Modeling urban growth in Kigali city Rwanda

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***Abstract*-The rapid demographic and uncontrolled spatial transformation have overloaded the capability of most cities management in developing countries. The growth of cities, if governed and supported by well informed policies, decision makers and stakeholders can help to address these challenges. Having a good understanding of the key drivers of the city's growth has proven to be a key instrument to manage urban growth. The study explores the capability of Logistic Regression model to identify the main drivers of Kigali city growth and to predict the future pattern of the city in next 26 years. Three scenarios were built, i.e. urban growth model for expansion (normal growth) and two densification (zoning implication) i.e. strict and moderate scenarios. LRMs regression and probability maps for the three scenario models were evaluated by means of Kappa statistic, ROC value and the percentage of 2014 built-up land cover predicted. These scenarios allowed predicting the future pattern of the city in 2025 and 2040. The results indicated that new urban developments in Kigali city will tend to be close to the existing urban areas, further from the CBD and wetlands but on low slope sites. 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.**

***Keywords*-Urban growth, GIS, Remote Sensing, Logistic Regression modeling, Kigali city, Rwanda**

I. Introduction

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). In recent years, the government of Rwanda has elaborated 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) 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 the implementation of these policies is still in process, it appears that the city growth pace remains. Besides, factors that are behind that growth are still unidentified (Manirakiza, 2012). 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 detect the main drivers controlling Kigali city growth. LR has been proven to be a suitable approach for urban growth modelling in such kind of fast growing cities (Huang et al., 2009).

Logistic Regression technique, one of the empirical-statistical methods can make a vital contribution in urban growth modelling studies (Pullar and Pettit, 2003; 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). 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. LRM is simple to interpret Field (2013); Moore. et al. (2009), suitable approach to evaluate critical areas for future urban development (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).

LR coupled with GIS and RS has been claimed to be a very effective tool for land cover/use change modelling, due to its explanatory power and spatial explicitness (Dendoncker et al., 2007). LR 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 modelling 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.

II. Material and methods

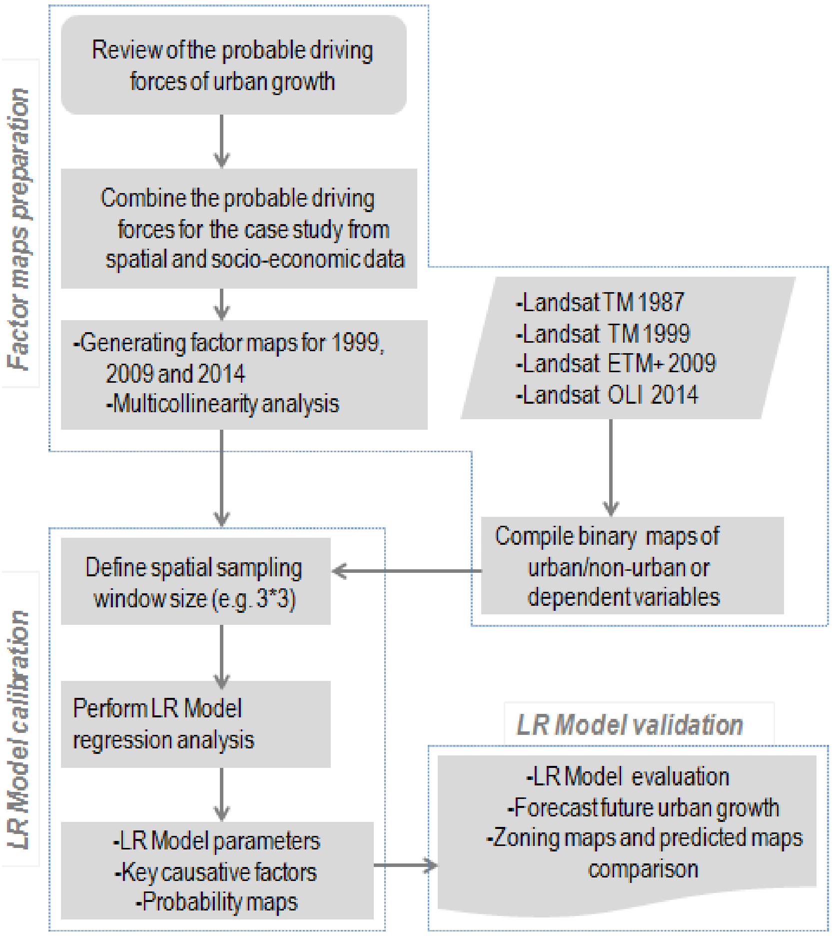
II.1. Remote sensing data and vector data

Type of Data	Time period	Source	Resolution	Projection	Purpose
Landsat TM	1987-05-Febuary	USGS	30 m	WGS_1984_UTM_Zone_36N	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	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	1:10000	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	
DEM, land use, 2025 and 2040 zoning...		Kigali city		GCS_ITRF_2005	Generating driving factors of urban growth

II.2. Methodology

Figure 1 highlights the steps passed through to come up with the meaningful drivers of Kigali city growth.

Figure 1: Flowchart showing procedures followed in LR M



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 (Field, 2013; Nong and Du, 2011). The general form of LR is showed by equation 1 (Cheng, 2003; Field, 2013; Hu and Lo, 2007; Huang et al., 2009; J.Padmavathi, 2012; Rogerson, 2015):

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 x_{1i} + b_2 x_{1i} + \cdots + b_n x_n)}} \qquad (1)$$

On the basis of factors listed from literature (Cheng, 2003; Dubovyk et al., 2011; Hu and Lo, 2007; Hu, 2004; Huang et al., 2009), explanatory variables were prepared for the LRM. 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.

Table 1: Explanatory variables that were 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	=	=	=
Neighbourhood 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

Figure 2: 1999 factor maps

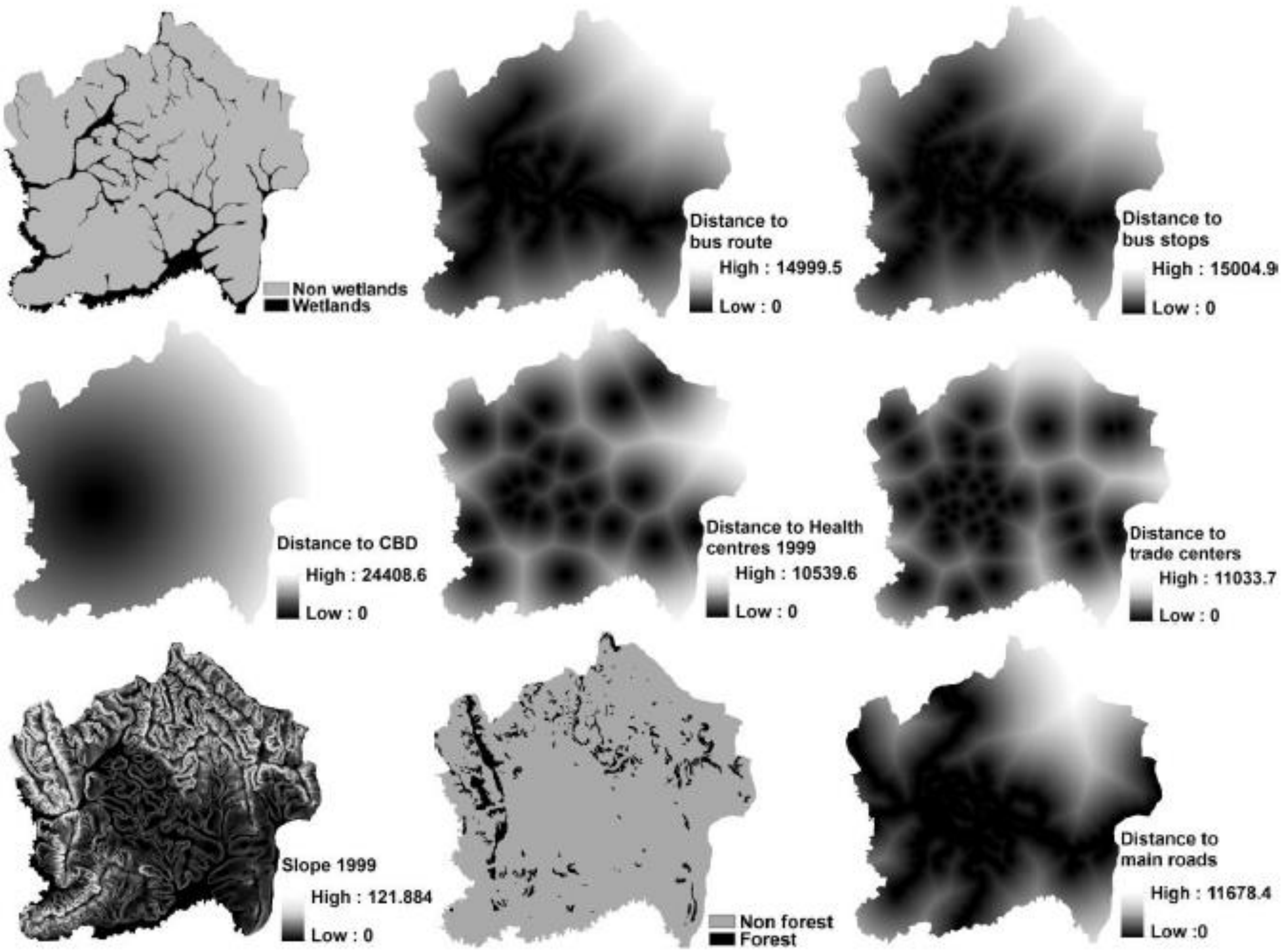
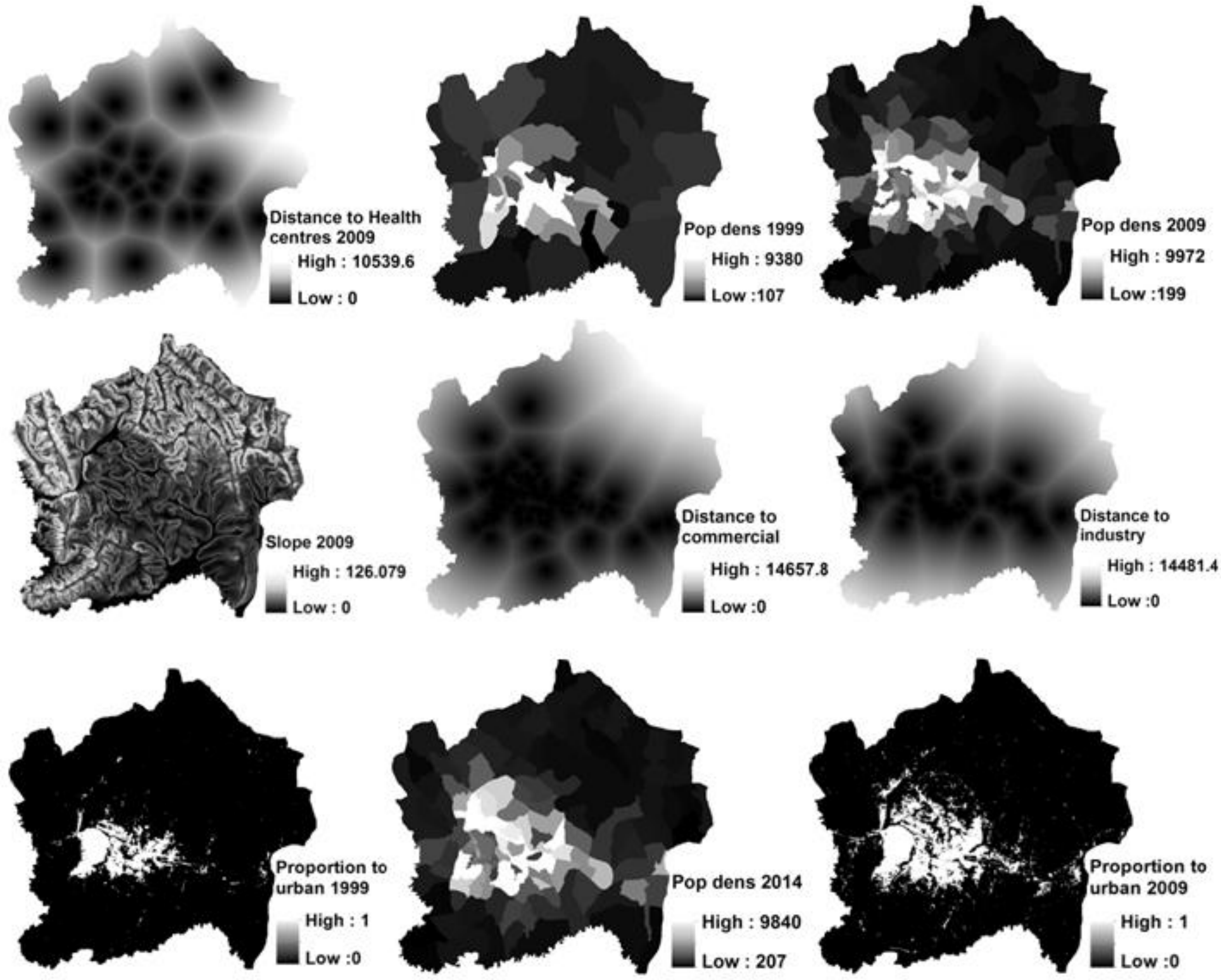


Figure 3: 2009 and 2014 factor maps



As suggested by (Cheng, 2003; Dubovyk et al., 2011; Hu and Lo, 2007; Hu, 2004; Huang et al., 2009; Munshi et al., 2014), multicollinearity test was performed to test variables correlation and their 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. Therefore they were excluded in the analysis.

Table 2: Multicollinearity test

	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

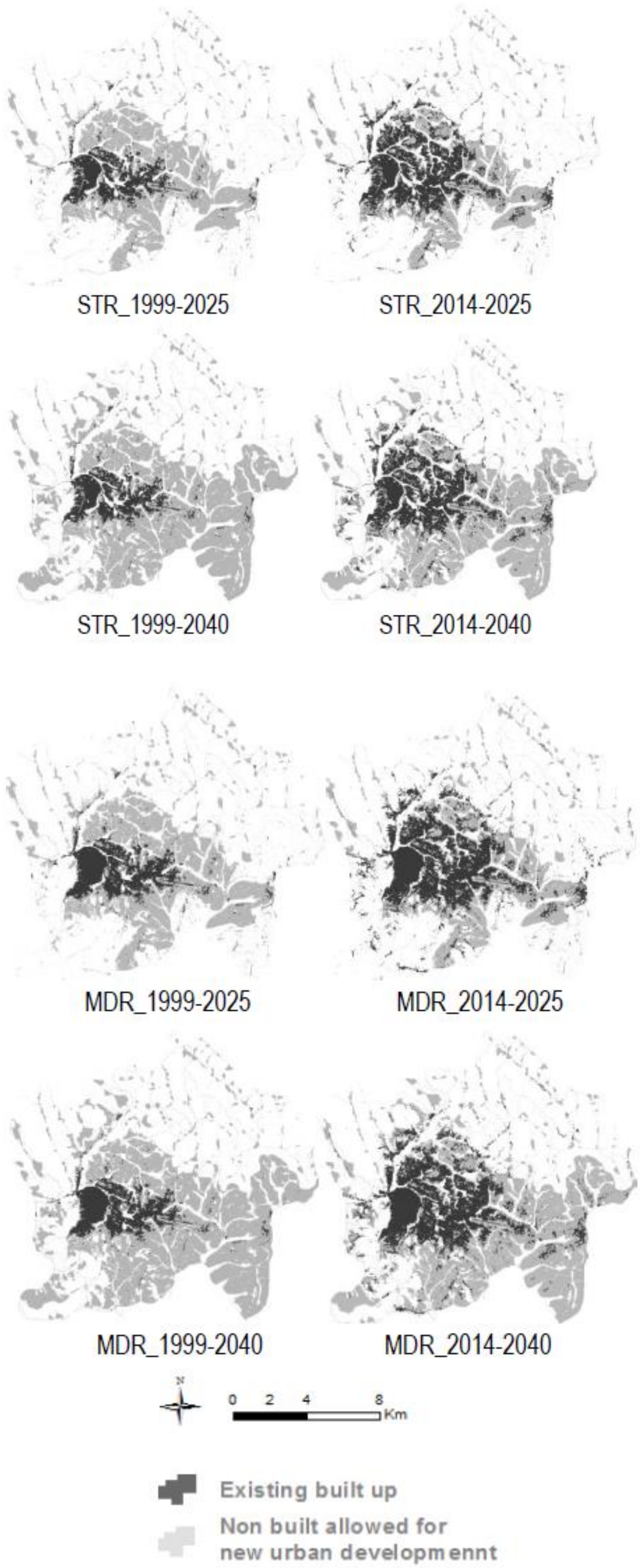
Using independent variables retained after multicollinearity analysis, 1999-2014, 1999-2009 LRMs and 2009-2014 expansion scenarios were built. On the first stage, all models were created using the 10 retained variables after multicollinerality check. Samples generated from initial LRM run were used to apply backward stepwise approach in SPSS and factors that had a sound influence on the model were detected. 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. To choose the window cell size for modelling, the number of significant factors, and model PCP were looked at. A 3*3 window size was selected for 1999-2014 LRMs and 2009-2014 expansion scenario and 5*5 window sizes was selected for 1999-2009 model. LRMs expansion scenario 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. This was done by comparing built-up of the current urban growth (reference image) and urban development predicted to the current situation (Hu and Lo, 2007; Huang et al., 2009). The best model was retained for densification model simulation and non-selected models were excluded.

Table 3: Statistical tests of LRMs expansion scenario

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	6	5	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

In LRMs for densification scenario, the proposed zoning for 2025 and 2040 were considered (Edaw et al., 2007; Surbana, 2012). Factors maps for the 2025 and 2040 zoning plan indicating land allowed to be developed or not were prepared. The 2025 and 2040 zoning factor maps were used to predict both 2025 period and 2040 situation respectively. 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).

Figure 4: Densification factor maps



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

III. Results

III.1. 1999-2014 LRM expansion scenario simulation

This model 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). 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.

Table 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

III.2. 1999-2009 LRM expansion scenario simulation

This final LRM 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. 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.

Table 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

III.3. 2009-2014 LRM expansion scenario simulation

The model was found at the fourth step after eliminating factors like distance to roads, forest cover and slope. 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.

Table 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 LRMs were significant at less than 5% of level of significance. 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 it can be seen that all variables had a different degree of influence of probability on 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 this way. For all models, it can be concluded that the proportion of urban in a neighbourhood 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.

1999-2014 LRM expansion scenario predicted 71.01% (71.92 km^2) of the total current built-up with 0.750 ROC value and 0.75 Kappa statistics. Hence this model was chosen as input for densification scenario.

Figure **Error! No text of specified style in document.**: Comparison of interpolated (2014 built-up prediction of 1999-2014 LRM expansion scenario) versus observed (reality) 2014 built-up cover.

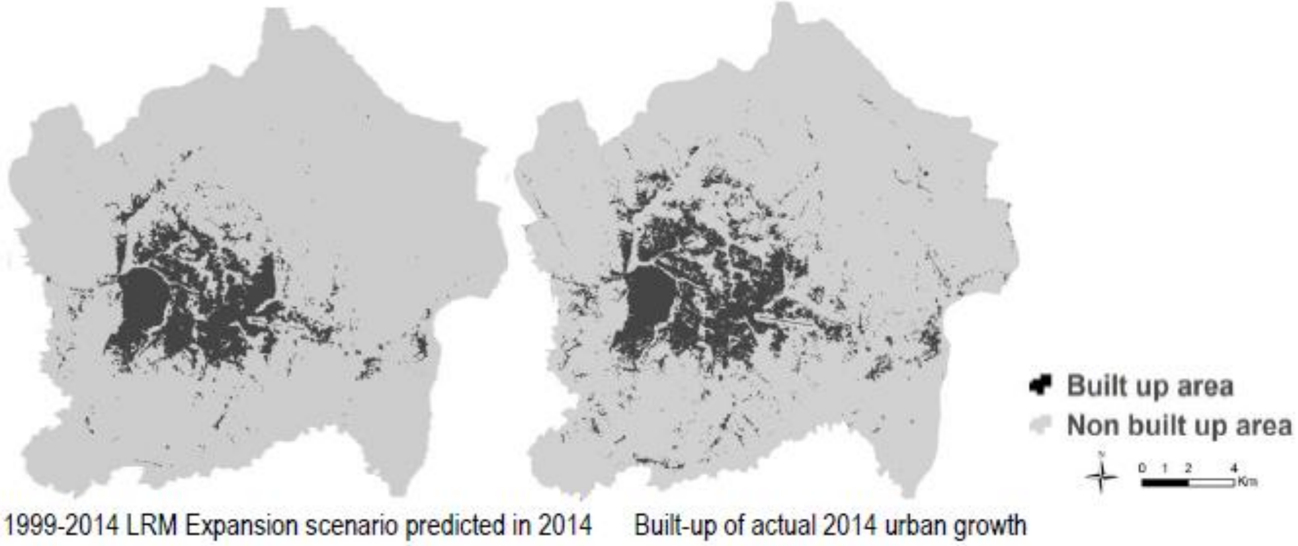
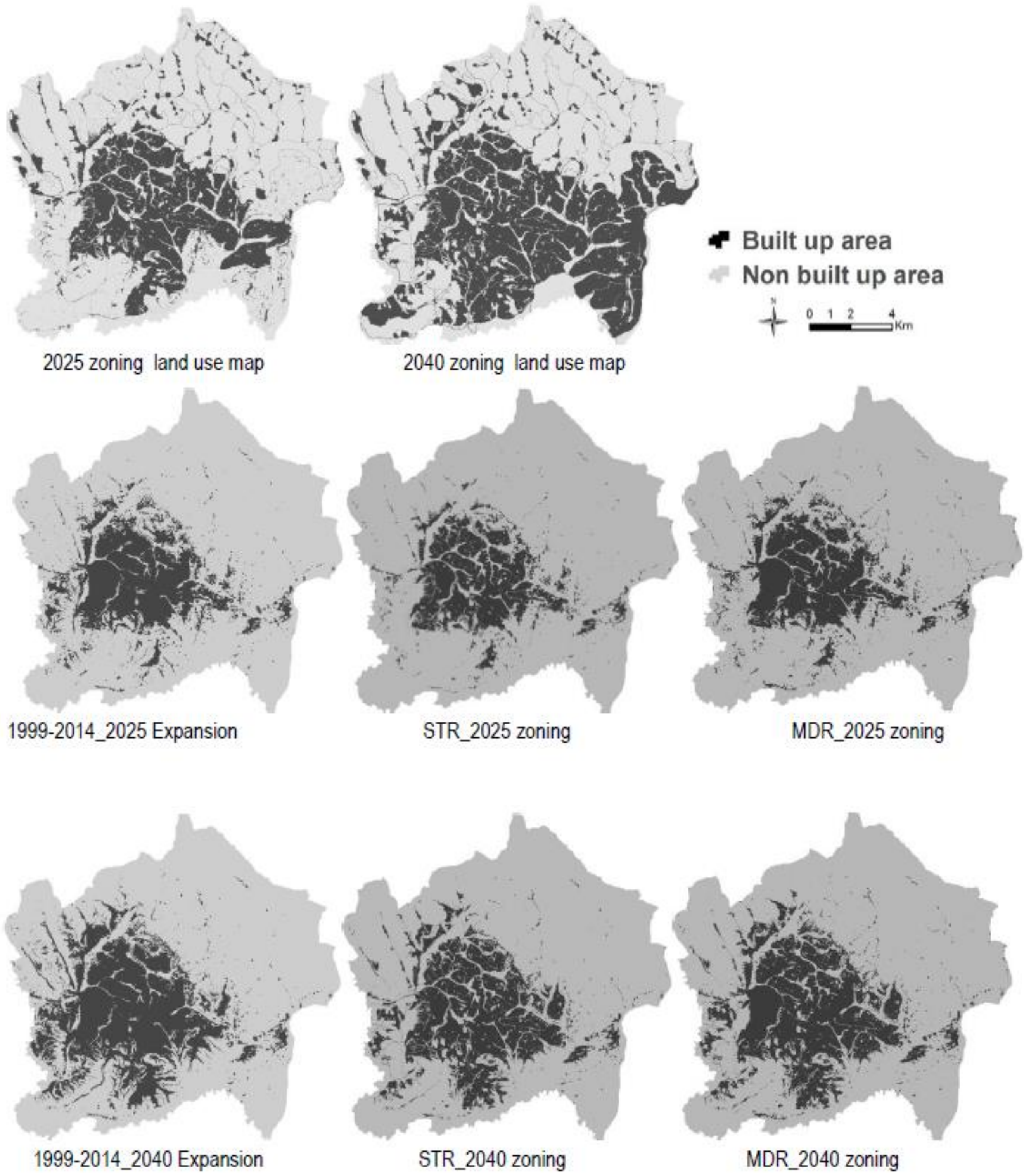


Table 7: Statistical test for LRMs expansion scenario

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

III.3.LRMs densification scenario and zoning implications

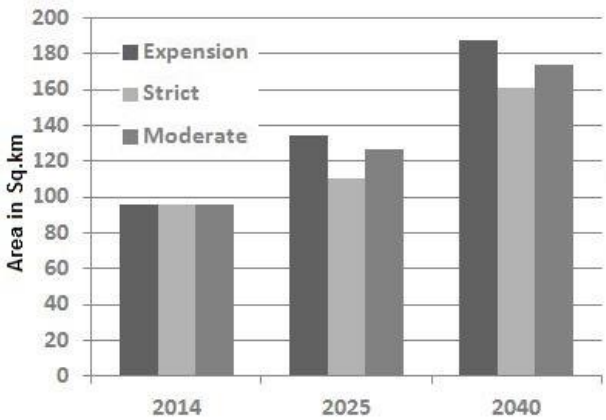
Figure 6: Comparison of interpolated 2025 and 2040 LRMs Expansion and Densification scenario



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

Expansion scenario is more compact, compared to other scenarios (refer to Figure 6). This is logical since expansion scenario tends to convert a higher amount of forest and wetlands into built-up. However, all three models tend to exclude urban units in the Eastern-Southern part of the city. By comparing patterns between 2025 and 2040 for both densification scenario and zoning maps, 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. In 2040, the city trend will be double the current situation if the current trend rate continues to be the same (Figure 7).

Figure 7: Built-up areas of different scenarios



IV. Discussion

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. 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. 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 modelling 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. Among factors Hu and Lo (2007) reported, neighbouring 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. Huang et al (2009) concluded that proportion to urban areas, zoning, and distance to roads were key drivers of New Castle city growth. Dubovyk et al (2011), found that slope and population density impacted the proliferation of informal settlement in Sancaktepe, Instanbul, Turkey.

The 1999-2014 LRMs both for expansion and densification scenarios predicted that if the current physical urban expansion rate 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. LRMs Kappa statistic and ROC 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 modelling, 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.

However, 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 any 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.).

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