QUANTIFYING URBAN GROWTH PATTERN IN DEVELOPING COUNTRIES USING REMOTE SENSING AND SPATIAL METRICS: A case study in Kampala, Uganda

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February, 2013

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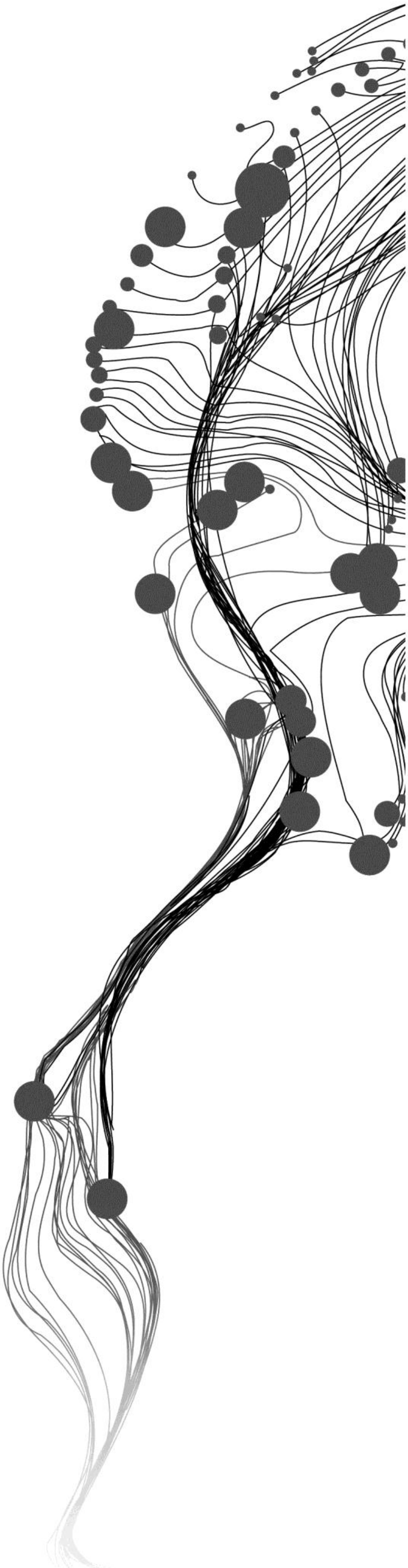

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A case study in Kampala, Uganda

GEZAHEGN AWEKE ABEBE
Enschede, The Netherlands, February, 2013

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ABSTRACT

Rapid urbanization and urban growth, particularly in the developing worlds, is continuing to be one of the crucial issues of global change in the 21st century affecting the physical dimensions of cities. This process, with no sign of slowing down, could be the most powerful and visible anthropogenic force that has brought about fundamental changes in urban land cover and landscape pattern around the globe. Understanding and quantifying the spatio-temporal dynamics of urban growth and its drivers in developing countries such as Kampala, Uganda, is critical to put forward appropriate policies and monitoring mechanisms on urban growth and make informed decision. In this study, the spatio-temporal patterns and processes of urban growth of Kampala and its drivers were investigated from 1989 to 2010 by using satellite remote sensing images, spatial metrics and logistic regression modelling.

Four different land cover maps derived from Landsat TM image of 1989, 1995, ETM+ 2003 and 2010 were used to evaluate a set of nine selected spatial metrics to reveal patterns and dynamics of urban growth in the study area. The computation of spatial metrics was conducted at two spatial scales. First, the summary descriptors of landscape heterogeneity at the city level are evaluated. Secondly, in order to better link the metric analysis to more specific locations, the study area is broken into six smaller individual 'regions' on the bases of administrative boundaries. Then, the changing patterns of urban growths over time are linked to the major physical driving forces in the study area via binary logistic regression modelling. Therefore, three models are built for 1989-1995, 1995-2003 and 2003-2010 study periods.

Results obtained from the synoptic analysis of built up area dynamics for the past two decades revealed that the city has been undergoing extensive urban growth processes. The growth was prolonging both from urban centre to adjoining non-built up areas in all direction, but mainly to the south-west, east and north direction alongside major transportation corridors. The total built up area in the city has grown from 73km² in 1989 to 325km² in 2010 at an average growth rate of 10, 14 and 4.4% per annum during 1989-1995, 1995-2003 and 2003-2010 study periods respectively. The study period from 1995 to 2003 was registered as the time at which the city experienced the highest urban growth. The analysis of spatial metrics at the city level revealed that the urban landscape has experienced a process of sprawling and fragmented development pattern particularly in the fringe areas while, the city centre underwent infill and edge expansion development processes. However, the region based analysis shows the Greater Kampala Metropolitan Area (GKMA) experienced different trend of development. The core area consolidated over time while the eastern region relatively underwent compact growth and the fringe areas show scattered growth pattern. This indicates the results of spatial metrics analyses at city level are not necessarily conclusive and decisions made fully depending on city level metrics analysis might be misleading.

The results of binary logistic regression model revealed that distance to major roads, distance to sub city centres, proportion of built up cell, distance to CBD, distance to satellite towns and slope were the major driving forces of urban growth at different time periods with varying level of significance and correlation. The importance of distance to CBD and distance to major roads decreased over time while distance to sub-city centres and proximity to highly urbanized cells become more important confirming the results of spatial metrics that show typical fragmentation and outward expansion. Quantifying urban growth patterns and development processes of the past trends can help better understand the dynamics of built up area and guide sustainable urban development planning of the future urban growth. Thus, the methods used in this research can deliver rich level of quantitative information on the development patterns and processes of the urban landscape.

Keywords: Urban growth; Spatial metrics, Remote sensing; Land cover change; Logistic regression.

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LIST OF ACRONNYM

ASTER	Advanced Space-borne Thermal Emission and Reflection Radiometer
CBD	Central Business District
CK	Central Kampala
EEA	European Environment Agency
ER	Eastern Region
ETM+	Enhanced Thematic Mapper-plus
GCP	Ground Control Points
GIS	Geographic Information Science
GKMA	Greater Kampala Metropolitan Area
GPS	Global Positioning System
IFM	Integrated Flood Management (Uganda)
ITC	International Training Centre (Faculty of Geo-Information Science & Earth Observation, University of Twente)
KCCA	Kampala Capital City Authority
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NEMA	National Environment Management Authority (Uganda)
NIR	Near Infra-Red
NR	Northern Region
PUR	Peri-Urban Region
RS	Remote Sensing
SPSS	Statistical Package for Social Sciences
SWR	South-Western Region
TM	Thematic Mapper
UBOS	Uganda Bureau of Statistics
UN	United Nations
UN-HABITAT	United Nations Human Settlements Program
USGS	United States Geological Survey
VHR	Very High Resolution
VIF	Variance Inflation Factor
WGS	World Geodetic System
WR	Western Region

1. INTRODUCTION

Urbanization has been a universal and important social and economic phenomenon taking place all around the world. This process, with no sign of slowing down, could be the most powerful and visible anthropogenic force that has brought about fundamental changes in land cover and landscape pattern around the globe. Rapid urbanization and urban growth, especially in the developing world, is continuing to be one of the crucial issues of global change in the 21st century affecting the physical dimensions cities.

1.1. Background

In the past few decades, urbanization and urban growth have drastically accelerated in many developing countries. According to United Nations; in 2011, 3.6 billion of the world's population (52%) were urban dwellers. Universally, the level of urbanization is expected to rise to 67% in 2050. In the less developed regions, the proportion of urban will rise from 47% in 2011 to 64% in 2050. In Africa alone the urban population is expected to triple from 414 million in 2011 to 1.2 billion 2050 (ibid).

In most countries; urbanization is recognized as a crucial phenomenon of economic growth and social change as it offers increased opportunities for employment, specialization, production and goods and services. This has initiated a large number of people to migrate from rural to urban area. As a result, cities are growing faster than ever (in physical dimension), being a huge centre for residence, industry, trade and investment, communications, infrastructure, social services etc. However, this growth also triggers numerous problems. Environmental pollution and degradation, increased environmental hazards such as flooding, population explosion, insufficient sanitation and water supply, transport problems, poor housing conditions, rising cost of living and wealth inequality, and increase in crime, and loss of fertile agricultural & wetlands are some of the most prominent negative effects of rapid urbanization and urban growth_(UN-HABITAT, 2012). If not managed properly, these may intimidate the sustainable development of cities in the long run (Dubovyk et al., 2011).

Recently, an increasing concerns about sustainable development have fostered a new interest of the international literature on the physical dimension of cities and, particularly, on the issues of urban growth pattern and urban form (J. Huang et al., 2007; Van de Voorde et al., 2009). Numerous studies have been conducted focusing on the phenomenon of urban sprawl and informal settlement and their adverse environmental and socio-economic consequences as opposed to the concept of compact and formal development (Dubovyk et al., 2011; A. Schneider & Woodcock, 2008). However, following the growing demand for empirical data and systematic analysis of urban growth processes and patterns, there is an increasing curiosity on the development of quantitative methods of urban analysis. It is significant to provide valuable information to help local and regional land use planners to better understand the urban growth process and make informed decision.

Urban growth patterns

Urban growth patterns are characteristic of spatial changes that take place in metropolitan areas (Aguilera et al., 2011). The spatial configuration and the dynamics of urban growth are important topics of analysis in the contemporary urban studies (Bhatta, 2012). Wilson et al. (2003) identified three major types of urban growth as: infill, expansion, and outlying. Infill development is a new development within remaining open spaces in already existing built up areas whereas expansion or sometimes called urban extension or edge expansion is a non-infill development extending the urban footprint in an outward direction sometimes called urban fringe development. Outlying or leap-frog development is a change from non-developed to developed land cover occurring beyond existing developed areas. Leap-frog development is also referred as urban sprawl as the expansion of urban area is in a way that demands the extension of public facilities. Tian et al. (2011) compared the spatial and temporal dynamic pattern of the urban growth for the five urban areas of Shanghai, Nanjing, Suzhou, Wuxi and Changzhou in the Yangtze River Delta region, China. The result of their research revealed during the 15 years, urban growth patterns were dramatically uneven over the three periods. The size distribution of the five urban areas became more even with the rapid urbanization process. The landscape metric analysis across concentric buffer zones indicates the coalescence process occurred during the rapid urban growth from 1990 to 1995 and the moderate growth period from 2000 to 2005, but different urban growth period between 1995 and 2000. This approach indicates that the coalescence process was the major growth model for the region and they conclude that the diffusion-coalesce dichotomy represent endpoints rather than alternate states of urban growth.

Remote sensing of urban areas

Several methods and techniques have been developed and applied to quantify and characterize the urban growth processes and patterns. Traditionally, visual interpretations of high-resolution aerial photographs were used to acquire comprehensive information for mapping of urban areas. This mapping technique is expensive and time consuming for the estimation of urban growth. However, with the gradual advancement and availability of high temporal and spatial resolution remote sensing imagery; the possibilities of monitoring urban problems with a better accuracy have become more promising. Hence, accurate mapping of urban environments and monitoring urban growth is becoming increasingly important at the global level (Guindon & Zhang, 2009).

Nowadays, there are several remote sensing satellite systems such as Landsat (TM & ETM+), ASTER, IKONOS, GeoEye, Quick bird, RapidEye, WorldView providing from medium to high and very high resolution imagery. It is also believed that remote sensing imagery is a powerful tool for acquiring data to analyse and map spatio-temporal land use change and urban growth process at different spatial scale (J. Huang et al., 2007; Yang & Lo, 2002; W. Yu et al., 2011). Particularly, in developing countries, remote sensing may provide fundamental observations of urban growth and environmental conditions that are not available from other sources (Miller & Small, 2003). Yet, it lacks the ability to fully describe the underlying urban processes (Herold et al., 2005).

Urban analysis using spatial metrics

Given much less attention than remote sensing, spatial metrics are useful tools to objectively quantify and describe the underlying structures and patterns of the urban landscape from geospatial data (Pham & Yamaguchi, 2011). Spatial metrics are essential to better understand the characteristics of a landscape. Equivalent to the name of spatial metrics, landscape metrics are widely used in landscape ecology to describe the ecological important relationships such as connectivity and adjacency of habitat reservoirs (McGarigal et al., 2002). When used in different field of studies, such as urban planning, landscape metrics referred to as “spatial metrics” (Herold et al., 2005). Though, this two phrases: ‘spatial metrics’ and ‘landscape metrics’ are used interchangeably on most published papers, in this research spatial metrics is used throughout.

Spatial metrics, in general, can be defined as ‘numerical indices to describe the structures and patterns of a landscape’ (O'Neill et al., 1988) as cited on (Bhatta, 2010, p. 87). Herold et al. (2003, p. 288) also defined spatial metrics as, “quantitative and aggregate measurements derived from digital analysis of thematic-categorical maps showing spatial heterogeneity at a specific scale & resolution". Both definitions emphasized on the quantitative nature of the metrics.

1.2. Justification

As discussed earlier, there are many reasons why urbanization processes have been a hot research area for several decades. One of the most important reasons for such an interest is that, the size and spatial configuration of an urban area directly impacts energy and material flows such as carbon emissions and infrastructure demands, and thus has direct or indirect consequences on the proper functioning of Earth as a system and on the quality of life of urban inhabitants. As the size of cities expands it begins to encroach on agricultural lands and natural areas (e.g. wetlands prone to environmental hazards such as flooding).

Although urban growth is an inescapable process, efforts can be made to protect natural resources, reduce natural hazards such as flooding and improve the livelihoods of urban dwellers through proper way of urban planning and management (Soffianian, 2010). To do so city planners, policy makers and resource managers need more advanced and quick techniques to acquire quantitative information on urban growth processes and patterns. It can facilitate the urgent establishment of management mechanisms and relevant policy interventions for proper allocation of resources and urban infrastructures based on empirical evidences. However, the available information on the city growth and evolution is insufficient and out-dated. This makes decision making process complex and less transparent. Therefore, quantifying urban growth processes and patterns is crucial to monitor urbanization and its impact on environment over time. However, they give insufficient information about spatial patterns of urbanization processes that characterize urban areas.

Remote sensing data can provide time series land-cover maps explicitly exhibiting the dynamics of urban growth; yet some underlying patterns and characteristics could not be visualized clearly. Spatial metrics, in the form of a succession of indices, can reliably quantify and represent the spatial-temporal patterns and processes of urban growth. They provide an improved description and understanding of the structure and morphology of heterogeneous urban areas. Moreover, spatial metrics provides a linkage to structure, pattern, processes and functionality in urban studies (Luck & Wu, 2002). Thus, remote sensing and spatial metrics are valuable tools to analyse urbanization processes and patterns empirically.

Therefore, assuming that urbanization will continue to be one of the major global environmental and social challenges in the foreseeable future, understanding and quantifying the changing patterns of urban growth is critical to put forward appropriate policies and monitoring mechanisms on urban growth.

1.3. Research problem

Urbanization in Uganda is relatively low compared to its neighbouring countries like Democratic Republic of Congo, Tanzania, Kenya and Rwanda, yet is dramatically increasing (UBOS, 2007). Rapid urban growth of Kampala is accompanied by high population growth, dramatic land use/cover change and social transformations (J. B. Nyakaana et al., 2007). Such rapid demographic and environmental changes in the past decades have resulted in environmental degradation, haphazard physical development, informal developments on wetlands, and poor land use planning practices (Mabasi, 2009). Influenced by topography, most of these growths are taking place in close proximity to wetlands which are prone to flooding (refer figure_2.3). This has aggravated the vulnerability of many inhabitants to natural disasters such as flooding and diseases (Stephen, 2009).

Basically, planning and management of urban spaces requires a comprehensive knowledge of the development process and physical dimension of cities (Klosterman, 1999). As discussed earlier (see section 1.4), most literature's on the analysis of the spatial characteristics of cites growths highlight the value of spatial metrics in the study of urban landscapes. However, Seto and Fragkias (2005) argue that, most of these studies focus on cities in the USA. Recently few studies have been conducted in Europe (Aguilera et al., 2011) and some Asian countries (Jain et al., 2011; Tian et al., 2011). However, less is studied in relatively fast growing cities of Africa using spatial metrics for quantifying urban growth patterns. Combined with remote sensing, spatial metrics can give better result than using either of them gives separately (Herold et al., 2003). Thus, it is worthwhile to expand the application of spatial metrics to fast growing African countries. This is particularly true for less developed Sub Saharan cities like Kampala, where the availability of spatial data is very limited.

Therefore, this study will investigate the spatio-temporal patterns of Kampala's urban growth and quantify the underlying spatial pattern of the urban landscape. Remote sensing and spatial metrics tools will be utilized to accomplish this task. The combined use of these tools is believed to lead to new levels of understanding of urban development process which can assist city planners and policy makers to make informed decision (Herold et al., 2005).

1.4. Research objectives

General objective:
The general objective of the study is to quantify the spatio-temporal trends and patterns of urban growth in fast developing Sub-Saharan African cities such as Kampala using satellite remote sensing and spatial metrics.

Specific objectives:
The specific objectives of this research are:

1) To analyse the extent and rate of spatio-temporal urban growth using multi-temporal satellite images.
2) To quantify the spatio-temporal pattern of urban growth and landscape fragmentation using spatial metrics.
3) To determine the major physical driving factors of urban growth.

1.5. Research questions

Based on the above research objectives, the following research questions were also posed to assist to analysis:

Questions for sub objective 1:

1) What are the changes in the land cover of Kampala?
2) What is the physical spatial extent & rate of urban growth?
3) What is/are the main growth directions?

Questions for sub objective 2:

1) How did the spatial pattern of urban growth change overtime?
2) What are the types of spatial urban growth patterns (infill, extension or leapfrog development)?
3) Did the urban area getting more fragmented over time?

Questions for sub objective 3:

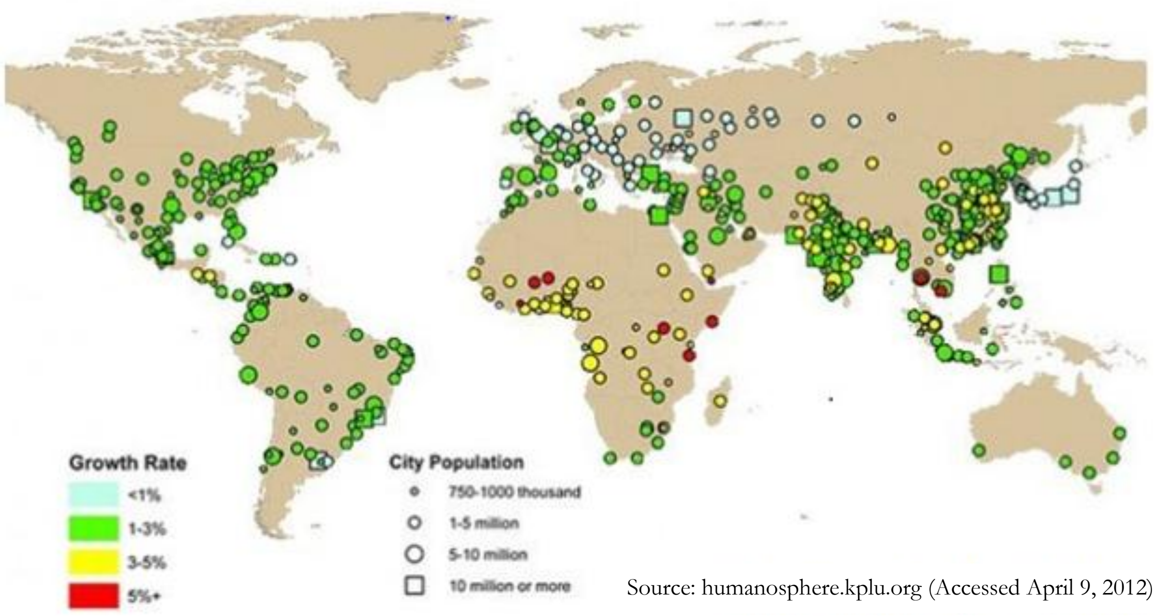
1) What are the major physical driving factors of urban growths in the study area?
2) How did these factors influence the urban growth process and pattern?
3) How do the driving factors relate to each other?

1.6. Context of the study area

Kampala, the capital city of Republic of Uganda, is one of the fastest growing cities of Sub-Saharan Africa with annual growth rate of 5.61% (J. B. Nyakaana et al., 2007). Figure_1.1 shows that Uganda is amongst the fastest growing urban area in the world and in Sub-Saharan Africa in 2012. Kampala is located at 00°18'49"N latitude and 32°34'52"E longitude (ARC_1960_UTM_Zone_36) geographic coordinate, 8km on the northern shore of Lake Victoria. It has a tropical wet and dry moderate climate. The city occupies an estimated area of 195 km² and at an average altitude of 1,120m above sea level. The form and structure of Kampala has been largely determined by the natural pattern of the landscape. It is situated on 20 low flat topped hills that are surrounded by wetland valleys, characterized by a huge amount of scattered informal settlements (UN-Habitat, 2008). These wet valleys are covered by papyrus swamps. Many of the papyrus swamps have been reclaimed and developed. They comprehend the central business district (CBD), slum dwellings and industrial zones. The hilltops have been reserved for institutional purposes such as universities and churches, prestigious buildings like State Lodge and other important installations like the Radio and TV masks, while the slopes have been used for various grades of commercial/office and residential buildings. The low laying areas are mostly dominated by informal settlements and slums. Subsequently, these areas of the city are frequently affected by flooding during rainy season.

Located in the central region of the country, Kampala absorbs 40% of the national urban population and 4.9% of the nation population (NEMA, 2002). Considering that the population was 330,700 in 1969, 1,208,544 million in 2002, and 1,811.794 in 2010, this signals the population of the city was dramatically increased. The Kampala suburbs are also experiencing rapid urbanization leading to development of satellite towns around the city (ibid). The City today has grown into a commercial, educational, cultural and administrative centre of Uganda. Currently, the urban population in Uganda is around 15% and is projected to reach 40% in 2025 of which the majority will be in Kampala City (Oonyu & Esaete, 2012).

Figure 1.1: Fast growing urban area in the world

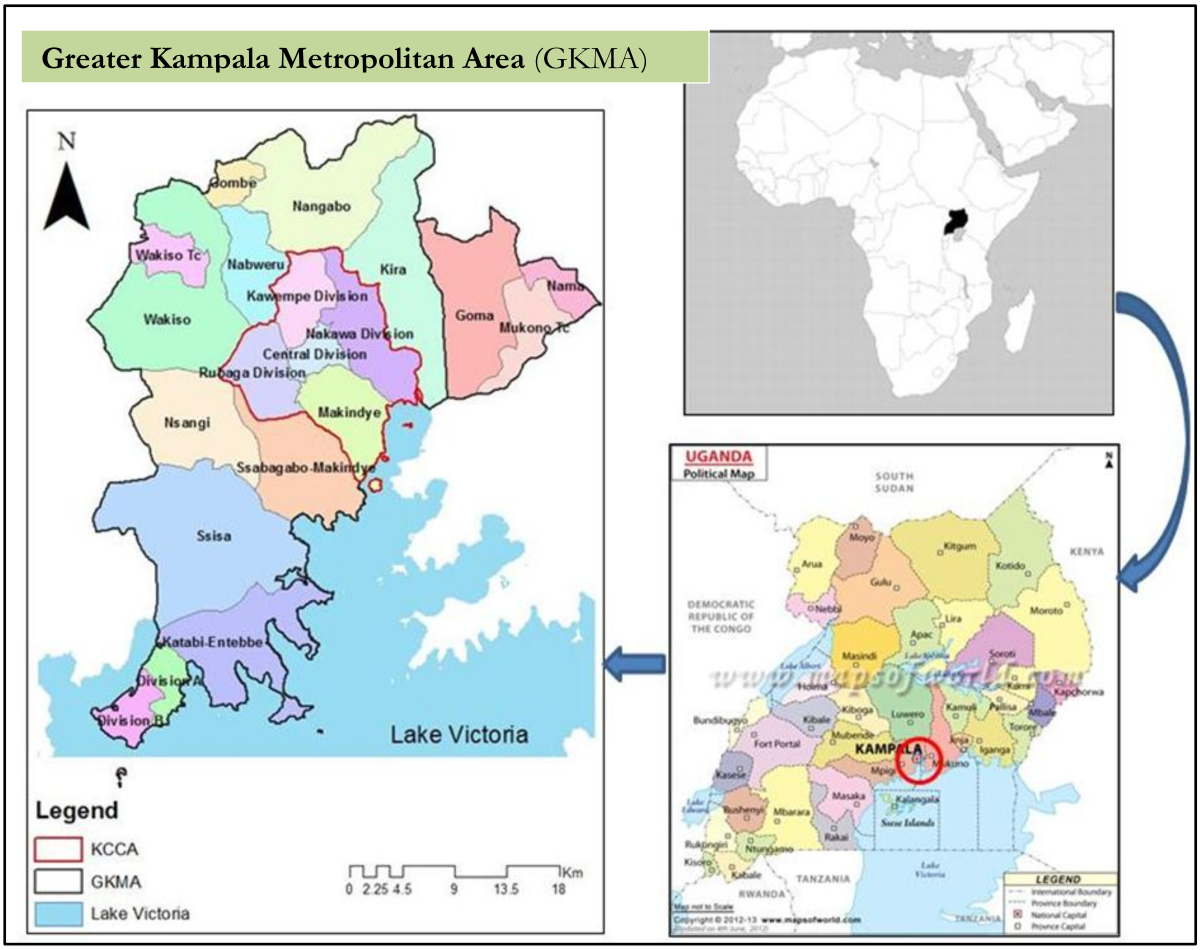


Source: humanosphere.kplu.org (Accessed April 9, 2012)

In the past two decades, Kampala has expanded beyond the administrative city boundary through seizing to the adjacent townships and rural areas (Vermeiren et al., 2012). Recently the administrative set up of the city has been changed to include the metropolitan area within the authority as it offers better opportunity to tackle some of the current problems in the metropolitan area (Oonyu & Esaete, 2012).

Today, the metropolitan Kampala covers up to 839 sq. km by engulfing the neighbouring satellite towns such as Mukono, Entebbe, Mpigi and Bombo and continuously converting the surrounding rural landscape in to urban area (J. B. Nyakaana et al., 2007). This study covers the Greater Kampala metropolitan area (GKMA) to analyse the spatio-temporal growth pattern of the city (refer figure_1.2). The GKMA is delineated based the draft final report prepared by Kampala Capital City Authority (KCCA) under the title "Updating Kampala Structure Plan and Upgrading the Kampala GIS Unit" which was made open for comment in November 2012. Accordingly, the GKMA includes already urbanized areas and those expected to be urbanized in the medium term, including the Municipal and Town Councils of Entebbe, Wakiso, Kira, Mukono and Nansana and parts of Wakiso and Mukono districts located between these town councils

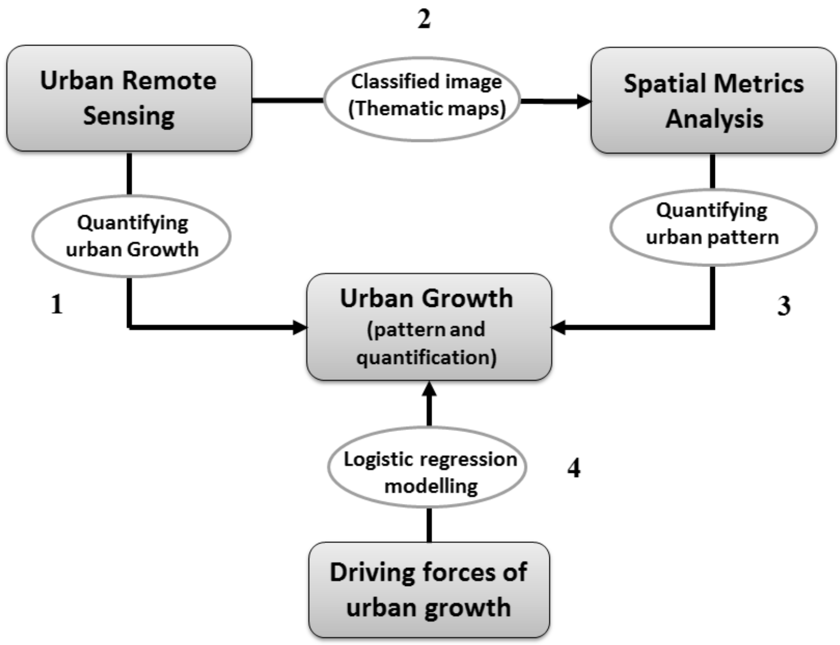
Figure 1.2: Geographical location of Kampala, Uganda



1.7. Conceptual framework

This study makes use of both remote sensing and spatial metrics methods to get a deeper insight into spatio-temporal urban growth processes and the underlying patterns. A simple conceptual framework is adapted from (Herold et al., 2005) see figure 1.3. The conceptual frame work is composed of three major elements interacting at different stages of the research. These are: remote sensing, spatial metrics & urban growth. The arrow no.1 shows the potential use of classified temporal remote sensing images to quantify urban growth. Whereas the arrow no. 2 shows interaction between urban remote sensing and spatial metrics, in which the output of classified remote sensing image is used as an input for spatial metrics computation (e.g. in FRAGSTATS) to quantify urban landscape fragmentation processes and patterns (arrow no. 3). Selected metrics (see section 3.4.1) are used to quantify urban growth pattern. These metrics are computed to quantify the spatial configuration of the urban landscape (e.g. size, shape, edge length, patch, density, fractal dimension) and the composition of the landscape, (e.g. richness, evenness, dispersion, contagion, diversity) (Gustafson, 1998). Finally, (arrow no. 4) binary logistic regression modelling is used to identify factors responsible for the changing patterns of urban landscape. The results of the entire analysis are used to discuss on how these methods can improve the better understanding of urban growth processes and patterns and can help urban planners and policy makers to put forward informed decision.

Figure 1.3: Conceptual framework for analysis of urban growth (Adapted from Herold et al., 2005 p.370)



1.8. Structure of the Thesis

The thesis is structured into five different sections in which the first section deals with the introduction to the research and mainly addresses the statement of problem, research objectives, research questions, the context of study area, conceptual frame work and organization of the thesis. The second section contains review of related literatures where the concept of urbanization and land cover change, urban remote sensing and spatial metrics, image classification techniques, spatio-temporal urban growth pattern, and urban landscape structures are reviewed. In section three, the data and methodology used in this study including methods of data collection and analysis, image classification method, accuracy assessment procedures, selection and description of metrics, definition of spatial domains, methods used for identification of major physical driving forces of urban growth, including variables used in logistic regression modelling, multicollinearity analysis method and methods of model evaluation are briefly discussed. Section four presents the results of data analysis and discussions including spatio-temporal urban growth analysis, presentation and interpretation of growth maps and spatial metrics, temporal patterns of land cover changes, intra urban comparison of metrics, logistic regression modelling and evaluation and interpretation of outcomes, identification of major driving forces of urban growth in the study area. In the last section, section five, conclusions are organized according to the research questions proposed in section one. Furthermore, the limitations of the research and some recommendation and future research directions are offered.

2. LITERATURE REVIEW

2.1. Introduction

The unprecedented growth of urban population and built-up area worldwide, have an enormous influence on natural landscape at different spatial scales (Herold et al., 2005). Land-use and land-cover changes are the process in which the natural environments such as forest and grasslands are replaced by human induced activities such as intensive agriculture and urbanization. This chapter reviews important literatures regarding land use/land cover change, urbanization, advances in remote sensing technology, classification methods, spatial metrics and their application in monitoring urban growth pattern and driving forces of urban growth and urban modelling techniques.

2.2. Land cover change

Human intervention and natural processes are responsible for the constant change in land cover all over the world. Land cover change is determined by the interaction in space and time between biophysical and human influences. Urbanization is a rapid land cover change process that produces different patterns depending on the proximity to large urban centres across the landscape (Wu, 2004). Many land cover change models have been used to identify the drivers assumed to affect conversions of land between built up and non-built up land cover categories. Information about urbanization, obtained from multiple multi-temporal images, can provide valuable knowledge about the patterns of urban growth and the probable factors driving the changes. This information is important for planners, policy makers and resource managers to make informed decisions. Nowadays decision makers are becoming more and more dependent on models of land use/cover change (Veldkamp & Verburg, 2004). Description and modelling of land systems is highly dependent on the availability and quality data (Tayyebi et al., 2010). The spatial dependency of land cover changes can be analysed by the integration of remote sensing and GIS techniques. These techniques have an efficient spatial capability to monitor urban expansion in urban areas.

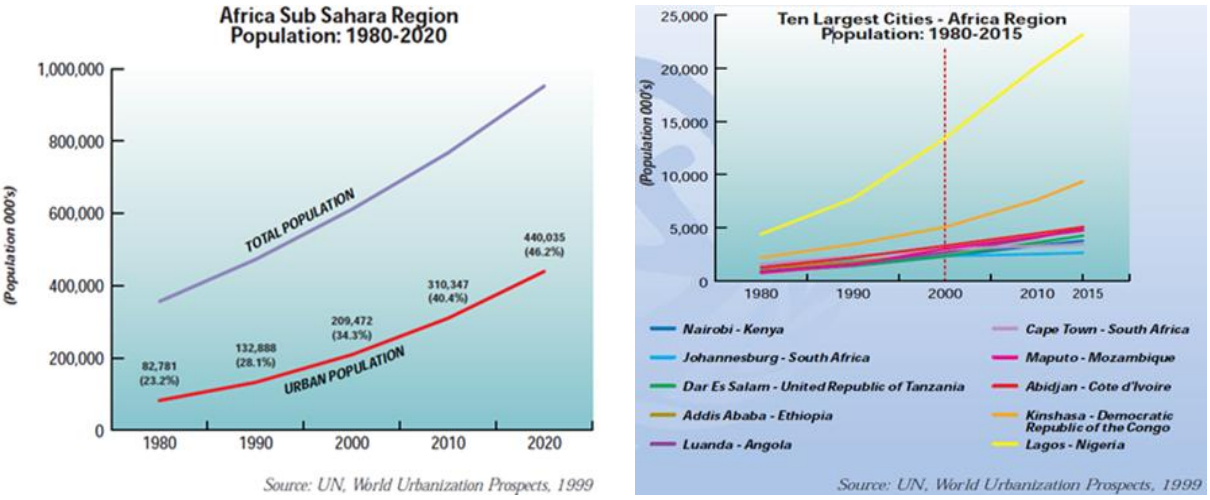
2.3. Urbanization and urban growth in sub –Saharan Africa

Definitions of ‘urban’ and ‘rural’ vary widely across Africa. Almost half the countries in Africa use a numerical definition to indicate the areas that qualify as urban. Many Sub-Saharan African countries use a population figure of 2,000 to distinguish between rural and urban settlements. However, the figure varies from 100 in Uganda to 20,000 in Nigeria and Mauritius (UN, 1999). For example, in Uganda the definition of urban areas has been changing over time. The 2002 Census defined urban areas as gazetted cities, municipalities and town councils as per the Local Government Act 2000, while the earlier censuses included ungazetted trading centers with more than 1,000 people as part of the urban population. The pattern of urbanization in West Africa differs somewhat from that in East Africa. In many West African countries there are few secondary cities, so the population is concentrated in one or a few large cities.

Population growth in East Africa is more evenly distributed over secondary and tertiary cities. But, primary cities are going through a period of rapid growth (UN-Habitat, 2009). The most important contributor to urbanization in both West and East Africa was until recently migration from rural areas. In Southern Africa natural population increase is already the most predominant cause of urbanization. Global economic processes have slowed down Sub- Saharan Africa with severe consequences for its urban areas. Africa is the only region of the world without a true newly industrializing economy. The failure to industrialize can partly be explained by external factors, but a variety of domestic factors must also be taken into account, including economic policies, the effects of personal rule, historical legacy, and the role of the state and low levels of literacy (UN, 1999).

Figure 2.1 below, shows that urban population in Sub Saharan African region is increasing at the rate of 6% per decade approximately (left hand side) and the ten largest and populous cities in Africa region (right hand side). It is easily to understand how fast these cities are growing just by comparing the population of these cities before and after 2000 from the graph.

Figure 2.1: Urbanization in Sub Saharan Africa



Trends and Patterns of Urbanization in Uganda

According to the State of Uganda Population Report (UNFPA, 2007) urbanization in Uganda is extremely low (12%) compared to its neighboring countries Kenya and Tanzania, which had 20% and 22% respectively of their population living in urban areas in 2002. In the same year, 88% of Ugandan population was predominantly living in rural areas, leaving about 12.3% in the urban areas as illustrated in Table 2.1 below.

Table 2.1: Trends in urban population in Uganda, 1980-2002 (Source: State of Uganda Population Report 2007)

Census Year	Population (Millions) Urban*	Population (Millions) Total	Percent of Population in Urban Areas	Urban Growth Rate (%)
1980	0.84	12.6	6.7	--
1991	1.65	16.7	9.9	6.1
2002	3.0	24.2	12.3	5.1

** The information for the 1980 and 1991 censuses have been recast to the 2002 definition of urban population, and are therefore different from figures published in earlier reports*

Table above shows that the urban population in Uganda was characterized by relatively high growth rate of 6.1% and 5.1% between 1980 and 1991 and between 1991 and 2002 respectively. However, there were regional variations in the distribution of the urban population. The level of urbanization is still very low in most of the regions with the exception of the Central region, which had 25% of its population residing in urban areas in 2002. The high level of urbanization in the Central region is due to Kampala City being the prime urban area. When Kampala is excluded from the Central region, the level of urbanization of the region falls from 25 percent to 9 percent. The level of urbanization rose substantially in the Northern region (from 5% to 9%) between 1991 and 2002, but declined in the Central and Eastern regions (UBOS, 2002). The percentage of the population in urban areas as enumerated in 2002 showed that 8 districts (Kampala, Luwero, Mukono, Busia, Jinja, Gulu, Kitgum and Nebbi) had urbanization rates above the national level (12.3%) (UBOS, 2002). The 2002 census clearly indicated that Kampala is 100 percent urban with a population of 1.2 million and is the largest urban center, in the country. It is also evident that the major urban areas in Uganda fall within what could be described as the "urban corridor", and are a reflection of the colonial policy of infrastructure development, especially the construction of the Kenya – Uganda railway as shown in figure below.

Figure 2.2: "Urban corridor" the Kenya – Uganda railway reflection of the colonial policy of infrastructure development

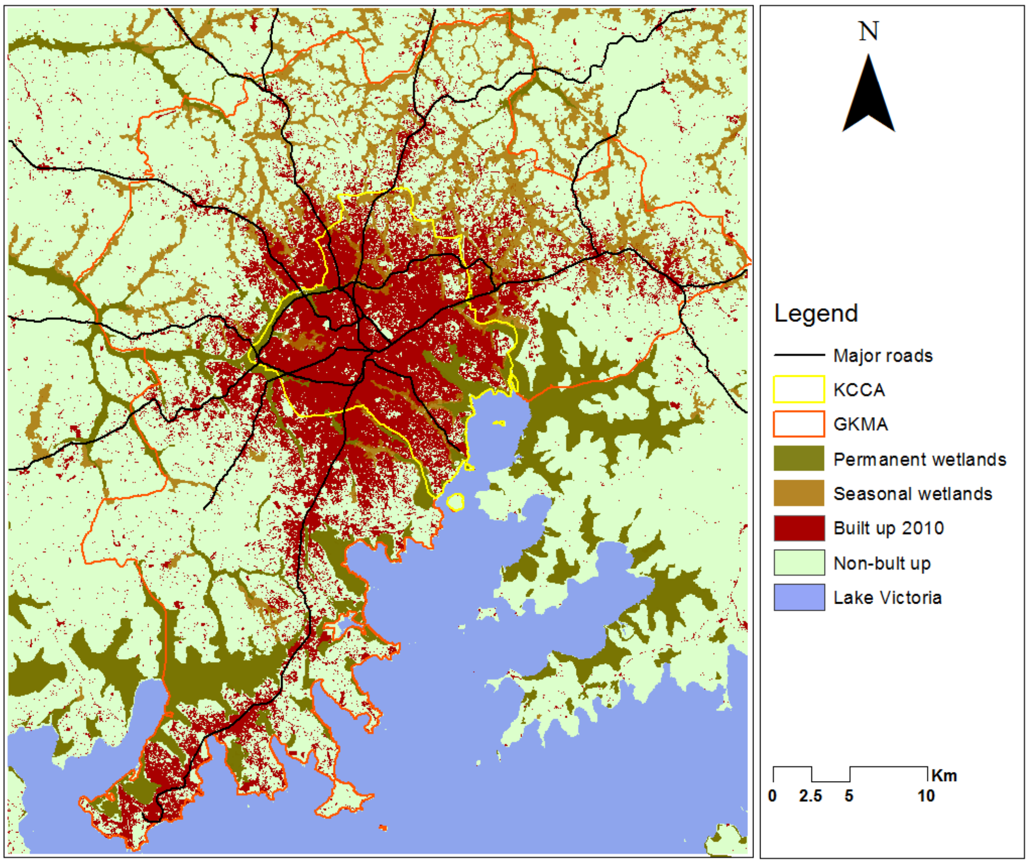
Source: Urban change in Uganda, a paper by Isolo Paul Mukwaya, 2004

Driving forces of Kampala's urbanization

The physical expansion of Kampala is mainly driven by urban population growth and demographic shifts in the form of rural-urban migration which has led to the formation of unplanned settlements within the city and at its periphery (Lwasa, 2004). Due to internal and international migration, high fertility rate (7.1%) and low mortality rate, the population of Kampala has been steadily growing since the last few decades exceeding the pace at which urban services and housing are provided (B. Nyakaana et al., 2004).

Economic transformation policies of Uganda which have mainly been pursued from and around the city through industrialization and the associated market forces of consumption derived from the population growth are also the other responsible factors for the urban expansion of Kampala. Due to these factors, the expansion in Kampala is steadily advancing at fast pace leading to engulfing of adjacent rural landscape and urban centers. However, the urban expansion a process of Kampala is accompanied by the proliferation of unplanned settlements and informal sectors with inadequate services and infrastructure as well as environmental sanitation problems. The conversion of environmentally sensitive non-urban land uses, such as wetlands & agricultural land, to urban uses with serious social and health problems mainly at the fringes of the city are the major consequence of unplanned and informal urban expansion in Kampala. Map presented in figure_2.3 shows the location of wetlands in the study area. This map is produced based on built up area 2010 and wetlands-1996 data obtained from (http://www.wri.org/publication/uganda-gis-data).

Figure 2.3: Wetlands location in GKMA (temporary and seasonal)



2.4. Remote sensing and urban growth

Many scientists, resource managers, and planners agree that, the future development and management of urban areas entail comprehensive knowledge about the on-going processes and patterns. As a result, understanding the urban growth patterns, dynamic processes, and their relationships and interactions is a key objective in the contemporary urban studies (e.g. Bhatta, 2009, 2010; Deng et al., 2009). Remote sensing is helpful tool to better understand the spatiotemporal trends of urbanization and monitor the spatial pattern of urban landscape compared to traditional socioeconomic indicators such as population growth, employment shifts, etc. (Jun et al., 2009). However, the availability of multi-temporal data is important to analyse the dynamics of land cover change over time and space. In order to detect the changes and patterns of different spatial phenomenon, it is important to make sure that the available images are acquired in the same season. This will help to avoid data inaccuracy generated due to seasonal variations. Nonetheless, it is difficult to find multi-date data taken at the same time of different years, particularly in tropical regions where cloud cover is prevalent (Mas, 1999). As a result the selection of temporal dimension is mostly dependent on the availability of good quality data at that particular time of interest. Particularly, this is true for developing countries.

Although challenged by different factors such as spatial and spectral heterogeneity of urban environments, remote sensing is an appropriate source of data for urban studies (Roberts & Herold, 2004). According to a report published by NASA, the advances in satellite-based land surface mapping are contributing to an improved understanding of the underlying forces of urban growth and sprawl, as well as issues relating to territorial management. Nowadays, the physical expansions and patterns of urban growth on landscapes can be distinguished, mapped, and analysed by using remote sensing data (Bhatta, 2010). Medium resolution Landsat images play the key role in the analysis of urban change at different spatial scale (e.g. Buyantuyev et al., 2010; Ding et al., 2007; Huang; et al., 2008)

Different studies have been conducted on urban change using medium resolution Landsat images. For instance, Yuan et al. (2005) used multi temporal Landsat images to analyse urban growth pattern and to monitor land cover changes of two twin cities in Minnesota metropolitan area. The result shows that it has been possible to quantify the land cover change patterns in the metropolitan area and demonstrate the potential of multi temporal Landsat data to provide an accurate and economical means to map and analyse changes in land cover over time. Yang and Lo (2002) used multi-temporal/multi-resolution satellite imageries to successfully extracted land use/cover data in the Atlanta, Georgia metropolitan area for the past 25 years. The result revealed that the loss of forest and urban sprawl have the major consequences of Atlanta's accelerated urban development. Tang et al. (2008) used multi temporal satellite images to analyse the dynamics of urban landscape in two petroleum-based cities: Houston, Texas in the United States and Daqing, Heilongjiang province in China. Accordingly, both cities expanded rapidly on the basis of the petroleum industries during the study period; however, under varying socio-political settings.

Shi et al. (2012) used three sets of Landsat Thematic Mapper (TM) images to characterize the growth types and analyse the growth density distribution in response to urban growth patterns in peri-urban areas of Lianyungang City. The result of this research depicted that, substantial arable lands were lost by urban growth in peri-urban & the pre-dominant growth types were edge-expansion and infilling growth respectively with important evidence of urbanization from a city's central core. Deka et al. (2012) showed that the integration of remote sensing (RS) and Geographical Information System (GIS) technique to effectively detect urban growth, emphasizing on the potential applicability of Landsat TM data in the urban studies at both regional as well as local level. This study also indicates the value of medium resolution Landsat images for analysis of urban growth at metropolitan scale, compared to the more resent VRH images.

2.5. Image classification methods

Classification in remote sensing involves clustering the pixels of an image to a relatively small set of classes, such that pixels in the same class are having similar properties. The majority of image classification is based on the detection of the spectral response patterns of land cover classes (Brito & Quintanilha, 2012). In order to utilize remote sensed images effectively, several image classification methods have been suggested and developed over the past decades. But there is no single ideal classification method for each and every remote sensing image (Tso & Mather, 2009). The choice of image classification method mostly depends on the objectives of the research, the nature of the image and the level of detail or accuracy required for specific application (Lillesand et al., 2008).

There are two broads of classification procedures: supervised classification unsupervised classification. Supervised classification is the process of assigning objects of unknown identity to one or more known features using training data. Maximum likelihood (ML) classification algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood). Better results can be achieved in supervised classification technique by taking more features and training samples from the study area. Training data are objects selected as representative samples of known features. In supervised classification prior knowledge of the ground cover is important to select training samples. The advantage of the ML classification algorithm is that it takes the variability of the classes into account by using the covariance matrix. However, the disadvantage of maximum likelihood classification arises from the time and effort required to prepare the training samples (Al-Ahmadi & Hames, 2009).

In unsupervised classification technique, an algorithm is chosen that will take a remotely sensed data set and find a pre-specified number of statistical clusters in multispectral or hyper-spectral space. Although these clusters are not always equivalent to actual classes of land cover, this method can be used without having prior knowledge of the ground cover in the study site (Mohd Hasmadi I et al., 2009). Contrary to the a priori use of analyst-provided information in supervised classification; unsupervised is a clustering of the data space without any information provided by any analyst. Analyst information is used only to attach information class (e.g. ground cover type) labels to the segments established by clustering. Clearly this is an advantage of the approach. However, the result of clustering is simply the identification of spectrally distinct classes in image data. These classes do not necessarily relate to the informational categories that are of interest to analyst. Hence, proper interpretation of these classes is required along with reference data that requires understanding of the concepts behind the classifier and familiarity with the area under analysis (Lillesand et al., 2008).

Maximum Likelihood classifier is one of the most popular and widely used types of image classification technique in remote sensing (Brito & Quintanilha, 2012). Several researchers have demonstrated the importance of supervised maximum likelihood classification technique for land cover change analysis. For example, Tang et al. (2008) analysed the spatiotemporal landscape dynamics of two petroleum-based cities: Houston, Texas in the United States and Daqing, Heilongjiang province in China. They used the conventional Maximum Likelihood Classification method to classify six multi-temporal satellite images. Yuan et al. (2005) used supervised maximum classification method to map and monitor land cover change using multi temporal Landsat Thematic Mapper (TM) data in the seven- county Twin Cities Metropolitan Area of Minnesota for 1986, 1991, 1998, and 2002. Zhou and Wang (2011) used maximum likelihood classifier to characterize the changing patterns and intensities of green space in Kunming, China from 1992 to 2009.

2.6. Remote sensing and change detection techniques

"Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times" (Singh, 1989, p. 989). Different change detection methods have been developed and documented over the past decades can be found in (D. Lu et al., 2004). All have their own advantage and disadvantage. Some of the most commonly used change detection methods have been discussed below.

Image differencing

Image differencing is one of the most widely used to determine changes between images, and has been used in a variety of geographical environments. The difference between two images is calculated by subtracting the imagery of one date from that of another, and generating an image based on the result. The subtraction results in large positive or negative values in areas of radiance change, and values close to zero in areas of no change. A critical challenge of this method is deciding where to place the threshold boundaries between change and no change pixels. This method is also sensitive to mis-registration and mixed pixels. To obtain good result, the two images must first be aligned so that corresponding points coincide. The complexity of image pre-processing needed before differencing varies with the type of image used.

Principal component analysis (PCA)

Principal component analysis is a technique used extensively in remote sensing images analysis in application well beyond that of change detection. PCA has been used for determining the intrinsic dimensionality of multi spectral imagery, data enhancement for geological application, and land cover change detection. This method is often used to reduce the dimensionality of the data without reducing its overall information content. However, estimation of the PCA projection from data has its own limitations. Its computational complexity makes it difficult to deal directly with high dimensional data, like satellite images. Second, the number of examples available for the estimation of the PCA projection is typically much smaller than the ambient dimension of the data and this can lead to over fitting of the projection.

Post classification comparison

Post classification comparison is the most intuitive methods of change detection, is GIS overlay of two independently produced classified images. The post-classification comparison can be used to identify not only the amount and location of change, but also the nature of change. The method can produce from-to information (D. Lu et al., 2004). However, the accuracy of the change detection is highly dependent on the accuracy of the classification result. The method reduces the need to perform geometric and atmospheric corrections (Jensen, 2005; Y. Liu et al., 2004)

Post-classification comparison is made on classified images. Mas (1999) suggested that post classification is often considered a priory to be the superior change detection method and is, therefore, used as the standard for evaluating the results of other methods. However, every inaccuracy in the individual data classification map will also be propagated in the final change detection map. Therefore, it is imperative that the individual classification maps used in the post-classification change detection methods be as accurate as possible. In addition to these the image classification stage of this method takes a long time because the accuracy of the classification needs to be high to get a good change detection result (D. Lu et al., 2004). The advantage of post-classification comparison is that it can provide from-to information which helpful to differentiate which land cove or land use class is changed to another class.

Change Vector Analysis (CVA)

Change vector analysis technique is an empirical method of detecting radiometric changes between multitudes of satellite images in any number of spectral bands. This method yields information about the degree and type of spectral changes by calculating a vector magnitude and direction in multispectral change space for each pixel (Balcik & Goksel, 2012). Like image differencing, a threshold indicating change and no change area also needs to be determined in this method (Lambin & Strahler, 1994). A particular advantage of the change vector analysis method is the potential capability to process any number of spectral bands desired. This is important because not all changes are easily identified in any single band or spectral feature. Nevertheless, since no effective method has been developed to handle more than two spectral bands (Kontoes, 2008).

Image Ratioing

Image ratioing is another method for change detection in which two images from two dates are divided band by band and pixel by pixel. If the ratio of two images is equal to 1, then no change has occurred, but if the ratio is greater than or less than one that means change has occurred. A threshold needs to be decided. The common way for deciding this has been to set a threshold value and then evaluating the change detection. Image ratioing produces images with a non-Gaussian distribution of pixel values and if a threshold is decided based on standard deviations from the mean, the change will not be equal on both sides. This feature of image ratioing has been criticized (D. Lu et al., 2004; Singh, 1989). One of the most common ratio is called Normalized Difference Vegetation Index (NDVI) is: (NIR-RED) / (NIR+RED) or simplified as NIR /RED. The advantage of image ratioing is that the effect of different Sun angles, shadows and topography is reduced, the disadvantage is the non-Gaussian distribution of the ratio image making threshold selection difficult (D. Lu et al., 2004).

Recently, numerous studies have indicated the use of post-classification comparison change detection technique for land cover change analysis in urban studies. Yin et al. (2011) used post-classification comparison to detect changes of Shanghai metropolitan area, China based on Landsat MSS, TM and ETM+ images from 1979, 1990, 2000 and 2009. By overlaying the classified images over each other they were able to compare the changes in pixels of the layers pixel-by-pixel. Alphan et al. (2009) used post-classification comparison change detection method to assess the land cover changes in Kahramanmaraş (K.Maraş) and its environs from multi temporal Landsat and ASTER imagery, respectively belong to 1989, 2000 and 2004. J. Liu et al. (2005) also used post-classification comparison to analyse and map the magnitude and pattern of China's changing landscape during the 1990s from Landsat TM images covering the entire county. They classified the images in to different land cover class identified. Then the classified images were compared using some statistical measurements.

2.7. Remote sensing and Spatial metrics metrics

As discussed above, the main strength of remote sensing technique lays on its capability to deliver spatially consistent data set that cover a wide range of spatial extent with both high and detailed spatio-temporal resolution, including historical time series data (Herold et al., 2005). Yet, it cannot provide full description of the underlying processes that are responsible for the changing patterns of urban landscape. To bridge this gap spatial metrics are used. The thematic land cover maps obtained from the analysis of Landsat TM and ETM+ images will used to further quantify and describe urban landscape pattern.

The interest to quantify landscape patterns are often driven by the premise that patterns are linked to ecological processes (Gustafson, 1998). Spatial metrics are expedient tools for quantifying spatial heterogeneity and to have better insight on how spatial structures impact the system interaction in a heterogeneous landscape. Heterogeneous landscape or spatial heterogeneity refers to the complexity and unevenness of a system property in time and space, spatial heterogeneity is considered synonymous of spatial pattern. A system property is any measurable entity, for instance the configuration of the landscape mosaic. Spatial structure is a major subset of the concept of spatial heterogeneity, usually referring to the spatial configuration of the system property (Turner et al., 1989).

Spatial metrics can provide rich numerical description of the landscape structure at patch, patch class or the whole landscape level (Herold et al., 2003). Spatial metrics can be categorized into three broad classes: patch, class, and spatial metrics (Bhatta, 2010). Patch is a relatively homogeneous area that differs from its surroundings (McGarigal & Marks., 1995). Patch metrics are computed for every patch in the landscape, class metrics are computed for every class in the landscape, and spatial metrics are computed for the entire landscape (Bhatta, 2010).

However, most spatial metrics are scale dependent and they are determined by the extent of spatial domain, the spatial resolution and the thematic definition of the map categories (Šímová & Gdulová, 2012). It is up to the user to define the landscape, including its thematic content and resolution, spatial grain and extent, and the boundary of the study area, based on the phenomenon under consideration before conducting any kind of metrics computation (McGarigal et al., 2012). Attention should be paid while comparing the value of metrics computed from landscapes that have been defined and scaled differently.

2.8. Analysing urban growth pattern using remote sensing & spatial metrics

Patterns are distinguished by spatial relationships among component parts in landscape metrics. A landscape pattern can be characterized by both its composition and configuration of its component parts (McGarigal & Marks., 1995). These two characteristics of a landscape can individually or in combination affect ecological processes.

A variety of metrics have been developed to quantify categorical map patterns in the past studies (see, for example McGarigal et al., 2002). Despite the availability of plenty of metrics, offered by different literature, to describe landscape structure, they are still categorized under the two major components, namely, composition and configuration of a landscape (Gustafson, 1998). Composition metrics is easy to quantify and can be defined as features related to the presence, proportion and the variety and richness of patch types within the landscape mosaic. Nevertheless, composition metrics does not consider the spatial character, arrangement, or location of patches within the mosaic. A variety of quantitative descriptors of landscape composition are available, but the principal measure of composition includes; the proportional abundance of each class in the entire landscape, patches richness, patches evenness, and patch diversity (McGarigal et al., 2002). Shannon's diversity index (SHDI), Shannon's evenness index (SHEI), dominance (DOM) and patch richness density (PRD) are some of the examples of commonly used composition metrics.

Conversely, configuration metrics is relatively more challenging to quantify. It refers to the spatial arrangement, character and position of patches within the class of patches or entire landscape (McGarigal & Marks., 1995). The principal aspects of configuration metrics includes: patch area and edge, patch shape complexity, core area, contrast, aggregation, subdivision, and isolation. Some of the most frequently used configuration metrics includes: number of patches (NP), percentage of landscape (PLAND), edge density (ED), landscape shape index (LSI), mean patch size (MPS) and number of patches (NP), largest patch index (LPI), total edge (TE), mean shape index (MSI), area-weighted mean fractal dimension (AWMFD), total core area (TCA), mean Euclidean nearest neighbour index (MNN), contagion (CONTAG), effective mesh size (MESH), aggregation index (AI).

Urban growth and land cover change has been the major topic concerning remote sensing applications (Masser, 2001). The spatial and temporal dimensions are major concerns of remote sensing in urban studies. To better understand the complexity of urban systems and its spatial and temporal dimensions, urban growth analysis need to be linked with land cover change model. Currently, there has been an increasing interest in applying remote sensing and spatial metrics techniques (see for example FRAGSTATS McGarigal et al., 2012) to analyse urban environment.

For instance, Kuffer and Barrosb (2011) used spatial metrics in a VHR remotely sensed images to analyse the morphology of unplanned urban settlements in Dar es Salaam and New Delhi. In this study, different sets of metrics were used for two case studies. After eliminating several highly correlating metrics, the authors selected a set of four metrics, i.e. is mean area, patch density, aggregation index and Shannon's diversity index for Dar es Salaam and a set of six metrics, i.e. effective mesh size, landscape division index, patch density, contagion, aggregation and Simpson's evenness index for Delhi. Both sets of metrics measure size, pattern and density. Finally, the sets of spatial metrics were combined using spatial multi-criteria evaluation to produce a composite index indicating areas of high likelihood of 'unplannedness' in the study area.

Jain et al. (2011) applied spatial metrics and gradient analysis method for quantifying and capturing changes in urban landscape using LISS III imagery of Gurgaon, India. The combination of landscape metrics, i.e. percentage of landscape, mean patch size, number of patches, landscape shape index and largest patch index have been used to quantify the patterns of urban growth in different directions of the city in terms of size, shape and complexity of development. Finally, they were able to demonstrate the potential of spatial metrics and gradient analysis to quantify the impact of regional factors on the growth pattern.

Pham and Yamaguchi (2011) showed the potential application of spatial metrics as secondary sources of information for supporting remotely sensed data and their use to characterize urban growth patterns of Hanoi, Vietnam. This study used the percentage of like adjacency (PLADJ) metric on the urban growth maps generated using maximum likelihood image classification technique to illustrate the changes in the urban structure in the study area. Six class-level landscape metrics, i.e. class area, number of patch, edge density, largest patch index, mean nearest neighbour distance and area weighted mean patch fractal dimension, were selected to characterize the urban the urban composition parameters of Hanoi.

Seto and Fragkias (2005) effectively compared the spatio-temporal pattern of urban land use changes in four Chinese cities, using three concentric zones and a set of landscape metrics. This study used a group of six spatial pattern metrics analysis indices namely: total urban area (UA), number of urban patches (NUMP), mean urban patch size (MPS), urban patch size coefficient of variation (PSCOV), urban edge density (ED) and area-weighted mean patch fractal dimension (AWMPFD). The results of this study indicate that urban form can be flexible over relatively short periods of time. Despite different economic development and policy background, the four cities exhibit common patterns in their shape, size, and growth rates, suggesting a convergence toward a standard urban form.

X. J. Yu and Ng (2007) used a combination of remote sensing images, spatial metrics and gradient analysis to analyse the spatial and temporal dynamics of urban sprawl in Guangzhou, China. The results of this study shows that landscape change in Guangzhou exhibits distinctive spatial differences from the urban centre to rural areas, with higher fragmentation at urban fringes or in new urbanizing areas. Population growth and rapid economic development were the two major driving forces of urban expansion in the study area. The authors were also able to demonstrate the importance of temporal data to reveal the complexity of landscape pattern and to capture the spatio-temporal dynamics of landscape changes.

Herold et al. (2005) explored the importance of spatial metrics in the study and modelling of urban land use change in Santa Barbara urban area, California, USA. Percentage of landscape (built up) (PLAND), patch size standard deviation (PSSD), contagion index (CONTAG), patch density (PD), edge density (ED), area weighted mean patch fractal dimension (AWMPFD) are the spatial metric growth signatures used in the study. According to the research, the growth of Santa Barbara develops outward from the original downtown core. Generally this study indicate that spatial metrics can be utilized for the detailed mapping of urban land use change at different geographic scales and can help infer a number of socioeconomic characteristics from remote sensing data.

Schneider et al. (2005) used remotely sensed data to map changes in land cover in the greater Chengdu area and to investigate the spatial distribution of urban development by using spatial metrics along seven urban-to-rural transects corridors of growth. Pham et al. (2011) explored and approach for combining remote sensing and spatial metrics to monitor urbanization, and investigate the relationship between urbanization and urban land use plans. The study examined four cities of Asia namely: Hanoi, Hartford, Nagoya and Shanghai, using Landsat and ASTER data. The results showed that the combined approach of remote sensing and spatial metrics provides local city planners with valuable information that can be used to better understand the impact of urban planning policies in urban areas.

Herold et al. (2005) stated that spatial metrics Combined with, time-series of high spatial resolution remote sensing data has the potential to characterize the dynamics of urban growth processes as well as it can reveal the spatial component in urban structure underlying the growth process (Herold et al., 2002). In this context remote sensing and spatial metrics are used in a complementary way to better understand the urban growth processes and patterns.

Jianguo Wu et al. (2011) analysed the spatio-temporal patterns of urbanization in two fast growing metropolitan regions in the United States using: Phoenix and Las Vegas. Based on historical land use data and landscape pattern metrics at multiple spatial resolutions they were able to characterize the temporal patterns of urbanization in the metropolitan regions. The results of this research showed that the two urban landscapes exhibited strikingly similar temporal patterns of urbanization with an increasingly faster increase in the patch density, edge density, and structural complexity of the landscape. That is, as urbanization continued to unfold, both landscapes became increasingly more diverse in land use, more fragmented in structure, and more complex in shape. Finally, the authors conclude that “a small set of spatial metrics is able to capture the main spatiotemporal signatures of urbanization, and that the general patterns of urbanization do not seem to be significantly affected by changing grain sizes of land use maps when the spatial extent is fixed”.

There are several methods to analyse and quantify the dynamics of urban growth patterns and processes. However the selection of method depends on the objectives of the problem on hand and the clear understanding of the different tools and techniques used for analysing urban environment. Several studies reviewed in this section indicate the value of medium resolution remote sensed satellite images and spatial metrics for the analysis of urban change.

2.9. Urban growth modelling

Rapid urban growth accompanied by land cover change, has become a global phenomenon observed all over the world. Several studies have endeavoured to understand the spatio-temporal pattern of land cover change and its driving forces (Allen & Lu, 2003; Veldkamp & Lambin, 2001). There are two broad categories of land change models developed over the past several decades (Hu & Lo, 2007). These are dynamic simulation based models and statistical estimation models. Simulation-based models such as

Cellular Automata (CA) attempts to capture the spatio-temporal pattern of urban change by incorporating spatial interaction effect in to the model However, the poor explanatory capacity of simulation models has limited the detail understanding and interpretability of urban growth dynamics with its potential driving forces (Luo & Kanala, 2008). Moreover, most dynamic simulation models are not capable of incorporating adequate socioeconomic variables (Hu & Lo, 2007).

Empirical models use statistical analysis to reveal the interaction between land cover change and explanatory variables and have much better interpretability than simulation models. For example, regression analysis can help to identify the driving factors of urban growth and quantify the contributions of individual variables and their level of significance (B. Huang et al., 2009; Luo & Kanala, 2008; Nong & Du, 2011). Binomial (or binary) logistic regression is a form of regression, which is used to model the relationship between a binary variable and one or more explanatory variables yielding dichotomous outcome (Hosmer & Lemeshow, 2004). Logistic regression is based on the concepts of binomial probability theory, which does not assume linearity of relationship between the independent and the dependent variables, does not require normally distributed variables, and in general has no strict requirements. In the context of urban growth modelling, logistic regression model was used to study the relationship between urban growth and biophysical driving forces (B. Huang et al., 2009). The conversion of non-urban to urban land use is considered as state 1, while the no conversion is indicated as state 0 in the same period of time. A set of independent variables are selected to explain the probability of non-urban land use to conversion to urban. The main purpose of urban growth modelling is to understand the dynamic processes responsible for the changing pattern of urban landscape, and therefore interpretability of models is the most important aspect the modelling process. The advantage of statistical models is their simplicity for construction and interpretation or their capacity to correlate spatial patterns of urban growth with driving forces mathematically. However, statistical models lack theoretical foundation as they do not attempt to simulate the processes that actually drive the change (Koomen & Stillwell, 2007).

3. DATA AND METHODOLOGY

3.1. Introduction

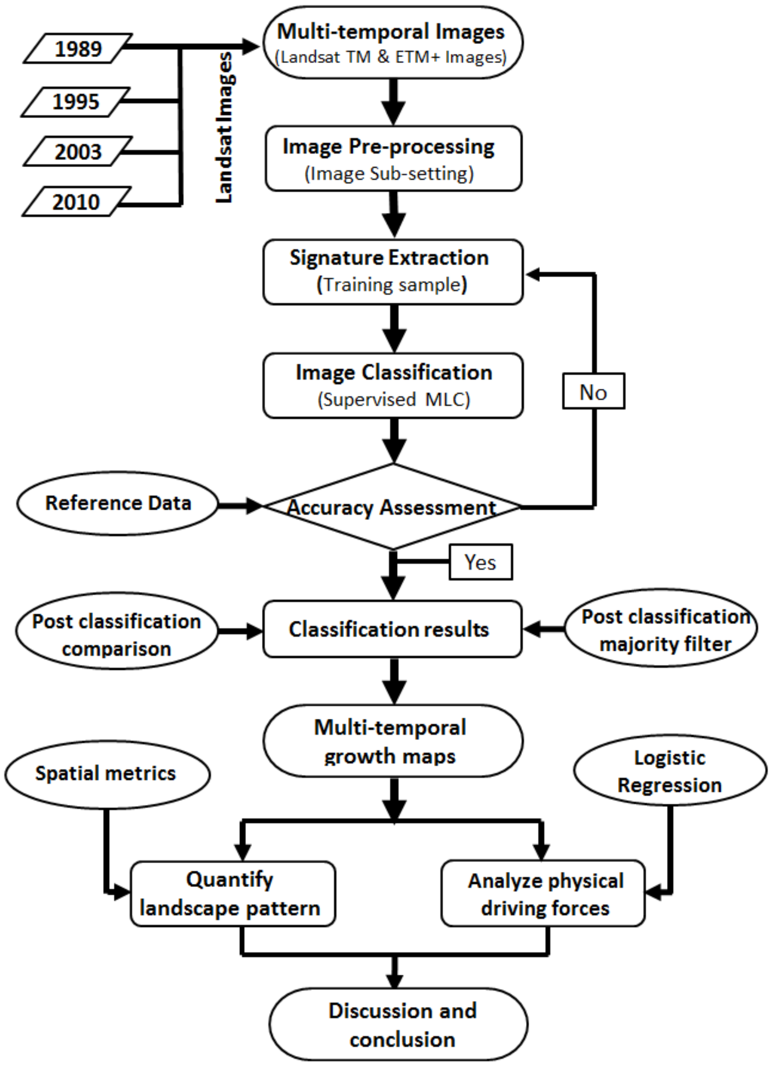
This chapter presents the available data, the overall methods, techniques, approaches and materials used to achieve the research objectives. It mainly explains the data sources and types, methods of field data collection, reference data used identification of driving forces of urban growth, image classification technique employed, and change detection methods used, accuracy assessment, selection of spatial metrics and list of software packages used in the research.

3.2. Research design and methodology

This research is conducted in three phases: pre fieldwork, fieldwork and post fieldwork phases. The first phase is a preparation phase which consists of research proposal development, including problem definition, formulation of research objectives and associated research questions, defining methods, identifying required data types, clearly defining data collection methods and preparing (field) work plans. The second phase is information and data gathering phase (fieldwork phase). In this phase, important data required to carrying out the research including primary and secondary data are collected during fieldwork. These includes interviewing local experts on the issues of urban growth driving forces, collecting ground truth data, visiting important places of the study area like city centre, new development sites, etc. to have the general impression of the study area. This task is carried out with the assistance of local dwellers. In the end, the collected data is processed, analysed and the finding are presented (post fieldwork phase) so as to meet the predefined objectives of the research, which is followed by conclusion and recommendation.

There are different kinds of methods, strategies and techniques to process input data in order to generate the anticipated research output in an efficient and consistent way with desired quality. However, the choice of appropriate methodology and specific technical arrangements are largely dependent on the availability of quality data, the desired inputs, the strength of logistic support including the software employed, researcher's experience and skill to manipulate and the necessary fund allocated for the task. The methodology incorporated in this study involves remote sensing image classification techniques as well as spatio-temporal analysis of spatial metrics and logistic regression methods. First, four multi-temporal sets of Landsat images (TM 1989 & 1995, ETM+ 2003 and TM 2010) covering the entire study area are used to produce the land cover map by using the maximum likelihood classification algorithm in ERDAS Imagine 2011 (Lillesand et al., 2008). Post-classification comparison is used to produce growth/change map, where the classified images are overlaid on top of each other in ArcGIS 10.1 using different spatial analyst tools. Consequently, the spatial extent and rate of urban growths are analysed and quantified. Then, the classified images are used as an input data in FRAGSTATS 4.1 (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of urban landscape. Finally, binary logistic regression model is built to identify the major physical driving forces responsible for the changing patterns of urban landscape in ArcGIS extension, Change Analyst software. A flow chart describing the general methodology used in this study is given below (see figure_3.1).

Figure 3.1: General methodology of the study



3.3. Data source and type

Different remote sensing and GIS data from different sources has been used in this research. Four medium resolutions Landsat TM images of 1989, 1995, 2003 (ETM+) and 2010 were used to detect urban land cover change patterns of the study area (see figure_3.2). These images were obtained from the United States Geological Survey (USGS) website as standard products, i.e. geometrically and radio-metrically corrected. In order to avoid the impact of seasonal variation, all images are selected from the same season in such a way that the cloud cover will not exceed 10%. The images are also of the same level of spatial resolution of 30m which makes it convenient for comparison of changes and patterns that occurred in the time under consideration. Additionally, two VHR images covering some pat of Kampala and obtained from ITC-IFM-Kampala geodatabase: one image generated from orthophotos (2004) with 50cm resolution and another one Quick bird image of 2010 with resolution 60cm are used to assist field observation data in training the images during classification. The DEM used to analyse driving forces of urban growth is downloaded from SRTM-USGS centre. Most GIS data such as location of satellite towns, Entebbe airport, sub-city centres, CBD and existing built up areas are derived VRH Google Earth image based on the information gathered from local experts during fieldwork period. Other data such as administrative boundaries, major roads and wetlands are obtained from open web sources such as (www.diva-gis.org), (www.ugandaspatialsolutions.com) and (www.wri.org) and from ITC-IFM-Kampala geodatabase. All dataset used in this study are geometrically referenced to the WGS 1984, UTM zone 36 projection systems. The detail description of the characteristics all images used in this study is summarized in tables 3.1 & 3.2 below.

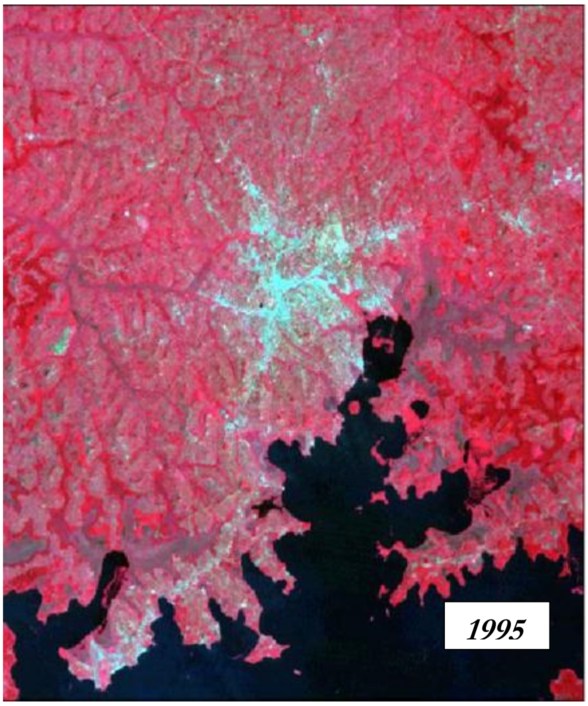
Table 3.1 List of satellite images (raster data) collected for the study area.

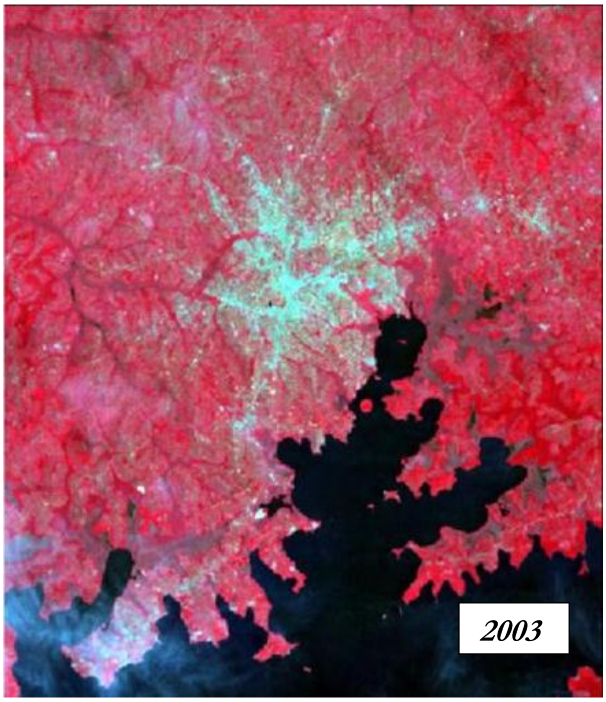
Satellite data	Acquisition date	Spatial resolution	Path/row	Data source
Landsat TM	1989/2/27	30 m	171/60	USGS
Landsat TM	1995/1/19	30 m	171/60	USGS
Landsat ETM+	2003/2/2	30 m	171/60	USGS
Landsat TM	2010/1/28	30 m	171/60	USGS
Image generated from orthophotos	2004	50cm	-	ITC/IFMKampala geodatabase
Quick bird image	2010	60cm	-	ITC/IFMKampala geodatabase
Topographic map (slope)	Raster	30cm	-	SRTM /USGS

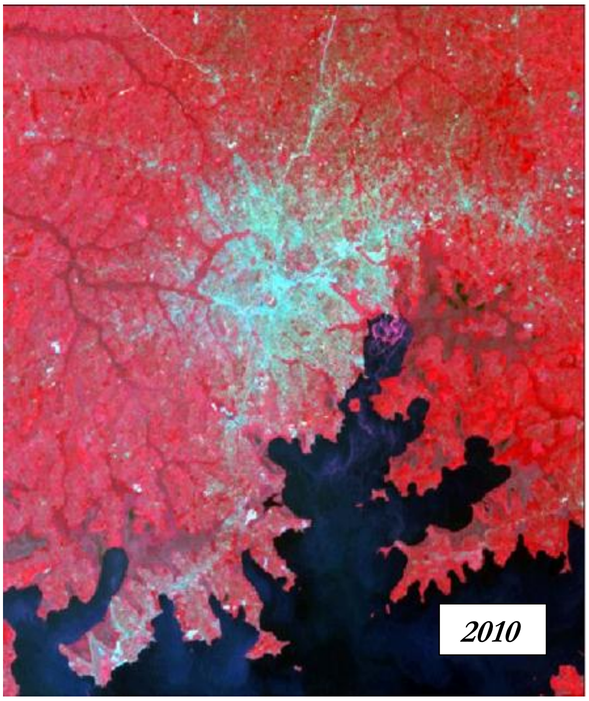
Table 3.2 List of spatial data (vector data) used for the study area

Spatial data	Format/type	Source
Satellite towns	Shape file	Derived
Major Roads	Shape file	IFMKampala geodatabase/ ITC
Enttebe Airport	Shape file	Derived
Sub-city centres	Shape file	Derived
CBD area	Shape file	Derived
Existing built-up area	Shape file	Derived
Administrative boundaries	Shape file	http://www.diva-gis.org
Wetlands	Shape file	http://www.wri.org

Figure 3.2: Landsat images covering the study area in 1989, 1995, 2003 and 2010







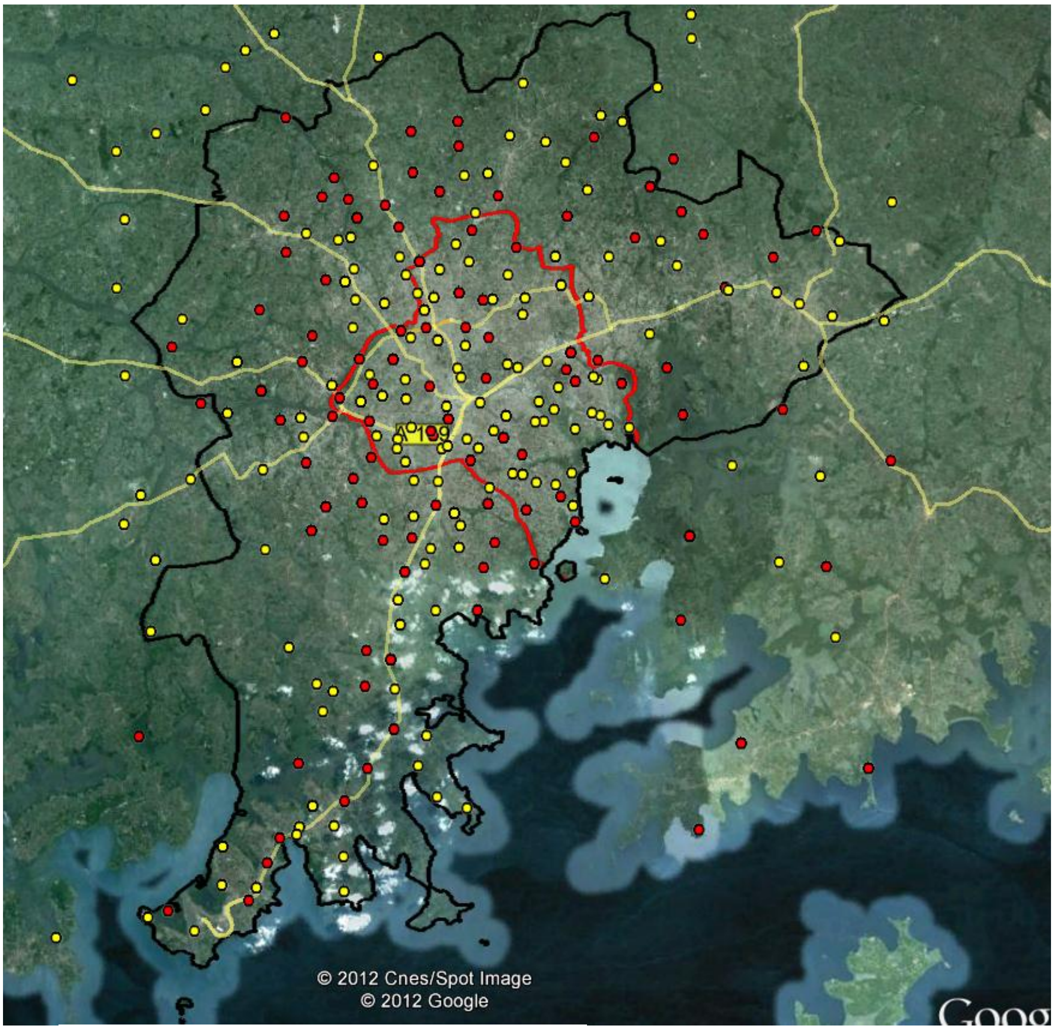
3.3.1. Field data collection

This research made use of both primary and secondary data to make sure that the objectives of the study are meet. Although some secondary data are collected from literature review and open source websites, yet important information and data are gathered from field work. The field work for the study was carried out from 15th of October, 2012 to 6th of November, 2012 in Kampala metropolitan area aiming at two major tasks relevant to the study as explained as below.

Reference data

One of the most important primary data required from field survey is ground truth data. It is used to assess the accuracy of classified land cover map. For this purpose the coordinates of 100 selected ground control points were collected to reinforce the 170 ground truth data obtained from previous work (Vermeiren et al., 2012). In total, 270 GCP are used to assess the accuracy of classified images (see figure 3.3). Simple stratified random sampling technique is used to determine the location of the new points. Handheld GPS Garmin E-trex 12 channel is used to collect the field data. Digital camera was also used to photograph the land cover material of visited sites. The data collection is carried out with the assistance of local people who has good knowledge the Kampala metropolitan area.

Figure 3.3: Location of reference data collected from field work.



LEGEND

Points from Vermeiren et al. (2012)

Points collected from fieldwork

Identifying the probable Physical driving forces of urban growth

The other most important task of the field work was to collect relevant information about driving forces of urban growth in the study area. This task is carried out in the form of interview with local experts like policy makers and city planners on the issues of urban growth driving forces. The main objective of the interview was to identify the major physical driving forces of urban growth in the study area. Beforehand, list of probable driving forces of Kampala's urban growth were identified based on literature review. The interview was conducted with two local experts in two different days. These are Dr. Shuib Lwasa, physical planner and lecturer, from Makere University, and Mr Ndiwalana Robert from KCCA physical planning department Kawempe division.

During the interview the list of probable driving forces of urban growths, which were identified from literature review, were presented by the researcher. Then the experts were interviewed with a guiding question to give their opinion based on their professional expertise & experience in the study area. The experts were given freedom to add or subtract from the given list of probable driving forces of urban growth identified from literature review. Finally, the researcher was able to identify the final list of physical driving forces of urban growth in the study area to be included in the logistic regression modelling. Accordingly, Thereby relevant information on identified driving factors such as the location of the main city centre (CBD) and economically active and important sub city centres where fast development has been observed in the past few years were identified on map.

3.3.2. Software's and Other Instruments Used

Erdas Imagine 2010, FragStats tool 4.1, ArcGIS 10.1, Change analyst Arc GIS plug in, Garmin E-trex 12 channel Hand held GPS & voice recorder are the tools used in this study.

3.4. Methods of data analysis

After collecting all the relevant primary and secondary data, the next task was to process and analysing the data. As discussed earlier this research applies remote sensing and spatial metrics techniques to quantify urban growth processes and patterns. Remote sensing image classification is a relevant method that can provide information on the extent and rate of urban growth whereas spatial metrics are computed based on the remote sensing image classification results to quantify the patterns of growth (Hai & Yamaguchi, 2008; Herold et al., 2003). Both together are believed to give better understanding of urban growth processes and patterns. The methods are also quick ways of acquiring relevant information where availability of spatial data is scarce such as in Sub-Saharan African countries. Apart from this binary logistic regression method has been used to identify the major physical driving forces of urban growth in the study area. Detail explanations on each method of data analysis are given in the subsequent sections.

3.4.1. Remote sensing Image classification

Four multi-temporal medium resolution Landsat images are used to analyse the urban growth trends and patterns of Kampala for the past 21 years. As described in section 3.3, all images are acquired geometrically corrected and geo-referenced. However, it is important to note that the 2003 ETM+ image has relatively more cloud cover (refer figure 3.2), which might affect the image classification process. Owing to its popularity and wide acceptance in remote sensing image classification (refer section 2.5), supervised maximum likelihood classification algorithm was applied in ERDAS IMAGINE 2010 software environment. Accordingly the images were classified in to different land cover classes which finally ended up generating four different year land-cover maps of the study area. In ML classification method, pixels with maximum likelihood are categorized into the corresponding class.

The land cover maps are composed of three major land-cover classes namely; built up, non-built up and water bodies. Each land cover classes comprise different land uses classes. The built up area consist of commercial, residential, road and impervious features, continuous and discontinuous urban fabric, residential, industrial and commercial units, road and railway networks and other associated lands, airports, parking lots, dump sites, construction sites, sport and leisure facilities, etc. while the non-built up area includes cropland (agriculture) land, parks, grasslands, forests, woodland shrubs, green spaces, wetlands, bare soil and others. The water body consists of lakes, artificial ponds, swimming pools and others.

Training samples were collected with the assistance of high resolution imageries of 2004 & 2010 (see table 3.1), and visual interpretation of very high resolution images of Google Earth are used for the two recent images of 2003 & 2010 whereas visual interpretation of the true colour composite of the Landsat TM image is used for 1989 and 1995 images. Finally, to improve the accuracy of the classified images, post classification majority filter is carried out in Arc GIS 10.1 using a 3x3 window size (eight surrounding neighbourhoods). Majority filter is a function that replaces cells in a raster based on the majority of their contiguous neighbouring cells. This is helpful to remove isolated and dispersed pixels from the classified image.

3.4.2. Accuracy assessment

In remote sensing-land cover mapping study, classification accuracy is most important aspect to assess the reliability the final output maps. The main purpose of assessment is to assure classification quality and user confidence on the product (Foody, 2002). In this study, the accuracy of the classification results for the year 2003 and 2010 are assessed using 270 randomly sampled ground truth points, obtained from fieldwork and from previous work by Vermeiren et al. (2012). However, since it has been difficult to get reference data for accuracy assessment of image 1989 and 1995, visual interpretation of the true colour composite of the Landsat TM image is used.

3.4.3. Change detection

The change detection method used in this analysis is the post classification comparison technique in which GIS overlay of two independently produced classified images in ARC GIS 10.1 (Alphan et al., 2009). The resulting land cover maps are then visually compared and change areas are simply those areas which are not classified the same at different times. This method is the most straightforward and intuitive change detection method. The advantages and disadvantages of this method are discussed in section 2.5 of this research. Following this method, maps are produced to show the newly built up area between each subsequent years, i.e. 1989-1995, 1995-2003 & 2003-2010 for the study area (Yang & Lo, 2002). In combination with class area spatial metrics, these make it possible to quantify the spatial extent and rate of urban growth over time in the study area. In this context, urban growth is considered as an increase in the physical extent of the built-up (urban) area. Thus, it is possible to interpret the city's growth directions by visualizing the multi-temporal land cover maps. In this study, post classification comparison is used to detect land cover change of the study area.

3.5. Quantifying urban growth pattern using spatial metrics

The processes of urbanization usually change the landscape pattern in urban regions. Such changes are mostly accompanied by decreasing the heterogeneity of landscape compositions and increasing landscape fragmentation by generating smaller patches (Yeh & Huang, 2009). Spatial metrics are useful tools to quantify the dynamic patterns of ecological processes. Changes in urban landscape pattern can be detected by using spatial metrics that quantify and categorize complex landscapes structure into simple and identifiable patterns.

3.5.1. Selection of Metrics and definition of spatial domain

Metrics are often used to quantify several aspects of spatial pattern. As a result, it is seldom to find a one-to-one connection between metric values and pattern. Indeed, most of the metrics describe similar aspect of landscape pattern and they are correlated among themselves (McGarigal et al., 2002). Some metrics are fundamentally redundant as they do not measure different qualities of spatial pattern. Some researchers have made an effort to recognize the most important aspects of landscape pattern for the purpose of categorizing a significant and independent set of metrics (e.g., Cushman et al., 2008; Riitters et al., 1995). These studies suggest that, agreement does not exist on the selection of individual metrics. Looking at the increasing advancement of quantitative metrics, it seems implausible that a single set of metrics exists to fully describe a landscape. Thus, the choice of metrics ultimately depends on the purpose of the problem under investigation and the nature of the landscape.

For this specific study a group of nine metrics are selected based on the literature review and the potential of each metrics to best describe urban pattern (Buyantuyev et al., 2010; Deng et al., 2009; Dietzel; et al., 2005; Herold et al., 2005; Herold et al., 2003). These are: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), area weighted mean patch fractal dimension (AWMPFD), contagion (CONTAG), Shannon's diversity index (SHDI) and Shannon's evenness index (SHEI). These metrics measure different and important aspects of the urban landscape. For example, CA measure absolute area of each land cover classes, number of patches measure the total of patches in the landscape or it is the measure of landscape fragmentation and heterogeneity, PD measure the number of patches per unit area, LPI is the measure of dominance, ED and AWMPFD measure the complexity of urban form, CONTAG measures the tendency of patches types to be spatially aggregated and SHDI & SHEI measures the diversity of landscape. These indices are computed for all (four years) land cover maps and compared temporally, to describe and quantify the spatial pattern of the urban land cover change both at landscape and class level. The detailed description of each metrics is given in the sections.

One of the most important issues in spatial metrics is defining the spatial domain of the study as it directly influences the spatial metrics. Particularly, in a comparative evaluation of intra-urban landscape structures, it is useful to disaggregate the urban environment into relatively homogenous spatial units that will serve as the spatial domains of the metric analysis. Spatial domain is the geographic extent under analysis and its sub-divisions. In some studies the extent of the study area determines the spatial domain. This research adopted the region based approach for metrics calculation, is used to further investigate the dynamics of urban area at disaggregate spatial scale, which is the easiest way to make intra-urban comparisons. Therefore, the study area is divided in to northern region to the Bombo road direction, eastern region to the Jinja road direction, Western region to Masaka-Kampala road direction & to Mityana road direction, south-western region to Entebbe road direction, central Kampala region and peri-urban regions which include parts outside GKMA (refer figure 4.6). These regions are created by dissolving the parishes (the smallest administrative unit in the study area) following the major roads and growth directions and the core city (KCCA), to create the desired unit of analysis.

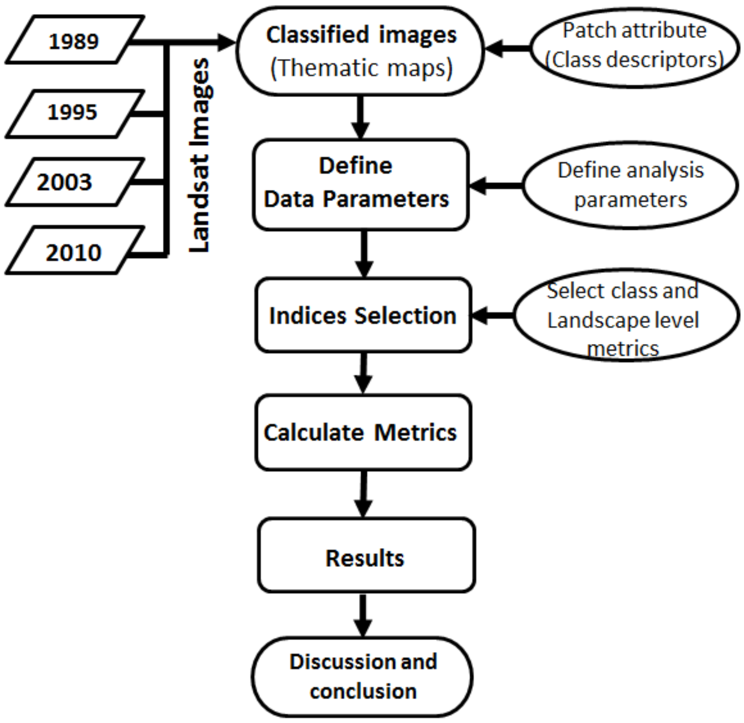
Thus, the analysis of spatial metrics is conducted at two different spatial scales. First, selected metrics are compute at the whole landscape or city level to obtain summary descriptor of landscape heterogeneity. Secondly, owing to the aggregating nature of spatial metrics over a large spatial scale, which might sometimes lead to misinterpretation of causal dynamics at disaggregated spatial scale like regions, administrative boundaries of the urban areas are used as a basis for disaggregating the study area into different regions as described above (Herold et al., 2003).

Accordingly, five among the selected nine metrics namely total areas (TA), number of patches (NP), patch density (PD), largest patch index (LPI) and area weighted mean patch fractal dimension (AWMPFD) are identified to describe pattern of urban growth at the whole landscape level. These metrics are initially selected based on their intuitiveness, ease interpretation and their ability to describe the composition and configuration of urban landscape pattern. Nevertheless, considering the fact that the growth of the city is going far beyond the metropolitan area, the analysis is conducted including areas outside GKMA, but only focusing on built up land cover class. Consequently, diversity and contagion metrics are excluded from the analysis at the whole landscape level as the thematic map contains only one class. For this kind of thematic map it is impossible to calculate the diversity and contagion metrics such as ED, CONTAG, SHDI and

SHEI. The decision to exclude non-built up area from the analysis is reached by considering no meaningful information can be extracted from the analysis of non-built up area at the whole landscape level. It would have been helpful if the analysis was limited to the GKMA administrative boundary in the meantime meaningful comparison can be made between the built up and no-built up classes. The extent of study area is defined based on its natural boundary, i.e. in such a way that to include the continuous built up land in and around the metropolitan area visible from satellite image.

However, unlike the analysis at the whole landscape level, all the selected (nine) metrics are used to evaluate landscape fragmentation in detail both at class and landscape level in the region based analysis. In such way six metrics: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED) and area weighted mean patch fractal dimension (AWMPFD are used quantify pattern at class level. The remaining three metrics: Contagions (CONTAG), Shannon's diversity index (SHDI) and Shannon's evenness index (SHEI) are used to quantify patterns at landscape level. In this case, it makes sense to evaluate both built up and non-built up classes since the regions are defined purposefully. This will help to quantify the detail pattern of urban land cover dynamics at regional level which will in turn facilitate the implementation of appropriate and different policy measures in the different study regions. The following figure3.3 shows the flowchart used to calculate metrics in FRAGSTATS.

Table 3.3: Detailed methodology used to derive spatial metrics



Generally, the selected metrics are supposed to describe the composition and configuration of the landscape pattern and they are computed for each land cover maps at the patch of classes and landscape mosaic level. Metrics at the class level are helpful for understanding how the landscape developed over time, whereas those at the landscape level provide aggregate information on the assessment of urban growth (McGarigal & Marks., 1995). All metrics are computed using public domain software FRAGSTAT 4.1 (McGarigal et al., 2012). The definitions and the significance the selected metrics is explained in the following section based on the documentation of the Fragstats software (McGarigal & Marks., 1995).

Class area (CA)

Class area is one of the most intuitive and straightforward metrics used to describe the pattern of urban growth in spatial metrics computation. It is sometimes known as total area implying the total area covered by a land cover class in hectares. In the context of this study CA/TA refers to the total area covered by either built up or non-built up area.

$\mathbf{CA} = \sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{a_{ij}} \left(\frac{\mathbf{1}}{\mathbf{10{,}000}}\right)$……………………………………………………………………...Equation 1
(class level metrics)

Units: Hectares

Range: CA > 0, without limit.

"CA approaches 0 as the patch type become increasing rare in the landscape. CA = TA when the entire landscape consists of a single patch type; that is, when the entire image is consists of a single patch.

Description: CA equals the sum of the areas (m) of all patches of the corresponding patch type, divided by 10,000 (to convert to hectares); that is, total class area" (McGarigal & Marks., 1995, p. 86). The class area (CA) metrics simply describes the growth of urban areas in terms of area or size.

Number of patches (NP)

The number of urban patches is the measure of discontinuous urban areas or individual urban units in the landscape. During the period of rapid urban nuclei development number of patch is expected to increase due to the emergence of new fragmented urban patches around the nuclei. Number of patches is an indication of the diversity or richness of the landscape. This index can be calculated and interpreted very easily. However, like other richness measures, this interpretation might give misleading results because the area covered by each class is not considered here. Even if a certain class covers only the smallest possible area, it is counted. The way to count the number of patches within a given landscape is:

NP=N…………………………………………………………………………………Equation 2
(class level metrics)

Units: None

Range: NP ≥ 1, without limit.

NP = 1 when the landscape contains only 1 patch.

Description: NP equals the number of patches in the landscape. Note, NP does not include any background patches within the landscape or patches in the landscape border (McGarigal et al., 2002).

The number of patches (NP) measures the extent of subdivisions of urban areas. NP being high when urban expansion is proportional to an increase in subdivided urban areas or when the landscape gets more fragmented and heterogeneous.

Patch density (PD)

Patch density is another measure of landscape fragmentation/spatial distribution of the patches of a land cover class which indicates the density of fragmented urban units within a specified area, (for example per hectares). This index is a good indicator of landscape fragmentation. Values of this indicator are affected by the size of the pixel and also the minimum mapping unit since this is the determining factor for delineating individual patches. Smaller mapping units imply more patches and therefore higher values. PD can increase or decrease based on different circumstances. For instance, when the number of small patches in the landscape increases without substantial increase of total landscape area, the PD will increase indicating more heterogeneous and fragmented urban development. Whereas, if the total landscape area increased without significant change in the number of urban patches, the patch density will degrease implying the formation of continuous urban surface due to the merging of smaller urban patches. However, if the number of patches and total landscape area increased together proportionally, there wouldn't be significant variation in PD for that landscape. Thus, it is important to pay attention while interpreting this measurement. A patch represents an area, which is covered by single land cover class. The patch density (PD) expresses the number of patches within the entire reference unit on a per area basis. It is calculated as:

PD=N/A (10,000) * (100)……………………………………………………………………Equation 3 (class level metrics)

Units: Number per 100 hectares

Range: PD > 0, without limit.

"Description: PD equals the number of patches in the landscape divided by total landscape area, multiplied by 10,000 and 100 (to convert to 100 hectares)" (McGarigal & Marks., 1995, p. 88).

Patch Density depends on the grain size, which is the size of the smallest mapping unit of the input data and the number of different categories. The index is a reflection of the extent to which the landscape is fragmented. This index is important for the assessment of landscape structures, enabling comparisons of units with different sizes.

Edge density (ED)

Edge density is another indicator of urban expansion level which measures the total length of the edge of the urban patches. It is computed by dividing the length of the urban boundary to the total landscape area. The total length of the edge of a land cover class (urban patch) increases with an increase in the land cover fragmentation. ED has direct relationship with NP. Similar to PD its value is affected by the pixel size and the minimum mapping unit since the smaller the mapping unit the delineation of the various patches will result in an increase of the edge length. Herein, the smallest mapping unit is pixel. An increment in the number of patches can certainly lead to the increase of Edge Density.

An edge is the border between two different classes. Edge density (in m/ha) or ratio of Perimeter/Area equal to the length (in m) of all borders between different patch types (classes) in a reference area divided by the total area of the reference unit. The index is calculated as:

ED=E/A (10,000)…………………………………………………………………………Equation 4 (class level metrics)

Units: Meters per hectare

Range: ED ≥ 0, without limit.

Description: "ED equals the sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares)" (McGarigal & Marks., 1995, p. 89). If a landscape border is present, ED includes landscape boundary segments representing true edge only (i.e., contrast weight > 0). If a landscape border is absent, ED includes a user-specified proportion of the landscape boundary.

Regardless of whether a landscape border is present or not, ED includes a user-specified proportion of background edge. In contrast, to patch density, edge density considers the shape and the complexity of the patches. Edge density is a measure of the complexity of the shapes of patches and similar to patch density an expression of the spatial heterogeneity of a landscape. In short edge density (ED) is a measure of the total length of urban patch edges.

Largest patch index (LPI)

The largest patch index (LPI) is the ratio of the area covered by the largest patch in the landscape divide by the total area of the landscape (Herold et al., 2002). This metrics describes the total area of land covered by the largest patch in the landscape expressed in percentage. LPI is a relative measure of all patches and this can be useful to compare different area (region) with varying spatial extent. It can be considered a measure of the fragmentation of the urban landscape into smaller discrete patches versus a dominant core. The LPI increases when the urban areas become more aggregated and integrated with the urban cores.

$$\mathbf{LPI} = \frac{\max_{j=1}^{n} (a_{ij})}{A} * \mathbf{100} \quad \text{......Equation 5}$$

(class level metrics)

Units: Percept (%)

Range: 0 < LPI ≤ 100

"LPI approaches 0 when the largest patch in the landscape is increasingly small. LPI = 100 when the entire landscape consists of a single patch; that is, when the largest patch comprises 100% of the landscape.

Description: LPI equals the area (m^2) of the largest patch in the landscape divided by total landscape area (m^2), multiplied by 100 (to convert to a percentage) " (McGarigal & Marks., 1995, p. 87); in other words, LPI equals the per cent of the landscape that the largest patch comprises.

Area weighted mean patch fractal dimension (AWMPFD)

The fractal dimension is a measure of patch shape complexity which describes the convolution and fragmentation of a patch as a perimeter-to-area ratio. It is estimated as the weighted mean value of the fractal dimension values of all patches of the same class. AWMPFD gives improved measure of class patch fragmentation as it averages the fractal dimensions of all patches by weighting larger land cover patches (Herold et al., 2003). The averaging of patches will reduce the overestimation of fractal dimension given the fact that the structure of smaller patches is often determined more by the spatial resolution of the image than by the spatial characteristics of natural or man-made features found in the landscape. Generally, when a patch has a compact regular form with a relatively small perimeter relative to the area the AWMPFD will be low. Conversely, if the patches are more irregular, complex and fragmented, the perimeter increases resulting in a higher fractal dimension (McGarigal et al., 2002). For instance, when a built up area starts to become saturated taking the shape of the urban blocks, AWMPFD will get lesser. This metrics is most likely to have less value, i.e. simple shape, for cities having compact and regular pattern of development such as grid iron pattern.

$$\mathbf{AWMPFD} = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{2\ln(.25p_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{A}\right)\right] \quad \text{......Equation 6}$$

Units: None

Range: 1 ≤ AWMPFD ≤ 2

A fractal dimension greater than 1 for a 2-dimensional landscape mosaic indicates a departure from a Euclidean geometry (i.e., an increase in patch shape complexity). AWMPFD approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

Description: AWMPFD equals the sum, across all patches, of 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2), multiplied by the patch area (m^2) divided by total landscape area; the raster formula is adjusted to correct for the bias in perimeter. In other words, AWMPFD equals the average patch fractal dimension (FRACT) of patches in the landscape, weighted by patch area.

Shannon's diversity index (SHDI)

Shannon's diversity index is a quantitative measure of the variety and relative abundance of patch types represented on the landscape. The composition component of pattern is typically quantified with diversity indices. The patch richness such as the number of land use or land cover classes in the landscape are the major aspects quantified using SHDI in urban planning.

$$\mathbf{SHDI} = -\sum_{i-1}^{m}(P_i{}^{\circ}\ln P_i) \quad \text{......Equation 7}$$

(Landscape level metrics)

Units: None

Range: SHDI ≥ 0, without limit

"SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity). SHDI increases as the number of different patch types (i.e., patch richness, PR) increases and/or the proportional distribution of area among patch types becomes more equitable.

Description: SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion" (McGarigal & Marks., 1995, p. 118).

Shannon's evenness index (SHEI)

Shannon's Evenness index is a quantitative measure of abundance or the area distribution of classes of different patch types. Generally, it is reported as the function of the maximum diversity possible for a given richness.

$$\mathbf{SHEI} = \frac{-\sum_{i-1}^{m}(P_i \circ \ln P_i)}{\ln m} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Equation 8}$$

(Landscape level metrics)

Units: None

Range: $0 \leq \text{SHEI} \leq 1$

"SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types become increasingly uneven (i.e., dominated by 1 type). SHDI = 1 when distribution of area among patch types is perfectly even (i.e., proportional abundances are the same).

Description: SHEI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion, divided by the logarithm of the number of patch types. In other words, the observed Shannon's Diversity Index divided by the maximum Shannon's Diversity Index for that number of patch types" (McGarigal & Marks., 1995, p. 120).

Contagion (CONTAG)

The contagion index measures the probability of neighbourhood pixels being of the same class and describes to what extent landscapes are aggregated or clumped (O'Neill et al., 1988). In other words contagion is the measure of adjacency. Landscape classes are described by a high contagion index; when the landscape consists of relatively large and contiguous patches. The presence of relatively greater number of small or highly fragmented patches in the landscape will result in low contagion index. For example, when an urbanized area becomes more amalgamated the contagion index will be high. As an urbanized area becomes more fragmentation into a larger number of individual urban units, the contagion index will be low.

$$\mathbf{CONTAG} = \left[1 + \frac{\sum_{i-1}^{m}\sum_{k=1}^{m}\left[(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right] \circ \left[\ln(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2\ln(m)}\right](100) \ldots\ldots\ldots\ldots\ldots\text{Equation 9}$$

(Landscape level metrics)

Units: Percept (%)

Range: $0 < \text{CONTAG} < 100$

"CONTAG approaches 0 when the distribution of adjacencies (at the level of individual cells) among unique patch types becomes increasingly uneven. CONTAG = 100 when all patch types are equally adjacent to all other patch types.

Description: CONTAG equals minus the sum of the proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). In other words, it is the observed contagion over the maximum possible contagion for the given number of patch types"(McGarigal & Marks., 1995, p. 121).

3.6. Logistic Regression modelling and driving forces of urban growth

3.6.1. Physical driving forces of urban growth

As an empirical estimation model, logistic regression modeling is a data-driven rather than a knowledge-based approach to the choice of predictor variables (Hu & Lo, 2007). In developing countries like Uganda the choice of predictor variables is highly depends on the availability of well-organized and good quality data. Particularly, socio-economic data's are the scarcest data in developing countries. Thus, to overcome the challenge, only physical driving forces of urban growths are considered in this study. Most of the spatial data's used to analyze the interaction between urban growth and driving forces are obtained from different open source webs such as USGS, www.Divagis.org, Google Earth, etc.

However, in this study, the selection of physical predictor variables is made systematically in two steps. First, the most probable driving forces urban growths are identified based on literature review (Cheng & Masser, 2003; B. Huang et al., 2009; Nong & Du, 2011; Tayyebi et al., 2010). Accordingly twelve predictors were identified and grouped into three categories: (1) environmental/site specific factors; (2) proximity factors; (3) neighbourhood characteristics factors. Most of the selected variables are in agreement with most dynamic simulation modeling practices, which usually reflect the determining factors of 'SLEUTH' (Slope, Land cover, Exclusion, Urban extent, Transportation, Hill-shade) as in Clarke's SLEUTH model (Clarke et al., 1997). These variables reveal the biophysical conditions, the spatial influences of major highways, economic activity centers, existing land cover status, etc. On the second step, based on the discussion made with local experts these driving forces are adapted to the local context. In the process some variables are added and at the same time some are removed from the list. The lists of these variables are given below.

Table 3.4: list of variables identified from literature review for logistic regression modelling

Type of factor	Variables	Nature
	Hazards	Dichotomous
Environmental/site specific factors	Slope	Continuous
	Soil type	Dichotomous
	Wetlands	Dichotomous
	Distance to CBD	Continuous
	Distance to satellite towns	Continuous
	Distance to sub city centres	Continuous
	Distance to major roads	Continuous
Proximity factors	Distance to minor roads	Continuous
	Distance to railways	Continuous
	Distance to water bodies	Continuous
	Distance to hills	Continuous
	Distance to Entebe Airport	Continuous
Neighbourhood characteristics	Proportion of urban land	Continuous
	Proportion of undeveloped land	Continuous

According to the discussion made with local experts, distance to CBD, distance from satellite town, distance to major roads, distance to minor roads, distance to Entebbe airport and proportion of urban land are major factors, whereas slope and wetlands are minor factors are and the rest are insignificant physical driving forces of urban growth in the study area. Thus, flood hazards, soil type, distance to railway, distance to water bodies, distance to hills and availability of developable land are removed from the list.

Generally, in this study, the probability of a land to convert from non-urban land to urban land is considered as a function of the identified predictor variables. Regression analysis, which will be discussed in the next section, is carried out to identify the degree of significance of each identified variables and to examine how they enhance or hinder urban growth/land cover change in the study area. The analysis is important to better understand the interaction between urban growth patterns and driving forces. It is also helpful for a variety of urban models which require selection of appropriate spatial variables for the modelling process.

3.6.2. Logistic regression modelling

In this study, the nature of the land cover change of a cell was considered as dichotomous: either the presence of non- urban–urban conversion (represented by value 1) or no change (represented by value 0). It was assumed that the probability of a non-built up cell changing to a built up cell would follow the logistic curve. The general formula of logistic regression is given as follows:

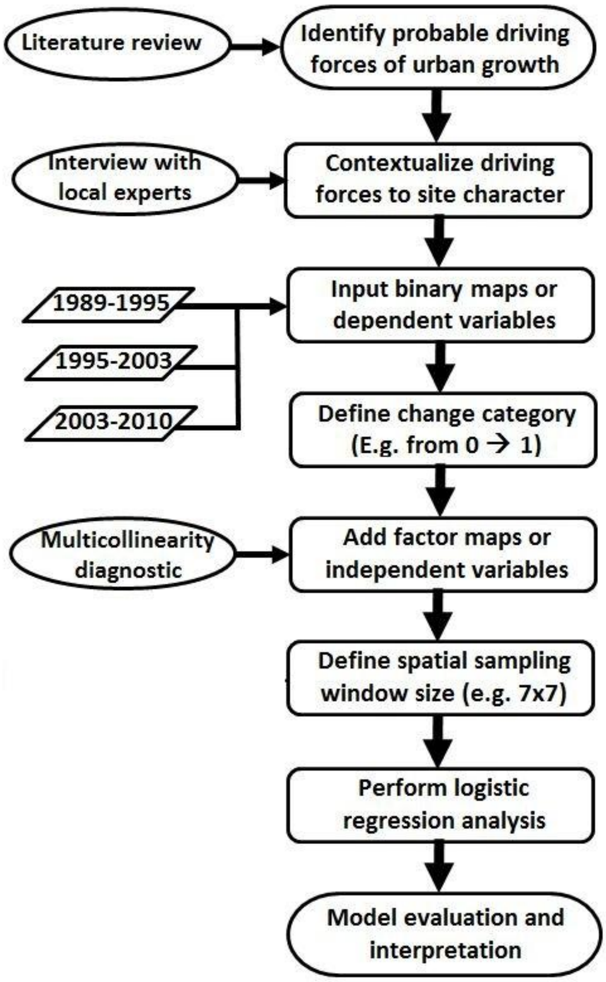
$$Y = a + b_1x_1 + b_2x_2 + \cdots + b_mx_m$$

$$y = \log_e\left({}^{P}\!/_{1-P}\right) = \log\mathrm{it}\ (P)$$

$$P(z = 1) = {}^{e^y}\!/_{1+e^y}$$

where x_1, x_2 …, x_m are explanatory variables. The utility function y is a linear combination of the explanatory variables representing a linear relationship. The parametersb_1, b_2,…, b_m are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 (z=1) means the occurrence of a new unit (i.e. the transition from a rural unit to an urban unit), and value 0 (z=0) indicates no change. P refers to the probability of occurrence of a new unit, i.e. z=1. Function y is represented as log it (P), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1. As the y value increases, probability P inevitably increases. ArcGIS extension software Change Analyst tool is used to conduct the logistic regression modelling. The flow chart showing general procedure followed in logistic regression modelling is given below (See figure_3.4).

Figure 3.4: Flow chart showing procedures followed in logistic regression modelling



3.6.3. Preparation of input data for logistic regression model

The independent variables or the factor maps for the regression analysis are prepared for the three different periods under study. These maps are prepared in ARC GIS 10.1 software environment. All the input data are in raster format in a cell size of 30X30 so as to match the resolution of Landsat images.

Dependent variables

In this model four binary land cover maps of 1989, 1995, 2003 & 2010 are used as dependent variables to carry out the logistic regression analysis. These maps are classified into two land cover classes 0 & 1. 0 represents non-built up land cover class whereas 1 represents built up land cover class. The conversion rule is based on the assumption that land cover only changes from non-built up to built-up land. This because of the fact that the possibility of land cover to change from built up to non-built up is very unusual or rare in developing countries like Uganda.

Independent variables

Nine independent variables are finally screened out based on literature review and discussion with local expertise to include in the model. However, as described in earlier section most land use/cover change models are data driven. Minor roads (as a major) and wetlands (as a minor) were identified as important physical driving force of urban growth both in literature and on discussion made with local expertise. However, due to unavailability of data that covers the whole study area the two independent variables are removed from the model. This reduced the total number independent variables from nine to seven. These variables are: proportion of urban land, slope, and distance from CBD, distance from Entebbe airport, distance from major roads, distance from sub city centres and distance from satellite towns. All of them are of the same resolution of 30X30m. Slope, distance from CBD, distance from Entebbe airport, and distance from satellite towns are the same for all study periods of 1989-1995, 1995-2003 & 2003-2010. The variables distance from major road and distance from sub city centres are the same for the first two study periods (1989-1995 & 1995-2003); however, these variables are different for the third study period (2003-2010). This is due to the fact that the northern bypass and some sub city centres were not present in the first two study periods or before 2003. The northern bypass is introduced in 2007 and since then it was assumed to have attracted development to the northern part of the study area. Sub city centres such as Mperere, Kasubi, Mbuye & Kisubi which are active and important economic sub city centres were not active and economically import before 2003. Proportion of built up land is obviously different for all the study periods and they are calculated based on land cover map.

The proportion of built up land (P_URBAN) is computed using a function focal statistics in Arc GIS. This function calculates the proportion of built up area within a neighbourhood of 7X7 window size for each pixel and assigns the central cell the mean value of all cells. The selection of the size of the neighbourhood window is based on the most widely used window size in dynamic simulation models where sizes are often 3 X 3, 5 X 5, or 7 X 7 (Hu & Lo, 2007). Slope map is derived from the ASTER digital elevation model (DEM) of 2011 obtained from USGS website. The image was resampled to a resolution of 30cm to match the resolution of land cover images. Distance to CBD (DIST_CBD), distance to Entebbe Airport (Dist_Entb), distance to major roads (Dist_Mjrd), distance to sub city centres (Dist_Scc) and distance to satellite towns (Dist_St) are computed in Arc GIS using Euclidean distance function. The function calculates the shortest distance from the centre of the source cell to the centre of each of the surrounding cells. These locations of the source cell or cells are represented by a point or line in Arc GIS. The values of all variables are standardized to 0-1 range.

3.6.4. Multicollinearity

Multicollinearity is a situation where two or more independent variables, are strongly correlated with each other than they are with the dependent variable (Field, 2009). The existence of multicollinearity in a model may cause very high standard error and low t-statistics, unexpected changes in coefficient magnitudes or signs, or insignificant coefficients despite a high R-square value. Such problems are misleading in the interpretation of outputs and will result in incorrect conclusions about associations between independent and dependent variables. Thus, to some extent performing multicollinearity analysis is the basis or a prerequisite for conducting multiple regression (Cheng & Masser, 2003).

The presence or the absence of multicollinearity is not a problem in multiple regressions, but rather the degree of presence matters. The higher the degree of multicollinearity, the greater will be the likelihood of the disturbing consequences of multicollinearity. There are several ways of detecting the manifestation of multicollinearity in a regression model. Variance-inflation factor (VIF) perhaps the most commonly used test is the other way of detecting multicollinearity in statistical analysis. The variance inflation factors measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. It has been shown that the variance inflation factor for the kth predictor is given by:

$$\mathrm{VIF}_k = \left(1 - R_k^2\right)^{-1}$$

where, R^2 is the R2-value obtained by regressing the kth predictor on the remaining predictors. Note that a variance inflation factor exists for each of the k predictors in a multiple regression model. In most scholarly articles and advanced statistical textbooks VIF>10 is regarded as a sign of severe or serious multi-collinearity (O'brien, 2007). There are a number of ways of dealing with multicollinearity problem (Field, 2009). The first, and most obvious, solution is to eliminate some of the highly correlated variables from the model. For instance, if two variables are highly collinear, then it means that they proving the same information. Thus, we can pick one variable to keep in the model and discard the other one. When unable to decide an appropriate variable to omit from the model, we can combine the variables into a reduced set of variables.

3.6.5. Model evaluation

The predicting capacity of the proposed models is evaluated based on Percentage Correct Prediction (PCP), which is a simple tool indicating how good the model is at predicting the outcome variable. The PCP statistic assumes that if the estimated p is greater than or equal to 0.5 then urban growth or change from 0 to 1 is expected to occur and automatically will be assigned 1. However, if the estimated p is less than 0.5 then urban growths is not expected to occur and automatically will be assigned 0. By assigning these probabilities 0s and 1s and comparing these to the actual 0s and 1s, the correct prediction, wrong prediction and overall percent correct prediction scores are calculated (Pampel, 2000). The result is obtained as cross-classified 2x2 table of the two categories of observed dependent variable with the two categories of predicted dependent variable.

A highly accurate model would show that most cases fall in a cell defined by 0 on both observed and predicted group membership and by 1 on both observed and predicted group membership. Relatively few cases fall into the cells defined by a mismatch of observed and predicted group membership. The overall summary of correct prediction, wrong prediction and percentage of correct prediction (PCP) is given in the preceding rows respectively. A perfect model would correctly predict a group membership for 100% of the cases. The PCP from 50 to 100% is considered as a crude measure of predictive accuracy (Pampel, 2000).

4. RESULTS AND DISCUSSIONS

4.1. Introduction

In this chapter the outcomes of this research are presented and discussed in detail sequentially. Starting from spatio-temporal quantification of urban growth, it goes through the most important findings of growth pattern analysis using spatial metrics. The pattern analysis is conducted both at citywide level and at regional scale. Most of the discussions are supported by maps, tables and illustrative graphs. The key factors responsible for the changing patterns of urban growths are presented and discussed through results of logistic regression modelling and driving forces.

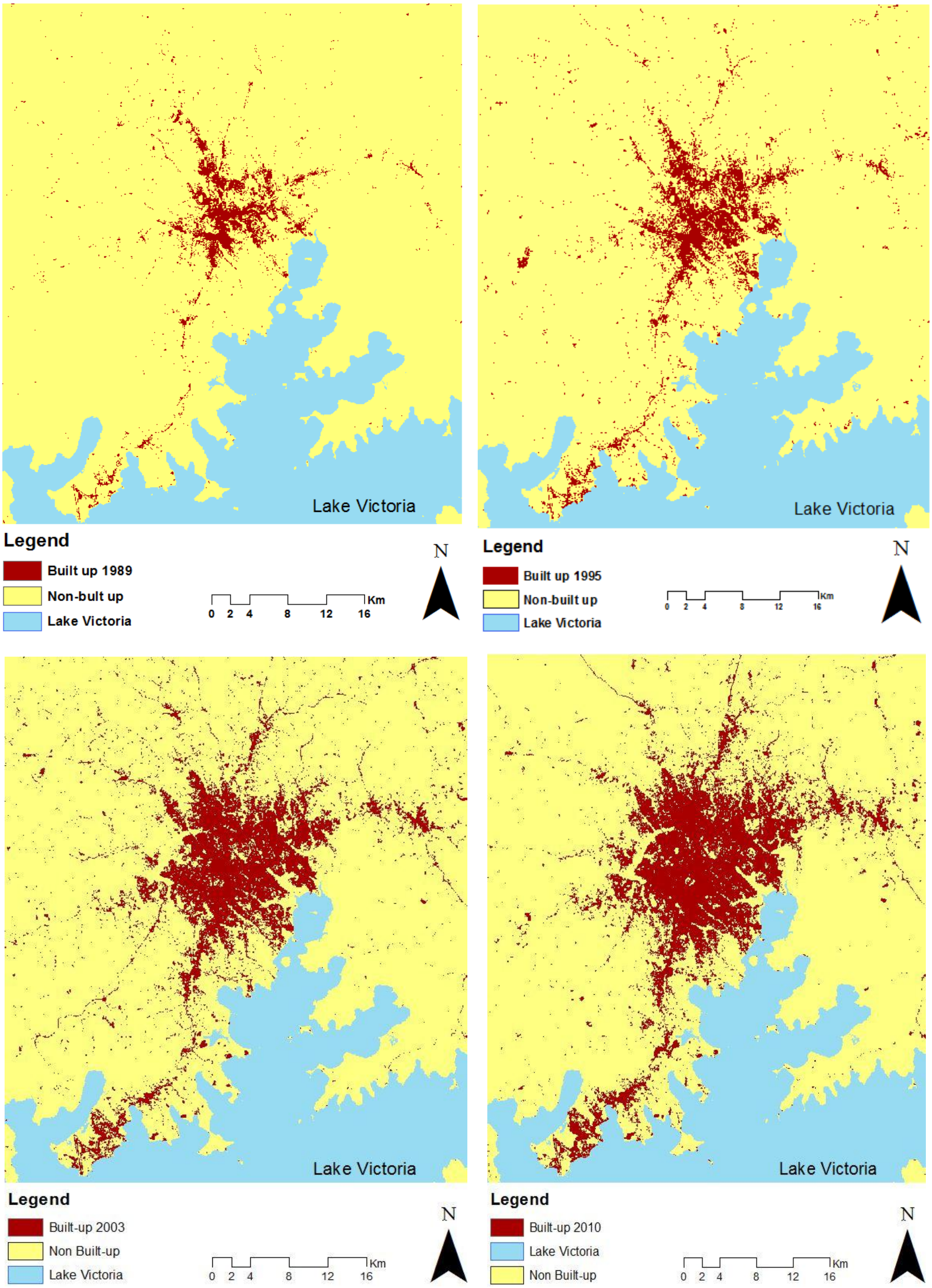
4.2. Results of image classification and accuracy assessment

According to the results of accuracy assessment the extraction of water body has relative higher accuracy in all images. Conversely, built-up class have the lower accuracy due to the mixed pixels in the classes. The small cloud covers observed around Entebbe airport and on some parts of image ETM+ 2003 might have influenced the accuracy of image classification as Landsat-7 ETM+ sensor have greater radiometric sensitivity compared to Landsat TM images. In addition to this, the Landsat-7 ETM+ sensor offers numerous improvements over the earlier generations of Landsat sensors such as Landsat-4&5 (Masek et al., 2001). The improved spectral information content of Landsat-7 ETM+ sensor could record small bright surfaces missed by Landsat-5 TM that has been manifested on Landsat ETM+ 2003 image in this study. The Relative Spectral Response (RSR) profiles of ETM+ and TM are given in figure_6.3. Thus, the results presented based on ETM+ 2003 image in this research are subject to the images inconsistencies described above. However, the overall accuracy of all images was found to be greater than 85%, which is considered as a good result for remote sensing image based analysis (Herold et al., 2005). The following table presents the accuracy of classified images for the different time periods. The results of image classification are given in figure_4.1.

Table 4.1 Results of accuracy assessment

Sensor	Acquisition date	Classified image	Over all accuracy	Kappa statistics
Landsat TM	2/27/1989	Built-up 1989	**85%**	0.70
Landsat TM	1/19/1995	Built-up 1995	**86%**	0.72
Landsat ETM+	2/2/2003	Built-up 2003	**88%**	0.78
Landsat TM	1/28/2010	Built-up 2010	**91%**	0.83

Figure 4.1: Results of image classifications



4.3. Spatio-temporal analysis of urban growth pattern using spatial metrics

The classification of the multi-temporal satellite images into built-up, non-built up and water body for the four different time periods of 1989, 1995, 2003 & 2010 has resulted in a highly simplified and abstracted representation of the study area (See figure 4.1). These maps show a clear pattern of increased urban expansion prolonging both from urban centre to adjoining non-built up areas along major transportation corridors. The maps show the spatio-temporal urban growth pattern in the study area. Post classification comparison of the classified images revealed the growth pattern of the city in different directions, the infilling of the open spaces between already built-up areas and the dynamics of urban expansion in the study area. However, it is important to assist the findings with statistical evidences as it is useful to describe the spatial extent and the different patterns of urban growths that have been occurring in the study area. This will help understand how the city is changing over time and to compare the various growth patterns taking place in different time periods quantitatively.

Spatial metrics are powerful tools to quantitatively describe and compare multi-date thematic maps. Five frequently used spatial metrics are selected based on literature review (refer section 3.5.1) for the synoptic analysis of built-up area dynamics over space and time at landscape level. The metrics are used to describe the trends and changing patterns of the actual built-up land extracted Landsat images. Detail discussion on metrics can be found on section 3.5.1 of this thesis. All metrics are computed only for the built up area. The outputs presented in table 4.3 were generated for the selected metrics in the form of numeric values for the whole study area in FRAGSTATS 4.1.

The results presented in table 4.3 shows that the total built-up area (TA) has grown from 7288ha in 1989 to 11695 in 1995, to 24811ha in 2003 and to 32456ha in 2010. The highest rate of urban growth is observed during the second period of urbanization (1995 to 2003) in which the built up area increased more than twice (112%) within 8 years (Table4.3). This is followed by 60% and 31% during the first (1989 to 1995) and the third (2003 to 2010) period of urbanization respectively. This indicates a more rapid urbanization has been taking place in the study area during the period of 1995 to 2003 compared to the two other periods. It could be also related to the change on land tenure system following the 1995 Constitution and the 1998 Land Act in Uganda, which gives legal recognition to private citizens who own land either under mailo, customary, leasehold and/or freehold tenures. Detail analysis on the land tenure system of Kampala is beyond the scope of this study.

Table 4.2: Analysis of Built-up Area expansion based on Total area (TA) metrics

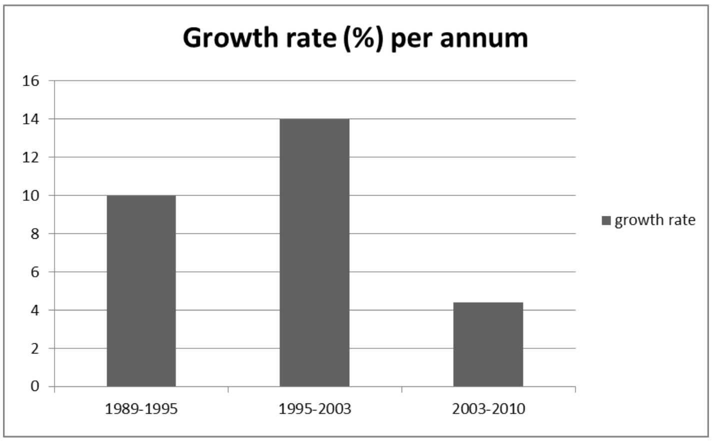
Study period	change(ha)	Change(%)	Time Span	growth rate/y	Average
1989-1995	4407	60	6yeras	10	
1995-2003	13116	112	8years	14	9.5
2003-2010	7645	31	7years	4	

Nevertheless, it should be also noted that the second period of urbanization covers the longest time span compared to the first and third periods. In terms of absolute land cover change in (ha) the second period 1995 to 2003 remains the highest witnessing the conversion of 13116ha of non-built up land to urban land. In contrast to the percentage change, the third study period (2003 to 2010) comes second with 7645ha land changed to built-up area followed by the first period of urbanization (1989 to 1995) where 4407ha land is changed to built-up area. Totally 25168ha of non-built up land has been converted to built-up land over the period 1989 to 2010. As the statistics obtained from the area metrics computation confirms, the built up area has been increasing at an average annual growth rate of 10, 14 & 4.4% during the periods 1989-1995, 1995-2003 & 2003-2010 respectively in the study area (refer figure_4.2).

Table 4.3 Results of spatial metrics calculation at the entire landscape level.

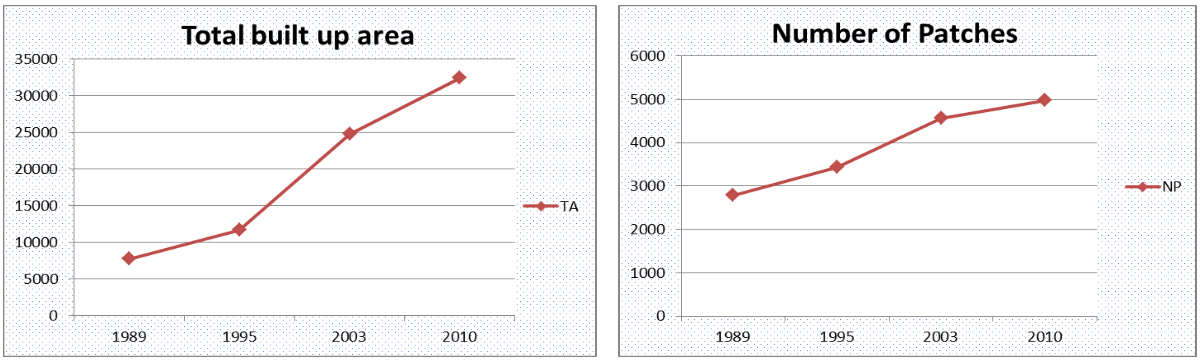
Greater Kampala Metropolitan Area (GKMA)						
Year/Metrics	LUC	TA	NP	PD	LPI	FRAC_AM
1989	Built up	7288	2786	36	53.0	1.26
1995	Built up	11695	3433	29	55.7	1.28
2003	Built up	24811	4560	18	63.4	1.26
2010	Built up	32456	4979	15	69.8	1.30

Figure 4.2 Built up area growth rate (%) per annum per study period.



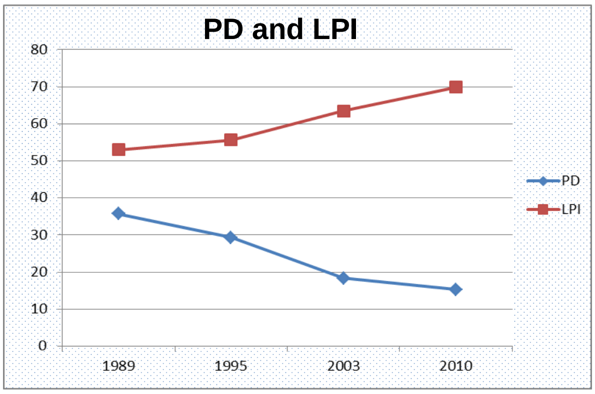
The rapid urban growth process in the study area has been revealed by the continuous rise of number of patches (NP) in the landscape throughout the study periods. This could be an indication of the heterogeneous and fragmented urban growth process taking place in the study area. Significant change in NP is observed during 1995 to 2003. However, the pick occurred in 2010 indicating the continuing development of scattered and fragmented urban patches in the study area. The situation can be attributed to the emergence of small and patchy built up patches around the periphery of the city and in peri-urban regions. This could happen as the city expands outward in the form of scattered development, the gap between the peri-urban regions and the urban core will decrease by increasing the attractiveness the peri urban area for development.

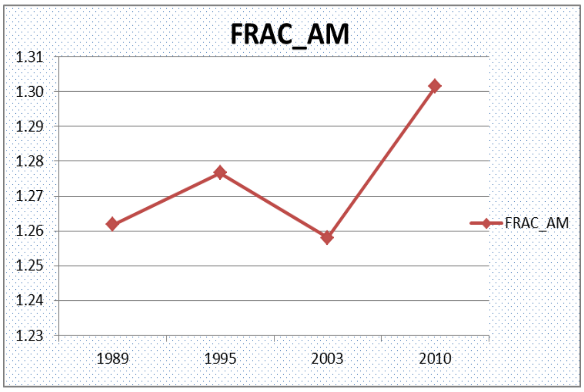
Figure 4.3: Graph showing total area (TA) & number of patches (NP) for the entire landscape area



The patch density (PD) continuously decreased from 36 in 1989 to 15 in 2010 throughout the study period. The highest reduction is observed during the second period of urbanization (1995-2003). These show that although the number of patches is continuously rising in the landscape, the built up area (TA) is increasing in much faster rate than NP. The phenomena can be observed from the slope of the two graphs (figure 4.3). Between 1995 & 2003 the slope of TA is steeper than the slope of NP in the same period on the graph. In other words, a decrease of patch density means that some patches located in close proximity to the city centre are merging with urban core to form a homogeneous urban fabric. The effect has been manifested on the increasing largest patch index (LPI), signifying the agreement between the metrics. Inherently, the dominant or largest patch in the landscape, which is supposed to be the urban core, is growing over time (Jun et al., 2009). Visual comparison of the classified images confirms the development of urban core in the form of infill and edge expansion (see figure_4.1 & 4.5). The gradual expansion of the urban core might have changed the city in to urban agglomeration. This could be one reason for the scattering and fragmented development of the city as urban agglomeration may push development away from the already established urban areas.

Figure 4.4: Graph showing patch density (PD), largest patch index (LPI) and FRAC_AM for the entire landscape area



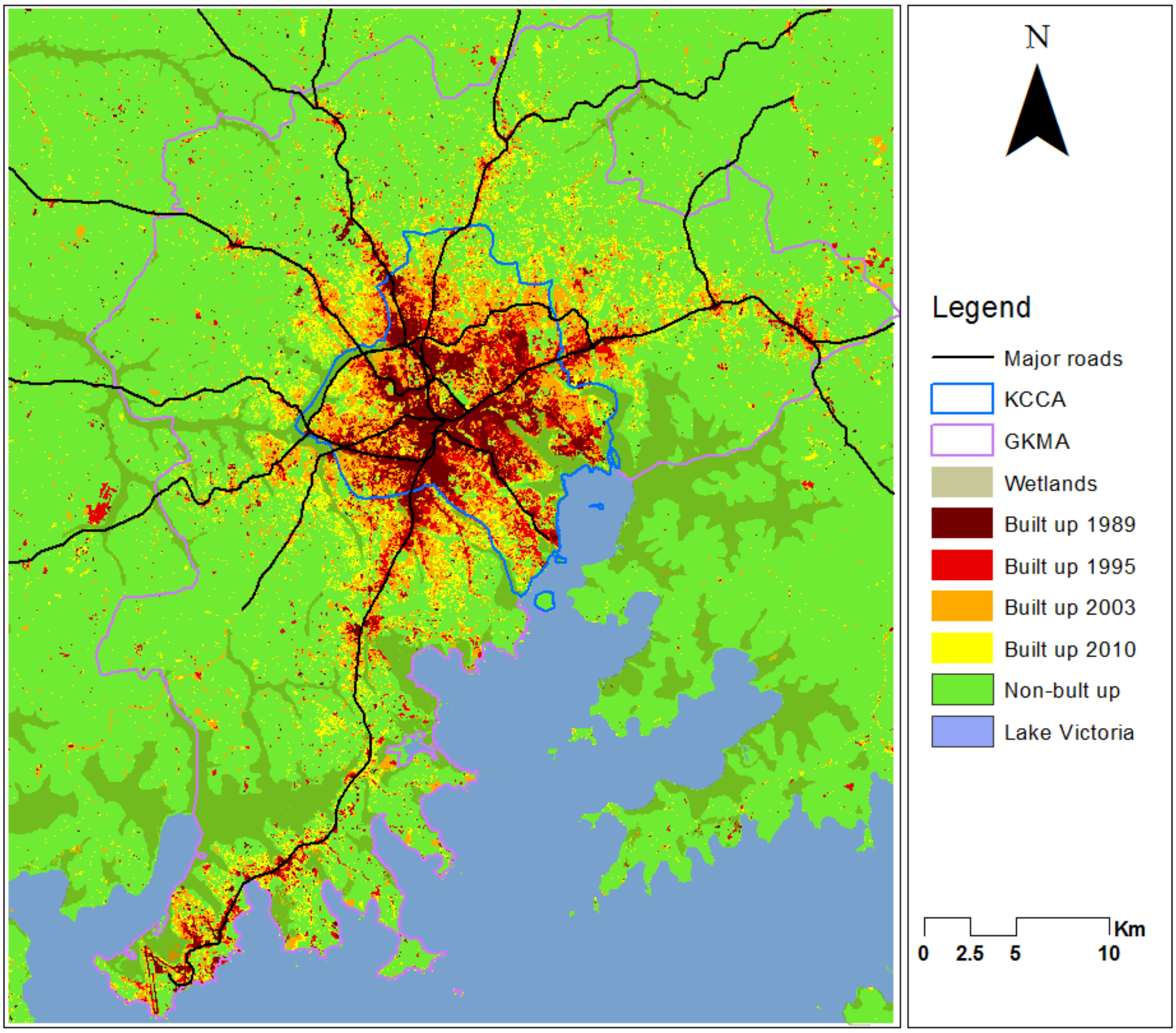


The area weighted mean patch fractal dimension (FRAC_AM/AWMPFD) is the measure of urban patch shape complexity which describes how patch perimeter increases per unit increase in patch area. In 1989, FRAC_AM was 1.26 which indicates that for a unit increase of patch area, the perimeter is increasing by 26% and by 30% in 2010. Nevertheless, during 1995-2003 FRAC_AM decreased from 1.28 to 1.26 which might be due to the merger of existing smaller urban patches in to relatively larger urban patches having simple geometric shapes (see figure_4.1). It could be also related to the stabilization and join up of built up area around the urban core into a simple and relatively regular urban form. Yet, looking at the highest value witnessed in 2010, it seems that the geometry of urban patches is getting more complex over time. This could be an indication of the prevalence fragmented low density development in the fringe areas (see figure_4.1). It is also important to note that topography might have played inevitable role for the fragmented development of the city particularly, large areas of wetlands can be found in particular in the Western and South-eastern part of Kampala (refer_2.3 & 4.5). The wetlands are not suitable areas for urban development, those they break the continuity and isolate or fragment the built up patches.

From the results of spatial metrics analysis of built up area it has been possible to quantify the trends and patterns of urban dynamics at the city level using the selected five metrics. Accordingly, three metrics namely: the total built up area (TA), number of urban patches (NP) and the largest patch index (LPI) showed consistent increasing trend while patch density (PD) exhibited a decreasing trend. Nevertheless the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with remarkable upturn in 2010. Despite the increasing trend of the largest patch index (urban core), the built up area remain getting more fragmented over time.

Generally, the spatio-temporal analysis of spatial metrics over the entire study area here described indicates that the urbanization has substantially changed the land cover of the study area, with a significant land conversion. Built up area has been undergoing fragmented development process in all study periods, with substantial increase of built up area during the second period of urbanization, 1995-2003. In addition to urban sprawl, which can be witnessed from the substantial increase in number of patches over time, patch density and the largest patch index also revealed that the city is experiencing infill and edge expansion around the urban core mainly during 1995-2003 (refer figure_4.5). The result of fractal dimension analysis also unveiled the increasing patch shape complexity of the study area except a slight decrease observed in 2003 which could be as a result of infill development or the merger of new patches with the existing patches during 1995-2003.

Figure 4.5: Spatio-temporal growth map of the study area (1989-2010)



4.4. Effect of classification accuracy and post procesing method on spatial metrics computation

Calculation of spatial metrics using land-cover maps extracted from remotely sensed data is becoming increasingly common (Wickham et al., 1997). To see the effects of classification accuracy and post classification technique implemented during image processing on the result of metrics calculation, this research compares two sets of classified images. The results illustrate the sensitivity of the metrics to the variation in the classification approach. The first set of images is based on the results obtained from this study and the second set of image is taken from the previous work of Vermeiren et al. (2012). Apart from the slight accuracy difference (see table 4.5), the major difference between these two set of images is that; the former one has applied post classification majority filter using 3x3 window size (see section 3.4.1) and the later one has applied post processed by imposing that non built-up area was never built-up in a previous time. Both data sets used maximum likelihood classification method.

Table 4.4 Results of landscape metrics: (upper) based on Vermeiren et al. (2012) and (lower) based on this research

Year/Metrics	LUC	TA	NP	PD	LPI	FRAC_AM
1989	Built up	6524	5969	91	33	1.23
1995	Built up	10427	7325	70	50	1.28
2003	Built up	21011	8752	42	66	1.33
2010	Built up	34298	13559	40	64	1.31
Greater Kampala Metropolitan Area (GKMA)						
Year/Metrics	LUC	TA	NP	PD	LPI	FRAC_AM
1989	Built up	7288	2786	36	53.0	1.26
1995	Built up	11695	3433	29	55.7	1.28
2003	Built up	24811	4560	18	63.4	1.26
2010	Built up	32456	4979	15	69.8	1.30

Table 4.5: Comparison of classification accuracy of the two sets of images

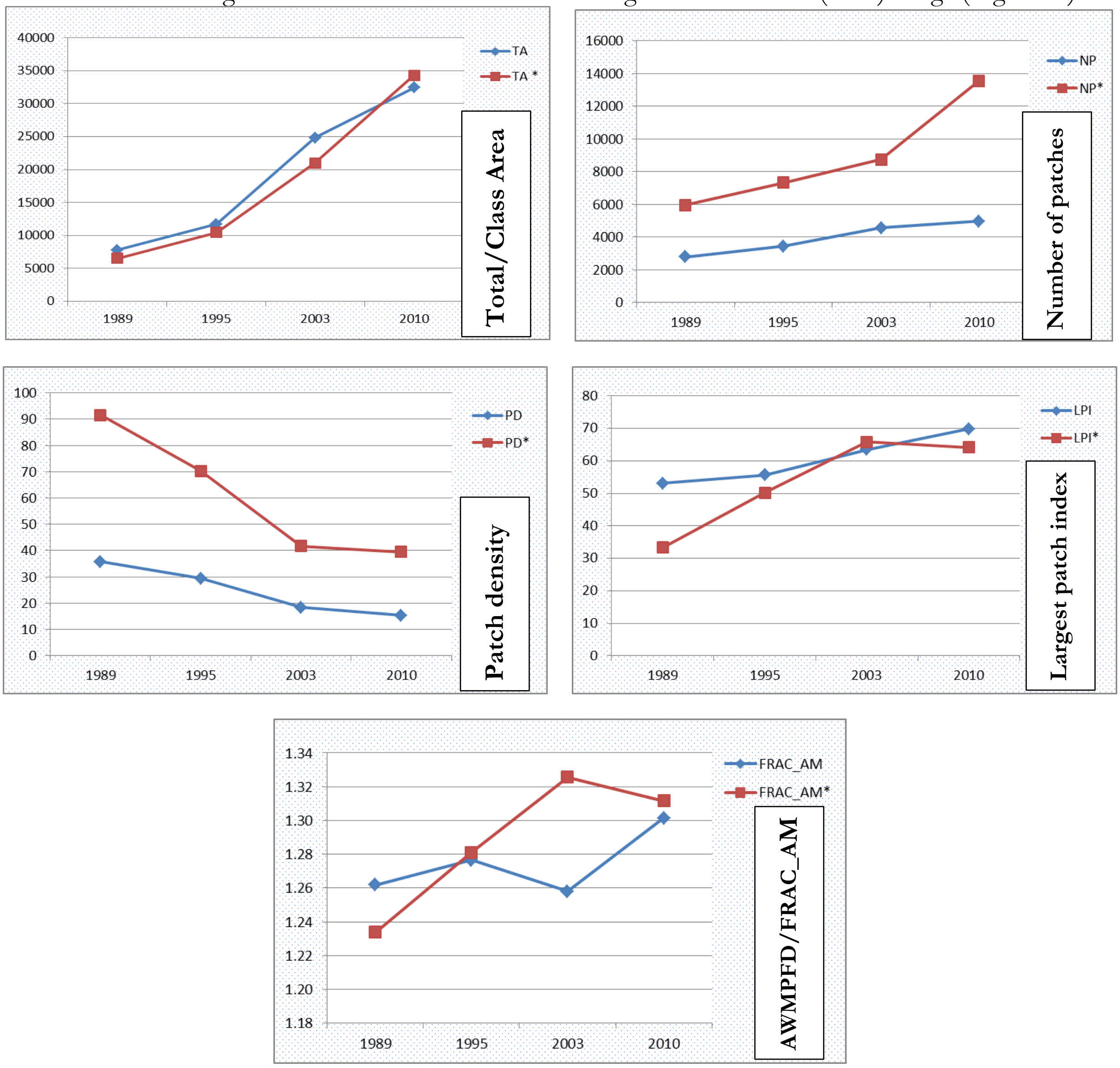
Sensor	Acquisition date	Classified image	Over all accuracy		Kappa statistics	
			My results	Vermeiren's result	My results	Vermeiren's result
Landsat TM	2/27/1989	Built-up 1989	**85%**	82%	**0.70**	0.66
Landsat TM	1/19/1995	Built-up 1995	**86%**	81%	**0.72**	0.60
Landsat ETM+	2/2/2003	Built-up 2003	**88%**	87%	**0.78**	0.74
Landsat TM	1/28/2010	Built-up 2010	**91%**	93%	**0.83**	0.84

The results presented in table 4.4 illustrates that using a majority filter has significant influence on the statistical value of all metrics computed in this analysis. For instance, number of patches (NP), decreased by more than half almost for all images. Patch density (PD) is the ratio of number of patches (NP) to total area (TA) and it showed decreasing trend when subjected to majority filter (see figure_4.6). Total area (TA) is inevitably influenced by filtering which can be proved by comparing the total area of built up area before and after filtering. However, total area (TA) is primarily subject to classification accuracy (Guofan & Wenchun, 2004). The largest patch index (LPI) is also the function of total area (TA) and showed increasing trend when filtering is applied (see figure_4.6). Fractal dimension (FRAC_AM) is seemingly negatively influenced by majority filtering. Due to the aggregating nature of filtering, smaller patches which were supposed to contribute to higher fractal dimension will be removed from the landscape. This also decreases the NP. Comparatively bigger patches have lower fractal dimension, i.e. lower complexity or simple shape.

Generally, interesting patter of correlation can be observed from the graphs (figure_4.6). Except for FRAC_AM there exists a kind of linear resembling correlation between corresponding pair of metrics. It was evident that the results of FRAC_AM for the three Landsat TM images, i.e. 1989, 1995 & 2010 is somehow comparable like the other metrics. The contrasting behaviour observed on FRAC_AM in 2003 could reflect the higher radiometric sensitivity of Landsat-7 ETM+ sensor on one hand and the advance in information content of the Landsat-7 ETM+ that could have contributed to mapping of smaller reflective objects resulting in increased spreading of built up pixels on image classification on the other hand . Therefore, the post-classification majority filter might have removed most of the spread out and isolated pixels and thus, reduction in fractal dimension. Base on the data and methods presented herein, the property of image 2003 (ETM+) have impact on FRAC_AM. However, the effect of post classification processing (majority filter) seems fairly uniform on most metrics values. But it is important to note that the classification accuracy of the two sets of images is somehow comparable. Owing to the better classification results achieved in this study, the analysis is preceded with the classification results of the present study. The results of Vermeiren et al. (2012) can be found on appendix section of this research.

Figure 4.6 Graph showing comparison between metrics calculated for the two sets of images.

NB: Metrics with * sign and in red are results obtained using Vermeiren et al. (2012) image (E.g. **TA***).



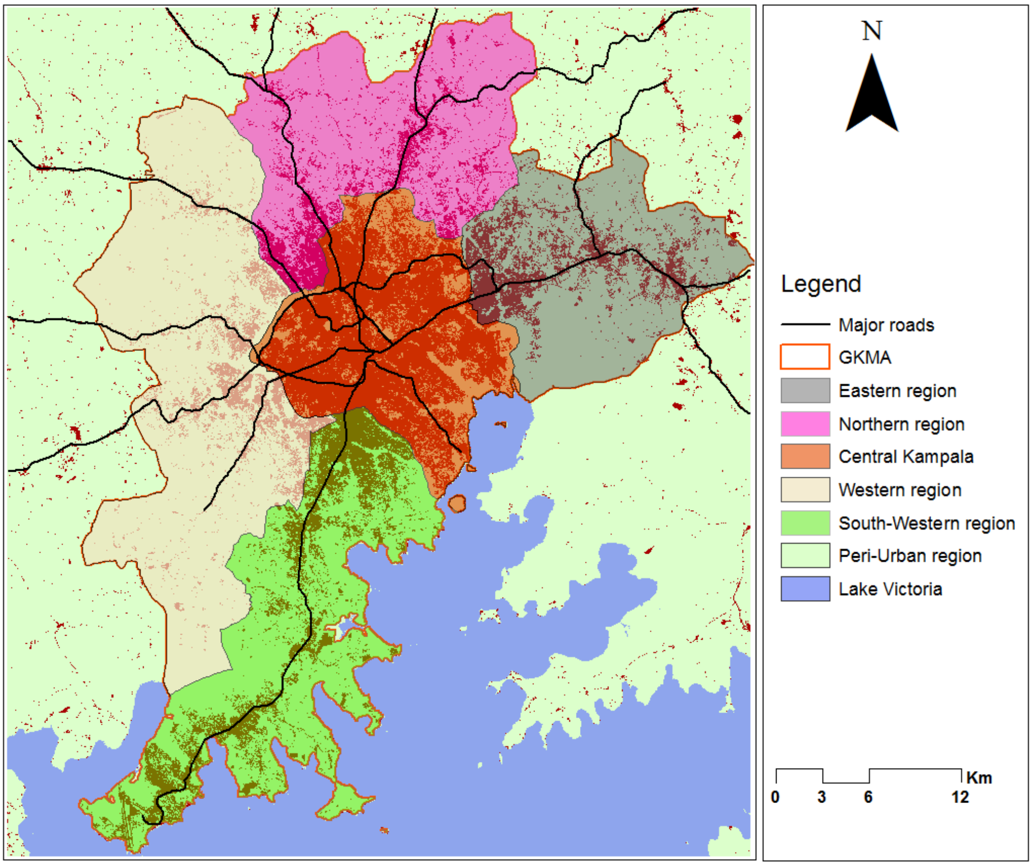
4.5. Region based analysis of growth pattern using spatial metrics.

Due to the aggregating property of metrics, quantification of urban pattern at a larger spatial scale, i.e. at the whole landscape level, may not provide sufficient insight to relate spatial patterns to the underlying causal processes. Besides, it is difficult to relate changes observed in the metrics to particular location in the landscape (Herold et al., 2003) at least not without visual interpretation. Therefore, it has been important to conduct detail analysis by dividing the metropolitan area in to different zones or regions. Different regions were aggregated using administrative boundaries at division level; the city is divided in to five analysis regions (see figure_4.7). Considering the observed growth dynamics beyond the metropolitan area, a sixth region called 'peri-urban region' is created. This has been useful to investigate the spatial development process of peri-urban or suburban areas. In this context, peri-urban region is the area located immediately outside the GKMA. Dissimilar to the other five regions this region is externally defined by the spatial extent of the study area. In terms of spatial extent most of the regions are of comparable except for the western region, which is slightly bigger than the other four regions of GKMA. The peri urban region is much larger than all regions. Unlike the analysis at the whole landscape level, in the region based analysis the thematic map is composed of two classes: built up and non-built up. This has been helpful to evaluate other properties of urban landscape such as diversity and Contagion yet, focusing on built up area dynamics. The metrics are computed in the recent version of FRAGSTATS (4.1). The list of divisions and their corresponding region are given in table 4.6 below.

Table 4.6: Administrative divisions making up regions

Region	Area (Km²)	Administrative divisions making up the region
Northern	203	Gombe, Nangabo, Nabweru and Northern part of Kira
South-western	238	Sabagabo-Makindye, Eastern part of Ssisa, Katabi-Entebbe, Divisions A and B
Eastern	182	Southern Kira, Goma, Mukuno Tc and Nama
Western	318	Wakiso Tc, Wakiso, Nsangi and Western part of Ssisa
Central Kampal	181	Central division, Kawempe, Makindye, Rubaga and Nakawa Divisions
Peri-urban	937	Outside GKMA

Figure 4.7: Map showing the five analysis regions for spatial metrics calculations



4.5.1. Northern region – Bombo road direction

Class level landscape pattern analysis

Table 4.7: Results of spatial metrics computation (northern region)

Northern region - Bombo road direction												
	CA		NP		PD		LPI		ED		FRAC_AM	
Year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	19861	**424**	10	**349**	0.05	**1.72**	97.89	**0.28**	8.41	**8**	1.16	**1.13**
1995	19687	**598**	9	**459**	0.04	**2.26**	97.04	**0.42**	11.71	**12**	1.19	**1.15**
2003	18023	**2262**	100	**727**	0.49	**3.58**	88.23	**2.94**	25.45	**25**	1.24	**1.18**
2010	16712	**3573**	174	**823**	0.86	**4.06**	45.31	**6.89**	36.68	**37**	1.25	**1.22**

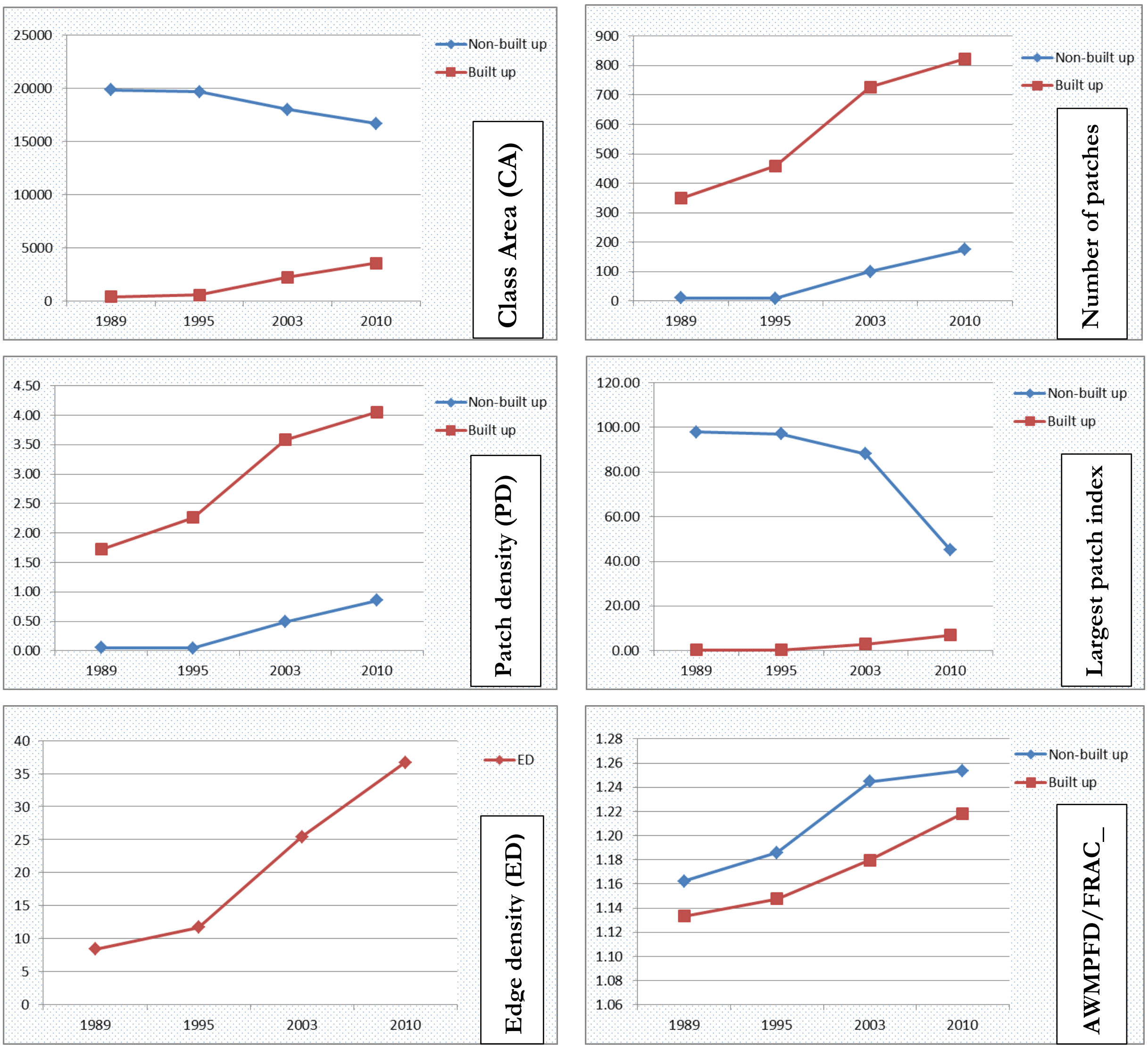
According to the results obtained from FRAGSTATS, the built up area has been considerably changed over time in the northern region (Bombo road direction) of the study area. During 1989-2010, 3149ha of non-built up land has been converted to built-up area with an average growth rate of 17% (150ha) per annum. In 1989 the built up land in the region has been only 424ha which constitute only 1.2% of the total area of the region (table 4.7). After six years in 1995 this figure changed to 598ha. Then, dramatically it increased to 2262ha in 2003. Although the period (1995-2003) covers the longest span of all the study periods under investigation, it is the period at which the highest urban change is observed in the study region. Finally, in 2010 the total built up area in the northern region reached 3573ha accounting for 17.6% of the total landscape in the region. The region is one of the most active areas in the GKMA hosting a variety of socio-economic activities. For instance Kawempe, where different industrial and commercial activities like private limited companies, hotels, markets and business are located, is found in this region. In addition to this, a major road (Bombo road) connecting the city to the satellite towns and northern regions of country is passing through this region. For these reasons, the total built up area (CA) is continuously increasing over time in the region.

Table 4.8: Temporal dynamics of built up area in northern region, based on class area (CA) metrics

Northern region - Bombo road direction					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	174	41	6	7	
1995-2003	1664	278	8	35	17
2003-2010	1311	58	7	8	

In 1989 the number of patches (NP) in the region was 349 and gradually increased to 459 in 1995, 727 in 2003 and finally reached 823 in 2010 (table 4.7). This indicates that during the urban growth process there has been a development and emergence of a number of small fragmented built up areas. According to the researcher's observation during fieldwork, this could be mainly attributed to the development of discontinuous urban patches and other impervious surface features due to uneven topography, hills and valley barrier, and swampy wetland cover (refer figure_2.3). In addition to this it is also possible that there might be a gradual development of new urban centres in the region. Similar an increasing trend is observed for patch density (PD) is over time. In 1989 PD was 1.72 then increased to 2.26 in 1995, 3.58 in 2003 and 4.06 in 2010. The total area of the landscape is much higher than the number of patches in the landscape; as a result the value of patch density is low. This is the manifestation of the non-built up area as a dominant land cover class in the landscape (refer figure_4.5). Nevertheless, patch density appears to increase over time indicating the fragmented development process of the built up area.

Figure 4.8: Graphs showing class level metrics computed for the Northern region - Bombo road direction



Like CA, NP and PD, the area occupied by largest patch has been increasing continuously throughout the study period in the region (see figure_4.8). The result obtained from FRAGSTATS reveals that the LPI has been 0.28 in 1989, 0.42 in 1995, 2.94 in 2003 and 6.89 in 2010 (table 4.7). This could be due to the amalgamation of small and isolated urban patches into a single patch and/or development of other urban patches around the existing built up area. The built up area is growing to the north direction as the continuation of the central Kampala region mainly following the major road. This indicates that most of the small isolated and fragmented urban sprawl and associated built ups were connected with the urban core.

The result of this study revealed, ED has increased from 8 in 1989 to 12 in 1995, to 25 in 2003 and to 37 in 2010 indicating that there has been significant urban expansion and emergence of various fragmented urban patches in the landscape. FRAC_AM has been 1.13 in 1989, 1.15 in 1995, 1.1 in 2003 & 1.22 in 2010 (table 4.7). The proximity of FRAC_AM value to one (1) in the earlier course of urbanization periods indicates; the built-up area was composed of patches having comparatively simple geometric shape in earlier periods. However, the increasing trend of FRAC_AM shows that this region is getting more fragmented and complex overtime.

Three metrics: Contagion (CONTAG), Shannon's diversity index (SHDI), and Shannon's evenness index (SHEI) were selected to analyse the overall condition of the landscape structure. Contagion (CONTAG) is the measure of the extent to which the different land cover classes are aggregated or clumped and it is expressed in percentage. High contagion results from the aggregation of patches of the same land cover classes.

Table 4.9: Spatial metrics computed at landscape level – Northern region

Northern region - Bombo road direction			
Year	**CONTAG**	**SHDI**	**SHEI**
1989	89	0.10	0.15
1995	85	0.13	0.19
2003	64	0.35	0.50
2010	52	0.47	0.67

Based on the result of the contagion analysis for the Northern region indicates a decreasing trend confirming the fragmented urban growth. Due to the domination of the landscape by the non-built up class in 1989 CONTAG were 89. This means patches of the non-built up class were highly aggregate together as it is clearly seen on figure 4.5. Conversely, in 2010 the value of CONTAG decline to 52 (table 4.9) indicating the increasing fragmentation of the landscape as a result of emergence of built up area between the contiguous non-built up classes. Shannon's diversity index (SHDI) also confirms the landscape is getting more diversified and rich with different patches over time. As a result the distribution of area between non-built up and built up area is relatively becoming more equitable or even over time as evidenced by increasing value of Shannon's evenness index (SHEI). Thus, all the metrics at landscape level confirms the northern region is getting more fragmented over time.

4.5.2. Eastern region – Jinja road direction

Class level landscape pattern analysis

The result of class area metrics analysis witnessed that urbanization has been considerably influencing the landscape in the eastern part of the study area. In 2010, the region constituted 16.6% of the total built up land in the greater Kampala metropolitan area (GKMA). However, built up area covered only 2.5% (450ha) of the region in 1989. After six years this figure increased to 4% (712ha) indicating the urbanization process in the eastern region. The most dramatic change is observed in 2003 when built up CA reached to cover 14% (2556ha) of the region (see table 4.10). The change is not surprising as this period covers the longest time span and besides it is the period at which the highest land cover change at the city level is observed. However, it logical to say the region might have absorbed the highest percentage urban growth that occurred in 2003 at the city. Relatively slower growth rate is observed in 2010. In total, Class area metrics shows 3333ha of non-built up land has been urbanized at a rate of 16% (159ha) per annum during the period 1989-2010 in this region with the highest growth rate during 1995-2003 (see table 4.10). The rate is comparable with the growth rate of the northern region, but it is much higher than the average growth rate of the city.

Table 4.10: Temporal dynamics of built up area in eastern region, based on class area (CA) metrics

Eastern region - Jinja road direction					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	262	58	6	10	
1995-2003	1844	259	8	32	16
2003-2010	1227	48	7	7	

Number of patches shows increasing trend illustrating the sprawling and fragmented growth of the built up area in the region. However, the increase in NP seems somehow slower than the increase of CA (table 4.11). This phenomenon is reflected by the density metrics PD & ED. The sprawling and fragmented growth can be confirmed from the lower values of patch density and edge density (table 4.11). In contrary, the largest patch index shows consistent increase throughout the study periods. These support the idea that the number of patches is growing in slower pace than the class area. This means the existing urban patches were growing in size together with the number of patches which indicates that the sprawling urban growth is followed by infill and edge expansion in this region. Between 1989 and 2010 the LPI grow from 1.21 to 10.19 (table 4.11).

Table 4.11: Results of spatial metrics computation (Eastern region)

Eastern region - Jinja road direction												
	CA		NP		PD		LPI		ED		FRAC_AM	
year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	17779	**450**	11	**221**	0.06	**1.21**	97.51	**1.21**	8.44	**8**	1.16	**1.22**
1995	17517	**712**	31	**339**	0.17	**1.86**	95.98	**1.62**	11.50	**11**	1.18	**1.19**
2003	15673	**2556**	94	**474**	0.52	**2.60**	84.10	**6.73**	24.20	**24**	1.23	**1.21**
2010	14445	**3783**	198	**536**	1.09	**2.94**	77.25	**10.19**	37.36	**37**	1.27	**1.24**

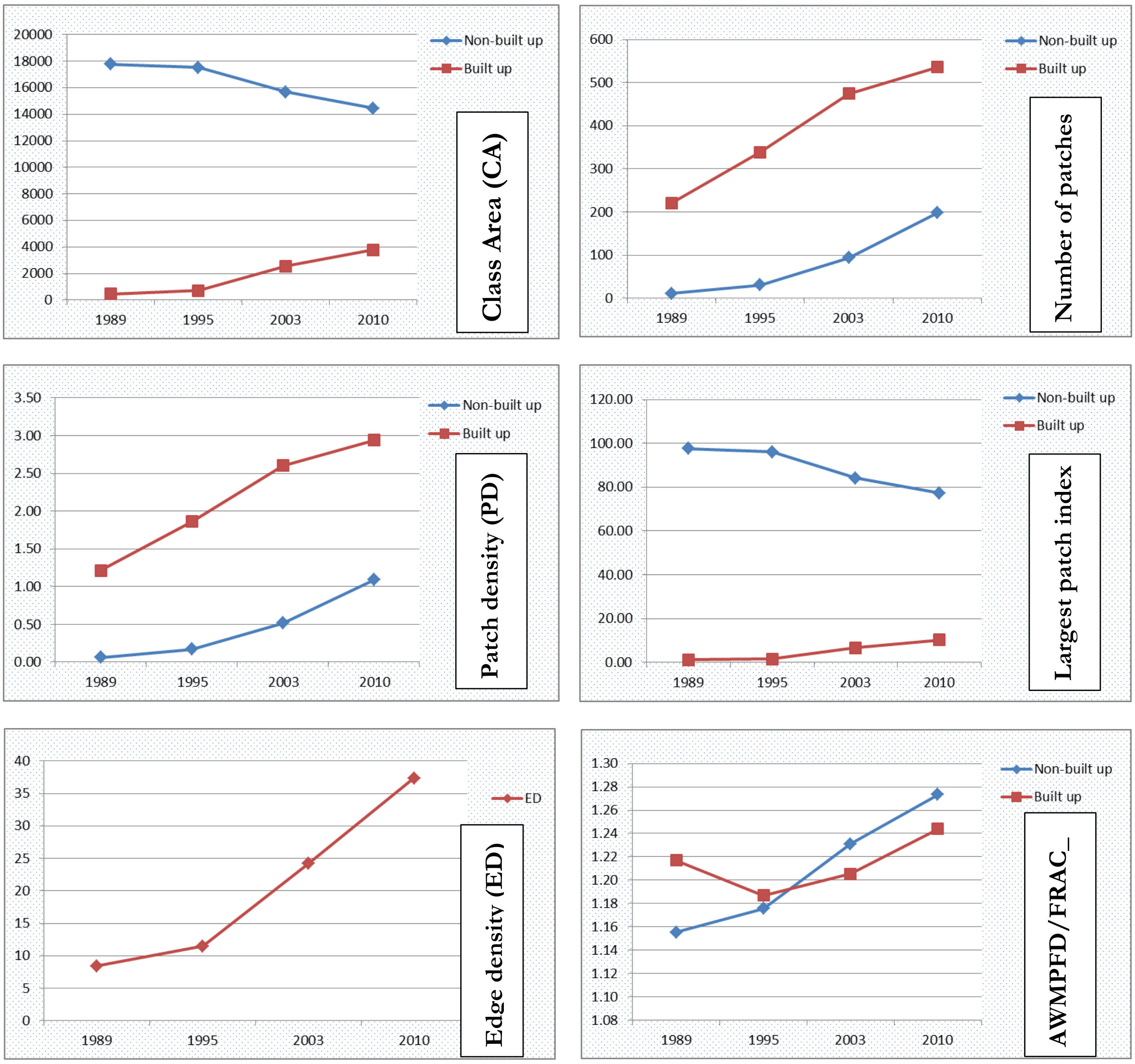
The growth of this region seems highly triggered by the presence of Jinja road, one of the major roads connecting Kampala to the Eastern part of the country and Kenya, and the close proximity between the city and the neighbouring satellite towns such as Mukono & Seeta. It is also the key route through which the import and export activities of the country are transported to and from Mombasa port in Kenya. In the early stage of urban development (1989) the built up area starts to expand from both the western and eastern part of the region. Then, it continues to spread along the Jinja road gradually infilling the open space between existing built up patches creating continuous urban fabric (see figure_4.5). It is evident that fragmented urban patches are observed in the northern and southern parts of the region as the time proceeds. This is confirmed by the area weighted mean patch fractal dimension (FRAC_AM) measure of the area. FRAC_AM showed increasing trend except for the period 1989-1995 showing the complex and fragmented development process of built-up areas in the region (figure_4.9).

Table 4.12: Spatial metrics computed at landscape level – Eastern region

Eastern Region - Jija road direction			
Year	CONTAG	SHDI	SHEI
1989	88	0.12	0.17
1995	83	0.17	0.24
2003	60	0.41	0.58
2010	48	0.51	0.74

Contagion (COTAGN) shows a gradual decline indicating the dispersed and low-density development pattern in the eastern region (table 4.12). As much of new built up patches develop in the region, the continuous non-built up land is interrupted resulting in fragmentation. Looking at SHDI and SHEI, it is evident that the landscape is also becoming more diversified with a variety of patch types and even distribution of class. SHDI is low in the early stages of urban development because of the dominance of the non-built up land cover class, hence low diversity of classes, whereas SHEI scored low value as there were no equitable distribution of classes in early stages of urbanization. The results of these metrics are in line with the metrics computed at individual class level.

Figure 4.9: Graphs showing class level metrics computed for Eastern region – Jinja road direction



4.5.3. Central Kampala region – KCCA

Class level landscape pattern analysis

The Central Kampala region or KCCA is the highly urbanized in all study periods. This is not surprising as KCCA is the core of the city. Based on class area (CA) metrics, in 1989 urbanized areas of KCCA region accounted for 26.6% (4827ha) of the total landscape area in the region (see table 4.14). During the period 1989-1995 the built up area increased by 45% (2168ha). However, the highest growth is observed during the period 1995-2003 where the built up area is increased by 74% (5198ha) (table 4.13). After two decades since 1989, the built up area take over the landscape accounting for 76.2% (13813ha) of the total area of the region. In total, 8986ha of non-built up land has been converted to built-up area over the period of 1989-2010 with an average growth rate of 6% (427ha) per year. During the period 2003-2010 relatively small change is detected signifying the gradual saturation of the city centre (table 4.14). However, it should be noted that growth rates and percentage change are relative measures of urban growth whereas change in (ha) is absolute measure of growth. In 2010 the built up area in KCCA region alone constitutes 42.5% of the total built up area in GKMA. This makes it the most urbanized region in the metropolitan area.

Table 4.13: Temporal dynamics of built up area in Central Kampala region, based on class area (CA) metrics

Central kampala - KCCA					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	2168	45	6	7	
1995-2003	5198	74	8	9	6
2003-2010	1619	13	7	2	

The intensive urban development process in this region is also manifested by the number of patches (NP). The number of patches consistently decreased from 697 in 1989 to 150 in 2010 demonstrating the merging of urban patches in to homogeneous urban fabric. The situation is also reflected by the gradual decline of patch density (DP) and dramatic growth of the largest patch index (LPI) in the landscape. This shows the agglomeration of urban core as a result of development pressure in and around KCCA.

The result of edge density (ED) and area weighted mean patch fractal dimension (FRAC_AM) metrics show similar trend for this region (table 4.14). Both indicate increasing trend between 1989 and 1995 and then decreased for the rest of study periods. The increasing trend can be associated with the partial integration of existing individual patches and probably the formation of fewer new patches during that period. Nevertheless, in the latter years both ED and FRAC_AM start to fall down indicating the amalgamation of individual patches into a bigger patch which suddenly give rise to the LPI (figure 4.10).

Table 4.14: Results of spatial metrics computation (Central Kampala region)

Central kampala - KCCA												
	CA		NP		PD		LPI		ED		FRAC_AM	
Year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	13291	**4827**	236	**697**	1.30	**3.85**	69.28	**20.67**	44.70	**45**	1.29	**1.29**
1995	11119	**6996**	437	**639**	2.41	**3.53**	20.20	**29.56**	57.89	**58**	1.26	**1.30**
2003	5917	**12194**	587	**204**	3.24	**1.13**	7.68	**65.16**	40.43	**40**	1.19	**1.28**
2010	4298	**13813**	601	**150**	3.32	**0.83**	4.55	**75.30**	35.68	**36**	1.17	**1.27**

The results of metrics analysis shows KCCA has been undergoing sprawling pattern of urban growth in the early urbanization periods; then continued to growth by edge expansion and infilling of the vacant space between fragmented patches in the later periods (see figure_4.5). This is witnessed by the continuous decreasing of NP & PD and by the continuous increasing of CA & LPI. This kind of development can potentially eat into public open spaces and wetlands as it may end up with no vacant space left over. Public open spaces and green areas have indispensable socio-economic and environmental value for the development of a city and for the quality of air in urban areas. If the infilling development process continues in the future, no doubt that KCCA region will be 100% built up area without leaving vacant land for open spaces. Thus, at this point it is important to think about the future of open spaces and green areas in the city centre. Policy makers and planners should critically think about the issue and come up with a planning scheme that protects the existing open spaces from encroachment or restrict any more merging of patch in the future. Although compact development is the motto of modern metropolitan growth as it promotes the best use of existing services, promote increased transit use and mixed use development, improve pedestrian accessibility, it should not be any more compact that could lead to congestion and loss of open spaces.

Figure 4.10: Graphs showing class level metrics computed for Central Kampala region – KCCA

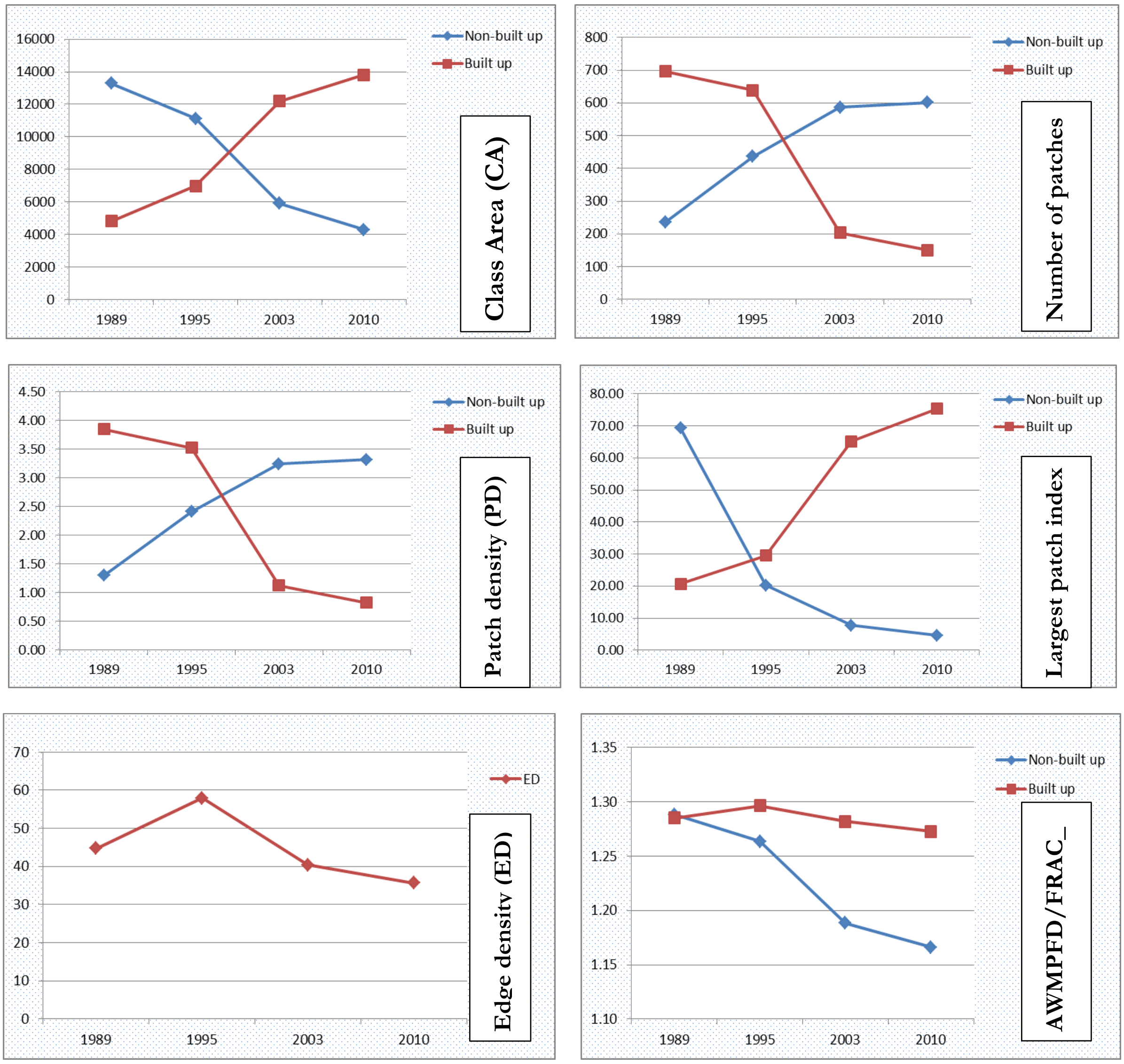


Table 4.15: Spatial metrics computed at landscape level – Central Kampala

Central Kampala (KCCA)			
Year	CONTAG	SHDI	SHEI
1989	41	0.58	0.84
1995	31	0.67	0.96
2003	38	0.63	0.91
2010	46	0.55	0.79

The central Kampala region has experienced different growth trends for the past 21 years. During the period of 1989-1995, CONTAG decreased from 41 to 31 indicating the fragmented urban growth process (table 4.15). However, from 1995 to 2010 CONTAG increased from 31 to 46 indicating the infilling of the open spaces between the non-built up patch and the merger of fragmented patches particularly those around the urban core. SHDI and SHEI reflected the similar trend, but opposed to contagion. In the early stage they show increasing trend and in the later periods appeared decreasing. These two metrics are also in agreement CONTAG. For three of the metrics presented here, 1995 seems the tipping point where the dominance of the non-built up land covers class start to decrease and the built up area starts to take over. It should be noted that SHDI & SHEI are expected to be low at early stage urbanization when the non-built up class is dominating and during period of rapid urbanization when the built up area takes over non-built up class. From table 4.15 the smaller values at the beginning and in the end are the reflections of this concept.

4.5.4. South-Western region – Entebbe road direction

Class level landscape pattern analysis

The South-Western – Entebbe road region is one of the rapidly urbanizing parts of the metropolitan area. In 2010, the total built up area in the region accounted for approximately 20% (6424ha) of the total built up land cover class in the GKMA metropolitan area (table 4.17). This makes it the second highly urbanized region in the metropolitan area next to central Kampala - KCCA region. In 1989, only 5.7% of the total area of the region is covered by urban. Later in 1995, the share of built up land cover class in the landscape increased to 9%. However, it takes eight years the built up area to double itself and to cover 18.43% (4389ha) of the total area of the region. This has been registered as the period at which the highest change is observed in the region with an average annual growth rate of 13% (table 4.16). Even though relatively slow growth rate it detected in 2010, considerable land has been converted from non-built up land to urban land cover. Generally, 5062ha of land has been changed to urban area with an average annual growth rate of 10% (241ha) for the past 21 years in this region (see table 4.16). This growth rate is somewhat comparable with the aggregate growth rate of the metropolitan area. It is worth mentioning that this region is somehow bigger in spatial extent than the northern, eastern and central Kampala region.

Table 4.16: Temporal dynamics of built up area in south-western region, based on class area (CA) metrics

South-western region - Entebbe road direction					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	818	60	6	10	
1995-2003	2208	101	8	13	10
2003-2010	2035	46	7	7	

The number of patches (NP) exhibits unique trend in this region indicating different development pattern over time. During the period 1989-1995, number of patches increased from 600 to 883 clearly indicating the emergence of new patches in the landscape as a result sprawling urban growth pattern in the region. Contrastingly, NP decreased from 883 to 713 during the period of 1995-2003. This shows the emergence of new connecting patches between fragmented urban patches along the Entebbe road. During this period the city underwent relatively compact type of development by infilling the space between built up along the Kampala-Entebe road. Unlike the other regions where urban expansion commonly appears as a continuation of the core city or central Kampala region, urban development in this region starts from the two extreme end directions: Entebbe airport and Kampala city. The two cities are located at 30.8km distance from each other (refer figure 4.5). However, the gap is gradually filled with contiguous and fragmented built up patches in a linear pattern. During 2003-2010, number of patches again increased from 713 to 846. This phenomenon can be associated with the expansion of the built up area in the form of branches extending from the main road to a land surrounded by wetlands and Lake Victoria (refer figure 4.5). This is also evidenced by the similar (increasing-decreasing-increasing) pattern observed on patch density (PD) for the periods 1989-1995, 1995-2003 and 2003-2010 respectively.

The measurements of largest patch index (LPI), edge density (ED) and area weighted mean patch fractal dimension (FRAC_AM) showed increasing trend over the entire study period (figure_4.11). LPI shows the gradual increasing size of the largest built up patch or the core area over time whereas ED and FRAC_AM indicates the increasing complicated geometric shape of patches due to fragmentation. Generally, Kampala-Entebbe road and topography have played significant role in shaping the urban growth pattern in this region. Lake Victoria, wetlands and unsuitable topographic nature are constraints of urban growth in the region (refer figure_2.3 & 4.5).

Table 4.17: Results of spatial metrics computation (South-western region)

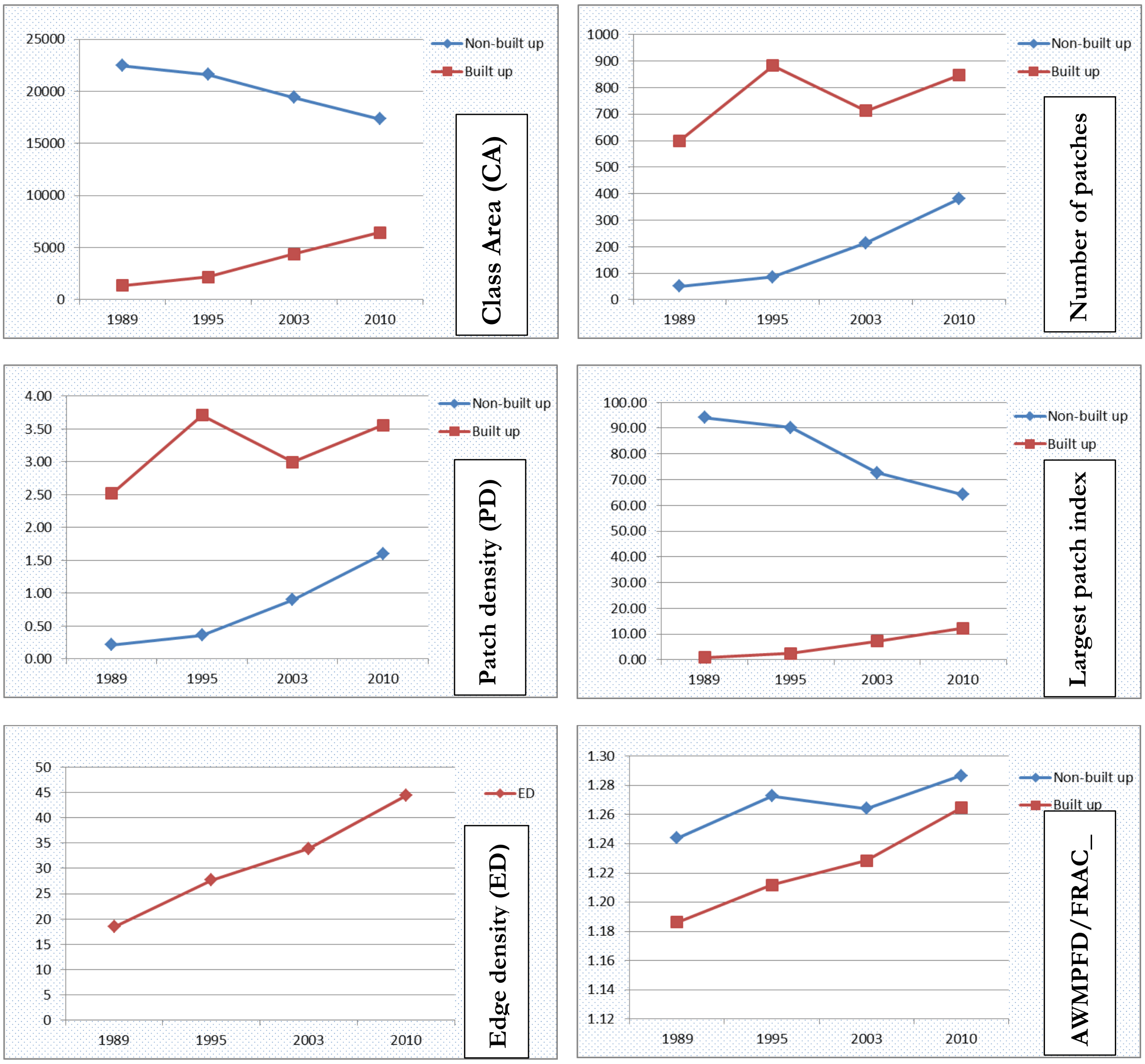
South-western region - Entebbe road direction												
	CA		NP		PD		LPI		ED		FRAC_AM	
Year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	22455	**1362**	51	**600**	0.21	**2.52**	94.14	**0.81**	18.43	**18**	1.24	**1.19**
1995	21616	**2180**	86	**883**	0.36	**3.71**	90.16	**2.41**	27.70	**28**	1.27	**1.21**
2003	19398	**4389**	214	**713**	0.90	**3.00**	72.69	**7.22**	33.89	**34**	1.26	**1.23**
2010	17357	**6424**	380	**846**	1.60	**3.56**	64.18	**12.21**	44.41	**44**	1.29	**1.26**

The results of metrics analysis at landscape level are consistent with the results of class level metrics (table 4.18). The probability of finding high adjacency between patches of different land cover classes is high during early stage of urbanization and decline when urban growth takes a sprawling pattern of development. Thus, higher values of CONTAG in this region is the result of the domination of the landscapes with a few large, contiguous patches of non-built up land cover class, whereas lower values generally characterize the gradual fragmentation process due to the domination of the landscapes with many small and dispersed built up patches. This observation is in line with the decreasing trends witnessed by SHDI and SHEI indicating the diversification of patch types and even distribution of area between land cover classes.

Table 4.18: Spatial metrics computed at landscape level – South western region

South-western region - Entebbe road direction			
Year	CONTAG	SHDI	SHEI
1989	77	0.22	0.32
1995	67	0.31	0.44
2003	52	0.48	0.69
2010	41	0.58	0.84

Figure 4.11: Graphs showing class level metrics computed for South-Western region – Entebbe road direction



4.5.5. Western region - Masaka & Mityana road direction

Class level landscape pattern analysis

Among the five regions making up the metropolitan area, western region is the least urbanized region with the highest rate of urban growth. In 1989 and 1995 the built up area occupied only 0.9% (288ha) and 1.3% (404ha) of the total area of the region (table 4.20). Nevertheless, it is important to note that this region is the largest region created for this research in the metropolitan area. In the earlier periods of urbanization (1989 & 1995), the region appears peri-urban in characteristics with few small pockets of built up patches dispersed in the landscape (see figure_4.5). During the period 1995-2003 this region underwent massive urbanization process as 1613ha of non-built up land is changed to build up land (399% change). This change is recorded as the highest percentage change in all study periods (see table 4.19 & 4.20). With the total built up area of 3117ha, the region form 9.6% of the total built up land in the whole study area in 2010. In sum, 2829ha of land has been changed to built-up area between 1989 and 2010 with an average annual growth rate of 21% (135ha).

Table 4.19: Table showing temporal dynamics of built up area in western region, based on class area (CA) metrics

Western region - Mityana & Masaka-Kampala road direction					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	116	40	6	7	
1995-2003	1613	399	8	50	21
2003-2010	1099	54	7	8	

The number of patches shows fluctuating trend suggesting the different development patterns taking place at different time in the region. In 1989 the number of patches were 522 and in 1995 declined to 382 indicating the merging of some urban patches. The following year (2003) NP considerably increased to reach 847. This is reasonable as it was the time at which the highest growth occurred in the region. The grow of built up area is mainly concentrated, along the shared boundary between the region and the urban core (KCCA) and following Masaka-Kampala road & Mityana road to the west direction. The concentrated and development observed in 2010 is an evidence for the reduction of NP. This signifies, relatively compact urban growth has occurred at that time. The slight changes perceived on PD during 2003-2010 study period is also in agreement with number of patches (NP) and largest patch index (LPI) for the same period as compact development reduces PD and increases LPI (see table 4.20). The urbanization occurred during 1989-1995 seems have not affected the ED, since the change in CA was relatively small. The consistent increasing trend observed on FRAC_AM shows the growing complexity of urban patches (see figure_4.12). The pattern of urban growth in this region give the impression that wetlands has played role in shaping the urban growth pattern in the western part of the study area. In the north-west & west direction, the core city is fortified by wetlands. As a result it has taken long time to break this barrier and urbanization to occur in this region. This could be because of different reasons. For instance, the lack adequate infrastructure to connect the region with the main city (KCCA). Another reason could be the increased distance from the city center on the top of inadequate infrastructures. As learnt from workshops and discussions made with different stakeholder during fieldwork, the complicated 'Buganda' land tenure system has also hindered the growth of the city in the west direction. But nowadays the region is experiencing rapid urban expansion in a disorganized and low-density sprawling pattern. This might create good opportunity for the encroachment of the greater part of wetlands located in this region. Thus, it is important to structure and reshape the existing messed up urbanized areas and prepare long term integrated development plan for the urban expansion to come the future.

Table: 4.20: Results of spatial metrics computation (Western region)

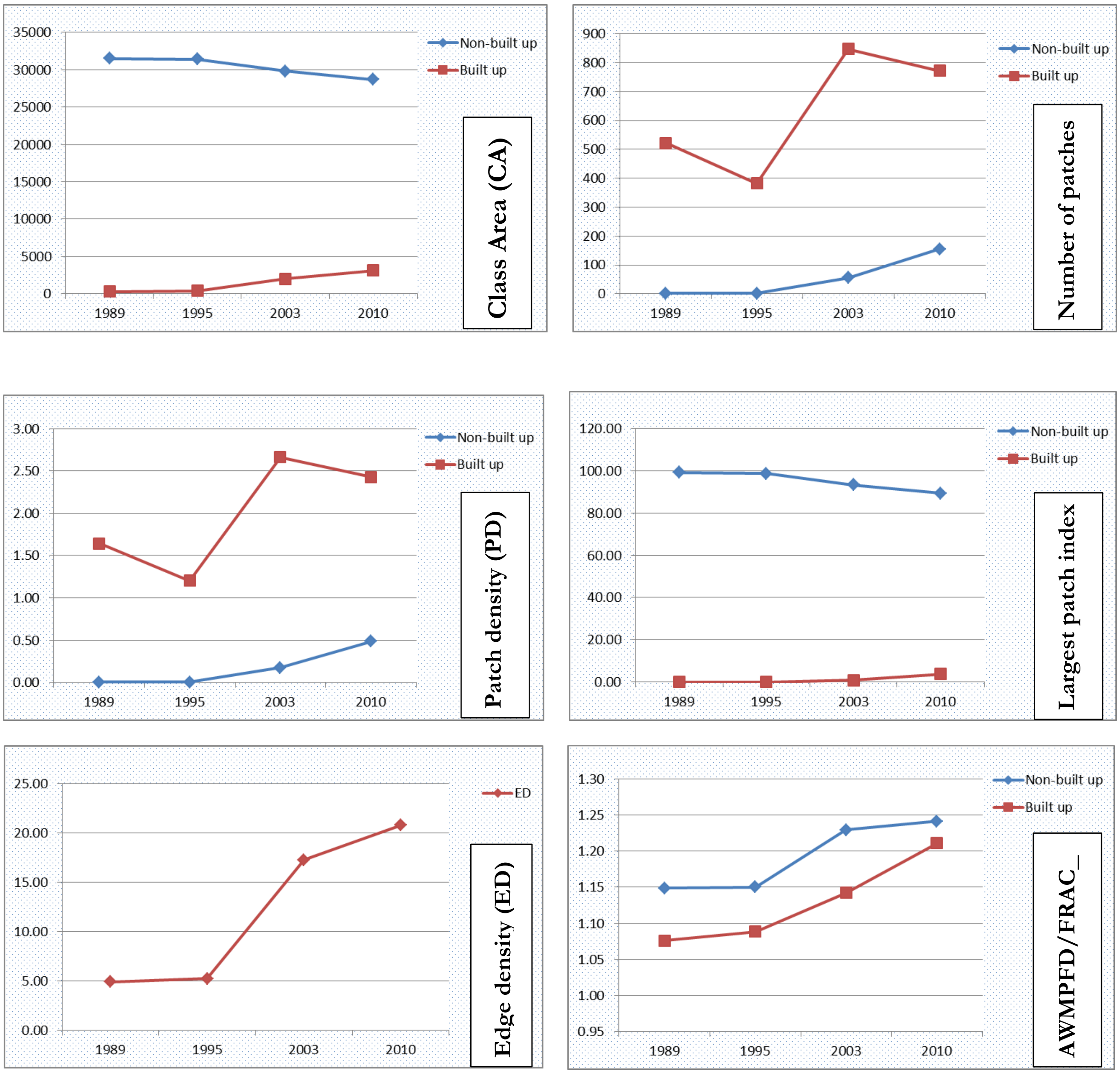
Western region - Mityana & Masaka-Kampala road direction												
	CA		NP		PD		LPI		ED		FRAC_AM	
Year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	31517	**288**	2	**522**	0.01	**1.64**	99.09	**0.05**	4.94	**5**	1.15	**1.08**
1995	31400	**404**	2	**382**	0.01	**1.20**	98.66	**0.10**	5.24	**5**	1.15	**1.09**
2003	29786	**2018**	56	**847**	0.18	**2.66**	93.27	**0.92**	17.26	**17**	1.23	**1.14**
2010	28687	**3117**	155	**772**	0.49	**2.43**	89.29	**3.82**	20.76	**21**	1.24	**1.21**

As the non-built up land cover class dominates the landscape in the earlier periods of urbanization, there were high probability of finding pixels of non-built up class adjacent to each other. As a result the value of the CONTAGN is high for year 1989 & 1995 (table 4.21). The slight variation of CONTAG in 1989 and 1995 imitates the small urban growth observed between these two years. In the latter two periods, significant change is witnessed by all metrics evaluated at landscape level. Both SHDI and SHEI increased together revealing the gradual diversification and even distribution of area among the land cover classes respectively.

Table 4.21: Spatial metrics computed at landscape level – Western region

Western region - Mityana-Masaka road direction			
Year	CONTAG	SHDI	SHEI
1989	94	0.05	0.07
1995	93	0.07	0.10
2003	76	0.24	0.34
2010	68	0.32	0.46

Figure 4.12: Graphs showing class level metrics computed for Western region – Masaka & Mityana road direction



4.5.6. Peri-urban region - Outside GKMA

A peri-urban area is a transition or interaction zone between urban and rural area where both activities are juxtaposed and landscape structures are subjected to rapid changes, due to human induced activities (Douglas, 2006). Although there are areas within the metropolitan area that possesses peri-urban character in nature, however, in this study only the region outside the metropolitan area is considered as a peri-urban region to see the long term effect of Kampala's urbanization. This region predominantly rural in character and the land is mainly used for agricultural activities, forest lands and rural settlements. However, recently, rapid urbanization and fast paced growth taking place in greater Kampala metropolitan area is transforming the character of the peri-urban areas. The growth of city is generally sprawling beyond the metropolitan boundary along the major transportation corridors extending from the city center to different regions of the country. To reveal the growth pattern of peri-urban region, a comparative analysis of metrics has been made at class and landscape level. The next section presents analysis of selected metrics.

The result of class area (CA) metrics analysis revealed that the peri urban region is growing fast over time. Although growth rate is relative measure as explained in earlier sections, the result of this analysis shows that annually, the peri-urban region has been growing with a faster rate (12%) than the annual growth rate of the city as whole (9%) (See table 4.22). In 1989 built up area in the region was only 361ha, which accounted for less than 1%. However, in 2010 the total built up area dramatically increased to 2029ha constituting 2% of the total landscape area of the region and 5.9% of the total built up land cover in the study area. In total, 1668ha of non-built up land has been changed to built-up area with an average annual growth rate of 12% (80ha) for the past two decades with the highest change being observed during the period 1995-2003.

Table 4.22: Temporal land built up area analysis in Peri-urban region

Peri-urban region - Outside GKMA					
Study period	change(ha)	Change(%)	Time Span(yr)	growth rate/yr	Average
1989-1995	386	107	6	18	
1995-2003	875	117	8	15	12
2003-2010	407	25	7	4	

The rapid urbanization process in the peri-urban region is also evidenced by the results obtained from NP and PD. The number of urban patches (NP) consistently increased throughout the study periods indicating the fragmentation of built up land cover class (see table 4.23). The increasing trend revealed by PD indicates, the number of built up patches per unit area is increasing over time as a result low density sprawling development pattern in peri-urban region. The largest patch index shows increasing trend except the sudden change observed in 1995 suggesting the merging of closely located built up patches over time. Edge density consistently increased throughout the study period signifying, the patches are getting more complex in shape over time as a result urbanization process. This is also witnessed by FRAC_AM.

Table 4.23: Results of spatial metrics computation (Peri-urban region)

Peri-urban region - Outside GKMA												
	CA		NP		PD		LPI		ED		FRAC_AM	
Year	Non-built	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up	Non-built up	Built up
1989	99428	**361**	374	**480**	0.37	**0.48**	67.70	**0.02**	1.80	**2**	1.13	**1.09**
1995	100442	**747**	457	**827**	0.45	**0.82**	66.49	**0.11**	3.13	**3**	1.16	**1.11**
2003	98360	**1622**	408	**1627**	0.41	**1.63**	66.56	**0.04**	6.48	**6**	1.19	**1.08**
2010	98446	**2029**	408	**2162**	0.41	**2.15**	45.56	**0.05**	7.85	**8**	1.17	**1.12**

Table 4.24: Spatial metrics computed at landscape level –Peri-urban region

Peri-urban region - Outside GKMA			
Year	CONTAG	SHDI	SHEI
1989	97	0.02	0.03
1995	95	0.04	0.06
2003	91	0.08	0.12
2010	89	0.10	0.14

The small variations recorded among all landscape level metrics indicate the dominance of one land cover class in the region. As expected, in peri-urban region the area covered by non-built up land cover is much higher than the area covered by built up land cover class. As a result Shannon's diversity index (SDI) is generally low. However, it is important to note that increasing trend is witnessed by both SHDI & SHEI, suggesting the region is getting more diversified and the distribution of area among classes is improving over time (see table 4.24). Conversely, the decreasing trend observed on CONTAG indicates the increasing fragmentation of the landscape. In other words, the built up patch is spreading over the landscape, which have resulted in disaggregation of non-built up land. Since the area covered by the built up cover is very small (<1 %) compared to the non-built up land cover class, the graphs for this region are not presented.

4.5.7. Intra urban growth comparison (1989-2010)

Class level metrics

Based on class area metrics, the central Kampala region (CK) and the south-western region (SWR) are the most urbanize region in the metropolitan area in all study periods. In 2010 these two regions together constituted more than 60% of the total built up land in the study area (see figure 4.14a). In terms of absolute growth rate (ha) the CK region is growing with 427ha per year while SWR is growing with 241ha each year. This is reasonable since central Kampala or KCCA is the heart of the city (CBD) and the country as whole, where different socioeconomic, commercial and administrative activities are accommodated. The south-western region or the Entebbe-Kampala road corridor is also the most dynamic urban expansion area due to the presence of Entebbe International airport (EBB), the principal international airport of Uganda which has been attracting development in the region. The eastern region (ER) and northern region (NR) are moderately urbanized, while the western region (WR) and the peri-urban region (PUR) are relatively less urbanized regions in a decreasing order.

However, in terms of average growth rate (%) the WR, NR and ER are the fastest growing regions in a decreasing order (see figure 4.14a & d) while the PUR, SWR and CK are growing with a relatively slower rate. As it can be observed from the bar chart (figure 4.14b), all regions except the central Kampala are growing with an average growth rate higher than the average growth rate of the study area as whole (GKMA). Despite their level of urbanization, all regions show a linear resembling increasing trend for CA metrics throughout the study period (see figure 4.13a) indicating the rapid urbanization process taking place in GKMA. In the earlier periods of urbanization, the latter four regions, i.e. ER, NR, WR & PUR, are almost starting from the same level of urbanization, but gradually the difference is getting larger.

The number of patches (NP) appeared highest for the peri-urban region and lowest for the CK in the latest periods of urbanization. This is also logical as peri-urban areas are expected to have dispersed and highly fragmented development pattern, whereas CK is the core of the city where the CBD and continuous urban fabric is found. However, the two most urbanized regions CK and SWR are the most fragmented regions in earlier period of urbanization, i.e., 1989. In 1995, SWR, PUR and CK were the most fragmented region in the study area with highest number of patches in a decreasing order (see figure 4.13b). CK and SR witnessed compact pattern of development in 2003 and 2010. Relatively, the eastern region (ER) underwent compact pattern of development mainly following the major transportation route. The up and down trends observed on NP in WR and SWR indicate the different development processes that take place in the region, i.e. fragmentation followed by infill and edge expansion.

NR and CK revealed increasing and decreasing trend for PD metrics throughout the study period. This indicates the northern region is undergoing continuous fragmented development process while the central Kampala is relatively undergoing compact development process. In 2010, NR, SWR and ER were the most fragmented regions in a decreasing order with the highest PD, whereas WR, PUR and CK take the lowest value indicating relatively low fragmentation. NR, ER and PUR unveiled linear increasing trend signifying the increasing amount of fragmented patches in the regions while KC showed decreasing trend. The largest patch index (LPI) exhibited similar trend with class area depicting the direct and proportional relationship between CA and LPI. Thus, those regions with high amount of built up area, i.e. CK, SWR, ER and NR are found to have large contiguous built up surface in their respective regions in a diminishing order since 1995. The central Kampala region is an outlier with high value for CA and LPI metrics, which is reasonable as CK is intensively urbanized region in the study area. However, SWR, ER, NR and PUR had relatively comparable value throughout the study periods (see figure 4.13a & d).

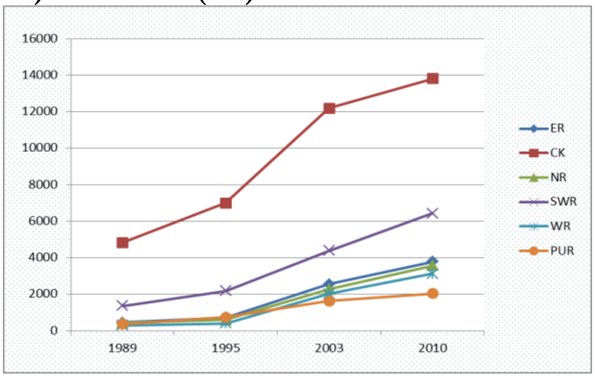
The two complexity measure metrics, edge density (ED) and area weighted mean patch fractal dimension (AWMPFD/FRAC_AM) metrics revealed that the most urbanized regions are composed of more complicated patches resulting in high value for perimeter-area ratio metrics. The first four most urbanized regions, i.e. CK, SWR, ER and NR had scored the highest value for ED metrics in a decreasing order in all study periods except in 2010 where SWR, ER and NR take over CK (see figure 4.13e). This could be the sign of stabilization of built up area in central Kampala region. Conversely, WR and PUR scored low value in a declining order in all study periods indicating the low level of urbanization, hence low fragmentation. ER and NR appeared overlapping throughout the study periods showing the comparable level of patch complexity in the two regions, which is somehow reflected by class area (CA). The peak value observed on CK in 1995 (see figure 4.13e) indicates the point at which the infill and edge expansion development starts in the region.

In all study periods, CK, SWR and ER scored the highest value for FRAC_AM in a decreasing order except in 1989 ER took over SWR. This might be attributable to the compact development pattern observed around satellite towns such as Mukono and Seeta during the earlier period of urbanization. In 1989 and 1995, the western region (WR) was less urbanized than the peri-urban region (PUR), which could be due to the complex land tenure system in the western region (Kiggundu & Mukiibi, 2011). NR, WR and PUR take the lowest value in a decreasing for FRAC_AM in the region signifying less urbanization compared with the other three regions.

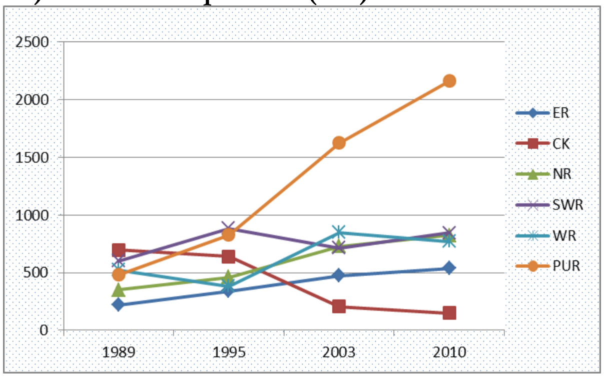
Generally, considering central Kampala region as the centre, the city is mainly growing to the south-west, east and north direction following the main transportation routes. In the west direction the growth appeared stagnant due to the topography and complex land tenure system in the region. However, in the recent years, the western region and the peri-urban region are growing in a faster rate than they used to grow before. This indicates high potential of urban expansion in the future in these regions.

Figure 4.13: Graphs illustrating intra urban metrics comparison at class level

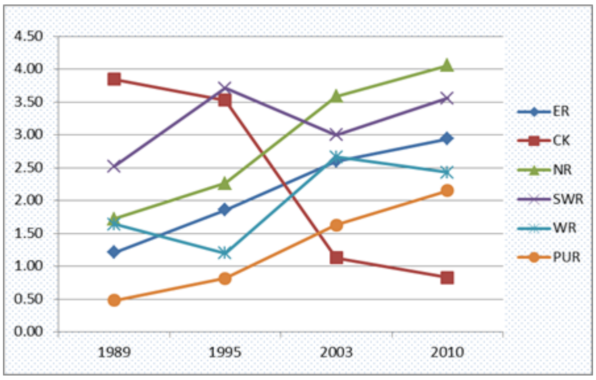
A) Class area (CA)



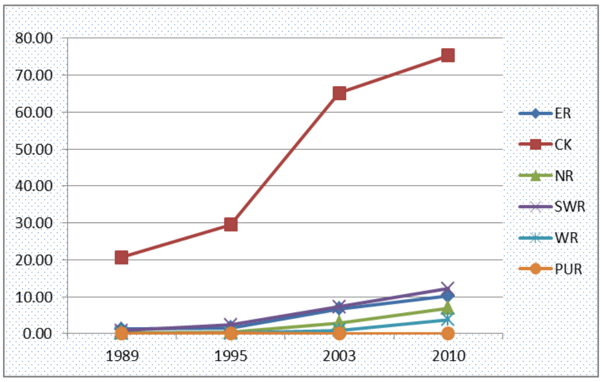
B) Number of patches (NP)



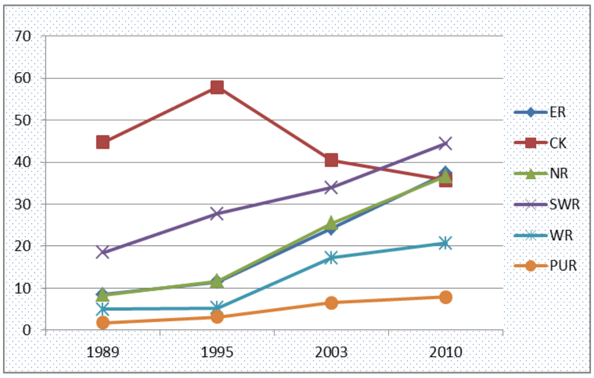
C) Patch density (PD)



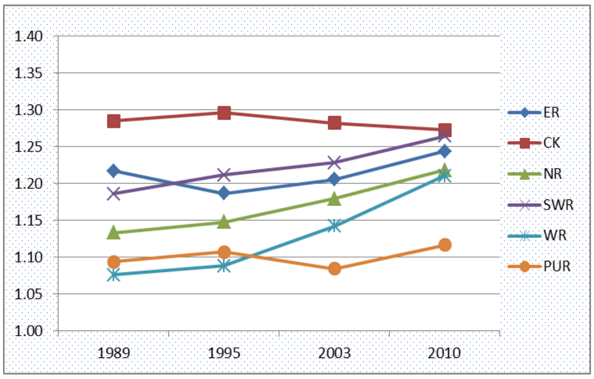
D) Largest patch index (LPI)



E) **Edge density (ED)**



F) AWMPFD/FRAC_AM



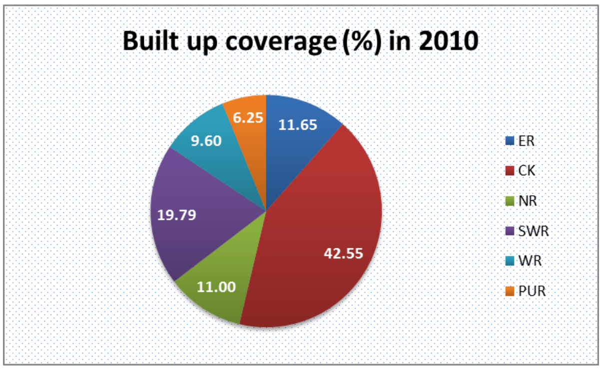
Shannon's diversity and evenness index showed similar pattern. This is rational since SHDI and SHEI are positively correlated. The value of a diversity index increases both when the number of classes increases and when the classes are evenly distributed in the landscape. Herein, the number of class classes is only two. Thus, it is convenient to easily understand the effect of one on the other. For instance, in 2010 SWR, CK and ER are the most diversified regions with the highest Shannon's diversity index in decreasing order. This means the abundance and distribution of patches is high in their respective landscapes. As a result, the classes are more evenly distributed giving higher Shannon's evenness index (SHEI). As the level of urbanization increases in the landscape, the diversity will increase and there will be equitable or even distribution of area among classes. All except CK exhibited increasing trend indicating the rapid urbanization process (see figure 4.15b & c). CK increased between 1989 and 1995 and decline or the rest of periods. This is a typical indicator of the dominance of built up area in the CK region after 1995, which is witnessed by CA metrics (see figure 4.10 CA graph).

Figure 4.14: Graphs and charts summarizing important urban growth statistical outputs.

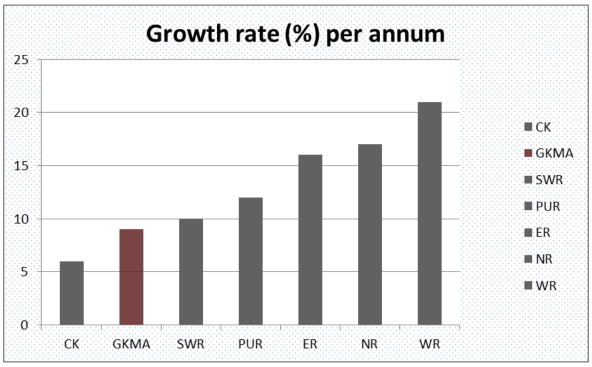
***Note: ER** – Eastern Region, **CK** – Central Kampala, **NR** – Northern Region, **SWR** – South-Western Region,*

***WR** – Western Region, **PUR** – Peri-Urban region*

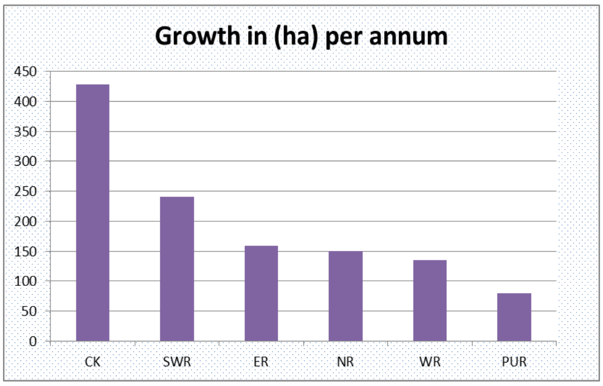
A) Pie chart showing contribution of each regions for the total built up area in GKMA



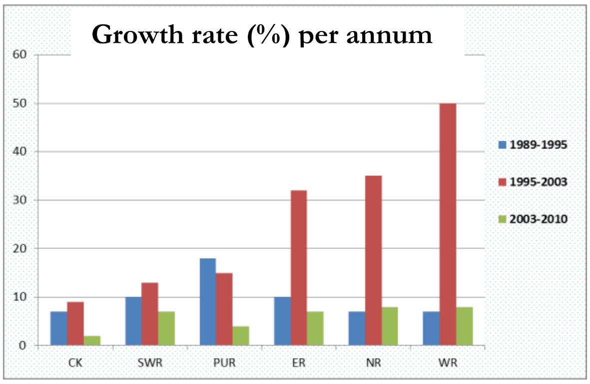
B) Bar chart indicating relative urban growth rate (%) per annum (1989-2010).



C) Bar chart indicating absolute urban growth rate (ha) per annum (1989-2010).



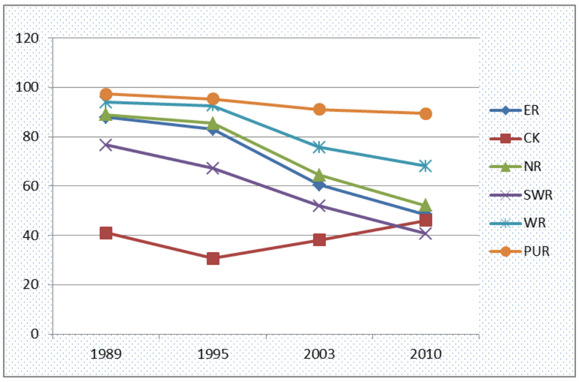
D) Bar chart indicating relative urban growth rate (%) per annum in each study periods.



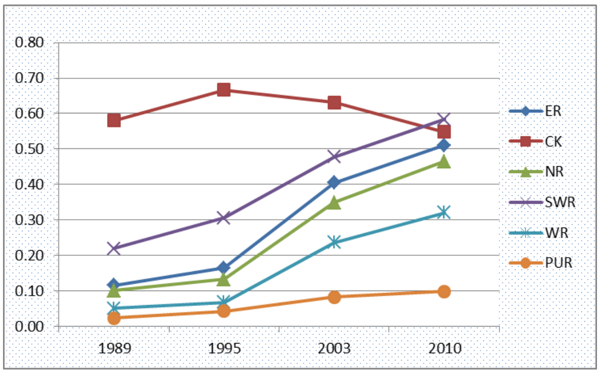
In contrast to diversity indexes, PUR, WR and NR scored high CONTAG value in a decreasing order. This could be attributed to the dominance of non-built up land in the regions. CONTAG metrics decreases when a landscape becomes more urbanized until it takes over the non-built up class and starts to fall down when the built up class becomes more dominant in the landscape. All except CK region showed decreasing trend indicating the increasing fragmented development process of the built up class. However, the decreasing trend observed on CK region during 1989-1995 (figure 4.14a) shows the fragmentation of the built up area during that period and the dominance of non-built up class, whereas, the increasing trend after 1995 shows the compact development process and the dominance of built up class.

Figure 4.15: Graphs illustrating intra urban metrics comparison at landscape level (1989-2010)

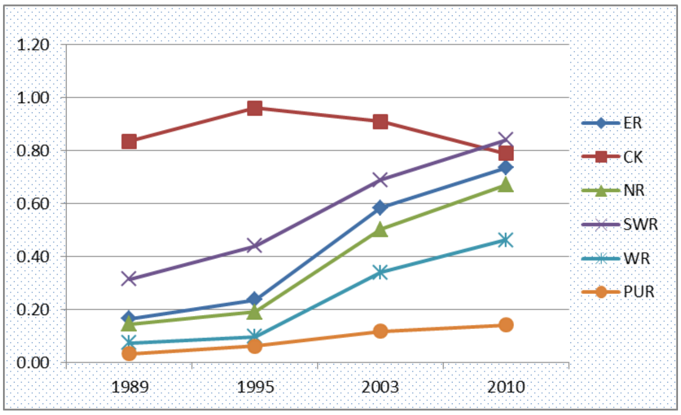
A) Contagion (CONTAG)



B) Shannon's diversity index (SHDI)



C) Shannon's evenness index (SHEI)



4.6. Results of logistic regression modelling

4.6.1. Variables used in the model

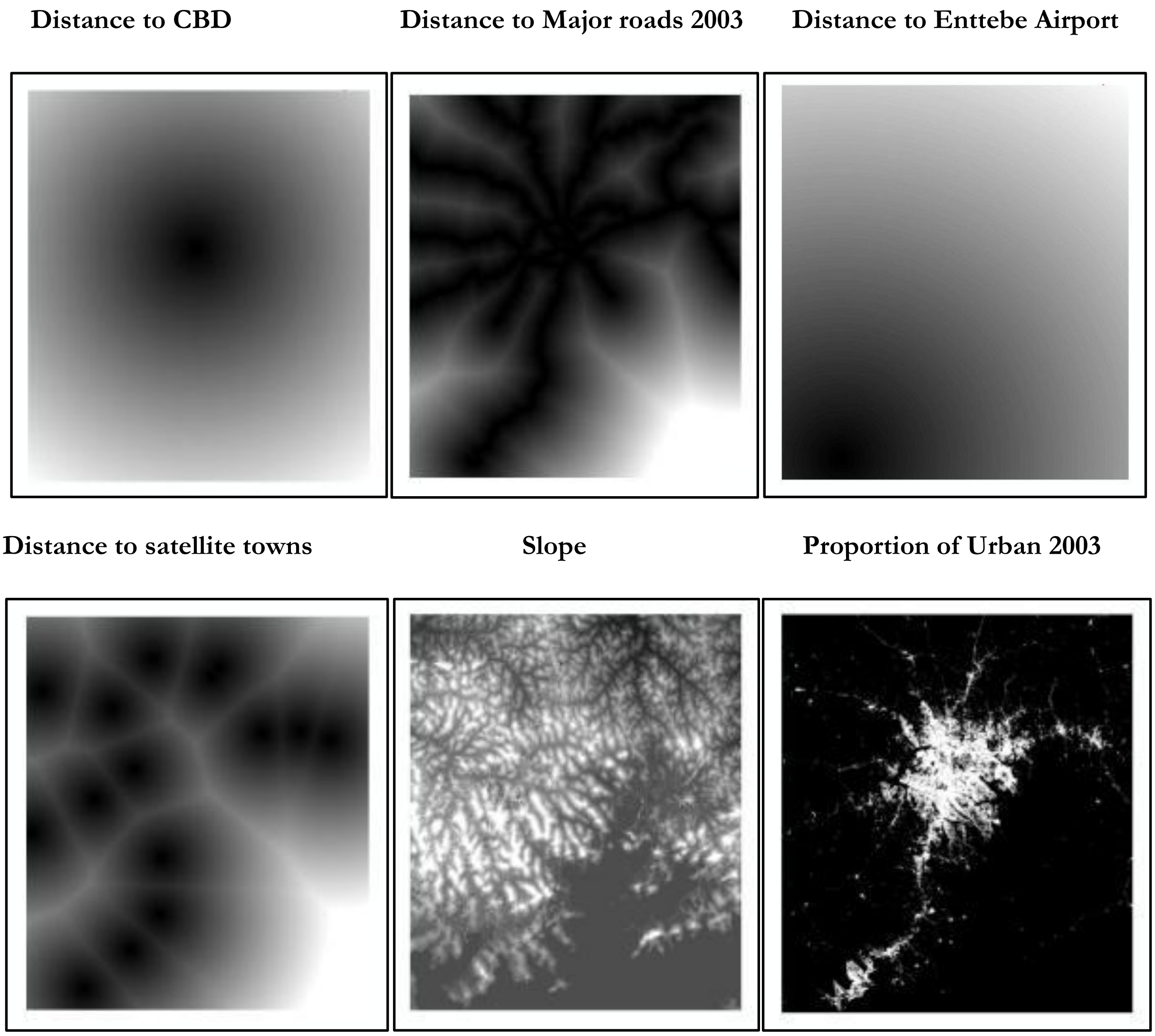
As discussed in previous chapter (section 3.6.2) the main purpose of logistic regression, in this study, is to understand and statistically quantify the interaction between urban growth and its drivers. In this model urban growth is considered as a dichotomous dependent variable to be explained as a function of seven predictor variables listed in table 4.25 below. Each cell in the dependent variable has only two categories, either to change to built-up cell (represented by 1) or remain as it is non-built up (represented by 0). Thus, the only change allowed in the model is from 0--->1. However, the seven predictor variables included in this model are continuous in nature.

The logistic regression analysis is conducted for three different time periods of 1989-1995, 1995-2003 & 2003-2010. The number of predictor variables used for all study periods are the same however, the information content is slightly different for few variable. For instance the proportion of built up land or cell is different for all study periods, whereas since the location of Entebbe airport is never changed from the very beginning distance from Entebbe airport is the same for all periods. For further information refer to 3.6.3 section of this research. List of all variables included in the regression model are summarized in table 4.25 and the raster layers of all independent variables used in the model are given in figure 4.15 below.

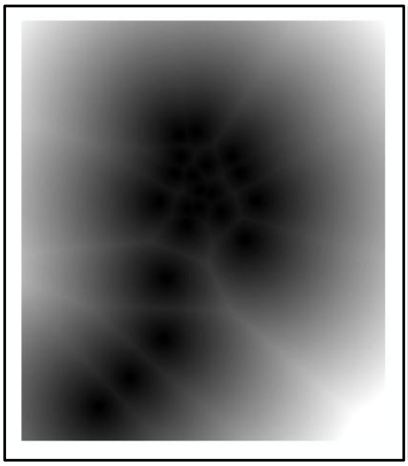
Table 4.25: List of variables used in the logistic regression model.

Variable	Meaning	Nature of data	Shape
Dependent			
Y	Land cover maps 1989, 1995, 2003 & 2010	Discrete	Polygon
Independent			
P_Urban	Proportion of urban land within 7*7 cell size	Continuous	Polygon
Slope	Slope	Continuous	Line
Dist_CBD	Distance to CBD	Continuous	Point
Dist_Entb	Distance to Enttebe Airport	Continuous	Point
Dist_Mjrd	Distance to major roads	Continuous	Line
Dist_Scc	Distance to sub city centers	Continuous	Point
Dist_St	Distance to satellite towns	Continuous	Point

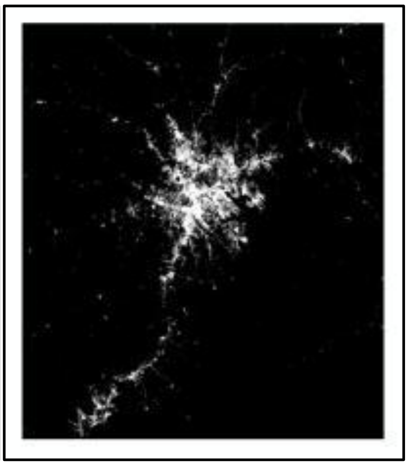
Figure 4.16: Raster layers of independent variables of the logistic regression.



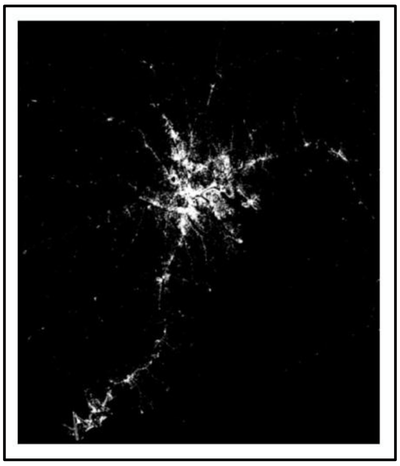
Distance to sub city centres 2003



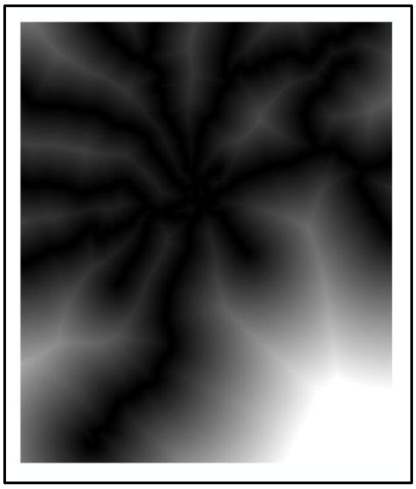
Proportion of Urban 1995



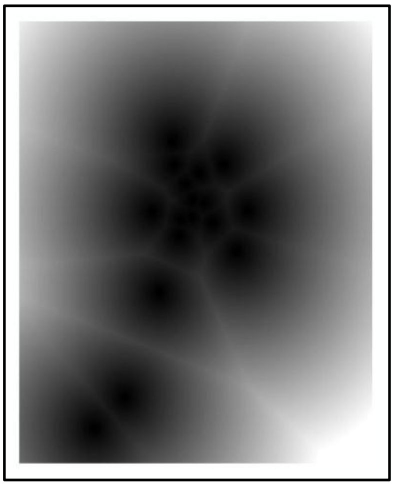
Proportion of Urban 1989

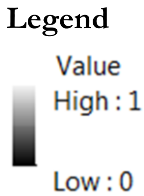


Distance to Major roads 1989&1995



Distance to sub city centres 1989





4.6.2. Multicollinearity analysis

To exclude redundant variables from the model and maintain the stability of coefficients, multicollinearity diagnostic has been conducted for each set of variables used in different time periods. The analysis is carried out in SPSS 21 statistical software package by regressing one of the independent variable against the remaining six variables in an iterative way. In this manner each variable is diagnosed for multicollinearity. Fortunately, none of the variables have scored variance inflation factor, VIF, >10. The analysis revealed that almost the entire variable scored VIF <5, which is a good result according to (Field, 2009). This shows that the proposed independent variables will measure different aspects of the dependent variable being modelled. The results of multicollinearity analysis for all study periods are summarized below.

Table 4.26: Results of multicollinearity analysis

Variables	Description	VIF (1989-1995)	VIF (1995-2003)	VIF (2003-2010)
P_Urban	Proportion of urban land	4.621	4.631	4.383
Slope	Slope (%)	4.072	4.180	4.228
Dist_CBD	Distance to CBD	3.031	3.076	3.171
Dist_Entb	Distance to Enttebe Airport	2.785	2.850	2.996
Dist_Mjrd	Distance to major roads	2.920	3.008	3.322
Dist_Scc	Distance to sub city centers	2.700	2.750	2.815
Dist_St	Distance to satellite towns	3.270	3.540	3.611

4.6.3. Model Results

Urban growth model 1989-1995 results

Model summary: Log Likelihood = -41752.4136, PCP =98.42%, Total sample size = 60236, Overall Model Fit: Chi Square = 77322.7016 with df=21 and P-Value=0.0000, 95% Confidence Intervals

Table 4.27: Estimated coefficients and odds ratios for the logistic regression model of 1989-1995

Variable	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
P_Urban	5.158638	0.23345	22.097435	0.0000*	173.927465
Slope	0.653646	0.381893	1.711594	0.0870**	1.922538
Dist_CBD	-2.276015	0.44471	-5.11798	0.0000*	0.102693
Dist_Entb	1.04521	0.370743	2.819233	0.0048*	2.843995
Dist_Mjrd	-9.296712	0.951923	-9.76624	0.0000*	0.000092
Dist_Scc	-5.264417	0.604664	-8.706345	0.0000*	0.005172
Dist_St	-0.080518	0.492371	-0.16353	0.8701	0.922639

Constant (a) = *-2.6091*

*Variables with * sign are significant at a=0.05* *Variables with ** sign are significant at a=0.1*

Table 4.27 presented above summarizes the regression results of 1989-1995 urban growth model. The results are generated by a binary logistic regression model using the maximum likelihood algorithm. Accordingly, five variables: proportion of urban land (P_Urban), distance to CBD (Dist_CBD), distance to Entebbe airport (Dist_Entb) distance to major roads (Dist_Mjrd) and distance to sub city centres (Dist_Scc) are significant at α=0.05 and the variable Slope is found to be significant at α=0.10. However, one variable (distance to satellite towns- Dist_St) has become insignificant in this model yielding higher p-value, which is 0.8701. Among the significant variables three of them: P_Urban, Dist_CBD and Dist_Entb are positively correlated with urban growth. The remaining three variables: Dist_CBD, Dist_Mjrd and Dist_Scc are negatively correlated with urban growth means that the higher the distance from these variables the lower is the probability of urban growth to occur or in other words urban growth tends to occur in close proximity to these variables. The relative significance of the predictor variables can be concluded from odds ratio. Odds ratios (OR) are important parameter for the interpretation of logistic regression modelling. It is an indicator of the change in odds resulting from a unit change in the predictor. Variables with higher odds ratio (>1) are regarded as highly influential variables in the model. Three variables: proportion of urban land (P_Urban), Slope and distance to Entebbe airport (Dist_Entb) are possessing OR>1 with z_Value significantly different from zero which indicates that the presence of these three variables has highly contributed to the growth of the city in that specific period.

Urban growth model 1995-2003 results

Model summary: Log Likelihood = -41125.1154, PCP=96.27%, Total sample size=59331 with an overall Model Fit: Chi Square = 69815.7459 with df = 21 and P-Value = 0.0000, 95% Confidence Intervals.

Table 4.28: Estimated coefficients and odds ratios for the logistic regression model of 1995-2003

Variable	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
P_Urban	6.797834	0.193304	35.166554	0.0000*	895.904251
Slope	3.03351	0.239342	12.674363	0.0000*	20.770015
Dist_CBD	0.217434	0.271437	0.801048	0.4231	1.242883
Dist_Entb	2.452809	0.233547	10.502402	0.0000*	11.620942
Dist_Mjrd	-5.751076	0.580022	-9.915275	0.0000*	0.003179
Dist_Scc	-8.295676	0.376278	-22.046667	0.0000*	0.00025
Dist_St	-2.162361	0.346399	-6.242397	0.0000*	0.115053

Constant (a) *= -3.2510* *Variables with * sign are significant at a=0.05*

The parameters of 1995-2003 growth models are summarized in table 4.28. The result of the regression modelling witnessed that all variables except distance to CBD (Dist_CBD) are found to be statistically significant at α=0.05. Interestingly, in similar fashion to the 1989-1995 model; proportion of urban land (P_Urban), Slope and distance to Entebbe airport (Dist_Entb) are observed positively correlated with urban growth. The other three variables: distance to major roads (Dist_Mjrd), distance to sub city centres (Dist_Scc) and distance from satellite towns (Dist_St) are negatively related to urban growth. However, distance from CBD which yielded p-value greater than 5%, had no significant contribution for urban growth in the study area during the period of 1995-2003. The level of significance of each variable can be determined based on their odds ratio. The variables proportion of urban land (P_Urban), slope, distance to Entebbe airport (Dist_Entb) had an odds ratio > 1 which indicating the presence of these variables the probability of urban growth is high.

Urban growth model 2003-2010 results

Model summary: Log Likelihood = -39360.3626, PCP=94.98%, Total sampling size= 56785, Overall Model Fit: Chi Square = 61892.8157 with df = 21 and P-Value = 0.0000, 95% Confidence Intervals

The results of the 2003-2010 regression modelling revealed that all predictors except distance to Entebbe airport are able to explain the dependent variable with different level of significance. Unlike the two other models presented earlier most of the predictor variables in this model are negatively related to urban growth. Proportion of urban land (P_Urban) and slope remains positively associated with urban growth. The odds ratio of these two variables is >1 indicating the presence of these variables yield high probability of urban growth.

Table 4.29: Estimated coefficients and odds ratios for the logistic regression model of 2003-2010

Variable	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
P_Urban	5.545203	0.139777	39.67181	0.0000*	256.006645
Slope	0.917092	0.216624	4.233571	0.0000*	2.502003
Dist_CBD	-1.939788	0.232614	-8.339098	0.0000*	0.143734
Dist_Entb	-0.178101	0.184528	-0.965171	0.3345	0.836858
Dist_Mjrd	-2.891817	0.435104	-6.646264	0.0000*	0.055475
Dist_Scc	-2.676289	0.282257	-9.481762	0.0000*	0.068818
Dist_St	-3.4041	0.309865	-10.985753	0.0000*	0.033237

Constant (a) *= -1.0448* *Variables with * sign are significant at a=0.05*

4.6.4. Model interpretation and discussion

As witnessed form the models, urban growth is more likely to occur in proximity of existing built up areas where the proportion of urbanized cell is high. This is true for all study periods under investigation. Proportion of urban land (P_Urban) is positively correlated with urban growth with an estimated coefficient of 5.158638, 6.797834 and 5.545203 and odds ratio of 173.927465, 895.904251 and 256.006645 for the study periods 1989-1995, 1995-2003 and 2003-2010 respectively. The odds ratios can be interpreted as; the probability of urban growth will increase with 173.927465, 895.904251 and 256.006645 with an increase of one urban cell is in the neighborhood for the periods 1989-1995, 1995-2003 and 2003-2010 respectively. The odds ratios of the independent variable P_Urban are far larger (>1) in all study period indicating that proportion of urbanized cell within a 7X7 window size is the major factors driving urban growth in the study area for all study periods.

Slope has been consistently significant and positively related to urban growth in all study periods. The estimated coefficients and odds ratios are 0.653646, 3.03351 & 0.917092 and 1.922538, 20.770015 & 2.502003 for the study periods 1989-1995, 1995-2003 & 2003-2010 respectively. For all study periods slope is positively related to urban growth, indicating the higher the slope of an area the higher probability to be occupied by a new built up cell. The likelihood of a non-built up cell to change to built-up cell is 1.922538 times, 20.770015 times & 2.502003 times as large as the probability of change in an area one per cent less in slope. This could be attributed to the hilly topographic nature of Kampala, where settlement on lower slope or close to wetlands is unfavourable due to the presence flood hazards and epidemic diseases like mosquito. Thus, steeper slopes were more preferred for settlement than low laying or wetland areas. During 1995-2003 most of the growths were taking place in areas relatively having high slope. However, the level of significance of slope during the period 1989-1995 has been at $\alpha=0.1$ having p-value 0.087 which makes it the only significant variable in all study period with $\alpha=0.1$. The rest of significant variables are important at the significance level of $\alpha=0.05$.

Distance to CBD (Dist_CBD) has been significant only for the periods 1989-1995 & 2003-2010 with significance level $\alpha=0.05$. However, it has been totally insignificant during the period 1995-2003. The estimated coefficients and odds ratios of Dist_CBD are -2.276015 & -1.939788, and 0.102693 (1/9.737762) & 0.143734 (1/6.957296) for the periods 1989-1995 & 2003-2010 respectively. The probability of urban growth in an area is estimated as 9.737762 times and 6.957296 as large as the probability of urban development in an area one unit further away from the nearest urban area for 1989-1995 & 2003-2010 study periods respectively. For both periods distance to CBD (Dist_CBD) is negatively correlated with urban growth indicating the higher the distance from CBD, the lower is the probability of urban growth to occur. Thus, areas within close proximity of the CBD were more favourable for urban development during 1989-1995 and 2003-2010 study periods. Proximity to CBD can provide a better access to facilities and services and reduces transportation cost; therefore people prefer to settle close to CBD. However, through time, CBD might lose its significance in attracting urban growth when the availability of developable land is scarce.

Entebbe airport is one of the variables that have been significantly correlated with urban growth in the study area particularly during 1989-1995 & 1995-2003 study periods. However, it had no more significant contribution for urban growth during the third period urbanization (2003-2010). In contrast to distance to CBD, distance to Entebbe airport (Dist_Entb) is positively correlated with urban growth at significance level of α=0.05 for the first two study periods (1989-1995 & 1995-2003). The estimated odds ratios are 2.843995 and 11.620942 for the two periods respectively which means that the odds of urban growth in area one unit farther away from Entebbe airport is estimated as 2.843995 times and 11.620942 times as large as that in area closer to the airport. The closer a cell is to Entebbe airport; the less likely it is to be urbanized. This could be attributed to unbalanced urban growth distribution revealed by spatial metrics analysis in section 4.5.7. In other words, since most of the growths were taking place closer to major roads, sub-city centres and where high proportion of built up cell is found, more developments were happening around the urban core (KCCA) compared to Entebbe airport area. It could be also the growths occurring along Kampala-Entebbe road were more concentrated (biased) to the Kampala side.

The models also show that urban growth has been significantly influenced by proximity to major road in all study periods. Similar to distance to CBD, this variable (Dist_Mjrd) is also negatively associated with urban growth. The estimated odds ratios for distance to major road (Dist_Mjrd) are 0.000092 (1/10869.5652), 0.003179 (1/314.5643) & 0.055475 (1/18.026138) for the study periods 1989-1995, 1995-2003 and 2003-2010 respectively. The likelihood of urban growth in an area closer to major roads is estimated as 10869.5652 times, 314.5643 times and 18.026138 times as large as the odds of urban development in an area a unit further away from major roads. Road is one of the major urban elements that facilitate movement of goods and people in urban areas and thus, influencing the spatial pattern of urban growth.

The variable distance to economically active sub city centres (Dist_Scc) has been affecting urban growth throughout the study periods with a significance level of 0.05. This variable (Dist_Scc) is also negatively related with urban growth in all study periods demonstrating the closer to sub-city centres the higher is the probability of urban growth to occur. The odds ratio for distance to sub city centres is 0.005172 (1/193.3488), 0.00025 (1/4000) and 0.068818 (1/14.531081) for the study periods 1989-1995, 1995-2003 and 2003-2010 respectively. These indicates that the odds of a non-built up cell to convert to a built-up cell within an area close proximity to active sub city centres is estimated as 193.3488 times, 4000 times and 14.531081 times as large as that in an area one unit further away from sub city centres for 1989-1995, 1995-2003 and 2003-2010 study periods respectively.

The results of the regression models revealed that distance from satellite towns (Dist_St) has influenced urban growth during the latter two study periods (1995-2003 and 2003-2010) at α=0.05. However, it had no significance during the period of 1989-1995. The coefficient and odds ratio of distance to satellite towns (Dist_St) is -2.162361 & -3.4041 and 0.115053 (1/8.691646) & 0.033237 (1/30.086951) for the periods 1995-2003 and 2003-2010 respectively. This shows that the probability of urban development to occur in an area close proximity to satellite towns is as 8.691646 times and 30.086951times as large as that in area one unit farther away from satellite towns for the study periods 1995-2003 and 2003-2010 respectively. This is reasonable as satellite town are located farther away from the city during earlier periods of urbanization and thus, they do not attract urban growth significantly.

4.6.5. Model evaluation

Model evaluation is an important step in logistic regression modelling. Change analysis software generates an output that could be used to evaluate the predictive power of the constructed model. Percentage correct prediction (PCP), the most commonly used type of evaluation method, is used in this study. It tells the percentage of correctly predicted pixels out of the sampled pixels in the model. The higher the PCP the higher is the predicting power of the model. This is helpful to identify which model to use for prediction when we have alternative models. Accordingly, the PCP of the three models, i.e. 1989-1995, 1995-2003 & 2003-2010 is 98.45%, 96.51% & 95.27% respectively, which is pretty good prediction power. The outputs of model evaluation analysis are presented below.

Table 4.30: Results of regression model evaluation

1989 to 1995

	Predicted			
Observed		0	1	Total
	0	2789110	5986	2795096
	1	39080	79321	118401
	Total	2828190	85307	2913497

Correct Prediction : 2868431

Wrong Prediction : 45066

Percentage of Correct Prediction (PCP) : ***98.45%***

1995 to 2003

	Predicted			
Observed		0	1	Total
	0	2659318	18799	2678117
	1	82766	152614	235380
	Total	2742084	171413	2913497

Correct Prediction : 2811932

Wrong Prediction : 101565

Percentage of Correct Prediction (PCP) : ***96.51%***

2003 to 2010

	Predicted			
Observed		0	1	Total
	0	2507443	21132	2528575
	1	116768	268154	384922
	Total	2624211	289286	2913497

Correct Prediction : 2775597

Wrong Prediction : 137900

Percentage of Correct Prediction (PCP) : ***95.27%***

4.6.6. Physical driving forces of Kampala's urban growth

Understanding the complex interaction between urban growth and its drivers over space and time is helpful to predict future urban development's and construct alternative scenarios. Despite the fact that availability of data is one of the major problems to conduct research in developing countries, it is evident that logistic regression model can be built based on few, but widely available spatially explicit data such as satellite images to provide relevant information for urban planners and policy makers (Fragkias & Seto, 2007). Thus, logistic regression urban growth modelling is an ideal approach to look at significant drivers of urban growth over time, particularly for developing countries. Different literatures has reported that driving forces of urban growth might differ based on the local context in which the development is taking place and the spatio-temporal dimension at which the analysis is considered (e.g. Cheng & Masser, 2003; B. Huang et al., 2009). In this study, three spatially explicit binary logistic regression models has been developed for 1989-1995, 1995-2003 and 2003-2010 study periods. The main purpose of the models is to figure out the major driving forces of urban growth and their level of significance in the study area.

Accordingly, the models were able to reveal significant driving forces of urban growth during the three study periods for the past 21 years.

Among the variables included in the 1989-1995 model, distance to major roads (Dist_mjrd) (-ve), distance to sub city centers (Dist_Scc) (-ve), proportion of built up cell (P_Urban) (+ve), distance to CBD (Dist_CBD) (+ve), distance to Entebbe airport (Dist_Entb) (+ve) and Slope (+ve) are found to be significant drivers of urban growth in a descending level of importance with their indicated sign of correlation with urban growth. However, distance to satellite towns (Dist_St) is found to be insignificant factor for this study period. This might be due to the wide gap between satellite towns and the city in the earlier stage of urbanization. According to Tobler's first law of geography "Everything is related to everything else, but near things are more related than distant things." The order of significance of the variables is also in a logical sequence as roads are major urban elements attracting urban growth in early stage of development.

During 1995-2003, distance to sub city centers (Dist_Scc) (-ve), proportion of built up cell (P_Urban) (+ve), distance to major roads (Dist_mjrd) (-ve), Slope (+ve), distance to Entebbe airport (Dist_Entb) (+ve) and distance to satellite towns (Dist_St) (-ve) are found to be significant driving forces of urban growth in a decreasing level of influence and with their indicated sign of correlation. Distance from CBD has been the fourth influential variable in the 1989-1995 model. However, in this model it is not any more significant. Following the rapid urban growth witnessed during 1995-2003 (refer section 4.3); the city has expanded outward to the periphery areas in all direction. This indicates developments were occurring in close proximity to sub city centers, existing built up areas and probably more closer to major roads than CBD. Consequently, the significance of distance to CBD (Dist_CBD) will be negligible or insignificant at all. Distance to sub-city centres (Dist_Scc) and proportion of built up cell (P_Urban) were the second and third influential variables in the 1989-1995 model, however they become the first and second important factors in the 1995-2003 model and distance to major roads (Dist_mjrd), the first important factor in the previous model takes the third place during the 1995-2003 period of urbanization.

Proportion of built up cell (P_Urban) (+ve), distance to satellite towns (Dist_St) (-ve), distance to major roads (Dist_mjrd) (-ve), distance to sub city centers (Dist_Scc) (-ve), distance to CBD (Dist_CBD) (-ve) and Slope (+ve) were significant drivers of urban growth in 2003-2010 study period in a decreasing sequence of importance with their designated sign of correlation with urban growth. Distance to Entebbe airport appeared insignificant in this model. However, distance to CBD becomes important variable in this model. This means most of the new growth tends to occur at the periphery of the city next to the already urbanized areas, i.e. edge expansion. However, there are also some infill developments that have been taking place closer to CBD during 2003-2010 period. Despite the introduction of the northern bypass in the third model, the major road (Dist_Mjrd) remains in the third place in this model. However, following the gradual expansion of the city, satellite towns become increasingly importance due to their proximity to the main city.

Slope has been attracting development in all study periods. This is due to the fact that Kampala is built on hilly topography. The variable becomes more significant factor in the period (1995-2003) than the previous period. This could be due to the fact that some land uses activities, such as high income residential land uses, may prefer relatively steeper slope for development pursuing safety and good view. However, it should be noted that slope may not necessarily attract development. For instance, given the hilly topography of Kampala (refer section 1.6), it can be assumed that relatively flat lands or foot slopes according to Vermeiren et al. (2012), which are suitable for development are already accompanied during the earlier period of urbanization. As a result, the lack of such suitable land in the city may push development to steeper slopes immediately found next to the existing built up area (P_Urban). Alternatively, it could be also the reflection of the increasing severity of flooding problem in low laying or wetland areas which might have pushed development to high slopes. This has been witnessed from the increasing level of significance of slope over time and positive relationship with urban growth in all study periods.

Assuming that distance to CBD might have been the most important variable above all before 1989, the pattern (order of significance) observed on the driving forces is reasonable. In early stage of urbanization roads are major urban elements structuring urban growth pattern followed by proximity to built-up area such as sub-city centers. Then, sub-city centers are created at the junction or nodes of roads. These sub-city centers eventually start to attract urban development around them. Gradually, when the availability of developable land in close proximity to CBD, major roads and sub-city centers become rare, the available land immediately next to existing built up area will be attractive. Some negative externalities such as congestion, overcrowdings, etc. due to the agglomeration of the city center might have pushed development away from established urban core (CDB).

The results of spatial metrics analysis can be also related to the findings of these models. The sprawling and fragmented development pattern witnessed during the early period of urbanization (1989-1995) could be driven by the major roads and economically active sub-city centres. This means, urban development has been taking place in all direction, mostly in South-West, East and North direction, following the major transportation routes and dispersed around sub-city centres. The proportion of built up cell and distance to CBD were also fair attracting urban growth during 1989-1995 study period.

During 1995-2003, the number of patches increased substantially, and therefore the city experienced rapid urban growth (refer section 4.3). The result of logistic regression analysis confirms that those growths were mostly driven by sub-city centres and existing built up areas. This is reasonable as the probability of finding developable land close to CBD and major roads is less, the locally distributed sub-city centres (Dist_Scc) and proportion built up area (P_Urban) will attract urban growths. However, it is important to note that there is still some development going on within close proximity to major roads although it is not as important as the growth taking place around sub-city centres and high proportion of built up areas. The variable slope confirms that following the rapid urban growth observed during 1995-2003, developments were taking place in relatively higher slope areas. The insignificance of distance to CBD during this period does not necessarily indicate the absence of development around CBD, because urban development is also taking place in close proximity to where high proportion of built up cell is found. This could be in the form of edge expansion at the edge of urban core, which can be confirmed from the increasing largest patch index (LPI) metric (refer section 4.3).

Interestingly, during 2003-2010 due to the lack developable land in close proximity to major roads and sub-city centres, the variable proportion of built up cell become the dominant factor attracting urban growth in the study area followed by distance to satellite towns (Dist_St). Yet, major roads remain the third important factor attracting urban growth. The position claimed by distance to satellite towns (Dist_St) is rational as the gap between the main city and satellite towns will decrease and thus, satellite towns become more attractive for development. The variable distance to CBD, which was insignificant in the previous period, become significant factor during 2003-2010 indicating that some infill development or redevelopments has been taking place in the city centre. This is reflected by the decreasing patch density (PD) and increasing largest patch index (LPI) during this period.

Given, the patterns observed during these three study periods, satellite towns will be the next significant drivers of urban growth in the foreseeable future. The top four driving forces of urban growth during the three different study periods are presented in table 4.31

Table 4.31: Major driving forces of urban growth in 1989-1995, 1995-2003 and 2003-2010 study periods

Study periods	Order of Significance	Major driving forces	Correlation with urban growth
	1st	Distance to major roads	Negative
1989-1995	2nd	Distance to sub city centers	Negative
	3rd	Proportion of built up cell	Positive
	4th	Distance to CBD	Negative
	1st	Distance to sub city centers	Negative
1995-2003	2nd	Proportion of built up cell	Positive
	3rd	Distance to major roads	Negative
	4th	Slope	Positive
	1st	Proportion of built up cell	Positive
2003-2010	2nd	Distance to satellite towns	Negative
	3rd	Distance to major roads	Negative
	4th	Distance to sub city centers	Negative

Generally, three variables: distance to major roads (Dist_Mjrd), distance to sub city centers (Dist_Scc) and proportion of built up cell (P_Urban), remain among the top four driving forces of urban growth in all study periods with varying order of significance. Distance to CBD (Dist_CBD), Slope and distance to satellite town (Dist_St) were among the top four drivers of urban growth at different time periods with varying (see table 4.31). Unfortunately, distance to Entebbe airport (Dist_Entb), which was included in the models based on the suggestion of local experts, was not among the top four driving forces of urban growth in all study periods. During 1989-1995 and 1995-2003 it was not found attracting growth or it has been pushing development away and during 2003-2010 it becomes insignificant at all. Although some attempts have been made to clarify the phenomenon, no strong logical reasoning or causal process could be found to explain how the variable distance to Entebbe airport become constraint for urban growth in this study.

4.7. Impact of urban growth on wetlands

As described in section 1.2 and 1.6, wetlands are common characteristics of the study area. Although they are considered minor driving forces of urban growth by local experts, an effort has been made to include wetlands in the logistic regression modelling at early stage of this research. Unfortunately, due to the lack of reliable data covering the study area the effort has been fruitless for long. Most recently, the researcher was able access data that covers the whole study area, but it was too late to include in the model. Therefore, it was decided to analyze the impact of urban growth on wetlands with in the remaining few days. Results of spatial metrics analysis revealed that wetlands have played considerable role in the fragmented development of the city particularly at the fringe areas. This could show the pressure of urban development that might have impacted wetland. Thus, quantifying and mapping the extent of urban growth that has been taking place in wetlands during 1989-2010 periods is worthy of consideration.

The quantification and mapping of wetlands encroachment is based on the data (wetlands-1996) obtained from (www.wri.org) “World Resource Institute”, an institute working on global climate change, ecosystem protection, environment, etc. According to this data wetlands are categorized in to permanent and seasonal wetlands. Permanent wetlands are those located near open water bodies and they are permanently waterlogged whereas seasonal wetlands are flooded during rainy seasonal and they are not flooded during dry season. It was believed that wetlands environmentally sensitive since they are home for high number of plant and animal species. Both permanent and seasonal wetlands are analyzed in this study. The analysis is conducted in ArcGIS using 'clip' spatial analyst tool. The built up area falling inside respective wet lands is clipped by the wetlands-1996 shape file for each year, i.e. 1989, 1995, 2003 & 2010, and the area is summed up separately (see table 4.32).

The results indicate 45ha, 118ha, 375ha and 658ha of permanent wetlands have been converted to urban (built up) area in 1989, 1995, 2003 and 2010 respectively. Most of the encroached wetlands are found inside and at fringe areas of KCCA (figure 4_17). This confirms to the suggestion given in region based analysis of central Kampala (CK) based on PD and LPI metrics. The bar chart presented in figure_4.17 illustrates seasonal wetlands were more vulnerable compared to permanent wetlands. This could be due the suitability of seasonal wetlands for settlement compared to permanent wetlands as they are dry for most part of the year. The result shows that 79ha, 183ha, 878ha and 1639ha of wetlands have been developed for urban use in 1989, 1995, 2003 and 2010 respectively. Seasonal wetlands are prominent in the north and north-eastern parts while permanent wetlands are more frequent in the western, south-western and south-eastern parts of the study area.

One observation made from this analysis is that the northern region is highly fragmented due to the presence of seasonal wetlands. More than 85% of wetland infringements are inside and around the core area (KCCA). This analysis also revealed that seasonal wetlands could be potential driver of urban growth than permanent wetlands as most of the urban growth has been taking place in seasonal wetlands (see table 4.32 & figure_4.17). More detailed analysis can still benefit to better understanding of wetlands condition which could assist decision making on proper management of wetlands for the future. The spatial location of encroach wetlands are mapped based on built up area 2010 (figure_4.18).

Table 4.32: Wetland encroachment in GKMA

Wetland Encroachment						
	Permanent wetlands			Seasonal wetlands		
Study period	Area(ha)	Change(ha)	Change (%)	Area(ha)	Change(ha)	Change (%)
1989	**45**	_	_	**79**	_	_
1995	**118**	**73**	**162**	**183**	**104**	**132**
2003	**375**	**257**	**218**	**878**	**695**	**380**
2010	**658**	**283**	**75**	**1639**	**761**	**87**

Figure 4.17: Urban growth dynamics in wetland areas (permanent vs. seasonal wetlands)

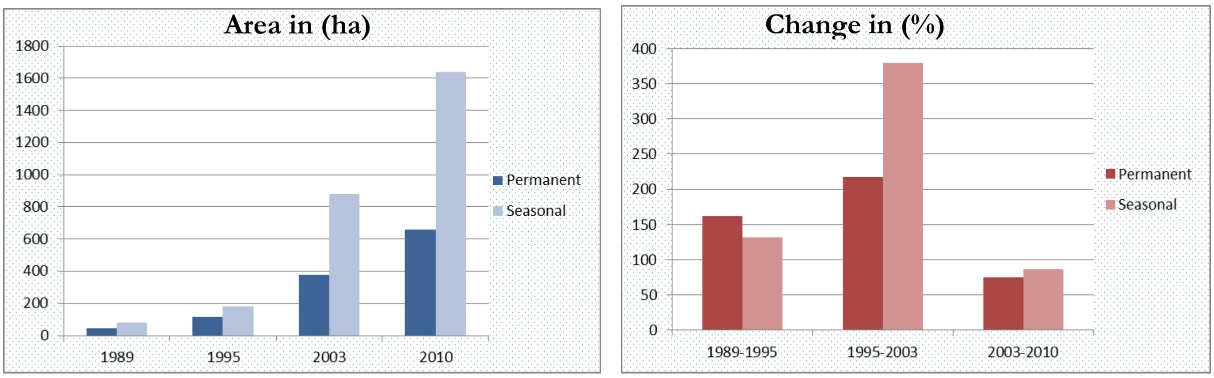
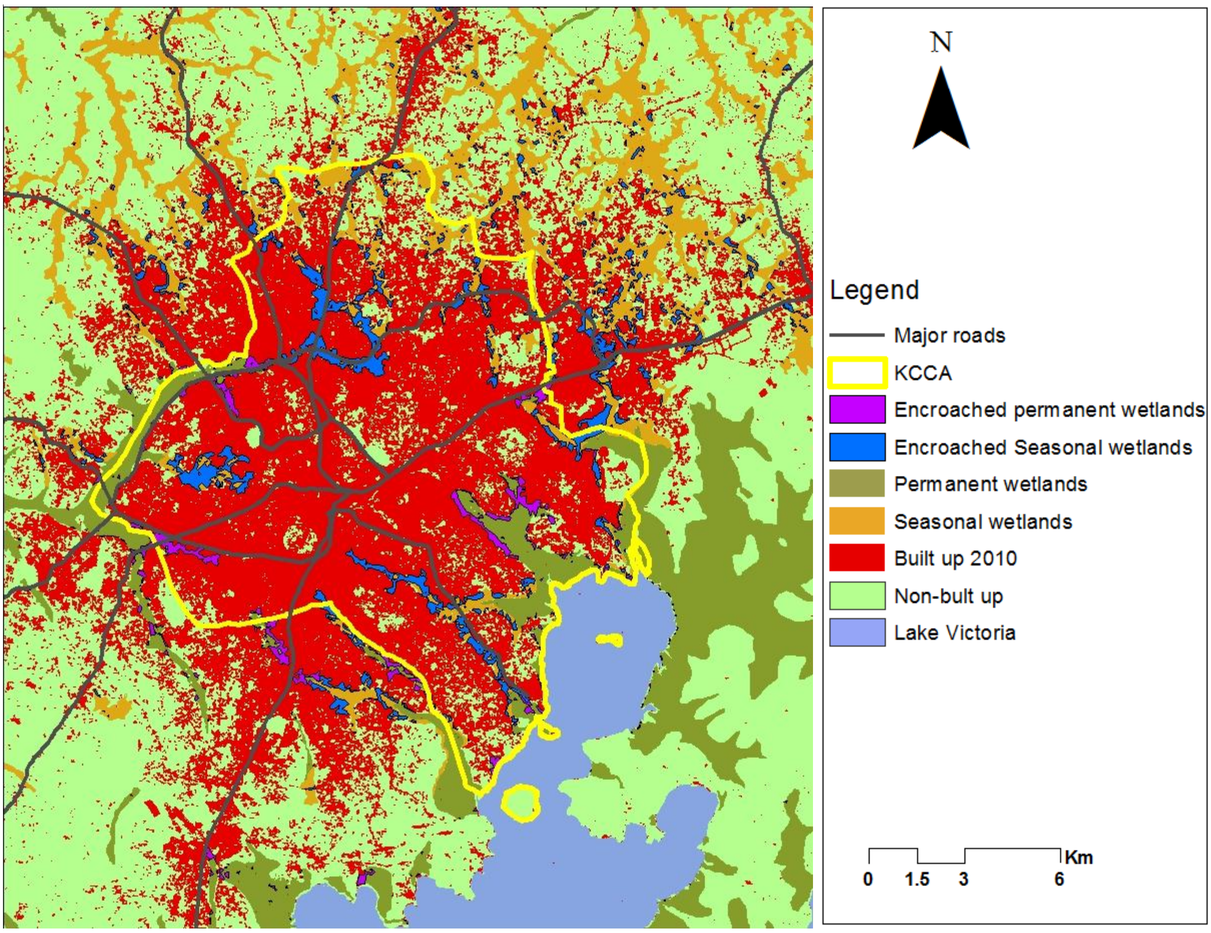


Figure 4.18: Map showing wetland infringement due to development pressure in Kampala (KCCA) area



5. CONCLUSION AND RECOMMENDATIONS

5.1. Introduction

Conclusions are structured based on the research objectives formulated. Specific conclusions are given per sub-objective so as to answer the formulated research questions. Then general conclusion is offered as per the general objective of the research. This will be followed by recommendation and indication of future research direction.

5.2. Conclusion

5.2.1. Specific conclusions and key findings

Sub-objective-1: To analyse the extent and rate of spatio-temporal urban growth using multi-temporal satellite images.

For the past 21 years, 1989-2010, Kampala (GKMA) has been undergoing extensive land cover change. The classification of multi-temporal satellite images of four different time periods, i.e. 1989, 1995, 2003 & 2010, in to built-up and non-built up land cover classes has resulted in a highly simplified and abstract representation of the study area. These maps show a clear pattern of increased urban expansion prolonging both from urban centre to adjoining non-built up areas in all directions mainly in the south-west, east and north direction alongside major transportation corridors. The synoptic analysis of spatio-temporal land cover change revealed that urbanization has significantly transformed the urban landscape of Kampala. The built up area in the city has grown from 73km² in 1989 to 325km² in 2010 at an average growth rate of 10, 14 and 4.4% per annum during 1989-1995, 1995-2003 and 2003-2010 study periods respectively. In total, 252km² of non-built up land has been converted to urban area. Thus, as per sub-objective-1 this research has successfully analysed and quantified the extent, rates and directions of spatio-temporal urban growth in the study area.

Sub-objective-2: To quantify the spatio-temporal pattern of urban growth and landscape fragmentation using spatial metrics.

Analysing the spatial extent and rate of urban growth and identifying the growth direction alone does not give sufficient insight in to the patterns of urban development processes, which are important to better understand urban pattern. To bridge this gap, spatial metrics are used in this study. Nine spatial metrics namely: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), area weighted mean patch fractal dimension (AWMPFD), contagion (CONTAG), Shannon's diversity index (SHDI) and Shannon's evenness index (SHEI) were used to evaluate the urban growth patterns and processes of Kampala city at class and landscape level. These metrics were selected based on literature so as to measure different aspects of the landscapes such as configuration, area, shape, etc.

The analyses of urban pattern were conducted at two spatial scales for the four different years described above. These are at city level and at sub city or regional level. Five metrics evaluated at city level, i.e. CA, NP, PD, LIP and FREC_AM, revealed the processes and patterns of urban growth over the entire study area indicating urbanization has substantially changed the landscape pattern of the study area, with a significant land conversion or formation of new patches and thereby increased fragmentation. Based on the number of patches (NP), built up area has underwent fragmented development process in all study periods with substantial increase of built up area (TA) occurred during the second period of urbanization, 1995 to 2003.

The decreasing trend witnessed by PD shows the merger of new patches with the existing ones, particularly, at the vicinity of urban core that eventually gives rise to the largest patch. The increasing trends observed on LPI throughout the study periods could reveal that the city centre or the core area has been relatively undergoing infill and edge expansion type of development process. Nevertheless the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with remarkable upturn in 2010. This illustrates, despite the increasing trend observed on the largest patch in the landscape (urban core), the built up area remain getting more complex and thus, fragmented over time mainly at the fringe areas. Unorganized development that could be due to poor planning scheme and topography such as hills and wetlands could have played inevitable role in the fragmented development process of the city.

In order to study the changing patterns and causal dynamics of urban landscape at more specific locations in the city, this research has developed a region based spatial metrics analysis. Accordingly the study area has been divided in to six spatially explicit regions namely: Northern Region (NR), South-Western Region (SWR), Eastern Region (ER), Western Region (WR), Central Kampala (CK) and Peri-Urban Region (PUR) based on the administrative boundary of the urban area. All the selected nine metrics are used to describe urban development patterns in each region at both class and landscape level. The synoptic analysis and comparison of class area (CA) metrics revealed CK, SWR, ER and NR are the first four highly urbanized regions in the study area in a diminishing order. In 2010 the central Kampala (CK) and the south-western region (SWR) together accounted for more than 60% of the total built up land in the study area. In the same year, the total built up area in CK covered more than three quarter of the total land in the region. However, in terms of average annual growth rate (%) WR, NR, ER and PUR are the first four rapidly urbanizing regions in the study area with a growth rate of 21%, 17%, 16% and 12% respectively.

The measurements from NP indicate CK as the only region with consistently decreasing number of patches indicating the infill and edge expansion or compact development pattern observed in the region. The SWR and ER showed increasing and decreasing trend for NP indicating the different development patterns in the respective regions. The remaining region reflected increasing trend in NP indicating the fragmented and low-density sprawling urban growth pattern. The PUR is found to be the most fragmented and low density region in the most recent periods. ER relatively exhibited compact pattern development with small variation in number of patches.

The results of PD and LPI are also consistent with NP. Both metrics witnessed that CK is the core of the city with the highest and outlying LPI value in all study periods advising critical condition of open spaces and wetlands in the city centre. This shows the need for planning strategy that promotes protection of environmentally sensitive area and vertical or height development in CK (KCCA) region. However, most of the other regions experienced increasing trend in PD and LPI suggesting the rapid development of fragmented patches and the merging of existing patches respectively in the fringe areas of the city. All regions, except CK, exhibited increasing trend in edge density (ED) indicating the fragmentation of the landscapes over time and space. Nevertheless, CK showed increasing trend in ED during 1989-1995, and consistently decreased since 1995 signifying the infill and edge expansion development process. The result of FRAC_AM is also in line with ED. Despite the decreasing FRAC_AM observed after 1995, the CK remains the most complex region in terms of fractal dimension followed by SWR, ER and NR. This could reveal the effect of topography, such as wetlands and hills, on geometry of patches and the disorganized pattern of development in the region.

Contagion (CONTAG) measured at landscape level demonstrate the less urbanized region such as PUR and WR are found to be more contiguous due to the dominance of non-built up patches in the landscapes. All regions, except CK, reflected decreasing contiguity indicating the fragmentation and sprawling urban growth process in the landscape over time. In 1995 central Kampala reached its minimum contagion, indicating the beginning of dominance of built up area in the region that eventually gave rise to CONTAG. The result of the two diversity indexes Shannon's diversity and Evenness index (SHDI and SHEI) is also in agreement with contagion metrics as highly contiguous landscape is expected to result in low diversity.

Sub-objective-3: To determine the main physical driving factors of urban growth pattern.

Finally, to better understand the interaction between the changing patterns of urban growth and its physical driving forces, binary logistic regression model has been built for three different time periods of 1989-1995, 1995-2003 & 2003-2010. The probable driving forces of urban growth are first identified and categorized in to site specific, proximity and neighbourhood factors based literature review, and then subjected to local experts to contextualize them to the specific study area. All models are subjected to multicollinearity analysis and found to yield VIF <10. The results of model evaluation indicate 98.45%, 96.51% and 95.27% for the 1989-1995, 1995-2003 and 2003-2010 models respectively indicating the high predicting capacities of the models.

The result of model 1989-1995 shows that distance to major roads (-ve), distance to sub city centers (-ve), proportion of built up cell (+ve) and distance to CBD (-ve) were the top four driving forces of urban growth with their indicated sign of correlation with urban growth. During 1995-2003, distance to sub city centres (-ve), proportion of built up cell (+ve), distance to major roads (-ve) and slope (+ve) were the top four driving forces of urban growth in the study area with their indicated sign of correlation urban growth, whereas proportion of built up cell (+ve), distance to satellite towns (-ve), distance to major roads (-ve) and distance to sub city centres (-ve) were found to be the top four drivers of urban growth during 2003-2010 study period with their indicated sign of correlation with urban growth.

The importance of proportion of built up cell, distance to sub-city centres and distance to satellite towns increased over time while the importance of distance to CBD and distance to major roads decreased over time. This confirms to the results of spatial metrics that show outward expansion accompanied by fragmentation at the fringe areas and condensation of the core. Most of the findings of the models built in this research are comparable with the results of similar works of (Hu & Lo, 2007; B. Huang et al., 2009; Vermeiren et al., 2012). If not policy measures are taken these factors will continue to play vital role in expanding the city in a disorganized way. Thus, the results of this model can help planners and policy makers better understand the drivers of urban growth in the study area and develop different alternative urban growth scenarios for the future development.

5.2.2. General conclusions

- In this study, it has been possible to successfully capture the changing subtleties of urban growth pattern both at metropolitan and at disaggregate urban regions level. At metropolitan scale, the city has experienced fragmented urban growth process, particularly, at the fringe areas with substantial built-up increase while, the city centre underwent relatively compact growth by infilling open spaces and through edge expansion over time.

- Based on number of patches, the region based analysis revealed different parts of the city have experienced different pattern of development. The Central region (KCCA) consolidated over time and the Eastern regions underwent relatively compact growth while the South-West and Western regions showed fragmentation followed by infill and edge expansion growth pattern. The Northern and the Peri-urban regions were the most fragmented or scattered regions of the city. This indicates the region based analysis can give more detailed information and therefore spatial metrics analyses at city level are not necessarily conclusive. Further sub division could give more improved level of information. However, decisions made fully based on city level analysis might be misleading as patterns of development in some regions of a city can potentially deviate from the pattern of development observed at the entire city level.

- Furthermore, this study has demonstrated the value of logistic regression analysis for understanding and identifying the potential causal factors responsible for the changing patterns of urban development processes learnt from spatial metrics analysis. Thus, proximity factors such as distance to major roads, distance to sub-city centres, proximity to built-up area, and distance to satellite towns were the major factors driving urban growth in the study area at different period of time with different level of significance. The importance of distance to CBD and distance to major roads decreased over time while distance to sub-city centres and proximity to highly urbanized cells become more important confirming the results of spatial metrics that show typical fragmentation and outward expansion.

- Using images acquired from different sensor (e.g. Landsat-7 ETM and Landsat-5 TM) for spatial metrics analysis could perhaps create consistency problem like ETM+ 2003 image in this study. Thus, although studies conducted in developing countries frequently suffer from the lack of data, as much as possible it is advisable to use consistent images acquired from the same sensor.

- Given the results presented in this study, remote sensing satellite images and spatial metrics coupled with logistic regression modelling are valuable tool for the analysis and extraction of information on urban growth patterns at different spatial scale and they can offer a comprehensive opportunity for the description of process, and facilitate intra urban comparison.

- Recently, Kampala Capital City Authority (KCCA) has released a draft version of the final report regarding Kampala Metropolitan Frame work (KPDF) and Kampala Physical Development Plan (KPDP). Thus, the result of this study could be an added value for evaluating and reinforcing the proposed physical development plan in the light of special metrics before implementation.

5.3. Future research directions

- To this end, this study has successfully explored the potential use of satellite remote sensing and spatial metrics in the light of quantifying the spatio-temporal urban growth patterns and processes in fast growing Sub-Saharan countries like Kampala, Uganda. However, results of this study are exclusive to the specific study area. Further researches are required on different Sub-Saharan cities to conclude on the efficiency and effectives of the tools for developing Sub-Saharan African countries.

- Since the quality of information extracted from spatial metrics is dependent on the quality of image classification, future studies could attempt to improve the classification accuracy the images used in this study, particularly, the accuracy of Landsat ETM+ 2003 image or perhaps use images from the same sensor, for instance all images from Landsat-TM. This could help solving the problem of image consistency.

- Owing to the spatial extent of the metropolitan area, it seems imperative to look at driving forces of urban growth at disaggregate spatial scale including more variables such as socio-economic and demographic variables and most importantly land tenure policy (system) and wetlands. This could reveal detail causal factors of urban growth pattern at local level and could give good explanation why Entebbe airport has been constraint or insignificant factor for urban growth in the study area. It could also reasonable to consider the Kampala-Entebbe road segment as a separate driving force in the future models. The region based method developed in spatial metrics analysis can be adopted for this purpose. However, the results of this model can be used as a base for future studies and can help planners and policy makers develop alternative urban growth scenarios.

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7. APPENDIX

Figure 7.1: Classification results of Vermeiren et al. (2012)

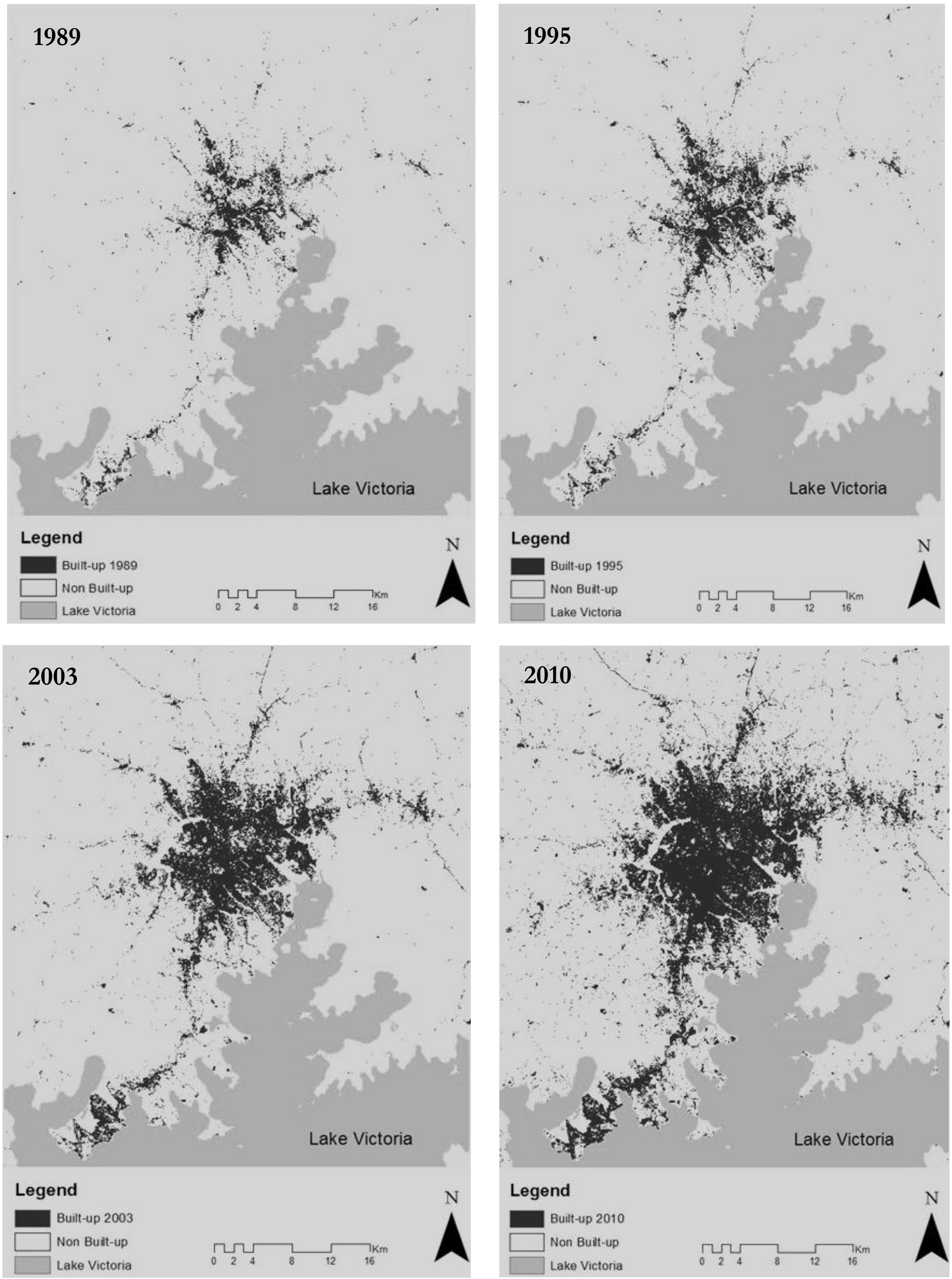
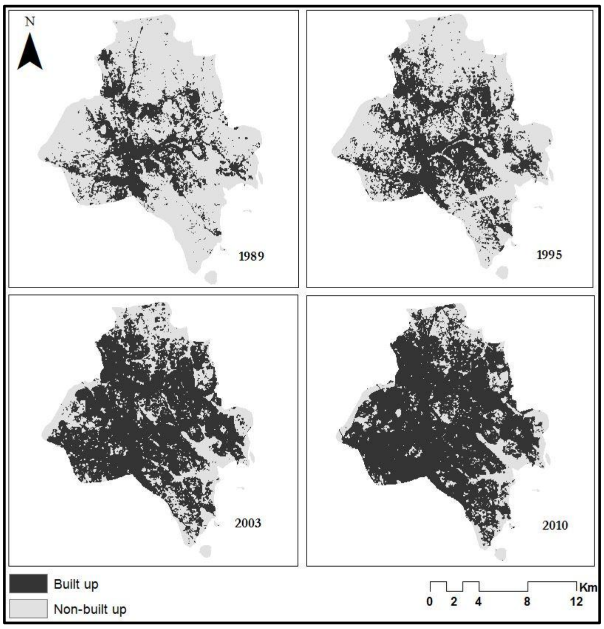
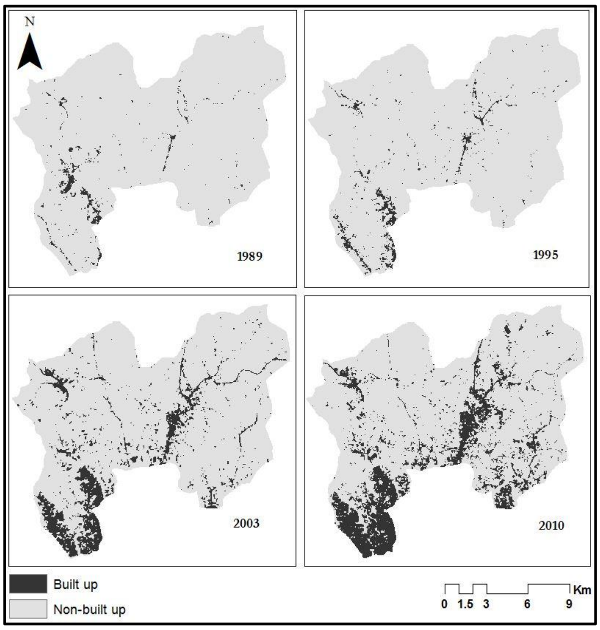


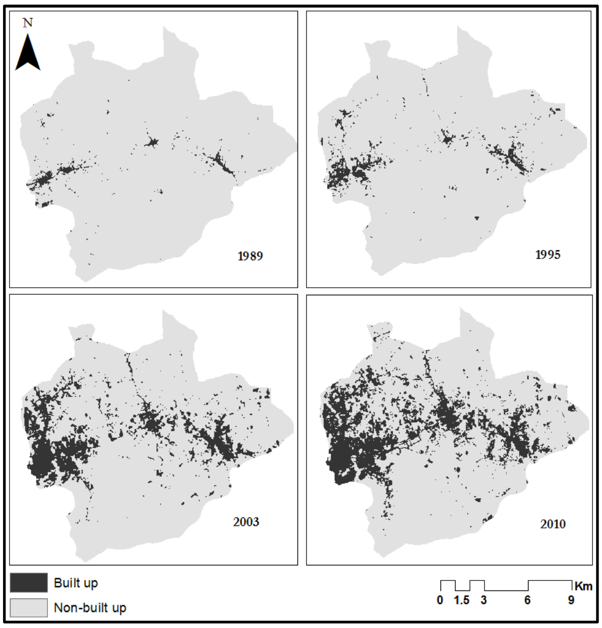
Figure 7.2 Disaggregate spatio-temporal regional maps of the study area.



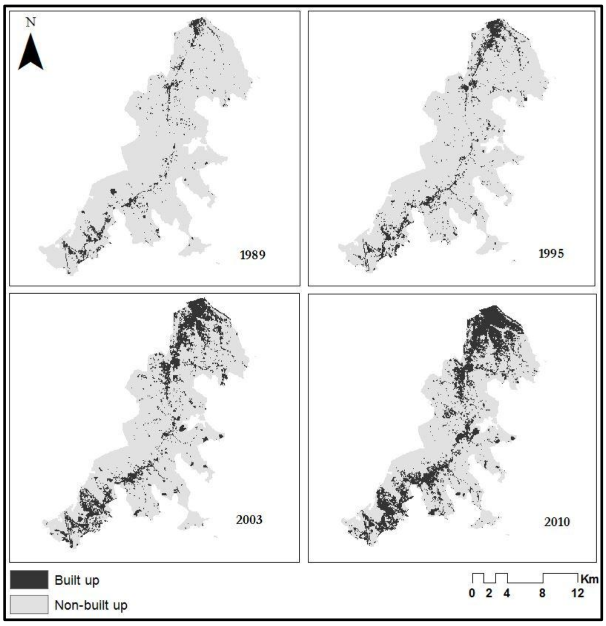
Central Kampala region (CK)



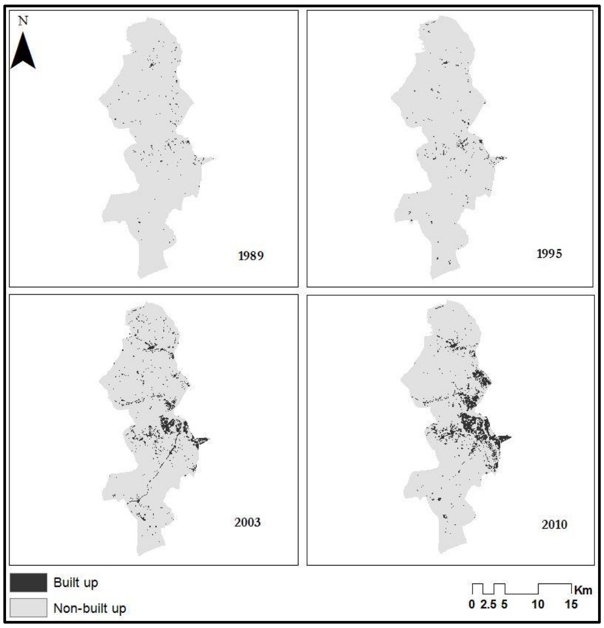
Northern region (NR)



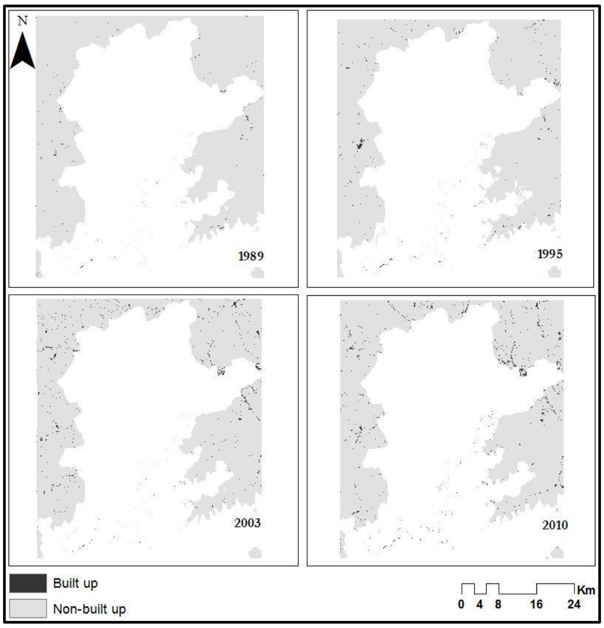
Eastern region (ER)



South-western region (SWR)



Western region (WR)



Peri-urban region (PUR)

Figure 7.3: Relative Spectral Response (RSR) profiles of Landsat-7 ETM+ and Landsat-5 TM (source: (Chander et al., 2005)