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Simulation on optimized allocation of land resource based on DE-CA model

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ABSTRACT

Optimization of land resource allocation is a research hot spot in land science. In this study, a new differential evolution-cellular automata (DE-CA) model was established. With this model, the quantitative structure of land-use was optimized with differential evolution algorithm (DEA). The results obtained were then used as the quantitative restraint condition of CA model to optimize the land-use spatial patterns. The application of this model successfully achieved the proper combination of land-use quantitative structure with the land-use spatial pattern, which overcame the problem in previous studies with particular emphasis on either optimization of land-use quantitative structure or optimization of spatial patterns in the field of optimization of land resource allocation. Finally, we applied the established DE-CA model to optimize the allocation of land resources for the year 2010 and 2020 based on 2005 and 2010, respectively, in Dawa County and Liaoning Province in northeast of China. The accuracy and reasonability of the optimized results were analyzed and assessed. The results showed that the overall accuracy of the optimized results was 84.56% with Kappa coefficient of 0.7860, indicating the good performance of the established DE-CA model. Furthermore, the simulated scheme was shown to be consistent with the real situation. Thus, this model can provide the references for formulation of the regional land-use planning and provide scientific basis for the substantial utilization of land.

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1. Introduction

Optimal allocation of land resources refers to the proper arrangement, design, combination, and planning of land resources at multiple levels and at different spatial scales to increase the land-use efficiency and beneficial results and maintain the relative balance of the land ecosystem so that the sustainable use of land resources can be achieved. Based on the land characteristics and land system principles, optimal allocation of land resources can be achieved by applying certain scientific principles, technological methods, and management measures (Benabdallah and Wright, 1992). The optimal goal of ecological economy can be achieved by optimal allocation of natural resources (Benabdallah and Wright, 1992). Recently, the contradiction between land supply and land demand has become increasingly obvious (Zhou et al., 2015). A variety of economical construction projects have already occupied a large amount of the high quality land, causing the imbalance of the land-use structures and the low efficiency of land-use (Zhou et al., 2015). This has imposed a serious threat to the safety of China's national land resources (Zhou et al., 2015). To scientifically and properly predict the supply demand of land-use, to effectively resolve the contradiction of land-use supply-demand, to optimally allocate the land resources, and to implement the measures of land saving and intensive use are essential for ensuring the requirement for the development of China's national economy.

Since 1990s, optimal allocation of land resource has been used as the important ways and measures for regional sustainable development and thus, has received increasing attention (Liu et al., 2014). Many investigators in China and other countries have conducted extensive studies from different aspects in this field. For instance, using a combination of the method of overall land-use planning based on Multi-objective Programming (MOP) and GIS, Wang et al. (2004) established an integrated and comprehensive GIS and Inexact-Fuzzy Multi-objective Programming (GIS/IFMOP) model and applied this model to optimize the land resource allocation in the watershed scale. Ralf and Alexey (2002) optimized

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the methodology for land-use based on spatially explicit landscape model. They developed a framework of procedures for numerical optimization in spatially explicit dynamic ecosystem simulation models and applied this model to quantitatively optimize farmland. Sergio et al. (2006) applied MOP model to investigate the allocation of land resource in the agricultural system for vegetable production in the areas surrounding Manila, the capital city of Philippine. They obtained the optimal eclectic solution from 23 Pareto efficiencies that were calculated by using the cluster analysis and constrained optimization method. Ines et al. (2008) established the GIS-based planning support system for allocation of rural land-use. Sadeghi et al., 2009Sadeghi et al. (2008) optimized the land-use structure in Brimvand watershed in Iran by using the multi-objective linear programming model. They provided the data of soil erosion, net benefit, and land capability maps as the inputs and formulated the objective functions and governing constraints in a multi-objective linear optimization problem and resolved the problem by using the simplex method with the assistance of ADBASE software package, and ultimately determined the optimal solution. Using single index, Peng and Liu (2014) estimated and analyzed the population burden of land resources and its restrictions in the capital metropolitan region and proposed the optimal strategies for the spatial distribution patterns of population. Feng et al. (2014) established the method for optimization of land-use structure in Tongling city based on different ecological conservation scales. Li et al. (2015) proposed an optimized regional land-use layout based on the CLUE-S model. In addition, other investigators used the coupling strategies of cellular automata and case reasoning, artificial neural network, and ant colony optimization (ACO) to compact simulation of urban land-use and obtained a number of satisfactory results (Li et al., 2009; Liu et al., 2010; Yang, 2009). In the studies mentioned above, most of the optimized models and methods for land-use have placed emphasis on the optimization of quantitative structure of land-use whereas no attention has been given to the methods for scientific and proper optimization of spatial patterns for land-use. This problem directly leads to the situation that the results obtained with these optimized structure models for land-use can hardly be implemented in geographical and spatial patterns for land-use in reality. While a number of investigators attempted to establish the models and methods for optimizing the spatial patterns for land-use based on several models, such as simulate annealing arithmetic method, ant colony optimization, genetic algorithm, multi-agent system and artificial neural network during the recent years, these methods are basically the relatively isolated, spatially optimized models. They cannot be used to resolve the problem of optimization for quantitative structure for land-use during the optimization process of spatial patterns for land-use. However, there have been few successful cases of the applications of the current studies results in practical (Liu et al., 2014). This is mainly due to the reason that a large majority of studies have been done with the focus mainly on either the optimization of land-use quantitative structure or on the optimization of land-use spatial patterns and few studies have been conducted with focus on the combination of both.

In this study, we selected Dawa county, Liaoning Province in northeast of China, as the study and established a new differential evolution-cellular automata (DE-CA) model. With this model, differential evolution algorithm (DEA) was used to optimize the quantitative structure of land-use and results obtained were then used as the quantitative restrain conditions and integrated into CA model to optimize the land-use spatial patterns for achieving the proper combination of optimization of land-use quantitative structure and the optimization of land-use spatial patterns. The results of this study can provide the valuable references for the formulation of land-use planning and can also provide the scientific basis for the substantial utilization of land in the studied area.

2. Model based on DE and CA

2.1. Differential evolution algorithm (DEA)

In the very recent years, there has been an ever-increasing interest in the area of a differential evolution algorithm (DEA) proposed by Rainer Storn and Kenneth Price (Storn and Price, 1995, 1997). The advantages of using DEA for solving the global design problems include global solution-finding property, powerful search capability, fewer control parameters, ease of use, and high convergence characteristics (Price et al., 2005; Rahnamayan et al., 2008; Noman and Iba, 2008; Lin et al., 2011). Like other evolutionary algorithms, DEA is a population-based and stochastic global optimizer that can work reliably in nonlinear and multimodal environments (Dhahri et al., 2012; Wang et al., 2012; Zou et al., 2013; Tsai, 2015).

DEA includes initial population, mutation, crossover, and selection. More specifically, the basic strategies of DEA can be described as the follows:

2.1.1. Initial population

Prior to conducting the major operational procedures, i.e., mutation, crossover, and selection with DEA, optimization of the location management needs to be carried out, i.e., the initial population in the NP (population for each generation) scale was randomly created in the definition domain space of the variable, the detailed equation was as the follows:

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

where, $x_{\mathrm{i,j}}$ is the J component of the i individual; $x_{\max}$ and $x_{\min}$ are the maximal value and the 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; j represents the individual serial number of the variable, j = 1,2,. . ..D.

2.1.2. Mutation

During the optimization process with DEA, the most basic mutation component is the differential vector derived from the parent generation. Each differential vector includes two different individual vectors (x_{r1}^t, x_{r2}^t). These differential vectors are calculated using the following equation:

$$D_{r1,2} = x_{r1}^t - x_{r2}^t, \tag{2}$$

where r_1, 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_i^t, the operational equation for mutation is expressed as follows:

$$v_i^{t+1} = x_{r3}^t + F\left(x_{r1}^t - x_{r2}^t\right), \tag{3}$$

where v_i^{t+1} represents the resulting variable vector; The r_1, r_2, $r_3 \in \{1, 2, \ldots, \mathrm{NP}\}$, represents 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.

2.1.3. Crossover

The operational procedures 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 by vector x_i^t, which can be determined by using the crossover probability factor CR. The detailed equations are as the follows:

$$u_{ij}^{t+1} = \begin{cases} v_{ij}^{t1+}, & \text{rand}(j) \le \text{CR or } j = \text{randn}(i) \\ x_{ij}^t, & \text{rand}(j) > \text{CR or } j \ne \text{randn}(i) \end{cases}, \tag{4}$$

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

2.1.4. Selection

The selection procedures were as follows: the resulting individual vector u_i^{t+1} obtained after mutation operation and crossover operation was compared with the original individual vector x_i^t, if the fitness of the experimental vector u_i^{t+1} was better than that of the original individual vector x_i^t, then it was 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; the detailed equations are as the follows:

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

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 the individual x_i^t; when $f(u_i^{t+1}) > f(x_i^t)$, the fitness of individual x_i^t is superior over that of the individual u_i^{t+1}.

2.2. Cellular automata (CA) model

CA is a dynamic network model in which the time, space, and state are individually separated and distinct. Both the spatial interactions and temporal causality are localized. With this model, the very simple states can be converted into rules and the extremely complicated states can be simulated and optimized in the way of evolving cellular automata from the bottom to the top.

The naturally dynamic CA has remarkable replicating properties and can create the dynamic spatial patterns at different temporal and spatial scales (Reine et al., 2014). CA is a powerful tool for understanding land-use systems and their inherent dynamic features (Benenson and Torrens, 2004), especially when they are used in combination with other tools, such as DEA.

CA focuses mainly on the local interactions of cellular with distinct temporal and spatial coupling features and the powerful computing capability of space, which is particularly suitable for the dynamic simulation and displays with self-organizing feature systems (Sang et al., 2011; Yang et al., 2014; Gong et al., 2015; Verstegen et al., 2014). The CA model can be expressed as follows:

$$S(t, t+1) = f(S(t), N), \tag{6}$$

where S is the set of limited and discrete cellular states; N is the cellular field; t and $t+1$ indicate the different times, and f is the transformation rule of cellular states in local space.

2.3. Integration of DE and CA

The advantages of CA model are that it can be used to conduct the simulation and evolution of the changes in land-use. However, it is relatively deficient in the ability to create the optimal land-use quantitative structure during the simulation process (Yang et al., 2015). Thus, in order to overcome this deficiency, in this study, we established DE-CA model by using differential evolution algorithm (DEA) to optimize the land-use quantitative structure and then used the results as the quantitative restriction conditions and integrated them into the CA model, and applied it to optimize the spatial patterns of land-use. The application of this new model for optimization of land resource allocation ensured the proper combination of optimization of land-uses quantitative structure with the optimization of the spatial patterns of land-use.

This model was applied to optimize the land resource allocation in this area. Starting from the current land-use status, the optimization of spatial patterns of land-use was achieved through the evolution of single cellular state. For N types of land-use, there might be $N \times N$ types of changes. Within certain period of optimization time, the transition of land-use types was influenced by many factors. Thus, each influencing factor needed to be analyzed. A serial of restriction conditions were added to the optimization model for controlling the optimization process so that the cellular state can be transited toward the expected direction and thus the optimization of the land-use in the entire region can be achieved.

During the transition process of cellular state, the cellular state was restricted by a number of factors including the location's characteristic variables, the adjacency coupling effect, ecological suitability, land-use inheritance, land-use transition restriction conditions, and random factors. Whether or not the cellular state can be converted could also be determined by the set conversion threshold and the quantitative restriction controlling index obtained by optimization using DEA. During the operational process with CA model, at the end of iteration, the results of iteration were checked, i.e., whether or not the areas of various land-use types reached the quantitative restriction control index. If they did not, then the operation was continued. Otherwise, the operation of CA model was stopped. The optimal results for the land-use spatial patterns in the studied area were finally obtained. The technological process of DE-CA model was shown in Fig. 1.

3. Case study

3.1. Studied area

Dawa County was selected as the study area because of the existence of representative ecosystem, which has rich land-use types, and can provide reliable data for simulation of the DE-CA model. It is located in southwest of Liaoning Province, and the north edge of Liaodong Bay. Its south and north are surrounded by Daliao river. Its west faces the Bohai Sea and Liaodong Bay. Geologically, this county is located between 121°48′E–122°21′E and 40°41′N–41°09′N and displays the typical characteristics of the coastal ecology. The total land area of the entire area is 1387 km^2. The topography of this county is flat with plenty of low-lying water. This is a coastal plain formed and developed by the deposits of in tidal flats from DaLiao Rive and Liao River. The mean annual precipitation is 647.3 mm. There is abundant water resource. DaLiao River, Liao River, Xinkai River and Shuangtaizi River flow through this area. The soil types in this area include mainly rice soil, meadow soil, and bog soil.

3.2. Data source and processing

The original raw data used in this study were the Landsat ETM+/TM remote sensing images acquired in the years of 2000,

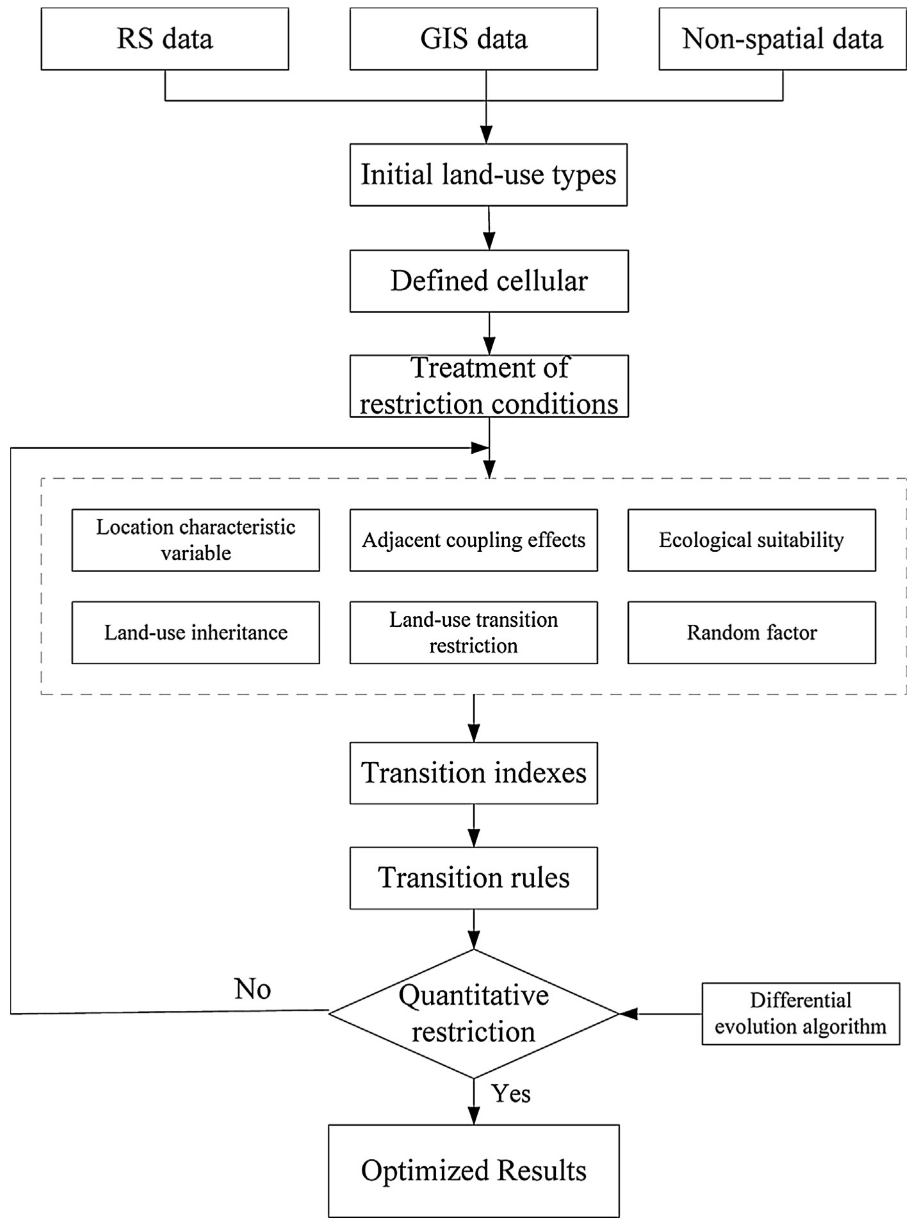

Fig. 1. Technological process of DE-CA model.

2005, and 2010 (Table 1). The topographic maps (1:100,000) of the year 2010, the current land-use status map (1:100000) of the year 2005, and land-use planning map (1:100,000) of the year of 2006–2020 and Digital Elevation Model (DEM) in 30 m resolution. In addition, the natural status data of meteorological, hydrological, soil, and vegetation and the statistical data of social-economic data in the studied area were also used (Table 1). Three Landsat TM images taken in each period in the study area were selected and montaged. The geometric registration of imagery was conducted using topographical map (1:100000) as the datum mark. The mosaic of remote sensing images was made using ENVI 4.8 software (Chen et al., 2015). 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 by using the ISODATA unsupervised classification. They were then combined into

Table 1
Data sources used in this study.

Acquisition	Data types	Spatial resolution	Data source
09-03-2000	7 ETM+	30 m	Computer network information center, Chinese Academy of Science
08-22-2005	TM5	30 m	Computer network information center, Chinese Academy of Science
09-20-2010	TM5	30 m	Computer network information center, Chinese Academy of Science
01-22-2010	DEM	30 m	Computer network information center, Chinese Academy of Science
07-28-2010	Topographic maps	1:100,000	Land Resources Bureau of Dawa County
02-03-2005	Land-use status map	1:100,000	Land Resources Bureau of Dawa County
2006–2020	Land-use planning map	1:100,000	Land Resources Bureau of Dawa County
2000–2010	Other data	–	Land Resources Bureau of Dawa County

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 studied 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 studied area were finally obtained. According to the ground data and the field survey data of the same period of time, cultivated land, construction land, forest land, wetland, waters, and tidal flats were randomly selected and their classification confusion matrix and Kappa coefficient were calculated. In addition, we calculated the producer's accuracy and user's accuracy of various types of land in the classified results of remote sensing imaging taken during three periods of investigation (Canran et al., 2007). Furthermore, the other natural status data and the statistical data of the social economy in the studied area were also collected and used for the establishment of restriction conditions for conducting the optimal allocation of the land resources.

3.3. Simulation process

3.3.1. Determining the constraints of land-use types number

In this study, when we optimized land resource allocation by using the established DE-CA model, we first used the differential evolution to optimize land-use quantitative structure and then integrated the results as the quantitative restriction conditions into CA model and optimized the land-use spatial patterns. According to the results of land-use classification described above, during the optimization process, the quantitative restriction conditions for land-use mainly included the restriction conditions for the areas of cultivated land, forest land, wetland, waters, tidal flat, and construction land. The quantitative restriction conditions were obtained by using DEA.

3.3.2. Determining the constraints of land-use types conversion

The essences of land resource optimal allocation are the transition of various land-use types and the spatial pattern distribution under various restriction conditions. In reality, the land-use types cannot be arbitrarily transited and changed. They are influenced by many factors. For example, Land Administration Law of the People's Republic of China has set some obligatory restrictions for controlling land-use. Furthermore, there exist some intrinsic restriction relationships among various land-use types. Thus, analysis of the land transition rules among different land-use types in the studied area can minimize the amount of work for transition of land-use types in cellular state during the optimization process and increase the transition efficiency. In this study, we analyzed the construction land transition restriction, wetland transition restriction, forest land transition restriction, cultivated land transition restriction, waters transition restriction, and tidal flat transition restriction and obtained six restriction conditions for the transition of land-use types.

3.3.3. Determination of CA filter

CA filters can produce a clear sense of the spatial weighting factor, which can be changed according to the current adjacent cellular state. The standard 3 × 3 contiguity filter was used as the neighborhood definition in this study, i.e., each cellular center is surrounded by a matrix space which is composed by 3 × 3 cellular to significantly impact the cellular changes (Yang et al., 2015).

3.3.4. Determining CA transition rules

3.3.4.1. The cellular state transition function. In this study, the cellular state transition rules in the CA model were mainly composed of six components: the effects of location characteristic of the variable, the adjacent coupling effects, the effects of ecological suitability, effects of land-use inheritance transition, the effects of restraint conditions for land-use type transition, and the effects of random factors. Thus, the restraint conditions can be converted into the transition indexes according to the nature of the effects of various factors. The transition indexes can be expressed as follows:

$$P^{t+1}_{(uz,i)} = L^t_{(uz,i)} \times N^t_{(uz,i)} \times E^t_{(uz,i)} \times I^t_{(uz,i)} \times C^t_{(uz,i)} \times R^t_{(uz,i)}, \tag{7}$$

where $P^{t+1}_{(uz,i)}$ is the transition indexes of cellular i from land type u to z at the period of time t to $t+1$; $L^t_{(uz,i)}$ is the effect of location characteristic variable of the transition of land type u to z of cellular i during the period of time t to $t+1$; $N^t_{(uz,i)}$ is the adjacent coupling effect of the transition of land type u to z of cellular i during the period of time t to $t+1$; $E^t_{(uz,i)}$ is the effect of ecological suitability of the transition of land type u to z of cellular i during the period of time t to $t+1$; $I^t_{(uz,i)}$ is the effect of land-use status inheritance of the transition of land type u to z of cellular i during the period of time t to $t+1$; $C^t_{(uz,i)}$ is the effect of restriction condition for the transition of land type u to z of cellular i during the period of time t to $t+1$; and $R^t_{(uz,i)}$ is the effect of random factors in the transition of land type u to z of cellular i during the period of time t to $t+1$.

3.3.4.2. Definition of transition rules. During the optimization process, the transition rules reflect the interactions among the cellular state. In equation (7), the adjacent coupling effect and the effects of location characteristic variable, ecological suitability, land inheritance, restriction of land-use type transition, and random factors on the cellular transition were taken into comprehensive consideration when the transition index was calculated. However, whether or not the cellular can be transited is determined by the threshold of transition probability $P_{\text{threshold}}$ and the quantitative restriction control index. The transition index P^{t+1} obtained after calculation was compared with the threshold value $P_{\text{threshold}}$, if $P^{t+1} \geq P_{\text{threshold}}$, then we judged that the land-use type transition in the cellular state i occurred during the period of time $t+1$; if $P^{t+1} \leq P_{\text{threshold}}$, then we judged that land-use type transition did not occur during the period of $t+1$; At the same time, for the cellular state transition, we also considered the land-use quantitative restriction. If the areas of various land-use types reached the quantitative restriction control indexes, the iteration was stopped; otherwise, the modeling operation was continued so that the optimal allocation of land resource allocation in the studied area can be finally obtained.

$$K = f(P^{t+1}_{(uz,i)}, P_{\text{threshold}}, S), \tag{8}$$

where K represents the optimal land-use spatial patterns; $P^{t+1}_{(uz,i)}$ is the transition index for the transition of land type u to z of cellular i during the period of time t to $t+1$; $P_{\text{threshold}}$ is the transition probability threshold values for quantitative restriction control index of the cellular i during the period of time t to $t+1$; S is the quantitative restriction control index; f is the transition function.

3.3.5. Model implementation

In this study, we established DE-CA model, which mainly included two parts. The first part was quantitative optimization of land-use, which was achieved by using DEA; the second part was the optimization of the land-use spatial patterns, which was achieved by using CA model.

Differential evolution algorithm (DEA) includes four major parameters, i.e., population size (NP), variable dimension (D), scale factor (F), and crossover probability (CR). Among them, based on the previous experiences, the values for F and CR were set as 0.5 and 0.9, respectively. It can be learnt from the results of land classification described above that the land-use types of the studied areas included six types, i.e., cultivated land, construction land, forest land, wetland, waters, and tidal flats. Thus, the number of variable dimension was 6. The population size (NP) was generally between 5 and 10D. In this study, the number was set as 10D and thus, NP = 60. DEA was achieved by programming under the VC + +6.0 environment. Among which, the variable dimension D was set as 6. The population size NP was set as 60. The value of crossover probability factor CR was set as 0.9 and the magnification factor *F* was set at 0.5. The maximal iterations were 500 (Wang et al., 2015). The year 2010 was taken as the base period and year 2020 was taken as the target year for optimization. After conducting independent operation and experiments many times, the results of the optimized land-use quantitative structure in 2020 in the studied area were finally obtained.

The part of CA model was achieved by using the Geographical Simulation and Optimization Systems (GeoSOS) developed by Sun Yat-Sen University (Guangzhou, China). GeoSOS can simulate, predict, optimize, and demonstrate the geographical patterns and spatial process. GeoSOS can resolve the problem of the seriously functional deficiency existing during the simulation and optimization of the spatial process with geographical information system. Based on the established model, we firstly input the base (mother) map of the optimized land- use status and then input the land-use quantitative structure obtained by using DEA and defined the quantitative restriction condition for the operation with this model, then calculated cellular transition index and defined the state transition rule. We conducted iterative computations based on the set preference order of the land-use types until the quantitative restriction conditions for various land-use types were satisfied. The optimized maps of the land-use spatial patterns were finally created.

4. Results and analysis

4.1. Results

Based on the data treatment described above, we applied the established DE-CA model to optimize the simulation of the regional land resource allocation in the studied area in 2010 and 2020. The optimal results in 2010 were shown in Fig. 2. Among them, the optimized results were obtained by the operation based on the land-use status map in 2005. The stopping criteria for iteration were the land-use quantitative restriction index of 2005–2010 that were obtained by one-factor analysis of the classification maps of the remote sensing images. The optimized results in 2020 were obtained by the operation based on the current land-use status map of 2010. By using the optimized results of quantitative structure of land-use obtained with DEA for 2020 as the stopping criteria for iteration and the optimal results were obtained after iteration for 500 times. It can be seen from Fig. 2 that the optimized results displayed the following characteristics:

(1) **The optimized results in 2010**: During the optimization process for the period of 2005–2010, the areas of construction land and waters were largely increased. The areas of cultivated land, tidal flats, forest land, and wetland were reduced to different extends (Table 2). Among them, the increased areas for construction land were mainly distributed in the areas surrounding the existing construction land and the developing areas along the roadways. The increased area of waters was mainly distributed the existing waters within the cultivated land and the surrounding areas as well as the western coastal zoon. The reduced area of cultivated land was mainly transited to the construction land and waters, which were mainly distributed in the tidal flats in the eastern coastal zoon. The reduced area of forest land was mainly transited to cultivated land, which was mainly distributed within the villages. The reduced area of wetland was transited to tidal flats, which were mainly distributed in wetland and the bordering zones between wetland and tidal flats. The transition of land-use types is consistent with the current reality status. The spatial patterns of various land-use types were basically similar to the patterns of land-use status map in 2010.

(2) **The optimized result in 2020**: During the optimization process for the period of 2010–2020, the areas of construction land and forest land were increased to a relatively large extent whereas the areas of cultivated land, tidal flats, and waters were reduced to different extends (Table 3). The area of wetland was not changed. Among them, the increased area of construction land was mainly distributed in the areas surrounding the exciting construction lands and in the developing areas along two sides of the roadways. The increased area of forest land was mainly distributed in the areas surrounding the existing forest land and two sides of roadways. The reduced area of tidal flats was transited to cultivated land, which was mainly distributed in the tidal flats in the eastern coastal edge. The reduced area of waters was mainly transited to cultivated land, which was mainly distributed in aquiculture area within the cultivated land. The inter-transition of these land-use types is consistent with the real situation. The spatial patterns of various land-use types are basically reasonable, indicating that the performance of the optimized model established in this study is quite good.

The results mentioned above were derived from the comprehensive consideration of the optimization of both the quantitative structure and spatial patterns of land-use. These optimized results basically meet the requirements for optimization of the land resource allocation in the studied area and can provide the reference for formulation and revision of land-use planning and can also provide the scientific basis for making the proper decision on substantial land-use.

4.2. Analysis on the Accuracy of the optimized results

In order to evaluate the accuracy/precision of the established DE-CA model, we analyzed the optimized spatial pattern of land-use. Currently, several methods, including visual comparison, fractal dimension, and confusion assessment method (CAM) were

Table 2
Optimization result of land-use quantitative structure in the year 2010 in the study area.

Land types	Status area (hm^2)	Proportion (%)	Optimized area (hm^2)	Proportion (%)	Change area (hm^2)	Proportion (%)
Cultivated land	65,134.00	46.96	62,768.29	45.25	−2365.71	−3.63
Forest land	2798.00	2.02	2279.78	1.64	−518.22	−18.52
Wetland	16,320.00	11.77	14,695.97	10.60	−1624.03	−9.95
Waters	13,054.00	9.41	14,281.84	10.30	1227.84	9.41
Tidal flats	23,040.00	16.61	22,905.71	16.51	−134.29	−0.58
Construction land	18,354.00	13.23	21,768.41	15.69	3414.41	18.60
Total	138,700.00	100.00	138,700.00	100.00	0.00	0.00

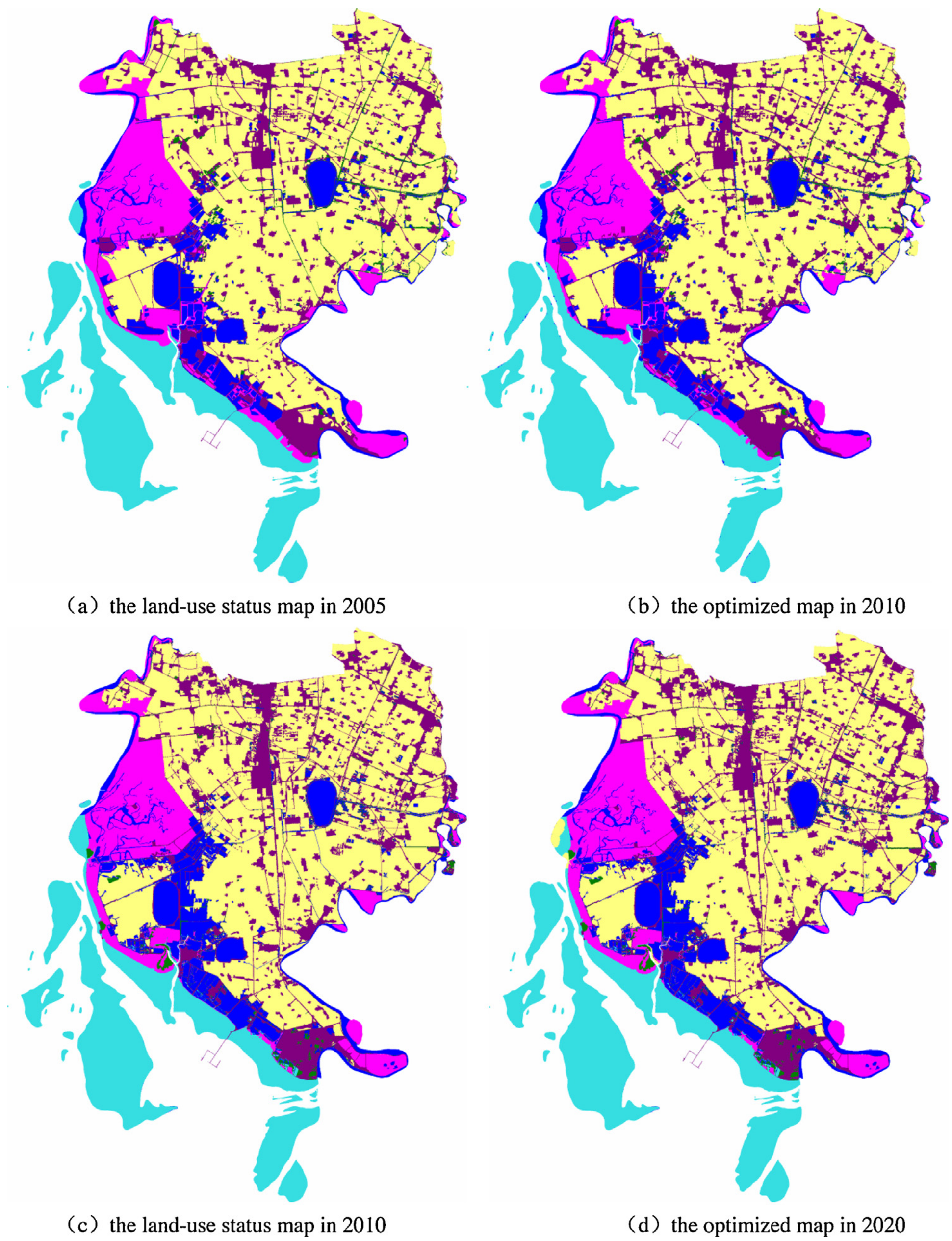

Fig. 2. Optimized results of maps of land-use status and spatial pattern in the study area.
Notes: The optimized results for the year 2010 were obtained by optimization of the land-use status map in 2005; the optimized results for the year 2020 were obtained based on the optimization of the land-use status map in 2010.

used to assess the accuracy of CA model. Among them, CAM is the most commonly used assessment method. With this method, the optimized results and the real classification results were composited and the accuracy was computed by point-by-point comparison, i.e., the confusion matrix was computed. In this study, we used this method to assess the accuracy of the optimized model.

In this study, we compared the optimized results obtained based on the land-use status map in 2005 with land-use status map (remote sensing images) of 2010 and computed the confusion

Table 3
Optimization result of land-use quantitative structure in the year 2020in the study area.

Land types	Status area (hm^2)	Proportion (%)	Optimized area (hm^2)	Proportion (%)	Change area (hm^2)	Proportion (%)
Cultivated land	62,768.29	45.25	62,687.39	45.20	−80.90	−0.13
Forest land	2279.78	1.64	2566.60	1.85	286.82	12.58
Wetland	14,695.97	10.60	14,695.97	10.60	0.00	0.00
Waters	14,281.84	10.30	13,823.65	9.97	−458.19	−3.21
Tidal flats	22,905.71	16.51	22,318.39	16.09	−587.32	−2.56
Construction land	21,768.41	15.69	22,608.00	16.30	839.59	3.86
Total	138,700.00	100.00	138,700.00	100.00	0.00	0.00

Table 4
Confusion matrix of the optimized results of 2010.

Ground truth classification	Waters	Cultivated land	Forest land	Construction land	Wetland	Tidal flats
Waters	5884	187	0	0	1202	320
Cultivated land	98	9350	31	478	879	552
Forest land	0	60	875	0	0	0
Construction land	0	662	4	6496	0	0
Wetland	284	0	0	0	6730	680
Tidal flats	127	0	0	0	505	3842

matrix (Table 4) with ENVI4.8 software (Chen et al., 2015). The results indicate that the overall accuracy of the optimized results was 84.5600% and Kappa coefficient was 0.7860. Therefore, it is feasible to apply this model to optimize the allocation of regional land resources and the results obtained can be acceptable.

4.3. Analysis on the rationality of the optimized results

In order to evaluate the rationality of the optimized results, we conducted comparative analysis in two aspects. Firstly, we compared the difference in the spatial patterns of land-use in term of the landscape patterns before and after optimization; Secondly, we conducted the overall analysis on the rationality of optimized results by comparing the optimized results with the real spatial patterns, including the real classification map of 2010 and the land-use planning map of 2020.

In order to analyze the difference in the optimized spatial patterns of land-use in term of the landscape patterns, we selected 8 landscape-pattern parameters including the patch number, the mean patch area, diversity, uniformity, predominance degree, fragmentation index, patch-shape index, and dispersion to assess the landscape characteristics of the optimized results from multiple aspects and contrasted the optimized results with the real classification results of the initial stage of the optimization. The detailed results were presented in Table 5.

It can be seen from Table 5 that the total patch numbers in the optimized results of 2010 and 2020 were increased slightly as compared to those of the land-use status maps of the corresponding years. Because the total areas were not changed, the mean patch areas displayed the decreasing trend. This is mainly due to the reason that during the optimization process with CA model, the effects of the random factors were taken into account. This led to the occurrence of sporadic patches in the optimized maps. At the same time, the increase in patch number made the optimized land-use spatial patterns more complicated. The landscape shape index that characterizes the complexity of the patch shape was increased. The fragmentation index that characterizes the fragmentation degree of the patch and dispersion that reflects the degree of dispersion of the patch displayed the increasing trends. In addition, the diversity that characterizes the abundances of land-use types and the uniformity that reflects the distribution uniformity of the patch displayed the increasing trends. The predominance that reflects the degree of the predominance of certain land-use types displayed a decreasing trend. These results indicate that the proportions of the various land-use types tend to be reduced and that various land-use types tended to be uniform. It can be seen from the characteristic changes in the optimized results and landscape patterns of land-use status described above that during the optimization process with the established DE-CA model, the total number of the patch in the studied area was increased to certain extend. This made the spatial structure and spatial patterns of land-use more complicated and at the same time, the uniform proportions of various land-use types in the studied area under the quantitative restriction conditions were also satisfied. The changes in these patterns are basically consistent with the real situation and also indicate that the optimized results obtained with the DE-CA model established in this study are reasonable and that this model is practical.

Furthermore, in order to analyze the rationality of the optimized results from the overall spatial patterns, we conducted the comparative analysis on optimized results of 2010 with the real classification maps of 2010, the optimized results of 2020 and the land-use planning maps of 2020. We found that the optimized spatial patterns were basically similar to real spatial distribution of land-use patterns and the direction of spatial pattern development of their major land-use types were basically similar as follows: (1) During the optimization for the period of 2005–2010 (Table 2), the area of the construction land was expanded mainly in the areas surrounding the existing construction land and developed along the roadways, which were mainly distributed around county, townships, villages, and along the roadways. The increased area of waters was mainly distributed in the farmland; the reduced cultivated land was mainly distributed around the villages. The reduced area of tidal flats was mainly distributed in the eastern coastal zoon nearby agricultural region. The reduced area of forest land was mainly distributed within the villages and their surrounding areas; the reduced area of wetland was mainly distributed in the edge of the wetland. (2) During the optimization for the period of 2010–2020 (Table 3), the area of the construction land was expanded mainly in the areas surrounding the existing construction land and developing areas along the roadways, reflecting the basic requirement of the development of construction; the increased area of forest land was mainly distributed along the roadway and the areas surrounding the townships, which was mainly used as the green space. The reduced area of the cultivated land was mainly distributed in the areas surrounding the construction land and two sides along the roadways; the reduced area of tidal flats was mainly distributed in the eastern coastal zoon nearby the agricultural region, which

Table 5
Contrast on landscape pattern indexes of the optimized results and land-use status in the study area.

Type	Patch number	Mean patch area (hm^2)	Diversity	Uniformity	Predominance	Fragmentation index	Patch shape index	Degree of dispersion
2005 Status map	5499	25.22	1.41	0.72	0.38	0.0036	1.28	0.75
2010 Optimized results	7054	19.66	1.42	0.74	0.36	0.0041	1.29	0.76
2010 Status map	7147	19.41	1.38	0.70	0.42	0.0046	1.26	0.77
2020 Optimized results	7284	19.04	1.49	0.83	0.41	0.0048	1.27	0.79

was mainly developed into the cultivated land. The reduced area of waters was mainly distributed in the central parts of the cultivated land, due to the transition of a part of aquiculture water surface into cultivated land. There was no change in wetland during the optimization process. These results indicate that the transition patterns of the land-use types are basically consistent with the real situation. The land-use layout is basically reasonable, indicating that the optimized model established in this study performs quite well.

However, it can be seen from the optimized maps for the years of 2010 and 2020 that because the effects of random factors were taken into account during the process of establishing DE-CA model, some sporadic patches that are not consistent with the real situation appeared in the optimized maps. For instance, some waters appeared in the edge of the tidal flats in the optimized maps for the year 2010; the transition of a piece of tidal flats into cultivated land was seen in the mid-west region nearby the western costal zoon in the optimized map for the year 2020. This is not consistent with the real situation because the tidal flats are usually selected for exploration in the eastern part nearby the agricultural region but not close to the costal zoon. Thus, this model needs to be improved in future study so that the optimized results obtained could be more scientifically sound and more reasonable/reliable. Generally, the optimized results obtained with the established DE-CA model are basically consistent with the requirement for optimal allocation of regional land-use. The reasonable optimal allocation plan for the regional land resources can be obtained.

5. Conclusions

In this study, a new DE-CA model was established. The quantitative structure of land-use was optimized with DEA. The results obtained were used as the quantitative restriction condition and integrated into CA model to optimize the spatial patterns of land-use. The application of this model ensured the proper combination of both the optimized quantitative structure with the optimized spatial pattern of land-use, which can overcome the problem of the particular emphasis on either optimization of quantitative structure of land-use or optimization of spatial pattern of land-use in previous studies in the field of land resource optimization.

The established model can be further optimized by using remote sensing imaging and other raster data. During the optimization process, the quantitative structure of land-use can be perfectly combined with spatial patterns optimization. This model can be used to resolve the problem existing in the complex optimization with multiple goals and multiple restriction conditions with relatively high accuracy and rationality. The established DE-CA model was applied to optimize the allocation of land resources for the year 2010 and 2020 in the studied area. The accuracy and reasonability of optimized results were analyzed and assessed. The experimental results indicate that performance of DE-CA model established in this study is quite good and application of this model can satisfy the demand for optimization of the land resource allocation under multiple restriction conditions in the studied area. The optimized results can provide the scientific basis for formulation of the regional land-use planning and for the substantial utilization of land.

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