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Computing ecosystem risk hotspots: A mediterranean case study

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ABSTRACT

In ecosystem management, risk assessment quantifies the probability and impact of events and informs on intervention priorities. Analytical models for risk assessment quantify the impact of natural and anthropogenic stressors on ecosystems. Traditional approaches evaluate single stressors, whereas complex models assess cumulative impacts of frequently interacting stressors and offer better accuracy at the expense of low cross-area re-applicability and long implementation times.

We introduce a versatile, re-useable, and semi-automated workflow designed for big data-driven ecosystem risk assessment, utilising spatiotemporal data from open repositories. It allows for a flexible definition of the stressors on which the risk under analysis depends. By applying cluster analysis, the workflow identifies different patterns of stressor concurrency, while statistical analysis highlights clusters of stressors likely linked to elevated risk. Ultimately, it generates geospatial risk maps and identifies spatial risk hotspots. The workflow methodology is independent of the geographical area of the application.

As a case study, we present risk assessments for the Mediterranean Sea, a region with intense anthropogenic pressures and significant climatic vulnerabilities. We used over 1.1 million open data from 2017 to 2021 and projections to 2050 under the RCP8.5 scenario (a high greenhouse gas emission scenario) at a 0.5° spatial resolution. Data included environmental, oceanographic, biodiversity variables, and manifest and hidden fishing effort distributions. Our workflow identified different types of high-risk hotspots, highlighting different concurrencies of habitat loss, overfishing, hidden fishing, and climate change stressors. High-risk hotspots concentrated in the Western Mediterranean, the Tyrrhenian Sea, the Adriatic Sea, the Strait of Sicily, the Aegean Sea, and eastern Turkey. Our results agreed with an alternative Fuzzy C-means-based method (with a 90% to 96% overlap over the years) and a Bayesian regression model (~80% overlap).

Our Mediterranean risk maps can facilitate the development of management and monitoring strategies, supporting the sustainable development and resilience of coastal zones, and can act as prior knowledge for ecosystem models and spatial plans.

1. Introduction

In ecosystem management, risk assessment is the activity of quantifying the probability of events and their impact (Holsman et al., 2017). Ecosystem management authorities rely upon risk assessment to assign different priorities to interventions. Practically, risk assessment is a set of methodologies that estimate the uncertainty and impact of natural and anthropogenic pressures (*stressors*) acting on the ecosystem (Côté et al., 2016). Assessments normally include indications for conservation and management strategies to dam the negative consequences of the stressors. In Marine Science, several studies have proposed assessment techniques to evaluate the risks to biodiversity and ecosystem services consequent to the interplay between environmental, ecological, and anthropogenic stressors (Crain et al., 2009; Galic et al., 2012; Borja et al., 2016; Scarcella et al., 2022; Simeoni et al., 2023; Tsikliras et al., 2023). Their results have also supported the socioeconomic debate in the context of the blue economy (Olsen et al., 2018; Klinger and Klinger, 2019; Klinger, 2023). Although traditional approaches evaluate the intensity and risks brought by one stressor at a time (Landis and Wiegers, 2005; Adger et al., 2018; Hobday et al., 2011), estimating the cumulative impact of multiple concurrent stressors through complex models can improve risk prediction (Halpern et al., 2012; Holsman et al., 2017; Coro et al., 2022a; Coro and Bove, 2022; Coro et al., 2024d; Barange, 2024).

Risk assessment for ecosystems can coarsely be distinguished into three (overlapping) categories. *Ecological risk assessment* evaluates the likelihood of adverse ecological effects of anthropogenic stressors,

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e.g., chemical (e.g., toxic compound release), physical (e.g., habitat destruction), and biological (e.g., invasive species, loss of prey base) (Lackey, 1994; Chen et al., 2013; Fletcher, 2015; Suter, 2016; Coro et al., 2024a). Ecosystem-based approaches rely on this information to address ecosystem restoration and ecosystem service enhancement (Fletcher, 2015; Holsman et al., 2017; Magliozzi et al., 2019; Piet et al., 2019; Coro, 2020b; Dimarchopoulou et al., 2021; Clark et al., 2022). *Environmental risk assessment* estimates the risks associated with the complex relation between environmental variables and stressors (Jones, 2001; Hope, 2006). For example, it identifies and evaluates the assets to reduce environmental risks to human health and ecosystems. Ecosystem-based management of coastal areas today relies upon the results of environmental risk assessment to estimate the impact of anthropogenic and natural perturbations on coastal habitats and communities (Dolan and Walker, 2006; Halpern et al., 2009a, 2010; Pandey and Jha, 2012; Samhouri and Levin, 2012; Cook et al., 2014; Samhouri et al., 2014; Himes-Cornell and Kasperski, 2015; McClanahan et al., 2015; Holsman et al., 2017). Finally, *climate risk assessment* evaluates the vulnerabilities of biodiversity and human societies to climate change (Holsman et al., 2017; Gaichas et al., 2018; Hodgson et al., 2019; Payne et al., 2021; Barange, 2024). Evaluations often include species assessment based on life-history traits, thermal preferences, and future projections of climatic conditions (Froese et al., 2016, 2017, 2020; Pita et al., 2021a; Roveri et al., 2022; Hidalgo et al., 2022; Froese et al., 2023; Barange, 2024).

Ecosystem risk assessment is an overall term comprising the risk categories presented above. It comprises three major stages (Cormier et al., 2013): The first stage, *risk identification*, identifies the vulnerabilities of ecological services. In this stage, specific analytic methodologies identify the stressors with the highest pressure on the ecosystem, based on their intensity, severity, spatial extent, and temporal duration. The second stage, *risk analysis*, explores the identified ecosystem vulnerabilities to determine the likelihood of occurrence of an identified risk. Risk analysis can include, for example, the likelihood that an invasive species outcompetes native species. The third stage, *risk evaluation*, is when competent authorities prioritise management actions according to the legal requirements and the general public perception of the risks.

1.1. Risks in the mediterranean sea

Risk assessment methodologies have been widely used in the Mediterranean basin, which is subject to extensive cumulative anthropogenic stressors and is sensible to climatic stressors, with different responses and adaptation by the subregions (Coro et al., 2020; Hilmi et al., 2021). Several scientific studies have highlighted the potential negative impact of climate change on the Mediterranean coastal and open-water ecosystems and the generally poor containment of stock exploitation by management policies (Rosa et al., 2012; Hidalgo et al., 2022). Assessments have highlighted an urgent need for flexible management policies at the entire basin and local scales to allow the adaptation of fisheries and other activities to climate change and counter resource degradation (Coll et al., 2012; Pennino et al., 2024). The vulnerability assets include habitat loss and degradation, natural resource extraction, pollution, eutrophication, alien species, and climate change (Coro et al., 2018; Moullec et al., 2019b; Piroddi et al., 2020; Schilling et al., 2024). The current interplay between these stressors is going to negatively impact health, food security, and ecosystems' status in the coming decades (Cramer et al., 2018).

In the Mediterranean Sea, industrial and small-scale fisheries have the highest intensity globally, with trawling involving at least 4500 vessels fishing for ~30,000 h annually (Mannini et al., 2005; Amoroso et al., 2018; FAO, 2020; Coro et al., 2022b, 2023b). Stocks are fished beyond biologically sustainable thresholds (Froese et al., 2018; Farahmand et al., 2023), and climate change threatens fisheries productivity by changing the presence and abundance of the stocks (Hilmi et al., 2021; Agnetta et al., 2022; Scannella et al., 2022b; Farahmand et al., 2023; Fiorentino et al., 2024). The loss of the Mediterranean biodiversity and stock richness would negatively impact the millions of people relying on fisheries and ecosystem services for their livelihoods (Coll et al., 2010; Lotze et al., 2011). Moreover, climate change fosters invasive species' entrance, especially from the Suez Canal, which exacerbates biodiversity change (Coro et al., 2018; Moullec et al., 2019a; Azzurro et al., 2022). Finally, coastal land use and uncontrolled building and pollution contribute to climate change and extreme climatic events (Satta et al., 2017; Malvarez et al., 2021).

Ecosystem approaches based on risk assessment have indicated directions for sustainably using Mediterranean resources and dam this scenario (Astles et al., 2006; Pita et al., 2021a). However, many approaches follow qualitative methodologies that do not differentiate the results among the Mediterranean subregions. Defining a clear picture of the significant stressors and their highest-intensity locations would be a significant step forward in assessing Mediterranean risks and improving the sustainable development of coastal zones (Bianchi and Morri, 2000; Stelzenmüller et al., 2010; Tsikliras et al., 2015; Satta et al., 2017; Malvarez et al., 2021; Piroddi et al., 2022).

1.2. Our proposal

We present a risk assessment *identification* and *analysis* methodology to highlight risks of overlapping high-intensity concurrent stressors. Our methodology allows a flexible selection of variables to consider as stressors. It visualises risks as geospatial maps, representing the areas with the highest overlap between intense stressor levels. Generally, our methodology solves a risk assessment problem through a variable selection procedure followed by clustering and statistical analysis. Its core is a statistical analysis over automatic data clustering. The methodology is independent of the application area and designed to process big data quickly. In the data preparation phase, open data of anthropic, climatic, oceanographic, environmental, biodiversity, and stock variables are aligned spatiotemporally. These variables can include static and dynamic variables. In a second phase, variable subsetting, combination and reprocessing define stressors related to the target risk of the analysis. Third, data clusters representing categories of stressors' overlap are extracted automatically. Fourth, clusters potentially associated with a high risk are identified through statistical analysis. Finally, the geospatial locations related to the high-risk clusters are identified, and geospatial high-risk hotspots are extracted.

The definition of the stressors is related to the type of risk to analyse. For example, addressing the risks of fishing in vulnerable ecosystems requires defining stressors related to fishing intensity, biodiversity, oxygenation, and nutrients. Our methodology does not include risk *evaluation* because it aims to produce advice for management authorities on areas that should receive greater attention, whereas it does not include planning and management actions.

As a case study, we applied our methodology to Mediterranean Sea data using more than 1.1 million open geospatial data of fishing activity, biodiversity, and environmental variables, with 2017 to 2021 temporal range. We also used projections to 2050 under the Representative Concentration Pathways (RCP) 8.5 scenario to simulate high greenhouse gas emission conditions, which are predicted to cause a decline of more than 10 per cent of the global exploitable fish biomass by mid-century (Barange, 2024). The analysed variables included environmental, oceanographic, biodiversity, and manifest and hidden fishing distributions, which we transformed into different groups of stressor variables. We produced one high-risk hotspot map for each stressor-variable group. These maps highlighted different concurrencies of potential habitat loss, overfishing, hidden fishing, and climate change stressors.

The main objective of the maps is to facilitate the development of management and monitoring strategies to support the sustainable development and resilience of coastal zones. Additionally, they can act as prior information for more complex risk-assessment models. The main limitation of our methodology is that it assumes the stressors to have equal weights (although weights can be simulated at the stressor definition). Moreover, concurrency is modelled as a linear combination of the stressor values, which is only a coarse approximation of the complex relations existing between the stressors. However, we demonstrate that the detected high-risk hotspots are overall similar to those by more complex models; we compared our results with those from alternative models using a fuzzy clustering algorithm and a Bayesian regression model, respectively. They reasonably agreed on most hotspots, although our methodology was less complex.

In summary, the novelties of our methodology can be summarised as follows:

- It transforms a risk assessment problem into a cluster and statistical analysis process;
- It can work on flexible definitions of stressors;
- It can cover different types of risk (ecological, environmental, climatic, ecosystem);
- It is an unsupervised model, i.e., it does not require pre-training;
- It can manage big data;
- It is independent of the application area;
- It produces prior information for complex risk-assessment models;
- It produces risk overviews useful for management and monitoring strategies.

The paper is organised as follows: Section 3 describes our methodology, the case study, and the evaluation methods. Section 4, reports a qualitative assessment of the results, a quantitative comparison with methodologies, and a model sensitivity analysis. Finally, Section 5 draws the conclusions.

2. The role of FAIR data and ecosystem models in risk assessment

The improved availability of Findable, Accessible, Interoperable, and Reusable (FAIR) data can facilitate risk assessment (Coro, 2020b; Coro et al., 2023a). For example, in European fisheries, the European Data Collection Framework has resulted in transversal data for risk assessment in the last ten years, including catch, fishing effort, stock population, and biodiversity data (Cervantes, 2016).

The availability of FAIR data allows for conducting sophisticated risk identification and analysis. In *risk identification*, FAIR remote-sensing data allow for studying trends in physical, chemical, and biological variables in the World's oceans at high spatiotemporal resolutions, and understanding their concurrency (Stelzenmüller et al., 2010; Roux et al., 2022; Farahmand et al., 2023). Recent advances in vessel data processing based on Automatic Identification Systems (AIS) provide knowledge on the spatial distribution of fishing effort in large areas (Coro et al., 2016a; Zennaro et al., 2021; Coro et al., 2023b). Moreover, machine-learning-based ecological niche models can produce reliable large-scale biodiversity perspectives over time by processing FAIR environmental and species-observation data (Coro et al., 2016b, 2024d,a).

FAIR data have also been used for *risk analysis*, to evaluate how much overfishing undermines stock productivity and whether active management policies support stock population rebuilding and overfishing damming (Colloca et al., 2013; Vasilakopoulos et al., 2014; Froese et al., 2018; Tsikliras et al., 2023). However, most studies have regional scales and seldom consider the interplay between fishing pressure and ecosystem change. The difficulty of producing large-scale assessments is due to non-homogeneous data availability, lack of standardisation, and poor open data accessibility across different countries (Colloca et al., 2017; BLUEMED Italian White Paper Working Group, 2018). These hindrances (*data gaps*) have also been highlighted by the European Scientific, Technical and Economic Committee for Fisheries (STECF) and by the General Fisheries Commission for the Mediterranean, which annually assess the status of overfishing to inform risk management (General Fisheries Commission for the Mediterranean, 2024; European Scientific, 2024).

Ecosystem models (EMs) can be used to fill these data gaps and assess the cumulative, large-scale overlap of climatic, environmental, and fisheries stressors while estimating their effects on the food web (Piroddi et al., 2022). Although EMs provide an excellent and valuable overview of cumulative ecosystem risks, they use stressor data that – for the limited data availability and long preparation times – are misaligned in time and usually perform aggregations over several decades and large spatial scales. Consequently, their results are flattened in time and space and only represent a general risk reference that might not be suitable for next-year predictions. The decade-aggregated data have indeed mean values that become obsolete in a few years at the current rates of climate change. Finally, EMs require long implementation times since they rely on expert-provided information. Therefore, although their analyses can be crucial for risk management they cannot provide predictions for emergency or urgent scenarios.

In summary, from the point of view of risk assessment, the current EM reusability is limited, the implementation times are long, and the validity is more suitable for assessing the scenario around the years of the results' publication. However, EMs might benefit from (prior) information provided by dynamic, flexible, and automatic assessments that can reproduce scenarios of rapid change from one year to another (Pita et al., 2021a; Campana et al., 2021; Pita et al., 2021b; Hidalgo et al., 2022), while requiring minimal expert intervention.

3. Methods

This section describes our workflow for risk identification and analysis (Section 3.1) and its application to the Mediterranean Sea (Section 3.2). Finally, it describes our evaluation methodology (Section 3.3).

3.1. Workflow

We present a risk identification and analysis methodology that can handle dynamically changing sub-regional scenarios and overcome several limitations highlighted in the previous section. Unlike other methods (Ramírez et al., 2018; Piroddi et al., 2022; Pennino et al., 2024), our methodology can quickly produce a temporal sequence of spatial perspectives, over a reference time frame, that highlight the dynamic evolution of the stressors' concurrency.

We designed our methodology in the spirit of big data processing, hypothesising that the available FAIR data contain valuable macroscopic patterns of potential risks (Zennaro et al., 2021). Should the data cover the entire range of anthropic, climatic, environmental, and biological stressors of the focus area, our method would produce a varied and complex perspective of the ecosystem risks associated. Our methodology does not include risk management aspects (*risk evaluation*), which are in the competencies of the authorities that might want to use our results.

Our semi-automatic methodological workflow is summarised in Fig. 1, which is explained step-by-step in the following sections. The corresponding software was entirely developed in R and is openly available (*Software and data availability* section).

3.1.1. Data preparation

Our workflow's input is a comma-separated-value (CSV) file table (Fig. 1-a). The table should include columns corresponding to geospatial variables related to the analysed ecosystem. Two columns should contain latitude and longitude information, i.e., coordinate pairs over the focus area whose numeric precision indicates the spatial resolution of the dataset. The other columns should correspond to variables of anthropic, climatic, environmental, and biological information, not necessarily corresponding to stressors at this stage. Each row thus

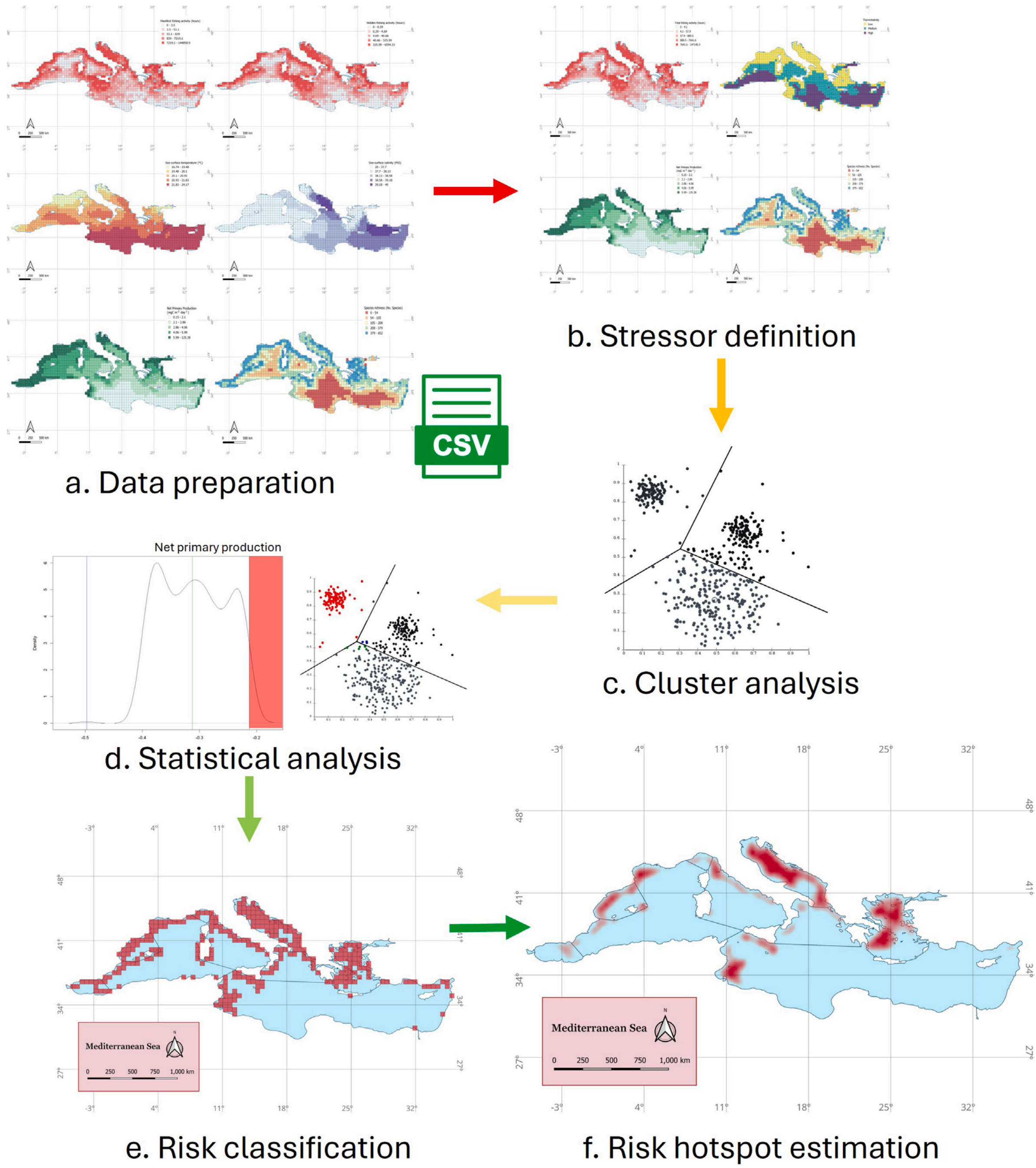

Fig. 1. Overall schema of our workflow.

represents the characteristics of a spatial *cell* (a raster *pixel*) in the focus area. The variables might include cell-wise estimations of fishing hours, number of species, temperature, salinity, depth, and distance from land. These data can come from heterogeneous sources, such as public repositories of FAIR environmental and climatic data (Tyberghein et al., 2012; Weatherall et al., 2015; Assis et al., 2018; Copernicus, 2020; CMEMS, 2022; Coro et al., 2023a), observation and habitat-distribution records (Grassle and Stocks, 1999; Scarponi et al., 2018; GBIF.org, 2024), and fishing effort estimates (Merten et al., 2016; Coro et al., 2023b, 2024d,b). In the data preparation phase, all data should be rasterised on the same spatial grid. The resolution of the grid should depend on the quality of the data (e.g., the spatial reliability of the information aggregation over the cells) and the target spatial accuracy of the assessment (e.g., large-scale vs regional-scale assessments). FAIR data are crucial in this phase to make data harmonisation times reasonable. Interoperability and accessibility features (e.g., using standards or software packages to retrieve the metadata and the data) and automatism allow for quickly gathering all the required data in a table, which can quickly be saved as a CSV file through GIS software (QGIS and QGIS, 2024; ArcGIS, 2024), or programmatically (e.g., through R), at a given spatial resolution (Santana et al., 2006; Candela et al., 2016; Coro et al., 2016b; de Andrade et al., 2020; Sillero et al., 2021; Coro et al., 2024d). The connection towards FAIR data repositories can remain active to guarantee a constant input data flow to our workflow for producing risk assessments periodically. FAIR data also allow for enhancing methodological transparency, i.e., for explaining the entire lineage that produced the assessments (Coro, 2020b; Campana et al., 2021).

3.1.2. Stressor definition

In the second phase, the user should reprocess the variables in the input table to represent *stressors* acting on the area (Fig. 1-b). From the point of view of the workflow, a *stressor* is a new variable whose *high* values either correspond to hostile forces affecting the ecosystem or to fragile conditions that withstand these forces. For simplicity, we also use the term *stressor* to indicate fragile-condition variables, in compliance with the broader definition of *stressor* as a factor of potential ecosystem balance and process alteration (Rapport et al., 1985; Sala et al., 2000; Gunderson et al., 2002; Grimm et al., 2008). In fact, although *stressor* is not a term usually referring to fragile conditions, the associated variables contain information on a potential cumulative stress for the ecosystem.

In the following, we report some example of stressor variables. *Fishing effort* (i.e., the hours vessel spend fishing) is a stressor because higher values might negatively affect stock biomass and repopulation. The *inverse of the distance of a cell from land* is another possible stressor if we want to assign greater attention to coastal locations, which are often subject to closures. Similarly, the *inverse of depth* would identify shallow waters as locations to put under attention. Another stressor can be *thermohaline circulation*, i.e., the combined effect of temperature and salinity on the circulation of seawater caused by temperature–salinity density gradients. A high thermohaline circulation can indeed reduce dissolved oxygen and alter biodiversity (Coro and Bove, 2022; Sisma-Ventura et al., 2021). *Low dissolved oxygen* is another potential stressor since hypoxia negatively affects species mortality, growth, and reproduction (Breitburg, 2002; Pollock et al., 2007; Wu, 2009). Likewise, a *high net primary production* – i.e., the organic material produced by photosynthetic organisms excluding the material they use for respiration – might indicate algae overblooming and, consequently, oxygen depletion (Smith et al., 1999; Anderson et al., 2002; Paerl and Otten, 2013).

The definition of stressors in our workflow depends on the type of risk analysis to conduct. For example, a *risk* scenario could be one of an area where intense fishing occurs in a high-biodiversity region with peculiar environmental conditions (e.g., with strong thermohaline circulation, high oxygen, and high net primary production). In such a scenario, human activities would potentially alter equilibrium and sustainability conditions by increasing pollution and reducing stocks and species biomass. Therefore, these areas should be identified as higher-risk areas because they might turn into hypoxic areas with low biodiversity. This definition of risk is associated with high oxygen and high biodiversity levels, different from other possible risk definitions over the same variables that might consider their inverse as stressors (e.g. when focussing on hypoxic or species-poor areas).

This flexibility in risk definition is a crucial difference with respect to other approaches (Coll et al., 2012; Osio et al., 2015; Ramírez et al., 2018; Hidalgo et al., 2018, 2022; Carmezim et al., 2022; Moullec et al., 2022; Piroddi et al., 2022). Depending on the target risk scenario to model, stressors can be single variables, inverse variables, or combinations because our method does not require the analysed scenario to represent an equilibrium condition. In EMs, instead, ecosystem state assessment is the main target and thus risks are usually assessed in averagely stable scenarios.

The second step of our workflow requires user intervention to define stressors based on input variable combinations. Given a *risk scenario*, the user should identify and build several contrasting factors that define or are highly related to the risk scenario. The next computational steps will analyse the concurrency of these factors. It should be possible for the user to calculate the stressors programmatically from the initial variables. Eventually, the stressor definitions should be added to the input data as new (m) additional columns. To make the stressors commensurable, they should be standardised, i.e. transformed so that the mean is 0 and the standard deviation is 1 ($s_i = \frac{x_i - \mu}{\sigma}$, $\forall i \in [1, m]$).

3.1.3. Cluster analysis

As the next step, our workflow considers the m stressor values associated with each spatial location as the elements of a real-valued vector in $\mathbb{R}^m$ (Fig. 1-c). The stressor values (with coordinates excluded) have similarities that can be calculated through their mutual distances in an m-dimensional vector space. Our workflow uses cluster analysis to identify groups of similar vectors in the stressors' space. In particular, it repeatedly executes a K-Means cluster analysis (*multi-K-means*) on the stressor vectors, with K between 2 and $number\ of\ vectors/2$ (i.e., up to the worst tolerated case of all clusters containing only two elements).

We configured each K-means execution to randomly select, in the initialisation phase, the centroids among the stressor vectors. This selection ended in K centroids very close to the data, representing plausible scenarios of stressor concurrencies. We also verified that a random selection often produced centroids far from real scenarios. The workflow executes K-means iterations up to convergence (i.e., with no maximum number of iterations) to produce stable centroids. Eventually, it selects the clusterisation with the lowest Bayesian Information Criterion (BIC). The BIC measures the K-means goodness-of-fit to the data while balancing model complexity with fitness. It penalises more complex models to avoid overfitting. The minimum BIC indicates the optimal K^* that corresponds to a good fit and a low model complexity. The processing steps and the mathematical definitions are reported in Algorithm 1.

Algorithm 1 Multi-K-means clustering of stressor vectors

N =number of stressor vectors
For $k \in [3, N/2]$

  Initialise k centroids as k randomly selected vectors $(\mu_1, \mu_2, .., \mu_k)$
  Execute the following steps up to *convergence condition*

    Assign each data point $\mathbf{x_i}$ to the nearest centroid based on Euclidean distance, i.e.
    $j = \arg\min_{1 \le j \le k} \|\mathbf{x_i} - \mu_j\|^2$

    with $\|\mathbf{x_i} - \mu_j\|^2$ being the squared Euclidean distance between $\mathbf{x_i}$ and μ_j.
    Recalculate the centroids as the barycenters of the cluster vectors:
    $\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i\ \forall j \in [1, k]$

    with C_j being the vector set of cluster j and $|C_j|$ its size
    If μ_j are equal to the ones of the previous step (no update) → *convergence condition* reached

  Calculate the total within-cluster sum of squares
  $\mathrm{WCSS}(k) = \sum_{j=1}^{k} \sum_{x_i \in C_j} \|x_i - \mu_j\|^2$

  Calculate the Bayesian Information Criterion
  $\mathrm{BIC}(k) = N\ log(\mathrm{WCSS}\ (k)/N) + p$

  with p $(= k \times m + 1)$ being the number of model parameters

Select the optimal clusterisation K^* as the one corresponding to the minimum BIC
$K^* = \arg\min_{3 \le k \le N/2} \mathrm{BIC}(k)$

Return K^*.

The output of the algorithm is the assignment of each stressor vector to one of the K^* clusters, and the report of the cluster centroids values.

3.1.4. Statistical analysis

As the next step, the workflow considers each stressor a random variable and estimates their distributions, i.e., the relative number of times each value occurs in the study area (Fig. 1-d). It calculates the density function of each variable through kernel density estimation (Parzen, 1962). The workflow uses a Gaussian kernel combined with Silverman's rule of thumb for bandwidth selection, which determines the smoothness of the density curve based on the standard deviation and the number of data points (Silverman, 2018). The stressor variables' distributions are generally not associable with known analytical forms of statistical distributions. Therefore, in compliance with other approaches (Cheung et al., 2004; Dureuil et al., 2018; Palma et al., 2019; Coro, 2020a; Coro and Bove, 2022; Coro et al., 2022a; Hodapp et al., 2023), our workflow uses a quartile subdivision to distinguish between *high-* and *non-high*-valued (i.e., medium and low valued) locations. The values over the third quartile (i.e., the 75th percentile) are considered high stressor values. Consequently, a stressor's high-value locations will be those with high values associated.

As a result, the high-value thresholds of each stressor are passed to the next step.

3.1.5. Risk classification

As an additional step, the workflow classifies each cluster as potentially associated with *high* risk or *non-high* risk (Fig. 1-e). Each cluster centroid has coordinates corresponding to the barycenters of the vectors belonging to the cluster. In our clustering analysis, a cluster centroid corresponds to plausible conditions in the study area; therefore, it can be classified as corresponding to a *high* or *non-high* risk location.

To classify risk for the centroids, our workflow first creates a string vector (H-vector) for each centroid. This vector contains an "H" in all vector positions whose corresponding stressor values are *high*. For example, if the first centroid vector element corresponds to fishing effort and its value is *high* (according to the fishing effort distribution), then the H-vector will contain "H" in the first position. The H-vector will contain the empty string in all *non-high* positions. To finally classifying the centroid risk — in compliance with other methodologies (Coro et al., 2016b; Froese et al., 2016; Coro et al., 2024d), the workflow uses a *voting-system consensus model*. If the centroid contains high values for most stressors, it and its cluster are classified as *high-risk*, and as *non-high-risk* otherwise, i.e.,

$$\begin{cases} |H-\text{vector}_H|/|H-\text{vector}| > 0.5 \rightarrow \text{high-risk} \\ |H-\text{vector}_H|/|H-\text{vector}| \leq 0.5 \rightarrow \text{low-risk} \end{cases}$$

with $|H-\text{vector}_H|$ being the number of "H" symbols in the vector, and $|H-\text{vector}|$ being the vector length (corresponding to the number of stressors). All vectors falling within at least one *high-risk* cluster are then labelled as *high-risk* vectors and their associated cells as *high-risk* cells.

As the result of this phase, the workflow adds a new column to the data table containing an "H" for each *high-risk* cell-row and an empty string for the others.

3.1.6. Risk hotspot estimation

As the final processing step, our workflow estimates *risk hotspots* in the study area (Fig. 1-f). Since our methodology is statistical and oriented to big data, its scope is to produce macro patterns of risk rather than cell-wise indications. Other studies have indeed shown that consensus models can produce reliable macro patterns (Coro et al., 2024a,d; Coro, 2024). The biases on the individual cells can indeed fade away when macroscopic patterns are produced through spatial aggregation (Weber et al., 2004; Queiroz et al., 2021).

Our workflow spatially aggregates the risk cells through spatial kernel density estimation. This technique generates a smooth density surface over the study area based on the spatial distribution of the high-risk cells. As the result, it creates a "heatmap" of high-risk areas.

In particular, our workflow uses a quartic kernel of the form

$$K(u) = \frac{15}{16}(1-u^2)^2 \quad \text{for} \quad |u| \leq 1$$

with $K(u) = 0$ for $|u| > 1$.

The algorithm first calculates the distance d_i between the grid point and a high-risk location (x_i, y_i). Second, it calculates the normalised distance $u_i = \frac{d_i}{h}$, where h is a radius (bandwidth) representing a spatial correlation. We set the radius to double the spatial resolution of the original data (e.g., 1° for 0.5° data) to keep the smoothed distribution closer to the cell-wise distribution and avoid long-range correlation artefacts. The final kernel function value for point (x_i, y_i) is the sum of all $K(u_i)$ values ($f(x_j, y_j) = \sum_i K(u_i)$), i.e., the summed influence of the proximity of high-risk cells on the analysed grid cell. The kernel function values over the third quartile (high values) across the grid covering the study area represent the risk hotspots.

Algorithm 2 summarises the processing phases from statistical analysis to hotspot estimation.

Algorithm 2 Estimation of high-risk hotspots

∀ stressor variable $S_i, i \in [1, N]$

  Calculate kernel density with Gaussian kernel ($KDE(S_i)$)

  Calculate and store the third quartile value $S_i^{thr} = \arg(KDE(S_i)_{|75p})$

∀ cluster centroid $\mu_j, j \in [1, K^*]$

  Create a string vector h_j with the same size as μ_j (H-vector)

  ∀ μ_j element $\mu_j[i], i \in [1, N]$

    If $\mu_j[i] > S_i^{thr} \rightarrow h_j[i] =$ "H"

  If $|H\text{-vector}_H|/|H\text{-vector}| > 0.5 \rightarrow C_j$ is a *high-risk* cluster

∀ *high risk* cluster $C_j \in \{\text{high-risk clusters}\}$

  ∀ stressor vector $s_g \in C_j$

    Get the spatial coordinates of the vector (x_g, y_g)

    Mark (x_g, y_g) as a *high risk* location if not marked yet

Create a new column in the input data table column named *risk*

∀ coordinate pair

  write the coordinate *mark* ("high risk" or empty string) in the *risk* column

Save the data table in a new CSV file

Apply spatial kernel density estimation to the *high-risk* coordinates, using quartic kernel and a $2\times spatial\,resolution$ radius → Produce kernel function ($f(x_j, y_j)$) estimates for each coordinate pair in the original table.

Save the spatial kernel density estimation as a new GeoTiff raster file

Visualise the hotspots as the values over the third quartile of the kernel function values.

3.2. Case study

We selected the Mediterranean Sea basin as a case study because of its peculiar and complex risks and stressors (Section 1). We searched for FAIR data on environmental, anthropic, biodiversity, stock richness, and climatic variables. The most extensive and high-quality data we found (and related sources) are summarised in Table 1, whose average values are shown in the Supplementary Material (Figures S1 and S2). A summary table with all the data for the Mediterranean Sea (containing over 1.1 million data) is also downloadable from the Supplementary Material.

In summary, our set of variables included annual distributions of net primary production, dissolved oxygen, temperature, salinity, thermohaline circulation, fishing activity, species and stock richness, distance from land, and depth. Most data came from oceanographic studies and ecological niche models. We selected these data because (i) the environmental variables were all manually verified by experts, (ii) the fishing effort distributions were obtained from high resolution

Table 1
Datasets of environmental, anthropic, biodiversity, stock, and climatic variables we used in our study, with the indication of their primary and secondary sources.

Variable name	Sub-specifications	Unit of measure	Time range	Original time resolution	Original spatial resolution	Primary source	Secondary source
Fishing activity	Hidden, total	h	2017–2022	Annual	0.01°	Coro et al. (2024b)	–
Depth	Mean	m	–	–	0.0042°	Weatherall et al. (2015)	–
Land distance	Water column	km	–	–	0.5°	Generated for the present paper	
Temperature	Sea-surface, sea-bottom	°C	2017–2021, 2050	Annual	0.5°	Coro et al. (2023a)	Tyberghein et al. (2012), Assis et al. (2018) and CMEMS (2022)
Salinity	Sea-surface, sea-bottom	PSS	2017–2021, 2050	Annual	0.5°	Coro et al. (2023a)	Tyberghein et al. (2012), Assis et al. (2018) and CMEMS (2022)
Dissolved oxygen	Sea-bottom	mmol m^{-3}	2017–2021, 2050	Annual	0.5°	Coro et al. (2023a)	Tyberghein et al. (2012), Assis et al. (2018) and CMEMS (2022)
Net primary production	Sea-surface	mgC m^{-3} day^{-1}	2017–2021, 2050	Annual	0.5°	Coro et al. (2023a)	Tyberghein et al. (2012) and Assis et al. (2018)
Species richness	Water column	No.	2017–2021, 2050	Annual	0.5°	Coro et al. (2024d)	–
Stock richness	Water column	No.	2017–2021, 2050	Annual	0.5°	Generated for the present paper from the data in Coro et al. (2024d)	–

vessel transmitted data bought from a data-collector company focussing on the Mediterranean, and (iii) the species distributions were punctually validated in other studies. Moreover, the environmental variables came from resources also used and validated in other risk assessment studies (Carmezim et al., 2022; Coro et al., 2023a, 2024a). Although the selected variables do not cover the entire range of Mediterranean anthropic, climatic, and biological stressors, they include fundamental variables for defining stressors.

In the following, we report details about the variables and their relations with Mediterranean stressors. The variables included cell-wise annual values between 2017 and 2021 at a 0.5° resolution. Data were reprojected at this resolution, through nearest neighbour resampling, when needed. Projections for 2050, under RCP8.5 – that simulate business-as-usual conditions – were available for all variables except fishing activity (Figure S3). Depth and distance from land were assumed static over the years. Species richness came from a combination of ensembles of machine learning-based native-range ecological niche models of over 1500 marine species (fishes and non-fishes) present in the Mediterranean (Coro et al., 2024d) (the list is available in the Supplementary Material). This dataset contains cell-wise species richness estimates, i.e., the number of species for which the cell is a native habitat. We extrapolated stock richness from this set by re-applying habitat-suitability count on the stocks known to be fished in the Mediterranean Sea. We asked regional experts of the EcoScope European project community to provide a list of species of commercial interest in their monitored areas (available in the Supplementary Material). We double-checked this list (of 96 species) on the FAO Global Record of Stocks and Fisheries (i-Marine, 2020) for further verification. Species richness (and stock richness, consequently) projection for 2050 was also available and allowed us to conduct climate change-related evaluations.

We estimated thermohaline circulation intensity classes (low, medium, and high) as an additional environmental variable because of its potential role in altering oxygen and biodiversity (Section 3.1.2). We first calculated the deltas of sea-surface and sea-bottom temperature (ΔT) and salinity (ΔS). Then, we standardised and summed the deltas (ΔTS). Finally, we extracted the quartiles of this sum to distinguish between low (<first quartile), high (>third quartile), and medium (in-between) values.

Fishing activity (trawling, in particular, which has the highest volumes) was available from other studies that quantified the manifest (known and monitored by authorities) and the estimated hidden activity distribution (related to non-monitored and illegal activities) (Coro et al., 2023b, 2024b). It was the only variable directly related to anthropic activity, whose role in Mediterranean ecosystem alteration is crucial (Halpern et al., 2008; Micheli et al., 2013; Coll et al., 2016; Bowler et al., 2020; O'Hara et al., 2021; Tuholske et al., 2021). Fishing activity is influenced by climate change and environmental stressors which alter its distribution (Raybaud et al., 2017; Schickele et al., 2021a,b; Hidalgo et al., 2022). In turn, it contributes to biodiversity and climate change in the Mediterranean (Crain et al., 2008; Halpern et al., 2009b; Côté and Darling, 2010; Froese et al., 2018). Overfishing can strongly alter stocks' productivity, influencing the entire trophic chain and energy flows (Christensen et al., 2014; Coll et al., 2016).

3.2.1. Definition of mediterranean stressors and risks

We conducted different types of risk assessments for the Mediterranean Sea based on the selected variables. In particular:

- **Annual total fishing pressure on species- and stock-rich areas in peculiar environmental conditions**: This assessment estimated the annual (2017–2021) risk in shallow, coastal, and species/stock-rich areas brought by high fishing pressure and thermohaline circulation. A high-intensity concurrency of these factors can indeed alter the ecosystem status from one year to another. For this risk assessment, we defined the following stressors: total fishing effort, species and stock richness, inverse distance from land and mean depth, sea-bottom dissolved oxygen, net primary production, and thermohaline circulation.
- **Annual total fishing pressure on species- and stock-rich areas**: This assessment – unlike the previous risk assessment – did not use thermohaline circulation and only focussed on species and stock richness in shallow and coastal waters subject to high fishing pressure.

- **Annual hidden fishing pressure on species- and stock-rich areas**: This risk assessment focussed on hidden fishing pressure (instead of total) to highlight the hidden (mostly illegal (Coro et al., 2024b)) pressure on species and stocks.
- **Time-averaged total fishing activity pressure on species and stock richness in peculiar environmental conditions**: This assessment studied stressor concurrency based on time-averaged values between 2017 and 2021. It represented a near-past summary of the risk.
- **Total fishing pressure on areas of future stock decrease**: For this assessment, we defined fishing stressor as the average fishing effort between 2017 and 2021, and compared it to the potential future stock decrease in 2050. The stock decrease was the inverse of the delta between the average 2017–2021 stock richness and the future (2050) stock richness. Therefore, we estimated the potential change in fishing regions due to an extensive future shift in stocks' presence, i.e., a potential threat to the current fishing distribution. This would result in new fishing regions, which might be also far from the current ones. Therefore, this risk analysis was meant to alert the countries and companies acting and investing in the regions.
- **Species richness change due to climate change**: This assessment highlighted which species-rich areas would likely lose habitat due to climate change. The selected stressors were species richness and its inverse delta in 2050. The ecological niche projections embedded the effects of habitat change due to climate change.
- **Stock richness change due to climate change**: This risk assessment was similar to the previous one but considered the effects of climate change just on stock habitat loss. It highlighted the areas where stock-related activities would likely change.
- **Climate change hotspots**: This risk assessment estimated the areas that would likely change their environmental conditions in the future. It was based on the deltas of sea-bottom dissolved oxygen, net primary production, and thermohaline circulation between a near past (average over 2017–2021) and 2050.

These eight risk assessments were just a subset of those that could be defined on the selected variables. They covered valuable risk prospects for monitoring authorities, and are usually considered in spatial planning and management decisions. For each risk definition, we produced cell-wise, high-risk classifications, and hotspot distributions.

3.3. Evaluation methodology

3.3.1. Qualitative analysis of the risk hotspots

As the first evaluation step, we qualitatively assessed the consistency of the produced risk hotspots. In particular, we qualitatively compared them with the assessments of other regional and basin-scale studies. We divided the comparisons by macro areas of risk hotspots emerging from our results.

3.3.2. Comparison with an alternative risk assessment method

As the second evaluation step, we quantitatively assessed the difference between our *time-averaged total fishing activity pressure on species and stock richness in peculiar environmental conditions* (hereafter named TFSSE) risk distribution with a similar assessment by Carmezim et al. (2022). This study evaluated the spatially explicit threats of anthropogenic and environmental stressors to fish-species richness. The authors modelled fish richness as a Poisson regression over a combination of covariate variables, which approximately correspond to our stressors. The selected stressors came from FAIR repositories and included sea-surface chlorophyll-a, phosphate concentration, salinity and temperature, bathymetry, distance from land, coastal impact and marine resource exploitation indexes, maritime activity, and fishing effort. The regression was solved through a Bayesian model initialised with general Gaussian and gamma prior distributions. The study produced a spatial distribution (at 0.1° resolution) representing the spatial effect (as a numeric *effect-index*) of the stressors on fish richness. One similarity between our selected stressors and those by Carmezim et al. (2022) is that several environmental variables came from the same data source (BioOracle (Tyberghein et al., 2012; Assis et al., 2018)). Moreover, the measured effect of the stressors on fish richness was conceptually similar to our TFSSE risk. However, the priors and the Poisson relation added explicit constraints on the stressors and fish richness, which could hardly be validated.

Since our workflow produced high-risk locations, we compared them with the locations of highest effect-index in Carmezim et al. (2022), i.e., the regions with values over the third quartile of the effect-index distribution. We compared the two spatial distributions through a 0.5° cell-wise comparison and measured the agreement on high-risk and non-high-risk locations ($\frac{\text{No. of cells with the same assessment}}{\text{No. of cells}}$). We also measured Cohen's kappa to evaluate the agreement with respect to chance agreement (Cohen, 1960).

In summary, we aimed to evaluate whether two different techniques measuring the concurrency of anthropogenic, biodiversity, and environmental stressors in delicate marine areas produced similar high-risk areas in the Mediterranean Sea. The emergence of similar regions would support the reliability of both assessments.

3.3.3. Model sensitivity analysis

Our workflow uses multi-K-means to cluster stressor vectors. We used an unsupervised learning strategy because we wanted vector groups to emerge directly from the data. We specifically wanted to avoid introducing prior information from outside, which would have skewed the results towards prior assumptions.

Several alternatives to multi-K-means are possible. For example, X-means (Pelleg et al., 2000) is an efficient alternative that produces very similar results. DBScan (Deng, 2020) is a density-based algorithm that can automatically infer the number of clusters but is inefficient for big data (Candela et al., 2015). All these models assign exclusive membership to a cluster for every vector. However, one possible criticism is that this assumption might be too strong for borderline vectors distant from their cluster centroids. Therefore, since our workflow performs risk assessment based on centroid classification, such classification might be unsuitable for these vectors.

We verified that multi-K-means classification was suitable for our case study by comparing the Mediterranean results for the TFSSE risk assessment with those obtained by substituting Fuzzy C-means (FCM) to multi-K-means (Dunn, 1973). FCM is a clustering algorithm that allows data points to belong to multiple clusters with varying degrees of membership. The algorithm calculates a degree of membership for each vector based on the distance to the cluster centroids. Compared to K-means, FCM recalculates the centroids based on a weighted average (instead of calculating barycenters), where the weights are the membership-degree values.

We used FCM as an alternative to multi-K-means and evaluated whether the results differed. We classified one vector as corresponding to a high-risk location if it had a high membership degree in at least one high-risk cluster. We assigned a high membership to vectors with a (normalised) membership degree of at least 30%.

A difference between the two approaches would indicate the presence of many borderline vectors falling in low-risk clusters, i.e., an underestimation of the high-risk locations. We calculated this difference year-by-year to evaluate similarity more accurately.

4. Results

4.1. Results of the qualitative analysis of the risk hotspots

The produced hotspot distributions for the risks defined in Section 3.2.1 depended on the choice of the stressors (Figs. 2 and 3).

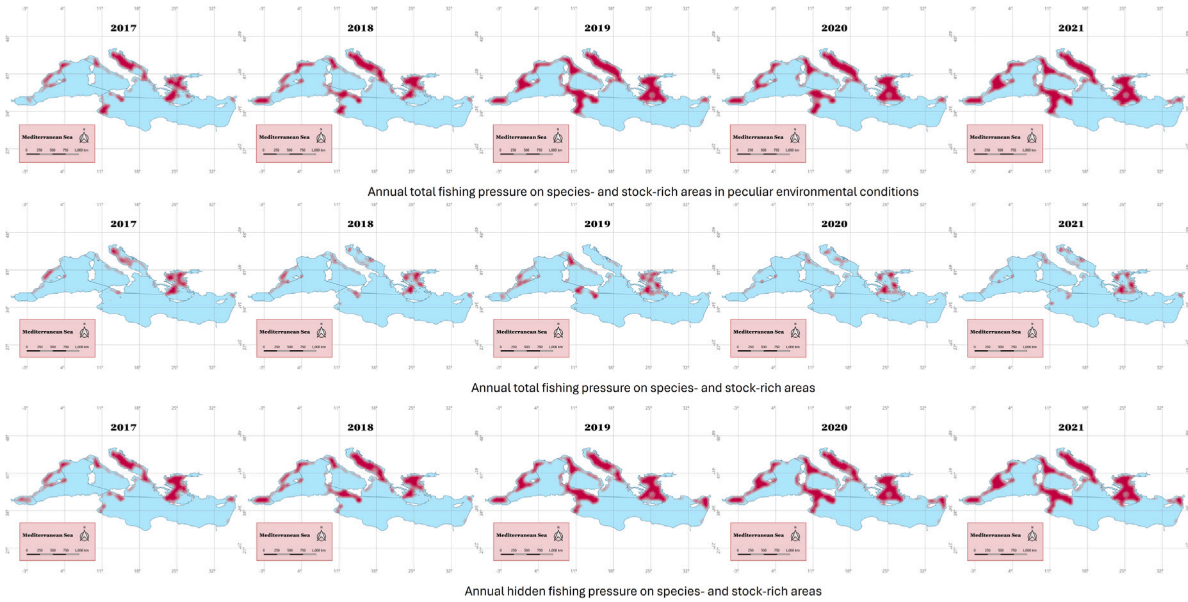

Fig. 2. Hotspots of annual risks, between 2017 and 2021, based on different definitions of the stressor variables. The maps display the values of the kernel density distributions over the third quartile (in red), with the other quartiles faded out. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

However, some macroscopic hotspot areas could be identified across all risk assessments (summarised in Table 2 along with their principal risk factors associated): the Western Mediterranean, the Tyrrhenian Sea, the Adriatic Sea, the Strait of Sicily, the Aegean Sea, and the Gulf of Alexandretta (eastern Turkey). The work of Carmezim et al. (2022) also detected most of these regions. Moreover, our hotspots agreed with many regional studies.

In the Western Mediterranean Sea, our hotspots mostly concentrated off the coasts of Spain and southern France. These areas are rich in biodiversity and stocks but also subject to intense fishing activity. Here, species richness was predicted to change (especially in the Catalan Sea) because of climate change, which would alter the current fishing distribution. These observations agree with regional studies highlighting habitat loss, degradation, and biodiversity change combined with intense fishing activity, especially in the Catalan Sea (Navarro et al., 2015; Calvo et al., 2011; Ramírez et al., 2021; Coll et al., 2024).

In the Tyrrhenian Sea, recurrent risk hotspots were the Ligurian Sea Cetacean Sanctuary and southern Italian coasts, where hidden fishing activity and climate change had major potential roles in affecting stock and species richness. Regional studies have indeed highlighted the potential risks of habitat degradation and species richness decrease, especially in the Ligurian Sea (Cattaneo-Vietti, 2018; Iacono et al., 2021). Factors possibly exacerbating such change are the touristic and industrial development, the intense port activities and the high urbanisation rage of the coasts that alter the environmental conditions and contribute to habitat unsuitability for the resident species (Sabatella et al., 2017).

The Adriatic Sea was a frequent hotspot across our maps. Apart from the deep area of the South Adriatic Pit, which is less subject to trawling, this basin is rich in species and stocks and is strongly stressed by fishing (including hidden fishing) (Coro et al., 2023b, 2024b). In particular, marine protected areas, offshore oil and gas platforms, and coastal areas are frequent targets of illegal fishing (Ferrà et al., 2023). Several regional assessments have also highlighted the concurrency of intense human activity and pollution (especially near the Po River's delta) in vulnerable benthic habitats and prohibited areas, and the intense fishing stressing already depleted stocks (Furlan et al., 2018, 2019; Gallina et al., 2020).

The Strait of Sicily included hotspots off the Italian coasts due to intense fishing (including hidden) in a highly stock and biodiversity-rich area subject to thermohaline circulation. Here, thermohaline circulation generates peculiar environmental conditions with the formation of dense water masses, which influence species presence (Béranger et al., 2004; Jarboui et al., 2022; Patti et al., 2022; Scannella et al., 2022a). According to our maps, the change in future environmental conditions would strongly influence this area's biodiversity, stocks, and fishing hotspots. This observation agrees with several regional expert studies that have suggested giving this area a higher priority in conservation management strategies (Di Lorenzo et al., 2018; Bonanno et al., 2018).

In the Aegean Sea, our maps highlighted the concurrency between intense fishing activity (especially hidden), stocks, and biodiversity, in agreement with other studies (Tsagarakis et al., 2010; Dimarchopoulou et al., 2022). Here, climate change would likely influence many species' habitats as also indicated by regional studies (Zittis et al., 2022; Chatzimentor et al., 2023; Voultsiadou et al., 2013). However, it might not affect fishing distribution which would mostly insist on climate-resilient habitats.

In the Gulf of Alexandretta, recurrent risk hotspots were due to intense hidden fishing in a stock- and species-rich area. This region is a recognised hotspot of illegal fishing activity regarding minimum catch size violations and the use of illegal fishing gears (Öztürk, 2015; Coro et al., 2024b). Our results also indicate that this scenario would not change due to climate change.

4.2. Results of the comparison with an alternative risk assessment

The comparison between our averaged TFSSE risk assessment and the map in Carmezim et al. (2022) highlighted a good level of agreement in key areas (Table 3 and Fig. 4). The overall agreement was 79.6% with a 0.41 kappa (moderate agreement Fleiss, 1971) (Table 3). Agreement regions included the regions off the Tunisian coasts, around Sardinia, the Balearic islands, and the southern French coasts. Moreover, the Adriatic, the Catalan Sea, the Aegean Sea (off Bosporus), the Ligurian Sea, and the southern Italian coasts were areas of particularly high agreement. In the Adriatic, both models recognised the South Adriatic Pit as less subject to stressor concurrency.

The middle Aegean Sea, instead, was not recognised as a risk hotspot by Carmezim et al. (2022). However, in this area their model had the highest uncertainty; therefore, agreement with our model cannot be excluded.

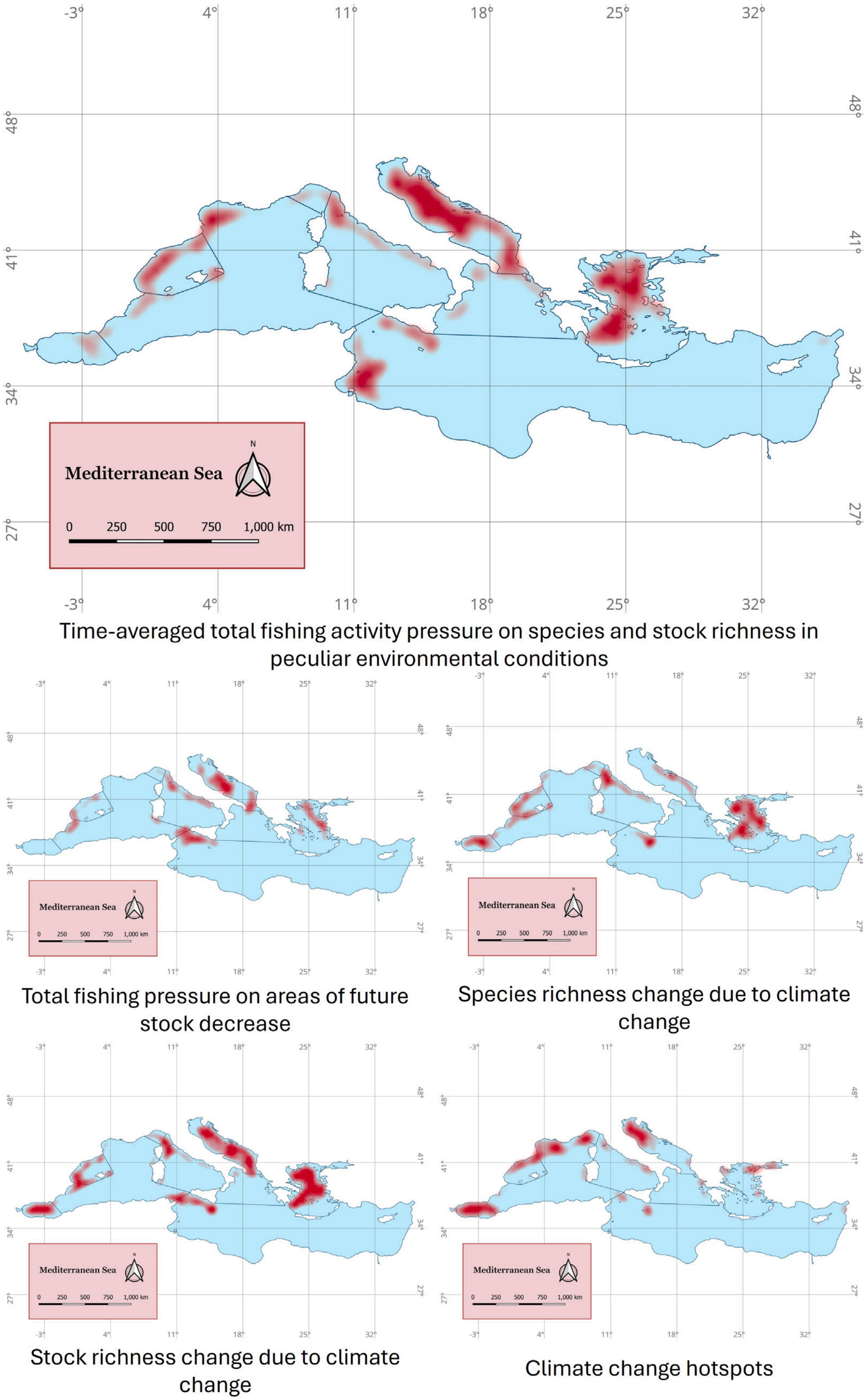

Fig. 3. Hotspots of time-averaged risks based on different definitions of the stressor variables. The maps display the values of the kernel density distributions over the third quartile (in red), with the other quartiles faded out. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

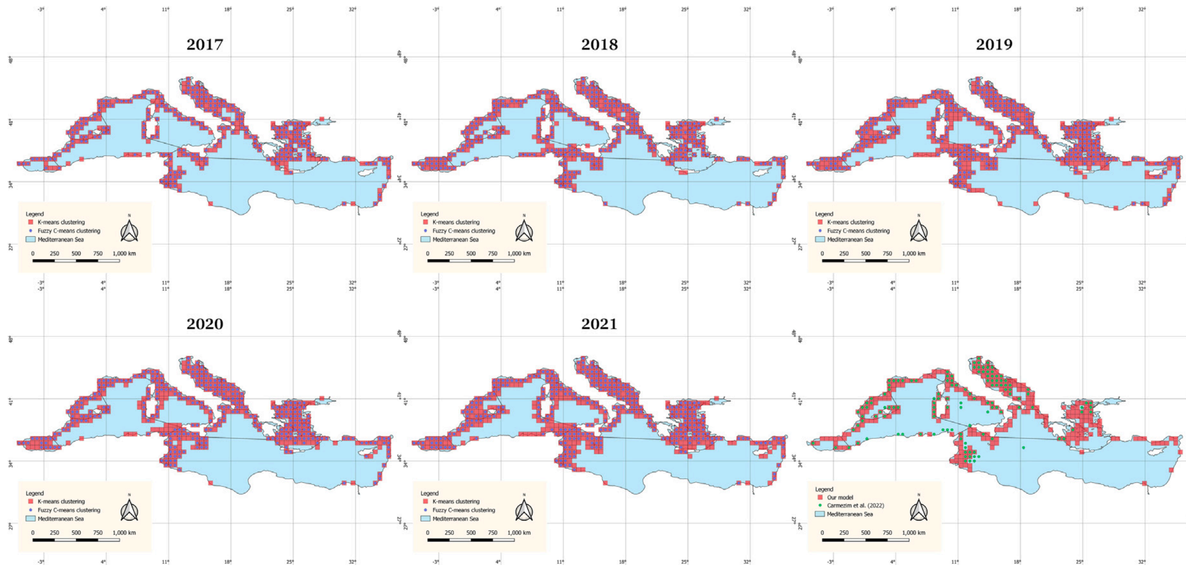

Fig. 4. Comparison between our method (K-means based) and other methodologies (Fuzzy C-Means clustering and Carmezim et al. (2022)) on the estimation of high-risk locations due to fishing activity pressure on species and stock richness in peculiar environmental conditions. The distributions have a 0.5° spatial resolution. In the comparison with Carmezim et al. (2022), our risk assessment was based on data averaged between 2017 and 2021.

Table 2
Summary of the principal Mediterranean risk areas emerging from our analysis, with their main sub-area and risk factors associated, and the potential future changes they would likely undergo.

Principal risk areas	Principal risk sub-areas	Main risk factors	Sub-regions subject to climate change effects	Potential future changes
Western Mediterranean	Spanish coasts (Catalan Sea) and southern French coasts	Intense total fishing pressure on biodiversity and stock-rich areas	Coastal areas	Habitat degradation, stock depletion, and fishing pattern change
Tyrrhenian Sea	Cetacean Sanctuary in the Ligurian Sea and southern Italian coasts	Intense hidden fishing pressure on biodiversity and stock-rich areas	Italian coasts	Habitat degradation, stock depletion, and fishing pattern change
Adriatic Sea	Northern and middle benthic areas, marine protected areas and offshore oil and gas platforms	Intense total and hidden fishing pressure on biodiversity and stock-rich protected areas	Northern area	Habitat degradation and stock depletion
Strait of Sicily	Italian coasts	Intense total and hidden fishing pressure on biodiversity and stock-rich protected areas; peculiar thermohaline circulation influencing species habitat	Northern and southern Italian coasts	Species and stock composition decline and fishing pattern change
Aegean Sea	Coastal areas	Intense total and hidden fishing pressure on biodiversity and stock-rich areas; climate change negative effects on biodiversity and stock composition	Northern coasts and the Bosporus	Habitat degradation and stock depletion
Gulf of Alexandretta (eastern Turkey)	Northern and eastern areas	Intense hidden fishing pressure on biodiversity and stock-rich areas	Syrian coasts	Stock depletion

Carmezim et al. (2022) did not recognise the Gulf of Alexandretta as a significant risk hotspot. However, in this area, our model was primarily driven by hidden fishing intensity, which the other model did not include among the variables.

Overall, considering that the two models used different premises and approaches, they largely agreed and highlighted very similar risk patterns.

4.3. Results of the model sensitivity analysis

The comparison between our TFSSE risk assessments and the ones using FCM indicated very high agreement between the two methods over all years (Table 3 and Fig. 4). The agreement across the years ranged between 89.6% and 95.9%, with kappa between 0.78 and 0.91 (from substantial to almost perfect Fleiss, 1971). The FCM distributions slightly overestimated the multi-K-means distributions.

The high similarity between the two models depended on a strong polarisation of the clusters, i.e., the cluster vectors were very close to their centroids. Consequently, most high-risk vectors often belonged to one cluster only, also in the FCM-based model. When they had more than one membership, they belonged to other high-risk clusters. Therefore, multi-K-means was a suitable unsupervised model for our evaluation case study.

5. Discussion and conclusions

We have presented a workflow for semi-automatically detecting hotspots of risk caused by the concurrent presence of ecosystem stressors. These stressors are defined upon environmental variables (e.g.,

Table 3
Agreement between our method and other methodologies (Carmezim et al. (2022) and Fuzzy C-Means clustering) on the estimation of high-risk locations due to fishing activity pressure on species and stock richness in peculiar environmental conditions. The agreement was calculated on 0.5° spatial resolution cells. In the comparison with Carmezim et al. (2022), our risk assessment was based on data averaged between 2017 and 2021.

	Agreement (%)	Cohen's kappa	Fleiss' interpretation of kappa
Carmezim et al. (2022)	79.6	0.41	Moderate agreement
Fuzzy C-means 2017	95.6	0.88	Almost perfect agreement
Fuzzy C-means 2018	96.0	0.91	Almost perfect agreement
Fuzzy C-means 2019	90.0	0.79	Substantial agreement
Fuzzy C-means 2020	92.8	0.84	Almost perfect agreement
Fuzzy C-means 2021	89.6	0.78	Substantial agreement

temperature, salinity, oxygen, net primary production), fishing activity (e.g., total and hidden), and species richness (e.g., marine species and fisheries stocks). One novelty is the management of risk assessment through clustering and statistical analysis, based on an adaptable definition of the stressors and the risks. Moreover, the unsupervised classification approach allows the workflow to be independent of the spatial area on which it is applied. Our workflow produces general risk-hotspot distribution prospects for monitoring purposes.

We applied the workflow to Mediterranean data to detect areas with a high risk of ecosystem change between 2017 and 2021. Moreover, using environmental and biodiversity projections to 2050, we assessed the potential change of fishing and marine species presence due to climate change. Finally, we highlighted areas of potential significant future environmental change.

The main findings include the identification of major high-risk hotspots in the Adriatic Sea, the Aegean Sea, the Strait of Sicily, the Tyrrhenian Sea, the Western Mediterranean, and eastern Turkey. Intense fishing on species- and stock-rich areas, potentially causing habitat degradation and biodiversity change, was the main risk condition across these areas. Intense hidden fishing was a defining condition for some hotspots, such as those in the Gulf of Alexandretta, the northern Tyrrhenian Sea, and the Adriatic Sea. Another risk factor was thermohaline circulation in biodiversity-rich areas such as the Strait of Sicily. In our analysis, climate change will significantly change the environment and biodiversity of benthic and coastal habitats, especially in the northern Adriatic and the Western Mediterranean, which will alter fishing patterns. These results agree with regional ecosystem change studies.

Most high-risk areas coincided with those highlighted by two different methodologies based on Fuzzy C-means and a Bayesian model, respectively. The substantial agreement (89.6% to 95.9% with kappa between 0.78 and 0.91) with the Fuzzy C-means-based model supported the suitability of our multi-K-means analysis for the case study. The moderate agreement (79.6% with a 0.41 kappa) with a Bayesian supervised model indicated that similar risk patterns were produced, although our process was less complex and did not require pre-training.

Generally, the compliance of our results with other studies and methodologies confirmed the hypothesis that an unsupervised model, such as our workflow, can extract valuable risk patterns in marine ecosystems from open and FAIR big data covering a varied spectrum of information. This concept aligns with other studies (Coro, 2020b; Campana et al., 2021; Coro et al., 2024b).

5.1. Result and workflow reusability

The open-access maps and data we produced contribute to the general understanding of the risks and trends of important driving forces acting in the Mediterranean. We have shown different perspectives on Mediterranean risks that would be useful for spatial planning and other risk assessment models (Russo et al., 2014). Our results would help management authorities support the sustainable use of marine resources in the Mediterranean and their conservation.

Generally, our workflow is a quick and effective tool to support management strategies also in areas other than the Mediterranean. It can produce reliable results at a basin level. The identified hotspots cannot guarantee cell-wise reliability (Queiroz et al., 2021). Rather, they represent aggregated areas potentially at risk, for which the intrinsic bias of big data processing could be accepted (Coro et al., 2024d,a,b). For higher-resolution risk assessment, our maps should be coupled with detailed regional and local investigations.

The maps provide useful prior knowledge to Ecosystem Models based on Bayesian Networks (BN-EMs) (Furlan et al., 2020; Häussler et al., 2020; Lyu et al., 2022, 2024; Wang et al., 2024). These models can incorporate our output as prior information into their nodes to simulate complex interactions between the stressors through the network. For example, BN-EMs can simulate the connections among the trophic chain, species interactions, stressor inter-dependency, and land use. Moreover, they can quantify the uncertainty on future ecosystem predictions (Franklin et al., 2011; Devarajan et al., 2020; Beger et al., 2022). Currently, building a BN-EM requires extensive work by experts, who can directly benefit from our methodology to automatise prior information definition.

5.2. Limitations and future work

One limitation of our method is that the stressors have equal weights, i.e., the centroids assume an equivalent pressure by each stressor. As a future extension, we will allow users to add weights to the stressors to better simulate pressures. Currently, stressor-weight can be simulated at the stressor definition level through a weighting factor on the standardised stressor values. However, from a methodological point of view, such factors are better defined at the model level.

Another limitation is that we modelled concurrency through Euclidean clustering, which internally uses an equal-weight linear combination of the stressor values. Although the statistical analysis improves the reliability of the model, the model itself cannot capture the complex relations between the stressors. Our future work will explore whether these complex relations can be extracted from high-risk clusters and if more complex functions can be used for vector clustering. For example, we will explore causal relations between the stressors to evaluate if a hierarchical schema of the variables can emerge from the data. Additionally, we will explore multi-variate inter-dependencies through deep learning models, such as Variation Autoencoders, which will enable the discovery of complex relations.

CRediT authorship contribution statement

Gianpaolo Coro: Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Laura Pavirani:** Writing – original draft, Validation, Software, Methodology. **Anton Ellenbroek:** Writing – original draft, Validation.

Software and data availability

The source code and all input and output data are available on the Zenodo repository at https://zenodo.org/records/12566786

The repository contains all tables and images, and data-manipulation scripts. It also includes the list of species used to estimate species and stock richness.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Laura Pavirani reports financial support was provided by Ministry of Education and Merit. Gianpaolo Coro reports financial support was provided by H2020 Food Security Sustainable Agriculture and Forestry Marine Maritime and Inland Water Research and the Bioeconomy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102918.

Data availability

The source code and all input and output data are available on the Zenodo repository at https://zenodo.org/records/12566786.

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