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Modelling and Simulating Urban Residential Land Development in Jiading New City, Shanghai

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Abstract This study develops an agent-based and spatial genetic algorithm framework called Population-driven Urban Land Development (PDULD) to simulate urban land development and population dynamics. In the model, household-life cycles promote their location and relocation desires and, thus, form local housing market demand. Land developers and local governments make optimal use of current land reserves to meet housing demands. Land development in an area is treated as a multi-goal optimization activity. Community cohesion theory is introduced into the model to illustrate the influence of the population on the spatial structure of urban land use. The study uses the Spatial Genetic Algorithm to help find the best land development choices to achieve social, economic, and environmental goals. The results show that the model simulates population distribution quite well and interprets the real land use at a neighborhood level with a reasonable accuracy. A historic data comparison indicates that government policies and increasing land prices have dominated the process of land development in Shanghai based on a case study of Jiading New City.

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Introduction

Cities are emerging as humanity's engines of creativity, wealth creation and economic growth (Bettencourt and West 2010). Despite the increasing importance of cities in human society, our ability to understand and manage them scientifically is still limited. While a variety of qualitative and quantitative methods have been adopted by urban planners and city administrators to generate plans and policies for urban resource allocation, imperative gaps still exist because of a lack of behavioral and dynamic realism in urban modelling (Batty 2008b; Heppenstall et al. 2016).

To address the gaps, urban geographers, computer scientists, and interdisciplinary researchers have made significant efforts to understand dynamic mechanisms behind urban growth and evolution by constructing diverse urban models. Due largely to the rapid advancement of computer technology, urban modellers have found that dynamic simulation models may have the power to delineate the process of urban structural evolution (Batty 1971; Couclelis 1986; White and Engelen 1993). Spatial simulation techniques such as Cellular Automata (CA) and Agent-based Modelling (ABM), have been introduced into urban land-use dynamics studies (Wahyudi and Liu 2016). The advantages of these methods are manifold, including their abilities to incorporate nonlinear, unorganized processes and cross-scale environments that can exhibit emergent properties, dynamic local interactions with spatial references, and indirect impacts and pattern-process linkages (Parker et al. 2003; Feng et al. 2016).

To date, studies on urban dynamics modelling can be classified into three main domains: theoretical modelling based on classical urban land-use theory, hybrid modelling combining land-use theories and empirical findings, and micro-simulation modelling driven by empirical data and specific case study (Huang et al. 2014). In terms of the theoretical modelling approach, researchers often adopt classic urban land-use theories to simulate the growth and expansion of urban land (Batty 2008a; Clarke et al. 1997; Clarke and Gaydos 1998; Batty and Xie 1994; White and Engelen 1993). For instance, Xu et al. (2007) built a CA model on the basis of the work of Dietzel et al. (2005) to test diffusion and coalescence theory in urban evolution; Sasaki and Box (2003) developed an agent-based model to verify von Thünen's location theory; and Filatova et al. (2009) established a bilateral agent-based land market model using the land-market and land price theory to test Alonso's mono-centric land price theory. Most of these studies are rooted in the classic land-use theories but fail to include social, political, and cultural factors in modelling individual decision-making processes in land development (SU 1998).

To address this deficiency, some researchers try to integrate empirical land development phenomenon, such as urban sprawl, urban gentrification, and various administrative policy into modelling and simulating land development processes, in addition to conventional land availability and suitability factors (Wu 1998; Li and Yeh 2000; Wu 2002; Yeh and Li 2002). In these models, local, regional and global constraint scores are used to re-estimate the development probabilities that are calculated from standard dynamic models. These models address the problem of neglecting the spatiality of institutional policies, planning and spatial administrative regulations, but they still overlook the heterogeneity characteristics in residential location and housing choice, local corporate land development strategy, and the involvement of government agents.

Microsimulation modelling method was firstly introduced in 1950s by Orcutt (1957) in an attempt to delineate the diversity of the US economic system. The technique operates at individual unit level and is capable of modeling heterogeneous behavioral activities. Using this method, researchers can incorporate demographic factors and integrate individual housing decision making into urban land development modelling (Waddell 2002; Waddell et al. 2003). It is well recognized that variations in housing preferences among individuals can give rise to an uneven spatial distribution in housing demand across a city space. Experimental studies have found a clear match between the revealed housing preferences and residence location choices (Levine et al. 2005). For example, to interpret residence choice effects on land development, Waddell developed the UrbanSim model (Waddell 2002; Waddell et al. 2003) to simulate the land-market interactions of households, firms, developers and public actors. Xie et al. (2007) constructed a dynamic household model to simulate how local household development leads to global urban landscape transformations, White et al. (2012) employed historic population and land-use data to evaluate neighborhood influences on urban land use dynamics. While these models all attempt to investigate the relationships between behavioral mechanisms of individual residents and land development processes across different scales, however, dynamic socio-economic characteristics of neighborhoods and decision mechanisms of households are rarely considered in the models. For instance, it is indicated that the existence of neighborhood spillover effects can limit the pace of urban land development (Wang 2016). In essence, these models fail to delineate the co-evolutionary processes of demographic transformation and land-use changes.

To solve the gaps in current urban modelling and improve urban land-use simulations, this study develops a theoretic model for the simulation of urban land-use growth that combines CA, ABM and spatial genetic algorithm (SGA) methods. In the model, citizen agents make their location and allocation decisions based on their socioeconomic characteristics. This decision-making process leads to changes in neighborhoods' social, economic, and environmental statuses. Government agents make development strategies and policies to balance citizens' needs and local sustainable development goals based on regional social, economic, and environmental conditions. The development strategies are then incorporated into multi-objective planning problems that are solved using optimization methods. SGAs are used to optimize those development strategies spatially, which determines urban land use development and redevelopment. Jiading New City, which was planned as a satellite city in metropolitan Shanghai, is selected to implement and verify the model in this study.

Following this introduction, a theoretical model of population-driven urban housing and land development is presented in section 2 and 3. The study will then introduce the study area and methods for data collection and analysis in section 4, followed by descriptions of model implementation, parameters estimation, and model verification in section 5. Model simulation results will be presented in Section 6. The paper concludes by discussing the findings and their implications.

Population-Driven Urban Land Development (PDULD) Framework

A dynamic urban system consists of land, buildings, populations, services, and their location-relocation activities (Semboloni 1997). From a housing development perspective, the process of land development of any area may originate from an addition of households, resulted from both natural population growth and migration. The increase in household number elevates local housing demand, and land developers and government administrators then work together to transfer land from non-residential to residential uses. After residential houses are built, household groups purchase and move into new homes based on their own financial and social status. Consequently, the socioeconomic characteristics of neighborhoods are altered. In this land-development process, two pairs of activities emerge to take important roles: land resource demand and supply and household decisions on housing location or relocation. Figure 1 presents a schematic illustration of how these two processes are related and modeled in this study.

For land resource demand and supply, several processes need to be considered. Firstly, the lifecycles of households initiate the formation of a general housing demand market (Mulder and Hooimeijer 1999). The varying residential family structures and financial resources present diverse requirements in the formed market (Logan et al. 2002). Finally, the household location and relocation decision-making activities will lead to the differentiation of housing needs in space (Carrion-Flores and Irwin 2004; Clark and Dieleman 1996).

In addition to the diverse demands generated by households, housing supplies are further shaped by land and housing developers and local governments. While land and housing developers attempt to maximize their economic returns by supplying sufficient housing units, local governments assess local land reserves for developing residential land and build houses to meet the demands to optimize

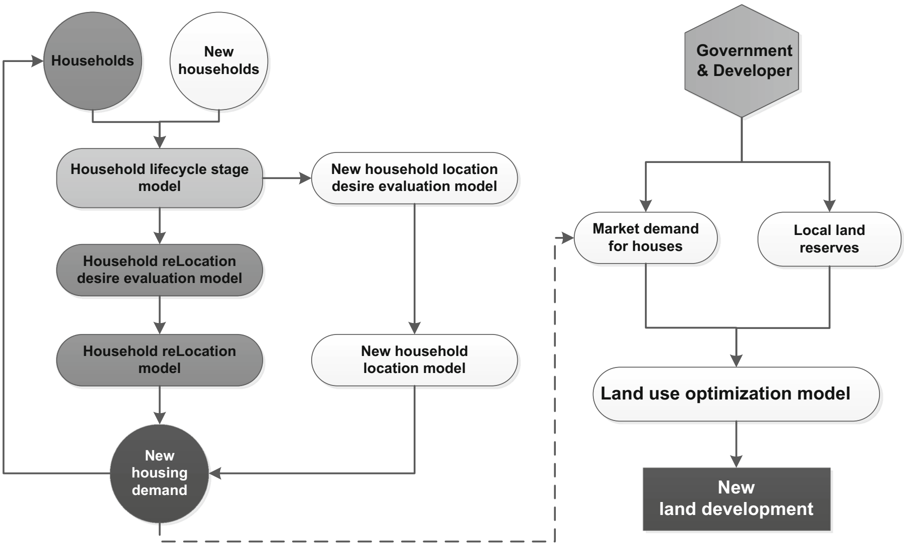

Fig. 1 Housing demand, land supply, and development

regional land use through land use planning and land-development goals (Wei 2002; Wei 2013) (Fig. 1). Therefore, the logic of modelling new land development from a housing market perspective needs to consider these factors in order to build a comprehensive and reasonably accurate simulation model. The following sections detail each element of the model.

Household Life Cycle Stage Model

Numerous measures can be employed to depict the social and financial status of an individual household. Age and revenue are two important ones (Mulder and Hooimeijer 1999; Abdullah et al. 2013). In the model, the age of a household head (A) increases with the lapse of simulation time. Assuming that an increase in household members may eventually create a need for a new or additional house unit, the probability of purchasing a house increases over time along with increasing age of household head. The yearly household revenue (R) also increases at a defined ratio (θ) with time lapse due to increasing seniority and, consequently, human capital in local labor markets.

Therefore, it can be defined that a household's savings at time $t+1$ (S_{t+1}) equals the sum of the previous year's savings S_t and the difference (μ) in yearly household revenue R_{t+1} minus annual housing expenses E_{t+1} and yearly mortgage payment M. The residence time TR_{t+1} in the current house begins when a household moves into the current dwelling and increases each year (Eq. (1)).

$$\begin{array}{l} A_{t+1} = \quad A_t + \quad 1 \\ R_{t+1} = \quad R_t^{*} \quad (1+\theta) \\ S_{t+1} = S_t + \mu^{*} R_{t+1} - E_{t+1} - M \\ TR_{t+1} = \quad TR_t + \quad 1 \end{array} (t = 0, 1, 2, \ldots, n), \tag{1}$$

where $n$is the maximum simulation years.

Meanwhile, a household could also move to another city or region, for reasons including employment, life cycle, housing, neighborhood, access, and other uncontrollable factors (Mulder and Hooimeijer 1999). The inter-region movement of a particular household is more accidental than determined. Therefore, a random value and threshold are defined to delineate this phenomenon. If a generated random value, Rnd, is larger than a predefined move-out threshold TH_O,the household will be removed from the model (Eq. (2)). Moreover, it is also possible that a household head (and, as such, the household) can die. Accordingly, the model assumes that the probability that a household head will die is proportional to his/her age:

$$H_i \begin{cases} die, out : if, e^{(-\kappa A_i)} < TH_A \\ move, out : if, Rnd > TH_O \end{cases}, \tag{2}$$

where A_i is the age of household H_i, κ is the corresponding coefficient, and TH_A is a predefined threshold for household die-out rate.

The average age, *VA*, and average revenue, *VR*, are employed to represent social and financial statuses of the neighborhoods under study:

$$\begin{aligned} VA_{j,t} &= \frac{\sum_j^n A_t}{N} \\ VR_{j,t} &= \frac{\sum_j^n R_t}{N} \end{aligned} \quad (j = 1, 2, 3 \ldots n), \tag{3}$$

where $j$denotes the current neighborhood and N is the total number of households.

Household Location/Relocation Desire Model

For any new migrant households who have already chosen to settle in an area, their location desire is set as full. For local households, their housing relocation desires can be reasonably assumed to relate to their feelings about their current neighborhood and their financial status (Liu et al. 2010; Liao et al. 2016). One of the important indicators about neighborhood feelings is neighborhood cohesion (Buckner 1988; Faludi 2010; Liu et al. 2010), which is reflected by the shared norms and values by the residents in a neighborhood and the network of trusting relationships. Empirically, household groups prefer to live near similar others (Ioannides and Zabel 2008). That means if there are big differences in the social and financial status between a household and its current neighborhood, the household may consider moving. The difference, D, between a household, i, and its neighborhood at time, t, is defined as follows:

$$D_{i,t} = \frac{|A_{i,t} - VA_t|}{\max(A_t - VA_t)} + \frac{|R_{i,t} - VR_t|}{\max(R_t - VR_t)}, \tag{4}$$

The household, H_i, will consider relocating if D_i is greater than a predefined neighborhood difference threshold, TH_D, and immediate household saving, S_i, is larger than new house down payment threshold, TH_S, as follows:

$$H_i \begin{cases} move : if \;\; D_i \geq TH_D \;\; and \;\; S_i > TH_S \\ stay : if \;\; D_i < TH_D \;\; or \;\; S_i < TH_S \end{cases}, \tag{5}$$

Household Location/Relocation Model

Many factors influence where people live, such as employment, income, perceived social exclusion, beliefs and values, their preferences for open space and other amenities, and commuting distance (Ng 2008). Although these factors mostly relate to individual attributes, location decisions are generally made by households, which may comprise single individuals or groups (Fontaine et al. 2014). Generally, higher neighborhood cohesion means greater stability (Schelling 2006), and most household members tend to prefer more cohesive neighborhood (Levy and Lee 2011). A neighborhood's cohesion rate can be defined as the sum of the standard deviations of all factors under consideration as follows (Buckner 1988):

$$C_{t,j} = std.\left(A_{t,j}\right) + std.\left(R_{t,j}\right), \tag{6}$$

where $C_{t,j}$ denotes the cohesion of neighborhood j at time t. The smaller the value, the higher the neighborhood cohesion. In the model, it is assumed reasonably that a household group will choose a more cohesive and equal neighborhood, for example, a neighborhood with small C and D values (Eq. (4) and (6)).

In addition to neighborhood cohesion, physical environment is another crucial factor that a household will consider in selecting a potential housing location. The physical environment may include transportation access, available public facilities, and housing quality (Levy and Lee 2011). Public transportation is important in metropolitan areas. Many cities around the world, especially in developing countries, operate under what is called transit-oriented development (Cervero and Day 2008). In addition, a city with a high development ratio usually has better public facilities and access to employment than do other areas (Hansen 1959). To consider these factors, this study uses the distance to metro as a transportation access indicator and the neighborhood development ratio (developed land divided by the total developable land in a neighborhood) as a public facility indicator.

Land Supply Model

Land supply is another prominent issue in modelling and simulating land use changes. Most models, especially those in the field of resources management, have failed to consider the factor of land supply (Verburg et al. 2002). A city's supply of land is limited by its natural conditions. Large slopes, water bodies, and other natural barriers define the available land for urban construction use. At the same time, the location of land in various parts of a city influences its developable probability (Rose 1989). Land parcels close to the urban center are more likely to be developed, whereas peripheral land parcels are less likely. This distance-decay phenomenon can be described as follows:

$$L = \sum_{i=1}^{n} s(i) * \exp(-\delta u), \tag{7}$$

where u represents the distance of land parcel i from the city center, $s(i)$ is the area of the land parcel i, L is the total land supply, and δ is a distance decay coefficient.

In addition, with limited land resources, a city usually constrains its yearly land use supply by planning periods. Therefore, we can define a city's yearly land supply, Y_t, as follows:

$$Y_t = L_t / T, \tag{8}$$

where L_t is the corresponding year land supply reserve and T is the total period for which the land development is planned. The volume of Y_t changes with time.

Land-Use Optimization Model

In a city, local governments and land use management specialists need to analyze the available land resources and make optimal area development strategies and plans based on social, economic, environmental, and ecological conditions. Urban-land owners (either government agents or private developers) can be assumed to be rational economic human beings who want to achieve the highest land sale revenue (Potepan 1996). According to the classic urban land-use theory, the closer a piece of land is to the central area, the higher its appraisal price (Alonso 1964). This is similar for main public facilities such as metro lines, schools, and hospitals. Therefore, land parcels close to urban centers and public facilities will generate higher development profits than the others, and therefore will receive higher development priority.

One key factor that urban administrators and government officials may consider in urban planning is land-development compactness. Often, low compactness is reflected in over-dispersed or leapfrog land-use patterns, also known as urban sprawl. Urban sprawl usually brings low land-use efficiency and high infrastructure and maintenance costs to a city (Brueckner and Fansler 1983). To land and housing developers, correspondingly, low compactness means high offsite and operating costs. To residents, compact land-use means low transportation costs and walkable, friendly environments (Levine and Frank 2007). Therefore, urban land-use compactness is one of the goals that both public and private agents hope to achieve in developing countries.

At the same time, a given neighborhood's social structure will also influence land development in its neighboring areas. High neighborhood cohesion and social and financial status will help attract more households to the area, and consequently, these areas could be more heavily promoted by private developers and local development authorities (Ding and Knaap 2002). In addition to these social and economic concerns, residential environment is another highly pressing issue in the land-development process. Maintaining certain amounts of green space usually creates better residential environments.

In sum, land development encompasses multiple social, economic, and environment goals. In this study, following a review of urban master planning, urban regulatory planning, and government land-use policy documents in the study area, we only consider land-development revenue, land-use compactness, neighborhood attractiveness, and environmental attractiveness as land development goals to simplify the model. Other factors, like local government and land developer's personal preferences and public-private partnership, have relatively minor impacts for land development in the study area. These goals in the model are specified as follows:

$$\begin{array}{c} LR = f_1(DI_C, DI_S), \\ LC = f_2(CC, CP), \\ LN = f_3(NC, NS), \\ LE = f_4(EG, EA). \end{array} \tag{9}$$

where LR is the land-development revenue, a function of land centricity (DI_C) and closeness to public transportation (DI_S), LC is the land-use compactness, a function of land-use concentration (CC) and land-use type compatibility (CP), LN is the neighborhood attractiveness, a function of neighborhood cohesion (NC) and household social and financial status (*NS*), and *LE* is the environmental attractiveness, which connects with public green spaces (*EG*) and agricultural land reserves (*EA*). During the processes of urban land-use planning and development, any given area is required not only to meet regional housing demand, but also to achieve the maximization of these social, economic, and environmental goals in order to provide better, more livable neighborhoods.

First, for *LR* of a land parcel *i*, this study assumes that the closeness to the central area (DI_C) and metro line (DI_s) positively affect the revenues of local governments and land developers (Ratner and Goetz 2013). Both distance effects decline exponentially with increased distance as follows:

$$LR_i = r_1 \exp(-\alpha_1 DI_C) + r_2 \exp(-\alpha_2 DI_S), \tag{10}$$

where $\alpha_1$and α_2 are distance decay coefficients and r_1 and r_2 are weights.

Second this study assumes that LC_i is positively related to CC_i and negatively related to CP_i as follows:

$$LC_i = s_1{}^{*}CC/M{-}s_2{}^{*}CP/M, \tag{11}$$

Where s_1 and s_2 are corresponding weights and M is the maximum number of land parcels. This study considers the eight neighboring cells (Moore Neighborhoods) of the land under consideration.

Third, this study assumes that LN_i, which is closely tied to neighborhood cohesion and neighborhood average revenue, is conversely related to C_t and VR_t as follows:

$$LN_i = t_1{}^{*}\exp(-C_t/C_M) + t_2{}^{*}\exp(-VR_t/VR_M), \tag{12}$$

where C_M is the immediate maximum neighborhood cohesion value, VR_M is the immediate maximum neighborhood average revenue, t_1 and t_2 are corresponding weights.

Finally, the study also assumes that LE_i is positively related to EG_t and negatively related to EA_t as follows:

$$LE_i = \varphi_1{*}EG_t{-}\varphi_2{*}EA_t, \tag{13}$$

where φ_1 and φ_2 are corresponding weights.

Potential land-development revenue, land-use compactness, neighborhood attractiveness, and environmental attractiveness all contribute to the suitability of a developable land parcel, $SUIT_i$, with different weights as follows:

$$SUIT_i = \omega_1 LR_i + \omega_2 LC_i + \omega_3 LN_i + \omega_4 LE_i \tag{14}$$

Study shows that in a planned economy, a city government makes its annual urban land supply plan based on several conditions: the previous year's land usage, the midterm urban land supply plan, the economic development results of the previous year, the economic predictions for the following year, and the land supply plans reported from local district governments (Qiu and Xu 2017; Xu 2004; Xu and Tan 2001).

Thereafter, land use administrators may evaluate developable land parcels and approve the most suitable parcels to be auctioned for development. Therefore, the total annual land supply is the optimal result of searching all potential land parcels as follows:

$$SUIT(L) = \max\left(\sum_{i=1}^{n} SUIT(i)\right) \tag{15}$$

Spatial Genetic Algorithms

As was noted in the previous section, land development requires to balance efficient resource use, environmental protection, economic development, and social equity (Cao et al. 2011). As formulated in Eq. (9), housing and land supply is proposed to optimize the development of available land to achieve development goals. Therefore, land-development models need to identify optimal solutions with multiple objectives.

Various methods and technologies, such as multi-criteria decision-based, simulation-based, and optimization-based models, have been proposed and applied to solve land allocation and optimization problems (Liu et al. 2015; Liu et al. 2014). Among them, spatial evolutionary optimization methods have the advantages of being able to incorporate many objectives and generate disparate spatial solutions (Ligmann-Zielinska and Jankowski 2010).

In SGA as shown in Fig. 2, a series of neighboring land parcels (cells) are selected as the chromosomes; different land-use combinations are then generated as parents for genetic reproduction. After this pairing, the "genes" (groups of parcels or cells) cross over to generate new pairs of chromosomes as children. Simultaneously, one parcel's land-use type could mutate to other types, and then better children will be selected for the next round of reproduction according to multi-optimization goals. This process can continue until the optimal land use combination is found (Cao et al. 2011; Liu et al. 2012; Liu et al. 2015).

For instance, cells (0), (1), (2), (3), (4) in Fig. 2 are selected as the chromosomes. Within the selected parent (1), cells (0), (2), and (4) are possible land parcels for development (the same for cells (1), (2), and (3) in parent (2)). Next, to the selected chromosome in parent (1) is a developed land parcel (5). Based on the parent (1) development choice, cell (5) only has one Moore neighbor (4-neighbour) (cell (2)). After pair-cell crossover (cells (0) and (4)), cell (5) has two Moore neighbors (cells (1) and (2)). In the case of land-use, generated child (1) is apparently more compact than parent (1) before the genetic operations. This method allows for randomly generating a group of possible land-use patterns as initial parents, using multiple land-development goals as objective functions, and completing the reproduction, crossover, and mutation processes to determine the optimal land-development order.

In a next step, the proposed PDULD model and SGA method were implemented and tested in one of the fastest-developing areas in Shanghai, Jiading New City.

Study Area and Data

Located at the tip of the Yangtze River Delta, Shanghai is the largest city in China by population. Jiading is one of the city's suburban districts and is located northeast of the

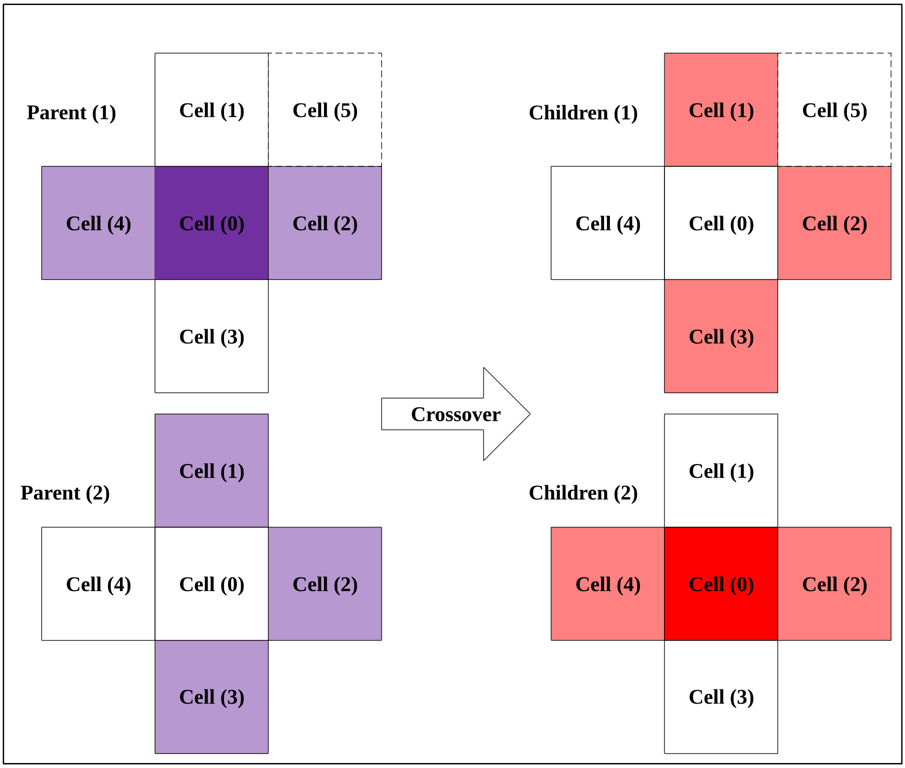

Fig. 2 Spatial genetic algorithm

central city (Fig. 3). The district has undergone a rapid pace of urban development over the past three decades. Its urbanized area has nearly tripled since 1990.

In the heart of Jiading district is Jiading New City (Fig. 3 left), which was planned as a satellite city as early as in the1960s. The original goal of the satellite city plan was to redistribute the over-crowded population in Shanghai's inner city proper. The initial 1959 urban master plan for Jiading New City described the area as a satellite city with 100 to 200

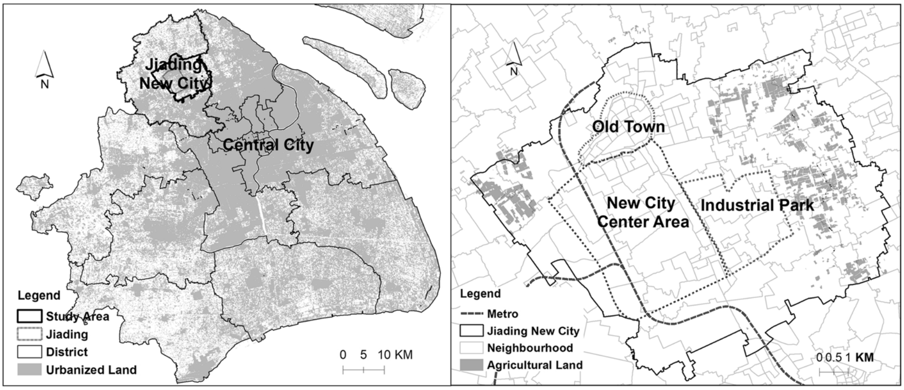

Fig. 3 Jiading New City

thousand people, along with certain industrial land uses and independent well-built public infrastructure. In the master plan that was compiled in the 1980s, Jiading New City was re-articulated as a satellite city with 200 to 300 thousand people. The population prediction was changed again to 800 thousand to one million people in 2004 due to the rapid urbanization and suburbanization in the surrounding areas of the Jiading New City.

Inside Jiading New City (Fig. 3 right) at the north end is the Jiading Old Town, with a long history of development. In the lower middle part is a planned industrial park. The east and west sides are agricultural land that is set aside for ecological protection, and the remainder, especially along the metro line, is the planned central area of Jiading New City for residential, commercial, public facility, and government uses.

According to the Shanghai Jiading New City Master Plan 2004–2010, the region represents one of the city's three new development hubs. It is a well-planned modern city with a rational allocation of resources and balanced strategic goals. Meanwhile, the current (2013) land-use map (Fig. 3 left) shows that most the land is developed and the area now is connected to Shanghai's central city proper. Therefore, the study of this case area provides a promising case for understanding land development in Shanghai in recent decades.

The empirical data include time-series Landsat Thematic Mapper (TM) satellite images from 1987, 1993, 2000, and 2010, historical thematic land-use maps, urban planning data, and social and economic statistics. The 30-m TM remote sensing data were obtained from the U.S. Geological Survey website (http://www.usgs.gov/), and a Random Forest Classifier, EnMap Box (van der Linden et al. 2015), was adopted to classify the remote sensing data into urban versus non-urban land use. Land-use survey data collected in 2002, 2006, and 2013 by Shanghai Government were obtained from the Shanghai Urban Planning and Land Use Administration Bureau to verify the classification results. Around 90% classification accuracy rate was achieved for each of 1987, 1993, 2000, and 2010 TM data. Historical urban land-use data were also used to calibrate, and validate the developed model. Statistical data were obtained from the Shanghai Municipality Statistics Bureau, and the urban planning data were obtained from individual urban planning departments. In addition, detailed 2000 and 2010 neighborhood-level population census data were used to project and model household location-relocation activities. Because only 2000 and 2010 population census data were available neighborhood-level for the city, this study used year 2000 as the start year for model simulation and used the 2013 land survey data to calibrate the model.

In addition to the land use and population data, an extensive field study of the area was carried out in the summer of 2015. We interviewed 11 urban planners, urban land use and planning administrators, and government officials to understand the land-development processes, government policies, and institutional organization and mechanisms of the city and the study area (Qiu and Xu 2017). Furthermore, we also conducted a questionnaire survey of 400 citizens about their household location-relocation choices. A field study was conducted to check the on-site implementation of the Jiading Master Plan, Jiading New City Detailed Plan, Jiading North Industry Park Plan, Juyuan Detailed Plan, and Nanxiang Detailed Plan to observe and confirm the neighborhood population, land use types, amenities and lifestyles. We walked around the focal areas of these plans and checked whether the plans matched the actual land use, populations, amenities and lifestyles of the residents in these areas. Video and photo images of the landscape and everyday street life were also taken randomly for analysis. The collected information assisted in a better understanding of the case study area.

Model Parameters and Calibration

The simulation is implemented in a Cellular Automata (CA) framework. To simulate the land-development process in Jiading New City, the study area was first divided into cells of 30×30 m^2 to match the 30 m spatial resolution of Landsat data. Because there were no population survey data from 2000, the urban land-use boundary of the classified 2000 Landsat 6 Enhanced Thematic Mapper imagery was used to subtract urban land in the 2002 land survey data, generating urban land uses as the initial stage of simulation. Land uses in simulation include residential, industrial, green space, agricultural, water, and public facilities. It is assumed that residential land use had a positive compatibility with green space and a negative compatibility with industrial land use.

I. Household status

As discussed in the PDULD model in the Section 2, households include both local and new migrant ones. All the variables and parameters are summarized in Fig. 4, Eq. (1).

Because there were no household-level population statistic data available for the area, we projected the household groups that lived in each residential cell using neighborhood population statistic data. Firstly, the number of male citizens age 25 years and older in each neighborhood; these were treated as the household heads. Each household head was then assigned an age (A) based on the male age group data from neighborhood-level statistics; next, the household heads were evenly distributed among the residential cells within each neighborhood. Each household head is treated as an agent, generating a total of 52,422 household agents to represent the total number of households in the study area in 2000. According to the Shanghai Statistical Year Books, the area enjoyed a 12% average annual household increase during the decade since 2000.

To estimate the annual revenue R and annual savings S of each household agent, we obtained the annual average household revenue, annual household increase rate (μ),

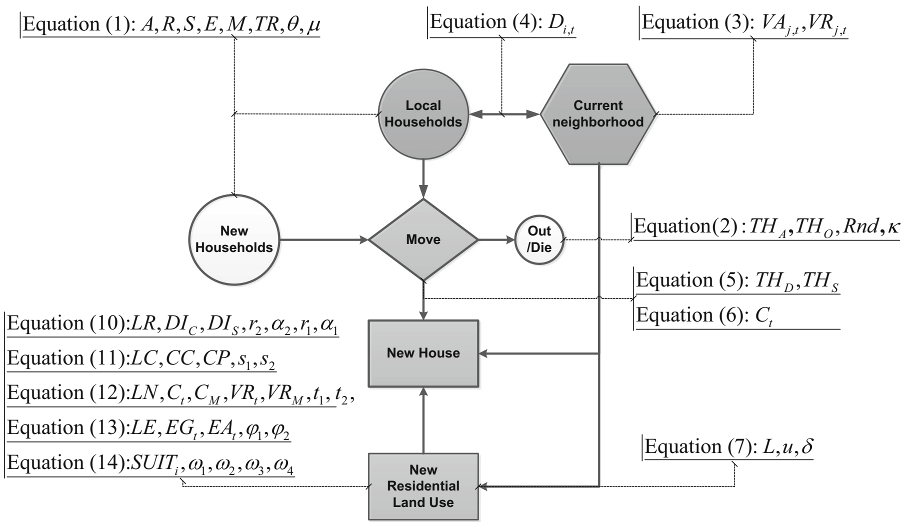

Fig. 4 Model and parameters

and household saving rate (θ) data from the 50 Years of Investment and Construction of the Shanghai Statistical Yearbook. In 2000, the average household revenue was 21,976 RMB, with an annual increase of 10% and an average household savings rate of 50%. To represent the variations among households, a random value for each household agent was generated using a random normal distribution (σ= 2197.6) based on the fact that more than 70% of household incomes were within 10% deviation from the 2000 average according to the yearbook. Moreover, the housing price that a household agent pays was set as 20 times the annual household income. The year 2000 down payment (E) on a new house was set as 50% of the housing price, and the yearly mortgage payment (M) was defined as the total mortgage amount divided by 20 years. The household agent's yearly savings rate was then set to 50% of the annual household income minus the annual mortgage payment. These assumptions are all grounded in our observations and surveys. For instance, the least expensive housing in Jiading in 2015 cost approximately 12,000RMB/m^2, and a 100 m^2 apartment costs 1.2 million RMB; meanwhile, the average annual salary in Jiading in 2015 was approximately 60,000 RMB, and the mortgage down payment was roughly 30% of the house price, five times the annual income. Both were defined based on multi-time-simulation-result observations. Thereafter, all household parameters required were known.

II. Neighborhood status

In addition to household agents, 114 neighborhood government agents were also generated to represent the studied 114 neighborhoods in Jiading New City. The simulation incorporated, for each neighborhood agent, the average household age (VA), the average household income (VR), and the calculation of the neighborhood cohesion value (C). All the variables in Eqs. (3) and (6) could be calculated automatically during the simulation.

III. Household activity

Local household agents, once they change their personal statuses, will check how they feel about the connection with their new neighborhoods. If the difference $D_{i,t}$ is larger than a defined threshold, TH_D, and household savings, S_t, is greater than the new house down payment threshold, TH_S, the household agent will consider moving out of that neighborhood to another one in the same region. Meanwhile, household agent's action generates a random number ($0 < =Rnd<=1000$) that is compared with a predefined threshold, TH_O, to determine whether the household will leave the region or not. In addition, each household agent will generate a probability value through Eq. (2) that can be compared with threshold, TH_A, to determine whether the agent (and thus the household) will die off.

All the variables were calculated in Eqs. (2), (4), and (5), except for κ, TH_D, TH_S, TH_O and TH_A. For age coefficient, κ, and threshold, TH_O, the model results revealed that by grouping household age from 10 to 1 and setting κ equals 1, TH_A equals 0.3, the annual death rate was close to the actual death rate of Jiading District (9 ‰ according to population statistics). The defined threshold, TH_S, is five times the average household income according to our field observations explained above. Neighborhood difference threshold TH_D is set as 0.5 based on multi-time-simulation-result observations. Lastly, the move-out threshold, TH_O, was set as 998 to correspond to the average 2‰ move-out rate in Jiading District.

IV. Land supply and development

With the increasing housing demand, new residential land needs to be developed. The annual land supply is defined through Eq. (7). Because the study area was divided into regular grids, the area of each cell (s_i) was defined. Moreover, Old Town Center was treated as the origin point because at the time of the study, it was still the center of the region, and the Euclidian distance (μ) was calculated for each land cell to Old Town Center. After multi-time simulations, the annual land supply Y was found to be close to the actual urban land increase rate when δ was close to the reciprocal of the maximum distance.

With all the developable land cells, the model used SGA to determine the best land development order. All the parameters in Eqs. (10), (11), (12), (13), and (14) had to be estimated. Once the most suitable land cells are chosen, houses will be built on them. To determine the number of houses that could be built on each residential cell, this study used floor area ratio data from Jiading New City Regulation Plan (2013) and kriging interpolation to generate the maximum construction volume surface of the study area. Next, the study assumed a normal apartment home size of 120 m^2 and divided the maximum construction volume to generate the maximum number of houses that could be built on each residential cell. Once new houses are built, household groups that wish to move will choose to move to the neighborhood with the most similar households (the smallest D).

All the land use maps and boundary data were first digitized and stored in the GIS database as vector data and were then converted into raster grids. To simulate land-development using the proposed models, the raster data were transformed into ASCII files, and then the ArcGIS Euclidean Distance tool was used to generate the distances from each cell to the metro lines and the city center. The generated raster distance data were also transformed into ASCII files with the same cell sizes as the others. After all the data were in place, the model was coded and run in one of the most popular simulation platforms, NetLogo (Wilensky 1999). The ASCII data files were imported into the model directly using the GIS extension in NetLogo.

To estimate the unknown parameters, this study employed R software and a GA to evaluate them with the help of the RNetLogo extension package (Thiele et al. 2012). As denoted in the following simplified source codes, a 14 × 10 data matrix (a) was first created to store all the possible values for the 14 unknown parameters. The NetLogo model *Residential Model.nlogo* was then called using *NLLoadModel* and *NLCommand* was used to assign the 14 global parameters to their possible solution values. After the model was run multiple times (*NLDoCommand*), an objective value was returned to the GA model. The GA model was run with real values, the initial parent population size set at 10, and maximum number of generations set at 20. The optimization objective of the GA method is to maximize the volume of cell-by-cell matched residential land cells between simulated data and actual 2013 land survey data. The result is a list of 14 estimated parameters (Table 1).

Simplified source codes:

library(RNetLogo, GA).

a1 < − seq(0, 1, by = 0.1)➔a14 < − seq(0, 10, by = 1).

a < − rbind(a1,a2,a3,a4,a5,a6,a7,a8,a9,a10,a11,a12,a13,a14).

NLStart(nl.path).
NLLoadModel("… /Residential Model.nlogo").
NLCommand("Setup").
NLCommand("set mu1", a[1,×1]) ➔ NLCommand("set Omiga4", a[14,×14]).
NLCommand("Initiate").
NLDoCommand(10,"RunModel").
NLCommand("GAResult").
return(NLReport("GAIResult"))}.
GA < − ga(type = "real-valued", fitness = function(x) + Rastrigin(x[1], ➔ x[14]), min = c(1, ➔ 1),max = c(12, ➔ 12), popSize = 10,maxiter = 20, monitor = TRUE).
summary(GA).

Simulation Results

Residential Land Use

Using the calibrated model parameters, our study simulated the residential land development and population dynamics in the study area. To verify the reliability of the simulation results, this study compares simulation results with actual land-use and population data. Figure 5 is the simulated urban residential land use of Jiading New City from 2002 to 2012. Figure 7 presents the maps of the spatial evolution of the actual and simulated residential land uses after 2000. During the period of 2000 to 2010, the total number of households in Jiading New City increased from 52,422 to 143,352, and the residential land use increased by 15.6 km^2.

The simulation results (Fig. 6 left) show that most of the land development activities are located around the surrounding areas of the old town and scattered around the lower part of the area. However, the actual residential land development map of the area from 2000 to 2010 (Fig. 6 right) shows that most housing construction is mainly concentrated in the surrounding area of the old town center and the planned new center areas. The actual increased residential land uses are more clustered spatially than the simulated results for the past 12 years.

To further analyze the accuracy of the simulation results and investigate the land development trajectories in the study area, we compared the simulated results with the actual land use changes, specifically by using the simulated neighborhood residential land increase volume minus real neighborhood residential land increase divided by real neighborhood residential land increase to generate the simulation result index. A positive result denotes overestimation and a negative result indicates underestimation.

The mapped results (Fig. 7) show that for 53% of neighborhoods, the differences in simulated and real land use were below 50%. Overestimation (greater than 50%) in the

Table 1 Predefined and estimated parameters

Parameter	r_1	r_2	α_1	α_2	s_1	s_2	t_1	t_2	φ_1	φ_2	ω_1	ω_2	ω_3	ω_4
Estimated value	0.1	0.2	800	700	0.2	0.3	0.7	0.1	0.4	1	0.1	0.8	0.4	0.9

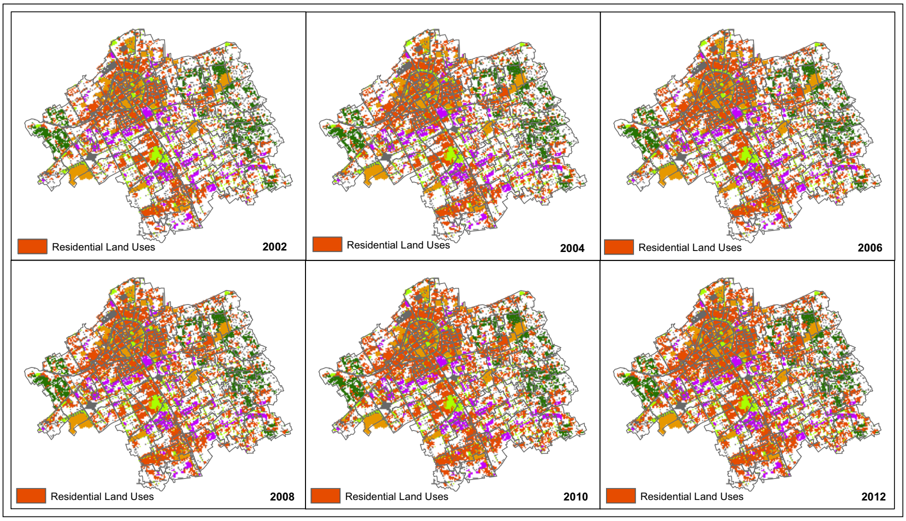

Fig. 5 Simulated residential land use from 2000 to 2012

simulation results occurred in 39 of 114 census enumeration areas, mainly concentrated around the eastern and inner Old Town areas. In reality, the eastern side of the area is mainly protected agricultural land, although there are many rural residential clusters of agricultural populations. Based on the simulation, more land should be developed for urban residential uses in this area with self-organized approaches. The Old Town areas are also very suitable for residential housing based on the simulation. However, these lands were primarily occupied by either commercial or public facility uses because the financial returns per unit from these uses exceed those from residences.

Household and Neighborhood Simulation Results

There were major neighborhood boundary changes in the study area during the period from 2000 to 2012. To compare the simulated household spatial distribution and census data, the study mapped the simulated 2012 household and the 2010 population census household densities (Fig. 8). The mapped spatial patterns show that the simulated

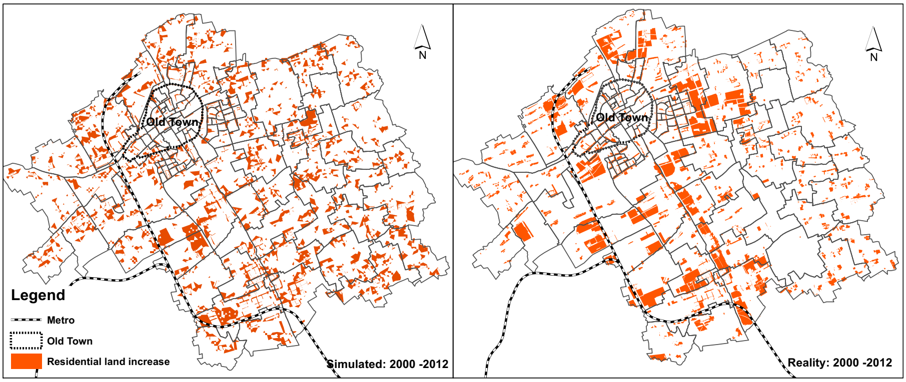

Fig. 6 Comparison between simulated and actual land use

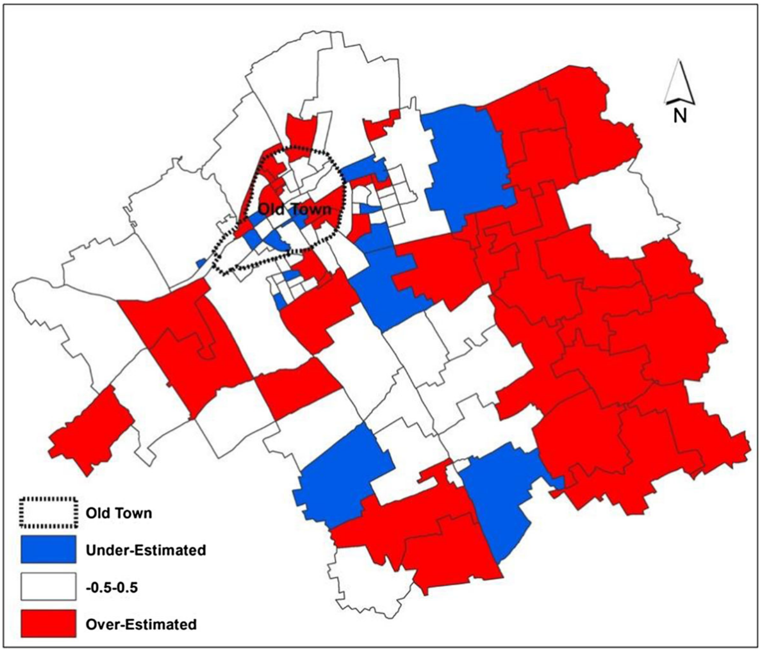

Fig. 7 The accuracy of simulation on neighborhood level

results matched the current household distribution quite well, with households in the study area highly concentrated around the Old Town.

During the simulation, the model also recorded the average household age and income and cohesion values in each neighborhood. The Fig. 9 box plot graphs of the average neighborhood age show that the average household age in the whole area is declining, which could be related to the continuous in-migration of young households to the area. Meanwhile, the differences in average household age among neighborhoods converged over time, a trend that was also reflected in Fig. 10. One exception was one of the neighborhoods located inside the Old Town (outlier in Fig. 9 and red arrow in Fig. 10); the average neighborhood age increased continuously during the simulated period.

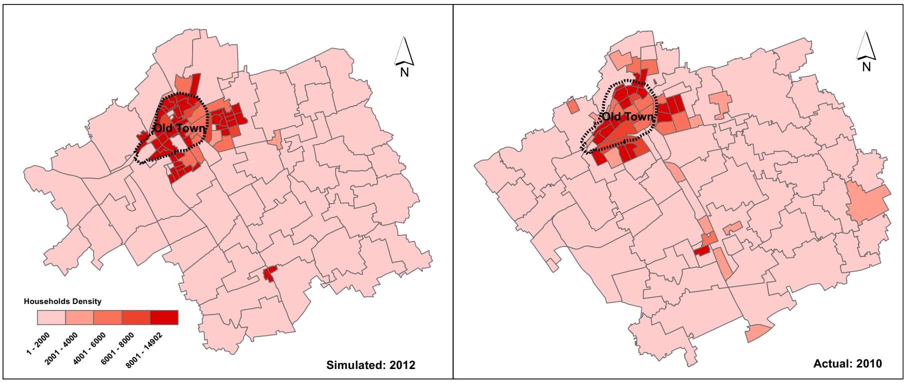

Fig. 8 Household density comparison between simulated and real uses

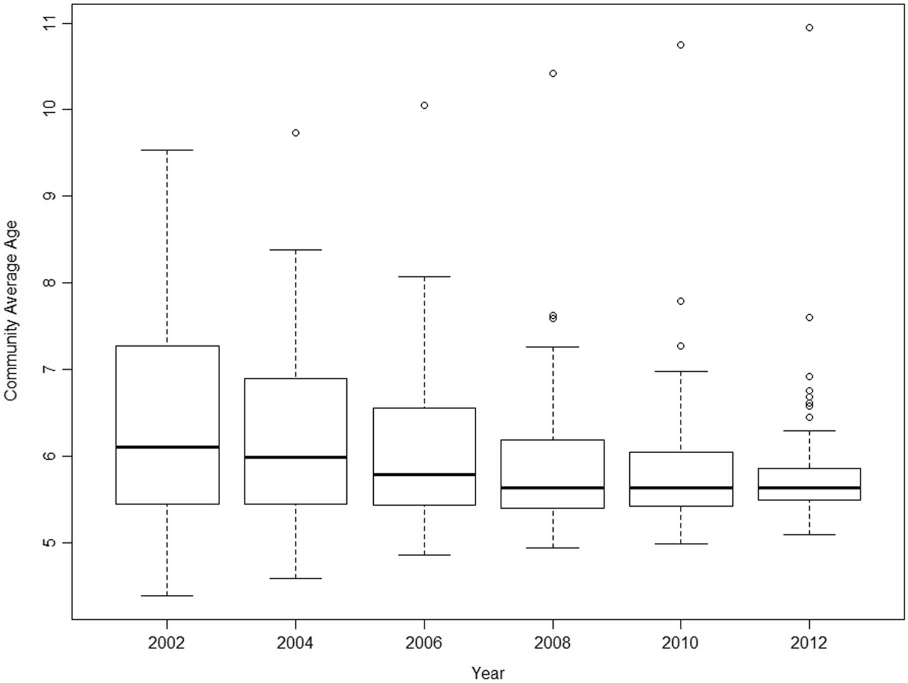

Fig. 9 Simulated residential neighborhood average age (circle-dots indicate outliers)

The Fig. 9 time series box plot graph and Fig. 10 neighborhood age maps also show that even though the general trend of average age differences across area neighborhoods decreased in the simulation, the age gaps still exist between the Old Town communities and rest of the region: The Old Town area has a relatively high average age.

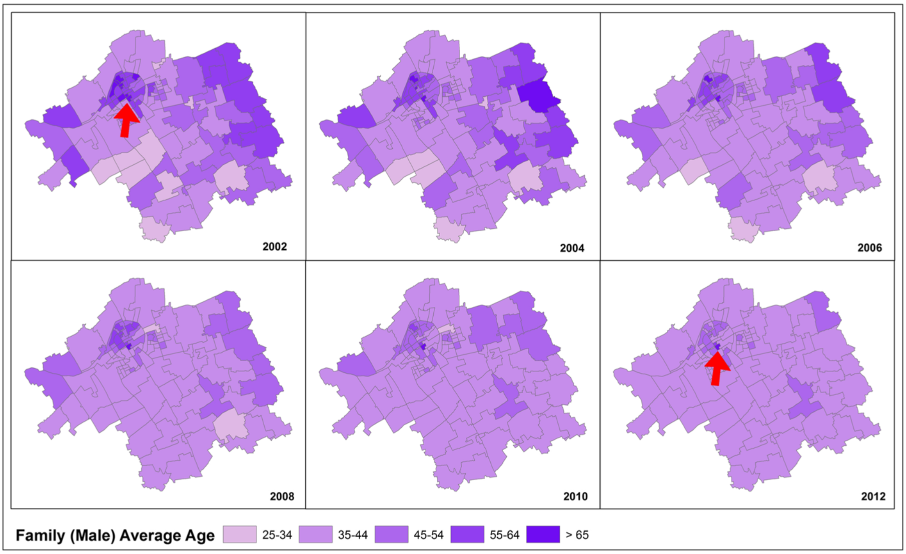

Fig. 10 The convergence of neighborhood average age

Contrary to the convergence of average age among neighborhoods, the average household income in the simulation diverged from 2000 to 2012 (Fig. 11) and the simulation results (Fig. 12) also show that neighborhood cohesion diverged during the study period.

Discussion and Conclusion

Land development modelling and simulation provides an important computational and visualization tool for assessing the impacts of future land demand for population and economic growth. It also provides a means for understanding complex causal relations and dynamic interactions among numerous factors ranging from economic, political, and social to environmental dimensions.

This study proposes a new simulation model of urban land-use growth and evolution that combined ABM, CA and SGA methods. The model is featured by a proposed population-driven urban land development framework. Within the model, a household group determines its housing location desires and then forms the local housing demand market, and land developers and local governments then make the optimal use of the current land reserves to meet these housing demands. In this process, land development in an area is treated as a multi-goal optimization process. A spatial genetic algorithm is used to help identify the best land development choice for achieving social, economic, and environmental goals of a given urban area.

In addition to environmental factors, this study introduces community cohesion theory into the model to illustrate the influence of populations on the spatial structure of urban land

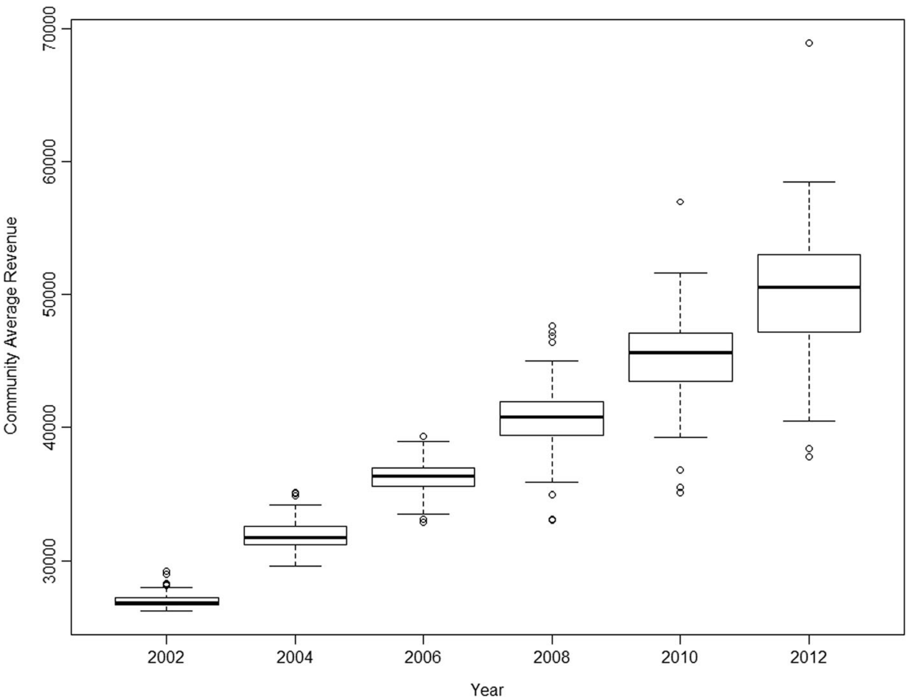

Fig. 11 Simulated residential neighborhood average revenue (circle-dots indicate outliers)

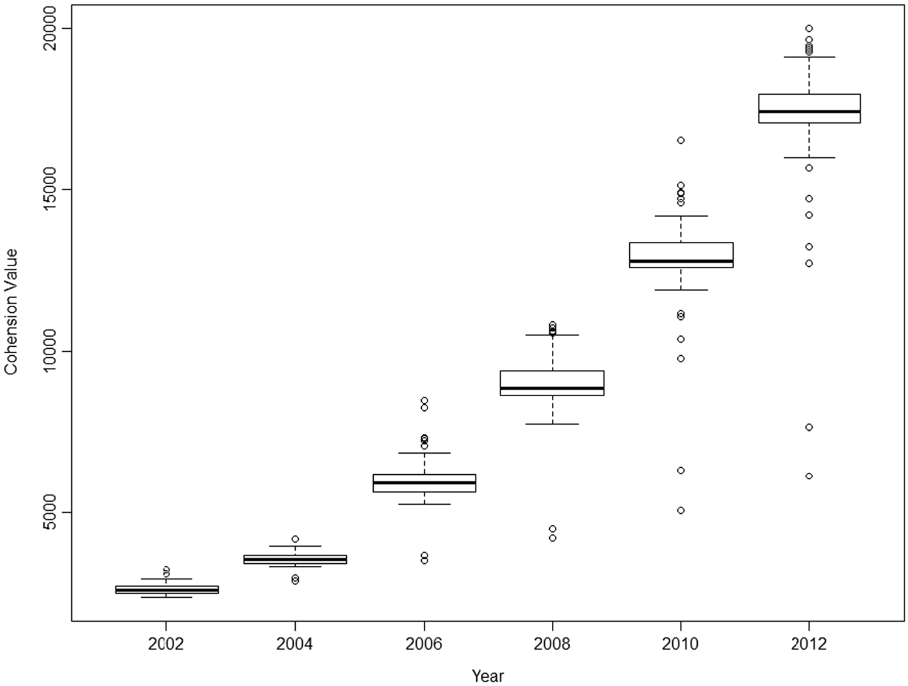

Fig. 12 Simulated residential neighborhood cohesion values (circle-dots indicate outliers)

use. In the model, household heads act as autonomic agents who assess the socioeconomic status of their current neighborhoods and can choose to relocate to other neighborhoods, and a given neighborhood's development status affects local land development activities. In this way, this study innovatively creates a dynamic evolutionary model that integrate both population and land-development dynamics in land development simulation.

Moreover, the study proposes a new parameter estimation method by using evolutionary algorithms. Sample data regression and multi-time experiments are among the main land use and cover change model parameter estimation methods (Couclelis 2001). These methods both are very time consuming and highly inaccurate. This study represents the first attempt to use evolutionary algorithms and historic data to estimate unknown parameters through multi-generation training. It opens a new window for future similar studies.

The simulation results show that the model interpret the real land use at the neighborhood level with a moderate success (53%). There are major (34%) overestimations around the eastern rural communities in the study area and the nearby outlying areas of Old Town Centre. The data comparisons show that the Old Town communities have all been built up. One of the main explanations is that these lands were dominated by commercial uses such as office buildings and other facilities, which out-compete residential land development. The neighborhood household simulation results match the current household distribution quite well. The average household revenue and cohesion of the neighborhoods in the study area diverge from 2000 to 2012, and average residential neighborhood age declines throughout the whole study area.

The modelling and simulation results in this study confirm the findings in the literature (SU 1998) that urban land use development is highly affected by a city's household social, economic, and environmental characteristics. However, two key issues emerge from this study: government intervention and land use profit competition.

As shown in the previous section, the land-use simulation results deviate heavily from the real land use in some of the study area, even though the simulated residential spatial distributions match with the reality well. The actual residential land use increases in the study area (Fig. 6) are clustered around the outskirts of the Old Town and the planned new center area of Jiading New City. Compared with the sparsely distributed land use in the simulation results, the actual residential land uses are in the form of large blocks. One of the major reasons for this clustered form is that the area is developed according to urban planning zoning and rezoning policies. The whole area is divided into several large functional zones and then subdivided into large land-use blocks. Each of these blocks is designed for residential, commercial, industrial, or recreation use. Inside the designed residential blocks are high-density apartment buildings. The mismatch between the actual land use and the population simulation results indicate that the region is regulated artificially by administration rather than a natural growth based on market processes.

Historic data and field studies show that the coexistence of urban development and redevelopment in the area. With the increasing population and decreasing developable land, the area's land value is increasing continuously. For instance, residential uses outcompete industrial uses in the planned industrial park, and industrial factories have had to move under both government and market pressures. The commercial uses outbid residential uses in the built-up areas around Old Town Centre in Jiading New City, as old houses were demolished or converted into uses for businesses, office buildings, and other land uses with high per-unit outputs. This process of urban redevelopment needs to be incorporated for better simulation results in the future.

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