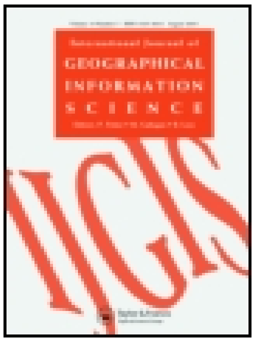

International Journal of Geographical Information Science

ISSN: 1365-8816 (Print) 1362-3087 (Online) Journal homepage: http://www.tandfonline.com/loi/tgis20

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INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE
https://doi.org/10.1080/13658816.2018.1502441

RESEARCH ARTICLE

Urban growth simulation by incorporating planning policies into a CA-based future land-use simulation model

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ABSTRACT

Urban land-use change is affected by urban planning and government decision-making. Previous urban simulation methods focused only on planning constraints that prevent urban growth from developing in specific regions. However, regional planning produces planning policies that drive urban development, such as traffic planning and development zones, which have rarely been considered in previous studies. This study aims to design two mechanisms based on a cellular automata-based future land-use simulation model to integrate different planning drivers into simulations. The first update mechanism considers the influence of traffic planning, while the second mechanism can model the guiding effect of planning development zones. The proposed mechanisms are applied to the Pearl River Delta region, which is one of the fastest growing areas in China. The first mechanism is validated using simulations from 2000–2013 and demonstrates that simulation accuracy is improved by the consideration of traffic planning. In the simulation from 2013–2052, the two mechanisms are implemented and yield more realistic urban spatial patterns. The simulation outcomes can be employed to identify potential urban expansion inside the master plan. The proposed methods can serve as a useful tool that assists planners in their evaluation of urban evolvement under the impact of different planning policies.

ARTICLE HISTORY
Received 21 December 2017
Accepted 16 July 2018

KEYWORDS
Urban growth simulation; CA-based FLUS model; planning policy; driving effects

1. Introduction

Land use and land cover are essential geospatial features that play an important role in many processes, such as sustainable development, environmental change and urban planning (Yu *et al*. 2013, Pekel *et al*. 2016, Li *et al*. 2017, Wang *et al*. 2017, Huang *et al*. 2018). In recent years, rapid urbanization has generated diverse and sophisticated urban land-use patterns at different scales (Li and Yeh 2001, Batty 2008, Liu *et al*. 2014, Kamusoko and Gamba 2015, Pekel *et al*. 2016; He *et al*. 2017). Urban or regional land-use distributions are not only determined by natural and socioeconomic drivers but are also affected by government-specified polices that cannot be stereotyped and that continuously change with additional urban development (Tian and Shen 2011, Lu

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et al. 2013). Therefore, simulating spatial changes in urban land use under the effect of various planning policies is significant for making effective decisions in urban growth management.

Urban growth modeling based on cellular automata (CA) has attracted considerable attention in recent decades (Tian and Shen 2011, Lu *et al*. 2013). As a spatially explicit discrete model, CA is extensively applied to the simulation of complex systems, such as urban growth modeling and geographical process simulation (Clarke and Gaydos 1998, Sohl and Sayler 2008, van Asselen and Verburg 2013). Multiple factors that affect urban development, such as socioeconomic drivers (Yao *et al*. 2017a), climate and topography (Li *et al*. 2017) and regional-scale land-use demand (Verburg and Overmars 2009), are incorporated into simulations to enable geo-CAs to more closely match the practical process of urban growth. In addition, to mine the relationships between urban forms and these driving factors, intelligent algorithms have often been applied to establish the transition rules for CA models (Feng *et al*. 2011). Such algorithms include decision trees (Li *et al*. 2014), support vector machines (SVMs) (Ke *et al*. 2017), random forests (RFs) (Kamusoko and Gamba 2015) and neural networks (Li and Yeh 2002, Dai *et al*. 2005, Lin *et al*. 2011). Land-use change simulations based on the CA model have yielded acceptable results in these studies, which proves that these approaches are applicable to simulating complex urban systems.

Although CA models are very effective at simulating large-scale urban expansion, urban growth under the effects of various factors in large areas can be very complex (Li and Yeh 2001, Li and Liu 2006). To render the simulation of urban growth closer to real-world outcomes, the CA model should not be restricted to considering socioeconomic effects; at the same time, it should take into account important factors such as policy and geographical constraints (Long *et al*. 2013), for example physical or legal characteristics that prevent a cell from experiencing urban growth. These characteristics can be regarded as constraints in CA models to simulate future urban forms while considering comprehensive urban development (Tayyebi *et al*. 2011, Liang *et al*. 2018). Therefore, in recent decades, additional research has considered the use of policy information for calibration or to guide the simulation process of a CA model. For example, Guy *et al*. (1997) proposed a constrained-CA model that integrates GIS and decision support tools for urban planning, Li and Yeh (2000) simulated urban expansion in Dongguan under the constraint of agricultural constraint scores, Yang *et al*. (2006) and Liu *et al*. (2010) used crop protection land to suppress urban land development in Shenzhen and the Pearl River Delta (PRD) and Liu *et al*. (2017a) simulated urban growth in China under the influence of major function zones by multiplying the urban probability by the development scores determined by experts. In addition, simulation research using agent-based models (ABMs) has added agricultural land preservation policies and urban containment policies to the planning agent to simulate urban growth under planning effects (Jjumba and Dragićević 2012). Other studies that have combined the CA model and the urban demand model also address policy goals on a macro scale, which enables these models to compare alternative planning and policy scenarios in terms of their effects on future land-use development (White and Engelen 2000, Barredo *et al*. 2003, He *et al*. 2006).

Although planning policies have been investigated by many researchers, most studies only consider institutions that maintain the states of cells that remain unchanged or that slow the development of urban land (Al-Ahmadi *et al*. 2009) or planning goals on a nonspatial scale (Huang *et al*. 2014). However, regional planning not only focuses on large-scale planning policies and specifies the regions in which construction is forbidden but also delineates the areas in which development is encouraged, such as the planning of development zones. The planning of traffic factors also guides the development direction of urban expansion, for example the planning of high-speed railway stations and subway stops. These planning drivers are commonly employed in regional planning and have a potential effect on future urban development (Dai *et al*. 2013, Lu *et al*. 2013, Sun 2016). They have received limited attention in previous studies (Clarke and Gaydos 1998, Li and Yeh 2000, 2002, Gong and Chen 2002, Liu *et al*. 2008, 2010, Liu and Liu 2008, Chen *et al*. 2014). Therefore, objectively modeling the effect of planning drivers on future urban growth is important for planners and managers to make appropriate decisions for future urban development.

This study aims to bridge this gap by proposing a method to integrate various planning driving effects in urban growth simulation. In this paper, a CA-based future land-use simulation (FLUS) model is employed to simulate urban growth in the PRD region in two phases: from 2010 to 2013 and 2013 to 2052. Based on the FLUS model, two mechanisms are proposed to tackle two major planning drivers in the simulation: the first mechanism is based on an artificial neural network (ANN) model that is employed to address the planning of traffic elements, and the second mechanism is based on randomly planted seeds (Chen *et al*. 2016) and is applied to address the planning of development zones. In this study, the master plan (Figure 4) in the PRD region is regarded as a planning development zone because it is proposed to guide the rational development of the city for long-term development and short-term construction (Gu *et al*. 2017). The two mechanisms are proposed to make the simulation models integrate more planning information and become more adaptive for estimating future urban forms. The simulation results can be used to evaluate the guiding effects of planning policies.

The remainder of this article is organized as follows. Section 2 provides the principles of the two novel mechanisms to address the planning effects. Section 3 describes the study region and lists the data in this study. Section 4 provides the experimental results and analyzes the effect of considering the planning components and comparing the simulation results with an urban area defined by master planning. The discussion and conclusions are given in Sections 5 and 6.

2. Method

The FLUS model has been successfully applied to the simulation of complex land-use and land-cover changes in China (Liu *et al*. 2017b) and on a global scale (Li *et al*. 2017) for modeling the dynamics of land cover changes for various human-related and natural environment driving forces. In this study, a modified version of the FLUS model is addressed using an updated mechanism to incorporate traffic planning and a random seeding mechanism to consider the planning of development zones.

2.1. *FLUS model*

The FLUS model is implemented by training an ANN model to obtain an urban probability-of-occurrence (PoO) surface and by using a spatial simulation process that is based on a CA model (Figure 1). An ANN is used to define the relationships between

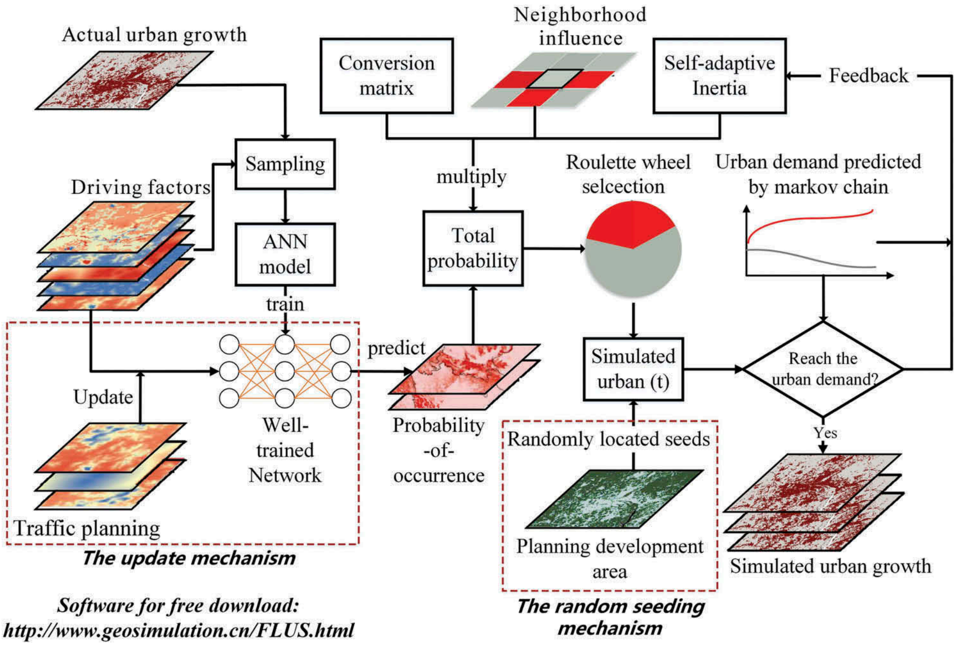

Figure 1. Basic structure of the modified FLUS model with the update mechanism and the random seeding mechanism for simulating urban growth.

historical land use and the various driving factors. The PoO surfaces derived from the ANN guide the placement of changes in land-use distribution. In the CA module, a self-adaptive inertia coefficient is used to adjust the total probability of urban land according to the total amount of urban area in the scenario. A roulette mechanism is designed to model the competition between urban land and nonurban land in each cell, which will make the FLUS model more capable of capturing the uncertainty and randomness of urban development (Liu et al., 2017; Chen *et al*. 2014). The simulation process is divided into several intervals, and the 'bottom-up' CA model and the 'top-down' urban demand forecasting model tightly couple with each other during the studied time series. These designs make the FLUS model more feasible for simulating complex and long-term land-use changes (Liu et al., 2017).

In our previous study, we used a system dynamic (SD) model as the 'top-down' urban demand forecasting module of the FLUS model (Liang *et al*. 2018). The SD model is able to provide urban demands in multiple planning scenarios by considering both human activities and natural ecological effects (Liu *et al*. 2017b). However, the structure of the SD model for projecting future urban demands is complex and requires large amounts of socioeconomic data to fit the relationship between various components and sub-modules (Liang *et al*. 2018). There is only one urban development scenario in this study, thus we can compare the simulation results with and without the proposed mechanisms under the same scenario. The Markov chain model is thus used as the 'top-down' model of the FLUS framework in this study. Markov chain is a method for projecting future land-use demands by determining transition probability of change from one category (e.g. nonurban land) to another category (e.g. urban land) from two periods of land-use data, which have been successfully employed by many simulation studies (Arsanjani *et al*. 2011, Yang *et al*. 2014). Although the Markov chain can only generate one urban development scenario, it is easier to use and only requires two periods of land-use data for the requirements of this study.

2.2. *Update mechanism based on an ANN model for traffic planning*

ANNs are a family of machine learning methods that are commonly employed to approximate the nonlinear and complex relationships between land-use patterns and their driving variables (Li and Yeh 2002, Dai *et al*. 2005, Zhang *et al*. 2015). Through iterations and feedback between the neurons of two different layers, an ANN can generate a PoO surface for a land-use type on each pixel for CA simulation (Pijanowski *et al*. 2005, He *et al*. 2018). Previous studies have proven that the ANN model is superior to ordinary regression methods, such as logistic regression (LR) (Lin *et al*. 2011), and they have been successfully applied to the analysis and modeling of land-use and land-cover changes (Dai *et al*. 2005). Therefore, this study constructs an update mechanism based on an ANN to address the influence of planning drivers into the PoO surface of the FLUS model. Figure 2 depicts a flowchart of the mechanism.

First, sampled land-use map data and historical driving force data are employed to train the ANN. The driving factors that will be updated are specified in this step (only driving factors with future planning schemes can be updated). Second, in the network prediction process, the historical driving forces in the specified layers are replaced with

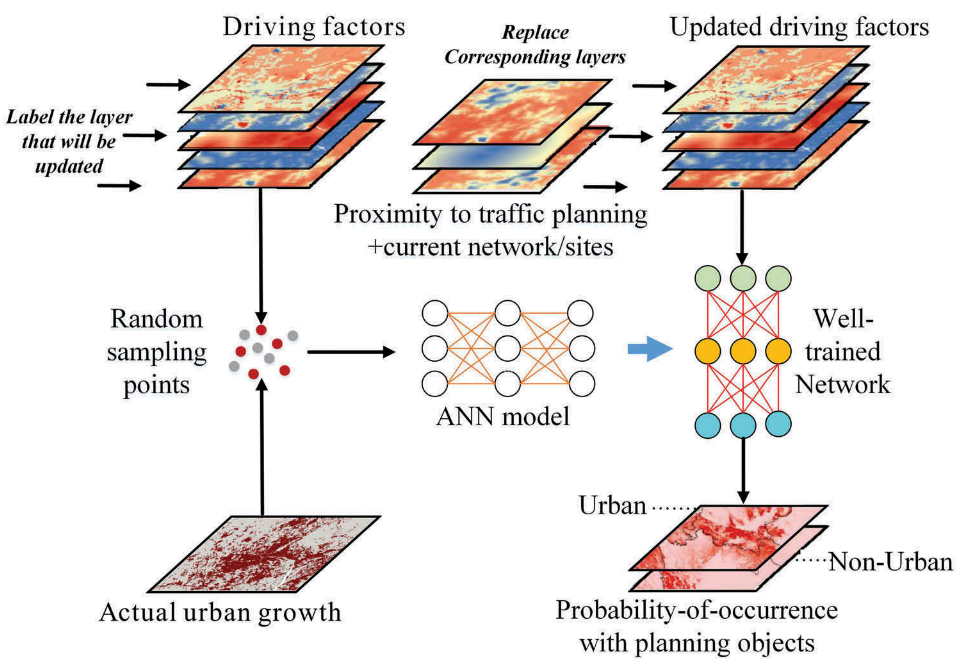

Figure 2. Schematic framework of the updated mechanism based on an ANN to consider the influence of traffic planning.

data that include both historical and future driving forces. For example, the proximity to future highway gates (including both the old highway gates and the newly planned highway gates) replaces the proximity to old highway gates. Other unchanged driving forces (e.g. DEM and slope) remain the same in this procedure. Finally, the model exports the urban PoO surface under the driving influences of the planning components. The design of this mechanism is based on the consideration that directly training the neural network with the planning drivers is unreasonable because these planning factors do not exist in the region, and the relationship between historic land use and future driving forces is incorrect. Therefore, the mechanism trains with the old driving forces and generates historical rules based on old data. However, planning drivers have a potential influence on urban development (Tian and Shen 2011, Lu *et al.* 2013). Thus, we choose to address this influence on the forecasting process of the ANN model by updating the corresponding driving force data.

2.3. *Random seeding mechanism for planning development zones*

A random seeding mechanism is proposed to model the potential influence of planning development zones (Figure 3) on urban growth. The seeding is carried out during the simulation process of the FLUS model. A nonurban cell that is located in the planning development zones is selected. If its PoO is greater than a random value within [0, 1], a seed is planted in the cell, which is similar to the study proposed by Chen *et al.* (2016). A planted seed will randomly increase the total probability of an urban area with the following rule:

$$\mathrm{TP_{urban}} = \begin{cases} (1+\mathrm{r}) \times TP_{\mathrm{urban}} \ \textit{if} \ (1+\mathrm{r}) \times TP_{\mathrm{urban}} \le 1 \\ 1 \ \textit{if} \ (1+\mathrm{r}) \times TP_{\mathrm{urban}} > 1 \end{cases}$$

where $\mathrm{TP_{urban}}$ denotes the total urban probability, and r is a random value between 0 and 1. This rule ensures that the $\mathrm{TP_{urban}}$ can be improved but is still within [0, 1]. Thus, the total urban probability in the planning development zones will be higher than the

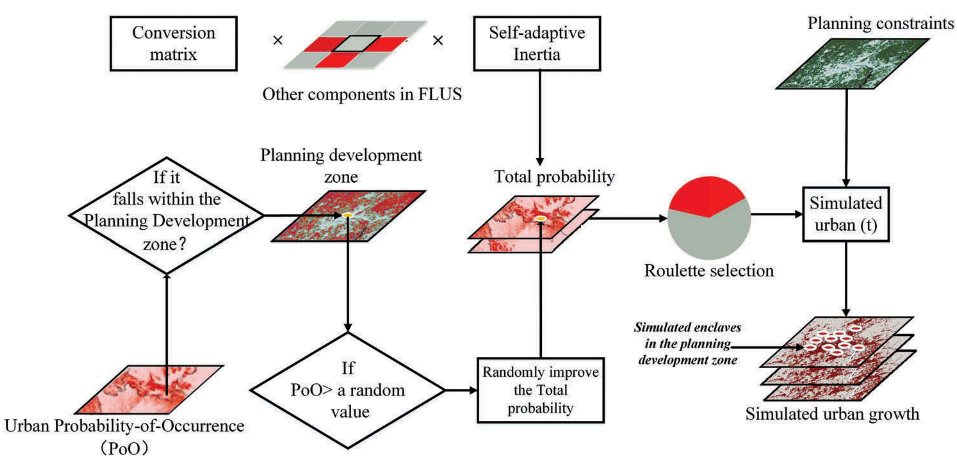

Figure 3. Flowchart of the random seeding mechanism for considering the influence on the planning development zone.

previous total urban probability, but it remains subject to the ANN-based PoO of this location because random seeds are likely to be planted in areas with a high urban PoO. This mechanism does not enable an urban pixel to be directly planted in the priority development area, but it provides a greater chance for these regions to develop enclaves even without nearby urban pixels. This mechanism overcomes one of the shortfalls of many traditional CA models – new urban land cannot be generated in a potential development zone if urban pixels do not exist within the range of the neighborhood in this region (Yang *et al*. 2006).

3. Study area and datasets

3.1. *Study area*

The proposed model was applied to the simulation of urban agglomeration development in the PRD in southern China (Figure 4). The area covers a total administrative area of approximately 54,000 km^2, with 7523 km^2 in the city proper and a total population of 57.15 million. This region includes four economically important cities in Guangdong Province (Guangzhou, Shenzhen, Foshan and Dongguan). Since 1978, China has witnessed a boom in the regional economy due to the economic reform policy and experienced rapid urbanization. The PRD has become one of the most developed regions in China with the highest per capita gross domestic product (Chen *et al*. 2013, Yao *et al*. 2017b). By 2013, the economic output of the PRD was $768 billion, which accounted for 9.33% of China's economy. This development has caused a

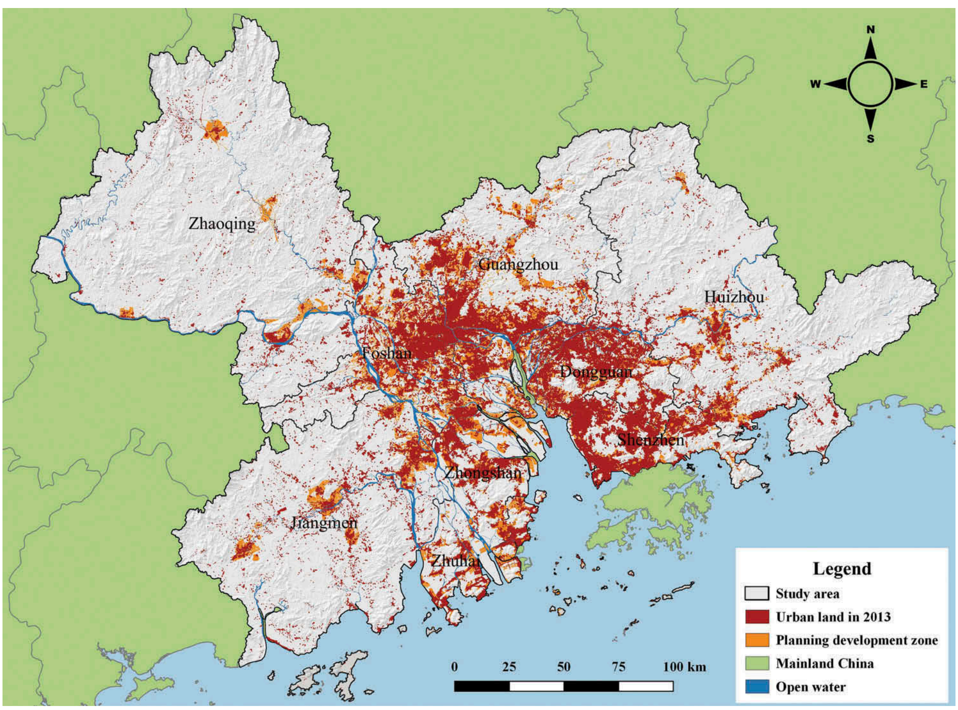

Figure 4. Study region of this research.

range of land-use problems, such as the permanent loss of agricultural land and forest, unreasonable urban sprawl (Yeh and Li 1999a) and related environmental issues (Yeh and Li 1998). Thus, China needs to formulate a sustainable development strategy to guide future urban growth and to propose appropriate policies to control encroachment on agricultural land (Yeh and Li 1999b). To facilitate decision-making with regard to the arrangement and planning of urban land-use distribution, an analysis of future land-use patterns with different government policies is critical.

3.2. *Data processing*

To analyze how spatial planning drives urban growth in the PRD area, historical land-use patterns from 2000, 2005, 2008, 2010 and 2013 and related physical, social and economic data are considered in the simulation. Data with a pixel size of 100 m × 100 m are applied in the PRD to account for different urban planning policies. Various driving forces that are considered include current driving factors such as the physical conditions (e.g. slope) of a site for development and the proximity to traffic networks/hubs (e.g. airports, highways, major roads, railway stations and ports, as well as proximity to town centers). The traffic planning drivers or planning constraints (e.g. primary farmland protection areas) are considered during the analysis experiment. These numeric variables were normalized to [0, 1]. The data from this study are listed in Table 1.

Table 1. List of data in this study and data sources.

Category	Data	Year	Data resource
Land use	Land-use data	2000–2013	CAS (http://www.resdc.cn)
Socioeconomic data	Population	2010	http://www.geodoi.ac.cn/WebEn/Default.aspx
	GDP	2010	
	Airports	2016	Baidu Map API (http://apistore.baidu.com/)
	Town centers	2016	
Terrain	DEM	2010	GDEMDEM (http://www.gscloud.cn/)
	Aspect	2010	Calculated from DEM
	Slope	2010	Calculated from DEM
All levels of road	National road	2015	PRD Master Plan (2014–2020)
	Provincial road		
	Highway gates		
	Highway		
	High-speed railway stations		
	Railway and high-speed railway		
	Main road		
	Urban road network	2016	Open Street Map (http://www.openstreetmap.org/)
Planning data	Planning high-speed railway stations	2013–2030	Traffic plan for Guangdong province (2000–2013, 2013–2030)
	Planning highway gates		
	Master planning in 2020	2020	PRD Master Plan (2014–2020)
	Primary farmland		
	Basic ecological line		

GDP: Gross domestic profit; PRD: Pearl River Delta.

4. Model implementation and results

In this study, 15 spatial driving factors and land-use patterns were selected to calibrate the ANN model for the PoO estimation for urban and nonurban land (see Table 1, with the exception of planning data). The BP-ANN (back propagation-ANN) model in this study is constructed of 15 neurons in the input layer (corresponding to 15 spatial driving factors), 30 neurons in the hidden layers and 2 neurons in the output layer (corresponding to urban and nonurban land). Two percent of the total pixels across the PRD region were randomly selected as the training dataset. The sampling data are normalized to the range of [0, 1] prior to training the network. The sigmoid function is selected as the activation function of the output layers to normalize the probability values to the range of [0, 1]. The learning rate and terminal condition of the ANN model are self-adaptive during the training process. In the simulation module, we used the 3 × 3 Moore neighborhood for the simulation. The neighborhood effect considered in this study is similar to that of traditional CA models, which can be measured by calculating the percentage of the urban cell in a 3 × 3 neighborhood (Liu *et al*. 2017b).

We divided the model implementation into two simulation periods: model calibration and validation and scenario simulation. The model calibration and validation is applied to the period from 2000–2013, and the scenario simulation is applied to the period from 2013–2052. In the model calibration and validation, the validity of incorporating the effects of traffic planning with the proposed updated mechanism is assessed. A series of experiments based on historical data (2000–2013) are arranged to test whether traffic planning is capable of improving the simulation accuracy of the FLUS model.

However, the effect of a planning development zone on simulation accuracy cannot be validated in this study because our study region – the new PRD region – was delineated by the Pearl River Delta Region Planning of Guangdong Province in 2014. Thus, a corresponding planning development zone for the validation period from 2000 to 2013 does not exist in the study region. Nevertheless, it is widely accepted that planning constraints can improve the simulation accuracy because they specify the areas that are not available for urban expansion, even though they may have a higher probability of increasing urban density (Li and Liu 2006, Yang *et al*. 2006). Similar to the effects of planning constraints, the planning development zone is very likely to improve the simulation accuracy because it defines the area where urban development is encouraged, even though it may have a relatively low PoO for urban areas, especially areas where the government's policies have a significant effect on urban development (Huang *et al*. 2017).

4.1. *Model calibration and validation*

4.1.1. *Simulation from 2000 to 2013*

This paper analyzes the influence of two traffic planning points on urban growth simulation in the PRD: planning high-speed railway stations and highway gates in the period from 2000 to 2013. We execute the first updated mechanism by adding the two planning traffic components to the ANN prediction process. Four types of influences of the two traffic planning components, separately or in combination, on the outputs of the ANN prediction (the PoO surfaces for urban land) are analyzed in this section. The generated urban PoO surfaces (PoOs) are displayed in Figure 5. Under the influence of the planning components,

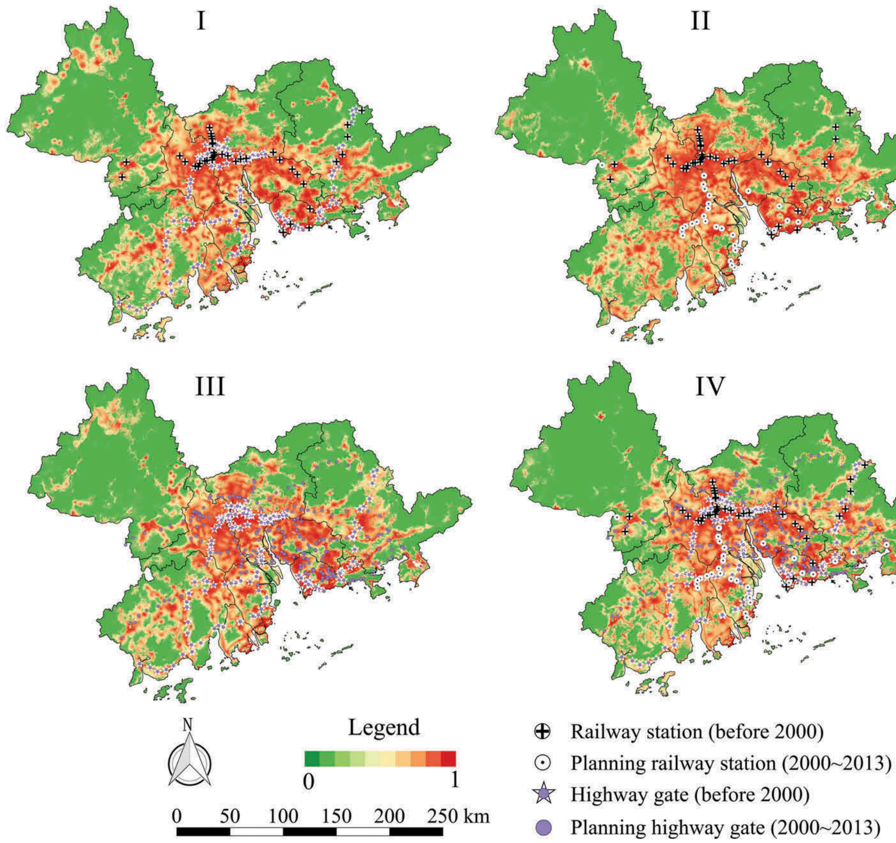

Figure 5. Urban probability-of-occurrence surfaces (PoOs) under the influence of the two planning traffic components separately or in combination. (I) PoO without the influence of planning policy; (II) PoO under the influence of high-speed railway station planning; (III) PoO under the influence of highway gate planning; (IV) PoO under the influence of high-speed railway station and highway gate planning.

we note that the probability distribution in spatial terms shows clear differences across the study area and that these differences will affect the simulation process of the CA model.

Based on the PoOs, we simulate urban growth from 2003 to 2013 under the influence of different traffic planning components. To enhance the simulation, actual land-use demands in 2005, 2008, 2010 and 2013 are employed to provide ‘top-down’ effects from the regional scale for the ‘top-down’ CA model during the simulation period, an approach that has been proven beneficial for improving simulation accuracy (Liu *et al.* 2017b). The historical land-use patterns in 2005, 2008, 2010 and 2013 are employed to validate the simulation results for the corresponding years.

Figure 6 shows the actual and simulated urban accuracies under the influence of different traffic planning policies in 2013. These simulated patterns are similar to the actual land-use patterns. Although the total distribution characteristics of the four simulated urban land-use patterns are similar, different planning policies yield different simulation accuracies.

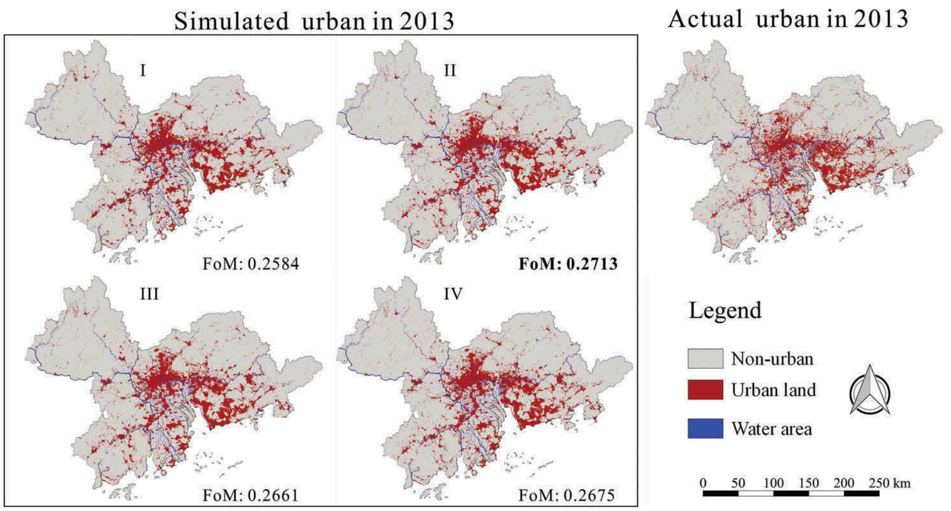

Figure 6. Simulated urbanization under the influence of the two traffic plans separately or in combination. (I) Simulated urban land without planning policy; (II) simulated urban land under the influence of high-speed railway station planning; (III) simulated urban land under the influence of highway gate planning; (IV) simulated urban land under the influence of high-speed railway station and highway gate planning.

4.1.2 *Accuracy evaluation*

The simulation results were validated using the 'figure of merit' (FoM) (Pontius *et al.* 2008) indicator to reflect cell-level agreement and pattern-level similarity. The FoM is calculated as follows:

$$F = B/(A + B + C + D)$$

where A is the area of error due to observed change predicted as persistence, B is the area corrected due to observed change predicted as change, C is the area of error due to the observed change predicted as change in the wrong category and D is the area of error due to observed persistence predicted as change. The FoM index is superior to the common kappa coefficient for assessing the accuracy of simulated changes (Pontius *et al*. 2004, 2008).

Figure 7 shows the FoM value used in each time period to test the influence of different planning policies on each simulation stage. All FoM values comprise the mean from 10 simulations. By comparison, the simulation results that only consider the planning of high-speed railway stations yield a higher FoM value each year than the FoM value obtained by the simulation pattern without considering any planning components (Figure 7(a)). The simulation under the influence of planned highway gates also obtained better accuracy each year (Figure 7(b)).

These experiments reveal that higher accuracy can be achieved by separately incorporating traffic planning elements into the proposed mechanism. To examine the effect of traffic planning, we test the simulation accuracy under the combined effect of planning highway gates and high-speed railway stations (Figure 7(c)). The combined effect of the two planning factors increases the simulation accuracy; the improvement is stronger than the effect of planning highway gates but is weaker than the effect of

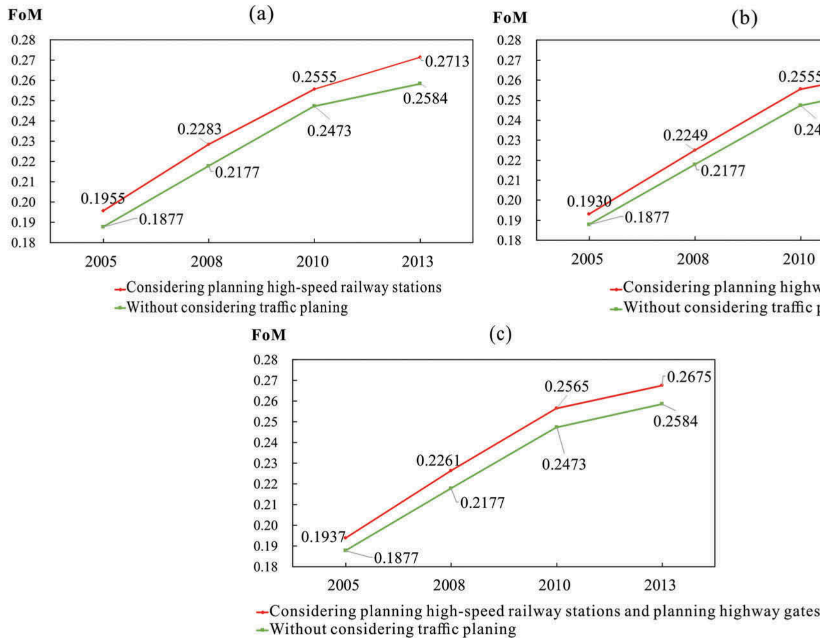

Figure 7. Simulated accuracy (FoM) comparison between simulated urban land without planning policies and (a) simulated urban land under the influence of high-speed railway station planning, (b) simulated urban land under the influence of highway gate planning and (c) simulated urban land under the influence of high-speed railway station and highway gate planning.

planning high-speed railway stations. This demonstrates that the combined effect of various traffic planning points can also help improve the simulation, but only addressing the most appropriate planning traffic point is most likely to achieve better accuracy.

4.1.3. *Analysis of the validation*

It is worth noting that when the combined effect of highway gates and railway stations is considered, the accuracy is lower than when only railway stations are considered. The reason for this result is likely to be the spatial heterogeneity and complexity of the PRD region. Batty *et al*. (1999) noted that cities are complex nonlinear systems involving spatial and sectoral interactions that cannot be easily modeled with the functionalities of current GIS software. In addition, the PRD region is a more complex system that includes nine cities with different development bases, development policies and development orientation. Therefore, under such complex nonlinear systems, the combined effect of multiple planning policies will probably result in some uncertainty regarding land-use change. It is possible that considering more planning factors will not significantly increase the simulation accuracy and may even produce worse results than considering fewer planning factors. A previous study also proved that simulation accuracy can be improved by considering fewer driving factors (Wang *et al*. 2016). However, the simulation accuracy of considering one or two planning factors is higher than without considering any planning driver, which indicates that our update mechanism is effective.

The comparison results suggest the importance of traffic planning in the simulation of future urban growth. Traffic planning points, such as high-speed railway stations or highway gates, are beneficial for improving the simulation accuracy. The simulation that only considers the planning of high-speed railway stations obtains the highest simulation accuracy and exhibits the best increasing trend (Figure 7(a)). The results also indicate that the driving effect of high-speed railway stations on urban development is stronger than the driving effect of highway gates in the PRD region from 2000 to 2013.

However, due to the lack of independent future spatial patterns of land use, it is difficult to calibrate and validate large-scale land-use models in a simulation of the future period (van Asselen and Verburg 2013). However, an evaluation of the simulation can be carried out by (1) conducting a scenario analysis in order to assess the applicability of the model or (2) testing the model performance against available datasets (Alcamo *et al*. 2011). Therefore, the scenario analysis of the simulation will be provided in Section 4.2, and the simulation results will be compared with master plan data in Section 4.3. Although these comparisons cannot be regarded as a full validation, they will provide an indication that the proposed methodology can successfully allocate land-use changes representing regional trends (Alcamo *et al*. 2011).

4.2. *Scenario simulation*

In the future simulation, the amount of future urban land use is first determined by a Markov chain, which has been successfully employed by many simulation studies (Arsanjani *et al*. 2011, Yang *et al*. 2014). The Markov model in this study is implemented to simulate the urban demand from 2013 to 2052 based on the analysis of the urban growth during the 2010–2013 period. The predicted urban areas in 2019 (8830.12 km^2), 2031 (10,150.9 km^2), 2040 (11,433.08 km^2) and 2052 (13,084.55 km^2) are selected to check the influence of planning policy on future urban development at different stages.

According to the comparison analysis, only considering the planning of high-speed railway stations in the PRD region is most likely to obtain the best simulation results. Therefore, this study only considers the planning of high-speed railway stations to project future scenarios. In addition, the priority development zones provided by the master plan in 2020 are addressed in the simulation process of the FLUS model. To better demonstrate the effect of considering planning drivers, we compare and analyze the simulation results with and without planning drivers in this section.

4.2.1. *Addressing the potential effect of traffic planning on the urban PoO*

In the process of spatial simulation, the urban PoO is calculated by a well-trained ANN model based on a land-use map and a set of driving factors in 2013. The PoO without any planning policy and the PoO under the influence of planning high-speed railway stations are depicted in Figure 8(I,II).

Under the effect of planning high-speed railway stations (Figure 8(II)), the urban PoO is more dispersed (Figure 8(I)) and spreads across most of the PRD region. The planning of high-speed railway stations tends to increase the urban PoO. For example, at the Nansha New Area, which is located south of Guangzhou, the urban PoO with the influence of the planning component (Figure 8(a2)) is significantly higher than the

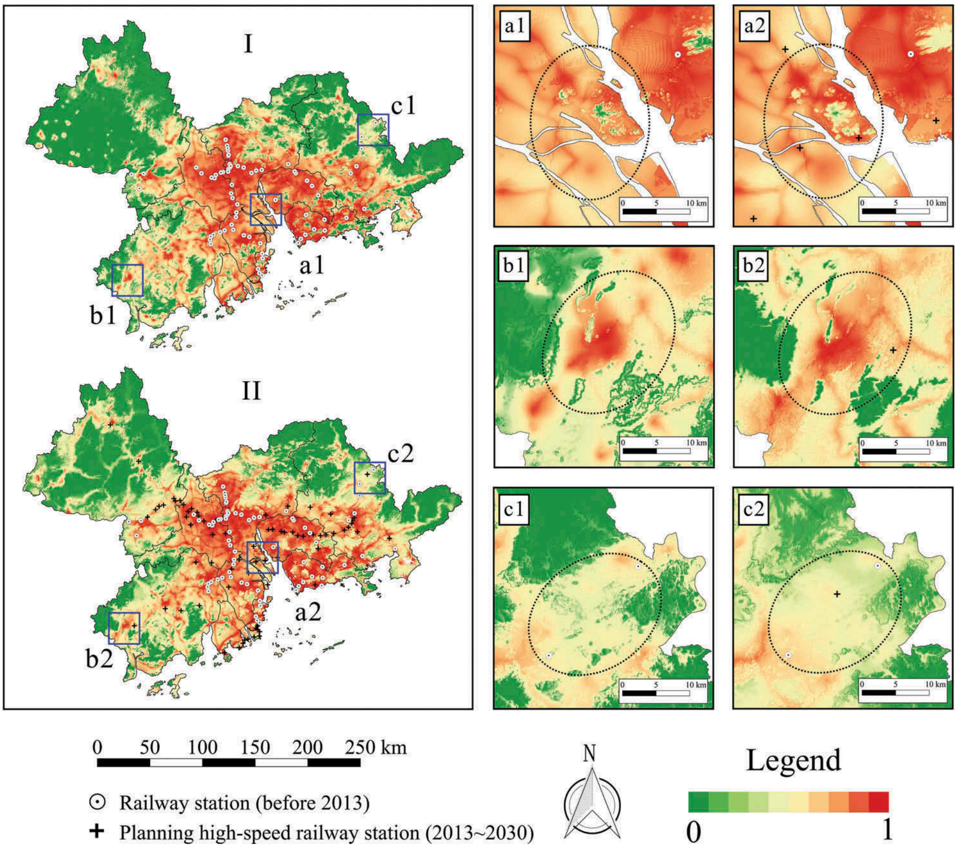

Figure 8. Urban probability-of-occurrence surface for future simulation, (I) PoO without any influence of planning policy; (II) PoO under the effect of high-speed railway station planning.

urban PoO without the influence of a planning policy (Figure 8(a1)), and these results can help simulate the southern development strategy specified by the Guangzhou government. Similarly, the effect of the planned station (Kaiping station) improves the total urban PoO of this region; however, the area near the planned station exhibits minimal signs of growth (Figure 8(b2)). This finding indicates that the influence of the planning policy measured by this method is nonlinear and spatially heterogeneous. This characteristic can also be observed by comparing panels c1 and c2 in Figure 8. This region is located at the edge of the PRD region and is far from the core area. Although a high-speed railway station (North Boluo station) is planned, the urban PoO does not exhibit significant changes around it. The analysis reveals that the proposed method can reflect the spatial heterogeneity and complexity of the planning effects.

4.2.2. *Addressing the effect of the planning development zone on spatial simulation*

In the future simulation from 2013 to 2052, the parameters of the FLUS model that were used to simulate urban growth are the same as the parameters of the validation stage. The basic ecological line policy and the primary farmland policy are considered in the future simulation as the planning constraints. Two scenarios are used for the future simulation. The first baseline scenario (Scenario I) is based on the PoO surfaces without any traffic planning. The second planning scenario (Scenario II) is based on the PoO surfaces under the potential influence of planned high-speed railway stations. Scenario I considers only the planning constraints. Scenario II considers not only the planning constraints but also the planning development zone (Figure 4) and traffic planning (Figure 8(II)). The simulation results in 2019, 2031, 2040 and 2052 are shown in Figure 9.

The comparison between Scenario I and Scenario II indicates that the spatial pattern differences between the two scenarios increase over time. The urban form of Scenario II (a2, c2) is more compact than the urban form of Scenario I (a1, c1), especially the regions of medium and small cities and towns around metropolitan areas (from the comparison between b1 and e1 and between b2 and e2). Because the planning development region attracts more newly developed urban land, the urban development in East Huizhou (Scenario II, d2) is not as fast as the urban development in Scenario I (d1) without any planning impacts. Additional details regarding the differences between the two scenarios are shown in Figure 10.

As depicted in Figure 10(a1,a2), consideration of the planning policies significantly changes the urban form and the development trajectory of the future simulation. Without considering that the planning development zone will produce centralized urban growth in the original urban areas, this phenomenon can be adequately suppressed by considering the planning development zone in the simulation. In the simulation of Scenario II, the area inside the planning development zone is developed at an earlier stage (refer to the simulated urban area from 2013 to 2019 in Figure 10(b1,b2)), which approaches the actual urban growth process, especially in the area in which urban development is significantly impacted by the local government. Under the scenario with the effects of planning policies, more urban growth in the Nansha development zone occurs in the period from 2019 to 2031 (Figure 10(c2)), which is in accordance with the southward development strategy of Guangzhou (http://www.gzlpc.gov.cn/hdjl/zjyj/201802/t20180224_1543000.html). Therefore, the consideration of planning polices not only helps the simulation model trace the real urban development trajectory, but it also improves the model's ability to identify future development hot spots and project complex urban growth patterns, such as enclave-growth and leap-growth.

4.3. *Evaluating the simulated urban area with the master plan*

The simulation results are compared with the master plan data to evaluate the urban growth trend projected by the proposed method and to validate the guiding effect of the planning development zone and traffic planning on urban development. The master plan data are determined by the Guangdong Provincial Government in the Pearl River Delta Region Planning Project from 2014 to 2020. The development of future urban land along the master plan is assessed in this section. Figure 11 shows a comparison of the master plan with the simulated urban land with and without the influence of planning drivers.

The differences between the master plan and the simulated pattern without the planning policy (Figure 11(a1,b1,c1)) in the simulation period are significant. Conversely, under the influence of planning drivers, urban development is similar to the master plan (Figure 11 (a2,b2,c2)) from 2013 to 2031. However, from 2031 to 2052, the amount of simulated urban

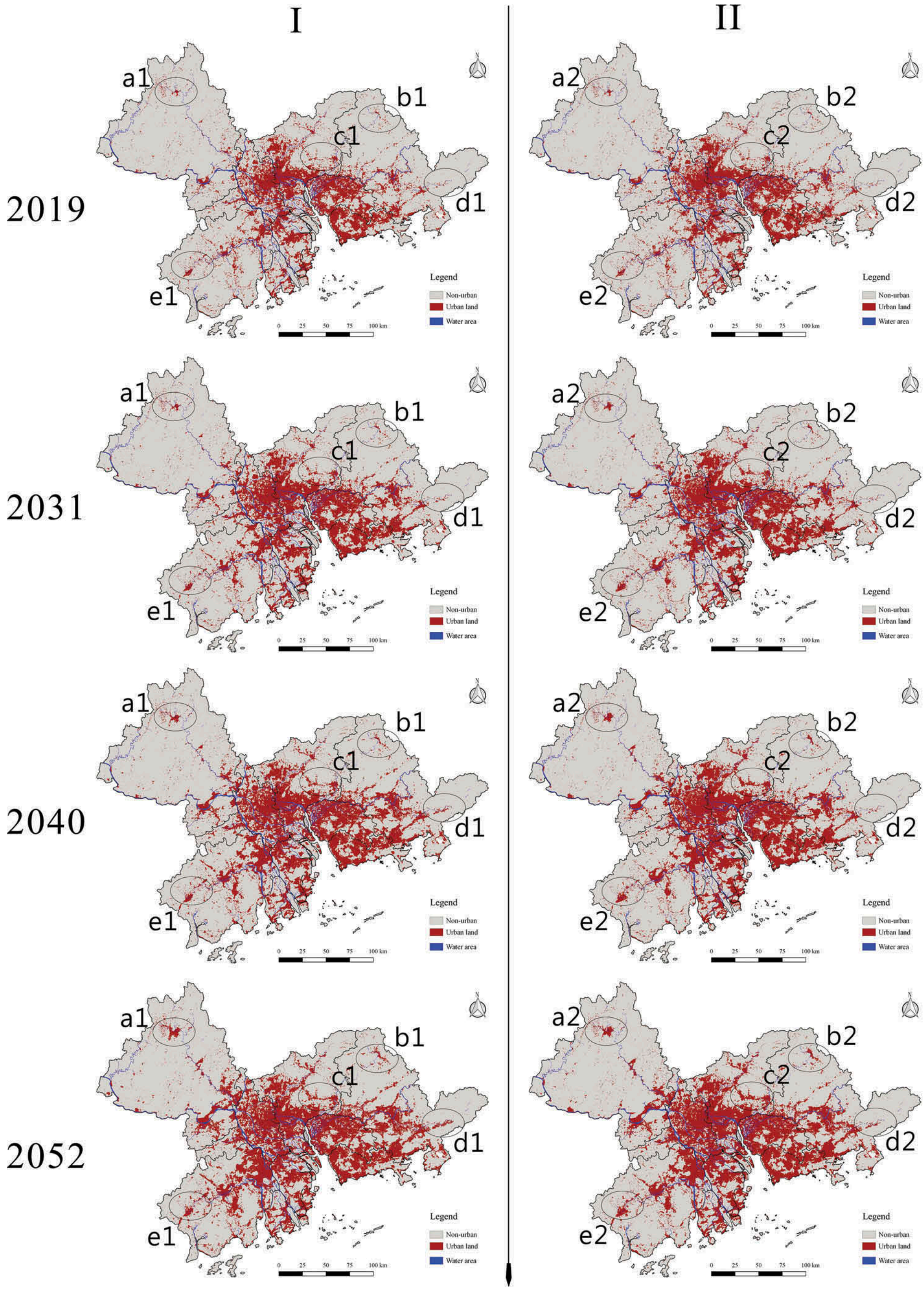

Figure 9. Simulated urban land use from 2013 to 2052. (I) Simulated urban land use without any planning policy; (II) simulated urban land use under the effect of high-speed railway station planning and development zone planning.

land exceeds the urban area determined by the 2020 master plan, which produces future urban patterns in the master planning area (Figure 11(a2,c2)). Although the master plan strongly guides the development of urban land, some regions inside the master planning

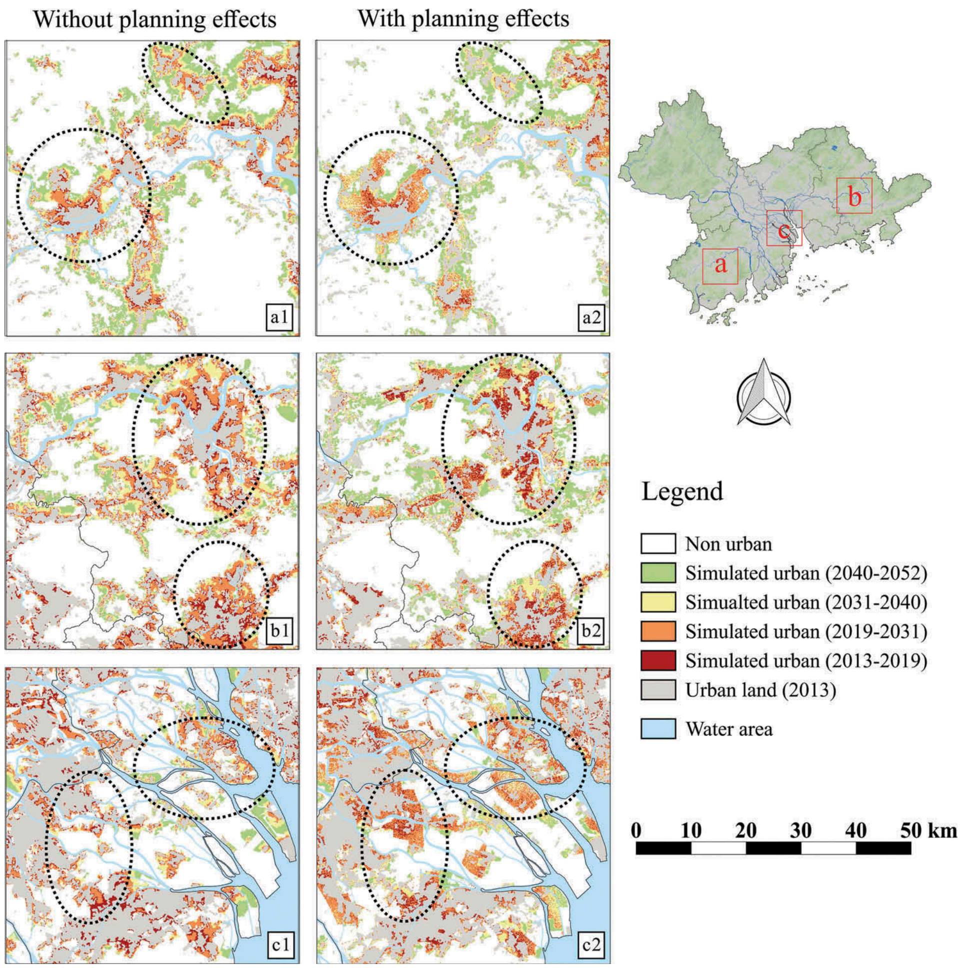

Figure 10. Development trajectories of simulated urban land use from 2013 to 2052 in the three regions in PRD. Panels (a1), (b1) and (c1) show the development trajectory without considering any planning policies; panels (a2), (b2) and (c2) show the development trajectory under the influence of the two planning policies.

area cannot develop into urban areas. Even if the consideration of traffic planning helps the PoO surface (Figure 8(II)) to expand across most of the PRD region, the urban PoO in this region remains too low to plant random urban seeds (Figure 11(a2,b2)). The simulation results under the influence of planning policies show that the urban expansion determined by master planning in 2020 is significantly larger than the simulated urban expansion projected by the FLUS model in the same year. The simulated urban expansion will approach the urban amount and urban form in approximately 2030. This comparison demonstrates that the urban growth simulated by the proposed methods can provide useful information about possible future changes.

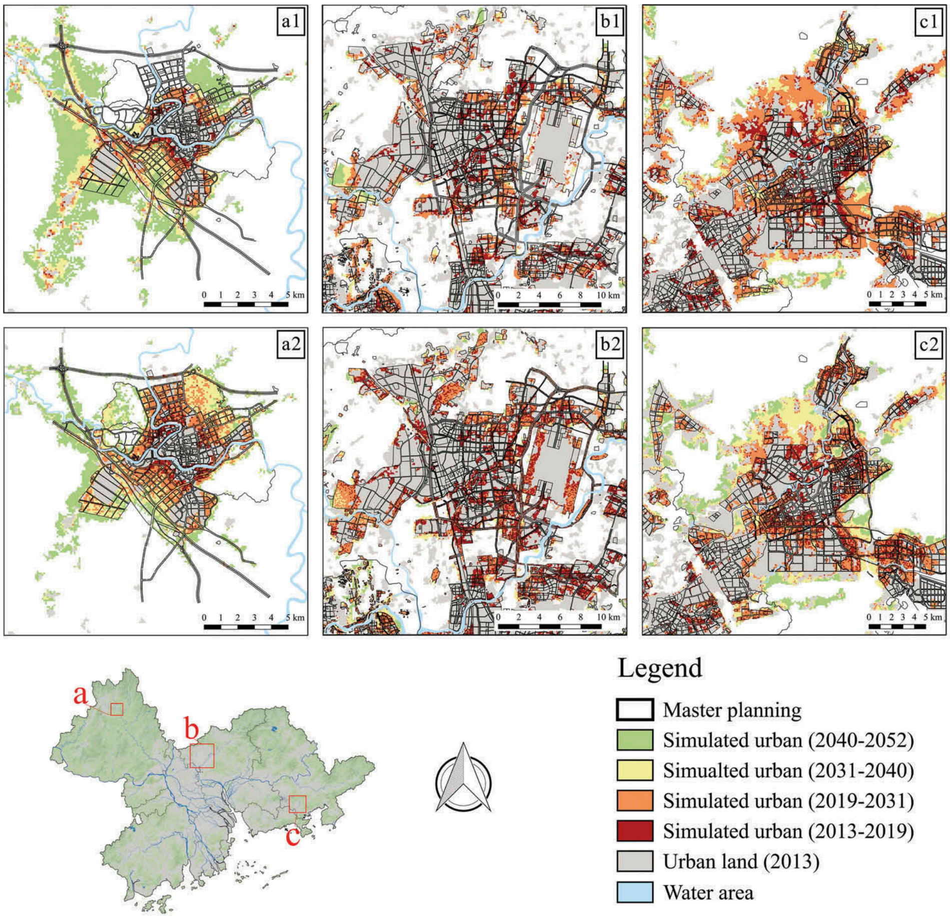

Figure 11. Comparing the simulation results with the master plan. Panels (a1), (b1) and (c1) show the comparison between the master plan and the simulation results without considering any planning policies; panels (a2), (b2) and (c2) display the comparison between the master plan and the simulation results under the influence of two planning policies.

5. Discussion

An important novelty of the methods presented in this article is the consideration of various planning driving factors such as traffic planning and planning development zones. The two proposed mechanisms can be integrated with the FLUS model in this study and with the probability-based traditional CA models (Li and Yeh 2001, Batty 2008, Kamusoko and Gamba 2015). For example, the update mechanism can be addressed in other supervised intelligent algorithms such as RF or SVM algorithms so that the modified RF-CA (Kamusoko and Gamba 2015) or SVM-CA (Ke *et al.* 2017) will be able to consider traffic planning in the simulation. Moreover, the random seeding mechanism can be easily addressed in the transition rules of the probability-based CA model by removing the roulette selection in the mechanism.

In a similar way, the proposed update mechanism can also be applied to probability-based ABMs, such as in the studies by Arsanjani *et al.* (2013) and Tan *et al.* (2015), which calculated the probability of development by using multi-criteria analysis and LR. The random seeding mechanism has the advantage that it does not directly plant urban cells in the study region but only changes the urban probability; the random seeding mechanism can also be transferred to probability-based ABMs, although the spatial processes of ABMs are usually more complex than those of CA models (Li *et al*. 2013).

This work is part of a series of urban growth studies using FLUS models. In the first study (Liu *et al*. 2017b), we proposed the FLUS for multi-type land-use change simulation. This study is the second part, in which we have proposed two mechanisms based on the FLUS model to integrate a set of planning driving effects in urban growth simulation. The validity of the modified FLUS model has been verified through contrast experimentation in this study. In the third study (Liang *et al*. 2018), the modified FLUS model proposed in this study is used to delineate the urban growth boundary, a useful planning policy for managing urban sprawl (Tayyebi *et al*. 2011), by coupling with a novel morphological method based on erosion and dilation. We believe that the FLUS series models can be effective tools for assisting urban planning and decision-making.

6. Conclusion

Planning policies are important factors that influence urban development. How urban growth is impacted by planning policies needs to be understood to better simulate the urban dynamics. In this paper, we present an approach that integrates the effects of various planning policies based on a CA-based land system change model – the FLUS model. To address the planning effects in the simulation in a more objective manner, we modified the original FLUS model by designing an updated mechanism and a random seeding mechanism for considering traffic planning points and planning development zones, respectively.

The proposed model was applied to simulate urban growth in the PRD region from 2000 to 2013 and from 2013 to 2052. We find that a higher simulation accuracy can be achieved by addressing traffic planning in the simulation. The consideration of high-speed railway station planning generates the highest accuracy and improves the performance of the FLUS model by approximately 5% in 2013 (Figure 7(a)). These results demonstrate the need to consider traffic planning in the simulation. Moreover, the simulation results for the future period from 2013 to 2052 indicate that the proposed methods can be effectively used to identify potential urban expansion inside the master plan. The spatial heterogeneity and complexity of the planning effects and a more diverse urban growth pattern can also be explicitly reflected by coupling the proposed mechanisms in the simulation.

In summary, this study explains how to incorporate planning policies into a land-use simulation model. The proposed methods improve the ability of the CA model to identify future development hot spots and to perform simulations that resemble real urban growth trajectories. The simulation results can be employed to evaluate the driving effect of a planning development zone and traffic planning. In short, the proposed mechanisms can help CA models to better simulate complex dynamic urban spatial and temporal changes and accurately predict and explain the development of cities, and these results should provide a valuable reference for future urban planners.

Acknowledgments

We sincerely thank two editors and two anonymous reviewers for their constructive suggestions that significantly strengthened this manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research was funded by the National Key R&D Program of China: [Grant Number 2017YFA0604404] and the National Natural Science Foundation of China: [Grant Number 41671398].

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References

Al-Ahmadi, K., *et al*. 2009. A Fuzzy Cellular Automata Urban Growth Model (FCAUGM) for the City of Riyadh, Saudi Arabia. Part 2: scenario testing. *Applied Spatial Analysis and Policy*, 2 (2), 85–105. doi:10.1007/s12061-008-9019-z

Alcamo, J., *et al*. 2011. Evaluation of an integrated land use change model including a scenario analysis of land use change for continental Africa. *Environmental Modelling & Software*, 26 (8), 1017–1027. doi:10.1016/j.envsoft.2011.03.002

Arsanjani, J.J., Helbich, M., and de Noronha Vaz, E., 2013. Spatiotemporal simulation of urban growth patterns using agent-based modeling: the case of Tehran. *Cities*, 32, 33–42. doi:10.1016/j.cities.2013.01.005

Arsanjani, J.J., Kainz, W., and Mousivand, A.J., 2011. Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. *International Journal of Image & Data Fusion*, 2 (4), 329–345. doi:10.1080/19479832.2011.605397

Barredo, J.I., *et al*. 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning*, 64 (3), 145–160. doi:10.1016/S0169-2046(02)00218-9

Batty, M., 2008. The size, scale, and shape of cities. *Science*, 319 (5864), 769–771. doi:10.1126/science.1151419

Batty, M., Xie, Y., and Sun, Z., 1999. Modeling urban dynamics through GIS-based cellular automata. *Computers Environment & Urban Systems*, 23 (3), 205–233. doi:10.1016/S0198-9715(99)00015-0

Chen, Y., *et al*. 2013. simulating urban form and energy consumption in the pearl river delta under different development strategies. *Annals of the American Association of Geographers*, 103 (6), 1567–1585. doi:10.1080/00045608.2012.740360

Chen, Y., *et al*. 2014. Modeling urban land-use dynamics in a fast developing city using the modified logistic cellular automaton with a patch-based simulation strategy. *International Journal of Geographical Information Science*, 28 (2), 234–255. doi:10.1080/13658816.2013.831868

Chen, Y., *et al*., 2016. Capturing the varying effects of driving forces over time for the simulation of urban growth by using survival analysis and cellular automata. *Landscape & Urban Planning*, 152, 59–71. doi:10.1016/j.landurbplan.2016.03.011

Clarke, K.C. and Gaydos, L.J., 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, 12 (7), 699–714. doi:10.1080/136588198241617

Dai, E., *et al*. 2005. Modeling change-pattern-value dynamics on land use: an integrated GIS and artificial neural networks approach. *Environmental Management*, 36 (4), 576–591. doi:10.1007/s00267-004-0165-z

Dai, G., Salet, W., and Vries, D.J., 2013. Why high-speed railway stations continue China's leapfrog urbanization: institutional parameters of urban development. *China City Planning Review*, 22 (1), 49–59.

Feng, Y., *et al*. 2011. Modeling dynamic urban growth using cellular automata and particle swarm optimization rules. *Landscape and Urban Planning*, 102 (3), 188–196. doi:10.1016/j.landurbplan.2011.04.004

Gong, P. and Chen, J., 2002. Assessment of the urban development plan of Beijing by using a CA-based urban growth model. *Photogrammetric Engineering & Remote Sensing*, 68 (10), 1063–1072.

Gu, C., Xiaohui, Y., and Jing, G., 2017. China's master planning system in transition case study on Beijing. *Paper presented at the 46th ISOCARP Congress*.

Guy, E., Roger, W., and Inge, U., 1997. *Integrating constrained cellular automata models, GIS and decision support tools for urban planning and policy making*. London: E&FN Spon, 125–155.

He, C., *et al*. 2006. Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China. *Applied Geography*, 26 (3–4), 323–345. doi:10.1016/j.apgeog.2006.09.006

He, J., *et al*., 2018. Mining transition rules of cellular automata for simulating urban expansion by using the deep learning techniques. *International Journal of Geographical Information Science*, 32 (10), 2076–2097.

He, J., Huang, J., and Li, C., 2017. The evaluation for the impact of land use change on habitat quality: a joint contribution of cellular automata scenario simulation and habitat quality assessment model. *Ecological Modelling*, 366, 58–67. doi:10.1016/j.ecolmodel.2017.10.001

Huang, J., *et al*., 2018. An ex-post evaluation approach to assess the impacts of accomplished urban structure shift on landscape connectivity. *Science of the Total Environment*, 622-623, 1143–1152. doi:10.1016/j.scitotenv.2017.12.094

Huang, Q., *et al*. 2014. Modeling the impacts of drying trend scenarios on land systems in northern China using an integrated SD and CA model. *Science China Earth Sciences*, 57 (4), 839–854. doi:10.1007/s11430-013-4799-7

Huang, Z., He, C., and Zhu, S., 2017. Do China's economic development zones improve land use efficiency? The effects of selection, factor accumulation and agglomeration. *Landscape and Urban Planning*, 162, 145–156. doi:10.1016/j.landurbplan.2017.02.008

Jjumba, A. and Dragićević, S., 2012. High resolution urban land-use change modeling: agent iCity approach. *Applied Spatial Analysis and Policy*, 5 (4), 291–315. doi:10.1007/s12061-011-9071-y

Kamusoko, C. and Gamba, J., 2015. Simulating urban growth Using a Random Forest-Cellular Automata (RF-CA) model. *Isprs International Journal of Geo-Information*, 4 (2), 447–470. doi:10.3390/ijgi4020447

Ke, X., *et al*. 2017. A CA-based land system change model: LANDSCAPE. *International Journal of Geographical Information Science*, 31 (9), 1798–1817. doi:10.1080/13658816.2017.1315536

Li, S., *et al*. 2013. Simulation of spatial population dynamics based on labor economics and multi-agent systems: a case study on a rapidly developing manufacturing metropolis. *International Journal of Geographical Information Science*, 27 (12), 2410–2435. doi:10.1080/13658816.2013.826360

Li, X., *et al*. 2017. A new global land-use and land-cover change product at a 1-km resolution for 2010 to 2100 based on human–environment interactions. *Annals of the American Association of Geographers*, 107 (5), 1040–1059. doi:10.1080/24694452.2017.1303357

Li, X. and Liu, X., 2006. An extended cellular automaton using case-based reasoning for simulating urban development in a large complex region. *International Journal of Geographical Information Science*, 20 (10), 1109–1136. doi:10.1080/13658810600816870

Li, X., Liu, X., and Yu, L., 2014. A systematic sensitivity analysis of constrained cellular automata model for urban growth simulation based on different transition rules. *International Journal of Geographical Information Science*, 28 (7), 1317–1335. doi:10.1080/13658816.2014.883079

Li, X. and Yeh, A.G., 2000. Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, 14 (2), 131–152. doi:10.1080/136588100240886

Li, X. and Yeh, A.G., 2002. Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, 16 (4), 323–343. doi:10.1080/13658810210137004

Li, X. and Yeh, G.O., 2001. Calibration of cellular automata by using neural networks for the simulation of complex urban systems. *Environment & Planning A*, 33 (8), 1445–1462. doi:10.1068/a33210

Liang, X., *et al*., 2018. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landscape and Urban Planning*, 177, 47–63. doi:10.1016/j.landurbplan.2018.04.016

Lin, Y., *et al*. 2011. Predictive ability of logistic regression, auto-logistic regression and neural network models in empirical land-use change modeling - a case study. *International Journal of Geographical Information Science*, 25 (1), 65–87. doi:10.1080/13658811003752332

Liu, X., *et al*., 2008. A bottom-up approach to discover transition rules of cellular automata using ant intelligence. *International Journal of Geographical Information Science*, 22, 1247–1269. doi:10.1080/13658810701757510

Liu, X., *et al*. 2010. Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata. *International Journal of Geographical Information Science*, 24 (5), 783–802. doi:10.1080/13658810903270551

Liu, X., *et al*. 2014. Simulating urban growth by integrating landscape expansion index (LEI) and cellular automata. *International Journal of Geographical Information Science*, 28 (1), 148–163. doi:10.1080/13658816.2013.831097

Liu, X., *et al*., 2017a. Simulating urban dynamics in China using a gradient cellular automata model based on S-shaped curve evolution characteristics. *International Journal of Geographical Information Science*, 32 (1), 73–101.

Liu, X., *et al*., 2017b. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, 168, 94–116. doi:10.1016/j.landurbplan.2017.09.019

Liu, Y. and Liu, X., 2008. Applying SLEUTH for simulating urban expansion of Hangzhou. *Journal of Natural Resources*, 7471 (5), 797–807.

Long, Y., *et al*., 2013. Urban growth boundaries of the Beijing metropolitan area: comparison of simulation and artwork. *Cities*, 31, 337–348. doi:10.1016/j.cities.2012.10.013

Lu, C., *et al*., 2013. Driving force of urban growth and regional planning: a case study of China's Guangdong Province. *Habitat International*, 40, 35–41. doi:10.1016/j.habitatint.2013.01.006

Pekel, J., *et al*. 2016. High-resolution mapping of global surface water and its long-term changes. *Nature*, 540 (7633), 418–422. doi:10.1038/nature20584

Pijanowski, B.C., *et al*. 2005. Calibrating a neural network-based urban change model for two metropolitan areas of the Upper Midwest of the United States. *International Journal of Geographical Information Science*, 19 (2), 197–215. doi:10.1080/13658810410001713416

Pontius, R.G., *et al*. 2008. Comparing the input, output, and validation maps for several models of land change. *The Annals of Regional Science*, 42 (1), 11–37. doi:10.1007/s00168-007-0138-2

Pontius, R.G., Huffaker, D., and 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

Sohl, T. and Sayler, K., 2008. Using the FORE-SCE model to project land-cover change in the southeastern United States. *Ecological Modelling*, 219 (1–2), 49–65. doi:10.1016/j.ecolmodel.2008.08.003

Sun, H., 2016. Study on the correlation between the hierarchical urban system and high-speed railway network planning in China. *Frontiers of Architectural Research*, 5 (3), 301–318. doi:10.1016/j.foar.2016.04.003

Tan, R., *et al*., 2015. A game-theory based agent-cellular model for use in urban growth simulation: a case study of the rapidly urbanizing Wuhan area of central China. *Computers, Environment and Urban Systems*, 49, 15–29. doi:10.1016/j.compenvurbsys.2014.09.001

Tayyebi, A., Pijanowski, B.C., and Tayyebi, A.H., 2011. An urban growth boundary model using neural networks, GIS and radial parameterization: an application to Tehran, Iran. *Landscape and Urban Planning*, 100 (1–2), 35–44. doi:10.1016/j.landurbplan.2010.10.007

Tian, L. and Shen, T., 2011. Evaluation of plan implementation in the transitional China: a case of Guangzhou city master plan. *Cities*, 28 (1), 11–27. doi:10.1016/j.cities.2010.07.002

van Asselen, S. and Verburg, P.H., 2013. Land cover change or land-use intensification: simulating land system change with a global-scale land change model. *Global Change Biology*, 19 (12), 3648–3667. doi:10.1111/gcb.12331

Verburg, P.H. and Overmars, K.P., 2009. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. *Landscape Ecology*, 24 (9), 1167–1181. doi:10.1007/s10980-009-9355-7

Wang, Y.X., *et al*., 2016. Simulation of land use dynamic change using selected driving factors based on the method of feature selection. In *International Conference on Materials Engineering, Manufacturing Technology and Control*.

Wang, Z., *et al*., 2017. Spatiotemporal variability of reference evapotranspiration and contributing climatic factors in China during 1961–2013. *Journal of Hydrology*, 544, 97–108. doi:10.1016/j.jhydrol.2016.11.021

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

Yang, Q., Li, X., and Shi, X., 2006. Cellular automata for simulating land use changes based on support vector machines. *Journal of Remote Sensing*, 34 (6), 592–602.

Yang, X., Zheng, X.Q., and Chen, R., 2014. A land use change model: integrating landscape pattern indexes and Markov-CA. *Ecological Modelling*, 283 (7), 1–7. doi:10.1016/j.ecolmodel.2014.03.011

Yao, Y., *et al*. 2017a. Simulating urban land-use changes at a large scale by integrating dynamic land parcel subdivision and vector-based cellular automata. *International Journal of Geographical Information Science*, 31 (12), 2452–2479. doi:10.1080/13658816.2017.1360494

Yao, Y., *et al*. 2017b. Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. *International Journal of Geographical Information Science*, 31 (4), 825–848. doi:10.1080/13658816.2016.1244608

Yeh, A.G. and Li, X., 1999a. Economic development and agricultural land loss in the pearl river delta, China. *Habitat International*, 23 (3), 373–390. doi:10.1016/S0197-3975(99)00013-2

Yeh, A.G. and Li, X.Y., 1998. Sustainable land development model for rapid growth areas using GIS. *International Journal of Geographical Information Science*, 12 (2), 169–189. doi:10.1080/136588198241941

Yeh, G.O. and Li, X., 1999b. Economic development, urban sprawl, and agricultural land loss in the pearl river delta,China. *Economic Geography*, 19 (1), 67–72.

Yu, Le., Wang, J., and Gong, P., 2013. Improving 30 m global land-cover map FROM-GLC with time series MODIS and auxiliary data sets: a segmentation-based approach. *International Journal for Remote Sensing*, 34 (16), 5851–5867. doi:10.1080/01431161.2013.798055

Zhang, X., *et al*., 2015. Proximate control stream assisted video transcoding for heterogeneous content delivery network. In *IEEE International Conference on Image Processing*, 2552–2555.