CORA Cork Open Research Archive
Cartlann Taighde Oscailte Chorcaí

Title	Seeing the whole coastline: Building and testing a comprehensive sustainable coastal vulnerability index
Authors	Chalençon, Emma;Cawkwell, Fiona;O'Shea, Michael;Murphy, Jimmy
Publication date	2026-08-01
Original Citation	Chalençon, E, Cawkwell, F, O'Shea, M & Murphy, J 2026, 'Seeing the whole coastline: Building and testing a comprehensive sustainable coastal vulnerability index', Applied Geography, vol. 193, 104075, pp. 1-17. https://doi.org/10.1016/j.apgeog.2026.104075
Type of publication	Article (peer-reviewed)
Link to publisher's version	https://www.scopus.com/pages/publications/105041139488 - 10.1016/j.apgeog.2026.104075
Rights	© 2026, authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/) - https://creativecommons.org/licenses/by/4.0/
Download date	2026-11-11 18:11:47
Item downloaded from	https://hdl.handle.net/10468/19573

UCC
University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Applied Geography 193 (2026) 104075

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Seeing the whole coastline: Building and testing a comprehensive sustainable coastal vulnerability index

Emma Chalençon [a,b,*], Fiona Cawkwell [a], Michael O'Shea [b], Jimmy Murphy [b]

[a] Department of Geography, University College Cork, T12 K8AF, Cork, Ireland
[b] MaREI Centre, Sustainability Institute, University College Cork, Ringaskiddy, P43 C573, Cork, Ireland

ARTICLE INFO

Handling Editor: J Peng

1. Introduction

Coastal zones are highly dynamic environments of critical ecological, economic, and social importance (Noor and Abdul Maulud, 2022; Šimac et al., 2023). However, these regions face increasing vulnerability due to a convergence of natural hazards, including sea-level rise, storm surges, erosion, and anthropogenic pressures (Kaniewski et al., 2016; Masselink and Lazarus, 2019; Pramanik et al., 2016). Climate change exacerbates these pressures, compromising the ability of coastal systems, human communities and natural ecosystems alike, to remain resilient and adaptive (Ummenhofer and Meehl, 2017).

In this context, assessing coastal vulnerability has become a global priority; the IPCC (The Intergovernmental Panel on Climate Change) (IPCC, 2007) and the European Environmental Agency (EEA), 2006; European Environmental Agency EEA, 2012 have emphasised the need for governments to assess vulnerability and adopt strategies that minimise exposure to climate risks while improving their ability to adapt. Yet, vulnerability is not merely a function of geophysical exposure to hazards. It emerges from the interactions of physical, social, economic, and environmental factors, operating across multiple scales and contexts (Noor and Abdul Maulud, 2022; Pantusa et al., 2018; Šimac et al., 2023). While a range of methodologies has been developed to capture this complexity, the Coastal Vulnerability Index (CVI) remains one of the most widely used tools (Gornitz, 1991; Thieler and Hammar-Klose, 2000). CVIs typically integrate physical parameters to discretise the coastline into zones of relative vulnerability (Rizzo et al., 2020; Ružić et al., 2019). Although efforts to incorporate socioeconomic dimensions date back to the early 2000s (Cutter et al., 2003; McLaughlin et al., 2002), their uptake within CVIs has remained inconsistent. CVIs have been repeatedly criticised for overemphasising biophysical exposure while neglecting the broader social and ecological systems that shape coastal vulnerability and adaptive capacity (Bukvic et al., 2020; Rocha et al., 2023).

Moreover, most CVIs remain opaque in their construction, rarely disclosing how indicator choices, weighting schemes, or aggregation formulae affect the outputs. This lack of methodological transparency undermines the reliability of results and limits their relevance for local decision-making (Bukvic et al., 2020; Oloyede et al., 2021). Calls for more holistic, transparent, and context-specific approaches have grown (Rocha et al., 2023; VanZomeren and Acevedo-Mackey, 2019), particularly those that integrate sustainability dimensions and align with evolving frameworks such as the IPCC's shift from vulnerability to risk-based assessments (Estoque et al., 2023; GIZ and EURAC, 2017).

Beyond coastal applications, Feizizadeh and Kienberger (2017) demonstrate how multi-criteria vulnerability assessment can include explicit sensitivity and uncertainty analysis. However, their framework is not specific to coastal systems and has not been applied to a CVI. Recent work has begun to explore transdisciplinary CVI frameworks that combine physical exposure with sociocultural, economic, and environmental indicators (Rocha et al., 2023). Yet Rocha et al. (2023), like many of the studies they review, aggregate social and economic aspects into a single "socioeconomic" dimension, which can obscure differences between social equity, cultural and ecological resilience, and economic capital. Moreover, the updated IPCC definition of vulnerability as a function of susceptibility to harm and the capacity to cope and adapt is rarely embedded explicitly in existing CVI frameworks (Estoque et al., 2023).

Chalençon et al. (2026) proposed a Sustainable Coastal Vulnerability

* Corresponding author. Department of Geography, University College Cork, T12 K8AF, Cork, Ireland.
E-mail address: emma.chalencon@ucc.ie (E. Chalençon).

https://doi.org/10.1016/j.apgeog.2026.104075
Received 6 October 2025; Received in revised form 30 May 2026; Accepted 1 June 2026
Available online 8 June 2026
0143-6228/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

Index (SCVI) that enables a comprehensive assessment of coastal vulnerability, one that distinguishes explicitly between sociocultural, economic and environmental susceptibility and aligns with the updated IPCC definition of vulnerability by not only capturing exposure but also incorporating adaptive capacity. That work provides a conceptual framework for rethinking coastal vulnerability as a place of "spatial coincidence" (Le Berre et al., 2022). It supports a more holistic understanding of coastal systems, helping to "see the whole coastline" and inform comprehensive sustainable local management.

This paper presents the first application of the SCVI proposed by Chalençon et al. (2026), to the coastline of County Cork, Ireland, a region with a predominantly coastal population, diverse ecosystems, and growing exposure to sea-level rise and storm-related hazards (Cork County Council, 2019). Using available spatial datasets, the SCVI is implemented in a GIS environment to generate vulnerability maps. A key contribution of this paper is a comprehensive sensitivity analysis, which evaluates how methodological choices influence index outcomes. This component, rarely addressed in CVI applications, enhances both the transparency and the robustness of the results. These developments demonstrate how a sustainability-focused, transdisciplinary CVI can offer more reliable, interpretable, and actionable insights for local coastal management, while remaining adaptable to variable data availability.

2. Methodology

2.1. Study area

This study focuses on the coastline of County Cork, west of Cork Harbour, in the southwest of Ireland (Fig. 1). The coastline extends for over 1100 km, including sandy beaches, rocky headlands, estuaries, dune systems, and saltmarshes (Neilson and Costello, 1999). These features contribute to the region's high environmental value but also expose it to significant coastal hazards, including erosion, storm surges, and projected sea-level rise, particularly in low-lying and sedimentary areas which are often the first site of landfall for weather systems approaching from the south-west across the Atlantic Ocean. The offshore wave climate along Ireland's Atlantic margin is energetic, but nearshore wave exposure is highly spatially variable: on exposed western headlands, average winter wave power at the 15 m isobath can reach 75 kW/m and average winter significant wave height up to 2.8 m. The tidal regime is semi-diurnal, with a mesotidal to locally macrotidal range of approximately 2.8–3.7 m, contributing to extensive intertidal areas and affecting the timing and severity of coastal flooding in low-lying estuaries and bays.

County Cork, with a population of 330,000 excluding Cork City (CSO, 2023), is home to a predominantly coastal population, with significant concentrations of human activity along the shoreline (Central Statistics Office CSO, 2016). Coastal settlements are socioeconomically diverse, ranging from historic towns to rural fishing communities, and the region's economy depends heavily on coastal locations for tourism, agriculture, and marine-based industries (Cork County Council, 2020). Cultural heritage is deeply embedded in the coastal landscape, with numerous archaeological and historical sites contributing to a strong sense of place (Cork County Council, 2022).

Ireland's approach to coastal management and vulnerability assessment has historically been fragmented, with limited national-scale integration, very limited coastal monitoring, and no dedicated coastal governance structure (Caloca-Casado, 2018; Devoy, 2008; Falaleeva et al., 2011; Farrell et al., 2021; O'Mahony et al., 2014). While the Geological Survey of Ireland (GSI) is developing (as of 2025) a national Coastal Vulnerability Index based on a modified Gornitz (1991) model, there remains a need for more comprehensive approaches. County Cork offers a highly relevant test case for advancing such methods.

2.2. Methodological framework: the multi-index approach

The SCVI presented here is structured as a modular, multi-index tool, integrating five thematic subindices (Fig. 2). The Coastal Hazard Index (CHI) characterises direct exposure to dynamic coastal processes. The Physical Susceptibility Index (PSI) reflects the intrinsic susceptibility of the physical landscape. The Sociocultural Susceptibility Index (ScSI) represents social, demographic, and cultural dimensions of vulnerability. The Economic Susceptibility Index (EcoSI) assesses the exposure and robustness of economic assets and infrastructure. The Environmental Susceptibility Index (EnSI) evaluates the ecological susceptibility of coastal habitats and ecosystems. These are organised into two composite dimensions: a Physical Vulnerability Index (PVI = CHI + PSI) and a Sustainable Susceptibility Index (SSI = ScSI + EcoSI + EnSI), which are then combined to produce the final SCVI. The framework is grounded in a transdisciplinary understanding of vulnerability that includes both exposure and adaptive capacity, aligning with the updated IPCC definition (IPCC, 2014; GIZ and EURAC, 2017). Exposure refers to the presence of human and environmental systems within the coastal zone that may be affected by coastal hazards. Sensitivity describes the degree to which these exposed systems may be affected, reflected in the classifications of the susceptibility parameters. Adaptive capacity, or resilience, represents the ability of these systems to cope with or respond to

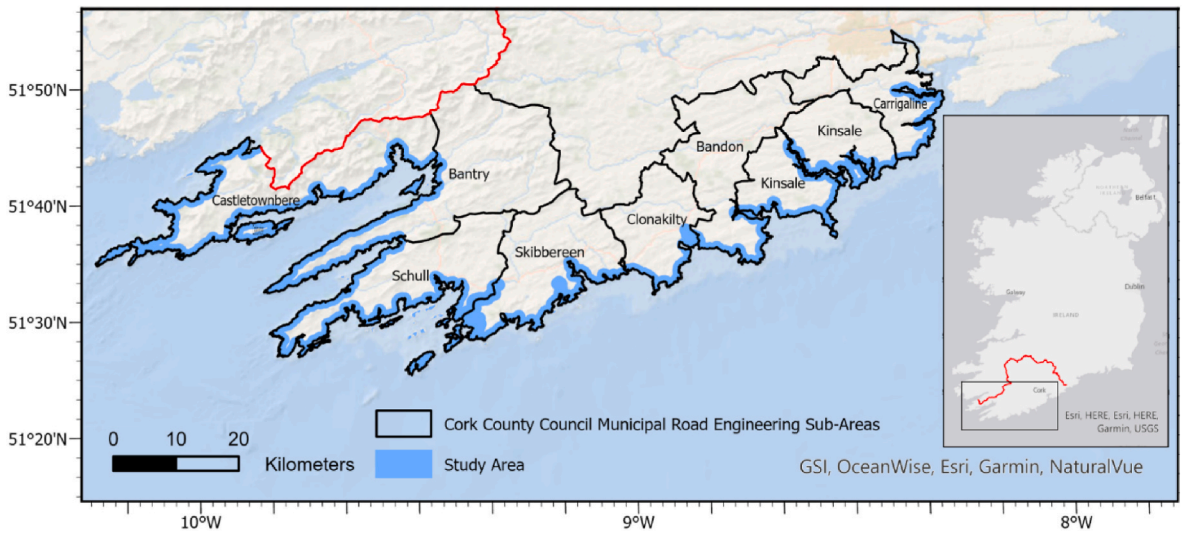


Fig. 1. Region of the County Cork coastline for which the SCVI was mapped, with the County Council municipal road engineering subareas shown.

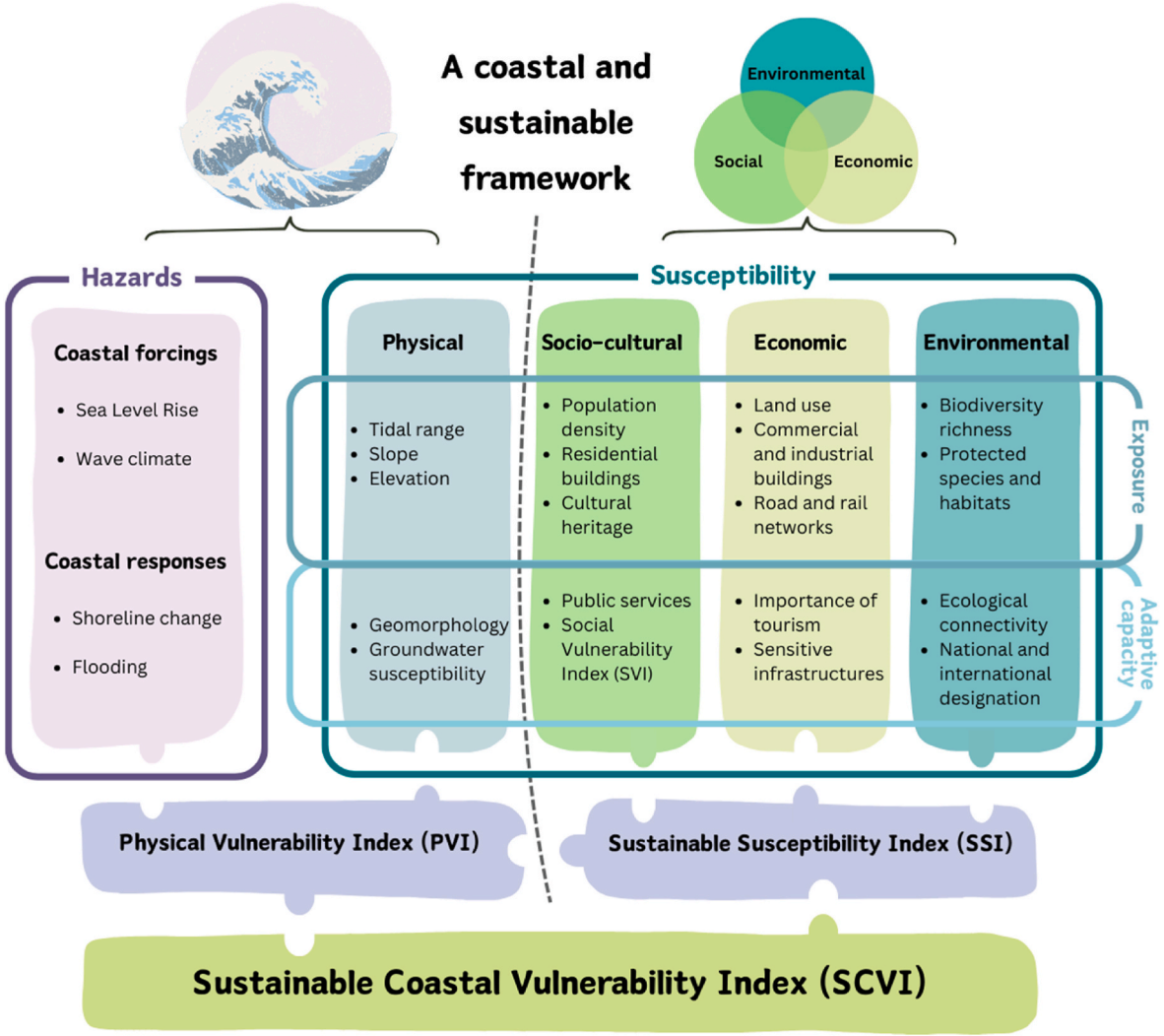


Fig. 2. The SCVI is a coastal and sustainable framework made of five subindices hazard- and susceptibility-focused which are used to calculate two components; the Physical Vulnerability Index (PVI) and the Sustainable Susceptibility Index (SSI). The combination of the two latter components forms the final SCVI.

impacts and is captured through indicators such as groundwater vulnerability, public services, social vulnerability, tourism dependency, or ecosystem protection status. The final SCVI is delivered in the form of a 50 m by 50 m grid, extending 1 km inland from the coastline, as an operational 'coastal strip', consistent with common practice in GIS-based coastal vulnerability mapping and related coastal-risk products (Jenkins et al., 2017, p. 18; Tanim et al., 2022), allowing the user to interrogate each individual cell and retrieve the vulnerability score per parameter and subindex.

2.3. Parameter selection and classification

The SCVI is applied here using parameters specific to County Cork, yet it is designed as a flexible and adaptable framework for broader applications. The conceptual "boxes" in Fig. 2 can be populated with context-appropriate indicators depending on data availability, scale and management priorities, provided the distinction between coastal forcings and responses, and between exposure and adaptive capacity within each susceptibility subsystem is maintained.

The SCVI presented here is a baseline assessment based on the most recent best-available spatial datasets for each parameter. As commonly encountered in applied coastal assessments, input layers are not fully harmonised to a single reference year, reflecting constraints in data availability. Most parameters describe slowly varying structural conditions, while the hazard component is explicitly scenario-capable: CHI inputs can be replaced with modelled projections for specific horizons to generate SCVI outputs for climate-change planning.

Table 1 provides an overview of the parameters selected for County Cork and their associated classification schemes. To maintain clarity in the main text, detailed descriptions of the rationale, data sources, preprocessing steps, and classification methods for each parameter are provided in Appendix A.

The coastal hazard component distinguishes between coastal forcings and coastal responses (Fig. 2). Coastal forcings describe the hydrodynamic conditions that drive coastal change. Relative sea-level rise (rSLR) expresses long-term changes in mean water level at the coast, which modulate the frequency and magnitude of extreme sea levels and can amplify both flooding and shoreline retreat. Wave climate summarises the nearshore wave regime, which governs the energy available along exposed coasts. Coastal responses capture how the shoreline and adjacent low-lying areas have reacted, or are likely to react, to these forcings. The long-term shoreline change rate (LRR) reflects the historical tendency of the coastline to erode or accrete. Finally, the coastal flooding layer represents the spatial extent and intensity of inundation under extreme water-level scenarios.

Physical susceptibility is described by tidal range, coastal slope, and elevation as exposure parameters, because microtidal, low-lying and gently sloping coasts have a larger area that can be inundated or eroded.

Table 1
Parameter sourcing, processing and classification.

Index	Parameter	Source	Data type	Classification					Data to Grid
				Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
Coastal Hazard	Relative Sea Level Rise (rSLR)	Geological Survey Ireland (GSI)	Point		4.9-5.4 (mm/yr)	5.4-5.7 (mm/yr)	>5.7 (mm/yr)		Closest
	Shoreline Change (LRR)	Chalençon et al., 2026: DSAS Linear Regression Rates from 5 automatedly detected vegetation lines (2000 to 2021) at a 10 m resolution	Point	>+ 0.27 (m/yr)	+0.27 to −0.27 (m/yr)	−0.27 to −0.5 (m/yr)	−0.5 to −1 (m/yr)	< −1 (m/yr)	Mode of the overlapping points or mode within 250 m
	Flooding (Flood)	Office of Public Works (OPW) National Coastal Flood Extents 2021 and Irish Coastal Wave and Water Level Modelling Study Coastal Area Potentially Vulnerable to Wave Overtopping (CAPO) extent Extreme Wave Events (O'Brien et al., 2018)	Polygon	Absence	1000-year return period	200-year return period	10-year return period	CAPO/ Extreme Wave	Maximum
	Wave Climate (WaveClim)	Average winter wave orientation and wave power (October-April 2000-2020) from a nearshore wave model at a 400 m resolution	Point	Wave power <5 kW/m and Incidence angle >75° Wave power <10 kW/m and not a sandy shore environment	Wave power <5 kW/m and Incidence angle >60° Wave power <10 kW/m and Incidence angle >75° Wave power <20 kW/m and not a sandy shore environment	Wave power <5 kW/m and Incidence angle >45° Wave power <10 kW/m and Incidence angle >60° Wave power <20 kW/m and Incidence angle >75° Wave power <50 kW/m and not a sandy shore environment	Wave power <5 kW/m and Incidence angle <45° Wave power <10 kW/m and Incidence angle >45° Wave power <20 kW/m and Incidence angle >60° Wave power <50 kW/m and Incidence angle >75° Wave power >50 kW/m and not a sandy shore environment	Wave power <10 kW/m and Incidence angle <45° Wave power <20 kW/m and Incidence angle <60° Wave power <50 kW/m and Incidence angle <75° Wave power >50 kW/m and Incidence angle <90°	Closest
Physical Susceptibility	Tidal range (Tide)	Geological Survey Ireland (GSI)	Point	>4.5	4.5 - 3.8	3.8 - 2.8	2.8 - 1.4	1.4 - 0.7	Mode of the overlapping points or mode within 250 m
	Slope (Slope)	OPW Coastal Aerial LiDAR Survey 2021 INFOMAR latest bathymetry dataset	Grid	>12%	9-12%	6-9%	3-6%	<3%	Mode
	Elevation (Elev)	OPW Coastal Aerial LiDAR Survey 2021	Grid	>6	3 to 5.9	2 to 2.9	1 to 1.9	<1.0	Mode
	Groundwater (GrWater)	GSI Groundwater vulnerability	Polygon	Low	Moderate	High	Extreme	Rock at surface/ Water	Maximum

(*continued on next page*)

Table 1 (*continued*)

Index	Parameter	Source	Data type	Classification					Data to Grid
				Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
	Geomorphology (Geomo)	GSI Quaternary Sediments Tailte Ireland - National Land Cover Map (2018)	Polygon	Bedrocks	Embankment/ Pier	Gravels/ Limestones/ Tills/Screes	Alluvium/ Silts/Clays/ Peats/ Lacustrine Sediments	Marshes/ Mudflats/ Sands/ Industrial/ Urban/ Landfill	Maximum
Sociocultural Susceptibility	Density (PopD)	Central Statistics Office (CSO) Census 2022	Polygon	<769 inhabitants/ km2	<3032 inhabitants/ km2	<5238 inhabitants/ km2	<8140 inhabitants/ km2	≥8140 inhabitants/ km2	Maximum
	Residential buildings (Resid)	Geodirectory	Point	Absence within 50 m				Presence within 50 m	Maximum
	Cultural heritage (Cult)	National Inventory of Architectural Heritage (NIAH) National Maritime Planning Framework National Monuments Service (NMS) Record of Protected Structures	Point	Absence within 50 m				Presence within 50 m	Maximum
	Public services (PServ)	Open Street Map (Schools, hospitals, healthcare facilities, fire stations, police stations, transport stations)	Point	Absence within 50 m				Presence within 50 m	Maximum
	Social Vulnerability (SVI)	Central Statistics Office (CSO) Census 2022 Irish Social Vulnerability to Environmental Hazards Index (ISVEHI) (McCullagh et al., 2025)	Polygon	< −1	> −1	> −0.5	>0.5	>1	Maximum
Economic Susceptibility	Land Use/Cover (LU)	Tailte Ireland - National Land Cover Map (2018)	Polygon	Waterbodies/ Exposed Rock and Sediments/ Mudflats	Treelines Forests/ Woodlands	Peat/Bog/ Hedgerows/ Bracken/ Scrub/Burnt areas/Heath/ Marshes/ Swamp/Dune	Grasslands/ Cultivated Land	Ways/ Artificial Surfaces/ Buildings	Maximum
	Commercial and industrial buildings (ComIndu)	Geodirectory	Point	Absence within 50 m				Presence within 50 m	Maximum
	Road and rail networks (Networks)	Cork County Council Road schedule Tailte Eireann - National Land Cover Map (Ways)	Polyline	Absence		Ways	Local roads	National and regional roads	Maximum
	Density of tourism infrastructures (Tourism)	Open Street Map (key: leisure, key: tourism; e.g. Surf school, B&B, or visitor centre)	Polygon	Absence	<2	<10	<20	>20	Maximum
	Sensitive infrastructures (Sensitive)	Environmental Protection Agency (EPA) Licensed facilities EPA Urban Waste Water Treatment Plant Location	Points	Absence within 50 m				Presence within 50 m	Maximum
Environmental Susceptibility	Biodiversity Richness (Biodiver)	Ecosystems Services, Mapping and Assessment	Grid	<400	<500	<600	<750	>750	Maximum

(*continued on next page*)

Table 1 (*continued*)

Index	Parameter	Source	Data type	Classification					Data to Grid
				Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	
	Protected species (Species)	National Pilot – National Parks & Wildlife Services (NPWS) 2017 Ecosystem Function Stock Map - Terrestrial Biodiversity Ecosystems Services, Mapping and Assessment National Pilot - NPWS 2017 Legally Protected and Policy Relevant Species Coincidence	Grid	<3300	<7950	<11,100	<15,150	>15,150	Maximum
	Ecological connectivity (Connect)	Ecosystems Services, Mapping and Assessment National Pilot - NPWS 2017 Contribution to ecological networks	Grid	Absence		Part of 1 ecological network	Part of 2 ecological network	Part of 3 ecological network	Maximum
	Designations (Designat)	NPWS (Special Areas of Conservation, Special Protection Areas, Natural Heritage Areas) Ramsar convention	Grid	Absence		International	European	National	Maximum

Geomorphology and groundwater susceptibility indicate adaptive capacity, reflecting the resistance of landforms to erosion and the vulnerability of coastal aquifers to saltwater intrusion. Sociocultural susceptibility uses population density, residential buildings and cultural heritage as exposure indicators, capturing people, housing and heritage assets, while public services and social vulnerability represent community-level capacity to prepare for, respond to and recover from coastal impacts. Economic susceptibility is characterised by land use/land cover, commercial and industrial buildings, and transport networks as exposure indicators, locating economic activities and critical infrastructure that may be directly damaged by flooding and erosion. Tourism infrastructure and sensitive infrastructure (such as wastewater treatment plants, energy facilities and hazardous industries) are included as adaptive-capacity indicators because they express how strongly local livelihoods and essential services depend on coastal assets and how much secondary risk may arise if these facilities are impacted. Environmental susceptibility uses biodiversity richness and the presence of protected or policy-relevant species as exposure indicators, identifying ecosystems and species of high conservation value at risk from coastal hazards, while ecological connectivity and the level of environmental protection indicate the capacity of ecosystems to maintain functions and benefit from conservation and recovery measures.

2.4. Weighting and aggregation

To determine the relative importance of the 23 parameters used in the Sustainable Coastal Vulnerability Index (SCVI), a structured Analytic Hierarchy Process (AHP) survey was conducted. The survey gathered input from 24 experts involved in the Cork coastline vulnerability assessment project, including representatives from academia (10), public authorities (6), governmental agencies (2) and consultancies (6). This large and balanced panel, with no single stakeholder group dominating, helped to minimise individual and institutional bias in the AHP process. Participants were asked to perform pairwise importance comparisons, to derive weights for each parameter within their respective subindices. The results of the survey were compiled and analysed to produce a final weighting table (Table 2), which was then used to calculate subindices. Each subindex was constructed through a weighted sum of its constituent parameters. This method was chosen for its transparency and ease of implementation, and to remain consistent across all components of the index. The implications of this aggregation choice are further evaluated through a sensitivity analysis presented in Section 3.3.

The five thematic scores were aggregated into two overarching components: the Physical Vulnerability Index (comprising CHI and PSI) and the Sustainable Susceptibility Index (comprising ScSI, EcoSI and EnSI) (Fig. 2). Each component was computed using a second-level weighted sum, with weights derived from the AHP survey (Table 2), with the exception of EnSI, where an initial weight of 32% disproportionately influenced the final SCVI rankings. Given the comparatively higher uncertainty and coarser resolution of the environmental datasets, this imbalance was interpreted as a potential source of methodological sensitivity rather than an intended outcome of the conceptual weighting scheme. The EnSI weight was therefore reduced to 20% as an uncertainty management step, preserving its importance while preventing it from disproportionately affecting the final SCVI outcomes. A simple sensitivity test comparing SCVI maps showed that, under the original weights the SCVI was more strongly correlated with EnSI than with the sociocultural or economic subindices ($r \approx 0.44$ vs 0.36–0.38), whereas after adjustment the influence of the three susceptibility dimensions became more balanced ($r \approx 0.32$ vs 0.46–0.49).

Finally, the SCVI score for each 50 m grid cell was calculated as the product of the Physical Vulnerability Index (*PVI*) and the Sustainable Susceptibility Index (*SSI*) scaled from 1 to 5 (eq. (1)).

Table 2
AHP derived weights. The Consistency Ratio (CR) indicates how consistent the judgments are in an AHP comparison matrix and should be below 10% for acceptable reliability. (*) These weights are not directly derived from the AHP survey.

Component	Parameter	AHP Weights	Consistency Ratio (CR) should be <10%
Coastal Hazard	Relative Sea Level Rise (rSLR)	18%	0.59%
	Shoreline Change (LRR)	30%	
	Flooding (Flood)	28%	
	Wave Climate (WaveClim)	24%	
Physical Susceptibility	Tidal range (Tide)	14%	0.67%
	Slope (Slope)	15%	
	Elevation (Elev)	32%	
	Groundwater (GrWater)	10%	
	Geomorphology (Geomo)	28%	
Physical Vulnerability	**Coastal Hazard Index (CHI)**	**60%**	N/A
	Physical Susceptibility Index (PSI)	**40%**	
Sociocultural Susceptibility	Density (PopD)	31%	1.56%
	Residential buildings (Resid)	19%	
	Cultural heritage (Cult)	7%	
	Public services (PServ)	23%	
	Social Vulnerability (SVI)	20%	
Economic Susceptibility	Land Use/Cover (LU)	11%	1.22%
	Commercial and industrial buildings (ComIndu)	12%	
	Road and rail networks (Networks)	33%	
	Density of tourism infrastructures (Tourism)	10%	
	Sensitive infrastructures (Sensitive)	33%	
Environmental Susceptibility	Biodiversity Richness (Biodiver)	27%	1.49%
	Protected species (Species)	30%	
	Ecological connectivity (Connect)	20%	
	Designations (Designat)	23%	
Sustainable Susceptibility	**Sociocultural Susceptibility (ScSI)**	**40%** *	N/A
	Economic Susceptibility (EcoSI)	**40%** *	
	Environmental Susceptibility (EnSI)	**20%** *	

$$SCVI = 1 + \frac{(PVI^{*}SSI) - 1}{6} \quad (1)$$

This multiplicative approach ensures that high SCVI scores only arise where physical vulnerability and systemic susceptibility co-occur. Unlike linear normalisation, the multiplicative form prevents compensation between dimensions, emphasising the spatial coincidence between coastal hazards and the vulnerability of assets, as advocated by Le Berre et al. (2022). Although the multiplicative combination resembles formulations commonly used in risk assessments, these assessments typically combine hazard probability, exposure, and potential consequences. In contrast, the SCVI focuses on characterising the susceptibility of coastal landscapes and socioecological systems under prevailing coastal hazard conditions. As such, the SCVI should be interpreted as a vulnerability index that can support risk screening and coastal planning, rather than a quantitative risk metric.

3. Results

3.1. Regional and local SCVI patterns

The SCVI was computed at a 50 m resolution within a 1 km coastal buffer (top panel of Fig. 12). Hotspots of very high vulnerability align with coastal towns characterised by dense populations and clustered infrastructure. A distinct spatial gradient is evident: cells closest to the shoreline typically exhibit higher vulnerability, while those farther inland tend to be classified as very low. Although proximity to the coast was initially included in Chalençon et al. (2026), it was removed after sensitivity testing revealed high collinearity with other variables. Nonetheless, the resulting SCVI pattern still captures the influence of coastal proximity, reinforcing the robustness of the index and the rationale for excluding a dedicated distance parameter. Estuarine areas also emerge as prominent hotspots of high and very high vulnerability. These environments are particularly susceptible due to their low elevation, dynamic geomorphology, and exposure to sea-level rise and storm surges. At the same time, estuaries have long been focal points of human settlement and economic activity, while also hosting ecologically important habitats, making them highly vulnerable from both socio-economic and environmental perspectives.

To further investigate how the five subindices are compounded, five sites were selected for closer examination (Fig. 12, A, B, C, D, E), reflecting a diverse range of coastal settings. This detailed analysis enables a more granular interpretation of how local characteristics drive vulnerability at finer spatial scales.

Across the five sites (Fig. 12), the CHI highlights high-energy wave-exposed beaches with a history of shoreline retreat and estuarine areas as hazard hotspots, with very high values at Allihies (A) and Barley Cove (B) on the west coast, as well as two distinct hazard zones at Owenahincha (Fig. 12, C3), more limited erosion-prone segments at Inchydoney (D), and shoreline retreat along the margins of Garretstown and Garrylucas (Fig. 12, E3). PSI is generally very high wherever low-lying, low-slope sandy beaches and dune systems occur, and also extends inland over estuarine wetlands at Owenahincha and the Old Head (Fig. 12, C4 and E4). Together, CHI and PSI show that the most physically vulnerable areas are exposed sandy shorelines and associated back-beach and estuarine systems.

Sociocultural and economic indices reveal more localised patterns. ScSI is typically moderate and concentrated behind the beaches, where residential areas, holiday apartments and caravan parks (Fig. 12, C5) or small settlements are present. It remains low at sites with sparse housing and low social vulnerability, such as Inchydoney (Fig. 12, D5). EcoSI, by contrast, picks out economic hotspots near roads, tourism-related businesses, resorts and sensitive infrastructure. These include, for example, localised high values close to a wastewater treatment plant and resort at Owenahincha (Fig. 12, C6), tourism accommodation and access roads at Barley Cove and Inchydoney (Fig. 12, B6 and D6), and the road network and commercial uses between Garretstown and Garrylucas (Fig. 12, E6). Overall, socioeconomic susceptibility is spatially confined but often closely aligned with back-beach infrastructure. Environmental susceptibility is more site-dependent. EnSI is generally limited at Allihies (Fig. 12, A7), where only a small hotspot emerges, but shows high values where biodiversity, protected species and overlapping designations converge. This is particularly evident at Barley Cove (Fig. 12, B7), where a Special Area of Conservation intersects with a Special Protection Area, around the estuary and dunes at Owenahincha (Fig. 12, C7), and across the dune and wetland systems at Inchydoney and the Old Head (Fig. 12, D7 and E7).

The composite SCVI integrates these dimensions. Very high SCVI values are found where exposed, erosion-prone sandy coasts and estuaries overlap with roads, buildings and tourism infrastructure, such as the northwestern part of Allihies, the Barley Cove estuary and Old Head tombolo beaches, the roads behind the Owenahincha beaches, the road and buildings immediately behind the Inchydoney dunes, and the back-

beach roads at Garretstown and Garrylucas. In all sites, SCVI hotspots emerge at the interface between highly sensitive coastal landforms and concentrated human use or environmental designations, rather than over the full extent of physically exposed shoreline.

3.2. Vulnerability class coverage and drivers of SCVI variability

The high and very high vulnerability classes in the study area cover approximately 57 km^2 and 13 km^2, respectively, accounting for 12% of the total area (Fig. 13). In contrast, low and very low vulnerability levels cover approximately 184 km^2 and 210 km^2, comprising 67% of the study area. Clonakilty is the municipal engineering subarea (Fig. 1) with the highest proportion of high and very high vulnerability (22%) (Fig. 13). Clonakilty town lies within a tidal estuary shaped by the Fealge River, bordered by extensive wetlands and low-lying terrain. These conditions inherently increase susceptibility to coastal hazards such as flooding, storm surges, and sea-level rise. The presence of the Inchydoney dune system further indicates active sedimentary dynamics that are vulnerable to erosion and morphological change under both natural and anthropogenic pressure. Additionally, the concentration of tourism

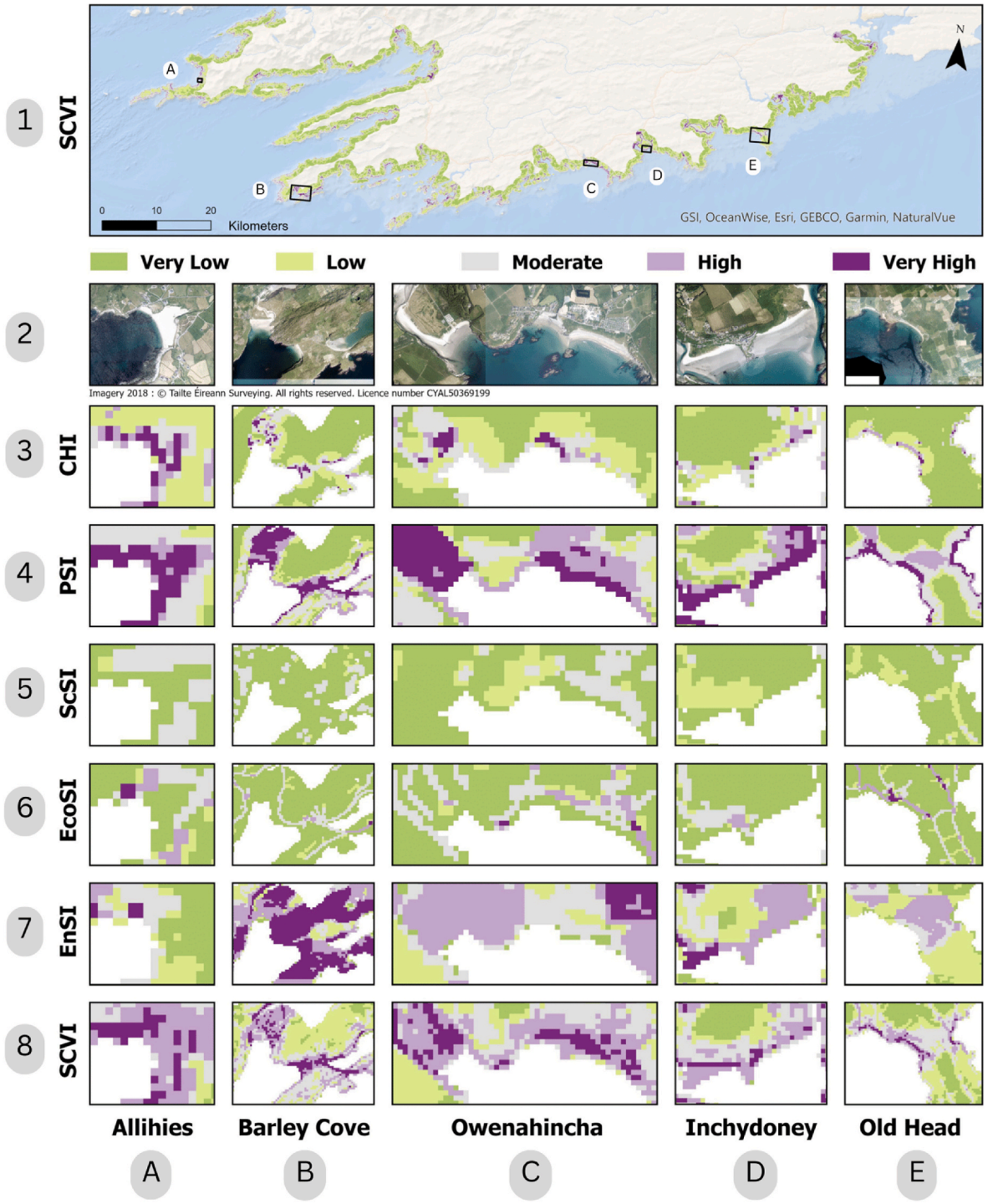


Fig. 3. Parameter redundancy and multicollinearity screening. Pairwise Pearson correlation matrices (top) and variance inflation factors (bottom) for the parameters comprising each subindex (CHI, PSI, ScSI, EcoSI, EnSI).

infrastructure in Clonakilty and around Inchydoney Beach, a designated Blue Flag site, increases exposure by placing high-value assets in hazard-prone coastal zones.

Using first-order variance propagation applied to $M = \text{PVI} \times \text{SSI}$, SCVI spatial variability is primarily driven by the physical component, with PSI contributing 37% and CHI 24% of total variance (61% combined). The remaining variability is explained by the sustainability susceptibility dimensions, led by EcoSI (18%) and ScSI (13%), while EnSI contributes 8%.

3.3. Sensitivity analysis

Evaluating the robustness and reliability of the SCVI framework requires more than just assessment of the final outputs and their interpretation in the context of features at each site, especially if the approach is to be transferable and scalable. It necessitates a closer examination of how the individual components of the index respond to methodological choices and data variability.

3.3.1. Parameter redundancy and collinearity

Potential redundancy among parameters was assessed using Pearson correlations and Variance Inflation Factors (VIFs) (Fig. 3). Following Pantusa et al. (2022), VIF values > 10 were treated as the indicative threshold above which multicollinearity may affect model estimates. In CHI, no strong correlations were observed; rSLR was the only variable exceeding the VIF threshold, primarily because it has no spatial variance, which can inflate VIF even in the absence of true collinearity. PSI showed only weak to moderate correlations (all r < 0.62), while all VIFs remained <7. In ScSI, population density and residential buildings had VIFs >10 due to spatial coincidence but were retained as complementary measures of social exposure. EcoSI displayed moderate correlation between land use and transport networks (r = 0.54) and elevated VIFs for land use and sensitive infrastructure linked to urban clustering; both were preserved due to distinct relevance. EnSI showed moderate correlations among biodiversity richness, designations and connectivity; biodiversity richness exceeded the VIF threshold but was retained for ecological relevance. Overall, no variables were removed at this stage, as overlaps were expected and each parameter contributed complementary information.

3.3.2. Aggregation methods

The second phase of the sensitivity analysis evaluated the influence of aggregation choices. At the subindex level, six aggregation operators were compared (Fig. 4). The baseline weighted-sum approach used in this study remained highly consistent with all alternatives (r > 0.89 for all subindices), with CHI, PSI and EcoSI showing particularly strong agreement (r > 0.95). ScSI and EnSI displayed slightly greater variation, but overall correlations remained high, indicating that subindex patterns are not strongly dependent on the chosen aggregation logic.

At the composite level (Fig. 5), three alternative SCVI formulations were tested to assess sensitivity to the overall aggregation structure. SCVI_WS corresponds to a weighted sum of the five subindices. SCVI_CHIx applies a multiplicative structure in which CHI scales a weighted sum of the remaining four subindices, increasing the emphasis on hazard exposure. SCVI_PVIx multiplies the Physical Vulnerability Index (PVI = CHI + PSI, weighted) by the Sustainable Susceptibility Index (SSI = ScSI + EcoSI + EnSI, weighted). Correlation matrices comparing these three formulations (Fig. 5) show strong agreement in both values and rankings (Pearson r > 0.89; Spearman ρ > 0.94), demonstrating that SCVI outputs are highly stable across plausible aggregation schemes.

3.3.3. Leave-one-out diagnostics

A leave-one-out analysis was used to quantify the influence of each parameter by recalculating its subindex and the composite SCVI after removing that parameter and measuring the mean change in outputs (Figs. 6 and 7). At the subindex level, all mean differences remained below 0.5, indicating that no single variable dominates any subindex. As expected, parameters with higher weights or distinctive spatial structure (elevation and geomorphology in PSI; protected species and environmental designation in EnSI) produced the largest shifts, reflecting their intended role.

At the SCVI level (Fig. 7), most parameters have limited influence on composite values (mean change < ±0.08) and rankings (rank shifts <18,000 across >200,000 cells), further supporting the overall robustness of the framework. The largest effects are associated with rSLR, elevation, sensitive infrastructure and protected species, which induce

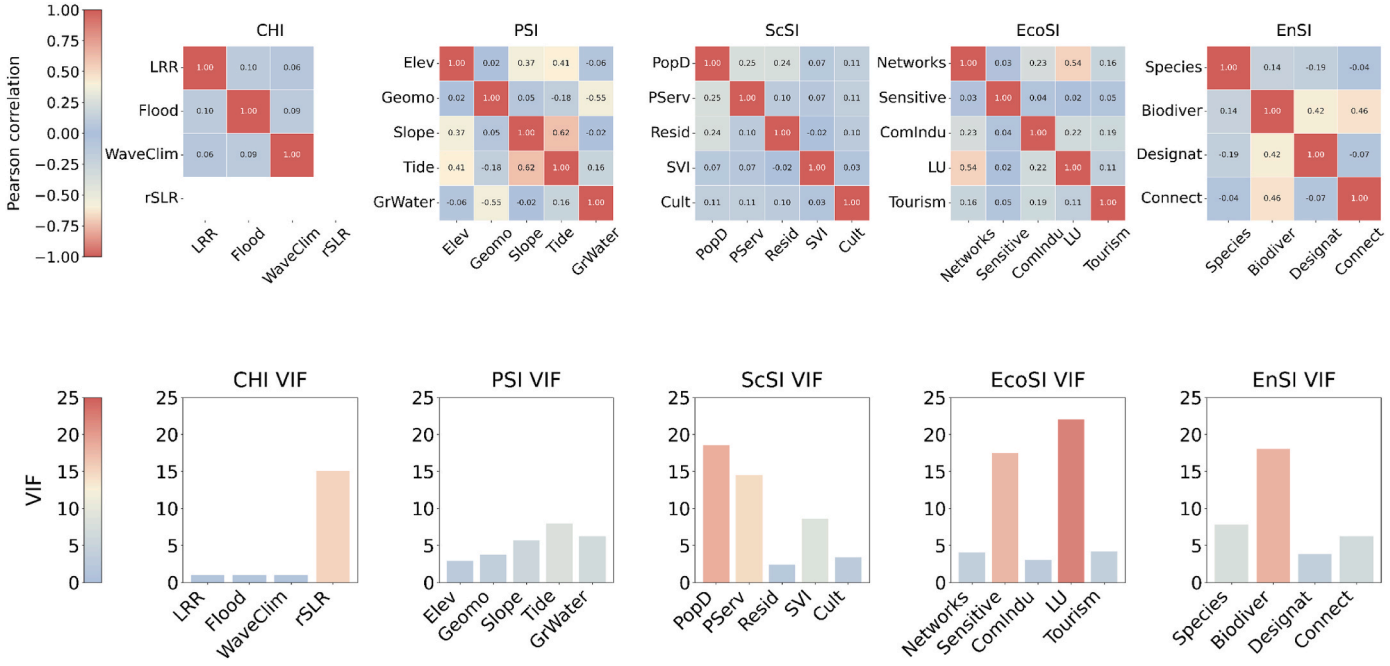


Fig. 4. Sensitivity of subindices to alternative aggregation operators. Pearson correlation matrices comparing subindex outputs computed using alternative aggregation methods (weighted sum, arithmetic mean, quadratic mean, geometric mean, harmonic mean, and product).

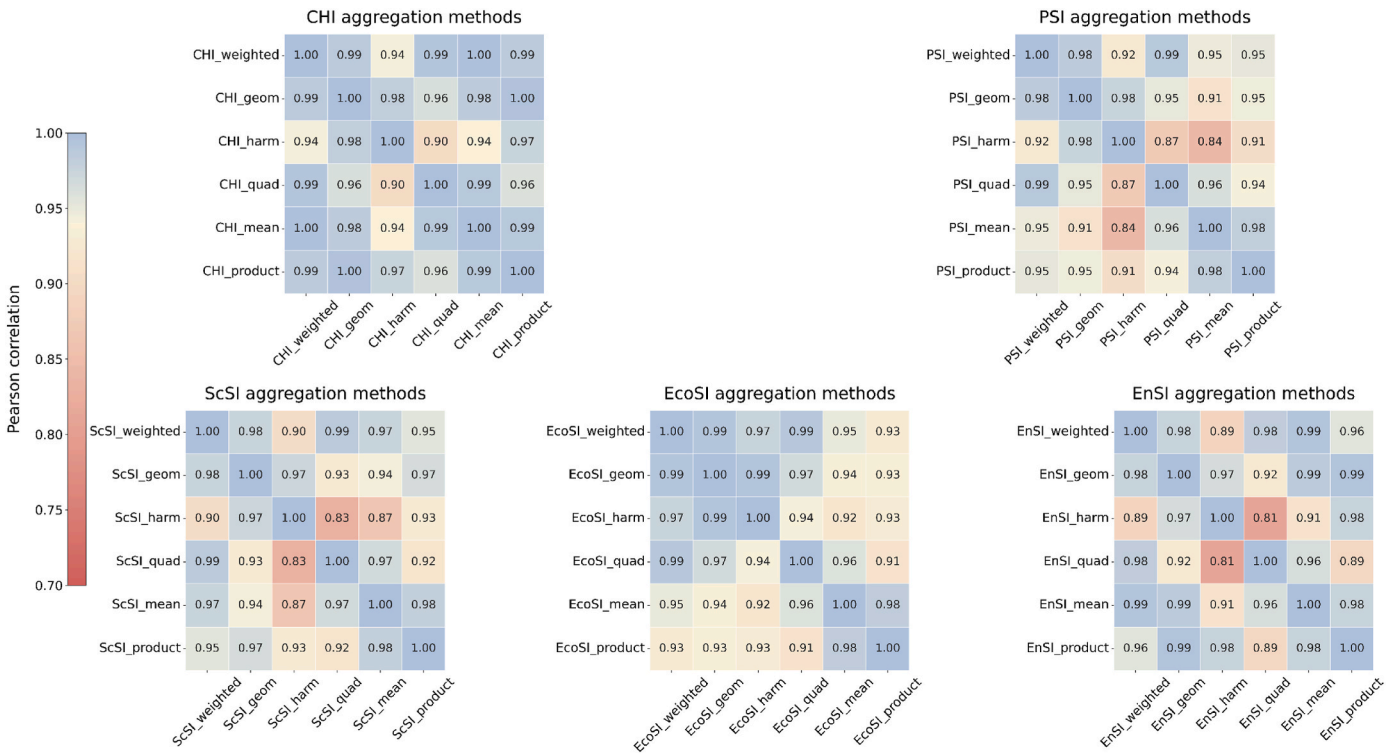


Fig. 5. Agreement between alternative SCVI aggregation formulations. Pearson (values) and Spearman (ranks) correlation matrices comparing SCVI outputs produced using three composite formulations (SCVI_WS, SCVI_CHIx, SCVI_PVIx).

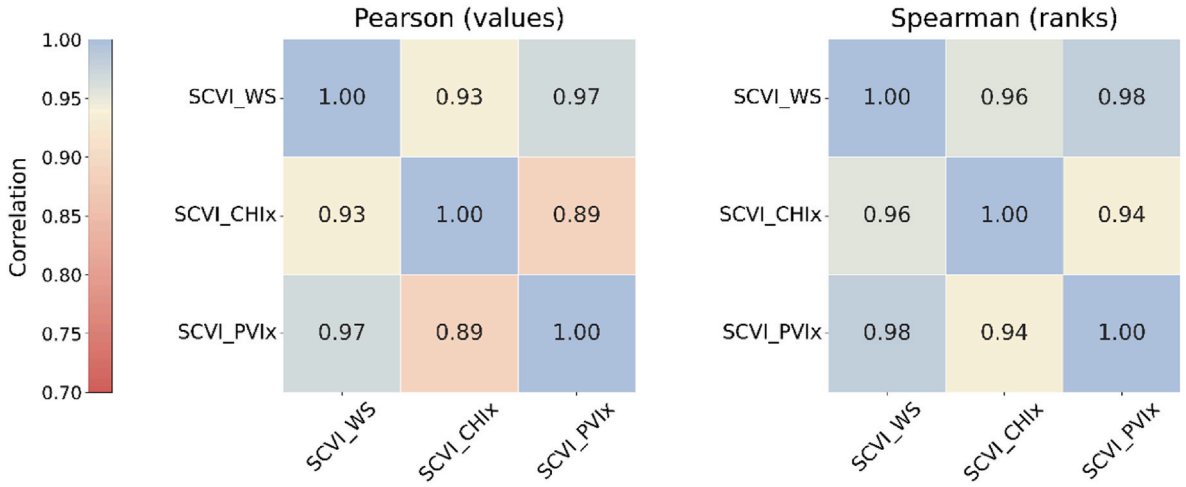


Fig. 6. Leave-one-out influence diagnostics. Mean absolute change in each subindex when one parameter is removed and the remaining weights are renormalised.

both score changes and local reordering, consistent with their relevance to hazard forcing, physical susceptibility, cascading infrastructure risk and ecological sensitivity.

Although rSLR is spatially uniform and has the lowest weight, its removal in the leave-one-out tests produces a notable effect for two reasons. First, rSLR contributes a constant baseline term to CHI that is present in every grid cell, so removing it shifts CHI, and therefore PVI and SCVI, systematically downward across the entire map. Additionally, in the leave-one-out procedure the remaining CHI weights are renormalised, increasing the relative influence of the spatially varying hazard layers (LRR, Flood, WaveClim), which can induce local reordering even when overall rank agreement remains high. Conversely, tourism density, cultural heritage and commercial/industrial buildings yield minimal changes when omitted, consistent with their lower weights and more localised contributions.

3.3.4. *Weights perturbations*

Uncertainty in weighting was evaluated using Monte Carlo simulations (1000 iterations) in which weights were perturbed while holding input datasets constant. At the subindex level, results indicate moderate but controlled sensitivity to weight variability (Fig. 8). ScSI was the most stable, showing the lowest dispersion, whereas EnSI exhibited the greatest variability and occasional outliers, consistent with its more spatially concentrated inputs and higher leverage seen in the leave-one-out analysis. PSI and EcoSI showed intermediate sensitivity, while CHI displayed comparatively low dispersion, reflecting its smaller parameter set and limited variability in weight allocation.

At the composite level, two Monte Carlo experiments were run:

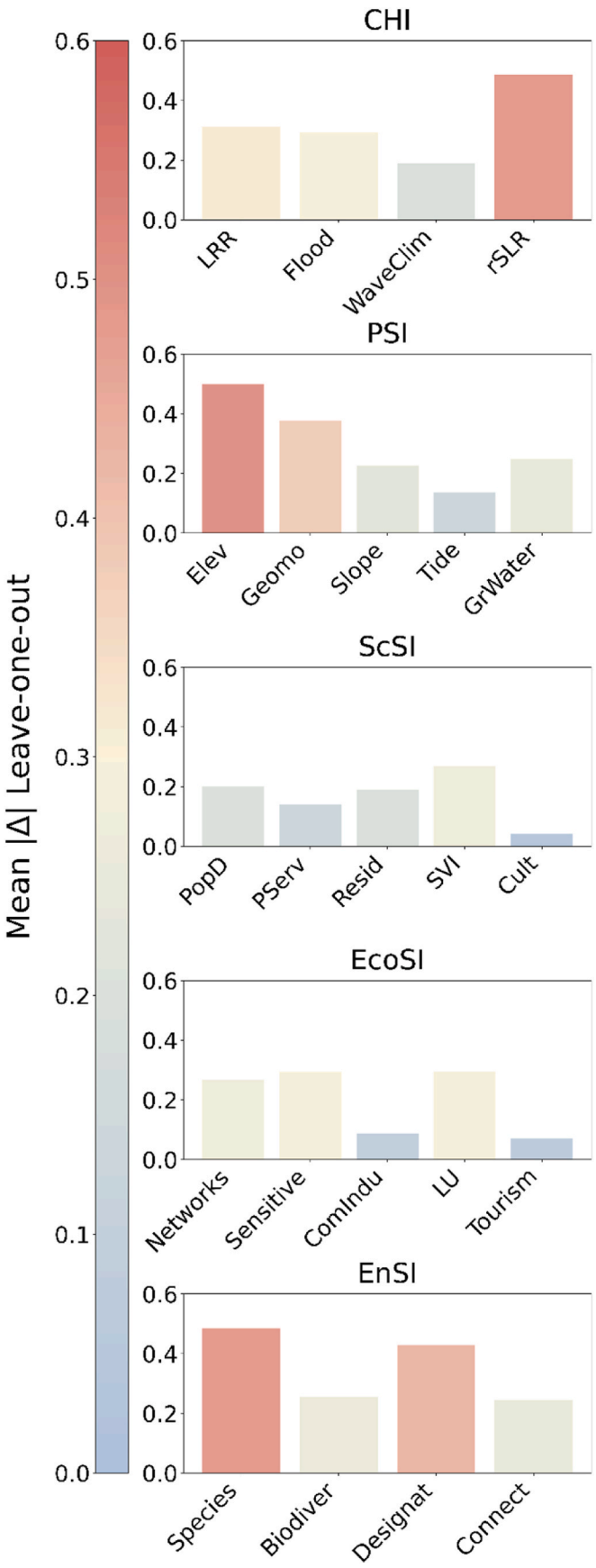


Fig. 7. Leave-one-out sensitivity of SCVI. Mean SCVI change (bars) and mean rank shift (line) observed when each input parameter is removed, and the index is recomputed.

perturbing parameter weights within subindices and perturbing subindex weights (Fig. 9). In both cases, SCVI value dispersion remained low (typically ± 0.25), indicating that plausible weight uncertainty introduces only modest changes in composite scores. Rank variability was higher, particularly under subindex-level perturbations, reflecting the influence of shifting balance across dimensions, but without evidence of systemic instability. Consistent with this, Table 3 shows high median rank agreement with the baseline (Spearman $\rho = 0.86–0.99$) and substantial class persistence for SCVI (median 73.75% of cells remaining in the same class), while hotspot persistence is moderate (median 49.08% overlap of the top 10% most vulnerable cells). Together, these results support the robustness of the weighting framework, while reinforcing the value of a rigorous participatory process, here implemented through AHP with 24 experts, because weighting choices still affect the precise spatial prioritisation of vulnerability.

3.3.5. *Classification methods*

The final sensitivity test examined how classification schemes affect the mapped distribution of vulnerability classes. Four common approaches, equal intervals, quantiles, Jenks natural breaks, and standard deviation, were applied and compared (Figs. 10 and 11). Results show consistent behaviour across indices: equal intervals tend to underrepresent higher vulnerability by concentrating most cells in low classes, whereas the standard deviation method shifts outputs toward higher classes and can overstate vulnerability beyond core hotspots. Quantiles produce more balanced class frequencies but may distort underlying structure by forcing equal-sized class populations. Overall, Jenks natural breaks provide the best compromise, preserving inherent groupings in the data while maintaining an interpretable class distribution, supporting its use for final map outputs. These comparisons also emphasise that classification is not neutral; it can materially influence how vulnerability is communicated and prioritised in planning, reinforcing the need for transparency in reporting map design choices.

From a decision-making perspective, the sensitivity analysis indicates that the spatial patterns of vulnerability identified by the SCVI are generally robust to methodological assumptions. The persistence of identified hotspots across multiple sensitivity scenarios suggests that priority areas for coastal management and adaptation are unlikely to be strongly dependent on specific methodological choices. These results support the use of the SCVI as a screening tool for identifying zones where further site-specific assessment or management interventions may be needed, while recognising that local scores should be interpreted as indicative rather than absolute measures of vulnerability.

4. Discussion

4.1. *Embedding sustainability in coastal vulnerability*

Most existing CVIs neglect less quantifiable but equally critical components such as cultural significance and ecosystem integrity. This study addresses that gap by incorporating subjective elements such as the place-based attachment to land noted by Devoy (2008), operationalised here through spatial proxies of cultural heritage, residential settlement patterns and community assets, and by integrating ecological value as intrinsically important. While references to sustainable development are common in the framing of CVIs, few studies translate that commitment into their actual methodologies. The SCVI departs from this trend by operationalising a sustainability-informed structure, explicitly representing social, economic, and environmental features as distinct components within both parameter selection and weighting. This directly addresses the omission of environmental dimensions criticised by Myers et al. (2019) and Falaleeva et al. (2013) as undermining long-term planning legitimacy.

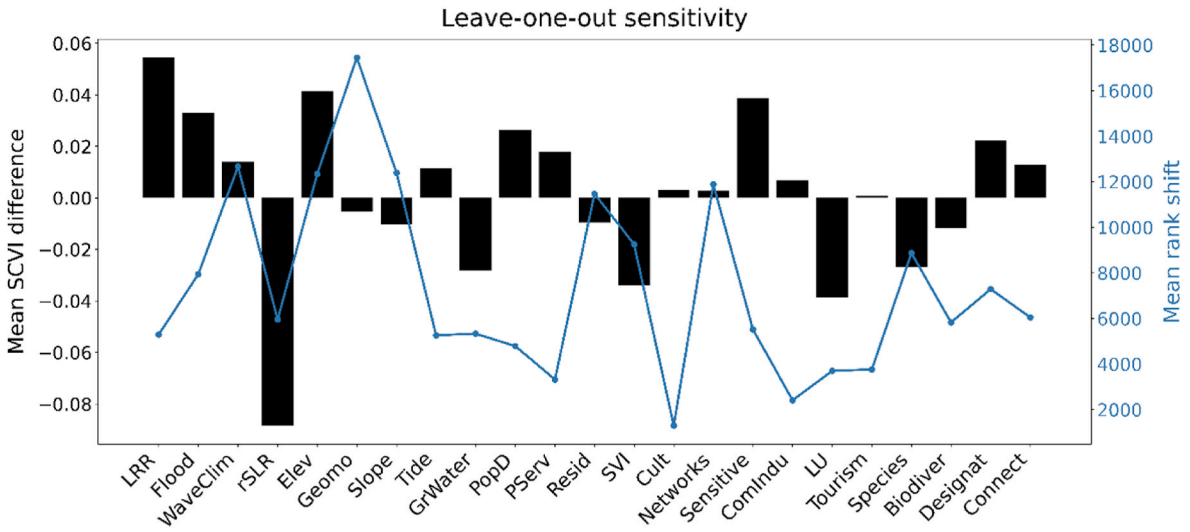


Fig. 8. Monte Carlo weight perturbations. Distribution of standard deviations of subindex values generated from 1000 Monte Carlo simulations in which within-subindex parameter weights are randomly perturbed (Dirichlet draws; weights positive and summing to one), with input datasets held constant.

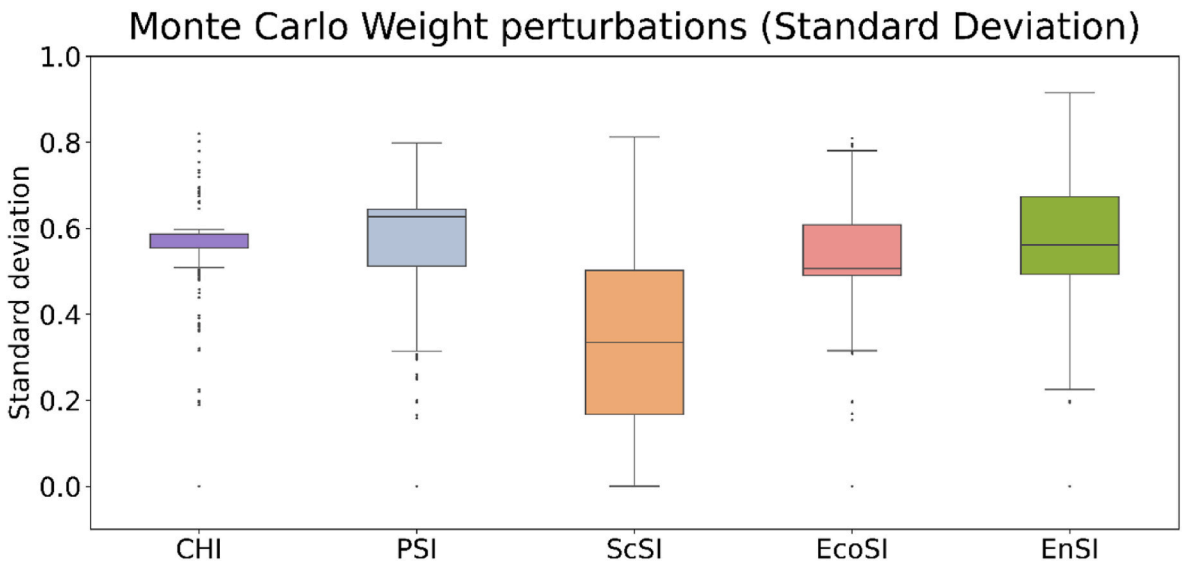


Fig. 9. Monte Carlo sensitivity of SCVI to weight uncertainty. Distributions of per-cell standard deviations in SCVI values and ranks across 1000 Monte Carlo simulations with (left) within-subindex parameter-weight perturbations and (right) subindex-weight perturbations (Dirichlet draws; weights positive and summing to one), with input datasets held constant.

Table 3
Stability of subindices and composite indices under Monte Carlo weight perturbations. Indices were recalculated using Monte Carlo simulations in which within-subindex parameter weights were randomly perturbed (Dirichlet draws, weights >0 and summing to 1), while input datasets were held constant; each simulation was compared to the baseline (AHP-derived) results.

Index	Median rank agreement with baseline (Spearman ρ)	Median share of cells in same class as baseline (%)	Median overlap of top 10% highest values with baseline (%)
CHI	0.99	82.50	62.90
PSI	0.89	49.01	49.07
ScSI	0.99	80.38	63.19
EcoSI	0.97	75.50	60.68
EnSI	0.91	49.19	58.45
PVI	0.91	65.38	68.30
SSI	0.88	65.34	51.35
SCVI	0.86	73.75	49.08

4.2. Ensuring transparency and methodological Rigour

VanZomeren and Acevedo-Mackey (2019) highlight the critical need for transparency in variable selection and data sourcing, and in the consequences of methodological decisions. This study responds by documenting each methodological choice and by explicitly quantifying sensitivity to common sources of uncertainty. As Harik et al. (2017) stressed, indices inevitably involve simplification of complex systems, but the scientific validity of such tools depends on honest disclosure of assumptions and limitations. The extensive sensitivity analysis reinforced this transparency by identifying where uncertainties existed and how they influenced final results; while correlation and VIF analyses are commonly used to remove variables with excessively high multicollinearity (Pantusa et al., 2022; Rahman et al., 2021), methods such as Leave-One-Out analysis (Raghavan Sathyan et al., 2018; Roy et al., 2024) and Monte Carlo analysis of AHP weights (Chen et al., 2011; Feizizadeh and Kienberger, 2017; Narra et al., 2019) are more rarely employed.

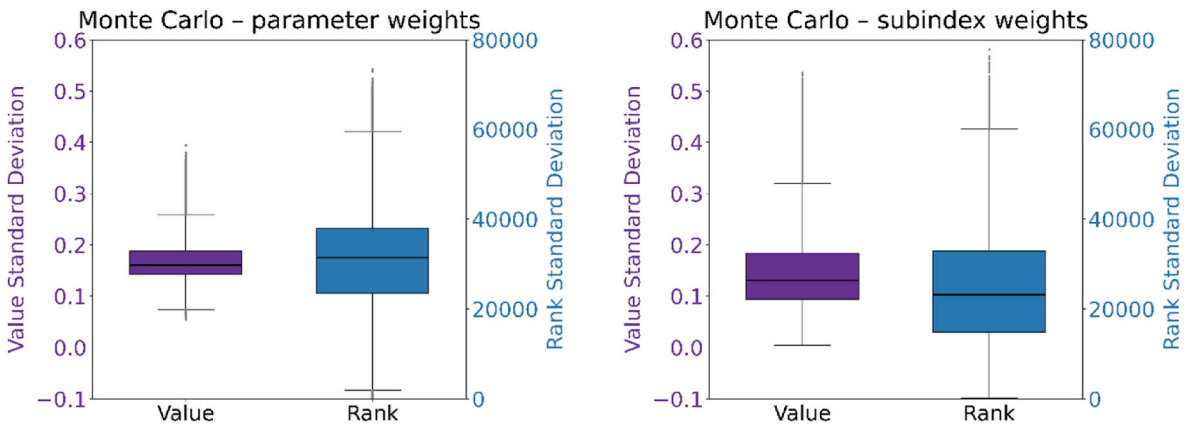


Fig. 10. Effect of classification schemes on vulnerability class distributions. Distributions of grid cells across five vulnerability classes under four common classification methods (equal intervals, quantiles, Jenks natural breaks, and standard deviation).

A remaining challenge is empirical validation. For composite vulnerability indices, "ground truth" is rarely available at comparable spatial and temporal resolution. Here, robustness testing is used to assess the internal stability of the SCVI under plausible methodological perturbations, rather than to provide external validation. Nonetheless, external validation remains a priority for future applications, for example through comparison with independent records of coastal flooding and erosion impacts, infrastructure disruption, emergency response logs, or targeted field verification of mapped hotspots.

4.3. Transferability and scaling

This study demonstrates that a detailed vulnerability index can be constructed from freely available data. The 50 m resolution of the SCVI aligns with recommendations by Gargiulo et al. (2020), who underscore the importance of spatial granularity in capturing meaningful local variation. However, the effective analytical resolution is constrained by the coarsest input datasets used in the index construction. As with many spatially aggregated indicators, results may also be influenced by scale effects associated with the Modifiable Areal Unit Problem (MAUP), where spatial patterns can vary depending on the resolution and aggregation of spatial units. The chosen grid resolution therefore represents a practical compromise between spatial detail and data availability, suitable for regional screening and planning applications but not intended to replace site-specific assessments. As Caloca-Casado (2018) noted, vulnerability assessments in Ireland are often hindered by sparse data and lack of coastal protection records. By leveraging existing datasets and expert input, many of these gaps were successfully addressed, resulting in the first comprehensive CVI for the Cork coastline, a region with both limited prior research and pressing management needs.

The study's international relevance lies in the transferability and scalability of the framework, not in the assumption that identical datasets exist everywhere. The SCVI is designed as a modular canvas (Fig. 2): its conceptual "boxes" can be populated with context-appropriate indicators depending on data availability, scale and decision needs, provided the structural logic of the framework is preserved: coastal forcing and coastal response parameters must both be represented, and each susceptibility subsystem (sociocultural, economic and environmental) should include indicators describing both the assets present and their sensitivity or adaptive capacity, with at least two parameters populating each conceptual component. This flexibility should be presented alongside clear caveats: fewer, older or coarser inputs increase uncertainty and may reduce the ability to distinguish local drivers of vulnerability.

4.4. A study with and for coastal managers

Bukvic et al. (2020) and Rehman et al. (2022) stress the importance of participatory methods in enhancing relevance and stakeholder trust. The AHP process not only guided the initial index design but was later tested through sensitivity analysis. Where necessary, weights were adjusted to reflect data uncertainty, such as the recalibration of the EnSI weight, demonstrating an adaptive and transparent use of expert input.

The SCVI is primarily a time-specific snapshot assembled from the best available datasets, resulting in some inputs being temporally inconsistent, an issue that is difficult to fully avoid in applied coastal assessments that combine a wide variety of different datasets. Importantly, the SCVI can be made time-relevant by substituting scenario-based hazard layers (sea-level rise time slices, projected wave climate, modelled flood extents, shoreline-change scenarios) to generate time-specific SCVI products, while keeping the susceptibility structure fixed or updating it as socioeconomic and environmental layers evolve. Doing so would allow managers to explore how hotspots shift under plausible futures, while retaining the interpretability of the current framework.

5. Conclusion

This study operationalised and evaluated a Sustainable Coastal Vulnerability Index (SCVI) for County Cork (Ireland), integrating coastal hazards with physical, sociocultural, economic and environmental susceptibility, and explicitly representing both exposure and adaptive capacity. The resulting maps highlight that the highest vulnerability areas are not simply found along the most exposed shorelines but are concentrated where hazards and sensitive coastal landforms spatially coincide with clustered infrastructure, settlements and high-value habitats. By combining a transparent GIS workflow with expert-derived weighting and a multi-stage sensitivity assessment, the SCVI provides a reproducible basis for coastal screening that can inform spatial planning and zoning, prioritise sites for monitoring and field verification, and help shape climate-resilience strategies by distinguishing hotspots driven by coastal forcing from those driven by systemic susceptibility. The SCVI should be interpreted as a decision-support screening tool rather than a deterministic prediction; future extensions through scenario-based hazard inputs would allow hotspot evolution to be assessed under climate change or human interventions, while the modular framework remains transferable provided structural logic is preserved and uncertainty communicated accordingly.

CRediT authorship contribution statement

Emma Chalençon: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal

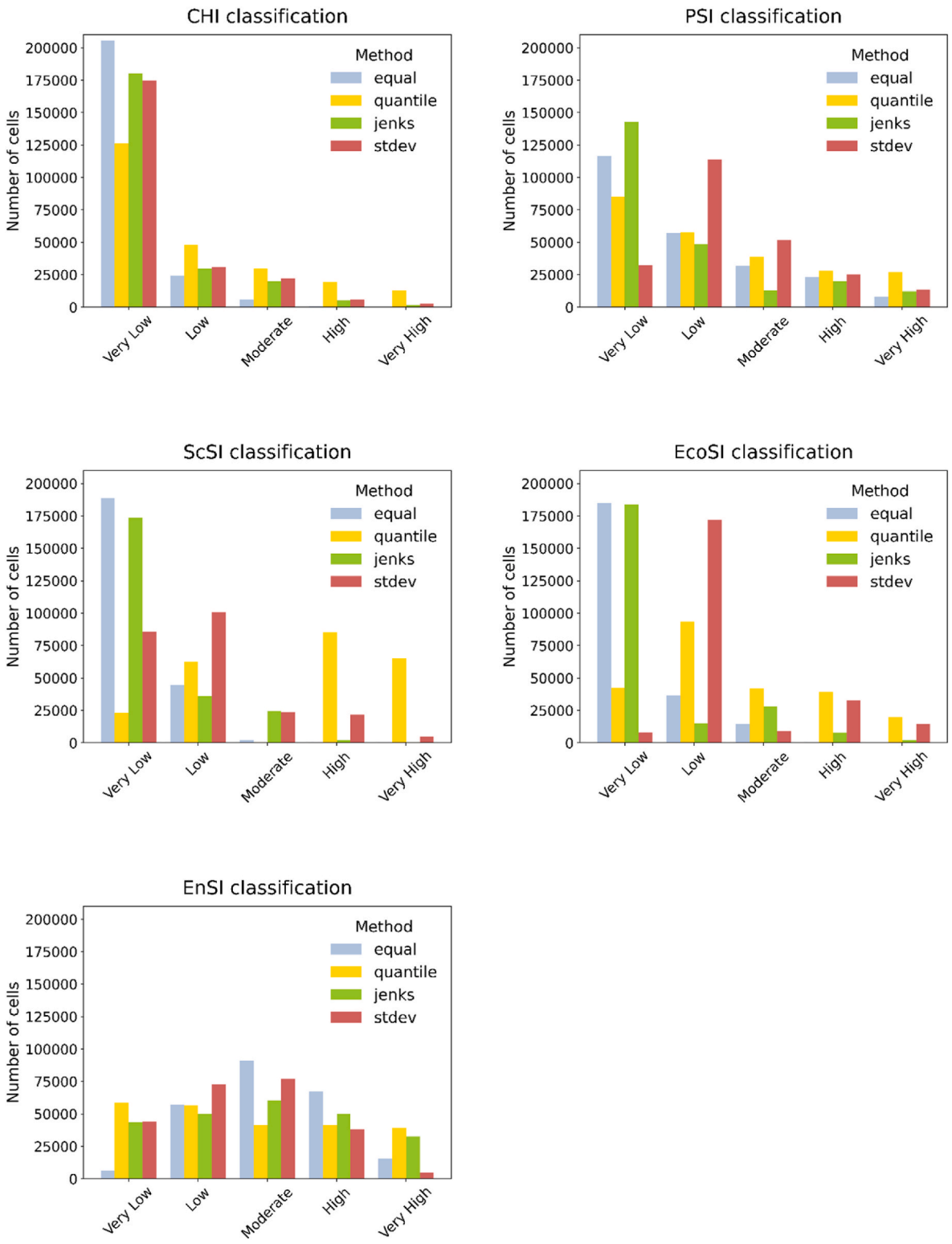


Fig. 11. Effect of classification scheme on SCVI class distribution. Distribution of grid cells across five vulnerability classes under four common classification approaches (equal intervals, quantiles, Jenks natural breaks and standard deviation), illustrating how class assignment can shift depending on the chosen mapping method.

analysis, Data curation, Conceptualization. **Fiona Cawkwell:** Writing – review & editing, Supervision, Methodology. **Michael O'Shea:** Writing – review & editing. **Jimmy Murphy:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Emma Chalencon reports financial support was provided by Cork County Council. If there are other authors, they declare that they have

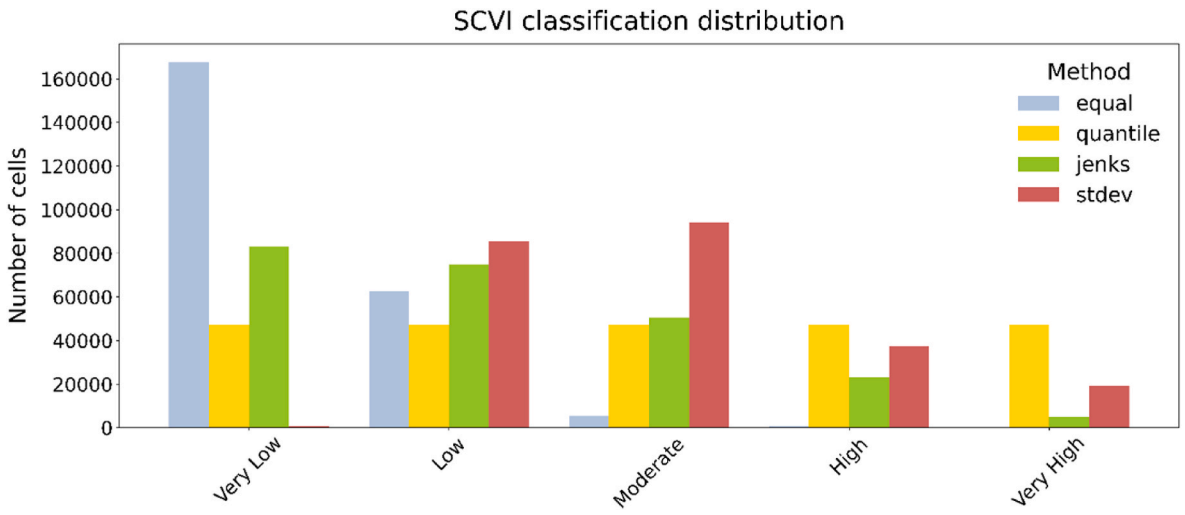


Fig. 12. Spatial distribution of the SCVI and its components along the Cork coastline. The top panel (1) presents the regional-scale SCVI classification. Below, detailed views are shown for five representative coastal sites ordered from west to east (left to right). Aerial imagery provides geographic context for each location (2). For each site, component scores are displayed: Coastal Hazard Index (CHI: 3), Physical Susceptibility Index (PSI: 4), Sociocultural Susceptibility Index (ScSI: 5), Economic Susceptibility Index (EcoSI: 6), and Environmental Susceptibility Index (EnSI: 7), along with the resulting SCVI (8). Scores range from Very Low (light green) to Very High (dark purple), illustrating spatial variability and the influence of local factors on coastal vulnerability.

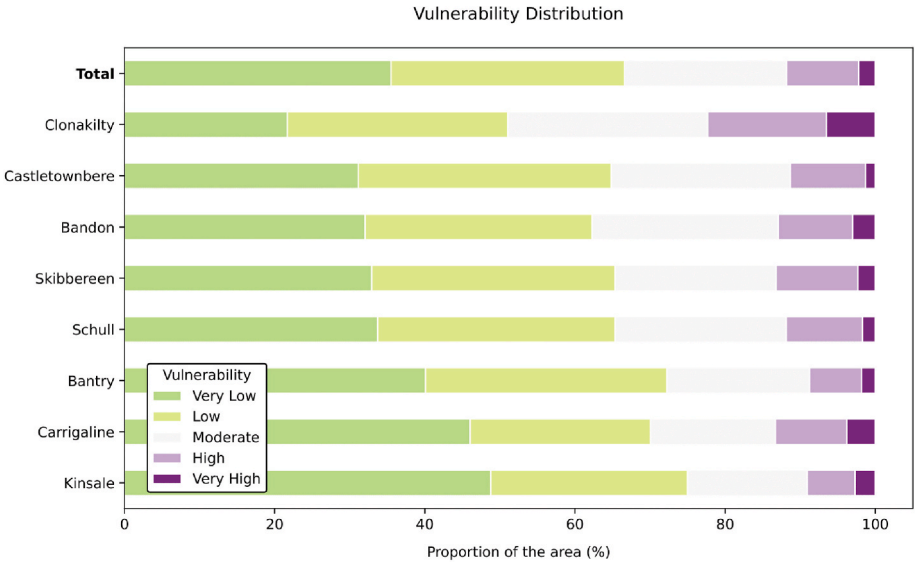


Fig. 13. Vulnerability distribution per municipal engineering sub area (%).

no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors gratefully acknowledge Cork County Council for funding this work through the Social Sustainability Infrastructure Programme (SSIP), as well as the Department of Environment, Climate and Communications under the Cork Coastline Vulnerability Assessment project (2022–2026). Special thanks are extended to Eamonn Mullaly and Tomas Kavanagh (Cork County Council) for facilitating access to Cork County Council and Geodirectory datasets; to David Fahey (Office of Public Works) for enabling early access to the latest OPW datasets; to Xavier Monteys (Geological Survey Ireland) for providing early access to updated GSI datasets; to Denise McCullagh and Walter Camaro for their support in accessing the latest outputs of the Irish Social Vulnerability to Environmental Hazards Index (ISVEHI); and to Ayşenur Karayel for producing and providing the nearshore wave modelling outputs.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2026.104075.

References

Bukvic, A., Rohat, G., Apotsos, A., & de Sherbinin, A. (2020). A systematic review of coastal vulnerability mapping. *Sustainability, 12*(7), 2822. https://doi.org/10.3390/su12072822

Caloca-Casado, S. (2018). *Coastal vulnerability assessment of co. Dublin and co. Wicklow to impacts of sea-level rise (PhD Thesis)*. National University of Ireland, Maynooth. https://mural.maynoothuniversity.ie/id/eprint/10245/1/PhD%20thesis%20Silvia%20Caloca%20Casado%202018.pdf.

Central Statistics Office. (2023). Press statement census of Population 2022 - Summary results Cork - CSO - Central statistics office. https://www.cso.ie/en/csolatestnews/pressreleases/2023pressreleases/pressstatementcensusofpopulation2022-summaryresultscork/.

Chalençon, E., Cawkwell, F., O'Shea, M., & Murphy, J. (2026). Beyond Coastal hazards and physical susceptibility: A Sustainable Coastal Vulnerability Index (SCVI) for the county Cork coastline, Ireland. In C. Coelho, C. Hallin, F. Sancho, & P. A. Silva (Eds.), *Coastal Dynamics 2025* (pp. 249–254). Nature Switzerland, Cham: Springer. https://doi.org/10.1007/978-3-032-15473-6_39.

Chen, H., Wood, M. D., Linstead, C., & Maltby, E. (2011). Uncertainty analysis in a GIS-based multi-criteria analysis tool for river catchment management. *Environmental Modelling & Software, 26*(4), 395–405. https://doi.org/10.1016/j.envsoft.2010.09.005

Cork County Council. (2019). *Cork county council climate adaptation strategy*. Retrieved from https://www.corkcoco.ie/sites/default/files/2021-11/cork-county-council-climate-adaptation-strategy-2019-2024-pdf.pdf.

Central Statistics Office (CSO). (2016). Census 2016 small area population statistics. https://www.cso.ie/en/census/census2016reports/census2016smallareapopulationstatistics/ [Accessed 25 June 2025].

Cork County Council. (2020). Economy and employment background document (No 6.). *Planning Policy Unit* (pp. 1–59). Retrieved from https://www.corkcoco.ie/sites/default/files/2022-04/economy-and-employment-pdf.pdf.

Cork County Council. Cork county development plan (No. Volume two Heritage and amenity). https://www.corkcoco.ie/sites/default/files/2022-06/volume-2-heritage-amenity.pdf.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly, 84*, 242–261. https://doi.org/10.1111/1540-6237.8402002

Devoy, R. J. N. (2008). Coastal vulnerability and the implications of sea-level rise for Ireland. *Journal of Coastal Research, 242*, 325–341. https://doi.org/10.2112/07A-0007.1

Estoque, R. C., Ishtiaque, A., Parajuli, J., Athukorala, D., Rabby, Y. W., & Ooba, M. (2023). Has the IPCC's revised vulnerability concept been well adopted? *Ambio, 52*(2), 376–389. https://doi.org/10.1007/s13280-022-01806-z

European Environmental Agency (EEA). (2006). *The changing faces of Europe's coastal areas*. Copenhagen: Luxembourg: Office for Official Publications of the European Communities. ISBN 92-9167-842-2. ISSN 1725-9177 © EEA. No 6/2006 http://www.vliz.be/projects/SAIL/eea_report_6_2006.pdf.

European Environmental Agency (EEA). (2012). Climate change impacts and vulnerability in Europe 2012. http://www.heritagecouncil.ie/fileadmin/user_upload/Publications/Marine/Climate_change_impacts_and_vulnerability_in_Europe_2012_Summary.pdf.

Falaleeva, M., Gray, S., O'Mahony, C., & Gault, J. (2013). *Coastal Climate Adaptation in Ireland: Assessing current conditions and enhancing the capacity for climate resilience in local coastal management (No. 28)*. EPA. Retrieved from https://www.epa.ie/publications/research/climate-change/CCRP_28.pdf.

Falaleeva, M., O'Mahony, C., Gray, S., Desmond, M., Gault, J., & Cummins, V. (2011). Towards climate adaptation and coastal governance in Ireland: Integrated architecture for effective management? *Marine Policy, 35*(6), 784–793. https://doi.org/10.1016/j.marpol.2011.01.005

Farrell, E. J., Smith, G., O'Hagan, A. M., & Tissier, M. (2021). *Building Coastal and marine resilience in Ireland (No. 429)*. EPA. Retrieved from https://www.epa.ie/publications/research/epa-research-2030-reports/Research_Report-429.pdf.

Feizizadeh, B., & Kienberger, S. (2017). Spatially explicit sensitivity and uncertainty analysis for multicriteria-based vulnerability assessment. *Journal of Environmental Planning and Management, 60*(11), 2013–2035. https://doi.org/10.1080/09640568.2016.1269643

IPCC. (2014). Summary for policymakers. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, & L. L. White (Eds.), *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral Aspects. Contribution of Working Group II to the fifth assessment report of the intergovernmental Panel on climate change* (pp. 1–32). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press. Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_summary-for-policymakers.pdf.

Gargiulo, C., Battarra, R., & Tremiterra, M. R. (2020). Coastal areas and climate change: A decision support tool for implementing adaptation measures. *Land Use Policy, 91*, Article 104413. https://doi.org/10.1016/j.landusepol.2019.104413

GIZ and EURAC. (2017). Risk supplement to the vulnerability sourcebook. *Guidance on how to apply the Vulnerability Sourcebook's approach with the new IPCC AR5 concept of climate risk*. Bonn: GIZ. Retrieved from https://www.adaptationcommunity.net/wp-content/uploads/2017/10/GIZ-2017_Risk-Supplement-to-the-Vulnerability-Sourcebook.pdf.

Gornitz, V. (1991). Global coastal hazards from future sea level rise. *Palaeogeography, Palaeoclimatology, Palaeoecology, 89*, 379–398.

Harik, G., Alameddine, I., Maroun, R., Rachid, G., Bruschi, D., Astiaso Garcia, D., & El-Fadel, M. (2017). Implications of adopting a biodiversity-based vulnerability index versus a shoreline environmental sensitivity index on management and policy planning along coastal areas. *Journal of Environmental Management, 187*, 187–200. https://doi.org/10.1016/j.jenvman.2016.11.038

IPCC. (2007). *Climate change 2007: Impacts, Adaptation and Vulnerability: Working Group II contribution to the fourth assessment report of the IPCC intergovernmental Panel on climate change. 4*. Cambridge University Press.

Jenkins, G. O., Mee, K., Richardson, J. F. M., Lee, K. A., Westhead, R. K., Carter, G. D., O'Jordan, H. M., & Payo, A. (2017). *User Guide British Geological Survey Coastal Vulnerability Dataset (Version 1)*. British Geological Survey Open Report. OR/17/025 https://nora.nerc.ac.uk/id/eprint/521682/1/OR17025.pdf.

Kaniewski, D., Marriner, N., Morhange, C., Faivre, S., Otto, T., & Van Campo, E. (2016). Solar pacing of storm surges, coastal flooding and agricultural losses in the Central Mediterranean. *Scientific Reports, 6*(1), Article 25197. https://doi.org/10.1038/srep25197

Le Berre, I., Meur-Ferec, C., Cuq, V., Guillou, E., Lami, T., Le Dantec, N., Letortu, P., Lummert, C., Philippe, M., Rouan, M., Noûs, C., & Hénaff, A. (2022). Systemic vulnerability of coastal territories to erosion and marine flooding: A conceptual and methodological approach applied to Brittany (France). *International Journal of Disaster Risk Reduction, 78*, Article 103122. https://doi.org/10.1016/j.ijdrr.2022.103122

Masselink, G., & Lazarus, E. D. (2019). Defining Coastal resilience. *Water, 11*(12), 2587. https://doi.org/10.3390/w11122587

McCullagh, D., Cámaro-García, W., Dunne, D., Nowbakht, P., Cumiskey, L., Gannon, C., & Phillips, C. (2025). Development of a social vulnerability index: Enhancing approaches to support climate justice. *MethodsX, 14*, Article 103290. https://doi.org/10.1016/j.mex.2025.103290

McLaughlin, S., McKenna, J., & Cooper, J. A. G. (2002). Socio-economic data in coastal vulnerability indices: Constraints and opportunities. *Journal of Coastal Research, 36*, 487–497. https://doi.org/10.2112/1551-5036-36.sp1.487

Myers, M. R., Barnard, P. L., Beighley, E., Cayan, D. R., Dugan, J. E., Feng, D., Hubbard, D. M., Iacobellis, S. F., Melack, J. M., & Page, H. M. (2019). A multidisciplinary coastal vulnerability assessment for local government focused on ecosystems, Santa Barbara area, California. *Ocean & Coastal Management, 182*, Article 104921. https://doi.org/10.1016/j.ocecoaman.2019.104921

Narra, P., Coelho, C., & Sancho, F. (2019). Multicriteria GIS-based estimation of coastal erosion risk: Implementation to Aveiro sandy coast, Portugal. *Ocean & Coastal Management, 178*, Article 104845. https://doi.org/10.1016/j.ocecoaman.2019.104845

Neilson, B., & Costello, M. J. (1999). The relative lengths of seashore substrata around the coastline of Ireland as determined by digital methods in a geographical information System. *Estuarine, Coastal and Shelf Science, 49*(4), 501–508. https://doi.org/10.1006/ecss.1999.0507

Noor, N. M., & Abdul Maulud, K. N. (2022). Coastal vulnerability: A brief review on integrated assessment in Southeast Asia. *Journal of Marine Science and Engineering, 10*(5), 595. https://doi.org/10.3390/jmse10050595

O'Brien, L., Renzi, E., Dudley, J. M., Clancy, C., & Dias, F. (2018). Catalogue of extreme wave events in Ireland: Revised and updated for 14 680 BP to 2017. *Natural Hazards and Earth System Sciences, 18*(3), 729–758. https://doi.org/10.5194/nhess-18-729-2018

Oloyede, M. O., Benson, N. U., & Williams, A. B. (2021). Climate change and coastal vulnerability assessment methods: A review. In *IOP conference series: Earth and environmental science* (Vol. 665), Article 012069. https://doi.org/10.1088/1755-1315/665/1/012069, 1.

O'Mahony, C., Kopke, K., Twomey, S., O'Hagan, A. M., & Gault, J. (2014). *Integrated Coastal Zone management in Ireland*. SWAN Research Project. Retrieved from https://swanireland.ie/wp-content/uploads/2020/08/Integrated-Coastal-Zone-Management-in-Ireland-SWAN-Report.pdf.

Pantusa, D., D'Alessandro, F., Frega, F., Francone, A., & Tomasicchio, G. R. (2022). Improvement of a coastal vulnerability index and its application along the Calabria Coastline, Italy. *Scientific Reports, 12*(1), Article 21959. https://doi.org/10.1038/s41598-022-26374-w

Pantusa, D., D'Alessandro, F., Riefolo, L., Principato, F., & Tomasicchio, G. (2018). Application of a coastal vulnerability index. A case Study along the Apulian coastline, Italy. *Water, 10*(9), 1218. https://doi.org/10.3390/w10091218

Pramanik, M. K., Biswas, S. S., Mondal, B., & Pal, R. (2016). Coastal vulnerability assessment of the predicted sea level rise in the coastal zone of Krishna–Godavari delta region, Andhra Pradesh, east coast of India. *Environment, Development and Sustainability, 18*(6), 1635–1655. https://doi.org/10.1007/s10668-015-9708-0

Raghavan Sathyan, A., Funk, C., Aenis, T., Winker, P., & Breuer, L. (2018). Sensitivity analysis of a climate vulnerability index - A case study from Indian watershed development programmes. *Climate Change Responses, 5*(1), 1. https://doi.org/10.1186/s40665-018-0037-z

Rahman, M., Ningsheng, C., Mahmud, G. I., Islam, M. M., Pourghasemi, H. R., Ahmad, H., Habumugisha, J. M., Washakh, R. M. A., Alam, M., Liu, E., Han, Z., Ni, H., Shufeng, T., & Dewan, A. (2021). Flooding and its relationship with land cover change, population growth, and road density. *Geoscience Frontiers, 12*(6), Article 101224. https://doi.org/10.1016/j.gsf.2021.101224

Rehman, S., Jahangir, S., & Azhoni, A. (2022). GIS based coastal vulnerability assessment and adaptation barriers to coastal regulations in Dakshina Kannada district, India. *Regional Studies in Marine Science, 55*, Article 102509. https://doi.org/10.1016/j.rsma.2022.102509

Rizzo, A., Vandelli, V., Buhagiar, G., Micallef, A. S., & Soldati, M. (2020). Coastal vulnerability assessment along the North-Eastern sector of Gozo Island (Malta, Mediterranean Sea). *Water, 12*(5), 1405. https://doi.org/10.3390/w12051405

Rocha, C., Antunes, C., & Catita, C. (2023). Coastal indices to assess sea-level rise impacts - A brief review of the last decade. *Ocean & Coastal Management, 237*, Article 106536. https://doi.org/10.1016/j.ocecoaman.2023.106536

Roy, S., Saha, M., Hasan, M. M., Razzaque, A., Sumaiya, N., Hoque, M. A.-A., Misiūnė, I., Ambrosino, M., & Depellegrin, D. (2024). Multi-pressure based environmental vulnerability assessment in a coastal area of Bangladesh: A case study on Cox's Bazar. *Geomatica, 76*(2), Article 100030. https://doi.org/10.1016/j.geomat.2024.100030

Ružić, I., Dugonjić Jovančević, S., Benac, Č., & Krvavica, N. (2019). Assessment of the coastal vulnerability index in an area of complex geological conditions on the Krk Island, Northeast adriatic Sea. *Geosciences, 9*(5), 219. https://doi.org/10.3390/geosciences9050219

Šimac, Z., Lončar, N., & Faivre, S. (2023). Overview of coastal vulnerability indices with reference to physical characteristics of the Croatian Coast of Istria. *Hydrology, 10*(1), 14. https://doi.org/10.3390/hydrology10010014

Tanim, A. H., Goharian, E., & Moradkhani, H. (2022). Integrated socio-environmental vulnerability assessment of coastal hazards using data-driven and multi-criteria analysis approaches. *Scientific Reports, 12*, Article 11625. https://doi.org/10.1038/s41598-022-15237-z

Thieler, E. R., & Hammar-Klose, E. S. (2000). *National assessment of coastal vulnerability to sea-level rise: Preliminary results for the U.S. Pacific Coast (No. 2000–178) Open-File Report*. U.S. Geological Survey. Retrieved from https://pubs.usgs.gov/publication/ofr00178.

Ummenhofer, C. C., & Meehl, G. A. (2017). Extreme weather and climate events with ecological relevance: A review. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 372*(1723), Article 20160135. https://doi.org/10.1098/rstb.2016.0135

VanZomeren, C., & Acevedo-Mackey, D. (2019). *A review of coastal vulnerability assessments: Definitions, components, and variables*. U.S.: Engineer Research and Development Center. Retrieved from https://hdl.handle.net/11681/33289.