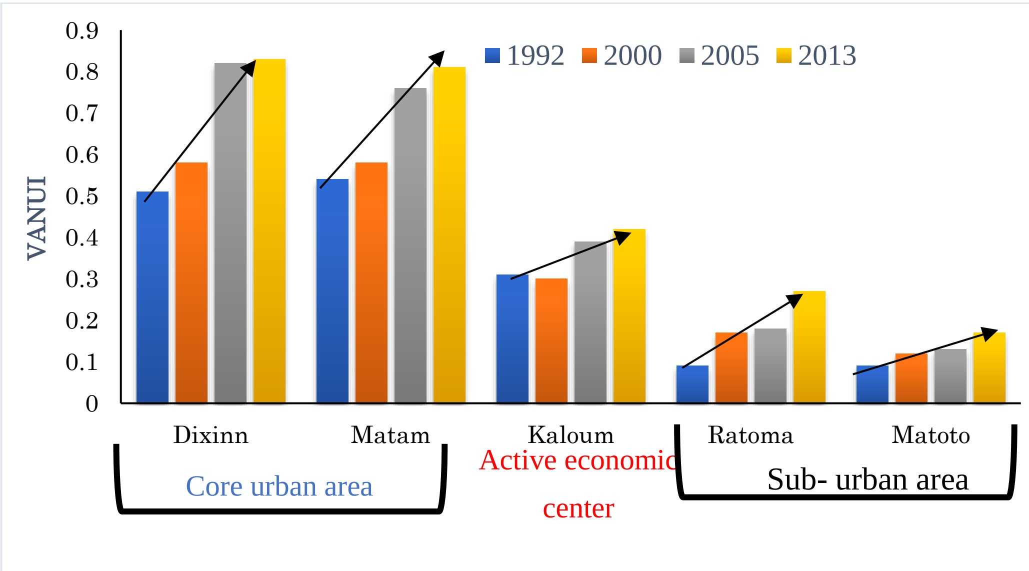


Figure 5.8 Nighttime light variation in each commune of Conakry from 1992 to 2013

Kaloum

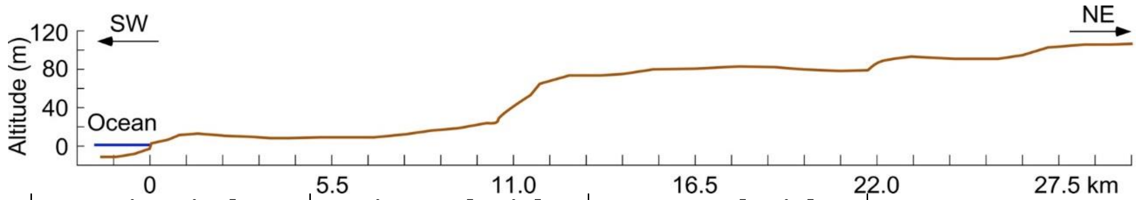
(Active economic center)

Dixin & Matam

(Core urban)

Matoto & Ratoma

(Suburban)



Historical development	**Since colonial period (1880-1984)**	**Post-colonial period (1984-2000)**	**Newest development (ca. 2000-)**
Major area use	Port, governmental offices, factories, administration, business, shopping centres	Residential houses, shopping stores, factories, cultural activities	Residential houses, crop fields, forests, mangroves
Population density 2014	4.6 persons/m^2	6.1-14.6 persons/m^2	3.5- 4.1 persons/m^2
VANUI 1992-2013	0.31-0.42	0.81-0.83	0.09-0.27

Figure 5.9 Topography and historical urban development in Conakry

6. Conclusions

6.1 Summary of the main findings

The main objectives of the present study were to examine the nature of LULC change in Conakry in 1986, 2000 and 2016, especially, an urban growth pattern; to examine the relations between urban growth and two categories of driving forces (i.e., socioeconomic and topographic); to model and predict future LULC change in Conakry based on the current LULC change pattern using the hybrid (CA-Markov) model and to discuss in more detailed the spatial and temporal nighttime lights pattern in each of the five communes of Conakry as proxy of urbanization and urban growth.

These objectives have been achieved by using different combinations of geospatial modeling and techniques. The first objective of this study was to generate accurate LULC maps using the supervised maximum likelihood classification technique, which is one of the most widely used LULC methods. Prior to LULC classification, the Normalized Difference Vegetation Index (NDVI) and the unsupervised classification were proceeded for the three Landsat data. These procedures have helped in improving and achieving relatively a good classification.

The classification accuracy was found 0.81,0.79 and 0.88 for 1986, 2000 and 2016 images respectively, which is above the minimum accuracy requirement set by the United States Geological Survey (USGS). The LULC classification results revealed significant increase in the urban areas and a substantial decrease in vegetation and bare ground respectively. Water area slightly increased over the study period, which may be due to seasonal variation, or the location of the study area as a coastal area.

The second objective had focused in exploring some driving forces of the urban growth in Conakry (i.e., socioeconomic and physical) using Logistic Regression Model (LRM). The LRM, although it’s lacked in temporal dynamic analysis, but it has been found as one the best models in understanding the relation between urban growth and its driving forces (Eyoh et al.; 2012, Liao et al.; 2014,Abubakr et al.; 2014). The choice of the variables included in this study was based on the literature review on urban growth studies and the result of the discussion with some personal resources of the Urban Planning Bureau (UPB) in Conakry.

Prior to running the LRM, the multicollinearity analysis, which checks the correlation among the explanatory variables was conducted using the hierarchical cluster analysis with a Pearson correlation coefficient. This step is important as it illustrates that the variables are not given same information, thus independent from each over. Multicollinearity test showed some multicollinearity issues particularly among variables (distance to industrial zones, distance of major roads, and the distance to the international airport). Thus, to avoid any multicollinearity problems, and select the best model for the LRM, the “step functions in R” was used, where the result is evaluated by using the Akaike Information Criteria (AIC). The AIC provides a means for model selection, and the best model is selected based on the least AIC value. In this study, the best model with the least AIC was generated with 6 explanatory variables.

The LRM result has revealed that the variables of elevation, population density, distance to major roads, distance to urbanized area and slope have resulted in the model with the best fit and high statistical significant. Suggesting that these variables have high influence on the urban growth process in Conakry. The validation of the model was conducted using the Relative Operating Characteristic (ROC), method which showed a high agreement (0.89) between the simulated urban growth probability map and the actual one.

The third objective was achieved by applying the hybrid Cellular Automata (CA) and Markov model to predict future LULC in Conakry based on the current growth pattern. First, the LULC maps of 1986 and 2000 were used to simulate the probability matrix and probability transition maps in 2016 using the Markov model. Next, the simulated 2016 LULC map generated through Markov model was compared with the current LULC map of 2016 for an accuracy assessment. The resulting accuracy assessment was conducted based on the relative operating characteristic (ROC), which result showed very high agreement (0.92) between the two maps. The projected LULC in 2025 showed that urban area in Conakry will continue to expand to the expense of vegetation cover and Bare ground.

The final goal was to use the Defense Meteorological Satellite Program ‘s Operational Line-scan System (DMSP/OLS) data to discuss in more detailed the spatial and temporal nighttime light variation in each of the 5 communes of Conakry, as proxy of urbanization and urban growth. The Vegetation Adjusted Night Urban Index (VANUI) indicator of urban nighttime light showed increasing pattern in nighttime lights in each commune of Conakry. However, there was a difference in the spatial and temporal VANUI distribution at the commune level. We found that, the urban core communes (Dixinn and Matam) characterized with higher population density, showed rapid increase and large VANUI values (0.81-0.83). The active economic and administrative center, the Kaloum commune showed values (0.31-0.42), while the sub-urban communes (Ratoma and Matoto) exhibited values (0.09-0.27). This difference in VANUI is explained by the difference of the historical development, which is strongly related to the topography (horizontal distance to the port) and the elevation of the city. However, the overall VANUI trends reveal increasing VANUI in each commune, suggesting, increasing urbanization and urban expansion in Conakry.

6.2 Contributions to knowledge

Significant technological advancement in data acquisition and processing in recent years has made it easier to analyze the spatial and temporal dynamics of the landscapes changes. The sustainable urban development of Conakry is critical for the overall socioeconomic and environmental development of Guinea. This study has focused on understanding the land-use and land-cover (LULC) change, especially an urban growth pattern in the capital Conakry, the most rapidly urbanizing city in Guinea and examining the driving factors of urban growth in the city.

Based on the major findings of this study, it is important to report that this research has contributed to the knowledge of the spatial and temporal LULC change, especially the rapid increase in the urban area to the detriment of the non-urban areas (vegetation and bare ground), which has impacted the ecosystem structures, functions, and dynamics, and threating the livelihood of Conakry's residents. Subsequently, this has assessed urban growth process at the commune level. In addition to the LULC change, this study has revealed important socioeconomic and physical driving factors of the urban growth process in Conakry. Understanding the spatial and temporal process of urban growth and the mechanisms that drive the dynamic process is fundamental to increase the effectiveness of managing the environmental sustainability.

This study concluded that the rapid urban growth has been led by both rapid population growth and extreme poverty in rural areas, which have resulted in migration into Conakry. Better management plans are needed not only for Conakry but also for the entire country. The results of this study will provide bases for assessing the sustainability and the management of the urban area and for taking actions to mitigate the degradation of the urban environment.

6.3 Limitations and suggestions for sustainable urban development

The methodology framework adopted in this study has demonstrated to be useful in monitoring and analyzing LULC changes in Conakry and in providing a support for decision making processes towards a sustainable environmental management. However, it is important to highlight that certain limitations have been noticed over the course of the study. In terms of LULC change analysis, the images used were derived from Landsat. However, some errors related to satellite remote sensing data may cause observations to fluctuate greatly. For example, changes and inconsistencies in the observed images resulted from different satellites related resolution (spatial, radiometric, spectral and temporal) of a sensor and from meteorological conditions in the study area at the time the data was recorded by the satellite.

These variations in urban landscape, as seen on the sensor of the satellite cannot be explained merely by remote sensing images. Besides that, another limitation of this study is the spatial resolution (30m) of the Landsat. With this spatial resolution, it was quite difficult to discern all the features and to achieve a very high classification as indicated by the results of the accuracy assessment. Future LULC studies in Conakry based on RS data and GIS technique should consider using very high-resolution satellite data to overcome such issue.

Furthermore, logistic regression model (LRM) was used to analyze the driving factors of the urban growth in Conakry, however, although LRM provided very high statistical significant of the urban growth drivers in Conakry, but we failed to integrate more variables which were difficult to incorporate into our model due to their non-spatial characteristics. Besides the factors used in this study, urban growth in Conakry is also strongly influenced by political, cultural, and other factors, Although, the good agreements between model results and actual maps were observed, it is suggested that more potential variables should be included in the future studies to improve the performance of spatial models and to evaluate the effects of these factors on urban growth in Conakry. This study suggests that the development of secondary urban centers is desirable for reasons of equity, and it might also have positive effects for economic growth. Regional cities development would reduce the severe imbalance among different regions in terms of access to urban facilities (i.e., education, and health care) and opportunities, especially employment.

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