MODELING URBAN GROWTH IN KIGALI CITY RWANDA

GILBERT NDUWAYEZU
February, 2015

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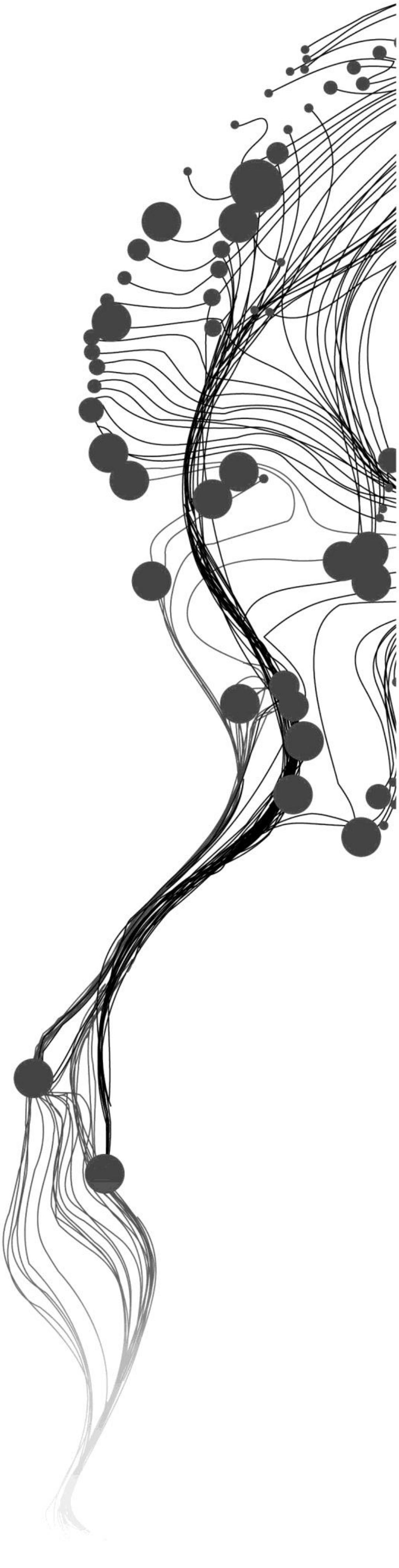

MODELING URBAN GROWTH IN KIGALI CITY RWANDA

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Urban Planning and Management

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ABSTRACT

In Kigali city, rapid urbanization and urban growth are recognized facts. The planning policy of urban areas in Kigali city has been disapproved of being ineffective. A likely reason of this inappropriate or lack of urban planning approaches was mainly approached to a limited understanding of the spatial- temporal patterns of the city and its dynamism. Moreover, the lack of appropriate techniques of urban growth modeling that can help in making valuable urban planning decisions is still critical.This study aims to determine the main driving forces behind the urban dynamics of Kigali city by coupling GIS and Logistic Regression (LR) model. This information is expected to support in determining the possible future directions of the city for the next 26 years, in turn, will form the basis of policy options/ decisions of the city.

Consistent set of land cover maps of Kigali city during the period 1987, 1999, 2009 and 2014 were generated. Pixel- based approach by Maximum Likelihood method was applied to classify Landsat images. As the purpose of the study was to look at built-up land cover only, from the land cover maps, built-up area were extracted and visualized. A remarkable trends and sprawl pattern was observed in urban areas in Kigali city in that, the rapid trend was more accelerated between 1987 and 2009 while it continued at a moderate pace up to 2014. Urban areas expanded mainly towards the Northern, Eastern and Southern directions. However, the Western part of the city was posed due to the area topography and environmental policy on protecting forests. The results also highlighted the implication of human related activities with regard to contributing to a decrease in natural reserves (forests and vegetation) for the period between 1987 and 2014.

The main drivers of Kigali city growth were identified according to both Logistic Regression model and local planning experts' views. The results indicated that new urban developments in Kigali city will tend to be close to the existing urban areas, hence a compact pattern. In addition, new urban development will have a tendency to occur further from the CBD and wetlands but on low slope sites. The model predicted that if the current physical urban expansion rates continues, urban development will expand towards Northern and Southern direction of the city rather than Western and Eastern parts. The new developments have a tendency to replace forest cover and wetlands in the Western part of the city and this constitutes a serious environmental threat to the city. The research suggests further study by using other important factors revealed by local urban planning experts like neighborhood of water and electricity, but not used because of data unavailability. This study should be repeated by coupling LRM with other micro-level approaches CA model or CommunityViz.

Key words: Urban growth, GIS and Remote Sensing, Logistic Regression modeling, Kigali city, Rwanda.

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"Commit your works to the Lord, and your thoughts will be established" Proverbs, 16:3.
"When There Seems No Way, God Will Make a Way" Isaiah, 43:16.

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
CA	Cellular Automata
DTM	Digital Elevation Model
DSM	Digital Surface Model
DTM	Digital Terrain Model
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographic Information System
IHS	Intensity, Hue and Saturation
LRM	Logistic Regression Modeling
MINALOC	Ministry of Local Governance
MINECOFIN	Minister for Finance and Economic Planning
MININFRA	Ministry of Infrastructures
MSI	Mean Shape Index
MSS	Multispectral Scanner
NIR	Near Infrared Band
NISR	National Institute of Statistics in Rwanda
OLI	Operational Landsat Imager
REMA	Rwanda Environmental Management Authority
RGB	Red, Green and Blue
RNRA	Rwanda Natural Resources Authority
ROC	Relative Operating Characteristic
RS	Remote Sensing
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
VHR	Very High Resolution

1. INTRODUCTION

The rapid demographic and uncontrolled spatial transformation have overloaded the capability of most cities management in developing countries (Linard et al., 2013). In those cities, the lack of strong spatial policies, disorganized urban sprawl accompanied by the high natural reserve consumption is the key characteristics. The growth of cities, if governed and supported by well informed, policies, decision makers and stakeholders, can help to address these challenges. However, having a good understanding of the key drivers of the city's growth dynamism has proven to be a key instrument to manage urban growth. Thus the focus of this research is to build a robust Logistic Regression model as a set of meaningful drivers of urban growth in Kigali city. This will allow determining the possible future directions of the city for the next 26 years. This chapter provides an introduction to the study, the problem statement and rationale of the research, the objectives and the research questions as well as the overall approach and the structure of the study.

1.1. Background and research justification

In the 21st century, rapid urbanization and urban growth have been one of the crucial issues of global change that affect the physical dimension of cities. In the past few decades, this has drastically accelerated in many developing countries. UN-HABITAT (2011) reported that 3.6 billion of the world's population (52%) was urban dwellers. Globally, the level of urbanization is expected to rise to 67% in 2050. In the less developed regions, the proportion of the urban area population is expected to rise from 47% in 2011 to 64% in 2050. In Africa alone the urban population is expected to triple from 414 million in 2011 to 1.2 billion 2050 (UN-HABITAT, 2011). This may lead to higher urbanization rates in Africa than in other regions of the world, with urban land cover growth of more than 12-fold between 2000 and 2050 in sub-Saharan Africa (Mohan, 2010).

Kigali city is one of the fastest growing cities in Africa (Civco et al., 2005). From its inception since 1907, the city has witnessed the remarkable spatial expansion, population growth and developmental activities such as building, road construction, deforestation and many other anthropogenic activities (REMA, 2013). In 1991, Kigali city only covered an area of 112 km^2 with 140,000 inhabitants. In 2012, the city expanded to a total population of 1,135,428 living in an area of 730 km^2 (NISR, 2012). This has resulted in increased land consumption and a modification and alterations in the status of land cover/use (REMA, 2013). Nowadays, Kigali city has witnessed a tremendous rapid urbanization whereby agricultural and forest lands in urban fringe zones have been occupied by city dwellers (Manirakiza, 2012). The causes are multiple. Kigali city's population is continuously increasing due to migration from the countryside, e.g. Migration of people from rural areas for employment and business opportunities are much higher compared to other Rwandan towns (NISR, 2012). Moreover, Niyonsenga (2012) stressed that high infrastructure accessibility is a root of such phenomenon.

In Kigali city, land use planning has been one of the main focus for the Government of Rwanda's decentralization policy (MINALOC, 2006, 2012). However, monitoring of land use changes became difficult as the size of towns has been changed over time. This issue is due to the extension of existing towns to almost the whole district size (Manirakiza, 2012). The up-to-date and accurate information on urban expansion is very much required for urban decision making (MININFRA, 2009). However, these urban centers lack adequate spatial information to support decision making on land cover/use planning

(Manirakiza, 2012). This, in turn, constitutes a challenge for better use of urban spaces MININFRA (2009), immediate actions of local authorities even may result in wrong decisions (Aibinu, 2001). In Kigali city, the planning policy of urban areas has been disapproved of being ineffective (Manirakiza, 2012). A likely reason of this inappropriate or lack of urban planning approaches was mainly approached to a limited understanding of the spatio-temporal patterns of the city and its dynamism (Aibinu, 2001). Moreover, the lack of appropriate techniques of urban growth modeling that can help in making valuable urban planning decisions is still critical (Edaw et al., 2007).

Logistic Regression technique, one of the empirical-statistical methods, estimates the probability that a particular event will occur where it analyzes relationships between a dichotomous dependent variable and metric or dichotomous independent variable (Pullar and Pettit, 2003). This method coupled with GIS and RS has been claimed to be a very effective tool for land cover/use change modeling, due to its explanatory power and spatial explicitness (Dendoncker et al., 2007). Logistic Regression provides an opportunity to analyze future development patterns based on the trends observed in the past, and it helps to quantify the contribution of the individual forces that drive land cover/use change, and thus provides the information needed to properly calibrate land cover/use change and urban growth models (Dendoncker et al., 2007). LR has been applied in the lot of urban growth studies (Arsanjani et al., 2013; Dendoncker et al., 2007; Dubovyk et al., 2011; Duwal, 2013; Hu and Lo, 2007; Munshi et al., 2014; Nong and Du, 2011). For example, LR has been applied in some East African cities by Abebe (2013) in Kampala, Uganda and Abebe (2011) in Dar es Salaam modeling urban growth and informal settlement development. In above studies the authors used one overall LR model to identify driving forces. The aim of the current study is to build different LR models to analyze the main determinants of Kigali city growth looking at how they changed over time and also how they contributed to the city change. Understanding and quantifying the spatial-temporal dynamics of urban growth and its drivers can help to better understand the dynamics of built-up area and guide sustainable urban development planning of the future urban growth in Kigali city.

1.2. Problem statement and research relevance

In Kigali city, rapid urbanization and urban growth are recognized facts (Civco et al., 2005). Socioeconomic and demographic trends, such as population growth, industrialization, land consumption and infrastructural development, have impacted on the state of the Kigali city expansion (REMA, 2013). Kigali city's current planning approach requires more data integration, multi-disciplinary and composite analysis regarding its urban expansion, and need faster and more precise information for all decision makers and stakeholders (Aibinu, 2001). In recent years, the government of Rwanda has elaborated and implemented a series of urbanization plans, policies and regulations to orient Kigali city growth toward a sustainable city (Manirakiza, 2012). Rwanda Vision 2020 plan, National Urban Housing Policy (2008), National Land Use Planning (2012), Kigali City Conceptual Master Plan (2008) and Kigali city Master plan (2013) are among the key policies that have been elaborated as a tool for making the Kigali city's future more sustainable (Surbana, 2012). However, implementation of these policies is still in process, it appears that the city growth pace remains. In addition, factors that are behind that growth are still undisclosed (Manirakiza, 2012). A better understanding of those factors that are governing the city growth is needed for a sustainable future of the city. Some attempts have been undertaken in quantifying urban growth of Kigali (Civco et al., 2005; Edaw et al., 2007). Empirical work is therefore needed to develop an approach to quantify the spatial-temporal patterns and to detect the main drivers controlling Kigali city growth. Kigali city expansion needs to be correlated with spatial, socioeconomic and demographic variables using a LR modeling approach. LR has been proven to be a suitable approach for urban growth modeling in such kind of fast growing cities (Huang et al., 2009). The study explores the capability of freely available

RS Landsat archived imageries that have been confirmed to monitor the urban growth pattern (Griffiths et al., 2010). LR models developed allow the creation of spatially detailed urban expansion forecasts for 2025 and 2040 for Kigali city, that were compared to the proposed 2025 and 2040 zoning plans. The results from the study can help city urban planners and decision makers to describe the future urban environment, leading to an improved understanding in the urban planning and management of the city.

1.3. Research objectives and research questions

1.3.1. General objective

The main objective of this research was to determine the main driving forces behind the urban dynamics of Kigali city by coupling GIS and Logistic Regression (LR) model. To achieve this main research objective, the following sub-objectives and research questions were answered in this research.

1.3.2. Specific objectives

1. To generate a consistent set of land cover maps of Kigali city during the period 1987, 1999, 2009 and 2014.
2. To build a Logistic Regression (LR) model of urban growth in Kigali city.
3. To predict future urban growth pattern in Kigali city.

1.3.3. Research questions

Objective one: *To generate a consistent set of land cover maps of Kigali city during the period 1987, 1999, 2009 and 2014.*

- How accurate the image classified using Landsat data?
- What are the main characteristics and trends of urban growth in Kigali city from 1987-2014?

Objective two*: To build a Logistic Regression (LR) model of urban growth in Kigali city.*

- What are the main drivers that condition the change of the urban area in Kigali city and what are their relative importances according to local urban planning experts' views?
- How did the driving forces contribute to the urban growth process and pattern in Kigali City?

Objective three: *To predict future urban growth pattern in Kigali city.*

- Where are the probable areas of future urban growth?
- What implications do the LR model outcomes have for urban development policy?
- What are the strengths and weaknesses of the LR modeling approach to urban growth prediction?
- What are the caveats, if any, should be placed on the use of the predictions?

1.4. Conceptual framework

As shown in Figure 1-1, this study will show the potential of combining GIS, RS and LR in urban growth modeling. GIS and RS techniques provide spatially consistent datasets that cover large areas with both high detail and high temporal frequency, including historical time series data. The urban growth results to its driving forces which shape a city toward a certain direction. GIS and RS help to know the land cover status based on historical archived RS imagery data. The land cover maps allow the analysis of urban growth patterns; quantification and preparation of binary maps (urban / non-urban) as basic inputs for urban growth modeling. For monitoring the city growth, dummy variables urban and non-urban data need to be extracted from the generated land cover maps. LR helps to detect and to analyze the main drivers behind the growth of the city. A long list needs to be compiled from both literature and local urban planning experts' views. The main driving forces detected (factor maps) need to be prepared in GIS. A

LR model helps to associate dichotomous dependent variable binary maps (urban / non-urban) with demographic and economic information (Factor maps) as products of RS techniques in a GIS environment. The generated urban growth probability maps help in predicting future urban direction of the city.

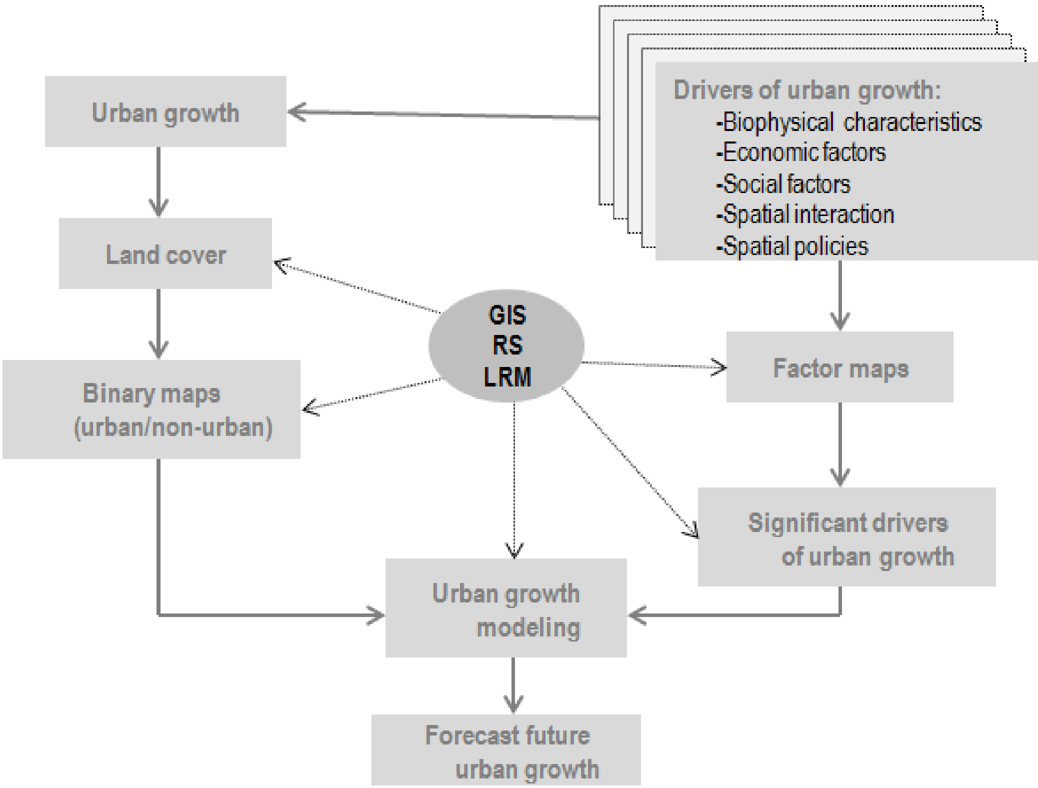


Figure 1-1: Conceptual framework.

1.5. Research structure

The present work has been organized in seven chapters and the outline of each chapter is mentioned below.

Chapter one comprises a general background of the research problem, justification and conceptual framework of the study. It includes also the main objective and sub-objectives, research questions and the overall research design of this study. Chapter two presents a review of the main determinants of urban growth and LR model. The main policies and institutions set to manage Kigali city growth as well as key concepts related to urban development are developed in Chapter three. The LR modeling methodological framework, model validation and evaluation are detailed in Chapter four. Chapter five contains results found in this study. The results are discussed in Chapter six. Conclusion and recommendations of this study are presented in Chapter seven.

Six appendices annexed at the end of this work contain various information used in this study. Appendix A gives a detailed description of secondary data collected is used in this work. The results of land cover classification maps of Kigali city are presented in Appendix B. The questionnaire used to obtain the main driving factors of urban growth in Kigali city is annexed as Appendix C. Appendix D contains a detail information about multicollinearity diagnosis. Probability maps of all LRMs excluded from further analysis are annexed as Appendix E. Lastly, variables retained after Backward stepwise procedure test are annexed as Appendix F.

1.6. Research design matrix

In the research matrix, the sources of data used, techniques for data collection and analysis for each research objective and questions are presented.

Sub-objectives	Research Questions	Techniques for data collection and analysis		Data source
		Survey techniques and data acquisition tools	Techniques of analysis	
1. To generate a consistent set of land cover maps of Kigali city during the period 1987, 1999, 2009 and 2014.	- How accurate the image classified using Landsat data? -What are the main characteristics and trends of urban growth in Kigali city from 1987-2014?	-Previous studies -Field work (Observations with taking truth ground samples) -ERDAS IMAGINE -ArcGIS 10.2.2 - Patch analyst -Land cover maps	-Literature review -GIS visualization -Excel analysis -Patch metric: Mean Shape Index (MSI)	-Books -Journals -Articles available, - ITC archives, -Kigali city province and in other institutions.
2. To build a Logistic Regression (LR) model of urban growth in Kigali city.	-What are the main drivers that condition the change of the urban area in Kigali city and what are their relative importances according to local urban planning experts' views? -How did the driving forces contribute to the urban growth process and pattern in Kigali city?	-Previous studies -Gaining urban expert knowledge using the interview -Different datasets (DEM, land use, Factor maps…) -ArcGIS 10.2.2 -Kigali city plans, policies and regulations.	-Literature review -GIS operations (Proximity, Extraction, reclass…) -SPSS using LRM	-Books -Journals -Articles available, - ITC archive, -Kigali city province and in other institutions.
3. To predict future urban growth pattern in Kigali city.	-Where are the probable areas of future urban growth? -What implications do the RL model outcomes have for urban development policy? -What are the strengths and weaknesses of the LR modeling approach to urban growth prediction? -What are the caveats, if	-Results from LRM (Probability maps) -Land cover maps -Change analyst	-Literature review -GIS overlay tools (intersection and erase) and visualization -LRM	-Content of analysis -Literature review

any, should be placed on
the use of the predictions?

2. THEORETICAL FUNDAMENTALS ON REMOTE SENSING FOR URBAN GROWTH AND LRM

This chapter provides theoretical fundamentals necessary to understand the mains concepts and theories used in this thesis. First, basics about land cover and land use change are given, followed by an overview on urban development and urbanization. Next, the methods of information extraction from RS data are introduced. Thereafter, the theories about the driving forces of urban growth are reviewed. In a final section, Logistic Regression Modeling and its applicability are explained.

2.1. Basic concepts on urban growth and urban development

Land cover/use change is a complex, dynamic process that links together natural and human systems (Koomen and Stillwell, 2007). Araya (2009) argued that understanding the urban land cover/use dynamics is one of the most complex tasks for sustainable urban planning and development. Understanding the present and past land cover/use in cities is essential before planning the locations of future land cover/use (Bauer et al., 2003). Moreover, information about existing conditions and past trends in land cover/use provides valuable insights on making better future land cover/use decisions (Haines et al., 2005). There are many key terms used in this study that need to be defined. Those include land cover and land use on the one hand and urban development, urban growth and urbanization on the other hand. Urban land use refers to the spatial distribution of city function, its residential communities or living areas, its industrial, commercial, and business districts or major work areas (Haines et al., 2005). The terms land use and land cover are not synonymous and literature draws attention to their differences so that they are used properly in land use and land cover change studies. Lesschen et al. (2005) defined land cover as "*the observed physical cover, as seen on the ground or through remote sensing, including the vegetation (natural or planted) and human constructions (buildings, etc.), that cover the earth's surface. Water, ice, bare land and salt flats or similar non-vegetated surfaces are included in land cover*". However, as defined by Briassoulis (2000), land use expresses" *the way in which, and the purpose for which, human beings employ the land and its resources*". Lesschen et al., (2005), expresses land use as "*a series of operations and associated inputs on land, carried out by humans, with the intention of obtaining products and/or benefits through using resources*". Other important terms of this work are urban development, urban growth and urbanization. Clark (1982) defined urban development as the process of emergence of a world dominated by cities and urban values and the main processes of urban development are urban growth and urbanization. Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as concentrations of population within a particular economy or society. Clark (1982) defines too urbanization as a spatial and social process which refers to the change of behavior and social relationships which occur in a society as a result of people living in towns and cities. The main focus of this study was to look urban growth within a spatial growth dimension but not its demographic pattern.

2.2. RS techniques for urban growth pattern extraction

(1) Pixel- based classification

The choice of classification method depends on the data available, but also requires knowledge about the area under investigation (Bakx et al., 2013; Lillesand and Kieffer, 2000). Supervised classification is applied if the land cover composition of the study is well known from field work or from other sources. In turn, when there is not enough knowledge of land cover classes unsupervised classification may be essential.

However, supervised classification can give tangible results when few classes need to be identified are selected (Sanchez and Canton, 1998). Essentially, both approaches only rely on spectral information, which is impossible for higher spatial resolution where each land cover type is made up of variable spectral pixel characteristics, and thus pixel information will give a little help. Object-oriented analysis may deal with this drawback. Based on the spectral information, this approach divides an image into spectrally homogenous parts that correspond to the image reality instead of classifying every pixel separately.

Pixel- based image classification is a method commonly applied to obtain thematic classes from multi-band RS images (ERDAS, 1999; Lillesand and Kieffer, 2000). It is the process of sorting pixels into a finite number of individual classes based on their spectral characteristics (Sanchez and Canton, 1998). This approach results in spectral classes where each pixel is assigned only to one class. In the supervised classification, pixels selected represent patterns or land cover features that the analyst well recognizes. Applying this approach, training samples of objects of interest are important. It can be identified from the image to be classified or with help from other sources, such as aerial photographs, ground truth data, topographic or cadastral maps. In the classification process a spectral class may be represented by several training classes. Using this approach, the knowledge of data and of the class desired is required before the classification process starts. The result of training is a set of signatures that defines training samples or cluster. Each signature corresponds to a class. Signatures can be parametric or non parametric. Parametric signature is based on statistical parameters such as the mean vector and the covariance matrix of the pixels that are in the training sample or cluster (ERDAS, 1999; Lillesand and Kieffer, 2000). A part of the standard attributes, a parametric signature includes the number of bands in the input image, the minimum and maximum data file value in each band for each sample (minimum vector and maximum vector), the mean data file value in each band for each sample or cluster (mean vector), covariance matrix for each sample or cluster and the number of pixels in the sample or cluster (ERDAS, 1999). However, non parametric signature is based on discrete objects (polygons or rectangles) in a feature space image. These feature space objects are used to define the boundaries for the classes during image classification. When both types of signatures are used during image classification process, class definitions are more analyzed and visualized that either type of signature used independently (Sanchez and Canton, 1998). There are several classification algorithms, but the commonly used parametric decision rules are Minimum Distance and Maximum Likelihood (Bakx et al., 2013; Lillesand and Kieffer, 2000; Sanchez and Canton, 1998). Minimum Distance algorithm calculates the distance between the measurement vector for the candidate pixel and the mean vector for each signature. The candidate cell is assigned to the class that qualifies as the closest one. Based on the equation 1, the Euclidean distances from a candidate feature vector to all the cluster centres are calculated (ERDAS, 1999):

$$SD_{xyc} \sqrt{\sum_{i=1}^{n} (\mu_{ci} - X_{xyi})^{2}} \quad ,\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[1]$$

where:

n = number of bands (dimensions); i = a particular band; c = a particular class; X_{xyi} = data file value of a pixel x, y in band i ; ci =mean of data file values in band i for the sample for class c and SD_{xyc} =spectral distance from pixel x, y to the mean of class c .

After spectral distance is computed for all possible classes and all possible values of c , the class of the candidate pixel is assigned to the class for which SD is the lowest. The advantages and disadvantages of the Minimum Distance are summarized in Table 2.1.

Table 2-1: Advantages and disadvantages of the Minimum Distance algorithm.

Advantages	Disadvantages
Since every pixel is spectrally closer to either one sample mean or another, there are no unclassified pixels.	Pixels that should be unclassified become classified.
Using this decision rule, the computation is fast.	This approach does not consider the variability of the candidate classes. In essence, this method is not widely used.

Maximum Likelihood algorithm is widely used in a lot of studies (Abebe, 2013; Duwal, 2013). ML is based on the probability that a pixel belongs to a particular class. In this decision rule, the probability is equal to all classes. The input bands have normal distributions. The equation of Maximum Likelihood algorithm is as follows (Bakx et al., 2013; ERDAS, 1999):

$$D = \ln(a_c) - [0.5\ln(|Cov_c|)] - [0.5(X - M_c)T(Cov_c^{-1})(X - M_c)] \quad \text{.................................[2]}$$

where:
D =weighted distance (likelihood); C = a particular class; X = measurement vector of the candidate pixel; M_c =mean vector of the sample of class c; a_c =percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from a priori knowledge); Cov_c =covariance matrix of the pixels in the sample of class c; $|Cov_c|$ =determinant of Cov_c (matrix algebra); Cov_c^{-1} =inverse of Cov_c (matrix algebra); ln = natural logarithm function and T =transposition function (matrix algebra).

Maximum Likelihood algorithm considers the cluster centers, but also the shape, size and orientation of the clusters. It calculates a statistical distance based on the mean values and the covariance matrix of the clusters. Maximum Likelihood allows the operator to define a threshold distance by defining a maximum probability value (Lillesand and Kieffer, 2000). The advantages and disadvantages of Maximum Likelihood are summarized in Table 2.2.

Table 2-2: Advantages and disadvantages of Maximum Likelihood algorithm.

Advantages	Disadvantages
Maximum Likelihood quantitatively evaluates both variance and covariance of the category spectral response patterns when classifying an unknown pixel	Maximum Likelihood classification takes a long time to compute. The computation time increases as the number of inputs bands increases.
It takes into account the variability of classes by using the covariance matrix.	Maximum Likelihood is parametric. This approach relies a lot on a normal distribution of data in each input band.
	Tends to overclassify signatures with relatively large values in covariance matrix. If there is a large dispersion of the pixels in a cluster or training sample, then the covariance matrix of that signature contains large values.

(2) Post classification approach

Classified data often manifest a "salt and pepper" of misclassified pixels due to the inherent spectral variability when applied pixel- based classification approach. Therefore, it is advantageous to aggregate the classified output to show only the dominant (correct) classified pixels (Dong et al., 2006). The most commonly used method is majority filtering, which involves the application of a moving window pixel kernel. Previous studies Dong et al. (2006) and the text book of Lillesand and Kieffer (2000) showed that smoothing image using major filtering is effective for removing misclassified pixels and eliminating noise in the post-classification of remote sensing image output. In pixel-based image classification, each pixel is only assigned to one class. However, during classification sometimes data may not fall into exactly one category or another. Fuzzy classification algorithm is one method that is more sensitive to the imprecise nature of that case (Dong et al., 2006; ERDAS, 1999). Fuzzy algorithm operation creates a single classification layer by calculating the total weighted inverse distance of all the classes in a 3*3, 5*5 and 7*7 moving window of pixels. In this process, a class with a very small distance value remain unchanged while classes with higher distance values change in the neighboring values. This is completed if there are a sufficient number of neighboring pixels with class values and small corresponding distance values. The following equation is used in the process (ERDAS, 1999):

$$T[k] = \sum_{i=o}^{s} \sum_{j=o}^{s} \sum_{l=o}^{n} \frac{w_{ij}}{D_{ijl}[k]}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3]$$

where: i = row index of window; j = column index of window; s =size of window (3, 5, or 7); l = layer index of fuzzy set; n = number of fussy layer used; W =weight table for window; k = class value; $D[k]$ = distance file value for class k; $T[k]$ = total weighted distance of window for class k. The center pixel is assigned the class with the maximum $T[k]$.

(3) Validation of the results

Remote Sensing image classified is based on samples of the classes defined. The quality of the classification result needs to be assessed as image classified is based on samples of those classes. Means that the output classified image need to be compared with true real world data (Lillesand and Kieffer, 2000; Sanchez and Canton, 1998). The most commonly cited measure of mapping accuracy is the overall accuracy, or proportion of correctly classified (PCC) derived from an error matrix. Overall accuracy is the number of the correct classified pixels divided by the total number of pixels checked. Another widely used indicator of accuracy assessment obtained from error matrix is the Kappa or k coefficient. The following equation is used to compute the kappa coefficient (Bakx et al., 2013; Lillesand and Kieffer, 2000):

$$k = \frac{N \sum_{i=1}^{r} Xii - \sum_{i=1}^{r} Xi + X + i}{N^2 - \sum_{i=1}^{r} Xi + X + i}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[4]$$

where:

r : The number of rows and columns in error matrix

Xii: The number of observations in row *i* and column *i*

Xi+: The marginal total of row i

X+i: The marginal total of column *i*

Xij: The number of observations in row *i* and column *j*

Xj+: The marginal total of row *j*

N: The total number of observations

Kappa coefficient indicates the proportionate reduction in error produced during the classification process compared with the error of a completely random classification. For instance, a value of 0.91 means that the classification process is avoiding 91 percent of the errors that a completely random classification produces.

(4) Change detection techniques

Several categories of change detection techniques have been developed such as algebra, classification based, visual analysis as well as GIS. Algebra technique includes all kinds of algorithms that are based on combining values of a pixel in subsequent images (Alkema et al., 2013). Algebra category includes image differencing, image rationing, vegetation index differencing, image regression and change vector analysis. This method is often used in detecting a very specific change, such as detection of forest fires, deforestation mapping as well as detecting vegetation change. However, applying algebra methods except vector analysis, a complete identification of the nature of the changes is absent means a complete matrix change is impossible. Classification- based change detection involves some kind of classification of separate or combined images. The most common technique in this category includes post- classification comparison approach. In post-classification comparison (the method used in this study), the images are classified separately and classification outputs images at different data are compared. Is the most method applied as it provides a complete change matrix (Lillesand and Kieffer, 2000). Visual analysis relies on the human eye in detecting an interpreting change. Time series images are displayed in different ways, such as multi-temporal color composites and animation. This method depends very much on analyst skills and its familiarity with the area (Alkema et al., 2013). In GIS based approach, maps and images are combined using GIS overlay tools. E.g the detecting changes in new buildings, parcel boundary or forest limits (Alkema et al., 2013).

(5) Concluding remarks

The analyst during image classification needs to be careful before applying filtering approach. Sometimes, this method can lead to information loss or distortion of classified image. Successive smoothing filtering can lose scattered data of a certain class, but keep compactly clustered data. Therefore, the application of this method must depend on the spatial level application and quality of data inputs.

2.3. Driving forces of urban growth

Having wide information about the drivers that are controlling the city expansion is necessary to assess the impact of future development (Verburg et al., 2004). Drivers have an impact on the future situation of a city (Thapa and Murayama, 2010). To identify key driving forces behind such land cover/use changes appropriate approaches are required (Verburg et al., 2004). There are a lot of researches conducted on analyzing drivers that governing the city's growth using different approaches as per Table 2-3. Some authors e.g. (Dubovyk et al., 2011; Hu and Lo, 2007; Huang et al., 2009; Nong and Du, 2011; Verburg et al., 2004) used statistical approach such as LR approach to determine the main drivers of land use change. Others Thapa and Murayama (2010) used mathematical method such as Analytic Hierarchy Process (AHP) approach. Within a statistical approach, land cover/use change (dependent variables) is explained as a function of a set of driving forces (independent explanatory variables). This section uses the concept matrix of Webster and Watson (2002) to review the literatures selected as per Table 2-3. Verburg et al., (2004) found that Dutch land use changes are conditioned by spatial policies in combination of accessibility measures, and neighborhood interactions. Hu and Lo (2007) concluded that in Atlanta city, Georgia, USA urban growth is influenced mostly by its neighborhood characteristics and distance to economy centres. However, Huang et al. (2009) concluded that population density, zoning, distance to roads, commercial centres, residential, and neighborhood characteristics are the key drivers of New Castle city growth. In addition, Nong and Du (2011) found that Jiayu county is expanding because of their roads accessibility, economic centres and higher population density. In their research on development on informal settlement in Sancaktepe, Istanbul, Turkey, Dubovyk et al. (2011) found that population density, slope, and neighborhood characteristics will be the main causes of proliferation on new informal settlement in the future. Last but not least, Thapa and Murayama (2010) found in their case study of the Kathmandu valley city, Nepal that economic opportunities, population density and political situation are key causes of this city expansion. It is seen that the authors not used the same list of the driving forces of urban growth in their analysis. Moreover, in the reviewed case studies, cities are not conducted with the same drivers in their expansion. Population density and the proportion of built-up in the surrounding area were seen as the common driver to all case studies reviewed. A combination of the above typology of driving forces differently described by different authors, gives a complete overview of the key causative factors of urban growth.

Table 2-3: Summary of reviewed driving factors which influence urban growth.

Author	(Verburg et al., 2004)	(Hu and Lo, 2007)	(Huang et al., 2009)	(Thapa and Murayama, 2010)	(Nong and Du, 2011)	(Dubovyk et al., 2011)
Case study	Netherlands	Atlanta, Georgia, USA	New Castle Delaware, USA	Kathmandu valley city, Nepal	Jiayu county, China	Sancaktepe, Istanbul, Turkey
Nature of research	Land use change modeling	Urban growth modeling	Urban growth modeling	Urban growth modeling	Urban growth modeling	Informal settlement development
Method used	Empirical statistical model/binomial logit model	Binary Logistic Regression	Binary Logistic Regression	Analytic Hierarchy Process approach	Binary Logistic Regression	Binary Logistic Regression
Biophysical factors	Altitude, ground water dynamics, soil characteristics	-	Slope	Slope, soils	Slope	Slope
Economic factors	A lot of socio-economic indices.	-	-	Economic opportunities and land market.	Industry and agriculture gross.	-
Social factors	Population density	Population density	Population density	Population density	Population density	Population density
Spatial interaction and neighborhood characteristics	All spatial interaction and neighborhood characteristics.	Distance to urban clusters, roads, bare land and grassland.	Proximity to roads, commercial site, residential centre and surrounding land.	Public services accessibility.	Index of distance to economic center and major roads.	Neighborhood characteristics, distance to roads, industrial sites and CBD.
Spatial policies	Spatial policies	-	Zoning	Plans and policies	-	-
Change occurred	Expansion of residential, industrial and commercial areas.	Expansion of built-up area	Expansion of built-up area	Expansion of built-up area	Expansion of built-up area	Proliferation of informal settlement

The major drivers	Most are spatial policies in combination of accessibility measures, and neighborhood interactions.	Neighborhood characteristics: bare land, grassland, forest, distance to economy countries.	Population density, zoning, distance to roads, commercial centers and residential, and neighborhood characteristics.	Economic opportunities, population density and political situation.	Road accessibility, economic centers and higher population density.	Population density, slope, and neighborhood characteristics.

2.4. LR Modeling

Land cover/use change models are tools to support the analysis of the causes and consequences of land cover/use change (Verburg et al., 2004). In addition, modeling land cover/use change helps understand the processes of continuing urbanization and can also be of value in informing policymakers of possible future conditions under different scenarios (Kelly et al., 2013). Over the past decades, research has sought to develop urban land cover/use models for forecasting future development, evaluating future plans, and identifying endangered natural areas (Dendoncker et al., 2007). Spatial modeling is popular in the last two decades due to increased computing power, improved availability of spatial data, and the need for innovative planning tools to help decision making (Herold et al., 2005). Few urban growth models have been developed for African cities because of the lack of data to implement such models (Linard et al., 2013).

Based on the temporal scale, there are two modeling approaches according to their process of land cover/use change simulation: micro- level and macro level modeling (Hu and Lo, 2007; Hu, 2004; Pullar and Pettit, 2003). Micro- level models are called also rule - / process-based models attempt to analyze patterns of land cover/use change as the aggregate outcome of many disparate individual land use decisions across space, of which there are Cellular Automata (CA) with the great capability to handle temporal dynamics (Hu and Lo, 2007). CA focuses on micro-spatial pattern, but using it is difficult to reflect macro-changes affected by social and economic factors (Hu and Lo, 2007). Moreover, it is difficult to define and implement appropriate rules for instance in multiple phenomena case studies (O'Sullivan and Torrent, 2000). On the other hand, macro-level models; empirical-statistic models are deterministic models which apply strict cause-effects relationships within a system to be modeled (Koomen and Stillwell, 2007). LR one of macro-level models overcomes CA barriers. Where it is difficult in CA model, LR integrates spatial and socioeconomic and demographic factors in an urban growth perspective. In addition, the computation requirements for LR models are not as intensive as for example for CA models. Eventually, the input data requirements are relatively easy to fulfil, making LR especially useful in developing countries where reliable data is often scarce (Arsanjani et al., 2013).

LR has been applied in a lot of urban growth studies discussed in section 1.1. LR may be binary or multinomial (Field, 2013). Binary LR is used to predict membership of only two categorical outcomes, and Multinomial logistic regression when you want to predict membership of more than two categories used in the model (Field, 2013; Hu and Lo, 2007; Huang et al., 2009). Binary LR (used in this study) is a type of regression analysis where the outcome variable is a dummy variable (coded 0, 1) means Yes or No or built-up and non-built in the context of the present study (Field, 2013; Nong and Du, 2011). LR model is simply a non- linear transformation of the linear regression where it transforms data using the

logarithmic transformation. The general form of LR is as follows (Cheng, 2003; Field, 2013; Hu and Lo, 2007; Huang et al., 2009; J.Padmavathi, 2012; Rogerson, 2015):
When there is only one predictor variable x_1, the LR equation from the probability of *Y* is predicted, is given by the equation 5:

$$P(Y) = \frac{1}{1+e^{-(b_0+b_1x_{1i})}} \quad ,\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...[5]$$

where *P (Y)* is the probability of *Y* is occurring, *e* is the base of natural logarithms, and the other coefficients form a linear combination much the same as in simple regression. The same as linear regression, there is a constant b_0, predictor variable x_1 and its weight or coefficient b_1. When there are several predictors, the equation becomes (Field, 2013):

$$P(Y) = \frac{1}{1+e^{-(b_0+b_1x_{1i}+b_2x_{1i}+\cdots+b_nx_n)}} \quad ,\ldots\ldots\ldots\ldots\ldots\ldots\ldots...[6]$$

where *P (Y)* is the probability of *Y* occurring, *e* is the base of natural logarithms, b_0 represents the overall occurrence (the overall incidence of built-up in this study); the variable b_1 represents the fraction by which the likelihood is altered by a unit change in x_1; b_2 is the fraction by which the likelihood is altered by a unit change in x_2… and so on.The estimated probability values lie between *0* and *1* where a value close to *0* means that *Y* is very unlikely to have occurred, the value close to *1* means that *Y* is very likely to have occurred. As the *y* value increases, the probability P increases as well. LR model is constructed by an iterative Maximum-Likelihood procedure (Hu and Lo, 2007; Nong and Du, 2011). LR uses Maximum Likelihood estimation to compute the coefficients for LR equation where it selects coefficients that make the observed values most likely to have occurred (Field, 2013; Nong and Du, 2011). This is a computerized dependent way that starts with arbitrary values of the regression coefficients (usually 0) and constructs an initial model for predicting the observed data. Maximum-Likelihood estimation is an interactive procedure that successively tries to get closer and closer to correct answer. Field (2013); Moore et al. (2009) proposed some parameters to assess the fitness of a model such as *the log-likelihood statistics, the deviance statistics, R-statistics* and *the Wald statistic* explained deeper in the methodology section. The latter assesses the contribution of predictors where the formers look at the characteristics of the whole model. In LR the measure of the log-likelihood is used to compare the observed and the predicted values to assess the robustness of the model using the equation 7 (Field, 2013):

$$\text{log- likelihood} = \sum_{i=1}^{N}[Y_i \ln(P(Y_i)) + (1-Y_i)\ln(1-P(Y_i))] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..[7]$$

The log-likelihood is based on summing the probabilities associated with the predicted and actual outcomes. This is an indicator telling how much unexplained information there is after the model has been fitted (Field, 2013; Moore. et al., 2009). The overall measure of how will the model fits, is given by the likelihood value. A model that fits the data well will have a small likelihood value. A perfect model would have a likelihood value of zero because the lager the value of the likelihood, the more unexplained observations there are. LR does not make any assumption of normality, linearity, and homogeneity of variance for the independent variables (Field, 2013; Nong and Du, 2011). Because it does not impose these requirements, it is preferred to discriminant analysis when the data does not satisfy the assumptions (Hu and Lo, 2007; Huang et al., 2009).

2.5. Application of RS and GIS in urban growth modeling

RS has facilitated robust up-to date urban growth pattern information to support essential information for sustainable urban planning and management. The spatial data obtained from RS must be processed and transformed into information, which can be displayed, analyzed and interpreted in a systematic and quick way (Trung et al., 2006). The images can be used to map anthropogenic and natural changes on the Earth over periods of several months to several years (Sanchez and Canton, 1998). The use of spatial data for sustainable management of cities has been recognized worldwide. However, in developing cities where access to required data is still difficult, Landsat has revealed as the potential free satellite imagery archive for quantifying urban growth patterns (Griffiths et al., 2010). Landsat images (RS data for the present work) have been applied to monitor urban growth in different cities: e.g.; Bauer et al. (2003) in Minnesota, USA; Araya (2009) in Portugal: Setúbal and Sesimbra; Hu and Lo (2007); Hu (2004) in Atlanta, Georgia, USA and recently Dubovyk et al. (2010) in Istanbul, Turkey and Duwal (2013) in Kathmandu Valley, Nepal. In this study, Kigali city was taken again as an example of application.

Landsat images are available from 1972 up to date in eight successive generations from Landsat one Multi spectral Scanner (MSS) to Landsat eight Operational Landsat Imager (OLI). Landsat six was never operating due to the fact that it did not reach the orbit. Therefore, a long time series of data is potentially available for analysis. However, Landsat can provide limited information (Sanchez and Canton, 1998). For example, it requires complex interpolation techniques processes to use some Landsat images that have been affected by some radiometric issues like striping and line drought.

Working with Landsat data, a selection of appropriate spectral bands is needed. Using all available bands may lie in the problem of band correlation. For classification purposes, correlated bands give redundant information and might disturb the classification process (Bakx et al., 2013). Although Landsat series has several bands, for urban studies application false color combination is needed where band 2 is blue, band 3 green and band 4 red Sanchez and Canton (1998) see Figure 4-4.

3. PLANNING POLICY AND URBAN DEVELOPMENT FOR THE CITY OF KIGALI

This chapter gives the background information about Kigali city in geographical, demographic and historical urban growth context. Then, the main policies, laws, plans, land use instruments and institutions of Kigali city' land use planning are introduced.

3.1. Historical growth and planning trend of Kigali city

Kigali city has existed since 1906 when Germany appointed Dr. Richard Kandt as the first imperial resident governor of Rwanda. He chose Nyarugenge hill as the site of the capital because of its central location in the country. Kigali eventually developed into a significant commercial centre because of its central position. It became a transit centre for commercial activities between Bukoba and Kigoma (in Tanganyika, now Tanzania) via Bujumbura and also between Kisangani in DRC and Kampala in Uganda. This development attracted many Arab and Indian traders to move from Nyanza, where the King's palace was, to Kigali. But after the Second World War, the Belgians maintained Kigali as the administrative centre for the whole country. Through this period from 1918 until 1962, Kigali city has grown and development took place. Different plans *"Plans quinquennaux de développement"* were elaborated. In 1964, a conceptual master plan "Schéma Directeur d'Aménagement Urbain de la ville de Kigali" was established. Only after 10 years the city spread beyond the area delimited in the 1964 plan, and a new plan was elaborated. During the next year, Kigali city continued to grow and by 1990's Kigali encompassed over 45 km², more than 20 times its original size in 1962. In 1991, a presidential order regulating the urban land use and housing was issued. After the 1994 genocide, Kigali continues to grow, spreading outwards from the original built area. Much of the development has occurred in natural areas such as wetlands and on steep slopes, areas typically protected and not suitable for development (Edaw et al., 2007). To control this urban phenomenon, new development measures were established to ensure urban expansion will occur in a sustainable way. Originally the city occupied the hills of Nyarugenge and Nyamirambo, which covered an area of about 200 hectares at the time of independence. Today, the city stretches from the centre: towards the east, covering the hills Kacyiru, Kimihurura, Nyarutarama, Remera and Kanombe, in the south bounding over the slopes of Mount Rebero, Gikondo, and Kicukiro and also towards the west over the slopes of mount Kigali, on slopes of Kabusunzu hills and Kimisagara. Finally, to the North, it reaches the slopes of Mount Jali and the hills of Gisozi and Gaculiro as per Figure 3-1.

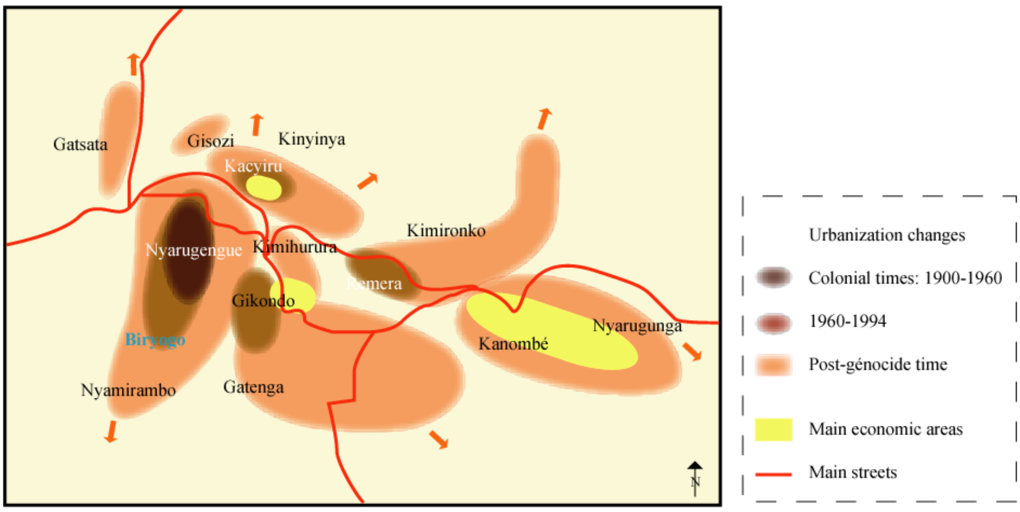


Figure 3-1: The spatial and temporal dynamics of Kigali city adapted from Michelon (2009).

3.2. Study area description and physical characteristics

Kigali city is situated between 29°43'0"E and 29°44'0"E of Longitude and 2°35'0"S and 2°37'0"S of Latitude. The city is built on hilly landscape sprawling across four ridges, separated from each other by large valleys in between. Kigali city is one among five provinces which composes the country of Rwanda. Kigali city is surrounded by the Northern Province on the North, Eastern Province on the East and South and Southern Province on the West. The elevation of the lower part is roughly 1400 m and the higher hills are at over 1845 m above the sea. The highest hill is Mount Kigali with 1850 m of latitude (see Figure 3-2). Over time, the city of Kigali has evolved by leaps from one hilltop to another (Michelon, 2009). This discontinuity is due to various constraints, namely the existence of flood plains, swamp and steep slopes. The settlements were mostly developed on gently sloping hillsides and on flattened hilltops. Nowadays Kigali city is subdivided into three districts; Gasabo, Kicukiro and Nyarugenge. Those 3 districts have 35 sectors, subdivided also into 161 cells. The cells also comprise a total number of 1061 imidugudu literally villages (REMA, 2013).

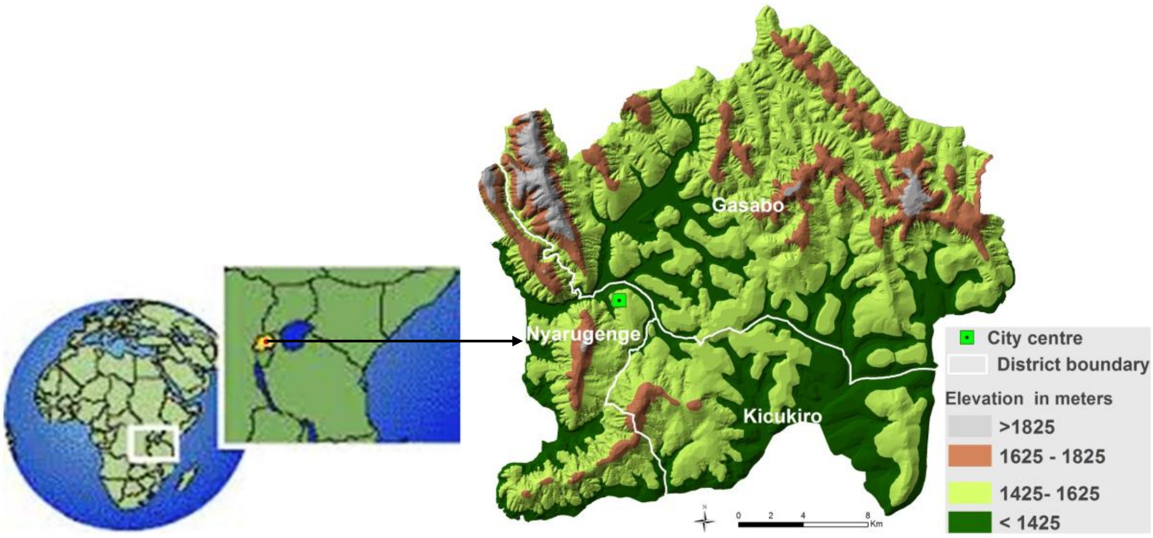


Figure 3-2: The location and topography of the study area.

Left picture downloaded from: http://www.worldtimeserver.com/current_time_in_RW.aspx?city=Kigali.

3.3. Demographic characteristics of Kigali city

Kigali has grown from a population of 6000 people in 1962 (when Rwanda gained its independence) to over 1 million inhabitants today as per Table 3-1. Such an increase of population in Kigali city was a result of the big migration of people from rural areas for employment and business opportunities. Moreover, the today's Kigali city is a result of its administrative boundaries that has been revised during the implementation of Decentralization policy which has resulted in the inclusion of some semi-urban areas which were previously not part of Kigali city. The first was a decree law N^0 11/97 of 27/04/1979 from which Kigali had 112 km^2. This was followed by the presidential order N^{0}896/90/of 27/11/1990 which conferred the city of Kigali a total area of 349 km^2. The third one was the law N^0 47/2000 of 19/12/2000 which had any impact on the spatial dimension of Kigali city but redefined its administrative entities. The last one was the law N^0 29/2005 of 31/12/2005 which gives the today's Kigali city a total area of 730 km^2 (Edaw et al., 2007; NISR, 2012).

Table 3-1: Population evolution in Kigali city in km² refers to its administrative area.

Year	Population	Area
1907	357	0.08
1945	6000	2
1960	6000	2.5
1978	117749	112
1991	235664	112
1994	350000	112
2000	605000	349
2005	851024	349
2006	930000	730
2009	1000000	730
2012	1135428	730

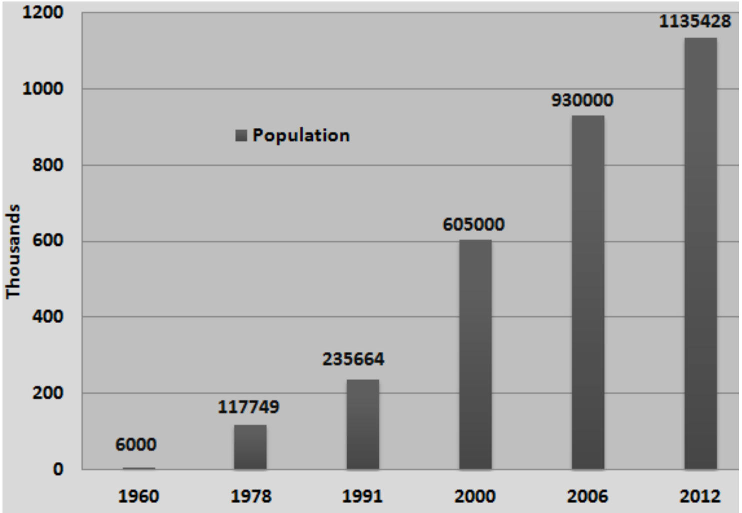


Figure 3-3: Demographic dynamics of Kigali city (REMA, 2013).

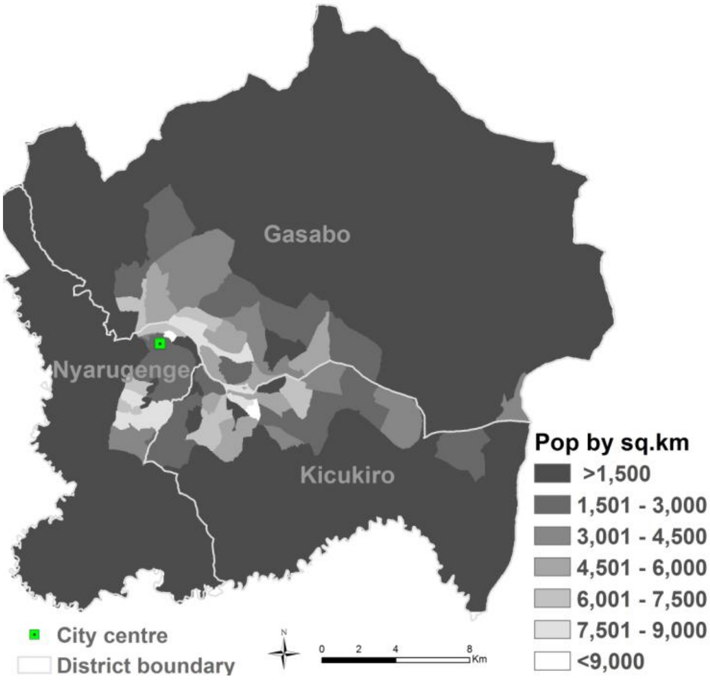


Figure 3-4: Population density of 2012 situation.

Kigali city is among fastest growing cities in Africa with a strong population growth with average annual growth rate of 4.0% (NISR, 2012). Table 3-1 shows the summary of the population figure from 1907 up to 2012. The corresponding Figure 3-3 was included to see population trends from 1960 up to 2012 the study time span. Furthermore, a breakdown of the population density for the three districts aggregated at cell level was visualized in Figure 3-4. Gasabo district is the most populated and fastest growing (5.2% growth rate) of the three districts while Nyarugenge is the least populated with 1.9 % average annual growth rate. This high population density is associated with high population growth rate due to the birth rates increase, immigration rates and transient population (Manirakiza, 2012). Table 3-1 and Figure 3-3 prove a big correlation between population growth and built-up areas in Kigali city. As can be seen in Figure 3-4, the most dense areas are located around the city's core, hence the highest population density is found in Nyarugenge district (average 2,127 persons per km²) and there is a noticeable decrease moving to the hinterlands. This population density is lower in Kicukiro district (average 1,918 persons per km²) and relatively lower in Gasabo district (average 1,237 persons per km^2). People are more concentrated towards the city centre and subcentres; few at the periphery.

3.4. Land use in Kigali city

Land use is a vital element for understanding urban activities. From Figure 3-5, it can be seen that the land use typology of Kigali city is grouped into urban and rural clusters. The total area occupied by urban areas was 12.1%, thus 88.40 km^2 and the remain portion (87.9%, thus 642,60 km^2) was rural. Built-up is a collection of different land use types like mixed use, commercial, industries, some infrastructures, public facilities, residential and governmental areas. Public facilities include education institutions, religious, civic, health facilities as well as cemeteries. The high-rise, medium-rise, low-rise and single family residential land can be distinguished. Commercial patches are mainly scattered in the core of the city. In past years, industrial sites which were closed to the wetlands were displaced currently on the new proposed sites as per Figure 3-5. Governmental land use combines government offices and military camps. Mixed use encompasses all vertical apartments containing more than one urban land use activities. Agriculture land occupies the biggest portion of the city's area (see Table 3-2 and Figure 3-5) followed by wetlands and forests respectively.

Table 3-2: 2012 land use types by percentage in Kigali city.

Land use type	Area in Km^2	%
Mixed use	0.19	0.03
Wetland	78.07	10.68
Agriculture	478.46	65.45
Commercial	3.00	0.41
Industries	4.14	0.57
Infrastructure	21.19	2.90
Forest	53.57	7.33
Recreational/Vacant spaces	7.38	1.01
Public Facilities	14.10	1.93
Residential	67.20	9.19
Governmental	2.20	0.30
Rivers/Lakes	1.50	0.21
Total	731.00	100.00

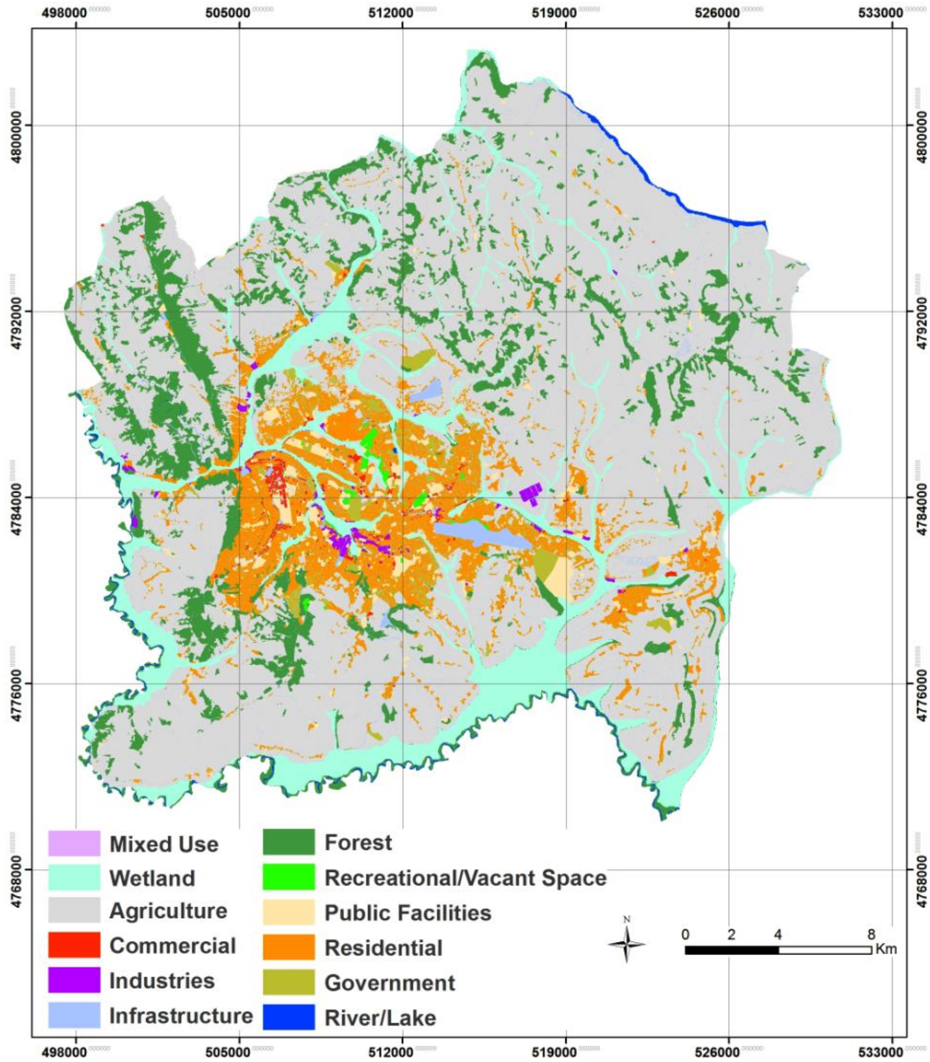


Figure 3-5: 2012 land use map.

3.5. Kigali city urban development and policy framework

Rwanda, like most developing countries, is facing many challenges in urbanization. To have a strong urban development control, improved policies, regulations as well as efficient institutions are needed. In this regard, a range of laws, policies, programs, visions and plans were issued after the 1994 genocide. Different policies, programs and regulations related to Kigali city growth were analyzed for gaining a good understanding on Kigali city current status. This study attempts to review the most vital on the country level like Rwanda vision 2020 (2002-2020), EDPRS (2008-2012); Land policy 2004, National human settlement policy 2004, National Urban housing policy 2008, Land law 2013, Condominium law 2012 and Land Use Planning and Development law 2012. On Kigali City scale, in 2013, Kigali City Master Plan was published followed by detailed physical plans of three districts of Kigali City. However, it is important to note that apart from Kigali City Master Plan, these laws, policies, plans are not specific to Kigali city but apply to all urban and rural lands.

(1) Rwanda vision 2020 (2002-2020)

Rwanda vision 2020 is a guiding document which specifies the main developments, policies, regulations that will be elaborated and implemented in all developmental domains from 2002 up to 2020. In regard to the urban development sector, in this vision a modern land law providing security of tenure and freedom of exchange was issued. Some paragraphs of "vision 2020" mentioned that: *"From now until 2010, each town will have regularly updated urban master plans and specific land management plans. The country will develop basic infrastructure in urban centres and in other development poles, enabling the decongestion of agricultural zones". "Rwanda will pursue a harmonious policy of grouped settlements based on economic activity. Rural settlements organized into active development centres will be equipped with basic infrastructure and services* (MINECOFIN, 2000)*".*

(2) EDPRS (2008-2012)

Economic Development and Poverty Reduction Strategy (EDPRS) is an implementation strategy for vision 2020. Its main actions are the improvement of living conditions of the poor people, economic infrastructure, promotion of good governance, development of the private sector and the institutional reinforcement. During EDPRS in urban development context, the focus was the management of the environment and optimal utilization of natural resources. Some paragraphs state that: *"A land use and management master plan will be developed by 2008. In the area of habitat and public assets management, emphasis will be put on the planning and development of improved rural and urban human settlements consistent with the contemplated sustainable land use and environmental protection schemes. Eleven city master plans will be prepared (making thirteen in total) by 2012* (MINECOFIN, 2007)*".*

(3) Land policy 2004

Land policy calls for rational use and proper management of national land resources. The policy also provides development of land use plans based on land suitability thus distinguishing the different categories of land and their purpose. In cities, this policy provides strategies for preventing the excessive use of space and urban outer expansion. This policy also encourages urban densification by adopting high-rise buildings and the reduction of the building plot size (MINITERE, 2004).

(4) National human settlement policy 2004 (updated version of 2009)

The main objective of this policy in the urban areas is to improve the settlement conditions of the urban population. In particular, this policy provides strategies for preventing the spread of chaotic buildings and of unplanned urban development. This policy ordered specifically the establishment of 2013 master plan and development plans for Kigali city that will take into consideration of the new urban extension zones (MININFRA, 2009).

(5) National urban housing policy 2008

National urban housing policy tried to improve and control urban development and the spatial expansion of cities in particular urban centres using spatial planning support systems. This policy aims at guiding objectives and priorities set in Vision 2020 and EDPRS in the urban housing domain. Mainly, this policy provides measures for preventing the formation of new unplanned settlements in cities and in Kigali city in particular (MININFRA, 2008).

(6) Land use planning and development law 2012

Land use planning and development law searches to prevent urban sprawl by promoting densification, multi-family residential settlement in rural and urban areas. This law limits illegal land use conversion and states that any use or change of land must be approved by the competent authority (Article 10). Any land use conversion must be based on this land use planning and other adopted plans and laws in force applicable in the matter (Article 12) (Republic of Rwanda, 2012b).

(7) Condominium law 2012

The main objective of condominium law is to reduce pressure on land and encourage vertical urban growth by stopping the progress of horizontal urban development. In this law, urban housing typologies would change moving away from the single typology of small single-storey family houses to multi-storey residential apartment (Republic of Rwanda, 2012a).

(8) Land law 2013

Together with the land policy, this law determines the management of land in Rwanda especially land allocation, acquisition use and land transfer. This law was elaborated as a tool for defining land rights, limitations and obligations of all land in Rwanda. In urban development perspective, It clarifies land use suitability; an area specific for each land use type (Article 2). Moreover, it recommends to use all land in a sustainable way (Article 62). The law orders the elaboration of the national land utilization plan and states that this must be respected at all the time (Article 66). This law argues that local specific master plans must be tied based on the district development plan and also in accordance with the national land use and development master plan (Republic of Rwanda, 2013).

(9) National Land use Master plan 2010-2020

NLUMP was elaborated to serve as the overall document that guides spatial and urban development directions on country level. For this, any other plan must be in line with this national plan, and only plans that conform to this national plan will be approved. In this plan, a national cadastral and land information system was established that will act as a tool for sustainable land use and spatial planning. The plan recommends detailed mapping of land use suitability at district level. These plans will define urban growth boundaries for each district that can assist in creating a sustainable balance between urban and rural area within a district. For Kigali city, it recommends the establishment of zoning regulations to control urban encroachment and urban land conversion (mainly agriculture to build-up) (RNRA, 2010).

(10) Kigali City Master Plan 2013

Kigali Master Plan 2013 is the final product of a long planned route started in 2007. It is based on the previous completed 2007 (Kigali Conceptual Master Plan). KCMP includes the Detailed Districts Master Plans for Nyarugenge, Gasabo and Kicukiro. This plan was developed to incorporate, harmonize and update all previously elaborated plans. These detailed district plans can now be referred to guide the development on an individual plot level. KCMP provides a long- term vision for the city. It sets up fundamental pillars of sustainable urban development, such as protection of wetland, slopes and forest areas. In addition, it contains detailed land use and zoning plans that will guide the city's urban development (see Figure 3-6 and 3-7). Zoning regulates the types of land uses, land development intensity, the setting and height of buildings on plot level. In this regard, the zoning plan is attended to provide a clear picture of what can and cannot be allowed on a particular land use type. Zoning of each district is composed of a zoning map and a set of zoning regulation. KCMP is designed in a way that the zoning map identifies specific zoning districts within a planning area based on its predominant land use in that area. Zoning regulations order the location of a building, building height as well as the maximum allowable development in a particular zone. Zoning regulations are grouped into permitted, conditional and prohibited uses. Permitted use gathers uses that comply with the desired use for the particular area and can be permitted to be developed within any particular zoning district. Conditional uses gather all activities that may create a significant traffic, noise, or other negative impacts on the surrounding neighborhood. Such identified uses can be permitted "conditionally" within a zone requiring the development to confirm to a set of conditions and standards as per the regulations which must be met at all the times. Each zoning district can allow different land uses, but compatible developments that are complementary in terms of use and scales. Prohibited use, assembles uses that are deemed prohibited, and includes activities that have been found to be incompatible with the particular zoning district. As shown in 3-6 and 3-7 Figures, 2013 KCMP provides proposed zoning maps for Kigali city's future growth in 2025 and 2040. These proposed plans are designed to guide changes in the city over the long term and gives physical form to its strategic vision (Surbana, 2012).

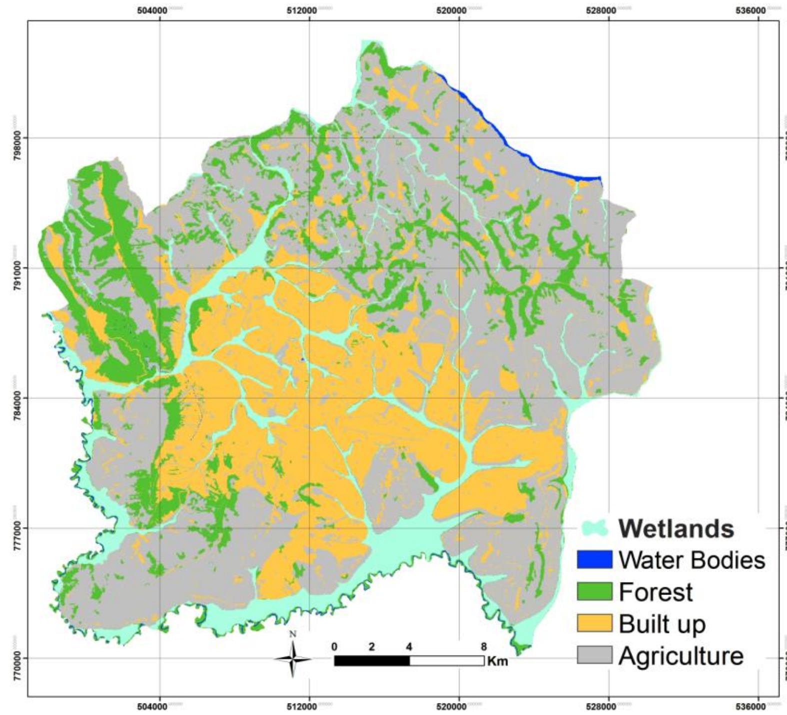


Figure 3-6: Proposed 2025 zoning land use map.

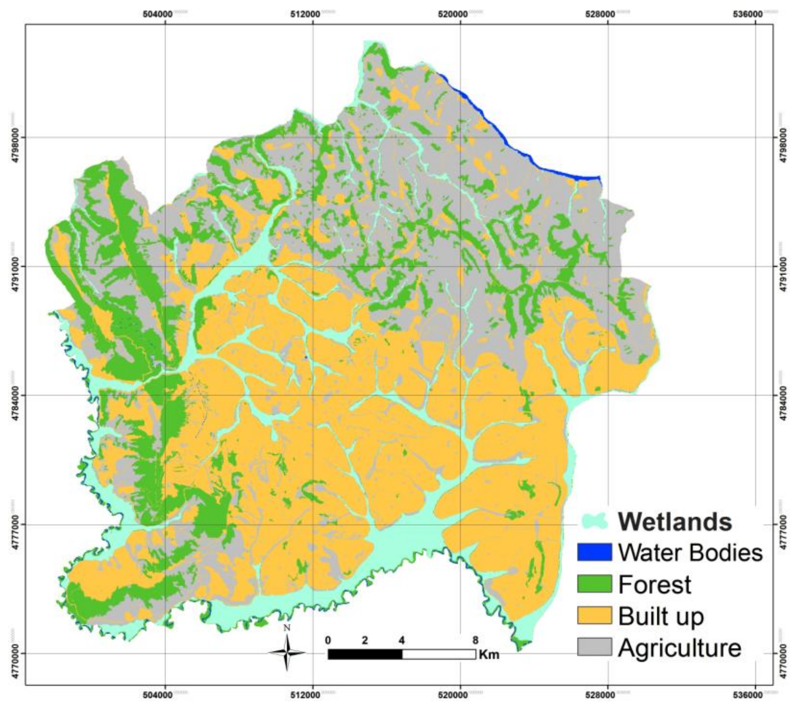


Figure 3-7: Proposed 2040 zoning land use map.

3.6. Policies instruments elaborated to control Kigali city growth

Kigali city sees as a rapid urban sprawl with low density development mushrooming particularly in the urban periphery (Edaw et al., 2007). It is in this regard that, Kigali city found it wise to put forward some policies and plans in order to protect open space and managing urban growth. Kigali city listed the land use policy instruments that will safeguard the open space and manage urban growth. Policy instruments used in Kigali city to manage urban growth are regulations, public acquisitions followed by incentives. In terms of regulations, the creation of buffers or controls distance between building and roads or streets was proposed. Kigali city stopped all construction on wetland and relocates all industrial zones located in wetlands (Gikondo in Kigali City) to the new planned zone "Kigali industrial zone" at Rusoro area. Public acquisition policy is a policy instrument used for protecting open space. This is used for creating recreational area and protecting the existing open space like forests, wetlands, etc. For an incentive based approach, Kigali city council gives leasehold plots for free taxes during 5 years for industrial activities. In addition, Kigali city offers new plots for free and plots without taxes during 3 years in the new industrial zone to the investors that had their business in the old industrial area. Moreover, the land allocated for agriculture or gardening is free of taxes, to protect open spaces. Non responsive instruments include demolition of illegal developments and paying fines for constructions that are contrary to the approved plans.

3.7. Kigali city institutional framework

In Rwanda, the institutional spatial planning domain is still evolving. This sector is characterized by significant structural changes and reforms. It involves different stakeholders, including governmental state institutions, NGOs, Civil society, the private sector, decentralized entities and donors. Responsibilities of the main vital government institutions for urban spatial planning concern are summarized in Table 3-3.

Table 3-3: Urban spatial planning structure in Rwanda

Institutions	Responsibilities	Actions
Ministry of infrastructure	MININFRA initiates, develops and implements related urban development policies and programs.	Monitoring and regulation, funding, policy making, technical support
1. Department of urban planning and human settlement	Elaboration of local urban plans and spatial planning policies.	
2. Rwanda Housing Authority	RHA advises the government on the formulation of the policy on housing, urban development and construction. It provides advice on all aspects of urban building, including land use suitability and construction procedures.	Housing technical support
Ministry of Natural Resources	MINIRENA ensures the protection and conservation of the environment and ensure optimal and rational utilization of natural resources for sustainable national development. Defines the overall land related policies.	Funding, policy making, land and technical support.
1. Rwanda Environmental Management Authority	REMA possesses the legal mandate for the national environmental protection, conservation, promotion and overall management, including all	Monitoring and regulations, implementation and

	advisory to the government on all matters important to the environmental concern. Monitors and supervises environmental impact assessment and other environmental related studies.	technical support
2. Rwanda Natural Resources Authority	RNRA is responsible for the management and the promotion of natural resources, composed by land, water, forests and geology. In land use domain, RNRA streamlines all policies regarding land transactions, approval of land use monitoring, implementation of land policies, national land use master plan, support local planners in all functions of spatial planning and survey.	Land technical support
Ministry of Local Government	Demarcation of urban boundaries and approval of local plans. Implementation of urban master plans and "imidugudu"policy for sustainable land use management.	Funding governance participation
District one stop centres	Land, housing and infrastructure planning, land allocation, construction permit assessment and approval, and local land use development control.	Monitoring, implementation and servicing

Source: Author, compiled from different documents related to urban development in Rwanda.

3.8. Concluding remarks

This chapter provides an overview of current policies implemented in directing the Kigali city growth. Local urban planning experts asked argued that;*"The current policies will reduce urban sprawl of the city and promote densification". "It will also require growth to be tied to infrastructure development".* However, other respondents claimed that the proposed plans focus on high and middle standing while the low standing for poors is given less priority. Therefore, the majority of low-income groups are unable to meet the standards set for high and middle-standing areas. This push them to settle in hazardous and in the non- planned peri-urban sites that in the long-term will finish by being incorporated in Kigali city through incessant urban extension. Several institutions are involved in the urban development sector. Although, Rwanda puts much effort in that sector, some issues are still present. There is a lack of clear definition and limitation of role and responsibilities and mandates of the institutions in the urban development process. As a matter of fact, all the above discussed institutions are responsible for funding and regulating spatial planning matters. This leads to the overlapping of tasks between institutions when implementing urban spatial planning policies and laws. To overcome this, there should be a good coordination among institutions. Moreover, all urban development institutions need to be merged instead of scattering these functions in my different institutions to avoid the present fragmented planning objectives.

4. DATA AND LOGISTIC REGRESSION MODEL INPUTS PROCESSING

This chapter gives detailed information about the data used and the methodological framework followed. First, an overview and workflow of data collection methods are given. Second, the defined way of generating input data is explained. Finally, LR model parameters and prediction inputs are explained.

4.1. Primary data collection

To obtain accurate and good data quality, primary data collection instruments need to be defined and checked beforehand. In this study, primary data relied on results from the questionnaire administrated to household heads, truth ground data and field index map preparation.

4.1.1. Questionnaire administration

The aim of the questionnaire was to collect the main drivers of Kigali city growth, their degree of importance on city growth that may have an impact on policies, plans and regulations of today's Kigali city morphology. A written list of questions was elaborated and administered to the local urban planning experts. Before administration of the questionaires, local urban planning experts were contacted to ensure their availability. Thereafter, the questionnaire was delivered to respondents and collected back after five days. In total, 15 respondents, including academicians, retired and technicians from different institutions (National university of Rwanda, Rwanda Housing Authority, Rwanda Natural Resources Authority, Ministry of Infrastructures and Kigali city) were interviewed. Additional information collected from local urban planning experts' views with regard to main drivers of Kigali city growth were an added value to build a robust LRM.

4.1.2. Truth ground data

GPS receiver was used for marking and recording coordinate points. Very High Resolution printed maps to locate the area visited and digital camera photo were used to take some field photos. Stratified sampling technique was used to capture 214 representative truth ground data and training samples. The area was subdivided into strata (see Figure 4-2 and 4-3) based on their interpretation elements such as homogenous tone and hue, texture, patterns, shape and size (Bakx et al., 2013; Kumar, 2005). In each stratum (one field sheet), random points in several places were marketed, recorded and categorized into their respective land cover classes which were built-up, bare, vegetation, forest and water. The below are GPS settings projection name and parameters used.

1. Name: WGS_84
2. Projection Name: Transverse_Mercator
3. Projection parameters
    - False_Easting: 500000
    - False_Northing: 5000000
    - Central_Meridian: 30
    - Scale_Factor: 0.9999
    - Latitude of Origin: 0

Figure 4-1: Different land covers of the study area.

4.1.3. Field index map preparation

One single A0 Kigali city map was not used due to the fact that all features were not readable in this format. To support field data collection, maps at a scale of 1:2000 were printed out using Map book created using Data Driven Pages tool in ArcGIS. It helped to generate a book of maps as a series of maps with similar themes that breaks a large area into smaller maps which all have the same scale. The final product was one Index map of 1:200,000 showing subdivided field sheets in A0 format and a series of 48 sheets at 1:20,000 in A2 format. The feature class of index polygon (created automatically), the feature class of the area to work on (Kigali city boundary) and VHR covers the concerned area were layers used to create the index map shown in Figure 4-2 and 4-3 respectively.

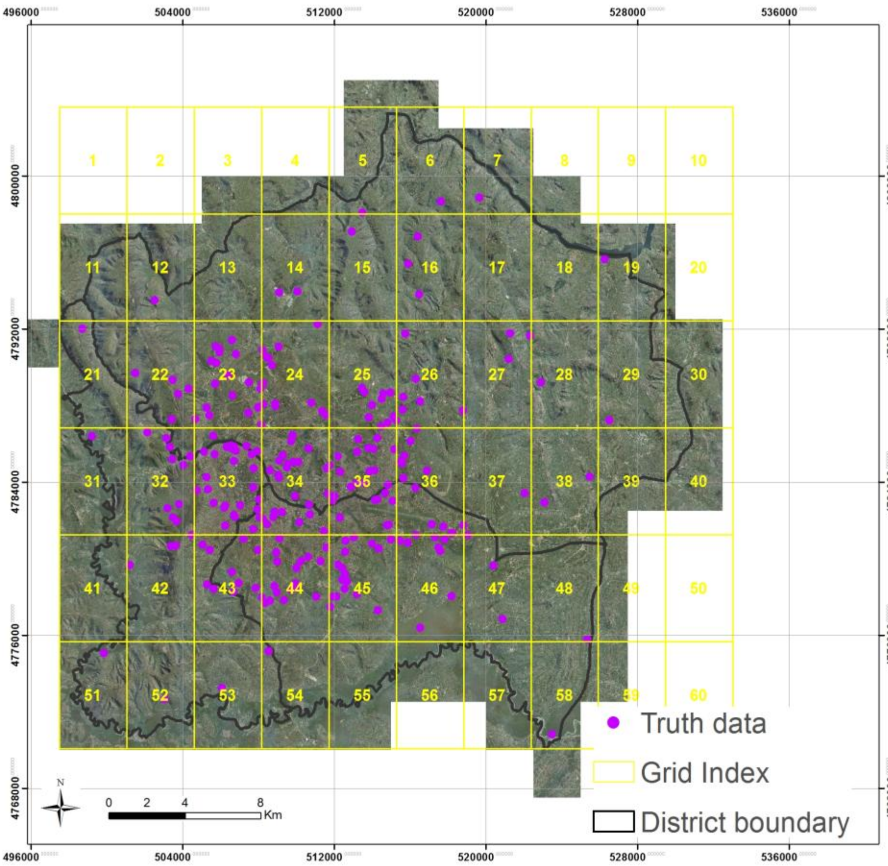


Figure 4-2: Kigali city index map.

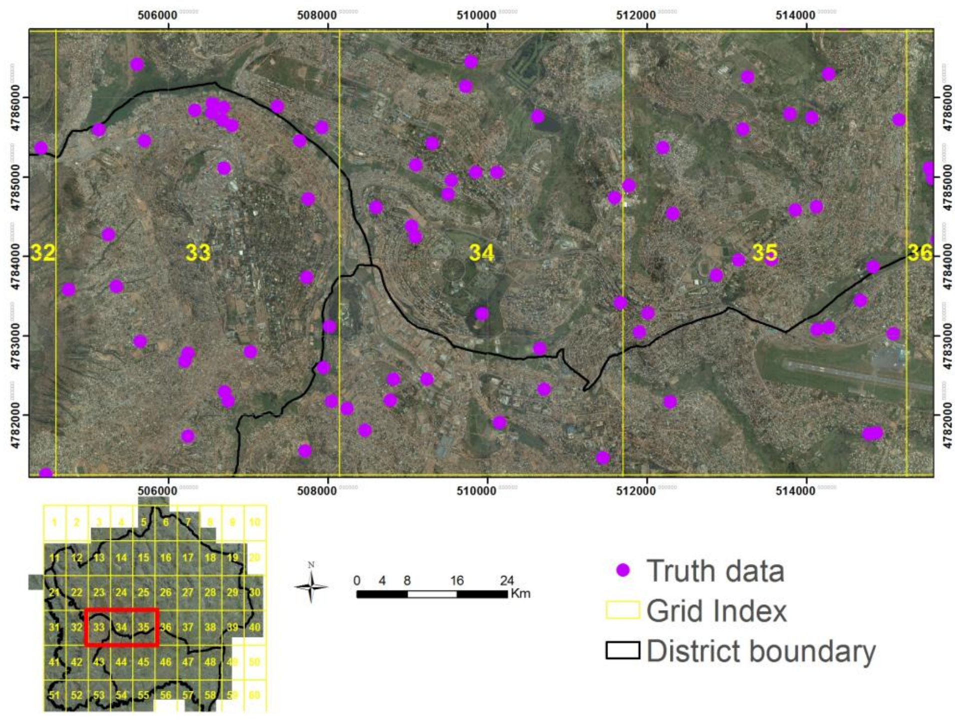


Figure 4-3: Kigali city field sheet.

4.2. Secondary data collection

Secondary data used in this study included spatial data; Remote Sensing (RS) imageries, base map components (land use maps, DEM, roads, wetlands, administrative boundary, health centres, markets), and other ancillary data; population statistical report, maps, reports, and other documents related to the study (*Appendix A*). For RS data, Landsat imagery (row 61, path 172) 1987, 1999, 2009 and 2014 were used to generate land cover maps. Therefore, 1986 topographic map, Kigali city Cadastral map designed in 1994, RGB aerial photography of 2008 (0.25 meters resolution), Google earth 2014 images (0.9 m resolution) were secondary data used during data collection.

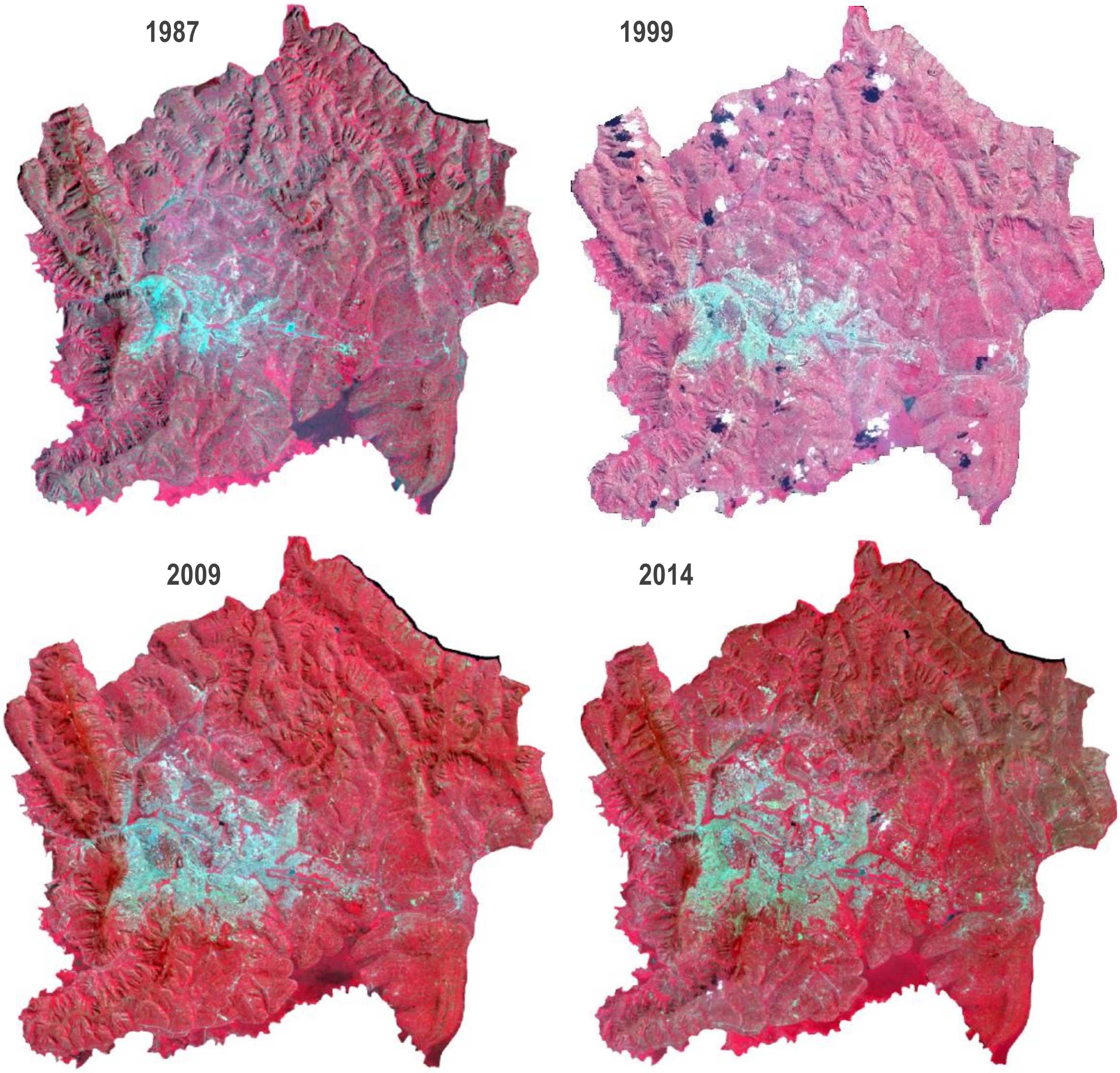


Figure 4-4: False color composite 432: Landsat TM (1987, 1999), Landsat ETM+ (2009) and Landsat OLI (2014) images of Kigali city.

4.3. Geoprocessing of data inputs and Logistic Regression Modeling

To build a LR model of urban growth pattern in Kigali city, a time series analysis and modeling were conducted using four different Landsat images from 1987 up to 2014. The selection of these periods was based on technological aspects such as Landsat image availability, radiometric (images without striping, line drought), atmospheric situation (images without clouds and hazes) and on Kigali city historical growth (different growth situations before 1994 genocide and post genocide period).

4.3.1. Generating a consistent set of land cover maps

Quantifying urban growth pattern passed through five essential stages: selection and preparation of RS image, image processing, image classification accuracy assessment and change detection (Bakx et al., 2013). Four Landsat TM (1987, 1999) Landsat ETM+ (2009) and Landsat OLI (2014) images downloaded from the United States Geological Survey (USGS) were used to extract land cover maps for Kigali city. The images downloaded were separate TIFF files bands larger than a Kigali city boundary. Mosaic and subset data were used to extract the Landsat images covering the study area for land cover classification. In the first step, the image combination of all bands; band 1 up to band 7 except band 6 and 8 were performed for Landsat TM and ETM+ and band 2 up to band 7 for Landsat OLI into ERDAS IMAGINE 2013 using layer stack tool. Moreover, for all time spans images subsets were created using the boundary of Kigali city. Clouds were nearly absent in the downloaded Landsat images except for the 1999 Landsat, which needed field observation to find out land cover type underneath clouds. The pixel based approach for all digital images were performed using supervised classification. By Maximum Likelihood Algorithm each pixel was classified and assigned the predominant land cover classes such as built-up areas, vegetation, bare soil, forest and water bodies. To select training areas the truth ground points that were collected during field work were used. Training sites were delimited by means of visual interpretation based on homogeneous patch identification, with the same color composite, local knowledge (local citizen) and using very high resolution images such as 1986 topographic map, 2008 aerial photography, 1994 Kigali city cadastral map and 2014 Google Earth image. The overall accuracy or proportion of correctly classified pixels (PCP) and Kappa statistic to assess the accuracy of land cover classified was performed. These were assessed using 214 randomly selected points. Noise pixels were appeared in the classified Landsat images. Post classification 3*3 moving window smoothing filter was applied to remove unneeded pixels to improve the classification accuracy. In ERDAS IMAGINE, fuzzy algorithm of 3*3 window size (eight surrounding neighborhood) followed by vector overlay rectification (using forest and wetlands datasets) were applied for Landsat classified images. Thereafter, post comparison approach was applied to quantify and analyze land cover changes occurred. The land cover maps that were classified separately were compared. Dummy variable inputs of the LR model were extracted from 1987, 1999, 2009 and 2014 land cover maps generated by grouping land cover into two categories which are urban and non urban as per Figure 4-5. To determine the pattern of the city, Patch Analyst by Mean Shape Index was calculated as detailed in section 5.1.

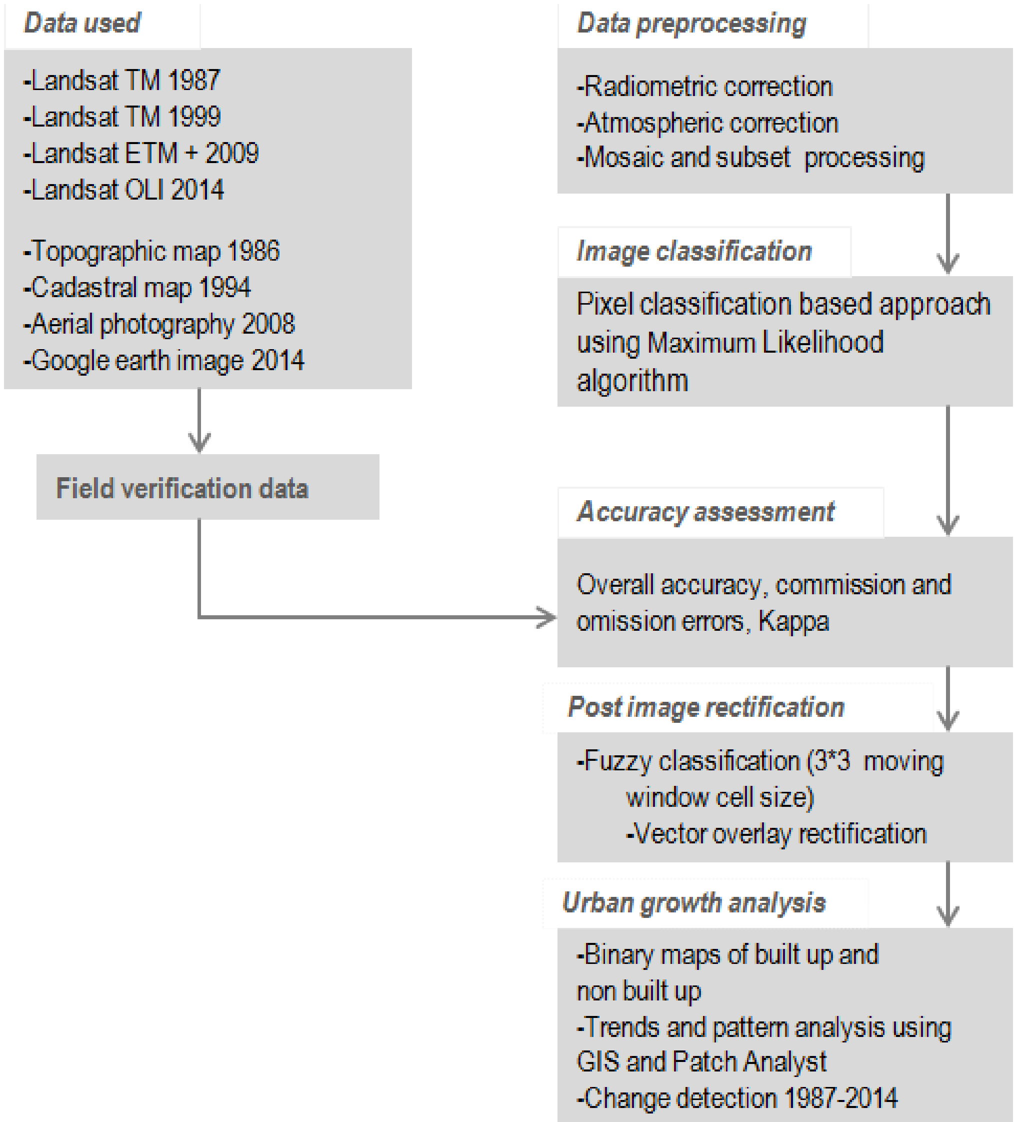


Figure 4-5: Urban growth mapping and change detection.

4.3.2. Identifying driving forces conditioning urban growth and preparation of input data for LRM

This study focused on identifying drivers contributing to the expansion of Kigali city. The idea was to know how good these explanatory variables can control the Kigali city growth. The assumption was that past behavior (land cover/use change) is indicative of future changes. The major drivers were identified from the literature and the views of local urban planning experts. The identified local urban planning experts provided us new variables not identified from the literature, but fundamental for Kigali city growth. A list of potentially useful independent variables was screened out. All variables were prepared into ArcGIS and resampled using the same resolution and projection. All datasets were geometrically registered using the World Geodetic System (WGS_1984_UTM_Zone_36N) coordinate system, of the used Landsat projection. Both dependent and independent variables were prepared in raster format, 30*30 meters cell size, the spatial resolution of Landsats classified.

According to Verburg et al. (2004) several factors that influencing the growth of an urban area were subdivided into four different broad categories. These are biophysical constraints and potentials, spatial policies and interaction characteristics factors.

(1) Bio-physical factors
Under these factors we include natural factors like slope, geology, soil types characteristics that may influence or constrain the development pattern of an urban area. The factor slope was selected under delimited data and used to check whether height had an influence on the development pattern of the city. Slope percentage was calculated from the DEM of 10*10 meters cell size processed from the DTM of 2009 aerial photography 0.25*0.25 meters of Kigali resampled into 30*30 meters the used Landsat cell size.

(2) Land use zoning factors
Among these factors, forest and wetland were selected with the assumption that wetlands had a connotation of being easily flooded and therefore they might not be developed for urban growth. Moreover, the forest was selected to check the environmental sensitiveness of Kigali city development. The used variables were extracted from the 2012 land use dataset and assumed that they remain constant in 1999 and 2009 years. They were selected by attributes and rasterized as dichotomous variables with 30*30 meters of cell size. Furthermore, commercial and industrial dummy variables were selected as potentials for urban growth. Moreover, 2025 and 2040 binary factors were extracted from 2025 and 2040 proposed land use zoning. These factors were incorporated in the model as scenario assumptions. In this study, three scenarios were considered; expansion scenario and densification (strict and moderate) scenarios. In the expansion scenario, 2025 and 2040 prediction models were constructed including all significant variables except the said zonings, while for densification (strict and moderate) scenarios, significant variables for the best expansion model including their respective zoning factors were incorporated in the model as well.

(3) Neighborhood characteristics
In spatial interaction and neighboring perspective, each development affects the conditions of the neighboring and distant locations (Verburg et al., 2004). Continuous factor maps were prepared representing the proportion of built-up in the year of 1999 and 2009. The factor map of 1999 was used in 1999-2009 expansion scenario model and the factor map of 2009 was used in 1999-2014 and 2009-2014 expansion scenario models. Here the assumption is that land cover only changes from non built-up to built-up where the inverse is rare in fast developing cities.

(4) Proximity characteristics
The Central Business District (CBD) such as main roads and subcentres were considered due to the fact that these CBD and sub centres have an influence on the urban growth, since it is assumed that the land is devoted to the use that generates the most returns; hence most commercial and industrial activities are developed along the development of the CBD. It is therefore assumed, unless proven otherwise, that the CBD has a great positive influence on the urban development pattern since most development will like to be closer to areas with employment opportunities and other social infrastructures. In this case, the road network of 2009 was considered and assumed that most developmental activities will like to be closer to major roads, therefore the road infrastructure has an influence on the development pattern.

The nature and significance of the relations between these explanatory variables and the response variable were tested for model robustness. Table 4-1 shows data that were included in LRM.

Table 4-1: Factors included in LRM.

Type of variable	Description	Nature of variable	1999	2009	2014
Dependent					
	1- Built-up 0-non built-up	Dichotomous	•	•	•
Independent					
Bio-physical influence	Slope in percentage	Continuous	•	=	=
Land use zoning	1- Forest; 0-none forest	Dichotomous	=	=	=
	1- Wetland; 0-none wetland	Dichotomous	=	=	=
Neighborhood characteristics	Population density (person/km^2)	Continuous	•	•	•
	Proportion of built-up land in the surrounding area	Continuous	•	•	•
Proximity characteristics	Distance to major roads	Continuous	=	=	=
	Distance to commercial areas	Continuous	=	=	=
	Distance to industrial sites	Continuous	=	=	=
	Distance to CBD	Continuous	=	=	=
	Distance to sub-centres	Continuous	=	=	=
	Distance to health centres	Continuous	•	•	•
	Distance to bus routes	Continuous	=	=	=
	Distance to bus stops	Continuous	=	=	=

- Assumed to be different for each year

= assumed to have the same value in each time span

Due to lack of 1987 data, RL models focused on data for 1999, 2009 and 2014 only. These factor maps are independent variables which are either dichotomous or continuous while the dependent one was dichotomous. Figure 4-6 highlights the steps passed through to come up with the meaningful drivers of Kigali city growth.

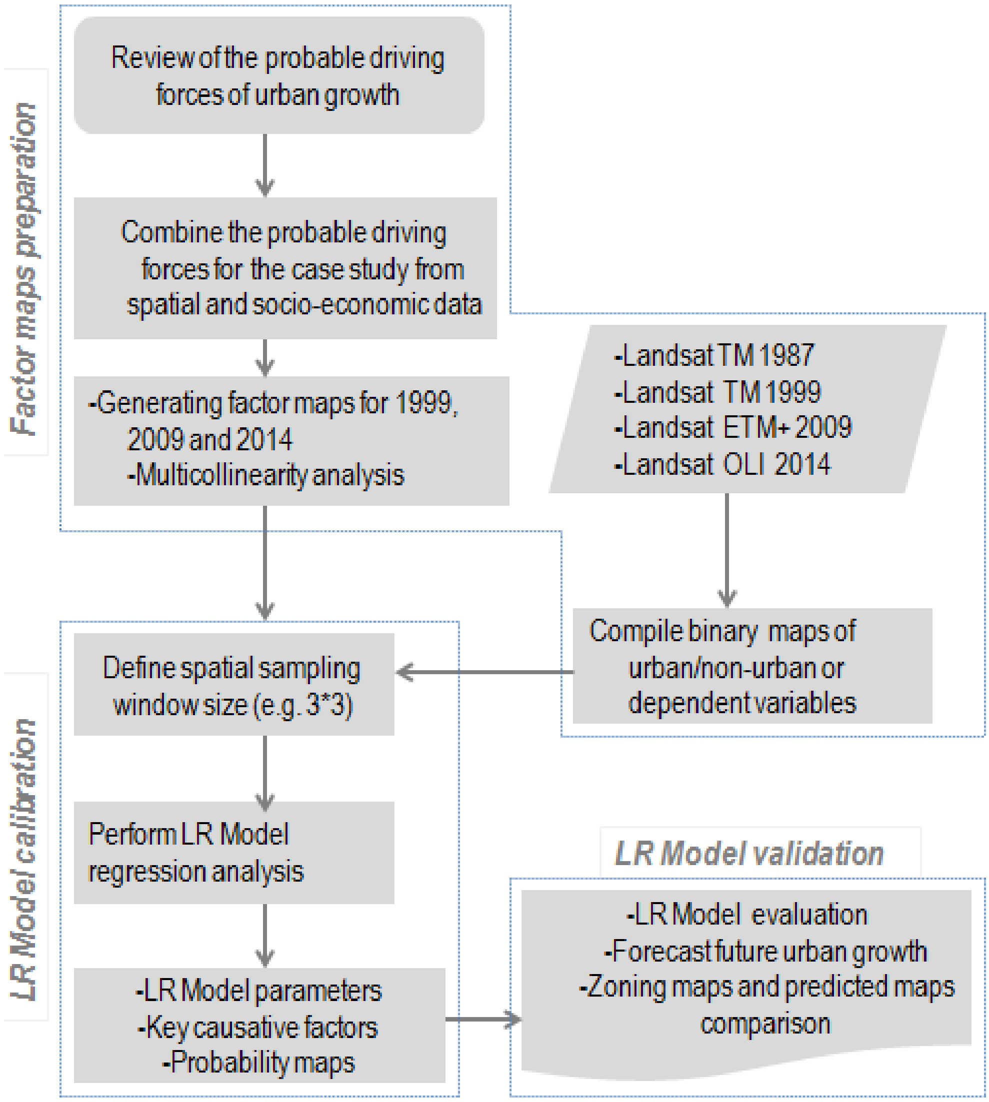


Figure 4-6: Flowchart showing procedures followed in LRM.

Apart from the aforementioned factors in Table 4-1, other factors considered as drivers of urban growth by local urban planning experts were not included in the model. This is because they were not available and their integration capability for extracting meaningful information was difficult. Firstly, a combination of 2009 Systematic Land Registration, business and legal response, proximity to workplace, family members and building material, security in Kigali city, level of services, job opportunities in the city, affordable cost, infrastructure upgrading and transport means were factors unveiled by respondents not included in the model because of the above reasons. Furthermore, some biophysical factors such as soil types, neighboring characteristics (regular water and electricity provision) as well as economic factors (land value) mentioned in the questionnaire were not also used.

In this case, four dummy land cover maps in the periods of 1987, 1999, 2009 and 2014 were used and were defined as 1 for built-up and 0 for non built-up. Then built-up was defined as the combination of vegetation, forest, bare land land cover types.

4.3.3. Build a Logistic Regression Model

As discussed in section 2.4, LRM has been used to model the relationship between the driving forces (independent variables) and built-up cover (dependent variables). In the LRM a positive sign coeffiecient parameter indicates that the explanatory variable helps to increase the probability of change and a negative sign implies the reverse effect (Cheng, 2003; Field, 2013; Rogerson, 2015).

4.3.4. Multicollinearity diagnosis

Multicollineality is a statistical analysis for the correlation detection among independent variables. When independent variables are correlated among themselves, multicollineality is said to exist (Cheng, 2003). There are some key problems that typically arise when these variables are highly correlated among themselves. Adding or deleting an explanatory variable changes significantly the regression coefficient and the estimated standard deviations of the regression coefficients become larger (Field, 2013; Moore. et al., 2009). Furthermore, it makes some variables statistically insignificant while they are significant. The most common diagnosis indicator to check for multicollinearity in LR modeling is to display Variance Inflation Factor (VIF). VIF is a measure of how much variance of the estimated regression coefficient increases if the explanatory variables are correlated.

$$VIF_j = \frac{1}{1-R_j^2}, \quad j = 1,2,\cdots k, \ldots\ldots\ldots\ldots\ldots\ldots [8]$$

where R^2j is the coefficient of determination of the regression of the j^{th} independent variable on the remaining *k-1* independent variables. The higher the value of *VIF* the greater is the degree of collinearity. Some authors suggest that if the *VIF is less than 10* there is strong evidence that collinearity is affecting the regression coefficients and consequently there are poorly estimated. During analysis, variables with the *VIF higher than 10* were removed from the model.

4.3.5. LRM parameters

To interpret results of LRM, odds ratio, model coefficients, Chi-square statistics and T-Ward statistics (z-value) parameters were used (Hu and Lo, 2007; Nong and Du, 2011). The odds of an urban growth occurring are defined as the probability of an urban growth occurring divided by the probability of that urban growth not occurring (Field, 2013). It is simply to calculate the proportionate change in odds by dividing the odds after a unit of change in the predictor by the odds before the change with equation 9 (Field, 2013; Moore. et al., 2009):

$$Odds\ ratio = \frac{Odds\ after\ a\ unit\ change\ in\ the\ predictor}{Original\ odds} \ldots\ldots\ldots\ldots\ldots\ldots [9]$$

This can be interpreted in terms of the change in Odds: if the value is greater than 1 then it indicates that as the predictor increases, the odds of the outcome occurring increase. Conversely, a value less than 1 indicates that as the predictor increases, the odds of the outcome occurring decrease (Field, 2013). Another way to assess the contribution of the predictor in LRM is to check the values of the Wald statistic (is sometimes called a z-statistic) (Field, 2013; Moore. et al., 2009). The idea behind is to know how well the model overall fits the data. Moreover, the individual contribution of predictors is discovered. This parameter follows the normal distribution, and is used to determine whether a variable is a significant predictor of the outcome. Equation 10 presents how the z-value is calculated:

$$Z = \frac{b}{SE_b} \quad \text{[10]}$$

Where, Z is the z-value, b is the value of a regression coefficient of the independent variable and SE_b is the associated standard error.

The goodness of fit of a LR Model is assessed based on its chi-square test values (Moore. et al., 2009). The chi-square statistic measures how much fits the observed values to the expected ones. The formula for the chi-square statistic is:

$$X^2 = \sum \frac{(observed\ value - expected\ value)^2}{expected\ value} \quad \text{[11]}$$

The Chi-square model was interpreted based on model p-values obtained on 0.05 level of significance. The null hypothesis was rejected if the estimated p-value is less than 0.05 which shows that on the model output, there is a significant influence of independent variables. When the null hypothesis accepted may prove the opposite effect. Applying backward stepwise method, the insignificant variables were eliminated while the significant factors were used in the model (Field, 2013; Moore. et al., 2009). The model results were statistical tables that were analyzed and probability maps of different coupled time spans were visualized.

4.3.6. LR Model validation and evaluation

It is important to check the adequacy of the model before it applied in the decision making purposes (Mayes, 2009). The idea is to check parameters' influence used in the model whether their influence should be reduced in the fitting process or revise the regression function (Mayes, 2009). Model statistics PCP, Kappa statistics were used to check the model goodness (Dubovyk et al., 2011; Huang et al., 2009; Nong and Du, 2011).

A more useful measure to assess the utility of the LRM is the Percentage of Corrected Predictions (PCP). It compares predicted group membership based on the logistic model to the actual, known group membership, which is the value for the dependent variable (Huang et al., 2009; Nong and Du, 2011). The formula of Percentage of the Corrected Predictions is;

$$PCP = \frac{Number\ of\ corrected\ predictions}{Total\ number\ of\ predictions} * 100 \quad \text{[12]}$$

As PCP rely on samples of prediction cells only, it is recommended to use an alternative measure to assess the model goodness (Dubovyk et al., 2011). Kappa statistic is another way to assess the accuracy of the model prediction which varies between -1 and 1. A value *less than 0* indicates a completely deviation between observed and expected agreement while the perfect agreement is shown by all values *higher than 0*. The model with 0 as the value indicates exactly what would be expected by chance (Lesschen et al., 2005). The Kappa statistic is:

$$K = \frac{P_o - P_c}{P_p - P_c} \quad \text{[13]}$$

where P_o is the observed proportion correct, P_c the expected proportion correct due to chance and Pp the proportion correct with perfect classification. In land use/cover change modeling, a kappa value higher than 0.5 can be considered as satisfactory. A value higher than 0.75 is very good to excellent, where values between 0.4 and 0.75 are fair to good. Values of 0.4 or less show poor agreement (Lesschen et al., 2005).

ROC is an excellent method commonly used to validate urban growth LRMs (Hu and Lo, 2007). ROC is a plot of the probability which measure the relationship between simulated real urban growth map and predicted urban growth map. ROC evaluates how well the pair of maps agrees in terms of the spatial location of urbanized pixels. Each point of ROC indicates the sensitivity and specificity pair of decision threshold procedure. The area under the ROC curve is a measure of how well urbanized pixels both in predicted map and actual situation spatially match. ROC values vary from 0.5 (absolute random assignment of probability) to 1 (perfect assignment of probability). A ROC value of 1 indicates a perfect spatial agreement match between the actual urban growth map and the predicted probability map. A ROC value of 0.5 is the agreement expected by chance (Cheng, 2003; Dubovyk et al., 2011). Probability maps were evaluated the best ones were used to forecast future urban growth in 2025 and 2040. After comparing the 2025 and 2040 expansion and densification scenario models with the existing zoning plans of Kigali city 2025 and 2040 some conclusions were drawn.

4.4. Workspace environments

This study used different computer programs such as ERDAS IMAGINE 2013 package for data processing IBM SPSS statistics 20 and Change Analyst tool were used for data analysis of the drivers of Kigali city growth. Patch Analyst software was used to characterize patterns of the city. Furthermore, ArcGIS was used to perform the densification and expansion trend between the forecasted urban growth models and the proposed designed 2025 and 2040 zoning plans.

5. URBAN GROWTH PATTERN AND LOGISTIC REGRESSION MODEL FINDINGS

In this section, the built-up area expansion between 1987, 1999, 2009 and 2014 was presented. The direction of urban growth and change detection were implemented using GIS tool. Post comparison approach was applied. The built-up between 1987 and 2014 was computed and the results were presented. Thereafter, several raster and vector layers were overlaid, to better visualize the results and for better trends and patterns' city interpretation.

5.1. Urban growth trends and pattern of Kigali city

In classifying Landsat images for 1087, 1999, 2009 and 2014, five classes were considered which were built-up, forest, bare soil, and vegetation as well as water bodies. To extract these five classes, more sub-categories were defined and merged into main five thematic categories. Built-up included pixels classified as roads and other infrastructures like airport, stadiums as well as other sport grounds. Bare land included bare land. Vegetation included grassland, and green vegetation and forest includes evergreen forest. Water samples were collected both from Kibagabaga artificial pond inside the hinterland and at Muhazi Lake in the Northern part of the city. In applying Maximum Likelihood algorithm, attention should be paid in the separability of samples. This concern was checked using the plot of ellipses of the training samples in the feature space. One of the main difficulties during classification was the confusion between built-up and forest in the Eastern part of the CBD, an area with low density having a mix between built-up and trees. As these two elements have similar responses, their distinction was a heavy task. Hence, several training samples were taken and fuzzy classification was applied.

The study also assessed the accuracy of the 1987-2014 classification. A total of 163 (72 for built-up, 63 for vegetation, 15 for forest, 10 for bare soil and 3 for water) truth ground data were taken and their land cover types were defined from field visual interpretation using VHR printed. The points were distributed throughout the area, following an almost stratified approach. High amount of points was collected where there is a high concentration of built-up area (see Figure 4-2). It has to reveal that truth ground data do not precisely go in hand with the classified sample as the VHR used during field work was for the date of September 2014, while the Landsat image is for January 2014. This mismatching may lead to the errors during accuracy assessment, as the same point may have different land cover types between those two dates. However, as the period between two dates is not significant in term of land cover change, this may not disfigure the results. For the results validation, an error matrix of each time span was computed. The overall accuracy was 84.23% for 1987 classified image, 86.51% in 1999, 88.34% for 2009 and 93.87 % in 2014.

Table 5-1: Accuracy assessment results.

Sensor	Classified image	Overall accuracy	Kappa statistics
Landsat TM	1987	84.23	0.76
Landsat TM	1999	87.51	0.79
Landsat ETM+	2009	88.34	0.81
Landsat OLI	2014	93.87	0.89

The purpose of the study was to look at built-up land cover only whereby land cover maps *(see Appendix C)* built-up area were extracted and visualized. A number of built-up pixels in each time span were quantified and the built-up area of each year was derived as depicted in Figure 5-1.

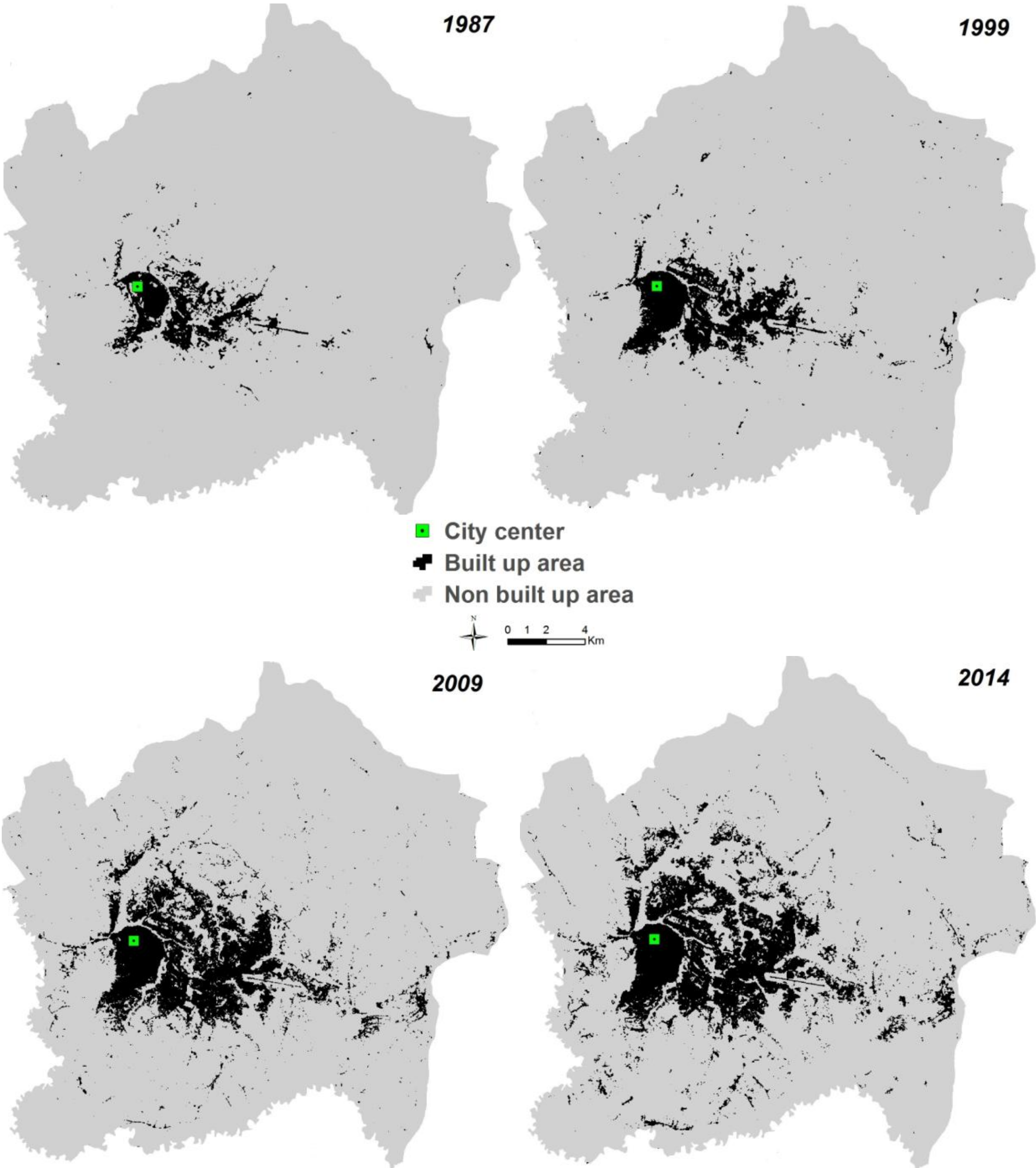


Figure 5-1: Built-up trends extracted from land cover maps classified.

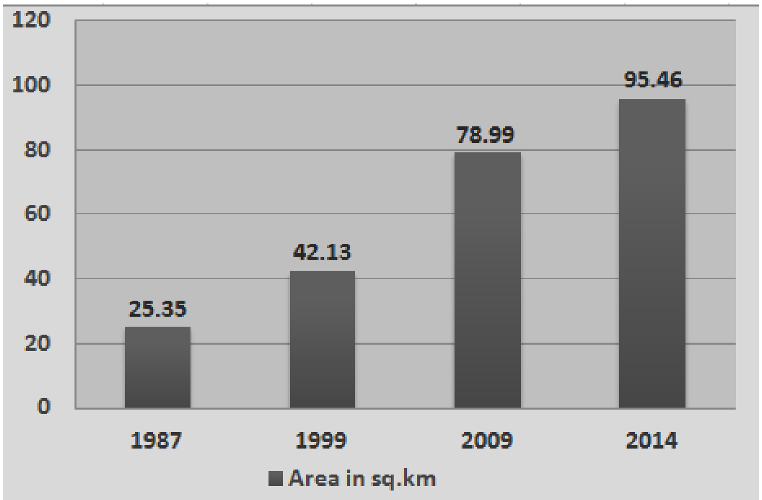


Figure 5-2: The built-up land cover trends in Kigali city.

This shows that the amount of urban growth and its increment during 1987-2014, Built-up area has increased considerably during this time. It doubled from 1987-1999 and 1999-2009 while there has been a gradual change between 2009 and 2014. The average annual growth rate from 1987 to 2014 was almost 10.24 %.

In general, the urban growth of Kigali city between 1987 and 1999 was sprawled but some dense areas can be observed. Some more compactness can be seen in the CBD and other existing built-up areas. The city became more sprawled in 1999 in comparison to 1987. In 2009, the urban sprawl decreased in some part of the city and in 2014 there was a bit more compactness in the many urban areas. Between 2009 and 2014, there was a remarkable extension trend in all sides of the city except the Western part. However, the tendency is higher to the Northern and Eastern sides while the Western was paused. In the Western direction of Kigali, the topography is critical for built-up since this part was protected by forests cover. Furthermore, some new built-up areas appeared in the hinterland of the Southern part. These are smaller and dispersed built-up patches compared to the Northern and Eastern development. The differences between the years 1987 and 2014 are of large magnitude, it can be said that the expansion pattern of Kigali city is horizontal and densification is very low. Rural lands have been converted into built-up areas due to the increase in urban activities (REMA, 2013). There is a big demand for land by the high number of offices, schools, industries built during last 27 years. Moreover, citizens constructed bungalows instead of high rise apartments. In the process of urbanization, apart from the CBD, new sub-centres were created and this multicentre development has been stated in the series of master plans elaborated for Kigali City.

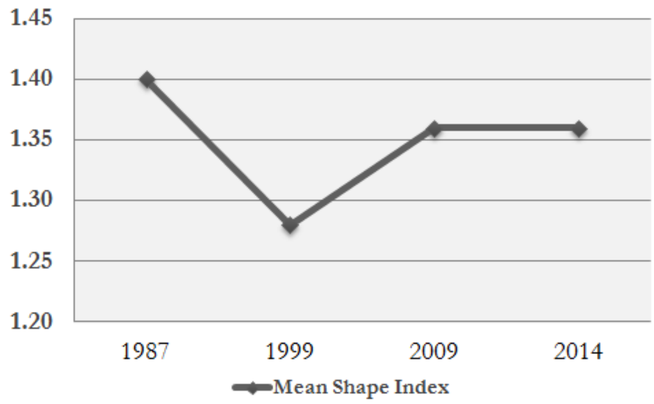


Figure 5-3: Sprawl and compactness pattern of Kigali city.

Patch metrics can also be used to explain the pattern (compactness and sprawl) in the urban areas. The Mean Shape Index gives information on the pattern of urban area. The MSI equal to 1 shows the maximally city's compactness and increases as the patch shape become more irregular (scattered). The pattern of Kigali city can be supported by patch analysis performed showed in Figure 5-3. The MSI was calculated for 4 times spans for the study and results reveals different situations. The decreasing value of MSI from 1987 to 1999 confirms the tendency of the city's compactness. However, from 1999 to 2009, the city sprawled to the hinterlands in all directions as the value of MSI increases. From 2009 to 2014, the city was posed. The reason is that recently, illegal developments were stopped and the city authority started vertical development campaign (Edaw et al., 2007; Surbana, 2012).

Figure 5-4 highlights the expansion development between 1987-2014. It indicated that the total new urban areas between 1987 and 2014 was 72.88 km². At 1987, the dense built-up areas were located near the city centre while in the next years settlements started to appear in the hinterland move to one hill to another as the site contains many wetlands in between. The built-up was slightly denser in Gasabo district with 40.60 km², while it was 12.52 km² and 20.36 km² Nyarugenge and Kicukiro districts respectively show some dispersion.

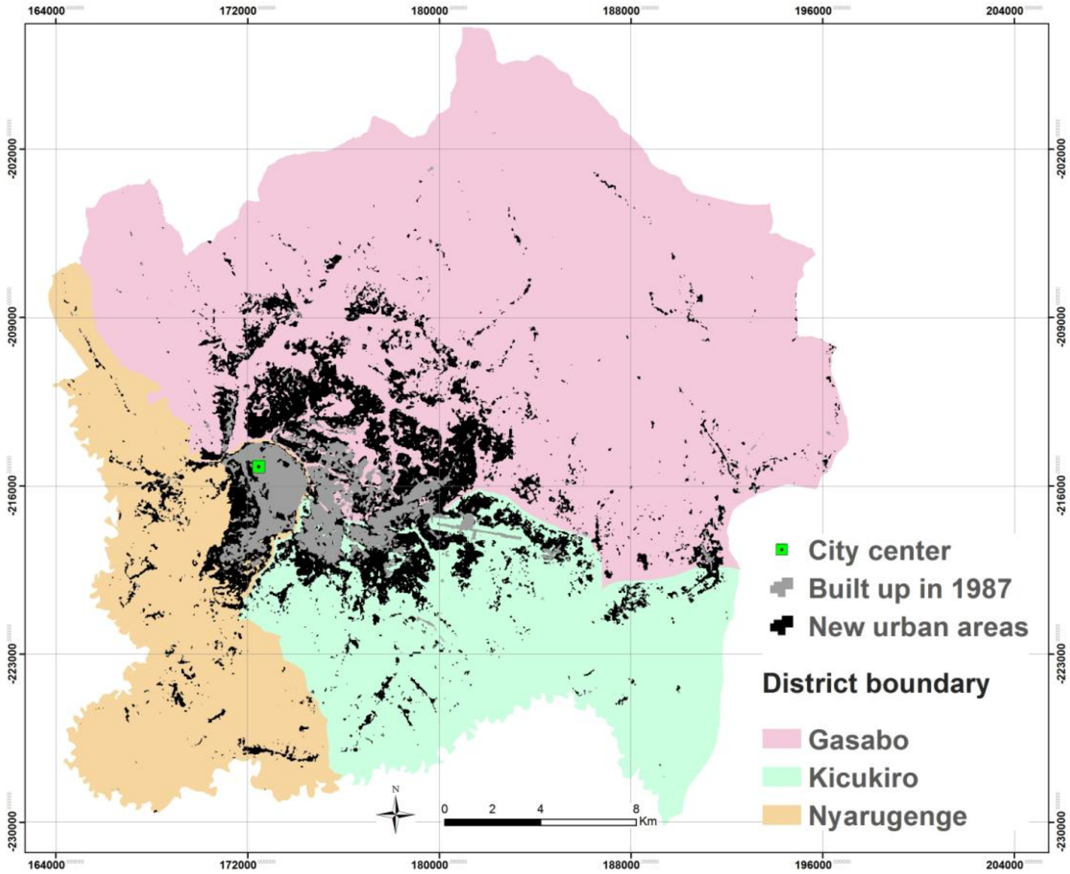


Figure 5-4: Expansion development between 1987-2014.

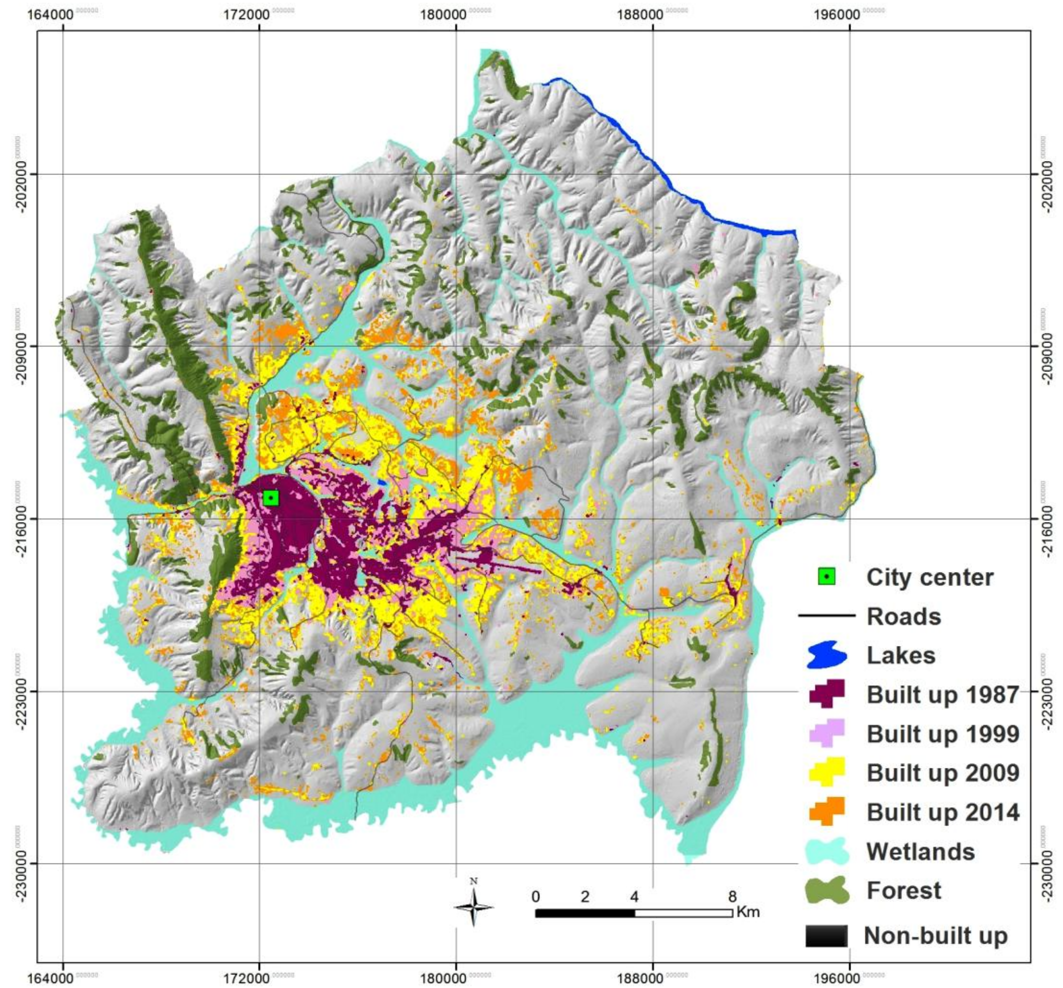


Figure 5-5: Spatial pattern of urban growth between 1987-2014.

Figure 5-5 shows that the main road network is overlaid into the built-up area of 1978, 1999, 2009 and 2014. It is noticeable that urban areas follow the main roads and evolve along them in the core of the city. As we move towards the hinterlands, urban areas are tracked in radius along the main road network. Moreover, it can be seen that some built-up area have evolved in protected zones in the forest on Kigali hill in the South and Jali hill in the North and within wetlands in some areas. The built-up of nearly three decades (27 years) shows a considerable built-up increase in two processes. The pattern of urban growth followed the linear development trend along the road network and infrastructure which drove growth in all roads' directions of the city.

5.2. Determining and quantifying LRM driving forces of urban growth

This section presents factors for the periods 1999-2014, 1999-2009 and 2009-2014 that were included in the LRM. However, the analysis of 1987 with other time spans was not performed due to the data unavailability. A preliminary test of independent variables (factor maps) was performed (multicollinearity diagnosis). Using different sampling window sizes, some statistical tests (Backward stepwise procedure, T-Wald-test) were performed to determine the significant drivers to be used and the best LRM was chosen. The results of the LRM were interpreted and the future prediction was carried out (for details see section 5.4).

On the basis of factors listed from literature (Cheng, 2003; Dubovyk et al., 2011; Hu and Lo, 2007; Hu, 2004; Huang et al., 2009) and refer to section 2.3, independent variables were prepared for the LRM. Table 4-1 and Figures 5-6, and 5-7 show the factors prepared to be used. All input variables had the same spatial extent (raster size row= 1092 and column= 1116), same projection (Transverse Mercator), coordinate system (WGS_1984_UTM_Zone_36N) and same cell size (30*30 meters).

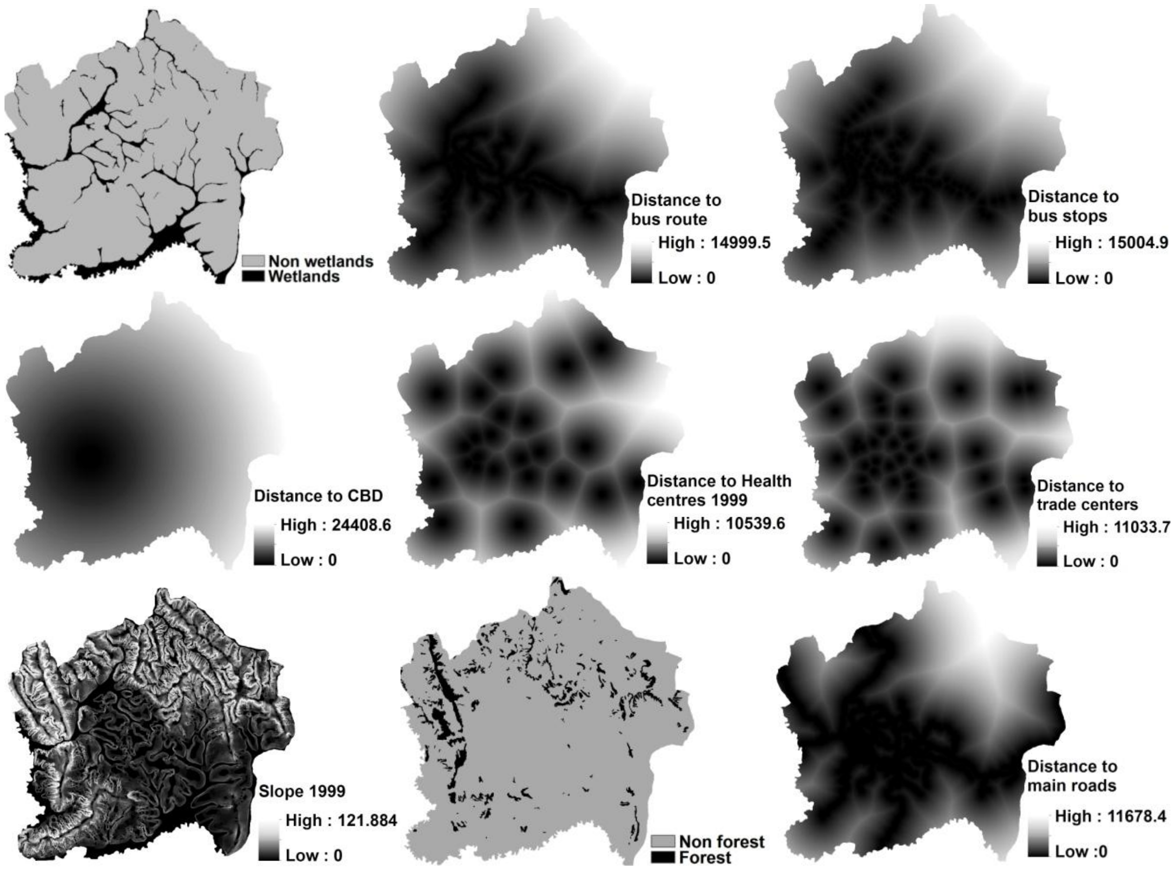
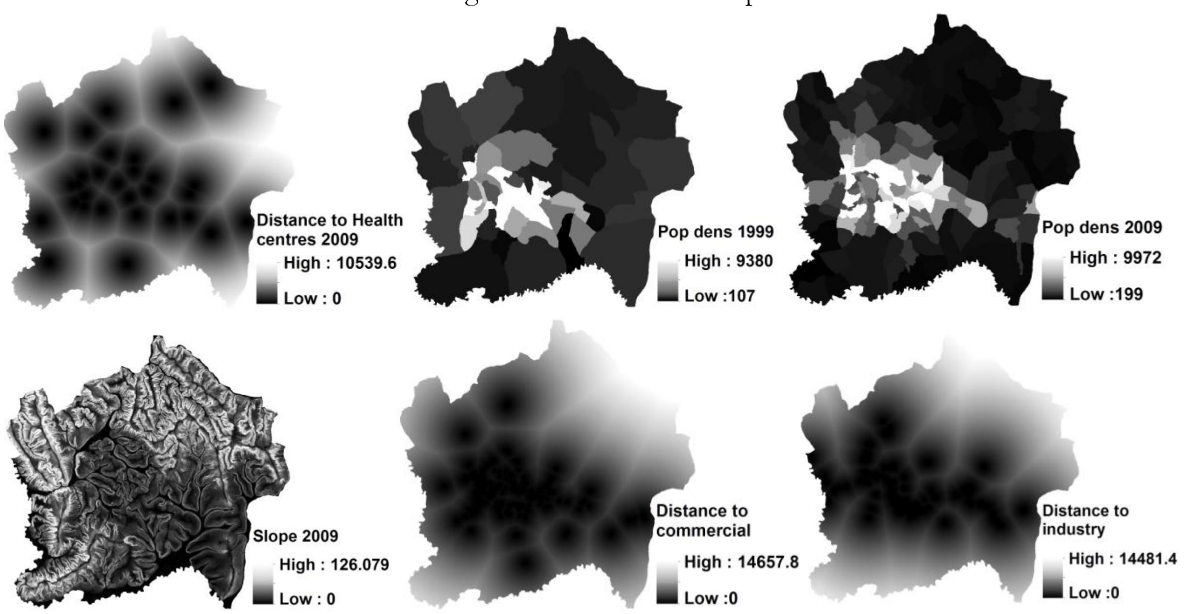


Figure 5-6: 1999 factor maps.



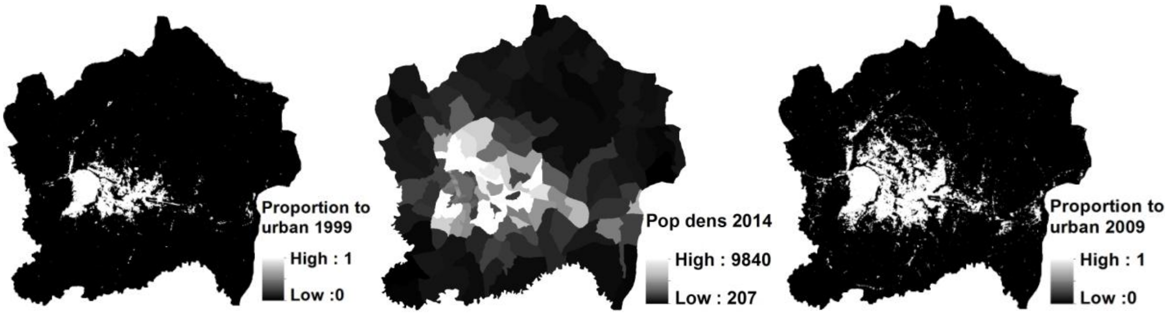


Figure 5-7: 2009 and 2014 factor maps.

As suggested by Cheng (2003); Dubovyk et al. (2011); Hu and Lo (2007); Hu (2004); Huang et al. (2009); Munshi et al. (2014), it is very important to test the correlation between independent variables to be included in the LRM. A test of multicollinearity was performed for all independent variables and the VIF was calculated. The test results showed that distance to bus routes, distance to bus stops and distance to commercial areas presented multicollinearity problems since their VIF was above 10 *(see Appendix E.1)*. Distance to bus routes was eliminated due to the fact that, in Kigali city, all bus routes are also main roads. Distance to bus stop and distance to commercial areas were eliminated in the latter step, this is because in each sub center there are commercial activities *(see Appendix E.3)*. However, another test performed for the remaining variables showed that there was no multicollinearity since the VIF was below 10 and therefore they were included in the analysis (Field, 2013; Moore. et al., 2009).

Table 5-2: Results of multicollinearity after eliminating bus routes, bus stops and commercial areas

	Description	VIF 1999-2014	VIF 1999-2009	VIF 2009-2014
X_1	*Distance to bus routes*	*Eliminated*	*Eliminated*	*Eliminated*
X_2	*Distance to bus stops*	*Eliminated*	*Eliminated*	*Eliminated*
X_3	Distance to CBD	3.126	3.472	3.384
X_4	*Distance commercial areas*	*Eliminated*	*Eliminated*	*Eliminated*
X_5	Distance to health centres	2.839	3.092	3.039
X_6	Distance to industry	4.000	4.350	5.079
X_7	Distance to main roads	2.946	3.693	3.677
X_8	Distance to trade centres	2.388	2.797	2.704
X_9	Proportion of urban in a surrounding area	1.576	1.726	1.820
X_{10}	Population density	1.666	2.093	2.024
X_{11}	Forests	1.244	1.245	1.262
X_{12}	Wetlands	1.219	1.220	1.280
X_{13}	Slope	1.542	1.505	1.589

5.3. LRModeling simulation

To characterize the future pattern of the city, three scenarios were performed, i.e. Urban growth model for expansion (normal growth) and two densification (zoning implication) scenarios. The urban growth model for expansion was performed for the 1999-2014, 1999-2009 and 2009-2014 time spans. However, an urban growth model for densification was computed using the best LRM expansion scenario selection chosen by mean statistical tests. Using the independent variables retained after multicollinearity analysis, 1999-2014, 1999-2009 LRMs and 2009-2014 expansion scenarios were built. On the first stage, all models were created using the 10 retained variables. Using Change Analyst, samples generated from LRM run were used to apply backward stepwise approach in SPSS and factors that had a sound influence on the model were detected. The nonsignificant ones were eliminated from the model. Factors retained after backward stepwise procedure were used to perform LRM regression. LRMs were built using different sample sizes varying from 3*3 up to 7*7. Finally, to choose the window cell size for modeling, the number of significant factors, and model PCP were looked at (see Table 5.3). A 3*3 window size was selected for 1999-2014 LRMs and 2009-2014 expansion scenario and 5*5 window size was selected for 1999-2009 model. LRMs regression and probability maps for the three selected expansion scenario models were evaluated by means of Kappa statistic, ROC value and the percentage of 2014 built-up land cover predicted. The best model was retained for densification model simulation and non-selected models were excluded (see all LRMs excluded *in Appendix E*).

Table 5-3: Statistical tests of LRMs expansion scenario on different sampling window size.

Criteria	1999-2014			1999-2009			2009-2014		
Window size	3*3	5*5	7*7	3*3	5*5	7*7	3*3	5*5	7*7
Significant drivers forces	5	4	5	5	4	5	7	6	4
PCP (built-up)	94.94	94.88	94.67	94.13	94.23	94.11	95.78	95.74	95.73

5.3.1. RLM expansion scenario

(a) 1999-2014 LRM expansion scenario simulation

The final 1999-2014 LRM was obtained on the sixth backward stepwise procedure after eliminating factors like forest cover, distance to trade centres, distance to industry, distance to main roads, and population density since their T-Wald statistic (p-values) were greater than the assigned confidence interval (greater than 5% level of significance) *see Appendix F*. The overall model was significant with chi-square of 91654.6792 and corresponding p-value of less than 0.0000 at the 1% level of significance. The sampling window size for this model was 3*3 since it has a higher number of significant factors and higher 94.94% of PCP comparing to other moving windows. The summary of the model is presented in Table 5-4.

Table 5-4: Variables in the equation of 1999-2014 LRM expansion scenario.

Variables	*b*	SE (*bi*)	z-value	T-Wald test (p-value)	O.R
Constant	-0.32880			-	-
CBD	-0.00015	0.000005	-31.841	0.000	0.999853
Health centres	-0.00017	0.000016	-10.636	0.000	0.999831
Slope	-0.04829	0.001799	-26.837	0.000	0.952861
Wetlands	-2.41260	0.098619	-24.463	0.000	0.089582
Proportion of urban	5.15426	0.064000	80.535	0.000	173.168106

(b) 1999-2009 LRM expansion scenario simulation

This final LRM (5*5 moving window size selected) was obtained on the sixth backward step after eliminating factors like forest cover, population density, distance to trade centres, distance to industries and distance to main roads. As mentioned in Table 5-5, five variables were significant with the p-value less than 5% level of significance. The overall model was significant with chi-square value of 16986.0256 and p-value of less than 0.0000 at the 1% level of significance. Different variables of this LRM have different probability degrees of influence on urban growth. The overall accuracy (PCP) was 94.23%, while Kappa value was 0.63.

Table 5-5: Variables in the equation of 1999-2009 LRM expansion scenario.

Variables	*b*	SE (*bi*)	z-value	T-Wald test (p-value)	O.R
Constant	1.63140			-	-
CBD	-0.00024	0.000008	-29.637	0.000	0.999753
Health centres	-0.00057	0.000030	-19.100	0.000	0.999428
Proportion of urban	6.66083	0.362504	18.374	0.000	781.203768
Wetlands	-2.50502	0.151870	-16.494	0.000	0.081673
Slope	-0.05047	0.002554	-19.7595	0.000	0.950780

(c) 2009-2014 LRM expansion scenario simulation

Among 10 variables included in the model, variables like distance to roads, forest and slope were eliminated after performing backward stepwise procedure. The model was found at the fourth step after eliminating factors like distance to roads, forest cover and slope. The sampling window of 3*3 was selected as it contains a higher number of drivers compared to other window sizes. This overall model was significant with chi-square of 88889.8764 and corresponding p-value of less than 0.0000 at the 1% level of significance. The PCP was 95.78 %, while Kappa value was 0.76. Hence, the model was not included for further analysis. The summary of the model is presented in Table 5-6.

Table 5-6: Variables in the equation of 2009-2014 LRM expansion scenario.

Variables	*b*	SE (*bi*)	z-value	T-Wald test (p-value)	*O.R*
Constant	0.427200			-	-
CBD	-6.7E-05	0.000006	-11.705	0.000	0.999933
Industry	-0.000170	0.000012	-13.841	0.000	0.999835
Trade centres	-0.000120	0.000022	-5.524	0.000	0.999980
Population density	0.000288	0.000013	6.694	0.000	1.000088
Health centres	-0.000200	0.000020	-10.027	0.000	0.999801
Wetlands	-2.083070	0.125171	-16.641	0.000	0.124548
Proportion of urban	5.913287	0.139958	42.250	0.000	369. 505638

All final LRMs expansion scenarios were constructed using 10 variables. All three LRMs were significant at less than 5% of level of significance. The variable increases the probability of urban growth if it has a positive sign or decreases the probability in case it has a negative sign. For the 1999-2014 model, the proportion of built-up land in the surrounding area has a positive effect on urban growth while distance to health centres, distance to the CBD, slope and wetlands were major determinants with negative effect on the urban growth occurrence; as closer (less distance) the more the likelihood of being built-up. Based on the values of *b* and O.R (Table 5-4), it can be seen that the 1999-2014 LRM for expansion' variables had a different degree of influence of probability on urban growth. Normally, a strong positive *b* value of the predictor indicates a strong positive relation between that predictor and urban growth. A negative large *b* value explains the strong negative impact of the predictor to the urban growth. Moreover, *b* can be linked to the values of O.R to explain the model variables influence to the urban growth. The proportion of built-up land in the surrounding area contains a coefficient *b* value of 5.15 and O.R value of 173.16. This implies that an increase of the proportion of built-up land in the surrounding area increases the likelihood or probability of urban growth. All resulting model parameters with an odds ratio greater than 1 and with positive *b* value can be interpreted in this way. All remaining variables (CBD and Health centres) have a negative *b* values and odds ratio less than 1. This implies that the higher distance from the CBD or health centres, the lower is the probability of urban growth and the lower distance from the CBD or health centres the higher is the probability of urban growth. Also, according to the estimated model parameters, slope and wetlands impact negatively urban growth occurrence. This indicates that new urban developments have a tendency to occur away from wetlands and on the low and gentle slope sites. 1999-2009 and 2009-2014 LRMs can be interpreted in the same way as 1999-2014 model. The strong positive relationship between the proportion of urban in a neighborhood area is logical in case of Kigali city. From (Figure 5.5), it can be seen that the new urban developments were mostly developed in a clustered pattern around the existing urban area. Surprisingly, proximity to the road network which is found as main driving factors in most similar urban development studies Huang et al. (2009); Nong and Du (2011); Verburg, et al. (2004) was not statistically significant in this study. The absence of paved (called main roads in this study) especially in the Northern and Southern part of the city: new developed areas after 1999 (refer to land cover maps Figure 5-1) might be related to the roads elimination in the model. Normally, urban developments tend to occur in the areas of higher road accessibility, which is common in most developing cities. Refer to Table 5-4, it can be concluded that the proportion of urban in a neighborhood area was the most important predictor of urban growth in Kigali city. Distance to the CBD, distance to health centres, slope and wetlands have low probability to influence urban growth. Table 5-7 presents the most three important factors for 1999-2014, 1999-2009 and 2009-2014 LRMs time spans. Table 5-8 presents the perceptions of local urban planning experts on drivers of urban growth in Kigali city. The proportion of built-up land in the surrounding area was among the best factors with a mode statistic ranked as a very high influential factor. Other important variables such as distance to the CBD, distance to the health centres slope and wetlands were found also to be the main drivers with a mode statistic ranked above moderate influence factors. All best variables with higher mode statistic were included in the models with the exception of soil types due to the lack of information regarding soil suitability and its contribution to urban developments in Kigali city. The land value variable was not used in the model as it is a proxy factor.

Table 5-7: The most important factors for 1999-2014, 1999-2009 and 2009-2014 LRMs.

	Time period of LRM		
Top three factors	1999-2014	1999-2009	2009-2014
First rank	The proportion of urban in a neighborhood area	The proportion of urban in a neighborhood area	The proportion of urban in a neighborhood area
Second rank	Slope	Slope	Population density
Third rank	Health centres	Health centres	Health centres

Table 5-8: Scores of variables according to local urban planning experts.

Rating scale (by mode statistic)			
Very high influence	=5	Low influence	=2
High influence	=4	Very low influence	=1
Moderate influence	=3	Not assigned	=0

Mode statistic

Probable driving force		5	4	3	2	1	0	Total
Bio-physical influence	Slope (site topography)	2	4	4	3	1	1	15
	Soil types	0	0	3	7	2	3	15
Spatial plans and policies	Land use zoning	8	3	1	0	3	0	15
	Protected land (eg: Wetlands, forest…)	3	2	4	2	4	0	15
Neighborhood characteristics	Proportion of built-up land in the surrounding area	7	4	3	1	0	0	15
	Population density	2	7	3	0	1	2	15
Proximity characteristics	Distance to major roads	8	5	1	0	1	0	15
	Distance to secondary roads	2	7	4	0	2	0	15
	Distance to industrial sites	4	4	4	1	1	1	15
	Distance to the CBD	6	3	4	1	1	0	15
	Distance to sub-centres	8	3	2	1	0	1	15
	Distance to primary schools	1	4	5	2	2	1	15
	Distance to secondary schools	1	5	3	3	2	1	15
	Distance to health facilities	2	3	5	2	2	1	15
	Distance to open markets	3	5	3	2	1	1	15
	Distance to bus stops	1	7	3	3	0	1	15
Economic factor	Land value	7	4	4	0	0	0	15

5.3.2. LRMs expansion scenario validation and prediction

In the LRM for urban growth, model validation and evaluation are performed by comparing built-up of the current urban growth (reference image) and urban developments predicted to the current situation (Hu and Lo, 2007; Huang et al., 2009). The assumption is that the present trend's rate and pattern will continue in the future. To choose the best LRM expansion scenario, PCP, Percentage of correct prediction, Kappa statistic and ROC values and the Percentage of current built-up predicts were calculated. Statistically and visually, 1999-2014 LRM expansion scenario shows a trend of a certain reality of urban growth over time based on the current situation model. This model predicted 71.01% (71.92 km^2) of the total current built-up with 0.750 ROC value and 0.75 Kappa statistic.

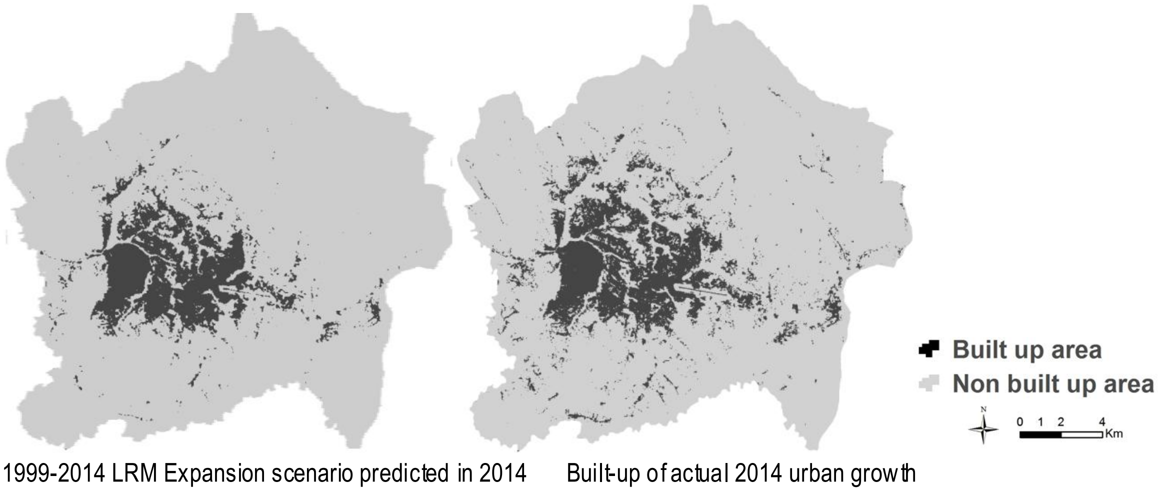


Figure 5-8: Comparison of interpolated (2014 built-up prediction of 1999-2014 LRM expansion scenario) versus observed (reality) 2014 built-up cover.

Table 5-9: Statistical test for LRMs expansion scenario.

Measure	1999-2014	1999-2009	2009-2014
Correct prediction	758761	748461	756949
PCP	94.82	93.96	94.82
Kappa statistic	0.75	0.63	0.76
% of 2014 Land cover Built-up predicted	75.46	72.07	77.48
ROC	0.750	0.716	0.754

Based on the visual and statistical pattern in Table 5-9 and Figure 5-8, the validation results let us conclude that 1999-2014 LRM leads to satisfying results in predicting the future pattern of the city. Therefore, the 1999-2014 model was chosen as input for densification model scenarios. It has a satisfactory Kappa and ROC values and a high percentage of correct cells pixels predicted. There is a moderate similarity between the model prediction and the actual situation pattern. However, the resulting prediction pattern is more compact than the actual 2014 land cover map. In addition, the 1999-2014 LRM was chosen with an assumption that it is a long period model; factors (independent and dependent variables) were updated in term of city trend and pattern. Independent variables like health centres (in term of counts) proportion of built-up in the neighboring were updated compared to 1999-2009 model. However, 2009-2014 model was found worse to predict the future pattern of the city. It tends to convert existing built-up into non built-up. It is a short time period compared to the others, there is a slight difference in term of trend and pattern between start and end year periods. Figure 5-9 shows LRM expansion scenario between 1999-2014 which was confirmed to both predict 2025 and 2040 Kigali city pattern and be used as additional inputs to build RLM densification scenario. All probability maps are binary showing built-up and non built-up areas.

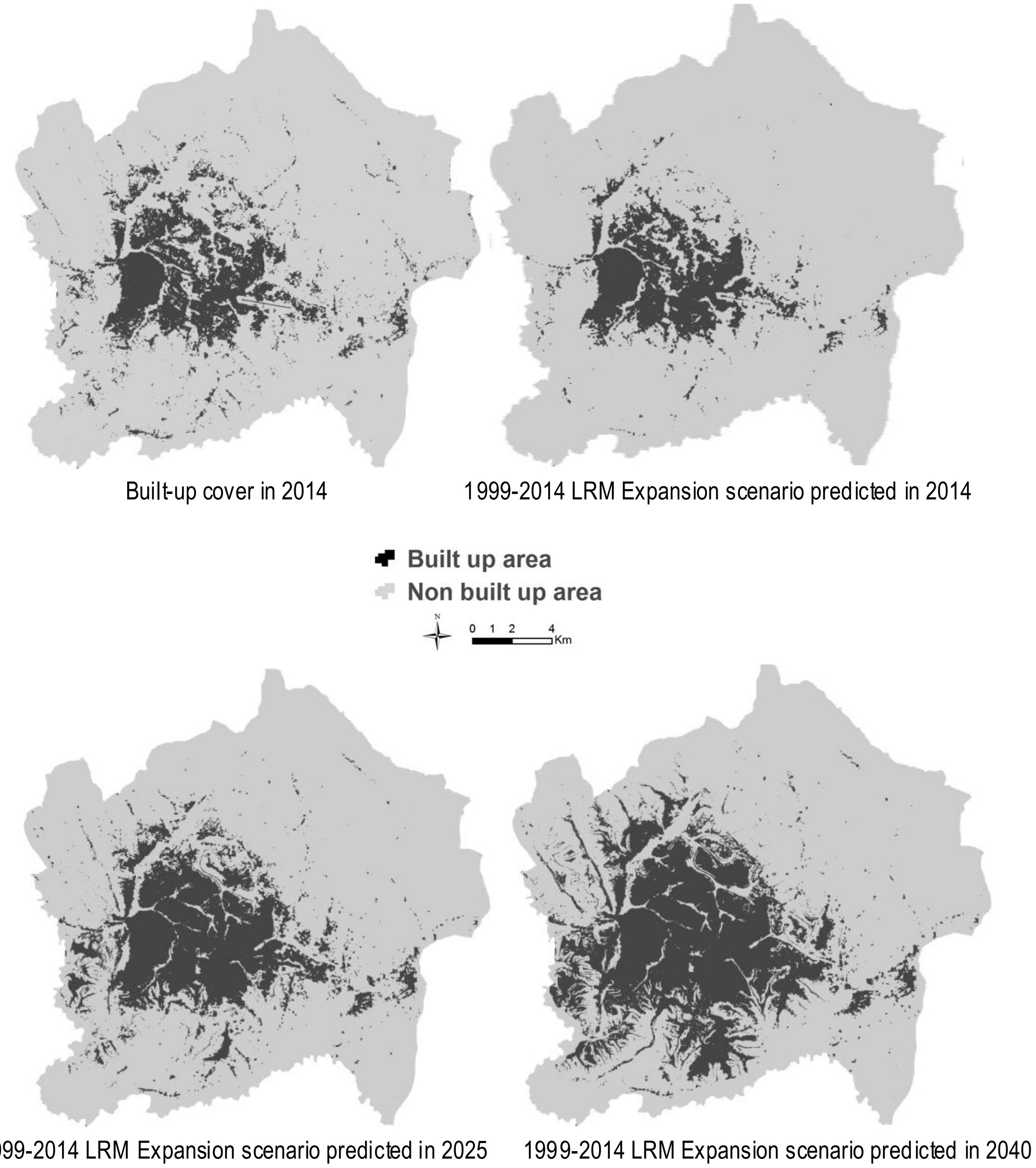


Figure 5-9: 1999-2014 LRM expansion scenario probability maps and 2014 built-up cover map.

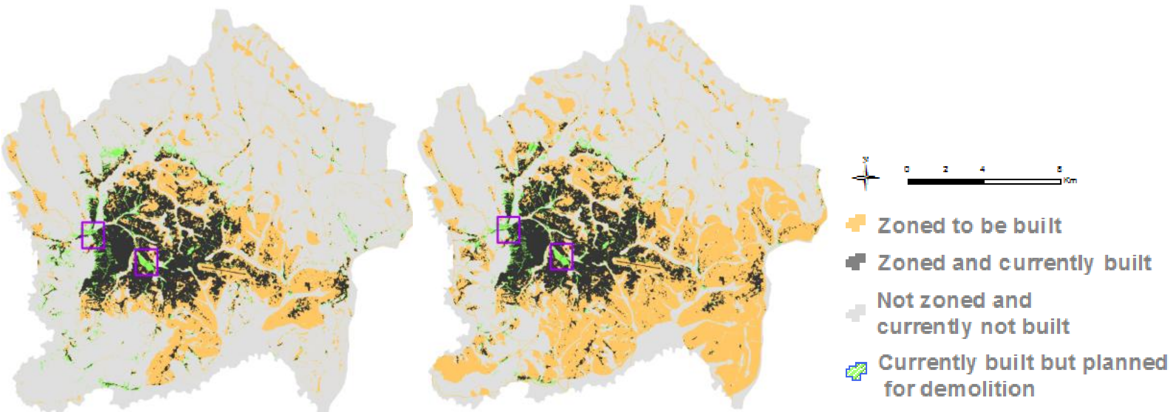
5.3.3. LRM densification scenario and zoning implications

In this study, the proposed zoning for 2025 and 2040 were considered (Edaw et al., 2007; Surbana, 2012). Factors maps for the 2025 to 2040 zoning plan indicating land allowed to be developed or not were prepared. The idea of using both expansion (normal growth or business as usual) and densification (zoning enforced) scenarios was because the city will continue to encourage people to build in the proposed zoning in the future. The zoning scenario implies that illegal constructions will be controlled in the future and proposed zonings will be respected. The 2025 and 2040 zoning factor maps were used to predict both 2025 period and 2040 situation respectively.

The idea behind the densification scenario was that new urban developments will tend to occur in the proposed zoned areas. Under this scenario, two sub- scenarios were simulated (strict zoning policy and moderate zoning policy). For each policy sub-scenario, the start and end year date dependent factor maps were prepared (1999 as initial year and 2014 as end year). Using ArcGIS from raster calculator, 1999 land cover was combined with 2025 and 2040 zoning binary map, 2014 land cover with 2025 and 2040 respectively. Four attributes were generated as zoned-currently built area, zoned but not currently built, not zoned currently built and not zoned currently not built. For the strict zoning sub-scenario, factor maps dichotomous dependent variables were prepared and given as 1 zoned-currently built area and 0 zoned-but not built (see Figure 5-10). However, not zoned-not built and not zoned but currently built were treated as no data. This implies that these areas are not assigned (not suitable) for future development. The assumption taken here is that the future city pattern will depend only on area allowed for allocation according to zoning policy. For moderate zoning, the same process was repeated but not zoned but currently built-up areas was combined with zoned- currently built and were given 1 as value. The idea behind the moderate zoning policy was to predict the future pattern of the city when existing built-up areas outside the zoning will not be demolished. The said areas to be demolished according to zoning policy includes formal residential and industrial area which are closed to wetlands, informal settlements close to protected forest mostly located in the Western and Southern part of the city on Mont Kigali and Mont Jali. The city planned afforestation and recreational activities in those places.

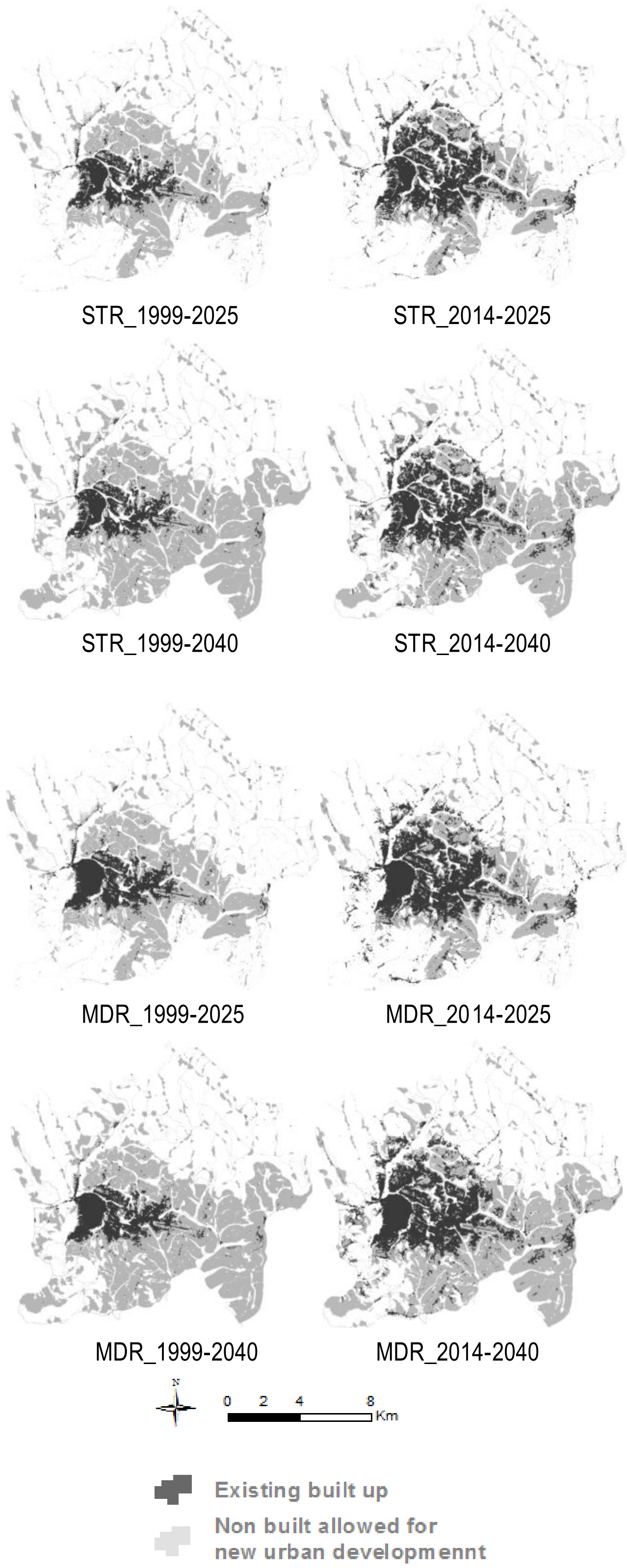
Industrial site in protected wetlands

Nyabugogo flooded area and protect forests



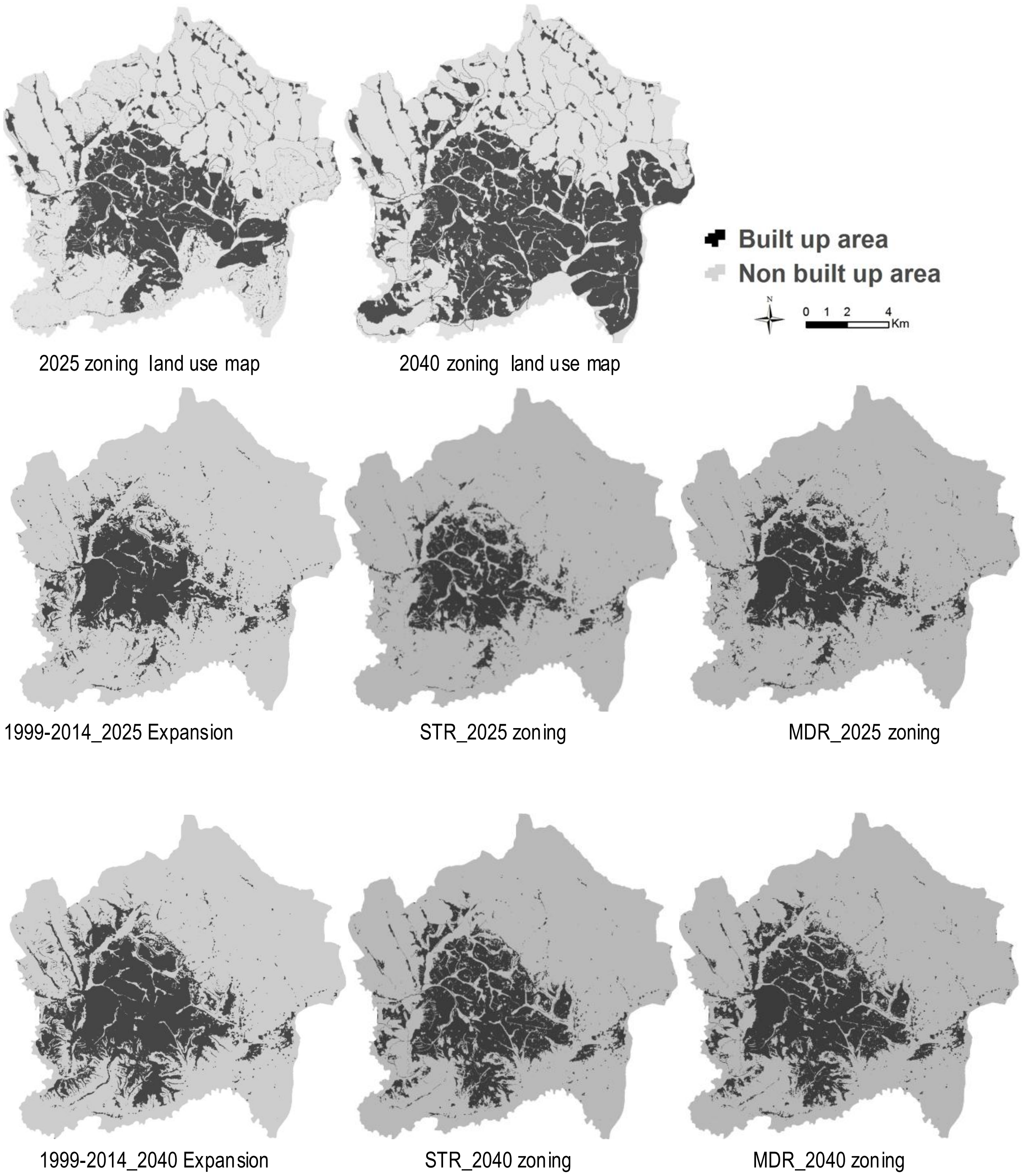
2014 land cover map combined with 2025 and 2040 zoning factor maps

Figure 5-10: Areas currently built but to be demolished according to zoning policy.



STR: Densification with strict zoning policy
MDR: Densification with moderate zoning policy

Figure 5-11: Factor maps prepared from 2025 and 2040 zoning maps; 1999 as initial year 2014 as end year.



STR: Densification with strict zoning policy;
MDR: Densification with moderate zoning policy

Figure 5-12: Comparison of interpolated 2025 and 2040 LRMs Expansion and Densification scenarios.

These scenarios allowed comparison of policy options and decisions since it compare and quantify the built-up areas between densification scenario model for planned areas in 2025 and 2040 (2012 Master Plan of Kigali city) as well as an expansion scenario model of the actually developed urban land predicted in 2025 and 2040. All three models have a nearly equal spatial match (see Figure 5-13b). Three scenarios generated have patterns characterized by a strong compactness of urban densities. Expansion scenario is more compact (see Figure 5-13a), compared to other scenarios. This is logical since expansion scenario tends to convert a higher amount of forest and wetlands land cover into built-up (see Table 5-10). However, all three models tend to exclude urban units in the Eastern-Southern part of the city. The area currently characterized by lower urban density and low health care accessibility which might be related to the model pattern found as shown in Figure 5-14. By comparing patterns between 2025 and 2040 for both densification scenario and zoning maps in Figure 5-13, it can be seen that LRMs for 2025 and 2040 densification scenario were quite spatially different from the proposed zoning maps. The three models tend to exclude urban units in the Eastern-Southern part of the city since the variables used in the model were not able to capture a pattern in that part of the city. Based on the current land use map in Figure 3-5, the Eastern-Southern part of Kigali city is mostly occupied by agricultural land therefore any of the variables can predict built-up in that location. This is because the place is not urbanized; no health centres and is located far from the CBD. Figure 5-14 shows the trend of the city up to 2040 and indicates that the city trend will be double the current situation if the current trend rate continues to be the same.

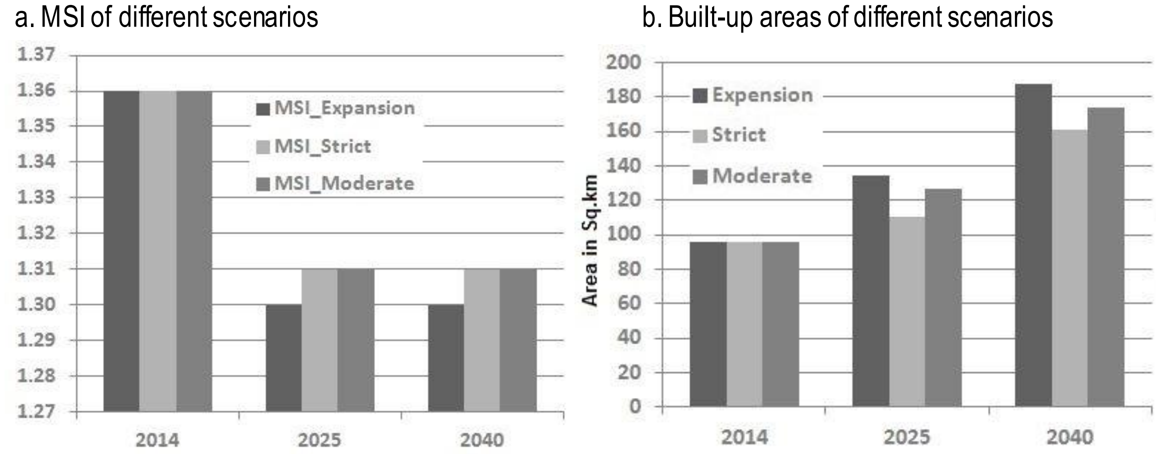
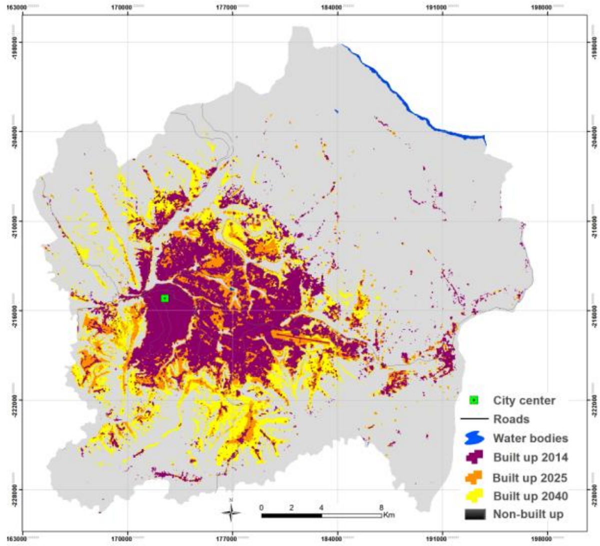


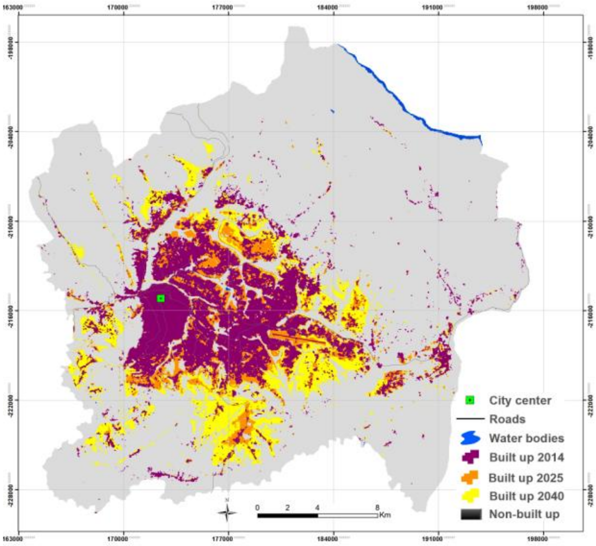
Figure 5-13: Expansion, Strict and Moderate scenarios comparison by mean of Mean Shape Index and built-up quantification in Km^2 of Kigali city urban growth.

Table 5-10: Type of converted forest and wetlands land cover into built-up in Expansion, Strict and Moderate scenarios in 2040 in Kigali city in km^2.

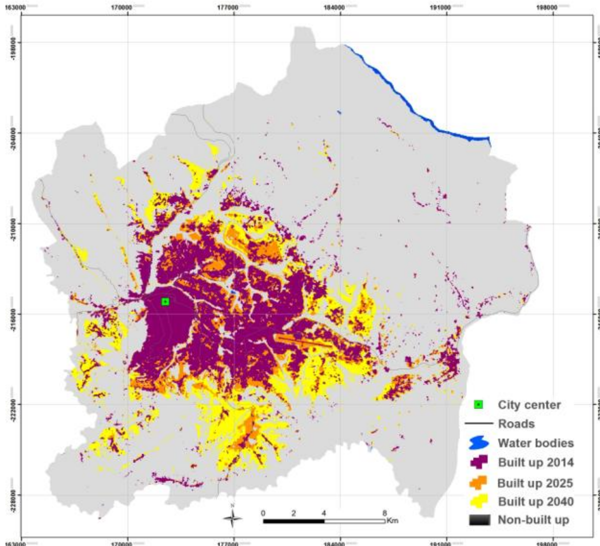
	2040 converted land cover in km^2	
Scenario	Forest	Wetlands
Expansion	4.20	3.76
STR	0.89	1.14
MDR	1.03	3.05



Expansion scenario



Strict scenario



Moderate scenario

Figure 5-14: Projected urban growth pattern of Kigali city (2014, 2025 and 2040); Expansion , Strict and Moderate scenarios.

6. REFLECTION ON RESULTS AND METHODOLOGICAL APPROACH

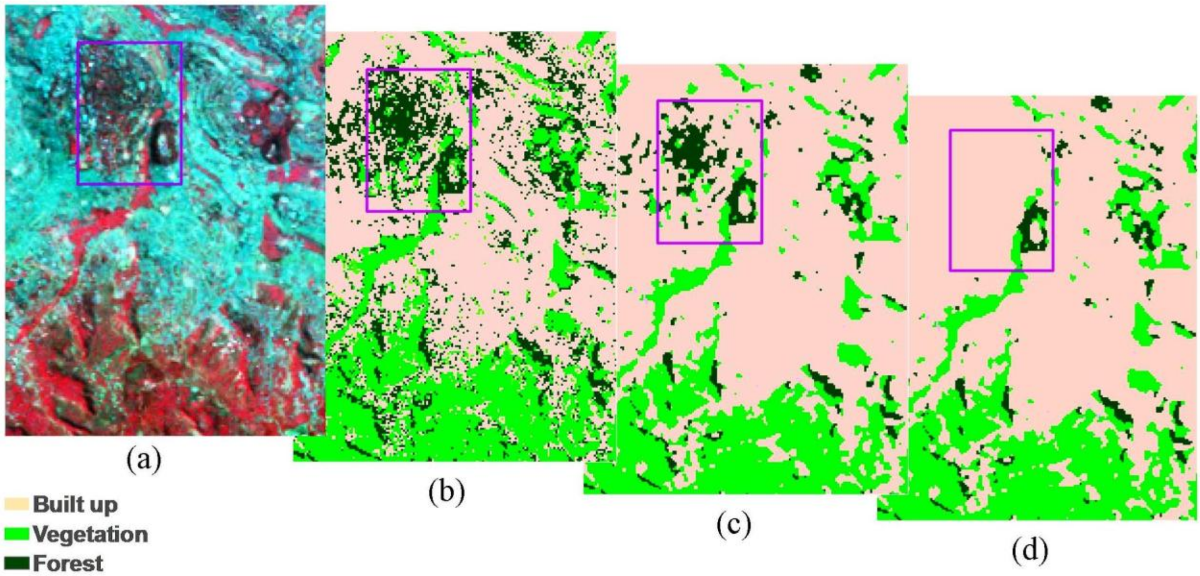
A better understanding of the factors affecting urban growth needs a formulation of effective urban development policy. This study examines the main driving forces conditioning expansion pattern of Kigali city in modeling perspective and its future spatial growth probability using scenarios and zoning implications. LR model was used to identify the socioeconomic and biophysical potentials and constraints that have impacted on urban growth and find the probable areas of built-up in Kigali city for the next 26 years.

6.1. Remote Sensing for urban growth pattern analysis

The results with Landsat images for urban growth pattern identified different land cover classes such as forest, vegetation, bare land, water bodies and built-up cover. For Remote Sensing data product, 80-85% overall accuracy appears to be satisfactory Treitz and Rogan (2004), while 70% Kappa statistics proves the agreement between the classification results with the reference data used for the assessment (Viera and Garrett, 2005). In this study, the 84.23%, 87.51%, 88.34% and 93.87% overall accuracy with 0.76, 0.79, 0.81 and 0.89 respectively kappa values were recorded, which were slightly higher than the threshold standard. The trends and patterns found were almost close to what was obtained in the previous studies for Kigali city urban growth quantification. For instance, Civco et al. (2005) classified two years and found a built-up spatial size of 15.56 km^2 to 45.73 Km^2 from 1984 to 1999 and Edaw et al. (2007) found between 15.19 km^2 and 45.13 km^2 in 1984 to 1999 and 65.63 km^2 in 2005. With reference to Figure 5-1 that highlights trends of built-up, this slight difference of 3 km^2 can be looked at validation techniques used (supervised and unsupervised classification approach) see section 2.3. Landsat images have been applied in other case studies to map out and model urban growth. Using the same approach and RS data even same land cover classes, similar results have been found by Duwal (2013) modeling urban growth in Kathmandu Valley, Nepal with a Kappa of 0.91, 0.83 and 0.86. In Uganda, with two land cover classes Abebe (2013) found a Kappa of 0.70, 0.72, 0.78, 0.83.

Therefore, the results from this work are consistent with classification of land cover maps. In these results using Landstat images, a remarkable trends and sprawl pattern (by change detection results and patch metrics analysis) was observed in urban areas in Kigali city in that, the rapid trend was more accelerated between 1987 and 2009 while it continued at a moderate pace up to 2014. The findings revealed that urban areas expanded mainly towards the Northern, Eastern and Southern directions. However, the Western part of the city was posed due to the area topography and environmental policy on protecting forests (see section 3.6). In general, the new urban areas lie mostly on previous vegetation and forest lands, and have not replaced areas covered by wetlands or forests in the Western and South-Western part of the city due to the environmental policy on wetland and forest protection. Visualizing land cover maps (built-up areas) with existing land use data, provides information on the relationship between urban expansion and other land use types. In this study, the Landsat classified maps overlaid with road networks and some zoning policy (wetlands and forests) showed that some built-ups have made a linear development along the main roads while protected zones (wetlands and forests) were left intact.

Having consistent data inputs can positively impact on the modeling results. This study explored the use of post classification approach Dong et al. (2006) by applying 3*3 moving window size and vector overlay rectification to improve Landsat image classification. This method was applied to improve built-up land cover in the low urban densities and to remove “salt and pepper” misclassified built-up pixels in wetlands and forests see Figure 6-1.



(a): Original Landsat OLI image 2014 false color composite 432; (b): Landsat OLI image 2014 classified; (c): Landsat OLI image 2014 classified after fuzzy classification (3*3 moving window size); (d): Landsat OLI image 2014 classified after vector overlay rectification.

Figure 6-1: Landsat OLI 2014 image post-processing classification in the low urban densities with the mixed-up of forest and built-up.

The analysis of different data on Landsat images allowed to obtain the inputs of urban growth modeling for four different years. The results helped not only to get LRM inputs, but also to describe the tendencies and the pattern of Kigali city growth in that period. Moreover, the patterns found proved the impact of the environmental policy on forest and wetlands protection in the Western and Southern part of the city on Mount Kigali and Mount Jali. The results also highlighted the implication of human related activities with regard to contributing to a decrease in natural reserves (forests and vegetation) for the period between 1987 and 2014. However, the wetland coverage has remained constant since 2009 to 2014 due to the efforts made by Kigali city, REMA and community for wetlands protection.

6.2. LRM for urban growth

LRM was applied in this study to determine the main driving forces that condition urban growth and predict future urban growth pattern in the study area in the next 26 years. The results of this study indicated that new urban developments in Kigali city will tend to be close to the existing urban areas, hence a compact pattern. This is logical for Kigali city due to the city experience of a massive horizontal urban growth pattern. This shows how important spatial policies (condominium law and 2012 Kigali City Master Plan) are to deal with horizontal growth and reduce its negative impact of adopting vertical urban growth pattern. It also shows that; new urban development will have a tendency to occur further from the CBD and wetlands but on low slope sites. This proves what have been found by Edaw et al. (2007), slope greater than 20% were deemed as unsuitable for urban development in Kigali city due to the fact that steep slope sites increase landslides, erosion, problems with road designs, construction and maintenance. Moreover, steep slope sites are less practicable in term of fire protection equipment and emergency vehicles in case of any risk occurrence. However, health centres impact the new urban development in a negative way. This can be linked with the efforts of the government of Rwanda on improving accessibility on health care facilities within an acceptable distance from the inhabitants (Surbana, 2012).

Drivers of urban growth may change from one case study to another, because of data availability Cheng (2003); resources Hu (2004); Huang et al. (2009) and modeling approach (Hu and Lo, 2007; Nong and Du, 2011). In the similar urban growth cities, factors proportion to urban areas, distance to the CBD and slope were reported as main drivers of urban growth see Table 2-3. Among factors Hu and Lo (2007) reported, neigbboring to urban area and distance to economic centres came at the first place as main driving forces of urban growth in Atlanta city, Georgia, USA. Moreover, Huang et al (2009) concluded that proportion to urban areas, zoning, and distance to roads were key drivers of New Castle city growth. Using the same approach, Dubovyk et al (2011), found that slope and population density impacted the proliferation of informal settlement in Sancaktepe, Instanbul, Turkey.

Empirical results from LRM used three scenarios to simulate the future built-up trends and patterns of the city, namely expansion scenario called normal growth (derived from past and present pattern of built-up area land cover) and densification scenario (simulated from the best 1999-2014 expansion scenario model and policy implication of 2025 and 2040 proposed zoning maps). The modeling was performed in Change Analyst software, an empirical statistical Planning Support System extension in the ArcGIS environment. Densification model was used to predict 2025 and 2040 of Kigali city built-up patterns. Both 2025 and 2040 prediction for expansion and densification scenarios model maps were compared with the proposed 2025 and 2040 zoning maps.

The 1999-2014 expansion scenario model predicted that if the current physical urban expansion rates continues, urban development will expand towards Northern and Southern direction of the city rather than Western and Eastern parts. The new developments have a tendency to replace forest cover and wetlands in the Western part of the city and this constitutes a serious environmental threat to the city (see Table 5-10). This 1999-2014 expansion scenario model selected was validated by means of Kappa statistic and ROC value whereby values of 0.75 for Kappa statistic and 0.750 for ROC showed the robustness of the results, which implies that the model was good to predict the real pattern of the future of Kigali city. In land use/cover change modeling, a kappa value higher than 0.5 can be considered as satisfactory (Lesschen et al., 2005). Kappa and ROC value found in this study can be compared to what have been found by (1) Dubovyk et al. (2011) with a Kappa of 0.50, 0.49, 0.65 with a ROC value of 0.81, 0.82 and 0.94; (2) Nong and Du (2011) with the ROC value of 0.891. The 0.75 and 0.750 kappa and ROC values found in this study can ensure the validity of the model built to predict the future urban growth of the city.

Three scenarios generated have patterns characterized by a strong compactness of urban densities. Expansion scenario is more compact (see Figure 5-13a), compared to other scenarios. This is logical since expansion scenario tends to convert a higher amount of forest and wetlands land cover into built-up while the policy scenarios will protect the land (see Table 5-10 and Figures 6-2 and 6-3). However, all three models tend to exclude urban units in the Eastern-Southern part of the city compared to proposed zoning maps (see Figure 5-12). The area currently characterized by lower urban density and low health care accessibility which might be related to the model pattern found as shown in Figure 5-14.

Figure 6-2: An area of wetlands that will be consumed by the expansion and policy scenarios

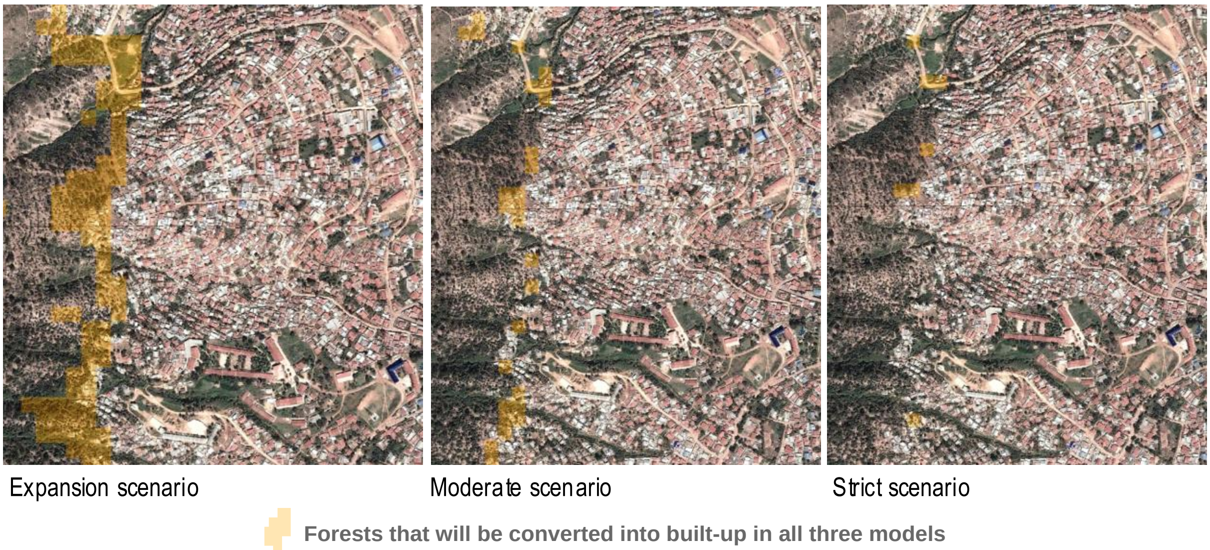


Figure 6-3: An area of forests that will be consumed by the expansion and policy scenarios

This study proves the potential of using socioeconomic data in macro-level urban growth modeling to better understand the dynamics of the future urban growth in Kigali city. LRM enabled the use of biophysical, demographic, socioeconomic and environmental data to evaluate future urban planning goals (proposed zoning in the 2025 and 2040 of the city of Kigali). Model built, predicted the future urban growth behavior of the city through scenarios, in turn, will form the basis of policy options/ decisions of the city.

6.3. The potential of using Logistic Regression in urban growth modeling

This empirical statistical approach (LRM), can make a vital contribution in urban growth modeling studies (Lesschen et al., 2005). LRM has shown its high capability to capture the probability of new urban developments that will take place in the future using less computer resources (Hu and Lo, 2007; Hu, 2004). Many authors claimed that LRM has a strong capability to not only incorporate biophysical influence (slope, land use/cover, transport, zoning) but also demographic and social variables to better understand human forces' ability in urban growth pattern (Hu and Lo, 2007). Nong and Du (2011) assured that by less computation resources, LRM calibration can allow multi-scale (different moving window sizes) simulations. Fundamentally, LRM is simple to interpret Field (2013); Moore. et al. (2009), suitable approach to evaluate critical areas for future urban developments (informal settlement proliferation or urban growth; i.e. areas that will be highly urbanized and not) Dubovyk et al. (2011); Duwal (2013) and to assess the impact of macro-level changes (e.g major roads, built-up areas, etc.) (Lesschen et al., 2005). However, LRM does not explain the underlying processes that lead to the micro factors of urban growth patterns. In principle, LRM behaves as a black box procedure. LRM lacks a self modifying approach so that the model variables can update themselves automatically. As a less temporal explicit modeling approach, LRM outputs probability maps contain information on where new developments will take place, but not when changes will occur (Cheng, 2003). LRM relies heavily on existing land cover/use history patterns (not urbanized areas with no history of land cover/use change). Hence, LRM meant for ideal situations (not absolutely real). A possible solution to deal with temporal dynamism, further researches would be combined with other model approaches like a CA model or other *What If* models (CommunityViz etc.). Results comparisons from different modeling approaches should be applied to point out weaknesses, strengths and a demand to reassess data and analysis procedures followed in one modeling approach or another (Lesschen et al., 2005).

6.4. Methodological issues

In modeling perspective, the method chosen should fit the research questions, data availability, time and resources (Lesschen et al., 2005). This study was subjected to the data constraints which is a serious problem in urban growth modeling in developing cities (Hu and Lo, 2007). The model relies on very limited factors therefore its outcomes should be looked at model inputs. All factors given by respondents to be considered as drivers of urban growth were not included in the model due to the data unavailability and their integration capability in LRM for extracting meaningful information (Table 5-7). Variables such as neighboring characteristics (regular water and electricity provision) were not incorporated in the model whereby their presence might have improved the model performance. In addition, compilation of data used suffers from processing anomalies of spatial and temporal resolution inconsistency. In this case, Landsat TM classified specifically for 1987 and 1999 lacked temporal consistent validation data (1986 topographic map used for 1987 and 1994 cadastral map used for 1999). Population densities were extrapolated and interpolated. Again, Landsat data (30*30 meters cell size resolution) lacked the capability to capture patterns on a micro level scale of change. However, using high resolution Remote Sensing data (1 meter resolution of IKONOS, 0.64 meters resolution of Quickbird) may remove classification anomalies (salt and pepper pixels of built-up and bare land), which could improve the pattern comparison and model performance. Dong et al. (2006) revealed that such comparisons can enable the study of urban growth on various scales, which can help in turn, taking urban growth decisions at different levels of urban development planning. The spatial analysis for this study was based on the 30*30 meters pixel size as the spatial resolution of Landsat images used in this research. Therefore, other variables used were resampled and conformed to this resolution for the model sensitivity. However, other resolutions from 10*10 meters to 20*20 meters need to be comparatively checked for the robustness analysis of this LRM study results in the future studies. LRM (Change Analyst) lacks the capability to analyze the data itself (to perform some analysis Change Analyst was coupled with other softwares i.e SPPS, Patch Analyst and ArcGIS), hence pushed changing data formats and locations which may be the source of some model outcomes' anomalies.

7. CONCLUSION AND FURTHER RESEARCH DIRECTIONS

7.1. Conclusion

Urban planning and management of cities in developing countries need adequate modeling tools for urban growth monitoring in time and space. This study is devoted to model urban growth by coupling GIS, RS, spatial metrics and Logistic Regression Model. LRM was applied in Kigali city to determine the main driving forces that condition the city expansion and predict future urban growth pattern in the study area in the next 26 years. For this study, multi scale data and from multi sources were used. There were three specific objectives in this study.

The first objective was *to generate a consistent set of land cover maps of Kigali city during the period 1987, 1999, 2009 and 2014*. Pixel- based approach by Maximum Likelihood method was applied to classify Landsat images. As the purpose of the study was to look at built-up land cover only, from the land cover maps, built-up area were extracted and visualized. A number of built-up pixels in each time span were quantified and the built-up area of each year was derived. With Landstat images classified, a remarkable trends and sprawl pattern was observed in urban areas in Kigali city in that, the rapid trend was more accelerated between 1987 and 2009 while it continued at a moderate pace up to 2014. The findings revealed that urban areas expanded mainly towards the Northern, Eastern and Southern directions. However, the Western part of the city was posed due to the area topography and environmental policy on protecting forests. The new urban areas lie mostly on previous vegetation and forest lands, and have not replaced areas covered by wetlands or forests in the Western and South-Western part of the city due to the environmental policy on wetland and forest protection on Mont Kigali and Mount Jali. The results also highlighted the implication of human related activities with regard to contributing to a decrease in natural reserves (forests and vegetation) for the period between 1987 and 2014. However, the wetland coverage has remained constant since 2009 to 2014 due to the efforts made by Kigali city, REMA and community for wetlands protection.

The second objective was *to build a Logistic Regression (LR) model of urban growth in Kigali city*. The results indicated new urban developments in Kigali city will tend to be close to the existing urban areas, hence a compact pattern. This is logical for Kigali city due to the city experience of a massive horizontal urban growth pattern. It also shows that; they will have a tendency to occur further from the CBD and wetlands but on low slope sites. This proves what have been found by Edaw et al. (2007), slope greater than 20% were deemed to be unsuitable for urban development in Kigali. However, health centres impact the new urban development in a negative way. This can be linked with the efforts of the government of Rwanda on improving accessibility on health care facilities within an acceptable distance from the inhabitants (Surbana, 2012). The results prove local urban planning experts wide understanding of the drivers of urban growth in Kigali city. There is a good match between best scored variables in both planners views and LR model results. The study results showed the changes of driving forces over all modeling time period from 1999 up to 2014. The proportion of urban densities in a neigborhood area, the slope and distance from health centres were found as most three important factors for 1999-2014 and 1999-2009 LRMs time spans, while population density was replaced slope for 2009-2014 LRM.

The last objective was *to predict future urban growth pattern in Kigali city*. The model predicted that if the current physical urban expansion rates continues, urban development will expand towards Northern and Southern direction of the city rather than Western and Eastern parts. All three models have a nearly equal spatial match but built-up cover for the expansion scenario will be higher with 187.9 km^2 compared to other densification scenarios. The new developments have a tendency to replace forest cover and wetlands in the Western part of the city and this constitutes a serious environmental threat to the city. This study proves the potential of using socioeconomic data in macro-level urban growth modeling to better understand the dynamics of the future urban growth in Kigali city. In addition, the study highlighted LRM strengths to evaluate zoning policy using scenarios. Model built, predicted the future urban growth behavior of the city through scenarios, in turn, will form the basis of policy options/ decisions of the city. However, LRM lacks a self modifying approach so that the model variables can update themselves automatically. Hence, LRM outputs probability maps contain information on where new developments will take place, but not when changes will occur. LRM relies heavily on existing land cover/use history patterns (not urbanized areas with no history of land cover/use change). Hence, LRM meant for ideal situations sometimes not absolutely real.

7.2. Further research directions

The predicted spatial urban developments are the outcomes of significant driving forces incorporated in the model. Further study might think about using other important factors revealed by local urban planning experts like neighborhood of water and electricity, but not included in this study's model because of data unavailability.

For being accurate for this kind of modeling, further research should make emphasis on using high resolution satellite data and a consistent temporal and spatial data.

A better understanding of the underlying processes regarding urban growth on micro- level (e. g the individual decisions in response to land use policies) may be essential to better analyze different urban growth patterns within a macro-level model. This study should be repeated by coupling LRM with other micro-level approaches CA model or CommunityViz.

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APPENDIX A: DESCRIPTION AND INDICATIVE OF SECONDARY DATA COLLECTED

Remote sensing data

Type of Data	Time period	Source	Resolution	Projection	Purpose
Landsat TM	1987-05-Febuary	USGS	30 m	WGS_1984_UTM_Zone_36N	Landsat imageries were used for preparing land cover maps.
Landsat TM	1999-08-July	USGS	30 m	WGS_1984_UTM_Zone_36N	
Landsat TM+	2009-25-June	USGS	30 m	WGS_1984_UTM_Zone_36N	
Landsat OLI	2104-14-January	USGS	30 m	WGS_1984_UTM_Zone_36N	
Aerial photography	2008	RNRA	0.25 m	GCS_ITRF_2005	High resolution images were used for verification of training sample sets.
Kigali city Topo map	1986	ITC/ RNRA	4 m	WGS_1984_UTM_Zone_36N	
Kigali city Cadastral map	1994	Internet[1]	1:10000	No projection (Georeferenced)	
Quickbird image	2004	CGIS-Butare	1m	WGS_1984_UTM_Zone_36N	
Google earth	2004	ITC	0.9m	D_WGS_1984	
Google earth	2005	ITC	0.9m	D_WGS_1984	
Google earth	2014	ITC	0.9m	D_WGS_1984	

1. http://www.lib.utexas.edu/maps/africa/txu-oclc-55668328-kigali-1994.jpg: Kigali original scale 1:10,000, Edition 4-DMA, Series Z922. U.S. Defense Mapping Agency, 1994.

Vector datasets

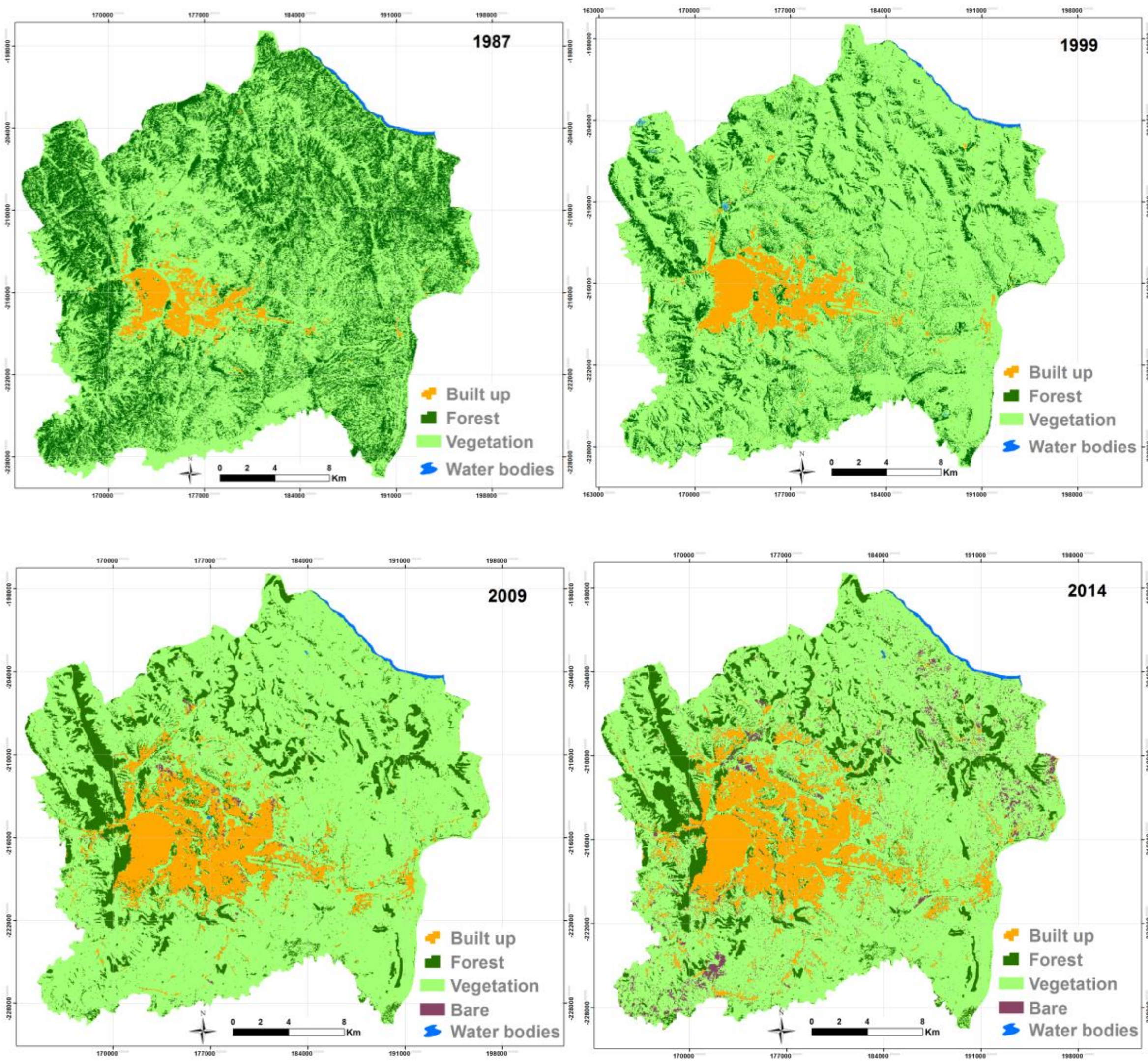
Type of Data	Time period	Source	Projection	Purpose
Base map of Rwanda and DEM (Slope generation)	2008	RNRA	GCS_ITRF_2005	Delineating study area extent and factor maps generation
Land use of Kigali city	2009	Kigali city	GCS_ITRF_2005	Delineating study area extent and factor maps generation
Road network Paved and unpaved roads	2008	ITC	GCS_Arc_1960	Driving factors of urban growth
Main markets	2008	CGIS-Butare	GCS_Arc_1960	Used as driving factors of urban growth
Land use: DEM Public services: Schools, Hospitals, post offices….	2005	ITC	GCS_Arc_1960	Reference for preparing land cover categories Public services were used as driving factors of urban growth
Economic areas: CBD, industrial area	2008	RNRA	GCS_ITRF_2005	Used as driving factors of urban growth
Soil types		RNRA	GCS_ITRF_2005	Used as driving factors of urban growth
Wetlands Updated	2014	Kigali city	GCS_ITRF_2005	Used as driving factors of urban growth
Zoning plan 2025	2013	Kigali city	GCS_ITRF_2005	Proposed zoning to be compared with the simulated model
Zoning plan 2040	2013	Kigali city	GCS_ITRF_2005	Proposed zoning to be compared with the simulated

			model	

Non spatial data

Type of Data	Time period	Source	Description	Purpose
Kigali city baseline (Socio economic characteristics)	1978, 2002, 2012	NISR	Population, land value, income, poverty rate, employment rate, of different time spans	To produce a population density map per ward level To produce the land value map
Kigali city conceptual master plan	2008	Kigali city		Have an overview on Kigali city's dynamism
Kigali city district master plans	2013	Kigali city		Have an overview on Kigali city's dynamism
Spatial policies Kigali city		Kigali city, RNRA, RHA	Vision 2020, EDPRS, KCMP, National land use and development master plan, National urban housing policy, Land policy, Urbanization and settlement policy, Land use planning and development law, The condominium law and Land law.	Have an overview on Kigali city's dynamism

APPENDIX B: LAND COVER CLASSIFICATION MAPS OF KIGALI CITY



APPENDIX C: LOCAL URBAN PLANNING EXPERTS' QUESTIONNAIRE

In this mode of collecting data respondents were contacted, a short introduction was given by the researcher to the respondents. A person (or face to face) interview was conducted using a questionnaire at the expense of other methods of data collection suggested by Bowling (2005), such as telephone interviews, self- assessed telephone recording and electronic or computer-based data collection.

This research focuses on determining factors which drive the urban growth and forecasting the future urban expansion pattern in Kigali city. In this regards, this interview will help to collect experts opinion about the driving factors of Kigali city growth. In addition, it will give the insight of the policies behind urban development in the city of Kigali. You are kindly asked to answer the questions below. The response given will be used only for the research purpose and confidentiality is assured.

A. IDENTIFICATION OF RESPONDENT	**ID Number…………………**
Respondent, function, address	Occupation/profession……………………………………………
	Position/duty ………………………………………………………..
	Address (Institution)…………………………………………………
	Email …………………………………………………………………...
B. EXPERIENCE IN PLANNING	
1. What it is your: a. Education background level…………………………………………………………… b. Highest degree……………………………………………………………………………. c. Field of studies………………………………………………………………………… d. Place of study…………………………………………………………………………….. e. Year of graduation………………………………………………………………………... 2. How long did you start working as a planner? (Specify years of)…………………………...	

C. PROBABLE DRIVING FORCES OF URBAN GROWTH

Please rate the listed factors which may influence urban growth (for the period before and after 1994 Genocide) as indicated below. If relevant factors are not mentioned in the list please specify.

Rating scale			
Very high influence	=5	Low influence	=2
High influence	=4	Very low influence	=1
Moderate influence	=3	Not assigned	=0

Probable driving force		**5**	**4**	**3**	**2**	**1**	**0**
1. Bio-physical influence	Slope (site topography)						
	Soil types						
If other please specify	Flooded area						
	………………………………………..						
2. Spatial plans and policies	Land use zoning						
	Protected land (eg: Wetlands, forest…)						

If other please specify	……………………………………..						
	……………………………………..						
	……………………………………..						
3. Neighborhood characteristics	Proportion of built-up land in the surrounding area						
	Population density						
	Regular water provision						
	Regular Electricity provision						
	……………………………………..						
If other please specify	Distance to major paved roads						
4. Proximity characteristics	Distance to unpaved roads						
	Distance to industrial sites						
	Distance to City Centre(Nyarugenge)						
	Distance to sub-centres (Kimironko centre, Kicukiro Centre, Gikondo…)						
	Distances to primary schools						
	Distances to secondary schools						
	Distance to health facilities						
	Distance to open markets (Nyabugogo, Kimisagara, Kabuga…)						
	Distance to bus stops						
If other please specify	……………………………………..						
	Land value (land price per parcel)						
5. Economic factors	……………………………………..						
If other please specify	……………………………………..						
6. Others not identified							

C. PLAN AND POLICIES OF URBAN GROWTH IN KIGALI CITY
1. Since 1984, what are the main plans, policies elaborated to control the growth of Kigali city?
………………………………………………………………………………………………………
………………………………………………………………………………………………………
………………………………………………………………………………………………………
2. What are the past policies that had an influence on the current shape of Kigali City?
………………………………………………………………………………………………………
………………………………………………………………………………………………………
………………………………………………………………………………………………………
3. Do you think that the current Kigali City Master Plan implemented, will control Kigali City future growth direction?
Yes ☐ No ☐
If Yes explain how?

……………………………………………………………………………………………………
……………………………………………………………………………………………………
……………………………………………………………………………………………………
4. How does the current planning approach control Kigali City growth?
……………………………………………………………………………………………………
……………………………………………………………………………………………………
……………………………………………………………………………………………………
5. What are the main types of policy instruments elaborated to control urban growth in Kigali City? (Incentive, Regulations, Non-responsive, Communicative or Mixed-instruments)
Eg: Non-responsive (punitive) instruments: Demolition of illegal building construction, paying fines…
……………………………………………………………………………………………………
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Thank you very much I will provide you the feedback when this research analysis completed!

APPENDIX D: MULTICOLLINEARITY DIAGNOSIS

E.1. Results of multicollinearity for all variables included

Variable	Description	VIF 1999-2014	VIF 1999-2009	VIF 2009-2014
X_1	*Distance to bus routes*	*1872.335*	*1820.273*	*1836.669*
X_2	*Distance to bus stops*	*1858.004*	*1796.896*	*1805.014*
X_3	Distance to CBD	4.905	4.816	4.958
X_4	*Distance commercial areas*	*18.201*	*15.158*	*15.011*
X_5	Distance to health centres	2.988	3.296	3.214
X_6	Distance to industry	6.600	7.067	7.891
X_7	Distance to main roads	4.412	6.670	4.414
X_8	Distance to trade centres	2.523	2.881	2.526
X_9	Proportion of urban in a surrounding area	1.942	1.760	1.647
X_{10}	Population density	1.557	1.787	1.743
X_{11}	Forests	1.241	1.244	1.247
X_{12}	Wetlands	1.222	1.223	1.226
X_{13}	Slope1999	1.582	1.549	1.581

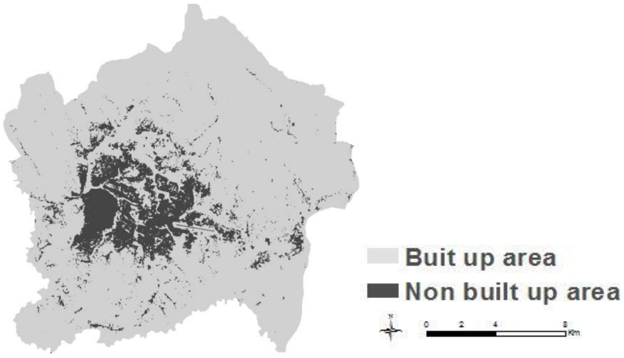
E.2. Results of multicollinearity after eliminating the bus routes

Variable	Description	VIF 1999-2014	VIF 1999-2009	VIF 2009-2014
X_1	*Distance to bus routes*	*Eliminated*	*Eliminated*	*Eliminated*
X_2	*Distance to bus stops*	*20.084*	*22.214*	*22.656*
X_3	Distance to CBD	4.900	4.812	4.747
X_4	*Distance commercial areas*	*18.015*	*15.090*	*14.915*
X_5	Distance to health centres	2.980	3.281	3.198
X_6	Distance to industry	6.429	6.920	7.656
X_7	Distance to main roads	4.390	6.583	6.387
X_8	Distance to trade centres	2.520	2.880	2.860
X_9	Proportion of urban in a surrounding area	1.893	2.121	2.463
X_{10}	Population density	1.556	1.786	1.858
X_{11}	Forests	1.241	1.243	1.258
X_{12}	Wetlands	1.216	1.219	1.251
X_{13}	Slope1999	1.579	1.548	1.644

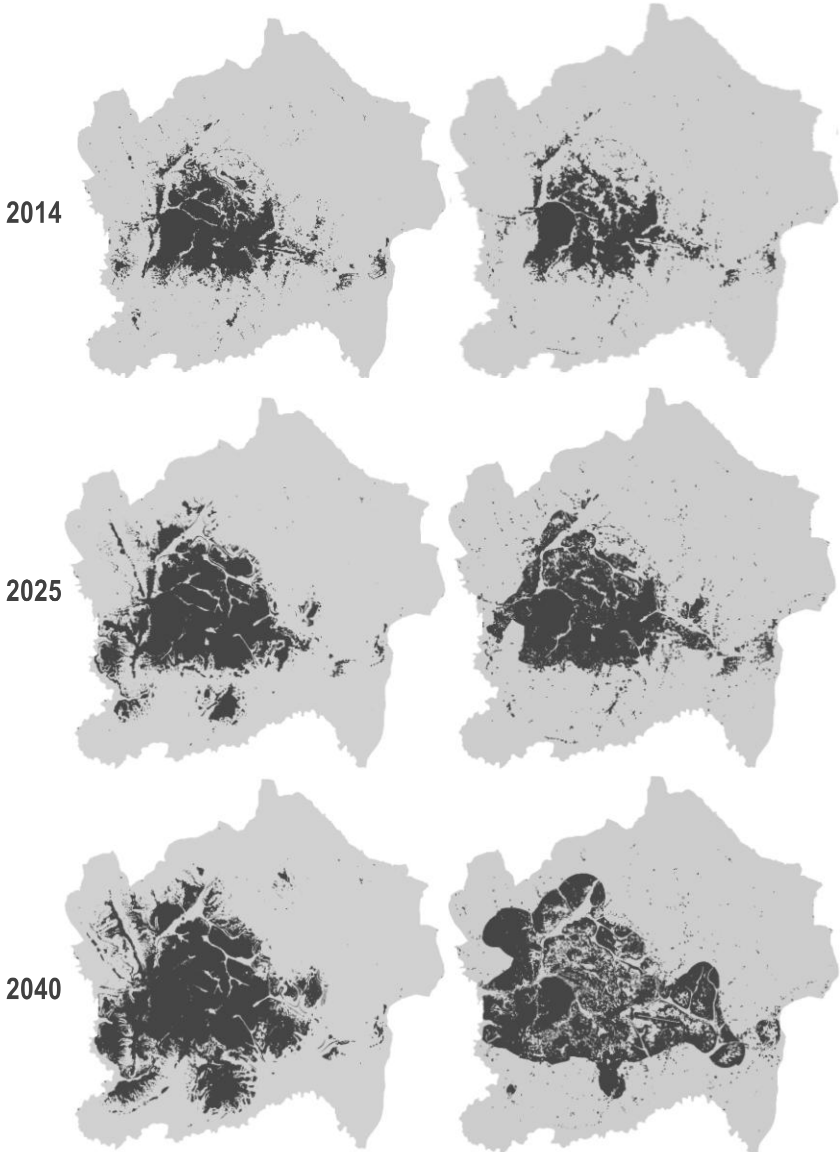
E.3. Results of multicollinearity after eliminating the bus routes and the bus stops

Variable	Description	VIF 1999-2014	VIF 1999-2009	VIF 2009-2014
X_1	*Distance to bus routes*	*Eliminated*	*Eliminated*	*Eliminated*
X_2	*Distance to bus stops*	*Eliminated*	*Eliminated*	*Eliminated*
X_3	Distance to CBD	3.749	3.674	3.656
X_4	*Distance commercial areas*	*13.732*	*13.793*	*13.370*
X_5	Distance to health centres	2.941	3.262	3.181
X_6	Distance to industry	5.831	6.168	6.653
X_7	Distance to main roads	4.325	5.826	5.666
X_8	Distance to trade centres	2.480	2.880	2.855
X_9	Proportion of urban in a surrounding area	1.872	2.098	1.793
X_{10}	Population density	1.493	1.717	1.793
X_{11}	Forests	1.240	1.243	1.258
X_{12}	Wetlands	1.216	1.218	1.251
X_{13}	Slope1999	1.564	1.540	1.641

APPENDIX E: 1999-2009 AND 2009-2014 LRMS EXPANSION SCENARIO PROBABILITY MAPS



Built-up cover in 2014



1999-2009 LRM Expansion

2009-2014 LRM Expansion

APPENDIX F: VARIABLES IN THE EQUATION OF 1999-2014 LRM

3*3 moving window

Variables not in the Equation[c]

			Score	df	Sig.
Step 2[a]	Variables	Forest	.096	1	.757
	Overall Statistics		.096	1	.757
Step 3[b]	Variables	Tradecentres	.193	1	.660
		Forest	.096	1	.757
Step 4[d]	Variables	Tradecentres	.162	1	.688
		Forest	.098	1	.755
		Industry	.209	1	.648
Step 5[e]	Variables	MainRoads	.874	1	.350
		Tradecentres	.055	1	.814
		Forest	.144	1	.704
		Industry	.792	1	.373
Step 6[f]	Variables	MainRoads	.741	1	.389
		Tradecentres	.104	1	.747
		Forest	.116	1	.733
		Popdens	1.205	1	.272
		Industry	.512	1	.474

a. Variable(s) removed on step 2: Forest.
b. Variable(s) removed on step 3: Tradecentres.
c. Residual Chi-Squares are not computed because of redundancies.
d. Variable(s) removed on step 4: Industry.
e. Variable(s) removed on step 5: MainRoads.
f. Variable(s) removed on step 6: Popdens.

5*5 moving window

Variables not in the Equation[c]

			Score	df	Sig.
Step 2[a]	Variables	Forest	3.005	1	.083
	Overall Statistics		3.005	1	.083
Step 3[b]	Variables	Forest	2.926	1	.087
		Popdens	.029	1	.865
Step 4[d]	Variables	Tradecentres	.099	1	.753
		Forest	2.867	1	.090
		Popdens	.022	1	.881
Step 5[e]	Variables	Tradecentres	.036	1	.849
		Forest	2.798	1	.094
		Popdens	.064	1	.800
		CBD	.285	1	.593
Step 6[f]	Variables	Industry	.518	1	.472

		Tradecentres	.100	1	.751
		Forest	2.612	1	.106
		Popdens	.006	1	.937
		CBD	.055	1	.815
Step 7[g]	Variables	Industry	.205	1	.651
		Tradecentres	.028	1	.868
		Forest	2.663	1	.103
		Wetlands	1.305	1	.253
		Popdens	.003	1	.959
		CBD	.199	1	.656

a. Variable(s) removed on step 2: Forest.
b. Variable(s) removed on step 3: Popdens.
c. Residual Chi-Squares are not computed because of redundancies.
d. Variable(s) removed on step 4: Tradecentres.
e. Variable(s) removed on step 5: CBD.
f. Variable(s) removed on step 6: Industry.
g. Variable(s) removed on step 7: Wetlands.

7*7 moving window

Variables not in the Equation[c]

			Score	df	Sig.
Step 2[a]	Variables	Forest	.047	1	.829
	Overall Statistics		.047	1	.829
Step 3[b]	Variables	MainRoads	.001	1	.972
		Forest	.047	1	.828
Step 4[d]	Variables	MainRoads	.001	1	.981
		Tradecentres	.002	1	.963
		Forest	.048	1	.827
Step 5[e]	Variables	MainRoads	.001	1	.981
		Tradecentres	.004	1	.950
		Forest	.047	1	.829
		Popdens	.813	1	.367
Step 6[f]	Variables	MainRoads	.000	1	.987
		Tradecentres	.010	1	.922
		Forest	.054	1	.816
		Popdens	.339	1	.561
		CBD	1.066	1	.302

a. Variable(s) removed on step 2: Forest.
b. Variable(s) removed on step 3: MainRoads.
c. Residual Chi-Squares are not computed because of redundancies.
d. Variable(s) removed on step 4: Tradecentres.
e. Variable(s) removed on step 5: Popdens.
f. Variable(s) removed on step 6: CBD.