**Marine Coastal Ecosystems Biodiversity and Services in a Changing World**

**MaCoBioS**

**Grant Agreement No 869710**

# Deliverable 2.1

# Multi-risk assessment in marine coastal ecosystems

WP 2 – Risk and adaptation of marine coastal socio-ecological systems

Lead beneficiary: Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici – Deliverable beneficiary: Stichting Wageningen Research

| Due date of deliverable | Month 20 (January 2022) | |
|---|---|---|
| Actual delivery date | 8th September 2023 | |
| Revision number | 01 | |
| Document status | Accepted by the EC | |
| Dissemination level | Public | |
| Role | Name | Organisation |
| Author/WP2 Co-leader | Elisa Furlan | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/WP2 Co-leader | Silvia Torresan | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Hung Vuong Pham | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Christian Simeoni | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Angelica Bianconi | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Cindy Cornet | University of Portsmouth (UoP) |
| Author/Task 2.1 contributor | Ewan Trégarot | University of Portsmouth (UoP) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| Role | Name | Organisation |
|---|---|---|
| Author/Task 2.1 contributor | Giorgia Verri | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Vladimir Santos Da Costa | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) |
| Author/Task 2.1 contributor | Catarina Fonseca | Fundação Gaspar Frutuoso (FGF) |
| Author/Task 2.1 contributor | Rafaela Tiengo | Fundação Gaspar Frutuoso (FGF) |
| Author/Task 2.1 contributor | Jessica Uchôa | Fundação Gaspar Frutuoso (FGF) |
| Author/Task 2.1 contributor | Stein Fredriksen | Universitetet i Oslo (UiO) |
| Author/Task 2.1 Leader | Erik Meesters | Stichting Wageningen Research (WR) |

## Abstract

Multiple activities are taking place across marine and coastal ecosystems without a full understanding of the composite interactions between natural and human-induced changes. The cumulative and synergistic impacts of these multiple threats (including climate change) are triggering complex and severe alterations of marine and coastal ecosystems' biodiversity and their capacity to supply services for human well-being. There is a need to reinforce the ecosystem risk concept to efficiently implement ecosystem-based assessment and management measures allowing us to better face multiple risks arising from the dynamic interplay between climate change and human-induced pressures.

Drawing on this need, this Deliverable aims to present the designed multi-risk assessment framework (MRAF) supporting the identification and prioritisation of cumulative impact pathways induced by interactive natural and anthropogenic pressures. Moreover, details on the iterative analytical process that serves as the cornerstone for the operational implementation of the MRAF across two MaCoBioS eco-regions (i.e., Mediterranean and Northern Europe) are also provided. This includes data pre-processing aimed at homogenising all input data for the subsequent model implementation through training, validation and testing phases. In particular, the potential of a Random Forest (RF) algorithm is exploited to better understand multi-risk underpinning marine coastal ecosystems' response to climate change impacts under both reference (2017) and future climate change scenarios for the 2050- and 2100-time windows and for the RCP4.5 and RCP8.5. The resulting GIS-based multi-risk scenarios from this task will be used as input data for the Nature-based solutions (NBSs) suitability modelling as envisaged in Task 3.3, identifying hot-spot risk habitats (e.g., seagrass meadows, kelp forests) where management actions and adaptation strategies would be best targeted.


**Keywords:** Multi-risk assessment, cumulative impacts, marine coastal ecosystems, ecosystem services and state, climate change, machine learning, Random Forest, scenario analysis, GIS maps, Mediterranean Sea eco-region, Northern Europe eco-region

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## List of abbreviations

| Acronym | Defintion |
|---|---|
| ARPA | Agenzia Regionale per la Protezione Ambientale (in Italy) |
| CBD | Convention on Biological Diversity |
| Cefas | Centre for Environment, Fisheries and Aquaculture Science (in the UK) |
| CGEDD | Conseil Général de l’Environnement et du Développement Durable (in France) |
| CMCC | Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (in Italy) |
| CIA | Cumulative Impact Assessment |
| CMEMS | Copernicus Marine Service |
| CNTE | Conseil National de la Transition Ecologique (in France) |
| COP | Conference of Parties |
| CSIC | Consejo Superior de Investigaciones Cientificas (in Spain) |
| CV | Cross-Validation |
| DEFRA | Department for Environment, Food & Rural Affairs (in the UK) |
| DT | Decision Tree |
| EU | European Union |
| IFREMER | Institut Français de Recherche pour l'Exploitation de la Mer (in France) |
| IMELS | Italian Ministry for the Environment Land and Sea |
| IPBES | Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services |
| IPCC | Intergovernmental Panel on Climate Change |
| ISPRA | Istituto Superiore per la Protezione e la Ricerca Ambientale (in Italy) |
| IUCN | International Union for Conservation of Nature |
| JNCC | Joint Nature Conservation Committee (in the UK) |
| MITECO | Ministerio para la Transición Ecológica y el Reto Demográfico (in Spain) |
| MCEs | Marine and coastal ecosystems |
| ML | Machine Learning |
| MMO | Marine Management Organisation (in the UK) |
| MPAs | Marine Protected Areas |
| MRAF | Multi-risk Assessment Framework |
| NAF(s) | National Adaptation Framework(s) |
| NAP(s) | National Adaptation Plan(s) |
| NAS | National Adaptation Strategy |
| NBSs | Nature-Based Solutions |
| NBSAPs | National Biodiversity Strategies and Action Plans |
| NGO(s) | Non-Governmental Organisation(s) |
| OECD | Organisation for Economic Co-operation and Development |
| PDP | Physical Development Plan |

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

| Acronym | Defintion |
|---|---|
| PNACC | Plan National d'Adaptation au Changement Climatique (in France) and Plan Nacional de Adaptación al Cambio Climático (in Spain) |
| RCP(s) | Representative Concentration Pathway(s) |
| RF | Random Forest |
| UK | United Kingdom |
| UN | United Nations |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |
| UNEP | United Nations Environment Programme |
| WP | Work Package |
| WWF | World Wide Fund for Nature |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

# Table of contents



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Introduction

Multiple activities are taking place across marine coastal ecosystems (MCEs) without a full understanding of the composite interactions between natural and human-induced changes. The cumulative and synergistic impacts of these activities and climate change are triggering complex and severe alterations of MCEs biodiversity and their capacity to supply services for human well-being. Drawing on this issue, Work Package 2 aims at reinforcing the ecosystem risk concept to efficiently implement ecosystem-based assessment and management measures allowing to better face multiple risks arising from the dynamic interplay between climate change and human-induced pressures.

In particular, Task 2.1 aims to develop and operationalise across two MaCoBioS eco-regions (i.e., Mediterranean and Northern Europe) a multi-risk assessment framework (MRAF) supporting a first-pass screening of cumulative impacts arising from the complex interplay between natural and anthropogenic pressures, affecting MCEs and their services provision. This framework allows the integration of heterogeneous indicators representing hazard (i.e., the potential occurrence of natural or human-induced physical events), exposure (i.e., the presence of ecosystems, environmental functions, services, and resources that could be adversely affected under the considered hazards), and vulnerability of the exposed MCEs to considered pressures (i.e., sensitivity and adaptive capacity). The expected outcome is a set of GIS-based multi-risk screening scenarios and indicators summarising key risk metrics and simplifying understanding and communication of risks induced by changing climate conditions and uses of MCEs.

To achieve this bold objective, as a first step, a conceptual MRAF is required to formalise the issue at hand, showing, in a systematic way, the relationships between the natural and anthropogenic sources of risk, the exposed coastal and marine targets (e.g., seagrass beds, coral reefs, kelp forests, mangroves, saltmarshes, and maërl beds), together with their vulnerability factors and the resulting environmental, physical, biological, and socio-economic impacts.

In this setting, this deliverable (D2.1) describes the progress throughout the development of the general MRAF, starting from the literature review to the organisation of the expert engagement workshop for the co-design of the framework, as well as its final implementation through the design and implementation of a Machine Learning (ML) model across two MaCoBioS eco-regions.

This report starts with an overview of the methodological approach applied to frame the conceptual framework under Task 2.1, including the review process of the state-of-the-art publications dealing with multi-risk and cumulative impact appraisal in MCEs (SECTION A – THEORETICAL BACKGROUND). Following a detailed description of the eco-region under investigation (including data available to describe key pressures and the selected ecosystems), SECTION B – METHODOLOGICAL DEVELOPMENT presents the workflow designed for co-design and operationalisation. Finally, SECTION C – APPLICATION describes all the operational steps applied to implement the designed model, and critically analyses the results of the RF model applied across the MaCoBioS eco-regions, highlights some pros and cons of this approach and provides some orientations for the next steps of the project.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Section A – Theoretical background

### 1. Assessment approached and applications for cumulative impacts and multi-risk appraisal in marine coastal ecosystems

Over the last decades, numerous and diverse issues leading to ecological implications have challenged both environmental scientists and decision-makers in the understanding of the relationships between social/economic interests and the associated environmental issues, requiring practical evaluation techniques building on interdisciplinary approaches. Risk assessment is a rather complex procedure that can help to analyse and manage a wide range of environmental issues, including those related to climate change. Different risk assessment methodologies have been developed to understand processes underpinning MCEs deterioration. When we embark on a multidisciplinary approach, dealing with multi-risk and cumulative impact appraisal in MCEs, these discipline-oriented theories become the empirical data of the conceptual framework analysis (Jabareen, 2009). Therefore, the first step of methodological development concerns the extensive systematic screening of the wide spectrum of multidisciplinary literature regarding the investigating question. Specifically, to explore the state-of-the-art CIA and multi-risk related studies and applications in MCEs, a multi-phase review process blending Scientometric and Systematic analysis of extant literature was performed. As shown in Figure 1. This analytical process comprises three main steps, including i) data collection based on a set of pertinent keywords for query; ii) Scientometric analyses to explore, evaluate and monitor the state of a particular research field (Geissdoerfer et al., 2017); and iii) Systematic review (based on the PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses - approach) for screening publications (details on the applied multi-phase review process are reported in Annex 2), and discuss them based on a set of comparison criteria. 692 publications were identified at the first stage (value obtained at the end of October 2020) of the publications collection, through the query search as detailed in Supplementary material Annex 1. By applying the PRISMA approach, this wide list was reduced to a limited set of 30 *'key papers'* (reported in Annex 4) selected based on their pertinence and relevance for the aim of this study.

Following a brief description of key results from the bibliometric review (Section 1.1), the following sections (Sections 1.2-1.6) present and discuss these publications (and related studies) exploring the type of methodological approaches and tools applied, as well as their relevance in terms of policy support under key EU and international regulatory frameworks, agreements, and strategies dealing with MCEs management and climate adaptation.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

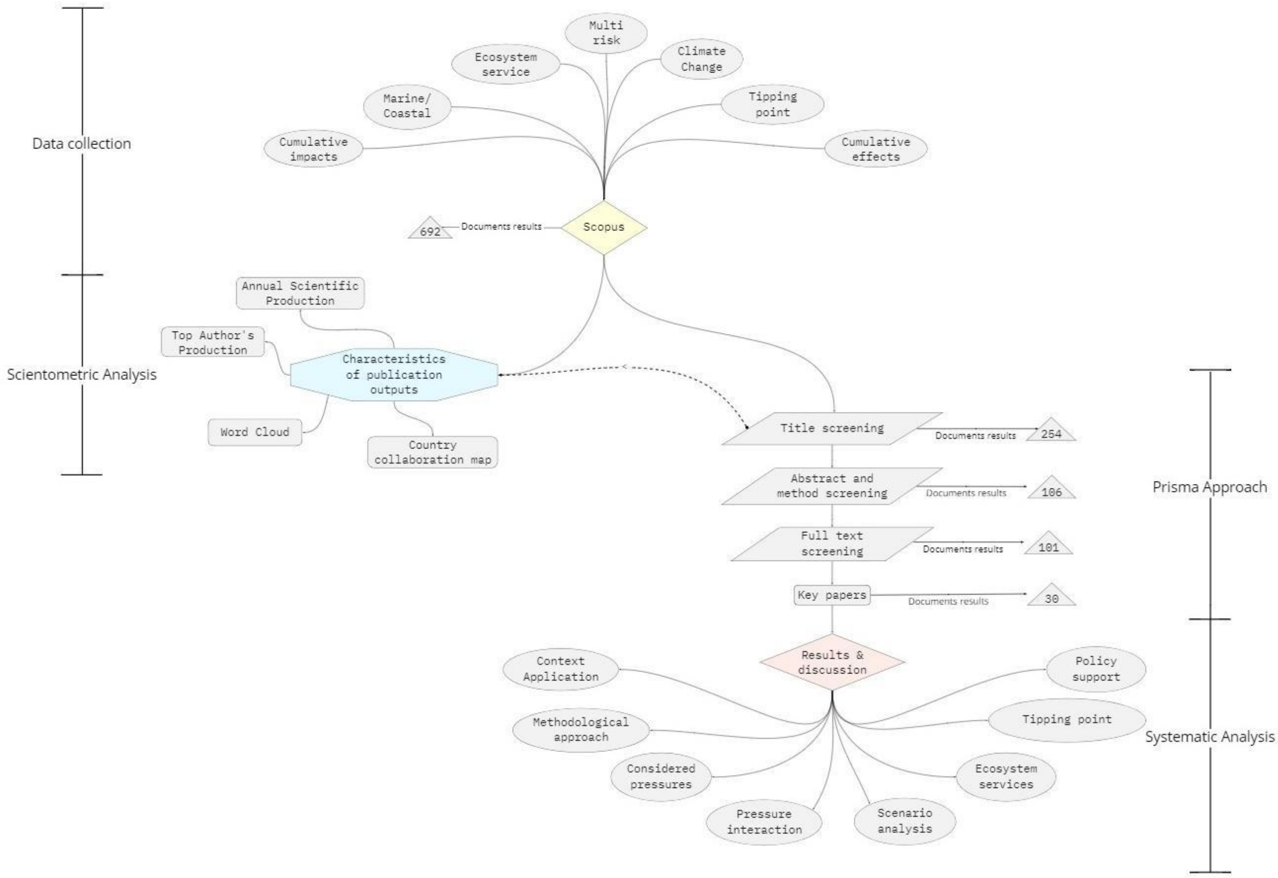



***Figure 1.*** *Methodological approach for the evaluation of existing studies and applications dealing with cumulative impact appraisal in marine coastal ecosystems.*

## 1.1 Characteristics of publication outputs

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 their 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). This information exported from Scopus was processed by applying the open-source *Bibliometrix* Package, designed for the statistic 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 recognize 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, then analytically processed through this R-based tool. In particular,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

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. All the analysis and graphs (i.e., annual scientific production, top authors' production over time, word-cloud, co-occurrence network, country collaboration map) are presented and discussed within Supplementary material Annex 3.

**Scientometric review**

A bibliometric review was performed by firstly applying a literature search in Scopus. This selection method led to the identification of 692 publications (value obtained at the end of March 2022) dealing with CIA in marine coastal ecosystems, for the 2000-2022 period. This process allowed the development of the Scientometric review (and related graphs) by processing the extracted bibliometric data (i.e., a BibTeX file of the 741 papers selected as input data) through the open-source bibliometrix R Package.

Afterward, the same Scientometric analysis was repeated by considering only the 254 papers obtained against the title-screening phase. This further evaluation allowed performing a more robust review, focusing only on a restricted number of preselected papers, thus avoiding non-significant documents (e.g., review 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 Annex 3).

The analysis of the 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 assessment carried out by Halpern et al., (2008). Up until then the number of publications was almost irrelevant (1-2 papers per year) but after this relevant CIA application, the yearly productions display a positive rising trend. The outputs provided by this analysis showed a further abrupt variation in 2014, which can be associated with the first period of the initial assessment of the MSFD concerning the current environmental status of EU marine waters, as well as the identification of environmental impacts induced by human activities on EU marine areas.

Overall, the number of CIA studies applied in MCEs increased continuously during the last decade, with an average number of publications of around 60 articles per year during the last 3 years. Focusing on the most influential authors (Annex 3 Figure S2), through the analysis of the author's production overtime, the pioneer of these applications, Halpern B.S., emerged also as the most productive author (with an overall number of 23 publications under 2000-2022 timeframe).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

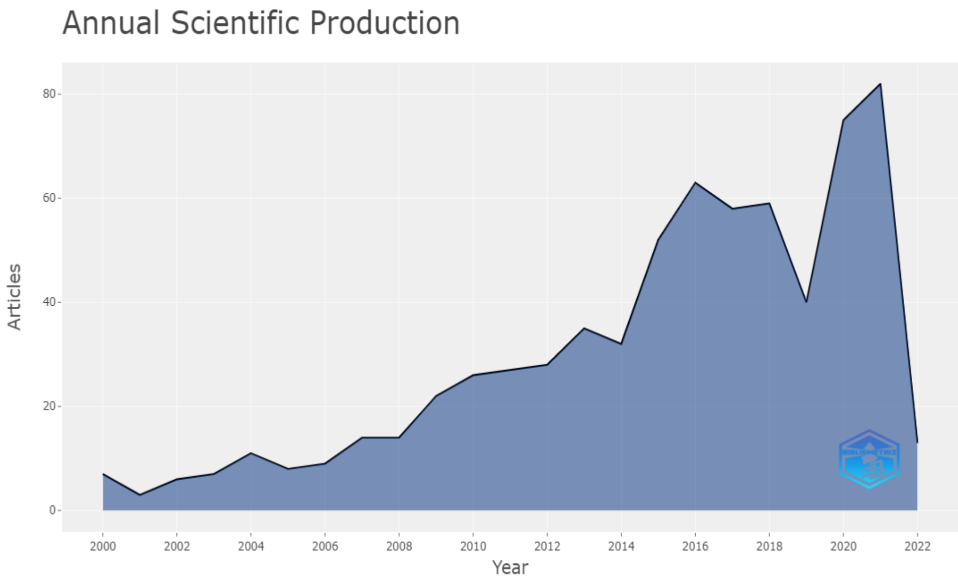



***Figure 2.*** *Number of publications, across the 692 papers obtained against the title-screening phase, applying CIA in marine coastal ecosystems during the 2000–2022 timeframe.*

Further, on the account of the analysis of the most frequent 50 author's keywords, besides those contained in the query string, the word cloud graph reveals as the main frequent author's keywords ecosystem-based management, marine spatial planning and climate change (Annex 3 Figure S3). In fact, not surprisingly, many CIA methods have been developed to support decision-makers and planners in the design of spatial plans for marine coastal ecosystems management and conservation/restoration under the ecosystem-based management approach (Menegon, et al., 2018), 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 coastal ecosystems and foresee potential alteration of biological, chemical, and physical processes (Furlan et al., 2020; Gissi et al., 2019) leading together to changes in ecosystem services flow.

Finally, another interesting graphical representation useful to detect scientific collaborations among countries applying CIA methods in marine coastal ecosystems was carried out through the analysis of the authors' affiliations related to the same publication. Analysing the extracted publications, the USA, Canada, UK and China emerged as the first countries approaching this specific topic. Then, over the 2000-2022 timeframe, collaborations among countries gradually increased according to the related rise in publications. Focusing on the last 5-year period (2015-2020, Figure S5), the resulting country scientific collaborations map appears in a dense network of interconnections among states, as a result of the increased international relevance of this specific research field.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

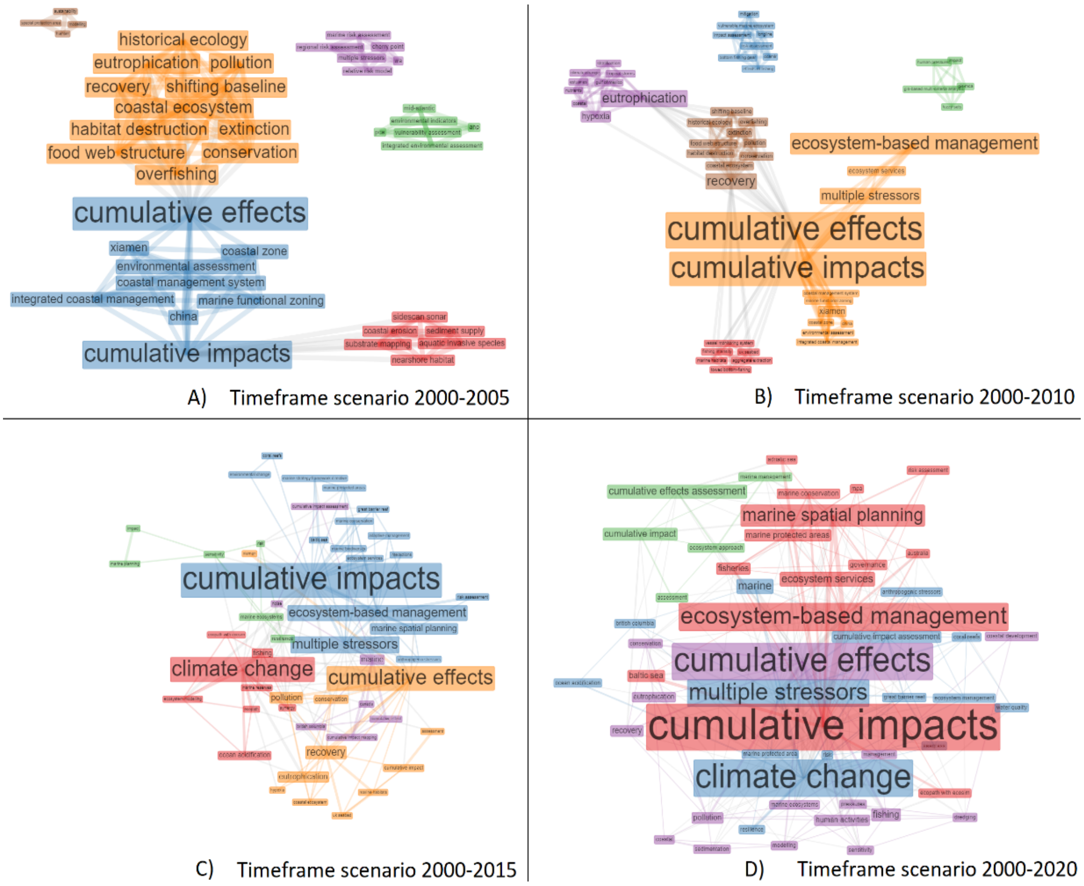



***Figure 3.*** *Word co-occurrence network graphs under four time slices: A) 2000-2005, B) 2000-2010, C) 2000-2015, D) 2000-2020.*

## 1.2 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 marine coastal ecosystems, is remarkable. GIS-based mapping, indicator/index (through the integration of several indicators representing the involved pressures and the presence and state of marine coastal ecosystems), numerical and ecological models, 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 by the bar chart Figure 4, 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 101 relevant papers) 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., 2018; 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-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

off among multiple uses, while supporting the sustainable use and conservation of marine coastal resources. Expert-based ranking (28 publications out of the selected 101 relevant papers) 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; Jones et al., 2018; Mach et al., 2017; Singh et al., 2017; Uusitalo et al., 2016); and iii) to analyse interactions among multiple pressures (Cook et al., 2014; Furlan et al., 2019a). On the other hand, differently from these studies mainly based on expert judgments, a step-wise risk-based approach is proposed by Piet et al. (2021) for a fully quantitative CIA integrating information for different sectoral human activities, pressures and ecosystem components.

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

[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)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

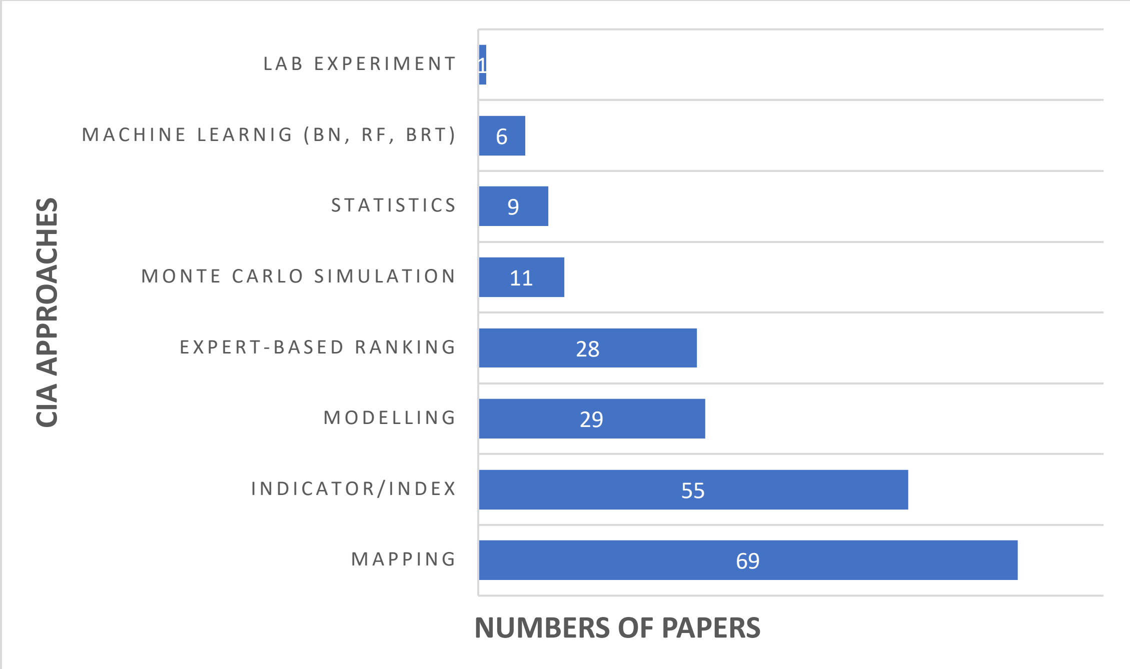



***Figure 4.*** *Bar chart summarising risk-based and CIA approaches and tools applied within the selected 101 relevant papers.*

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, Piet et al. (2021) carried out a confidence assessment, providing an overview of the quality and adequacy of the available data and information underpinning CIA application. In particular, this assessment was based on a hierarchy confidence classification, structured with different levels and criteria applied to different methodological aspects (e.g., data processing, spatio-temporal resolution and coverage, etc.), and elements integrated in each phase i.e., activities, pressure and ecosystem component, including their relations. Whereas, 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

[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)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

overall cumulative impacts, provides useful information to support the identification of conservation priorities, as required by marine coastal laws.

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 across the publications (as illustrated in Figure 5). 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). Among the risk-based studies, Piet et al. (2021) introduced the concept of "risk of impact" as assessment endpoint of their step-wise approach. 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.

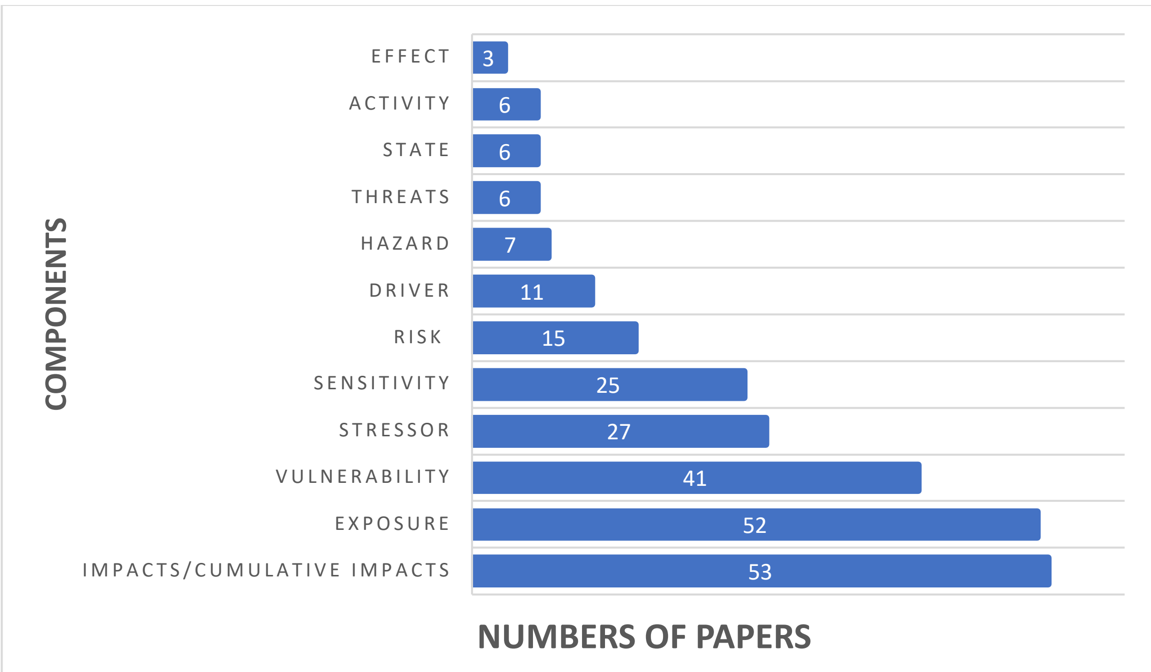



***Figure 5.*** *Bar chart summarising key components applied within CIA and risk-based methodological frameworks in the 101 selected papers.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## 1.3 Scenario analysis for healthy marine and coastal ecosystems

Exploring in advance changes in cumulative impacts against different climate conditions or management goals 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., 2019a; Jonsson et al., 2021; Magris et al., 2021). Consequently, researchers have begun applying different tools (e.g., Bayesian network models) integrating scenario analysis into CIA-related studies to understand ecosystems' responses to a changing future. The majority of CIA methodologies applied across the 101 selected papers 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. idealized 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 4 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); 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 the next 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 the potential futures of marine resources and ecosystems conditions within the analysed case study area. 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" scenario, most authors evaluated potential changes in cumulative impacts under the implementation of several management measures (as already tested in Corrales et al., 2018), allowing to compare the expected environmental effects of different plan alternatives. For instance, Stelzenmüller et al., (2010) operationalized a Bayesian Belief Network–GIS framework to evaluate cumulative impacts under three different 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., scenarios more in accordance with the target posed by MSFD 2008/56/EC). The comparison between the Business As Usual (BAU) 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 Lānaʻi, 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 goods and services capacity. With a similar perspective, Furlan et al., (2020) applied a GIS-based Bayesian network approach to evaluate the probability of cumulative impacts under four

[3] Intergovernmental Panel on Climate Change

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

*"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. On the one hand, *sea surface temperature* emerged as the most considered among the exogenic variables (Furlan et al., 2019a; Ihde & Townsend, 2017; Singh et al., 2020), followed by *precipitation* (Uusitalo et al., 2016), *ocean acidification* (Ainsworth et al., 2011; Fulton et al., 2009; Singh et al., 2020), 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., 2020) have been integrated into CIA-related scenario analysis to simulate how changes in their range can contribute to increasing the vulnerability of MCEs.

## 1.4 Incorporating ecosystem services perspective into CIA

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 for a limited amount of time against adverse effects. 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., 2020). 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 service 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 ecosystem services categories, '*regulating and maintenance*' resulted as the most analysed marine ecosystem services category (i.e., 50%), followed by provisioning and cultural services, respectively (Figure 6).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

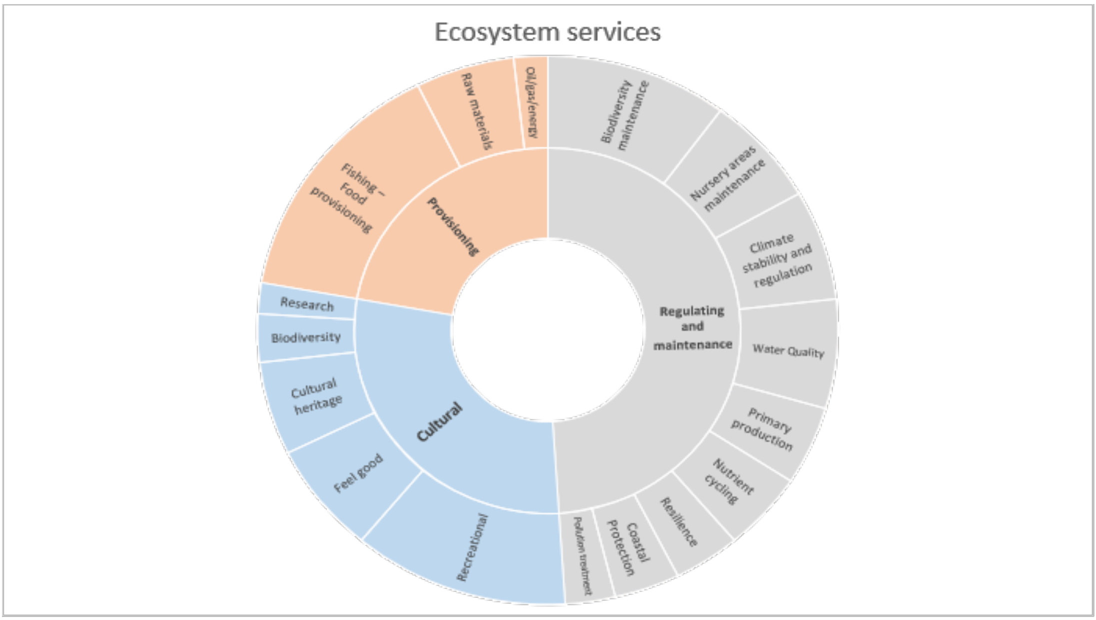



***Figure 6.*** *Radial chart summarising key marine ecosystem services frequency applied for integrating and modelling ecosystem services within CIA methodologies in the marine environment. The nineteen marine ecosystem services extracted from the reviewed publications were divided according to the CICES v5.1 (Haines-Young & Potschin-Young, 2018).*

The assessment method of ecosystem functions and services, varies greatly from subjective evaluation to expert judgement 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 judgement, 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 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 actions that will reverse, mitigate, or prevent ecosystem degradation and sustain benefit 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-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

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) then used the Ecosim foodweb model and analysed future scenarios (2010-2060) considering multiple pressures. The authors provided robust modelling that really 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 considering the cumulative impact of multiple threats, considering their 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, providing meaningful support to decision- and policymakers for MSP (Hansen & Bonnevie, 2020; Muñoz et al., 2018). As such, many softwares (e.g., InVEST, CORSET, HIReefSim, and Ecosim, EwE) and models (e.g., CARE, MES-Threat, and MES-Capacity) have been developed as Decision-Supporting Tools. However, methodological approaches, published within the investigated timeframe (2000-2022), rarely considered all three marine ecosystem services categories, but often 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 the positive/negative feedback between anthropogenic and climate-related pressures, the ecological condition of marine habitats, and ecosystem services.

## 1.5 When cumulative impacts lead to an ecological tipping point

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 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

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

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 1.2, 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, 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

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

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.

## 1.6 Policy support for risk management and climate adaptation in marine and coastal socio-ecological system

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, 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 overtime 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 strategies and drive future research and effective ecosystem-based management (Marzloff et al., 2016). By incorporating scenario methodologies, CIA could support long term planning by showing how different strategies could improve the provision of marine ecosystem services (e.g., using scenario methodologies) (Farella et al., 2020; Weijerman et al., 2018). Lastly, CIA may increase transparency in planning decisions. CIA also enables policy makers 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 policy makers 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 101 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

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

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 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 interventions (such as marine protected areas or fishing management alternatives) within their CIA methodology to understand what kind of 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 which have inconsistent language, interpretation and parametrisation which limits the effective use of CIA to effectively support management and policy making (Judd et al., 2015; J. 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 base line to enable management decisions (Hansen & Bonnevie, 2020).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Section B – Methodological development

### 1. Case studies description

The main objective of this study is to develop and analyse multi-risk scenarios, induced by the interplay among anthropogenic and climate-related pressures, affecting MCEs and their services capacity within the MaCoBioS eco-regions. To achieve this bold objective, a huge amount of data able to spatially resolve all MRAF components and feed the model development is needed. Following a detailed description of key environmental and ecological features of the Mediterranean and Northern Europe, the following paragraphs will introduce and describe all data and information (both data representing endogenic and exogenic pressures, as well as detailed information on conditions/health of the analysed ecosystems) collected across two MaCoBioS eco-regions.

#### 1.1 Description and characterization of the Mediterranean eco-region

The Mediterranean Sea (Figure 7) is a semi-enclosed basin surrounded by 22 countries belonging to 3 different continents (Europe, Asia and Africa). Its basin extends from 30° to 45°N and from 6° W to 36° and covers almost 2.6 million km2, with a coastal length of about 46,000 km (Piroddi et al., 2015). It is linked to the Atlantic Ocean in the west by the Strait of Gibraltar, to the Black Sea in the north by the Bosporus and the Dardanelles, and to the Red Sea in the south by the Suez Canal. Among the enclosed seas, it is the deepest, due to its narrow continental shelves and a large area of open sea, where much of the basin can be classified as deep-sea (maximum depth of 5,200 m and average depth of 1,430 m) (Cramer et al., 2020).

The Mediterranean Sea is generally oligotrophic except for some areas where strong river flows, vertical mixing, and upwelling phenomena occur, such as the Gulf of Lions, Strait of Sicily, Algerian coastlines, southern Adriatic, Ionian Sea, Aegean Sea, and Rhodes Gyre. A gradient of biological production increasing from south to north and from east to west can be observed, with phosphorus, rather than nitrogen, being the limiting nutrient, especially towards the eastern basin (Piroddi et al., 2015), and showing an inverse correlation with temperature and salinity (UNEP, 2014). Indeed, salinity averages 37.5-39.5 PSU (Coll et al., 2010) and shows a gradient from west to east, following the increase in temperature from 12,8°C-13,5°C in the western part of the basin, to 13,5°C-15,5°C in the eastern ones (Cramer et al., 2020), and the resulting rise in evaporation and related decrease in water level. Overall, the Mediterranean is described as a temperate sea, with a considerable portion that can be categorised as deep-sea, and characteristic homeotherms from 300-500 m to the bottom where, unlike the Atlantic Ocean, there are no thermal boundaries (Coll et al., 2010).

In terms of climate, the Mediterranean region is characterised by hot, dry summers and mild winters, with increasing gradients of temperature from north to south and from west to east (UNEP, 2014). On the other side, annual precipitation ranges from 100 mm in some southern Mediterranean countries to 1,500 - 2,000 mm in the northern Mediterranean (Brondizio et al., 2019; Coll et al., 2010). The most outstanding climatic processes that influence the Mediterranean region are the North Atlantic Oscillation (NAO), East Atlantic (EA) pattern, East Atlantic–West Russia (EA–WR) pattern and the Mediterranean oscillation (MO) (IPCC, 2021).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

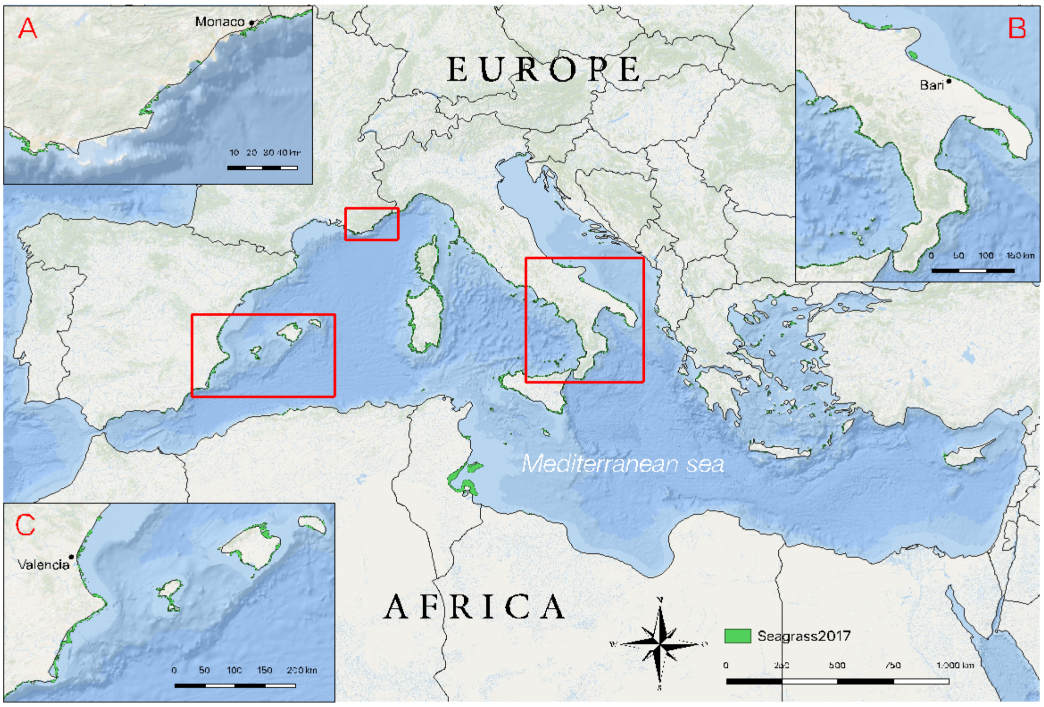



***Figure 7.*** *The Mediterranean eco-region, focus A: Monaco and South-East France coast; Focus B: South Italy; Focus C: Valencia Sea area and the Balearic Islands.*

From a biodiversity point of view, although the Mediterranean represents only a small fraction of the global ocean surface (0,82%), it hosts about 25% of the global marine primary production and 7% of global marine biodiversity (Coll et al., 2010; Moullec et al., 2019). Indeed, the Mediterranean basin is described as a biodiversity hotspot due to the presence of a high number of different ecosystems (e.g., seagrasses, coralligenous outcrops, maerl beds, submarine canyons and deep-sea structures) hosting more than 17,000 species (Brondizio et al., 2019; Coll et al., 2010), including about 18% of the global macroscopic biodiversity. The marine biodiversity of the Mediterranean Sea is primarily derived from the Atlantic Ocean, but more recent pressures, such as the increment of shipping activities, the opening of the Suez canal and the rising of temperature, have caused the introduction, adaptation and survival of both temperate and subtropical indigenous species coming from the Red Sea and the Atlantic Ocean, which are consistently growing in the presence (Coll et al., 2010; Cramer et al., 2020; Martin et al., 2015). However, these high biodiversity results to be strongly threatened by both managed endogenous and unmanaged exogenous pressures. The former ones come from within a system and require local, regional, and/or international management to act on their causes and consequences. In contrast, the second ones are raised from outside the system, and we cannot address the causes of change but only address the consequences (e.g., climate change, geomorphic isostatic activity) (Michael Elliott et al., 2015). These pressures contribute together to shape severe cumulative impacts (J. A. Lonsdale et al., 2020), especially on marine and coastal ecosystems located at the land-sea interface, where the complex interaction between terrestrial and marine systems makes these ecosystems particularly prone to multi-risk scenarios.

### 1.1.1 Key pressures

Multiple interactive drivers significantly affect the Mediterranean Sea (Micheli et al., 2013), both directly, i.e., unequivocal influences on ecosystems processes (e.g. degradation of aquatic habitats, climate change, pollution, Invasive Alien Species (IAS), resources extraction), and indirectly (e.g.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

demographic, economic, socio-political, cultural, religious, technological, legislative and financial drivers) (Bazairi, H. et al., 2010; Cramer et al., 2020).

According to the classification provided by the Mediterranean Experts on Climate and Environmental Change network (MedECC), direct drivers can be divided into the following four macro-categories: i) climate change, ii) pollution, iii) land and sea use changes, and iv) non-native species. Table 1 reports the most influential pressures related to each of these four macro-categories, also providing a short description of how these affect coastal marine ecosystems.

As far as **climate drivers** are concerned, according to the 6th IPCC Report, scientists are observing changes in the climate in every region on Earth and across the whole climate system (IPCC, 2021). Many of the changes observed in the climate are unprecedented in thousands of years, and some of the alterations that already occurred (e.g., Sea Level Rise - SLR) have been irreversible over hundreds to thousands of years (IPCC, 2021). The climate change we are already experiencing will increase with additional warming, affecting every region on Earth in multiple ways and increasingly exacerbating the impact of other drivers on nature and human well-being (IPCC, 2021). According to a synthesis of various studies, the fraction of species at risk of extinction due to climate change is 5% at 2°C warming and climbs to 16% at 4.3°C warming (IPBES, 2019; IPBES & IPCC, 2021). In this context, the Mediterranean region has been described as a major climate change hotspot (Coll et al., 2010; Tuel & Eltahir, 2020). For all its characteristics, such as the small size, the geographical location and the residence of water in the basin of approximately 100 years, the Mediterranean Sea is very sensitive and quickly responding to climate change, ocean acidification, and other direct and indirect human-induced perturbations and/or anthropogenic influences (e.g., fishing, sea use change, demographic development) (Giorgi, 2006), which are proportionally stronger in the Mediterranean than in any other sea in the world (Criado-Aldeanueva & Soto-Navarro, 2020). The most impactful climate drivers in the Mediterranean are represented by sea surface temperature and sea level rise, precipitation and extreme events, including marine heatwaves, storm surges and flood events, ocean water acidification and changes in salinity (Table 1).

When focusing on **'pollution'**, we can observe that the Mediterranean eco-region results to be mainly threatened by oxygen-depleting substances, heavy metals, persistent organic pollutants (POPs), hydrocarbons, microorganisms, nutrients introduced by human activities, and marine litter (UNEP/MAP, 2012). These pollutants flow into the basin/sea via a variety of sources such as discharge sites and landfills on land, surface river runoff, atmospheric deposition, and maritime activities like shipping, mining, and oil and gas development (UNEP/MAP and Plan Bleu, 2020). The leading causes are unsustainable **land and sea uses**, which include rising coastal and terrestrial development, fishing, aquaculture, and agriculture (with fertiliser and pesticide use), livestock management, forestry, mining and energy production (IPBES, 2019), further contributing to the overexploitation of natural resources of the Mediterranean Sea (Piroddi et al., 2017). Basin's landscapes and uses have changed throughout millennia, with the rate of change accelerating significantly since the second half of the twentieth century, particularly around the coasts, having consequences in terms of habitat fragmentation and damages, leading to biodiversity loss and biological homogenisation (Cramer et al., 2020).

Finally, many non-indigenous species (NIS), including vertebrates, invertebrates, and primary producers, have been established in the Mediterranean Sea, especially in the eastern side of the basin (Martin et al., 2015), causing drastic and rapid changes in its biota. The main drivers of NIS invasions are expanding trade networks, increased human mobility, continued habitat degradation, and climate change, which is linked to phenomena such as tropicalisation and meridionalisation (Brondizio et al., 2019; IPBES, 2019; IPBES & IPCC, 2021). The eastern Mediterranean is the most heavily affected and shows the most severe environmental effects, with more than 50% of NIS in the Mediterranean arriving through the corridor of the Suez Canal, as well as from the ballast water of ships due to

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

expanding trade networks (UNEP/MAP and Plan Bleu, 2020). However, these Indo-Pacific species do not stop in the eastern part of the basin, and it is possible to observe meridionalisation phenomena, i.e., the northward expansion of species that usually thrive in the southern part of the basin, due to the warming of sea waters (Tsiamis et al., 2018).

All these pressures tend to interact with each other through synergistic or antagonistic pathways (Battista et al., 2017). Together, they contribute to generating cumulative impacts on ecosystems, threatening their functioning, capacity, and productivity, and thus resulting in a reduction in ecosystem services flow and capacity for human well-being.

Mediterranean key pressures are listed and described in Supplementary material Annex 5.

### 1.1.2 Seagrasses ecosystems: key environmental features and vulnerabilities to climate risks

The EU Habitats Directive (92/43/EEC) defines habitat as "*the terrestrial or aquatic area differentiated by its geographical, abiotic and biotic characteristics, in which species live in any state of their life cycle.*" Drawing on this definition, various methods have been developed over time to classify European and Mediterranean Sea habitats and two main classification systems have been adopted: the EUNIS and the Barcelona Convention (UNEP/MAP, 2012) approaches. Both combine physical and biological information to define different habitats based on specific bionomic areas and substrate types (Montefalcone et al., 2021).

As previously brought up, thanks to its peculiar features and the presence of numerous habitats with different characteristics, the Mediterranean represents a hotspot of marine biodiversity. Indeed, despite its oligotrophic feature, it presents a high marine species richness, counting about 17,000 species, with a high presence rate of endemics (Coll et al., 2010; Costello et al., 2010). Particularly, coastal areas and continental shelves, usually above 200m depth, host the greatest diversity. The highest richness is represented by the Animalia group with approximately 11,500 species, with the most significant contribution coming from the subphylum Crustacea (13.2%), phyla Mollusca (12.4%) and Annelida (6.6%) (Piroddi et al., 2015). Among endemic species, the highest percentages are represented by Porifera (48%), followed by Mysidacea (36%). Among the vertebrates inhabiting the Mediterranean then, there are 650 marine species of fish (mainly actinopterygians - 86%), nine species of marine mammals and three species of sea turtles (Coll et al., 2010; Piroddi et al., 2020). Important for structuring especially hard-bottom benthic communities, shallow sandy and muddy environments are usually too turbid for light to penetrate the sediment.

Belonging to photosynthetic organisms, we find as more present endemism seaweeds and seagrasses (22%) (Coll et al., 2010). Seagrasses are flowering plants that produce seeds and grow by the production of new leaves and extension of their underground rhizomes through the substrate, creating complex, rich and highly productive habitats. Although in the Mediterranean basin the photic zone reaches a maximum depth of 150 m (Maes et al., 2020), seagrasses are mainly located in shallow water (up to 40-50 meters depth) (UNEP, 2020; Weatherdon et al., 2017), where there is the right amount of light to allow their photosynthetic pigments to perform photosynthesis (Boon et al., 2017). The collective term "seagrasses" encompasses more than 70 species around the world. Nevertheless, in the Mediterranean Sea, only seven species can be found that are *Posidonia oceanica* (representing 23% of all shallow bottoms) (Castejón-Silvo & Terrados, 2012), *Cymodocea nodosa*, *Zostera marina*, *Zostera noltii*, *Ruppia cirrhosa*, *Ruppia maritima*, and *Halophila stipulacea* (Belluscio et al., 2013; Ruiz et al., 2015). In the map in Figure 7, the distribution of seagrasses beds in the Mediterranean is reported, based on Emodnet and UNEP data for 2016, 2017 and 2018[4]. Seagrasses demographic

[4] https://data.unep-wcmc.org/datasets/7; http://gis.ices.dk/geonetwork/emodnet-seabedhabitats/eng/catalog.search#/metadata/39746d9c-4220-425c-bc26-7cb3056c36a5

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

dynamics are mainly driven by the interactions between several biophysical parameters such as temperature, salinity, hydrodynamics, depth, substrate and light availability (O'Brien et al., 2018). Based on the UNEP (2020) definitions, key requirements for seagrass growth can be summarised into three main classes: i) habitat suitability: depth, sediment substrate, temperature and water movement; ii) water quality: adequate light for photosynthesis (high minimum light requirements, 4.4 – 29% of surface irradiance), salinity and absence of toxicants; iii) grazing and recruitment processes: suitable assemblages of grazing animals, water movement to transport seeds and vegetation fragments (UNEP, 2020). Seagrass habitats play a key ecological role in the marine environment, providing a long list of valuable ecosystem services such as food security, climate change mitigation, ocean acidification buffer (covering only 0.1% of the ocean floor, they efficiently store up to 18% of the world's ocean carbon) (UNEP, 2020), contribution to fisheries by supporting food webs, enrichment of biodiversity by providing valuable nursery habitat, nutrients cycling, absorption of pollutants by filtrating water, diseases control, protection against coastal erosion and tourism (Campagne et al., 2014; Kawabara & Acharya, 2020).

Despite the recognised importance of these ecosystems as contributors to human well-being, only 26% of their distribution is covered by marine protected areas (a lot less compared to other ecosystems, like coral reefs or mangroves) (Kawabara & Acharya, 2020). Moreover, the increase in threats affecting estuaries and seas was one of the main reasons behind the abrupt reduction of seagrass extent from 1869 to 2016, with almost 30% of global seagrass beds lost during that period (Campagne et al., 2014). This pattern accelerated within the EU in the second half of the twentieth century, rising from a reduction rate of "0.9%" yr-1 in the 1940s to a peak of about "34%" in the 1970s, before slowing to lower rates in the 1980s ("–27.0%" decade-1), 1990s ("–16.1%" decade-1) and 2000s ("–8.3%" decade-1). More recently, some areas experienced a reversal trend, with a positive net change rate in seagrass surfaces (de los Santos et al., 2019). However, most of these species show a low recovery rate (O'Brien et al., 2018). For this reason, the full recovery of seagrass beds is usually considered irreversible in a human timescale (Telesca et al., 2015).

As introduced in Section 2.2.1, overall, seagrasses in the Mediterranean are experiencing a faster rate of warming than the rest of the oceans (Coll et al., 2010). Although all photosynthetic species are affected by warming, the data emphasise that *Posidonia oceanica* is one of the most vulnerable species to future climate change (Chefaoui et al., 2018), with an alarming risk of extinction under scenarios of severe warming (Balzan et al., 2019). Due to its low water temperature tolerance and endemic status, *Posidonia oceanica* could face functional extinction (decrease in density by more than 90%) in the western Mediterranean by the middle of this century (Jordà et al., 2012). Under the same scenario, *Cymodocea nodosa* would lose "only" 46.5% of suitable habitat (Chefaoui et al., 2018). Most of these declines are linked to water quality degradation (26%) due to climate-related impacts, wasting disease (25%), coastal modification (16%), mechanical damage (14%), and other causes (12%) (de los Santos et al., 2019). The climate threats include rising temperatures, ocean acidification, sea level rise and increased frequency and intensity of extreme weather events. At the same time, the mechanical damages are mainly linked to dredging, boating, shipping accidents, fishing (especially trawling), harvesting, aquaculture activities and invasive species (especially grazing animals) (UNEP, 2020). Looking at the regression of this ecosystem in the Mediterranean, mostly affected surfaces correspond to areas of medium or high human footprint (e.g., proximity to fishing ports, urbanised areas, coast with altered sedimentary/hydrologic regimes) and near river mouths on the continental coastline (Telesca et al., 2015).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

### 1.1.3 Seagrasses: ecosystem services and functions

According to the Millennium Ecosystem Assessment, ecosystem services are "*the benefits that people derive from ecosystems*" (MEA, 2005). According to the Common International Classification of Ecosystem Services (CICES) v5.1 (Haines-Young & Potschin-Young, 2018), ecosystem services are classified into three main categories: provisioning, regulation & maintenance and cultural. Ecosystem services can be further classified based on the different aspects featuring the ecosystem services concept, which are capacity, flow, and benefits. Where the "capacity" is described as the natural potential of the ecosystem to provide a specific service; the "flow" is the actual use of the service (Grizzetti et al., 2019); and the "benefits" are the direct or indirect values associated with human well-being (MEA, 2005).

In this setting, seagrasses provide fundamental ecosystem services, contributing to fish production, water filtering and recreational activities. Most of these can be directly appreciated and quantified (e.g., the quantity of dead leaves that are used in numerous areas such as compost and for roof insulation, the amount of biomass from their leaves and rhizomes that represent food for multiple fish and invertebrates), but some others, chiefly regulating and maintenance services are less evident (Grizzetti et al., 2016). Focusing on the endemic Mediterranean *Posidonia oceanica*, this is one of the most productive and valuable ecosystems in the overall Mediterranean basin (Chefaoui et al., 2018), and it plays an important role in providing food for multiple fishes and invertebrates, harbouring species, protecting coasts, while improving water quality (e.g., water filtration/purification) and mitigating climate change effects (e.g., carbon sequestration) (Vacchi et al., 2016). Using the classification developed by Boudouresque (2016), Drakou (2017) and UNEP (2020), and following the CICES v5.1 classification, Table 1 summarises the main ecosystem services provided by seagrass beds.

As detailed in Table 1, seagrasses can filter, cycle, and store materials such as nutrients (e.g., nitrogen) and pollutants through their leaves and roots, stabilising the sediment concentration in the soft bottom while decreasing the turbidity (Boudouresque et al., 2016) and improving water quality.

Although this ecosystem plays a key role in the assimilation of chemical and physical pollutants, it is not only limited to these. Indeed, seagrasses can also remove microbiological contaminants from water, such as bacterial pathogens and viruses that could affect invertebrates, fish, or humans (UNEP, 2020), and they can produce bioactive secondary metabolites with antibacterial and antifungal properties. For instance, in the Mediterranean Sea, *Posidonia oceanica* beds can store heavy metals in the sediments for millennia, while in intensive oyster farming, seagrasses act as natural biofilters for the ammonium produced by shellfishes (UNEP, 2020). Due to their bioaccumulation capacity, and their sensitivity to environmental changes (Campagne et al., 2014), the seagrass bed is described by the EU Water Framework Directive (WFD, 2000/60/EC) as an indicator of coastal water quality for the Mediterranean Sea.

Focusing on regulation and maintenance of ecosystem services, seagrass beds are considered the most significant ocean carbon sinks in the world, with a high capacity for taking and storing carbon in the sediment (Castejón-Silvo & Terrados, 2012; UNEP, 2020), also known as 'blue' carbon (Mcleod et al., 2011). They show a high potential in mitigating climate change and benefiting the entire globe. Despite covering a worldwide surface that is one to two orders of magnitude smaller than terrestrial forests (Mcleod et al., 2011), and thanks to their trapping capacity of suspended particles and associated organic carbon, seagrasses are expected to store 19.9 Pg of organic carbon per year (UNEP, 2020). The anoxic conditions of the sediments promote the preservation of sedimentary organic carbon ($C_{org}$), resulting in the production of substantial carbon deposits that, if left undisturbed, can last for millennia (Ruiz et al., 2015; UNEP, 2020). Hence, the loss of seagrass beds leads to a reduction in carbon sequestration and storage capacity, resulting in increased $CO_2$ emissions from

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

soil $C_{org}$ deposit remineralisation. Some studies quantified this potential release at up to 299 Tg carbon per year at current rates of seagrasses losses (UNEP, 2020).

In addition, certain seagrass necromasses from, e.g., *Posidonia oceanica*, generate a unique habitat called matte, which is made up of dead rhizomes, roots, and sediments filling interstices (Boudouresque et al., 2016; Pergent et al., 2012). It can be found midway between soft and hard bottoms, and it has a role in the carbon sequestration flux with consequences for the oxygen net production (Röhr et al., 2016).

***Table 1.*** *Ecosystem services supplied by seagrass beds.*

| CICES ES Section | CICES division | CICES class | Description |
|---|---|---|---|
| **Provisioning** | Biomass | Wild plants (terrestrial and aquatic, including fungi, and algae) used for nutrition | Food provisioning; their leaves and rhizomes represent food for multiple fishes and invertebrates, as a basis for the food web |
| | | Fibres and other materials from wild plants for direct use or processing (excluding genetic materials) | Dead leaves are used as building insulation, as compost, bioindicator, industrial water waste absorbents and for roof isolation |
| **Regulation and maintenance** | Transformation of biochemical or physical inputs to ecosystems | Filtration/sequestration/storage/accumulation by micro-organisms, algae, plants, and animals | They are natural filters for pathogens, heavy metals and nutrients |
| | Regulation of physical, chemical, and biological conditions | Hydrological cycle and water flow regulation (Including flood control and coastal protection) | They prevent coastal erosion and protect from flooding, also attenuating the bottom stress |
| | | Maintaining nursery populations and habitats (Including gene pool protection) | They represent the habitat of a lot of marine species, including endangered and protected ones. They support fisheries by providing nursery habitats for fish, bivalve and crustacean species. They also provide life cycle maintenance exporting necromasses toward close habitats |
| | | Regulation of chemical composition of atmosphere and oceans | They can sequester carbon and act as storage for large amounts of carbon sediments. Linked to carbon sequestration, they can produce oxygen contributing to acidification mitigation |
| **Cultural** | Direct, in-situ and outdoor interactions with living systems that depend on the presence in the environmental setting | Characteristics of living systems that enable activities promoting health, recuperation or enjoyment through active or immersive interactions | They provide the opportunity for recreational tourism activities (e.g., diving, recreational fishing) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

In terms of coastal protection ecosystem services, seagrass beds play an important role in hydrodynamic attenuation and sediment retention, contributing to protecting coastal areas from the effects of climate change, including flooding, storm surges, as well as beaches from erosion (Boudouresque et al., 2016). More precisely, their rhizomes and roots stabilise the sediment and defend from erosion, while their leaves can attenuate currents, flow velocity and wave energy supporting sedimentation (Vacchi et al., 2016). Furthermore, the interactions between marine species and the abiotic seafloor lead to a substantial impact on benthic communities, influencing not only initial colonisation but also subsequent assemblages of the associated fauna (Vacchi et al., 2016).

In addition, some seagrass species, such as Posidonia, produce banquettes (UNEP, 2020), which are thick heaps of beach-cast seagrass material. These banquettes create a distinctive habitat playing a role in the geomorphic evolution of beaches under normal wave conditions and can contribute to stabilising dunes while protecting the shoreline from erosion by reducing wave motion and wave force (Boudouresque et al., 2016; Campagne et al., 2014; Ruiz et al., 2015; UNEP, 2020).

### 1.1.4 Available data for the Mediterranean eco-region

The operationalisation of the MRAF for cumulative impact appraisal in the Mediterranean eco-region requires the collection and pre-processing of a huge amount of heterogeneous data able to represent 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 were 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[5], useful to frame the case study area boundary, was retrieved from the EMODnet database[6]. Then, 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.), as detailed in the MRAF (Section 3), were retrieved from the Copernicus Marine Environment Monitoring Service (CMEMS)[7]. This platform provides free and open scientifically assessed ocean data across the global ocean to enable marine policy implementation and scientific innovation. In addition to these stressors, the spatial layer on the "kinetic energy at the seabed due to currents" was retrieved from the EMODnet Platform[8]. In particular, this indicator (and the related metrics –mean of annual 90th percentile) were calculated by the EMODnet Seabed Habitats project consortium exploiting CMEMS products. As far as the shipping traffic map is concerned, the map on the vessel traffic density (hours per square km per month), was collected from the EMODnet Human Activities database web portal[9]. Additionally, to evaluate the influence of human coastal activities and urban areas on seagrasses' health and distribution, several indicators and metrics related to the distance to the 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 located along the Mediterranean coasts

[5] The EMODnet Digital Terrain Model (DTM) has been generated for European sea regions (36W,15N; 43E,90N) from selected bathymetric survey data sets, composite DTMs, Satellite Derive Bathymetry (SDB) data products, while gaps with no data coverage were completed by integrating the GEBCO Digital Bathymetry.
[6] https://www.emodnet-seabedhabitats.eu/
[7] https://marine.copernicus.eu/
[8] www.emodnet-seabedhabitats.eu
[9] www.emodnet-humanactivities.eu

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

were gathered from Global Fishing Watch[10]. On the other hand, the minimum distance of each seagrass polygon to the closest main cities and river mouths has been calculated by applying the Haversine[11] formula (building on two different datasets containing information on major rivers and cities located close to the Mediterranean Sea shores, respectively).

Finally, for what concerns data on ecosystems' health and biodiversity, different seagrasses distribution maps across the Mediterranean eco-region were collected. In particular, data from a broad range of UNEP-WCMC global biodiversity standardized databases for the year 2017 were combined with the seagrass coverage layer produced by EMODnet Seabed Habitats (for the years 2016, 2017, 2018) to obtain the most complete representation of seagrasses distribution in the investigated marine region. Additionally, occurrence records of species and their metadata (e.g., taxonomic, geographic, time, data quality) were retrieved from the Ocean Biodiversity Information (OBIS)[12] System, supporting the calculation of biodiversity indices[13].

Data selected for the MRAF operationalisation in the Mediterranean eco-region are summarized in Table 2, also detailing metadata based on the following criteria: i) unit of measure and data format, ii) spatial and temporal resolutions, iii) data sources/web-reference.

[10] https://globalfishingwatch.org/data-download/
[11] Angular distance between two points on the surface of a sphere.
[12] https://obis.org/manual/access/
[13] https://iobis.github.io/notebook-diversity-indicators/

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

*Table 2. Available GIS-based dataset for the application of the multi-risk approach in the Mediterranean Sea eco-region.*

| | Indicator | Unit of measure | Data format (NetCDF, Shape, raster, etc.) | Spatial resolution | Temporal resolution | Sources (reference/ web link) |
|---|---|---|---|---|---|---|
| **Basic information** | Bathymetry | [m] | Raster file | 800 meters | Static | EMODnet (https://www.emodnet-bathymetry.eu/) |
| **PRESSURES' DATA** | | | | | | |
| **Endogenic pressures** | Seagrass distance from port | [km] | Raster file | / | Static | Global Fishing Watch (https://globalfishingwatch.org/data-download/) |
| | Seagrass distance from shore | [km] | Raster file | / | Static | |
| | Seagrass distance from the nearest river mouth | [km] | Raster file | / | Static | Calculated from HydroSHEDS hydrography dataset (http://gaia.geosci.unc.edu/rivers/) |
| | Seagrass distance to cities | [km] | Raster file | / | Static | Calculated from Copernicus (https://land.copernicus.eu/local/urban-atlas) |
| | NH4 | [mmol m-3] | NetCDF | 0.042degree x 0.042degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/?option=com_csw&view=details&product_id=MEDSEA_MULTIYEAR_BGC_006_008) |
| | NO3 | [mmol m-3] | NetCDF | 0.042degree x 0.042degree | Daily-mean | |
| | PO4 | [mmol m-3] | NetCDF | 0.042degree x 0.042degree | Daily-mean | |
| | Dissolved oxygen (O2) | [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 (https://resources.marine.copernicus.eu/product- |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | |
|---|---|---|---|---|---|---|
| | Light attenuation | [mmol m-3] | NetCDF | 0.042degree x 0.042degree | Daily-mean | detail/OCEANCOLOUR_GLO_OPTICS_L4_REP_OBSERVATIONS_009_081) |
| | Shipping traffic (Density) | [hours km-2 year-1] | GeoTIFF | 1 km x 1 km | Monthly | EMODnet (https://www.emodnet-humanactivities.eu/) |
| **Exogenic pressures** | Sea surface temperature | [Kelvin] | NetCDF | 0.05 degree x 0.05 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/?option=com_csw&view=details&product_id=SST_MED_SST_L4_REP_OBSERVATIONS_010_021) |
| | Ocean acidification | [pH] | NetCDF | 0.042 degree x 0.042 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_BGC_006_008) |
| | Salinity | [PSU] | NetCDF | 0.042 degree x 0.042 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_PHY_006_004) |
| | Spectral significant wave height | [m] | NetCDF | 0.042 degree x 0.042 degree | Hourly-instantaneous | CMEMS (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_WAV_006_012) |
| | Wind wave period | [s] | NetCDF | 0.042 degree x 0.042 degree | Hourly-instantaneous | CMEMS (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_WAV_006_012) |
| | 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 (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_PHY_006_004) |
| | Northward Sea Water Velocity | [m s-1] | NetCDF | 0.042 degree x 0.042 degree | Daily-mean | |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | |
|---|---|---|---|---|---|---|
| | Kinetic energy at the seabed due to currents | [N m-2] | Raster file | 1/24 degree horizontal resolution | Monthly-mean | EMODnet Seabed Habitats (https://www.emodnet-seabedhabitats.eu/) |
| | Sea level rise (Sea surface height) | [m] | NetCDF | 0.042 degree x 0.042 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/MEDSEA_MULTIYEAR_PHY_006_004) |
| **ECOSYSTEM DATA** | | | | | | |
| **Marine coastal ecosystem condition** | Seagrass distribution | [poligon occurance ] | ESRI Shapefile | \ | Static | UNEP WCMC global distribution seagrass (https://data.unep-wcmc.org/datasets/7) |
| | | | ESRI Shapefile | \ | Static | EMODnet Seabed Habitats (https://www.emodnet-seabedhabitats.eu/) |
| | Biodiversity | Shannon index [H] | ESRI Shapefile | hex grid | Static | Calculated from OBIS (https://obis.org/manual/access/) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

### 1.1.5 Future climate scenarios (RCP4.5 and RCP8.5)

Once the RF is trained, validated, and tested, it can be used for scenario analysis This analysis involves developing different multi-risk scenarios based upon climate projections derived from numerical models. With respect to the Mediterranean eco-region, the designed model will first be implemented with baseline data for the present climate. These data are representative of the real conditions of the system in the selected year (information collected and provided by CMEMS, as presented in the previous section) at the Mediterranean scale. After this first step of model training and validation, the RF algorithm will be tested against the reference scenario: i.e., a scenario representing the physical conditions resulting from the observed climate (dataset provided by CMCC). Compared to the baseline, this data is the resulting output of the CMCC Regional Earth System Model -RESM in the framework of the MedCORDEX initiative (CMCC-MedCORDEX) by extracting the window from 1998 to 2017.

The CMCC Med-CORDEX RESM covers the Mediterranean Sea and a small part of the Atlantic Ocean with a mesoscale permitting horizontal resolution 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 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).

Finally, a set of GIS-based multi-risk scenarios will be produced through the integration of climate change scenarios, which simulate the future conditions of oceanic parameters, under different Representative Concentration Pathways (IPCC, 2013).

In this study, future projections were extracted from numerical models. Specifically, these included projections of SST+MHWs, Salinity, and SSH (Table 3) that were extracted from the stabilization scenario (RCP4.5) and under the “business as usual” scenario (linked to very high greenhouse gas emissions - RCP8.5) Here, the projection years are 2031 to 2050 and 2081 to 2100, respectively (Table 3). These sea state variables/indicators allow simulation of their future impacts on MCEs biodiversity in the Mediterranean eco-region. The variables/indicators were also calculated for a baseline period (1998 to 2017), in order to better compare the scenarios and calculate the projections.

Sea state variables/indicators for the scenario analysis in the Mediterranean eco-region are summarized in Table 3, detailing information on i) variable ii) indicator considered iii) ID of the scenarios, iv) time windows of baselines and scenarios, and v) RCP and timeframe (regarding future scenarios).

Further investigations will integrate local scale scenarios in smaller-scale case studies within T2.3. For example, the Italian local case study will examine the potential future impacts to the Marine Protected Area of Torre Guaceto on a wider set of scenarios and indicators, including those linked to the biogeochemical cycle.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 3.*** *Scenarios available for the Mediterranean eco-region.*

| Variable | Indicators | ID | CMEMS Reanalises Baseline | Medcordex CMCC Baseline | Future scenarios | |
|---|---|---|---|---|---|---|
| | | | | | RCP Scenario | Period considered |
| Sea Surface Temperature | Mean<br>STD<br>95 Percentile<br>Minimum | A | 1998 to 2017 | 1998 to 2017 | RCP 4.5 | 2031 to 2050<br>2081 to 2100 |
| | | | 1998 to 2017 | 1998 to 2017 | RCP 8.5 | 2031 to 2050<br>2081 to 2100 |
| Marine heat waves | Duration<br>Number/year<br>Intensity | | 1998 to 2017 | 1998 to 2017 | RCP 4.5 | 2031 to 2050<br>2081 to 2100 |
| | | | 1998 to 2017 | 1998 to 2017 | RCP 8.5 | 2031 to 2050<br>2081 to 2100 |
| Salinity | Mean<br>STD<br>5 Percentile<br>Minimum | B | 1998 to 2017 | 1998 to 2017 | RCP 4.5 | 2031 to 2050<br>2081 to 2100 |
| | | | 1998 to 2017 | 1998 to 2017 | RCP 8.5 | 2031 to 2050<br>2081 to 2100 |
| Sea surface height | Mean | C | 1998 to 2017 | 1998 to 2017 | RCP 4.5 | 2031 to 2050<br>2081 to 2100 |
| | | | 1998 to 2017 | 1998 to 2017 | RCP 8.5 | 2031 to 2050<br>2081 to 2100 |

## 1.2 Description and characterization of the Northern Europe eco-region

The Northern Europe eco-region as understood in this project corresponds to a subregion defined by the Celtic Seas, the Greater North Sea including the English Channel and the Kattegat, parts of the Norwegian Sea and the Barents Sea (Figure 8). It includes the following countries: Ireland, the United Kingdom, France, Belgium, the Netherlands, Germany, Denmark, Sweden and Norway, and their dependent areas (i.e., the Channel Islands that are Guernesey, Jersey and Sark, the Isle of Man). The eco-region extends from 47° to 74°N and from 18°W to 32°E, and covers about 2.2 million km2 with a coastal length of about 88 000 km. It is openly connected to the North Atlantic Ocean in the west and the Greenland Sea in the north, and linked to the Baltic Sea in the east through the Skagerrak and the Kattegat.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

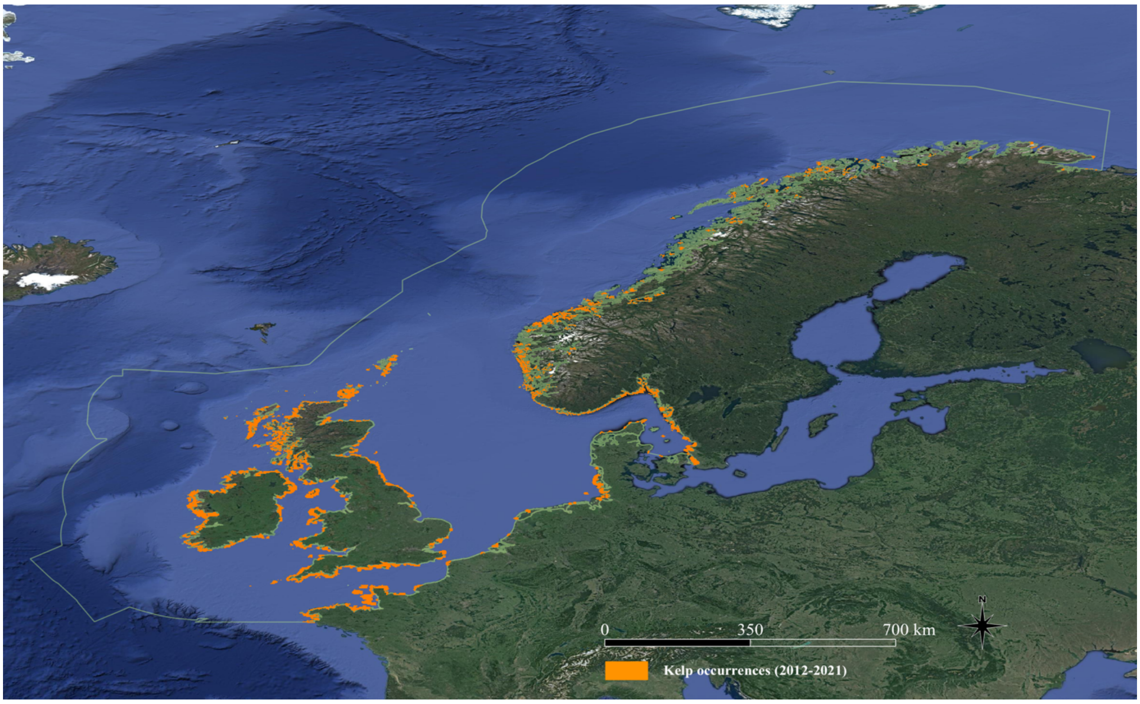



***Figure 8.*** *The Northern Europe eco-region.*

Because the eco-region is composed of inter-connected open seas across a larger latitudinal range than the Mediterranean Sea, its geomorphological, oceanological and climatological characteristics are much more varied.

Starting from the western part of the eco-region, the Celtic Seas region covers a transitional zone of continental shelf between the Atlantic Ocean and coastal waters, with the Rockall Trough further acting as an important pathway for warmer and more saline waters to more northerly basins such as the Norwegian sea. While most of the region is relatively shallow (<200m depth), the Rockall Trough is 1500 to 2300m deep, and the most western part of the region dip to 4500m depth in the Atlantic Ocean. As such, the oceanographic and climatic conditions of the Celtic seas are strongly influenced by the Northeast Atlantic Ocean, with the North Atlantic Oscillation (NAO) indirectly affecting the seas' sea surface temperature and salinity through its influence on storm tracks, westerly winds and oceanic circulation (ICES, 2022a). While in the summer strong thermal stratification leads to nutrient depletion in the upper mixed layer, resulting in low integrated rates of primary production (Marañon et al., 2005), vertical flow induced by currents on both sides of the mostly south-to-north seasonal front features results in biogeochemical and production hotspots with carbon export that sustain bottom communities (ICES, 2022a).

The Greater North Sea region then covers the Northern European continental shelf and is relatively shallow overall (ca. 50% of the area is no deeper than 50m) only dipping to more than 800m in the Norwegian Trench in the north-east (ICES, 2022b). It is a temperate, semi-enclosed continental shelf sea connected to the Celtic Seas and the Norwegian Sea in the North (ICES, 2022b). Variations in bathymetry and water inflows influence and drive the sub-regional differences observed in the water column stratification. Indeed, the English Channel in the south is usually mixed under the influence of wind, tidal currents and water inflow from the Atlantic. It is to the southern part of the North Sea, which is even more strongly mixed because of its shallow waters, tidal currents, and large river inputs (ICES, 2022b). The east and north of the sub-region are predominantly stratified, on the other hand, because of the lesser influence of tidal currents and stronger influence of water inflow from the Atlantic in the north conditioned by the NAO (ICES, 2022b).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

The Northern Europe eco-region also covers part of the Norwegian Sea corresponding more or less to the Norwegian exclusive economic zone. This part of the Norwegian Sea is relatively shallow, mostly covering the continental shelf (ICES, 2022c). It connects to the Greater North Sea to the south and to the Barents Sea to the east, constituting a transition zone with the Norwegian Atlantic Current, forming in the Norwegian Trench in the North Sea as an extension of the Gulf Stream and the North Atlantic Current, bringing warm and saline waters from the Atlantic in the south, and the cold and fresh Arctic waters in the north-east (ICES, 2022b, c). As such, the Atlantic Multidecadal Oscillation (AMO) affects the long-term climate variability of the area (ICES, 2022c). Finally, our Northern Europe eco-region also covers a small part of the Barents Sea north of the Norwegian sea, covering the continental shelf along the coast of Norway. Depth and oceanographic conditions in the area are still very similar to the one observed in the parts of the Norwegian Sea described above in its north-eastern range. It is worth noticing, though, that the variations in the NAO strongly affect the sea-ice cover in this area (and the more extended Barents Sea) (ICES, 2021).

The oceanographic conditions found in this eco-region allow the support of relatively complex food webs that span 4-5 trophic levels. These levels span from primary producers to top predators represented by many emblematic species such as sharks, seabirds, seals, dolphins and whales (ICES, 2021, 2022a, b, c). Those food webs have been significantly affected in the past decades mostly by the combined impacts of fishing pressure and environmental changes (ICES, 2021, 2022a, b, c), with species of commercial interest now being listed as Critically Endangered on the IUCN List of Threatened Species, such as the flapper skate and blue skate (*Dipturus spp.*) in the Celtic Seas (ICES, 2022a). Commercial fish stocks declined or shifts are almost ubiquitous in the eco-region (ICES, 2021, 2022a, b, c), while significant declined has also been observed in top predator species, such as in the Norwegian Sea where the Common guillemot (*Uria aalge*) is at high risk of extinction as a breeding species in the area, or where a lower pup production observed for hooded seals (*Cystophora cristata*), grey seals (*Halichoerus grypus*) and harp seals (*Pagophilus groenlandicus*), with similar trends in the Barents Sea (ICES, 2021, 2022c).

In the present section, following a detailed description of the main endogenic and exogenic pressures affecting the Northern Europe eco-region, details on the ecological and physical features characterising the marine and coastal ecosystem investigated in this study, i.e., kelp forests, as well as key ecosystem services they can provide, are also reported.

### 1.2.1 Key pressures

Like the Mediterranean Sea, the Northern European seas are significantly affected by multiple interactive drivers, that could similarly be classified into the following four categories: i) climate change, ii) pollution, iii) land and sea use changes, and iv) non-native species; and summarised in Table 4.

The main driver of **climate change** identified at the scale of the eco-region is the increase in temperature, including sea surface temperature (SST). According to the IPCC (Gutiérrez et al., 2021), SST in the region should increase by 0.5 to 1.0°C between 2040 and 2100 under scenario SSP1-2.6 and by 0.7 to 3.3°C between 2040 and 2100 under scenario SSP5-8.5. In the Celtic seas, an increase of 0.5°C has already been observed since 1975 potentially leading to a decrease in dinoflagellates and primary production, with repercussions for higher trophic levels (ICES, 2022a). Over the same period, the SST in the Greater North Sea has increased by more than 1.0°C in congruence with alterations of dinoflagellates and copepods populations and their phenology (ICES, 2022b). The deepening of demersal fish communities observed is also coherent with this temperature increase (ICES, 2022b). In the Norwegian Sea then, the warm phases associated with the Atlantic Multidecadal Oscillation

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

(AMO) have grown warmer and the cold phases less cold, and while it is expected these changes are affecting marine trophic webs of the area, this remains to be investigated (ICES, 2022c). Finally, the last decade has been the warmest observed in the Barents Sea with potential effects on plankton and fish populations although this remains to be investigated (ICES, 2021). The Northern Europe eco-region is also expected to be affected by a reduction in sea ice concentration for its northernmost part (-0.2% to -1.0% between 2040 and 2100 under scenario SSP1-2.6, and -0.6% to -2.6% over the same period under scenario SSP5-8.5; Gutiérrez et al., 2021), an increase in precipitations, acidification and sea-level rise (SLR). For instance, it is expected that, even when the accretion rate could be enough to keep up with SLR, coastal development would hamper salt marshes to cope with this pressure by preventing their landward migration in the UK (Boorman, 1992), a phenomenon better known as "coastal squeeze" (e.g., Doody, 2013).

When looking at **pollution** then, the whole eco-region is threatened by the introduction of contaminating compounds from various sources. In the Celtic Seas and the Greater North Sea, the main sources of contaminations are industrial, urban (coastal and wastewater), and agricultural run-off as well as atmospheric deposition, shipping, fisheries, tourism and recreation, oil and gas extraction, aquaculture, and renewable energy instalments, and many of the contaminants are long lasting with nearly all marine ecosystems being affected to some degree (ICES, 2022a, b). However, many sources of inputs are regulated, monitored, and managed within the eco-region leading to downward trends for some contaminants (ICES, 2022b). The Norwegian and Barents Seas, while being relatively "cleaner", are still affected by human activities in coastal areas (e.g., aquaculture), the local oil and gas industry and ship fuel emissions, but also from sources outside the region (introduced through long-range transport), causing toxicity for marine organisms and food webs (ICES, 2021, 2022c). The Celtic Seas and Greater North Sea are further affected by marine litter from various origins related to land and sea uses such as fishing (e.g., nets, ropes, buoys) and tourism and recreation (e.g., food and drinks packaging, cigarette buts), with the most dominant material found being plastic (macro, micro and nano), and effects on marine life remaining poorly known but supposing ranging from entanglement to microplastic contamination (ICES, 2022a, b). Finally, the Celtic Seas are also impacted by nutrient and organic enrichment from agriculture, urban wastewater and atmospheric deposition mostly, but also from shipping, aquaculture and land-based industry, which contribute to localised coastal eutrophication (ICES, 2022a). However, it seems that management measures in the area have proven relatively successful as supported by the observed reductions in Nitrogen and Phosphorus (ICES, 2022a). The innermost areas of the Norwegian Sea are also potentially impacted by nutrient and organic enrichment, notably coming from aquaculture. Indeed, it has been estimated that fish farms on the Norwegian Sea's coasts can release large amounts of nutrients similar to that of a little town, which impacts local ecosystems such as kelp forests (Haugland et al., 2021).

The Northern Europe eco-region is also strongly impacted by **land and sea uses**, the main one being the extraction of species, and in particular commercial fisheries with landings counted in millions of tones across the eco-region (e.g., 2 million of tonnes in the Greater North Sea or 1 million of tones in the Norwegian Sea; ICES, 2022a, c). Commercial fisheries further have a strong impact on the eco-region through high rates of by-catch on sometimes vulnerable species, with trawling gears and nets presenting a risk for some elasmobranch of conservation concern in the Celtic Sea, longline fisheries presenting a risk for seabirds offshore and nets for diving birds, seals and dolphins more inshore (e.g., an average of 2900 harbour porpoises per year taken in a gillnet in the Norwegian Sea between 2006 and 2018; ICES, 2022c). Mink whales are also still actively fished in the Norwegian Sea, although the number of whaling vessels is decreasing, and ship strike has been identified as an additional threat to marine mammals in the eco-region (ICES, 2022c). Finally, recreational fisheries also represent a significant activity in the Celtic Sea and the Greater North Sea covering a wide range of platforms

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

and gears and including hand collecting/harvesting on the shore, particularly on both sides of the English Channel (ICES, 2022a, c). The second main pressure in the eco-region then is the physical disturbance of the seabed through abrasion, resuspension or removal of the substrate, and deposition, mostly from mobile bottom-trawl fishing gear and offshore oil and gas operations, but also to some extent from other activities such as aquaculture, tourism/recreation, coastal infrastructure, hydrodynamic dredging, shipping (anchoring), and cable burial (ICES, 2021, 2022a, b, c). For the 2018-2021 period, it was estimated that mobile bottom trawls were deployed over nearly 1.11 million km$^2$ across the eco-region, i.e., half of its total surface area. Of this area, the Greater North Sea is the most severely impacted with approximately 85% of its surface area swept by this type of gear (ICES, 2022b). These activities are mostly affecting benthic communities causing additional mortality through, for example, collisions with bottom-contacting mobile and set fishing activities. Finally, underwater noise linked to human activities has also been highlighted mostly in the Greater North Sea and Norwegian Sea, with seismic surveys to search for oil and gas and sonars from naval exercises noted as the main sources, although many other sources can be found such as ship traffic or offshore windfarms (ICES, 2022b, c).

Finally, the threat from **non-native species** is ubiquitous across the eco-regions, with the main vectors cited as shipping, mostly through ballast water and hull fouling, and contaminants and parasites on animals (primarily associated with aquaculture) (ICES, 2021, 2022a, b, c). It can be noted that some introductions of non-native species were voluntary, such as the introduction of the red king crab in the Barents Sea to provide a resource for fishing, but that is now considered invasive (ICES, 2021). The northward migration of some species (e.g., fish, copepods) potentially under the effect of rising temperatures has also been noted, although the exact causes of such migrations remain unclear because the underlying mechanisms are usually quite complex. While 470 non-native and cryptogenic species have been recorded since 1950 with an increasing annual discovery rate since the 1990s in the Greater North Sea, the monitoring of non-native species and their impact on local communities has been relatively poor and fragmented across the eco-region (ICES, 2021, 2022a, b, c).

***Table 4.*** *Key pressures affecting the Northern Europe eco-region.*

| | | Celtic Seas | Greater North Sea | Norwegian Sea | Barents Sea |
|---|---|---|---|---|---|
| Climate change | Rising sea-surface temperature | ✓ | ✓ | ✓ | ✓ |
| Pollution | Introduction of contaminating compound | ✓ | ✓ | ✓ | ✓ |
| | Marine litter | ✓ | ✓ | | |
| | Nutrient and organic enrichment | ✓ | | ✓ | |
| Land and sea uses | Extraction of species | ✓ | ✓ | ✓ | ✓ |
| | Physical disturbance to the seabed | ✓ | ✓ | ✓ | ✓ |
| | Underwater noise | | | ✓ | |
| Non-native species | | ✓ | ✓ | ✓ | ✓ |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

### 1.2.2 Kelp forest ecosystems: key environmental features and vulnerabilities to climate risks

Kelps are large brown algae or seaweed of the orders Laminariales and Tilopteridales, made of a holdfast that anchors them to the seafloor through a branched root-like structure and a stipe with blades that have a leaf-like structure. They can grow in monospecific or mixed assemblages forming sometimes extensive underwater forests with complex three-dimensional structures providing food, shelter, and habitat for a wide variety of species from invertebrates to fish, mammals and seabirds, and are thus considered as ecosystem engineers. Kelp forests can be found around the world in nutrient-rich rocky coastal marine environments under sub-tropical, temperate, and sub-polar latitudes (Figure 9) and are considered as one of the most diverse and productive ecosystems of the world (UNEP, 2023). This latitudinal distribution is constrained by light but also by temperature in their poleward range and by nutrients and competition in their temperate range (Yesson et al., 2015; Wernberg et al., 2019). Furthermore, like seagrasses in the Mediterranean, kelps are usually found in relatively shallow waters but can found up to 40-50 meters deep in Northern Europe (exceptionally deeper), where they are constrained by light as photosynthetic organisms.

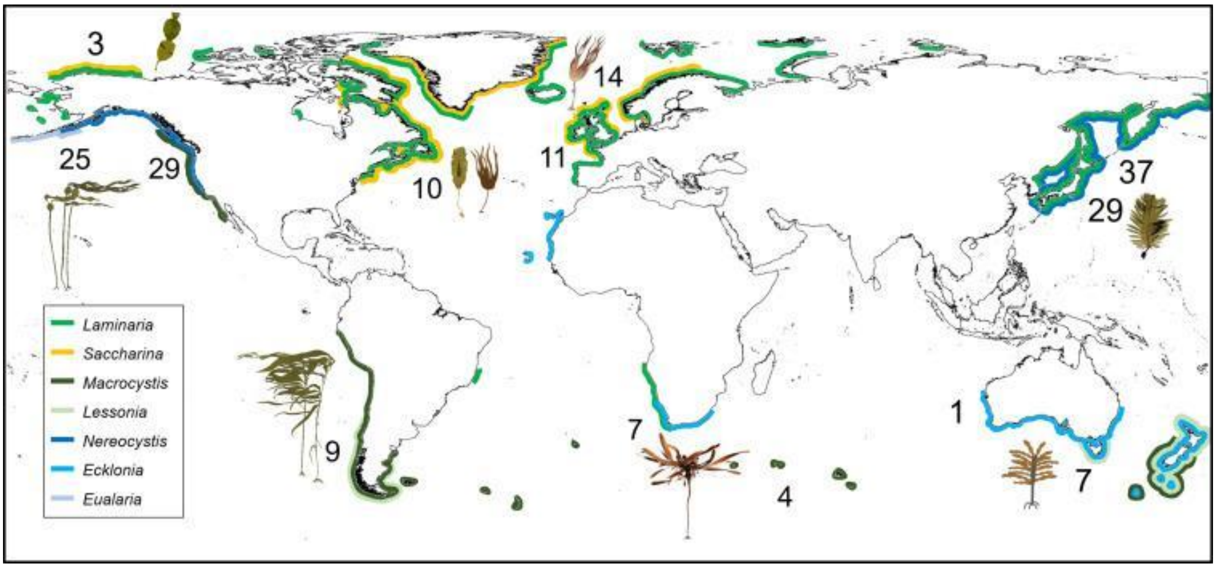



***Figure 9.*** *Global distribution of kelps. Coloured lines indicate the distribution of kelp genera and numbers indicate kelp species in each area. From Wernberg et al. 2019.*

Kelp populations can be spatially and temporally highly dynamic due to varied and complex drivers (e.g., Smale et al., 2013; Trowbridge et al., 2013) but also to the specificity of their lifecycle. Indeed, kelps reproduce through the development of specialised reproductive tissue on the blade of the adult algae (or sporophyte) that will release flagellated zoospores, which will then disperse before settling on the seafloor and developing into male or female gametophytes. The female gametophyte will then be fertilised by the gametes released by male gametophytes, and finally develop into a juvenile sporophyte that will grow into an adult sporophyte (Wernberg et al., 2019). Each life cycle stage (i.e., gametophyte and sporophyte) may then be affected differently by environmental stressors (see Bartsch et al., 2008). Overall, it is largely acknowledged that sea water temperature increase, including the increased number of marine heatwaves, related to climate change is one of the main drivers of kelp populations trends observed across Northern Europe (e.g., Araújo et al., 2016; Deliverable 1.3; UNEP, 2023, Wernberg et al., 2019; Smale 2020). Northern European kelps are also under threats from overfishing through the perturbation of the trophic web, i.e., a decrease in coastal

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

fish stocks leading to an increase of grazers such as sea urchins (Deliverable 1.3, Arújo et al., 2016, Wernberg et al., 2019; UNEP, 2023). Although this last pressure has mainly been reported in Norway, localised events have also been reported in France, Denmark and the UK (Norderhaug and Christie, 2009). Kelp harvesting has also been discussed as a potential threat along with bottom trawling that can further create physical disturbance to kelp ecosystems (Deliverable 1.3, Christie et al., 1998). Other threats in Northern Europe include eutrophication and freshwater run-offs from land, and the expansion of invasive species such as *Undaria pinnatifida* that displace native species (Deliverable 1.3, Araújo et al., 2016, Wernberg et al., 2019; UNEP, 2023).

While it exists more than 30 genera and more than 100 species (Wernberg et al., 2019), 7 main species are identified in our Northern Europe eco-region (Yesson et al., 2015): *Alaria esculenta*, *Laminaria digitata*, *Laminaria hyperborea*, *Laminaria ochroleuca*, *Saccharina latissima*, *Saccorhiza polyschides, Saccorhiza dermatodea* and *Undaria pinnatifida*. In Northern Europe, the following trends have been observed for each species.

*Alaria esculenta* is a circumpolar species that can be found from the south of the Point du Raz, France, to Svalbard (Araújo et al., 2016). The species usually grows in the upper sublittoral and is therefore particularly vulnerable to increased temperatures, although it may also be found at greater depths. However, limited data showed no significant decrease of the species in the northern limits of its distribution and only small-scale variations around the UK (Araújo et al., 2016).

*Laminaria digitata* present a similar distribution to *Alaria esculenta*, being found from Britany, France, to Svalbard (Araújo et al., 2016). The species has been declining in the southern limits of its distribution, having completely disappeared from the French coastline of the English Channel and Dover Strait (Araújo et al., 2016). On the other hand, it seems to be striving in the northern limits of its distribution where its biomass has been increasing in shallow sublittoral waters between 2.5 and 5m since the mid-1990s (Araújo et al., 2016; Düsedau et al. 2022), although these northernmost populations also indicated a high-temperature sensitivity (Liesner et al., 2020).

*Laminaria hyperborea* has a more extended distribution, from Portugal to the Murman coast in Russia (Araújo et al., 2016). The species has been decreasing in the southern limits of its distribution with reports of populations disappearing or moving to a greater depth around the Iberian Peninsula (Araújo et al., 2016), while Smale et al. (2022b) reported a replacement by *Laminaria ochroleuca*, a warm water species, in southern England. Further north, populations have been reported as increasing in the North Sea around the island of Helgoland, and stable in the Skagerrak and southwest Norway, but heavily degraded in mid to north Norway due to heavy grazing by sea urchins (Araújo et al., 2016). However, it seems that these last populations of L. hyperbora are starting to recover thanks to increased temperatures that favour the northern migration of crab species, such as *Cancer pagurus* and *Carcinus maeans*, that predate on sea urchins (Christie et al., 2019).

The warm water species, *L. ochroleuca,* is a warm water species able to tolerate temperatures up to 25°C that can be found from the Strait of Messina in Italy to the southern coasts of the UK, and to depth up to 80m (Araújo et al., 2016). While there has been reports of population decrease in the northern coasts of France, the species has been developing in the UK (replacing *L. hyperborea* as stated above) and has even been reported recently in Ireland (Schoenrock et al., 2019), with expectations of northern expansion as temperatures keep increasing (Assis et al., 2018).

Not unlike *L. hyperborea*, *Saccharina latissima* exhibits an extended distribution, ranging from Portugal in the South to Svalbard in the North (Araújo et al., 2016). While the species also exhibits populations trends similar to *L. hyperborea* in the southern part of its range, with reports of populations disappearing or moving to greater depth around the Iberian Peninsula, and in the northern part of its range, with populations being decimated by sea urchin grazing in mid and north Norway, it has also exhibited decrease and/or shift to deeper waters in the English Channel and the Dover

Strait, around Helgoland in the North Sea, and southwest Norway (Araújo et al., 2016). It has been suggested that the main drivers of the southwest Norway populations decrease were heat waves together with increased nutrients and particle pollution (Filbee-Dexter & Wernberg 2018, Filbee-Dexter et al. 2020). Also, similarly to *L. hyperborea*, the species seems to have started to recover in mid and north Norway more recently, thanks to increased temperatures that favour the northern migration of crab species, such as *Cancer pagurus* and *Carcinus maeans*, that predate on sea urchins (Christie et al., 2019).

*Saccorhiza polyschides* is distributed from the Strait of Messina in Italy to the Lofoten archipelago in Norway (Araújo et al., 2016). There are few data on the trends of this species' populations, but it is generally regressing in Southern Europe and in some localities on the northern coast of France. Relatively stable populations on the northern coast of the Iberian Peninsula and on southern French coasts (Araújo et al., 2016). *Saccorhiza dermatodea* is a northern species only found in the northern part of Norway and on Svalbard (Rueness 1977, Fredriksen et al. 2019).

*Undaria pinnatifida* is a species native from Northern Asia that was voluntary introduced via cultivation into the Mediterranean Sea and Brittany, France in the 1970s and 1980s. Since then, it has spread from coastal Italy to the UK (Araújo et al., 2016) and Northern Ireland where it was reported in the early 2010s (Minchin and Nunn, 2014). The species exhibits a wide temperature tolerance (Morita et al., 2006) which could facilitate its expansion northward of its current range into Northern Europe.

These changes are expected to continue and even accelerate as climate keeps changing and human activities keep intensifying, and while the main drivers of these changes are relatively well identified, the cumulative impacts of these stressors on kelp populations remain uncertain (Wernberg et al., 2019).

### 1.2.3 Kelp forests: key services and functions

Kelps are ecosystem-forming species that, as such, provide food, shelter and habitat for a wide variety of species. They support rich and complex food webs from which humans benefit food and material. Their dense, three-dimensional structure they form further shelter coastlines from storms and waves energy, and their high productivity contribute to absorb and sequester carbon from the atmosphere making them particularly valuable ecosystems when it comes to adapting to and mitigating the effect of climate change. Kelps therefore provide many significant ecosystem services, some of which might appear more obvious and easier to assess like food provisioning, others being less evident and more difficult to evaluate such as regulating and maintenance services covering for instance the nursery function, carbon sequestration, water treatment or coastal protection, and cultural services covering for instance recreative activities and tourism or the source of inspiration for the arts. Table 5 summarises the main ecosystem services provided by kelp forests, following the CICES v5.1 classification.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 5.*** *Ecosystem services supplied by kelp forests.*

| CICES ES Section | CICES division | CICES class | Description |
|---|---|---|---|
| **Provisioning** | Biomass | Cultivated and wild plants (terrestrial and aquatic, including fungi, algae) grown for/used for nutritional purposes | Kelps have been historically harvested and are cultivated for food and food supplement such as vitamins. |
| **Provisioning** | Biomass | Fibres and other materials from cultivated and wild plants for direct use or processing (excluding genetic materials) | Kelps are harvested and cultivated to produce insulating material, alginates, cosmetics, fertilizer, etc. |
| **Provisioning** | Biomass | Cultivated and wild plants (terrestrial and aquatic, including fungi, algae) grown/used as a source of energy | Kelps have been recently used to develop biofuels (although this use remains rare). |
| **Regulation and maintenance** | Transformation of biochemical or physical inputs to ecosystems | Filtration/sequestration/storage/accumulation by microorganisms, algae, plants, and animals | Kelps have been known to filter nutrients, in particular nitrogen and phosphorus from run-offs and aquaculture/mariculture farms. They also have the potential to filter pathogens and accumulate heavy metals. |
| **Regulation and maintenance** | Regulation of physical, chemical, biological conditions | Hydrological cycle and water flow regulation (Including flood control and coastal protection) | They prevent coastal erosion and protect from flooding, also attenuating the bottom stress by attenuating wave energy. |
| **Regulation and maintenance** | Regulation of physical, chemical, biological conditions | Maintaining nursery populations and habitats (Including gene pool protection) | They represent the habitat of a lot of marine species, including endangered and protected ones. They support fisheries providing nursery habitats for fish, bivalve and crustacean species. |
| **Regulation and maintenance** | Regulation of physical, chemical, biological conditions | Regulation of chemical composition of atmosphere and oceans | Kelp biomass is exported, via frond shedding, to the deep sea where sediments have little direct contact with human activities, which means the carbon exported this way can be trapped and stored for centuries. |
| **Cultural** | Direct, in-situ and outdoor interactions with living systems that depend on the presence in the environmental setting | Characteristics of living systems that enable activities promoting health, recuperation or enjoyment through active or immersive interactions | They provide the opportunity for recreational tourism activities (e.g., diving, recreational fishing) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

In terms of **provisioning services**, kelps have been historically cultivated and harvested for food (e.g., *Unadria pinnatifida* commonly known as 'wakame', *Saccharina latissima* commonly known as 'sugar kelp' or 'kombu') and food supplements (e.g., vitamins), but also for raw and processed material such as insulating material, cosmetics, fertilizer, or alginates that are widely used in pharmaceutical products, like pill coatings or toothpaste, and food production, including ice cream or beer. More recently and although this venture remains in its very early stages, kelps have also been explored as an option to produce biofuels (Lin et al., 2019; https://www.macrofuels.eu/copy-of-seaweed-cultivation-2).

In terms of **regulating and maintenance services**, four main categories of services have been highlighted. First, kelps play an important role in reducing the effects of climate change through carbon sequestration. Indeed, like plants on land, kelps photosynthesise to grow, absorbing carbon dioxide in the process. Healthy kelps can grow fast (e.g., *Macrocystis pyrifera* can extend by up to 60cm/day during its growing season) and export much of their biomass, via frond shedding (that is the stipe and blade part of the algae), to the deep sea. Because deep-sea sediments have little direct contact with human activities, this "blue carbon" can be trapped and stored for centuries (e.g., Bayley et al., 2021; Pedersen et al., 2021; Smale et al., 2022a). Secondly, as mentioned in the previous section, kelps form complex three-dimensional habitats providing shelter and food for many species from invertebrates to fish, mammals and seabirds (Teagle at al., 2017). Some species, such as *Laminaria hyperborea* in particular, can be overgrown by epiphytes and host more than 100 different (Christie et al. 2009, Teagle et al., 2017; Wernberg et al., 2019). These epiphytes provide an additional dimension to the kelp forest and, in turn, support many other animals with shelter, food and raw materials (Teagle et al., 2017; Christie et al., 2019; Smale et al., 2022b). Kelp forests therefore play an important role in supporting biodiversity and fisheries as many species of commercial interest also use these ecosystems for at least part of their life cycle such as the Atlantic cod, *Gadus morhua* (Wernberg et al., 2019; Smale et al., 2013). The three-dimensional structure of kelp forests further interferes with water movements, attenuating wave energy and reducing the velocity of breaking waves providing a buffer during storm surges, but also potentially reducing coastal erosion and sand and pebbles movement from adjacent areas (UNEP, 2023). While this potential has been relatively well documented for other coastal ecosystems such as mangroves or coral reefs, it has been less studied for kelps. However, a study in Norway has shown that *Laminaria hyperborea* could reduce wave heights by up to 60% (UNEP, 2023). Overall, the wave-dampening potential of kelp forests will depend on the kelp species present (morphology, size, density, community assemblage, etc.) and understorey associated species, but also on the geomorphology, depth and oceanographic parameters of the area, meaning the service will vary according to the location (UNEP, 2023). Finally, kelps have been known to filter nutrients, in particular, nitrogen and phosphorus from run-offs and aquaculture/mariculture farms (Kim et al., 2015; Marinho et al., 2015; Umanzor and tephens, 2023; Xu et al., 2023). They also have the potential to filter pathogens and accumulate heavy metals (Ratcliff et al., 2016).

Lastly, kelp forests provide many **cultural services** which remain largely unvalued because of a lack of data and mean of evaluation. Yet they have an important role in supporting recreational activities (e.g., scuba diving and recreational fisheries) and tourism, further providing a source of inspiration for the arts, and a study subject for education and research, among many other cultural services (UNEP, 2023).

### 1.2.4 Available data for the Northern Europe eco-region

Like for the Mediterranean eco-region, the operationalisation of the MRAF for cumulative impact appraisal in the Northern Europe eco-region requires the collection and pre-processing of a considerable amount of heterogeneous data able to represent spatial distribution and intensity of both endogenic and exogenic pressures (Michael Eliott et al., 2020), as well as detailed information on ecosystem's health and biodiversity. To this aim, different open-source web-data platforms were screened for this eco-region as well (e.g., Copernicus Services, EMODnet and GBIF data), paying particular attention to the availability of high spatio-temporal resolution data.

As for the Mediterranean eco-region, bathymetric data[14], useful to frame the case study area boundary, was first retrieved from the EMODnet database[15]. Then, focusing on the most relevant stressors affecting kelp forests in the Northern Europe eco-region, data on both endogenic (e.g., 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.), as detailed in the MRAF (Section 3), were retrieved from the Copernicus Marine Environment Monitoring Service (CMEMS)[16]. Additional to these stressors, the spatial layer on the "kinetic energy at the seabed due to currents" was retrieved from the EMODnet Platform[17]. In particular, this indicator (and the related metrics –mean of annual 90$^{th}$ percentile) were calculated by the EMODnet Seabed Habitats project consortium exploiting CMEMS products. As far as the shipping traffic map is concerned, the map on the vessel traffic density (hours per square km per month), was collected from the EMODnet Human Activities database web portal[18]. Additionally, to evaluate the influence of human coastal activities and urban areas on kelps distribution, two indicators and metrics related to the distance to the human settlements have been retrieved and pre-processed. Specifically, two open-source layers representing the distance from ports and shores located along the Northern European coasts were gathered from Global Fishing Watch[19].

Finally, for what concerns data on ecosystems' distribution, and contrary to the Mediterranean eco-region, no homogeneous and/or large-scale kelps distribution maps adapted to such analysis are available across the Northern Europe eco-region. Instead, occurrence records of species and their metadata (e.g., taxonomic, geographic, time, data quality) were retrieved from the Global Biodiversity Information Facility (GBIF)[20] database for the years from 2012 to 2021 and for the following kelp species: *Alaria esculenta*, *Laminaria digitata*, *Laminaria hyperborea*, *Laminaria ochroleuca*, *Saccharina latissima*, *Saccorhiza polyschides, Saccorhiza dermatodea* and *Undaria pinnatifida*.

Data selected for the MRAF operationalisation in the Northern Europe eco-region are summarised in Table 6, also detailing metadata based on the following criteria: i) unit of measure and data format, ii) spatial and temporal resolutions, iii) data sources/web-reference.

---

[14] The EMODnet Digital Terrain Model (DTM) has been generated for European sea regions (36W,15N; 43E,90N) from selected bathymetric survey data sets, composite DTMs, Satellite Derive Bathymetry (SDB) data products, while gaps with no data coverage were completed by integrating the GEBCO Digital Bathymetry.

[15] https://www.emodnet-seabedhabitats.eu/

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

[17] www.emodnet-seabedhabitats.eu

[18] www.emodnet-humanactivities.eu

[19] https://globalfishingwatch.org/data-download/

[20] https://www.gbif.org

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 6.*** *Available GIS-based dataset for the application of the multi-risk approach in the Northern Europe eco-region.*

| | Indicator | Unit of measure | Data format (NetCDF, Shape, raster, etc.) | Spatial resolution | Temporal resolution | Sources (reference/ web link) |
|---|---|---|---|---|---|---|
| **Basic information** | Bathymetry | [m] | Raster file | 800 meters | Static | EMODnet (https://www.emodnet-bathymetry.eu/) |
| **PRESSURES' DATA** | | | | | | |
| **Endogenic pressures** | Kelps distance from port | [km] | Raster file | / | Static | Global Fishing Watch (https://globalfishingwatch.org/data-download/) |
| | Kelps distance from shore | [km] | Raster file | / | Static | |
| | NO3 | [mmol m-3] | NetCDF | 0.25degree x 0.25degree | Monthly-mean | CMEMS (https://resources.marine.copernicus.eu/?option=com_csw&view=details&product_id=GLOBAL_REANALYSIS_BIO_001_029) |
| | PO4 | [mmol m-3] | NetCDF | 0.25degree x 0.25degree | Monthly-mean | |
| | O2 | [mmol m-3] | NetCDF | 0.25degree x 0.25degree | Monthly-mean | |
| | Chl-a | [mg m-3] | NetCDF | 0.25degree x 0.25degree | Monthly-mean | |
| | Secchi depth (ZSD) | [m] | NetCDF | 0.042degree x 0.042degree | Monthly-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/OCEANCOLOUR_GLO_OPTICS_L4_REP_OBSERVATIONS_009_081) |
| | Light attenuation | [m-1] | NetCDF | 0.042degree x 0.042degree | Monthly-mean | |
| | Shipping traffic (Density) | [hours km-2 year-1] | GeoTIFF | 1 km x 1 km | Monthly | EMODnet (https://www.emodnet-humanactivities.eu/) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | |
|---|---|---|---|---|---|---|
| **Exogenic pressures** | Sea surface temperature | [Kelvin] | NetCDF | 0.05degree x 0.05degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/?option=com_csw&view=details&product_id= SST_GLO_SST_L4_REP_OBSERVATIONS_010_011) |
| | Ocean acidification | [pH – unit-less] | NetCDF | 0.25degree x 0.25degree | Monthly-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_MULTIYEAR_BGC_001_029) |
| | Salinity | [PSU] | NetCDF | 0.083degree x 0.083degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_REANALYSIS_PHY_001_030) |
| | Spectral significant wave height | [m] | NetCDF | 0.2degree x 0.2degree | 3-hourly-instantaneous | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_MULTIYEAR_WAV_001_032) |
| | Wind wave period | [s] | NetCDF | 0.2degree x 0.2degree | 3-hourly-instantaneous | |
| | Spectral significant wind wave height | [m] | NetCDF | 0.2degree x 0.2degree | 3-hourly-instantaneous | |
| | Eastward Sea Water Velocity | [m s-1] | NetCDF | 0.083degree x 0.083degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_REANALYSIS_PHY_001_030) |
| | Northward Sea Water Velocity | [m s-1] | NetCDF | 0.083degree x 0.083degree | 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 (https://www.emodnet-seabedhabitats.eu/) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | |
|---|---|---|---|---|---|---|
| | Sea level rise (Sea surface height) | [m] | NetCDF | 0.083 degree x 0.083 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_REANALYSIS_PHY_001_030) |
| | Sea ice concentration (sea ice area fraction) | [unit-less] | NetCDF | 0.25 degree x 0.25 degree | Daily-mean | CMEMS (https://resources.marine.copernicus.eu/product-detail/GLOBAL_ANALYSISFORECAST_PHY_CPL_001_015) |
| | Sea ice thickness | [m] | NetCDF | 0.25 degree x 0.25 degree | Daily-mean | |
| **ECOSYSTEM DATA** | | | | | | |
| **Marine coastal ecosystem condition** | Kelp species occurences | [point occurrences ] | txt file | \ | Static | GBIF (https://www.gbif.org) |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

### 1.2.5 Future climate scenarios

Similar to the procedure employed for the Mediterranean eco-region, once the RF model developed for the North Europe eco-region has been trained, validated, and tested, it will be leveraged for scenario analyses. This analysis will utilize the climate model provided through the Copernicus Climate Change Service (C3S) platform[21].

The specific model used has been generated employing the marine ecosystem model known as ERSEM v15.06 (European Regional Seas Ecosystem Model), in conjunction with the regional ocean circulation models named POLCOMS (Proudman Oceanographic Laboratory Coastal Ocean Modelling System). Following the same procedure applied in the Mediterranean eco-region, the RF algorithm will be used against the reference and future scenarios. Unlike the long-term reference considered in the previous section (1998-2017), here the baseline dataset includes the 2006-2017 time window due to the limited data availability of the above model.

In this study, based on the available dataset, projections of dissolved oxygen will be extracted from two future scenarios, the intermediate scenario (RCP4.5) and the “business as usual” scenario (RCP8.5). Here, the projection years are 2031 to 2050 and 2081 to 2100, respectively. This sea state indicator allows us to simulate its future impacts on MCEs biodiversity in the North Europe eco-region.

[21] https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-marine-properties?tab=overview

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

## 2. MRAF Conceptual framework

Building on knowledge and terminologies as acquired under the preliminary systematic review of the state-of-the-art publication focusing on CIA and multi-risk-based methodologies and applications (Section A), the co-design of the general MRAF aims at unrevealing the complex interplay between natural and anthropogenic pressures affecting MCEs and their services. This phase is highly iterative and includes the tight involvement of all MaCoBioS Experts during the theorization of the MRAF, as framed under an Expert engagement workshop organized on the 24th of March, 2021. In the following paragraphs, the methodology for the co-design of the general MRAF is reported in Section 2.1 while the outcome is reported in Section 2.2.

### 2.1 Co-design of the general MRAF

The MRAF was designed iteratively through different phases (Figure 11) including the: i) collection of preliminary information from the Ahaslide questionnaire (i.e., pre-event phase) allowing to set up the forthcoming thematic World Café discussions and feed the initial set-up of the MRAF; ii) World Café discussions (i.e., during the event phase), organized within the WP2 expert-based workshop to connect multiple ideas and perspectives under three main topics i.e. pressures affecting MCEs, vulnerability and adaptive capacity of MCEs and ecosystem services provision in MCEs; iii) integration of all inputs into the MRAF under a co-design process (i.e., post-event phase).

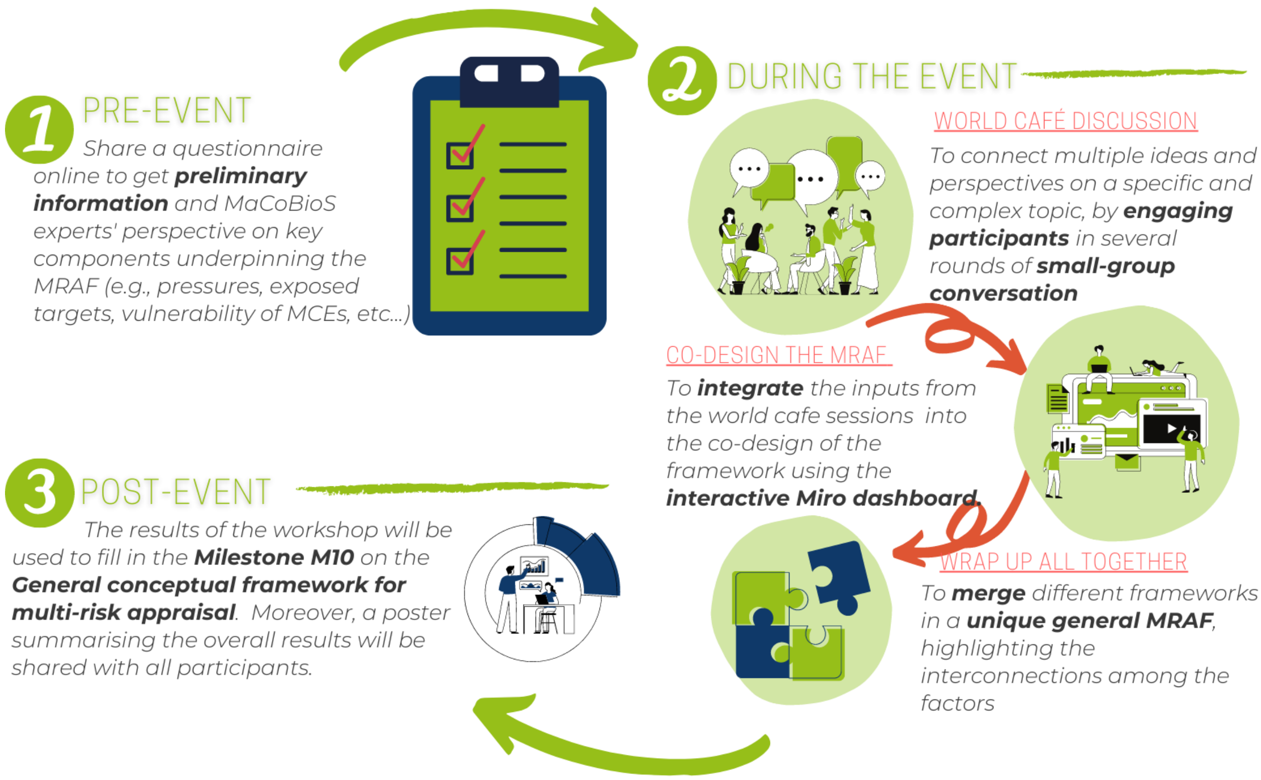



***Figure 11.*** *The methodology for the co-design of the general MRAF.*

As far as the questionnaire of the pre-event phase is concerned, the survey aims to i) identify human-made and climate-related pressures affecting MCEs, together with their potential synergies; ii) characterize the vulnerability of MCEs to the identified pressures (both in terms of sensitivity and

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

adaptive capacity); iii) integrate ecosystem services concepts into the multi-risk assessment framework. The MaCoBioS'experts actively responded to the questions and provided valuable information in different formats (e.g., proposing new pressures, vulnerability, and ecosystem services-related indicators, while scoring their relevance. For example, Figure 12 reports the results of the two questions related to the vulnerability topic.

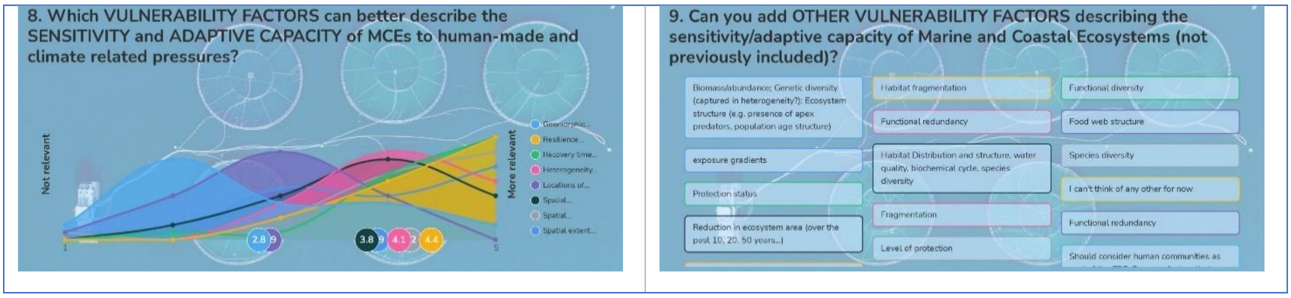



***Figure 12.*** *Results from the Ahaslide questionnaire of the pre-event phase under the "vulnerability" topic.*

Specifically, resilience and recovery time of the community were identified as the most important vulnerability factors (i.e., with a score of 4.4 out of 5 for both) by the MaCoBioS experts, while geomorphology setting and the locations of wetlands and river mouths were the least relevant (i.e., with a score of 2.8 and 2.9 out of 5, respectively). Besides the predefined vulnerability factors, participants provided a list of 13 new vulnerability indicators, in which functional redundancy and biodiversity were mentioned more than one time by experts. Similar results were obtained for the other topics addressed in the questionnaire. Finally, these contributions were cleaned up to avoid repetition and overlapping and feed the round table discussion of the world café session. Similar results for the human- and climate-related pressures affecting MCEs, and ecosystem services are reported in Supplementary material Annex 6 and Annex 7 respectively.

Regarding the world café session, participants contributed iteratively to fine-tune and further integrate the list of indicators and proxy indicators allowing to analyse and spatially represent pressures, vulnerability, and ecosystem services patterns in MCEs) while scoring their relevance versus the MaCoBioS MCEs of concern. For example, Table 7 reports the output of the discussion related to the ecosystem services topic throughout three consecutive rounds of discussion.

***Table 9.*** *Results of the World Café discussion for the "Ecosystem services" topic.*

| No | Ecosystem | Seagrass beds | Coral reefs | Kelp forests | Mangroves | Saltmarshes | Rhodolith beds | Fish | Marine mammals |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Sea food | fish, potential harvestable biomass, | biomass of conch/fish/lobster | 4 | biomass of conch/fish/lobster | 2 | | 5 | |
| 2 | Raw material | | 4 | | 5 | | | | |
| 3 | Coastal protection | water flow (proportion of reduces currents) | Prop. Wave energy attenuation, Protected area | Prop. Wave energy attenuation, Protected area | Prop. Wave energy attenuation, Protected area | Prop. Wave energy attenuation, Protected area | | | |
| 4 | Water purification | denitrification rate, | | | 4 | 5 | | | |
| 5 | Recreation | | additional income generated by diving / recreational fishing | | | | | 5 | 5 |
| 6 | De-stressing or mental health | | | | | | | | |
| 7 | Tourism | 2 | additional income generated by diving / recreational fishing | | additional income generated by diving / recreational fishing | | | 5 | 5 |
| 8 | Energy | | | | 4 | | | | |
| 9 | Carbon sequestration | blue carbon storage in seagrass sediments | | 4 | blue carbon storage in seagrass sediments | 5 | | | nutrient dispersal across water columns supporting plankton growth and CO2 capture |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Specifically, besides the eight predefined ecosystem services (as emerged from the pre-event questionnaire, e.g. seafood, raw material, coastal protection, water purification, recreation, de-stressing or mental health, tourism, and energy), carbon sequestration was identified as the most relevant service (as the result of the first round), especially for seagrass beds, saltmarshes, kelp forests, and marine mammals (as the results of the second round). Participants also ranked the relative relevance of the identified ecosystem services to each MCEs and proposed several proxy indicators (e.g., fish, potential harvestable biomass for seafood; denitrification rate for water purification) to quantify the corresponding ecosystem servives value. A similar approach was applied to the topics of pressure and vulnerability to frame different components of the general MRAF. Similar results for the human- and climate-related pressures affecting MCEs, and vulnerability are reported in Supplementary material Annex 8 and Annex 9, respectively.

After the 3-rounds discussion of the World Café session, inputs obtained in terms of a list of climate-related and anthropogenic pressures, vulnerability factors, and ecosystem services-related indicators were used to feed the co-design of the MRAF by 3 distinct groups of MaCoBioS experts. Each group was moderated by a different team of moderators and supporters, thus resulting in 3 frameworks (see Figure 13, Figure 14 and Figure 15 for Group 1, Group 2, and Group 3, respectively) diverging in terms of selected components and the connections/links among them.

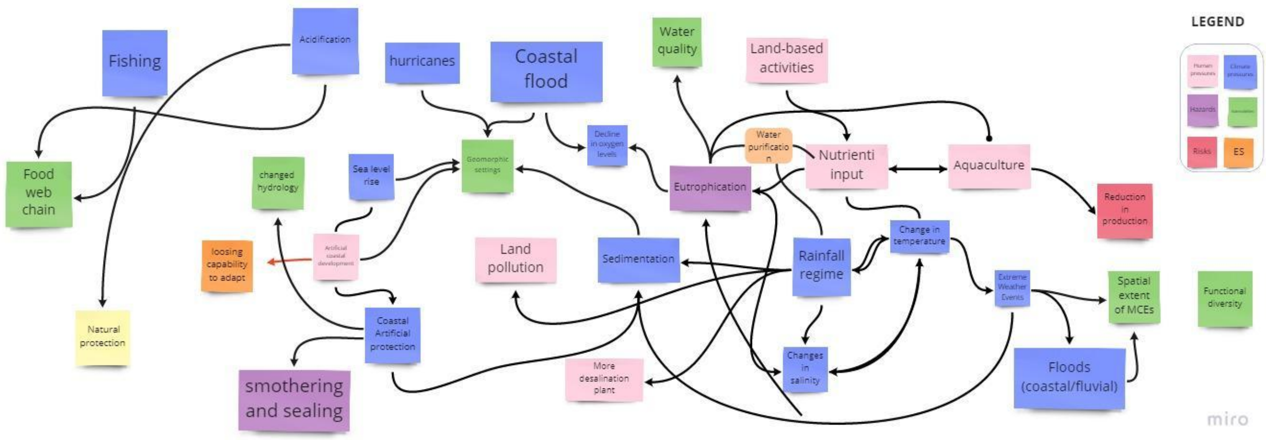



***Figure 13.*** *General MRAF developed by group 1 during the WP2 experts engagement workshop.*

Specifically, group 1 designed their MRAF proceeding with an in-depth analysis of all potential interconnections among different pressures, hazards, vulnerabilities, and related risks and ecosystem services flow (see Figure 13). In particular, this team started with the inclusion of some of the most relevant climate-related pressures (e.g., coastal flood, acidification, changes in temperature, and rainfall regime) affecting MCEs, as already discussed during the world café sessions on the thematic 'pressures'. Afterwards, mainly focusing on the eutrophication process, experts tried to better detail and disentangle all connections (lines without arrows) and effects (arrows) among the different components included in the framework. Interesting aspects resulting from the discussion are the integration of coloured arrows (red or green) representing, respectively, any negative or positive effects of that measure on a specific ecosystem service, as well as the distinction between natural and artificial adaptation measures (e.g., coastal artificial protection vs natural protection). Finally, as can be seen from Figure 13, due to time constraints, the resulting output from this group is only a snapshot of the whole MRAF but illustrates in detail all interconnections among a reduced list of components.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

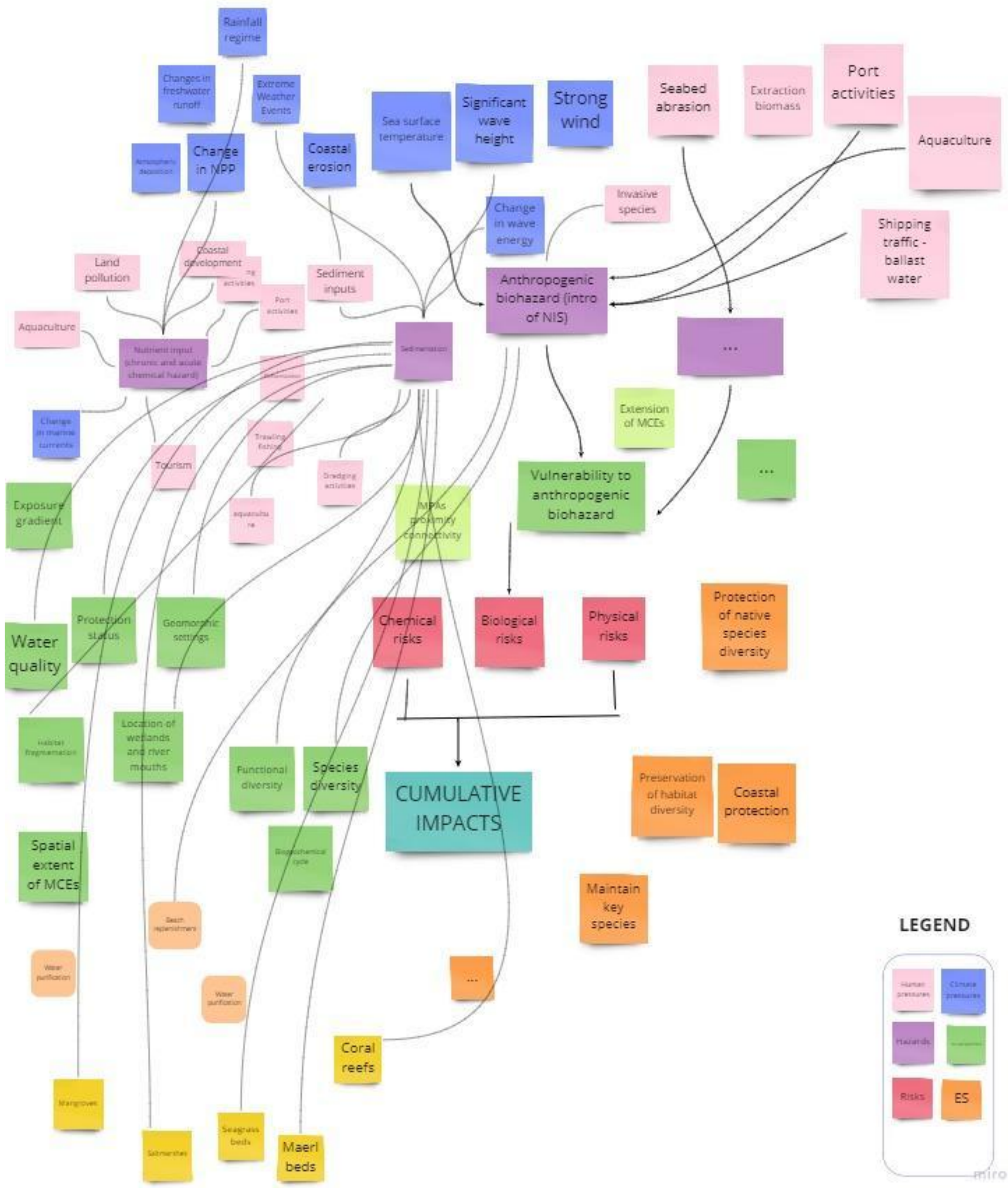



*Figure 14.* General MRAF developed by group 2 during the WP2 experts engagement workshop.

As far as group 2 is concerned, experts started to fill in the empty dashboard with the whole set of pressures and vulnerability factors, as obtained from the Ahaslide questionnaire and the World Café discussions (see Figure 14). These pressures were clustered and then connected to the relevant hazards (e.g., chronic, and acute chemical hazards, sedimentation, and anthropogenic biohazards). Among these, 'sedimentation' was identified as the most connected node, linking to many climates- and human-related pressures (e.g., dredging activities, aquaculture, and sediment inputs) and vulnerability factors (e.g., geomorphic setting, protection status, water quality, and location of wetlands and river mouths) (see Figure 14). Group 2 also tried to identify the linkages of these components to some MCEs and their provided ecosystem services (e.g., beach replenishment). Nevertheless, interconnections among pressures and vulnerability factors were not considered.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

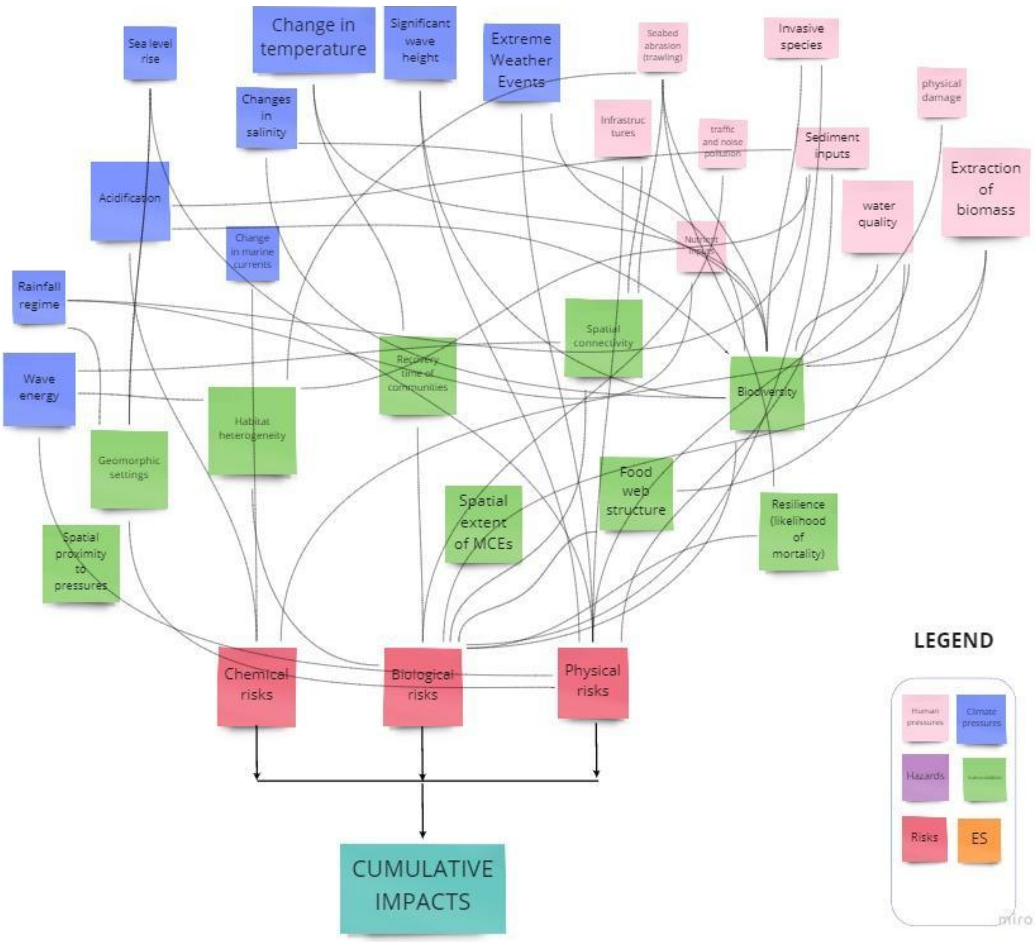



***Figure 15.*** *General MRAF developed by group 3 during the WP2 experts engagement workshop.*

Finally, group 3 started with the identification, selection, and grouping of the most important pressures and vulnerability factors to be linked to 3 key risks affecting MCEs i.e., chemical, biological and physical risks (e.g., "physical risk" was connected to some sea-based and coastal man-made pressures such as dredging activities, recreational activities, coastal development, offshore wind farms, mineral extraction, etc.) (see Figure 15). As far as vulnerability factors are concerned, "biodiversity" was selected as a key indicator representative of a subset of more detailed biodiversity-related factors (e.g., functional diversity, species diversity, and genetic diversity). In the end, group 3 selected 9 climate-related pressures, 9 human-related pressures, and 9 vulnerability factors, all included in the final MRAF (see Figure 15). Then, the connections among these components were established by the expert's suggestions gained during the workshop. Overall, "biodiversity" was the most connected vulnerability-related variable, especially linked to man-made pressures, thus highlighting the human effect on biodiversity. Also, it can be seen from Figure 15 as the biological risk was the most connected risk among those considered, followed by physical and chemical risk. Nevertheless, group 3 did not establish interconnections among pressures due to the time constraint under the MRAF co-design session. This limitation can be solved by integrating some of the connections as identified within the MRAF designed by Group 1.

As can be seen from the above conceptual frameworks (see Figure 13, Figure 14 and Figure 15), each group approached differently during the MRAF co-design (i.e., focusing only on connections among selected variables, considering all sets of variables, or clustering variables based on risks of concern e.g., chemical and biological) and had variation in the final results even though the initial set of variables was the same. Each approach shows pros and cons regarding the complexity and

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

completeness of the framework. For instance, the links/connections among pressures as highlighted by Group 1 can be integrated into the framework designed by Group 2 and Group 3, thus allowing to complement of the missing information. Similarly, the clustering of variables as made by Group 3 could help to simplify the complexity of networks developed by Group 1 and Group 2. Therefore, it requires merging different frameworks into a unique general MRAF, highlighting the interconnections among factors in the post-event phase. The result of this process is presented in the following paragraph.

## 2.2 Final insights from the workshop: towards the operationalisation of the MRAF in the following sections

As a result of the 3 Group sessions devoted to the co-design of the conceptual MRAF, several insights and shared patterns and difficulties emerged. First, everything is connected in a complex marine coastal socio-ecological system (pressure, vulnerability, and ecosystem services). Moreover, the co-designed frameworks provide a good example of interlinked frameworks, where concepts from both DPSIR and risk-based frameworks are integrated to analyse complex dynamics underpinning MCEs processes under a holistic approach. Indeed, as can be observed in see Figure 13, Figure 14 and Figure 15, each co-designed framework showed as all components are connected to each other into a continuous flow characterizing complex processes underpinning MCEs conditions. In addition, during this exercise researchers outlined "vulnerability" as a function of exposure, sensitivity, and adaptive capacity, requiring different indicators to represent ecosystem conditions based on the scale of the application.

Second, among the above-mentioned components, vulnerability resulted as the trickiest topic to be integrated into MRAF because it is the result of a wide range of economic, social, cultural, institutional, political and psychological factors that shape people's lives and the environment that they live in. Therefore, it tends to mean different things to different people and because it is often described by a variety of terms such as "lack of capacity", "fragility", "weakness", etc. Even though with the same way of understanding, different fields of expert would identify different factors of vulnerability with different levels of detail.

Third, the main novelty of these frameworks relies on the integration of ecosystem services indicators cross-cutting all the MRAF components, mainly considered as drivers of MCEs state changes (with positive or negative effects), and thus not just as an assessment endpoint of the overall risk appraisal process. This integration in the MRAFs also allows to clarify and highlighting MCEs variations and change trajectories which can, in turn, influence the final risk level (Stelzenmüller et al. 2018; Menegon et al., 2018). For instance, "biological regulation" and "water purification" are some of the ecosystem services indicators considered in this phase which, through their regulating task, may mitigate the effects of some pressures and, thus, reduce the overall risk.

Finally, variables identified in the designed MRAFs will drive the data collection across the MaCoBioS eco-regions. The eco-region-specific MRAFs, adapting to each eco-region based on the data availability and the ecosystem of concern, will be reported in Section 4. Thanks to its ability to learn from data and understand highly nonlinear behaviours, the designed ML-based model will be applied to disentangle some of the complex interrelations discussed during the workshop and support the overall risk appraisal process.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## 3. Material and methods – ML model for MRAF operationalisation

As emerged from the review of CIA approaches and their applications for integrated management of MCEs (Section A - 1.2), ML-based methods can provide an alternative approach to characterize complex environmental systems and to provide reliable quantification of the impacts of the interacting climate-driven and local/global anthropogenic factors affecting MCEs.

In this context, the operationalisation of the designed MRAF requires the selection and development of a ML-based model able to deal with the integration of heterogeneous data, in terms of: i) spatio-temporal resolutions, ii) data sources (models, monitoring surveys, remote sensing, etc.), iii) various fields (integration of features representing oceanographic/atmospheric data, human activities, biodiversity health, ecosystem services, etc.). Moreover, this model needs to be flexible enough to allow the simulation of future climate (RCPs) scenarios (Section 3.6).

Therefore, according to the aim of this analysis and the data availability, in the present study, the RF algorithm has been selected thanks to its potential (Section 3.3), including its inherent ability to explore the complex nexus between multiple stressors and the ecological response (represented with multiple indicators) of MCEs. Further to a short description of the family and the main characteristics of the selected algorithm (Sections 3.1 and 3.2), the following sections describe the model architecture specifically designed (including its main operative steps) for the MRAF operationalisation across the MaCoBioS eco-regions (Section 3.5), as well the overall process underpinning the scenario analysis (Section 3.6).

### 3.1 Decision tree

The decision tree is a supervised learning model used for classification and regression problems (Muhammad & Yan, 2015). Particularly, the decision tree algorithm creates a model that can predict a value or class label by learning simple decision rules inferred from the model input data (Mitchell, 1997). This model can be explained as a collection of rules of the if-then type. It can be described with a tree structure (Figure 16) in which the first node, or the root node, is followed by the decision node and leaf node. The decision node, as noted in the name, acts as the decision-making node, since this is the point at which the node divides further according to the best feature of the sub-group. The final node (or the leaf node) is then the one that holds the final decision.

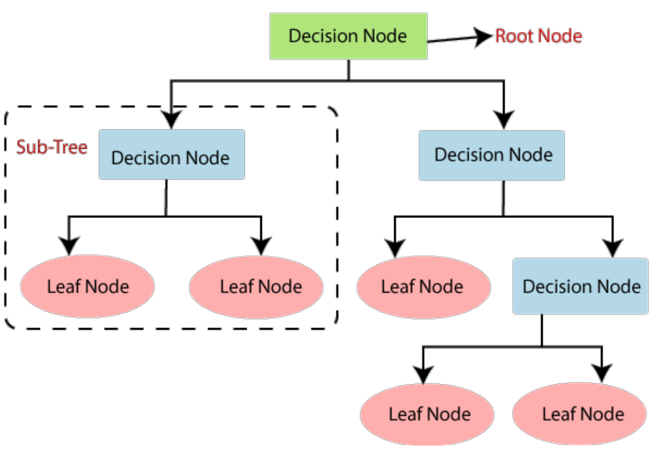



***Figure 16.*** *Decision tree structure. Source: Arain et al. (2021).*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

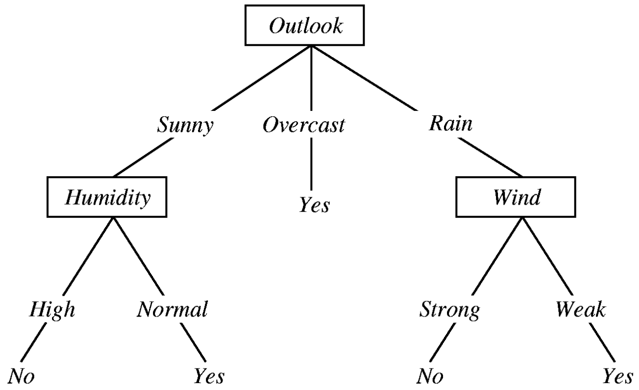



***Figure 17.*** *Typical learned decision tree that classifies if a day is suitable for playing tennis. Source: Mitchell (1997).*

For example, the tree in Figure 17 classifies an instance that allows to decide if a certain day is suitable (or not) for playing tennis based on several variables, i.e., Outlook, Wind, and Humidity. Particularly, the classification of an instance occurs in the following way: it starts from the root; selects the attribute linked to the current node; and follows the branch associated with the value of that attribute in the instance; if a leaf has been reached, the label associated with the leaf is returned, otherwise the process is repeated starting from the current node. For example, the following table represents a dataset consisting of: i) weather information of the last 14 days, including Outlook, Humidity, and Wind; ii) whether a match was played or not on a particular day, labeled as "Yes" or "No" in the variable called PlayTennis.

***Table 10.*** *Dataset for the PlayTennis concept. Inspired by Mitchell (1997).*

| Day | Outlook | Humidity | Wind | PlayTennis |
|---|---|---|---|---|
| D1 | Sunny | High | Weak | No |
| D2 | Sunny | High | Strong | No |
| D3 | Overcast | High | Strong | Yes |
| D4 | Rain | High | Weak | Yes |
| D5 | Rain | Normal | Weak | Yes |
| D6 | Rain | Normal | Strong | No |
| D7 | Overcast | Normal | Strong | Yes |
| D8 | Sunny | High | Weak | No |
| D9 | Sunny | Normal | Weak | Yes |
| D10 | Rain | Normal | Weak | Yes |
| D11 | Sunny | Normal | Strong | Yes |
| D12 | Overcast | High | Weak | Yes |
| D13 | Overcast | Normal | Weak | Yes |
| D14 | Rain | High | Strong | No |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Using the decision tree, it needs to classify, based on historical data in the table, whether the game will happen if the weather condition is:

- *Outlook = Sunny*
- *Humidity = High*
- *Wind = Strong*

The instance (*Outlook = Sunny*, *Humidity = High*, *Wind = Strong*) can be classified as follows by referring to the tree in Figure 14. The *Outlook* attribute is associated with the root, therefore, since *Outlook = Sunny* in the example, the *Sunny* branch is followed; the *Humidity* attribute is associated with the node reached and therefore, being *Humidity = High* in the example, the *High* branch is followed, thus, reaching the leaf node and obtaining the *NO* classification.

In general, decision trees represent a disjunction of conjunctions of constraints on the attribute values of instances. Each path from the tree root to a leaf corresponds to a conjunction of attribute tests, and the tree itself to a disjunction of these conjunctions. For example, the decision tree shown in Figure 17 corresponds to the expression (*Outlook* = *Sunny* **and** *Humidity* = *Normal*) **or** (*Outlook* = *Overcast*) **or** (*Outlook* = *Rain* **and** *Wind* = *Weak*) for the label *YES* (Mitchell 1997).

As mentioned previously, the decision tree is a tree structure that will have nested nodes, the subdivision of the nodes is called recursive partitioning, and takes place based on a threshold value. In addition to the threshold value, to divide a node there is a need to select an attribute defined as optimal to split a node and the various decision tree learning algorithms differ above all from how the optimal attribute is selected. For instance, the ID3 algorithm, uses entropy and information gain as the criterion to measure the impurity of a node, while the CART algorithm, used both in regression and classification problems, uses the Gini index as a measure of impurity.

## 3.2 Ensemble methods

Ensemble methods are machine learning methods that build a series of predictive models (often called weak learners or base models) and combine their results into a single prediction in order to obtain a more accurate and robust model (Zhou, 2019). Theoretically, ensemble methods are justified by the bias-variance trade-off (Valentini & Dietterich, 2004). The classification error is composed of two parts: bias, the accuracy of the classifier with respect to training data; and variance, the accuracy of the classifier when trained on different training sets. This latter is the variability in the model prediction and refers to the changes in the model when using different portions of the training data set. Often, these two components have a trade-off relationship: models with low bias tend to have high variance and vice versa. Knowing that the average has a smoothing (variance-reducing) effect, the goal of ensemble systems is to create several models with relatively fixed bias and then combine their outputs by averaging to reduce the variance. This increases the accuracy of the model: assuming that models make different errors on each sample, but generally agree on their correct classifications. Averaging the model outputs reduces the error by averaging out the error components (Zhang & Ma,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

2012). There are three major kinds of algorithms that aim at combining weak learners: i) **bagging**[22]; ii) **boosting**[23]; iii) **stacking**[24].

### 3.3 Random Forest algorithm

Random Forest is one of the most advanced ML techniques used to solve classification and regression problems among supervised learning algorithms (AhmedK et al., 2013). It is a tree-based ensemble model where each tree is based on a collection of random variables. From a computational point of view, RFs are regarded as attractive because they are relatively fast to train and predict (Zhang & Ma, 2012). Secondly, they depend only on a few tuning parameters. Finally, they can be used directly for high- dimensional problems. They also provide measures of variable importance, differential class weighting, missing value imputation (Zhang & Ma, 2012). As stated before, RF is an ensemble predictor that uses a bagging strategy, so deep trees, fitted on bootstrap samples, are combined to produce an output with lower variance. In addition to choosing instances, however, a RF also incorporates random feature subspacing techniques (Ho, 1998). When growing each tree, instead of only sampling over the observations in the dataset to generate a bootstrap sample, it also samples over features and keeps only a random subset of them to build the tree. A training sample created using the random subspace method thus contains all the original example instances, each one with the same randomly reduced feature space. Sampling over features has indeed the effect that all trees do not look at the exact information to make their decisions and, as a consequence, it reduces the correlation between the different returned outputs. It is another way to achieve the independence of models. Predicting output values for novel instances with a RF predictor involves each individual ensemble member votes for the most probable output according to its learned decision rule. The ensemble members' votes are tallied and aggregated into a common ensemble output. As detailed in the following paragraph, some important features and properties of RF include, out of bag data (Section 3.3.1), variable importance (Section 3.3.2) and weighting (Section 3.3.3).

#### 3.3.1 Out-of-bag data

The probability that a particular sample will not be chosen in a single random draw from the full data set is $\frac{N-1}{N}$. So, the probability that a sample will not be chosen in a tree, which is a bootstrap sample consisting of $N$ draws, is $\left(\frac{N-1}{N}\right)^N = \left(1-\frac{1}{N}\right)^N$. In the limit of large $N$, this expression gets a limit below:

$$\frac{lim}{N \to \infty}\left(1-\frac{1}{N}\right)^N = \frac{lim}{N \to \infty}\left(1+\frac{-1}{N}\right)^N = e^{-1} \approx 0.368$$

So, 36.8% of the samples in each tree are out-of-bag (Chernick & LaBudde, 2014).

The "out-of-bag data" are highly useful for estimating generalisation error and variable importance.

[22] **Bagging**: several instances of the same base model are trained in parallel, independently from each other's, on different bootstrap samples and then aggregated in an averaging process (Wen & Hughes, 2020);

[23] **Boosting**: several instances of the same base model are trained sequentially so that, at each iteration, the way to train the current weak learner depends on the previous weak learners and more especially on how they are performing on the data (Wen & Hughes, 2020);

[24] **Stacking**: different types of weak learners are fitted independently from each other, and a meta-model is trained on top of that to predict outputs based on the outputs returned by the base models (Wen & Hughes, 2020).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Let $T$ be a training set consisting of examples with an output variable $y$ and corresponding input $x$. Let $f(x,T)$ be a predictor and a given loss function $L(y,f)$ measures the error in predicting $y$ by $f$. Let $T_{k,B}$ be the bootstrap training sets and $f(x,T_{k,B})$ be the predictors. These predictors are aggregated in an appropriate way to form the bagged predictor $f_B(x)$. For each $(y,x)$ in the training set, the predictors are aggregated only over those $k$ for which $T_{k,B}$ does not contain $y,x$. These out-of-bag predictors are denoted by $f_{OB}$. Then the out-of-bag estimate for the generalization error is the average of $L(y, f_{OB}(x))$ over all examples in the training set (Breiman, 1996).

### 3.3.2 Variable importance

Most ML tasks help find the most accurate model and identify which of the input variables are the most important to make better predictions as well (Louppe et al., 2013). In this context, RF offers several mechanisms for evaluating the importance of an input variable, and therefore improves the model interpretability. Let $\Delta i(s,t) = i(t) - p_L i(t_L) - p_R i(t_R)$ be the impurity decrease of a binary split $s \in Q$ dividing node $t$ into a left node $t_L$ and a right node $t_R$. $p_L$ (resp., $p_R$) is the proportion $\frac{N_{t_L}}{N_t}$ (resp., $\frac{N_{t_R}}{N_t}$) of learning samples from $L_t$ going to $t_L$ (resp., to $t_R$) and where $N_t$ is the size of the subset $L_t$. The importance of a variable $X_j$ for predicting $Y$ is evaluated by adding up the weighted impurity decreases $p(t)\Delta i(s_t,t)$ for all nodes t where $X_j$ is used, averaged over all trees $\phi_m$ (for $m = 1, \dots, M$) in the forest:

$$Imp(X_j) = \frac{1}{M}\sum_{m=1}^{M} \sum_{t\in\phi_m} 1(j_t = j)[p(t)\Delta i(s_t,t)]$$

where $p(t)$ is the proportion $\frac{N_t}{N}$ of samples reaching $t$ and where $j_t$ denotes the identifier of the variable used for splitting node $t$. This measure is known as the Mean Decrease Impurity Importance (MDI). Another way to evaluate the importance of a variable $X_j$ is by measuring the Mean Decrease Accuracy (MDA) of the forest when the values of $X_j$ are randomly permuted in the out-of-bag samples. The latter measure is also known as the Permutation Importance, that for regression is computed by this formula:

$$Imp(X_j) = E_{\pi_j}\left\{\frac{1}{N}\sum_{(x'_i,y_i)\in\pi_j(L)} L\left(\frac{1}{M^{-i}}\sum_{l=1}^{M^{-i}} \varphi_{L^{m_{k_l}}}(x'_i), y_i\right)\right\}$$

$$\hookrightarrow -\frac{1}{N}\sum_{(x_i,y_i)\in L} L\left(\frac{1}{M^{-i}}\sum_{l=1}^{M^{-i}} \varphi_{L^{m_{k_l}}}(x_i), y_i\right)$$

where $\pi_j(L)$ denotes a replicate of L in which the values of $X_j$ have been randomly permuted, and where $m_{k_1}, \dots, m_{k_{M^{-i}}}$ denote the indices of the trees that have been built from a bootstrap replicate that do not include $(x_i, y_i)$; for classification is derived similarly as in regression, except that the out-of-bag average predictions are replaced with the class which is the most likely, as computed from the out-of-bag class probability estimates. Its rationale is that randomly permuting the input variable $X_j$ should break its association with the response $Y$. Therefore, if $X_j$ is in fact associated with $Y$, permuting its values should also result in a substantial increase of error, as here measured by the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

difference between the out-of-bag estimates of the generalization error. That is, the larger the increase of error, the more important the variable, and vice-versa (Louppe et al., 2013).

### 3.3.3 Weighting

When faced with unbalanced data in which some classes are much smaller than others, large classes may be predicted correctly while small classes are predicted incorrectly, although the classifier achieves high performance. RF has an effective method to weigh classes and to give balanced results in unbalanced datasets. Particularly, it is possible to change the weight of each class, assigning to the minority class a greater weight, that is, a higher misclassification cost. Class weights are used to weigh the Gini criterion in the splitting stage of the tree and in leaf nodes to make predictions. The class prediction of each leaf node is determined by the "weighted majority vote", that is the weighted vote of a class multiplied by the number of cases associated with that specific class at the terminal node. The final class prediction for RF is achieved by aggregating the weighted vote from each individual tree, where the weights are in turn average weights in the leaf nodes (Chen et al., 2004).

## 3.4 Multi-output classification

Multi-class-multi-output classification is a classification problem in which a single estimator handles several joint classification tasks. It is also known as multitask classification. Both the number of targets and the number of classes per target are greater than two. This can be defined both a generalisation of the multi-label classification problem, which only considers binary attributes, as well as a generalization of a multi-class classification problem, where only one target is considered. RF supports the multi-output multi-class classification, being made up of decision trees which, in turn, support it. With respect to the normal structure and to the normal functioning of the decision tree described in Section 3.1, the multi-output problems require memorising $n$ output values instead of one in the leaf nodes and require that the splitting criteria is averaged on $n$ output.

## 3.5 Model design for the MaCoBioS eco-regions

Focusing on the core of the MRAF operationalisation, in this project, the open-source software Python (https://www.python.org), with its specific libraries devoted to RF (Section 3.3), was used to develop, train, validate, and test the RF model developed for the MaCoBioS focus eco-regions. As represented in Figure 18, the RF model is composed of two main parts/layers: i) a top/input layer, relying on the data representing proxy indicators for the identified key threats/pressures affecting the ecosystems of concern in each eco-region (i.e., the most representative ecosystem per eco-region). Technically, they represent the RF model predictors; ii) a bottom/output layer based on the aggregation of the main ecosystem state indicators. In this case, they are RF model responses.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

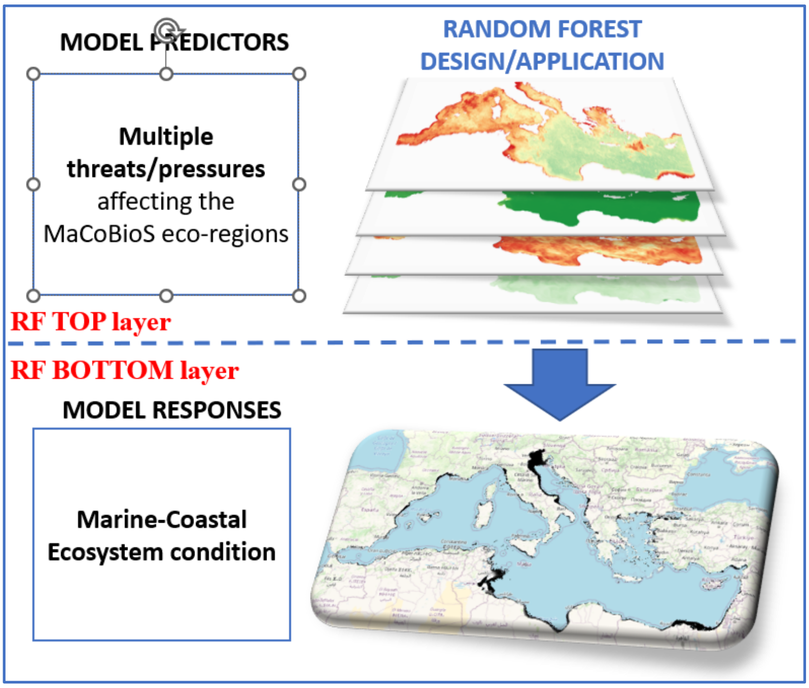



***Figure 18.*** *RF conceptual model for the MaCoBioS eco-regions: a) TOP layer of the model: multiple threats/pressures affecting focus eco-regions; b) BOTTOM layer of the model: Marine-Coastal Ecosystem condition integrating state indicators.*

More precisely, this model allows integrating a set of yearly-based indicators (included in the RF top layer) standing for all the most relevant pressures (e.g., nutrient input, sea surface temperature, salinity, etc.) affecting MCEs. On the other side, a set of indicators have been calculated and included in the model to understand, as much as possible, ecosystems condition (based on data availability and constraints at the eco-regional scale) and disentangle the complex interrelations with the identified pressures. For instance, three indicators have been calculated for characterizing both MCEs' state and biodiversity for the Mediterranean eco-region (i.e., biodiversity level, spatial distribution and connectivity). The full list of indicators and related metrics calculated for the Mediterranean eco-region is reported in Annex 10. Details on the technical procedures applied for their mapping and analysis are described in Section 4, also reporting some examples of the related output (i.e., maps and descriptive statistics).

From an operative perspective, as represented in Figure 19, the design of the RF follows a precise analytical workflow.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

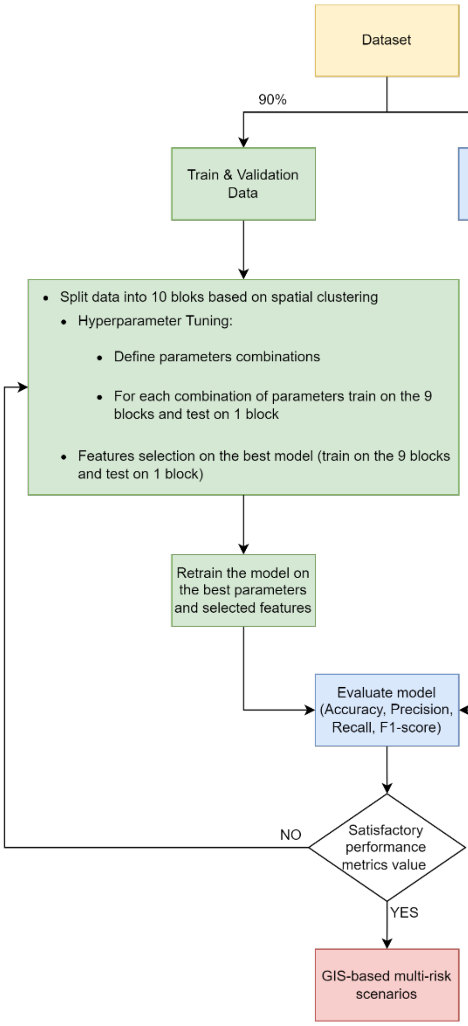



***Figure 19.*** *The flowchart of the RF implementation in the MaCoBioS eco-regions.*

Specifically, once the available data for the MaCoBioS eco-regions (Sections 1.1.4, 1.2.4) are pre-processed and analysed, the dataset to be used for the model development can be created. Then, to move on training and testing stages, the dataset needs to be split into two main folds, i.e., training (90% of the whole observations) and test sets (10% of the whole observations). Particularly, the training set is used to fit the parameters of the model, while the test is used to evaluate the model fit on the training set. To reduce overfitting (i.e., when the model shows high performance in predicting training data, but fails to predict new data) the training set is also split into training and validation sets. Then, after some iterative processes, the best model configuration (by means of the hyperparameters tuning and feature selection) can be implemented to move on to scenario analysis and produce a set of related GIS-based multi-risk scenarios.

### 3.5.1 RF model training and validation

#### *3.5.1.1 Tuning, feature selection and spatial cross-validation*

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 will be applied. This method belongs to the family of resampling methods (James et al., 2013). Within this study, a spatial cross-validation will be adopted to alleviate the problem of data 'spatial partitioning'.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

In particular, due to the data autocorrelation (points/pixels close to each other are, generally, more similar than points/pixels further away; Getis et al., 2004), by using random samples, the IDD (Independent and Identically Distributed Data) assumption it would be violated since samples are not statistically independent.

To solve this issue, the case study area will be partitioned into different spatial blocks. More precisely, to create different spatial areas, pixels within the whole case study area will be clustered by the KMeans algorithm in n spatial blocks until reaching a good spatial partitioning of observations upon manual inspection. This partitioning strategy leads to a bias-reduced assessment of the predictive performance, helping to avoid overfitting.


***Figure 20.*** *Representation of the default cross-validation vs. spatial cross-validation.*

Blocks representing sub-areas of the case study will be used for 10-fold cross-validation. This spatial cross-validation will be used also to research the best architecture of the model (i.e., the architecture that maximises the accuracy of the model in the validation set). This procedure is called hyperparameters tuning, in which one or more parameters of the model are optimized, under an iterative process, to find the best configuration. Particularly, a simple strategy for optimizing hyperparameters is a greedy approach: vary one hyperparameter at a time and measure changes in the model performance. However, in this way, we can capture only the way in which the different values of a single hyperparameter behave in the context of a single instance of the others, therefore it cannot be considered an accurate method (Andonie, 2019). For this reason, there are two systematic approaches: Grid Search (GS) and Random Search (RS).

In the first approach (GS), it is possible to define a search space as a grid of hyperparameter values and evaluate every position in the grid. in the second approach (RS), it is possible to define a search space as a bounded domain of hyperparameter values and randomly sample points in that domain. The problem with GS is that the number of joint values grows exponentially with the number of hyperparameters, so RS will be used in this study that, using the same number of trials, generally produces better results than GS (Andonie, 2019). More specifically, the RS is an iterative process in which a fixed number of possible combinations of parameters are sampled from the parameter space, following a particular distribution (grid). In this study, for each combination, the model will be trained by performing the spatial cross-validation mentioned above. In the end, the combination that obtains the highest accuracy on the validation test will be selected. Once the best hyperparameters are selected, the feature selection, i.e., the process of identifying the most relevant features, is performed.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

To choose the best features, the spatial cross-validation needs then to be performed again and a recursive elimination of the features follows. This method is part of the family of wrapper methods, in particular, it is a sequential backward selection algorithm that starts from the complete set of variables and removes one feature at a time whose removal provides the lowest decrease in predictor performance (Chandrashekar & Sahin, 2014).

### 3.5.2 RF model testing

Finally, after the model training and validation, the RF model can be analysed against the remaining testing dataset (10% of the total dataset) to evaluate the performance of a trained classifier. Specifically, to get more insight into model performance, in addition to accuracy, precision and recall, also the F1 score will be 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** will be 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:

$$F1\_Score = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

## 3.6 Scenario analysis

Once the RF is trained, validated, and tested, it can be used for scenario analysis. This phase involves the development and analysis of various multi-risk scenarios based on different climate projections obtained from numerical models, specifically extracted for the investigated areas (Section 1.1.5 and 1.2.5). The validated RF model enables simulations that evaluate which hotspot risk areas will be potentially more impacted by the projected climate variations. This model was used to evaluate the

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

ecological response of the system under both an individual, pairwise combination, and cumulated scenario, as these pressures act upon marine and coastal ecosystems simultaneously, causing complex interactions which might exacerbate or mitigate the overall effects. This analysis aims to detect the dominant stressors, their non-linear effects, and finally the interactions among stressors. Consequently, this understanding could help to evaluate the risk reduction and associated ecological benefits expected from reducing pressure from stressors by the implementation of management actions and mitigating strategies.

This iterative analysis is described in the following steps. First, one variable was substituted from the original dataset to evaluate its influence on the selected ecosystem. This procedure was then repeated for all the available metrics of Salinity, SSH, SST with MHWs. Then, all possible combinations of two (e.g., SST + Salinity, SST + SSH, etc.) and three scenarios (i.e., ABC with all available scenarios integrated into the model) have been tested to evaluate their future impacts under pairwise combination, and cumulated scenarios.

This stepwise approach took into account the complex interactions of the model predictors with those previously selected in the scheme. For each step, the variations in terms of marine coastal ecosystem conditions were assessed and compared to the previous step to envision differences/anomalies of the outputs and the positive/negative interactions of the stressors ranging from antagonism to synergism.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## 4. Data pre-processing and analyses across MaCoBioS eco-regions

Having defined the RF conceptual model for the Mediterranean and Northern Europe eco-regions, a data pre-processing task is needed to homogenize all input data for the next model development steps. Accordingly, this Section breaks down into three sub-paragraphs reporting, respectively for the two analysed eco-regions, the data pre-processing phase, as well as main statistics on the indicators and metrics that will be used to feed the RF model.

### 4.1 Data pre-processing

The dataset for the experiments requires data preparation and data-preprocessing procedures, as the representation and the quality of the data are the main success factors of a ML algorithm (Kotsiantis et al., 2006). To pursue this task, it was first necessary to frame the study area. In the Mediterranean, this meant taking into account that the reference year 2017 shows a more complete seagrasses ecosystem coverage in the whole Mediterranean Sea. As emerged in the literature, seagrasses are mainly located in shallow water, within 40-50 meters of depth (UNEP, 2020). Therefore, a bathymetry layer up to 50 meters of depth was defined as the case study area (Figure 21). In the Northern Europe eco-region, a bathymetry layer up to 100 meters of depth was defined as the case study area (Figure 22), considering the literature reported observations of *Saccorhiza polyschides* at a maximum depth of 84 meters in the Atlantic, even though such observations remain rare (Araújo et al., 2016), and the relative coarseness of the bathymetry layer where areas of steep slope would be lost. Furthermore, considering the topography of the very shallow North Sea, a big part of the continental shelf was further removed, as depth is not the only parameter limiting kelps distribution and the likelihood that kelps occur in this open-sea area is close to null (Yesson et al., 2015). Then, all data collected for RF model development from different open-source data platforms were pre-processed to homogenize their different spatial resolutions into a 4 km-based raster grid.

Then, as already introduced in Section 3.5, for each of the selected environmental indicators (Section 1.1.4 and 1.2.4), a set of yearly-based metrics (e.g., minimum, maximum, standard deviation, etc. – Annex 10) were calculated (and mapped) with the procedures and examples as detailed in the following paragraphs.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

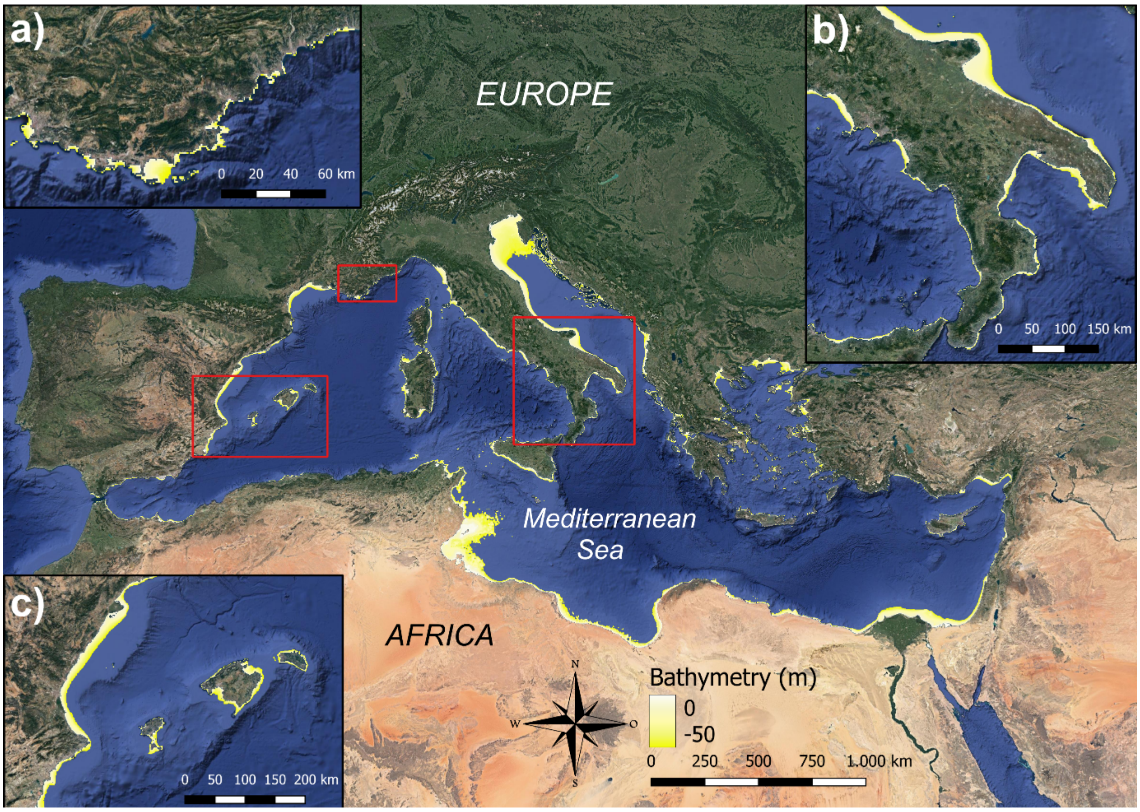



***Figure 21.*** *Case study area corresponding to a bathymetry layer up to 50 meters depth.*

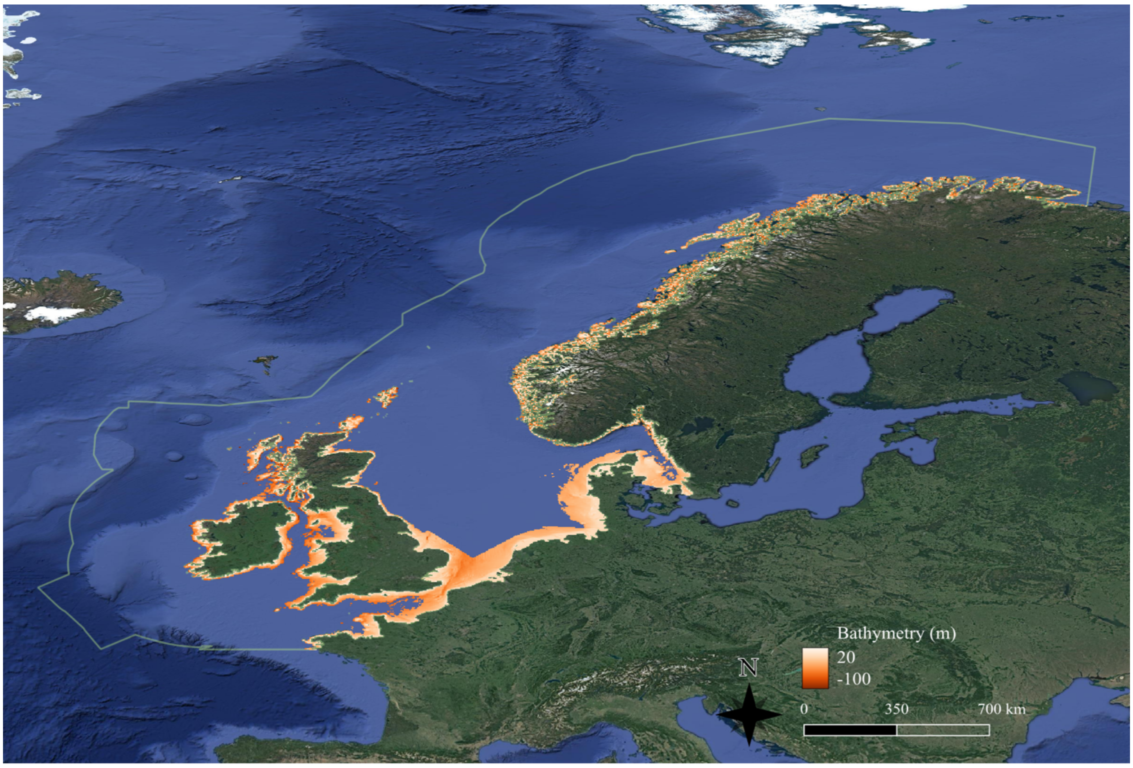



***Figure 22.*** *Case study area corresponding to a bathymetry layer up to 100 meters depth.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

### Model predictors

As regards to 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 (Section 1.1.4 and 1.2.4), making available data of the selected indicators, was processed through the *xarray* library[25] allowing to manipulate the data and calculate aggregated metrics. Some examples of the resulting output from this process (i.e., spatial maps in the form of raster files) are displayed in Figure 23 and 24.

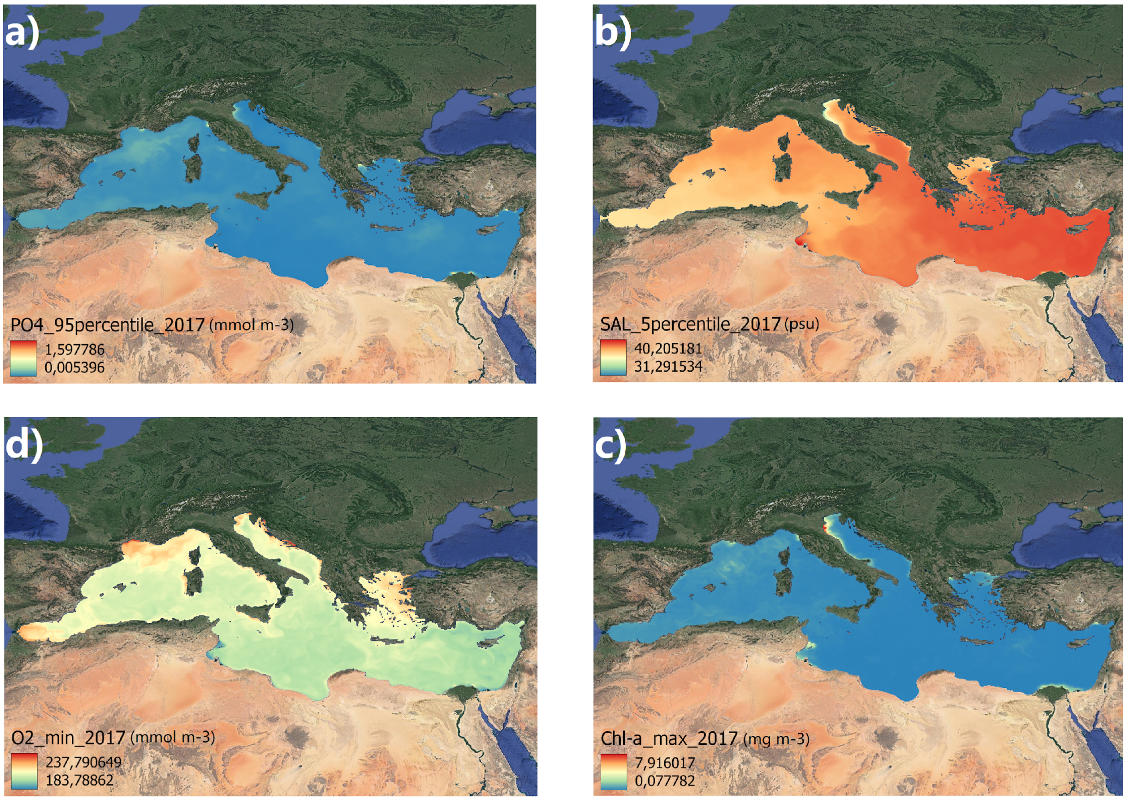



***Figure 23.*** *Maps representing some of the pressures-related maps calculated for the Mediterranean eco-region. a) 95° percentile of phosphorus; b) 5° percentile of salinity; c) minimum of dissolved oxygen; d) maximum of chlorophyll-a.*

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

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

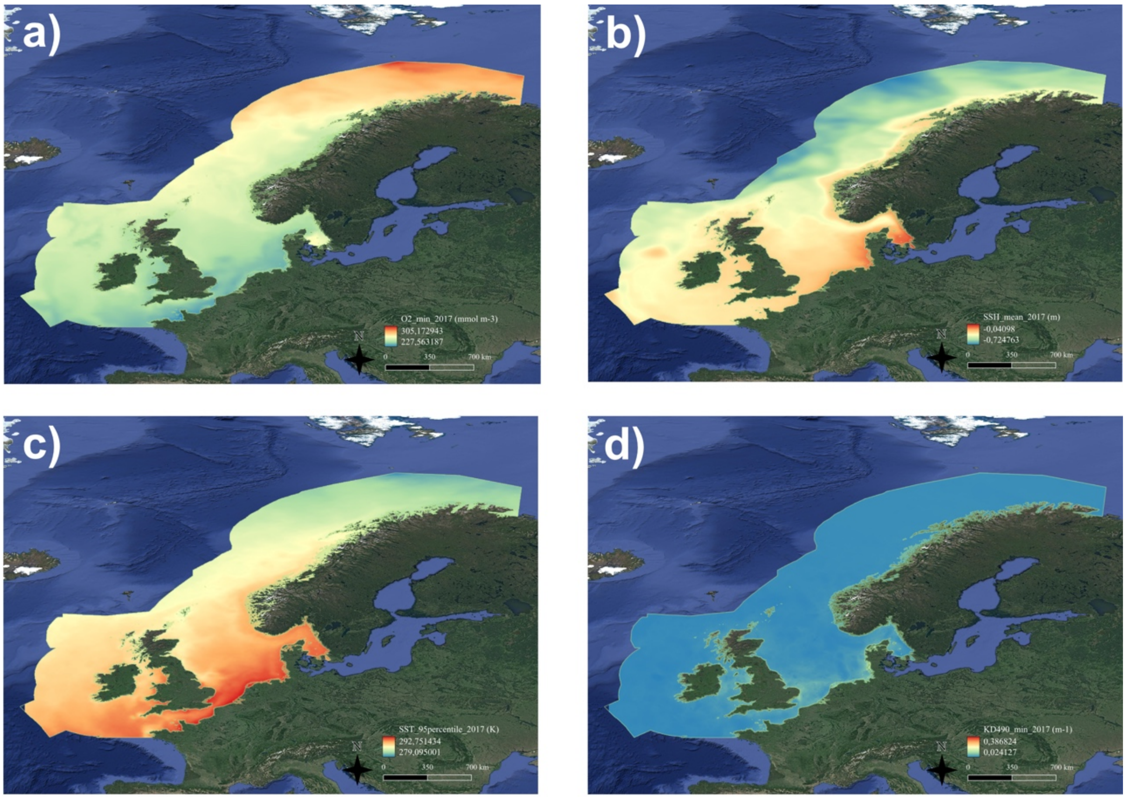



***Figure 24.*** *Maps representing some of the pressures-related maps calculated for the Northern Europe eco-region. a) minimum of dissolved oxygen; b) mean sea surface height (SSH); c) 95th percentile of sea surface temperature (SST); d) minimum light attenuation coefficient (KD490).*

As far as pressures related to coastal developments are concerned, the distance of seagrasses meadows to the closest major river mouths and urban areas was calculated by applying the Haversine distance formula, implemented in Python by means of the following libraries: *geopandas*[26], *geocube*[27], *rasterio*[28] and *xarray*[29]. The resulting maps from these calculations are reported in Figure 25.

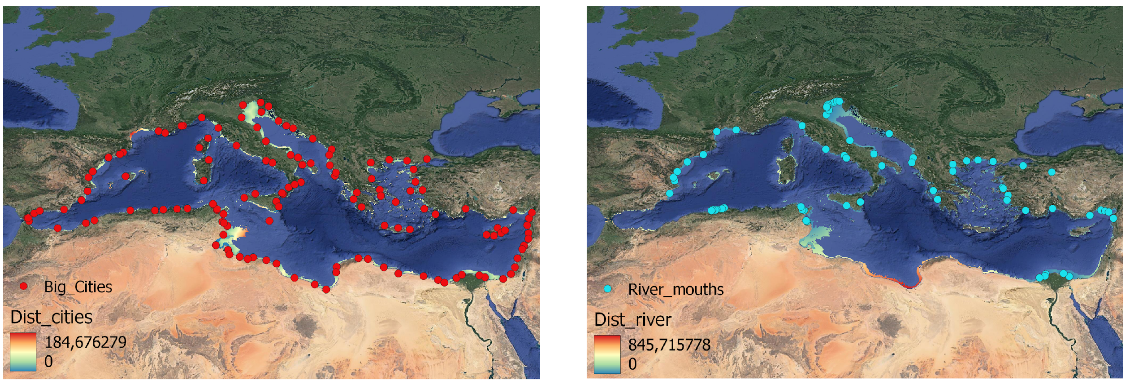



***Figure 25.*** *Plots of the distance from big cities (left panel) and distance from river mouths (right panel).*

[26] https://geopandas.org/en/stable/
[27] https://corteva.github.io/geocube/stable/
[28] https://rasterio.readthedocs.io/en/latest/
[29] https://xarray.pydata.org/en/stable/index.html

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

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 variables (Section 1.1.4 and 1.2.4). Focusing on marine coastal ecosystem condition variables, as far as seagrasses' distribution is concerned, by applying the *QGIS*[30] zonal statistics[31] plugin, the percentage of seagrasses coverage within each 4km pixel of the case study was calculated. In Northern Europe then, the kelp occurrences extracted from GBIF were manually "cleaned", i.e., removing occurrences with geospatial issues, duplicates, etc. The spatial points layers thus obtained were then rasterized to a 4km resolution using the 'rasterize' function of the 'raster' R package[32]. To improve the spatial representation of kelp forests based on these observations, interpolation using inverse distance weighting was applied to the layer using the 'idw' function of the 'gstat' R package[33], and the result was then classified into 2 classes (0 = absent, 1 = present).

Furthermore, in the Mediterranean, ecosystem biodiversity, was also considered as an indicator of seagrass beds condition and the Shannon diversity index (also known as the Shannon-Wiener diversity index) was selected. As defined within the Ocean Biodiversity Information System (OBIS), the Shannon index is a mathematical measure of species diversity in a given community, assuming that all species are represented in a randomly selected sample. It is calculated based on the following equation (Shannon, 1948):

$$Shanon\ index = \sum_{i=1}^{s} \quad p_i * ln\ ln\ p_i$$

Where: pi: defined as n/ni

n: as the total number of records in the raster cell and

ni: as the total number of records for the ith-species in the raster cell

s: as the number of species

In this application, the Shannon Index was calculated by following the steps reported in the notebook biodiversity indicator[34] provided by OBIS. This calculation was implemented in the R environment using several libraries such as "arrow" and "dplyr" for reading the occurrence data; "dggridR" and "dggs" for creating a discrete global grid; and finally, "gsl" for calculating the metrics. The result of this calculation is reported in Figure 26.

To calculate the seagrasses **connectivity** pattern, as already applied for the distance to rivers and major cities, the Haversine formula was applied. The results of this calculation are reported in Figure 27.

---

30 (https://qgis.org/en/site/)

31 (https://docs.qgis.org/2.18/en/docs/user_manual/plugins/plugins_zonal_statistics.html)

32 (https://cran.r-project.org/web/packages/raster/raster.pdf)

33 (https://cran.r-project.org/web/packages/gstat/gstat.pdf)

34 https://iobis.github.io/notebook-diversity-indicators/

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

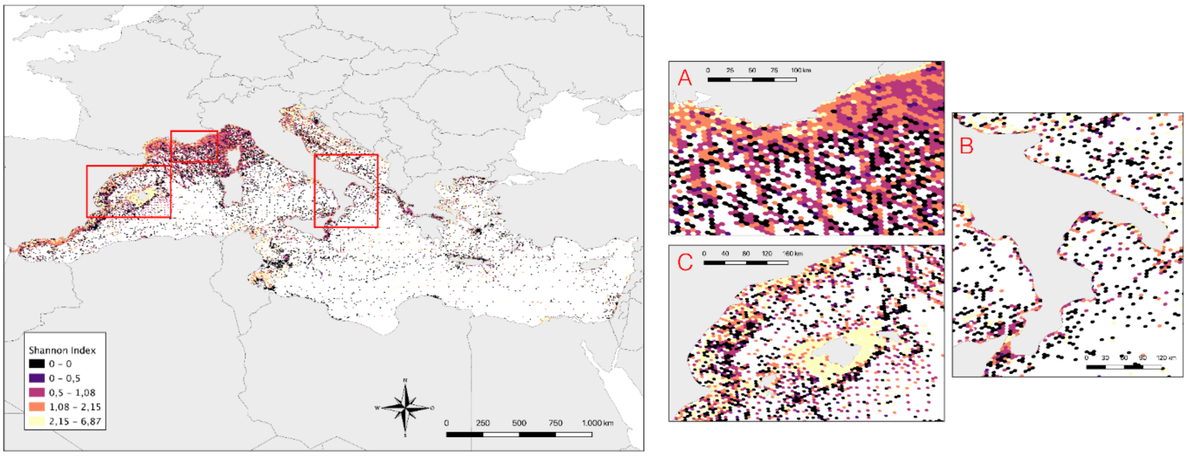



***Figure 26.*** *Shannon index map.*

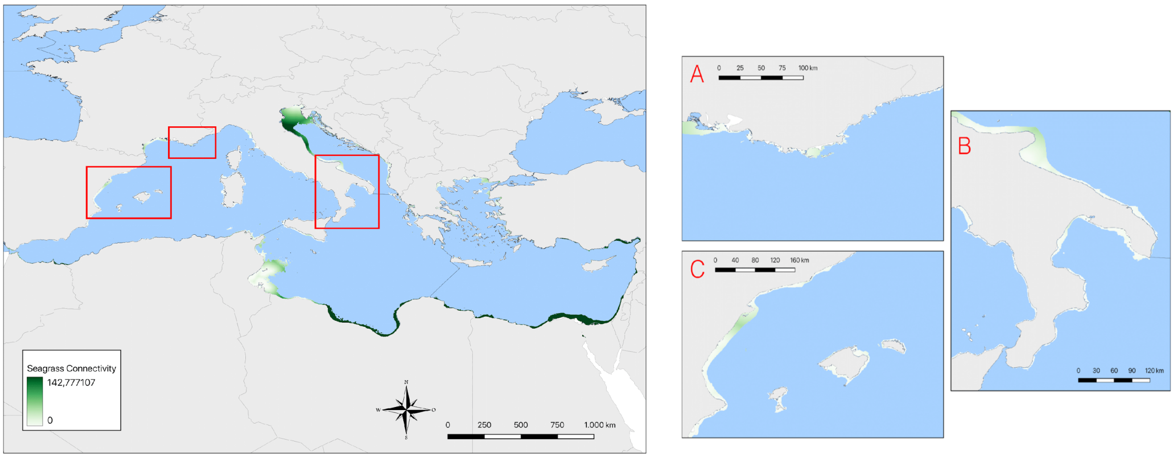


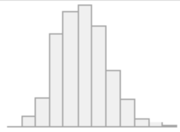
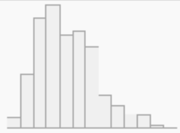
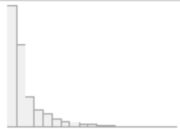
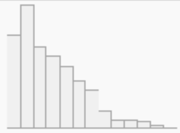
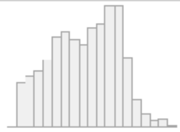
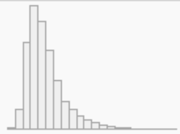
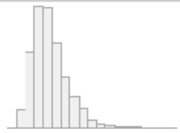
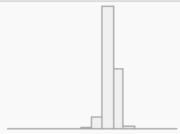
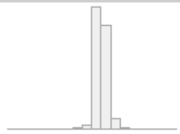
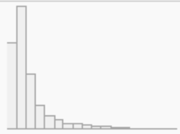

***Figure 27.*** *Connectivity pattern of seagrasses in the Mediterranean Sea.*

## 4.2 Data analysis

In the Mediterranean eco-region, according to the spatio-temporal resolution of the available data covering the selected case study area (Section 1.1.4), the final dataset includes 10367 observations, of which 9330 will be devoted for the model training and validation phases, whereas the excluded 1037 for the final testing phase. Data exploration is the first step in data analysis to unravel, through ad-hoc data visualization tools and statistical techniques (e.g., correlation analysis), dataset characteristics and initial patterns.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 11.*** *Summary of the main statistics and distributions of some model predictors in the Mediterranean eco-region.*

| No | Variable | Abbreviation | Stats / Values | Graph |
|---|---|---|---|---|
| 1 | Yearly minimum oxygen concentration [mmol m-3] | O2_min [numeric] | Mean (sd) : 207 (8.7)<br>min ≤ med ≤ max:<br>183.8 ≤ 206.7 ≤ 237.1<br>IQR (CV) : 12.3 (0) |  |
| 2 | Yearly 5 percentile oxygen concentration [mmol m-3] | O2_5percentile [numeric] | Mean (sd) : 232.9 (10.9)<br>min ≤ med ≤ max:<br>212.2 ≤ 231.7 ≤ 270.7<br>IQR (CV) : 15.4 (0) |  |
| 3 | Yearly 90 percentile Chlorophyll-a concentration [mg m-3] | CHL.a_90percentile [numeric] | Mean (sd) : 0.4 (0.4)<br>min ≤ med ≤ max:<br>0.1 ≤ 0.2 ≤ 3.7<br>IQR (CV) : 0.3 (1.1) |  |
| 4 | Yearly minimum Secchi depth value [mmol m-3] | ZSD_min [numeric] | Mean (sd) : 6.6 (4.6)<br>min ≤ med ≤ max:<br>1.3 ≤ 5.5 ≤ 25.5<br>IQR (CV) : 6.9 (0.7) |  |
| 5 | Yearly 5 percentile Secchi depth [mmol m-3] | ZSD_5percentile [numeric] | Mean (sd) : 17.3 (7.4)<br>min ≤ med ≤ max:<br>1.9 ≤ 18 ≤ 36.8<br>IQR (CV) : 12 (0.4) |  |
| 6 | Yearly maximum Eastward Sea Water Velocity [m s-1] | uo_max [numeric] | Mean (sd) : 0.2 (0.1)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 1<br>IQR (CV) : 0.1 (0.6) |  |
| 7 | Yearly maximum Northward Sea Water Velocity [m s-1] | vo_max [numeric] | Mean (sd) : 0.2 (0.1)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 0.9<br>IQR (CV) : 0.1 (0.5) |  |
| 8 | Yearly mean Northward Sea Water Velocity [m s-1] | vo_mean [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>-0.5 ≤ 0 ≤ 0.3<br>IQR (CV) : 0 (-2.8) |  |
| 9 | Yearly mean Eastward Sea Water Velocity [m s-1] | uo_mean [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>-0.5 ≤ 0 ≤ 0.4<br>IQR (CV) : 0 (24) |  |
| 10 | Yearly 5 percentile Light attenuation [mmol m-3] | KD490_5percentile [numeric] | Mean (sd) : 0.1 (0)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 0.4<br>IQR (CV) : 0 (0.7) |  |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Table 11 reports the main statistic (including minimum, mean and maximum values) and distribution of the considered model predictors. More details about all metrics are included in Supplementary material (Annex 11 and Annex 12).

Similarly, to better understand the variability and dispersion of the available future scenarios, some further data explorations by means of boxplots have been carried out. More precisely, Figure 28 gives a good indication of how values in the baseline, reference and future scenarios are spread out. Across the analysed metrics, it is possible to observe a remarkable increase in SST under the worst-case scenario (RCP8.5), delivering an increase of about 4 °C by 2100, relative to the SST in the year 2017. Instead, looking at the salinity 5th percentile, the studied metrics show a stable evolution with an average salinity close to 38 PSU throughout this century.

Further illustrations, showing the comparison between the historical and baseline of the available metrics are included in Supplementary material (Annex 13).

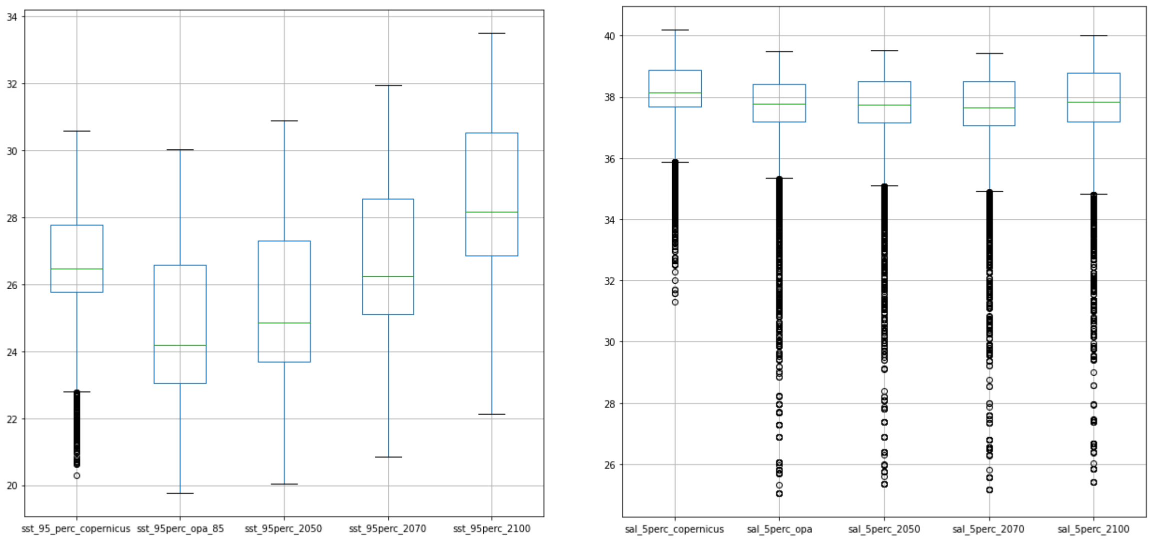



***Figure 28.*** *Boxplots displaying the distribution and range of baseline (Copernicus data), reference and future scenarios (RCP8.5 - provided by CMCC) of: left) Sea surface temperature 95 percentile [°C]; right) salinity 5 percentile [PSU].*

After the visual exploration aimed at understanding the size and some basic characteristics of the data, a correlation analysis was performed to measure the strength of the linear relationship among the analysed variables, and try to identify some relationships, patterns, significant connections, as well as features contributing very less in predicting the output. Accordingly, in this study, the threshold (i.e., degree of dependence) selected to remove highly correlated features/variables (as they do not convey extra information) from the RF model is equal to or higher than 0,85. Coherently, as can be observed in Figure 29, the resulting correlation matrix highlighted as most of the correlation coefficients greater than the selected thresholds usually refer to metrics representing the same variable, as between CHL-a_max and CHL-a_90percentile or between kd490_min and KD490_5percentile. More precisely, by means of this analysis, the following metrics have been removed from the further steps:

- *'CHL-a_max',*
- *'KD490_min',*
- *'SAL_min',*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

- *'NH4_95percentile',*
- *'NH4_min',*
- *'NO3_5percentile',*
- *'NO3_95percentile',*
- *'NO3_min',*
- *'OA_mean',*
- *'PO4_95percentile'.*

Therefore, one of the advantages of this analysis is the possibility of reducing the complexity of the designed RF model and the computational cost/time required for its final implementation. Besides these high-correlated variables, among the water quality parameters, Chl-a resulted to be correlated with all included nutrients (especially with NH4 – degree of correlation around 0.7): this outcome was predictable since eutrophication (Chl-a can be used as a proxy of eutrophication processes) is a process mainly driven by enrichment of water by nutrients, especially compounds of nitrogen and/or phosphorus (EC, 2008). Generally, these nutrients lead to an increase in micro and macro algal biomass and consequently to a trophic imbalance in the entire ecosystem. This phenomenon manifests itself in altered water colour and transparency due to high concentrations of microalgae (phytoplankton), and explains the close relationships between light attenuation (algae blooms block sunlight from penetrating to the seagrass canopy and Chl-a (Dennison et al., 1993). Finally, as expected, Chl-a is also high correlated with sea surface temperature, since among all the ecological factors influencing phytoplankton growth, the temperature is undoubtedly one of the most important.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

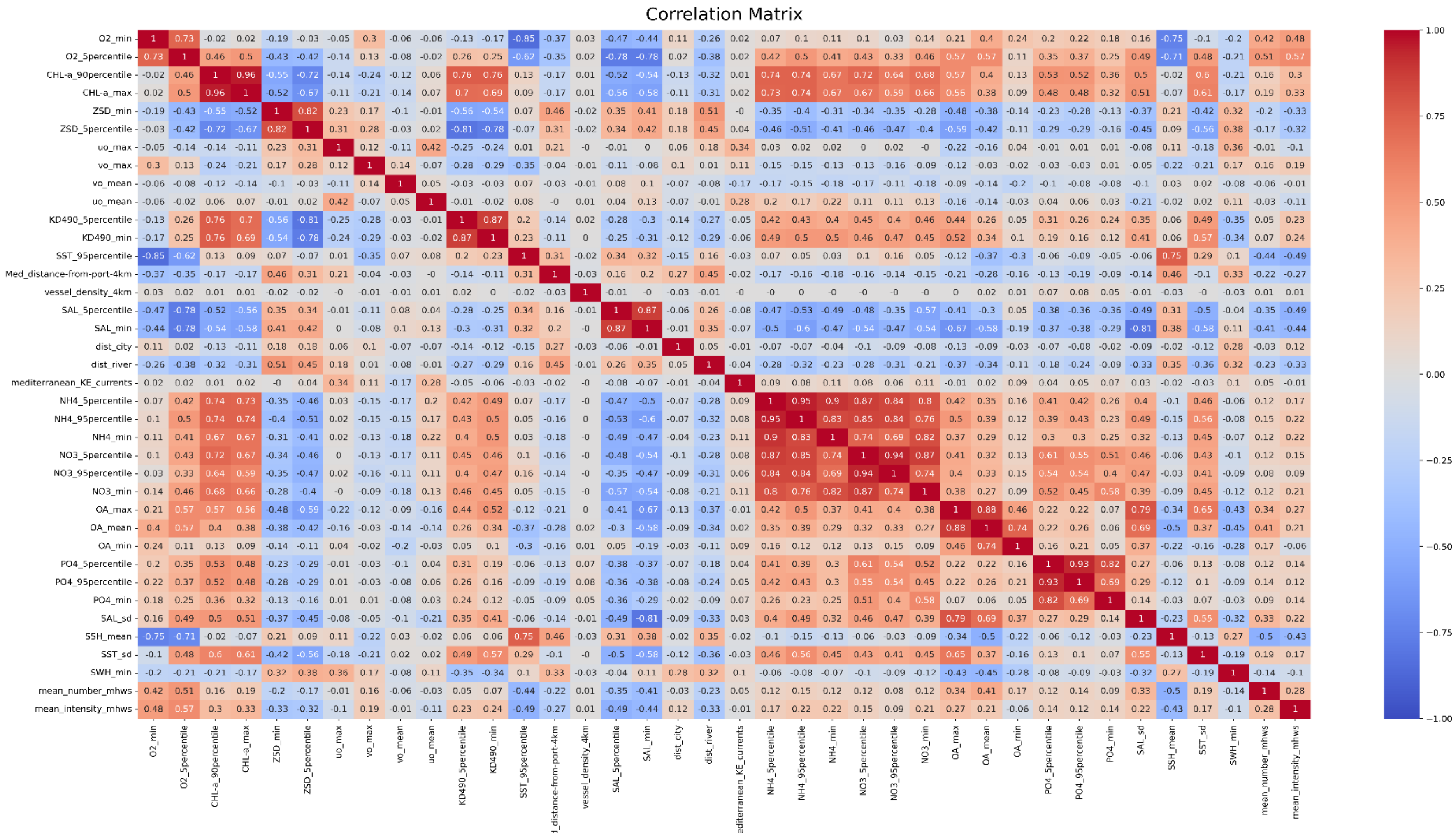


***Figure 29.*** *Plot of the correlation matrix, depicting the correlation among the variables in the Mediterranean eco-region.*

In the Northern Europe eco-region then, according to the spatio-temporal resolution of the available data covering the selected case study area (Section 1.2.4), the final dataset includes 24217 observations, of which 21795 will be devoted for the model training and validation phases, whereas the excluded 2422 for the final testing phase

After the visual exploration aimed at understanding the size and some basic characteristics of the data, a correlation analysis was also performed to measure the strength of the linear relationship among the analysed variables, and try to identify some relationships, patterns, significant connections, as well as features contributing very less in predicting the output. Accordingly, in this study, the threshold (i.e., degree of dependence) selected to remove highly correlated features/variables (as they do not convey extra information) from the RF model is also equal to or higher than 0,85. By means of this analysis, the following metrics have been removed from the further steps:

- *'SD_mean',*
- *'KD490_5percentile',*
- *'KD490_mean',*
- *'Chl_mean',*
- *'NO3_95percentile',*
- *'NO3_max',*
- *'NO3_mean',*
- *'O2_mean',*
- *'OA_min',*
- *'PO4_95percentile',*
- *'PO4_max',*
- *'PO4_mean',*
- *'PO4_min',*
- *'SAL_mean',*
- *'SAL_sd',*
- *'SWH_mean',*
- *'VHM0WW_max',*
- *'VTM01WW_max',*
- *'ICEConc_mean',*
- *'ICEThick_max',*
- *'ICEThick_mean',*
- *'SST_sd',*
- *'Ave_Fishing_Hours'.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

# 5. Results

## 5.1 RF implementation in the Mediterranean eco-region

This section reports the output of the RF implementation (as described in Section 3.5). In particular, Section 5.1.1 shows the identified best model configurations useful to improve the model performances of the designed model across the training and validation phases, as well as discusses the results obtained from the final testing phase (showing tables and graphs resulting from the applied metrics, i.e., recall, accuracy, precision and F1) (Section 5.1.2), as well as the resulting maps from the scenario analysis (Section 5.1.3).

### 5.1.1 Model training and validation

First, in order to perform the spatial cross-validation technique (Section 3.5.1), 10 groups have been created from the clustered blocks so that the same group does not appear in two different sets (train and validation). Then, the standard 10-fold cross-validation was applied to search for the best parameters, identify the most relevant predictor variables, and validate the model.

To implement the hyperparameter tuning (Section 3.5.1.1) the scikit-learn[35] Python open-source machine learning library was used. This library provides techniques to tune model hyperparameters. Specifically, it provides the RandomizedSearchCV for random search (Section 3.5.1), which is the technique employed in this study. Firstly, a hyperparameter space was created to be used to make the possible combinations. In particular, a list of possible values has been set for: i) n_esimator: the number of trees in the forest; ii) min_samples_split: the minimum number of observations required to split a node; iii) max_depth: the dimension of the longest path between the root node and the leaf node. The remaining parameters have been set equal to the default parameters except for the class_weight parameter (i.e., weights associated with classes) which has been set as 'balanced'. Looking at the distribution of the three classes of the response variable (i.e., seagrass distribution), it is unbalanced, therefore, thanks to the class weighting of the RF (Section 3.3.3), the weight of the classes is automatically assigned inversely proportional to their frequencies in the input data. In particular, let y be the specified class, and the weight is given by the (number of observations)/(number of classes * number of occurrences of y in the input data). Table 12 summarizes the hyperparameter settings:

***Table 12.*** *Hyperparameter settings.*

| | Parameter | List/value |
|---|---|---|
| **Optimized hyperparameters** | n estimator | [100,150,200,250]<br>[30,40,50,60,70,80] |
| | max_depth | [5,8,10,13,15] |
| | min_samples_split | [5,8,10,13,15] |
| **Fixed hyperparameters** | min_samples_leaf | 1 (default) |
| | class_weight | 'balanced' |
| | max_features | 'auto' (default) |

[35] https://scikit-learn.org/stable/

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Table 13 lists the tested hyperparameters, and the related best values, determined through this process to improve the predictive accuracy.

***Table 13.*** *Hyperparameter tuning results.*

| HYPERPARAMETER TUNING RESULTS | | |
|---|---|---|
| n_estimator | max_depth | min_samples_split |
| 50 | 13 | 10 |

The parameter related to the minimum number of samples required to be at a leaf node (i.e., min_samples_leaf) was increased from 1 to 4 to avoid overfitting and improve overall model performance.

Once the best hyperparameters were selected, the feature selection process (Section 3.5.1) was performed. Particularly, this iterative process started with all the model predictors included as input variables, hence, the model was trained on the initial set of features and the ranking of each feature was obtained through variable importance (Section 3.3.2). Then, the least important features were pruned from the current set of features. The procedure was recursively repeated on the pruned set until the features that did not reduce the accuracy of the prediction were selected. As can be observed in Figure 30, this process identified 19 relevant model predictors, discarding 9 variables from the initial 28.

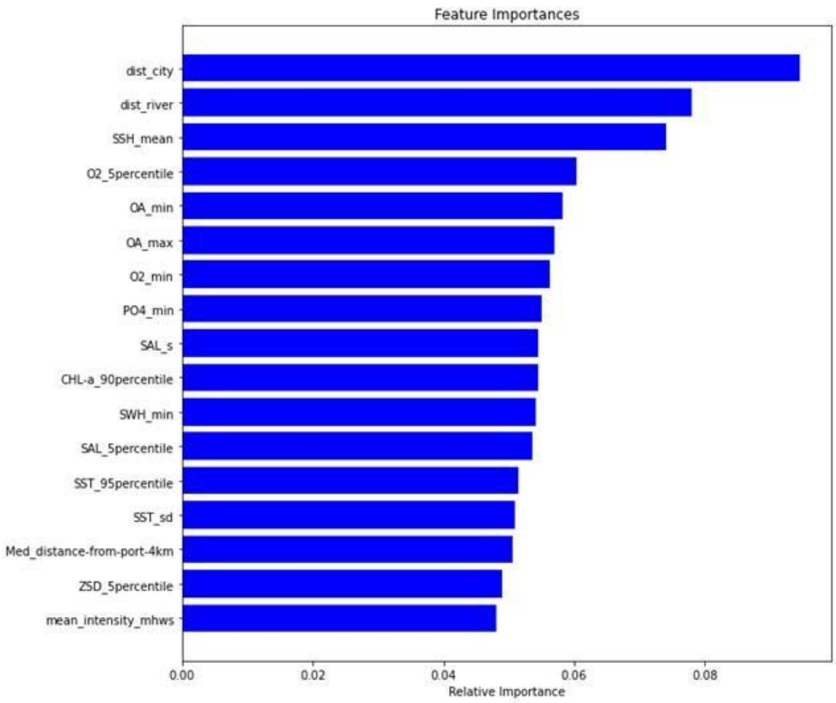



***Figure 30.*** *Contributions of the 19 most relevant model predictors for predicting the MCEs' condition/biodiversity according to the RF model.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

The RF model, adjusted with 19 predictors, explained the largest proportion of the overall model capability to predict the Mediterranean Sea condition. The contribution of the most relevant model predictors ranged between almost 0.05 for the 5 percentile of Secchi depth and the mean of intensity of marine heat waves (respectively, "ZSD_5percentile" and "mean_intensity_mhws") to around 0.085-0.09 for the distance from major cities (i.e., the most relevant one). The resulting output from the feature importance is consistent with the main threats influencing seagrasses' health and distribution (UNEP, 2020). Indeed, seagrass growth and productivity are mainly regulated by the quantity and quality of light reaching the seagrass bed; therefore, changes in water transparency (or turbidity/light attenuation) can influence seagrass abundance and distribution. As already described in Section 1.1.2, light stress is attributed to nutrients and pollution loads, often driven by urban, industrial and agricultural run-off, as well as to coastal development (UNEP, 2020). This explains the high ranking of distance from major cities and rivers, as well as some nutrient concentration-related variables. Additionally, temperature, oxygen and salinity are important abiotic factors that influence seagrass health and productivity. Seagrass photosynthesis is positively correlated with temperature until the optimal value is reached; afterwards, moving beyond this critical threshold, the performance starts to drop off sharply. At the same time, an increase in photosynthesis causes faster growth and therefore higher respiration rate. This can compromise the net primary production and lead to a negative carbon balance (Galli et al., 2017; Marín-Guirao et al., 2016).

### 5.1.2 RF model testing

In this application, the RF model exhibited a notable level of accuracy in predicting the condition of the Mediterranean Sea on the input data (model predictors). The final overall model predictive accuracy for new observations during the testing phase reached 0.82. More precisely, the specific accuracies resulted for the 3 output indicators were: 0.89 regarding the seagrass distribution, 0.71 for the Shannon index and 0.86 for connectivity.

In addition, as explained in Section 4.5.2, the F1 scores were examined to gain insight into model performance. The resulting model performances comparing the RF performance against all the response variables are reported in Table 14. Differences in the performance across the response variables and the related classes can be observed. Moreover, relatively simple plots depicting the confusion matrix were developed (Figure 31) to illustrate how many predictions were assigned correctly, incorrectly, and where the RF got confused. In Figure 31, the rows represent the predicted labels, and the columns represent true labels. Values on the diagonal represent the percent (dark blue highlights high values, whereas white represents values close to 0%) of the right assignation (i.e., where the predicted label matches the true label). Values in the other cells represent instances where the classifier mislabelled an observation; the rows reveal what the classifier predicted, and the columns show what the right label was.

Overall, these results show good performances in predicting the first and the third classes, whereas the second class is more frequently misclassified. Looking at the model predictors, our model presents higher performances in predicting connectivity, with high values for each class. However, the Shannon index is predicted with lower accuracy, with the final F1 score between 0.57 to 0.80. In sum, the implemented model shows compelling results in estimating model predictors against historical data, thus, making it ready for the simulation of future climate change scenarios (e.g., climate scenarios with increasing water temperatures, sea level rise, and variations in sea surface salinity.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 14.*** *Model performances.*

| | Seagrass distribution | | | Shannon index | | | Connectivity | | |
|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 |
| Class 1 | 0.98 | 0.92 | 0.95 | 0.87 | 0.73 | 0.80 | 0.99 | 0.91 | 0.95 |
| Class 2 | 0.31 | 0.60 | 0.41 | 0.50 | 0.64 | 0.57 | 0.75 | 0.66 | 0.70 |
| Class 3 | 0.81 | 0.71 | 0.76 | 0.65 | 0.71 | 0.68 | 0.60 | 0.93 | 0.73 |

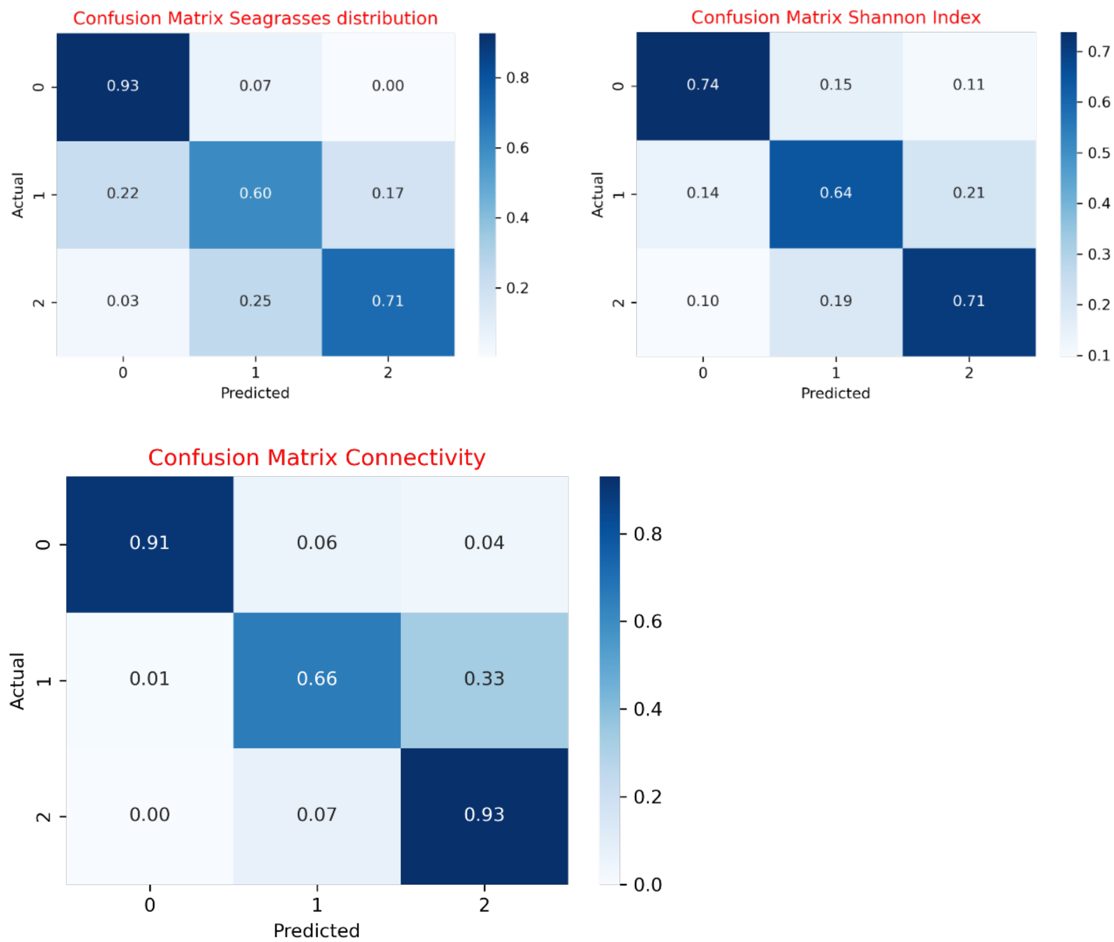



***Figure 31.*** *Resulting confusion matrix of a) Seagrass distribution, b) Shannon index, c) Connectivity.*

### 5.1.3 Scenario analysis

The last phase of the RF implementation is the scenario analysis, which allows the simulation of potential impacts arising from climate-related scenarios envisioned for the investigated area (Section 3.6). To accomplish this goal, the model was enriched with various metrics corresponding to the RCP4.5 and RCP8.5 scenarios and subjected to thorough testing. Specifically, various simulations were conducted for the Mediterranean eco-region, taking into account variations in SST + MHWs, Salinity and SSH. The aim was to assess potential changes in the ecological condition of the selected

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

case study area, with a specific focus on seagrass. Coherently, the first set of simulations was aimed at evaluating anomalies in seagrass distribution between reference and future scenarios. Once all the available metrics were tested under an individual scenario, a combination of these indicators was tested to discover evidence for differences in stressor interaction ranging from synergism to antagonism. Based on the RF model, combined scenarios SC-AB, SC-AC and SC-ABC lead to higher seagrass shrinkages compared to influence of individual pressures (Figure 32). In particular, the model predicts the shrinkage of more isolated seagrass meadows (from moderate presence to absence), where area characterized by a good distribution seems to be resilient to these impacts. Additional results (and related illustrations) on the influence of pressures on connectivity and the Shannon index (illustrating the anomalies between reference and future scenarios under both mid- and long-term timeframes) can be found in the Supplementary material (Annex 14).

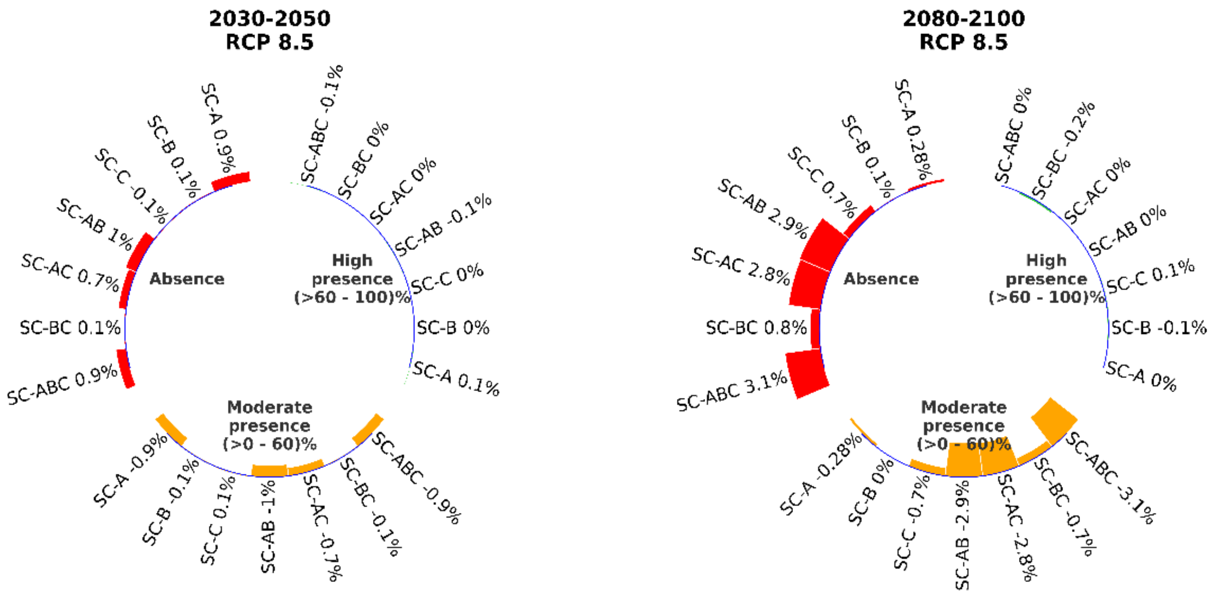



***Figure 32.*** *Circular bar plot showing anomalies between reference (1998-2017) and future scenarios for seagrass distribution. The tested scenarios include: i) individual scenarios (SC-A: SST, SC-B: SAL and SC-C: SSH); ii) coupled scenarios (i.e., SC-AB: SST+SAL, S C: SST+SSH and SC-BC: SAL+SSH); iii) all available scenarios together (i.e., SC-ABC: SST+SAL+SSH).*

Future variations of the Shannon index were analysed to examine potential effects induced by the selected scenarios on the ecosystem biodiversity. The analysis revealed that the comparison between reference and simulated scenarios showed more significant changes compared to the previous indicator (connectivity). Overall, more relevant changes are triggered under the long-term scenario, although in both timeframes, relevant anomalies emerged.

When shifting focus to the indicators, projected variations in SST triggered the most relevant losses in species diversity (reduction close to 20% reduction under the BAU scenario) in the Mediterranean Sea in 2100. Instead, SSH seems to have reduced effects on species diversity compared to SST. However, these two scenarios seem to induce even more relevant effects when considered cumulatively despite the model predicting ecological benefits arising from the projected SAL variations.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

When comparing the circular bar plots (Figure 32) displaying the anomalies in the seagrass connectivity, similarities are observed with the outputs obtained for the seagrass distribution. In fact, the expected variations are less remarkable (anomalies between 0 and 4%), as well as combined scenarios showed signs of being characterized by interactive behaviours, e.g., synergisms lead to higher effects (SC-AC) compared to simple additive ones. Finally, also for the connectivity, the designed model foresees reduced ecological benefits associated with the projected SAL variations under both timeframes and scenarios.

Furthermore, the selection of the RF was also linked to its potential to **spatially** predict and map future conditions of MCEs under different scenarios. Following the same procedure, a set of maps displaying all the anomalies for the 3 output indicators for both timeframes and scenarios have been produced and reported in Supplementary material (Annex 15).

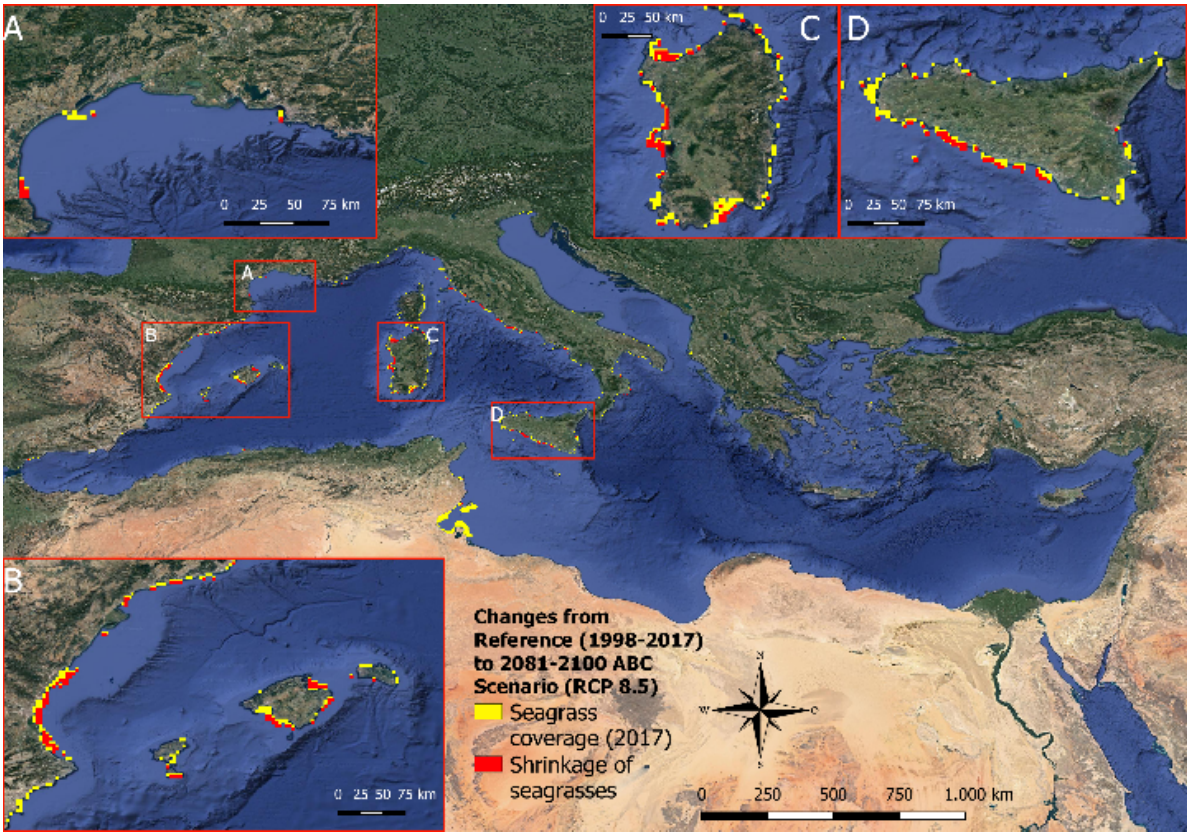



***Figure 33.*** *Map illustrating future changes from reference to the long-term ABC RCP8.5 scenarios for the seagrass distribution.*

Overall, according to the different climate impact intensities represented by investigated RCPs scenarios, the model predicts a more severe risk under the long-term scenarios. Specifically, within the 2031-2050 timeframe (Supplementary material - Annex 15), under both RCP4.5 and RCP8.5 scenarios, the overall pattern of cumulative impacts and risk distribution are similar in terms of overall changes and spatial variations. In terms of spatial distribution, meadows surrounding the Balearic Islands and the French coastline appear to be the most impacted regions under the "cumulative" scenario in the short-term time horizon.

The declining trend is consistent with previous studies (Houngnandan et al., 2020) focused on the French coast, where the Eastern part presented higher disturbances due to anthropogenic pressures.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

When examining the long-term scenario (2081-2100), in both RCP's, meadows shrinkage emerged across the entire Mediterranean basin. In particular, the meadows at lower depths (between 25 and 50 m depth) appeared to be the most affected. This trend is more remarkable along the French coast (Figure 33, B) and the south coast of Sicily (Figure 33, D). The differences between RCP4.5 and RCP8.5 are linked to the meadows in the northwestern part of Sicily and the western part of the French coast. While the results for the RCP4.5 predict a fragmented distribution with the presence of some persistent areas, the scenario linked to the RCP8.5 shows almost a complete loss of this ecosystem over these two areas.

In sum, biodiversity variations under the cumulative scenarios reveal numerous areas exhibiting a significant decline in species diversity compared to the reference scenario (Figure 33). This decline is especially pronounced along the Italian and Spanish coasts, as well as in proximity to Tunisia. Finally, it is worth noting that no specific trends or regions leading to a substantial reduction in seagrass connectivity can be identified. The resulting map shows only a few scattered or isolated areas across the Mediterranean basin will be triggered by a reduction of connectivity across the tested scenarios.

## 5.2 RF implementation in the Northern Europe eco-region

Following a structure analogous to that presented for the Mediterranean region, this section introduces the outcomes of the RF implementation, as outlined in Section 3.5. Specifically, Section 5.2.1 elucidates the best model configurations that have been identified during both the training and validation phases. Then, Sections 5.2.1 and 5.2.2 present the conclusions derived from the final testing phase, as well as the resulting maps (Section 5.2.3) from the scenario analysis.

### 5.2.1 Model training and validation

To implement the RF, the same procedure described for the Mediterranean eco-region was adopted (Section 5.1.1). A list of possible values has been set for: i) n_esimator: the number of trees in the forest; ii) min_samples_split: the minimum number of observations required to split a node; iii) max_depth: the dimension of the longest path between the root node and the leaf node; iv) min_samples_leaf: the minimum number of samples required to be at a leaf node. The remaining parameters have been set equal to the default values except for the class_weight (i.e., weights associated with classes). In fact, during the training process, the model was evaluated by setting this parameter as 'balanced' and a better performance on the recognition of the presence of kelp forest was reached. This result may be due to the fact that the classes of the response variable are moderately unbalanced, therefore, thanks to the class weighting of the RF (Section 3.3.3), the weight of the classes is automatically assigned inversely proportional to their frequencies in the input data. The following table summarises the hyperparameter settings:

***Table 15.*** *Hyperparameters setting.*

| | *Parameter* | *List/value* |
|---|---|---|
| *Optimized hyperparameters* | *n_estimator* | *[20,30,50,70,90,110,120]* |
| | *max_depth* | *[4,6,8,10,12]* |
| | *min_samples_split* | *[2,4,6]* |
| | *min_samples_leaf* | *[1,2]* |
| *Fixed hyperparameters* | *class_weight* | *'balanced'* |
| | *max_features* | *'auto' (default)* |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

The tested hyperparameters, and the related best values, determined through this process to improve the predictive accuracy, are listed in the following table:

***Table 16.*** *Hyperparameter turning results.*

| *HYPERPARAMETER TUNING RESULTS* | | | |
|---|---|---|---|
| *n_estimator* | *max_depth* | *min_samples_split* | *min_samples_leaf* |
| *110* | *10* | *4* | *2* |

Once the best hyperparameters are selected, the feature selection process (Section 3.5.1) is performed as described in Section 5.1.1. Figure 34 shows the most relevant model predictors identified by the feature selection process, discarding 16 variables from the initial 27. Moreover, it is also presented the importance of each input variable. Specifically, the contribution of the most relevant model predictors ranged between almost 0.05 for the 5th percentile of nutrients to 0.30 for the distance from shore (i.e., the most relevant one). The resulting output from the feature importance is consistent with the main environmental parameters influencing kelp forests' condition and distribution (Yesson et al., 2015; Wernberg et al., 2019; UNEP, 2023). Indeed, like seagrasses, kelps growth and productivity are mainly regulated by the quantity and quality of light reaching the algae (e.g., Yesson et al., 2015); therefore, the height of the water column (reflected by 'SSH') and changes in water transparency (or turbidity/light attenuation. reflected by 'Secchi Depth - SD', and 'KD490') can influence their abundance and distribution. As already described in Section 2.2, kelps are also threatened by eutrophication and freshwater run-offs, which can be caused by urban, industrial and agricultural run-off, but also aquaculture, atmospheric deposition, shipping, etc., which introduce nutrients and other pollution loads within the Northern Europe eco-region (ICES, 2021, 2022a, b, c). This explains the high ranking of distance from shore and port (as an indicator of exposure), as well as some nutrient concentration-related variables ($PO_4$ and $NO_3$) we observed here. Although nutrients are essential for the growth of kelp forests that can drive their distribution in their temperate range south of the eco-region (Yesson et al., 2015; Wernberg et al., 2019), eutrophic conditions benefit turfs communities and epiphytes. Turf communities tend to trap sediment, preventing the settlement of kelp, while the development of epiphytes on the kelps reduce the amount of light for the kelp. Additionally, temperature ('SST') and oxygen ('$O_2$') are important abiotic factors that influence kelp productivity (Crowder et al., 2019; Yesson et al., 2015), with SST increase, including the increased number of marine heatwaves, related to climate change being recognized as one of the main drivers of kelp populations trends observed across the eco-region (e.g., Arújo et al., 2016, UNEP, 2023). In fact, kelp not only performs photosynthesis but respiration too, so hypoxia can be harmful to the kelp and their associated fauna (e.g., grazers, decomposers, predators). In addition, the cumulative effects of low oxygen and upwelling-associated fluctuations in pH ('OA') and temperature could have profound effects on the faunal communities that drive the structure and function of kelp ecosystems (Crowder et al., 2019).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

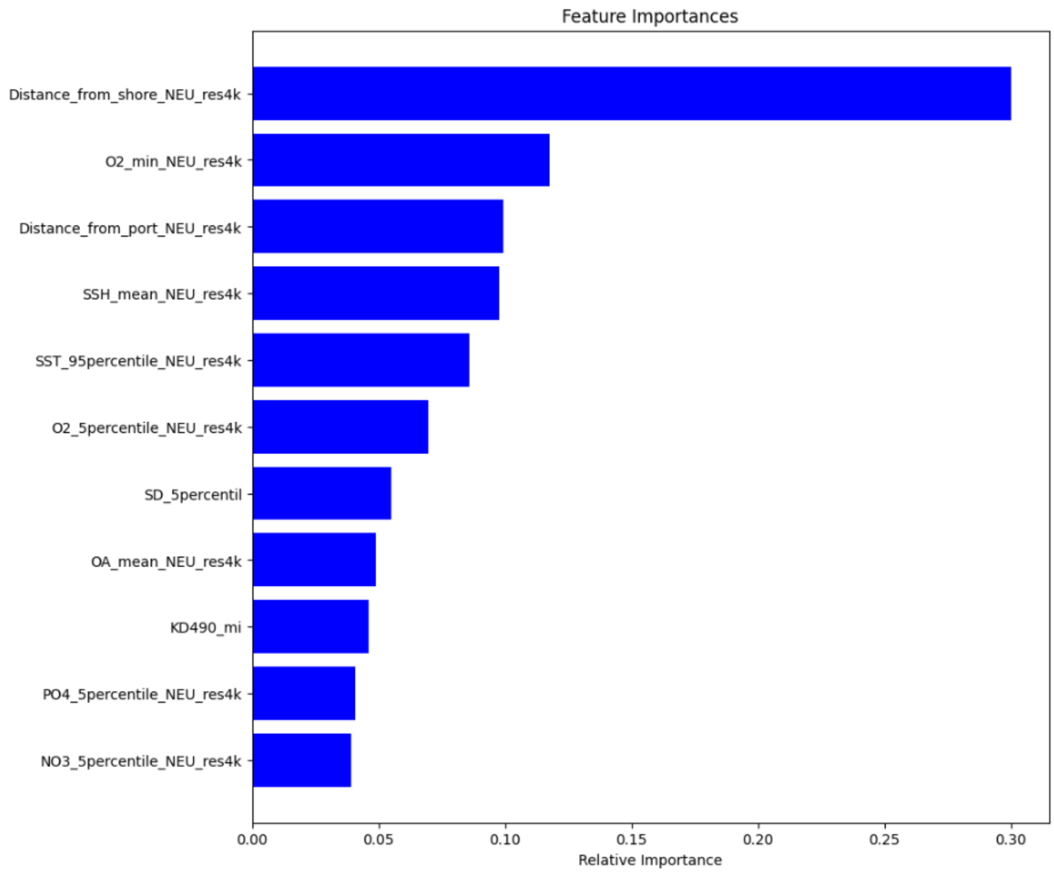



***Figure 34.*** *Contributions of the 11 most relevant model predictors for predicting the Kelp Forest distribution according to the RF model.*

### 5.2.2 RF testing

The RF model showed a very good level of accuracy in predicting the distribution of Kelp forests against several pressures in the Northern Europe case study. During the testing phase, the model obtained an accuracy of 0.88 in predicting new observations (i.e., test set). In addition, also precision, recall and F1-score were evaluated, and the results are shown in Table 17. It is possible to see that the model has very good performances in both classes, in fact, the F1-score reaches 0.91 for class 0, while for class 1 is equal to 0.83. The model specialises in recognising the presence of kelp forest as demonstrated by the value of recall in class 1, at the expense of lower precision. Indeed, it classifies 15% of observations of the test set as class 1 instead of class 0 as it is visible from the confusion matrix (Figure 35). Despite a lower precision, his result should be considered satisfactory because the goal is to admit no error about the presence of the kelp forest rather than the opposite.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

***Table 17.*** *Model performances.*

| | Kelp forests distribution | | |
|---|---|---|---|
| | Precision | Recall | F1 |
| Class 0 (Absence) | 0.97 | 0.85 | 0.91 |
| Class 1 (Presence) | 0.74 | 0.94 | 0.83 |

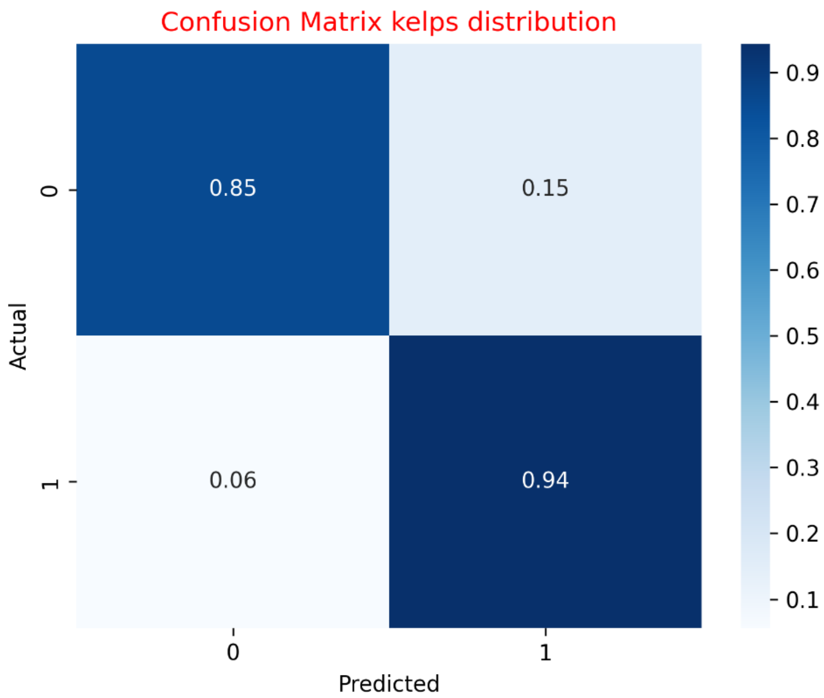



***Figure 35.*** *Resulting confusion matrix of Kelp forests distribution.*

### 5.2.3 Scenario analysis

To perform the scenario analysis phase, several simulations were conducted for the Northern Europe eco-region. Specifically, based on variable importance (Figure 34), metrics related to the most important variable for which future projections are available were calculated. Particularly, the minimum and fifth percentile of oxygen for the 2050 and 2100 timeframes were computed using projections for 4.5 and 8.5 RCPs. Once the metrics were calculated, they were substituted to the initial dataset and the model results in terms of changes in kelp forests distribution were evaluated. For example, in the histogram in Figure 36 it is possible to see the variation of kelp forests under future oxygen changes (Scenario A) in 2100 with RCP 8.5. Although some absence pixels have become presence pixels, in general, a reduction of the area covered by kelp forests can be noted. It is possible to see in spatial terms this shrinkage in the map in Figure 37. The main reduction is in the coasts of Denmark and Norway and some disappearance is also on the coasts of the United Kingdom.

While knowledge on kelp forest populations trends is fragmented and lacking in some areas of Northern Europe, the decline observed between the southern coast of Norway and the Skagerrak and

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

on the coasts of the United Kingdom is coherent with past trends observed (Araújo et al., 2016; UNEP, 2023). The underlying reasons of this shrinkage in respect to oxygen projections used are unclear though and potentially complex. Indeed, kelps are generally not believed to be particularly vulnerable to deoxygenation, at least directly, because they are photosynthetic organisms, however, almost no studies exist on the effects of climate-driven hypoxia on these organisms. But because kelps are photosynthetic organisms that also respire, they are thus still likely to be impacted to some extent by oxygen depletion. It is further believed that the interplay between climate-driven hypoxia and other climate-driven stressors such as ocean acidification and warming could then have an overall negative impact on kelp forests, although effects would vary locally on a small spatial scale and depending on the species considered (Crowder et al., 2019). For instance, it has been observed that warming can cause an increase in metabolic demand and in respiration rates compared to photosynthesis, while hypoxia would inhibit respiration rates through oxygen depletion on the other hand. If both co-occur, one might expect a sharp decline in kelps net primary production at least. Considering that a broad-scale mortality of sugar kelp, *Saccharina latissima*, has been linked to an increase in the frequency of marine heatwaves in the Skagerrak and southern Norway (Filbee-Dexter et al., 2020), the co-occurrence of oxygen depletion predicted in the area could explain the shrinkage of kelp forests we observed in the area. Ocean acidification then can benefit photosynthesis, which would tend to counterbalance the negative effects of hypoxia. The effects of hypoxia on kelps are therefore complex to predict and highly context-dependent. Considering sea surface temperature and ocean acidification were also identified as important variables of the model, future developments regarding the Northern Europe eco-region will be particularly interesting when it will become possible to integrate further scenarios and observe the cumulative effect of multiple pressures in the future.

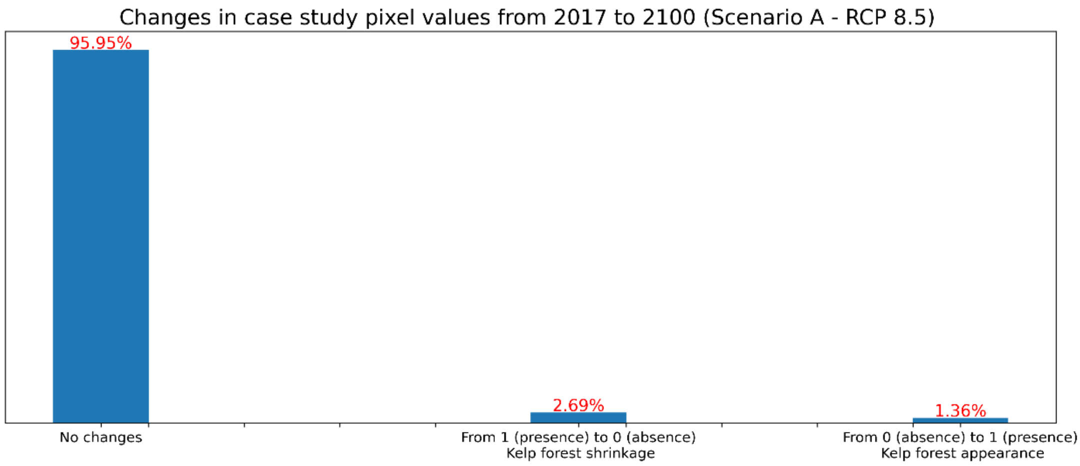



***Figure 36.*** *Histogram showing changes in the North Europe case study pixel values for the Scenario A (oxygen variations) in the 2100 timeframe for RCP 8.5.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

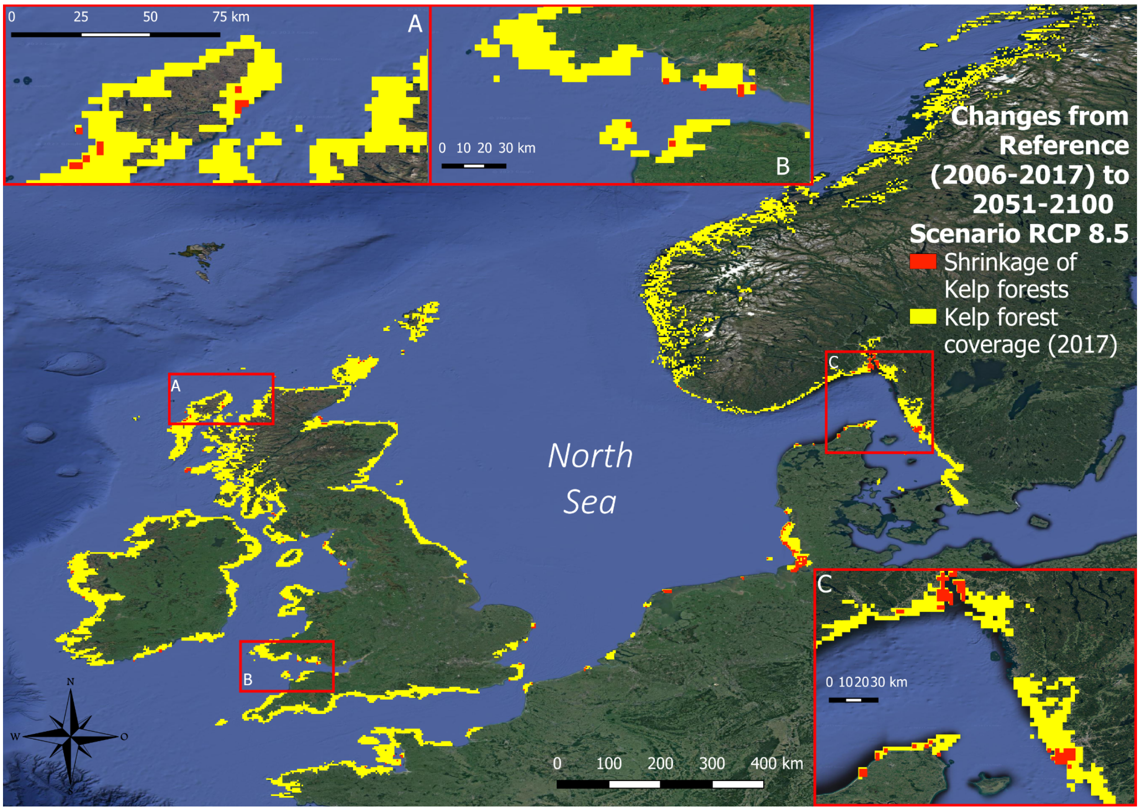



***Figure 37.*** *Map illustrating future changes from reference to the long-term A RCP 8.5 scenario for the Kelp forests distribution.*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Conclusion

Understanding the complex interplay and the effects of multiple human-made and climate-related pressures (Furlan et al., 2019; Halpern et al., 2008) is a key challenge to support decision-makers in the achievement of environmental and sustainability objectives (EEA, 2019). The cumulative and synergistic impacts of these activities and climate change are triggering complex and severe alterations of MCEs biodiversity and their capacity to supply services for human well-being. Drawing on these, the main aim of Task T2.1 was the co-design and operationalisation of a general MRAF and specific eco-regional-MRAFs aimed at unrevealing the complex interplay between the most relevant pressures affecting MCEs conditions across two MaCoBioS eco-regions. To achieve these bold objectives, a stepwise approach was carried out across the lifetime of T2.1, including literature review, co-design of the MRAFs with stakeholders and experts, and the implementation of specific eco-regional-MRAFs using ML. From the operationalisation of stepwise approach in the Mediterranean and Northern Europe eco-regions, several key insights emerged during the iterative process with all MaCoBioS experts for the MRAF co-design.

First, it can be observed from the literature review that methodological approaches and frameworks dealing with cumulative and multi-risk appraisal in MCEs have increased significantly since 2008, after the publication of Halpern et al. (2008). From this point onward the majority of work was carried out building upon the foundations of Halpern et al (2008). Avenues of research employed indicator/index-based methods, ranking the pressures-ecosystem vulnerability nexus through expert-based judgment (e.g., with sampling surveys/questionnaires) when data were not available. In many cases, these data gaps were due to a lack of regional and local scale data on ecosystem vulnerability to specific pressures). Recently, with the progressive digital transformation and the increased availability of spatio-temporal data for marine and coastal environmental monitoring and management (e.g., remote sensing data), authors now have the possibility to design and test new methods (e.g., advanced ML-based models) to evaluate the effect of multiple pressures affecting MCEs. These methodological and digital improvements allow the integration of big data that are essential to disentangle complex inter-relationships and feedbacks between multiple endogenic and exogenic pressures. These pressures lead in concert to cumulative impacts and the resulting changes in MCEs ecological condition.

Building on the results of the literature review, an expert engagement workshop was organised for the co-development of the MRAF. The workshop sought to reinforce the ecosystem risk concept to then efficiently implement ecosystem-based assessment and management measures. This, in turn, more easily helps to mitigate multiple risks arising from the dynamic interplay between climate change and human-induced pressures. It emerged from the workshop that all risk components (pressure, vulnerability, and ecosystem services) are connected in a complex marine coastal socio-ecological system. Among these components, vulnerability is the most difficult to identify, while ecosystem services can be considered as a cross-cutting concept throughout the risk and DPSIR framework. The outcome of this workshop drove the data collection and implementation of the specific MRAFs across the MaCoBioS eco-regions.

Finally, ML-based risk assessment models were implemented to analyse interactions among stressors as well as evaluate the risk reduction and associated ecological benefits expected from reducing pressure from stressors. These, in turn then guide the implementation of management actions and mitigating strategies. Different configurations of the RF model were designed and implemented across the MaCoBioS eco-regions. Scenarios related to the variation in SST, Salinity, MHWs, and SSH were simulated in the Mediterranean eco-region. This was done to test the capacity of the designed ML-based model to better understand multi-risk underpinning MCEs' response to future climate impacts. The final models showed good potential for not only capturing these relationships,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

but for evaluating the most relevant ones driving changes in MCEs' conditions as well. More precisely, results showed that the ecological condition is mainly threatened by human-related pressures linked to coastal development and to changes in nutrient concentration. Both of which can trigger cascading effects on the potential light reaching the seabed. As for Northern Europe, future variations in dissolved oxygen were simulated, as it is one of the most important variables for the region's representative ecosystem. In this case study, the model proved capable of capturing the relationships between cumulative impacts of the stressors. In particular, the interplay between remaining pressures and oxygen in the future showed a worrying decline in the ecosystem consistent with past trends. The insights gained from working within these two eco-regions, as well as the data prerequisites, revealed that extending the same approach to the Caribbean eco-region would not be feasible within the project's timeframe. The absence of extensive and homogeneous data able to represent both pressures and the coral reef distribution at the eco-regional level did not allow for the implementation of the RF model across all the MaCoBioS eco-regions.

Overall, despite limitations inherent to data availability at this large scale, this ML-based approach provided useful predictive insight on possible future ecological conditions and the nexus underpinning MCEs' response to multiple pressures, including climate change. The continuous progress in understanding cumulative impacts, also thanks to ML models allowing to 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. The resulting GIS-based multi-risk scenarios from this Task will then be used as input data for the NBSs suitability mapping (Task 3.3). Moreover, they will be the starting point for the local MRAF operationalisation aimed at identifying hot-spot risk habitats (e.g., seagrass meadows, mangroves) where management actions and adaptation strategies supported, or inspired, by nature would be best targeted.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Bibliography

AhmedK, A., Aljahdali, S., & Naimatullah Hussain, S. (2013). Comparative Prediction Performance with Support Vector Machine and Random Forest Classification Techniques. *International Journal of Computer Applications*, *69*(11), 12–16. https://doi.org/10.5120/11885-7922

Ainsworth, C. H., Samhouri, J. F., Busch, D. S., Cheung, W. W. L., Dunne, J., & Okey, T. A. (2011). Potential impacts of climate change on Northeast Pacific marine foodwebs and fisheries. *ICES Journal of Marine Science*, *68*(6), 1217–1229. https://doi.org/10.1093/icesjms/fsr043

Allan, J. D., McIntyre, P. B., Smith, S. D. P., Halpern, B. S., Boyer, G. L., Buchsbaum, A., Burton, G. A., Campbell, L. M., Chadderton, W. L., Ciborowski, J. J. H., Doran, P. J., Eder, T., Infante, D. M., Johnson, L. B., Joseph, C. A., Marino, A. L., Prusevich, A., Read, J. G., Rose, J. B., … Steinman, A. D. (2013). Joint analysis of stressors and ecosystem services to enhance restoration effectiveness. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(1), 372–377. https://doi.org/10.1073/pnas.1213841110

Andersen, J. H., Al-Hamdani, Z., Harvey, E. T., Kallenbach, E., Murray, C., & Stock, A. (2020). Relative impacts of multiple human stressors in estuaries and coastal waters in the North Sea–Baltic Sea transition zone. *Science of the Total Environment*, *704*, 135316. https://doi.org/10.1016/j.scitotenv.2019.135316

Andersen, J. H., Halpern, B. S., Korpinen, S., Murray, C., & Reker, J. (2015). Baltic Sea biodiversity status vs. cumulative human pressures. *Estuarine, Coastal and Shelf Science*, *161*(4), 88–92. https://doi.org/10.1016/j.ecss.2015.05.002

Andonie, R. (2019). Hyperparameter optimization in learning systems. *Journal of Membrane Computing*, *1*(4), 279–291. https://doi.org/10.1007/s41965-019-00023-0

Araújo RM, Assis J, Aguillar R, Airoldi L, Barbara I, Bartsch I, Bekkby T, Christie H, Davoult D, Derrien-Courtel S, Fernandez C, Fredriksen S, Gevaert F, Gundersen H, Le Gal A, Leveque L, Mieszkowska N, Norderhaug KM, Oliveira P, Puents A, Rico JM, Rinde E, Schubert H, Strain EM, Valero M, Viard F, Sousa-Pinto I. 2016. Status, trends and drivers of kelp forest in Europe: an expert assessment. Biodivers. Conserv. 25:1319- 1348.

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/J.JOI.2017.08.007

Armstrong, C. W., Vondolia, G. K., Foley, N. S., Henry, L. A., Needham, K., & Ressurreicao, A. M. (2019). Expert assessment of risks posed by climate change and anthropogenic activities to ecosystem services in the deep North Atlantic. *Frontiers in Marine Science*, *6*(MAR), 1–11. https://doi.org/10.3389/fmars.2019.00158

Assis J, Araujo MB, Serrao EA. 2018. Projected climate changes threaten ancient refugia of kelp forest in the North Atlantic. Glob.Change Biol. 2018;24:e55-e66. DOI: 10.1111/gcb.13818

Baas, J., Schotten, M., Plume, A., Côté, G., & Karimi, R. (2020). Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative Science Studies*, *1*(1), 377–386. https://doi.org/10.1162/qss_a_00019

Balzan, M. V., Pinheiro, A. M., Mascarenhas, A., Morán-Ordóñez, A., Ruiz-Frau, A., Carvalho-Santos, C., Vogiatzakis, I. N., Arends, J., Santana-Garcon, J., Roces-Díaz, J. V., Brotons, L., Campagne, C. S., Roche, P. K., de Miguel, S., Targetti, S., Drakou, E. G., Vlami, V., Baró, F., & Geijzendorffer, I. R. (2019). Improving ecosystem assessments in Mediterranean social-ecological systems: a DPSIR analysis. *Ecosystems and People*, *15*(1), 136–155.

https://doi.org/10.1080/26395916.2019.1598499

Bartsch, I., Wiencke, C., Bischof, K., Buchholz, C.M., Buck, B.H., Eggert, A., Feuerpfeil, P., Hanelt, D., Jacobsen, S., Karez, R., Karsten, U., Molis, M., Roleda, M.Y., Schubert, H., Schumann, R., Valentin, K., Weinberger, F., Wiese, J., 2008. The genus Laminaria sensu lato: recent insights and developments. Eur. J. Phycol. 43, 1–86.

Bayley, D., Brickle, P., Brewin, P., Golding, N. and Pelembe, T., 2021. Valuation of kelp forest ecosystem services in the Falkland Islands: A case study integrating blue carbon sequestration potential. One Ecosystem, 6, 1-18. DOI:10.3897/oneeco.6.e62811

Batistič, S., & van der Laken, P. (2019). History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations. *British Journal of Management*, *30*(2), 229–251. https://doi.org/10.1111/1467-8551.12340

Battista, W., Karr, K., Sarto, N., & Fujita, R. (2017). Comprehensive Assessment of Risk to Ecosystems (CARE): A cumulative ecosystem risk assessment tool. *Fisheries Research*, *185*, 115–129. https://doi.org/10.1016/j.fishres.2016.09.017

Bazairi, H., Ben Haj, S., Boero, F., Cebrian, D., De Juan, S., Limam, A., Lleonart, J., Torchia, G., and Rais, C. (2010). The Mediterranean Sea Biodiversity: state of the ecosystems, pressures, impacts. *Unep-Map-Rac/Spa*, 100.

Belluscio, A., Panayiotidis, P., Gristina, M., Knittweis, L., Pace, M. L., Telesca, L., Criscoli, A., Apostolaki, E., Gerakaris, V., Fraschetti, S., Spedicato, M. T., Lembo, G., Salomidi, M., Mifsud, R., Fabi, G., Badalamenti, F., G., G., Alagna, A., Ardizzone, G. D., … Valavanis, V. (2013). Seagrass beds distribution along the Mediterranean coasts. Mediterranean Sensitive Habitats (MEDISEH) Final Report,. *DG MARE Specific Contract SI2.600741*, *April*.

Ben Rais Lasram F., Hattab T., Halouani G., Romdhane M.S., Le Loc'H F., A. C. (2016). Cumulative human threats on fish biodiversity components in Tunisian waters. *Mediterranean Marine Science*, *17*(1), 190–201. https://doi.org/10.12681/mms.1373

Blanfuné, A., Boudouresque, C. F., Verlaque, M., & Thibaut, T. (2019). The ups and downs of a canopy-forming seaweed over a span of more than one century. *Scientific Reports*, *9*(1), 1–10. https://doi.org/10.1038/s41598-019-41676-2

Bonnevie, I. M., Hansen, H. S., & Schrøder, L. (2020). SEANERGY - a spatial tool to facilitate the increase of synergies and to minimise conflicts between human uses at sea. *Environmental Modelling and Software*, *132*(March). https://doi.org/10.1016/j.envsoft.2020.104808

Boon, A., Uyarra, M. C., Heiskanen, A.-S., van der Meulen, M., Galparsoro, I., Viitasalo, M., Stolte, W., Garmendia, J. M., Murillas, A., & Borja, Á. (2017). *Mapping and assessment of marine ecosystem services and link to Good Environmental Status - Background document to the Roadmap for an integrated approach to a marine MAES. May*. https://doi.org/10.13140/RG.2.2.28660.35204

Boorman, L.A, 1992. The environmental consequences of climatic change on British salt marsh vegetation. Wetlands Ecology and Management, 2, 11–21. https://doi.org/10.1007/BF00178130

Boudouresque, C. F., Pergent, G., Pergent-Martini, C., Ruitton, S., Thibaut, T., & Verlaque, M. (2016). The necromass of the Posidonia oceanica seagrass meadow: fate, role, ecosystem services and vulnerability. *Hydrobiologia*, *781*(1), 25–42. https://doi.org/10.1007/s10750-015-2333-y

Breiman, L. (1996). Out-of-Bag Estimation. *New Zealand Medical Journal*, *128*(1425), 97–100.

Brodersen, M. M., Pantazi, M., Kokkali, A., Panayotidis, P., Gerakaris, V., Maina, I., Kavadas, S.,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Kaberi, H., & Vassilopoulou, V. (2018). Cumulative impacts from multiple human activities on seagrass meadows in eastern Mediterranean waters: the case of Saronikos Gulf (Aegean Sea, Greece). *Environmental Science and Pollution Research*, *25*(27), 26809–26822. https://doi.org/10.1007/s11356-017-0848-7

Brondizio, E. S., Settele, J., Díaz, S., & Ngo, H. T. (2019). Global Assessment Report on Biodiversity and Ecosystem Services | IPBES. In *ipbes secretariat -Germany*.

Campagne, C. S., Salles, J. M., Boissery, P., & Deter, J. (2014). The seagrass Posidonia oceanica: Ecosystem services identification and economic evaluation of goods and benefits. *Marine Pollution Bulletin*, *97*(1–2), 391–400. https://doi.org/10.1016/j.marpolbul.2015.05.061

Castejón-Silvo, I., & Terrados, J. (2012). Patterns of spatial variation of nutrient content, epiphyte load and shoot size of Posidonia oceanica seagrass meadows (Mediterranean Sea). *Marine Ecology*, *33*(165–175). https://doi.org/10.1111/j.1439-0485.2011.00477.x

Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. *Computers and Electrical Engineering*, *40*(1), 16–28. https://doi.org/10.1016/j.compeleceng.2013.11.024

Chefaoui, R. M., Duarte, C. M., & Serrão, E. A. (2018). Dramatic loss of seagrass habitat under projected climate change in the Mediterranean Sea. *Global Change Biology*, *24*(10), 4919–4928. https://doi.org/10.1111/GCB.14401

Chen, C., Liaw, A., & Breiman, L. (2004). Using Random Forest to Learn Imbalanced Data. *Discovery*, *110*, 1–12.

Chernick, M. R., & LaBudde, R. A. (2014). *An Introduction to Bootstrap Methods with Applications to R*.

Christie H, Fredriksen S, Rinde E., 1998. Regrowth of kelp and colonization of epiphyte and fauna community after kelp trawling at the coast of Norway. Hydeobiologia 375/376:49-58.

Christie H, Andersen GS, Bekkby T, Fagerli CW, Gitmark JK, Gundersen H, Rinde E., 2019. Shifts between sugar kelp and turf algae in Norway: Regime shifts or fluctuations between different opportunistic seaweed species? Front. Mar. Sci. 6:72. doi: 10.3389/fmars.2019.00072

Clark, D., Goodwin, E., Sinner, J., Ellis, J., & Singh, G. (2016). Validation and limitations of a cumulative impact model for an estuary. *Ocean and Coastal Management*, *120*, 88–98. https://doi.org/10.1016/j.ocecoaman.2015.11.013

Clarke Murray, C., Agbayani, S., & Ban, N. C. (2015). Cumulative effects of planned industrial development and climate change on marine ecosystems. *Global Ecology and Conservation*, *4*, 110–116. https://doi.org/10.1016/j.gecco.2015.06.003

CMEMS. (2020). Ocean State Report. *Journal of Operational Oceanography*, *4*.

Coll, M., Piroddi, C., Steenbeek, J., Kaschner, K., Lasram, F. B. R., Aguzzi, J., Ballesteros, E., Bianchi, C. N., Corbera, J., Dailianis, T., Danovaro, R., Estrada, M., Froglia, C., Galil, B. S., Gasol, J. M., Gertwage, R., Gil, J., Guilhaumon, F., Kesner-Reyes, K., … Voultsiadou, E. (2010). The biodiversity of the Mediterranean Sea: Estimates, patterns, and threats. *PLoS ONE*, *5*(8). https://doi.org/10.1371/journal.pone.0011842

Colléter, M., Valls, A., Guitton, J., Gascuel, D., Pauly, D., & Christensen, V. (2015). Global overview of the applications of the Ecopath with Ecosim modeling approach using the EcoBase models repository. *Ecological Modelling*, *302*, 42–53. https://doi.org/10.1016/j.ecolmodel.2015.01.025

Cook, G. S., Fletcher, P. J., & Kelble, C. R. (2014). Towards marine ecosystem based management in South Florida: Investigating the connections among ecosystem pressures, states, and services

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

in a complex coastal system. *Ecological Indicators*, *44*, 26–39. https://doi.org/10.1016/j.ecolind.2013.10.026

Cooper, P. (2013). Socio-ecological accounting: DPSWR, a modified DPSIR framework, and its application to marine ecosystems. *Ecological Economics*, *94*, 106–115. https://doi.org/10.1016/j.ecolecon.2013.07.010

Cornwall, C. E., & Eddy, T. D. (2015). Effects of near-future ocean acidification, fishing, and marine protection on a temperate coastal ecosystem. *Conservation Biology*, *29*(1), 207–215. https://doi.org/10.1111/cobi.12394

Corrales, X., Coll, M., Ofir, E., Heymans, J. J., Steenbeek, J., Goren, M., Edelist, D., & Gal, G. (2018). Future scenarios of marine resources and ecosystem conditions in the Eastern Mediterranean under the impacts of fishing, alien species and sea warming. *Scientific Reports*, *8*(1), 1–16. https://doi.org/10.1038/s41598-018-32666-x

Costello, M. J., Coll, M., Danovaro, R., Halpin, P., Ojaveer, H., & Miloslavich, P. (2010). A census of marine biodiversity knowledge, resources, and future challenges. *PLoS ONE*, *5*(8). https://doi.org/10.1371/journal.pone.0012110

Cramer, W., Guiot, J., & Marini, K. (2020). *MedECC - Climate and Environmental Change in the Mediterranean Basin, First Mediterranean Assessment Report* (W. Cramer, J. Guiot, & K. Marini (eds.)).

Criado-Aldeanueva, F., & Soto-Navarro, J. (2020). Climatic indices over the mediterranean sea: A review. *Applied Sciences (Switzerland)*, *10*(17). https://doi.org/10.3390/app10175790

Crowder, L.B., Ng, C.A, Frawley, T.H., Low, N.H.N., Micheli, F., 2019. 8.3 The significance of ocean deoxygenation for kelp and other macroalgae. In 'Laffoley, D. & Baxter, J.M. (eds.) (2019). Ocean deoxygenation: Everyone's problem - Causes, impacts, consequences and solutions. Gland, Switzerland: IUCN. xxii+562pp.

de Juan, S., Hewitt, J., Subida, M. D., & Thrush, S. (2018). Translating Ecological Integrity terms into operational language to inform societies. *Journal of Environmental Management*, *228*(September), 319–327. https://doi.org/10.1016/j.jenvman.2018.09.034

de Juan, S., Thrush, S. F., & Hewitt, J. E. (2013). Counting on β-Diversity to Safeguard the Resilience of Estuaries. *PLoS ONE*, *8*(6), 1–11. https://doi.org/10.1371/journal.pone.0065575

de los Santos, C. B., Krause-Jensen, D., Alcoverro, T., Marbà, N., Duarte, C. M., van Katwijk, M. M., Pérez, M., Romero, J., Sánchez-Lizaso, J. L., Roca, G., Jankowska, E., Pérez-Lloréns, J. L., Fournier, J., Montefalcone, M., Pergent, G., Ruiz, J. M., Cabaço, S., Cook, K., Wilkes, R. J., … Santos, R. (2019). Recent trend reversal for declining European seagrass meadows. *Nature Communications*, *10*(1), 1–8. https://doi.org/10.1038/s41467-019-11340-4

Dennison, W. C., Orth, R. J., Moore, K. A., Stevenson, J. C., Carter, V., Kollar, S., Bergstrom, P. W., & Batiuk, R. A. (1993). *Assessing_Water_Quality_with_Submersed_Aquatic_Vegetation.pdf* (pp. 86–94).

Depellegrin, D., Menegon, S., Farella, G., Ghezzo, M., Gissi, E., Sarretta, A., Venier, C., & Barbanti, A. (2017). Multi-objective spatial tools to inform maritime spatial planning in the Adriatic Sea. *Science of the Total Environment*, *609*, 1627–1639. https://doi.org/10.1016/j.scitotenv.2017.07.264

Depellegrin, D., Menegon, S., Gusatu, L., Roy, S., & Misiunė, I. (2020). Assessing marine ecosystem services richness and exposure to anthropogenic threats in small sea areas: A case study for the

Lithuanian sea space. *Ecological Indicators*, *108*(April 2019). https://doi.org/10.1016/j.ecolind.2019.105730

Domínguez-Tejo, E., Metternicht, G., Johnston, E., & Hedge, L. (2016). Marine Spatial Planning advancing the Ecosystem-Based Approach to coastal zone management: A review. *Marine Policy*, *72*, 115–130. https://doi.org/10.1016/j.marpol.2016.06.023

Doody, J.P., 2013. Coastal squeeze and managed realignment in southeast England, does it tell us anything about the future? Ocean & Coastal Management, 79, 34-41. https://doi.org/10.1016/j.ocecoaman.2012.05.008.

Douvere, F., & Ehler, C. N. (2008). New perspectives on sea use management: Initial findings from European experience with marine spatial planning. *Journal of Environmental Management*, *90*(1), 77–88. https://doi.org/10.1016/j.jenvman.2008.07.004

Drakou, E. G., Liquete, C., Beaumont, N., Boon, A., Viitasalo, M., & Agostini, V. (2017). Applying Ecosystem Service Mapping in Marine. *AREAS Bbok*, *January*.

Düsedau L, Fredriksen S, Brand M, Savoie S, Jungblut S, Molis M, Niklass C, Buschbaum C, Bischof K, Batrsch I., 2022. Macroalgal biodiversity and biomass of Kongsfjorden through time and space. Poster Svalbard Science Forum 2022.

EC, E. P. A. O. T. C. (2008). The marine strategy framework directive, DIRECTIVE 2008/56/EC. *Journal of Water Law*, *19*(3), 95–97.

EEA. (1999). Environmental indicators: Typology and Overview. *European Environmental*.

EEA. (2019). The European environment - state and outlook 2020: knowledge for transition to a sustainable Europe. In *European Environment*. https://doi.org/10.2800/96749

Elliott, M., Burdon, D., Atkins, J. P., Borja, A., Cormier, R., de Jonge, V. N., & Turner, R. K. (2017). "And DPSIR begat DAPSI(W)R(M)!" - A unifying framework for marine environmental management. *Marine Pollution Bulletin*, *118*(1–2), 27–40. https://doi.org/10.1016/j.marpolbul.2017.03.049

Elliott, Michael, Borja, A., & Cormier, R. (2020). Activity-footprints, pressures-footprints and effects-footprints – Walking the pathway to determining and managing human impacts in the sea. *Marine Pollution Bulletin*, *155*(April), 111201. https://doi.org/10.1016/j.marpolbul.2020.111201

Elliott, Michael, Borja, Á., McQuatters-Gollop, A., Mazik, K., Birchenough, S., Andersen, J. H., Painting, S., & Peck, M. (2015). Force majeure: Will climate change affect our ability to attain Good Environmental Status for marine biodiversity? *Marine Pollution Bulletin*, *95*(1), 7–27. https://doi.org/10.1016/j.marpolbul.2015.03.015

Fang, X., Li, X., Xiang, Y., Hao, C., Zhao, Y., & Zhang, Y. (2020). Cumulative impact of anthropogenic nutrient inputs on lagoon ecosystems — A case study of Xincun Lagoon, Hainan, China. *Regional Studies in Marine Science*, *35*, 101213. https://doi.org/10.1016/j.rsma.2020.101213

Farella, G., Menegon, S., Fadini, A., Depellegrin, D., Manea, E., Perini, L., & Barbanti, A. (2020). Incorporating ecosystem services conservation into a scenario-based MSP framework: An Adriatic case study. *Ocean and Coastal Management*, *193*(October 2019), 105230. https://doi.org/10.1016/j.ocecoaman.2020.105230

Fernandes, M. da L., Esteves, T. C., Oliveira, E. R., & Alves, F. L. (2017). How does the cumulative impacts approach support Maritime Spatial Planning? *Ecological Indicators*, *73*(2017), 189–

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

202. https://doi.org/10.1016/j.ecolind.2016.09.014

Filbee-Dexter K, Wernberg T., 2018. Rise of turfs: A new battlefront for globally declining kelp forest. BioScience 68, No.2. doi:10.1093/biosci/bix147

Filbee-Dexter K, Wernberg T, Grace SP, Thormar J, Fredriksen S, Narvaez CN, Feehan CJ, Norderhaug KM., 2020. Marine heatwaves and the collapse of marginal North Atlantic kelp forest. Sci. Rep. 10:13388. DIO org/10.1038/s41598-020-70273-x

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., & Holling, C. S. (2004). Regime shifts, resilience, and biodiversity in ecosystem management. *Annual Review of Ecology, Evolution, and Systematics*, *35*(June 2014), 557–581. https://doi.org/10.1146/annurev.ecolsys.35.021103.105711

Fu, C., Xu, Y., Guo, C., Olsen, N., Grüss, A., Liu, H., Barrier, N., Verley, P., & Shin, Y. J. (2020). The Cumulative Effects of Fishing, Plankton Productivity, and Marine Mammal Consumption in a Marine Ecosystem. *Frontiers in Marine Science*, *7*(September), 1–19. https://doi.org/10.3389/fmars.2020.565699

Fulton, E. A., Gray, R., Sporcic, M., Scott, R., & Hepburn, M. (2009). Challenges of crossing scales and drivers in modelling marine systems. *18th World IMACS Congress and MODSIM 2009 - International Congress on Modelling and Simulation: Interfacing Modelling and Simulation with Mathematical and Computational Sciences, Proceedings*, *July*, 2108–2114.

Furlan, E., Slanzi, D., Torresan, S., Critto, A., & Marcomini, A. (2020). Multi-scenario analysis in the Adriatic Sea: A GIS-based Bayesian network to support maritime spatial planning. *Science of the Total Environment*, *703*, 134972. https://doi.org/10.1016/j.scitotenv.2019.134972

Furlan, E., Torresan, S., Critto, A., Lovato, T., Solidoro, C., Lazzari, P., & Marcomini, A. (2019a). Cumulative Impact Index for the Adriatic Sea: accounting for interactions among climate and anthropogenic pressures. *Science of The Total Environment*.

Furlan, E., Torresan, S., Critto, A., Lovato, T., Solidoro, C., Lazzari, P., & Marcomini, A. (2019b). Cumulative Impact Index for the Adriatic Sea: Accounting for interactions among climate and anthropogenic pressures. *Science of the Total Environment*, *670*, 379–397. https://doi.org/10.1016/j.scitotenv.2019.03.021

Galli, G., Solidoro, C., & Lovato, T. (2017). Marine heat waves hazard 3D maps and the risk for low motility organisms in a warming Mediterranean Sea. *Frontiers in Marine Science*, *4*(MAY), 1–14. https://doi.org/10.3389/fmars.2017.00136

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production*, *143*, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Getis, A., Anselin, L., Lea, A., Ferguson, M., & Miller, H. (2004). Spatial Analysis and Modeling in a GIS Environment. *Research Agenda for Geographic Information Scienc*, 157–96.

Giorgi, F. (2006). Climate change hot-spots. *Geophysical Research Letters*, *33*(8), 1–4. https://doi.org/10.1029/2006GL025734

Gissi, E., Fraschetti, S., & Micheli, F. (2019). Incorporating change in marine spatial planning: A review. *Environmental Science and Policy*, *92*(August 2018), 191–200. https://doi.org/10.1016/j.envsci.2018.12.002

Gkadolou, E., Stithou, M., & Vassilopoulou, V. (2018). Human pressures and carbon assessment of posidonia oceanica meadows in the aegean sea: Limitations and challenges for ecosystem-based management. *Regional Science Inquiry*, *10*(3), 73–86.

Grizzetti, B., Lanzanova, D., Liquete, C., Reynaud, A., & Cardoso, A. C. (2016). Assessing water ecosystem services for water resource management. *Environmental Science and Policy*, *61*, 194–203. https://doi.org/10.1016/j.envsci.2016.04.008

Grizzetti, B., Liquete, C., Pistocchi, A., Vigiak, O., Zulian, G., Bouraoui, F., De Roo, A., & Cardoso, A. C. (2019). Relationship between ecological condition and ecosystem services in European rivers, lakes and coastal waters. *Science of the Total Environment*, *671*, 452–465. https://doi.org/10.1016/j.scitotenv.2019.03.155

Gutiérrez, J.M., R.G. Jones, G.T. Narisma, L.M. Alves, M. Amjad, I.V. Gorodetskaya, M. Grose, N.A.B. Klutse, S. Krakovska, J. Li, D. Martínez-Castro, L.O. Mearns, S.H. Mernild, T. Ngo-Duc, B. van den Hurk, and J.-H. Yoon, 2021: Atlas. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L.Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K.Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press. Interactive Atlas available from Available from http://interactive-atlas.ipcc.ch/

Haines-Young, R., & Potschin-Young, M. B. (2018). Revision of the common international classification for ecosystem services (CICES V5.1): A policy brief. *One Ecosystem*, *3*, 1–6. https://doi.org/10.3897/oneeco.3.e27108

Halpern, B. S., Frazier, M., Afflerbach, J., Lowndes, J. S., Micheli, F., O'Hara, C., Scarborough, C., & Selkoe, K. A. (2019). Recent pace of change in human impact on the world's ocean. *Scientific Reports*, *9*(1), 1–8. https://doi.org/10.1038/s41598-019-47201-9

Halpern, B. S., Walbridge, S., Selkoe, K. A., Kappel, C. V., Micheli, F., D'Agrosa, C., Bruno, J. F., Casey, K. S., Ebert, C., Fox, H. E., Fujita, R., Heinemann, D., Lenihan, H. S., Madin, E. M. P., Perry, M. T., Selig, E. R., Spalding, M., Steneck, R., & Watson, R. (2008). A global map of human impact on marine ecosystems. *Science*, *319*(5865), 948–952. https://doi.org/10.1126/science.1149345

Hammar, L., Molander, S., Pålsson, J., Schmidtbauer Crona, J., Carneiro, G., Johansson, T., Hume, D., Kågesten, G., Mattsson, D., Törnqvist, O., Zillén, L., Mattsson, M., Bergström, U., Perry, D., Caldow, C., & Andersen, J. H. (2020). Cumulative impact assessment for ecosystem-based marine spatial planning. *Science of the Total Environment*, *734*, 139024. https://doi.org/10.1016/j.scitotenv.2020.139024

Hansen, H. S., & Bonnevie, I. M. (2020). A Toolset to Estimate the Effects of Human Activities in Maritime Spatial Planning. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 12252 LNCS*. Springer International Publishing. https://doi.org/10.1007/978-3-030-58811-3_38

Harris, L., Nel, R., Holness, S., & Schoeman, D. (2015). Quantifying cumulative threats to sandy beach ecosystems: A tool to guide ecosystem-based management beyond coastal reserves. *Ocean and Coastal Management*, *110*, 12–24. https://doi.org/10.1016/j.ocecoaman.2015.03.003

Hayes, E. H., & Landis, W. G. (2004). Regional ecological risk assessment of a near shore marine environment: Cherry Point, WA. *Human and Ecological Risk Assessment*, *10*(2), 299–325. https://doi.org/10.1080/10807030490438256

Ho, T. K. (1998). The random subspace method for constructing decision forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *20*(8), 832–844.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

https://doi.org/10.1109/34.709601

Hodgson, E. E., & Halpern, B. S. (2019). Investigating cumulative effects across ecological scales. *Conservation Biology*, *33*(1), 22–32. https://doi.org/10.1111/cobi.13125

Houngnandan, F., Kefi, S., & Deter, J. (2020). *Identifying key-conservation areas for Posidonia oceanica seagrass beds The environment , more than direct human activities , influences the spatial configuration of Posidonia oceanica seagrass beds in France*. 0–16.

ICES. 2021. Barents Sea Ecoregion – Ecosystem overview. In Report of the ICES Advisory Committee, 2021. ICES Advice 2021, Section 5.1, https://doi.org/10.17895/ices.advice.9438.

ICES. 2022a. Celtic Seas Ecoregion – Ecosystem overview. In Report of the ICES Advisory Committee, 2022. ICES Advice 2022, Section 7.1, https://doi.org/10.17895/ices.advice.21731615

ICES. 2022b. Greater North Sea ecoregion – Ecosystem overview. In Report of the ICES Advisory Committee, 2022. ICES Advice 2022, Section 7.1, https://doi.org/10.17895/ices.advice.21731912

ICES. 2022c. Norwegian Sea ecoregion – Ecosystem overview. In Report of the ICES Advisory Committee, 2022. ICES Advice 2022, Section 12.1, https://doi.org/10.17895/ices.advice.21731726

Ihde, T. F., & Townsend, H. M. (2017). Accounting for multiple stressors influencing living marine resources in a complex estuarine ecosystem using an Atlantis model. *Ecological Modelling*, *365*, 1–9. https://doi.org/10.1016/j.ecolmodel.2017.09.010

IPBES. (2019). *IPBES Global Assessment Summary for Policymakers*.

IPBES, & IPCC. (2021). *Scientific outcome*. 234.

IPCC. (2014). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandre*. Cambridge University Press.

IPCC. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen,. *Cambridge University Press*, *In Press*, 3949.

Jabareen, Y. (2009). Building a Conceptual Framework: Philosophy, Definitions, and Procedure. *International Journal of Qualitative Methods*, *8*(4), 49–62. https://doi.org/10.1177/160940690900800406

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: With Applications in R. *Springer*.

Jones, A. R., Doubleday, Z. A., Prowse, T. A. A., Wiltshire, K. H., Deveney, M. R., Ward, T., Scrivens, S. L., Cassey, P., O'Connell, L. G., & Gillanders, B. M. (2018). Capturing expert uncertainty in spatial cumulative impact assessments /631/158 /631/158/2445 article. *Scientific Reports*, *8*(1), 1–13. https://doi.org/10.1038/s41598-018-19354-6

Jonsson, P. R., Hammar, L., Wåhlström, I., Pålsson, J., Hume, D., Almroth-Rosell, E., & Mattsson, M. (2021). Combining seascape connectivity with cumulative impact assessment in support of ecosystem-based marine spatial planning. *Journal of Applied Ecology*, *58*(3), 576–586. https://doi.org/10.1111/1365-2664.13813

Jordà, G., Marbà, N., & Duarte, C. M. (2012). Mediterranean seagrass vulnerable to regional climate warming. *Nature Climate Change*. https://doi.org/10.1038/NCLIMATE1533

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Judd, A. D., Backhaus, T., & Goodsir, F. (2015). An effective set of principles for practical implementation of marine cumulative effects assessment. *Environmental Science and Policy*, *54*, 254–262. https://doi.org/10.1016/j.envsci.2015.07.008

Katsanevakis, S., Tempera, F., & Teixeira, H. (2016). Mapping the impact of alien species on marine ecosystems: The Mediterranean Sea case study. *Diversity and Distributions*, *22*(6), 694–707. https://doi.org/10.1111/ddi.12429

Kawabara, T., & Acharya, M. (2020). Seagrasses, the forgotten ecosystem. *UN Environment Foresight Brief*, *19*(2007), 1–9.

Kim, J.K., Kraemer, G.P., Yarish, C., 2015. Use of sugar kelp aquaculture in Long Island Sound and the Bronx River Estuary for nutrient extraction. Marine Ecology Progress Series, 531, 155-166. doi: 10.3354/meps11331

Korpinen, S., & Andersen, J. H. (2016). A global review of cumulative pressure and impact assessments in marine environments. *Frontiers in Marine Science*, *3*(AUG), 1–11. https://doi.org/10.3389/fmars.2016.00153

Korpinen, S., Laamanen, L., Bergström, L., Nurmi, M., Andersen, J. H., Haapaniemi, J., Harvey, E. T., Murray, C. J., Peterlin, M., Kallenbach, E., Klančnik, K., Stein, U., Tunesi, L., Vaughan, D., & Reker, J. (2021). Combined effects of human pressures on Europe's marine ecosystems. *Ambio*, *50*(7), 1325–1336. https://doi.org/10.1007/s13280-020-01482-x

Kotsiantis, S., Kanellopoulos, D., & Pintelas, P. E. (2006). Data preprocessing for supervised leaning. *International Journal of …*, *1*(2), 1–7. https://doi.org/10.1080/02331931003692557

Li, T., Bai, J., Yang, X., Liu, Q., & Chen, Y. (2018). Co-occurrence network of high-frequency words in the bioinformatics literature: Structural characteristics and evolution. *Applied Sciences (Switzerland)*, *8*(10), 1–14. https://doi.org/10.3390/app8101994

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Journal of Clinical Epidemiology*, *62*(10), e1-34. https://doi.org/10.1016/j.jclinepi.2009.06.006

Lonsdale, J. A., Nicholson, R., Judd, A., Elliott, M., & Clarke, C. (2020). A novel approach for cumulative impacts assessment for marine spatial planning. *Environmental Science and Policy*, *106*(September 2019), 125–135. https://doi.org/10.1016/j.envsci.2020.01.011

Lonsdale, J., Weston, K., Blake, S., Edwards, R., & Elliott, M. (2017). The Amended European Environmental Impact Assessment Directive: UK marine experience and recommendations. *Ocean and Coastal Management*, *148*, 131–142. https://doi.org/10.1016/j.ocecoaman.2017.07.021

Louppe, G., Wehenkel, L., Sutera, A., & Geurts, P. (2013). Understanding variable importances in Forests of randomized trees. *Advances in Neural Information Processing Systems*, 1–9.

MA. (2005). Millennium Ecosystem Assessment General Synthesis Report:"Ecosystems and Human Well-being". In *Assessment of Climate Change in the Southwest United States: A Report Prepared for the National Climate Assessment*. https://doi.org/10.5822/978-1-61091-484-0_1

Mach, M. E., Wedding, L. M., Reiter, S. M., Micheli, F., Fujita, R. M., & Martone, R. G. (2017). Assessment and management of cumulative impacts in California's network of marine protected areas. *Ocean and Coastal Management*, *137*, 1–11.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

https://doi.org/10.1016/j.ocecoaman.2016.11.028

Maes, J., Teller, A., Erhard, M., Condé, S., Vallecillo, S., Barredo, J. ., Paracchini, M. ., Abdul Malak, D., Trombetti, M., Vigiak, O., Zulian, G., Addamo, A. ., Grizzetti, B., Somma, F., Hagyo, A., Vogt, P., Polce, C., Jones, A., Marin, A. ., … Orgiazzi, A. . F. U. O. . S.-M. F. (2020). *Mapping and Assessment of Ecosystems and their Services: An EU ecosystem assessment Supplement (Indicator fact sheets)*. https://doi.org/10.2760/519233

Magris, R. A., Costa, M. D. P., Ferreira, C. E. L., Vilar, C. C., Joyeux, J. C., Creed, J. C., Copertino, M. S., Horta, P. A., Sumida, P. Y. G., Francini-Filho, R. B., & Floeter, S. R. (2021). A blueprint for securing Brazil's marine biodiversity and supporting the achievement of global conservation goals. *Diversity and Distributions*, *27*(2), 198–215. https://doi.org/10.1111/ddi.13183

Morita, T., Kurashima, A., Maegawa, M., 2006. Temperature requirements for the growth of young sporophytes of Undaria pinnatifida and Undaria undarioides (Laminariales, Phaeophyceae). Phycological Resarch51(4): 266-270.

Manea, E., Bianchelli, S., Fanelli, E., Danovaro, R., & Gissi, E. (2020). Towards an Ecosystem-Based Marine Spatial Planning in the deep Mediterranean Sea. *Science of the Total Environment*, *715*, 136884. https://doi.org/10.1016/j.scitotenv.2020.136884

Marín-Guirao, L., Ruiz, J. M., Dattolo, E., Garcia-Munoz, R., & Procaccini, G. (2016). Physiological and molecular evidence of differential short-Term heat tolerance in Mediterranean seagrasses. *Scientific Reports*, *6*(January), 1–13. https://doi.org/10.1038/srep28615

Martin, J., Henrichs, T., & Eea. (2015). The European Environment: State and Outlook 2015: Synthesis. In *European Environment*.

Marzloff, M. P., Melbourne-Thomas, J., Hamon, K. G., Hoshino, E., Jennings, S., van Putten, I. E., & Pecl, G. T. (2016). Modelling marine community responses to climate-driven species redistribution to guide monitoring and adaptive ecosystem-based management. *Global Change Biology*, *22*(7), 2462–2474. https://doi.org/10.1111/gcb.13285

Mcleod, E., Chmura, G. L., Bouillon, S., Salm, R., Björk, M., Duarte, C. M., Lovelock, C. E., Schlesinger, W. H., & Silliman, B. R. (2011). A blueprint for blue carbon: toward an improved understanding of the role of vegetated coastal habitats in sequestering CO2. *Front Ecol Environ 2011;*, *9(10)*, 552–560. https://doi.org/10.1890/110004

McQuatters-Gollop, A., Mitchell, I., Vina-Herbon, C., Bedford, J., Addison, P. F. E., Lynam, C. P., Geetha, P. N., Vermeulan, E. A., Smit, K., Bayley, D. T. I., Morris-Webb, E., Niner, H. J., & Otto, S. A. (2019). From science to evidence - how biodiversity indicators can be used for effective marine conservation policy and management. *Frontiers in Marine Science*, *6*(MAR), 1–16. https://doi.org/10.3389/fmars.2019.00109

MEA. (2005). Millennium Ecosystem Assessment MEA, 2005. Ecosystem and Human Well-Being, General Synthesis. In *Island Press, Washington D.C.* https://doi.org/10.3897/zookeys.715.13865

Menegon, S., Depellegrin, D., Farella, G., Gissi, E., Ghezzo, M., Sarretta, A., Venier, C., & Barbanti, A. (2018). A modelling framework for MSP-oriented cumulative effects assessment. *Ecological Indicators*, *91*(December 2017), 171–181. https://doi.org/10.1016/j.ecolind.2018.03.060

Menegon, S., Depellegrin, D., Farella, G., Sarretta, A., Venier, C., & Barbanti, A. (2018a). Addressing cumulative effects, maritime conflicts and ecosystem services threats through MSP-oriented geospatial webtools. *Ocean and Coastal Management*, *163*(June), 417–436. https://doi.org/10.1016/j.ocecoaman.2018.07.009

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Menegon, S., Depellegrin, D., Farella, G., Sarretta, A., Venier, C., & Barbanti, A. (2018b). Addressing cumulative effects, maritime conflicts and ecosystem services threats through MSP-oriented geospatial webtools. *Ocean and Coastal Management*, *163*(March), 417–436. https://doi.org/10.1016/j.ocecoaman.2018.07.009

Micheli, F., Levin, N., Giakoumi, S., Katsanevakis, S., Abdulla, A., Coll, M., Fraschetti, S., Kark, S., Koutsoubas, D., Mackelworth, P., Maiorano, L., & Possingham, H. P. (2013). Setting Priorities for Regional Conservation Planning in the Mediterranean Sea. *PLoS ONE*, *8*(4). https://doi.org/10.1371/journal.pone.0059038

Miller, M. J., Feunteun, E., & Tsukamoto, K. (2016). Did a "perfect storm" of oceanic changes and continental anthropogenic impacts cause northern hemisphere anguillid recruitment reductions? *ICES Journal OfMarine Science*, *73*, 43–56. https://doi.org/10.1093/icesjms/fsv063

Mingers, J., & Leydesdorff, L. (2015). A review of theory and practice in scientometrics. *European Journal of Operational Research*, *246*(1), 1–19. https://doi.org/10.1016/j.ejor.2015.04.002

Mitchell, T. (1997). *Machine Learning*. https://doi.org/https://www.worldcat.org/oclc/61321007.

Montefalcone, M., Tunesi, L., & Ouerghi, A. (2021). A review of the classification systems for marine benthic habitats and the new updated Barcelona Convention classification for the Mediterranean. *Marine Environmental Research*, *169*(May), 105387. https://doi.org/10.1016/j.marenvres.2021.105387

Moullec, F., Velez, L., Verley, P., Barrier, N., Ulses, C., Carbonara, P., Esteban, A., Follesa, C., Gristina, M., Jadaud, A., Ligas, A., Díaz, E. L., Maiorano, P., Peristeraki, P., Spedicato, M. T., Thasitis, I., Valls, M., Guilhaumon, F., & Shin, Y. J. (2019). Capturing the big picture of Mediterranean marine biodiversity with an end-to-end model of climate and fishing impacts. *Progress in Oceanography*, *178*(December 2018), 102179. https://doi.org/10.1016/j.pocean.2019.102179

Muhammad, I., & Yan, Z. (2015). Supervised Machine Learning Approaches: a Survey. *ICTACT Journal on Soft Computing*, *05*(03), 946–952. https://doi.org/10.21917/ijsc.2015.0133

Mulrow, C. D. (1994). Rationale for systematic reviews. *British Medical Journal*, *309*(6954), 597–599. https://doi.org/10.1136/bmj.309.6954.597

Muñoz, M., Reul, A., Gil de Sola, L., Lauerburg, R. A. M., Tello, O., Gimpel, A., & Stelzenmüller, V. (2018). A spatial risk approach towards integrated marine spatial planning: A case study on European hake nursery areas in the North Alboran Sea. *Marine Environmental Research*, *142*(July 2018), 190–207. https://doi.org/10.1016/j.marenvres.2018.10.008

Norderhaug, K. M., & Christie, H. C., 2009. Sea urchin grazing and kelp re-vegetation in the NE Atlantic. Marine Biology Research, 5(6), 515-528.

O'Brien, K. R., Waycott, M., Maxwell, P., Kendrick, G. A., Udy, J. W., Ferguson, A. J. P., Kilminster, K., Scanes, P., McKenzie, L. J., McMahon, K., Adams, M. P., Samper-Villarreal, J., Collier, C., Lyons, M., Mumby, P. J., Radke, L., Christianen, M. J. A., & Dennison, W. C. (2018). Seagrass ecosystem trajectory depends on the relative timescales of resistance, recovery and disturbance. *Marine Pollution Bulletin*, *134*(September 2017), 166–176. https://doi.org/10.1016/j.marpolbul.2017.09.006

Oguz, T., & Gilbert, D. (2007). Abrupt transitions of the top-down controlled Black Sea pelagic ecosystem during 1960-2000: Evidence for regime-shifts under strong fishery exploitation and nutrient enrichment modulated by climate-induced variations. *Deep-Sea Research Part I:*

*Oceanographic Research Papers*, *54*(2), 220–242. https://doi.org/10.1016/j.dsr.2006.09.010

Okey, T. A., Alidina, H. M., & Agbayani, S. (2015). Mapping ecological vulnerability to recent climate change in Canada's Pacific marine ecosystems. *Ocean and Coastal Management*, *106*, 35–48. https://doi.org/10.1016/j.ocecoaman.2015.01.009

Otto, S. A., Niiranen, S., Blenckner, T., Tomczak, M. T., Müller-Karulis, B., Rubene, G., & Möllmann, C. (2020). Life Cycle Dynamics of a Key Marine Species Under Multiple Stressors. *Frontiers in Marine Science*, *7*(May). https://doi.org/10.3389/fmars.2020.00296

Pedersen, M.F., Filbee-Dexter, K., Frisk, N.L., Sárossy, Z. and Wernberg, T., 2021. Carbon sequestration potential increased by incomplete anaerobic decomposition of kelp detritus. Marine Ecology Progress Series, 660, pp.53-67. https://doi.org/10.3354/meps13613

Pergent, G., Bazairi, H., Boudouresque, C. F., Buia, M. C., Clabaut, P., Harmelin-Vivien, M., Mateo, M. A., Montefalcone, M., Morri, C., Orfanidis, S., Pergent-Marini, C., Semroud, R., Serrano, O., & Verlaque, M. (2012). *Mediterranean Seagrass Meadows : Las praderas de Magnoliofitas marinas del mar Mediterráneo: resiliencia y contribución a la mitigación del cambio climático, Resumen / Mediterranean Seagrass Meadows : Resilience and Contribution to Climate Change Mitigati*.

Piet, G. J., Tamis, J. E., Volwater, J., de Vries, P., van der Wal, J. T., & Jongbloed, R. H. (2021). A roadmap towards quantitative cumulative impact assessments: Every step of the way. *Science of the Total Environment*, *784*, 146847. https://doi.org/10.1016/j.scitotenv.2021.146847

Piroddi, C., Coll, M., Liquete, C., Macias, D., Greer, K., Buszowski, J., Steenbeek, J., Danovaro, R., & Christensen, V. (2017). Historical changes of the Mediterranean Sea ecosystem: Modelling the role and impact of primary productivity and fisheries changes over time. *Scientific Reports*, *7*(March). https://doi.org/10.1038/srep44491

Piroddi, C., Coll, M., Steenbeek, J., Moy, D. M., & Christensen, V. (2015). Modelling the Mediterranean marine ecosystem as a whole: Addressing the challenge of complexity. *Marine Ecology Progress Series*, *533*, 47–65. https://doi.org/10.3354/meps11387

Piroddi, C., Colloca, F., & Tsikliras, A. C. (2020). The living marine resources in the Mediterranean Sea Large Marine Ecosystem. *Environmental Development*, *36*(August). https://doi.org/10.1016/j.envdev.2020.100555

Polovina, J. J. (1984). Model of a coral reef ecosystem. *Coral Reefs*, *3*(1), 23–27. https://doi.org/10.1007/bf00306137

Quemmerais-Amice, F., Barrere, J., La Rivière, M., Contin, G., & Bailly, D. (2020). A Methodology and Tool for Mapping the Risk of Cumulative Effects on Benthic Habitats. *Frontiers in Marine Science*, *7*(November), 1–27. https://doi.org/10.3389/fmars.2020.569205

Ratcliff, J.J., Wan, A.H.L., Edwards, M.D., Soler-Vila, A., Johnson, M.P., Abreu, M.H., Morrison, L., 2016. Metal content of kelp (Laminaria digitata) co-cultivated with Atlantic salmon in an Integrated Multi-Trophic Aquaculture system. Aquaculture, 450, 234-243. https://doi.org/10.1016/j.aquaculture.2015.07.032.

Roca, G., Romero, J., Farina, S., Martínez-Crego, B., & Alcoverro, T. (2017). *Using seagrasses to identify local and large-scale trends of metals in the Mediterranean Sea*. https://doi.org/10.1016/j.marpolbul.2017.09.021

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Röhr, M. E., Boström, C., Canal-Vergés, P., & Holmer, M. (2016). Blue carbon stocks in Baltic Sea eelgrass (Zostera marina) meadows. *Biogeosciences*, *13*(22), 6139–6153. https://doi.org/10.5194/bg-13-6139-2016

Ruiz, J., M. Guillén, J. E., Ramos Segura, A., & Otero, M. . (2015). Atlas de las praderas marinas de España. *Observación Medioambiental*, *15*, 235–255.

Schoenrock KM, O´Callaghan T, O´Callaghan R, Krueger-Hadfield SA. 2019. First record of Laminaria ochroleuca Bachelot de la Pylaie in Ireland in Béal an Mhuirthead, county Mayo. Mar. Biodiv. Records 12-9. https://doi.org/10.1186/s41200-019-0168-3

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Journal of the Franklin Institute*, *23*(3). https://doi.org/10.1016/s0016-0032(23)90506-5

Singh, G. G., Eddy, I. M. S., Halpern, B. S., Neslo, R., Satterfield, T., & Chan, K. M. A. (2020). Mapping cumulative impacts to coastal ecosystem services in British Columbia. *PLoS ONE*, *15*(5), 1–23. https://doi.org/10.1371/journal.pone.0220092

Singh, G. G., Sinner, J., Ellis, J., Kandlikar, M., Halpern, B. S., Satterfield, T., & Chan, K. M. A. (2017). Mechanisms and risk of cumulative impacts to coastal ecosystem services: An expert elicitation approach. *Journal of Environmental Management*, *199*, 229–241. https://doi.org/10.1016/j.jenvman.2017.05.032

Smale, D.A., Burrows, M.T., Moore, P., O'Connor, N., Hawkins, S.J., 2013. Threats and knowledge gaps for ecosystem services provided by kelp forests: a northeast Atlantic perspective. Ecology and Evolution, 3(11), 4016-4038.

Smale, D.A., 2020, Impacts of ocean warming on kelp forest ecosystems. New Phytol, 225: 1447-1454. https://doi.org/10.1111/nph.16107

Smale, D.A., Pessarrodona, A., King, N. and Moore, P.J., 2022a. Examining the production, export, and immediate fate of kelp detritus on open-coast subtidal reefs in the Northeast Atlantic. Limnol Oceanogr, 67: S36-S49. https://doi.org/10.1002/lno.11970

Smale DA, Teagle H, Hawkins SJ, Jenkins HL, Frontier N, Wilding C, King N, Jackson-Bue M, Moore PJ., 2022b. Climate-driven substitution of foundation species causes breakdown of a facilitation cascade with potential implications for higher trophic levels. J Ecol. DOI: 10.1111/1365-2745.13936

Smith, D. J., & Rodríguez-Labajos, B. (2021). Turning the wheel away from biophysical indicators in coastal zone management: Towards a stakeholder-based systemic framework. *Ecological Indicators*, *125*(March), 107527. https://doi.org/10.1016/j.ecolind.2021.107527

Soto-Navarro, C. A., Harfoot, M., LL Hill, S., Campbell, J., Campos Santos, H.-C., Mora, F., Pretorius, C., Kapos, V., Allison, H., & Burgess, N. (2019). *Building a multidimensional biodiversity index*.

Stelzenmüller, V, Lee, J., Garnacho, E., & Rogers, S. I. (2010). Assessment of a Bayesian Belief Network–GIS framework as a practical tool to support marine planning. *Marine Pollution Bulletin*, *60*(10), 1743–1754.

Stelzenmüller, Vanessa, Coll, M., Cormier, R., Mazaris, A. D., Pascual, M., Loiseau, C., Claudet, J., Katsanevakis, S., Gissi, E., Evagelopoulos, A., Rumes, B., Degraer, S., Ojaveer, H., Moller, T., Giménez, J., Piroddi, C., Markantonatou, V., & Dimitriadis, C. (2020). Operationalizing risk-based cumulative effect assessments in the marine environment. *Science of the Total Environment*, *724*, 138118. https://doi.org/10.1016/j.scitotenv.2020.138118

Stelzenmüller, Vanessa, Coll, M., Mazaris, A. D., Giakoumi, S., Katsanevakis, S., Portman, M. E., Degen, R., Mackelworth, P., Gimpel, A., Albano, P. G., Almpanidou, V., Claudet, J., Essl, F.,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Evagelopoulos, T., Heymans, J. J., Genov, T., Kark, S., Micheli, F., Pennino, M. G., … Ojaveer, H. (2018). A risk-based approach to cumulative effect assessments for marine management. *Science of the Total Environment*, *612*, 1132–1140. https://doi.org/10.1016/j.scitotenv.2017.08.289

Stock, A., Haupt, A. J., Mach, M. E., & Micheli, F. (2018). Mapping ecological indicators of human impact with statistical and machine learning methods: Tests on the California coast. *Ecological Informatics*, *48*(March), 37–47. https://doi.org/10.1016/j.ecoinf.2018.07.007

Stock, Andy, Crowder, L. B., Halpern, B. S., & Micheli, F. (2018). Uncertainty analysis and robust areas of high and low modeled human impact on the global oceans. *Conservation Biology*, *32*(6), 1368–1379. https://doi.org/10.1111/cobi.13141

Sutherland, M., Lane, D., Zhao, Y., & Michalowski, W. (2007). Estimating marine cumulative effects using spatial data: an aquaculture case study. *Geomatica*, *61*, 43–54. https://doi.org/10.1080/13657300903351636

Teagle, H., Hawkins, S.J., Moore, P.J., Smale, D.A., 2017. The role of kelp species as biogenic habitat formers in coastal marine ecosystems. Journal of Experimental Marine Biology and Ecology, 492, 81-98. https://doi.org/10.1016/j.jembe.2017.01.017.

Teichert, N., Borja, A., Chust, G., Uriarte, A., & Lepage, M. (2016). Restoring fish ecological quality in estuaries: Implication of interactive and cumulative effects among anthropogenic stressors. *Science of the Total Environment*, *542*, 383–393. https://doi.org/10.1016/j.scitotenv.2015.10.068

Telesca, L., Belluscio, A., Criscoli, A., Ardizzone, G., Apostolaki, E. T., Fraschetti, S., Gristina, M., Knittweis, L., Martin, C. S., Pergent, G., Alagna, A., Badalamenti, F., Garofalo, G., Gerakaris, V., Louise Pace, M., Pergent-Martini, C., & Salomidi, M. (2015). Seagrass meadows (Posidonia oceanica) distribution and trajectories of change. *Scientific Reports*, *5*, 1–14. https://doi.org/10.1038/srep12505

Thrush, S. F., Hewitt, J. E., Dayton, P. K., Coco, G., Lohrer, A. M., Norkko, A., Norkko, J., & Chiantore, M. (2009). Forecasting the limits of resilience: Integrating empirical research with theory. *Proceedings of the Royal Society B: Biological Sciences*, *276*(1671), 3209–3217. https://doi.org/10.1098/rspb.2009.0661

Thrush, S. F., Hewitt, J. E., Gladstone-Gallagher, R. V., Savage, C., Lundquist, C., O'Meara, T., Vieillard, A., Hillman, J. R., Mangan, S., Douglas, E. J., Clark, D. E., Lohrer, A. M., & Pilditch, C. (2021). Cumulative stressors reduce the self-regulating capacity of coastal ecosystems. *Ecological Applications*, *31*(1), 1–12. https://doi.org/10.1002/eap.2223

Thrush, S. F., Hewitt, J. E., Parkes, S., Lohrer, A. M., Pilditch, C., Woodin, S. A., Wethey, D. S., Chiantore, M., Asnaghi, V., De Juan, S., Kraan, C., Rodil, I., Savage, C., & Van Colen, C. (2014). Experimenting with ecosystem interaction networks in search of threshold potentials in real-world marine ecosystems. *Ecology*, *95*(6), 1451–1457. https://doi.org/10.1890/13-1879.1

Tičina, V., Katavić, I., & Grubišić, L. (2020). Marine Aquaculture Impacts on Marine Biota in Oligotrophic Environments of the Mediterranean Sea – A Review. *Frontiers in Marine Science*, *7*(April), 1–11. https://doi.org/10.3389/fmars.2020.00217

Trowbridge, C., Little, C., Dlouhy-Massengale, B., Stirling, P. & Pilling, G., 2013. Changes in brown seaweed distributions in Lough Hyne, SW Ireland: a long-term perspective. Botanica Marina, 56(4), 323-338. https://doi.org/10.1515/bot-2013-0036

Tsiamis, K., Zenetos, A., Deriu, I., Gervasini, E., & Cardoso, A. C. (2018). The native distribution

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

range of the European marine non-indigenous species. *Aquatic Invasions*, *13*(2), 187–198. https://doi.org/10.3391/ai.2018.13.2.01

Tuel, A., & Eltahir, E. A. B. (2020). Why Is the Mediterranean a Climate Change Hot Spot? *Journal of Climate*, *33*(14), 5829–5843. https://doi.org/10.1175/JCLI-D-19-0910.1

Tulloch, V. J. D., Turschwell, M. P., Giffin, A. L., Halpern, B. S., Connolly, R., Griffiths, L., Frazer, M., & Brown, C. J. (2020). Linking threat maps with management to guide conservation investment. *Biological Conservation*, *245*(November 2019). https://doi.org/10.1016/j.biocon.2020.108527

Turschwell, M. P., Tulloch, V. J. D., Sievers, M., Pearson, R. M., Andradi-Brown, D. A., Ahmadia, G. N., Connolly, R. M., Bryan-Brown, D., Lopez-Marcano, S., Adame, M. F., & Brown, C. J. (2020). Multi-scale estimation of the effects of pressures and drivers on mangrove forest loss globally. *Biological Conservation*, *247*(May), 108637. https://doi.org/10.1016/j.biocon.2020.108637

Umanzor S, Stephens T., 2023. Nitrogen and Carbon Removal Capacity by Farmed Kelp Alaria marginata and Saccharina latissima Varies by Species. Aquaculture Journal, 3(1), 1-6. https://doi.org/10.3390/aquacj3010001

UNEP/MAP. (2012). State of the Marine and Coastal Mediterranean. *UNEP/MAP – Barcelona Convention*, 96.

UNEP/MAP and Plan Bleu. (2020). United Nations Environment Programme/Mediterranean Action Plan and Plan Bleu (2020). State of the Environment and Development in the Mediterranean. Nairobi. In *Environmental Science and Technology* (Vol. 16, Issue 8). https://doi.org/10.1021/es00102a607

UNEP. (2014). Horizon 2020 Mediterranean Report. In *EEA - UNEP/MAP joint report* (Issue 6).

UNEP. (2020a). *Out of the blue: The value of seagrasses to the environment and to people* (M. P. (GRID-Arenda) (ed.)).

UNEP. (2020b). *Out of the Blue the Value of Seagrasses*.

UNEP United Nations Environment Programme (2023). Into the Blue: Securing a Sustainable Future for Kelp Forests. Nairobi.

Uusitalo, L., Korpinen, S., Andersen, J. H., Niiranen, S., Valanko, S., Heiskanen, A. S., & Dickey-Collas, M. (2016). Exploring methods for predicting multiple pressures on ecosystem recovery: A case study on marine eutrophication and fisheries. *Continental Shelf Research*, *121*, 48–60. https://doi.org/10.1016/j.csr.2015.11.002

Vacchi, M., De Falco, G., Simeone, S., Montefalcone, M., Morri, C., Ferrari, M., & Bianchi, C. N. (2016). State of Science Biogeomorphology of the Mediterranean Posidonia oceanica seagrass meadows. *Earth Surface Processes and Landforms*, *42*(42–54). https://doi.org/10.1002/esp.3932

Valentini, G., & Dietterich, T. G. (2004). *Bias-Variance Analysis of Support Vector Machines for the Development of SVM-Based Ensemble Methods*. *5*, 725–775. https://doi.org/10.1007/3-540-45428-4_22

van Nes, E. H., Arani, B. M. S., Staal, A., van der Bolt, B., Flores, B. M., Bathiany, S., & Scheffer, M. (2016). What Do You Mean, 'Tipping Point'? *Trends in Ecology and Evolution*, *31*(12), 902–904. https://doi.org/10.1016/j.tree.2016.09.011

Wang, Z. B., Van Maren, D. S., Ding, P. X., Yang, S. L., Van Prooijen, B. C., De Vet, P. L. M.,

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Winterwerp, J. C., De Vriend, H. J., Stive, M. J. F., & He, Q. (2015). Human impacts on morphodynamic thresholds in estuarine systems. *Continental Shelf Research*, *111*, 174–183. https://doi.org/10.1016/j.csr.2015.08.009

Weatherdon, L., Friedrich, L., Martin, C., & King, S. (2017). Experimental Seagrass Ecosystem Accounts : A pilot study for one component of marine ecosystem accounts. *European Union 2018*.

Weijerman, M., Veazey, L., Yee, S., Vaché, K., Delevaux, J. M. S., Donovan, M. K., Falinski, K., Lecky, J., & Oleson, K. L. L. (2018). Managing local stressors for coral reef condition and ecosystem services delivery under climate scenarios. *Frontiers in Marine Science*, *9*(NOV), 1–16. https://doi.org/10.3389/fmars.2018.00425

Wen, L., & Hughes, M. (2020). Coastal wetland mapping using ensemble learning algorithms: A comparative study of bagging, boosting and stacking techniques. *Remote Sensing*, *12*(10). https://doi.org/10.3390/rs12101683

Wernberg, T., Krumhansl, K., Filbee-Dexter, K., & Pedersen, M. F., 2019. Chapter 3. Status and trends for the world's kelp forests. In 'World Seas: an Environmental Evaluation', 2nd edn. (Ed. C Sheppard.), Academic Press, pp. 57–78. https://doi.org/10.1016/B978-0-12-805052-1.00003-6.

White, L., Donohue, I., Emmerson, M. C., & O'Connor, N. E. (2018). Combined effects of warming and nutrients on marine communities are moderated by predators and vary across functional groups. *Global Change Biology*, *24*(12), 5853–5866. https://doi.org/10.1111/gcb.14456

Willsteed, E. A., Birchenough, S. N. R., Gill, A. B., & Jude, S. (2018). Structuring cumulative effects assessments to support regional and local marine management and planning obligations. *Marine Policy*, *98*(July), 23–32. https://doi.org/10.1016/j.marpol.2018.09.006

Xue, X., Hong, H., & Charles, A. T. (2004). Cumulative environmental impacts and integrated coastal management: The case of Xiamen, China. *Journal of Environmental Management*, *71*(3), 271–283. https://doi.org/10.1016/j.jenvman.2004.03.006

Xu, S., Yu, Z., Zhou, Y., Yue, S., Liang, J., Zhang, W., 2023. The potential for large-scale kelp aquaculture to counteract marine eutrophication by nutrient removal. Marine Pollution Bulletin, 187, 114513. https://doi.org/10.1016/j.marpolbul.2022.114513.

Yesson, C., Bush, L., Davies, A., Maggs, C., & Brodie, J., 2015. The distribution and environmental requirements of large brown seaweeds in the British Isles. Journal of the Marine Biological Association of the United Kingdom, 95(4), 669-680. doi:10.1017/S0025315414001453

Zhang, C., & Ma, Y. (2012). Ensemble Machine Learning: Methods and Applications. *Springer*.

Zhou, Z.-H. (2019). *Ensemble Methods: Foundations and Algorithms*.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

**Supplementary material**

**Annex 1: Query string performed in Scopus (search date: October 2020)**

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")).

**Annex 2: Methodological approach for the evaluation of existing studies and applications dealing with cumulative impact appraisal in MCEs**

**Data collection**

Peer-reviewed literature dealing with cumulative and multi-risk appraisal in MCEs was 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 in Scopus a search query combining the following keywords: '*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 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 Annex 1). The resulting list of papers published between the 2000-2020 timeframe (the search was limited to this period because this specific research topic acquired a wide attention just in the 2000s) and their connected records (e.g., information including title, author and author keywords, affiliations, etc.), was exported as a Bibtex file for a qualitative and quantitative analysis through the *Bibliometrix* R Package (Aria & Cuccurullo, 2017; Mingers & Leydesdorff, 2015), as well as the subsequent systematic review.

**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). This information exported from Scopus was processed by applying the open-source *Bibliometrix* Package, designed for the statistic 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 recognize gaps across research fields.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

**Systematic review – selection of 'key papers'**

Following a preliminary identification of major focal topics made through the Scientometric analysis, a Systematic review was then applied. This review process consists of a rigorous methodological examination of the identified scientific literature (as detailed in "Data collection"), 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 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 allowing to ensure a transparent and complete analysis and reporting from each review phase.

This process reduces the list of papers (646 publications) previously selected through the keywords' query applied in the Scopus database ("Data collection") through different phases, including: i) First publications' screening based on the title's pertinence to the topic of concern and review objectives (resulting in 238 publications); ii) Second screening based on reading the abstracts and methodological sections of publications remaining from the original list (100 documents were selected); iii) Further screening through the reading of the full papers. During this process, 5 papers emerged not in line with the objective of this review and, hence, removed from the final statistics; iv) Selection of the most relevant publications 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 30 "key papers" against a set of comparison criteria.

Particularly, the whole set of comparison criteria aims at clarifying the main features of the reviewed CIA-related methodological approaches, specifying: a) the case study area including details on the scale of analysis; b) the 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) the components analysed through the CIA-related methods, including specification on pressures (with their interactions), exposed environmental targets and vulnerability factors (or indicators) integrated in the study; d) the presence/absence of climate change/management future scenario analysis; e) the ecosystem services integrated into the CIA framework, also clarifying the type of ecosystem services considered in the study (i.e., provisioning, regulation & maintenance, and cultural services); f) the integration of ecological tipping point concept into the CIA 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 evaluating methodological approaches and frameworks dealing with CIA and multi-risk assessment in MCEs. 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 exchange to better evaluate selected papers from different perspectives, as well as identify key challenges that need to be addressed in future CIA and multi-risk assessment frameworks.

**Annex 3: Results and insights from the Scientometric review**

As described in Section A, the Scientometric review was performed by first applying a literature search in Scopus. This selection method led to the identification of 646 publications (value obtained at the end of October 2020) dealing with CIA in marine and coastal ecosystems, during the investigated 2000-2020 timeframe period. This process allowed to develop of the first Scientometric review (and related graphs) by using the bibliometric data of the 646 selected as input data for analysis through the open-source *Bibliometrix* R Package. Afterwards, the same Scientometric analysis was

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

repeated by considering only the 238 papers obtained against the title-screening phase, as implemented under the Systematic review. This allowed performing a more robust review, focusing only on a restricted number of preselected papers, thus avoiding non-significant documents (e.g., review 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 646 and 238 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 and their linkages' evolution across different timespans (e.g., 2000-2005, 2000-2010; 2000-2015; 2000-2020); v) the country collaboration networks' evolution under different time slices (i.e., 2000-2005, 2005-2010; 2010-2015; 2015-2020).

**Annual scientific production**

The analysis of the annual scientific production allowed examining the number of publications per year from 2000 to 2020, 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 six years (from 2014 to 2020) can be observed, which overall, they account for more than half of the whole literature of concern (from 20 to 37 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) laid the way for other CIA applications (Korpinen & Andersen, 2016; Quemmerais-Amice et al., 2020), following his same approach (or similar ones).

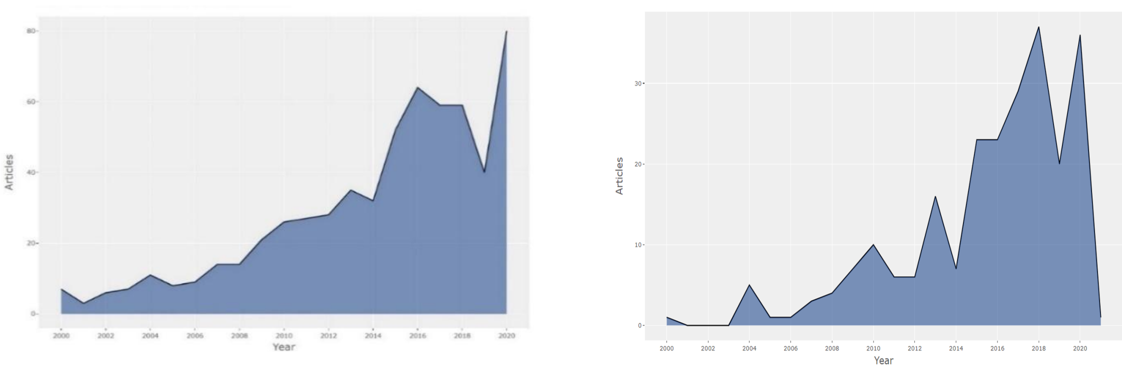



***Figure S1.*** *Number of publications applying CIA in marine and coastal ecosystems during the 2000–2020 timeframe (left: across the 646 papers, right: across the 238 papers).*

**Top authors' production over time**

The analysis of the author's production over time 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 2000-2020 timeframe. Moreover, the colour of the 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 2000-2020 timeframe, Halpern B.S. emerged as the main author

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

(with an overall number of 18 publications from 2008) applying a systematic procedure for evaluating the cumulative impact from multiple pressures/activities on MCEs.


***Figure S2.*** *Top 20 authors' production over the time (left: across the 646 papers, right: across the 238 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., Stelzenmuller V., Andersen J.H., Depellegrin D. 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 2000-2020 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.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710


***Figure S3.*** *Word Cloud analysis illustrates the main author's keywords (left: across the 646 papers, right: across the 238 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 the Annex 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 surprisingly, 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, Depellegrin, Farella, Sarretta, et al., 2018b), 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; 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 from 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., 2020).

**Co-occurrence network**

The relationship of co-occurrence keywords is one of the most important aspects of mapping scientific knowledge, widely used in text mining, social networks and environmental analysis, as well as in the field of biology (Li et al., 2018). Relationships between keywords generate a family (or cluster) of co-occurrence sets (e.g., author keywords) that can be viewed as a snapshot of the information space during a determined timeframe, allowing to understand past and future challenges, methods and strategies enabling future implementation. The resulting co-occurrence networks

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

(graphs) are built based on a co-occurrence matrix, collecting relationships between any two high-frequency keywords. To get some insights from this co-occurrence matrix (and resulting network map), we need to consider the following elements and characteristics: i) the presence/absence of nodes reveals the importance of the cluster, while their size in the overall network allows distinguishing the importance degree; ii) the edge enables to identify the interrelationship between keywords; iii) the spatial distribution of keywords is driven by their centrality role (or the minor – peripheral- relevance) within the selected list of publications; iv) clusters of keywords are identified by a different colour (Batistič & van der Laken, 2019; Li et al., 2018).

Analysing the co-occurrence networks developed in the frame of this study (four different networks according to four-time slices, 2000-2005, 2000-2010, 2000-2015, 2000-2020, Supplementary Figure S4), during the first timeframe 2000-2005, we noticed a fragmented network, where the keywords used by authors are grouped into six clusters. Specifically, focusing on the network extracted after title-screening (238 papers), three minor clusters are isolated by the other interconnected network, and relate to risk model and assessment (violet cluster), vulnerability assessment (green cluster) and specially protected areas (brown cluster). Furthermore, three clusters are interconnected by a network that links ecosystem features (orange), methodological approach (blue) and pressure (red). In particular, the blue cluster plays a key role during this time-slice, showing the keywords 'cumulative effects' and 'cumulative impacts' as links with the orange and red clusters. During the second timeframe (2000-2010, Supplementary Figure S4B), four clusters out of six are linked in a network focusing on cumulative effects/impacts and ecosystem-based management procedures. Similarly, within the third timeframe (2000-2015, Supplementary Figure S4C), was confirmed the priority direction of the key topic considered in the previous timeframe, but were added increasing attention to "climate change" and "multiple stressors" keywords.

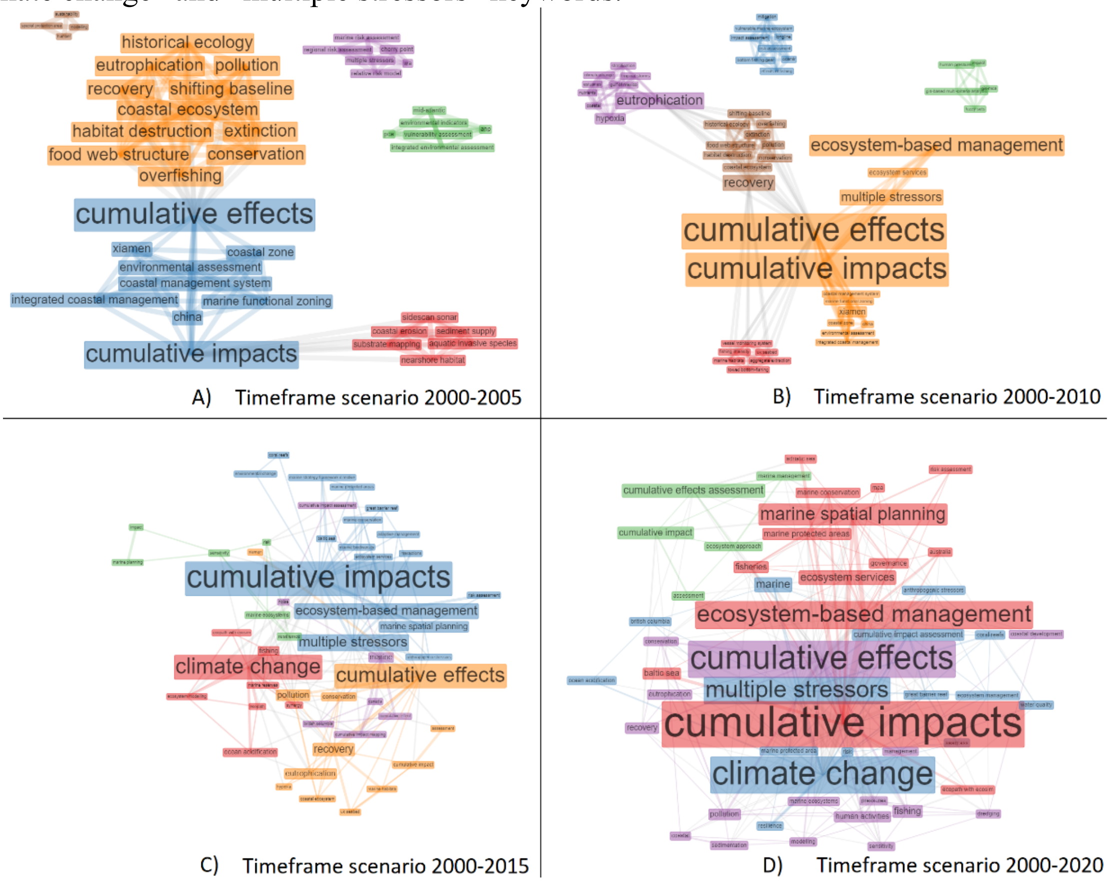



***Figure S4.*** *Word co-occurrence network graphs under four time slices: A) 2000-2005, B) 2000-2010, C) 2000-2015, D) 2000-2020 (above: across the 646 papers, below: across the 238 papers).*

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

Moreover, as can be noted, all clusters start to be interconnected in a single network connecting the aforementioned five more relevant keywords. This increase in interconnection (as a result of the increase in publications), can be observed also in the fourth time slice (2000-2020, Supplementary Figure S4D). Focusing on keywords, this last plot displays an increasing focalization on these five main topics, proved by the larger size of these keywords their centrality in the network. Finally, it is interesting to observe the increasing relevance in time of the 'marine spatial planning' keyword. Indeed, observing the network, although it is further from the centre, MSP could be considered at the same level as the other five keywords in terms of dimensions and, for that reason, we can assume it covers a relevant role within this research field. In fact, this is a relevant procedure promoted by EU policies (e.g., MSP directive) to support decision-makers and managers in the achievement of ecological, economic, and social objectives in the management of marine space and resources.

## 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, 2005-2010, 2010-2015, 2015-2020), thus allowing us to understand the evolution of collaboration networks over time (Supplementary Figure S5).

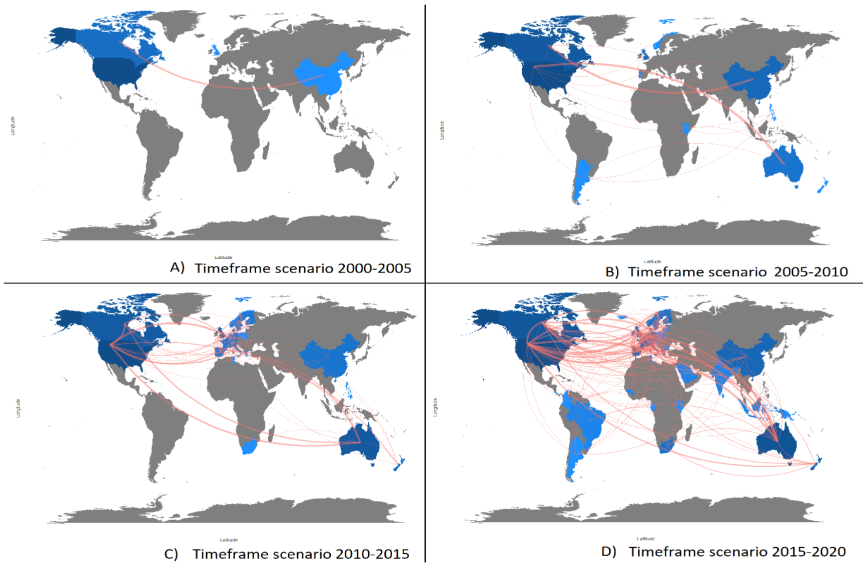



***Figure S5.*** *Country collaboration maps under four time-slices: A) 2000-2005; B) 2005-2010; C) 2010-2015; D) 2015-2020 (above: across the 646 papers, below: across the 238 papers).*

Specifically, during the first time slice (Supplementary Figure S5A), with only seven papers published, the first countries approaching CIA in marine and coastal ecosystems were the USA, Canada, the UK and China. Moreover, during this period only one interconnection emerged between USA and China. In the following 2005-2010 time period (Supplementary Figure S5B), 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-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

continental states (as illustrated by the high number of red lines in Supplementary Figure S5C). In the last five years, 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 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.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Annex 4: Table reporting the resulting output from the systematic review in terms of 'key papers' dealing with the application of CIA in MCEs

| Article detail | | CIA conceptual frameworks and methodological approaches | | | Healthy marine coastal ecosystems under a changing climate – Scenario analysis | | Ecosystem Services into CIA frameworks | | When cumulative impacts lead to ecological tipping point | Policy support for risk management and climate adaptation in MCEs |
|---|---|---|---|---|---|---|---|---|---|---|
| Authors | Location | Type of method | Components | Interactions (Y/N) | Y / N | Type of scenario | Y / N | Considered services: Provisioning (P), Regulating and Maintenance (R), Culture (C), functioning (F) | Considering tipping point Y / N | Considering policy (management actions) Y / N |
| (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 chronic and acute chemical hazards; rising nutrient input; management measures and adaptation strategies needed to reduce cumulative impacts. | 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 |
| (A. Stock et al., 2018) | 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 applying a conflict matrix) | Y | (P) Nursery area, Habitat. (R) Nursery area maintenance; (F) Resistance; resilience; sensitivity | N | Y |
| (Menegon, et al., 2018) | 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; | N | N |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Nursery; Biodiversity; (C) Cognitive benefits; Leisure; Feel good/warm glove; | | |
| (Menegon, et al., 2018) | 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:<br><br>(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; Commercial Demersal/pelagic Fishing; Energy; Finfish/Shellfish aquaculture; (R) Coastal Protection; (C) Coastal Aesthetics and recreation (kayak, boating, camping, dive sites) | N | N |

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (Fu et al., 2020) | British Columbia, Canada | Modelling; | Driver; Pressure; Risk; Cumulative impact; | Y | Y | Favourable (from fish perspective) high fish population biomasses; halving fishing mortality rate; doubling plankton biomass and halving marine mammal biomass; Unfavourable (from fish perspective) low fish population biomasses; fishing mortality doubled; halved plankton biomass; and marine mammal biomass doubled; attempt to address the variations of specific indicators to CC pressures (i.e., SST) | 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 of 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 |
| (Andy 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 |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| (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: modified the current loadings of the Status Quo model: 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 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 |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Annex 5: Mediterranean key pressures

| PRESSURE | DESCRIPTION |
|---|---|
| **CLIMATE DRIVERS** | |
| **Sea surface temperature (SST) increase** | Annual mean SST will increase by 0.43-1.17°C in a century under the SSP1-2.6 scenario, and by 2.01-4.07°C under SSP5-8.5 (IPCC, 2021). Seawater temperature has affected and will continue affecting the distribution and abundance of native and alien species in the future, with severe ecological effects on the invaded environments (e.g., global extinction of native species, altered food chains) (Jordà et al., 2012). |
| **Sea level rise** | It results mainly from the thermal expansion of oceans and glaciers melting (IPBES & IPCC, 2021). Although SLR doesn't assume a homogeneous pattern across the globe, it is possible to calculate a continuous rising rate of more than 3 mm/year in recent decades (Brondizio et al., 2019; Cramer et al., 2020). This rate is faster than the one observed in the past two millennia and is likely to accelerate (Cramer et al., 2020). In fact, the Sea Level, compared to data from the late 20th century, is projected to increase from 28-55cm under the very low GHG emissions scenario, SSP1-1.9, to 98-188cm under the very high scenario, SSP5-8.5, by the end of the 21st century (IPCC, 2021). |
| **Precipitation** | The major trend that can be observed is a decrease in winter precipitation since the second half of the 20th century, especially in the central and southern parts of the Mediterranean. According to this trend, precipitation is expected to decrease in most of the regions, with an average rate of reduction of about 4% per degree of global warming (Cramer et al., 2020). |
| **Extreme events** | These events (such as marine heat waves, storm surges and flooding events) will become more frequent and intense, particularly in the northern Mediterranean. In particular, the largest marine heat waves detected since 1982 occurred in 2003, 2012, 2015, and 2017 (Grizzetti et al., 2016) but according to the RCP8.5 scenario, they will increase in spatial extension, duration, frequency and intensity (Cramer et al., 2020; IPCC, 2021). |
| **Ocean water acidification** | According to thermodynamic calculations of the IPCC emission scenarios, at the end of the century in the Mediterranean basin pH could decrease from 0.1 pH units, under the RCP2.6. scenario, to 0.4, follow the most pessimistic scenario RCP8.5 (IPCC, 2014). |
| **Salinity** | According to the worst IPCC RCP8.5 scenario, for the end of the century, the sea surface salinity anomalies will range from -0.18 to +0.16 psu (Cramer et al., 2020; Soto-Navarro et al., 2019) |
| **POLLUTION** | |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

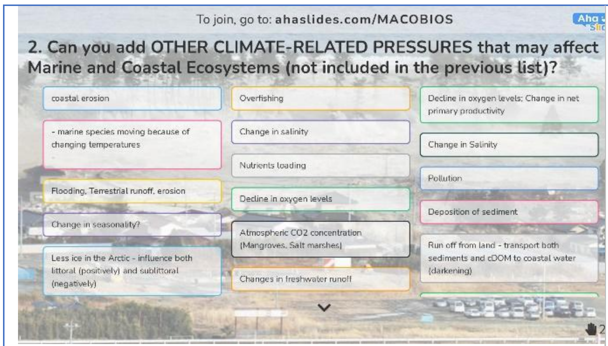
| | |
|---|---|
| **Atmospheric particulate matter** | PM concentrations in the Mediterranean region result much higher than the limit values given in the WHO guidelines (Brondizio et al., 2019; UNEP/MAP, 2012), particularly across Italian and Greek cities (e.g. Vicenza, Cremona, Athens), as well as in the eastern part of the Mediterranean basin. |
| **Plastic (macro/micro/ nano)** | In the Mediterranean Sea, the average density of plastic is one element per 4m2 (Cramer et al., 2020). Of particular concern is the exposure to MP (Micro Plastic) (size <5 mm) by numerous taxa, especially in the coastal zone, which occurs mainly through ingestion. In addition, persistent organic pollutants and alien species are also transported with plastics. |
| **Nutrient enrichment** | Soil erosion due to agriculture is leading to a high increase in water bodies nutrient fluxes, mainly nitrogen and phosphorus, which have risen 4 to 20 times in the last 10 years (CMEMS, 2020), following decreasing levels eastward from Gibraltar to the Levantine Sea. Nutrient enrichment in the Mediterranean Sea can cause a strong increase in phytoplankton growth and biomass, leading to eutrophication processes. Impacts are even worst in presence of harmful or toxic algal blooms, which can cause disease, mortality and socio-economic impacts related to fisheries, aquaculture, tourism and human health. |
| **Gaseous pollutants** | Due to road traffic emissions, the Mediterranean basin is one of the regions of the world with high concentrations of gaseous air pollutants such as nitrogen dioxide, sulphur dioxide and ozone (UNEP, 2014). |
| **Other pollutants** | Such as trace metal elements (MTEs) like cadmium, chromium, copper, lead, nickel, zinc, and mercury, polycyclic aromatic hydrocarbons (PAHs) and pesticides (PAIs). They tend to remain in the environment and concentrate in organisms, posing a threat to plants, animals, and ecosystems, as well as constituting a major health risk to humans (Roca et al., 2017). |
| **CHANGE IN LAND AND SEA USE** | |
| **Coastal Development** | The coastal environment has been one of the most affected by urbanization in recent decades (Smith & Rodríguez-Labajos, 2021). This is also due to the dramatic increase in tourism in the last 20 years, which has tripled globally (Brondizio et al., 2019), bringing numerous economic benefits with negative cascading effects on the marine coastal ecosystem. |
| **Overfishing and unsustainable fishing** | Data showed that due to the increase in SST and decrease in oxygen availability (IPBES, 2019), a shift in fish populations and a decrease in fish size is occurring. Furthermore, overfishing is causing a further decrease in stock biomass (Brondizio et al., 2019). |

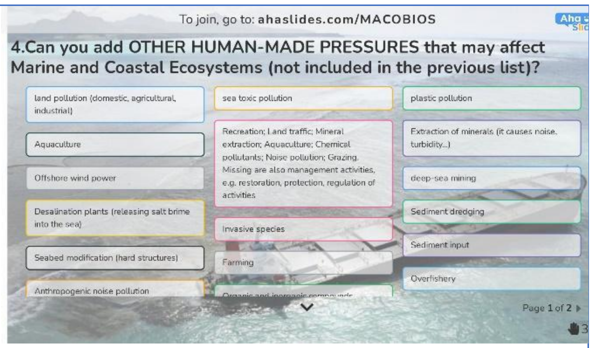
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | |
|---|---|
| **Aquaculture** | There are a large number of impacts on the local scale mainly related to effects on the seabed biocenosis under aquaculture facilities (most of the invertebrate species are phytophagous pests that cause damage to crops and forests), behavioral changes in local wildlife, genetic changes in wild fish populations (Tičina et al., 2020) and nutrient enrichment, which can cause a high increase in phytoplankton and harmful algae (Cramer et al., 2020). |
| **NON INDIGENOUS SPECIES (NIS)** | |
| **Tropicalization** | The appearance of numerous allochthonous species within the Mediterranean basin entering through the Suez Canal or the Strait of Gibraltar. In the past, these species seemed to remain confined to areas close to their zones of ingress, while now they are increasingly present in the northern area of the Mediterranean due to rising sea temperatures (Cramer et al., 2020; UNEP/MAP, 2012). |
| **Meridionalisation** | The increase in the proportion of native thermophilic species of Boreo-Atlantic origin. These species, after entering the Mediterranean during the glacial period, had become established in the northern and colder parts of the basin and now, unable to move further north due to rising temperatures, may quickly disappear (Coll et al., 2010). |
| **Marine transport** | The two most likely routes of initial introduction of organisms into the Mediterranean Sea via marine transport are through ballast water and ship hulls. The first includes mainly plants and invertebrates (often as seeds or in resting stages such as cysts or eggs), while the second principally takes in account sedentary species that attach to hulls (Katsanevakis et al., 2016). |

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

## Annex 6: Results from the Ahaslide questionnaire of the pre-event phase under the “pressures” topic




## Annex 7: Results from the Ahaslide questionnaire of the pre-event phase under the “ecosystem services” topic



This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

## Annex 8: Results of the World Café discussion for the “Pressures” topic

| | | Proxy Indicator 1 | Proxy Indicator 2 | Proxy Indicator 3 | Proxy Indicator 4 | Proxy Indicator 5 | Proxy Indicator 6 |
|---|---|---|---|---|---|---|---|
| CLIMATE-RELATED PRESSURES | Change in Temperature | degree heating weeks (thermostress | Past stress events | geochemical proxies | Sclerochronological data from marine calcifiers | Geochemical data from marine calcifiers | |
| | Sea Level Rise | | | | | | |
| | Extreme Weather Events | Unusual warm events - 95° percentile | Past stress events | | | | |
| | Changed Marine Currents | | | | | | |
| | Rainfall Regime | Sclerochronological data from marine calcifiers | Geochemical data from marine calcifiers | | | | |
| | Acidification | saturation values in the water | DHW | geochemical proxies | Sclerochronological data from marine calcifiers | Geochemical data from marine calcifiers | |
| YOUR INPUTS ON CLIMATE-RELATED PRESSURES | Coastal erosion | water turbidity from satellite images | spatial patterns of coastline | shipping traffic - intensity | | | |
| | Change in wave energy | | | | | | |
| | Changes in salinity | geochemical proxies | Sclerochronological data from marine | Geochemical data from marine | | | |
| | Marine species migration | latitudinal changes vs latitudinal limits | | | | | |
| | Reduced ice caps in the Arctic | | | | | | |
| | Decline in oxygen levels | | | | | | |
| | Changes in seasonality | | | | | | |
| | Atmospheric CO2 concentration | | | | | | |
| | Changes in freshwater runoff | amount of vegetation | DTM | water turbidity | salinity changes | Sclerochronological data from marine calcifiers | Geochemical data from marine calcifiers |
| | Changes in NPP | | | | | | |
| | Deposition of sediments | | | | | | |
| | Changes in wind regime | | | | | | |

## Annex 9: Results of the World Café discussion for the “Vulnerability” topic

| | | | MCEs | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | x | | | | | | | | | |
| | Sensitivity | Adaptive capacity | Seagrass beds | Coral reefs | Kelp forests | Mangroves | Saltmarshes | Rodolith beds | Fish | Marine mammals |
| Geomorphic setting | x | | x | x | | x | x | x | | |
| Likelihood of mortality (proxy or delete (?)) | x | | | | | | | | | |
| Resilience | | x | | | | | | | | |
| Recovery time of community (shift to proxy of resilience) | | | | | | | | | | |
| Heterogeneity abiotic | | | | | | | | | | |
| Heterogeneity biological | | | | | | | | | | |
| Locations of wetlands and river mouths | | | | | | | | | | |
| Spatial connectivity among MCEs | | | x | | | | x | | | |
| Spatial proximity of a MCE to the source of the | | | | | | | | | | |
| Spatial extent of MCEs | | | | | | | | | | |
| Biodiversity index | | | x | | | | | | | |
| Exposure gradients | | | | | | | | | | |
| Level of protection | | | | | | | | | | |
| Reduction in ecosystem area (over the past 10, 20, 50 years...) | | | | | | | | | | |
| Functional redundancy | x | | | | | | | | | |
| Fragmentation | | | | | | | | | | |
| ~~Species diversity~~ | | | | | | | | | | |
| Functional diversity | | x | | | | | | | | |
| Habitat fragmentation | | | | | | | | | | |
| Biomass/abundance | | | | | | | | | | |
| Genetic diversity | | | x | | | | | | | |
| Ecosystem structure | | | | | | | | | | |
| Cover and density | | | | | | | | | | |

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 869710

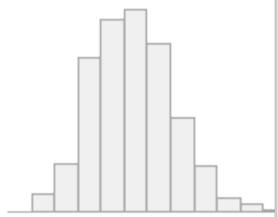
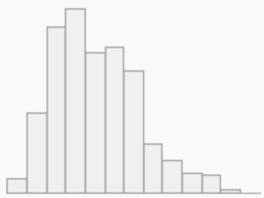
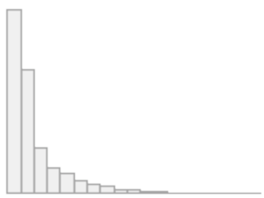
## Annex 10: Full list of indicators and related metrics considered for the Mediterranean eco-region

| | 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 |
| | NH4 | NH4 min |
| | | 5percentile |
| | | 95percentile |
| | NO3 | |
| | | NO3 min |
| | | 5percentile |
| | | 95percentile |
| | PO4 | PO4 min<br><br>5percentile |
| | | 95percentile |
| | O2 | O2min |
| | | 5percentile |
| | Chl-a | Chl-a max |
| | | 90percentile |
| | Secchi depth (ZSD) | SDmin |
| | | 5percentile |
| | Light attenuation | KD490min |
| | | 5percentile |
| | Shipping traffic (Density) | yearly mean vessel density |
| **Exogenic pressures** | Sea surface temperature | 95percentile |
| | | SST standard deviation |
| | | number_MHW |
| | | importance_MHW (duration and intensity) |
| | pH | pH min |
| | | pH mean |
| | | pH max |
| | Salinity | SAL min |
| | | SAL standard deviation |
| | | 5percentile |
| | Max Significant Wave Height | SWH max |
| | Wind component | WHM0_WW max |
| | | VTM01_WW min |

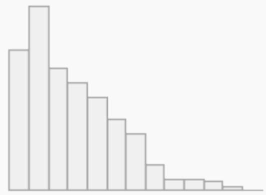
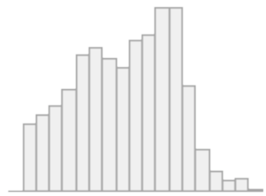
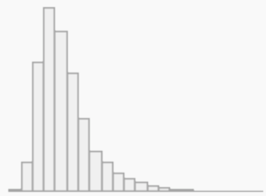
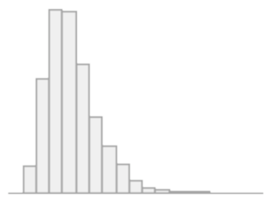
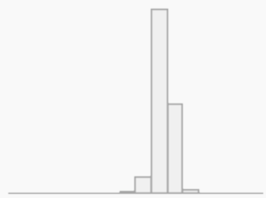
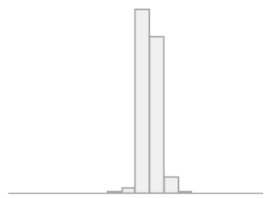
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | |
|---|---|---|
| | 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 |
| **Marine coastal ecosystem condition** | Areal extent/surface | Percentage of presence |
| | Spatial distribution | Pattern of connectivity |
| | Species richness | Shannon index |

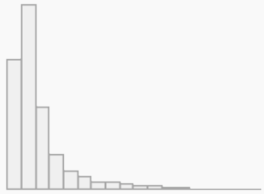
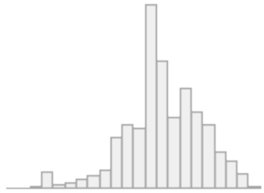
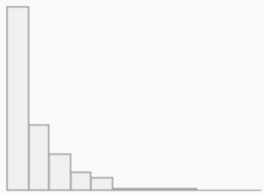
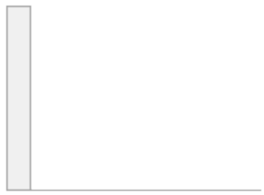
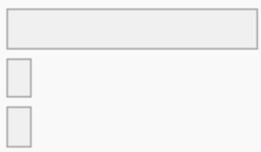
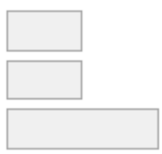
**Annex 11: Summary of the range and distribution of the considered Mediterranean model predictors and responses**

| No | Variable | Abbreviation | Stats / Values | Graph |
|---|---|---|---|---|
| 1 | Yearly minimum oxygen concentration [mmol m-3] | O2_min [numeric] | Mean (sd) : 207 (8.7)<br>min ≤ med ≤ max:<br>183.8 ≤ 206.7 ≤ 237.1<br>IQR (CV) : 12.3 (0) |  |
| 2 | Yearly 5 percentile oxygen concentration [mmol m-3] | O2_5percentile [numeric] | Mean (sd) : 232.9 (10.9)<br>min ≤ med ≤ max:<br>212.2 ≤ 231.7 ≤ 270.7<br>IQR (CV) : 15.4 (0) |  |
| 3 | Yearly 90 percentile Chlorophyll-a concentration [mg m-3] | CHL.a_90percentile [numeric] | Mean (sd) : 0.4 (0.4)<br>min ≤ med ≤ max:<br>0.1 ≤ 0.2 ≤ 3.7<br>IQR (CV) : 0.3 (1.1) |  |

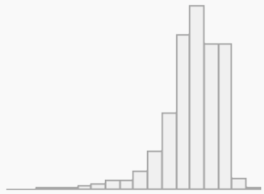
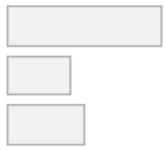
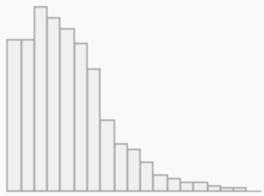
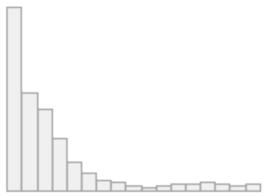
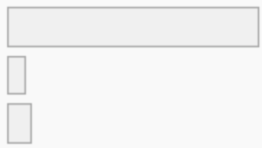
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | |
|---|---|---|---|---|
| 4 | Yearly minimum Secchi depth value [mmol m-3] | ZSD_min [numeric] | Mean (sd) : 6.6 (4.6)<br>min ≤ med ≤ max:<br>1.3 ≤ 5.5 ≤ 25.5<br>IQR (CV) : 6.9 (0.7) |  |
| 5 | Yearly 5 percentile Secchi depth [mmol m-3] | ZSD_5percentile [numeric] | Mean (sd) : 17.3 (7.4)<br>min ≤ med ≤ max:<br>1.9 ≤ 18 ≤ 36.8<br>IQR (CV) : 12 (0.4) |  |
| 6 | Yearly maximum Eastward Sea Water Velocity [m s-1] | uo_max [numeric] | Mean (sd) : 0.2 (0.1)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 1<br>IQR (CV) : 0.1 (0.6) |  |
| 7 | Yearly maximum Northward Sea Water Velocity [m s-1] | vo_max [numeric] | Mean (sd) : 0.2 (0.1)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 0.9<br>IQR (CV) : 0.1 (0.5) |  |
| 8 | Yearly mean Northward Sea Water Velocity [m s-1] | vo_mean [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>-0.5 ≤ 0 ≤ 0.3<br>IQR (CV) : 0 (-2.8) |  |
| 9 | Yearly mean Eastward Sea Water Velocity [m s-1] | uo_mean [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>-0.5 ≤ 0 ≤ 0.4<br>IQR (CV) : 0 (24) |  |
| 10 | | | Mean (sd) : 0.1 (0) | |

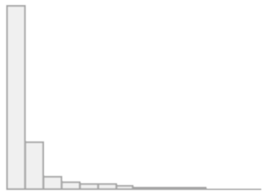
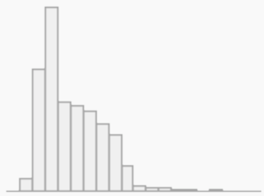
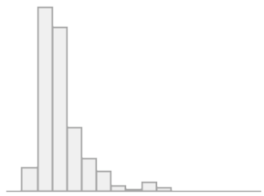
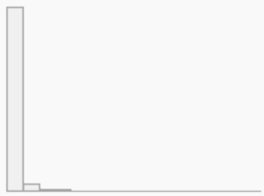
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | |
|---|---|---|---|---|
| | Yearly 5 percentile Light attenuation [mmol m-3] | KD490_5percentile [numeric] | min ≤ med ≤ max:<br>0 ≤ 0 ≤ 0.4<br>IQR (CV) : 0 (0.7) |  |
| 11 | Yearly 95 percentile Sea surface temperature [Kelvin] | SST_95percentile [numeric] | Mean (sd) : 299.8 (1.7)<br>min ≤ med ≤ max:<br>293.4 ≤ 299.6 ≤ 303.7<br>IQR (CV) : 2 (0) |  |
| 12 | Seagrass distance from port [km] | Med_distance.from.port.4km [numeric] | Mean (sd) : 27.6 (32.3)<br>min ≤ med ≤ max:<br>0 ≤ 16 ≤ 234<br>IQR (CV) : 31.7 (1.2) |  |
| 13 | Yearly Shipping traffic [hours km-2 year-1] | vessel_density_4km [numeric] | Mean (sd) : 6.4 (147.4)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 10883.9<br>IQR (CV) : 0.4 (23) |  |
| 14 | Seagrass distribution [poligon occurance] | seagrass_distribution [numeric] | Mean (sd) : 0.2 (0.6)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 2<br>IQR (CV) : 0 (2.4) |  |
| 15 | Level of connectivity [km] | connectivity [numeric] | Mean (sd) : 1.3 (0.8)<br>min ≤ med ≤ max:<br>0 ≤ 2 ≤ 2<br>IQR (CV) : 2 (0.7) |  |
| 16 | | | Mean (sd) : 38.1 (1) | |

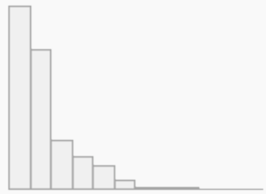
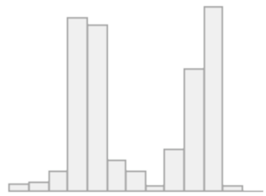
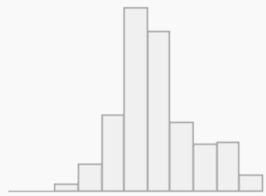
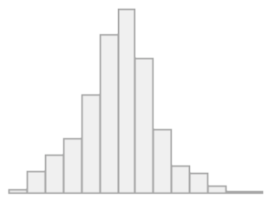
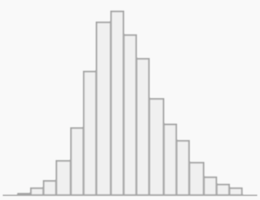
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | |
|---|---|---|---|---|
| | Yearly 5 percentile Salinity [psu] | SAL_5percentile [numeric] | min ≤ med ≤ max:<br>31.6 ≤ 38.1 ≤ 40.2<br>IQR (CV) : 1.2 (0) |  |
| 17 | Yearly species richness | shannon_index [numeric] | Mean (sd) : 0.7 (0.8)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 2<br>IQR (CV) : 2 (1.1) |  |
| 18 | Seagrass distance from major cities [km] | dist_city [numeric] | Mean (sd) : 45.6 (32.5)<br>min ≤ med ≤ max:<br>0 ≤ 40.6 ≤ 184.7<br>IQR (CV) : 41 (0.7) |  |
| 19 | Seagrass distance from major rivers [km] | dist_river [numeric] | Mean (sd) : 158 (189.8)<br>min ≤ med ≤ max:<br>0 ≤ 93 ≤ 845.7<br>IQR (CV) : 154.1 (1.2) |  |
| 20 | Annual Carbon sequestration | carbon_sequestration [numeric] | Mean (sd) : 0.2 (0.6)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 2<br>IQR (CV) : 0 (2.6) |  |
| 21 | Annual Denitrification | denitrification [numeric] | Mean (sd) : 0.2 (0.6)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 2<br>IQR (CV) : 0 (2.4) |  |
| 22 | | | Mean (sd) : 2.7 (6.6) | |

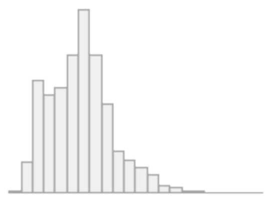
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | |
|---|---|---|---|---|
| | Annual Kinetic energy at the seabed due to currents | mediterranean_KE_currents [numeric] | min ≤ med ≤ max:<br>0 ≤ 0.7 ≤ 150<br>IQR (CV) : 1.6 (2.5) |  |
| 23 | Yearly 5 percentile Ammonium concentration [mmol m-3] | NH4_5percentile [numeric] | Mean (sd) : 0.3 (0.4)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 2.8<br>IQR (CV) : 0.1 (1.3) |  |
| 24 | Yearly maximum ocean acidification concentration [pH] | OA_max [numeric] | Mean (sd) : 8.2 (0)<br>min ≤ med ≤ max:<br>8.1 ≤ 8.2 ≤ 8.5<br>IQR (CV) : 0.1 (0) |  |
| 25 | Yearly minimum ocean acidification concentration [pH] | OA_min [numeric] | Mean (sd) : 8 (0)<br>min ≤ med ≤ max:<br>7.9 ≤ 8 ≤ 8.2<br>IQR (CV) : 0 (0) |  |
| 26 | Yearly 5 percentile Phosphorus concentration [mmol m-3] | PO4_5percentile [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 0.8<br>IQR (CV) : 0 (2.3) |  |
| 27 | Yearly minimum Phosphorus concentration [mmol m-3] | PO4_min [numeric] | Mean (sd) : 0 (0)<br>min ≤ med ≤ max:<br>0 ≤ 0 ≤ 0.4<br>IQR (CV) : 0 (2.2) |  |

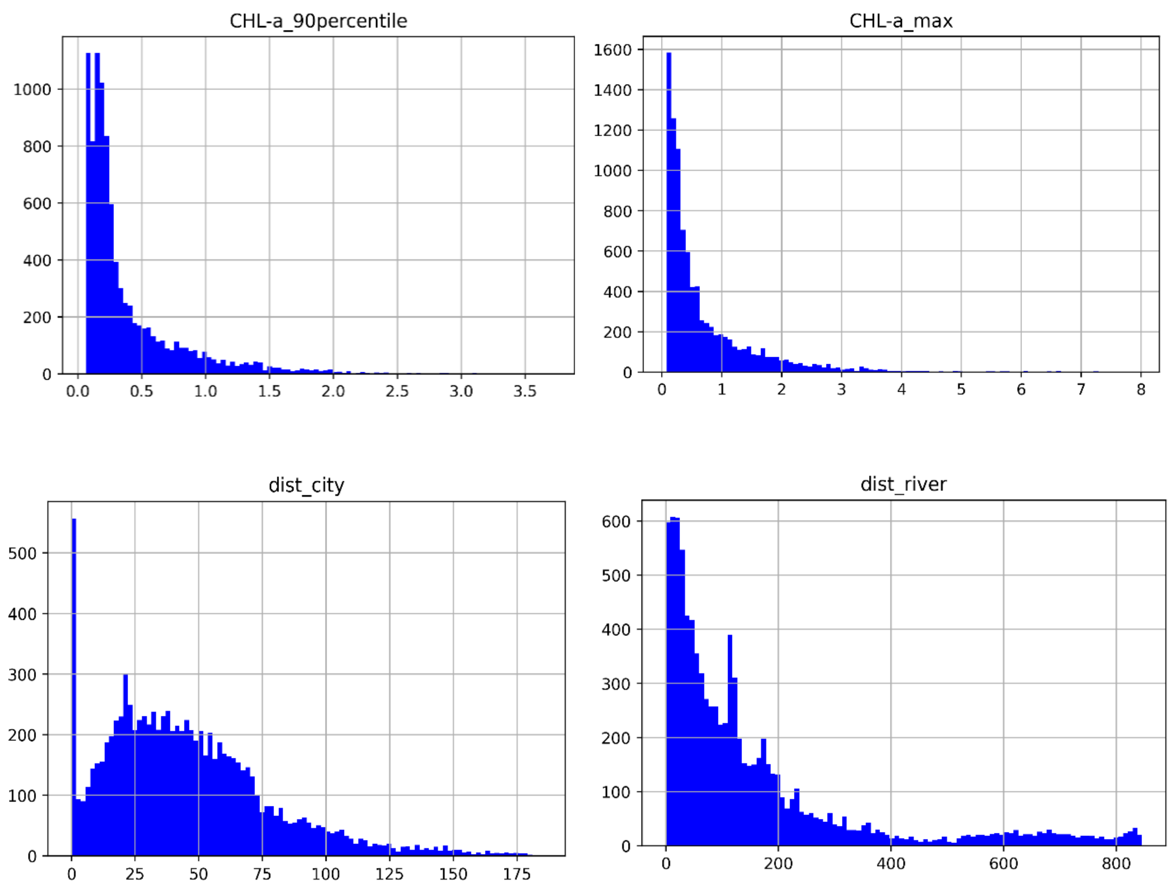
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

| | | | | |
|---|---|---|---|---|
| 28 | Yearly standard deviation Salinity [psu] | SAL_sd [numeric] | Mean (sd) : 0.3 (0.3)<br>min ≤ med ≤ max:<br>0 ≤ 0.2 ≤ 2.2<br>IQR (CV) : 0.3 (0.8) |  |
| 29 | Yearly mean Sea level rise value [m] | SSH_mean [numeric] | Mean (sd) : -0.3 (0.1)<br>min ≤ med ≤ max:<br>-0.5 ≤ -0.4 ≤ -0.2<br>IQR (CV) : 0.1 (-0.2) |  |
| 30 | Yearly standard deviation Sea surface temperature [Kelvin] | SST_sd [numeric] | Mean (sd) : 4.7 (0.8)<br>min ≤ med ≤ max:<br>1.9 ≤ 4.6 ≤ 6.9<br>IQR (CV) : 1 (0.2) |  |
| 31 | Yearly minimum Significant wave height [m] | SWH_min [numeric] | Mean (sd) : 3.1 (1)<br>min ≤ med ≤ max:<br>0.3 ≤ 3.1 ≤ 6.8<br>IQR (CV) : 1.2 (0.3) |  |
| 32 | Number of marine heat waves | mean_number_mhws [numeric] | Mean (sd) : 1.8 (0.3)<br>min ≤ med ≤ max:<br>0.9 ≤ 1.8 ≤ 2.8<br>IQR (CV) : 0.4 (0.2) |  |
| 33 | Intensity of marine heat waves | mean_intensity_mhws [numeric] | Mean (sd) : 1.7 (0.3)<br>min ≤ med ≤ max: | |

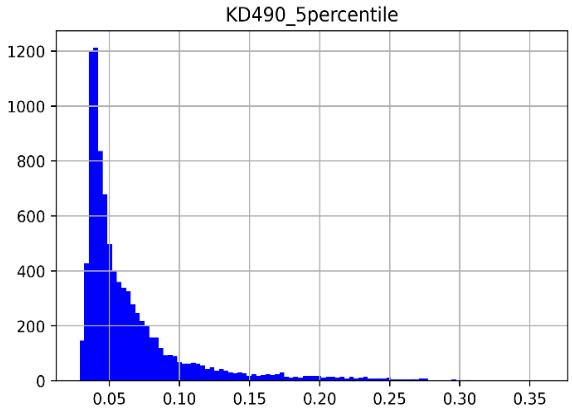
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

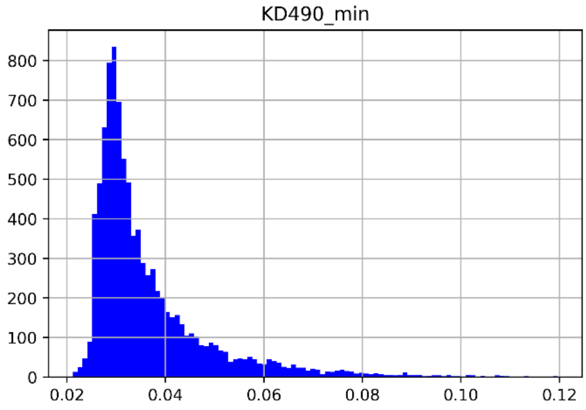
| | | | | |
|---|---|---|---|---|
| | | | 1.2 ≤ 1.7 ≤ 3.2<br><br>IQR (CV) : 0.4 (0.2) |  |

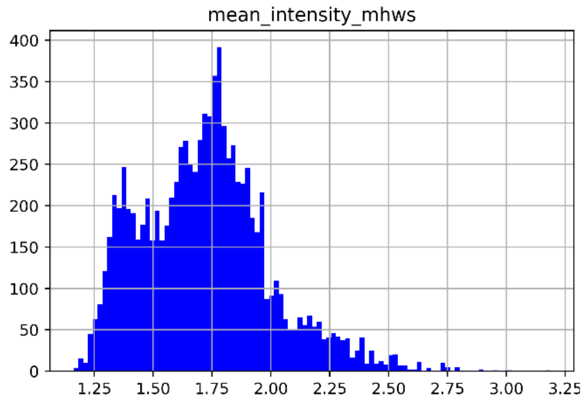
## Annex 12: Distribution of the Mediterranean model predictors

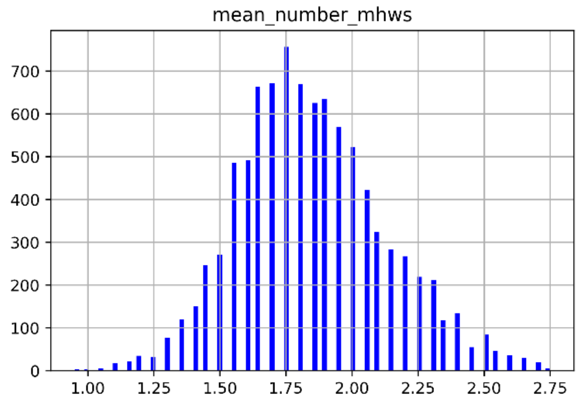


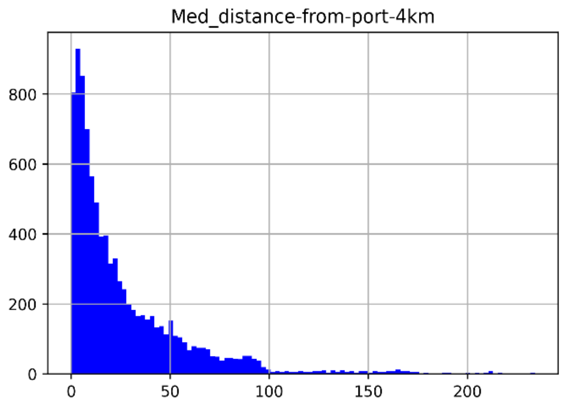

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

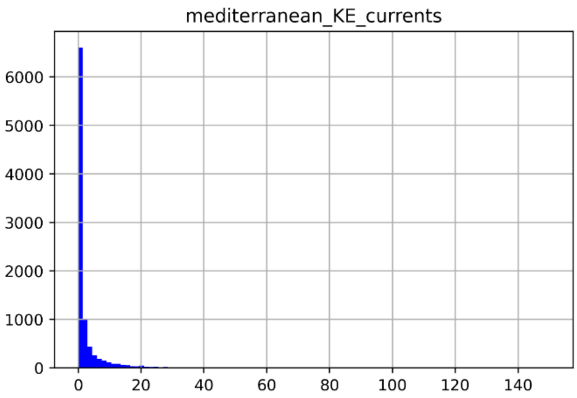


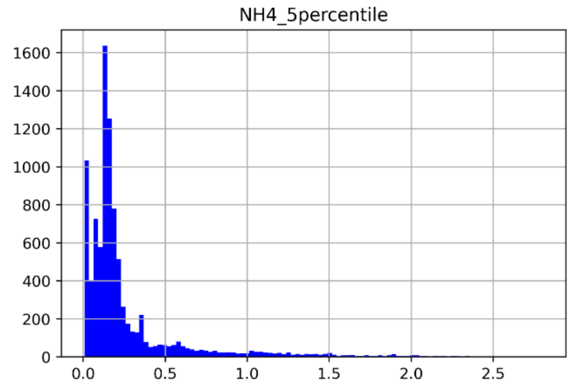



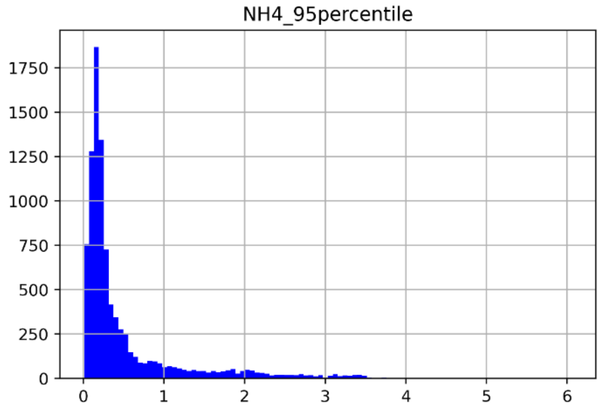



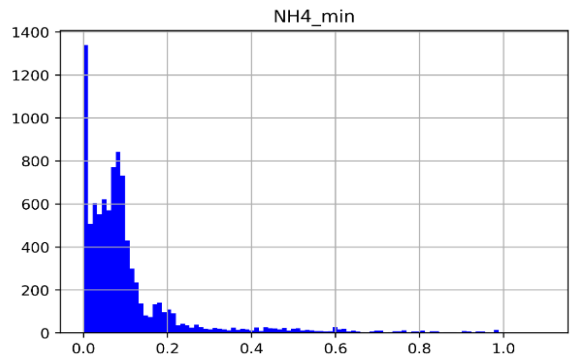



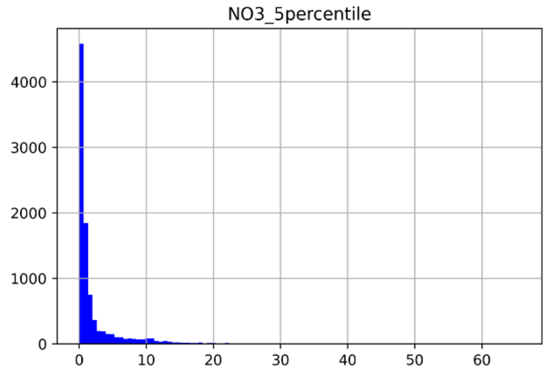



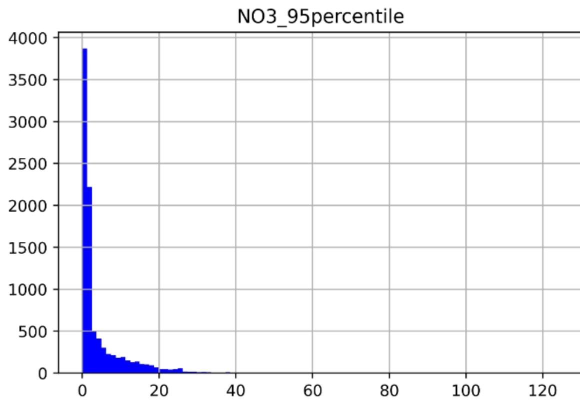

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

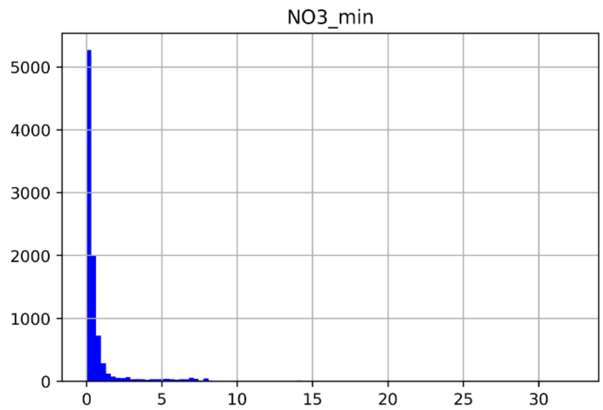


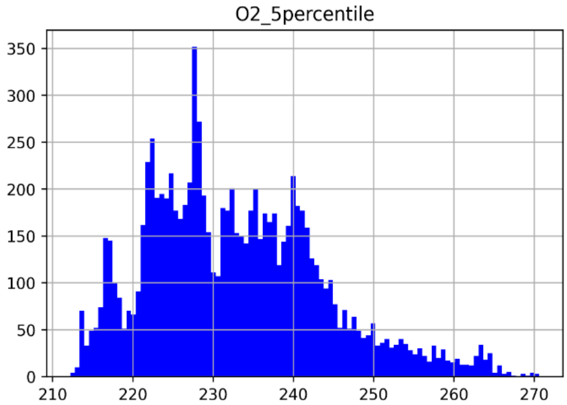



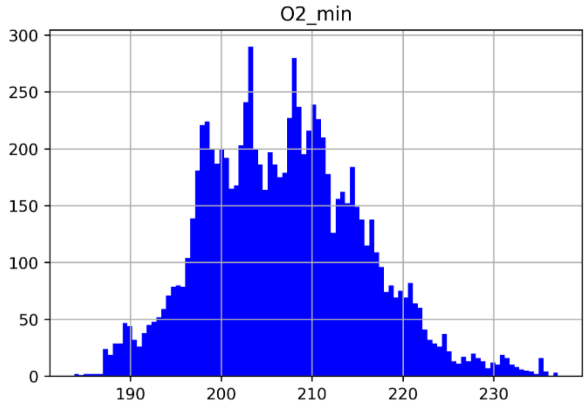



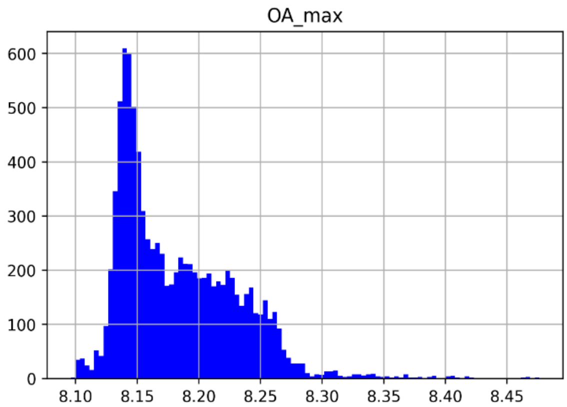



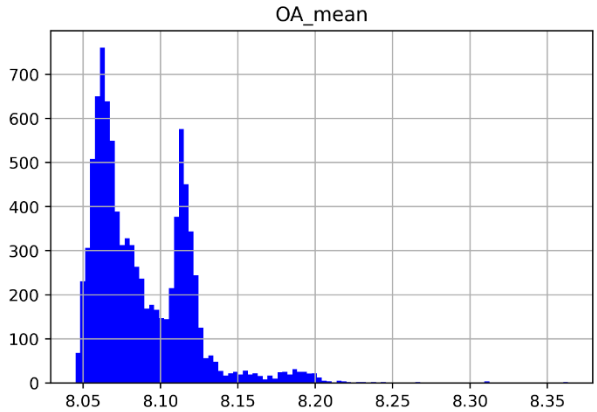



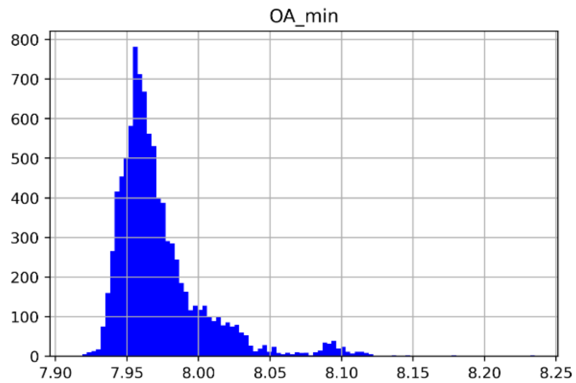

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

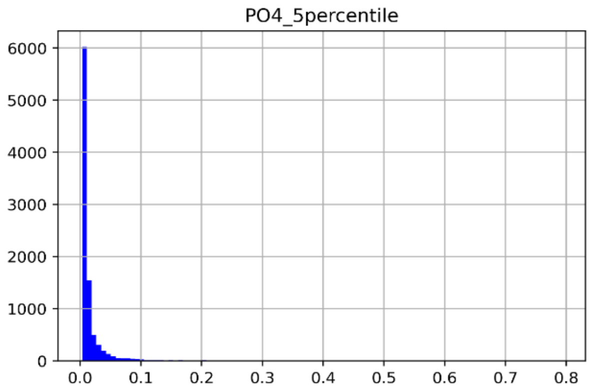


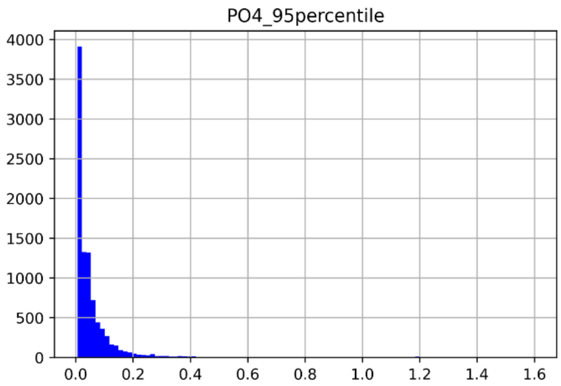



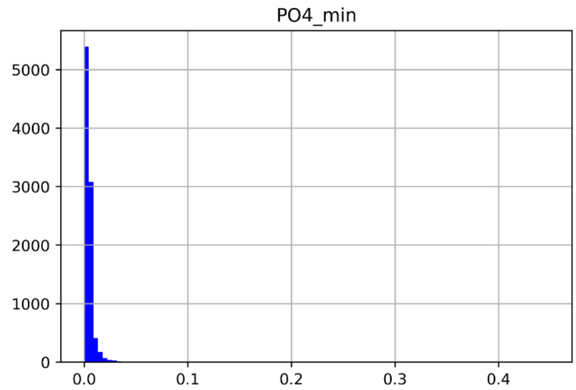



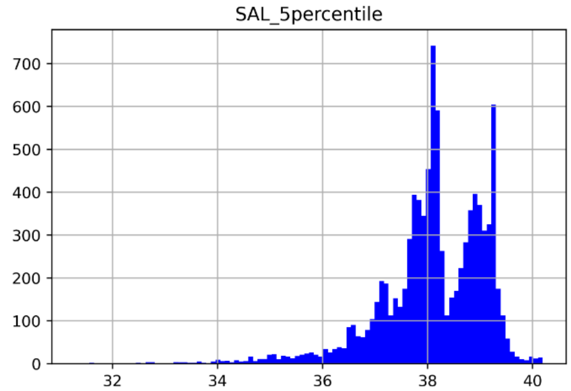



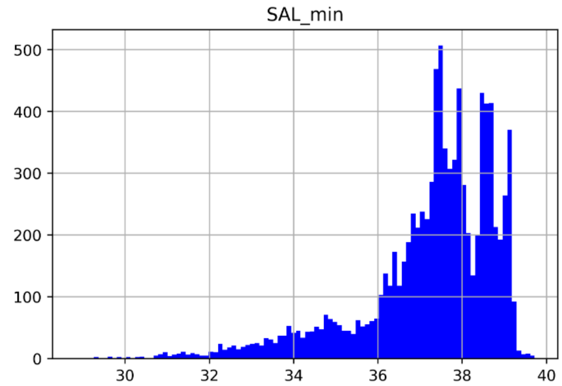



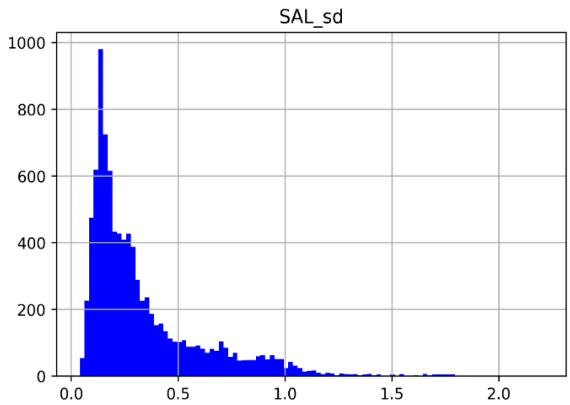

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

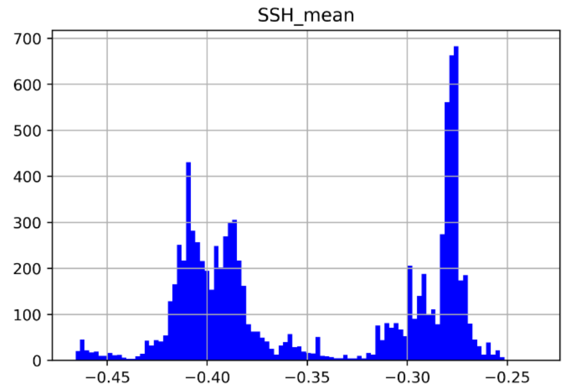


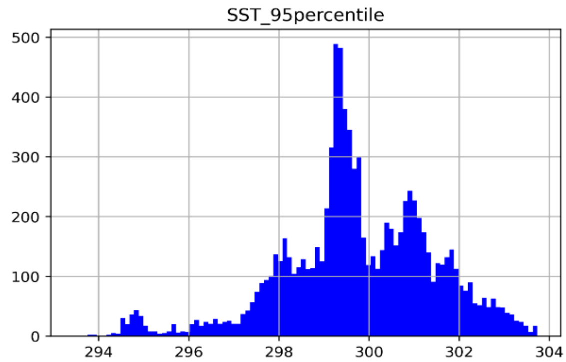



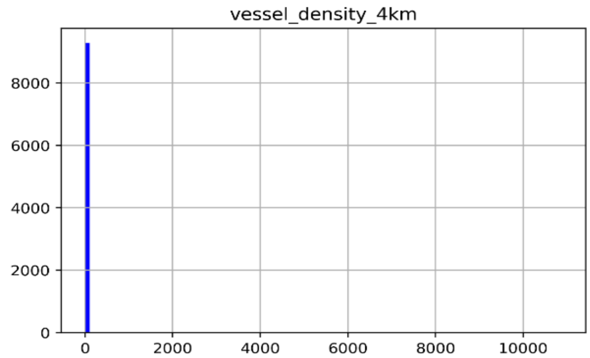



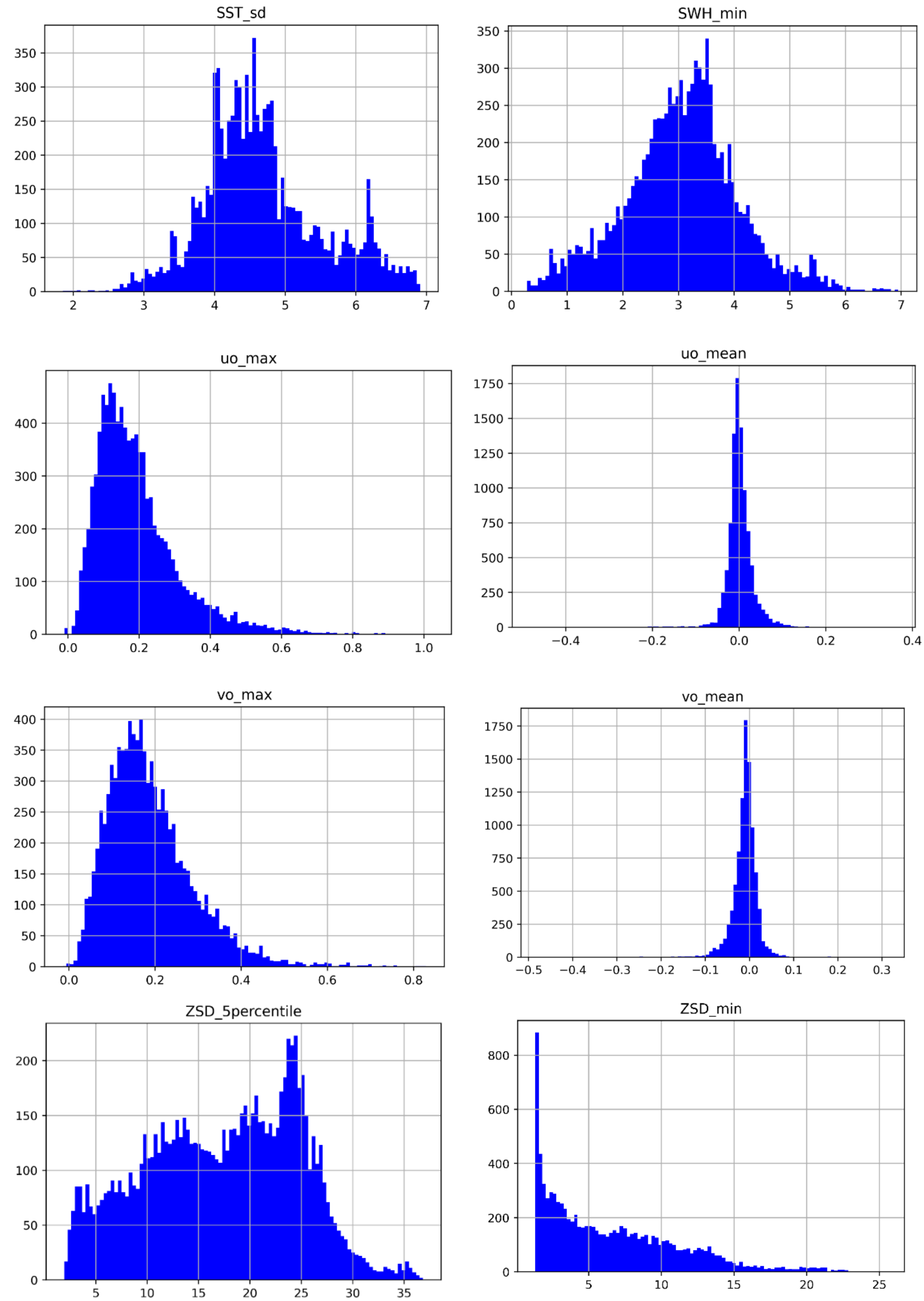



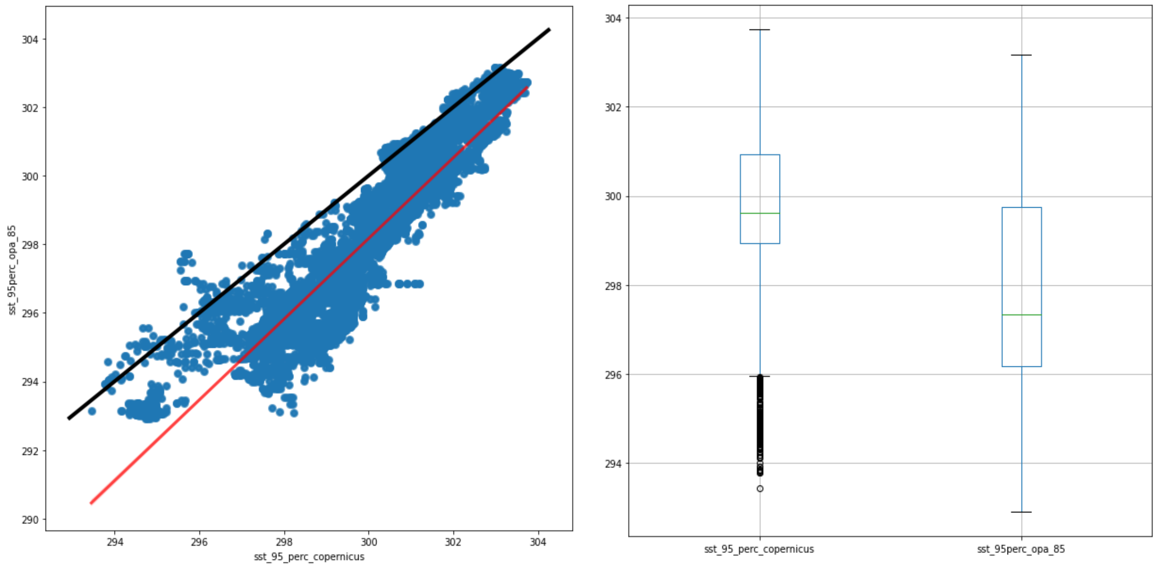

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710



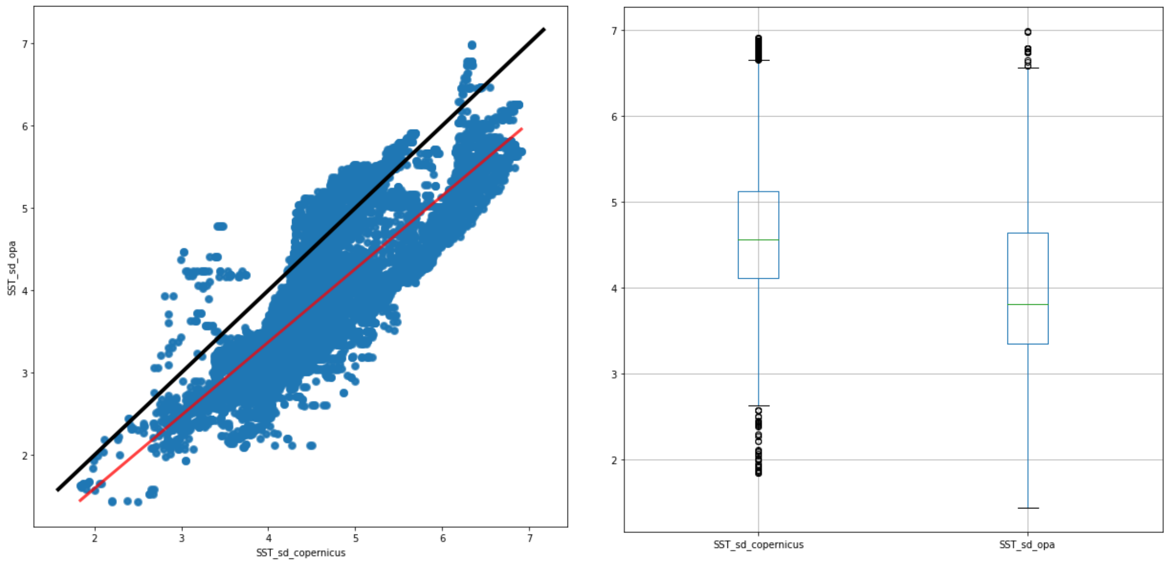

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

# Annex 13: Comparison between Baseline and Reference for the Mediterranean model

## 1- SST_95 percentile_2017 (Copernicus vs CMCC_RCP8.5 data)

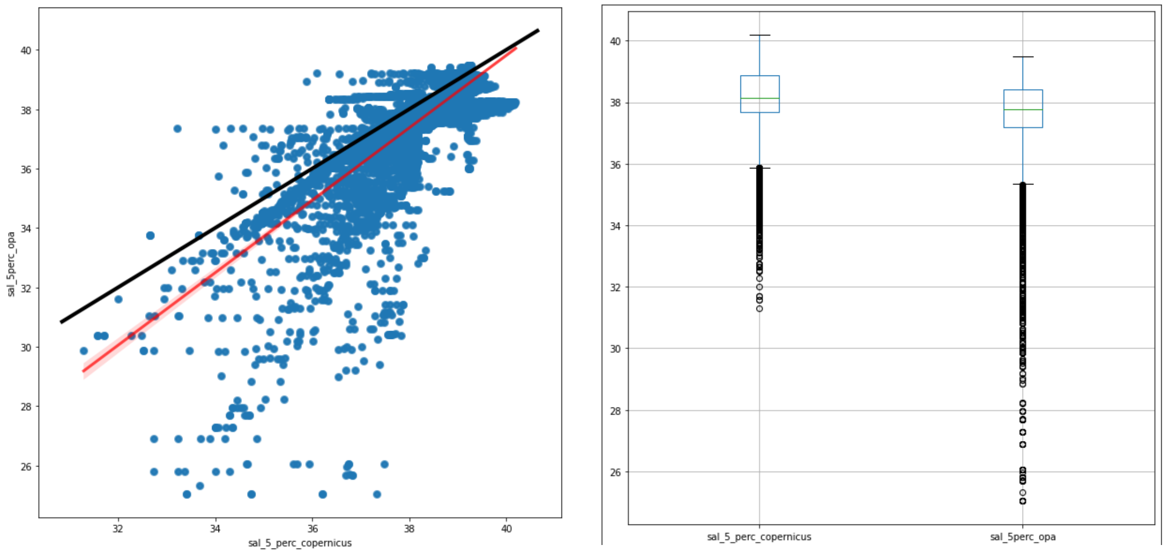



## 2- SST_standard deviation_2017 (Copernicus vs CMCC_RCP8.5)

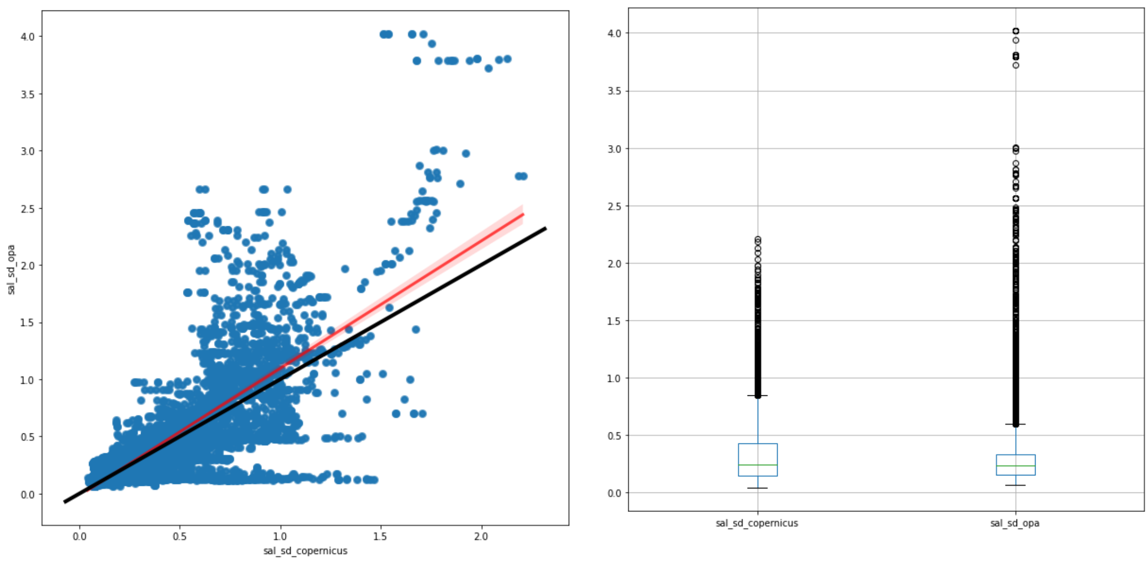



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

3- **SALINITY_5percentile_2017 (Copernicus vs CMCC_RCP8.5)**

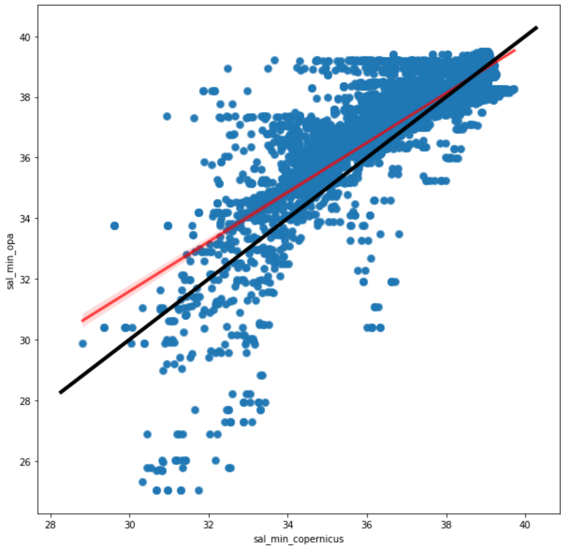


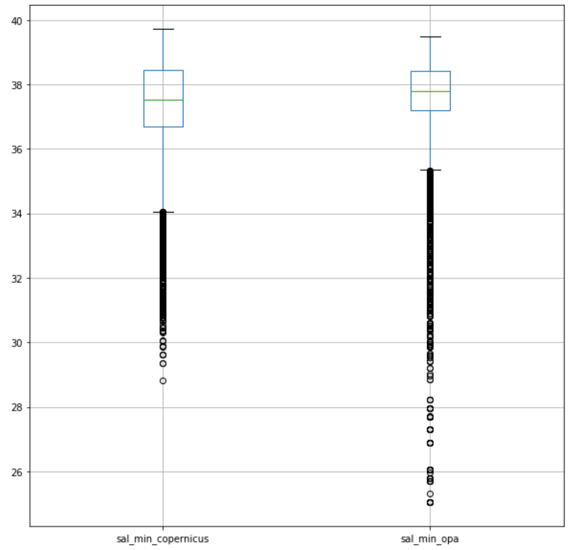

4- **SALINITY _ standard deviation_2017 (Copernicus vs CMCC_RCP8.5)**



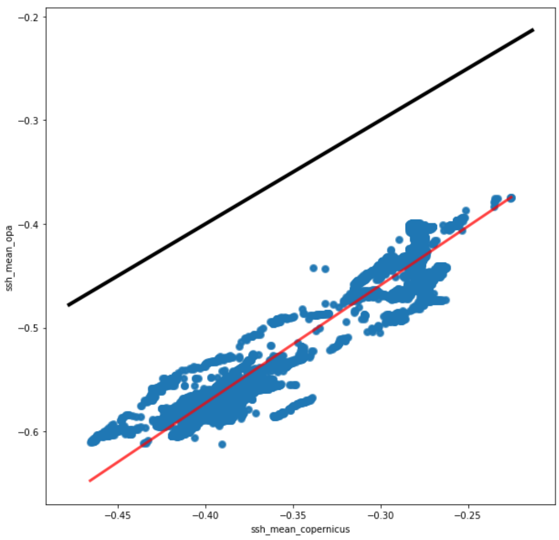

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

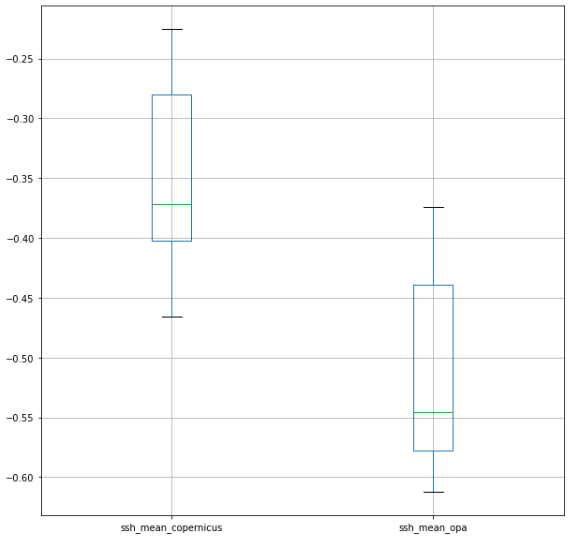
5- **SALINITY _ minimum_2017 (Copernicus vs CMCC_RCP8.5)**




6- **SSH_mean_2017 (Copernicus vs CMCC_RCP8.5)**

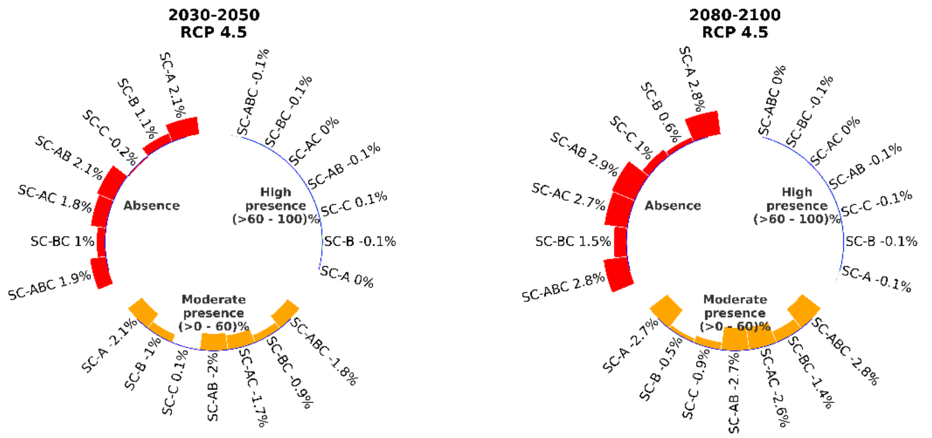


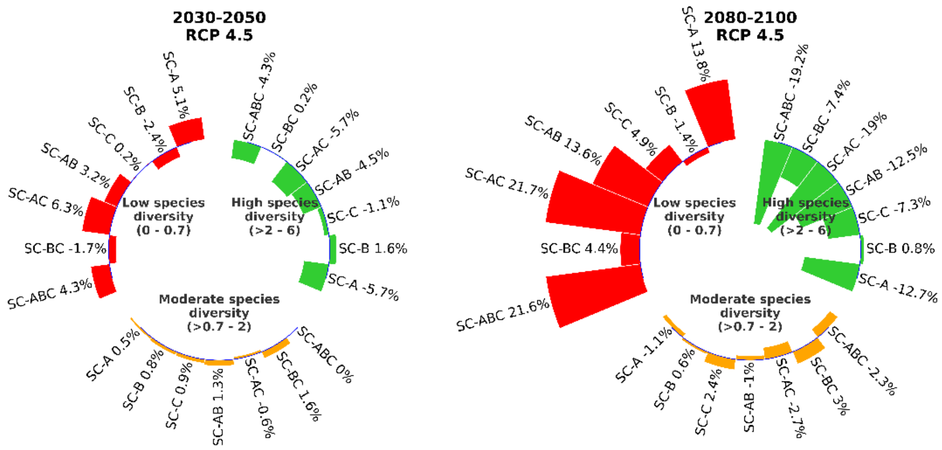

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

# Annex 14: Results from the scenario analysis in the Mediterranean: circular bar plot showing the anomalies between reference and future scenarios for all the 3 outputs

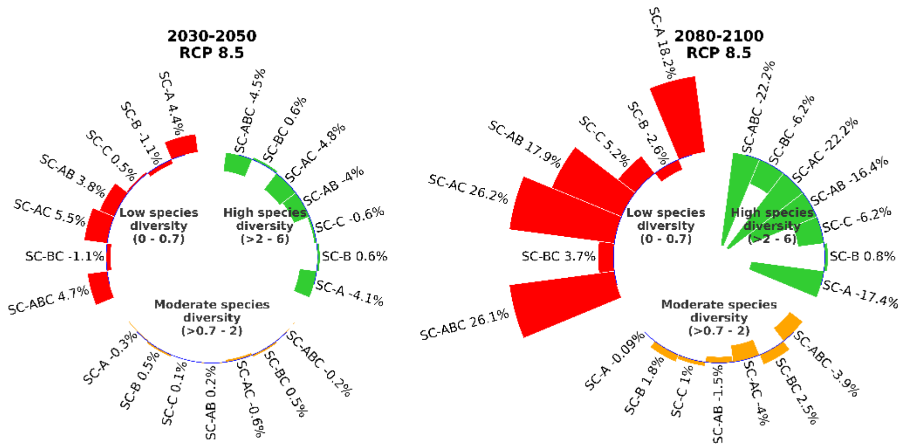
**Seagrass distribution: anomalies between reference and future scenarios**



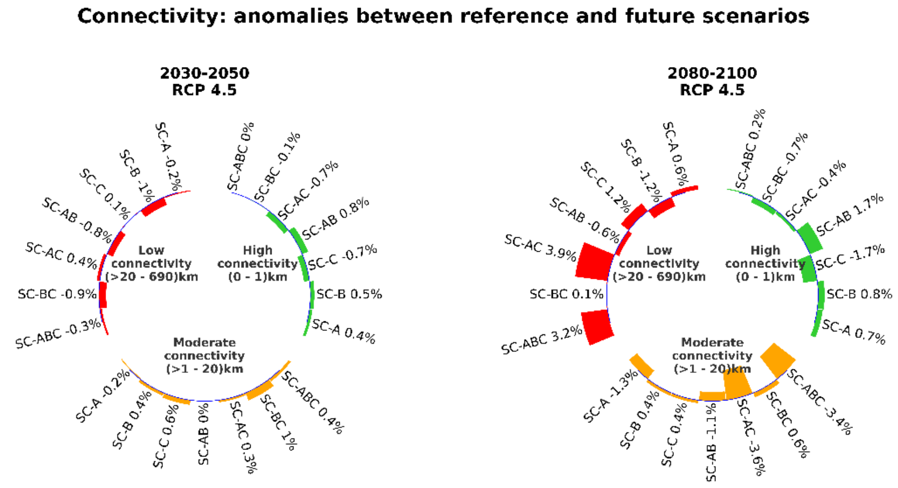

**Shannon index: anomalies between reference and future scenarios**

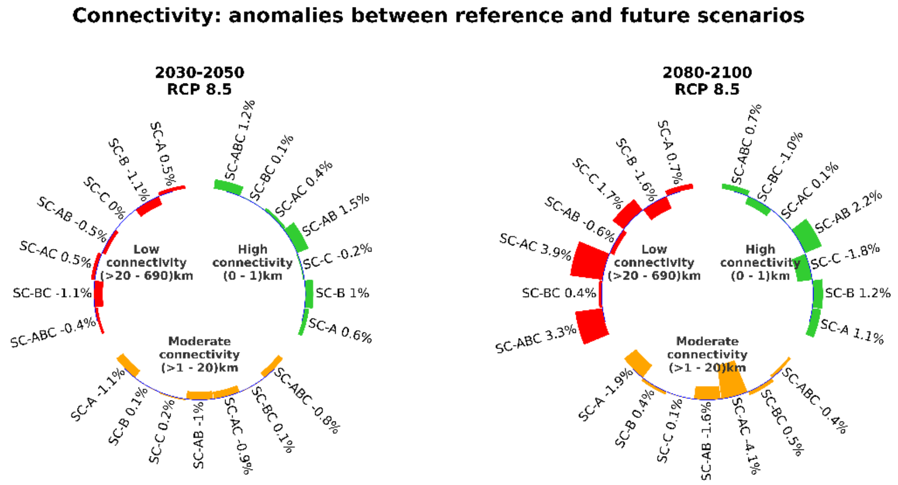



**Shannon index: anomalies between reference and future scenarios**




This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710



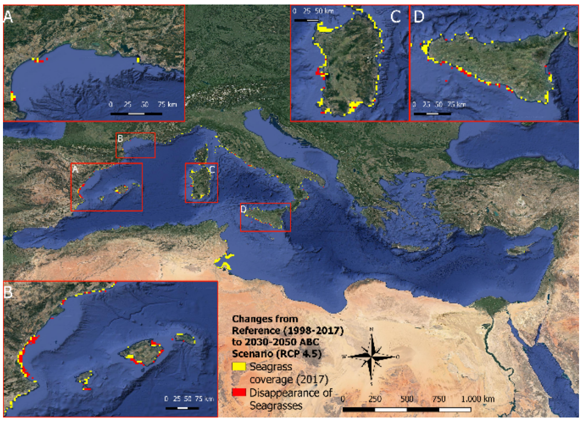

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

**Annex 15: Spatial representation of the anomalies between reference (1998-2017) and future scenarios for all the Mediterranean RF model outputs.**

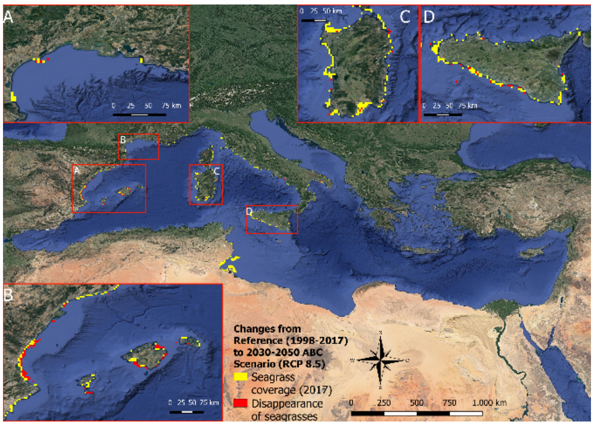
The tested scenarios include: i) individual scenarios (SC-A: SST, SC-B: SAL and SC-C: SSH); ii) coupled scenarios (i.e., SC-AB: SST+SAL, SC-AC: SST+SSH and SC-BC: SAL+SSH); iii) all available scenarios together (i.e., SC-ABC: SST+SAL+SSH).

**Seagrass meadows shrinkage under ABC scenario analysis (2030-2050)**

**RCP 4.5**

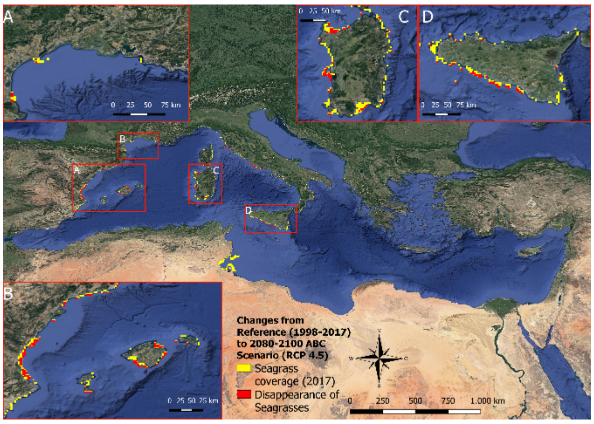



**RCP 8.5**

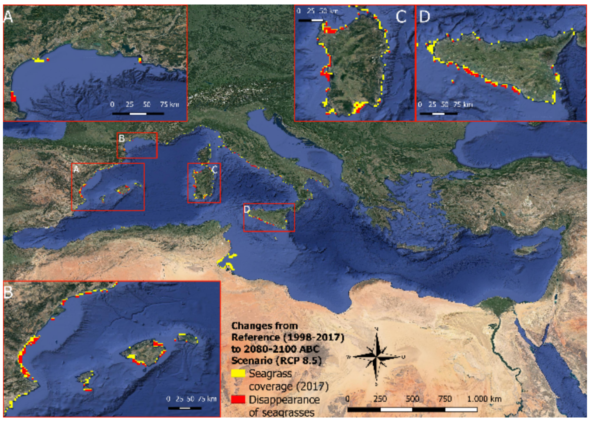



**Seagrass meadows shrinkage under ABC scenario analysis (2080-2100)**

**RCP 4.5**



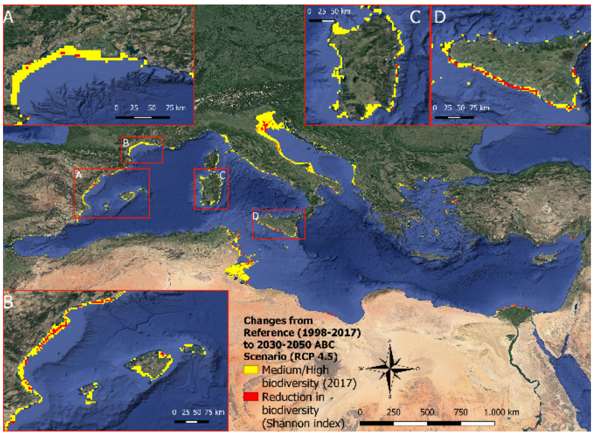

**RCP 8.5**



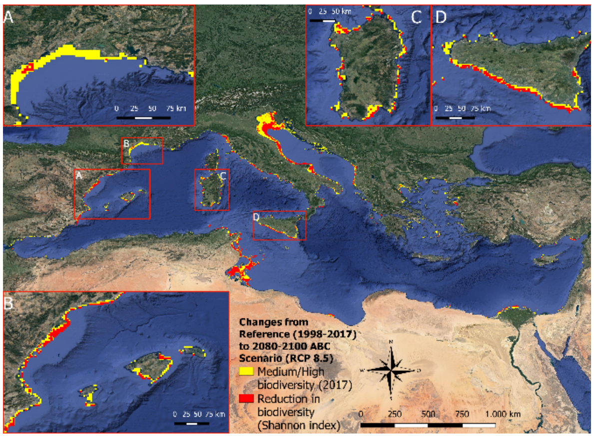

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

**Variations in biodiversity under ABC scenario analysis (2030-2050)**

**RCP 4.5**

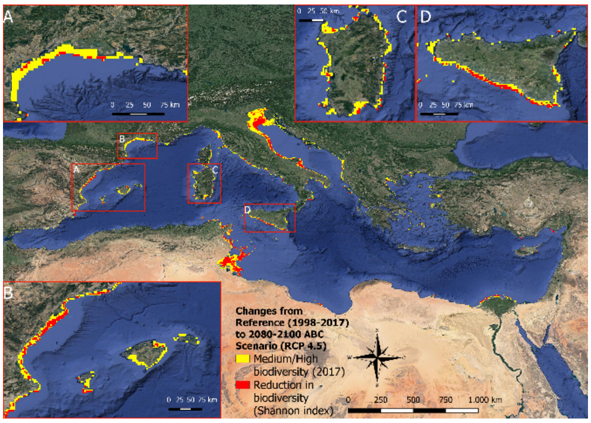



**RCP 8.5**

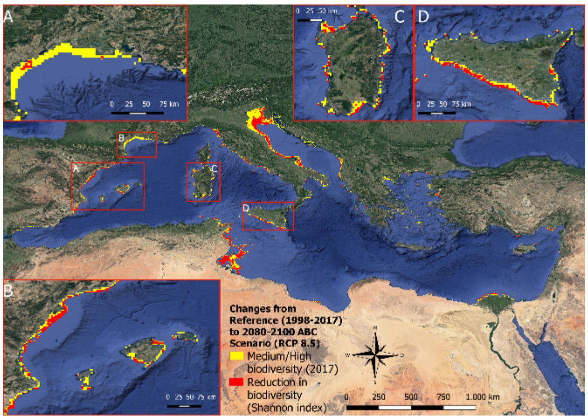



**Variations in biodiversity under ABC scenario analysis (2080-2100)**

**RCP 4.5**

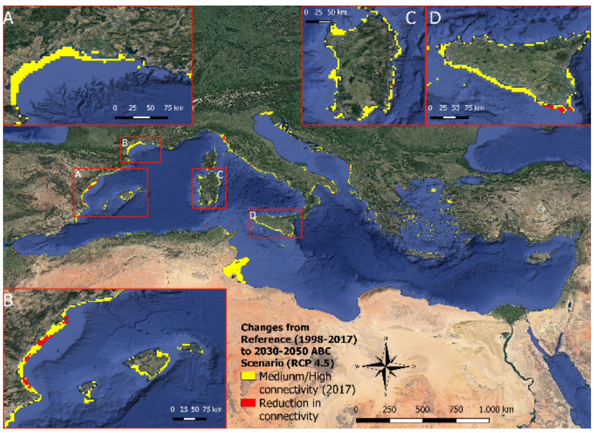



**RCP 8.5**

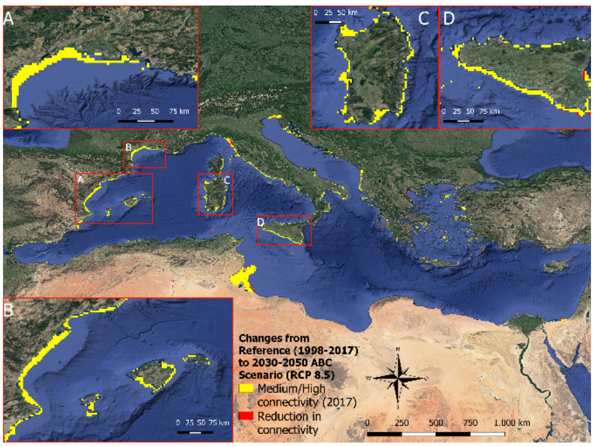



**Variations in connectivity under ABC scenario analysis (2030-2050)**

**RCP 4.5**



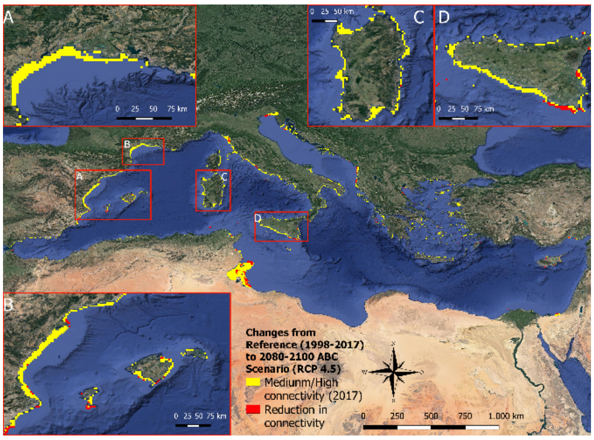

**RCP 8.5**



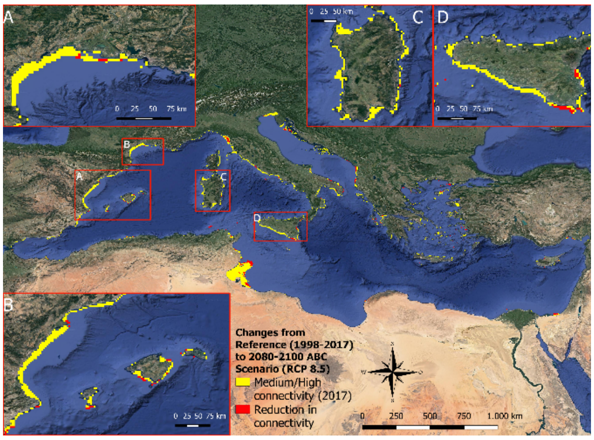

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710

**Variations in connectivity under ABC scenario analysis (2080-2100)**

**RCP 4.5**




**RCP 8.5**




This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869710