The International Journal of Life Cycle Assessment (2026) 31:69
https://doi.org/10.1007/s11367-026-02626-z

OCEAN RESOURCES & MARINE CONSERVATION

Development of characterization factors for Peruvian fish stocks within the fisheries impact pathway framework

Rubén Manrique-Muñante[1] · **Alejandro Deville**[1] · **Ramzy Kahhat**[1] · **Ian Vázquez-Rowe**[1]

Received: 31 October 2025 / Accepted: 3 March 2026

Abstract

Purpose Biodiversity impacts of the Peruvian fisheries, strongly influenced by El Niño-Southern Oscillation (ENSO), are not fully covered by current life cycle impact assessment (LCIA) models. While the recently developed Fisheries Impact Pathway (FIP) accounts for the impacts of marine biotic resource depletion, key methodological challenges, such as temporality, critical for impact assessment in dynamic fisheries, remain unattended. In the current study, we aim to develop characterization factors (CFs) for 10 relevant Peruvian fishing stocks, including Peruvian anchoveta, using an enhanced FIP framework.

Methods The methodological framework includes 1) optimization of CMSY++ performance using an exhaustive statistical analysis, to provide reliable estimates for subsequent CF calculations; 2) calculation of CF time series under an Exclusive Economic Zone (EEZ) approach; and, 3) statistical evaluation of enhanced CFs comprising typical uncertainty and sensitivity analyses, along with other tests addressing ecological soundness and stock management; and, 4). application of CFs in case studies to quantify biodiversity impacts from fishing for direct and indirect human consumption.

Results and discussion Enhanced CFs deviate up to 4 orders of magnitude from previously reported values, usually showing lower values. These CFs also exhibit weak-moderate statistical correlation with typical ENSO indices, with sea level anomalies showing the strongest relationship. Furthermore, case studies framed in the Peruvian EEZ confirm the relevance of the enhanced CFs, unveiling significant differences in fishing impacts of stocks destined to direct human consumption during years with El Niño and La Niña events, and additional LCIA impacts, ranging from 0.1% to 61% in fishmeal and fish oil production among plants of a major producer, during years 2019 and 2021. Together, these findings suggest that addressing temporality is critical to refine LCA results, especially in systems with highly dynamic parameters.

Conclusions and recommendations The enhanced CF time series more accurately represents stock population dynamics, under fluctuating climatic stressors and management regimes, than the original FIP method. Thus, our method responds to the call of international LCA guidelines for regionalized and temporally explicit impact assessment. We recommend using these CFs to assess biotic resource depletion in Peruvian seafood and aquaculture systems, and extending our methodology to other EEZs affected by similar ecosystem dynamics and fishing pressure.

Keywords Anchoveta · Biodiversity loss · Biotic resource depletion · LCA · Fisheries · Stock assessment

1 Introduction

Biodiversity is crucial for a healthy biosphere in view of the different functional roles' species perform and the ecosystem stability they can attain (IPBES 2019). However, biosphere integrity is one of the six planetary boundaries that had been transgressed in the Anthropocene (Richardson et al. 2023). In this context, the current extinction rate has been estimated to be 100–1,000 times the natural background rate (Cowie et al. 2022), with the number of threatened species reaching 46,337 in 2024 (IUCN 2024).

Communicated By Arnaud Hélias

✉ Ian Vázquez-Rowe
ian.vazquez@pucp.edu.pe

[1] Peruvian Life Cycle Assessment Network (PELCAN), Department of Engineering, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, San Miguel 15088, Peru

Food systems, through their production, distribution and consumption patterns, are considered the main cause of this biodiversity decline given the chemicals, energy, land and water use, and unsustainable practices employed (Benton et al. 2021). Among these systems, seafood is attracting attention as its nutritional profile can be exploited to improve food security and because it contributes to local and national economies, especially in coastal regions. Seafood value chains rely on wild capture fisheries and aquaculture. In 2022, global captures amounted to 91 million tonnes, and, for the first time, these were surpassed by aquaculture production, 94 million tonnes (FAO 2024), revealing the importance of inputs such as fishmeal and fish oil (FMFO) to meet the requirements of this growing sector. Despite this transition in seafood production, over 37% of the 442 stocks analyzed remain unsustainably exploited (FAO 2024). These factors, along with the fact that many coastal communities rely on small-scale fisheries and that aquafeed mainly arrive from the ocean (Farmery et al. 2022) indicate that fisheries biodiversity impacts cannot be disregarded and require urgent attention, particularly in prominent fishing nations like Peru (Deville et al. 2025).

1.1 Peruvian fisheries: challenges regarding biotic resource depletion

Peru is one of the most important fishing nations globally (Majluf et al. 2024), with important fisheries within its exclusive economic zone (EEZ), especially Peruvian anchoveta (*Engraulis ringens*), which is the largest fishery worldwide by volume (Gozzer-Wuest et al. 2021). Industrial and artisanal fleets target this species, and landings are almost exclusively reduced to produce FMFO, an important ingredient for aquafeed (PRODUCE 2024), with only a minor fraction of catch directed to direct human consumption – DHC (De La Puente et al. 2020). In recent decades, *ca.* 95% of landed anchoveta has been directed to FMFO production (PRODUCE 2024), consistently supplying 15–20% of global FMFO (EUMOFA 2021). Peruvian fishmeal (FM) is mainly exported to Asia (Coayla et al. 2023), whereas much of the fish oil (FO) is exported to countries such as China, United States, Chile, or Norway (PRODUCE 2024).

Despite the prominence of the anchoveta fishery, other species are exploited in the Peruvian EEZ and destined mainly for DHC, contributing to *ca*. 20% of annual landings and yielding 2600 million US$ in exports revenue in 2023 alone (PRODUCE 2024). These species include several pelagic species, such as jack mackerel (*Trachurus murphyi*), bonito (*Sarda chiliensis*) or chub mackerel (*Scomber japonicus*), hake (*Merluccius gayi*), which is an important demersal species caught by midwater trawling (PRODUCE 2024), jumbo squid (*Dosidicus gigas*), and calico scallop (*Argopecten purpuratus*) (Sánchez Durand and Gallo Seminario 2009). These species represent an important fraction of the economic revenue of the Peruvian fishing industry, with the contribution of jumbo squid in a similar range to that of anchoveta (Christensen et al. 2014).

Species population is a key variable to measure when aiming to systematically assess biological diversity loss in a given environmental compartment (Jetz et al. 2019). The seasonal fluctuation of climatic conditions in the Peruvian marine system, the growing fishing pressure by industrial and artisanal fleets, and the regulation through quota systems are critical factors that affect stock abundance in the Peruvian EEZ. Although Peruvian upwelling supports high productivity (Mogollón & Callil 2017), positive temperature shifts caused by El Niño phenomena trigger fluctuations in abundance of Peruvian anchoveta, and other commercial stock populations (Alheit and Niquen 2004; Chavez et al. 2003), as illustrated in Fig. 1. The effect El Niño has on stock abundance and landed catch depends on its conditions and types (Bertrand et al. 2020). Extreme and Eastern Pacific El Niño events drive pelagic species to evade warm currents typical of northern Peruvian by moving closer to the shore, delaying their biomass recovery (Bertrand et al. 2020). Under Central Pacific and moderate El Niño conditions, negative effects on most pelagic species biology are observed, except for sardine (Cárdenas 2009). Demersal species like hake are drawn closer to the coast but driven by higher oxygen concentrations (Chavez et al. 2008). Regarding invertebrates, the abundance of jumbo squid is negatively affected by prey availability rather than the sea surface temperature typical of El Niño and La Niña events (Argüelles et al. 2008; Waluda et al. 2006).

Growing fishing pressure in Peru's EEZ can be illustrated by two historic episodes of biodiversity decline in the anchoveta stock. The Peruvian FMFO industry started in the 1950s and expanded rapidly, contributing to economic growth (Wintersteen 2021). Therefore, El Niño Southern Oscillation (ENSO), together with unregulated overfishing, led the industry to collapse in 1972 (Alheit and Niquen 2004), taking decades for the stock to recover a healthy state. While a similar event occurred in 1998, new enforced quota systems based not only on economic yield but in real stock status have allowed the anchoveta stock to remain relatively healthy (Wintersteen 2021). In fact, the amount of anchoveta that can be captured seasonally is dictated by the government, following the advice of the Peruvian Marine Institute (IMARPE). An individual quota system has been established for the industrial fleet since 2009 (2008). Thereafter, in 2017, a total allowable catch limit was also set for the artisanal fleet (2017). An important feature stated in this latter document is linked with the allowed redirection of discards from the artisanal fleet that do not comply with human

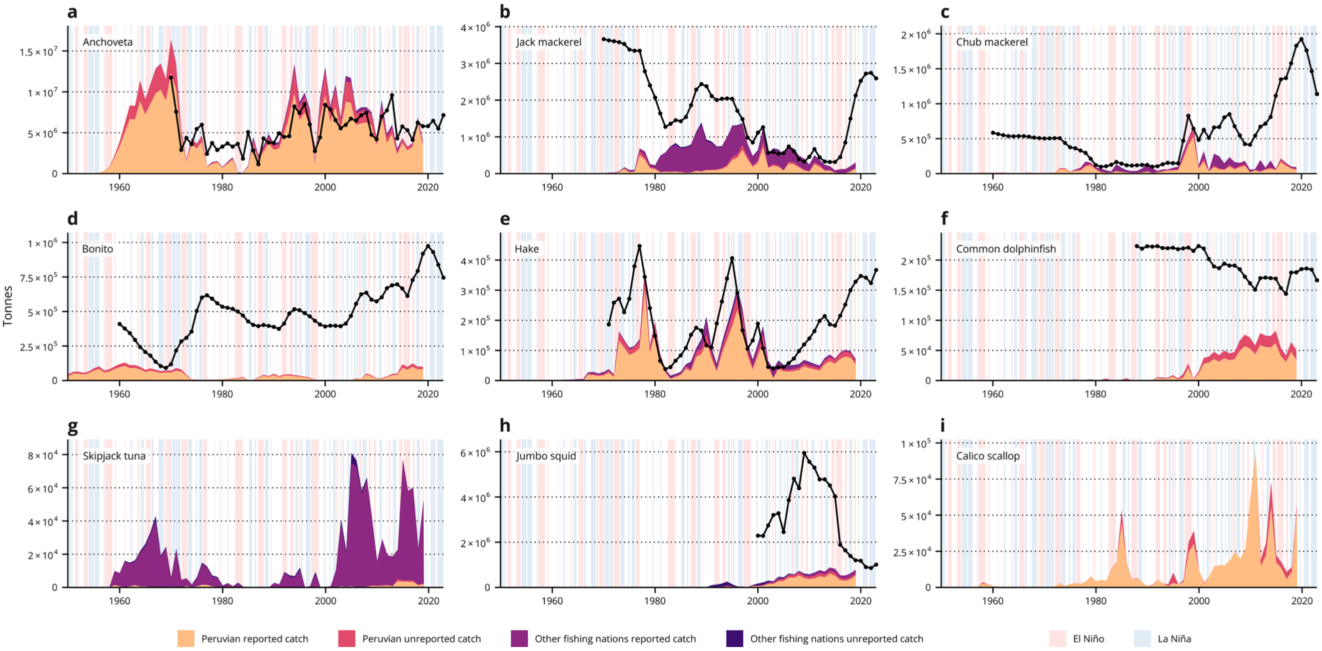


Fig. 1 Biomass (solid lines with data points) and reconstructed catch (colored area), in tonnes, for nine commercially relevant species within the Peruvian Exclusive Economic Zone – EEZ (log scale). To facilitate analysis of fluctuation over time, red and blue shadings indicate months when moderate to extreme El Niño events and moderate to extreme La Niña events occurred, respectively (Takahashi et al. 2014). Biomass was obtained from IMARPE (2024a) and catch from sea Around Us project (Pauly et al. 2020)

consumption standards towards FMFO production. Strategies to attain sustainability in the management of Peruvian fisheries include IMARPE scientific advice, regulatory frameworks addressing fishing quotas, total allowable catch and fishing gears (Arias-Schreiber 2012). Regardless negative repercussions of overexploitation on marine biodiversity (Jaureguiberry et al. 2022), sustainability of the anchoveta stock has been maintained over time thanks to precautionary and adaptive fishing management (Castillo et al. 2025).

This evidence demonstrates that the Peruvian anchoveta fishery, along with other nationally managed commercial fish species (e.g., giant squid or chub mackerel), is highly influenced by fishing pressure, management policies and the climatic fluctuations related to the pseudo-cyclical behavior of the ENSO phenomenon (Bertrand et al. 2020). This behavior implies that far from showing a dichotomous pattern, ENSO effects are highly variable in terms of intensity and length, and, therefore, the effects on marine biota and, more specifically, commercial fishing species, are highly variable across historical time series. Therefore, we argue that these considerations highlight the need under certain circumstances of computing EEZ-oriented approaches to develop a time series of CFs accounting for fish stock depletion within a comprehensive impact assessment framework.

1.2 Life cycle assessment: a comprehensive approach to measure biodiversity loss from marine biotic resources depletion

Life Cycle Assessment (LCA) has emerged as a standardized approach to evaluate the environmental footprint along the life cycle of products or goods (ISO 2006) through the aggregation of elementary flows in impact categories (Valente et al. 2024), including, among others, biodiversity impacts (Hellweg et al. 2023; Marques et al. 2017).

A detailed review of recent LCA indicators for biodiversity loss revealed that a limited number of life cycle impact assessment (LCIA) methods incorporates sufficient marine ecosystem metrics as impact categories (Bergman et al. 2025), and even fewer account for exploitation of marine resources (Damiani et al. 2023). For instance, ReCiPe (Huijbregts et al. 2017) only includes two impact categories within the ecosystem quality area of protection (AoP) that represent an impact pathway related to the marine environment (i.e., marine eutrophication and marine ecotoxicity), denoting a problem when aiming at identifying the direct impacts and damages on marine biodiversity (Bergman et al. 2025). The past few years, however, have been relatively prolific in terms of new models to characterize marine-related environmental impacts (Bergman et al. 2025), although their use in LCA case studies or their availability in broader assessment methods is still limited. Methods in these categories aim at refining the assessment of biodiversity loss in the marine environment, such as biotic resource depletion (Hélias et al. 2023; Bach et al. 2022), seabed damage (Woods & Verones 2019; Préat et al. 2021), invasive species (Verones et al. 2023) and plastic emissions to the ocean (Corella-Puertas et al. 2023; Hajjar et al. 2024).

The extraction of biotic resources from the ocean through fishing activities is the fishery-specific category that has evolved the most in recent years, as overfishing has been considered the major driver of biodiversity loss in aquatic ecosystems (Hald-Mortensen 2023). Most of the models in this category are based on stock assessments (see Table 1), which require parameters such as catch, biomass, intrinsic population growth, carrying capacity, or maximum sustainable yield - MSY (Brown et al. 2025). These data are commonly obtained from the stock status assessments conducted by regional or national fishing authorities to monitor the sustainable management of specific fisheries (Costello et al. 2016). Other models estimate free net primary production that represent the amount of carbon equivalents removed that will not be available to the biochemical processes in the ecosystem (Langlois et al. 2014, 2015). Models based on distance-to-target (Bach et al. 2022) and distance-to-nature (Farmery et al. 2017) assess proximity to specific science- or policy-related targets and pristine conditions.

Among the models shown in Table 1, the Fisheries Impact Pathway (FIP) can be considered as one of the most advanced within the metrics relying on stock assessments (Brown et al., 2025), given its ability to account for fish stock population dynamics, its global applicability and stock-level granularity, and the use of the broadly accepted potentially disappeared fraction of species (PDF) of species as an endpoint unit (Stanford-Clark et al. 2024). With endpoint CFs for more than 5000 stocks distributed in FAO major fishing areas worldwide, it represents one of the most recent refinements of a series of studies (Hélias et al. 2018, 2023). These CFs are available at regional and global scales, accounting for the effects of discarding unwanted by-catch. The authors used the open-source algorithm CMSY+, an updated version of the code presented by Froese et al. (2017), to overcome lack of data in stocks from fisheries with limited available information. As of late 2024, and for the first time, an indicator that quantifies impacts of fish extraction from wild-capture fisheries (i.e., Stanford-Clark et al. 2024) was included in a holistic multi-impact category assessment method, Impact World+ v2.1 (CIRAIG 2023).

1.3 Current research needs addressing temporal dynamics in fisheries impact pathway (FIP) LCA method

Despite the step forward in aligning LCA impact pathways for the overexploitation of wild-capture fisheries provided by the series of publications that led to a final method by Stanford-Clark and colleagues (2024), we have identified a series of methodological aspects that could be included within the framework to account for temporal, geographical and statistical considerations in fisheries management. Firstly, the original FIP method does not reflect in-depth time-dependent variability of fish stocks, although it does recommend the use of a moving average based on several years and regular updates (Stanford-Clark et al. 2024). Peruvian stocks are driven by climatic temporal fluctuations linked to the pseudo-cyclical ENSO phenomenon (Bertrand et al. 2020), suggesting that static CFs may significantly misrepresent LCA impacts on marine biota. Even though dynamic CFs (here denoting time differentiated CFs or annual CFs) for other impact categories exist (Beloin-Saint-Pierre et al. 2016; Levasseur et al. 2016), fisheries currently lack robust dynamic CFs for assessing impacts on marine biodiversity (Emanuelsson et al. 2014; Langlois et al. 2014).

Secondly, the original FIP method employs large FAO fishing areas suitable for global consistent assessment, neglecting national management regimes (Stanford-Clark et al. 2024). Analysis at an EEZ level would better capture distinct fishery policies, particularly for transboundary stocks where competitive access compromise stock populations (Liu and Molina 2021; Østhagen et al. 2020). This spatial resolution refinement could be interpreted as regionalization within the marine environment, which remains a challenge for the LCA community (Pfister et al. 2020).

Thirdly, while the statistical analysis of the CMSY++ algorithm addresses convergence, residual and prior-to-posterior analyses, model performance can be further explored to include a wider number of criteria to provide more reliable estimates, therefore improving CF certainty. These include retrospective pattern analysis, which reveals differences between catch-only and data-rich models (Wang et al. 2025); hindcasting analysis, that enables examination of model consistency relative to observed abundance data (Derhy et al. 2024); biological plausibility analysis, which uses biological knowledge to judge final model estimations credibility (Bouch et al. 2021); and jittering analysis, detecting optimal input parameter combinations (Cai et al. 2023). In addition, optimized model performance can be achieved when abundance indices are included in modeling (Zhai et al. 2020), a procedure not implemented in Stanford-Clark et al. (2024).

Therefore, in this study we revisit the FIP method on overexploitation of wild-capture fisheries with the aim of providing enhanced endpoint level CF temporal series for relevant Peruvian fishing stocks, including anchoveta, within the national EEZ. Based on this general objective, we intend to respond whether a higher level of granularity in these CFs from a spatial, temporal and statistical

Table 1 Fishery-specific Life cycle impact assessment (LCIA) models within biotic resource use impact category. CF= characterization factor.

LCIA model	Assessment	Characterization factor	Units	Midpoint/Endpoint	Fish stocks assessed	References
Lost Potential Yield	Stock assessment	Lost Potential Yield (LPY)	$\text{kg}_{\text{lost yield}} \cdot \text{kg}^{-1}_{\text{catch}}$	Midpoint	31 stocks	Emanuelsson et al. (2014)
		Overfishing through fishing mortality (OF)	$\text{kg}_{\text{fished in excess}} \cdot \text{kg}^{-1}_{\text{sustainable catch}}$	Midpoint		
		Overfishedness of biomass (OB)	$\text{kg}_{\text{biomass in excess}} \cdot \text{kg}^{-1}_{\text{remaining biomass}}$	Midpoint		
Depleted Stock Fraction	Stock assessment	Depleted Stock Fraction (DSF)	t^{-1}	Midpoint	4093 FAO stocks, 2065 species, 50 ISSCAAP group of species in 26 FAO major fishing areas	Hélias et al. (2018)
		[Ecosystem quality endpoint CF]	$\text{Species} \cdot \text{year} \cdot \text{kg}^{-1}_{\text{catch}}$	Endpoint	5000 stocks from 40 FAO major fishing areas	Hélias et al. (2023) Stanford-Clark et al. (2024)
		[Ecosystem quality endpoint CF]	$\text{PDF}_{\text{reg}} \cdot \text{year} \cdot \text{kg}^{-1}_{\text{catch}}$	Endpoint		
		[Ecosystem quality endpoint CF]	$\text{PDF}_{\text{glo}} \cdot \text{year} \cdot \text{kg}^{-1}_{\text{catch}}$	Endpoint		
Ecological Scarcity Method	Distance-to-target assessment	Depleted Stock Fraction	$\text{Eco-points} \cdot \text{kg}^{-1}$	Single score (ecopoints)	150 stocks from 15 FAO fishing areas	Frischknecht et al. (2021)
Distance-to-target approach	Distance-to-target assessment	Stock in the sea (SIS)	$\text{Eco-points} \cdot \text{t}^{-1}$	Single score (ecopoints)	10 species/stocks from 5 FAO fishing areas	Bach et al. (2022)
		Fish manager (FM)	$\text{Eco-points} \cdot \text{t}^{-1}$	Single score (ecopoints)		
		Target pressure (TP)	$\text{Eco-points} \cdot \text{t}^{-1}$	Single score (ecopoints)		
		Production based regional midpoint approach (RMA)	$\text{Eco-points} \cdot \text{t}^{-1}$	Single score (ecopoints)		
		Consumption based regional midpoint approach (RMA)	$\text{Eco-points} \cdot \text{t}^{-1}$	Single score (ecopoints)		
Biotic Natural Resources (BNR) impact assessment	Distance-to-target assessment at species level	Biotic-resource extraction impact assessment at the species level	$\text{year} \cdot \text{t}^{-1}_{\text{wet weight}}$	Midpoint	69 sustainably fished stocks and 58 overexploited stocks distributed in 88 marine provinces	Langlois et al. (2014)
	Productivity assessment at ecosystem level	Biotic-resource depletion impact assessment at the ecosystem level	$\text{year} \cdot \text{t}^{-1}_{\text{wet weight}}$	Midpoint		
Sea use impact assessment	Productivity assessment	Biotic Natural Resource Depletion (BNRD)	$\text{kg C-eq} \cdot \text{kg}^{-1}_{\text{catch}}$	Midpoint	34 groups of species distributed in 5 ecosystems	Langlois et al. (2015)
Naturalness Degradation Indicator (NDI)	Distance to nature assessment	Naturalness Degradation Indicator (NDI)	$\text{m}^2 \cdot \text{kg}^{-1}_{\text{catch}}$	Midpoint	Northern Australia prawn fishery	Farmery et al. (2017)

perspective affects environmental impact of fishing stock removal and subsequent LCA results. For this, our specific objectives are to (1) optimize stock assessment modeling using comprehensive statistical criteria; (2) calculate CF temporal series (2007–2023) for anchoveta, jack mackerel, chub mackerel, bonito, hake, common dolphinfish, skipjack tuna, jumbo squid and calico scallop, all of them in the Peruvian EEZ; (3) conduct enhanced CF temporal series statistical evaluation including uncertainty, sensitivity, correlation with typical ENSO ecological indicators and hierarchical clustering analyses; and (4) apply the dynamic CFs in representative LCA case studies to quantify how interannual stock variability affect biotic resource depletion impacts. It is expected that this methodological framework will allow fishery scientists and managers to compute fisheries and aquafeed environmental impacts for the novel biotic resource depletion LCA category for Peruvian case studies in different years and provide guidance for CF calculation in other EEZs with fluctuating stock population.

2 Methods

The methodological framework is organized in five sections. Firstly, we detailed data requirements for the enhancement (Sect. 2.1). Secondly, we optimized the CMSY++ package performance, employed in the original FIP model, to guarantee the reliability of its estimates used in subsequent CF calculations (Sect. 2.2). Thirdly, we used optimal modeled parameters as inputs to calculate enhanced CF time series that integrate stock abundance and catch annual fluctuations driven by climatic events, fishing pressure and national policy interventions (Sect. 2.3). In a fourth step, the resulting CF time series were subjected to statistical evaluation addressing uncertainty and sensitivity, along with further correlation and hierarchical clustering analyses to obtain valuable information concerning the ecological meaning of the CFs (Sect. 2.4). Finally, we explore the practical implications of these novel CFs applying them to a real-world case study, at both national and company scales in Peru during years with and without El Niño phenomena to evaluate changes of impacts on marine biodiversity (Sect. 2.5).

2.1 Data collection

Annual data on catch and biomass for the nine species assessed were gathered from the Sea Around Us project (Pauly et al. 2020) and through online query (IMARPE 2024a). For CMSY++ performance assessment, reference parameters of population increase rate (r), carrying capacity (K), MSY, biomass and fishing mortality at MSY (B_{MSY} and F_{MSY}) were sourced from IMARPE (2024a). In the absence of confidence intervals for these parameters, lower and upper bounds were set at 50 and 150% of their reported values. More details on the information provided by IMARPE are found in Table S1–S2 in the Supporting Material (SM).

Calculation of enhanced CFs used the total number of marine species of 247,410 (WoRMS Editorial Board 2025) and Peruvian EEZ shapefiles (Flanders Marine Institute 2023). Statistical correlation for ecological validation required time series of sea surface temperature (SST) anomalies (SIOFEN 2025), as well as time series on atmospheric pressure, eastward sea water velocity, northward sea water velocity, sea level, salinity, dissolved oxygen, nitrate, phosphate, chlorophyll, phytoplankton, and net primary productivity (NPP) (Copernicus 2025).

For the DHC case study, landings data were used to calculate environmental impacts (IMARPE 2024a). Energy and protein content were obtained from national food composition tables (INS 2023), Avadí et al. (2014), technical sheets (ITP 2007), product information (Exalmar 2025) and other sources (Fitia 2025). Annual DHC production was obtained from IMARPE (2024a), PRODUCE (2024) and wholesale fish markets data (PRODUCE 2025). All primary data for this first case study are found in Table S3. For the FMFO case study, landed catch, FMFO outputs and allocation data were sourced from Deville et al. (2025).

2.2 Assessment conducted by CMSY++ package

The quantification of CFs relies on key fisheries biological parameters such as biomass, maximum intrinsic rate of population increase, and carrying capacity (Stanford-Clark et al. 2024). To estimate these parameters, we used the CMSY package, an R-based algorithm that applies Monte Carlo simulations to model fish population dynamics (Froese et al. 2017). The CMSY package is especially useful for data-deficient fisheries, as some fisheries still depend on mathematical models rather than direct methods like hydroacoustic surveys due to economic constraints (Froese et al. 2017). Two methods can be applied when using the CMSY algorithm. While the first method, Catch-MSY (CMSY), uses only stock captures to estimate fisheries reference points, the second one, the Bayesian Schafer Model (BSM), uses abundances indices (e.g., biomass and catch per unit of effort, CPUE) in addition to catch for the same purpose. In this study, we used the updated version of the CMSY package, called CMSY++ (Froese et al. 2023) applying both methods to estimate biomass, maximum intrinsic rate of population increase, and carrying capacity.

2.2.1 Data preparation

Prior to the CMSY++ modeling, data curation was carried out to complete, when possible, missing values for biomass and catches of the stocks. Regarding biomass, jumbo squid presented two missing values (i.e., years 2017 and 2023). The biomass of 2017 was interpolated using 2018 and 2019 values. For 2023 we retained the same number of specimens from the 2020 assessment (IMARPE 2023). However, the average weight of individual squids decreased from 5.81 kg in 2020 (IMARPE 2021) to 4.97 kg in 2023 (IMARPE

2024b), resulting in lower biomass estimate for 2023. Thus, we calculated the biomass in tonnes by applying a ratio between the average weights in those years. This adjustment ensured our 2023 estimate reflects the change in the population total biomass, even if the number of squid were identical. Regarding catch, Sea Around Us data records ended in 2019. An estimation of catch for 2020–2023 was carried out multiplying landings by the average catch-to-landings ratio from 2015 to 2019 (IMARPE 2024a; PRODUCE 2024). For most stocks, biomass data availability aligned with catch records. However, biomass time frames covered shorter periods than landings for common dolphinfish and jumbo squid, whereas no biomass estimates were available for skipjack tuna and scallop.

2.2.2 CMSY++ model configuration

To obtain the most accurate parameters resulting from the CMSY++ estimation, we defined two scenarios (A and B, as shown in Table 2). Scenario A referred to the original method from Stanford-Clark et al. (2024), in which the model was informed only by including catch and maximum intrinsic rate of population increase. In Scenario B we adjusted priors, including combinations of initial, intermediate and final biomass to carrying capacity (B/K) ratio, and integrated biomass indices to inform the model. Furthermore, since many of the Peruvian fisheries have experienced shifts in policies in recent decades (see Table S4 in the SM), we defined two approaches with two different time frames for modeling (Table 2). The first time frame considered the whole historical data for catch and biomass we could collect, which was up to 2023. The second time frame considered the data from the year a policy change was observed to the last year 2023.

Like any other surplus production model, establishing prior distributions for diverse parameters is of utter importance for the modeling process (Froese et al. 2023). Prior lower and upper limits of intrinsic rate of population increase, r, for a given stock were set in a way that included all previous ranges documented for fish stocks in Fishbase (Froese and Pauly 2024) and mollusk stocks in SeaLifeBase (Palomares and Pauly 2024) (see Table S5 in the SM). The CMSY++ algorithm from Froese et al. (2023) was adapted using Rstudio (R Core Team 2023) to save relevant information, such as B, F, B/K, MSY, B/B_{MSY}, and F/F_{MSY} ratios from posterior distributions.

Table 2 Scenarios and approaches of time frame analysis used to set up the CMSY++ package in this study

Scenario	Entire time frame	Reduced time frame
A	Catch Maximum intrinsic rate of population increase (r)	Catch Maximum intrinsic rate of population increase (r)
B	Catch Maximum intrinsic rate of population increase (r) 30 combinations of initial, intermediate and final Biomass to carrying capacity (B/K) Biomass indices (B) [a]	Catch Maximum intrinsic rate of population increase (r) 30 combinations of initial, intermediate and final Biomass to carrying capacity (B/K) Biomass indices (B)[a]

For skipjack tuna (*K. pelamis*) and calico scallop (*A. purpuratus*), biomass historical records provided by IMARPE were not available. For the rest of the stocks, IMARPE biomass estimations were included

2.2.3 Analysis of CMSY++ outcomes with statistical criteria

Since stock assessments determine biological reference points relevant for fisheries management (Punt et al. 2023), errors in fisheries modeling can lead to severe consequences in marine biodiversity (Carvalho et al. 2021). Thus, rigorous statistical criteria are crucial to avoid inaccuracies and ensure model and stock status reliability. Hence, once the algorithm was run under our established conditions, the modeling outcomes were subjected to diagnostic tools (Table 3) to evaluate the feasibility of the model and to select the best fit based on standards from Carvalho et al. (2021) and Kokkalis et al. (2024). The criteria proposed allow the modeling process to find optimized estimates (i.e., convergence) near the observed values (residual analysis), while including prior knowledge and data (prior to posterior analysis). They also identify the risk of finding inconsistencies relative to the values observed (retrospective analysis) as well as to naive predictions (hindcasting analysis). In addition, one key criterion of the diagnosis toolbox proposed (biological meaning) is linked to the biological implications of the fisheries reference points estimated by the assessment. Within each criterion, we set metrics (some of which were statistical tests) to assess model performance using an acceptance threshold suggested by Kokkalis et al. (2024). The number of accepted tests originated a percentage of compliance for each criterion. The model with a higher number of accepted tests (i.e., the model with 100% compliance) was selected to be the optimal model for the stock assessed. In the event of a tie, we selected the model with r, K, MSY, B_{MSY} and F_{MSY} parameters closer to values reported in literature by inspecting the biological meaning criterion.

2.3 Calculation of temporal series for enhanced characterization factors - CFs

The FIP model stands out for its scientific robustness because it includes the fraction of stock removed from the ocean as an effect factor (Hélias et al. 2018) multiplied by a fate factor that includes the proportion of current biomass to a pristine-condition biomass, and the intrinsic growth rate of the stock (Hélias et al. 2023). Stanford-Clark et al. (2024) suggest that a continuing recalculation of their CFs

Table 3 List of criteria and subcriteria used in model evaluation. In this study, 7 criteria were proposed to evaluate model performance according to state-of-the-art tools. Each criterion is evaluated using their own metrics, which can be statistical tests per se or can be defined quantitative properties under an acceptance threshold. Number of tests and how the degree of compliance were determined are also described

Criteria	Meaning	Metrics	Acceptance threshold	Application in this study	Compliance
Convergence	Equilibrium distributions for Markov Chain Monte Carlo (MCMC) distributions meet a definite and optimized point	Heidelberger & Welch test	p-value >0.05 and $\varepsilon<0.1$ for each of the r and K chains	6 tests (3 for each r chain and 3 for each K chain)	100% for 8/8 tests
		Gelman-Rubin test	$R<1.01$ for r chains and for K chains	2 tests (1 for the group of r chains and 1 for the group of K chains)	
Residuals	Difference between the observed biomass and predicted biomass (i.e., residuals) should be random distributed and their RMSE should be low	Root mean squared error (RMSE) calculation	RMSE <0.3	1 test	100% for 3/3 tests
		Wald-Wolfowitz test	p-value >0.05	1 test	
		Presence of outliers	Number of outliers $=0$	1 test	
Prior-to-posterior distributions	The distribution after the observations (posterior distribution) should be informed by data and the distribution before the observations (prior distribution)	Posterior-to-prior variation ratio (PPVR)	PPVR <1	6 tests for each parameter (r, K, MSY, and B/K at the start, intermediate and end of the time frame)	100% for 12/12 tests
		Posterior-to-prior variation of mean (PPVM)	$\lvert log_{10}PPVM \rvert<1$	6 tests for each parameter (r, K, MSY, and B/K at the start, intermediate and end of the time frame)	
Retrospective analysis	Model-dependent inconsistencies in relative biomass (B/B_{MSY}) and relative fishing mortality (F/F_{MSY}) found in estimations with increasing periods of data (Mohn, 1999)	Mohn's rho calculation	$a \leq \rho \leq b$ for each B/B_{MSY} and F/F_{MSY} for 5 and 7 years analysis with •$a=-0.15$ and $b=0.20$ for longer-lived species •$a=-0.22$ and $b=0.30$ for shorter-lived species	4 tests	100% for 4/4 tests
Hindcasting analysis	Model-free inconsistencies in biomass found in estimations with increasing periods of data (Kell et al. 2016)	Mean absolute squared error (MASE) calculation	MASE <1 for LnB and B/B_{MSY} for 3 and 5 years analysis	4 tests	100% for 4/4 tests
Biological meaning	Output parameters should be within expected intervals in view of the historical biological reference points provided by competent bodies (e.g., governmental institutions) or other stock assessment studies.	Parameter r within algorithm prior distribution	$r_{alg,\ min} \leq r \leq r_{alg,\ max}$	1 test	100% for 8/8 tests
		Same order of magnitude in B/B_{MSY} and F/F_{MSY}	$\log_{10}\left[\frac{(B/B_{MSY})_{uci}}{(B/B_{MSY})_{lci}}\right]<1$ and $\log_{10}\left[\frac{(F/F_{MSY})_{uci}}{(F/F_{MSY})_{lci}}\right]<1$	1 test	
		Maximum B in time series lower than K	$B_{max}<K$	1 test	
		Parameters r, K, MSY, B_{MSY} and F_{MSY} within literature prior distributions	$r_{lit,\ min} \leq r \leq r_{lit,\ max}$ $K_{lit,\ min} \leq K \leq K_{lit,\ max}$ $MSY_{lit,\ min} \leq MSY \leq MSY_{lit,\ max}$ $B_{MSY,\ lit,\ min} \leq B_{MSY} \leq B_{MSY,\ lit,\ max}$ $F_{MSY,\ lit,\ min} \leq F_{MSY} \leq F_{MSY,\ lit,\ max}$	5 tests	

should be done to preserve the validity of this impact category. In our study, CF recalculation denoted integration of statistical, spatial and temporal enhancements into the CF quantification process, to account for the dynamic behavior of fisheries. Enhanced CFs were computed following Eq. 1, where C is catch, K is the stock carrying capacity, r is the maximum intrinsic rate of population increase, B is the stock biomass, n is the global number of marine species and $f_{Reg\rightarrow Glo}$ is a factor that converts regional to global PDF.

$$CF = f_{Reg\rightarrow Glo} \times \frac{C \times K}{r^2 \times B^3} \times \frac{1}{n} \tag{1}$$

Empirical probability distributions of r and K were derived from CMSY++ package outputs. To generate the biomass (B) distribution, we applied a scaling factor to the CMSY++ biomass estimated distribution for each year. The scaling factor was established as a ratio between the biomass value provided by IMARPE and the biomass median value obtained from CMSY++. A triangular distribution was assumed for catch, thus avoiding normal distribution, which is rarely observed in catch patterns or other biological processes in fishery contexts. Using the Latin Hypercube Sampling (LHS) technique (McKay et al. 1979) we then generated 100,000 data points to capture input parameters uncertainty, while maintaining computational efficiency. The sample size was determined by iterative testing to stabilize median and quantiles estimates, minimizing variability induced by the sampling technique. Thereafter, this variability was quantified using the coefficient of variation.

Following Stanford-Clark et al. (2024), the $f_{Reg\rightarrow Glo}$ was calculated by three approaches: Global Extinction Probabilities (GEP) (Verones et al. 2022), proportion of the biomass in each stock to the biomass of the whole stocks of a given species (i.e., Relative Endemicity, RE, conversion factor), and the distance of the stock actual biomass to natural conditions represented by the stock carrying capacity (i.e., Species Specific, SS, conversion factor). GEP are the result of complex global assessments (e.g., conducted by IUCN) that imply significant efforts for which values were developed for broad species groups (Kuipers et al. 2019). Stock catch data spanning 10 consecutive years is needed for RE and SS factors calculation. However, many fisheries lack consistent records for their stocks. In view of these limitations, we decided to maintain conversion factors as constant values over time. The GEP values at cell level from Verones et al. (2024) were summed within the boundaries of each EEZ, obtained from the Flanders Marine Institute (2023) to obtain GEP conversion factors for this study. The RE and SS conversion factors required biomass and carrying capacity of the species in every other stock for their calculation. Hence, both were modeled using reconstructed catch data up to the year 2019 (Pauly et al. 2024). We emulated the catch-only CMSY++ configuration of Stanford-Clark et al. (2024). We acknowledge this is a value choice that differs from the methodology proposed in Sect. 2.2.2 and, therefore, will be discussed later. To analyze the effect of using single year landings and average landings for 3 and 5 years in fisheries impact calculation, we quantified 3 sets of CFs for the model selected in Sect. 2.2.3.

2.4 CF statistical evaluation

2.4.1 Uncertainty analysis

Qualitative uncertainty used a pedigree matrix assessing scientific reliability, model completeness, temporal specification, geographical specification and input data characteristics of the enhanced LCIA methods (Qin et al. 2020), while quantitative uncertainty was addressed using dispersion factors (k), which is a metric derived from the proportion of the order of magnitude from the 97.5th and 2.5th percentiles (Slob, 1994). For the latter, the k values were compared between original FIP model and the enhanced CF distributions.

2.4.2 Sensitivity analysis

Spearman's rank correlation tests were conducted to detect statistical associations between enhanced CF time series for each stock and two indicators related to their corresponding catch and biomass temporal series: C/MSY and B/K. Moreover, we assessed the effects of deliberate perturbations in catch and biomass on CF values for the anchoveta stock.

2.4.3 Statistical correlation analysis

The CF time series were analyzed for two purposes: 1) to validate environmental soundness by testing whether CF fluctuations correspond to wider climatic and ecological drivers of ENSO (Sanchez-Matos et al. 2024); and 2) to explore if available oceanographic data could serve as potential proxies for future CF estimation (Langlois et al. 2015). We used Spearman's rank correlation coefficient to detect associations between enhanced CF time series and typical ENSO indicators focused on the Peruvian EEZ. This non-parametric test was selected because it does not require the data to follow a normal distribution (Kraemer et al. 2003; Puth et al. 2015) The indicators were the Oceanic Niño Index, ONI (Bamston et al. 1997; Huang et al. 2017), El Niño Coastal Index, ICEN (Takahashi et al. 2014), and Coastal Laboratory Index, LABCOS (Quispe and Vásquez 2015). While the three indices classify El Niño in weak, moderate, strong and very strong events, and La Niña in weak, moderate and strong events, based on SST anomalies as monthly averages, they differ in the scale at which they are applied: ONI is a macroscale index (i.e., Niño region 3.4), ICEN is a regional index (Niño region 1+2), and LABCOS is a local index (Peruvian coastal waters). Other climatic and ecological indicators at the EEZ scale comprised: atmospheric pressure, eastward sea water velocity, northward sea water velocity, sea level, salinity, dissolved oxygen, nitrate, phosphate, chlorophyll, phytoplankton and net primary productivity (NPP). Spearman's tests required the same temporal scale; hence, indicators measured at daily or monthly basis were annually averaged.

2.4.4 Hierarchical clustering analysis

For the purpose of analyzing similar enhanced CFs behavior among the stocks, hierarchical clustering analysis (HCA) was applied to regional and global CF temporal series. After data standardization, the dissimilarity matrix was created using Euclidean distance, as the most common distance metric applied, and dynamic time warping, as an emerging measure, appropriate to analyze temporal series (Javed et al. 2020). The clusters were formed using Ward's method (Ward 1963), with the optimal number of clusters determined by the elbow method and validated by silhouette analysis. All data processing, including visualization using a dendrogram, were implemented in Rstudio (R Core Team 2023).

2.4.5 Effect of catch aggregation on enhanced CFs

The Wilcoxon signed-rank test (Wilcoxon 1945) and rank-biserial correlation test (Cureton 1956) were conducted to analyze differences in medians between enhanced CFs computed using single landings and moving averages (3- and 5-year averages). Given the considerable sample sizes, datapoints were reduced using the LHS technique. This resampling of CFs continued until both Wilcoxon and rank-biserial correlation outputs were stabilized (i.e., 1000 and 100 datapoints).

2.5 Application of enhanced CFs to assess biotic resource depletion in the Peruvian EEZ

A first case study aims to provide information about environmental impacts related to the extraction of commercially relevant wild fish stocks from the Peruvian EEZ. This case study seeks to quantify the biodiversity-related impacts of fishing in the national marine region that holds the largest fishery in the world. System boundaries included the fishing stage (i.e., extraction and landing) of the nine species abovementioned, although separate assessments were performed for the northern and southern Peruvian anchoveta stocks. The functional unit (FU) was determined as 100 g of protein content in the edible portion of the final DHC product (i.e., fresh, cured, canned and frozen) delivered to the entire Peruvian population (i.e., 33,725,000), in years portraying El Niño and La Niña oceanic conditions (2013 and 2015, respectively). Those years were selected according to the ICEN index, which is the indicator the Multisectorial Committee for the Study of El Niño (ENFEN) designated to analyze the intensity of ENSO events in Peru (ENFEN 2012).

A second case study analyzed the variation of environmental impacts of FMFO production at a reduction plant in northern Peru, using the enhanced CFs to expand a recently conducted LCA on FMFO production (Deville et al. 2025). The motivation for conducting this case study is the empirical data gap accounting for biodiversity-related impacts of the major wild capture fishery (i.e., Peruvian anchoveta), as well as our interest to test the calculated CFs. System boundaries included the fishing stage, processing and transportation of FMFO to the importing countries. The FU was established as 1 tonne of FM and 1 tonne of FO produced and delivered to the importing country in 2019 and 2021, which were the years for which primary data were available.

In terms of LCIA, the first case study included landings of stocks and production of edible DHC products (in tonnes) as elementary flows. The impact assessment focused exclusively on the FIP. Thus, the mean, minimum and maximum values of the CFs from this study and from the original FIP method (Stanford-Clark et al. 2024), in $\text{PDF}_{\text{global}}\times\text{year}\times\text{tonne}^{-1}$, were used to compute the environmental impacts on biodiversity. Mass and energy allocations were considered.

For the second case, the assessment focused on the ecosystem quality AoP. Impacts from conventional impact categories (e.g., climate change, acidification, or eutrophication) were obtained from Deville et al. (2025). Similarly to the previous case study, impacts within the biotic resource depletion category were calculated following both original and revisited FIP approaches, and using three sets of global CFs (GEP-, RE- and SS-based). However, here we only used mean CF values, and, in addition, we converted $\text{species}\times\text{year}\times\text{tonne}^{-1}$ available in Deville et al. (2025) to the $\text{PDF}\times\text{year}\times\text{tonne}^{-1}$ unit to allow direct comparison with our results. Energy allocation was considered.

In both case studies, as the CFs were not available in commercial LCA software, impact quantification was carried out in spreadsheet software and the Rstudio environment (R Core Team 2023).

3 Results and discussion

3.1 Selection of models with optimal CMSY++ performance

Models under each scenario present varying degrees of compliance with each criterion. In general, higher levels of criteria fulfillment were observed when biomass indices and combination of initial, intermediate and final B/K priors were included, under a short period of analysis (scenario B), as shown in Table 4. This fact suggests that input information is relevant to model optimization using CMSY++ algorithm in Peruvian stocks, which seems reasonable since additional information supports a better fit of empirical data. Similar trends in model optimization were found in South Atlantic Ocean blue shark stock assessment (Kindong et al. 2022) but were not observed in other stocks as little tunny – *Euthynnus alletteratus* (Konoyima et al. 2024).

Almost every stock achieved 100% compliance in the convergence criterion (see Tables S6–S7 in the SM). It is likely that the number of steps used (i.e., 60,000 steps) are enough to obtain a finite and optimal value of r-K pairs for the model even for stocks poor in data (Froese et al. 2017). Prior-to-posterior analysis and retrospective analysis presented a high percentage of compliance after convergence, with the former being another aspect addressed by the diagnostic tools implemented in CMSY++ (Froese et al. 2017). The absence of consistent retrospective patterns in the stock assessment suggests the model remains stable as new data is added gradually. The biological meaning criterion presented varied fulfillment degree as the percentages fall mostly in the 50–99% range with less cases with percentages in the <50 and 100% ranges. This was a critical criterion as it assesses how close the estimated parameters and biological reference points from the model are to other reliable assessments from competent institutions. Although the CMSY++ modeling was informed by priors and abundance indices, a complete fulfillment was not possible in this criterion due to the approach this modeling package is based on. While the CMSY++ modeling procedure is based on biomass and catch, the reference assessments were conducted under integrated approaches that included data on size or age that allow even more precise estimations, as explained by Dichmont et al. (2021). Residual analysis and hindcasting analysis, both linked with accuracy against observed data (RMSE and MASE metrics), showed the lowest compliance rates. Pronounced deviations of estimated biomass indices from reference biomass values sourced from IMARPE can be explained by the differences in stock assessment methods and the ability to include an expanded pool of input parameters into those methods.

The common dolphinfish and scallop stocks complied with almost all subcriteria tests (see Table 4). The relatively shorter lifespans of these species might align better with CMSY++ assumptions of steady state population dynamics (Froese et al. 2017). While the vertical distribution in the marine environment and the migratory behavior (Arntz and Tarazona 1990; Barahona et al. 2017) may be causing catchability to fluctuate in species with lower subcriteria compliance (e.g., jack mackerel). Thus, r and K estimations are not closer to other assessments' outcomes. Despite this variability, a major part of our estimations in this stock complied with the criteria proposed. The statistical analysis was validated by visual inspection of key model performance metrics. For instance, Fig. 2 shows the behavior of residuals, prior-and-posterior distributions for r and K and retrospective patterns for B/B_{MSY} and F/F_{MSY} (a-f), together with complementary equilibrium curve and Kobe plot (g-h).

To calculate the enhanced CFs, the model with a higher degree of criteria compliance within each stock was selected to gather the population increase (r) and carrying capacity (K) parameters. The northern-central anchoveta stock presented the highest values for parameters r, K, MSY, B_{MSY} and $_{FMSY}$ among the stocks assessed (Table 5 and Table S8). The upwelling of the Humboldt Current System, with the rapid rate of population increase, and the short lifespan of anchoveta are the driving factors that sustain the huge biomass of this stock, allowing it to deal with strong fishing pressures (Chavez et al. 2008). The higher nutrient content of Peruvian northern-central waters (Bruland et al. 2005) along with its optimal climatic conditions (e.g., temperature and oxygen concentrations) for anchoveta growth (Castillo et al. 2025), results in lower productivity of the southern anchoveta stock compared to its northern-central analogue. In any case, the southern anchoveta stock still presents high MSY, K and B_{MSY} values within the stocks analyzed. This northward distribution of anchoveta has proven to be due to the affinity to cold waters, although seasonal behavior has also been observed (Castillo et al. 2015). A balance between MSY and lower exploitation might explain jack mackerel ranking in terms of K and B_{MSY}. In the common dolphinfish stock, the relatively strong fishing pressure it can support (F_{MSY}) can be attributed to its relatively high resilience. This species feeds on other smaller species, not plankton, thus, a lower trophic efficiency is expected in its food web and, as a consequence, lower B_{MSY} (Pincay-Espinoza and Varela 2022). Moderate fishing pressure on hake along with its relatively low K indicate that this stock might be susceptible to overfishing (Guevara-Carrasco and Lleonart 2007). Although skipjack tuna is a commercial species that exhibits significant landings, its resilience is short, making this stock more sensitive to fishing pressure. Thus, a lower F_{MSY} is observed for this species.

Table 4 Comparison of criteria compliance for representative stocks in the Peruvian Economic Exclusive Zone (EEZ) between the original Fisheries Impact Pathway (FIP) methodology (Stanford-Clark et al. 2024) and the enhanced methodology proposed in the current study

Stock (Scientific name)	Scenario	Time frame of analysis	Convergence (8 subcriteria)	Residuals (3 subcriteria)	Posterior-prior (12 subcriteria)	Retrospective (4 subcriteria)	Hindcasting (4 subcriteria)	Biological meaning (8 subcriteria)	Total subcriteria compliance
Anchoveta, northern-central stock (*E. ringens*)	A	1960 – 2023	8	0	10	2	0	4	24 of 39 (61.5%)
	B	2007 – 2023	8	2	12	4	2	7	35 of 39 (89.7%)
Anchoveta, southern stock (*E. ringens*)	A	1960 – 2023	8	0	10	2	1	4	25 of 39 (64.1%)
	B	2007 – 2023	8	1	12	4	0	5	30 of 39 (76.9%)
Jack mackerel (*T. murphyi*)	A	1950 – 2023	8	0	10	0	0	3	21 of 39 (53.9%)
	B	2002 – 2023	8	1	11	4	0	2	26 of 39 (66.7%)
Chub mackerel (*S. japonicus*)	A	1950 – 2023	8	0	10	4	0	2	24 of 39 (61.5%)
	B	2002 – 2023	8	2	12	4	1	5	32 of 39 (82.1%)
Bonito (S. chiliensis)	A	1950 – 2023	8	0	11	4	0	3	26 of 39 (66.7%)
	B	2007 – 2023	8	1	12	4	1	4	30 of 39 (76.9%)
Hake (*M. gayi*) [a]	A	1953 – 2023	8	0	10	1	0	2	21 of 32 (65.6%)
	B	2003 – 2023	8	1	11	4	0	2	26 of 32 (81.3%)
Common dolphinfish (*C. hippurus*)	A	1954 – 2023	8	0	12	4	0	4	28 of 39 (71.8%)
	B	2001 – 2023	8	2	12	4	2	8	36 of 39 (92.3%)
Skipjack tuna (*K. pelamis*) [b]	A	1950 – 2023	8	0	11	2	0	1	22 of 27 (81.5%)
	B	2003 – 2023	8	0	12	2	0	2	24 of 27 (88.9%)
Jumbo squid (*D. gigas*)	A	1950 – 2023	8	0	10	1	0	3	22 of 39 (56.4%)
	B	2007 – 2023	8	0	12	4	0	4	28 of 39 (71.8%)
Calico scallop (*A. purpuratus*) [b]	A	1953 – 2023	8	0	10	4	0	1	23 of 27 (85.2%)
	B	2007 – 2023	8	0	12	4	0	2	26 of 27 (96.3%)

Literature values for r, K, MSY, B_{MSY} and F_{MSY} were not available

Biomass historical records were not available. Thus, biomass estimations from the CMSY method were used

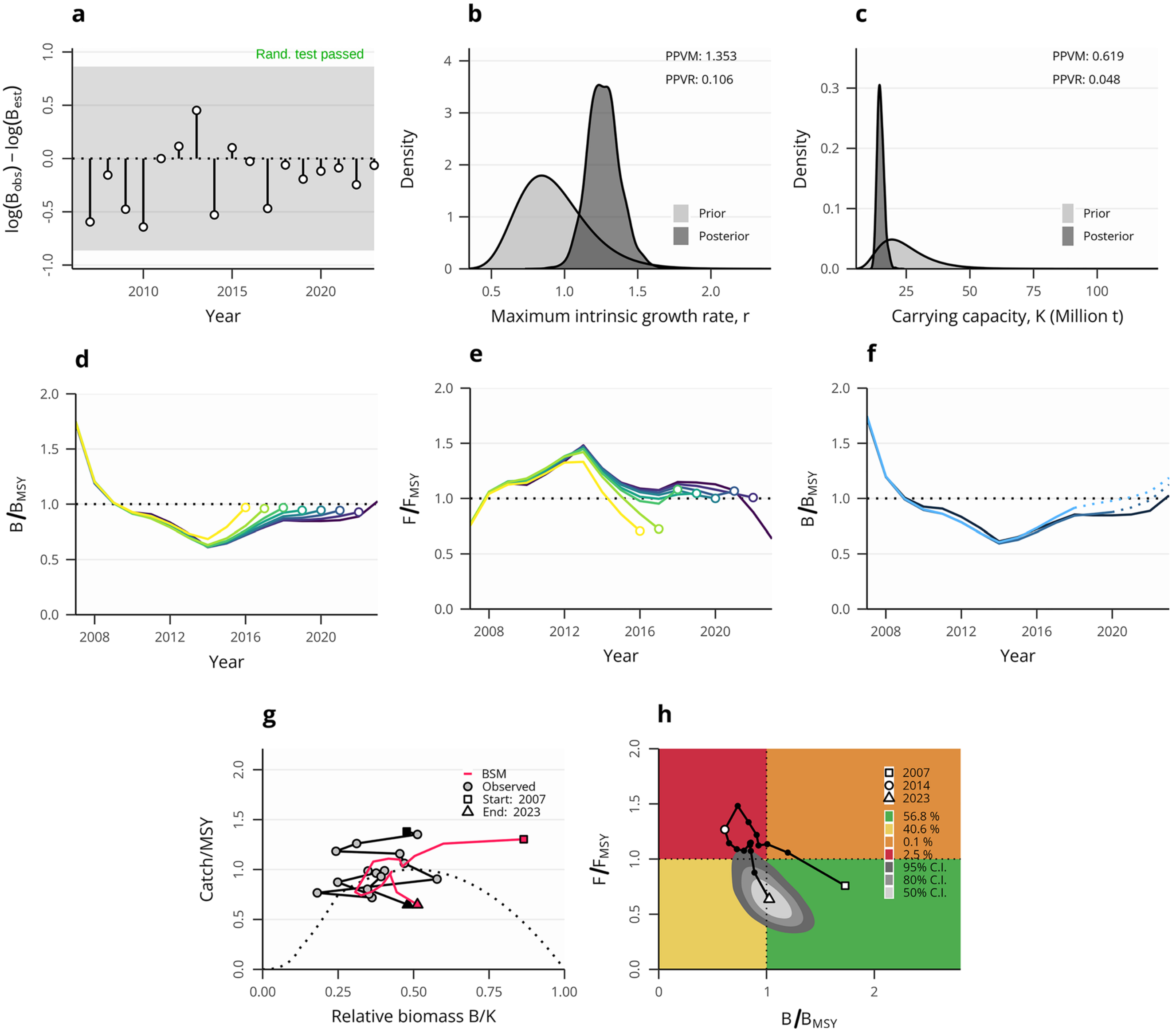


Fig. 2 Illustration of statistical analysis conducted for CMSY++ model performance of northern-central anchoveta. The figure shows residual analysis (**a**), prior-to-posterior analysis of r and K parameters (b and c), retrospective analysis for B/B_{MSY} and F/F_{MSY} (d and e), hindcasting analysis (**f**), along with equilibrium curve (**g**) and Kobe plot (**h**) typical of CMSY++ package

3.2 Temporal series of enhanced characterization factors (CFs) for Peruvian stocks

3.2.1 GEP, RE and SS conversion factors to achieve global PDF units

Prior to the computation of enhanced CF temporal series, conversion factors from regional to global PDF units at EEZ level for Peru and other nations were calculated. GEP values in the marine ray-finned fish category ranged from 8.47×10^{-9} to 6.89×10^{-2} (dimensionless, see Figure S1 and Figure S2a). Considering all species and EEZ that entered the quantification process, RE and SS factors distribution ranged from 8.56×10^{-10} to 8.83×10^{-1} (Figure S2b) and from 1.06×10^{-9} to 1.31 (Figure S2c), respectively. Looking at the Peruvian stocks, the GEP values were, on average, two orders of magnitude lower than RE and SS factors (Tables S9–S11) given that IUCN groups of species from GEP are more widespread around the globe than single species from the latter approaches.

3.2.2 Overview of enhanced regional and global characterization factors (CFs)

Once the estimation of regional-to-global PDF conversion factors was executed, four sets of CF time series (1 regional

Table 5 Maximum intrinsic rate of population increase (**r**) and carrying capacity (K) estimated outputs resulting from optimal CMSY++ models in this study. These estimates were used to calculate enhanced characterization factors (CFs) for representative fishery stocks in the Peruvian Exclusive economic Zone (EEZ)

Stock	r **(year^{-1})**	K (million tonnes)
Anchoveta (*E. ringens*), northern-central stock	1.303 (1.101–1.529)	12.132 (10.469–14.437)
Anchoveta (*E. ringens*), northern-central stock	0.825 (0.552–1.140)	2.379 (1.852–3.631)
Jack mackerel (*T. murphyi*)	0.489 (0.342–0.619)	2.902 (2.184–3.821)
Chub mackerel (*S. japonicus*)	0.255 (0.185–0.344)	1.707 (1.396–2.134)
Bonito (*S. chiliensis*)	0.244 (0.175–0.345)	1.447 (1.126–1.91)
Hake (*M. gayi*)	0.879 (0.755–1.01)	0.431 (0.386–0.491)
Common dolphinfish (*C. hippurus*)	1.118 (0.827–1.514)	0.232 (0.204–0.27)
Skipjack tuna (*K. pelamis*)	0.202 (0.121–0.279)	0.401 (0.291–0.722)
Jumbo squid (*D. gigas*)	0.828 (0.511–1.052)	2.337 (1.834–3.377)
Calico scallop (*A. purpuratus*)	0.986 (0.661–1.246)	0.273 (0.213–0.407)

and 3 global) were obtained for each stock. A non-parametric distribution of CFs was obtained for each year, set of CF time series and stock (see Figure S3, which shows quantile-quantile plots of the CF distributions for northern-central anchoveta, using single year catch). Sampling of 100,000 data points were sufficient to stabilize the distribution metrics, reducing the coefficient of variation for median and other quantiles to ≤1% across all stocks (Table S12).

Typically, the CFs showed lower median values than those previously reported in the original FIP (Fig. 3), with regional CF values larger than those from the three global approaches (Table S13 and Figures S4–S13 in the SM). Within regional CFs, hake and jack mackerel presented higher values with medians in the order of $10^{-11} - 10^{-9}$ PDF×year×tonne^{-1}. In the group of GEP-, RE- and SS-based CFs, hake and jack mackerel remained as leaders, but now with 10^{-13}–10^{-10} PDF×year×tonne^{-1}. The stocks of southern anchoveta, jack mackerel, hake and jumbo squid showed more dispersed CFs, suggesting higher susceptibility to temporal variability. The lower CF values appear to be reasonable as employed biomass, catch, carrying capacity and regional-to-global conversion factors are limited by the geopolitical boundaries of the EEZ, and other policy-oriented strategies such as total allowable catch and quota systems.

Although the enhanced CFs are on average below previous reference values, in the years 2009, 2011 and 2014–2016, CF values are substantially higher, getting closer to the reference value extracted from the original FIP impact category, and in some cases surpassing it (Fig. 3). This pattern tends to indicate higher impacts in years under El Niño oceanic conditions for certain stocks (e.g., anchoveta, jack mackerel and bonito). Notably, CFs from the jumbo squid stock converge to the reference value in recent years, suggesting an increasing pressure over this species. In contrast, mackerels, hake and scallop stocks showed CFs that diverged from reference values in recent years, pointing towards a decreasing pressure on these species.

3.3 Statistical evaluation of the characterization factors (CFs)

3.3.1 Uncertainty in the enhanced characterization factors (CFs)

Uncertainty sources of the CFs are mainly propagated in the Monte Carlo simulations employed in the CMSY++ algorithm, which outputs include estimations of key parameters such as the intrinsic rate of population increase, r, carrying capacity, K and biomass, B, with their corresponding confidence intervals.

From a qualitative perspective, the model's scientific reliability scored 1 (low uncertainty) given its basis on a model which has been included in the IMPACT World+ framework (CIRAIG 2023) and the integration of further statistical filters to improve model fit (Table 6). However, the limited stock coverage (only 10 out of 37 commercial stocks) resulted in a score of 5 (high uncertainty). Temporal specification was assigned 1 (low uncertainty), as the annual CFs capture the fisheries dynamics and address the biological reference points for each stock. Although the CFs granularity was mainly at EEZ level, regional variations within the EEZ boundaries are observed, particularly in northern-central and southern marine stocks like anchoveta. Thus, geographic specification scored 2 (moderately low uncertainty). Given the limitation to distinguish estimated from hydroacoustic biomasses in the abundance data provided by IMARPE, the input data characteristics also scored 2 (moderately low uncertainty).

From a quantitative perspective, dispersion factors (k) using single year landings ranged from 1.62 to 6.61, with lower values for jack mackerel and northern-central anchoveta and higher values for scallop and skipjack tuna (Table 7). A similar trend was observed when using 3-year averages. In both cases, the enhanced regional CFs showed lower k values than those reported by the original FIP for almost every stock, except for skipjack tuna. This is probably due to the larger uncertainty typical of the catch-only CMSY method used also in the original FIP framework, and the fluctuating skipjack tuna catch in the initial 2000s,

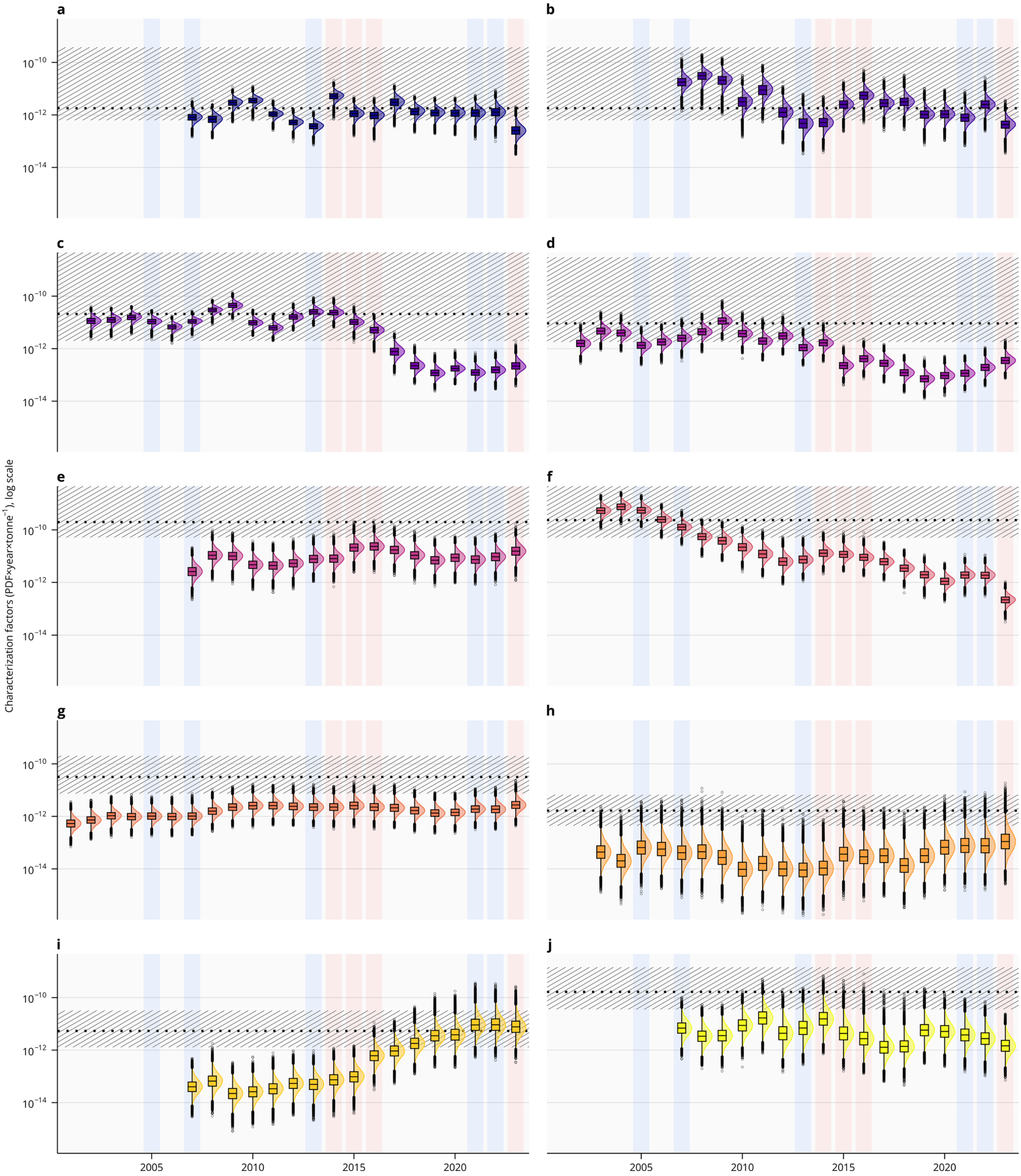


Fig. 3 Temporal series of enhanced characterization factors (CFs) for northern-central anchoveta (**a**), southern anchoveta (**b**), jack mackerel (**c**), chub mackerel (**d**), bonito (**e**), hake (**f**), common dolphinfish (**g**), skipjack tuna (**h**), jumbo squid (**i**) and calico scallop (**j**), recalculated using single year catch and relative endemicity (RE) conversion factors. Red and blue shadings indicate years with annual mean ICEN values > +0.5 (warm years) and <−0.7 (cold years). Dotted black lines and stripped patterns represent median values from the fisheries impact pathway with their corresponding confidence intervals

Table 6 Uncertainty assessment using the pedigree matrix for enhanced characterization factors (CFs) regarding relevant Peruvian fishing stocks

Criteria	Score[a]		Geometric Standard Deviation (GSD)
Reliability of underlying science	2	Moderately low uncertainty	1.11
Model completeness	5	High uncertainty	1.55
Temporal specification	1	Low uncertainty	1.00
Geographical specification	2	Moderately low uncertainty	1.09
Input data characteristics	2	Moderately low uncertainty	1.07

According perceived uncertainty in LCA characterization factors (Qin et al. 2020)

Table 7 Uncertainty assessment using dispersion factor (**k**) and differences in order of magnitude (OM_{diff}) between the 97.5th and 2.5th percentiles from regional enhanced characterization factor (CF) distributions. A centered 3-year moving average was used for a consistent of comparison

Stock	Catch used	Current study		Fisheries Impact Pathway	
		k	OM_{diff}	k	OM_{diff}
Anchoveta, northern-central stock	Single year	1.77 - 2.60	0.50 - 0.83	-	-
	3-year average	1.78 - 2.58	0.50 - 0.82	19.81	2.59
Anchoveta, southern stock	Single year	2.56 - 3.32	0.82 - 1.04	-	-
	3-year average	2.58 - 3.31	0.82 - 1.04	19.81	2.59
Jack mackerel	Single year	1.62 - 2.38	0.42 - 0.75	-	-
	3-year average	1.62 - 2.37	0.42 - 0.75	48.28	3.37
Chub mackerel	Single year	2.15 - 2.28	0.66 - 0.72	-	-
	3-year average	2.15 - 2.27	0.66 - 0.71	43.14	3.27
Bonito	Single year	2.54 - 2.79	0.81 - 0.89	-	-
	3-year average	2.54 - 2.79	0.81 - 0.89	25.84	2.82
Hake	Single year	1.99 - 2.60	0.60 - 0.83	-	-
	3-year average	1.99 - 2.62	0.60 - 0.84	42.06	3.25
Common dolphinfish	Single year	2.23 - 2.46	0.70 - 0.78	-	-
	3-year average	2.24 - 2.45	0.70 - 0.78	5.19	1.43
Skipjack tuna	Single year	5.07 - 6.61	1.41 - 1.64	-	-
	3-year average	5.10 - 6.41	1.41 - 1.61	5.09	1.41
Jumbo squid	Single year	3.40 - 4.61	1.06 - 1.33	-	-
	3-year average	3.42 - 4.58	1.07 - 1.32	4.55	1.32
Calico scallop	Single year	3.63 - 5.38	1.12 - 1.46	-	-
	3-year average	3.61 - 5.38	1.12 - 1.46	6.30	1.60

which broadened the distributions of r, K and biomass. The order of magnitude ranges of the 97.5th and 2.5th percentiles, in our study, also showed lower values than the original FIP (Table 7).

3.3.2 Sensitivity in the enhanced characterization factors (CFs)

The variability of the CFs in time is explained primarily by their significant (p-value < 0.05) and moderate-strong (Spearman's rho near -1 or $+1$) correlations with relative biomass indices (Table 8). Biomass estimation is a critical step towards a precise characterization of the impact related to biotic resource depletion in the marine environment. However, many fisheries lack these data because of the technical and logistical requirements to carry out biological assessments and, thus, they draw upon the use of modeling software. Surplus production models (e.g., CMSY++ and SPiCT), when tested in data-rich stocks, provide not so robust outcomes in comparison with more sophisticated assessments (Bouch et al. 2021). Hence, fisheries population dynamics modeling is still a challenge to bear with and LCA modeling for this impact pathway will rely heavily on fish stock modeling advances.

The updated CFs respond to perturbations in both biomass and landed catch. Given that biomass is an estimated parameter, it is crucial to examine the effects of potential overestimation in CF calculation. If biomass were only 80 and 50% of the current estimates, regional CFs could increase up to 1.95 and 8.00 times their current value, respectively. Moreover, under a combined situation of 50% lower biomass and 20% increase in catch, CF values could rise by almost one order of magnitude (9.60 times as compared to the reported values). In this latter case, an El Niño event in the Peruvian EEZ (e.g., 2015) would yield a CF of 1.29×10^{-11} PDF×year×tonne^{-1} for northern-central anchoveta, noting a new peak in the CF time series for the stock.

3.3.3 Statistical correlation of enhanced CFs and ENSO indicators

Significant correlations using Spearman's rank correlation coefficient were identified between CF time series and the climatic parameters of sea level and dissolved oxygen for

Table 8 Sensitivity analysis of enhanced characterization factors (CFs) towards catch-maximum sustainable yield (C/MSY) and relative biomass (B/K) ratios. Statistically significant correlations ($p < 0.05$) are shown in bold with Spearman's rho coefficients in parentheses, indicating where annual CF variations are systematically associated to the input parameters used in their recalculation

Stock	Annual catch		3 year moving average	
	C/MSY	B/K	C/MSY	B/K
Anchoveta, NC stock	0.486 (−0.18)	0.492 (−0.18)	0.133 (−0.38)	0.384 (−0.23)
Anchoveta, S stock	**0.030** **(0.53)**	**0.046** **(−0.49)**	0.213 (0.32)	0.064 (−0.46)
Jack mackerel	0.363 (−0.20)	**0.000** **(−0.73)**	0.156 (−0.31)	**0.000** **(−0.78)**
Chub mackerel	**0.042** **(0.44)**	**0.000** **(−0.86)**	0.601 (0.12)	**0.000** **(−0.91)**
Bonito	**0.005** **(0.65)**	0.326 (0.25)	**0.013** **(0.59)**	0.098 (0.41)
Hake	0.404 (−0.19)	**0.000** **(−0.97)**	0.241 (−0.27)	**0.000** **(−0.98)**
Common dolphinfish	**0.000** **(0.76)**	**0.000** **(−0.78)**	**0.007** **(0.55)**	**0.000** **(−0.82)**
Skipjack tuna	**0.000** **(0.94)**	**0.007** **(−0.57)**	**0.000** **(0.78)**	**0.006** **(−0.58)**
Jumbo squid	**0.048** **(0.49)**	**0.000** **(−0.90)**	0.052 (0.48)	**0.000** **(−0.90)**
Calico scallop	**0.000** **(0.90)**	0.094 (−0.42)	0.069 (0.45)	**0.000** **(−0.81)**

most of the stocks (see Table 9). Regarding SST anomalies, significant correlations were observed only for bonito when observing the regional (ICEN) and local (LABCOS) indices. Other stocks with significant statistical association were common dolphinfish with atmospheric pressure, skipjack tuna with nitrate concentrations and, once again, bonito with phosphate concentrations. Although some of these correlations are documented (Bertrand et al. 2020), the use of annual scale CFs and climatic variables is not appropriate to detect the expected statistical associations with sufficient resolution.

Given significant correlation across stocks, sea level and dissolved oxygen could be explored as proxies in LCIA modeling. Changes in oxygen solubility due to elevated oceanic temperatures represent a robust proxy for global warming as this indicator shows minimal variability over time (Garcia-Soto et al. 2021). Dissolved oxygen can also be exploited to monitor eutrophication since this metric includes biota decomposition, respiration and photosynthetic activity (Coffin et al. 2018). Concerning sea level, Global Sea level rise Potential (GSP) arises as a metric which quantifies oceanic thermal expansion caused by anthropogenic emissions (Sterner et al. 2014). To our knowledge, existing LCIA models are yet to address these impact pathways.

3.3.4 Grouping stocks based on clustering analysis of CF time series

In the hierarchical clustering analysis, although the elbow method and silhouette analysis indicated two optimal groups (see Figures S13–S16 in the SM), the defined behavior of the CF time series allowed an improved analysis using four clusters. Using the Euclidean distance, the first group is formed by common dolphinfish and bonito with CFs marked by growing, extreme and slow fluctuations (see Fig. 4a and Figure S17). The second group, formed by jumbo squid and skipjack tuna, shows consistent growth without extreme values. Calico scallop and northern-central anchoveta stocks form the third group, showing highly extreme values, with relatively fast CF value fluctuations. The last group, formed by hake, southern anchoveta, chub mackerel and jack mackerel is characterized by decreasing CFs through time with peaks in the period 2014–2016. Dynamic time warping refined the clustering within groups by distinguishing the more varied pattern of southern anchoveta CFs from the stable pattern shown by hake, chub mackerel and jack mackerel CFs. It also identified behavioral similarities between CFs from the first and second groups formed using Euclidean distance (Fig. 4b and Figure S18).

The joint analysis of CF temporal series and clustering analysis may suggest that fishery management of some species has been successful. For instance, after decades of high fishing pressure, hake started to show signs of recovery in 2012 (Avadí et al. 2018), and this is observed with a lower CF value in that year. In contrast, growing landings for other species, such as jumbo squid and skipjack tuna (IMARPE 2024a), coupled with reports of illegal, unreported and unregulated (IUU) fishing from foreign fleets entering the Peruvian EEZ (Muñoz-Sovero et al. 2026), may have contributed to a gradual increase in the CFs of this species through time.

An interesting insight emerges when comparing our CFs between 2022 and 2023. Despite 2023 experiencing a strong El Niño phenomenon, which typically hampers anchoveta, hake and jumbo squid abundance through elevated, positive anomalies in SST (Bertrand et al. 2020), no significant increase in CFs or decrease in biomass indices were observed relative to 2022. These facts may stem from the pre-El Niño periods that are defined to conduct IMARPE's hydroacoustic surveys to provide biomass estimations (Castillo et al. 2024). If these seasonal windows are not aligned with the lowest point in biomass decline, reported estimates would not reflect the true population status, remarking the challenges raised by synchronizing surveys with climatologic stressors to avoid overestimations in stock abundance.

Table 9 Results for Spearman rank correlation between enhanced characterization factor (CF) temporal series and indices of sea surface temperature (SST) anomalies, along with other physical and biochemical parameters monitored within Peru's EEZ. *p*-values < 0.05 (in bold together with Spearman's rho in parenthesis) show statistically significant correlations, allowing the rejection of the hypothesis of no relationship between annual CFs and annual mean parameters

Parameters[a]	Anchoveta, NC stock	Anchoveta, S stock	Jack mackerel	Chub mackerel	Bonito	Hake	Common dolphinfish	Skipjack tuna	Jumbo squid	Calico scallop
Oceanic Niño Index (ONI) [b]	0.815	0.353	0.556	0.986	0.056	0.311	0.579	0.797	0.978	0.504
El Niño Coastal Index (ICEN)	0.619	0.952	0.368	0.587	**0.010 (0.61)**	0.915	0.074	0.801	0.896	0.286
Coastal Laboratories (LABCOS)	0.918	0.465	0.352	0.133	**0.002 (0.70)**	0.078	0.111	0.457	0.184	0.084
Atmospheric pressure	0.417	0.222	0.271	0.662	0.181	0.650	**0.046 (−0.42)**	0.559	0.758	0.918
Eastward sea water velocity	0.158	0.532	0.086	0.160	0.453	0.302	0.166	0.454	0.808	0.694
Northward sea water velocity	0.567	0.384	0.146	0.355	0.141	0.575	0.445	0.263	0.701	0.374
Sea level	0.933	0.081	**0.017 (−0.50)**	**0.001 (−0.68)**	**0.001 (0.72)**	**<0.001 (−0.72)**	**0.010 (−0.52)**	0.567	**0.006 (0.64)**	**0.016 (−0.57)**
Salinity	0.358	0.547	0.721	0.240	0.405	0.375	0.264	0.964	0.751	0.722
Dissolved oxygen	0.801	**0.031 (0.52)**	**0.038 (0.45)**	**0.039 (0.44)**	0.227	0.124	0.564	**0.022 (−0.50)**	**0.025 (−0.54)**	0.492
Nitrate	0.188	0.952	0.740	0.294	0.900	0.810	0.058	**0.034 (−0.46)**	0.395	0.209
Phosphate	0.300	0.168	0.379	0.214	**0.031 (−0.52)**	0.372	0.144	0.143	0.073	0.115
Chlorophyll	0.130	0.425	0.382	0.824	0.507	0.703	0.740	0.849	0.918	0.660
Phytoplankton	0.115	0.855	0.262	0.651	0.318	0.978	0.633	0.658	0.613	0.646
Net Primary Productivity (NPP)	0.240	0.903	0.101	0.236	0.395	0.679	0.993	0.793	0.492	0.456

Sea Surface Temperature (SST) anomalies were sourced from SIOFEN (2025), while other oceanographic indicators were sourced from Copernicus (2025)

ONI index was derived from Multivariate ENSO Index (MEI.v2)

3.3.5 Influence of landings on characterization factors (CFs)

Results from the Wilcoxon test indicated that the choice of single year catch or moving averages (3- and 5-year) yield statistically significant differences in CF distributions across all stocks for *ca.* 40% of the years analyzed within each stock (Table S14). Confirming these results, the rank-biserial correlation analysis showed negligible-small effect size in years without statistical differences ($0 \leq r < 0.3$), and mostly medium-large effect size in years characterized by statistical differences ($0.3 \leq r$). Figure 5 shows differences in northern-central anchoveta CFs using single year and moving averages, in particular, for the events that occurred in 2013 (strong La Niña) and 2015 (strong El Niño).

Considering annual variability in fish stocks dynamics, especially those affected by climatic phenomena, and the need for consistently updating CFs to support adaptive fishery management, we recommend the use of single year catch for CF recalculation. This value choice is preferable since center-aligned moving averages introduce time lags and trailing moving averages decrease responsiveness to recent fluctuations in catch and biomass.

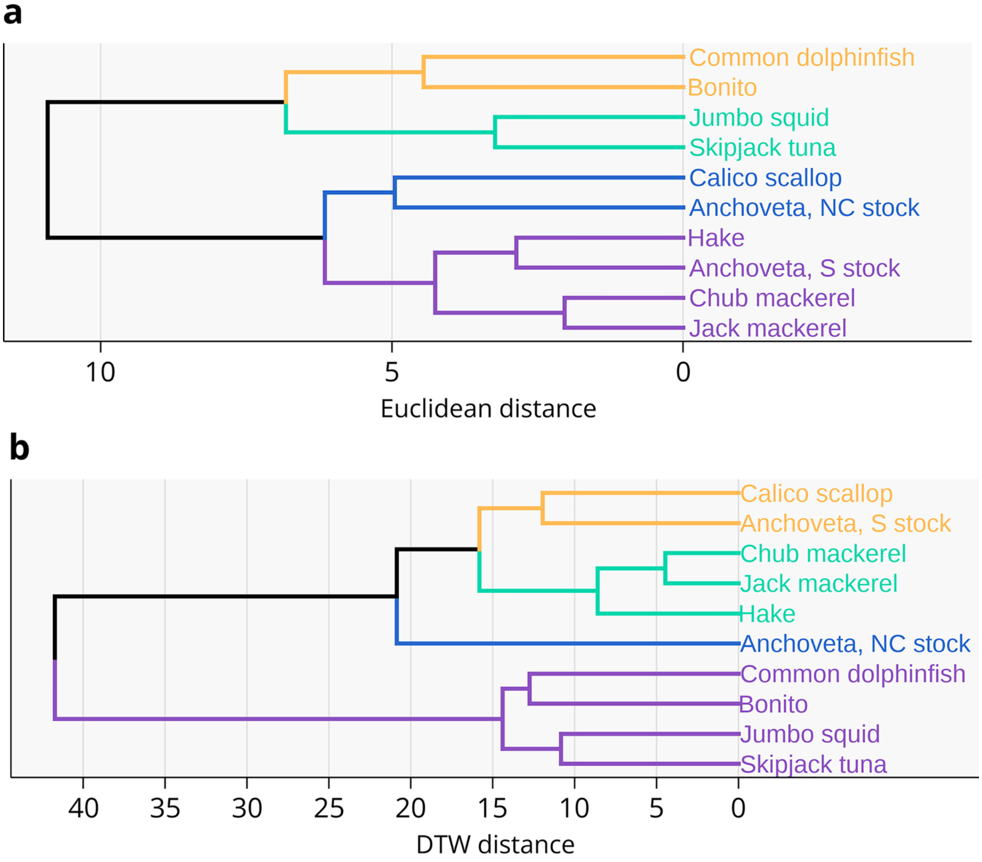
3.4 Key insights from case study results

3.4.1 Environmental impacts on stocks for direct human consumption (DHC)

Environmental impacts were lower than those obtained through the original FIP framework regardless of the allocation approach. When applying energy allocation with RE-based global CFs, anchoveta exhibited the highest impacts for fresh DHC products, followed by the impacts of cured jack mackerel, chub mackerel, bonito and hake in both 2013 and 2015 (Fig. 6). As the impacts are distributed among the annual outputs of a given product, higher PDF×year per functional unit (FU) were obtained for the noted processing DHC procedures.

When the CFs from this study were used, impacts of anchoveta were only 21–36% of the impacts resulting from the original FIP CFs. In the case of chub mackerel, bonito and hake, the percentages are even lower representing 3–12% of original CFs. However, our refined methodology yielded higher impacts in jack mackerel for 2013, at 1.2 times the value obtained when applying the original FIP framework. The lack of data on environmental impacts in PDF×year or

Fig. 4 Clusters formed by either one of the two approaches to calculate distance in hierarchical clustering analysis, i.e., Euclidean (**a**) and dynamic time warping, DTW (**b**), and applying logarithmic adjustment followed by Ward's method to the enhanced regional characterization factors (CFs) of each evaluated stock



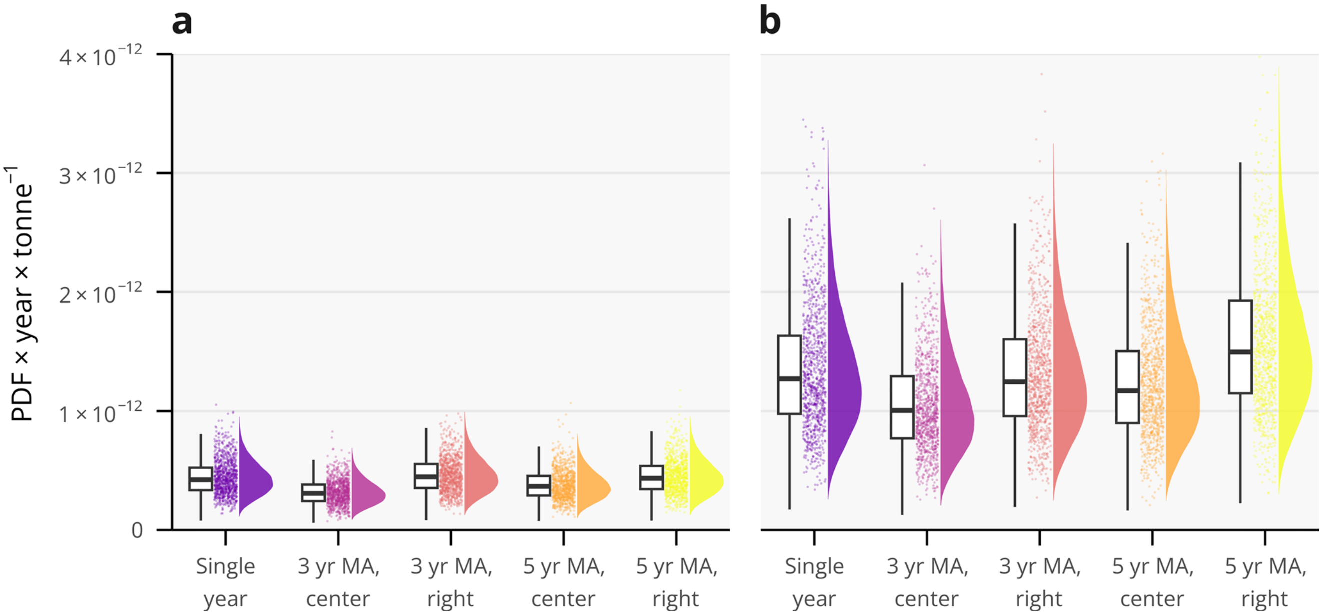
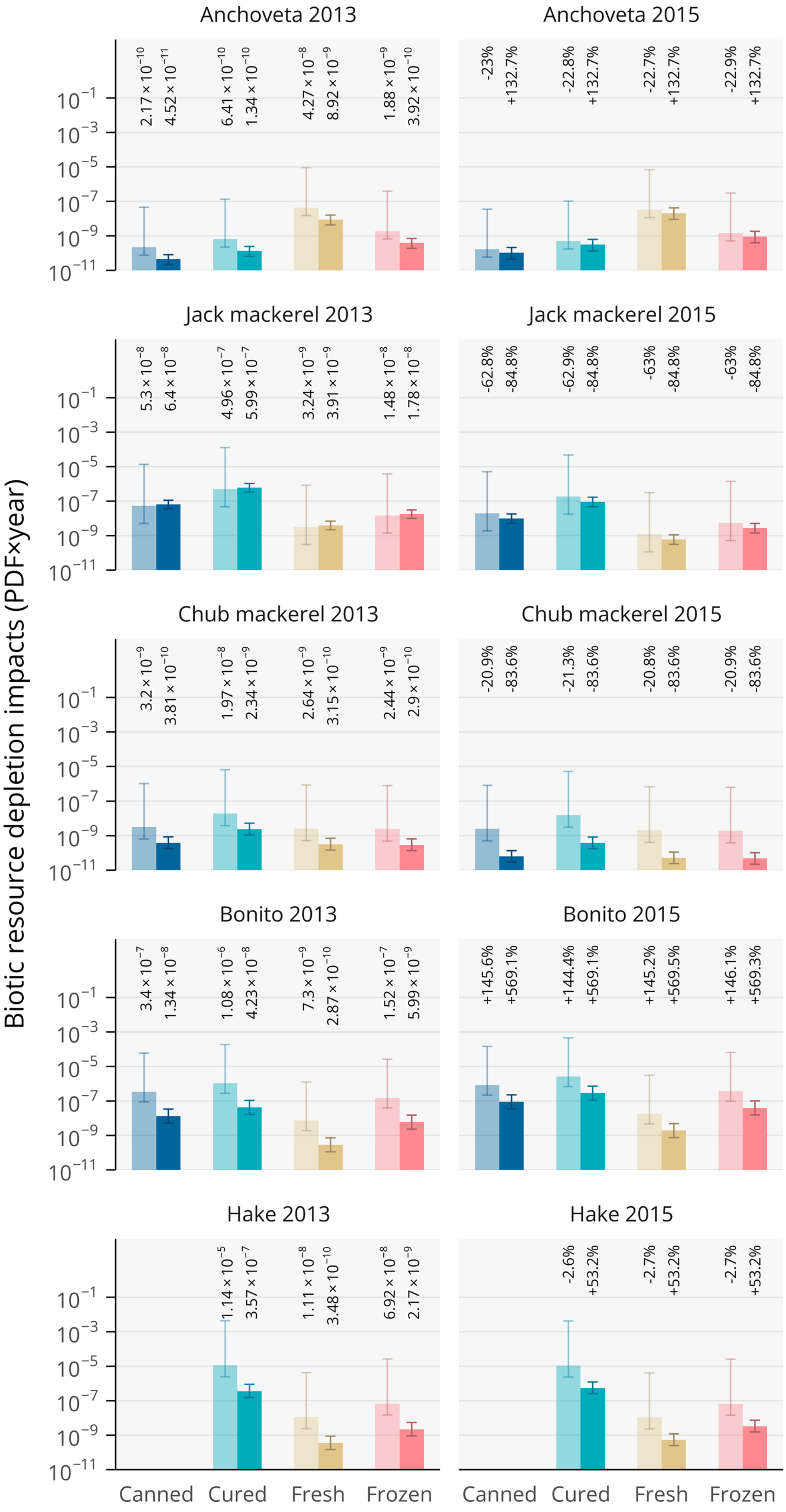


Fig. 5 Distribution of characterization factors (CFs) using different catch values (1 single year, 3- and 5- year moving averages) for northern-central anchoveta stock within Peru's Exclusive economic Zone (EEZ), corresponding to 2013 (**a**) and 2015 (**b**) years

Fig. 6 Marine biotic resource depletion impacts, per 100 g of protein supplied to the Peruvian population (i.e., 33,725,000), through direct human consumption (DHC) products from five species caught in Peruvian waters. Impacts were calculated using global characterization factors (CFs) based on relative endemicity (RE), from original fisheries impact pathway – FIP (transparent columns) and the enhanced method from this study (solid columns). Impacts for 2015 are expressed in relative increments relative to their corresponding 2013 values



species×year regarding LCA of DHC anchoveta production (Avadí et al. 2014) limit the discussion regarding the increment of the impacts due to stock removal from the ocean.

Impacts of anchoveta, bonito and hake stocks rose 53–570% across all DHC products from 2013 to 2015, using enhanced CFs from the current study. In contrast, jack and chub mackerels exhibited a decrease of *ca*. 84% in impacts from 2013 to 2015. The higher energy content of fresh chub mackerel (compared to jack mackerel) results in more distributed impacts for its fresh products, whereas the small cured production volume of jack mackerel explains its disproportionate impact per FU. Since these species share similar fishing regulations, potential management deficiencies during El Niño events (e.g., 2015) may have occurred.

Comparable temporal trends were observed when other global CFs and a mass allocation method were employed to compute environmental impacts for DHC products (Table S15). Even though similar PDF×year values were also identified with global CFs, impacts using GEP-based CFs were two orders of magnitude lower given that the regional-to-global conversion factor was significantly lower than the other two conversion factors in this study.

The methodological improvements of employing annually differentiated CFs enabled detection of interannual variability that was previously masked by the use of static CFs. This temporal resolution is valuable for fisheries management in nutrient-rich ecosystems like the Humboldt Current, where climate phenomena, such as El Niño perturbations, can dramatically alter stock abundance and distribution.

3.4.2 Impacts of fishmeal and fish oil (FMFO) production

Using an energy allocation perspective, the increase in environmental impacts for the ecosystem quality AoP caused by the extraction of anchoveta from the ocean was variable depending on the CFs applied. When the GEP global CFs are used, the increment is minimal, representing only 0.1%-9% of the impacts relative to the original ReCiPe values without this category (see Figure S22). However, when using the other two approaches (i.e., RE and SS global CFs), the impact is much larger, accounting for 18%-61% of the total ReCiPe impacts (see Fig. 7 and Figure S23). This pattern is reasonable as the methodological differences involve extinction probabilities up to two orders of magnitude lower than the other conversion factors. SS generates lower impacts since the deviation of Peruvian anchoveta stocks' from pristine conditions remained smaller than the average deviation observed in other stocks assessed.

Although our methodology yields lower impacts overall, impacts from the processing plant at Ilo, located in the southern region of Peru, are systematically lower to other plants in the northern-central territory of Peru. This is linked with the values of southern anchoveta CFs which are slightly below their northern-central counterpart, highlighting the difference in population dynamics between both stocks.

Our revisited CFs revealed a decrease in fishmeal environmental impacts from 2019 to 2021 (Table S16), representing lower proportions relative to values previously reported (Deville et al. 2025). This is due, in part, to La Niña oceanic conditions that in 2021 promoted exceptional anchoveta biomass, particularly in the southern region, causing a distinct biodiversity impact despite the high resilience of anchoveta. Fish oil did not conform to the patterns mentioned above, as fish oil production is strongly conditioned by other variables, such as fat content of the anchoveta.

It is worth highlighting that the FIP model, a methodology with static CFs in time based on FAO stock captures, reflects higher impacts on biodiversity than our methodology: while the original FIP increase impacts by 41–61%, our approach results in only an 18–49% increase. This divergence suggests a previous overestimation particularly for the Peruvian anchoveta fishery.

We reckon that the enhanced CFs allow precise analysis of the contribution of individual processing plants to marine biodiversity loss. The divergence between northern and southern anchoveta stocks highlights that, when required, a higher level of granularity can be applied to identify impact differences between production systems. Apart from facility-level impact quantification, the enhanced dynamic CFs support temporal and spatial management during climate anomalies using the sensitivity that static CFs cannot provide. Thus, we recommend employing dynamic CFs when data availability allows it to better capture the environmental impacts on biodiversity.

3.5 Characterization factor (CF) regionalization and temporalization in fisheries

The importance of incorporating regionalization in LCIA has been highlighted recurrently for conventional mainstream impact categories (Frischknecht et al. 2019) and is beginning to be implemented in marine-specific impact categories, such as microplastic emissions to the marine environment (Hajjar et al. 2024) or seabed impact (Woods and Verones 2019). In the case of the FIP model, how a nation manages its fisheries under its jurisdiction will have profound implications on stock sustainability and on underlying biological diversity. For instance, the stricter quotas IMARPE set after the very strong El Niño event in 1998 helped the stock to recover faster (Arias-Schreiber 2012). This gains relevance when multiple factors (e.g., climate change) redistribute an international shared stock to enter a specific EEZ (Bjørndal et al. 2024), or when integrated efforts from different nations are required to promote the

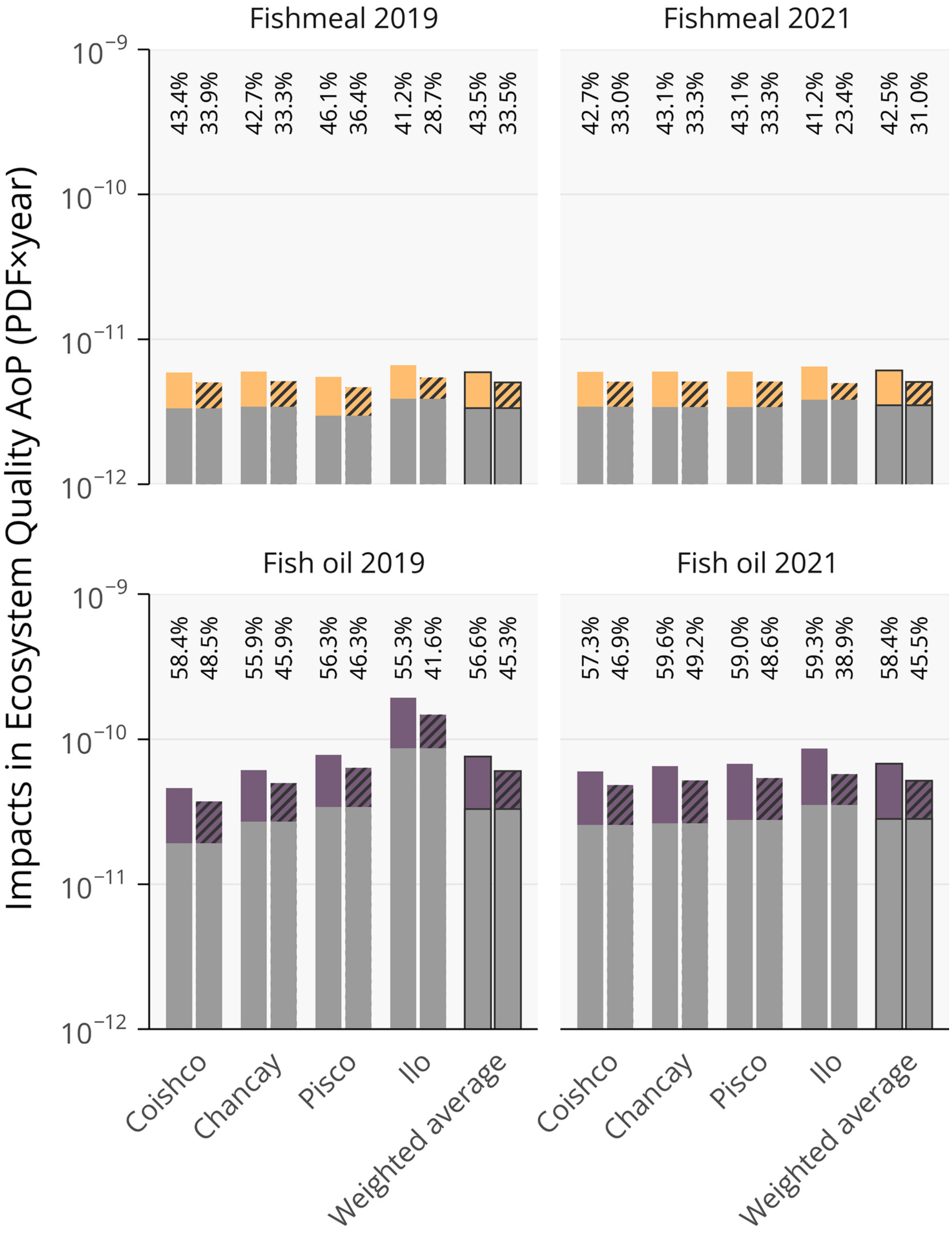


Fig. 7 Comparative ecosystem quality impacts per 1 tonne of fishmeal and 1 tonne of fish oil produced by four processing plants and delivered to the importing country in 2019 and 2021. Impacts were assessed using three methods: ReCiPe (gray bars; Deville et al. 2025), the original fisheries impact pathway – FIP (solid colored bars; Stanford-Clark et al. 2024) and the enhanced method from this study (striped colored bars). Impacts of marine biotic resource depletion were quantified using global characterization factors (CFs) based on relative endemicity (RE) factors, with results for fishmeal, and fish oil shown in yellow and purple, respectively. Numerical values above bars indicate percentage contribution of stock removal to the total ReCiPe impact

recovery of an almost depleted stock, such as the case of jack mackerel in the South Pacific (Rodriguez and Urrutia 2020).

We argue that a regionalized approach to quantify biotic resource depletion in the marine realm is about contextualizing the environmental impact assessment, rather than confining species to physical or geopolitical boundaries. This means linking CFs to specific ecological conditions, and to some extent climatic factors, that influence stock dynamics. Under this framework, an overexploited stock in a hostile ecosystem would suffer pronounced impacts per tonne removed as compared to a sustainably exploited stock. Using the EEZ as a boundary for this contextualization allows diverse stakeholders to measure the effectiveness of national fishery policies (e.g., marine protected areas or restrictive quota systems) that would remain undetected using coarse CFs.

Limitations due to temporality have been detected in LCA since early years of its development (Owens 1997) and more recent systematic reviews have delved into how temporal dynamism should be modeled in the methodology (Lueddeckens et al. 2020). Previous studies have included dynamic inventories related to the biotic resource depletion caused by fisheries (Emanuelsson et al. 2014; Langlois et al. 2015). However, to the best of our knowledge, our study is novel in providing dynamic CFs within the marine environment for a long time series. The susceptibility of biomass and catch to fishing pressure and policy implementations over time make CF quantification a critical step towards environmental assessment that better reflects the dynamism of the fisheries. Ignoring these methodological aspects can lead to erroneous policies that cause detrimental ecological effects decades later.

3.6 Considerations for applying the enhanced framework in other exclusive economic zones (EEZs)

Even though this study assesses biotic resource depletion impacts within Peruvian maritime boundaries, our statistical, spatial and temporal enhancements may be applied in other EEZs, depending on a set of conditions. The statistical criteria assessing CMSY++ performance is applicable to any fishery using this algorithm, as its estimations provide reliable CFs. Although certain criteria (i.e., residual, hindcasting and biological plausibility) require independent biomass data, model functioning can be improved even in lack of such data, as demonstrated by skipjack tuna and calico scallop.

Including temporal variability through dynamic CFs is relevant for fisheries with oscillating catch and abundance, such as those affected by climate or policy changes. However, we recommend quantifying CF time series instead of assuming static CFs in light of two complications when predicting CF behavior over time: 1) stable catch records are not a proxy for stable CFs, as changes in fishing effort and environmental conditions can alter other CF data inputs; and 2) the stable enhanced CFs we calculated (e.g. skipjack tuna) were not necessarily linked to similar catch trends.

The importance of using an EEZ approach was discussed in Sect. 3.5, yet we emphasize that this approach is only viable where national data on stock status exists, e.g., from reported catch and hydroacoustic surveys or other independent assessments. In this context, the EEZ approach is less suitable for highly migratory stocks, international fisheries, and situations lacking national abundance indices. While intuitive, using national landings data to calculate CFs would underestimate biotic resource depletion since catches cover reported and unreported stocks from both national and foreign fleets.

The enhanced methodology should be prioritized for fish stocks influenced by climatic systems that induce immediate and long-term changes in population dynamics and fishery patterns. These systems include ENSO, Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), Indian Ocean Dipole (IOD), and Southern Annular Mode (SAM) (Mondal et al. 2024; Salinger 2013). Examples include changes in spatial or temporal distribution of North Sea cod (Engelhard et al. 2014), yellowfin tuna in the Indo-Pacific (Wu et al. 2022), and sardinella in the Northwest African coast (Sarre et al. 2024).

To extend our methodological enhancements to other EEZs, LCA practitioners should follow an implementation protocol (Figure S24 in the SM). The ideal scenario requires data on catch temporal series of ≥17 years, independent biomass estimates for the same period, and biological parameters extracted from the literature (i.e., r, K, MSY, BMSY, FMSY). In data-limited situations, modeling is still viable with only catch series of ≥10 years and prior distributions for r and K. However, in these cases, some statistical criteria (residual, hindcasting, and biological plausibility analyses) cannot be fully applied, resulting in less robust enhancements with higher uncertainty.

3.7 Limitations of the study

Firstly, the spatial resolution of landing data was limited by national-level aggregation for each stock except for anchoveta, preventing more resolved geographical analysis. Secondly, the lack of biomass data for skipjack tuna and scallop interfered with residual analysis, hindcasting analysis and biological meaning criteria within the model performance evaluation, leading to higher uncertainty in the computation of their CFs. Moreover, we estimated confidence intervals for IMARPE biomass data by extrapolating proportions from 2.5th and 97.5th percentiles of biomass calculated under the CMSY method of the CMSY++ package. A third aspect is the absence of annual reporting on by-catch, discards, and IUU fishing in the Peruvian EEZ (Muñoz-Sovero et al. 2026), at least for recent years, which implied that these components could not be incorporated into our impact assessment and can potentially distort the enhanced CFs.

Methodologically, the study faced three main difficulties. The CMSY++ algorithm required a 7-year retrospective data window beyond our study time frame to meet statistical testing requirements. We hypothesize that advancing in time, our methodology will generate results that better fit empirical data. Although the CMSY++ model is robust, it carries assumptions that may not be suitable for stocks experiencing heavy exploitation pressure.

Furthermore, factors that allow conversion from regional to global PDF units had some constraints. GEP values lacked uncertainty quantification, while RE and SS calculations relied on averaged biomass indices due to varying temporal coverage of data across EEZs (Pauly et al. 2024). In this regard, there was also a trade-off with the RE and SS factors, which did not follow the procedure proposed in this study. In practice, processing 30 runs (corresponding to different initial, intermediate and final B/K prior combinations) for >350 stocks required computational power that was beyond our current resources. Thus, we focused on relative proportions of stock biomass and stock distance to nature, (K-B)/K, to calculate RE and SS factors, which meant only one run for each stock.

Although the CFs presented in our study are notably useful and innovative in the field of LCA, they cannot capture ecosystem-level effects, such as food web interactions, due to heavy fishing. These aspects remain beyond our scope despite being recommended in ILCD guidelines (European Commission et al. 2010), discussed by Brown et al. (2025) and incorporated in a recent study by Stanford-Clark et al. (2025). Besides, the absence of economic allocation parameters for DHC fisheries limited the scope of the first case study. Finally, the dynamic nature of fisheries needs annual recalculation of CFs (integrating enhanced r, K, and B estimates), demanding critical computational resources that might limit practical implementation.

4 Conclusions

This study enhanced the FIP model by refining spatial, temporal and statistical methodological foundations, to provide endpoint CFs for a series of significant Peruvian fishing stocks within the national EEZ. These refinements revealed inter-annual variability in biotic resource depletion impact assessment in fisheries affected by ENSO variability, fluctuating fishing pressure at sub-stock level (northern-central and central anchoveta), and shifting management policies. Therefore, this study advances the field towards international LCA guidelines, such as those from UNEP-SETAC, requesting for context-specific LCIA.

For CF enhancements, CMSY++ model performance was optimized using convergence, residuals, prior-to-posterior, retrospective, hindcasting and biological plausibility statistical criteria. Optimal performances were achieved by incorporating biomass time series, adjusted r and B/K priors and by reducing the time frame of analysis (Section 3.1). Although the whole time frame accounts for the entire population dynamics, the increasing number of statistical criteria met supports the use of a shorter period for more accurate estimates.

The resulting CF time series for Peruvian fisheries fluctuated over time, with consistently lower values than the original FIP values (Section 3.2). Moreover, the uncertainty analysis conducted revealed less dispersion in CF distributions in the current study. The sensitivity analysis indicated CFs are strongly correlated to biomass and catch, which implies that the use of moving averages can hide interannual variability of the CFs. Although correlations with typical ENSO parameters were weak-moderate, peak CF values were observed during certain El Niño years, indicating the influence of climate phenomena on higher environmental impacts. However, this relationship is complex: while strong associations with sea level and dissolved oxygen were observed, the response was not uniformly positive or negative across stocks and other ENSO indicators. Subsequently, hierarchical cluster analysis classified the stocks in those recovering from heavy fishing (e.g., hake), under growing pressure (e.g., jumbo squid), and showing CF variability with extreme values. Together, these statistical tests demonstrate our method better reflects population dynamics, fisheries management, and climatic influence than the original FIP model, yet also indicates enhanced CFs cannot fully disentangle complex and nonlinear influence of climatic temporal fluctuations (Section 3.3).

The application of our enhanced CFs in the DHC production case study revealed that impacts for several stocks fluctuate between climatic events (El Niño vs. La Niña), indicating trends that static CFs cannot distinguish. For the FMFO case study, the method showed lower impacts relative to the original FIP framework, and differentiated fisheries impacts at facility level. Therefore, our method can provide valuable information for certification, labeling, corporate decisions, and fishery policy interventions in the seafood and aquafeed sectors (Section 3.4).

Our study suggests that accounting for both spatial differentiation (e.g., between EEZs) and temporal variability in fisheries LCAs is critically important, as climatic drivers and divergent management policies affect stock status unevenly (Section 3.5). For this reason, we recommend using the method proposed to recalculate CFs based on single-year catch data for the Peruvian EEZ when production systems being analyzed, such as the case studies presented here, require a rigorous quantification of marine biotic depletion impacts (e.g., DHC seafood LCAs in Peru or aquaculture studies that rely heavily on Peruvian FMFO). However, this recommendation may not apply for more generalist LCA studies (e.g., human diets). We also recommend following principles outlined in Section 3.6 for deciding which enhancements can be applied to different EEZs, while also considering the data limitations discussed in Section 3.7.

For future research, we recommend building CF temporal series for other stocks for which this perspective could be meaningful. In the case of the Peruvian EEZ, this will require improved stock abundance data acquisition, as this is a critical factor that drives the CMSY++ performance and, thus, compromises CFs reliability. Finally, to move beyond single species impacts, we suggest integrating ecosystem-level models to account for species interactions (e.g., food web interactions).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11367-026-02626-z.

Acknowledgements The authors work in the BAMBOO and RAINFOREST projects that have received funding from the European Union's Horizon Europe research and innovation programme under grant agreements no. 101059379 and 101081744, respectively. Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them. The authors wish to thank Francesca Verones, Stephan Pfister, and Chloe Stanford-Clark for valuable scientific discussion.

Author contributions Rubén Manrique-Muñante: investigation, validation, resources, methodology, formal analysis, writing (original draft); Alejandro Deville: methodology, resources, formal analysis, writing (review and editing); Ramzy Kahhat: formal analysis, supervision, validation, writing (review and editing); Ian Vázquez-Rowe: conceptualization, formal analysis, supervision, funding acquisition, project administration, validation, writing (review and editing).

Funding Open access funding provided by Pontificia Universidad Catolica del Peru.

Data availability Data will be made available on request.

Declarations

Competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Alheit J, Niquen M (2004) Regime shifts in the Humboldt Current ecosystem. Prog Oceanogr 60(2–4):201–222

Argüelles J, Tafur R, Taipe A, Villegas P, Keyl F, Dominguez N, Salazar M (2008) Size increment of jumbo flying squid Dosidicus gigas mature females in Peruvian waters, 1989-2004. Prog Oceanogr 79(2–4):308–312

Arias-Schreiber M (2012) The evolution of legal instruments and the sustainability of the Peruvian anchovy fishery. Mar Policy 36(1):78–89

Arntz WE, Tarazona J (1990) Effects of El Niño 1982–83 on benthos, fish and fisheries off the South American Pacific coast. Elsevier Oceanogr Ser 323–360

Avadí A, Adrien R, Aramayo F V, P (2018) Environmental assessment of the Peruvian industrial hake fishery with LCA. The Int J Life Cycle Assess 23(5):1126–1140

Avadí A, Fréon P, Quispe I (2014) Environmental assessment of Peruvian anchoveta food products: is less refined better? The Int J Life Cycle Assess 19(6):1276–1293

Bach H V, Muhl A, M et al (2022) Assessing overfishing based on the distance-to-target approach. The Int J Life Cycle Assess 27:573–586

Bamston AG, Chelliah M, Goldenberg SB (1997) Documentation of a highly ENSO-related SST region in the equatorial pacific: research note. Atmos-Ocean 35(3):367–383

Barahona SP, Chávez DSO, Baza RWQ (2017) High genetic connectivity and population expansion of Scomber japonicus in the northern Humboldt Current System revealed by mitochondrial D-Loop region sequences. Rev Peru Biol 24(2):163–174

Beloin-Saint-Pierre D, Levasseur A, Margni M, Blanc I (2016) Implementing a dynamic Life cycle assessment methodology with a case study on domestic hot water production. J Ind Ecol 21(5):1128–1138

Benton T, Bieg C, Harwatt H, Pudasaini R, Wellesley L (2021) Food system impacts on biodiversity loss: three levers for food system transformation in support of nature. In Chatham House. https://www.chathamhouse.org/2021/02/food-system-impacts-biodiversity-loss

Bergman K, Gröndahl F, Hasselström L, Strand Å, Thomas JBE, Hornborg S (2025) Integrating biodiversity impacts into seafood life cycle assessments: pathways for improvement. The Int J Life Cycle Assess 30(3):477–490

Bertrand A, Lengaigne M, Takahashi K, Avadí A, Poulain F, Harrod C (2020) El Niño Southern Oscillation (ENSO) effects on fisheries and aquaculture. FAO eBooks

Bjørndal T, Lindroos M, Munro G (2024) The cooperative management of internationally shared fish stocks in a world of instability. Mar Policy 160:105961

Bouch P, Minto C, Reid DG (2021) Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks. ICES J Mar Sci 78(1):264–276

Brown E, Vázquez-Rowe I, Ulrich C, Asselin A-C, Casonato C, Ferrara N, Ardente F, Garcia-Herrero L (2025) Exploring environmental impact methodologies to quantify fish stock exploitation and seabed impacts of fishing: evaluating LCA and Non-LCA approaches. Publications Office of the European Union. https://publications.jrc.ec.europa.eu/repository/handle/JRC142085

Bruland KW, Rue EL, Smith GJ, DiTullio GR (2005) Iron, macronutrients and diatom blooms in the Peru upwelling regime: brown and blue waters of Peru. Mar Chem 93(2–4):81–103

Cai K, Kindong R, Ma Q, Tian S (2023) Stock assessment of chub mackerel (Scomber japonicus) in the Northwest Pacific using a multi-model approach. Fishes 8(2):80

Carvalho F, Winker H, Courtney D, Kapur M, Kell L, Cardinale M, Schirripa M, Kitakado T, Yemane D, Piner KR, Maunder MN, Taylor I, Wetzel CR, Doering K, Johnson KF, Methot RD (2021) A cookbook for using model diagnostics in integrated stock assessments. Fish Res 240:105959

Castillo P, Madureira L, Marangoni J, Gerlotto F, Guevara-Carrasco R (2015) Variability in distribution and aggregation behavior of the Peruvian anchovy (Engraulis ringens) analyzed using a fifteen year long series of acoustic surveys (2000-2014). In IEEE/OES Acoustics in underwater Geosciences Symposium, Brazil, 9781467370202

Castillo PR, Bouchon M, Grados D, Guevara R (2024) Actores que intervienen para recomendaciones de la cuota de pesca en la anchoveta (Engraulis ringens) en Perú. Bol Inv Mar Cost 53(2):9–28

Castillo PR, Xu H, Cuadros G, Grados D, Valdez C, Cornejo R, Pozada-Herrera M (2025) Spatial structure and decadal spatio-temporal distribution of the anchoveta (Engraulis ringens) in the marine ecosystem of the Peruvian Current between 1985 and 2024. Fish Oceanogr 34(6):70–88

Chavez FP, Bertrand A, Guevara-Carrasco R, Soler P, Csirke J (2008) The northern Humboldt Current System: brief history, present status and a view towards the future. Prog Oceanogr 79(2–4):95–105

Chavez FP, Ryan J, Lluch-Cota SE, Ñiquen CM (2003) From anchovies to sardines and back: multidecadal change in the Pacific Ocean. Science 299(5604):217–221

Christensen DLP V, Sueiro S, Steenbeek JC, Majluf J, P (2014) Valuing seafood: the Peruvian fisheries sector. Mar Policy 44:302–311

CIRAIG (2023) IMPACT world report changes. https://github.com/CIRAIG/IWP_Reborn/tree/master/Report_changes. Retrieved June 4, 2025

Coayla E, Bedón Y, Rosales T, Jiménez L (2023) Industrial marine fishing in the face of climate change in Peru. J Mar Sci 1–10

Coffin MRS, Courtenay SC, Pater CC, van den Heuvel MR (2018) An empirical model using dissolved oxygen as an indicator for eutrophication at a regional scale. Mar Pollut Bull 133:261–270

Copernicus (2025) Copernicus marine services. https://marine.copernicus.eu/access-data/. Retrieved October 28, 2025, from

Corella-Puertas E, Hajjar C, Lavoie J, Boulay A (2023) MarILCA characterization factors for microplastic impacts in life cycle assessment: physical effects on biota from emissions to aquatic environments. J. Clean. Prod 418:138197

Costello C, Ovando D, Clavelle T, Strauss CK, Hilborn R, Melnychuk MC, … Leland A (2016) Global fishery prospects under contrasting management regimes. Proc Natl Acad Sci USA 113(18):5125–5129

Cowie RH, Bouchet P, Fontaine B (2022) The sixth Mass extinction: fact, fiction or speculation? Biol Rev 97(2):640–663

Cárdenas G (2009) Análisis de series de tiempo de los indicadores biológicos, pesqueros y poblacionales de la sardina, Sardinops sagax sagax (Jenyns, 1842), en función de la variabilidad ambiental y la pesca [PhD Thesis, Universidad Nacional Mayor de San Marcos

Cureton EE (1956) Rank-biserial correlation. Psychometrika 21(3):287–290

Damiani M, Sinkko T, Caldeira C, Tosches D, Robuchon M, Sala S (2023) Critical review of methods and models for biodiversity impact assessment and their applicability in the LCA context. Environ Impact Assess Rev 101:107134

De La Puente S, De La Lama RL, Benavente S, Sueiro JC, Pauly D (2020) Growing into poverty: reconstructing Peruvian small-scale fishing effort between 1950 and 2018. Front Mar Sci 7

Derhy G, Elkalay K, Rincón MM, Khalil K (2024) Stochastic surplus production and length-based assessment models to compare maximum sustainable yield advice for the Moroccan Atlantic chub mackerel. Front Mar Sci 11

Deville A, Vázquez-Rowe I, Avadí A, Miranda F, Kahhat R (2025) Identifying current trends in the environmental impacts linked to fishmeal and fish oil production in Peru. Aquaculture 600:742239

Dichmont CM, Deng RA, Dowling N, Punt AE (2021) Collating stock assessment packages to improve stock assessments. Fish Res 236:105844

D. S. N° 005-2017-PRODUCE (2017) Reglamento de Ordenamiento Pesquero del Recurso Anchoveta para Consumo Humano Directo. Diario Oficial El Peruano. https://busquedas.elperuano.pe/dispositivo/NL/1509249-2

D. S. N° 021-2008-PRODUCE (2008) Ley sobre límites máximos de captura por embarcación. Gobierno del Perú. https://www.gob.pe/institucion/produce/normas-legales/6526341-21-2008-produce

Ec JRC, IES (2010) International reference Life cycle data System (ILCD) handbook: framework and requirements for Life cycle impact assessment models and indicators. Publications Office of the European Union. https://publications.jrc.ec.europa.eu/repository/handle/JRC48211

Emanuelsson A, Ziegler F, Pihl L, Sköld M, Sonesson U (2014) Accounting for overfishing in life cycle assessment: new impact categories for biotic resource use. The Int J Life Cycle Assess 19(5):1156–1168

ENFEN (2012) Definición operacional de los eventos El Niño y La Niña y sus magnitudes en la costa del Perú [Nota Técnica, 3p]. Comité Técnico del Estudio Nacional del Fenómeno El Niño. http://met.igp.gob.pe/elnino/enfen/ICEN-Nota_Tecnica.pdf

Engelhard GH, Righton DA, Pinnegar JK (2014) Climate change and fishing: a century of shifting distribution in North Sea cod. Glob Chang Biol 20(8):2473–2483

EUMOFA (2021) Fishmeal and fish oil - production and trade flows in the EU. European Union

Exalmar (2025) Pesquera Exalmar S.A.A. https://www.exalmar.com.pe/. Retrieved October 1, 2025, from

FAO (2024) The state of world fisheries and aquaculture. Blue Transformation in action

Farmery AK, Alexander K, Anderson K, Blanchard JL, Carter CG, Evans K, Fischer M, Fleming A, Frusher S, Fulton EA, Haas B, Ck M, Murray L, Nash KL, Pecl GT, Rousseau Y, Trebilco R, Van Putten IE, Mauli S, … Nowak B (2022) Food for all: designing sustainable and secure future seafood systems. Rev Fish Biol Fish 32(1):101–121

Farmery AK, Jennings S, Gardner C, Watson RA, Green BS (2017) Naturalness as a basis for incorporating marine biodiversity into life cycle assessment of seafood. The Int J Life Cycle Assess 22:1571–1587

Fitia (2025) Fitia App. https://fitia.app/es/. Retrieved September 30, 2025, from

Flanders Marine Institute (2023) Maritime boundaries geodatabase: maritime boundaries and exclusive economic zones (200NM), version 12. https://www.marineregions.org/. Retrieved February 11, 2025, from

Frischknecht et al (2021) Swiss Eco-Factors 2021 according to the Ecological Scarcity Method Methodological fundamentals and their application in Switzerland. Umwelt-Wissen, Bern

Frischknecht R, Pfister S, Bunsen J, Haas A, Känzig J, Kilga M, Lansche J, Margni M, Mutel C, Reinhard J, Stolz P, Van Zelm R, Vieira M, Wernet G (2019) Regionalization in LCA: current status in concepts, software and databases-69th LCA forum, Swiss Federal Institute of technology, Zurich. The Int J Life Cycle Assess 24(2):364–369. 13 September, 2018

Froese R, Demirel N, Coro G, Kleisner KM, Winker H (2017) Estimating fisheries reference points from catch and resilience. Fish Fish 18(3):506–526

Froese R, Pauly D (Eds.) (2024) FishBase ver. 10/2024. https://www.fishbase.org/. Retrieved January 6, 2025, from

Froese R, Winker H, Coro G, M&quot P, Tsikliras AC, Dimarchopoulou D, Touloumis K, Demirel N, Vianna GMS, Scarcella G, Schijns R, Liang C, Pauly D (2023) New developments in the analysis of catch time series as the basis for fish stock assessments: the CMSY++ method. Acta Ichthyol Piscat 53:173–189

Garcia-Soto C, Cheng L, Caesar L, Schmidtko S, Jewett EB, Cheripka A, Rigor I, Caballero A, Chiba S, Báez JC, Zielinski T, Abraham JP (2021). An overview of Ocean climate change indicators: sea surface temperature. Ocean Heat Content, Ocean pH, Dissolved Oxygen Concentration, Arct Sea Ice Extent, Thickness Volume, Sea Level Strength The AMOC (Atl Meridional Overturning Circ). Front Mar Sci 8

Gozzer-Wuest R, Alonso-Población E, Tingley GA (2021) Identifying priority areas for improvement in Peruvian fisheries. Mar Policy 129:104545

Guevara-Carrasco R, Lleonart J (2007) Dynamics and fishery of the Peruvian hake: between nature and man. J Mar Syst 71(3–4):249–259

Hajjar C, Bulle C, Boulay A (2024) Life cycle impact assessment framework for assessing physical effects on biota of marine microplastics emissions. The Int J Life Cycle Assess 29(1):25–45

Hald-Mortensen C (2023) The main drivers of biodiversity loss: a brief overview. J Ecol Nat Resour 7(3):000346

Hellweg S, Benetto E, MaJ H, Verones F, Wood R (2023) Life-cycle assessment to guide solutions for the triple planetary crisis. Nat Rev Earth Environ 4(7):471–486

Hélias A, Langlois J, Fréon P (2018) Fisheries in life cycle assessment: operational factors for biotic resources depletion. Fish Fish 19(6):951–963

Hélias A, Stanford-Clark C, Bach V (2023) A new impact pathway towards ecosystem quality in life cycle assessment: characterisation factors for fisheries. The Int J Life Cycle Assess 28(4):367–379

Huang B, Thorne PW, Banzon VF, Boyer T, Chepurin G, Lawrimore JH, Menne MJ, Smith TM, Vose RS, Zhang H (2017) Extended reconstructed sea surface temperature, version 5 (ERSSTV5): upgrades, validations, and intercomparisons. J Clim 30(20):8179–8205

Huijbregts MA, Steinmann ZJ, Elshout PM, Stam G, Verones F, Vieira M, … Van Zelm R (2017) ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. The Int J Life Cycle Assess 22:138–147

IMARPE (2021) Informe Correspondiente al Oficio N° 199-2021-IMARPE/PCD. https://www.gob.pe/es/i/2056728. Retrieved February 12, 2025, from

IMARPE (2023) Situación del Calamar Gigante Durante Enero - Julio 2023, y Perspectivas de Explotación Para Agosto - Diciembre de 2023. https://www.gob.pe/es/i/4843163. Retrieved February 12, 2025, from

IMARPE (2024a) Acceso a la información pública. IMARPE - Instituto Del Mar Del Perú. https://www.imarpe.gob.pe/imarpe/accesoinformacion/. Retrieved March 15, 2024, from

IMARPE (2024b) Indicadores Biológicos, Pesqueros y Poblacionales del Calamar Gigante Dosidicus gigas y Perspectivas de Pesca Para el 2024. https://www.gob.pe/es/i/5631998. Retrieved February 12, 2025, from

INS (2023) Tablas peruanas de composición de alimentos. https://hdl.handle.net/20.500.14196/1773. Retrieved November 5, 2025, from

IPBES (2019) Global assessment report on biodiversity and ecosystem services of the intergovernmental science-Policy platform on biodiversity and ecosystem services. https://zenodo.org/records/6417333. IPBES secretariat

ISO (2006) Environmental management - life cycle assessment - principles and framework (ISO Standard No. 14040: 2006). https://www.iso.org/standard/37456.html

ITP (2007) Investigación y Desarrollo de Productos Pesqueros: Fichas Técnicas. https://es.scribd.com/document/476409141/FICHAS-TECNICAS-pdf. Retrieved September 30, 2025, from

IUCN (2024) Summary statistics. The IUCN red list of threatened species. https://www.iucnredlist.org/resources/summary-statistics. Retrieved January 30, 2025, from

Jaureguiberry P, Titeux N, Wiemers M, Bowler DE, Coscieme L, Golden AS, Guerra CA, Jacob U, Takahashi Y, Settele J, Díaz S, Molnár Z, Purvis A (2022) The direct drivers of recent global anthropogenic biodiversity loss. Sci Adv 8(45)

Javed A, Lee BS, Rizzo DM (2020) A benchmark study on time series clustering. Mach Learn Appl 1:100001

Jetz W, McGeoch MA, Guralnick R, Ferrier S, Beck J, Costello MJ, Fernandez M, Geller GN, Keil P, Merow C, Meyer C, Muller-Karger FE, Pereira HM, Regan EC, Schmeller DS, Turak E (2019) Essential biodiversity variables for mapping and monitoring species populations. Nat Ecol Evol 3(4):539–551

Kell LT, Kimoto A, Kitakado T (2016) Evaluation of the prediction skill of stock assessment using hindcasting. Fish Res 183:119–127

Kindong R, Wu F, Tian S, Sarr O (2022) How well do ‘catch-only’ assessment models capture catch time series start years and default life history prior values? A preliminary stock assessment of the South Atlantic Ocean blue shark using a catch-based model. Animals 12(11):1386

Kokkalis A, Berg C, Kapur M, Winker H, Jacobsen NS, Taylor MH, Ichinokawa M, Miyagawa M, Medeiros-Leal W, Nielsen J, Mildenberger T (2024) Good practices for surplus production models. Fish Res 275:107010

Konoyima KJ, Kindong R, Zhu J (2024) A paradigm shift: using catch and abundance indices to assess the impact of tuna purse seiner FAD and FSC fishing on the stock status of little tunny in the Northeast Atlantic Ocean. Fish Sci 90(2):139–160

Kraemer HC, Morgan GA, Leech NL, Gliner JA, Vaske JJ, Harmon RJ (2003) Measures of clinical significance. J Am Acad Child Adolesc Psychiatry 42(12):1524–1529

Kuipers KJJ, Hellweg S, Verones F (2019) Potential consequences of regional species loss for global species richness: a quantitative approach for estimating global extinction probabilities. Environ Sci Technol 53(9):4728–4738

Langlois J, Fréon P, Delgenes J, Steyer J, Hélias A (2014) New methods for impact assessment of biotic-resource depletion in life cycle assessment of fisheries: theory and application. J. Clean. Prod 73:63–71

Langlois J, Fréon P, Steyer J, Delgenès J, Hélias A (2015) Sea use impact category in life cycle assessment: characterization factors for life support functions. The Int J Life Cycle Assess 20(7):970–981

Levasseur A, Cavalett O, Fuglestvedt JS, Gasser T, Johansson DJ, Jørgensen SV, Raugei M, Reisinger A, Schivley G, Strømman A, Tanaka K, Cherubini F (2016) Enhancing life cycle impact assessment from climate science: review of recent findings and recommendations for application to LCA. Ecol Indic 71:163–174

Liu OR, Molina R (2021) The persistent transboundary problem in marine natural resource management. Front Mar Sci 8

Lueddeckens S, Saling P, Guenther E (2020) Temporal issues in life cycle assessment-a systematic review. The Int J Life Cycle Assess 25(8):1385–1401

Majluf P, Matthews K, Pauly D, Skerritt DJ, Palomares MLD (2024) A review of the global use of fishmeal and fish oil and the fish in. Fish Out Metr. Sci Adv 10(42)

Marques A, Verones F, Kok MT, Huijbregts MA, Pereira HM (2017) How to quantify biodiversity footprints of consumption? A review of multi-regional input-output analysis and life cycle assessment. Curr Opin Environ Sustain 29:75–81

McKay MD, Beckman RJ, Conover WJ (1979) A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21(2):239

Mogollón R, Calil PH (2017) On the effects of ENSO on ocean biogeochemistry in the northern Humboldt Current System (NHCS): a modeling study. J Mar Syst 172:137–159

Mohn R (1999) The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. ICES J Mar Sci 56(4):473–488

Mondal S, Ray A, Boas M, Navus S, Lee M, Dey S, Barman KK (2024) Can the delayed effects of climatic oscillations have a greater influence on global fisheries compared to their immediate effects? PLoS One 19(8):e0307644

Muñoz-Sovero E, Kahhat R, Deville A, Ita-Nagy D, Gonzales D, Montero A, Vázquez-Rowe I (2026). The use of remote sensing to detect illegal, unreported and unregulated (IUU) tuna fishing activities in the Peruvian Exclusive economic Zone. Mar Policy 190:107213

Østhagen A, Spijkers J, Totland OA (2020) Collapse of cooperation? The North-Atlantic mackerel dispute and lessons for international cooperation on transboundary fish stocks. MAST 19(2):155–165

Owens JW (1997) Life-cycle assessment: constraints on moving from inventory to impact assessment. J Ind Ecol 1(1):37–49

Palomares MLD, Pauly D (2024) SeaLifeBase ver. 12/2024. https://www.sealifebase.org. Retrieved January 7, 2025, from

Pauly D, Zeller D, Palomares MLD (2024) Sea Around Us. https://www.seaaroundus.org/. Retrieved February 11, 2025, from

Pfister S, Oberschelp C, Sonderegger T (2020) Regionalized LCA in practice: the need for a universal shapefile to match LCI and LCIA. The Int J Life Cycle Assess 25:1867–1871

Pincay-Espinoza JE, Varela JL (2022) Spatial- and size-related shifts in feeding habits of the common dolphinfish (coryphaena hippurus) in the Southeast Pacific Ocean. Environ Biol Fishes 105(2):313–326

Préat N, Lefaible N, Alvarenga RA, Taelman SE, Dewulf J (2021) Development of a life cycle impact assessment framework accounting for biodiversity in deep seafloor ecosystems: a case study on the clarion clipperton fracture Zone. Sci Total Environ 770:144747

PRODUCE (2024) Anuario Estadístico Pesquero y Acuícola 2023. https://www.producempresarial.pe/anuario-estadistico-pesquero-y-acuicola-2023/. Retrieved February 11, 2025, from

PRODUCE (2025) Abastecimiento Diario de Recursos Hidrobiológicos a los Mercados Mayoristas Pesqueros. https://app.powerbi.com/view?r=eyJrIjoiNjg0MmI0Y2ItZGE3Mi00NGRjLThkYjgtOTNlY2M0MzNkMmZhIiwidCI6ImMzNGNjOGM2LTJiMjctNDA0Mi1hMGE2LWI3OWZiMmM0NDE4NyIsImMiOjR9. Retrieved October 2, 2025, from

Punt AE (2023) Those who fail to learn from history are condemned to repeat it: a perspective on current stock assessment good practices and the consequences of not following them. Fish Res 261:106642

Puth M, Neuhäuser M, Ruxton GD (2015) Effective use of Spearman's and Kendall's correlation coefficients for association between two measured traits. Anim Behav 102:77–84

Qin Y, Cucurachi S, Suh S (2020) Perceived uncertainties of characterization in LCA: a survey. The Int J Life Cycle Assess 25(9):1846–1858

Quispe J, Vásquez L (2015) Índice "LABCOS" para la caracterización de eventos El Niño y La Niña frente a la costa del Perú, 1976-205. Boletín Trimestral Oceanográfico 1(1–4):12–16. https://hdl.handle.net/20.500.12958/2957

R Core Team (2023) R: a language and environment for statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Richardson K, Steffen W, Lucht W, Bendtsen J, Cornell SE, Donges JF, Drüke M, Fetzer I, Bala G, Von Bloh W, Feulner G, Fiedler S, Gerten D, Gleeson T, Hofmann M, Huiskamp W, Kummu M, Mohan C, Nogués-Bravo D, … Rockström J (2023) Earth beyond six of nine planetary boundaries. Sci Adv 9(37)

Rodriguez S, Urrutia O. Nicklin, S, Cornwell, B & Trowbridge, L (Eds.) (2020) Successful science-based fisheries management in the South Pacific. A better world, vol 6. Human Development Forum, pp 45–47. ISBN 978-1-9160325-0-7

Salinger MJ (2013) A brief introduction to the issue of climate and marine fisheries. Clim Change 119(1):23–35

Sanchez-Matos J, Vázquez-Rowe I, Kahhat R (2024) Are Peruvians moving toward healthier diets with lower environmental burden? Household consumption trends for the period 2008-2021. J Ind Ecol 28(5):1147–1164

Sarre A, Demarcq H, Keenlyside N, Krakstad J, Ayoubi SE, Jeyid AM, Faye S, Mbaye A, Sidibeh M, Brehmer P (2024) Climate change impacts on small pelagic fish distribution in Northwest Africa: trends, shifts, and risk for food security. Sci Rep 14(1):12684

SIOFEN (2025) Servicio de Información Oceanográfica del Fenómeno del Niño. https://siofen.imarpe.gob.pe/principal/indices-climaticos. Retrieved November 11, 2025, from

Slob W (1994) Uncertainty analysis in multiplicative models. Risk Anal 14(4):571–576

Sánchez Durand, Gallo Seminario M (2009) Status of and trends in the use of small pelagic fish species for reduction fisheries and for human consumption in Peru. In: Hasan MR, Halwart M (eds) Fish as feed inputs for aquaculture, vol 518. FAO, pp 325–370. https://www.fao.org/4/i1140e/i1140e00.htm

Stanford-Clark C, Bulle C, Loiseau E, Helias A (2025) Ecosystem-scale biodiversity in fisheries life cycle impact assessment. Environ Sci Technol

Stanford-Clark C, Loiseau E, Helias A (2024) Fisheries impact pathway: making global and regionalised impacts on marine ecosystem quality accessible in Life cycle impact assessment. Sustainability 16(9):3870

Sterner E, Johansson DJA, Azar C (2014) Emission metrics and sea level rise. Clim Change 127(2):335–351

Takahashi K, Mosquera K, Reupo J (2014) El Índice Costero El Niño (ICEN): historia y actualización. Boletín técnico: Generación de modelos climáticos para el pronóstico de la ocurrencia del Fenómeno El Niño. Inst Geofísico del Perú 1(2):8–9. http://hdl.handle.net/20.500.12816/4639

Valente A, Vadenbo C, Fazio S, Shobatake K, Edelen A, Sonderegger T, … Ingwersen WW (2024) Elementary flow mapping across life cycle inventory data systems: a case study for data interoperability under the global Life cycle assessment data access (GLAD) initiative. The Int J Life Cycle Assess 29(5):789–802

Verones F, Gjedde P, Koslowski M, Woods JS, Lonka R, Stadler K (2023) MarINvaders: a web toolkit of marine species for use in environmental assessments. Ecosphere 14(11)

Verones F, Kuipers K, Núñez M, Rosa F, Scherer L, Marques A, Michelsen O, Barbarossa J V, Pfister B, Dorber S, M (2022) Global extinction probabilities of terrestrial, freshwater, and marine species groups for use in Life cycle assessment. Ecol Indic 142:109204

Verones F, Kuipers K, Núñez M, Rosa F, Scherer L, Marques A, Michelsen O, Barbarossa J V, Pfister B, Dorber S, M (2024) Global extinction probabilities of terrestrial, freshwater, and marine species groups. Data Set]. Zenodo. https://doi.org/10.5281/zenodo.14499582

Waluda CM, Yamashiro C, Rodhouse PG (2006) Influence of the ENSO cycle on the light-fishery for Dosidicus gigas in the Peru Current: an analysis of remotely sensed data. Fish Res 79(1–2):56–63

Wang K, Li Q, Zhang C, Xu B, Ren Y (2025) Enhancing catch-based stock assessment in data-limited fisheries with proxy CPUE indicators in the Yellow Sea. Sci Rep 15(1):11043

Ward JH (1963) Hierarchical grouping to optimize an objective function. J Am Stat Assoc 58(301):236

Wilcoxon F (1945) Individual comparisons by ranking methods. Biom Bull 1(6):80

Wintersteen KA (2021) The fishmeal revolution. In University of California Press eBooks

Woods JS, Verones F (2019) Ecosystem damage from anthropogenic seabed disturbance: a life cycle impact assessment characterisation model. Sci Total Environ 649:1481–1490

WoRMS Editorial Board (2025) World register of marine species. https://www.marinespecies.org. Retrieved February 18, 2025, from

Wu Y, Lan K, Evans K, Chang Y, Chan J (2022) Effects of decadal climate variability on spatiotemporal distribution of Indo-Pacific yellowfin tuna population. Sci Rep 12(1):13715

Zhai L, Liang C, Pauly D (2020) Assessments of 16 exploited fish stocks in Chinese waters using the CMSY and BSM methods. Front Mar Sci 7