

Article

Interpretation and Comprehensive Evaluation of Regional Water–Land–Energy Coupling System Carrying Capacity

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Abstract: Previous studies on carrying capacity have primarily focused on measuring agricultural production conditions while neglecting the coupling effects among production conditions, production materials, and the external environment (the coupling effects of agricultural water, soil, energy, and the external environment). Therefore, this paper introduces the concept of the carrying capacity of a regional agricultural water–land–energy coupling system (WLECS); develops an evaluation framework comprising 27 indicators from the perspectives of stability, collaboration, and resilience and constructs an improved random forest model based on the red-billed blue magpie optimizer (RBMO). Finally, it is applied to the evaluation of WLECS carrying capacity in China’s main grain producing area (Heilongjiang Province). The results demonstrate that the constructed RBMO-RF model exhibits stability and reasonableness with high fitting accuracy. The collaboration weight accounts for the highest proportion (0.438), indicating that the collaboration within the subsystem has the greatest impact on the carrying capacity. In terms of time scale, the WLECS carrying capacity in Heilongjiang Province shows an upward trend, characterized by three stages: a “low-level fluctuation period”, a “growth period”, and a “rapid growth period”. In terms of spatial scale, the overall spatial pattern is low in the West and high in the East, and stable in the North and South. The key driving factors are the effective irrigation index, indirect water footprint, and agricultural water-land matching degree. The research results demonstrate the carrying capacity of the WLE coupling system holds significant implications for formulating regional agricultural resource optimization allocation plans and promoting agricultural sustainable development.

Keywords: carrying capacity; red-billed blue magpie optimizer; random forest; coupling system



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1. Introduction

Water, land, and energy are important natural resources for maintaining the operation of social systems. They are also the core of regional agricultural system production [1,2]

and the material basis for human survival and livelihood [3]. Rapid social and economic development, accelerated urbanization, continuous population growth, energy depletion, and environmental degradation have created significant challenges. These factors have resulted in issues such as resource crowding out, shortages, and regional structural disruptions of water, land, and energy in agricultural production. Consequently, these problems are likely to intensify the imbalance between industrial structure adjustment and resource supply and demand [4]. Current demand and resource use trajectories are threatening to undermine the inclusiveness and sustainability of development. For example, by 2050, the Food and Agriculture Organization (FAO) projects a 70 per cent increase in food production, and the World Energy Council (WEC) projects a 100 per cent increase in energy supply. These trajectories must be curbed by a more efficient use of resources and reduced wastage, as well as demand management. However, there exists a close and complex coupling relationship among agricultural water, land, and energy [5]. Clarifying the mechanism of the water–land–energy coupling system (WLECS) in agricultural production [6] and conducting research on the agricultural water–land–energy coupling system carrying capacity (WLECSCC) will help promote resource conservation, improve production efficiency, alleviate the imbalance between resource supply and demand, ensure food security, and achieve sustainable regional economy development.

The term “carrying capacity” originally referred to a physical quantity in mechanics, namely the maximum (limit) load that an object can withstand without sustaining damage [7]. It was initially borrowed by disciplines such as demography, applied ecology, and population biology [8–11], all of which utilized the concept of “upper limit of quantity”. Subsequently, the FAO and the United Nations Educational, Scientific and Cultural Organization (UNESCO) organized large-scale studies on carrying capacity, and proposed various definitions and quantification methods [12]. This led to a new wave of research on carrying capacity.

Currently, the primary research methods for studying carrying capacity can be categorized into three main approaches: the empirical formula method, the index system evaluation method, and the system analysis method [13,14]. The empirical formula method offers the advantage of relatively simple calculations, but its disadvantage is that it inadequately considers the interrelationships among resources, the environment, the economy, and society. The indicator system evaluation method excels in its deep application of mathematical theories, yet it faces challenges in standardizing indicator selection [15,16]. The system analysis method accounts for the complexity and systematic nature of the resource–economy–society ecology, but it involves complex calculations and faces difficulties in application and promotion [17,18]. In summary, considering the inherent properties of carrying capacity, the index system evaluation method is the mainstream research approach in the current academic community. However, for the carrying capacity of complex agricultural production systems, previous studies have either focused on the relationship between the constraints of single water or land resources and social, economic, and natural systems or integrated water and land resource systems for evaluation. Not only does this ignore the impact of energy systems beyond natural conditions on agricultural production, but it also fails to consider the complex nonlinearity and feedback relationships among the interactions of various subsystems. Additionally, it lacks a comprehensive evaluation of WLECSCC from an integrated management perspective of factor coordination, departmental collaboration, and system control. Against this background, conducting regional agricultural WLECSCC evaluation research is of significant importance for alleviating the imbalance between resource supply and demand under the existing agricultural planting model.

To address the complex WLECSCC evaluation problem, we first need to analyze the intrinsic relationships within a coupled system. Based on this analysis, we should design an indicator system with minimal information overlap among the evaluation indicators, objectively determine the weights of these indicators, and finally use intelligent algorithms to optimize model accuracy, thereby enhancing the rationality of the evaluation results. The entropy weight method for determining indicator weights offers the advantages of objectivity, simplicity in operation, and effective reflection of the indicator differentiation ability, making it widely used in multi-objective evaluation fields [19–21]. With the development of artificial intelligence, machine learning methods have been widely applied in multi-objective evaluations of agricultural areas [22,23]. Machine learning can automatically analyze and extract patterns from multidimensional data, using these patterns to predict unknown data with high accuracy and the ability to handle complex nonlinear problems [23]. An evaluation simulation model is constructed using machine learning, with the evaluation index threshold serving as the input variable and the carrying capacity threshold serving as the output variable. The measured index data are substituted into the constructed model as the input source, and the output source obtained is the required evaluation target [22]. The evaluation results are not only scientifically sound and reasonable but can also efficiently identify key driving factors. However, a disadvantage is that the modeling process is relatively complex, and the selection of modeling methods and model parameters can directly influence the accuracy of the measurement results. The models that are currently used most in the field of multi-objective evaluation are projection pursuit (PP) [24], artificial neural networks (ANNs) [25], support vector machines (SVMs) [26], and extreme learning machines (ELMs) [27]. The accuracy of the PP model is overly dependent on the projection direction and has poor stability. The ANN model's fitting process suffers from issues of overfitting and becoming trapped in local minima. The SVM model's function is excessively complex and inconvenient to operate. The ELM model randomly initializes the weights between the input layer and the hidden layer, and the hidden layer is too high, which adversely affects the generalization performance of the model. The random forest (RF) model offers several advantages, including simple operation, excellent performance, fast convergence speed, minimal parameter tuning requirements, automatic identification of feature importance, high tolerance to data noise, and strong anti-interference and anti-overfitting capabilities [28]. Consequently, it is widely used in multi-objective evaluation. Therefore, this paper selects the random forest model as the evaluation model.

In the traditional random forest model, the number of decision trees N and the number of candidate split attributes m are two key parameters that significantly influence the model's accuracy [29]. Before the N value reaches its optimal point, a larger N generally improves model performance. The m value determines the ability of the decision tree and the correlation between them [29]. Therefore, to enhance the performance of the random forest model, it is essential to determine the optimal values for N and m . The RBMO algorithm has the advantages of automation, global search, fitness evaluation, and performance improvement in model parameter optimization problems, and has been well applied in practice. To address the challenge of optimal parameter selection in the traditional RF model, this paper introduces the red-billed blue magpie optimizer (RBMO) [30]. An improved RF model based on the RBMO algorithm was constructed, utilizing the RBMO algorithm to automatically optimize the N and m parameters, thereby enhancing the accuracy of the RF model.

Based on this, this paper proposes the concept of WLECSCC and constructs the RBMO-RF model using Heilongjiang Province, China's primary grain-producing region, as the research base. This study aims to alleviate the imbalance between the supply and demand for water, land, and energy under the current agricultural planting model and provide guidance for decision-makers in formulating more effective water, land, and energy allocation plans. The primary potential contributions of this study are as follows:

- (1) The concept of regional WLECSCC is proposed;
- (2) A set of regional WLECSCC evaluation indicators are constructed based on the principles of stability, collaboration, and resilience;
- (3) The RBMO-RF model is constructed to analyze the spatiotemporal characteristics of regional WLECSCC;
- (4) The driving mechanisms underlying WLECSCC are analyzed using the RBMO-RF model.

2. Study Area Overview and Methods

2.1. Study Area

Heilongjiang Province, located in northeastern China between 121°11' and 135°05' east longitude and 43°26' and 53°33' north latitude, encompasses 12 prefecture-level cities, including Harbin, Qiqihar, and Mudanjiang, and the Greater Khingan Range Region (Figure 1). It has a total area of 473,000 km² and serves as a major agricultural province and energy-producing province, as well as an important industrial base in China. It has a temperate continental monsoon climate, with four major water systems—the Heilongjiang River, Songhua River, Wusuli River, and Suifen River—as well as two major black soil regions: the Sanjiang Plain and the Songnen Plain. Due to its unique land properties and hydrological and climatic conditions, Heilongjiang Province has become China's largest commercial grain production base, ranking first in the country in grain output. It serves as the “ballast stone” of China's food security. Due to the excessive pursuit of short-term economic benefits in recent years and the long-term focus on reclamation, while neglecting management, a series of resource and environmental issues have emerged. These include an imbalance in the agricultural water use structure, deterioration of water environment quality, decline in arable land fertility, and low agricultural energy utilization efficiency. The current agricultural development model has strayed from the sustainable development trajectory of “green agriculture”. Against this background, clarifying the characteristics of the WLECS in Heilongjiang Province and conducting research on the WLECSCC will help to coordinate the relationship between agricultural water, land, and energy resources and formulate a more effective allocation plan for these resources, as well as promoting the sustainable use of regional agricultural resources and the green development of agricultural economy. In addition, Heilongjiang Province is located in one of the world's three major black soil conservation areas. Conducting research on the WLECSCC in this region plays an essential role in ensuring global food security, sustaining the fertility of black soil farmland, and facilitating the dissemination of agricultural technology.

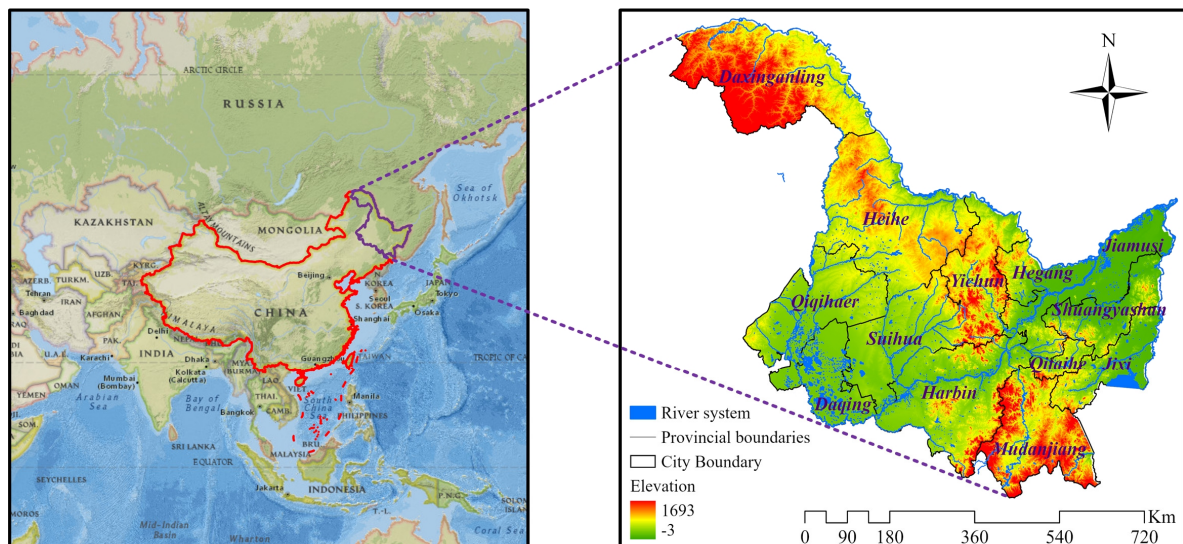


Figure 1. Geographical divisions of Heilongjiang Province.

2.2. Data Source

Data were collected from the “Heilongjiang Statistical Yearbook” (2004–2022), published by the Heilongjiang Provincial Bureau of Statistics, China. Additionally, data from the “Heilongjiang Provincial Water Resources Bulletin” (2004–2022) and the “Heilongjiang Provincial Water Resources Comprehensive Annual Report” (2004–2022) were obtained from the Heilongjiang Provincial Water Resources Department. After sorting and calculating, we obtained data on water resources, land resources, energy, and other indicators for 19 years across 13 cities and districts in Heilongjiang Province, China. Relevant economic indicators were deflated and utilized for the analysis of WLECSCC-related issues.

2.3. Methodology

2.3.1. Analysis of the Connotation of WLECSCC

Agricultural production depends on natural conditions and the input of agricultural production materials. The agricultural system can only operate cyclically by relying on water, land, and energy inputs. Water is an essential substance and medium for crop growth and photosynthesis; land provides a place and nutrient source for crops; and energy serves as the power source for the operation of the agricultural system. The three major elements of agriculture, water, land, and energy, cover the raw materials, sites, and power of regional agricultural production [31], and form the core components of the regional agricultural economic system through water cycles, land use, and energy consumption. There are complex influences or conversion relationships in this system, including “water–land”, “water–energy”, and “land–energy” [1]. Regarding “water–land”, the construction of agricultural irrigation and drainage projects and the application and development of water-saving technologies and water-saving policies will change the land-use type. At the same time, non-point source pollution generated by agricultural planting will affect land quality and thus affect the land use structure. As for “water–energy”, agricultural water extraction, water supply, water use, and drainage consume a lot of energy. At the same time, the production or extraction process of agricultural energy, such as seeds, fertilizers, pesticides, and diesel, requires a lot of water resources. As for “land–energy”, agricultural land use and land fertility maintenance require large amounts of energy, and agricultural energy extraction and the construction of its supporting facilities require land investment. Changes in land-use types caused by social development will affect water distribution and circulation. Hydropower will generate new energy, and some

agricultural and sideline products will be converted into biomass energy to change the energy utilization structure. The interactions between these factors comprise complex nonlinear and feedback relationships [31], thus forming a regional agricultural water–land–energy coupling system (WLECS).

A WLECS not only involves the interconnection and interaction of the three major systems within it, namely the water system, land system, and energy system, but is also closely related to the external social–economic–environmental system, together forming the main body of the regional agricultural economic system. Among these, the WLECS is the core of agricultural production, supporting agriculture as an important foundation for human economic and social development. The social–economic–environmental system provides external driving forces for the WLECS, while the WLECS can also exert coercive effects on it. Therefore, it is particularly important to clarify the system coupling mechanism and understand the functions and influencing factors of each subsystem. In this process, water, land, and energy are the main bodies of the WLECS and the basic production and exchange units of materials and energy, while the carrying capacity determines the upper limit of the balanced development of the WLECS. Therefore, conducting research on WLECSCC evaluation is of great significance for optimizing regional water, land, and energy allocation, coordinating the relationship among the three and promoting the sustainable development of the regional economy.

Referring to the previous research results [4,7,13,14,32,33], WLECSCC is defined here as follows: “At a certain historical development stage, based on the foreseeable technological, economic and social development levels, with sustainable development as the principle and with the maintenance of healthy ecological environment development as the condition, the maximum capacity of regional population growth and economic development under the premise that regional agricultural water, land and energy resources are rationally developed and utilized”. Taking into account the complex nonlinear and feedback relationship between the WLECS and the external environment, WLECSCC is decomposed into “stability”, “collaboration”, and “resilience”, among which “stability” is characterized by the resource endowment and efficient utilization carrying capacity of each subsystem of water resources, land resources, and energy resources; “collaboration” is characterized by the carrying capacity of dependency transformation and interaction of each subsystem; and “resilience” is characterized by the carrying capacity of each subsystem to resist the external environment and absorb the driving force of the external environment. The connotations of the WLECSCC are shown in Figure 2.

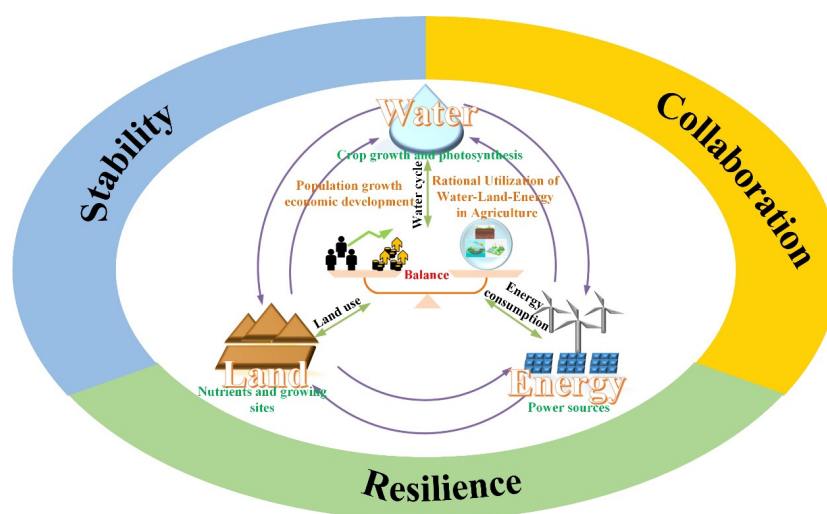


Figure 2. WLECSCC connotation framework.

2.3.2. Construction of Evaluation Index System

Scientifically constructing an indicator system is the key to evaluating WLECSCC. Traditional indicator screening methods mainly include theoretical analysis and expert consultation. The idea of constructing the indicators in this article was based on using theoretical analytical thinking. The specific steps in this process are as follows: consult a large amount of research, grasp the research direction, build a research framework, explain the research connotations, and select evaluation indicators. References [31–36] selected typical and representative evaluation indicators. On this basis, based on the principles of scientificity, necessity, operability, pertinence, and policy relevance, and based on the connotation analysis of WLECSCC and the characteristics of Heilongjiang Province, 27 indicators that can reflect the WLECSCC of Heilongjiang Province were selected with “stability”, “collaboration”, and “resilience” as the criteria. The evaluation index system is shown in Figure 3.

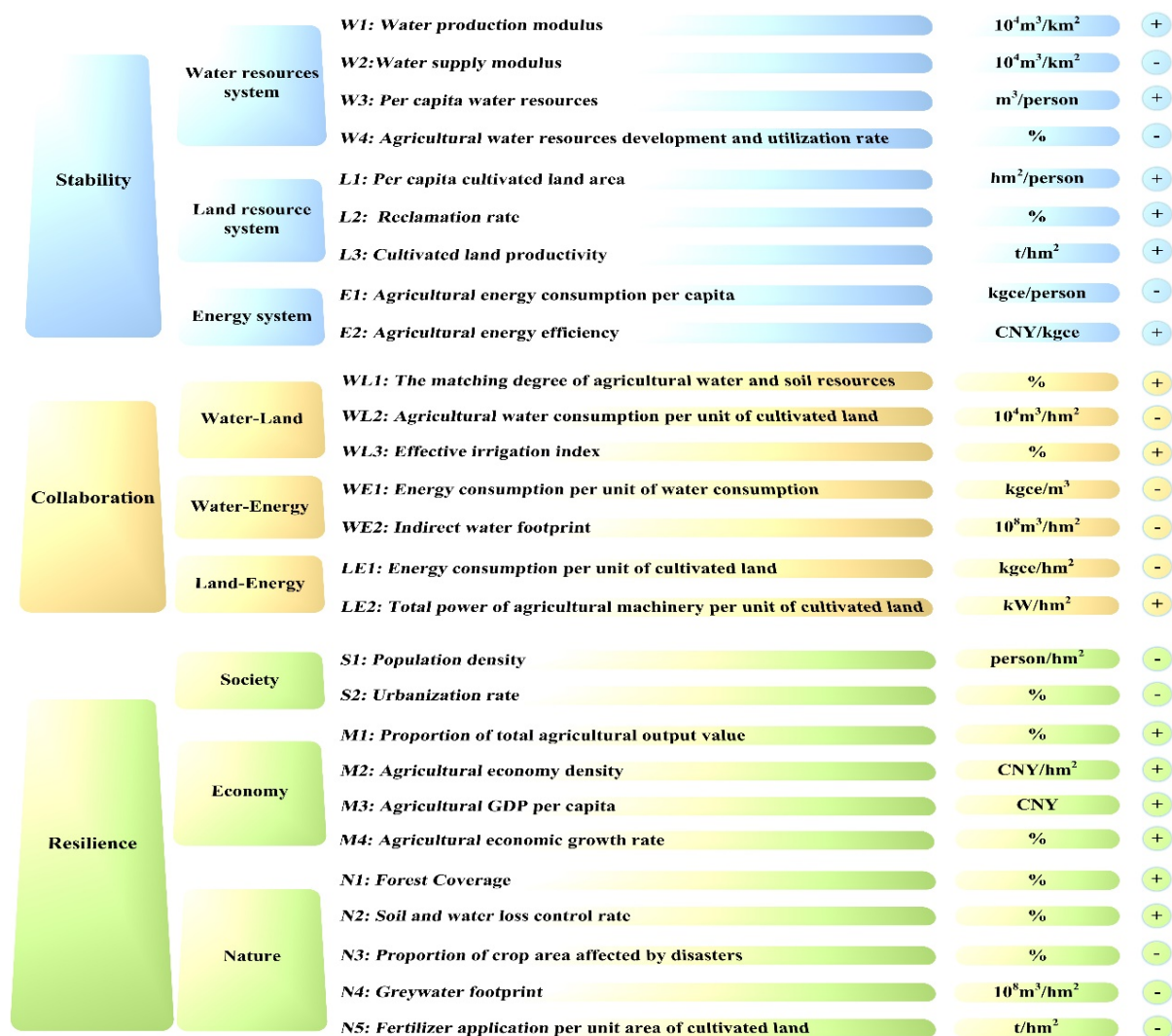


Figure 3. WLECSCC evaluation index system. Note: In this figure, “+” indicates a positive indicator and “−” indicates a negative indicator. The simplified naming of indicators adopts the method of listing subsystems in alphabetical order. In order to distinguish energy from economic indicators, economic indicators are represented by “M”.

2.3.3. Normalization of Indicators

After normalization, the indicators can accelerate algorithm convergence, improve model accuracy and algorithm stability, and eliminate the impact of the different dimensions of evaluation indicators of each system. Compared with other normalization methods, the max–min method is frequently employed in scenarios where the data range is known. It offers the advantages of simplicity, ease of use, and preservation of the proportional relationships between data points. It has been extensively utilized in neural networks and other machine learning models. The process is detailed in the literature [29]. The indicator data in this study were comprehensively detailed, and the final evaluation was conducted using machine learning techniques. Accordingly, this research employed the max–min normalization method to standardize the evaluation indicators.

2.3.4. Determination of Indicator Weights

The entropy weighting method is an objective weighting method. In information theory, entropy is a measure of the degree of disorder in a system, used to determine weights, where the larger the entropy value, the smaller the amount of information provided by the indicator and the smaller the weight of the indicator, and vice versa. In the field of multi-objective evaluation, in order to avoid subjective weighting, the entropy weight method is widely used to determine the weights of evaluation system indicators. The main process of determining the index weight via the entropy weight method is as follows: data standardization, entropy value calculation, weight calculation, and weighted evaluation. The process will not be described here, and the detailed process can be found in the literature [37].

2.3.5. Random Forest Model

RF is an ensemble learning model based on decision trees [38]. The basic idea is to use multiple independent decision trees to form an ensemble decision tree, and the performance is determined by the number of decision trees N and the splitting attribute m . RF can improve prediction accuracy without significantly increasing the calculation load and is insensitive to multicollinearity. The results are relatively robust to missing data and unbalanced data. Please refer to the literature for the detailed steps of this process [39].

2.3.6. Red-Billed Blue Magpie Optimizer

The red-billed blue magpie optimizer (RBMO) is a new type of swarm intelligence optimization algorithm proposed by Shengwei Fu in 2024. This algorithm is based on the cooperation and competition mechanism of red-billed blue magpies when foraging to find the optimal solution. Compared with traditional algorithms, RBMO has the advantages of fast convergence speed, high accuracy, and strong robustness [30]. The steps are as follows:

Step 1: Randomly generate a set of solutions (called a population), where each solution corresponds to the position of a red-billed blue magpie, and set the parameters of the algorithm, such as population size, maximum number of iterations, etc.

$$X_{i,j} = (UB - LB) \cdot Rand_1 + LB \quad (1)$$

where X is an individual red-billed blue magpie; UB and LB are the upper and lower intervals of the problem to be solved; and $Rand_1$ is a random number between 0 and 1.

Step 2: Simulate the process of the red-billed blue magpie looking for food and update the position as follows:

$$X^i(t+1) = X^i(t) + \left(\frac{1}{p} \cdot \sum_{m=1}^p X^m(t) - X^{rs}(t) \right) \cdot Rand_2 \quad (2)$$

$$X^i(t+1) = X^i(t) + \left(\frac{1}{q} \cdot \sum_{m=1}^q X^m(t) - X^{rs}(t) \right) \cdot Rand_3 \quad (3)$$

where t is the number of iterations; p represents the number of randomly selected red-billed blue magpies; X^m represents the randomly selected red-billed blue magpie individuals; q represents the randomly selected red-billed blue magpie population; and X^{rs} represents the randomly selected search agent.

Step 3: Simulate the process of a red-billed blue magpie attacking its prey and update the position as follows:

$$X^i(t+1) = X^{food}(t) + CF \cdot \left(\frac{1}{p} \cdot \sum_{m=1}^p X^m(t) - X^i(t) \right) \cdot Rand_{n_1} \quad (4)$$

$$X^i(t+1) = X^{food}(t) + CF \cdot \left(\frac{1}{q} \cdot \sum_{m=1}^q X^m(t) - X^i(t) \right) \cdot Rand_{n_2} \quad (5)$$

where X^{food} is the food's location; $CF = (1 - (\frac{t}{T}))^{(2 \times \frac{t}{T})}$; and $Rand_{n_1}$ and $Rand_{n_2}$ represent random numbers based on the standard normal distribution.

Step 4: Simulate the process of the red-billed blue magpie storing food and update the position as follows:

$$X^i(t+1) = \begin{cases} X^i(t) & \text{if } fitness_{old}^i > fitness_{new}^i \\ X^i(t+1) & \text{else} \end{cases} \quad (6)$$

where $fitness_{old}^i$ and $fitness_{new}^i$ represent the fitness values of the red-billed blue magpie before and after the update.

2.3.7. RBMO-RF Model Construction

Let N and m in the RF model be the search objects of the red-billed blue magpie, and the specific process is as follows:

Step 1: Collect relevant evaluation index data and divide them into a training set and test set;

Step 2: Initialize the red-billed blue magpie individuals; that is, N and m of the random forest model;

Step 3: Set $RMSE$ as the objective function;

Step 4: Based on Formulas (2) and (3), the red-billed blue magpie searches for food;

Step 5: Based on Formulas (4) and (5), the red-billed blue magpie attacks its prey;

Step 6: Based on Formula (6), the food storage operation of the red-billed blue magpie is performed;

Step 7: Determine whether the algorithm has reached the termination condition. If so, repeat Step 4–Step 6.

Step 8: Output the optimal individual of the red-billed blue magpie; that is, N and m of the random forest model.

The regional WLECSCC evaluation process based on the RBMO-RF model is shown in Figure 4.

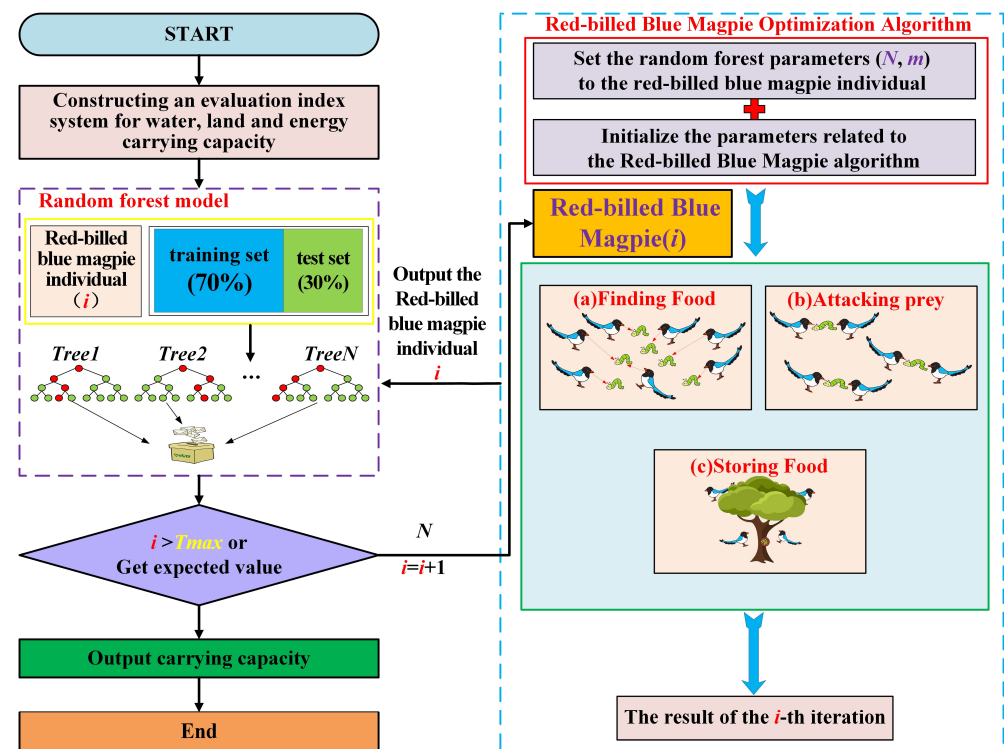


Figure 4. WLECSCC evaluation process based on the RBMO-RF model.

2.3.8. Model Performance Test

Different models were used to evaluate the WLECSCC, and the evaluation results of different models were ranked. The evaluation results were then summed up and re-ranked to obtain the final relatively reasonable ranking. The Spearman rank correlation coefficient of the relatively reasonable ranking of different models was calculated as the rationality coefficient of the evaluation model results [36].

$$R = \frac{1}{\alpha} \cdot \sum_{i=1}^{\alpha} P_i \quad (7)$$

where R is the model rationality coefficient, α is the number of model runs, and P_i is the Spearman rank coefficient.

Sample entropy can be used to analyze the complexity of time series. The lower the complexity, the higher the stability of the model evaluation results.

$$S = \frac{w}{\sum_{i=1}^w SE(\text{Result}_w)} \quad (8)$$

where S is the model stability coefficient, SE is the sample entropy, and Result_w is the α th evaluation result of the model in the w th region.

2.3.9. Mann–Kendall Test

The Mann–Kendall (M-K) is a nonparametric statistical method for analyzing time series data. It can analyze whether the data trend is monotonically rising or falling, does not require the data to follow a specific distribution, and is not affected by outliers [40]. Therefore, this paper used the Mann–Kendall test to evaluate the trend changes in WLECSCC in Heilongjiang Province from 2003 to 2021. When $Z > 0$, it means that the carrying capacity is on an upward trend. When $Z < 0$, it means that the carrying capacity is on a downward trend. When $|Z| > 1.96$, the trend change in the carrying capacity is significant ($p < 0.05$). When the standard normal distribution statistic UF intersects the reverse sequence statistic

UB, the point is considered to be a mutation point [36]. For details on the calculation process of the M-K test, see [41].

3. Results

3.1. Determination of Evaluation Index Level

The determination of the grading standards for evaluation indicators is an important topic of research on WLECSCC evaluation. At present, there is no unified standard for WLECSCC evaluation. With reference to relevant studies [42–44], the natural discontinuity method is adopted and combined with the actual situation in Heilongjiang Province, and the grading standard of WLECSCC evaluation indicators in Heilongjiang Province is determined. The grades are set from I to V. The higher the grade, the greater the WLECSCC. The results are shown in Table 1.

Table 1. Index classification standards.

Indicator	I	II	III	IV	V
W1	<10.87	[10.87, 21.90)	[21.90, 37.90)	[37.90, 47.75)	≥ 47.75
W2	≥ 8.59	[5.02, 8.59)	[2.78, 5.02)	[1.04, 2.78)	<1.04
W3	<1491.36	[1491.36, 4465.49)	[4465.49, 9300.34)	[9300.34, 21,563.3)	$\geq 21,563.3$
W4	≥ 1.07	[0.553, 1.07)	[0.293, 0.553)	[0.107, 0.293)	<0.107
L1	<0.222	[0.222, 0.3)	[0.3, 0.406)	[0.406, 0.574)	≥ 0.574
L2	<0.09	[0.09, 0.362)	[0.362, 0.477)	[0.477, 0.563)	≥ 0.563
L3	<1.525	[1.525, 2.455)	[2.455, 3.503)	[3.503, 4.786)	≥ 4.786
E1	≥ 411.79	[228.55, 411.79)	[140.37, 228.55)	[89.26, 140.37)	<89.26
E2	<48.25	[48.25, 73.96)	[73.96, 107.92)	[107.92, 173.80)	≥ 173.80
WL1	<0.0598	[0.0598, 0.155)	[0.155, 0.250)	[0.250, 0.421)	≥ 0.421
WL2	≥ 0.200	[0.194, 0.200)	[0.144, 0.194)	[0.040, 0.144)	<0.040
WL3	<0.164	[0.164, 0.322)	[0.322, 0.596)	[0.596, 1.126)	≥ 1.126
WE1	≥ 21.790	[6.939, 21.790)	[1.664, 6.939)	[0.560, 1.664)	<0.560
WE2	≥ 4.982	[2.635, 4.982)	[1.435, 2.635)	[0.571, 1.435)	<0.571
LE1	≥ 1916.21	[1013.46, 1916.21)	[599.67, 1013.46)	[344.11, 599.67)	<344.11
LE2	<2.05	[2.05, 3.44)	[3.44, 5.12)	[5.12, 7.31)	≥ 7.31
S1	≥ 1.513	[0.955, 1.513)	[0.729, 0.955)	[0.397, 0.729)	<0.397
S2	≥ 0.731	[0.596, 0.731)	[0.528, 0.596)	[0.388, 0.528)	<0.388
M1	<0.129	[0.129, 0.219)	[0.219, 0.322)	[0.322, 0.500)	≥ 0.500
M2	<71.81	[71.81, 150.27)	[150.27, 248.95)	[248.95, 425.06)	≥ 425.06
M3	<4703.02	[4703.02, 8655.16)	[8655.16, 14,115.45)	[14,115.45, 21,275.1)	$\geq 21,275.1$
M4	<0.044	[0.044, 0.194)	[0.194, 0.571)	[0.571, 1.116)	≥ 1.116
N1	<15.43	[15.43, 25.00)	[25.00, 40.20)	[40.20, 65.00)	≥ 65.00
N2	<0.227	[0.227, 0.369)	[0.369, 0.521)	[0.521, 0.752)	≥ 0.752
N3	≥ 0.517	[0.376, 0.517)	[0.242, 0.376)	[0.131, 0.242)	<0.131
N4	≥ 228.08	[69.09, 228.08)	[39.47, 69.09)	[16.34, 39.47)	<16.34
N5	≥ 0.150	[0.111, 0.150)	[0.0813, 0.111)	[0.0534, 0.0813)	<0.0534

Note: In the tables, the darker color shading indicates a higher load-carrying grade, which signifies a greater carrying capacity. This principle applies consistently to Tables 2 and 3 as well. In addition, please refer to Figure 3 for the meaning and dimension details of the indicators in the table.

Table 2. *SI, CI, RI, and WLECSCC grading evaluation intervals.*

Index	I	II	III	IV	V
<i>SI</i>	<1.417	[1.417, 2.759)	[2.759, 3.202)	[3.202, 4.329)	≥4.329
<i>CI</i>	<1.714	[1.714, 2.754)	[2.754, 3.147)	[3.147, 4.636)	≥4.636
<i>RI</i>	<1.662	[1.662, 2.809)	[2.809, 3.107)	[3.107, 4.215)	≥4.215
<i>WLECSCC</i>	<1.629	[1.629, 2.774)	[2.774, 3.146)	[3.146, 4.425)	≥4.425

Table 3. *WLECSCC grades during different stages in various regions of Heilongjiang Province.*

Area	Simulation Results			Evaluation Level		
	First Stage	Second Stage	Third Stage	First Stage	Second Stage	Third Stage
Harbin	2.676	2.880	3.075	II	III	III
Qiqihar	2.605	2.635	2.812	II	II	III
Jixi	2.908	3.124	3.253	III	III	IV
Hegang	3.157	3.417	3.698	IV	IV	IV
Shuangyashan	3.001	3.168	3.093	III	IV	III
Daqing	2.753	3.025	3.177	II	III	IV
Yichun	2.962	3.114	3.312	III	III	IV
Jiamusi	2.831	3.101	3.096	III	III	III
Qitaihe	2.812	2.810	2.789	III	III	III
Mudanjiang	2.963	3.089	3.104	III	III	III
Heihe	2.661	2.857	3.005	II	III	III
Suihua	2.582	2.765	3.026	II	II	III
Daxing'anling	2.818	3.153	3.256	III	IV	IV

3.2. Determination of Grade Simulation Interval

The threshold values of each indicator in Table 1 are input into the RBMO-RF model to obtain the grading evaluation intervals of the stability index (*SI*), synergy index (*CI*), resilience index (*RI*), and WLECSCC index. The system level is set to I–V. The higher the level, the greater the system carrying capacity. The results are shown in Table 2.

3.3. Analysis on the Spatiotemporal Variation Characteristics of WLECSCC in the Province

As can be seen from Figure 5a, in terms of the overall trend, the *SI* of Heilongjiang Province showed an upward trend from 2003 to 2021, but with certain volatility. It has two stable periods and two mutation points. The stable periods occurred in 2010–2012 and 2014–2018, respectively. The first mutation point occurred in 2009, which is also the maximum point, with an *SI* of 3.230. The second mutation point occurred in 2013. The lowest value occurred in 2007, with an *SI* of only 2.381. As shown in Figure 5b, the *CI* has an obvious cyclical growth pattern, displayed in 2003–2010, 2011–2012, and 2013–2021. The *CI* is stable in these periods, being 2.636, 2.883, and 3.130, respectively. As can be seen from Figure 5c, the *RI* showed a trend of first increasing and then decreasing in 2003–2006, 2007–2009, and 2010–2013, with a short period of stability in 2013–2014; the *RI* showed a steady growth trend from 2015 to 2021, and the maximum point occurred in 2021 at 3.000.

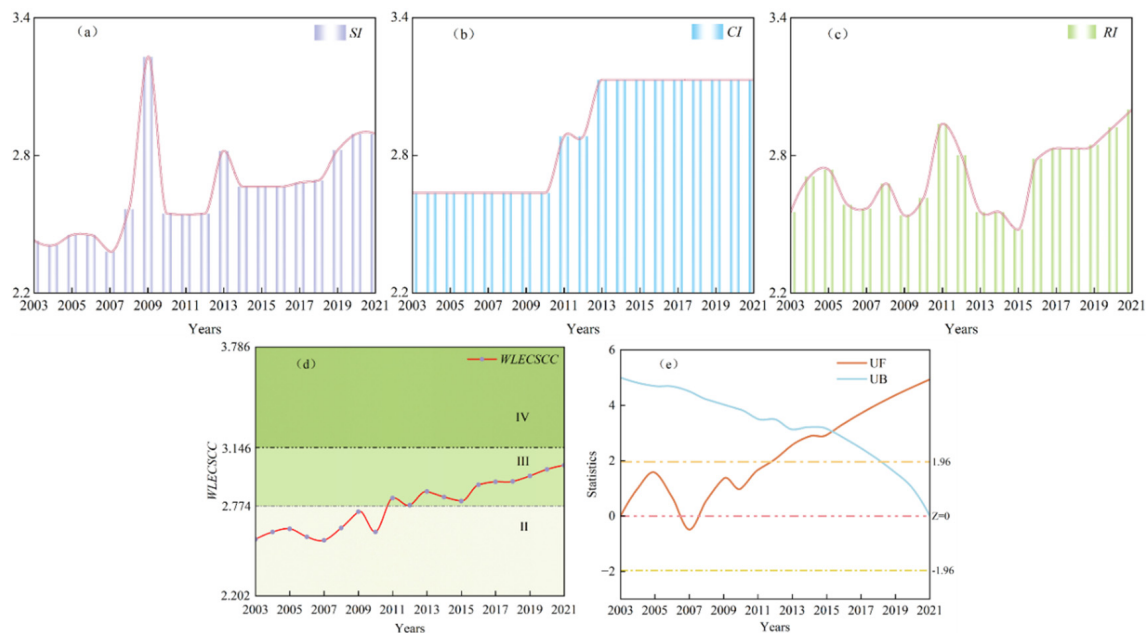


Figure 5. (a–c) Trend changes in *SI*, *CI*, and *RI* in Heilongjiang Province from 2003 to 2021; (d) trend changes in *WLECSCC* in Heilongjiang Province from 2003 to 2021; (e) MK test results of *WLECSCC* in Heilongjiang Province from 2003 to 2021.

The M-K test was used to analyze the trend of *WLECSCC* in Heilongjiang Province. The results are shown in Figure 5e. As can be seen from Figure 5d,e, the *WLECSCC* in Heilongjiang Province showed an upward trend from 2003 to 2021, with certain fluctuations. The UF value from 2003 to 2006 was $[0, 1.96]$, indicating that the *WLECSCC* had an insignificant upward trend. The UF value in 2007 was $[-1.96, 0]$, indicating that *WLECSCC* showed an insignificant downward trend, and the *WLECSCC* in 2007 was the lowest during the study period, with a value of 2.556. The UF value from 2008 to 2011 was $[0, 1.96]$, indicating that *WLECSCC* had an insignificant upward trend. The UF value of *WLECSCC* from 2011 to 2021 was greater than 1.96, indicating that *WLECSCC* showed a significant upward trend at this time. In addition, the two curves UF and UB intersect between 2015 and 2016, indicating that *WLECSCC* began to mutate at this time, with its upward trend becoming more obvious. It reached its highest level in 2021 at 3.0331. The changing trend of *WLECSCC* can be divided into three stages. The first stage (2003–2011) is the “low-level fluctuation period”, the second stage (2012–2015) is the “growth period”, and the third stage (2016–2021) is the “rapid growth period”.

3.4. Analysis on the Spatiotemporal Variation Characteristics of the *WLECSCC* in Cities

3.4.1. Analysis on Interannual Variation Characteristics of the *WLECSCC* in Cities

Taking all prefecture-level cities in Heilongjiang Province as the research objects, the changes in *WLECSCC* are divided into three stages: the first stage (2003–2011), the second stage (2012–2015), and the third stage (2016–2021). The indicator data of the three stages were substituted into the RBMO-RF model to obtain the carrying capacity simulation results and evaluation levels of each region in the three stages. The results are shown in Table 3.

As shown in Table 3, from 2003 to 2011, 2012 to 2015, and 2016 to 2021, the *WLECSCC* grade changes in Jiamusi, Qitaihe, Mudanjiang, and Hegang showed a “stable” characteristic. Jiamusi, Qitaihe, and Mudanjiang remained at level III, and Hegang remained at level IV. The changes in the *WLECSCC* levels of Suihua, Qiqihar, Jixi, and Yichun showed a “stable first, then increasing” characteristic. From 2003 to 2015, the carrying capacity levels of Suihua and Qiqihar were stable at level II and rose to level III from 2016 to 2021. From

2003 to 2015, the carrying capacity levels of Jixi and Yichun were stable at level III and rose to level IV from 2016 to 2021. The changes in the WLECSCC levels of Heihe, Harbin, and Daxing'anling showed the characteristics of "increasing first and then stabilizing". The carrying capacity levels of Heihe and Harbin increased from level II to level III from 2012 to 2015 and remained at level III from 2012 to 2021. The carrying capacity level of Daxing'anling increased from level III to level IV from 2012 to 2015 and remained at level IV from 2012 to 2021. Daqing's WLECSCC grade shows a "full-range growth" feature, with the carrying capacity grade rising from level II to level III and then to level IV. The WLECSCC grade of Shuangyashan showed a "fluctuating" characteristic, with the carrying capacity grade rising from level III to level IV and then dropping to level III.

From the analysis of the overall development trend, the WLECSCC distribution in various regions was between level III and IV, accounting for 82.1%, and level II accounted for only 17.9%, indicating that the overall WLECSCC level in Heilongjiang Province is good. By comparing the simulation results of level II WLECSCC in different periods, their values are all distributed in the right half of the level II interval [2.202, 2.774), being very close to the lower limit of level III, 2.774. Among them, 71.4% of level II is upgraded to level III. Further analysis shows that when the level simulation result is greater than 2.635, WLECSCC can jump to level III in the later period, and 2.635 is exactly 95% of the lower limit of level III. Similarly, by comparing the simulation results of level III WLECSCC in different periods, the values are distributed in the right half of the level III interval [2.960, 3.146), accounting for 60.9%. The stability of level III is good. When the level simulation result is greater than 3.114, the WLECSCC can jump to level IV in the later period. A value of 3.114 is 99% of the lower limit threshold of level IV. By comparing the simulation results of level IV WLECSCC in different periods, the minimum value is 3.153 and the maximum value is 3.698, and the values are all distributed in the left half of the level IV interval [3.146, 3.786), which proves that the level IV WLECSCC is not high, and the level IV carrying capacity is relatively vulnerable. In the later stage, it is necessary to further rationally allocate resources and strengthen technical control to maintain the current level. In summary, there is no level V WLECSCC in the various regions in Heilongjiang Province from 2003 to 2021, and the risk of fluctuations in the carrying capacity level still exists, with huge potential for improvement. It is worth further analyzing the key driving mechanisms within the WLECSCC and identifying its key driving factors, which will help decision-makers to formulate better resource allocation plans.

3.4.2. Analysis on Spatial Variation Characteristics of WLECSCC in the City

In order to more intuitively analyze the spatial variation characteristics of WLECSCC, the spatial distribution maps of WLECSCC levels in Heilongjiang Province as a whole and in three time periods were drawn, as shown in Figure 6.

As shown in Figure 6a, the *SI* of Jixi, Daqing, Jiamusi, Harbin, and other cities is at a relatively low level and has weak stability, indicating that the water resource, land resource, and energy resource subsystems in these regions have high levels of resource development and demand, and the issue of resource supply imbalances is more prominent. In contrast, the *SI* levels in Yichun, Heihe, and Daxinganling are better, indicating that the degree of resource development and utilization in these areas is low and the internal carrying risk of resources is low. It can be seen from the trend line that the overall change trend in different periods is relatively consistent.

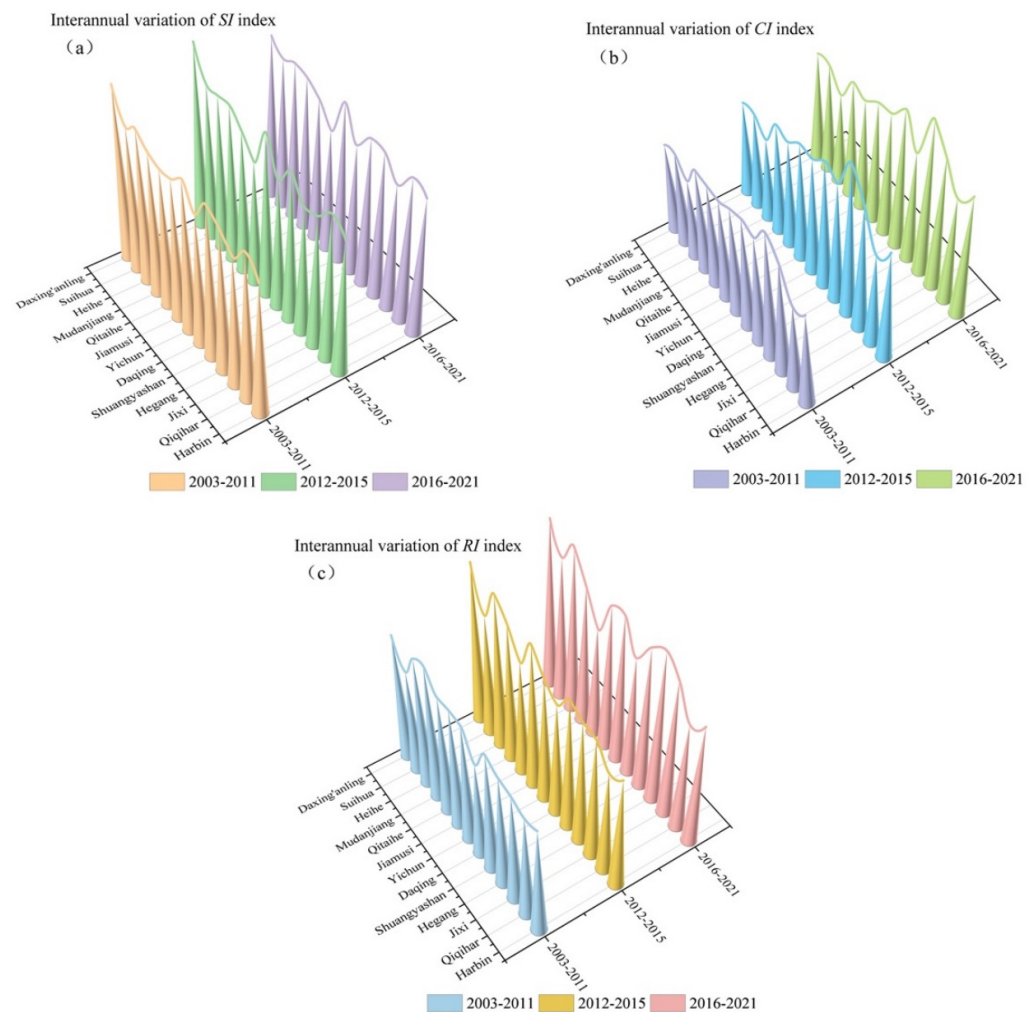


Figure 6. Spatial distribution characteristics of WLECS *SI*, *CI*, and *RI* in various cities in Heilongjiang Province at different times: (a) *SI*; (b) *CI*; (c) *RI*.

As shown in Figure 6b, the *CI* levels of Hegang and Daqing are relatively high, while the *CI* level of Heihe is relatively low, indicating that the resource utilization structure and matching pattern of Hegang and Daqing are more reasonable, while Heihe has problems in resource allocation. Except for Shuangyashan, where the *CI* showed a downward trend from 2016 to 2021, the *CI* of other cities showed an upward trend in different periods, indicating that various cities and districts in Heilongjiang Province are developing healthily in terms of resource allocation.

As can be seen from Figure 6c, compared with the overall development trends of the *CI* and *SI*, the overall change in the *RI* has an obvious fluctuation trend. Among the cities, Qiqihar showed a downward trend in the second stage, the trend for Jiamusi and Mudanjiang declined slightly in the third stage, Qitaihe showed a continuous downward trend, and the rest of the cities showed an upward trend. This shows that Qitaihe lacks the ability to resist natural disasters and external interference, and its social, economic, and environmental systems are facing great challenges and difficulties. It should increase investment in agricultural science and technology and environmental protection to improve this situation.

As can be seen from Figure 7a, from 2003 to 2021, the areas in Heilongjiang Province with low WLESCC levels were Suihua in the central region and Qiqihar in the western region, and the area with the highest WLESCC level was Hegang in the northeastern region at level IV. The rest of the areas had a WLESCC at level III. The overall WLESCC

level showed a spatial pattern of “low in the west, high in the east, and stable in the north and south”.

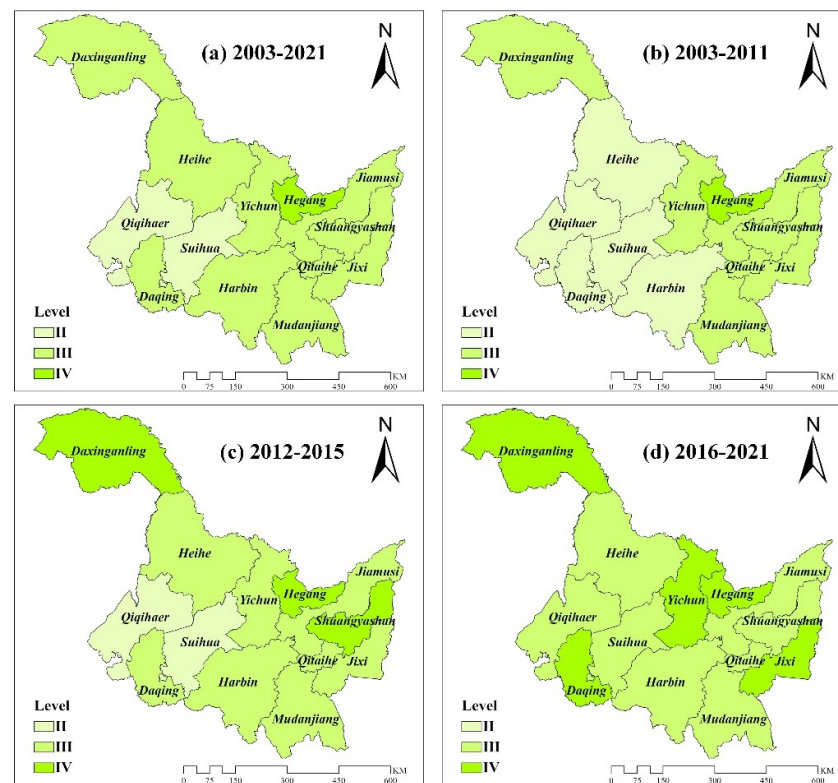


Figure 7. Spatial distribution characteristics of WLECSCC in various cities in Heilongjiang Province during different periods: (a) 2003–2021; (b) 2003–2011; (c) 2012–2015; (d) 2016–2021.

As shown in Figure 7b, from 2003 to 2011, the areas in Heilongjiang Province with a low WLECSCC level were located in the western and central regions, with level II accounting for 38.46% and level III accounting for 53.85%. Hegang was the only area with a level IV WLECSCC during this period. The overall WLECSCC level showed a trend of “increasing from west to east”.

As shown in Figure 7c, from 2012 to 2015, the overall WLECSCC level showed a trend of “radiating from the middle to all directions”. Level II accounted for 15.38% and level III accounted for 61.54%. Compared with 2003–2011, the transition rate for level II reached 60%, Shuangyashan and Daxing’anling jumped from level III to level IV, and Hegang continued to maintain its level IV WLECSCC. The WLECSCC level increased well during this period.

As shown in Figure 7d, the overall WLECSCC level from 2016 to 2021 showed a “fluctuating growth” trend. From northwest to southeast, the spatial pattern was “high–low–high–low–high”, and from southwest to northeast, the pattern was “high–low–high”, with level III accounting for 61.54% and level IV accounting for 38.46%. Compared with 2012–2015, the carrying capacity during this period increased significantly, with Suihua and Qiqihar rising from level II to level III; Daqing, Yichun, and Jixi jumping from level III to level IV; and Daxing’anling and Hegang continuing to maintain their level IV WLECSCC, while Shuangyashan dropped from level IV to level III.

3.5. Key Driving Factor Analysis

The RBMO-RF model is used to calculate the weights of the criterion layer, the sub-system layer, and each indicator, and the indicator weights are arranged in descending order, with the cumulative weight thresholds set at 25%, 50%, and 75%, respectively. On

this basis, the indicator levels are divided into very critical, critical, relatively critical, and generally critical according to the cumulative weights. The results are shown in Figure 8.

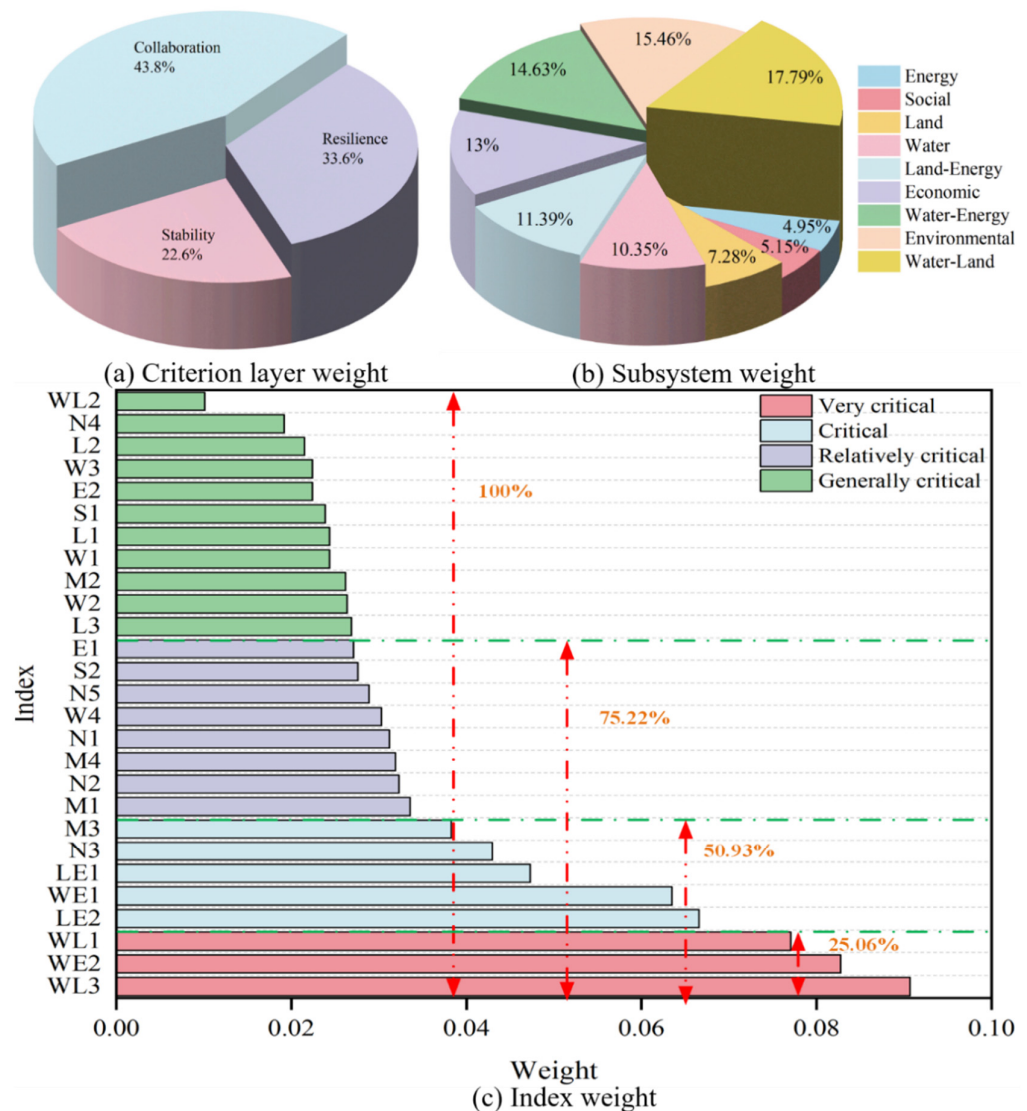


Figure 8. Analysis of importance of different levels: (a) Quasi-measurement layer; (b) subsystem; (c) indicator.

As shown in Figure 8, in terms of the criterion layer weights, the weights of stability, collaboration, and resilience are 0.226, 0.438, and 0.336, respectively, and the weight of collaboration weight is the highest, indicating that the degree of collaboration of each subsystem has the greatest impact on WLECSCC. In terms of subsystem weights, the cumulative weights of the water–land resource system, environmental system, water–energy system, and economic system exceed 60%, indicating that Heilongjiang Province’s WLECSCC is not only affected by the coordinated allocation of resource endowments but also by the degree of economic development and environmental protection. This shows that even when resource endowments are not abundant, regional WLECSCC can be improved by optimizing resource allocation plans, improving scientific and technological competitiveness, and paying attention to environmental protection. In terms of indicator weights, the cumulative weights of the first 3, 8, and 16 indicators are 25.06%, 50.93%, and 75.22%, respectively, exceeding the cumulative weight threshold. Therefore, WL3, WE2, and WL1 are set as “very critical indicators”, LE2, WE1, LE1, N3, and M3 are set as “critical

indicators”, M1, N2, M4, N1, W4, N5, S2, and E1 are set as “relatively critical indicators”, and the remaining indicators are set as “general critical indicators”.

4. Discussion

4.1. Feasibility of WLECSCC Research

Water resources, land resources, and energy resources are the basic resources for human life. The connection, dependence, and constraint relationships between them will inevitably affect the regional industrial structure and resource supply and demand adjustments and further affect economic development and regional stability. Regional agricultural production cannot be separated from the coordinated configuration among the three. Clarifying the coupling relationship among the three is a prerequisite for optimizing the configuration plan and maintaining green agricultural development. The WLECSCC concept and evaluation method proposed in this paper are important links in optimizing the allocation of regional water, land, and energy resources. In 2011, the Bonn Conference in Germany first proposed that there is a complex feedback relationship between water security, food security, and energy security, which triggered a wave of research on the interdependence and trade-offs between these three resources in the nexus relationship and laid the foundation for the study of the mechanism of multi-factor coupling systems [45]. The literature focuses on the study of the regional “water–soil–energy–carbon” coupling mechanism, providing a new theoretical perspective for revealing the coupling relationship between multiple resources and their environmental effects [3]. The literature measures the safety assessment and joint risk probability of the “water–soil–energy” system and clarifies the interactive relationships within the water–soil–energy coupling system [1]. In addition, the theoretical research on carrying capacity in a mature field has been transformed from utilizing a single-factor to a multi-factor integrated perspective. The traditional single-factor research on water, land, and energy carrying capacity obviously does not meet the actual needs of real-life systems. The resource and environmental carrying capacity is closely related to the level of regional social and economic development and human interference. Scholars have conducted many theoretical and empirical studies on the carrying capacity of individual resource subsystems and local related resource systems. The existing research results on the relationship between resource and environmental carrying capacity and social development are rich and solid.

However, this article did not fully consider factors such as climate change, government policies, and global economic trends when designing the indicator system. This shows that the properties of WLECSCC are complex and require more thinking and research in the future. Meteorological conditions such as precipitation and temperature are closely related to the basin hydrological cycle, and through the hydrological cycle process, they further affect the total amount of available water resources and water environment capacity in the basin. Government policy changes have far-reaching impacts on water management, land use planning and energy extraction, which in turn will change the existing agricultural system. Global international trade and competition will also intensify competition for agricultural products and lead agricultural production towards a development model of efficient resource utilization.

In summary, the important foundation laid by many scholars in the field of multi-objective evaluation from the perspective of multi-factor, multi-system, and multi-scale integration provides theoretical support and guidance for the proposal of the WLECSCC concept and evaluation method in this paper.

4.2. Model Comparison

4.2.1. Model Accuracy

To evaluate the performance of the RBMO-RF model, we assessed the RBMO-RF model, the PSO-RF model, and the random forest model using different parameters, namely $N = 500$, $m = 1$, $\sqrt{M}$, $(\log_2(M) + 1)$. The mean square error (MSE), mean absolute error (MAE), mean absolute percentage error ($MAPE$), and determination coefficient (R^2) were used as model performance evaluation indicators. Each model was run 50 times, and the average values of the performance evaluation indicators of the above models were calculated. The results are shown in Figure 9.

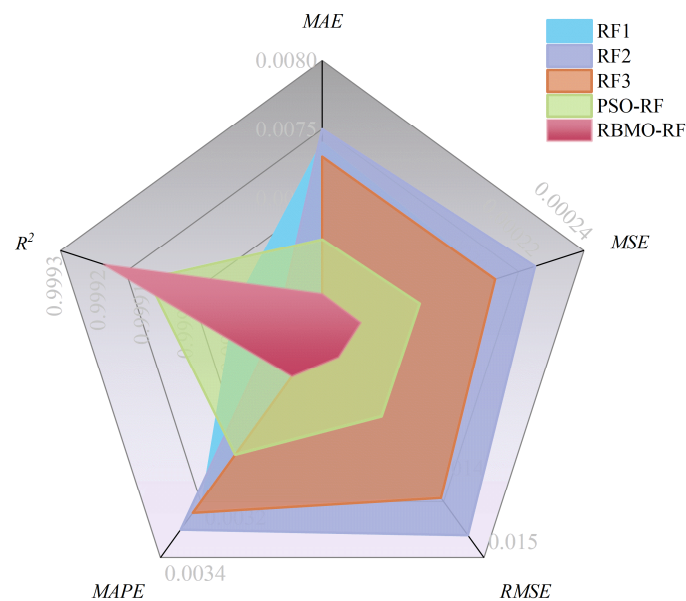


Figure 9. Model performance comparison.

As shown in Figure 9, compared with the PSO-RF, RF1, RF2, and RF3 models, the RBMO-RF model has different degrees of optimization in its MAE , MSE , $RMSE$, $MAPE$, and R^2 values. Its MAE decreased by 5.27%, 13.91%, 16.11%, and 13.73%; its MSE decreased by 13.86%, 19.91%, 13.99%, and 13.99%; its $RMSE$ decreased by 6.28%, 13.24%, 16.28%, and 13.23%; its $MAPE$ decreased by 9.34%, 13.89%, 15.99%, and 15.22%; and its R^2 increased by 0.01%, 0.03%, 0.04%, and 0.05%, respectively. In summary, the RBMO-RF model is a more accurate evaluation method.

4.2.2. Comparison of Evaluation Results of Different Models

The RBMO-RF, PSO-RF, RF1, RF2, and RF3 models were used to evaluate the WLEC-SCC in Heilongjiang Province and various cities. All models were run 50 times. On this basis, the rationality coefficient and stability coefficient of the five models were calculated using Formulas (7) and (8). The detailed results are shown in Table 4.

Table 4. Rationality coefficient and stability coefficient of each model.

Model	RBMO-RF	PSO-RF	RF1	RF2	RF3
R	0.989	0.956	0.941	0.923	0.950
S	2.148	1.571	1.494	1.139	1.531

It can be seen from Table 4 that compared with the PSO-RF, RF1, RF2, and RF3 models, the rationality coefficient R of the RBMO-RF model increased by 3.45%, 5.10%, 7.15%, and 4.11%, respectively, while the stability coefficient S increased by 36.73%, 43.78%, 88.59%,

and 40.30%, respectively. Compared with other models, the WLECSCC evaluation results of the RBMO-RF model have obvious advantages in stability and rationality.

4.3. Discussion of Evaluation Results

4.3.1. Analysis of Evaluation Results of the *SI*, *CI*, and *RI*

As for the provincial *SI*, although there is a certain degree of volatility, it shows an overall upward trend, with the maximum point occurring in 2009. By checking the weight ratios of the subsystems of water resources, land resources, and energy resources and the inter-annual changes in indicators, it was found that the water resource subsystem had the highest weight, with a value of 10.35%. In 2009, the W1 indicator changed significantly, increasing by 114.22% compared with 2008. According to the 2009 Heilongjiang Water Resources Bulletin, the increase in the total amount of water resources in Heilongjiang Province accounted for 83.05%, exceeding the multi-year average of 23.2%. The abundant precipitation greatly supplemented the total amount of water resources in the province, causing the *SI* to reach a maximum value that year. Similarly, by checking the 2007 Heilongjiang Water Resources Bulletin, it was found that Heilongjiang Province experienced a dry year that year, with the total water resources decreasing by 23.608 billion m³ compared with the previous year, resulting in the *SI* reaching a minimum value that year.

The *CI* reflects the synergy between the water and land, water and energy, and land and energy subsystems. Based on the cyclical growth trend of the inter-provincial *CI*, it can be seen that the synergy between the subsystems in Heilongjiang Province is developing in a benign manner. By comparing the weights of specific indicators and the interannual variation patterns, it was found that the two indicators with the largest fluctuations were WL3 and LE2, both of which promoted the *CI*. Compared with 2003–2010, the average growth rates of the two indicators in 2011–2012 and 2013–2021 were 71.57% and 30.73% and 102.45% and 59.93%, respectively.

In terms of the *RI*, the fluctuations are quite obvious. The *RI* reflects the effects of economic environment and human interference on each subsystem, and the leap-like changes conform to the laws of nature. Analysis of specific indicators revealed that M3 and N3 are the main controlling factors. Due to the unpredictability of the N3 factor, it has an inhibitory effect on the *RI*. However, with economic growth and improvements in human environmental awareness, the increase in agricultural technology and environmental protection investment will slow down the inhibitory effect of the N3 factor, which is also the reason for the overall upward trend of the *RI*.

4.3.2. Analysis of Carrying Capacity Index Evaluation Results

Through the M-K test earlier in this article, it can be seen that the change in carrying capacity shows three stages. The first stage (2003–2011) is the “low-level fluctuation period”, the second stage (2012–2015) is the “growth period”, and the third stage (2016–2021) is the “rapid growth period”. The changes in WLECSCC levels in Jiamusi, Qitaihe, Mudanjiang, and Hegang showed a “stable” characteristic. Jiamusi, Qitaihe, and Mudanjiang remained at level III, and Hegang remained at level IV, while the WLECSCC levels of Suihua and Qiqihar were upgraded from level II to level III from 2016 to 2021. Analyzing the changes in *SI*, *CI*, and *RI* during this period, compared with 2003–2015, the average increase rates were 0.14%, 11.96%, and 24.39% and −1.83%, 15.73%, and 2.70%, respectively. It can be seen that the growth of *CI* and *RI* promoted the improvement of the carrying capacity level, and the negative growth of *SI* and the low increase in *CI* and *RI* resulted in Qiqihar’s comprehensive carrying capacity index being lower than that of Suihua. Similarly, the average increase rates of Jixi and Yichun were −3.78%, 6.96%, and 16.31% and 0.90%, 6.65%, and 18.08%, respectively. The changes in WLECSCC levels in Heihe, Harbin, and Daxinganling showed

a “first increase and then stable” characteristic. From 2012 to 2015, the carrying capacity levels of Heihe and Harbin increased from level II to level III. Upon analyzing the changes in *SI*, *CI*, and *RI* during this period, it was found that the average increase in each index was 0.31%, 2.14%, and 17.01% and 1.07%, 14.57%, and 2.23%, respectively. The reason why the WLECSCC remained at level III from 2016 to 2021 was that all indexes showed an upward trend. The same is true for Daxing'anling. Daqing is the only city with full-process growth. The average increase in *CI* and *RI* was 19.35% and 20.96%, and the increase in each segment was 11.17%, 16.49%, 7.37%, and 3.84%, respectively. The growth in the second stage was obvious, which caused the overall carrying capacity to jump to the lower threshold of level IV. The growth in the third stage was general, but the level jumped to level IV, indicating that the level IV carrying capacity was not high and there was a risk of decline, which was consistent with the comprehensive evaluation results of the model.

5. Conclusions

This study takes Heilongjiang Province, China's main grain-producing area, as the research area and constructs a regional WLECSCC evaluation index system. Based on this, the RBMO-RF model was used to analyze the spatiotemporal variation characteristics and driving mechanisms of WLECSCC in the study area from 2003 to 2021. The specific conclusions are as follows:

The *SI*, *CI*, and *RI* all show an upward trend. The *SI* is greatly affected by the water resource subsystem. The growth of the *CI* indicates that the synergy among the subsystems in Heilongjiang Province has developed benignly. The change in the *RI* is greatly affected by the environmental subsystem and has a certain degree of uncontrollability.

The weights of stability, collaboration, and resilience are 0.226, 0.438, and 0.336, respectively, indicating that the degree of collaboration of each subsystem has the greatest impact on WLECSCC; through the cumulative weight threshold, WL3, WE2, and WL1 are judged as “very critical indicators”, indicating that the level of WLECSCC is not only affected by the coordinated allocation of resource endowments, but the degree of economic development and environmental protection also cannot be ignored.

The M-K test shows that the WLECSCC shows an overall upward trend, but with certain stage changes. The period of 2003–2011 was a period of low-level fluctuations, 2012–2015 was a period of growth, and 2016–2021 was a period of rapid growth.

In terms of model performance, the *R* and *S* of the RBMO-RF model are 0.989 and 2.148, respectively, which are higher than those of other models, indicating that its evaluation results are more stable and reasonable.

6. Research Deficiencies and Prospects

6.1. Research Deficiencies

Due to the complexity of the WLE coupled system, the existing research framework does not comprehensively consider climate change, socio-political factors, and global economic trends. It is inevitable that some factors will be overlooked due to the lack of existing knowledge and the impact of technological levels. In addition, the unique dynamic integration properties of carrying capacity require a complete and related dynamic monitoring network of system elements to assist various departments in sharing information.

6.2. Research Prospects

In the future, as production levels and human environmental awareness improve, the level of coordination and cooperation among departments will improve, which will make up for the information omissions caused by insufficient real-time monitoring. In addition, with the continuous development of artificial intelligence, an endless stream

of new high-quality intelligent algorithms will emerge, machine learning will become more mature, and the mixed-parameter adjustment of multiple algorithms will further improve the accuracy of model evaluation. Future research will focus on designing a more comprehensive and scientific evaluation indicator system and further exploring the universality of better evaluation models in other regions. Finally, carrying capacity research always serves the purpose of regulation, and future research should focus on formulating carrying capacity regulation plans based on driving mechanisms.

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References

1. He, G.; Zhang, S.; Yang, X.; Bao, K.; Zhang, Y. Safety evaluation and joint risk probability calculation of Water-Land-Energy systems in Anhui Province. *J. Saf. Environ.* **2024**, *24*, 4094–4106. [\[CrossRef\]](#)
2. Wang, F.; Chen, M.; Cao, Y.; Yang, Y. Network characteristics of water-land-energy-carbon correlation system of nine provinces along the Yellow River Basin. *Adv. Sci. Technol. Water Resour.* **2024**, *44*, 31–37.
3. Zhao, R.; Liu, Y.; Tian, M.; Ding, M.; Cao, L.; Zhang, Z.; Chuai, X.; Xiao, L.; Yao, L. Impacts of water and land resources exploitation on agricultural carbon emissions: The water-land-energy-carbon nexus. *Land Use Policy* **2018**, *72*, 480–492. [\[CrossRef\]](#)
4. Ren, S.; Fu, Q.; Wang, K. Regional agricultural water and soil resources carrying capacity based on macro-micro scale in Sanjiang Plain. *Trans. Chin. Soc. Agric. Eng.* **2011**, *27*, 8–14.
5. Zhong, H.; Zhang, S.; Zhang, X.; Yu, Y.; Li, D.; Wang, S.; Xiao, J.; Tian, P. Water-land-energy efficiency and nexus within global agricultural trade during 1995–2019. *Sci. Total Environ.* **2024**, *951*, 175539. [\[CrossRef\]](#)
6. Aktymbayeva, A.; Nuruly, Y.; Artemyev, A.; Kaliyeva, A.; Sapiyeva, A.; Assipova, Z. Balancing nature and visitors for sustainable development: Assessing the tourism carrying capacities of Katon-Karagay National Park, Kazakhstan. *Sustainability* **2023**, *15*, 15989. [\[CrossRef\]](#)
7. Zuo, Q.; Zhang, X. Dynamic carrying capacity of water resources under climate change. *J. Hydraul. Eng.* **2015**, *46*, 387–395.
8. Del Monte-Luna, P.; Brook, B.W.; Zetina-Rejón, M.J.; Cruz-Escalona, V.H. The carrying capacity of ecosystems. *Glob. Ecol. Biogeogr.* **2004**, *13*, 485–495. [\[CrossRef\]](#)
9. Chapman, E.J.; Byron, C.J. The flexible application of carrying capacity in ecology. *Glob. Ecol. Conserv.* **2018**, *13*, e00365. [\[CrossRef\]](#)
10. Sayre, N.F. The genesis, history, and limits of carrying capacity. *Ann. Assoc. Am. Geogr.* **2008**, *98*, 120–134. [\[CrossRef\]](#)
11. Daily, G.C.; Ehrlich, P.R. Population, sustainability, and Earth's carrying capacity. *BioScience* **1992**, *42*, 761–771. [\[CrossRef\]](#)
12. Zhang, L.; Li, W.; Liu, X.; Wang, W. Carrying capacity: Origin, development and prospective. *Acta Ecologica Sinica* **2009**, *29*, 878–888.

13. Wang, J.; Jiang, D.; Xiao, W.; Chen, Y.; Hu, P. Study on theoretical analysis of water resources carrying capacity: Definition and scientific topics. *J. Hydraul. Eng.* **2017**, *48*, 1399–1409.
14. Zuo, Q. Review of research methods of water resources carrying capacity. *Adv. Sci. Technol. Water Resour.* **2017**, *37*, 1–6.
15. Peng, T.; Deng, H. Evaluating urban resource and environment carrying capacity by using an innovative indicator system based on eco-civilization—A case study of Guiyang. *Environ. Sci. Pollut. Res.* **2021**, *28*, 6941–6955. [[CrossRef](#)]
16. Liu, Z.; Ren, Y.; Shen, L.; Liao, X.; Wei, X.; Wang, J.J. Analysis on the effectiveness of indicators for evaluating urban carrying capacity: A popularity-suitability perspective. *J. Clean. Prod.* **2020**, *246*, 119019. [[CrossRef](#)]
17. Liu, B.; Qin, X.; Zhang, F. System-dynamics-based scenario simulation and prediction of water carrying capacity for China. *Sustain. Cities Soc.* **2022**, *82*, 103912. [[CrossRef](#)]
18. Hu, G.; Zeng, W.; Yao, R.; Xie, Y.; Liang, S. An integrated assessment system for the carrying capacity of the water environment based on system dynamics. *J. Environ. Manag.* **2021**, *295*, 113045. [[CrossRef](#)]
19. Li, Z.; Luo, Z.; Wang, Y.; Fan, G.; Zhang, J. Suitability evaluation system for the shallow geothermal energy implementation in region by Entropy Weight Method and TOPSIS method. *Renew. Energy* **2022**, *184*, 564–576. [[CrossRef](#)]
20. Li, X.; Wang, K.; Liu, L.; Xin, J.; Yang, H.; Gao, C. Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. *Procedia Eng.* **2011**, *26*, 2085–2091. [[CrossRef](#)]
21. Song, M.; Zhu, Q.; Peng, J.; Gonzalez, E.D.S. Improving the evaluation of cross efficiencies: A method based on Shannon entropy weight. *Comput. Ind. Eng.* **2017**, *112*, 99–106. [[CrossRef](#)]
22. Li, X.; Li, H.; Liu, D.; Fu, Q.; Li, M.; Faiz, M.A.; Ali, S.; Li, T.; Khan, M.I. Connotation analysis and evaluation index system construction of regional agricultural soil and water resource composite system harmony. *J. Clean. Prod.* **2020**, *263*, 121438. [[CrossRef](#)]
23. Zhang, Z.; Zhang, L.; Liu, D.; Sun, N.; Li, M.; Faiz, M.A.; Li, T.; Cui, S.; Khan, M.I. Measurement and analysis of regional water-energy-food nexus resilience with an improved hybrid kernel extreme learning machine model based on a dung beetle optimization algorithm. *Agric. Syst.* **2024**, *218*, 103966. [[CrossRef](#)]
24. Friedman, J.H.; Tukey, J. A projection pursuit algorithm for exploratory data analysis. *IEEE Trans. Comput.* **1974**, *100*, 881–890. [[CrossRef](#)]
25. Hopfield, J.J. Neural networks and physical systems with emergent collective computational abilities. *Proc. Natl. Acad. Sci. USA* **1982**, *79*, 2554–2558. [[CrossRef](#)]
26. Osuna, E.; Freund, R.; Girosi, F. An improved training algorithm for support vector machines. In Proceedings of the Neural networks for signal processing VII. In Proceedings of the 1997 IEEE Signal Processing Society Workshop, Piscataway, NJ, USA, 23–25 June 1997; pp. 276–285.
27. Huang, G.-B.; Zhu, Q.-Y.; Siew, C.-K. Extreme learning machine: A new learning scheme of feedforward neural networks. In Proceedings of the 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No. 04CH37541), Budapest, Hungary, 25–29 July 2004; pp. 985–990.
28. Iverson, L.R.; Prasad, A.M.; Matthews, S.N.; Peters, M. Estimating potential habitat for 134 eastern US tree species under six climate scenarios. *For. Ecol. Manag.* **2008**, *254*, 390–406. [[CrossRef](#)]
29. Wang, C.; Wang, K.; Liu, D.; Zhang, L.; Li, M.; Khan, M.I.; Li, T.; Cui, S. Development and application of a comprehensive assessment method of regional flood disaster risk based on a refined random forest model using beluga whale optimization. *J. Hydrol.* **2024**, *633*, 130963. [[CrossRef](#)]
30. El-Fergany, A.A.; Agwa, A.M. Red-Billed Blue Magpie Optimizer for Electrical Characterization of Fuel Cells with Prioritizing Estimated Parameters. *Technologies* **2024**, *12*, 156. [[CrossRef](#)]
31. Zhao, R.; Li, Z.; Han, Y.; Milind, K.; Zhang, Z.; Ding, M. The coupling interaction mechanism of regional water-land-energy-carbon system. *Acta Geogr. Sin.* **2016**, *71*, 1613–1628.
32. Zhan, C.; Wu, D.; Yang, R. Comprehensive evaluation of energy resources capacity in Guangxi. *Ecol. Sci.* **2018**, *37*, 131–137.
33. Liu, B.; Shao, M.A. Modeling soil–water dynamics and soil–water carrying capacity for vegetation on the Loess Plateau, China. *Agric. Water Manag.* **2015**, *159*, 176–184. [[CrossRef](#)]
34. Li, H.; Zhou, W.; Zhuang, Y.; Ma, C.; Liu, B. Agricultural water and soil resources matching patterns and carrying capacity in Yanan City. *Trans. Chin. Soc. Agric. Eng.* **2016**, *32*, 156–162.
35. Jia, Z.; Cai, Y.; Chen, Y.; Zeng, W. Regionalization of water environmental carrying capacity for supporting the sustainable water resources management and development in China. *Resour. Conserv. Recycl.* **2018**, *134*, 282–293. [[CrossRef](#)]
36. Wu, D.; Zhang, Z.; Liu, D.; Zhang, L.; Li, M.; Khan, M.I.; Li, T.; Cui, S. Calculation and analysis of agricultural carbon emission efficiency considering water–energy–food pressure: Modeling and application. *Sci. Total. Environ.* **2024**, *907*, 167819. [[CrossRef](#)] [[PubMed](#)]
37. Ni, J.; Li, P.; Wei, C.; Xie, D. Potentialities evaluation of regional land consolidation based on AHP and entropy weight method. *Trans. Chin. Soc. Agric. Eng.* **2009**, *25*, 202–209.
38. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [[CrossRef](#)]

39. Strobl, C.; Malley, J.; Tutz, G. An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychol. Methods* **2009**, *14*, 323. [[CrossRef](#)]
40. Chen, Y.; Shen, H.; Wang, X.; Zhao, W.; Pan, Z.; Wang, J.; Li, S.; Han, D. Assessment Method for Urban Energy Carbon Emission Peak Based on Mann-Kendall Trend Test. *J. Shanghai Jiaotong Univ.* **2023**, *57*, 928–938.
41. Shi, Y.; Niu, F.; Lin, Z.; Luo, J. Freezing/thawing index variations over the circum-Arctic from 1901 to 2015 and the permafrost extent. *Sci. Total. Environ.* **2019**, *660*, 1294–1305. [[CrossRef](#)]
42. Lu, Y.; Geng, Y.; Liu, Z.; Cote, R.; Yu, X. Measuring sustainability at the community level: An overview of China's indicator system on National Demonstration Sustainable Communities. *J. Clean. Prod.* **2017**, *143*, 326–335. [[CrossRef](#)]
43. Qiu, W.; Liu, Y.; Lu, F.; Huang, G. Establishing a sustainable evaluation indicator system for railway tunnel in China. *J. Clean. Prod.* **2020**, *268*, 122150. [[CrossRef](#)]
44. Alem, D.; Bonilla-Londono, H.F.; Barbosa-Povoa, A.P.; Relvas, S.; Ferreira, D.; Moreno, A. Building disaster preparedness and response capacity in humanitarian supply chains using the Social Vulnerability Index. *Eur. J. Oper. Res.* **2020**, *292*, 250–275. [[CrossRef](#)]
45. Lin, Z.; Liu, X.; Chen, Y.; Fu, B. Water-food-energy nexus: Progress, challenges and prospect. *Acta Geogr. Sin.* **2021**, *76*, 1591–1604.

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