

Fishery nutrient profiles provide practical guidance for nutrition-sensitive small-scale fisheries management in Timor-Leste

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Small-scale fisheries are a crucial source of nutrient-dense aquatic foods in low- and middle-income countries, yet practical tools to manage these fisheries to optimize nutritional outcomes in an ecosystem approach remain limited. Here, we present an analytical framework and predictive model of fishery nutrient profiles under typical multi-species multi-gear situations. Using 6 years of catch data from Timor-Leste, we modelled how different fishing methods, habitats, vessel types and seasons influence the yield of nutrients of public health significance. Our results demonstrate that fishing method and habitat are strong predictors of catch nutritional profiles. Importantly, we show that different combinations of fishing strategies can achieve similar nutritional outcomes, indicating complementary management pathways to enhance nutrient availability for communities while balancing ecological, economic and human wellbeing goals. This replicable framework provides actionable insights for nutrition-sensitive fisheries management and offers data-driven guidance for policies aimed at improving food and nutrition security in low- and middle-income countries.

The evolving vision of sustainability and food systems transformation requires the need to minimize the ecological impact of every fish caught and maximize its societal benefit¹. In low- and middle-income countries (LMICs) and among populations vulnerable to malnutrition and diet-related diseases, that societal value may best be realized by maximizing the contribution of fisheries to nutrition and health. This can be achieved by minimizing waste and loss² and by managing the fishery to supply the micronutrients most needed to support nutrition and healthy diets in the populations accessing that aquatic food³. The specific management of nutrient flows in agriculture has long been highlighted^{4,5}, and recent studies emphasize the role of blue foods specifically in providing diets that improve social, environmental and human health outcomes^{6,7}. Fish and other harvested

aquatic animals comprise thousands of species, and while they all have similarly high protein content, they have very different micronutrient compositions^{8–10}. This offers the possibility of managing fisheries to optimize the supply of the nutrients most lacking and most needed to improve the health outcomes of human diets. The nutrient yield from most of the world's marine and inland fisheries could be better targeted¹¹, and nutrient-sensitive fisheries management (NSFM) that also incentivizes maintenance of biodiverse ecosystems could be a pivotal strategy within this transformation¹² but remains largely theoretical¹³.

While there is advocacy for biodiversity conservation (and corollary protection of nutrient diversity) in small-scale fisheries (SSFs), NSFM proposes the integration of nutritional goals to sustain fish

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populations and ecosystems whilst also contributing to human health and wellbeing¹⁴. This approach recognizes the crucial role that aquatic foods play in providing essential nutrients^{9,11}, addressing micronutrient deficiencies^{8,15–17} and improving diets—particularly among vulnerable populations^{13,18–20}—and seeks to optimize the nutritional benefits from fisheries. Fish and other aquatic foods are rich in bioavailable protein and iron as well as a key source of essential nutrients, such as omega-3 fatty acids, vitamin A, calcium and zinc, critical for early childhood development and overall health²¹. Such contributions cannot be overstated in the context of LMICs, which suffer most from micronutrient deficiencies (including 1.5 billion women and children globally²²) and from stunting (affecting 148 million children in 2022²³). Recent efforts that complement NSFM approaches to improve nutrition in the Global South include a framework on nutrition-sensitive fisheries governance¹², trade and foreign fishing assessments on nutrients' relocation²⁴, spatial analyses of aquatic food flows to inform nutrition-sensitive policies²⁵ and analyses examining the integration of fisheries, food security and nutrition policies^{26–30}. Despite the potential, there has been limited effort to translate this into practical fisheries management tools for LMICs to enhance nutrition within an Ecosystem Approach to Fisheries (EAF)¹². Managing fisheries for multi-species maximum nutrient yield has been suggested, theoretically working through a framework for nutrient-based reference points in specific contexts³¹, but in data- and capacity-limited contexts, an approach to implement this and inform policies is still lacking.

SSFs account for 40% of the global reported catch from capture fisheries³² and play a crucial role in food and nutrition security in LMICs^{8,9,11,33}. SSFs are often subsistence³⁴, targeting a wide range of species with multiple gears across ecologically diverse habitats, beyond commercially lucrative species³⁵. These mixed-species fisheries are too complex and data-poor for conventional fisheries management of single-species stock assessments that estimate the maximum sustainable yield (of generic fish protein) in tons. Conventional fisheries management tends to overlook the intricate species interactions and competition, leading to highly selective strategies that can disrupt ecosystem balance and reduce overall productivity³⁶. EAF aims to balance ecological, economic and human wellbeing goals, providing a more sustainable and resilient fisheries management framework^{37–39} that tacitly advocates for nutrient diversity. However, this multi-dimensionality of EAF policies makes it hard to implement and evaluate, especially in data-constrained scenarios such as SSFs of LMICs.

Data remain a crucial part of EAF and is critical in managing fisheries for recovery and sustainability⁴⁰, yet the quality and resolution of data from SSFs hamper evidence-based fisheries management. However, emerging digital advancements support robust data systems for SSF monitoring^{41,42} and present new opportunities for synthesized management tools, such as incorporating nutritional or climatic considerations. *Peskas* is one such open-source software for managing and visualizing SSF data and has become the official fisheries national monitoring system of Timor-Leste^{43,44}. Moreover, data on nutrient composition of aquatic foods have only recently become available^{8,9}. LMICs such as Timor-Leste, where stunting and micronutrient deficiencies such as anaemia are rife⁴⁵ and child and maternal dietary quality remain poor⁴⁶, could benefit from data-driven NSFM approaches to optimize the nutritional contributions of SSFs.

Using a 6-year catch data series⁴⁴ (77,438 fishing trips) linked to NutrientFishbase and the Global Food Composition Database for Fish and Shellfish nutrient composition databases⁴⁷, we developed an NSFM framework. We selected women of reproductive age (WRA) for nutrient analysis, a standard reference group in nutrition-sensitive fisheries research^{11,17}, representing a large, nutritionally vulnerable group targeted by public health interventions. Our approach modelled the relationship between catches from different fishing methods and corresponding nutritional outcomes, offering a tool to visualize and optimize catch nutrient supply. The framework can be replicated using

multi-species fisheries catch data from other contexts, while the model enables applied policy recommendations.

Results

Nutrient supply from SSFs

Our analysis confirmed that small pelagic fishes, particularly mackerels, flying fish and sardines/pilchards, were the most important contributors to recommended human dietary intake, providing relatively high concentrations of essential nutrients such as protein, zinc, calcium, omega-3 fatty acids, iron and vitamin A, compared with other fish groups (Fig. 1a). Marine invertebrates typically caught by gleaners, such as crabs, cockles and octopus, ranked particularly high in nutrient density, illustrating the potential of a diverse range of aquatic foods in enhancing dietary quality. Small pelagic fishes contributed most to the overall nutrient yield, owing to their higher nutrient density and volumes caught (Fig. 1b). By linking nutrient density to catch landing prices, we found that small pelagic fishes were also the most affordable, priced at under US\$2 per kilogram. In contrast, larger pelagic fishes such as tuna/bonito were more expensive despite their modest nutritional density (Fig. 1c).

Different marine habitats and fishing gears influenced nutrient yields considerably (Fig. 1d and Extended Data Fig. 1). Results show that deploying fish aggregating devices (FADs) enhances the capture of species high in calcium, iron and omega-3, key nutrients for addressing micronutrient deficiencies in the region. Catches from reef habitats also showed high average nutrient density, with notable contributions from vitamin A and calcium.

Fisheries' contribution to healthy diets

Approximately 62.9% of Timorese WRA (337,144, approximately one-quarter of the population) could potentially meet their protein balanced recommended nutrient intake (RNI) from edible annual catches, assuming seafood was distributed equitably among WRA (29.4 g day⁻¹). Catches from SSFs have the potential to contribute the RNI of zinc to 31.3% of WRA and to 18.3% and 16.4% for calcium and omega-3, respectively (Extended Data Table 1). In recognition that single-nutrient analyses are of limited usefulness for quality diets, we present findings for multiple nutrient combinations. In Timor-Leste, where animal protein and micronutrient intakes are estimated to be below requirements^{46,48}, marine catches could supply the RNI for four nutrients to ~55,000 WRA, and to ~22,000 for the six examined nutrients. In terms of satisfying the national food-based dietary guidelines' recommendation of 250 g of cooked fish per adult per week⁴⁹, current fisheries production has the potential to contribute to two-thirds, 65.4%, of all WRA (Extended Data Table 2). Municipal-level totals show that five municipalities catch enough fish to exceed the recommended quantities for WRA in the local population (Extended Data Fig. 2), suggesting trade and distribution opportunities with deficit municipalities and highlighting the need to develop nutrition-oriented value chains. Whilst current catches can support WRA's nutrition, a substantial supply gap remains for meeting the broader population's needs from aquatic foods.

FNP prediction

Using clustering techniques (elbow and silhouette methods) on nutrient density data from the Dili and Atauro municipalities of Timor-Leste, we identified three distinct fishery nutrient profiles (FNPs) applicable to both gill nets and other gears datasets (Extended Data Fig. 3). These profiles cluster fishing trips on the basis of the nutrient density of their catches (Box 1) and were statistically significant, as confirmed by permutational multivariate analysis of variance (PERMANOVA) analysis (Extended Data Table 3). Figure 2 illustrates the distribution of nutrient density scores (NDS) among these profiles for each gear type, highlighting variations in nutrient contributions across different fishing methods. In the gill nets dataset (Fig. 2a), FNP-3 stood out with the

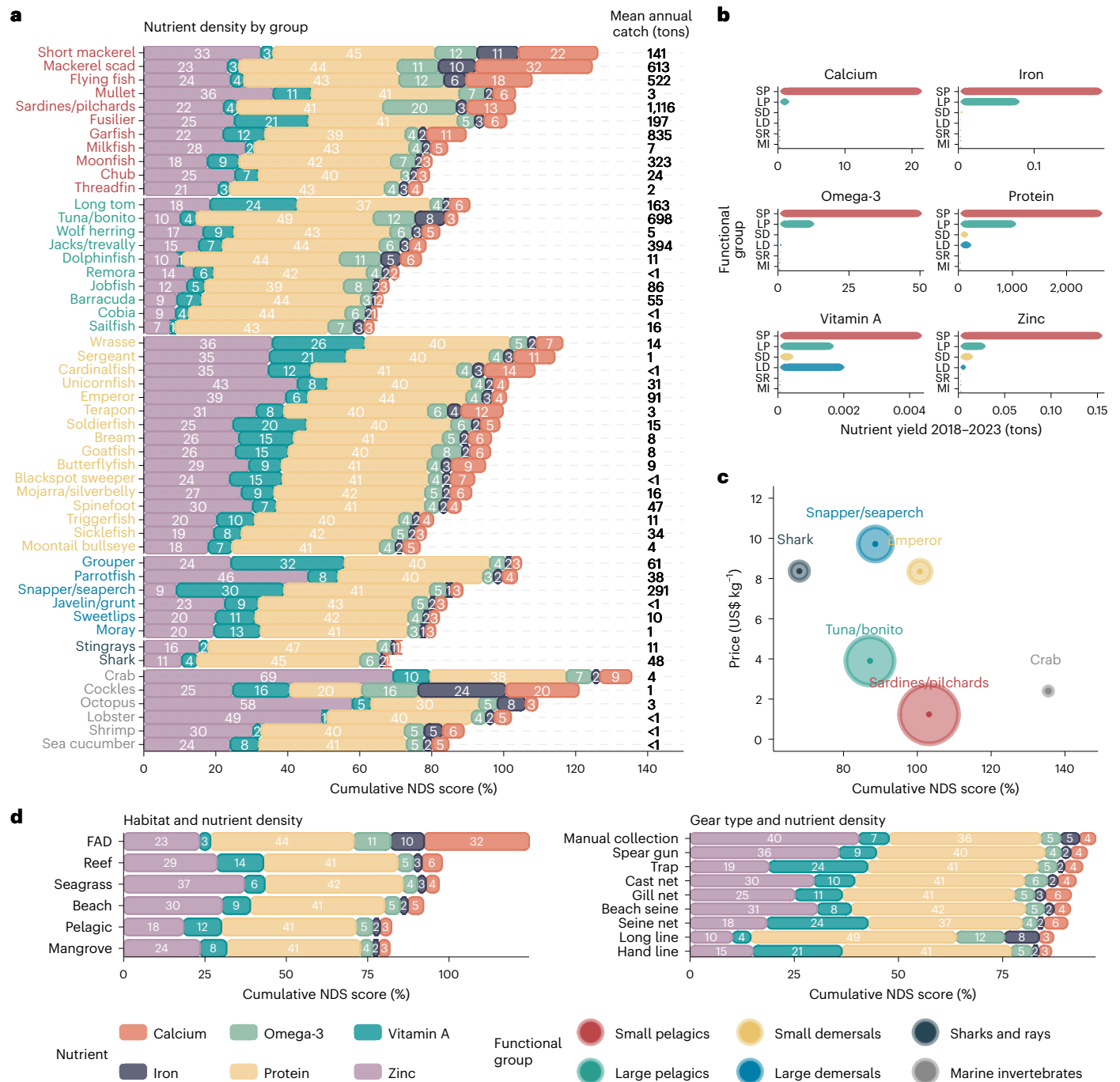


Fig. 1 | Nutrient density, nutritional yield and affordability of marine foods from Timor-Leste fisheries. a, d, The bars show the percentage contribution of a 100-g serving of raw edible flesh from marine foods to daily RNI for six nutrients for WRA (19–50 years old), where each bar is the mean RNI contribution across all species that form each functional group (a) or the combination of species typically caught relative to habitat and gear type (d), weighted by their contribution to total catch. The cumulative NDS (x axis) is the sum of the percentage contributions for the six nutrients. The plot in a ranks functional fish groups by cumulative NDS: small pelagic teleost fish (red), large pelagic (green), small demersal (yellow), large demersal (blue), sharks and rays (black) and marine invertebrates (grey). Bars are colour-segmented by nutrient, with white labels indicating the percentage contribution of each nutrient. Mean annual edible catch (metric tons, 2018–2023) is shown at the end of each bar, with

transparency scaled to relative catch contribution. **b,** The cumulative nutritional yield (edible metric tons) from 2018 to 2023 for small pelagic (SP), large pelagic (LP), small demersal (SD), large demersal (LD), sharks and rays (SR) and marine invertebrates (MI), defined as the supply volume of calcium, omega-3, iron, protein, vitamin A and zinc; values for the lower four functional groups are very small relative to the other groups on this scale. **c,** A comparative analysis of NDS versus economic accessibility for key fish groups. The scatter plot relates cumulative NDS (x axis) to median landing price per kilogram (y axis) for the most important fish group within each functional category. The dot size reflects the relative catch percentage of each group, serving as an index of affordability and availability. **d,** The NDS for habitats (left) and gear types (right), based on a 100-g portion. Bars are colour-segmented by nutrient, with white labels showing each nutrient's percentage contribution.

BOX 1

FNPs: what are these and why are they useful?

- (1) An FNP describes a characteristic pattern of nutrients that consistently appears in the catches from a specific fishery. In this study, FNP is defined by the specific composition and concentrations of six key nutrients: calcium, iron, omega-3, protein, vitamin A and zinc.
- (2) FNPs are defined by clustering fishing trips according to the nutrient composition of their catch. This grouping identifies trips with similar nutrient densities, revealing consistent nutritional patterns across the catches. The profiles are statistically validated to ensure each cluster represents distinct nutritional characteristics, serving as a reliable analytical tool for optimizing the nutritional contributions of fisheries.
- (3) Single-nutrient analyses are of limited relevance for public health nutrition, as food-based approaches considering the whole-of-diet have overcome reductionist approaches that focus on specific nutrients⁹⁶ or single food commodities²⁷. FNPs support this perspective and focus on a combination of multiple nutrients of public health concern.

highest levels of calcium, iron and omega-3 fatty acids, surpassing FNP-1 and FNP-2. FNP-2 was notably higher in vitamin A compared with the other profiles. While protein levels were consistent across all profiles, FNP-1 exhibited higher zinc levels than FNP-2 and FNP-3. In the dataset for other gears (Fig. 2b), FNP-2 demonstrated markedly higher levels of protein, omega-3 and iron. In contrast, FNP-1 and FNP-3 showed elevated levels of zinc and vitamin A. Calcium distribution was even among all profiles.

The extreme gradient boosting (XGBoost) models accurately predicted FNPs on the basis of fishing gear (mesh size in the gill nets model), habitat, season and vessel type. The gill nets model achieved an area under the curve (AUC) score of 0.92 and the other gears model achieved an AUC of 0.91 (Extended Data Fig. 4). The other gears model demonstrated slightly better reliability in classification, particularly in its accuracy and specificity (Extended Data Table 4), effectively distinguishing FNPs across different fishing methods.

Feature importance (Extended Data Fig. 5) showed that in the gill nets model, the interaction between habitat and mesh size was the most influential, with mesh size alone also contributing considerably. In the other gears model, gear type was the most influential predictor, closely followed by its interaction with habitat. Shapley additive explanations (SHAP) values then revealed how those top predictors influenced the outcome of each FNP. Gill nets mesh sizes <40 mm were associated with FNP-2 and FNP-3 across various habitats (Fig. 3a). FNP-2 showed higher predictive influence in reefs, beaches and pelagic areas, indicating a strong likelihood of predicting this FNP when fishing in these environments. FNP-3 was also associated with smaller mesh sizes, particularly within pelagic zones, followed by mangroves and FADs. At mesh sizes ranging from 40 to 60 mm, FNP-3 was predominant, especially in reefs and FADs. In addition, FNP-1 showed some association within the 40–60 mm mesh size range, particularly in pelagic habitats and, to a lesser extent, in mangroves. Between 60 and 80 mm, FNP-1 became more characteristic across all habitats, especially in littoral environments such as seagrass, reefs and beaches. Larger mesh sizes were predominantly associated with FNP-2, especially in mangrove and reef habitats.

When excluding gill nets, SHAP analysis revealed strong associations between specific gear types and FNPs (Fig. 3b). FNP-1 was

associated with spearfishing in reef and seagrass habitats, which exhibited the highest predictive influence and, to a lesser extent, gleaning. FNP-2 was strongly linked to long lines, especially in pelagic, FAD and mangrove areas, indicating a robust association between this gear type and the FNP-2 profile. For FNP-3, seine nets had the strongest predictive contribution across multiple habitats, including beach, reef and FAD zones. Hand lines also contributed to FNP-3 but with a weaker influence.

Discussion

SSFs are crucial for the livelihoods, culture and wellbeing of half a billion people globally¹¹ and contribute substantially to the RNI of populations^{34,50}. Our study presents an analytical framework and predictive model designed to guide nutrition-sensitive SSF management strategies, fostering interagency cooperation and policy coherence across fisheries, health, environmental and social inclusion domains.

Nutrition profiles associated with fish catches are highly relevant in countries where malnutrition is a critical concern, such as LMICs. Timor-Leste has one of highest child stunting rates globally, 47%⁴⁵, and widespread anaemia⁴⁸—typically caused by dietary iron deficiency and particularly affecting women⁵¹. Aquatic foods offer rich sources of micronutrients and omega-3 fatty acids^{8–10}, essential for optimal brain development⁵²; their consumption is associated with improved child health⁵³ and reductions in micronutrient deficiencies⁹. Our framework enables countries with marine or inland SSFs to integrate nutrition goals into fisheries policies, helping address these health burdens. Importantly, it provides a practical tool to visualize and quantify the nutritional value of fisheries outputs, offering actionable data for policy and programmatic decisions.

Small pelagic fishes are productive, affordable and nutritious and should be promoted among nutritionally vulnerable groups, underscoring their role in improving healthy diets, as also found in other LMICs^{17,54–56}. Nearshore FADs are well documented to increase access to tunas and small pelagic species for Pacific coastal fishers^{57–60}, which can improve fish consumption when combined with social behaviour change interventions⁶¹ and be a productive and cost-effective investment⁶². We found that catches of small pelagic fishes from FADs increased the yield of calcium, omega-3 and iron, as shown in FNP-3 using gill nets. If deployed close to shore, FADs can be sustainably fished using existing methods and redistribute fishing pressure away from reef-associated fisheries in response to improved catch rates⁶³. This can contribute to reef recovery and the retention of nutrient-rich and diverse reef species for small-scale and women-dominated fisheries such as gleaning⁶⁴. Redirecting fishing efforts towards these systems indicates an opportunity to align livelihoods, nutrition and conservation goals.

The framework can inform multi-sectoral strategies in LMICs with SSFs, such as investing in FADs and linking trade networks with government-endorsed nutrition programmes, such as mother support groups⁶⁵ or school meals⁶⁶. Our analysis of nutrient yield relative to women's recommended intake highlights how fisheries production can meet populations' nutritional needs. In Timor-Leste, this analysis revealed supply gaps that can be addressed through sustainable fisheries and aquaculture development^{61,62,67}. These findings support the integration of nutrition objectives into fisheries policy, advancing the agenda for NSFM.

Mesh size and gear types, in conjunction with habitat, were reliable predictors of FNPs, illustrating how different combinations of fishing strategies can achieve similar nutritional yields. For instance, gill nets with <40-mm mesh in pelagic and mangrove habitats—catching sardines and flying fish—or 50.8 mm in reef and FAD zones—catching short mackerels and scads—returned the highest concentrations of calcium, iron and omega-3 (FNP-3). Combining these configurations in management interventions, such as pairing FAD deployments with distribution of 50.8-mm nets, enhances the likelihood of obtaining FNP-3, as indicated by our predictive models. Long lines in pelagic habitats—catching

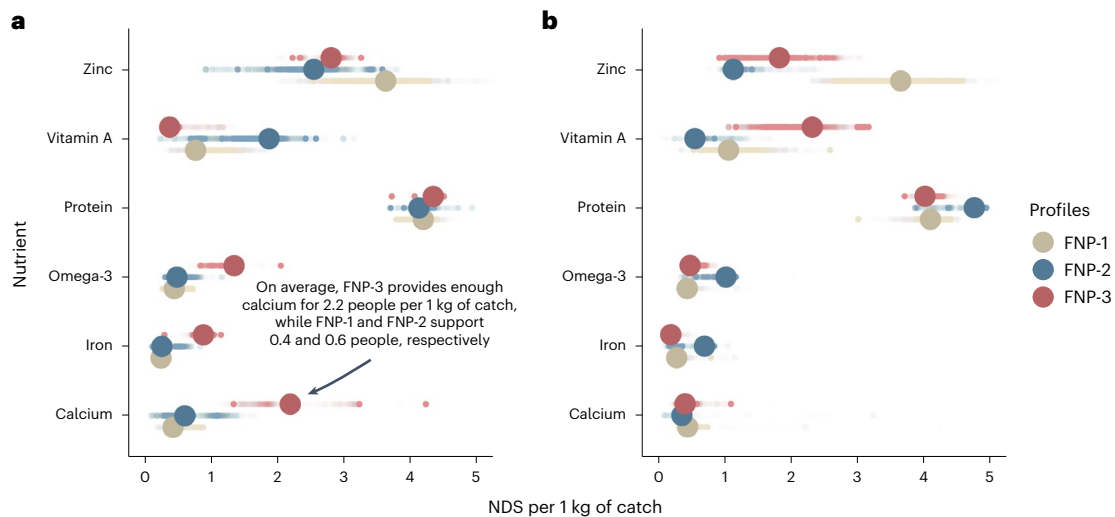


Fig. 2 | Distribution of cumulative NDS among the FNPs from *k*-means clustering in the Dili and Atauro municipalities. **a, b, Plots delineating the NDS per 1 kg of catch using exclusively gill nets (**a**) and other gears (**b**) for various nutrients across the identified *k*-means clusters ($N = 3$), indicating contributions**

to the RNI. Each large point represents the mean NDS for a specific nutrient in each profile, while the smaller points illustrate the total distribution of the NDS within each profile.

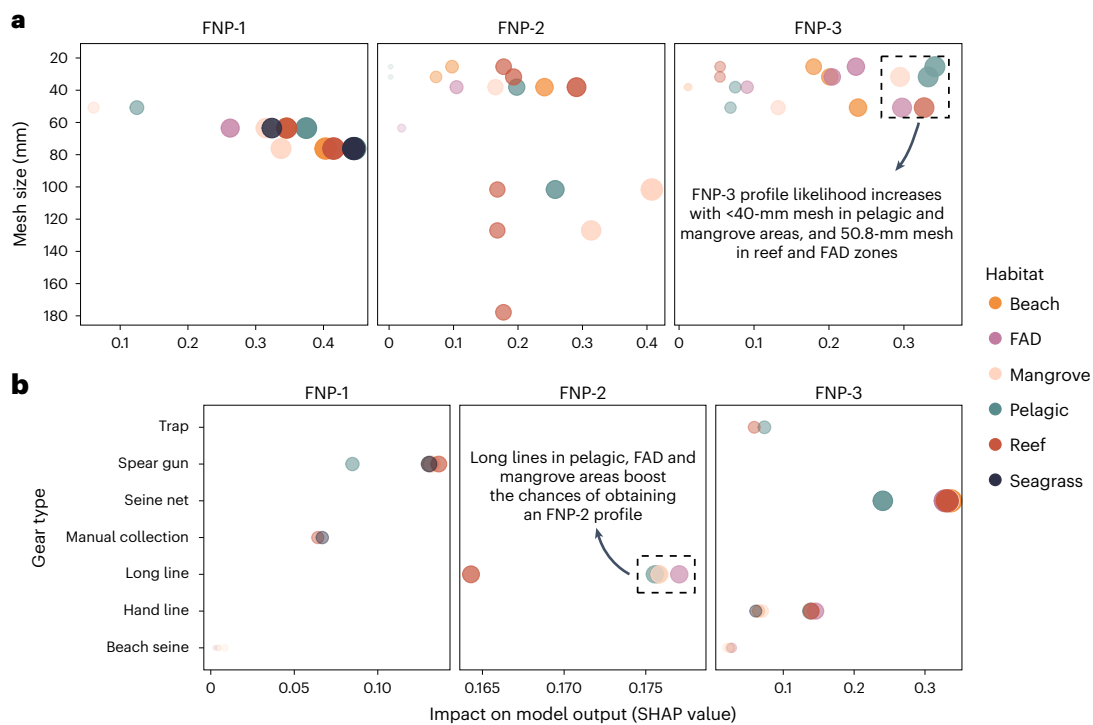


Fig. 3 | Differential influence of mesh size and gear type from XGBoost models. **a**, The impact of mesh size on the probability of observing various FNPs on the basis of the habitat. Each sub-panel corresponds to a specific FNP (FNP-1, FNP-2 and FNP-3), showing how the contribution of mesh size to the prediction changes across a range of sizes. Data points are colour-coded by habitat (beach, pelagic, FAD, mangrove, reef and seagrass), illustrating how the effect of mesh size varies between environments. The y axis represents mesh size ranges, while the x axis shows the strength of the contribution of mesh size to the prediction of each

FNP, represented by SHAP values. **b**, The role of gear type in predicting FNPs, with habitats influencing the effectiveness of each gear. Each sub-panel corresponds to a specific FNP, with gear types listed on the y axis. The x axis represents the strength of each gear type's contribution to the prediction of a specific FNP. Larger and more opaque points denote gear types (or mesh sizes for gill net data) with higher SHAP values and stronger contribution to the predictions for each FNP in different habitats.

jacks/trevally and tuna/bonito—returned the highest levels of protein, omega-3 and iron (FNP-2). Promoting government-led capacity building focused on the most nutrient-dense gear-habitat combinations and their regulation could enhance the nutrient yields of catches in different environments. Fisheries managers require a range of tools to

meet the challenges posed by climate change and overfishing, while understanding the balance of gear selectivity and fishing pressure can potentially increase the resilience of marine ecosystems^{36,68}.

Traditional management paradigms, such as maximum sustainable yield, are predominantly single-species oriented and fall short

in multi-species data-poor SSF settings⁶⁹. SSFs require a different approach owing to high species diversity, diverse gear usage and daily fisher decision-making^{37,70}. In this setting, fishing trips represent a practical management unit, reflecting individual fishers' decisions about these parameters, and associated livelihood considerations, such as optimizing catch per unit effort. By focusing on fishing patterns at the trip level, our FNP framework links nutritional outcomes to operational realities of fishers, providing actionable guidance on gear regulation, habitat management and capacity building.

Our results support distributing fishing effort across diverse habitats and gear types to optimize nutrient gains. This aligns with the balanced harvest concept, which explicitly addresses EAF as a measurable indicator, and where moderate fishing mortality on each usable (and societally acceptable) ecological group in proportion to its production can increase total long-term sustainable yields while minimizing impacts on ecosystem structure⁷¹. While implementation challenges exist^{72,73}, balanced harvest principles may emerge naturally in SSFs, where demand and prices are evenly distributed across species^{74–76}. Yet, to achieve a balance between optimizing nutrient harvests and sustainable yields while conserving ecosystem structure—and with it, biodiversity—we suggest FNPs would be best used as a heuristic tool, rather than a prescriptive management system.

For instance, FNPs can inform incentive-based and participatory governance strategies. In contexts where regulatory capacity (for example, mesh size enforcement or spatial closures) is limited, as in Timor-Leste, FNPs can guide the design of social and economic incentives—such as nearshore FAD deployment, value chain development for nutrient-dense species or integration with nutrition programmes—aligning local fishing practices with broader ecological and nutritional goals. Grounded in the lived realities of SSF communities, this tool offers a scalable pathway to integrate fisheries, health and social inclusion policies.

The framework provides a modelling approach for data-driven nutrition-sensitive SSF planning and management, complementing previous efforts^{16,31}. Our primary contribution to NSFM is methodological; we propose an approach that links nutrient outcomes to specific fishing patterns—defined by gear, habitat and species combinations—at the scale of individual fishing trips. This reframes the core management question in multi-species SSF from 'how much to fish?' towards 'how to fish?', providing a more ecologically and socially relevant basis for decision-making. While applying the model in other countries may be constrained by data availability, open-source tools such as Peskas reduce technical and financial barriers to digital SSF monitoring⁴⁴. As more LMICs invest in data systems, including vessel tracking, digital logbooks and citizen science initiatives, the feasibility of implementing this framework at scale increases⁷⁷.

Future research should investigate ecological (for example, habitat and stock degradation caused by certain gear types and fishing strategies), economic (for example, gear costs and fuel efficiency as catch per unit effort factors) and social (for example, employment, gender equity and governance) considerations to refine FNP-based management strategies. Analyses addressing these integrated objectives would substantially advance the applicability of NSFM policies.

Limitations

Our approach depends on the availability of time series of species- and gear-specific catch data, so modelling with data from other contexts may not be equally robust. For data-scarce and capacity-constrained contexts, options such as the Peskas software⁴⁴ are available. Nutrient composition values used include Bayesian estimates; future analyses would benefit from using primary data on aquatic foods' nutrient content from a country or region, including ways to prepare and consume them. Limited gleaning data availability underestimates its nutritional contributions, as 'marine invertebrates' in Fig. 1 are particularly nutrient-dense; this women-led non-commercial fishery contributes

to coastal nutrition security, but its inclusion in fisheries monitoring is limited by normative barriers^{78,79}. Purchasing power, distribution and consumption patterns shape who benefits from fisheries' nutrient yields; inclusive policies are critical to overcome structural and social barriers and ensure equitable access to aquatic foods.

There is a need for fisheries policies that maximize micronutrient mass⁸⁰. Nations with substantial fisheries exports should prioritize domestic production for national consumption, especially where nutritionally vulnerable populations exist. But just as with broader ecosystem approaches and multi-species management, the major challenge to NSFM is implementation. We have demonstrated that a nutrition modelling approach can provide practical and applicable intervention points for NSFM. Improved data on food-critical fisheries focused on catch volumes, fishing methods and composition, as well as local nutrient data, will be important for practical implementation of NSFM. Finally, there is a need for national policymakers to shift attention away from production and revenue as indicators of fisheries development success and, instead, emphasize the role of 'blue foods' for social, environmental and human health outcomes²⁷.

Methods

Study site and fisheries characterization

The SSF sector of Timor-Leste plays a modest role in the country's formal economy yet is crucial for food security. Comprising approximately 4,554 vessels, the fleet is predominantly motorized (about 60%) and consists of canoes (40%)⁸¹. Fishing activities are primarily nearshore, targeting fringing coral reefs and the pelagic forereef zone within 5 km of the coast. The most common fishing gear employed is gill nets, which catch a diverse composition of fish species. More selected gear types used in reef areas include gleaning, speargun, hook and line, long line and seine nets. In the pelagic, FADs are utilized in some areas to concentrate small pelagic fish and make them easier to catch.

SSFs make crucial contributions to the livelihoods of coastal communities, particularly in rural areas where poverty rates are higher. Fishing not only provides income but also serves as a vital source of nutrition in a country with one of the highest malnutrition rates globally⁴⁵. The average annual catch is estimated at 6,781 tons, with municipalities such as Atauro, Lautem, Bobonaro and Manatuto being the most productive. The catch composition is diverse, with larger fish species fetching higher market prices, particularly in Dili, where proximity to the capital reduces transportation costs.

The fisheries sector provides crucial resilience to system shocks such as the COVID-19 pandemic, where resilience was attributed to limited export activities and a modest tourism sector, which insulated local fisheries from broader economic shocks⁸¹. The Peskas monitoring system, developed in partnership with the Timor-Leste Ministry of Agriculture and Fisheries, has enhanced data collection and management, allowing for better decision-making and sustainable practices within the sector.

As Timor-Leste continues to invest in its fisheries sector, it is essential to balance modernization efforts with the needs of local communities, ensuring that initiatives address food security, dignified livelihoods and environmental sustainability. The ongoing development of the SSF sector can serve as a model for other Small Island Developing States facing similar challenges.

Analysis overview

First, we analysed the nutritional characteristics of Timor-Leste SSFs through descriptive analyses of (1) the nutritional density of the main species caught (by functional group and volume), (2) the cumulative yield (by nutrient from overall catches), (3) the affordability of key species vis-à-vis their nutrient density and (4) the nutrient density of catches (by marine habitat and gear type). This is the proposed NSFM analytical framework, which evaluates the nutritional properties of the overall fisheries composition (species/groups), their relative

importance (production), accessibility (price) and key fisheries parameters (habitat and gears).

For analyses involving cumulative nutrient yields, we applied group-specific edible portion coefficients (Extended Data Table 5) to estimate the share of total catch weight that is typically consumed. These coefficients, derived from FAO Fisheries technical paper no. 309 (T0219E)⁸² and the Aquatic Foods Composition Database⁸³, reflect raw edible fractions (mainly muscle tissue, with skin and soft bones where commonly consumed).

Second, we estimated the contributions of marine catches to human nutrition by assessing the number of people meeting the RNI and the recommended quantity of fish from the national food-based dietary guidelines, which are crucial for integrating public health nutrition policies. We focused on a population subgroup that requires more nutrient-rich diets, WRA, and conducted the analyses nationally and sub-nationally. This theoretical exercise illustrates how catches by geography can contribute to dietary quality of subpopulations and highlights opportunities for fish distribution between regions to maximize nutritional impact and equity gains. We present the percentage of WRA achieving 20% of the daily RNI for the six modelled nutrients from SSF catches¹¹. This acknowledges that an adequate diet should include diverse food groups, and that fish alone is neither a realistic nor desirable sole source of 100% of a person's RNI. Dietary diversity guidelines recommend consuming foods from at least five food groups⁸⁴, and aquatic foods should be promoted as part of a diverse and balanced diet. We refer to the 20% RNI measure as 'balanced RNI'.

Third, we proposed a method to model nutrition scenarios for managing SSFs. This involved identifying and validating FNP specific to the fishery. We then predicted FNP outcomes on the basis of fishing gear, habitat, season and vessel type. Last, we explored how gear types and habitats interact to shape FNPs.

Data used

We utilized fishing catch data obtained from Peskas (<https://timor.peskas.org>), an open-source web portal offering insights into Timor-Leste SSFs⁴⁴. This platform compiles catch data collected by local enumerators alongside vessel tracking data, enabling temporal and spatial analysis of fishing patterns. To date, the dataset comprises over 85,000 records of fishing trips along the Timor-Leste coastline, encompassing information about the fishing habitat, gear type used, number of fishers involved, catch composition, catch weight and economic value. Launched in 2016 through a collaboration with the Timor-Leste Ministry of Agriculture and Fisheries, Peskas functions as a near-real-time, low-cost, open-access monitoring system primarily targeting SSFs⁴³. Data are continuously processed and validated according to a defined workflow. For this study, we used data collected from January 2018 to December 2023 ($n = 77,438$).

Nutritional values for catch data were derived using the Fishbase Nutrient Analysis Tool⁸⁵. This tool employs a Bayesian hierarchical model, incorporating phylogenetic information to represent the interconnectedness of fish species, and trait-based data, reflecting critical aspects such as fish diet, thermal regime and energy demands. It predicts muscle flesh concentrations of seven essential nutrients: calcium, iron, omega-3 fatty acids, protein, selenium, vitamin A and zinc, for global marine and inland fish species. The nutritional yield for each catch was ascertained by merging edible weight estimates for 55 fish groups defined according to the ASFIS List of Species for Fishery Statistics Purposes⁸⁶ with the model's nutrient concentration predictions. We used the median nutrient concentrations (calcium, iron, omega-3 fatty acids, protein, vitamin A and zinc) for each species within the fish groups as a representative indicator of each fish group's nutritional value. For non-fish groups such as octopuses, squids, cockles, shrimps, crabs and lobsters, where NutrientFishbase repository models lacked nutritional data, we used raw edible-portion values from the Global Food Composition Database for Fish and Shellfish⁴⁷. Values for selenium were

excluded from the analysis because its exceptionally high contributions to nutritional requirements across species obscured other results, and it is not considered a nutrient of major public health concern.

Finally, for each fishing trip, we calculated the NDS¹¹ as the sum of RNI-equivalent contributions of six key nutrients per kilogram of catch. For each species in the landed catch, we multiplied its catch weight by the modelled nutrient concentration per 100 g of edible muscle, converted those masses into percentages of the RNI for WRA (19–50 years old)⁸⁷ and then summed across calcium, iron, omega-3 fatty acids, protein, vitamin A and zinc to produce the trip-level NDS. By evaluating the combined contributions of calcium, iron, omega-3 fatty acids, protein, vitamin A and zinc, we were able to provide a broad assessment of the nutritional value of the catch. The RNI calculations are based on several assumptions. Protein requirements are based on World Health Organization (WHO) recommendations of $0.83 \text{ g kg}^{-1} \text{ day}^{-1}$ for adult females and assume an average body weight of 55 kg (ref. 88). This body weight is based on an observed mean body mass index of 20.6 for adult women in Timor-Leste⁴⁸ and an assumed mean height of 163 cm based on WHO growth standards. Omega-3 polyunsaturated fatty acid requirements are based on Food and Agriculture Organization recommendations of 0.5–2% (taken at the midpoint of 1.25%) of dietary energy from omega-3s for adults⁸⁹, assuming an average energy requirement of $8,700 \text{ kJ day}^{-1}$ for a 55-kg adult female and physical activity level of 1.6 (ref. 88). Iron, zinc, calcium and vitamin A requirements are based on Food and Agriculture Organization/WHO global recommendations for an adult female aged 19–50 years, assuming a 10% dietary bioavailability of iron and a moderate bioavailability of zinc⁸⁷.

Modelling and analyses

To investigate the impact of gear type, habitat, season and vessel type on the nutritional quality of catches in SSFs, we applied a combination of *k*-means clustering and machine learning techniques. We used high-resolution fisheries data from Dili and Atauro, two municipalities with the most complete and reliable trip-level records, and organized the dataset into two subsets: one focusing on gill net usage and the other encompassing all other gear types. The other gear category included hand and long lines, cast and seine nets, beach seines, traps and manual collection (gleaning). Because gill nets were the majority of recorded trips, we separated gill nets and other gear to ensure adequate sample sizes for clustering and subsequent modelling. In this classification, FADs were treated as artificial habitats rather than gear types, since multiple fishing gears (for example, long lines, gill nets and seine nets) can be deployed around them. This segmentation was essential for analysing the differential impacts of various fishing gear types on the nutritional outcomes of the catches.

As a first step, we employed *k*-means clustering to establish consistent FNPs across the datasets. Fishing trips were grouped on the basis of similarities in their RNI-equivalent contributions of six essential nutrients—calcium, iron, omega-3 fatty acids, protein, vitamin A and zinc. This clustering revealed patterns in nutrient levels, grouping fishing trips with similar nutritional characteristics. The optimal number of clusters, determined to be three distinct FNPs, was identified using the elbow and silhouette methods, which assess the compactness and separation of clusters.

To validate the consistency and significance of the identified FNPs, we conducted a PERMANOVA⁹⁰. This analysis tested whether nutrient profiles within the same cluster were significantly more similar to each other than to those in different clusters, thereby confirming the robustness of our clustering approach.

After clustering, we developed two XGBoost models to predict FNPs using key fishing-trip attributes—gear type, habitat, season and vessel type—to assess how these factors influenced catch nutritional quality. XGBoost was chosen for its high predictive accuracy and its ability to capture complex nonlinear relationships and feature interactions, particularly when some gear-habitat combinations are rare. For

the gill net model, predictors included mesh size (to capture variations in catch composition owing to different net sizes), habitat, their interaction (to capture combined effects), quarter of the year (reflecting seasonal variations) and vessel type (distinguishing between motorized and non-motorized boats). For the other gear model, predictors were gear type, habitat, their interaction, quarter of the year and vessel type.

Both datasets were divided into training (80%) and testing (20%) sets to build and evaluate the models. We applied tenfold cross-validation on the training set to enhance the models' accuracy and generalizability, reducing the risk of overfitting⁹¹. Model tuning involved dynamically adjusting parameters such as the number of trees, tree depth, learning rate, loss reduction, sample size and early stopping criteria to optimize performance. The performance of the XGBoost models was assessed using several metrics, including accuracy, the area under the receiver operating characteristic curve, sensitivity (recall) and specificity. We obtained gain-based feature-importance rankings from each model to identify the most influential predictors.

Next, we calculated SHAP values⁹² for the predictors ranked highest by gain-based feature importance to interpret their influence on FNP outcomes in each model. SHAP values offer a unified approach to explain the output of machine learning models by quantifying the contribution of each feature to prediction and determining the direction of its impact. In the gill net subset, we focused on the impact of mesh size and habitats on FNPs. This analysis offered insights into how selecting certain mesh sizes could influence the nutritional quality of catches in different environmental contexts. For the other gear subset, we examined how gear type and habitat influenced FNP predictions. SHAP values allowed us to dissect the combined effect of specific gear types in particular habitats on the nutritional outcomes.

All statistical analyses were performed in R (version 4.3.3) using the built-in stats package (version 4.3.3) for *k*-means clustering, the vegan package (version 2.6-6.1) for PERMANOVA (adonis2) and the tidymodels metapackage (version 1.2.0) for building and tuning XGBoost models. SHAP values were computed with the kernelshap package (version 0.7.0).

Statistics and reproducibility

This study is based on an observational dataset of 77,438 fishing trips recorded between January 2018 and December 2023 through the Peskas monitoring system in Timor-Leste. Sample size was determined by the full availability of validated trip-level records collected during this period; therefore, no statistical method was used to predetermine sample size. All records meeting basic data completeness requirements for trip-level habitat, gear and catch information were included in the analyses. No data were excluded from the analyses, with the exception of fishing trips missing essential metadata required for modelling (for example, missing gear or habitat labels), for which exclusion criteria are reported in the Methods. Because the study uses observational monitoring data, randomization and blinding were not applicable. The analyses were not randomized and investigators were not blinded to allocation during analyses or outcome assessment. To evaluate reproducibility, the complete dataset, preprocessing scripts and analytical workflows used to generate the NDS, identify FNPs and train and validate the machine learning models are openly available (Data availability and Code availability). Reproducibility was further supported through standardized workflows for data cleaning and validation in Peskas, the use of 80/20 training–test splits and tenfold cross-validation for XGBoost models and independent validation of clustering via PERMANOVA. The robustness of clustering was assessed using elbow and silhouette methods to determine optimal cluster number, and cluster significance was evaluated using PERMANOVA. Model reproducibility is supported by transparent hyperparameter tuning and reporting of performance metrics, including area under the receiver operating characteristic curve, accuracy, sensitivity and specificity, for both gill nets and other gear models.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All data supporting the findings of this study are openly available. The raw and processed fisheries datasets, nutrient composition tables and derived analytical outputs used for clustering, machine learning analyses and municipal nutritional yield estimates are available via Zenodo at <https://doi.org/10.5281/zenodo.17541325> (ref. 93) and via GitHub at <https://github.com/WorldFishCenter/timor.nutrients> (ref. 94). The repository includes input data, metadata and documentation describing data structure and processing steps. No restrictions apply to data access.

Code availability

All code used to process the fisheries and nutrient data, generate the NDS, perform *k*-means clustering, train and evaluate the machine learning models and reproduce the figures and tables in this study is available via GitHub at <https://github.com/WorldFishCenter/timor.nutrients> (ref. 94) and <https://worldfishcenter.github.io/timor.nutrients/index.html> (ref. 95). The repository contains annotated scripts, workflow documentation and instructions for reproducing the analyses.

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Author contributions

L.L., A.T. and G.B.-P. designed and conceptualized the study. V.S. and J.D.R.L supported data collection and stakeholders' engagement. L.L. and H.A. developed statistical methods and performed the analyses and the visualizations. L.L., A.T. and G.B.-P. wrote the first draft. J.B. and J.K. provided expert input on specific topics. All authors reviewed and approved the final paper. A.T. supervised this work.

Competing interests

The authors declare no competing interests.

Additional information

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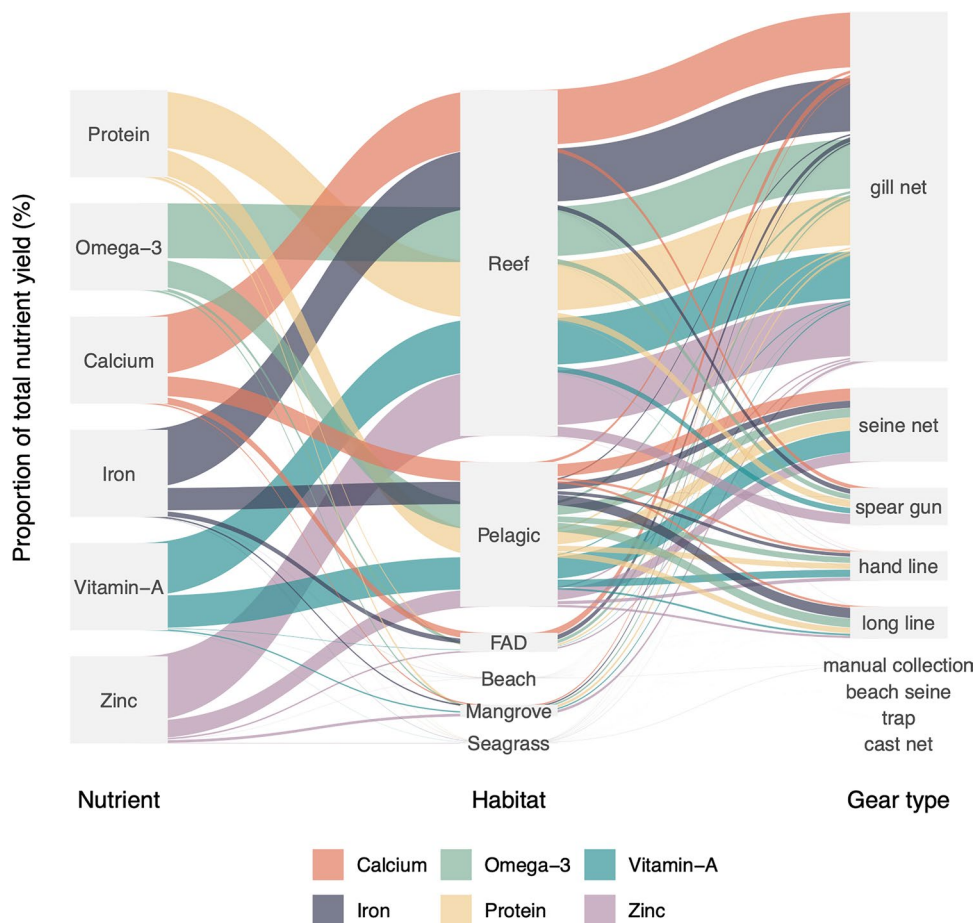
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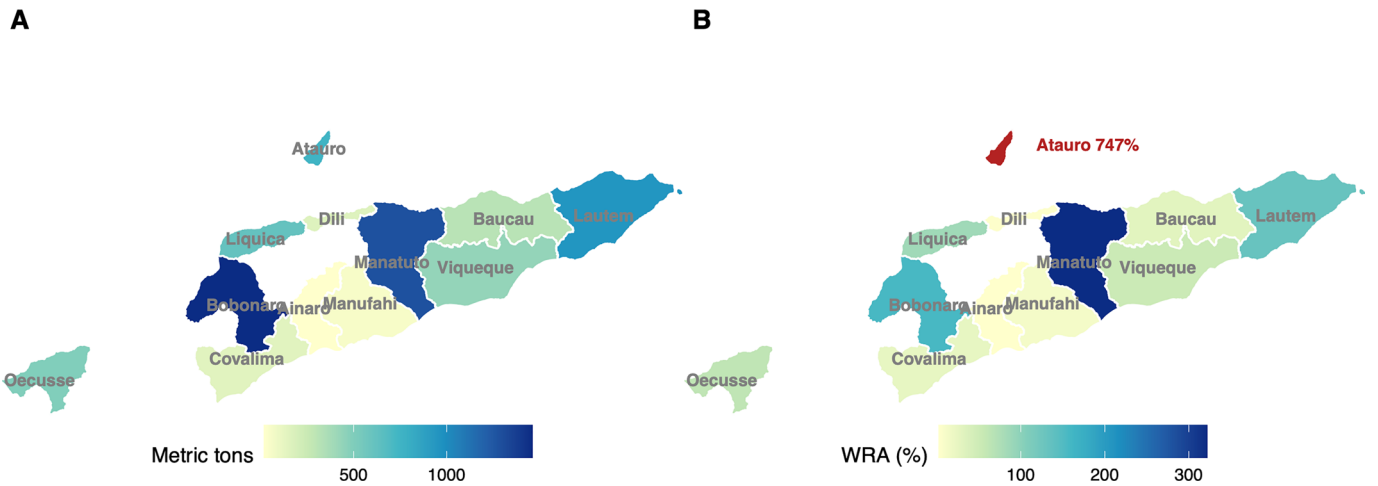
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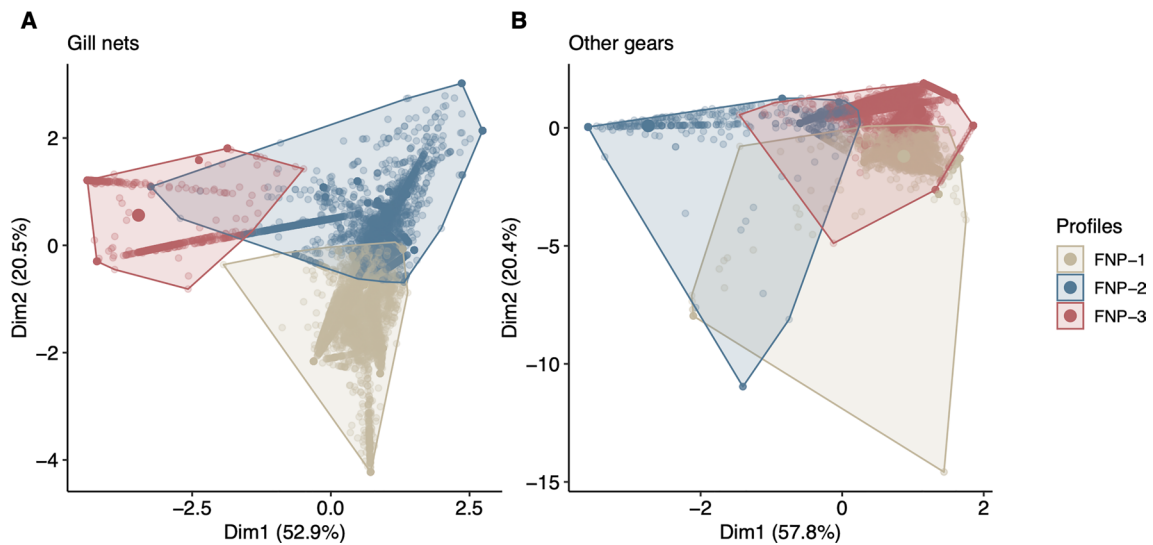
Extended Data Fig. 1 | Sankey diagram illustrating the relative distribution of key nutrients across marine habitats and their extraction by fishing gear. The figure shows the flow of six essential nutrients from primary habitats

(reef, deep, FAD, nearshore and mangroves) to the main fishing gears used in Timor-Leste's small-scale fisheries, highlighting the dominant pathways contributing to nutrient supply.



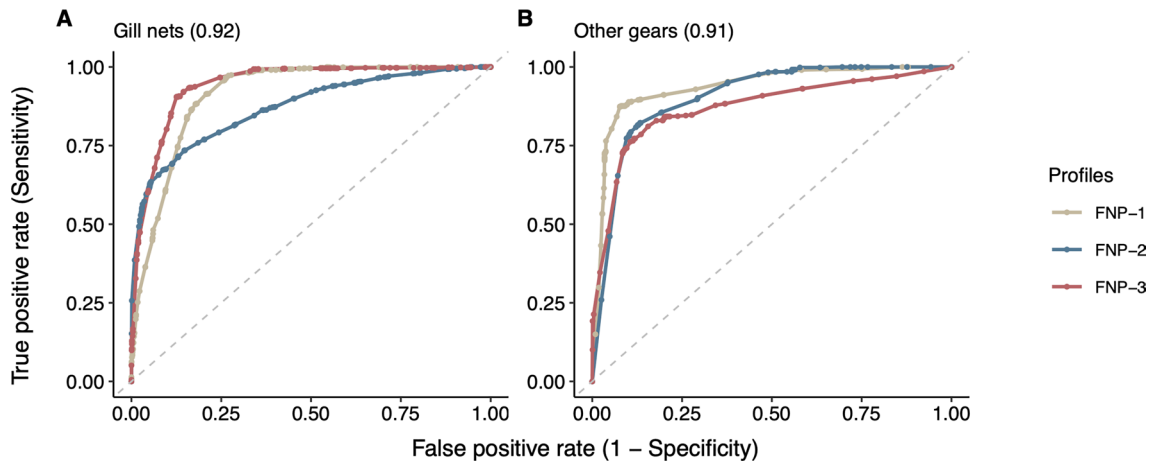
Extended Data Fig. 2 | Timor-Leste small-scale fisheries production and contributions to dietary fish recommendations. (A) Annual marine small-scale fisheries catch by municipality (2020–2022 average), expressed in metric tons (Mt), with a total national production of 6,688 Mt. (B) Percentage of Women of Reproductive Age (WRA) whose recommended annual edible fish intake could be met based on current catches. Five municipalities (Atauro, Bobonaro,

Lautem, Manatuto, Liquica) produce surplus catches, indicating potential for redistribution to municipalities with deficits. Atauro is highlighted in red due to its disproportionately high catch relative to other municipalities. Basemap data were obtained from the Timor-Leste Subnational Administrative Boundaries (COD-AB-TLS) dataset (HDX), distributed under CC BY 3.0 IGO.



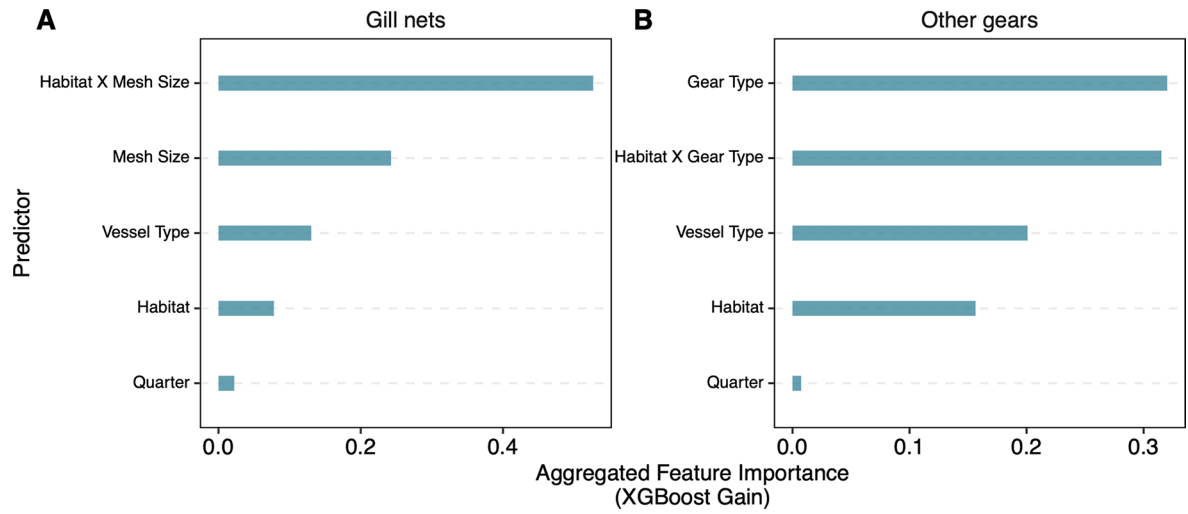
Extended Data Fig. 3 | Fishery nutrient profile-based clustering of fishing trips by gear category in Dili and Atauro municipalities. Each plot presents a k-means clustering analysis of fishing trip observations, grouped by their nutritional contributions to the recommended nutrient intake (RNI) for six nutrients. The panels display data subsets for gill nets (**A**) and all other gear types (**B**), specifically. The scatter plots within each panel are charted in a two-dimensional space defined by the first two principal components, with the axes

denoting the percentage of explained variance. Points are color-coded to denote distinct Fishery Nutrient Profile clusters derived from the k-means algorithm. Convex hulls define the periphery of each cluster, providing insight into the cluster density and separation. Convex hulls around the clusters aid in visualizing the distribution and delineation of Fishery Nutrient Profile groupings across different fishing methods.



Extended Data Fig. 4 | Receiver Operating Characteristic (ROC) curves for evaluating the performance of a cluster-based XGBoost classification model. Panel **A** shows ROC curves for gill nets, and Panel **B** for other gear data. Each curve represents one of the three Fishery Nutrient Profiles (FNPs) obtained from the classification, with different colors marking each profile. The curves display the model's performance in distinguishing the profiles, with each point

depicting the balance between correctly identifying a profile (sensitivity) and the rate of incorrect identifications (1-specificity). A curve's closeness to the top-left corner denotes higher classification precision, while proximity to the diagonal dashed line indicates a performance no better than random chance. Numbers in parentheses indicate the overall ROC Area Under the Curve (AUC) performance score.



Extended Data Fig. 5 | Aggregated feature importance (XGBoost gain) for predicting nutritional outcomes across fishing gears. Panel **A** presents feature importance for gill nets, with predictors including habitat, mesh size, vessel type, and the interaction between habitat and mesh size. Panel **B** shows feature

importance for all other gear types, with predictors including gear type, habitat, vessel type, and the interaction between habitat and gear type. The x-axis denotes the aggregated gain, with higher values indicating greater predictor influence on model accuracy.

Extended Data Table 1 | Proportion of Women of Reproductive Age (WRA) in Timor-Leste meeting nutrient requirements from marine catches

Geography ^a	Protein (%)	Zn (%)	Ca (%)	Omega-3 (%)	Vit A (%)	Fe (%)	Number of WRA: 4 nutrients	Number of WRA: 6 nutrients
National	62.9	31.3	18.3	16.4	11.7	6.5	55,389	21,955
Ainaro	1.2	0.5	0.3	0.5	0.2	0.1	51	17
Atauro	712.1	434.7	121.3	97.3	271.2	61.6	3,117	1,583
Baucau	35.9	18.9	21.0	11.3	3.3	6.5	3,504	1,023
Bobonaro	203.2	105.2	55.2	61.7	30.3	16.3	13,688	4,042
Covalima	27.9	14.6	14.4	7.3	3.9	5	1,288	688
Dili	4.4	2.2	1.0	0.8	1.2	0.3	974	292
Lautem	159.6	71.9	54.6	28.7	39.1	20	6,315	3,230
Liquiça	88.8	43.9	30.0	25.0	9.1	11.5	5,164	1,880
Manatuto	355.1	176.5	117.1	136.	35.2	40.5	13,879	4,172
Manufahi	13.2	6.6	5.6	4.7	1.8	1.6	659	224
Oecusse	119.5	57.9	19.4	18.6	29.2	9.5	3,735	1,829
Viqueque	65.8	22.5	8.1	9.8	21.6	3.5	1,773	633

The table shows the percentage of WRA meeting 20% of daily recommended nutrient intake (RNI) and the number of WRA meeting the full RNI for four and six nutrients, based on the edible portion of marine catches at national and municipal levels. Calculations are based on estimated marine catches per coastal municipality and 2022 census data on women of reproductive age (15–49 years). Marine catches represent averaged annual values for 2020–2022 (kg), derived from the number of fishing boats reported in the 2021 Timor-Leste boat census, the average number of fishing trips per boat, and mean landing weights for each fish group.

Extended Data Table 2 | Women of Reproductive Age (WRA) meeting annual fish intake recommendations from the edible portion of marine catches in Timor-Leste

Geography ^a	Annual marine catches (Mt) ^b (average 2020-22)	Edible portion ^c of annual marine catches (Mt) ^b (average 2020-22)	Number of WRA ^d	WRA that would meet FBDG recommendations ^e	
				Percentage	Number
National	6,688	3,621	337,144	65.4	220,457
Ainaro	21	10	16,925	3.6	609
Atauro	751	392	2,570	928.6	23,866
Baucau	313	165	31,006	32.4	10,046
Bobonaro	1,460	827	24,798	203.0	50,350
Covalima	149	81	17,643	28.0	4,932
Dili	161	87	97,447	5.4	5,297
Lautem	950	444	16,151	167.4	27,032
Liquiça	612	347	20,657	102.3	21,126
Manatuto	1,281	741	11,852	380.6	45,114
Manufahi	57	32	14,030	13.9	1,948
Oecusse	491	262	19,250	82.9	15,951
Viqueque	438	227	18,094	76.4	13,820

The table estimates how many WRA could meet the recommended annual quantity of edible fish based on Food-Based Dietary Guidelines. Marine catch values represent averaged annual production (2020–2022) in Metric tons, derived from the 2021 Timor-Leste boat census, average trips per boat, and mean landing weights for each fish group. To estimate the edible share of total catch, we applied group-specific edible portion coefficients (Extended Data Table 5), sourced from FAO Fisheries Technical Paper No. 309 (T0219E)³³ and the Aquatic Foods Composition Database (AFCD)³⁴, which reflect raw edible fractions (primarily muscle tissue, with skin and soft bones where commonly consumed). Population estimates of women aged 15–49 are based on the 2022 Timor-Leste Census. Dietary recommendations assume 100g of cooked fish two to three times per week for adults³⁵, equivalent to approximately 45g/day or 16.4kg/year of raw fish.

Extended Data Table 3 | Results of PERMANOVA analysis evaluating the homogeneity of Fishery Nutrient Profiles within clusters of fishing trips, categorized by gear type (gill net, other gears)

Data subset	Term	df	Sum of squares	R ²	Statistic	p-value
Gill net	Clusters	4	14899.02	0.81	10879.56	< 0.001
	Residual	10166	3480.46	0.19		
	Total	10170	18379.48	1		
Other gears	Clusters	4	10871.14	0.85	7753.61	< 0.001
	Residual	5477	1919.79	0.15		
	Total	5481	12790.93	1		

The analysis details include degrees of freedom (df), sum of squares, R-squared values (R²), PERMANOVA statistics, and p-values for each cluster and residual variance. The R² values indicate the proportion of variance explained by the clusters.

Extended Data Table 4 | Performance metrics for XGBoost model across fishing data subsets

Metric	Description	Gill nets	Other gears
ROC AUC Score	Measures overall model performance, with 1 being perfect	0.92	0.91
Accuracy	Proportion of correct predictions	0.76	0.8
Kappa Statistic	Agreement between predicted and actual values beyond chance	0.62	0.7
Recall	Ability to correctly identify positive cases (true positives)	0.77	0.81
Specificity	Ability to correctly identify negative cases (true negatives)	0.88	0.9
Precision	Likelihood that positive prediction is correct	0.74	0.8
Negative Predictive Value	Likelihood that negative prediction is correct	0.87	0.9
Youden's J Index	Sum of sensitivity and specificity minus 1, indicating effectiveness	0.65	0.71
Balanced Accuracy	Average of sensitivity and specificity	0.82	0.86
Detection Prevalence	Proportion of cases predicted as positive	0.33	0.33
F-measure	Harmonic mean of Precision and Recall	0.75	0.8

The table provides the predictive performance metrics of an XGBoost classification model for two distinct subsets of fishing gill nets and other gear data. The metrics collectively reflect the model's ability to discriminate between Fishery Nutrient Profiles, its overall accuracy, and the balance between the sensitivity and specificity for each subset.

Extended Data Table 5 | Edible portion coefficients (as percentage of total catch weight) for marine aquatic food groups reported in Timor-Leste

FAO alpha3code	Family	Catch name	Edible portion (%)	Reference
SLV	-	Lobster	30.0	FAO T0219E
SWX	-	Seaweed	100.0	AFCD
CUX	-	Sea cucumber	50.0	FAO T0219E
RAX	Scombridae	Short mackerel	57.0	AFCD
SDX	Carangidae	Mackerel scad	53.0	AFCD
CGX	Carangidae	Jacks/Trevally	53.0	AFCD
TUN	Scombridae	Tuna/Bonito	57.0	AFCD
CJX	Caesionidae	Fusilier	60.0	FAO T0219E
CLP	Clupeidae	Sardines/pilchards	60.0	AFCD
GZP	Hemiramphidae	Garfish	38.0	FAO T0219E
YDX	Holocentridae	Soldierfish	65.0	FAO T0219E
BEN	Belonidae	Long tom	38.0	FAO T0219E
SNA	Lutjanidae	Snapper/seaperch	56.0	AFCD
SPI	Siganidae	Spinefoot	72.0	FAO T0219E
GPX	Serranidae	Grouper	50.0	FAO T0219E
EMP	Lethrinidae	Emperor	54.0	FAO T0219E
PWT	Scaridae	Parrotfish	45.0	FAO T0219E
TRI	Balistidae	Triggerfish	36.0	AFCD
FLY	Exocoetidae	Flying fish	58.0	FAO T0219E
SUR	Acanthuridae	Unicornfish	50.0	FAO T0219E
MOJ	Gerreidae	Mojarra/Silverbelly	70.0	FAO T0219E
LWX	Lutjanidae	Jobfish	56.0	AFCD
WRA	Labridae	Wrasse	60.0	AFCD
BAR	Sphyrnidae	Barracuda	54.0	FAO T0219E
KYX	Kyphosidae	Chub	50.0	FAO T0219E
OCZ	Octopodidae	Octopus	79.0	AFCD
MOO	Menidae	Moonfish	65.0	FAO T0219E
BWH	Priacanthidae	Moontail bullseye	52.0	FAO T0219E
LGE	Leiognathidae	Ponyfish	78.0	FAO T0219E
MOB	Nemipteridae	Bream	51.0	FAO T0219E
MHL	Pempheridae	Blackspot sweeper	75.0	FAO T0219E
GOX	Mullidae	Goatfish	50.0	FAO T0219E
MUL	Mugilidae	Mullet	50.0	FAO T0219E
THO	Terapontidae	Terapon	55.0	FAO T0219E
SKH	Carcharhinidae	Shark	35.0	FAO T0219E
GRX	Haemulidae	Sweetlips	48.0	FAO T0219E
MUI	Muraenidae	Moray	70.0	FAO T0219E
DSF	Pomacentridae	Sergeant	80.0	AFCD
PEZ	-	Shrimp	57.0	FAO T0219E
IHX	Chaetodontidae	Butterflyfish	85.0	AFCD
APO	Apogonidae	Cardinalfish	83.0	AFCD
IAX	Sepiidae	Cuttlefish	63.0	FAO T0219E
BGX	Haemulidae	Javelin/Grunt	48.0	FAO T0219E
SFA	Istiophoridae	Sailfish	60.0	FAO T0219E
CBA	Rachycentridae	Cobia	60.0	FAO T0219E
CRA	-	Crab	25.0	FAO T0219E
DOX	Coryphaenidae	Dolphinfish	53.0	FAO T0219E
MIL	Chanidae	Milkfish	61.0	FAO T0219E
THF	Polynemidae	Threadfin	50.0	FAO T0219E
COZ	Cardiidae	Cockles	18.0	FAO T0219E
ECN	Echeneidae	Remora	50.0	FAO T0219E
PUX	Triacanthidae	Tripodfish	52.0	FAO T0219E
DOS	Chirocentridae	Wolf herring	40.0	FAO T0219E
SRX	-	Stingrays	26.0	FAO T0219E
DRZ	Drepaneidae	Sicklefish	50.0	FAO T0219E

Values represent the raw, edible fraction of the animal, primarily consisting of muscle tissue and, in some cases, skin and soft bones when commonly consumed. Edible portion values were compiled from the FAO Fisheries Technical Paper No. 309 (T0219E)⁸⁴ and the Aquatic Foods Composition Database (AFCD)⁸⁴, using species- or family-level.

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Software and code

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Data collection

The data were collected using Peskas, a custom-built, open-source fisheries monitoring system developed in collaboration with the Timor-Leste Ministry of Agriculture and Fisheries. Peskas is an automated analytics tool that records fishing trip data, including catch composition, weight, gear type, and fishing location. The platform is publicly accessible at <https://timor.peskas.org>, and the source code is available on GitHub at <https://github.com/WorldFishCenter/peskas.timor.data.pipeline>

Data analysis

Data analysis was performed using R software (R 4.5.1), the list of packages used is accessible at <https://github.com/WorldFishCenter/timor.nutrients/blob/main/DESCRIPTION>. The complete data analysis code is available in a public GitHub repository at <https://github.com/WorldFishCenter/timor.nutrients> and <https://worldfishcenter.github.io/timor.nutrients/>

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The raw and processed fisheries datasets, nutrient composition tables, and derived analytical outputs used for clustering, machine learning analyses, and municipal nutritional yield estimates are archived on Zenodo (<https://doi.org/10.5281/zenodo.17541325>) and available as a public GitHub release at <https://github.com/WorldFishCenter/timor.nutrients>. The repository includes input data, metadata, and documentation describing data structure and processing steps. No restrictions apply to data access.

Human research participants

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Reporting on sex and gender	No human research participants were involved in this study. The analysis was conducted using fisheries catch data collected through the Peskas system. Therefore, there was no disaggregation of data based on sex or gender, and no sex- or gender-based analyses were performed.
Population characteristics	This study did not involve human research participants.
Recruitment	No human participants were recruited for this study. The data used were collected through routine fisheries monitoring by local enumerators using the Peskas system.
Ethics oversight	Ethics approval was not required, as the study used secondary data from fisheries monitoring systems without any direct involvement of human research participants.

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

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Ecological, evolutionary & environmental sciences study design

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Study description	This study involved quantitative analysis of fisheries catch data to model the nutrient profiles of small-scale fisheries in Timor-Leste. Using six years of fisheries data, we applied machine learning techniques to predict nutrient outcomes based on fishing gear, habitat, season, and vessel type. The study aimed to develop a practical framework for nutrition-sensitive fisheries management in low- and middle-income countries.
Research sample	The research sample consisted of fisheries catch data collected through the Peskas system. This dataset included over 75,000 fishing trips recorded between January 2018 and December 2023, covering various gear types, habitats, and catch compositions. The sample represents the small-scale fisheries sector in Timor-Leste, which is crucial for food security and livelihoods in the region.
Sampling strategy	No formal sample-size calculation was performed, as this study utilized a complete dataset of recorded fishing trips from the national fisheries monitoring system.
Data collection	Data were collected through Peskas, a government-endorsed, open-source system for monitoring small-scale fisheries. Local enumerators recorded data on fishing trips, including gear type, catch composition, weight, and economic value. Data collection was conducted systematically at landing sites across the country.
Timing and spatial scale	Data collection covered the period from January 2018 to December 2023, with records from various fishing locations along the coast of Timor-Leste. The data represent the national catch from small-scale fisheries over this six-year period.
Data exclusions	No data were excluded from the analysis. All available records from the Peskas system were used.
Reproducibility	The analyses were conducted using publicly available data and code, which are accessible in the GitHub repository at https://

Reproducibility

Randomization

Blinding

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