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A Cloud Model-Based CRITIC-EDAS Decision-Making Approach with Linguistic Information for Marine Ranching Site Selection

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Abstract: Modern marine ranching construction has drawn growing attention of relevant planning authorities and enterprises with the potential value of oceans becoming apparent. To satisfy the demand for a successful marine ranching construction, site selection is considered as the first and fundamental procedure. This work aims to help planning authorities find the optimal marine ranching site by introducing a methodological evaluation framework for solving this critical problem. Firstly, the advanced CRiteria Importance Through Inter-criteria Correlation (CRITIC) method is extended by using a cloud model to determine the relative importance of attributes in marine ranching site selection problems. Secondly, the Evaluation based on Distance from Average Solution (EDAS) method is developed by integration with the cloud model to obtain the ranks of alternative sites for marine ranching construction. The proposed cloud model-based CRITIC-EDAS method considers the fuzziness and randomness of the linguistic terms given by experts simultaneously to ensure the scientificity and rationality of decision making. Finally, a real-world marine ranching site selection problem is solved by using the proposed model, where the efficiency and reliability of the proposed model are verified according to the comparison with other traditional multi-attribute decision-making methods.

Keywords: marine ranching site selection; cloud model; CRITIC method; EDAS method

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1. Introduction

With the potential value of oceans becoming apparent, coastal countries attach great importance to the conservation, protection and sustainable utilization of marine resources [1]. As an effective measure for fishery resource enhancement and ecological restoration, marine ranching has received increasing attention all over the world [2–4]. Marine ranching has experienced two versions: the version 1.0 was characterized by the placement of artificial reefs and the proliferation and release of fishery resources based on farming, ranching and engineering techniques; the version 2.0 was characterized by ecologicalization and informatization with the purpose of protecting the environment and enhancing fishery resources. Nowadays, with the development of digitalization and systematization, China pays great effort to establish modern marine ranching, a novel pattern which can be considered as marine ranching version 3.0. In November 2021, China officially released the first national standard for marine ranching building, the 'Technical Guidelines for Marine Ranching construction', indicating that marine ranching 3.0, a type of whole-area aquatic pasture covering both fresh water and sea water, is coming.

On the premise of ensuring the safety of the environment and fishery resources, modern marine ranching promotes coordinated development of marine ranching, energy exploitation, tourism, facility-based breeding and other industries. It has been suggested to implement a development pattern conducive to the entire industrial chain covering site selection, layout, habitat restoration, resource conservation, safety assurance and integrated development, thus boosting global aquatic ecological ranching [5]. It is clear that in the industrial chain of modern marine ranching construction, site selection is the first and fundamental step, which is directly related to the success of the project [6]. A poorly executed site selection for marine ranching may affect ecosystem functions and services with negative environmental, social and economic consequences [7]. Therefore, the main aim of this research study is to evaluate alternative sites for marine ranching and select an optimal site by using a multi-attribute decision-making technique.

1.1. Aims of This Study

This study intends to address the modern marine ranching site selection problem from the MADM perspective. Marine ranching 3.0 is a new fussiness pattern, which integrates environmental protection, resource conservation and sustainable production of fishery resources to supply high-quality protein and ensure the security of the offshore ecosystem. Although a few research studies are devoted to the site selection problem of artificial reefs, they are not applicable for modern marine ranching, so both a practical and a methodological evaluation framework for solving modern marine ranching site selecting problems is still missing. Therefore, an index system for marine ranching evaluation with five primary indices and sixteen secondary indices has been identified, which aims to provide a practical framework for relevant planning authorities to be used when evaluating feasible sites for modern marine ranching. Also, this study aims to introduce an advanced multi-attribute decision-making approach for determining the optimal marine ranching site. The approach is based on the integration of the CRiteria Importance Through Inter-criteria Correlation (CRITIC) method and the Evaluation based on Distance from Average Solution (EDAS) method with linguistic information by introducing a cloud model theory. The proposed cloud model-based CRITIC-EDAS approach can also be used to solve other complex multi-attribute decision-making problems in reality. In addition, this research proposes real-world guidelines for selecting the optimal site for modern marine ranching by using a case study of the city of Yantai in China. In the real case, Yantai intends to construct a novel marine ranching complex with the functions of marine culture, sea sightseeing, leisure fishing, ocean science, and supplying seafood as well as sea accommodation. The rendering for the main building of the marine ranching complex is depicted in Figure 1, the Chinese character identification of the image is the project name. and six marine areas have been selected as alternative sites for the marine ranching construction as shown in Figure 2.

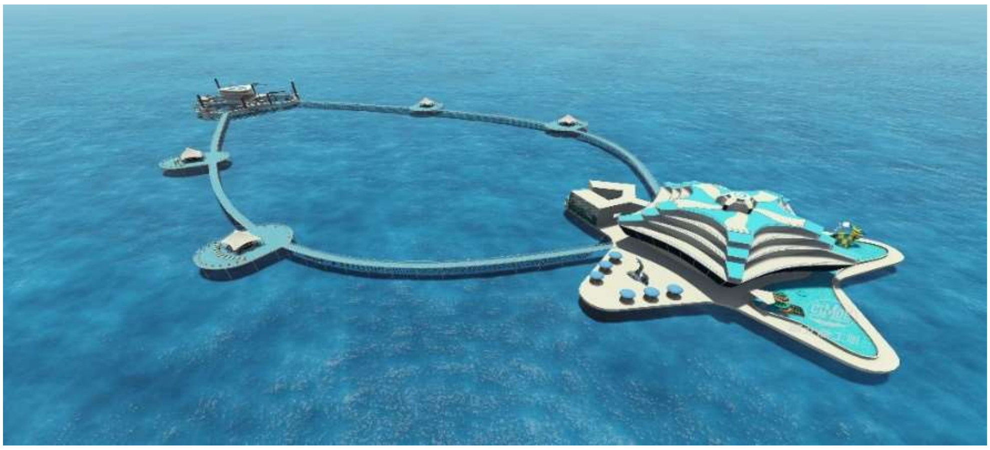

Figure 1. A rendering of the marine ranching complex.

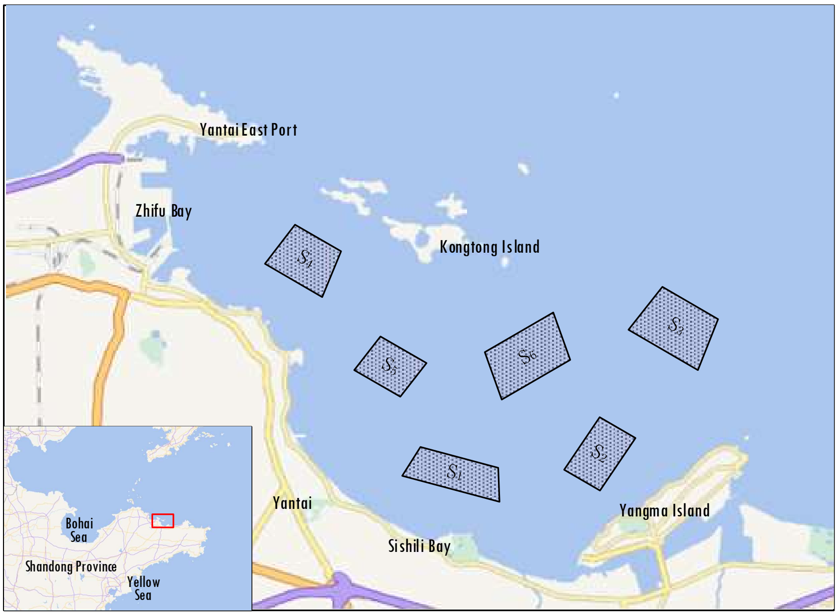

Figure 2. The geographical positions of six alternative marine ranching sites.

1.2. Motivation for Developing a Cloud Model-Based CRITIC-EDAS

Owing to the external environment's variability and complexity and to human cognition incompleteness, it is difficult for experts to quantify their cognition with a precise number. For example, a precise number of plant plankton biomass of a marine ranching site can only be obtained at some fixed monitoring points, and it may lose some critical information such as the dynamics and variance of the index. Therefore, linguistic terms have become popular tools in modeling various decision-making problems in reality, as people tend to rely on language to express their opinion rather than exact numbers. For example, natural language such as 'extremely low' or 'too high' can be used by decision makers to deliver their cognition about the plant plankton biomass of marine ranching sites with fuzziness and uncertainty. Linguistic decision-making problems can be divided into three main types of research: linguistic computational models based on membership functions [8,9], linguistic symbolic models based on ordinal scales [10,11] and two-tuple linguistic models [12,13]. Another character of marine ranching site selection problems is the randomness of data. The first linguistic model can only describe fuzziness but not randomness, and the last two linguistic models cannot produce a clear description of either fuzziness or randomness. Therefore, the cloud model theory is introduced to solve linguistic MADM problems [14].

The cloud model theory, a description of the qualitative concept, is developed on the fundamentals of the probability theory and the fuzzy set theory and manipulates the issue that membership degrees are accurate in the fuzzy set theory through allowing a stochastic disturbance of the membership degree encircling a determined central value [15]. More specifically, the cloud model employs a large number of discrete points to depict the vagueness and randomness of experts' uncertain preferences, and then uses three quantitative numerical characteristics to describe the distribution of elements, in which the objective and interchangeable transformation between qualitative concepts and quantitative values becomes possible. Due to the advantage of the cloud model in reflecting fuzziness and randomness simultaneously, it has been successfully employed to construct extended MADM methods such as cloud AHP [16], cloud TOPSIS [17], cloud VIKOR [18] and cloud CoCoSo [19], and applied in solving realistic practices such as sustainable supplier selection, informatization project evaluation, online education satisfaction assessment, vulnerability assessment for urban road network traffic systems and so on [20–23]. Some typical MADM methods combined with the cloud model are summarized in Table 1.

Table 1. Related studies combining the cloud model with MADM methods.

MADM Methods	Evaluations	Applications	Reference
AHP	Intervals	Select a house by home buyers	[16]
TOPSIS	Linguistic terms	Online education satisfaction assessment	[20]
VIKOR	Linguistic terms	Evaluate the risk of an informatization project	[18]
CoCoSo	Linguistic terms	Select a trusted cloud service provider	[21]
Complex network	Crisp numbers	Vulnerability assessment for traffic systems	[22]
TOPSIS	Rough numbers	Sustainable supplier selection	[23]

The CRITIC method, a well-known multi-attribute decision-making technique proposed by Diakoulaki, was developed to calculate the relative importance of attributes and alternatives in decision-making processes [24]. CRITIC takes into account the standard deviation (S.D.) and correlation coefficient (C.C.) to determine the significance and impact of each attribute on the overall decision outcome, which considers the fluctuation of data to synthesize the weight values of attributes, and helps to reduce the negative impact of the extreme values of weights of individual data within the evaluation system [25]. Recently, CRITIC has been extensively extended to interval-valued intuitionistic fuzzy [26], linguistic Pythagorean fuzzy [23], probabilistic uncertain linguistic [27], Fermatean fuzzy [28], picture fuzzy [29] and type-2 fuzzy [30] environments, as listed in Table 2. Hence, an extension of the CRITIC method with the cloud model is still missing. A combination of CRITIC and the cloud model can be valuable for researchers and practitioners as the existing CRITIC methods are unable to handle fuzziness and randomness of realistic decision-making problems [31–33]. To fill this significant research gap, this study introduces a cloud model-based CRITIC method to determine the importance of evaluation attributes for marine ranching site selection [34,35].

Table 2. Studies related to the CRITIC method.

Environments	Applications	Reference
Interval-valued intuitionistic fuzzy sets	Transportation mode selection	[16]
Linguistic Pythagorean fuzzy sets	Industrial waste management technique selection	[20]
Probabilistic uncertain linguistic sets	Site selection for hospital constructions	[27]
Fermatean fuzzy sets	-	[21]
Picture fuzzy sets	Wearable health technology selection	[29]
Type-2 fuzzy sets	Site selection for nursing homes	[30]

EDAS is one of the recently developed methods for alternative prioritization in various complicated multi-attribute decision-making problems [36]. In traditional distance-based methods such as TOPSIS and VIKOR, the best alternative is determined by using the distances to positive ideal solutions (PIS) and negative ideal solutions (NIS). However, in many realistic MADM problems, lower distance to PIS and higher distance to NIS would not guarantee to get the optimal solution [37]. Therefore, EDAS utilizes two distance measures named positive distance from average value and negative distance from average value to determine the ranking order. As it provides a robust ranking of alternatives, a simple algorithm and calculation swiftness, EDAS has turned into one of the popular and frequently used method to efficiently tackle realistic complex decision-making problems, and been extended by implementing different uncertainty sets, such as fuzzy sets [38], probabilistic hesitant fuzzy sets [19], q-rung orthopair fuzzy sets [39], linguistic intuitionistic fuzzy sets [40], picture fuzzy soft sets [24], and interval-type 2 fuzzy sets [41], as listed in Table 3. However, all the extended EDAS models only represent uncertainties such as fuzziness, imprecision and vagueness, and they cannot handle decision-making problems with fuzziness as well as randomness. To fill this important research gap, this study introduces a cloud model-based EDAS method to rank alternatives and reveal the optimal marine ranching site.

Table 3. Studies related to the EDAS method.

Environments	Applications	Reference
Fuzzy sets	Supplier selection	[16]
Probabilistic hesitant fuzzy sets	Selection of commercial vehicles and green suppliers	[20]
Q-rung orthopair fuzzy sets	Supplier selection in the defense industry	[24]
Linguistic intuitionistic fuzzy sets	Selection of houses and travel destinations	[21]
Picture fuzzy soft sets	Robotic agrifarming	[24]
Interval-type 2 fuzzy sets	Route selection of petroleum transportation	[30]

1.3. Contribution of This Study

The main objective of this study is to construct a multi-attribute group decision-making technique that can assist governments and enterprises in evaluating and selecting optimal marine ranching sites. The main contributions of this research, which might also be viewed as its distinctive strengths or benefits, can be depicted as follows:

- This study constructs a methodology for marine ranching site selection by considering fuzziness and randomness simultaneously. Existing decision-making approaches for marine ranching site selection only take into account the fuzziness of data, while the data collected by detectors and the linguistic terms given by experts are random due to the dynamics and volatility of sample points and human cognition. Therefore, a cloud model is first introduced to reveal the fuzziness and randomness of data in marine ranching site selection problems.
- A new method for determining the relative importance of attributes in marine ranching site selection problems is proposed by integrating CRITIC and the cloud model. The collected evaluation values are transferred from linguistic terms into corresponding clouds, and then the CRITIC approach is extended to handle these clouds in order to obtain the weights of attributes.
- A novel model, named cloud model-based EDAS, is developed to determine the ranks of alternatives in marine ranching site selection problems. The proposed model obtains the final evaluation scores of alternative sites in the form of clouds, which reserve the fuzziness and randomness of evaluation results in order to determine the optimal alternative for marine ranching site selection in a scientific way.
- A real-world marine ranching site selection problem in the city of Yantai is solved by using the cloud model-based CRITIC-EDAS model. Firstly, an evaluation attribute system for modern marine ranching site selection problems is determined from a comprehensive perspective, and then, by transforming linguistic evaluation values into clouds, the proposed model is utilized to obtain the optimal site for marine ranching in Yantai city.
- A comparison of the proposed model with the existing approaches is conducted in the same case to demonstrate its superiority and consistency.

1.4. Organization of This Study

This research is structured as follows: Section 2 presents the preliminaries. Section 3 explores a comprehensive framework of the cloud model-based CRITIC-EDAS model for marine ranching site selection. In Section 4, a real-world case study of the city of Yantai is explored, with an extensive comparative analysis with other methods. Section 5 presents the conclusions and implications.

2. Preliminaries

In this section, the definitions and some of the operations and measures of the cloud are illustrated, and then the concept and properties of linguistic variables are outlined.

2.1. Cloud Model

The cloud model theory, derived from the probability theory and the fuzzy set theory, is an artificial intelligence approach that can reflect the fuzziness and randomness of concepts in human knowledge. It allows a stochastic disturbance of the membership degree encircling a determined central value rather than a fixed number.

Definition 1 [14]. *Let U be the universe of discourse and T be a qualitative concept in U. If $x \in U$ is a random instantiation of concept T, which satisfies $x \sim N\left(Ex,\ En'^2\right)$ and $En' \sim N\left(En,\ He^2\right)$, and if the certainty degree of x belonging to concept T satisfies*

$$y = e^{-\frac{(x-Ex)^2}{2(En')^2}} \tag{1}$$

then the distribution of x in the universe U is called a normal cloud (given as 'cloud' in the remainder of the paper), which can be generally denoted as $(Ex,\ En,\ He)$, and the cloud drop can be denoted as (x, y).

Figure 3 illustrates the cloud $(10, 10, 1)$ with 600 cloud drops. It can be seen that the thickness of the cloud is uneven, which reflects the randomness and fuzziness of the normal cloud. The overall quantitative properties of a concept are described by the cloud using three numerical characteristics: (1) expectation (Ex), the mathematical expectation that the cloud drops belong to a concept in the universe; (2) entropy (En), which illustrates the uncertainty measurements of a qualitative concept, specifically randomness and fuzziness [37]; and (3) hyper entropy (He), the degree of uncertainty of En, i.e., the second-order entropy of the entropy. Additionally, the coverage and discrete degree of clouds have obvious differences: the larger the entropy, the larger the distribution range; the larger the hyper entropy, the bigger the discrete degree [38].

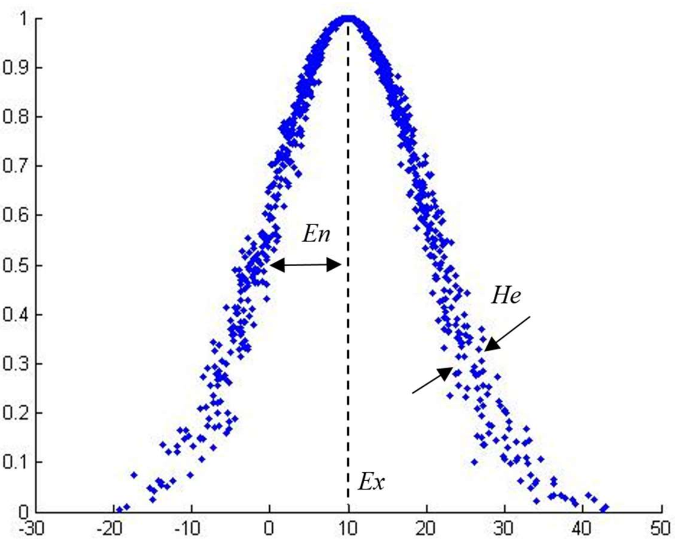

Figure 3. A cloud $(10, 10, 1)$ with 600 cloud drops and its numerical characters.

Definition 2 [39]. *Let $A(Ex_1, En_1, He_1)$ and $B(Ex_2, En_2, He_2)$ be two arbitrary clouds in the domain U. Some basic operations between cloud A and cloud B are defined as follows:*

(1) $A + B = \left(Ex_1 + Ex_2, \sqrt{En_1^2 + En_2^2}, \sqrt{He_1^2 + He_2^2}\right)$
(2) $A - B = \left(Ex_1 - Ex_2, \sqrt{En_1^2 + En_2^2}, \sqrt{He_1^2 + He_2^2}\right)$
(3) $A \times B = \left(Ex_1Ex_2, \sqrt{(En_1Ex_2)^2 + (En_2Ex_1)^2}, \sqrt{(He_1Ex_2)^2 + (He_2Ex_1)^2}\right)$
(4) $\lambda A = \left(\lambda Ex_1, \sqrt{\lambda}En_1, \sqrt{\lambda}He_1\right)$
(5) $A^\lambda = \left(Ex_1^\lambda, \sqrt{\lambda}Ex_1^{\lambda-1}En_1, \sqrt{\lambda}Ex_1^{\lambda-1}He_1\right)$

Especially when $En = He = 0$, a cloud $(Ex,\ En,\ He)$ degenerates to a numerical number. In other words, a numerical number a can be expressed as a cloud $(a,\ 0,\ 0)$. Therefore, the operations between a cloud $A(Ex, En, He)$ and a numerical number a can be obtained by using $(a,\ 0,\ 0)$ according to Definition 2.

Definition 3 [40]**.** *Assume that Ω is the set of all clouds and $w_i(Ex_i, En_i, He_i)$ $(i = 1, 2, \cdots, n)$ is a subset of Ω, a mapping of CWAA: $\Omega^n \to \Omega$ is defined as the cloud-weighted arithmetic averaging (CWAA) operator by*

$$CWAA(A_1, A_2, \cdots, A_n) = \left(\sum_{i=1}^n w_iEx_i, \sqrt{\sum_{i=1}^n w_iEn_i{}^2}, \sqrt{\sum_{i=1}^n w_iHe_i{}^2}\right) \tag{2}$$

where $w = (w_1, w_2, \cdots, w_n)$ is the associated weight vector of $A_i(Ex_i, En_i, He_i)$, satisfying $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$.

In particular if $w = \left(\frac{1}{n}, \frac{1}{n}, \cdots, \frac{1}{n}\right)$, then the $CWAA$ operator degenerates to the CAA operator as

$$CAA(A_1, A_2, \cdots, A_n) = \left(\frac{1}{n}\sum_{i=1}^n Ex_i, \frac{1}{\sqrt{n}}\sqrt{\sum_{i=1}^n En_i{}^2}, \frac{1}{\sqrt{n}}\sqrt{\sum_{i=1}^n He_i{}^2}\right) \tag{3}$$

Definition 4 [41]**.** *Given a cloud drop (x, y), its contribution to concept T can be measured by the score function $s = xy$. Regarding a cloud $A(Ex,\ En, He)$ with n cloud drops (x_i, y_i), we denote the expected value $\hat{s}(A)$ as the overall score for cloud A to concept T as follows:*

$$\hat{s}(A) = \frac{1}{n}\sum_{i=1}^n x_iy_i \tag{4}$$

Wang et al. proposed a method based on Monte Carlo simulation by using the forward generator of the cloud to obtain the expected value $\hat{s}$. And using Definition 4, the comparison method between clouds can be obtained as the following: with regard to two clouds A and B, if $\hat{s}(A) \geq \hat{s}(B)$, then $A \geq B$.

Definition 5 [42]**.** *Let $A(Ex_1, En_1, He_1)$ and $B(Ex_2, En_2, He_2)$ be two arbitrary clouds in the domain U. The Hamming distance between the two clouds can be defined as follows:*

$$D^H(A, B) = \left|\left(1 - \frac{En_1 + He_1}{Ex_1}\right)Ex_1 - \left(1 - \frac{En_2 + He_2}{Ex_2}\right)Ex_2\right| \tag{5}$$

2.2. Linguistic Variables

The concept of linguistic variables is used to deal with the cases which are too complex or too ill-defined to be reasonably represented by quantitative expressions [17].

Definition 6 [43]**.** *Let $L = \{L_i | i = -g, \ldots, 0, \ldots, g,\ g \in N^*\}$ be a finite and totally ordered discrete linguistic term set, where L_i represents a possible value for a linguistic variable. Then, the linguistic term set L has the following characteristics:*

(1) *The set is ordered: $L_i > L_j$ if and only if $i > j$;*

(2) *There is the negation operator:* $neg(L_i) = L_{-i}$.

For example, a set of seven terms L can be defined as follows:

$$L = \{L_{-3} = \text{very poor},\ L_{-2} = \text{poor},\ L_{-1} = \text{moderately poor},\ L_0 = \text{moderate},$$
$$L_1 = \text{moderately good},\ L_2 = \text{good},\ L_3 = \text{very good}.\}$$

So far, there are two perspectives to transform linguistic variables into clouds. One is using the golden ratio to generate the values of expectation, entropy and hyper entropy [18], the other is obtaining the characters by use of a linguistic scale function [18]. In this paper, we improve the former one by using the linguistic term sets with symmetric subscripts.

Definition 7. [44]. *Assume that the effective domain* $U = [Xmax_{min}]$ *and let* $L = \{L_i | i = -g, \ldots, 0, \ldots, g,\ g \in N^*\}$ *be a linguistic term set. Then, the* $2g + 1$ *basic clouds can be generated based on the golden segmentation method as follows:*

$$A_{-g}(Ex_{-g}, En_{-g}, He_{-g}),\ A_{-(g-1)}\left(Ex_{-(g-1)}, En_{-(g-1)}, He_{-(g-1)}\right),\ A_0(Ex_0, En_0, He_0), \ldots$$
$$, A_g(Ex_g, En_g, He_g),$$

where

$$Ex_i = X\frac{i+g}{2g}min_{max\,min};$$
$$En_0 = 0.382(Xmin_{max};\ En_i = En_0/\left(0.618^{|i|}\right),\ i = -g, \cdots, 0, \cdots, g;$$
$$He_i = He_0/\left(0.618^{|i|}\right),\ i = -g, \cdots, 0, \cdots, g.$$

Note that the effective domain $U = [Xmax_{min}]$ and He_0 need to be designated in advance.

Example 1. *Given the universe* $U = [10,\ 20]$ *and* $He_0 = 0.02$, *then a 5-label linguistic term set* $L = \{L_{-2} = poor,\ L_{-1} = moderately\ poor,\ L_0 = moderate, L_1 = moderately\ good,\ L_2 = good\}$ *can be transformed into five clouds as*

$$A_{-2}(10, 0.667, 0.052),\ A_{-1}(12.5, 0.412, 0.032),\ A_0(15, 0.255, 0.02),$$
$$A_1(17.5, 0.412, 0.032) \text{ and } A_2(20, 0.667, 0.052).$$

And the depictions of the five clouds are given in Figure 4.

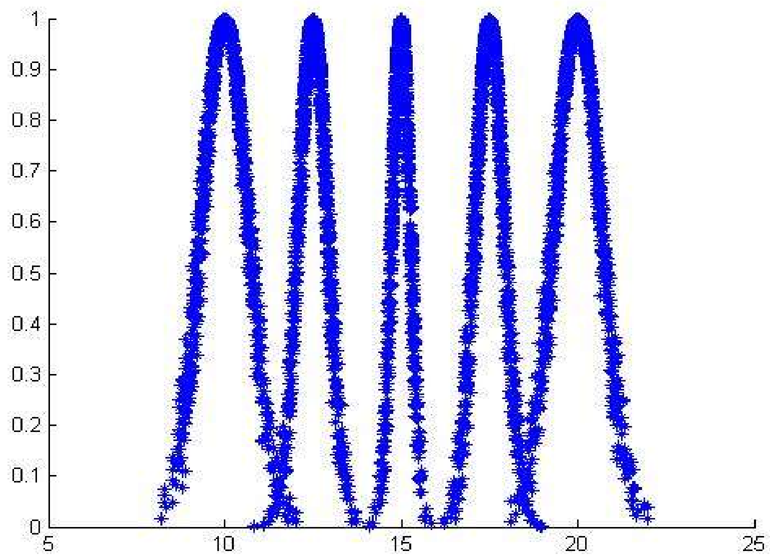

Figure 4. Clouds derived from a 5-label linguistic term set (where $U = [10,\ 20]$ and $He_0 = 0.02$).

3. An Innovative CRITIC-EDAS Approach Based on the Cloud Model

In this section, we focus on discussing a novel MAGDM approach for site selection for marine ranching. Firstly, the framework of the proposed model is depicted; then, a cloud model-based CRITIC method for weighting attributes and a cloud model-based EDAS method for ranking alternatives are illustrated.

3.1. Framework of the Proposed Model

The proposed model in this section is divided into two phases. The first one is a cloud model-based CRITIC method for calculating the weight of attributes for marine ranching site selection, and the second one is a cloud model-based EDAS method for evaluating and ranking alternative marine ranching sites. The specific procedure of the proposed model is depicted in Figure 5.

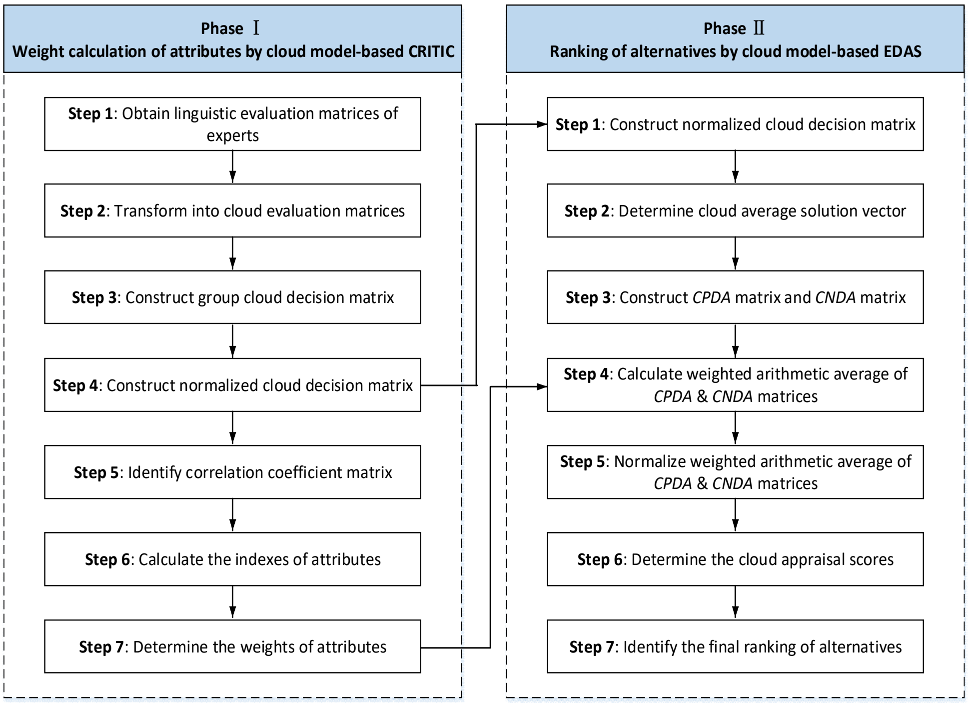

Figure 5. The framework of cloud model-based CRITIC-EDAS approach.

3.2. Cloud Model-Based CRITIC Methodology

The CRITIC method, an objective weighting method, was first proposed by Diakoulak in 1995 [45]. In this section, an extension to the classical CRITIC method is presented by using the cloud model. The procedure of the cloud CRITIC is illustrated as follows.

Step 1. Obtain the linguistic evaluation matrix of expert e_k.

Gather the information from experts in the form of linguistic variables and form decision matrices for each expert. For the kth decision maker e_k $(k = 1, 2, \cdots, s)$ we have the linguistic evaluation matrix as

$$D_k = \begin{pmatrix} L_{11}^k & L_{12}^k & \cdots & L_{1n}^k \\ L_{21}^k & L_{22}^k & \cdots & L_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ L_{m1}^k & L_{m2}^k & \cdots & L_{mn}^k \end{pmatrix} \tag{6}$$

where L_{ij}^k is an assessment value for the ith alternative with respect to the jth attribute, a linguistic variable assigned by the kth expert.

Step 2. Transform to cloud evaluation matrices.

Determine the label of a linguistic term set and transform linguistic variables into clouds by using Definition 7. Then, the linguistic evaluation matrix D^k of expert e_k can be transformed into a cloud evaluation matrix as

$$D'_k = \begin{pmatrix} \left(Ex^k_{11}, En^k_{11}, He^k_{11}\right) & \left(Ex^k_{12}, En^k_{12}, He^k_{12}\right) & \cdots & \left(Ex^k_{1n}, En^k_{1n}, He^k_{1n}\right) \\ \left(Ex^k_{21}, En^k_{21}, He^k_{21}\right) & \left(Ex^k_{22}, En^k_{22}, He^k_{22}\right) & \cdots & \left(Ex^k_{2n}, En^k_{2n}, He^k_{2n}\right) \\ \vdots & \vdots & \vdots & \vdots \\ \left(Ex^k_{m1}, En^k_{m1}, He^k_{m1}\right) & \left(Ex^k_{m2}, En^k_{m2}, He^k_{m2}\right) & \cdots & \left(Ex^k_{mn}, En^k_{mn}, He^k_{mn}\right) \end{pmatrix} \tag{7}$$

where $\left(Ex^k_{ij}, En^k_{ij}, He^k_{ij}\right)$ is the transformed cloud used to assess the ith alternative with respect to the jth attribute by the kth expert.

Step 3. Construct a group cloud decision matrix.

Denote the weights of experts as $\omega = (\omega_1, \omega_2, \cdots, \omega_s)$. By using the cloud-weighted arithmetic averaging ($CWAA$) operator as Equation (2), we can aggregate s cloud evaluation matrices D'_k $(k = 1, 2, \cdots, s)$ and generate an integrated group cloud decision matrix as

$$A = \left[A_{ij}\left(Ex_{ij}, En_{ij}, He_{ij}\right)\right]_{m\times n} = \begin{pmatrix} A_{11}(Ex_{11}, En_{11}, He_{11}) & A_{12}(Ex_{12}, En_{12}, He_{12}) & \cdots & A_{1n}(Ex_{1n}, En_{1n}, He_{1n}) \\ A_{21}(Ex_{21}, En_{21}, He_{21}) & A_{22}(Ex_{21}, En_{21}, He_{21}) & \cdots & A_{2n}(Ex_{21}, En_{21}, He_{21}) \\ \vdots & \vdots & \vdots & \vdots \\ A_{m1}(Ex_{m1}, En_{m1}, He_{m1}) & A_{m2}(Ex_{m2}, En_{m2}, He_{m2}) & \cdots & A_{mn}(Ex_{mn}, En_{mn}, He_{mn}) \end{pmatrix} \tag{8}$$

where

$$A_{ij}(Ex_{ij}, En_{ij}, He_{ij}) = CWAA(A^1_{ij}, A^2_{ij}, \cdots, A^s_{ij}) = \left(\sum_{k=1}^{s} \omega_k Ex^k_{ij}, \sqrt{\sum_{i=1}^{n}\left(\omega_k En^k_{ij}\right)^2}, \sqrt{\sum_{i=1}^{n}\left(\omega_k He^k_{ij}\right)^2}\right) \tag{9}$$

Step 4. Construct a normalized cloud decision matrix.

The group cloud decision matrix given in Equation (8) is normalized, both for benefit type attributes and cost type attributes, by using Equation (10):

$$B_{ij} = \begin{cases} \dfrac{A_{ij} - \underset{i}{min}(Ex_{ij})}{\underset{i}{max}(Ex_{ij}) - \underset{i}{min}(Ex_{ij})}, & \text{for beneficial attributes} \\ \dfrac{\underset{i}{max}(Ex_{ij}) - A_{ij}}{\underset{i}{max}(Ex_{ij}) - \underset{i}{min}(Ex_{ij})}, & \text{for cost attributes} \end{cases} \tag{10}$$

where B_{ij} denotes the normalized cloud for the ith alternative with respect to the jth attribute. $\underset{i}{max}(Ex_{ij})$ and $\underset{i}{min}(Ex_{ij})$ represent, respectively, the maximal expectation and the minimal expectation among the clouds under the jth attribute.

Then, we can obtain the normalized cloud decision matrix as

$$\begin{aligned} B &= \left[B_{ij}\left(Ex_{ij}, En_{ij}, He_{ij}\right)\right]_{m\times n} \\ &= \begin{pmatrix} B_{11}(Ex_{11}, En_{11}, He_{11}) & B_{12}(Ex_{12}, En_{12}, He_{12}) & \cdots & B_{1n}(Ex_{1n}, En_{1n}, He_{1n}) \\ B_{21}(Ex_{21}, En_{21}, He_{21}) & B_{22}(Ex_{21}, En_{21}, He_{21}) & \cdots & B_{2n}(Ex_{21}, En_{21}, He_{21}) \\ \vdots & \vdots & \vdots & \vdots \\ B_{m1}(Ex_{m1}, En_{m1}, He_{m1}) & B_{m2}(Ex_{m2}, En_{m2}, He_{m2}) & \cdots & B_{mn}(Ex_{mn}, En_{mn}, He_{mn}) \end{pmatrix} \end{aligned} \tag{11}$$

Step 5. Identify the correlation coefficient.

In traditional CRITIC, the conflicting relationships between attributes are captured with the help of the Pearson correlation. Székely et al. introduced a distance-based correlation measure [46], and then many research studies developed a D-CRITIC method from the perspective of distance correlation [47]. Therefore, by using Hamming distance measures between clouds in Definition 5, a distance-based correlation coefficient, ρ_{jk}, among all attributes is introduced as follows

$$\rho_{jk} = \frac{\sum_{i=1}^{m} D^H\left(B_{ij}, \overline{B}_j\right) D^H\left(B_{ik}, \overline{B}_k\right)}{\sqrt{\sum_{i=1}^{m} D^H\left(B_{ij}, \overline{B}_j\right)^2 \sum_{i=1}^{m} D^H\left(B_{ik}, \overline{B}_k\right)^2}} \tag{12}$$

where $\overline{B}_j$ and $\overline{B}_k$ denote the mean values of the jth and kth attributes by using the CAA operator in Equation (3) as $\overline{B}_j = CAA\left(B_{1j}, B_{2j}, \cdots, B_{mj}\right)$ and $\overline{B}_k = CAA\left(B_{1k}, B_{2k}, \cdots, B_{mk}\right)$.

The distance-based correlation coefficient ρ_{jk} provides a numerical value that indicates the degree of association of the jth attribute with the kth attribute. The value satisfies $\rho_{jk} \in [0, 1]$, providing a scale for measuring the relationship among attributes. In this step, the symmetrical distance-based correlation coefficient matrix is formed as $\left[\rho_{jk}\right]_{n \times n}$.

Step 6. Calculate the index of each attribute.

Compute the information content represented in the index of the jth attribute as follows:

$$I_j = \sigma_j \sum_{k=1}^{n} \left(1 - \rho_{jk}\right) \tag{13}$$

where σ_j indicates the standard deviation of the jth attribute, which is defined as

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} D^H\left(B_{ij}, \overline{B}_j\right)^2}{m-1}} \tag{14}$$

Step 7. Determine the weights of attributes.

The weight of the jth attribute can be calculated as

$$w_j = \frac{I_j}{\sum_{j=1}^{n} I_j} \tag{15}$$

3.3. Cloud Model-Based EDAS Methodology

Ranking alternatives and selecting the best one is another critical process in MADM problems. In this section, an extension to the classical EDAS method is presented, where the cloud model is incorporated. The procedure of the cloud EDAS is depicted as follows.

Step 1. Construct a normalized cloud decision matrix.

Gather the information from experts in the form of linguistic variables, and, by using the procedure of Step 1–4 in Section 3.2, the normalized group cloud decision matrix B can be constructed as follows:

$$\begin{aligned} B &= \left[B_{ij}\left(Ex_{ij}, En_{ij}, He_{ij}\right)\right]_{m \times n} \\ &= \begin{pmatrix} B_{11}(Ex_{11}, En_{11}, He_{11}) & B_{12}(Ex_{12}, En_{12}, He_{12}) & \cdots & B_{1n}(Ex_{1n}, En_{1n}, He_{1n}) \\ B_{21}(Ex_{21}, En_{21}, He_{21}) & B_{22}(Ex_{21}, En_{21}, He_{21}) & \cdots & B_{2n}(Ex_{21}, En_{21}, He_{21}) \\ \vdots & \vdots & \vdots & \vdots \\ B_{m1}(Ex_{m1}, En_{m1}, He_{m1}) & B_{m2}(Ex_{m2}, En_{m2}, He_{m2}) & \cdots & B_{mn}(Ex_{mn}, En_{mn}, He_{mn}) \end{pmatrix} \end{aligned} \tag{16}$$

Step 2. Determine the cloud average solution vector.

The cloud average solution vector can be expressed as

$$CAV = [CAV_1, CAV_2, \cdots, CAV_n]_{1 \times n} \tag{17}$$

where CAV_j indicates the cloud average solution of the jth attribute, which is denoted as

$$CAV_j = CAA\left(B_{1j}, B_{2j}, \cdots, B_{mj}\right) \tag{18}$$

Actually, CAV_j is the mean value $\overline{B}_j$ in the cloud CRITIC method. In order to keep consistent with the traditional EDAS, we still use CAV_j in the proposed approach to indicate the cloud average solution of the jth attribute.

Step 3. Construct the cloud positive distance from the average matrix and the cloud negative distance from the average matrix.

Calculate two important distance measures, the cloud positive distance from average ($CPDA$) and the cloud negative distance from average ($CNDA$), both for benefit type attributes and cost type attributes as follows:

$$CPDA_{ij} = \begin{cases} \dfrac{max\left(0, \left(B_{ij} - CAV_j\right)\right)}{Ex_{CAV_j}} & \text{for benefit attributes} \\ \dfrac{max\left(0, \left(CAV_j - B_{ij}\right)\right)}{Ex_{CAV_j}} & \text{for cost attributes} \end{cases} \tag{19}$$

$$CNDA_{ij} = \begin{cases} \dfrac{max\left(0, \left(CAV_j - B_{ij}\right)\right)}{Ex_{CAV_j}} & \text{for benefit attributes} \\ \dfrac{max\left(0, \left(B_{ij} - CAV_j\right)\right)}{Ex_{CAV_j}} & \text{for cost attributes} \end{cases} \tag{20}$$

where Ex_{CAV_j} is the expectation of the cloud CAV_j.

After obtaining the two cloud distance measures from the average of all the evaluation information in B, the $CPDA$ matrix and the $CNDA$ matrix can be determined as follows:

$$CPDA = \begin{pmatrix} CPDA_{11} & CPDA_{12} & \cdots & CPDA_{1n} \\ CPDA_{21} & CPDA_{22} & \cdots & CPDA_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ CPDA_{m1} & CPDA_{m2} & \cdots & CPDA_{mn} \end{pmatrix} \tag{21}$$

$$CNDA = \begin{pmatrix} CNDA_{11} & CNDA_{12} & \cdots & CNDA_{1n} \\ CNDA_{21} & CNDA_{22} & \cdots & CNDA_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ CNDA_{m1} & CNDA_{m2} & \cdots & CNDA_{mn} \end{pmatrix} \tag{22}$$

Step 4. Calculate the weighted arithmetic average of $CPDA$ and $CNDA$.

The weighted sums of $CPDA$ and $CNDA$ for each alternative can be calculated by using the $CWAA$ operator shown in Equation (2), respectively, as follows:

$$SCP_i = CWAA(CPDA_{i1}, CPDA_{i2}, \cdots, CPDA_{in}) \tag{23}$$

$$SCN_i = CWAA(CNDA_{i1}, CNDA_{i2}, \cdots, CNDA_{in}) \tag{24}$$

SCP_i represents the weighted sum of the positive distance of the ith alternative from the average solution, SCN_i represents the weighted sum of the negative distance of the ith alternative from the average solution. And the weights of attributes can be obtained by cloud CRITIC.

Step 5. Normalize the values of SCP_i and SCN_i.

The normalized weighted sum values of $CPDA$ and $CNDA$ can be obtained as follows:

$$NSCP_i = \frac{SCP_i}{\max\limits_i (Ex_{SCP_i})} \tag{25}$$

$$NSCN_i = 1 - \frac{SCN_i}{\max_i(Ex_{SCN_i})} \tag{26}$$

where $\max_i(Ex_{SCP_i})$ represents the maximal expectation of the clouds among the weighted sum of $CPDA$, and $\max_i(Ex_{SCN_i})$ represents the maximal expectation of the clouds among the weighted sum of $CNDA$.

Step 6. Determine the cloud appraisal scores.

The cloud appraisal score for the ith alternative can be calculated as

$$CAS_i = \frac{NSCP_i + NSCN_i}{2} \tag{27}$$

Step 7. Determine the final ranking of alternatives.

Generate cloud drops of CAS_i based on Monte Carlo simulation by using the forward generator of the cloud, and calculate the expected score value $\hat{s}(CAS_i)$ for the ith alternative by using Equation (4) in Definition 4. Arrange expected score values in descending order, and then the alternative with the highest expected score value is chosen as the best choice.

4. Case Study: Marine Ranching Site Selection in Yantai

4.1. Problem Description

In order to protect natural ecosystems and enhance fishery resources, marine ranching has been widely promoted as a novel production pattern of marine economy. China attaches great importance to the development of modern marine ranching from version 1.0 to version 3.0, which is a new business form, by integrating environmental protection, resource conservation, and sustainable production of fishery resources to supply high-quality protein and ensure the security of the offshore ecosystem. Whether marine ranching can play a role or not is intensively related to various factors derived from the ecological environment and the social environment. Therefore, evaluating different areas and selecting an optimal site for establishing marine ranching are the crucial procedures.

In recent years, Shandong province has been regarded as a strategic area for high-quality economic and social development in China. As the central city of Shandong Peninsula approved by the State council, an important port city around the Bohai Sea, and a national historical and cultural city, Yantai is identified as a city vigorously developing marine economy. By December 2022, Yantai had established 46 provincial marine ranching demonstration zones and 20 national marine ranching demonstration zones. With the increasing demand for marine ranching 3.0, Yantai intends to construct a novel marine ranching complex with the functions of marine culture, sea sightseeing, leisure fishing, ocean science, and supplying seafood as well as sea accommodation. According to the preliminary investigation, six marine areas in Yantai have been selected as alternative sites for marine ranching construction. The rendering for the main building of the marine ranching complex and the sea areas of six alternative sites are depicted as shown in Figures 1 and 2, respectively.

The marine ranching site selection problem can be illustrated as the following:

(1) Six marine areas were identified beforehand as alternative sites for further evaluation, which are denoted as $S = \{S_1, S_2, S_3, S_4, S_5, S_6\}$.

(2) A committee composed of five experts was formed, denoted as $E = \{e_1, e_2, e_3, e_4, e_5\}$. All the experts are professionals in marine economy, consisting of two enterprise managers, two governmental staff members and one college professor. In order to reserve their evaluation information impartially, we consider that each expert plays an equally important role, so the relative importance vector of the experts is $\omega = (0.2, 0.2, 0.2, 0.2, 0.2)$.

(3) The decision committee collects the data according to the evaluation index system as shown in Figure 6. The evaluation index system contains 5 primary indices and 16 secondary indices, which can be acquired by corresponding monitors. Table 1 shows the collected data of S_1 among all the secondary indices. In order to reduce complexity and interactivity among different secondary indices, experts evaluate each alternative from five primary indices by using linguistic terms according to the specific data of secondary indices. And the five primary indices are denoted as five attributes in the marine ranching site selection problem:

- Physical environment (C_1);
- Chemical environment (C_2);
- Biological environment (C_3);
- Engineering environment (C_4);
- Social environment (C_5).

(4) Collect the specific data of all the alternatives on 16 secondary indices, and then experts evaluate alternatives on 5 primary attributes by using the following 7-label linguistic terms:

$$L = \{L_{-3} = extremely\ poor,\ L_{-2} = very\ poor,\ L_{-1} = poor,\ L_0 = medium,\ L_1 = good,\ L_2 = very\ good,\ L_3 = extremely\ good\}.$$

Here, 'good' indicates that alternatives perform well in the attributes and 'poor' indicates that alternatives perform badly in the attributes.

Take S_1 for example. The data of S_1 on 16 indices are detected and collected as shown in Table 1, and then five experts evaluate S_1 from five attributes according to the specific data independently. Then, linguistic evaluating values of five experts are listed in the last five columns of Table 4. At last, we can obtain the group linguistic evaluation information as depicted in Table 5.

Table 4. Attributes for marine ranching site selection.

	Primary Indices	Secondary Indices	Data of Indices	e_1	e_2	e_3	e_4	e_5
S_1	Physical environment	Average depth	14.8 m	*G*	*M*	*G*	*VG*	*M*
		Sediment particle size	0.2 mm					
		Dissolved oxygen	5.45 mg/L					
	Chemical environment	Inorganic nitrogen	1.67 mg/L	*VG*	*EG*	*VG*	*VG*	*G*
		Sulfide content	63 mg/kg					
		Active phosphate	0.032 mg/L					
	Biological environment	Plant plankton biomass	125×10^4 ind/m^3	*G*	*VG*	*M*	*M*	*G*
		Zooplankton biomass	76.3 mg/m^3					
		Benthic biomass	89.7 g/m^2					
		Chlorophyll A	3.78 mg/m^3					
	Engineering environment	Bottom load	1.2 t/m^2	*EP*	*VP*	*VP*	*VP*	*VP*
		Silt thickness	0.61 m					
		Seabed slope	4.1 m					
	Social environment	Fishery resource density	48 kg/m^2	*M*	*P*	*M*	*G*	*P*
		Distance to scenic spots	7.8 km					
		Distance to submarine pipeline	12.1 km					

Table 5. Linguistic assessment information of marine ranching sites from five experts.

	C_1	C_2	C_3	C_4	C_5
S_1	L_1, L_0, L_1, L_2, L_0	L_2, L_3, L_2, L_2, L_1	L_1, L_2, L_0, L_0, L_1	$L_{-3}, L_{-2}, L_{-2}, L_{-2}, L_{-2}$	$L_0, L_{-1}, L_0, L_1, L_{-1}$
S_2	L_1, L_2, L_0, L_1, L_1	$L_{-1}, L_{-2}, L_{-2}, L_{-2}, L_{-1}$	L_3, L_3, L_3, L_2, L_3	$L_{-2}, L_{-3}, L_{-2}, L_{-2}, L_{-2}$	L_0, L_1, L_1, L_1, L_0
S_3	$L_{-2}, L_{-3}, L_{-2}, L_{-1}, L_{-2}$	L_1, L_1, L_2, L_1, L_1	L_3, L_2, L_3, L_3, L_2	L_2, L_1, L_2, L_2, L_1	L_2, L_1, L_0, L_1, L_1
S_4	L_2, L_1, L_1, L_2, L_2	L_2, L_2, L_3, L_2, L_2	L_2, L_1, L_1, L_0, L_1	L_1, L_1, L_1, L_2, L_1	$L_{-1}, L_{-2}, L_{-2}, L_{-2}, L_{-1}$
S_5	L_2, L_1, L_2, L_2, L_2	$L_0, L_1, L_1, L_{-1}, L_0$	L_2, L_1, L_1, L_2, L_0	$L_{-1}, L_0, L_{-1}, L_1, L_0$	L_3, L_2, L_1, L_2, L_2
S_6	$L_{-1}, L_{-2}, L_{-1}, L_{-1}, L_{-1}$	L_2, L_2, L_1, L_3, L_2	$L_{-1}, L_{-1}, L_{-1}, L_0, L_{-2}$	L_1, L_2, L_1, L_1, L_1	L_1, L_0, L_0, L_0, L_1

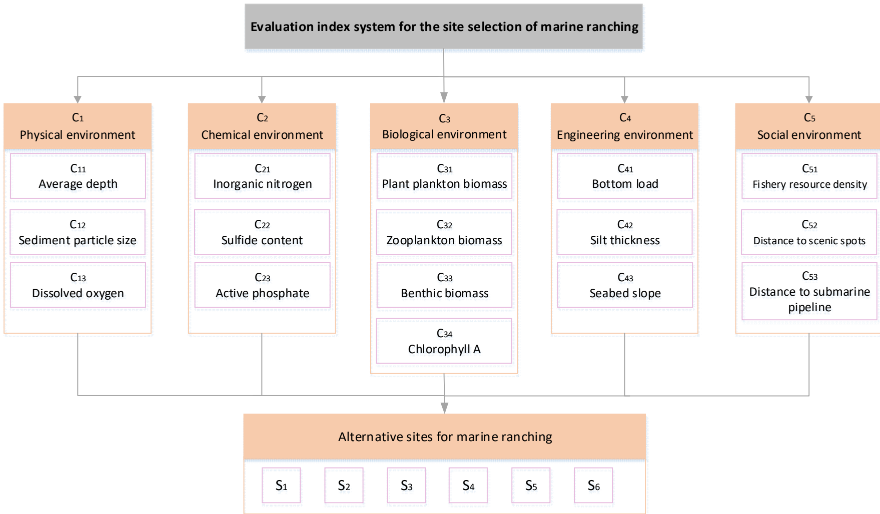

Figure 6. Evaluation index system for marine ranching site selection.

4.2. Assessing the Significance of Attributes Using Cloud CRITIC

Step 1. Collect the linguistic evaluation information of experts as described in Table 2.

Step 2. Transform the linguistic evaluation matrix of each expert into a cloud evaluation matrix. Given the universe $[Xmax_{min} = [0, 10]]$, the 7-label linguistic term set can be transformed to seven clouds by using the transformation rule in Definition 7. Selecting $He_0 = 0.01$, the transformed clouds are depicted in Table 6.

Table 6. Transformation from 7-label linguistic terms to clouds.

Linguistic Terms	Clouds
EP	(0.000, 0.771, 0.042)
VP	(1.667, 0.476, 0.026)
P	(3.333, 0.294, 0.016)
M	(5.000, 0.182, 0.010)
G	(6.667, 0.294, 0.016)
VG	(8.333, 0.476, 0.026)
EG	(10.000, 0.771, 0.042)

Step 3. Compile all decision matrices and create an aggregated cloud decision matrix $A = \left[A_{ij}\left(Ex_{ij}, En_{ij}, He_{ij}\right)\right]_{m \times n}$. In these cases, we consider that the all the experts possess the same significance; therefore, we use the *CAA* operator depicted in Equation (3) to aggregate cloud evaluation information. The group cloud decision matrix is shown in Table 7.

Table 7. Aggregated cloud decision matrix.

	C_1	C_2	C_3	C_4	C_5
S_1	(6.333, 0.305, 0.017)	(8.333, 0.522, 0.028)	(6.333, 0.305, 0.017)	(1.334, 0.548, 0.030)	(4.667, 0.255, 0.014)
S_2	(6.667, 0.322, 0.018)	(2.333, 0.413, 0.023)	(9.667, 0.722, 0.039)	(1.334, 0.548, 0.030)	(6.000, 0.255, 0.014)
S_3	(1.667, 0.522, 0.028)	(7.000, 0.338, 0.018)	(9.333, 0.669, 0.036)	(7.667, 0.413, 0.023)	(6.667, 0.322, 0.018)
S_4	(7.667, 0.413, 0.023)	(8.666, 0.548, 0.030)	(6.667, 0.322, 0.018)	(7.000, 0.338, 0.018)	(2.333, 0.413, 0.023)
S_5	(8.000, 0.446, 0.024)	(5.333, 0.255, 0.014)	(7.000, 0.363, 0.020)	(4.667, 0.255, 0.014)	(8.333, 0.522, 0.028)
S_6	(3.000, 0.338, 0.018)	(8.333, 0.522, 0.028)	(3.333, 0.322, 0.018)	(7.000, 0.338, 0.018)	(6.000, 0.255, 0.014)

Step 4. Normalize the aggregated cloud assessment information by using Equation (10). The normalized cloud decision $B = \left[B_{ij}\left(Ex_{ij}, En_{ij}, He_{ij}\right)\right]_{m\times n}$ is conducted as shown in Table 8.

Table 8. Normalized cloud decision matrix.

	C_1	C_2	C_3	C_4	C_5
S_1	(0.737, 0.211, 0.007)	(0.947, 0.207, 0.011)	(0.474, 0.121, 0.007)	(0.000, 0.218, 0.012)	(0.389, 0.104, 0.006)
S_2	(0.790, 0.223, 0.007)	(0.000, 0.164, 0.009)	(1.000, 0.287, 0.016)	(0.000, 0.218, 0.012)	(0.611, 0.104, 0.006)
S_3	(0.000, 0.361, 0.011)	(0.737, 0.134, 0.007)	(0.947, 0.266, 0.014)	(1.000, 0.164, 0.009)	(0.722, 0.132, 0.007)
S_4	(0.947, 0.285, 0.009)	(1.000, 0.218, 0.012)	(0.526, 0.128, 0.007)	(0.895, 0.134, 0.007)	(0.000, 0.169, 0.009)
S_5	(1.000, 0.308, 0.010)	(0.474, 0.101, 0.006)	(0.579, 0.144, 0.008)	(0.526, 0.101, 0.006)	(1.000, 0.213, 0.012)
S_6	(0.210, 0.234, 0.007)	(0.947, 0.207, 0.011)	(0.000, 0.128, 0.007)	(0.895, 0.134, 0.007)	(0.611, 0.104, 0.006)

To demonstrate the process behind the values in Table 8, we provide a calculation example specifically for B_{11} in the normalized cloud decision matrix. The maximal value and minimal value for C_1 are $A_{51}(8.000, 0.446, 0.024)$ and $A_{31}(1.667, 0.522, 0.028)$, respectively, and then we can transfer A_{11} to a normalized value B_{11} by using Equation (10) as

$$B_{11} = \frac{(6.333, 0.305, 0.017) - (1.667, 0.522, 0.028)}{8.000 - 1.667} = (0.737, 0.211, 0.007)$$

Step 5. Calculate the distance correlation coefficient among all attributes.

The specific procedure of calculating correlation coefficients is shown in Tables 9–11. Firstly, by using the *CAA* operator shown in Equation (3) we can obtain the mean value $\boldsymbol{B_j}$ for attribute $\boldsymbol{C_j}$, as illustrated in Table 9. Then, the Hamming distance between each cloud assessment and the corresponding mean value is depicted by using Equation (5), as shown in Table 10. By using Equation (12), we can obtain the correlation coefficient matrix shown in Table 11.

Table 9. The mean values of attributes.

$\overline{B}_1$	$\overline{B}_2$	$\overline{B}_3$	$\overline{B}_4$	$\overline{B}_5$
(0.614, 0.275, 0.009)	(0.684, 0.177, 0.010)	(0.588, 0.192, 0.010)	(0.553, 0.167, 0.009)	(0.556, 0.144, 0.008)

Table 10. Aggregation of the Hamming distance $\left(B_{ij}, \overline{B}_j\right)$.

	C_1	C_2	C_3	C_4	C_5
S_1	0.1893	0.2315	0.0394	0.6057	0.1252
S_2	0.2299	0.6703	0.3123	0.6057	0.0971
S_3	0.7019	0.0979	0.2818	0.4508	0.1794
S_4	0.3230	0.2732	0.0061	0.3769	0.5820
S_5	0.3523	0.1305	0.0415	0.0433	0.3712
S_6	0.3607	0.2315	0.5203	0.3769	0.0971

Table 11. Correlation coefficient matrix.

	C_1	C_2	C_3	C_4	C_5
C_1	1.0000	0.6160	0.7393	0.7865	0.7357
C_2	0.6160	1.0000	0.6860	0.8766	0.5713
C_3	0.7393	0.6860	1.0000	0.7275	0.3138
C_4	0.7865	0.8766	0.7275	1.0000	0.5981
C_5	0.7357	0.5713	0.3138	0.5981	1.0000

Taking the correlation coefficient ρ_{12} between C_1 and C_2 for example, we have

$$\rho_{12} = \frac{0.1893 \times 0.2315 + 0.2299 \times 0.6703 + \cdots + 0.3607 \times 0.2315}{\sqrt{(0.1893^2 + 0.2299^2 + \cdots + 0.3607^2) \times (0.2315^2 + 0.6703^2 + \cdots + 0.2315^2)}} = 0.6160$$

Step 6. Calculate the index I_j by using Equation (13), which is illustrated in Table 12. To provide a clear understanding of how to obtain the index of each attribute, we use C_1 as an example.

Table 12. The values of indices and weights of attributes.

	σ_j	I_j	w_j
C_1	0.4336	0.4866	0.1956
C_2	0.3627	0.4534	0.1823
C_3	0.3003	0.4605	0.1851
C_4	0.4946	0.5001	0.2010
C_5	0.3296	0.5870	0.2360

Firstly, we calculate the standard deviation of C_1 by using Equation (14) as

$$\sigma_1 = \sqrt{\frac{0.1893^2 + 0.2299^2 + 0.7019^2 + 0.3230^2 + 0.3523^2 + 0.3607^2}{6-1}} = 0.4336$$

Then, the index of attribute C_1 can be determined as

$$I_1 = 0.4336 \times ((1-1.0000) + (1-0.6160) + (1-0.7393) + (1-0.7865) + (1-0.7357)) = 0.4866.$$

Step 7. Calculate the weights of attributes by using Equation (14); the results are described in the last column of Table 12.

For example, the weight of C_1 can be calculated as

$$w_1 = \frac{0.4866}{0.4866 + 0.4534 + 0.4605 + 0.5001 + 0.5870} = 0.1956$$

Therefore, we can determine the weight vector of the marine ranching site selection problem as

$$W = (0.1956, 0.1823, 0.1851, 0.2010, 0.2360).$$

4.3. Evaluating Alternatives Using Cloud EDAS

After obtaining the weights of attributes, a cloud model-based EDAS method is implemented to evaluate the alternative sites for marine ranching.

Step 1. Similar to the procedure depicted in the cloud CRITIC, the normalized group cloud decision matrix can be constructed as shown in Table 8.

Step 2. Calculate the cloud average solution of each attribute, which is equivalent to the mean value in the cloud CRITIC. Therefore, we can obtain the cloud average solution vector as depicted in Table 13.

Table 13. The cloud average solution vector.

CAV_1	CAV_2	CAV_3	CAV_4	CAV_5
(0.614, 0.275, 0.009)	(0.684, 0.177, 0.010)	(0.588, 0.192, 0.010)	(0.553, 0.167, 0.009)	(0.556, 0.144, 0.008)

Step 3. Calculate the cloud positive distance from average ($CPDA$) matrix and the cloud negative distance from average ($CNDA$) matrix as described in Equations (19) and (20) by using the Hamming distance measure shown in Equation (5). The results are depicted in Tables 14 and 15.

Table 14. The cloud positive distance from average ($CPDA$) matrix.

	C_1	C_2	C_3	C_4	C_5
S_1	(0.200, 0.443, 0.014)	(0.385, 0.330, 0.018)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)
S_2	(0.286, 0.452, 0.014)	(0.000, 0.000, 0.000)	(0.701, 0.450, 0.025)	(0.000, 0.000, 0.000)	(0.100, 0.238, 0.013)
S_3	(0.000, 0.000, 0.000)	(0.077, 0.269, 0.015)	(0.612, 0.428, 0.023)	(0.809, 0.315, 0.017)	(0.300, 0.261, 0.014)
S_4	(0.543, 0.506, 0.016)	(0.461, 0.339, 0.019)	(0.000, 0.000, 0.000)	(0.619, 0.289, 0.016)	(0.000, 0.000, 0.000)
S_5	(0.629, 0.527, 0.017)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.800, 0.345, 0.019)
S_6	(0.000, 0.000, 0.000)	(0.385, 0.330, 0.018)	(0.000, 0.000, 0.000)	(0.619, 0.289, 0.016)	(0.100, 0.238, 0.013)

Table 15. The cloud negative distance from average ($CNDA$) matrix.

	C_1	C_2	C_3	C_4	C_5
S_1	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.194, 0.296, 0.016)	(1.000, 0.369, 0.020)	(0.300, 0.238, 0.013)
S_2	(0.000, 0.000, 0.000)	(1.000, 0.292, 0.016)	(0.000, 0.000, 0.000)	(1.000, 0.369, 0.020)	(0.000, 0.000, 0.000)
S_3	(1.000, 0.579, 0.018)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)
S_4	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)	(0.104, 0.301, 0.016)	(0.000, 0.000, 0.000)	(1.000, 0.297, 0.016)
S_5	(0.000, 0.000, 0.000)	(0.308, 0.247, 0.013)	(0.015, 0.313, 0.017)	(0.048, 0.263, 0.014)	(0.000, 0.000, 0.000)
S_6	(0.657, 0.461, 0.014)	(0.000, 0.000, 0.000)	(1.000, 0.301, 0.016)	(0.000, 0.000, 0.000)	(0.000, 0.000, 0.000)

We still take $CPDA_{11}$ and $CNDA_{11}$ as examples to illustrate the specific calculation procedure. As C_1 is a benefit attribute, the two cloud distances can be calculated as

$$CPDA_{11} = \frac{max(0,(0.737,0.211,0.007)-(0.614,0.275,0.009)))}{0.614} = \frac{(0.123,0.347,0.011)}{0.614} = (0.200,0.443,0.014)$$

$$CNDA_{11} = \frac{max(0,(0.614,0.275,0.009)-(0.737,0.211,0.007))}{0.614} = \frac{(0.000,0.000,0.000)}{0.614} = (0.000,0.000,0.000)$$

Step 4. According to the CWAA operator shown in Equation (2) as well as the weight vector determined by the cloud CRITIC, the weighted arithmetic averages of $CPDA$ and $CNDA$ for each alternative can be calculated as shown in Table 16.

Table 16. The result of SCP_i and SCN_i for alternatives.

	SCP_i	SCN_i	$NSCP_i$	$NSCN_i$	CAS_i
S_1	(0.109, 0.241, 0.010)	(0.308, 0.239, 0.013)	(0.303, 0.402, 0.016)	(0.197, 0.386, 0.021)	(0.250, 0.394, 0.019)
S_2	(0.209, 0.301, 0.014)	(0.383, 0.207, 0.011)	(0.580, 0.502, 0.023)	(0.000, 0.335, 0.018)	(0.290, 0.427, 0.021)
S_3	(0.361, 0.288, 0.016)	(0.196, 0.256, 0.008)	(1.000, 0.480, 0.026)	(0.490, 0.414, 0.013)	(0.745, 0.448, 0.021)
S_4	(0.315, 0.296, 0.013)	(0.255, 0.194, 0.011)	(0.872, 0.494, 0.021)	(0.334, 0.313, 0.017)	(0.603, 0.413, 0.019)
S_5	(0.312, 0.287, 0.012)	(0.068, 0.208, 0.011)	(0.864, 0.478, 0.019)	(0.821, 0.336, 0.018)	(0.843, 0.413, 0.019)
S_6	(0.218, 0.223, 0.012)	(0.314, 0.242, 0.010)	(0.605, 0.372, 0.020)	(0.182, 0.390, 0.015)	(0.393, 0.381, 0.018)

To demonstrate the process behind the values in Table 16, we calculate SCP_1 and SCN_1, for example, as follows:

$$\begin{aligned}
SCP_1 &= CWAA((0.200, 0.443, 0.014), (0.385, 0.330, 0.018), \cdots, (0.000, 0.000, , 0.000)) \\
&= (0.1956 \times 0.200 + 0.1823 \times 0.385 + 0.1851 \times 0.000 + 0.2010 \times 0.000 + 0.2360 \times 0.000, \\
&\sqrt{0.1956 \times 0.443^2 + 0.1823 \times 0.330^2 + 0.1851 \times 0.000^2 + 0.2010 \times 0.000^2 + 0.2360 \times 0.000^2}, \\
&\sqrt{0.1956 \times 0.014^2 + 0.1823 \times 0.018^2 + 0.1851 \times 0.000^2 + 0.2010 \times 0.000^2 + 0.2360 \times 0.000^2}\Big) \\
&= (0.109, 0.241, 0.010)
\end{aligned}$$

$$\begin{aligned}
SCN_1 &= CWAA((0.000, 0.000, 0.000), (0.000, 0.000, 0.000), \cdots, (0.300, 0.238, 0.013)) \\
&= (0.1956 \times 0.000 + 0.1823 \times 0.000 + 0.1851 \times 0.194 + 0.2010 \times 1.000 + 0.2360 \times 0.300, \\
&\sqrt{0.1956 \times 0.000^2 + 0.1823 \times 0.000^2 + 0.1851 \times 0.296^2 + 0.2010 \times 0.369^2 + 0.2360 \times 0.238^2}, \\
&\sqrt{0.1956 \times 0.000^2 + 0.1823 \times 0.000^2 + 0.1851 \times 0.016^2 + 0.2010 \times 0.020^2 + 0.2360 \times 0.013^2}\Big) \\
&= (0.308, 0.239, 0.013)
\end{aligned}$$

Step 5. Normalize the weighted arithmetic averages by using Equations (25) and (26); the results are depicted in the right columns of Table 16.

For example, $NSCP_1$ and $NSCN_1$ can be obtained as follows:

$$NSCP_1 = \frac{(0.109, 0.241, 0.010)}{0.361} = (0.303, 0.402, 0.016),$$

$$NSCN_1 = 1 - \frac{(0.308, 0.239, 0.013)}{0.383} = (0.197, 0.386, 0.021).$$

Step 6. The cloud appraisal scores of the marine ranching sites are depicted in the last column of Table 16 and are obtained with the help of Equation (27) based on the arithmetic average of SCP_i and SCN_i.

We still use CAS_1 as an example:

$$\begin{aligned}
CAS_1 &= \tfrac{(0.303,0.402,0.016)+(0.197,0.386,0.021)}{2} \\
&= \left(\tfrac{0.303+0.197}{2}, \sqrt{\tfrac{0.402^2+0.386^2}{2}}, \sqrt{\tfrac{0.016^2+0.021^2}{2}}\right) \\
&= (0.250, 0.394, 0.019).
\end{aligned}$$

Step 7. In order to compare the cloud appraisal scores and determine the ranking of marine ranching sites, we generate cloud drops and calculate the expected score value for each alternative. With different numbers of cloud drops, the expected scores and final rankings are depicted as shown in Table 17. The results in Table 17 illustrate that, according to different numbers of cloud drops, the ranking of the alternatives by expected scores can be determined as: $S_5 \succ S_3 \succ S_4 \succ S_6 \succ S_2 \succ S_1$. Thus, S_5 should be selected as the best site to establish marine ranching. The cloud appraisal scores of the six alternatives are plotted as shown in Figure 7.

Table 17. The ranking with different numbers of cloud drops.

	S_1	S_2	S_3	S_4	S_5	S_6	Ranking
n = 5000	0.181	0.204	0.529	0.425	0.599	0.278	$S_5 \succ S_3 \succ S_4 \succ S_6 \succ S_2 \succ S_1$
n = 10,000	0.179	0.203	0.526	0.426	0.597	0.277	$S_5 \succ S_3 \succ S_4 \succ S_6 \succ S_2 \succ S_1$
n = 50,000	0.177	0.205	0.526	0.426	0.595	0.278	$S_5 \succ S_3 \succ S_4 \succ S_6 \succ S_2 \succ S_1$
n = 100,000	0.177	0.205	0.527	0.425	0.597	0.279	$S_5 \succ S_3 \succ S_4 \succ S_6 \succ S_2 \succ S_1$

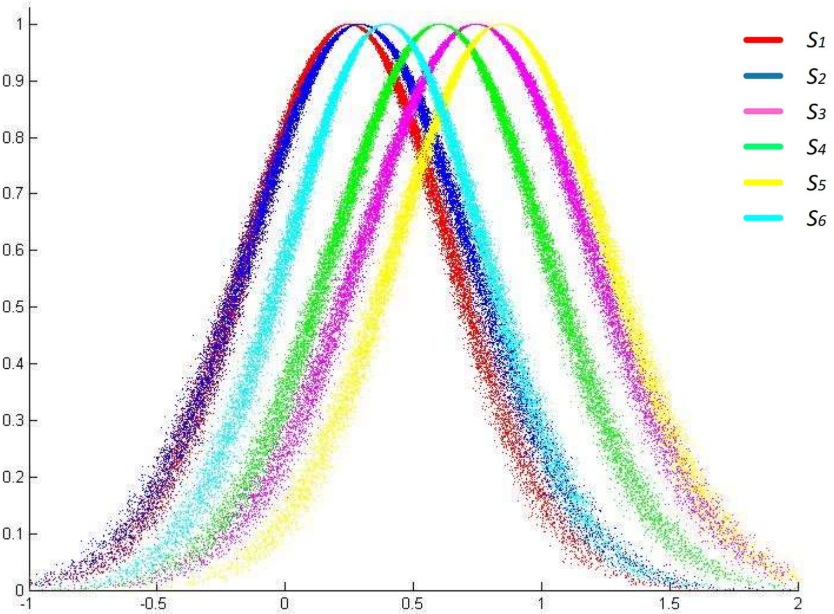

Figure 7. Cloud appraisal scores of six alternatives (with normalized universe $U = [0, 1]$ and $He_0 = 0.01$).

4.4. Comparison and Discussion

To illustrate the effectiveness and superiority of the proposed cloud model-based CRITIC-EDAS approach in this study, it is necessary to compare the proposed approach with some mature methods commonly used in existing studies and some newer methods for verification. In this paper, the same case is applied to the following multi-attribute group decision-making methods: linguistic TOPSIS [48], fuzzy VIKOR [49], probabilistic linguistic EDAS [44] and probabilistic linguistic MABAC [50], cloud TOPSIS [20] and cloud VIKOR [18]. The results obtained from different methods are shown in Table 18 and Figure 8.

Table 18. Comparison of the ranks of the alternatives according to different methods.

Alter.	L-TOPSIS	F-VIKOR	PL-MABAC	PL-EDAS	C-TOPSIS	C-VIKOR	Proposed Method
S_1	6	5	5	6	5	6	6
S_2	5	6	6	4	6	4	5
S_3	3	3	2	3	2	2	2
S_4	2	2	3	2	3	3	3
S_5	1	1	1	1	1	1	1
S_6	4	4	4	5	4	5	4

From Table 18 and Figure 8 we can find an accordant result that the alternative S_5 is always chosen as the optimal alternative in the marine ranching site selection problem, while there are some changes in the ranking of the other alternatives. According to the ranking results in Table 18, it is clear that S_3, S_4 and S_5 occupy the first three positions in the rankings of all the selected methods with S_5 as the optimal one, and S_1, S_2 and S_6 occupy the last three positions in the rankings of all the selected methods. Derived from L-TOPSIS, F-VIKOR and PL-EDAS, S_4 is superior to S_3 in the rankings; while all the cloud model-based models (C-TOPSIS, C-VIKOR and the proposed method) consider S_4 as inferior to S_3 in the rankings. It illustrates that, based on most traditional MADM methods, S_4 performs a little better than S_3 according to the evaluation among attributes, while by using cloud models, the fuzziness and randomness of the evaluation information are both considered. According to the cloud models, the evaluation information of S_3 contains lower fuzziness and randomness than that of S_4. Therefore, from the perspective of a cloud model, S_3 is better than S_4.

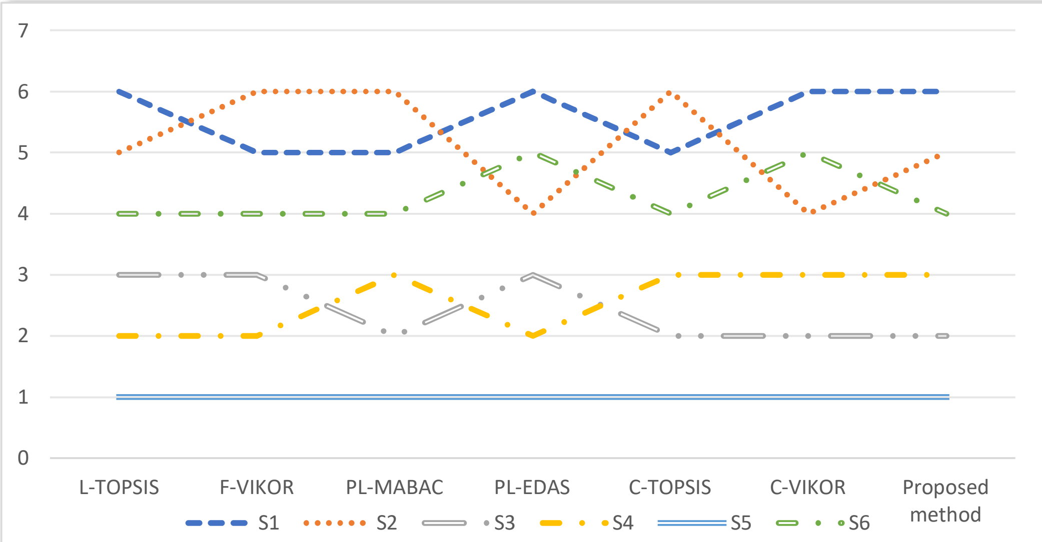

Figure 8. Rankings of alternatives among different methods.

In order to establish the connection between the results derived from different methods, ref. [51] used Spearman's correlation coefficient (SCC) as an indicator to interpret the relationship between two different approaches. So, in this paper, the pairwise comparison method SCC is used to obtain the statistical significance of the results of different methods and to verify the effectiveness of the proposed method. Table 19 represents the SCCs which show the connection between the results of the proposed method and the selected MADM models. There is a consensus that an SCC greater than 0.8 indicates a strong relationship between variables. The results in Table 19 depict that all of the SCCs between the proposed method and other selected MADM models are in the range of [0.886, 1], indicating the effectiveness and credibility of proposed method in this paper.

Table 19. SCCs of the ranks derived from different methods.

MADM Models	L-TOPSIS	F-VIKOR	PL-MABAC	PL-EDAS	C-TOPSIS	C-VIKOR	Proposed Method
L-TOPSIS	1.000	0.943	0.886	0.943	0.886	0.886	0.943
F-VIKOR	-	1.000	0.943	0.829	0.943	0.771	0.886
PL-MABAC	-	-	1.000	0.771	1.000	0.829	0.943
PL-EDAS	-	-	-	1.000	0.771	0.943	0.886
C-TOPSIS	-	-	-	-	1.000	0.829	0.943
C-VIKOR	-	-	-	-	-	1.000	0.943
Proposed method	-	-	-	-	-	-	1.000

5. Conclusions

The evaluation and selection of marine ranching sites has become a significant issue with the rapid develop of marine economy and great importance of marine ecology protection. This study introduces the cloud model to extend multi-attribute decision-making methods in order to help relevant planning authorities and enterprises determine the optimal sites for marine ranching construction.

To handle this issue, an integrated CRITIC-EDAS method based on the cloud model is developed. Firstly, the cloud model-based CRITIC method is formulated to determine the objective importance of the evaluation attributes for marine ranching site selection. Secondly, the cloud model-based EDAS is proposed to evaluate the alternatives and reveal the optimal marine ranching site. Thirdly, the proposed method is employed to solve a real-world practice of marine ranching site selection in the city of Yantai and it considers the fuzziness and randomness of data. Finally, the cloud model-based CRITIC-DEAS is compared with traditional decision-making methods to demonstrate the efficiency, reliability and superiority of the proposed model. The comparison analysis shows that the underlying principle behind the proposed model is acceptable to the managers and decision makers, as it is more suitable to reflect the characteristics of fuzziness and randomness of experts' preferences in the real-world marine ranching site selection process.

There are numerous advantages of this study. First, the cloud model is introduced to describe the fuzziness and randomness of the evaluation information in marine ranching site selection problems, and it proposes a novel manner in dealing with real-world decision-making problems by considering the uncertainty and probability simultaneously. Second, a novel multi-attribute decision-making approach named cloud model-based CRITIC-EDAS is developed, which is the first attempt to integrate CRITIC and EDAS with a cloud model to obtain the relative importance of attributes and the rank of alternatives from the perspective of probability. Thirdly, a real-world marine ranching site selection problem in the city of Yantai is solved by using the proposed model, where the efficiency and reliability are verified according to the comparison with other traditional MAMD methods.

However, there also inevitably exist some limitations of the proposed model. The model only considers the decision-making problems with linguistic terms, and various well-known MADM methods can also be extended with the cloud model. In future research, the study should be extended in several directions: (1) the transformation from many linguistic terms such as probabilistic linguistic terms, multi-granularity linguistic terms and probabilistic uncertain linguistic terms to clouds should be explored to expand the range of applications in real-world decision-making problems; (2) many traditional MADM methods, such as CCSD, ITARA, TODIM and CORPAS should be extended by using the cloud model to demonstrate the randomness of data and obtain more scientific results; (3) a theoretical extension of the cloud model should be taken into account in future studies by considering some classical probability and statistics theories, such as other distribution functions and Bayesian methods [52]. Referring to the application of the proposed model, it is potentially applicable to solve real-word multi-attribute decision-making problems in other research areas such as evaluation of sustainable transportation, renewable energy source selection, green supplier selection, evaluation of medical centers and so on. Another idea is to determine the clouds by using a backward cloud generator mentioned in Ref. [15], where the clouds can be generated directly from big data in real-world problems. For example, after collecting a massive amount of data with fuzziness and randomness during hydrologic monitoring, meteorological monitoring, equipment health monitoring, etc., clouds can be determined and processed by the proposed model to help governments or enterprises making valuable decisions for commercial value.

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