Modelling Uncertainties in Long-Term Predictions of Urban Growth: A Coupled Cellular Automata and Agent-Based Approach

Ahmed M Mustafa, Ismail Saadi, Mario Cools and Jacques Teller

Abstract

Modelling the growth of urban settlements is of considerable interest for different applications, amongst which integrated flood management. This study aims at modelling urban growth for a long time horizon up to 2100 and to integrate the model outcomes with a hydrological model for the same time horizon. Forecasting land-use change over such time frames entails very significant uncertainties. In this regard, the main focus of this paper is attributed to the handling of uncertainty in an urban growth model. To this end, we examine a Monte Carlo Simulation method, which is integrated in the proposed urban growth model. Transition probabilities for each non-urban cell are estimated by a coupled Cellular Automata-Agent-Based approach. The results help to handle uncertainty over long time horizons and to assess the increment in degree of uncertainty at every time-step.

A. Mustafa (Corresponding author) • I. Saadi • M. Cools • J. Teller
LEMA, University of Liège, Liège, Belgium
Email: a.mustafa@ulg.ac.be

1. Introduction

Across the globe, urban settlements are growing rapidly, which leaves urban planners with a continuous challenge of planning a livable urban system. Modelling this growth is of considerable interest to different disciplines including flood management. Several studies indeed stated that for many river basins, exposure to flood risks may considerably increase during the 21st century as a result of a combination of climate and land-use changes. It is important in this respect to evaluate flood risks at different time horizons by coupling land-use changes and hydrological models. Several scenarios have been proposed to anticipate future climate change and its related impacts on rain and water surface levels. These scenarios are typically considering long-term time horizons, i.e. 2050-2100, as this is the appropriate time frame for analyzing such effects (Bates et al. 2008).

This paper presents an urban growth model for a long time horizon up to 2100 in order to couple the model outcomes with a hydrological model for the same time horizon. Predicting long-term future of urban growth remains an elusive goal. Urban development depends on technological, economic, social and cultural factors that cannot be modelled in a linear manner. In addition, eventual future extreme events such as economic collapses and shifts in weather conditions are hard to predict. In the context of making predictions of responses under never observed conditions requires the coupling of deterministic physics-based and stochastic components. To this end, this paper focuses on handling uncertainty in urban growth models. Generally, uncertainties can be considered as a component of fuzziness or randomness (Wang et al. 2013). A number of scholars analyzed uncertainties in land-use models using randomness (e.g. García et al. 2011; Maria de Almeida et al. 2003; Mustafa et al. 2014; Wu 2002). Al-Ahmadi et al. (2009) and Wang et al. (2013) introduced fuzziness in their models.

Several approaches have been proposed to simulate urban growth in grid-based data; among which Cellular Automata (CA) and Agent-Based (AB) models are the most common approaches (e.g. Bert et al. 2011; Mitsova et al. 2011; Puertas et al. 2014; Ralha et al. 2013). Traditional CA models are based on an extrapolation of past observations using spatial inferences; they are based on the implicit assumption that people's behaviors would be maintained over time. Such an assumption is acceptable for short time horizons, but not applicable to longer ones (more than 30 years). For instance, landowners may resort to speculative motives for hoarding land, in anticipation of potential development such as initializing of new roads. AB models are modelling agents as goal-oriented entities capable of responding to their environment and taking autonomous action, where these agents may represent households, firms, etc. It has been therefore considered to integrate potential variations of agent behavior through an AB model. At cell level, in grid-based data, CA can best consider the local factors through cell neighbors effects whereas AB could consider global factors; such as urban development attractiveness (UDA) which depends on distance to cities, slope, etc.; through simulation of agents' behavior.

We propose an approach that integrates CA and AB models for simulating future urban growth scenarios. Furthermore, a Monte Carlo Simulation (MCS) method has been introduced in the model that allows better handling of uncertainty. In this paper, we explore the effects of uncertainties about agents' behavior due to global factors. The effects of uncertainties about local factors and the expected growth of households and related jobs has been maintained constant throughout simulations, although they are obviously other components of uncertainty.

In order to stress the role of uncertainty, the number of agents included in the model has been deliberately limited to three categories: urban developers (UrbA) represents households, firms and some farmers who decided to stop being farmers, farmers (FarmA) and government (GovA). The UrbA and FarmA will seek appropriate cells to develop or to retain in the current state based on profit maximization; the GovA will permit or prevent new urban developments. The AB model calculates transition probability combining three layers that define cell probability for urban development: a neighborhood weight (NBW), agriculture-urban externalities (Ag-UrbW) and the UDA. The NBW and Ag-UrbW layers are developed using a CA model. Other factors and parameters are automatically generated by a logistic regression analysis and an MCS algorithm to model the effect of uncertainty upon land-use change, in terms of attractiveness. The effect of the stochastic component is addressed by comparing different model runs, and focuses on the analysis of the effect of an MCS used to incorporate the stochastic component in the model. The main contribution of this paper is to highlight the handling of uncertainty over time in urban growth models.

2. Methodology

2.1. Study area

The model framework is applied to Ourthe river basin located in Wallonia, in the southern part of Belgium. It occupies an area of 2,140 km^2 and consists of 37 administrative municipalities. It has 664,744 inhabitants in 2013 (IWEPS 2013). The landscape is composed of 214,005 cells of 100x100 m^2. The geography of the area goes from flat to hilly with altitude ranges from

+47 to +618 m above the sea level. The largest metropolitan area is Liège city with population of 195,931 in 2013 (IWEPS 2013). The Ourthe River is a 165 km long river in the Ardennes in Wallonia. It is formed at the confluence of the Ourthe Occidentale (Western Ourthe) and the Ourthe Orientale (Eastern Ourthe), west of Houffalize. After the confluence of the two Ourthes, the Ourthe flows in north direction. It flows into the river Meuse in the city of Liège (Fig. 1).

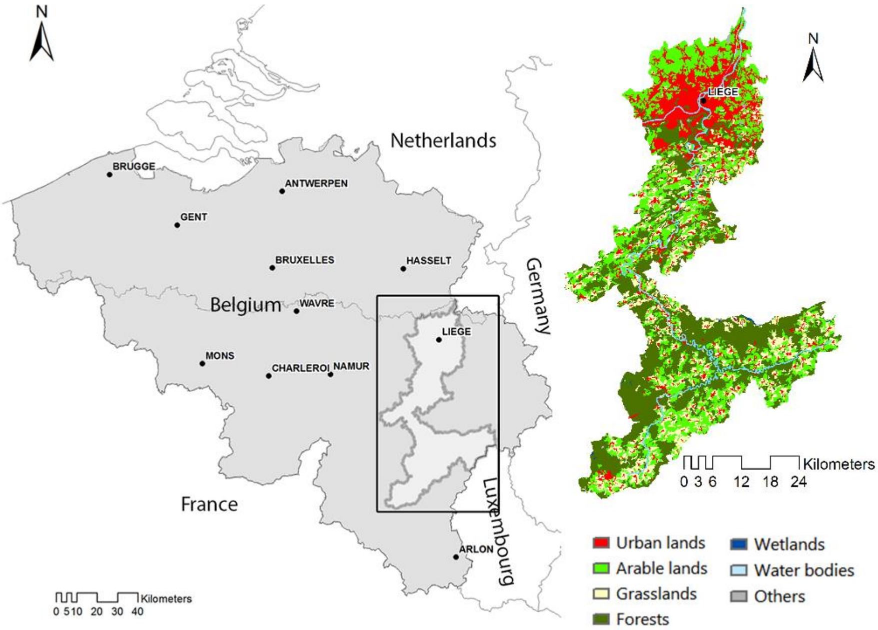

Fig. 1. Study area and land-use map of 1990

2.2. Data

The CORINE Land-Cover (CLC) datasets provide a detailed inventory of the biophysical land cover in Europe using 44 classes. It is made available by the European Environment Agency (EEA) (http://www.eea.eu.int/products) at a resolution of 100 and 250m² grid cells. A 100m² CLC of 1990 and 2000 are used in this paper to apply the model framework. The CLC 44 classes have been reclassified into seven general classes (Fig.1). The Navteq streets of 2002 dataset has been used to calculated Euclidean distances to four functional road classes (1: high speed roads, 2: quick travel between and through cities, 3: moderate speed travel within cities and 4: moderate speed travel between neighborhoods).

Euclidean distances to cities have been calculated using the major 11 Belgian cities (Fig.1). Access to jobs has been calculated using the number of jobs available within 20km for each municipality.

2.3. Urban growth model

Urban development is a product of both physical constraints and human decision-making behavior. Therefore, a coupling of CA and AB is highly suitable to encapsulate urban development possibility at a specific location. The model target is to simulate urban growth from 1990 to 2100. The model is first calibrated and validated with real observed data of 1990 and 2000 and it is then used to project possible future urban growth at a 2100 time horizon.

In the study area, 176,183 cells could be converted into urban land-use between 1990 and 2000. The real amount of developed urban cells over those ten years is 4,730. In the model, each time-step represents one year which would be adequate in a model of land-use change (White and Engelen 2000).

The model is based on two modules: a demand module and a transition probability module. The demand module calculates the quantity of change for urban lands at each time-step. Widely, two methods have been used to estimate urban land demands (i) linear extrapolation of the past change trend (e.g. Pontius et al. 2004) and (ii) socioeconomic factors to estimate future growth (e.g. White and Engelen 2000). In this paper, we have linearly extrapolated the change between 1990 and 2000.

In our model, the development of non-urban cells are done by UrbA and controlled by GovA. FarmA, owning undeveloped arable and grasslands cells, will decide to keep or to sell their own cells. Moreover, a number of farms will decide to stop being farmer and change to UrbA. If a cell state is urban in time-step t_n, it automatically remains the same in the next time-steps. Three land-use classes can only be changed into an urban land-use class; arable lands, grasslands and forests. All other land-uses will be introduced in the model as constraints.

2.3.1. Transition probability module

The transition probability module is the core element of the model representing decision-making criteria of agents to select target cells for development. It employs CA and AB approaches to calculate the transition probability for each non-urban cell.

Agents state variables

At the initialization of the model, the real land-use map of 1990 is uploaded into the model, the parameters are set, and the agents are created. FarmA controls all arable and grasslands. GovA controls other land-uses except urban lands and sets zoning constraints for the entire study area based on three categories, in terms of urban development, permitted (urban zones), permitted under strict circumstances (arable, grassland and forest) and forbidden (wetlands, water bodies and other classes). GovA sets zones using a zoning plan developed by the Walloon authorities. UrbA calculates the demand for future urban development and starts seeking cells to develop.

Agents' movement and interaction

UrbA will start seeking appropriate cells to develop until meet the required demand. It starts selecting an undeveloped cell randomly, wherever it starts, it assesses the score of the current cell. Agents record the positions and the states of the visited cells and learn each other.

When UrbA determined which cells to develop, it has to ask for a permission from GovA. GovA considers that zoning of land is not always strictly enforced in Belgium. If a cell is located in a permitted zone, GovA will give the permission automatically, otherwise a sort of competition will be carried out to determine the winner. The winner of the competition depends on the number of times that GovA has lost cells in the previous competitions. We used logistic regression analysis to define the rule of zoning. The odds ratio of zoning is around 12 which means that it is around 12 times more likely to find new urban cells in urban zones than other zones. Thus, we assumed that at each time-step, GovA will give permissions for at most 8% of the amount of required cells to be developed outside urban zones. In addition, under this rule, the available urban zones cannot meet the required urban cells up to 2100. GovA detects that the current zoning plan might cover only 40 years to come. In this paper, we do not specify a complete model. In the complete model, GovA will establish different scenarios for developments. There are some efforts to set a number of new regulations in Wallonia with respect to the development of new residential areas, called settlement cores, which proposed to reduce the housing density from about 10 households/ha (Marique et al. 2011) to more than 20 households/ha in 2100 (Beckers et al. 2013) and GovA considers such regulations. However, in this paper, GovA will give a permission for development in permitted under strict circumstances zones to meet the requested urban cells after 40 time-steps.

Decision to take

Once all agents finish the search, they have to decide which cells to develop. A number of scholars consider various parameters representing decision-making criteria of agents to select cells for development using qualitative and/or quantitative approaches (e.g. Matthews et al. 2007; Parker and Meretsky 2004; Ralha et al. 2013). A quantitative approach is introduced here to parametrize the decision-making criteria. When UrbA has the opportunity to make a decision regarding land-use, the agent first forms an urban development expected value for each undeveloped cell. This expected value represents the profitability score that the agent expects to obtain from the undeveloped cell based on his own knowledge. The agent knows the demand curve for urban activity and understands the profit-maximizing of global and local factors.

UrbA tries to select cells with the best score at each time-step using a utility function as the following formula:

$$score^t_{c_{i,j}} = n^t_{c_{i,j}} \, g^t_{c_{i,j}} \tag{1}$$

where $score^t_{c_{i,j}}$ is the profitability score of urban development assigned to cell $c_{i,j}$ at time t, $n^t_{c_{i,j}}$ is the local urban development probability according to neighborhood effects on the cell and $g^t_{c_{i,j}}$ is the global probability according to geo-physical and socio-economic factors. We assumed that $n^t_{c_{i,j}}$ and $g^t_{c_{i,j}}$ have the same relative weight. Indeed, the integration between local and global parameters is normally done using the same weight for both (e.g. Mustafa et al. 2014; Poelmans 2010; Wu 2002). When UrbA selects an arable or grassland cell to develop, FarmA will make a decision to sell or maintain it. In this paper, we assumed that FarmA imitates the land-use of neighbors and also tends to maximize short-term profits. Therefore, it is highly affected by its urban neighbors. We assumed that the FarmA cell is impacted, in terms of agriculture profits, by a negative spatial externality generated by urban cells. This externality results in a loss ω by the neighbor urban cells.

$$\omega^t_{c_{i,j}} = 1 / nu^t_{c_{i,j}} \tag{2}$$

where $\omega^{t}_{c_{i,j}}$ is the loss of agriculture profitability and $nu^{t}_{c_{i,j}}$ urban neighborhood effects on the agriculture land. FarmA will then compare the loss value with profitability of urban development at time *t* as follows:

$$FarmDecision^{t+1}_{c_{i,j}} = \begin{cases} accept, & \omega^{t}_{c_{i,j}} > score^{t}_{c_{i,j}} \\ reject, & \omega^{t}_{c_{i,j}} \leq score^{t}_{c_{i,j}} \end{cases} \tag{3}$$

Three criterion layers, namely, NBW ($n^{t}_{c_{i,j}}$), Ag-UrbW ($\omega^{t}_{c_{i,j}}$) and UDA ($g^{t}_{c_{i,j}}$) have been generated.

NBW and Ag-UrbW layers

In human-based systems, the idea of locality is hard to define clearly, since agents are aware of their surroundings in a wide space. Thus, it is desirable to set a neighborhood large enough to capture the operational range of the local processes being modelled (White and Engelen 2000). In some land-use change models (e.g. Poelmans 2010; White and Engelen 2000; Wu 2002) the neighborhood is defined as all surrounding cells within a radius between three to eight cells. In this paper, we consider a search window of 5x5 cells Moore neighborhood. The neighboring weights are based on the calibrations reported on another study (Poelmans and Van Rompaey 2010) that defines the interaction effects, representing push and pull forces, between different land-use classes that done for the northern part of Belgium.

The CA models are based on a purely microscopic approach, i.e., they are originally built upon a basic unit of behavior. Hence, it reasonably captures the interaction between land and developer at a very local scale. CA address the change in space as state changes and simulate the state changes through immediately neighboring cells (Wu 2002).

A pure CA model has been applied to set the NBW factor for each cell at time *t* according to the following formula:

$$n^{t}_{c_{i,j}} = \sum_{i=1}^{i=N} {}_{x} \sum_{i=1}^{i=N} {}_{d}\, w_{lxd} \tag{4}$$

where N is a number of neighbors and w_{lxd} is the weighting parameter applied to land use l at position x in distance zone d.

CA model is applied also to set Ag-UrbW. We considered the effect of urban neighbors using the same search window of 5x5 cells with the following formula:

$$nu^{t}_{c_{i,j}} = \sum_{i=1}^{i=N} {}_{x} \sum_{i=1}^{i=N} {}_{d} w_{urbxd} \tag{5}$$

where w_{urbxd} is the weighting parameter applied to urban land-use. All parameters are based on the calibrations reported on Poelmans and Van Rompaey (2010).

UDA layers

The UDA is driven by different factors such as slope, accessibility, population growth, employment potential, investment in infrastructure, etc. (Al-Ahmadi et al. 2009; Cammerer et al. 2013).

A binomial logistic regression (logit) model has been therefore developed in order to measure the relative contribution of each factor, focusing on changes from non-urban to urban cell. This type of regression analysis is usually employed in estimating a model that defines the relationship between one or more independent variable(s) to the binary dependent variable. The input dependent variable (Y) is a binary map of real non-urban/urban changes between 1990 and 2000 and the independent variables (X_n) are selected urban growth driving forces in the study area. The model considers distance to four road classes, distance to major cities, slope, access to jobs and zoning as X_n for the logit. Logit analysis yields coefficients for each X_n based on a sample of data (observations). These coefficients are then interpreted as weights in a formula that generates a UDA map depicting the probability of each cell to be developed into urban as:

$$g^{t}_{c_{i,j}} = \frac{\exp(\alpha + \sum_{n} \beta_n X_n)}{1 + \exp(\alpha + \sum_{n} \beta_n X_n)} \tag{6}$$

where α is the intercept and β_n are the regression coefficients. The model was calibrated using a random sample in order to minimize the spatial autocorrelation after standardization of the X_n. The goodness-of-fit was evaluated using Relative Operating Characteristic (ROC) procedure.

2.3.2. Handling uncertainty

In this paper, we put a strong focus on handling uncertainties to simulate urban growth in 2100. Land-use change models are always subject to uncertainties due to limited human knowledge, complexity of urban system and limitation of technology. In our research, we only consider uncertainty due to the future values of the exogenous factors that are not well predictable by nature. There is another type of uncertainty that propagated due to errors in the model's inputs. As mentioned earlier, in this paper, we focus on the uncertainties due to global factors.

The UDA layer is computed based on the coefficients of the selected drivers of development attractiveness that represent agents' behaviors. These coefficients are based on a maximum likelihood estimation procedure. In order to capture an enormous range of agents' behaviors, in terms of attractiveness, an MCS algorithm is launched to generate 1000 different sets of coefficients. Each set of coefficients represents a random of 8000 observations (4.5% of the study area with an equal number (4000) of 0 (no-change) and 1 (change) values of the independent variable *Y*). By using a range of possible values for the coefficients, we can capture a more realistic picture of agents' responses. Selecting a value from the 1000 different sets of coefficients to compute different UDA layer at each time-step can be done by using a measure of central tendency or by selecting a value from the samples randomly. The mean value of the 1000 coefficients, through one run of the model, were -0.0003, -0.0288, -0.0210, -0.3967, -0.4971, 0.0001, 0.5773 and 2.4871 for slope, distance to road class1, road class2, road class3, road class4, distance to city, access to jobs and zoning, respectively.

Fig. 2 shows that the distance to roads, slope and zoning have extreme variation in responses, whereas other variables seem to have less variation in responses. In order to better capture these kinds of variation, the model randomly selects a value of each coefficient set. In other words, at each time-step, the model will be supplied with a new UDA that may represent normal or extreme responses. A stochastic process of this kind never repeats itself. Several runs would be necessary to get a full idea of the distribution of different outputs. This process does not ensure that the degree of uncertainty is changeable over the entire simulation period from 1990 to 2100. That is not the case in reality as the far future involves more uncertainties. Our contribution here is to handle uncertainty degree with time. To this end, in addition to MCS, we proposed to introduce a uniform random variable in our model. At each time step, the computed score for each cell is used to determine whether a transition takes place or not by comparing it with a uniform random number that is drawn over a fixed range associated with cells score and if the number is less than the appropriately cell score, a transition to urban land takes place as the following formula:

$$change^{t+1}_{c_{i,j}} = \begin{cases} urban, & score^{t}_{c_{i,j}} \geq unifrand \\ non\text{-}urban, & score^{t}_{c_{i,j}} < unifrand \end{cases} \qquad (7)$$

where $change^{t+1}_{c_{i,j}}$ is the change decision at next time-step and *unifrand* is a uniform random value within range (minimum, maximum). Wu (2002) defines this range between the minimum and maximum probability scores.

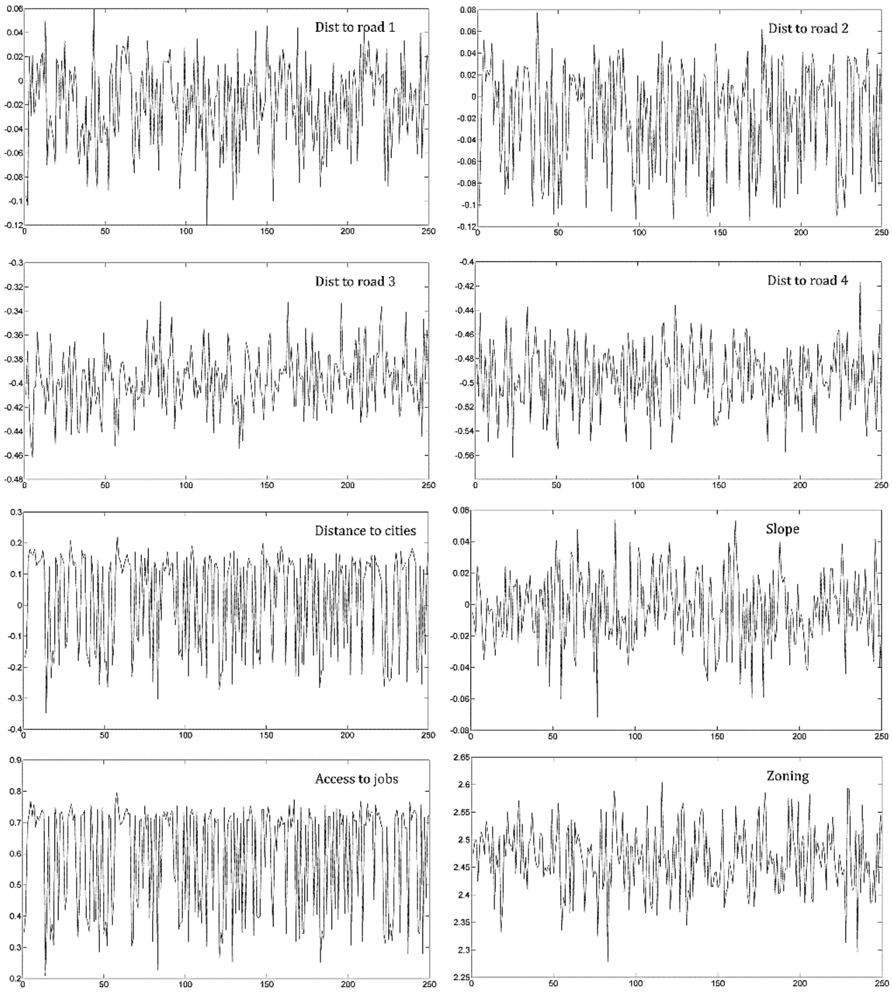

Fig. 2. Logit coefficients (y axis) for a sample of 250 runs (x axis)

We propose that this range controls the degree of uncertainty with time. To do this, the agents sort their score list for the cells in descending order, with the most suitable cell at the top of the list. Normally, agents then select the top-scoring cells from their sorted list and develop them until meet the requested demand without considering uncertainty. In the case of uncertainties, agents will select randomly one cell in the set of cells with best scores, the size of which is initially determined by the demand and subsequently increased to include more possibilities.

The maximum range of *unifrand* is fixed to the score of top-scoring cell and the values of minimum are a cumulative increment of 1% (*rand0.01*), 10% (*rand0.1*), 20% (*rand0.2*), 50% (*rand0.5*), 100% (*rand1*), 500% (*rand5*) or 1000% (*rand10*) of the score assigned to the last requested cell to develop at time-step t_n in the sorted list. Further, it takes the minimum score of cells (*rand_min*).

For instance, considering *rand0.01* case, there are 473 cells (4730 change between 1990 and 2000; 473 per time-step) should be changed each time-step. The sorted score list has values between 1 (the top rank) and 0, and therefore the maximum value of *unifrand* is 1 and the minimum is the score of the cell 473, 473+5 (473x0.01~5), 478+5, etc at time-step 1, 2, 3, etc. In other words, the model selects the best scored cells at the beginning and then enters more cells in the selection competition with time. This way, our model is a truly deterministic model at the beginning and turns slowly to stochastically model with time-steps.

3. Model calibration and validation

The most common method of calibrating urban growth models has been by sensitivity analysis. In this method, the model is run with different of parameter values and the results are compared.

First, the ten different UDA maps that produced between 1990 and 2000 in one run have been evaluated using ROC. The ROC compares the outcomes of Eq. 6 to a map with the observed changes of the urban land between 1990 and 2000 and its value should range between 0.5 (random fit) and 1 (perfect fit). ROC values range from 0.781 to 0.789. ROC values higher than 0.70 are considered as a reasonable fit (Cammerer et al. 2013; Jr and Lemeshow 2004).

The validation of the model is the process of measuring the accuracy of the simulated result against real world observations (Mustafa et al. 2014). To produce a large number of simulations requires heavy computation. In our case study we have a grid of 579x1027 cells, and the model algorithm is very computationally intensive. As a result, we could run the model 4500 times with different ranges of *unifrand* (500 runs for each).

The different runs of the model performance without introducing *unifrand* (*no_rand*) and with different ranges of *unifrand* of 2000 are compared to the real 2000 land-use map in order to assess the best way to handle the increment degree of uncertainty with time-steps.

In order to evaluate our model, we used one of the common methods to compare two maps, a cell-to-cell agreement due to location. This method produces a stringent test of simulation as it measures on a cell basis. Urban growth model validation might also rely on evaluating how a model simulates spatial properties, e.g., landscape compactness and isolation. The overall agreement due to location for a number of previous studies is ranging between 92.7% and 76% for the all urban cells (Poelmans 2010; Wu 2002). One simulation of *no_rand* runs shows an accuracy of 92.5% for all urban cells.

Fig. 3 shows simulated 2100 urban growth and pattern comparison between 2100 simulations using *rand0.1* (correlated pattern) and *rand_min* (scattered pattern).

Table 1 lists the cell-to-cell accuracy of only newly simulated urban cells in 2000. As shown in table 1, rand0.1, presenting the best result with a mean accuracy 33.648%. no_rand and rand0.01 achieving 33.646% and 33.643% respectively. The result reveals a downward trend in accuracy with other parameters.

Table 1. Accuracy (%) for newly urban cells of 2000 (simulated vs. real) of 500 runs for each parameter

	1	2	3	4	5	6	7	8	9
Min	33.38	33.30	33.24	33.07	32.66	31.95	27.74	25.84	22.11
Max	33.87	34.06	34.16	34.10	33.98	33.38	29.73	29.03	24.80
Mean	33.65	33.64	33.65	33.56	33.23	32.54	28.80	27.20	23.54
SD	0.12	0.15	0.17	0.20	0.25	0.27	0.41	0.50	0.46

. 1.*no_rand*, 2. *rand0.01*, 3.*rand0.1*, 4.*rand0.2*, 5.*rand0.5*, 6.*rand1*, 7.*rand5*, 8.*rand10*, 9.*rand_min*, SD.*standard deviation*

Finally, we proposed to simulate 2100 urban growth using rand0.1 as it gives one of the best results and also represents a reasonable increment of uncertainty with time.

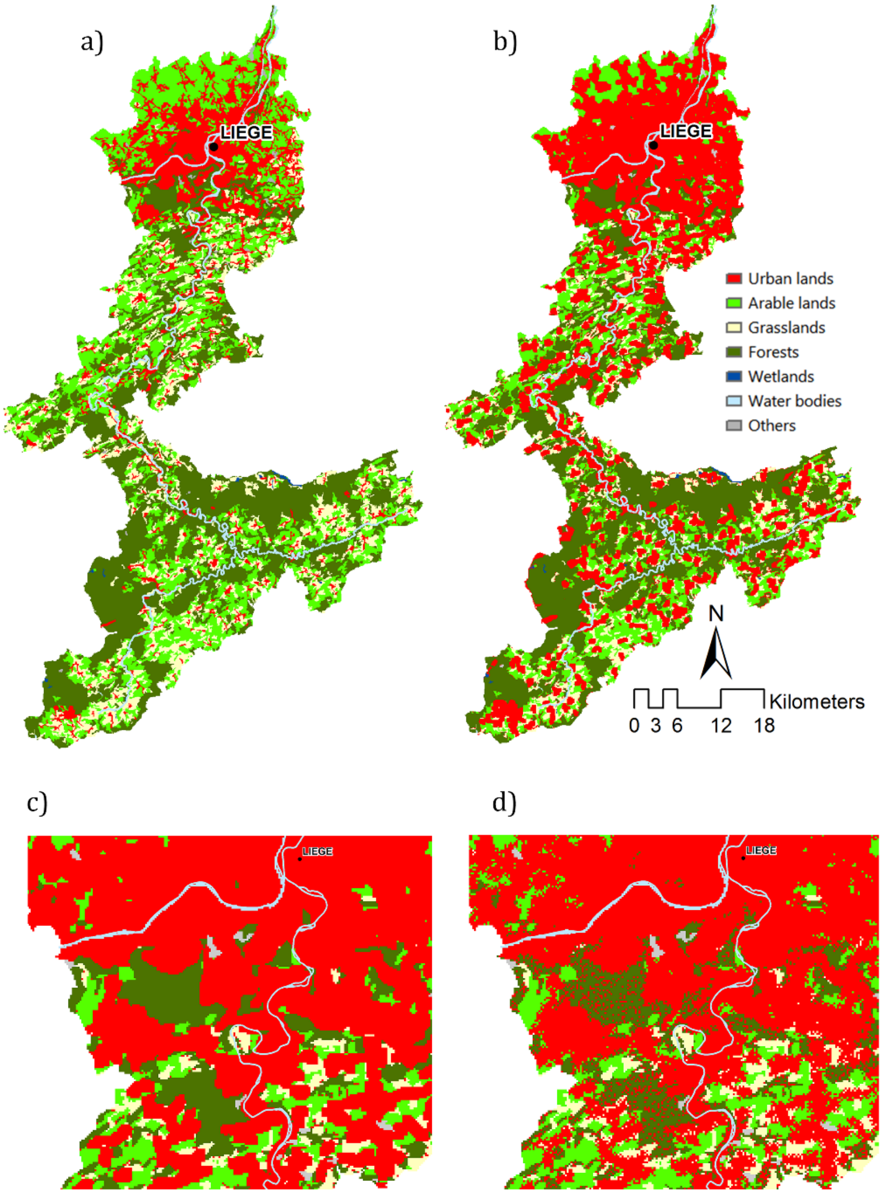

Fig. 3. a. Real land-use map of 1990, **b.** Simulated land-use map of 2100 using rand0.1, **c.** Simulated pattern of 2100 using *rand0.1*, **d.** Simulated pattern of 2100 using *rand_min*

4. Discussion and conclusions

Urban growth models simulate a situation in the future. Bearing in mind the high level of complexity of urban environments, such models should be built on a robust modeling strategy.

In this paper, we proposed a CA-AB integrated model to capture the relation between developer and landscape at different spatial scales in order to simulate a 2100 expected growth pattern. Dealing with uncertainties in this kind of modelling becomes essential.

An MCS algorithm has been employed here to analyze the most suitable way to introduce the appropriate degree of randomness. A cell-to-cell location validation technique has been used to evaluate the model results. It provides statistical information of how well allocation procedures succeeded. The results bring to light that the model accuracy is highly affected by combining stochastic and deterministic components.

Finally, this paper points to the need to perform analyses of urbanization process that best suits the dynamics of our analyzed area. However, there are some urban driving forces that might be lacking. Future work will focused on including more variables to build UDA layer and to handle uncertainties due to local factors.

Acknowledgments: The research was funded through the ARC grant for Concerted Research Actions, financed by the Wallonia-Brussels Federation.

References

Al-Ahmadi, K., See, L., Heppenstall, A., & Hogg, J. (2009). Calibration of a fuzzy cellular automata model of urban dynamics in Saudi Arabia. Ecological Complexity, 6(2), 80–101. doi:10.1016/j.ecocom.2008.09.004

Bates, B., Kundzewicz, W. Z., Wu, S., & Palutikof, J. (2008). Climate Change and Water (Technical Paper of the Intergovernmental Panel on Climate Change) (p. 210). Geneva: IPCC Secretariat. https://docs.google.com/file/d/0B1gFp6Ioo3akcFFFeGRRVFNYM0E/edit. Accessed 12 August 2014

Beckers, A., Dewals, B., Erpicum, S., Dujardin, S., Detrembleur, S., Teller, J., et al. (2013). Contribution of land use changes to future flood damage along the river Meuse in the Walloon region. Nat. Hazards Earth Syst. Sci., 13(9), 2301–2318. doi:10.5194/nhess-13-2301-2013

Bert, F. E., Podestá, G. P., Rovere, S. L., Menéndez, Á. N., North, M., Tatara, E., et al. (2011). An agent based model to simulate structural and land use changes in agricultural systems of the argentine pampas. Ecological Modelling, 222(19), 3486–3499. doi:10.1016/j.ecolmodel.2011.08.007

Cammerer, H., Thieken, A. H., & Verburg, P. H. (2013). Spatio-temporal dynamics in the flood exposure due to land use changes in the Alpine Lech Valley in Tyrol (Austria). Natural Hazards, 68(3), 1243–1270. doi:10.1007/s11069-012-0280-8

Évolution de la population. (n.d.). IWEPS. http://www.iweps.be/evolution-de-la-population/. Accessed 18 June 2014

García, A. M., Santé, I., Crecente, R., & Miranda, D. (2011). An analysis of the effect of the stochastic component of urban cellular automata models. Computers, Environment and Urban Systems, 35(4), 289–296. doi:10.1016/j.compenvurbsys.2010.11.001

Jr, D. W. H., & Lemeshow, S. (2004). Applied Logistic Regression. John Wiley & Sons.

Maria de Almeida, C., Batty, M., Vieira Monteiro, A. M., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2003). Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. Computers, Environment and Urban Systems, 27(5), 481–509. doi:10.1016/S0198-9715(02)00042-X

Marique, A.-F., De Meester, T., & Reiter, S. (2011). Energy requirements and solar availability in suburban areas: the influence of built density in an existing district. Presented at the CISBAT 2011 - Clean Tech for Sustainable Buildings. http://orbi.ulg.ac.be/handle/2268/98454

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: a review of applications. Landscape Ecology, 22(10), 1447–1459.

Mitsova, D., Shuster, W., & Wang, X. (2011). A cellular automata model of land cover change to integrate urban growth with open space conservation. Landscape and Urban Planning, 99(2), 141–153. doi:10.1016/j.landurbplan.2010.10.001

Mustafa, A., Saadi, I., Cools, M., & Teller, J. (2014). Measuring the Effect of Stochastic Perturbation Component in Cellular Automata Urban Growth Model. Procedia Environmental Sciences, 22, 156–168. doi:10.1016/j.proenv.2014.11.016

Parker, D. C., & Meretsky, V. (2004). Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. Agriculture, Ecosystems & Environment, 101(2–3), 233–250. doi:10.1016/j.agee.2003.09.007

Poelmans, L. (2010). Modelling urban expansion and its hydrological impacts (Unpublished PhD dissertation). Katholieke Universiteit Leuven, Leuven.

Poelmans, L., & Van Rompaey, A. (2010). Complexity and performance of urban expansion models. Computers, Environment and Urban Systems, 34(1), 17–27. doi:10.1016/j.compenvurbsys.2009.06.001

Pontius, R. G., Huffaker, D., & Denman, K. (2004). Useful techniques of validation for spatially explicit land-change models. Ecological Modelling, 179(4), 445–461. doi:10.1016/j.ecolmodel.2004.05.010

Puertas, O. L., Henríquez, C., & Meza, F. J. (2014). Assessing spatial dynamics of urban growth using an integrated land use model. Application in Santiago Metropolitan Area, 2010–2045. Land Use Policy, 38, 415–425. doi:10.1016/j.landusepol.2013.11.024

Ralha, C. G., Abreu, C. G., Coelho, C. G. C., Zaghetto, A., Macchiavello, B., & Machado, R. B. (2013). A multi-agent model system for land-use change simulation. Environmental Modelling & Software, 42, 30–46. doi:10.1016/j.envsoft.2012.12.003

US EPA, C. C. D. (n.d.). Future Climate Change. Overviews & Factsheets,. http://www.epa.gov/climatechange/science/future.html. Accessed 18 February 2015

Wang, H., He, S., Liu, X., Dai, L., Pan, P., Hong, S., & Zhang, W. (2013). Simulating urban expansion using a cloud-based cellular automata model: A case study of Jiangxia, Wuhan, China. Landscape and Urban Planning, 110, 99–112. doi:10.1016/j.landurbplan.2012.10.016

White, R., & Engelen, G. (2000). High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Computers, Environment and Urban Systems, 24(5), 383–400. doi:10.1016/S0198-9715(00)00012-0

Wu, F. (2002). Calibration of stochastic cellular automata: the application to rural-urban land conversions. International Journal of Geographical Information Science, 16(8), 795–818. doi:10.1080/13658810210157769