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Original Research

Simulating Land Use Structure Optimization Based on an Improved Multi-Objective Differential Evolution Algorithm

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Abstract

Optimizing land use structure is currently a hot research topic in the land resource management field. In this study, we constructed a new land use structure optimization model based on the improved multi-objective differential evolution algorithm. This model made improvements in two aspects of the classic differential evolution algorithm, i.e., control parameters and adaptive strategies. On this basis, we established a multi-objective function by taking ecological benefits and economic benefits as the objectives. According to the real situation of the study area, we established multiple constraint conditions and finally established an improved multi-objective differential evolution model. By taking the year 2010 as the base period, we simulated an optimized land use quantitative structure in 2020 for the study area and compared this optimized structure with classic linear programming. The experimental results showed that although the annual ecological benefits in the study area decreased by 5,105,300 yuan, the annual economic benefits increased by 69,133,500 yuan, and the annual total benefits increased by 20,878,300 yuan – an increase of 0.44%. This showed that the land use structure obtained by using the optimization model proposed in this paper was more reasonable. The results indicated that the model established in this study possessed quite good properties and could meet the requirements for the regional land use structure optimization under multiple constraint conditions. The optimized results can provide the scientific basis for formulating appropriate measures for regional land resources use.

Keywords:differential evolution algorithm, land use structure, optimization, land resource management

Introduction

Land use structure optimization, also known as land use quantitative structure optimization, refers to an optimization process during which one or multiple benefits are taken as the optimizing objectives under a series of constraints of a certain region. This is to allocate the regional land resources into various types of land use so that proper arrangements of the regional land resources can be achieved temporally and quantitatively.

In the recent years, many investigators have launched their studies with a focus on modeling and methodologies

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for the environment, ecology, agriculture, and land use structure optimization. Deb et al. [1] recognized a few recent efforts and discuss a number of viable directions for developing a potential EMO algorithm for solving multi-objective optimization problems. Gobeyn et al. [2] presents a methodology, illustrated with the example of river pollution in Ecuador, using a simple genetic algorithm to identify well performing SDMs by means of an input variable selection. Herzig A. et al. [3] used the Land-Use Management Support System to assess land-use development scenarios for the potential irrigable areas Black Creek and White Rock in the Ruamahanga catchment. The results show that intensification and expansion of dairy farming and arable cropping increased production levels, but also nitrate leaching and greenhouse gas emissions. Ibrahim et al. [4] have proposed an improved NSGA-III algorithm, called EliteNSGA-III, to improve the diversity and accuracy of the NSGA-III algorithm. This algorithm maintains an elite population archive to preserve previously generated elite solutions that would probably be eliminated by NSGA-III's selection procedure. Valcu et al. [5] assessed empirically how agricultural lands should be used to produce the highest valued outputs, which include food, energy, and environmental goods and services. In addition, some investigators have applied the linear programming method to perform studies on land use structure optimization [6]. Based on their studies on the suitability of optimal linear programming for land use planning, Piyush Kumar et al. [7] constructed a mixed integer linear programming approach for land use planning that limit urban sprawl. Mahmoud M. et al. [8] aims at developing novel algorithms through hybridizing Tabu search (TS), genetic algorithm (GA), GRASP, and simulated annealing (SA) and examining their quality and efficiency in practice. The outputs showed that the quality and efficiency of LLTGRGATS were slightly better than those of SVNS, and it can be considered as a favorable tool for the land-use planning process. Tomasz Noszczyk et al. [9] studied changes in areas of four land use variables in the Małopolska Voivodeship of Poland using statistical methods. The results show significant dependence of the current land use values on the past values from the previous two years.

In general, while a large number of research results in the field of land use structure optimization have been obtained in both China and other countries and some practical application results have also been obtained, many problems and shortcomings still remain. A majority of the previous studies mainly applied such mathematical models as linear programming method, objective programming methods, and systemic dynamic method etc. and integrated these methods for optimization. However, these methods are difficult for resolving the complicated multi-objective optimization problem under constraint conditions. The differential evolution algorithm is a random, parallel, and direct searching algorithm. It is suitable to be applied in solving the complicated optimization problems that cannot be solved with traditional and routine mathematical optimization methods. It has been successfully applied in some fields owing to its easy usefulness, robustness, and powerful ability of global optimization.

Land use structure optimization involves multi-objective and multiple constraints. Differential evolution algorithm has the characteristics of solving complex problems, and has a promising potential to be applied in land use structure optimization. In recent years, some investigators began applying the differential evolution algorithm in conducting optimal crop cultivation planning [10-11] and have obtained some successful results. However, few studies with a focus on the regional land use structure optimization have been reported. In China, the differential evolution algorithm has been mainly applied in the fields of artificial intelligence, chemical industry, biology, data mining, and image treatment, etc. No studies with a focus on the application of differential evolution algorithms in land use structure optimization have been reported in the literature. While a lot of research results have been obtained with differential evolution algorithm since it was proposed, as compared to other evolution algorithms, it exhibits more obvious advantages in solving the optimization problem of biology and agriculture. However, there is still plenty of room for further improvement for this algorithm, i.e., this algorithm needs to be further improved and perfected regarding parameter optimization.

The goal of this paper is to optimize the structure of land use in Dawa County, China, in 2010-2020 and propose an approach to optimize land use structure. To this end, the improved multi-objective differential evolution algorithm was established and the model that optimized the structure of land use in the study area was developed.

Material and Methods

Study Area

Dawa County was selected as the study area due to its rich land-use types that include cultivated land, construction land, forest land, wetland, waters, and tidal flats, and can provide reliable data for simulating the improved differential evolution algorithm. The results obtained in Dawa County by applying the model proposed in this paper can be extended to other regions there are more or fewer land-use types.

Dawa County is located in southwest Liaoning Province. Its west faces the Bohai Sea and Liaodong Bay. Geologically, Dawa is located between 121°48′E-122°21′E and 40°41′N-41°09′N and displays the typical characteristics of coastal ecology. The total land area of the entire area is 1,387 km^2. A reasonable land use structure is very important for regional land resource management.

Table 1. Data sources used in this study.

Acquisition	Data types	Spatial resolution	Data source
09-20-2010	TM5	30 m	Computer network information center, Chinese Academy of Science
07-28-2010	Topographic maps	1:100000	Land Resources Bureau of Dawa County
2000-2010	Non-spatial data	—	Land Resources Bureau of Dawa County

Data

The acquisition date of a topographic map with a scale of 1:100,000 and other non-spatial data was 2010 (Table 1). So, the Landsat TM remote sensing images used in this study were acquired in 2010 (Table 1) in order to maintain the consistency of data acquisition date. In addition, the natural status data of meteorological, hydrological, soil, and vegetation, and the statistical data of social-economic data in the study area were also used (Table 1). Three Landsat TM images taken in the study area were selected and montaged. The geometric registration of imagery was conducted using a topographical map (1:100000) as the datum mark. The mosaic of remote sensing images was made using ENVI 5.0 software [12]. The images were classified by relying mainly on unsupervised classification with the assistance of visual interpretation. During the classification process, the images were firstly and automatically classified into 15 types using the ISODATA unsupervised classification. They were then combined into six types of land that were needed (cultivated land, construction land, forest land, wetland, waters, and tidal flats) to obtain the preliminary classification results in the study area. These preliminary results were further treated after classification. According to the field survey results, GPS data, the current land use status map, and other related data, the confusion pixels and misclassification pixels were modified by visual interpretation. The classification results of land-use in the study area were finally obtained. Furthermore, the other natural status data and the statistical data of the social economy in the study area were also collected and used for the establishment of restriction conditions for conducting the optimal allocation of the land resources.

Methods

Principle of Differential Evolution Algorithm

In recent years, there has been an ever-increasing interest in the area of a differential evolution algorithm proposed by Rainer Storn and Kenneth Price [13-14]. The advantages of differential evolution algorithm for solving global design problems include global solution-finding property, powerful search capability, fewer control parameters, ease of use, and high convergence characteristics [15-18]. The differential evolution algorithm is a population-based and stochastic global optimizer that can work reliably in non-linear and multimodal environments [16-19].

Differential evolution algorithm includes initial population, mutation, crossover, and selection. More specifically, the basic strategies of a differential evolution algorithm can be described as follows:

Initial Population

Prior to conducting the major operational procedures, i.e., mutation, crossover, and selection with a differential evolution algorithm, optimizing the location management needs to be carried out, i.e., the initial population in the NP (population for each generation) scale is randomly created in the definition domain space of the variable [17], the equation is as follows:

$$x_{i,j} = x_{\min} + rand(0,1) \times (x_{\max} - x_{\min}) \quad (1)$$

…where $x_{i,j}$ is the J component of the i individual; X_{max} and X_{min} are the maximal and minimal value of the variable, respectively; rand (0.1) is the random number of the even distribution above the [0,1] region; i represents the individual serial number of the population, I = 1,2, ….NP; and j represents the individual serial number of the variable, j = 1,2,….D [26].

Mutation

During the optimization process with differential evolution algorithm, the most basic mutation component is the differential vector derived from the parent generation. Each differential vector includes two different individual vectors (x^t_{r1}, x^t_{r2}) [26]. The equation is as follows:

$$D_{r1,2} = x^t_{r1} - x^t_{r2} \quad (2)$$

…where r_1 and r_2 are the serial numbers of two different individual vectors among the population of the t generation. The resulting differential vector is combined with another randomly selected individual vector to form a variable vector. For every target vector x^t_i, the equation is as follows:

$$v_i^{t+1} = x^t_{r3} + F(x^t_{r1} - x^t_{r2}) \quad (3)$$

…where v_i^{t+1} represents the resulting variable vector; r_1, r_2, r_3, $\in$ {1,2,...,*NP*} represent the integers that are different from each other and also different from the serial numbers of the target vector i. Thus, the population size (NP) ≥ 4 is generally needed. *F* represents the magnification factor and the range of numerical value is [0, 2], which is used to control the magnification magnitude of differential vectors [26].

Crossover

The procedure of crossover of the variable vector v_i^{t+1} resulted from the mutation operation with the corresponding individual vector from the parent generation of the population to create the experimental individual vector x_i^t from the parent generation of the population to generate the experimental individual vector u_i^{t+1}. In order to ensure the evolution of x_i^t into the next generation, the contribution of at least one u_i^{t+1} vector must be firstly ensured through random selection. For the other individual vectors, whether the contribution to vector u_i^{t+1} is made by either vector v_i^{t+1} or vector x_i^t, which can be determined by using the crossover probability factor CR (Wang, 2015). The equations are as follows:

$$u_{ij}^{t+1} = \begin{cases} v_{ij}^{t+1}, & rand(j) \leq CR \ \ or \ \ j = randn(i) \\ x_{ij}^{t}, & rand(j) > CR \ \ or \ \ j \neq randn(i) \end{cases} \tag{4}$$

…where *rand*(*j*) is the random number within the [0,1] region; *j* is the variable *j*; and *CR* represents the crossover probability factor and its values of range is generally set as [0,1]. *rand*(*j*) ∊ [1,2,...,*D*], represent the serial number of the randomly selected dimension variable [26].

Selection

The selection procedures are as follows: the resulting individual vector u_i^{t+1} obtained after mutation operation and crossover operation is compared with the original individual vector x_i^t, if the fitness of the experimental vector u_i^{t+1} is better than that of the original individual vector x_i^t, then it is selected as the new individual and kept until the next generation of the population. Otherwise, the original vector x_i^t would be used as the new individual and kept until the next generation population. Taking the minimized target function value as an example [26], the equations are as follows:

$$x_i^{t+1} = \begin{cases} u_i^{t+1}, & f(u_i^{t+1}) < f(x_i^t) \\ x_i^{t+1}, & f(u_i^{t+1}) \geq f(x_i^t) \end{cases} \tag{5}$$

…where $f(u_i^{t+1})$ and $f(x_i^t)$ are the fitness (the target function values) of the individuals u_i^{t+1} and x_i^t. When, $f(u_i^{t+1}) < f(x_i^t)$, the fitness of individual u_i^{t+1} is better than that of x_i^t; when $f(u_i^{t+1}) > f(x_i^t)$, the fitness of individual x_i^t is superior to that of u_i^{t+1} [26].

Improved Differential Evolution Algorithm

Improving Control Parameters

The differential evolution algorithm mainly involves four controlling parameters, including population size (NP), number of individual (variable) dimensions (D), differential vector zooming factor (F), and crossing rate (CR). Compared with NP and D, F and CR have a higher impact on optimization property of this algorithm. Among them, the dimensional number of variable D can be generally determined according to the real problem; the population size NP is usually between 5D and 10D. The value of zooming factor F is set as [0, 2] and the value of crossing rate CR is set as [0, 1].

In recent years, many investigators have conducted studies on the adaptability of determining the parameters for differential evolution algorithms [18-22] while aiming to determine the parameters that are independent from the optimization problem and to enable the controlling parameters to change their adaptability within the specified range during the evolution process. In this study, based on the current studies, we proposed the improvement strategy for two controlling parameters, zooming factor F and crossing rate CR, aiming to make the optimized results obtained more reasonable.

The Adaptability of Zooming Factor F

Previously, some researchers selected the fixed coefficient for zooming factor in differential evolution algorithm, i.e., the zooming factor was unchanged from the beginning to the end during the optimization process. By doing so, the factor may cause more interference, and it is relatively difficult to determine the proper parameters. Thus, it is necessary to formulate the adaptability strategy for zooming factor F. This strategy can provide the optimal F value for each solution. In this study, we applied the adaptability strategy for zooming factor proposed by Wu [27].

The basic idea of this strategy is that according to three individuals randomly selected during the mutation operation, the corresponding positions in the searching space derived from adaptability adjust the size of the zooming factor F [27]. If these randomly selected individuals are closer to each other in the searching space, the differential vector generated will be smaller and at the same time, the disturbance quantity of various dimensional strategy variables is also smaller. In this case, the larger value for zooming factor F should be selected. Otherwise, because the disturbance quantity is small, it does not play a role in mutation, leading to the early falling into the regional searching in the early stage of evolution [27]. If the positions of three randomly selected individuals in the searching space are more disperse, the value of differential vector generated will be too large, and the disturbance quantity of various dimensional strategy variables is larger. In this case, the smaller value for zooming factor should be selected to control the larger disturbance quantity. This will be favorable for conducting regional searching with this algorithm [27]. Therefore, the selected value for zooming factor F should be adaptive. The changes of factor F can be adjusted according to relative positions in the searching space of two individuals, and the differential vector can be adjusted dynamically so that the regional searching and global searching can reach a balanced state and the uncertain influence caused by an artificially assigned factor can be avoided [27]. The details of adaptability strategy are as follows:

$$F_i = F_l + (F_u - F_l)\frac{f_b - f_a}{f_c - f_a} \tag{6}$$

…where f_a, f_b, and f_c, are the adaptabilities (target function values) of individual vectors x_a^t, x_b^t, and x_c^t, respectively. Among which, three randomly selected individuals that are used for mutation are ranked in order according to the size of their adaptabilities. The vector of the individual with the best adaptability is designated as x_a^t, the vector of the individual with the second best adaptability is designated as x_b^t, and the vector of the individual with the worst adaptability is designated as x_c^t [27]. F_l and F_u are the upper and lower limits of zooming factor F, respectively. The value for F_l is usually set as 0.1, and the value of F_u is usually set as 0.9. F_i is the zooming factor of adaptability and its values can be between [0.1,0.9] and can be changed with the adaptable changes in the relative positions of x_a^t and x_b^t in the vector space [27].

Adaptability of Crossing rate (CR)

Crossing rate (CR) can affect the diversity through controlling the selection of vector for individuals in the specie population and thus can affect the searching speed and the successful rate of the differential evolution algorithm [28]. In the beginning stage, a relative small value for CR should be selected and this is favorable for preventing premature and for maintaining the population species diversity. But in the later stage of searching, the larger value for CR should be selected. This can enhance the regional searching capability of this algorithm [28]. Based on this idea, Huang proposed a crossing rate-enhancing strategy [28]. This study made an improvement on the basis of this method and proposed a crossing rate adaptable strategy. The details of this crossing rate adaptable strategy are as follows:

$$CR_i = CR_l + (CR_u - CR_l)\frac{g+1}{G+1} \tag{7}$$

…where CR_i is the adaptive crossing rate; CR_u and CR_l are the upper limit and the lower limit of the CR, respectively. The value of CR_l is usually 0.3, and the value of CR_u is 0.9. Of course the values for CR_u and CR_l can be determined according to the practical problem; g is the iterative algebra and G is the maximal iterative algebra during the evolution process.

Improving Mutation Strategy

The standard mutation strategy of differential evolution algorithm is DE/rand/1/bin, as shown in equation (3). In this mutation operation, x^t_{i1}, x^t_{i2}, and x^t_{i3} are three individual vectors randomly selected from the species populations that differ from each other. In recent years, some researchers have made many improvements to the DE/rand/1/bin. Among them, the DE/best/1/bin is the most commonly used. The detailed equation of DE/best/1/bin is as follows:

$$v_i^{t+1} = x_{best}^t + F(x_{r1}^t - x_{r2}^t) \tag{8}$$

…where v_i^{t+1} is the mutation vector generated; r_1, r_2 ∈ {1, 2, …, NP} are the integral numbers that are different from each other and are different from the currently target vector serial number i ; and x^t_{best} is the most superior individual in the current generation of the species population. This improved mutation strategy takes x^t_{best} as the mutation base vector and is no longer random searching and thus is favorable for enhancing the conversion speed of differential evolution algorithm.

Technological Process of Improved Differential Evolution Algorithm

The improved differential evolution algorithm mainly included the steps of the initial species population (improvement and determination of control parameters),

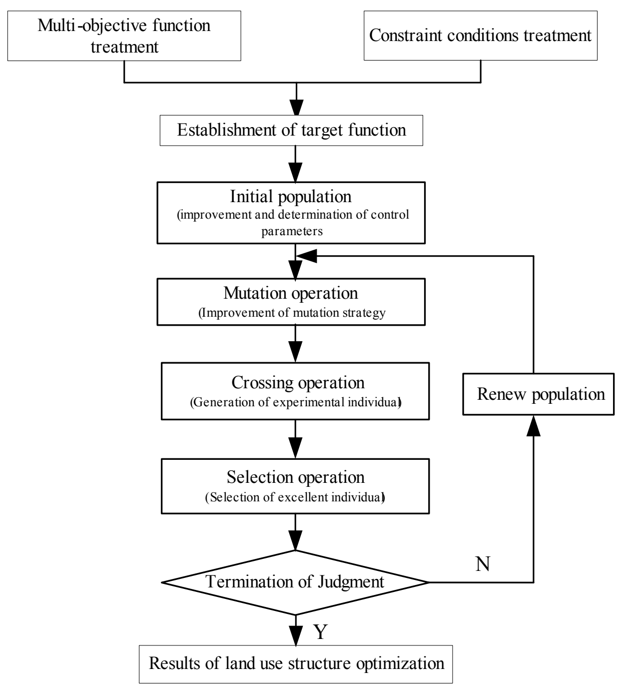

Fig. 1. Technological process of the model.

mutation (improvement of mutation strategy), crossing, and selection, etc. The detailed procedures are shown as the following flow scheme (Fig. 1).

Establishing Multi-Objective Function and Processing of Constraints in the Differential Evolution Algorithm

Multi-Objective Function Establishment

By focusing on the target optimization problem, in 1896, Italian economist Pareto proposed the first solution method from the mathematical prospective, i.e., Pareto optimal solution [18]. Because of the better results generated with this method, the multi-objective optimization problem started drawing the attentions of some investigators [19-20]. In particular, since the differential evolution algorithm was proposed, a number of investigators have proposed various target function treatment methods around this evolution algorithm [21-22]. To sum up, they can be divided into two types:

Pareto-Based Method

Currently, a majority of multi-objective differential evolution algorithms are Pareto-based [33-34, 36]. They can be divided into two subtypes, i.e. predominant type and sorted by class type. Between both subtypes, the Pareto-predominant type is the standard for selection of the most optimal solution in the differential evolution selection mechanism. Pareto-sorted by class subtype is mainly used in the process of ranking the species populations with differential evolution algorithm. This method generates the better results in seeking the solution for two dimension or three-dimension target optimization problems. However, with the increase in the number of target dimensions, the quality of optimization results may be dramatically reduced. In addition, the calculation process is complicated and the applications of the results are sometimes not so intuitive.

Non-Pareto-Based Method

The essence of this method is to convert the multi-objective optimization problem into single-objective optimization problem and then conduct optimization with the single-objective optimization method [35]. These multi-objective optimization methods mainly include the weighted sum method, **ε**-constraint method, goal programming, and game theory, etc. [33-34, 36]. Among them, the most commonly used is the weighted sum method. Its basic idea is as follows: each optimization target is given a corresponding weight. The importance of each optimized target in the total optimization target is adjusted according to the weight of each target and finally converted to the multi-objective into a single-objective optimization problem. The principle of this method is simple, easy to operate, and can basically converge the most optimal solution. Thus, in this study, we selected the weighted sum method to the treat multi-objective function with a differential evolution algorithm. The basic principles of the weighted sum method are described as follows. The detailed equation is as follows:

$$\min \text{ (or max)} : f(X)$$

$$F(X)=\sum_{i=1}^{k} w_i f_i(X) \tag{9}$$

…where F(X) is the new optimized function; k is the number of target function; and w_i is the weight value of the ith target function, which generally meets $\sum_{i=1}^{k} w_i = 1$. Because the weight value of each target differs, the multi-objective optimization results can be obtained through adjusting the value of weight coefficient in different situations.

Constraints Processing

The penalty function method is the most commonly used method for obtaining the solution for the constraint optimization problem. Its basic idea is to use a penalty factor to punish constraint function and then the obtained penalty term is added to the optimized target function and thus a non-constraint generalized target function is formulated. The solution for the newly formulated generalized target function is obtained with the optimized algorithm, and the most optimized solution is finally obtained under the action of the penalty term [27]. The constraint optimization problem is generally expressed as follows:

$$\min \text{ (or max)} : f(X)$$

$$s.t. \quad \begin{aligned} & g_i(X) \le 0, i = 1,2,...,l \\ & h_j(X) = 0, j = 1,2,..., p \end{aligned} \tag{10}$$

…where $f(X)$ refers to target function, $g_i(X)$ refers to inequality constraint, and $h_j(X)$ refers to equality constraint. Generally, during the treatment process, equality constraint is first converted to inequality constraint. The detailed method is as follows: relaxation factor ε is first introduced. For equality constraint, h(X) = 0; then the equality constraint is converted to inequality constraint using relaxation factor ε $|h(X)|<\varepsilon$. In general, ε is a very small positive number and its value is generally the real number of 10^{-3} or 10^{-4}. On this basis, the generalized objective function is as follows:

$$F(X) = f(X) + \delta(t) * h(X) \tag{11}$$

…where $F(X)$ refers to the generalized objective function, $f(X)$ refers to the original objective function; $\delta(t)*h(X)$ refers to the penalty term, $\delta(t)$ refers to penalty strength, and $h(X)$ refers to the penalty factor. If penalty strength $\delta(t)$ is a constant and is unchanged during the optimization process, it is known as the stationary penalty function method; if δ(t) is changed during the optimization process, it is known as the non-stationary penalty function method. The non-stationary penalty function method has more advantages than the stationary penalty function method because during the calculation process, the penalty strength $\delta(t)$ can be continuously changed with the iteration number t, and provide certain flexibility for the entire opptimization process and make the problem-solving process more rapid. In this study, we applied the improved non-stationary multi-stage assignment penalty function proposed by Wu [27] to treat the constraint conditions. The mathematical expression is as follows:

$$h(X)=\sum_{i=1}^{m}\theta(p_i(X))p_i(X)^{r(p_i(X))} \tag{12}$$

$$p_i(X)=\max\{0,g_i(X)\} \tag{13}$$

$$r(p_i(X))=\begin{cases}1, & p_i(X)<1\\ 2, & p_i(X)\geq 1\end{cases} \tag{14}$$

$$\theta(p_i(X))=\begin{cases}5, & p_i(X)<0.001\\ 10, & p_i(X)\leq 0.1\\ 15, & p_i(X)\leq 1\\ 30, & others\end{cases} \tag{15}$$

$$\delta(t)=t\sqrt{t} \tag{16}$$

…where Equation (12) is used for calculating the penalty factor; Equation (13) is for calculating the violation degree of constraint conditions; Equation (14) is for calculating penalty strength; equation (15) is for calculating multi-stage assignment function; and equation (16) is for the continuing adjustable penalty strength with the change in the number of iterations.

Method Application

Determining Various Parameters for the Improved Differential Evolution Algorithm

The parameters of differential evolution algorithm mainly include population size (NP), number of variable dimension (D), zooming factor (F), and crossing rate (CR). Among them, F and CR were determined by using adaptable strategy Equation (6) and Equation (7) described above, respectively. It can be known according the land classification described above. Six types of land in the study areas included cultivation land, forest land, wetland, waters, intertidal zone, and construction land. Thus, the dimensional number of viable D is 6; the species population size NP was between 5D and 10D. In this study, 10D was selected, i.e. NP = 60.

Establishing the Optimized Model Based on Improved Multi-Objective Differential Evolution Algorithm

(1) Setting variables

According to the results of land classification, the land types of the study area included cultivation land, forest land, wetland, waters, intertidal zone, and construction land. Thus, the variables for land use structure optimization model were set as follows: x_1 (cultivation land), x_2 (forest land), x_3 (wet land), x_4 (waters), x_5 (intertidal zone), and x_6 (construction land). To seek the solutions for optimization results is to find out the quantitative structure of six variables when the objective functions reach the maximum values.

(2) Establishing multi-objective functions

The ultimate objective of land use structural optimization is to achieve the harmonization and unification of three aspects, i.e. ecological benefits, economic benefits, and social benefits, i.e., aiming to achieve the maximal comprehensive benefits. In this study, because of the lack of data and the difficulty of quantitation, the social benefit was temperately excluded. The ecological benefits and economic benefits were mainly taken into account. Thus, there are mainly two target functions, i.e., the maximization of ecological benefits and the maximization of economic benefits. The multi-objective target optimization problem was finally converted to single-objective target optimization using the weighted sum method.

– Objective Function I: maximizing ecological benefits.

One of the objectives of land use structure optimization is to maximize ecological benefits. The calculation process for maximizing benefits is that the area of each type of land use be multiplied by the corresponding ecological service value per unit area; and then sum up and the regional total ecological benefits is finally obtained. The detailed equation is as follows:

$$\max:\ f_1(X)=\sum_{i=1}^{6}(x_i\times p_i) \tag{17}$$

…where x_i is the i type of land use; p_i is ecological service value per unit area of the i type of land use. According to the results calculated by Wang [23], p_1 was 6920 yuan/hm^2, p_2 was 11940 yuan/hm^2; p_3 was 10820 yuan/hm^2, p_4 was 7640 yuan/hm^2, p_5 was 7610 yuan/hm^2, and p_6 was 0 yaun/hm^2.

– Target function II: maximizing economic benefits

Another objective of land use structural optimization is to reach the maximization of economic benefits.

The calculation process of the maximization of economic benefits is that the area of each type of land use is multiplied by the corresponding economic benefits per unit area and then sum up. The regional total economic benefits were finally obtained. The detailed calculation equation is as follows:

$$\max: f_2(X)=\sum_{i=1}^{6}(x_i \times q_i) \tag{18}$$

…where x_i is the i type of land use type; q_i is the economic benefit per unit area of the i type of land use type. According to the data reported in the literature [24]. The economic benefit per unit area of each type of land use was comprehensively determined as follows: q_1 was 30000 yuan/hm^2, q_2 was 4000 yuan/hm^2, q_3 was 500000 yuan/hm^2, q_4 was 27000 yuan/hm^2, q_5 was 2000 yuan/hm^2, and q_6 was 100000 yuan/hm^2, respectively.

– Establish multi-objective functions

In this study, we applied the weighted sum method to treat the multi-objective function in differential evolution algorithm. With this method, each target function is given a weighted coefficient and the multi-objective target optimization problem was converted into a mono-objective optimization problem. The key to this method is to determine the weight for each objective function. The goal of this study was to conduct land use structural optimization under the conditions that reflect the priority of ecological benefits and economic benefits. In this study, we applied the expert consultant to determine the weighted coefficient. The weight of target function I (maximization of ecological benefits) finally obtained was w1 = 0.65 and that of target function II (maximization of economic benefits) was w2 = 0.35. The final multi-objective optimized function was expressed by the following equation:

$$\max: f(X)=\sum_{i=1}^{2} w_i f_i(X) = 0.65\times f_1(X) + 0.35\times f_2(X) \tag{19}$$

…where f(X) is the finally optimized objective function. During the optimization problem-solving process, only the value of objective function was needed to be considered.

Establishing Constraint Conditions

The constraint conditions for land use structural optimization were established according to several aspects, including natural conditions, land use status, the overall planning of land use (2006-2020), and the construction planning of ecological county (2008-2020) and the 12 5-year plans for the national economy and social development, food safety, and economic development in the study area. Taking the year 2020 optimization objectives as an example, the constraint conditions mainly included the 8 aspects as follows:

– Constraint of total land area

The sum of various land uses should be equal to the total land area of the study area, i.e.,

$$\sum_{i=1}^{6} x_i = 138700.00 \text{ hm}^2 \tag{20}$$

– Constraint of cultivation land area

With the social and economic development of the study area, the cultivation land area still displayed a decreasing trend. However, in order to guarantee the total yield of food production and ensure food safety, it is necessary to maintain certain areas of cultivation land. According to the general planning of land use in the study area, the cultivation land will be maintained at ≥ 61675.00 hm^2 until 2020. Thus, the cultivation land area constraint was:

$$61675.00\text{hm}^2 \le x_1 \le 62768.29\text{hm}^2 \tag{21}$$

– Constraint of forest land area:

According to “Planning of Construction Dawa Ecological County (2008-2020),” within the period of this planning, the large scale of tree planting and forestation will be performed and the forest land area will be increased, i.e.:

$$x_2 \ge 2279.78\text{hm}^2 \tag{22}$$

– Constraint of wetland area:

According to the planning for construction of ecological county of the study area, strict measures will be taken to protect the wetland during the planning period. Thus, during the optimization period of 2010-2020, the wetland area will be maintained at or less than its current status, i.e.:

$$x_3 \le 14695.97\text{hm}^2 \tag{23}$$

– Constraint of waters area:

The waters in the study area mainly included natural water surface area and artificial aquatic cultivation area. According to the overall planning of land use and planning of construction of ecological county, the natural water surface is protected and at the same time the artificial aquatic cultivation area is properly controlled or reduced. Thus, during the optimization period of 2010-2020, the water surface area will be smaller than its current status, i.e.:

$$x_4 \le 14281.84\text{hm}^2 \tag{24}$$

– Constraint of intertidal zone area

According to the results of evaluation of the importance of the general planning of land use and ecological land use, the intertidal zone area in the study area will be properly explored under the conditions of ecological protection of the coastal intertidal zone. However, in order to protect the ecological environment of the study area, the intertidal zone in the study area cannot be explored in an unlimited way. According to the planning for construction of ecological county, the intertidal zone area will be maintained at more than 22318.39 hm^2. Thus, the constraint conditions for the intertidal zone area are as follows:

$$22318.39\text{hm}^2 \le x_5 \le 22905.71\text{hm}^2 \tag{25}$$

– Constraint of construction land area

According the launch of the increase/decrease linkage project in the social and economic development and urban/rural construction land use, the construction area in the study area will be increased. However, according to the general planning of land use in the study area, the construction land area cannot exceed 22608 hm^2 during the optimization period of 2010-2020. Thus, the construction land use area will be larger than the current status (21768.41hm^2), but smaller than the controlled quota (22608.00hm^2), i.e.:

$$21768.41\text{hm}^2 \le x_6 \le 22608.00\text{hm}^2 \tag{26}$$

– Non-negative constraint conditions

That is the values of all the areas of various types of land use were not negative.

$$x_i \ge 0\,, \quad \text{i=1 2 ... 6} \tag{27}$$

Results and Discussion

Results

The establishment of a model in this study was achieved by programming under the VC^{++}6.0 environment. Among which, the dimensional number of variable was set as 6, the species population size was set as 60, the zooming factor F and crossing rate CR were determined through adaptability proposed in the study, and the maximal iteration number was 500. By taking the year 2010 as the base period and 2020 as the objective year to be optimized, we finally obtained the results of the land use quantitative structural optimization and the comparative analysis of the benefits before and after optimization, as shown in Tables 2 and 3.

Optimization Results of Land *Use Structure*

It can be seen from Table 2 that after optimization, the land use structures were as follows: cultivation land area was 62687.39 hm^2, accounting for 45.20% of total area; forest land area was 62687.39 hm^2, accounting for 1.85% of total area; wetland area was 14695.97hm^2, accounting for 10.60% of total area; water areas were 13823.65hm^2, accounting for 9.97% of total area; intertidal zone area was 22318.39 hm^2, accounting for 16.09% of total area; and construction land area was 22318.39 hm^2, accounting for 16.30% of total area. Comparing the optimized results with land use status in 2010, it can be seen that after optimization, the cultivation land area was reduced by 80.90 hm^2 (0.13%); the forest area was increased by 286.82 hm^2 (12.58%); the wetland area was maintained the current status without change; the water area was reduced by 458.19 hm^2 (3.21%); the intertidal zoon area was reduced by 587.32hm^2 (2.56%); and the construction area was increased by 839.59hm^2 (3.86%). Generally, among six types of land

Table 2. Optimization result of land use quantitative structure in 2020 in the study area.

Variable	Land type	Area at current status (hm^2)	Proportion (%)	Optimized area (hm^2)	Proportion (%)	Increased/ decreased area (hm^2)	Proportion (%)
x_1	Cultivation land	62768.29	45.25	62687.39	45.20	-80.90	-0.13
x_2	Forest land	2279.78	1.64	2566.60	1.85	286.82	12.58
x_3	Wet land	14695.97	10.60	14695.97	10.60	0.00	0.00
x_4	Waters	14281.84	10.30	13823.65	9.97	-458.19	-3.21
x_5	Intertidal zoon	22905.71	16.51	22318.39	16.09	-587.32	-2.56
x_6	Construction land	21768.41	15.69	22608.00	16.30	839.59	3.86
Sum	Total land area	138700.00	100.00	138700.00	100.00	0.00	0.00

Note: because the optimization process of differential evolution algorithm may bring certain randomness, the optimized results will be fluctuated up and down within a small range; the data presented in the figure are the average values of several times of optimization use, only the intertidal zoon area was unchanged. The forest area and construction areas will be increased somewhat while cultivation land area, water, and intertidal zoon area were reduced to different extents.

It can be seen from the land use structure after optimization in the study area that the cultivation land area was reduced by 80.90 hm^2, which was only reduced by 0.13% as compared to cultivation land use status in 2010. This is consistent with the situation that during the planning period, the cultivation land area should be larger than inventory cultivation land area and smaller than status area. The forest area after optimization was increased by 286.82 hm^2. This is in agreement with the guiding idea that the large scale of tree planning and forestation will be launched in the study area for construction of an ecological county. The increase in forest land area is favorable for enhancing regional ecological benefits and can effectively improve the local ecological environment. Additionally, among the land types for ecological land use, because the wet land, natural waters, and intertidal zoon are all naturally formed, it is difficult for artificial construction. Thus, in order to protect the regional ecological environment, to increase the forest land area is a major way to protect the environment. After optimization, the wetland area was neither increased nor decreased. According to the planning for construction of ecological county in the study area, a large amount of manpower and material will be put and strict ecological protection measures and will be applied to protect wetland. Furthermore, from the planning prospective, wetland has good ecological and economic benefits. Thus, in order to reach optimal comprehensive benefits, theoretically, it is reasonable to maintain the wetland area. After optimization, the water area and intertidal zone area were reduced by 3.21% and 2.56%, respectively. Although these two types of land use belong to ecological land use and have relatively high ecological benefits, because the study area has maintained relatively high speed of social and economic development during the planning period, a relatively high and rigid demand for the construction land use should be maintained. Thus, under the prerequisite of the ecological protection, a part of artificial cultivation water surface will be converted into other types of land use and part of the intertidal zoon will be further explored and utilized. After optimization, the area of construction land use was increased by 3.86%. From the planning prospective, although construction land use does not have ecological benefits, it does have relatively high economic benefits. In order to reach the maximal total benefits of target objectives, it certainly needs to increase the area for construction. This is in accord with demands for general land use planning and the rapid social and economic development of the study area.

Table 3. Comparative analysis on benefits of land use structure optimization before and after in the study area.

Land type	Situation in 2010				Optimized results in 2020				Changing range			
	Area (hm^2)	Ecological benefits (10 thousand)	Economic benefits (10 thousand)	Total benefits (10 thousand)	Area (hm^2)	Ecological benefits (10 thousand)	Economic benefits (10 thousand)	Total benefits (10 thousand)	Ecological benefits (10 thousand)	Economic benefit (10 thousand)	Total benefits (10 thousand)	Proportion (%)
Cultivation land	62768.29	43435.66	188304.87	94139.88	62687.39	43379.67	188062.17	94018.55	-55.98	-242.70	-121.33	-0.13
Forest land	2279.78	2722.06	911.91	2088.51	2566.60	3064.52	1026.64	2351.26	342.46	114.73	262.76	12.58
Wet land	14695.97	15901.04	734798.50	267515.15	14695.97	15901.04	734798.50	267515.15	0.00	0.00	0.00	0.00
Waters	14281.84	10911.33	38560.97	20588.70	13823.65	10561.27	37323.86	19928.17	-350.06	-1237.11	-660.53	-3.21
Intertidal zoon	22905.71	17431.25	4581.14	12933.71	22318.39	16984.29	4463.68	12602.08	-446.95	-117.46	-331.63	-2.56
Construction land	21768.41	0.00	217684.10	76189.44	22608.00	0.00	226080.00	79128.00	0.00	8395.90	2938.57	3.86
Sum	138700.00	90401.32	1184841.49	473455.38	138700.00	89890.80	1191754.84	475543.21	-510.53	6913.35	2087.83	0.44

Note: The total benefits presented in this table were calculated by summing up the ecological benefits and economic benefits and multiplied by the weighted coefficients

Optimization Result of Benefits

As can be seen from Table 3, after optimization, due to the reduction of cultivation land area, the ecological, economic, and total benefits in the study area were reduced by 559.8, 2427.0, and 1213.3 thousand yuan, respectively. After optimization, the forest land area was increased on a large scale. Furthermore, ecological benefits land economic benefits of the forest land were increased by 3424.6 and 1147.3 thousand yuan, respectively. The total benefit of forest land was increased by 2627.6 yuan, which was increased by 12.58%. On one hand, the increase in forest land is favorable for increasing the stability of the ecological system; on the other hand, it also compresses the space of land supply between food safety and construction land. After optimization, the wetland area was unchanged. Thus, the ecological benefits and economic benefits of wetland were also unchanged. After optimization, the ecological, economic, and total benefits of the water were reduced by 3500.6, 12371.1, and 6605.3 thousand yuan, respectively. In addition, after optimization, the ecological, economic, and total benefits of the intertidal zoon were reduced by 4469.5, 1174.6, and 3316.3 thousand yuan, respectively. For construction land, the economic and total benefits were increased by 83959.0 and 29385.7 thousand yuan, respectively. In term of the optimized results, the increases in forest land and construction land area, under the conditions of unchanging total area; it is unavoidable to reduce the other types of land use. Because we need to take regional food safety into consideration, the range of the reducing cultivation land area is relatively limited. Moreover, the wetland area was unchanged. Thus, during the optimization process, it is unavoidable to reduce a part of the artificial water and the intertidal zone area. These are the comprehensively balanced results during the optimization process. It can be seen from Table 3 that after optimization, the annual ecological benefits in the study area were reduced by 5105.3 thousand yuan while the annual economic benefits were increased by 69133.5 yuan. The regional annual total benefit was increased by 20878.3 thousand yuan, which was increased by 0.44%.

In general, the rapid social and economic development in the study area leads to the construction land use compressing ecological land use continuously. After optimization, the land use structural scheme still maintained the increase in the regional total benefits. This scheme not only meets the requirement for protection of the ecological environment but at the same time also meets the requirement for its rapid social and economic development.

Discussion

In order to verify the feasibility of the improved multi-objective differential evolution algorithm proposed in this study, we compared the results obtained with this algorithm with those obtained with the classic linear programming method. Among which, the linear programming method was achieved via the optimization function in the Matlab7.0 environment. The year 2010 was taken as the base period while the year of 2020 was taken as the objective year to be optimized. The optimized results obtained with two methods were presented in Table 4 as follows.

It can be seen from Table 4 that under the situation when the objective function and various constraint conditions are the same, the optimized results obtained with the improved differential evolution algorithm are the same as those obtained with the linear programming method, indicating that it is feasible to apply the improved differential evolution algorithm in land use structure optimization and that the optimized results obtained with it are reliable [27]. Additionally, it can also be seen from the optimization process that the procedures for the improved differential evolution algorithm is simpler and clearer and that operational efficiency is higher and is more robust [25-26, 27]. However, because the scale of optimization problem and the degree of complicity are not so big, the advantages of the differential evolution algorithm are still not fully demonstrated [28-29]. It is believed that in seeking a solution for a more complicated non-linear optimized problem, the differential evolution algorithm will display more advantages than the linear programming method. In the follow-up study, we will select regions with more land use types and more complex changes as

Table 4. Comparison of differential evolution algorithm and linear programming optimization.

Land type	Situation in 2010		Optimized results with differential evolution in 2020		Optimized results with linear programming method in 2020	
	Area (hm^2)	Proportion (%)	Area (hm^2)	Proportion (%)	Area (hm^2)	Proportion (%)
Cultivation land	62768.29	45.25	62687.39	45.20	62687.39	45.20
Forest land	2279.78	1.64	2566.60	1.85	2566.60	1.85
Wet land	14695.97	10.60	14695.97	10.60	14695.97	10.60
Waters	14281.84	10.30	13823.65	9.97	13823.65	9.97
Intertidal zone	22905.71	16.51	22318.39	16.09	22318.39	16.09
Construction land	21768.41	15.69	22608.00	16.30	22608.00	16.30
Sum	138700	100.00	138700	100.00	138700	100.00

the study area, and verify the proposed model of land use structure optimization from other aspects in order to improve it.

Conclusions

In this study, we established a land use structure optimization model based on an improved multi-objective differential evolution algorithm. The improvements were made on the classic differential evolution algorithm in two aspects, i.e., the controlling parameters and mutation strategy and established multi-objective functions by taking economic and ecological benefices as the objectives. According to the actual situation of the study area, we established multiple ecological constraint conditions and finally established an improved multi-objective differential evolution algorithm. We found the solution for the optimal land use quantitative structure for the study area and made a comparison between the optimized results with those obtained with the classic linear programming. The experimental results showed that the annual total benefits increased by 20,878,300 yuan, an increase of 0.44% in the study area. This showed that the land use structure obtained by using the optimization model proposed in this paper was more reasonable.

The results indicated that the model established in this study has quite good properties and can meet the requirement for regional land use structure optimization under multi-constraint conditions. The models constructed in the study may undoubtedly support the process of optimizing land use structure. They facilitate determining possible land use planning and taking appropriate corrective actions, if necessary. These can provide the basis for formulating regional land use planning and the sustainable use of land resources.

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Conflict of Interest

The authors declare no conflict of interest.

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