A Land Use Spatial Allocation Model based on Ant Colony Optimization

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Abstract

Land use spatial allocation is a space optimization to improve the land use efficiency by distributing different land use types under the limits of regional land use structure according to specific planning objectives in spatial and temporal scales(Zhang et al. 2012). It is very complex because it need to consider not only numerous spatial factors, attributes and constraints,but also multiple and often conflicting objectives(Chen et al. 2010 and Cao et al. 2011). Therefore providing an effective method for decision-makers to determine effects and costs of solutions in different scenarios becomes increasingly important(Loonen et al. 2007).

Many optimizing methods have been used to deal with the land use spatial allocation problems. These methods can be classified into two categories: mathematical programming models and Heuristic methods. Mathematical programming models,e.g. linear programming model(Campbell et al. 1992 and Aerts et al. 2003) and mixed-integer programming model(Crohn et al. 1998), require that all variables, constraints, objectives have strict mathematical definition, while land use spatial allocation is a complicated geographic process which involves a large number of constraints, complex spatial relationships and game decision-making by stakeholders,making it difficult to meet the conditions of the mathematical programming models. Heuristic methods hardly have any restrictions regarding the formulation of the variables, constraints and objectives, and they are able to provide alternatives for decision-makers according to the optimization objectives(Loonen et al. 2007). In many researches,heuristic algorithms such as genetic algorithm(Stewart et al. 2004 and Cao et al. 2011), simulated annealing(Duh et al. 2007 and Sante-Riveira 2008), particle swarm optimization(Masoomi et al. 2012 and Liu et al. 2012) combining with multi-objective optimization techniques,can generate diversified land use planning scenarios to provide decision support.These researches provide a new approach to solve land use spatial allocation problems(Cao et al. 2011).

Ant colony optimization (ACO), which was first proposed by Dorigo et al. (1991), solve optimization problems,such as routing problems, assignment problems and traveling salesman problem, by simulating ants' behaviours of selecting the best route from a food source to their nest.Li xia et al.(2009,2010,2011 and 2012) introduced

improved ant colony optimization into the land use planning ,their results suggest that ACO is effective when it is applied to these problems.

As a space optimization problem,land use spatial allocation have difficulty in articulating and specifying(Tong et al. 2012). Under this circumstances a land use spatial allocation model based on global search capability and information feedback mechanism of ant colony algorithm is proposed in this paper(fig. 1): Construction graph, a complete weighted graph made up of components which are composed of land units(N) and land use types(T), is built firstly for modeling land use spatial allocation problem.Secondly the behaviors of artificial ants(including component selection, pheromone updating and objective function) are improved so that the solution could be found quickly in the seraching space. Finally,ant colony generates optimized solutions by reconciling the conflicts between different planning objectives.

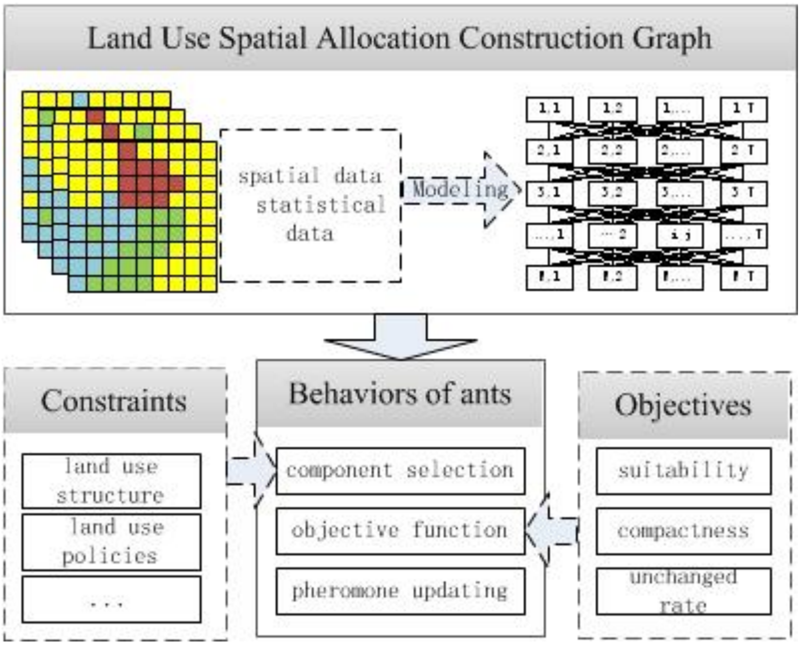

Figure 1 Block diagram

Our study focuses on Gaoqiao Town of Fuyang City in Zhejiang Province(fig. 2). The model maximizes land use suitability(equation 2),spatial compactness(equation 3) and unchanged rate(equation 4) based on a variety of constraints, e.g. optimal land use structure and land use policies, land use suitability and spatial compactness are normalized within the range [0, 1] using the equation 5.

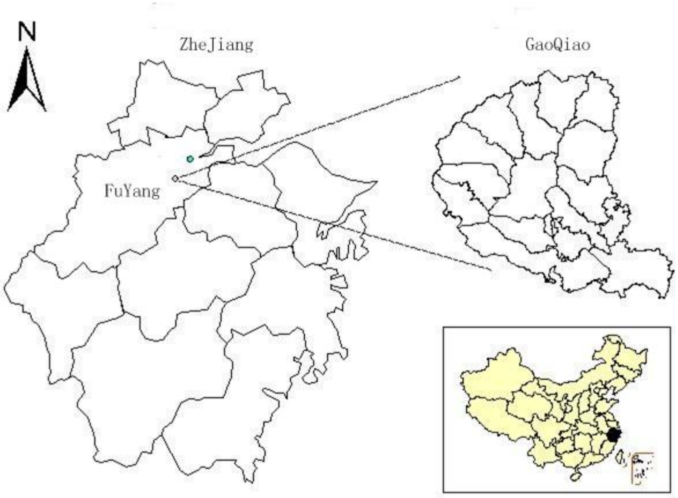

Figure 2 Location of the study area

$$f_k = W_s f_{suitability}(k) + W_C f_{compactness}(k) + W_U f_{unchanged}(k) \quad (1)$$

$$f_{suitability}(k) = \sum_{i=1}^{n} S_{ij} \quad (2)$$

$$f_{compactness}(k) = \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} \quad (3)$$

$$f_{unchanged}(k) = \frac{n_{unchanged}}{n} \quad (4)$$

$$N_{norm} = (N - N_{min}) / (N_{max} - N_{min}) \quad (5)$$

The results suggest that this model can obtain the optimized land use spatial pattern in different sets of sub-objective weights and different development scenarios: with the constraint of land use structure(table 1), land use types distribute more reasonable(table 3 and fig 3) by different sets of sub-objective weights(equation 1 and table 2);In different development scenarios(table 4),the model encourage areas of land use types in line with the development direction increase(fig 5 and table 5) to meet different development needs by setting relative dominance of different land use types $W_{dominance}$ adding to the component selection probability P_{ij} (equation 6). Table 1 shows the influence of the relative dominance, The quantity of cropland increases with the relative moderate until reach the limit caused by land use suitability and neighborhood.

Land Use Type	Cropland	Garden	Forestland	Ruarl Residential Areas	Town	Barren	Others
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 1 land use structure

ID	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 2 Different sets of sub-objective weights

ID	$f_{suitability}$	$f_{compactness}$	$f_{unchanged}$	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

Table 3 Value of objectives with respect to different sets of sub-objective weights

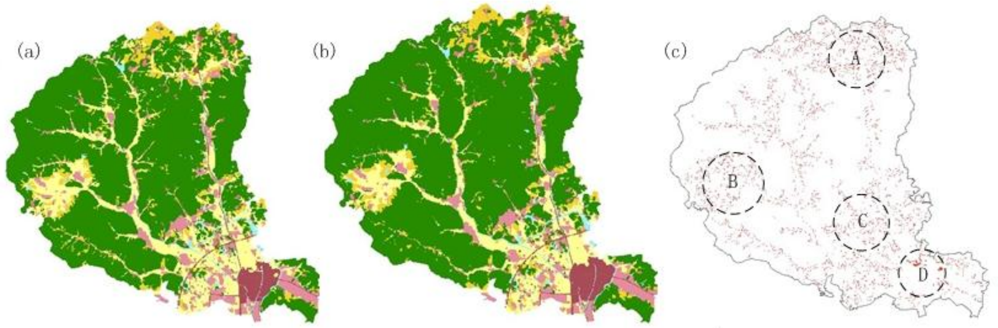

Figure 3 Overlay result:(a) The actual land use map; (b) the optimal land use spatial patterns obtained in weighted ID 5; (c) the distribution of changed units.

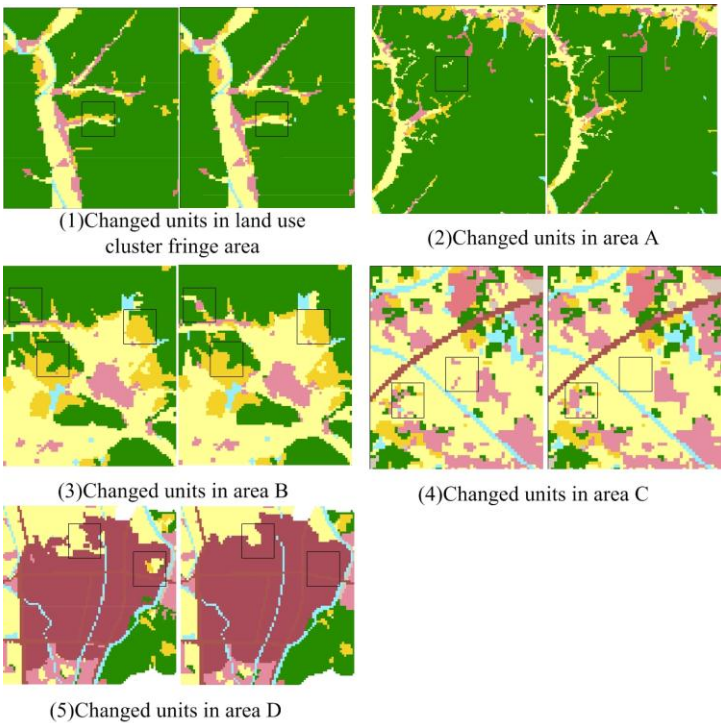

Figure 4 Changed units in different areas

$$P_{ij} = [P_{AS}(C_{ij}) \times P_{neighbourhood}(C_{ij})^{\mu}] \times P_{constraint}(C_{ij}) \times W_{dominancey}(C_{ij}) \quad (6)$$

Scenarios	Cropland	Garden	Forestland	Ruarl 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 4 Different development scenarios

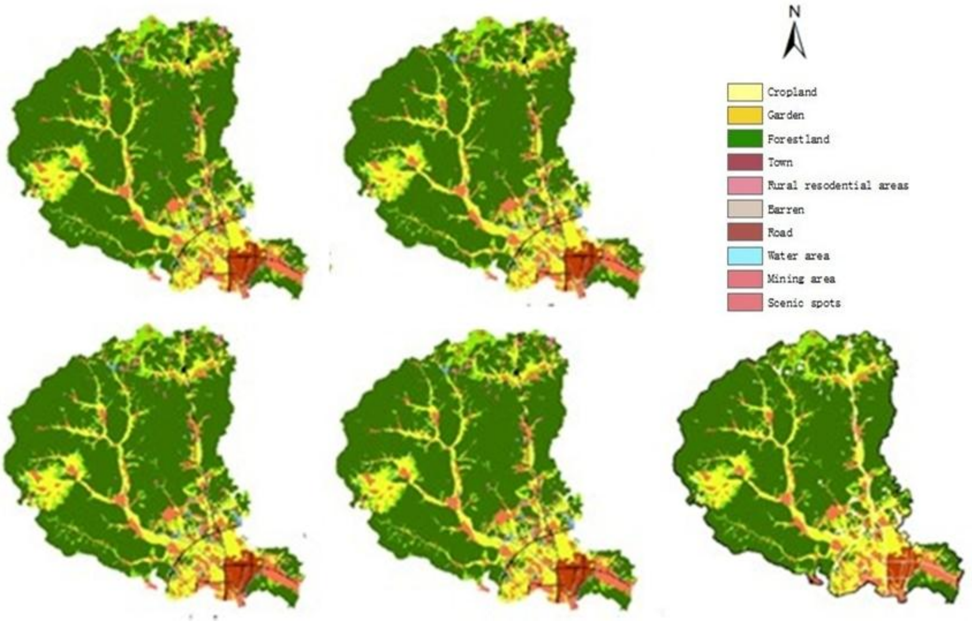

Figure 5 the optimal land use spatial patterns obtained in different development scenarios

scenarios	Cropland	Garden	Forestland	Ruarl 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

Table 5 Statistics of the optimal land use spatial patterns obtained in different development scenarios

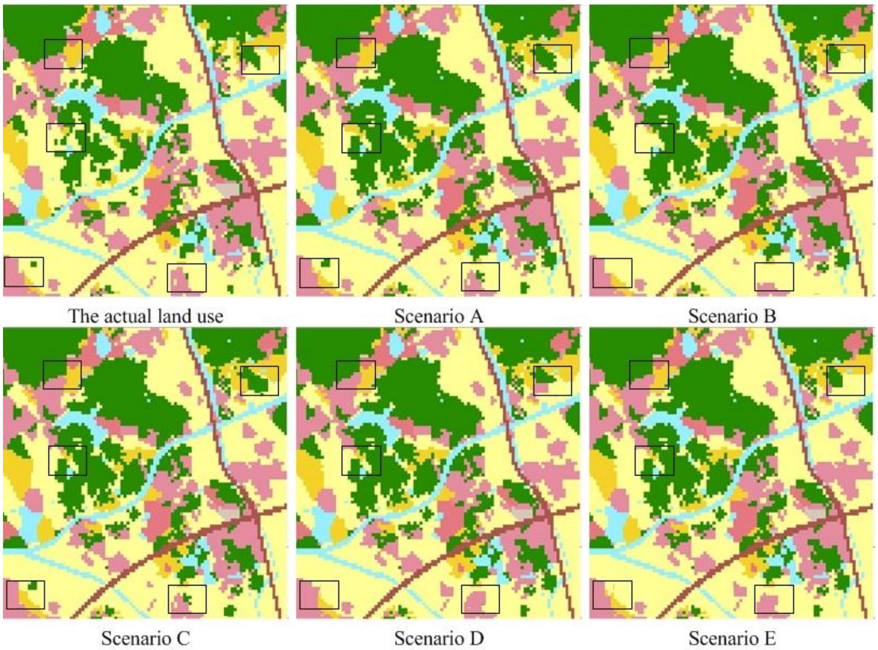

Figure 6 Changed units in different development scenarios

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

Table 6 Different sets of relative dominance of Cropland

keywords Land Use Spatial Allocation, Ant colony optimization, Construction graph

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