Ecological Modelling 257 (2013) 11–24

Contents lists available at SciVerse ScienceDirect

Ecological Modelling

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

# Combining system dynamics and hybrid particle swarm optimization for land use allocation

Xiaoping Liu*, Jinpei Ou, Xia Li, Bin Ai

*School of Geography and Planning, and Guangdong Key Laboratory for Urbanization and Geo-simulation, Sun Yat-sen University, Guangzhou 510275, PR China*

ARTICLE INFO

*Article history:*
Received 9 October 2012
Received in revised form 22 February 2013
Accepted 23 February 2013

*Keywords:*
Land use allocation
System dynamics
Hybrid particle swarm optimization

ABSTRACT

Urban land use spatial allocation is crucial to lots of countries that are usually under severe environmental and demographic pressures, because it can be used to alleviate some land use problems. A number of models have been proposed for the optimal allocation of land use. However, most of these models only address the suitability of individual land use types and spatial competition between different land uses at micro-scales, but ignore macro-level socio-economic variables and driving forces. This article proposes a novel model (SDHPSO-LA) that integrates system dynamics (SD) and hybrid particle swarm optimization (HPSO) for solving land use allocation problems in a large area. The SD module is used to project land use demands influenced by economy, technology, population, policy, and their interactions at macro-scales. Furthermore, particle swarm optimization (PSO) is modified by incorporating genetic operators to allocate land use in discrete geographic space. The SDHPSO-LA model was then applied to a case study in Panyu, Guangdong, China. The experiments demonstrated the proposed model had the ability to reflect the complex behavior of land use system at different scales, and can be used to generate alternative land use patterns based on various scenarios.



## 1. Introduction

Urbanization in China has been accelerating with the rapidly growing economies and massive immigration to cities since the adoption of economic reform and open-door policy in 1978. Urban areas expanded by almost 100% from 1996 to 2005 (National Bureau of Statistics). The rapid urbanization process has involved the conversion of natural ecosystems, farmland, water, and vegetation into urban areas. However, the lack of appropriate land use planning has given rise to a series of environmental problems, including the encroachment of agricultural land, destruction of sensitive ecosystems, environment pollution, soil erosion, severe flooding, and reduction of biodiversity (Seto et al., 2002; Li and Liu, 2008; Liu et al., 2011). These problems have negatively affected sustainable land development. The spatially optimal allocation of land resources is crucial in these regions that are usually under severe environmental strains because it can be used to alleviate some land use problems in rapidly growing cites (Li and Liu, 2008).

Land resource allocation is a spatial optimization problem, where the planner tries to reconcile multiple conflicting interests as rationally and transparently as possible by manipulating the proportions and locations of land uses (Carsjens and Van Der Knaap, 2002). There are some conflicts in land use decision making because the involvement of people has interests in the same land parcels for incompatible land uses (Bojórquez-Tapia et al., 1994; Li and Liu, 2008). These conflicts greatly complicate land resource allocation. Furthermore, the planner must also take into account both site (e.g. suitability, cost, environmental impacts) and aggregation (e.g. shape, contiguity, compactness) attributes (Cova and Church, 2000). The complexities of searching for a solution considerably increase if a region is very large and a fine spatial resolution of data is used (Stewart et al., 2004). As a result, there is an urgent need for an effective tool that can assist planners in determining the optimal allocation of land use.

To date, a number of approaches have been developed for the computation of the optimal allocation of land use (Wright et al., 1983; Williams and Revelle, 1998; Stewart et al., 2004). Linear programming (LP) may be the earliest among such methods. Cocks and Baird (1989) applied LP to address multiple reserve selection problems in South Australia. The LP method can ensure optimal solutions, but finding a solution within a reasonable amount of time is difficult. Eastman et al. (1995) proposed the iterative relaxation (RI) method to solve land use allocation problems involving conflicting objectives. The limitation of RI is its lack of a compactness constraint (Chen et al., 2010). Recently, many researchers resorted to heuristic algorithms, which are more efficient for

* Corresponding author. Tel.: +86 15802012393.
*E-mail address:* yiernanh@163.com (X. Liu).

0304-3800/$ – see front matter. Crown Copyright © 2013 Published by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ecolmodel.2013.02.027

solving complex spatial optimization problems (Xiao et al., 2007). For instance, Brookes (2001) developed a site allocation method by integrating region growing techniques and genetic algorithm (GA). Xiao et al. (2002) used GA and GIS to generate alternatives for multi-objective site search problems. Matthews (2001) explored the potential of GA in assisting the planner in generating land use mapping to achieve multiple objectives. Another heuristic method widely used to solve spatial allocation problems is called simulated annealing (SA). Bos (1993) used SA to create forest management zones. Martínez-Falero et al. (1998) presented SA algorithms for allocating agricultural activities. Another example of the use of SA in generating land use spatial allocation alternatives is provided by Aerts and Heuvelink (2002), their model both minimizes development costs and maximizes spatial compactness of land use. Santé-Riveira et al. (2008) extended SA algorithms with varying temperature to solve multiple land use optimization problem.

Despite successful examples in solving spatial allocation problems, most of these studies mainly focus on allocating land resource for a small region. For example, in the experiment of Xiao et al. (2002), each solution only has ten cells. Verdiell et al. (2005) applied the SA method to select and design a National Park, but the study region has an area of only 900 cells. Solving spatial optimization problems with increased study area size is a challenge. Thus, the exploration of an efficient optimization approach for land use allocation in large areas may result in useful practical applications.

A more severe problem with land resource spatial allocation is that these models only address the suitability of individual land use types and spatial competition between different land uses at micro-scales. There is a lack of macro-scale socio-economic variables, such as regional economic inequality, population migration and policy influences. Land use change is in fact determined by the interaction in space and time of socio-economic and physical components at different scales (He et al., 2005). As a top-down approach, system dynamics (SD) blends the art of traditional management with the science of feedback control. It is particularly suited to the investigation of socioeconomic driving forces and the simulation of complex systems (Han et al., 2009). SD can describe the complicated connections among each element and predict changes in complex systems change under different “what if” scenarios. In recent years, SD has been used successfully to solve geographical problems, including environmental management (Mashayekhi, 1990), water resource planning (Ford, 1996), regional environmental management (Guo et al., 2001), land use analysis (Liu et al., 2007) and urban development (Han et al., 2009). However, it has disadvantages when dealing with a mass of spatial data, and cannot incorporate spatial factors into the system. Therefore, considering the advantages and disadvantages of SD and land use allocation approaches, the integration of land use spatial allocation models with system dynamics models is urgently needed.

This research proposes a novel approach based on the integration use of system dynamics and hybrid particle swarm optimization (HPSO) for solving land use allocation problem in a large area. Particle swarm optimization (PSO), which simulates the social behavior of bird flocks, is a population-based stochastic optimization algorithm for finding optimal regions of complex search spaces through the interaction of particles. Successful applications of PSO to various problems, such as function optimization, pattern recognition, and data mining, have demonstrated its potential. Many studies have demonstrated that PSO is highly robust and can offer different routes through the problem hyperspace than other evolution algorithms (Boeringer and Werner, 2004). However, very few studies of PSO focused on discrete combinatorial optimization because the original PSO is customized to continuous function value optimization (Yin, 2006). Land use allocation belongs to a typical discrete combinatorial optimization problem, which cannot be solved by the original PSO directly. Hence, this article proposed a hybrid strategy embedding discrete crossover and mutation operator into the PSO algorithm to tackle spatial combinatorial optimization problems.

The contribution of this article is twofold. First, we present an integrated system dynamics (SD) and hybrid particle swarm optimization (HPSO) model for land use allocation. Through the SD module, macro-level socio-economic variables and driving forces are taken into account. Then, the HPSO module is used to generate optimal land use patterns based on suitability map and spatial constrains. Second, the original PSO is customized to continuous function value optimization. In this article, PSO is modified by incorporating discrete genetic operators to be suitable for solving spatial combinatorial optimization problems.

The remainder of this article is organized as follows. Section 2 reviews basic PSO. Section 3 describes land use allocation problem formulation. Section 4 provides the details of the proposed SDHPSO-LA model. In Section 5, we present the experimental results and discussion. Finally, a conclusion is given in Section 6.

## 2. Basic PSO algorithm

Particle swarm optimization (PSO) is a population-based optimization technique proposed by Kennedy and Eberhart in 1995. It is based on a metaphor of social interaction such as bird flocking and fish schooling. In PSO, a candidate solution for a specific problem is called a particle. Each particle moves through the problem space with a velocity, which is dynamically adjusted by its own moving experience and those of its companions. Similar to GA, PSO also has a fitness function that evaluates the position of the particle. The best position found by each particle is called the personal best ($p_{id}$), and the best position with the highest fitness value among all the particles obtained is called the global best ($p_{gd}$). The PSO algorithm completes the optimization process through following the personal best ($p_{id}$) and the global best ($p_{gd}$). At each time step, all particles are updated by the following equations (Kennedy and Eberhart, 1995):

$$V_{id}(t+1) = \omega \cdot V_{id}(t) + c_1 \cdot r_1 \cdot (p_{id} - X_{id}(t)) + c_2 \cdot r_2 \cdot (p_{gd} - X_{id}(t)) \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{2}$$

where $t$ is the number of iterations; $i$ is the particle number, $d$ is the component number which represents the dimension of particles; $V_{id}$ and $X_{id}$ are positions and velocities of particles respectively, $\omega$ is called inertia weight, which is employed to control the influence of the previous history of velocities on the current velocity; $c_1$ and $c_2$ are two positive constants, called cognitive learning rate and social learning rate respectively; $r_1$ and $r_2$ are uniformly distributed random numbers between 0 and 1. $p_{id}$ is the local best solution found by the $i$th particle, where $p_{gd}$ represents the global best. The PSO algorithm is terminated once the best position of all the particles cannot be improved further after a sufficiently large number of generations.

## 3. Land use allocation problem formulation

If we suppose that the study area is to be allocated into $K$ different land use types, and the observed region is denoted as a two-dimensional grid of cells arranged into $R$ rows and $C$ columns, then the land use allocation problem is how to assign a specific land use to each individual cell $(i, j)$, so that the resulting land use map optimally achieves the planning objectives. Generally, there are several important planning objectives for land use allocation (Stewart et al., 2004; Siitonen et al., 2003), such as selecting a given area of land, maximizing land use suitability, and achieving the best spatial objectives (compactness or compatibility). In our research, these planning objectives are expressed by the following equations (Stewart et al., 2004; Liu et al., 2012):

$$Max\sum_{k=1}^{K}\sum_{i=1}^{R}\sum_{j=1}^{C}Suit_{ijk}x_{ijk} \tag{3}$$

$$Min\sum_{i=1}^{R}\sum_{j=1}^{C}dist_{ij}\cdot x_{ijud} \tag{4}$$

$$Max\sum_{k=1}^{K}\sum_{i=1}^{R}\sum_{j=1}^{C}c_{dom_{ij}k}\cdot x_{ijk} \tag{5}$$

$$Max\sum_{k=1}^{K}Comp_{k} \tag{6}$$

$$Comp_k=\frac{L_{kMaxSum}-L_{kSum}}{L_{kMaxSum}-L_{kMinSum}} \tag{7}$$

$$\sum_{k=1}^{K}x_{ijk}=1 \quad \forall i=1,\ldots,R,\quad j=1\ldots,C \quad x_{ijk}\in\{0,1\} \tag{8}$$

$$\sum_{i=1}^{R}\sum_{j=1}^{C}x_{ijk}=Q_k \quad \forall k=1,\ldots,K \tag{9}$$

where $Suit_{ijk}$ is the suitability of the $k$th land use, $x_{ijk}$ equals 1 if land use $k$ is allocated to cell $(i, j)$, and equals 0 otherwise. $dist_{ij}$ is the distance of cell $(i, j)$ to its nearest developed area. $x_{ijud}=1$, if undeveloped land at location $(i, j)$ is converted into developed land; and $x_{ijud}=0$ otherwise. $dom_{ij}$ is the dominant land use type within the neighborhood of cell $(i, j)$. $c_{dom_{ij}k}$ is the compatibility index between land use $dom_{ij}$ and $k$. $Comp_k$ is the compactness of the $k$th land use. $L_{kSum}$ is the sum of perimeter of land use $k$. Once the area is known, the most compact form is circular and the minimum sum of perimeter of land use $k$ ($L_{kMinSum}$) can then be calculated. On the contrary, if the selected sites are separate from each other, the maximum sum of perimeter of land use $k$ ($L_{kMaxSum}$) can be obtained. $Q_k$ is a pre-specified percentage of land use $k$ in the entire area. Eq. (3) maximizes the total suitability of land use map, i.e., it is considered optimal that each land use is allocated to the most suitable land. Eq. (4) minimizes the distance of new development to already developed sites. Eq. (5) maximizes the compatibilities between land use of cell $(i, j)$ and its neighborhood. Eqs. (6) and (7) maximize the spatial compactness of a land use. The compact pattern of land use can improve efficiencies in land source and energy utilizations because less infrastructures and other services are needed (Gabriel et al., 2006). Eq. (8) ensures that only one land use can be allocated to each cell. Eq. (9) specifies the percentages of different land use types for the allocation to meet. Land allocation problems are often complex because conflicting objectives are involved. Generally, a simple additive weighting method is employed to create a composite score to solve a multi-objective problem:

$$U=\sum_{k=1}^{K}(a\cdot Suit_k+b\cdot c_{domk}+c\cdot Comp_k-d\cdot dist)\times\quad\forall a+b+c+d=1 \tag{10}$$

where $U$ is a composite score incorporating all objectives; and $a$, $b$, $c$ and $d$ are the weights of suitability, compatibility, compactness, and distance to developed land, respectively.

## 4. Integrating SD with HPSO for land use allocation (SDHPSO-LA)

The SDHPSO-LA model consists of two components, system dynamics (SD) and hybrid particle swarm optimization (HPSO), for allocating land use. The SD module is used to project the land use scenario demands influenced by population, economy, technology and policy at the national or regional scale. The HPSO algorithm is the land use allocation module, which allocates the regional level demands to individual grid cells with the consideration of land use suitability and spatial objectives (compactness or compatibility) using HPSO. The general structure of SDHPSO-LA model is shown as Fig. 1.

### *4.1. The system dynamics module for projecting land use demands*

The SD methodology is a simulation technique that models large-scale, complex socio-economic systems using stocks and flows, and by explicitly including feedback loops (Sterman, 2000). It attempts to understand how the physical processes, information flows, and managerial policies interact to create the dynamics of the variables of interest (Vlachos et al., 2007). Many researchers have noted that SD was particularly suited to model land use systems (Forrester, 1969). It is because that land use systems is a complex system, which is determined by the interaction of different human factors.

In this article, the proposed SD model aims to simulate the land use scenario demands. The SD model basically consists of three sub-models, namely population, economy and land use. Population sub-models are essential because they can influence other sectors. This sub-model, mainly referred to the quantity of population, is comprised of usual and mobile population. The annual increase in total population is attributed to the natural increasing people and immigrants. Economy sub-model, reflecting the economic development, also has a strong correlation with population and land use. In this sub-model, GDP (gross domestic product) act as a critical indicator that directly affects the change in the value of employment posts and industry investments. Land use sub-model is assumed to be composed of three parts: residential, industrial, and commercial land. Residential land is estimated by multiplying urban population with urban residential land per capita, while the commercial land and industrial land are mainly estimated by the change with the GDP of service industries and the GDP of industries respectively. Relevant formulas for estimating urban land demands are listed as follows:

$$RL(t)=95+0.004\cdot(TP(t)\cdot ALPP\cdot 10^{-6})^{2.35} \tag{11}$$

$$IL(t)=38.1+0.147\cdot IOV(t)\cdot LMIO(t) \tag{12}$$

$$CL(t)=25+0.23\cdot\ln(ACLP(t)\times 10^{-3})\cdot\ln(TII(t)\times 10^{-1})\cdot\ln(TP(t)\times 10^{-5}) \tag{13}$$

$$LMIO(t)=0.025\cdot\exp\left(\frac{1}{1.1\cdot TI+1.8\cdot SII(t)\times 10^{-5}}\right) \tag{14}$$

$$ACLP(t)=\frac{0.5\cdot GDP(t)}{TP(t)} \tag{15}$$

where $RL(t)$, $IL(t)$ and $CL(t)$ are the area of residential, industrial and commercial land at time $t$, respectively. $TP(t)$, which is derived from the population sub-model, represents the total population at time $t$. $GDP(t)$ represents the gross domestic product at time $t$. $ALPP$ is the average living space per capita. $IOV(t)$ represents the industrial output value at time $t$. $LMIO(t)$ means the coefficient of land area

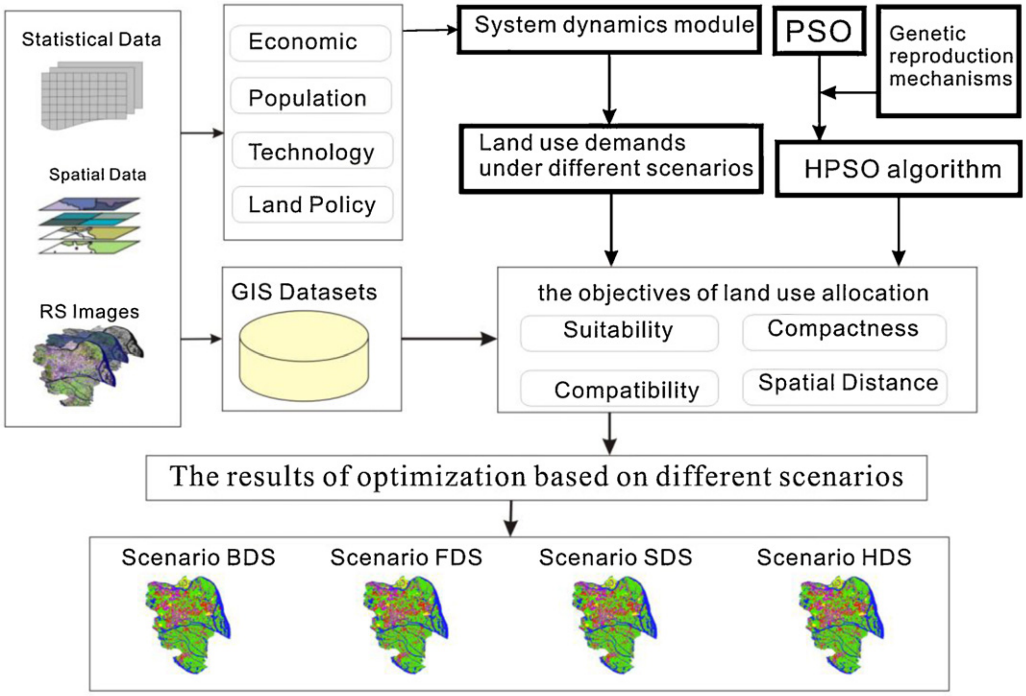


**Fig. 1.** The general structure of the SDHPSO-LA model for generating land use patterns.

from million in industrial output at time $t$, which is estimated based on the technical inputs ($TI$) and the second industrial investment ($SII$). $ACLP(t)$ represents the average consumption level per capita at time $t$, which is defined as a half of GDP per capita. $TII(t)$ represents the tertiary industry investment at time $t$. The values of $IOV$, $SII$, $TII$ are mainly obtained from GDP in economy sub-model.

The SD model was constructed by using the software of Vensim, which is designed using a visualization process that allows model builders to conceptualize, document, simulate, and analyze models of dynamic systems (Forrester, 1961). The structure of the SD model is shown in Fig. 2. Land use demand is driven by different "what-if" scenarios controlled by different socio-economic factors at regional scales.

## 4.2. The HPSO algorithm for the spatial allocation of land use

PSO is an efficient and effective global optimization algorithm widely applied to nonlinear function optimization (Eberhart and Shi, 2001; Cagnina et al., 2004). The original PSO is customized to continuous function value optimization (Kennedy and Eberhart, 1997). However, the spatial allocation of land use is a discrete combinatorial optimization problem (Ligmann-Zielinska et al., 2008). Thus, this article further modified and extended the PSO algorithm with embedding genetic operator for solving land use allocation problems.

### 4.2.1. Particle representation

Particles correspond to candidate solutions to the underlying problem. Hence, we use the particle to represent the solution of land use allocation by a two-dimension integer array. In this article, the array size is equal to the size of the study region ($R \times C$). As illustrated in Fig. 3, there are $K$ types of cells, and the number of each type cells is equal to the corresponding number for each land use. The code of the cell corresponds to its land use type. For example, the codes for industrial, residential, and commercial are 1, 2, and 3, respectively. At the start of optimization, these types of land use cells are randomly positioned in the study region ($R \times C$) for each particle.

### 4.2.2. Hybrid strategy

In PSO, each particle flies to a better position, which is a randomized weighted sum of vectors based on its personal and global best positions (Eqs. (1) and (2)). This property is perhaps desired for continuous optimization problems. However, it hinders the solution exploration for discrete combinatorial optimization (Yin, 2004; Esmin et al., 2005). The meanings of concepts such as trajectory and velocity are difficult to be represented in a discrete space. The solution to this dilemma is to express the discrete combinatorial problems in a binary notation and find an optimizer that can operate on two-valued functions to improve the PSO for handling these problems (Kennedy and Eberhart, 1997). However, land use allocation is an optimization problem that deals with multiple types of land use in two-dimensional space, and is very difficult to be expressed in a binary notation. Some studies indicated that the optimal solution may be obtained by a recombination of the cells in the discrete combinatorial space instead of a weighted sum of the vectors (Zhi et al., 2004; Yin, 2006; Shi et al., 2007). Genetic algorithm (GA), as a search heuristic that mimics the process of natural evolution, provides a mechanism for exchanging and recombining information (such as land use cells) among good-quality individuals (Stewart et al., 2004). Hence, to facilitate the applicability of PSO to land use allocation problems, we propose a new particle adjustment rule with genetic reproduction mechanisms, namely crossover and mutation. The improved formula is described as follows:

$$X_{id}(t+1) = Rand(X_{id}(t)) + \alpha \cdot Cross(P_{id}(t), X_{id}(t)) + \beta \cdot Cross(P_{gd}(t), X_{id}(t)) \quad (16)$$

where $X_{id}$ is the positions of particle $i$; $P_{id}$ is the local best solution found by the $i$th particle, while $P_{gd}$ represents the global best; $\alpha$ and $\beta$ are two random integers. $Cross(\,)$ is the strategy of cross operation corresponding to a crossover among $X_i$, $P_i$, and $P_g$ such that the particle can exchange land use cells with personal and

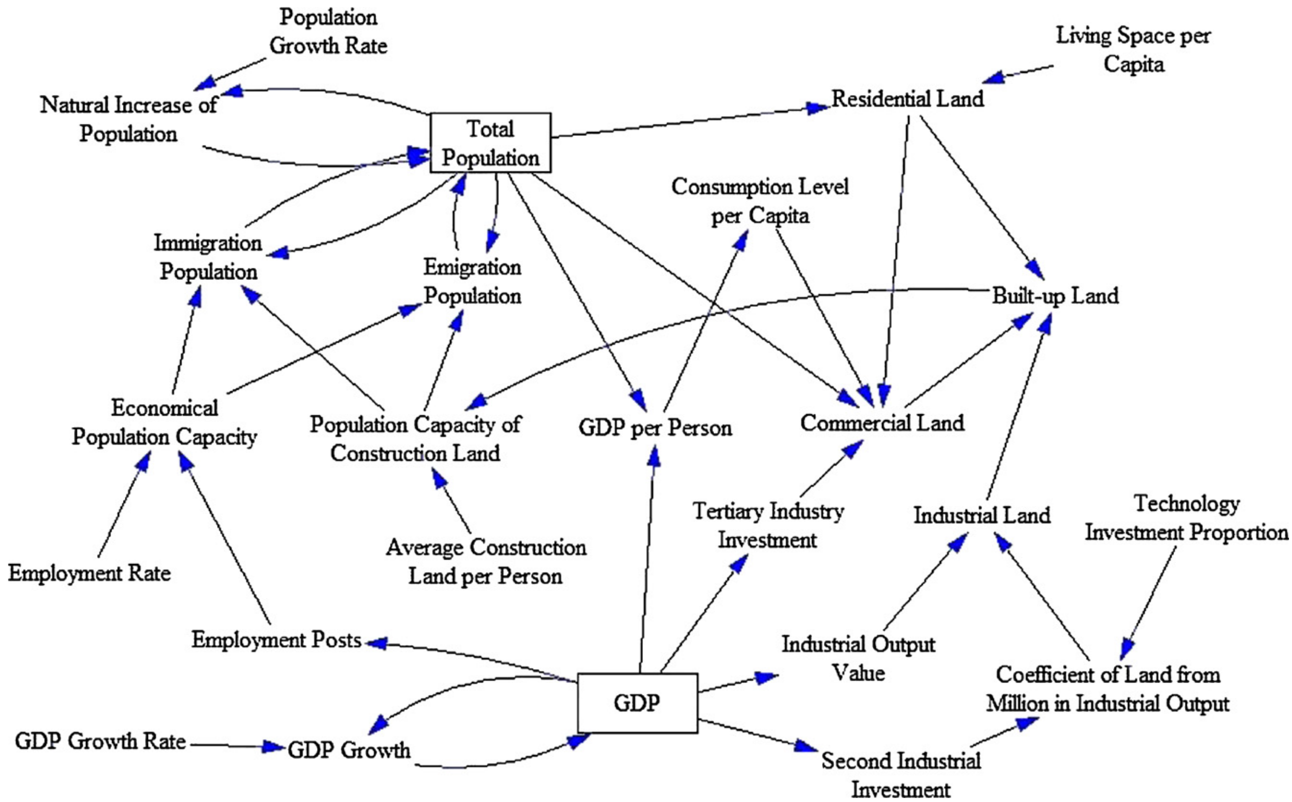


**Fig. 2.** The framework of land use scenario demands based on system dynamics.

global best experiences. As illustrated in Fig. 4, a cross operation between particles $X_i$ and $P_i$ has been explained in detail. First, we randomly choose an area $D$ in particles $X_i$ and $P_i$, respectively. Each area has the same size (the value is equal to $\alpha$) and position in particle space. All the cell types of the selected area then in particle $X_i$ are transformed into the same cell type of the selected area in particle $P_i$. Finally, considering the consistency of land use, particle $X_i$ need to modify and make sure the cell numbers of each land use type unchanged as same as before. For example, after the transformation process in particle $X_i$, two cells where the land use is type-3 are increased, whereas the one cell where the land uses are type-1 and type-2 are decreased. To avoid this mistake, two cells where the land use is type-3 in particle $X_i$ are randomly picked out and assigned as type-1 and type-2, respectively.

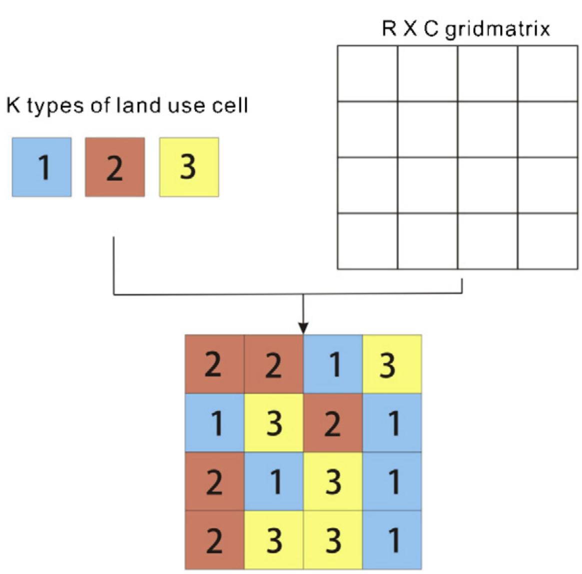


**Fig. 3.** The representation of each particle corresponding to the solution of land use allocation.

*Rand*( ) is the strategy of mutation operation corresponding to the mutation performed in GAs. In the strategy, we randomly select two cells with different land uses in particle $X_i$, and exchange the type for each other by allocating the land use (Fig. 5).

Accordingly, Eq. (16), as a new particle adjustment rule, is analyzed in terms of two important aspects. First, cross operations were performed on particle $X_i$, local best solution $P_i$ and global best solution $P_g$. These operations facilitate the particle exchange of land use cells with local and global best solutions, such that particle $X_i$ can update itself by obtaining local and global information. Second, particle $X_i$ was adjusted by mutation operation to maintain the particle diversity. Each particle can learn from individual and global best experiences to update and improve itself by the cross and mutation operations. These steps overcome the limitation of the original PSO in the discrete combinatorial space by the new particle adjustment rule with the genetic recombination mechanism. Hence, the proposed algorithm named HPSO is more suitable than the original algorithm for solving land use allocation problems.

### 4.2.3. The procedures of HPSO

For solving land use allocation problems, the detailed procedures of the proposed HPSO are presented as follows:

Step 1: **Initialization**. A swarm of particles are initially created with size $n$, each of which is a two-dimensional integer array corresponding to a candidate solution to the underlying problem. Set $t = 0$.

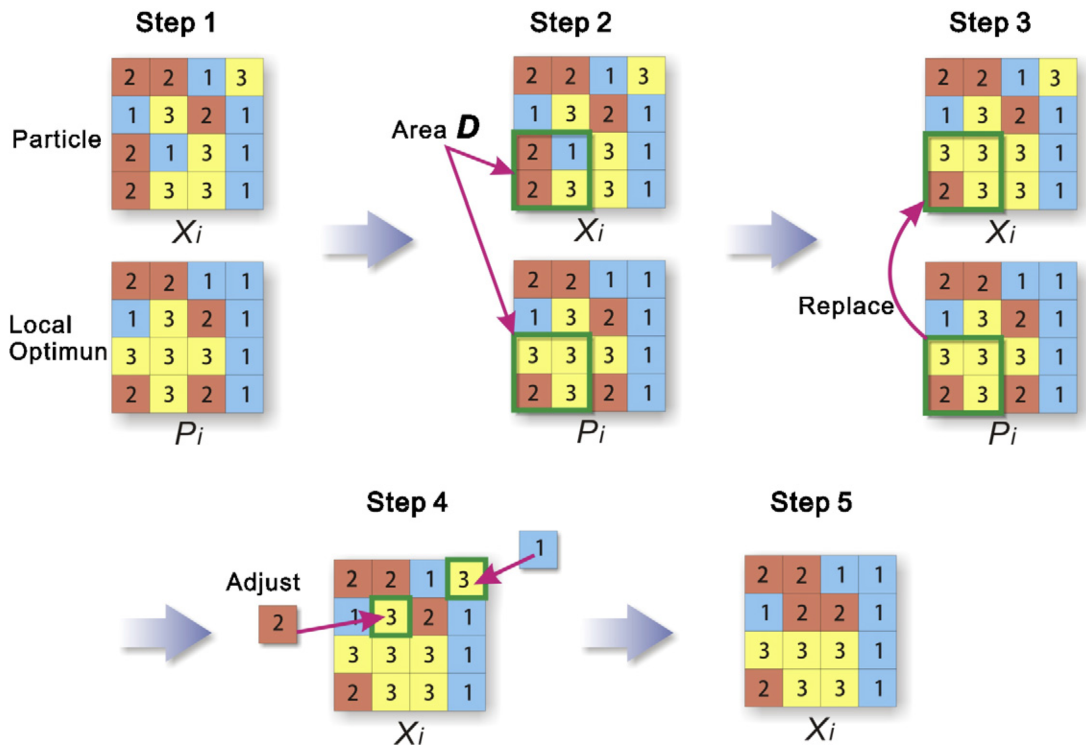


**Fig. 4.** The strategy of cross operation for the SDHPSO-LA model.

Step 2: **Evaluation**. The fitness values of all particles are evaluated using Eq. (10).
Step 3: **Determine the best position**. The fitness evaluation of the particle is compared with its best fitness value ***pbest***. If the current value is better than ***pbest***, then the ***pbest*** value is set to be equal to the current value, and the particle individual best position $P_i$ equals the current position. Similarly, the best position $P_g$ of the swarm visited so far is determined by the whole swarm.
Step 4: **Update of particles**. Each particle position is updated using Eq. (16). However, not all new particles produced are improved by the update mechanism. To accelerate the convergence speed and make particles more efficient in exploring the solution space, we take an improved measure as follows: for each particle $X_i$, if the fitness value of the position of the new particle is better than that of the individual best position $P_i$ of the particle, particle $X_i$ accepts the new position.
Step 5: **Termination. Set** $t = t + 1$. If $t < t_{max}$, Step 2 follows; otherwise, the procedure is terminated.

Finally, the best particle $P_g$ of the swarm is an optimal solution to the land use allocation problems when the procedure is terminated.

## 5. Implementation and results

The SDHPSO-LA model was applied to solve land use allocation problem of Panyu, a city in South China. The modeling contains three general steps: (1) data processing and mapping, which respectively generates the suitability and the spatial distance of each urban land use, as well as the compatibility of adjacent land uses; (2) projecting land use demands under different scenarios using the SD module, which generates proportions of different land uses that need to be met by the allocation; and (3) allocating land uses to cells based on the planning objectives using the HPSO algorithm.

The proposed model was implemented using the software of Vensim and Visual C#. All experiments were run on a PC with Intel(R) Core(TM) 2, 2.33 GHz CPU, 2.00 GB RAM, and Windows 7 OS.

### 5.1. The study area

Panyu city is selected to test the proposed model. The city, with an area of 786 km$^2$, is situated at the centre of the Pearl River

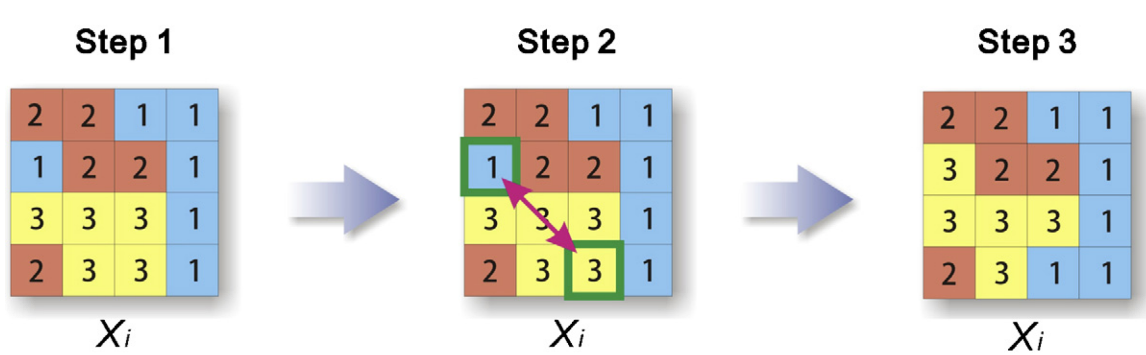


**Fig. 5.** The strategy of mutation operation for the SDHPSO-LA model.


**Fig. 6.** Location of Panyu in the Pearl River Delta.

Delta (PRD) in Guangdong Province, one of the fastest developing regions in China (Fig. 6). With the implementation of the Reform and Opening-Up Policy, the city has undergone rapid economic development and urban sprawl, thereby losing a large amount of agricultural land due to rapid urban development and poor land management (Yeh and Li, 1999), consequently, a series of land use problems has arisen. Therefore, sustainable land use patterns of Panyu city are very crucial for local environmental and economic planning. As a serviceable tool for land use management, the optimal allocation of land use plays an important role in fully exploiting the potential of land use, as well as keeping the land ecosystem balance (Bourne, 1969; Verburg et al., 1999; Andrew, 2002). Thus, we apply the SDHPSO-LA model to identify optimal allocation for land uses in Panyu city.

### 5.2. Data processing and mapping

The study area consists of an analysis of 131,093 cells, with a ground resolution of 100 m. We generalize current land use in the area into five categories, namely, industry, commerce, residence, undeveloped (such as agriculture and orchards) and restricted land (such as water, ecological preservation zone) (see Fig. 7). Except for restricted land use, which is about 132.91 $km^2$ according to local government regulations, only four land uses (industry, commerce, residence and undeveloped land) are convertible, whereas the undeveloped land represents open-space areas that may be converted into urban areas (industry, commerce, and residence).

Land use suitability analysis is the process of estimating the fitness of a given tract of land for a specific use (Pereira and Duckstein, 1993; Steiner et al., 2000; Jacek, 2004). In this study, the spatial suitability of each type of land use was derived based on a weighted overlay of 14 factors in Table 1 (Huang et al., 2012). Then, the associated weights of each factors were obtained through the analytic hierarchy process (AHP), which is a decision-making theory of measurement in a multi-criteria evaluation problem through pair-wise comparisons that relies on the experiences of experts to derive priority scales (Thomas, 1990; Saaty, 2005). Thus, with the aid of the AHP method, the factors and their weights obtained for different land uses are listed in Table 1. Then land use suitability (Fig. 8) was created by integrating the above factors and weights using the ArcGIS 9.3 spatial overlay analyst function.

As one of the planning objectives for land use allocation, the distance to already developed areas can embody the effect of urban development attractiveness (Batty and Xie, 1994). To ensure that future social economic activities occurred close to existing developed areas, some proximity distance maps need to be used. The distance maps were generated using ArcGIS 9.3 Spatial Analyst

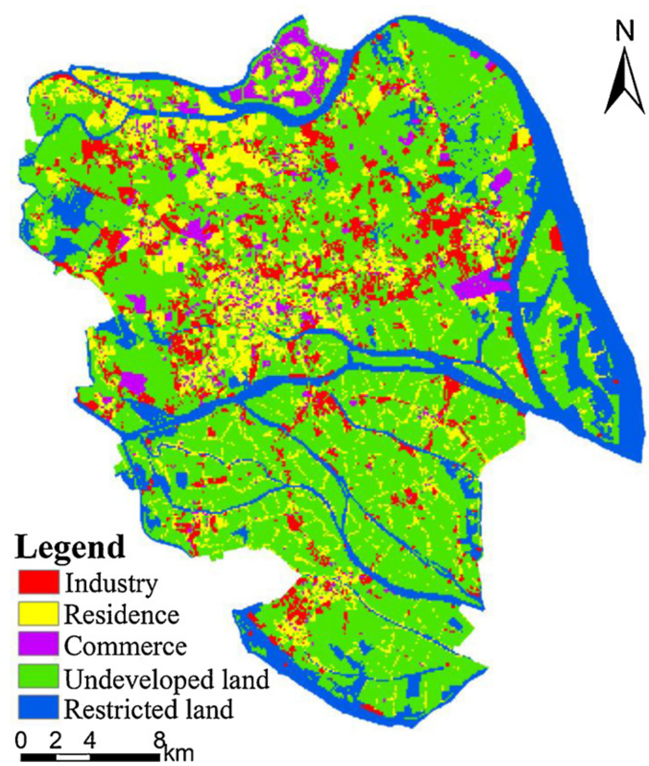


**Fig. 7.** Land use map input in the case study.

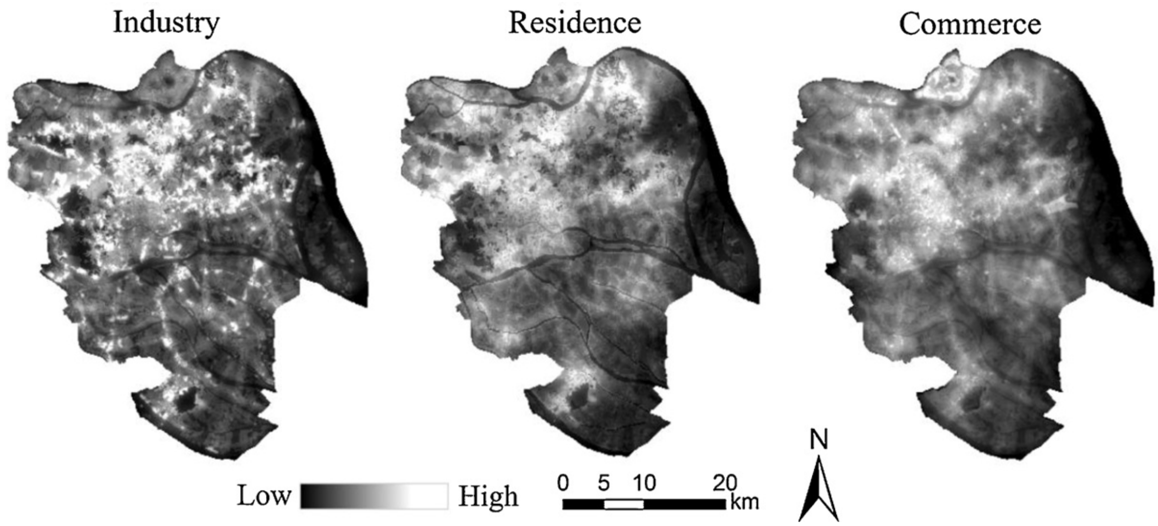


**Fig. 8.** The suitability maps for industry, residence, and commerce respectively.

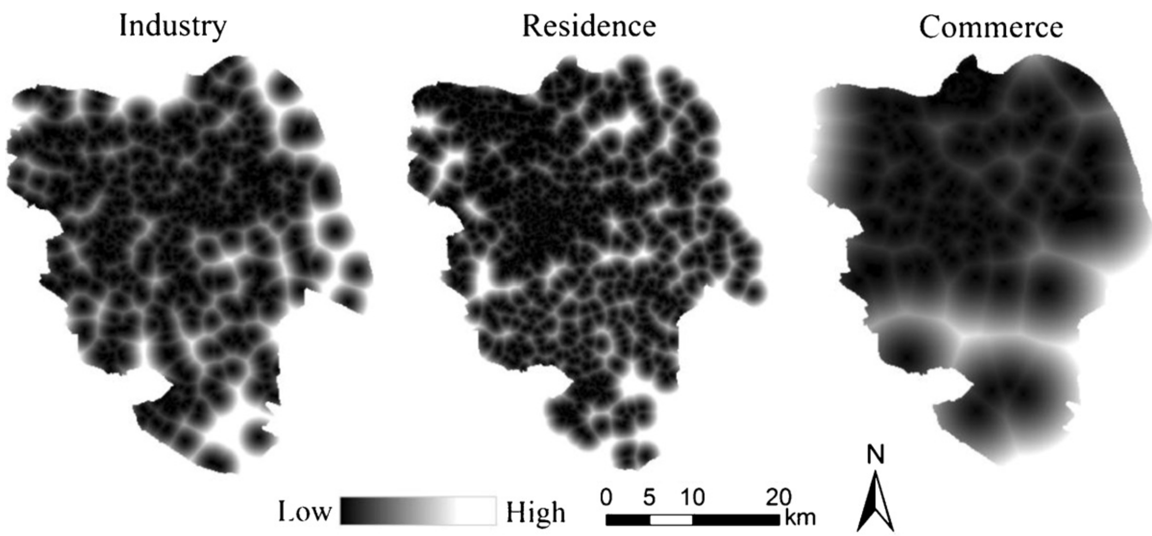


**Fig. 9.** The distance to developed areas of industry, residence, and commerce respectively.

Euclidean Distance function. The value ranges of these spatial variables are normalized into 0–1(Fig. 9).

The compatibility of land uses means the degree to which two or more land use types co-exist (Libby and Sharp, 2003; Taleai et al., 2007). There are different kinds of spatial externalities among various land use types (Hughes and Sirmans, 1992). However, these relationships of externalities can be positive or negative (Willis et al., 1998; Espey and Lopez, 2000). For instance, placing an industrial land use adjacent to residential land uses causes some negative externalities due to the pollution made by industrial activity. Therefore, the location and allocation of land to each land use type should be designed to minimize undesirable impacts among adjacent land uses. The purpose is to protect the health, safety, and welfare of the community by reducing noise, air, and visual pollution, as well as increase the usability and value of the lands by maximizing positive externalities. In this study, the compatibility of land uses was acquired based on personal communication with the experts and urban planners (Table 2). The compatibility value range is [0.0, 1.0], where higher values indicate more compatibility.

**Table 1**
Weights of factors for each of the three land uses.

| Factors | Industry | Residence | Commerce |
|---|---|---|---|
| Slope | 0.1253 | 0.1124 | 0.1266 |
| Elevation | 0.0867 | 0.0827 | 0.0935 |
| Geological disaster potential | 0.1427 | 0.1479 | 0.1461 |
| Distance to towns | 0.0675 | 0.1029 | 0.1251 |
| Distance to highways | 0.1669 | 0.0764 | 0.0528 |
| Distance to roads | 0.1553 | 0.0886 | 0.1035 |
| Density of green surfaces | 0.0286 | 0.0923 | 0.0297 |
| Proximity to river | 0.0254 | 0.0227 | 0.0169 |
| Proximity to industry | 0.1622 | 0.0119 | 0.0135 |
| Proximity to commerce | 0.0236 | 0.1054 | 0.1753 |
| Proximity to residence | 0.0108 | 0.1568 | 0.1170 |
| Sum | 1 | 1 | 1 |

### 5.3. *Land use demands based on different scenarios*

Before conducting the experiment for land use allocation optimization, land use demands of Panyu city in the forecast period need to be obtained. With the historical data of statistical yearbooks and land resources investigation of Panyu city, we investigated the influence of economic development, population growth, technology investment and policy changes on the demand for each land

**Table 2**
The compatibility of land uses.

| Land use | Industrial | Residential | Commercial | Undeveloped | Restricted |
|---|---|---|---|---|---|
| Industrial | 1 | 0 | 0.2 | 1 | 0.1 |
| Residential | 0 | 1 | 0.8 | 1 | 0.9 |
| Commercial | 0.2 | 0.8 | 1 | 1 | 0.5 |
| Undeveloped | 1 | 1 | 1 | 1 | 1 |
| Restricted | 0.1 | 0.9 | 0.5 | 1 | 1 |

use. Then, land use demands from 2008 to 2030 under different scenarios can be created by using the SD module.

### 5.3.1. *Parameter selection*

The modeling scenarios are constructed based on a series of parameters that greatly influence the system. By adjusting these parameters, land use demands under different scenarios can be generated from the SD module. As discussed in Section 4.1 above, four parameters (GDP growth rate, population growth rate, technology investment proportion, and living space per capita) were chosen as system control variables according to the development conditions that mainly affect the current structure of land use in Panyu. Different values were assigned to parameters according to the historical statistical data of Panyu to generate various development scenarios for the city in 2030. The parameters setting for each system dynamics model scenario is listed in Table 3.

Table 3 indicates that the size of the city increases as the level of economic development rises. Consequently, urban sprawl increases the demand for commercial and industrial land. Meanwhile, agricultural land requires reduction to accommodate urban sprawl. Thus, economic development has an important impact on land use change. Three scenarios for Panyu's economic development in the next over 20 years are design as follows: (1) booming-oriented development, in which the GDP of Panyu is expected to grow rapidly at the rate of 18%; (2) steady development, in which the GDP growth rate is maintained at the current level of 12%; and (3) conservative development, in which the GDP growth rate is set to 8%.

The population increase undoubtedly leads to higher demand for residential areas and living space. Panyu city currently experiences decline in both fertility and mortality, and population growth rate dropped from 7.02‰ in 2000 to 5.67‰ in 2010. In this study, we established three modes of population growth to simulate Panyu's population development situation in 2030: high-speed growth, steady growth, and low-speed growth. The population growth rate for each mode is listed in Table 3.

Technology development is a key factor that influences industry production. Increased investment in technology can improve industrial productivity, relieving agricultural pressure from the increasing demand of people living. In addition, increased investment can also improve urban land use efficiency and reduce land resource consumption. We established two technology development scenarios for the next 20 years, based on the current technology investment in Panyu. One scenario involves the improvement of investment level and strengthening of technology development; the other involves maintaining the original investment level. The latter indicates that technology investment proportion will remain at the current level of approximately 30%.

Land policy is generally implemented to regulate land use, which is an important human factor that directly affects change in urban land use. Living space per capita is mainly selected to represent the influence of land policy implementation in simplifying the complex model. In this study, we also presented three scenarios for Panyu land development over the next 20 years or so. In the first scenario, land use in Panyu experiences a vigorous development, in which the living space reaches 35 $m^2$ per capita. In the second scenario, moderate development with economic demand and resource protection considered is presented. In the third scenario, urban expansion is restricted to protect land resources, and living space is limited to 25 $m^2$ per capita.

### 5.3.2. *Scenarios design*

By the combination of different value of four parameters above: GDP growth rate, population growth rate, technology investment proportion, and living space per capita, the SD module was used to construct four modeling scenarios for the land use demands according to the actual situation of socio-economic development and land use in Panyu. These scenarios represent the future development of Panyu at different local socio-economic and policy-making levels. Table 4 summarizes the combination of the different values of the four parameters in each given scenario.

*5.3.2.1. Scenario 1: Baseline Development Scenario (BDS).* BDS, for predicting land use demands, is based on the trajectory of past development of Panyu. In this scenario, the current trends of economic and population development are assumed to continue. According to the present circumstance of land use in Panyu, the value of living space per capita is also held at the constant level of 30 $m^2$ per capita.

*5.3.2.2. Scenario 2: Fast Development Scenario (FDS).* FDS is constructed to maximize of socio-economic benefits in Panyu. In this

**Table 3**
The scenarios parameter settings for system dynamics model.

| Driving force | Manipulated variable | Parameter value | Remark |
|---|---|---|---|
| Economic | GDP growth rate (%) | 18 | Booming development-oriented (E1) |
| | | 12 | Steadily development-oriented (E2) |
| | | 8 | Conservative development-oriented (E3) |
| Population | Population growth rate (‰) | 7 | High-speed growth (P1) |
| | | 5 | Steady growth (P2) |
| | | 3 | Low-speed growth (P3) |
| Technology | Technology investment proportion (%) | 35 | Improve input level (T1) |
| | | 30 | Maintain the original level (T2) |
| Land policy | Living space per capita ($m^2$ per capita) | 35 | Vigorous development (L1) |
| | | 30 | Moderate development (L2) |
| | | 25 | Strict protection (L3) |

**Table 4**
The combination of different value of the four parameters in each given scenario.

| Scenario | GDP growth rate (%) | Population growth rate (‰) | Technology investment proportion (%) | Living space per capita ($m^2$ per capita) | Remark |
|---|---|---|---|---|---|
| BDS | 12 | 5 | 30 | 30 | Baseline development mode (E2P2T2L2) |
| FDS | 18 | 8 | 30 | 35 | Fast development mode (E1P1T2L1) |
| SDS | 8 | 3 | 35 | 25 | Slow development mode (E3P3T1L3) |
| HDS | 12 | 5 | 35 | 35 | Harmonious development mode (E2P2T1L1) |

scenario, the economy and population continue to increase at a higher speed. Furthermore, the influence of the progress in science and technology, as well as the improvement in the living condition of resident, were also taken into account in this scenario to predict the land use demands in Panyu.

*5.3.2.3. Scenario 3: Slow Development Scenario (SDS).* Contrary to FDS, the main purpose of SDS is to protect agriculture and orchards as much as possible. Undeveloped land (agriculture and orchards) is strictly limited to conversion into urban land by local government regulation. The GDP growth rate, population growth rate, and living space per capita are assumed to be at the lowest level with regard to the future urban development, except for the technology investment proportion.

*5.3.2.4. Scenario 4: Harmonious Development Scenario (HDS).* To balance the appropriate ecological and socio-economic benefits, HDS is constructed as a more human-oriented and sustainable urban development mode with a trade-off analysis between economic development and land conservation. The speed of economic and population growth are held at their current rate. At the same time, to promote land use efficiency, the proportion of technology investment is assumed to have more input in industry, and the living condition and environment of residents are also improved by considering people orientation. Hence, the living space per capita is set to a maximum value of 35 $m^2$ per capita.

### 5.3.3. *Results of scenario simulations*

According to these four different scenarios discussed above, the SD module was used to project the land use demands under four different development options, which derived via the adjustment and combination of various control variables. The simulation process and results for land use demands were depicted in Fig. 10 and Table 5.

Fig. 10 clearly shows the change in each land use demands under different scenarios. The amount of each urban land use continues to increase from 2008 to 2030. Among the scenarios, the growth range of urban land use demand in FDS is largest in the forecast period, but that in SDS is smallest. Table 5 illustrates the forecasting land use demands of Panyu in 2030, wherein urbanization in BDS is shown to consume more undeveloped land than SDS, but less than FDS. Under FDS, more cropland and open space are occupied to pursue economic development. Under HDS, the amount of urban land area is about 294.04 $km^2$, roughly similar to that in BDS (283.44 $km^2$). The demand for industrial land in HDS is only about 76.35 $km^2$, which is much less than one in BDS. However, the number residential and commercial lands of the former are higher than those of the latter.

## 5.4. *Implementation of the model*

After obtaining land use demands by the SD module, we used the HPSO module to optimize land use pattern based on these land

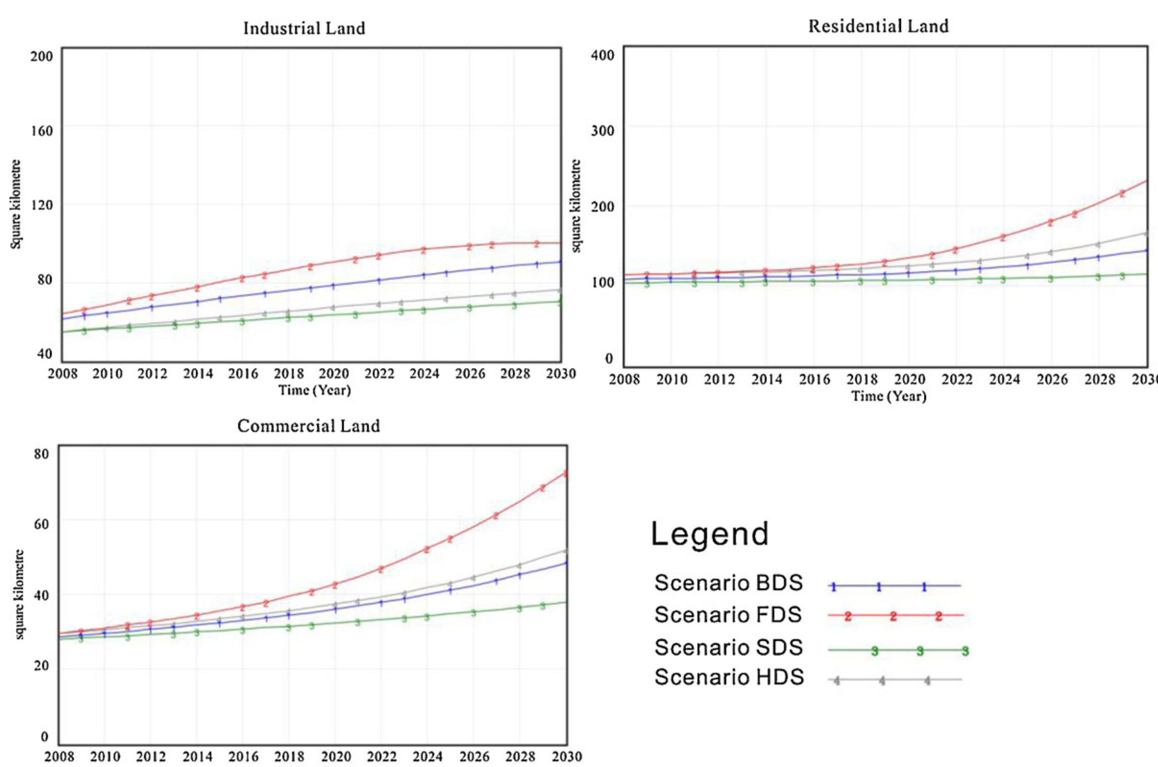


**Fig. 10.** The simulation process and results of land use demands under different scenarios.

**Table 5**
The land use demands for Panyu in 2030 under different scenarios.

| Scenario | Industrial | Residential | Commercial | Undeveloped | Restricted |
|---|---|---|---|---|---|
| BDS | 90.5892 | 144.46 | 48.3873 | 358.5542 | 132.9084 |
| FDS | 99.9388 | 230.823 | 72.7322 | 238.4967 | 132.9084 |
| SDS | 70.2365 | 114.537 | 38.0375 | 419.1797 | 132.9084 |
| HDS | 76.3503 | 165.857 | 51.8363 | 347.9471 | 132.9084 |

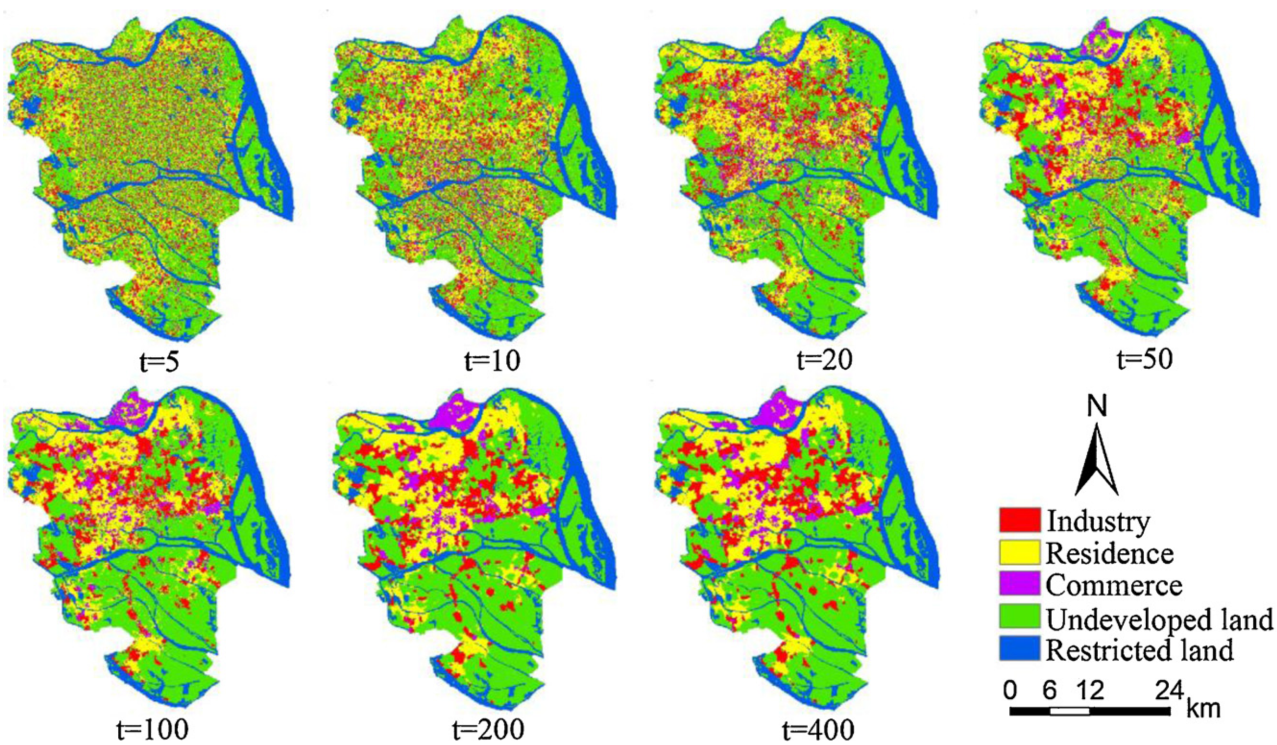


**Fig. 11.** The optimization process of land use pattern by using SDHPSO-LA model in BDS.

use demands. In the HPSO algorithm, a swarm of 50 particles are adopted, and the maximum iteration number ($t$) is set to 400. By considering the trade-off between the four objectives (suitability, compatibility, compactness, and distance to developed land) in the SDHPSO-LA model, the weight values of $a$, $b$, $c$ and $d$ are all set to 0.25.

To prove the feasibility of the proposed model, an optimization process of land use allocation under BDS was first carried out (Figs. 11 and 12). The series of images in Fig. 11 shows the optimum outputs from different iterations. Initially, each cell of land use is randomly located in the study region. As the iterations progress, the formulated patterns appear to be increasingly compact. A close inspection reveals that after 100 iterations, most land use cells are at locations that have balanced combinations of suitability, compatibility, compactness, and distance to developed land. The land use pattern started to stabilize after 200 iterations. Finally, the optimum pattern of Panyu land use is presented in the last image. Fig. 12 illustrates a change in the utility values of the optimum outputs from the objective function as the iterations progress (specified by BDS). The curve shows that the value rapidly increases in the early stage of the optimization, gradually becomes stable, and finally levels out after 200 iterations. The search will spend about 15 min by using a computer with Intel(R) Core(TM) 2, 2.33 GHz CPU. From the spatial distribution of land uses in Fig. 11, the patterns of industrial, residential, and commercial land are very compact, conforming to the urban planning concept of promoting compact land use form. Thus, the proposed model is proven to be an appropriate method for land use optimization allocation, and can provide decision-making support for planners of land resource management.

According to the land use demands generated from four scenarios by SD, we further carried out scenarios for the optimization of Panyu land use allocation. As can be seen in Fig. 13, the optimization results of BDS, FDS, SDS, and HDS are successfully produced to show the spatial distribution of all future urban land uses in 2030. From the comparison of these optimization results, there are some obvious similarities and differences among the spatial patterns of land use in each scenario. First, the allocations of industrial,

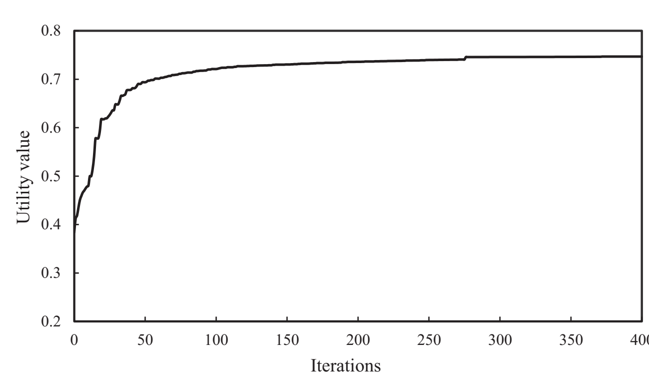


**Fig. 12.** Utility improvement with iterations by the proposed SDHPSO-LA model in BDS.

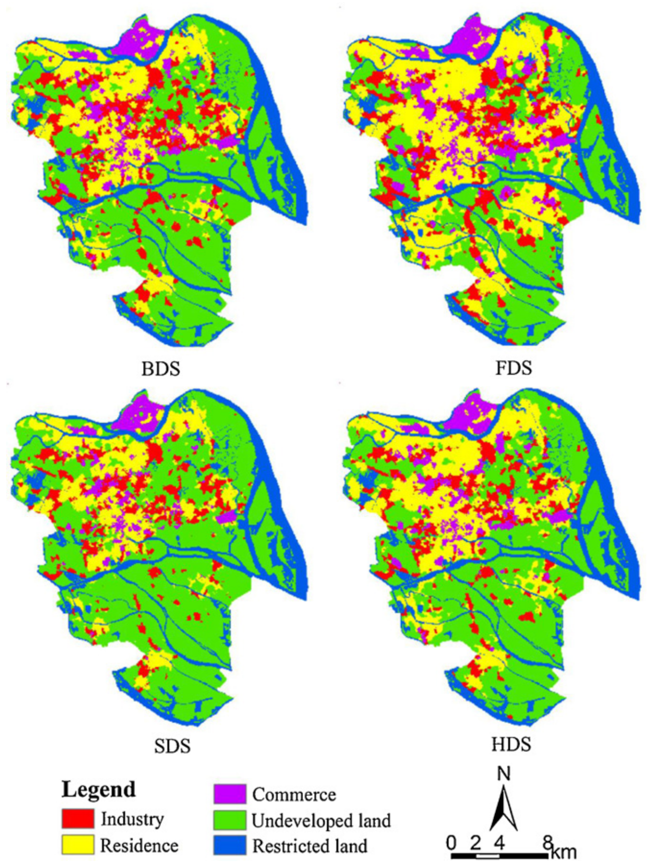


**Fig. 13.** Comparison of optimization results between scenario BDS, FDS, SDS, and HDS.

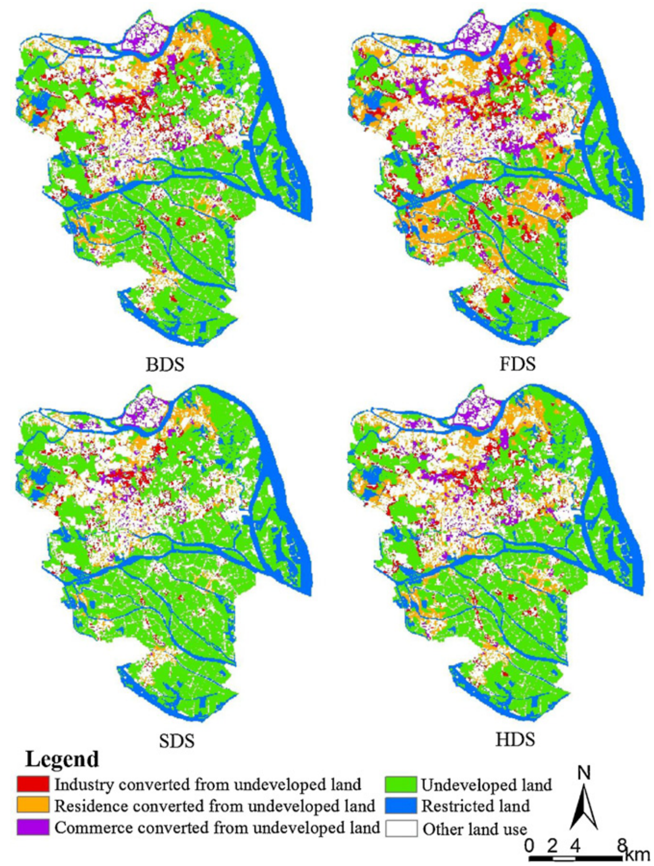


**Fig. 14.** Comparison of the land conversions from undeveloped land to industrial, residential and commercial land under different scenarios.

residential, and commercial lands have almost the same pattern and mainly located at the north of Panyu. Most of the southern area is undeveloped land used for agricultural development. Among four scenarios, the spatial distribution of the allocated future urban development under FDS expands and occupies the largest amounts of Panyu areas to meet the need of socio-economic development. The land consumptions for residence and industry are especially strengthened to encroach and engulf more undeveloped land (agriculture and orchards). In contrast, the urban land use optimization follows a mode based on strictly confined land use in SDS, where agriculture and orchards are well protected. Indeed, urban areas in this scenario increase the least, which is the result of forbidding the occupation of some undeveloped lands, and can influence economic development. As regards BDS, most land use allocation is expected to occur within and around the appropriate places in accordance with the planning objectives. However, the spatial distribution of future urban development for HDS differs from that for BDS in some ways, mainly due to the difference between the land demand for residence and industry in the two scenarios. The above results derived by various scenarios can provide decision makers with references for land use management, both in numerical assignments as well as spatial and temporal scales from 2008 to 2030.

### 5.5. Analysis of scenario results

The actual land use in 2008 and the optimization pattern allocation in each scenario were compared based on spatial overlay analysis to provide spatial patterns of land conversion from undeveloped land to industrial, residential, and commercial land (Fig. 14). Such that the land use change of Panyu in the future under different "what-if" of urban policies can be examined and analyzed to help us to understand the dilemma of urban development.

Fig. 14 indicates that the socio-economic development of BDS following the current trend increases the demand for urban land (283.44 $km^2$) in 2030. Newly increased urban land is predicted to occupy the undeveloped land around the original urban land in 2008, which is roughly similar situation to that of HDS (Fig. 14). However, a notable difference in demand for residential and industrial land use exists between BDS and HDS. For example, the amount of industrial land encroaching undeveloped land in BDS (35.40 $km^2$) is more than that in HDS (28.58 $km^2$), whereas the amount of residential land encroaching undeveloped land in the former (56.04 $km^2$) is much less than that in the latter (69.21 $km^2$). Such a land use pattern in BDS can easily cause problems in the residential environment. These problems include housing pressure arising from population growth, as well as air and noise pollution from factories. Therefore, BDS is not the best option for Panyu's future development.

With regard to FDS, exhaustion of the supporting ability of land resource in Panyu is predicted after Panyu's rapid development over the next two decades. For instance, the sum of residential and industrial land areas is about 176.44 $km^2$ in 2008 but is expected to increase to approximately 330.76 $km^2$ in 2030. In particular, the area of undeveloped land converted to residential land, which mostly occurs in the northeastern and southern parts of Panyu is expected to reach 120.99 $km^2$. This scenario may be contributory to socio-economic development as well as the improvement of residential space. However, the rapid development of the city also indicates a loss of vast agricultural and forestal land. In the long run, the negative effects resulting from the occupation of expansive land resource far outweighs the economic benefits. Therefore, the development of FDS negatively affects the sustainability of land use in Panyu.

By contrast, SDS provides alternative urban land use optimization in Panyu in which strict urban planning policy is implemented to restrict the expansion of urban land (Fig. 14). In this scenario, the smallest urban areas increase among the four scenarios is reported, that is, only 15.27 $km^2$ from 2008 to 2030. Fig. 14 shows that a small area of undeveloped land north of the city is allocated to residential and industrial uses. Most undeveloped land in the south reflects no change in status from 2008 to 2030. These characteristics of land use change due to restricting the occupation of some undeveloped land parcels can also have a serious negative impact on socio-economic development because of lack of support for land resources. Thus, this scenario does not contribute to the sustainable development of Panyu.

In HDS, with the demand of socio-economic development and land conservation considered, urban land in Panyu is predicted to increase by 86.51 $km^2$ from 2008 to 2030. In this scenario, more technological advances are introduced into industry to improve land use efficiency and protect undeveloped land from being despoiled. Contrary to the BDS scenario, a reasonable size of residential land in HDS (165.86 $km^2$) can relieve the pressure of the increasing demand from residents. Hence, this human-oriented and sustainable urban development scenario among the four scenarios seems the most suitable for Panyu' development.

In summary, the analysis of scenarios indicates that land use pattern is driven by economic and social forces and restricted by land policies. In future, the development of Panyu city has to face a dilemma of the continuous urban expansion versus limited land resource. Effective planning and management must be implemented to solve this dilemma, and the proposed model provides a convenient method to examine and analyze relevant policies in land planning and management spatially and explicitly.

## 6. Conclusion

Land use change is a complex process involving the interaction in space and time of socio-economic and physical components at different scales. In the past, a number of models have been applied to land use spatial allocation but only address micro-scale interaction. Macro-level socio-economic variables and driving forces are seldom considered in these models. With the combination of system dynamics (SD) and hybrid particle swarm optimization (HPSO), a novel land use allocation model named SDHPSO-LA, is presented in this article. Different from the previous works, the proposed model addresses cross-scale interactions in land use modeling. At first, the SDHPSO-LA model projected land use demands by the SD module, which considered the regional economic inequality, population migration, policy influences and their interactions at macro-scales. Then, hybrid particle swarm optimization (HPSO) module was used to generate optimal land use pattern based on suitability map and spatial constrains at micro-scales.

As a heuristic method, PSO has been proven as an effective algorithm for solving complex combination optimization problems. The original PSO is customized to continuous function value optimization. However, land use allocation belongs to a typical discrete combinatorial optimization problem. The original PSO cannot directly solve this problem. In this article, PSO is modified by incorporating discrete genetic operators, namely crossover and mutation, so that it can be suited to solve spatial combinatorial optimization problems. Moreover, the hybrid strategy accelerates the convergence speed so that PSO can solve land use allocation problems in large areas.

The SDHPSO-LA model was then applied to the creation of optimal land use patterns in Panyu, a rapidly developing region in China, which is involved an area of 131,093 cells. Four scenarios of land use pattern in 2030, namely BDS, FDS, SDS and HDS, have been successfully generated by using this proposed model. Each scenario takes about 15 min for finding a near-optimal solution. This indicates that the SDHPSO-LA model is an efficient optimization technique for generating alternative land use patterns. The successful application of the SDHPSO-LA model indicates that it can reflect the complex interactions in land use system at both macro-scales and micro-scales. Furthermore, the model also enables planners and stakeholders to test and compare the gains under different scenarios. Indeed, the model is a useful exploratory tool for generating alternative land use patterns.

## Acknowledgements

This study was supported by the National Natural Science Foundation of China (Grant No. 41171308), the National Natural Science Foundation of China (Grant No. 40901187) and the Key National Natural Science Foundation of China (Grant No. 40830532).

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2013.02.027.

## References

Andrew, R.S., 2002. Spatial optimization for managed ecosystems. Regional Science and Urban Economics 32 (4), 541–542.
Aerts, J., Heuvelink, G.B.M., 2002. Using simulated annealing for resource allocation. International Journal of Geographical Information Science 16, 571–587.
Batty, M., Xie, Y., 1994. Research article. Modelling inside GIS: Part 1. Model structures, exploratory spatial data analysis and aggregation. International Journal of Geographical Information Systems 8 (3), 291–307.
Boeringer, D., Werner, D., 2004. Particle swarm optimization versus genetic algorithms for phased array synthesis? IEEE Transactions on Antennas and Propagation 52 (3), 771–779.
Bojórquez-Tapia, L.A., Ongay-Delhumeau, E., Ezcurra, E., 1994. Multivariate approach for suitability assessment and environmental conflict resolution. Journal of Environmental Management 14, 187–198.
Bos, J., 1993. Zoning in forest management: a quadratic assignment problem solved by simulated annealing. Journal of Environmental Management 37, 127–145.
Bourne, L.S., 1969. A spatial allocation-land use conversion model of urban growth. Journal of Regional Science 9 (2), 261–272.
Brookes, C.J., 2001. A genetic algorithm for designing optimal patch configurations in GIS. International Journal of Geographical Information Science 15, 539–559.
Cagnina, L., Esquivel, S., Gallard, R., 2004. Particle swarm optimization for sequencing problems: a case study. In: Proceedings of the IEEE Conference on Evolutionary Computation, pp. 536–541.
Carsjens, G., Van Der Knaap, W., 2002. Strategic land-use allocation: dealing with the spatial relationships and fragmentation of agriculture. Landscape and Urban Planning 58 (2–4), 171–179.
Chen, Y.M., Li, X., Liu, X.P., 2010. An agent-based model for optimal land allocation (AgentLA) with a contiguity constraint. International Journal of Geographical Information Science 24 (8), 1269–1288.
Cocks, K., Baird, I., 1989. Using mathematical programming to address the multiple reserve selection problem: an example from the Eyre Peninsula, South Australia. Biological Conservation 49, 113–130.
Cova, T.J., Church, R.L., 2000. Exploratory spatial optimization in site search: a neighborhood operator approach. Computers & Operations Research 24, 401–419.
Eberhart, R.C., Shi, Y., 2001. Particle swarm optimization: developments, applications and resources. In: Proceedings of the 2001 Congress on Evolutionary Computation, vol. 1, pp. 81–86.
Esmin, A.A.A., et al., 2005. A hybrid particle swarm optimization applied to loss power minimization. Power Systems 20 (2), 859–866.
Espey, M., Lopez, H., 2000. The impact of airport noise and proximity on residential property values. Growth and Change 31 (3), 408–419.
Ford, A., 1996. Testing snake river explorer. System Dynamics Review 12 (4), 305–329.
Forrester, J.W., 1961. Industrial Dynamics. The MIT Press, Cambridge, MA.
Forrester, J.W., 1969. Urban Dynamics. The MIT Press, Cambridge, MA.
Gabriel, S.A., Faria, J.A., Moglen, G.E., 2006. A multiobjective optimization approach to smart growth in land development. Socio-Economic Planning Sciences 40, 212–248.

Guo, H., et al., 2001. A system dynamics approach for regional environmental planning and management: a study for the Lake Erhai Basin. Journal of Environmental Management 61, 93–111.
Han, J., et al., 2009. Application of an integrated system dynamics and cellular automata model for urban growth assessment: a case study of Shanghai, China. Landscape and Urban Planning 91, 133–141.
He, C.Y., et al., 2005. Developing land use scenario dynamics model by the integration of system dynamics model and cellular automata model. Science in China Series D: Earth Sciences 48 (11), 1979–1989.
Huang, K.N., et al., 2012. An improved artificial immune system for seeking the Pareto front of land-use allocation problem in large areas. International Journal of Geographical Information Science iFirst, 1–15.
Hughes, W.T., Sirmans, C.F., 1992. Traffic externalities and single-family house prices. Journal of Regional Science 32 (4), 487–500.
Jacek, M., 2004. GIS-based land-use suitability analysis: a critical overview. Progress in Planning 62 (1), 3–65.
Kennedy, J., Eberhart, R.C., 1995. Particle swarm optimization. In: IEEE International Conference on Neural Networks (ICNN'95), vol. 4, IEEE Press, pp. 1942–1947.
Kennedy, J., Eberhart, R.C., 1997. A discrete binary version of the particle swarm algorithm. In: IEEE International Conference on Systems, Man, and Cybernetics, Computational Cybernetics and Simulation, vol. 5, pp. 4104–4108.
Li, X., Liu, X.P., 2008. Embedding sustainable development strategies in agent-based models for use as a planning tool. International Journal of Geographical Information Science 22, 21–45.
Libby, L.W., Sharp, J.S., 2003. Land-use compatibility, change, and policy at the rural–urban fringe: insights from social capital. American Journal of Agricultural Economics 85 (5), 1194–1200.
Ligmann-Zielinska, A., et al., 2008. Spatial optimization as a generative technique for sustainable multiobjective land-use allocation. International Journal of Geographical Information Science 22 (6), 601–622.
Liu, Y., et al., 2007. An integrated GIS-based analysis system for management of lake areas in urban fringe. Landscape and Urban Planning 82, 233–246.
Liu, X.P., Li, X., Tan, Z.Z., 2011. Zoning farmland protection under spatial constraints by integrating remote sensing, GIS and artificial immune systems. International Journal of Geographical Information Science 25 (11), 1829–1848.
Liu, X.P., Li, X., Shi, X., 2012. A multi-type ant colony optimization (MACO) method for optimal land use allocation in large areas. International Journal of Geographical Information Science, http://dx.doi.org/10.1080/13658816.2011.635594.
Matthews, K., 2001. Applying Genetic Algorithms to Multi-Objective Land-Use Planning. PhD Thesis. The Robert Gordon University, Aberdeen, UK.
Martínez-Falero, E., et al., 1998. Optimization of spatial allocation of agricultural activities. Journal of Agricultural Engineering Research 69 (1), 1–13.
Mashayekhi, A.N., 1990. Rangeland destruction under population growth: the case of Iran. System Dynamics Review 6 (2), 167–193.
Pereira, J.M.C., Duckstein, L., 1993. A multiple criteria decision-making approach to GIS-based land suitability evaluation. International Journal of Geographical Information Systems 7 (5), 407–424.
Saaty, T.L., 2005. Analytic Hierarchy Process. Encyclopedia of Biostatistics. John Wiley & Sons, Ltd., New York.
Santé-Riveira, I., et al., 2008. Algorithm based on simulated annealing for land-use allocation. Computers & Geosciences 34, 259–268.
Seto, K., et al., 2002. Monitoring land-use change in the Pearl River Delta using Landsat TM. International Journal of Remote Sensing 23, 1985–2004.
Shi, X.H., et al., 2007. Particle swarm optimization-based algorithms for TSP and generalized TSP. Information Processing Letters 103 (5), 169–176.
Siitonen, P., Tanskanen, A., Lehtinen, A., 2003. Selecting forest reserves with a multiobjective spatial algorithm. Environmental Science and Policy 6, 301–309.
Steiner, F., et al., 2000. Land suitability analysis for the upper Gila River watershed. Landscape and Urban Planning 50 (4), 199–214.
Sterman, J.D., 2000. Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill, Irwin, USA.
Stewart, T.J., Janssen, R., van Herwijnen, M., 2004. A genetic algorithm approach to multiobjective land use planning. Computers & Operations Research 31 (14), 2293–2313.
Taleai, M., et al., 2007. Evaluating the compatibility of multi-functional and intensive urban land uses. International Journal of Applied Earth Observation and Geoinformation 9 (4), 375–391.
Thomas, L.S., 1990. How to make a decision: the analytic hierarchy process. European Journal of Operational Research 48 (1), 9–26.
Verburg, P.H., et al., 1999. A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. Ecological Modelling 116 (1), 45–61.
Verdiell, A., Sabatini, M., Maciel, M., Iglesias, R., 2005. A mathematical model for zoning of protected natural areas. International Transactions in Operational Research 12, 203–213.
Vlachos, et al., 2007. A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains. Computers & Operations Research 34, 367–394.
Willis, K.G., et al., 1998. A review of cost–benefit analysis as applied to the evaluation of new road proposals in the U.K. Transportation Research Part D: Transport and Environment 3 (3), 141–156.
Williams, J.C., Revelle, C.S., 1998. Reserve assemblage of critical areas: a zero-one programming approach. European Journal of Operational Research 104, 497–509.
Wright, J., Charles, R., Cohon, J., 1983. A multi objective integer programming model for the land acquisition problem. Regional Science and Urban Economics 12, 31–53.
Xiao, N., Bennett, D.A., Armstrong, M.P., 2002. Using evolutionary algorithms to generate alternatives for multiobjective site-search problems. Environment and Planning A 34, 639–656.
Xiao, N., Bennett, D.A., Armstrong, M.P., 2007. Interactive evolutionary approaches to multiobjective spatial decision making: a synthetic review. Computers, Environment and Urban Systems 31, 232–252.
Yeh, A.G.O., Li, X., 1999. Economic development and agricultural land loss in the Pearl River Delta, China. Habitat International 23 (3), 373–390.
Yin, P.Y., 2004. A discrete particle swarm algorithm for optimal polygonal approximation of digital curves. Journal of Visual Communication and Image Representation 15 (2), 241–260.
Yin, P.Y., 2006. Genetic particle swarm optimization for polygonal approximation of digital curves. Pattern Recognition and Image Analysis 16 (2), 223–233.
Zhi, X.H., et al., 2004. A discrete PSO method for generalized TSP problem. In: Proceedings of 2004 International Conference on Machine Learning and Cybernetics.