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Multi-scenario analysis in the Apulia shoreline: A multi-tiers analytical framework for the combined evaluation and management of coastal erosion and water quality risks

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ABSTRACT

Ongoing climate change is causing threats to coastal areas, according to scenarios of Intergovernmental Panel on Climate Change (IPCC). The coastal areas are becoming highly exposed to erosion as a direct consequence of natural and anthropogenic processes that occur at different spatial-temporal scales. Against this interplay, coastal managers are calling for integrated tools supporting a multi-scenario evaluation of risks arising from natural and anthropogenic stress. A multi-tier analytical framework, exploiting the openly available Earth Observation databases, was developed, allowing the combination of remote sensing, GIS and Bayesian Network to evaluate the probability and uncertainty of coastal erosion risks and connected water quality variation, against '*what-if*' scenarios, representing different management measures (i.e., Nature-Based Solution) and climate change impacts (e.g., higher incident waves due to increased storminess). Based on the available data for the Municipality of Ugento (Italy), the designed framework was applied over the 2009–2018 timeframe, allowing to capture local-scale shoreline erosion dynamics and driving forces. Results from scenario analysis revealed, to a minor extent, a nexus between oceanographic drivers, shoreline evolution, and water quality changes, with increasing probability of high erosion/accretion and higher turbidity under the simulated rising maximum significant wave height. However, the implementation of Nature-Based Solutions (i.e., circular approach exploiting beached Posidonia oceanica leaves) resulted in significant positive effects, stabilizing the shoreline by reducing high erosion and accretion rates. Despite data constraints, outcomes of the performed assessment could represent valuable information to drive adaptive policy pathways in the context of coastal management along the Ugento shoreline.

1. Introduction

It is widely recognized among the scientific community that climate change is leading to severe impacts on terrestrial and marine ecosystems worldwide in a variety of ways (IPCC, 2022). Sea-level rise (SLR) and variations in the pattern, frequency, and intensity of extreme events, are expected to increase extreme sea levels, flooding and erosion processes along European and, in particular, Mediterranean coastal areas in the future (Vousdoukas et al., 2017). Climate change might also be associated to changes in the stormy wind and wave patterns in terms of the prevailing direction affecting a coastal area. Belušić Vozila et al. (2019) analysed climate change scenarios in Southern Adriatic and concluded that the Scirocco events (east-southeast to south south-east winds) increase in frequency and magnitude in relation to the Bora events (north-northeast to east-northeast winds), signifying a major change in wind direction. The expected modifications in the meteo-marine climate may redistribute the wave energetic balance, altering regimes from longshore to cross-shore sediment transport, leading to changes in the erosional and depositional patterns.

Under this ongoing complex scenario, coastal areas are also

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experiencing relevant pressures resulting from a variety of anthropogenic activities linked to coastal economic development (e.g., touristic activities, infrastructures) and connected land-use changes (e.g., urbanization) (Halpern et al., 2019; Lonsdale et al., 2020; Stock et al., 2018). The resulting impacts of this complex interplay among climate-related and man-made pressures consist in coastal risks, which are caused by the dynamic interactions between climate-related hazards, exposure and vulnerability of human society, species or affected ecosystems (IPCC, 2023). Among coastal risks, erosion processes have been defined by the United Nations Office for Disaster Risk Reduction (UNISDR) as the loss of coastal lands due to the net removal of sediments or bedrock from the shoreline (UNISDR, 2017). As a matter of fact, the dynamic evolution of the shoreline (both under accretion and erosion trends) leads to cascading effects on human (i.e., human lives, economic sectors, activities and infrastructure) and natural systems such as water bodies (e.g., changes in water quality linked to rising turbidity), as well as the related biodiversity loss, reduced species survival, and species shift which, in turn, will affect ecosystems services flow and generate socio-economic damages (UNDP, 2011; IPCC, 2014).

In this framework, coastal authorities are faced with the challenging task of balancing coastal development with risk management, while ensuring the implementation of EU recommendations and directives for integrated coastal zone management (ICZM) and adaptation planning (Furlan et al., 2018; Garmendia et al., 2017; European Comission, 2013; European Commission, 2013; UNEP, 2009). An integrated approach to coastal management is needed to tackle coastal erosion processes and their cascading impacts, merging both technical and scientific studies to identify, on one side, the main drivers contributing to coastal imbalance and, on the other side, to design appropriate monitoring actions for understanding trends and the required structural measures, following the order of priority resulting from the risk level.

Drawing on this need, different tools and methods have been developed so far by the research community to evaluate coastal erosion phenomena occurring along shorelines, lagoons, and river mouths, and to monitor the consequent water quality changes against this physical process. Among these, the most commonly applied methodology is the Coastal Vulnerability Index (CVI), an easy-to-use index-based approach structured to support the combination of multiple physical, morphological, and socio-economic indicators into a single vulnerability measure Furlan et al., 2019; Furlan et al., 2021a,b; Gornitz, 1991; Mclaughlin and Cooper, 2010; Pantusa et al., 2018; Torresan et al., 2020). Recently, more sophisticated methods have been developed, including Bayesian Network (BN) approaches and, among others, Machine Learning techniques to observe and analyze coastal evolution trends (Calkoen et al., 2021; Fogarin et al., 2023; McAllister et al., 2022), allowing the integration of heterogeneous information (e.g., physical and chemical data, expert judgment) into a single model. The first BN approach focusing on the analysis of coastal vulnerability to erosion processes was proposed by Gutierrez et al. (2011), developing a BN model including variables representing key erosion driving forces (e.g., SLR rate, mean wave height, tidal phases), boundary conditions (e.g., geomorphic settings, coastal slope) and the long-term shoreline change rate as assessment endpoint of the network. A key added value of Gutierrez's study was also the spatial visualization of the resulting output, depicting the probability distribution of shoreline changes in 2378 coastal segments along the US Atlantic coast, and against simulated scenarios depicting worst relative SLR changes (i.e., in the range of 2.95–3.15 m and 3.16–4.1 m).

This preliminary BN approach was then fine-tuned by other authors, designing different BN configurations by changing the numbers of boundary conditions and the states associated with each variable (Poelhekke et al., 2016), or integrating into the model a node specifically devoted to the spatial representation of the investigated coastal areas (Narayan et al., 2015; Poelhekke et al., 2016; Sanuy et al., 2018). Consequently, Jäger et al. (2017) expanded the BN model by including an additional set of nodes representing different environmental and human receptors that could be potentially affected by coastal erosion impacts. More recent studies further improved the BN approach integrating variables concerning coastal management measures (e.g., beach nourishment, nature-based solutions), to evaluate the effectiveness of different strategies to prevent and mitigate coastal erosion impacts (Giardino et al., 2019; Plomaritis et al., 2017). Other studies tried to analyze and predict water quality and nutrient changes (e.g., salinity, temperature, DO, and chlorophyll) under different climate scenarios, exploiting BN capabilities to overcome the uncertainty of forecasts (Jafari Nodoushan, 2018; Kotta et al., 2009; Zennaro et al., 2021). However, despite these advancements, the analysis of dynamic and joint evolution of physical, oceanographic, environmental, and chemical phenomena, remains a major issue among the research community.

To fill this gap in extant literature and research, the main objective of this paper is to design a multi-tier analytical framework allowing to evaluate interrelations among oceanographic dynamics and the resulting shoreline and water quality changes against different climate and management scenarios (e.g., implementation of Nature-Based Solutions – NBS). Moving forward traditional applications for coastal erosion risk and vulnerability assessment (Gutierrez et al., 2011; Harris et al., 2022; Jäger et al., 2017; Plomaritis et al., 2018; Poelhekke et al., 2016; Sanuy et al., 2018; Sanuy et al., 2020), the analytical framework here proposed combines capabilities offered by remote sensing, Geographic Information System (GIS) and BN to evaluate the probability and uncertainty of coastal erosion risks and connected water quality variation in the Ugento case study (Apulia region, Italy), exploiting the huge amount of data released under e.g., Copernicus services. Particularly, data on shoreline trend, as extracted from RapidEye satellite images[1] under the 2008–2019 timeframe, are integrated into a unique BN model with oceanographic and water quality data (e.g., significant wave height, sea level, particulate matter) made available by Copernicus Marine Service (CMEMS)[2] over the same period. Under this multi-tier approach the high volume and variety in *big data* stored in online databases for environmental monitoring and applications, is exploited to investigate multifaceted coastal erosion risks and provide support for Integrated Coastal Zone Management (ICZM) and climate adaptation in the investigated site.

This study represents the first attempt in which a hybrid analytical framework is developed to investigate a dynamic conceptualization of coastal erosion risks, taking also into account the potential risk reduction effect induced by the implementation of NBS along the coast.

Following the characterization of the case study area and the available data to inform the BN approach (Section 2), the multi-tier analytical framework is detailed in Section 3.2, followed by a narrative description of the main findings resulting from its application in the Ugento case (Section 4). Finally, the concluding section highlights the strengths and weaknesses of the proposed approach in the context of ICZM and adaptation planning, while suggesting future model improvements to respond to other EU directives related to water resource assessment and management (Section 5).

2. Description and characterization of the case study area

2.1. The Apulia region shoreline and the pilot case of the municipality of Ugento, Italy

The Apulia region is located in South-Eastern Italy, in a strategic position in the center of the Mediterranean, bordering the Adriatic Sea to the East and the Ionian to the South-West. Cities with higher population density are mainly located along the coast where, during the summer season, the population increases further for tourism (e.g., Bari, Taranto, Brindisi, Gallipoli) (Buongiorno and Intini, 2021). In fact,

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[1] https://earth.esa.int/eogateway/missions/rapideye

[2] https://marine.copernicus.eu/

Apulia is the Italian region with the longest coastal extension of about 970 km (Regione Puglia, 2018), most of which is flat and sandy. Second only to Sicily and Sardinia, Apulia's coastal development attracts an increasing number of tourists worldwide (Del Vecchio and Passiante, 2017). On the other hand, 13.8% of the region, and the connected marine space, is characterized by the presence of valuable natural protected areas (Buongiorno and Intini, 2021; De Giosa et al., 2019), featured by the presence of ecosystems playing a crucial role in the conservation of biodiversity and genetic resources (e.g., Regional park of Ugento). The median nearshore slope in the investigated areas varies from 0.003 (Torre Mozza) to 0.0055 (Fontanelle and Lido Marini) (Athanasiou et al., 2019).

With the main aim of monitoring coastal erosion processes affecting the whole region, several studies have been performed within both national and regional plans. In particular, results of the Italian shoreline evolution conducted by the Italian Institute for Environmental Protection and Research) (Barbano et al., 2006; Istituto Superiore per la Protezione e la Ricerca Ambientale, 2009)highlighted an average coastal setback for 21.4% of the shoreline under the 1950–2000 observed period. However, the most recent Regional Coastal Plan (RCP) environmental analysis (Regione Puglia, 2018) showed that 4.6% of the overall Apulia coast is retreating (about 45 kilometers of extention). The most intense erosive phenomena occurred before 1992, with a decreasing trend in the following period (Regione Puglia, 2018). Despite this comforting trend, coastal areas are still suffering heavy erosion processes, coinciding with those that have already experienced strong setbacks. Specifically, in the frame of the RCP, erosion processes of sandy shores were evaluated under the 1992–2017 timeframe, considering seven different Physiographic Units (PU), defined in the RCP itself as the stretches of the coastline in which the solid transport (i.e., all the sediments and materials that contribute to shoreline formation), due to wave motion and littoral currents, is confined (Comune di Ugento, 2015; Regione Puglia, 2018). Considering a 10 m-wide buffer zone and a 2005–2017 timeframe, 129 km of sandy coast (33.2%) were found to be affected by erosion processes. Moreover, to identify areas with a higher level of criticalities, a 30-m buffer evaluation was also performed focusing exclusively on the retreating coast already recognized under the previous analysis (i.e., 129 km of Apulia shoreline). As a result, PU5 (i.e., from Otranto to Gallipoli) was the most affected by erosive phenomena, with an overall retreating rate of about 12–18%. In particular, the Municipality of Ugento (Fig. 1) was one of the most affected municipalities in PU5 and in the Apulia region, with about 1.5 km of eroded coast against an overall extension of about 13 km (ISTAT, 2011). The shoreline is mainly sandy at the low ground level, with rocks only in the northern area of the municipality. Behind the coastal area, there are numerous artificial basins surrounded by rural landscapes, featured by olive groves and vineyards on low hills (Gennaio et al., 2001), whose associated industries are flourishing. The economy of these regions is based on the primary sector, the transformation of its products, and the tourism sector. Specifically, the latter has expanded considerably in the last decade, making the area of Ugento, especially Torre San Giovanni and the related marinas, an appreciated destination for summer tourists. However, in the last decades, its shoreline has experienced the impacts of several extreme storm surge events (e.g., events that occurred from October to December 2011), which have led to progressive coastal retreatment, especially around the marina of

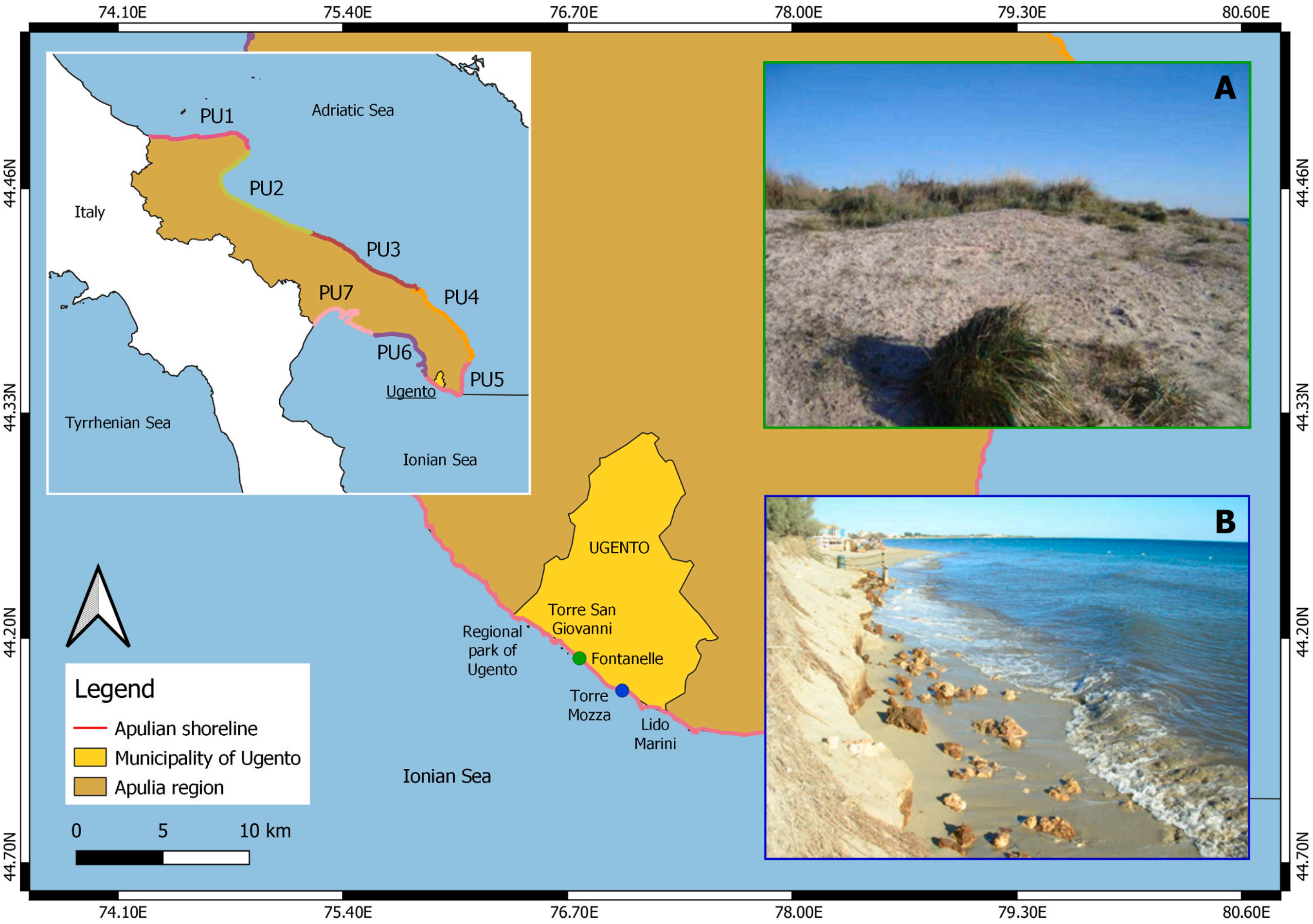

Fig. 1. Case study area of the Municipality of Ugento (Apulia region, Southern Italy). Focus on A) NBS implemented along the coast of Località Fontanelle; B) erosive phenomena occurred along the shoreline of Torre Mozza.

Torre Mozza (Fig. 1; about 1.5 km of sandy beach has been eroded within the 2005–2017 timeframe; Regione Puglia, 2018), as well as of anthropogenic pressures (e.g., touristic development, building of resorts and infrastructure) and a lack of sediment provision coming from the inland (Mastronuzzi and Sansò, 2017; De Santis and Caldara, 2015).

Moreover, these extreme storm events heavily impact the coastal mass budget, causing a remarkable sediment transport and deposition of sandy materials moved by currents, with increased suspended matter. The analysis of wave and wind parameters in the southern parts of the case study area indicates that the most prevalent wave directions are the one from S-W and S (see Supplementary Material **SM11** for more details). In general, storm events result in significant high wave heights above 4 m in the offshore marine area of Ugento. Yet, the orientation of the Torre Mozza and the Lido Marini beach promotes the long-shore sediment transport from the induced wave energy. Particularly, storms can trigger longshore sediment transport by reshaping the limited volumes of sediment, which are eroded and then transported with the flow (Normandeau et al., 2020). Consequently, the presence of suspended matter can limit the penetration of natural light in the water column, hence decreasing biological processes (e.g., primary production) (Mi et al., 2020). This outcome is also confirmed through the direct analysis of both physical and chemical indicators (e.g., suspended particulate matter – SPM, diffuse attenuation – KD), as retrieved for the investigated area (Badewien et al., 2009).

To address these issues, many NBS have been implemented in this area by the Apulia Region and the Municipality itself. Among them, the reconstruction of eroded and degraded dunes along the Ugento coastline (Fig. 1), a project started in 2007, represents the most significant measure put in place by the local authority to protect beaches from natural processes (e.g., storm surges; Pasquali et al., 2019), as well as anthropogenic pressures (e.g., touristic development, infrastructural construction) and the deficit of inland sediment supply (Mastronuzzi and Sansò, 2017; De Santis and Caldara, 2015), ensuring their maintenance and restoration for the local touristic activities in summer. More specifically, the municipality adopted a novel circular approach to NBS implementation within its coastal management schemes (see Supplementary Material **SM7**). Physical and ecological processes in the Posidonia beach are evaluated as a holistic system, systematically preserved and restored, contributing to regulate the morphology of the coast while ensuring the maintenance of the main local economic activity in the area. A reuse-depollute-prevent coastal climate-related impacts approach is taken to restore dunes with circular integration of natural waste (Posidonia beached leaves) along the shoreline (Liviello et al., 2014; Moretti et al., 2016).

2.2. Data collection for the case study

The implementation of risk-based methodologies requires the collection and processing of a huge amount of heterogeneous information, including data from climate and hydrodynamic models to characterize hazard scenarios, as well as land-use datasets (including the identification of coastal infrastructures) supporting the identification and characterization of potentially exposed targets and their vulnerabilities. Accordingly, with the main aim of evaluating both shoreline movement and connected changes in water quality, in-depth research and collection of GIS-based datasets expressing spatio-temporal changes in parameters were performed, paying specific attention to their spatial resolution and homogeneous coverage for the case study. A variety of physical and environmental (e.g., currents, waves, winds) and anthropogenic drivers (e.g., localization of infrastructures) were retrieved to spatially characterize the main stressors contributing to a negative coastal balance in the case study and identify the potentially exposed targets (Table 1).

3. Multi-tier analytical framework for coastal erosion risks assessment and management

A multi-tier analytical framework was developed to analyze coastal erosion risks in the Ugento case study. The methodology composes of two main analytical tiers (Fig. 2): **Tier 1** "*Data analysis*" (Section 3.1), focusing on shoreline changes analysis under the 2009–2018 time frame and correlating this data with oceanographic and water quality information observed over the same period; Tier 2 "*BN model for coastal erosion risk assessment and management*" (Section 3.2), with BN development and application for scenario analysis at the case study level.

3.1. Tier 1: Data analysis

The first tier of the proposed analytical framework comprises two different sub-phases, including i) extraction and evaluation of the historical shoreline evolution trend (2009–2018 timeframe) through satellite imagery, and ii) pre-processing of both oceanographic and water quality variables as retrieved from CMEMS (Section 3.1.2).

3.1.1. Historical shoreline evolution trend

The analysis of the shoreline evolution (SEV) trend comprises (i) the coastline extraction from open-source satellite images (as indicated in Table 1) and (ii) the evaluation of the Net Shoreline Movement (NSM) in terms of meters of advancing or retreating coasts among years.

As far as coastline extraction is concerned, historical RapidEye satellite images with a spatial resolution of 5 m were retrieved freely from the Planet Explorer Beta website,[3] covering the 2009–2018 period. The advantages of using RapidEye satellite images to analyze SEV lie in their spatio-temporal coverage and the enhancement of the spatial resolution compared to other open-source satellite imagery (e.g., 30 m of the Landsat 4–5 TM).

Specifically, based on the matching of the same tidal range (to allow for comparability of the extracted shoreline) and the clarity from cloud cover, RapidEye images were selected for the following dates: 07/05/2009, 24/08/2012, 28/10/2013, 06/08/2015, and 20/07/2018. Image selection was based on: (a) clarity from cloud cover; (b) the correct georeference; (c) the seasonality (all images were retrieved in the summer months); (d) tidal effect (all images were retrieved during tidal neaps). The shoreline extraction methodology was validated using a reference coastline extracted by the higher resolution GeoEye-1 image, with spatial resolution 0.46 m in the panchromatic and 1.84 m in RGB NIR bands. The distance between respective RapidEye shorelines of the same period was estimated using vertical transects (at 2 m distance). The average error was estimated at 1.6 m.

The Semi-Automatic Classification Plugin (SCP) in QGIS (Congedo, 2018), was then applied for coastline extraction (see Supplementary Material **SM1** and **SM2**, showing results for the Ugento shoreline and the Torre Mozza hotspot, respectively). Consequently, the analysis of SEV trend was carried out by applying the Digital Shoreline Analysis System tool (Thieler et al., 2009), which allows the historical evaluation of shoreline throughout the years, also considering the related errors and uncertainties (Genz et al., 2007), and automatically tracing transects along the shoreline with a distance defined by the user. In the frame of this study, among SEV indicators provided by the tool (i.e., End Point Rate, Net Shoreline Movement, Linear Regression Rate), NSM was selected to report the distance between the reference (e.g., 2009) and the current/most recent shoreline. This value is calculated for all the above-defined transects, and results for the case study are outlined in Section 4.1.

3.1.2. Oceanographic and water quality data processing

Oceanographic and water quality indicators were downloaded from

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[3] www.planet.com/explorer/

Table 1
Metadata of the dataset available for the implementation of risk-based methodologies in the Apulia shoreline case study.

Data type	Spatial domain	Publish Year	Spatial resolution	Temporal resolution	Timeframe	Data Format	Reference/Link
Base map data							
Administrative Boundaries	Global	2015	/	/	/	Shapefile	http://gadm.org
Coastline	Europe	2015	/	/	/	Shapefile	https://www.eea.europa.eu/data-and-maps/data/eea-coastline-for-analysis-1
Oceanographic data							
Sea surface height above geoid (m)	Med Sea	2018	~ (6.9 ×6.9) km	daily	1987-2018	NetCDF	https://doi.org/10.25423/MEDSEA_REANALYSIS_PHYS_006_004
Eastward sea water velocity (m/s)	Med Sea	2018	~ (6.9 ×6.9) km	daily	1987-2018	NetCDF	
Northward sea water velocity (m/s)	Med Sea	2018	~ (6.9 ×6.9) km	daily	1987-2018	NetCDF	
Wave direction propagation (^{o})	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	https://doi.org/10.25423/CMCC/MEDSEA_HINDCAST_WAV_006_012
Significant wave height (m)	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	
Sea surface wave mean period (s)	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	
Wind wave direction (^{o})	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	
Significant wind-induced wave height (m)	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	
Sea surface wind-induced wave mean period (s)	Med Sea	2019	~ (4.6 ×4.6) km	hourly	2006-2019	NetCDF	
Water quality data							
Suspended Particulate Matter (mg/m^{3})	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	https://doi.org/10.48670/moi-00281
Diffuse attenuation (m^{-1})	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	
Reflectance	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	
Absorption coefficient (m^{-1})	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	
Particulate backscattering (m^{-1})	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	
Secchi transparency depth (m)	Global	2017	(4 ×4) km	monthly	1997-2019	NetCDF	
Nature-based solutions	Ugento	2018	User-defined	yearly	2009-2018	Shapefile	(Comune di Ugento, 2014;Regione Puglia, 2018)
Socio-economic data							
Infrastructures	Ugento	2018	User-defined	yearly	2009-2018	Shapefile	(Regione Puglia, 2018)
Remote sensing data							
RapidEye satellite images	Global	2019	(5 ×5) m	daily	2009-2018	Raster	www.planet.com/explorer/

Copernicus CMEMS for the 2009–2018 time-window (as detailed in Section 2.2), and the raw grid-based data was pre-processed to homogenize their spatio-temporal resolution for the whole case study. Specifically, as far as the temporal integration is concerned, the original data was aggregated by using the Climate Data Operators commands (Schulzweida, 2018), calculating the monthly mean to capture seasonal-based patterns across both oceanographic and water-quality variations, as well as the monthly-based maximum for the variables concerning the significant wave height and significant wind-induced wave height to detect extreme events within the investigated timeframe. Moreover, the oceanographic data related to the offshore wave parameters (i.e., significant wave height, wave direction from and wave mean period), were used to calculate the incident wave energy at the breaker zone along the shoreline (IWE; U.S. Army Corps, 2008).

The final output of this process consists of a matrix where lines indicate the IDs of all transects located along with the case study of the Ugento shoreline (so-called cases in BN approaches), and columns indicate the considered variables. Based on this matrix, a correlation analysis was developed to select the most relevant variables while discarding the highly correlated ones and, in turn, reducing the complexity of the designed BN model and the computational time required for its implementation. As detailed in the Supplementary Material **SM4** and **SM5**, SPM and KD were selected as WQ-related assessment endpoints, as their correlation with the oceanographic drivers is the highest, representing great influence from these variables, and among the assessment endpoints is the lowest, detailing different aspects of WQ.

3.2. Tier 2: BN model for coastal erosion risk assessment and management

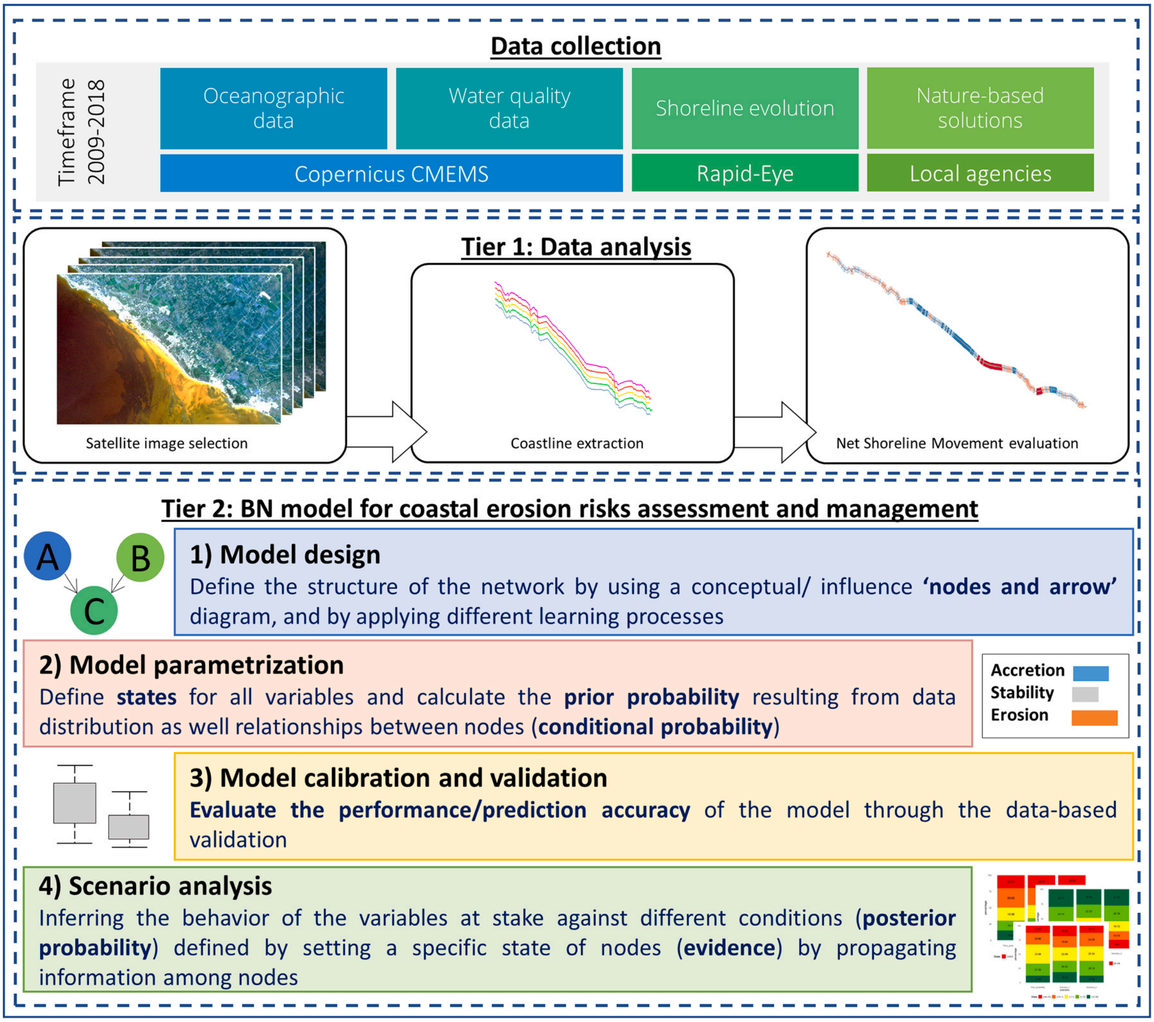
BN are probabilistic graphical models, widely used for knowledge representation and reasoning under uncertainty within natural resource management (Pollino and Henderson, 2010).

They are based on Bayes' theorem of probability to propagate information between nodes, which states that the likelihood of an event, relied on prior knowledge of conditions, might be related to the event, as expressed in the following equation (Bayes, 1763):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

where $P(A)$ and $P(B)$ are the probabilities of observing A and B without regard to each other,$P(A|B)$ is the probability of observing the event A given that the event B is true, and $P(B|A)$ is the probability of observing the event B given that the event A is true.

The development of the BN tailored for the Ugento case study was implemented through four consecutive operative phases, including



1) Model design

Define the structure of the network by using a conceptual/ influence **'nodes and arrow'** diagram, and by applying different learning processes

2) Model parametrization

Define **states** for all variables and calculate the **prior probability** resulting from data distribution as well relationships between nodes (**conditional probability**)

3) Model calibration and validation

Evaluate the performance/prediction accuracy of the model through the data-based validation

4) Scenario analysis

Inferring the behavior of the variables at stake against different conditions (**posterior probability**) defined by setting a specific state of nodes (**evidence**) by propagating information among nodes

Fig. 2. Operative steps underpinning the multi-tiers analytical framework designed for the Ugento shoreline case study.

model design and parameterization, model calibration and validation, and scenario analysis, as detailed in the following Sections 3.2.1, 3.2.2, and 3.2.3, respectively.

3.2.1. BN model design and parametrization

The first methodological step for the implementation of the BN approach concerns the model design, where links between variables are detailed to build a causal structure. Within this study, a DPSIR-based conceptual framework was designed showing pathways of interaction between oceanographic dynamics and human-made pressures resulting in environmental, physical, and socio-economic impacts on the exposed coastal systems (e.g., shoreline and water quality change; Supplementary Material **SM6**). The framework was then converted into a "boxes and arrows" diagram representing the initial expert-based BN model (Section 4.2.1), where "arcs" (i.e., casual correlation) connect "nodes" (i.e., variables), building a directed acyclic graph (DAG; Furlan et al., 2020). BN conceptual models can be also inferred by applying different learning techniques, allowing for the automatic extraction of the network structure (i.e., structure learning) by looking at the relationships among variables (Scutari, Marco, 2017). Specifically, four different structure learning techniques were applied (i.e., *Grow-Shrink* (GS) and *Incremental Association* (IAMB) and *hill-climbing* (hc) and *tabu search (tabu)* to verify potential connections among variables that might integrate into the expert-based BN framework. The outputs from their application comprise the list of suggested connections (or DAGs) based on the input data (see Supplementary Material **SM10**), which need, however, further considerations and experts' judgment for setting the final BN structure.

The model resulting from this overall process represents the BN initial condition and the level of evidence of the relationships among variables considered in the investigated coastal system (Furlan et al., 2020).

Building on the parameter and structure learning, the conditional probabilities among BN variables can be learned directly from the BN input dataset (Ji et al., 2015).

3.2.2. BN model validation

Model validation is a crucial step to assess the model's predictive accuracy and reliability, which can be fulfilled by applying two different methods: i) data-based evaluation, measuring the predictive accuracy of the BN model by calculating the model errors as false outcomes of the predicted nodes (e.g., assessment end-points) using an independent set of observed data; ii) qualitative evaluation, expert judgment or outcomes comparison with peer-reviewed literature or similar models/ applications.

In this work, the accuracy of the model was checked by performing the k-fold cross-validation (k-cv), estimating the prediction error of the designed BN model, in terms of probability of misclassification of unlabeled instances (Rodrìguez et al., 2010; Stone et al., 1974). Through this method, the training dataset is trained uniformly and randomly partitioned into k-folds of equal size. The model is tested using '*k–1*' folds and the prediction error can then be estimated by testing the model in the remaining set of folds, taking the mean errors of all the iterations.

3.2.3. Scenario analysis

The last phase of the BN development concerns the scenario analysis, which allows for the simulation of potential '*what-if*' scenarios, including potential changes in climate (e.g., different oceanographic boundary conditions) and management measures envisioned for the investigated area to mitigate coastal erosion risks (i.e., implementation of new coastal infrastructures and NBS).

To this aim, two different inference methods may be performed, namely 'diagnostic' (or 'bottom-up') and 'prognostic' (or 'top-down') inference (Scutari, 2010). Within this study, building on the prognostic inference approach, two scenarios were envisioned for the case study area. Specifically, considering information from pivotal discussion with the municipality of Ugento (as the relevant stakeholder involved in the design of the BN model for the investigated area), as well as climate change projections (i.e., increasing the magnitude of coastal waves), these scenarios are defined as follows:

Scenario 1 (SC1): A rapid changing world.

Can higher significant wave height influence the energy at the breaking zone and, as a consequence, lead in a variation of the sedimentary budget?

Climate change is leading to an increase of extreme events occurrences (e.g., storms, sea-level rise, variation of ecosystems; Furlan et al., 2021a,b; Lionello et al., 2017; McClelland et al., 2018). The purpose of this scenario is to assess the potential effects exclusively of storminess, on the investigated coastal environment, by setting a 100% probability to the higher class of the oceanographic driver related to the maximum significant wave height (MWAH), i.e., the class with wave heights higher than 5 m, in line with recent studies suggesting an increase in significant wave height under climate change scenarios (Caloiero et al., 2020; Sánchez-Arcilla et al., 2016). Accordingly, the defined evidence is propagated from the parent node on WAH to its child ones (e.g., IWE and then both the assessment endpoints), focusing the analysis on the connected cascading risks in terms of SEV and variations in WQ parameters.

Scenario 2 (SC2): Green is the new black.

What are the required management measures to reduce coastal erosion risks along the Ugento shoreline?

As far as management scenarios are concerned, during the latest decades, the Ugento shoreline has been restored by implementing a set of NBS, including beach nourishment and restoration of dune systems, as well as artificial structures (i.e., groins and breakwaters). Accordingly, building on the input of the municipality of Ugento, this scenario aims to simulate the implementation of further management measures along the coast, assuming NBS scaling-up to face rising coastal erosion risks. Specifically, the probability of NBS located along the coast was set equal to 100%, envisioning a sustainable development pathway for the Ugento shoreline in line with the objectives of the ICZM protocol (OECD, 1997), the recent EU Green Deal, and the EU strategies on Biodiversity and Climate Change (European Comission, 2013; European Commission, 2013). Accordingly, the set evidence is propagated from the NBS node to

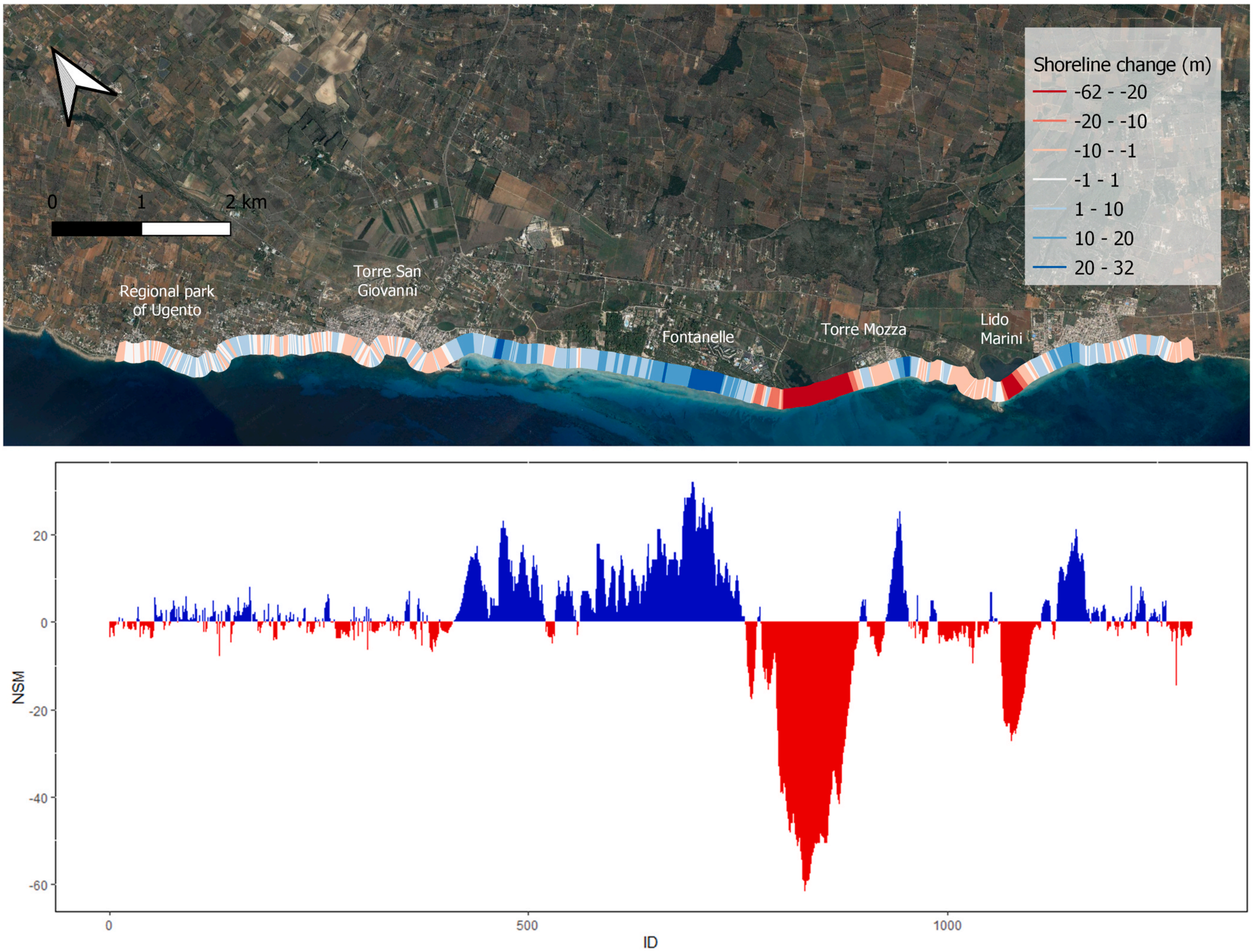


Fig. 3. Spatial and graphical representation of the Net Shoreline Movement (NSM) indicator as extracted from the DSAS tool application in the Ugento case study under the 2009–2018 temporal range.

its child ones, investigating changes in the probability distributions of the SEV and WQ nodes.

4. Results and discussion

As described in Section 3, the proposed analytical framework was organized into two main interconnected tiers, and the following sections outline their respective results. Specifically, the shoreline evolution trend analysis is presented in Section 4.1, whereas Section 4.2 highlights result of the BN model application for coastal erosion risk assessment and management.

4.1. Tier 1: Data analysis

As detailed in Section 3.1, the shoreline evolution analysis was performed to assess the historical erosive trend of the Ugento coast (Fig. 3) and identify hotspot areas showing higher changes both in erosion and accretion patterns.

The spacing between transects was set equal to *10m* to capture the high spatial variability of input data and to get a smoother visualization of the final outputs.

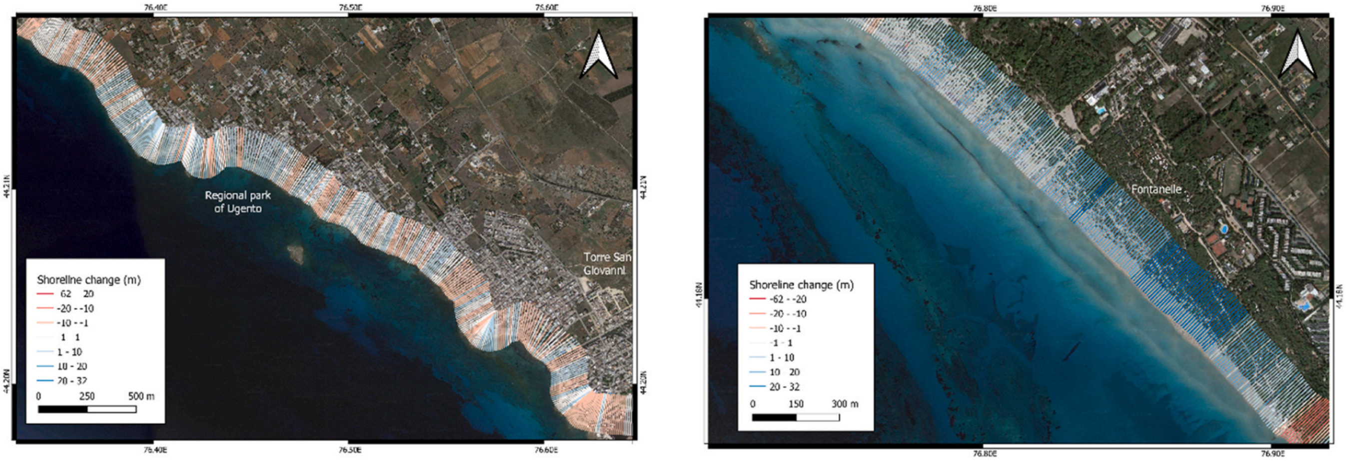
The analysis highlighted four main areas showing different evolutionary trends along the coast (Fig. 3). Specifically, in the northernmost area along the *Regional park of Ugento*, the coastal area is predominantly stable (i.e., [−1,1]m class, represented with transects in white color in Fig. 4-A) for the whole investigated period, due to its rocky geomorphology. Along the sandy beaches of Fontanelle shoreline is advancing (transects in blue color in Fig. 4-B) mainly due to the management measures put in place by local authorities (Apulia region and Municipality of Ugento) to reduce coastal erosion risk (e.g., NBS as detailed in Supplementary Material SM7 and artificial protections). On the other hand, the sandy beach of Torre Mozza turned out to be the most affected area by erosion (Fig. 4-C). Finally, the sandy shore of Lido Marini features a mixed trend, erosion beside the drainage channel and advancing along the southernmost area of the municipality (Fig. 4-D).

4.2. Tier 2: BN model for coastal erosion risk assessment and management

As mentioned in Section 3.2, the proposed BN model was implemented under several consecutive operative phases. The following sections detail results obtained for each step, including model design and parametrization (Section 4.2.1), model validation (Section 4.2.2), and scenario analysis (Section 4.2.3).

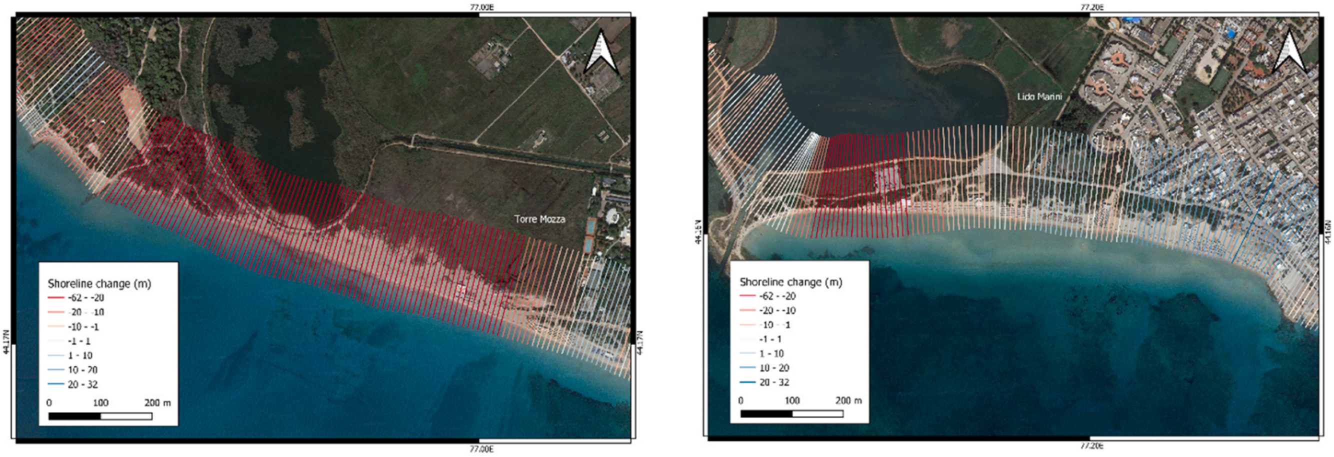
4.2.1. Model design and parametrization

Building on the developed DPSIR framework (see Supplementary Material **SM6**), the preliminary expert-based BN model was designed (see Supplementary Material **SM8**), composed of parent nodes related to oceanographic boundary conditions and management measures, as well



(A) Regional park of Ugento

(B) Fontanelle



(C) Marina of Torre Mozza

(D) Lido Marini

Fig. 4. Results of the DSAS tool application in the area of the Regional park of Ugento (A), beaches of Fontanelle (B), the Marina of Torre Mozza (C), and Lido Marini (D) – municipality of Ugento.

as three assessment endpoints representing shoreline and WQ changes (see Supplementary Material **SM3**). Specifically, oceanographic variables were selected based on literature review (Gutierrez, 2011; Jäger et al., 2017; Plomaritis et al., 2017) and expert judgment by TRITON project partners. Accordingly, the node related to IWE was integrated into the BN model together with its driver variables (i.e., wave height and wave direction), as they jointly influence the sediment transport along the shoreline resulting in accretion and erosion processes (Anastasiou and Sylaios, 2016). On the other hand, the management nodes (i. e., infrastructures and NBS) were chosen following the strategies and plans implemented by the municipality under the 2009–2018 timeframe. Specifically, the construction of artificial protections, as well as the rehabilitation of the dune system through the storage and deposition of Posidonia oceanica leaves (see Supplementary Material **SM7**), helped together to reduce beach erosion in the investigated site by minimalizing sea wave energy during storms and strong winds (ISPRA, 2009). Finally, the assessment endpoints of the BN model (i.e., SEV, SPM, KD) were selected to quantify physio-chemical processes against coastal erosion phenomena, as well as changes in the coastline (see Supplementary Material **SM1**). However, the framework was highly driven by oceanographic dynamics, as well as the availability of homogeneous data (Section 2.2), thus constraining the analysis and limiting the selection of variables. In particular, among the WQ indicators included in the Copernicus CMEMS portal, SPM and KD coefficients were selected as WQ assessment endpoints, as they were able to represent light and mass components while outlining a high correlation with the SEV trend. Specifically, these are able to identify the quality of light and the quantity of sediments washed away by storms and extreme events along the whole Ugento Municipality, as well as within the Torre Mozza hotspot (see Supplementary Material **SM4** and **SM5**). More specifically, SPM refers to both organic and mineral particles in suspension in the water's mixed layer, and KD to light intensity at a specified wavelength attenuated within the water column. Therefore, these variables give an indication of water clarity and living conditions of some important marine ecosystems in the study area (e.g., sea grass meadows).

Once the expert-based model has been set, the input data were organized into discrete values, in order to be integrated into the designed BN model (i.e., *discretize* function in R). Specifically, the number of states for each variable (or node) depended on its natural characters (e.g., continuous or Boolean values; see Supplementary Material **SM9**). Consequently, the expert-based BN conceptual model was trained against different structure learning techniques (Section 3.2.1), highlighting some undirect arcs, as well as new connections often not representing real-world natural processes, as observed in the expert-based framework (Plomaritis et al., 2017; Poelhekke et al., 2016; Sanuy et al., 2018), thus discarded.

As represented in Fig. 5 showing the final BN structure, only the suggested connection from MWAH to MWIH was selected, since wave height is highly connected to the wind-induced wave height (Tucker and Pitt, 2001). Building on the final BN model, conditional probabilities among variables included in the network were learned, calculating probabilities based on the frequency of observed data (Fig. 5).

4.2.2. Model validation

Once the BN model has been defined and all variables have been parametrized, the validation process follows to estimate the BN model prediction error (i.e., classification error) in terms of misclassification of unlabeled instances (Rodrìguez et al., 2010; Stone et al., 1974). Fig. 6 illustrates the resulting output of this process applied to the final BN model, reporting its average prediction error (Scutari, Marco, 2017)

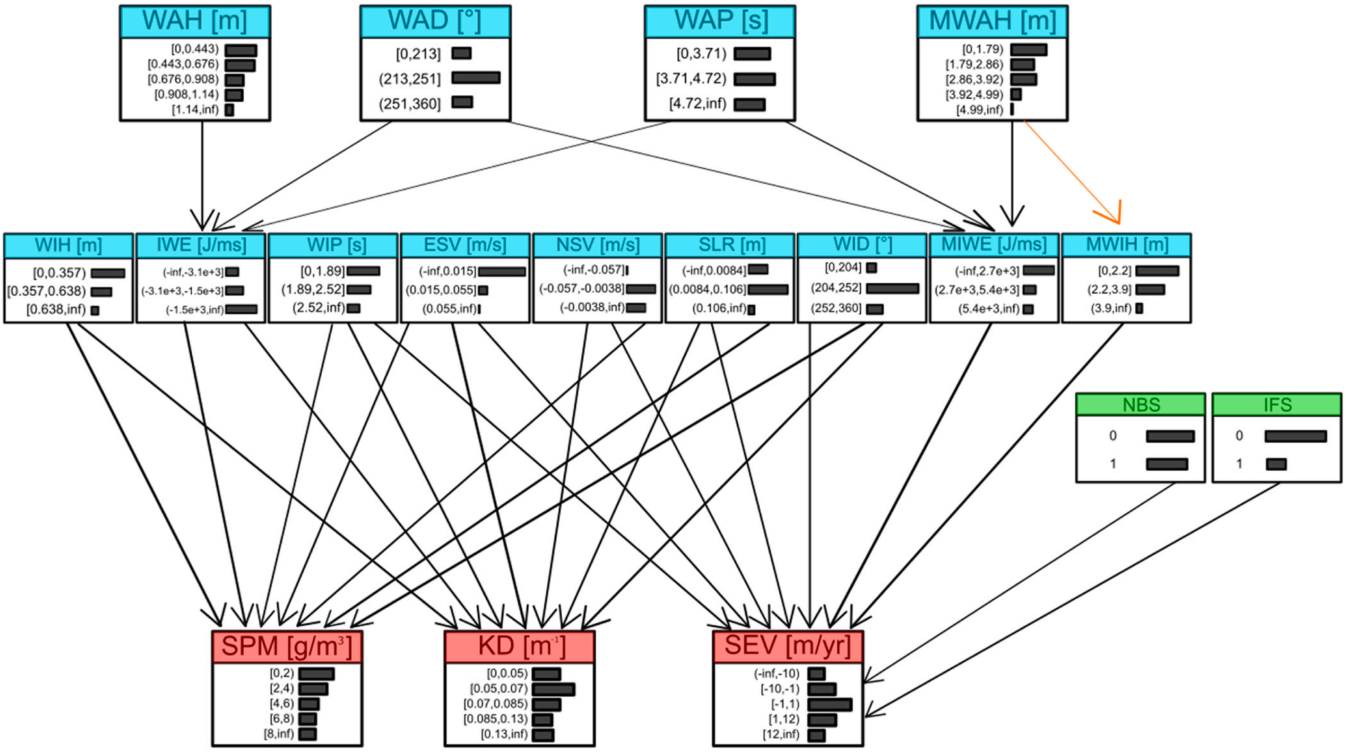


Fig. 5. Final BN model used for the scenario analysis in the Ugento shoreline case study. The black and orange arcs indicate the connection before and after the structural learning process, respectively. The black bars indicate the marginal distributions associated with all variables, and related states, included in the network (see Supplementary Material **SM9** for more details related to the classes of each input variable). Legend: ESV - Eastward Sea water Velocity; IFS – infrastructures; IWE – incident wave energy at the breaker zone; KD – diffuse attenuation; MIWE – max incident wave energy at the breaker zone; MWAH – max significant wave height; MWIH – max significant wind-induced wave height; NBS – nature-based solutions; NSV – Northward sea water velocity; SEV – shoreline evolution; SLR – sea-level rise; SPM – suspended particulate matter; WAD – wave direction from; WAH – significant wave height; WAP – sea surface wave mean period; WID – wind-induced wave propagation direction; WIH – significant wind-induced wave height; WIP – sea surface wind-induced wave mean period.

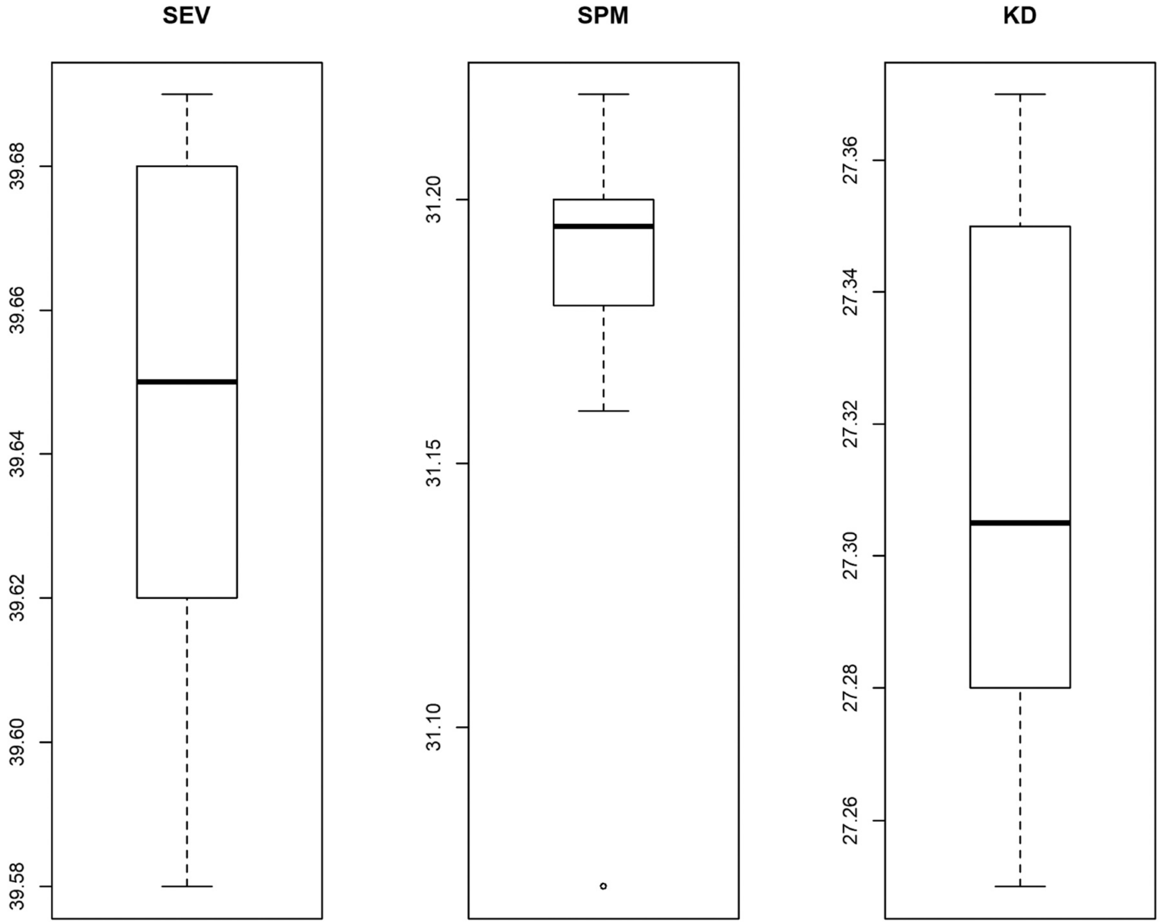


Fig. 6. Boxplot reporting the prediction error of the final BN model for its assessment endpoints (i.e., shoreline evolution (SEV), suspended particulate matter (SPM), and diffuse attenuation (KD)).

across the three assessment endpoints. The model was validated by performing the 10-fold cross-validation method (i.e., k = 10).

As can be observed, the mean classification error across the 10 defined folds was about 39.6%, 31.2%, and 27.3% for the SEV, SPM, and KD, respectively. Accordingly, this outcome confirms that the final BN model could get the right prediction of about 60%, 69%, and 73% for the assessment endpoints.

4.2.3. Scenario analysis

As explained in Section 3.2.3, the last phase of the proposed multi-tier approach consists of the scenario analysis, which was performed aiming at analyzing the probability of the assessment endpoints under

SEV KD SPM

🟥	High erosion: (-inf,-10) meters	Very high turbidity: [0.13,inf) m^{-1}	Very high presence: [8,inf) gm^{-3}
🟧	Moderate erosion: [-10,-1) m	High turbidity: [0.085,0.13) m^{-1}	High presence: [6,8) gm^{-3}
🟨	Stability: [-1,1) m	Moderate turbidity: [0.07,0.085) m^{-1}	Moderate presence: [4,6) gm^{-3}
🟩	Moderate accretion: [1,12) m	Clear water: [0.05,0.07) m^{-1}	Low presence: [2,4) gm^{-3}
🟩	High accretion: [12,inf) m	Very clear water: [0,0.05) m^{-1}	Very low presence: [0,2) gm^{-3}

Fig. 7. Results of scenarios analysis for the assessment endpoints, i.e., shoreline evolution (SEV), diffuse attenuation (KD) and suspended particulate matter (SPM), compared to the prior probability (the first bar of each sub-figure). Legend: SC1: Rapid changing world; SC2: Green is the new black.

different climate and management scenarios. Taking into account the inherent complexity and uncertainty of the analyzed coastal system, the framework could support a sound evaluation of physical and water quality-related risks, arising from coastal erosion processes (e.g., shoreline retreatment, increased water turbidity). Specifically, Fig. 7 includes three different bar charts which represent the results of the scenario analysis against BN assessment endpoints (i.e., SEV, KD, SPM). Specifically, within each bar chart, the first bar refers to the prior probability (i.e., probability of the unperturbed condition to occur), whereas the second and the third to the simulated scenarios (i.e., SC1 – *A rapid changing world*, SC2 – *Green is the new black*).

Scenario 1 (SC1): Rapid changing world.

This scenario was designed to assess the effects of potential changing climate conditions (e.g., intensity and duration of storms, and sea-level rise) on the coastal environment of concern, assigning 100% probability to the highest state of the oceanographic pressure related to the significant wave height (WAH) and maximum significant wave height (MWAH), corresponding to a potential increase in extreme coastal flood events during the last decade (Section 2.1). Accordingly, the defined evidence was propagated from the parent nodes WAH and MWAH to their child nodes (i.e., IWE, and to the assessment endpoints).

As far as SEV is concerned, the most significant changes can be observed in the ‘stable’ class (Fig. 7), with a reduction of almost 10% of stable coast. Interestingly, this change was converted into the most unstable classes, i.e., an increase of 6.3% for the ‘high erosion’ state and 6.3% for the ‘high accretion’ state. The magnitude and frequency of natural extreme weather events and sea level would alter the hydrodynamic process and, consequently, the morphological dynamics (i.e., erosion and accretion) along the shores. Specifically, increased extreme events under the ‘*Rapid change world’* SC1 could lead to higher wave height and energy at the breaker zone, which would trigger higher erosion rates and, in turn, higher sediment mass transport in some areas of the coast. The designed BN model, which has been implemented in combination with the shoreline analysis within the proposed multi-tier hybrid framework, does not allow to recognize the specific area where the shoreline will experience the erosion/accretion pattern, due to the data aggregation made under the model development. However, we can deduce that the expected pattern will follow the trend already observed from the remote sensing-based SEV analysis (see Supplementary Material **SM1**). Specifically, as detailed in Section 4.1, most of the eroded areas have been experiencing a high erosion rate (e.g., overall retreating of about 60 m in Torre Mozza). On the other hand, this pattern is converted into an advancing process along the Fontanelle hamlet, due to the presence of artificial protections limiting sediment transport (i.e., groins and breakwaters), as well as the implementation of beach nourishment and NBS. This phenomenon has been also recognized on various coasts across the globe: Scardino et al. (2020) found that changes in vertical (e.g., wind direction, wave high, etc.) and horizontal components of sea level (e.g., water velocity and sediment budget), together with human activities, result in different erosion and accretion rates, as experienced along the Gulf of Taranto (Apulia region, Italy). Moreover, Vieira et al. (2020) recognized that the installation of coastal protection measures (i.e., emerged and submerged detached breakwaters) strongly influences hydro- and morpho-dynamics by dispersing the energy of significant waves at the breaker zone.

Interestingly, a balance between the increased rate of ‘high erosion’ and ‘high accretion’ states can be observed as a result of the remobilization processes towards new equilibrium profiles of the shoreline via sedimentation flux (Bourriquen et al., 2016). Based on the probability distribution of data used for the BN training, we can assume that, while the northern area (i.e., Regional park of Ugento) will remain mostly stable due to its rocky conformation, the sandy coasts of Fontanelle and Torre Mozza will experience high accretion and erosion, respectively.

Regarding the WQ nodes, a similar trend can be observed for both SPM and KD variables. Specifically, for the latter was observed a total increase of about 4% for the ‘turbidity’ classes, which, in turn, led to a decrease of the same amount of the ‘clear water’ classes. Accordingly, SPM node highlighted an increase of about 5% in the presence of sedimentary budget (i.e., ‘high presence’ and ‘very high presence’ classes; see Supplementary Material **SM9)**.

Noticeably, the magnitudes of changes for the WQ parameters were less significant than those observed for SEV. This behavior confirmed as changes in the oceanographic boundary conditions would lead to more severe physical impacts on the SEV rather than to the WQ, which are governed by more complex biological/oceanic processes (Durán and Beiras, 2013) instead of physical, hydrological, and morphological dynamics mainly driving modifications in the shorelines (Bourriquen et al., 2016; Vieira et al., 2020).

Scenario 2 (SC2): Green is the new black.

This scenario was designed to simulate management objectives, assuming that the municipality of Ugento, in line with the recent Biodiversity strategy and EU Green Deal targets (European Commission, 2019), would move on NBS upscaling to reduce coastal erosion risks. Accordingly, the probability of the presence of NBS along the Ugento shoreline was set equal to 100%, thus replicating the human efforts to protect the coast and its surroundings.

It can be seen from Fig. 7, as the implementation of NBS (e.g., dune restoration) in the ‘*Green is the new black’* SC2 could lead to a reduction of the stable class, and conversion into the two intermediate classes reflecting the impact of the implementation of new coastal protection solutions.

The dune rehabilitation strategy implemented during the last decade along some specific areas of the Ugento shoreline (e.g., in Fontanelle, see Supplementary Material **SM7**), had an important role in the reconfiguration of the beach profile, as well as in the dune formation and stabilization. As shown from the data used for the BN training (Fig. 8), the implementation of NBS along Fontanelle proved to be efficient in preventing coastal erosion. SC2 confirms that this sedimentation trend (moderate accretion class; [1,12] m) will persist also in the future. On the other hand, the southern coastal area, from Torre Mozza to Lido Marini, is more prone to erosion, and this pattern has been clearly evident for decades (Comune di Ugento, 2015). Consequently, NBS and artificial protections (i.e., groins and breakwaters) were established, but they have not been able to counteract the eroding pattern along the southern coast. This trend can be seen due to the shoreline orientation changes between the northern and southern part of the municipality, playing a key role in determining the dynamic morphological changes. Therefore, SC2 also outlines an increase of the moderate erosion class, since the orientation of the southern coast is more exposed to incoming waves/storm surge events. As a results, current management measures have not been able to stabilize the entire coast of the investigated municipality. For this reason, further and continuous adaptive solutions are needed, particularly where extreme events have a greater negative impact on the shoreline due to its orientation.

Moreover, NBS show their wider benefits in increasing the resilience of marine and coastal areas under long-term programs (Castellari et al., 2021; O’Leary et al., 2023). Accordingly, NBS-related benefits under the SC2 upscaling strategy were minor in terms of shoreline stabilization in the investigated area. However, this management scheme can be enhanced within the EU climate policies, providing an increased ambition and policy coherence on adaptation planning, aimed at strengthening resilience and reducing vulnerability to climate change and extreme events (European Commission, 2021).

Concerning WQ variables, both KD and SPM remain almost stable across the defined classes. The only fluctuations were noticed between the classes of cleat and very clear water, as well as the presence of SPM in the water column (between 2% and 4%). Meanwhile, there were not any significant trends in other classes for both variables. These minor changes implied that NBS would not significantly influence WQ variables, since they are mainly driven by more complex biological, oceanic processes rather than hydrodynamic and morphological ones. A similar pattern was also observed by Cooke et al. (2020) also highlighting as

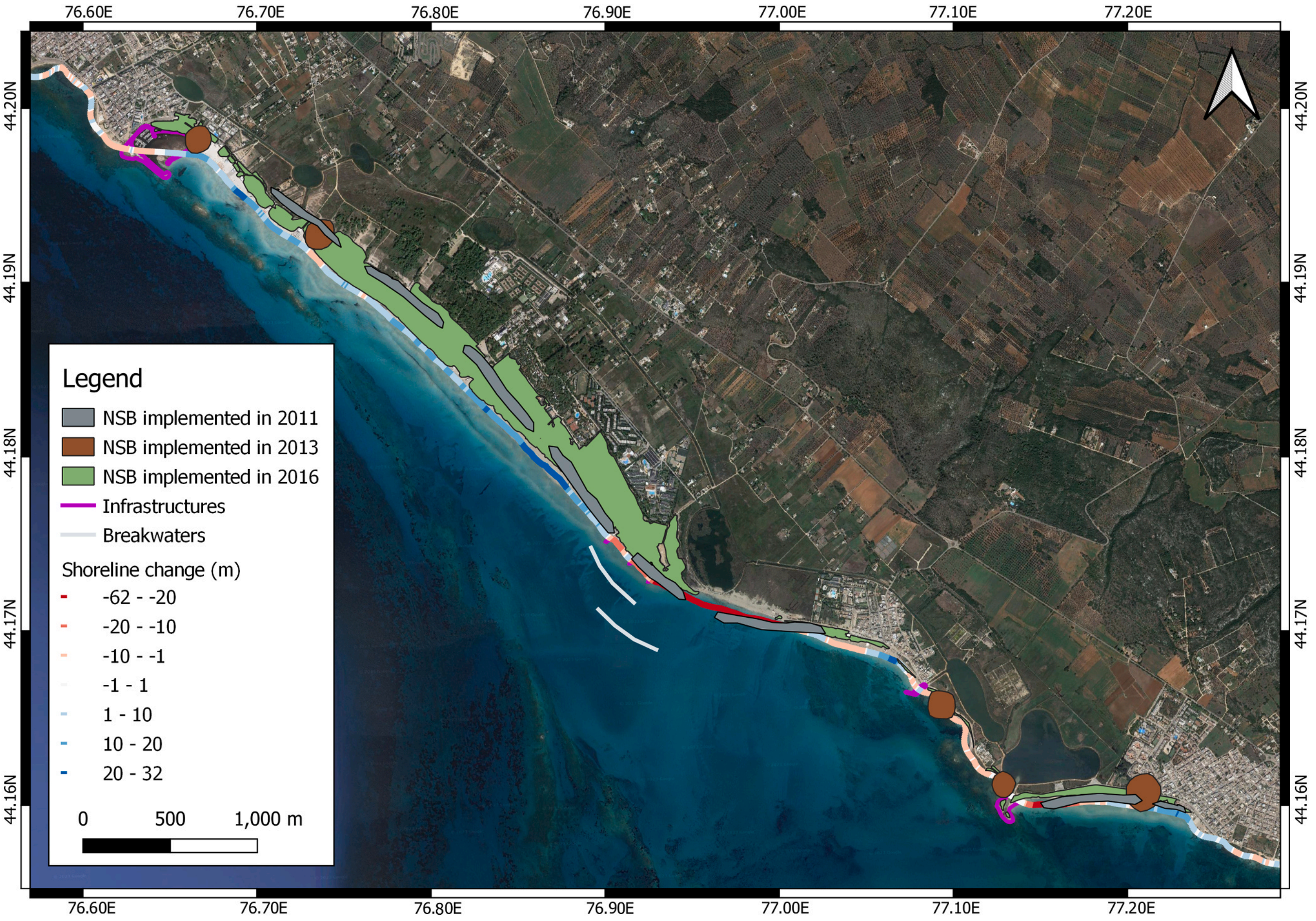


Fig. 8. Spatial representation of the NSM indicator against the management measures (i.e., NBS, breakwaters and infrastructures) implemented during the investigated timeframe (2009–2018).

there was not any significant ecological improvement after two years of the implementation of backshore sand nourishments of ocean beaches.

5. Conclusion

This paper presented a multi-tier analytical framework able to support a joint analysis of the shoreline evolution (SEV) in time, and the probability (and related uncertainties) of coastal erosion risks under different *'what-if'* scenarios. Specifically, two scenarios were simulated for the Ugento shoreline (Apulia region - Italy), testing the capability of the proposed GIS-based BN model to assess the potential consequences of climate change scenarios (i.e., rising sea level and increasing storm occurrence), as well as management measures needed to counteract the coastal erosion (e.g., the implementation of NBS), as required by the ICZM protocol. This application represents an attempt to apply a hybrid framework to support ICZM and decision-making in the Apulia region by providing a quick evaluation of shoreline changes and 'what-if' scenario analysis to identify the main drivers of coastal erosion risks in terms of SEV and WQ variation, supporting adaptation planning in the investigated area, recognized as one of the most vulnerable areas in the Apulia region to coastal erosion phenomena.

The resulting output from both the historical shoreline trend analysis, as well as the BN-based scenario analysis, revealed, even if to a minor extent, a connection between changes in the oceanographic boundary conditions (i.e., max significant wave height) and the resulting shoreline and WQ variation (i.e., SPM, KD), with increasing probability of erosion/accretion along the coast and higher turbidity.

From a methodological point of view, the multi-tier approach represents a flexible tool for interdisciplinary studies, in which spatial data from oceanographic, physical, geomorphological, and environmental domains are integrated to assess the multi-faceted nature of coastal erosion risks. Specifically, the designed BN model can assimilate both expert knowledge and information mined from data retrieved on the investigated area from multiple sources (e.g., numerical models, satellite data for environmental status monitoring, etc.). Consequently, the proposed approach facilitates the understanding of the network of interdependencies among the key variables of the system at stake, also quantifying the degree of relationship among them. Furthermore, the flexibility of the proposed approach lies on the possibility to update the model with more highly detailed and local-scale data as they become available, increasing model efficacy and reliability for the assessment of local-scale phenomena (e.g., coastal erosion processes and linked water quality changes) and management of related impacts. Accordingly, the biggest limitation of this approach mainly relates to data availability. Specifically, starting from historical data, erosion hotspot areas were detected, allowing to identify where adaptive measures are needed. On the other hand, according to both historical trends and scenario analysis, carried out within this study, the implementation NBS could be an effective and suitable solution to address coastal erosion. However, continuous monitoring and rehabilitation of dunes are required to reduce well-known impacts occurring along the investigated case study.

In fact, even in presence of high spatial resolution of satellite images to estimate the shoreline evolution, the input data concerning oceanographic parameters (e.g., the max significant wave height) has significantly constrained the assessment, due to their coarse spatial resolution (from 4 to 6 km), limiting the overall input data available for a 13 km-long shoreline. However, this can be improved leveraging innovative artificial intelligence techniques aimed at assessing meteo-marine parameters (Scardino et al., 2022). Moreover, considering that the network also explored WQ variations, other variables closely influencing WQ (e.g., precipitation and temperature) should have been included in the developed BN. However, the availability of data for these variables, featured by a limited spatial resolution (8 km), did not allow for their proper integration in the designed model.

As far as the BN structure is concerned, it is important to underline that the direct acyclic and static nature of the developed BN brings about some other critical limitations in modeling more complex synergies and temporal changes (and cascading effects) naturally occurring in dynamic coastal ecosystems since no loops and feedbacks are allowed in BN models. Finally, for what concerns the parametrization of the network, the discretization of the possible values assumed by the considered variables poorly represents dynamic environmental processes acting in a continuous probability distribution in both space and time dimensions.

Credit authorship contribution statement

Maria Katherina Dal Barco: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft and review editing. **Elisa Furlan**: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft and review editing. **Hung Vuong Pham**: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft and review editing. **Silvia Torresan**: Funding acquisition, Project administration. **Konstantinos Zachopoulos**: Data curation, Methodology, Visualization. **Nikolaos Kokkos**: Data curation, Methodology, Visualization. **Georgios Sylaios**: Conceptualization, Validation, Supervision, Writing review editing. **Andrea Critto**: Conceptualization, Validation, Supervision, Writing review editing.

Declaration of Competing Interest

All the authors declare that they have no known competing financial interests or personal relationships that could had influenced the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2023.103665.

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