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Land-Use Spatial Optimization Based on PSO Algorithm

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Abstract The optimization of land-use spatio-structure is one of the most important areas of land use management; constructing a spatial optimization model that is based on the micro spatial unit in a bottom-up mode plays an important role in coupling the quantity structure and spatial structure effectively. The objective of this research is to develop a land use spatial optimization model based on particle swarm optimization to make spatial decision in land use management. The model is implemented using real datasets to emulate the process of spatial structure optimization in order to get the best landscape pattern under the control of decision environments. Simulation results revealed that the particle swarm optimization model has the ability to utilize the quantity and spatial structure. Furthermore, the result demonstrated that it can be used to stimulate the landscape pattern in designing the appropriate optimization environment, which could land quantity target to the basic spatial units effectively and provide appropriate spatio-structure for regional land use space layout decision making.

Keywords PSO; land-use spatial allocation; intelligent agent; GIS

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Introduction

Realizing the sustainable utilization of land resources is a very important issue of land resources management with the accelerated process of industrialization and urbanization, which has weakened agricultural sustainable development of resources because of nonagriculturalization and ecological environment deterioration. Meanwhile, the land resource structure optimization allocation also gets further study as the important research content of sustainable

development. According to the characteristics of land resource and its suitability assessment and based on certain scientific technology and management, the land resource configuration optimization can get land resources within the area more reasonable arrangement and spatial distribution to achieve a certain economic, social, and ecological targets to improve the efficiency of land use, maintain the relative equilibrium of land ecosystem, and realize the sustainable utilization of land resources.^[1]

It is very important to use this model to optimize the land use structure. Land resource optimization alloca-

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tion is a complicated engineering system, which is a multiple-target multilevel continuous decision-making process; land resource configuration optimization model is also in the constant development and improvement. It has formed a number of models, such as linear programming, multiobjective and multicriteria optimization decision system dynamics, landscape ecology, spatial logistic regression, genetic algorithm (GA), and cellular automata (CA) model.^[2-5] Land resources optimization allocation also breaks the traditional simple quantity structure optimization, turning to study the spatial structure, and tend to coupling them. However, it appears very difficult to simulate effectively due to the complexity and the space characteristics of the geographical landscape system, where it is difficult to get the ideal effect by some simple model; thus, land resources optimization allocation methods are also steering to geographic information science and intelligent information processing technology from the simple mathematical model in order to optimize regional land use space structure in bottom-up model at microcosmic space level of land use. However, how to match the land use goal to the corresponding space unit effectively in micro level remains to be a difficult technical problem, and the conventional models in quantity processing or treatment of space have certain limitation. The development of intelligent geographic information technology provides important technical support for spatial decision making in land resources optimizing process.^[6-14] Thus, combining the intelligent geographic information technology with land optimization model and constructing intelligent land optimization model to realize the reasonable allocation of land resources both in quantity and space has become a hotspot to these researchers concerned, and it also promotes the development of scientific research about the land use optimization.

The two typical kinds of space optimization models, namely, cellular automata and genetic algorithm,^[15-21] also have their limitations though they are widely used at present. Though genetic algorithm can make global optimization with the coding of each land use map spot, its efficiency of managing high dimensional space information is slightly inadequate, and this disadvantage reflects more obvious espe-

cially when thousands of land use decision space is concerned. Cellular automata have the advantage in spatial evolution timing simulation, but the cell is susceptible to neighborhood and conversion rules. Meanwhile, the model is very weak in the cytoplasm optimization ability, and the spatial evolution results may not achieve global optimization, so new cell model that is under the control of multiobjective constraints or meta cell based on agent has become a new development direction.^[22-24] Therefore, a model that can effectively couple quantity structure and spatial structure in microlevel in terms of land use from bottom-up approach becomes a research focus, and the intelligent processing of spatial information provides the solving tool for this optimization pattern undoubtedly.^[25,26] Particle swarm optimization (PSO) is a kind of evolutionary algorithm^[27] that can optimize decision-making by using the information sharing mechanism between particles. At present, some scholars have taken particle swarm into space optimization fields, such as Du, and other researchers used the spatial optimal decision research with particle swarm algorithm.^[28-30] This paper brings a land use spatial optimization model based on the study of mechanism of particle swarm algorithm in order to couple the land resources optimization allocation quantity target and spatial structure effectively.^[31-34] A detailed explanation is given about the design ideas and key technology when using this model. A county area was selected as a case study area to test the optimizing ability of this model thru experiments.

1 PSO for land-use spatial optimization

1.1 Model design ideas

Particle swarm algorithm requires distributing particles random in solution space, and particles update their position and velocity through P_b that is the historical optimum value and P_g that is the global optimum value. All the particles are controlled by inertia weight to search for the optimal solution constantly. Each land-use map spot is abstracted to a particle by its center of gravity or other represent points when PSO is taken into land-use spatial optimization. Par-

ticles constantly fly to adjust their position as to the optimum value of history that is called P_b and the current global optimum values that is called P_g , which both are determined by the fitness function of the particle that is abstracted form land-use map spots.

All the particles work together until they meet the iterative requirements or other limiting conditions, and then, the particles position vector is just the optimization result. The PSO model of land-use spatial optimization is shown in Fig.1.

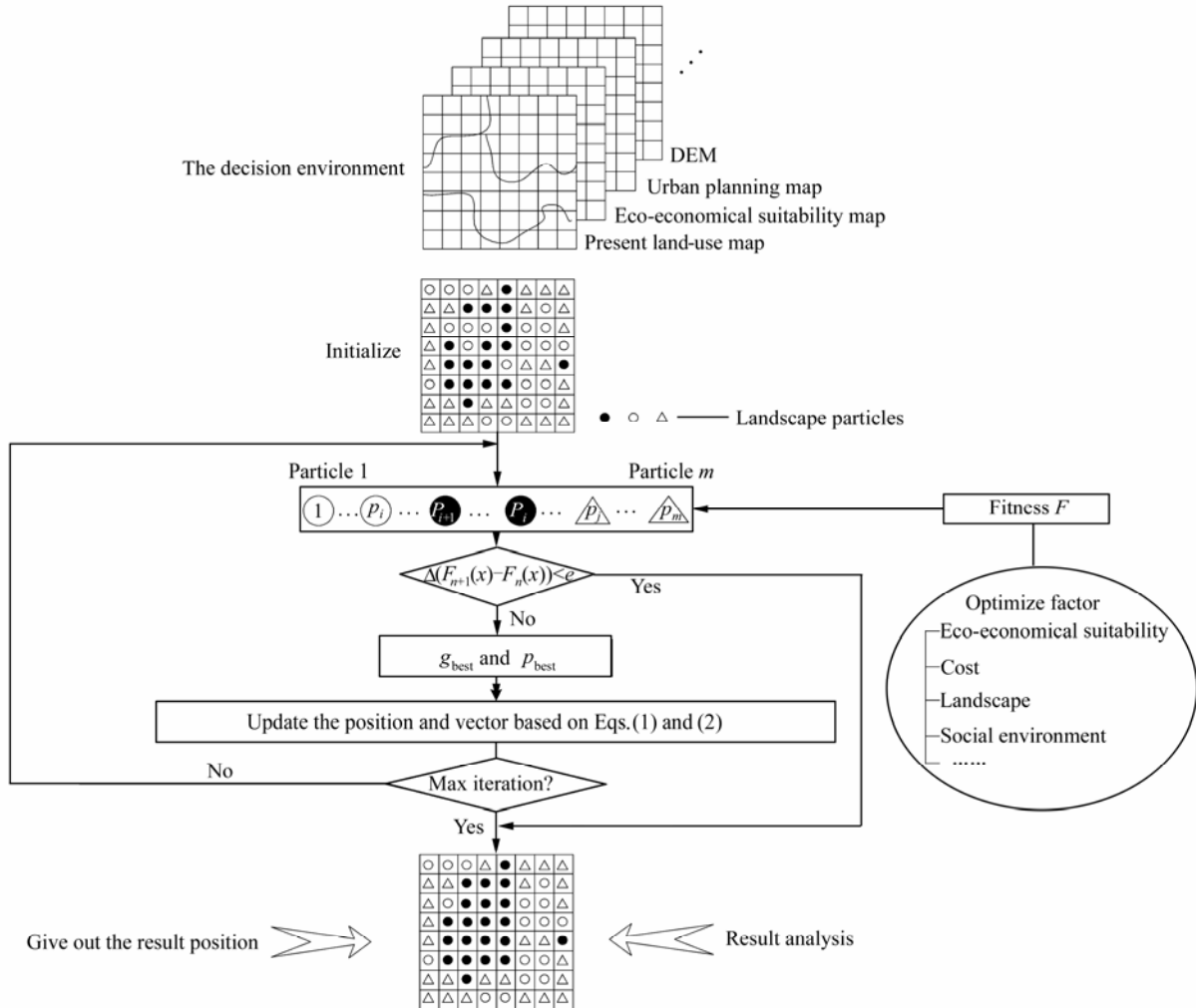


Fig. 1 The model of land-use spatial optimization based on PSO

1.2 Key technology of the model realization

PSO model of land-use spatial optimization is to abstract the land-use map spots into particles that search for their optimal locations in the space by the iterative computation. The particles update their velocity and location with the historical optimum value P_b , which is the particle's own best value in history, and the global optimum value P_g , which is the optimal value of all the optimal values of the similar particles in history. These two values compose the information center for the particles to update their positions. The historical optimum value is the succession of its own information; the global optimum value is

the information sharing between particles; and the particles control their own flight according to the two values. We can use updating rule of inertia weight function to calculate the velocity, and the function is shown in Eq.(1):

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_{1j}(t)[p_{ij}(t) - x_{ij}(t)] + c_2 r_{2j}(t)[p_{gj}(t) - x_{ij}(t)] \quad (1)$$

For function of position adjustment, we have

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

Where $i=1,2,\dots,n; t=1,2,\dots,I_{\max}-1$; t is the iteration times; I_{\max} represents the largest number of iterations; $\omega(t)$ is the inertia weight when it runs to t

times; $r()$ is a random value between $[0,1)$; c_1, c_2 represent different inertia weights; p_{bj} are the historical optimum values of appropriateness; p_{gj} are the historical global values; and σ are modified parameters of location.

1.2.1 Fitness function

The land-use spatial optimization aims to implement the various types of land use in specific space^[31-33] and perform suitability evaluation to the positions of various types of particles that are created at random. Every particle follows the optimal particle that is evaluated by the fitness function to update their positions and velocity to search the optimal location in the solution space. Fitness function is an important parameter for particles to update their positions, and it not only reflects the factors that impact the spatial optimization but also reflects the information shared between the particles, and the fitness of each particle can be described in the following multiobjective programming model:

1) Fee of land use change

$$\text{Minimize } C_k = \sum_{i=1}^n c_{ik} x_{ik} \quad (3)$$

2) Ecological suitability

$$\text{Minimize } S_k = \min_{i|x_{ik}=1} (s_{ik} x_{ik}) \quad (4)$$

3) Landscape pattern

$$\text{Minimize } Z_k = \sum_{i|x_{ik}=1, j|x_{jk}=0, j \in T_i} \sum_{h=1}^{n_{ij}} l_{ijh} x_{ik} \quad (5)$$

$$F = (C_k, M_k, Z_k) \quad (6)$$

This is subject to

$$A_{1k} \leq \sum_{i=1}^n a_i x_{ik} \leq A_{2k}, x_{ik} \in \{0,1\} \quad (7)$$

Where n is the total number of land units; c_{ik} is the expense that required to turn the land-use from the present type into k for the i -th units; s_{ik} is suitability evaluation index for the i -th units used as k -th type; T_i is the set made up of adjacent units of the i -th units; n_{ij} is number of the public edge of unit i and unit j ; l_{ijh} is the length of h -th public edge between unit i and unit j ; a_i is the area of land unit i ; A_{1k} and A_{2k} are the total area of the upper and lower limits for the k -th land-use type, respectively; $x_{ik}=1$ if unit i is just k -th land-use type, or $x_{ik}=0$; C_k is the object of expense for the land-use changes; S_k is the suitability target for

the k -th land-use type; Z_k is the shape target for land units, which represents the compaction of land units; and F is comprehensive evaluation for all the particles' fitness.

1.2.2 Inertia weight

Inertia weight is an important parameter that controls the inertia of particles' velocity, and its role is to balance the particles' capabilities of global and local search. The most popular one is the inertia weight decreasing linearly formula proposed by Shi, which is shown as Eq.(8), ω_{\max} is the largest weight and ω_{\min} is the smallest; t is the current iteration times; and I_{\max} is the total number of iterations for the algorithm. The weight will be getting smaller and smaller with the iteration proceeding. The larger inertia weight can enhance the PSO's capability of global search at the beginning, which can make the particle explore in a large region and approximate to the optimal solution location quickly, while the smaller inertia weight can strengthen the PSO's capability of local search in the late stage, which needs the particle to slow down for precise local search.

$$\omega(t) = \omega_{\max} - t(\omega_{\max} - \omega_{\min}) / I_{\max} \quad (8)$$

1.2.3 Location updating mechanism

As mentioned above, the particles that represent certain types of land use are searching for their most appropriate location in the land-use space, so the best way is to limit every particle to fly between the representative points, such as gravity of each land-use spot, which will guarantee that each particle just represents one land-use spot during each position updating. If particles update their velocity by Eq.(1), we can see that the updating velocity of one particle is a random value, which cannot guarantee that the particles just land in next gravity center in accordance with Newton's mechanics.^[35-37] However, we will not allow particles to update their velocity in the discrete space completely, which will destroy the information sharing. In this paper, the particles updated their position based on the rule that states that particles use the ID number of the land use space to update the location indirectly, as shown in Fig.2, and this requires the particles to update locations in accordance with the random velocity first and then

modify the location of the random result with the rule, as described in the Eq. (2).

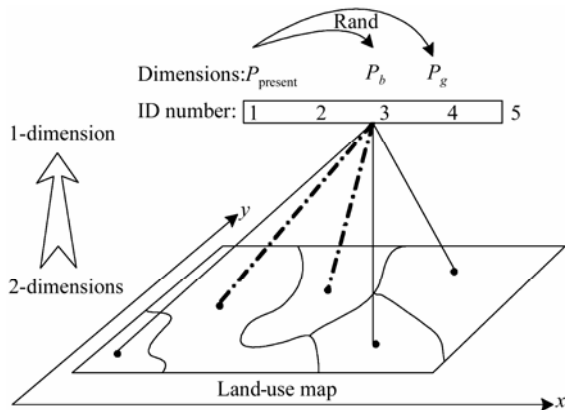


Fig. 2 Position updating rules

The location updating the rule mentioned above can deal with the issue of updating the location of one particle, but if two or even more particles fall on the same spot according to the updating rule, which particle should the spot be accepted? Therefore, the game theory should be considered between two or more particles when using the updating rule.

2 Case study

2.1 Study area

Huangmei is a county that is located in the junction of Hubei, Anhui, and Jiangxi Province of China, in the northern is the east of Dabie Mountain and southern is the Yangtze River (Fig.3), from north to south, a three-level step-wise tilt. Location advantage is very superior, which is known as the eastern gateway of Hubei Province. For nearly a decade, the land use changes significantly because of society and rapid economic development.

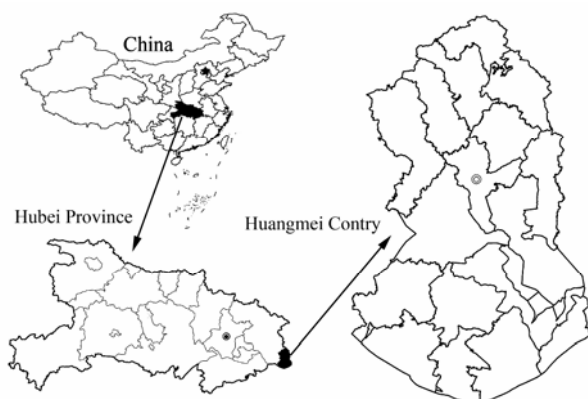


Fig. 3 Location of study area

2.2 Model application

Based on the secondary land-use categories and quantity structure stated by land planning, a county was chosen as the optimization object to verify the model under the framework mentioned above. The current land-use map is shown in Fig.4, and the parameters are set in accordance with the one previously introduced. We just select the maximum number of iterations that is set 150 as the iteration termination conditions in order to make the model with a high operating efficiency, and the maximum flying speed is limited at one tenth of the total numbers of land use spots. The updating of location is decided by optimum game under the control of the position updating rule, which makes sure that when two particles or more compete for the same land-use spot, the victor is the particle that has the highest fitness value. The fitness value is computed by function Eqs.(3) to (7). The optimal solution of PSO is shown in Fig. 5.



Fig. 4 Map of present land use

Judging from the experiments, the results of land use with particle swarm optimization mainly depends on two primary factors that are decision unit space and the optimization decision environment. Land use



Fig. 5 Map of optimization land use

spatial optimization has two basic patterns, namely, grid and vector. Grid is suitable for fine space scale to do land types convert research with the rule shape, and the vector is suitable for optimization in a large-scale space with easy operation, but it may lead to unreasonable land use spot for conversion, for example, the area of A in Fig.5, which are unsuitable for construction land because they are far away from city. The secondary factor is the decision environment, because the particle is changing their positions mainly according to the fitness value, and the optimizing effect is better with a better decision environment. The area of B in Fig.5 is expected to construction land, but the optimization map does not give the right results because we did not set the conditions.

3 Conclusion

The space structure optimization is an important aspect of land-use planning and a difficult point for it. With traditional planning methods, it is difficult to solve this problem because land-use planning is a multiobjective, external, and spatial decision-making sys-

tem project. In this paper, PSO land-use optimization model is brought forward based on information-sharing mechanisms and characteristics of global optimization. The case study has shown that this method could be used in land-use spatial optimization and also has the following characteristics: (1) Good intelligence. The particle can just take the code of conduct of the particles into consideration and have regard to both quantifiable and nonquantifiable factors. The particles can search their best position in the land use space. (2) Simple implementation. Compared with the genetic algorithm that involves complexity coding, the particle swarm optimization is able to finish all the operations just according to two values.

At the same time, this model also has some shortcomings that need to be improved later: (1) Location updating mechanism. Particle swarm algorithm itself requests that the distribution of particles is completely random, and how to better fusion particle swarm group flight behavior and land utilization spatial relationship is the next breakthrough place. Although we propose the gravity center and the updating rule to deal with it, they cannot deal with the losing of information as well as the issue of the games between particles. (2) Algorithm efficiency. The particles mainly do spatial analysis in practical applications, and the computation is growing geometrically with the number of map spots increase, which has been the bottleneck to extend the model in bigger regions and more sophisticated space scale, for instance, in 1: 10000 decision space to set a bottom-up emerging type optimization. To solve these problems, relevant literatures have given us good directions, such as the parameter modification, the parallel computation, the coordination-grid computation, the grid-vector integration data model, etc. In short, this model can be used to simulate the landscape pattern and its evolution by designing appropriate spatial distribution pattern of particles group. However, how to deal with the discrimination space as well as the algorithm efficiency and behavior of particles is the key point that we need to solve. This paper has primarily made some progress in research on the PSO model, but we need plentiful future work to make it an intelligent decision support system of spatial optimization. Although the model has very good space search abil-

ity, how to take the particle swarm with continuous space into the discrete space of the vector map spots, information-sharing mechanisms, the relationship between particle quantity and area, and the games between particles that are not complete yet need further study.

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Notes to Contributors

Contributions are welcomed on one of the following subjects or in related areas:

- | | | |
|-------------|------------------|--------------------------|
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| ★ GPS | ★ Geo-surveying | ★ Engineering surveying |
| ★ RS | ★ Photogrammetry | ★ Mapping apparatus |
| ★ Cartology | ★ Graphics | |

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