Chapter 17
A Framework to Probe Uncertainties in Urban Cellular Automata Modelling Using a Novel Framework of Multilevel Density Approach: A Case Study for Wallonia Region, Belgium

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Abstract Urban expansion models are widely used to understand, analyze and predict any peculiar scenario based on input probabilities. Modelling and uncertainty are concomitant, and can occur due to reasons ranging from–discrepancies in input variables, unpredictable model parameters, spatio-temporal variability between observations, or malfunction in linking model variables under two different spatio-temporal scenarios. However, uncertainties often occur because of the interplay of model elements, structures, and the quality of data sources employed; as input parameters influence the behavior of cellular automaton (CA) models. Our study aims to address these uncertainties. While most studies consider neighborhood effects, timestep and spatial resolution, our study uniquely focuses on the susceptibility of multi density classes and varying cell size on uncertainty. Hence this chapter offers a theoretical elucidation of the concepts, sources, and strategies for managing uncertainty under various criteria as well as an algorithm for enumerating the model's accuracy for Wallonia, Belgium.

Keywords Uncertainty analysis · Urban CA modelling · Urban densification

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17.1 Introduction

Over the last few decades, pressures on land availability brought on by urbanization has become a central issue, particularly for developing countries. The enormous land requirement to serve a rapidly expanding urban population has presented significant impediments to economic prosperity, social inclusion, and environmental protection (Angel et al. 2021; Jiang et al. 2022). Various modelling methods have been developed in recent years to handle various urban challenges which differ in approach and underlying principles (Li and Gong 2016). For example, several statistical and geospatial urban models have been designed to analyze the relationship between driving forces and urban land change, and predict its future development, including Agent-based models (ABM) (Zhang et al. 2010), logistic regression (Mustafa et al. 2018a), cellular automata (Almeida et al. 2003; García et al. 2013), and Conversion of Land use and its effects (CLUE) model (Verburg et al. 2014). Urban planners and decision-makers can better comprehend the environmental and socioeconomic elements that encourage urbanization trends thanks to the application of these urban development models (Batisani and Yarnal 2009).

In general, CA is viewed as a bottom-up urban model from which emergent patterns of land use change are produced from 'simple' transition rules, which is in line with the core principles of complexity science; the interactions of simple subsystems lead to the formation of complex systems (Lu et al. 2019). Uncertainty can be measured through probability distribution and involves risks. Uncertainty with a known events of possible outcomes and quantifiable probability involves risk which are known as objective risks while the one whose outcomes are purely reliant on human judgements are known as subjective risk (Loucks et al. 2005). Model's uncertainty can be a causative effect of various type of errors. The error can occur due to model parameters or input variables. Vardoulakis et al. (2002) has used different dispersion model as he suggests that it is impossible to assess the uncertainty of a model based on discrete values of input variables. On the other hand, Gar-On and Li (n.d.) in their work have experimented with errors in acquiring and applying GIS data sources that are used as a input variables while simulating numerous CA models, thus helping to achieve realistic and accurate results.

Urban CA models, like any other urban models, are subject to numerous sources of uncertainty which are difficult to disentangle. Uncertainty might be viewed as a measure of how much we distrust the concepts and abstractions we use to represent the real world. An archetypal urban CA model is made up of four parts: transition rules, neighborhood configuration, simulation time (time step), and stochastic perturbation (Yeh and Li 2006). Due to the complex characteristics among each component, urban CA results may be sensitive to variations in parameter settings and adopted approaches (García et al. 2011; Li et al. 2014). These inaccuracies will spread during CA simulation and have an impact on the results of the simulation. In order to do this, the effects of source errors and error propagation on simulation outcomes must be assessed. While, Uncertainty is crucial because it enhances the model's accuracy and account the variability in inputs, and allows folding up the uncertainty of input into the set ofoutput values (*Sensitivity and Uncertainty–Center for Systems Reliability* 2022). Conversely, sensitivity analysis examines the model's resilience, and evaluates the influence of a model's assumptions, thus concluding that inputs with greater impact on output sensitivity provide the effect of interactions between input components. Hence, uncertainty analysis seeks to quantify the ambiguity in a model's result. The purpose of sensitivity analysis is to determine how variation in input values corresponds to variance in output measurements. It is done by altering one or more input variables, and measuring the effect on output measurements (*Sensitivity and Uncertainty–Center for Systems Reliability* 2022).

The simplicity with which CA models may currently be integrated and programmed in raster-based geographic information system (GIS) systems (Kocabas and Dragicevic 2006), as well as with other methodologies like agent-based or multi-criteria assessment (Batty 2016; Wu 2016), is one reason why they are receiving more and more focus. Simple rules can be used in CA models to produce complicated patterns (Wolfram 2002). By configuring fundamental CA model components including cell states, cell size, neighborhood size and type, transition rules, and temporal increments, it is feasible to properly reflect spatial complexity and the dynamics of urban development change (Torrens and O'Sullivan 2022; White and Engelen 2000; Yen and Li 2016). Among these, spatial extent is frequently linked to a specific research case, preventing it from having the universal property of spatial scale sensitivity during CA-based land use change simulation. There haven't been enough studies to date that have carried out a systematic investigation of the consequences of changing the CA model design's constituent parts during the calibration process (Wu et al. 2019). While most papers deal with several kind of model-based or input-oriented uncertainties and their sensitivity towards cellular automata modelling, we have attempted to present in our work a theoretical prototype of evaluation taking into consideration a multi-level density approach. It involves changing input variables and observing their error propagation, but under different urban built-up density classes, thus helping the original data to remain untouched and resulting in realistic model simulation outputs.

In the remainder of the paper, we provide background information on various types of uncertainty analysis based on cell size, transition rules and density classes. In Sect. 17.3, we explain the methodology for analyzing uncertainty based on urban CA models in a univariate method and how it can be implemented for Wallonia region, Belgium. Subsequently, in Sect. 17.4 we present results and discuss the influence of cell size, transition rules and density class on the model output. In Sect. 17.5, we conclude by providing a list of future tasks that can be implemented in order to investigate sensitivity and uncertainty analysis using urban CA model.

17.2 Background

When applied to real cities, urban CA models are prone to errors and uncertainty. Uncertainty in geospatial data might be unavoidable when developing a realistic simulation. However, differing combinations of neighborhood size, type, and spatial resolution can have an impact on simulation outcomes. By perturbing spatial variables and analyzing the error terms in the simulation results, one may easily scrutinize error propagation in urban simulation. The variability in the model output is quantified by uncertainty analysis (UA), and the distribution of this uncertainty across the model input factors is examined by sensitivity analysis (SA) (Crosetto and Tarantola 2010; Saltelli et al. 1999). Sensitivity analysis examines the link between input and output information in a model and pinpoints the sources of variation that affect model outputs. Uncertainty can come from a variety of sources, including errors and approximations in the measurement of the input data, parameter values, model structure, and model solution techniques. Input errors and model flaws both spread during the simulation process in CA simulation.

While prior research has offered an examination of CA model behavior in relation to modifying the model components, several recent studies have focused on the topic of errors and uncertainties associated with CA models. Variations in cell size, transition rule, and multi-level density classes have been explored in the current literature. In order to examine how uncertainty affects simulation outcomes for the Ourthe River basin in Wallonia, Belgium, Mustafa et al. (2014) employed a stochastic component. This component addressed how randomness propagates in urban growth models. The model was validated using cell-to-cell allocation and validated using landscape matrices. The findings showed that as stochastic perturbation size grows, the accuracy of the model declines, starting with extremely tiny perturbations. Feng and Liu (2013) introduced a unique geographic-based CA model that incorporates sensitivity analysis techniques to optimize transition rules that were first constructed using logistic regression. Menard and Marceau also explored how spatial scale affected the results of the CA model in relation to the spatial resolution and a typical CA neighborhood layout. They expanded on their study even further and introduced VecGCA (Moreno et al. 2008), a new object-based geographical cellular automata model. This model was a versatile and effective tool for simulating changes in land use and cover as well as other spatiotemporal occurrences that suggested object geometry alterations. VecGCA ensured a more accurate portrayal of geographic space (as well as growth of the items constituting it) by being independent of cell size, neighborhood arrangement, and landscape configuration by incorporating a dynamic neighborhood.

17.2.1 Approaches in Evaluating Uncertainty Based on Scale Effects: A Multiscale Approach

Scale may be understood as a continuum across which things, patterns, and processes can be seen and connected (Marceau 2014). In relative space, scale is a variable that is inextricably tied to the spatial entities, patterns, forms, as well as functions, processes, and rates under consideration. In absolute space, scale refers to a practical, standard system used to divide geographical space into an operational spatial unit (Samat 2006). Marceau (2014), on the other hand, provides a concept of scale that is generally accepted when discussing urban CA models and relates it to the absolute and relative depiction of space.

The scale problem has been addressed using a variety of methods. It runs the gamut of from straightforward scale analysis methods like geographic variance, local variation, and texture analysis, to more intricate methods like semi-variograms and fractals (Chen and Henebry 2009; García-Álvarez et al. 2019a, b; Young et al. 2021; Zhang et al. 2019). According to earlier research by Kok and Veldkamp (2001) on the impact of modifying scale in a LUCC model for Central America, increasing the resolution from 15*15 km to 75*75 km enhanced the model's explanatory power (r^2) but had no discernible impact on the explanatory factors. In their study of the behavior of several urban development rules at various cell sizes in the well-known SLEUTH (Clarke 2008) model, Jantz and Goetz (2007) came to the conclusion that the resolution of the cells had a significant role in the performance of the model, and that some urban growth rules produced significantly greater growth at coarser resolutions than at finer ones. Although their results are highly unique to the SLEUTH model, the conclusion is that neighborhood effects for urban land, which are essential to all CA models, may vary non-linearly across scales.

17.2.2 Scenario Description and Impacts of Uncertainty on Transition Rules

Transition rules in CA model are essentially designed such that a cell's future state depends on both its current state and the state of its surroundings (Liu 2008; Stevens et al. 2007; Ward et al. 2003). In order to characterize land-use transition potential of a cell, many driving mechanisms for urban landuse change have been discovered, mapped, and implemented in GIS (Liu et al. 2008; Wu 2010). These driving forces or factors may be divided into three major groups of variables: socioeconomic, geophysical, and accessibility and have been listed in Table 17.1 (Chakraborty et al. 2022; Mustafa et al. 2018a, b, c).

Many transition rules, including those based on Markov chains (Kamusoko et al. 2009), neural networks (Li and Yeh 2010b), genetic algorithms (Shan et al. 2008), ant colony optimization (Liu et al. 2010), cuckoo search algorithms (Cao et al. 2015), particle swarm optimization (Feng et al. 2018), and data mining (Li and Yeh 2010a), have been developed based on various intrinsic principles of land use conversion. Although a CA-Markov only models land use changes using a constant time step (Pontius and Malanson 2007), one significant advantage is that it simultaneously predicts the trajectory of land use change among various categorical states (Li et al. 2016). It also simulates spatio-temporal dynamic changes (Jenerette and Wu 2001)

Table 17.1 Varied metrics of senstivity analysis used in the past

S.No	Publication	Metric	Aspect	Study area	KEY strength
1	Jantz and Goetz (2007)	Scale Sensitivity	Scale	Washington, DC–Baltimore	Scale as an integral issue during each phase of a modelling effort
2	Kocabas and Dragicevic (2006)	Neighborhood sensitivity	Neighborhood	San Diego region, USA	Exploratory method of sensitivity analysis that can be used in a gen-eral context to examine and assess CA model errors and uncertainties
3	Feng and Liu (2013)	Transition sensitivity	Transition rules	Shanghai, China	Model the multiple land-use changes and spatial ecological processes using SA optimisation algorithm
4	Ménard and Marceau (2016)	Scale sensitivity	Scale	Maskoutains region (Quebec, Canada)	Finer exploration of cell size sensitivity by using a stochastic geographic cellular automata (GCA) model
5	Moreno et al. (2008)	Neighborhood sensitivity	Neighborhood	Quebec, Canada	Size sensitivity by allowing the representation of space as a collec-tion of geographic objects by im-plementing a novel VectorGCA

(continued)

Table 17.1 (continued)

S.No	Publication	Metric	Aspect	Study area	KEY strength
6	Samat (2006)	Scale sensitivity	Scale	Seberang Perai region, Penang State, Malaysia	GIS based CA model using multi-criteria evaluation (MCE) suitability index map
7	Ward et al. (2003)	Transition sensitivity	Transition rules	Queensland, Australia	Address strategic planning and management issues by integrating regional and local scale models
8	Wu (2010)	Transition sensitivity	Transition rules	Guangzhou, South China	Stochastic CA model for rural–urban land conversion using Monte Carlo process

that attempt to improve the simulation accuracy as much as possible. Mustafa et al. (2021) forecasted future land use changes in New York City by introducing a multi-objective Markov Chain Monte Carlo (MO-MCMC) that considered multiple allocation objectives. They concluded that the model can bring analytical and simulation approaches into the planning process, and simulate trade-offs between different LULC visions.

17.3 Materials and Methods

17.3.1 Study Area

Wallonia, located in the southern part of Belgium, accounts for 55% of total area of the country with a coverage of 16,844 km^2 (Mustafa et al. 2018a), as shown in Fig. 17.1. It predominantly consists of the French speaking area and is mostly characterized by peri-urban areas. Despite its large areal extent, Wallonia comprises of only one third of the total Belgian population. The important urban centers of Wallonia are Liege, Mons, Namur, and Charleroi. The urban density of the region has a peculiar pattern of sparse settlements in most of the outskirts with populated inhabitants mostly in the metropolitan centers (Li et al. 2015).

This area mostly stretches from Eastern part (e.g., Liege) along the industrial zones to the west in Mons. Wallonia, with its urban development design, makes it

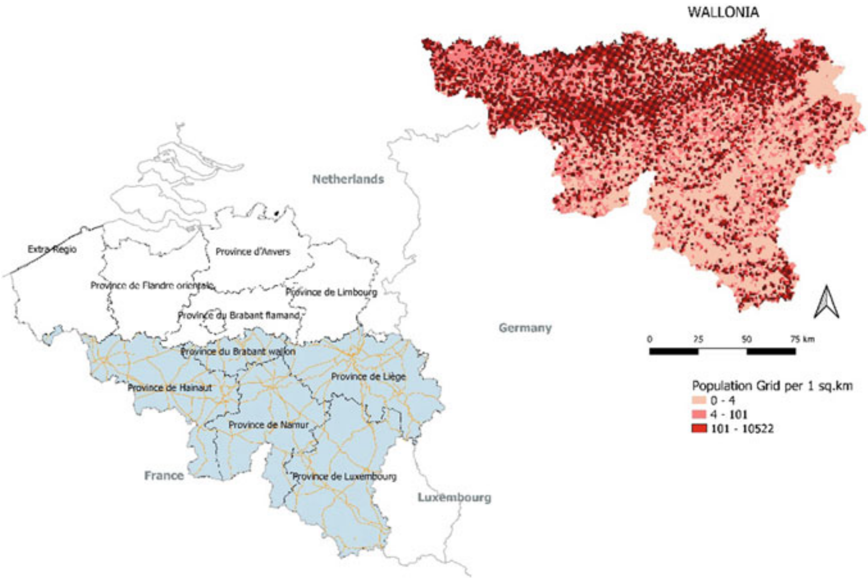

Fig. 17.1 Wallonia region (southern Belgium) with population grid per sq.km

useful for studying dispersed urbanization patterns. It is also an area that has been less researched in the CA urban growth literature. Hence this region was selected for modelling urban densification, along with its associated uncertainties.

17.3.2 Conceptual Framework

In Fig. 17.2, we show our conceptual method which includes our diverse datasets and modelling structures. This includes our previous study that used a novel approach. In this work (Mustafa et al. 2018b), a temporal Monte Carlo method (TMC) was proposed to study the uncertainty over time for Liege, Wallonia, with a study being conducted between year 1990 and 2010 for a short term simulation This is different from other models that use randomness in order to study uncertainity. Further, this model was subsequently extended for a longer term till year 2100.

Our literature study showed that the basic necessities for a standard CA model involved implementing neighborhood effect, transition rules and cell size for simulating development in future. García-Álvarezet al. (2019a, b) and Gar-On Yeh usually concentrate on technical uncertainty, which takes into account usual errors related to spatial scale or raster data classification. While it is evident from literature that uncertainty can be due to input variables, it is important to note that driving factors are also crucial. A range of socioeconomic, physical, accessibility and environmental variables have been considered, which when calibrated using a logit model, can

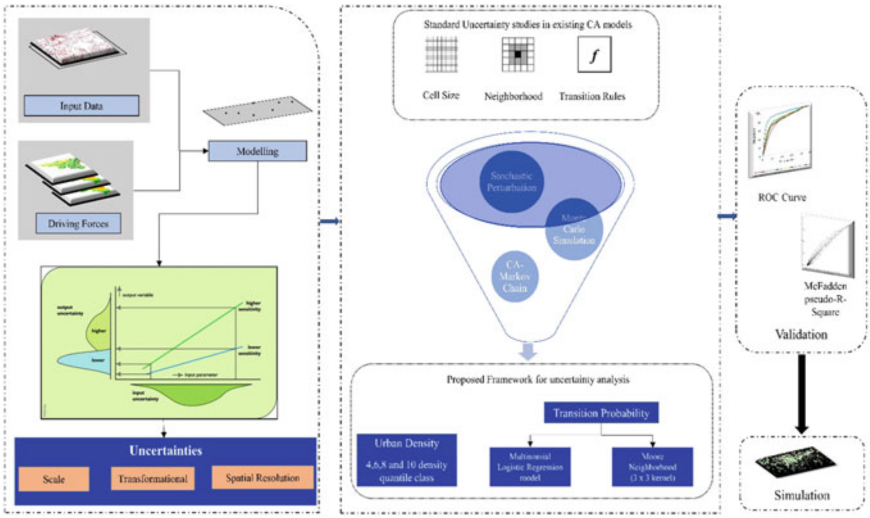

Fig. 17.2 Conceptual methodological framework for uncertainty analysis. *Source* partly adapted from (Loucks et al. 2005)

help provide better validation. Therefore, while most studies have the tendency of following a traditional input-based or model-based study, it is imperative to consider uncertainties of spatial allocation as well (Mustafa et al. 2018b).

By observing the land use pattern at time t and time t + 1, the calibration process aims to derive the coefficients or parameter values for CA transition rules. Using a multinomial logistic model, the likelihood of development may be determined when there are numerous factors. The probability is calculated by comparing land use changes in CA over a longer time period than one cycle. The estimated transition probability of a randomly chosen cell is compared with a uniform random number within a dynamic range at each time-step. The methodologies of Wu et al. as well as Mustafa et al. (2018a), were used to determine the transition probabilities (2002). Mathematically, the transition probability P for cell *i* at time-step *t* can be calculated as follows:

$$Pi^t = \left(Pi^d\right) \times \left(Pi^n\right)^t \times con(.)$$

where $\left(Pi^t\right)$ is the urbanization probability based on driving forces, $(Pi^n)^t$ is the neighborhood interaction, and $con(.)$ Is restrictive constant for land use change.

Hence, as a part of our previous research, we attempted to carry out the study on a vector based Cadastral data which was further converted into raster format at a scale of 100*100 m representing different density classes for urban built up development. Since most of the uncertainty studies on CA model involves urban expansion as their phenomenon, It is crucial to take into account the uncertainty that occurs as a result of change in density classes of different combinations across time and space. This is the main objective for our hypothesis.

17.4 Observation and Assessments

In this section, we highlight the different strategies that have been suggested till now, with ultimate goal for dealing with uncertainty analysis using CA. The purpose of CA models is to truly portray urban and land-use patterns by reflecting their changes over time. Considering that complexity is a state between order and chaos, and that creating complexity necessitates the introduction of the proper amount of randomness in the models, it becomes vital to assess the best strategy for doing so. Different strategies are consequently required for a thorough analysis of uncertainty because there is no single method that can analyze all sorts of uncertainty. For this reason, the paper explored the uncertainty analysis in a multivariate approach.

Comparing the model's predictions to actual data in order to determine its level of uncertainty is the process of validating a cellular automata (CA) model of urban expansion. This might involve contrasting the simulated urban land-use patterns, population density, and other spatial aspects of the city with actual data in the context of urban growth modelling. Comparing the simulated land-use patterns to satellite imagery or other remote sensing data is a typical method for evaluating a CA model of urban expansion (Chaudhuri and Clarke 2014) This may be done by visualizing a comparison between the satellite picture and the generated land-use map. Another strategy is to contrast crucial model statistics with actual data, such as the percentage of urban land.

Comparing the model's predictions against those of other models or data sources is another method of model validation. An official census or other sources of demographic information can be used to compare the model's estimates of population density, for instance. The model's performance may also be evaluated in relation to other urban growth models that employ other techniques or premises. By repeatedly running the model with various initial conditions or parameter values and comparing the outcomes, the degree of uncertainty may be assessed. This can assist pinpoint the model's sources of uncertainty and show how sensitive the model is to changes in the inputs.

Although transition rules and transition probability are essential to CA modelling, CA models are also influenced by neighborhood configuration and scaling behavior, as well as scaling behaviors of transition probability (Dahal and Chow 2015; Feng and Tong 2018). As a result, even though transition rules and transition probability are crucial to CA modelling, they are not the only factors that have an impact on simulation results (Gao et al. 2020). However, there is a relationship between model performance and the amount of change across the simulation time. As discussed previously, typical CA models include a variety of intrinsic model uncertainties that are connected to the neighborhood, cell size, computation time, transition rules, and model parameters (Gar-On Yeh and Li n.d.).

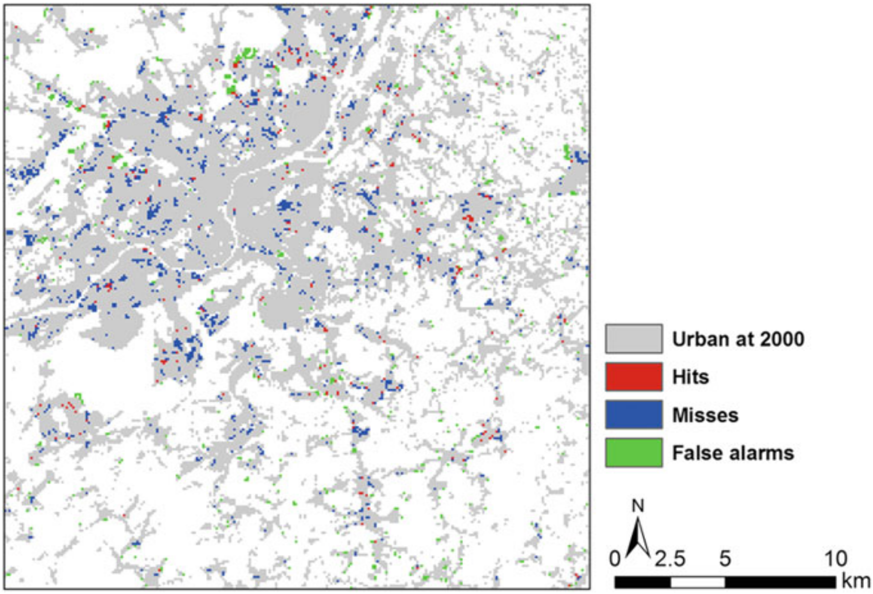

Fig. 17.3 The hits, misses, false alarms during the validation time interval for Liege metropolitan

When applied to a local context, such as Wallonia, Mustafa et al.(2018b) proposed a Time Monte Carlo (TMC) method to introduce randomness in land use change models with the aim of modelling spatial allocation uncertainty. By analysing (a) the hits (H) which indicate that the areas of expansion on the observed map were simulated as expansion, it evaluated the allocation performance; (b) misses (M) that indicate that the areas of expansion on the observed map were simulated as no changes; (c) false alarms (FA), indicating that the no-changes in the observed map were simulated as expansion; and (d) correct rejections (CR), indicating that the areas of no-change in the observed map were simulated correctly (Fig. 17.3).

Mustafa et al. (2018b) further transformed the transition probability of each cell by comparing it with the largest available probability at each time-step, following Wu's (2010) study. Mathematically it can be written as:

$$Pi'^{t} = Pi^{t} \exp\left[\delta(1 - Pi^{t}/\max\left(P^{t}\right)\right]$$

where Pi'^{t} is the updated transition probability for cell i at time-step t, Pi^{t} is the original probability, δ is a dispersion term, and $\max(P^{t})$ finds the maximum transition probability at time-step t. The dispersion term in a cellular automata (CA) simulation is used to measure the degree of variation or spread in the density of the system at different levels. The density of a CA system refers to the number of active or "on" cells at a given time, and the dispersion term is used to measure how this density varies across different spatial scales or levels. This information can then be used to influence the behavior of the simulation, for example by adjusting the rules for

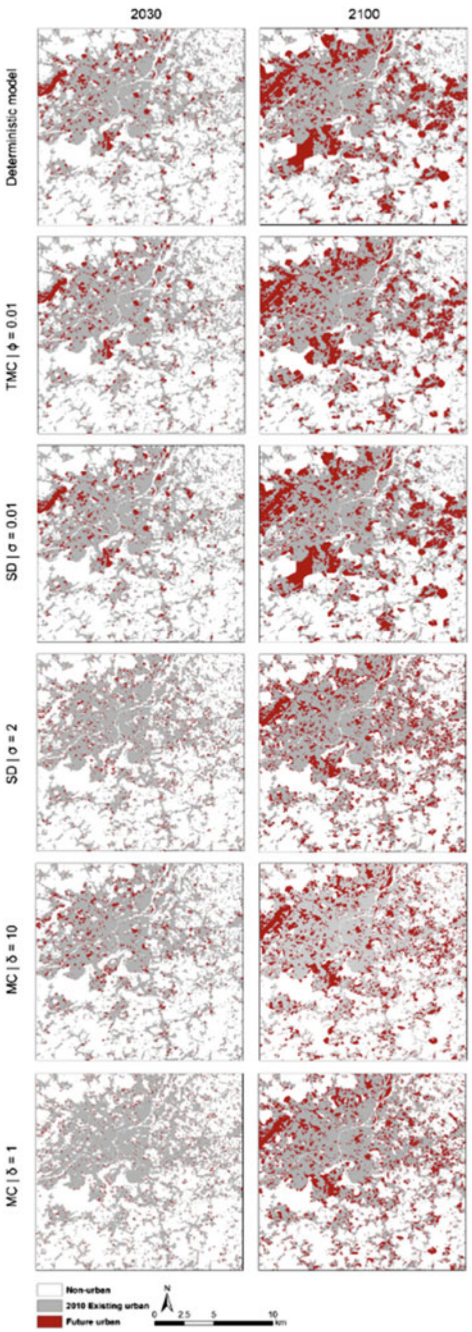

Fig. 17.4 2030 and 2100 simulations for different configurations for Liege metropolitan

cell activation or interaction based on the observed density variations. The skewed probability curve's form is controlled by the dispersion parameter.

To further investigate the model's performance, different values of δ have been used to generate future urban patterns for 2030 and 2100 (Fig. 17.4). At early time-steps (like 2030), the proposed TMC model generates simulations that are comparable to the outcomes from deterministic models, with minor changes. However, the model generates results different from a deterministic-equation based simulation model as it predicts further into the future.

17.5 Conclusion

In this study, we demonstrate the uncertainty with regards to CA model for analyzing urban complexities. This uncertainty is mostly a result of different cell size, neighborhood dynamics and transition rules. Which is why the uncertainty can be model input-based or model parameter based. Because our work involves urban densification, it is crucial to understand the effect of density classes on uncertainty. Hence, we proposed a theoretical framework explaining the establishment of uncertainty in models through past works carried out for Liege. We employed the TMC model to evaluate uncertainty, and forecasted urban development for 2030 and 2100. In our future research, we will extend the current study that shows uncertainty resulting from applying a CA model based on multi-level urban density to a larger area. Further, as a part of our future work, we intended to apply the model uncertainty for simulating residential densification. Finally, a simplified CA-MCMC (Cellular Automata Monte Carlo) simulation could be used for other parts of Belgium, for example the Brussels capital region, and Flemish and Wallon Brabant. Also, unlike the usual variables that are commonly used for such studies (e.g., cell neighborhood and cell size), novel variables like cell density was applied in our study. Thus, going forward this research framework will facilitate in adding a different dimension to uncertainty studies in urban modeling, specifically in studying densification while achieving valid simulation results.

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