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GIS-MCDM-Based Approach to Site Selection of Wave Power Plants for Islands in China

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Abstract: On-site development of wave energy resources is a promising way to overcome power-shortage problems on islands. It is necessary to select suitable islands to deploy wave power plants, which are influenced by multiple factors related to resources, technology, economy, society, and environment. This study develops a two-stage decision framework to identify feasible islands and determine priority order based on geographic information systems (GIS) and multicriteria decision-making (MCDM). In the exclusion stage, unfeasible marine areas are excluded based on exclusion criteria and feasible island alternatives are identified. In the evaluation stage, alternatives are evaluated by evaluation criteria using the combined weighting method and the technique for order of preference by similarity to ideal solution (TOPSIS)-grey relation analysis (GRA) method. As the combined weighting method is based on the fuzzy group decision-making (GDM)-analytic hierarchy process (AHP) and the entropy method, it can effectively reduce subjective deviation. The proposed framework is applied in Shandong Province. It identifies 13 inhabited islands feasible for constructing wave power plants, among which Daguan, South Changshan, and Xiaoguan are the optimal ones. Sensitivity analysis is performed to verify the feasibility of the proposed framework. The results show that it is effective and could provide reference for practical engineering.

Keywords: site selection; GIS; MCDM; wave power plants; island alternatives

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1. Introduction

Against the background of rising environmental concerns and the depletion of fossil energy reserves, renewable energy resources are expected to be an important part of the world's future energy supply [1–3]. Marine energy, as a type of renewable energy with wide distribution, abundant reserves, and broad development prospects, has received considerable attention in many coastal countries around the world [4,5]. Wave energy is one of the major forms of marine energy, with strong predictability, high stability, and significantly higher density than other marine-energy sources [6,7]. Research has shown that the world's available wave energy could reach 2 billion kW, equivalent to twice the current total power generation [8]. At present, the harnessing and exploitation of wave energy in China is still in the research and development stage. To promote wave energy development, there has been an urgent push for research on selecting satisfactory wave power plant sites. Appropriate site selection is the prerequisite for wave energy industrialization, and it directly affects electricity-generation capacity and future socioeconomic benefits [9,10].

At present, the harnessing and exploitation of wave energy is often applied on islands that are far from the shore [11,12]. Because of the limitations of power-grid access, a large number of inhabited islands currently face power-shortage problems, which has placed great constraints on local economic development and population growth [13,14]. With island development becoming more and more important, the construction of reliable and affordable island power systems has become an urgent task [15,16]. The local development and utilization of wave energy resources around inhabited islands will be a promising path [17]. Considering the high construction costs of wave power plants, it is necessary to select feasible islands and determine their prioritization for the deployment of wave power plants.

Selecting a wave power plant site involves multiple factors related to resources, technology, economy, society, and environment; it is usually regarded as a complex multi-criteria decision-making (MCDM) problem. Applying MCDM to site-selection decision-making can support dealing with multiple, often conflicting criteria in a structured way, allowing different preferences to be considered. Another excellent tool, geographic information systems (GIS), can help decision-makers carry out the collection, storage, management, calculation, analysis, and visualization of geo-referenced data [18]. In previous studies of renewable-energy site selection, GIS has been frequently combined with MCDM to form decision-support tools to exclude unsuitable sites based on restrictions or to calculate site-suitability indexes based on the established criteria system [19–22].

Moreover, some scholars try to carry out research from multi-objective planning, and the most widely used method is data envelopment analysis (DEA) [23]. DEA is a methodology based on linear programming to measure the relative efficiency of homogenous decision-making units (DMUs) with multiple inputs and multiple outputs [24,25]. Wang et al. (2022) proposed a combined method based on DEA, Grey Analytic Hierarchy Process (G-AHP), and Grey Technique for Order Preference by Similarity to Ideal Solution (G-TOPSIS) for solar PV power plants site selection, in which DEA was used in the first phase to select high-efficiency locations based on various measurable criteria [26]. Pambudi et al. (2019) presented a hierarchical fuzzy data envelopment analysis model for identifying suitable locations for the construction of wind farms in the Indonesian archipelago [27]. However, in the evaluation process, DEA focuses on economic cost and power generation efficiency, and can only perform quantitative analysis [28,29]. On the other hand, each DMU obtains the weights from the most favorable aspect, and it will cause these weights to be different with different DMUs so that the characteristics of each DMU lack comparability, and the results obtained in this way may be not reliable.

In terms of energy sources, previous studies of site selection have mainly focused on solar, onshore wind, and offshore wind power; few, however, have investigated wave power. To the best knowledge of the authors, there has been no research on site selection for wave power plants for islands in the existing literature. This is likely because the harnessing and exploitation of solar and wind energy have entered the development stage in terms of industrialization and practical use, and wave energy is still in the research and development stage, or the early stage of industrialization. Therefore, research on site selection for wave energy is of great significance for making progress in the industrialization of renewable energy.

A few studies investigating wave power plant site selection have been conducted in various areas. Ghosh et al. (2016) employed analytic hierarchy process (AHP) to obtain evaluation criteria weights and then used an artificial neural network to determine a suitability index for wave-energy-conversion device site selection in the UK and Jamaica [30]. Abaei et al. (2017) developed a new site-selection decision method to estimate the expected utility of different sites for wave power plants in Tasmania; the approach was based on a Bayesian network model and could be extended to influence diagrams [31]. Vasileiou et al. (2017) used GIS and AHP to obtain evaluation criteria weights and employed weighted linear combination (WLC) to determine suitable areas for hybrid offshore wind and wave energy systems in Greece [32]. Gradden et al. (2016) proposed a GIS-based approach for the site selection of hybrid wind and wave energy platforms along the Atlantic-facing coasts of Europe [33]. Shao et al. (2020) employed GIS, AHP, and WLC methods to calculate a suitability index and drew a suitability map for constructing wave energy power stations in Qingdao, China [34]. Nobre et al. (2009) proposed a framework based on a combination of reclassification and weighting procedures in a GIS environment. In that framework, expert experience and WLC were applied to determine suitability for wave farm deployment in an area off the southwest coast of Portugal [35]. Flocard et al. (2016) determined criteria weights based on expert experience and obtained a suitability index for wave energy converter site selection using WLC [36].

The literature review reveals that a few studies have undertaken large-scale site selection for wave power plants based on a combination of GIS and MCDM methods. Those studies have primarily been limited to obtaining regional suitability indexes or classes for wave development. It appears, however, that no studies have considered small-scale site selection to determine the priority order of feasible site alternatives. Yet, large-scale and small-scale site selection are both essential components of research on site-selection decision-making. Moreover, in previous studies, criteria weighting and alternatives evaluation have been regarded as two core and troublesome stages that affect the decision results. Some researchers have done effective work on these two stages; nevertheless, certain problems remain to be solved, as outlined below.

(1) In published studies, AHP is the most common weighting method [37]. As a subjective weighting method, AHP relies on experts' subjective judgment to give a comparative matrix and determine criteria weights. However, the process has difficulty on avoiding subjective deviations caused by factors such as insufficient expert knowledge or experience, which affect the reliability of the weighting results.

To reduce subjective deviations and improve reliability, some researchers have attempted to improve traditional AHP by integrating it with other approaches. Integrating fuzzy theory with AHP can determine criteria weights by considering fuzzy linguistic variables from decision-makers. Sánchez-Lozano et al. expressed expert-group opinions using triangular fuzzy numbers (TFNs) and then used them in the AHP method [38]. Ayodele et al. proposed interval type-2 fuzzy AHP, which reduces uncertainty in decision-making processes [39,40]. A few researchers have combined subjective and objective weighting methods to determine criteria weights; this approach can not only consider subjective expert judgment but also reflect information in the data itself [41].

(2) Currently, the alternative evaluation methods in wave energy site selection research are mainly limited to WLC. WLC is a classical, simple, straightforward MCDM method. In recent years, it has been popularized and applied to many decision-making problems. However, it has also been criticized because its mathematical model is not sufficiently clear. Accordingly, many MCDM methods have been proposed and employed. Among them, TOPSIS (technique for order preference by similarity to an ideal solution), which has a clear mathematical model, is generally considered to be the most scientific and convenient one. Currently, this method has been used in several studies of solar energy site selection and wind energy site selection, but never been used in the field of wave energy site selection.

Sánchez-Lozano et al., used traditional TOPSIS to assess alternatives for solar power plants [42]. Several researchers used fuzzy TOPSIS to evaluate alternatives [43–47]. Fang et al. proposed an extended TOPSIS method to rank the order of photovoltaic power plant sites [43]. Sánchez-Lozano employed two different MCDM methods, TOPSIS and Elimination and Choice Expressing the Reality TRI (ELECTRE-TRI), to evaluate and classify suitable locations for solar farms; that study also examined the differences and similarities between the two methods [44].

Despite the popularity and application of TOPSIS, it still has some limitations and needs to be improved. In alternative evaluation, the classical TOPSIS method only considers the distances to the best and worst ideals while ignoring other dimensions.

This study develops a two-stage decision framework based on GIS and MCDM for wave power plant site selection for islands, and applies it in Shandong, China. The framework solves the aforementioned problems and its innovation lies in the following aspects:

(1) It includes both large-scale site selection and small-scale site selection. The first stage aims to exclude unfeasible marine areas and identity island alternatives for constructing wave power plants. The second stage aims to evaluate island alternatives to determine priority order.

(2) A combined weighting method is proposed to determine criteria weights, based on a combination of subjective and objective weighting methods. The subjective weighting method consists of fuzzy theory, AHP, and group decision-making (GDM). The objective weighting method employs the entropy method, which handles information from an objective standpoint. The proposed weighting method avoids subjective bias and improves the accuracy of the results; meanwhile, it overcomes the shortcomings of single subjective or objective weighting methods.

(3) An integrated TOPSIS-GRA (grey relation analysis) approach is proposed for alternative evaluation of wave power plant locations. In this approach, the distance used in the TOPSIS method is employed to represent the position similarity between alternatives. The grey relational grade used in GRA is mainly employed to describe the shape similarity between alternatives.

The rest of this paper is organized as follows. Section 2 establishes a criteria system for site selection, including exclusion and evaluation criteria. Section 3 presents the decision framework for site selection and introduces GIS, the combined weighting method, and TOPSIS-GRA. Section 4 presents a case study of Shandong Province to identify the suitable islands for the siting of wave power plants; sensitivity analysis is performed as well. Finally, the conclusions and outlook are presented in Section 5.

2. Criteria System

The site selection of wave power plants for islands is influenced by plenty of factors. After studying much research on site selection decision making and consulting experts, exclusion and evaluation criteria for wave power plant site selection are confirmed as follows; detailed data sources are provided in Section 4.1.

2.1. Exclusion Criteria

To exclude islands unsuitable for wave energy development, exclusion criteria are established based on the existing literature, the actual situation of the islands, and expert opinions. These criteria take technical, economic, social, and environmental factors into consideration.

2.1.1. Marine Ecological Red Line

To maintain marine ecological health and security, China has designated important marine ecological function areas as key control areas; these are called “marine ecological red line” (MERL). All development activities that might affect ecosystems are prohibited or restricted in MERL areas [48]. Considering these restrictions and environmental factors, areas covered by MERL are excluded for wave energy development.

2.1.2. Wave Power Density

Wave power density (WPD) is an important technical criterion for evaluating wave energy resources considering both wave height and wave period. As an exclusion criterion, the lowest WPD value should meet the technical feasibility requirements of wave-energy-generation devices.

2.1.3. Water Depth

For economic and technical reasons, water depth (WD) imposes many space restrictions on wave power plants site selection. The type and installation method of wave energy generation devices and cost-related issues (e.g., wiring, operating, and maintenance costs) are all affected by WD [49,50].

2.2. Evaluation Criteria

To determine the preference order of islands, 14 evaluation criteria related to resource, natural, economic, social and environmental factors are identified to evaluate island alternatives. Table 1 presents the classifications of evaluation criteria.

Table 1. Evaluation criteria.

First-Level Criteria	Second-Level Criteria	Benefit/Cost	Qualitative/Quantitative
Resource criteria	Wave power density (WPD) (kW/m)	B	Quantitative
	Wave height (WH) (m)	B	Quantitative
Natural criteria	Seabed geology (SG)	B	Qualitative
	Water depth (WD) (m)	C	Quantitative
	Coastal erosion (CE)	C	Qualitative
	Geological disaster (GD)	C	Qualitative
Economic criteria	Distance from the shore (DS) (m)	C	Quantitative
	Distance from the port (DP) (m)	C	Quantitative
	Population served (PS)	B	Quantitative
Social/environmental criteria	Fishing potential (FP)	C	Qualitative
	Tourism potential (TP)	C	Qualitative
	Shipping density (SD)	C	Qualitative
	Policy encouragement (PE)	B	Qualitative
	Electricity demand (ED)	B	Qualitative

2.2.1. Resource Criteria

Resource conditions are critical for the economic viability and technical feasibility of wave power plants. WPD and wave height are both benefit criteria, and they are important resource criteria for wave energy resource evaluation [32–36]. These two criteria are used to describe how much wave energy is available for wave-energy generation at a site. The greater the WPD and wave height, the more suitable it is for wave energy development.

2.2.2. Natural Criteria

Natural criteria affect the construction and operation of wave power plants for islands, including WD, seabed geology, coastal erosion, and geological disaster. Seabed geology is a benefit criterion, while WD, coastal erosion, and geological disaster are cost criteria. WD limits the type and placement of wave energy generation devices. Installing wave energy generation devices in areas with a large WD will increase foundation costs and technical difficulties [30,32,33]. Seabed geology affects the installation of energy generation devices and submarine cables [49,51,52]. It is very valuable for selecting a suitable seabed geology for installing wave energy generation devices. After that, a developer can determine the appropriate slope, installation location, and connection route to the coast for installation. Coastal erosion indicates the soil erosion of a near-shore beach zone [30,52,53]. Installing wave energy generation devices around areas with severe coastal erosion will increase the difficulty of construction and reduce the stability of power generation. Geological disaster refers to the frequency of geological disasters around the island; areas with a high frequency of geological disaster are not suitable for constructing wave-energy power plants [52].

2.2.3. Economic Criteria

Economic criteria affect the construction and operation costs of wave power plants. They include distance from the shore, distance from the port, and population served. Distance from the shore and distance from the port are cost criteria, and population served is a benefit criterion. Distance from the shore is related to operation and maintenance costs; being far from the shore increases the cost of maintaining wave energy generation devices [32–34]. Distance from the port affects construction and installation costs; areas close to ports are better for constructing wave power plants because the related costs will be comparatively low [32,33,35,36]. Population served refers to the population of the island served by the wave power plant [32]. It reflects the number of potential energy consumers; the larger the population served, the more urgent the power demand of the island.

2.2.4. Social/Environmental Criteria

Wave power plants may affect social benefits and environmental conditions around islands. Social/environmental criteria include fishing potential, tourism potential, shipping density, policy encouragement, and electricity demand. Fishing potential, tourism potential, and shipping density are cost criteria; policy encouragement and electricity demand are benefit criteria. Areas with high fishing potential and tourism potential are less suitable for wave energy development. Constructing wave power plants in areas with good fishing potential will affect the normal economic activities of island residents [36,54] Meanwhile, wave-energy-generation devices also cause visual and noise disturbances for tourists, which will affect the economic benefits of local tourism [30,55,56]. The deployment of wave-energy-generation devices should not disturb primary shipping routes since the probability of collision with the devices will increase [30,32,33,36]. Policy encouragement is important for achieving a successful, long-lasting wave power plant since a reliable institutional policy framework can promote constructing wave power plants [47,57,58]. The island population, infrastructure construction, distance from the shore, and current energy supply situation determine the island's power demand [59–61]. The greater the demand for power, the more urgent the need for construction.

After quantifying the above qualitative criteria through reclassification, vector normalization (VN) is further employed to normalize all criteria values. The purpose of normalization is to eliminate differences between attributes in dimensionality and order of magnitude. Normalization can affect the decision result by affecting the diversity of attribute data (DAD) [62]. VN does not change DAD and is considered to be the best normalization method for TOPSIS. The formula for VN is

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}, (i = 1, \dots, m, j = 1, \dots, n). \tag{1}$$

where x_{ij} represents the attribute value of ith alternative against jth criterion, x_{ij}^{*} represents the normalized attribute value, m represents the number of alternatives, and n represents the number of criteria.

3. Methodology

3.1. Decision Framework for Site Selection

The decision-making process for site selection consists of two stages: exclusion stage and evaluation stage. Figure 1 shows the decision-making framework.

Stage 1: Exclusion stage

This stage aims to exclude unfeasible marine areas and identify feasible islands through exclusion criteria sets. GIS is introduced in this stage to handle spatial data. In this study, GIS datasets for MERL, WPD, WD are established, each dataset can generate a thematic map. By superimposing these maps, unfeasible marine areas and feasible island alternatives are identified.

Stage 2: Evaluation stage

To rank island alternatives, MCDM methods are employed in this stage. After identifying feasible islands in the study area, the island alternatives are evaluated based on 14 evaluation criteria using the combined weighting method and TOPSIS-GRA. Criteria weights are obtained by the combined weighting method, including fuzzy GDM-AHP and entropy method. After obtaining the criteria weights, TOPSIS-GRA is used to rank the islands.

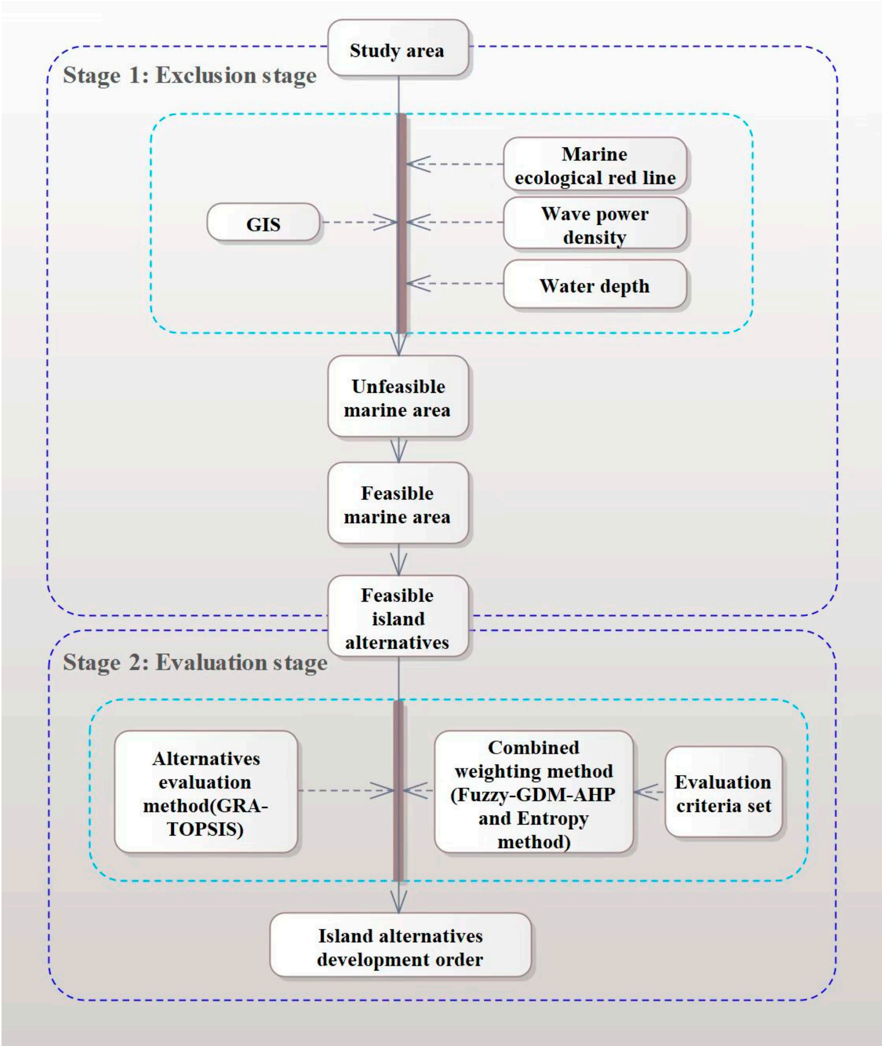

Figure 1. Decision-making framework for site selection.

3.2. GIS

GIS is an information system used to deal with data, maps, and spatial information [63]. GIS tools can support planning and decision making in site-selection problems [64–67]. In this study, GIS is used to exclude unfeasible marine areas by three exclusion criteria related to economic, technical, and social constraints. Inverse distance weighted (IDW) interpolation and Euclidean distance in GIS are used to obtain 100 m $\times$ 100 m raster datasets of WPD, WD. After obtaining the raster data of the exclusion criteria, the Boolean overlay operation is employed in the overlay analysis in GIS to exclude unfeasible areas. After that, islands feasible for constructing wave power plants are identified for subsequent study.

3.3. Combined Weighting Method

In total, 4 first-level criteria and 14 s-level criteria are set for site selection. Fuzzy GDM-AHP is used for the determination of first-level criteria weights. The entropy method is utilized to determine second-level criteria weights.

3.3.1. Fuzzy GDM-AHP

AHP is a well-known MCDM method invented by Saaty as a decision-making tool; it is widely used for its simple calculation process and straightforward theory [68]. Traditional AHP has some shortcomings, such as subjective deviations, insufficient reliability, and an inability to reflect human thinking processes. To overcome these shortcomings, fuzzy set theory and GDM theory are introduced into AHP to determine the first-level criteria weights.

Fuzzy set theory was introduced by Zadeh to deal with vague, imprecise, and uncertain problems [69]. Fuzzy decision-making is a rational decision-making method that considers human subjectivity. In a fuzzy environment, linguistic variables are transformed into TFNs, which take the ambiguity and uncertainty of expert judgment into account [70]. By integrating TFNs into AHP, decision-making processes can be described more accurately.

Expert judgment is the most important part of the AHP method. To reduce the bias of individual expert evaluation and make the evaluation results more objective, GDM theory is introduced into the calculation of evaluation criteria weights [71]. By selecting experts from different fields and empowering them according to their importance, the advantages of expert judgment can be maximized, and the accuracy and reliability of results can be improved [72].

The process of calculating evaluation criteria weights through fuzzy GDM-AHP is as follows [73]:

(1) Establish a fuzzy pairwise comparison matrix:

Let $F = [c_{kv}]_{n \times n}$ be the matrix for n criteria against the goal. c_{kv} is a fuzzy set representing the relative importance of criterion k over v. Then, assume $c_{kv} = \frac{1}{c_{vk}}$.

Figure 2 shows the possible assessment values of c_{kv} in the pairwise comparison matrix, represented as TFNs [74].

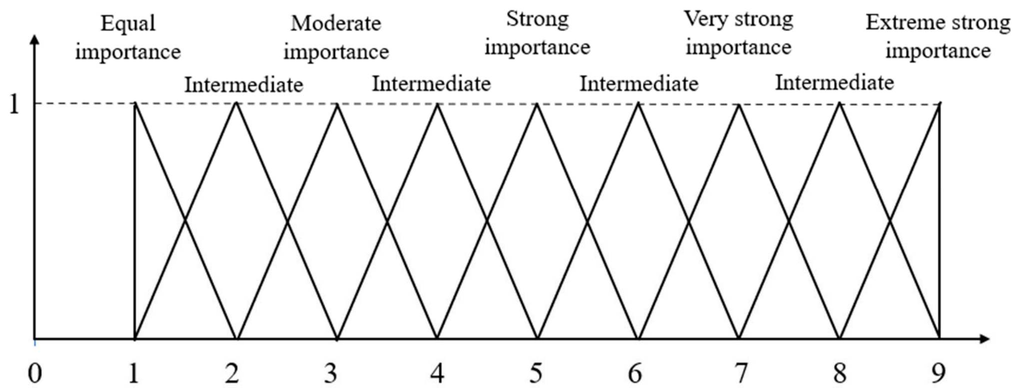

Figure 2. Degree of influence and corresponding TFNs for expert assessment.

(2) Synthesize judgements using GDM:

There are t experts forming an expert set $E = \{E_1, E_2, \cdots, E_t\}$; the weights of experts are $\{e_1, e_2, \cdots, e_t\}$. Let $c_{kv}^{(t)} = \left(l_{kv}^{(t)}, m_{kv}^{(t)}, u_{kv}^{(t)}\right)$ be a TFN representing the relative importance of c_k over c_v judged by DM_t. After GDM, let $c_{kv} = (l_{kv}, m_{kv}, u_{kv})$ be the aggregated relative importance of c_k over c_v judged by all experts. c_{kv} can be calculated as follows:

$$l_{kv} = l_{kv}^{(1)e_1} l_{kv}^{(2)e_2} \cdots l_{kv}^{(t)e_t}; \tag{2}$$

$$m_{kv} = m_{kv}^{(1)e_1} m_{kv}^{(2)e_2} \cdots m_{kv}^{(t)e_t}; \tag{3}$$

$$u_{kv} = u_{kv}^{(1)e_1} u_{kv}^{(2)e_2} \cdots u_{kv}^{(t)e_t}. \tag{4}$$

(3) Calculate the fuzzy weights of the criteria:

The geometric normalized average method can be used to calculate the fuzzy weights of criteria. Where the values are fuzzy, not crisp, the weight vector will be achieved through the following formula:

$$(w_{lk}, w_{mk}, w_{uk}) = \frac{\left(\prod_{v=1}^{n}(l_{kv}, m_{kv}, u_{kv})\right)^{1/n}}{\sum_{k=1}^{n}\left(\prod_{v=1}^{n}(l_{kv}, m_{kv}, u_{kv})\right)^{1/n}}, \tag{5}$$

where (w_{lk}, w_{mk}, w_{uk}) is the fuzzy weight of the k-th criterion.

(4) Defuzzify the fuzzy weights:

Fuzzy sets are difficult to compare directly because they are partially ordered rather than linear or strictly ordered crisp values. So, we defuzzify the obtained weights to calculate the crisp value of each criterion weight as follows:

$$w_{FCk} = \frac{w_{lk} + 4w_{mk} + w_{uk}}{6}. \tag{6}$$

where w_{FCk} is the crisp weight of the k-th first-level criterion.

3.3.2. Entropy Method

The entropy method is used to calculate criteria weights according to the size and difference degree of the value of the sample data [75,76]. The larger the entropy, the smaller the influence of the evaluation criterion on decision-making; that is, the weight of the criterion is smaller. The process for calculating the weight of the evaluation criteria by the entropy method is as follows:

(1) Normalize the decision matrix:

Different criteria can be of different scales. A given decision matrix should first be transformed into a dimensionless space via

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n), \tag{7}$$

where p_{ij} is the probability of the j-th criteria in the i-th alternative.

(2) Calculate the entropy of the j-th criteria:

$$E_j = -\mathrm{K} \sum_{i=1}^{m} p_{ij} \ln p_{ij}, \tag{8}$$

$$\mathrm{K} = \frac{1}{\ln m}, \tag{9}$$

where E_j is the entropy of the j-th criteria, and K is the coefficient.

(3) Calculation of objective weights:

$$w_{SCj} = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)}. \tag{10}$$

where w_{SCj} is the weight of the j-th second-level criterion.

3.3.3. Combined Algorithm

To obtain the criteria weights for site selection, a combined weighting algorithm is proposed, which is to solve the weights of the first- and second-level criteria respectively. The first-level criteria weights are calculated by fuzzy GDM-AHP, the second-level criteria weights are calculated by the entropy method, and the combined weight is calculated by the following:

$$w^{*}_{Cj} = w_{FCk} \cdot w_{SCj(k)}. \tag{11}$$

where w^*_{Cj} is the combined weight of the j-th criterion, w_{FCk} is the weight of the k-th first-level criterion, and $w_{SCj(k)}$ is the weight of the j-th second-level criterion under the k-th first-level criterion.

3.4. TOPSIS-GRA

This study proposes a novel hybrid method integrating TOPSIS and GRA to obtain the optimal site for a wave power plant.

TOPSIS method, first developed by Hwang and Yoon [77], is commonly used for addressing the rank issue. The basic idea of TOPSIS is that the best decision is the one that is closest to the ideal situation and farthest from the non-ideal situation. Although TOPSIS is widely used in many fields, it has some shortcomings. TOPSIS introduces two reference points and ranks alternatives by comparing the distances from alternatives to these points. It can express the position similarity between alternatives, but it does not consider the shape similarity between the alternatives. The GRA method was originally developed by Deng and is suitable for making decisions in multiple-attribute situations [78]. The limitation of TOPSIS can be overcome by the grey relation coefficient of the GRA model [79,80]. The combination of TOPSIS and GRA measures the relations among alternatives based on the degree of similarity or difference in both the position and shape of the alternatives.

The process for TOPSIS-GRA is as follows:

(1) Calculate the weighted normalized decision matrix:

$$v_{ij} = w^*_{Cj} \cdot x^*_{ij} (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n), \tag{12}$$

$$V = (v_{ij})_{m\times n} = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix}, \tag{13}$$

where v_{ij} denotes the weighted normalized criterion value of the j-th criterion in the i-th alternative.

(2) Determine the positive ideal solutions (A^+) and negative ideal solutions (A^-):

$$A^+ = \{v_1^+, \dots, v_n^+\} = \left\{ \left(\max_i v_{ij}, j \in J \right) \left(\min_i v_{ij}, j \in J' \right) \right\}, \ (i = 1, \dots, m), \tag{14}$$

$$A^- = \{v_1^-, \dots, v_n^-\} = \left\{ \left(\min_i v_{ij}, j \in J \right) \left(\max_i v_{ij}, j \in J' \right) \right\}, \ \left(i = 1, \dots, m\right), \tag{15}$$

where J and J' refer to the benefit criteria set and cost criteria set, respectively.

(3) Calculate the Euclidean distance d_i^+ and d_i^- of each alternative from positive ideal solutions (PIS) and negative ideal solutions (NIS):

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2}, \ (i = 1, \dots, m), \tag{16}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2}, \ (i = 1, \dots, m), \tag{17}$$

where d_i^+ is the distance from alternative i to PIS, and d_i^- is the distance from alternative i to NIS.

(4) Calculate the grey relational coefficients:

Based on the weighted normalized decision matrix, the grey relational coefficient between the i-th alternative and the PIS with respect to the j-th criterion is calculated as follows:

$$r_{ij}^{+} = \frac{\underset{i}{min}\underset{j}{min}\left|v_{ij} - v_j^{+}\right| + \rho\underset{i}{max}\underset{j}{max}\left|v_{ij} - v_j^{+}\right|}{\left|v_{ij} - v_j^{+}\right| + \rho\underset{i}{max}\underset{j}{max}\left|v_{ij} - v_j^{+}\right|}, \tag{18}$$

$$R^{+} = \left[r_{ij}^{+}\right]_{m\times n}, \tag{19}$$

where ρ is the distinguishing coefficient, and R^{+} is the grey relational coefficient matrix with PIS. In this study, the distinguishing coefficient is set as 0.5.

Similarly, the grey relational coefficient between the i-th alternative and the NIS with respect to the j-th criterion can be obtained as follows:

$$r_{ij}^{-} = \frac{\underset{i}{min}\underset{j}{min}\left|v_{ij} - v_j^{-}\right| + \rho\underset{i}{max}\underset{j}{max}\left|v_{ij} - v_j^{-}\right|}{\left|v_{ij} - v_j^{-}\right| + \rho\underset{i}{max}\underset{j}{max}\left|v_{ij} - v_j^{-}\right|}, \tag{20}$$

$$R^{-} = \left[r_{ij}^{-}\right]_{m\times n}, \tag{21}$$

where R^{-} is the grey relational coefficient matrix with NIS.

(5) Calculate the grey relational grade:

The grey relational grade is used for the overall evaluation of alternatives depending on all criteria. It is defined as the average value of relational coefficients at different criteria. For the i-th alternative, the grey relational grades from PIS and NIS are given as follows:

$$g_i^{+} = \frac{1}{n}\sum\nolimits_{j=1}^{n} r_{ij}^{+}; \tag{22}$$

$$g_i^{-} = \frac{1}{n}\sum\nolimits_{j=1}^{n} r_{ij}^{-}. \tag{23}$$

(6) Calculate a new relational grade:

Normalize the Euclidean distances and grey relational grades obtained from Equations (5) and (7), as follows:

$$D_i^{+} = \frac{d_i^{+}}{maxd_i^{+}},\ D_i^{-} = \frac{d_i^{-}}{maxd_i^{-}},\ G_i^{+} = \frac{g_i^{+}}{maxg_i^{+}},\ G_i^{-} = \frac{g_i^{-}}{maxg_i^{-}}; \tag{24}$$

$$S_i^{+} = \alpha D_i^{-} + \beta G_i^{+}; \tag{25}$$

$$S_i^{-} = \alpha D_i^{+} + \beta G_i^{-}. \tag{26}$$

Among them, the larger the values of D_i^{-} and G_i^{+}, the closer the alternative is to the positive ideal solution in position and shape. The larger the values of D_i^{+} and G_i^{-}, the closer the alternative is to the negative ideal solution in position and shape. In the above formulas, α and β are the weights of position and shape, respectively, in the calculation of the similarity degree of the alternative and ideal solutions, reflecting the decision-maker's preference for position and shape factors. In this study, α and β are both set as 0.5.

The new relational grade is as follows:

$$Z_i = \frac{S_i^{+}}{S_i^{+} + S_i^{-}}. \tag{27}$$

(7) Rank alternatives according to the values of Z_i:

The order of alternatives is ranked according to the value of relative closeness to each of the alternatives. A greater value of Z_i indicates a higher priority in the alternatives.

4. Case Study

4.1. Study Area

In the "Marine Renewable Energy Development Plan" in China, Shandong Province is positioned as a key area for marine renewable energy development [51,58,81]. It borders the Bohai Sea and the Yellow Sea, with a coastline of approximately 3345.41 km, rich in wave energy resources. It has a developed marine economy, and there is a huge demand for energy due to busy marine activities along the coast. At the same time, Shandong Province has gathered many powerful marine science research institutes and related enterprises in China, which is an important condition for the development and utilization of wave energy [82].

Shandong Province has jurisdiction over 589 islands, among which 32 are inhabited. Given the distance from the mainland, the economic activities of the inhabited islands are severely restricted by power dilemmas [83]. In addition, traditional power-generation modes are costly and cause serious pollution. Clean wave energy can be easily obtained around islands, which will not cause pollution and can greatly alleviate the power-shortage problems in the islands [84].

This study investigated site selection for wave power plants for the inhabited islands of Shandong Province. Based on locations and development conditions, the latitude and longitude of the study area (Figure 3) are selected from 34°24′ N to 38°58′ N and 117°34′ E to 123°37′ E. Considering the requirements for the accuracy of the results, the evaluation units in the study area are divided into 100 m × 100 m grids. Table 2 shows the data description and source of each criterion.

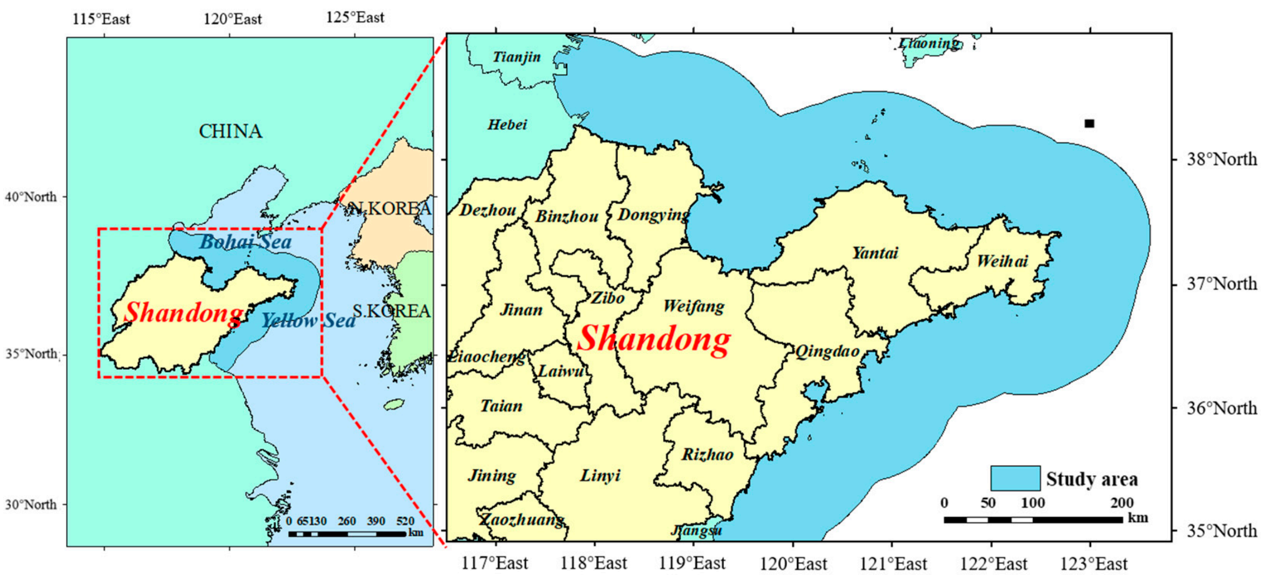

Figure 3. Study area.

Table 2. Data descriptions and sources of criteria.

Criterion	Data Description	Data Resource
Marine ecological red line	Vector data	Yellow Sea and Bohai Sea Marine Ecological Red Line Delineation Plan, released by Shandong Provincial People's Government
Wave power density	Average wave power density of Shandong Province in 39 years; 100 m ×100 m grid data (kW/m)	General Bathymetric Chart of the Oceans (GEBCO) and European Center for Medium Weather Forecast (ECMWF)
Wave height	Average wave height of Shandong Province in 39 years; 100 m ×100 m grid data (m)	General Bathymetric Chart of the Oceans (GEBCO) and European Center for Medium Weather Forecast (ECMWF)
Seabed geology	Score 1–9; the higher the score, the better the seabed geology	China Offshore Ocean Atlas (submarine topography and landforms)
Water depth	100 m ×100 m grid data (m)	General Bathymetric Chart of the Oceans (GEBCO)
Coastal erosion	Score 1–9; the higher the score, the greater the degree of coastal erosion	China Island History (Shandong Volume)
Geological disaster	Score 1–9; the higher the score, the greater the frequency of geological disaster	China Island History (Shandong Volume)
Distance from the shore	100 m × 100 m grid data (m)	Shortest Euclidean distance to the land coastline in ArcGIS
Distance from the port	(m)	Shortest Euclidean distance to the major ports (obtained from the Transportation Department of Shandong Province) in ArcGIS
Population served	Amount of island population	Statistical Yearbooks released by the government
Fishing potential	Score 1–9; the higher the score, the greater the fishing potential	Marine Ecological Environmental Protection Plan, released by the Ecological Environment Department of Shandong Province
Tourism potential	Score 1–9; the higher the score, the greater the tourism potential	Marine Ecological Environmental Protection Plan, released by the Ecological Environment Department of Shandong Province
Shipping density	Score 1–9; the higher the score, the higher the shipping density	Marine Ecological Environmental Protection Plan, released by the Ecological Environment Department of Shandong Province
Policy encouragement	Score 1–9; the higher the score, the greater the policy encouragement	Shandong Province Island Protection Plan, released by the Department of Oceans and Fisheries of Shandong Province
Electricity demand	Score 1–9; the higher the score, the greater the electricity demand	China Island History (Shandong Volume) and Statistical Yearbook released by the government

4.2. Exclusion of Unfeasible Areas

In this study, unfeasible marine areas are excluded by three exclusion criteria. The MERL of Shandong Province includes 10 types of areas: marine nature reserves; special marine protected areas; important estuarine ecosystems; important coastal wetlands; important fishery waters; special protected islands; natural landscape and historical and cultural heritage areas; important coastal tourist areas; important sandy shorelines; and sand source protected sea area [85,86]. All of these areas should be excluded. The Simulating Waves Nearshore (SWAN) model is used to simulate the wave field, and the 39-year average WPD distribution in the study area could be obtained by calculation [87,88]. WPD data are point feature data with an accuracy of $1' \times 1'$. Considering the existing wave-energy-generation devices and the data for Shandong Province, marine areas with a WPD lower than 1 kW/m are regarded as undeveloped sea areas [87]. WD data are point-feature data with an accuracy of 0.1° × 0.1°. Considering currently available technology and installation types, areas with a WD greater than 50 m are excluded. The exclusion range of each criterion is shown in Table 3.

Table 3. Exclusion range of each criterion.

Exclusion Criteria	Exclusion Range
Marine ecological red line	All
Wave power density	<1 kW/m
Water depth	>50 m

ArcGIS software is used for overlay analysis. The thematic map of unfeasible areas is obtained by superimposing the respective maps of these three criteria. Figure 4 shows a different thematic map for each exclusion criterion. Figure 5 shows the unfeasible and feasible marine areas determined by the combination of the three maps.

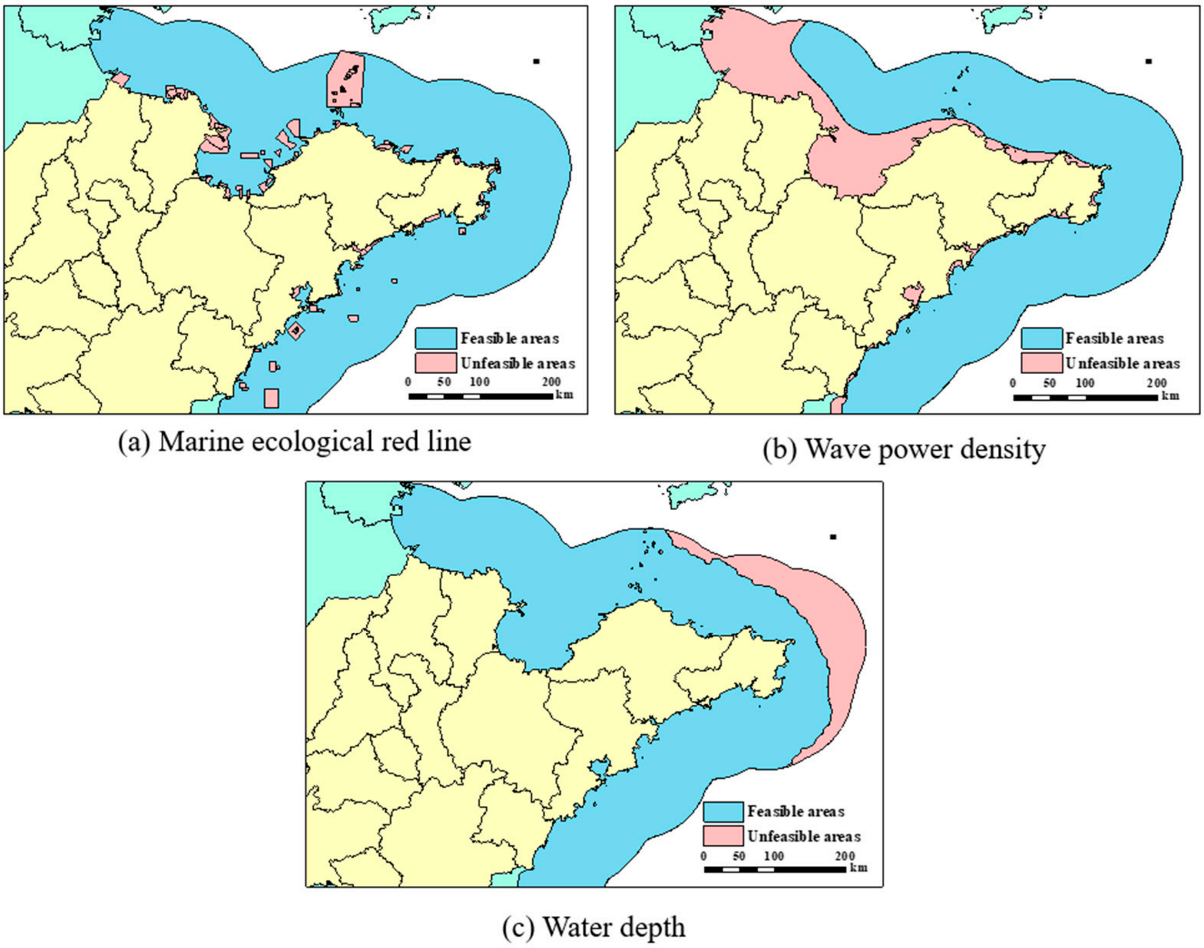

Figure 4. Unfeasible areas based on the three exclusion criteria.

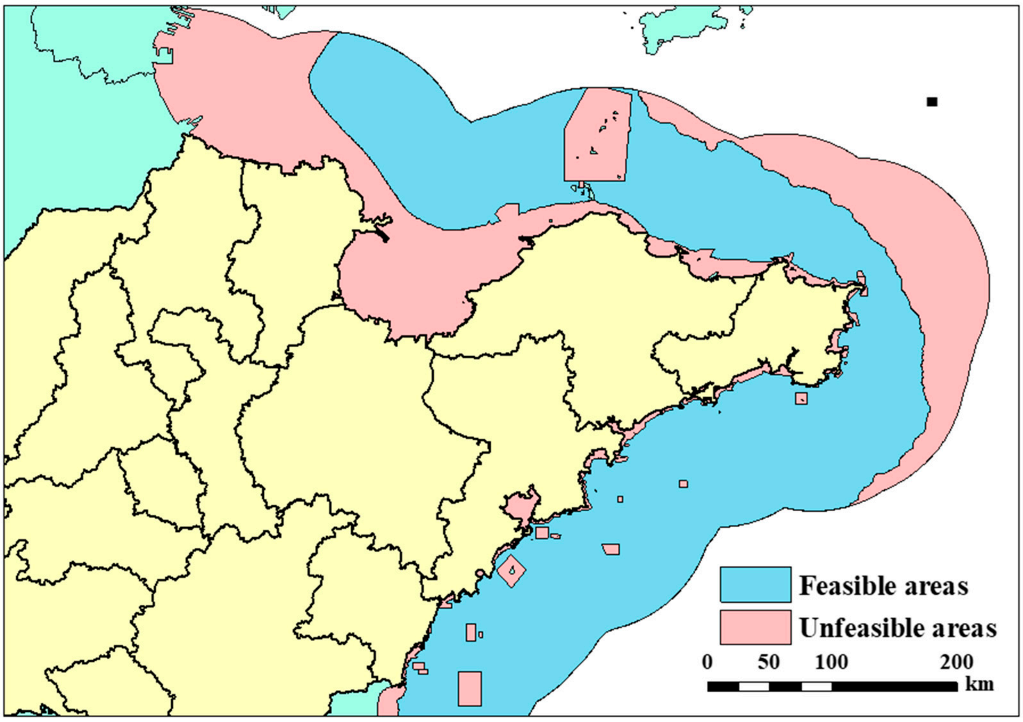

Figure 5. Unfeasible areas and feasible areas.

4.3. Feasible Islands Identification and Data Acquisition

After excluding the unfeasible parts of the study area, thirteen inhabited islands that can feasibly develop wave energy are identified: South Changshan, North Changshan, Temple, Daheishan, Xiaoheishan, Jiming, Nanhuang, East Little Qingdao, Zhucha, Muguan, Daguan, Xiaoguan, and Zhaitang, which constitute alternative set $A = \{A_1, A_2, \cdots A_{13}\}$. A_1, A_2, A_3, A_4, A_5 are located in the northern part of Yantai. A_6, A_7, A_8 belong to Weihai, and the other five islands are located in the east and south of Qingdao. Figure 6 shows the distribution of the thirteen island alternatives for constructing wave power plants.

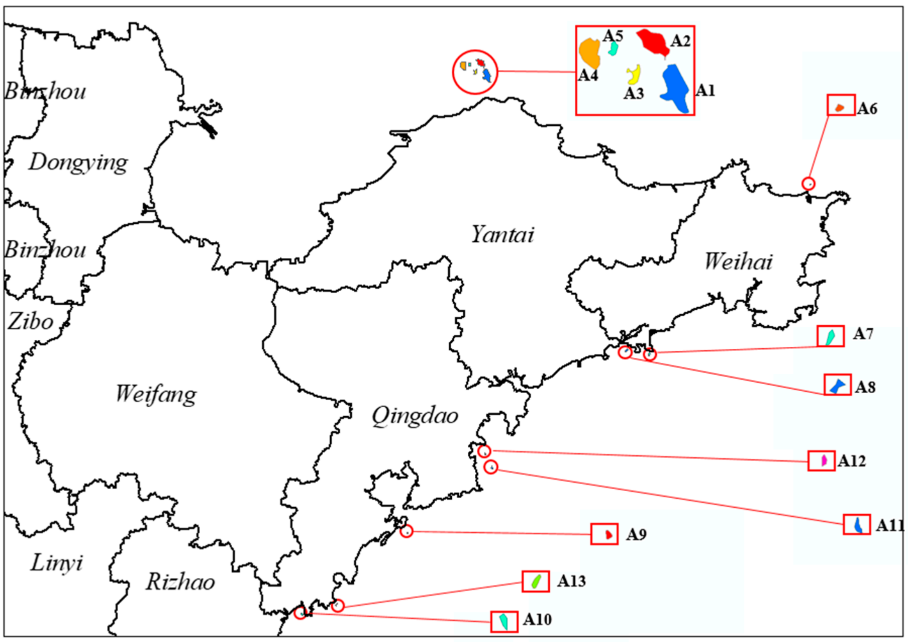

Figure 6. Thirteen island alternatives for constructing wave power plants.

Through data investigation, on-site observation, and numerical simulation, the at tribute values of the evaluation criteria of each alternative are obtained, as shown in Table 4.

Table 4. Attribute value matrix.

Alternatives	Island	WPD	WH	SG	WD	CE	GD	DS	DP	PS	FP	TP	SD	PE	ED
A_1	South Changshan	1.0402	0.7734	4	11.1637	5	6	5884.52	9428.9	24400	8	8	8	8	7
A_2	North Changshan	1.1703	0.8282	4	12.4547	5	7	6288.24	1839.7	3300	7	7	6	8	7
A_3	Temple	1.0698	0.7727	4	11.33	4	3	5637.07	1561.9	1700	8	7	7	6	6
A_4	Daheishan	1.1477	0.8261	3	12.1661	6	5	5440.56	2064.25	1500	7	7	6	6	6
A_5	Xiaoheishan	1.1491	0.8213	3	12.4229	7	3	5801.7	2144.13	270	7	7	6	8	5
A_6	Jiming	1.2674	0.8411	3	24.3263	4	3	3161.31	412.32	200	4	5	7	4	3
A_7	Nanhuang	1.3127	0.6818	6	6.9741	3	6	9395.83	98.77	520	6	4	5	4	2
A_8	East Little Qingdao	1.2463	0.5634	6	7.4281	3	6	10,623.75	211.82	300	5	4	4	4	3
A_9	Zhucha	1.7929	0.7446	5	18.0511	5	4	1979.26	400.12	560	4	4	2	7	4
A_{10}	Muguan	1.2549	0.5589	4	11.2361	5	3	3434.31	138.52	180	7	4	8	5	2
A_{11}	Daguan	2.2626	0.7583	4	11.1103	6	4	5200.64	975.35	120	3	5	5	7	3
A_{12}	Xiaoguan	2.0068	0.6483	4	5.8069	6	5	5179.35	936.13	100	3	6	5	7	2
A_{13}	Zhaitang	1.6374	0.7475	6	15.8693	4	3	5216.56	130.14	1100	4	4	4	8	4

4.4. Determination of Criteria Weights

The evaluation criteria weights are determined by the combined weighting method. First-level criteria weights can be solved based on the fuzzy GDM-AHP method. Second-level criteria weights are calculated based on the entropy method.

(1) Determination of first-level criteria weights

The first-level criteria weights are calculated by Equations (2)–(4). Matrices of pairwise comparisons are created based on five experts in the fields of economics, marine energy technology, and the social sciences, using a fuzzy scale from (1,1,1) to (8,9,9). Expert weights are specified as $(0.3,\ 0.3,\ 0.2,\ 0.1,\ 0.1)$. Appendix A shows the fuzzy pairwise comparison matrix generated by the five experts. Table 5 shows the fuzzy values of the first-level criteria weights. Through defuzzification and normalization, the weights calculated by Equation (6) are $(0.4896,\ 0.1779,\ 0.1286,\ 0.2038)$.

Table 5. Fuzzy values of the first-level criteria weights.

w_1	(0.2772, 0.4966, 0.8208)
w_2	(0.1102, 0.1740, 0.3148)
w_3	(0.0735, 0.1305, 0.2146)
w_4	(0.1217, 0.1990, 0.3663)

The calculation results show that resource criteria account for almost 50% of the weight. It means resource criteria are the most important and should be considered more in the site-selection process. Resource criteria have always been the most important criteria in decision making for renewable energy power plant site selection [23,25,28,29]. The weight of social/environmental criteria is the second largest at 20.38%, indicating that the external conditions of social/environmental criteria can restrict or promote site selection to a certain extent. The weights of natural criteria and economic criteria are 17.79% and 12.86%, respectively, indicating slightly less importance.

(2) Determination of second-level criteria weights

The second-level criteria weights are calculated by Equations (7)–(10). Figure 7 shows the calculation results. From the calculation results, it can be seen that the weight of WPD under resource criteria is much larger than that of WH, indicating that WPD has a greater impact on site selection. The weight of PS under economic criteria accounts for 70.69%, indicating its high importance among economic criteria.

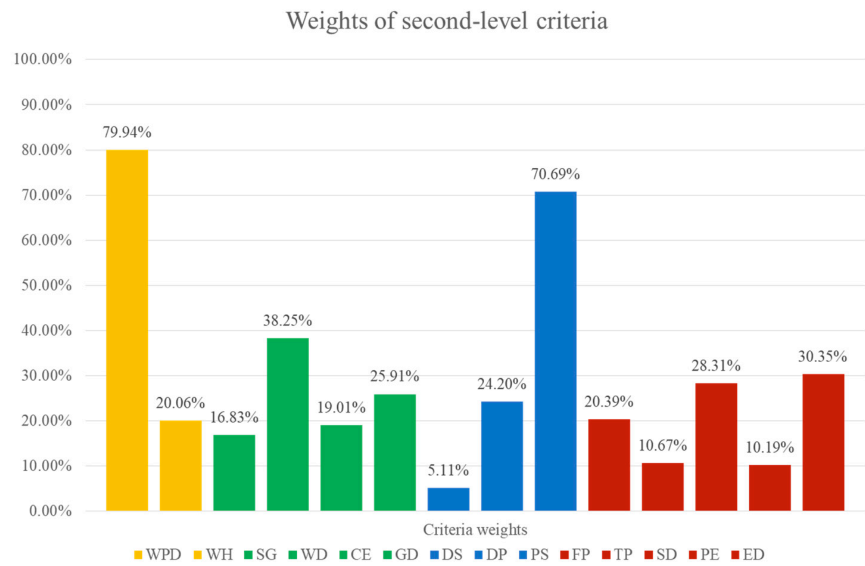

Figure 7. Weights of second-level criteria.

(3) Determination of combined criteria weights

Figure 8 shows the combined weights based on Equation (11). According to the calculation results, the weight of WPD is the largest at 39.14%. As a resource criterion, WPD plays a vital role in the process of site selection. The criteria weights of WD and population served are close to 10%, indicating that these two criteria also have a relatively large impact on site selection. At the same time, the weights of other criteria are relatively small, and the impact on overall decision making is relatively small, but their role in the process of site selection should not be ignored.

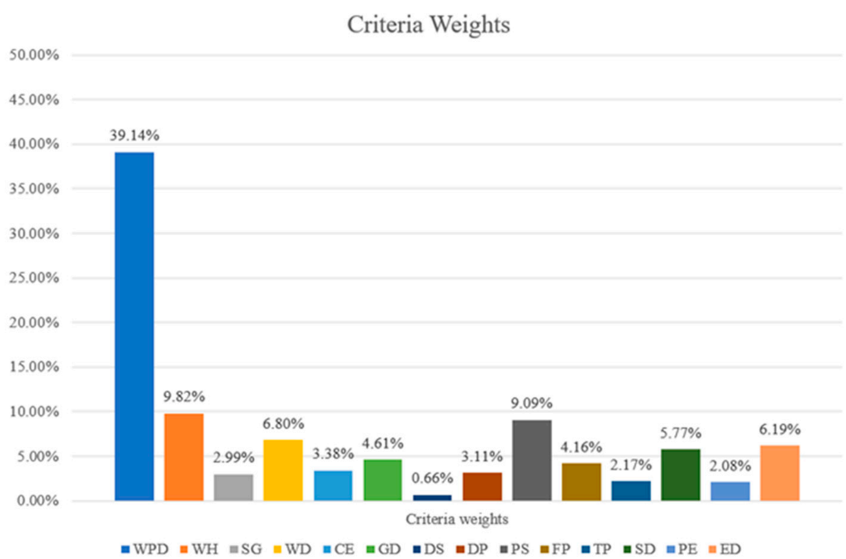

Figure 8. Criteria weights.

4.5. Evaluation of Feasible Islands

The 13 identified inhabited islands of Shandong Province are evaluated and ranked using TOPSIS-GRA to determine the precedence sequences for development. Table 6 shows the final results and rankings of the 13 islands, obtained on the basis of Section 3.4.

Based on the complete assessment results obtained by the proposed decision framework, the top five optimal islands are Daguan, South Changshan, Xiaoguan, Zhucha, and

Zhaitang, respectively. Daguan is found to be the best site for establishing a wave power plant owing to its optimal wave energy conditions and good other features. The National Ocean Technology Center established a hybrid solar–wind–wave independent power system on Daguan in 2010 [89]. To some extent, this also shows that the resources and social environmental conditions of Daguan are suitable for wave energy development.

Table 6. Ranking of site alternatives.

Rank	d_i^+	d_i^-	r_i^+	r_i^-	Z_i	Alternatives	Island
1	0.7638	1.0000	1.0000	0.9409	0.5399	A11	Daguan
2	0.7596	1.0000	1.0000	0.9779	0.5351	A1	South Changshan
3	0.7866	0.8272	0.9727	0.9560	0.5081	A12	Xiaoguan
4	0.7809	0.6613	0.9820	0.8871	0.4963	A9	Zhucha
5	0.8273	0.5627	0.9852	0.9256	0.4689	A13	Zhaitang
6	0.9291	0.4041	0.9554	0.9696	0.4173	A7	Nanhuang
7	0.9278	0.3442	0.9495	0.9247	0.4112	A2	North Changshan
8	0.9859	0.3803	0.9553	0.9738	0.4053	A8	East Little Qingdao
9	0.9688	0.3311	0.9313	0.9982	0.3909	A10	Muguan
10	0.9989	0.3096	0.9409	0.9780	0.3875	A3	Temple
11	0.9729	0.2994	0.9387	0.9940	0.3863	A4	Daheishan
12	0.9732	0.2990	0.9373	0.9921	0.3861	A6	Jiming
13	1.0000	0.2905	0.9401	1.0000	0.3809	A5	Xiaoheishan

South Changshan ranks second. It has the largest population served and the best social and environmental conditions. Given the large number of residents, the island is in urgent need of developing wave power plants to alleviate power pressures. Xiaoguan has the second-largest WPD and the smallest WD, leading it to the third place. Ranking fourth, Zhucha has the smallest distance to ports, and it performs relatively well for WPD and wave height. Finally, Zhaitang ranks fifth, performing best for distance to the shore and performing relatively well for WPD and population served.

4.6. Sensitivity Analysis

In decision making, various uncertain issues affect decision accuracy, such as the different risk attitudes of DMs, different weights of evaluation criteria, and different MCDM methods for the final ranking. Hence, it is necessary to test the sensitivity of the ranking results.

4.6.1. Varying Expert Weights

A sensitivity analysis based on equal expert weights is performed, as shown in Figure 9. The results obtained from equal expert weights are very similar to the original results. It is worth noting that the top nine islands remain unchanged, and only two islands have changed in development order. Therefore, the ranking results remain stable for variable expert weights.

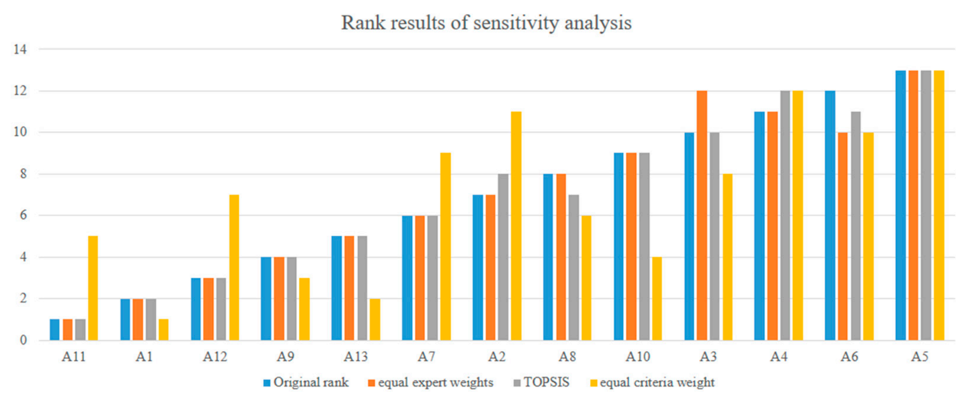

Figure 9. Ranking results of the sensitivity analysis.

4.6.2. Varying Criteria Weights

Because the criteria weights affect the final results, equal criteria weights are set to test its impact on the decision results. Figure 9 shows the final rankings. With the adjustment of the criteria weights, the ranking results change accordingly. The rankings of all alternatives fluctuate within five ranks. A1 performed best in population served; when the criteria weights are equal, it ranks first. A11, A1, A9, and A13 still perform fairly well, ranking among the top five. A5 is still last with equal criteria weights. When criteria weights are equal, the order of islands will inevitably change since resource conditions are the decisive criteria for site selection. A significant reduction in resource condition criteria will inevitably change the ranking results, reflecting the characteristics of sensitivity. Therefore, when the importance of criteria is quite different, it is necessary to find a suitable algorithm to solve the criteria weights.

4.6.3. Varying the Ranking Method

Different MCDM methods have different calculation principles, and the obtained ranking results might also be different. TOPSIS is used to rank islands to test the universality of the results. Figure 9 shows that the ranking of islands is generally stable, and the top six optimal islands remain unchanged. The results under TOPSIS change only four alternatives; A2, A8, A4, and A6 are changed in the development order. This comparative analysis demonstrates the practicability of the proposed model.

5. Conclusions

To address the problems of wave-power-plant site selection for islands in China, this study proposed a two-stage decision framework, including both large- and small-scale site selection, based on a combination of GIS, fuzzy GDM-AHP, entropy method and GRA-TOPSIS. This approach enabled us to identify feasible islands and determine priority order. The main contributions of this study were as follows:

- While the combined weighting method was used to obtain criteria weights, the subjective bias, which was the shortcoming of single subjective weighting method, was largely reduced. The loss of decision information was reduced by employing TFNs to represent the attitudes of experts; in addition, a combination of GDM theory and entropy method made decision making more reliable and reduced the ambiguity in actual problems.
- TOPSIS and GRA were combined to rank island alternatives, considering both position similarity and shape similarity between alternatives. As TOPSIS-GRA used the grey correlation degree, as well as distances from the alternatives to PIS and NIS, to construct a new relative closeness for ranking alternatives, the decision-making accuracy was improved.
- The proposed framework was applied in Shandong Province. A total of 13 feasible inhabited islands were identified for constructing wave power plants. The top five optimal islands were Daguan, South Changshan, Xiaoguan, Zhucha, and Zhaitang, in order. These results could provide a reference for decision-makers to build wave power plants. Sensitivity analysis was employed by varying the expert weights, criteria weights, and ranking methods. The results demonstrated that the proposed framework was effective and feasible.

The proposed methodology framework can be generally applied to other energy sources by changing the criteria system. Future research on wave power plants site selection can be conducted as follows: first, attribute values can be used in the fuzzy environment to improve the precision of the results. Second, while the fuzzy sets in this paper are TFNs, the trapezoidal fuzzy numbers, intuitionistic fuzzy sets and interval hesitant fuzzy sets can be used in subsequent research to improve the flexibility of fuzzy sets in dealing with fuzzy and uncertain problems.

Author Contributions: Conceptualization, M.S. and S.Z.; methodology, M.S.; software, S.Z.; validation, S.Z., J.S. and Z.H.; formal analysis, J.S.; investigation, S.Z. and J.S.; resources, M.S., Z.H. and Z.S.; data curation, Z.S.; writing—original draft preparation, S.Z.; writing—review and editing, M.S. and C.Y.; visualization, C.Y; funding acquisition, M.S. and J.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Fuzzy pairwise comparison matrix of expert 1 (Weight: 0.3).

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1, 1, 1)	(1, 2, 3)	(3, 4, 5)	(1, 2, 3)
C_2	(1/3, 1/2, 1)	(1, 1, 1)	(1, 1, 2)	(1, 1, 2)
C_3	(1/5, 1/4, 1/3)	(1/2, 1, 1)	(1, 1, 1)	(1/3, 1/2, 1)
C_4	(1/3, 1/2, 1)	(1/2, 1, 1)	(1, 2, 3)	(1, 1, 1)

Table A2. Fuzzy pairwise comparison matrix of expert 2 (Weight: 0.3).

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)
C_2	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 1, 2)	(1/2, 1, 1)
C_3	(1/4, 1/3, 1/2)	(1/2, 1, 1)	(1, 1, 1)	(1/4, 1/3 1)
C_4	(1/4, 1/3, 1/2)	(1, 1, 2)	(2, 3, 4)	(1, 1, 1)

Table A3. Fuzzy pairwise comparison matrix of expert 3 (Weight: 0.2).

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(2, 3, 4)
C_2	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 2, 3)	(1, 1, 1)
C_3	(1/5, 1/4, 1/3)	(1/3, 1/2, 1)	(1, 1, 1)	(1/2, 1, 1)
C_4	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 1, 2)	(1, 1, 1)

Table A4. Fuzzy pairwise comparison matrix of expert 4 (Weight: 0.1).

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1, 1, 1)	(3, 4, 5)	(3, 4, 5)	(1, 2, 3)
C_2	(1/5, 1/4, 1/3)	(1, 1, 1)	(1, 1, 1)	(1/2, 1, 1)
C_3	(1/5, 1/4, 1/3)	(1, 1, 1)	(1, 1, 1)	(1/2, 1, 1)
C_4	(1/3, 1/2, 1)	(1, 1, 2)	(1, 1, 2)	(1, 1, 1)

Table A5. Fuzzy pairwise comparison matrix of expert 5 (Weight: 0.1).

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1, 1, 1)	(3, 4, 5)	(3, 4, 5)	(3, 4, 5)
C_2	(1/5, 1/4, 1/3)	(1, 1, 1)	(1, 1, 2)	(1/2, 1, 1)
C_3	(1/5, 1/4, 1/3)	(1/2, 1, 1)	(1, 1, 1)	(1/3, 1/2, 1)
C_4	(1/5, 1/4, 1/3)	(1, 1, 2)	(1, 2, 3)	(1, 1, 1)

Table A6. Fuzzy pairwise comparison matrix by GDM.

	Resource Criteria (C_1)	Natural Criteria (C_2)	Economic Criteria (C_3)	Social/Environmental Criteria (C_4)
C_1	(1.0000, 1.0000, 1.0000)	(1.7617, 2.8137, 3.8367)	(2.6564, 3.6693, 4.6762)	(1.5784, 2.6253, 3.6457)
C_2	(0.2606, 0.3554, 0.5676)	(1.0000, 1.0000, 1.0000)	(1.0000, 1.1487, 2.0237)	(0.7071, 1.0000, 1.2311)
C_3	(0.2138, 0.2725, 0.3764)	(0.4941, 0.8706, 1.0000)	(1.0000, 1.0000, 1.0000)	(0.3453, 0.5451, 0.8123)
C_4	(0.2743, 0.3809, 0.6335)	(0.8123, 1.0000, 1.4142)	(1.2311, 1.8346, 2.8958)	(1.0000, 1.0000, 1.0000)

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