LAND-USE SPATIAL OPTIMIZATION MODEL BASED ON PARTICLE SWARM OPTIMIZATION

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ABSTRACT:

The optimization of land-use structure is the core of optimizing the allocation of land resources, including the optimization of quantity and space. However, traditional methods such as multi-objective programming model, gray system, landscape ecology are very difficult to make the space structure and the quantity structure unified effectively. To avoid the deficiencies mentioned above, this paper brings forward the land-use space optimization model based on particle swarm evolutionary algorithm. The results show that this model can analyze the data of multidimensional discrete decisionspace with good space search features and high accuracy in parallel. It can implement the quantity structure of land in a specific geographical space effectively and realize the optimization of regional land-use.

INTRODUCTION

The optimization of land-use structure is the core of optimizing the allocation of land resources, which has long been widely concerned by many researchers. It has formed a number of decision methods based on quantity structure optimization such as Linear Programming, Multi-objective Optimization, Multi-criteria Optimization and System Dynamics etc, and spatial optimization methods which include Landscape Ecology and Cellular Automata (CA) model(Lv C Y etc，2006 and Liu R X etc,2005 and Xu X B etc,2007). However, the traditional optimization models of land resources are mostly limited to optimize the structure of quantity or space, lacking the effective unification of the quantity structure and space structure. The development of computer technology and geography information has offered a strong technical support for the analysis of spatial data when making spatial optimization decision for land-use. Combine the mathematical methods with GIS and realize the reasonable allocation of the 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. At present, there have been several models such as Multi-objective Genetic Algorithm (Dong P J etc, 2003) and Multi-objective Cellular Automata (Dong P Jie etc, 2008), etc. Although genetic algorithm has strong capability of global optimization, it involves complicated map spot coding, which makes the program difficult to realize, and it doesn’t have strong capability of spatial correlation; the multi-objective cellular automaton model performs timing simulation by CA based on the results of multi-objective optimization, which can not realize trans-space search. Particle Swarm Optimization (PSO) is a kind of evolutionary algorithms, derived from the research on the predation behavior of bird flock and it is able to analyze the data of multidimensional discrete decisionspace in parallel. Some scholars have already introduced the particle swarm optimization into spatial optimization, such as Du *Guoming*, Chen *Xiaoxiang* and Li *Xia* did the research about location decision using particle swarm optimization algorithm in 2006, which verified the feasibility of making spatial optimization based on PSO; Yu *Yan* and He *Jianhua* brought forward the thought that combining the game theory with particle swarm optimization to make spatial optimization of land-use. In this paper, we try to resolve the unification of quantity structure and space structure of land-space effectively based on PSO.

1 PSO FOR LAND-USE SPATIAL OPTIMIZATION

1.1 Model design ideas

Particle swarm algorithm requires distributing points (particles) random in solution space and particles update their position and velocity through *Pb* that is the optimal value of the history and *Pg* that is the global optimal value. All the particles are controlled by inertia weight to search for the optimal solution constantly. When PSO is taken into land-use spatial optimization, each land-use map spot is abstracted to a particle by its center of gravity and each particle has its own species，including i, location x and y. The particles of same species (such as construction land) constitute the subsystem of particle swarm system and all the particles make up the particle swarm system. Each kind of particles searches their optimal values in solution space through the information sharing of interspecific and intraspecific. If the target region is made up of n map spots, then initialize all the map spots into n

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particles, k species. Particles constantly fly to adjust their position as to the optimal value of history that is called *Pb* and the current global optimum values that is called *Pg*, which are determined by the fitness function. All the particles work together till meet the iterative requirements, and then the particles' position vector is just the optimization result. PSO model of land-use spatial optimization is shown as Figure 1.

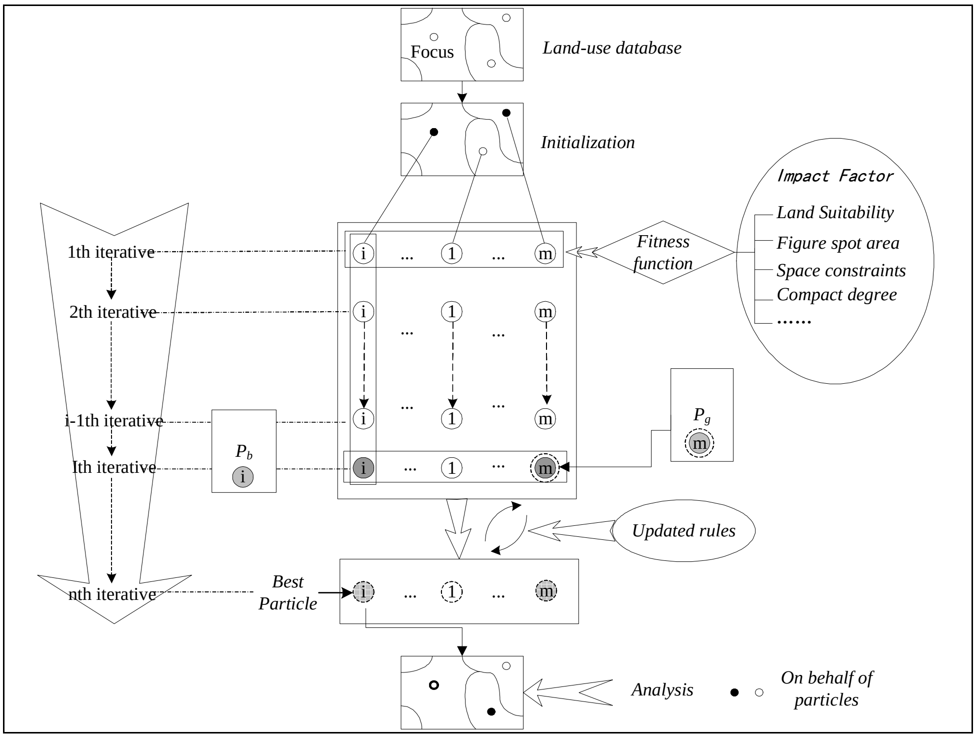

Figure.1 The model of land-use spatial optimization based on PSO

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 *Pb* which is the particle's own best value in history and the global optimum value *Pg* 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 and 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 as the formula (1):

$$\begin{cases} \upsilon_{xi}(t+1)=\omega(t)\upsilon_{xi}(t)+c_1*rand()*(p_{bx}(t)-x_i(t))+c_2*rand()*(p_{gx}(t)-x_i(t)) \\ \upsilon_{yi}(t+1)=\omega(t)\upsilon_{yi}(t)+c_1*rand()*(p_{by}(t)-y_i(t))+c_2*rand()*(p_{gy}(t)-y_i(t)) \end{cases} \tag{1}$$

Function of position adjustment:

$$\begin{cases} x_i(t+1)=x_i(t)+\upsilon_{xi}(t+1)+\sigma_1 \\ y_i(t+1)=y_i(t)+\upsilon_{yi}(t+1)+\sigma_2 \end{cases} \tag{2}$$

Where: $i=1,2,\cdots,n$; $t=1,2,\cdots,I_{\max}-1$, t is the iteration times and $I_{\max}$ represents the largest number of iterations; $\omega(t)$ is the inertia weight when it runs to t times; $rand()$ is a random value between $[0,1)$; c_1,c_2 represent different inertia weights; $p_{bx}(t), p_{by}(t)$ are the historical optimum values of appropriateness on x-axis and y-axis; $p_{gx}(t), p_{gy}(t)$ are the historical global values on x-axis and y-axis; σ_1,σ_2 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, and perform suitability evaluation to the positions of various types of particles which are created at random. Every particle follows the optimal particle which 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, otherwise particles will fall into a dilemma of single-objective optimization. Land-use spatial optimization is a problem of multi-objective optimization, and the fitness of each particle can be described as the following multi-objective programming model (Liu H T etc, 2006 and Guo P etc, 2005):

$$Minimize\ C_k = \sum_{i=1}^{n} c_{ik} x_{ik} \tag{3}$$

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

$$Minmize\ \ Z_k = \sum_{i|x_{ik}=1,\ j|x_{jk}=0,\ j\in T_i} \sum_{h=1}^{n_{ij}} l_{ijh} x_{ik} \tag{5}$$

$$F = (C_k, M_k, Z_k) \tag{6}$$

Subject to:

$$A_{1k} \le \sum_{i=1}^{n} a_i x_{ik} \le A_{2k}\ ,\ x_{ik} \in \{0,1\} \tag{7}$$

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; $A1k$ and $A2k$ is the total area of the upper and lower limits for the k-th land-use type; 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; 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 showed as formula (8), $\omega_{\max}$ is the largest weight and $\omega_{\min}$ is the smallest; t is the current iteration times; $I_{\max}$ 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.

1.2.3 The location updating mechanism

As mentioned above, the particles which 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 gravity centers of each land-use spot, which will guarantee each particle just represents one land-use spot during each flight. If particles update their velocity by formula (1), we can see that the updating velocity of one particle is a random value, which can not guarantee the particles just land in next gravity center in accordance with Newton's mechanics. However, we won't 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 nearest neighbor rule that requires the particles to update locations in accordance with the random velocity first, then modify the location of the random result with nearest neighbor rule as is described in the formula (2).As is shown in Figure 2, the particle may update its location to point A, which is not out of the primary spot, therefore, the particle should modify its location from A to A1; meanwhile, the particle may also fly out of the primary spot but did not exactly fall into the gravity center of next land-use spot, for example, it reaches point B, so in accordance with the nearest neighbor rule, the particle should be modified from B to B1.While the particle update its position in accordance with the nearest rules from B to B1 can not guarantee the point B1 is the gravity center of land-use spot which contains point B because of the special shape of spot.

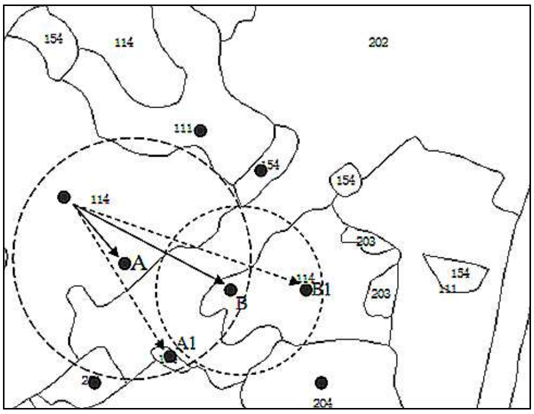

Figure.2 Sketch map of location update

The nearest neighbor rule can deal with the issue of updating the location of one particle, but if two or even more particles fall on the same gravity center according to the nearest neighbor rule, and which particle should the spot accepted? Therefore, the game theory should be considered between neighbor particles when using the nearest neighbor rule. Secondly, a class of particles represents a land use, so the total area of a special land-use is different according to the particles' updating, so we should control the scope of the total area in the fitness function in order to reflect the flexible mechanism of land area control well.

2 THE PROCESS OF LAND-USE SPATIAL OPTIMIZATION BY PSO

The land-use spatial optimization is to find the best combination of land-use by combining the computational intelligence with GIS technology on the base of data. The main process of PSO land-use spatial optimization model is as follows (Du G M etc, 2006 and Zheng X W,2008):

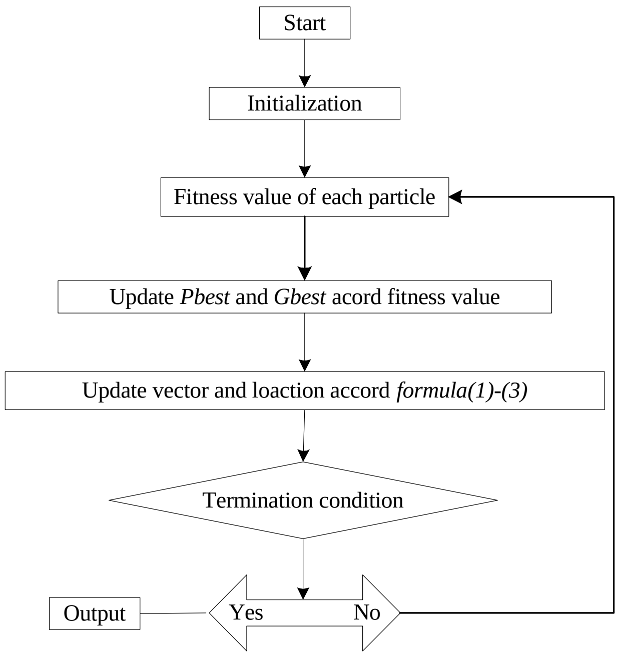

Figure.3 Flow chat of PSO model

1) Extracting GIS data

The essence of land-use spatial optimization by PSO is to carry out arithmetic operations on the land-use spot with the support of GIS platform, so a lot of factors should be considered about the optimization process such as the results of land suitability evaluation, area and perimeter of map spots, the limits of each land type in area and so on. All the factors that impact land spatial optimization must be collected into database to meet the need of spatial analysis.

2) Set parameters of PSO

These parameters include the number of particles *n*, type *k*, the maximum speed of the particles in the direction of *x* and *y*, the acceleration weight *c1* and *c2* and the largest number of iteration I_{max}.

3) Initialize the position, velocity and attribute of each particle

The initialization is a key job when optimize land-use, and how the particles are created has a significant impact on the PSO model. Each particle is flying in space with information in the optimization model. The position of each particle is randomly distributed when initialize, so we should initialize *n* particles which are flying to search their optimal locations until termination conditions are met. In this study there is some difficult work because of the uncertain shape of map spots which bring a lot of inconvenience to initialization and updating of the particles' location. Each particle flies in space to search a map spot suitable for it, and he updating of each particle should be limited between gravity centers of map spots in order to ensure that each particle is on behalf of a single spot at its each flight. However, we can not make this model in the discrete space completely, or the information sharing between particles will be destroyed. In this experiment, the particles first update their locations at the random speed and then modify their location with the nearest neighbor rule, so we should get all map spots' gravity centers and store them in the database then initialize each particle's location in the database. The initialization type *k* is a factor of statistical relationship between the particles' number and the average area of the map spots, and both the area of map spots and the regeneration area of particles are uncertain, so the scope of area should be controlled. And the initializing velocity can be directly expressed as fellows:

$$\begin{cases} \upsilon_{xi} = rand * \upsilon_{x\max} \\ \upsilon_{yi} = rand * \upsilon_{y\max} \end{cases} \tag{9}$$

Where: υ_{xi} and υ_{yi} represent the speed of particles in the direction of *x* and *y*.

4) Calculate inertia weight

The inertia weight is calculated according to the formula (8), where: *t* is the iteration times and $t = 1, 2, \cdots, I_{\max}$, $I_{\max}$ is the largest number of iterations. $\omega_{\max}$ is the maximum inertia weight which is usually set 0.9 and $\omega_{\min}$ is the minimum inertia weight which is usually set 0.4. As to the formula (8), we can see that the inertia weight decreases linearly with the iteration times. From the whole process of the optimization, the pre-expansion of search need a large inertia weight while the latter stage needs a smaller inertia weight because the particles mainly search in the vicinity of the optimal solution.

5) Calculate the fitness value for each particle

The fitness value of each particle is calculated according to the formula (3) - (7).

6) Select current optimum value and global optimum value

To the optimal spatial distribution of land-use, the current optimum value *Pb* is the largest fitness value of particle of the history before the *t*-th iterations which could be described as Max*F(t)* and global optimal value *Pg* is the maximum optimal value of the current optimal value of all the types of particles which could be described as Max*Pb*, where $t = 1, 2, \cdots, I_{\max}$.

7) Update each particle's velocity and the current location

The particle should be updated its velocity and location according to the current optimum value *Pb* and the global optimum values *Pg* under the control of the nearest neighbor rule. In order to prevent particle's velocity from increasing infinitely and presenting a disordered state, a group of constraints should be added which are described as follows:

$$\begin{cases} \upsilon_i = \upsilon_{\max} & \text{if } \upsilon > \upsilon_{\max} \\ \upsilon_i = -\upsilon_{\max} & \text{if } \upsilon < -\upsilon_{\max} \end{cases} \tag{10}$$

Maximum velocity of flight limits the speed of particles, which determines the particle's searching accuracy in the search space. If the value is too large, the particles are easy to miss the optimal location; while if the value is too small, the particles fly slowly and are easy to fall into local search and can not get global optimal solution.

8) Check the conditions of termination

If the iteration times exceeds the largest iteration number (it is an experience value, for example I_{max}=150), then the process stops iterating. This condition is used to terminate the cycle compulsorily in order to prevent the process fall into dead circulation. What's more, we can also use other termination conditions such as controlling the average error of accuracy etc. The particles' vector location that corresponds with the global optimum value we get at last is the optimal combination of the target types of land-use.

9) Mapping and Analysis

When the particle swarm meets the termination conditions, the particles' position vector is the location of the target types of land-use in space. This model is suitable for land-use spatial optimization because it can optimize on the micro level such as land-use spot.

3 CASE STUDY

A township land-use planning was chosen as the optimization object to verify the model under the framework mentioned above. The current land-use map is as shown in Figure 4 which has a total of 781 map spots and the experiment is supported by MO2.4 and VB6.0; other parameters are set in accordance with previously introduced. We just select the maximum number of iterations which 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 height of the region. The updating of location is decided by optimum game under the control of the nearest neighbor rule, which makes sure that when two particles or more compete for the same land-use spot, the victor is the particle which has the highest fitness value. The fitness value is computed by function formula (3) to (7). The optimal solution of PSO is shown in Figure 5, and from the results we can see that all the particles have reached their optimal centers. For example, the unutilized land is developed if the cost is reasonable; the land around the city is generally agricultural land. Overall, the layout in line with the principle of concentration and the area is controlled in the flexible framework, and the spatial structure is reasonable too. But there are also some problems, such as some long and narrow plots are zoned for general agricultural land which is not suitable in the space and the total area of each kind are varying at each flight.

Compared with other models, PSO has significant advantages: the particle can make cross-space search under the control of fitness value which breaks the restrictions that limits in neighborhood and can make the quantity structure and space structure close-coupled. Although the model has very good space search ability, how to use the particle swarm from vector space to discrete space and information-sharing mechanisms, the number and area of particles and the games between particles need further study.

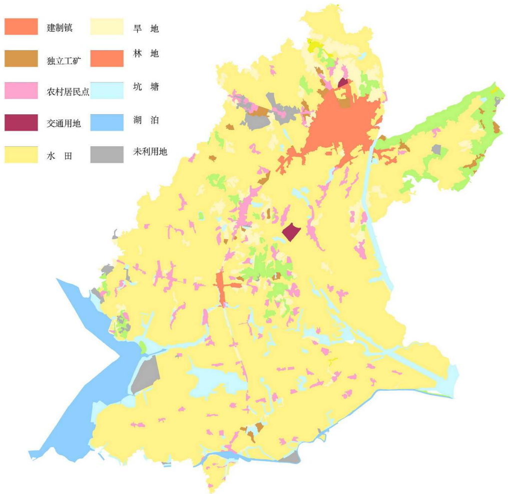

Figure.4 The current map of land-use

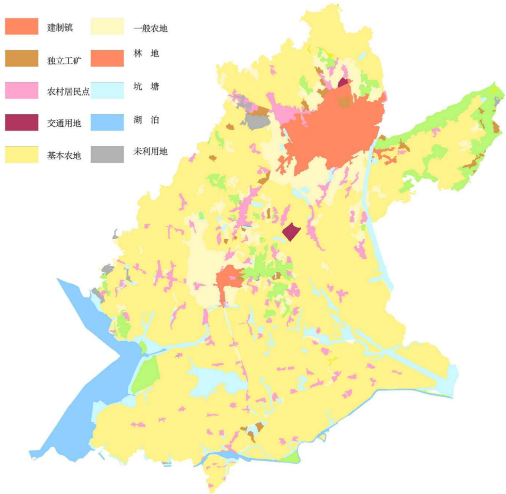

Figure.5 The optimization map of land-use

4 SUMMARIES

The space structure optimization is an important aspect of land-use planning and a difficult point for it. Traditional planning methods are difficult to solve this problem because land-use planning is multi-objective, external and spatial decision-making system project. In this paper, PSO land-use optimization model is brought forward based on information-sharing mechanisms and the characteristics of global optimization. The case study has shown that this method has following advantages: 1) Good intelligence. The particle can just take the code of conduct of the particles into consideration and have regard to both quantified factors and non-quantifiable factors. The particles can make discrete jumping searching, too. 2) Simple implementation. Compared with the genetic algorithm which 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 which need to be improved latter: 1) Location updating mechanism. Particle swarm algorithm itself requests the distribution of particles is completely random, but there is no continuous state in land-use space. All particles are advancing by leaps and bounds. Although we propose the nearest neighbor rule to deal with it, the rule can not deal with the loosing 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. To solve these problems, relevant literatures (Wang J W etc, 2009 and Wang W L etc,2007 and Gong Q,2008)have given us good directions, such as modifying the parameters, quantum PSO, grid computing and grid-vector data model, etc. In short, PSO has strong space search ability, could deal with non-constant factors and couples the structure of quantity and space effectively. However, how to deal with the discrimination space as well as the algorithm efficiency is the key point that we need to solve.

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Overall， land-use planning plays an important role in China's land resource management and economic macro-control. The techniques and methods of land-use planning should be improved constantly, which has better prediction ability, high credibility and accurate spatial location, to meet the development of land-use planning.

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