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Simulating Multi-Objective Spatial Optimization Allocation of Land Use Based on the Integration of Multi-Agent System and Genetic Algorithm

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ABSTRACT: In this study, under the constraint of resource-saving and environment-friendliness objective, based on multi-agent genetic algorithm, multi-objective spatial optimization (MOSO) model for land use allocation was developed from the view of simulating the biological autonomous adaptability to environment and the competitive-cooperative relationship. The model was applied to solve the practical multi-objective spatial optimization allocation problems of land use in the core region of Changsha, Zhuzhou, Xiangttan city cluster in China. The results has indicated that MOSO model has much better performance than GA for solving complex multi-objective spatial optimization allocation problems and it is a promising method for generating land use alternatives for further consideration in spatial decision-making.

Key words: Land use allocation, Multi-objective, spatial optimization, Multi-agent system, Genetic algorithm, Resource-saving, Environment-friendliness

INTRTODUCTION

Nowadays, the rapid socio-economic development has produced enormous material interests, however, the unreasonable land use allocation has also led to a series of serious resource and environment problems, and affected seriously sustainable land use (Verburg, *et al*., 1999; Peng, *et al*., 2006; Li and Liu, 2008). Thus, developing a spatial optimization allocation model of regional land use will have important significance to scientific planning and rational management of land use. Owing to multifaceted nature of land use allocation, spatial optimization allocation model should aim at finding a set of high-performing alternatives instead of just one solution (Duh and Brown, 2007; Xiao, *et al*., 2007; Zhang and Armstrong, 2008; Ligmann-Zielinska, et al., 2008). As a type of general global optimization algorithm, genetic algorithm (GA) has been widely used for numerical optimization, combinatorial optimization and travelling salesman problems. And many researchers have been trying to apply this method to solve the multi-objective land use allocation problems quantitatively (Feng and Lin, 1999; Balling, *et al*., 1999; Matthews, 2001; Xiao, *et al*., 2002; Stewart, *et al*., 2004; Holzkamper and Seppelt, 2007; Janssen, *et al*., 2008). All the above studies indicate that GA is effective in solving multi-objective spatial optimization allocation problems of land use. However, the main problem of GA is that it may be trapped in the local optima of objective functions when the optimization problems are too complicated. And it's more possible to obtain local optimal solutions and increase convergence time with increase of the complexity of problems and search space of algorithms. In the meantime, it is difficult to incorporate human and social factors in GA. Therefore, it's necessary to develop more intelligent algorithms for the solution of multi-objective spatial optimization allocation problems of land use.

Artificial life methods inspired by complexity science has witnessed a significant development and been applied extensively (Chebeane and Echalier, 1999; Liu, *et al*., 1997). As one of these methods, multi-agent system has been successfully applied to build dynamic representations of geographical systems (Parker, *et al*., 2003; Manson, 2005, 2006; Evans, *et al*., 2006; Evans and Kelley, 2008; Brown, et al., 2005, 2008; Brown and Xie, 2006; Xie and Batty, 2007), especially in representing spatial allocation of land use (Benenson, 1998; Arentze and Timmermans, 2003; Saarloos, *et al*., 2005; Li and Liu, 2007, 2008). The multi-agent system has a cell structure which can make each agent achieve optimization in its neighborhood areas respectively instead of in the whole system to ensure the population

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diversity. This enables it to avoid being trapped in the local optima of the objective functions, which is very helpful when applying GA to solve multi-objective optimization issues (Cardon, *et al*., 2000; Cao, *et al*., 2007). As a consequence, compared with application of GA alone, the integration of multi-agent system and GA can give rise to better solutions for multi-objective spatial optimization allocation of land use. There are as yet no published studies on the integration of both techniques as an assistant decision-making tool for implementing the initiative of sustainable land use. In this study, MOSO model, which includes four evolutionary operators for land use allocation, was developed from the view of simulating the biological autonomous adaptability to environment and the competitive-cooperative relationship. The model was applied to the solution of the practical multi-objective spatial optimization allocation problems of land use in the core area of Changsha, Zhuzhou, Xiangttan city cluster in China, where land use in urban areas is characterized by inefficient low-density and extensive patterns (Yeh and Li, 1999; Liu, *et al*., 2006, 2008). The simulation results have indicated that the model can produce satisfactory optimized results.

MATERIALS & METHODS

Spatial optimization allocation of land use should not only take saving land resource by the greatest degree and increasing the utilizing efficiency into consideration, but also take improving the environmental benignity of adjacent land uses as much as possible into consideration. Thus, in this study, the general objective of MOSO model is resource-saving and environment-friendliness. In order to enhance model's operability, referring to Ligmann-Zielinska, *et al*., (2008), we set corresponding sub-objectives and constraints for resource-saving and environment-friendliness objectives respectively, which are described as follows:

Resource-saving objective:

$$\text{Minimize } \sum_{j\in U}\sum_{m} dist_j x_{jum} \tag{1}$$

$$\sum_{j=1}^{n} p_{lm} x_{jk} \tag{2}$$

Environment-friendliness objective:

Minimize

$$\sum_{j\in U}\sum_{m}(1-c_{d_j m})\ x_{jum}\ \text{ÿ} \sum_{j\in D}\sum_{m\neq e_j}(1-c_{d_j m})\ x_{je_j m} \tag{3}$$

Subject to

$$\sum_{m\neq e_j} x_{je_j m} \leq 1; \forall j \in D \tag{4}$$

$$\sum_{m} x_{jum} \leq 1; \forall j \in U \tag{5}$$

$$s_j + \sum_{i\in B_j}\sum_{m} x_{ium} \geq b\sum_{m} x_{jum}; \forall j \in U \tag{6}$$

$$x_{jum} \in \{0,1\}; x_{je_j m} \in \{0,1\}; x_{jk} \in \{0,1\} \tag{7}$$

Some notations:

j 1, 2, …, n; cell locations.

n Total number of cells in the study area.

l, m 1, 2, … k; types of land uses.

k Total number of land use type.

u Undeveloped land use.

U Set of cells of undeveloped land.

D Set of developed cells; all subsets of D are mutually disjoint.

B_j Set of j's neighbors that are undeveloped.

e_j Existing land use of cell j.

c_{lm} Estimated compatibility index between land uses l and m. in the model, l is represented by d_j.

d_j Dominant urban land use type within the neighborhood of cell j.

s_j Number of initially developed cells within j's neighborhood.

$dist_j$ Distance of location j to its nearest developed area (in cells).

p_{lm} Cost of changing land use l to m.

b Minimum required number of neighbor cells that are developed after allocation.

Variables:

x_{jum} =1, if undeveloped land at location j is changed to m; and 0 otherwise.

$x_{je_j m}$ =1, if current land use e_j at location j is changed to m; where $m \neq e_j$, and 0 otherwise.

x_{jk} =1, if type of land use at location j is changed; and 0 otherwise.

Objective (1) and (2) are resource-saving objectives. Objective (1) minimizes the distance of new development to already developed sites, in order to shift the low-density and extensive pattern of land use to intensive pattern and improve the efficiency of land use; Objective (2) minimizes the total cost of land use conversion. Objective (3) is environment-friendliness objective, minimizing the environmental incompatibilities between cell j and its neighbors in order to promote the development of environment-friendly land use pattern. Constraints (4) and (5) guarantee that only one type of land use is allocated to cell j; Constraint (6) ensures connectivity and compactness of land use, guaranteeing that the number of initially developed cells within j's neighborhood is no less than b, which makes the undeveloped land use inside the urban areas be allocated.

Zhong, *et al*., (2004) combined multi-agent system with genetic algorithm to form a new algorithm, multi agent genetic algorithm (MAGA), to solve global optimization problems (Zhong, *et al*., 2004). This algorithm inspired by multi-agent system overcomes the limitation of computation time to some extent, so we try to use MAGA to provide solutions for multi-objective spatial optimization allocation of land use in MOSO model. However, it is worth while to note that there exist many different types of agent in the course of multi-objective spatial optimization allocation of land use, such as resident agents, peasant agents, compared with the fact that all agents in MAGA are the same type. Moreover, the structure of agent in MAGA is too simple to describe complex rule and behavior of agents participating in spatial optimization allocation of land use, and the value of agents' energy can not be simply measured with the negative value of the objective function because of the characteristic of multi-objective in the course of spatial optimization allocation of land use. Consequently, the MAGA must be modified in order to make MAGA with the ability to solve problems of multi-objective spatial optimization allocation. In this study, the modified MAGA is named M-MAGA. In M-MAGA, all agents exist in a cell-like environment, L, which is called an agent cell. The size of L is $L_{size} * L_{size}$, where L_{size} is an integer. Within the cell environment, each individual is considered as an agent with energies, adaptabilities and behaviors, and different types of agents have different behaviors. Energy level of agents can be represented by fitness value that is obtained by fitness function transformed from the objective functions. In M-MAGA, an agent is considered as an entity that can essentially sense and react on the environmentÿand the structure of agent exerts a great influence on fitness function. According to characteristics of agent in the course of land use spatial decision, the structure of agent can be defined as follow:

Agent =<type, decision variable, decision parameter, fitness> (8)

As can be seen, structure of agent in M-MAGA includes four properties. Type refers to all kind of agents taking part in the spatial allocation of land use, such as residents and enterprisers, etc; decision variable and parameter represent the selected decision factors by agents and their weights respectively; fitness refers to the adaptability, which is determined by agent's competitiveness. Different types of agents have different decision variables and decision parameters.

In MOSO model, agents compete and cooperate with others, achieving the evolution of each generation through crossover, mutation, death and self-learning operation. Four evolutionary operators, including neighborhood competition operator, neighborhood crossover operator, mutation operator and self-learning operator, are designed to simulate agents' evolutionary behaviors. In these operators, energy of agents changes with the evolutionary behavior of agents. In order to make computation more convenient, we use equation (9) to represent agents' main properties on which the evolutionary operators are performed. Type, decision variable and fitness are input to the operators in the terms of additional properties, not participating in actual computation, but the fitness value changes with the decision parameter.

$$L_{i,j} = (l_1, l_2, ..., l_n) \tag{9}$$

In formula (9), $L_{i,j}$ represents the agent located at cell (i, j); l_1, l_2,...l_n represent the decision parameters of corresponding decision variables chosen by agents respectively; n is the number of decision variables.

Different to MAGA, neighborhood competition behaviors include internal competition and external competition in M-MAGA. Internal competition behaviors occurred on agents with the same type, and external competition behaviors occurred on agents with different types. Suppose that neighborhood competition operator is performed on the agent $L_{i,j} = (l_1, l_2, ..., l_n)$, $Max_{i,j} = (m_1, m_2, ..., m_n)$ is the agent with maximum energy among the neighbors of $L_{i,j}$. If Energy ($L_{i,j}$)>Energy ($Max_{i,j}$), can can still live in the agent lattice; it dies otherwise, and the cell-point will be occupied by $Max_{i,j}$. If agent type of $Max_{i,j}$ is the same as $L_{i,j}$, $Max_{i,j}$ will generate a new agent agent $New_{i,j} = (e_1, e_2, ..., e_n)$, then $New_{i,j}$ is put on the cell-point, as can be seen in formula (10). If agent type of $Max_{i,j}$ is not the same as $L_{i,j}$, $Max_{i,j}$ is first mapped onto [0,1] according to formula (11), then $New_{i,j}' = (e_1', e_2', ..., e_n')$ is determined by formula (12), finally $New_{i,j}$ is obtained by mapping $New_{i,j}'$ back to $[\bar{x}_k, \underline{x}_k]$ according to formula (13).

$$e_k = \begin{cases} \bar{x}_k & (m_k + U(-1,1) \times (m_k - l_k)) < \underline{x}_k \\ \underline{x}_k & (m_k + U(-1,1) \times (m_k - l_k)) > \bar{x}_k, \\ m_k + U(-1,1) \times (m_k - l_k) & others \end{cases}$$

$$k = 1, \ldots n \quad (10)$$

In formula (10), $U(-1,1)$ is random number on (-1,1), $[\bar{x}_k, \underline{x}_k]$ is the search space.

$$\mathrm{m_k}' = (m_k - \underline{x}_k)/(\bar{x}_k - \underline{x}_k), k = 1, \ldots n \quad (11)$$

$$New_{i,j}' = (m_1', \ldots, m_{i_1}' - 1,\ m_{i_2}', m_{i_2}' - 1, \ldots, m_{i_1}' + 1, m_{i_1}', m_{i_2}' + 1, \ldots, m_n'), 1 < i_1 < n, 1 < i_2 < n, i_1 < i_2 \quad (12)$$

$$e_k = \underline{x}_k + e_k' \cdot (\bar{x}_k - \underline{x}_k), k = 1, \ldots, n \quad (13)$$

Neighborhood crossover operator is used to simulate the cooperation behavior of agents. Compared with neighborhood crossover operator in MAGA, the neighborhood crossover operator in M-MAGA takes advantage of elitist strategy in order to make population evolve to the best solutions more quickly and reduce the unnecessary random degradation. Although this strategy will cause the reduction of population diversity to some extent, it can be compensated by mutation operator. In the neighborhood of $L_{i,j}$, if agent type of $Max_{i,j}$ is the same as $L_{i,j}$, this operator is performed on $L_{i,j}$, and $Max_{i,j}$ to achieve the purpose of cooperation. In this process, neighborhood crossover operator generates two new agents, one of which with larger fitness survives. This kind of process takes place for m (m <5) times. Finally, the agent *Max* with maximum energy is selected to replace$L_{i,j}$, if Energy(*Max*) > Energy($L_{i,j}$,); no replacement otherwise.

As a result of some sudden factors, the decision parameters of agent in the course of land use spatial optimization decision may mutate. Therefore, we use mutation operator to express this situation. Different to MAGA, the interchange mutation operator is taken to describe agents' mutation behaviors in order to improve efficiency of algorithm in M-MAGA. In interchange mutation operator, after randomly choosing two positions in agent $L_{i,j}$, new agent $L_{i,j}' = (b_1, b_2, \ldots, b_n)$ is generated from agent $L_{i,j} = (l_1, l_2, \ldots, l_n)$ through interchanging corresponding parameters in these two positions. The concrete operation is described as follow:

$$b_k = \begin{cases} l_k, U(0,1) \geq P_m \\ (\ldots, l_q, l_{p+1}, \ldots, l_{q-1}, l_p \ldots), U(0,1) < P_m \end{cases} \quad (14)$$

Where $k = 1, \ldots, n$, $U(0,1)$ is random number on (0,1), P_m is mutation probability.The self-learning operator can be considered as a small scale M-MAGA, being performed on the best agent in each generation to simulate the behavior of self-learning to improve its own energy. The operator in M-MAGA is the same as MAGA, and for more details, see Leung and Wang, *et al*., (2001). In M-MAGA, all agents of the population are ranked with the priority method according to their fitness to each objective function, and then getting the total fitness. $Z(i)(i = 1,2,\ldots,n)$ represents the objective function and n is the number of objectives. For each objective, agent X_j ($j = 1,2,\ldots,N$) will form a collating sequence Y according to the magnitude of the objective function values of $Z_i(X_j)$. For objective i, fitness of agent X_j is calculated according to,

$$F_i(X_j) = \begin{cases} (N - Y_i(X_j))^2 & Y_i(X_j) > 1; \\ kN^2 & Y_i(X_j) = 1; \end{cases}$$

$$i = 1,2,\ldots,n; j = 1,2,\ldots,N \quad (15)$$

In the formula, *N* is the total number of agents; X_j is the j^th agent in the population; Y_i refers to X_j's serial number in the collating sequence *Y(* X_j *);* represents's fitness for objective *i*. Total fitness of agent X_j *(j=1, 2, …,N)* will be obtained according to,

$$Fit(X_j) = \sum_{i=1}^{n} F_i(X_j) \quad (16)$$

Where *n* is the total number of the objective functions; $Fit(X_j)$ is X_j's total fitness for all objectives. It's self-evident that those agents with higher total fitness value can obtain lager fitness, which makes agents enjoy more opportunities of evolution.

In order to keep the diversity of the population and avoid genetic drift, the niche technology based on sharing mechanism is introduced to decrease the replication of similar individuals. The radius of ecological niche (σ_{share}) can be determined by formula (17).

$$\mathrm{N}\sigma_{share}^{n-1} - \frac{\prod_{i=1}^{n}(F_i(X_j) + \sigma_{share}) - \prod_{i=1}^{n} F_i(X_j)}{\sigma_{share}} = 0 \quad (17)$$

In formula (17), *n* is the total number of the objective functions; *N* is the total number of agents.

After sharing with other agents, $Fit(X_j)$, total fitness of agent X_j, is obtained by formula (18).

$$Fits(X_j) = \frac{Fit(X_j)}{\sum_{k=1}^{N} s(X_j, X_k)} \tag{18}$$

In formula (18), $Fits(X_j)$ is total fitness of X_j to all objectives after its sharing, $s(X_j, X_k)$ is agents' sharing coefficient which can be calculated through formula (19), where X_k stands for the k[th] agent and N total number of agents

$$s(X_j, X_k) = \begin{cases} 1 - \dfrac{d}{\sigma_{share}}, & d \le \sigma_{share} \\ 0, & d > \sigma_{share} \end{cases} \tag{19}$$

In formula (19), the denotation of σ_{share} is the same as that in formula (17) and d is shared searching radius which can be calculated through formula (20).

$$d = \sqrt{\sum_{i=1}^{n} (F_i(X_j)) - F_i(X_k))^2} \tag{20}$$

In the formula, n is total number of objective function and denotation of $F_i(X_j)$ and $F_i(X_k)$ is the same as that in (15).

During the course of spatial optimization allocation of land use, agent cell's suitability to expected land use objective of agent located at this cell has certain effect on the agent's total fitness. Taken such effect into consideration, an agent's total fitness is determined by,

$$Fits(X_j)^* = k \cdot Fits(X_j) \cdot P(X_j) \tag{21}$$

In the formula (21), *k* is a constant on [1, 2], $P(X_j)$ representing agent X_j's decision satisfaction to suitability of the cell can be calculated by formula (22).

$$P(X_j) = \sum_{k=1}^{l} w_k f_k \tag{22}$$

In the formula (22), l represents number of decision variables; w_k represents decision weight; f_k represents decision parameter of corresponding decision variable.

RESULTS & DISCUSSION

Changsha, Zhuzhou, Xiangttan city cluster is located at Hunan province in central China, which is a national comprehensive reform test area to build the resource-saving and environment-friendliness society (henceforth two-oriented-society). According to the requirement of two-oriented-society, land use in the test area should meet the dual objectives of saving land resource and pursuing a friendly environment, therefore, a fast spatial optimization allocation mechanism of land use are needed. Based on the above objectives, therefore, we select the core part of the city cluster--Changsha city to do empirical research on multi-objective spatial optimization allocation of land use using MOSO model.

The data for the application includes remote sensing data, GIS data, social and economical statistics, environmental statistics, etc. Remote sensing data include TM data of the year 2005; GIS data include land use map in 2005, general land use planning of Changsha city (1997-2010), general urban planning of Changsha city (2003-2020), transportation map, and public facilities map, land price map, as well as digital elevation model. Social-economical statistics are mainly consisted of Changsha population statistics as well as income statistics of urban residents from 1993 to 2005. Environmental statistics include public reports on environment quality and environment quality statistical yearbook of Changsha from 2000 to 2005.

Current land use in the study area was generalized into such main five types as residential land, commercial land, industrial land, undeveloped land, as well as restricted land (including hill, water, greenland areas), and the size of land use cell is defined as 30m×30m. 3×3 neighborhood structure is used for the model, and parameter b- minimum required number of neighbor cells that are developed after allocation-as 3. According to presupposition, every land use cell in this model only can be assigned an agent. Based on the ratio of population to land area from 1993 to 2005, demand of residential land, commercial land as well as industrial land in 2010 were obtained with GM(1,1) model, which are separately 69.42045.85030.39 km^2. And based on this, the number of resident agents, industrial agents as well as commercial agents can be determined in 2010. One thing to add is that an agent here represents the average population or number of enterprises accommodated in a 30m×30m cell. After that, these agents were stochastically allocated to corresponding land use cell in 2005 according to their types. What are generated in this step are the model's parent generation individuals, namely, initial solution of the model. In this study, three types of agents were defined which are separately resident agents, commercial enterprise agents as well as industrial enterprise agents. Meanwhile, to demonstrate the internal heterogeneity and diversity of agents of the same type in the course of decision-making, we categorized resident agents into three subgroups, the low-income class (income < 12,000 RMB/year), the middle-income class (12,000 RMB/year < income < 50,000 RMB/year), and the high-income class (income > 50,000 RMB/year), industrial enterprises into two subgroups, the environment pollution class and pro-environmental class according to pro-environment level and commercial enterprise into two subgroups, the department stores class and retail outlets class according to their size. Decision variables and decision parameters vary with agent type. In this study, resident agents' main decision behavior is selection of appropriate location for residence, and that of enterprise is selection of appropriate location for its expansion. Slope, land price, environmental value, transportation accessibility, planning completeness level as well as industrial agglomeration level are provided for agents to choose as decision variables. The choices of various agents are demonstrated in Table 1 with decision parameters obtained through AHP method. With reference to Table 1 and formula (22), $P(X_j)$ can be determined. The calculation of fitness follows the approach described in formula (21). During the course of these calculation, function value of objective (1) was obtained by calculating the distance from agent cell to its nearest developed land use cell, function value of objective (2) according to development cost of land use conversion, the standard of which was demonstrated in Table 2, and function value of objective (3) from sum of environmental compatibility between agent cells within the 3×3 neighborhood area. Environmental compatibility between various land use types was represented in Table 3. The flow of performing evolutionary operators is represented as Fig.1.

Table 1. Agents' decision variable and decision parameters

Agents' Decision variable	Agents' decision parameters						
	Resident Agents			Industrial enterprise Agents		Commercial enterprise Agents	
	High-income	Middle-income	Low-income	pro-environmental	environment pollution	Department store	Retail outlet
S	0.113	0.082	0.051	0.124	0.112	0.112	0.135
L	0.149	0.209	0.343	0.225	0.251	0.201	0.261
E	0.315	0.243	0.114	—	—	0.087	0.054
P	0.180	0.194	0.157	0.129	0.154	0.133	0.096
T	0.243	0.272	0.335	0.286	0.270	0.244	0.299
I	—	—	—	0.236	0.213	0.223	0.155

Notations: S, Slope; L, land price; E, environmental value; T, transportation accessibility; P, planning completeness level; I, industrial agglomeration level.

Table 2. Standard of land development cost of land use conversion (unit: 10,000 RMB per cell)

	Industrial land	Residential land	Commercial land
Industrial land	—	0.20	0.20
Residential land	0.90	—	0.90
Commercial land	0.45	0.45	—
Undeveloped land	1.80	1.80	1. 80

Table 3. Environmental compatibility between adjacent land use types

	Undeveloped land	Restricted land	Residential land	Commercial land	Industrial land
Undeveloped land	1.0	1.0	1.0	1.0	1.0
Restricted land	1.0	1.0	1.0	0.5	0.0
Residential land	1.0	1.0	1.0	0.7	0.0
Commercial land	1.0	0.5	0.7	1.0	0.2
Industrial land	1.0	0.0	0.0	0.2	1.0

Note: environmental compatibility ranges from 0.0 to 1.0; 0.0 means incompatibility and compatibility increases with the value.

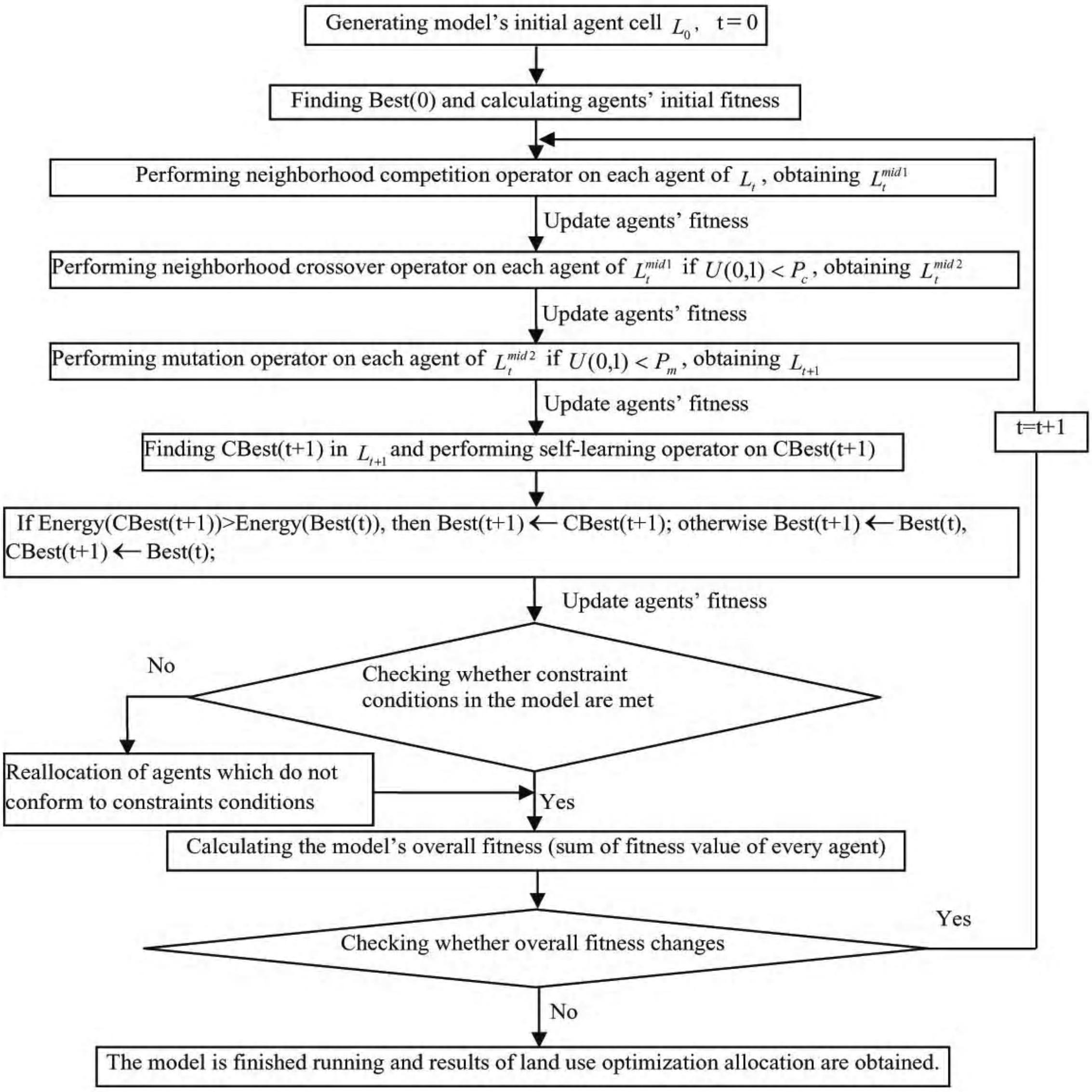

Fig. 1. Flow chart of performing evolutionary operators

Note: In the Figure, L_t represents the agent cell in the tth generation, and L_t^{mid1} and L_t^{mid2} are the mid-cells between L_t and L_{t+1}. Best(t) is the best agent among L_0, L_1, …,L_t , and CBest(t) is the best agent in L_t. and P_m are the probabilities to perform the neighborhood crossover operator and the mutation operator.

Fig.2 represents the simulation results of land use optimization allocation during the different runtime of the model, in which T=0 stands for the model' initial state and T=400 stands for the 400th iteration. The ultimate spatial optimization allocation results in 2010 is shown in Fig 3(b). Compared with spatial pattern of land use in 2005 before optimization (Fig 3(a)), it's obvious that spatial pattern of land use after optimization is denser and more compact, and a notable decrease of vacant land inside land patches and spot land use patches in suburb area can be observed. In addition, it is also observed that space agglomeration level of the same land use type is higher, and that main expansion pattern of newly-increased urban land is internal filling with avoidance of overexpansion of urban land.

Model validation is usually required when optimization models are applied to the simulation of land use optimization allocation. In this study, the proposed model was assessed in two ways: (1) comparing the optimized patterns with land use patterns before optimization; (2) comparing the simulated optimized patterns between MOSO model and the standard GA.

In combination with objective functions of the model, the quantitative assessment was carried out

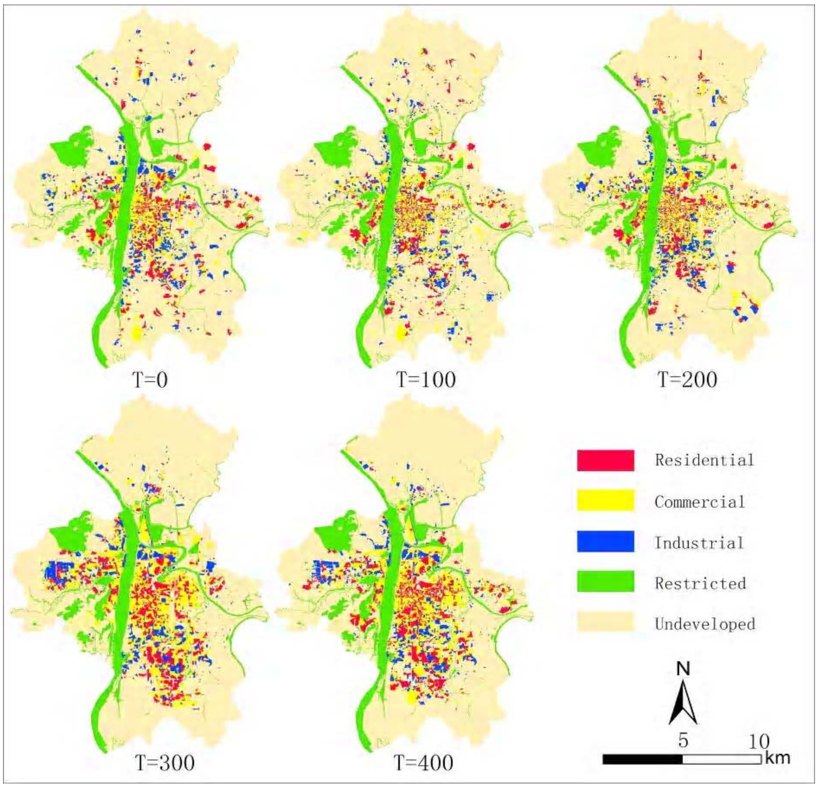

Fig. 2. Simulation of land use optimization allocation in Changsha in 2005–2010

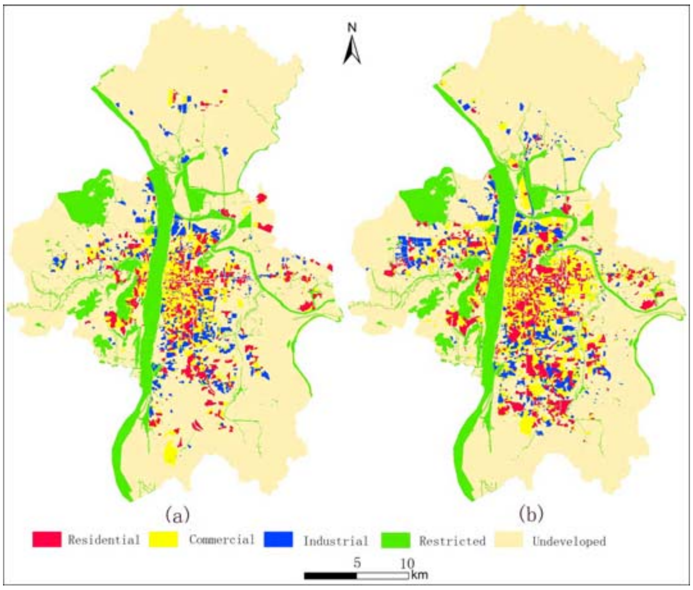

Fig. 3. Comparison of spatial patterns of land use before and after spatial optimization. (a) spatial patterns before spatial optimization; (b) spatial patterns after spatial optimization.

by using some landscape metrics, which are mainly used to measure overall compactness of a certain land use patch, namely, land resource saving degree. These landscape metrics include Mean Patch Fractal Dimension (MPFD), Mean Euclidean Nearest-Neighbor Distance (MNN), and Aggregation Index (AI) (McGarigal, *et al*., 2002). They are obtained by using a landscape analysis software, FRAGSTATS 3.3

(McGarigal, *et al*., 2002). In addition, environmental compatibility index (EC) is employed to assess environmental friendliness level of land use patch. EC is illustrated in the following formula in which e_i stands for patch i 's environmental compatibility with its land use cells within neighbor area and n stands for number of patches.

$$EC = \frac{\sum_{i=1}^{n} e_i}{n} \tag{23}$$

Table 4 shows the assessment of spatial patterns of resident land, industrial land as well as commercial land before and after optimization. It is observed from the table that values of MPFD, MNN of each land use type is lower after optimization while those of AI and EI are higher, which proves that spatial patterns of land use has notably improved in patch adjacency, connectivity, aggregation, compactness as well as environmental compatibility after optimization and subsequently verifies that overall resource-saving and environment-friendliness level of optimized allocation results is higher than that of before optimization. To further validate the model's feasibility, the performances of MOSO model were compared with those from the standard GA on the basis of the same objective functions (Fig.4 and Fig.5). It is observed from Fig.4 that spatial patterns of land use generated through MOSO model is more regular and compact than that generated through standard GA. Meanwhile it is observed from Fig.5 that, for the same study area, that total fitness values obtained through the standard GA and MOSO model are separately 14.88 and 16.75, which reflects an increase of 12.57% in total fitness values of MOSO model than the standard GA model.

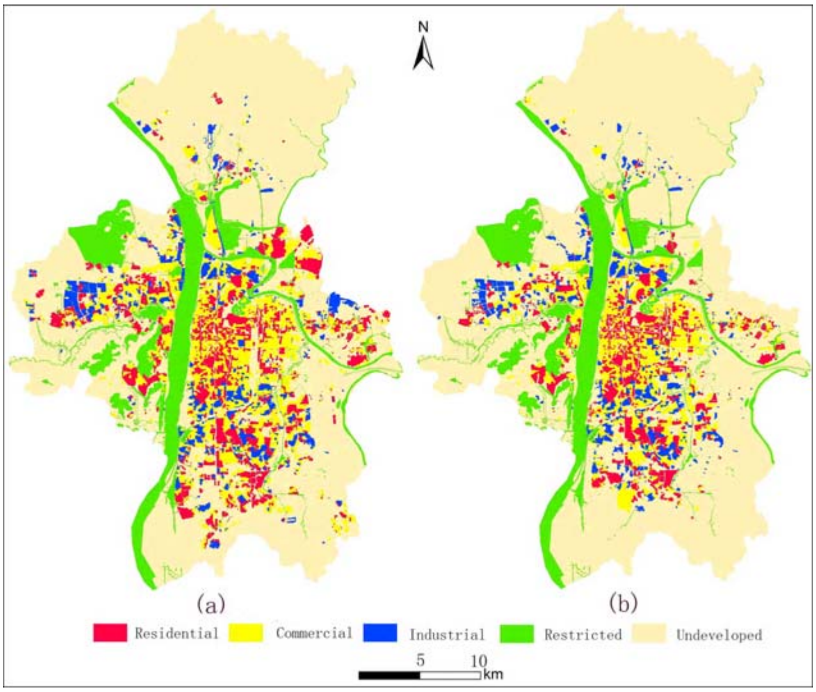

Fig. 4. Comparison of optimized allocation results. (a) using the standard GA model; (b) using MOSO model

Table 4. Assessment of spatial patterns before and after optimization

		MPFD	MNN	AI	EI
A (before optimization)	Resident land	1.127	145.321	65.876	0.642
	Industrial land	1.438	169.245	38.214	0.677.
	Commercial land	1.267	149.687	57.929	0.708
B (after optimization)	Resident land	1.006	132.514	70.381	0.771
	Industrial land	1.349	155.455	45.112	0.734
	Commercial land	1.105	138.663	68.475	0.769

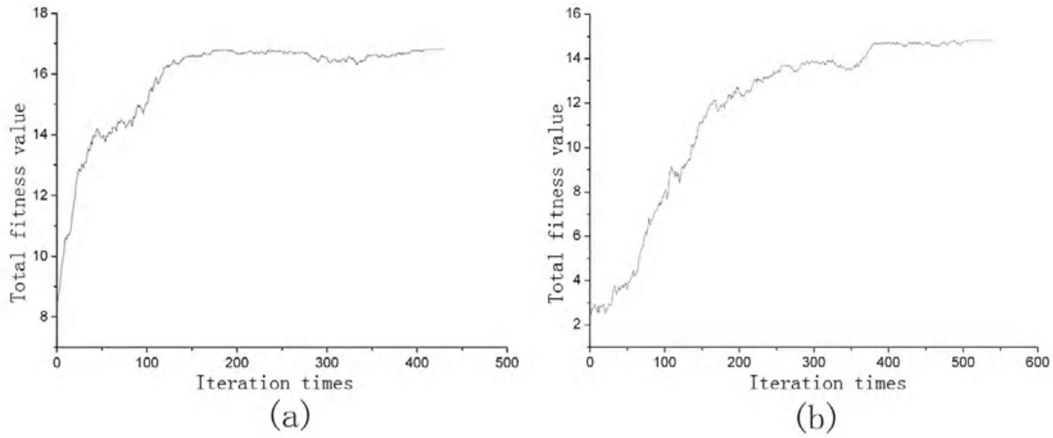

Fig. 5. Comparison of convergence curves. (a) convergence curve of MOSO model; (b) convergence curve of the standard GA.

Table 5. Assessment of optimized spatial patterns produced from the standard GA model using landscape metrics

	MPFD	MNN	AI	EI
Resident land	1.008	140.976	66.803	0.689
Industrial land	1.412	158.74	40.257	0.694
Commercial land	1.208	141.53	60.445	0.723

In addition, assessment of optimized spatial patterns of land use produced from the standard GA model using landscape metrics is shown in Table 5. By comparing Table 5 with Table 4(b), it is obvious that MPFD, MNN of each land use type in Table 5 are higher than those in Table 4(b), which proves that optimized allocation results obtained from MOSO model is more superior than that from the standard GA model in overall resource-saving and environmental-friendliness level. This is because the behavior of various players in the actual world can be well addressed based on agent-based approach. In additionÿiteration time of MOSO model and standard GA model are separately 3.31 hours and 8.57 hours, which reflects an improvement of 61.38% in running efficiency of MOSO model than the standard GA model and proves a faster convergence rate of MOSO model than that of standard GA model. All the observations above together indicated MOSO model is a promising method for generating land use alternatives for further consideration in spatial decision-making.

CONCLUSION

The technique of spatial optimization allocation of land use is important for government and land use planners to formulate sustainable land development strategies. The complexity, and indeed the multi-objective, of land use spatial optimization allocation problems has been widely recognized (Balling, *et al*., 1999; Stewart, *et al*., 2004; Holzkamper and Seppelt, 2007; Janssen, *et al*., 2008). In this study, under the constraints of general objective of resource-saving and environment-friendliness, based on multi-agent genetic algorithm, MOSO model of land use allocation was developed from the view of simulating the biological autonomous adaptability to environment and their competitive and cooperative relation. In the model, corresponding sub-objectives and constraints according to resource-saving and environment-friendliness objectives were set; structure and evolutionary operators of agents were designed based on multi-agent genetic algorithm; and the niche technology based on sharing mechanism was introduced to calculate fitness of agents. Changsha city was selected for testing this proposed model. The proposed model includes three types of agents-resident agents, industrial enterprise agents, commercial enterprise agents. Different types of agents can compete and cooperate with each other in the course of spatial optimized allocation of land use and different types of agents have different decision variables. The experiment has indicated that optimized spatial patterns of land use can be simulated based on MOSO model. By comparing landscape metrics of spatial patterns of land use before and after optimization, the validation was carried out. The analysis has indicated that the model can produce satisfactory optimized results and the overall resource-saving and environment-friendliness level of land use allocation results were improved after optimization.

This model also performed better than the standard GA models in simulating spatial optimization allocation of land use in the study area. This is because the behavior of various players in actual world can be well addressed by the agent-based approach. Extensive conversions and quick changes in urban land use took place in Chinese cities. Consequently, it is urgent to form sustainable land use pattern using techniques of spatial optimization allocation. Spatial optimization allocation of land use is an intricate process of multi-objective decision behavior. Although the objective of resource-saving and environmental friendliness has been taken into consideration in this study, more and more complex objectives such as policy and resource constraints are possible ones in need of consideration in the course of spatial optimization allocation. Therefore, in the actual application of the model, objective systems should vary with real situations according the principle of adaptation to local conditions. In addition, uncertainties from models such as scales and neighborhood structures will also affect the application of these agent-based models, which will be explored in further studies.

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