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GIS supported optimal site selection for coastal structure integrated wave energy converters

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Abstract

There is an urgent need for adaptative engineering for more resilient coastal communities, and coastal structure integrated wave energy converters (CSI-WECs) are a promising solution. CSI-WECs are wave energy converters (WECs) that are built into coastal protection structures, such as breakwaters. These devices provide the dual benefits of coastal protection and local energy production, and unlike other WECs, maximizing energy production is not always the main objective. CSI-WECs are located near the shore where the wave resource is lower; thus, site selection for these devices differs from typical offshore WECs. Other attributes of a site that may be more important than wave power include existing coastal structures, port proximity, electric transmission line proximity, and the location of disadvantaged communities. Geographic information system (GIS) interfaces can be used to easily visualize geospatial data that represent these various criteria important for determining optimal marine energy sites. Multi-criteria decision analysis (MCDA) is a geospatial analysis method that allows for the evaluation of multiple, usually overlapping, criteria. This project applies GIS-based MCDA methods to two distinct case studies in Puerto Rico and California for CSI-WEC site selection. The two study sites contrast in terms of wave resource, coastal hazards, and local energy needs. This research demonstrates the utility of applying an MCDA framework within GIS to facilitate efficient site selection for devices with unique characteristics in different use cases.

Keywords: GIS; Decision Science; Marine Energy, Site Selection; Coastal Protection

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1. Introduction

The sea level along the U.S. coastline is expected to rise 10–12 inches (0.254–0.3 meters) on average over the next 30 years due to anthropogenic climate change [1]. Furthermore, as storms increase in frequency and intensity, coastal communities will be at greater risk of flooding from storm surges. Coastal protection structures, such as breakwaters and seawalls, are often used to mitigate the impact of coastal storms. Fourteen percent of the U.S. shoreline is hardened with protective structures and is predicted to increase to protect coastal areas against the impacts of climate change [2]. Coastal defense structures are effective against storms but have high construction and maintenance costs [3]. One strategy to reduce lifetime costs is to integrate wave energy converters into existing or planned defense structures. The protective function of coastal structures remains the primary purpose of coastal structure integrated wave energy converters (CSI-WECs), and any generated energy is an additional local benefit.

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The site selection for wave energy converters (WECs) generally focuses on maximizing potential power generated from the local wave energy resource. CSI-WECs are sited near shore where the wave resource is reduced, necessitating different site selection requirements than traditional WECs. Furthermore, CSI-WECs can function as non-grid-connected devices, where they are not connected to the larger utility-scale grid but instead directly power some local activity. For example, they can serve as an emergency backup generator after storms, power desalination systems for drinking water, or power local port operations. These functions can all contribute to a community's coastal resiliency. Other attributes of a site that may be more important than wave power include existing coastal structures, port proximity, electric transmission line proximity, and the location of disadvantaged communities.

One of the primary tools that allows for this type of intersecting analysis is a geographic information system (GIS), which is computer software that allows for the visualization and manipulation of geospatial data. GIS-integrated analytical tools can be used to analyze typically incompatible data types crucial for identifying optimal marine energy sites [4, 5]. Multi-criteria decision analysis (MCDA) is one geospatial analysis method that allows for this evaluation of multiple, usually overlapping, criteria. The MCDA framework has been used extensively in Europe for solar and wind projects to help identify locations with greater energy resources and less social impact [4, 5]. However, it has yet to be used extensively for marine energy projects.

This project applies GIS-based MCDA to identify suitable CSI-WEC sites in Puerto Rico and California, locations that differ in wave resource, coastal hazards, and local energy needs. This research showcases how GIS-based MCDA methods streamline site selection for marine energy devices in diverse case studies.

The two locations selected for analysis in this study were Puerto Rico and California. Puerto Rico was selected due to its vulnerability to hurricanes and the unique energy insecurity that is prevalent in island communities. Past hurricanes have devastated the island and disrupted energy access for long periods [6]. Numerous communities outside the main metro areas experienced power outages and damaged infrastructure during these storms, with recovery efforts persisting for years [7, 8]. Climate change is causing increasing intensity and frequency of hurricanes [7]. CSI-WECs could provide coastal resiliency in these communities by supporting their ability to respond to and recover from disasters. The site selection analysis for Puerto Rico incorporates social justice data to incorporate the potential benefits of CSI-WECs for communities that are at most risk from climate change.

California was selected because of the immense wave energy resource and extensive shoreline. California's wave energy resource is 140 terawatt hours per year (TWh/yr), enough to power 13 million homes [10]. Recent research indicates that up to 75% of California's beaches are at risk of complete erosion from sea level rise by 2100 [11]. Coastal protection structures have been widely used to slow coastal erosion and protect commercial and residential areas; however, many of these structures have aged and require major repairs or replacement. The Center for Climate Integrity Resilient Analytics projected that costs could total $22 billion for future coastal structure development [12]. CSI-WECs can provide coastal protection [13], fostering coastal resiliency with fortifying coastal defenses and with local clean energy generation. California's site selection analysis will consider the location of jetties and the wave energy resource to identify areas with both a high energy production potential and high coastal erosion rates.

2. Methods

2.1. Criteria selection

In Puerto Rico, the criteria selected for analysis were the omnidirectional wave power [14, 15], proximity to cities [16], proximity to transmission lines [17], proximity to ports [18], proximity to Justice40[1] climate change and energy disadvantaged communities [19], and military danger and restricted zones [20]. The Puerto Rico analysis included two specific datasets representing energy disadvantaged communities and climate change disadvantaged communities. Military danger and restricted zones were selected as exclusionary criteria. Marine protected areas were considered, but not included due to the nature of CSI-WEC technology being essentially onshore.

In California, the criteria selected for analysis were omnidirectional wave power [21], proximity to cities, proximity to transmission lines, proximity to ports, proximity to public jetties [22], proximity to power plants [23], and proximity to Justice40 disadvantaged communities. The analysis used a comprehensive Justice40 dataset that included all eight categories. In California, no exclusionary criteria were used.

[1] Justice40 is a federally funded initiative that has mandated environmental justice action. The geospatial data set identifies disadvantaged communities, defined as communities that are underserved, marginalized, or overburdened by pollution. This is measured with different indicator datasets; the eight categories are climate change, energy, health, housing, legacy pollution, transportation, water and wastewater, and workforce development.

2.2. Criteria weighting

A fundamental part of the MCDA process is the weighting of criteria, which evaluates the relative importance of each criterion. The most frequent renewable energy site selection method is the analytical hierarchical process (AHP) method, which is a hierarchical approach to complex decision-making [24, 25]. AHP is popular because it provides a structured approach to quantifying complex and subjective judgements [26]. The AHP method was created by Thomas Saaty [27] and involves assigning values to pairwise comparisons that represent the relative importance of one criterion over another. These values are listed in Table 1 and are used to create a pairwise comparison matrix. Within the matrix, the values in each column are summed. Then the matrix is normalized by dividing each point in the matrix by the column's sum to create values from 0 to 1. Finally, the average of each row is calculated. The output is a criterion weighting, which represents the criterion's overall importance compared to all other criteria. To validate the criteria weightings and test for robustness, a consistency index (CI) and consistency ratio (CR) were calculated using Equation 1 and Equation 2 [26]:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \text{(Eq. 1)} \qquad\qquad CR = \frac{CI}{RI} \quad \text{(Eq. 2)}$$

where λ_{max} is the maximum eigenvalue of the matrix, and n is the number of criteria in the matrix. RI is the random index, a standard value derived from the size of the matrix. This value was calculated by Saaty [27], who created a table of RI values based on matrix size. This value increases with matrix size. A CR greater than 10% indicates that there are logical inconsistencies in the pairwise comparisons and the analysis should be repeated [26]. AHP analysis was conducted in the computer programming language Python.

Table 1. AHP value scale chart based on Saaty's methodology [27].

Intensity of Importance	Definition	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one criteria over another
5	Essential or strong importance	Experience and judgment strongly favor one criteria over another
7	Very strong importance	A criteria is favored very strongly, and its dominance is demonstrated in practice
9	Extreme importance	The criteria favoring one activity over another is of the highest order of affirmation
2, 4, 6, 8	Intermediate values	

2.3. GIS and MCDA methods

After the selection of the study areas and specific criteria, data were imported and clipped to the extent of the study location using the ESRI GIS software ArcMap 10.8.2 [28]. The study area extent was 3.0 nautical miles from the coastline for both Puerto Rico and California. The Euclidean distance tool was used to calculate the proximity for feature class data, providing the distance between the layer feature and each raster cell. To allow for the compilation of the data layers, each layer was normalized to a standard scale of 0 to 1, where 1 is considered the highest rank, and 0 is the least desirable. This was done with the raster calculator using Equation 3:

$$Raster = 1 - \frac{Raster - Raster\ Minimum}{Raster\ Maximum - Raster\ Minimum} \qquad \text{(Eq. 3)}$$

In ArcGIS, the data layers were combined using the Weighted Sum tool. The criteria rankings from the AHP analysis were used to weight each data layer. After the analysis was completed, exclusionary areas were overlaid to remove locations classified as unsuitable. The resulting raster mapped the suitability of sites in the study area. For both study areas, the raster was displayed using the standard deviation stretch.

3. Results

3.1. Puerto Rico

Figure 1a displays the criteria weights used during the suitability analysis that were calculated from an AHP analysis. The highest weighted criteria were the Justice40 energy and climate change disadvantaged communities. The calculated CR of 4.1% confirms that the criteria matrix was consistent, meaning that the pairwise comparisons were logically coherent and free from contradictions. Fig. 1b displays the Puerto Rico site suitability results. There is a span of highly suitable sites from San Juan along the north shore to the northwest coast. Additionally, the analysis identified a few sites along the southern coast as highly suitable. These areas have lower wave energy resources compared to the northern parts of the island and are more remote, but are adjacent to vulnerable communities, according to Justice40 data. Including this Justice40 data reveals hotspots that otherwise would not have been considered, and they represent areas that need coastal protection and clean energy access.

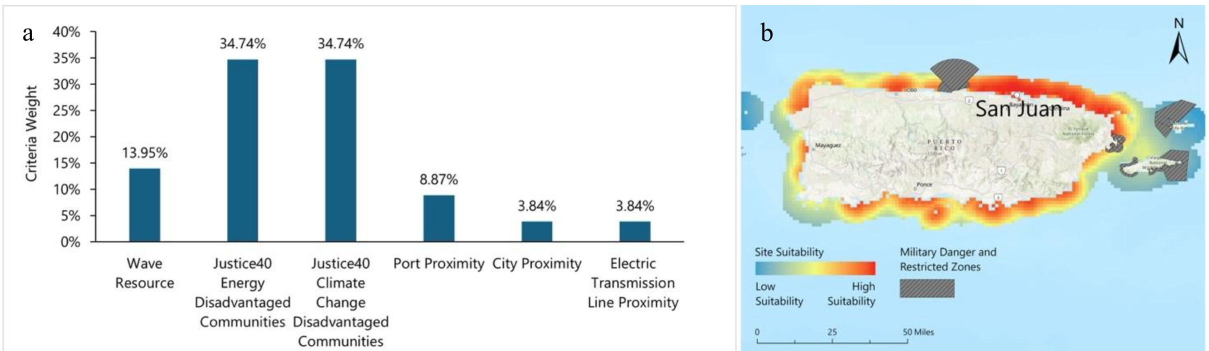

Fig. 1. (a) Puerto Rico criteria weightings calculated from the AHP analysis; (b) Puerto Rico site suitability map. Blue represents low suitability and red represents high suitability. Military danger and restricted zones are gray.

3.2. California

The criteria weights used during this suitability analysis are represented graphically in Fig. 2a. Based on the results of the AHP analysis, the highest weighted criterion was the omnidirectional wave power. The CR was 6.7%, which indicates that the criteria weight matrix was consistent, and the pairwise comparisons are rational and without logical inconsistencies. Fig. 2b displays the California site suitability results. The analysis identified both highly suitable and not suitable sites, underlining the utility of GIS for refining potential sites. A few highly suitable areas stand out from the initial analysis: in northern California near Eureka and Noyo Bay, San Francisco, Santa Cruz, and San Diego. Two locations were selected for further examination: Noyo Bay (Site A) and Eureka (Site B) are mapped in Fig. 3. These maps display the surrounding infrastructure and omnidirectional wave power. The location of a jetty along the bay (Fig. 3a) suggests that the area has historically required coastal protection, demonstrating the need for a CSI-WEC. However, the lack of nearshore high-resolution wave data limits the ability to estimate a WEC's power potential. Fig. 3b shows that in Eureka there are multiple jetties that could be replaced by or upgraded to a CSI-WEC. Two power plants located along the coast could provide grid access for the energy produced.

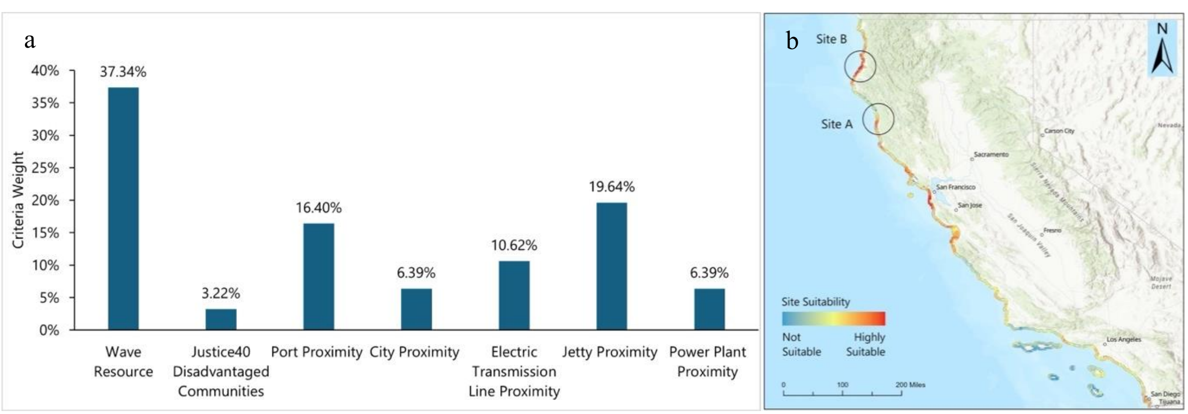

Fig. 2. (a) California criteria weightings calculated from the AHP analysis; (b) California site suitability analysis. Blue symbolizes low suitability and red symbolizes high suitability. Two sites are identified for further analysis, Noyo Bay (Site A) and Eureka (Site B).

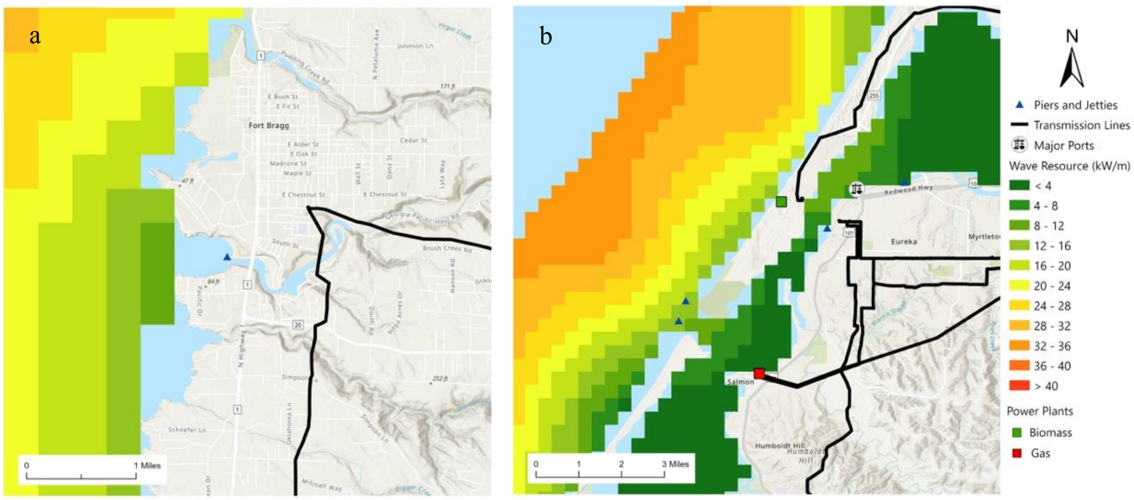

Fig. 3. (a) Map of Noyo Bay, California, depicting the omnidirectional wave power (kilowatts per meter [kW/m]), electric transmission lines, and piers and jetties; (b) Map of Eureka, California, depicting the omnidirectional wave energy (kW/m), electric transmission lines, piers and jetties, and power plants.

4. Conclusion

This study demonstrated how GIS-based MCDA methods optimize marine energy site selection. These analyses used six or seven spatial datasets, as these were determined sufficient to answer the research questions with limited computational resources. However, the inclusion of more data would further narrow down the hotspots as determined by the analyses. For example, data on seafloor substrate, bathymetry, and extreme sea states impacts which WEC archetypes are appropriate in certain locations. Identifying this early in a project timeline would aid in streamlining projects and accelerating the deployment of devices because fewer sites would have to be evaluated. Additionally, integrating additional social, environmental, and economic geospatial data into future research for marine energy projects is essential for comprehensive analysis. This ensures that other marine activities in an area are proactively considered and that stakeholders from a variety of user groups can be engaged as early as possible in a project. For example, without including such data, a location may be identified as an ideal location for deployment even if it may be a critical habitat for a sensitive species or a culturally vital fishing location for the local community. This methodology can therefore ensure that marine renewable energy is a component of multi-use marine spatial planning while preventing some potential conflicts among stakeholders of various user groups.

The flexibility of GIS-based MCDA means that this methodology can be used whenever locations must be down-selected and there are sufficient spatial data. Within the renewable energy industry, for example, evaluating different kinds of resource data within a region can help isolated rural and island communities identify the optimal energy source and subsequent technology. For example, a community may be content to leverage their local wave resource, but this resource may not be consistent or strong enough to adequately meet that community's needs, and therefore a hybrid system may be more appropriate. Additionally, the technology readiness level of marine energy devices across the industry is relatively low compared to devices used to harness other energy resources, such as solar and wind. Pairing an established technology with a more nascent technology reduces the risks of relying on one technology and resource in a clean energy transition.

Comprehensive GIS-based MCDA analyses that include different resource datasets, environmental data, site characterization data, and socioeconomic data can identify ideal locations for renewable energy development without using computationally intensive and mathematically complicated optimizations. This approach can allow for input and engagement from multiple user groups. The visualization of spatial data in this methodology also simplifies the collaboration process between stakeholders as the data are in a format that is easier for the general public to interpret than numerical data. Narrowing down optimal sites and enabling easier and quicker collaboration among user groups is crucial for scaling up the world's renewable energy portfolio to meet global climate targets.

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