SPATIAL-STATISTICAL MODELLING OF URBAN GROWTH IN GREATER KUMASI METROPOLITAN AREA, GHANA

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February, 2014

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ABSTRACT

Greater Kumasi Metropolitan Area area has over the past two decades experienced rapid urban growth. This situation has resulted in the expansion of the area into surrounding districts. Associated impacts of this are loss of agricultural lands and livelihoods. To gain an insight into the spatio-temporal dynamics of growth the driving forces behind this growth need to be studied and analysed. This study has attempted to quantitatively reveal the relationships between possible drivers of the growth of the metropolitan area using spatial statistical logistic regression and to simulate future growth trends based on the empirical trends studied. This made use of remote sensing imagery for 1986, 2001 and 2014 coupled with GIS to map the spatio-temporal growth trends of the study area. Three growth types were identified: edge-expansion, infilling and outlying in the study area.

A review of literature coupled with consultations with experts assisted in identifying locally relevant driving forces of the areas growth. To investigate the relative contributions of these factors, two models are constructed, evaluated and validated. The results from the models indicated that distance to urban cluster, distance to CBD, distance to major roads and the proportion of urban cells in 7x7 neighbourhood which are common to both time periods have been among the top four drivers of urban growth in both cases though with varying levels of influence. These drivers of growth were used to predict the future growth of the city.

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1. BACKGROUND OF STUDY

1.1. Introduction

The phenomenon of urbanisation, viewed from the perspective of costs and benefits could best be described as a "double edged-sword". At the global and local spheres, this phenomenon has come to be accepted as a fact of life and hence the question is not whether urbanisation should or should not take place but how well to urbanise. An understanding of the drivers of urbanisation is key to managing the process. This research aims to contribute to this understanding through a spatial-statistical modelling of urban growth in Greater Kumasi, the fastest growing metropolitan area in Ghana.

1.2. Justification

Over the past half century, the rapid growth of urban populations in cities across the globe has pushed the phenomenon of urbanisation into the limelight. Urbanisation has become a major concern for international aid agencies, a hot topic among urban planners and the theme of conferences (Akrofi, 2006) and learned papers (Cheng & Masser, 2003; Vermeiren, Van Rompaey, Loopmans, Serwajja, & Mukwaya, 2012). The world has been rapidly urbanising and for the first time in history, more than half the world's population is living in towns and cities (UN-HABITAT, 2013)

Though a global phenomenon, the urbanisation process of the developed world in the immediate past century has been fundamentally different from that of the developing world. Varis, Biswas, Tortajada, & Lundqvist (2006) have cited two important reasons as underlying the different processes of urbanisation between the developed and the developing world. The first difference is the rate of growth. Growth of cities in the developed world over the immediate past century has been a gradual process (Henderson, 2002; Varis et al., 2006). Much of the population growth that occurred in cities like London and New York was spread over a span of a century whereas the rapid growth experienced in the developing nations happened in the post-1950 period (Biswas, Lundqvist, Tortajada, & Varis, 2004). For example only 60 years back, the proportion of people living in urban centres in the developed nations slightly exceeded their developing counterparts by 4% (UN-HABITAT, 2013). This trend has now changed, with the developing world now urbanising at an unprecedented pace. Today more than seven out of every ten urban dwellers in the world are found in the developing world. Besides, of the additional world population that is expected between 2000 and 2015, nearly one billion is projected to be urban dwellers and 91% of this figure will be living in cities of the developing world (UN-HABITAT, 2002). The second major difference is that as developed nations urbanised in their relatively slow pace, the growth of their economies kept pace with urbanisation, thus providing them with adequate leverage and capacity to meet the consequent challenges and demands of an urbanising world. Conversely, declining economic performance of the developing countries incapacitated them to effectively cope with the challenges of massive urbanisation (Henderson, 2002; UN-HABITAT, 2013; Varis et al., 2006)).

A number of studies posit that among the developing regions, contrary to the general trend of urbanisation in the developing world, Africa's urbanisation rates are slowing or even counter-urbanising (Potts, 2012). Moreover, UN-HABITAT (2013) has projected that by 2025 Africa will be the least urbanised with 45% of its population being urban. These regional averages, it should be noted mask the high urban growth rates of some countries in the sub-Saharan African region. Confirming this fact, UNFPA (2007) observed that the timing and rhythm of urbanisation oscillates considerably among less developed regions and further noted that general trends conceal wide local variations by country and by city.

Countries in Sub-Saharan Africa have been undergoing rapid urbanisation fuelled by the demographic processes of natural population growth and migration (Andersson & Jirström, 2013 ; Akrofi, 2006). A consequence of this rapid growth is the expansion of most African cities beyond their administrative boundaries into the urban-rural continuum, a process termed peri-urbanisation (Oduro, 2010; UNFPA, 2007). The urban periphery is a transitional zone with a continuous wave of land use/cover transformations unleashed by the rapid growth of cities (Oduro, 2010; Ravetz, Fertner, & Nielsen, 2013; UNFPA, 2007). These land use/cover changes in the city fringes are often reflected in a dynamic, diverse, chaotic and unregulated pattern of development (Kombe, 2005; Oduro, 2010; UNFPA, 2007) resulting from inadequate resources, weak governance structures and systemic failures in urban development control policies (Cobbinah and Amoako, 2012; Kombe, 2005)). The land cover conversions taking place at as a result of urbanisation leaves too much to be desired as vegetation cover and farmlands are converted to built-up (UNFPA, 2007) areas causing loss of livelihoods and environmental degradation (Cobbinah & Amoako, 2012; Kim, 2012; Kombe, 2005; UNFPA, 2007). These and other negative impacts of rapid urbanisation are key issues of global concern. In the 2013 Millennium Development Goals (MDGs) report, for instance, it is stated that due to world's growing population forests are disappearing at a rapid pace and that the largest net loss of forest cover has occurred in South America and Africa-around 3.6 million hectares and 3.4 million hectares per year correspondingly, over the period from 2005 to 2010 (UNITED NATIONS, 2013).

1.3. Study area

Kumasi is the second largest city in Ghana and is located in the transitional forest zone about 270km north of the national capital. It has a total landmass of 254 sq. kilometres, stretching between latitude 6.35°- 6.40°N and longitude 1.30° - 1.35°W, with an elevation which ranges between 250 - 300 meters above sea level. The city is the fastest growing city in Ghana with a growth rate of 5.6%. The resultant rapid and uncontrolled expansion has extended the urban footprint beyond the city's administrative boundaries into the surrounding districts namely Afigya-Kwabre, Kwabre East, Ejisu-Juaben, Bosomtwe, Atwima-Kwanwoma and Atwima-Nwabiagya. The city together with its six adjoining districts covering a landmass of approximately 2481 sq. kilometres forms the Greater Kumasi Metropolitan Area[1], though not a formally recognised administrative entity. The study area extent will cover this conurbation as Kumasi exerts influence on these adjoining districts. The study area is shown in the Figure 1.

1.4. Urbanisation in Greater Kumasi

In the last six decades Ghana has had its share of urban population growth. The proportion of the total population living in urban areas which was 8% in 1921, rose to 13% by 1948 through 23% in 1960, 29% in 1970 and 32% in 1984 and reached 44% in 2000 (Ghana Statistical Service, 2005). The urban population is projected to reach 65% by 2030 (Catherine, Raghunath, Eghoff, and Boakye, 2008). Kumasi, with a population of 2,035,064 is Ghana's fastest growing city with an annual growth rate of 5.4 percent between 1984 and 2010 (Cobbinah and Amoako, 2012; Oduro, Ocloo, & Peprah, 2014) which exceeds both the regional and national population growth rates of 2.7 and 2.4 respectively (Ghana Statistical Service, 2005). As Kumasi lacks the needed capacity and resources to effectively and sustainably manage its fast pace of growth, the situation has culminated into rapid spatial expansion of the city's urban footprint that is encroaching into rural areas. The built-up area of Greater Kumasi Metropolitan Area (GKMA) in 2012 was approximately 401.2 sq. km which more than quadrupled the built-up area of 1972 (98 sq. km). The

[1] The conurbation is also referred to as Greater Kumasi Sub-Region and these are used interchangeably

contiguously built-up area which extended beyond the city's boundary in 2012 was 46.4% up from 3.6% in 1972. The areas experiencing this encroachment have over the years undergone major land-use and socio-economic transformations culminating in a mix of urban and rural residents and an unplanned spread of completed, partially completed and uncompleted and empty buildings situated around the frontiers of the indigenously established rural communities now easily accessible to the centre of Greater Kumasi (Afrane and Amoako, 2011). The pattern reveals an uncontrolled and low density peripheral growth (Catherine et al., 2008).
Kumasi has become the nucleus of an evolving metropolitan region that comprises the old city and the six adjoining districts as shown in Figure 1 above. In 2010 the sub-region registered a combined population of 2,764,091 of which 73.6% lived in the Kumasi metropolis. Most of the settlements in the adjoining districts of the Greater Kumasi conurbation serve as dormitory towns for both the indigenous and migrant populations alike who commute to work in the city (Oduro et al., 2014).

Given the challenges posed by rapid urban growth and the associated sprawl, several studies have been conducted looking into different dimensions of the phenomenon. Cobbinah and Amoako (2012) the following key drivers of growth in the sub-region ; improved transportation links, the price of land, increasing immigration trends and the application of land use planning policies at the metropolitan level. Other similar works have pointed to other drivers underlying the growth of the study area, for example land values, government policies (Amoateng, Cobbinah, and Owusu-Adade , 2013), proximity to work, facilities and services (Acheampong and Anokye, 2013). Analysis of the drivers of urban growth in these studies is however qualitative as the quantification of the relative influences of these drivers on urban growth is yet to be explored.

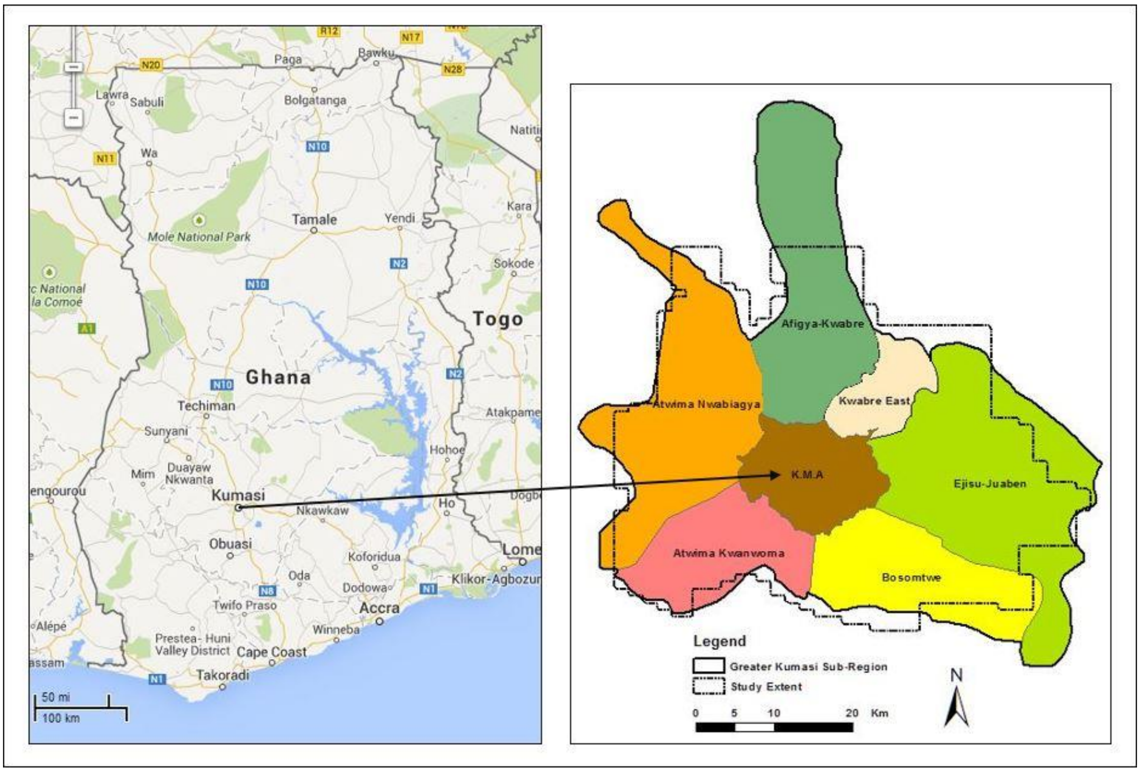

Figure 1: Map showing study area

1.5. Research Problem

Rapid population growth in many African cities have resulted in the ever increasing demand for land to meet the concomitant housing needs and other associated uses. This phenomenon is reflected in the fast expansion of these cities into the urban periphery usually in an unplanned and chaotic manner. The pace of urbanisation in Ghana is taking place within a context in which the growth of cities and towns is occurring with little or no direction (Government of Ghana, 2012). For instance, the fast and unplanned physical expansion of Greater Kumasi and the associated haphazard land use pattern have resulted in environmental degradation and loss of livelihoods among others.

As pointed out in the background of this study, several studies have cited a variety of driving forces underlying the fast pace of urbanisation in Kumasi. Reference to these drivers is however anecdotal as there is no quantitative analysis of these drivers in relation to urban growth. This research aims to fill this void through a spatial-statistical modelling of the growth of the city.

1.6. Objectives and Research questions

Main Objective

To identify and analyse the key drivers of urban growth in Kumasi

Sub-objectives and research questions

1. To analyse the spatio-temporal pattern of urban growth in Kumasi over the time period 1986-2014
   - What are the changes in the land cover of Kumasi?
   - What is the spatial extent and rate of urban growth?
   - What is the pattern of growth over time?

2. To model urban growth based on key driving forces
   - What are the spatial driving forces of urban growth in Greater Kumasi?
   - What is the individual contribution of each of the drivers to urban growth?
   - How reliable is the logistic regression (LR) model?
   - How does the LR model compare to previous studies on urban growth drivers?

3. To predict the future spatial growth pattern of Kumasi for 2023 and 2033.
   - Where are the probable areas for future growth?
   - What is the influence of proposed public investment on future growth

1.7. Conceptual Framework

Urbanisation is a dynamic process transforming the morphological and socio-economic identities of cities over time. Urbanisation is a term to describe urban growth. There are two inter-related interpretations of urbanisation- (1) physical growth of an urban area and (2) movement of people of people from rural to urban areas (Huang and Sin, 2010). In this study however, urban growth is used to refer to the physical growth of an urban area. This process of growth is usually triggered and fuelled by an interplay of several factors which may vary by type and significance across space and time. Rapid urbanisation unleashes pressures in the form of competing and increasing demands for land for further development and this is reflected in the land cover/ land-use conversions taken place in major cities over time thereby turning non-built up land into built-up. Urban growth is usually manifested in varying patterns and this is a consequence of the interaction of the various kinds of driving forces (Xu et al., 2007). Five types of urban growth-infilling, expansion, linear development, sprawl and large-scale projects-have been distinguished by Camagni, Gibelli, and Rigamonti (2002). Wilson, Hurd and Civco (2002) also identified five types of urban growth: infill, expansion/urban fringe development, isolated growth, linear branching and clustered branching. Although different writers use different terminologies to refer to the typology of growth, the connotations are however essentially the same (Xu et al., 2007).

The study area, largely exhibits monocentric pattern of development with development spreading out in all directions in the form of edge-expansion and mainly along major roads radiating from the city centre (Oduro et al., 2014) as shown in the figure below. The peripheral areas of Greater Kumasi exhibits sprawl in the form of leapfrogging and clustered sprawl which are together considered as outlying growth since these developments are detached from pre-exsiting developed patches. There is also infill development in vacant parcels in the core area.

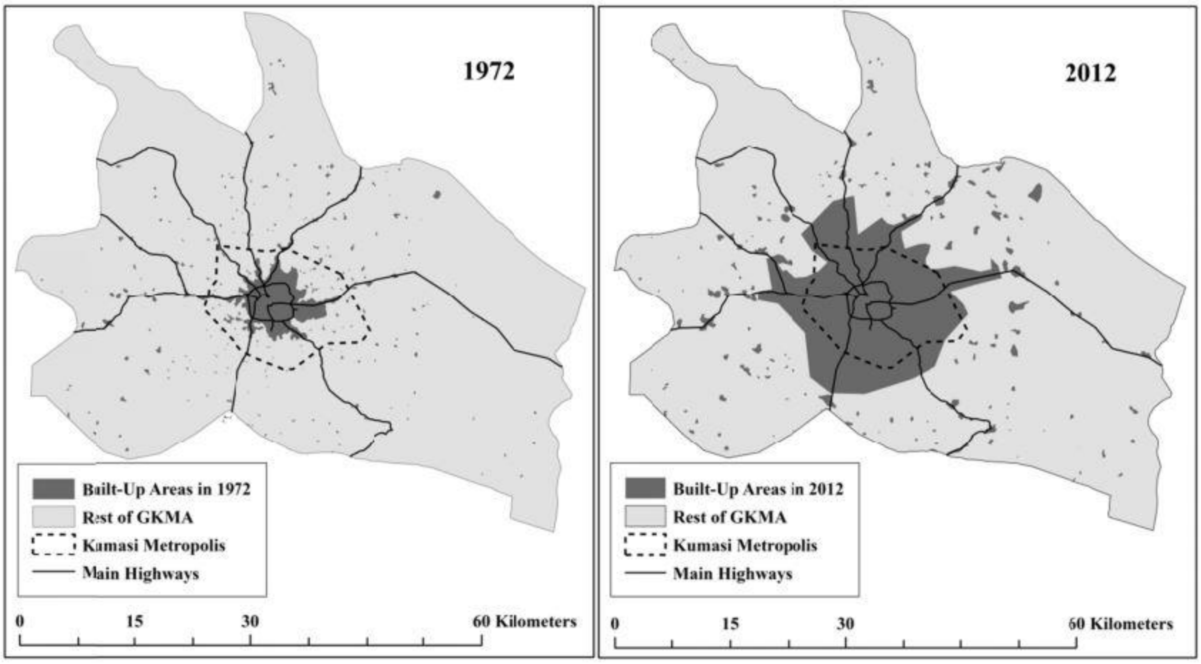

Figure 2: Built-up area of GKMA in 1972 and 2012

(Source: Oduro et al., 2014)

Figure 3 represents the conceptual framework which sets the stage for this research. Within this framework are key concepts such as urbanisation, urban growth patterns, remote sensing, driving forces of urban growth and logistic regression modelling. Urbanisation unleashes pressures on land in the form of competing demands for land. The competing demands are reflected in land cover conversions (in this case conversions between non-urban and urban land). Remote sensing plays a key role in mapping these conversions over time to detect the land cover changes and hence urban growth which. Urban growth occurs in three forms in the study area and selected spatial metrics are used to analyse the different forms of urban growth. Finally binary logistic regression modelling is used to identify the driving forces of urban growth in the study area and to project future growth situation based on the drivers of growth.

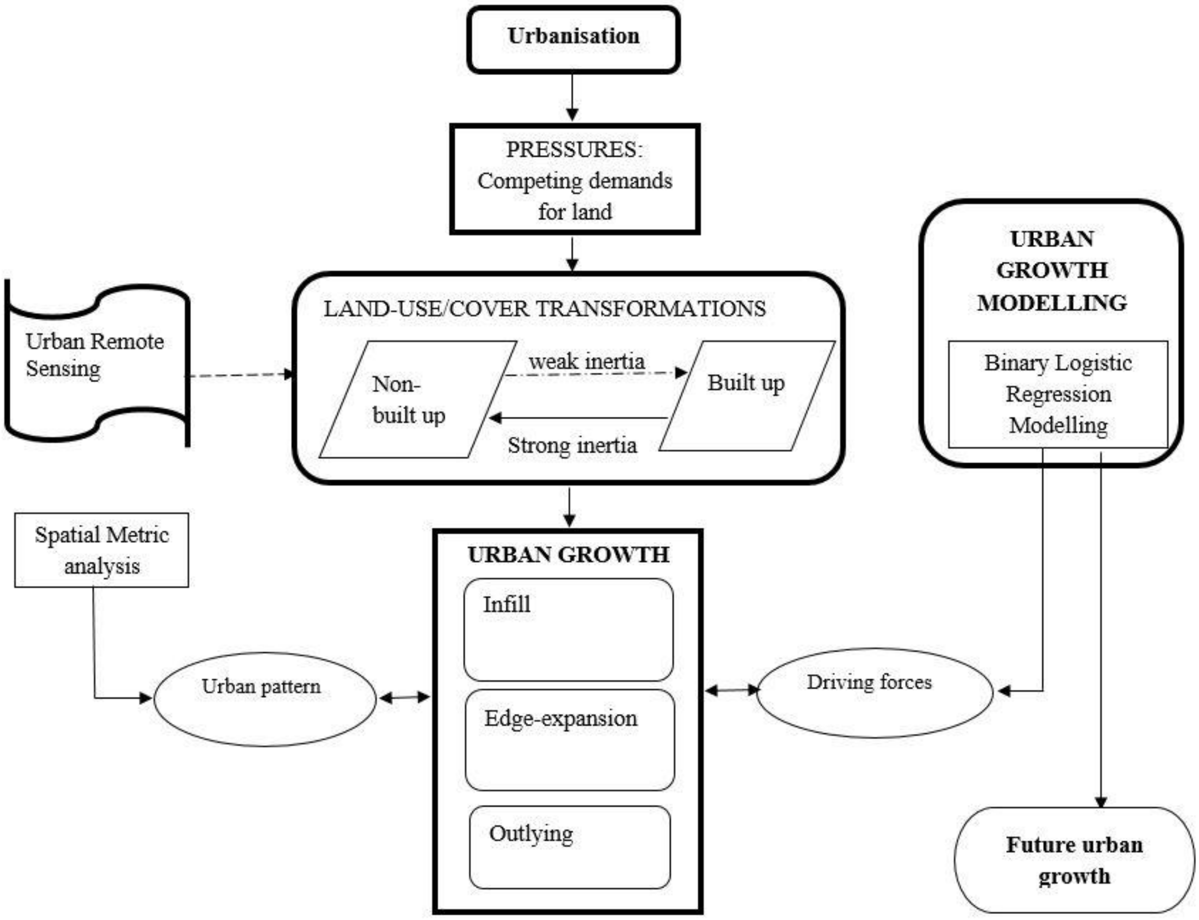

Figure 3: Conceptual framework

1.8. Thesis Structure

Chapter 1: Introduction
This chapter will provide general information on global urbanisation trends and then narrows down to the context of the study area. This will set the background for the research and subsequently the research problem and objectives, research questions and conceptual framework.

Chapter 2: Review of literature
This chapter focuses on the review of historical and current urban development policies in the study; the application of remote sensing to monitoring urban growth, the application of spatial metrics in understanding urban growth patterns, urban growth modelling approaches and driving forces of urban growth.

Chapter 3: Methodology
In this chapter areas of focus are overview of data collection and detailed explanation of the methods and techniques employed for data analysis. Methods for analysing the spatio-temporal patterns of urban growth and the logistic regression model for identifying key drivers of urban growth will be discussed here.

Chapter 4: Results and discussions
This chapter presents analysis of results and main findings from the research. This shall include analysis of results from spatio-temporal analysis of urban growth pattern, relationship between urban growth and driving factors and probable locations of future growth.

Chapter 5: Conclusions and Recommendations
This chapter will conclude the researching by presenting a summary of the key findings and indicating possible directions for further research.

2. LITERATURE REVIEW

2.1. Introduction

This chapter focuses on the review of historical and current urban development policies in the study; the application of remote sensing to monitoring urban growth, the application of spatial metrics in understanding urban growth patterns, urban growth modelling approaches and driving forces of urban growth.

2.2. Urban development policies/plans

Formal development planning process started in Kumasi with the design of the 1945 plan drawn by Maxwell Frye and Jane Drew. This planned was based on Ebenezer Howard's garden city model which had gained popularity in the western world at the time (Quagraine, 2011). The plan envisioned and therefore gave Kumasi its accolade, the "Garden City of West Africa". In line with its ultimate vision of a green city, the plan provided for the creation of green belts and urban parks (Schmidt, 2005). The planned also proposed a central area ringed by low-density suburbs. The built-up area was to be interspersed by green spaces along many shallow river valleys owing to the city's topography (Quagraine, 2011).

To realise the lofty ideals of the garden city concept, five urban parks were created. These were however located father away from residential areas and were thus underutilised. This notwithstanding, the designation of green belts along streams and the creation of urban parks gave Kumasi its nickname the "Garden City of West Africa".

In 1963 a new plan was made similar to the one before it (1945 Plan). A key feature of this plan is a ring road around the existing built up area and plans to extend out around and beyond the many villages close to the city. Provisions for industrial, commercial and residential land uses were also made. Until recently, when the 2007 master plan was made, this plan had been the only instrument designed to guide and control urban development (Amoako & Korboe, 2011). The provisions in the plan, as Cobbinah & Amoako (2012) noted implied a level of control over development which the city's planning authorities have always lacked due partly to financial and human resource constraints, but mainly because the allocation of land for development rests with the Asantehene[2] through sub-chiefs (Owusu & Asamoah, 2005).

In Greater Kumasi, when any area is declared as a statutory planning area, the norm is that, the Survey Department upon the request of the Town and Country Planning Department (TCPD) prepares the necessary base maps. However due to inadequate funding and weak human resource base, the Survey Department have often failed to respond to this request. Consequently, the sub-chiefs of the areas concerned engage the services of private surveyors to demarcate the land and prepare base maps for the areas and copies of these are sent to the TCPD and the Lands Commission. With the base maps, TCPD prepares layouts for the areas showing the various land uses. The copies of the layouts are forwarded to the sub-chiefs who in turn contract surveyors to demarcate plots after which the chiefs start to allocate these plots for development (Owusu and Asamoah, 2005). In most cases land allocation and development begin before the TCPD could consider and approve the layout. Even when approval is given by the TCPD, land allocations do not mostly comply with the layouts.

[2] The King of the Ashanti Region of Ghana.

Land use and development control are enforced under the layout plan system based upon which development permit consisting of both planning and building permits is issued. After lease right is transferred from the chief to the plot buyer, he submits an application for confirmation (planning permit) of his plot in the layout to the TCPD and subsequently site and building plans are submitted for a building permit. Having acquired land from the chief, many developers proceed to develop without permits. It is estimated that unauthorised houses totalled 80% as of 2002 (TCPD, 2013). Land developments without permits usually take one of the following forms; building expansion/annexation; encroachment of buildings in water ways and conservation areas; disorderly developments in suburban areas without planning schemes. Oppong & Brown, (2012) have revealed that many of these unauthorised buildings have seen their way to completion and continue to exist even when the Town and Country Planning Department served the developers in question notices to produce permit or stop work and in some cases to demolish the structure altogether. This situation clearly underscores the weak enforcement of planning regulations. Thus in the parts of the sub-region where there are planning schemes, physical developments to a large extent are not in line with the provisions of this plan.

In recent years the contiguous built up area of Kumasi city has extended into adjoining suburban areas and as a result the supply and improvement of urban infrastructure such as roads, solid waste management has become a daunting task requiring joint efforts of Kumasi and the districts surrounding it. The urbanisation of Kumasi has therefore become an issue of regional significance. In the light of the city's current urbanising trend, the Government of Ghana with technical assistance from Japan International Cooperation Agency (JICA) has drawn a Comprehensive Urban Development Plan to span 2013-2033 for the Greater Kumasi Sub-region. This plan has two main components; a sub-regional development framework which is an indicative plan showing the desired development in the next 20 years (2013-2033) and; a 15-year structure plan (2013-2028) for Greater Kumasi conurbation (the area to contiguously urbanised by the target year). The Comprehensive Urban Development Plan seeks to achieve; economic development; social development and poverty reduction and; environmental conservation and disaster management. The master plan for the conurbation prescribes land uses at the sub-regional level and a long term framework for guiding the future development of the sub-region (TCPD, 2013).

From the foregoing it can be deduced that, a strong level of cooperation between the traditional authorities and government planning institutions coupled with political commitment is indispensable to the sustainable development and management of the growth of the sub-region.

2.3. Remote Sensing and GIS in urban growth studies

Urban-land cover change is the spatio-temporal-reflection of urban growth. Such change is influenced by a set-of social, economic, and political factors. An understanding of the spatio-temporal patterns of urban growth by urban planners, policy makers is key to effectively managing the urban growth process.

Remote sensing especially satellites provide a rich source of data for studying the spatiotemporal variations of environmental parameters. Remotely sensed imagery have been used in a myriad of applications from reconnaissance, military and civil applications, monitoring land use/land cover changes, to urban planning (Perumal and Bhaskaran, 2010). Multitemporal remotely sensed data play an indispensable role in monitoring the spatiotemporal trends of urbanisation.

Remote sensing offers a convenient and excellent source of data from which up-to-date information on urban land cover can be extracted and analysed. One of the most frequent objectives of urban studies is to provide a land use map which combines information on the recent and actual situation to enable informed urban management operations. Remote sensing has always made such information available with the help of visual interpretations and more recently digital processing (Baudot, 1993)

Advances in remote sensing technology has brought in its wake remarkable improvements in the availability of higher resolution satellite imageries (Jhawar, Tyagi, & Dasgupta, 2012). High resolution remotely sensed imagery such as IKONOS, Quickbird, Cartosat, World View have been instrumental in documenting the growth of urban areas quantitatively and in some cases qualitatively when coupled with ancillary data sets (Netzband, 2010)

The output of remote sensing is usually an image of the scene being observed. The information required for a more comprehensive analysis may not always be provided by remote sensing and thus other spatial attributes from various sources (such as survey data, topographical maps or archived data) need to be integrated with remote sensing data (Jhawar et al., 2012) . GIS techniques have proved very useful in the integration of remote sensing data with other spatial data and their combined analysis.

The application of GIS and remote sensing in urban growth studies is evident in the wealth of research on the subject. For instance (Bhatta, 2012; Cheng & Masser, 2003; Dubovyk, Sliuzas,& Flacke, 2011; Duwal, 2013; Hu and Lo, 2007; Huang, Zhang, & Wu, 2009; Jhawar et al., 2012; Netzband, 2010; Sun et al., 2013; Vermeiren et al., 2012; Wilson et al., 2002; Xu et al., 2007; Baudot, 1993). These studies used remote sensing coupled with other GIS techniques to extract land cover/land use information.

Remote sensing is based on distinguishing land cover classes based on the differences in their spectral reflectances (Angel, Sheppard, & Civco, 2005). A key application of remotely sensed data is to generate a classification map of meaningful features or land cover classes in a scene. Hence the end product may be a thematic map of land use, vegetation types among others. The section that follows throws light on some of the methods of image classification.

2.3.1. Urban land cover extraction using image classification techniques.

Image classification in remote sensing involves the categorisation of pixels (i.e basic units of an image) found in remotely sensed data into classes by grouping identical pixels into categories of user interest (Perumal & Bhaskaran, 2010). The idea underpinning land cover classification using digital remote sensing data is that pixels from within the same land cover class tend to form groups in multispectral feature space and that groups of pixels from different classes tend to separate from one another in multispectral feature space (Angel et al., 2005). The majority of image classification is based on variations in spectral response patterns of land cover classes (Angel et al., 2005; Eastman, 2001) though other variables such as vegetation indices, textural and contextual information may also be used. The performance of image classification therefore depends very much on; the presence of unique signatures in the band set used to extract the land cover classes of interest and; the ability to reliably differentiate these spectral reflectances from other signatures that may be present. Generally, there are two classification paradigms pixel-based (i.e where pixels are grouped based on similar reflectance properties) and object-oriented classification (i.e where classification is based on homogenous segments corresponding to distinct objects.

The pixel-based classification which is used in this study has two common classification approaches: supervised and unsupervised. In the supervised classification the user first defines samples of the land cover classes of interest called training sites which are then used to extract signatures for clustering the pixels

(Eastman, 2001; Perumal & Bhaskaran, 2010). Ground truthing and local knowledge of land cover types in the area under study are thus a very useful in supervised classification. In an unsupervised classification, no advance information is needed about the classes of interest as a clustering algorithm automatically groups pixels based on similar reflectance properties.

2.4. Spatial metrics in urban growth pattern analysis

2.4.1. Urban growth types

Urbanisation as discussed in previous sections of this work is fuelling the expansion of the population/geographical size of urban areas. The physical development of cities is influenced by an interplay of several factors such as topography, economic and social activities, policies and plans, soil characteristics and population which drive the urban growth process and result in different typologies of growth (Cheng, 2003; Xu et al., 2007)

Urban growth occur in a variety of ways as documented in several studies. Cheng (2003) identified various types of urban growth-sprawling or compact, dispersed or clustered, continuous or leapfrog, spontaneous or self-organising, planned or organic. Sprawling is an ambiguous term that lacks a common definition (Bhatta, 2012). However a general understanding of sprawl views urban sprawl as characterised by unplanned and uneven pattern of growth especially on city fringes and peripheral areas leading to inefficient use of resources. The compact city which is often contrasted with sprawl is characterised by high density, centralised development with a spatial mix of functions (Burgess, 2004). Scattered or dispersed growth exhibits a pattern where development is patchy, speckled and spread out (Cobbinah and Amoako, 2012). Leapfrogging exhibits a discontinuous pattern of development away from and older central core with the areas of development interspersed with vacant land (Batty, Chin, & Besussi., 2002).

Wilson et al., (2002) categorised urban growth into infill, expansion, and outlying with outlying further subdivided into isolated, linear branch and clustered branch. Five types of urban growth-infilling, expansion, linear development, sprawl and large-scale projects-have been distinguished by Camagni et al. (2002). Although different writers use different terminologies to refer to the typology of growth, the connotations are however essentially the same (Xu et al., 2007).

According to Xu et al., (2007), three main types of urban growth are documented: infilling, edge-expansion and outlying growth which will be adopted because of their relevance to the study area. Infilling means the non-built up area surrounded by built up urban being converted to urban. Edge-expansion also called urban fringe development, refers to the newly developed urban area spreading out from the fringe of existing urban patches. Outlying growth means that new urban patches are formed and have no direct spatial connection with the existing urban patches.

Regarding the aforementioned growth typologies it could be discerned from the literature reviewed that one cannot draw a clear dichotomy among them as some of these are interrelated and sometimes may be used interchangeably. For instance some of these growth types are considered as different forms of sprawl (Michael Batty et al., 2002) such as clustered development, scattered or dispersed development, leapfrogging and ribbon development (Cobbinah and Amoako, 2012).

Greater Kumasi like other urban regions exhibits a number of these growth typologies but a different magnitudes. However in this study, the dominant type of growth characteristic of the study area are considered. As pointed out in Section 1.7, the contiguously built up area of the city in all directions from the city centre to engulf previously rural communities. This depicts an edge-expansion form of growth. The other forms of growth evident in the study area are infilling and outlying growth. Figure 4 shows how these growth types are spatial manifested.

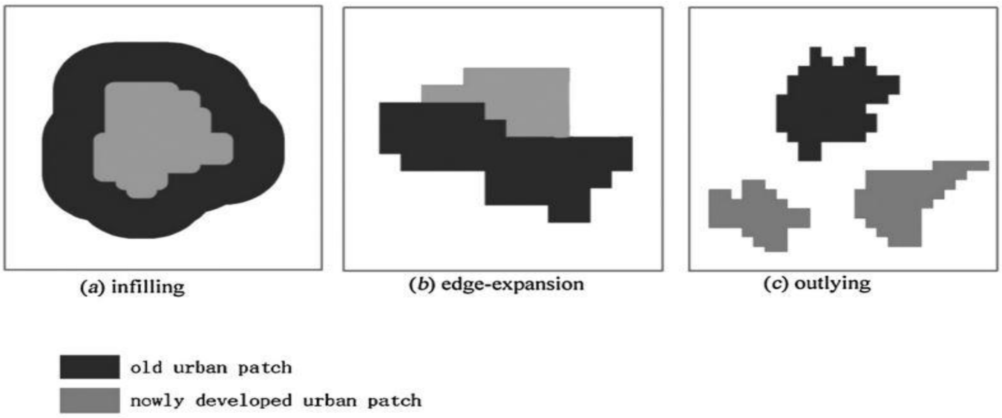

Figure 4: Spatial manifestation of urban growth typologies

Source: Adapted from *Sun, Wu, Lv, Yao, and Wei (2013)*

2.4.2. Spatial metrics

Spatial metrics are quantitative indices used to analyse spatial patterns of a landscape (Herold, 2001). These indices are commonly applied in landscape ecology (Gustafson, 1998). However in recent times these metrics have been applied to study the urban environment (Herold, Goldstein, & Clarke, 2003). Spatial metrics have been coupled with remote sensing and GIS to study urban growth patterns.

Spatial metrics coupled with remote sensing and GIS is a key analytical tool for gaining an insight into urban growth dynamics. Sun et al. (2013) applied spatial metrics coupled with remote sensing and GIS to distinguish the pattern of urban growth typologies in the city of Guangzhou, China. Spatial metrics are many and some of these do not have explicit meanings in relation to the behaviour of urban patches (Nong et al., 2014). Commonly used indices for analysing urban growth are; Landscape Expansion Index, Landscape Shape Index, Patch Density, Euclidean Nearest Neighbour Distance and Mean Patch Size, Largest Patch Index, Number of Patches (Nong et al., 2014; Sun et al., 2013; Xu et al., 2007).

Spatial metrics are many with strong correlations between several of them and thus contain redundant information (Bhatta, 2012). There is no specific set of spatial metrics for fully describing a landscape (Sun et al., 2013). The choice of metrics depends on the problem under study. In this study, only those that provide an insight into the identified growth types have been selected. A key consideration in the calculation of spatial metrics is the definition of the spatial domain for metrics calculation as this influences the metrics. Spatial domain is the geographic extent under investigation and its sub-divisions. The definition of the spatial domain depends on the problem under investigation. In some researches such as Xu et al., (2007) the study area extent is used as the spatial domain. For other studies, the entire landscape is subdivided into relatively homogenous units which will then serve as the spatial domains of the metric analysis (Martin Herold, Couclelis, & Clarke, 2005)

2.5. Urban growth modelling

Urban growth models are tools that help unveil the complex suite of driving forces of urban which are influencing urban spatial patterns. There are several modelling approaches that can be applied to model land-use change. These techniques have been studied and applied in different areas for example Markov Chain Analysis (Lopez, Bocco, Mendoza, & Emilio, 2001), Artificial Neural Networks (Yeh & Li, 2002)Cellular automata (CA) (Batty, Xie, and Sun, 1999; Liu and Phinn, 2003; Wu, 1998; Wu, 1997) logistic regression (Chen, Lu, and Fan, 2012; Vermeiren et al., 2012; Xie et al., 2005). In spite of the varying levels of success demonstrated by these techniques, they are also limited in certain regards. For example the most markov models are best the descriptive analysis rather than the making predictions (Lopez et al., 2001).

CA provide provides an effective tool for dynamic process modelling benefiting from its simplicity and strong capacities for scenario simulation (Clarke & Gaydos, 1998). These models however focus on the simulation of spatial patterns rather than the interpretation of the spatio-temporal processes of land-use change. Besides the approach is time consuming (Clarke & Gaydos, 1998; Xu et al., 2007).

Among the broad range of modelling techniques, logistic regression (LR) modelling has been found to be a more effective tool for land use change analyses due to its interpretative power and spatial explicitness (Cheng and Masser, 2003). The LR method is also capable of establishing functional relationships between land-use change probabilities and the drivers of change (Xu et al., 2007).

Additionally, LR models are not as computationally involving as CA models and input data requirements are relatively easy to meet (Xie et al., 2005) making them especially useful for data-scarce developing countries. Examples of the application of LRM can be found in Cheng & Masser (2003), Dubovyk et al. (2011), Duwal (2013), Eyoh & Nihinlola (2012), Hu and Lo (2007), Huang & Sin (2010).

The LR modelling approach however is not without weaknesses. Since the LR is an empirical approach it lacks the element to capture spontaneity in its predictions (Ahmed et al., 2014). Statistical models also lack a theoretical underpinning as they fail to explain the processes that actually drive land use change (Koomen & Stillwell, 2007)

2.5.1. Driving Forces of urban growth

In general land use change is influenced by a variety of factors (Xie, Huang, Claramunt, & Chandramouli, 2005). No single set of factors can explain the urban growth dynamics in different places since the contexts are not the same. Different driving forces have been identified in various land use studies, among them are demographics, socio-economic factors, transport system and effects of the natural environment (Acheampong & Anokye, 2013; Ahmed, Bramley, & Verburg, 2014; Cobbinah & Amoako, 2012; Duwal, 2013; Hu & Lo, 2007). These researches and others have indicated four primary factors as driving land use change in an area. They are; socio-economic factors; biophysical constraints and potentials; neighbourhood characteristics and; institutional factors in the form of spatial policies.

The socio-economic factors may include, employment opportunities and population growth, among others (Cheng & Masser, 2003). Generally, there is lack/scarcity of spatially encoded data at the local level in developing countries and in place of this some researches use other data such as distribution of employment opportunities, urban centres as proxy for the socio-economic variables (Ahmed et al., 2014). Several studies have used proxy variables in the absence of actual data (Ahmed et al., 2014; Cheng & Masser, 2003; Dubovyk, Sliuzas, & Flacke, 2011; Duwal, 2013; Hu & Lo, 2007; Huang et al., 2009; Vermeiren et al., 2012).

Biophysical constraints or potentials refer to characteristics and processes of the natural environment. These include climatic and weather conditions of an area (e.g rainfall, temperature, and wind), topography, landforms, soil types, and water resources. These characteristics to large extent influence the suitability of land for a particular use (Verburg, Eck, Nijs, Dijst, & Schot, 2004). Hence in studying the drivers of urban growth biophysical factors cannot be discounted. This further explains why several land use modelling studies attempt to investigate the influences of these factors for instance slope (Dubovyk et al., 2011; Duwal, 2013; Hu & Lo, 2007) on growth.

Analysis of spatial interactions have also contributed to understanding urban land use patterns. Neighbourhood effects have been shown to drive urban growth since urban growth patterns to a very large extent depends on the availability of usable sites. The likelihood of development on a site varies not only on its own availability for development but also influenced by neighbouring land uses (Cheng & Masser, 2003). Thus in urban growth modelling spatial interactions are accounted for by incorporating a neighbourhood function as one of the variables influencing the location preference. The neighbourhood variable reflects the spatial effects (promotion or constraints) of neighbouring pixels.

The influence of these factors is often determined by an inductive approach, that is using multivariate statistical technique (e.g. linear or logistic regression) (Ahmed et al., 2014).

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3. METHODOLOGY

3.1. Introduction

This chapter illustrates in detail the data, methods and techniques as well as approaches and materials employed to achieve the research objectives

3.2. Research Methodology

This research is divided into three broad phases. Phase one which centres on problem identification and the establishment of a conceptual framework of urban growth, its patterns, associated driving forces and the methods of modelling this relationship using land use modelling techniques.

In the second phase, relevant data and information in the form of primary and secondary data for carrying out this research was collected during fieldwork from 26th September -25th October, 2014. Interviews with experts (i.e. urban planners, academicians among others) (See appendix C) on the phenomenon of urban growth, its drivers and pattern was conducted. Other secondary data such as spatial plans, spatial data, and demographic data were obtained from government/non-government institutions. Field observations were conducted to collect ground truth data for image classification.

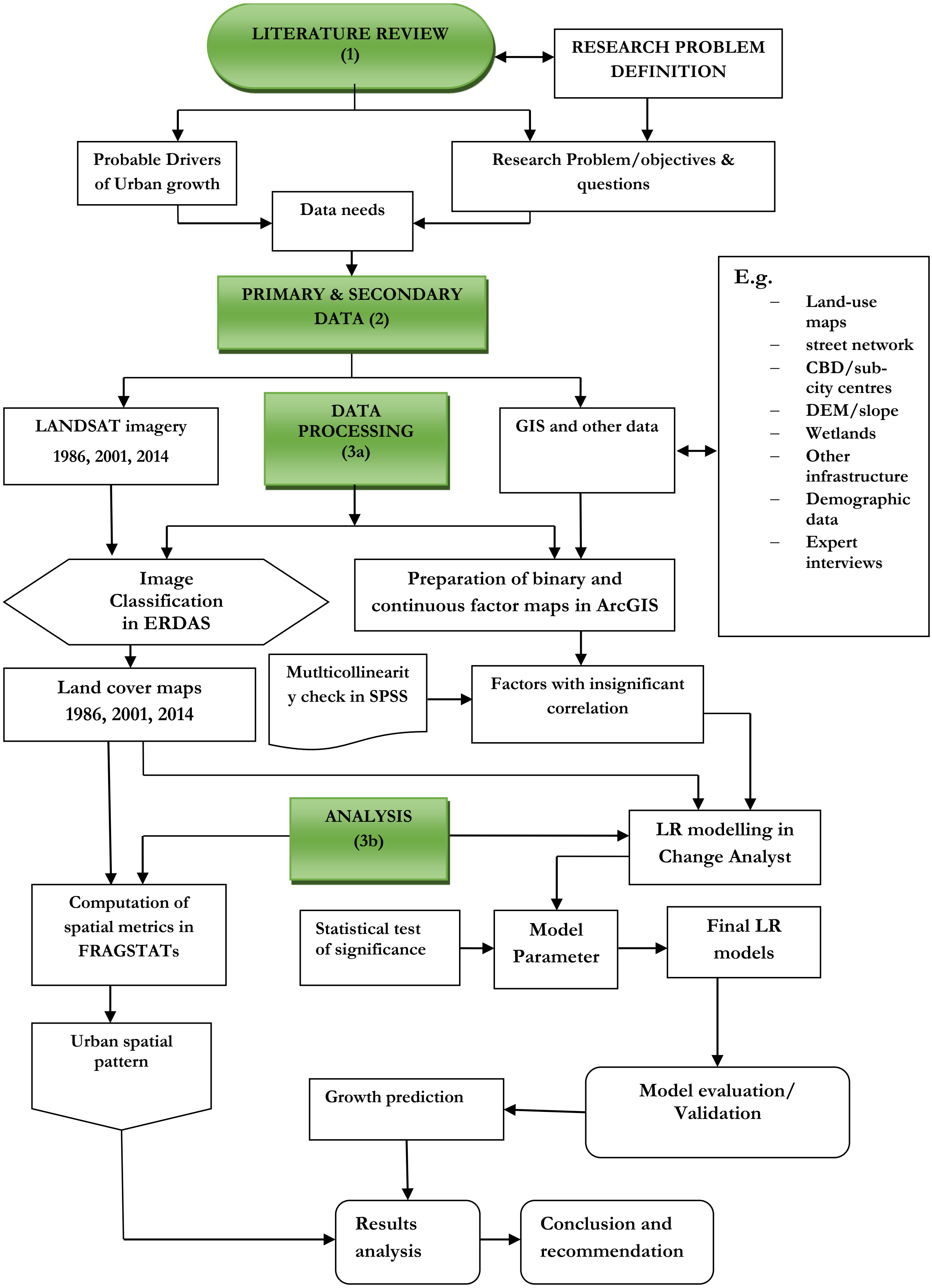
The final phase (phase three) of the work consist of preparation the collected data and analysing them in the light of the objectives of the study. Google earth was used to help in classifying LANDSAT imagery to generate land-cover maps and for accuracy assessments. The land-cover maps were used to prepare binary maps of urban and non-urban classes. Factor maps for the identified driving forces were prepared using the spatial data obtained. The land-cover maps were used to generate relevant spatial metrics in FRAGSTATs software for the analysis of spatial patterns of urban growth. Driving forces of urban growth in the study area were identified by constructing a logistic regression model which relates land-cover changes over time to the driving forces. The results spatial metrics and the LR models were analysed and discussed. Figure 5 below captures the steps just described.

3.3. Data Source and type

Primary Data Collection

Primary data took the form of interviews with experts and ground-truthing of training samples for land cover classification accuracy assessment. Experts were chosen based on their in-depth knowledge of urban growth in the study area. Seven experts, 3 from Centre for Settlement Studies, 3 from KNUST Department of Planning and the Metropolitan Director of Town Planning were successfully interviewed. A semi-structured interview approach was adopted with the discussion focussing on specific drivers of Greater Kumasi's growth, their relative significance and direction of influence as well as the growth typologies characteristic of the study area. The average time spent with experts was about 30-40 minutes. For purposes of accuracy assessment, sample locations were identified and visited in the field for land cover verification. 135 points were generated using stratified random sampling method which were used to train the data.

Figure 5: Flowchart of methodology



Secondary data collection

Different remotely sensed and GIS data obtained from different sources are used in this work. Three medium resolution Landsat TM images for the years 1986, 2001 and 2014 were download from USGS website as standard products to be used for land cover change detection. The choice of these years is motivated by the fact that studies have shown that Greater Kumasi started to experienced much of its growth during 1984 to 2010 (Cobbinah and Amoako, 2012; Oduro, Ocloo, & Peprah, 2014). To understand future trends of growth a knowledge of past trends is indispensable. Secondly the years were chosen because of availability of relatively good quality satellite imagery for these years. The images are of the same spatial resolution (30m) to make for easy comparison of changes. Very High Resolution (VHR) Google Earth image coupled with field observation was used in generating training samples for classifying the Landsat images except for the 1986 image which doesn't have any reference data. All data used in this study are geometrically referenced to the WGS 1984, UTM Zone 30N. Other ancillary data for this research were obtained from other institutions as shown in the Tables 1, 2&3 below.

Table 1: Data compiled for research

Data	Time period	Data Source
Land cover (Landsat TM/ETM+)	*1986, 2001, 2014*	USGS
Conservation areas	*1986, 2001*	Forestry Commission
Land use maps	*2000, 2012*	Town and Country Planning Department
Roads	*1988, 2000*	Departments of Urban Roads KMA
CBD/sub-city centres	*2000*	Town and Country Planning Department
Demographic data plus reports	*2000*	Ghana Statistical Service
Spatial plans (land-use plan)	*2007 Structure plan and Spatial plan of Greater Kumasi metropolitan Area (2013-2033)*	Kumasi Metropolitan Assembly

Table 2: List of remotely sensed data

Image	year	Resolution	Source	Path/row	Purpose
Landsat TM	1986	30m	USGS	194/55	For extracting land cover
Landsat ETM+	2001	30m	USGS	194/55	For extracting land cover
Landsat	2014	30m	USGS	194/55	For extracting land cover
DEM			SRTM/USGS		Used as a driving factor of urban growth

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Table 3: Vector dataset

Data	Year	Format	Purpose
Administrative boundary	2000, 2013	Shapefile	Delineating study area extent
Road network	1988, 2000	Shapefile	Road layers are used to drive factor maps by calculating to Euclidean distance to roads.
Conservation areas	1972, 2001	Shapefile	Conservation areas include forest reserves and wetlands which considered unbuildable. This is used to derive a dichotomous factor maps
Ward boundaries	2000,	Shapefile	For generating population density factor map
Land use map	2000, 2012	Shapefile	Maps depicting major land uses with categories such as industrial areas, education, water bodies, residential etc. These were used as reference for preparing land cover categories.
CBD/sub-city centres	1986, 2000	Shapefile	Used to prepare factor maps which indicate proximity to CBD/sub-city centres.

Statistical data

Statistical data consist of population data for the 1984 and 2000. Census data are available at district level for 1984 and at ward level for 2000. Ward boundaries are available only for 2000 in vector format.

3.4. Identifying and Analysing urban growth typologies

3.4.1. Image Classification

One of the objectives of this study is to analyse and understand the urban growth typologies over the chosen time steps. The first step towards this objective was to classify the satellite imagery so as to generate maps of the land cover classes of interest in this case urban, non-urban, and water bodies. Detailed description of these classes is given below (Table 4);

Both supervised and unsupervised classification were done to generate the above land cover classes. Two of the images, namely 2001 and 2014 were classified using supervised classification because these two times have reference data. Training samples, collected with the help of Land use maps of 2000 and 2012 and very high resolution images from Google Earth are used for 2001 and 2014 Landsat images while the land cover classes for 1986 were derived using visual image interpretation techniques of the false colour composite of bands 4, 3 and 2 of the Landsat TM image coupled with expert knowledge of the study landscape during that time. Some of the experts namely Mr. Joseph Edusei, Professor Romanus Dinye and the Director of Town Planning, Mr. Emmanuel Christian Coffie provided valuable information on the land cover types existing during that time. The image was printed in colour on an A-3 sheet and this was presented to the experts to indicate by sketching sample polygons on each identified land cover. The knowledge obtained from this was used in generating training sites in ERDAS IMAGINE to supervise the classification of the image.

Table 4: Description of land cover types

Code	Land cover type	Description
1.	Urban	This class consist of the urban fabric, roads, residential, commercial, and industrial and other built up lands.
2.	Nonurban	Consist of farmlands, grasslands, bare land, forests and other vegetation
3.	Water bodies	This consists of lakes, streams, ponds, rivers and reservoirs

3.4.2. Classification Accuracy Assessment

Accuracy assessment is in remote sensing image classification quantitatively tells the reliability or otherwise of the classification results (Angel et al., 2005). This is done by comparing the classified pixels with some form of reference data which provides detail information of the land cover types in the area of interest. In this project, the accuracies for the classification results of the years 2001 and 2014 are assessed using 135 randomly sampled ground truth points. As indicated earlier, the 1986 image has no reference data and hence visual image interpretation using the false colour composite of bands 4, 3 and 2 was used. What further facilitated the interpretation is the fact that, cloud cover percentage of the image is less than 10 and even these areas lie outside the extent of the study area and besides the land cover classes could easily be distinguished visually. According to the (NGDSC, n.d.) the false colour combination makes vegetation appear as red tones, brighter reds which show more the growing vegetation. Soils with no or sparse vegetation range from white (sand, salt) to greens or browns depending on moisture and organic matter content. Water appears blue; clear water will be dark blue to black while shallow waters or waters with high sediment concentrations are lighter blue. Urban areas will appear blue towards grey. This knowledge coupled with insights from experts was used to assign land cover classes to the 135 sample points for subsequent accuracy assessment.

3.4.3. Post-classification Change detection

Change detection is necessary for understanding and visualising the land cover conversions between any multitemporal images. It indicates which land cover type has changed in what time and where. In this study the land cover changes over time were detected using the matrix function in ERDAS IMAGINE. Two independently classified images (1986-2001 and 2001-2014) were loaded in the matrix dialog of ERDAS IMAGINE to produce a change map together with a change matrix (derived from the raster attribute) which shows the class-to-class conversions between the time periods under study.

3.4.4. Distinguishing and analysing growth typologies

Identifying growth types

Three growth typologies namely, infilling, edge-expansion and outlying growth have been agreed upon by experts as characterising the study area over the time periods under study. To distinguish between these growth typologies, a quantitative method as used in the study of Xu et al., (2007) would be applied in this study. Their study used the landscape expansion index, *S*, which is the ratio between the *length,* L_c of the common boundary of a newly grown urban area and the existing/pre-growth urban patches and the *perimeter, P* of the newly grown area to determine the typology of growth that has occurred over time. The relation is mathematically expressed as follows:

$$S = \frac{L_c}{P}$$

Urban growth type is defined as infilling when $S \geq 0.5$, edge-expansion when $0 < S < 0.5$ and outlying when $S = 0$ which indicates no common boundary. Thus an infill development refers to newly developed urban patch surround by at least 50% old urban area whereas edge-expansion refers to a newly developed urban area spreading out from an existing urban area and surrounded by less than 50% of the existing urban (Sun et al., 2013). Newly grown urban areas depicting these typologies were identified by following the steps captured in the flowchart below (Figure 6) . The first step is to convert the classified land cover maps from raster to polygons and extract the urban classes. To determine the types of growth between the study periods, the urban areas of the start time (u_1 e.g. 1986) and the end time (u_2 e.g. 2001) are intersected to generate the existing urban at 2001 (u_3). The growth (u_4) over 1986-2001 is generated by erasing u_3 from u_2. After the erase operation in ArcGIS, apparently separate polygons may still be classified as one polygon and this makes the generation of common boundaries difficult. To avoid this u_4 is exploded into unique polygons (u_5). u_5 is intersected with u_3 and the line output feature type should be selected and this will result in the common boundaries (L_c) between existing urban (u_3) and the growth (u_5). The separate polygons (u_5) are joined to their respective common boundaries (L_c) based on a common field ID. This way the boundary each polygon shares with existing built-up can be identified in the attribute of the joined feature. The above formula can then be applied to distinguish which polygons belong to which growth type.

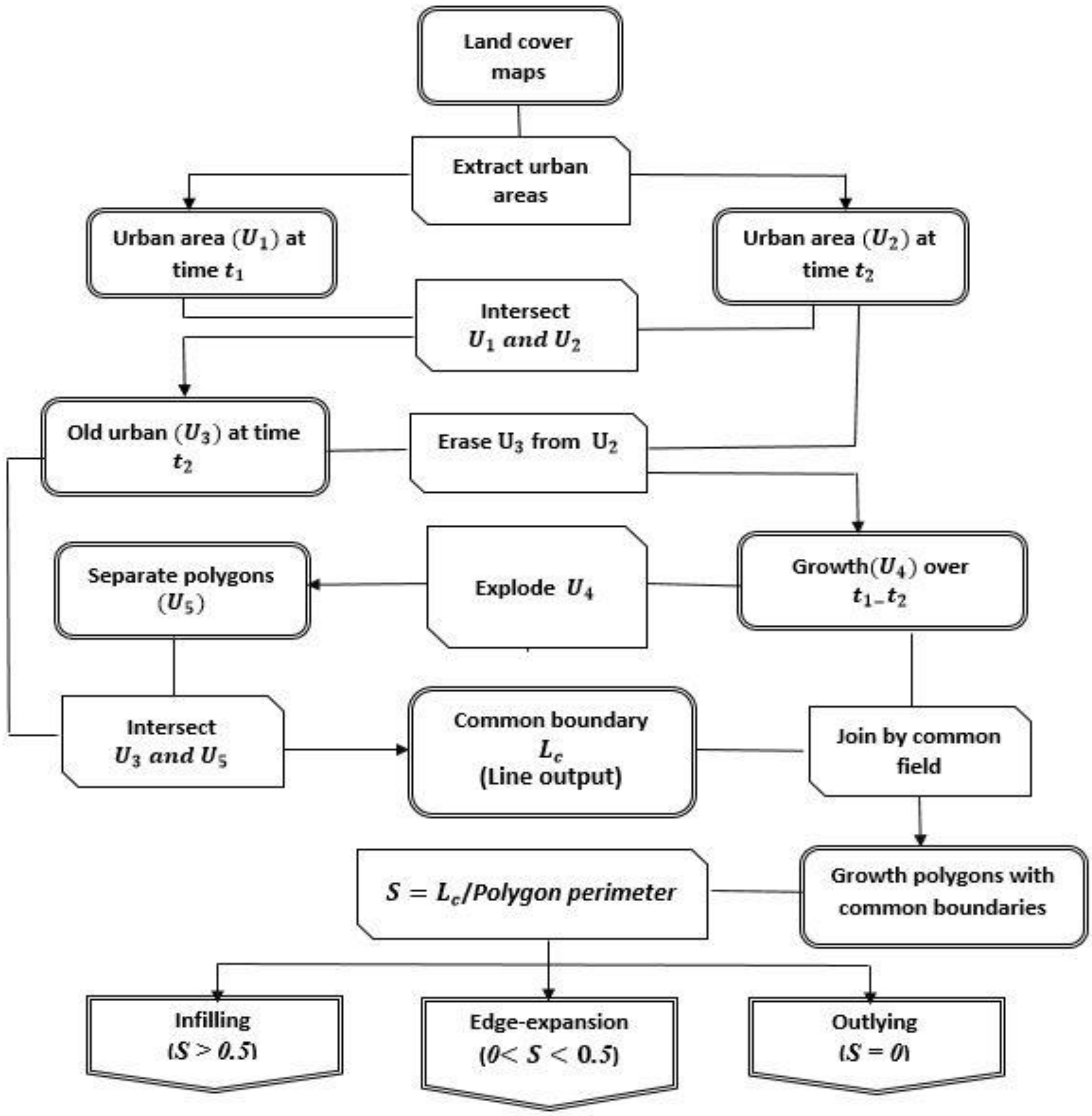

Figure 6: Flowchart for identifying urban growth types

3.4.5. Analysis of growth types using spatial metrics

Spatial metrics are quantitative indices for objectively quantifying the structure and pattern of an urban landscape. They are critical in the description and analysis of urban form and its changes (Herold, Goldstein, and Clarke, 2003). Spatial metrics are many with strong correlations between several of them and thus contain redundant information (Bhatta, 2012). Frequently used metrics for spatial pattern analysis are patch size, number of patches and density, edge length and density, fractal dimension, nearest neighbour distance, contagion among others (Herold, Couclelis, and Clarke, 2005). There is no specific set of spatial metrics for fully describing a landscape (Sun et al., 2013). The choice of metrics depends on the problem under study. In this study, only those that provide an insight into the identified growth types have been selected. A key consideration in the calculation of spatial metrics is the definition of the spatial domain for metrics calculation as this influences the metrics. Spatial domain is the geographic extent under investigation and its sub-divisions. The definition of the spatial domain depends on the problem under investigation. In some researches such as Xu et al., (2007) the study area extent is used as the spatial domain. For other studies, the entire landscape is subdivided into relatively homogenous units which will then serve as the spatial domains of the metric analysis (Herold et al., 2005). One other approach may be to construct buffered zones which allows for analysis at much disaggregate level than when the entire landscape is serving as the spatial domain for analysis. This approach also provides an insight into the gradient changing characteristics of growth. (Nong et al., 2014). This is usually the case for comparative evaluation of intra-urban structures such as found in Abebe (2013 and Herold et al. (2003). In order to gain a deeper understanding of the spatial and temporal dynamics of urban growth, GIS-buffer analysis is used in this study which involves the creation of circular buffer zones around the urban core until it completely covered the spatial extent of the study area. The geometric centre of the urban core in 1986 was used as the origin in creating the buffer zones.

The following metrics have been found to be significant in analysing the patterns of urban growth. These metrics are calculated at the class level.

Patch density

Patch density measures landscape heterogeneity/the spatial distribution of patches of a land cover class and is lowest when the urban landscape is highly fragmented (Sun et al., 2013). The patch density is a very good indicator of urban landscape fragmentation. Values for this metric are however influenced by certain factors such as pixel size and the minimum mapping unit. Smaller mapping units imply more patches and hence higher values .For instance, if the total landscape area is does not change significantly, an increase in the number of small urban patches will indicate a more heterogeneous and fragmented urban development. Conversely, an increase in total landscape area with no or insignificant change in the number of patches will imply the formation of a continuous urban patch as the density value will decrease. There might also exist a situation in which the number of patches and the total landscape would simultaneously vary proportionally in the same direction in which case there would be no significant change in the patch density value for that landscape.

Largest patch Index (LPI)

The largest patch index (LPI) is the proportion of the total landscape area covered by the largest patch. The range for this metric is defined in percentage by $0 < LPI \leq 100$. This index approaches zero when the largest patch of the corresponding patch type is increasingly small (McGarigal, 2014). LPI is 100 when the entire landscape is dominated by a single patch of the corresponding patch type. The LPI increases when the urban patches become aggregated and integrated with the urban core.

Area-weighted Mean Euclidean Nearest Neighbour Distance (AWMENND)

Euclidean nearest neighbour distance measures the distance from a patch to the nearest neighbouring patch based on edge-to-edge distance (that is, using simple Euclidean geometry). This measure is the simplest measure of patch isolation. *AWMENND* approaches 0 as the distance to the nearest neighbour decreases.

The above metrics are useful measures of patch isolation, aggregation and density and thus are useful for analysing the growth patterns of the study area over time. The basis of the spatial metric calculation is a thematic map representing a landscape comprised of spatial patches categorized in different patch classes. In this study, the landscape heterogeneity (i.e. the patch categories) is represented in two classes: urban and non-urban. The spatial metrics were calculated using the public domain software, FRAGSTATS 4.2. Table 5 presents the list of the chosen metrics, their units of measurement and ranges.

Table 5: Spatial metrics used in the study

Metric	Unit	Range
Patch density (NP)	Number per 100 ha	PD > 0
Number of Patches (NP)	None	NP ≥ 1
Largest patch Index (LPI)	Percent	0 < LPI ≤ 100
Area-weighted Mean Euclidean Nearest Neighbour Distance(ENN)	Meters	ENN>0

3.5. Logistic Regression modelling and driving factors of urban growth

3.5.1. Driving factors of urban growth

The LR modelling approach is data-driven, and hence a list of probable driving factors (the independent variables) have been compiled from literature and from discussions with experts during field work The factors were grouped under four broad categories; *site specific characteristics*, *proximity variables*, *neighbourhood characteristics*, *plans/policies in the area* and *other*. During the interactions with experts in the field the list of factors compiled from literature were discussed in-depth to unearth the relative importance and directions of influence of each individual factor and to adapt these factors to the local environment. Experts also had the opportunity to indicate other factors which they thought were significant in driving growth. The discussions resulted in the generation of locally relevant drivers of urban growth as show in Table 6

Table 6: Selected drivers of urban growth

Category	Factors	1986-2001		2001-2014
Site specific characteristics	Population density	•		✓
	Waterways		=	
	Educational land use	✓		✓
	Slope	✓	=	✓
Proximity characteristics	Distance to major roads	✓		✓
	Distance to CBD		=	
	Distance to existing urban cluster	✓		✓
	Distance to sub-urban centres	•		✓
Neighbourhood Characteristics	Proportion of urban land in a surrounding neighbourhood (7x7 cell window)	✓		✓

- • Not available or relevant during the period
- ✓ Not the same for both study periods
- = Assumed to be the same for both study periods

3.5.2. Logic underlying the selection of driving factors for modelling

Population density

For the period in between 1972 and 2010 population density was higher within 2km away from central Kumasi and declines with distance from the city centre (Oduro et al., 2014). There is intensive and densified land development in areas of high population density in the form of infilling, redevelopment of old buildings (i.e. reconstruction, increasing number of floors) due to scarcity of land to accommodate the increasing population. The result is the expansion of the urban footprint into the surrounding districts in the form of edge-expansion and outlying development. This resulted in the emergence of sub-urban centres which are beginning to attract the new developments(TCPD, 2013).

Distance to major roads

The major roads that traverse the metropolitan area drive and direct the growth of Greater Kumasi. Besides connecting GKMA to parts of the country, these roads provide commuters with easy access to the city centre. This implies that living close to these roads facilitates resident's ability to commute to the city centre. Population density within 2km of a major road is very high compared to areas far away from major roads (Oduro et al., 2014). Since population growth leads to physical development it could be reasoned that development would mostly likely be high at a distance close to major roads and decrease with distance away from major roads. This fact was corroborated by experts during fieldwork

The road network as of 1972 is used as a factor in the 1986-2001 model. The reason underlying inclusion of this variable is that major road investments in and around Kumasi occurred during the 1990s. These investments involved the repaving and reconstruction of city streets and improvements in arterial roads connecting central Kumasi to other districts and regional capitals. Thus road infrastructure investments mainly focused on improving the existing road network, for instance parts of the following roads were widened and changed from two-lane into dual carriageways: the Kumasi-Accra Highway and the Kumasi-Obuasi Road. The Kumasi-Techiman Road was also repaved in 1998. These investments in roads was part of the move to develop and improve the infrastructure base of districts so as to operationalise the 1988 decentralisation programme which had just been implemented to politically, administratively and fiscally transfer authority to the local level.

Distance to CBD

Major economic points and key services are located in the CBD such as the central market, Adum shopping centre and a point of many job opportunities. These economic centres attract people from within and beyond the Ashanti region and thus areas in close proximity to the CDB have high level of attraction for development.

Distance to sub-urban centres

In 1984 there were no urban communities in five of the surrounding districts within the Greater Kumasi Sub-Region namely; Bosomtwe, Afigya Kwabre, Awima Nwabiagya, Kwabre East and Atwima Kwanwoma. By the year 2000 new urban centers emerged in these surrounding districts following the spatial expansion of Kumasi's built up area into the surrounding districts (TCPD, 2013). The emergence of these centres did not however come with shift in economic activities. In all the adjoining districts except Kwabre East and Afigya Kwabre, primary industry still had the largest proportion of economically active population as of year 2000. These sub-centres are mainly playing the role of dormitory towns are therefore desirable locations for residential developments for low-income immigrants/indigenes who cannot afford land in the city centre. Land speculations and some negative locational attributes of Central Kumasi such congestion have made these sub-centres prime locations for development (Acheampong & Anokye, 2013).

Neighbourhood effects
Neighbourhood effects have been shown to drive urban growth since urban growth patterns to a very large extent depends on the availability of usable sites. The likelihood of development on a site varies not only on its own availability for development but also influenced by neighbouring land uses (Cheng & Masser, 2003). Thus in urban growth modelling spatial interactions are accounted for by incorporating a neighbourhood function as one of the variables influencing the location preference. The neighbourhood variable reflects the spatial effects (promotion or constraints) of neighbouring pixels.

Zoning
Areas considered unbuildable are wetland areas. As a result areas within 100m buffer (set by Ministry of Lands and Natural Resources) around these wetlands are not allowed to be developed by law. However, enforcement of planning regulations is very weak and thus these and other regulations are flouted as structures are put up on these areas. Physical development have spread and has not spared ecologically sensitive areas such as rivers, streams, waterlogged areas and open spaces. Areas zoned as forest reserves however have remained unaffected by the physical growth of the sub-region and these reserves include the Owabi and Bobiri wildlife reserves. These reserves as well as the Kumasi airport buffer zone are masked out of all the factor maps since physical developments are prohibited in these areas.

There are also pockets of land within which physical developments are controlled. These areas are lands that were acquired in the 1950s for the establishment of educational and research institutions. They include: the Kwame Nkrumah University of Science and Technology, Council for Scientific and Industrial Research, Kwadaso Agricultural Research Station, Kumasi Girls Secondary School and Opoku Ware Secondary School. Thus though physical growth is rapid in the sub-region, these areas are an exception (Afrane & Amoako, 2011). To account for these areas in the model, a dichotomous independent factor representing the presence (value of 1) of educational/research institution or otherwise (value of 0) is included.

3.5.3. Preparation of input data for logistic regression modelling

Dependent variables
These driving factors of urban growth consist of dichotomous or continuous variables in the form of factor maps driven from the data collected. These are prepared for two time periods 1986-2001 and 2001-2014. The choice of driving factors is limited by data availability and this could introduce some level of uncertainty into the modelling results. In this study the nature of land cover change is regarded as dichotomous; either the presence of urban or non-urban which is considered to be a function of the identified driving factors. The binary dependent variable takes the value 1 as urban and 0 as non-urban.

Independent variables

Population data is available at ward level for year 2000 with the respective population densities of each ward. This data exist in vector format. The 2000 population data is used to generate the population density factor map for 2001 with the assumption that the population statistics would not have under gone any noticeable changes within a span of one year that is from 2000 to 2001. The population density factor map of 2001 was generated by converting the vector layer to raster with 30m cell size. No population data exist at ward level for the year 1986 and hence population density is not considered as a variable in the 1986-2001 model.

To account for neighbourhood effects in the models, the proportion of urban land is calculated using the focal statistics tool in ArcGIS. In this study the proportion of urban land within a 7x7 rectangular neighbourhood is computed using the focal function. In many studies an arbitrary neighbourhood size is used and only the direct neighbourhood of a location is considered (Verburg, de Nijs, Ritsema van Eck, Visser, & de Jong, 2004). The studies of Duwal (2013) and Abebe (2013) used a 7x7 rectangular neighbourhood while Cheng and Masser (2003) adopted a circular neighbourhood of radius 500m.

All distance variables such as distance to major roads, distance to CBD, distance to urban cluster, and distance to suburban centres are computed in ArcGIS using Euclidean distance tool. The tool calculates the minimum distance from the selected factors to each of each the surrounding cells. Slope was generated from the DEM (Digital Elevation Model).

Though experts interviewed indicated that urban development does not spare water ways and other open spaces such as river which are not allowed to be developed by law, the are incorporated into the model to investigate whether or not they are a constraint to urban growth. Waterways are included in the models as dichotomous variables (presence waterway = 1, absence of waterway= 0)

All input data are in raster format and either continuous or dichotomous (with values of 0 or 1). The continuous variables have been standardised to 0 – 1 range.

3.5.4. Multicollinearity diagnostics

An issue that needs to be checked in the independent variables is multicollinearity among the variables which is present when there exists a strong correlation between two or more independent variables. Perfect correlation exist between two or more variables when they have a correlation coefficient of 1 or -1. Highly correlated predictors lead to redundancy of some independent variables. Multicollinearity could result in high standard errors and difficulty in assessing the individual importance of a predictor (Field, 2013).

It should be noted that the presence or otherwise of multicollinearity is not the problem because perfect multicollinearity and less than perfect multicollinearity are very rare situations in real-life. What rather matters is the level of multicollinearity. The higher the level of correlation between the variables, the more unreliable the model estimates would be. Multicollinearity should therefore be checked among the independent variables and reduced to a reasonable level. There different ways of checking for multicollinearity between independent variables. This study uses the Variance Inflation Factor (VIF) which is a very good indicator of the level of correlation among independent variables. The VIF measures the inflation in estimated regression coefficients resulting from collinearity between independent variables. An independent variable with VIF>10 is a cause for concern (Field, 2013) as this points to serious multicollinearity (O'brien, 2007). Therefore in this study only variables with VIF<0 are included in the models.

3.5.5. Sampling scheme

Spatial dependence of spatial data needs to be considered when employing logistic regression to model urban growth. To avoid unreliable parameter estimation, spatial dependence should be tackled. A spatial sampling scheme to reduce spatial autocorrelation among the sampled sites can serve this purpose. This study employs the Change Analyst software which uses a sampling scheme that combines systematic sampling and stratified random sampling. Such combination is utilized, as systematic sampling is effective in reducing spatial dependence, while stratified random sampling is efficient in representing population (Ahmed, Bramley, and Verburg, 2014; Xie et al., 2005). In this study a 5x5 non-overlapping sampling window is used after a number other window sizes (3x3, 7x7, 9x9) which resulted in less or no significant variables were tried.

3.5.6. Logistic regression model

Logistic regression has been used widely to relate the outcomes of a categorical dependent variable to a set of independent variables which can be continuous and/or dichotomous. In this study a binary logistic regression model is applied to analyse the relationship between urban growth in the study area and a list of probable driving forces and to simulate future urban growth. The nature of land cover change of a cell is considered as binary: either the presence of urban (value of 1) or non-urban (value of 0). It is assumed that the probability of a non-urban cell changing to an urban cell would follow the logistic curve. The general formula of logistic regression is as follows:

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

$$y = \log_e(P/_{1-P}) = \log\text{it}\,(P)$$

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

where $x_1,\ x_2, \dots\dots\dots\dots.., x_n$ are explanatory variables and the utility function *y* represents a linear relationship between y and the list of explanatory variables. The parameters $b_1,\ b_2,\ \dots\dots.., b_n$ are the regression coefficients to be determined. The binary response variable is z which takes the value of either 0 or 1. The value, z=1 indicates the occurrence of a new unit (that is a transition from non-urban to urban) and z=0 denotes no change. P refers to the probability of occurrence of a new unit, that is z=1. Function y is represented as the logit (P) that is the log (to base e) of the odds or likelihood ratio that the dependent variable is 1. An increase in the value of y inevitably results in a corresponding increase in the probability P. The role of each explanatory variable on the probability P is denoted by the regression coefficients with the signs (positive or negative) of the coefficients indicating the direction of influence of each variable. A positive coefficient means that an increase in the value of its associated variable means an increase in likelihood of change from non-urban to urban. Conversely, with a negative coefficient, when its associated variable increases the likelihood of change from non-urban to urban is reduced. Logistic regression modelling is implemented in ArcGIS extension software-*Change Analyst*.

Logistic regression parameters

The Change Analyst software computes a number of statistics which can be used to assess the robustness and the performance of the model's estimated parameters

Odds ratio (O.R): The odds ratio is very key to the interpretation of logistic regression (Field, 2013). It indicates a change in odds (in this case a change in the odds of a non-urban cell becoming urban) emanating from a unit change in the independent variable. O.R is computed as the odds after a unit change in the independent variable divided by the original odds and its value ranges from 0 to positive infinity. An O.R>1 means that as the independent variable increases the odds of the outcome occurring increases as well. Conversely an O.R< 1 indicates that as the independent variable increases the odds of the outcome occurring decreases. An O.R of 1 means that a change in the independent variable has no influence on the outcome variable and thus such a variable should be removed from the model.

Chi-square statistic: Another statistic worthy of note is the Chi-square statistic. The Chi-square statistics evaluates the goodness of fit of the logistic regression model (LRM). The Chi-square is given by the formula:

$$x^2 = \sum \frac{(observed\ count - model\ count)^2}{model\ count}$$

Where x^2 is Chi-square. Observed values are the true values of the cell whereas model count are the predicted values of the same cell from the model. The Chi-square tests the null hypothesis that all independent variables have and odds ratio of 1 and thus have no use in explaining the dependent variable. Related to the chi-square statistic is a corresponding p-value which is compared to a chosen significance level (in this case $\alpha = 0.05$ significance level). If the p-value is less than α, then the null hypothesis is rejected as this is an indication that at least one of the independent variables significantly contributes to the dependent variable. A p-value greater α confirms the null hypothesis.

Wald-statistics (z-value): The Wald statistic gives information on the individual contributions of the independent variables. It indicates whether the coefficient of an independent variable is significantly different from zero. The Wald statistic is used to determine whether an independent variable significantly influences the outcome.

3.5.7. Model Evaluation and Validation

There are a variety of approaches for evaluating urban growth models. Among these are the ROC (Relative Operating Characteristic) statistic as used in the studies by Hu & Lo (2007), Ahmed et al. (2014), Dubovyk et al. (2011). Other commonly used approaches are Kappa (Eyoh & Nihinlola, 2012) and Percentage of Correct Prediction (PCP) (Abebe, 2013; Xie et al., 2005). The Change Analyst software which is used in this study automatically computes the PCP. This study combines the PCP with kappa as this combination provides a more objective assessment of the models' performance (Dubovyk et al., 2011).

Percentage of Correct Predictions (PCP)

After estimating the coefficients of the independent variables in the models, they are used to predict a known situation for evaluation and validation purposes. The PCP measures what percentage of the real situation is correctly predicted by the model. The PCP value shows the model's predictive power (Huang & Sin, 2010). The following formula is used in computing the PCP (Christensen, 1998):

$$PCP = \frac{(a + d)}{n} \times 100$$

Where a is the number of correctly predicted occurrences, d is the number of predicted absences which are correctly predicted and n denotes the total number of observations.

Kappa:

According Lesschen et al. (2005), regression models' performance for trend extrapolation can be validated by using it to predict the outcome variable for other data besides the data used for fitting the model. The kappa statistic is an indicator of a model's prediction accuracy and it measures the agreement between the predicted situation and a reference data (actual situation) and the agreement that may occur by chance (Munroe, Southworth, & Tucker, 2002). It ranges between 0 (completely inaccurate) and 1 (perfectly accurate). Pontius (2000) distinguished three variants of kappa: Kappa for no information (k_{no}), Kappa for location (k_{loc}), and kappa for quantity ($k_{quan}/\mathrm{K}_{Histo}$). K_{no} represents an overall index of agreement. K_{quan} is an index that measures agreement in terms of quantity while k_{loc} only quantifies agreement in terms of location. Pontius (2000) considers a kappa value greater than 0.5 as satisfactory for land use change modelling.

3.5.8. Simulating future urban growth

Probable areas of urban growth in the future were mapped using the best of the two models. The 2001-2014 model was used in the predictions of urban growth for 2023, 2033 given that this model is built on variable which are most current relative to the 1986-2001 model.

3.6. Possibilty of errors

The logistic regression model like other land use models is not free from errors. Firstly the model's predictive power is not 100% because it does not account for all driving forces of urban growth. Besides predictions of future growth can be flawed by spontaneous land use changes since this approach (LRM) only extrapolates past urban growth trends into the future. Errors may also result from GIS operations such Euclidean distance calculations.

3.7. Tools used

The tools used for data processing and analyses in this work include ArcGIS 10.2.2, ERDAS IMAGINE 2014, Change Analyst software (Huang & Sin, 2010), Fragstats 4.2 (McGarigal, Cushman, Neel, & Ene, 2002), Map Comparison Kit 3 and IBM SPSS Statistics 22.

4. RESULTS AND DISCUSSIONS

In this chapter the results of the research are presented and analysed in detail. A comparative analysis of the growth typologies that are characteristic of the two time steps under investigation is presented here. This supported by maps, tabular and graphic illustrations coupled with selected spatial metrics which offers a deeper understanding of the spatio-temporal dynamics of these growth typologies. Another integral section of this chapter is the discussion of the results of the logistic regression models, model evaluation and predictions of future growth. Comparisons is also made here between this study on and other related studies on urban growth drivers.

4.1. Results of image classification

The respective accuracies of the classified images are shown in table 7 below. The overall accuracies though different are satisfactory for remote sensing image based analysis. The kappa statistics indicate the reliability of the classification results (that is the extent to which the classification results match with the reference data). The higher the value the more reliable the results. In Kundel and Polansky (2003) kappa values in the range 0.61-0.80 indicate substantial agreement whereas the range of 0.81-1.00 signifies an almost perfect agreement. In the light of the foregoing, the kappa values obtained here indicate that the classified images significantly depict the land cover classes into which they were classified and thus could be used for further analysis. The classified maps are shown in Figure 7 and areas of each land cover class across the years are also displayed in Table 8.

Table 7: Results of accuracy assessment

Land cover class	1986		2001		2014	
	Producer's	User's	Producer's	User's	Producer's	User's
Urban	100	89.62	76.19	88.89	81.82	97.83
Non-urban	66.67	100	94.12	87.91	98.61	87.65
Water	100	100	87.5	87.5	100	100
Overall accuracy	91.85		88.15		91.85	
Kappa statistics	0.80		0.76		0.8	

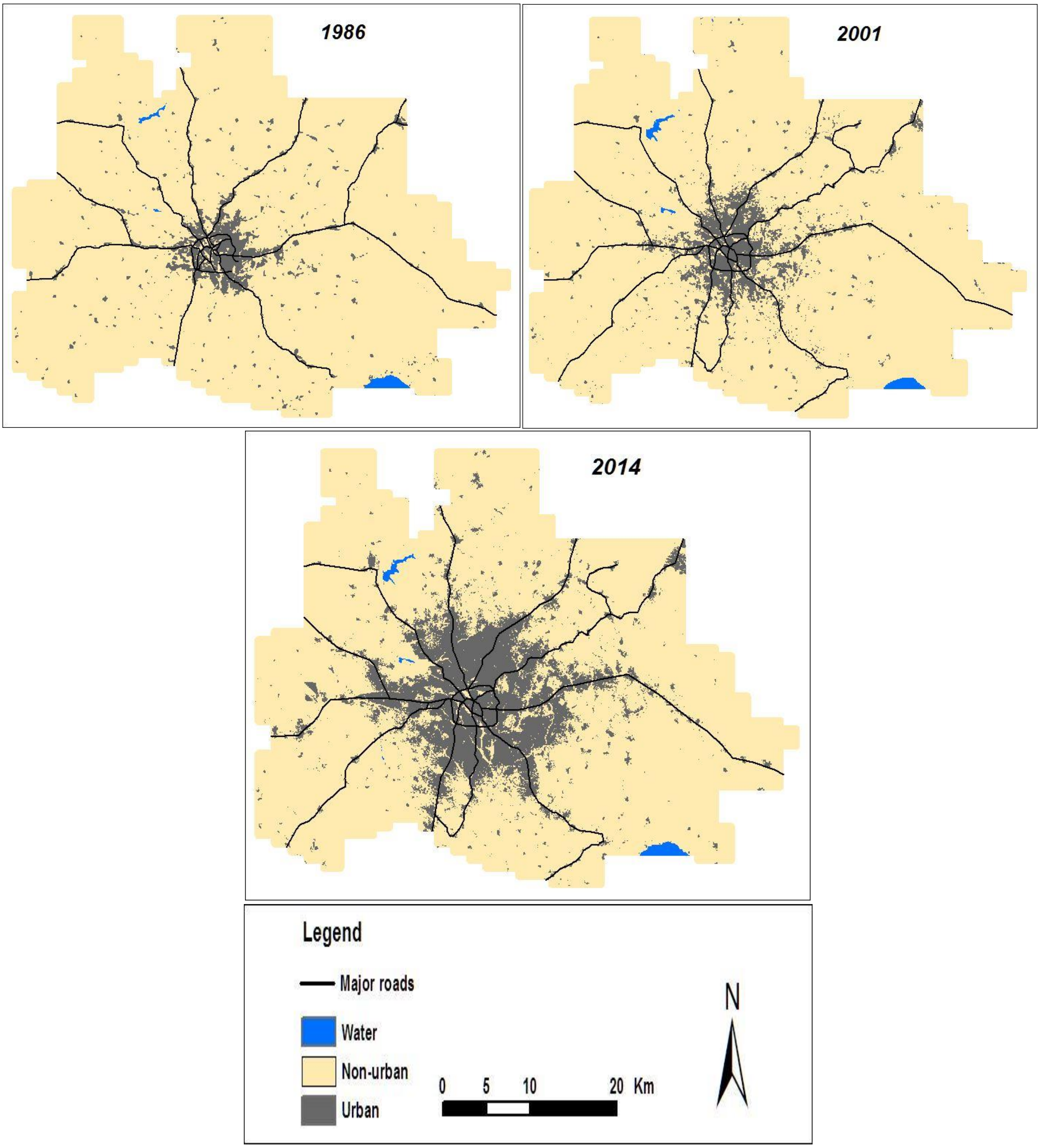

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Figure 7: Land cover maps from image classification

Year	**Area (km²)**			**Total Area (km²)**
	Urban	Non-urban	Water	
1986	120	2345	9	2474
2001	182	2282	10	2474
2014	410	2053	11	2474

Table 8: Land cover classes

4.2. Trend in land cover change between 1986 and 2014

During the two time spans under study, changes were noted from one land cover type to the other and this is graphically revealed in Figures 8 and 9. This study only focuses on changes between the urban and non-urban classes. During the period 1986-2014, the urban area registered a continuous and rapid increase in size in the metropolitan area. In 1986 the urban area was 120.7 km^2 (5.0% of the study area) and this figure more than tripled to 410 km^2 (representing 16.6% of the study area) in 2014. The mean annual growth rates in the two time steps, 1986-2001 and 2001-2014 registered a significant difference. Of the total area that had undergone change in both time steps, the conversion from non-urban to urban land was predominant and thus occupied a substantial proportion of the changes observed. As can be seen from Table 4.2, the statistics suggest that some 95km^2 of non-urban land which is approximately 59% of the total land cover change, had been used for urban development during the period 1986-2001. The non-urban to urban land conversion in the period 2001-2014 was 244.7km^2 and this more than doubled its counterpart in the previous time step (Table 4.2). Though the urban land cover witnessed an increase in both periods, the spate of growth during the second time step was greater as shown in table of land cover change statistics (Table 9). Urban land was increasing at a rate of 6.4km^2 per annum during the first time step while the 2001-2014 period recorded an annual increases in urban land cover at the rate of 18.8km^2. Urban growth tends to spread out from the city centre and extends into the surrounding districts in an axial fashion thus following the direction of the major roads. Over 90% of the land areas in the six adjoining districts in the Greater Kumasi Metropolitan Area are covered by forests and agricultural lands (TCPD, 2013). Hence the fast pace of Kumasi City's expansion into these surrounding districts is resulting in the loss of forests and agricultural lands as already pointed out in other studies (Afrane & Amoako, 2011; Cobbinah & Amoako, 2012; Koranteng & Zawia-nied, 2008)

Another land cover conversion worthy of note and which also rates second in order of the magnitude of change in both time steps is the transition from urban to non-urban land cover. Approximately 34km^2 and $15km^2$ (Table 9) of urban land changed to non-urban during the periods 1986-2001 and 2001-2014 respectively.

This change from urban to non-urban land could largely be attributed to the tearing down and redevelopment of old buildings. In the study area particularly the CBD and other sub-centres, traditional poor and low-income residential housing which are located on prime lands are remodelled or completely razed down to pave way for properties with modern architecture. Neighbourhoods experiencing redevelopments and teardowns are Suame, Bantama, oforikrom/Afful Nkwanta, Amakom among others (Oppong & Brown, 2012). In many cases the tearing down and redevelopment is done without due considerations of planning regulations. This is due to the fact that the planning institutions are not adequately resourced to live up to their mandates. This has in turn culminated into the proliferation of unauthorised structures.

Table 10: Land cover change statistics

Changes in land cover	**Area**			
	1986-2001		2001-2014	
	km^2	%	km^2	%
Non-urban to Urban	94	77	244	94
Urban to Non-urban	34	23	15	6
Total	122	100	259	100

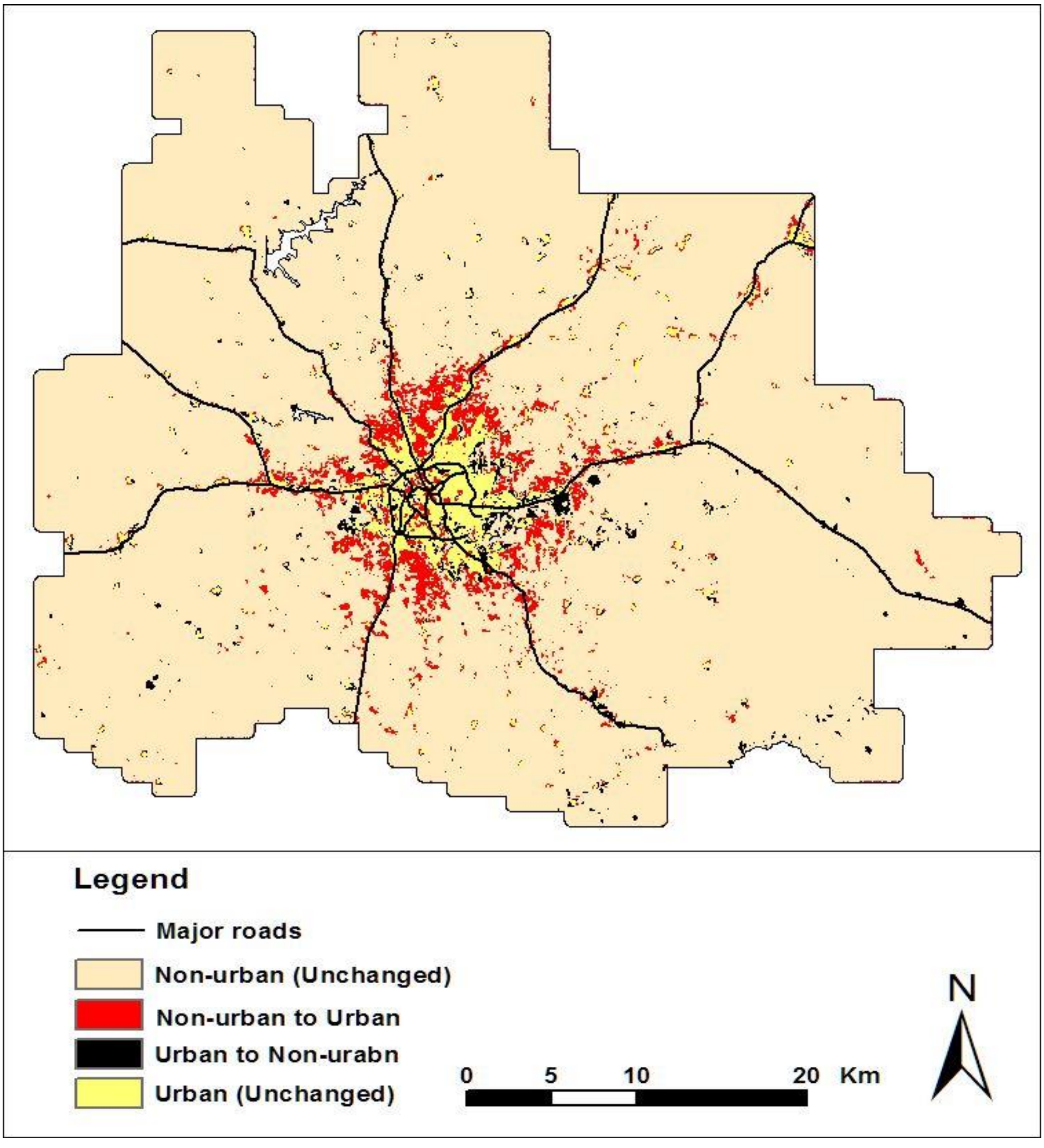


Figure 8: Conversion between land cover classes (1986-2001)

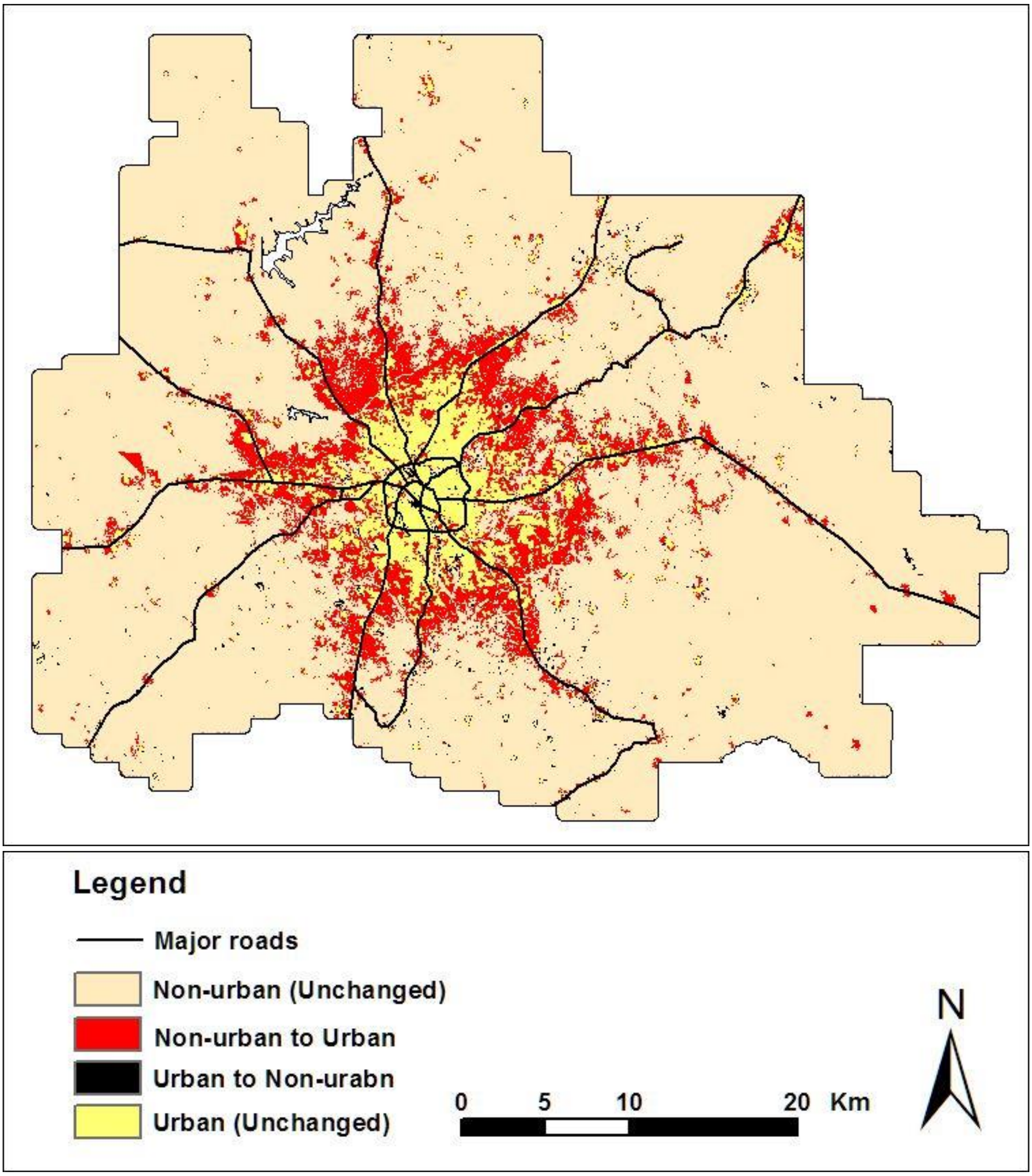


Figure 9: Conversions between land cover classes (2001-2014)

4.3. Urban growth typologies

The land cover change maps graphically show the spatio-temporal urban growth pattern of the sub-region. Three urban growth types were identified namely; infilling, edge-expansion and outlying and the respective contributions of each of them is tabulated Table 11 below. These growth types were distinguished using the Landscape Expansion Index (LPI) which computes the ratio of the shared boundary between newly grown patches to the perimeter of the previous urban footprint. Detailed explanation of how these growth types are detected is given under chapter on methodology. The three growth types are illustrated in Figures 10 & 11.

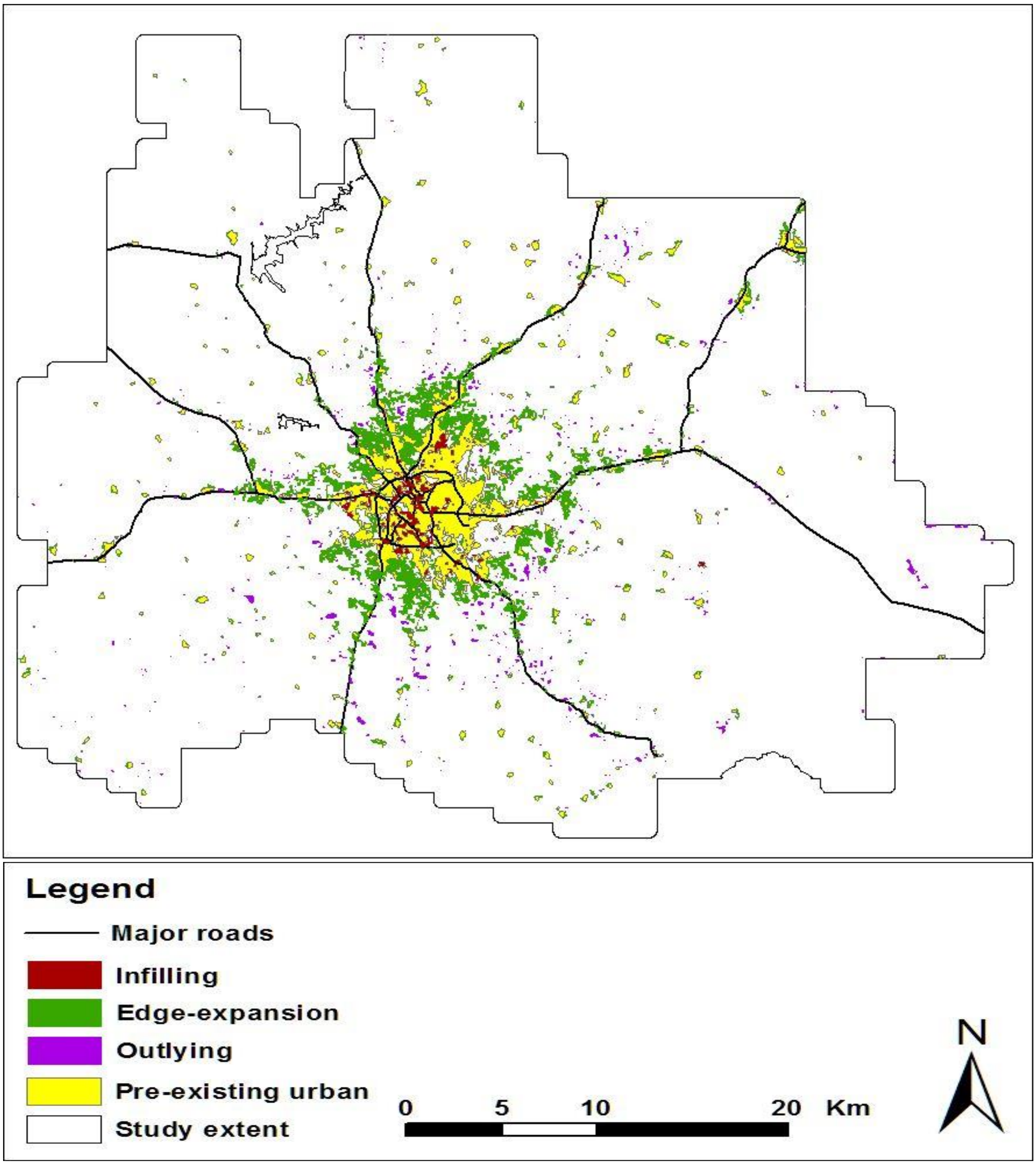


Figure 10: Urban growth typologies (1986-2001)

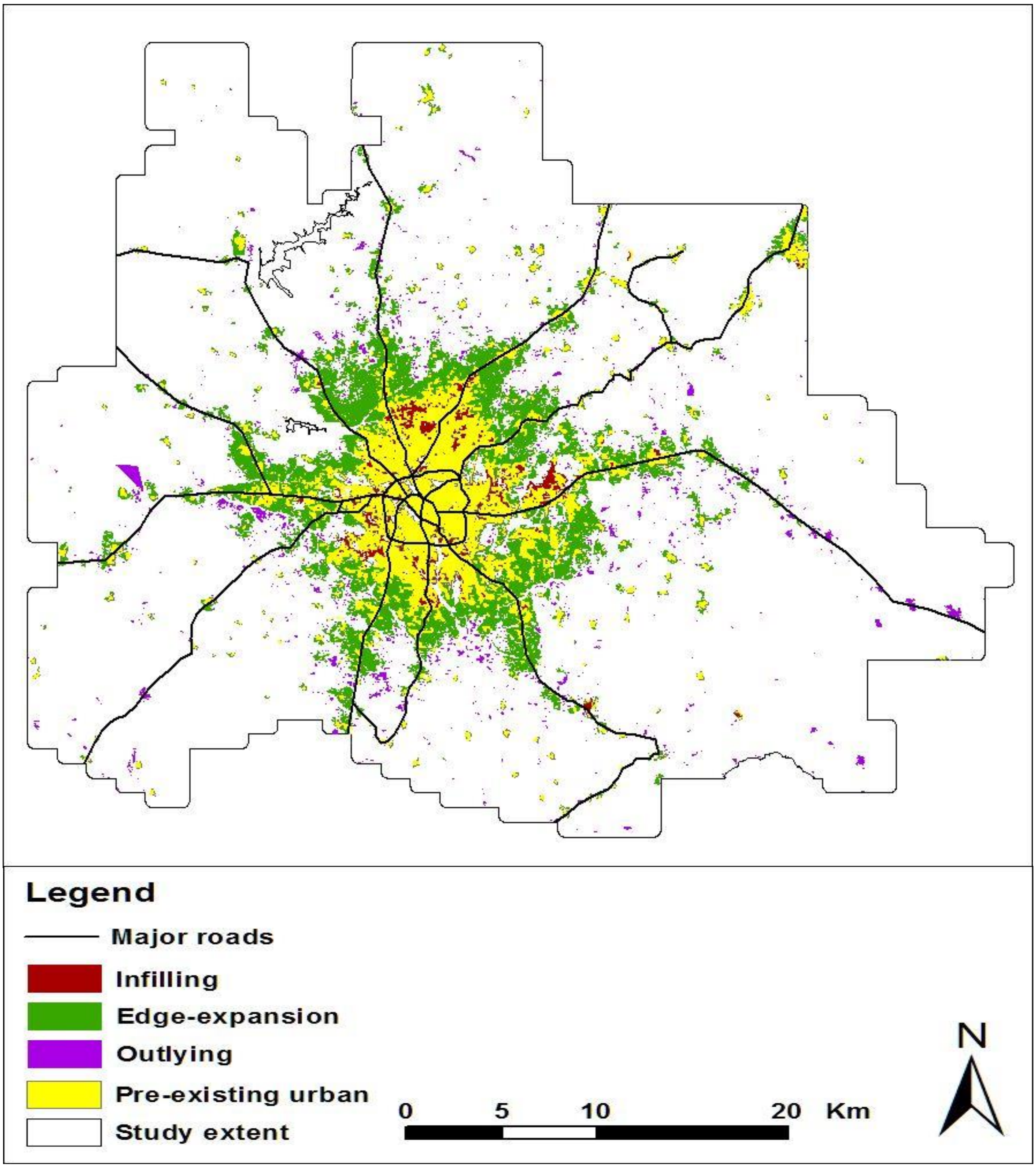


Figure 11: Urban growth typologies (2001-2014)

During 1986-2001, the total growth was 94 km² (Table 12). An area of 7km² covering 7% of the total growth occurred through infilling of vacant parcels within the urban core (Figure 10). About 78% of the growth was occurring in the form of edge-expansion and this new developments extended from the edges of pre-existing urban area and along the major transportation route. Outlying growth during the period constitutes 15% of overall urban growth. The share of the three growth types of overall growth during 1986-2001 is suggestive of the conclusion that, edge-expansion was the predominant form of growth followed by outlying and infill developments in order of magnitude. All the three types of growth more than doubled during 2001-2014 with the order of dominance in terms of contribution to overall growth still remaining the same for that period. Overall urban growth was 244 km² of which 79.5%, 12.7% and 7.8% represented the proportions of edge-expansion, outlying and infill growth respectively. In terms of absolute urban growth as well as the annual rate of change, the second time-step witnessed rapid urbanisation within a time span of thirteen years at a rate faster than that of the previous time period. This variations in growth between the time steps could largely be attributed to population growth. Available population statistics indicate that the population of Greater Kumasi Metropolitan Area grew at the rate of 2.5% per annum between 1984-2000 whereas the annual growth rate between 2000-2010 was 3.1% (TCPD, 2013).

Table 12: Growth types and their share of total growth

Growth type	1986-2001		2001-2014		1986-2014	
	km^2	$km^2/year$	km^2	$km^2/year$	km^2	$km^2/year$
Infilling	7	0.5	19	1.5	26	0.9
Edge-expansion	73	5	194	15	267	9.5
Outlying	14	0.9	31	2.4	45	1.6
Overall growth	94	6.3	244	18.8	338	26

In order to gain a deeper understanding of the spatial and temporal dynamics of urban growth, GIS-buffer analysis is used in this study which involves the creation of circular buffer zones (Figure 12) around the urban core until it completely covered the spatial extent of the study area. The geometric centre of the urban core in 1986 was used as the origin in creating the buffer zones. A width of 5km buffer interval was defined was defined to encompass the urban core, central Kumasi. Within each buffer zone the percentage of each growth type was computed and analysed to understand their gradient changing characteristics. This approach provides an understanding in growth pattern across space and time. It thus helps in identifying which locations are dominated by what type of growth.

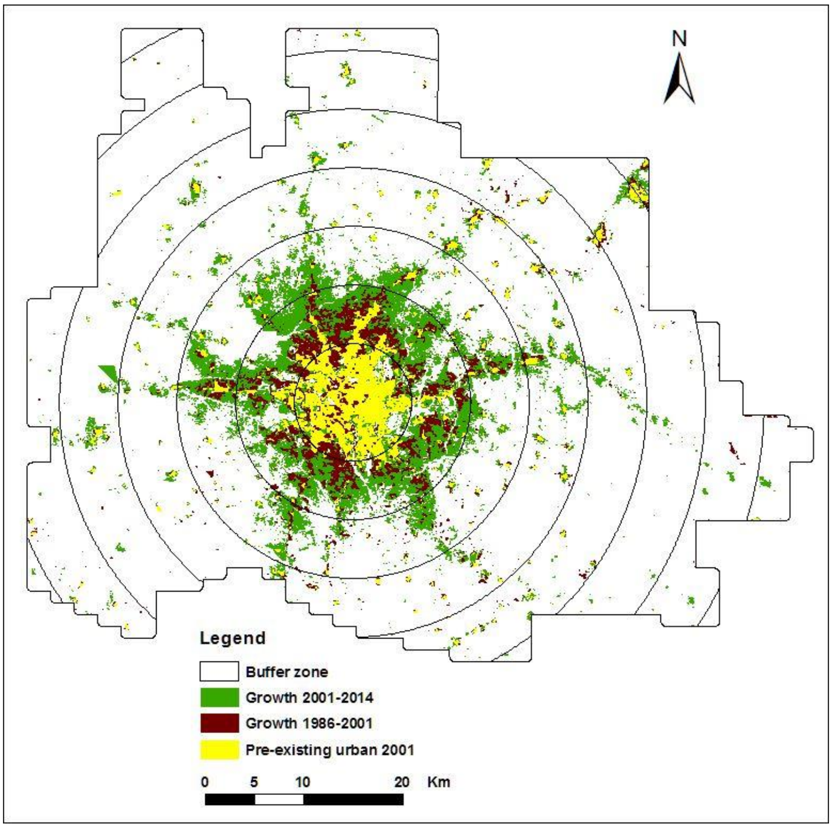


Figure 12: Multiple buffer zones of 5km interval from Kuma

Across all the 8 buffer zones and over the two time steps, each of the three growth types showed distinct patterns as clearly depicted in Fig. 13. In the first period (1986-2001), the 0-5 km buffer zone was dominated by edge-expansion (7.4km²) growth followed by infill (5.8km²) and outlying (0.08 km²) growth. As one moves away from the first zone into the second zone which is 5-10 km away from Central Kumasi, the trend changes, with infill development registering a fall of about 86% of its previous value (from 5.8km² to 0.8km²) while edge-expansion still the predominant type of growth, sharply increased by more than five times its value in zone 5 to 48 km², followed by outlying development which also recorded an increase from 0.08km² to 5.2km². Areas located within 20-35km from Central Kumasi were dominated by outlying growth followed by edge-expansion and infill development in order of dominance. After peaking in zone 10 edge-expansion started to fall but still maintained its dominance until zone 20 where outlying growth became dominant growth type.

In the second period (2001-2014) edge-expansion increased both in size and in sphere of dominance. Edge-expansion in zone 5 was 48km² during 1986-2001 and almost doubled to 90.8 km² in the period 2001-2014 within the same zone (zone 5) but this time the sphere of dominance spanned from zone 5 to zone 25 beyond which outlying dominated. It could be discerned from Fig. 13 that during the first period (1986-2001), the infill type of growth was mostly concentrated within the Central Kumasi as this is encompassed in the 5km buffer zone while the zone immediately next to zone 5 recorded the highest growth mainly through edge-expansion. However, during the second period (2001-2014) the area of infill development in zone 10 increased slightly to 10.8 km² from 0.8 km² in the previous time-span and was next to edge-expansion in terms of dominance. It can thus be reasoned that the outlying growth areas in the period 1986-2001 had grown in size by 2014 through edge-expansion and began to fuse together through the infilling of vacant lands inwards.

In general it can be inferred from the patterns across the zones that urban growth peaked in zone 10 during both periods of 1986-2001 and 2001-2014. From the first period to the second period urban growth increased in zone 15 mainly through edge-expansion. These trends in urban growth confirms the assertion of the Town and Country Planning Department that the most urbanised area in the surrounding districts in the period 1984-2010 is within 10-15 km radius from Central Kumasi (TCPD, 2013). Zone 10-15 can therefore be regarded as the hot-zone of urban growth during the period 1986-2014. It is also observed that as the time went by the sphere of influence of edge-expansion development extends into zones hitherto less developed. For instance zone 20 was dominated by outlying growth which assumed an area of 13 km² during 1986-2001 while edge-expansion and infill developments covered 3.7 km² and 0.04 km² respectively. During 2001-2014 edge-expansion was the leading growth type with an area of 19 km² while outlying growth dropped to 5. 6 km² from its initial figure of 13 km². It could be argued that much of the growth in this zone (buffer zone 20) during 2001-2014 was outward expansion of the old urban areas.

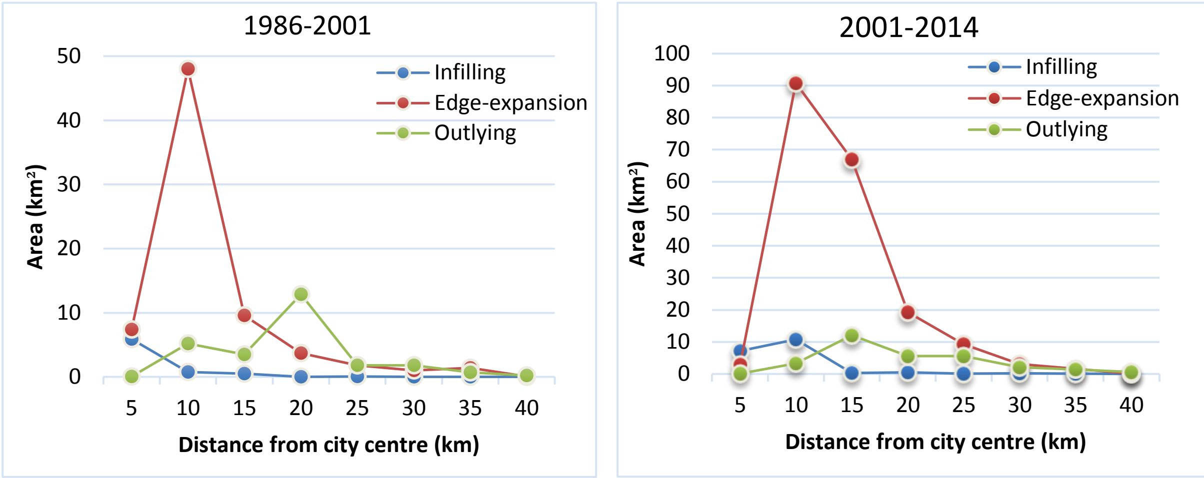


Figure 13: Proportion of urban growth across different buffer zones

4.4. Spatial metrics

Spatial metrics as quantitative indices can help quantify the spatial characteristics of a landscape. In this work, four selected spatial namely Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI) and Area-Weighted Mean Euclidean Nearest Neighbour Distance (AWMENND) are used for analysed growth patterns. These metrics have proved useful in analysing urban growth patterns in several studies such as Herold et al., (2005), Nong et al., (2014), Sun et al., (2013) and Xu et al., (2007) among others are used. The metrics were first computed for the entire study area as shown in Table 4.7 below. They were again calculated for the buffer zones to unveil the intra-urban growth patterns.

Table 13: Spatial metrics of entire study area

Year	NP	PD	LPI	AWMENND
1986	551	0.15	2.05	268.31
2001	1181	0.33	2.79	135.14
2014	3047	0.84	8.40	72.47

Table 13 shows the spatial metrics calculated for the whole study area. These metrics quantify the spatial pattern at an aggregate level relative to metrics at the buffer zone level (Figure 14). All the indices at entire landscape level have shown an upward trend over the two periods except for the Area-weighted Mean Euclidean Nearest Neighbour (AWMENND) which decreased over time. The Number of Patches (NP) in 1986 was 551 which rose through 1181 in 2001 to 3047 in 2014. The increasing number of urban patches is indicative of new urban developments over the time periods in question as new urban nuclei emerge which points to outlying growth. However the pattern in the other indices strongly suggest that these patches were growing in size over time through infilling and edge-expansion. Patch density (PD) measures fragmentation and is lowest when the landscape is dispersed (Sun et al., 2013). PD increased steadily with accelerating urban growth and this shows that urban growth is getting more and more aggregated over time. In 1986 PD was 0.15 and rose to 0.84 in 2014 from 0.33 in 2001. Patch aggregation could also be inferred from the fact that AWMENND has also registered a falling trend over time. The AWMENND in 2014 is 72.47 which represents a reduction by 50% and 46% of the AWMENND values in 1986 and 2001 respectively. The downward trend of the area-weighted Euclidean nearest-neighbour distance depicts the coalescence of urban patches. This process of coalescence could be attributed to the infilling and edge-expansion that characterise the growth of the study area. The LPI also registered an increasing trend over the periods under study and this suggest that some urban patches become fused into the dominant urban patch over time.

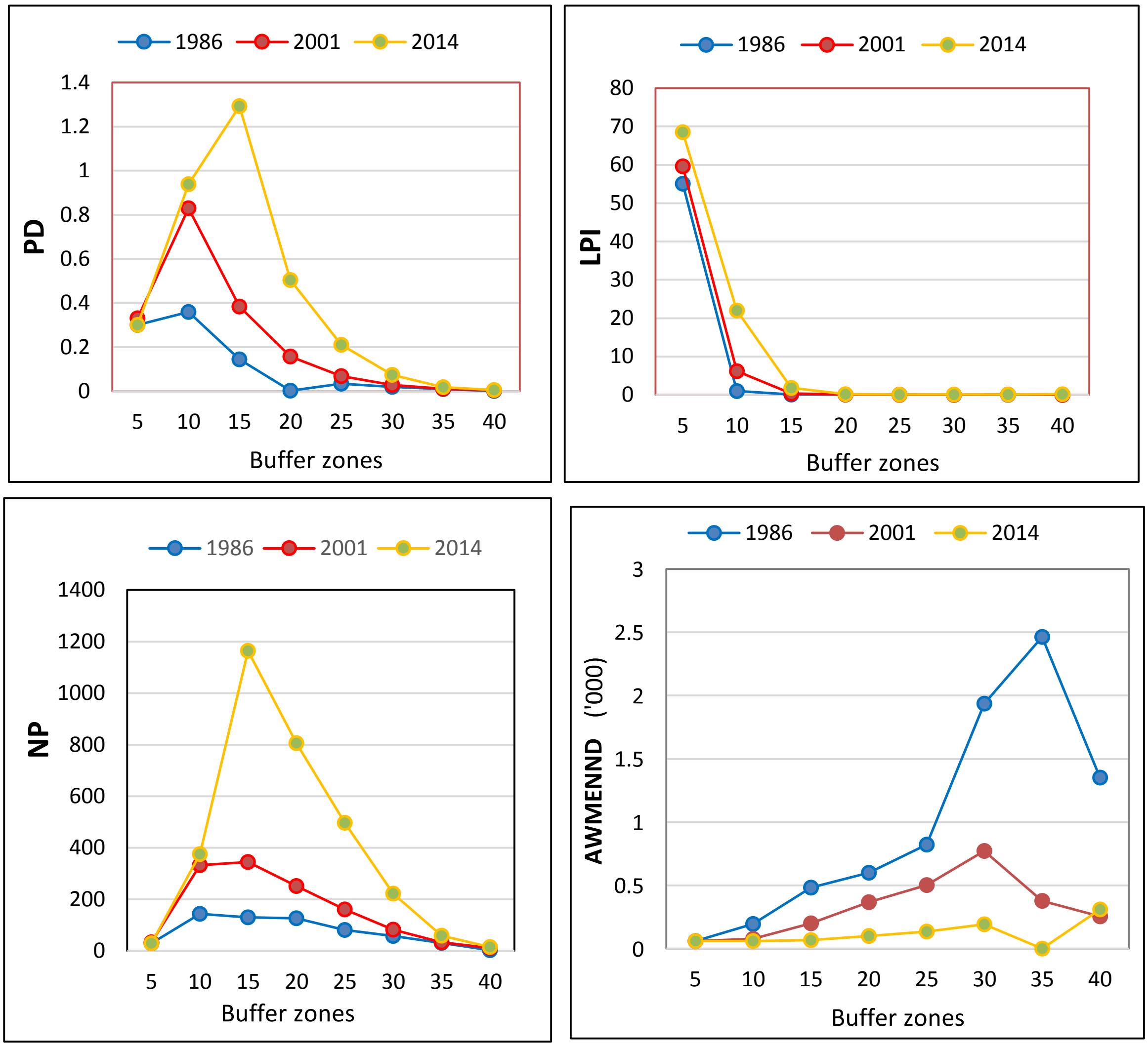


Figure 14: Spatial metrics across different buffer zones

At the buffer zone level (Figure 14), the metrics show some variations with the pattern observed at the aggregate level (that is, the entire landscape). This indicates that intra-urban variations are concealed when the metrics are computed for entire landscapes. The purpose of disaggregating the study area for spatial metric computation is to unearth these variations for a better understanding of the growth patterns. The PD of 1986, 2001 and 2014 are 0.3, 0.33 and 0.3 respectively in zone 5. PD increases, reaches a peak and then starts to decline and this trend in PD is generally the same for all the years. However within the zones differences in values of the metrics exist across the years. For instance in zone 10 where PD reached its peak across the zones for both 1986 and 2001, The PD values were 0.36 and 0.83 for 1986 and 2001 respectively. The upward trend of the PD value over this period could be linked to increase in number of patches from 144 in 1986 to 332 in 2001. The increase in PD is an indication patch aggregation as evidenced in the dominance of edge-expansion (see Fig. 13) in this zone. Between 2001 and 2014 the PD had risen from 0.83 to 0.94 (in zone 10). During this period the predominant form of growth continued to be edge-expansion except that infilling this time superseded outlying growth and this could explain why LPI increased from 6.2 to 22 during the period (2001-2014). Thus following the outward expansion between 1986-2001, infill growth filled some of the vacant land inwards. In 2014 both PD and NP peaked in Zone 10-15 scoring 1.3 and 1164 respectively. The predominant growth in this zone between 2001-2014 still remained edge-expansion.

The AWMENND across all the zones for 1986 were higher than their counterparts in 2001 and 2014. The AWMENND is an index of landscape configuration and it deals explicitly with the relative locations and arrangements of patches. Thus the decreasing trend observed over time across the zones is an indication of either edge-expansion or infill or both. Also for each of the years under investigation it could be seen that the AWMENND generally tends to increase with distance away from the city centre. This points to the more compact and dense development of the city which decreases as distance from the city centre increases. This trend could be attributed to the fact that proximity to Central Kumasi matters to businesses and commuters which in turn result from the fact that Central Kumasi is the dominant socio-economic centre in the entire region. Residents and economic activities therefore tend to locate as close as possible to Central Kumasi.

4.5. Results of logistic regression models

This section presents the results from the logistic regression models. The regression analysis in this study is conducted for two time steps namely 1986-2001 and 2001-2014. The number and type of independent variables used for each of the two time steps is not exactly the same due to unavailability of data. It should also be noted that there are some independent variables used for both time steps but with varying levels of information content such as distance to major roads, distance to existing urban cluster and proportion of urban area in a 7x7 cell neighbourhood. Distance to CBD is however the same for the two time periods. Table 14 below shows the list of variables used in the models. The factor maps used in generating the model results are shown in in Figures 16 &17

Table 14: List of independent variables

Variable	Meaning	Nature of variable
Y	Dependent variable	Dichotomous (urban=1, Non-urban=0)
X_1	Population density	Continuous
X_2	Proportion of urban area in a 7x7 neighbourhood	Continuous
X_3	Distance to CBD	Continuous
X_4	Distance to major roads	Continuous
X_5	Distance to sub-urban centres	Continuous
X_6	Slope	Continuous
X_7	Distance to urban cluster	Continuous
X_8	Rivers/streams	Dichotomous (presence-1; absence-0)
X_9	Educational landuse	Dichotomous (presence-1; absence-0)

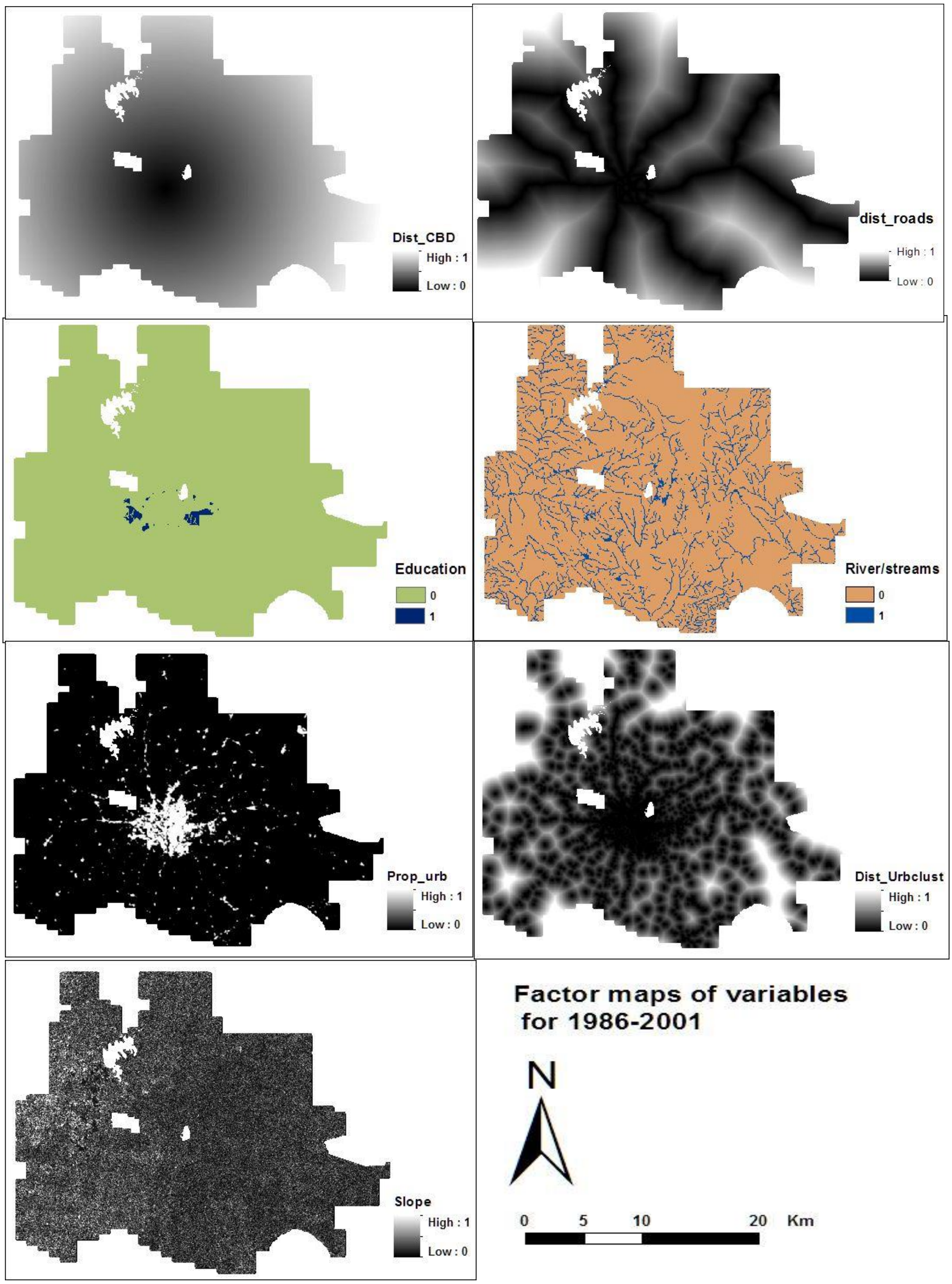
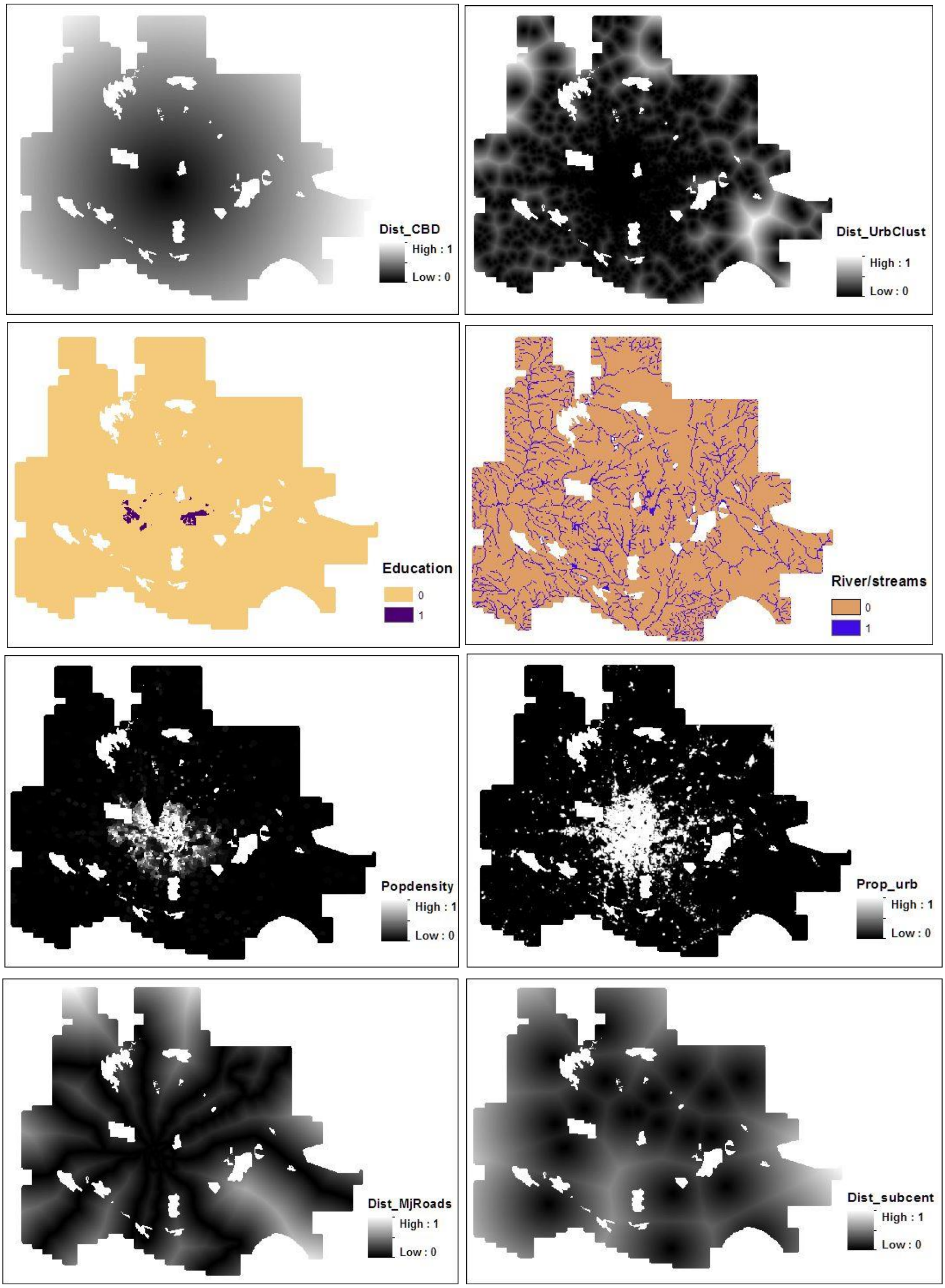
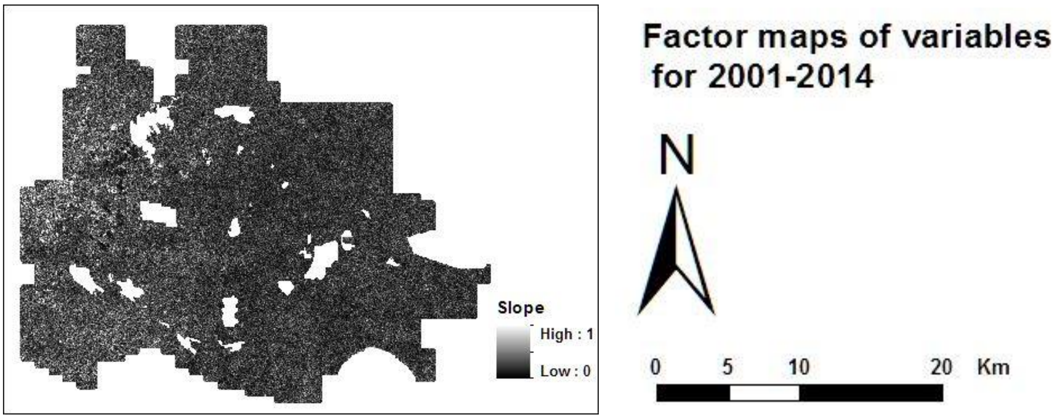


Figure 15: Factor maps 1986-2001

Figure 16: Factor maps 2001-2014





4.6. Multicollinearity check

As mentioned earlier, presence of collinearity among the independent variables could result in misleading estimates of coefficients of independent variables. Variance Inflation Factors (VIFs) was computed for all the variables in SPSS. The aim is to eliminate variables with very serious levels of collinearity. The results are shown in Tables 15 below. The results indicate that none of the independent variables is highly correlated with the other as shown by their respective VIFs. All the variables have a VIF of less than 10. A VIF>10 is a cause for concern and variables with VIF in this range should be eliminated in any regression model. The fact that all the variables considered scored a VIF<0 is an indication each of these independent variables uniquely contributes to the outcome variable.

Table 15:Results of multicollinearity diagnostics

Variable	Meaning	VIF (1986-2001)	VIF (2001-2014)
X_1	Population density	*	1.210
X_2	Proportion of urban area in a 7x7 neighbourhood	1.058	1.222
X_3	Distance to CBD	1.433	2.144
X_4	Distance to major roads	1.217	1.376
X_5	Distance to sub-urban centres	*	1.473
X_6	Slope	1.005	1.008
X_7	Distance to urban cluster	1.302	1.466
X_8	Rivers/streams	1.001	1.004
X_9	Educational land-use	1.026	1.041

*Variable not available for the time step

4.7. Model results

1986-2001 Model (Model A)

Model summary: Log likelihood = -70684.3769, PCP = 96.32%, p-value = 0.0000, Sample size = 101976
Overall Model Fit: Chi-square = 120570.4401, df = 21, Confidence Interval = 95%

Table 16 gives a summary statistics of the relevant model parameters. All seven independent variables are statistically significant at α = 0.05 since each has a p-value < α. From the seven variables, all the independent variables, distance to CBD(X_3), distance to major roads (X_4), slope (X_6), distance to urban cluster (X_7) , rivers/streams (X_8), educational land use (X_9) with the exception of (X_2) (i.e. the proportion of urban land in a 7x7 neighbourhood) have a negative relation to urban growth due to their negative coefficients. For variables which have a positive correlation with urban growth, an increase in their values will cause more growth to occur. The opposite is true for variables which have a negative relation with growth. The variable, proportion of urban land (X_2) has a positive coefficient which indicates that then an increase in the value of this variable contributes to the growth of the sub-region during the time period under discussion (1986-2001).

Table 16: 1986-2001 Model parameters

Variable	Coefficient	Standard error	z-value	T-test (p)	Odds ratio (O.R)
Constant	1.9036	-	-	-	-
X_2	3.478639	0.192021	18.115940	0.0000	32.415566
X_3	-8.566252	0.166796	-51.357760	0.0000	0.000190
X_4	-3.341958	0.194654	-17.168687	0.0000	0.035368
X_6	-3.128251	0.504418	-6.201699	0.0000	0.043794
X_7	-14.436409	0.447170	-32.283927	0.0000	0.000001
X_8	-1.165402	0.075655	-15.404100	0.0000	0.311797
X_9	-2.582380	0.171278	-15.077156	0.0000	0.075594

2001-2014 Model (Model B)

Model summary: Log likelihood = -66551.8334, PCP = 92.44%, p-value = 0.0000, Sample size = 96014 Overall Model Fit: Chi-square = 95411.9424, df = 27, Confidence Interval = 95%.

In Table 17 below, all the independent variables are statistically significant at α = 0.05 since each of them records a p-value < α. In this model, population density (X_1) and proportion of urban land in a 7x7 cell neighbourhood (X_2) have are directly related with urban growth. The rest, distance to CBD (X_3), distance to major roads (X_4), distance to suburban centres (X_5), slope (X_6), distance to existing urban cluster (X_7), rivers/streams (X_8) and educational land use (X_9) are inversely related with urban growth.

Table 17: 2001-2014 Model Parameters

Variable	Coefficient	Standard error	z-value	T-test (p)	Odds ratio (O.R)
Constant	2.7169	-	-	-	-
X_1	56.093934	4.352708	12.887135	0.0000	2.298E+24
X_2	3.718815	0.168669	22.048058	0.0000	41.215540
X_3	-7.050380	0.118137	-59.679593	0.0000	0.000867
X_4	-5.132515	0.157398	-32.608503	0.0000	0.005902
X_5	-0.849203	0.103322	-8.218993	0.0000	0.427756
X_6	-1.141389	0.334162	-3.415678	0.0000	0.319375
X_7	-9.858499	0.269642	-36.561455	0.0000	0.000052
X_8	-1.102231	0.049762	-22.150075	0.0000	0.332129
X_9	-1.165330	0.098015	-11.889310	0.0000	0.311820

4.7.1. Model interpretation and discussions

The fitted models' estimated coefficients and their respective odds ratios are indispensable in the interpretation of the models. The estimated coefficient of an independent variable in logistic regression represents the expected change in the log odds of the outcome variable per unit increase in the value of the independent variable, keeping all other variables constant at a certain value. Mathematically, the exponential function of the regression coefficient is the odds ratio with one unit increase in the associated independent variable. The relative contributions of each independent variable is examined the coefficients and the associated odds ratio. A variable with an odds ratio of 1 means that an increase/decrease in its value has no effect on the outcome variable and such a variable should be eliminated. A variable with an odds ratio of less than 1 indicates that with an increase in its value the odds of the outcome occurring will decrease. An odds ratio of greater 1 means that the odds of the outcome happening will increase following an increase in value of the said independent variable. Odds ratios less than 1 are difficult to interpret and can be misleading. An odds ratio of less than one is only an indication that the odds of the outcome occurring will decrease following a unit increase in the independent variable. It does not tell by how much the odds of the outcome will decrease. Based on this, (Osborne, 2006) recommended that analyses be based on odds ratios greater than 1 by taking the inverse of the odds ratio and reversing the interpretation of the results.

Andresen (2009) argues that the odds ratio is a measure of relativity and does not tell anything about absolute change in the outcome variable. It is therefore difficult to determine among a list of independent variables, which one of them has the highest influence on the outcome variable based only on odds ratio. Andresen therefore suggested that, both relative and absolute effects should be accounted for to make a complete analysis. This can be ensured by complementing the odds ratios with the respective coefficients. The estimated coefficients indicate the change in log odds as a result of a unit increase in the independent variable. The coefficients thus give an indication of the magnitude of change of the outcome variable following a unit increase in the independent variables. This study therefore combines the two to give a better interpretation and discussion of the models' results.

Model A

In the model the variable, proportion of urban land within a 7x7 cell window (X_2) is the only variable with O.R > 1 and also doubles as the variable with the highest odds ratio. From Table 4.7 above X_2 has an estimated coefficient of 3.479 and an associated O.R of 32.416 which are the highest of all the 7 variables. This is an indication that variable X_2 in comparison to the rest, made the highest contribution to urban growth during 1986-2001. The O.R of X_2 could be interpreted as follows: an increase of one urban cell in the neighbourhood (7x7 cell window) would correspondingly increase the odds of urban growth by 31.416. The three growth typologies that have been identified and quantified for the period under investigation (1986-2001) also confirms the model results. It can be recalled that the major growth type during this period was edge-expansion. This and the infill growth type only occur in an area surrounded by an existing built-up area. Hence, the presence of these growth typologies could in part be linked to this factor (X_2).

From the model it could be deduced that urban growth has a high probability of occurring in close proximity to CBD as shown by the O.R recorded for this variable. The model showed the variable, distance to CBD (X_3) with an O.R of 0.000190 or $1/5263.2$ .This means that the likelihood of urban growth in an area closer to the CBD is estimated as 5263.2 times the odds of urban development in an area which is a unit distance further away from the CBD. Distance to CBD is negatively related with urban growth because of its negative coefficient (-8.566252). The coefficient suggests that the log odds of urban growth occurring will reduce by 8.566252 with a unit increase in distance away from the CBD. Expressed another way, a unit decrease in distance from the CBD will result in an increase in log odds of urban growth occurring by 8.566252. The CBD hosts major services and key economic centres such as the Kejetia/central market, Adum shopping centre within the sub-region. The CBD is also a major centre of employment. These features make the CBD and areas closer to it more attractive for development. People and businesses therefore tend to locate within the CBD or closer to it.

Distance to major roads (X_4) is one of the variables which is negatively associated with urban growth. This variable has an odds ratio of 0.035368 or 1/28.27. This indicates that the farther away from the CBD the less probable an area is to be developed. In other words, the probability of urban growth in an area closer to a major road is 28.27 times as high as the probability of growth in an area which is a unit distance further away from a major road. The estimated coefficient of this variable is-3.341958 indicating that an increase in log odds of urban growth will be associated to a unit decline in distance to major roads. The role of proximity to major roads in the growth of Greater Kumasi is evidenced by the orientation of its physical expansion. Development tends to follow the axial pattern of the main transport routes.

Slope (X_6) has been identified by the model to be negatively related with urban growth. This factor has an O.R of 0.043794 (1/22.8342) with an estimated coefficient of -3.128251. This indicates the odds of growth in an area with a 1 percent decrease in slope is 22.8342 times as high as the odds of growth in an area with a unit increase in slope. A unit reduction in slope will cause log odds of urban growth to increase by 3.128251

Distance to existing urban cluster (X_7) has the largest negative relation to urban growth with O.R of 0.000001 (1/1000000). This indicates the high tendency for urban growth to be located in close proximity to existing built-up areas. The O.R demonstrates that the odds of urban growth in an area closer to existing urban cluster is 1000000 times as high as that of an area which is a unit distance further away from the existing built-up. The coefficient of X_7 is -14.436409 and this in absolute terms is greater than coefficients of the remaining variables. The value of the coefficient means that a unit increase in distance away from the existing urban area will decrease the log odds of urban growth by 14.436409 and the vice versa. This factor could be linked to the edge-expansion and infilling types of growth which identified during the 1986-2001 period. The reason being that these forms of growth occur in an area already surrounded by some proportion of existing built-up.

Two of the variables namely, rivers/streams (X_8) and educational land use (X_9) are dichotomous and both are inversely related to urban growth due to their negative coefficients. The odds ratios of the two variables are 0.311797 (1/3.207215) and 0.075594 (1/13.228563) respectively. Their odds ratios with imply that the odds of urban development will reduce on waterways and educational land compared to otherwise. In the case of rivers/streams the probability of urban growth on areas without river/stream is 3.207215 times as large as the probability of growth on river/streams. The odds of development on non-educational land is estimated as 13.228563 as large as the odds of growth on educational land. The statistics presented here show that physical development on rivers/streams and areas zoned for education is restricted. Developments however takes place in both cases. Developments occur on educational lands but this is controlled and regulated by authorities of these institutions. Physical development within 100 metre buffer around rivers/streams is outlawed. Despite this, developments are occurring in this prohibited zone. This is one of the main causes of flooding in the study area since the illegal developments block waterways. Campion (2012), noted that, flooding in the flood prone neighbourhoods of the sub-region particularly Kumasi is the result of the physical expansion of built up areas into lands hitherto regarded as wetlands.

Model B

With the exception of population density (X_1) and proportion of urban land (X_2), the rest of the independent variables are negatively related to urban growth. This model includes two variables which were not considered in model A. They are population density (X_1) and distance to suburban centres(X_5). The rest ($X_2, X_3, X_4, X_6, X_7, X_8, X_9$) are the same as the ones used in model A except factor updates in some of the variables such as proportion of urban land (X_2), distance to major roads (X_4) and distance to urban cluster (X_7). The role factors with negative association to urban growth in model B is the same in principle as that of A. For this reason, only the new variables will be discussed here.

Population density (X_1) is a key driver of urban growth in the study area as can be seen in Table 17. This view is shared by the experts that were interviewed (Appendix A) on the growth of the sub-region. The odds of urban growth will increase by 2.298E+24 times following a unit increase in population density. A unit increase in population density is expected to increase the log odds of urban growth by 56.093934. In the study of Oduro et al. (2014), they found that population density was directly linked to urban growth in the sub-region. Among the nine factors considered in the period 2001-2014, population density possesses the highest odds ratio and estimated coefficient and therefore contributes more to the sub-region's growth than the rest.

The model results (Table 17) indicate that proximity to suburban centres is indeed driving urban growth. Distance to suburban centres (X_5) is negatively linked with growth with an O.R of 0.427756 ($1/2.3378$) and this implies that the odds of having urban growth a unit distance closer to suburban centre is 2.3378 times as higher as the odds of growth a unit distance further away.

Comparison of models A and B

The comparison here is based on the factors which the two models have in common. In model B, Proportion of urban land in a 7x7 cell neighbourhood (X_2) rates second in terms of contribution to urban growth. This factor has an estimated coefficient of 3.718815 and a corresponding odds ratio of 41.215540 ($1/0.024263$) signifying that for an additional urban cell within the neighbourhood, the odds of growth will be 41.23 times as high as the likelihood of growth in a neighbourhood with a one unit reduction in urban cell. The factor , X_2 in both models is positively related with urban growth and has increased in importance over time as can be seen in the increase in both coefficient and odds ratio of the variable over the two time steps . That is, the factor witnessed an increase in estimated coefficients from 3.478639 (in model A) to 3.718815 (in model B) and a corresponding increase in O.R from 32.415566 (in model A) to 41.215540 (in model B). This factor has a relation with edge-expansion and infilling discussed earlier. Edge-expansion more than doubled over the two periods (see Table 12) and as this type of growth continues to dominate, the factor, X_2 will accordingly continue to be relevant in driving urban growth.

Proximity to CBD as shown by X_3 , continued to exert influence on urban growth. With an O.R of 0.000867($1/1153.4$), the probability of urban growth on a non-urban cell closer to CBD is 1153.4 times as large as the probability of growth on a cell a unit distance further away from the CBD. Though proximity to CBD continue to drive urban growth, its contribution to urban growth has declined over time. For instance the period 1986-2001 the likelihood of urban growth in an area closer to the CBD was 5263.2 as large as the odds of growth in an area a unit distance further away from CBD. This compared to the situation in 2001-2014 shows a decline in the contribution of factor X_3. The absolute value of the coefficient of X_3, in model A is 8.566252 which declined to 7.050380 in model B. One of the reasons that could be attributed to this decline in contribution to growth is the emergence of new suburban centres during 2001-2014. By the year 2000 new suburban centres emerged in the surrounding districts of Central Kumasi following the spatial expansion of Kumasi's built up area into these districts (TCPD, 2013). These sub-centres are mainly playing the role of dormitory towns and are therefore desirable locations for residential developments for low-income immigrants/indigenes who cannot afford land in the CBD. Other factors such as land speculations and some negative locational attributes of Central Kumasi such congestion have made these sub-centres prime locations for development (Acheampong & Anokye, 2013).

Model A suggests that with a 1 percent fall in slope the odds of urban growth will be 22.8342 as high as the likelihood of growth in an area with 1 percent increase in slope. In model B however, the odds of growth occurring is shown in an area with a 1 percent decrease in slope to be 3.1311(1/0.319375) as large as otherwise. The absolute value of the estimated coefficient for slope (X_6) for model A is 3.128251 which falls to 1.141389 in model B. It can be inferred from the two models that, physical developments during 1986-2001 was taking place on areas with relatively gentle slopes. The 2001-2014 period witnessed a very rapid and massive expansion urban expansion in the Greater Kumasi Sub-Region. This explained why the absolute value of the slope's coefficient reduced from 3.128251 (in 1986-2001) to 1.141389 (in 2001-2014) indicating that as relatively flat slopes are occupied by urban expansion, new developments tend to spread into areas hitherto not developed probably due to their hilly terrain. The views of expert on influence of slope however seems to contradict the models' results as they hold that slope is insignificant in driving urban growth. This view cannot be entirely accepted neither can it be holistically rejected. The topography of the study area is undulating with a slope that rarely exceeds 7.5% (Brook & Dávila, 2000). Expert views on the influence of slope is based on the observation that physical development generally appear to be occurring on all fronts of the terrain. Since statistical models deal with quantities, they have the ability to capture subtle relations which such generalisations fail to capture. Therefore, based on the model results, this study argues that the slope of the terrain in the study area has a significant relation with its physical growth though it has declined over the two time steps under study.

Urban growth as depicted in model B, similar to model A, continues to be driven by proximity major roads and existing urban cluster. In model B, distance to major roads (X_4) have odds ratios of 0.005902 (1/169.434) compared 0.035368 or 1/28.27 in A. This shows an increase in the level of influence of X_4 on urban growth in the 2001-2014 period. The coefficients of X_4 in the two models (A & B) support this assertion. As the built-up area of the sub-region expands it mimics the axial layout of the major roads (see Fig. 4.3 and Fig. 4.4) thereby confirming the model's results and experts assertion that proximity to major roads is a significant driver of growth.

Proximity to existing urban cluster (X_7) also decline in role with odds ratio of 1000000 (1/0.000001) in model A as compared to 19230.77 (1/0.000052) in model B. The coefficients also decreased in absolute terms from 14.436409 in model A to 9.858499 in B. This trend in X_7 over the time steps as noted earlier could be attributed to the emerging role of suburban centres in urban growth.

Educational land use (X_9) and rivers/streams (X_8) remain negatively related to urban growth in model B as in model A. However, there have been some changes in odds ratios over the time-steps under study. Factor X_8 has an odds ratio of 0.332129 (Table 4.8). This indicates that the odds of urban growth occurring on areas other than rivers/streams is 3.011 (1/0.332129) as large as the odds of development occurring on rivers/streams. In model A, the odds of urban growth on non-river/stream areas is estimated as 3.2072 (1/0.311797) times more likely than on a river/stream. Factor X_9 in model B has odds ratio of 0.311820 (1/3.207) indicating that the odds of development on non-educational land is 3.207 as large as the odds of growth on area earmarked for educational use. In model A, the odds of urban growth on a non-educational land is shown to be 13.2286 (1/0.075594). The coefficient of factor X_9 in absolute terms in model A is 2.582380 compared 1.165330 in model B. This decline in the absolute values of the coefficients could mean that friction to development on educational land has reduced over time especially in light of the fact that educational institutions keep developing new infrastructure to meet growing demand.

Table 18 below presents the urban growth drivers in the two time steps in order of importance. Each of the variables has two possible dimensions, that is, increasing or decreasing values in the case of the continuous variables and presence and non-presence in the case of the dichotomous variables. Since the focus of this research is to study the factors driving urban growth, the ranking of the variables is done considering only that dimension of the factor which drives growth. For instance it is found the closer to the CBD the more likely growth is to occur. Hence distance is ranked based on the odds ratio and coefficient associated with a unit decrease in distance to the CBD. The ranking of the rest of the variables is based on this principle.

Table 18: Ranking of driving forces of growth

Period	Meaning	Rank	Direction of influence
1986 To 2001	Distance to urban cluster	1st	Negative
	Distance to CBD	2nd	Negative
	Proportion of urban cells in a 7x7 neighbourhood	3rd	Positive
	Distance to major roads	4th	Negative
	Slope	5th	Negative
	Educational land use	6th	Negative
	Waterways	7th	Negative
2001 To 2014	Population density	1st	Positive
	Distance to urban cluster	2nd	Negative
	Distance to CBD	3rd	Negative
	Distance to major roads	4th	Negative
	Proportion of urban cells in a 7x7 neighbourhood	5th	Positive
	Slope	6th	Negative
	Educational land use	7th	Negative
	Zoning (waterways)	8th	Negative
	Suburban centres	9th	Negative

Generally, from the ranking above the distance to urban cluster, distance to CBD, distance to major roads and the proportion of urban cells in 7x7 neighbourhood which are common to both time periods have remained among the top four drivers of urban growth in both cases though with varying order of ranking. Population density is ranked they most important driver in the second period. The significance of these aforementioned driving forces therefore statistically confirms expert opinions (see Appendix A) regarding the significant drivers of Greater Kumasi's growth. The difference between the models' results and expert views lies in the influence of slope, suburban centres and zoning (rivers/streams) to the growth of the sub-region which experts think do not have a significant impact on growth while the study results suggest the contrary.

4.8. Model evaluation and validation

Validation is the assessment of the predicted modelling results (Lesschen et al., 2005). Evaluating the model's predictive capacity builds confidence in the model. This study uses Kappa and Percentage of Correct Predictions (PCP) for evaluating the performance of the models.

PCP

The PCP is computed in Change Analyst. The tables below (Table 4.9 and Table 4.10) show the PCP values for the two models.

Table 20: Model evaluation results (Model A)

	Predicted			
		0	1	Total
Observed	0	2392163	46814	2438977
	1	79882	121118	201000
	Total	2472045	167932	2639977

Correct Prediction : 2513281
Wrong Prediction : 126696
Percentage of Correct Prediction (PCP) : 95.20%

Table 19: Model Evaluation results (Model B)

	Predicted			
		0	1	Total
Observed	0	2063012	50850	2113862
	1	145842	303250	449092
	Total	2208854	354100	2562954

Correct Prediction : 2366262
Wrong Prediction : 196692
Percentage of Correct Prediction (PCP) : 92.33%

For the purposes of validation the models were used to predict the actual situation of the end year. Model A and B were used to predict the growth of 2001 and 2014 respectively to validate their performance for trend extrapolation. The maps were compared in Map Comparison Kit for validation (see output in Fig. 4.11). The comparison of Model A with actual situation resulted in overall kappa value = 0.63, kappa for location (k_{loc}) = 0.69 and Kappa for quantity (k_{Histo}) = 0.91. The results for model B are: overall kappa value = 0.73, kappa for location (k_{loc}) = 0.77 and Kappa for quantity (k_{Histo}) = 0.94. The overall kappa value in both cases is higher than 0.5 and this shows that the models' predictive capacities are representative of the reality simulated and hence satisfactory for land use modelling (Pontius, 2000). On the basis of the kappa statistics model B is the best model compared A since it has a higher kappa value.

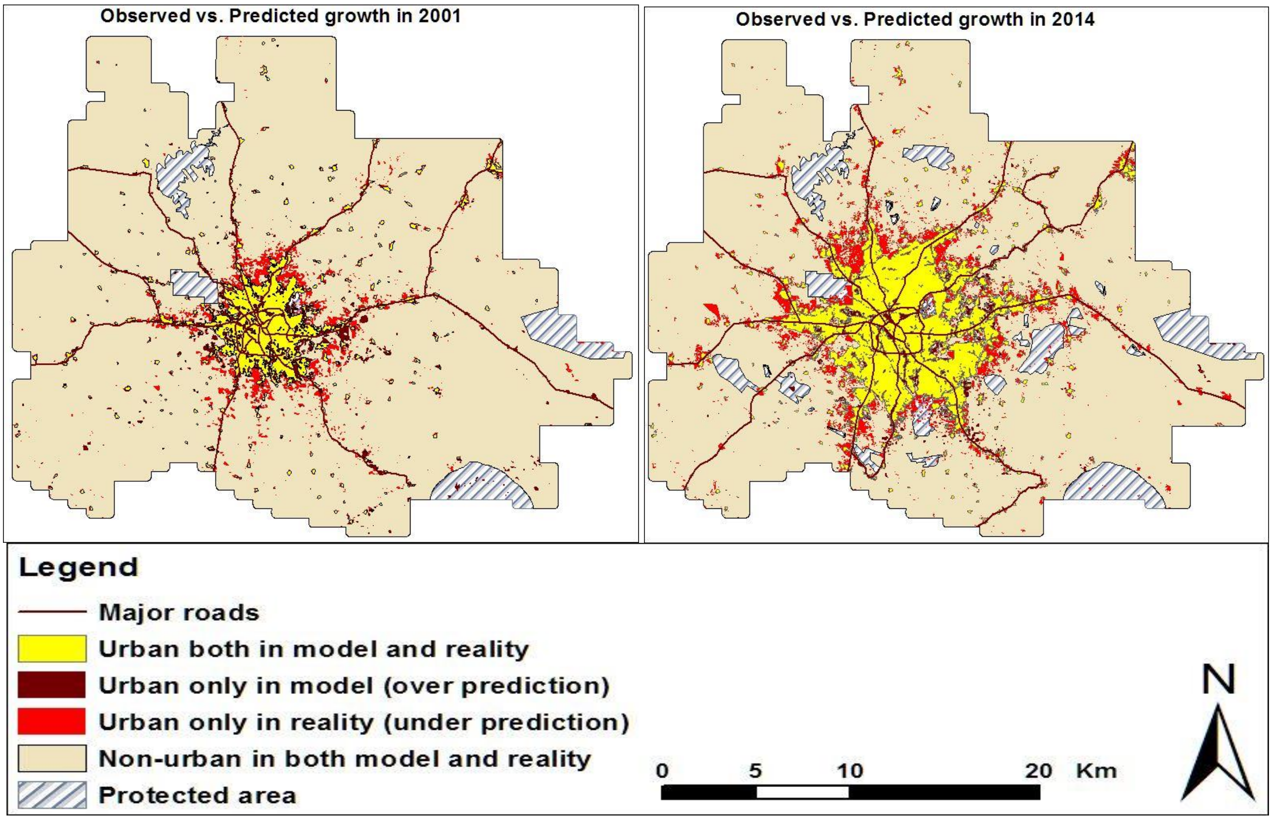


Figure 17: Model prediction vs. reality

Figure 18 above shows that, the models fall short in the cases of over-prediction and under prediction. This is to be expected as models are a simplification of real life which no model can ever mimic to the minutest detail.

4.8.1. Probable areas of future urban growth

Future areas of urban growth have been simulated based on model B. The factor maps for model B and their respective estimated coefficients including the model's constant were used to calculate an urban growth probability map which depicts the probabilities of urban growth occurring on a cell in the future. The probability map (Figure 19) is reclassified into five classes to distinguish between which areas have a high tendency for growth than others. The probability map shows high tendency for new physical developments to be located within the urban core and this tendency registers a declining trend with increasing distance from the core area. As can be observed from Figure 20, urban growth is expected to be located closer to major roads. This is in line with the finding that urban growth is driven by proximity to major roads.

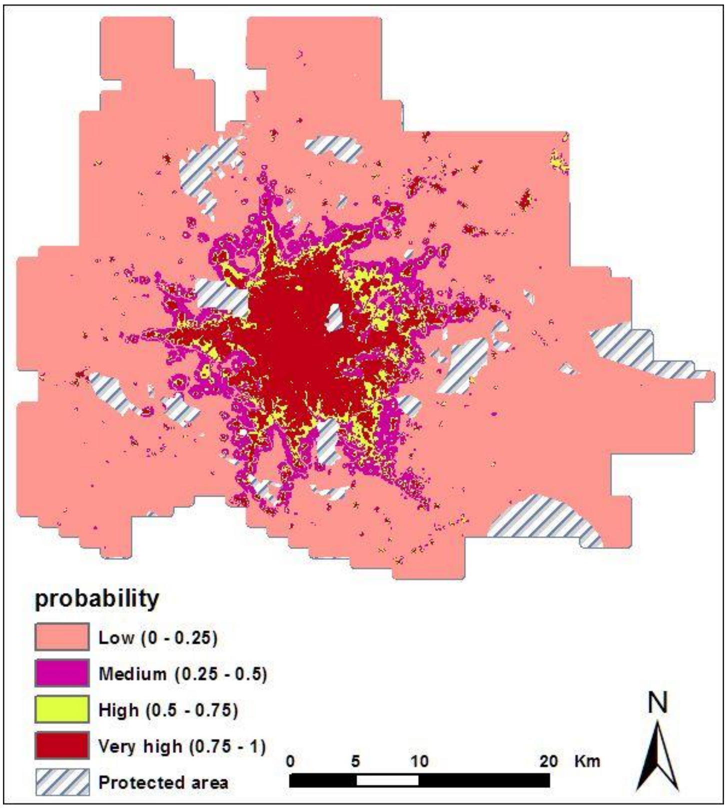


Figure 18: Urban growth probability map

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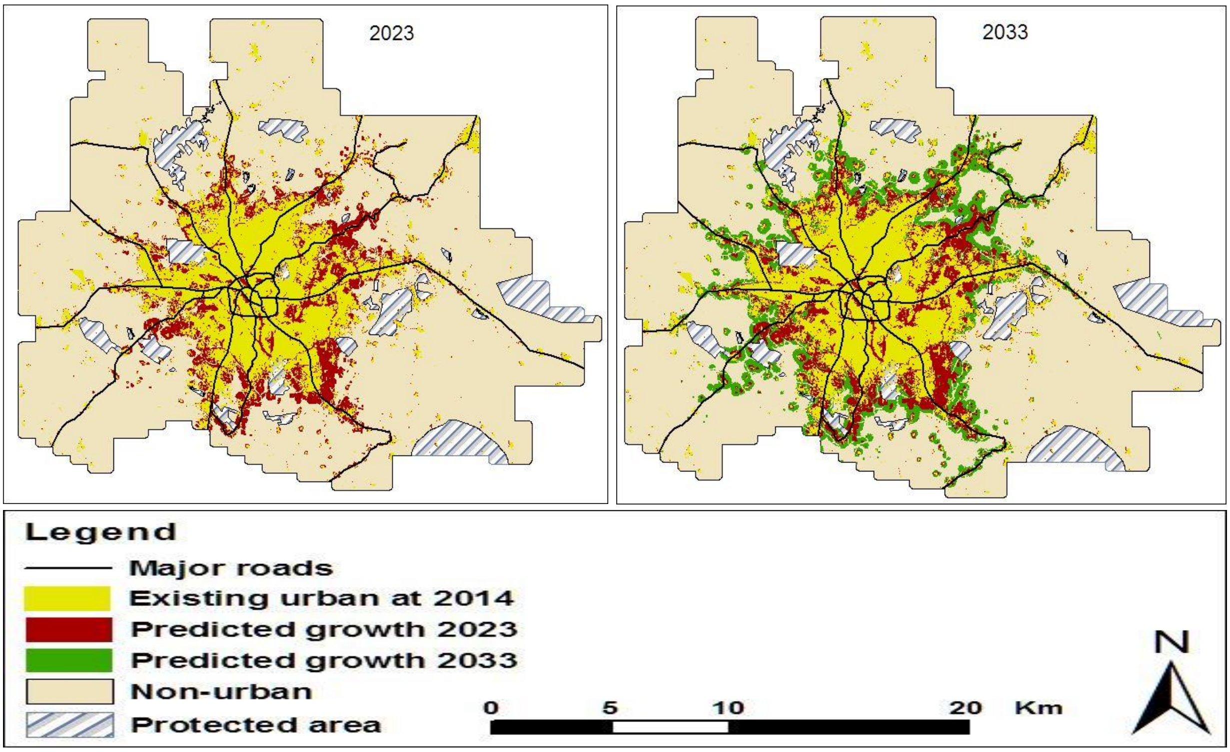

Figure 19: Probable areas of future growth

4.8.2. Influence of public investment on urban growth

The model results as explained earlier have shown that public investments such as roads have an influence on urban growth. This means that planned public investments on roads can be expected have an influence on the growth of the sub-region. As part of the 2013-2033 Comprehensive Urban Development Plan for Greater Kumasi, there a number planned road projects to be carried out during the period. These include a new Outer Ring Road and extensions to the existing road network (TCPD, 2013). The new roads are incorporated into the regression model to understand how planned investments can influence urban growth. These roads are expected to be fully operational by 2021. For this reason, it is assumed that they will only have significant impact on Greater Kumasi's growth from 2021 onwards. As a result, the model generated (see Table 21) by incorporating the proposed roads is used to predict the situation of 2033.

Model results (Model C)

Model summary: Log likelihood = -66551.8334, PCP = 92.17%, p-value = 0.0000, Sample size = 96014 Overall Model Fit: Chi-square = 95411.9424, df = 27, Confidence Interval = 95%.

Table 21: Model Parameters (Model C)

Variable	Coefficient	Standard error	z-value	T-test (p)	Odds ratio (O.R)	VIF
Constant	2.4747	-	-	-	-	
X_1	55.401162	4.241865	13.060568	0.0000	1.149E+24	1.212
X_2	3.697352	0.164581	22.465263	0.0000	40.340334	1.223
X_3	-7.202111	0.119483	-60.277346	0.0000	0.000745	2.230
X_4 *	-3.957256	0.229248	-17.261917	0.0000	0.019115	1.590
X_5	-0.759958	0.105673	-7.191598	0.0000	0.467686	1.499
X_6	-0.721217	0.331836	-7.191598	0.0298	0.486160	1.009
X_7	-10.770233	0.265817	-40.517541	0.0000	0.000021	1.467
X_8	-1.036211	0.049176	-21.071565	0.0000	0.354797	1.004
X_9	-1.022631	0.097822	-10.453983	0.0000	0.359647	1.042

*Updated factor

A comparison of Table 17 with Table 21 reveals variation in statistics between models B and C. This is due to the inclusion of the proposed roads. All variables have witnessed a reduction in coefficients (in terms of their absolute values) including the updated factor, distance to major roads (X_4), except distance to CBD (X_3) and existing urban cluster (X_7). Thus the incorporation of planned investments in our model has caused the influence of distance to major roads to decline. The odds ratio of the updated variable is 0.019115 (1/52.315) compared to the odds ratio before update, 0.005902 (1/169.43). The focus of this study is the nearness to major road. Comparing models B and C, it can be said that odds of urban growth in close proximity to major roads will fall. This seems to contradict what is observed in Figure 21 as new developments in the scenario simulated, appear along the new roads. The white rings on the map (Figure 21) point to these developments. However, a closer look at the figure reveals that these new developments are adjacent to existing built up (in this case the 2033 predicted growth without proposed roads). This explains why the influence of proximity to urban cluster has increased with the inclusion proposed roads. In Table 21, it is estimated that, with the updated factor, an area in close proximity to existing urban cluster is 47619 (1/0.000021) as likely to be developed as an area a unit distance further away from existing urban cluster.

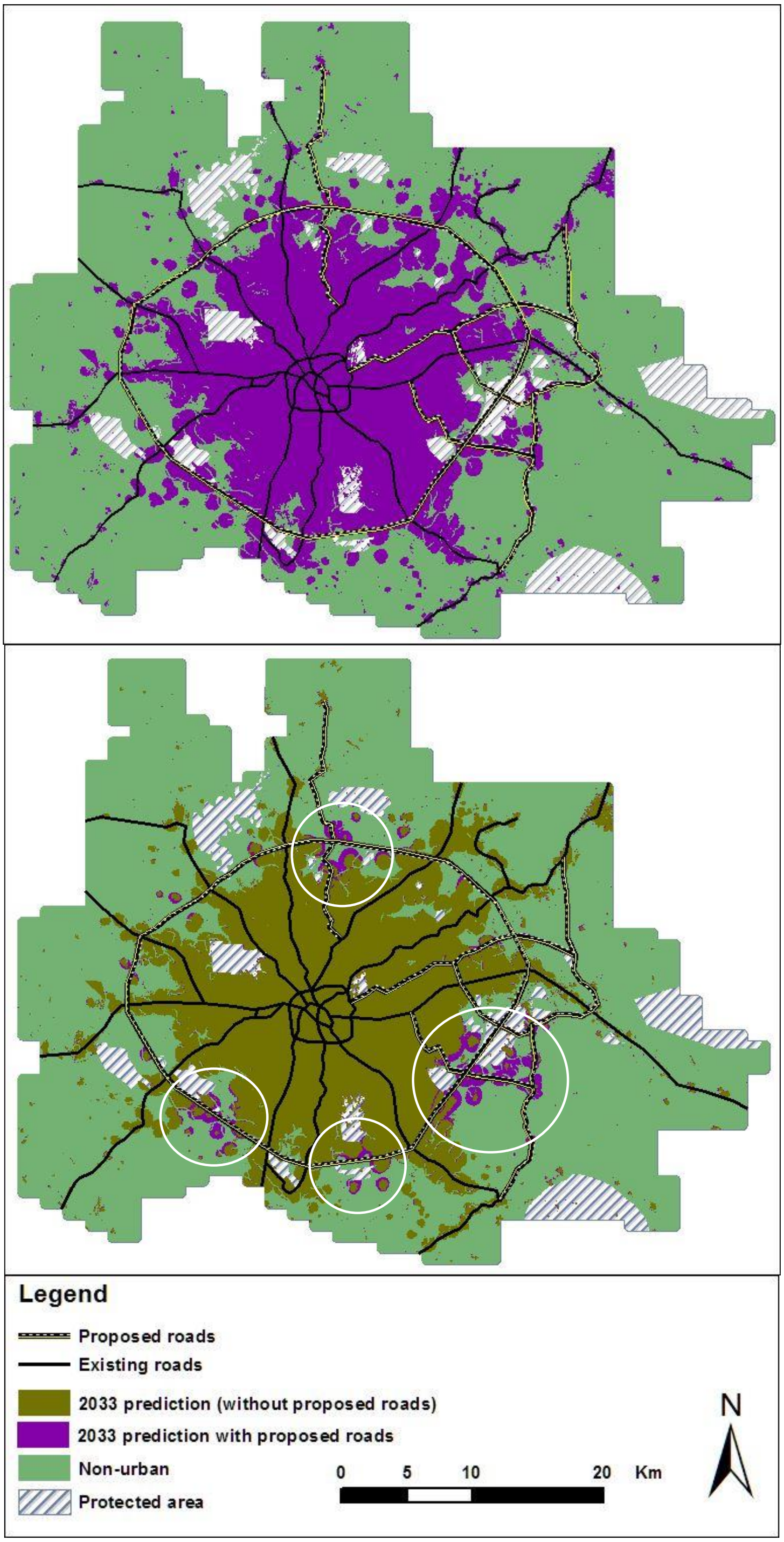

Figure 20: Simulated growth with proposed roads

Prior to the inclusion of proposed roads in the model, the odds of growth in an area a unit closer to existing urban cluster was 19230.8 ($1/0.000052$). It can be said here that this increase in the role of factor X_7, is partly due to the inclusion of new roads. Parts of the proposed roads are closer to or traverse the existing built up thus making these areas (existing built-up) highly accessible and prime locations for new developments. It can therefore be argued that as existing built up areas attract development due to accessibility by proposed roads, the model attributes these developments to proximity to existing urban cluster. This is supported by the fact that the two factors, distance to major roads (X_4) and existing urban cluster (X_7) are negatively correlated (see Appendix B). The CBD has similar impact on the updated factor due to its negative correlation with roads.

4.9. Comparing LR results with other studies

This section attempts to relate to LR models constructed in this study with those of other studies on urban growth drivers in times of findings and limitations. Several studies have applied the LR modelling technique to model the relationship between urban growth and its drivers. Such studies have revealed a variety of context-specific drivers of urban growth for instance most urban growth studies reveal, population density proportion of existing built up, distance to major roads as key driving forces (Cheng, 2003; Duwal, 2013; Fang, Gertner, Sun, & Anderson, 2005; Hu & Lo, 2007; Huang & Sin, 2010) though the level of influence of these factors may vary from one context to the other. This study have also reported the aforementioned driving forces as significant in driving Greater Kumasi's growth but with varying levels of influence compared to their counterparts as identified in the studies being refers to.

The models' evaluation and validation was done using Kappa statistics and PCP. Model A produced PCP value of 95.2% and Kappa value of 0.63 while B produced PCP value of 92.33% and Kappa value of 0.73. Both statistics confirms the good predictive capacity of the models. These values also compare favourably with results from similar studies for Cheng & Masser (2003) had PCPs of 75.7, 81.4 and 83 for three different models while Dubovyk et al. (2011) constructed three models with PCPs of 84.9, 84.72, 82.97 and corresponding kappa values of 0.54, 0.61 and 0.59. Future predictions were made with a limited number of factors and hence there is possibility of uncertainty in the model's prediction as it does not capture all drivers due to data constraints.

This research uses 30x30m resolution for modelling as used in other studies (Chen, Lu, & Fan, 2012; Duwal, 2013; Vermeiren et al., 2012). Spatial logistic regression is sensitive to issues of scale, both temporally and spatially. For example observed patterns vary with the level of resolution. Patterns at one level of resolution may be masked at lower or higher levels (Lesschen et al., 2005). Spatial extent influences the contribution of variables. Smaller extents allow for the incorporation of specific variables for the area under study (Verburg & Chen, 2000). The choice of scale however depends on the purpose of the study and the level of detail that needs to be explored.

5. CONCLUSIONS

5.1. Introduction

This study has a main objective, which is to identify and analyse the key drivers of urban growth in Greater Kumasi Sub-Region. This chapter presents conclusions drawn from the analysis of study the results. The conclusions drawn are based on the sub-objectives of the research. Following this, future research directions are recommended.

5.2. Sub-objective specific conclusion

Sub-objective 1: To analyse the spatio-temporal pattern of urban growth in Kumasi over the time period 1986-2014

It is found from the results that the spatial extent of the built-up area has increased over the time-steps under investigation. Three growth typologies have characterised the growth of the sub-region namely, edge-expansion, infilling and outlying growth. Much growth occurred during the second period of the study (2001-2014) compared to the first (1986-2001). Though shorter in span in relation 1986-2001, the period 2001-2001 (a 13-year period) witnessed an increase in urban land cover of 224km² which more than doubled the 94km² which occurred during the second period. Of the total growth quantified in both periods it is found that edge-expansion have been predominant in both periods of time. Considering the different time spans of the two study periods it can be concluded that urban growth occurred at fast pace and higher rate in 2001-2014 compared to 1986-2014. The edge-expansion form of growth spreads out from existing built-up areas and as this growth takes place vacant pockets of land are left inwards which are later developed through infill.

Sub-objective 2: To model urban growth based on key driving forces

A list of possible was compiled from literature review and based on expert opinions. The logistic regression modelling technique as use in this study proved useful in relating these drivers to the growth of the sub-region and their relative influences on growth. The results showed that in both period under study some four key factors have been at working in driving the expansion of the sub-region's built-up area. These four factors are, distance to urban cluster, distance to CBD, distance to major roads and the proportion of urban cells in 7x7 neighbourhood which are common. For the period 2001-2014, population density was the most important driver of urban growth. The results of the two model's statistically confirmed expert's view on these drivers, that they are significant drivers though the model's ranking and experts' ranking differ to some extent. The model and experts' opinion concurred that population density is the most important driver of urban growth in the period 2001-2014. However, whereas the model rated distance to suburban centres and slope as significant factors, they were ranked insignificant according opinions of experts. The study however concludes that the two variables are significant since quantitative analyses such as this one are capable of unearthing subtle relations among variables.

Sub-objective 3: To predict the future spatial growth pattern of Kumasi for 2023 and 2033

After generating statistically significant models, the model built on 2001-2014 was used to simulate the future growth situation of the sub-region for 2023 and 2033 based on trends between 2001 and 2014. Since the model predicts based on past trends, future growth as simulated by the model is expected to occur along major roads similar to axial development pattern observed in the two time steps under study. This study also attempted to model a scenario where new roads are constructed to see how new investments would likely influence growth. It was expected that since major roads have been influential in the past they would increase in their influence with the addition of new roads. After adding proposed roads the new model (model C) predicted new growth which did not occur in the model's prediction without new roads. The results of the new model how however suggests that roads are not as influential in the new model (model C) as in model B. This study concludes that the seeming contradiction observed in the prediction of model C could arise out of correlations among the variables: distance to roads has negative correlation with distance to urban cluster and distance to CBD though not so serious for the purposes of logistic regression modelling.

5.3. Future research avenues

- This research used the logistic regression approach to analyse the driving forces of urban growth. Future studies can be done within the time frames used here, with the CA modelling method to see how the results will compare with is obtained here.

- Further studies could also attempt to construct LR models for the growth typologies identified in this study. This could help reveal which specific factors are influencing these growth types.

- The influence of urban growth on other land uses has not been explored. Future research can explore can explore this area through the use of multinomial LR modelling approach to unearth the impact of urban growth on different land cover conversions.

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6. APPENDICES

Appendix A: Expert views on driving factors of growth

Variable	Significance					Rating
	Highly significant 5	Significant 4	Neutral 3	Insignificant 2	Highly Insignificant 1	
Population density	6	1	0	0	0	4.9
Distance to urban cluster	4	3	0	0	0	4.6
Distance to CBD	1	6	0	0	0	4.1
Distance to major roads	5	2	0	0	0	4.7
Proportion of urban cells in a 7x7 neighbourhood	2	5	0	0	0	4.3
Slope	0	0	5	0	2	2.4
Distance to water supply lines	0	0	4	3	0	2.6
Distance to minor roads	3	4	0	0	0	4.4
Suburban centres	0	3	2	2	0	3.1
Zoning (conservation areas/protected area)	0	4	0	3	0	3.1

Appendix B

Correlation Matrix

		Constant	Factor_1	Factor_2	Factor_3	Factor_4	Factor_5	Factor_6	Factor_7	Factor_8	Factor_9
Step 1	Constant	1.000	-.277	-.149	-.701	-.222	-.285	-.338	-.163	-.165	-.157
	Factor_1	-.277	1.000	-.106	.247	.010	-.049	.006	.097	-.107	-.056
	Factor_2	-.149	-.106	1.000	-.073	.031	-.033	.008	.365	-.009	.003
	Factor_3	-.701	.247	-.073	1.000	.037	-.039	-.032	-.203	.120	.206
	Factor_4	-.222	.010	.031	.037	1.000	-.135	-.021	-.134	.022	.014
	Factor_5	-.285	-.049	-.033	-.039	-.135	1.000	-.039	-.015	-.025	-.096
	Factor_6	-.338	.006	.008	-.032	-.021	-.039	1.000	-.031	.024	-.020
	Factor_7	-.163	.097	.365	-.203	-.134	-.015	-.031	1.000	.015	.021
	Factor_8	-.165	-.107	-.009	.120	.022	-.025	.024	.015	1.000	.088
	Factor_9	-.157	-.056	.003	.206	.014	-.096	-.020	.021	.088	1.000

Appendix C: List of Experts interviewed

No.	Name	Institution
1	Prof. Romanus Dinye	Head, Centre for Settlement Studies, Kumasi
2	Dr. Michael Poku Boansi	Senior Lecturer, KNUST, Kumasi
3	Dr. Theresa Baah-Enumh	Lecturer, Department of Planning KNUST
4	Mr. P.K.B Asamoah	Senior Research Fellow, Center for Settlement Studies, Kumasi.
5	Mr. Prince Anokye	KNUST, department of Planning
6	Mr. Joseph Edusei	Senior Research Fellow, Centre for Settlement Studies.
7	Mr. Emannuel Christian Cofie	Director, Town and Country Planning, Kumasi