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Mapping the Unheard: Analyzing Tradeoffs Between Fisheries and Offshore Wind Farms Using Multicriteria Decision Analysis

Zhenlei Song,^a  Piers Chapman,^b Jian Tao,^c Ping Chang,^b Huilin Gao,^d Honggao Liu,^e Christian Brannstrom,^a and Zhe Zhang^f 

^aDepartment of Geography, Texas A&M University, USA; ^bDepartment of Oceanography, Texas A&M University, USA; ^cDepartment of Visualization, Texas A&M University, USA; ^dDepartment of Civil and Environmental Engineering, Texas A&M University, USA; ^eHigh Performance Research Computing (HPRC), Texas A&M University, USA; ^fDepartment of Geography and Department of Electrical and Computer Engineering, Texas A&M University, USA

Identifying offshore wind energy sites involves analyzing multiple variables, such as wind speed, proximity to the coastline, and sociocultural factors. This complex decision-making process often involves many stakeholders, resulting in conflicting data and goals. Decision analysis that promotes collaboration, transparency, understanding, and sustainability is key. This study presents a unique model of human–environment interaction that reconciles different perspectives and visualizes the balance between fisheries and wind power. Using three multicriteria decision models (weighted aggregated sum product assessment [WASPAS], technique for order of preference by similarity to ideal solution [TOPSIS], and analytical hierarchy process [AHP]), we analyze the decision mix for wind farm selection and assess the impacts on fisheries using historical data. Our approach was applied to an upwelling system in California, generating ten tailored decision scenarios for different stakeholder groups. The results showed that adaptation scores for specific call areas in northern California decreased when the weight of fishery factors increased, and there was a tendency for high-scoring areas to shift southward as fishery parameters increased. The results of the sensitivity analysis showed that the first-order sensitivity scores of WASPAS were better correlated with the weights compared to TOPSIS, whereas the second-order sensitivity scores were generally lower, indicating a reduced interdependence of our model. *Key Words:* human–environment interactions, multicriteria decision-making, offshore wind energy, site selection, sustainability.

Offshore wind energy represents one of the largest potential renewable energy sources in the United States. Developing an offshore wind generating capacity is one of the essential steps for reducing global warming (Mekonnen and Gorsevski 2015). The Biden–Harris administration announced plans in February 2022 to generate 30 gigawatts of energy from offshore wind by 2030 nationally (The White House 2022). At the same time, California has set aggressive decarbonization goals, including ambitious renewable portfolio standards and a target of 100 percent carbon-free power generation by 2045. In 2021, California Governor Gavin Newsom signed a bill mandating an offshore wind-energy development plan in federal waters from the California Energy Commission (Garner and

Maroon 2022). The Energy Commission was required to establish the maximum feasible capacity for offshore floating wind turbines by 1 June 2022. The California grid operator is currently struggling with “duck curve” challenges, which means the demand peaks in the morning and evening while the supply peaks at noon, requiring nonsolar power generation (or electricity storage), such as offshore wind, to meet evening peak demand for electricity.

One significant problem in offshore development is identifying appropriate sites for wind energy farms (Mekonnen and Gorsevski 2015). Determining wind farm sites is a challenging, complex, and protracted process that requires the evaluation of many different criteria, such as wind and geophysical conditions and environmental impacts (Tegou, Polatidis, and

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CORRESPONDING AUTHOR Zhe Zhang  zhezhang@tamu.edu

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Haralambopoulos 2010; Grassi, Chokani, and Abhari 2012). Research in the eastern United States has shown the importance of stakeholder engagement at all stages of offshore wind farm development in the interest of increasing procedural fairness and a “chain of trust” between stakeholders and developers (Dwyer and Bidwell 2019; Ferguson et al. 2021; Gonyo et al. 2021). Offshore wind farms could have significant negative impacts on ocean ecosystems (Wahlberg and Westerberg 2005; Thomsen et al. 2006; Mooney, Andersson, and Stanley 2020). For example, Mooney, Andersson, and Stanley (2020) discussed the impacts of the entire lifetime of wind turbines on marine species’ habitats by applying physical modeling. Haggett et al. (2020) pointed out that the opinions of fishing industry representatives should be strongly considered when determining the sites for offshore wind power. Many researchers, however, discussed the issues related to social and political perspectives. They claimed that a holistic information platform is needed to visualize all the variables in making such complex decisions when building an offshore wind farm. Numerous studies have indicated that establishing offshore wind energy infrastructures could interact with fisheries in complex ways. Some interactions could be negative, but others can potentially contribute to the ecosystem, such as providing new habitats for marine life. Still, a pressing need exists for improved dialogue and cooperation between the fisheries and energy sectors, largely due to the current lack of information platforms that can foster effective collaborative decision-making processes.

Multicriteria decision-making (MCDM) has been applied to renewable energy site selection problems, which evaluates candidates from multiple locations based on multiple criteria (Shao et al. 2020). The most common criteria include (1) natural or marine reserve areas, (2) military areas, (3) distance from shore, and (4) wind speed (Mekonnen and Gorsevski 2015; Fetanat and Khorasaninejad 2015; Y. Wu et al. 2016; Chaouachi, Felix Covrig, and Ardelean 2017; Mahdy and Bahaj 2018; B. Wu et al. 2018; X.-Y. Zhang et al. 2018; Russell, Bingaman, and Garcia 2021). The third component can be explained from a construction cost perspective: The closer to the coastline, the higher the transmission line efficiency, and the lower the transportation costs during construction and maintenance costs during operational phases. From the aspect of

high transmission efficiency, wind farms are primarily located close to the coastline. At the same time, these areas are commonly associated with the dense distribution of military bases and nature reserves. Therefore, the conflict decision objectives associated with offshore wind energy development come from several perspectives, such as maintaining military services, sustaining fishery and marine ecosystems, and maximizing the offshore wind energy construction portfolio.

In the MCDM analysis, developing a weighting method plays an important role. Several weighting methods have been commonly used in MCDM, including the analytical hierarchy process (AHP; Chaouachi, Felix Covrig, and Ardelean 2017; Mahdy and Bahaj 2018; B. Wu et al. 2018), weighted aggregated sum product assessment (WASPAS; Zavadskas et al. 2012; Mekonnen and Gorsevski 2015; Chaouachi, Felix Covrig, and Ardelean 2017), and technique for order of preference by similarity to ideal solution (TOPSIS; Z. Zhang et al. 2018). Many previous studies in offshore wind energy site selection applied the fuzzy MCDM algorithms, such as the fuzzy AHP used in Sánchez-Lozano, García-Cascales, and Lamata (2016) to tackle a common problem: how to give a decision-making solution that is acceptable to all parties when the opinions and priorities conflict when selecting the best location to implant an onshore wind farm.

Research gaps still exist, however, regarding the ability to use MCDM to handle collaborative (or participatory) decision-making processes in the offshore wind energy application area. First, it is challenging to identify and quantify criteria and weightings, which depend on how much the decision-makers know about the area and their preferences. Second, most spatial decision support systems are focused on areas with only limited decision variables and rules, which cannot be used where there are conflicting decision objectives. For instance, industry energy managers might consider the wind speed variable as the most important in deciding the location of a wind farm, and environmental agency managers might think likewise regarding the distance to the natural reserve areas. Finally, there exist barriers to knowledge-sharing and communication among different decision-makers. Decision-making in offshore energy site selection problems requires the cooperation of a group of stakeholders, including

domain experts, engineers, system developers, fishery and energy industry managers, and application users. Therefore, more advanced methods to collect, integrate, interpret, and visualize decision variables from different parties of interest are critical to both energy management and sustainable fishery.

In this research article, we aim to investigate the following research questions:

1. Are there overlaps or conflicts between expected fishing efforts, bycatch, protected species, and human activities such as offshore energy development, and can management decisions mitigate them?
2. Can we find spatial solutions for balancing the trade-offs between Energy Commission goals and the sustainability of fisheries and conservation of ecosystems?

In this article, we developed a participatory decision support information system using MCDM models and advanced visualization techniques to illustrate trade-offs between fishery management and offshore wind energy development. This decision information system enables different decision-makers, such as fishing and offshore energy industry managers, policymakers, researchers, and environmental protection agency officers, to make risk-informed decisions when developing a new offshore wind farm.

Background Theory

This section introduces the background and theories used to implement the decision support information system. In this application, we help decision-makers to find suitable locations for building offshore wind energy infrastructure by considering the impacts on fisheries and marine ecosystems. MCDM theory combines all the decision criteria to form an overall evaluation score for offshore wind location selection problems.

Multicriteria Decision Analysis

Multicriteria decision analysis (MCDA) is a mathematical decision-making framework that combines many decision criteria to meet one or several objectives that support decision-making (Shao et al. 2020). In the weighted sum method (WSM), given a set of m alternatives, denoted as $A_1, A_2, A_3, \dots, A_m$, and a set of n decision criteria, denoted as $C_1, C_2, C_3, \dots, C_n$, it is assumed that a decision-maker has to determine the weight value ω_{ij} (for

$i=1,2,3, \dots, m$ and $j=1, 2, 3, \dots, n$) of each alternative in terms of each criterion (Fishburn 1967). For each row of data set X with x_j values are defined, along with the criteria weight matrix W (the weight of the relative performance of the decision criteria). Usually, these weights are normalized to add up to one, and the alternatives are ranked. If there are m alternatives and n criteria, the score calculated using WSM for the i th decision alternative can be represented as Equation 1 (Fishburn 1967; Thakkar 2021), where ω_{ij} is the weight for the j th criteria in the i th decision alternative; x_j is the data value of the j th column (attribute); and Q_i^{WSM} is the WSM score for the i th decision alternative.

$$Q_i^{WSM} = \sum_{j=1}^n \omega_{ij} * x_j \quad (1)$$

The weighted product method (WPM) is similar to the WSM. The main difference is that instead of addition in the model, there is multiplication. Each alternative is compared with the others by multiplying a number of ratios, one for each criterion. Each ratio is raised to the power equivalent of the relative weight of the corresponding criterion (Triantaphyllou and Mann 1989). In WPM, under the same problem conditions, the score for the i th decision alternative can be expressed as Equation 2, where ω_{ij} represents the weight for the j th criteria in the i th decision alternative; x_j represents the data value of the j th column (attribute); and Q_i^{WPM} represents the WPM score for the i th decision alternative (Thakkar 2021).

$$Q_i^{WPM} = \prod_{j=1}^n x_j^{\omega_{ij}} \quad (2)$$

The WSM and WPM are widely used in MCDM processes, but each has limitations. WSM's main disadvantage is its assumption of additive criteria, overlooking potential interactions, whereas WPM assumes criteria are multiplicative, which might neglect interactions and distort results with zero values. The WASPAS method seeks to balance these models' strengths and weaknesses by providing a weighted average of both approaches, offering more comprehensive and flexible decision-making outcomes (Zavadskas et al. 2012). WASPAS is preferred to the variety of available methods because of its ability to increase the accuracy of ranking. WASPAS leads to the highest accuracy of estimation for optimization of the weighted aggregate function. It combines two well-known methods—the WSM and the WPM—to provide a method with

accuracy greater than the original two methods, with an optimization of the aggregation being conducted (Thakkar 2021). WASPAS uses a λ value to coordinate the output share of the two models, which generally defaults to 0.5 out of 1; that is, equal reception of the outputs from WSM and WPM. The weighted score value calculated using the WASPAS method can be expressed in Equation 3, where ω_{ij} represents the weight for the j th criteria in the i th decision alternative; x_j represents the data value of the j th column (attribute); and Q_i^{WASPAS} represents the WASPAS score for the i th decision alternative (Thakkar 2021).

$$Q_i^{\text{WASPAS}} = \lambda \sum_{j=1}^n \omega_{ij} * x_j + (1 - \lambda) \prod_{j=1}^n x_j^{\omega_{ij}} \quad (3)$$

In this project, the decision alternatives refer to a set of combinations of weights corresponding to criteria. These criteria represent four environmental factors, including wind speed at 90 m, along with statistics on fishing landings for 2019 to 2021, for a total of seven decision criteria. These are used to gauge the feasibility of constructing a wind turbine at specific locations. The WASPAS method serves as the primary algorithm for assessing the suitability of diverse locations within the study area. A key innovation of this research involves the integration of two additional algorithms—AHP and TOPSIS—alongside the WASPAS method in creating our Web-based, participatory decision support system. This allows users to compute adaptive scores for weight combinations aligning with their preferences. We explore these two algorithms and their respective roles within our modeling framework in the subsequent sections.

Analytic Hierarchy Process

In addition to the WASPAS model (described in the last section), the AHP was used as another weighting method for constructing the MCDM model. AHP has been applied in different fields, such as planning, selecting the best alternative, and resource allocations (Vaidya and Kumar 2006; Chaouachi, Felix Covrig, and Ardelean 2017; Mahdy and Bahaj 2018; Wu et al. 2018). AHP involves breaking down a decision problem into a hierarchy of criteria and alternatives. The hierarchy consists of a goal at the top, followed by a set of criteria that contribute to the achievement of the goal.

These criteria are further divided into subcriteria, forming a hierarchical structure. Once the hierarchy is established, pairwise comparisons are made between the elements of each level (Saaty 1977). In the AHP analysis, users construct a pairwise weighting matrix, wherein each element signifies the relative importance of one criterion compared to another during the decision-making process. The weighting vector is the feature vector of the matrix corresponding with the maximum nonzero feature value.

1. Constructing pairwise weighting matrix. The AHP pairwise weights matrix is shown in Table 1.
2. Feature vector

$$Aw = \lambda_{\max} w \quad (4)$$

3. Normalization

$$w_{\text{AHP}} = \frac{w}{\|w\|} \quad (5)$$

4. Consistency check.

The ideal pairwise weighting matrix is supposed to be a consensus matrix, but the constraints are strict for practical application. Thus, to ensure the error is within the acceptable range, the consensus index (CI) and random consensus index (RI) were introduced. CI measures the consistency of the pairwise comparisons. It is calculated as $(\lambda - n)/(n - 1)$, where λ is the maximum eigenvalue of the pairwise comparison matrix, and n is the number of criteria, as shown in Equation 6, where λ is the feature value and n is the order number.

$$CI = \frac{\lambda - n}{n - 1} \quad (6)$$

RI is used to measure the consistency of judgment matrices; it is derived from many randomly filled matrices that are the same size as the judgment

Table 1. Analytical hierarchy process (AHP) weight matrix

	A1	A2	A3	A4	A5	A6
A1	1	$w1/w2$	$w1/w3$	$w1/w4$	$w1/w5$	$w1/w6$
A2		1	$w2/w3$	$w2/w4$	$w2/w5$	$w2/w6$
A3			1	$w3/w4$	$w3/w5$	$w3/w6$
A4				1	$w4/w5$	$w4/w6$
A5					1	$w5/w6$
A6						1

Table 2. Analytical hierarchy process (AHP) random consensus index (RI) statistics

N	1	2	3	4	5	6	7	8	9
RI	0	0	0.52	0.89	1.12	1.24	1.36	1.41	1.49

matrix we are examining. The values of RI are fixed and vary according to the size of the matrix, as shown in Table 2 (Saaty 1988).

Consensus ratio (CR) serves as a measure of how consistent the judgments have been relative to large samples of purely random judgments as shown in Equation 7. Provided CR falls within an acceptable range (lower than 0.1), the weight matrix entered by the user can be incorporated as input into the decision model. Subsequently, the output suitability scores will be updated and visualized.

$$CR = \frac{CI}{RI} \quad (7)$$

The AHP method, with its matrix of pairwise compared weights, proves more effective as a direct, user-oriented approach to obtaining weights than using an array of absolute weights. In this project, AHP was used as another method for setting a weight for evaluation criteria for this application.

The Technique for Order of Preference by Similarity to Ideal Solution

TOPSIS is an MCDM method used to evaluate and rank alternatives based on their proximity to an ideal solution (Uzun et al. 2021). The procedure of TOPSIS application in this study includes the following steps.

1. Construct the normalized matrix. Let matrix $\mathbf{X}$ represent the initial data sample matrix. The matrix $\mathbf{Z}$ represents the normalized data matrix, as shown in Equation 8.

$$\begin{aligned} \mathbf{X} &= \begin{bmatrix} x_{11} & \cdots & x_{1m} & \vdots & \ddots & \vdots & x_{n1} & \cdots & x_{nm} \end{bmatrix} \\ z_{ij} &= \frac{x_{ij}}{\sqrt[n]{\sum_{i=1}^n x_{ij}^2}} \\ \mathbf{Z} &= \begin{bmatrix} z_{11} & \cdots & z_{1m} & \vdots & \ddots & \vdots & z_{n1} & \cdots & z_{nm} \end{bmatrix} \end{aligned} \quad (8)$$

2. Identify positive and negative ideal solutions (PIS and NIS). Among all the samples, pick the best and the worst scenario for each feature to form the best and the worst case vectors. Here, V^+ (the output vector of PIS) and V^- (the output vector of NIS) are identified

in Equation 9, where $v_{ij} = \omega_j z_{ij}$; $i = 1, \dots, m$; $j = 1, \dots, n$; $\sum_{j=1}^n \omega_j = 1$. The PIS maximizes the benefit criteria and minimizes the cost criteria, whereas the NIS maximizes the cost criteria and minimizes the benefit criteria.

$$\begin{aligned} V^+ &= (v_1^+, v_2^+, v_3^+, v_4^+, \dots, v_n^+) = [[\max_i v_{ij}]] \\ V^- &= (v_1^-, v_2^-, v_3^-, v_4^-, \dots, v_n^-) = [[\min_i v_{ij}]] \end{aligned} \quad (9)$$

3. Calculate the Euclidean distance to the PIS and NIS in Equation 10.

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^m (v_j^+ - v_{ij}^+)^2} = \sqrt{\sum_{j=1}^m (v_j^+ - \omega_j z_{ij}^+)^2} \\ D_i^- &= \sqrt{\sum_{j=1}^m (v_j^- - v_{ij}^-)^2} = \sqrt{\sum_{j=1}^m (v_j^- - \omega_j z_{ij}^-)^2} \end{aligned} \quad (10)$$

4. Evaluate the closeness of samples and best and worst cases. The closeness of each sample and the best and worst cases is calculated in Equation 11:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad 0 \leq C_i \leq 1 \quad (11)$$

The alternatives are ranked based on their relative closeness. The alternative with the highest relative closeness value is considered the most favorable choice. The greater C_i is, the closer each sample is to the best case. The TOPSIS method facilitates a good understanding of how closely a model's characteristics align with an ideal solution, as determined by a specific set of weights and the encompassing data set. Its robustness, validity, and inherent intuitiveness make it a favored instrument for post hoc evaluation and validation, especially following the selection of weights. Within the scope of our current project, TOPSIS is leveraged twofold: first, as an evaluative measure assessing the efficacy of weight combinations procured through a multistakeholder interest-balancing exercise corresponding to each decision alternative; second, as an intrinsic decision-support algorithm within the Web application, paralleling the roles of WASPAS and AHP methods.

Sensitivity Analysis

Sensitivity analysis refers to the process of examining the impact of changes in criteria weights or alternative evaluations on the overall decision outcome. It is a valuable technique for assessing the robustness and stability of the decision-making

process (Saltelli et al. 2004; Z. Zhang et al. 2018). A numeric value often represents the sensitivity of each input called the sensitivity index (Iwanaga, Usher, and Herman 2022): (1) First-order indexes measure the contribution of the output variance by a single model input alone; (2) second-order indexes measure the contribution of the output variance caused by the interaction between two model inputs; and (3) total-order index measures the contribution of the output variance caused by a model input, including both its first-order effects (the input varying alone) and all higher order interactions (Herman and Usher 2017). In practice, the total-order index is commonly used when discovering the effects of each decision criterion on the decision modeling outputs. The second-order indexes are used when discussing the correlation between different decision criteria in MCDM problems.

In this project, we applied sensitivity analysis to these three MCDM models to help understand how sensitive the decision outcomes are to changes in criteria weights or alternative evaluations. Through sensitivity analysis, we can identify the most impactful criterion (as suggested by the first-order SA index) and pair of criteria (as indicated by the second-order SA index) under the influence of weight combinations specific to each decision alternative.

Methodology

Data Sources

The following factors have been considered for modeling the trade-offs between fisheries and offshore wind energy development to ensure the running efficiency and legality of the site selection and construction: (1) wind speed at a 90-m height, (2) distance to shorelines, (3) the distances to military bases, and (4) natural protected area locations (Fetanat and Khorasaninejad 2015; Mekonnen and Gorsevski 2015; Chaouachi, Felix Covrig, and Ardelean 2017; Mahdy and Bahaj 2018; Y. Wu et al. 2016; B. Wu et al. 2018; X. Zhang et al. 2018). This project was developed based on the National Science Foundation-funded Convergence Accelerator-Networked Blue Economy project, where our team has conducted sixteen interviews with fishery managers, policymakers, and scientists regarding sustainable fishery management strategies. Many interview participants have pointed out the

concerns regarding the impacts of building offshore wind energy on marine ecosystems and fishery production. In addition to the previously mentioned variables, we included fishery landing statistics data collected from 2019 to 2021 in the decision-making model (California Department of Fish and Wildlife 2022). We collected annual average offshore wind speed for the Pacific Coast (California, Oregon, and Washington) at a 90-m height from the National Renewable Energy Laboratory (AWS Truepower/NREL 2011) and the shoreline and military bases map from public databases released by the National Transportation Atlas Databases 2014 (NTAD2014) and U.S. Geological Survey.

Study Area

Our study area is in California, where floating offshore wind is emerging as a promising source of renewable energy generation for the state. The development of floating offshore wind energy in California will diversify the state's energy portfolio and provide an opportunity for good-paying jobs and statewide economic benefits (California Energy Commission 2019). On 18 August 2016, the federal Bureau of Ocean Energy Management (BOEM) published a Request for Interest in California Offshore Wind in response to an unsolicited lease request. Two years later, BOEM published a Call for Information and Nominations from companies interested in commercial wind energy leases within the proposed areas of central and northern California (BOEM 2018). In addition, BOEM sought public input on the potential for wind energy development in the Call Areas. On 25 May 2021, the Departments of the Interior and Defense and the State of California announced their agreement to advance areas for wind energy development offshore the northern and central coasts of California, enabling a path forward for the Humboldt Call Area and areas within and adjacent to the Morro Bay Call Area. BOEM published the Morro Bay East and West Extensions—Call for Information and Nominations in the *Federal Register*, which initiated a forty-five-day public comment period. BOEM accepted industry nominations and public comments until 13 September 2021. The coastal fishing region in the Pacific California area was divided into 615 equal segments, each approximately 550 km². This specific area dimension was derived from the average

of three proposed call areas from 2018 (BOEM 2018). Consequently, each polygon can symbolize a prospective call area.

This study aims to evaluate the adaptability of established offshore wind energy areas by considering multiple geophysical, environmental, and fishery management factors. More than 8,000 random weight combinations were generated and processed using the WASPAS as the primary weighting algorithm. This approach facilitated the calculation of score rankings for the three designated call areas under diverse weight combinations. Subsequently, the scores corresponding to the polygons within these call areas were organized in descending order. An analysis of the weight combinations leading to higher scores on the corresponding polygons was then undertaken. This evaluation helped identify which parameters were more skewed and hence which stakeholder groups were more prominently represented by such weight combinations. The intent was to infer the degree to which the interests of all parties are incorporated in the decision-making process concerning the given call areas. The outcomes of this section are further elucidated in the results section.

Experiments

The proposed study categorizes the seven evaluation criteria into two distinct classifications. Category 1 (C1) encompasses parameters such as wind speed at a 90-m height, distance from the shoreline, proximity to military installations, and distance from marine nature reserves. These parameters primarily cater to the interests of energy planning authorities that aim to enhance the operational efficiency of wind turbines and curtail costs associated with construction and operation. Category 2 (C2) incorporates parameters like fishing statistics from 2019 to 2021 that are predominantly of concern to corporate executives and research scholars. The primary objective of this research is to model and visualize the trade-offs between fisheries and offshore wind farms to assist the decision-making process in constructing a new offshore wind site. Table 3 demonstrates a simulated weight matrix for the MCDM model. The study constructed five distinct sets (L1–L5) with a total of ten alternative strategies (L1_a–L5_b), each to showcase an array of decision-making strategies. Each set embodies unique weight ratios,

which signify diverse weight allocations for the two types of parameters, with each alternative within the set demonstrating distinct weight distribution among parameters within the same category. To provide an illustrative example, decision alternatives L1_a and L4_b possess divergent weight allocations. L1_a attributes 90 percent and 10 percent weights to categories C1 and C2, respectively, maintaining a uniform weight distribution within the corresponding parameter groups. Conversely, L4_b assigns 60 percent and 40 percent weights to categories C1 and C2, respectively, with weight distributions of (7:7:3:3) within the parameters of C1 and (1:2:3) within the parameters of C2.

Figure 1 exemplifies the user input via the WASPAS simulating the L1_a alternative delineated in Table 3. The coastal fishing region in the Pacific California area was divided into 615 equal segments, each approximately 550 km². This specific area dimension was derived from the average of three proposed call areas from 2018 (BOEM 2018). Consequently, each polygon can symbolize a prospective call area. Normalization of the weights ensures their sum equals one, with the resultant scores depicted on the right indicating each polygon's suitability for offshore wind turbine construction. On submission, the map undergoes an update to spotlight the vulnerable areas derived from the user-selected criteria and weightings via the chosen MCDA algorithms. Similarly, Figures 2 and 3 embody analogous user inputs for the L4_b alternative using AHP and L5_b alternative via TOPSIS, respectively. The weight sets in Table 3 undergo normalization; however, this process is not obligatory for user interface inputs. The SWING Weighting method (Zilinskas 2001; Patel, Vashi, and Bhatt 2017) was used in this experiment. It allows users to assign weights ranging from 0 (least preferred) to 100 (most preferred), facilitating a more intuitive weighting of the different criteria. Consequently, the output suitability scores are normalized within a scale of 0 to 1.

Results

By generating multiple (more than 8,000) random weight combinations, we did a mixed qualitative–quantitative study of multiple regions, including existing call areas. We found among all weight combinations as input, a higher focus on

Table 3. Criteria and weights of different alternatives

		C1				C2		
		Wind speed 90 m (<i>w1</i>)	Distance to shoreline (<i>w2</i>)	Distance to military bases (<i>w3</i>)	Distance to natural protected areas (<i>w4</i>)	Landing stats 2019 (<i>w5</i>)	Landing stats 2020 (<i>w6</i>)	Landing stats 2021 (<i>w7</i>)
L1	<i>a</i>	0.225	0.225	0.225	0.225	0.03333	0.03333	0.03333
	<i>b</i>	0.315	0.315	0.135	0.135	0.01667	0.03333	0.05
L2	<i>a</i>	0.2	0.2	0.2	0.2	0.06667	0.06667	0.06667
	<i>b</i>	0.28	0.28	0.12	0.12	0.03333	0.06667	0.1
L3	<i>a</i>	0.175	0.175	0.175	0.175	0.1	0.1	0.1
	<i>b</i>	0.245	0.245	0.105	0.105	0.05	0.1	0.15
L4	<i>a</i>	0.15	0.15	0.15	0.15	0.13333	0.13333	0.13333
	<i>b</i>	0.21	0.21	0.09	0.09	0.06667	0.13333	0.2
L5	<i>a</i>	0.125	0.125	0.125	0.125	0.16667	0.16667	0.16667
	<i>b</i>	0.175	0.175	0.075	0.075	0.08333	0.16667	0.25

Fishing Area Selection

Fishing Areas :

Multi-Criteria Weights Assignment

WASPAS

Weight of Wind Speed 90m :

Weight of Shoreline Distance :

Weight of Military Distance :

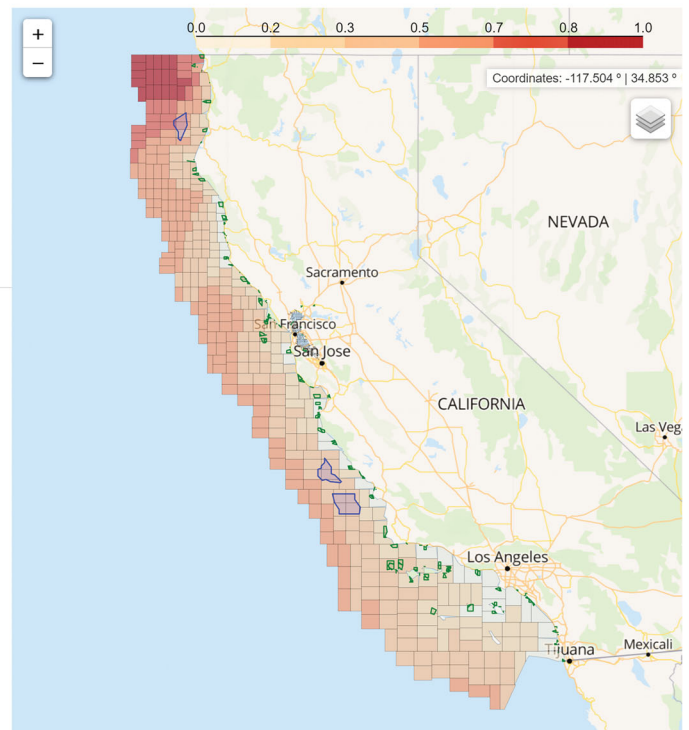
Weight of Protected Area Distance :

Weight of Landing in 2019 :

Weight of Landing in 2020 :

Weight of Landing in 2021 :

Map

**Figure 1.** An illustration of the human–ocean interaction tool user interface.

nonfishery criteria (e.g., wind speed, etc.) is highly positively correlated with a higher suitability score for the existing northern California call area near Eureka. To be quantitative, to position the Eureka call area in the top 5 percent of the suitability score, the weighting strategy required scaling the nonfisheries weight sum to approximately three times the sum of the fisheries weights, as shown in Figure 4. The areas with higher suitability scores

can be found if the weights on fisheries criteria are increased, as shown in Figure 5. These findings suggest that the decision-making process for the call area near Eureka did not adequately factor in the potential impacts on fisheries following the wind farm's construction. It is further noted that with increased consideration for fisheries, additional areas in the vicinity become more suitable for wind power site locations.

WASPAS

AHP

TOPSIS

AHP

1	1	0.42857143	0.42857143	0.31746032	0.63492063	0.95238095
1	1	0.42857143	0.42857143	0.31746032	0.63492063	0.95238095
2.33333333	2.33333333	1	1	0.74074074	1.48148148	2.22222222
2.33333333	2.33333333	1	1	0.74074074	1.48148148	2.22222222
3.15	3.15	1.35	1.35	1	2	3
1.575	1.575	0.675	0.675	0.5	1	1.5
1.05	1.05	0.45	0.45	0.33333333	0.66666667	1
Submit						

Figure 2. Analytical hierarchy process (AHP) weighting user interface.

WASPAS	AHP	TOPSIS
TOPSIS		
Weight of Wind Speed 90m : 0.175		
Weight of Shoreline Distance : 0.175		
Weight of Military Distance : 0.075		
Weight of Protected Area Distance : 0.075		
Weight of Landing in 2019 : 0.08333		
Weight of Landing in 2020 : 0.16667		
Weight of Landing in 2021 : 0.25		
Submit		

Figure 3. Technique for order of preference by similarity to ideal solution (TOPSIS) weighting user interface.

Wind energy site selection decisions are often made based on multiple constraints. For example, industry practitioners prioritize wind plant efficiency and cost-effectiveness. As such, preferred locations are those with a minimum average wind speed of 7 m/s at a 90-m altitude and a safe distance from military zones and coastlines. In contrast, fishing communities favor areas rich in marine biodiversity and high-yield catches, placing a high emphasis on the impact of wind farm construction on local wildlife habitats. This dichotomy presents a challenge for traditional decision-support models to find a balanced solution. Consequently, we have applied the MCDM approach across five scenarios, each reflecting a different criterion of focus. The suitability scores for these scenarios are illustrated in Figures 6 through 15. We have also designed a Web-based GIScience application, an interactive tool enabling users to set their weights using a range of

multicriteria techniques. The areas highlighted in Figure 5 represent potential sites for the construction of new offshore energy platforms. The application allows users to select multiple fishing areas and assign weights to different criteria to ascertain a location's suitability score for wind farm construction. As evident in Figures 6 through 15, polygon shading intensity indicates the suitability score, with darker shades denoting higher scores. From left to right, these results were calculated using the WASPAS, AHP, and TOPSIS methods, respectively. The graphical outcomes depicted in Figures 6 through 15 can be analyzed in two ways. First, we have a longitudinal evaluation of the five distinct decision alternative groups, ($L1$, $L2$, $L3$, $L4$, and $L5$). Within this context, the weightings vary from a $C1:C2$ ratio of 90:10 to a more balanced ratio of 50:50. The visualization indicates that areas with higher suitability scores typically transition from the north to the south. Second, there is an intragroup comparison of the decision alternatives (designated as Lx_a and Lx_b). When compared to the evenly distributed intragroup weighting set (Lx_a), the non-uniform intragroup weighting set (Lx_b) demonstrates that the outcomes of suitability scores are more geographically focused.

Discussion

Stakeholders within the fisheries sector have voiced significant concerns regarding the potential implications for both fisheries and ecosystems when expansive offshore energy platforms are constructed. A pressing need exists for the creation of a comprehensive decision-support platform. This platform should encapsulate all requisite information for both the fisheries and energy sectors, to aid informed decision-making about

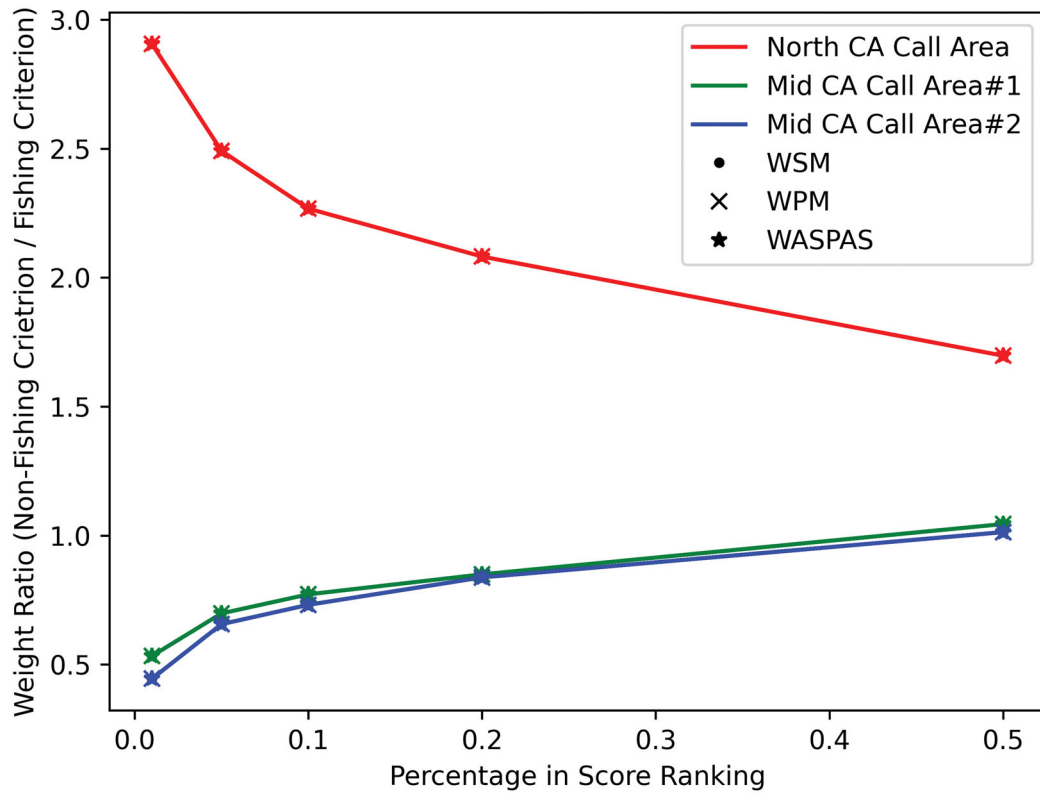


Figure 4. Weight ratio (nonfishery criterion/fishery criterion) with respect to percentage in ranking. *Note:* WSM = weighted sum method; WPM = weighted product method; WASPAS = weighted aggregated sum product assessment.

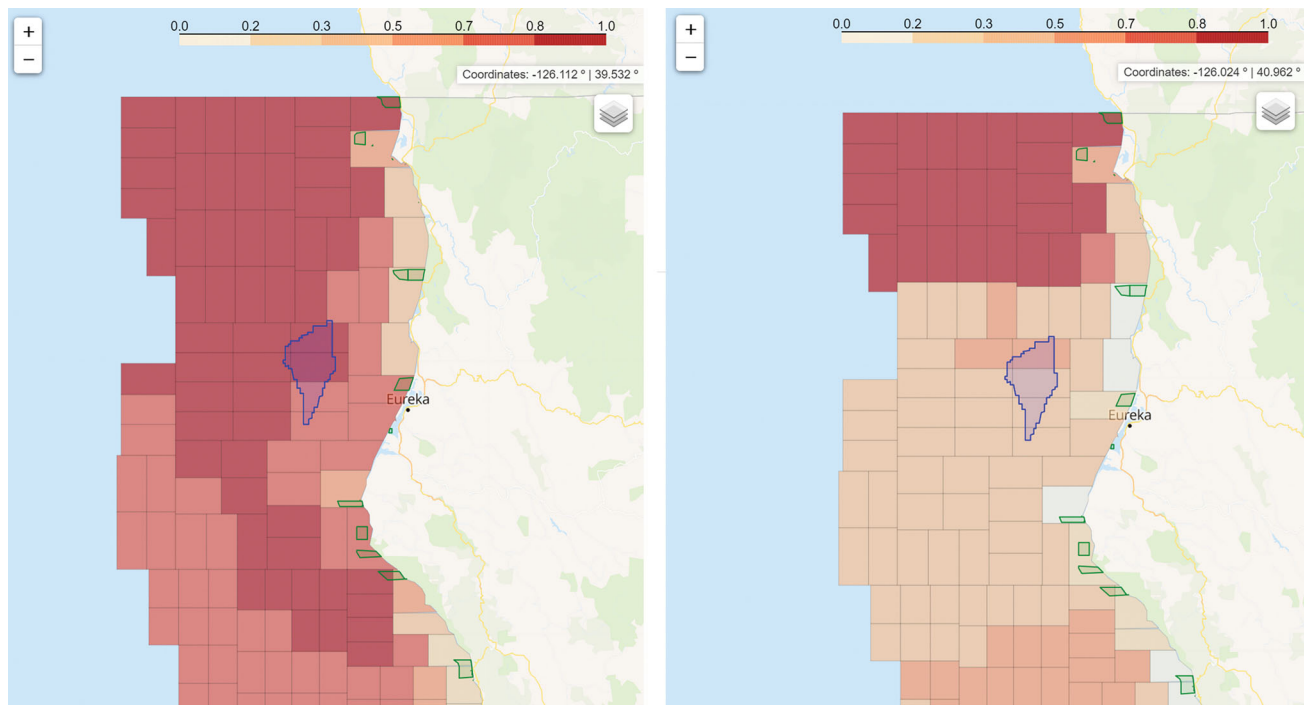


Figure 5. Suitability score visualization of Eureka Call Area of emphasizing nonfishery criteria (left) versus with consideration of fishery criteria (right).

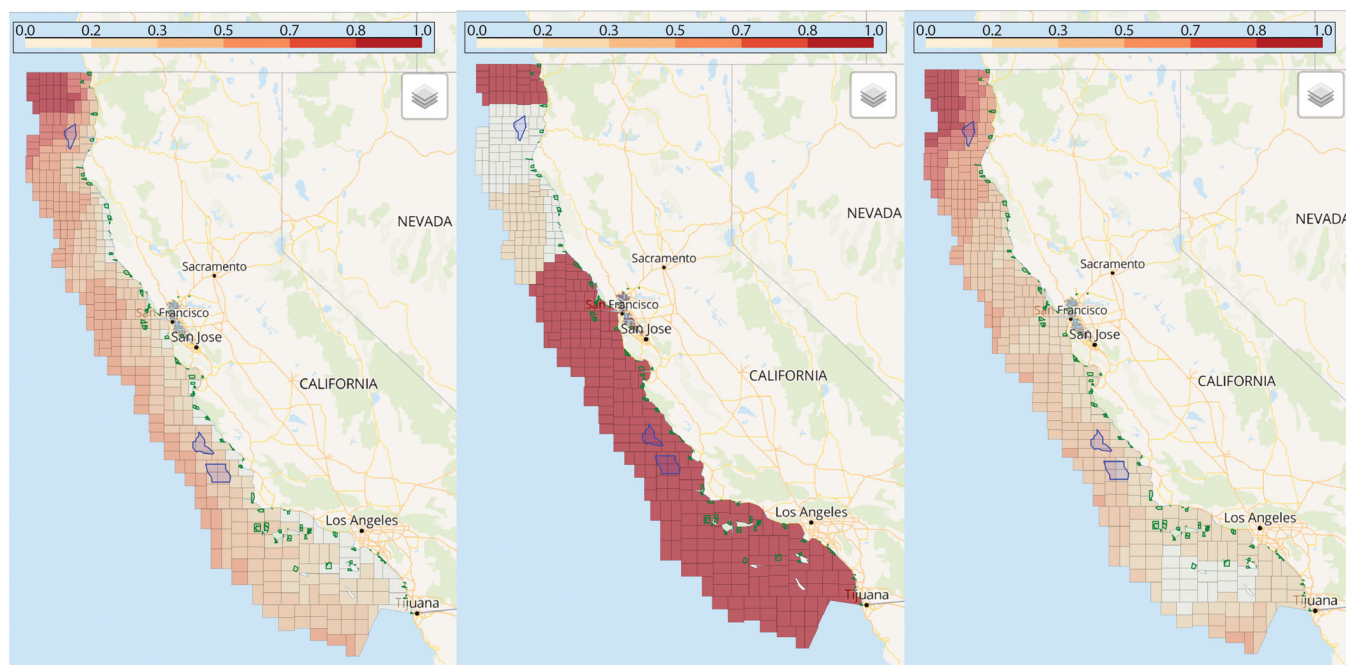


Figure 6. Suitability scores using decision alternative *LI_a* for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

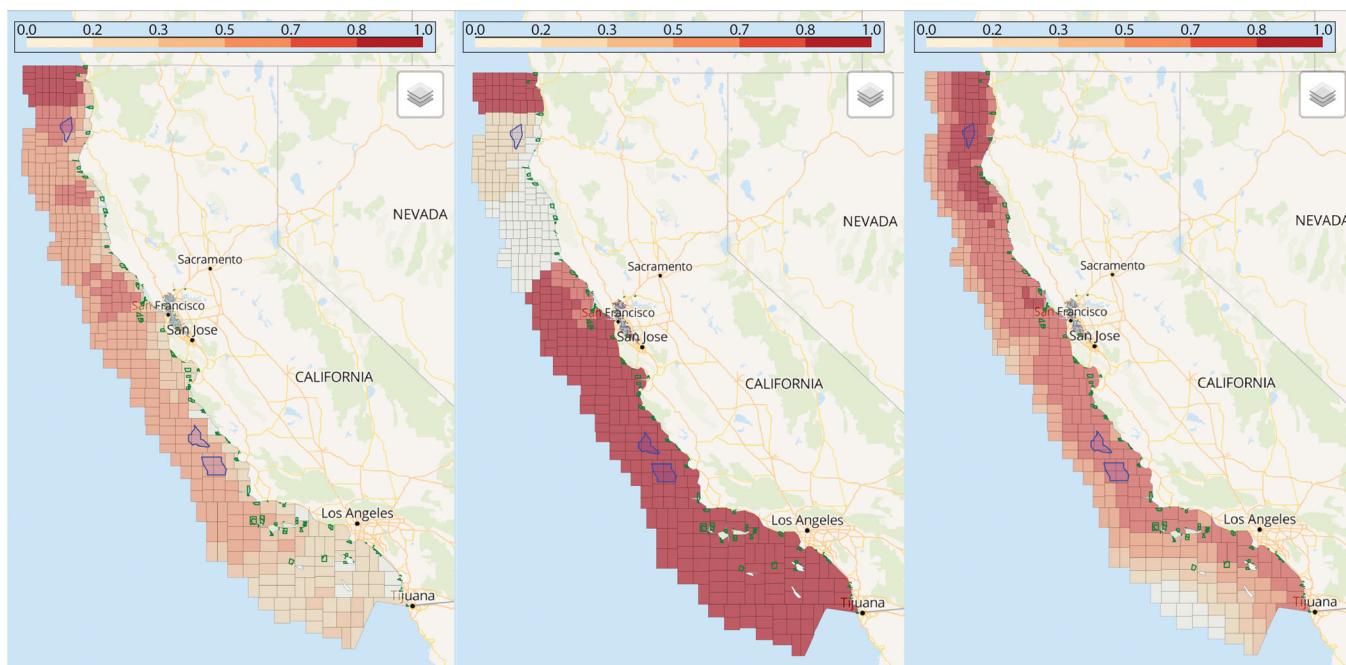


Figure 7. Suitability scores using decision alternative *LI_b* for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

the construction of offshore wind energy infrastructures, while concurrently minimizing environmental impacts. In this study, a model employing MCDA algorithms is introduced. This model integrates and synthesizes a range of crucial geospatial data along with fisheries statistics to compute suitability scores for

distinct areas, such as offshore wind site locations, forming the model's output. The developed model yields several pertinent applications:

1. The work reveals that the extant call area in the vicinity of Eureka failed to consider the potential adverse effects on fisheries during the decision-making process.

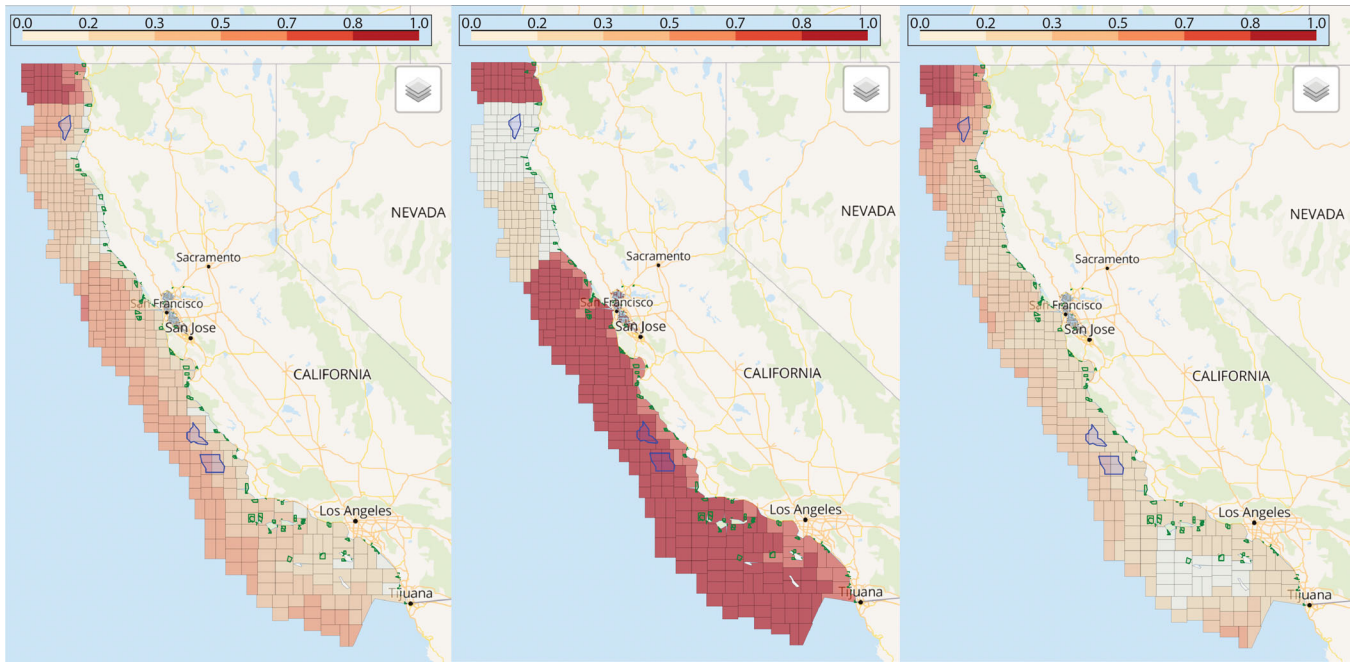


Figure 8. Suitability scores using decision alternative $L2_a$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

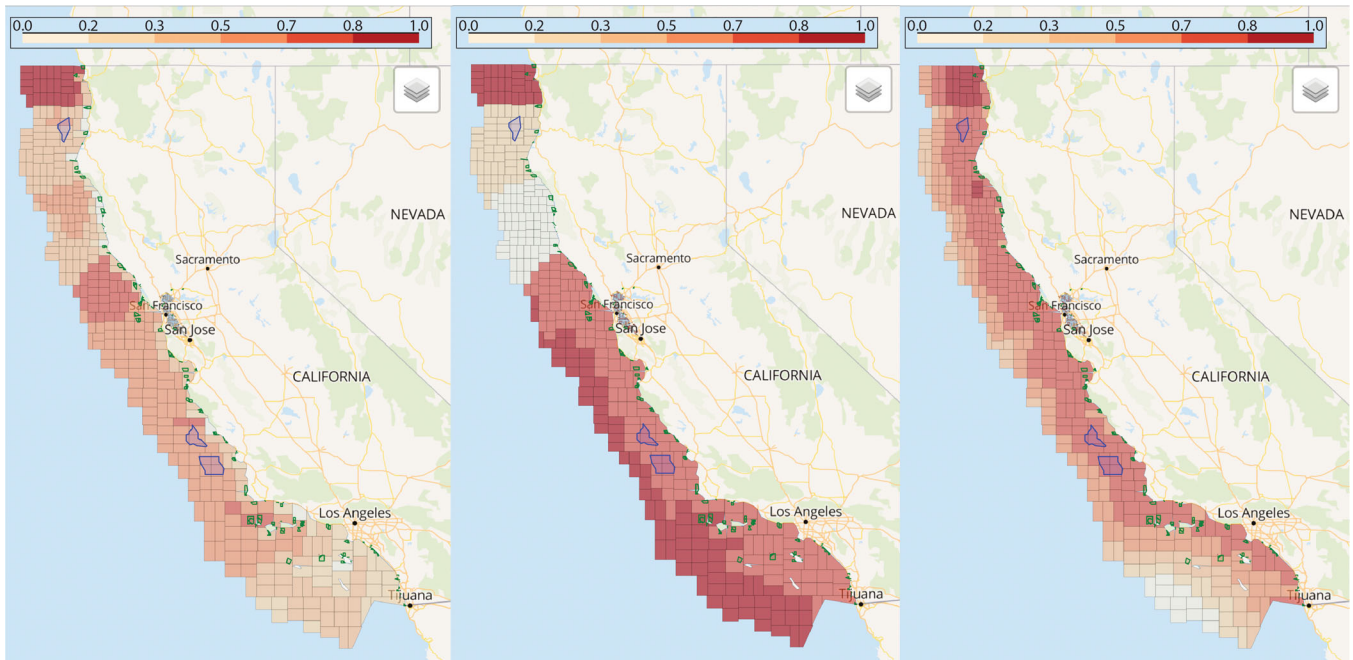


Figure 9. Suitability scores using decision alternative $L2_b$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

2. A variety of weight combination sets were provided as recommendations, indicative of decision choices catering to different stakeholders' focus. In each recommendation, the areas yielding the highest scores were highlighted.
3. A collaborative spatial decision support platform was constructed. This platform enables users to configure weight combinations more flexibly, thereby promoting a decision-making process that optimizes benefits for all concerned parties.

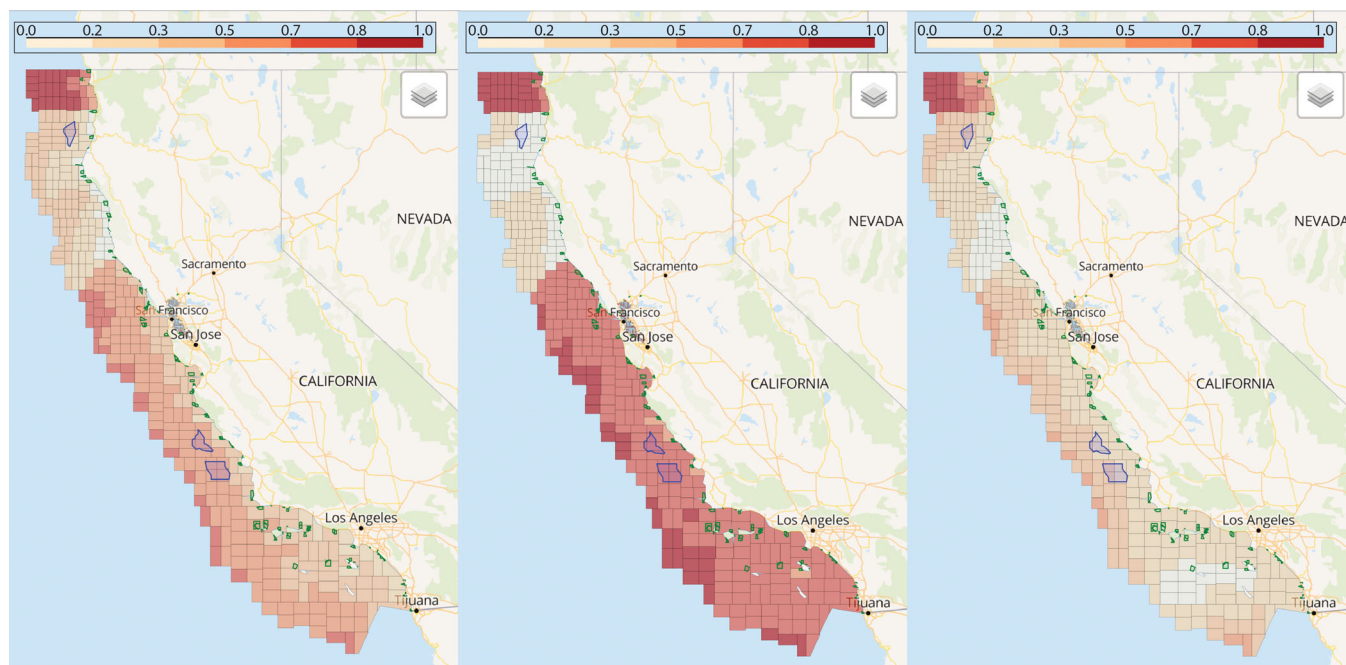


Figure 10. Suitability scores using decision alternative *L3_a* for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

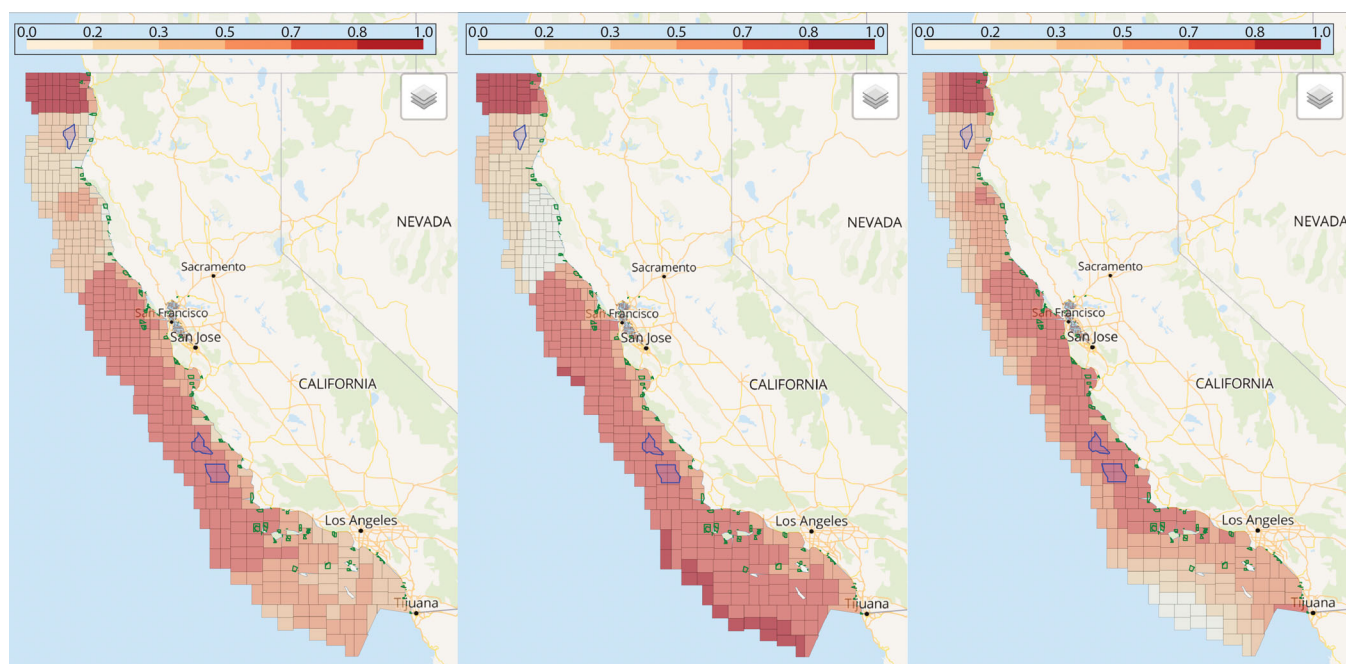


Figure 11. Suitability scores using decision alternative *L3_b* for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

In this section, the previously mentioned methods and conclusions are validated and evaluated mainly using sensitivity analysis (Simanaviciene and Ustinovichius 2010).

To illustrate how different criteria affect decision model outputs, we conducted a sensitivity analysis of all MCDM models using an open-sourced Python

Library SALib (Herman and Usher 2017; Iwanaga, Usher, and Herman 2022). The AHP method is particularly suited to capturing user inputs and converting them into combinations of weights; we executed a statistical evaluation of the outcomes from both first- and second-order sensitivity analyses. These analyses were derived using two MCDA algorithmic models, namely

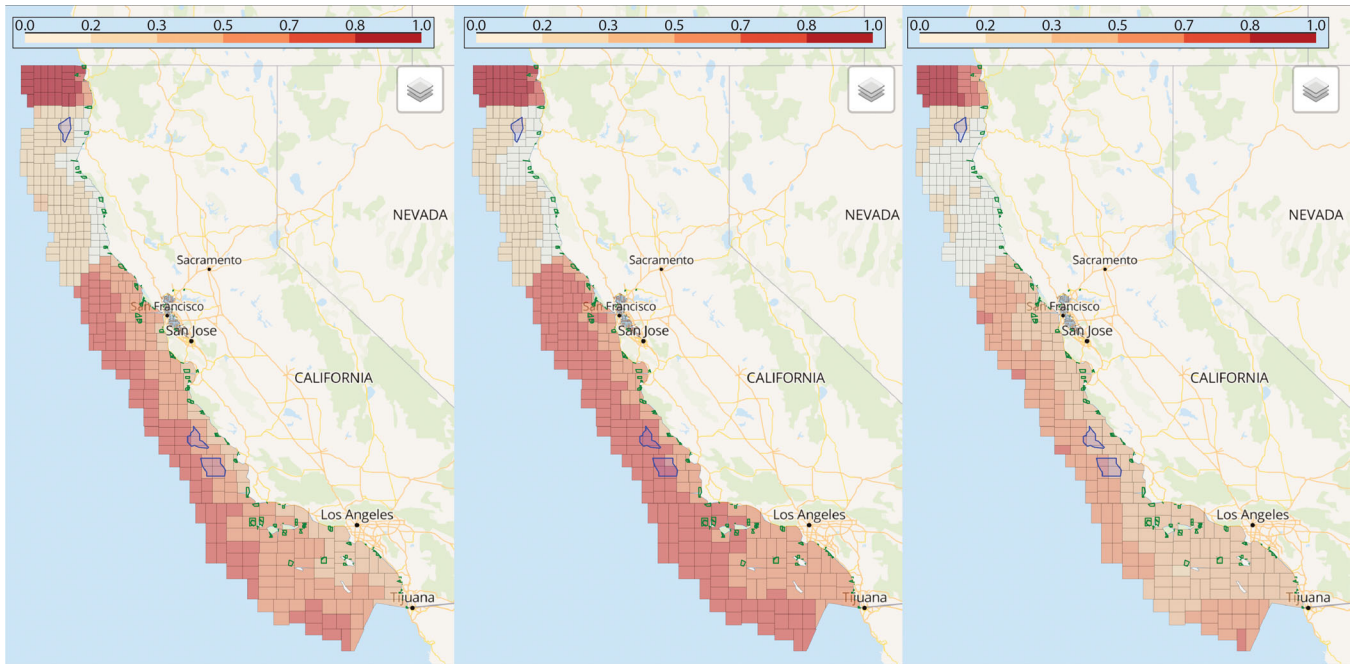


Figure 12. Suitability scores using decision alternative $L4_a$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

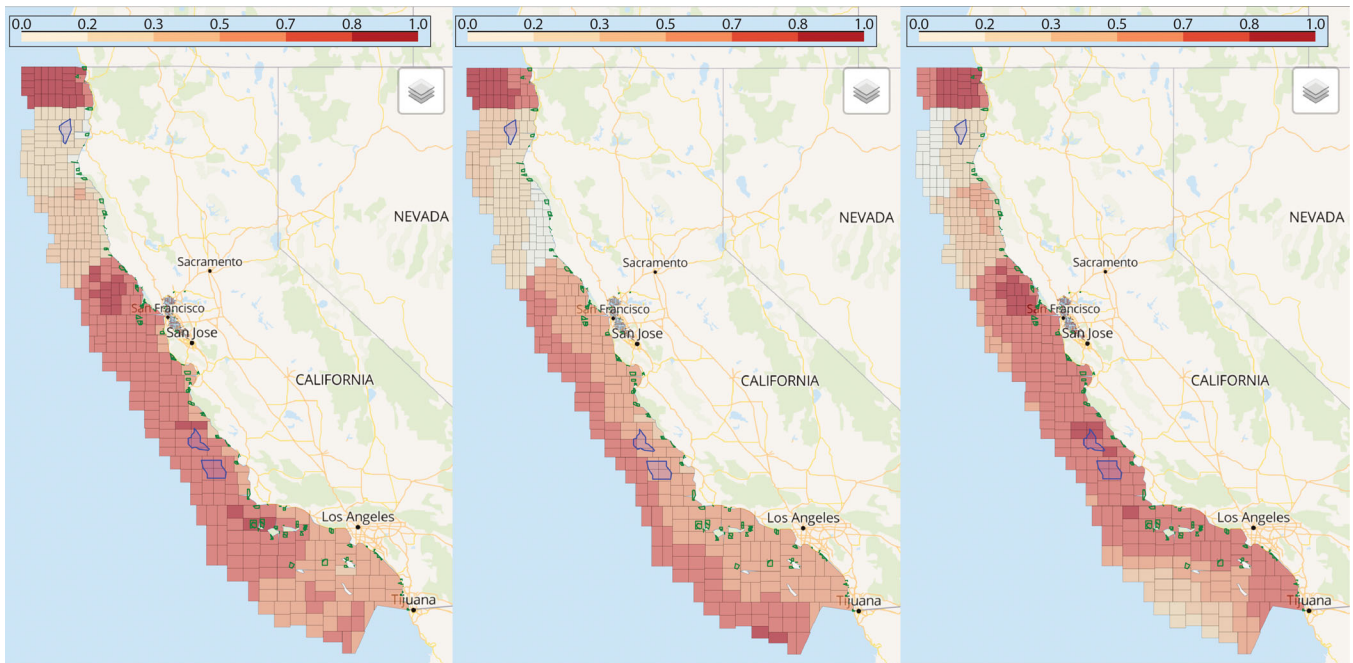


Figure 13. Suitability scores using decision alternative $L4_b$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

the WASPAS and TOPSIS. In sensitivity analysis, the first-order sensitivity index ($S1$ value) quantifies the impact of an individual criterion on the ultimate outcome, taking both the data and the model into account. As such, the $S1$ value in an MCDA model generally displays a strong positive correlation with its corresponding weight value. The correlation between the $S1$ values and their respective weight values under

the WASPAS and TOPSIS models is illustrated in Figure 16. The graphical representations indicate that both $S1$ values maintain a roughly linear positive correlation with weight values. The WASPAS method, however, offers a superior linear fit between $S1$ values and weights as compared to the TOPSIS method. This implies that the influence of a single criterion overall is more diffused in the TOPSIS model.

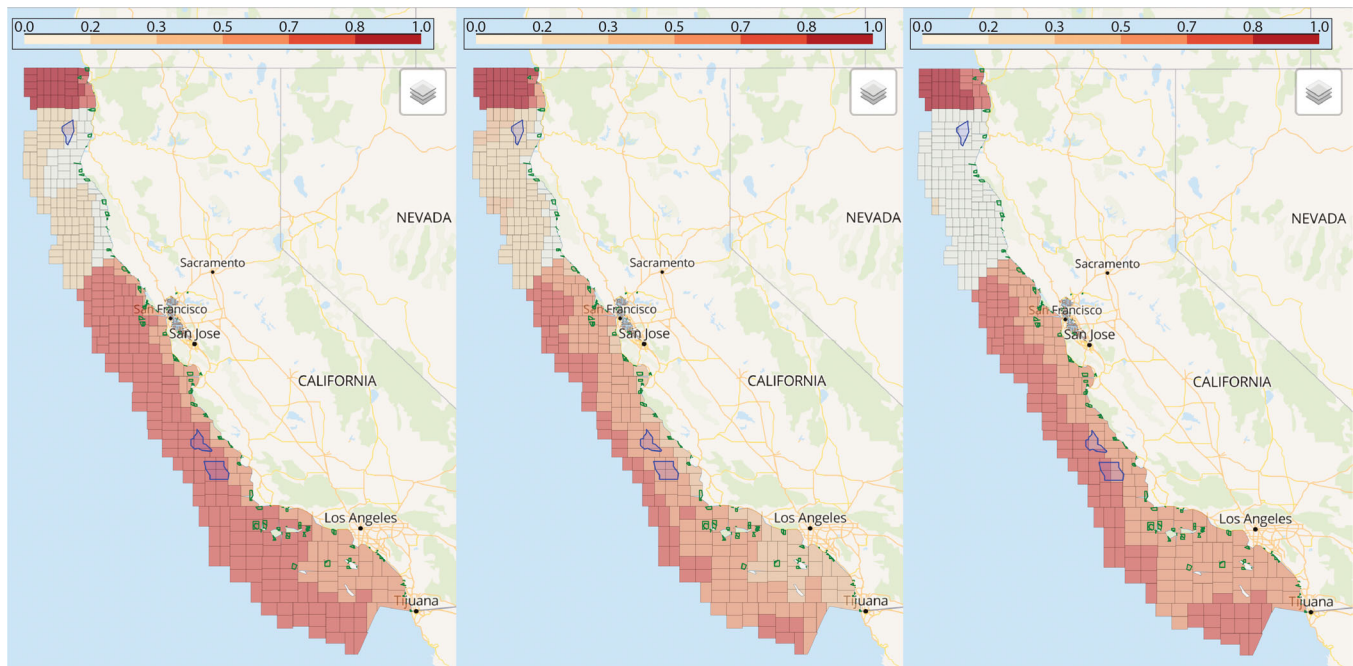


Figure 14. Suitability scores using decision alternative $L5_a$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

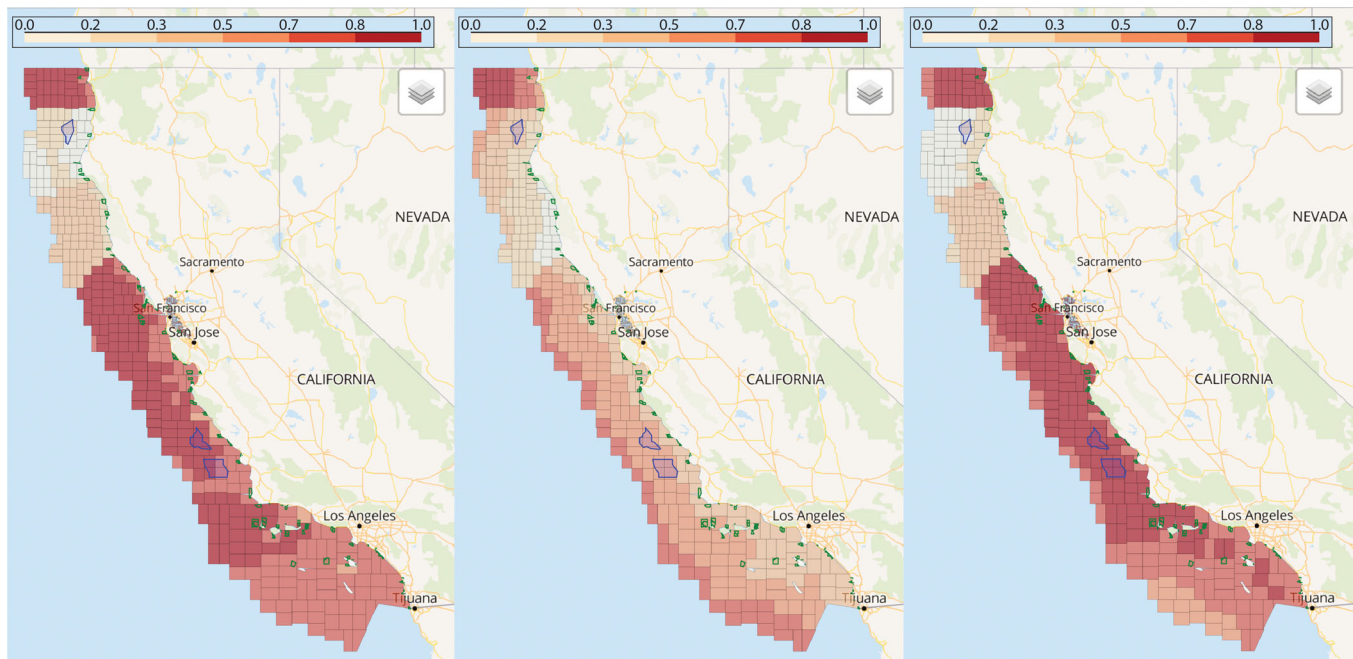


Figure 15. Suitability scores using decision alternative $L5_b$ for various algorithms. (A) WASPAS; (B) AHP; (C) TOPSIS.

In sensitivity analysis, although the first-order sensitivity index ($S1$) quantifies the impact of individual criteria on the outcome, the second-order sensitivity index ($S2$) gauges the combined influence of pairs of criteria. To visualize these $S2$ values for the two employed algorithms, we construct two upper triangular matrices, as illustrated by the heat

map in Figure 17. Notably, all $S2$ values are less than 10^{-3} , suggesting negligible interdependence between criteria. The homogeneity of these values further underscores the absence of data redundancy and criterion interdependence in our selection and regression processes. In the future, more indicators, including sea water temperature, sea floor depth, and

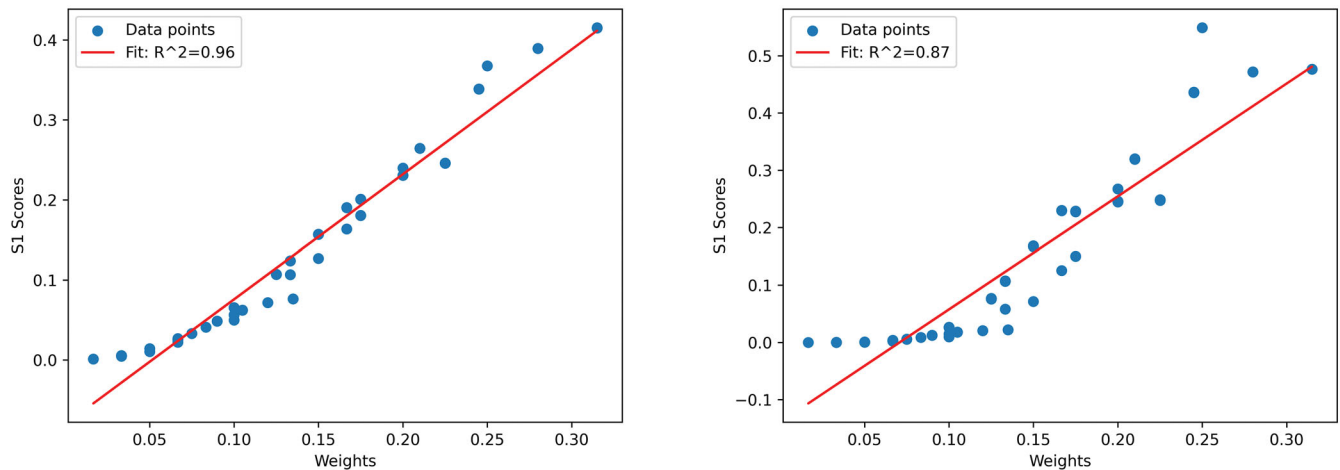


Figure 16. Relationship between first-order sensitivity analysis indexes and multicriteria decision analysis weights using WASPAS (left) and TOPSIS (right).

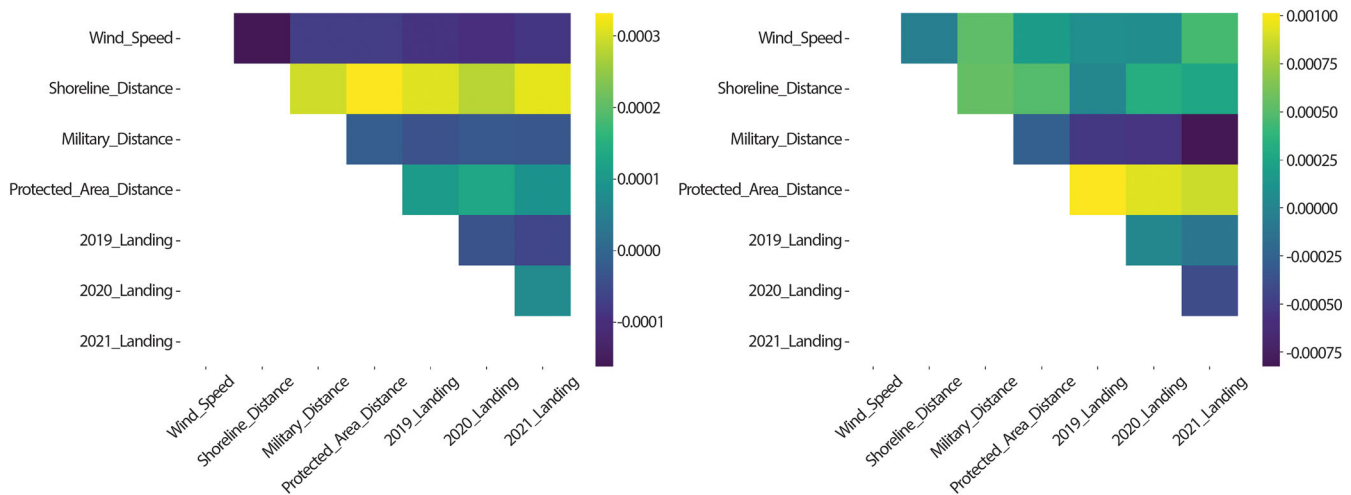


Figure 17. Second-order sensitivity scores heat map using WASPAS (left) and TOPSIS (right).

habitat movement data, could be combined into this proposed MCDM model to achieve compatibility for different groups of stakeholders. The flexibility and portability of this application make it adaptable to other geographic regions.

Conclusion

In this study, we implemented a Web-based spatial decision support framework, which integrated three types of MCDA models (WASPAS, AHP, and TOPSIS), and various indicators important in making decisions on offshore wind energy site selection and fishery landing statistics (California Department of Fish and Wildlife 2022) to enable a more efficient spatial decision-making process. There are three

major advantages of this MCDM. First, this proposed framework enables multivariate spatial data analytics by which multiple types of data sets can be combined into a single spatial decision-making platform. Second, conflicting decision goals are common issues in offshore wind energy plant site selection. In this article, besides the multicriteria baseline decision model (WSM), two types of MCDM models (AHP and TOPSIS) were adopted, where indirect decision criteria can be combined to meet several objectives and aid in complex decision-making problems. Third, this application supports collaborative decision-making by developing an interactive user interface in that users can assign weights for different criteria to reach a common goal in energy and fishery management. This tool provides a communication bridge between decision-makers and

practitioners in the fishery and wind energy fields to help them develop more sustainable management strategies.

Disclosure Statement

No potential conflict of interest was reported by the authors.

ORCID

Zhenlei Song  <http://orcid.org/0009-0007-5205-3808>

Zhe Zhang  <http://orcid.org/0000-0001-7108-182X>

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ZHENLEI SONG is a Graduate Research Assistant in the Department of Geography, Texas A&M University, College Station, TX 77843. E-mail: songzl8_950606@tamu.edu. His research interests include geospatial modeling for decision-making support and geospatial cyberinfrastructure.

PIERS CHAPMAN is Professor Emeritus in the Department of Oceanography, Texas A&M University, College Station, TX 77843. E-mail: piers.chapman@tamu.edu. His research interests include nutrient cycling in coastal areas, the oceanography of upwelling and other low-oxygen regions, and marine oil pollution.

JIAN TAO is Assistant Professor in the School of Performance, Visualization, and Fine Arts, Texas A&M University, College Station, TX 77843. E-mail: jtao@tamu.edu. He is affiliated with the Texas A&M Institute of Data Science, the Department of Electrical & Computer Engineering, the Department of Nuclear Engineering, and the Department of Multidisciplinary Engineering

Technology at Texas A&M University. His research interests include computational physics, high-performance computing, parallel programming, numerical algorithms, computational framework, data analytics, machine learning, and workflow management.

PING CHANG is Professor in the Department of Oceanography, Texas A&M University, College Station, TX 77843. E-mail: ping@tamu.edu. His research interests include climate dynamics and climate prediction, as well as global and regional climate modeling.

HUILIN GAO is Professor in the Department of Civil & Environmental Engineering, Texas A&M University, College Station, TX 77843. E-mail: hgao@tamu.edu. Her research interests include hydrometeorology, hydroclimatology, hydrological modeling, satellite remote sensing, climate change, and water resources management.

HONGGAO LIU is Executive Director of High-Performance Research Computing, Texas A&M University, College Station, TX 77843. E-mail: honggao@tamu.edu. He is also affiliated with the

Department of Geography as graduate faculty. His research interests include chemical engineering, computational fluid dynamics, high-performance computing, numerical simulation and modeling, computational and data sciences, artificial intelligence and machine learning, and cyberinfrastructure.

CHRISTIAN BRANNSTROM is Professor in the Department of Geography, Texas A&M University, College Station, TX 77843. E-mail: cbrannst@geog.tamu.edu. His research interests include social and political aspects of renewable energy and unconventional fossil fuels in Texas.

ZHE ZHANG is Assistant Professor in the Department of Geography and the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843. E-mail: zhezhang@tamu.edu. Her research interests include GIScience and within it, a focus on cyberinfrastructure, knowledge-driven spatial decision-making, spatial uncertainty modeling, human-centered geospatial artificial intelligence, and social sensing.