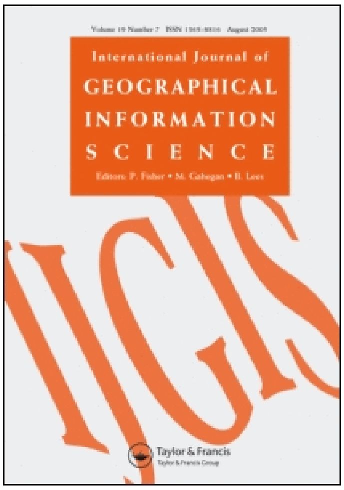

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An agent-based model for optimal land allocation (AgentLA) with a contiguity constraint

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Spatial optimization is complex because it usually involves numerous spatial factors and constraints. The optimization becomes more challenging if a large set of spatial data with fine resolutions are used. This article presents an agent-based model for optimal land allocation (AgentLA) by maximizing the total amount of land-use suitability and the compactness of patterns. The essence of the optimization is based on the collective efforts of agents for formulating the optimal patterns. A local and global search strategy is proposed to inform the agents to select the sites properly. Three sets of hypothetical data were first used to verify the optimization effects. AgentLA was then applied to the solution of the actual land allocation optimization problems in Panyu city in the Pearl River Delta. The study has demonstrated that the proposed method has better performance than the simulated annealing method for solving complex spatial optimization problems. Experiments also indicate that the proposed model can produce patterns that are very close to the global optimums.

Keywords: agents; land allocation; spatial optimization; contiguity

1. Introduction

Massive conversion of agricultural land use into urban land use in rapid growing countries has caused a series of environmental problems, such as soil erosion, floods, and deprivation of future land supply (Li and Liu 2008). There is an urgent need for the development of planning tools for alleviating land-use conflicts in these regions under multiobjectives. Land-use planning is a process of allocating different activities to specific units within a region. Land allocation relates to not only what to do but also where to do it (Stewart *et al.* 2004). It is regarded as a complex planning problem because of involving both site attributes (e.g., suitability, cost, and environmental impacts) and aggregation attributes (e.g., shape, contiguity, and so on) (Cova and Church 2000). The complexities and difficulties of searching for a solution will enormously increase if a region is very large and a fine resolution of data is used (Stewart *et al.* 2004). In most situations, space is modeled under a raster framework, on which the suitability of the given land use is mapped. Suitability maps serve as a crucial aid for solving land-use planning problems. However, when the objective is to locate a region rather than individual cells, it is insufficient with mere suitability maps for the optimization (Brookes 1997). A fragmented pattern will be produced without incorporating other constraints in the optimization (Yeh and Li 1998). Thus, extra heuristics

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for searching feasible alternatives are required for satisfying shape constraints such as compactness.

Techniques that deal with this sort of problems are used to adopt a centralized approach (Matheya *et al.* 2008). For example, Yeh and Li (1998) proposed a sustainable land development model using geographic information system (GIS) to balance present land consumption and the stock of land for future urban growth. However, these approaches cannot handle too much spatial complexity (Matheya *et al.* 2008). Efforts have been made to solve these difficult planning problems. For instance, Eastman *et al.* (1995) described a method to allocate land use in a raster environment involving conflicting objectives. The limitation of this method is the lack of compactness constraint. Inspired by the region growing techniques in image processing (Sonka *et al.* 1993), Brookes (1997) proposed a site allocation method, which was further developed by incorporating a genetic algorithm (Brookes 2001). However, this method mainly optimizes a patch rather than a pattern. Xiao *et al.* (2002) also used the evolutionary algorithm to tackle patch optimization problems. In this method, each solution (a site) has a fixed size, for example, 10 cells, and then the shape and location 'mutates' over the time dimension, subject to several constraints. Stewart *et al.* (2004) employed the genetic algorithms to optimize land-use planning alternatives, but the experiments were only implemented in 20×20 and 40×40 grids. Ligmann-Zielinska *et al.* (2005) developed the sustainable multiobjective land-use allocation (SMOLA) model and further enhanced it with hop-skip-jump (HSJ) method (Brill *et al.* 1982). Santé-Riveira *et al.* (2008) extended the simulated annealing (SA) as a land allocation optimization method that was implemented in a large area. This method requires very intensive computation, although it can produce better optimization results than other conventional methods.

Multiagent systems (MASs), as well as cellular automata (CA), belong to the range of simulation approaches. They have been applied to spatial process modeling, urban process modeling in particular (Torrens and Benenson 2005), such as urban growth (Clarke and Gaydos 1998), land-use changes (White *et al.* 1997, Li and Yeh 2002), fractal urban forms (White and Engelen 1993, 1994), and urban settlement patterns (Bura *et al.* 1996, Sanders *et al.* 1997). Compared to CA, MAS has the advantages of directly modeling the behaviors and interactions among individual decision-makers (Parunak *et al.* 2006). Benenson (1998) proposed an MAS model to simulate urban residential dynamics. An entity-based approach was used to study residential segregation of Yaffo, Tel Aviv (Benenson *et al.* 2002). As stated by Li and Liu (2007), CA models have difficulty in reflecting complex interactions between individuals and the environment; therefore, they proposed a model integrating CA and MAS to simulate the residential development of Guangzhou, China. Besides the simulation of residential dynamics, MAS is also preferable for the simulation of land-use changes. For example, Manson (2005, 2006) employed MAS to explore the land-use changes in Southern Yucatan, Mexico. Xie *et al.* (2007) developed an agent-based model to simulate 'Deskota' in China. There are other applications for land use/cover change (LUCC) simulation using MAS (Parker *et al.* 2003).

There are few reports on the use of MAS for optimizing land allocation. Ward *et al.* (2003) integrated an optimization model into CA to simulate and evaluate two converse planning scenarios. The role CA plays in their study is to spatially realize the optimization amount of new development derived from the optimization model. Similarly, Li and Liu (2008) use sustainable development strategies to determine the respective quantity of land for growth in each period, leaving the job of spatial allocation to an integration model of CA and MAS. These two applications emphasize more on optimizing the amount of given land use by projecting from other factors, such as population, and constraints of shape are also absent.

Actually, optimal land allocation with a contiguity constraint is not a new problem. Aerts *et al.* (2003) have tried to use linear programming (LP) to solve the joint cost-compactness optimization of land allocation. As one typical deterministic optimization technique, LP can ensure the optimal solution, but the computation time is far beyond acceptable when it is applied to real data. Thus, the resolution of spatial data has to be restrictively coarse. As reported by Aerts *et al.* (2003) in their research, the method is not feasible to be implemented in an area that is larger than 30 × 30 cells. However, real applications usually involve the use of spatial data much larger than 30 × 30 cells, and coarsening the data will inevitably lose the details of spatial information.

This study develops an agent-based optimization model for solving land allocation problems. A simple set of behavioral rules is proposed for the formulation of the optimal land allocation pattern that maximizes both land-use suitability and compactness. Although SMOLA is quite advanced on the subject of land allocation optimization, this model mainly optimizes land-use patterns by using the factors of compatibility and proximity but compactness is loosely involved (Ligmann-Zielinska *et al.* 2008). This proposed agent-based model (AgentLA) is to produce optimal land allocation patterns by including the compactness factor as one important objective. Moreover, the outcomes of many optimization models are not always the global optimums or close to the global optimums because of the complexities. The objective of this study was to generate patterns that are very close to the global optimums according to the collective efforts of agents. The proposed model is first validated by using two sets of artificial data (with pre-known optimal patterns). A further comparison to LP model is performed using a small subset of land-use suitability map. Finally, this model is used to generate land allocation alternatives of conservation area in Panyu, a rapid growing region in the Pearl River Delta, China.

2. The multiagent model for optimization

In conventional MAS models, agents are considered as movable individual entities like households (Benenson 1998), developers (Li and Liu 2007), or pedestrians (Dijkstra and Timmermans 2002). In this study, an agent is used to identify a single unit of the given land use to be allocated. Figure 1 depicts the methodologies of AgentLA. Initially, a population of agents are generated with random positions. The population size of agents is equal to the given amount of land use to be located. Each step of the simulation consists of two tasks: the decision for the allocation of each agent and the assessment of the simulated pattern. Each agent will use a fitness function to assess a potential site for relocation. An agent will move to a better location based on the assessment of the site. After all agents have made their decisions, the whole simulated pattern will be evaluated through an overall fitness function involving suitability and compactness factors. Such iterations will continue until the improvement of the fitness function gets stable.

Before a further specification of the model, the meanings of some important notions (Figure 2) are listed below for better understanding:

- A *cluster* is a group of spatially connected agents of the same type;
- An *isolated agent* refers to a cluster that is made up by only one agent;
- A *boundary agent* means that it has less than four neighboring agents of the same type in its von Neumann neighborhood; and
- *Nonboundary agents* represent the agents inside a cluster.

2.1. Definition of agents' behavior with multiobjectives

A fitness function is defined to measure whether a position is worth occupying by an agent. The objective is to maximize both land-use suitability and compactness of the pattern created

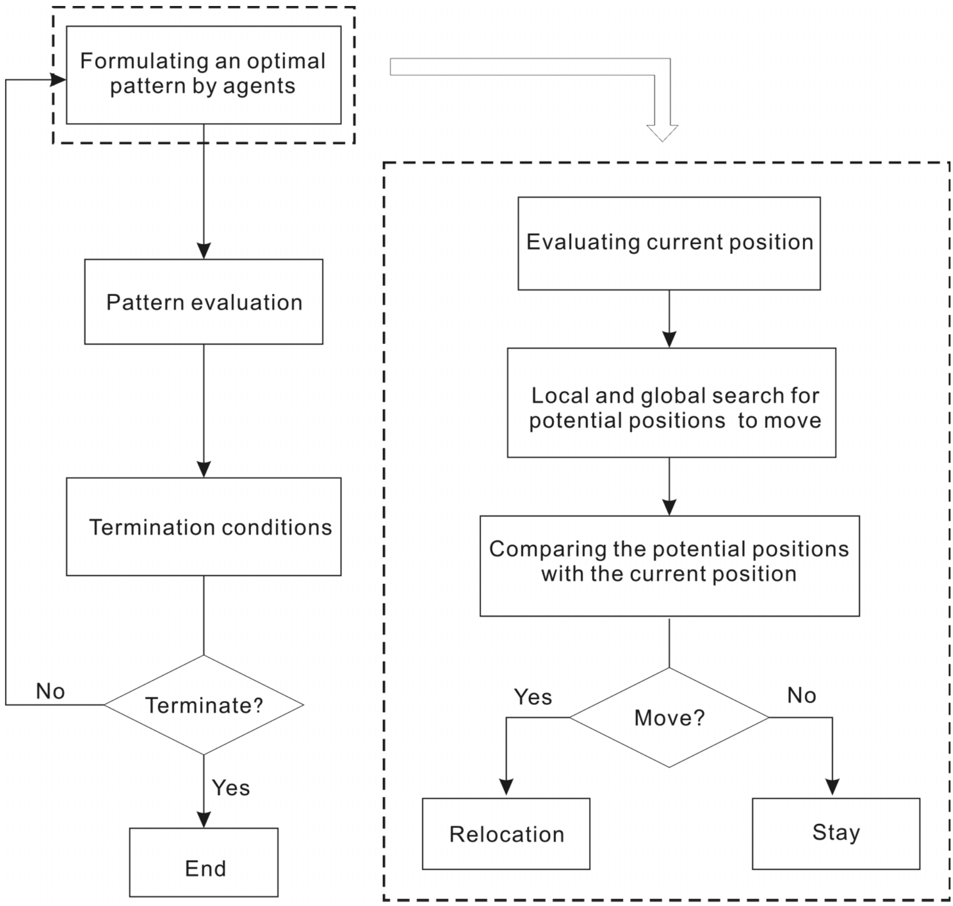


Figure 1. Optimization procedure of AgentLA.

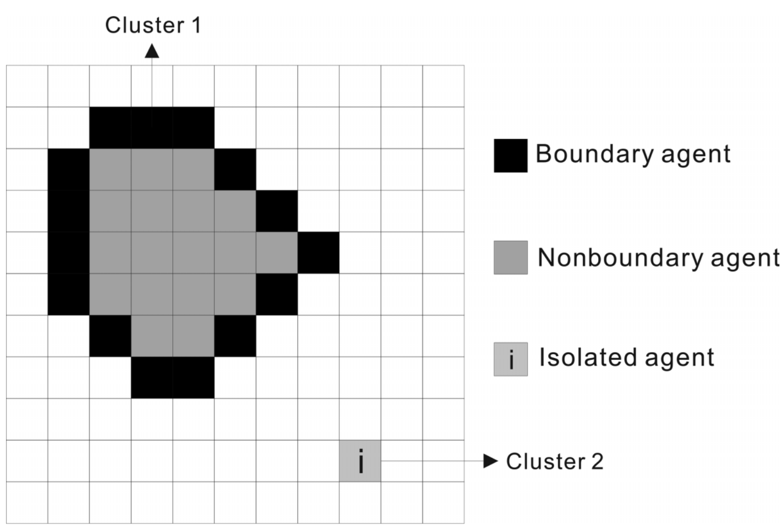


Figure 2. Cluster, boundary agent, nonboundary agent, and isolated agent.

by the simulation. This involves two spatial variables: the land-use suitability value and the spatial efficiency. The fitness function is thus formulated by using a linear combination of these two variables as follows:

$$f = w_v v + w_c c \tag{1}$$

where v is the land-use suitability value, c is the spatial efficiency, and w_v and w_c are their weights, respectively ($w_v + w_c = 1$).

This expression is quite straightforward and easy to implement for agent-based modeling. An agent takes into account both land-use suitability and spatial efficiency when evaluating a position for allocation. The former variable requires a suitability map that can be conveniently prepared by using GIS. The latter encourages agents to attach with each other and become a cluster. Specifically, this variable can be expressed through the following equation:

$$c = \frac{\sum_{i \in \Omega} x_i \exp(-d_i/-\gamma)}{\sum_{i \in \Omega} \exp(-d_i/-\gamma)} \tag{2}$$

where x_i is a binary variable which equals to 1 if cell i is occupied and to 0 otherwise. Ω represents the Moore neighborhood of the central agent. d_i is the Euclidean distance from cell i to focal agent. γ is a compensation parameter that ranges from 1 to 10. The specification of c is favorable to fasten the formation of agent cluster, and the modeling bias created by rectangular neighborhood can be eliminated as well, because of the introduction of the distance variable d_i.

The relationship among agents is cooperation instead of competition. In the optimization, agents help each other to assemble an optimized pattern rather than competing with each other for satisfying their individual objective. This mechanism is similar to those of swarm optimization, such as particle swarm optimization and ant colony optimization. For example, ant intelligence has been applied to the solution of a lot of spatial optimization problems (Li *et al.* 2009a, b). The cooperation between these agents is crucial for finding the optimal solution.

In this proposed model, each agent is used to identify one unit area for a specific land-use type. The objective is to allocate each agent to a place that is worth occupying. There are no conflicts such as several agents contesting for the same place. It is because there are enough locations for accommodating these agents. These agents just need to cover all positions that are meant to be occupied, but regardless of who occupies a place first.

The cooperation among agents is achieved according to a spatial search strategy. The search for a position is based on local information and global information. First, we define the neighborhood of an agent as its local searching range. Agents search and evaluate all vacant positions within their neighborhood to look for the best position. However, this strategy of using only local information may have some problems. If there is more than one peak in the entire region, agents are likely to get trapped in some locally high fitness positions after several iterations. As illustrated by Figure 3a and b, the area enclosed by the white line is of high suitability value, but not as high as the brightest area roughly bounded by the green line. Assuming agents are distributed randomly at the beginning (Figure 3a), only if they search for a better position according to local information, the pattern may finally evolve into the one shown in Figure 3b – one cluster in the highest suitability area, whereas the other gets stuck in the less bright area, although apparently there

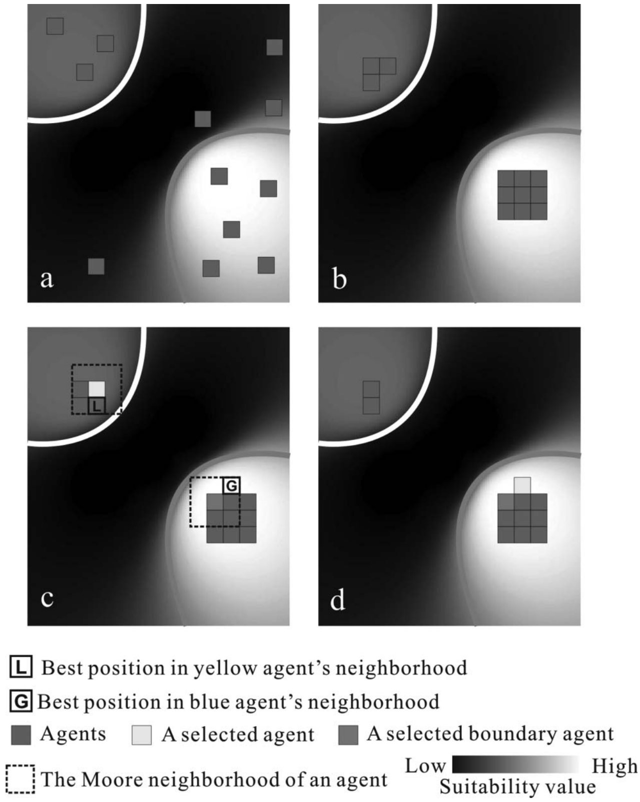


Figure 3. Formulation of agent clusters.

are plenty of better positions within, which is encircled by the green line. Therefore, a proper amount of global information is required. This is the so-called cooperation strategy.

Stated by Tobler's first law of geography, near things are more related than distant things (Tobler 1970). Empirically, the distribution of land-use suitability in most actual cases obeys this law. Inspired by this concept, an effective local and global search strategy is adopted to inform the agents to move properly: Randomly select a boundary agent from the population, and then identify the vacant position of the highest fitness value within this boundary agent's neighborhood. As an example, Figure 3 assumes that there are 12 agents, and their initial positions are randomly chosen. The brightest area in the southeast part of the region has the highest suitability value, enclosed by a green line. The area within the white line is darker but brighter than the narrow corridor diagonally across the region. The predicted optimal pattern should be a single cluster formed by all 12 agents and should be located in the brightest area. However, if agents only perform the local neighborhood search, the modeling outcome is likely to be two separated clusters that are far from the expected optimum (Figure 3b).

The local and global search strategy can help avoid the trapping to a local optimum. Suppose the selected agent (shown in yellow in Figure 3c) is in search of a better position for relocation. First, the agent looks for vacant position of the highest fitness value within its local Moore neighborhood, denoted as Pos_L (Figure 3c, the grid with a label 'L'). Then, another boundary agent is randomly chosen globally (the one in blue in Figure 3c). The best vacant position within the Moore neighborhood of this global boundary agent will be identified, denoted as Pos_G (Figure 3c, the grid with a label 'G'). Pos_L and Pos_G are compared, and the better one becomes the target position for potential relocation. If the target position has a higher fitness value than the current position, the migration probability P is computed by using the following equation:

$$P = \frac{\exp(\Delta)}{\exp(\Delta_{\max})} \tag{3}$$

where Δ represents the difference of fitness value between the target position and the current position and $\Delta_{\max} = 1$.

A random value r is generated as a pointer: if r is greater than P, then it will migrate to the target position (Figure 3d); otherwise, the agent will stay at its current position:

$$\begin{cases} r > P, & \text{move} \\ r \leq P, & \text{stay} \end{cases} \tag{4}$$

The outcomes of this model should be very sensitive to the specification of weights w_v and w_c. Theoretically, when w_v is set to 0, the simulation is only based on the criterion of spatial efficiency. As a result, the pattern is likely to evolve from initially dispersed distribution to eventually a compact one. Under this circumstance, agents' decisions are independent of the suitability value, and consequently the location of the resulted cluster is completely uncertain. On the contrary, when w_v is set to 1.0, it means that agents only take into account the suitability value. Then, the most suitable positions in terms of the suitability will ultimately be occupied by these agents. These positions are fixed once the suitability map is given. Therefore, no matter how many times the model is operated, the outcome will be the same. Thus, when the weight w_v moves from 0 to 1.0, the randomness of the outcome reduces and vice versa.

Another effect brought about by shifting the value of w_v is rather straightforward. Generally in real circumstance, it is hardly possible to draw a pattern that covers the most suitable area as well as maintaining the most compact shape at the same time. The spatial characteristics of the simulation outcomes may differ significantly according to various configurations of the weights w_v and w_c. When w_v is extremely low, the resulting pattern will show the greatest compactness regardless of the suitability value. Conversely, if w_v is set exceedingly high, the resulting pattern will be most scattered. Apparently, such an extreme scenario is not the best alternative. The optimized patterns cannot be obtained unless an appropriate configuration of weights that best compromises suitability value and spatial efficiency is determined.

2.2. *Evaluating the simulated pattern*

The final simulated pattern will be evaluated through an F function. Because there are two main objectives to achieve, that is, conserving the most suitable positions while keeping the spatial efficiency, this function is defined as follows:

$$F = \mathrm{SV} - \mathrm{SL} \tag{5}$$

$$\mathrm{SV} = \sum_{i=1}^{n} \frac{v_i}{V_{\mathrm{MaxSum}}} \tag{6}$$

$$\mathrm{SL} = \frac{L_{\mathrm{Sum}} - L_{\mathrm{MinSum}}}{L_{\mathrm{MaxSum}} - L_{\mathrm{MinSum}}} \tag{7}$$

where n is the size of population, V_{MaxSum} is the sum of the suitability value of the most suitable cells, and $\sum_{i=1}^{n} v_i$ is the total suitability value of the selected cells currently occupied by agents. SV is the ratio of $\sum_{i=1}^{n} v_i$ to V_{MaxSum}, measuring how well the objective of site attribute is achieved.

SL is used to measure the dispersion of the simulated pattern. It is common sense that once the area is known, the most compact form would be circular and its perimeter is shortest. The minimum sum of perimeter (L_{MinSum}) can then be calculated when the area of planning land use is known. On the contrary, if agents separate from each other, the maximum sum of perimeter L_{MaxSum} will be obtained. L_{Sum} represents the sum of perimeter of the current pattern. In short, the wellness of the resulted pattern increases when SV is higher and SL is smaller.

3. Model implementation and results

AgentLA is developed by using Java and RePast 3.0, an open source toolkit for agent-based modeling. (A free version of AgentLA for academic use can be downloaded at http://www.geosimulation.cn/AgentLA/.) This model is first tested by applying it to three sets of hypothetical data because they allow easy identification of the optimization effects. The results are shown and discussed in Section 3.1. Thereafter, the model is implemented in Panyu, one of the fastest developing regions in the Pearl River Delta, China, for creating the conservation area for natural vegetation protection.

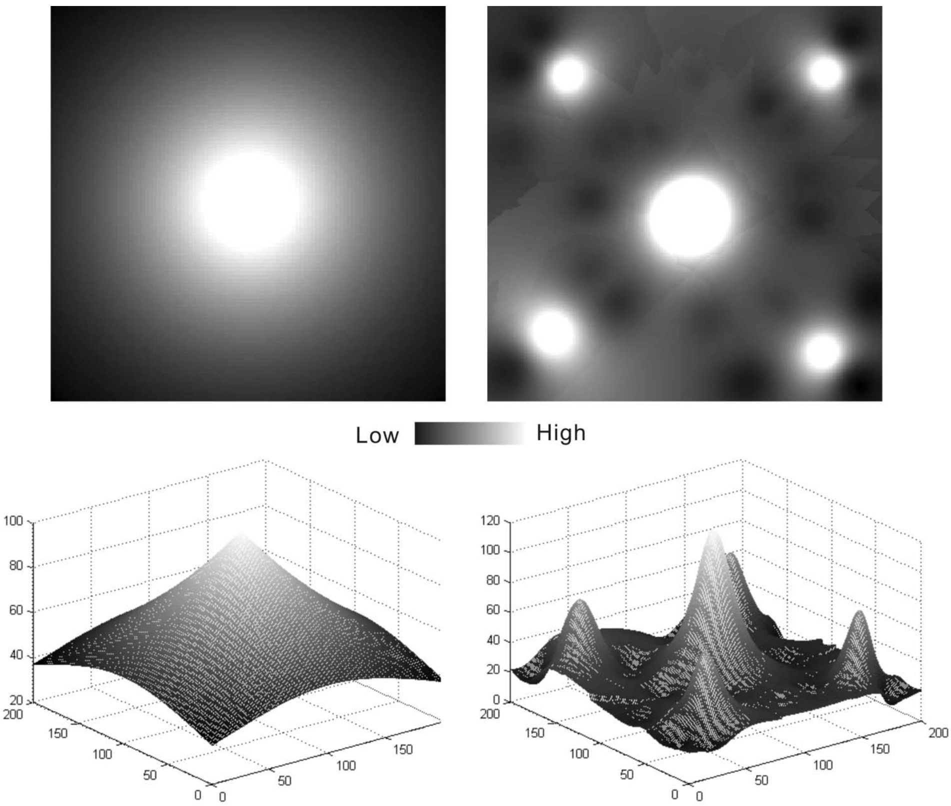
3.1. Identification of the effects for hypothetical data

The preliminary test of the proposed model is divided into two parts. First, the model is examined by using two hypothetical data, that is, suitability layers with monocentric and polycentric distributions, respectively. In these two experiments, the size of the agent population is set to 800 and the local search window is 7 × 7. The data size of suitability layers is 200 × 200 in a raster format (Figure 4). Test data-set 1 has a monocentric form in the suitability map. It has the highest suitability value in the central part, generated by an exponentially decline function (Figure 4a). The suitability map was created using the following function:

$$S_{\mathrm{t}} = 100 \times \mathrm{Exp}(-d_{\mathrm{c}}) \tag{8}$$

where S_{t} is the suitability value in test data-set 1 and d_{c} is the normalized distance to the center.

Test data-set 2 has a polycentric form in the suitability map that consists of a larger area of the highest suitability value in the center and four smaller ones of the highest suitability values near the corners (Figure 4b). The central part of the highest suitability is designed to have enough area for the land allocation so that the optimization effect can be easily identified. Therefore, the optimal pattern is expected to form just in the central part for



(a) Test data 1 (Monocentric) (b) Test data 2 (Polycentric)

Figure 4. Test data-sets for verifying AgentLA.

these two data-sets. The experiments will examine whether the proposed model can generate such a pattern after sufficient iterations of simulation.

Figure 5 shows the optimization results of test data-sets 1 and 2. It is found that agents rapidly assemble into a single cluster only after 50 iterations of simulation. Although the simulated pattern does not fit the central part perfectly as predicted, it becomes almost the same as the known optimal after several hundreds of iterations. Test data-set 2 is a little more complicated, of which the central part has the highest suitability value, whereas another four minor 'hills' exist near the corners. This distribution can help to examine whether the proposed model will stop at a local optimum. In this experiment, some agents did locate in the areas of less high suitability value in the early several iterations, but then the pattern evolves very quickly, and almost all agents congregate at the center after 15 iterations. Eventually, the pattern stabilizes after 50 iterations. F values of these two final outcomes are both very close to 1.0, indicating a significant approach to the optimal pattern (Table 1). These two data-sets seem quite simplified. The advantage is that the optimal patterns are known for convenient verification of the proposed model. To illustrate the spatial consistency, the simulation results are overlapped with the known optimal patterns; and roughly 96% of areas in both simulation results are shared with the optimal patterns.

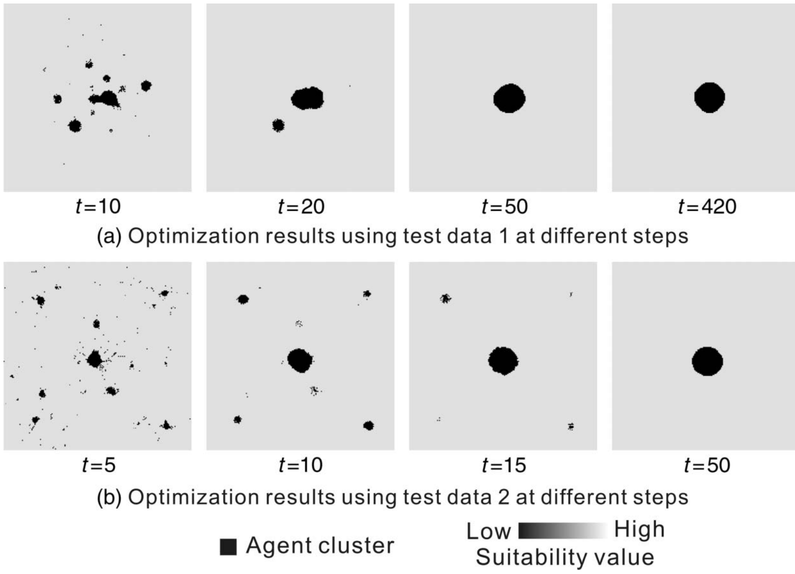


Figure 5. Optimization results using test data-sets 1 and 2.

Table 1. *F* value of the optimized patterns in Figure 5.

Test data-set 1		Test data-set 2	
$t = 10$	0.7346	$t = 5$	0.3194
$t = 20$	0.9243	$t = 10$	0.8114
$t = 50$	0.9823	$t = 15$	0.9187
$t = 420$	0.9891	$t = 50$	0.9889

The second experiment is to compare the optimization results between the proposed model and LP model developed by Aerts *et al.* (2003), using a small subset of real suitability map, namely 10×10 (Figure 6a).

As one typical deterministic optimization technique, LP can ensure the optimal solution, although it can only be used for a small data-set. Thus, the validity of the proposed model can

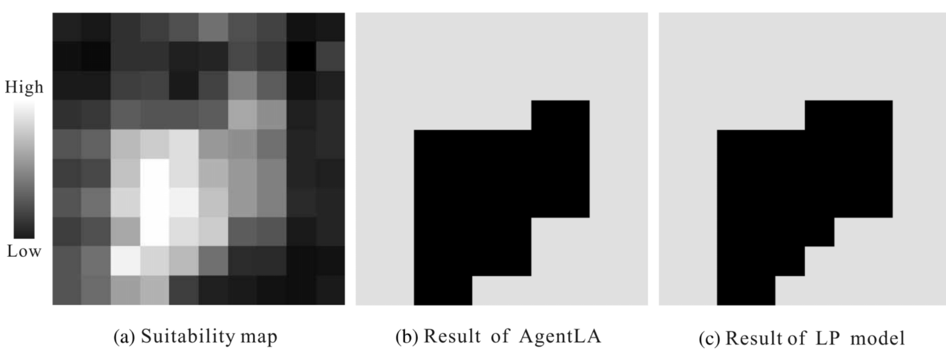


Figure 6. Comparison of optimization results between AgentLA and LP.

be further confirmed by comparing the optimization result to the one produced by LP model. The region is restricted to only 100 cells because LP model is not efficient and feasible to solve land allocation optimization problems for large areas (Aerts *et al.* 2003). As described by Aerts *et al.* (2003), given an area which is divided into $N \times M$ cells and K different land uses, x_{ijk} equals 1 if land use k is assigned to cell (i, j) and equals 0 otherwise. S_{ijk} represents the suitability value of cell (i, j) for land use k and T_k is the total amount of cells to be allocated as land use k. The variable y_{ijk} measures the similarity to land-use type k in the neighborhood of cell (i, j). The overall objective is to maximize total suitability value and compactness, subject to a set of constraints:

Maximize:

$$w_1 \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{M} S_{ijk} x_{ijk} + w_2 \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ijk} \tag{9}$$

where:

$$b_{ijk} = x_{i-1jk} + x_{i+1jk} + x_{ij-1k} + x_{ij+1k} \tag{10}$$

$$y_{ijk} = b_{ijk} x_{ijk} \tag{11}$$

subject to:

$$\sum_{k=1}^{K} x_{ijk} = 1 \quad x_{ijk} \in \{0, 1\} \tag{12}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{M} x_{ijk} = T_k \tag{13}$$

$$y_{ijk} \leq 4 x_{ijk} \tag{14}$$

$$y_{ijk} \leq x_{i-1jk} + x_{i+1jk} + x_{ij-1k} + x_{ij+1k} \tag{15}$$

$$y_{ijk} \geq x_{i-1jk} + x_{i+1jk} + x_{ij-1k} + x_{ij+1k} - 4(1 - x_{ijk}) \tag{16}$$

$$y_{ijk} \geq 0 \tag{17}$$

$$\forall k = 1, \ldots, K, \quad i = 1, \ldots, N, \quad j = 1, \ldots, M \tag{18}$$

The comparison of the optimization results between AgentLA and LP is illustrated in Figure 6b and c. Although the size of the subset data is much smaller, the distribution of the suitability values is much complicated. The LP model developed by Aerts *et al.* (2003)

concerns suitability values and compactness, as the proposed model does. Moreover, LP guarantees the outcome is a true optimum. As shown in Figure 6, the optimized results of these two models are quite consistent (only with a slight difference). This has clearly confirmed the validity of AgentLA if some degree of approximation is allowed.

3.2. Application in the pearl river delta

Panyu city in the Pearl River Delta has been selected for the experiment of land allocation optimization (Figure 7). A series of land-use problems driven by rapid urban development and land speculation in this region have been reported in many studies (Yeh and Li 1997, Li and Yeh 2000). Seto *et al.* (2002) estimated that, between the period 1988 and 1996, urban land use increased more than 300%, and approximately a quarter of new urban areas originated from natural vegetation and water. A great amount of natural vegetation in Panyu has been encroached by urban land use, causing a series of environmental problems. There is an urgent demand for conserving the natural vegetation to sustain the environmental quality and more importantly, the ecological functions for human welfare and further development, such as food supply, sources of materials, waste treatment, space for receiving economic activities, and so on (Costanza *et al.* 1997). In this application, the model described above is used for producing optimal conservation area for natural vegetation protection. The entire process is divided into two steps: (1) suitability mapping constrained by a set of criteria, using spatial analysis functions of GIS; and (2) various scenarios with different model configurations are generated and compared with each other to determine the most satisfactory results.

Figure 7. Location of Panyu in the Pearl River Delta.

Pointed out by Malczewski (2004) in a review on GIS-based land-use suitability analysis, the term 'land-use suitability analysis' can be extended into a broader sense that includes site search problems. However, in this study, the land-use suitability analysis (mapping) is referred in particular to quantification of different units (e.g., a pixel/cell) in the study area suiting the given activity, that is, conservation for natural vegetation.

A raster GIS provides the spatial data for producing the land-use suitability map (Figure 8). These spatial data include the normalized difference vegetation index (NDVI) value, three proximity variables (distance to towns, distance to highways, and distance to roads), slope, and focal density of urban cells. A 30-m digital elevation model (DEM) file is used to produce the slope of the region. The focal density of urban cells is calculated by using the neighborhood of 7×7. Finally, the resolution of all these data is downgraded to 100 m (76,516 cells in total). The value ranges of these spatial variables are normalized into 0–1 for calculating the land-use suitability map.

NDVI has been widely used for researches relevant to vegetation, such as vegetation abundance estimation (Hurcom and Harrison 1998), vegetation succession (Zhao *et al.* 2009), and gross primary production estimation (Wu *et al.* 2009). In this study, the NDVI value, denoted as $S_{\text{vegetation}}$, is used to detect which land units deserve conservation. The potential of future development should also be considered because environmental

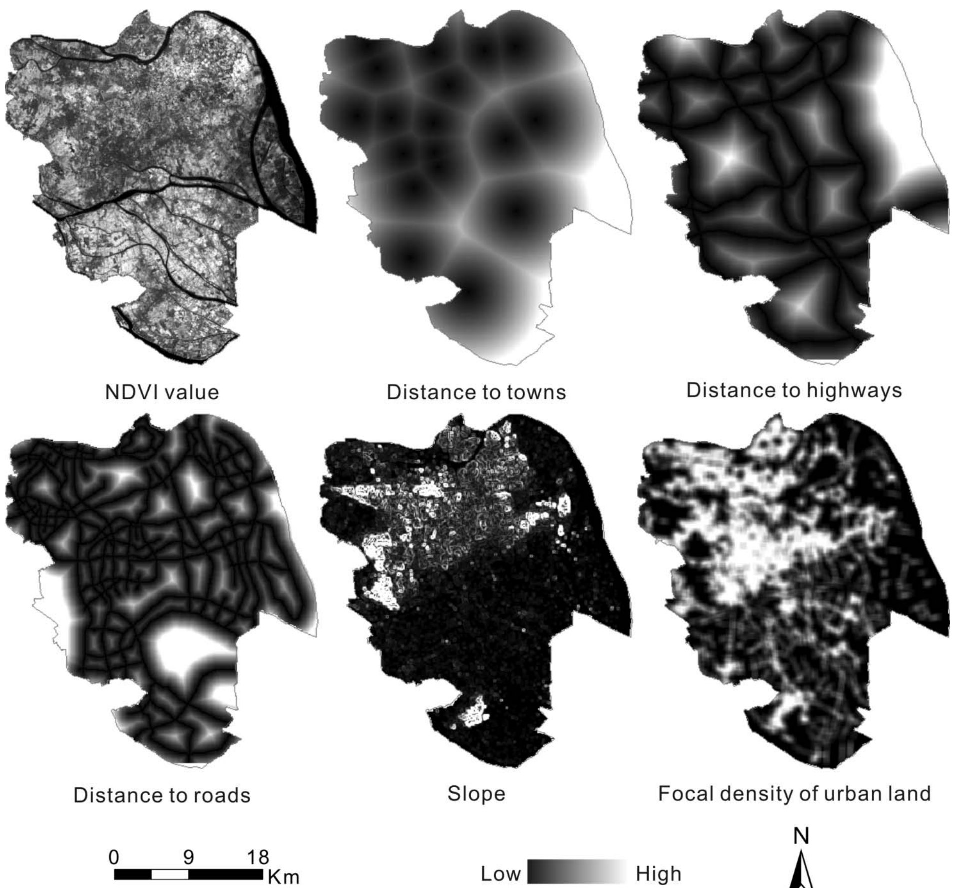


Figure 8. Spatial data for mapping land suitability using raster GIS.

conservation should not totally deny future economic development. Therefore, the development potential, denoted as S_{dev}, is estimated using the following equation:

$$S_{\text{dev}} = w_{\text{h}}(1 - d_{\text{h}}) + w_{\text{r}}(1 - d_{\text{r}}) + w_{\text{t}}(1 - d_{\text{t}}) - w_l l + w_\rho \rho \tag{19}$$

where d_{h}, d_{r}, and d_{t} respectively represent normalized distance to highways, roads, and towns; l is the slope and ρ is the focal density of urban land in a 7×7 neighborhood; w_{h}, w_{r}, w_{t}, w_l, and w_ρ are the weights and are subject to $w_{\text{h}} + w_{\text{r}} + w_{\text{t}} + w_l + w_\rho = 1$

Finally, the suitability value of conservation for each cell is calculated by the following equation:

$$S = S_{\text{vegetation}} - S_{\text{dev}} \tag{20}$$

Figure 9 illustrates the suitability map ($w_{\text{h}} = 0.25$ $w_{\text{r}} = 0.25$ $w_{\text{t}} = 0.2$ $w_l = 0.1$, and $w_\rho = 0.2$) and the optimization results by using 2000 agents with w_v varied from 0 to 1. In

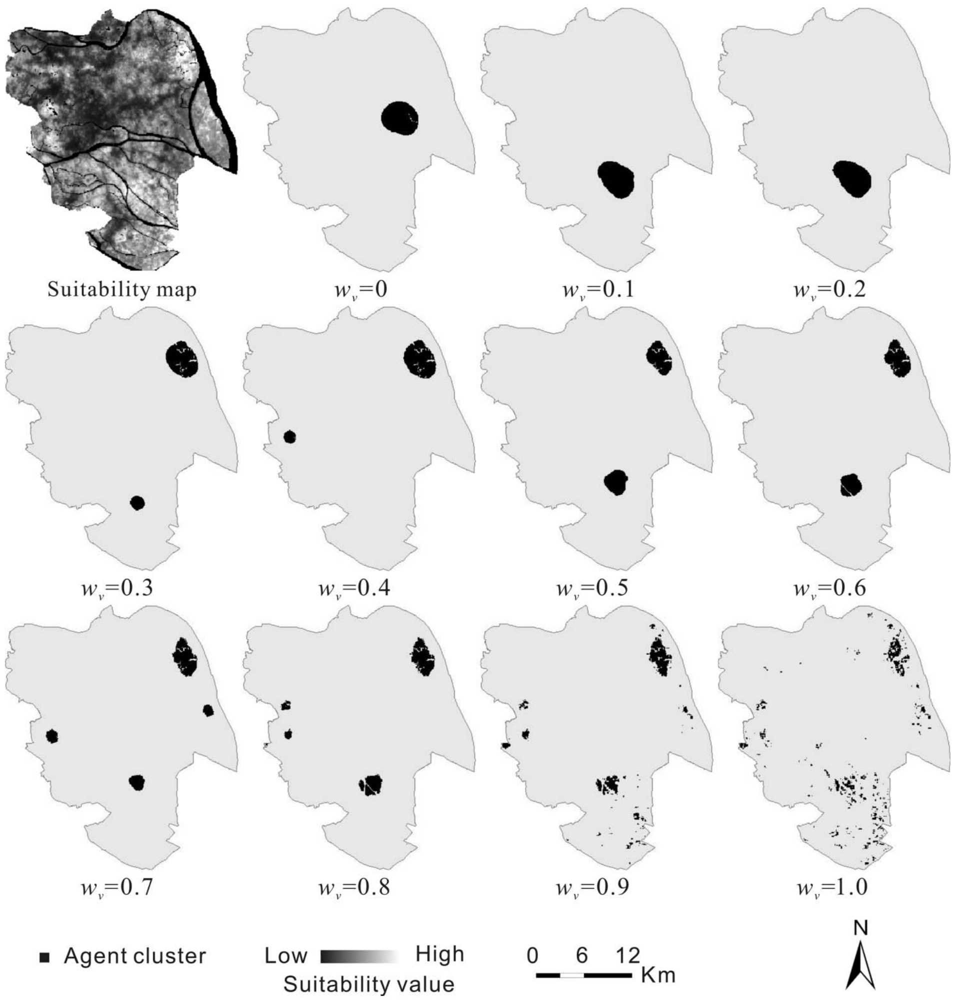


Figure 9. Optimization results using different w_v values.

this simulation, when w_v is less than 0.3, the outcomes all exhibit a pattern of great compactness (only one cluster). When the value of w_v rises, for example, 0.4–0.8, the suitability value becomes more important for the simulation. Hence, the compactness of the pattern reduces, but a larger amount of total suitability value is obtained. When w_v is set closer to 1.0, the simulated pattern becomes more fragmented because the importance of suitability value is dominant over spatial efficiency in the fitness function. The F values of these patterns are computed by using Equation (5), and a histogram is set up in Figure 10. It shows that the F value becomes the highest when w_v falls between 0.5 and 0.8.

As mentioned in Section 2.1, the randomness of outcomes reduces if the value of w_v is increased. This is confirmed by a series of simulation with $w_v = 0.0$, $w_v = 0.7$, and $w_v = 1.0$. Each set of simulation is carried out five times, and the respective results are overlapped, as illustrated in Figure 11 and Table 2. The trend is very clear that the repetitiveness of outcomes rises from nearly negligible (as $w_v = 0.0$) to almost totally coincident (as $w_v = 1.0$). When w_v is set to 0.7, the uncertainty of distribution of the pattern exists mainly in the southern part of the region, whereas a major cluster is observed in the northeast.

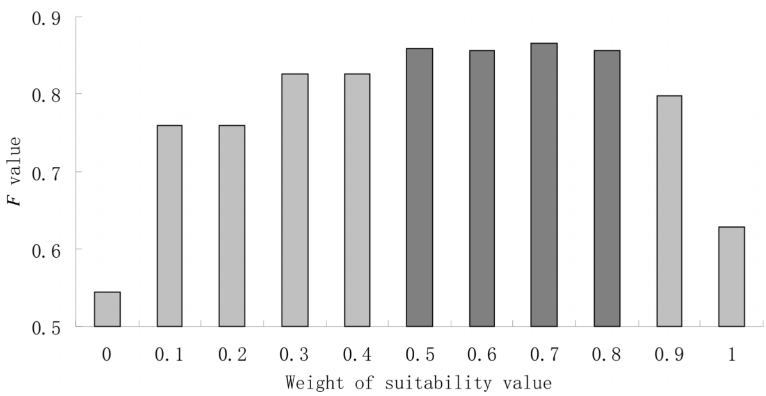


Figure 10. Evaluation of the optimized patterns based on F value.

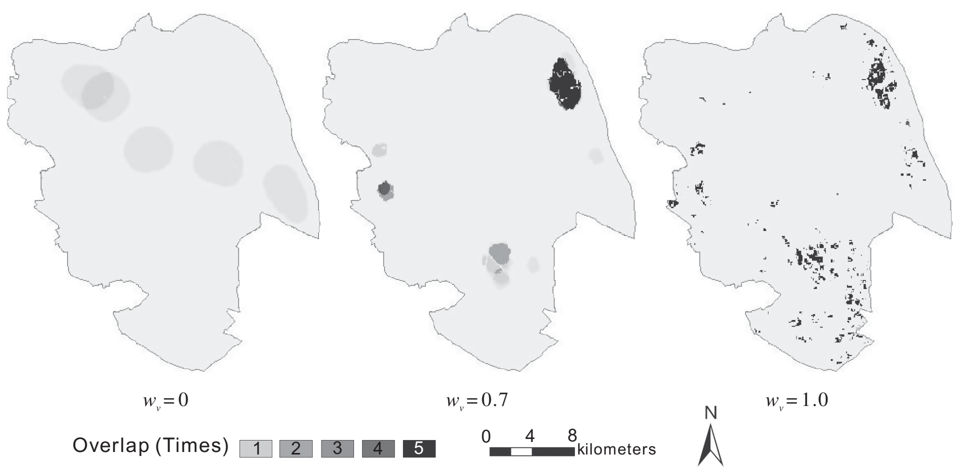


Figure 11. Randomness of optimization with regard to different w_v values.

Table 2. Cell counts grouped according to overlap.

	Overlap counts				
w_v	1	2	3	4	5
0	8044	978	0	0	0
0.7	824	648	538	194	1098
1.0	47	44	43	104	1864

Three more simulations are carried out by using 8000, 15,000, and 23,000 agents, roughly equivalent to 10, 20, and 30% of the study area, to generate more realistic planning alternatives of conservation area for natural vegetation. The optimized patterns are shown in Figure 12a. Meanwhile, another heuristic method for land allocation optimization, the SA algorithm, developed by Santé-Riveira *et al.* (2008), is performed to make a comparison because LP cannot be applied to this large data-set. This method also involves suitability and compactness (Santé-Riveira *et al* 2008). Thus, the comparison mainly examines whether the effectiveness and efficiency of AgentLA are more suited for solving practical problems.

Briefly, the SA algorithm is performed through the following steps. At the beginning of the procedure, a random configuration was generated and the initial value of the objective

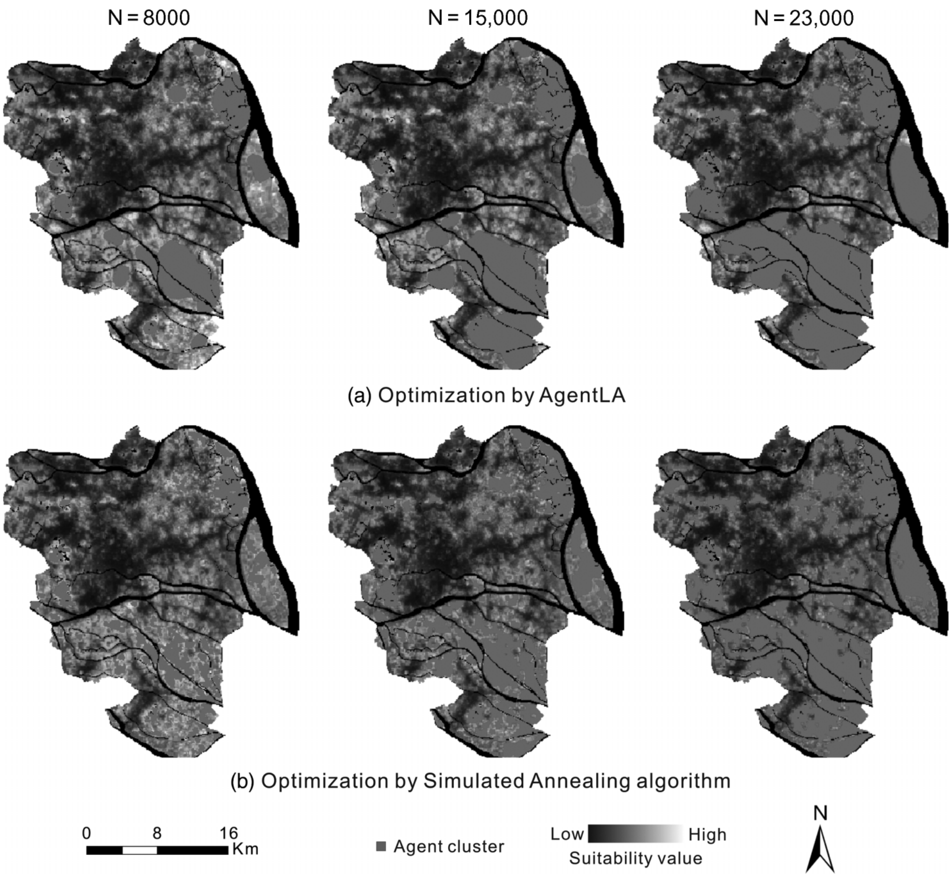


Figure 12. Comparison between AgentLA and SA algorithm.

Table 3. Performance of AgentLA and simulated annealing (SA) algorithm.

		Agent counts		
		8000	15,000	23,000
F value	AgentLA	0.8798	0.9036	0.9112
	SA algorithm	0.8136	0.8586	0.8877
Time/s	AgentLA	956	1500	2091
	SA algorithm	2787	3104	3763

function (Equation 5) was obtained, denoted as F(0). To generate a trial solution, a small perturbation was added. Then, the value of the objective function was calculated for the trial configuration, denoted as F(1). If the difference between F(0) and F(1) is greater than 0 then accept this trial configuration; otherwise the probability of acceptance is calculated using the exponential function: Exp[(F(1)-F(0))/T]. We set the initial value of temperature $T = 100$, and the cooling constant = 0.98. T decreases at each step when multiplied by the cooling constant. In this way, the acceptance probability of worse solution becomes smaller and eventually reaches the global optimal solution.

All these calculations are performed on the same PC with 2 Gb of memory and an Intel Pentium D CPU (3.4 GHz). Figure 12 shows the respective optimization results of both methods, and Table 3 summarizes the results of the F value and time cost. The patterns generated by SA have lower F values than that produced by AgentLA. Moreover, the computation time of AgentLA is far less than SA in all three cases. This indicates that MAS has better computation efficiency.

4. Conclusion

This article has demonstrated a new function of MAS for solving complex optimization problems. Agents are used to create optimal patterns with a contiguity constraint for planning purposes. The objectives are to maximize the total amount of land-use suitability and the compactness of patterns. During the optimization, the relocation of an agent to a location is decided by two spatial variables: land-use suitability of this location and the total spatial efficiency. The final optimized patterns are created according to the collective behaviors of these agents.

The proposed model is first examined through two sets of hypothetical data with different spatial distributions of land-use suitability: monocentric and polycentric. In the former case, the pattern quickly converged into a form very close to the known optimum. In the latter case, there are several subpeak areas of suitability. Some small agent clusters were formed around these peaks in the early stages, but these clusters were soon decomposed and eventually formed right at the center with an expected shape. The F values for these two cases are very close to 1.0, indicating the formation of almost the optimal patterns. An LP model that can guarantee an optimum is used to further examine the validity of this proposed model. The comparison between the optimized results of LP and AgentLA shows a great consistency of these results. This indicates the effectiveness of AgentLA for solving complex optimization problems. Although AgentLA may not guarantee an exact optimum, it can provide an approximate one in a convenient way.

Some may suspect, from the perspective of the game theory, the guarantee of producing even an approximated optimum using MAS. It is because MAS may lead to a Nash equilibrium rather than an optimum under the game theory. The most distinctive characteristic between this proposed model and that discussed in the game theory is the relationship/interaction among the individuals. In the game theory, such relationship/interaction is more frequently interpreted as competition. In our model, however, the optimized pattern is a result of the cooperation by agents. Actually, swarm intelligence, such as ant colony optimization, has been used to solve a lot of optimization problems according to this cooperation strategy (Li *et al.* 2009a, b).

The proposed method is used to produce the optimal conservation area for natural vegetation protection in Panyu, a rapidly urbanized region. The experiments with various sets of model configuration reveal that this model can produce the most satisfactory results when w_v falls between 0.5 and 0.8. A comparison to another heuristic method, the SA algorithm, is further performed. The result indicates that AgentLA has better effectiveness and efficiency. This method is more suited for solving land allocation optimization problems. This study mainly aims at spatial optimization of single land-use type. The complexity of optimization for multiple land-use types increases enormously because of involving more spatial variables and interdependent relationships. This proposed model should be extended to handle these issues in our future studies.

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