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Review

Evaluation of decision-support tools for coastal flood and erosion control: A multicriteria perspective

Andrés M. Enríquez-Hidalgo [a,b,c,*], Andrés Vargas-Luna [a,c], Andrés Torres [a,c,d]

[a] Civil Engineering Department, Engineering School, Pontificia Universidad Javeriana, Colombia
[b] Laboratori d'Enginyeria Marítima, Universitat Politècnica de Catalunya (LIM/UPC)–Barcelona Tech, Spain
[c] Ciencia e Ingeniería del agua y el ambiente Research Group, Pontificia Universidad Javeriana, Colombia
[d] Instituto Javeriano del Agua, Pontificia Universidad Javeriana, Carrera 7a No. 40-62, Bogotá, Colombia

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ABSTRACT

Coastal areas face significant challenges due to natural and anthropogenic changes, such as sea level rise, extreme events and coastal erosion. The coastal management requires the consideration of socioeconomic and environmental factors to address these variables. The selection of an appropriate Decision Support Tool (DST) based on decision matrix method plays a crucial role in implementing coastal management strategies to tackle climate change-related issues. This has posed considerable challenges for decision-makers, aligning with the Sustainable Development Goals (SDG). This review provides an overview of the practical experience in the application of DSTs for coastal erosion and flood risk, emphasizing the use of Multi-Criteria Decision Analysis (MCDA). DST choice depends on the coastal archetype, including its geographical features and sociocultural context. The purpose is to clarify how the integration of DSTs maximizes flexibility and supports the implementation of future Decision Support System (DSS) tailored to the needs of coastal cities with development pathways (DP). This review assesses different MCDA methods, highlighting their applicability, utility, and integration in coastal management, while evaluating each method's strengths, weaknesses, and specific applications, with a focus on sustainability and resilience. The review highlights the necessity of expert knowledge in accurately defining criteria and weighting factors to ensure that the chosen MCDA method reflects the complexities of the coastal environment. Depending on the scenario, methods like PROMETHEE and ELECTRE are recommended for their flexibility and robustness in handling complex decision-making processes, especially in data-rich and well-structured environments. In contrast, TOPSIS and AHP are suitable for scenarios with limited information or requiring minimal interaction with decision-makers. For more challenging contexts, where computational resources and expertise are constrained, methods like MAUT, VIKOR, and TODAIM emerge as viable alternatives due to their adaptability and reduced reliance on extensive datasets.

1. Introduction

Coastal zones are dynamic regions significantly influenced by natural phenomena and human activities, exacerbated by climate change effects, posing significant challenges to decision-making processes regarding their vulnerability, hazard assessment, and exposure (CNR-ISMAR et al., 2020; Lawrence et al., 2019a; N. G. Rangel-Buitrago et al., 2015; Xu et al., 2023). Coastal systems are complex, with non-linear interactions, thus understanding the processes and responses to climate-induced changes is vital for effective risk management strategies or development pathways (DP) such as hard engineering measures, soft engineering measures, sediment-based measures, nature-based measures, adaptation of the built environment, advancement, and retreat (Glavovic et al., 2022; N. Rangel-Buitrago et al., 2018). Additionally, climate change impacts such as sea level rise (SLR), salinization, changes in wind patterns, waves, and coastal circulation, increase the risk of erosion and flooding (Akash et al., 2024; Wainwright et al., 2015).

While traditional adaptation strategies like coastal "hardening" exist, there is growing awareness of their issues (New et al., 2022). The emergence of a need for long-term, passive solutions that focus on strengthening the resilience of these communities, especially during extreme events is required, highlighting that a growing recognition exists that focusing on long-term, passive solutions and building

* Corresponding author. Civil Engineering Department, Engineering School, Pontificia Universidad Javeriana, Colombia.
E-mail address: enriquez_andres@javeriana.edu.co (A.M. Enríquez-Hidalgo).

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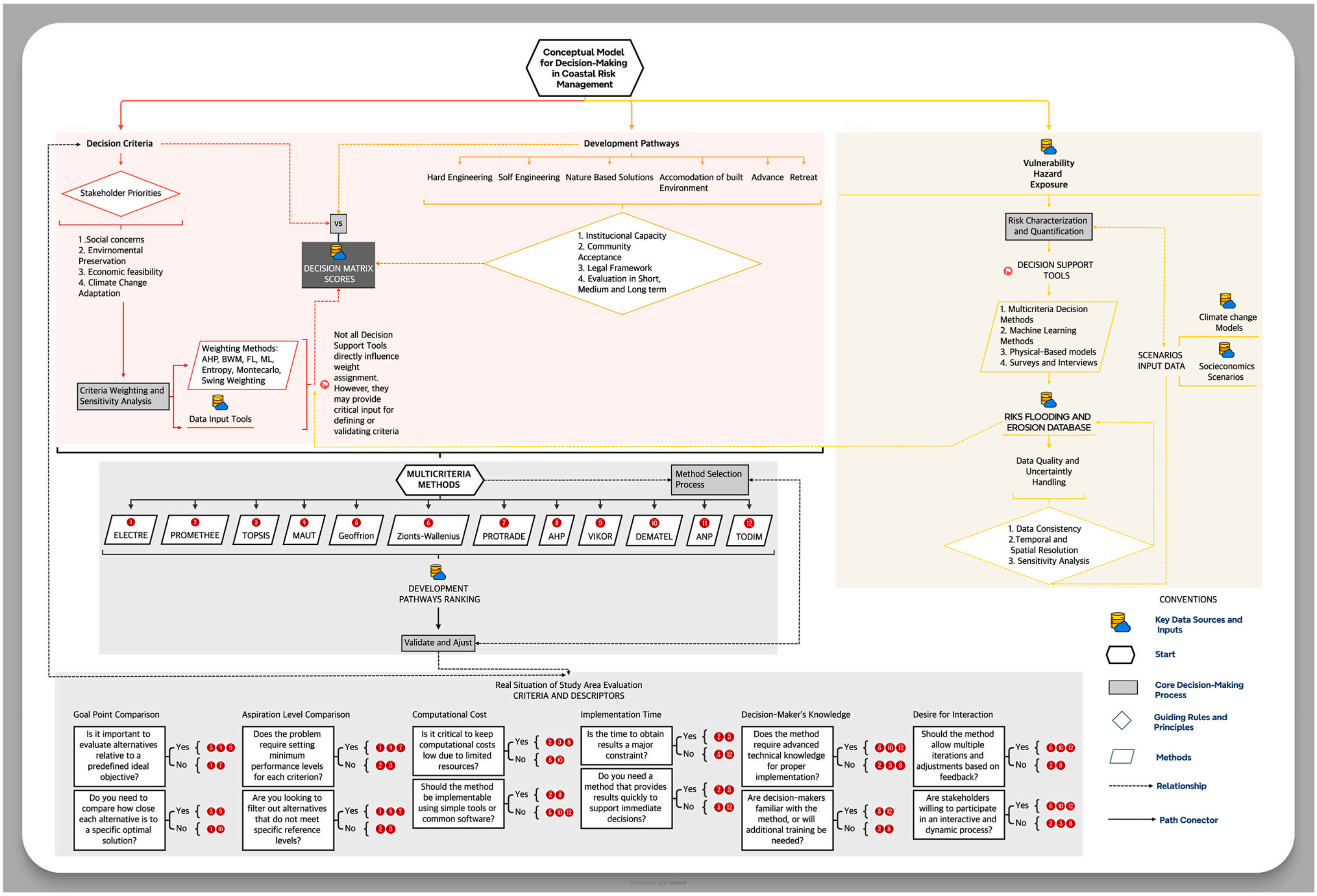

Fig. 1. Conceptual model for selecting decision-support methods for flooding and erosion management.

governance capacities, could foster climate-resilient growth (Glavovic et al., 2022; New et al., 2022; O'Neill et al., 2022; Schipper et al., 2022). However, an "adaptation gap" remains, as most interventions being reactive responding to incidents, problems and risks as they appear and materialize (Kao et al., 2023; Wainwright et al., 2015).

Factors such as city archetype, socioeconomic conditions, as well as cultural, political, and institutional considerations, are critical for the success of these strategies in specific areas. To quantify these factors, the literature concludes that relying solely on a single DP is inadvisable. Instead, the integration of DSTs with DP becomes pivotal (Glavovic et al., 2022; Haasnoot et al., 2019). The review of the efficiency of combining data-driven and model-based DSTs with DP has not yet been developed, but the application of hybrid strategies, which integrate hard and soft protection measures, are considered efficient and cost-effective, subject to the specific archetype of the area (Dovie and Pabi, 2023; Toimil et al., 2020; Wang et al., 2021). Consequently, the analysis of hybrid strategies using the results of DST methods based in decision matrix evaluation, combined with a graphical user interface (GUI), can result in the creation of what is referred to as a DSS (Narne et al., 2024; Terribile et al., 2024).

There are two types of DSTs. The first type provides a comprehensive representation of environmental, socioeconomic, and cultural aspects within various coastal archetypes (De Valck et al., 2023), its primary aim to capture dominant phenomena and provide relevant indices representing flood and coastal erosion risks across different timescales and specific contexts (Barzehkar et al., 2021a; Dovie and Pabi, 2023; Glavovic et al., 2022). Each tool, which includes MCDA, machine learning, and physics-based models, possesses different requirements and levels of uncertainty (Asiri et al., 2024; Toimil et al., 2020; Wang et al., 2021).

The second type comprises decision matrix-based DSTs such as ELECTRE (*ELimination Et Choix Traduisant la REalité*), PROMETHEE (*Preference Ranking Organization Method for Enrichment Evaluation*), TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*), MAUT (*Multi-Attribute Utility Theory*), Geoffrion method, Zionts-Wallenius method, PROTRADE (*Probabilistic Trade-off Development method*), AHP (*Analytic Hierarchy Process*), VIKOR (*VlseKriterijumska Optimizacija I Kompromisno Resenje*), DEMATEL (*Decision-Making Trial and Evaluation Laboratory*), ANP (Analytic Network *Process*), and TODIM (*Tomada de Decisão Interativa Multicritério*), which use the outputs from the risk characterization DSTs (e.g., flood and erosion indices translated into scores and assigned appropriate weights to criteria) to create Decision Support Systems (DSS). These DSTs expand decision-making beyond the usual reactive, economically driven protocols based on cost-benefit principles and rigid engineering approaches (Cooper and McKenna, 2008; Kao et al., 2023). The selection of the appropriate DSTs depends on factors such as data requirements, ease of application, and associated uncertainty (Asiri et al., 2024; Smith et al., 2000).

As such, the purpose of an adequate results of decision matrix-based DSTs involves overcoming several challenges that have not yet been fully resolved: (i) the selection of appropriate method for the case study (Barzehkar et al., 2021b); (ii) the integration and coupling of risk, vulnerability, and resilience indicators (Barzehkar et al., 2021b; Mohammadifar et al., 2023; Walling and Vaneeckhaute, 2020); (iii) the propagation (cascading) of uncertainties originating from different sources (e.g., emission scenarios, climate models, downscaling techniques, coupled morphodynamic-wave models, and data) (Barzehkar et al., 2021b; H. Sun et al., 2024; Walling and Vaneeckhaute, 2020).

In the face of these challenges, it is crucial to review the

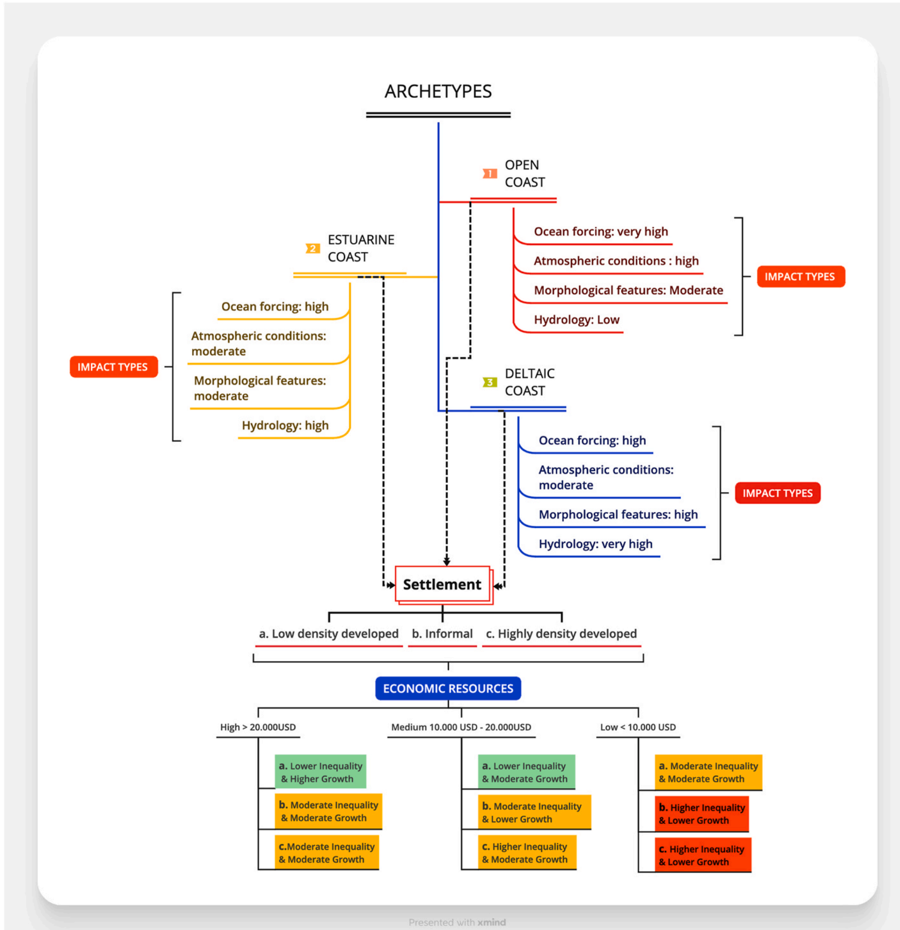

Fig. 2. Level of inequality, growth, and impacts of coastal archetypes.

methodologies approach for the implementation of the first type of DSTs in the management of coastal zones. Barzehakar et al. (2021a) provide a benchmark review for the construction of coastal indices calculated through these tools, essential for managing data variability, planning scale, and processing capacity. Studies such as Gudiyangada et al. (2020) emphasize the practical dimensions of applying various existing DSTs for flood susceptibility mapping, highlighting how Machine Learning methods demonstrate slightly better predictive performance compared to MCDA methods. Similarly, Asiri et al. (2024) applied AHP with fuzzy logic to evaluate coastal flood vulnerability, while Sapiega and Zalewska (2024) employed a physically-based coupled model to generate high-resolution wave data using SWAN and predict sediment transport and beach flooding through the coupling of the SWANOneSed sediment transport model. This approach was aimed at characterizing flood hazards during storms.

There is significant research focused on coupling, integrating, and combining different DSTs with the sole purpose of characterizing vulnerability, hazard, and exposure to flooding and occasionally erosion in coastal zones. These studies emphasize that, across the three described approaches Machine Learning, MCDA, and physically based models all findings consistently agree that when two or all three approaches are combined, the results for prediction and classification improve substantially (Akash et al., 2024; Asiri et al., 2024; Terribile et al., 2024; Xu et al., 2023).

However, the calculation of coastal indices with this kind of DST is not sufficient to choose a DP. It is necessary to evaluate the performance of each known DP based not only on flood risk indices but also on criteria such as climate change adaptation, environmental, social, and economic impact (Lawrence et al., 2019b; Narne et al., 2024). This Multi-Criteria Decision Analysis (MCDA) based on decision matrix-based DSTs approach reduces uncertainty in decision-makers' preferences and supports the development of future DSS with graphical user interfaces (GUI) that classify DPs within decision matrices, allowing for the identification and ranking of those most effective in mitigating flood and erosion risks across various planning horizons (Fei et al., 2019; Walling and Vaneeckhaute, 2020).

The absence of a clear and standardized guide for selecting and integrating these tools into environmental management, specifically in coastal risk management, remains an evolving topic of interest in the current era. For instance, Abounaima et al. (2020) highlight that over four decades of research have attempted to compare these DSTs, concluding that "a direct comparison between the two methods is normally far from common sense and becomes subjective." Nevertheless, rational methods, such as correlations between the results of different methods, have shown that ELECTRE II outperforms TOPSIS in terms of environmental preservation and protection performance across EU states. In this context, Allah Bukhsh et al. (2019) emphasize the challenge of choosing a DST among MAUT, AHP, and ELECTRE III for infrastructure management (e.g., prioritizing maintenance needs), which not only involves technical requirements but also social and economic developments. They highlight that a software-based approach facilitates the scalability of these methods, finding a consistent trend in their results.

For coastal zones, Wu et al. (2020), applied PROMETHEE to select an optimal site for offshore wind power stations (OWPS), developing a theoretical and methodological framework for decision-making in response to the deficiencies of integrated coastal management. They noted that previous research on MCDM problems has overly focused on

Table 1
Decision-support tools characteristics.

Method	Advantages	Disadvantages	Success Cases	References
Analytical Hierarchical Process (AHP)	Structured and validated; effective for pairwise comparisons	Limited flexibility; subjective variable selection.	Beach erosion sensitivity indicators.	Díaz-Cuevas et al. (2020).
Weighted Linear Combination (WLC)	Integrates socioeconomic factors effectively	Assumes variable linearity; weak in spatial predictions	Flood plain management.	Mokrech et al. (2012).
Fuzzy Logic (FL)	Reduces uncertainty; incorporates expert input	Requires significant expertise for membership functions	Development of coastal vulnerability indices for areas prone to flooding and erosion.	Mullick et al. (2019)
CoastSat (GEE)	Efficient for long-term shoreline analysis.	Limited to sandy coasts; ~10 m horizontal accuracy	Retrieving shoreline positions over time for any sandy coast worldwide.	Vos et al. (2019).
Bayesian Networks (BN)	Models complex causal relationships effectively	Computationally intensive; requires data harmonization	Risk analysis and GIS output mapping of flood and erosion risk.	Furlan et al. (2020)
Artificial Neural Networks (ANN)	Handles large datasets; adapts to complex patterns.	"Black box" models; low interpretability.	Used in predictive modeling in various fields, including coastal erosion patterns.	Peponi et al. (2019)
Physically-Based Models	Accurate simulation of physical processes.	High computational demand; input data often unavailable.	Applied in predicting the impact of coastal storms sea-level rise and wave patterns.	Sun et al. (2021)

the mathematical complexity of the methods while neglecting rationality, rendering conventional methods unable to meet the requirements for OWPS site selection. Furthermore, they justified the choice of PROMETHEE for resolving the problem of attribute differences. Finally, concerning physical flood susceptibility and measuring changes in the physical vulnerability of coasts, Mondal et al. (2024) highlight and justify the use of AHP, as recent studies of this type have utilized the same method (Ali et al., 2019; Arif et al., 2023; Bera and Maiti, 2021; Ghosh et al., 2023; Kaya and Derin, 2023; Mohanty et al., 2023).

This knowledge gap, originating from the application of these tools often without a rational justification for method selection, is what we close with this research. Through a conceptual model (Fig. 1), we provide developers and decision-makers with a practical guide to selecting a method adapted to the specific needs of flood and erosion management in coastal zones.

Each section of this review addresses these aspects, starting with the evaluation of coastal flooding and erosion management (Chapter 2) and continuing with the description of the most effective DSTs for representing vulnerability, exposure, and risk (Chapter 3). Subsequently, Development Pathways (DPs) are analyzed, highlighting the advantages and disadvantages of their application based on coastal archetypes, planning horizons, and levels of development (Chapter 4). Then, the review explores MCDA techniques based on decision matrix DSTs for constructing and evaluating a Decision Support System (DSS), detailing the steps required to apply each method and how expert judgment and uncertainty reduction improve the assessment of DP performance (Chapter 5). Finally, the review analyzes the process for selecting the appropriate MCDA method based on the specific decision problem, considering relevant descriptors for coastal flooding and erosion, and evaluating each method according to applicable criteria in coastal decision-making (Chapter 6).

2. Flood risk management and coastal erosion

Coastal flooding and erosion are significant sources of coastal risk, often studied separately due to their complex interactions across different spatial and temporal scales (Penning-Rowsell et al., 2014). Flood and drought-related risks, identified as top global concerns in 2023 by the World Economic Forum (World Bank Group, 2023), result from the interplay of socioeconomic and environmental factors, particularly impacting coastal regions. Additionally, coastal erosion is closely linked to sea-level rise (SLR), whether caused by extreme events, chronic erosion, or land loss due to increased flooding (Pollard et al., 2019).

Coastal flooding is the temporary inundation of land typically not submerged and coastal erosion is defined as the net removal of material from one coastal location to another (N. G. Rangel-Buitrago et al., 2015), both driven by natural and anthropogenic factors such as changes in wave energy, reduced sediment supply (Bomer et al., 2020), accelerated global SLR, local land subsidence (Pollard et al., 2019), population density growth (Luo et al., 2013), asset concentration in coastal zones (Melby et al., 2020) and potential climate changes (Glavovic et al., 2022). Understanding these trends is crucial for informed decision-making regarding mitigation and adaptation (Cooper and McKenna, 2008; Pollard et al., 2019; N. Rangel-Buitrago et al., 2018).

Managing flooding risk and coastal erosion is challenging due to the intricate interactions among coastal drivers, morphological responses, and risk factors. Although often treated separately, it is essential to consider them together as they are interconnected. According to Spencer and Brooks (2019), three key expressions of this interaction are identified: (i) coastal morphology modifies flood hazard, (ii) future flood risk depends on the changing position of the coast, (iii) simultaneous occurrence of erosion and flooding events. These interactions are influenced by the coastal archetypes, representing different geomorphological characteristics, urban growth patterns, economic resources, and inequalities that creates unique exposure and vulnerability; additionally, climate change further compounds these risks (Glavovic et al., 2022; Hanson and Nicholls, 2020).

Fig. 2 depicts the degree of risk based on the coastal archetype, highlighting that estuaries and deltas have a higher hydrological risk compared to open coasts. This classification is crucial for understanding the differential vulnerabilities these regions experience, which directly informs the selection of appropriate DPs (Glavovic et al., 2022). It also classifies the level of growth and inequality based on the density of occupation within the archetypes and the level of economic development using the Urban Annual Gross Domestic Product per Capita (USD, 2020), further influence the resilience or vulnerability of coastal settlements. Understanding these variations is key to selecting the most suitable MCDA methods for decision-making, as areas with higher inequality and informal growth (highlighted in red) are more vulnerable and require different management strategies compared to regions with low-density development and higher economic resources (highlighted in green).

3. How are DST configured to obtain coastal indices for managing erosion and flooding in coastal cities?

3.1. *Methodologies for evaluating hazard, vulnerability, exposure, and risk*

Different methods have been used for coastal management by specifying and prioritizing vulnerable areas and classifying them based on evaluation criteria provided by experts (Adem Esmail y Geneletti, 2018). For example, MCDA has been used with methods such as Analytic Hierarchy Process (AHP), Fuzzy Logic (FL), Weighted Linear Combination (WLC), Bayesian Networks (BN), Artificial Neural Networks (ANN) and physical based models to enhance its capabilities by incorporating different types of information, availability, and quality. This combination can provide optimal results depending on the decision-makers'

Table 2
Coastal indices.

Index	Description	Advantages	Disadvantages	References
Coastal Vulnerability Index (CVI)	Represents potential deterioration around the coast, including physical, environmental, and socioeconomic factors. Classification depends on case study and current situation. Calculation involves WLC of CCVI, CFVI, and SEVI.	Provides a comprehensive scenario of vulnerability. Combines multiple factors (physical, environmental, socio-economic).	Classification depends on case study and current situation. Socioeconomic variables need re-evaluation for each case study.	(Barzehkar et al., 2021a; Yariyan et al., 2020; Mullick et al., 2019; N. Rangel-Buitrago et al., 2018; Mclaughlin and Cooper, 2010)
Coastal Exposure Index (CEI)	Evaluates socio-economic criteria and classifies at-risk targets based on flooding and erosion risk. Quantification involves using water level maps and MCDA method for assigning weights to each criterion.	Classifies at-risk targets effectively. Uses socio-economic criteria and water level maps.	Requires accurate water level maps. Relies on socio-economic criteria which might vary.	(Barzehkar et al., 2021a; Bagdanavičiūtė et al., 2019; Mullick et al., 2019)
Coastal Risk Index (CRI)	Derived from CVI and CEI, reflecting current and future hazards. Provides numerical basis for classifying coastal sections and identifying regions of higher risk.	Reflects relevant characteristics of the study area. Combines CVI and CEI for a holistic risk assessment.	Dependent on the quality of CVI and CEI data. Might not cover all relevant hazards.	(Barzehkar et al., 2021a; Bagdanavičiūtė et al., 2019; Mullick et al., 2019).
Coastal Area Index (CAI)	Developed under MCDA approach. Transforms dataset pixels into utility values based on environmental sensitivity, assigns weights based on land-use planning, and calculates CAI using WLC.	Transforms dataset pixels into utility values. Uses MCDA approach for environmental sensitivity.	Utility values and weights need validation. Requires good spatial resolution for accurate results.	(Barzehkar et al., 2021a; Dhiman et al., 2018, 2019).
Coastal Resilience Index (CoRI)	Measures urban coastal system's capacity to cope with hazardous events. Articulated into four subsystems: socioeconomic, physical, functional, and geomorphological. Uses AHP for weighting indicators and quantifying urban coastal resilience.	Measures urban coastal system's capacity with a focus on four subsystems. Uses AHP for weighting indicators. Utilizes vector data, which is advantageous with good information.	Uses vector data, which is a disadvantage in areas with limited information. Complex weighting and aggregation process.	(Gargiulo et al., 2020; Roy et al., 2019)

specific situation (Barzehkar et al., 2021b).

The DSTs compilation that have been applied to different coastal archetypes indicates that the knowledge gap of the lack of a "standard guide," as indicated in various studies (Barzehkar et al., 2021a; N. Rangel-Buitrago et al., 2018), has been filled. It can be stated that all studies on flood and coastal erosion risk management now include the mandatory use of a GIS engine combined with a multicriteria analysis tool that encompasses the process of data collection, normalization, weighting, and integration of different physical and socioeconomic variables specific to the archetype. Now the problem in flood and erosion risk management lies in the lack of a guide that includes the DST vs DP to obtain useful results for decision-makers. Table 1 presents the DST methods along with their application characteristics, which are contingent upon the available data, technical expertise, socioeconomic development, and the management level chosen by decision-makers for the application of specific decision processes. This DST provide outputs that can be distinguished as maps at a specific spatial resolution, with different variables and indices of interest representing a categorical measure of the influencing factors on coastal archetypes.

3.2. Coastal indices as DSTs

The integration of factors and processing with DSTs leads to the creation of coastal indices that represent the degree of vulnerability, exposure, and threat in coastal zones. The review indicates that several indices exist; however, the most advanced ones are presented in Table 2.

4. Development pathways (DP) in coastal archetypes

DP approach can facilitate long-term thinking, anticipate maladaptive consequences and blockages, and address dynamic risk vs. unrelenting and potentially high SLR. This approach can also frame adaptation as a series of manageable steps over time, using a combination of hard, soft, and nature-based interventions to implement strategies that protect, accommodate, regress, and advance, either individually or in combination depending on the context (Du et al., 2020). DP can be adjusted to new information on SLR and other climate risks, considering economic, environmental, social, institutional, technical, or other objectives. In cases of rapid SLR, it may be necessary to implement a short-term protection strategy to buy time for the implementation of more transformative and lasting strategies (Morris et al., 2020). There is a high agreement that combining and sequencing adaptation interventions can reduce risk over time. Additionally, incremental interventions can help spread costs and minimize risk if options to adapt to changing conditions are kept open (Du et al., 2020).

In the Mediterranean context, where tourism and historical infrastructure are key economic pillars, hard engineering measures have been vital for safeguarding coastal cities with high cultural value and population density. For instance, in Venice, Italy, the MOSE system was designed not only to mitigate flooding but also to protect the city's tourism-driven economy and cultural heritage. This billion-euro project reflects the importance of prioritizing highly specialized technical solutions in urban coastal archetypes with significant cultural significance (Focardi and Pepi, 2024). Similarly, in Alexandria, Egypt, open-coast archetypes have seen the implementation of cement barriers to protect vulnerable communities from flooding. While these measures are effective in the short term, they highlight significant limitations in resource-constrained open-coast settings. The local population, heavily reliant on fishing and maritime trade, faces additional challenges due to ecosystem degradation and the loss of marine habitats caused by these barriers (Focardi and Pepi, 2024).

Moving to soft engineering and sediment-based interventions, the Yangtze River estuary offers a compelling example. Sediment replenishment and wetland restoration not only mitigated flood risks but also improved livelihoods by enhancing water quality and supporting fishing-dependent communities. This case demonstrates how socioeconomic objectives can be integrated into such measures, showcasing the critical interplay between ecological restoration and community resilience (Long et al., 2024).

In terms of nature-based solutions, estuarine live coasts exemplify the efficacy of green engineering approaches. These interventions are particularly relevant for estuaries, where ecosystem services such as carbon sequestration and biodiversity preservation align closely with local cultural and environmental values. For example, wetlands in the

Table 3
Development pathways characteristics.

DP	Recommended Archetype	Advantages	Disadvantages	Time of Application
Hard Engineering Measures	Open coasts, estuaries, and deltas, particularly in urban areas and vulnerable zones where immediate protection is crucial.	Immediate protection in critical areas; rapid and effective solution; high confidence in preventing immediate damage.	High cost; additional measures may be needed for salinization and habitat loss; may become unsustainable with progressive sea-level rise.	Short to medium term
Soft Engineering and Sediment-Based Measures	Open coasts, suitable for gradual adaptation over time, more appropriate for medium-term adjustments.	More flexible and less costly adaptation than hard engineering measures; suitable for gradual changes and managing erosion and flood risks.	Limits based on allowable sand reserves; environmental impacts and high costs; must align with the highest sea-level rise rates.	Medium term
Nature-Based Measures	Deltas and estuaries, where natural ecosystems can be utilized for coastal protection and provide long-term benefits.	Risk reduction over time; long-term ecosystem services benefits; effective protection using natural ecosystems.	Requires site-specific knowledge and science-based design; potential conflict with land occupation and use demands.	Medium to long term
Accommodation of the Built Environment	Already developed areas and cities preparing for minor sea-level changes in the short term.	Rapid adaptation in developed areas; preparation for short-term minor sea-level changes.	Effective for current conditions and minor sea-level changes; may require future transformative strategies.	Short term
Advance	Densely populated areas with limited land, suitable for cities with sufficient economic capital and needs for territorial expansion.	Creates new land from the sea; reduces inland risk; accommodates population growth and urban expansion.	Significant negative impact on coastal ecosystems and livelihoods; substantial financial and material resources needed; may be subject to land subsidence.	Long term
Retreat	All coastal zones, especially those with limited resources for other forms of adaptation.	Long-term strategy; involves relocation of populations and assets; can be considered for all coastal areas.	Breaks cultural ties with the coast; adverse socioeconomic effects if not planned inclusively; requires land availability.	Long term

United States and China serve as natural buffers, reducing storm surges and erosion while sustaining local fishing economies. The successful integration of community participation with science-based design in these cases has ensured the long-term sustainability of these measures (Long et al., 2024). However, the implementation of such measures varies across archetypes. Densely populated deltas often encounter land-use conflicts, necessitating careful sociopolitical negotiations. Conversely, open coasts provide greater flexibility for large-scale restoration projects, emphasizing the importance of tailoring interventions to regional socioeconomic contexts (Long et al., 2024).

When accommodating the built environment, coastal regions in France, the UK, and Ireland have employed building elevation as an adaptive response to SLR. In France, the aftermath of Cyclone Xynthia in 2010 spurred changes in coastal adaptation policies, leading to mandatory refuge areas for properties in high-risk zones. This strategy is deeply rooted in local governance and social norms, supported by national funding mechanisms such as the "Fonds de Prévention des Risques Naturels Majeurs," which mitigate economic burdens for property owners (Long et al., 2024). By contrast, the UK and Ireland adopt decentralized models where local planning authorities define adaptation strategies based on spatial planning and local risk assessments. While these measures align with technical resilience, they face social challenges, such as ensuring equitable access to funding and maintaining community cohesion in flood-prone areas (Long et al., 2024).

For managed retreat, examples from Fiji highlight significant cultural disruptions, including the loss of ancestral lands and sacred sites. Village relocations strained community cohesion, underscoring the spiritual connections residents maintain with their homeland. These cases reveal governance gaps, such as the insufficient inclusion of diverse community voices in decision-making processes. In Houston, Texas, managed retreat programs exposed socioeconomic disparities in resettlement outcomes. Low-income neighborhoods subjected to buyout programs often faced greater displacement distances and weaker social network continuity compared to wealthier communities. These disparities underscore the critical need for equitable frameworks that prioritize social capital preservation and fair compensation mechanisms (Dalton et al., 2024).

Finally, in regions like China's Bohai Sea and Jiangsu coastal areas, port reclamation exemplifies the "Advance" strategy, where land is expanded into the sea to meet economic demands. Zhu et al. (2024) highlight that port reclamation represented 13.5% of China's total reclamation activities between 2000 and 2020, contributing over 60% to the country's GDP. However, this strategy has incurred significant ecological costs, including the loss of 22,000 km^2 of wetlands since 1949, impacting biodiversity and disrupting sedimentary and hydrological processes (Zhu et al., 2024). Social and cultural contexts further compound these challenges. In Jiangsu Province, port reclamation prioritized industrial development and urbanization over traditional livelihoods such as fishing, leading to cultural displacement and reduced access to marine resources. Ecologically, areas like the Bohai Sea exhibit reduced carrying capacities due to habitat loss and altered ocean currents, posing long-term risks for fisheries and biodiversity. Sustainable reclamation models are essential to address these issues, including integrating nature-based solutions such as mangrove planting into reclamation projects to mitigate biodiversity loss and enhance coastal resilience (Zhu et al., 2024).

Considering these examples, Table 3 displays the principal attributes of Development Pathway applications aligned with temporal planning and specific coastal archetypes, including their general considerations and archetype recommendations across different planning horizons.

5. Multicriteria decision analysis (MCDA) for selecting development pathways (DP) in coastal erosion and flood management

In this chapter, we describe the methods by which a DST can be applied through the integration of the criteria defined in chapter 3 (coastal indices) with the alternatives defined in chapter 4 (DP: development pathways). Additionally, for coastal risk management, new criteria are added that reflect the potential impact of the DPs considering cultural, social, and economic aspects not included in the coastal indices. These criteria include effectiveness in reducing flooding and erosion, environmental and social sustainability, costs and resources required to implement and maintain the DP, adaptation to climate change and coastline variation, impact on biodiversity and coastal ecosystems, impact on the lives of local communities, compliance with local, regional, and national regulations, and implementation time. Therefore, the following section explains how these methods integrate coastal criteria with DPs.

Firstly, ELECTRE methods aim to identify a set of acceptable solutions by considering the degree to which one alternative outranks another. The most prominent ones are ELECTRE I, II, III, and IV. Although they share a similar structure, they exhibit important differences. ELECTRE I is a procedure that reduces the size of the set of non-

Table 4
Common First steps for implementing decision-support methods.

STEPS	DESCRIPTION
1) Construction of the Decision Matrix	This involves listing all the alternatives and their performance across various criteria. For example, performance can be measured on a scale of 1–5 on the criteria defined above
2) Normalization of the Decision Matrix	This step ensures that all criteria are comparable. Common normalization techniques include min-max normalization, z-score normalization, or vector normalization.
3) Construction of the Weighted Normalized Decision Matrix	Weights are assigned to each criterion based on their relative importance.

dominated solutions to a smaller number, while ELECTRE II, III and IV produce a complete ranking of all alternatives (Fei et al., 2019). The method is highly useful and applicable in coastal management due to its ability to handle multiple criteria and complex comparisons between alternatives. In the context of the defined criteria, ELECTRE allows for a detailed evaluation of each DP by calculating concordance and discordance indices. ELECTRE facilitates the identification of alternatives that best meet a set of weighted criteria. It is crucial to validate these indices through expert knowledge input to ensure that the evaluations adequately reflect the complexity and particularities of the coastal environment (Zhou et al., 2022).

Respect to PROMETHEE methods, there are designed to handle complex decision problems by comparing alternatives through pairwise preference relations. It is particularly useful in contexts where decision-makers need to evaluate multiple, often conflicting criteria (Wu et al., 2020). To apply PROMETHEE to coastal management, consider a set of development pathways (DPs) evaluated against criteria such as effectiveness in reducing flooding and erosion, environmental sustainability, and implementation costs. Each criterion is assigned a weight reflecting its importance, and preference functions are defined based on expert input. The pairwise comparisons of DPs are then performed to calculate preference indices, positive and negative flows, and net flows, ultimately leading to a ranking of the DPs. However, the selection of preference functions can be subjective and may influence the results. Additionally, PROMETHEE requires detailed pairwise comparisons, which can be computationally intensive for many alternatives. Despite these limitations, PROMETHEE provides clear and interpretable rankings and handles both qualitative and quantitative criteria flexibly, making it an excellent choice for coastal management.

Similarly, TOPSIS method involves a systematic process that considers both the positive and negative aspects of the alternatives to determine their relative closeness to an ideal solution. The ideal solution represents the best values for each criterion, while the negative ideal solution represents the worst values. The method aims to find the alternative that is closest to the ideal solution and farthest from the negative ideal solution, indicating the most favorable option (Wątróbski et al., 2022). TOPSIS provides decision-makers with a structured and quantitative approach to evaluating and ranking alternatives based on multiple criteria. However, TOPSIS has certain disadvantages. The use of Euclidean distance to measure the closeness to the ideal solution may not always accurately reflect the decision-makers' preferences. Another limitation is that TOPSIS does not account for direct preference relationships between alternatives. Lastly, the method assumes that criteria can compensate for each other, which might not be appropriate in situations where certain criteria are crucial and cannot be offset by. The method allows for a detailed evaluation of each development pathway (DP) by comparing their performance relative to the ideal and negative ideal solutions. This comparison is crucial for identifying the most effective and sustainable solutions in managing coastal areas. By validating the criteria and weights through expert knowledge input, TOPSIS ensures that the evaluations accurately reflect the complexities and specificities of the coastal environment.

Table 5
Specific steps for applying each decision-making method.

ELECTRE	*4) Calculation of Concordance and Discordance Matrices	Concordance measures the degree to which an alternative is at least as good as another, while discordance measures the degree to which an alternative is worse than another. Respect to concordance index calculation, involves for each pair of alternatives (A, B), the concordance index $\boldsymbol{c}(\boldsymbol{A},\boldsymbol{B})$ is calculated by summing the weights of criteria where A is preferred over or equal to B. On the other side, discordance index $\boldsymbol{d}(\boldsymbol{A},\boldsymbol{B})$ is calculated by evaluating the maximum difference in criteria where B is better than A.
PROMETHEE	4) Calculation of Preference Indices	Calculate the pairwise preference index for each pair of alternatives. The preference index $\pi(a,b)$ indicates the degree to which alternative a is preferred over alternative b for each criterion.
	5) Calculation of positive and Negative Flow	Compute the positive flow (ϕ^+) and negative flow (ϕ^-) for each alternative. The positive flow measures how much an alternative is preferred over all others, while the negative flow measures how much all others are preferred over it. $\phi^+(a) = \frac{1}{n-1}\sum_{b\neq a}\pi(a,b)$ *and* $\phi^-(a) = \frac{1}{n-1}\sum_{b\neq a}\pi(a,b)$
	*6) Calculation of Net Flow	Determine the net flow (φ) for each alternative, which is the difference between the positive and negative flows: $\phi(a) = \phi^+(a) - \phi^-(a)$
TOPSIS	4) Determination of the Ideal and Negative Ideal Solutions	Identify the best and worst values for each criterion. The ideal solution consists of the maximum (or minimum for cost criteria) values, while the negative ideal solution consists of the minimum (or maximum for cost criteria) values.
	5) Calculation of the Closeness Coefficient	Measure the distance of each alternative from the ideal and negative ideal solutions using a distance measure, such as Euclidean distance: $D_i^+ = \sqrt{\sum_{j=1}^{n}\left(w_j\left(x_{ij}-x_j^+\right)\right)^2}$ *and* $D_i^- = \sqrt{\sum_{j=1}^{n}\left(w_j\left(x_{ij}-x_j^-\right)\right)^2}$ Where D_i^+ is the distance of alternative i from the ideal solution, D_i^- is the distance of alternative i from the negative ideal solution, w_j is the weight of criterion j, x_{ij} is the normalized performance score of alternative i for criterion j, x_j^+ is the ideal value for criterion j, and x_j^- is the negative ideal value for criterion j.
	*6) Calculation of the Relative Closeness	Determine the relative closeness of each alternative to the ideal solution: $C_i^* = \frac{D_i^-}{D_i^+ - D_i^-}$ Where C_i^* is the relative closeness of alternative i to the ideal solution.
MAUT	4) Utility Function Development	Develop a utility function for each criterion to transform performance measures into utility scores. Common utility functions include linear, logarithmic, and exponential functions. These functions should be calibrated to reflect the decision-maker's risk preferences and value trade-offs. Calibration can be done using historical data or eliciting preferences from decision-makers.
	5) Calculation of Utility Scores	Calculate the utility score for each alternative by aggregating the weighted utility scores of all criteria. This is typically done using a weighted sum model:

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Table 5 (*continued*)

		$U(A) = \sum_{i=1}^{n} w_i U_i(x_i)$ where $U(A)$ is the overall utility of alternative A, w_i is the weight of criterion i, and $U_i(x_i)$ is the utility score of criteria i for alternative A.
Geoffrion Method	4) Formulation of the Linear Programming Model	Develop a linear programming model that represents the decision problem. This model typically includes an objective function that needs to be maximized or minimized, representing the overall utility or preference $\textit{Maximize or Minimize } Z = \sum_{i=1}^{n} w_i x_i$ Where Z is the objective function, w_i are the weights of the criteria and x_i are the normalized performance scores of the alternatives. $a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n \leq b_1$ Where a_{ij} are the coefficients representing the contribution of alternative i to criterion j, and b_1 is the limitation or resource available for that criterion.
	5) Solving the Linear Programming Model	Use linear programming techniques to solve the model. This involves finding the optimal solution that maximizes or minimizes the objective function while satisfying all constraints
	*6) Sensitivity Analysis	Perform sensitivity analysis to understand how changes in the weights or criteria affect the optimal solution. This helps in assessing the robustness of the solution.
Zionts-Wallenius Method	4) Preference Elicitation (Interactive Iterations)	Engage the decision-maker to express preferences between different pairs of alternatives. This step involves presenting pairs of alternatives and asking the decision-maker which one is preferred and by how much.
	5) Adjustment of Weights (Interactive Iterations)	Based on the feedback, adjust the weights of the criteria to reflect the decision-maker's preferences more accurately. This step may involve recalculating the weights using methods such as pairwise comparisons
	6) Update of Decision Matrix (Interactive Iterations)	Recalculate the normalized and weighted decision matrix with the updated weights.
	7) Determination of the Preferred Solution	Identify the alternative that best aligns with the decision-maker's preferences based on the updated weights and criteria
	*8) Sensitivity Analysis	Perform sensitivity analysis to understand how changes in the weights or criteria affect the preferred solution. This helps in assessing the robustness of the solution.
PROTRADE	4) Selection of Reference Points	Define reference points or aspiration levels for each criterion. These reference points represent the desired levels of performance for each criterion and serve as benchmarks for evaluating the alternatives
	5) Calculation of Deviations	Calculate the deviations of each alternative from the reference points. The deviation for a criterion is the difference between the performance of an alternative and the reference point. For example, for a criterion C_j, the reference point R_j could be the maximum desired value: $R_j = \max\{x_{ij} \mid i = 1, 2, \ldots, m\}$ The calculation of deviations d_{ij} for each alternative A_i and criterion C_j is calculated as $d_{ij} = \lvert x_{ij} - R_i \rvert$ Where x_{Ij}, is the normalized performance score of alternatives A_i, for criterion C_j.
	*6) Aggregation of Deviations	Aggregate the deviations across all criteria to obtain an overall deviation score D_i for each alternative. This can be done using a weighted sum approach, where weights represent the relative importance of each criterion.
AHP	*4) Calculation of the Consistency Ratio	Verify the consistency of the pairwise comparisons using the formula: $CR = \frac{CI}{RI}$ Where CI is the Consistency Index and RI is the Random Index. If $CR < 0.$ indicates acceptable consistency.
VIKOR	4) Determination of the Ideal and Negative Ideal Solutions	Identify the best and worst values for each criterion.
	5) Calculation of the Closeness Coefficient	Measure the distance of each alternative from the ideal and negative ideal solutions using a distance measure.
	*6) Calculate the Compromise Index (Q)	Combine the distances to calculate the compromise index Q, which reflects the balance between individual regret and collective satisfaction. The formula is as follows: $Q_i = v\frac{S_i - S^*}{S^- - S^*} + (1 - v)\ \frac{R_i - R^*}{R^- - R^*}$ Where v = Compromise parameter, typically set to 0.5, representing the weight of the decision-making strategy (majority rule vs. individual regret minimization), S_i = Sum of the normalized weighted distances for alternative iii to the ideal solution, S^* *and* S^- = Minimum and maximum values of S_i, R_i = Maximum normalized weighted distance for alternative i to the ideal solution, R^* *and* R^- = Minimum and maximum values R_i respectively.
DEMATEL	4) Calculate the Direct-Relation Matrix	Determine the direct influence of each criterion on others through expert evaluation or data. Assign values on a predefined scale. This results in a matrix A, representing the direct influences.
	5) Generate the Total-Relation Matrix	Compute the total-relation matrix T, which includes both direct and indirect influences. This step uses the normalized direct-relation matrix N, derived from A. The formula is: $T = N\,X\,(I - N)^{-1}$ Where I is the identity matrix, and T provides the overall influence of each criterion.
	*6) Analyze the Total-Relation Matrix	Extract insights from T to identify the key drivers and dependencies among criteria. This involves computing prominence ($D + R$) and relation ($D-R$), where D is the sum of rows and R is the sum of columns in T. Prominence indicates the importance of a criterion, and relation classifies criteria as causes or effects.
ANP	4) Develop Pairwise Comparison Matrices	For each cluster (criteria, alternatives, or sub-criteria), construct pairwise comparison matrices using expert input or stakeholder feedback. Evaluate the relative importance of each element with respect to others in the same cluster using a Satty scale This step generates multiple pairwise comparison matrices for both criteria and their interdependencies.
	5) Calculate the Supermatrix	Form the initial supermatrix by organizing the local priorities derived from the pairwise comparisons into a matrix structure. The supermatrix includes all clusters and their relationships, representing the influence of each element on others.

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Table 5 (*continued*)

	*6) Normalize and Compute the Weighted Supermatrix	Normalize the supermatrix so that the sum of each column equals 1, ensuring consistency. Then, calculate the weighted supermatrix by raising it to a sufficiently large power until convergence is reached, resulting in the limiting matrix. This final matrix provides the global priorities of the elements, which are then used to rank the alternatives.
TODIM	4) Calculate the Relative Dominance of Each Alternative	For each criterion, compute the dominance of every alternative A_i over every other alternative A_j.This is done using a piecewise function based on the Prospect Theory value function, which captures the decision−maker's perception of gains and losses. The dominance δ_{ij} for each pair of alternatives is calculated as: $\delta_{ij} = \sum_{k=1}^{n} w_k . V_{ij}^k$ Where w_k is the weight of criterion k, V_{ij}^k is the value function of alternative i over j under criterion k.
	5) Aggregate the Dominance Scores	Aggregate the dominance values across all criteria to compute the overall dominance score for each alternative. This involves summing the dominance scores δ_{ij} across all criteria, providing a single dominance value for each alternative in the decision matrix.
	*6) Normalize the Dominance Scores	Normalize the aggregated dominance scores to make them comparable across alternatives. The normalized scores are used to prioritize and rank the alternatives before final evaluation. This method highlights the psychological aspects of decision-making, particularly the decision-maker's attitude toward risk and trade-offs.

Note. * Last step in each method, before ranking the alternatives. Steps 1, 2, and 3 for each method are described in Table 4.

Likewise, MAUT evaluates the alternatives based on multiple criteria by transforming them into a single utility value (Arena et al., 2022). This approach is particularly useful when decision-makers need to consider various attributes simultaneously and balance trade-offs between them. MAUT provides a structured framework to quantify the preferences of decision-makers and to rank the alternatives based on their overall utility scores (Smith et al., 2000). The method allows for a detailed evaluation of each development pathway (DP) by transforming the performance measures into comparable utility scores, thus facilitating informed decision-making. MAUT is particularly useful because it allows for the explicit modeling of preferences and trade-offs among criteria. However, it has certain disadvantages. The development of utility functions can be complex and may require significant input from experts to accurately reflect the decision-makers' preferences. The assignment of weights to criteria, which is inherently subjective, can also influence the final ranking. Additionally, the method assumes that the utility scores are additive, which might not always be appropriate in situations where criteria are interdependent or have non-linear relationships.

In the same vein, Geoffrion method utilizes linear programming techniques to handle multi-criteria decision problems. This method focuses on finding an optimal solution by exploring the trade-offs between different criteria and identifying the best compromise solution. The formulation of the linear programming model can be complex and may require significant input from experts to accurately reflect the decision problem. Additionally, the method assumes linear relationships between criteria, which may not always be appropriate in real-world scenarios where non-linear relationships exist. Despite these limitations, the Geoffrion method remains a powerful tool for informed decision-making in coastal management.

Furthermore, Zionts- Wallenius Method is a MCDA approach that incorporates interactive techniques to find the most preferred solution. This method is particularly useful when decision-makers need to engage in an iterative process to refine their preferences and criteria weights dynamically. The Zionts-Wallenius method facilitates the decision-making process by involving the decision-maker in each step to provide feedback and adjust preferences (Doumpos et al., 2019). The Zionts-Wallenius method is highly applicable in coastal management due to its interactive nature, which allows decision-makers to refine their preferences dynamically. However, the Zionts-Wallenius method also has certain limitations. The iterative process can be time-consuming and may require significant involvement from decision-makers, which might not always be feasible. Additionally, the method relies heavily on the accuracy of the decision-makers feedback, and inconsistencies in preferences can affect the final outcomes.

The Reference Point Method (PROTRADE) focuses on evaluating and ranking alternatives based on direction-based preferences. This method is particularly useful for decision problems where the direction or trend of improvement is more important than the exact numerical values of the criteria. The Reference Point Method involves the use of reference points or aspiration levels to guide the decision-making process (Ge et al., 2023).

AHP is an MCDA method that structures complex decisions into a hierarchy of criteria and alternatives, enabling pairwise comparisons to derive priority weights (Saaty, 1980). In coastal management, AHP aids in evaluating development pathways (DPs) by integrating criteria like cost, environmental impact, and social acceptance. It's effective for incorporating stakeholder input and building consensus. However, AHP assumes criteria independence and may face inconsistencies due to subjective judgments in comparisons (Arda et al., 2024).

VIKOR is a MCDA technique that prioritizes compromise solutions, focusing on minimizing the maximum regret of decision-makers across multiple criteria. This method is especially effective in addressing conflicting objectives, as it calculates the closeness of each alternative to the ideal solution and ranks them accordingly. For coastal management, VIKOR facilitates the identification of development pathways (DPs) that best balance trade-offs among economic, environmental, and social sustainability goals. By evaluating the performance of DPs relative to ideal and anti-ideal solutions, decision-makers can identify robust strategies for flood and erosion mitigation. However, VIKOR requires the careful selection of weights and parameters, which can introduce subjectivity. Additionally, the method assumes that decision-makers are willing to compromise, which may not always align with stakeholder priorities in diverse coastal contexts (Nair et al., 2024).

The DEMATEL method is a decision-making tool designed to visualize and analyze the relationships among criteria, allowing for the identification of influential and dependent factors. This method constructs a direct influence matrix to reveal the strength and direction of interrelationships among criteria, making it particularly useful for complex systems like coastal management. In this context, DEMATEL can clarify the interdependencies between criteria such as environmental sustainability, costs, and social acceptance of DPs. The insights provided by DEMATEL allow decision-makers to focus on critical criteria that drive the success of coastal adaptation strategies. While DEMATEL excels in mapping causal relationships, it relies heavily on expert judgment, which can introduce biases. Additionally, the method requires significant computational effort to process the influence matrix, especially when applied to large datasets or numerous criterion (Alikhani, 2024).

ANP extends the capabilities of AHP by considering the interdependencies and feedback among criteria, providing a more comprehensive framework for multi-criteria decision-making. This method is highly applicable in coastal management, where criteria such as cost, social acceptance, and environmental impact are often interrelated. By constructing a network of criteria and sub-criteria, ANP facilitates the evaluation of DPs in a holistic manner, capturing the complex interconnections inherent in coastal systems. However, ANP can be

Table 6
MCDA methods for coastal management.

Method	Characteristic	Advantage	Disadvantage	Input Data	Output Data	Implementation/ Indices	Empirical examples
ELECTRE	Outranking method, uses concordance and discordance indices.	Handles multiple criteria, identifies acceptable alternatives.	Complexity in calculation and interpretation of indices.	Decision matrix, criteria weights.	alternatives based on outranking relations.	Concordance $(c(i,j))$, discordance $(d(i,j))$.	ELECTRE was applied in Southern Italy to prioritize erosion-prone coastal areas, effectively balancing socioeconomic and environmental criteria for sustainable management (Rahimi Juneghani and Nooraie, 2024)
PROMETHEE	Outranking method, uses pairwise comparisons with preference functions.	Provides clear ranking, handles both qualitative and quantitative criteria.	Selection of preference functions can be subjective, computationally intensive for large datasets.	Decision matrix, criteria weights, preference functions.	Ranking of alternatives based on net flow.	Positive flow (ϕ^{+}), Negative flow (ϕ^{-}), Net flow (φ)	PROMETHEE was used to rank coastal management strategies in Tunisia, balancing ecological preservation with socioeconomic development goals (Plataridis and Mallios, 2024)
TOPSIS	Evaluates closeness to an ideal solution and distance from a negative ideal.	Easy to understand and implement, useful in various contexts.	Sensitive to normalization, does not consider direct relationships.	Decision matrix, criteria weights.	Ranking of alternatives based on closeness coefficient.	Distance to ideal solution (D_i^{+}), negative (D_i^{-}).	TOPSIS ranked coastal vulnerability in the Marmara Gulf, prioritizing segments based on socio-economic and physical criteria (Arda et al., 2024)
MAUT	Transforms criteria into single utility values.	Explicitly models preferences and trade-offs.	Complexity in utility function, subjectivity in weights.	Decision matrix, criteria weights, utility functions.	Ranking of alternatives based on utility scores.	Utility score $(U_i(x_i))$, weighted sum.	MAUT was applied to the Aghsu watershed in Azerbaijan to evaluate land-use scenarios, integrating social, economic, and environmental criteria to identify the most sustainable solutions (Ikram et al., 2024)
Geoffrion	Uses linear programming to optimize an objective function.	Structured, quantitative, evaluates multiple criteria.	Complexity in model formulation, assumes linear relationships.	Decision matrix, criteria weights, objective function, constraints.	Ranking of alternatives based on optimal solution.	Objective function (Z), linear constraints $(a_{ij}x_i) \leq b_i$.	The Geoffrion method using linear programming optimized flood risk management in Bandar Abbas, prioritizing interventions based on hazard, vulnerability, and exposure metrics (Asiri et al., 2024)
Zionts-Wallenius	Interactive method based on decision-maker preferences.	Allows dynamic refinement of preferences.	Iterative process can be lengthy, depends on accurate feedback.	Decision matrix, initial weights, decision-maker feedback.	Ranking of alternatives based on adjusted preferences.	Pair comparison, weight adjustment.	Using the Ziont-Wallenius iterative process, the article models climate change adaptation for sustainable coastal zones, integrating GIS and AHP to prioritize climate change indicators. It identifies Al-Alamein New City as a case study, focusing on key parameters like geology and topography to inform adaptive strategies. (Marzouk and Azab, 2024)

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Table 6 (*continued*)

Method	Characteristic	Advantage	Disadvantage	Input Data	Output Data	Implementation/ Indices	Empirical examples
PROTRADE	Uses reference points or aspiration levels.	Clarity in objectives, useful for specific goals.	Subjectivity in selecting reference points, linear aggregation.	Decision matrix, criteria weights, reference points.	Ranking of alternatives based on deviations from reference points.	Deviations (d_{ij}), weighted sum of deviations (D_i).	PROTRADE was applied in Fairbourne, North Wales, to analyze managed retreat strategies, focusing on claims-making processes to address sociopolitical challenges (Hilson and Arnall, 2024)
AHP	Hierarchical decomposition of decisions.	Handles qualitative and quantitative data.	Time-consuming for large datasets.	Decision matrix, pairwise comparisons.	Ranking based on priority weights	Pairwise comparison matrix, Consistency Ratio (*CR*).	AHP weighted criteria in the Marmara Gulf, identifying high-risk zones through expert-driven pairwise comparisons (Arda et al., 2024)
VIKOR	Compromise ranking method prioritizing closeness to the ideal solution	Balances conflicting criteria effectively	Requires normalization, sensitive to weights	Decision matrix, criteria weights	Ranking of alternatives based on compromise solution	Proximity to ideal solution index (*S, R, Q*)	VIKOR prioritized flood-prone sub-watersheds in the Mahe River Basin, India, using morphometric factors to classify risk levels (Nair et al., 2024)
DEMATEL	Analyzes interrelationships among criteria	Visualizes complex causal relationships	Requires expert judgment, sensitive to bias	Decision matrix, pairwise comparisons	Influence map and ranking of criteria	Total influence matrix (*T*), direct and indirect effects	DEMATEL identified and ranked construction risks along the Caspian Sea coast, highlighting geological risks as the most critical (Alikhani, 2024)
ANP	Extends AHP to handle interdependencies among criteria	Accounts for feedback and interrelationships	Computationally intensive, requires consistency checks	Decision matrix, pairwise comparisons, criteria interdependencies	Weighted priorities and ranking of alternatives	Supermatrix (*W*), weighted and limit matrices	ANP-GIS assessed flood sensitivity in Guangdong, China, integrating hazard, exposure, and vulnerability for coastal resilience planning (Lyu et al., 2024)
TODIM	Applies a value function to calculate dominance among alternatives based on losses and gains relative to a reference point	Reflects decision-makers' risk preferences; intuitive loss-aversion modeling	Sensitive to the choice of the reference point; complex calculations for large datasets	Decision matrix, criteria weights, reference point	Ranking of alternatives based on dominance values	Dominance degree (d_{ij}) calculated for each pair of alternatives	TODIM optimized groundwater management in the Nowshahr-Nur aquifer, prioritizing scenarios to mitigate saltwater intrusion (Alizadeh et al., 2023)

computationally intensive, and the development of pairwise comparisons for interconnected criteria requires significant expertise and effort. Despite these challenges, ANP offers decision-makers a robust tool for prioritizing DPs while accounting for the dynamic interactions between criteria in coastal contexts (Lyu et al., 2024).

TODIM is a MCDA approach based on prospect theory, which evaluates alternatives by considering the perceived gains and losses of decision-makers relative to a reference point. This method is particularly effective in contexts where stakeholders have varying risk preferences, as it integrates psychological factors into the decision-making process. For coastal management, TODIM provides a nuanced evaluation of DPs by weighting criteria according to their perceived importance and calculating dominance values for each alternative. The method's ability to incorporate risk perception makes it well-suited for scenarios involving uncertain climate impacts. However, TODIM requires detailed input data and careful calibration of reference points, which can be challenging in data-limited environments. Additionally, the method's reliance on subjective judgments may affect its robustness and repeatability in practice (Alizadeh et al., 2023).

Table 4 presents the common steps that should be followed when applying any of the methods. Table 5 then details the specific steps required for each method, which should be applied after completing the steps outlined in Table 4.

All the methods analyzed in this chapter aim to derive the final ranking of alternatives. In ELECTRE, this is achieved by evaluating the outranking relations, considering the degree of outranking to identify the most acceptable solutions based on the decision-maker's preferences. PROMETHEE ranks alternatives based on their net flow values, with the highest net flow indicating the most preferred option. TOPSIS uses the closeness coefficient to rank alternatives, selecting the option with the highest value as the most favorable. MAUT ranks alternatives by their overall utility scores, identifying the one with the highest utility as the best fit for the set of weighted criteria. The Geoffrion method ranks alternatives based on their performance in the linear programming model, choosing the best compromise solution. The Zionts-Wallenius method and PROTRADE employ iterative processes to rank

Table 7
Decision matrix for coastal flooding and erosion: General framework for DST methods.

Criteria/Development Pathway	Hard Engineering Measures (A_1)	Sediment-Based Measures (A_2)	Nature- Based Measures (A_3)	Accomodation of the Built Environment (A_4)	Advance (A_5)	Retreat (A_6)	Alternative j (A_j)
Effectiveness in reducing flooding and erosion (C_1) (w_1 ↑)	1–5: Normalized score for each criterion in relation to each alternative, covering all possible combinations. A score of 1 indicates the least favorable performance, while a score of 5 represents the most favorable performance for the given criterion.						
Environmental and Social sustainability (C_2) (w_2 ↑)							
Costs and resources required to implement and maintain the solution (C_3) (w_3 ↓)							
Adaptation to climate change and variation of the coastline (C_4) (w_4 ↑)							
Impact on biodiversity and coastal ecosystems (C_5) (w_5 ↓)							
Impact on the lives of local communities (C_6) (w_6 ↑)							
Compliance with local, regional and national rules and regulations (C_7) (w_7 ↑)							
Implementation time (C_8) (w_8 ↓)							
Coastal indices (C_9) (w_9 ↓)							
Criterion i (w_i: ↑ or ↓)							

Note.
C: Criteria.
W: Weights.
A: Alternatives.
↑ Higher values receive higher scores.
↓ lower values receive higher scores.
Source. The authors.

alternatives, aligning consistently with the decision-maker's preferences to determine the most favorable option. Table 6 highlights the most relevant characteristics of each DST discussed in this review.

6. Selecting the most appropriate MCDA method for coastal flooding and erosion management: criteria and descriptors

Based on existing literature and some of our own proposals, a five-step framework is presented to guide decision-makers in choosing the most suitable multi-objective techniques for coastal management. This framework combines established knowledge with suggestions that are tailored to the specific challenges of the coastal environment, with the aim of improving the practical application of DSTs in these scenarios.

Step 1 Define a List of Available Multi-Objective Techniques: The application of MCDA methods in the development of DSS allows for the integration of various factors, both quantitative and qualitative, providing a comprehensive evaluation of potential management alternatives (Doumpos et al., 2019). The methods available for this review are shown in Fig. 1. If a method is not based on this decision matrix, it cannot be effectively applied or may not be suitable for use in this context.

The criteria selected in the decision matrix (Table 7) are grounded in an integration of literature that addresses coastal management from multiple perspectives. Cooper and McKenna (2008) highlight how the allocation of public resources to protect private property in areas affected by erosion generates social justice conflicts. These conflicts underscore the need to balance local interests with national priorities, proposing that a sustainable evaluation should consider both the social impact and the economic implications of decisions. This duality forms the core of criteria such as environmental and social sustainability (C_2) and the impact on local communities (C_6), which align with debates on equity in coastal management.

In a broader context, McLaughlin and Cooper (2010) emphasize how, in densely populated urban areas, the high value of infrastructure justifies defense at all costs. This reinforces the relevance of economic criteria (C_3) while also introducing elements related to climate change adaptation (C_4), given the growing exposure of these areas to extreme events. Penning-Rowsell et al. (2014) challenge this perspective by noting that the spatial scale of analysis directly affects the perception of vulnerability. While national-scale management may mask local vulnerabilities, more granular analyses enable the identification and prioritization of resources in critical areas. This approach translates into criteria such as resource allocation (C_3) and regulatory compliance (C_7), which are essential to ensuring equitable and effective implementation of strategies.

N. Rangel-Buitrago et al. (2018) delve into the requirements for sustainable coastal management, emphasizing the importance of criteria such as coastal zoning, hazard assessment (C_1), and the conservation of coastal ecosystems (C_5). These elements are particularly relevant in contexts where human occupation and poor adaptation practices exacerbate risks. More recently, Asiri et al. (2024) highlight how combining methods such as AHP with machine learning algorithms enables better capture of flood and erosion hazards, as well as social vulnerability (C_6), integrating these factors into climate change scenarios.

Table 7 illustrates the general structure of a decision matrix, where each score representing the performance of a Development Pathway (DP) is normalized on a 1–5 scale. The assignment of weights to each criterion depends on their relative importance, which varies depending on the specific objectives of coastal management and the socio-environmental context. For example, the role of assigning appropriate weights to reflect the trade-offs between ecological, social, and economic priorities has been emphasized (Ayan et al., 2023). Criteria such as costs, implementation time, and impact on biodiversity and coastal ecosystems are often weighted towards minimization (indicated by a downward arrow), meaning that lower values receive higher scores. Conversely, criteria like effectiveness in reducing flooding and erosion, environmental and social sustainability, adaptation to climate change, impact on local communities, and compliance with regulations are weighted for maximization (indicated by an upward arrow), emphasizing their desirability (Passos Neto et al., 2023).

The conceptual model developed in this study highlights various weighting methods, including Analytical Hierarchy Process (AHP), Best

Table 8
Descriptors for coastal management.

No	Descriptor	Description*	Applies*	Reason*
A	Finite set of discrete alternatives	A predefined list of distinct options that can be individually selected.	Yes	Discrete alternatives are essential for coastal management solutions, as they allow for a clear definition and comparison of different options.
B	Continuous alternatives	Options that are not discrete but fall along a continuous spectrum.	Yes	Some management strategies might require continuous variables, such as adjusting the intensity or scale of interventions along a spectrum.
C	Ordinal attributes	Attributes that can be ranked in a specific order but not measured precisely.	No	An ordinal ranking system is less precise for evaluating the combination of alternatives in coastal management scenarios where a cardinal ranking provides more detailed insights
D	Ordinal ranking of alternatives sought	A ranking system that places options in order based on preference or importance.	No	A more precise evaluation requires cardinal rankings, which allow for numerical quantification and are better suited for coastal management scenarios.
E	Cardinal ranking of alternatives sought	A ranking system that uses precise numerical values to evaluate options.	Yes	A cardinal ranking is necessary for precise numerical evaluation and for effectively combining different management alternatives.
F	Portfolio of discrete alternatives sought	A selection of several distinct options considered together as a group.	Yes	Coastal management often involves selecting a combination of projects, making a portfolio approach appropriate for comprehensive management.
G	Single stage decision problem	A decision problem that is addressed in a single phase or step.	No	Given the complexity of coastal management problems, they often require multiple stages for thorough assessment and implementation.
H	Multi stage decision problem with changing preferences	A decision problem that requires multiple phases and may involve evolving preferences.	Yes	Coastal management often involves multiple phases, where preferences may evolve due to changing environmental or socio-economic conditions.
I	Large number of objectives or discrete alternatives	A scenario with many different goals or a large number of distinct options.	Yes	Coastal management typically involves numerous goals or a wide range of alternatives, necessitating a method that can handle such complexity.
J	Need for highly refined solution	A solution that needs to be very detailed and accurate.	Yes	Coastal management requires solutions that are detailed and precise to effectively address the specific challenges.
K	Decision maker reluctant to express preference explicitly	A situation where the decision maker is unwilling to state their preferences clearly.	No	It is assumed that decision-makers in this context are willing and able to clearly express their preferences, making this descriptor unnecessary.
L	Decision maker experiences difficulty in conceptualizing hypothetical trade-offs or goal levels	A scenario where the decision maker struggles to understand hypothetical trade-offs or set goals.	Yes	Due to the complexity of coastal management, decision-makers may struggle with understanding hypothetical scenarios and require clear, straightforward evaluations.
M	Decision maker preferences for marginal rates of substitution among objectives not independent of absolute levels of objective attainment	Preferences for trade-offs among objectives that depend on the levels of achievement.	Yes	In coastal management, it's important to evaluate trade-offs accurately based on the actual levels of objective achievement.
N	Need for decision maker understanding of method	The decision maker needs to understand the method being used for it to be effective.	No	The focus here is on ensuring decision-makers understand the results of the method, rather than needing detailed knowledge of the method itself.
O	Limited time with decision maker available	Limited availability of the decision maker's time to engage in the process.	Yes	Decision-makers in coastal management may have limited availability, so it's crucial to use methods that can efficiently accommodate their time constraints.

Note: * The authors have supplemented the table with specific information on coastal management.
Adaptet from: (Doumpos et al., 2019; Al-Shemmeri et al., 1997).

Table 9
Evaluation of MCDA methods according to applicable descriptors.

DESCRIPTOR		METHOD											
		ELECTRE	PROMETHEE	TOPSIS	MAUT	Geoffrion	Zionts-Wallenius	PROTRADE	AHP	VIKOR	DEMATEL	ANP	TODIM
A	Finite set of discrete alternatives	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
B	Continuous alternatives	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
E	Cardinal ranking of alternatives sought	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
F	Portfolio of discrete alternatives sought	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
H	Multistage decision problem with changing preferences	✔	✔	✔			✔		✔	✔	✔	✔	✔
I	Large number of objectives or discrete alternatives	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
J	Need for highly refined solution	✔	✔		✔		✔	✔					
L	Decision maker experiences difficulty in conceptualizing hypothetical trade-offs or goal levels	✔	✔	✔	✔	✔	✔		✔	✔	✔	✔	✔
M	Decision maker preferences for marginal rates of substitution among objectives not independent of absolute levels of objective attainment						✔			✔		✔	
O	Limited time with decision maker available	✔	✔	✔		✔			✔	✔	✔	✔	✔

Worst Method (BWM), Fuzzy Logic (FL), Monte Carlo Simulations, Entropy Weighting, Machine Learning (ML), and Swing Weighting. These methods are complemented by tools such as surveys, interviews, and participatory workshops, which ensure stakeholder engagement and contextual relevance. Entropy Weighting is particularly effective in data-rich scenarios due to its objectivity and scalability, while AHP provides a structured framework well-suited for scenarios involving extensive stakeholder interaction. Swing Weighting offers flexibility in prioritizing criteria based on decision-makers' preferences (Mahmudah et al., 2024).

National-scale analyses often prioritize regulatory compliance and broad economic impacts, while local-level decisions focus on community vulnerability and ecosystem conservation (Penning-Rowsell et al., 2014). Similarly, tailoring weighting methods to the spatial and temporal context of the management objectives is essential to avoid sub-optimal resource allocation and reduced effectiveness in addressing coastal risks (Asiri et al., 2024). Integrating stakeholder perspectives through participatory methods enhances the legitimacy of the decision-making process by aligning technical priorities with community values (Cooper and McKenna, 2008).

Step 2 Formulate the Decision Problem: The existing body of research on MCDA in environmental management (water use, conservation, risk management, etc.) (Bascetin, 2007; Lawrence et al., 2019b; Luo et al., 2013; Mclaughlin and Cooper, 2010; Ranasinghe, 2016; Sheng and Zou, 2017; Zhou et al., 2022) provides a solid foundation for its applicability to problems of coastal flooding, erosion, and ecosystem quality. Although there is no existing literature on the application of the reviewed MCDA methods to these specific coastal issues, this review outlines clear steps to apply these methods in choosing among DP to address such problems effectively.
Step 3 Examine descriptors for relevance: Table 8 indicates the 15 descriptors used to select an appropriate method for decision-making (Doumpos et al., 2019; Al-Shemmeri et al., 1997). In the context of managing coastal flooding and erosion, the necessary descriptors are evaluated to determine which ones are essential for addressing these issues. It is noted that descriptors C, D, G, K, and N are not required for this type of problem.
Step 4 Screen the list of the multi-objective decision aiding techniques: All the reviewed methods are generally applicable to the management of coastal flooding, erosion, and ecosystem quality. ELECTRE, PROMETHEE, and TOPSIS effectively handle multiple criteria and manage portfolios of alternatives, making them suitable for complex decision-making scenarios. However, descriptors that involve handling marginal rates of substitution among objectives (M) do not apply to ELECTRE, PROMETHEE, and TOPSIS, as these methods are not specifically designed for this purpose. Additionally, TOPSIS may not require highly refined solutions (J) in all cases.

Multi-attribute utility methods and the Geoffrion method support detailed evaluations and handle multiple stages, making them suitable for complex coastal management decisions. However, these methods may not need multiple stages with changing preferences (H) and defining utility functions can be time-consuming (O). The Zionts-Wallenius method effectively manages trade-offs among objectives, but requires constant updates to objectives, which may not be feasible for all decision makers (O). The reference point method supports detailed evaluations and managing portfolios, but it may not need multiple stages (H) and defining specific goals can be complex (L). Therefore, these descriptors do not apply to these methods in the context of coastal management (see Table 9).

Step 5. Select most appropriate method.

In coastal management, achieving objectives such as reducing flooding and erosion in coastal areas requires careful consideration of the available methods, as discussed in this review (Penning-Rowsell et al., 2014). Each method has unique strengths that make it more

Table 10
Filtered criteria matrix: Evaluating method-specific compliance with non-fulfilled criteria in coastal management.

Criteria Type	Criteria	ELECTRE	PROMETHEE	TOPSIS	MAUT	Geoffrion	Zionts	PROTRADE	AHP	VIKOR	DEMATEL	ANP	TODIM
Non-mandatory Binary Criteria	Comparison to goal point	×	×	×	×	×	✓	✓	✓	✓	✓	✓	✓
	Comparison to aspiration level	×	×	×	×	×	✓	✓	✓	✓	✓	✓	✓
Technique-dependent Criteria	Computational cost	Medium	High	Medium	Low	Medium	High	Medium	Low	Medium	High	Very High	Medium
	Implementation time	Medium	High	Medium	Low	Medium	High	Medium	Low	Medium	High	Very High	Medium
	Interaction time	Low	Low	Low	Medium	Medium	Very High	Medium	Medium	Medium	High	Very High	Medium
	Decision-maker's knowledge	Medium	Medium	Medium	Very High	Very High	Very High	Medium	Medium	Medium	High	Very High	Medium
	Level of decision-maker's knowledge	Medium	Medium	Medium	Very High	Very High	Very High	Medium	Medium	Medium	High	Very High	Medium
	Time available for interaction	Low	Low	Low	Medium	Medium	High	Medium	Medium	Medium	High	Very High	Medium
	Desire for interaction	Medium	Medium	Medium	Very High	Very High	Very High	Medium	Medium	Medium	High	Very High	Medium

appropriate for certain contexts. In the context of environmental management, it is explicit how DST can be chosen based on mandatory binary criteria, non-mandatory binary criteria, MCDA technique-dependent criteria, and application-dependent criteria (Al-Shemmeri et al., 1997). These criteria have the ability to eliminate methods for creating a future DSS when they do not meet the following requirements (Köksalan et al., 2011; Allah Bukhsh et al., 2019; De Smet, 2019; Doumpos et al., 2019; Wu et al., 2020; Abounaima et al., 2020; Zhou et al., 2022).

It is important to highlight that all the methods analyzed in this study fully meet the mandatory binary criteria (handle qualitative criteria and handle discrete sets). Regarding the non-mandatory binary criteria, all methods fulfill the criteria of direct comparison, complete ranking, and cardinal ranking. In terms of technique-dependent criteria, all methods meet the criteria of consistency of results and robustness of results. Finally, concerning the application-dependent criteria, all methods satisfy the criteria of the number of objectives and confidence in preference structure. After this filtering process, Table 10 indicates which remaining criteria are met by each method.

Fig. 3 illustrates the steps for managers, engineers, and researchers to construct and select the best Decision Support Tool (DST) for a future Decision Support System (DSS) based on criteria for coastal flooding and erosion in the face of climate change. This highlights the inclusion of spatial information in coastal indices, supported by multi-criteria techniques, machine learning, and physically based models that are evaluated in a decision matrix with the development pathways for the application of DSTs and ranking of DPs. It emphasizes that the choice of DST depends on the descriptors associated with the type of management to be carried out and the criteria that must be met to achieve management objectives, which can justify the selection of specific DSTs.

7. Conclusions

- A rational analysis, although not strictly objective, can provide clear guidance for selecting Decision Support Tools (DST) by integrating specific criteria. The conceptual model developed in this research enables the selection of the most suitable MCDA method by linking key descriptors such as computational cost, decision-maker knowledge, implementation time, and interaction dynamics. This approach considers fundamental aspects such as flood and erosion risk characterization to rank Development Pathways (DP) based on socio-economic sustainability, climate change adaptation, and cultural preservation criteria, ensuring that decisions align with stakeholder priorities and the needs of the coastal environment.
- Given the specific challenges associated with coastal flooding and erosion where multiple, often conflicting criteria must be balanced, and the decision-making context is highly complex PROMETHEE, ELECTRE, and VIKOR emerge as particularly suitable methods. Their ability to handle diverse types of data, incorporate decision-makers' preferences, and provide robust and stable results makes them highly effective for these scenarios. PROMETHEE and ELECTRE excel in ranking alternatives comprehensively, leveraging pairwise comparisons to evaluate and prioritize diverse management strategies systematically and transparently. Meanwhile, VIKOR stands out for its capacity to address conflicting criteria by focusing on a compromise solution, which is particularly useful in scenarios requiring consensus among stakeholders.
- For coastal areas where information is limited, and the decision-maker's knowledge level and desire for interaction are minimal, TOPSIS is recommended. The method provides a straightforward and clear approach to decision-making, requiring less subjective judgment in comparison to methods like MAUT. Its simplicity in implementation and ease of understanding makes it particularly suitable for situations where decision-makers need to quickly evaluate alternatives based on a set of predefined criteria, even with minimal interaction and lower levels of expertise.

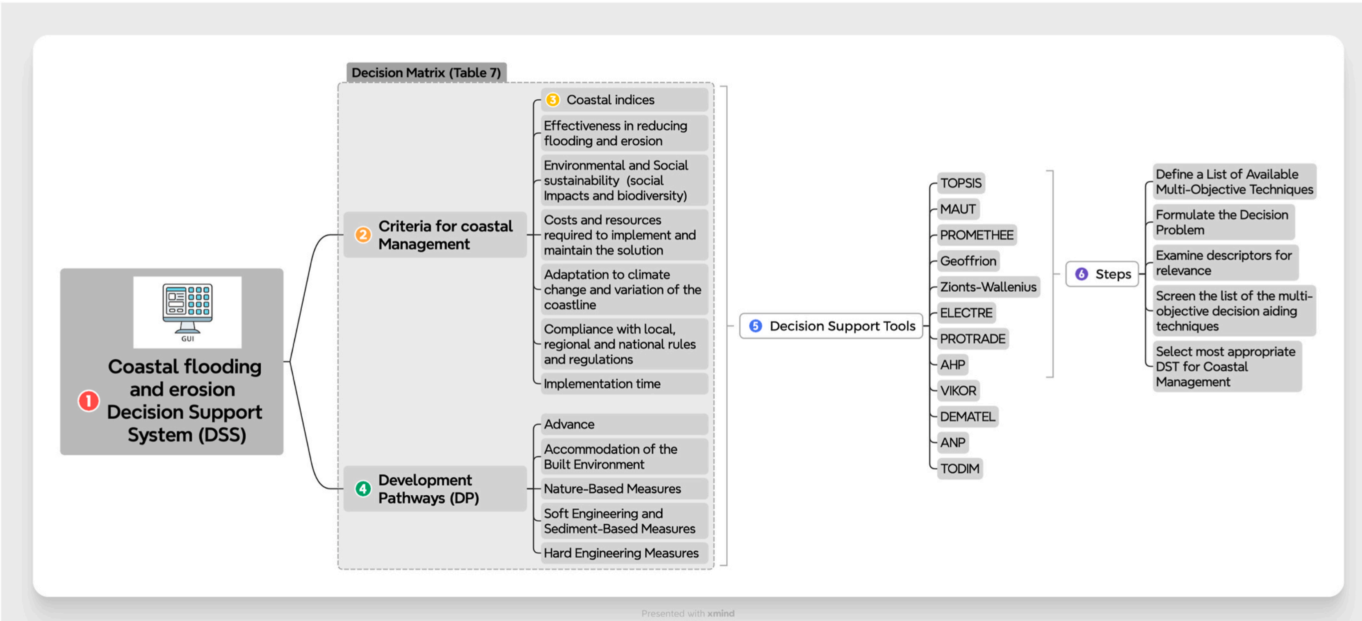

Fig. 3. Steps for Constructing and Selecting the Optimal Decision Support Tool (DST) for Coastal Management.
Note: The markers numbered 1 to 7 correspond to the chapters developed in this article.

- For coastal areas with limited information, minimal decision-maker knowledge, and low levels of interaction, methods like TOPSIS and MAUT are highly recommended. The decision-making framework outlined in Fig. 1 emphasizes the use of targeted questions to assess whether computational simplicity, minimal interaction, or straightforward implementation is required. For scenarios where the response is affirmative, TOPSIS emerges as an optimal choice due to its straightforward approach, requiring fewer subjective judgments and enabling rapid evaluation of alternatives. Conversely, if a more comprehensive evaluation of preferences is needed, MAUT offers the flexibility to model trade-offs among criteria effectively. Both methods align well with low-resource environments, providing practical solutions for evaluating development pathways (DPs) based on predefined criteria, even when expertise and stakeholder engagement are limited
- While PROTRADE provides clarity in defining objectives and is effective for targeted, straightforward goals, its suitability heavily depends on the decision-making context. Factors such as the complexity of coastal risks, the decision-maker's level of expertise, and the available computational resources significantly influence its applicability. The inherent subjectivity in selecting reference points and the method's reliance on linear aggregation of deviations introduce uncertainties that may undermine its effectiveness in scenarios requiring robust, precise decisions, such as coastal flooding and erosion management. Consequently, PROTRADE may be better suited for cases with well-defined aspirations and fewer conflicting criteria. When these conditions are not met, other methods that integrate non-linear and more flexible approaches, like PROMETHEE or ELECTRE, may offer greater reliability and applicability in dynamic coastal environment

8. Recommendations

Although this study does not specifically highlight the advantages of hybridizing MCDA methods, the conceptual model and decision framework presented here serve as a foundational step for evaluating whether hybridization is necessary. By thoroughly analyzing the descriptors and criteria such as computational cost, decision-maker knowledge, and interaction needs stakeholders can assess whether a single method suffices or if combining approaches would add value. This ensures that decisions prioritize relevance and efficiency, avoiding unnecessary complexity while maintaining focus on achieving practical and optimal outcomes for coastal management.

CRediT authorship contribution statement

Andrés M. Enríquez-Hidalgo: Writing – original draft, Visualization, Investigation, Formal analysis, Conceptualization. **Andrés Vargas-Luna:** Supervision. **Andrés Torres:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) utilized [ChatGPT 3.5] in order to [facilitate English review]. Subsequent to employing this tool/service, the author(s) thoroughly reviewed and edited the content as required and assume(s) full responsibility for the publication's content.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Andres M Enriquez reports a relationship with Fundación WWB para la investigación that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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