Modelling Urban Expansion: A Multiple Urban-Densities Approach

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***Abstract*— Most existing spatio-temporal urban expansion models consider urban land-use as a binary process, through the identification of urban versus non-urban areas. The main aim of this study is to analyze and model the expansion of multiple urban densities in Wallonia, Belgium. To this end, this study employs a multinomial logistic regression model that enables to visualize the consequence of different urban densities expansion. Cadastral datasets of years 2000 and 2010 are used to set four urban classes (non-urban, low-density, medium-density and high-density urban). Besides, several socio-economic, geographic and political driving forces dealing with urban development were operationalized to create maps of urban expansion probability for each urban density class. These probability maps are then utilized to predict future urban expansions for years 2020 and 2030. The model is validated using relative operating characteristic method for different urban classes. Our results suggest that different urban densities expansions are mainly linked to zoning status, neighboring areas that are urban and accessibility. Most importantly, this study highlights that the contribution of different driving forces to urban expansion process varies along with urban density.**

Keywords- multinomial logistic regression; urban expansion; urban densities; driving forces.

I. INTRODUCTION

Rapid urbanization is one of the crucial global issues affecting the physical features of the Earth. As a consequence, a series of urban expansion modelling approaches has been proposed. Most existing urban expansion models are based on a regular grid composed of square cells of dimension between 30x30m to 300x300m [1]–[6]. Typically, these models address urban expansion as a binary process, through the identification of urban versus non-urban land-uses. Most urban cells at these dimensions comprise a mix of different land-uses. For instance, a cell classified as urban land-use may covered by 60% built-up surface and 40% open-space surface. This causes an erroneous estimation of urban expansion pattern. This paper proposes an urban expansion model that enables modelling three urban classes: low-density urban, medium-density urban and high-density urban. Cadastral datasets (CAD) are used to set urban densities. The MLR is employed to model future urban expansion in Wallonia, Belgium. Frist, urban land-use maps are prepared for years 2000 and 2010 based on CAD data. Next, the MLR model is applied to correlate the observed urban expansion pattern for different urban densities with a number of indicators related to distances, topological, neighborhood, socioeconomic factors and land-use policies. Finally, the MLR's outcomes will be utilized to model urban expansion scenarios for years 2020 and 2030 based on linear extrapolation of observed urban expansion between 2000 and 2010. Relative operating characteristic (ROC) method validates the MLR's outcomes.

This paper focuses on assessing the change from non-urban land-use (reference class) into one of urban density classes. The paper is organized as follows. Section II introduces the case study area, urban expansion model and data. Section III wraps up the results and discussions. Section IV concludes the paper findings.

II. MATERIAL AND METHODS

A. Study area

Wallonia (south Belgium) is landlocked, accounts for 55% of the territory of Belgium with a total area of 16,844 km². It comprises five provinces: Hainaut, Liège, Luxembourg, Namur, and Walloon Brabant. The main urban areas are Charleroi, Liège, Mons and Namur. They are all characterized by a historical city-center, around which the urban development expanded. The total population in 2010 was 3,498,384 inhabitants that makes up a third of Belgium population (Fig. 1).

B. Outline of the model

The analysis presented here consists of two main parts: (I) estimating probability maps of three urban classes (low, medium and high-density urban) versus non-urban class and (II) develop future urbanization scenarios for years 2020 and 2030.

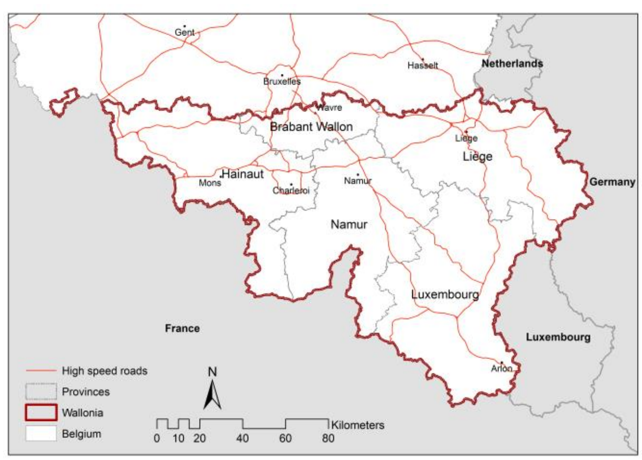

Figure 1. Study area.

The dependent variables (changes from non-urban to one of urban density classes) for the MLR model is defined using CAD. CAD is a vector dataset representing buildings in two dimensions as polygons. Each building comes with different attributes from which the construction date is the most important attribute for our study. Using the construction date, two urban land-use raster-grids were generated for 2000 and 2010 years. First, CAD vector data were rasterized at a very fine cell dimension 2x2m. The rasterized cells were then aggregated to obtain a 50x50m raster-grid. Thus, each aggregated cell has a density value that exhibits the number of rasterized 2x2m cells. The magnitude of density value is then used to represent four urban classes: (class0) non-urban, (class1) low-density urban, (class2) medium-density urban and (class3) high-density urban. Geometrical interval classification method is used to set thresholds that define urban land-use classes (table I). This classification scheme works fairly well on continuous data.

TABLE I. URBAN CLASSES DENSITY RANGE IN NUMBER OF 2X2M CELLS (% OF 50X50M CELL AREA).

Class	***Minimum***	***Maximum***
Class0 (non-urban)	0	25 (4)
Class1 (low-density)	25 (4)	56 (9.12)
Class2 (medium-density)	57 (9.12)	174 (28)
Class3 (high-density)	175 (28)	625 (100)

The independent variables for the MLR model (X), urbanization driving forces, are selected based on expert knowledge of our study area as well as on literature review [6][7]. Table II summarizes the complete list of the selected urbanization driving forces. A zoning map (land-use policy) was developed by discerning the zones where urban development is not permitted and the zones that are designated for urban based on the regional development plan. All data used in this study is represented at 50x50m raster-grid square. The independent variables are measured in different units and therefore we standardized all continuous X. If some of X comparatively measure the same phenomena, then strong collinearities will cause the erroneous estimation of the MLR's parameters. Consequently, a multicollinearity test was examined in the initial stage using the variance inflation factors (VIF). Montgomery and Runger (2003) recommended that the VIFs should not exceed 4. The VIF test results for all X suggest that the variables digital elevation model (DEM) and slope measure the same phenomena and that is also represented between population density and employment rate. In a refining stage, the DEM and employment rate variables have been suppressed. The VIF values for the refining stage implies that all X variables included in this stage show a very low degree of multicollinearity and therefore are introduced in the MLR. Both dependent and independent variables may exhibit spatial autocorrelation, which may have biased the results of the regression analysis [9]. These issue can be addressed through a data sampling approach [5][7]. For the model calibration, 45000 cells were randomly selected. Cells that were urban in 2000 were not included in the samples.

TABLE II. LIST OF SELECTED URBANIZATION DRIVING FORCES.

Driver	***Name***	***Unit***
X1	DEM	Meter
X2	Slope	Percent rise
X3	Distance to Road1 (high-speed roads)	Meter
X4	Distance to Road2	Meter
X5	Distance to Road3	Meter
X6	Distance to Road4 (local roads)	Meter
X7	Distance to railway stations	Meter
X8	Distance to high-populous cities	Meter
X9	Distance to medium-populous cities	Meter
X10	Number of class1 cells within a 5x5 window	Number
X11	Number of class2 cells within a 5x5 window	Number
X12	Number of class3 cells within a 5x5 window	Number
X13	Population density	inh/km²
X14	Employment rate	Percent
X15	Zoning	Binary (0 non-urban, 1 urban)

The general form of the MLR can be represented as, given K_0 (non-urban class) as the reference class:

$$\log\left(\frac{P(Y=k_1)}{P(Y=k_0)}\right) = \alpha_{k_1} + \beta_{k_1 1} X_1 + \beta_{k_1 2} X_2 + \ldots + \beta_{k_1 n} X_n$$

$$\ldots \tag{1}$$

$$\log\left(\frac{P(Y=k_n)}{P(Y=k_0)}\right) = \alpha_{k_n} + \beta_{k_n 1} X_1 + \beta_{k_n 2} X_2 + \ldots + \beta_{k_n n} X_n$$

where $\log\left(\frac{P(Y=k_n)}{P(Y=k_0)}\right)$ is the natural logarithm of class k_n against the reference class, α is the intercept, β is the regression coefficients of class k_n. The probabilities of each class can be calculated with the following formula:

$$P(Y=k_0) = \frac{1}{1 + e^{\log(k_1)} + \ldots + e^{\log(k_n)}}$$

$$\ldots \tag{2}$$

$$P(Y=k_n) = \frac{e^{\log(k_n)}}{1 + e^{\log(k_1)} + \ldots + e^{\log(k_n)}}$$

III. RESULTS AND DISCUSSIONS

Fig. 2 shows different urban density classes of the observed 2000 urban land-use. High-density urban lands are concentrated in the existing urban centers. Medium-density lands tend to be located around cities in suburbs and low-density lands tend to be found in rural and remote locations.

The MLR's outcomes are probability of urbanization maps for each class based on vectors of regression coefficients β and intercepts α. Table III gives the MLR's results. All explanatory variables are statistically significant on one or more urban classes.

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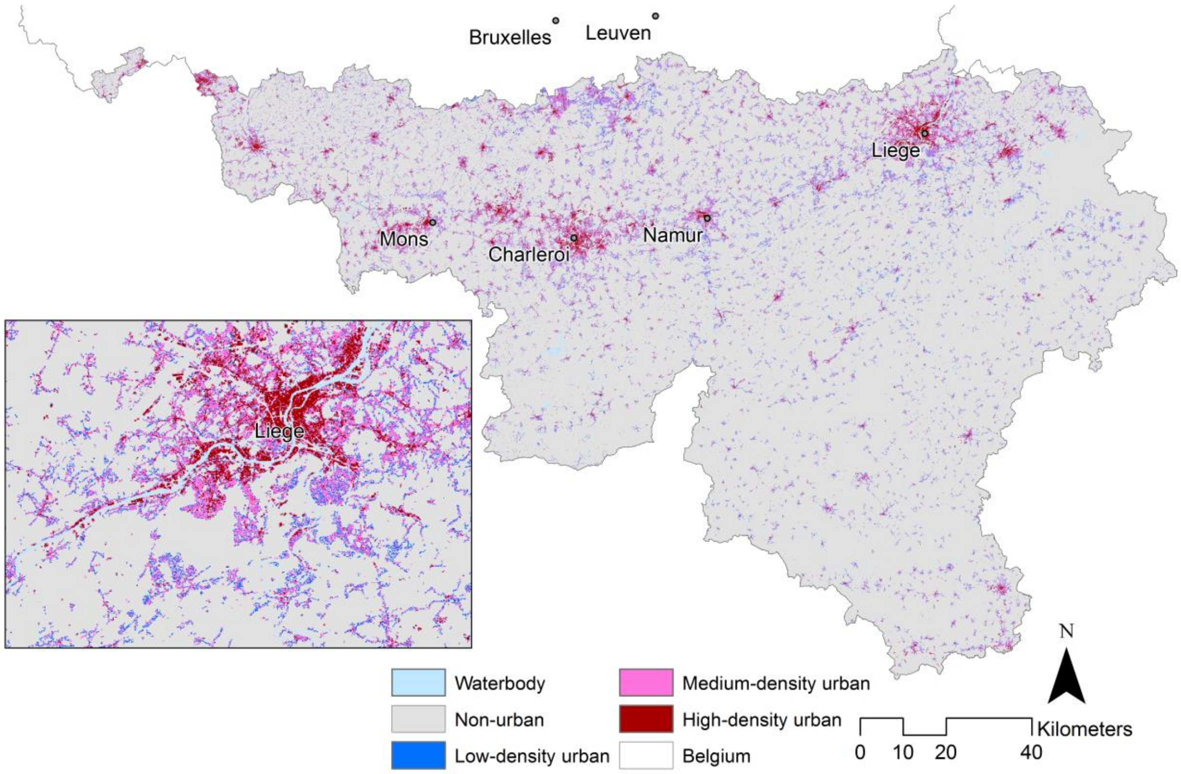

Figure 2. Urban density classes of 2000.

TABLE III. THE COEFFICIENTS (B) OF THE MLR MODEL (CLASS0 IS THE REFERENCE CLASS).

Driver	*Class1*	*Class2*	*Class3*
Intercept	-2.869	-2.979	-3.381
X1	N.I.	N.I.	N.I.
X2	0.036	-0.148*	-0.141*
X3	-0.038	-0.125*	-0.534*
X4	-0.004	-0.112*	-0.350*
X5	-0.137*	-0.160*	-0.238*
X6	-0.356*	-0.306*	-0.160*
X7	0.097*	0.001	-0.174*
X8	0.006	0.053*	0.122*
X9	-0.054*	-0.104*	-0.069*
X10	0.391*	0.305*	-0.024
X11	0.153*	0.151*	0.036*
X12	0.091*	0.214*	0.460*
X13	0.000	0.147*	0.138*
X14	N.I.	N.I.	N.I.
X15	3.317*	2.930*	2.692*
* Indicate significance at P <= 0.05 level N.I. not included			

The impact of different drivers varies along with urban density. Urban expansion of all urban density classes are extremely correlated with zoning status (X15). Distances to Road1 and Road2 (X3 and X4) have a noticeable impact on the development of high density projects (class3). The impact of distance to Road4 (X6), is generally decreasing with increasing urban densities.

The ROC-values of the probability maps of 2000-2010 are 0.94, 0.93 and 0.88 for classes 1, 2 and 3 respectively. That means the probability maps can be used for reliable predictions of the future urban expansion patterns.

The assessed probability maps for the period 2000–2010 have been used to generate spatially-explicit urbanization scenarios for 2020 and 2030 by (I) quantifying the necessary area for future expansion for each urban density class and (II) selecting the cells with the highest values from urbanization probability maps for each class until the required areas are met. This generates urban expansion map for each 2020 and 2030. Next, the expansion maps are combined with the 2010 actual map to produce the urban distribution map. Waterbodies, that are defined using zoning plan, are introduced as a constrained.

The future necessary areas for each density class are calculated on the basis of a linear extrapolation of the actual urban expansion between 2000 and 2010. The urban area is expected to increase, given the actual 2010 urban area, to 3.6% in 2020 and to 10.1% in 2030. The percentage of each urban density class expansion to the total expansion between 2000 and 2010 were about 56% low-density, 35% medium-density and 9% high-density lands. These percentages are then used to estimate the required urban lands in 2020 and 2030 for each urban density class (Fig. 3).

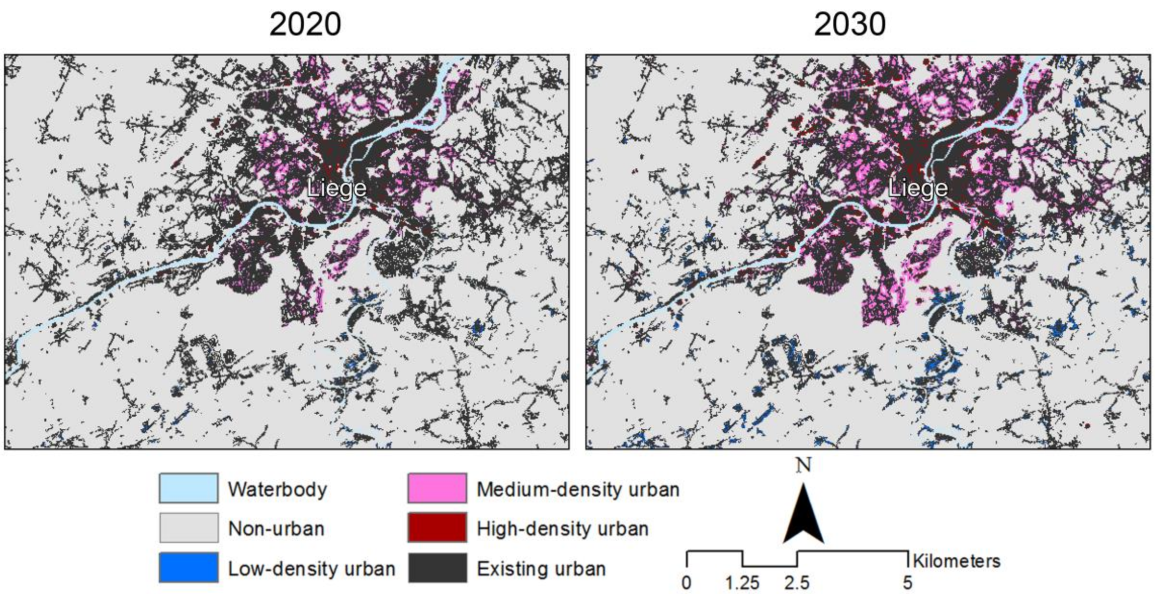

Figure 3. Developed scenario for the Liège metropolitan area.

IV. CONCLUSIONS

This paper employs the MLR model to examine drivers of urban expansion in Wallonia (Belgium) and to forecast near-future urban expansion using Belgian cadastral data (CAD). Four classes, non-urban, low-density, medium-density and high-density urban, are defined as dependent variables for the MLR. Urban expansion for each urban class versus non-urban class is predicted for 2020 and 2030 based on 2000 and 2010. Several variables are selected and introduced in the MLR model as independent variables. It was found that all the independent variables have impacts on urban expansion in Wallonia, but their relative importance are varied with density. However, it can be concluded that policies, number of existing urban lands within neighborhood and accessibility are the most important determinants of urban expansion process. A validation of the MNL showed that the model's outcomes allows to predict future urban expansion patterns with a relatively high explanatory power.

Based on liner extrapolation of urban expansion between 2000 and 2010, expansion scenarios are proposed to simulate 2020 and 2030 urban patterns. This study's findings would help decision makers and urban planners in enhancing understanding of urban expansion in Wallonia. Most importantly, it can serve as input to hydrological modelling.

Finally, future extension of this research will be dedicated to analyze the urbanization process within existing medium and low-density urban areas instead of only studying the change from non-urban to one of urban density classes.

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