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Comprehensive Evaluation Model for Resettlement Site Selection in Karst Areas Using Multiobjective Particle Swarm Optimization

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ABSTRACT Resettlement site selection is a systematic project constrained by multiple geographic, social, and economic factors, and site selection in karst mountainous areas is even more complicated. The key step in resettlement site selection is to reduce the uncertainty and inaccuracy of evaluation models. This study constructed an evaluation index system of a model for resettlement site selection in karst mountainous areas from multiple aspects, including karst rocky desertification environment, degree of geological hazard development, resource and environmental carrying capacity, transportation and economic development potential, as well as relocation cost. A hierarchical model was applied to classify the indices, determine the weighted optimal solution of the eigenvectors in matrices, and evaluate the suitability. A new algorithm for model parameter inference was developed based on four objectives, including achieving suitable ecoenvironment capacity, ensuring production and development, controlling relocation cost, and meeting the comprehensive requirements. The objective functions and constraints of the model with four objectives were also established. To address this problem, the multiobjective particle swarm algorithm was applied, and a novel concept of ‘‘noninferior solution set’’ was proposed. The objective functions and constraint conditions of the algorithm were optimized and improved from four aspects: parameter setting, representativeness of particles, noninferior solution set storage, and selection of global noninferior solution set. Guanling County, an area in Guizhou Province with a typical development of karst rocky desertification, was selected as the study site. The latest data for land use mapping were adopted as the smallest evaluation unit, and the improved multiobjective particle swarm algorithm was employed in evaluating the resettlement site selection within this area. The improved algorithm was applicable to a wide range of multiobjective optimization problems.

INDEX TERMS Resettlement site selection, karst mountainous area, multiobjective, particle swarm algorithm.

I. INTRODUCTION

Settlement site selection in karst mountainous areas is a complex systematic project that faces many challenges, and it is also a multiconstraint, multiobjective optimization problem [1], which is highly non-trivial due to the geological background of extensive karst development. Specifically, in karst mountainous areas, disturbance and destruction by excessive social and economic activities of mankind have caused severe soil erosion, extensive exposure of bedrock, substantial decline in land productivity, and land surface being prone to land degradation similar to a barren landscape [2]. Improper site selection in these types of areas will have a relatively great social impact. For a large resettlement population from large-scale water conservancy projects, resettlement issue is essential to the success of the entire

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migration process of the involved population and the life and property safety of a vast number of immigrants. The key to addressing the site selection issue is to establish an effective and feasible evaluation index system and the corresponding evaluation method to comprehensively assess the suitability of the resettlement area in terms of geological conditions, resources, and environment [3]–[5]. Currently, research on evaluation methods of resettlement site selection has primarily focused on the Three Gorges Project, South-to-North Water Diversion, and other large-scale water conservancy projects. To the best of our knowledge, there lacks in-depth research on karst and other geomorphological backgrounds [6], [7].

First, in-depth research is required when selecting the location of resettlement sites due to the sensitivity and fragility of the environment in karst mountainous areas [8], and it needs to be carried out with greatest care and effort because the safety of the life and the property of the people to be relocated depend on the selected sites. In addition, the complexity of the karst environment increases the difficulty and intricacy of the evaluation of the entire resettlement site selection [9]. For a long period of time, karst mountainous areas have formed a highly developed landscape with dissolution of carbonate rocks and rocky desertification [10]. Natural conditions impose multifaceted influence on the selection of resettlement sites, with the facets inextricably linked, which not only reflect the extraordinary craftsmanship of nature but also post great challenges to scientific and engineering calculations. Various aspects need to be considered to construct an evaluation index system for resettlement sites selection, such as rocky desertification environment, development degree of geological hazards, carrying capacity of resources and the environment, transportation and economic development potential, and cost of relocation in the karst mountainous areas [11]. Scientific research and engineering practice with higher accuracy and depth are required to ensure the proper selection of resettlement sites [9].

Based on the above objectives, the research content of this paper has at least the following contribution significance in this field:(1) Through this study, the influencing factors of resettlement site selection in karst areas are systematically analyzed, and the corresponding evaluation index system is established to provide support for scientific evaluation. (2) In the typical complex karst mountain area resettlement site selection problem, the artificial intelligence algorithm is proposed for the first time to analyze and evaluate the problem. (3) Based on the special objective background, a multi-objective improved swarm intelligence algorithm is proposed to study the site selection of reservoir resettlement, and the corresponding strategies and methods are improved, which provides a new way for the calculation of site selection of reservoir resettlement in karst areas. (4) Taking Guanling County, Guizhou Province, a typical karst landform area, as an example, engineering practice is carried out according to the proposed algorithm strategy, and a variety of algorithms are compared to test the research results, which provides a reference model for the application of more projects in the future.

II. RELATED WORK

Optimal site selection has always been a hot research topic, which is essentially a sophisticated mathematical problem with multi constraints. There are also plenty of studies on related algorithms, from traditional optimization methods (e.g., heuristic algorithm [12] and enumeration method [13]) to relevant evolutionary artificial intelligence algorithms (e.g., neural network algorithms [14] and support vector machines [15]) and to the emerging swarm intelligence algorithms (e.g., particle swarm algorithm [16], artificial immune algorithm [17], and ant colony algorithm [18]). Many of these methods have been applied and thoroughly verified in practice. However, there are few studies on intelligence algorithms for the selection of resettlement sites, especially in the context of the complex and fragile ecological environment in karst mountainous areas.

With the development of computer technology, artificial intelligence has sprung up and been going through rapid development [19]. It has become an important technology for modern scientific research and been widely applied in many fields, such as project analysis and regional evaluation. As one type of artificial intelligence algorithms, BP neural network has the advantages of high-speed calculation and learning, capable of theoretically approximating any nonlinear continuous function. It has demonstrated appealing performance in prediction and evaluation in complex decision-making situations [20]. Nie [21] applied BP neural network algorithm to investigate the site selection and evaluation of logistic centers. The site location and evaluation of logistic centers established according to the BP neural network could objectively reflect the mapping relationship between the distribution capacity of the logistics center and the key elements affecting site selection. A site selection model was established, which was able to objectively analyze the distribution capacity of established networks and provide decision-making guidance to the location and relocation of logistic centers. Wong *et al.* [22] investigated the site selection of clothing manufacturing factories based on neural network models and proved that neural network models were of decent practicability and operability in selecting the location of clothing manufacturing factories.

Currently, as engineering challenges become more complex, with ever-increasing degree of nonlinearity, it has become increasingly more difficult to solve complex problems with one single method. Artificial neural networks and support vector machines will eventually be transformed into optimization problems. In other words, the final training accuracy of the abovementioned two methods depends entirely on the results of parameter optimization. If the parameter optimization falls into a local optimum, it will directly lead to low fitting accuracy. Due to the high degree of nonlinearity associated with the problems, traditional optimization methods cannot completely meet the practical needs in terms of the accuracy and convergence speed. Therefore, more researchers have been trying to combine multiple methods, especially swarm intelligence optimization methods, to obtain a better solution [23].

Without centralized control and global models, swarm intelligence optimization algorithms take advantage of crowd distribution to perform search. These methods can find the optimal solutions of complex optimization problems more quickly than traditional optimization methods, thereby providing new ideas and methods for searching the optimal solutions for complex issues. Rongrong *et al.* [24] conducted an in-depth study on site selection of highway central stations based on immune genetic algorithm and proposed a theoretical framework for selecting highway central station sites. The factors that impacted the site selection of highway central stations were utilized to set the targets and establish the model for selection highway central station sites. The model was further transformed, and immune genetic algorithm was applied to obtain the solution for the model and the optimal scheme of site selection. Tao [25] investigated the site selection of TD-SCDMA base stations based on immune optimization algorithm and verified the feasibility and practicability of the model and algorithm in the application of TD-SCDMA base station site selection using specific examples. Zhi *et al.* [26] applied a hybrid particle swarm algorithm to logistics center site selection. They established a mathematical model, utilized particle swarm algorithm and queuing theory to deal with time and resource constraints in process optimization, and applied heuristic algorithm to optimize the transportation issue. Finally, the algorithm was verified by a product test, and the results showed that the method is effective. Gong *et al.* [27] Ammar *et al.* [28] Shao *et al.* [29] Zhang *et al.* [30] Zhang *et al.* [31] proposed to study multi-objective optimization algorithm based on different strategies.

Overall, a systematic approach has not been formed for the site selection problems. Currently, more research has been conducted by evaluation methods, while less was done by optimization models. In terms of the research on site selection by evaluation methods, there are qualitative studies but less quantitative research. Regarding the optimization model research, there are more application studies based on basic site selection models, but there is less research involving theoretical innovations. In view of the model research, there are more plane site selection studies but less works on network location research. In recent years, the relatively advanced site selection studies have mostly focused on site selection of logistics centers, followed by public facilities. Due to the special environmental background and population displacement management scenario of resettlement in karst mountainous areas, research is rare in this field.

III. METHODOLOGY

A. EVALUATION INDEX SYSTEM

Based on the resources and environmental conditions in karst mountainous areas, especially in areas with extensive and thorough development of carbonate rock dissolution and rocky desertification, an evaluation index system for determining the suitability of resettlement sites for displaced population was established. The weights of the proposed evaluation indices were calculated using relevant quantitative calculation methods. According to certain site selection principles with a focus on the selection process, the primary influencing factors were comprehensively and systematically analyzed to reflect the basic needs of the displaced population in karst mountainous areas. Based on the existing research results, the environmental background and conditions in these areas were examined, which was combined with the requirements of the Guizhou ecological resettlement general plan and the rocky desertification control plan to be applied to the initial selection of the influencing factors of the indices. Through field study, the initial influencing factors were screened. Then, the selected index factors were modified through consulting with experts to ensure their rationality, which were finally utilized to establish an evaluation index system for the site selection of resettlement areas for the displaced population in karst mountainous areas. Corresponding quantitative calculation methods were used to calculate the weight of the evaluation indices.

According to the formed index system and the environmental background and conditions of the study area, the development pattern and influencing factors of individually selected operators in the study area were arranged and analyzed to generate digital outcomes and discover their corresponding level distribution patterns.

The purpose and goals of the resettlement are to eliminate serious environmental threats to the displaced population, as well as to improve their living conditions and economic situations after the resettlement. At least two objective functions, namely, the survival-based optimal site selection function and the development-based optimal site selection function, are needed for the resettlement site selection. Additionally, the penalty term coefficients are introduced to combine multiple objective functions into a single objective function to obtain the optimal solution.

Through survey and related data analysis, six major factors and fourteen basic evaluation indices were determined for estimating the suitability of resettlement sites (Table 1). In particular, the six factors include geological environmental factors, natural disaster development factors, karst environmental factors, land water source factors, transportation factors, and economic development potential. The fourteen basic evaluation indices are surface slope, engineering geological rock formation types, development degree of flood and drought hazards, development degree of geological hazards, degree of karst development, development degree of rocky desertification, external transportation readiness, internal transportation readiness, per-capita cropland area, cropland quality and grade, water quality, water quantity, industrial and agricultural resources, and tourism resources.

In this paper, the optimization transformation and algorithm implementation are carried out from four aspects:

TABLE 1. Suitability evaluation index system of resettlement site selection in karst areas.

Index system	Primary index	Secondary index
1	Geological environmental factors	Geological slope
2		Rock formation type
3	Natural disasters	Development degree of flood and draught hazards
4		Development degree of geological hazards
5*	Karst environment	Degree of karst development
6		Development degree of rocky desertification
7	Land and water resource	Per-capita cropland area
8		Cropland quality and grade
9		Water quantity
10		Water quality
11		Readiness of internal transportation system
12	Transportation factor	Readiness of external transportation system
13	Economic potential	Industrial and agricultural resources
14		Tourism resources

* Evaluation index system for resettlement site selection in karst areas

parameter setting, particle representativeness, non inferior solution group storage and global non inferior solution group selection. Especially, in order to realize the proposed "land class aggregation + internal difference" optimization strategy, all data are aggregated on the basis of land use map data as the smallest unit, In order to scientifically determine the initial population particles.

The distribution of some indices is listed in Figs. 1–6.

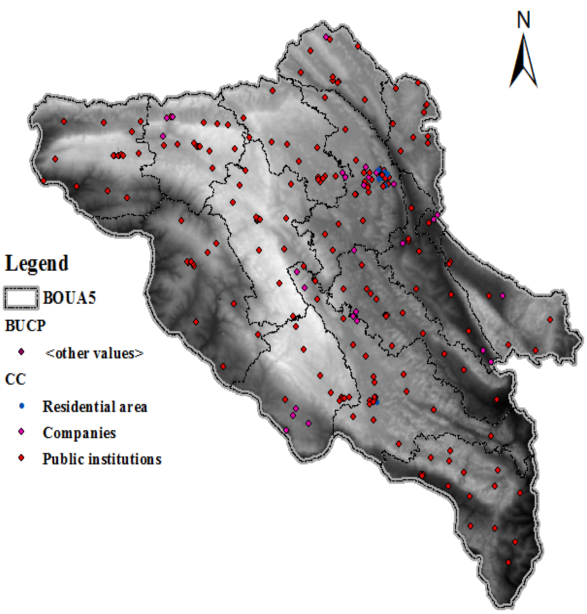

FIGURE 1. Distribution of infrastructure development in Guanling county.

(According to the relevant land slope grading standards, it is divided into four grades: degree 1-5 is flat slope, degree 5-15 is gentle slope, degree 15-25 is slope, and degree >25 is steep slope.)

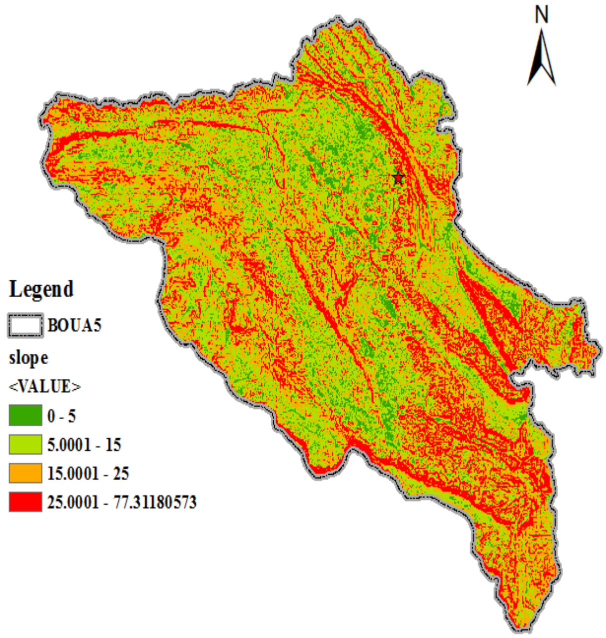

FIGURE 2. Slope map of Guanling county.

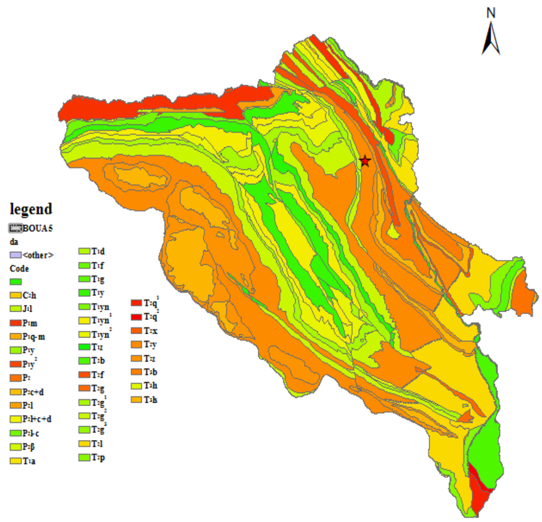

FIGURE 3. Strata distribution in Guanling county.

First, classification grades were set up for the resettlement site evaluation system. According to relevant references and actual conditions, four grades were established, including: (I) suitable, (II) relatively suitable, (III) suitable threshold, and (IV) poorly suitable. The grade of evaluation indices should be comprehensively determined, taking into consideration the grade of the object to be evaluated (Table 2).

(a): Geological slop; (b): Rock formation types; (c): Rock formation types; (d): Development degree of geological hazards; (e): Degree of karst; (f): Development degree of rocky; (g): Per-capita cropland area; (h): Cropland quality and grade; (i): Water quantity; (j): Water quality; (k): Readiness of

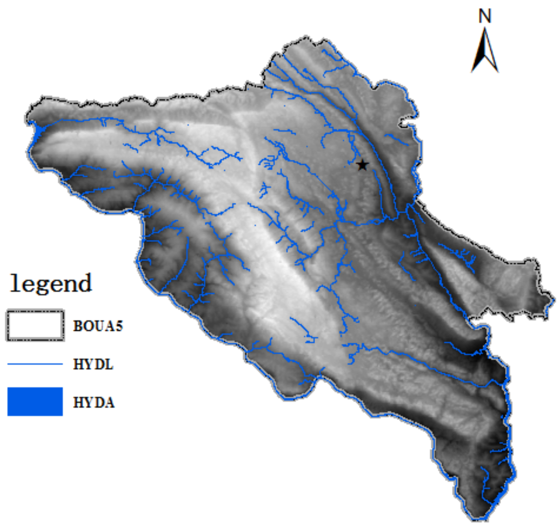

FIGURE 4. Hydrological map of Guanling county.

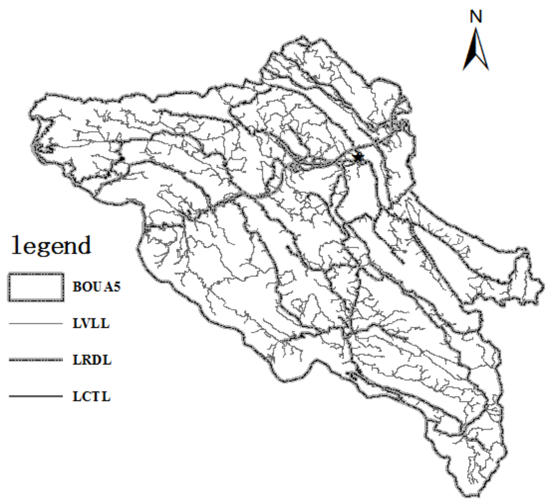

FIGURE 5. Transportation map of Guanling county.

internal transportation system; (l): Readiness of external transportation system; (m): Industrial and agricultural resources; (n): Tourism resources.

B. ALGORITHM

Particle swarm optimization (PSO) is an optimization algorithm established based on swarm intelligence simulation shares many similarities with evolutionary algorithms such as genetic algorithm. It needs to initialize the population, calculate the fitness values, and iterate through evolution. Compared with genetic algorithms, the advantages of particle swarm algorithm include that it is relatively easy to code, and there are only a few parameters for adjustment, making it applicable to engineering projects. However, there are also problems associated with traditional particle swarm algorithm. For example, the initial population might not be reasonably determined, which may lead to local optima, the single objective determination is not suitable for practical engineering projects, or there exist random global optima.

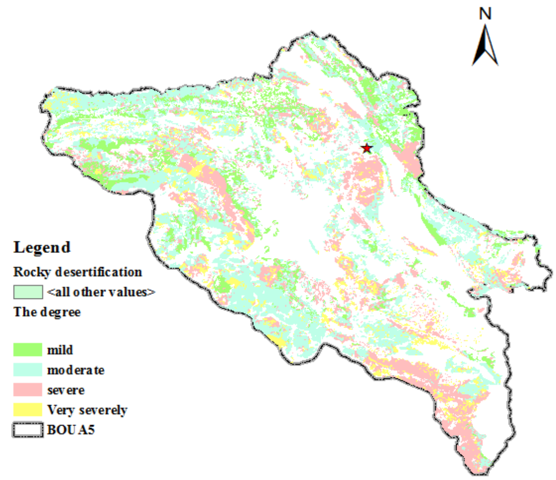

FIGURE 6. Rocky desertification in Guanling county.

TABLE 2. Detailed grade classification of evaluation indices.

No.	Indices	Suitable (I)	Relatively suitable (II)	Suitable threshold (III)	Suitable threshold (III)
1	(a)	<5	<15	<25	>25
2	(b)	Hard blocky rocks	Relatively hard	Soft and hard	Soft clastic
3	(c)	None	100 years	50 years	>50 years
4	(d)	None	Low	Medium	High
5	(e)	None	Sub-karst	Mild-karst	Complete
6	(f)	None	Mild	Medium	Severe
7	(g)	2	1.5	1	<1
8	(h)	Grades 1–4	Grades 5–8	Grades9–12	Grades 13–15
9	(i)	Abundant	Relatively abundant	Normal	Poor
10	(j)	I	II	III	<III
11	(k)	Hardened road	Gravel road	Dirt road	No road
12	(l)	0–2 km	2–5 km	5–8 km	>8 km
13	(m)	Abundant	Relatively abundant	Normal	Poor
14	(n)	Abundant	Relatively abundant	Normal	Poor

*Slope classification can be classified according to the slope classification of detailed geomorphological maps used by the Commission of Geomorphological Survey and Geomorphological Cartography of the International Union of Geography. The cultivated land quality grade refers to "China cultivated land quality grade investigation and assessment", the water quality and quantity refers to "surface water environmental quality standard" (GB3838-2002); The development degree of flood and drought disasters should refer to the Classification Standard of Major Natural Disasters in China.

According to the characteristics of the resettlement site selection in karst mountainous areas, PSO has been proposed to solve the site selection optimization problem.

As the resettlement site selection is a complex social and economic issue, the task here is not to simply find the unique and optimal solution. Different decision makers will have distinct understanding of the issues and various decision objectives. Multiobjective algorithm models can be used to generate a set of optimal solutions which, as noninferior solutions, are then sorted and calculated, so that multiple subobjectives can be optimized as much as possible in a coordinated fashion.

The evaluation results of traditional data models were analyzed. In combination with the natural mechanisms of karst landscape and rocky desertification, the study was carried out using parameter settings, multiobjective noninferior solution storage, evaluation strategies, and sample selection. Various strategies such as centering on rapid convergence, avoiding local extrema, in-depth search, and extensive development have been considered. According to the complexity of the real situation, appropriate strategies have been proposed to improve the algorithm model and complete the global optimization.

1) PROBLEM ANALYSIS

Due to the complexity and fragility of karst environment, the objectives of site selection for resettlement in the karst area need to meet the needs of project construction, ecoenvironmental capacity limitation, and sustainable development. Accordingly, three target scenarios were proposed, and the objective functions were established with corresponding dimensions, as follows: (a) suitability of ecological environment capacity, (b) guarantee of production and economic development, (c) controllability of relocation costs, and (d) comprehensive requirements.

2) OBJECTIVE FUNCTIONS

a: OBJECTIVE FUNCTION OF THE ECOENVIRONMENTAL CAPACITY

Ecoenvironmental protection is the basis of resettlement site selection in karst areas. The evaluation of ecoenvironmental protection is a comprehensive assessment on land resources, involving a multitude of factors and requiring comprehensive consideration of ecoenvironmental suitability grade indices, such as topography and degree of karst development. It is expressed in the following equation:

$$\mathrm{F(e)} = \frac{\sum_i^I S_i M_i}{\sum_i^I M_i} \tag{1}$$

where i is the id of land figure, I is the count of all land figure, F(e) is the objective function of ecoenvironmental protection, S is the suitability grade of the ecological environment of the evaluated region, and M is the land area of the evaluated region.

b: OBJECTIVE FUNCTION OF ECONOMIC GUARANTEE

To achieve a better development of production and the well-being of the displaced population in the resettlement site, the selected site should have industrial and agricultural infrastructure (including tourism resources) and accessible transportation. The equation is expressed as follows:

$$\mathrm{F\,(d)} = \frac{\sum_i^I (R_i + J_i)\, M_i}{\sum_i^I M_i} \tag{2}$$

where i is the id of land figure, I is the count of all land figure, F(d) is the objective function of production and economic development, R is the industrial and agricultural development coefficient of the selected site, J is the accessibility of internal and external transportation systems, and M is the area of the evaluated region.

c: OBJECTIVE FUNCTION OF CONTROLLABLE RELOCATION COST

With the project quality remaining stable, the resettlement cost is controlled by the land area of the resettlement site, the construction cost per unit area of the selected site, and the moving distance. It is expressed in the following equation:

$$\mathrm{F\,(s)} = \frac{\sum_i^I (T_i M_i + D_i E_i)}{\sum_i^I M_i} \tag{3}$$

where i is the id of land figure, I is the count of all land figure, F(s) is the objective function of the controllable relocation cost, T is the construction cost per unit area of the selected site, D is the relocation distance, E is the unit transportation cost, and M is the land area of the evaluated region.

d: OBJECTIVE FUNCTION OF COMPREHENSIVE REQUIREMENTS FOR RESETTLEMENT SITE SELECTION

The objective function of comprehensive requirements for resettlement site selection is expressed as follows:

$$\mathrm{F(a)} = W_e \frac{\mathrm{F\,(e)}}{\mathrm{F\,(e)_{max}}} + W_s \frac{\mathrm{F\,(s)_{min}}}{\mathrm{F\,(s)}} + W_d \frac{\mathrm{F\,(d)}}{\mathrm{F\,(d)_{max}}} \tag{4}$$

where F(a) is the total objective function and $\mathrm{W_e}$, $\mathrm{W_s}$, and $\mathrm{W_d}$ are the corresponding weighting coefficients. As all three objectives are equally important, their weighting coefficients are all set to 1.

3) ESTABLISHMENT OF CONSTRAINTS

The objective functions were constructed under certain constraints. Based on the real situation, this study mainly includes the following two constraints: suitability constraints and the capacity constraints of the relocation plots.

a: SUITABILITY CONSTRAINTS

It is hereby determined that the average suitability of the selected sites should be greater than the suitability threshold, expressed as follows:

$$\mathrm{G} = \frac{\sum_i^I S_i M_i}{\sum_i^I M_i} \tag{5}$$

where G is the threshold of suitability, i is the id of land figure, I is the count of all land figure.

b: CONSTRAINTS ON THE CAPACITY OF THE RELOCATION PLOTS

With the land use plot as the smallest evaluation unit, the selected relocation site should be the optimal combination of multiple plots, and the combined area should meet the relocation area requirements, described as follows:

$$\mathbf{S} < \sum_i^I M_i \tag{6}$$

where S is the minimal required relocation area, i is the id of land figure, I is the count of all land figure.

4) OPTIMIZATION ALGORITHM

a: OPTIMIZATION OF PARAMETER SETTINGS

The solution of the algorithms is generally the optimal solution for a single index. Affected by multiple factors, the resettlement site selection is a comprehensive problem, which needs to be determined based on the real situation. Therefore, this study proposed the concept of the optimal solution set based on single index optimization of the original algorithm. This optimal solution set is a two-dimensional array [X, Y], where X is the optimal solution of the dominant index and Y is the comprehensive solution of the nondominant factors. For example, if the ecoenvironmental capacity of a project is set as the dominant index X, then Y is the comprehensive result combining the production and development guarantee and the controllable relocation costs.

The scientific setting of algorithm parameters directly affects the search ability and performance of the algorithm. The primary parameters of the algorithm that need adjustment include population size V, learning factors C1 and C2, inertia weights Wmax and Wmin, and iteration number T. After multiple experiments and analyses, at the county scale, the improved parameters of this algorithm should be set as follows: population size of 100, learning factor C1 as 0.5 and C2 as 0.5, inertia weight W maximum value at 0.5 and minimum value at 0.1, iteration number at 100, and storage size of noninferior solutions as 6.

b: REPRESENTATIVE OPTIMIZATION OF PARTICLES

A more reasonably distributed initial particle population will lead to faster calculation and more accurate results. This paper proposed a strategy of "land clustering + internal difference" to determine the population particles, that is, lands of the same type are clustered as a large area and the number of particles are assigned based on the area of the land. Also, equidistant difference is performed within the large area. This can ensure that the population particles cover all land types, and each land type is fully covered.

c: OPTIMIZATION OF NONINFERIOR GROUP STORAGE

In terms of the determination of the optimal solution set proposed in this paper, it is necessary to examine and compare the optimal solution sets [X, Y] separately, with the dominant index as the major basis. When the difference of the nondominant comprehensive index is twice the difference of the dominant index, both sets of solutions will be stored as noninferior solutions, that is, when $X - Xp < (Y) / 2$, [X, Y] and [Xp, Yp] are both stored as noninferior solutions.

For multiobjective particle swarm algorithm, the storage optimization of noninferior solutions is a critical step. It is essential to establish a reasonable storage mechanism, including the limitation of scale and the establishment of updating and iterating mechanisms. After analysis and testing, the scale of noninferior solution within a county was determined to be 6. The updating mechanism was established as follows: when the number of noninferior solutions is below the limit, the solutions will be directly stored; when the limit is reached, the new noninferior solution should be compared with the existing solutions to determine whether there is a dominating relationship and whether it should replace an existing solution in the storage or be discarded.

d: OPTIMIZATION OF GLOBAL OPTIMAL SOLUTION SET

In search of solutions for a multiobjective optimization problem, each iteration produces a set of noninferior solutions. Among the many noninferior solutions, one set of noninferior solutions must be selected as the learning sample of the global optimal particle. Generally, multiobjective PSO randomly selects a noninferior solution set from an external archive as the global optimal solution. However, with this approach, the noninferior solution sets in the dense area have a greater chance to be chosen as the global optimum, thus losing the population diversity. To ensure the diversity of solutions and the balance of the distribution of noninferior solution sets, this paper proposed "the noninferior solution set of the largest area of relevant land type based on constraints" as the global optimal solution set. Comparison showed that the global optimal solution set was consistent with the local optimal solution set.

After the abovementioned algorithm was improved and optimized, the county's land use classification data were utilized to calculate the parameters with map spot as the smallest evaluation unit. Then, the particle swarm algorithm was applied to finish multiobjective function calculation. The implementation flow and the pseudocode of the algorithm are shown in Figs. 7 and 8, respectively.

IV. EXPERIMENT ANALYSIS

A. TEST AREA OVERVIEW

Guanling County is located in the southwest of the central part of Guizhou Province and west of Anshun City. It is on the east bank of the Beipan River in the upper reaches of the Pearl River, with a typical karst topography. The geographical coordinates are 105°15'–105°49' E and 25°34'–26°05' N, and the land area is 1,468.00 km2. It is surrounded by Zhenning Autonomous County in the northeast, Beipan River in the northwest, which separates it from Jinglong County, Xingren County, and Zhenfeng County, and the Liuzhi Special Zone in the northwest. The landforms are complex and diverse, with large elevation gaps. Carbonate rocks are widely distributed, and karst landforms and normal landforms are staggered in this area. Shafts, stalagmites, funnels, depressions, valleys, hills, peaks, and stone forests appear everywhere, with abundant caves and underground rivers. In the county, the proportion of agricultural population is high, accounting for 90.38% of the total population. The high proportion of agricultural population, relatively densely distributed residents,

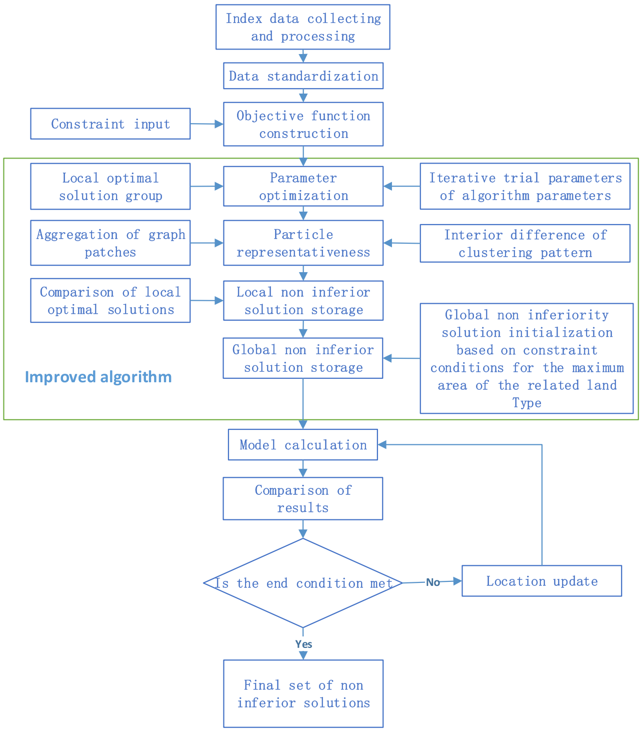

FIGURE 7. Flowchart of resettlement site selection in karst areas based on multiobjective particle swarm optimization algorithm.

```
%--------------- Algorithm -------------------------------------
var sel=0
 %Target model selection,0 Comprehensive,1 Ecological environment
 %capacity,2 Production development,3 Relocation cost
 % Initializing individuals
 var x=cluster(class); % Cluster difference
 var v=rand(N,D)*(Vmax-Vmin)+Vmin;
% Initialization of individual noninferior solution set position and
%noninferior solution set
 var p[]=x;
 var pbest[]=ones(N,1);
  for i=1:N
 var pbest[](i)=func1(x(i,:)); % Model calculation
  end
% Initialization of global optimal position solution set and noninferior
% solution set
var g[]=ones(1,D);
  var gbest[]=inf;
  for i=1:N
  if (pbest(i)<gbest)
  g=p(i,:);
  var gbest[]=pbest[](i);
  end
  end
 var gb=ones(1,T);
% Iteration according to the equations until reaching the precision
% requirements or the iteration number
```

FIGURE 8. Pseudocode of the algorithm.

large number of people living in poverty, low per-capita cropland, and much unusable land have created substantial conflicts and aggravated land rocky desertification.

B. CALCULATION RESULTS

According to the different initialized population particles, 50 times of experimental analysis and calculation are carried out respectively. The statistical analysis shows that the effectiveness of the whole algorithm is more than 98% due to the strategy of "ground class aggregation + internal difference". Six noninferior solution sets were selected in the test site based on the calculation of objective functions of the model using optimized particle swarm algorithm. The specific distribution is shown in Figs. 9–12.

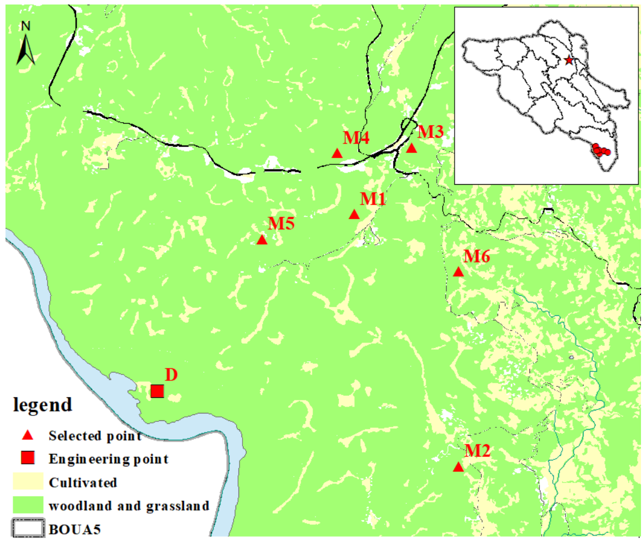

FIGURE 9. Selected resettlement sites in the karst areas based on comprehensive requirements.

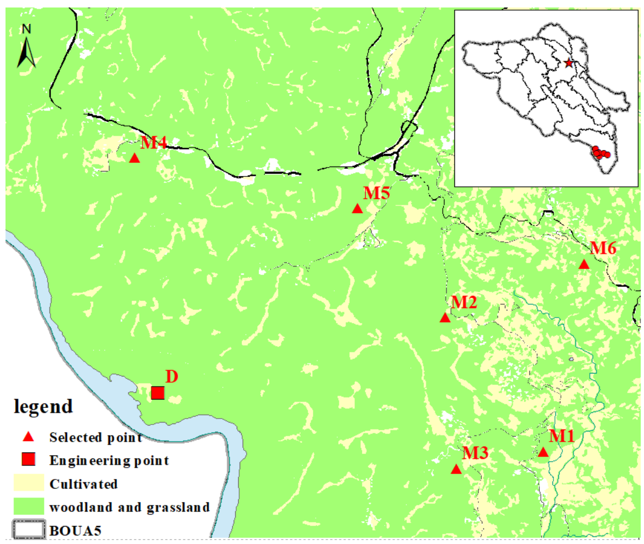

FIGURE 10. Selected resettlement sites in the karst areas based on eco-environmental capacity.

The calculation results of individual resettlement sites are shown in Tables 3–6.

In terms of convergence speed, the optimized multiobjective PSO algorithm has an evident advantage over traditional

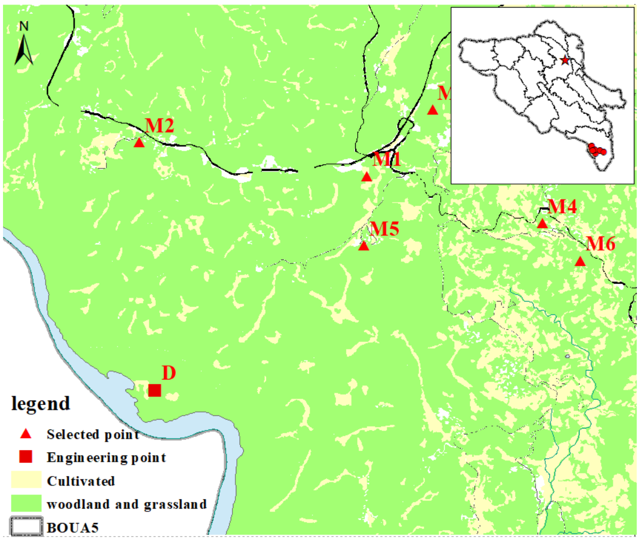

FIGURE 11. Selected resettlement sites in the karst areas based on guarantee of production and development.

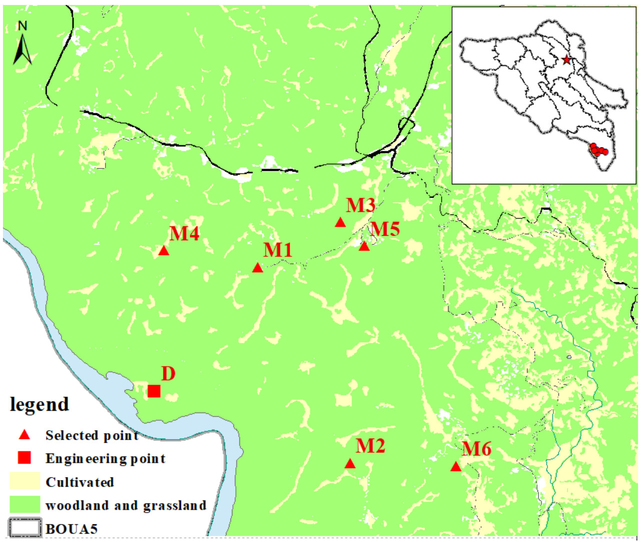

FIGURE 12. Selected resettlement sites in the karst areas based on relocation costv.

TABLE 3. Noninferior solution sets based on comprehensive requirements.

Test area	Dominant index	Ecoenvironmental capacity	Production & development	Relocation cost
M1	0.82	0.83	0.75	0.88
M2	0.81	0.81	0.79	0.84
M3	0.80	0.79	0.84	0.78
M4	0.81	0.80	0.82	0.80
M5	0.81	0.78	0.82	0.82
M6	0.79	0.82	0.79	0.75

* THE NONINFERIOR SOLUTIONS WERE NOT SORTED

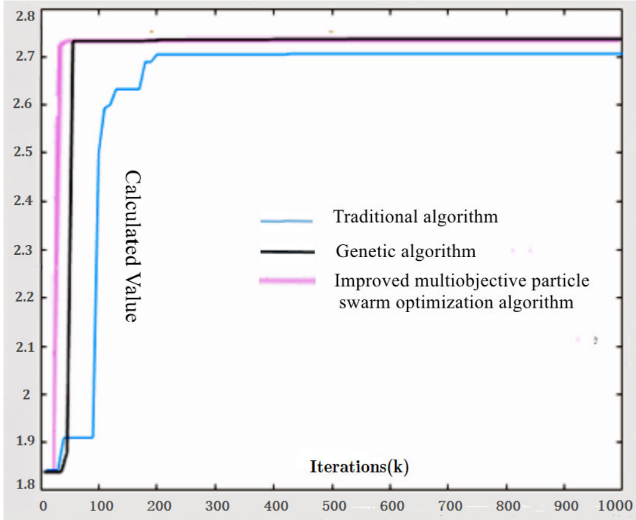

FIGURE 13. Comparison of the improved multiobjective particle swarm optimization algorithm with traditional particle swarm optimization algorithm and genetic algorithm.

TABLE 4. Noninferior solution sets based on ecoenvironmental capacity requirements.

Test area	Dominant index	Other comprehensive indices
M1	0.82	0.75
M2	0.80	0.73
M3	0.81	0.71
M4	0.80	0.72
M5	0.78	0.77
M6	0.80	0.70

TABLE 5. Noninferior solution sets based on guarantee of production and development.

Test area	Dominant index	Other comprehensive indices
M1	0.83	0.72
M2	0.82	0.73
M3	0.80	0.74
M4	0.78	0.75
M5	0.79	0.75
M6	0.77	0.76

TABLE 6. Noninferior solution sets based on relocation cost.

Test area	Dominant index	Other comprehensive indices
M1	0.82	0.70
M2	0.81	0.71
M3	0.80	0.74
M4	0.82	0.71
M5	0.80	0.75
M6	0.78	0.70

methods and genetic algorithm in selecting the resettlement sites in karst mountain areas, showing a significant effect on the convergence speed (Fig. 13).

The computational complexity of the optimized multi-objective particle swarm optimization algorithm is obviously better than that of the traditional calculation method and genetic algorithm, its time complexity respectively:

$$T^{1(n)} = a^{2*}n \quad T^{2(n)} = m^{2*}n \ (a > m)$$

T1(n) is the time complexity of the traditional algorithm; T2(n) is the time complexity of the improved multi-objective particle swarm optimization algorithm; A is the total number of individuals; M is the number of particle swarm samples; N is the number of calculated impact factors.

V. CONCLUSION

To address the uncertainty, low accuracy, and lack of research studies on resettlement site selection in karst mountainous areas, this study constructed an evaluation index system for resettlement site selection in these areas from multiple aspects including karst rocky desertification environment, degree of geological hazard development, resource and environmental carrying capacity, transportation and economic development potential, and relocation cost. A hierarchical model was applied to classify the indices, determine the weighted optimal solution of the eigenvectors in matrices, and assess the suitability. The algorithm of the model was developed based on four objectives including achieving suitable ecoenvironment capacity, ensuring the production and development, controlling relocation cost, and meeting the comprehensive requirements. The objective functions and constraints of the model with four objectives were also established. To address this problem, the particle swarm algorithm was applied, and the "noninferior solution set" was proposed. The objective functions and constraint conditions of the algorithm were optimized and improved in four aspects: parameter setting, representativeness of particles, noninferior solution set storage, and selection of global noninferior solution set. To validate the proposed model and algorithm, Guanling County, an area in Guizhou Province with a typical karst rocky desertification development, was selected as the test site. The latest land use map spot data were used as the smallest evaluation unit, and the improved multiobjective particle swarm algorithm was employed in evaluating the resettlement site selection within this area. The results are summarized as follows:

In terms of the accuracy of the results, the model calculations in the four scenarios were consistent with the actual natural, social, and economic conditions and reasonably reflected the requirements of resettlement site selection. The selected sites were quite different under various requirements, reflecting the necessity and further research study of the model's algorithm. At the same time, due to the adoption of the strategy of "land clustering + internal difference," the scientific distribution of the particle swarm was guaranteed, therefore improving the accuracy of the results.

Regarding practicability, this study proposed a model algorithm for four scenarios, which can be expanded accordingly. The concept of "optimal solution group" was also proposed to meet the realistic needs, which adequately reflects the objective conditions and promotes relevant engineering applications in the field.

The article "optimal solutions group" realistic demand, but also to a certain extent, increased the complexity of algorithm, but still can obtain good results, is to apply the "hierarchical aggregation" strategy "to class aggregation + internal difference of particle swarm initialization method, hierarchical aggregation and distribution of the particle swarm of combining the problems worth further optimization study, improve the efficiency and accuracy of algorithm.

In terms of limitations, the three objective functions selected and established in this paper are representative to some extent, but can not fully meet all requirements. The main factors affecting these limitations are as follows: (1) Different requirements of each project and region lead to differences in objective functions and constraint conditions; (2) the quantitative scale of each index factor data.

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