Landscape and Urban Planning 177 (2018) 47–63

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method

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ARTICLE INFO

Keywords:
Urban growth boundaries (UGBs)
UGB-FLUS model
Planning scenarios
Cellular automata
Erosion and dilation

ABSTRACT

Urban growth boundaries (UGBs) have been commonly regarded as a useful tool for controlling urban sprawl. There is a need to create models that can establish plausible UGBs for fast growing regions. Previous methods have merely focused on establishing a single UGB scenario over different time intervals, but rarely considered the influences of macro policy (e.g., future urban demand) and spatial policy (e.g., master plan) for regional planning. However, the spatial patterns of urban expansion are significantly affected by regional planning. In this paper, a CA-based method called the future land use simulation (FLUS) is applied to the delineation of UGBs. We argue that the delineation needs to integrate the top-down approach with CA for projecting complex land use changes under designed scenarios. The system dynamics model (SD) and cellular automaton model (CA) were interactively coupled in the FLUS model during the projection period. The top-down SD is used to project scenarios that relate to macro policy and socioeconomic status, and the bottom-up CA accounts for urban growth simulations under the influence of different driving factors and spatial planning policies. A morphological technology based on erosion and dilation is further proposed to generate the UGBs from the FLUS model's simulated urban forms. The proposed UGB-FLUS model was applied to the establishment of UGBs in the Pearl River Delta region (PRD) from 2020 to 2050. The results demonstrate that the method can support urban planning by generating feasible patterns for UGBs under different planning scenarios.

1. Introduction

Urban sprawl, which arises from the rapid growth of the economy and population, has become a major challenge for sustainable urban development worldwide (Yao et al., 2016, 2017; Hashem & Balakrishnan, 2015; Liu et al., 2014). For assisting urban planning, methods or models are required to guide and constrain urban area growth (Long, Han, Lai, & Mao, 2013). Urban growth boundaries (UGBs) have been a common tool used by planners to control urban development in open spaces, protect superior rural areas that make significant contributions to the urban environment from development, and promote efficiency in urban management, especially where there is residential development in established and planned suburban areas (Gennaio, Hersperger, & Burgi, 2009). Moreover, this planning tool is also important for increasing the density of urban services and reducing urban infrastructure costs (Tayyebi, Perry, & Tayyebi, 2014). A recent study was carried out by Long, Han, Tu, and Shu (2015) regarding planner designed UGBs, and they reported that UGBs were effective in containing human mobility and activity. In addition, the control function of UGBs increases over time during urban development, and the effect of UGBs is clearly stronger in exurban areas than in central urban (Long, Gu, & Han, 2012). Therefore, the UGBs will play an increasingly important role in the future of new urban land management.

UGBs are most often established in high growth areas such as metropolitan areas. The earliest UGB can be traced back to the green belt in London in the 1930s (Nelson & Moore, 1993). In recent decades, UGBs were first adopted widely in the United States (Hepinstallcymerman, Coe, & Hutyra, 2011; Jun, 2004) and then, they were gradually brought into other countries such as China (Han, Lai, Dang, Tan, & Wu, 2009), India (Venkataraman, 2013), Canada (Gordon & Vipond, 2005), Albania (Carter, 1992), Australia (Coiacetto, 2007), Switzerland (Gennaio et al., 2009), etc. To date, UGBs are being used by

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https://doi.org/10.1016/j.landurbplan.2018.04.016
Received 23 September 2017; Received in revised form 8 February 2018; Accepted 30 April 2018

an increasing number of local governments in various countries around the world to direct urban growth (Ma, Li, & Cai, 2017). As UGBs attract an increasing amount of attention, there are also a growing number of requirements to develop efficient and feasible techniques to define those boundaries for different applications. However, many UGBs are delineated by conventional methods that are only based on the personal experience of planners, which may lead to the lack of an adequate scientific basis and quantitative support (Long et al., 2013). Land use suitability evaluation models used to evaluate UGBs based on a series of spatial factors, e.g., topography and traffic conditions (Cerreta & Toro, 2012) have also been widely used in previous studies (Bhatta, 2009). Although easy to implement, these methods ignore the urban landscape characteristics, which will have negative effects for establishing elaborate urban boundaries (Cao, Huang, Wang, & Lin, 2012; Ma et al., 2017). Moreover, many geographic factors that drive urban change operate across different spatial and temporal scales in a very complex way (Tayyebi, Pijanowski, & Pekin, 2011; Tayyebi, Pijanowski, & Tayyebi, 2011). Suitability evaluation models commonly fail to reflect these relationships and interactions, which may result in UGBs failing to realistically accommodate future urban expansion (Tayyebi, Pijanowski, & Pekin, 2011; Tayyebi, Pijanowski, & Tayyebi, 2011).

To overcome the disadvantages of the abovementioned studies, many researchers have established UGBs by adopting the cellular automaton (CA) model. The CA model differs from previous models (manual method and suitability evaluation model) in its ability to represent spatial interactions implemented in the immediate neighborhood or the hierarchical structure of the neighborhood (Li et al., 2017a). CA can simulate the dynamics of urban growth at the landscape level (Verburg & Overmars, 2009). Through iterations and updates, CA can efficiently incorporate the interactions between urban growth and its corresponding geographic driving factors (Clarke & Gaydos, 1998). Thus, by using the CA model, UGBs can be generated from the simulation results in these studies. For example, Tayyebi, Pijanowski, & Pekin, 2011; Tayyebi, Pijanowski, & Tayyebi, 2011 proposed two rule-based CA models for the Tehran metropolitan area, which can directly predict the size and shape of urban boundaries. Long et al. (2012) delimited UGBs for the Beijing region using a constrained CA and compared the results to those established in the city master plan. The results show that CA is a helpful planning tool for the establishment of UGBs. Some of the researchers have tried to combine CA with intelligent algorithms such as logistic regression (Hu & Lo, 2007), artificial neural networks (Tayyebi, Pijanowski, & Pekin, 2011; Tayyebi, Pijanowski, & Tayyebi, 2011), particle swarm optimization (Feng, Liu, Tong, Liu, & Deng, 2011), and ant colony optimization algorithms (Ma et al., 2017). In addition, a recent study also proposed CA models based on partial least squares (PLS-CA) regression or generalized pattern search (GPS-CA) which can better explain the dependent variables and reduce simulation uncertainties. These CA models also have great potential to improve the CA-based UGB delineating method (Feng, 2017; Feng, Liu, Chen, & Liu, 2016). In summary, the use of these intelligence algorithms allows CA models to simulate the local interaction between land use patterns and various driving factors (Li & Yeh, 2002; Lin, Chu, Wu, & Verburg, 2011; Liu, Xia, Shi, Zhang, & Chen, 2010).

CA-based UGB models have made superior progress compared to previous UGB methods. However, the spatial patterns of urban expansion are significantly affected by regional planning on both regional and local scales (Lu, Wu, Shen, & Wang, 2013; Tian & Shen, 2011). Most of the previous UGB models only focused on the local “bottom-up” effect of the CA model but ignored the “top-down” effect at the regional scale. The large-scale influences usually refer to the future demand for economic development and population increase that determine the future amount of urban land in a region (Verburg & Overmars, 2009). The local effects are indicative of interactions and feedback between land use patterns and multiple spatial driving forces, which include the road network, geographical locations, terrain conditions, etc. (van Asselen & Verburg, 2013; Verburg, 2006; Verburg, Ellis, & Letourneau, 2011). On both scales, these effects are influenced by the development policies of a region (Gao, Wei, Chen, & Chen, 2014), and the urban area dynamics are largely determined by forces that are exogenous to land allocation. Therefore, the influence of regional planning on both scales should be considered by coupling the “bottom-up” CA model with a ‘top-down’ approach (Verburg, van de Steeg, Veldkamp, & Willemen, 2009; Xiang & Clarke, 2016). However, there are no previous studies that attempted to build a UGB model by integrating both the macro urban demand and local dynamics.

Additionally, the ways in which different planning policies influence the spatial patterns of urban areas and future UGBs under various scenarios is of great importance for decision makers to assess the outcome and impact of different policies (Chen, Li, Liu, & Ai, 2014). For example, Long et al. (2012) incorporated urban planning to simulate a planning-strengthened scenario in Beijing to help illustrate the impact of urban planning on urban expansion. In addition, considering planning factors in the urban simulation can be employed by decision makers in the early stages of policy making; this operation provides an inexpensive and effective way for planners to obtain helpful information about the influences of different development policies or planning scenarios on urban development, which may prevent poor urban designs (Clarke, 2014). With this information, planners can better adjust the direction of urban development by modifying corresponding planning factors and planning policies, as well as delineating more appropriate UGBs. Most of the previous research only attempted to build UGBs under a single scenario, in specific time nodes or by a set of model parameters (Ma et al., 2017; Tayyebi et al., 2014; Inkoom, Nyarko, & Antwi, 2017). However, a very limited number of studies have tried to establish UGBs for large-scale and fast-developing areas under various planning scenarios. Another challenge in delineating UGBs is that some cities with amazing development speed show fractal characteristics in urban land forms, spatial form and landscape organization (Yuan, 2005). An example of this is the Pearl River Delta area in China. This results in UGBs in these areas potentially comprising numerous polygons and even showing a dispersed form. When delimiting the UGBs, polygons with low compactness and a small area should be eliminated, as they are not feasible for urban development. This indicates that the results of the simulation model cannot be directly used as final UGBs. Previous studies established UGBs based on CA simulation, which was mainly through manual modification (Long et al., 2013). Such modification is quite subjective and inconvenient to use. The effective establishment of UGBs from the CA model simulation results remains unresolved for practical problems.

In this paper, a novel UGB delineation framework is presented, in which UGB-FLUS is proposed to tackle these problems. This framework is implement by two steps: 1) urban growth simulation with a future land use simulation (FLUS) model and 2) delineating UGBs based on the simulated urban growth. The FLUS model is a CA-based method that is integrated with a top-down approach to solve UGBs problems. This FLUS model has been proven effective for projecting complex land use changes under various design scenarios (Liu, Liang, Li, & Xu, 2017). By using this FLUS model, the visions of planners can be embedded as the constraints or drivers for creating UGBs. In the second step, we proposed a component based on the theory of erosion and dilation to improve the effects of generating plausible UGBs from the simulation results, because traditional methods cannot effectively remove the small and dispersed urban patches. This method is used to merge and connect the cluster of urban blocks into one large area and simultaneously eliminate the small and isolated urban patches. The application of this proposed framework is carried out in the Pearl River Delta (PRD), which is one of the fastest growing regions in China.

2. Methods

The UGB-FLUS framework involves several techniques. First, a spatial simulation model based on the theory of cellular automaton

(CA)—the FLUS model (Liu et al., 2017)—is used to project the spatial distribution changes in urban land use for the PRD region. This model has been successfully tested in the simulation of land use and land cover change in China (Liu et al., 2017), as well as on the global scale (Li et al., 2017b). In this study, we further modify the FLUS model so that it can be suitable for UGB delineation. The improvement includes the use of morphological erosion and dilation to generate plausible UGBs.

2.1. The FLUS model

As a CA-based model, the FLUS model can represent spatial interactions that are implemented in the neighborhood and adequately incorporate the feedback between system elements through iterations and updates, as does the traditional CA. However, the conversion rules of the CA model can be very complex in urban simulations under the influence of various driving factors, both at the large and local scales. Thus, we implement three steps in the FLUS model to handle such complexity: 1) a "top-down" land use demand model using system dynamics (SD); 2) a "bottom-up" spatial modeling component using cellular automaton (CA); and 3) an integration mechanism to interactively couple the above two steps. The large-scale information from the SD module is used to constrain the spatial modeling at each time interval.

2.1.1. Land use demand projection using system dynamics (SD)

The SD model is characterized by its ability to simulate and analyze the behavior of complex systems through feedback loops between different modules and variables. The land use system is complex and is influenced by many anthropogenic and biophysical driving forces. Thus, the interactions between the physical components, socio-economic change, and managerial policies to create future urban growth can be understood by establishing an urban growth SD model (Liu, Ou, Li, & Ai, 2013). Currently, the SD model is widely applied for exploring the influence of policy making on urban growth.

In this study, an SD model is developed to project the future demands of urban growth under different scenarios by taking a series of factors (e.g., population, macroeconomic drivers and technological progress) into account that are associated with urban growth. The feedback and interactions between different elements of the SD model can be defined by empirical formulas or tables that are fitted with the statistical data in this study (Liu et al., 2013). Data for building the inside empirical formulas of the SD model are from statistical yearbooks from the study region in recent years. The material and information flow of the developed SD model are presented in Fig. 1.

Three tightly coupled sub-modules consist of the urban growth SD model, the population module, the economy module and the land use module. In this model, the population, GDP (gross domestic product) and technical progress act as the three most essential indicators that directly or potentially affect the change in industry and service investments, and they will ultimately affect the amount of urban areas soon. In the land use sub-model, urban land is assumed to be composed of three parts: residential, industrial, and commercial land. Each subcategory of urban land is separately linked to the population module or economic module. The structure of the proposed SD model can help decision makers understand how the physical processes, information flow, and planning policies interact to create the dynamics of urban growth.

2.1.2. Urban growth allocation using cellular automaton (CA)

A modified CA model that is quite different from the traditional CA is implemented to explicitly simulate the long term spatial trajectories of urban growth (Fig. 2). The CA allocation method is implemented in two steps: 1) an artificial neural network is used to train and estimate the probability-of-occurrence surfaces for urban land on a specific grid cell, and 2) an elaborate self-adaptive inertia and competition mechanism addresses the competition and interaction among urban land and non-urban land.

We chose to base FLUS on an ANN (artificial neural network) because the ANN algorithm was proven to be an effective way to map the complex, nonlinear relationship between historical land use and various ancillary data sources, and it is stronger than other simple methods such as the logistic regression (Lin et al., 2011; Zhang, Li, Li, Zhao, & Zhang, 2015). Through the application of the ANN model, the institutional factors, market incentives, road planning, traffic site planning, etc. can be regarded as components for generating a probability-of-occurrence surface for future urban forms. In addition, the placement of changes in land use distribution is guided by the value of the probability-of-occurrence surface on each pixel. In this study, the ANN model will be trained with the current driving forces, and then, the future traffic networks (including the planning traffic network) are considered by replacing the current traffic networks in the prediction process of the ANN model. A similar operation to address the future changes in driving factors has been adopted in the CLUE-s series model (Verburg et al., 2002).

In the second step, the mechanism of self-adaptive inertia and competition is adopted in the FLUS modeling process. This can enhance the model's ability to simulate randomness and uncertainty in land use change and strengthen the connection between "top-down" effects from land use demands and "bottom-up" influences from local scale competition. In this mechanism, we define a self-adaptive inertia coefficient to auto-adjust the inheritance of the urban land on each grid cell, which is according to the differences between future urban areas and current urban areas (iteratively changed). This coefficient is defined as follows:

$$Inertia_k^t = \begin{cases} Inertial_k^{t-1} & \text{if} \quad |D_k^{t-1}| \leqslant |D_k^{t-2}| \\ Inertial_k^{t-1} \times \frac{D_k^{t-2}}{D_k^{t-1}} & \text{if} \quad 0 > D_k^{t-2} > D_k^{t-1} \\ Inertial_k^{t-1} \times \frac{D_k^{t-1}}{D_k^{t-2}} & \text{if} \quad D_k^{t-1} > D_k^{t-2} > 0 \end{cases} \tag{1}$$

where k is a value of 1 or 2, which means that only two land uses (urban land and non-urban land) are considered in the simulation. $Inertia_k^t$ represents the inertia coefficient for land use type k at iteration time t. The D_k^{t-1} represents the difference between land use demand and allocated area at time t − 1. because the inertia coefficient is only defined for the land use type occupying the grid cell, if the potential land use type k is not the same as the current land use type c, the inertia coefficient of land use k will be defined as 1 and will have no effect on the total probability of land use type k for this grid cell.

Through these two steps, the combined probability of all land use types at each specific grid cell can be estimated with the following equation:

$$TP_{i,k}^t = P_{i,k} \times \Omega_{i,k}^t \times Inertia_k^t \times con_{c\rightarrow k} \tag{2}$$

where $TP_{i,k}^t$ is the combined probability of grid cell i for conversion from the original land use into the target k at iteration time t (only non-urban land can be converted to urban land in this study); $P_{i,k}$ denotes the probability-of-occurrence of land use type k on grid cell I, which was generated by the ANN algorithm; $\Omega_{i,k}^t$ denotes the neighborhood effect of land use type k on grid cell i at time t; and $con_{c\rightarrow k}$ is a transition matrix that defines the possibility of conversion from the original land use type c to the target k (1 denotes possible conversion and 0 denotes impossible conversion).

A roulette selection mechanism is developed to establish the competition between different land uses after estimating the combined probability. In this study, the comparison is between urban land and non-urban land. Through a roulette selection, a land use category with a higher value of combined probability is more likely to change, but those with relatively lower values still have a chance to convert. Thus, the diversity, uncertainty, and complexity of land use change is reflected. This mechanism is important for simulating the leapfrog growth of urban land that may appear in urban development (Chen, Li, Liu, Ai, &

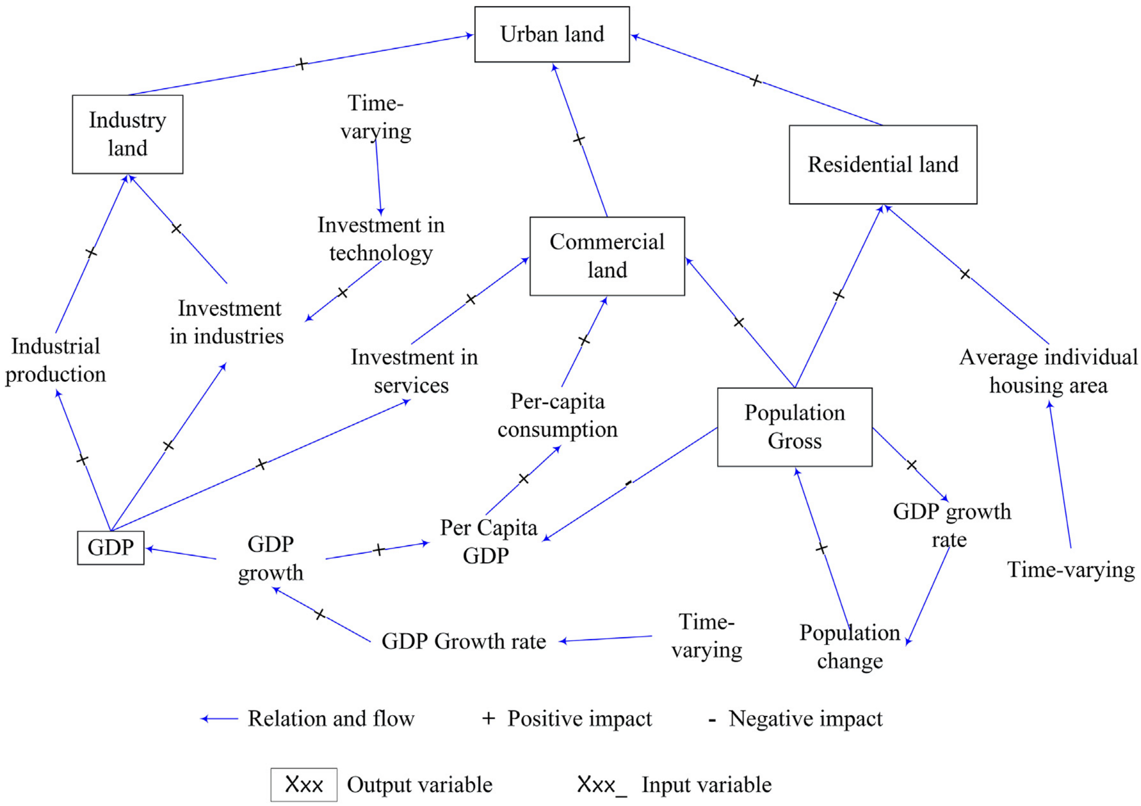

Fig. 1. The interactions between different factors in the system dynamics.

Li, 2016). In addition, to model the driving effects of planning urban areas (e.g., priority development region or urban area in the master plan), random planted seeds (Chen et al., 2014, 2016; Clarke & Gaydos, 1998), which is based on probability-of-occurrence (Chen et al., 2014, 2016) are sent to the future urban areas, and thus, the new urban land is more likely to spread out from the seeds in planning urban areas. The schematic diagram of the spatial allocation of the FLUS model is shown in Fig. 2.

2.1.3. Integration of the SD model with the CA model

In the FLUS model, two primary modules are tightly integrated to facilitate the simulation of urban growth (Fig. 3). To exclude such integration, the FLUS model divides the simulation period into many intervals (e.g., each interval lasts for one year). The future land use demand comes from the SD model in the current interval that is used to guide the CA model simulation until the urban growth meets the current demand. Then, the simulated land use pattern from the previous time node, together with the driving factors in the new stage, are used to project the land use change in the next interval under the guidance of land use demand. This reciprocal interaction continues throughout the simulation period and generates the final spatial characteristics of urbanization. The tight coupling between the SD and CA models helps the FLUS model to be more effective in projecting the cross-scale dynamics, as well as more reliable in simulating long term land use change (Liu et al., 2017).

2.2. Delineating the UGBs based on the simulation results

This article establishes UGBs from the simulation results of the FLUS model by applying the combination of two very common morphology operators, dilation and erosion. It is a novel method that applies a closing operation followed by an opening operation based on dilation and erosion and has been proposed for UGB delineation. An erosion followed by a dilation constructs an opening operation. In contrast, a closing operation is a dilation step followed by an erosion step. The general structure of the UGB delineation method is illustrated in Fig. 4.

2.2.1. The dilation and erosion

The morphology-based dilation and erosion has a strong mathematical basis in set theory. The dilation of a set of points X by a structuring element B is defined (Narayanan, 2006) as follows.

$$X \oplus B = X + b = \{ x + b : (x \in X) \& (b \in B)\} \tag{3}$$

Erosion is the dual of dilation. The erosion of a set of points X by a structuring element B is defined as follows.

$$X \ominus B = X - b = \{z : (B + z) \subseteq X\} \tag{4}$$

where X is the binary simulation that only includes urban and non-urban land. The structuring element B is an n × n (n is an odd number) sliding window, but the four pixels at the corners of the square are not included (Fig. 4). This structuring element shape makes the boundaries of dilation or erosion less rectangular and closer to the approximate border lines of urban blocks. The origin of the structuring element moves through the urban pixels during the erosion process. If not all pixels in the structuring element are urban pixels, the urban pixels at the origin of the structuring element will be removed during the erosion process. In contrast, the dilation process turns all the non-urban pixels in the structuring element into urban pixels when the origin of the structuring element moves around the urban pixels.

Erosion can remove the small and dispersed urban patches with low compactness because a very small urban patch is not feasible for designating UGBs. In addition, dilation can bridge the gaps and connect the clusters of urban blocks that are suitable for incorporation into UGBs.

2.2.2. Opening and closing

However, the delineation of UGBs should meet the above two requirements (delete isolated patches and fill gaps between urban clusters). Therefore, we need to use the dilation and erosion methods in

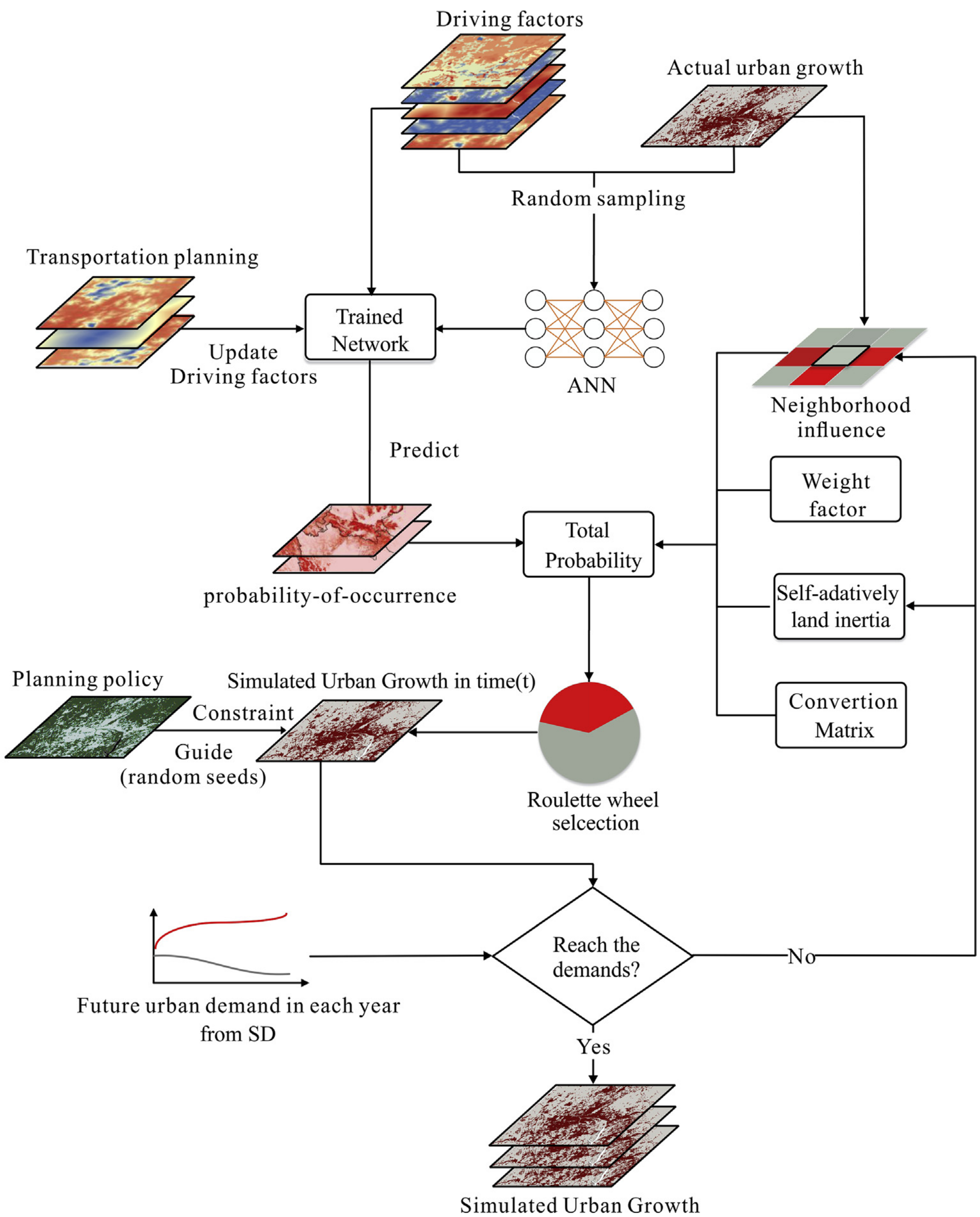

Fig. 2. The schematic framework of the cellular automaton (CA) local allocation.

combination. The application of an erosion followed by a dilation using the same structuring element is referred to as an opening operation. The erosion step in an opening will remove isolated urban patches, as well as the boundaries of urban blocks, and the dilation step will restore most of the boundary pixels without restoring the noise. Opening tends to "open" small gaps or spaces between objects touching in an image. Opening is defined by the following equation:

$$X\circ B = (X\ominus B)\oplus B \tag{5}$$

Closing is similar to opening except that the dilation is first performed, which is followed by the erosion using the same structuring element. A closing is more effective at filling small gaps in an image and "closing" them. Closing is defined by the following equation:

$$X\cdot B = (X\oplus B)\ominus B \tag{6}$$

The opening operation tends to shrink the urban pixels, because the substance of the opening is the intersection between X and B. Instead, the closing operation creates the union of X and B, and thus, this expands the number of urban pixels. Both operations can smooth object boundaries in an image.

Because opening and closing have their specific functions mentioned above, this study first applied the closing operation to connect the adjacent urban blocks, and then, the opening is used to delete the isolated small urban parcels that are not appropriate for delineation into UGBs. In theory, the combination of opening and closing can ensure the final UGB area will not heavily deviate from the planning target.

3. Study area and data sources

3.1. Study area

The PRD region is in southern China and encompasses an area of 54,000 km^2; it is widely recognized as one of the most developed regions in China (Fig. 5). Since the implementation of reform and opening in recent decades, the PRD region has successfully developed into an economic, cultural and traffic center for south China. At the same time, the PRD has experienced rapid urbanization with the fast growth of GDP and population. Thereby, this raises a series of land use problems such as the permanent loss of agricultural land (Yeh & Li, 1997a,b),

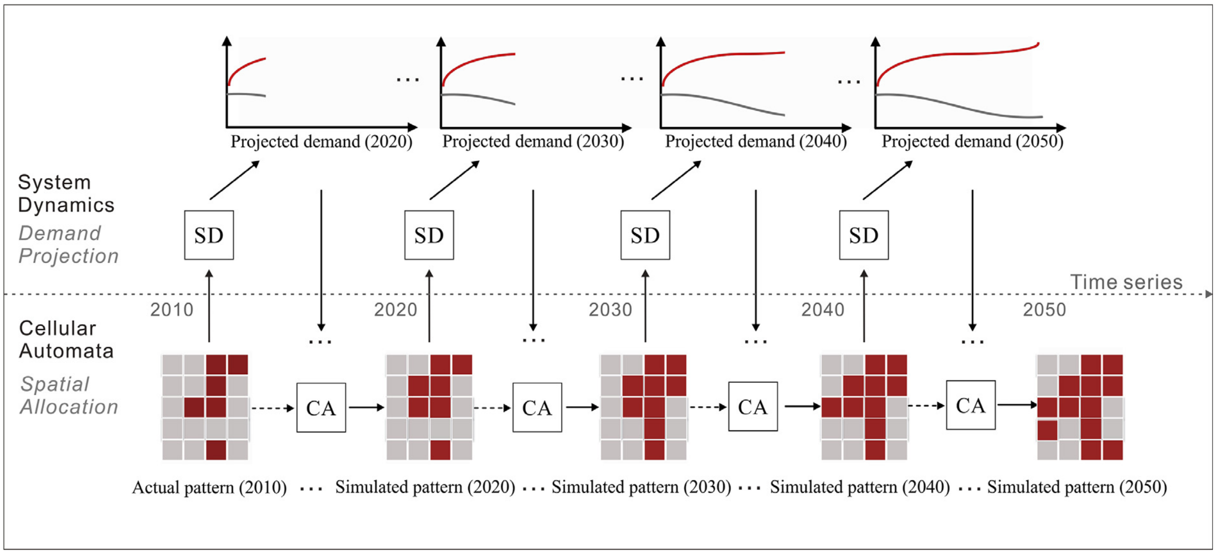

Fig. 3. Interactive coupling mechanism of the SD and CA models.

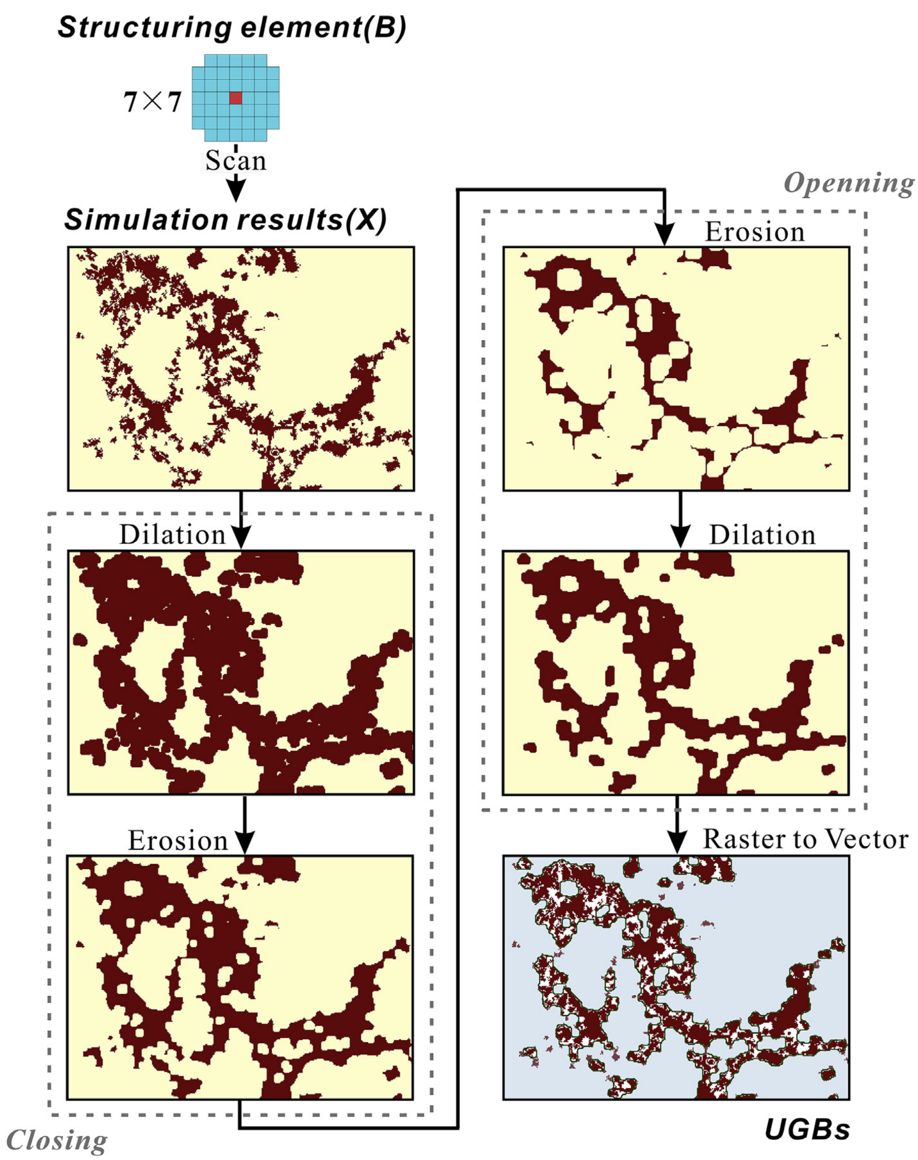

Fig. 4. Flow diagram of the morphological method based on erosion and dilation.

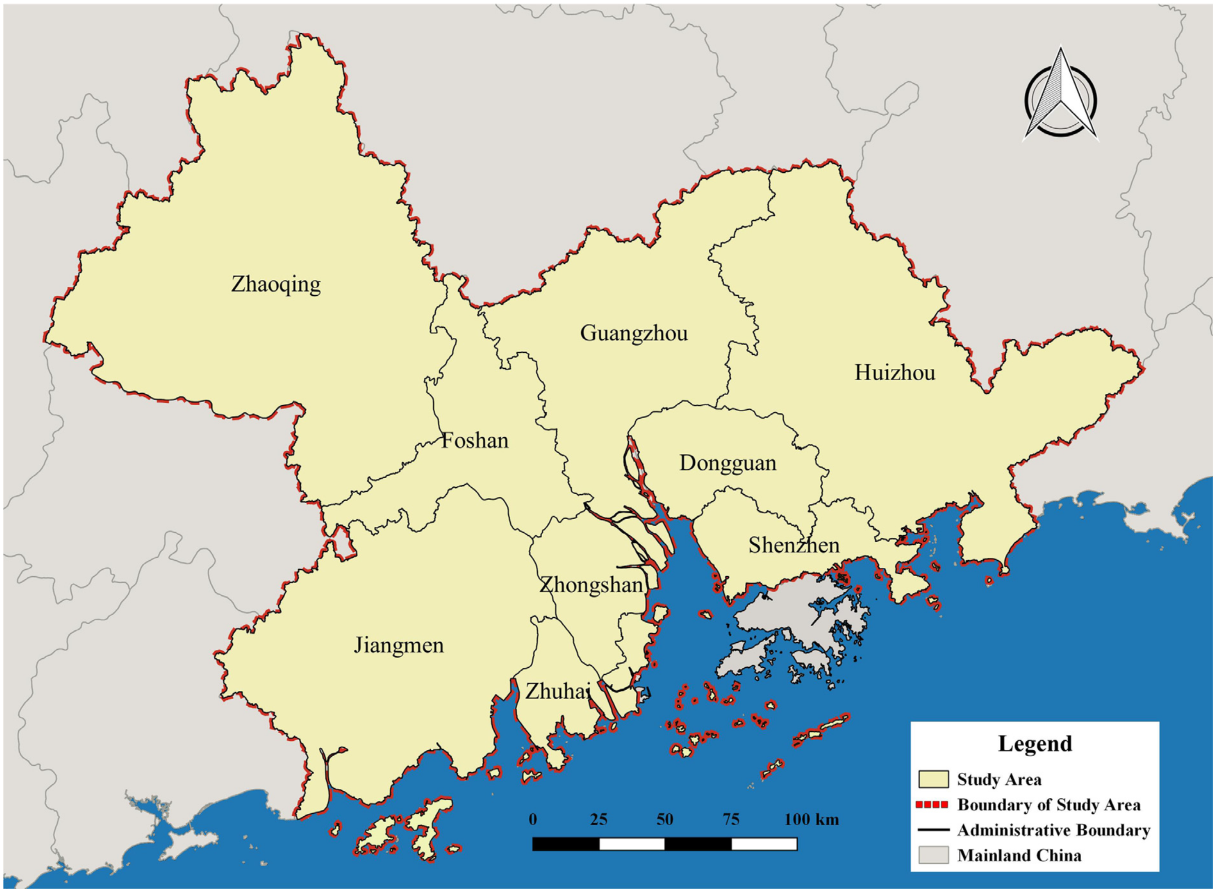

Fig. 5. The Pearl River Delta region as the study area for creating UGBs using the FLUS model.

unreasonable urban sprawl (Yeh & Li, 1997b), and related environmental issues (Yeh & Li, 1998). Soon, the PRD region is most likely to maintain a medium-high-speed of development according to the Pearl River Delta Region Planning (http://www.gdupi.com/prd2014/), especially in the regions of medium and small cities and towns around metropolitan areas. In this context, reasonable planning of urban growth boundaries is necessary to appropriately control urban development in the PRD region.

3.2. Data sources

To analyze the relationship between land use patterns and the driving factors in the PRD area, 2010 land use patterns and data on related physical, social, and economic dimensions are considered in the simulation. A FLUS model was applied in the PRD to account for different urban planning policies. In addition, various driving forces were considered in the simulation for better reflecting the distribution changes of urban land. These data include DEM, slope, distance to all levels of roads, distance to town centers, etc, and other drivers for planning traffic or planning constraints (e.g., primary farmland protection areas). All these land use data were converted to a cell size of $100 \times 100\,\mathrm{m}^2$ with a total of 13,000,932 cells. The data required for building the FLUS model is listed in Table 1.

4. Implementation and results

4.1. Planning scenarios

One of the purposes of this study is to simulate urban growth under the designed scenarios that closely link to planning policies in terms of space and quantity. We developed six scenarios under different spatial planning policies; these scenarios and spatial policies are very typical and commonly used in regional planning in other areas (Al-Ahmadi, Heppenstall, Hogg, & See, 2009). All spatial planning policies are shown in Fig. 6.

According to the different influences of various spatial forces on corresponding scenarios, the six scenarios are named as follows: (i) the Baseline Scenario; (ii) the Economic Zoning Development Scenario; (iii) the High-speed Railway Station-centered Development Scenario; (iv) the Master Plan Scenario; (v) the Sustainable Urban Development Scenario; and (vi) the Excessive Urban Growth Scenario. These scenarios are described in detail below.

1) Baseline Scenario

In the first scenario, the future land use pattern of the PRD region was predicted based on the urban growth rate in recent years without any land policies to constrain or promote zonal growth. Therefore, it was referred to as the baseline or default scenario. The implication of this scenario is that the metropolitan area is growing as a "bottom-up" system (e.g., self-organizing from the cell or neighborhood scale) without spatial planning policies to affect the layout of the city.

2) Economic Zoning Development Scenario

The second scenario was similar to the baseline except for population and GDP zoning regulations. Under this scenario, the counties with the fastest growing economies and populations in recent years were considered, and they attract more urban growth and minimize urban sprawl around metropolitan areas. This scenario was used to assess the urban growth change pattern under the control and guidance of the policy that gives priority to developing the most potential areas.

Table 1
List of data used in this study.

Category	Data	Year	Data resource
Land use	Land use data	2010	CAS (http://www.resdc.cn)
Socioeconomic data	Population	2010	The Census in 2000 and 2010
	GDP	2000–2016	The Statistic yearbooks from 2000 to 2016
Location	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 roads	National road	2015	PRD Master Plan (2014–2020)
	Provincial road		
	Highway		
	Railway		
	Urban road network	2016	Open Street Map (http://www.openstreetmap.org/)
Planning data	Planning high-speed railway stations	2030	Traffic plan for Guangdong province (2013–2030)
	Planning high-speed railway		
	Master plan in 2020	2020	PRD Master Plan (2014–2020)
	Primary farmland		
	Basic ecological line		

3) High-speed Railway Stations-centered Development Scenario

China is entering the high-speed railway age with increasing miles of high-speed rails across the country in recent decades. The PRD region is one of the most developed areas in respect to building high-speed railway systems. In a previous study, it was noted that the rapid rise of the high-speed railway had fast development momentum at a much earlier stage of urbanization in China (Tang, Savy, & Doulet, 2011), and the improvement of the high-speed railway network will also promote the urbanization process and development stage of urban agglomeration (Monzón, Ortega, & López, 2013). According to transportation planning for the PRD region, between 2013 and 2030, there are more than 30 new high-speed railway stations and 15 high-speed railways or intercity rails (more than 1700 km) that will be built across the PRD region (http://www.gdupi.com/prd2014/). In this scenario, the urban form is assumed to be largely driven by the influence of the existing and planned passenger stations along high-speed railways.

4) Master Plan Scenario

According to the master plan (2014–2020), urban agglomeration in the PRD region is going to set out on a path of sustainable and balanced development. In addition, the urban areas in the region will develop in a more compact way in the future. With major efforts to develop weak areas in the PRD region, the population in the metropolitan area is attracted and scattered by the surrounding fast-developing cities. Although a detailed urban development plan has been made, the real development of urban agglomeration will not strictly go with the urban plan (Long et al., 2012). Therefore, this scenario is aiming to analyze the future urban form under the influence and constraint of the master plan.

5) Sustainable Urban Development Scenario

The rapid growth of urban areas has caused serious environmental land resource problems, because urban sprawl is usually accompanied by lots of agricultural land loss and a waste of land resources (Yeh & Li, 1998). To assess how sustainable development measures control and direct urban growth, we developed a scenario aimed at predicting the urban form in the PRD region by taking the planning objectives of building a sustainably developed region into account. In this scenario, baseline urban growth is applied but with the constraints of environmental policy. Different environmental urban policies include prime farmland protection areas, which are basic ecological lines that were devised to promote sustainability through harmony with the environment.

6) Excessive Urban Growth Scenario

This scenario assumed the PRD metropolitan area would attract more immigrants because of great economic development from 2010 to 2050. The urban development of both the PRD metropolitan area and the surrounding cities are experiencing rapid growth. This scenario was used to examine where potential areas of rapid sub-urbanization around the PRD metropolitan area will occur.

In addition, to generate the future amounts of urban areas under the six designed scenarios, an SD model (Fig. 1) was built based on the socioeconomic data for the PRD region from 2000 to 2016 (Table 1) using Vensim software (http://vensim.com/). The SD model has three inputs: population growth rate, GDP growth rate and technical progress, and future urban demands under different scenarios can be generated with this model by using different combinations of the three parameters. The values are set according to the planning policies under the designed scenarios. For example, 1) the Baseline Scenario corresponds to three median values of growth rate, 2) three fast growth rates are given to the Excessive Urban Growth Scenario and yield the greatest quantity of urban land, and 3) the lowest population growth rate is given to the Sustainable Urban Development Scenario to reduce the environmental stress. This generates a minimum area of urban land among all scenarios, and fast technical progress contributes to maintaining a medium speed of GDP growth under this scenario.

In addition, other scenarios yield different amounts of urban land by changing the values of one or more parameters under the Baseline Scenario. For instance, 4) we assume that the GDP growth under the Economic Zoning Development Scenario is faster than the Baseline Scenario, because more efforts are being made to develop counties under this scenario. 5) For the High-Speed Railway Station-centered Development Scenario, the values of population growth rate and technical progress are greater than the Baseline Scenario because more technical progress contributes to the fast development of the transportation industry, and a developed transportation industry brings more population growth. In addition, 6) the development parameters under the Master Plan Scenario are set according to the macro planning goal for 2020 that the economy will grow at a high-speed, and population growth will be controlled at a low-level. The planning polices, scenario parameters and urban demands generated by the SD model for each scenario are summarized in Table 2.

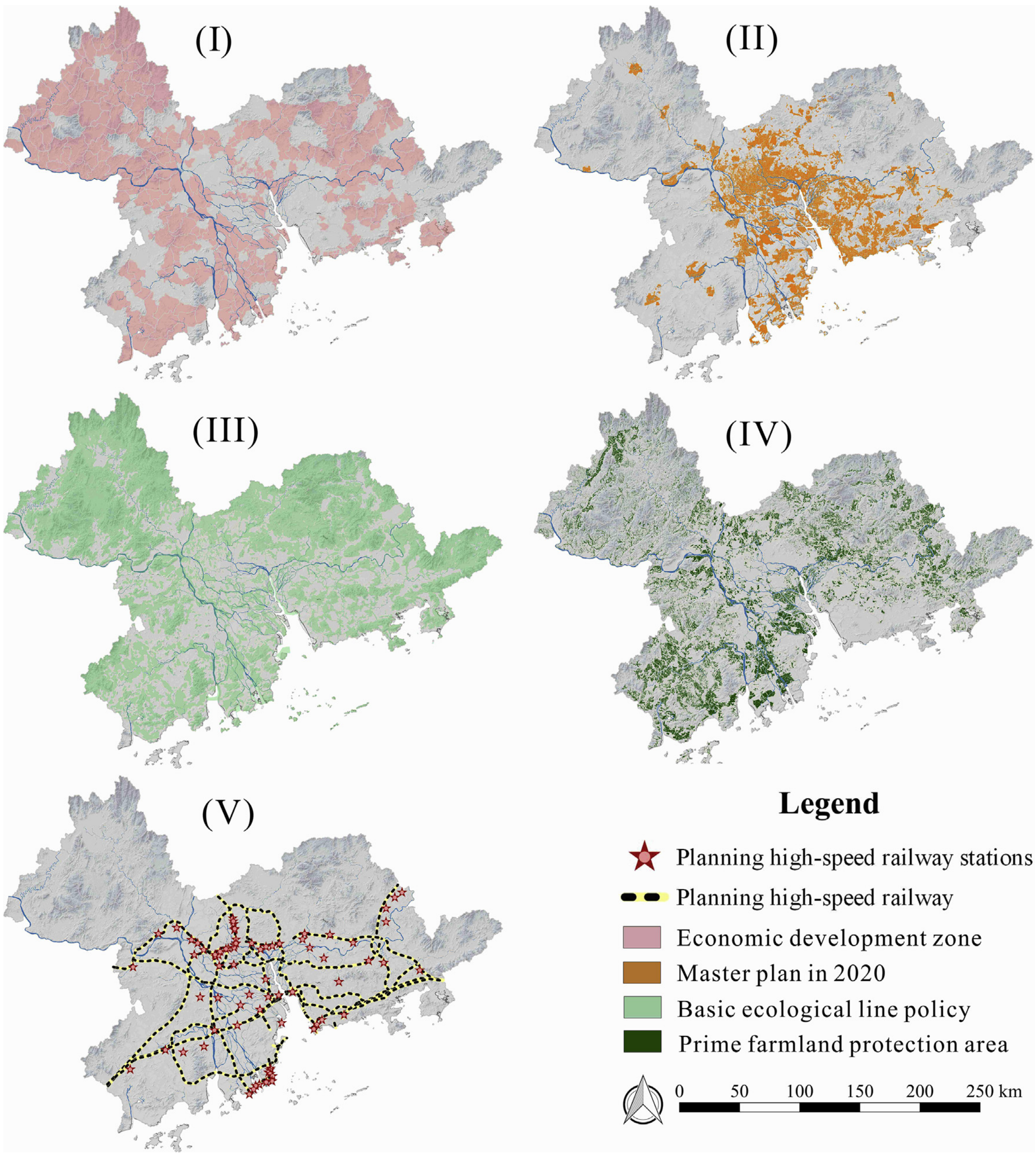

Fig. 6. Spatial planning policies used in this study: (I) the economic development zone, (II) the master plan, (III) the basic ecological line policy, (IV) the prime farmland protection area, and (V) the planned high-speed railway stations and high-speed railway.

4.2. Spatial simulation and results

Based on the six planning scenarios designed for urban development, the FLUS model is implemented in our study area, and the simulation results were generated. There were 10 spatial driving factors and land use patterns used in 2010 that are listed in Table 1 (except the planning data and socioeconomic data), and these data were selected to train the ANN model for the probability-of-occurrence estimate for urban and non-urban areas. The back-propagation ANN (BP-ANN) model used in this study is constructed by 10 neurons in the input layer (corresponding to 10 spatial driving factors), 15 neurons in the hidden layers, and 2 neurons in the output layer (corresponding to urban and non-urban areas). A total of 10% of the pixels were randomly selected as a training dataset across the PRD region. The sampling data is normalized to the range of [0, 1] before training the network. The sigmoid function is selected as the activation function for output layers to normalize the probability values to the range of [0, 1]. The learning rate and terminal conditions 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 of the FLUS model. The initial inertia coefficients for the first iteration are set to 1 and will self-adaptively evolve according to Eq. (1) during the CA iteration. All the parameters are the same for all scenarios. Fig. 7 show the predicted urban shape of the PRD area under the six different scenarios, which are described below.

1) Baseline Scenario

The future urban form generated by the baseline growth scenario is shown in Fig. 7(I). The characteristics of urban growth in this scenario can be described as a combination of edge-expansion development on the metropolitan fringe and expansion along the roads surrounding the cities. This means that the most important factors for urban growth in this scenario are the attraction of large cities and the major

Table 2
Values of different parameters under various planning scenarios in the Pearl River Delta.

Scenarios (2010–2050)	Planning policy	Scenario parameters	Growth rate (scenario variables)	Urban Demand (km^2) (SD outputs)
Baseline Scenario	NAN	Population growth rate	4‰–5‰(median)	11,498.83
		GDP growth rate	7%–16%(median)	
		Technical progress	0.3%(median)	
Economic Zoning Development Scenario	Economic development zone	Population growth rate	4‰–5‰(median)	11,509.42
		GDP growth rate	> 16%(fast)	
		Technical progress	0.3%(median)	
High-speed Railway Stations-Centered Development Scenario	High-speed railway stations and High-speed railway	Population growth rate	> 6‰(fast)	12,231.42
		GDP growth rate	7%–16%(median)	
		Technical progress	> 0.7%(fast)	
Master Plan Scenario	Master plan in 2020	Population growth rate	3‰–4‰(slow)	11,540.09
		GDP growth rate	> 16%(fast)	
		Technical progress	0.7%(fast)	
Sustainable Urban Development Scenario	Prime farmland	Population growth rate	3‰–4‰(slow)	10,099.89
	Protection area and Basic ecological line policy	GDP growth rate	7%–16% (median)	
	Basic ecological line policy	Technical progress	> 0.7%(fast)	
Excessive Urban Growth Scenario	High-speed railway	Population growth rate	> 6‰(fast)	13,217.96
	Prime farmland	GDP growth rate	> 16% (fast)	
	Economic development	Technical progress	> 0.7%(fast)	

transportation arteries that link large cities and surrounding towns. Under such a disorganized condition, the superior non-urban land (including agricultural land, protected areas, and forest land) that is near metropolitan areas, which is very important for providing ecosystem functions, are easy to exploit in urban development. The compactness of the urban form is therefore at the cost of urban sustainability and city environmental quality. The urban sprawl of the surrounding towns is disconnected from the metropolitan area and shows fragmented clusters to the north and southwest of the region. Moreover, leapfrog development can also be seen in different parts of the developed areas.

2) Economic Zoning Development Scenario

This scenario examines the impact of a policy that gives priority to the fast-developing counties with the most potential to absorb the future population and GDP growth in the PRD region (Fig. 7(II)). The urban land can grow faster in these counties than the major urban areas. The process of decentralization dominated urban development during the simulation period, and therefore, this provides new opportunities for the surrounding small and medium-sized cities. Compared to the Baseline Scenario that expanded around the metropolitan area of the PRD region, the urban development of this scenario is more compact and concentrated around the new development centers. The development pattern of this scenario can reduce the pressure of the population in metropolitan areas, as well as benefit the narrowing economic differences between developed and developing areas.

3) High-speed Railway Station-centered Development Scenario

Fig. 7(III) shows the results for this scenario by taking the distance to planned high-speed railways and high-speed railway stations into account in the ANN prediction process (as shown in Fig. 2). This scenario is characterized by showing edge-expansion in predicting urban growth, which is similar to the Baseline Scenario. However, because of the influence of the future high-speed railway and stations, the new urban land is more likely to occur near the planned high-speed railway stations, and the diminishing trend of urban growth from the metropolitan area to the surrounding area is weaker than the Baseline Scenario. Additionally, the driving effect of high-speed railways on urban growth in the east PRD (e.g., Huizhou) is larger than the western region (e.g., Jiangmen). This is because the city of Huizhou has a better economic foundation and is closer to Guangzhou and Shenzhen, which are the most developed areas in the PRD region. This means that Huizhou will have more development opportunities than Jiangmen under such a development pattern. It also demonstrates that the impact of high-speed railways on regional urban growth is not homogeneous.

4) Master Plan Scenario

Fig. 7(IV) shows the results of experiments with the new planned urban area including the policies that follow the master plan from 2014 to 2020. Thus, the urban shape exported by the FLUS model will be similar to the urban planning form in the master plan, but because there are no other spatial policies to constrain the urban expansion, the real urban area will not be completely developed within the region delimited by the master plan. Similar to the Baseline Scenario, significant urban growth is found at the north, west and southwestern fringes of Guangzhou and Foshan (the developed areas in the PRD) under this scenario, which indicates that urban expansion around Guangzhou and Foshan is the overall trend of future development in the PRD region. However, under the management of the master plan, urban sprawl along major transportation paths is efficiently restrained, and the shape of the new urban area is more compact and regular, especially in the developing area (Zhaoqing, Jiangmen) of this region.

5) Sustainable Urban Development Scenario

The urban growth under a sustainable development policy is under restrictions of the primary farmland policy and the basic ecological line policy (Fig. 7(V)). The urban pattern area in this scenario shows restrained growth in the metropolitan area. The stringent environmental protection measures not only limit the amount of future urban areas,

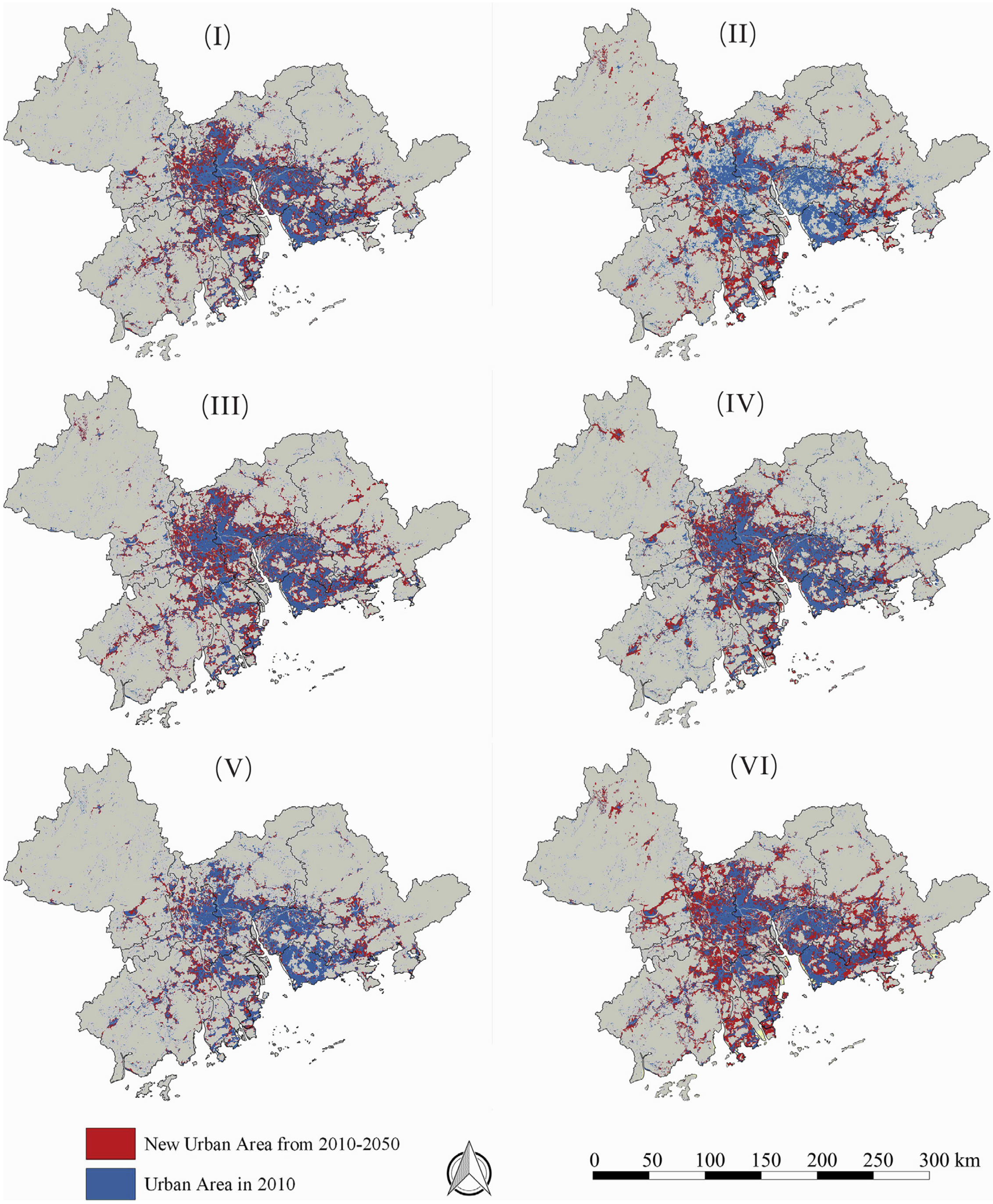

Fig. 7. Simulated urban development of PRD areas under (I) the Baseline Scenario, (II) the Economic Zoning Development Scenario, (III) the High-speed Railway Station-centered Development Scenario, (IV) the Master Plan Scenario, (V) the Sustainable Urban Development Scenario and (VI) the Excessive Urban Growth Scenario.

which results in the least amount of urban area for these scenarios, but they also guide the direction of urban development. The new urban areas are absorbed into the western part (Huizhou) and eastern part (Jiangmen) of the PRD region, which is different from the previous scenarios where urban growth occurred near the edges of metropolitan areas (mostly around Guangzhou and Foshan).

6) Excessive Urban Growth Scenario

This scenario aims to estimate the potential areas for development if further excessive urban growth occurs but under a primary farmland policy, which is to keep enough cultivated land to feed the increasing population (Fig. 7(VI)). Urban growth under this scenario is divided into two development stages. The first stage is from 2010 to 2030; this stage is similar to the Baseline Scenario but with more rapid GDP and population growth, which thus results in a relatively high urban growth rate. The second stage is from 2030 to 2050 and has a development strategy similar to the Economic Zoning Development Scenario, in which the cities around the metropolitan area with high economic potential and high-speed railway stations are given priority for development. Therefore, this scenario has the characteristics of both the Baseline Scenario and the Economic Zoning Development Scenario. This scenario was able to examine where potential areas of rapid urbanization occur in the PRD area.

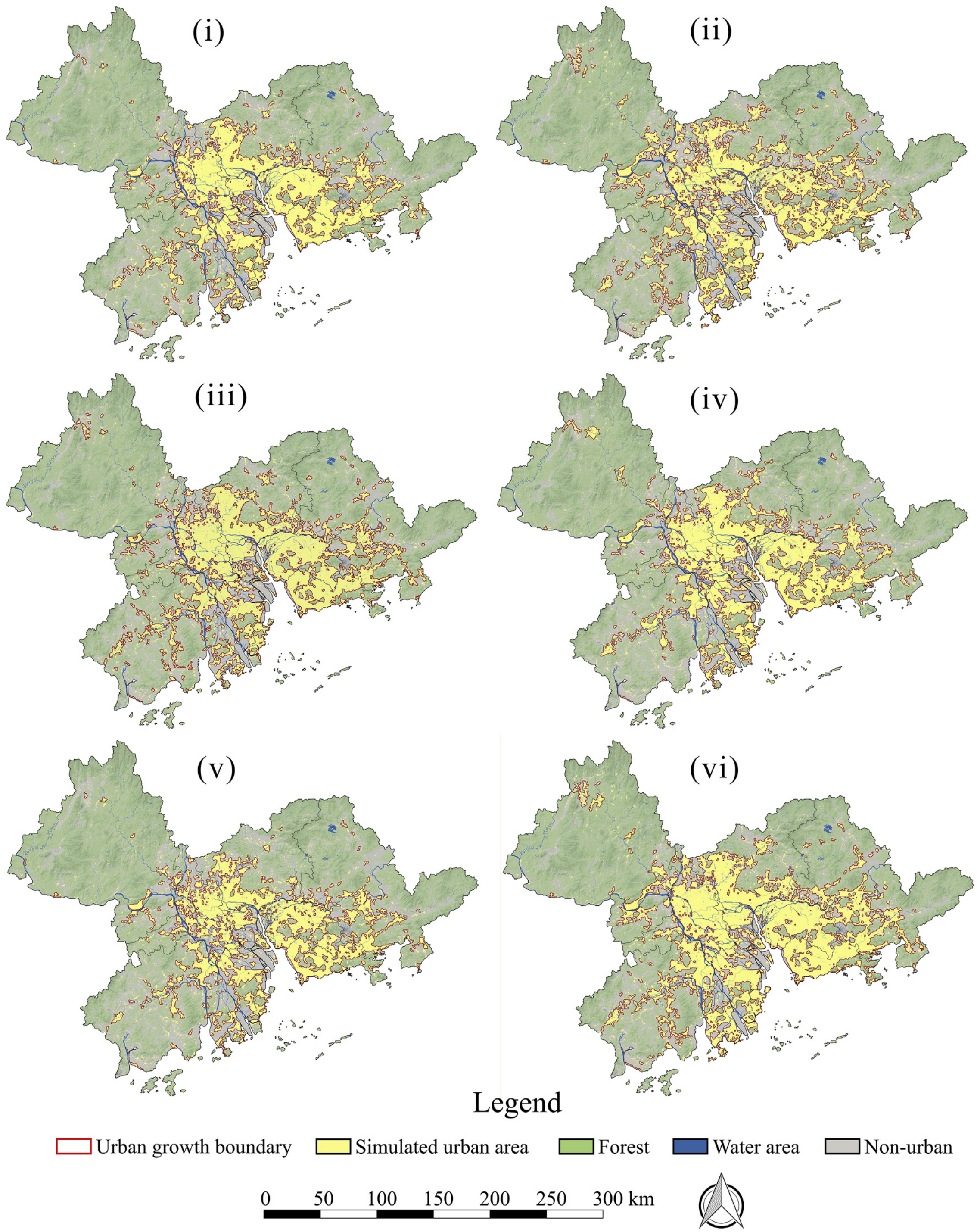

Fig. 8. The UGBs for the PRD region under the six planning scenarios: (i) the Baseline Scenario; (ii) the Economic Zoning Development Scenario; (iii) the High-Speed Railway Station-centered Development Scenario; (iv) the Master Plan Scenario; (v) the Sustainable Urban Development Scenario and (vi) the Excessive Urban Growth Scenario.

4.3. Establishing UGBs

The UGBs of the PRD region are established according to the simulations of the FLUS model in the present study through the morphological method described in this section, which is shown in Fig. 8. The size of the slide windows for the structuring elements of erosion and dilation are set to 7 × 7 in this study. The generated UGBs in raster format are converted to vector format with GIS software, and the small UGB patches that are less than 5 square kilometers are removed.

These results show that the UGB delimiting method successfully transforms the simulation results of the CA model into available UGBs for regions of fast development. The proposed method remains the spatial distribution characteristics of the simulation patterns under various scenarios (as shown in Fig. 8), which are important for decision makers when creating appropriate policies for regional plans in city agglomerations and individual cities.

Fig. 9 shows an example of the delineated UGBs for six locations within the PRD region under the six planning scenarios. These examples give a good indication of how the new UGB delineation method is based on erosion and dilation performs. Fig. 9(a) and (d) show that the UGBs

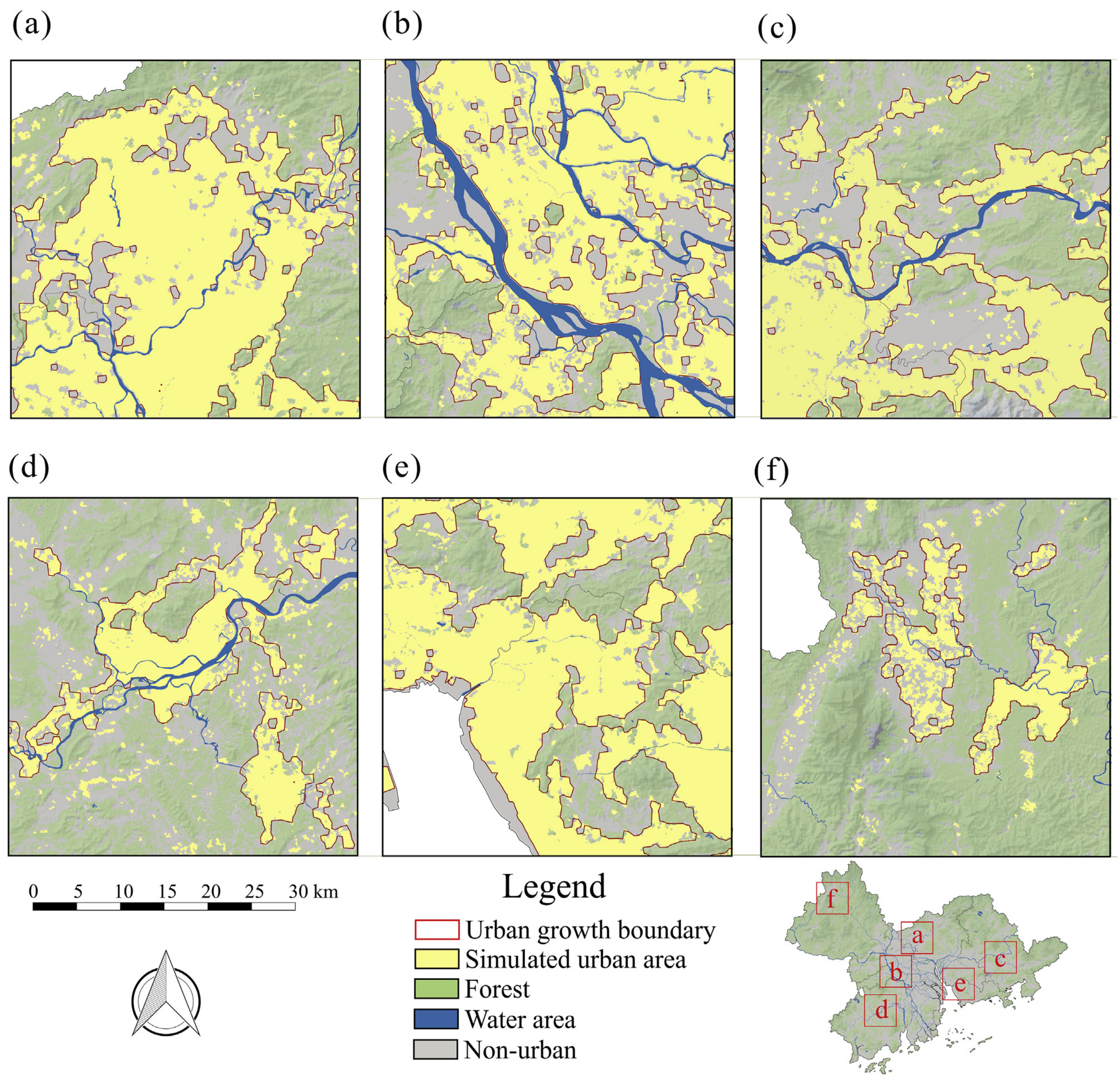

Fig. 9. UGBs for six areas for 2050 and 2015 for different scenarios: (a) area a under the Baseline Scenario; (b) area b under the Economic Zoning Development Scenario; (c) area c under the High-Speed Railway Station-centered Development Scenario; (d) area d under the Master Plan Scenario; (v) area e under the Sustainable Urban Development Scenario and (vi) area f under the Excessive Urban Growth Scenario.

generated by this method can well encase not only the large urban areas but also the irregular and angular urban blocks. In addition, the non-urban land surrounded by urban areas includes many superior rural areas and small woodlands that are beneficial for adjusting the urban ecological environment and contributing to a better quality of life for city inhabitants. These areas can be identified and preserved by the UGBs delineated by the proposed method (Fig. 9(b) and (e)). Moreover, the UGBs in Fig. 9(c) and (f) indicate that this method can delete the small and dispersed urban patches that have low compactness, and effectively integrate the cluster of urban patches into a large area defined by UGBs.

4.4. Area statistics and analysis

Fig. 10 shows a comparison of the simulated UGBs with the simulated urban areas. The common feature of the designed scenarios is that in most cities, the area of delineated UGBs tends to be larger than the original simulated urban areas, especially in developed region such as Guangzhou, Foshan, Shenzhen and Dongguan. In this region, the urban form is compact, and this delineated method tends to enclose the simulated urban form.

However, the Sustainable Urban Development Scenario tends to be contrary to other scenarios because this scenario generates many dispersive and small urban patches, which may be eliminated by the morphological erosion and dilation method. For example, in most scenarios in Zhaoqing, which is an area with a relatively low economic foundation, the UGB area is larger than the simulated urban areas. However, under the sustainable development scenario, the simulated urban areas are much larger than the UGBs. To summarize, this method tends to generate larger UGBs in developed areas that have a compact urban form, and smaller UGBs are delineated in developing areas that have a disperse urban pattern. Table 3 shows the area comparison

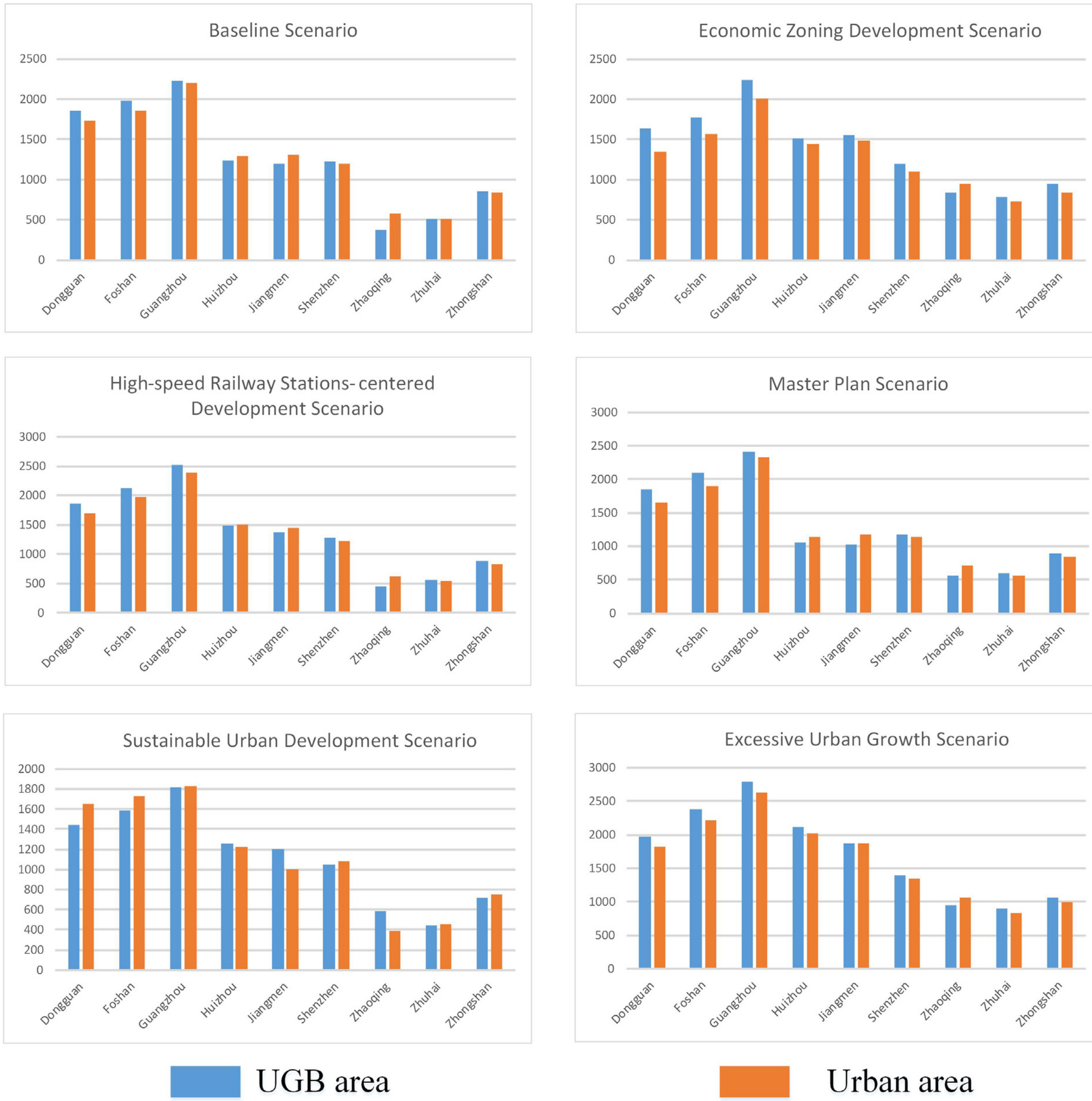

Fig. 10. Simulated urban area and UGB area of each city in the PRD region (area unit: km^2).

Table 3
Area comparison between delineated UGBs and simulated urban areas in PRD region.

Scenario	2050 UGB area	2050 urban area	Percentage difference
Baseline Scenario	11475.45	11498.83	−0.20%
Economic Zoning Development Scenario	12495.22	11509.42	+8.57%
High-speed Railway Stations-Centered Development Scenario	12540.61	12231.42	+2.53%
Master Plan Scenario	11765.35	11540.09	+2.0%
Sustainable Urban Development Scenario	10060.42	10099.89	−0.40%
Excessive Urban Growth Scenario	138019.52	132217.96	+4.39%

between delineated UGBs and simulated urban areas in the PRD region. The UGB area of the cities in the PRD in most scenarios are similar to the simulated urban areas in the whole region, which proves that the proposed method will not heavily change the planned urban demand (planning objective) of a region under most scenarios. However, the biggest difference occurs under the Economic Zoning Development Scenario because this scenario (Table 3) creates many aggregated urban clusters, which are merged into a large UGB block by the UGB delineated method and results in a relatively larger difference.

4.5. *Comparing simulated UGBs with planned UGBs*

The UGBs simulated by the FLUS model are validated with the planner designed UGBs. We used the master plans as the planners' UGBs because the new PRD region still does not have official UGBs, and the master plan can guide the urban growth as UGBs do, to a certain extent (Long et al., 2012; Lu et al., 2013; Tian & Shen, 2011). The UGBs under the Baseline Scenario and Master Plan Scenario are selected for comparison with the planner designed scenarios. We used the simulated UGBs in 2030 for both scenarios, because the predicted urban area is the nearest to the urban area defined by master planning. To better reflect the subtle urban spatial structure, we employed 3×3

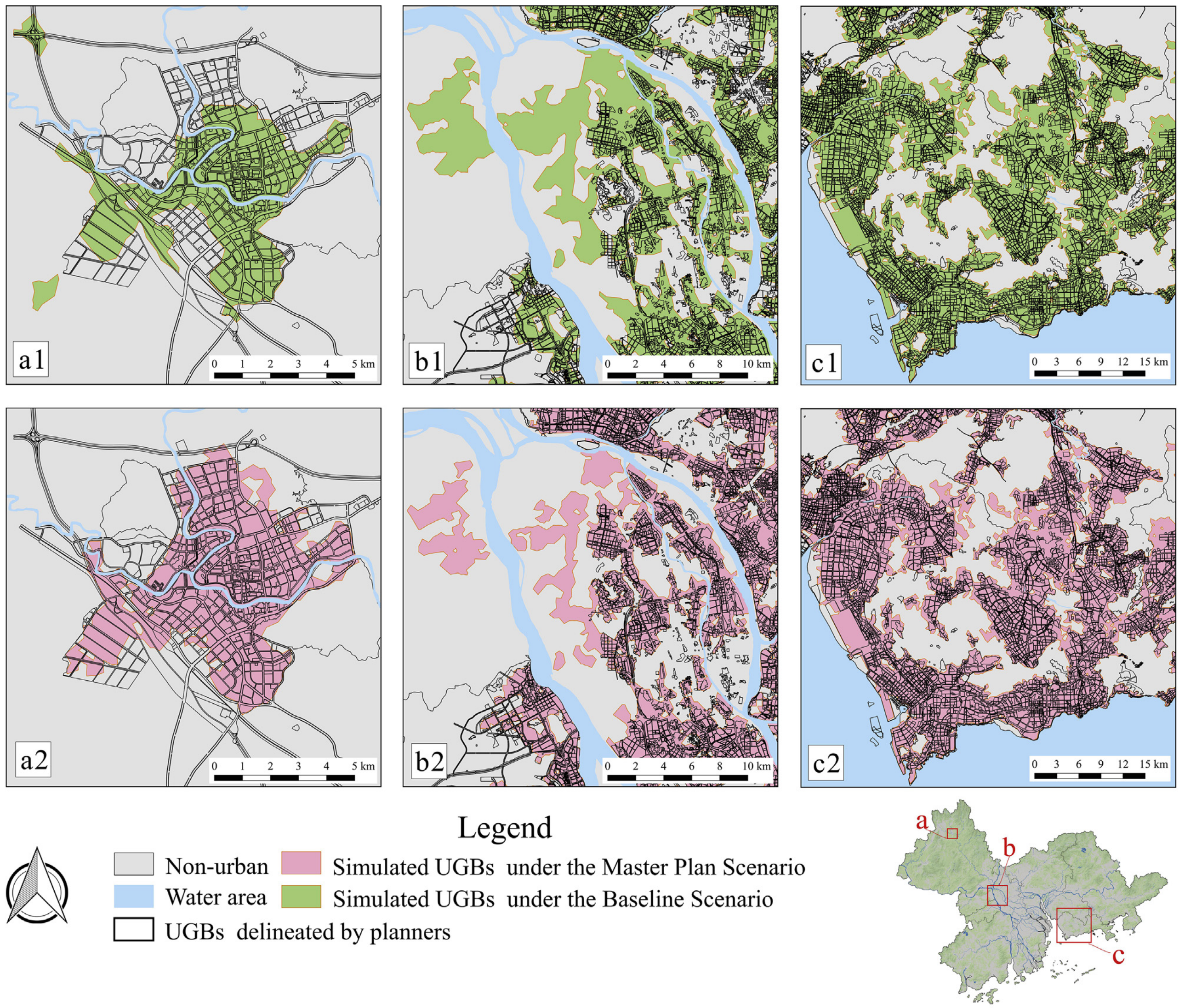

Fig. 11. Simulated UGBs under the two scenarios in contrast with the planned UGBs.

structuring elements of erosion and dilation to generate the simulated UGB. Fig. 11 shows a comparison of the planners' UGBs and the simulated UGBs under the two chosen scenarios.

There are significant differences between the two scenarios of simulated UGBs (Fig. 11a1 and a2, b1 and b2). Although without the influences of planning policies, the simulated UGBs under the Baseline Scenario still have the same development trend as the planners' UGBs (Fig. 11a1). Compared to the UGBs from the Baseline Scenario, the UGBs under the Master Plan Scenario are closer to the planner designed UGBs (Fig. 11a2 and c2). However, differences still exist; for example, some areas delineated by planner's UGBs are unable to be developed as urban areas during the simulation period under the influences of the master plan (Fig. 11a2) because the urban probability-of-occurrence is too low to generate a new urban area in this region. This demonstrates that the UGBs delineated by the proposed method can be used to identify the high development potential areas and the regions with relatively low development potential inside the planner's UGBs. In addition, both simulated UGBs can supplement the planners' UGBs because they delineate the potential development region out of the planner's UGBs (Fig. 11b1 and b2). The simulated UGBs under the two scenarios are very similar in the core area of the PRD region (e.g., Shenzhen, Fig. 11c), which has a greater amount of urbanization. In general, the proposed method serves as an effective support tool for assisting planners to establish UGBs by considering various spatial preferences.

5. Conclusions

In this study, a UGB-FLUS method is proposed to support the planning process in a complex, urbanized region such as the PRD, which is composed of a CA-based FLUS model and a morphological UGB delineation technique. A case study in the PRD area was developed to demonstrate how urban patterns under different scenarios can be generated using this method.

This model successfully creates different urban forms under different planning policies such as the "High-speed Railway Station-centered Development Scenario", the "Master Plan Scenario", the "Sustainable Urban Development Scenario" growth patterns, etc. that have their respective characteristics, which are quite different from each other. This study indicates that the FLUS model can provide useful knowledge for understanding urban development processes, as well as assisting land use planning by incorporating objectives in the simulation. This enables planners and managers to assess the future outcome of current planning policies for large regions, as well as investment choices before they are put into action.

While most CA-based UGB models are not designed to efficiently establish the edges of the urban area from the CA simulations, one of the objectives of this paper was to develop a method for determining the future urban boundary location based on simulation results instead of artificial modification. Thus, in the UGB-FLUS method, a morphological method based on erosion and dilation, in which a closing operation is first applied and is then followed by an opening operation, is proposed for handling the binary simulation results. Within this method, the closing process is first used to fill gaps between urban blocks, and then, these gaps are "closed". The opening process removes the dispersive and small construction land patches around cities that are not suitable for delineation into UGBs. The combination of closing and opening makes the UGBs more compact and smooth. It remains the spatial distribution characteristics of the simulation results under different scenarios that determine the UGBs where future urban areas are most probable to occur under the corresponding scenarios.

In summary, the proposed UGB-FLUS method can be used to pinpoint specific locations where it is appropriate to delineate UGBs under different planning policies, which is very useful for rapid urban growth areas, particularly in urban agglomerations with complex urban boundaries like the PRD region. Moreover, this UGB method can provide vital information for regional planning because the risk to social development and environmental quality is quite different under various planning policies. The delineation of the UGB for the PRD area based on the FLUS-UGB model provides a new and easily understood way of defining where urban growth will be encouraged or not permitted. This study shows that the FLUS and UGB-FLUS software (available for download at http://www.geosimulation.cn/flus.html) can conveniently explore the possible patterns of future urban changes or multiple land use changes under the influence of different human and natural effects and under different planning policies.

Acknowledgments

This research was funded by the National Key R&D Program of China (No. 2017YFA0604404 and 2017YFA0604402), the National Natural Science Foundation of China (Grant No. 41671398), and the Key National Natural Science Foundation of China (Grant No. 41531176).

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