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Modeling the dynamics and walking accessibility of urban open spaces under various policy scenarios

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HIGHLIGHTS

- Open space and urban land are interactively attractive in the simulation.
- Simulated OS is evaluated with walking accessibility and population coverage rate.
- Different mean sizes and time-lags of OS are considered in the simulation.
- OS-CA is an effective tool for assessing the policies for creating new OS.

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ABSTRACT

Open spaces (OSs) in urban areas play a vital role in providing space for habitat conservation and recreation, improving the mental health of urbanites. OSs consist of complicated elements, such as parks, green landscapes and public squares. Few studies have simulated the dynamics of OS with a complete set of these elements. This study proposes a new Open-Space simulation model using cellular automata (OS-CA). A system dynamics model is used to generate scenarios for creating new OS with different construction time-lags. The spatial simulation of OS is allowed to interact with the urban dynamics, constrained by the policies controlling different mean sizes of new OSs. The effectiveness of creating new OS is assessed using the walking accessibility and the population coverage rate. The OS-CA was applied to Dongguan, South China, and validated with multi-source data. The OS simulation from 2015 to 2030 shows that the longer time-lag in building new open spaces, the higher the demand for open space will be in the future. We found that new open spaces are most likely to appear at places near rivers, forests, wetlands, lakes, along the roads, road intersections, or near residential areas. With the growth of OS, the increase rate of OS population coverage becomes slower than that of walking accessibility. We suggest that governments building more small OS within the central urban areas while constructing larger and fewer OS outside of the core urban areas to help improve the overall service level of OS. The OS-CA is available for download at https://github.com/HPSCIL/Open-Space-Cellular_Automata.

1. Introduction

Open space (OS) in urban areas is created with the purposes of improving the quality of life of urban residents, and providing places for recreation activities (Giles-Corti et al., 2005; Liu et al., 2019). The OS includes urban green spaces, parks, public squares, trails, courtyards, and other developed natural spaces (Maruani & Amit-Cohen, 2007; Thompson, 2002). Establishing more OS has often been considered an

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approach to improve many ecological functions, social interactions, aesthetics, and cultural heritage (Haaland & van den Bosch, 2015; Rottle, 2016). For example, some OSs (e.g., parks, urban wetlands) can alleviate the urban heat island effect and improve thermal comfort (Sun et al., 2017), and some green spaces can also reduce the severity of air pollution (Helbich et al., 2019; Zhou et al., 2011). With a rise in the desire for a better living environment in cities, OSs have increasingly played an important role in urban development and planning in recent decades (Juhola, 2018; Lewis et al., 2009), and the demand for OS has increased significantly (Liu et al., 2020; Yung et al., 2016).

Previous research has mainly focused on the social and/or ecological effects of urban OS on the urban environment. For example, Lewis et al. (2009) studied the effects of open-space conservation policies on residential development density; Nutsford et al., (2013) explored the relationships between proximity to urban green spaces and human mental health; Derkzen et al. (2015) quantified the urban ecosystem services based on fine-resolution data for urban green space in the Netherlands; and Masoudi and Tan (2019) used a series of landscape metrics to measure the effects of the spatial pattern of urban green spaces on urban land surface temperature in Singapore.

Some other studies aim to develop planning tools for urban OS planning, which can help planners achieve multiple goals for sustainability (Juhola, 2018). For example, Maruani and Amit-Cohen (2007) reviewed nine types of commonly used models of open space planning and their guiding principles, and pointed out some of their merits and limitations as planning tools. Lindholst et al. (2016) discussed tools for mapping the recreational and social values of green spaces, while Juhola (2018) proposed an element scoring approach which includes a list of greening factors commonly used in urban planning. In terms of planning tools, Yeh and Chow (1996) proposed a location-allocation approach to assist public open space planning by identifying the best sites for facilities, and Zhou et al. (2011) used a computational fluid dynamics model to develop spatial planning of OS from the perspective of oxygen concentration. However, only a few studies have attempted to assist the conservation and planning of OS through spatio-temporal modeling (Haaland & van den Bosch, 2015).

Spatio-temporal modeling in geography provides insights into geographical processes at a variety of scales (Amiri et al., 2009; Guo et al., 2005; He et al., 2020). A temporal series covering the spatial evolution of landscape patterns before and after the impact of government policies would be particularly useful for managers to control the spatial layout of regional land uses (Turner, 1990). By simulating open space creation on both local and city levels, we can understand the dynamic nature of the development of open space better, and enhance its visualization to evaluate policy implications for the distribution of OS (BenDor et al., 2013). It is worth noting that OS is not a simple object with a single land cover type. The land cover of open space can be impervious surface (e.g., squares), shallow water (wetland parks) and vegetated land (e.g., ecological parks). Hence, our simulation of OS is different from other studies that only focus on the simulation of single green space, water and forest objects (Soares-Filho et al., 2002, 2006; Mitsova et al., 2011). Meanwhile, our simulation of OS pays more attention to the creation of new OS; thus, it can help urban planners to identify suitable places for establishing new open spaces from multiple relevant land cover types.

Previous studies have simulated a single element (e.g. parks, greenbelt) of open space with Cellular Automata (CA) models, as CA models are effective tools for simulating the spatio-temporal dynamics and interactions of land use change (Clarke & Gaydos, 1998; Pontius et al., 2008; Zhai et al., 2020). For example, BenDor et al. (2013) have developed a method based on the Regional Urban Growth model (RUG) to explore the spatial allocation of urban parks (public, recreational open spaces) given different municipal and county investment decisions. Park et al. (2017) simulated greenbelt elimination using the SLEUTH model. Liu et al. (2020) used a CA based future land use simulation model (FLUS) (Liang, Liu, Li, Zhao et al., 2018; Liang, Liu, Li, Chen et al., 2018) to simulate the future layout of green space and public plazas in Xuchang, northern China. A machine learning method (Neural Network) was used in this study to analyze the relationship between open spaces and multiple land use change driving factors. Nevertheless, many important components of open spaces, for example, public squares, meeting plazas, roadside spaces, etc., have not been considered in the existing literature. Few if any, studies exist to simulate the development of all OSs components to assist open space planning in fast-developing cities.

What size of OS the urban planners should build is an important topic for OS planning. Bolitzer and Netusil (2000) have pointed out that each additional acre of open space is estimated to significantly increase housing price, while the size of the area decreases the per hectare value of OS (Brander & Koetse, 2011). Therefore, simulating the spatial distribution of OS under different mean sizes of OS is very useful for forecasting and controlling property prices and land values in a city. In addition, if holding the total demand of OS constant, different mean sizes of OS will lead to diverse distribution patterns and different overall walking accessibility to the OSs. To appropriately determine the future mean area of OSs is of great value for increasing the amenity levels of urban residents. However, to our knowledge, few studies have simulated the future distribution pattern of OS spatio-temporally under different mean sizes of OS. Nor have previous studies evaluated the walking accessibility of OSs under different mean sizes of OS.

Here, we highlight the need of simulating the complex dynamics of urban open spaces across space and time under different construction policies of urban OS. An integrated CA model that couples the “top-down” demand prediction model and “bottom-up” interactions between open spaces and urban land is proposed. The model structure can translate policies and planning into parameterized scenarios such that their effects on OS development can be investigated (Huang et al., 2014). First, we constructed a dynamic land use sub-model for OS to model the interactions among socio-economic factors from the “top-down” component and to predict the future demands of open spaces and urban land. Then, we developed a cellular-automaton sub-model for OS to simulate the creation of the open spaces and urban growth by spatially considering the “bottom-up” effect. The CA sub-model can simulate the future distribution pattern of OS under the policies of building different mean sizes of OS, which can help planners make suitable plans for new urban open spaces that are not addressed by other models. The two sub-models were tightly coupled with each other in the simulation process. The modeling approach was demonstrated with a simulation of multiple scenarios for Dongguan, a fast-developing city in southern China. We also proposed a method based on the minimum bounding rectangle to determine the gates or access points of each open space for assessing the walking accessibility and population coverage rate of OS. We expect that the method and results of this study can effectively support the planning of open spaces in any fast-developing urban region.

2. Study area and datasets

2.1. Study area

Dongguan is situated in the central part of Guangdong Province, south China, located between 22°39′N-23°09′N and 113°31′E-114°15′E. The city had a total population of 8.39 million in 2018, which includes 32 towns and covers 2465 km^2 (Fig. 1). The topography in Dongguan changes from hills in the southeast to alluvial plains in the northwest and the elevation ranges from 0 to 559 m. Dongguan land use in 2018 was 35% urban land, 13% agricultural land, 25% forestland, and 27% water area (Sun et al., 2018). Dongguan is adjacent to Guangzhou and Shenzhen, two of the most developed cities in China, such that it is a city with developed traffic, business, high-tech industries, tourism, services and modern industries. Over the past two decades, the urbanization rate in Dongguan has reached 88.82% (Chen et al., 2014). Against this

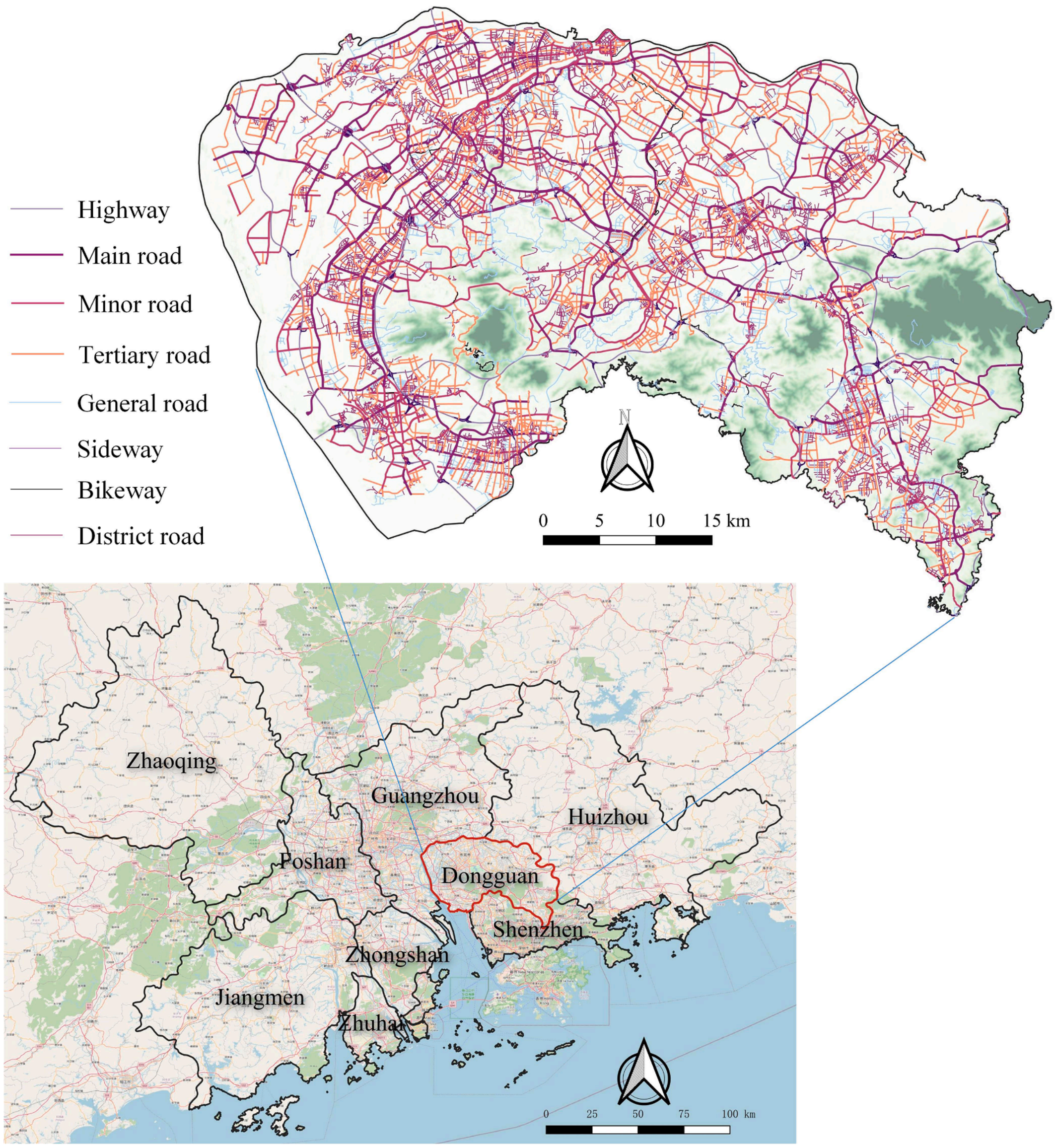

Fig. 1. Spatial location of the Dongguan study region.

background, the development of new open spaces should match the rapid urbanization to satisfy the increasing needs of urban residents in Dongguan. The government of Dongguan proposed the *Plan of Beautiful Dongguan Construction* in 2018, which highlights the need to accelerate the construction of parks, green spaces and waterfront spaces, and for improving the quality of forest parks, wetland parks, and agricultural gardens (http://www.dg.gov.cn/zwgk/zfgb/szfwj/content/post_2421477.html). Therefore, it is important for urban designers to guide the reasonable layout of new and existing open spaces in Dongguan using objective methods.

2.2. Data

First, we used statistical data for each town of Dongguan from 2010 to 2015 to establish a sub-model for predicting the future demand for OS. These data came from the website of the Census Bureau of Dongguan, the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and zonal statistics from land-use data. Statistical indicators included the area of open space, urban and non-urban area, urban and rural population, Gross Domestic Product (GDP), total agricultural output, and the density of road networks. Other spatial data were also collected, including administrative boundaries, city centers, data about town centers, elevation data and population distribution. The spatial distribution of the population in 2015 was obtained from the WorldPop global population dataset (https://www.worldpop.org/methods/populations).

Another set of spatial data were collected to develop the OS-CA model. We derived the open space for 2015 by integrating the patches of open spaces obtained from Baidu Map and the land use data provided from the detailed plan of Dongguan (Fig. 2). These data are obtained from land investigations and visual interpretation, which are very reliable data for building a complete data set for open space. The urban land in Dongguan was from the subset of a Global Human Settlement Layer (GHSL) dataset (Pesaresi et al., 2013). The GHSL data has a relatively high resolution (30 m) and a high total accuracy of >90% (https://ghsl.jrc.ec.europa.eu/). The Basic Ecological Line Policy in Dongguan was also considered in our study to constrain urban development in Dongguan. The water area in 2015 was extracted from Landsat imagery by Pekel et al. (2016), and this map was used in this study to prevent the open water from converting into urban land (www.global-surface-water.appspot.com/).

The development of new open spaces is not only determined by their

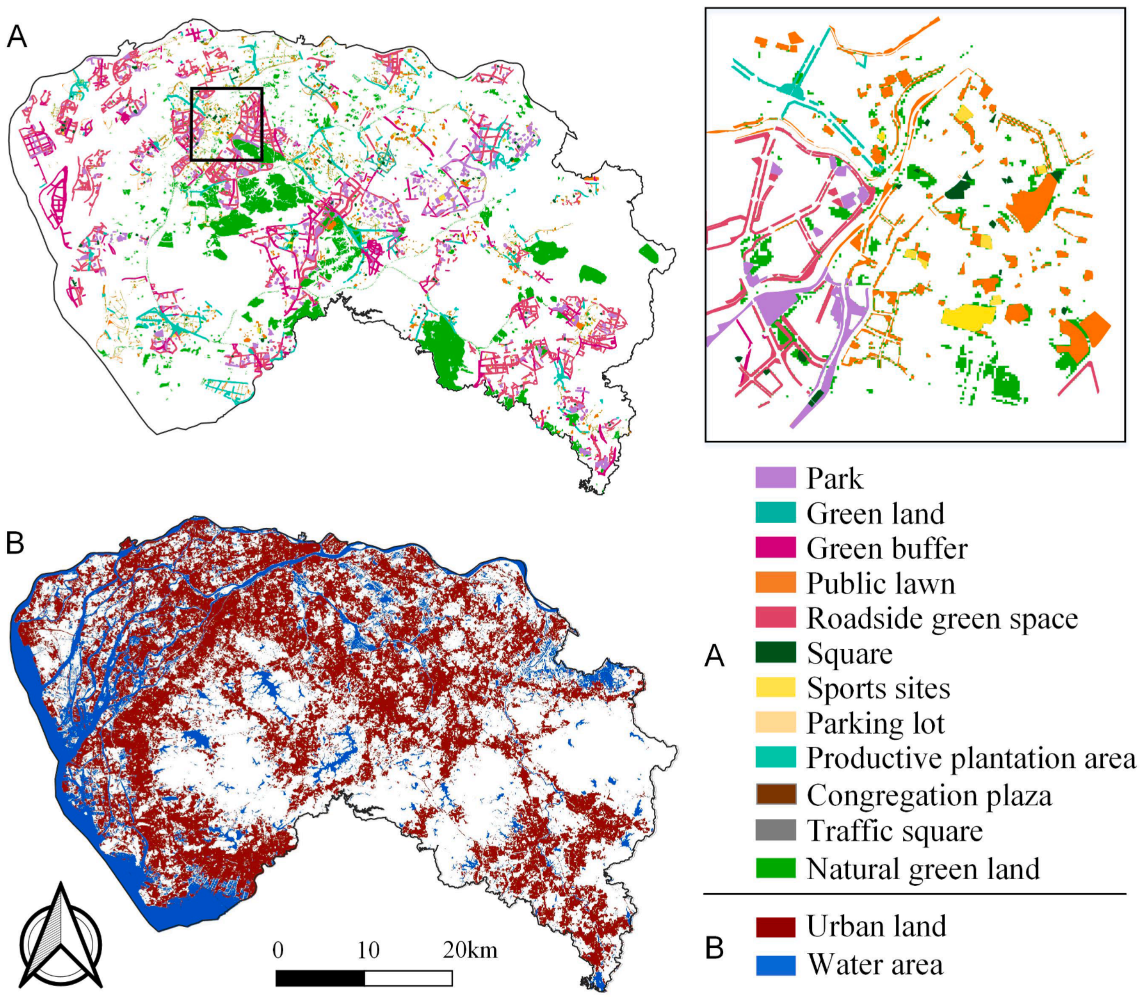

Fig. 2. (A) The 2015 open spaces in Dongguan (provided by the Detailed Plan); (B) the 2015 urban land and water areas in Dongguan.

accessibility or locations, but also by many other aspects such as the availability of recreational facilities, markets, restaurants, health (medical institutions), locations of work places (e.g., factories) and population distribution (Derkzen et al., 2015; Hofmann et al., 2012; Thompson, 2002; Yung et al., 2016). To consider the influences of socio-economic factors and infrastructure on the development of open space we collected a set of POIs from the Baidu Map API (lbsyun.baidu.com/), including restaurants, hotels, markets, factories, places of entertainment, medical facilities, parks, public restrooms, public places and bus stations. We calculated the kernel density (High density POIs) and proximity map (Low density POIs) of these POIs as the driving factors of land use change. In addition, road networks were regarded important driving factors in the development of both urban land and open space. The data for road networks were obtained from OpenStreetMap (www.openstreetmap.org). We calculated the Euclidean distance as the proximity factors of each level of the road network. All the land use data, spatial policy data and spatial driving factors were resampled to a uniform resolution of 30 m (Fig. 3).

3. Methods

The OS-CA model consists of a systems dynamics sub-model and a cellular automaton sub-model for OS. The former is applied to projecting the future demand for open space and urban land under the interactions among multiple socio-economic factors (i.e., top-down process); and the latter is used to simulate the creation of new open spaces driven by infrastructure and socio-economic drivers (i.e., bottom-up process). Then we evaluated the simulation result with multi-source data (Baidu Base Map and street scenes) and assessed the walking accessibility of OS under different scenarios.

3.1. A systems dynamics sub-model for OS

We constructed a dynamic sub-model for OS within a systems dynamics framework, which is a co-evolution system for the open spaces, urban land, and non-urban land. The dynamic sub-model for OS considers many indicators that are closely related to the open spaces, including historical population (both urban and rural population), GDP, road network density, and the proportions of the agriculture, industrial, and service sectors (Fig. 4). The estimation of the population and GDP of the sub-model is according to the following equation:

$$P(t+1) = P(t) + \Delta P \cdot dt \tag{1}$$

$$\Delta P = P(t) \cdot R_p \tag{2}$$

$$G(t+1) = G(t) + \Delta G \cdot dt \tag{3}$$

$$\Delta G = G(t) \cdot R_g \tag{4}$$

where $P(t)$ and $G(t)$ denote the population amount and GDP of the study region, respectively; ΔP and ΔG are the changes in the population and GDP at time t; and R_p and R_g represent the rate of change of the population and GDP respectively. The prediction of the area of open space is according to the method proposed by BenDor et al. (2013).

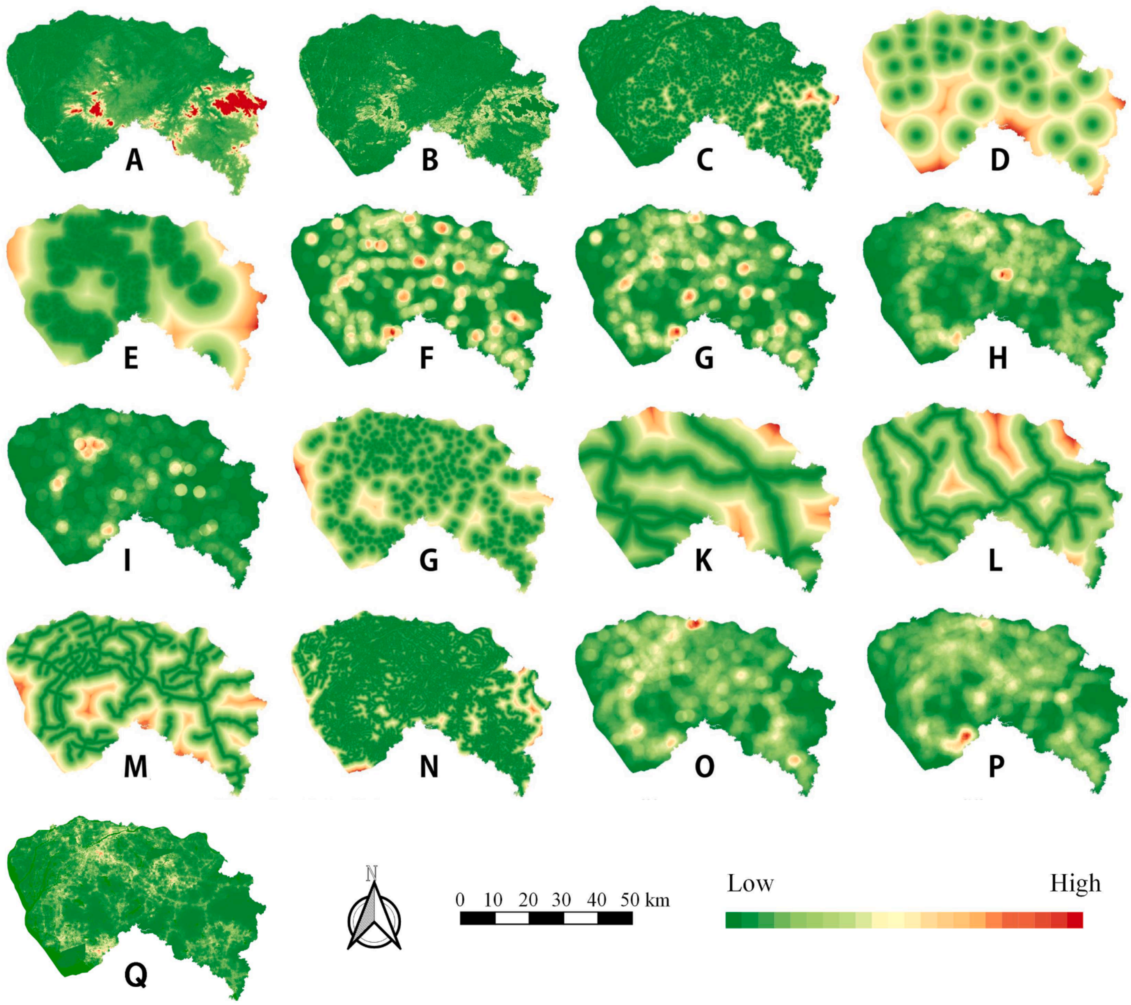

Fig. 3. Driving factors in this study, include a set of POI data that represents the infrastructures and socio-economic factors (Panel (E, F, G, H, I, J, O, P)): (A) Terrain; (B) Slope; (C) Proximity to rivers; (D) Proximity to town centers; (E) Proximity to recreational facilities; (F) Density of markets; (G) Density of restaurants; (H) Density of factories; (I) Density of public restrooms; (J) Proximity to medical institutions; (K) Proximity to highways; (L) Proximity to main roads; (M) Proximity to minor roads; (N) Proximity to other roads; (O) Density of intersections; (P) Density of bus stations; (Q) Population distribution.

$$\mathrm{R}_{OS}(\mathrm{t}+1) = \mathrm{Time}-\mathrm{lag}\left(\frac{D_{OS}-A_{OS}(t)}{A}, dl\right) \tag{5}$$

$$= \mathrm{R}_{OS}(\mathrm{t}) + \left(\frac{D_{OS}-A_{OS}(t)}{A} - \mathrm{R}_{OS}(\mathrm{t})\right)/\mathrm{dl}$$

$$\mathrm{A}_{OS}(\mathrm{t}+1) = \mathrm{A}_{OS}(\mathrm{t}) + A_{OS}(t)^{*}\mathrm{R}_{OS}(\mathrm{t}) \tag{6}$$

$$\mathrm{LoS}(\mathrm{t}) = \frac{A_{OS}(t)}{\mathrm{P}(\mathrm{t})}\mathrm{LoS}(\mathrm{t}) \rightarrow \mathrm{LoS}_{goal} \tag{7}$$

where $\mathrm{LoS}(\mathrm{t})$ is the level of the service of open spaces; LoS_{goal} is the goal of the $\mathrm{LoS}(\mathrm{t})$ which is set by the model builder; A is the total area of the study region; $A_{OS}(t)$ is the area of open spaces at time; $\mathrm{R}_{OS}(t)$ is the growth rate of the open spaces; and dl is the mean time-lag between the moment of deciding to construct new open spaces and the time of opening these open spaces to residents. The area of urban land is assumed to be a function of population, GDP, and the density of the road network (Clarke & Gaydos, 1998; Deng et al., 2010; Fragkias & Seto, 2009). We used multiple linear regression to fit their relationship with the urban area in the study region. The best fit formula used to calculate the urban area was as follows:

$$\mathrm{A}_u(\mathrm{t}) = 0.31 \times dp(t) - 2.29 \times \mathrm{RoD}(\mathrm{t}) + 6.92 \times pGDP(t) + 183.74 \tag{8}$$

where $\mathrm{A}_u(\mathrm{t})$ represents the area of urban land at time t; $dp(t)$ is the density of population; $\mathrm{RoD}(\mathrm{t})$ denotes the density of road networks, which is from the statistical yearbook; and $pGDP(t)$ is the GDP per capita. The area of non-urban land was estimated according to the rural population and the output value of agriculture:

$$\mathrm{A}_{nu}(\mathrm{t}) = 1525.29 - 1.15 \times 10^{-5} \times \mathrm{rP}(\mathrm{t}) - 0.0023 \times \mathrm{aG}(\mathrm{t}) \tag{9}$$

where $\mathrm{A}_{nu}(\mathrm{t})$ denotes the area of non-urban land at time t; $\mathrm{rP}(\mathrm{t})$ represents the rural population; and $\mathrm{aG}(\mathrm{t})$ is the total agricultural output. The indicators mentioned above interact to generate the future demand for open space.

3.2. A cellular-automaton sub-model for OS

A cellular-automaton sub-model for OS was developed to spatially allocate the future open spaces to individual cells. The sub-model first uses an artificial neural network (ANN) to quantify the complex non-linear relationships between the end-term land-use pattern and a set of driving factors (Li & Yeh, 2002). The advantage of ANNs is that they are capable of learning and fitting complex relationships between input data and training targets through a number of learning-recall iterations (Pijanowski et al., 2005). The ANN model will output the probability-of-occurrence surfaces of open spaces, urban land, and non-urban land. The

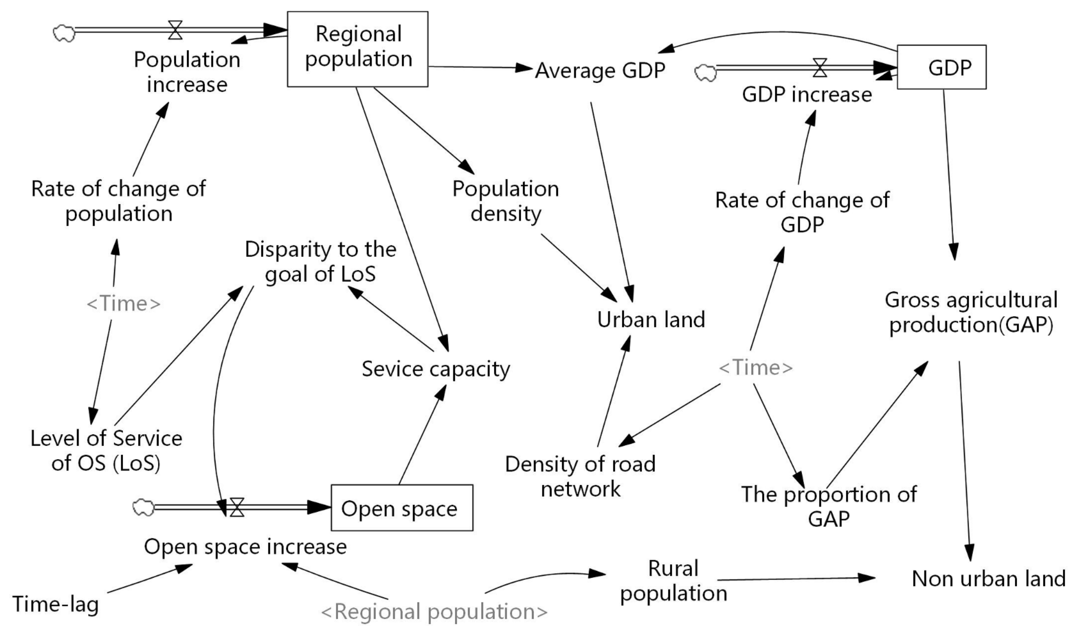

Fig. 4. The structure of the dynamic sub-model for OS, which is driven by a set of socio-economic factors.

sub-model can thus simulate the development of new open spaces and other land use types on these probability-of-occurrence surfaces. The mining framework of transition rules for the CA model based on ANN is commonly used in many simulation studies (Cao et al., 2019; Liang, Liu, Li, Zhao et al., 2018; Liang, Liu, Li, Chen et al., 2018; Pijanowski et al., 2005). Based on these probability-of-occurrence surfaces, a CA model that considers the emergence, competition, and inter-attraction between open space and urban land is proposed to model the co-evolution of open space and urban land (see Fig. 5).

3.2.1. Interactions and competition

The OS-CA also considers the interactions and inter-attraction between open space and urban land. The interactions lay in the competition between open spaces, urban land and non-urban land. The three land use types compete with each other through a random roulette wheel process, which is constructed by the normalized total probability of each land use type (Liu et al., 2017). The land use type selected by the roulette wheel will account for the cell in the next iteration. The formula for calculating the total probability of land use type k can be expressed as follows:

$$TP_{i,k}^{t} = P_{i,k} \times \Omega_{i,k}^{t} \times D_{k}^{t} \tag{10}$$

where $P_{i,k}$ is the probability-of-occurrence of land use type k at location i, as exported from a neural network model (Liang, Liu, Li, Zhao et al., 2018; Liang, Liu, Li, Chen et al., 2018); D_k^t represents the impact of the future demand for land use type k, which is a self-adaptive driving coefficient that depends on the gap between the current amount of land at iteration t and the target demand of land use k; and $\Omega_{i,k}^t$ denotes the neighborhood effects of land unit i, which are the cover proportions of the land use components of k within the following neighborhood. The self-adaptive method of D_k^t is as follows:

$$D_k^t = \begin{cases} D_k^{t-1} & \text{if } \ |G_k^{t-1}| \le |G_k^{t-2}| \\ D_k^{t-1} \times \dfrac{G_k^{t-2}}{G_k^{t-1}} & \text{if } \ 0 > G_k^{t-2} > G_k^{t-1} \\ D_k^{t-1} \times \dfrac{G_k^{t-1}}{G_k^{t-2}} & \text{if } \ G_k^{t-1} > G_k^{t-2} > 0 \end{cases} \tag{11}$$

where G_k^{t-1} and G_k^{t-2} are the differences between the current amount of, and future demand for, land use type k at the $t-1$th and $t-2$th iteration. This self-adaptive mechanism has proven to be an efficient method for simulating the competition and co-evolution of multiple land use types (Li et al., 2017; Liu et al., 2017).

3.2.2. Emergence of new open space

The emergence of open spaces and urban land is according to a stochastic patch generation mechanism based on probability-of-occurrence surfaces (Chen et al., 2013; Liang et al., 2020; Sohl et al., 2007). The number of new open spaces is determined by the following equation:

$$N_{os}(t) = \frac{D_{os}(t)}{M_{os}} \tag{12}$$

where $N_{os}(t)$ is the number of new open spaces at time t; $D_{os}(t)$ represents the demand for open space; M_{os} is the mean patch size of open space. For each simulation stage, the OS-CA will randomly plant $N_{os}(t)$ seeds of open spaces in the study region according to the probability-of-occurrence surfaces of open space. When the value of the probability-of-occurrence of open space is larger than a random number ranging from 0 to 1, a seed cell of open space is planted and the neighborhood effect in formula (10) is replaced by another random value R_x ranging from 0 to 1:

$$TP_{i,k}^{t} = \begin{cases} P_{i,k=OS} \times R_1 \times D_{k=OS}^{t} & \text{if } \ Con(OS_{old}, N_d) = 0 \text{ and } P_{i,OS} > R_2 \text{ and } th_{OS} \\ P_{i,k=U} \times R_3 \times D_{k=U}^{t} & \text{if } \ Con(OS_{new}, N_d) > 0 \text{ and } P_{i,k=U} > R_4 \\ P_{i,k} \times \Omega_{i,k}^{t} \times D_k^t & \text{all others} \end{cases} \tag{13}$$

where OS means the open space, U is urban land; and th_{OS} represents the lowest threshold for generating open spaces. The OS_{old} denotes the existing open space before simulation, and the OS_{new} represents the simulated open space in the simulation process. $Con(OS_x, N_d)$ is a counting function for OS_x inside an $N_d \times N_d$ window, N_1 is an odd number so that the search window has a core cell. The first condition of formula (13) means the OS-CA does not allow the seeds of new open space to grow within the $N_d \times N_d$ search window of the existing cells of open space (OS_{old}). In this way the existing open spaces before simulation will not expand, and the new open spaces will not be too close to the existing open spaces. The second condition of formula (13) reflects that

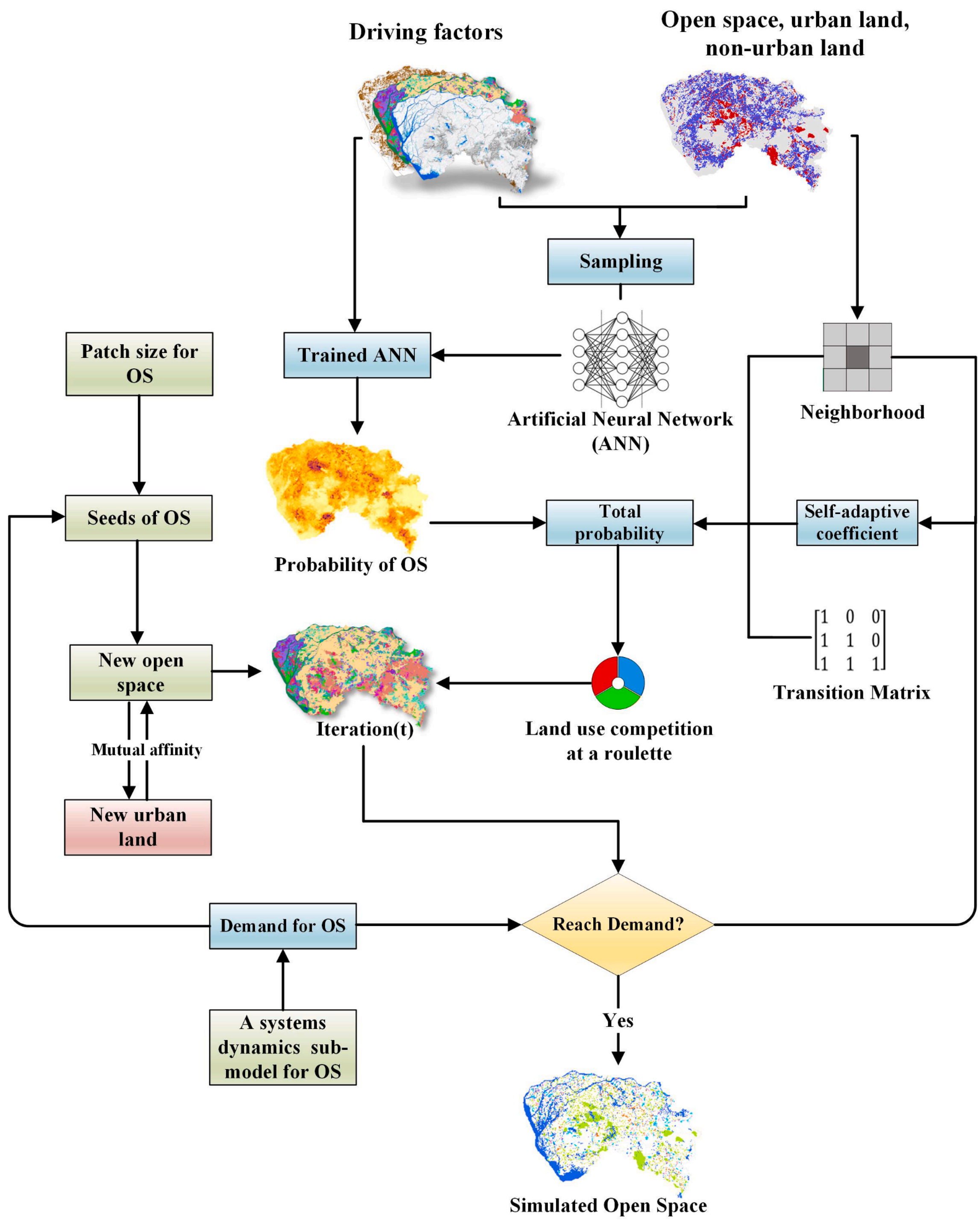

Fig. 5. The schematic framework of the cellular-automaton sub-model for OS.

the new open spaces will attract the spontaneous growth of new urban land (e.g., residential communities constructed by estate agents) inside an affected region with a size of $N_d \times N_d$. The area of these new open spaces and urban land will freely grow until they meet the future demand $D_{os}(t)$.

3.2.3. Inter-attraction between open space and urban land

In addition, in the process of urban development, not only will the open space attract the growth of urban land, but the new urban land also produces new demand for open space in local regions (Wu & Plantinga, 2003). Thus, we designed an inter-attraction process in the simulation of the OS-CA model (Fig. 6). This mechanism is established based on the probability surfaces or attractiveness surfaces. In a previous study, the attractiveness surface was defined as the sum of weighted driving factors, the weights being determined by the planners, which may bring some subjectivity into the modeling process (BenDor et al., 2013). For this study, we used ANN to generate the probability-of-occurrence surfaces of urban land and open space, which not only avoids bringing in the subjectivity of planners but also can consider more interactions between urban land and open space.

First, we assume the region of inter-attraction of a cell of open space or urban land is also an $N_d \times N_d$ window. When a new cell of open space emerges, it improves the total probability of the occurrence of urban land inside the $N_d \times N_d$ neighborhood window with a non-linear

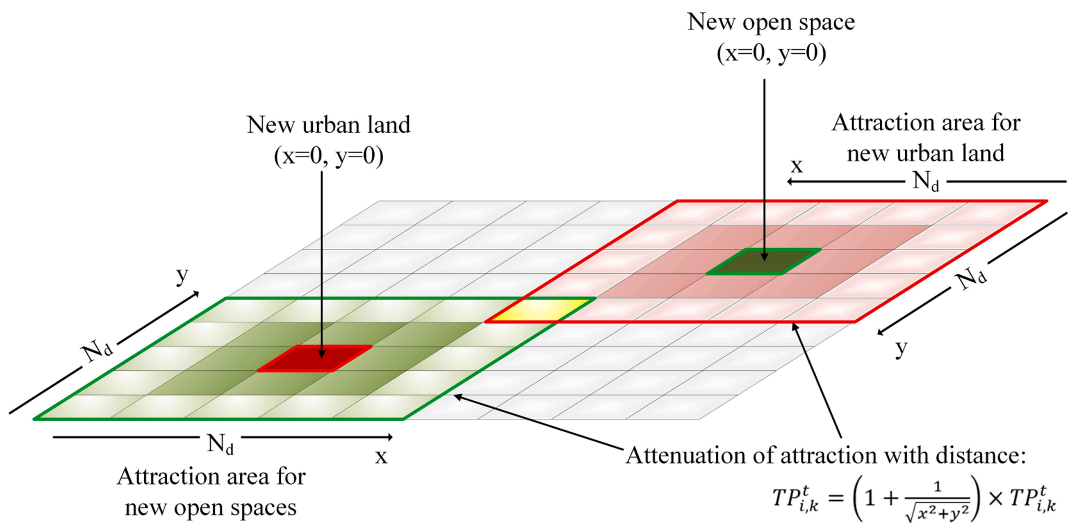

Fig. 6. The sketch map of the inter-attractions between open space and urban land.

function, which is different from the previous study that used a linear function (BenDor et al., 2013):

$$TP_{i,k}^t = \left(1 + \frac{1}{\sqrt{x^2+y^2}}\right) \times TP_{i,k}^t \quad 1 \le x,\ y \le \frac{N_d - 1}{2},\ k = OS \text{ or } U \tag{14}$$

where $TP_{i,k}^t$ represents the total probability of urban land caused by the new open space; x and y are the coordinate indices of the cells within the $N_1 \times N_1$ window, and the core cell is the origin of the coordinate system. Thus the $\frac{1}{\sqrt{x^2+y^2}}$ is the inverse distance from a cell to the core cell within the window. The closer to the core cell (open space), the higher the increase of the total probability of urban land. Similarly, the urban land also attracts the new open space with the same rule.

3.3. Model validation and scenario development

3.3.1. Validation of the dynamic sub-model for OS

We first calibrated the dynamic sub-model for OS with a trial-and-error method and validated its prediction accuracy with statistical data using the following formula:

$$\mathrm{RE(t)} = \frac{|\mathrm{SV(t)} - \mathrm{HV(t)}|}{\mathrm{HV(t)}} \times 100\% \tag{15}$$

where RE(t) is the relative error of the prediction at time t; SV(t) is the simulated value; HV(t) is the historical value; and |*| means selecting the absolute value. We used the statistical data from 2010 to 2015 to validate the predicted areas of open space, urban land, and non-urban land in Dongguan (Table 1). The relative errors of the prediction values were all less than 7%, which indicates that the dynamic sub-model for OS proposed in this study can reproduce the historical trajectory of open space and urban land in Dongguan. Therefore, we can use the sub-model to predict the future demands for open space, urban land, and non-urban land.

3.3.2. Scenario development

In the simulation step, the population and urban area were set according to the Master plan in Dongguan from 2016 to 2030. Oxford Economics reported in 2014 that the GDP in Dongguan will reach 1919.1 billion Chinese yuan in 2030 (Oxford Economics, 2014). The time-lag in the baseline scenario was set to 1 year, and the growth rate of the goal in the level of service of the open space (LoS_{goal}) was set to 10% per 5 years (initial value 33.69 m^2/per year in 2015). Since all the spatial data were created or resampled to a uniform resolution of 30 m, the mean area of open space was set to 0.9 ha (10 cells). The window size of inter-attraction between open space and urban land was set to 11 (N_d), which means the attractive area of an open space cell is a 330 m × 330 m square and the least distance between old and new cells of open space is 150 m. Two groups of scenarios were set in this study. Scenarios in the first group have different mean time-lags for building new open spaces, including 1-year, 3-years, 5-years and 10-years.

The mean time-lags under different scenarios refer to the systems dynamics model proposed by BenDor et al. (2013). According to the statistical data in Dongguan, the patch sizes under different scenarios refer to the mean patch size of open spaces in Dongguan in 2015 (1.22 ha, 13.56 cells). We take 10 cells (0.9 ha, less than the 2015 mean value) and 25 cells (2.25 ha, approximate twice the mean value) as the mean patch sizes of the first and second scenarios. The mean patch sizes under the last two scenarios are set as 50 (4.5 ha) and 100 (9 ha), which are double and quadruple the values in the second scenario respectively.

Table 1
Validation of the simulated results of the dynamic sub-model for OS with real land use amounts from 2010 to 2015.

Variables (km^2)		2010	2011	2012	2013	2014	2015
Open space	HV(t)	154.98	174.39	200.37	203.31	202.86	278.07
	SV(t)	152.93	168.65	193.82	199.02	212.64	259.47
	RE(t)	1.32%	3.29%	3.27%	2.11%	4.82%	6.69%
Urban land	HV(t)	859.62	849.61	839.40	850.65	862.81	805.14
	SV(t)	829.12	839.98	840.44	844.17	833.25	811.20
	RE(t)	3.55%	1.13%	0.12%	0.76%	3.43%	0.75%
Non-urban land	HV(t)	1098.45	1089.05	1073.28	1059.09	1047.38	1029.84
	SV(t)	1131.00	1104.43	1078.79	1069.87	1067.16	1042.38
	RE(t)	2.96%	1.41%	0.51%	1.02%	1.89%	1.22%

Other parameters were the same as the parameters used in the baseline scenario. The construction time-lags and mean OS area thus represented the policies chosen by the urban managers.

The trajectories of future open space and urban land is shown in Fig. 7. We found that the area of open space in 2030 under the 1-year and 3-years time-lags were almost the same. The former created an open space area of 416.73 km^2 while the latter produced an open space area of 422.80 km^2. The two trajectories have different growth trends though. New open spaces will appear much earlier in the 1-year time-lag trajectory. The demand for open space under the 1-year time-lag scenario shows a pattern of phased development. Compared to the 1-year time-lag trajectory, the curve under the influence of the 3-year time-lag is steeper. Besides, under the 5-years and 10-years time-lag scenario, the growth of open space at the early stage is very limited, but the demands for open space will grow rapidly after the construction time-lag. Overall, the trajectories of open space under all the scenarios show an 'S' shape growth curve. Thus, the amount of open space will tend to be more stable after a period of rapid growth.

In the simulation process, a three-layer back propagation ANN was used to explore the relationships between land use distribution and the multiple driving factors. We set 10 nodes for the hidden layer of the ANN model and trained it with a 3% sample. Finally, it was used to derive the probability-of-occurrence surfaces for all land use types (open spaces, urban land and non-urban land). Fig. 8 shows the probability-of-occurrence surfaces in Dongguan. Driven by the demands of the three land use types (Fig. 7), the OS-CA was used to spatiotemporally simulate the creation of open space under the group of scenarios with different time-lags based on the probability-of-occurrence surfaces (Fig. 8). We validated the probability surface of open space with the relative operating characteristic (ROC) curve (Pontius & Schneider, 2001; Pontius & Si, 2014; Pontius & Parmentier, 2014). The area under the curve was 0.704, which is an acceptable precision for the ANN model.

3.3.3. Validation with multiple source data under the baseline scenario

We first simulated the development of open space under the baseline scenario from 2015 to 2020, and validated some of the simulated open spaces with multiple source data (Fig. 9). We examined the locations, street scenes, and high-resolution imagery for four simulated open spaces in 2020, corresponding to the types of open spaces simulated. The locations of the new open spaces were validated using Baidu Map (https://map.baidu.com/). The street scenes in Fig. 9 are obtained from the Internet. The high-resolution imagery comes from Google Maps (www.google.com/maps).

The location of Fig. 9(a) is a newly-built national wetland park that adjoins Huayang Lake. The OS-CA model can not only accurately predict its location, but also simulate a similar pattern to the actual form of the national wetland park. The OS-CA simulated that most of the national wetland park will be formed from 2020 to 2025, which is different from the true period for building the wetland park (2015–2020). However, considering that the simulation process of the OS-CA model has some randomness, the error in the time period is acceptable. Fig. 9(b) shows a simulation result of another location in Changping town, Dongguan. The OS-CA model also successfully simulated the open space created along the roads: the Hexi park, which was opened in June 2018. Despite the fact that Hexi park was dismantled at the end of 2019 because of land use problems, the government planned to transform it into an

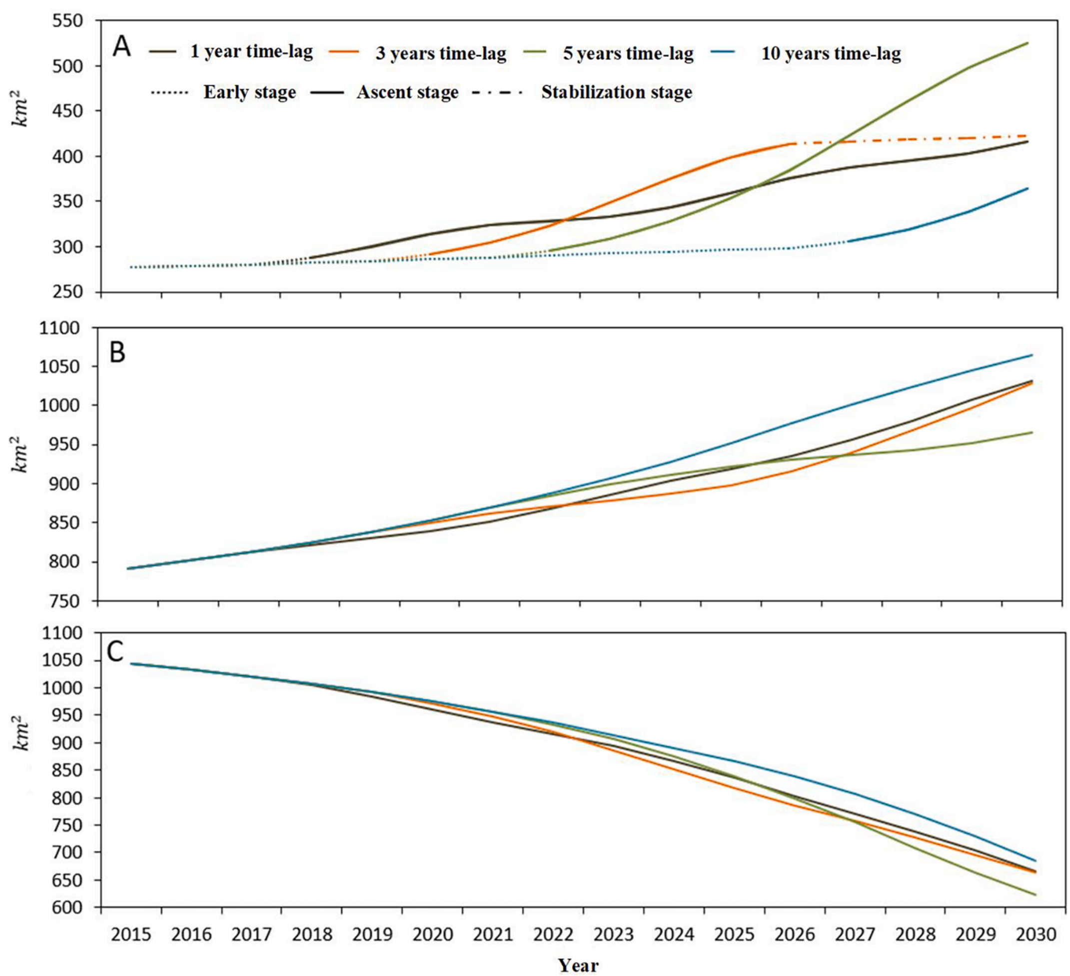

Fig. 7. The predicted demand for open space (A), urban land (B), and non-urban land (C) under different scenarios.

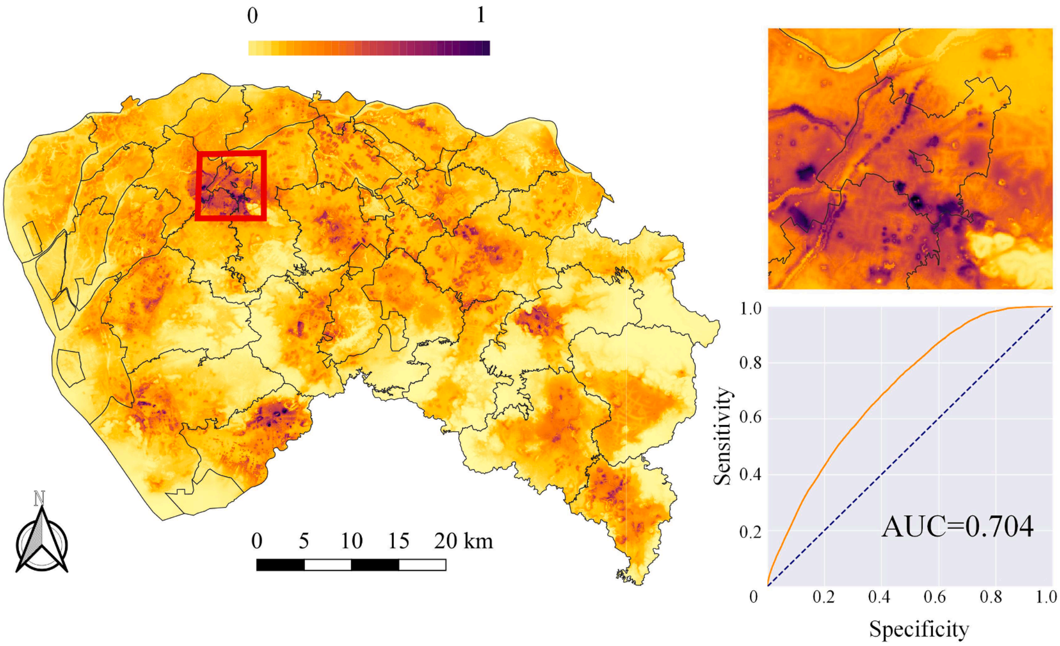

Fig. 8. Probability-of-occurrence surfaces for open space.

agricultural sightseeing garden, which is another kind of open space.

Fig. 9(c) shows the indoor open space predicted by the OS-CA model, which is located at the intersection of two avenues in Dongguan. This open space is an art exhibit on the 5th floor of a commercial building, namely the Minying art museum. This museum was formed to improve the art exchange in Dongguan at the end of 2018. It is a free pavilion that follows the trend of placing cultural elements into shopping centers in China. The OS-CA model accurately predicted its occurrence at this location during 2015–2020. Fig. 9(d) shows a new open space that emerges inside a residential area identified by the OS-CA model. This open space was built in 2017, and is a water park built inside a residential area. These cases indicate that the OS-CA model can identify the locations that are suitable for building new open spaces.

3.4. Assessment of the walking accessibility of OS

Most of the residents' activity inside the open spaces are spontaneous. Van Hecke et al. (2018) pointed out that citizens who live close to the open spaces tend to have more physical activities. Therefore, distance to open space is an important factor for citizens to decide whether they will do outdoor activities and which open spaces to visit. In this study, we used walking accessibility to measure the convenience degree of the citizens in Dongguan for going to open spaces. The coverage of walking accessibility (CWA) is the sum of the buffer of the entry points to open spaces within a comfortable distance for walking. The ratio between the overlapping area of the CWA and urban land and the total urban area in Dongguan is the ratio of the coverage of walking accessibility (RCWA) (Geoghegan, 2002). To calculate the RCWA in Dongguan, we assume that the comfortable walking distance to the gates or entry points of an open space for residents is 300 m and that a comfortable walking time is 5 min. After that, we overlap the CWA with the population distribution data to calculate the population coverage of OS under different scenarios. The future distribution data for the population in 2030 is from a study by Chen, Li, Huang, Luo, & Gao, 2020.

However, it is hard to determine the locations of the gates to the open spaces, especially the simulated open spaces. To approximately determine potential gates for each open space, we regarded each open space as a polygon. Then we computed a minimum bounding rectangle for each polygon. The open space polygons will have at least four touching points with their minimum bounding rectangle (Fig. 10). These touching points are regarded as the candidate gates to the open space.

Considering that only very large open spaces have more than one gate, we determined how many gates to expect for each open space according to its area (Table 2). Then the location of the entry points for each open space were randomly determined from the four potential gate locations.

4. Results

4.1. Simulation of new OS with different construction time-lags

The simulations of new OS under different scenarios are presented in Figs. 11 and 12. The simulated results showed that the new open spaces tend to emerge at regions outside of the central urban area. Fig. 11 shows the simulated open spaces under the influence of different construction time-lags. We found that new open spaces tend to appear at places that are already covered with forest. As shown in Fig. 11(A-I), a new open space will appear where there was originally an agricultural garden, which is a piece of productive plantation land that has not been regarded as open space for it is not free. Yet the location is well suited for developing into an open space. Some other new open spaces occur near the river (Fig. 11(D-III)). This kind of open space is a trail along the river, which is commonly seen in the cities of South China. In addition, the areas near the residential area also have a probability of developing into open space (Fig. 11(C-III)). As time progresses and the demand for open spaces grows, new open spaces appear in the hilly area which is covered by natural forest (Fig. 11(B-II)).

4.2. Simulation of OS with different mean sizes

The simulation results under the four scenarios are shown in Fig. 12. We found that the smaller the mean area of open space, the more dispersed is the distribution pattern of open space. According to formula (12), scenario A tends to generate more open spaces than the other scenarios, and most of them are small open spaces. Scenario B shows an alternative distribution of both large and small open spaces. More large open spaces will be formed under Scenarios C and D in the period from 2020 to 2025 because the growth rate of open space in this period is greater than that in 2015 to 2020 and 2025 to 2030.

Fig. 9. Validating the simulated open spaces in Dongguan from 2015 to 2020 with Baidu locations, street scenes, and high-resolution imagery.

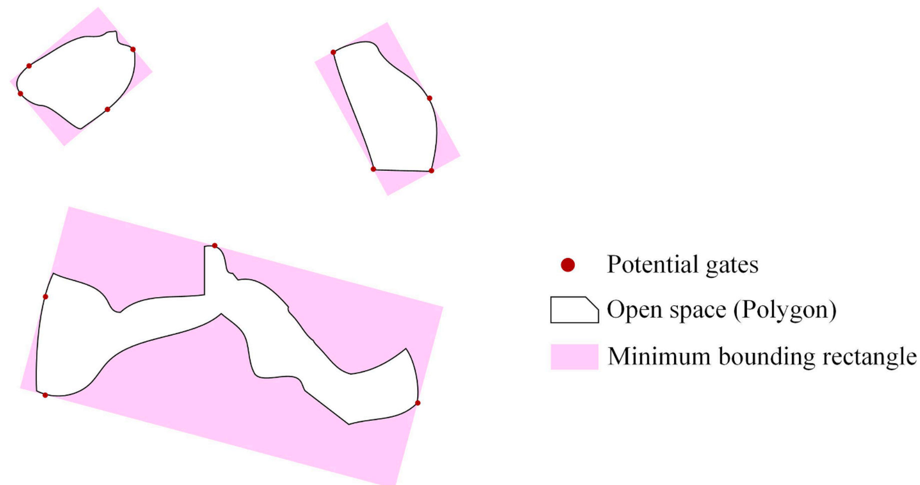

Fig. 10. Examples for determining the potential gates for each open space within the minimum bounding rectangle.

Table 2
Rules to determine the number of gates for each open space according to its size.

Number of pixels (N)	Area of OS (AOS)	Number of gates
$N \leq 10^2$	AOS $\leq$ 9 ha	Randomly select 1
$10^2 < N \leq 20^2$	9<AOS $\leq$ 36 ha	Randomly select 2
$20^2 < N \leq 40^2$	36<AOS $\leq$ 144 ha	Randomly select 3
$N > 40^2$	AOS > 144 ha	4

4.3. Walking accessibility for the simulated OS

We measured the 2015 and 2030 walking accessibility and the coverage rate of the population of open spaces in Dongguan under the different scenarios from 2015 to 2030 (Table 3). We found that the walking accessibility of OS under all the scenarios were significantly improved (Table 3). An average area of 10 cells (0.9 ha) will increase the ratio of the coverage of walking accessibility and the coverage rate of population in Dongguan by 20.54% and 12.96% from 2015 to 2030, respectively. The scenario with a mean area of open space of 100 cells (9 ha) has the lowest coverage ratio of walking accessibility and coverage rate of population (increases of only 10.13% and 6.76%, respectively), indicating that building more small open spaces (lower mean open space size) is likely to gain a higher coverage of walking accessibility for the citizens and a higher coverage rate of the population. Moreover, with the construction of more open spaces, the improvement of the walking accessibility is higher than the improvement of the population coverage rate (Table 3).

5. Discussion

Important information can be revealed in simulations. For example, the group of scenarios (Fig. 7(A)) derived from the SD model with different time-lags can simulate the time-lag of the growth of open space in Dongguan due to site selection, examination, approval, bidding, publicity, and construction. From the comparison between different time-lag scenarios, we find that if the efficiency of constructing new open space is too low (with a relatively long time-lag of constructing new open space), the demand for open space by residents will accumulate and show a trend of reactive growth. The longer the time-lag in building new open spaces, the more demand for open space the study region will face in the future. This result indicates that the low efficiency in building new open spaces will lead to extra demand for open space in the future, which is a kind of waste of resources. If the extra demand is not fulfilled by the government, the quality of life of the residents will decrease.

From the results of the spatio-temporal simulation of OS, we find that the new open spaces tend to emerge at regions outside of the central urban area. This is because the central urban area has limited space for building new open spaces, and the new open spaces tend to appear at places that are already covered with vegetation, which agrees well with the study proposed by Tu, Huang, Wu, and Guo (2020). We also found that if the government builds more small open spaces, the distribution pattern of open space would be more dispersed and the walking accessibility to open spaces would be higher. In contrast, a lack of small open spaces may lead to a lower accessibility of open space for urbanites, a waste of land resources, duplicate functionality of the open spaces, and even green space inequality. The results under different scenarios show that new open spaces in Dongguan tend to appear in the places that are already covered with forest or are near a river (Fig. 11(D-III)). New open spaces can also emerge in hilly areas (Fig. 11(B-II)), as forest parks. In summary, the new open spaces are most likely to appear at places near a river, forest, wetland or lake, along roads or at road intersections, or near residential areas.

We find that with the construction of more open spaces, the improvement of the walking accessibility is higher than the improvement of the population coverage rate (Table 3). This is due to the fact that the central urban areas with higher population density have limited space for building new open spaces, so new open spaces tend to emerge in the regions with relatively low population density, which leads to a decrease in the efficiency of services of open space. Therefore, we recommend that governments build more small open spaces within the central urban areas to improve the overall walking accessibility of open space, which will help to improve the service level and population of new open spaces. As Wu and Plantinga (2003) have pointed out, the residents may derive greater benefits from more dispersed forms of open space.

Although we recommend creating more small open spaces within the central urban areas to improve the overall walking accessibility for open space, it is worth noting that the recreational, ecological, and economic functions of small open spaces are reduced as well. The smaller open spaces are unlikely to become popular tourist spots in a city. Giles-Corti et al. (2005) have pointed out that larger OSs are associated with higher levels of walking activities. Therefore, the urban designer should balance the accessibility and socio-economic functions of open spaces for multiple users (e.g., walkers, sports participants, picnickers), for example, a certain amount of larger open spaces can be built outside the core urban areas. These suggestions can help urban planners to balance the availability of open spaces where citizens can experience leisure as rapid urbanization continues (Sushinsky et al., 2017). Additionally, larger open spaces have lower per hectare land values (Brander &

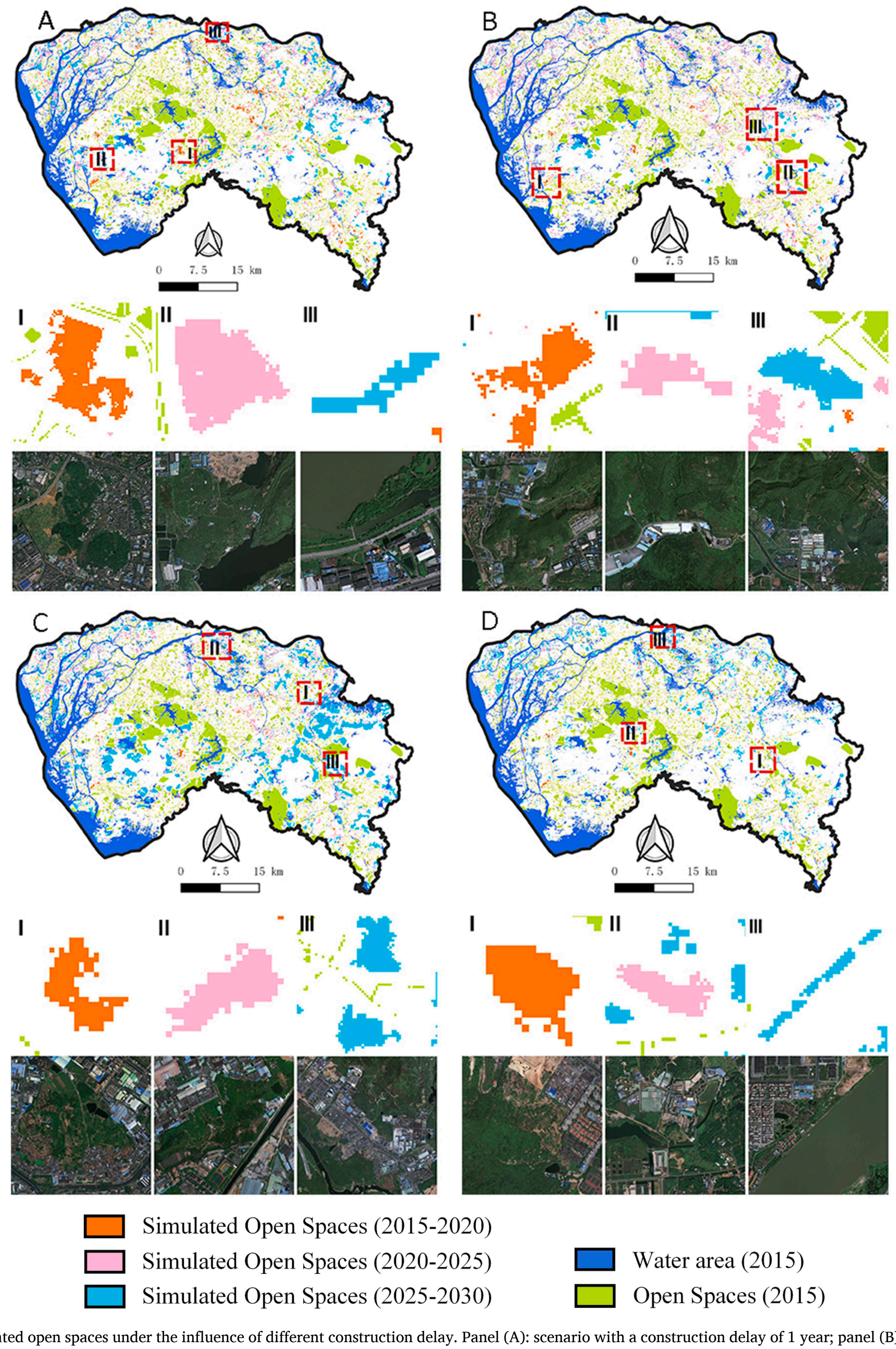

Fig. 11. Simulated open spaces under the influence of different construction delay. Panel (A): scenario with a construction delay of 1 year; panel (B): scenario with a construction delay of 3 years; panel (C): scenario with a construction delay of 5 years; and panel (D): scenario with a construction delay of 10 years.

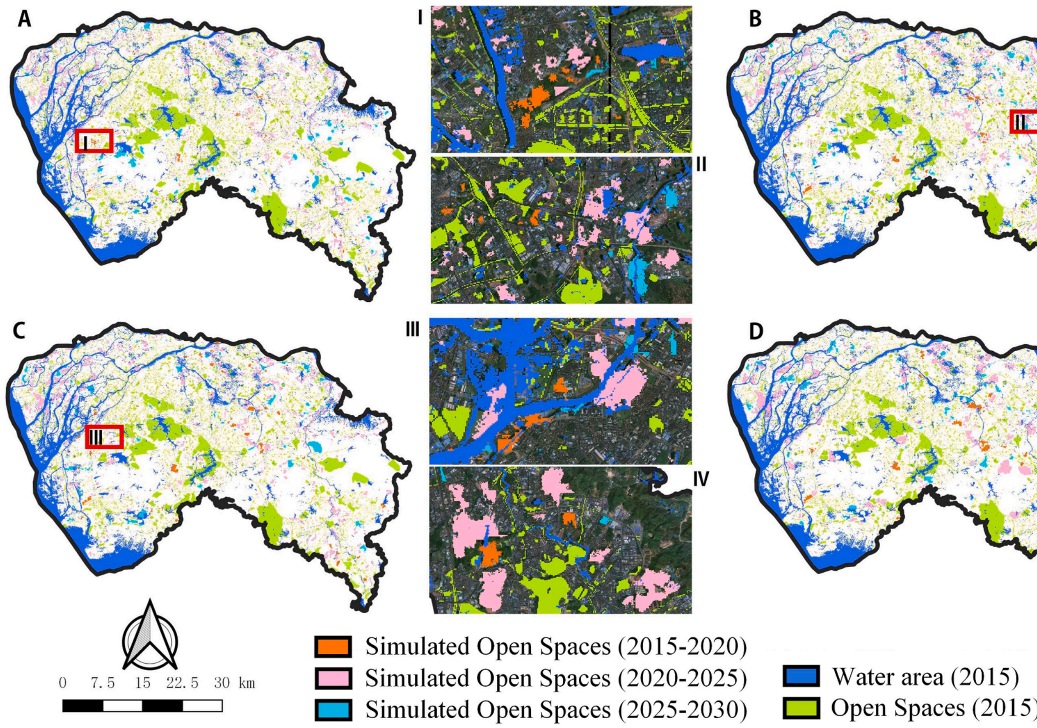

Fig. 12. Simulated open spaces under the scenarios of different mean area of open space. Panel (A): scenario with a mean OS area of 0.9 ha; panel (B): scenario with a mean OS area of 2.25 ha; panel (C): scenario with a mean OS area of 4.5 ha; and panel (D): scenario with a mean OS area of 9 ha.

Table 3
Future walking accessibility under different mean size scenarios of open spaces.

Scenario with different mean area	Coverage of walking accessibility (km^2)	Coverage rate (%)	Improvement of coverage rate (%)	Coverage rate of population (%)	Improvement of the population coverage (%)
2015 open space	370.63	54.13	–	29.31	–
10 cells	660.20	74.67	20.54	42.27	12.96
25 cells	615.06	71.56	17.43	40.70	11.39
50 cells	568.30	68.33	14.20	38.45	9.14
100 cells	509.24	64.26	10.13	36.07	6.76

Koetse, 2011), but the size of the open space has a positive and statistically significant influence on home sale prices (Bolitzer & Netusil, 2000). Our recommendation that building more small open spaces within the central urban areas while constructing larger open spaces outside of the core urban areas can help the government control the rise of housing prices and save financial funds for constructing new open spaces.

In our future work, we will improve the OS-CA model with state-of-the-art classification algorithms (e.g., deep learning methods) to simulate the creation of the different components of open spaces shown in Fig. 2, to identify what specific categories of the OS will emerge in the study region by considering more high-dimensional spatio-temporal features. More complex drivers, for example, house prices and urban renewal policy, will be taken into account in our further study.

6. Conclusion

Open spaces provide important recreational and communication functions for citizens. To fulfill the rapid increase in the demand for urban open space, urban designers should make suitable city planning policies to balance the growth of urban land and the co-development of open space. Existing studies only simulated one single component of OS, for example, parks, and have ignored other subsets of OS. This article presented an OS-CA approach to simulate the development of all OSs components from 2015 to 2030 in Dongguan. Some specific designs have to be incorporated, which are not presented in traditional CA models, for example: 1) the emergence mechanism of new open space to simulate the spontaneous growth of open spaces; 2) the inter-attraction mechanism between open space and urban land; and 3) using different construction time-lags and mean size of OS.

To predict the co-development of urban land and open space with of socio-economic development, we propose a dynamic sub-model for OS and urban land under the interactions of a series of factors, including GDP, population, industrial development, and road network density. The sub-model can accurately predict the amount of open space and urban land for the historical period from 2010 to 2015 (the relative error was less than 5%). The development of open space and urban land from 2015 to 2030 was projected with the cellular automaton sub-model for OS under different scenarios. Scenarios with different time-lags were used to simulate the development of open spaces under the influence of different time costs caused by planning, approval, construction, etc. The trajectories of open space under all the scenarios tend to be stable after a period of growth. The demand for open space under the 1-year time-lag scenario shows a pattern of phased development. The curve under the influence of the 3-years time-lag is steeper than the one under the 1-year time lag scenario. The curves under the 5-years and 10-years time-lag scenario will grow rapidly after the construction time-lag and generate more demand of OS.

By considering a set of infrastructural and socio-economic factors derived from POIs, the OS-CA model was used to simulate the emergence and mutual affinity of new open spaces in urban land under different scenarios. The simulated open space in 2020 under the baseline scenario was validated with the true locations, street scenes, and high-resolution imagery for the same year. We also developed a 'different mean area of open space' series of scenarios in the spatial simulation process, to explore the relationship between the sizes of open spaces and overall walking accessibility to open spaces, which is very important for the welfare of urban residents but cannot be addressed by previous models. Finally, we proposed an evaluation method based on a minimum bounding rectangle to compare the current and future walking accessibility and population coverage rate of open spaces in Dongguan, and calculated the improvement of walking accessibility and population coverage rate under different scenarios (Table 3).

The model proposed in this study can accurately anticipate the locations that best suit the building of new open spaces. The OS-CA model is applicable for exploring the impacts of various infrastructural and socio-economic factors on future open space dynamics. The future planning of open space in Dongguan will need to deal with questions such as 'How do open spaces distribute across the region with different mean sizes?' and 'How is the demand for open space growth met under the influence of different efficiencies of construction?' The OS-CA is an effective tool for addressing these problems, and is of great importance for assisting urban managers and designers to make suitable plans for new urban open spaces, including parks, squares, walkways, green belts, and museums. To facilitate OS simulation, the OS-CA used is available for download at https://github.com/HPSCIL/Open-Space-Cellular_Automata.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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