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Exploring inter-relations among Climate Change - Water Quality - Seagrass ecosystems and their Services in the Mediterranean region.

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LIST OF ABBREVIATIONS

Acronym	Definition
BRF	Balanced-Random Forest
CIA	Cumulative impact assessment
CMEMS	Copernicus Marine Service
GB	Gradient Boosting
DO	Dissolved oxygen
DTO	Digital Twin of the Ocean
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
MARITIME	MAchine leaRnIng-based CumulaTive Impact AssessMEnt
MCEs	Marine and coastal ecosystems
ML	Machine learning
MPA	Marine protected area
MRA	Multi-risk assessment
NO_3	Nitrate
PO_4	Phosphate
RCP	Representative Concentration Pathway
RF	Random Forest
SAL	Salinity
SSH	Sea Surface Height
SST	Sea Surface Temperature
UNEP	United Nations Environment Programme
XGB	Extreme Gradient Boosting

ABSTRACT

The cumulative impacts on marine and coastal ecosystems (MCEs) are intensifying due to the interplay between climate change and human-induced pressures, leading to water quality degradation, biodiversity loss, and declining ecosystem services capacity. My PhD aims to address these issues (and their complex nexus) in three phases. First, I conducted a systematic review of cumulative impact assessment approaches and applications applied across different marine regions to evaluate the combined effect of multiple stressors affecting MCEs. In the second phase, I developed a multi-risk assessment framework operationalized with a machine learning (ML) model to assess the risk of cumulative impacts (hereafter referred to as MARITIME - MAchine leaRnIng-based CumulaTive Impact AssessMEnt) on Mediterranean seagrass meadows under current and future climate scenarios projected for 2050 and 2100. The third phase refines this modelling framework at a local scale, focusing on the Apulia region (Italy). This final part provides a detailed analysis of seagrass spatio-temporal responses to present and future cumulative impacts. Remote sensing was instrumental in producing maps of the seagrass distribution at higher resolutions from 2014 to 2021, maps which were then used to train the ML model. The overall MARITIME results of these investigations indicate a progressive decline in seagrass meadows across the different climate change scenarios, posing increasing risks to some ecosystem services these meadows can provide in the future. Moreover, this loss of seagrass meadows could lead not only to a reduction in their potential to support climate adaptation and mitigation but also to the release of buried carbon storage, potentially transforming a coastal region from carbon sinks to a temporary source of carbon emissions.

1) INTRODUCTION

1.1 MOTIVATIONS AND OBJECTIVES

The health of MCEs is fundamental to maintaining the balance of the Mediterranean region's environmental and socio-economic systems (Korpinen et al., 2021; Micheli et al., 2013). Seagrass meadows, coral reefs, and Maërl beds, among others, serve as natural barriers against coastal erosion, support fisheries, and act as carbon sinks, mitigating the impacts of climate change (Buonocore et al., 2020; Pergent-Martini et al., 2021). Despite their critical role, these ecosystems are increasingly threatened by the cumulative pressures from human activities and climate change (Furlan et al., 2020; Hansen & Bonnevie, 2020; Menegon et al., 2018). In the Mediterranean, where biodiversity hotspots coexist with densely populated coastal areas, the interplay between local stressors (such as pollution, overfishing, and habitat degradation) and global phenomena such as rising sea temperatures and ocean acidification is accelerating ecosystem decline (Furlan et al., 2019; IPCC, 2023b).

Addressing these threats requires robust tools capable of assessing the combined effects of multiple stressors on MCEs. Traditional cumulative impact assessments (CIA) lack the complexity needed to evaluate such interactions and predict future scenarios, especially under evolving climate change conditions. This research aims to fill this gap by developing and operationalise a multi-risk assessment framework that can i) understand and map the effects of multiple pressures on a selected MCE across multiple scenarios; ii) investigate the potential interactive behaviours among pressures to capture ecosystem response and effects on ecosystem services capacity; iii) identify areas where ecosystems are at risk of disappearance from, or may expand into as a result of, future changes where local management solutions, such as blue Nature-based Solutions, could be targeted.

By integrating ML, specifically the Random Forest (RF) algorithm, this framework enables a deeper understanding of how seagrass ecosystems respond to multiple stressors (including climate change) over space and time. The designed framework allows for the integration of a wide range of heterogeneous indicators that represent three fundamental risk dimensions: hazard, exposure, and vulnerability (Adger, 2006; IPCC, 2018). In addition to assessing these risk dimensions, the framework is designed to evaluate potential cascading effects in the capacity of MCEs to provide essential services, such as carbon sequestration. This aspect is particularly crucial, as shifts in ecosystem service capacity can have long-term consequences for biodiversity conservation, climate change mitigation and the socio-economic benefits derived from these ecosystems.

The outcome of this integrated approach is a set of GIS-based multi-risk scenarios and indicators that summarize key risk metrics. These outputs are crucial for simplifying the understanding and communication of risks induced by changing climate conditions and human pressures on MCEs. By providing spatially explicit insights into risk distribution, the framework supports policymakers and marine managers in identifying hot-spot risk areas and prioritizing actions to mitigate the impacts of multiple stressors, particularly in contexts where resources are limited. As part of this scenario analysis, potential synergistic behaviours between pressures were also evaluated, enabling a more comprehensive understanding of how combined stressors may amplify or mitigate their effects on seagrass health and resilience. This integrated evaluation enhances predictive accuracy, offering valuable insights into managing ecosystem risks under various stress scenarios.

In this frame, the thesis provides a global overview of cumulative impact assessments, identifying gaps in current methodologies for evaluating the combined effects of human activities and climate change on MCEs. The second and third sections operationalize the multi-risk framework developed by applying it at two different scales: an initial screening at the eco-regional scale focusing on the Mediterranean basin and a more detailed local scale application (with the support of remote sensing technique) centred on the Apulia region (Italy). These two applications aim to test the ML-CIA modelling framework across varying spatio-temporal

resolutions and assess its potential for replicability and scalability, providing insights into how effectively it can be used for both broader and more localized conservation and management efforts.

The methodology was developed within the H2020 European Project MaCoBioS (Marine Coastal Ecosystems Biodiversity and Services in a Changing World, https://macobios.eu/) carried out in collaboration with the Foundation “Centro Euro-Mediterraneo sui Cambiamenti Climatici” (CMCC, http://www.cmcc.it).

1.2 THESIS STRUCTURE

This thesis is structured in 3 main sections, corresponding to the three independent research papers (each addressing three specific research questions). Coherently, after a short introduction describing the relevance of the ongoing effects of cumulative impacts on MCEs' health and their capacity to provide ecosystem services, the thesis will include:

Section A – State-of-the-art knowledge on cumulative impact assessment approaches and applications applied across different marine regions to evaluate the combined effect of climate and anthropogenic stressors affecting MCEs. This section corresponds to the review paper '*Evaluating the combined effect of climate and anthropogenic stressors on marine coastal ecosystems: Insights from a systematic review of cumulative impact assessment approaches'* (already published *in Science of the Total Environment*).

Section B - Building on the insights and the research gaps that emerged from the previous review, this section will focus on the operationalization of the multi-risk assessment framework designed for the Mediterranean region through the development of an ML-based model supporting heterogeneous data integration (e.g. most of them from Copernicus CMEMS), for a sound evaluation of cumulative impacts on seagrass distribution under both reference and future mid (2050) and long-term (2100) climate scenarios. This section corresponds to the Second paper, titled "*The Big Picture: appraising the risk of cumulative impacts on seagrass meadows in the Mediterranean Sea*" (currently under revision by the *Ecological Informatics Journal*).

Section C - Recognizing the limitations posed by the resolutions of the data used for the initial risk screening in the development of the CIA ML-based model for the Mediterranean Sea, the final section of the thesis explores remote sensing techniques to achieve a more detailed spatio-temporal characterization of ecosystem state changes (e.g., variations in seagrass coverage over multiple years). Accordingly, this section includes the remote sensing output (analyses started during the secondment at the University of the Azores/IVAR Academy in the Azores), along with the multi-risk-based modelling framework, operationalized through ML techniques applied to a spatio-temporal dataset. Tested ML algorithms were developed to enhance the understanding of the processes and dynamics underlying the spatio-temporal variations in the health status of the seagrass ecosystem, in response to key pressures in the Apulia case study (Italy). As with the previous chapters, this section aligns with the third paper, "*Harnessing machine learning for transformative adaptation planning: modelling the risk of cumulative impacts on seagrasses across time and space*" (currently under finalization).

Finally, general conclusions will highlight the significance of this thesis in advancing knowledge within the investigated research field.

SECTION A:

FIRST PAPER

Evaluating the combined effect of climate and anthropogenic stressors on marine coastal ecosystems: insights from a systematic review of cumulative impact assessment approaches

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ABSTRACT

Cumulative impacts increasingly threaten marine and coastal ecosystems. To address this issue, the research community has invested efforts on designing and testing different methodological approaches and tools that apply cumulative impact appraisal schemes for a sound evaluation of the complex interactions and dynamics among multiple pressures affecting marine and coastal ecosystems.

Through an iterative scientometric and systematic literature review, this paper provides the state of the art of cumulative impact assessment approaches and applications. It gives a specific attention to cutting-edge approaches that explore and model inter-relations among climatic and anthropogenic pressures, vulnerability and resilience of marine and coastal ecosystems to these pressures, and the resulting changes in ecosystem services flow. Despite recent advances in computer sciences and the rising availability of big data for environmental monitoring and management, this literature review evidenced that the implementation of advanced complex system methods for cumulative risk assessment remains limited. Moreover, experts have only recently started integrating ecosystem services flow into cumulative impact appraisal frameworks, but more as a general assessment endpoint within the overall evaluation process (e.g. changes in the bundle of ecosystem services against cumulative impacts). The review also highlights a lack of integrated approaches and complex tools able to frame, explain, and model spatio-temporal dynamics of marine and coastal ecosystems' response to multiple pressures, as required under relevant EU legislation (e.g., Water Framework and Marine Strategy Framework Directives). Progress in understanding cumulative impacts, exploiting the functionalities of more sophisticated machine learning-based approaches (e.g., big data integration), will support decision-makers in the achievement of environmental and sustainability objectives.

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Introduction

Marine and coastal ecosystems (MCEs) play a crucial role for society by regulating climate, providing food resources and contributing to well-being (Albert et al., 2020; EEA, 2019b). However, most of these ecosystems (e.g., seagrass meadows, coral reefs and Maërl beds) across the globe have been significantly altered by multiple human-related drivers (e.g., overexploitation of fish, shellfish and other organisms, land- and sea-based pollution, aquaculture) (IPBES, 2020). In addition, the complex interplay between anthropogenic and climate-related pressures (e.g., rising sea temperature sometimes resulting in marine heatwaves, increased occurrence of climate and weather extremes, ocean acidification, etc.) is increasingly exacerbating the cumulative impacts across all MCEs, undermining their resilience to consecutive perturbations and their capacity to provide ecosystem services (EEA, 2019; IPBES, 2019; IPCC, 2019). Specifically, cumulative impacts cause a reduction in the health and resilience of MCEs (Beusen et al., 2022; IPBES, 2019), and consequently increase their overall vulnerability to additional external pressures (Berrouet et al., 2018; Salomidi et al., 2012).

In that context, in the early 2000s, the research community started developing methodological approaches and tools for the assessment of cumulative impacts and multi-risk scenarios (hereafter CIA methods). These arised from the complex interaction between human activities (e.g., shipping traffic, fishing) and climate change (e.g., sea surface temperature , ocean acidification) affecting MCEs, and aimed to support decision-makers in the identification of sustainable management strategies (Halpern et al., 2008; Hayes & Landis, 2004). Policies at the international and EU level (UN-SDGs, EU Water Framework Directive, EU Maritime Spatial Planning, Green Deal initiative, Biodiversity Strategy for 2030), and the related definition of environmental targets, requires a comprehensive review to identify suitable existing methodological approaches and tools for managing cumulative impacts and risk to support their implementation and achievement of goals.

The objective of this paper is to provide an in-depth review of CIA and multi-risk assessment (MRA) approaches and applications, jointly applying a Scientometric and systematic literature review of publications identified during the 2000-2022 period (March 2022). The integration of both review approaches allows descriptive analysis and network extraction of the conceptual structure (and terminologies) underpinning this research field, while mapping and systematically analysing its theoretical/methodological trends, as well as gaps and challenges ahead. This review is the first done at this scale, comparing studies against multidisciplinary research questions and related comparison criteria (e.g., ecosystem services component, integration of the ecological tipping point concept), embracing both environmental, ecological, technical/methodological and policy/management perspectives. Particularly, it tries to respond to 3 main research questions*: i) Which are the key methodologies and scientific information/tools that the research community can apply to evaluate the effects of human activities and climate change on MCEs? ii) How has the complexity of stressors on MCEs (e.g., synergism, antagonism) been integrated into CIA/MRA frameworks to identify tipping points and the resilience of ecosystems? iii) What are the benefits and barriers of CIA/MRA applications to support real-world implementation of adaptation and restoration actions in MCEs and achieve policy targets (e.g., Good Environmental Status)?* Other recent global reviews have mainly focused on identifying methodological similarities among analysed studies (Blakley & Russell, 2022; Gissi et al., 2021; Halpern et al., 2019; Halpern & Fujita, 2013; Jones, 2016; Korpinen & Andersen, 2016; Stelzenmüller et al., 2018), as well as exploring some specific aspects into CIA and MRA frameworks and tools for MCEs (e.g., investigation of tipping points, shift changes, Decision Support Systems supporting CIA) (McClenachan et al., 2020; Menegon et al., 2018a; Thrush et al., 2021). This investigation extends the abovementioned perspectives and merges them together to frame and drive the review process and identify key challenges

and gaps, as well as research horizons ahead. The paper gives elements of comparison for scientists and policy makers who aim to use CIA and MRA methods and tools to evaluate and monitor environmental targets in MCEs, while highlighting the best available knowledge and data.

The paper is structured in 3 sections. A preliminary overview on the methodological approaches and the related data acquisition process underpinning the literature review is given in Section 1. The main results obtained from the review are presented in Section 2, while a discussion, in Section 3, highlights the main findings and key relevant challenges and proposes some pathways for improvement.

1. Data acquisition and review methods

A multi-phase systematic literature review was performed to get an overall picture of the current state-of-the-art regarding scientific studies and applications focused on CIA and multi-risk appraisal in MCEs. Specifically, as shown in Figure 1, the methodological approach is comprised of three main steps, including i) data collection, ii) Scientometric analyses; and iii) Systematic analyses (based on the PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses - approach), as described in the following paragraphs 1.1-1.2 and 1.3, respectively.

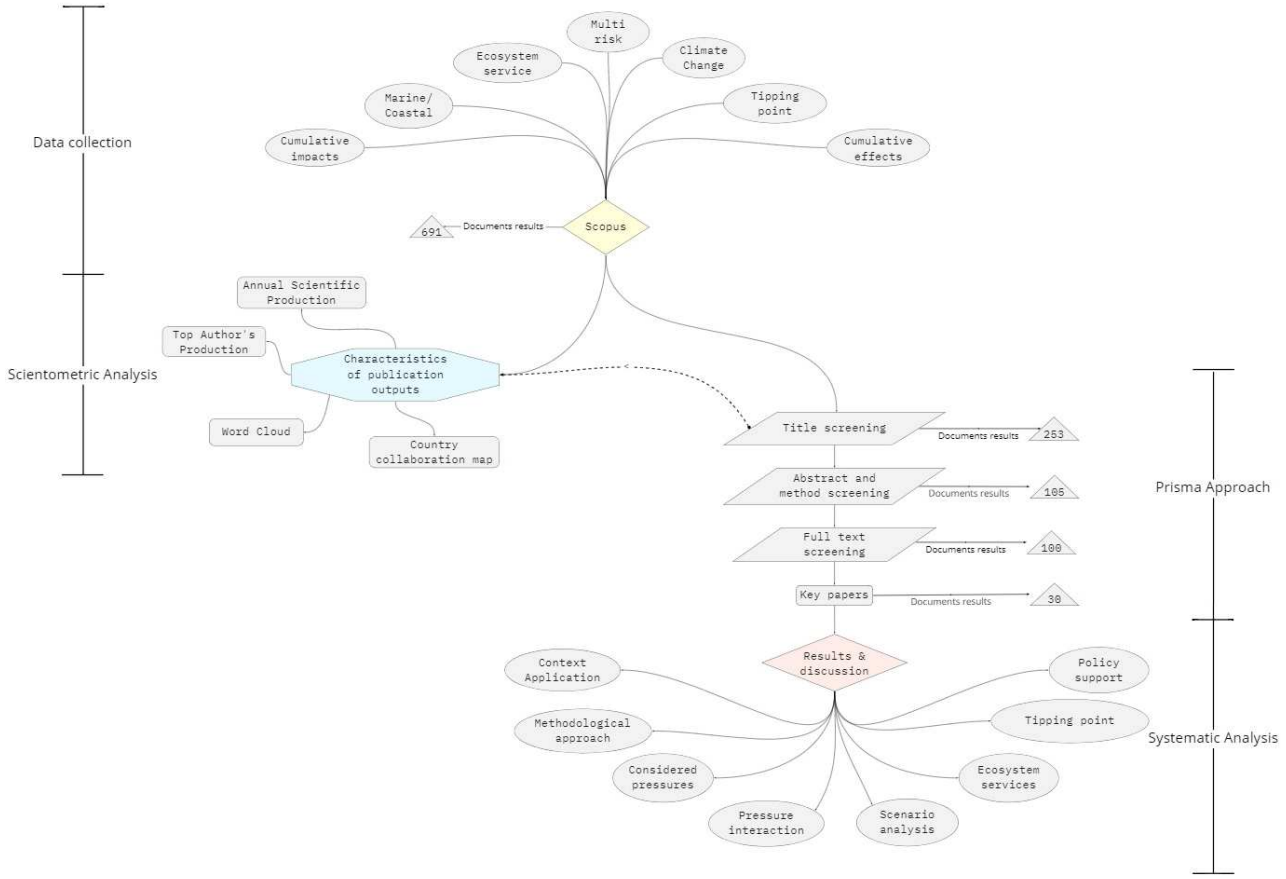


Figure 1: Methodological approach for the evaluation of existing studies and applications dealing with cumulative impact assessment in marine and coastal ecosystems.

1.1 Data collection

Peer-reviewed literature dealing with cumulative impact and multi-risk appraisal in MCEs was systematically searched using Scopus, a source-neutral abstract and citation database developed by independent subject matter experts. The Scopus database is considered the largest curated bibliographic abstract and citation database (Baas et al., 2020), and it was selected as the main source of information for this review. Specifically, building on the objectives of this paper, we performed a search query combining the following keywords in Scopus: '*cumulative impact, cumulative effect, marine coastal ecosystem, marine coastal environment, ecosystem service, multi risk, climate change, ecological tipping point*' through appropriate Boolean operators ("AND", "OR", "NOT"). This set of keywords allows to define the scope of the search and, therefore, identify a comprehensive list of relevant applications integrating methodological approaches for cumulative and multi-risk appraisal in MCEs (the query string is detailed in Supplementary Material SM1, whereas Supplementary Material SM5 provides updated definitions (and related References) of the introduced keywords). More precisely, the first part of the query string – *(("cumulative impact*" OR "cumulative effect*") AND ("marine" OR "coastal" AND "ecosystem*" OR "environment"))* - allows to already select all those publications including at least "cumulative impact/effect" keywords and, therefore, also those papers reporting "cumulative impact/effect assessment" keywords. Moreover, as detailed through the research questions included in the Introduction, the final query contains the keyword "multi-risk" (and not "risk-based assessment/approach") since the key objectives of this review is to give specific attention to novel frameworks and tools allowing to explore and model inter-relations among multiple pressures, and the diverse responses of ecosystems to the latter. The resulting list of papers published between the 2000-2022 timeframe (the search was limited to this period because this research topic started getting attention from the early 2000s) and their connected records (e.g., information including title, author and author keywords, affiliations, etc.) were exported as a Bibtex file for a qualitative and quantitative analysis through the Bibliometrix R Package (Aria & Cuccurullo, 2017; Mingers & Leydesdorff, 2015), and subsequently, the systematic literature review (Section 1.3).

1.2 Scientometric analysis

The Scientometric analysis explores, evaluates and monitors the state of a particular field of research, meta-analytically evaluating the development of a predefined research area to identify its key components and underlying theoretical frameworks (Geissdoerfer et al., 2017). This quantitative analysis takes advantage of the main metadata related to each paper: citation information (such as the author's name, document title, year, and citation count), bibliographical information (e.g., affiliations, publisher, and editor), abstract and keywords (e.g., the authors' keywords and the index keywords). The information exported from Scopus was processed by applying the open-source *Bibliometrix* Package, designed for the statistical R software (Aria & Cuccurullo, 2017). *Bibliometrix* is a web-based application for bibliometric and co-citation analysis able to achieve comprehensive science mapping analysis of scientific literature (Aria & Cuccurullo, 2017) (http://bibliometrix.org/biblioshiny), thus supporting an overarching understanding and interpretation of network patterns, as well as recognising gaps across research fields.

Building on the workflow shown in Figure 1, a preliminary screening of papers, based on the title's pertinence to the review topic of concern allowed to better focus the bibliometric analysis on a restricted list of relevant papers that were then analytically processed through this R-based tool. In particular, this kind of review allows the identification of major focal topics, trends and gaps, while discovering and visualizing the evolution of the topic through the 2000 – 2022 period (Section 2). All the analysis and graphs (i.e., annual scientific

production, top authors' production over time, word-cloud, country collaboration map) are presented and discussed within Supplementary Material SM3.

1.3 Systematic literature review - selection of 'key papers'

Following a preliminary identification of major focal topics made through the Scientometric analysis, a systematic literature review was then applied. This review process consists of a rigorous methodological examination of the identified scientific literature (as detailed in Section 1.1), allowing to separate the insignificant, unsound, or redundant publications from the salient and critical ones that are worthy of further investigation (Mulrow, 1994). Specifically, the systematic literature review has been performed based on the PRISMA approach (Moher et al., 2009), consisting of a pyramidal analysis composed of an iterative stepwise process following a predefined checklist that ensures a transparent and complete analysis and reporting from each review phase.

This process reduced the list of papers (691 publications) initially selected through the keywords' query applied in the Scopus database (Section 1.1) through different phases, including i) publications' screening based on the title's pertinence to the topic of concern and review objectives (resulting in selected 253 publications); ii) Screening based on reading the abstracts and methodological sections of publications remaining from the original list (105 documents were selected); iii) Further screening through the reading of the full papers. During this process, 5 papers were removed from the final statistics as they were not in line with the objective of this review. The table with the full list of 100 papers resulting from the review stage 2 is reported in the Supplementary material SM4; iv) Selection of the most relevant publications (30 "key papers") on the topic of concern based on an in-depth reading of the whole papers (including sections devoted to results' analysis and discussion); v) Comparison and discussion of the final list of "key papers" against a set of comparison criteria.

The comparison criteria aim to clarify the main features of the reviewed CIA-related methodological approaches, specifying the: a) case study area, providing details on the scale of the analysis; b) name of the method assigned by authors, together with the specific type of analytical approach applied (e.g., mapping, indicator/index, machine learning, Bayesian network); c) components analysed through the CIA and MRA-related methods, including specification on pressures (with their interactions), exposed environmental targets and vulnerability factors (or indicators) integrated in the study; d) presence/absence of climate change/management scenario analysis; e) ecosystem services component, as a part of CIA/MRA frameworks, including the type of ecosystem service considered (i.e., provisioning, regulation & maintenance, and cultural services); f) integration of the ecological tipping point concept into the CIA/MRA analysis; g) evidence for use of CIA approaches for integrated management of MCEs.

This iterative process (including the selection of specific comparison criteria) was applied under tight cooperation among 14 MaCoBioS (H2020, https://macobios.eu/) partners, jointly collaborating under this review. Participants, covering multifaceted fields of environmental/marine sciences and chemistry, risk assessment, ecological and physical modelling and maritime spatial planning and management, enabled an interdisciplinary knowledge exchange to systematically review selected papers against different perspectives, as well as identify key challenges that need to be addressed in future CIA and MRA frameworks.

More details on the comparison criteria co-selected by MaCoBioS partners are reported in the Supplementary material SM3.

2. Results of the review

2.1 Characteristics of publication outputs: insights from the Scientometric review

The Scientometric methodological approach, as described in Section 1.1, allowed extracting and processing bibliometric data from the initial set of 691 papers selected as input data by applying the open-source bibliometrix R Package under the 2000-2022 timeframe. Moreover, the same Scientometric analysis was repeated by considering only the 253 papers obtained against the title-screening phase, as implemented under the systematic literature review (Section 1.3). This further evaluation allowed for a more robust review, focusing only on a restricted number of preselected papers, thus avoiding non-significant documents (e.g., reviews papers or publications not focusing on the topic of concern of this review) for the scope of this study (a detailed description of the Scientometric analysis is available within Supplementary Material SM3).

Analysis of annual scientific production (number of papers per year) allowed the recognition of 2008 as a turning point in this particular research field (Figure 2), mostly due to the global-scale study carried out by Halpern et al. (2008). After this relevant CIA application, yearly production displays a positive rising trend overall, although the abrupt increase in 2014 may be associated with the first period of the initial assessment of marine environmental status under the MSFD. Overall, the number of studies applied in MCEs continuously increased during the last decade, with around 60 articles published per year on average during the last 3 years.

Focusing on the most influential authors (Supplementary material SM3), through the analysis of the author's production overtime, the pioneer of these applications, Halpern B.S., also emerged as the most productive author (with an overall number of 23 publications on this topic, under the 2000-2022 timeframe).

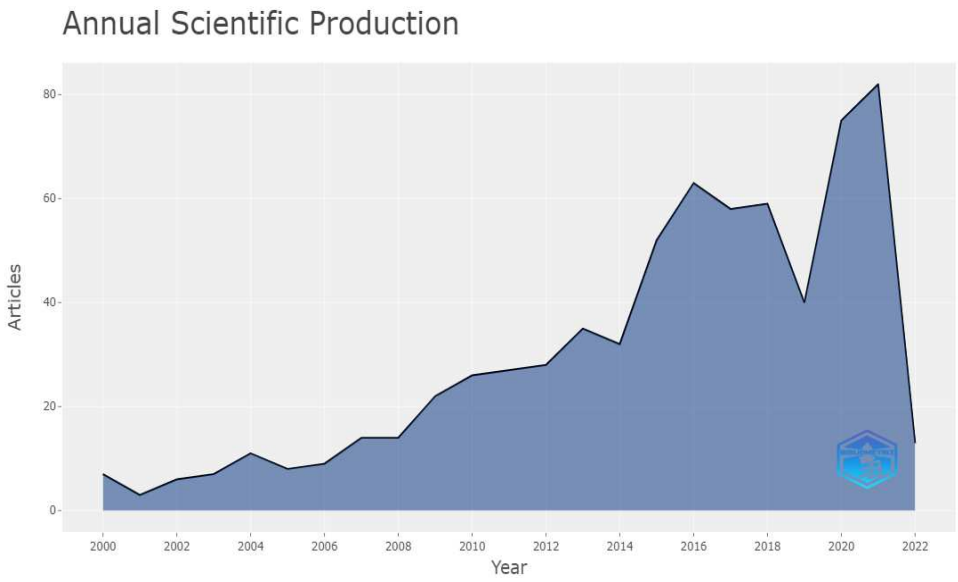


Figure 2: Number of publications (n=691) applying cumulative impact assessment in marine and coastal ecosystems during the 2000–2022 timeframe

Further, word cloud analysis of the most frequent 50 author's keywords, together with those contained in the query string, reveals "ecosystem-based management", "marine spatial planning" and "climate change" to be the most frequently used keywords (Supplementary material SM3). This is unsurprising given many CIA methods have been developed to support decision-makers and planners in the design of spatial plans for MCEs management and conservation/restoration under the ecosystem-based management approach (Menegon, et al., 2018b), as promoted by the Maritime Spatial Planning (MSP), Marine Strategy Framework

Directive and Convention on Biological Diversity regulatory frameworks (Andersen et al., 2015; Domínguez-Tejo et al., 2016; Manea et al., 2020). Recently, climate change threats have also started to be considered across many regulatory frameworks (e.g., MSP), and methodological approaches have recently started integrating this concept to assess and model future environmental conditions of MCEs, and foresee potential alteration of biological, chemical and physical processes (Furlan et al., 2020; Gissi et al., 2019). Finally, analysing scientific collaborations among countries applying CIA methods in MCEs, it was observed that the USA, Canada, UK and China emerged as the first countries approaching this specific topic, with collaborations among countries increasing in the last decade according to the related rise in publications.

2.2 Cumulative Impacts Assessment in marine and coastal socio-ecological systems: key output from the systematic literature review

100 articles (as reported in the Supplementary Material SM4) were systematically reviewed by all MaCoBioS partners, focusing on the type of methodological approaches, as well as the main components employed across these methods (e.g., ecosystem services and tipping point evaluation). The following Sections report the resulting output of this review process, comparing CIA applications exploring and modelling the vulnerability and resilience of MCEs under future scenarios, as well as the assessment of ecological tipping points and changes in the ecosystem service flow (Sections 2.2.1-2.2.4). Finally, Section 2.2.5 discusses the integration of CIA approaches, and their results, in the planning and management processes of MCEs (hence, it clarifies the relevance of this review in terms of policy support against key regulatory frameworks, agreements and strategies dealing with MCEs management). 30 selected 'key papers', part of this set of publications is reported in Table 1, presenting up-to-date methods and integrating most of the concepts previously reported (e.g., ecosystem services and tipping point evaluation).

Table 1: Results from the systematic literature review in terms of 'key papers' dealing with the application of cumulative impact assessment in marine and coastal ecosystems.

Article detail		CIA conceptual frameworks and methodological approaches			Healthy MCEs under a changing climate – Scenario analysis		Ecosystem Services evaluation		Tipping point evaluation	Policy support for MCEs management
Authors	**Location**	**Type of method**	**Components**	**Interactions (Y/N)**	**Y/ N**	**Type of scenario**	**Y/N**	**Considered ES: Provisioning (P), Regulating and Maintenance (R), Culture (C), functioning (F)**	**Considering tipping point Y / N**	**Considering policy (management actions) Y / N**
(Jonsson et al., 2021)	Baltic Sea	Indicator /index; Mapping	Pressure; Exposure; Sensitivity; Cumulative impact	N	Y	Different MSP scenarios.	N		N	Y
(Furlan et al., 2020)	Adriatic Sea	Bayesian Network	Pressure; Hazard; Vulnerability; Risk; Cumulative impact	Y	Y	4 "what if" scenarios: i) new MPAs; ii) increasing SST within anthropogenic chemical hazards; rising nutrient input; management measures and adaptation strategies.	N		N	N
(Halpern et al., 2019)	Global	Mapping; Indicator/index	Stressor; Exposure; Vulnerability; Cumulative impact	N	N		N		N	N
(Furlan et al., 2019)	Adriatic Sea	Mapping; Indicator/index	Hazard; Exposure; Vulnerability; Risk; Pressure; Cumulative impact	Y	Y	Rising temperatures for the 2035-2050 scenario under the RCP 8.5: exogenic variable (SST); endogenic variables (Chl-a variations; chemical and biological impact)	N		N	N
(Stock et al., 2018a)	California Coast	Mapping; Machine Learning; Indicator/index; Statistics	Stressor; Exposure	N	N		N		N	N
(Muñoz et al., 2018)	Spanish contiguous zone	Indicator/index; Mapping; Modelling;	Driver; Pressure; Sensitivity; Vulnerability; Exposure; Risk	N	Y	Future conflicts among activities (were estimated by applying a conflict matrix)	Y	(P) Nursery area, Habitat. (R) Nursery area maintenance; (F) Resistance; resilience; sensitivity	N	Y
(Menegon, et al., 2018b)	North-Adriatic Sea	Mapping; Indicator/index; Ranking; Statistics	Pressure; Exposure; Sensitivity; Risk; Cumulative impact	N	N		Y	(P) Food provisioning; Raw materials; (R) Air and water quality; disturbance protection; Photosynthesis; Nutrient cycling; Nursery; Biodiversity; (C) Cognitive benefits; Leisure; Feel good/warm glove;	N	N
(Menegon, et al., 2018a)	Adriatic Sea	Mapping; Indicator/index; Monte Carlo Simulation	Pressure; Exposure; Sensitivity; Cumulative impact	Y	N		N		N	N

(Battista et al., 2017)	Karimunjawa (Indonesia); Cantilan (Philippines)	Indicator/index; Ranking	Stressor; Vulnerability; Exposure; Risk	Y	N		Y	(R) Coastal protection; Erosion control; Water purification; Maintenance of fisheries and wildlife; Nutrient cycling; Carbon sequestration; Biodiversity; (C) Tourism, recreation, education, and research; (F) System recovery potential; connectivity; resistance to impact; functional redundancy and diversity.	N	N
(Uusitalo et al., 2016)	Baltic Sea	Bayesian Network; Mapping; Expert-based scoring	Pressure; Exposure; Vulnerability; Cumulative impact	N	Y	3 scenarios: (1) business-as-usual scenario (current or recent nutrient loading and fishing mortality levels are maintained, but no further restrictions are implemented); (2) a 30% cut in the pressures (nutrient inputs and fishing mortality); (3) 60% cuts in the pressures.	N		N	N
(Hayes & Landis, 2004)	Point Roberts; Drayton Harbor; Birch and Lummi Bays; Cherry Point	Ranking; Mapping; Monte Carlo Simulation	Stressor; Exposure; Risk; Effect	N	N		N		N	N
(Halpern et al., 2008)	Global	Mapping	Driver; Vulnerability; Exposure; Cumulative impact	N	N		N		N	N
(Singh et al., 2020)	The coast of British Columbia, Canada	Modelling; Mapping; Expert-based scoring; Ranking	Driver; Ecosystem service	N	Y	3˚C SST increase and 0.3 pH decrease for 2100: exogenic variable (temperature, ocean pH); endogenic variables (oil-spill)	Y	(P) Commercial Demersal/pelagic Fishing; Energy; Finfish/Shellfish aquaculture; (R) Coastal Protection; (C) Coastal Aesthetics and recreation (kayak, boating, camping, dive sites)	N	N
(Fu et al., 2020)	British Columbia, Canada	Modelling;	Driver; Pressure; Risk; Cumulative impact;	Y	Y	High & low fish population biomasses; halving fishing mortality rate; doubling plankton biomass and halving marine mammal biomass; Unfavourable (from fish perspective); fishing mortality doubled; halved plankton biomass; and marine mammal biomass doubled.	Y	(P) Total fish biomass of all-trophic-level species; the biomass of higher-trophic-level fish species	Y	Y
(Hammar et al., 2020)	Swede	Mapping; Indicator/ index; Expert-based scoring	Pressure; Exposure; Cumulative impact; Sensitivity	N	Y	MSP scenarios 2020-2030: i) MSP proposals developed after extensive stakeholder dialogue; ii) Eco-alternative plans safeguarding ecological functions to achieve GES status; compared to no implemented MSP simple projection from current industry trends;	N		N	Y
(Turschwell et al., 2020)	Global Mangrove	Bayesian Network; Modelling; Mapping	Driver; Pressure; Impact; State; Response	Y	N		N		N	Y
(Tulloch et al., 2020)	Global	Mapping; Indicator/ index	Stressor; Exposure; Vulnerability; Cumulative impact	N	Y		N		N	Y

(Fang et al., 2020)	Xincun Lagoon, Hainan, (China)	Indicator/ index; Mapping; Modelling	Activity; Pressure; Vulnerability; Cumulative Impact	Y	Y	Different vulnerability (μ value) from mangroves, seagrass beds and other areas	N		N	Y
(Hansen & Bonnevie, 2020)	Baltic Sea	Mapping; Indicator/index	Pressure; Exposure; sensitivity; Cumulative impact	Y	Y	Scenarios where ecosystems might become endangered, areas where competition/ conflict might arise, and areas where synergies might cause potential for co-location	N		N	Y
(Stock et al., 2018)	Global ocean	Modelling; Monte Carlo uncertainty analysis	Stressor	N	N		N		Y	
(Corrales et al., 2018)	Israeli Med. continental shelf	Modelling; Monte Carlo uncertainty analysis	Pressure; Cumulative impact	Y	Y	2010-2060. Warming - RCP2.6 (Scn5), RCP4.5 (Scn6) and RCP8.5 (Scn7); Endogenic: Fishing effort - Kept at 2010 levels or New Israeli regulations; Trophic groups biomass; Alien species: biomass Forced or not		(P) Total biomass; Forage fish/ Invertebrate/ Predatory biomass; Kempton's index; Total catch; (F) Mean Trophic Level of the catch; and of the community; Total System Throughput; Finn's Cycling Index; Path length	Y	Y
(Weijerman et al., 2018)	Maui Nui (an islands complex), Hawai'i	Modelling; Mapping	Hazard; Exposure; State; Cumulative Impact	Y	Y	RCP 8.5 with High/low sediment mitigation; existence adding random MPAs; high/low bleaching events	Y	(P) Fisheries production (potential provisioning service); (R) State of the reef; Trophic integrity of the reef (supporting service)	N	Y
(Ihde & Townsend, 2017)	Chesapeake Bay (USA)	Modelling; Indicator/index	Stressor; Exposure	Y	Y	50-year projections: a 1.5 ◦C increase in water temperature, removal of 50% of Marsh biomass), removal of 50% of SAV biomass, a 25% reduction in nitrogen and a 20% reduction in sediment inputs	Y	(F) Modelisation of change of 3 species important for fisheries in the area	N	Y
(Clark et al., 2016)	Tauranga Harbour estuary (New Zealand)	Mapping; Indicator/index; Expert judgment	Stressor; Vulnerability; Exposure; Cumulative impact	N	N		N		N	N
(Teichert et al., 2016)	North-East Atlantic	Statistical analyses; Machine Learning	Stressor; State	Y	N	Simulation of Ecological quality ratio (EQR) restoration benefits	N		Y	Y
(Lasram et al., 2016)	Tunisia's EEZ	Mapping; Indicator/index; Expert-based ranking	Threats; Pressure; Exposure; Vulnerability; Cumulative impact	N	N		Y	(F) Functional biodiversity	N	Y
(Marzloff et al., 2016)	South-eastern Australia	Modelling	Impact; Exposure; State	Y	Y	Qualitative predictions under alternative scenarios about species poleward redistributions and/or management interventions. Exogenic variables: range shifts, species relocation	N		N	Y

(Clarke Murray et al., 2015)	Marine waters of British Columbia (Canada)	Mapping; Indicator/index	Stressor; Vulnerability; Exposure; Cumulative impact	N	Y	Four scenarios: (1) Current, (2) Climate change, (3) Planned developments, and (4) Combined Current + Climate + Planned.	N		N	N
(Harris et al., 2015)	South Africa	Mapping; Indicator/index	Threats	N	N		N		Y	N
(Okey et al., 2015)	Canada's Pacific marine areas	Mapping; Expert-based scoring	Pressure; Vulnerability; Exposure; Sensitivity; Impact	Y	N		N		N	N

2.2.1 Conceptual frameworks and methodological approaches

The multiplicity of risk-based and CIA approaches applied by the research community to evaluate the effects of human activities (such as fishing, seabed extraction, transport, etc.) and climate change on MCEs (as detailed in the Supplementary Material SM4) is remarkable. GIS-based mapping, indicator/index (through the integration of several indicators representing pressures and the presence and state of MCEs), numerical and ecological models, Machine Learning (ML), or expert-based ranking are some of the most applied methods to analyse and modelling environmental impacts from local to global stressors, while providing support for sustainable management and adaptation pathways.

As summarised in Figure 3, most of the analysed approaches build on the methodological framework developed by Halpern et al. (2008), mapping the spatial distribution and intensity of human activities, at the global scale, over several ecological components and ecosystems (e.g., coral reefs, seagrass beds, mangroves, rocky reefs). Specifically, in this reference approach, final predicted cumulative impact scores are calculated by multiplying the normalised value of pressures' intensity with expert-based weights, representing each ecosystem type's sensitivity to these pressures. Similarly, always drawing on the Halpern et al. (2008) study, most of the reviewed applications (55 out of 100 relevant papers – as reported in the Supplementary material SM3) build on an indicator/index-based approach (Bonnevie et al., 2020; Halpern et al., 2019), sometimes integrated into ML-based methods (Furlan et al., 2020; A. Stock et al., 2018b; Teichert et al., 2016; Turschwell et al., 2020). The wide application of both mapping and indicator/index-based methodologies is also due to the requirements posed by both the EU and international regulatory frameworks (e.g., MSFD and MSP directives, UNCLOS), which require analysing and locating human activities and their drivers to reduce spatial conflicts and trade-off among multiple uses, while supporting the sustainable use and conservation of marine coastal resources. Expert-based ranking (28 publications out of the selected 100 relevant papers – as reported in Supplementary material SM4) is also frequently applied for several purposes, including i) to consider experts' perception in the evaluation of the risk linked to human and climate-induced impacts (Armstrong et al., 2019; Brodersen et al., 2018)); ii) to estimate ecological vulnerabilities to pressures (Clark et al., 2016; A. R. Jones et al., 2018; Mach et al., 2017; Singh et al., 2017; Uusitalo et al., 2016b); and iii) to analyse interactions among multiple pressures (Cook et al., 2014; Furlan et al., 2019).

Within CIA approaches, quite a large set of applications are also carried out using ecological (Cornwall & Eddy, 2015; Ihde & Townsend, 2017) and conceptual models (Cook et al., 2014) to evaluate cumulative impacts of human activity at the ecosystem level. Among these, Cornwall & Eddy (2015) applied Ecopath with Ecosim (EwE) ecological/ecosystem model, a food web model that considers energy flows between functional groups of species. Similarly, Fu et al. (2020) evaluated how stressors cumulatively affect modelled species using the *Object-oriented Simulator of Marine Ecosystems* (OSMOSE) model. Finally, ML-based methods emerging among methodologies being applied across marine coastal realms, thanks to the recent increase in data availability for environmental monitoring and management (i.e., 'Big data'[1]). In this context, Stock et al. (2018) compared the predictive performance of ten statistical and ML algorithms (e.g., Classification and Regression Trees, Random Forests and Boosted regression trees) to understand whether these models could make accurate predictions of ecological indicators representing MCEs' condition (i.e., kelp biodiversity, fish biomass, and rocky intertidal biodiversity) of California coast. Similarly, Teichert et al. (2016) operationalised a Random Forest model to explore the complex structure of non-linear inter-relations between multiple stressors (both anthropogenic and climate change), and the ecological response of biological systems to these stressors. In particular, this model has been used to investigate the effect of stressors interactions on

[1] Big data, defined as '*high volume, high velocity, and/or high variety data that require new processing paradigms to enable insight discovery, improved decision making, and process optimisation*' (Beyer and Laney, 2012)

fish ecological status in European estuaries, as well as to evaluate the ecological benefits arising from the implementation of restoration actions.

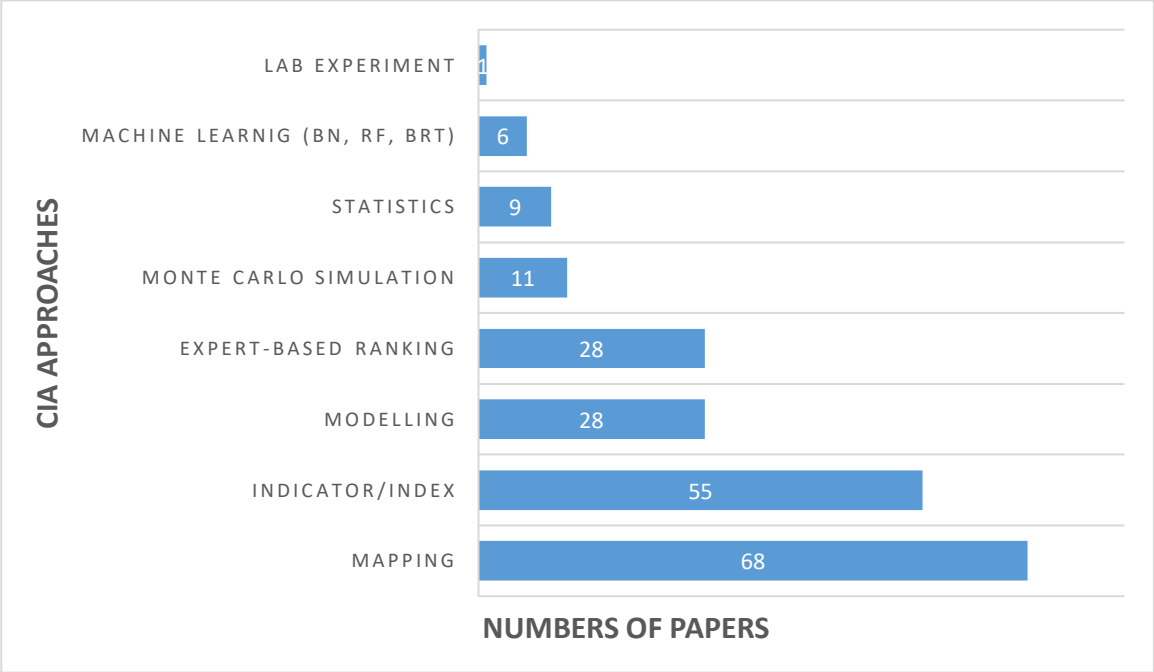


Figure 3: Summary of risk-based and cumulative impact assessment approaches and tools applied within the selected 100 relevant papers.

Another ML-based application was developed by Furlan et al. (2020), coupling Bayesian Network approaches (BN^2) with a GIS tool, to evaluate cumulative impacts under different idealised scenarios. In this study, BNs allowed the consideration of multiple variables (e.g., stressors, assessment end-points) and types of data (e.g., quantitative and qualitative) from heterogeneous data sources and disciplines (e.g., probabilistic quantities elicited from expert knowledge, empirical data, mathematical representations) within the same analytical framework.

Across these studies, some authors also integrate statistics and mathematical techniques to better detect uncertainties associated with several factors (e.g., incomplete and inaccurate data availability, linearity, aggregation of different factors, etc.), providing more robust analysis and, in turn, reducing the possibility of unsustainable management decisions. For instance, Stock et al. (2018) implemented uncertainty analysis, using Monte Carlo simulations, to identify robust high- and low-impact areas on the global oceans (considering the effects of 7 factors of uncertainties simultaneously, including their interactions). Similarly, using Monte Carlo simulations with 1000 runs, Andersen et al. (2020) evaluated the robustness of the impact index and stressor ranking for Danish marine waters, considering the possible weaknesses in data quality and the effects of model assumptions. More precisely, they ranked 35 stressors according to their contribution to the cumulative impact score, aggregated for the North Sea-Baltic Sea transition zone. This methodology, i.e., identifying and ranking the most influential stressors contributing to the overall cumulative impacts, provides useful information to support the identification of management and conservation priorities, as required by marine coastal laws.

[2] Bayesian Network: a family of ML-based algorithms providing an intuitive graphical structure by combining principles of Graph theory and Probability theory; (Pearl & Russell, 2011; Pollino et al., 2007)

Regardless of the applied methodological approach, the operationalisation of risk-based and CIA methodologies requires a strong linkage between all components and processes underpinning impacts and changes in MCEs' state and ecosystem services flow. Specifically, looking at the key elements integrated into CIA methodologies, the review has identified different and fragmented components (better described in the Supplementary Material SM5) across the publications (as illustrated in Figure 4). This is due to the specific terminologies applied by different research communities (e.g., risk, ecology, chemistry-related communities), making it difficult to identify mainstream components. Still, most of the key components considered overall are in line with those integrated by Halpern et al. (2008) in his index, as a direct consequence of the methodological framework applied, i.e., the predicted cumulative impact scores are calculated as a function of the intensity of the selected "drivers", the presence/absence of marine ecosystems ("exposure") and their "vulnerability" to pressures. Exposure and vulnerability are among the most cited concepts being integrated across different methodological approaches for CIA applying risk-based frameworks (IPCC, 2014). Finally, another set of terminologies, such as "state" and "response", is linked to the other conceptual framework of greatest interest for CIA and risk assessment works, i.e., the DPSIR (Driver-Pressures-State-Impact-Response) framework (EEA, 1999), together with its more recent modifications (e.g., DPSWIR, Driving Force-Pressure-State-Impact-Well-being-Response; (Cooper, 2013)). In general, these terminologies, and especially those representing triggering factors (i.e., variables that explain the occurrence of the analysed phenomena/effect), are often applied by authors for explaining the same (or similar) concepts (e.g., pressure, driver, stressor, and threat). This amplifies the redundancy of components integrated into the same analytical method, and creates general confusion and misunderstandings due to the different use of the same terminologies (see Section 3. Discussion for further details).

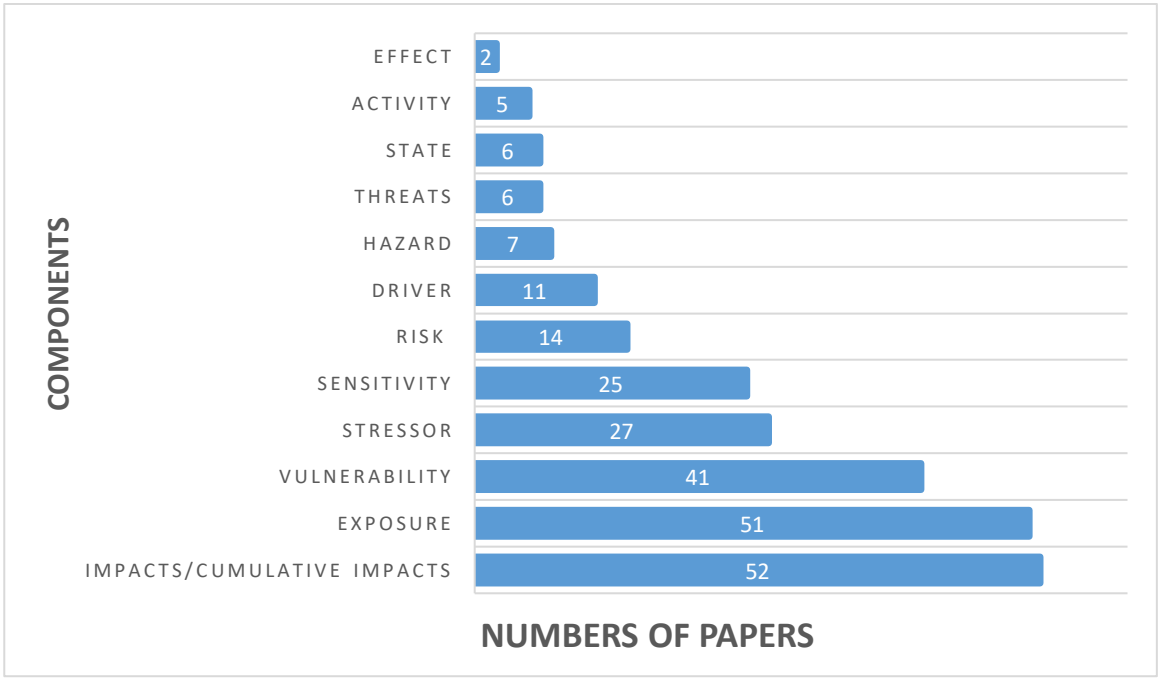


Figure 4: Summary of key components applied within cumulative impact assessment and risk-based methodological frameworks in the 100 selected papers

2.2.2 Scenario analysis for healthy marine and coastal ecosystems

Exploring changes in cumulative impacts against different climate conditions or management goals before they happen can be a crucial task to provide support to policymakers and planners involved in the design of sustainable marine spatial plans and climate adaptation strategies (Corrales et al., 2018; Furlan et al., 2019; Jonsson et al., 2021; Magris et al., 2021). Consequently, researchers have begun applying different tools (e.g., Bayesian network models) and integrating scenario analysis into CIA-related studies to understand ecosystems' responses to a changing future. The majority of CIA methodologies applied across the 100 selected papers (see the full list in Supplementary material SM4) focus on a snapshot in time based on recent/current conditions. Only 23 papers evaluated changes in cumulative impacts against different climate or management scenarios.

Within these 23 papers, it is possible to identify two main research streams: i) studies exploring variations in cumulative impacts against different climate scenarios (e.g., temperature variation) usually based on projections from numerical models (IPCC, 2014); ii) applications integrating "what if" scenarios (i.e. idealised scenarios based on narratives) to evaluate cumulative impacts changes under the effects of different environmental patterns and socio-economic pathways (e.g., simulating the potential consequences of different management measures).

Focusing on the first research stream, only four studies referred to the IPCC[3] Representative Concentration Pathways (RCP) describing four different 21st-century GHG emissions trajectories (i.e., RCP2.6, RCP4.5, RCP6, and RCP8.5), based on a possible range of raising radiative forcing pathways (IPCC, 2014). Among these, Otto et al. (2020) focused on the intermediate GHG emission scenarios (i.e., RCP4.5 and RCP6), whereas Furlan et al. (2019) and Weijerman et al. (2018) on the worst one (i.e., RCP8.5). Corrales et al. (2018) tested the impact of a continued increase in sea temperatures on the Israeli Mediterranean continental shelf over 50 years (2010 - 2060), taking into account three GHG emission scenarios (i.e., RCP 2.6, 4.5, and 8.5). Moreover, future scenarios accounting for a new set of fishing regulations currently being implemented, and a continued increase in alien species biomass were tested to assess potential futures of marine resources and ecosystem conditions within the analysed case study area. As described in Section 3.2.4., the resulting output of this analysis showed collapsed conditions for different species (a sign of potential tipping points) according to the investigated scenarios.

Of those publications exploring "what-if" scenarios, most evaluated potential changes in cumulative impacts under the implementation of several management measures (as already tested in Corrales et al., 2018) to compare the expected environmental effects of different plan alternatives. For instance, Stelzenmüller et al. (2010) operationalised a Bayesian Belief Network–GIS framework to evaluate cumulative impacts under three different spatial planning objectives and related management measures (e.g., relocation of fishing pressure). Similarly, Hammar et al. (2020) evaluated the environmental effects of two different sets of idealized MSP scenarios for 2030, namely (i) negotiated plans (i.e., MSP proposals developed after extensive stakeholder dialogue) and (ii) eco-alternative plans (i.e., a scenario more in accordance with the target posed by MSFD 2008/56/EC). The comparison between a Business As Usual scenario and different planning options (and scenarios) detected some alterations in the final cumulative impact score, making it possible to evaluate how these impacts could be amplified or reduced under different management measures. With a focus on the Hawaiian Islands of Maui, Molokai, and Lāna'i, Weijerman et al. (2018) developed fifteen scenarios, combining different settings in land- and marine-based management and climate-related stressors (under the RCP8.5) to better understand future variation in the coral reef ecosystem services provision. Similarly,

[3] Intergovernmental Panel on Climate Change

Furlan et al. (2020) applied a GIS-based Bayesian network approach to evaluate the probability of cumulative impacts under four *"what-if"* scenarios representing different marine management options (i.e., how impacts change due to the establishment of new MPAs) and climate conditions (i.e., potential rising sea temperature) envisioned for the Adriatic Sea. The results of the simulated scenarios provided some insights on the management programs/measures required to achieve Good Environmental Status targets, as required under relevant EU legislation (e.g., an integrated approach in MSP emerged as the most effective way to substantially reduce cumulative impacts on the Adriatic Sea).

Finally, looking at the overall picture of papers applying scenario analysis, a wide range of both endogenic (i.e., managed pressures or those emanating within the system) and exogenic pressures (i.e., unmanaged pressures are those emanating from outside the system) have been investigated by authors under the simulation of future changes. S*ea surface temperature* emerged as the most considered exogenic variable (Furlan et al., 2019; Ihde & Townsend, 2017; Singh et al., 2020b), followed by *precipitation* (Uusitalo et al., 2016), *ocean acidification* (Ainsworth et al., 2011; Fulton et al., 2009; Singh et al., 2020b), and *salinity* (Otto et al., 2020). A wide range of endogenic variables representing biological disturbance (e.g., shipping traffic as the main vector of non-indigenous species introduction; Fu et al., 2020; Weijerman et al., 2018) and chemical pollution (e.g., oil spill, eutrophication; Fulton et al., 2009; Furlan et al., 2020; Singh et al., 2020b) have been integrated into CIA-related scenario analysis to simulate how changes in their range can contribute to increase the vulnerability of MCEs.

2.2.3 Incorporating the ecosystem services perspective into CIA frameworks

Ecosystem services are the benefits people obtain from ecosystems and are essential to people's well-being (MA, 2005). The magnitude and sustainability of the use of these services depend on the functioning of the ecosystem. Changes to ecosystem conditions or ecosystem processes such as the ones that generally result from cumulative impacts will naturally lead to changes in the capacity to deliver ecosystem services, although human culture and ingenuity may buffer adverse effects for a limited amount of time. Therefore, CIA of various human activities and stressors on ecosystem services is crucial to understand supply (i.e., biophysical means) and service (i.e., delivery to people) provision.

CIA methodological approaches generally evaluate how human activities affect species and habitats, neglecting how multiple activities affect the capacity of the whole ecosystem to provide direct and indirect benefits to human well-being (Depellegrin et al., 2017; Singh et al., 2020b). This is even more true in the marine environment. Indeed, less than a quarter of the reviewed articles (n=21) incorporate the ecosystem services perspective. Since the term 'ecosystem services' is relatively new, increasing in popularity since the Millennium Ecosystem Assessment (MA, 2005), the integration of ecosystem services into the CIA framework only started with one of the most straightforward marine ecosystem services, i.e., fisheries yield, in 2007 (e.g., Sutherland et al., 2007). It was only in 2014 that a bundle of ecosystem services (provisioning, regulating and maintenance, and cultural – considering the Common International Classification of Ecosystem Services classification or 'CICES' v5.1, Haines-Young & Potschin-Young, (2018)) were included in a CIA framework by Cook et al. (2014). However, the trend has changed over the past few years. Based on the frequency of marine ecosystem services considered in the investigated studies under the three above-mentioned ES categories, '*regulating and maintenance*' resulted as the most analysed marine ecosystem services category (i.e., 50%), followed by provisioning and cultural services, respectively (Figure 5).

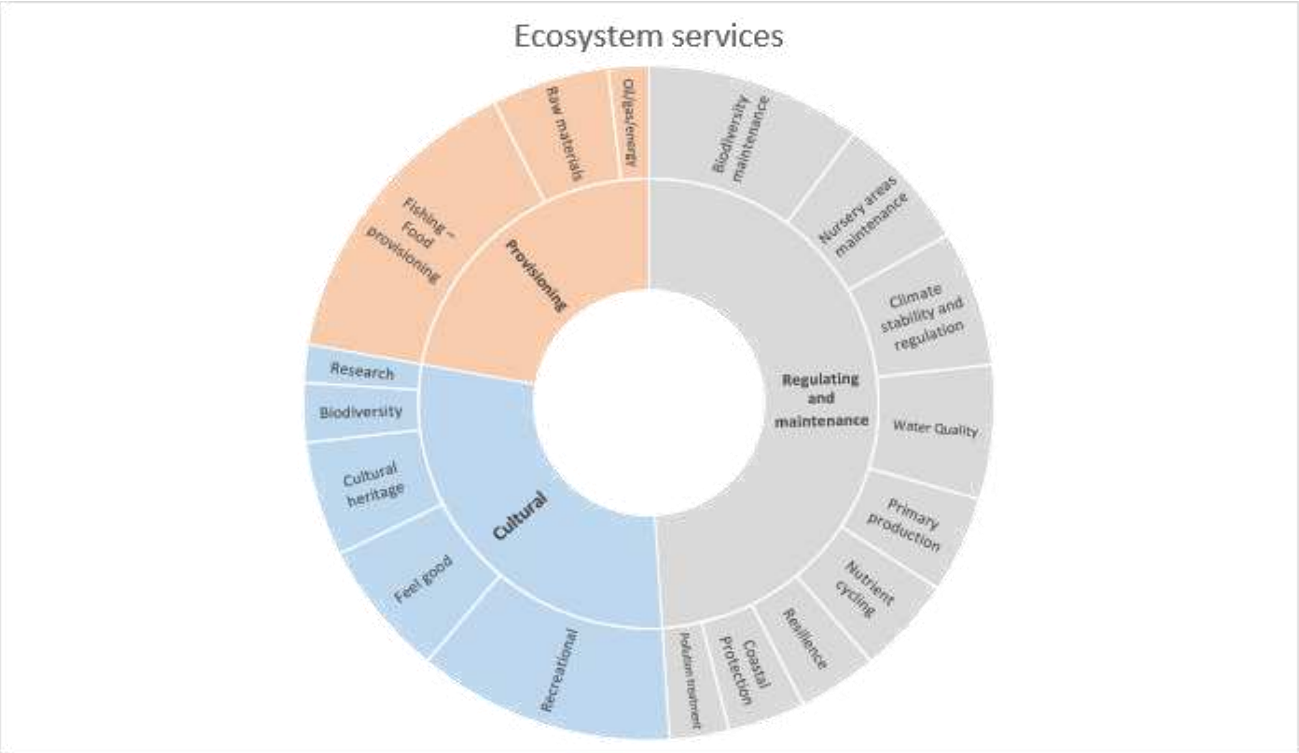


Figure 5: Marine ecosystem services frequency applied for integrating and modelling ecosystem services within cumulative impact assessment methodologies in the marine environment. The nineteen marine ecosystem services extracted from the reviewed publications were divided according to the CICES v5.1 (Haines-Young & Potschin-Young, 2018)

The assessment method of ecosystem functions and services varies greatly from subjective evaluation to expert judgment to quantitative assessments; however, most are qualitative or semi-quantitative at best, considering that data availability is often a problem. Therefore, most recent methods based their appraisal on expert judgment, considering that areas covered by determined EUNIS habitat may contribute to enrich the ecosystem services capacity of MCEs (Depellegrin et al., 2017; Farella et al., 2020; Menegon et al., 2018b). The spatial coverage of data available for relevant stressors may also limit the inclusion of stressors that are likely to have a significant impact on a studied MCE. For example, Allan et al. (2013) were able to include 34 of 50 anthropogenic stressors identified. Although including 34 anthropogenic stressors is already a great achievement, having to put aside 16 of them is concerning. They also focused on the spatial distribution of the stressors and not on the distribution of their impacts because assessment of impacts of stressors at the ecosystem level was not feasible. Another challenge for the CIA is the type of relationship between stressors and impacts. Generally, only linear responses are considered, probably due to a lack of data. Thus, twice as much stressor is assumed to double the impact. Additionally, interactions between stressors are mostly not assessed or, at best, assumed to be additive. To summarise, there appears to be a significant lack of knowledge with respect to the impacts of and interactions between multiple stressors acting simultaneously within an ecosystem.

In addition, stressor and condition maps usually consider only one snapshot in time. However, the policy question is not only about the presence or absence of a stressor or habitat but about the changes in the pressure, state, and, more importantly, the benefits to people such as fishing, recreation, or coastal protection that may be more meaningful to decision-makers and the public (Bockstael et al., 2000; Yee et al., 2014). This is where scenario analysis is useful to identify the best management actions that will reverse,

mitigate, or prevent ecosystem degradation and sustain benefits to society. Few studies applied scenario analysis whilst accounting for ecosystem services into a CIA framework. Weijerman et al. (2018) used a spatially-explicit biophysical ecosystem model – the Hawai'i Reef dynamics Simulator (HIReefSim) based on the Coral Reef Scenario Evaluation Tool (CORSET) – to evaluate socio-ecological trade-offs of land-based vs. marine-based management scenarios, and local- vs. global-scale stressors and their cumulative impacts on coral reefs. Fu et al. (2020) used an individual-based spatially explicit ecosystem modelling platform OSMOSE (Object-oriented Simulator of Marine Ecosystems) to investigate the cumulative effects of fishing, plankton biomass change, and marine mammal consumption on the dynamics of some commercially important fish species and the whole British Columbia marine ecosystem. The authors calibrated the model based on data acquired from 1940 to 2018 and applied scenario simulations for the past 20 years (1998-2018). Recently, Corrales et al. (2018) used the Ecosim foodweb model and analysed future scenarios (2010-2060), considering multiple pressures. The authors provided robust modelling that takes interactions between pressures into account. While Ecopath with Ecosim (EwE) has been widely used since its first use in 1984 (Polovina, 1984), it requires the collection, compilation and harmonisation of various types of information (Colléter et al., 2015), which might be difficult in data-poor regions. Where data are lacking then, the Comprehensive Assessment of Risk to Ecosystems (CARE) model, developed by Battista et al. (2017), allows the cumulative impact of multiple stressors and interactions that may result in synergistic or antagonistic impacts, on whole-ecosystem productivity, functioning, and ecosystem services.

From all the above results, the incorporation of marine ecosystem services into a CIA approach has been increasing and allows not only to analyse conflicts between cumulative pressures of human activities and marine habitats but also to reveal conflicts and synergies among uses and services, thereby providing meaningful support to decision- and policy makers for MSP (Hansen & Bonnevie, 2020; Muñoz et al., 2018). As such, many software (e.g., InVEST, CORSET, HIReefSim, and Ecosim, EwE) and models (e.g., CARE, marine ecosystem services -Threat, and marine ecosystem services -Capacity) have been developed as Decision-Support Tools. However, methodological approaches published within the investigated timeframe (2000-2022) rarely considered all three marine ecosystem services categories and instead focused on single ecosystem services, such as carbon sequestration provided by the seagrass species *Posidonia oceanica* (Gkadolou et al., 2018) or the potential provisioning of fish according to the condition of coral reefs (Weijerman et al., 2018). Yet, looking at a single ecosystem service in a CIA framework could misguide decision-makers. Moreover, across the analysed papers, the ecosystem services component has been integrated into the different CIA frameworks as an additional assessment endpoint without considering the potential influence of specific ecosystem services in reducing/mitigating the effect of both endogenic and exogenic pressures while increasing the resilience of MCEs to further perturbations. Much research is still needed to understand those positive/negative feedbacks between anthropogenic and climate-related pressures, the ecological condition of marine habitats and ecosystem services.

2.2.4 When cumulative impacts lead to ecological tipping points

Resilience represents an insurance against potentially adverse changes in the performance of ecosystem functions – and ultimately on the delivery of ecosystem services. Thus, the concepts of ecological resilience in relations to ecosystems services should be intertwined into CIA & risk assessment frameworks, offering insurance against the loss of valued functions (Folke et al., 2004; Thrush et al., 2009). The assessment of resilience, or loss of resilience, of a system subjected to cumulative pressures and risk scenarios requires metrics that forewarn approaching thresholds of change well in advance so that management actions can be

implemented (de Juan et al., 2018). However, key knowledge gaps remain in terms of defining exactly how close a system is to a threshold of change and what the research community can actually measure in natural ecosystems to better understand resilience and advert of drastic change (de Juan et al., 2013). Van Nes et al. (2016) proposed that the term 'tipping point' should simply be used for any situation where accelerating change caused by positive feedback (although they propose no value is assigned, only a sign) drives the system to a new state. Then, the management of cumulative impacts needs to uptake the information on how close a system is to a tipping point (Thrush et al., 2021), and incorporate this concept into MRA frameworks.

The systematic literature review exposed the slow uptake of ecosystem metrics informing the risk of approaching a tipping point under a MRA framework. Six publications mentioned the topic (i.e., tipping point, threshold, shifting baseline concepts); however, none of these actually implemented or proposed an approach that encompassed the tipping points assessment. Among these, as already mentioned in Section 2.2.1, Fu et al. (2020) applied an ecosystem model (OSMOSE) focused on a set of commercial fish species and their (predatory-prey) interaction with other species. They assessed two temporal scenarios (a favourable and un-favourable one) considering fishing drivers (fishing, change in plankton biomass and change in mammal biomass) in a cumulative fashion (synergistic, antagonistic, etc.), and then evaluated consequences on the commercial species biomass. Therefore, this study takes an ecosystem approach by considering the cumulative effects of three drivers (i.e., fishing, change in plankton and mammal biomasses) and assesses temporal changes in commercial fish biomass (ecosystem service provision) against each scenario; nevertheless, the OSMOSE model is basically focused on fishery activities and their management, so it fails to adopt an integrative cumulative impact perspective inherent to a CIA. On the other hand, due to the huge amount of data required to represent the trophic interactions and life-history dynamics of the species of interest, this approach does not specifically address tipping points. Similarly, Stock et al. (2018) explored impact maps taking into account cumulative (non-linear) effects, highlighting the need to incorporate uncertainty appraisal into MRA frameworks (considering as baseline Halpern et al., 2008), as there is high uncertainty in evaluating interactive behaviours of multiple stressors over ecosystems. In this work, the authors run 3000 simulations for cumulative human impact maps to identify the frequency of selection of different cells in the "vulnerability" categories. The resulting outputs showed a relatively high standard error in the assignations. They discussed "thresholds" but only related to the robustness of the model vulnerability level assignation. Finally, among the selected papers, Corrales et al., (2018) investigated future changes in marine resources by applying an ECOSIM model. They tested the effects of new fishing regulations with predictions on invasive species under IPCC scenarios (RCPs 2.6, 4.5 and 8.5), addressing the effects of stressors both separately and in a cumulative fashion. They addressed the effects of stressors separately but also in a cumulative way, exploring temporal changes in the predicted biomass of fish species. Even though they did not specifically explore thresholds of change, these thresholds could be approximated from the predicted biomass curves.

Other studies, selected in the Scopus search but discarded after applying the selection criteria (basically because these papers address an ecological problem – regime shifts – but do not incorporate the problem into management) were successful in identifying environmental limits or ecosystem tipping points. However, these studies have in common the availability of long temporal series (some starting in the 1950s) of very large gradient experiments. Both scenarios are not feasible for an operational assessment protocol as they are limited to highly rich data case studies. Among these, Oguz & Gilbert (2007) analysed long-term data (1960-2007) of the pelagic system in the Black Sea to detect regime shifts under fishery exploitation and nutrient enrichment scenarios. Similarly, other long temporal series (starting in the 1950s) have been

detected by Miller et al. (2016) to explore the causes of anguillid eel populations' decline under cumulative stressors (damp construction, overfishing, pollution, etc.) and by Wang et al., (2015) to address threshold of change in estuary systems. Other studies detected regime shifts of marine rockpool communities in a mesocosm experiment (White et al., 2018), changes in Cystoseira populations linked to increased anthropogenic pressures in the northwest Mediterranean (Blanfuné et al., 2019), and environmental limits for the communities (regarding sedimentation and nutrient input) through a large-scale experiment (experimental impact conditions in 15 estuaries) (Thrush et al., 2021).

To our knowledge, there is no published study that effectively incorporates the assessment of ecosystem thresholds of change or tipping points into CIA-MRA frameworks. Despite the importance of identifying approaching thresholds in ecological science, the complexity of empirically defining threshold levels for multiple interacting stressors (Thrush et al., 2014) hampers the selection of metrics that can be systematically incorporated into regular ecosystem assessments. In order to manage ecosystems to avoid the loss of functions (and therefore services), CIA and MRA frameworks need to understand (and embrace) the mechanism linking stressors to ecosystem consequences – with special attention on tipping points (Hodgson & Halpern, 2019; Stelzenmüller et al., 2020). After all, one of the main objectives is to avoid reaching regime shifts, or thresholds of change, where ecological and societal values are gradually degraded until the properties of ecosystems are no longer recognised.

2.2.5 Policy support for risk management and climate adaptation in marine and coastal socio-ecological systems

There is increasing recognition of CIA methods' relevance in supporting policy and management of MCEs. CIA can theoretically support policy and management in several ways. First, by providing a spatial perspective on the major pressures and threats which impact a specific area over time, the CIA may improve the capacity of decision-makers to prioritise appropriate management strategies, such as marine spatial planning, protected area establishment, restoration, etc. (e.g., Jones et al., 2018; Tulloch et al., 2020). Second, by evaluating over time how CIA changes according to variations of data on multiple pressures (e.g., temperature, nutrient input, etc.) (Furlan et al., 2020), CIA may support the assessment of the effectiveness of different management strategies and drive future research and effective ecosystem-based management (Marzloff et al., 2016). By incorporating scenario methodologies, the CIA could support long-term planning by showing how different management strategies could improve the provision of marine ecosystem services (e.g., using scenario methodologies) (Farella et al., 2020; Weijerman et al., 2018). Lastly, the CIA may increase transparency in planning decisions. CIA also enables policymakers to better balance the benefits and consequences of marine coastal plans and policies prior to implementation (Hammar et al., 2020). Moreover, it can be used as a tool to support policymakers to communicate scientific evidence (for instance, through maps) on which management strategies and decisions are based, thus providing a larger degree of transparency before and during stakeholder consultations (McQuatters-Gollop et al., 2019).

Despite the potential holistic application of CIA methods in policy and management, the current review reveals that most of the literature concerning CIA in coastal and marine ecosystems do not consider policy or management actions. Of the 100 papers reviewed, the majority (about 70%) do not consider policy or management actions, while only 30% mention this.

Out of the 30% of studies that consider policy and management actions, most of those evaluating the environmental status of the European seas refer to the MSFD (2008/56/EC) as a relevant policy and MSP as a process of analysing and allocating the spatial and temporal distribution of anthropogenic activities (Brodersen et al., 2018; Fernandes et al., 2017; Gkadolou et al., 2018; Hammar et al., 2020; Hansen & Bonnevie, 2020; Jonsson et al., 2021; Korpinen et al., 2021; Manea et al., 2020; Willsteed et al., 2018). Similarly, authors that operationalised these assessment frameworks in other marine coastal areas worldwide (e.g., Xiamen and British Columbia, respectively in China and Canada), referred to other national/local policies. For instance, Ihde & Townsend, (2017) developed scenarios considering both reductions in Nitrogen and sediments inputs to reflect the nutrient and sediment goals required under the US EPA specifications for the Total Maximum Daily Load Regulations (USA EPA, 2010). On the other hand, Xue et al. (2004) presented the assessment of cumulative environmental impacts and the implementation of integrated coastal management (implemented as part of the Regional Programme for the Prevention and Management of Marine Pollution in the East Asian Seas) within the harbour of Xiamen, China. In this study, authors combined policy and planning, including legislative and enforcement mechanisms, with scientific knowledge support.

The literature review also reveals a lack of empirical evidence on how or if CIA methodologies or approaches have influenced management processes of MCEs. The reviewed papers mainly highlight the theoretical contributions of CIAs to guide policies and decision making for the management of MCEs, while a few engaged with providing nuance on management interventions based on the CIA application. For example, Hammar et al. (2020) mention one clear example where CIA has been integrated into marine spatial planning in practice. In this case, a national marine spatial planning strategy in Sweden has been developed using a CIA-based GIS application to evaluate the expected effectiveness of precautionary measures in marine planning and for comparing different locations of new activities. Some other papers assessed alternative management interventions (such as marine protected areas or fishing management alternatives) within their CIA methodology to understand what kind of management strategies are necessary to effectively manage impacts within their study scope (Fu et al., 2020; Jones et al., 2018; Marzloff et al., 2016). MCEs are complex adaptive systems that translate into management and policy challenges (Willsteed et al., 2018).

CIA in marine spatial planning may improve the capacity of planners to address environmental impacts. However, integrating CIA into ecosystem-based management requires a structured and transparent approach with common terminology, methods and the setting of baselines (Andersen et al., 2020). This review found that, at present, there are a variety of principles and definitions underpinning CIAs that have inconsistent language, interpretation, and parametrisation which limits the effective use of CIA to effectively support management and policy making (Judd et al., 2015; Lonsdale et al., 2017; Willsteed et al., 2018). To enable more effective decision making, there is a need for comprehensive CIA methodologies that not only focus on the impacts of human activities on ecosystems, but that assess how different human impacts interact with each other and contribute to environmental change. The latter can provide a more realistic baseline to enable management decisions (Hansen & Bonnevie, 2020).

3. Discussion

The results of this review have provided insights into the CIA and MRA approaches and applications developed in literature. This section provides a reflection on different aspects of this specific research field. In particular, building on the information extracted from the 100 selected papers (papers reported in the SM3 of Supplementary Material), this section discusses the potentials, limitations and barriers of the analysed frameworks and related applications, providing recommendations for future research and improvements.

3.1 Diving into a sea of terminologies

Over the last decades, numerous and diverse issues leading to ecological implications have challenged both environmental scientists and decision-makers in understanding the relationships between social/economic interests and associated environmental issues, requiring practical evaluation techniques building on interdisciplinary approaches. Environmental risk and impact assessments are rather complex procedures that can help to analyse and manage a wide range of environmental issues, including those related to climate change. Different assessment approaches and frameworks have been developed so far in order to understand the processes underpinning MCEs deterioration. As observed in this review, most of these methods apply a stepwise (and cyclic) approach, starting from the definition of the problem toward the impact/risk identification, analysis, and evaluation. Particularly, the definition of the issue of concern, including the identification of all relevant stressors (sources of risk), the potential exposure pathways, and the harm (losses) that might result from exposure to hazard (impacts), is the first step for an effective evaluation process. However, the definition of "risk" may vary across different research fields. Many disciplines dealing with risk assessment showed different perspectives about its definition, as well as on components to be included in the process of its calculation. This review also highlighted substantial discrepancies in the risk and cumulative impact-related literature, fragmented into many disciplinary streams, with different definitions evolving within each research community. In this setting, at least two distinct conceptual frameworks for environmental risk and impact analysis have been recognised: the DPSIR and the risk-based framework (building on the IPCC definitions, where risk results from the interaction among hazard-exposure-vulnerability), with related assessment components. Terminologies vary within the reviewed studies which apply diverse conceptual frameworks but essentially refer to the same assessment procedure: i.e., an additive approach to map and analyse the potential effects of multiple human pressures on marine species, habitat and ecosystems. Moreover, a lack of clarity in the use of some terms has been identified with e.g., "stressors", "threats", "drivers", and "pressures" terms considered sometimes interchangeably.

Recently, some authors tried to manage this 'sea of terminologies' by framing exhaustive glossaries and conceptual frameworks bridging concepts from several research streams (Elliott et al., 2017; Judd et al., 2015; Stelzenmüller et al., 2018). Joint efforts and tight cooperation between the research community and the European Commission could lift the main uncertainties, as well as better understand how to achieve a standard and consensus framework (ensuring collaboration across geographic boundaries, disciplines and sectors) that incorporates cross-border multi-risk management.

3.2 AI for complex marine and coastal ecosystems

Assessing and managing multi-risks posed by interactive anthropogenic and natural drivers is one of the major challenges that the research community is currently facing. The inherent complexity of MCEs and the limited knowledge of spatio-temporal dynamics underpinning their functioning, health and resilience, represent major obstacles to precisely identify hot-spot risk areas requiring targeted interventions. Within the investigated publications, non-linear relationships and interactive effects induced by multiple activities/pressures are poorly explored (Battista et al., 2017; Corrales et al., 2018; Furlan et al., 2019; authors usually applied additive models to evaluate synergies among pressures, as proposed by Halpern et al., 2008), due to the limited capability of traditional approaches (e.g., indicators and index-based method, multi-criteria decision analysis) to capture and mapping these complex dynamics and the resulting MCEs response. To overcome these limitations, the research community has started to apply new methodological approaches and tools leveraging the most recent advances in hardware and computer science, including the application of techniques exploiting capabilities offered by Artificial Intelligence (AI, e.g., machine and deep learning models) to solve a wide range of complex environmental issues (Bui et al., 2020; Peterson et al., 2020). Thanks to the current digitisation of European and international society and the consequent availability of a huge amount of data for environmental observation and monitoring (e.g., remote sensing data from Copernicus Sentinels, USGS Earth Explorer, among others), AI-based models represent an alternative approach to investigate complex environmental systems. Moreover, by providing all the information necessary for achieving Trustworthy AI (e.g., inform SHs regarding the system's capabilities and limitations, as well as provide an exhaustive description of the data is being integrated in the model and the ways in which it is being used) (EC, 2019; Felzmann et al., 2020), these methods support the evaluation of complex (and even unknown) interactions between interacting climate-driven and local/global anthropogenic factors affecting MCEs (Teichert et al., 2016), needed to provide a sound quantification of cumulative impacts. In particular, as emerged from the reviewed studies, these models can be used to i) identify the most influential pressures driving severe changes in MCEs condition (Teichert et al., 2016); ii) model and predict a wide range of individual and combined effects among different pressures, including the analysis of antagonistic/additive/synergistic behaviours (Furlan et al., 2019); iii) model and evaluate multiple scenarios accounting for diverse climate patterns (e.g. changes in the precipitation regime, rising sea temperatures) (Furlan et al., 2020), use of MCEs resources and services, management measures (e.g. restoration activities, implementation of artificial protections) (Stelzenmüller et al., 2010; Teichert et al., 2016; Uusitalo et al., 2016b) and governance pathways.

3.3 Dealing with a shifting baseline

In the current context of global warming and ecological crisis, there is an increasing demand for approaches that can forecast future cumulative impacts of multiple stressors (Fu et al., 2020; Hammar et al., 2020; Muñoz et al., 2018). This study highlighted that the current CIA application is mainly focused on the present condition of MCEs. This is due to the complexity and variability of these environments, as well as to the lack of detailed information on their responses to multi-risk scenarios. In highly variable marine and coastal environments, this is made even more challenging due to 'shifting baselines' in any ecosystem components (e.g., species shifts, changes in hydrographic patterns, and human activities), making it difficult to detect the long-term effects of such changes and identify cumulative impacts-prone areas requiring adaptation and restoration measures (Duarte et al., 2009; Michael Elliott et al., 2015).

This is a key scientific challenge that must be considered when setting targets for the evaluation of Good Environmental Status (GES) as required by the MSFD (EC, 2008), since improved scenario analyses,

integrating these shifting baselines, are relevant to drive the formulation of possible mitigation measures for reaching the objective of GES (Elliott et al., 2015).

In the context of predicting the future, as also emerged in Zennaro et al. (2021), the current digital transformation is showing high predictive potential to evaluate and manage short-, medium- and long-term multi-risk and cumulative impact scenarios under climate change. Specifically, long-range planning, informed by climate and "*what if*" scenarios analysis, enables marine managers to predict and explore a range of potential alternative futures to identify appropriate management measures while avoiding actions that could lead to further alterations of MCEs. As a consequence, the design of advanced models able to accommodate 'shifting baselines' due to climate change, as well as a wide range of potential short-term societal responses (e.g., including monitoring and measures; Swaney et al., 2012), will represent key tools for addressing integrated adaptation pathways, providing a more holistic view of the management of current global warming and ecological crises.

3.4 A broader perspective on Good Environmental Status

This section discusses how authors dealing with CIA and MRA in European marine coastal ecosystems framed their approaches (including key indicators integrated) under these regulatory frameworks, as well as identifies challenges that need to be addressed in future CIA frameworks to support EU better the implementation and achievement of the relevant EU acquis (e.g. MSFD and MSP directives). In particular, the main goal of the MSFD is to achieve GES of EU marine waters. GES is described through 11 descriptors (i.e., state descriptors that characterise marine biodiversity and pressure descriptors that relate to human-induced pressures), the level of achievement of which determines whether GES is achieved or not. Measures of those descriptors could feed CIA frameworks, which in return could pave the way toward disentangling the effect of single and multiple pressures on the state of MCEs and their contribution to people. Pressures on the marine environment act in various ways, changing the state of the environment, which subsequently modify or impact the ecosystem goods and services provided and the well-being of humans. Policymakers at local, regional, and national levels can decide to respond by acting on the Driving Forces, Pressures, State and Welfare (see Cooper 2012) by implementing policy tools, for instance, economic incentives supporting environmental stewardship and less impactful use. These policies, however, require qualitative and/or quantitative evidence to justify them and to monitor their effects on the ecosystem. This requires a lot of data, starting with ecological data on the state of marine ecosystems. However, to understand the state of an ecosystem, baselines need to be established, a critical step for the sound assessment of ecological status (Borja et al., 2012). Indeed, one ecosystem may present different states whilst being "healthy", depending on natural environmental conditions (e.g., wave exposure, sedimentation load, current, temperature). Long-term monitoring allows the detection of changes or phase shifts as long as the selected indicators are sensitive enough to disturbances. However, the selection of the right indicators is still under debate for many coastal ecosystems. Moreover, in addition to state indicators, other indicators are required to assess the functions and the provision of ecosystem services and it is only recently that the assessment of ecosystem services started to include the ecological condition to adjust the production function (Culhane et al., 2019; Failler et al., 2015; Trégarot et al., 2017) or to assess the risk or vulnerability to ecosystem services supply (Culhane et al., 2019; Trégarot et al., 2021). The relationships between ecological conditions and the delivery of ecosystem services are complex (Grizzetti et al., 2019) in such a way that a well-preserved ecosystem does not necessarily coincide with a high level of ecosystem services delivery. For instance, a degraded coral reef will see its service of water purification increase substantially due to the overgrowth of macroalgae that have a much higher nutrient uptake rate than coral species (Den Haan et al., 2016). However, other services will

decrease (recreational activities, coastal protection, provision for food, etc.). Understanding the thresholds at which ecological phase shifts are observed, and understanding the implication of these phase shifts, is crucial to linking changes in the ecological condition and delivery of services, and incorporate these links into CIA, and working towards integrated approaches to avoid reaching ecological tipping points (Hodgson & Halpern, 2019; Stelzenmüller et al., 2020). Accordingly, considering a broad bundle of ecosystem services within CIA and MRA frameworks is essential to avoid misguiding outcomes.

3.5 Obstacles for CIA implementation into policy

Despite the increasing and wide application of CIA and MRA methods in research, their use and application are still limited and there is little empirical evidence that the results of their application are integrated into policy discourse. For CIA to be of practical use, it needs to account for the complexity of socio-ecological systems and the transboundary character of many MCEs within which human activities take place, as well as the different responses across multiple administrative jurisdictions. This requires more coherence between methodologies over time, agreement on terminologies and principles (Willsteed et al., 2018), but also finding tools to account for and address transboundary pressures (for instance, climate change, ocean acidification, pollution).

For better integration of CIA into policy, more empirical studies are also required to test data needs and usefulness of CIA in delivering the desired spatial and temporal resolution relative to identified indicators and management goals (Willsteed et al., 2018). CIA methodologies have a better chance to be implemented if they are embedded in already existing decision-making and planning processes for climate change adaptation and management of MCEs (Hammar et al., 2020). However, there seem to be a few persisting obstacles that prevent decision-makers from making full use of methodologies and tools developed by academia (Kirchhoff et al., 2013). To help overcome this gap between knowledge production and its use, researchers might need to improve communication and engagement with policy actors and develop approaches able to better integrate institutional, economic, and cultural constraints (Bednarek et al., 2015). In this sense, for CIA methodologies to be applied in practice, it is important that evaluation pathways are conducted through a process that ensures coordination and synergies among different actors, policies, and programs at different scales and layers.

4. Conclusions

In this study, a theoretical review of the state of the art of methodological approaches and frameworks already developed by the scientific community for cumulative and multi-risk appraisal in MCEs was performed. Specifically, an iterative scientometric and systematic literature review of relevant studies was carried out to recognise trends and gaps in this specific research field, providing a comprehensive analysis and discussion of the existing literature over the past 20 years. More than 700 articles were initially identified, which were carefully screened to finally select a comprehensive set of 100 papers, representative of the most relevant CIA-related studies and applications for MCEs.

As the first remark, the performed review showed a meaningful increase in publications from 2008, when Halpern B.S. analysed for the first time the relationships and cumulative effects of multiple pressures affecting MCEs. Afterward, building on this milestone approach, authors started integrating into their study an increasing number of pressures (frequently in line with the list of pressures listed within the MSFD) using indicator/index-based methods, while ranking the pressures-ecosystem nexus through expert-based

judgment (as proposed in the Halpern B.S. approach). In the last decade, with the progressive digital transformation, new methods (data-driven approaches including, e.g., Bayesian Networks and Random Forest models) have been developed and tested to evaluate the effect of multiple pressures affecting MCEs. Moreover, following recent EU policy and international agreements (e.g., EU 2030 Biodiversity strategy, Sustainable Development Goals), the ecosystem services perspective started to be integrated into CIA frameworks as a further assessment endpoint within the overall evaluation process.

Drawing on these outputs, this review identified key challenges that need to be addressed in future CIA frameworks to provide more accurate guidance to policymakers for sustainable coastal ecosystem management. The first challenge for the research community is to develop and test cutting-edge approaches (e.g., ML-based models) able to capture/evaluate the complex and non-linear inter-relationships among multiple pressures affecting MCEs, which increase the level of complexity and uncertainties underpinning the design of integrated management plans. Dynamics are neglected in most of the reviewed studies, where the combined effect of different pressures was modelled "just" under an additive fashion, thus without considering potential synergistic or antagonistic interactions. Solving these limitations depends on the research progress of multi-source monitoring techniques needed to characterise and monitor the quality of the environment. Indeed, spatio-temporal data for marine and coastal environmental monitoring and management (e.g., satellites, drones) are becoming increasingly available. Consequently, authors now have the possibility to design and train more sophisticated data-driven models that allow integrating heterogeneous data to disentangle complex (and even unknown) interactions between human activities, the climate system, the ecosystems and the services they provide. In addition, this would also support the implementation of multivariate scenario analysis, which is useful for estimating the potential ecosystems' response to the effect of different environmental and social patterns. Similarly, this review also revealed a lack of consideration of the potential influence of specific ecosystem services in reducing/mitigating the effect of both endogenic and exogenic pressures while increasing the resilience of MCEs to further perturbations. In particular, some authors only recently started integrating into CIA frameworks the ecosystem services flow component, but only as an additional assessment endpoint within the overall assessment process (i.e., potential ecosystem services losses or degradation against cumulative impacts scenarios). The reason behind this limited and latest integration can be traced back to the recent international definition of marine ecosystem services under the CICES classification supporting ecosystem service mapping and capital ecosystem accounting.

Importantly, the current review revealed a reduced consideration of policy or management actions and their potential empirical evidence on how these CIA methodologies have influenced the management processes of MCEs. Most of the studies just mentioned the theoretical contributions of CIAs to guide policies and decision-makers within the management of the analysed ecosystems. Greater efforts should be made to improve synergies between the research community and stakeholders (including policymakers) from local to national and international levels.

Finally, progress in understanding cumulative impacts, particularly through ML models, which can help improve the overall understanding of environmental systems behaviour, might help to identify some relevant trends potentially representing ecosystem thresholds of change or approaching tipping points. Overall, these advances would reinforce, on one side, the current systemic knowledge and, on the other, provide more accurate CIA future scenarios allowing to drive more robust adaptation planning in MCEs.

SUPPLEMENTARY MATERIAL (SM) FIRST PAPER

Supplementary material SM1: Query string performed in Scopus (search date: March 2022)

TITLE-ABS-KEY (("cumulative impact*" OR "cumulative effect*") AND ("marine" OR "coastal" AND "ecosystem*" OR "environment")) OR (("cumulative impact*" OR "cumulative effect*" AND ("ecosystem service*" OR "multi-risk*" OR "multi risk*" OR "climate change" OR "ecological tipping point*" OR "policy support" OR "ecosystem health" OR "ecosystem condition" OR "ecosystem vulnerability" OR "safe operating space" OR "adaptive capacity" OR "resilience")) AND ("marine" OR "coastal" AND "ecosystem*" OR "environment")).

Supplementary material SM2: List and description of the comparison criteria

Class of criteria	Comparison criteria	Descriptions
Article detail	Main information of the paper	These criteria specify the authors, title, year of publication, source of the papers and the type of document (i.e., article, letter, review, proceedings paper, report) of all 95 papers.
	Case study area	Case study area including details on the scale of analysis and where possible the specific location where the method was applied.
CIA conceptual frameworks and methodological approaches	Method	The name of the method assigned by authors (or the generalized name e.g., CEA, CIA) together with the specific type of analytical approach applied (e.g., mapping, indicator/index, machine learning, etc.). It also specifies the components analysed through the CIA-related methods (e.g., hazard, exposure, vulnerability, risk, etc.).
	Pressure/hazard interaction	This includes specifications on pressures integrated into the study (e.g., commercial shipping, invasive species, ocean acidification, SST) and the potential evaluation of their interactions (detailing the list of interactions).
	Exposed targets	The exposed environmental targets, such as coastal seagrasses, reefs, wetlands, etc.
	Vulnerability factors/indicators	the vulnerability factors (or indicators) used to describe their sensitivity (or adaptive capacity) to multiple pressures (e.g., ecosystem state indicators, substrate composition, spatial extent and recovery times of habitats, etc.).
Healthy marine coastal ecosystems under a changing climate	Scenario analysis	The presence/absence of climate change/management future scenario analysis (yes/no), detailing the investigated timeframe (for both baseline and future scenarios) and the endogenic and exogenic variables modelled under these scenarios (e.g., rising SST under the 2050 timeframe scenario).
Ecosystem Services into CIA frameworks	Ecosystem Service assessment	The ecosystem services integrated into the CIA framework (yes/no), also clarifying the type of ES considered in the study (i.e., provisioning, regulation & maintenance, and cultural services)
When cumulative impacts lead to ecological tipping point	Considering tipping point	The integration of ecological tipping point concept into the CIA analysis (yes/no), detailing the investigated variables and thresholds.
Policy support for risk	Considering policy	Evidence for use of CIA approaches for integrated management of

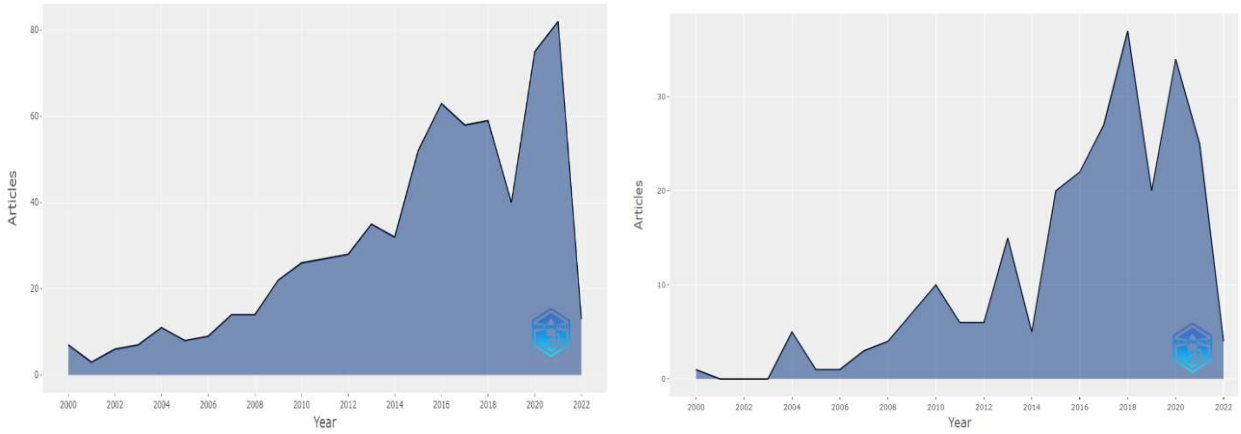
management and climate adaptation in MCEs	(management actions)	marine coastal ecosystems

Supplementary material SM3: Results and insights from the Scientometric review

As described in Section 2.1, the Scientometric review was performed by firstly applying a literature search in Scopus. This selection method led to the identification of 691 publications (value obtained at the end of March 2022) dealing with CIA in MCEs, during the investigated 2000-2022 timeframe period. This process allowed to develop the first Scientometric review (and related graphs) by using the bibliometric data of the 741 selected as input data for analysis through the open-source *bibliometrix* R Package. Afterward, the same Scientometric analysis was repeated by considering only the 253 papers obtained against the title-screening phase, as implemented under the Systematic review (Section 2.3). This allowed performing a more robust review, focusing only on a restricted number of preselected papers, thus avoiding non-significant documents (e.g., reviews papers or publications not focusing on the topic of concern of this review) for the scope of this study. Hereafter, the main findings from the performed Scientometric review (both for the 691 and 253 papers) are reported, highlighting i) the annual scientific production; ii) the most relevant authors; iii) the most frequent authors' keywords; iv) the most relevant keywords; v) the country collaboration networks' evolution under different time slices (i.e., 2000-2005, 2006-2010; 2011-2015; 2016-2022).

Annual scientific production

The analysis of the annual scientific production allowed examining the number of publications per year from 2000 to 2022, thus getting some insights on the progressive relevance and trends in CIAs methods and applications across MCEs. Specifically, as shown in Supplementary Figure S1, a relevant positive increase in publications during the last eight years (from 2014-2022) can be observed, which overall, they account for more than half of the whole literature of concern (from about 30 to 80 papers per year). Moreover, it is evident a gradual increase in publications since 2008. In fact, with his global-scale assessment, Halpern et al., (2008) (the pioneer of these applications) has laid the way for other CIA applications (Korpinen & Andersen, 2016; Quemmerais-Amice et al., 2020), following his same approach (or similar ones).

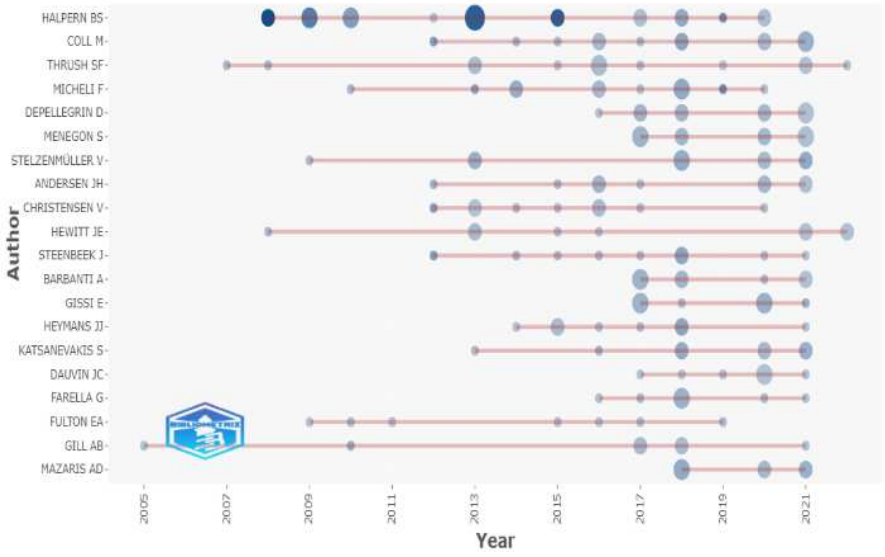


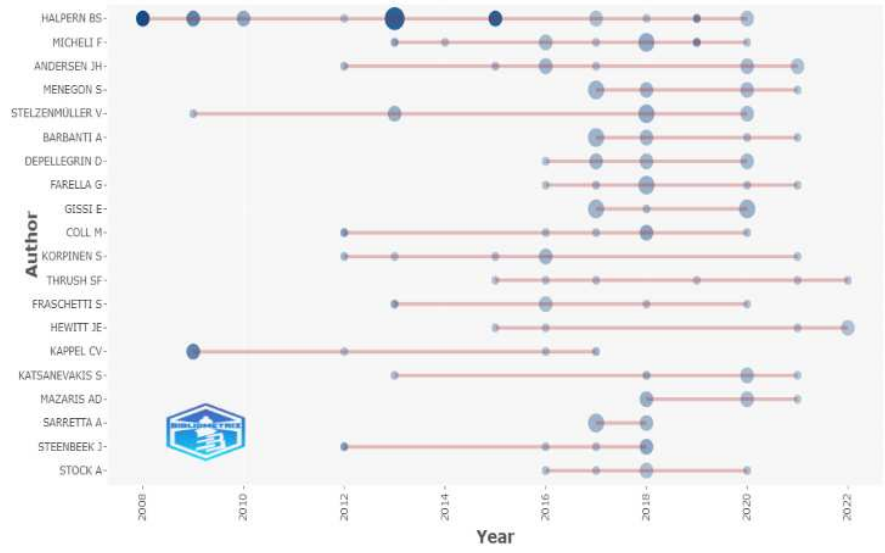
SUPPLEMENTARY FIGURE S1: NUMBER OF PUBLICATIONS APPLYING CIA IN MARINE AND COASTAL ECOSYSTEMS DURING THE 2000–2022 TIMEFRAME (LEFT: ACROSS THE 691 PAPERS, RIGHT: ACROSS THE 253 PAPERS).

Top authors' production over the time

The analysis of the author's production overtime allows integrating information concerning the number of contributions and the quotations authors have received through the years. This is analysed by means of the graph as presented in

Supplementary Figure S2, showing the top 20 authors with the higher contribution to CIA in MCEs. Focusing on the symbols applied in the graph, the size of the dots is proportional to the number of publications per year. Accordingly, it is possible to see when and how many articles these authors published in the 2000-2022 timeframe. Moreover, the colour of dots is proportional to the overall document's citations received by the author per year (i.e., dark blue dots correspond to the most cited papers). On the other hand, the red line per author represents the production time between the first document published and the last one, allowing us to understand the frequency of publication per author over the last two decades. In particular, considering the top 20 author's production under the 2000-2022 timeframe, Halpern B.S. emerged as the main author (with an overall number of 20 publications from 2008) applying a systematic procedure for evaluating the cumulative impact from multiple pressures/activities on MCEs.





SUPPLEMENTARY FIGURE S2: TOP 20 AUTHORS' PRODUCTION OVER THE TIME (UP: ACROSS THE 691 PAPERS, DOWN: ACROSS THE 253 PAPERS). THE RED LINE SIGNS THE PUBLICATIONS PERIOD OF THE AUTHOR, WHILE THE SIZE OF THE DOT SIGNIFIES THE RELEVANCE OF PAPERS PUBLISHED WITHIN THE CIA.

The two blue dots in the Halpern BS timeline highlight this researcher as the most cited author through the investigated timeframe, recognizing him as the most prominent author dealing with CIA methodology applied in MCEs. Along with Halpern B.S., the first 5 main authors are Micheli F., Andersen J.H., Depellegrin D, Stelzenmuller V.. However, even though they are among the most productive authors, developing CIA-related methodologies for the longest time, we can see a reduced frequency in publications and a lower number of citations compared with Halpern B.S.

Word Cloud

The Word cloud graph analyses the most frequent 50 author's keywords used among the whole set of papers published during the 2000-2022 timeframe. Looking at the resulting figure generated from this analysis (words are distributed on a shape similar to an ellipse, Supplementary Figure S3, it can be seen a gradient in word size. In particular, the most frequent words are presented with the biggest font and are positioned towards the centre of the ellipse.



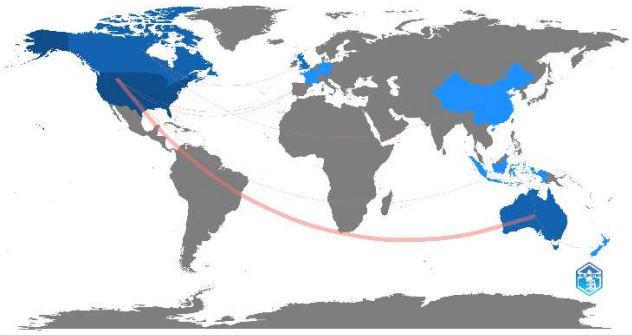
SUPPLEMENTARY FIGURE S3: WORD CLOUD ANALYSIS ILLUSTRATES THE MAIN AUTHOR'S KEYWORDS (LEFT: ACROSS THE 691 PAPERS, RIGHT: ACROSS THE 253 PAPERS). THE BIGGEST SIZE AND THE CENTRALITY POSITION OF KEYWORDS INDICATE THE MOST IMPORTANT KEYWORDS EMPLOYED BY AUTHORS WITHIN THE CIA IN MARINE AND COASTAL ECOSYSTEMS.

As we might expect, the figure discloses as main frequent author's keywords, those contained in the query string (explained within Section 2.1) such as cumulative impacts, cumulative effects. Furthermore, besides these keywords, ecosystem-based management (EBM), marine spatial planning and climate change emerged as the keywords most frequently used by authors. In fact, not surprising, many CEA and CIA methods have been developed to support decision-makers and planners in the design of spatial plans for MCEs management and conservation/restoration under the ecosystem-based management approach (Menegon et al., 2018a), as promoted by the MSP, MSFD and CBD regulatory frameworks (Andersen et al., 2015; Domínguez-Tejo et al., 2016; Manea et al., 2020). Recently, also climate change threats have started to be considered across many regulatory frameworks (e.g., MSP), and methodological approaches which started integrating this concept to assess and model future environmental conditions of marine and coastal ecosystems and foresee potential alteration of biological, chemical and physical processes (Furlan et al., 2020; E. Gissi et al., 2019) leading together to changes in ecosystem services flow. In fact, a key pillar of the ecosystem-based management approach is also the assessment of the range of marine ecosystem services which society can benefit from healthy marine and coastal ecosystems (Douvere & Ehler, 2008; M. Elliott et

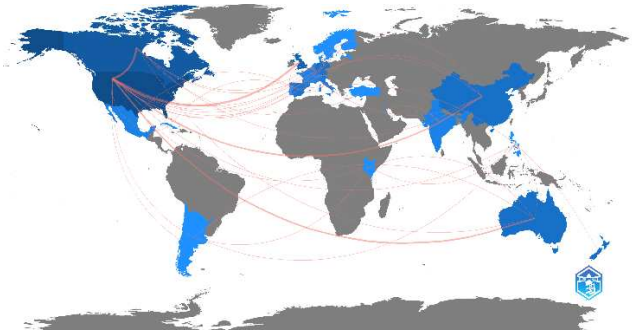
al., 2017; Farella et al., 2020). However, nowadays marine ecosystem services are poorly considered in CIA approaches, and this aspect is also reflected in the word cloud where marine ecosystem services doesn't appear as a focal keyword, since only recently started to be explored within the CIA methods (Depellegrin et al., 2020; Farella et al., 2020; Singh et al., 2020a).

Country collaboration map

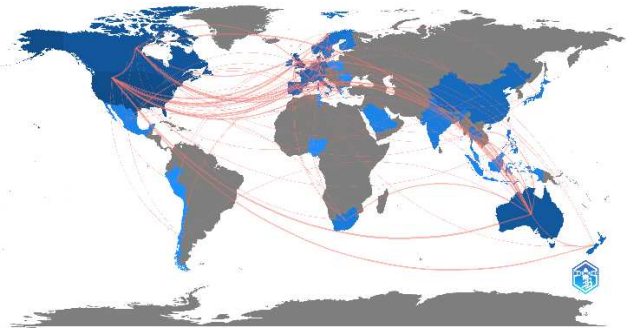
The evaluation of scientific collaborations among countries applying CIA methods in marine and coastal ecosystems is performed by analysing the authors' affiliations related to the same publication. Specifically, through this analysis, the number of documents in which there is at least one co-author from a different research institute is calculated. The country scientific collaborations graphic was performed, similarly to the previous analysis, under four different timeframes (i.e., 2000-2005, 2006-2010, 2011-2015, 2016-2022), thus allowing to understand the evolution of collaboration networks over time (Supplementary Figure S4).



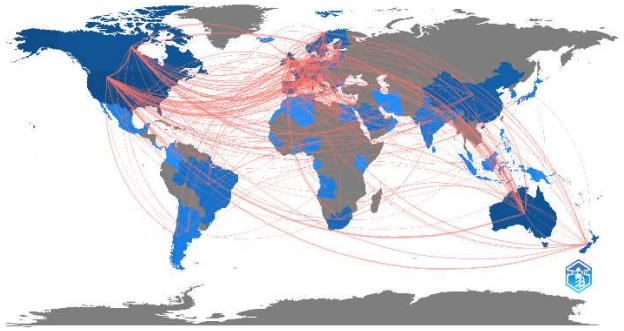
A) Timeframe scenario 2000-2005



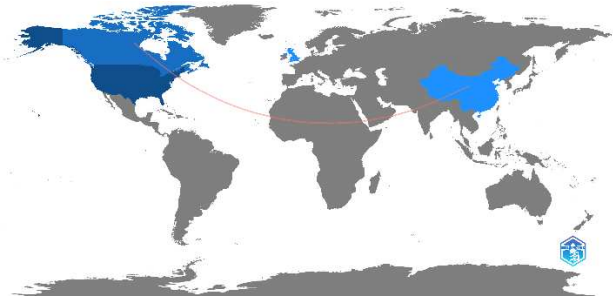
B) Timeframe scenario 2006-2010



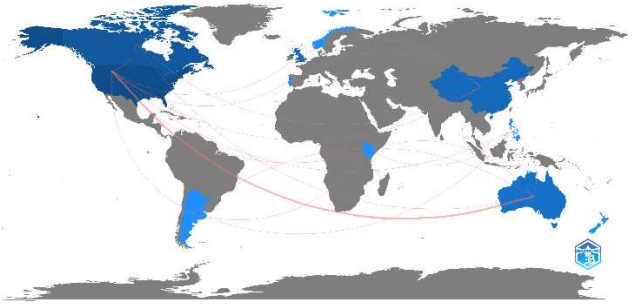
C) Timeframe scenario 2011-2016



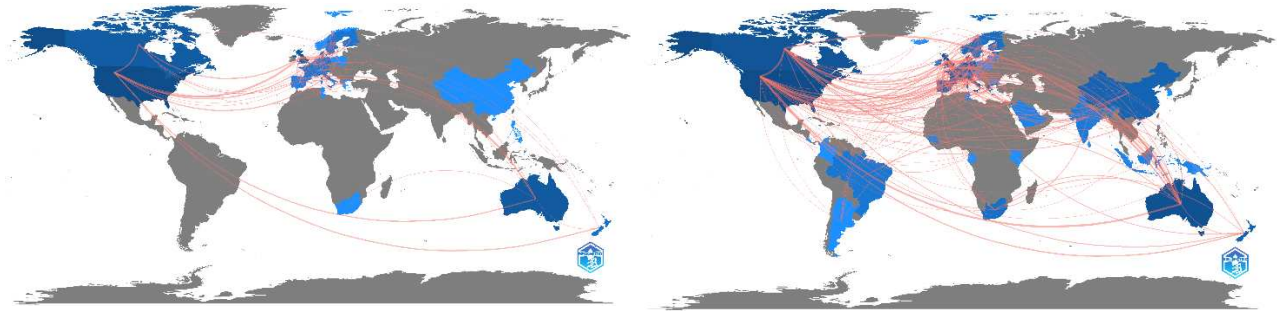
D) Timeframe scenario 2016-2022



A) Timeframe scenario 2000-2005



B) Timeframe scenario 2006-2010



C) Timeframe scenario 2011-2016 D) Timeframe scenario 2016-2022

SUPPLEMENTARY FIGURE S4: COUNTRY COLLABORATION MAPS UNDER FOUR TIME-SLICES: A) 2000-2005; B) 2006-2010; C) 2011-2015; D) 2016-2022 (ABOVE: ACROSS THE 691 PAPERS, BELOW: ACROSS THE 253 PAPERS).

Specifically, during the first time slice (Supplementary Figure S4A), with only seven papers published, the first country approaching CIA in marine and coastal ecosystems are USA, Canada, UK and China. Moreover, during this period only one interconnection emerged between USA and China. In the following 2006-2010 time period (Supplementary Figure S4B), collaborations among countries gradually increased according to the related rise in publications (with new contributions from Oceania, South America and central-east Africa). Instead, during the third timeframe period, many European States started developing collaborative CIA approaches with extra-continental states (as illustrated by the high number of red lines in Supplementary Figure S4C). In the last timeframe, we can observe a dense network of interconnections among states, as a result of the increased international relevance of this specific research field. Finally, the present plots also pointed out the lack of contribution of some relevant coastal States situated mainly in the north and south-west Asia, southeast Europe, Africa, South America, Mexico, the Caribbean area and Greenland. Therefore, further advancement of such approaches, as well as a better understanding of the potential impacts posed by multiple drivers, could be pursued by also fostering new collaborations with coastal and marine researchers and local stakeholders, in order to shape different CIA frameworks specifically designed and operationalized for site-specific marine and coastal ecosystems and connected environmental issues.

Supplementary material SM5: List of main terminologies

Terminology	Description	References
DPSIR framework		
Drivers/driving forces	They represent natural and anthropogenic forces that can drive variations in the state of socio-ecological systems(s). Drivers/driving forces, in turn, may exert intentionally or unintentionally 'pressures'.	(Neves et al., 2008)
Pressure	Pressures can broadly be described as the means through which drivers are actually expressed, i.e. the way they may interfere, perturb and alter socio-ecological systems(s), then causing an effect (or multiple ones) on any of its/their part.	(Neves et al., 2008; Oesterwind et al., 2016)
State/state change	The state is the actual condition of a system(s) and its components, established in a certain area and under a specific time frame. It can be quantitatively-qualitatively described based on physical (e.g. temperature, light), biological (e.g. genetic-, species-, community-, habitat-levels), and chemical (e.g. nitrogen level, atmospheric gas concentration) characteristics.	(Oesterwind et al., 2016)
Impact	Consequences of system(s) state change in terms of substantial environmental and/or socio-economic effects which can be both, positive or negative.	(Oesterwind et al., 2016)
Responses	Responses are the reactions by the society and policymakers triggered by the impacts, and may target drivers, pressures, state/state changes or impacts.	(Maxim, 2009)

RISK-based framework		
Hazard	The potential occurrence of natural or human-induced physical or chemical events or trends that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources.	(IPCC, 2018)
Exposure	The presence of people, livelihoods, ecosystem and their services, infrastructure, or economic, social, or cultural assets located in places that could be adversely affected by natural or human-induced hazards.	Adapted from IPCC, (2018)
Vulnerability	It represents the propensity or predisposition of a community, system, or asset to be adversely affected by a certain hazard. In a broad sense, it should include economic, social, geographic, demographic, cultural, institutional, governance, and environmental factors. Vulnerability encompasses a variety of concepts and elements including exposure to external impacts, sensitivity or susceptibility to harm, lack of capacity to cope and adapt.	(Adger, 2006; IPCC, 2018)
Risk	The potential for adverse consequences from climate and human-related hazard for socio-ecological systems, resulting from the interactions between the hazard and the vulnerability and exposure of the affected system. Risk integrates the likelihood of exposure to a hazard and the magnitude of its impact. It can be expressed in probabilistic or relative/semi-quantitative terms.	Adapted from IPCC, (2018)
Other key terminologies		
Cumulative Impacts/Effect	Ecosystem components may be affected by a wide range of pressures at the same time, but not necessarily featured by the same effect and extent. These multiple pressures, being frequently overlaid, can lead to cumulative (the sum of the effects) and interactive effects, resulting in combinations that may be synergistic, when the sum of the effects is increased, or antagonistic in case effects may decrease or cancel each other	(Patrício J., 2014)
Ecosystem Based Management	The comprehensive integrated management of human activities based on the best available scientific knowledge about the ecosystem and its dynamics, in order to identify and take action on influences that are critical to the health of marine ecosystems, thereby achieving sustainable use of goods and services and maintenance of ecosystem integrity	(OSPAR-HELCOM, 2003; ICES, 2003)
Ecosystem Services	Ecosystem services are the contributions that ecosystems make to human well-being. These services are final in that they are the outputs of ecosystems (whether natural, seminatural or highly modified) that most directly affect the well-being of people. A fundamental characteristic is that they retain a connection to the underlying ecosystem functions, processes and structures that generate them.	(Haines-Young, R. and Potschin, M., 2013)
Endogenic Drivers	Endogenic drivers: or managed pressures are those emanating from within the system under study (a sea area, an estuary) and which we can control (e.g., port activities, aquaculture, shipping traffic, ports activities, oil-spill, site-specific human activities carried out within an area, anthropogenic biological hazard, chronic and acute chemical hazards).	(Elliott et al., 2015; Furlan et al., 2019)
Exogenic Drivers	Exogenic drivers are those emanating from outside the system (globally or from catchment) which are not under our control when managing a particular system.	(Elliott et al., 2015; Furlan et al., 2019)
Sensitivity	Susceptibility of an ecosystem component to a specific pressure. The concept of sensitivity accounts for the ecosystem components' recovery potential, resistance and resilience with respect to certain pressure and related effects.	(Laffoley et al., 2000; Tillin et al., 2010; Stelzenmüller et al., 2018)
Stressors	Events and trends, often not climate-related, that have an important effect on the system exposed and can increase vulnerability to climate-related risk.	(IPCC, 2018)

Section B

SECOND PAPER

The Big Picture: appraising the risk of cumulative impacts on seagrass meadows in the Mediterranean Sea

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ABSTRACT

Human well-being and societal resilience are deeply tied to marine coastal ecosystems, yet they are threatened by multiple endogenic and exogenic pressures. In this study, a new MAchine leaRnIng-based CumulaTive Impact AssessMEnt (MARITIME) model is implemented and operationalised through the Random Forest algorithm to better understand the risk of cumulative impacts on seagrass meadows in the Mediterranean Sea and their cascading effects on the capacity to deliver ecosystem services for this key blue carbon ecosystem under a reference state (2017) and future climate change scenarios (RCP4.5 and RCP8.5). The results indicate a shrinkage of seagrass meadows, particularly at lower depths, and a decline in related ecosystem services capacity by both 2050 and 2100. This trend is notably severe across the entire Mediterranean basin under the long-term scenario. Such shrinkage may trigger further impacts, including the release of buried carbon, potentially transforming Mediterranean coastal areas from carbon sinks into sources of carbon emissions - a phenomenon likened to a 'carbon bomb'.

UNDER REVISION in the Journal "Ecological Informatics"

1. Introduction

Marine and coastal ecosystems (MCEs) are crucial for human well-being by providing essential life-support functions and services (Albert et al., 2020; EEA, 2019a). However, most MCEs, such as seagrass meadows, coral reefs, and mangrove forests, are under cumulative stress from various human activities, including coastal development and pollution. Moreover, the complex interplay between anthropogenic and climate-related pressures (e.g., ocean warming and acidification) is increasingly exacerbating the risk of cumulative impacts across these socio-ecological systems (He, 2023; Tiffany H. Morrison et al., 2019). The Mediterranean Sea ecosystems have not been spared from this intense pressure (Korpinen et al., 2021; Micheli et al., 2013), jeoparding their health and resilience, and reducing biodiversity and ecosystem services (Beusen et al., 2022; EEA, 2019a; IPBES, 2019; IPCC, 2019).

To address this challenge, the research community has started designing and applying spatially referenced cumulative impact/effect assessment (CIA/CEA) approaches and tools, adapting analytical frameworks (Furlan et al., 2020; Hansen & Bonnevie, 2020; Menegon et al., 2018) for local and regional applications. These methods have been applied to several coastal and marine areas to support the assessment and mapping of the distribution of key pressures and their potential combined effects on marine life and ecosystem health, as well as the cascading effects on their capacity to provide services (Korpinen & Andersen, 2016; Simeoni et al., 2023). Since the inception of this approach (Simeoni et al., 2023), most CEA/CIA applications have built on an index-based methodological framework (Halpern et al., 2008), calculated by aggregating information on the pressures' intensity and the sensitivity (usually based on expert-based weightings) of analysed ecosystems to these pressures. Recent studies have tested more complex methods to improve these analyses. Specifically, Machine Learning (ML) applications have been implemented to assess changes in the environmental and ecological status of MCEs against multiple pressures (Furlan et al., 2020; A. Stock et al., 2018b; Teichert et al., 2016; Turschwell et al., 2020). ML applications leverage algorithms such as Random Forest (RF) and Bayesian Networks to analyse and extrapolate patterns from spatio-temporal big data. These algorithms are advantageous for their ability to analyse non-linear structures, handle complex phenomena, manage large datasets at different spatial and temporal scales, and address missing data in environmental fields (Bui et al., 2020).

Drawing on these state-of-the-art methodologies, the main aim of this work is to develop a cutting-edge risk assessment model that allows: *i) a multi-scenario assessment of environmental impacts arising from changing oceanographic and climate conditions, ii) unravelling the mechanisms by which multiple stressors influence MCEs condition and responses, iii) investigating the interrelations between climate change and human-made pressures, variations in the MCEs conditions, and the cascading effects on the ecosystem services capacity.*

To achieve these objectives, this study presents a new MARITIME model designed to support a sound comprehensive evaluation of the risk of cumulative impacts affecting ecosystems at an ecoregional scale. As illustrated in Figure 6, the MARITIME model is composed of two macro-layers: i) a top/input layer, relying on data representing proxy indicators for the identified key threats/pressures, such as shipping traffic, nutrient input, changes in temperature and salinity regimes, and ii) a bottom/output layer, integrating an indicator of seagrass distribution (the model response explaining the ecosystem condition) along with two derived indicators depicting the potential capacity for carbon sequestration and denitrification.

The developed MARITIME model, implemented through a RF algorithm, allows the identification of the most important stressors, i.e., variables that substantially contribute to accurate predictions, and elucidates their relationships with the response variables (it analyses how these stressors interact and cumulatively influence the response variables under study). Additionally, the model predicts seagrass distribution under future

scenarios representing changes (i.e., anomalies between future and reference periods) in the pressures' distribution and intensity.

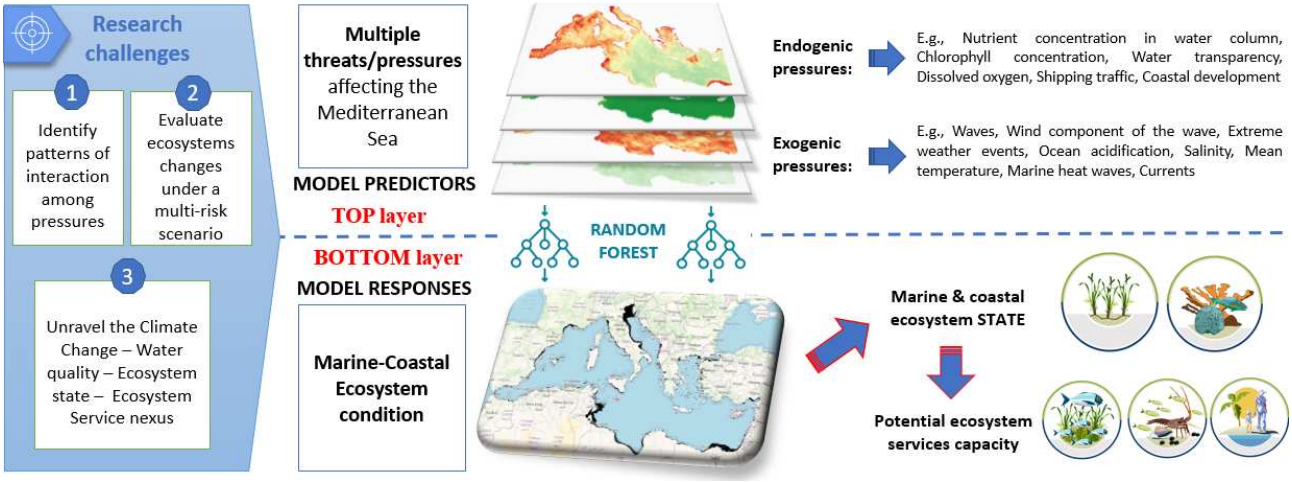


FIGURE 6: MARITIME MODEL FRAMING IN THE MEDITERRANEAN SEA. LEFT PANEL: CHALLENGES/RESEARCH QUESTIONS UNDERPINNING THE STUDY; RIGHT PANEL: RF CONCEPTUAL MODEL FOR THE MEDITERRANEAN SEA.

To evaluate the seagrass ecosystem's responses to climate change conditions, this model has been implemented with the historical conditions of the Mediterranean Sea in the reference period (1998 – 2017, see more details in Section 2.1 "Data collection"). Then, it has been trained, validated, and tested through various iterative analyses, including hyperparameter tuning, feature selection, spatial-cross validation, and model performance evaluation. Finally, a set of GIS-based multi-risk scenarios have been produced by integrating future conditions of key environmental parameters under different Representative Concentration Pathways (RCPs): the stabilisation scenario RCP4.5 and the "business as usual" scenario RCP8.5 (IPCC 2013). Projections of Sea Surface Temperature (SST), Marine Heat Waves (MHW), Salinity (SAL), and Sea Surface Height (SSH) have been extracted from available climate models for the Mediterranean region, covering two different timeframes: i) short-term from 2031 to 2050, and ii) long-term from 2081 to 2100.

This multi-risk scenario analysis has been implemented using a stepwise approach to investigate the complex interactions among the selected model predictors. For each step, variations in seagrass distribution between reference conditions and future scenarios have been assessed and compared to the previous step to identify differences or anomalies potentially linked to the synergistic/antagonistic interactions among stressors. Initially, the simulation considered all stressors together (i.e., the cumulative scenario SC-ABC) which includes simultaneously all future variations in SC-A: SST+MHWs, SC-B: SAL and SC-C: SSH. Subsequently, these indicators have been tested individually (SC-A, SC-B, and SC-C) and in pairs (SC-AB, SC-AC, SC-BC), allowing for comparisons with the initial scenario.

2. METHODS

2.1 Data collection

The operationalization of the MARITIME framework necessitates the collection and pre-processing of a vast amount of heterogeneous data capable of representing spatial distribution and intensity of both endogenic and exogenic pressures (Michael Elliott et al., 2020), as well as detailed information on ecosystems' health and biodiversity. To this aim, different open-source web-data platforms have been screened (e.g., Copernicus

Services, EU-Atlas of the Sea, Worldclim, UNEP and EMODnet data), paying particular attention to the availability of high spatio-temporal resolution data.

As a first step, bathymetric data, essential for delineating the boundaries of the case study area, has been retrieved from the EMODnet database (https://www.emodnet-seabedhabitats.eu/). Subsequently, focusing on the most relevant stressors affecting seagrasses meadows in the Mediterranean region, data on both endogenic (i.e., variables regarding nutrients load, dissolved oxygen, water transparency, turbidity, and Chl-'a') and exogenic pressures (e.g., sea surface temperature, pH, marine currents, waves, etc.), have been retrieved from Copernicus Marine Service (CMEMS). Additionally, the spatial layer indicating the "kinetic energy at the seabed due to currents" (and the related metrics – mean of annual 90th percentile) has been retrieved from the EMODnet Platform (www.emodnet-seabedhabitats.eu). This indicator allows for an understanding of how underwater currents influence sediment transport and seabed stability, which are critical factors for seagrass habitat health. Regarding shipping traffic, data on vessel traffic density (hours per square km per month) has been collected from the EMODnet Human Activities database web portal (www.emodnet-humanactivities.eu). Furthermore, to evaluate the influence of human coastal activities and urban areas on seagrass health and distribution, several indicators and metrics related to the proximity to human settlements (e.g., ports, shores, main cities, and river mouths) have been retrieved and pre-processed. Specifically, two open-source layers representing the distance from ports and shores along the Mediterranean coasts have been gathered from Global Fishing Watch (https://globalfishingwatch.org/data-download/). On the other hand, the minimum distance of each seagrass meadow to the nearest major cities and river mouths has been calculated using the Haversine formula based on datasets containing information on major rivers and cities near the Mediterranean Sea shores.

Finally, different seagrass distribution maps across the Mediterranean ecoregion have been compiled for data on ecosystems' health and biodiversity. Data from a broad range of UNEP-WCMC global biodiversity standardized databases for the year 2017 has been combined with the seagrass coverage layer produced by EMODnet Seabed Habitats (for 2016, 2017, 2018) to obtain the most complete representation of seagrasses distribution in the investigated marine region. The whole set of reference data (indicators and related metadata) selected for the MARITIME operationalization in the Mediterranean Sea eco-region is provided in Supplementary Table SM3.

Moving from the reference to the scenario analysis, projections from regional climate models have been integrated into the RF model. More precisely, the CMCC Med-CORDEX RESM covers the Mediterranean Sea and a small part of the Atlantic Ocean, with a mesoscale permitting horizontal resolutions for both the atmospheric (i.e., 12km) and the ocean (i.e., 6.5km) components. The atmospheric code is COSMO-CLM, while the ocean component is based on the NEMO code. The model for the land surface and near-surface soil column is Veg3d LSM. Three climate simulations have been carried out, one of them in historical mode (1960-2005) and the others in projection mode (2006-2100 RCP 4.5 and RCP8.5).

2.2 Data preprocessing

The dataset required for operationalizing the model undergoes several data preparation and pre-processing steps, which are crucial for ensuring the representation and quality necessary for ML-based algorithms to succeed (Kotsiantis et al., 2006). To pursue this task, the study area has been delineated, prioritizing the reference year 2017 as it shows more complete data availability in seagrasses ecosystem coverage across the entire Mediterranean Sea. According to literature, seagrasses predominantly inhabit shallow waters, typically within depths of 40-50 meters (UNEP, 2020b). Consequently, a bathymetry layer up to 50 meters deep has

been used to delineate the selected to define the case study area, ensuring it falls within the typical seagrass habitat range. However, depth itself was not included as an indicator in the table of metrics used for training, validation, and testing the RF model (as reported in Supplementary material SM1). Subsequently, all data collected for RF model operationalization have been pre-processed to homogenize their different spatial resolutions into a uniform 4 km-based raster grid. Moreover, a series of yearly-based metrics (such as minimum, maximum, standard deviation, etc.) have been calculated for each of the environmental indicators selected. These steps ensure that the data are appropriately formatted and optimized for integration into the MARITIME model. This facilitates robust analysis and accurate prediction of seagrass distribution and ecosystem responses under various scenarios.

Looking at the response variable, seagrass distribution depends on the presence or absence of seagrass meadows. Class 0 corresponds to the absence of seagrass (value = 0). Data in the range (0, median] are assigned to class 1 ("moderate presence"), while data in the range (median, maximum] are assigned to class 2 ("high presence"). This classification allows a more detailed understanding of seagrass distribution within the coarse 4km-based raster grid. More details on the calculation and mapping of model predictors and responses are reported in Supplementary material SM2.

2.3 Model selection

As emerged in Simeoni et al. (2023) and Zennaro et al. (2021) , the RF algorithm started to be used in the frame of climate change risk assessment and CIA studies for modelling and understanding of the ecological response of water bodies to multiple stressors. Building on these applications, this study focused on the design and implementation of an RF multi-class classification problem, in which a key indicator representing environmental condition of seagrass meadows (considered by means of an indicator representing the seagrass distribution) is classified. More precisely, this algorithm was chosen across the wide range of available ML-based algorithms for its versatility and powerful features which make it highly suitable for a wide range of classification and regression problems (AhmedK et al., 2013). This model is particularly effective because it is computationally efficient, allowing for relatively fast training and prediction (Zhang & Ma, 2012). Additionally, it requires minimal parameter tuning, which simplifies its application, even for high-dimensional datasets. Moreover, it fits with the specific needs of this application as it can handle missing values seamlessly, assign different weights to classes to manage imbalances, and provide insights into variable importance, which is crucial for understanding the contribution of individual features.

Another important factor in choosing RF is its capability to support scenario analysis (Teichert et al., 2016). It allows testing how potential variations in inputs (e.g., climate-related variables) can influence the output (such as seagrass meadows, corals, etc), making it highly relevant for evaluating the future impacts of various climatic and human-related stressors. This capacity to analyze and predict outcomes under different configurations is essential for understanding risks and planning more robust adaptive strategies.

Furthermore, RF leverages an ensemble approach that enhances predictive performance. By combining multiple decision trees, each trained on randomly sampled data and features, it achieves robust predictions with reduced variance. The inclusion of random feature subspacing ensures that trees are less correlated, further improving the model's reliability.

Finally, RF offers spatial representation capabilities, enabling predictions to be visualized in the form of maps. This facilitates the communication of findings to stakeholders by providing an intuitive and visually engaging way to interpret and present results.

2.4 Model operationalization

From an operative perspective, the design of the RF follows a precise analytical workflow, from model development to training and testing, and finally, scenario analysis. Specifically, once the available data for the selected eco-region are pre-processed and analysed, the dataset to be used for the model development can be created. To proceed with training and testing, the dataset is split into two sets: 90% of the total data for training and 10% for testing. The training set fits the model, while the test set evaluates the final model's performance. Then, after some iterative processes, the best model configuration can be implemented to move to the scenario analysis and develop a set of related GIS-based multi-risk scenarios. To get a consistent estimation of the RF model performances, that are not biased by a specific configuration of training and test set, a cross-validation method has been applied. Particularly, in this study, a spatial cross-validation approach has been implemented to address the issue of data 'spatial partitioning' (Roberts et al., 2017). This technique has been employed to account for the inherent autocorrelation in the data, where points/pixels nearby tend to exhibit greater similarity compared to those further apart (Getis et al., 2004). Using random samples alone would violate the assumption of Independent and Identically Distributed Data (IDD), as the samples would not be statistically independent. The study area has been divided into distinct spatial blocks to overcome this challenge, ensuring a more robust and reliable analysis. More precisely, to create different spatial areas, pixels within the whole case study area have been clustered by the KMeans algorithm in *n* spatial blocks until a good spatial partitioning of observations is reached upon manual inspection. Blocks representing sub-areas of the case study have been used for 10-fold cross-validation. This spatial cross-validation has also been used to research the best architecture of the model (i.e., the architecture that maximizes the model's accuracy in the validation set). Once the best hyperparameters have been selected, the feature selection, i.e., identifying the most relevant features, has been performed. To choose the best features, the spatial cross-validation needs to be performed again, and a recursive elimination of the features follows. Finally, the scenario analysis was carried out by calculating anomalies between the reference scenario (1998 to 2017) and future scenarios. Both circular bar plots and spatial maps have been structured to highlight the projections' anomalies and better compare the scenarios.

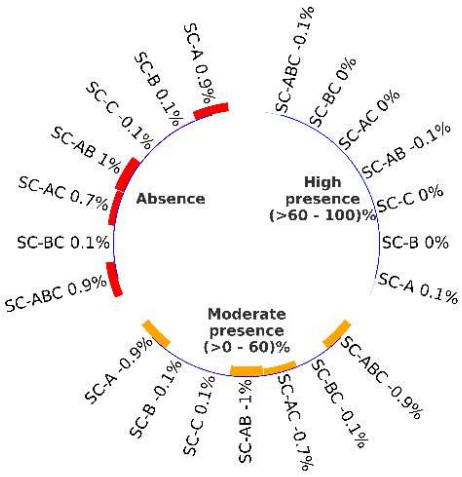
3. Results

3.1 Predicting future distributions of seagrass meadows under different climate conditions

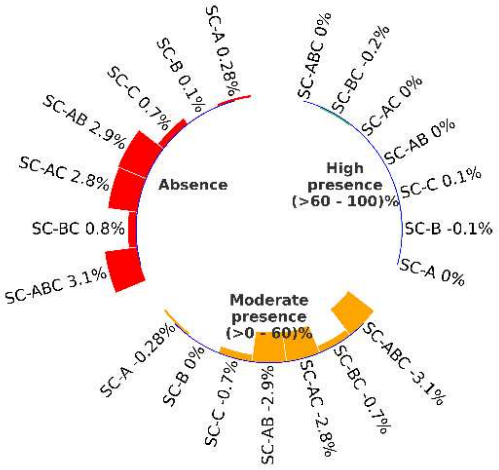
Overall, the MARITIME model predicts a more severe risk of cumulative impacts under long-term scenarios across different RCPs. Within the 2031-2050 timeframe, both RCP4.5 and RCP8.5 scenarios show similar overall changes and spatial variations. More precisely, climate-related forcings are projected to cause a 6-12% potential shrinkage in seagrass meadows (under RCP8.5 and RCP4.5 scenarios, respectively), mainly in the "moderate presence" class. This decline corresponds to an 800-1600 Km2 reduction across the Mediterranean basin. In terms of spatial distribution, as depicted in Figure 2c and Supplementary Material SM6, the meadows surrounding the Balearic Islands and the French coastline appear to be the most risk-prone regions under the cumulative scenario (SC-ABC) in the short-term time horizon (see panels A and B of Figure 7c).

FIGURE 7: FUTURE CHANGES IN SEAGRASS DISTRIBUTION FROM THE REFERENCE PERIOD TO THE SHORT (2031-2050)- AND LONG-TERM (2081-2100) UNDER THE RCP8.5 SCENARIOS

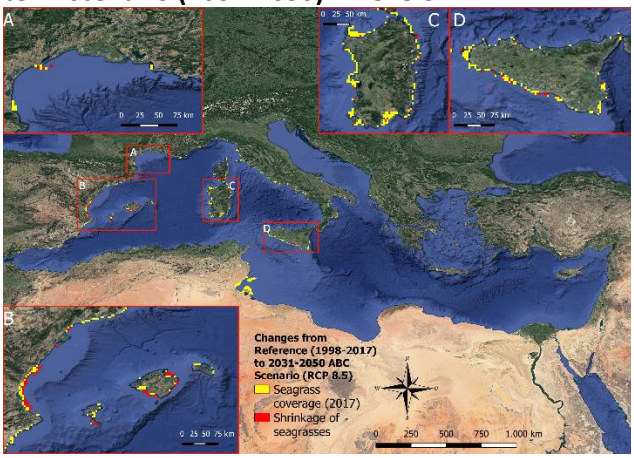
a) **2031-2050 - RCP8.5**



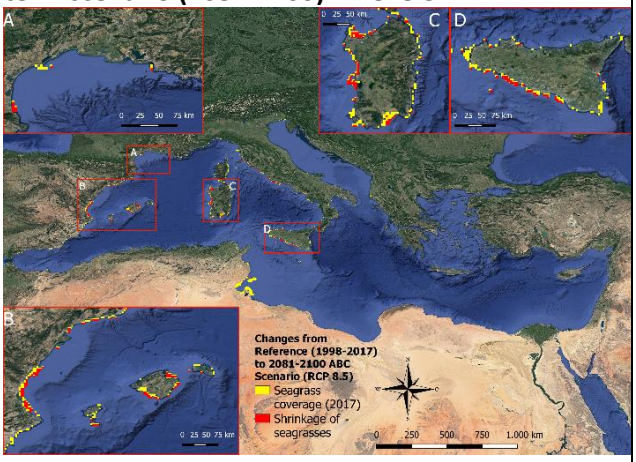
b) **2081-2100 – RCP8.5**



c) Seagrass meadows shrinkage under the short-term scenario (2031-2050) – RCP8.5



d) Seagrass meadows shrinkage under the long-term scenario (2081-2100) – RCP8.5



a,b, Anomalies between reference period (1998-2017) and future scenarios for seagrass distribution. The tested scenarios include i) individual scenarios (SC-A: SST+MHWs, SC-B: SAL, and SC-C: SSH); ii) paired scenarios (i.e., SC-AB, SC-AC, and SC-BC; iii) cumulative scenario (i.e., SC-ABC); **c,d**, Future changes of seagrass distribution from reference for the cumulative scenario of the RCP8.5.

Looking ahead to the 2081-2100 timeframe under both RCP scenarios, the model predicts a worsening in meadow shrinkage throughout the Mediterranean basin. The MARITIME model predicts that nearly 3% of the whole case study (i.e., all pixels considered in this analysis) will shift to the absence class (Figure 7b), indicating the relative decline of seagrass conditions. Because seagrass beds are restricted to benthic shallow waters, this decrease, which might appear relatively limited at the Mediterranean basin level, is substantial at the seagrass ecosystem dimension. This reduction corresponds to about 20% of the current seagrass distribution. This shrinkage of seagrass is predominantly associated with isolated meadows or patchy meadows, with a predicted reduction of nearly 50% of meadows classified under the "moderate presence" class (Figure 8). In absolute terms, this translates to a potential reduction of about 2500 Km^2 in seagrass distribution compared to the reference period, with a minor difference of 100-150 Km^2 between RCP4.5 and RCP8.5. To provide a better perspective on the scale of this decline, the estimated area is roughly equivalent to losing approximately two-thirds of the land area of Mallorca Island in Spain.

Spatially, the meadows at the deeper bathymetry (i.e., between 25 and 50 m depth) are expected to be the most affected. This trend is particularly notable along the French coast and the southern coast of Sicily, as shown in panels B and C of Figure 7d. Comparing RCP4.5 and RCP8.5, the most significant differences are observed in the northwestern part of Sicily and the western part of the French coast. Despite these two notable differences, a greater loss is expected under the RCP8.5 scenario at the Mediterranean scale compared to RCP4.5. The decline in the spatial distribution of seagrass meadows will also lead to a progressive process of reduced connectivity between meadows, which, in turn, will contribute to raising the vulnerability of patches to further pressures.

3.2 Untwisting a sea of complex interactions

The multi-risk scenario analysis leverages ML capabilities to explore the complex structure of relationships between stressors and their impacts on the seagrass ecosystem. As highlight in (Furlan et al., 2019; Simeoni et al., 2023), only a few studies have attempted to investigate these complex pathways of interactions and identify synergistic and/or antagonistic combinations. Typically, authors dealing with CIA/CEA approaches apply additivity to resolve and model cumulative impacts, as proposed by (Halpern et al., 2008). An additive effect refers to the simplest combination of two or more agents/stressors, where the total effect is the sum of the individual components' effects. On the other hand, interactions occur when combined stressors deviate from the 'additivity expectation', requiring further analysis to model and represent cumulative effects accurately (Beusen et al., 2022). Synergistic effects are one such possible interaction where the combined effect of multiple components exceeds the sum of their individual effects. Conversely, antagonistic interactions occur when the combined effect is less than the sum of the individual effects (Crain et al., 2008; Halpern et al., 2008; Roell et al., 2017).

On the circular bar plots (Figure 7a, b), which represent both potential positive (future increase in seagrass coverage) and negative (seagrass meadow shrinkage) effects of simulated scenarios on seagrass distribution, the influence of SST, SAL, and SSH on the response variable can be quantified. Under the short-term horizon (2031 – 2050), the model shows minor variations for both individual and coupled scenarios. In the long-term horizon (2081-2100), the RCP8.5 scenario shows some potential synergistic effects among pressures, as coupled pressures scenarios result in higher seagrass shrinkages compared to the sum of their individual effects. Specifically, future scenarios of SST and SAL individually trigger minor changes in seagrass distribution if considered separately (up to 0.3%). However, when these two variables are considered together, nearly 1,500 km^2 of seagrass are predicted to disappear (up to 3% of the case study). In contrast, the projected sea level rise appears to have a minor impact on seagrass distribution, even when considered alongside the other environmental variables. Changes of approximately 0.1% have been predicted for all scenarios related to SSH.

3.3 Implications on the potential ES capacity against analysed risks

From a social, economic, and management perspective, the results of the MARITIME model are crucial when considering the services provided by seagrass meadows. These ecosystems offer fundamental services that contribute to human well-being and address several societal challenges. Particularly in terms of regulation and maintenance services, seagrass beds are among the most significant ocean carbon sinks globally, with a high capacity for capturing and storing carbon in the sediment (Castejón-Silvo & Terrados, 2012; UNEP, 2020a) also known as 'blue' carbon (Mcleod et al., 2011), although this capacity can be significantly compromised by environmental stressors such as macroalgal blooms and habitat degradation (Liu et al., 2020; Serrano et al., 2021). This ability positions seagrass meadows as key species in mitigating climate change by absorbing large amounts of atmospheric carbon and providing coastal protection against erosion and storm surges, thereby offering dual benefits for climate change mitigation and adaptation.

In this study, two regulating services (i.e., carbon sequestration and denitrification potential) have been calculated. First, the carbon sequestration has been evaluated based on the surface area covered by meadows and their average carbon sequestration rate per year range between 7.7 and 84.4 g C/m2 as a function of depth, following the equation y = −40.5 x ln(depth) + 145.5, reflecting reduced meadow density due to light attenuation (Pergent-Martini et al., 2021). This appraisal has been conducted for both the reference period and future climate change scenarios, estimating a potential reduction in carbon sequestration of 0.5-3.5% in the short term (2031-2050) and around 6% by the end of the century, depending on the RCP scenario considered. Similarly, the denitrification potential of seagrass has been estimated by a constant denitrification rate of 13,500 tN/km2/year per meadow-covered surface unit (Mateo & Romero, 1997). Analysis of the reference period and future scenarios indicates an overall reduction in denitrification potential spanning from 6-12% in the short term and around 20% in the long term.

Beyond their roles in geomorphological and ecological processes, healthy seagrass meadows also act as natural barriers that effectively absorb and mitigate hydrodynamics forces at the seabed. By dampening the intensity of waves and currents, seagrasses contribute to coastal protection by reducing erosion processes (e.g., helping sediment transported in the seawater to accumulate on the seafloor), stabilizing the shoreline and, as a consequence, protecting coastal populations and infrastructures near the shore from the increasing force of the sea caused by sea-level rise.

4. DISCUSSION & CONCLUSIONS

Understanding the complex interplay and the effects of multiple stressors (Furlan et al., 2019; Halpern et al., 2008; Zennaro et al., 2021) is a key challenge for improving the management of marine and coastal areas and supporting the implementation and achievement of related environmental and sustainability policies (Beusen et al., 2022; EEA, 2019b). As recently emphasised by the Intergovernmental Panel on Climate Change (IPCC) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), climate change and biodiversity degradation must be considered together, as recent studies recognised the interdependence of climate, ecosystems, and biodiversity, and human societies (IPBES, 2019; IPCC, 2022). Assessing these effects and the nexus among different systems' components is a particularly complex task that requires advanced modelling tools and methods. This study aims to bridge this gap by developing an ML model to better investigate these research challenges and untwisting interactive patterns in socio-ecological systems. Being a data-driven model, the MARITIME model provides a scientific understanding and mapping of the effects and associated ecological benefits or detriments expected from different climate scenarios without relying on surveys or workshops where experts score the sensitivity of each ecosystem type to each stressor. According to the data availability and the model design, as well as thanks to the iterative processes conducted during the training and validation phases, the MARITIME model achieved an overall prediction accuracy of approximately 0.89 in estimating seagrass distribution. Additional metrics such as precision, recall, and the F1 score have been examined to gain deeper insights into the model's performance. The full list of indicators and corresponding yearly-based metrics, along with details on the technical procedures applied for their analysis and mapping, as well as further information on future improvements are provided in the "Data processing" (Section 2.1) and "Navigating complexities in modelling" sub-sections, and Supplementary material SM1-SM2. The final model performance, based on the tested evaluation metrics, is documented in Supplementary material SM4-SM5.

Navigating complexities in modelling

The quality of data for training, testing, and scenario analysis significantly influences the accuracy and complexity of the MARITIME model. Ensuring data coherence represents an essential concern when dealing with CEA and risk assessment approaches, which require heterogeneous data/variables to adequately capture the complexity of socio-ecological systems across broad geographical scales. Combining and homogenizing data from various sources and platforms is essential but challenging due to differences in spatio-temporal resolution and the availability of information, especially along the African coast. In the reference scenario, limitations in data availability not only limited the number of variables considered but also impacted the overall model accuracy and the understanding of relationships between predictors and the seagrass distribution. Similarly, in the scenario analysis, complex interactions have been investigated with a limited combination of variables due to data projection constraints. Enhancing the analysis with a broader range of future pressure indicators could strengthen the model's predictive capacity and provide deeper insights into cumulative and cascading effects.

Moreover, the flexibility of the MARITIME model allows for transferability and scalability across different marine ecoregions with varying ecosystems, climatic conditions, and anthropogenic influences. Initially applied to the Mediterranean ecoregion, focusing on seagrass ecosystems, it was later adapted to the North European ecoregion (targeting kelp forests) within the EU2020 Macobios project (Furlan et al., 2023). These case studies demonstrated the model's flexibility across diverse spatial locations and marine ecosystems.

Nevertheless, the proposed assessment could be further reinforced at finer scales by integrating the temporal dimension into the reference scenario (i.e., to analyse the time-dependent variation of seagrass habitats in response to environmental and anthropogenic pressures over different years). This could be achieved through advanced frameworks like coupling numerical models with cutting-edge data-driven models such as Graph Neural Networks, enabling more nuanced exploration of ecosystem behaviours and human impacts on marine coastal ecosystems. This would also allow for a deeper investigation of the potential reduction in the ecosystem functioning and service provision. Moreover, it could support the assessment of potential tipping points, which, at this scale and with only one year of training data, cannot be reliably evaluated, thus improving our understanding of critical thresholds and ecosystem resilience.

Future investigations aim to bolster environmental process analysis and assess the impacts of diverse pressures, capturing their interactions and cascading effects across multiple timeframes and at local scales. This approach seeks to leverage more precise spatio-temporal data (e.g., monitoring data, satellite imagery) to enhance model robustness. By unravelling the nexus between climate change, water quality, and marine biodiversity, the MARITIME model can inform conservation strategies, support local adaptation efforts, and guide policy development. These efforts are crucial for maintaining ecosystem service provision, preserving carbon storage in sediments, and bolstering the resilience of marine ecosystems against environmental changes.

From blue carbon to carbon bomb: risks of seagrass degradation

Despite the discussed limitations related to data availability and matchability at the Mediterranean scale, the implemented ML-based approach offers useful predictive insights into possible future ecological conditions and the nexus among climate change, water quality, and marine and coastal biodiversity, underpinning MCEs' response to multiple pressures, including climate change. Policymakers and marine managers can use the information from the MARITIME model to identify hot-spot risk areas to prioritize, which is particularly valuable when capacity and resources are limited. The MARITIME model thereby supports the successful management of the Mediterranean Sea.

More precisely, the MARITIME model identified areas with good coverage of seagrass (Figure 7b) as resilient to the effects of the considered pressures, as almost all areas labelled as high presence do not suffer significant changes. Nevertheless, even these most resilient meadows could undergo habitat degradation, with potential reductions evidenced by indicators such as leaf bundle density (bundle/m2), leaf area per bundle (cm^2/bundle), etc.

Managing the carbon stock of seagrass is a key challenge for tackling climate change, both positively through carbon sequestration capacity and negatively through the risk of releasing carbon stored in the past. Part of the absorbed carbon can be efficiently buried in the sediment, leading to mid-term and long-term carbon sequestration, making the seagrass ecosystem a significant blue carbon ecosystem (Johannessen, 2022; Macreadie et al., 2021). Among the worldwide seagrass species, *Posidonia Oceanica*, endemic to the Mediterranean Sea, is notable for producing a massive below-ground biomass composed of roots and rhizomes, known as matte. The matte may have accumulated over hundreds of years and be several meters high (Romero et al., 1994). A living seagrass meadow, built slowly but continuously with a resilient matte and thick leaves canopy, reduces currents and wave energy, minimising erosion. In contrast, degraded, patchy, or dead seagrass meadows leave the exposed matte vulnerable to erosion. Similar to how permafrost melting mobilises carbon stores (Jin & Ma, 2021; Treat & Frolking, 2013), the dead seagrass matte in the Mediterranean Sea could constitute a kind of 'carbon bomb' with the risk of releasing this stock of carbon stored over ages by remineralization process (Figure 8).

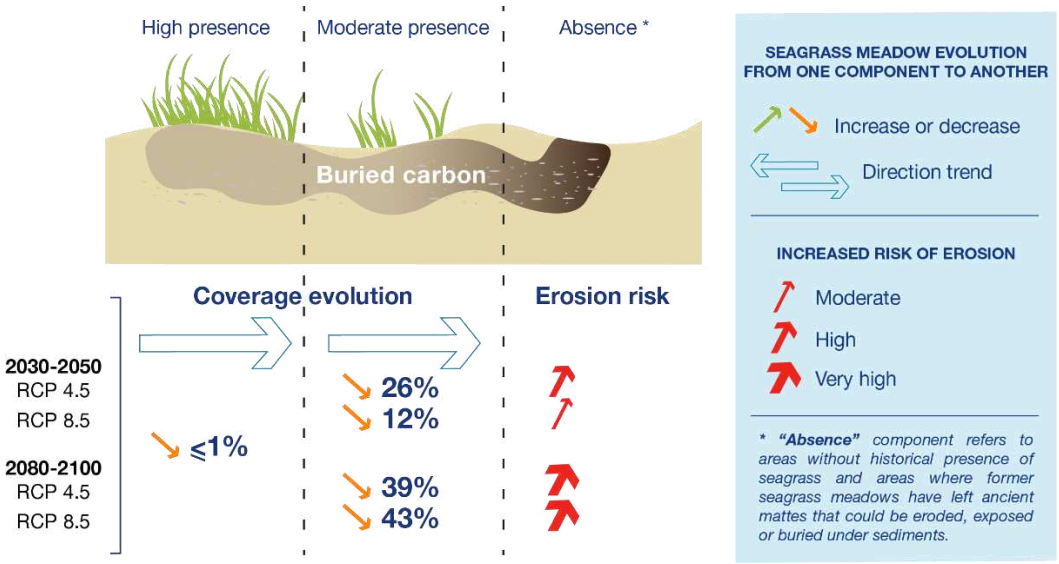


FIGURE 8: SEAGRASS MEADOW EVOLUTION AND EROSION RISK

To mitigate these risks, implementing Nature-Based Solutions and restoration efforts is crucial. For instance, (Calvo et al., 2021) highlight the potential of seagrass restoration on dead matte, emphasizing the restoration of these critical ecosystems to enhance their resilience and carbon sequestration capabilities. Furthermore, integrating a blue carbon strategy is essential for preserving and enhancing the carbon sequestration potential of seagrass ecosystems (Fakhraee et al., 2023). This strategy should encompass protection measures for existing seagrass meadows, active restoration projects, and policies to reduce the pressures leading to seagrass degradation. By incorporating blue carbon strategies into broader climate and environmental policies, the natural carbon sequestration capacity of seagrass meadows can be leveraged, thereby contributing significantly to global climate change mitigation efforts.

Supplementary material SM1: List of considered indicators and related yearly-based metrics included in the model to represent pressures and MCEs state.

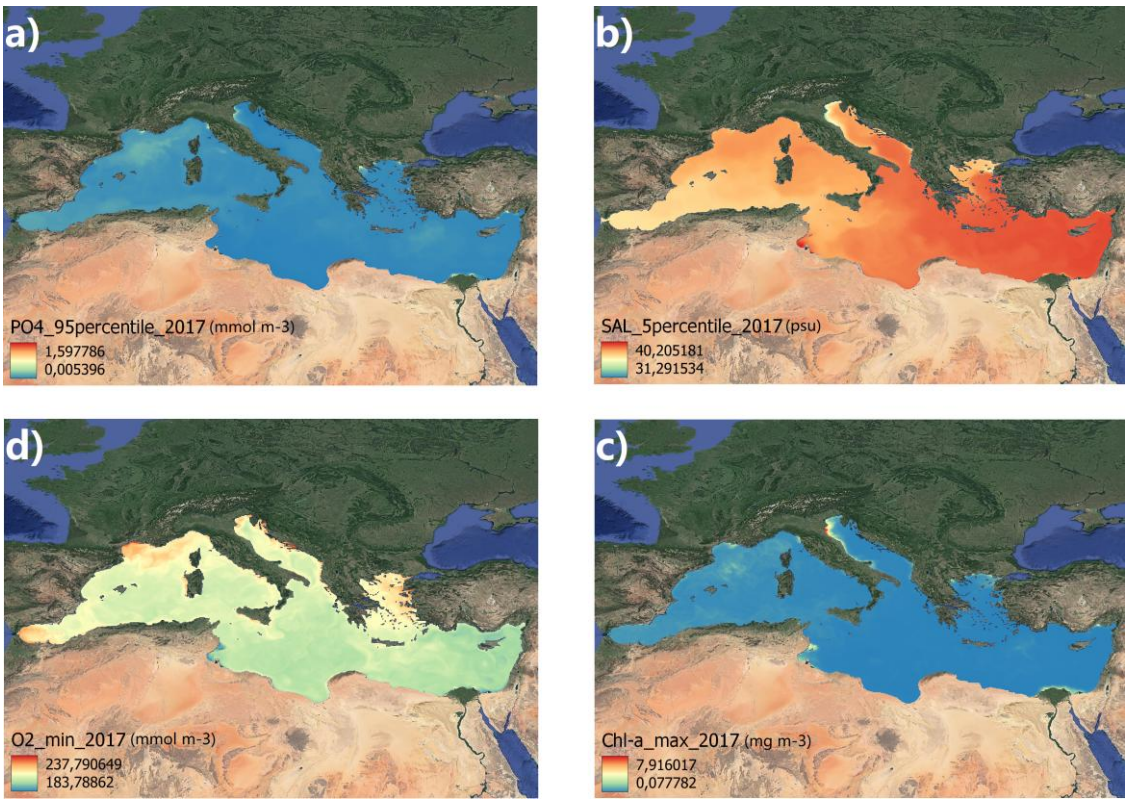
	Indicator	Metrics
RF TOP LAYER - MODEL PREDICTORS		
Endogenic pressures	Seagrass distance from port	Derived from the source
	Seagrass distance from shore	Derived from the source
	Seagrass distance from the nearest river mouth	Calculated through haversine distance
	Seagrass distance to cities	Calculated through haversine distance
	NH_4	NH_4 min
		NH_4 5percentile
		NH_4 95percentile
	NO_3	NO_3 min
		NO_3 5percentile
		NO_3 95percentile
	PO_4	PO_4 min
		PO_4 5percentile
		PO_4 95percentile
	O_2	O_2 min
		O_2 5percentile
	Chl-a	Chl-a max
		Chl-a 90percentile
	Secchi depth (ZSD)	ZSD min
		ZSD 5percentile
	Light attenuation	KD490 min
		KD490 5percentile
	Shipping traffic (Density)	yearly mean vessel density
Exogenic pressures	Sea surface temperature	SST 95percentile
		SST standard deviation
		number_MHW
		Importance_MHW (duration and intensity)
	pH	pH min
		pH mean
		pH max
	Salinity	SAL min
		SAL standard deviation
		SAL 5percentile
	Max Significant Wave Height	SWH max
	Eastward Sea Water Velocity (uo)	uo yearly mean
		uo max
	Northward Sea Water Velocity (vo)	vo mean
		vo max
	Kinetic energy at the seabed due to currents	Ke 90th percentile

	Sea level rise (Sea surface height)	SSH mean
RF BOTTOM LAYER - MODEL RESPONSES		
MCE condition	Areal extent/surface	Percentage of presence

Supplementary material SM2: Procedure carried out to calculate and map yearly-based metrics linked to the selected model predictors and responses.

Model predictors

As regards the model predictors (i.e., the exogenic and endogenic pressures), metrics were calculated using Python codes. In particular, each NetCDF file, as collected from different open-source portals, making available data of the selected indicators, was processed through the *xarray* library[4] allowing the manipulation of the data and calculation of aggregated metrics. Some examples of the resulting output from this process (i.e., spatial maps in the form of raster files) are displayed in Supplementary Figure S9.

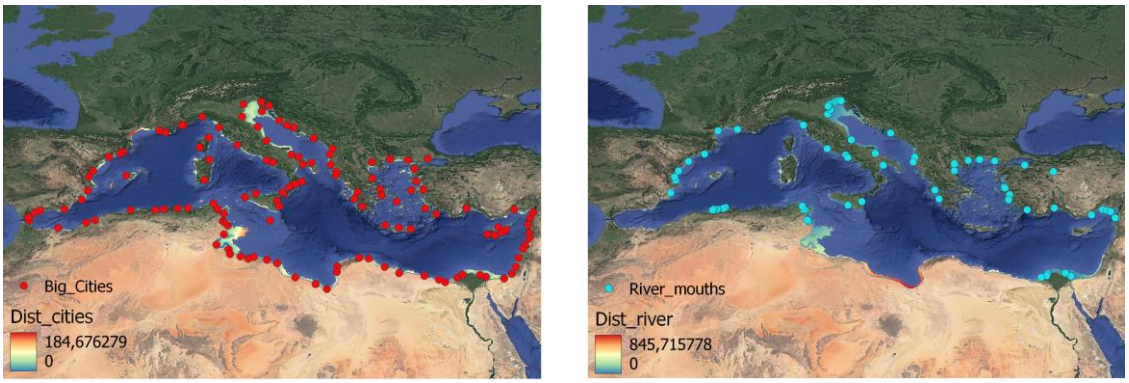


SUPPLEMENTARY FIGURE S9: MAPS REPRESENTING SOME OF THE PRESSURES-RELATED MAPS CALCULATED FOR THE MEDITERRANEAN ECO-REGION. A) 95° PERCENTILE OF PHOSPHORUS; B) 5° PERCENTILE OF SALINITY; C) MINIMUM OF DISSOLVED OXYGEN; D) MAXIMUM OF CHLOROPHYLL-A

As far as pressures related to coastal development are concerned, the distance of seagrasses meadows to the closest major river mouths and urban areas was calculated by applying the Haversine distance formula,

[4] https://xarray.pydata.org/en/stable/index.html

implemented in Python by means of the following libraries: *geopandas*[5], *geocube*[6], *rasterio*[7] and *xarray*[8]. The resulting maps from these calculations are reported in Supplementary Figure S10.



SUPPLEMENTARY FIGURE S10: PLOTS OF THE DISTANCE FROM BIG CITIES (LEFT PANEL) AND DISTANCE FROM RIVER MOUTHS (RIGHT PANEL).

At this stage, looking at the overall dataset, the selected variables were characterized by different spatial resolutions. To deal with this issue, it was decided to homogenize them to the same resolution by rescaling all input to 4 km spatial resolution (i.e., to the most common one among the input variables). This process allowed us to perform some statistical analysis (e.g., correlation, distribution) among these variables.

Model responses

Once the overall process of predictive variables' calculation was completed, similar procedures were carried out for the response variable. Focusing on marine coastal ecosystem condition variables, as far as seagrasses' distribution is concerned, by applying the *QGIS*[9] zonal statistics[10] plugin, the percentage of seagrasses' coverage within each 4km pixel of the case study was calculated.

Supplementary material SM3: Available GIS-based dataset for the application of the multi-risk approach in the Mediterranean Sea eco-region

	Indicator	Unit of measure	Data format	Spatial resolution	Temporal resolution	Sources
Basic information	Bathymetry	[m]	Raster file	800 meters	Static	EMODnet
	Administrative boundaries					
PRESSURES' DATA						
Endogenic pressures	Seagrass distance from port	[km]	Raster file	/	Static	Global Fishing Watch

[5] https://geopandas.org/en/stable/
[6] https://corteva.github.io/geocube/stable/
[7] https://rasterio.readthedocs.io/en/latest/
[8] https://xarray.pydata.org/en/stable/index.html
[9] (https://qgis.org/en/site/)
[10] (https://docs.qgis.org/2.18/en/docs/user_manual/plugins/plugins_zonal_statistics.html)

	Seagrass distance from shore	[km]	Raster file	/	Static	
	Seagrass distance from the nearest river mouth	[km]	Raster file	/	Static	Calculated from HydroSHEDS hydrography dataset
	Seagrass distance to cities	[km]	Raster file	/	Static	Calculated from Copernicus
	NH_4	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	CMEMS
	NO_3	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	
	PO_4	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	
	Dissolved oxygen (O_2)	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	
	Chl-a	[mg m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	
	Secchi depth (ZSD)	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	CMEMS
	Light attenuation	[mmol m-3]	NetCDF	0.042degree x 0.042degree	Daily-mean	
	Shipping traffic (Density)	[hours km-2 year-1]	GeoTIFF	1 km x 1 km	Monthly	EMODnet
Exogenic pressures	Sea surface temperature	[Kelvin]	NetCDF	0.05 degree x 0.05 degree	Daily-mean	CMEMS
	Ocean acidification	[pH]	NetCDF	0.042 degree x 0.042 degree	Daily-mean	CMEMS
	Salinity	[PSU]	NetCDF	0.042 degree x 0.042 degree	Daily-mean	CMEMS
	Spectral significant wave height	[m]	NetCDF	0.042 degree x 0.042 degree	Hourly-instantaneous	CMEMS
	Wind wave period	[s]	NetCDF	0.042 degree x 0.042 degree	Hourly-instantaneous	CMEMS
	Spectral significant wind wave height	[m]	NetCDF	0.042 degree x 0.042 degree	Hourly-instantaneous	
	Eastward Sea Water Velocity	[m s-1]	NetCDF	0.042 degree x 0.042 degree	Daily-mean	CMEMS
	Northward Sea Water Velocity	[m s-1]	NetCDF	0.042 degree x 0.042 degree	Daily-mean	
	Kinetic energy at the seabed due to currents	[N m-2]	Raster file	1/24 degree horizontal resolution	Monthly mean	EMODnet Seabed Habitats

	Sea level rise (Sea surface height)	[m]	NetCDF	0.042 degree x 0.042 degree	Daily-mean	CMEMS
ECOSYSTEM DATA						
Marine coastal ecosystem condition	Seagrass distribution	[poligon occurance]	ESRI Shapefile	\	Static	UNEP WCMC global distribution seagrass
			ESRI Shapefile	\	Static	EMODnet Seabed Habitats

Supplementary material SM4: Model training

In this application, the standard 10-fold cross-validation was applied to search for the best parameters, identify the most relevant predictor variables and validate the model. Once the best hyperparameters were selected, the feature selection process was performed. This process identified 19 most relevant model predictors explaining the larger proportion of the overall model capability to predict the Mediterranean Sea condition, discarding 9 variables from the initial 28 (10 yearly-based metrics were removed by the correlation analysis due to their high correlation with other metrics).

Supplementary material SM5: Performance evaluation of model prediction

Finally, to get more insight into model performance, in addition to accuracy, precision and recall, also the F1 score was examined, as most of the response variables have an unbalanced distribution of classes. Model accuracy returns the number of classifications the model correctly predicts divided by the total number of predictions made. Mathematically, model **accuracy** is expressed as follows:

$$Accuracy = \frac{TP + TN}{(TP + FP + TN + FN)}$$

Where TP stands for "True Positives," FP for "False Positives," TN for (True Negatives) and FN for (False negatives). Recall (also known as sensitivity) highlights the number of members of a class that the classifier identified correctly, divided by the total number of members in that specific class. Mathematically, model **recall** is defined as follows:

$$Recall = \frac{TP}{TP + FN}$$

On the other hand, model **precision** (also called positive predictive value) is the ratio between the True Positives and all the Positives. Mathematically, it is defined as follows:

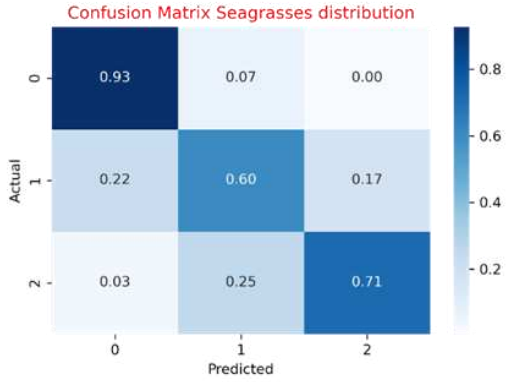
$$Precision = \frac{TP}{TP + FP}$$

Finally, the **F1 score** has been also calculated. This score is the weighted average of Precision and Recall, providing a way to express both concerns with a single score. As a consequence, this evaluation metric takes both false positives and false negatives into account. F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Mathematically, the F1 score is defined as follows

$$F1_Score = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

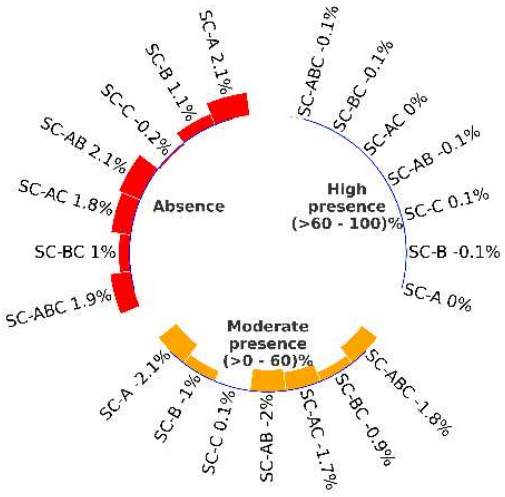
Supplementary material SM5: Model performances

	Seagrass distribution		
	Precision	Recall	F1
Class 1	0.98	0.92	0.95
Class 2	0.31	0.60	0.41
Class 3	0.81	0.71	0.76

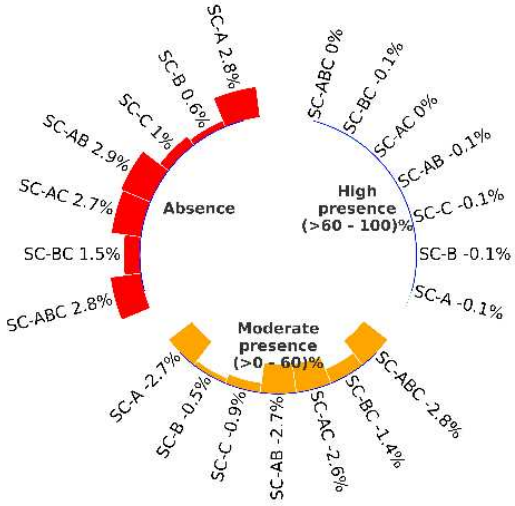


Supplementary material SM6: Circular bar plot and spatial representation of the anomalies between reference (1998-2017) and future scenarios for seagrass distribution under RCP4.5. The tested scenarios include: i) individual scenarios (SC-A: SST, SC-B: SAL and SC-C: SSH); ii) coupled scenarios (i.e., SC-AB: SST+SAL, SC-AC: SST+SSH and SC-BC: SAL+SSH); iii) all available scenarios together (i.e., SC-ABC: SST+SAL+SSH)

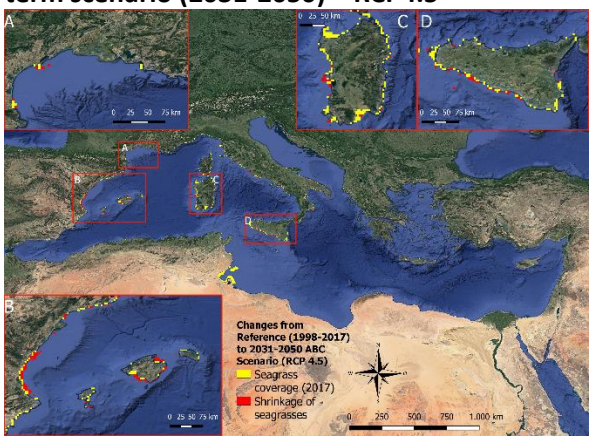
a) 2031-2050 – RCP4.5



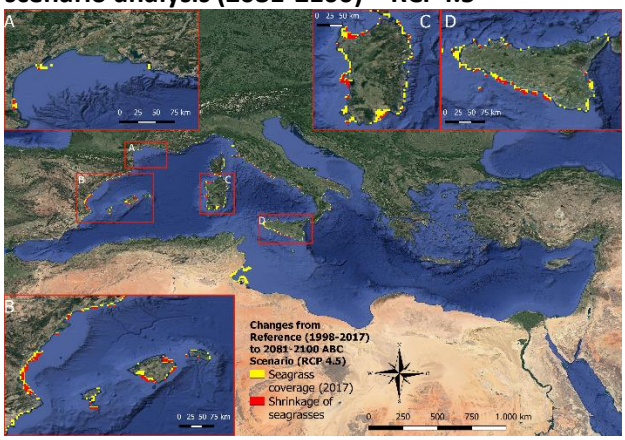
b) 2081-2100 – RCP4.5



c) Seagrass meadows shrinkage under the mid-term scenario (2031-2050) – RCP4.5



d) Seagrass meadows shrinkage under the long-term scenario analysis (2081-2100) – RCP4.5



SECTION C:

THIRD PAPER

Harnessing machine learning for transformative adaptation planning: modelling the risk of cumulative impacts on seagrasses across time and space

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ABSTRACT

Globally, MCEs play a critical role in supporting overall ecological well-being and human health. Yet, their ecological integrity is facing escalating threats stemming from multiple risks induced by the complex interplay between endogenic (e.g. coastal development, shipping traffic) and exogenic (e.g., increasing sea temperature, shoreline degradation) pressures. Evaluating the risk of cumulative impacts arising from these interactions presents a significant hurdle in meeting Sustainable Development Goals and biodiversity objectives while also impeding the implementation of ecosystem-based management strategies in marine coastal regions. To this aim, a risk-based modelling framework, operationalized by two ML models applied to a spatio-temporal dataset, was developed following most of the Digital Twin of the Ocean (DTO) implementation phases, a cutting-edge digital representation that mirrors the real ocean environment. The Digital Twin is essentially an interactive and dynamic replica of ocean systems, utilizing vast amounts of data from satellites, marine sensors, and advanced modelling. By integrating artificial intelligence and ML, this Digital Twin can simulate the behaviour and interactions of marine ecosystems in real time. Hence, the developed application aims to support a better understanding of the processes and dynamics underpinning spatio-temporal variations of the health status of the investigated ecosystem (i.e., seagrass beds) against selected key pressures in the Apulia region (Italy) case study.

In this application, two ML algorithms, an RF and an Extreme Gradient Boosting (XGB), were trained, validated, and tested exploiting a diverse array of data sources, including open-source data platforms (e.g., Copernicus Services) and remote sensing-based data. Remote sensing played a pivotal role in getting high-resolution spatio-temporal distribution maps of seagrass meadows within the 2014-2021 timeframe. In

particular, the analysis relied on imagery from the Landsat satellite constellation (i.e., Landsat 8), enabling the delineation and monitoring of seagrass habitats' spatial and temporal dynamics and, in turn, capturing how seagrass beds have responded to environmental or anthropogenic factors over the selected timeframe. Finally, a future scenario analysis was performed by integrating projections from climate numerical models for sea surface temperature, salinity, sea level rise, and some biogeochemical variables under the 2050 timeframe into the validated RF and XGB models. The results and the overall workflow presented help identify future trends (the models predict a reduction of the seagrass coverage across the different scenarios) relevant to designing effective conservation measures and highlight the importance of addressing critical data quality gaps to improve ML model predictive performance.

The manuscript is planned for submission to a high-impact, Q1 peer-reviewed journal in the first semester of 2025.

1. Introduction

MCEs are among the most productive yet vulnerable interfaces on the planet, creating a hub of capital of ecological services that bolster human well-being and biodiversity (IPCC, 2023a). These dynamic systems are critical for numerous species, including humanity, providing essential services ranging from carbon sequestration to serving as nurseries for marine life (Saraswathi et al., 2023). However, the increasing pressures from human activities and climate change (WMO, 2023) pose unprecedented threats to these fragile habitats. The intricate interplay between endogenic stressors, such as coastal development and shipping traffic, and exogenic forces, like increasing sea surface temperatures and ocean acidification, is leading to a cumulative impact that threatens the MCEs' spatial distribution, ecological integrity, and functioning.

The complexity of the risks posed by the synergistic effects of multiple stressors presents a significant challenge in implementing effective ecosystem-based management strategies. In this context, intense research started focusing on Cumulative (or combined) Impact/Effect Assessment (hereafter jointly referred to as CIA) on MCEs (Furlan et al., 2020; Halpern et al., 2008; Simeoni et al., 2023). CIA are methodical procedures that attempt to identify, evaluate, and predict the significance of multiple impacts on a specified target. Recent ML-based CIA studies have assessed interaction types between stressors in marine ecosystems; however, they have only looked at specific stressor pairs (Simeoni et al., 2024; Teichert et al., 2016). Moreover, indicator/index-based methods and more advanced data-driven approaches usually assess the overall cumulative impact, focusing only on a specific snapshot in time. Hence, by looking at many stressor combinations and considering the temporal component (this can be achieved by filling the gap in the spatio-temporal data representing marine and coastal environments), new CIA studies are expected to produce more accurate predictions of spatio-temporal variations of the studied targets (e.g., seagrass habitats) in response to cumulative pressures.

Building on the MARITIME modelling framework developed in the previous chapter, this new investigation attempts to improve the abovementioned perspectives by integrating remote sensing and ML techniques (i.e., leveraging diverse data sources). This advanced multi-phase modelling approach enables the analysis and prediction of ecosystem changes, considering data representing historical variations in ecosystems across different areas and under an extended period. By harnessing open-source data platforms such as Copernicus Services, field monitoring campaigns, and particularly, satellite images, the ML-based application provides a more comprehensive understanding of the spatio-temporal distribution of seagrass meadows. Remote sensing technologies are revolutionizing ecological monitoring, providing unprecedented insights into environmental dynamics (especially used to quantify the health and density of vegetation using the normalized difference vegetation index or to assess land-cover changes). In recent studies, satellite imageries started to be processed to extract MCEs extent (including seagrass distribution), offering critical data for coastal ecosystem management (Tamondong et al., 2021; Traganos et al., 2018, 2022; Trinh & Takeuchi, 2020). Among the different constellations, Landsat[11] provides a wealth of data for monitoring land use, vegetation health, and environmental changes on a global scale. In this study, the Landsat 8 satellite has been instrumental in delineating and monitoring the seagrass' spatio-temporal dynamics (extracting different maps of the meadows distribution), supporting the assessment of the seagrass' responses to environmental and anthropogenic pressures over the 2014-2021 timeframe. Drawing on this, the main aim of this new MARITIME study is to integrate this temporal component in the assessment, deepening the understanding of the spatio-temporal variations of MCEs, with a focus on the seagrass ecosystem in the Apulia region (southern Italy). As previously performed at the eco-regional level, also this local-scale risk assessment has been operationalized by RF and XGB algorithms: algorithms selected for their ability to manage complex spatio-temporal datasets. This makes them invaluable tools that can be employed to predict environmental

[11] https://landsat.gsfc.nasa.gov/

conditions or analyse the impact of various natural and human-related stressors on environmental distribution (e.g., predict the future ecosystems' presence/absence). For instance, they can be used to forecast/project air and water quality levels based on meteorological data and emissions or to classify land cover types from satellite imagery (X. Wang et al., 2019; Zennaro et al., 2024). Recently, RF has been tested to explore the complex structure of non-linear inter-relations between multiple stressors and the ecological response of biological systems to these stressors (Simeoni et al., 2023; A. Stock et al., 2018a; Teichert et al., 2016). In this study, it is applied in two subsequent phases: first, as a classifier to process Landsat 8 images and discriminate the seabed cover among sand, seagrass, and deep waters. This processing task produced eight GIS-based maps representing the annual seagrass distribution in the Apulia region from 2014 to 2021. These maps serve as input for operationalising the MARITIME model, which uses a variation of the classical RF and Gradient Boosting (GB) algorithms, respectively the BRF and XGB, specifically designed to address the class imbalance problem. By leveraging remote sensing and ML, the presented methodology incorporates most of the operational phases of a DTO and aims to contribute to its development at broader scales, such as the European DTO. Furthermore, the scenario analysis in the local scale assessment extends the experiment presented in Chapter 2 by integrating not only projections from climate numerical models for SST, SAL and SSH but assessing also the impact of future variations in Dissolved Oxygen (DO/O_2), pH, NO_3 and PO_4 for 2043-2050 timeframe. These projections are crucial for understanding the potential future conditions/health status of the ecosystem under investigation and for planning adaptive management strategies that consider projected future climate change forcings.

Following a brief introduction to the case study area (Section 2), the paper describes the operative phases adopted (highlighting the related data acquisition and their processing) for the CIA (Section 3), as well as the main results of the trained, validated, and tested model under the reference and future scenario analysis (Section 4). The final discussion (Section 5) and conclusions report relevant challenges and propose research pathways for further improvements.

2. Unravelling the Apulian and coastal landscape

The Apulia region is the most south-eastern one (between 41°53'N - 39°48'N and 14°49'E - 18°35'E), occupying the 'heel' of the 'boot' of Italy. This region is renowned not only for its rich cultural heritage but also for its diverse and valuable MCEs (ISPRA, 2022[12]). With its longest coastline in the Italian peninsula (a region with more than 800 km coastline), the Apulia region borders the Adriatic Sea to the East, the Ionian Sea to the South-East, and the Strait of Otranto and the Gulf of Taranto to the South (Figure 11).

The climate is typically Mediterranean, with hot, dry, and sunny summers and mild, wet winters (Lionello et al., 2012). This climate fosters a diverse array of flora and fauna, including endemic species adapted to the coastal environment (Mannino et al., 2017). The marine environment is rich in life, with seagrass meadows and coral reefs supporting a rich diversity of fish, crustaceans, and marine invertebrates (Balestri et al., 2021). Additionally, the coastal waters are frequented by marine mammals such as sea turtles (https://mysea.it/), adding to the area's ecological significance (Cirelli et al., 2018).

[12] https://www.isprambiente.gov.it/files2023/pubblicazioni/stato-ambiente/ambiente-in-italia-annuario-2022.pdf

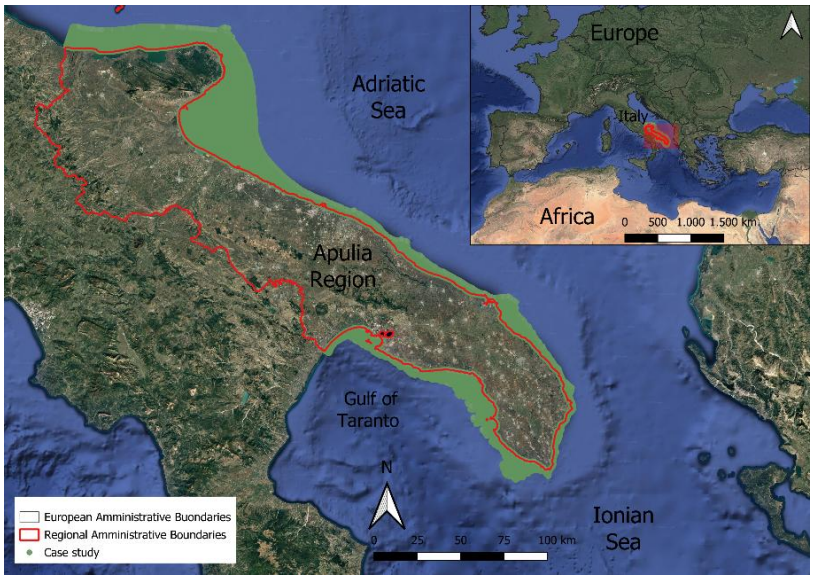


FIGURE 11: THE APULIAN CASE STUDY AREA

Focusing on seagrass meadows, this ecosystem is among the most productive and ecologically significant MCEs, playing a crucial role in marine biodiversity, carbon sequestration, and coastal protection (UNEP, 2020a). These submerged flowering plants provide habitat for a wide range of marine species, supporting both local fisheries and broader marine food webs (Ramesh et al., 2019). Seagrasses also contribute significantly to carbon storage, playing a key role in mitigating climate change by sequestering large amounts of carbon in coastal sediments (Mazarrasa et al., 2018). Despite their importance, seagrass meadows are under significant threat. Anthropogenic activities such as coastal development, pollution, and nutrient runoff have led to widespread degradation (Trégarot et al., 2024). In this context, climate change exacerbates these issues through rising water temperatures and sea levels, which negatively impact seagrass health (Simeoni et al., 2024). Eutrophication, driven by nutrient inputs, further promotes harmful algal blooms, which block sunlight and cause oxygen depletion, leading to seagrass loss (Mcleod et al., 2011). Conservation and restoration efforts are critical, as studies show that restored seagrass meadows can regain their carbon sequestration capacity, supporting global climate mitigation strategies. In the Apulia Region, seagrass and other ecosystems are protected through a variety of designations and regulatory frameworks aimed at preserving biodiversity and promoting sustainable use. Notably, the region is home to two national parks, the Alta Murgia National Park and Gargano National Park, and hosts 2 of the 29 Marine Protected Areas (MPAs) of Italy, the MPA of Torre Guaceto[13] and the MPA of Porto Cesareo[14]. The marine conservation framework is further strengthened by Sites of Community Importance (SICs) and Special Protection Areas (ZPSs) (Council Directive 92/43/EEC and Directive 2009/147/EC). Marine SICs in Apulia include important habitats such as Posidonia oceanica meadows. Notable marine SICs in Apulia are the "Secche della Meloria" and the "Fondali tra Punta Penna e Punta Aderci," which support diverse marine life and unique underwater landscapes. Meanwhile, Apulia's ZPS areas, such as the "Saline di Margherita di Savoia," provide critical habitats for numerous bird species, including flamingos, herons, and various shorebirds. These areas often overlap with SICs, creating a comprehensive protection framework for both avian and other forms of biodiversity (Nature 2000).

[13] https://www.rac-spa.org/node/890
[14] https://www.mite.gov.it/pagina/aree-marine-istituite

3. Data and methods

To support a local-scale assessment and improve understanding of the processes driving spatio-temporal variations in the studied ecosystem (i.e., seagrass beds) within the Apulia case study (Italy), a multi-phase modelling framework was developed and applied. This framework is divided into three consequent phases, which are detailed in sections 3.1 to 3.3, where the first phase, described in **Section 3.1: Data Collection**, focuses on gathering datasets from diverse sources such as satellite imageries, Copernicus, and EMODnet, covering 2014–2021 reference period. Once the data is collected, it undergoes preprocessing to prepare it for modelling (**Section 3.2: Data Preprocessing**). This phase includes two key parallel steps: the computation of yearly-based metrics of key pressures (Phase 2A) acting on the seagrass ecosystems and the processing of satellite images to extract relevant information on seagrass distribution (Phase 2B) using Google Earth Engine. This ensures the datasets are standardized and ready for the subsequent phase, which involves the implementation of the BRF and XGB models (**Section 3.3: BRF & XGB training, validation, and testing**). This step follows a typical ML workflow, including data partitioning, training, validation, and testing, to ensure robust and accurate predictions. Once the trained model achieves satisfying performance in the testing phase, it can be used to assess the impact of future environmental and climatic conditions on the seagrass habitats present in the case study area (**Section 3.4: Scenario analysis**).

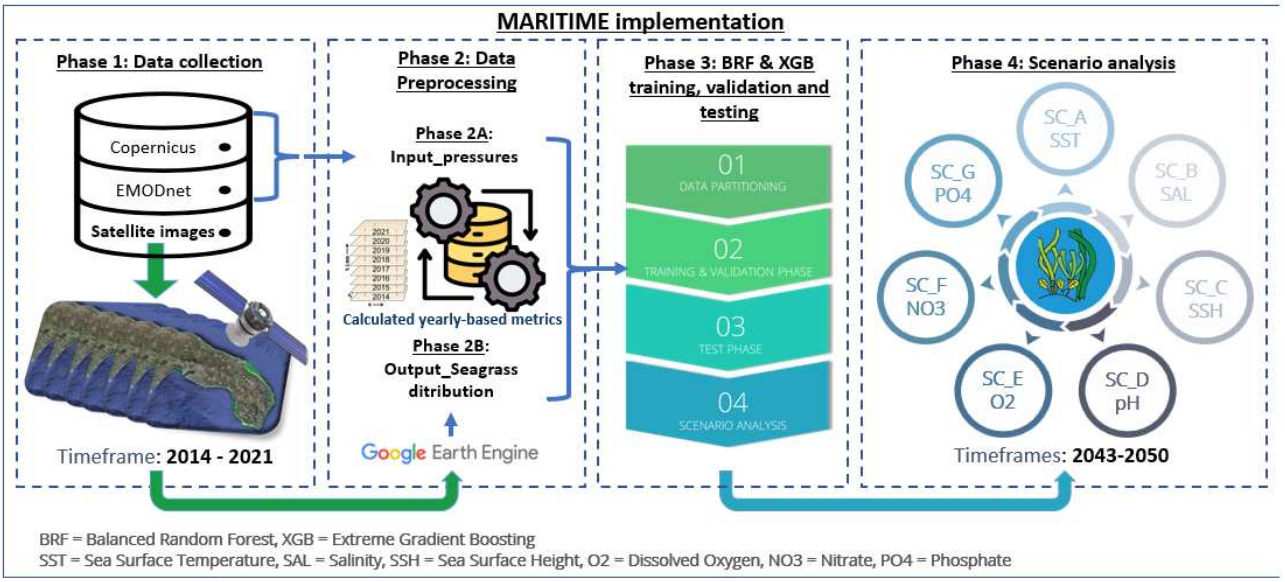


FIGURE 12: OPERATIVE STEPS UNDERPINNING THE RISK-BASED CIA MODELLING FRAMEWORK DESIGNED FOR THE APULIA CASE STUDY.

As illustrated in Figure 12, each phase builds upon the previous one, creating a continuous framework for understanding and predicting the dynamics of the analysed ecosystem under varying environmental pressures. Further details on the methods and results are provided in their respective sections.

3.1 Phase 1: Data collection

The implementation of the modelling framework begins with the dataset collection and its integration into the MARITIME. By combining open-source datasets, such as Copernicus Services, and satellite data, the amount of data available for the ML algorithms increases, henceforth, enhancing the predictive capacity of the model. The integration of remote sensing data provides large-scale data (at a regional scale) that bridges critical knowledge gaps left by limited in-situ observations. By enabling continuous assessments of seagrass coverage, this cutting-edge technology helps identify historical trends, quantify spatio-temporal changes, and

improve the understanding of these ecosystems' responses to environmental and human-related stressors, which is vital for their conservation and management.

TABLE 2: AVAILABLE DATASET FOR THE APPLICATION OF THE MARITIME IN THE APULIAN REGION

TIMEFRAME	DATA SOURCE	YEARS	VARIABLES	MODEL/COLLECTION
REFERENCE	CMEMS	2014-2021	Salinity (SAL), Sea Surface Temperature (SST)	MEDSEA_MULTIYEAR_PHY_006_004
			Light attenuation (KD490), Secchi Depth (ZSD)	OCEANCOLOUR_GLO_BGC_L4_MY_009_104
			Sea Surface Height (SSH)	GLOBAL_MULTIYEAR_PHY_001_030
			Chlorophyll-a (CHL), Ammonium (NH_4), Nitrate (NO_3), Phosphate (PO_4), Dissolved Oxygen (O_2), pH	MEDSEA_MULTIYEAR_BGC_006_008
	CLMS	2014-2021	Distance from cities & rivers	Calculated through haversine distance from the CLMS
	UNEP	2017	Seagrass distribution	UNEP-WCMC, Short FT (2021)[15]
	REMOTE SENSING	2014-2021		LANDSAT 8
	MaCoBioS project	2021		FIELD CAMPAIGN
FUTURE	CMCC-MEDCORDEX	2043-2050	SST, SAL, SSH	CMCC Regional Earth System Model (RESM)
	CS3 CLIMATE DATA		O_2, pH, PO_4, NO_3.	POLCOMS

More precisely, for the operationalization of the model, Copernicus data was widely utilized, downloading critical oceanographic variables for the considered timeframe within the Copernicus Marine Service (CMEMS) (Table 2). These variables, such as SST, SSH, and SAL, serve as input data for the ML prediction models, enabling precise analyses of marine conditions' influence on the seagrass ecosystem over the selected case study. Similarly, the distances from the cities and rivers were calculated (using the haversine distance) starting from the land cover products of the Copernicus Land Monitoring Service (CLMS). Moving towards the MARITIME response variable, Landsat 8 (one of the latest satellites in the Landsat series, more details in Section 3.2.2) images were processed to retrieve the distribution of seagrass meadows in the coastal areas of the Apulia region in the 2014–2021 timeframe. As described in Phase 2, open-source data downloaded from UNEP, field observations close to the MPA of Torre Guaceto, and data provided by local stakeholders have been used as auxiliary data for the validation of these remote sensing outputs. Finally, transitioning from the reference period to the future scenarios, projections from regional climate models were integrated into the RF and XGB models. Multi-risk scenarios were developed by combining climate change projections and simulating future conditions of oceanic and biogeochemical parameters under different RCPs (IPCC, 2013). This study focuses on key variables, including SST, SAL, SSH, O_2, pH, PO_4, and NO_3, extracted from numerical models. These projections were extracted from both the stabilization scenario (RCP4.5) and the high-emission "business as usual" scenario (RCP8.5), covering the mid-term (2043-2050) timeframe.

[15] https://data.unep-wcmc.org/datasets/7

3.2 Phase 2: Data pre-processing

3.2.1 Phase 2A: model predictors

All input datasets (i.e., variables representing key endogenic and exogenic pressures) used for the analysis underwent rigorous pre-processing to ensure data quality and consistency. This operative phase involved calculating specific annual metrics for each variable, applying the same metrics defined in Simeoni et al. (2024). These metrics include mean, maximum, minimum, standard deviation, 5^{th} and 95^{th} percentiles, depending on the nature of the variable and its relevance to seagrass dynamics. The full list of indicators and corresponding metrics are reported in Supplementary Material SM1. Additionally, any missing data points were carefully removed. By applying the same pre-processing steps across all eight years of baseline data, the input dataset was consistently structured, reducing the risk of bias and enhancing the robustness of the analysis. This consistency was particularly important for capturing spatio-temporal patterns, as it ensured that variations in the data reflected real environmental changes rather than inconsistencies in data preparation. The pre-processed datasets were then spatially aligned to a common grid (100 m grid), allowing for uniform integration and analysis within the ML framework. In the scenario analysis, all metrics of each variable are consistent with those calculated during the training phase for the reference period (2014-2021). These projections ensure a comprehensive understanding of the future physical and biogeochemical dynamics of the case study area under different climate scenarios (Section 4.3).

3.2.2 Phase 2B: model response

On the other side, the response variable of the MARITIME framework was retrieved by processing satellite images. In particular, in this study, the overall remote sensing-based data collection process leverages the Landsat Program, as the first one among the series of Earth-observing satellite missions jointly managed by NASA and the U.S. Geological Survey (USGS), along with high-performance cloud computing, supervised ML, web-based visualization tools, and the human-driven creation of extensive training datasets for validating the ML results. All these elements are supported by the cloud infrastructure provided by Google Earth Engine[16] (Figure 13). Landsat 8[17] is equipped with the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), capturing data across nine spectral bands. These bands range from visible to shortwave infrared regions, with a spatial resolution of 30 meters for multispectral and 15 meters for panchromatic bands. The consistent availability of Landsat 8 imagery allowed for creating a comprehensive time-series dataset, making it possible to track temporal variations in seagrass distribution across multiple years, thereby enabling a detailed analysis of changes over time induced by multiple interacting pressures.

An RF algorithm was employed to classify the multi-annual Landasat-8 mosaic at 30 m resolution (Breiman, 2001). The focus was on building a classifier with three classes: a) sandy seabeds, b) seagrasses, and c) optically deep water. Expert photointerpretation of satellite images was used to label polygons representative of each class.

Afterwards, open-source data (UNEP), field observations, data provided by local stakeholders (such as the Apulian Regional Agency for Environmental Prevention and Protection – ARPAP and the Torre Guaceto Management Consortium) and Interreg-med EU projects (e.g., AMARE[18] project), and results presented by Traganos et al. (2022) were used to validate the RF outputs. Finally, the distribution of seagrass beds between 2014 and 2021 throughout the first 25 m of depth (as performed in Poursanidis et al. (2019); Traganos et al.

[16] https://earthengine.google.com/
[17] https://www.usgs.gov/landsat-missions/landsat-8
[18] https://amare.interreg-med.eu/

(2022)) was extracted and exported in raster files. This depth range was extracted using the EMODnet Bathymetry Digital Terrain Model (DTM)[19] for the European Seas of 2018.

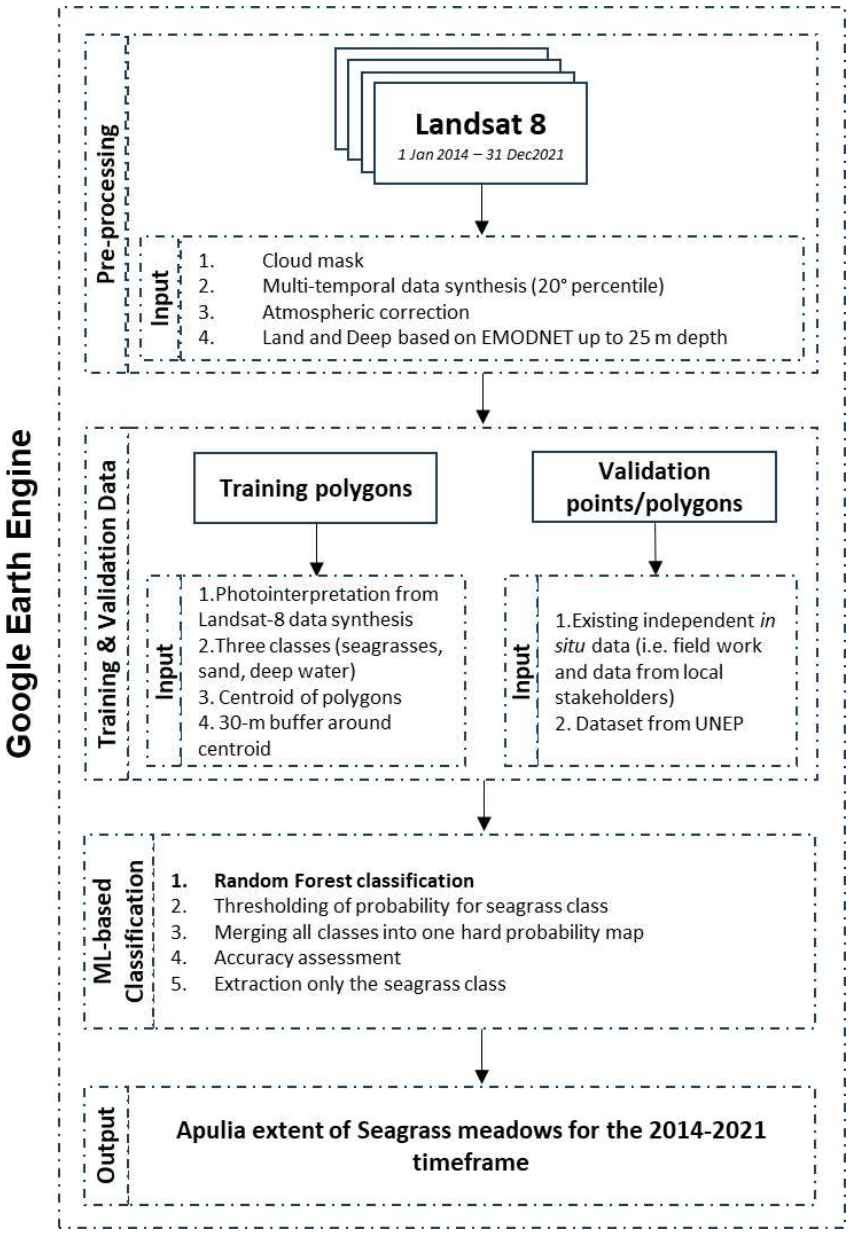


FIGURE 13: SCHEMATIC WORKFLOW ADAPTED FROM TRAGANOS ET AL. (2022)

The final output of this phase is a series of raster files generated for each of the eight years analyzed, where each pixel was classified as either 0 (absence) or 1 (presence), indicating the distribution of seagrass beds at 30 spatial resolutions. This binary classification provides a clear representation of seagrass presence for the whole selected reference period.

[19] https://www.emodnet.eu/newhigh-resolution-digital-terrain-model

3.3 Phase 3: Machine Learning models for modelling the risk of cumulative impacts

Building upon the methodology developed and detailed in Simeoni et al. (2024), this study evaluates the scalability of the MARITIME modelling framework at a local scale. The focus is on testing its applicability at different spatial and temporal scales (ranging from a snapshot in time at an eco-regional scale to multiyear analysis at the local scale), assessing its capacity to provide robust insights into cumulative impacts and ecosystem dynamics across broader or more localized regions. To achieve this, two different ML algorithms, RF and XGB were employed to test this modelling framework in the Apulian case study.

More specifically, by building on the decision trees, RF enhances the predictive performance by creating an ensemble of multiple trees, where each tree relies on a random selection of data variables. While a single decision tree can provide clear and interpretable results, RF improves robustness and reduces overfitting by combining the outputs of numerous trees, each trained on a subset of data. This algorithm is a powerful ML technique for classification and regression problems within supervised learning (AhmedK et al., 2013). RFs are computationally appealing because they are relatively fast to train and predict, require minimal tuning, and handle high-dimensional data effectively (Zhang & Ma, 2012). They also offer additional advantages, such as measuring variable importance (i.e., helping identify the most relevant stressors), handling differential class weights, spatially representing the outputs, and imputing missing values.

On the other hand, GB is an ensemble learning method that combines multiple weak learners to improve overall performance, reduce errors, and enhance predictive accuracy. As a supervised ML algorithm, it builds models sequentially, with each new model correcting the errors of the previous ones. This is achieved by fitting decision trees to the residuals (errors) of the previous models, and optimizing performance through gradient descent. The final prediction is obtained by combining the outputs of all models, resulting in a strong ensemble that reduces bias and variance.

Hence, both algorithms are ensemble learning methods based on decision trees, but they differ in their approach. RF constructs multiple decision trees independently and aggregates their predictions through bagging (it involves training multiple models independently on random subsets of the data, and aggregating their predictions through voting or averaging), which helps reduce variance and enhance model stability. In contrast, GB builds trees sequentially, where each new tree corrects the errors of the previous ones using boosting techniques, leading to a more refined predictive model.

RF is designed to lower variance by averaging multiple decision trees, making it a robust method that effectively prevents overfitting. However, this often comes at the cost of slightly lower predictive accuracy. On the other side, GB, by focusing on minimizing residual errors in a sequential manner, can achieve superior predictive performance. Nevertheless, it is more susceptible to overfitting if not properly regularized or tuned. Computational efficiency is another key distinction between the two methods. Since RF grow trees independently, it is highly computationally efficient, making it well-suited for large datasets as in this assessment. In contrast, GB, due to its sequential nature, requires more computational resources and is typically slower, particularly when training on big data. In this context, XGB, a more advanced and optimized version of GB, addresses this issue by using an exact greedy algorithm and histogram-based splits for faster computations. These optimizations make XGB significantly more efficient than standard GB (similar to RF as will be described in Section 4.2) while maintaining or even improving predictive accuracy. Drawing on this potential, the XGB library [20]has been used for computation.

[20] https://xgboost.readthedocs.io/en/stable/

3.3.1 Operationalizing the modelling framework – RF & XGB training, validation & testing

The final model operationalization process was divided into three key sub-phases: training, validation, and testing. In the initial training and validation phases, the RF and XGB models were fine-tuned to optimize their performance by adjusting hyperparameters, ensuring they could generalize well across different data subsets. During the training phase, the RF and XGB models were trained on 70% of the total dataset previously pre-processed. Hyperparameter tuning was conducted to optimize key parameters such as the number of trees, maximum tree depth, and minimum samples required for a split. After completing these training and validation phases, the performance of the designed BRF and XGB models can be evaluated using the remaining testing dataset, which in this study represents 30% of the total data. To gain deeper insights into the models' effectiveness, different performance metrics such as accuracy, precision, recall, F1-score and ROC/AUC were examined (Supplementary Materia SM2).

3.4 Phase 4: Scenario analysis

Once the RF and XGB are trained, validated, and tested, they can be used for scenario analysis. Building upon the methodology outlined and applied in Simeoni et al. (2024), this phase involves the development and analysis of various multi-risk scenarios (RCP4.5 and RCP8.5 under the 2050 timeframe) based on different climate projections obtained from numerical models, to assess the impacts of environmental changes on the studied ecosystem. Variations in seagrass distribution were evaluated across 7 different climate change scenarios: SC_A: SST, SC_B: SAL, SC_C: SSH, SC_D: pH, SC_E: O_2, SC: F: NO_3, SC_G: PO_4. This approach enables the assessment of the potential future seagrass expansion or shrinkage associated with variations of singular stressors.

4. Results

4.1 Phase 1-2: Remote sensing outputs

The resulting outputs of the applied methodological remote sensing workflow are presented in Figure 14 through GIS-based maps and a statistical breakdown of the results within the processed period. More precisely, the graph illustrates the distribution of seagrasses across different years from 2014 to 2021, expressed in terms of the number of pixels classified as seagrass. The general trend shows a slight increase in seagrass coverage in the processed period, rising from approximately 200-250 km² in the first three years to about 350 km² in the following years, resulting in an overall increase of about 100-150 km². These results reflect changes in environmental conditions, anthropogenic pressures, or potential methodological factors influencing classification accuracy. In particular, a notable peak was observed in 2019, where the number of seagrass pixels exceeded 600,000, corresponding to a total area of approximately 550 km², significantly higher compared to other years. This could indicate an actual environmental phenomenon, a data artefact, or other influencing factors. Since the analysis relies on multi-temporal Landsat 8 data, the spike could be partially influenced by differences in data quality, cloud cover reduction, or improved data availability for that year. To minimize this influence and reduce related uncertainties, the RF-based classification was exported as a probability-based output, and only predictions with a probability exceeding 60% were considered valid. This threshold ensured higher confidence in the identified areas, thereby reducing noise and false positives.

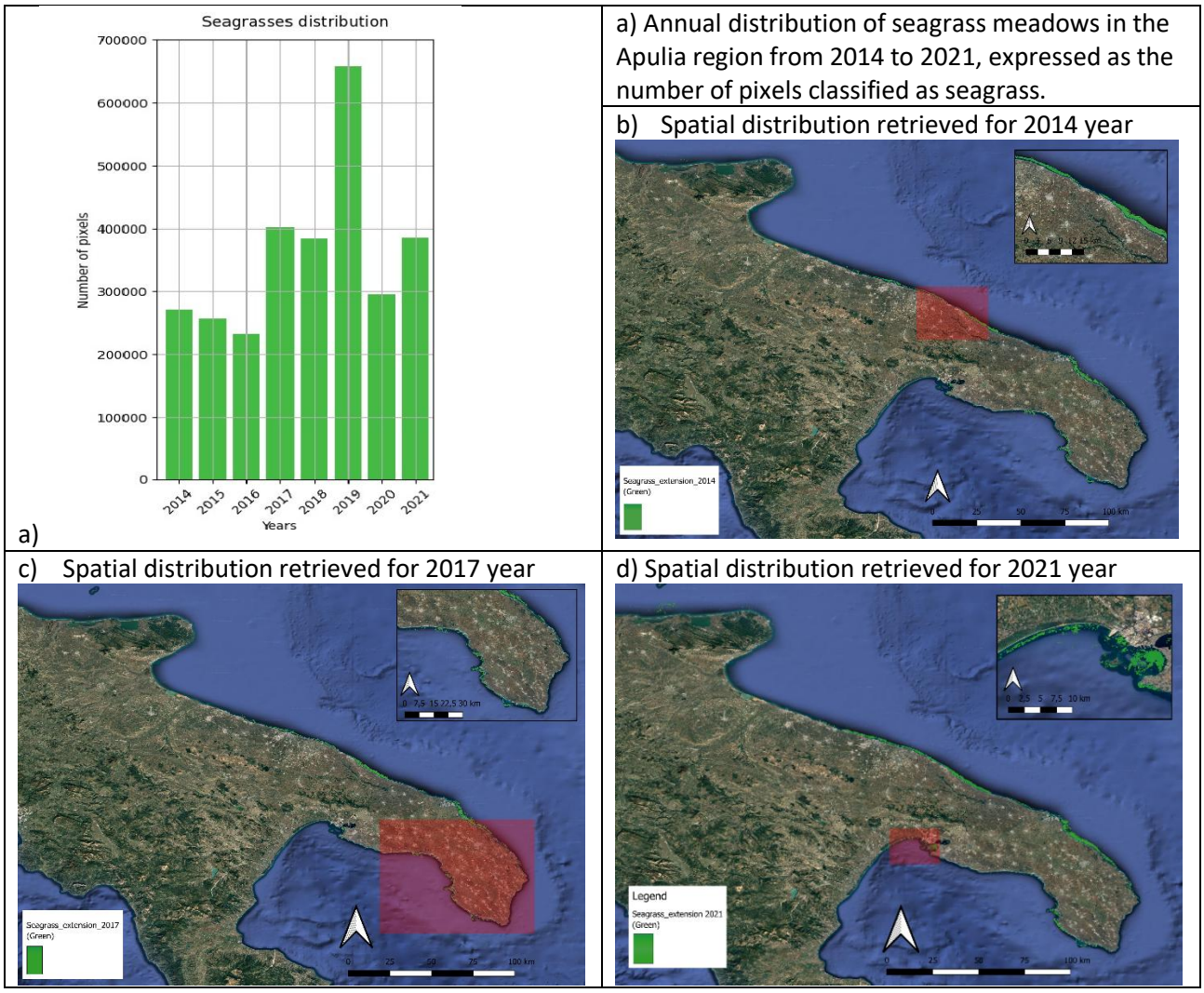


FIGURE 14: (A) ANNUAL DISTRIBUTION OF SEAGRASS MEADOWS IN THE APULIA REGION FROM 2014 TO 2021, EXPRESSED AS THE NUMBER OF PIXELS CLASSIFIED AS SEAGRASS. *(B, C, D)* SPATIAL DISTRIBUTION MAPS FOR THE YEARS 2014, 2017, AND 2021, HIGHLIGHT THE TEMPORAL EVOLUTION OF SEAGRASS COVERAGE IN THE APULIA REGION.

The final probability maps illustrate the spatial extent of seagrass meadows located in regions of shallow water (0-25 meters of depth) (Figure 14b-d), providing additional insights into the seagrass dynamics in this area (maps at higher sizes and resolutions are provided in the Supplementary Material SM3). In 2014 (Figure 14b), seagrass coverage appeared limited, particularly in coastal zones around the Gargano and the Gulf of Taranto. The overall spatial distribution among the different years appears quite homogeneous, with a slight recovery in coverage progressing from 2014 to 2017 and 2021 (Figure 14d), potentially reflecting improved environmental conditions or localized restoration efforts. Notably, in line with other studies, Landsat data predict a minimal presence of seagrass meadows in the northernmost area around Gargano throughout the entire timeframe (2014–2021). In Traganos et al. (2022), no seagrass meadows are detected in this specific area, as that study focuses exclusively on *Posidonia oceanica*. However, the observation obtained from the RF classifications aligns with UNEP data, which report the presence of seagrass meadows dominated by *Cymodocea nodosa* in this area. This suggests that the absence of detected meadows in Traganos et al. (2022) may be due to the exclusion of Cymodocea nodosa from their analysis rather than an actual lack of seagrass. Validation against available independent datasets demonstrated the reliability of this approach, especially in localized areas, such as the MPA of Torre Guaceto, where high-quality in-situ data was available for this task.

4.2 Phase 3: Performances comparison of BRF and XBG in the validation phase

The comparison of model performance began with the implementations of the traditional RF and GB (Figure 15). Both models performed well in terms of accuracy, with RF slightly outperforming GB across all the other metrics. Precisely, RF demonstrated superior precision (i.e., it is better at minimizing false positives), higher recall (highlighting its strength in identifying positive cases), as well a higher F1 score, reflecting a better overall balance between the two. Additionally, RF outperformed GB in ROC-AUC, showcasing a stronger ability to distinguish between the positive and negative classes across various thresholds. Thus, RF emerged as the stronger model in this setup, particularly in scenarios requiring balanced performance and high precision.

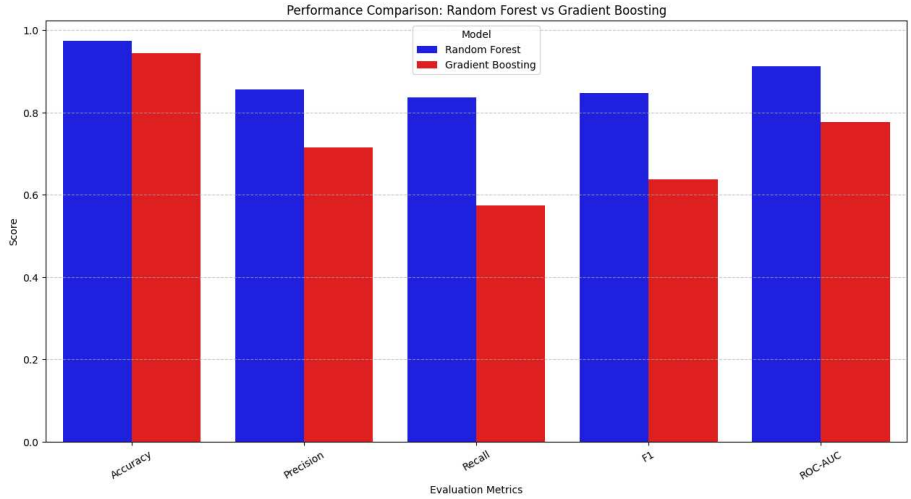


FIGURE 15: PERFORMANCE COMPARISON OF RANDOM FOREST AND GRADIENT BOOSTING MODELS

Afterwards, the models were adapted to handle class imbalance (and their performance shifted due to changes in how the algorithms weigh different classes during training) as in this study, approximately 90% of observations fell under the "seagrass absence" class, while only ~10% belonged to the "seagrass presence" class. Such imbalances can lead to biased predictions in scenario analysis, as standard models tend to prioritize the majority class, resulting in a strong underestimation of seagrass presence across different configurations. To mitigate this issue, a specialized version of the RF, the BRF, was employed. This algorithm, implemented through the *imbalanced-learn* Python library (Lemaître et al., 2017), enhances the standard RF by applying a class-balancing strategy during training. In a conventional RF, each tree is trained on a bootstrap sample that often mirrors the original class distribution, reinforcing the existing imbalance. Conversely, BRF modifies this approach by ensuring that each tree is trained on an equal number of instances from both classes, thereby improving sensitivity to the minority class while maintaining the strengths of traditional RF. This method reduces the bias towards the majority class, leading to a more accurate classification of environmental conditions.

As result, BRF applies class weighting to ensure that minority-class instances (1 – the presence of seagrass beds) have a stronger influence during training. This allows BRF to maintain high accuracy and precision, demonstrating its robustness in addressing majority-class dominance while minimizing false positives (Figure 16). On the other hand, Imbalanced Handling GB, which typically incorporates techniques such as weight adjustments or specialized loss functions, showed a significant improvement in recall. This suggests that while BRF effectively balances accuracy and precision, Imbalanced Handling GB enhances the detection of the minority class, making it particularly useful for identifying seagrass presence in highly imbalanced scenarios. Despite this, BRF achieved a higher F1 score, indicating a better balance between precision and recall. Interestingly, the ROC-AUC values of both models are comparable, suggesting that both perform well in distinguishing between classes overall.

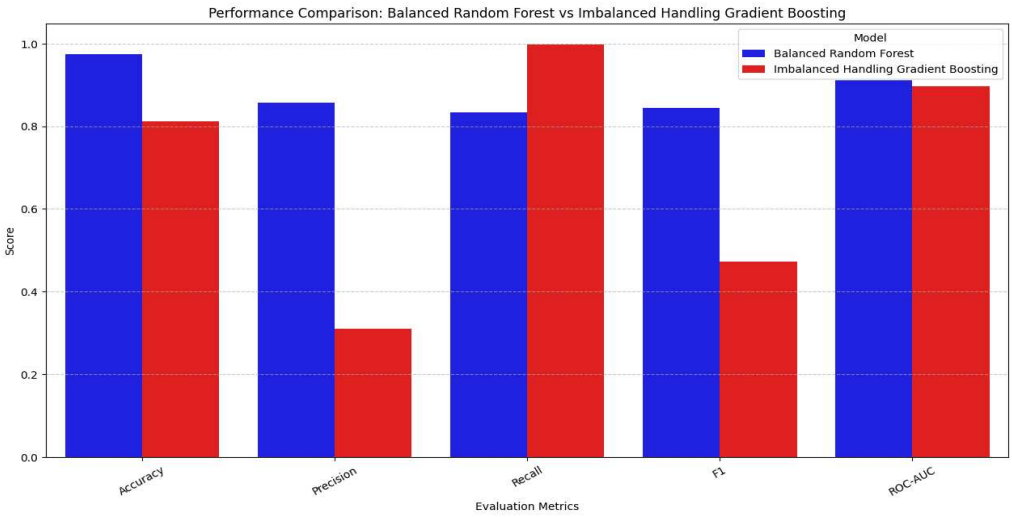


FIGURE 16: PERFORMANCE COMPARISON OF BALANCED RANDOM FOREST AND IMBALANCED HANDLING GRADIENT BOOSTING

Finally, the two models were compared in terms of computational efficiency (Figure 17). Such a comparison of training times between XGB and RF revealed a significant computational advantage for XGB. More specifically, as the number of estimators increases (from 100 to 500), the training time normally grew for both models, but RF experienced an exponential increase, reaching thousands of seconds, while XGB remained within a much lower range. This highlights a major computational burden for RF, making it less practical for large-scale applications. However, while RF may exhibit slightly better performance in certain cases, XGB outperforms in terms of computational efficiency. Unlike RF, which trains trees independently, XGB builds trees sequentially, leveraging optimized techniques such as histogram-based splits and parallelized computation. This approach significantly accelerates training, making XGB much faster, especially when handling large datasets.

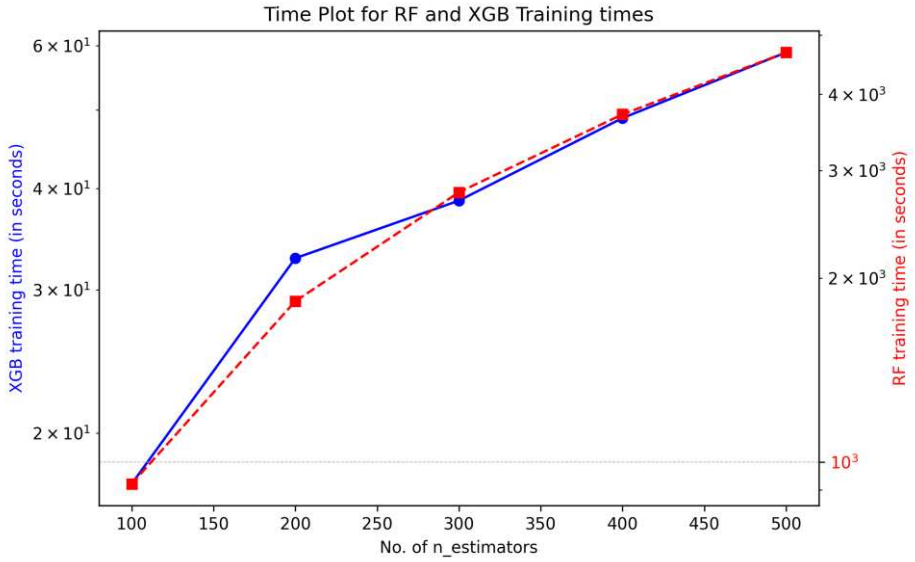


FIGURE 17: TRAINING TIME COMPARISON BETWEEN RF AND XGB MODELS FOR DIFFERENT NUMBERS OF ESTIMATORS. THE RF TRAINING TIME IS SHOWN IN RED (RIGHT AXIS), WHILE THE XGB TRAINING TIME IS SHOWN IN BLUE (LEFT AXIS)

Overall, given these satisfactory results, where the BRF and XGB models have shown reliable capabilities to assess current seagrass distributions under multiple endogenic and exogenic pressures, they could be applied to scenario analyses to predict the impacts of future environmental changes on the investigated ecosystem.

4.3 Phase 4: Will Apulian seagrasses withstand future environmental changes?

The results of the scenario analysis were obtained by calculating the mean probability to estimate the percentage of seagrass presence in each of the tested scenarios (i.e., SC_A, SC_B, etc). In particular, rather than relying on a standard percentage calculation based on pixel classification, a probabilistic approach was adopted due to the intrinsic nature of the RF and XGB models. These ML models generate predictions with varying degrees of uncertainty; therefore, the probabilistic values of each class were averaged to derive a mean probability score. This methodology provides a more robust assessment of model confidence, ensuring a more reliable estimation of seagrass presence or absence under future environmental conditions.

Looking at the predicted distributions, as displayed in Figure 18 and in Supplementary Material SM4, overall, the ML models predict a slight decline in seagrass presence in 2050 for both RCP 4.5 and RCP 8.5 compared to the last available historical year (2021). This suggests that near-future projected environmental changes investigated by testing the variation of physical and biogeochemical WQ parameters may negatively affect seagrass distribution in the studied area. The similarities in projections across both scenarios could be attributed to the relatively small differences in the key environmental metrics between RCP 4.5 and RCP 8.5 before mid-century. Notably, the divergence between these scenarios becomes more pronounced after 2050, as highlighted by IPCC (2021).

In particular, consistent with the findings reviewed by Trégarot et al. (2024), global warming (represented with the SST variable), sea level rise and salinity changes, are predicted to exert a negative impact on seagrass distribution, with a reduction around 1-2% of the total area retrieved in 2021. Sea level rise (SC_C), on the other hand, alters light availability, and, as also observed in Pergent et al. (2015) & Simeoni et al. (2024), the potential reduction can be associated to a reduction in light penetration to the seabed which can in turn diminish photosynthetic activity of the meadows, ultimately leading to increased mortality, particularly at the deeper edges of meadows. Moving towards SC_D, as ocean acidification progresses (i.e., decreasing pH), the models predict a contraction of this ecosystem, likely driven by physiological stress that could affect seagrass resilience and overall condition. Finally, among the 7 scenarios presented, nutrient enrichment emerged as among the key drivers of seagrass decline. Model predictions indicate that projected NO_3 and PO_4 variations could result in a loss of approximately 3% of the total Apulia seagrass distribution in 2050 compared to 2021. This finding underscores the importance of managing eutrophication and maintaining the good environmental status (as required by the EU Marine Strategy Framework Directive), to mitigate further degradation of these critical marine habitats.

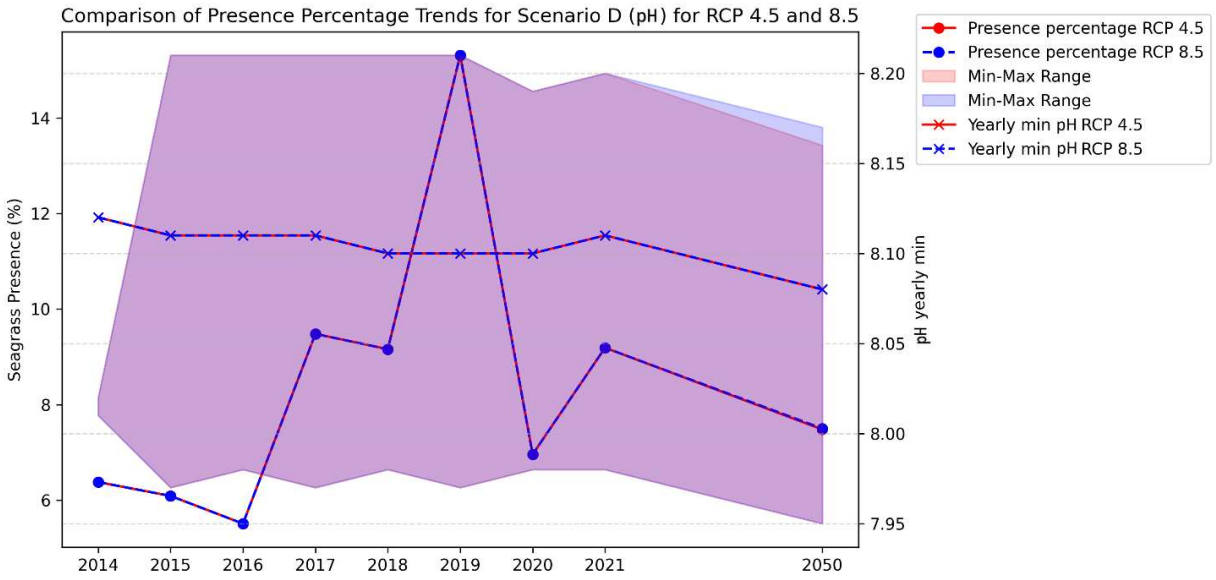


FIGURE 18: SEAGRASS PRESENCE (%) UNDER FUTURE PH VARIATIONS – RCP4.5 & RCP8.5

4.3.1 Performance comparison of BRF and XBG in the prediction phase

In the scenario analysis, the performance and efficiency of the XGB and RF models were evaluated under different conditions, focusing on the predicted presence/absence of seagrass beds and the computational prediction times. The plot comparing predicted presence percentages under SC_C (SSH variations) under both RCP 4.5 and 8.5 highlights some differences between the two ML models (Figure 19). The scenarios developed with the XGB algorithm, both for RCP4.5 and RCP8.5, maintain relatively stable predicted presence values around 8.40 to 8.43%, showing only a slight decrease as the number of estimators increases. In contrast, the RF algorithm predicted lower percentages, with RCP4.5 and RCP8.5 producing values below 8.20%. The scenarios under the RF model exhibited a small initial increase in presence prediction before declining as the number of estimators grew. Overall, XGB consistently predicted higher "presence" percentages than RF, with only a slight gap between the two RCP scenarios.

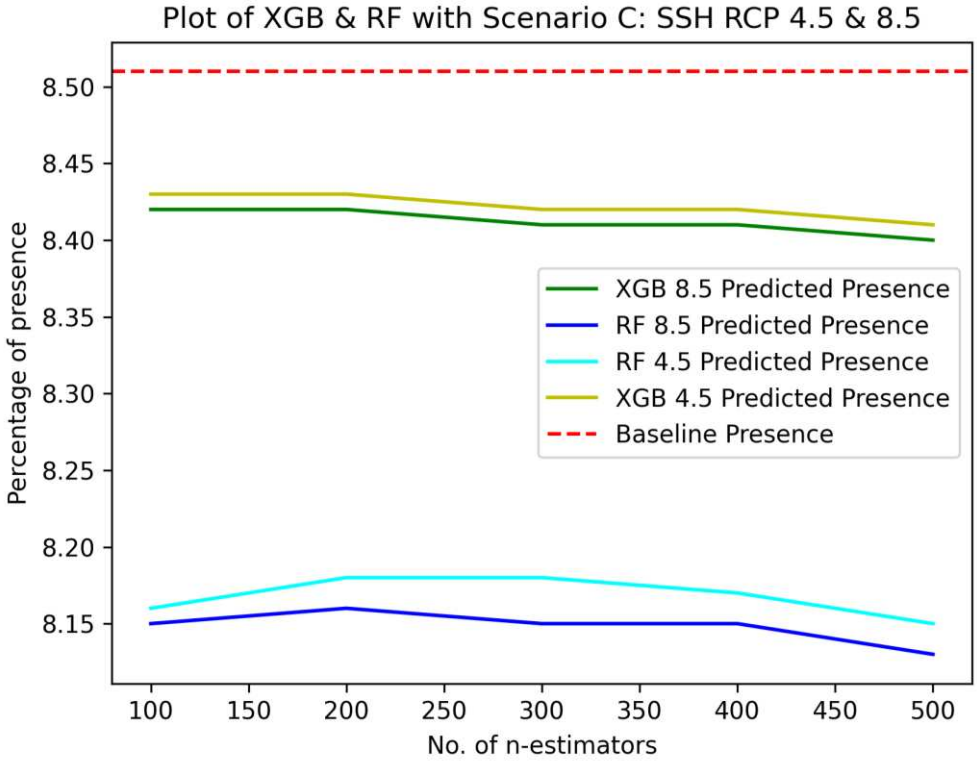


FIGURE 19: COMPARISON OF PREDICTED SEAGRASS PRESENCE PERCENTAGES USING XGB AND RF MODELS UNDER SCENARIO C: SSH UNDER BOTH RCP 4.5 & 8.5 SCENARIOS.

Instead, when analyzing the efficiency of the two models (Figure 20), the prediction times followed a similar trend to those observed during the training phase (Figure 17). While both models experienced increasing prediction time as the number of estimators grew, RF consistently required more time than XGB. This further reinforces XGB's advantage in computational efficiency, ensuring faster inference while maintaining strong predictive performance. Overall, in real-world applications such as climate risk assessment, where both speed and accuracy are critical, XGB provides a more scalable and efficient solution, making it a strong candidate for large-scale environmental modelling.

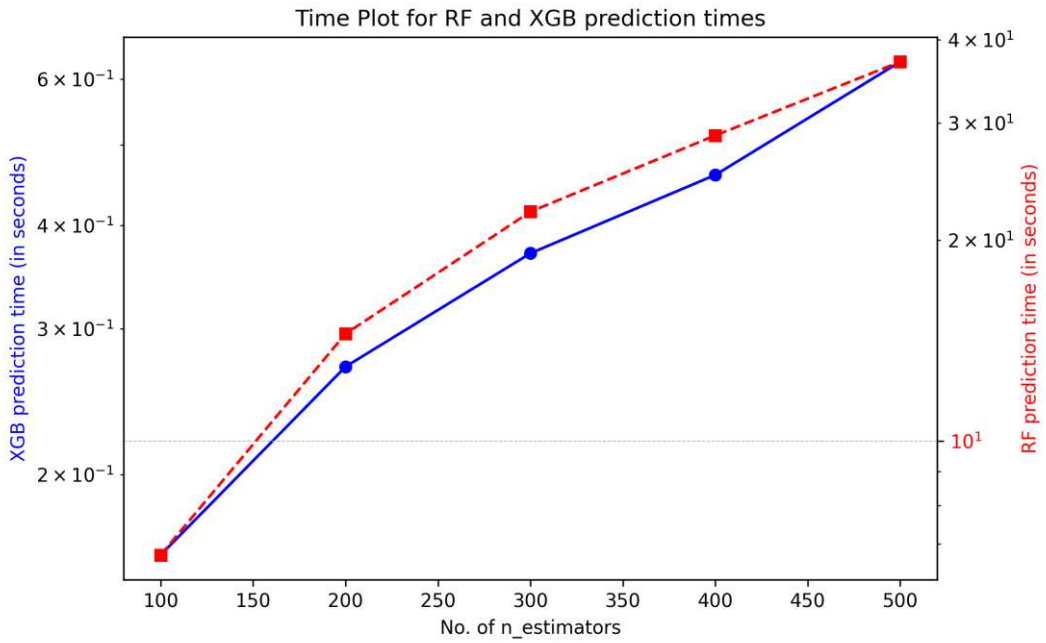


FIGURE 20: PREDICTION TIME COMPARISON BETWEEN RF AND XGM MODELS FOR DIFFERENT NUMBERS OF ESTIMATORS. THE RF PREDICTION TIME IS SHOWN IN RED (RIGHT AXIS), WHILE THE XGB PREDICTION TIME IS SHOWN IN BLUE (LEFT AXIS)

5. Discussion

5.1 Role of remote sensing and unmanned vehicles in CIA applications

Integrating remote sensing and unmanned vehicles is significantly advancing the monitoring and management of different systems, including the coastal and inland aquatic environments. Remote sensing technologies, such as satellite observations, can provide large-scale insights into not only terrestrial phenomena but also oceanic and coastal dynamics, encompassing physical (e.g., SST, ocean currents), chemical (e.g., chlorophyll-a, turbidity levels), and biological (e.g., algal bloom events, habitat distribution) processes. However, their utility is often limited by atmospheric distortions, cloud cover, and difficulties in capturing subsurface data (Aasen et al., 2018). Unmanned vehicles, including autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and unmanned surface vehicles (USVs), can effectively bridge this data gap by enabling high-resolution, real-time data collection even in remote or hazardous environments (Mohsan et al., 2023).

These vehicles, equipped with cutting-edge sensors like multispectral and hyperspectral cameras, LiDAR, thermal imaging systems, and side-scan sonars facilitate detailed exploration and monitoring of tidal and underwater habitats such as mangroves, seagrass meadows and corals. Focusing on seagrass beds, these technologies can enhance the accuracy of mapping this ecosystem by detecting variations in patch distribution and density, especially in lower bathymetric zones (i.e. where accurate mapping using satellite imagery is more difficult). Additionally, 3D seafloor mapping technologies, including laser scanners and multibeam sonars, are revolutionizing the accuracy and detail of underwater surveys (Igbinenikaro et al., 2024). This capability is particularly critical for assessing biodiversity, habitat health, and seafloor topography, providing essential data for calculating ecosystem services such as carbon sequestration, habitat provisioning, and nutrient cycling (Canonico et al., 2019). The mobility and flexibility of unmanned platforms allow for frequent, cost-effective, and minimally invasive surveys, thus enhancing data accuracy while reducing ecological disturbance. Furthermore, integrating unmanned technologies with human divers,

especially in high-value areas like MPAs, can offer highly detailed assessments in shallow water, where specialized divers can capture nuanced ecological data and verify remote observations. This combination can enable comprehensive habitat evaluations, as required by the recent Nature Restoration Regulation (EU, 2024), that are vital for effective management and conservation efforts.

Moreover, integrating unmanned aerial vehicles with surface and underwater platforms, along with satellite data, offers the potential for synergistic, multi-scale monitoring that can be managed through cutting-edge deep learning models (Section 5.2). This integrated approach could not only improve the spatio-temporal resolution of data collection (which is particularly relevant in dynamic coastal and underwater regions (Aasen et al., 2018)) but also provide relevant data to validate predictions derived from satellite imageries. By leveraging the increased volume and accuracy of data from unmanned vehicles, these platforms can support the upscaling of monitoring efforts, enabling the generation of increasingly accurate predictions at regional, national, and even global scales. Therefore, emerging underwater survey technologies, supported by artificial intelligence and ML, have the potential to enhance the overall understanding of underwater environments further. These technologies enable researchers and managers to train CIA models with more precise and high-quality data, leading to more accurate risk assessment predictions and improved evaluations of current and potential future ecosystem services.

5.2 The MARITIME model evolution: future horizons

The current MARITIME modelling framework developed by Simeoni et al. (2024) and tested here at a local scale, provides a solid basis for better understanding and managing MCEs. The transformation from a static model to one that accounts for temporal dynamics represents a major improvement. In particular, the generated multi-annual maps retrieved from remote sensing deeply enrich the training dataset, thereby increasing the model's accuracy and robustness.

However, the model could be further expanded by incorporating multi-ecosystem dynamics and interactions. In the thesis, the MARITIME modelling framework has finally been set up with a focus only on the seagrass ecosystem. However, MCEs are highly interconnected, with processes and species often spanning multiple environments and ecosystems. Therefore, by integrating these multi-ecosystem interactions, the model could offer a more holistic view of local and even regional dynamics.

Moreover, expanding the temporal range of historical data for training, validation, and testing (Section 5.1) would significantly improve the predictive accuracy and precision of the implemented ML-based models. This step is particularly crucial in studies examining the effects of long-term environmental changes, such as climate change impacts, where a broader temporal scope is essential to capture gradual trends, seasonal variabilities, and potential tipping points. A more extended historical/baseline dataset would enable the model to better identify patterns of ecosystem resilience or shifts, providing a more robust framework for predicting future changes under the influence of climatic pressures at different intensities.

Another crucial enhancement is the inclusion of socio-economic factors. Human activities such as fishing, shipping, and coastal development significantly impact MCEs. Hence, incorporating socio-economic indicators such as touristic flows and already implemented regulatory frameworks (e.g., ZPS, SIC, and MPAs) would enable the ML-based model to capture better the complex interplay between ecological health and human activities. This integration would also support scenario planning, allowing the testing of different conservation actions. For instance, by training the model with data on MPAs and the related status of the ecosystem before and after their implementation, the MARITIME modelling framework could even evaluate the potential benefits of establishing new MPAs or expanding existing ones, supporting efforts to achieve the “30x30” conservation target (Dinerstein et al., 2019).

Looking ahead, drawing on the previous section, the growing availability of high-resolution data from diverse sources offers a transformative opportunity. These technologies, equipped with advanced sensors, can provide more detailed data on various ecological parameters, from seafloor mapping to biological productivity. The model could also be expanded to account for the ocean's vertical variability. Many key ecological processes occur across different ocean layers, from the surface to the bottom. A multi-layer approach would improve the representation of vertical interactions, such as nutrient cycling and thermal stratification. Using a graph network structure to incorporate all these diverse datasets and to model several depth layers could facilitate an effective assessment of ecosystem services and the simulation of dynamic connections between different depths, enhancing the understanding of the ocean's ecological and biogeochemical system. Together, these expansions will enable a more accurate, dynamic, and holistic evaluation of the complex inter-relations among climate change- water quality - MCEs and ecosystem services capacity and flow, increasing the MARITIME's capacity to inform sustainable marine management strategies.

5.3 Leveraging Digital Twin technology for CIA of seagrass ecosystem resilience

The model developed aligns with the principles of the DTO (EC, 2022), which combines ocean observations, artificial intelligence, and advanced modelling operating on high-performance computers, allowing for a deeper understanding of ocean dynamics. More precisely, Digital Twin technology involves creating a detailed, dynamic virtual model of a physical entity, which in this case is the seagrass ecosystem. This digital representation mirrors the real-world ecosystem's behaviour, condition, and response to various human-induced pressures and environmental factors in near real time. To enhance its predictive accuracy, it would be important to integrate controlled experimental studies into the DTO alongside physical dynamics. By adding information on how ecosystem health varies under different stressor intensities, such as temperature increase, nutrient enrichment, pollution, and ocean acidification, the DTO can gain deeper information into species-specific adaptive capacities and resilience mechanisms. This integration would support the identification of early warning signals of ecosystem increase/decline and help determine potential tipping points beyond which recovery may become unlikely.

Following the DTO modelling framework, the multi-phase analytical approach presented in this chapter adheres to most of the DTO operational phases: the initial phase focused on data acquisition and collection (Section 3.1), where a variety of data sources were utilized, including open-source data platforms (e.g., Copernicus Services) and remote sensing-based data. Then, following data acquisition, the preparation phase ensured that the collected datasets were retrieved and pre-processed for subsequent ML analyses. The integration of remote sensing in this phase further strengthens the capacity of this modelling methodology to track ecosystem changes. Afterwards, an ML-based modelling framework, operationalized by a BRF and an XGB, was employed to model the data. However, this first release lacks the final development of the Digital Twin visualization interface, which enables interactive representation, visualization, and assessment of cumulative impacts on MCEs.

Hence, the integration of a fully developed DTO interactive visualization interface is a crucial next step for the MARITIME modelling framework to enable users to interact directly with the model. This would allow for real-time scenario analyses, where different stakeholders can input and test different "what-if" scenarios (e.g., reduction or increase of specific human-induced pressures, introduction of new adaptation measures, etc.) and immediately observe the potential benefits or impacts, supporting evidence-based decision-making. Therefore, by making complex data more accessible and understandable, it transforms the MARITIME model from a purely data-centric tool into a comprehensive, actionable platform that can support environmental governance and marine management practices, such as the design and implementation of blue nature-based solutions.

Conclusions

This study attempts to analyse seagrass variations along the Apulia region, exploring the intricate relationships between seagrass spatio-temporal dynamics and the selected endogenic and exogenic factors impacting this ecosystem. To reach this goal, the MARITIME modelling framework presented in Chapter 2 (Simeoni et al., 2024) was adapted and reapplied at a local level with the support of remote sensing technology. The implemented methodological workflow with the integration of remote sensing allowed for regional spatio-temporal mapping of this ecosystem. In particular, by leveraging the Landsat satellite constellation, the methodology employed in this study resulted in a high-resolution delineation of seagrass meadows (i.e., 30 meters of spatial resolution) for the 2014-2021 timeframe, which allowed tracking of their spatio-temporal dynamics. Looking at the whole reference period, the analysis revealed good coverage of seagrass meadows along the Apulia region, except for the Gargano area, where only sparse patches were detected. Overall, a nearly stable trend emerged, with total coverage increasing slightly from 2014 to 2021.

The obtained spatio-temporal dynamics partially addressed critical gaps in the quality of available datasets representing MCEs for the MARITIME model, a longstanding challenge also highlighted in Simeoni et al. (2024). Previously, the training process was constrained to a single snapshot in time due to the limited data available representing seagrass meadows at the eco-regional level. Overall, integrating remote sensing analyses and related outputs within a CIA framework represents a step forward compared to previous approaches. In this context, two ML models, RF and XGB, were trained on diverse datasets, including these remote sensing data, to predict future seagrass distribution changes. The designed scenarios were tested by evaluating climate forcings (sea temperature increase, sea level rise, ocean acidification, salinity and oxygen variation and nutrient enrichment) individually, each contributing to a decline. The most impacting environmental stressor is predicted to cause a potential shrinkage of the seagrass meadows in Apulia by up to 3% in 2050 compared to 2021.

The ongoing increasing availability of datasets with progressively finer spatial and temporal resolutions opens new opportunities for further advancements. A step forward would be retrieving such data for a longer period and at even lower resolutions, extracting additional biophysical parameters of the ecosystem, such as leaf density, canopy height, or biomass, which are essential for accurately estimating the potential ecosystem services that seagrass meadows can provide to human wellbeing. Furthermore, integrating water quality data, such as turbidity, sea temperature, chlorophyll-a concentration, pH, or nutrient levels, at the same resolutions as the seagrass data would provide an even more comprehensive understanding of the direct effects of these factors on ecosystem variations. In parallel, with the increasing availability of these data from numerical models, remote sensing and other vehicles, a further challenging improvement of the proposed modelling framework is the design of more sophisticated ML models capable of efficiently handling large volumes of data with heterogeneous spatio-temporal resolutions. Finally, creating a user-friendly platform for conducting CIAs could significantly increase the accessibility of complex environmental and climatic datasets, usually difficult for stakeholders (such as regional and local decision-makers) to manage. Such a platform would minimize the need for advanced programming skills by automating critical tasks, including data preprocessing and preparation, thereby streamlining workflows and reducing the time required to produce actionable insights. This dual approach, refining models and simplifying workflows, represents a crucial pathway toward more inclusive and efficient tools for marine ecosystem management. From a regulatory perspective, it offers a valuable framework for analyzing complex spatio-temporal dynamics of water quality under varying conditions and timeframes, supporting decision-makers and managers in identifying key drivers of ecosystem deterioration. Moreover, it can support the achievement of EU environmental policies, including the Water Framework and Marine Strategy Framework Directives, the EU Restoration Law (recently adopted as part of the European Green Deal), and the broader Agenda 2030 goals. By integrating advanced modelling and remote sensing, these tools enhance the ability to assess degradation, guide restoration efforts, and ensure more effective, science-driven conservation strategies.

Supplementary material SM1: List of considered indicators and related yearly-based metrics included in the MARITIME model to represent pressures and seagrass state.

	Indicator	Metrics
RF TOP LAYER - MODEL PREDICTORS		
Endogenic pressures	Seagrass distance from the nearest river mouth	Calculated through haversine distance
	Seagrass distance to cities	Calculated through haversine distance
	NH_4	NH_4 min
		NH_4 5percentile
		NH_4 95percentile
	NO_3	NO_3 min
		NO_3 5percentile
		NO_3 95percentile
	PO_4	PO_4 min
		PO_4 5percentile
		PO_4 95percentile
	O_2 Chl-a Secchi depth (ZSD)	O_2 5percentile 90percentile ZSD min
		ZSD 5percentile
	Light attenuation	KD490 min
		KD490 5percentile
Exogenic pressures	Sea surface temperature	SST 95percentile
		SST standard deviation
	pH	pH min
		pH mean
		pH max
	Salinity	SAL min
		SAL standard deviation
		SAL 5percentile
	Sea level rise (Sea surface height)	SSH mean
RF BOTTOM LAYER - MODEL RESPONSES		
MCE condition	Areal extent/surface	Presence/Absence

Supplementary material SM2: classification metrics tested

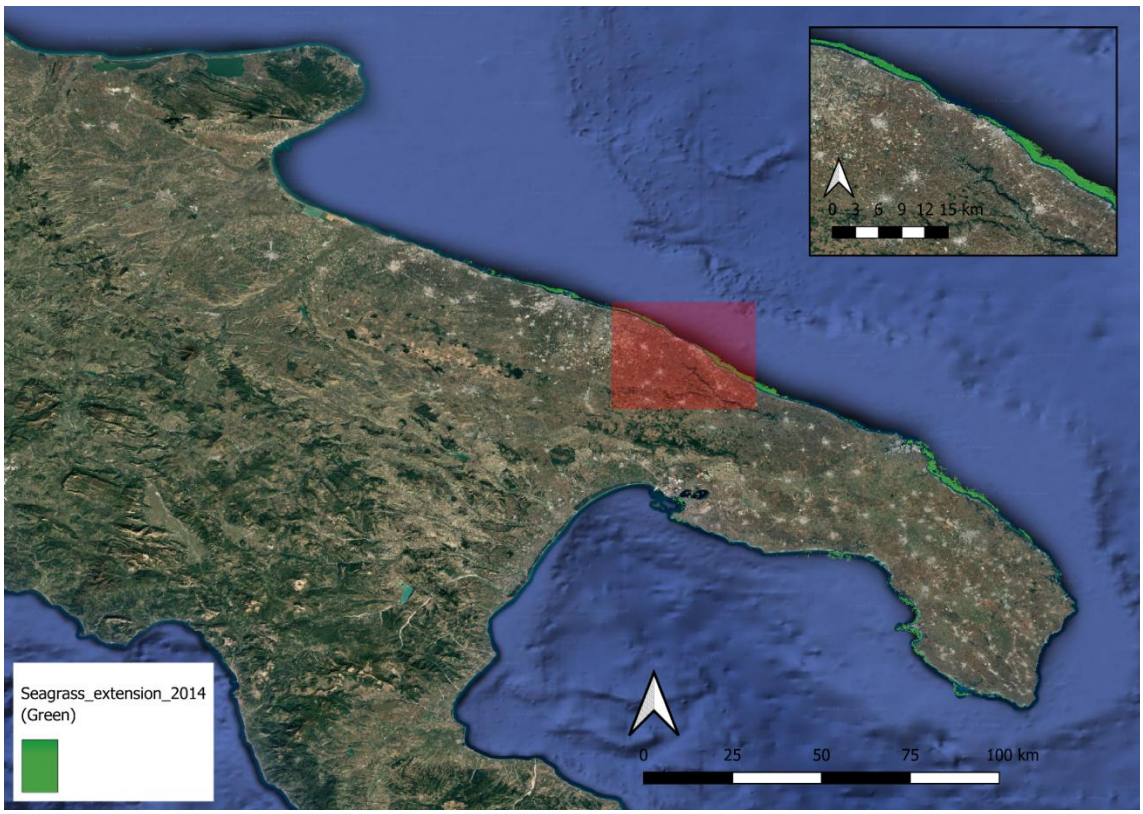
Metric name	Formula	Code
Accuracy	$\frac{TP + TN}{(TP + FP + TN + FN)}$	*sklearn.metrics.accuracy_score()*
Recall	$\frac{TP}{TP + FN}$	*sklearn.metrics.recall_score()*
Precision	$\frac{TP}{TP + FP}$	*sklearn.metrics.precision_score()*
F1-score	$2 * \frac{Precision * Recall}{Precision + Recall}$	*sklearn.metrics.f1_score()*
ROC-AUC	*The area under the ROC curve (plots TPR vs. FPR)*	*sklearn.metrics.roc_auc_score()*

Where TP stands for "True Positives," FP for "False Positives," TN for (True Negatives) and FN for (False negatives). As expressed in the formula, model accuracy measures the proportion of correct predictions made by the model out of all predictions. It is calculated by dividing the number of correct classifications by the total number of predictions. Recall (also known as sensitivity) instead highlights the number of members of a class that the classifier identified correctly, divided by the total number of members in that specific class. On the other hand, model precision (also called positive predictive value) is the ratio between the True Positives and all the Positives, whereas the F1-score represents the harmonic mean of Precision and Recall, providing a single score that balances both concerns.

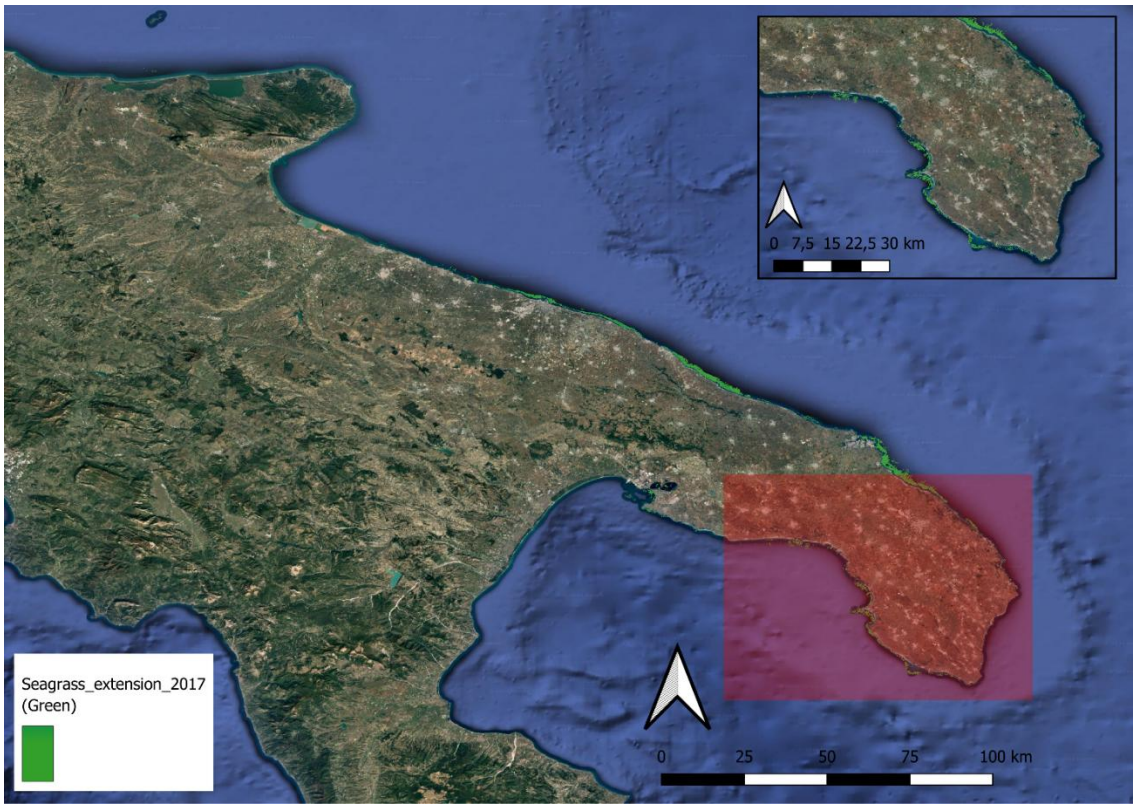
Finally, the ROC (Receiver Operating Characteristic) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different classification thresholds, illustrating how well the two tested models distinguish between classes. The AUC (Area Under the Curve) quantifies this ability, where an AUC of 1.0 represents a perfect model, 0.5 indicates random guessing, and values below 0.5 suggest worse-than-random performance. These metrics were evaluated due to the class imbalance issue, as described in Section 4.2. In this specific case with the dataset highly skewed, accuracy can be misleading. For instance, in a scenario like this application, where approximately 90% of the samples belong to a single class (class 0), a naive model that always predicts the majority class would achieve 90% accuracy while lacking true predictive power. In contrast, ROC/AUC provides a more robust evaluation by measuring the model's ability to distinguish between classes, making it a more reliable metric in such cases. Additionally, ROC/AUC is valuable for assessing the ranking ability of a model, as it evaluates how well the model assigns higher scores to positive instances compared to negative ones, independent of a specific classification threshold.

Supplementary material SM3: Spatial distribution maps for 2014, 2017, and 2021 years

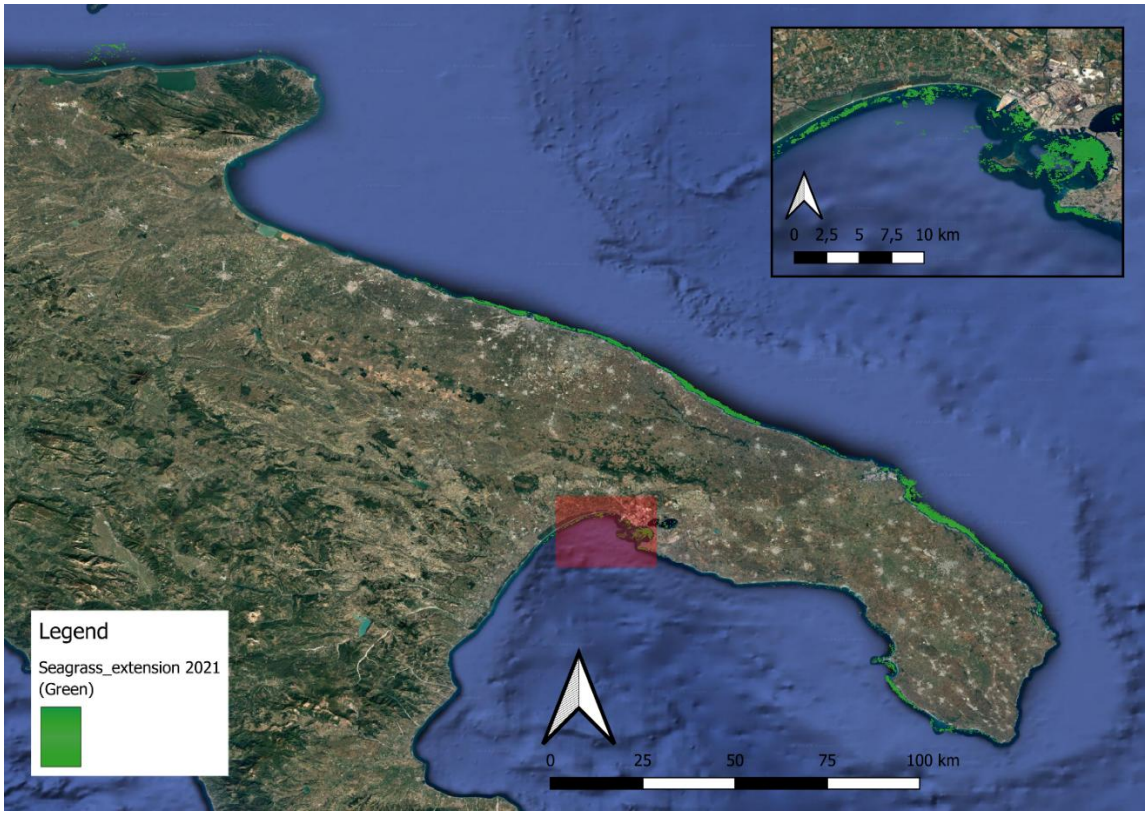
a) Spatial distribution retrieved from Landsat 8 for 2014 year



b) Spatial distribution retrieved from Landsat 8 for 2017 year

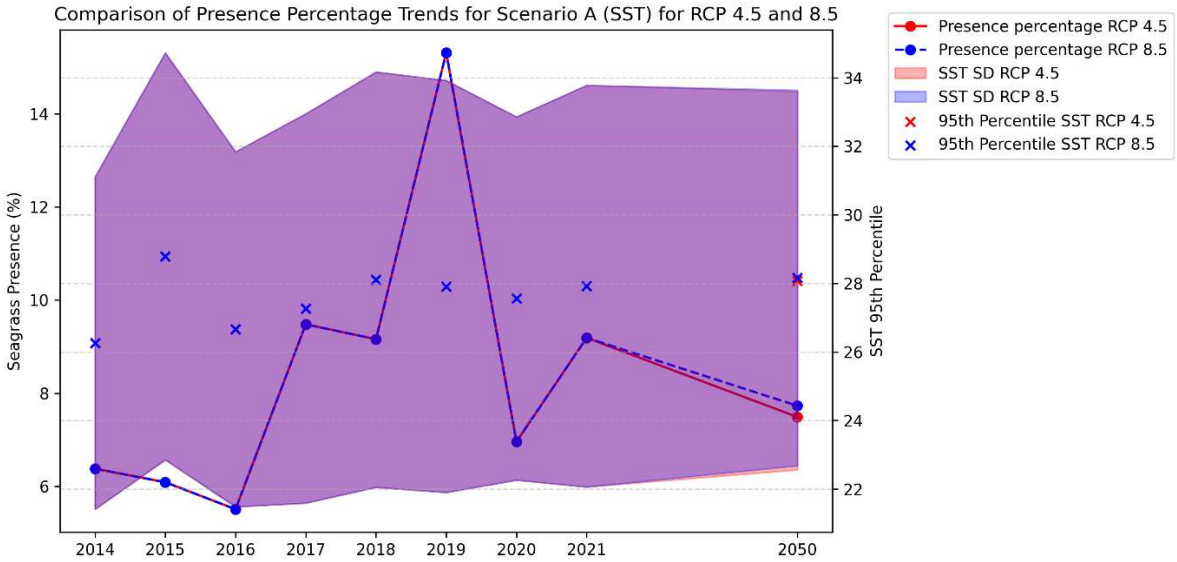


c) Spatial distribution retrieved from Landsat 8 for 2021 year

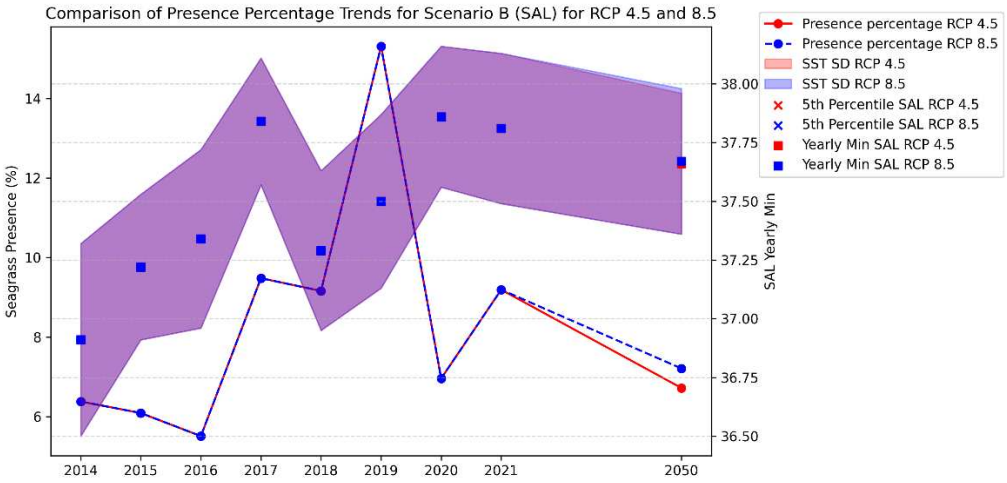


Supplementary material SM4: Projected seagrass presence under future SST, SAL, SSH, O_2, pH, NO_3 and PO_4 variations

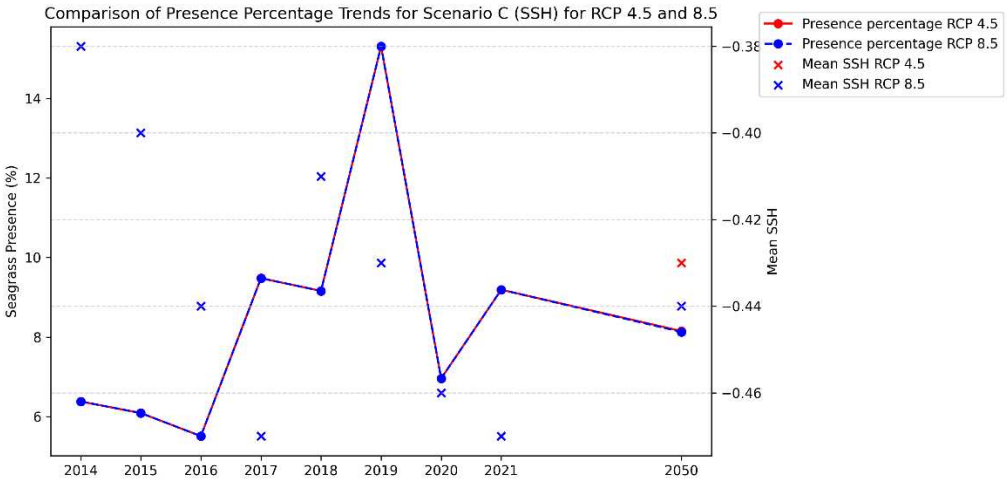
a) Seagrass presence (%) under future SST variations – RCP4.5 & RCP8.5



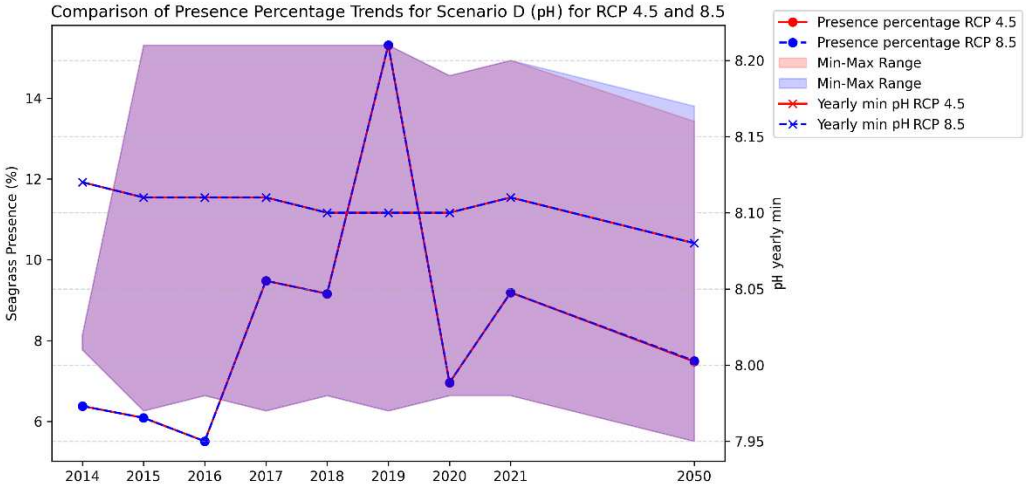
b) Seagrass presence (%) under future SAL variations – RCP4.5 & RCP8.5



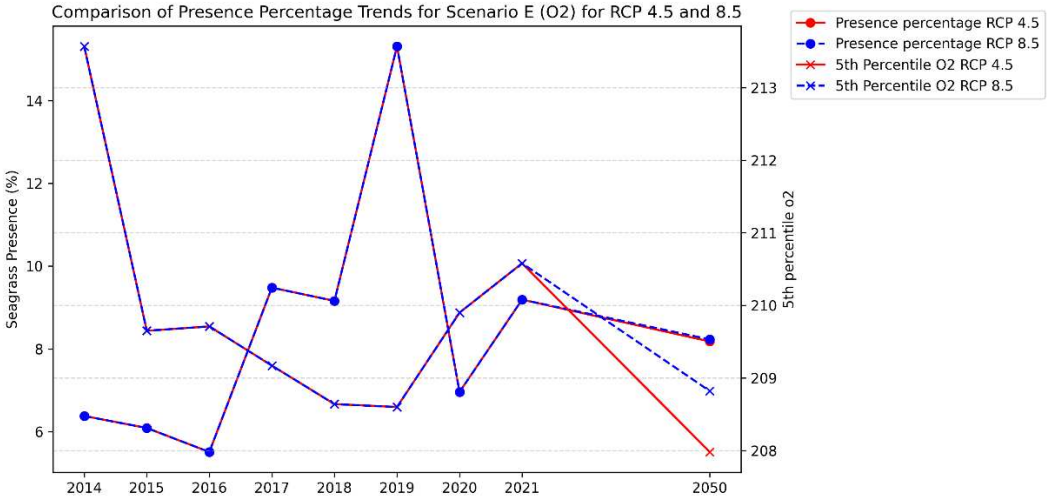
c) Seagrass presence (%) under future SSH variations – RCP4.5 & RCP8.5



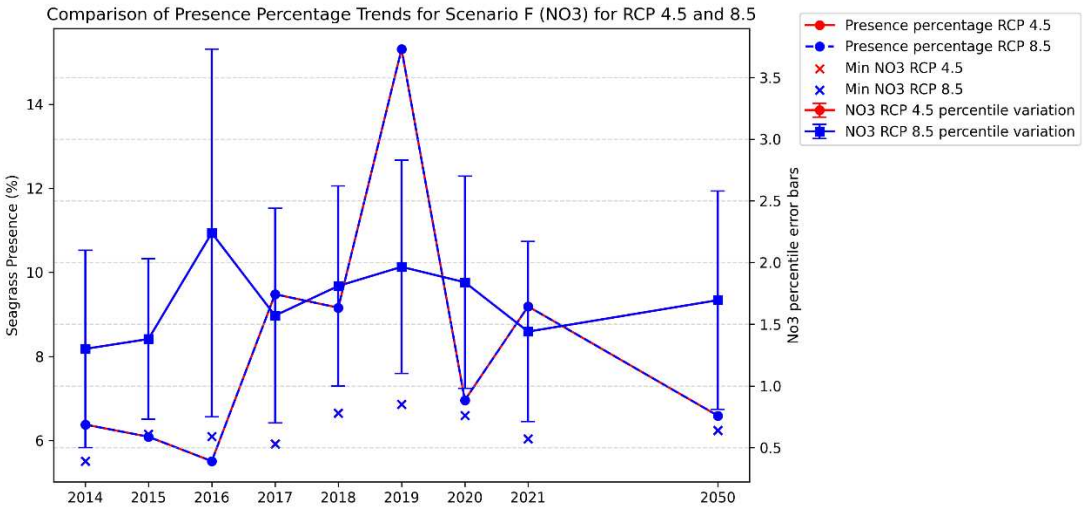
d) Seagrass presence (%) under future pH variations – RCP4.5 & RCP8.5



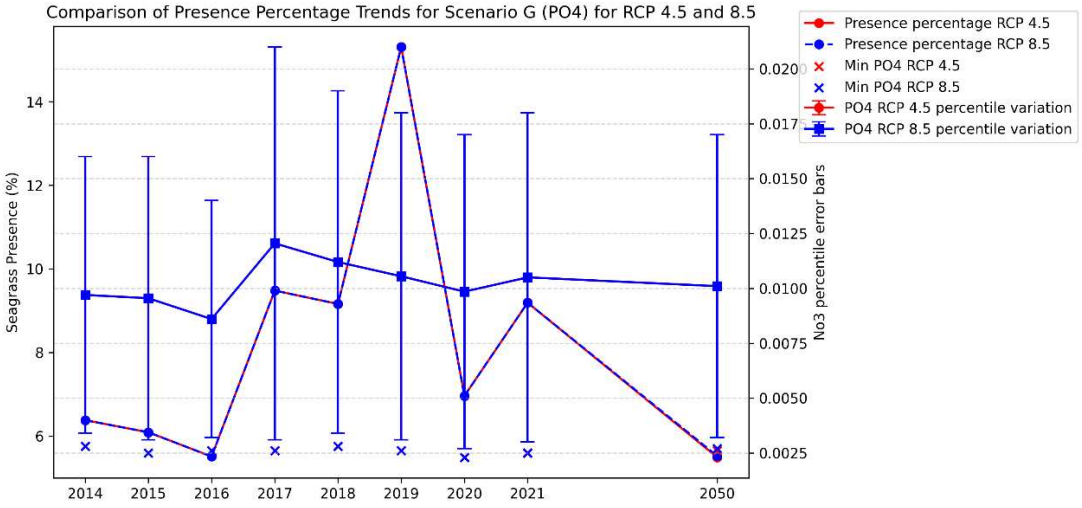
e) Seagrass presence (%) under future O_2 variations – RCP4.5 & RCP8.5



f) Seagrass presence (%) under future NO_3 variations – RCP4.5 & RCP8.5



g) Seagrass presence (%) under future PO_4 variations – RCP4.5 & RCP8.5



DISCUSSION AND CONCLUSIONS

The health of MCEs is critical to the stability of both environmental and socio-economic systems, particularly in regions like the Mediterranean, where biodiversity hotspots and densely populated coastal areas coexist. However, MCEs are increasingly vulnerable to the cumulative effects of climate change and human activities. Climate-related changes such as rising sea temperatures, ocean acidification, extreme weather events, and anthropogenic pressures like pollution, overfishing, and coastal development are rapidly transforming these ecosystems. These cumulative impacts pose a significant challenge for effective ecosystem management, as the interactions among multiple stressors are often complex and dynamic, requiring advanced assessment methodologies for their evaluation.

This thesis investigates the cumulative impacts on MCEs, specifically focusing on seagrass meadows, and evaluates the potential of ML as a tool for supporting the assessment of these impacts. The research is structured around three main questions: (i) *What is the current state of knowledge of key methodologies and scientific information/tools that the research community can apply to evaluate the effects of human activities and climate change on MCEs?* (First Paper); (ii) *Where is management most urgently needed to reduce and mitigate regional and local pressures?* This question focuses on identifying hot-spot risk areas by analyzing the spatial and temporal distribution of key stressors. In this research, this overarching question is addressed by developing and applying a cutting-edge ML-based modelling framework that leads to the third question: iii) *can an ML-based modelling framework identify patterns of interaction among endogenous and exogenous pressures at different spatio-temporal scales, as well as evaluate ecosystem changes under multi-risk scenarios?* (Second and Third Papers).

By addressing these questions, the thesis aims to provide a deeper understanding of how seagrass ecosystems respond to cumulative pressures and to explore the utility of ML in enhancing the accuracy and precision of these assessments. Last, the research seeks to contribute valuable insights that can inform decision-making frameworks for the sustainable management of coastal environments, ensuring that ecosystem services such as carbon sequestration are maintained despite the projected increase of climate change pressures.

Breaking down these bold objectives into more specific and operative research activities, the first paper in this thesis provides a comprehensive review of the methodologies and scientific tools currently used to assess the impacts of climate change and human activities in marine and coastal areas. This review identifies significant gaps in existing CIA frameworks, particularly in their ability to integrate ecosystem services and to model complex and non-linear inter-relationships interactions between multiple stressors affecting MCEs under both a reference scenario and under different climate change future scenarios. The findings underscore the importance of adopting more sophisticated methodologies, such as ML-based modelling frameworks, to address these gaps and improve predictive capabilities.

Building on these research challenges, a conceptual multi-risk assessment framework was initially created to outline the issue. This framework systematically identifies the interactions between natural and human-induced risks, the marine and coastal targets at risk (such as seagrass beds, coral reefs, kelp forests, mangroves, saltmarshes, and Maërl beds), along with their vulnerability factors and associated environmental, physical, and biological impacts. In this setting, the second paper presents the design and implementation of a general MARITIME modelling framework, which can be adapted and applied across different case studies and scales, as well as with multiple targets/assessment endpoints. Building on this general framework, the second and third papers operationalize this ML-based modelling framework in the Mediterranean under different climate scenarios. In particular, the second paper applies the framework at an eco-regional scale, focusing on the whole Mediterranean Sea. The outcomes demonstrated good potential for evaluating the most relevant pressures driving changes in seagrass distribution at the eco-regional level

(through the variable importance) with results highlighting that human-related pressures, particularly those linked to coastal development and changes in nutrient concentrations, pose significant threats to the ecological condition of seagrass meadows. Furthermore, the analysis of interactions between different pressures, such as SST, SAL, and SSH, revealed potential synergies that could exacerbate ecosystem degradation. These interactions suggest that multiple stressors may amplify their combined impacts, accelerating the loss of seagrass habitats and compounding cascading effects on biodiversity, ecosystem services, and carbon storage. Understanding and addressing these synergies is crucial for mitigating long-term degradation and reducing the risk of releasing stored carbon as a consequence of seagrass shrinkages.

The third paper refines this approach by applying the MARITIME modelling framework to a local-scale study. Here, the methodology is further enhanced with remote sensing data, which enables a detailed examination of seagrass distribution over an 8-year timeframe. This integration allows the two implemented models (RF and XGB) to incorporate additional layers of information, which in turn helps to identify spatio-temporal patterns. Considering the limitations linked to data availability, remote sensing, combined with the acquisition of new data from diverse advanced instrumentation (such as unmanned vehicles), could represent a turning point for future CIA. These approaches could significantly advance predictive capabilities when analyzed through increasingly sophisticated ML models, supported by more powerful computational capacities. This, in turn, would enable more precise identification of ecosystem responses to cumulative pressures, improving the accuracy of predictions. Moreover, it could help assess potential tipping points, which are currently difficult to estimate due to the current limitations of available data, thereby enhancing our ability to anticipate critical ecosystem shifts and implement timely management strategies and related conservation measures.

Overall, through the exploration of these three research questions, this thesis aims to produce a significant contribution to the growing body of knowledge on CIAs and the application of artificial intelligence and ML to environmental risk assessment. By addressing key gaps in the understanding of MCEs health conditions and the pressures these ecosystems are facing, the findings and limitations encountered underscore the critical importance of integrating advanced monitoring and modelling approaches and techniques, such as graph neural network models, into decision-making frameworks. These methodologies enable more accurate predictions of ecosystem responses to the combined impacts of climate and human pressures, offering practical tools for sustainable management. Despite limitations inherent to large-scale data availability (partially addressed through the integration of remote sensing data at a local scale), this MARITIME approach has provided valuable predictive insights into the future ecological conditions of MCEs. As demonstrated, this modelling framework can be transferred and replicated across different case studies, scales, and ecosystems. However, the successful application of the MARITIME across case studies requires fine-tuning key variables and representative metrics to accurately characterize ecosystem conditions and the main climatic and anthropogenic drivers, ensuring the reliability of model outputs. In addition to these specific modelling achievements, it has also facilitated the investigation and analysis of the intricate nexus between climate change, water quality, seagrass ecosystems, and their services in the Mediterranean region. The model was specifically designed to allow information to flow across all components of this nexus, accounting for cascading effects from one factor to another, to the final assessment endpoint. Furthermore, the integration of developed GIS-based multi-risk scenarios with other analyses (e.g., the suitability mapping of Nature-Based Solutions) can support managers in implementing targeted transformative adaptation strategies and related actions that consider both ecological and socio-economic dimensions of MCEs management.

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