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A Land-use Spatial Allocation Model Based on Modified Ant Colony Optimization

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ABSTRACT: Land-use spatial allocation is a multi-objective collaborative spatial optimization method for rational use of the land use. Based on global search capabilities and the information feedback mechanism of ant colony optimization (ACO), a land-use spatial allocation model (ACO-LA) is proposed. FirstlyFirst, a construction graph is built for modeling the land-use spatial allocation problem. SecondlySecond, the behaviors of artificial ants are improved so that the solution can be foundobtained quickly in the searchingsearch space. Finally, the ant colony generates optimized solutions by reconciling the conflicts between different planning objectives or by setting the relative dominance of different land-use types. Our study focuses on Gaoqiao Town of Fuyang City in Zhejiang Province, China. The model maximizes the land-use suitability and spatial compactness~~,~~ and minimizes the cost of changing the land use, based on a variety of constraints, e.g., the optimal land-use structure and land-use policies. The results suggest that this model can obtain an optimized land-use spatial pattern from different sets of sub-objective weights and different development scenarios. With the constraint of the land-use structure, the land-use types can be distributed more reasonably by different sets of sub-objective weights. In different development scenarios, the model encourageencourages areas of land-use types in line with the development direction, adapting to meet different development needs by setting the relative dominance of the different land-use types, $W_{dominance}$, which is added to the component selection probability P_{ij}.

Key words: Land-use spatial allocation, ACO, Construction graph, Solution component, Scenario simulation

INTRODUCTION

The management of land resources can significantly affect the quality of the environment and the sustainable development (Aerts *et al.,* 2005; Wang *et al.,* 2012; Bragagnolo 2013). Land-use spatial allocation is a spatial optimization undertaken to improve the land-use efficiency by distributing different land-use types under the limits of the regional land-use structure, according to specific planning objectives, at various spatial and temporal scales (Zhang *et al.,* 2012). It needs to consider not only numerous spatial factors, attributes, and constraints, but also multiple and often conflicting objectives (Chen *et al.,* 2010; Cao *et al.,* 2011). Therefore, providing an effective method for decision-makers to determine the effects and costs of solutions in different scenarios becomes increasingly important (Loonen *et al.,* 2007).

Many different optimization methods have been used to deal withsolve land-use spatial allocation problems. These methods can be classified into three categories: multi-criteria evaluation evaluation-based models, mathematical programming models, and heuristic methods. Multi-criteria evaluation evaluation-based models (Carver *et al.,* 1991; Eastman

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et al., 1998; Feizizadeh *et al.,* 2012) couple multi-criteria evaluation techniques with GIS to allocating allocate the most suitable land-use type with the highest evaluation value to each unit, . these These models have a drawback when solve solving multi-suitability problems because they all have nolack a global objective function to choose select the optimal solution (Liu *et al.,* 2012). Mathematical programming models, e.g., the linear programming models (Campbell *et al.,* 1992; Aerts *et al.,* 2003) and the mixed-integer programming models (Crohn *et al.,* 1998), require that all the variables, constraints, and objectives have a strict mathematical definition; however, land-use spatial allocation is a complicated geographic process which that involves a large number of constraints, complex spatial relationships, and game decision-making by stakeholders, making it difficult to meet satisfy the conditions of the mathematical programming models. Heuristic methods have hardly anyfew restrictions regarding the formulation of the variables, constraints, and objectives, and they are able to provide alternatives for decision-makers based on , according to thetheir optimization objectives (Loonen *et al.,* 2007). In many studies, heuristic algorithms, such as genetic algorithms (Stewart *et al.,* 2004; Cao *et al.,* 2011), simulated annealing (Duh *et al.,* 2007; Sante-Riveira 2008), immune systems (Liu *et al.,* 2011), and particle swarm optimization (Masoomi et al. 2012; Liu *et al.,* 2012), have been combined with multi-objective optimization techniques and can generate diversified land-use planning solutions under different scenarios, to provide decision support. These studies have provided a new approach to solving land-use spatial allocation problems (Cao *et al.,* 2011).

Ant colony optimization (ACO), which was first proposed by Dorigo et al. (1992), is used to solve optimization problems, such as routing problems (Blum *et al.,* 2005; Lai *et al.,* 2012), scheduling problems (Rajendran *et al.,* 2004; Deng *et al.,* 2011), and traveling salesman problems (Dorigo *et al.,* 1997; Bianchi et al. 2002), by simulating ants' behaviors when selecting the best route from a food source to their nest. Li et al. (2009, 2010, 2011, and 2012) introduced improved ant colony optimization into land-use planning, and their results suggest that ACO is effective when it is applied to these problems.

As a spatial optimization problem, land-use spatial allocation is not easy to model when applying heuristic methods (Tong *et al.,* 2012). Among other issuess, land-use spatial allocation is under the guidance of guided by land-use structure, which is oftfen flexible because they it is are influenced by the evolution of the planning region. Under these circumstancesIn this context, a land-use spatial allocation model based on a global search capability and the information feedback mechanism of an ant colony algorithm is proposed in this paper. The model uses solution components and a construction graph to modeling land-use spatial allocation problems, and modifies artificial ants' behavior for to simulating simulate decision -makers to generate the optimum solutions. Under a given land-use structure constraint, the optimum land-use spatial solution is searched by for using different sets of sub-objectives. MeanwhileIn addition, to meet the demand of land use of different regional development directions, we employ the relative dominance to simulate the area fluctuation of different land-use types. As a case study, we applied this model to the creation of land allocation alternatives in Gaoqiao Town, Zhejiang Province, China to validate the proposed model.

MATERIALS & METHODS

The study area lies in the north of Fuyang City, Zhejiang Province, 20 km from Hangzhou, with a total area of 104.03 square kilometers (Fig. 1). The average annual precipitation reaches is 1452.5 mm. The territory is rich in tourism resources and natural resources, and its economic and social development index ranked 200th in the national "Top Thousand Towns", 34th in Zhejiang Province's "Top Hundred Towns", and 8th in Hangzhou's "Top Ten Towns.". The economic development of the town has also resulted in problems with the excessive growth expansion of construction land, extensive land use, and land pollution. In order tTo achieve the goal of sustainable development, there is an urgent need to promote the intensive use of land, and along with the protection of natural resources and the environment.

The data consist of statistical data and spatial data, which are summarized in Table 1. Statistical data, including economic, social, and ecological data, are employed to determine the optimal land-use structure. The spatial data comprise an actual land-use map, land suitability evaluation maps, and restrictive maps, including a slope map, which are all projected in a Gauss-Krüger projection, datum and spheroid Xi'an 1980, at the scale of 1: 10000. These maps are converted into a grid of 166260 cells of 25×25 m.

Table 1. Data for the spatial allocation modeling

Type	Data
Spatial data	Land suitability evaluation maps Land-use map Average slope map
Statistical data	Economic, social, and ecological statistical data, land demand of land uses and population, demand for food, labor and water

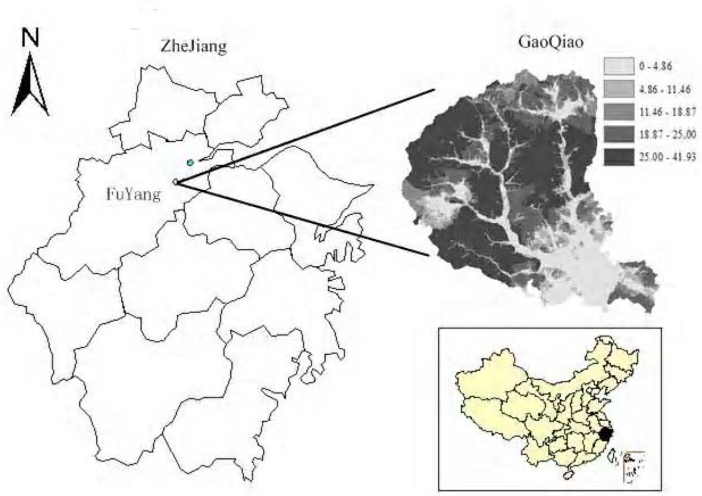

Fig. 1. Location of the study area

The study area has ten land-use types: cropland, garden, forest, rural residential areas, town, road, water, mining, scenic spots, and barren areas. We have excluded road, water, mining, and scenic spots as they are usually not convertible. Land suitability evaluation maps for cropland, garden, forest, rural residential areas, and town were acquired obtained to determine the most suitable use of the land units. The suitability for each land-use type is classified into three four levels: high suitability, suitable, low suitability, and unsuitable, and the values of the levels from high to low equal 4, 3, 2, and 1, respectively.

The decision variable of for land-use spatial allocation problems is the land-use unit, and its state is the land-use type, . so Therefore, we call designate the component, which is the basic unit of solution, the a combination of a unit and a land-use type. ACO is used to choose select the land-use type for a unit, that meanswhich involves selecting a component for the unit, and then adding the solution component selected, which consists of the unit and its land-use type, as chosen by ACO, to the solution under construction until a complete solution is generated. ACO-LA uses a construction graph, a complete weighted graph made up of the components, for modeling the land-use spatial allocation problems.

Artificial ants build solutions by moving on the construction graph and selecting components for the solution according to the component selection mechanism (Dorigo *et al.,* 2006). After all the ants form a solution, the ant colony chooses the best of all the ants' solutions on the grounds ofusing an objective function value. MeanwhileIn addition, the ants update their artificial pheromones in the light of theusing a pheromone update mechanism at the end of each iteration, in order to exchange information and guide the search of the next iteration (Fig. 2). Through Through improving the components of the selection mechanism, the solution selection mechanism, and the ACO pheromone update mechanism of ACO, the model becomes more effective in obtaining the optimized land-use spatial pattern.

Land-use spatial allocation is the procedure of allocating a suitable land-use type to each land unit (Zhang *et al.,* 2012), so such that each component (C_{ij}) of the optimized solution is made up of a land unit (U_i) and its land-use type (T_j). All these components constitute the land-use spatial allocation construction graph G_C, and the weight of each solution component is the heuristic value, which equals the suitability of land-use type j of land unit i. To allocate the land-use types, artificial ants sequentially search each unit and choose a component satisfying all the constraints for the unit, e.g., they choose C_{32} for unit 3, which means indicates unit 3 is used for garden, and add the selected solution component to the partial solution under construction until artificial ants traverse all units (Fig. 3). And meanwhileIn addition, they release pheromones on the components in their solution.

When solving land-use spatial allocation problems, the artificial ant simulates behaviors of the decision-maker to in choose choosing land-use types for each land unit. As mentioned before, when allocating a land-use type to the units, the artificial ants have to consider the attributes and the neighborhood of the units, so the probability P_{ij} of components C_{ij} being chosen by the ants is modified as in Equation 1.

$$P_{ij} = [P_{AS}(C_{ij}) + P_{neighbourhood}(C_{ij})] \times P_{constraint}(C_{ij}) \quad (1)$$

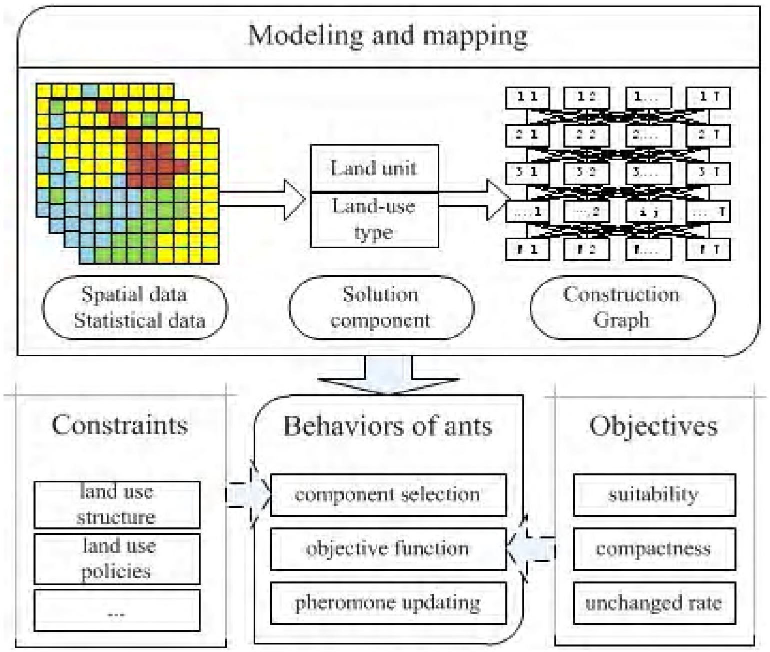

Fig. 2. Block diagram of ACO-LA

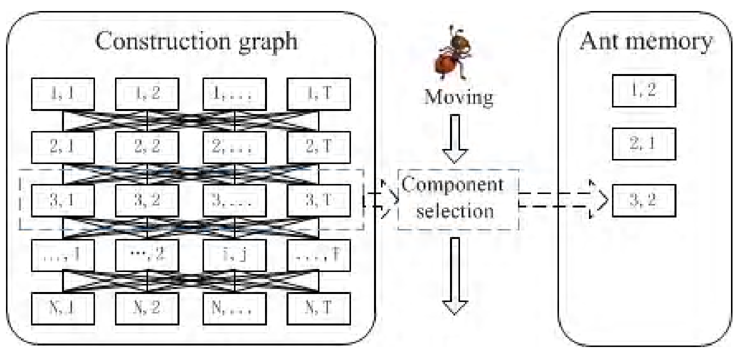

Fig. 3. Construction graph and component selection mechanism (N is the ID of the units, and T is the ID of the land-use type)

where $P_{AS}(C_{ij})$ is the probability calculation method of the ant system (Equation 2). $P_{neighbourhood}(C_{ij})$ is the ratio of land-use type j in the eight-neighborhood of unit i, . the The land-use type of the neighborhood is determined by the original pattern and optimal pattern of current iteration if they are changed in the optimization process . $P_{constraint}(C_{ij})$ equals 0 or 1, as determined by the constraints (Table 2 & 3). When unit i can be converted to land-use type j, its value is 1, and otherwise, it is 0.

where τ_{ij} is the amount of pheromone on components C_{ij}, ; η_{ij} is the heuristic value of the components C_{ij}, which equals the suitability of land-use type j of land unit i, ; and α and β are the parameters of ACO, which have a significant effect on the ACO performance of ACO.

Typically, regional land-use has different emphases because of the different regional development directions, so that the land-use structure is flexible. In this case, the areas of the land-use types will fluctuate

$$P_{AS}(C_{ij}) = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{m \in allowed_k} [\tau_{im}]^{\alpha}[\eta_{im}]^{\beta}} & , j \in allowed_k \\ 0 & , j \notin allowed_k \end{cases} \tag{2}$$

$$P_{ij} = [P_{AS}(C_{ij}) \times P_{neighbourhood}(C_{ij})^{N}] \times P_{constraint}(C_{ij}) \times W_{superiority}(C_{ij}) \tag{3}$$

Table 2. Land-use structure

Land-use type	Cropland	Garden	Forest	Rural residential areas	Town	Barren	Others
ID	1	2	3	4	5	6	7
Area	1675.05	634.39	6662.96	773.49	233.69	26.73	401.58
Land units count	26758	10134	106437	12356	3733	427	6415

Table 3. The constraints of the land-use spatial allocation

ID	Constraints
1	The preservation of basic farmland: cropland in the basic farmland areas should not to be converted to other land-use types
2	The policy of grain for green: return cropland of which the slope is more than 25 degrees to forest
3	Prohibit abandonment: no land-use types should be converted to barren land
4	Town, road, water, mining, and scenic spots are not convertible
5	The expansion of a town shall be within the boundaries of the construction area
7	Area constraint: the areas of the land-use types must meet the area of the land-use structure constraint

to meet the development needs (the change area is limited to †plus or minus 10% of the land-use structure, for the protection of theto ensure stability). We add the relative dominance of the different land-use types, $W_{dominance}$, to the component selection probability P_{ij} (Equation 1) to generate solutions for different development scenarios (Equation 3).

Each artificial ant represents one possible solution; the ant colony has to choose the best one by reconciling the conflicts between multiple objectives. The three objectives of the land-use spatial allocation proposed in this paper are to maximize the land suitability ($f_{suitability}$) and spatial compactness ($f_{compactness}$), and minimize the cost (f_{cost}). The objective $f_{suitability}$ ", which is a guide in the land-use spatial allocation, is employed to make ensure that each area of land is used for a suitable use when the land is suitable for multiple uses (Yeh and Li 1998) (Equation 4). The objective $f_{compactness}$ encourages land units with the same use type to assemble in a cluster (Aerts *et al.,* 2003) (Equation 5). The objective f_{cost} is to minimize the cost of changing the land use. We adopted the unchanged rate, the percentage of unchanged units in all units, which indirectly measuring measures the cost caused by the land-use type conversion, which is difficult to quantify (Equation 6). Objective $f_{suitability}$ and objective $f_{compactness}$ are normalized within the range [0, 1] using Equation 7. We employ a weighting method to deal with address the multiple objectives (Equation 8).

$$f_{suitability}(k) = \sum_{i=1}^{n} S_{ij} \tag{4}$$

where k is the ID of the ants, i ~~is~~ the ID of the unit, n ~~is~~ the count of the units, and S_{ij} ~~is~~ the suitability of land-use type j of land unit i.

$$f_{compactness}(k) = \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} \tag{5}$$

where j is the ID of the land-use type, and m is the count of the land-use types.

$$f_{cost}(k) = \frac{n_{unchanged}}{n} \tag{6}$$

where $n_{unchanged}$ is the count of the units that did not change their use.

$$N_{norm} = (N - N_{min}) / (N_{max} - N_{min}) \tag{7}$$

$$f_k = W_s f_{suitability}(k) + W_C f_{compactness}(k) + W_U f_{unchanged}(k) \tag{8}$$

where W_S, W_C, and W_U are the weights of the three objectives, respectively.

After all the ants have constructed their solutions, the pheromone intensity of each component is updated at the end of each iteration, according to the following mechanism (Equations 9 and 10). First, the pheromone intensity will evaporate at a certain rate (ρ), and then the pheromone intensity of component C_{ij} will increase if C_{ij} is in the solution. During the optimization process, the more pheromone that is present on C_{ij}, the more likely C_{ij} is choosed chosen by ants (Equation 2).

$$\tau_{ij} \leftarrow (1 - \rho)\,\tau_{ij} + \Delta\tau_{ij} \tag{9}$$

$$\Delta\tau_{ij} = \begin{cases} f_k, & C_{ij} \text{ is in ant' solution} \\ 0, & otherwise \end{cases} \quad (10)$$

where f_k is the objective function value of ant k.

RESULTS & DISCUSSION

The proposed land-use spatial allocation model based on ACO was employed to optimize the land-use spatial allocation pattern of the study area. The parameter values of the model are listed in Table 4.

Table 4. The parameter values of the model

M	α	β	ρ
35	1	1	0.5

As the optimization objectives may conflict with one another, we can generate the optimum solutions by setting objective weights of the objectives to emphasize different objectives (Liu *et al.,* 2012). Table 5 lists the different weights we applied to the three objectives. For example, options 1, 2, and 3 are a single-objective optimization that, only maximizes the land-use suitability or spatial compactness, or minimizes the cost of changing the land use. For options 4–7, the combinations are 1:1:1, 2:1:1, 1:2:1, and 1:1:2. The results in Table 6 indicate that different sets of objective weights have provide the best performance in reconciling the conflicts between the three objectives. Options 1–3 consider only one objective, and the optimum pattern is unreasonable. Options 4–7 get obtain the optimal pattern by considering the trade-off between suitability, compactness, and conversion cost.

Table 5. Different sets of objective weights

Option	W_S	W_C	W_U
1	1.00	0.00	0.00
2	0.00	1.00	0.00
3	0.00	0.00	1.00
4	0.34	0.33	0.33
5	0.50	0.25	0.25
6	0.25	0.50	0.25
7	0.25	0.25	0.50

Table 6. Values of the objectives with respect to different sets of objective weights

Option	$f_{suitability}$	$f_{compactness}$	f_{cost}	f
1	0.8623	0.3241	0.9123	0.8623
2	0.7422	0.4235	0.9087	0.4235
3	0.7456	0.3306	0.9427	0.9427
4	0.7841	0.3793	0.9397	0.701864
5	0.8238	0.3656	0.9291	0.735575
6	0.8174	0.3907	0.9247	0.630875
7	0.8168	0.3746	0.9386	0.76715

The economic development of the study area has led to unreasonable land use. We need to emphasize the suitability objective, so option 5 is more in line with the development of the region. Fig. 4 shows the overlay results of the optimal patterns of option 5 (Fig. 4-b) and the actual land-use map (Fig. 4-a). A total of 7.09% of the units are concentrated in the marginal areas of the land-use clusters, and regions A, B, C, and D have changed uses (Fig. 4-c). Units in the margins of the land-use clusters have changed because of the multi-suitability for multiple land uses and the neighborhood (Fig. 5-1). Region A is located in the northern mountainous area with lots ofabundant forest, small rural settlements, and arable land, and the converted units are mainly farmland distributed in on the slopes more than 25 degrees, which are converted to forest (Fig. 5-2). Region B is located in the plains of the western mountains, the main area of cropland and gardens. In this region, some forest in good condition is converted to cropland and garden (Fig. 5-3). Region C is located in the southern plains, like region B, and rural settlements, cropland, and garden are the main land-use types in this area. Here, some scattered settlements are converted into cropland, garden, and other land-use types, and some cropland, garden, and forest land-use types around settlements are also converted to settlements. At the same time, a small amount of forest with good conditions is converted to cropland and garden (Fig. 5-4). Region D is Gaoqiao Town, and the town increases through internal transformation and external expansion to meet the needs of the urban development. Villages in the town, some settlements, and other land units surrounding the town are converted to construction land (Fig. 5-5). The parameter settings for ACO, including the number of ants M, α, β, and ρ, will affect the performance of the algorithm, even for the same problem with different data. The optimal parameter settings need a number of experiments to determine the values.

As shown in Fig. 6, the objective function value increases when the number of ants increases from 5 to 35, and then remains basically stable. The pheromone intensities of the components are equalized when an excessive number of ants is are used, and that leads to more time being required to find the optimal solution. In the experiment, when M=35, the value of the objective function reaches a maximum.

The parameters α and β will affect the component selection probability. Parameter α is a thereaction of the influence of the pheromone intensity on the component selection; . the The greater its the value of this parameter, the more likely it is that components which that have been chosen before will be selected, but the searching randomness of ACO-LA will

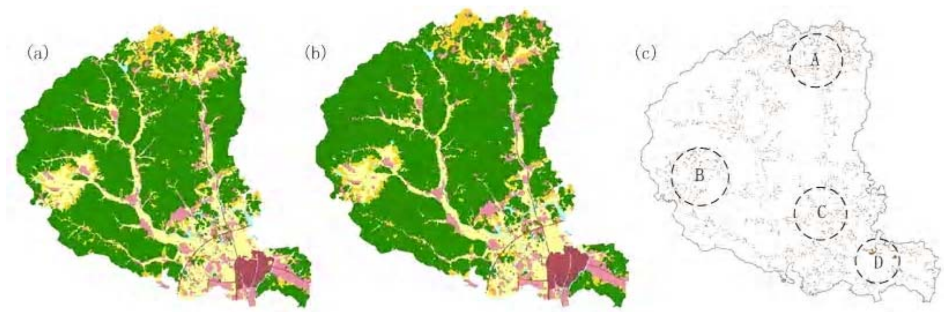

Fig. 4. Overlay result: (a) The actual land-use map; (b) the optimal land-use spatial patterns obtained in weighted option 5; and (c) the distribution of the changed units

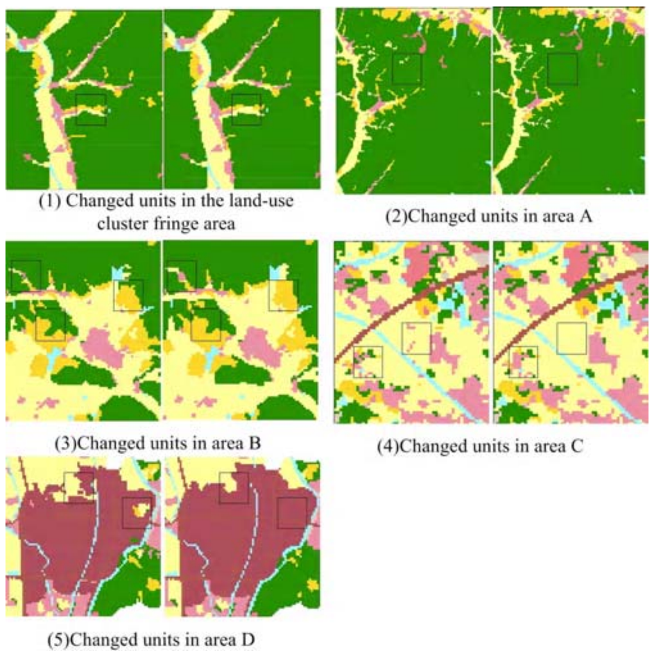

Fig. 5.Changed units in the different areas

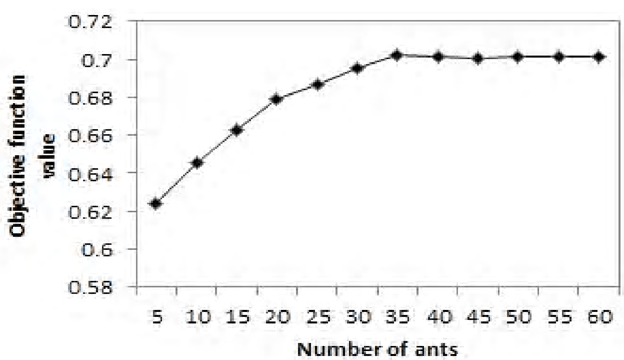

Fig. 6. Influence of the number of ants on the objective function value

decrease. Conversely, if the value is too small, the algorithm is easily trapped at a local optimum. While Though parameter β is a the reaction of the influence of the heuristic value on the component selection, the role of certainties are more powerful in component selection when β is increased, but, meanwhilesimultaneously, the randomness of the search is reduced, resulting in a local optimum. As shown in Fig. 7 in the form of a surface plot (Liu *et al.*, 2012), when α=1 and β=1, the value of the objective function reaches a maximum.

The parameter ρ will affect the global search ability and convergence speed of the algorithm. When ρ<0.5, the performance of ACO-LA improves as the value increases, but when ρ > 0.5, as the value increases further, the remaining pheromone intensity of each component decreases. Consequently, the speed of the convergence is increased, but the global search capability is weakened, and the algorithm is more likely to fall into a local optimum. When ρ = 0.5, good results have beenare achieved (Fig. 8).

To obtain the optimized land-use spatial pattern of different regional development directions, Table 7 lists five development scenarios by that involve setting the relative dominance of the different land-use types, according to equation 3. Scenario A is a balanced development with all the relative dominance values equal to 0.2. Scenario B is the development of cropland protection, and the relative dominance of cropland is 0.4, and the relative dominance of other others land-use types are is 0.15. Scenario C is eco-development, and the relative dominance of cropland is 0.2, garden and forest are 0.3, and the other land-use typess are 0.1. Scenario D is the development of rural construction, in which the relative dominance of cropland and rural residential areas is 0.35. Scenario E is urban-–rural integration development, and the relative dominance of rural residential areas and towns is 0.35.

Table 8 lists the statistics of the optimal land-use spatial patterns (Fig. 9) obtained in the different development scenarios. The number of units increases with the relative dominance. This is because a greater relative dominance makes results in the corresponding component being more likely to be selected by the ants. Therefore, adjusting the relative dominance of the land-use types is a means of influencing the component selection, and has an important impact on generating alternatives.

We selected five typical regions to compare the land-use spatial patterns obtained in the different development scenarios (Fig. 10). We can see that the

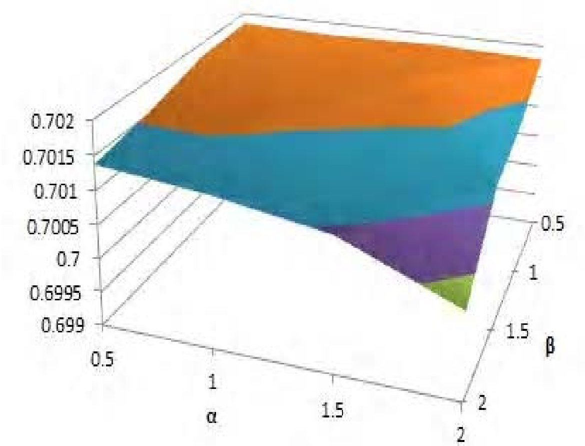

Fig. 7. Influence of α and β on the objective function value

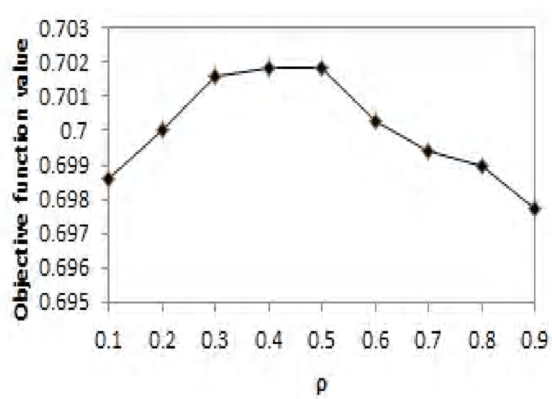

Fig. 8. Influence of ρ on the objective function value

Table 7. Different development scenarios

Scenarios	Cropland	Garden	Forest	Rural residential areas	Town
A	0.2	0.2	0.2	0.2	0.2
B	0.4	0.15	0.15	0.15	0.15
C	0.2	0.3	0.3	0.1	0.1
D	0.35	0.1	0.1	0.35	0.1
E	0.1	0.1	0.1	0.35	0.35

Table 8. Statistics of the optimal land-use spatial patterns obtained in the different development scenarios

scenarios	Cropland	Garden	Forest	Rural residential areas	Town	WS	WC	WU	$f_{(0.34/0.33/0.33)}$
A	26357	10343	106937	12356	3733	0.7834	0.7747	0.9182	0.852007
B	27438	10135	106784	11832	3537	0.7794	0.7793	0.9164	0.852165
C	26874	11358	107329	10536	3629	0.7941	0.7763	0.9207	0.856173
D	27135	10145	105273	13597	3576	0.7752	0.776	0.9135	0.849648
E	25536	10626	106012	13479	4073	0.7869	0.7757	0.9215	0.853527

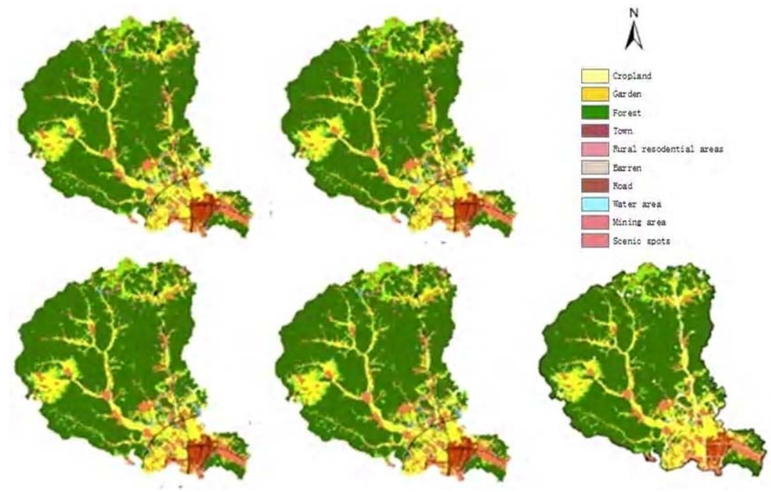

Fig. 9. The optimal patterns obtained in the different development scenarios

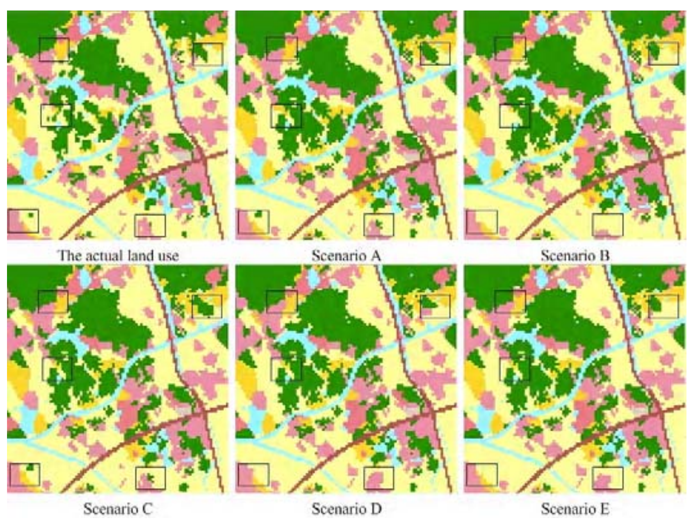

Fig. 10. Changed units in the different development scenarios

Table 9. Different settings of the relative dominance for cropland

ID	Relative dominance of cropland	Cropland units count
1	0.1	26295
2	0.2	26593
3	0.3	26742
4	0.4	26918
5	0.5	27322
6	0.6	27487
7	0.7	27452
8	0.8	27466
9	0.9	27453
10	1	27446

units located in the margins of cluster areas have more choices, because of the multi-suitability and the neighborhood, and the land use with a greater relative dominance is more likely to be allocated to these units. In order tTo analyze the impact of the dominance on the numbers of the different land-use types, we gradually increase the relative dominance of cropland while the others are kept unchanged (equal to 0.1). As shown in Table 9, with the increase in cropland dominance, the number of cropland units gradually increases, until the dominance of cropland is increased to 0.6, where the number stabilizes. There are two reasons for this. Firstly,: the area constraints. Secondly, and the impact of the suitability and the neighborhood. The amount of land suitable for cropland is limited, and at the same time not all the units suitable for cropland are converted to arable land at the same time, because because of the neighborhood. It follows that the increased dominance will lead to the number of units of the corresponding land-use type gradually increasing until it is close to the area constraint or the number of cells defined by the suitability and neighborhood.

CONCLUSIONS

Land-use spatial allocation is a complex composite geographic process, and the traditional mathematical models have difficulty in resolving such problems. The introduction of heuristic algorithms for such problems has brought aboutgenerated new ideas. This paper presents a land-use spatial allocation model based on modified ant colony optimization. The modifications comprise include the use of a construction graph for the land-use spatial allocation problems, and an improved component selection mechanism, solution selection mechanism, and pheromone update mechanism for ACO.

Our study focuses on Gaoqiao Town, with 166260 cells, and employs three objectives: maximization of the land-use suitability, maximization of and spatial compactness, and minimization of the cost of changing the land use, based on a variety of constraints, to obtain the optimal land-use spatial pattern. As the results of the land-use spatial allocation showdemonstrate, the relative weights of 2:1:1 for three sub-objectives is are adopted for the study area, and the changed units, accounting for 7.09% of the total area, are mainly distributed in the marginal areas of the land-use clusters and 4 regions for increasing objective function value and constraints. The optimal algorithm parameter settings, M=35, α=1, β=1 and ρ = 0.5, are determined after many tests. And tThe proposed model can then efficiently and effectively find determine the optimal solutions with different sets of relative dominance for different development scenarios. When the gradually increase the relative dominance of cropland is gradually increased, we find that the number of cropland units gradually increases and reaches the limit caused by the area constraints, the impact of the suitability and the neighborhood.

In this paper, we take suitability as the heuristic value of for ACO, and the optimization results of the model are dependent on the accuracy of the land suitability evaluation. Therefore, any future work should focus on the setting of the heuristic value, and employing more additional economic, social, and environmental objectives and constraints.

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