frontiers in Marine Science

TYPE Original Research
PUBLISHED 03 September 2026
DOI 10.3389/fmars.2026.1900311

Check for updates

OPEN ACCESS

EDITED BY
Pablo Presa,
University of Vigo, Spain

REVIEWED BY
Wilma Latuny,
University of Pattimura, Indonesia
Mohamed Ibrahim Hassan Farag,
Helwan University, Egypt

*CORRESPONDENCE
Fabio Falsone
fabio.falsone@cnr.it

RECEIVED 04 June 2026
REVISED 29 July 2026
ACCEPTED 04 August 2026
PUBLISHED 03 September 2026

CITATION
Falsone F, Calabrò M, Gancitano V, Garofalo G, Geraci ML, Gjoni V, Lauria V, Sardo G, Scannella D, Vitale S and Fiorentino F (2026) A decision-tree framework for the sustainable management of emerging fisheries and fishing innovations.
Front. Mar. Sci. 13:1900311.
doi: 10.3389/fmars.2026.1900311

COPYRIGHT
© 2026 Falsone, Calabrò, Gancitano, Garofalo, Geraci, Gjoni, Lauria, Sardo, Scannella, Vitale and Fiorentino. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

A decision-tree framework for the sustainable management of emerging fisheries and fishing innovations

Fabio Falsone[1,2]*, Monica Calabrò[1,2], Vita Gancitano[1], Germana Garofalo[1], Michele Luca Geraci[1], Vojsava Gjoni[1,2], Valentina Lauria[1,2], Giacomo Sardo[1], Danilo Scannella[3], Sergio Vitale[1,2] and Fabio Fiorentino[1,4]

[1]Institute for Marine Biological Resources and Biotechnology (IRBIM), National Research Council CNR, Mazara del Vallo, TP, Italy, [2]National Biodiversity Future Center (NBFC), Palermo, Italy, [3]Italian Institute of Environmental Protection and Research, Palermo, Italy, [4]Department of Integrative Marine Ecology, Stazione Zoologica Anton Dohrn (SZN), Palermo, Italy

Introduction: Technological innovation in fisheries can rapidly alter exploitation patterns, often outpacing the capacity of regulatory systems to respond and increasing the risk of stock depletion or collapse. To address this challenge, this study presents a Decision-Tree Framework (DTF) designed to support precautionary and adaptive management when new fishing gears or substantial changes in fishing practices emerge.

Methods: The DTF combines an automated landing-based screening pathway, applied when at least six consecutive annual observations are available, with a structured expert-supported pathway for shorter time series or cases in which technological innovation is already recognised. The framework is implemented in R and as an interactive Shiny application. The performance of the automated landing-based screening component was evaluated through simulations representing abrupt and gradual increases in landings under alternative time-series lengths, effect magnitudes, observation noise levels and temporal autocorrelation conditions. The framework was applied to two contrasting Mediterranean case studies: the silver scabbardfish (*Lepidopus caudatus*) multi-gear fishery and the Mediterranean swordfish (*Xiphias gladius*) trap-line fishery.

Results: Simulation and case-study results show that the DTF can provide early warning signals of potentially unsustainable exploitation and offer transparent guidance for precautionary management actions, even where conventional stock assessments are limited or unavailable. Retrospective application to the scabbardfish fishery indicates that the DTF would have identified an early diagnostic signal and supported the consideration of precautionary management measures, while application to the swordfish fishery demonstrates consistency with precautionary policy decisions adopted under data-limited conditions.

Discussion: Overall, the DTF represents a proactive decision-support tool that operationalizes precautionary and adaptive management principles, enhances transparency in decision-making, and has the potential to support the management of emerging fisheries across diverse contexts, subject to further validation.

KEYWORDS

adaptive management, data-limited fisheries, decision-support framework, emerging fisheries, fisheries management, fishing technology, Mediterranean Sea, precautionary approach

1 Introduction

Effective fisheries management is essential to prevent stock overexploitation and the economic collapse of fisheries, and to ensure that governance systems can respond proactively to changes in fishing practices. Failures in this regard destabilize the fishing sector and threaten food security and coastal livelihoods, thereby posing significant challenges for fisheries governance and policy-making (e.g., Dao et al., 2024; March and Failler, 2022). In response to these challenges, the European Union's Common Fisheries Policy (CFP; Reg. UE 1380/2013) and the General Fisheries Commission for the Mediterranean (GFCM) 2030 Strategy for sustainable fisheries and aquaculture in the Mediterranean and the Black Sea aim to regulate fishing activities to ensure conservation and sustainable exploitation of fisheries resources in European and Mediterranean fisheries, respectively. The most advanced management framework in the Mediterranean region is represented by multiannual management plans (MAPs) adopted by the EU and the GFCM. These binding plans incorporate measures like catch/effort limits, spatio-temporal closures and technical regulations, focusing on long-term sustainability and preventing/reverting overfishing through precautionary and adaptive approaches.

Unlike regions where Total Allowable Catches (TACs) are the primary management tool, the multispecies nature of most Mediterranean fisheries makes the implementation of TACs particularly challenging (Smith and Garcia, 2014). As a result, effort control has become the most widely adopted strategy to limit fishing mortality, shaping the regional governance model (Lleonart and Maynou, 2003). Regulatory measures include restrictions on fleet activity (fishing days) and capacity (GT and engine power), supplemented by technical measures such as minimum conservation reference sizes (MCRS), mesh size regulations, minimum depth requirements (EU Reg. 1241/2019), and seasonal or spatial closures aimed at protecting sensitive species or life stages (Mendoza et al., 2010; Stergiou et al., 2016; Bellido et al., 2017; Fiorentino and Vitale, 2021; Geraci et al., 2023). Although the overall level of fish stock overexploitation in the Mediterranean has decreased over the past decade (FAO, 2025), these strategies have not been sufficient to prevent persistent overfishing. This is partly due to difficulties in ensuring consistent implementation across the Mediterranean, reflecting institutional fragmentation and uneven regulatory capacity among coastal states, as well as limited information on fishing effort and catches from non-EU countries (Marsaglia et al., 2025). Nevertheless, approximately 52% of commercial stocks in the Mediterranean Sea remain overexploited, highlighting a persistent gap between scientific advice and management outcomes (FAO, 2025). This situation reflects ineffective controls on fishing effort, insufficient implementation of scientific advice, and shortcomings in current management measures (Cardinale et al., 2017). In addition, several countries face challenges in establishing effective monitoring, control, and surveillance (MCS) systems to combat illegal, unreported, and unregulated (IUU) fishing (FAO, 2022).

These challenges are not confined to the Mediterranean Sea but they are also evident in other regions of the world (e.g. Indonesia, India, several West African countries, and the North Kenya Banks) where newly established or expanding fisheries, often arising from declines in traditional target species and broader socio-economic changes, are frequently characterized by limited data availability and evolving management frameworks (Sherman et al., 2018; Kamau et al., 2021).

The fisheries management literature has consistently emphasized the need for precautionary and adaptive approaches in such contexts (Garcia et al., 2018; FAO, 2020). Delayed or inadequate regulation can lead to stock depletion and fishery collapse (Hutchings and Reynolds, 2004; Hilborn et al., 2020; Falsone et al., 2021), particularly for slow-growing and late-maturing deep-sea species (Morato et al., 2006) and small pelagic populations with key roles in marine food webs (Mullon et al., 2005; Pikitch et al., 2012). Similar consequences have been documented in the Indo-Pacific, where IUU fishing costs billions of dollars annually, affects coastal livelihoods and food security, and can contribute to local stock collapses (Wilcox et al., 2021). In Lake Malawi, increased fishing effort and the use of illegal small-mesh seine nets led to intensive harvesting of juveniles, reduced spawning biomass and recruitment capacity, and ultimately triggered the collapse of tilapia stocks (Malasha, 2003). Across these examples, fishing pressure increased through technological innovation, market shifts, or expansion into new resources before adequate governance responses were implemented. Such dynamics reinforce the importance of adopting precautionary, proactive, and adaptive management approaches for emerging fisheries.

In this study, the term "*emerging fisheries*" refers to both the development of entirely new fisheries targeting previously unexploited resources and the expansion of existing fisheries, understood as the introduction of new or more efficient fishing gear or substantial modifications to established fishing practices. In cases of expansion, technological innovations can substantially increase catchability and fishing mortality without necessarily being accompanied by changes in nominal fishing effort. Consequently, landings may increase abruptly while the fishery continues to operate under regulatory frameworks designed for previous fishing practices. Emerging fisheries pose specific management challenges. Standard monitoring systems may not be designed to detect technological innovation or rapid exploitation of new species promptly, allowing increases in fishing mortality to remain unnoticed until overfishing becomes evident.

Despite the growing recognition of the need for precautionary and adaptive fisheries management, robust and operational tools for the timely identification of emerging fisheries and the provision of evidence-based decision support remain limited, increasing the risk of stock depletion. Several decision-tree approaches have been proposed in fisheries science (e.g., Hart and Fay, 2020; Harford et al., 2019; Harford, 2020; Dowling et al., 2023), providing structured guidance under uncertainty, but none examines the potential impacts of fisheries undergoing rapid transitions driven by technological innovation and the associated governance and regulatory challenges.

To address this gap, this study develops and validates a Decision-Tree Framework (DTF) conceived as a governance-oriented decision-support tool that assists managers in identifying, justifying, and implementing proactive and precautionary regulatory responses for emerging fisheries, including contexts where data availability may be limited.

The proposed DTF is primarily intended for application in fisheries where: (i) a stock has already been exploited and historical information on landings is available, allowing observed changes to be interpreted relative to a known exploitation baseline; and (ii) the introduction of a new fishing gear or practice modifies catchability within an existing fishery. In addition, the framework can also be applied in more data-limited contexts. When at least six consecutive annual landing observations are available, the automated landing-based screening pathway can be used. When the available series is shorter, the framework follows an alternative pathway based on fishing-effort information, other available fishery evidence and structured expert judgement. To evaluate the quantitative performance of the automated screening component and define the conditions under which it is most informative, this component was tested through simulations representing abrupt and gradual increases in landings under alternative time-series lengths, effect magnitudes, observation noise levels and temporal autocorrelation conditions.

To illustrate its operational utility, the DTF is applied retrospectively to two Mediterranean case studies: (i) the collapse of the silver scabbardfish (*Lepidopus caudatus, Euphrasen, 1788*) fishery following unregulated gear innovation, and (ii) the precautionary limitation of trapline use in the swordfish (*Xiphias gladius*, Linnaeus, 1758) fishery through restricted experimental authorisation. By integrating early diagnostics, adaptive pathways, and explicit expert judgement, the DTF illustrates how a transparent decision pathway could support precautionary recommendations and earlier consideration of management responses in emerging fisheries.

2 Materials and methods

2.1 Rationale and implementation of the decision-tree framework

The Decision-Tree Framework (DTF) is a structured decision-support tool designed to detect and manage risks arising from the introduction of new fishing gears or substantial changes to existing fishing practices within established fisheries. The framework emerged from evidence demonstrating that the introduction of new fishing technologies, in the absence of prompt and specific regulatory action, can quickly reshape exploitation dynamics and, in some cases, precipitate depletion or collapse.

The DTF is explicitly grounded in the precautionary principle. Its primary objective is not to estimate stock status with high analytical precision, but rather to provide an operational, transparent, and reproducible pathway for identifying situations in which technological change may have increased fishing mortality beyond sustainable levels. In this role, the framework functions as a screening and guidance tool, supporting timely management responses when conventional assessment approaches are not yet available or feasible.

The framework was initially developed as a conceptual flowchart to formalize expert decision logic and ensure internal consistency across applications, using Canva (2025). It was subsequently implemented in the R programming environment (R Core Team, 2023) within RStudio (RStudio Team, 2023) to enable standardized and reproducible analyses. Finally, the DTF was deployed as an interactive Shiny application to further enhance accessibility and usability for fisheries managers, researchers, and other stakeholders.

2.2 Conceptual structure and decision logic of the DTF

The DTF is structured as a hierarchical decision pathway comprising several decision nodes, each addressing a distinct diagnostic or management objective (Figure 1). At each step, information is used to reduce uncertainty and narrow the diagnosis. The initial pathway depends on whether technological innovation is already recognised and on the availability of landing data. When a new fishing gear or practice is already known, the framework proceeds directly to its technical and management evaluation. When the innovation is not known, fisheries with at least six consecutive annual landing observations enter the automated screening pathway, whereas shorter series enter an alternative pathway based on fishing-effort information, other available fishery evidence and structured expert judgement. This combined approach reflects how fisheries management works in practice and enhances transparency by documenting where and how quantitative analysis and expert judgement are used. The decision nodes and indicators were selected to represent the sequence of management questions that arise when a new gear or operational practice is suspected: verification of whether the innovation is already known; assessment of landing-data availability; detection of an anomalous landing pattern when the quantitative screening pathway is applicable; expert-supported evaluation of fishing patterns when the available series is shorter; verification of technological change; evaluation of stock-status information; assessment of the adequacy of existing management; and selection of precautionary actions.

The nodes were derived from the precautionary-management logic described above and from governance failures documented in the case-study literature (e.g. Falsone et al., 2021), and were refined iteratively to avoid redundant branches and ensure that each node leads to a defined information requirement or management response.

The framework operates through a stepwise process summarized as follows:

- determining whether the introduction of a new or substantially modified fishing gear or practice is already known;
- assessing whether at least six consecutive annual landing observations are available for the automated screening component;
- applying automated landing-based screening when this minimum requirement is met, or proceeding through an alternative expert-supported pathway based on effort and other fishery information when the available series is shorter;
- examining time series of abundance data for the selected species, derived from both fishery-independent biomass

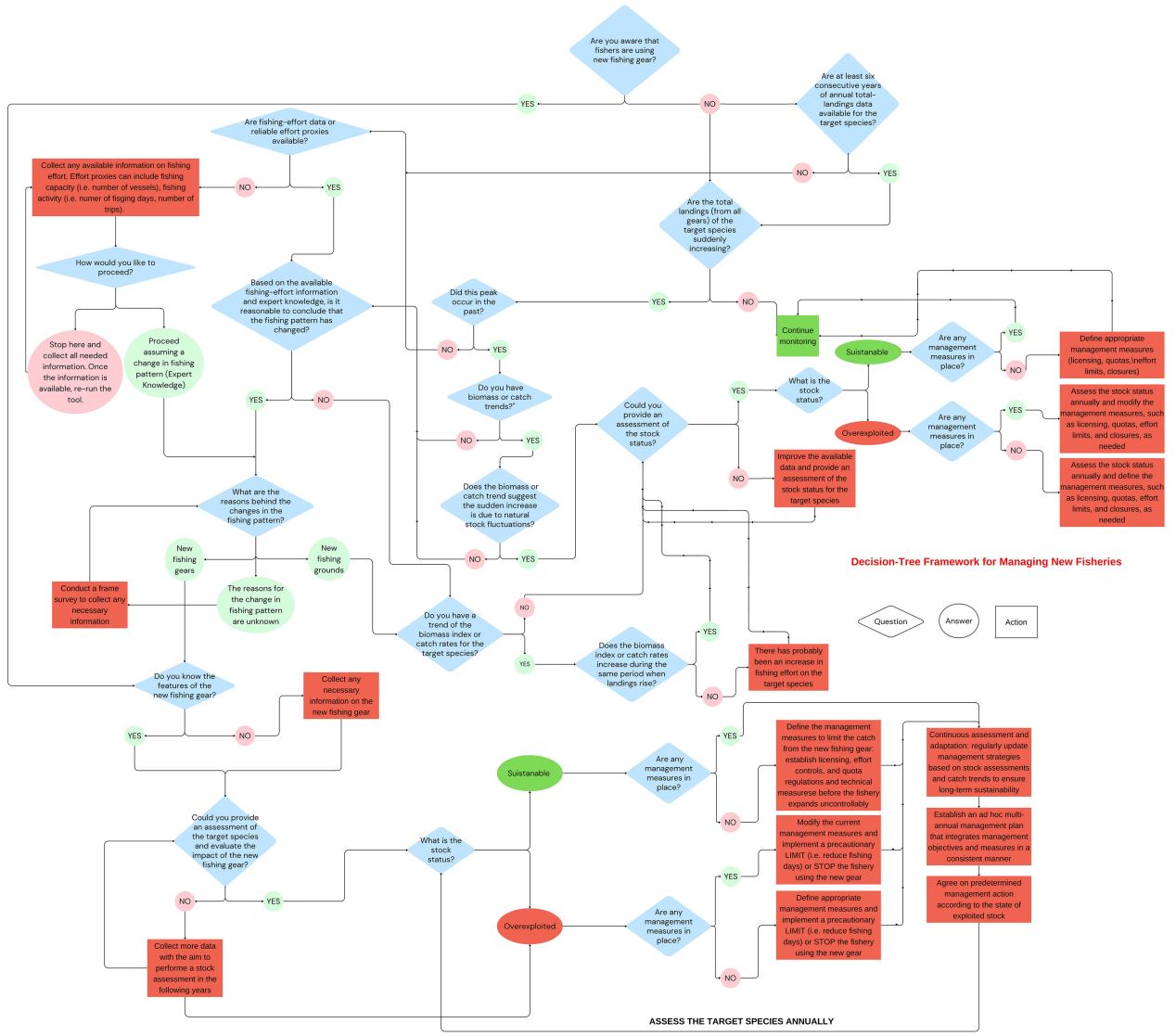


FIGURE 1
Conceptual structure of the decision-tree framework for emerging fisheries and fishing innovations. In light blue, the questions to answer; in green, the situations where a new fishing gear or pattern is probably not developing; and in orange, the actions needed to prevent unsustainable exploitation of fishery resources.

indices and fishery-dependent catch rates, to determine whether observed increases reflect stock fluctuations or the introduction of new fishing practices;

- conducting structured expert assessment and targeted data collection, including frame surveys, harbour observations, fisher interviews, gear inspections and the examination of fleet, effort and fishing-ground information, to verify whether fishing practices have changed and identify their possible causes;
- implementing precautionary measures at an early stage, including fishery authorizations, effort controls, and catch limits, before the increase in fishing mortality becomes uncontrolled;
- defining in advance the management actions corresponding to different states of stock exploitation;
- updating management strategies through continuous assessment within an adaptive framework to ensure long-term sustainability;
- developing *ad hoc* multi-annual management plans that coherently integrate objectives and regulatory measures.

Annual landings were selected as the initial quantitative indicator because they are often the first consistently available signal in established fisheries. When a new fishing gear or practice has not already been formally recognised, the DTF first assesses whether at least six consecutive annual landing observations are available. If this requirement is met, total landings are examined through the automated screening component to identify sudden and persistent increases. When a diagnostic signal is detected, the framework evaluates whether a similar pattern occurred previously, whether it

may reflect stock variability and whether changes in fishing effort or practices provide a plausible explanation. Supplementary abundance indices, catch rates and documented expert evidence are then used to interpret the screening signal. When fewer than six consecutive annual observations are available, the automated screening component is not applied. Instead, the DTF proceeds through an alternative pathway in which available information on fishing effort, fleet activity, fishing grounds, catch rates and other fishery characteristics is evaluated using structured expert judgement. This pathway determines whether there is sufficient evidence that fishing practices or exploitation patterns may have changed and identifies any targeted data-collection needs. When the introduction of a new or substantially modified fishing gear or practice is already formally recognised, the landing-data availability and automated screening nodes may be bypassed. The process then moves directly to the collection of detailed information on the gear and fishing practices in use. Depending on data availability and the degree of novelty of the fishery, landing data are combined with fishery-independent abundance indices and/or commercial catch rates to support stock-status evaluation. For sustainably exploited stocks, monitoring is maintained and existing regulations are confirmed, even where they are not yet specifically adapted to the new gear. For overfished stocks, existing measures are revised or new measures are introduced, including fishery authorisation, effort or catch limits, and spatial or temporal closures. Where formal stock assessment is not possible, the DTF prioritises data collection and applies conservative interim management measures.

For eligible time series, the landing-based screening component uses operational quantitative thresholds rather than standard biological reference points. Minimum percentage increases, effect-size thresholds, composite-score values, statistical-support requirements and persistence criteria were evaluated through the simulation calibration described in Section 2.6 under alternative false-positive-rate constraints. These calibrated criteria apply only to the automated screening pathway and are not used to determine progression through the short-series expert-supported pathway. The selected configuration is therefore an operational early-warning setting whose performance depends on time-series length, observation noise, temporal autocorrelation and the form of the underlying change. These assumptions and limitations are reported explicitly, and the Shiny application documents the diagnostic evidence supporting each candidate breakpoint.

2.3 Role and standardisation of expert judgement

Expert judgement is used at predefined decision nodes where quantitative information is insufficient to determine the appropriate pathway. When automated landing-based screening is applicable, expert judgement complements, rather than replaces, the quantitative analysis by interpreting the detected signal within its fishery-specific context, including changes in gear, fishing practices, effort, fishing grounds, stock dynamics and data reliability. When fewer than six consecutive annual landing observations are available, it supports the alternative diagnostic pathway using the available fishery information (Table 1).

To improve transparency and limit subjectivity, each expert-based decision should document the supporting evidence,

TABLE 1 **Decision components in the DTF that require expert judgement and supporting evidence.**

DTF decision component	Role of expert judgement	Supporting evidence and bias-control measures
Selection of the initial diagnostic pathway	Verify whether the landing series meets the minimum requirement for automated screening and, when it does not, assess whether effort information, reliable proxies and other fishery evidence are sufficient to proceed through the expert-supported pathway.	Number and continuity of annual landing observations; information on changes in reporting or data collection; availability of effort data or proxies; explicit documentation of missing information and the rationale for the selected pathway.
Interpretation of the automated landing signal	Assess whether a detected increase in landings is plausibly linked to increased catchability, effort redistribution, market or reporting changes, or natural stock variability.	Landing trends, CPUE where available, survey abundance indices, fleet dynamics, effort data, and market or regulatory information; explicit recording of alternative explanations, uncertainty and confidence.
Short-series assessment of changes in fishing patterns	When fewer than six consecutive annual landing observations are available, assess whether effort information, reliable proxies and other documented evidence suggest that fishing practices or exploitation patterns may have changed.	Number of vessels, fishing days, trips, gear units, fishing capacity, catch rates, changes in fishing grounds, harbour observations, fisher interviews, logbooks and management records; assessment by more than one expert where possible and explicit documentation of confidence and uncertainty.
Recognition and characterisation of new or modified fishing practices	Determine whether a new fishery, gear, gear modification or operational practice is present and whether it may substantially alter efficiency, selectivity, catchability or access to the resource.	Frame surveys, harbour interviews, vessel and gear observations, gear specifications, fishing grounds, depth, mesh or hook characteristics, electronic devices, logbooks, fisher knowledge and inspection reports; use of predefined technical criteria and direct observations where possible.
Assessment of stock-status information and uncertainty	Decide whether the available information is sufficient to evaluate stock status and the potential effects of the new fishing practice, or whether the pathway should proceed using precautionary assumptions and targeted data collection.	Fishery-independent surveys, commercial catch rates, biological sampling, length- or age-structure data, previous assessments and gear-specific catch or bycatch information; predefined criteria for data sufficiency and documentation of missing information.
Evaluation of management adequacy and response	Assess whether existing measures are adequate for the observed or suspected exploitation pattern and identify feasible interim precautionary or adaptive management responses.	Current regulations, authorisations, licensing systems, effort and catch limits, spatial or temporal closures, monitoring and compliance information, and socio-economic context; documentation of confidence, disagreement and reassessment needs.

confidence level and plausible alternative interpretations. Where experts disagree, the sources of disagreement should be recorded and, where possible, addressed through structured discussion or a formal elicitation process. Expert judgement is therefore treated as a formal and documented source of information rather than as informal opinion (Martin et al., 2012; Morgan, 2014; Hemming et al., 2018).

2.4 Automated detection of peaks and breakpoints in landings

When a new or substantially modified fishing gear or practice is not already known and at least six consecutive annual landing observations are available, the DTF enters the automated landing-based screening pathway. This screening step identifies potential signals of innovation-driven change rather than providing definitive evidence of technological innovation, overfishing or stock status. The analytical module identifies peaks and candidate breakpoints in landing time series and provides an objective and reproducible answer to the decision node: "Does the automated landing-based screening identify a sudden and persistent increase in total landings?" The six-year requirement applies exclusively to this quantitative component. When fewer than six consecutive observations are available, the framework proceeds through the expert-supported pathway described in Sections 2.2 and 2.3. For eligible time series, all candidate breakpoint years are evaluated by comparing landings before and after each potential breakpoint. For each candidate split, normality of the pre- and post-breakpoint observations is assessed using the Shapiro–Wilk test (Shapiro and Wilk, 1965), while homogeneity of variance is evaluated using the Fligner–Killeen test (Fligner and Killeen, 1976). A one-sided Student's *t*-test is used when both assumptions are supported; otherwise, a one-sided Wilcoxon rank-sum test is applied (Wilcoxon, 1945; Mann and Whitney, 1947; H_A: values after the breakpoint are greater than those before it; α=0.05). Because candidate segments may contain as few as three observations, the assumption tests are treated as diagnostic indicators rather than definitive assessments. The selected test and its diagnostic results are therefore reported transparently. The magnitude of change is additionally quantified using Cohen's *d* (Cohen, 1988), calculated as:

$$d = \frac{M_2 - M_1}{SD_{pooled}}$$

Where M_2 and M_1 are the means of the two groups, and SD_{pooled} is the combined standard deviation of the two groups.

To integrate statistical evidence and effect magnitude into a single diagnostic indicator, a composite score is computed for each candidate breakpoint as:

$$\text{Score} = (1 - p) \times |d| \times (\Delta\% / 100)$$

where p is the p-value from the selected one-sided comparison, d is Cohen's d, and Δ% is the percentage increase in mean landings after the candidate breakpoint.

Because multiple candidate breakpoint years are screened within each time series, p-values are not interpreted as confirmatory evidence from independent hypothesis tests. Instead, they are used as one component of an operational ranking procedure, together with effect size and relative increase in landings, to identify candidate transition years requiring further investigation.

The Ljung-Box test and lag-1 autocorrelation are used to evaluate temporal dependence in the landing series (Ljung and Box, 1978). As temporal autocorrelation can affect inferences drawn from fisheries time-series data and fishery-dependent indicators, it is not considered to invalidate the screening procedure in itself. Rather, it is reported as a diagnostic feature of the time series and used to qualify the interpretation of p-values (Pyper and Peterman, 1998; Maunder and Punt, 2004). When temporal dependence is detected, the breakpoint is therefore primarily interpreted as an early-warning signal requiring further investigation rather than as definitive evidence of a structural change in exploitation dynamics.

The breakpoint associated with the highest composite score is retained as the most plausible diagnostic signal of a change in landings that may be consistent with a technology-driven increase in catchability. When such a signal is detected, it triggers progression through the subsequent DTF nodes, where its possible causes and management relevance are evaluated using expert judgement and supplementary fishery information. When no signal is detected, continued monitoring and periodic repetition of the analysis are recommended. Importantly, this automated breakpoint analysis is not intended to provide definitive evidence of stock status, nor to replace formal stock assessment methods. Rather, it provides a standardised, transparent, and reproducible diagnostic entry point into the decision framework, supporting the early identification of changes in fishing practices and the activation of precautionary management responses when evidence suggests that exploitation dynamics may have shifted.

2.5 Shiny application

The DTF has been implemented as an interactive Shiny web application to facilitate its operational use and to ensure transparency, standardisation and reproducibility of the decision-making process. The application is publicly available at https://decisiontreetool.shinyapps.io/dtf-shiny/ and provides a guided interface that allows users to upload landing data, identify the appropriate initial diagnostic pathway and navigate the subsequent decision nodes. The source code, simulation scripts, example data and manuscript figures are publicly available at https://github.com/FabioFalsone/DTF-emerging-fisheries.

Upon data upload, the application checks the format, number and continuity of the annual observations. Series comprising at least six consecutive annual observations enter the automated landing-based screening pathway, whereas shorter or non-consecutive series are redirected to the expert-supported pathway based on fishing-effort information, reliable proxies and other available fishery evidence.

For each eligible candidate breakpoint, the application reports the Shapiro–Wilk results for the pre- and post-breakpoint segments, the Fligner–Killeen test, the selected one-sided comparison test, its p-value, mean landings before and after the breakpoint, sample sizes, percentage increase, Cohen's *d*, Ljung–Box and lag-1 autocorrelation diagnostics, and the composite score. Results are

presented through annotated landing trajectories and a table containing all evaluated candidate breakpoints. The supported candidate with the highest composite score is retained as the principal diagnostic signal and guides progression through the subsequent expert-supported decision nodes.

The application also displays the selected decision pathway and corresponding management recommendation and allows users to export the decision-tree diagrams, statistical outputs and textual summaries. A worked example based on the silver scabbardfish (*L. caudatus*) case study illustrates the interaction between automated screening and expert-supported decisions.

Finally, the application allows users to export all outputs, including: (i) high-resolution PNG and PDF diagrams of the decision tree generated via Graphviz with the selected pathway highlighted, and (ii) bullet-point summaries of the decision pathway in plain text or PDF format. Together, these features ensure a fully documented, traceable and reproducible decision-support process that can be applied consistently across fisheries experiencing rapid technological change.

To improve usability and facilitate adoption by first-time users, the application also includes a fully worked example based on the silver scabbardfish (*L. caudatus*) case study. This example allows users to explore a pre-filled decision pathway and corresponding outputs, including graphical representations of the decision tree, diagnostic plots, and management recommendations. The example is intended to illustrate the expected behaviour of the tool, clarify the interpretation of intermediate results, and demonstrate how quantitative diagnostics and expert-based decision nodes interact within the framework. By providing a guided example, the application supports self-contained exploration of the DTF without requiring prior familiarity with the underlying methodology or immediate access to user-specific data.

2.6 Simulation-based validation and sensitivity analysis

To evaluate the operating characteristics of the automated landing-based screening component, an independent Monte Carlo simulation framework was developed using repeated stochastic simulations under controlled conditions (Metropolis and Ulam, 1949). The simulation analysis was designed to quantify the conditions under which the automated screening component provides reliable early-warning signals.

Simulated landing time series were generated under five scenarios that were representative of emerging fisheries and technology-driven changes in fishing practices, namely: (1) no change; (2) an abrupt moderate increase; (3) an abrupt strong increase; (4) a gradual expansion; and (5) an expansion followed by a peak and a decline. The simulation design varied five main factors: time-series length (set to 8, 10, 15, 20 or 30 years), temporal autocorrelation (simulated using an AR(1) process with φ = 0, 0.3 or 0.6), observation noise (represented by coefficients of variation of 0.10 and 0.25), magnitude of change (represented by effect multipliers of 0.40, 0.80 and 1.25), and breakpoint position (placed at 30%, 50% or 70% of the time series). Representative examples of the simulated trajectories, including the influence of temporal autocorrelation and observation noise, are provided in Supplementary Figure 1.

The simulation workflow consisted of two sequential phases. In the first phase, 20,000 simulated time series were generated by randomly sampling combinations of the above-described simulation factors. This calibration phase was used to screen alternative DTF threshold settings and composite-score weighting schemes. The threshold combinations included alternative minimum percentage increases in landings, minimum absolute effect sizes, and minimum score values. There were also requirements relating to statistical support and persistence criteria based on the number of positive post-breakpoint differences. We compared four weighting formulations of the composite score: equal weighting of the p-value, effect size, and percentage increase; effect-priority weighting; percentage-increase-priority weighting; and a formulation excluding the p-value component. Candidate configurations were ranked using an operational utility criterion, which was defined as the proportion of useful detections within ±2 years, minus a penalty for false-positive detections. The configurations were evaluated under false-positive-rate constraints of 0.05, 0.10 and 0.15.

In the second phase, the selected configurations were evaluated using a full factorial performance design. For each combination of scenario, time-series length, autocorrelation, observation noise, effect magnitude and breakpoint position, 100 stochastic replicates were generated. The DTF was applied to each series using the automated breakpoint-detection routine implemented in the Shiny application. Because the true transition boundary was known, the estimated transition year could be compared directly with the simulated reference year.

Performance was evaluated using complementary classification metrics. Detection rate, equivalent to recall, was defined as the proportion of series with a true change in which the DTF detected a transition. The false-positive rate was the proportion of no-change simulations in which a transition was incorrectly detected, whereas the false-negative rate was the proportion of changed series in which no transition was detected. Precision was defined as the proportion of detected transitions corresponding to true simulated changes, and the F1-score as the harmonic mean of precision and recall, balancing missed detections and false alarms (van Rijsbergen, 1979; Sokolova and Lapalme, 2009).

Temporal accuracy was evaluated only when a true change was present and detected. Temporal error was calculated as the estimated transition year minus the true boundary, with positive and negative values indicating delayed and early detection, respectively. Mean temporal error assessed directional bias, mean absolute error quantified average deviation regardless of direction, and root mean squared error gave greater weight to large errors. Detections were also classified as useful when they occurred within ±1 or ±2 years of the true transition boundary, indicating whether the signal was sufficiently close to the onset of change to support early management action.

Finally, sensitivity analyses examined whether the performance of the automated landing-based screening component depended on the selected thresholds or on the four composite-score weighting schemes, or was instead driven by the magnitude, direction and persistence of the increase in landings.

3 Results

Results are presented in two complementary stages. First, simulation experiments were used to evaluate the performance and operational limits of the automated landing-based screening component under alternative landing trajectories, time-series lengths, effect magnitudes, observation-noise levels and temporal autocorrelation conditions. Second, the framework was applied retrospectively to two Mediterranean fisheries to illustrate its operation under contrasting conditions of data availability, technological innovation and institutional recognition. The silver scabbardfish and swordfish trap-line cases were used to examine the decision pathways generated by the DTF and their consistency with documented fishery outcomes and management responses.

3.1 Simulation performance of the automated landing-based screening component

The simulation analysis revealed that the performance of the automated landing-based screening component depended on the type and rate of change in the simulated landing trajectory. The framework performed best under abrupt and relatively rapid expansion scenarios. Abrupt strong increases showed the highest useful-detection rate, with 98% of detections occurring within ±2 years of the true simulated transition boundary, whereas the corresponding rate was 71% for abrupt moderate increases (Figure 2A). Detailed results across time-series lengths, effect magnitudes and autocorrelation levels are provided in Supplementary Figure 2. Representative simulated trajectories under different scenarios, observation-noise levels and autocorrelation conditions are shown in Supplementary Figure 1.

Performance was lower for more complex or gradual changes. The useful-detection rate was 59% for the expansion-followed-by-peak-and-decline scenario and 26% for gradual expansion (Figure 2A). Temporal accuracy followed the same general pattern. Median temporal error was close to zero for abrupt moderate and abrupt strong increases, with mean absolute errors of 0.4 and 0.2 years, respectively. In contrast, the expansion-followed-by-peak-and-decline scenario showed a modest positive temporal error and a mean absolute error of 1.4 years, while gradual expansion showed the largest delay and a mean absolute error of 3.9 years (Figure 2C). More detailed distributions of temporal error across time-series lengths and autocorrelation levels are presented in Supplementary Figure 3. These results suggest that the DTF is better suited to identifying abrupt or relatively rapid shifts in exploitation patterns than to detecting slow monotonic trends.

False-positive performance depended primarily on observation noise and temporal autocorrelation. Under low observation noise (CV = 0.10), false-positive rates remained close to zero across all time-series lengths and autocorrelation levels. Under higher observation noise (CV = 0.25), false-positive rates increased, particularly when temporal autocorrelation was strong, reaching or slightly exceeding the 10% reference level under some conditions (Figure 2B). The calibration analysis also revealed a trade-off between useful detection and false-positive control across alternative threshold configurations (Supplementary Figure 5). However, the four composite-score weighting schemes produced very similar utility distributions and broadly overlapping detection–false-positive trade-offs (Supplementary Figures 4, 5). This indicates that the performance of the automated landing-based screening component was not strongly determined by a single weighting choice or by the inclusion of the p-value component alone, but rather by the combined evidence of the magnitude, direction and persistence of the increase in landings.

3.2 Retrospective case-study applications

The DTF was applied retrospectively to two Mediterranean fisheries that experienced technological innovation under different data-availability and governance contexts. The first case examines the silver scabbardfish (*L. caudatus*) fishery in the Strait of Sicily, where technological innovation was not formally recognised until after the fishery collapse. The second focuses on the trap-line fishery for Mediterranean swordfish (*X. gladius*), where technological change was immediately known but quantitative information on gear-specific impacts was limited. For each case study, the results document the detection or recognition of innovation-driven changes, the decision pathway followed through the DTF, and the consistency of the framework recommendations with documented fishery outcomes and management responses.

3.2.1 Case study 1: the silver scabbardfish fishery in the Strait of Sicily

The fishery for silver scabbardfish off the southern coast of Sicily in the Central Mediterranean provides a clear example of the management challenges associated with rapid technological innovation. This resource was traditionally exploited using longlines, but in the early 1990s fishers based in Sciacca introduced a new semi-pelagic trawl net, locally known as the *spatolara* (Falsone et al., 2021). This gear, characterised by a vertical opening of 5–8 metres, allows the efficient capture of scabbardfish by exploiting the species' midwater distribution.

The *spatolara* fleet expanded rapidly, increasing from a single vessel in 1993 to ten vessels by 2007, with reported landings peaking at approximately 1,200 tonnes in 2011. This expansion occurred in the absence of a dedicated management plan, and the uncontrolled increase of fishing effort led to overexploitation of the stock. By 2018, landings had declined to 169 tonnes per year, supported by only one remaining active vessel (Falsone et al., 2021). Available evidence from recent MEDITS scientific surveys indicates that the stock has not yet recovered, suggesting that it remains vulnerable and currently unable to support additional fishing pressure from this gear (MEDITS, unpublished data, 2024).

The retrospective application of the DTF to this case study illustrates how the framework would have identified a strong diagnostic signal consistent with a technology-driven change in exploitation dynamics under the precautionary approach. Automated analysis of landing data identified a significant breakpoint in 2006 (Figure 3). Mean landings increased by 143% when comparing the periods 2004–2006 and 2007–2018, a sharp

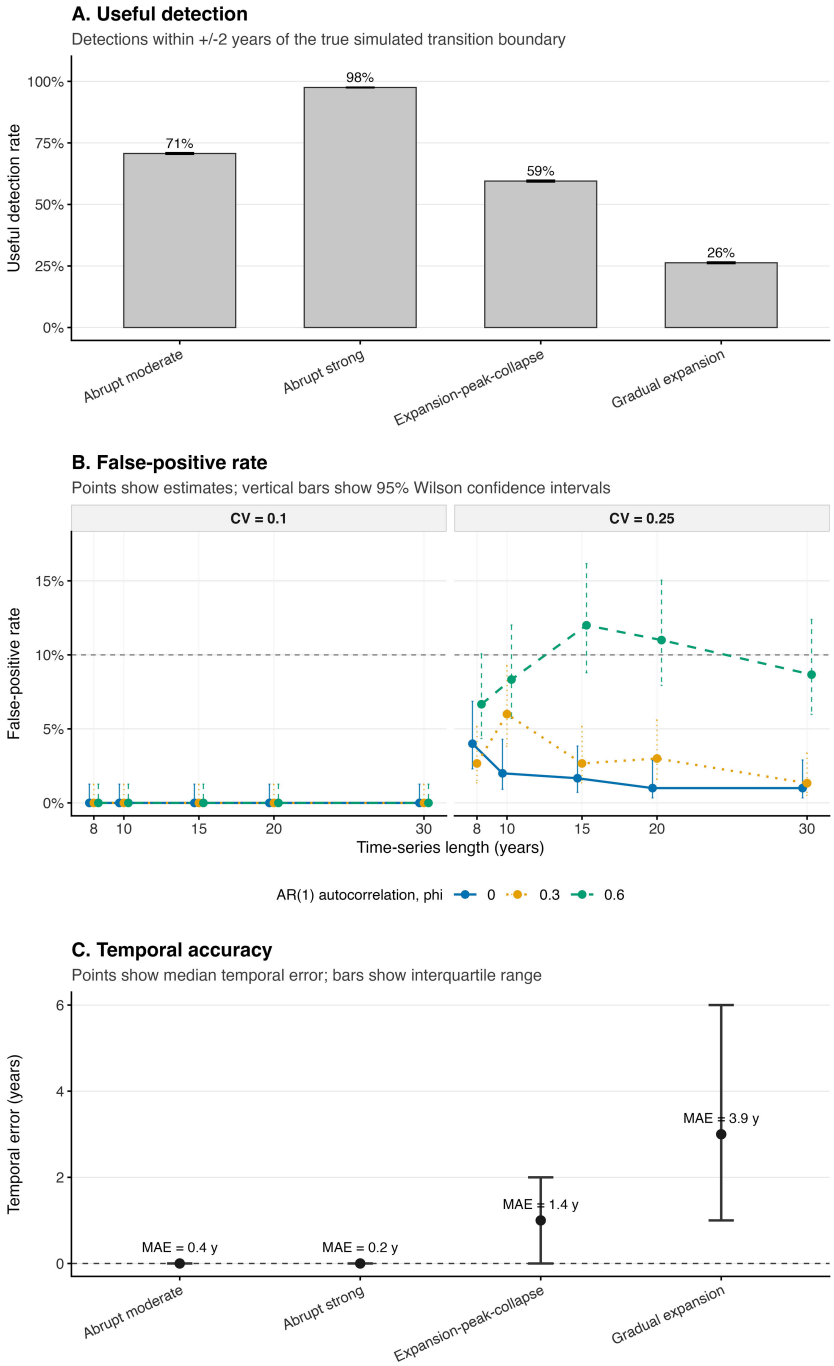


FIGURE 2
Summary of the performance of the automated landing-based screening component across simulated landing scenarios. **(A)** Useful-detection rates within ±2 years of the true transition boundary. **(B)** False-positive rates under different observation-noise levels, time-series lengths and AR(1) autocorrelation values; bars indicate 95% Wilson confidence intervals and the dashed line marks the 10% reference threshold. **(C)** Temporal accuracy across scenarios; points show median temporal error, bars indicate the interquartile range and labels report mean absolute error.

increase that is consistent with the rapid expansion of the spatolara fishery. According to the DTF logic, the detection of this breakpoint would have triggered subsequent diagnostic steps, including verification of the introduction of new fishing gear and evaluation of stock status.

Given the overexploited condition of the stock and the absence of specific regulatory measures at the time, the DTF pathway (Figure 4) would have guided the adoption of early precautionary management actions, such as limits on fishing effort, catch quotas, mesh size regulations, and fishery closures. Under high-risk conditions, the framework would also have indicated the need to consider the precautionary suspension of the fishery, subject to regular review. Although retrospective application cannot demonstrate causality or establish whether the collapse would have been avoided, the case shows that a formalised precautionary pathway could have supported earlier regulatory consideration, even in the absence of a complete stock assessment, before exploitation reached unsustainable levels.

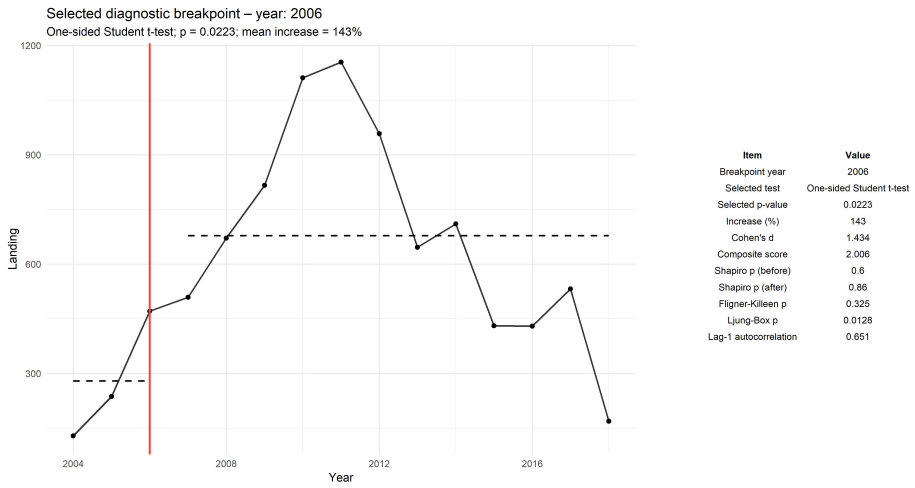


FIGURE 3
Statistical breakpoint analysis of silver scabbardfish (Lepidopus caudatus) landings in the Strait of Sicily. The red line indicates the detected breakpoint (2006), while the black dashed lines represent the mean landings before and after the breakpoint.

3.2.2 Case study 2: the trap-line fishery of swordfish

Another illustrative case concerns the use of trap-line gear to catch swordfish in the Mediterranean Sea. This fishing gear consists of six to eight concentric nylon rings surrounding a central bait, which is sometimes fitted with an LED light. Swordfish become entangled in the line when attacking the bait (Garibaldi et al., 2024). Recent scientific studies (ICCAT, 2024), based on technical reports and fishing plans submitted in 2024 to the ICCAT Scientific Committee under Recommendation 16–05 and describing the recent use of this gear in the Mediterranean swordfish fishery (notably by fleets operating in Spain, Italy and Portugal), have noted that this gear represents a novel technique. Although still limited, available evidence indicates that this device may improve swordfish catch rates while offering greater selectivity and reducing bycatch of non-target species, including seabirds and turtles, compared with traditional longlines (Báez et al., 2026). However, its rapid adoption, largely driven by its superior catch efficiency, was accompanied by immediate concerns regarding its potential impact on an already exploited stock. Unlike the silver scabbardfish case, the presence and use of a new fishing gear targeting swordfish were already known at the time of management concern. Because the technological innovation was already explicitly recognised, the DTF bypasses the initial landing-based screening and proceeds directly to the evaluation of the technical characteristics and potential impacts of the new gear. As illustrated in Figure 5, the framework therefore focuses on confirming the technical characteristics of the gear, assessing the exploitation status of the stock, and determining whether appropriate management measures are already in place. Given the limited availability of quantitative information and the known overexploited status of the swordfish stock in the Mediterranean (ICCAT, 2020), the DTF adopts a precautionary management perspective. In the absence of robust and gear-specific assessments, the framework indicates that conservative assumptions should be applied when evaluating the potential impacts of the new fishing practice. Under these conditions, the DTF would guide managers towards modifying existing management measures and implementing precautionary limits, such as reducing fishing days or temporarily suspending the use of the new gear, pending regular reassessment as additional information becomes available. By explicitly linking innovation-driven risks to precautionary management responses, the DTF provides a transparent and traceable justification for restrictive measures under uncertainty, including precautionary limits on trap-line use through restricted experimental authorisation, while supporting consistency with long-term sustainability objectives.

4 Discussion

4.1 Simulation performance and operational implications

This study presents a DTF as a novel decision-support framework for detecting and managing potential fish stock collapse due to the introduction of new fishing practices within established fisheries. Although developed primarily for this purpose, the DTF can also be applied to entirely new fisheries targeting previously unexploited resources. The six-year minimum requirement applies exclusively to the automated landing-based screening component and should not be interpreted as a waiting period before the framework can be used. When shorter series are available, the DTF remains operational through the expert-supported pathway based on fishing-effort information, reliable proxies, other fishery evidence and targeted data collection.

The core value of the framework lies in its capacity to facilitate early, proactive, and precautionary management responses aimed at minimizing the risk of unsustainable exploitation (Figure 1). The strength of the DTF lies in its flexibility and adaptability across a range of information contexts, rather than being limited to data-limited situations alone. Depending on data availability, the framework can operate using landing data as a diagnostic trigger before



FIGURE 4
Application of the decision-tree framework (DTF) to the case of the silver scabbardfish (Lepidopus caudatus) fishery off the southern coast of Sicily. The blue boxes represent the diagnostic questions guiding the evaluation pathway, the black text indicates the corresponding answers at each step, and the green box reports the management recommendation.

progressively integrating additional sources of information, such as fishery-independent abundance indices, commercial catch rates, and expert knowledge. This integration of multiple information sources, together with stakeholder engagement, provides a transparent and adaptive basis for fisheries management, allowing real-time information on fishing effort, gear modifications, and operational practices to inform management decisions and strengthen governance.

Alongside these strengths, the simulation results further clarify the operational domain and limitations of the proposed framework.

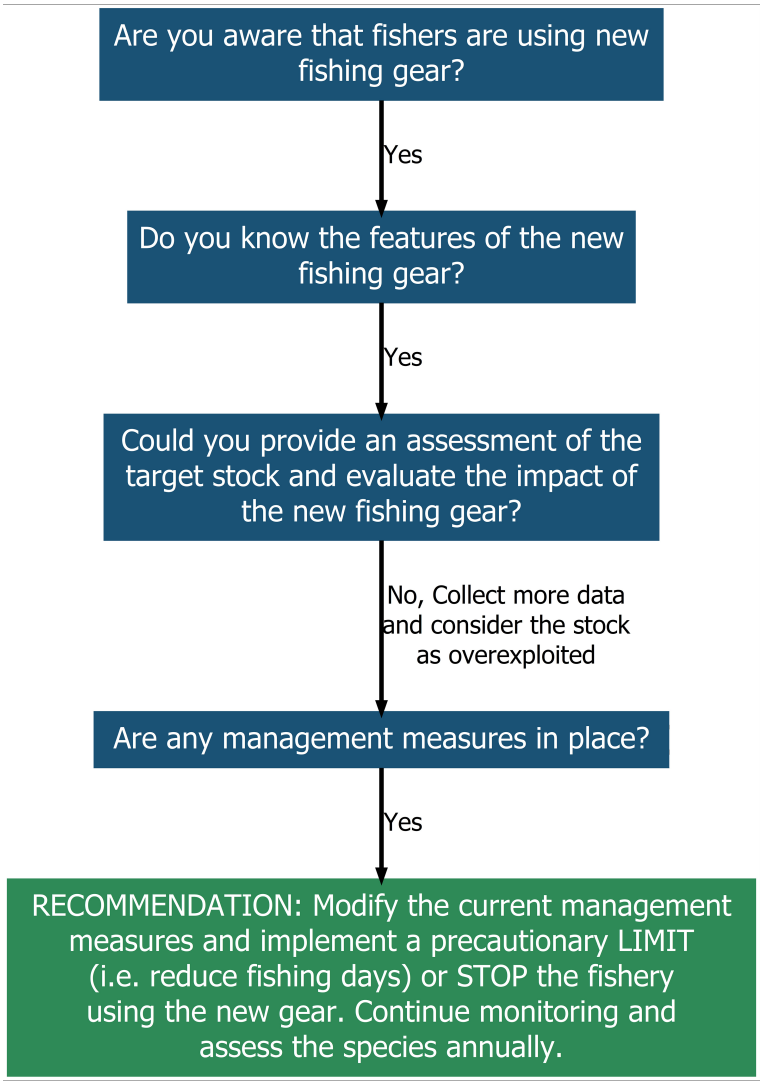


FIGURE 5
Application of the decision-tree framework (DTF) to the swordfish (Xiphias gladius) trap-line fishery in the Mediterranean Sea. The blue boxes represent the diagnostic questions guiding the evaluation pathway, the black text indicates the corresponding answers at each step, and the green box reports the management recommendation.

The automated landing-based screening component should not be interpreted as a general-purpose change-point detector, but as an early-warning procedure designed to identify relatively rapid changes in exploitation patterns that may be associated with emerging fisheries or technological innovation. This distinction is important because the framework performed well under abrupt and relatively rapid expansion scenarios, whereas performance decreased under gradual expansion, especially when temporal accuracy was considered. In slow-developing trends, the change in the underlying process may become detectable only after several years, particularly when observation noise and temporal autocorrelation are high. Under such conditions, the DTF output should be interpreted cautiously and complemented with trend-based analyses, fishery-independent information and expert knowledge.

The sensitivity analyses also support the use of the composite score as an operational ranking metric rather than as a formal inferential statistic. Similar performance across alternative weighting schemes indicates that the identification of candidate transition years was not highly dependent on a single arbitrary weighting choice. The comparable behaviour of the formulation excluding the p-value component further suggests that the diagnostic signal was primarily driven by the magnitude and persistence of the increase in landings. This is consistent with the intended precautionary role of the DTF, in which statistical evidence is considered together with effect size, temporal pattern and contextual information from the fishery.

4.2 Case-study insights

The operational implications of the framework are illustrated by two complementary Mediterranean case studies. In the silver scabbardfish fishery, Falsone et al. (2021) showed how the adoption of new gear, combined with increased fishing effort and inadequate monitoring, assessment, control and surveillance, contributed to rapid expansion and eventual fishery collapse. The retrospective DTF application indicates that a strong and persistent breakpoint in

landings could have triggered investigation of its causes and earlier recognition of the new gear. In the absence of specific management measures, the resulting pathway would have supported precautionary actions such as effort limits, quotas, seasonal closures or, under high-risk conditions, temporary suspension subject to regular review. Although the retrospective analysis cannot establish causality or determine whether collapse would have been avoided, it demonstrates how the DTF could have provided an earlier and more transparent basis for precautionary decision-making.

The swordfish trap-line case represents a different setting because the technological innovation was already formally recognised. The DTF therefore proceeds directly to evaluation of the gear and stock exploitation status. Given that Mediterranean swordfish was already considered overexploited (ICCAT, 2020), the framework would support restrictive precautionary measures. The limitation of trap-line use through restricted experimental authorisation is consistent with the precautionary management pathway identified by the DTF, illustrating the framework's ability to support decisions that are aligned with existing management objectives.

Together, the two cases illustrate complementary functions of the framework: early detection when technological change has not yet been institutionally recognised, and transparent regulatory justification when the innovation is known but its impacts remain uncertain.

4.3 Methodological context and complementarity with existing tools

From a fisheries governance perspective, the Decision-Tree Framework (DTF) addresses a critical gap: the limited capacity of regulatory systems to respond proactively and coherently to technological innovation. By explicitly linking early diagnostic signals to predefined regulatory responses, the DTF operationalises precautionary and adaptive management principles widely endorsed in international fisheries policy (e.g. FAO, 1995; Garcia, 1996; Hilborn et al., 2001). Importantly, the framework improves decision traceability, transparency, and accountability, thereby supporting stakeholder communication and compliance in situations where precautionary restrictions may be contested (e.g. Jentoft, 2000; Degnbol et al., 2006; FAO, 2014). Although developed in a Mediterranean context, the DTF has the potential to be transferred to a wide range of governance settings in which innovation-driven fisheries challenge existing management bodies.

A key strength of the DTF is its specific focus, distinguishing it from broader tools described in the literature. Several examples reinforce the relevance of decision-tree approaches in fisheries management and decision-making under uncertainty. Harford et al. (2019) developed a multi-indicator decision tree for the recreational red abalone (Haliotis rufescens) fishery in California, combining catch-MSY and length-based spawning potential ratio (LB-SPR) into a structured pathway that guided harvest control rules and was tested through management strategy evaluation. Similarly, Dowling et al. (2023) describe the FishPath decision-support tool, which uses structured questionnaires and hierarchical decision trees to identify appropriate combinations of data collection methods, assessment approaches, and management measures, particularly in data- and capacity-limited contexts. To clarify the relationship between FishPath and the DTF proposed here, their main objectives, inputs, outputs and domains of application are compared in Table 2.

This comparison highlights that the DTF is not intended to replace broader frameworks like FishPath, but to address a narrower and more operationally specific management problem that remains largely unexplored in the literature. Whereas FishPath supports the identification of suitable harvest-strategy components across data collection, assessment and management measures, the DTF provides a landing-based early-warning entry point for fisheries undergoing rapid technological change or emerging fishing patterns. Its added value lies in linking an observed quantitative signal to a predefined precautionary decision pathway.

Similarly, other contributions in the literature, while not explicitly structured as decision trees, provide complementary tools. Ralston et al. (2011) proposed a meta-analytic approach to quantify uncertainty in stock assessments and catch advice. Although not formulated as a decision tree, such approaches could be integrated as modules within a DTF, contributing to the refinement of decision rules under uncertainty. Likewise, Harford et al. (2021) introduced a multi-indicator framework for data-limited fisheries, which offers important guidance for indicator selection and integration but does not explicitly adopt a decision tree structure. These approaches nevertheless could contribute to the development of DTFs by strengthening their diagnostic components.

Furthermore, standard risk-based approaches such as Productivity Susceptibility Analysis (PSA) and Ecological Risk Assessment (ERA) address related but distinct decision problems (Patrick et al., 2010; Hobday et al., 2011). PSA ranks the relative vulnerability of stocks using productivity and susceptibility attributes, whereas ERA frameworks evaluate ecological risk by combining exposure with the consequences of fishing. These approaches are particularly useful for prioritising species or ecosystem components when conventional assessments are unavailable. Rather than replacing these methods, the DTF complements them by adding a temporal and governance-oriented dimension that detects or recognises changes in exploitation practices and links those signals to predefined precautionary responses. Consequently, PSA or ERA outputs could be effectively used as supplementary evidence at DTF nodes concerning stock vulnerability, ecological consequences and the adequacy of management measures.

More broadly, the DTF complements existing decision-support frameworks by addressing an earlier stage of the management process, namely the timely recognition of emerging fisheries or technology-driven shifts before conventional stock assessment and harvest-strategy evaluation become feasible.

4.4 Broader limitations and future directions

Beyond the simulation-specific limitations, a broader limitation concerns the expert-supported pathway, particularly when short landing series are available. Although the DTF requires documentation of supporting evidence, confidence and disagreement,

TABLE 2 Complementarity between FishPath and the proposed decision-tree framework in relation to emerging fisheries and technology-driven exploitation changes.

Dimension	FishPath	Proposed DTF	Added value of the DTF
Primary objective	Guides the identification of suitable harvest-strategy components for data- and capacity-limited fisheries (Dowling et al., 2023).	Provides early-warning and precautionary decision support for fisheries undergoing rapid exploitation changes.	Focuses on a specific and operationally urgent management problem: emerging fisheries and technology-driven shifts.
Scope	Broad framework covering data collection, assessment approaches and management measures.	Targeted management framework linking landing-based diagnostics, expert judgement and predefined precautionary pathways.	More operational for rapid screening when technological innovation or new gear adoption is suspected.
Input information	Uses a structured questionnaire on biological, ecological, operational, economic and governance characteristics of the fishery.	Uses landing time series, supplementary abundance or catch-rate information, and expert knowledge on fishing practices and gear changes.	Adds a quantitative diagnostic entry point based on observed changes in landings.
Analytical component	Does not directly detect breakpoints or transitions in landing time series.	Includes an automated breakpoint-screening module to identify candidate transition years in landings.	Converts an observed increase in landings into an explicit early-warning trigger.
Decision pathway	Identifies feasible harvest-strategy options and highlights assumptions, caveats and constraints.	Links detected or known innovation-driven changes to precautionary management actions through a stepwise decision tree.	Provides a direct pathway from signal detection to management response.
Best suited for	Designing or refining harvest strategies across diverse data-limited fisheries.	Detecting and managing emerging fisheries, new fishing gears or rapid changes in catchability.	Useful as a first-response screening tool before or alongside broader harvest-strategy planning.
Main limitation	May be less direct for detecting rapid technology-driven changes in landings.	Narrower than FishPath and not intended to design a full harvest strategy.	The two tools are complementary rather than substitutes.

broader application will require further standardisation of elicitation and reporting procedures. Future versions of the Shiny application could include structured expert forms, confidence scores and procedures for recording alternative interpretations.

Finally, the present study evaluates the framework using two Mediterranean case studies and a simulation design focused on landing trajectories. Future applications across a broader range of fisheries, regions, governance systems, and data contexts will be essential to evaluate the transferability, robustness, and practical applicability of the framework. Reproducibility and future development are supported by the public availability of the Shiny application code, simulation scripts, example data and Supplementary Materials in a versioned GitHub repository (https://github.com/FabioFalsone/DTF-emerging-fisheries), thereby facilitating independent evaluation, refinement, and wider adoption of the framework.

5 Conclusion

This study presents a Decision-Tree Framework (DTF) designed to support the precautionary and adaptive management of emerging fisheries and those undergoing rapid technological or operational change. The DTF provides two complementary diagnostic entry pathways. When at least six consecutive annual landing observations are available, an automated screening component identifies potential changes in landings. When shorter series are available, an expert-supported pathway uses fishing-effort information, reliable proxies and other fishery evidence. Both pathways subsequently converge at the same diagnostic and management nodes.

The simulation analysis defines the operational domain of the automated landing-based screening component, which performed best under abrupt and relatively rapid expansion scenarios. Conversely, performance was weaker under gradual expansion and under conditions of high observation noise and strong temporal autocorrelation. Therefore, the framework should be interpreted as a screening and decision-support tool, rather than as a substitute for formal stock assessment or a general-purpose change-point detection model. Its outputs should be considered as early-warning signals requiring further investigation rather than as definitive evidence of structural change or stock status.

The two Mediterranean case studies demonstrate the framework's various applications. In the silver scabbardfish fishery, retrospective application of the DTF shows that it would have identified an early diagnostic signal in landings and supported consideration of precautionary management measures before the decline became evident. In the swordfish trap-line fishery, the DTF provides a structured rationale for precautionary restrictions in situations of uncertainty, where the use of new fishing gear was already known, but gear-specific information on catchability and impact on fishing mortality was limited. These examples demonstrate how the DTF can organise available evidence and make the reasoning behind precautionary decisions more explicit.

A key strength of the DTF lies in its ability to link a quantitative diagnostic signal to a predefined precautionary decision pathway. This makes the framework particularly useful when conventional stock assessments are unavailable, delayed, or not well-suited to rapid changes in fishing practices. However, the framework remains dependent on the quality of the available information and transparent expert interpretation at specific decision nodes. Any applications should therefore further standardise expert elicitation, confidence scoring and reporting procedures, and evaluate the transferability of the DTF across fisheries, regions, governance systems and data contexts.

Overall, the DTF contributes to a shift from reactive to proactive management of emerging fisheries. Implementing it as

an interactive Shiny application enhances transparency, traceability and reproducibility. The public availability of the application code, simulation scripts, example data and Supplementary Materials through a versioned repository supports its future use, testing and development. While further applications are required, the framework offers managers a practical tool for identifying early risk signals and justifying precautionary responses before exploitation patterns become unmanageable.

Data availability statement

The landing time series and input data used to reproduce the analyses are provided within the tutorial included in the Shiny application and as example data in the accompanying repository. The Decision-Tree Framework is implemented in R and deployed as an interactive Shiny application at https://decisiontreetool.shinyapps.io/dtf-shiny/. The source code for the Shiny application, the automated breakpoint-detection routine, the Monte Carlo simulation and sensitivity analyses, example input data, main-text figures and supplementary materials are publicly available at https://github.com/FabioFalsone/DTF-emerging-fisheries.

Author contributions

FFa: Supervision, Validation, Data curation, Formal analysis, Methodology, Visualization, Conceptualization, Software, Investigation, Writing – review & editing, Writing – original draft. MC: Validation, Visualization, Writing – review & editing. VGa: Writing – review & editing, Visualization, Validation. GG: Supervision, Validation, Writing – review & editing, Visualization. MG: Writing – review & editing, Validation, Visualization. VGj: Writing – review & editing, Validation, Visualization. VL: Visualization, Validation, Writing – review & editing. GS: Writing – review & editing, Visualization, Validation. DS: Writing – review & editing, Visualization, Validation. SV: Visualization, Validation, Supervision, Writing – review & editing. FFi: Validation, Supervision, Conceptualization, Visualization, Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This study was carried out within the framework of the Italian National Programs developed in accordance with the European Data Collection Framework.

Acknowledgments

The authors would like to warmly thank all the technical staff of the CNR in Mazara del Vallo for their support in data collection during the MEDITS and CAMPBIOL modules.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fmars.2026.1900311/full#supplementary-material

References

Báez, J. C., Alegría, A., Moreno, J., Borrego-Santos, R., Salmerón, F., García-Barcelona, S., et al. (2026). Development and results of the pilot project on the efficacy of traplines/loops in the Spanish longline fleet in the ICCAT Area. *Collect. Vol. Sci. Pap. ICCAT* 83, SCRS/2026/051, 1–7.

Bellido, J. M., García-Rodriguez, M., García-Jiménez, T., González-Aguilar, M., and Carbonell-Quetglas, A. (2017). Could the obligation to land undersized individuals increase the black market for juveniles: evidence from the Mediterranean? *Fish Fish.* 18, 185–194. doi: 10.1111/faf.12166

Canva (2025). *Canva: Online Graphic Design Platform*. Available online at: https://www.canva.com (Accessed October 6, 2025).

Cardinale, M., Osio, G. C., and Scarcella, G. (2017). Mediterranean Sea: a failure of the European fisheries management system. *Front. Mar. Sci.* 4, 72. doi: 10.3389/fmars.2017.00072

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences. 2nd ed* (Hillsdale, NJ: Lawrence Erlbaum Associates).

Dao, Y., Yusnaldi, Y., and Kusuma, K. (2024). An analysis of destructive fishing as an anthropogenic disaster in coastal areas: a maritime security perspective. *Nation State J. Int. Stud.* 7, 144–161. doi: 10.24076/nsjis.v7i2.1633

Degnbol, P., Gislason, H., Hanna, S., Jentoft, S., Nielsen, J. R., Sverdrup-Jensen, S., et al. (2006). Painting the floor with a hammer: technical fixes in fisheries management. *Mar. Policy* 30, 534–543. doi: 10.1016/j.marpol.2005.07.002

Dowling, N. A., Wilson, J. R., Cope, J. M., Dougherty, D. T., Lomonico, S., Revenga, C., et al. (2023). The FishPath approach for fisheries management in a data- and capacity-limited world. *Fish Fish.* 24, 212–230. doi: 10.1111/faf.12721

Falsone, F., Scannella, D., Geraci, M. L., Gancitano, V., Vitale, S., and Fiorentino, F. (2021). How fishery collapses: the case of Lepidopus caudatus in the Strait of Sicily (central Mediterranean). *Front. Mar. Sci.* 7, 584601. doi: 10.3389/fmars.2020.584601

FAO (1995). *Code of Conduct for Responsible Fisheries* (Rome: FAO).

FAO (2014). *Voluntary Guidelines for Securing Sustainable Small-Scale Fisheries in the Context of Food Security and Poverty Eradication* (Rome: FAO).

FAO (2020). *The State of World Fisheries and Aquaculture 2020* (Rome: FAO). doi: 10.4060/ca9229en

FAO (2022). *The State of Mediterranean and Black Sea Fisheries 2022* (Rome: FAO). doi: 10.4060/cc3370en

FAO (2025). *The State of Mediterranean and Black Sea Fisheries 2025. General Fisheries Commission for the Mediterranean* (Rome: FAO). doi: 10.4060/cd7701en

Fiorentino, F., and Vitale, S. (2021). How can we reduce the overexploitation of Mediterranean resources? *Front. Mar. Sci.* 8, 674633. doi: 10.3389/fmars.2021.674633

Fligner, M. A., and Killeen, T. J. (1976). Distribution-free two-sample tests for scale. *J. Am. Stat. Assoc.* 71, 210–213. doi: 10.1080/01621459.1976.10481517

Garcia, S. M. (1996). "The precautionary approach to fisheries and its implications for fishery research, technology and management," in *Fao Fish. Tech. Pap*, (Rome: FAO), vol. 350.

Garcia, S. M., Rice, J., Ye, Y., and Charles, A. (2018). *Rebuilding of Marine Fisheries. Part 1: Global Review* Vol. 630/1 (Rome: FAO Fish. Aquac. Tech. Pap).

Garibaldi, F., Di Natale, A., and Zava, B. (2024). A new challenge for assessing the swordfish fishery: the use of an innovative fishing gear. *Collect. Vol. Sci. Pap. ICCAT* 81, 1–9.

Geraci, M. L., Sardo, G., Scannella, D., Falsone, F., Di Maio, F., Gancitano, V., et al. (2023). Exploring the feasibility of technological transfers of two by-catch reduction devices in crustacean bottom trawling of the central Mediterranean. *Front. Mar. Sci.* 10, 1011605. doi: 10.3389/fmars.2023.1011605

Harford, W. J. (2020). *Management Strategy Evaluation: Recreational Red Abalone Management Strategy Integration* (Miami, FL: Report for California Fish and Game Commission).

Harford, W. J., Amoroso, R., Bell, R. J., Caillaux, M., Cope, J. M., Dougherty, D., et al. (2021). Multi-indicator harvest strategies for data-limited fisheries: a practitioner guide to learning and design. *Front. Mar. Sci.* 8, 757877. doi: 10.3389/fmars.2021.757877

Harford, W. J., Dowling, N. A., Prince, J. D., Hurd, F., Bellquist, L., Likins, J., et al. (2019). An indicator-based decision framework for the northern California red abalone fishery. *Ecosphere* 10, e02533. doi: 10.1002/ecs2.2533

Hart, A. R., and Fay, G. (2020). Applying tree analysis to assess combinations of ecosystem-based fisheries management actions in management strategy evaluation. *Fish. Res.* 225, 105466. doi: 10.1016/j.fishres.2019.105466

Hemming, V., Burgman, M. A., Hanea, A. M., McBride, M. F., and Wintle, B. C. (2018). A practical guide to structured expert elicitation using the IDEA protocol. *Methods Ecol. Evol.* 9, 169–180. doi: 10.1111/2041-210X.12857

Hilborn, R., Maguire, J.-J., Parma, A. M., and Rosenberg, A. A. (2001). The precautionary approach and risk management: can they increase the probability of successes in fishery management? *Can. J. Fish. Aquat. Sci.* 58, 99–107. doi: 10.1139/f00-225

Hobday, A. J., Smith, A. D. M., Stobutzki, I. C., Bulman, C., Daley, R., Dambacher, J. M., et al. (2011). Ecological risk assessment for the effects of fishing. *Fish. Res.* 108, 372–384. doi: 10.1016/j.fishres.2011.01.013

Hutchings, J. A., and Reynolds, J. D. (2004). Marine fish population collapses: consequences for recovery and extinction risk. *BioScience* 54, 297–307. doi: 10.1641/0006-3568(2004)054[0297:MFPCCF]2.0.CO;2

ICCAT (2020). *Report of the Standing Committee on Research and Statistics (SCRS)* (Madrid: ICCAT).

ICCAT (2024). Mediterranean swordfish fishing plans submitted in 2024 (Rec. 16-05). ICCAT Working Document PA4_802/2024.

Jentoft, S. (2000). The community: a missing link of fisheries management. *Mar. Policy* 24, 53–59. doi: 10.1016/S0308-597X(99)00009-3

Kamau, J. N., Jacobs, Z. L., Jebri, F., Kelly, S., Kimani, E., Makori, A., et al. (2021). Managing emerging fisheries of the North Kenya Banks in the context of environmental change. *Ocean Coast. Manage.* 209, 105671. doi: 10.1016/j.ocecoaman.2021.105671

Ljung, G. M., and Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika* 65, 297–303. doi: 10.1093/biomet/65.2.297

Lleonart, J., and Maynou, F. (2003). Fish stock assessment in the Mediterranean: state of the art. *Sci. Mar.* 67, 37–45. doi: 10.3989/scimar.2003.67s137

Malasha, I. (2003). "Colonial and postcolonial fisheries regulations: the cases of Zambia and Zimbabwe," in *In Management, Co-Management or No Management? Major Dilemmas in Southern African Freshwater Fisheries. 2. Case Studies*. Eds. E. Jul-Larsen, J. Kolding, R. Overå, J. R. Nielsen and P. A. M. van Zwieten (FAO, Rome), 253–266. Available online at: https://www.fao.org/4/y5056e/y5056e13.htm. FAO Fisheries Technical Paper No. 426/2 (Accessed May 11, 2026).

Mann, H. B., and Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *Ann. Math. Stat.* 18, 50–60. doi: 10.1214/aoms/1177730491

March, A., and Failler, P. (2022). Small-scale fisheries development in Africa: lessons learned and best practices for enhancing food security and livelihoods. *Mar. Policy* 136, 104925. doi: 10.1016/j.marpol.2021.104925

Marsaglia, L., Parisi, A., Libralato, S., Miller, N. A., Davis, P., Paolo, F. S., et al. (2025). Shedding light on trawl fishing activity in the Mediterranean Sea with remote sensing data. *ICES J. Mar. Sci.* 82, fsae153. doi: 10.1093/icesjms/fsae153

Martin, T. G., Burgman, M. A., Fidler, F., Kuhnert, P. M., Low-Choy, S., McBride, M., et al. (2012). Eliciting expert knowledge in conservation science. *Conserv. Biol.* 26, 29–38. doi: 10.1111/j.1523-1739.2011.01806.x

Maunder, M. N., and Punt, A. E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fish. Res.* 70, 141–159. doi: 10.1016/j.fishres.2004.08.002

Mendoza, M., García, T., and Baro, J. (2010). Using classification trees to study the effects of fisheries management plans on the yield of Merluccius merluccius in the Alboran Sea (western Mediterranean). *Fish. Res.* 102, 191–198. doi: 10.1016/j.fishres.2009.11.010

Metropolis, N., and Ulam, S. (1949). The Monte Carlo method. *J. Am. Stat. Assoc.* 44, 335–341. doi: 10.1080/01621459.1949.10483310

Morato, T., Watson, R., Pitcher, T. J., and Pauly, D. (2006). Fishing down the deep. *Fish Fish.* 7, 24–34. doi: 10.1111/j.1467-2979.2006.00205.x

Morgan, M. G. (2014). Use (and abuse) of expert elicitation in support of decision making for public policy. *PNAS* 111, 7176–7184. doi: 10.1073/pnas.1319946111

Mullon, C., Fréon, P., and Cury, P. (2005). The dynamics of collapse in world fisheries. *Fish Fish.* 6, 111–120.

Patrick, W. S., Spencer, P., Ormseth, O., Cope, J., Field, J., Kobayashi, D., et al. (2010). Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. *Fishery Bull.* 108, 305–322. doi: 10.1177/0002716284475001036

Pikitch, E. K., Boersma, P. D., Boyd, I. L., Conover, D. O., Cury, P., Essington, T., et al. (2012). *Little Fish, Big Impact: Managing a Crucial Link in Ocean Food Webs* (Washington, DC: Lenfest Ocean Program).

Pyper, B. J., and Peterman, R. M. (1998). Comparison of methods to account for autocorrelation in correlation analyses of fish data. *Can. J. Fish. Aquat.Sci.* 55, 2127–2140. doi: 10.1139/f98-104

Ralston, S., Punt, A. E., Hamel, O. S., DeVore, J. D., and Conser, R. J. (2011). A meta-analytic approach to quantifying scientific uncertainty in stock assessments. *Fish. Bull.* 109, 217–231.

R Core Team (2023). *R: A Language and Environment for Statistical Computing* (Vienna: R Foundation for Statistical Computing).

RStudio Team (2023). *Rstudio: Integrated Development Environment for R* (Boston, MA: RStudio PBC).

Shapiro, S. S., and Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika* 52, 591–611. doi: 10.1093/biomet/52.3-4.591

Sherman, K. D., Shultz, A. D., Dahlgren, C. P., Thomas, C., Brooks, E., Brooks, A., et al. (2018). Contemporary and emerging fisheries in The Bahamas: conservation and management challenges, achievements and future directions. *Fish. Manage. Ecol.* 25, 319–331. doi: 10.1111/fme.12299

Smith, A. D., and Garcia, S. M. (2014). Fishery management: contrasts in the Mediterranean and the Atlantic. *Curr. Biol.* 24, R810–R812. doi: 10.1016/j.cub.2014.07.031

Sokolova, M., and Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Inf. Process. Manage.* 45, 427–442. doi: 10.1016/j.ipm.2009.03.002

Stergiou, K. I., Somarakis, S., Triantafyllou, G., Tsiaras, K. P., Giannoulaki, M., Petihakis, G., et al. (2016). Trends in productivity and biomass yields in the Mediterranean Sea large marine ecosystem during climate change. *Environ. Dev.* 17, 57–74. doi: 10.1016/j.envdev.2015.09.001

van Rijsbergen, C. J. (1979). *Information Retrieval. 2nd ed* (London: Butterworths).

Wilcox, C., Mann, V., Cannard, T., Ford, J., Hoshino, E., and Pascoe, S. (2021). *A Review of Illegal, Unreported and Unregulated Fishing Issues and Progress in the Asia-Pacific Fishery Commission Region* (Rome: FAO). doi: 10.4060/cb2640en

Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bull.* 1, 80–83. doi: 10.2307/3001968