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Machine learning-based prediction of passive gears from vessel tracking data in small-scale multi-gear fisheries

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ABSTRACT

Small-scale fisheries (SSF) play a crucial role in the Mediterranean Sea, contributing significantly to coastal livelihoods, employment, food security, and local economies. These fisheries are highly diverse and often operate with multiple passive gears within a single trip, targeting different species based on season, market demand, and fisher preference. This gear diversity, combined with the absence of trip-level gear reporting, poses a challenge for accurate monitoring, gear-specific effort estimation, and sustainable management. This study presents a Machine Learning-based approach to predict the type of fishing gear used during individual hauling events from high frequency vessel tracking data.

Tracking data were collected from 10 SSF multi-gear vessels based in Ancona (Italy) between January 2023 and March 2024, and over 7000 hauling events were detected from a total of 1634 trips. Each event was labelled through fisher validation and expert-informed spatial analysis. Predictive models – Ridge Classifier, Logistic Regression, Decision Tree, Random Forest, and Extreme Gradient Boosting – were trained and tested using various sets of predictors. Two classification levels were explored: i) gear categories (nets vs. pots) and ii) specific gear types (i.e., gillnets, trammel nets, and three types of pots).

With fewer predictors and optimized tuning, Random Forest reached 95% test accuracy for *gear category* and Extreme Gradient Boosting achieved 86% for *specific gear* type classification, successfully maintaining low levels of overfitting. The shared, reproducible hauling event-level approach offers a scalable tool for automated gear classification in multi-gear fisheries and contributes to more precise monitoring, management, and traceability in small-scale coastal systems.

1. Introduction

Small-scale fisheries (SSF, vessels under 12 m in length and not using towed fishing gears, as defined in the CE Regulation N° 508/2014 - European Commission, 2014) are usually underrepresented in marine spatial planning, management plans and Blue Growth initiatives, even if their role is often not marginal (Basurto et al., 2025; Cohen et al., 2019; Percy and O'Riordan, 2020). SSF support the livelihoods of 1 in 12 people worldwide – nearly half of them women – while generating 44% (US77.2 billion) of the total economic value of global fisheries (Basurto et al., 2025). Given their role in food security and poverty reduction, particularly in developing countries, their active inclusion in marine spatial planning and management initiatives is key to achieving broader sustainability goals (Bitoun et al., 2024; FAO, 2021). However, a significant challenge in this regard has been the historical scarcity of comprehensive data for this fleet (FAO, 2021).

While a huge amount of spatial information is now available for large-scale fisheries (LSF, vessels greater than 12 m in length) thanks to tracking devices (e.g., AIS – Automatic Identification System (Armelloni et al., 2021; Bernabé et al., 2023; De Souza et al., 2016; Ferrà et al., 2018; Le Guyader et al., 2017; Natale et al., 2015; Tassetti et al., 2019), VMS – Vessel Monitoring System (Amoroso et al., 2018; Bastardie et al., 2010; Doherty et al., 2021; Russo et al., 2014)) and remote-sensing technologies (e.g., SAR – Synthetic Aperture Radar (Galdelli et al., 2021; Rodger and Guida, 2023)), the application of these methodologies to SSF is still limited. However, in Europe, the adoption of Regulation

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(EU) 2023/2842 (Control Regulation - European Commission, 2023) on 22 November 2023 marked a significant step forward enhanced fisheries control, requiring all vessels, including those under 12 m, to be equipped with tracking devices for regular position reporting. This measure aims to improve monitoring, ensure compliance with the Common Fisheries Policy, and promote sustainable fishing practices (European Commission, 2009). In many countries, pilot projects are supporting the transition by encouraging the adoption by the fishers (Behivoke et al., 2021; Galparsoro et al., 2024; James et al., 2018; Jerome and Mohamed, 2023; Mendo et al., 2023; Rufino et al., 2023; Tassetti et al., 2022) of low-cost and low-burden positioning systems, and numerous initiatives have been set up at international, national or regional levels to make SSF fleet tracking compulsory (MMO, 2024; BLE, 2018; Del Olmo, 2006; Consejo de Gobierno, 2016; Consell de Govern, 2019; Gobierno de Cantabria, 2020).

Nevertheless, the mandatory collection of SSF positional information is just a starting point, as harmonized protocols for data collection, processing and analysis are required to enhance the scientific foundation for SSF fisheries management across Member States (ICES, 2022, 2023; Mendo et al., 2024).

Recently, tracking technologies have provided insights into the individual fishing strategies, revealing a significant and often overlooked heterogeneity in fishers' spatial and temporal fishing behaviours that contrasts aggregated fleet-level analyses (Frawley et al., 2021; Rodriguez-Albala et al., 2024; Russo et al., 2011). Indeed, fishers' operational choices are shaped by a complex set of factors that go beyond catch maximization (Boonstra and Hentati-Sundberg, 2016; Cheng et al., 2023; Salas and Gaertner, 2004; Warner et al., 2025). Understanding this individual-level variability is crucial for effective fisheries management, as non-uniform fleet displacements in time and space can lead to differing impacts in coastal areas. This awareness could empower the development of tailored management interventions, optimizing resource allocation and enhancing long-term sustainability for both fisheries and marine ecosystems (Frawley et al., 2021). Shedding light on the spatial extent and intensity of small-scale fishing activities may also facilitate greater SSF involvement into decision-making processes (FAO, 2021).

Concerning the technical side, statistical methods have long been employed to analyse tracking data, offering precious intuitions into spatial patterns and fisher behavior. More recently, Artificial Intelligence (AI) algorithms have significantly enhanced this analysis, enabling more precise and automated interpretations of large and complex datasets (Welch et al., 2024). These advanced techniques are particularly effective at recognizing relationships, making them well-suited for tasks such as identifying fishing activities from vessel trajectories. By integrating traditional statistical methods with AI, researchers can improve both the accuracy and efficiency of detecting fishing behaviours (Behivoke et al., 2021; Cardiec et al., 2020; Frawley et al., 2021; Mendo et al., 2023; Samarão et al., 2024).

The novelty of this study lies in its shift of focus from trip-level analysis to the multiple hauling events (gear retrieval moments). In the study area, SSF vessels frequently use multiple gear types during a single trip defined as port departure to return (Tassetti et al., 2022). This multi-gear approach makes conventional trip-level analysis insufficient and prone to information loss; therefore, analyzing data at the hauling-event level allowed for more accurate identification of gear use.

Within this framework, the paper introduces ensemble AI models to predict which specific fishing gears were used during each hauling event within multi-gear fishing trips. Decision Trees, Random Forests, and Extreme Gradient Boosting algorithms were chosen for their balance between predictive power and computational efficiency, avoiding both overly simplistic linear models and computationally demanding deep learning techniques (Hastie et al., 2005). This choice also allowed for a comprehensive comparison across a spectrum of algorithmic complexity. Two statistical models (i.e., Ridge Classifier and Logistic Regression) were added for comparison with traditional methods. While previous studies have already applied machine learning (ML) to fishing gear recognition in commercial fisheries, these efforts have primarily focused on identifying active gears (De Souza et al., 2016; Marzuki et al., 2018; Srisukkham et al., 2021) or distinguishing between active and passive gears (Kim and Lee, 2020; Rodriguez-Albala et al., 2024; Russo et al., 2011). However, the category of "passive gears" (i.e., those relying on the movement of the target species toward stationary gear) encompasses a wide range of devices that differently influence fishers' operational behaviours, spatial fishing patterns and catch selectivity. These gears also exhibit distinct functional characteristics, such as the single wall of netting and gilling mechanism for gillnets, the three layers of netting for trammel nets, and the rigid structures with funnel entrances often baited for pots, among others (Scanu et al., 2020). The code developed for predicting gears was shared at the *Figshare* repository (available at https://doi.org/10.6084/m9.figshare.29647448, Lattanzi et al., 2025), supporting reproducibility and transferability to other multi-gear contexts.

2. Materials and methods

2.1. Data acquisition and pre-processing

Fishing trips were recorded using GNSS tracking devices (i.e., Global Positioning System, GPS) installed onboard 10 small-scale fishing vessels operating from the Ancona harbour (Marche Region, Italy, Fig. 1A). These vessels are authorized to use passive gears (mainly GNS – Set gillnets, GTR – Trammel nets, and FPO – Pots, FAO, 2021) that are selected depending on several factors, such as target species, market demand, and fishing season. These drivers collectively influence vessel behavior in space and time. Passive gears involve two distinct operations: deployment (*setting*) and retrieval (*hauling,* Fig. 1B), typically after a soak period that depends on the factors previously mentioned, as well as prevailing weather and sea conditions. Additionally, the use of fishing gear is governed by specific regulations that impose technical/numerical constraints and regulate the overall fishing effort exerted at sea (Tassetti et al., 2022).

Data collection was carried out in collaboration with the local small-scale fishing organization, and its architecture and system design were described by Tassetti et al., 2022. Geo-positional observations were collected between January 2023 and March 2024, with vessel positions transmitted at 60-s intervals. A total of 1634 trips were identified using the code provided by Mendo et al., 2024.

Once identified, each fishing trip was mapped and shown to fishers, who provided information on the gear or gears they used. Indeed, multiple gear types were often deployed within a single trip, reflecting the polyvalent nature of these SSF vessels. Fishing gears were labelled at two different levels of analysis: i) gear category, distinguishing between Nets (Set gillnets, *GNS* + trammel nets, *GTR*) and Pots (*FPO*), and ii) five specific gear, namely *GNS, GTR* and three different types of *FPO,* known as "*cogolli*" (cuttlefish pots, mainly targeting *Sepia officinalis*), "*nasse*" (crustacean pots, mainly targeting *Squilla mantis*) and "*cestini*" (gastropod pots, mainly targeting *Tritia mutabilis*). Fig. 2 shows the different fishing gears and their associated target species, along with example vessel trajectories depicting typical fishing trips for each gear type.

Each event was labelled through fisher validation (in terms of the gear type they used) and expert-informed spatial analysis (in terms of the operational status, from here on identified as: *fishing* = hauling / *not_fishing* = setting or navigation). Clarifying the position, timing, and type of each fishing events enabled the calculation of the so-called "*soak time*", a reliable metric for estimating fishing effort of passive gears. To calculate it, the code by Mendo et al., 2023 was tested and adapted for the case study. This algorithm matches two phases, *setting* and *hauling,* of the same fishing event across consecutive trips based on spatial overlap and leveraging highly resolved geospatial tracking data. If successfully coupled, each hauling event inherits the relative soak time, and this will

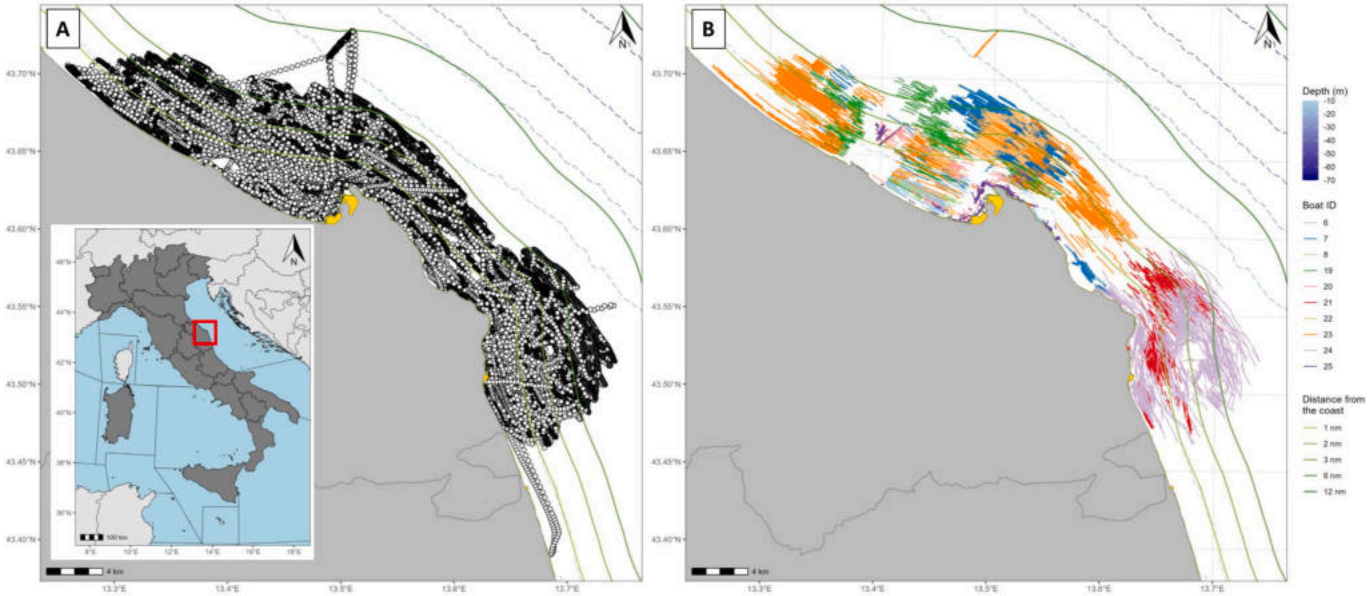


Fig. 1. Map of the study area – Ancona harbour, Marche Region, Italy. A) GPS points from all 1634 tracked small-scale fishing trips ($n = 10$ vessels). B) Detected fishing events ($n = 7164$), categorized by vessel ID.

be valuable for fishing gear prediction.

Lastly, pre-processing involved data cleaning, where hauling events that were too short or exhibited unrealistic soak time values were removed (e.g., nets retrieval exceeding 72 h). Supplementary Material S1 displays a chart summarizing all steps involved in GPS data pre-processing.

The resulting dataset of labelled hauling events was then used as the input for statistical and ML models seeking to predict the fishing gear used in each event.

2.2. Feature engineering

Two distinct sets of variables were extracted at the hauling event level and investigated to identify the most informative predictors to be used in classification models (Table 1): variables represented by mean values (highlighted in green), and variables represented by relative frequencies across predefined intervals (highlighted in orange). Both sets were combined with fixed predictors (white-shaded in Table 1), which were included in all model configurations. This allowed for a comprehensive evaluation of model performance across these different predictor configurations.

A logarithmic transformation ($log(x + 1)$, enforced before *MinMax* scaling to the [0,1] interval – Table 1) was applied to the numerical features, because most of them exhibited a positive skewness with the clear occurrence of outliers. This pre-processing step was taken as a precaution despite models demonstrated sufficient robustness to outliers even when using the untransformed data (see Supplementary Materials S2 and S3).

Fishing license information was excluded from the set of predictor variables, as it was either outdated, general, or unreliable. For instance, a license simply indicating the use of “passive gear” does not provide sufficient detail to distinguish between different gear types. Moreover, Italian regulations currently exempt fishers with vessels under 10 m from logbook obligations (European Commission, 2009), meaning they are not required to report the specific gears used on each trip.

2.3. Models development and optimization

Three ML algorithms were used to predict the fishing gear employed during each hauling event (Boehmke and Greenwell, 2019): Decision Trees (*Dtree*), Random Forests (*RaFo*) and Extreme Gradient Boosting (*XGBo*). *Dtree* provides simple, interpretable rules through hierarchical splits. *RaFo* improves accuracy by combining multiple de-correlated trees with minimal tuning. *XGBo* builds sequential shallow trees that correct previous errors, offering high performance through an efficient, scalable framework. These algorithms were selected to balance predictive power with computational efficiency, positioning them between simpler linear approaches and more complex deep learning frameworks. While a basic weak learner such as a decision stump (i.e., a single-split decision tree) lacked the capacity to capture the dataset's inherent non-linear relationships, deep learning models, conversely, were deemed unnecessarily complex and computationally demanding given the size and structure of the available data. The chosen algorithms span a range of algorithmic complexity, from interpretable methods to highly optimized ensemble techniques, enabling a comprehensive assessment of performance across varying degrees of model sophistication. Furthermore, to provide a comprehensive performance baseline and clearly contextualize the added value of the advanced ML approaches, the analysis included comparisons against fundamental statistical models, such as Ridge Classifier (*Ridge*) and Logistic Regression (*LoRe*). This comparison serves as a crucial yardstick, offering readers - particularly those familiar with traditional fisheries science modelling - a direct measure of when and how the complexity of advanced ML methods is justified.

Fig. 3 sums up the model development process:

1. Data Preparation: from the initial pool of 1634 fishing trips, only those hauling events with available soak time information were retained (7164 matched observations).
2. Data Splitting: data was divided into 70% train, 20% validation, and 10% held-out test set to ensure an unbiased final evaluation.
3. Model Optimization via Nested Cross-Validation: an inner 5-fold cross-validation (within each outer fold) performed hyperparameter tuning via Randomized Search, while an outer 5-fold cross-validation estimated model performance during development.
4. Final Evaluation: the best model was assessed on the completely unseen 10% test set.
5. Sensitivity Analysis: Permutation Feature Importance (PFI) identified crucial features for model interpretability.

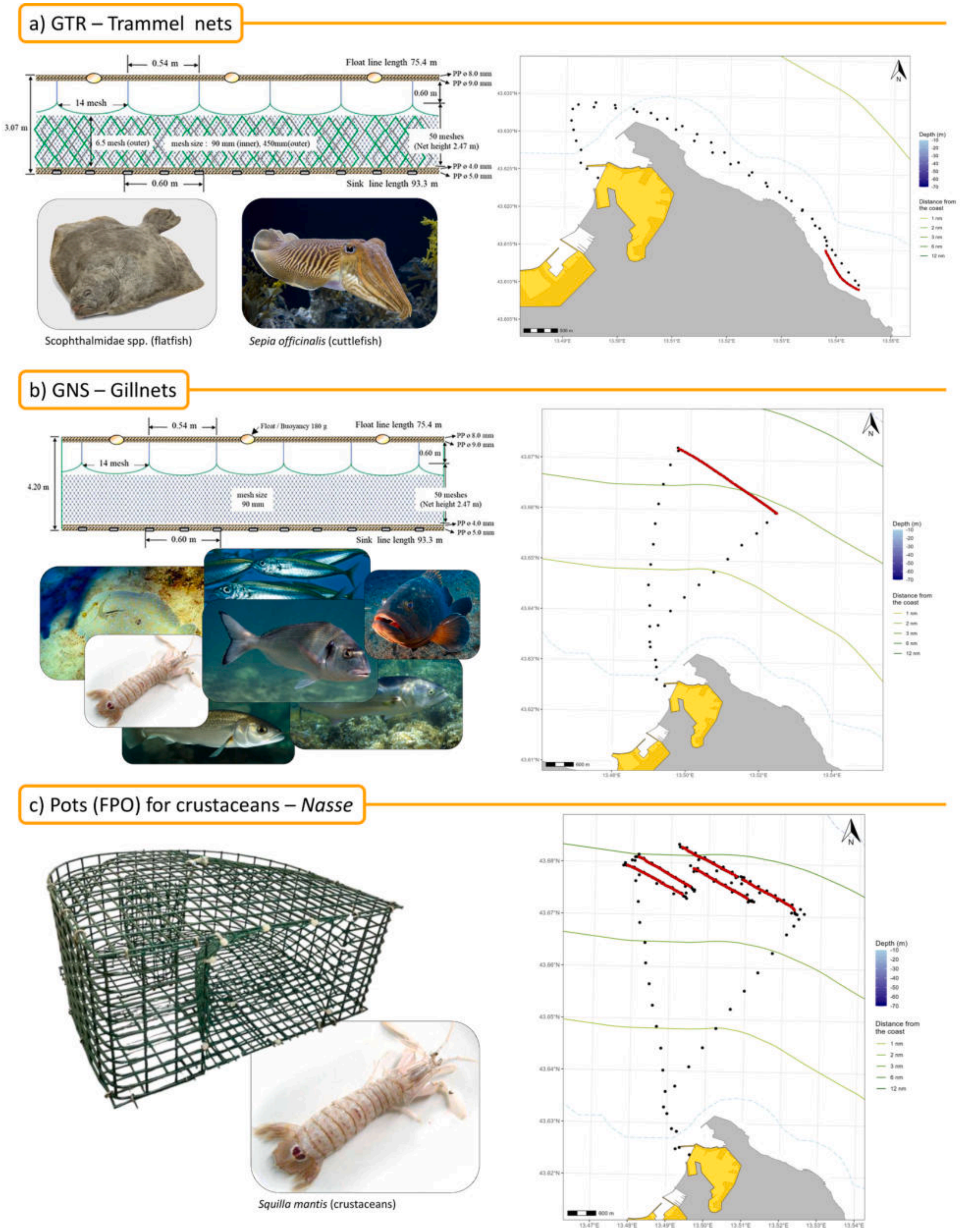
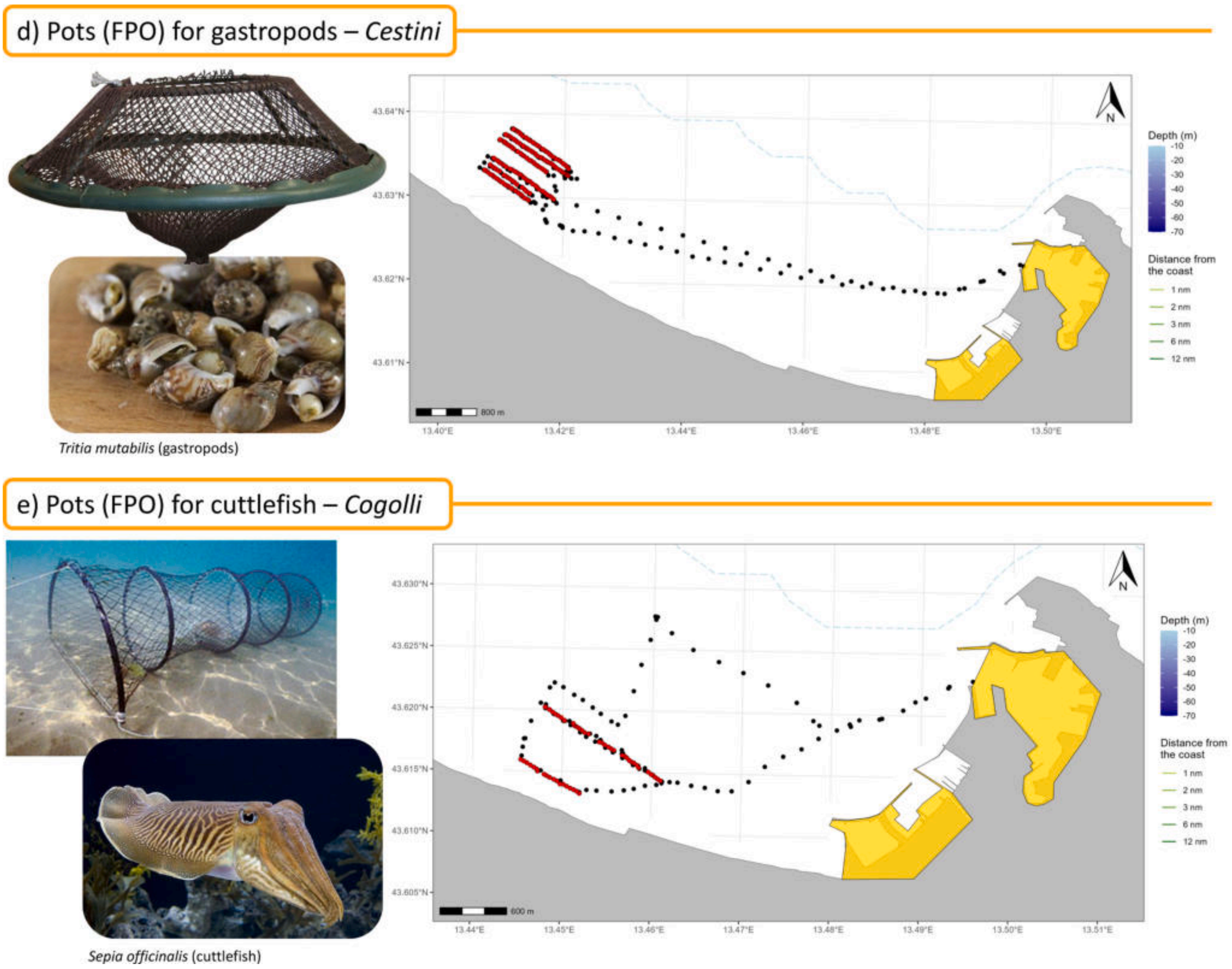


Fig. 2. Overview of the fishing gears (and related main target species) used by the SSF fleet in the study area. Example vessel trajectories from GPS tracking data illustrate typical fishing patterns for each gear type.


d) Pots (FPO) for gastropods – *Cestini*

Tritia mutabilis (gastropods)

e) Pots (FPO) for cuttlefish – *Cogolli*

Sepia officinalis (cuttlefish)

Fig. 2. (*continued*).

6. Selection of the best model: selection prioritized a balance between strong performance on test set and minimal overfitting during cross-validation.
7. Fine-tuning: the selected model was subsequently re-trained using 70% training and 30% testing split, with hyperparameters refined as necessary to further optimize predictive performance.

Additionally, class imbalance posed a significant challenge at both levels of analysis, as certain gears – nets and *cogolli* – were underrepresented in the dataset (Fig. 5). To effectively address this issue while ensuring model stability and code efficiency, a class-weighted loss function was employed during training. This technique intrinsically adjusts the loss contribution of each observation based on its class frequency, effectively prioritizing minority classes. This method was selected after comparative testing with alternative strategies, including the Synthetic Minority Over-sampling Technique (SMOTE, Lemaître et al., 2017). Results demonstrated that both apporaches produced yielded comparable performance, confirming the models' robustness. Consequently, the class-weighted approach was chosen for its simpler implementation. Detailed evidence of class-weighted models' robustness against class imbalance is documented in the Supplementary Material S3.

Moreover, model performance was assessed using two distinct hyperparameter sets (Fig. 4): (1) a default configuration and (2) an optimized configuration identified via randomized search (RandomSearchCV from Python's scikit-learn package - Pedregosa et al., 2011). This comparison was crucial for evaluating the impact of parameter choice. The default settings, often highly flexible, posed an elevated risk of overfitting – where a model captures noise and quirks in the training data rather than generalizable patterns. Consequently, while the default set might achieve superior performance on the specific test data, this comes at the expense of broader generalizability. Conversely, the optimized set was specifically tuned to stricter parameter values, aiming to find the best balance between performance and stability.

Overall, both level of analysis – *gear category* and *specific gear* – were tested under four model configurations, combining varying numbers of predictors and degrees of tuning flexibility (see Fig. 4):

- *Gear category* level:
    - o Fewer predictors (9 variables: white+green-shaded in Table 1) with optimized tuning;
    - o Fewer predictors (9 variables: white+green-shaded in Table 1) with default tuning;
    - o More predictors (18 variables: white+orange-shaded in Table 1) with optimized tuning;
    - o More predictors (18 variables: white+orange-shaded in Table 1) with default tuning.
- *Specific gears* level:

Table 1
Variables evaluated to predict the gear employed in each hauling event. Green-shaded variables represent mean values, while orange-shaded variables represent relative frequency distributions across defined intervals. Only one of these two groups was used at a time, while white-shaded variables were included in all model configurations. Two input sets were tested: i) green-shaded+white predictors and ii) orange-shaded+white predictors.

Variable (predictor)	**Description**	**Type**	**Transformation**
Haul Distance from the Coast	Mean distance of the hauling event from the coast	Numerical	Preprocessed using a log(x+1) transformation, followed by Min-Max scaling to the [0,1] interval
distcost_1	Classes for vessel distance from the coast during the hauling event - Calculated distance of each GPS position from the coastline	Numerical	Cumulate sum is equal to 1
distcost_2			
distcost_3			
distcost_4			
*distcost_5**			
Haul Speed	Mean speed of the vessel during the hauling event	Numerical	Preprocessed using a log(x+1) transformation, followed by Min-Max scaling to the [0,1] interval
speed_1	Classes for vessel speed during the hauling event - Calculated speed (dx/dt) in knots (kn)	Numerical	Cumulate sum is equal to 1
speed_2			
speed_3			
*speed_4**			
Main Substrate	The most frequent substrate type recorded during the hauling event	Categorical (5 values)	One-hot encoded**
substrate_1 *(coastal and continental shelf sands)*	Classes for bottom substrate type in correspondence of the hauling event	Numerical	Cumulate sum is equal to 1
substrate_2 *(pelytic sands)*			
substrate_3 *(very sandy mudstone)*			
substrate_4 *(sandy mudstone)*			
substrate_5 *(mudstone)*			
Estimated Soak Time	Fishing hours during which the gear remains underwater (between coupled *setting-hauling*)	Numerical	Preprocessed using a log(x+1) transformation, followed by Min-Max scaling to the [0,1] interval
Haul length	Length (m) of the hauling event	Numerical	Preprocessed using a log(x+1) transformation, followed by Min-Max scaling to the [0,1] interval
Haul order	Sequential position of the hauling event within a trip (e.g., 1 = first hauling event, 2 = second, etc.)	Numerical	-
Month of the year	Month during which the trip is carried out	Categorical	One-hot encoded**
Hour of the day	Hour of the day during which the trip is carried out	Categorical	One-hot encoded**
Gear Change	Logical flag indicating if the fisher is switching (TRUE) or not (FALSE) fishing gear during the trip	Categorical	One-hot encoded**

* *distcost_5* and *speed_4* intervals are not present for the *gear category* level of analysis.
Note that intervals are slightly different for the analysis based on i) *gear category* and ii) *specific gears*.
** One-hot encoding transforms categorical variables into a numerical format by creating new binary columns for each unique category. For each instance, only the column corresponding to its category is marked '1', with others '0'.

- o Fewer predictors (9 variables: white+green-shaded in Table 1) with optimized tuning;
- o Fewer predictors (9 variables: white+green-shaded in Table 1) with default tuning;
- o More predictors (20 variables: white+orange-shaded in Table 1) with optimized tuning;
- o More predictors (20 variables: white+orange-shaded in Table 1) with default tuning.

2.4. *Performance metrics and generalization assessment*

For the model performance evaluation, the following metrics were calculated: Overall Accuracy (proportion of correctly classified instances across all classes), Precision (average precision per class, weighted by class support); Recall (average recall – sensitivity – per class, weighted by class support), and F1-Score (harmonic mean of precision and recall, weighted by class support; useful for imbalanced class distributions).

Correlation heatmaps for both predictors sets and levels of analysis (Supplementary Material S4) displayed Pearson correlation coefficients among numerical predictors (first $\log(x + 1)$ transformed and

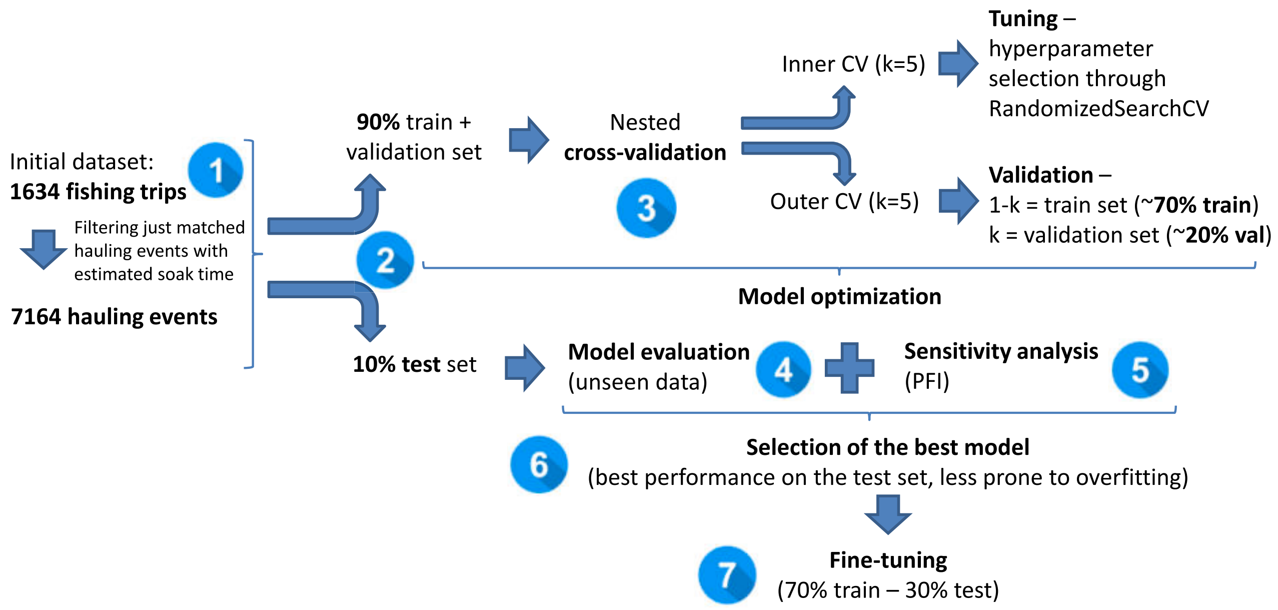


Fig. 3. Workflow of the model development process.

A Set of default parameters

```
param_grids = {
        'Dtree': {
            'clf__max_depth': [None],
            'clf__min_samples_leaf': [1],
            'clf__criterion': ['gini'],
            'clf__class_weight': [class_weight_dict]
        },
        'RaFo': {
            'clf__n_estimators': [100],
            'clf__max_depth': [None],
            'clf__max_features': ['sqrt'],
            'clf__min_samples_leaf': [1],
            'clf__bootstrap': [True],
            'clf__class_weight': [class_weight_dict]
        },
        'XGBo': {
            'clf__subsample': [1.0],
            'clf__colsample_bytree': [1.0],
            'clf__n_estimators': [100],
            'clf__max_depth': [6],
            'clf__learning_rate': [0.3],
            'clf__reg_alpha': [0],
            'clf__reg_lambda': [1],
            'clf__gamma': [0],
            'clf__min_child_weight': [1]
        },
        'LoRe': {
            'clf__penalty': ['l2'],
            'clf__C': [1.0],
            'clf__class_weight': [class_weight_dict],
            'clf__solver': ['saga'],
            'clf__l1_ratio': [None]
        },
        'Ridge': {
            'clf__alpha': [1.0]
        }
    }
```

B Set of optimized parameters

```
param_grids = {
        'Dtree': {
            'clf__max_depth': [3, 5, 7, 10],
            'clf__min_samples_leaf': [10, 20, 50, 100],
            'clf__criterion': ['gini', 'entropy'],
            'clf__class_weight': [class_weight_dict]
        },
        'RaFo': {
            'clf__n_estimators': [500, 1000, 2000],
            'clf__max_depth': [7, 10, 15, 20],
            'clf__max_features': ['sqrt', 0.5],
            'clf__min_samples_leaf': [5, 10, 20],
            'clf__bootstrap': [True],
            'clf__class_weight': [class_weight_dict]
        },
        'XGBo': {
            'clf__subsample': [0.5, 0.6, 0.7, 0.8, 0.9],
            'clf__colsample_bytree': [0.5, 0.6, 0.7, 0.8],
            'clf__n_estimators': [1000, 2000, 3000],
            'clf__max_depth': [3, 4, 5],
            'clf__learning_rate': [0.005, 0.01, 0.03, 0.05],
            'clf__reg_alpha': [0.0, 1, 10, 50, 100],
            'clf__reg_lambda': [1, 10, 50, 100],
            'clf__gamma': [0.0, 0.5, 1],
            'clf__min_child_weight': [5, 10, 20, 50]
        },
        'LoRe': {
            'clf__penalty': ['l2', 'l1', 'elasticnet'],
            'clf__C': [0.0005, 0.001, 0.01, 0.1, 1.0],
            'clf__class_weight': [class_weight_dict],
            'clf__solver': ['saga'],
            'clf__l1_ratio': [0.25, 0.5, 0.75, None]
        },
        'Ridge': {
            'clf__alpha': [0.1, 1.0, 10.0, 50.0, 100.0, 500.0, 1000.0]
        },
    }
```

Fig. 4. Default Hyperparameter Configurations Used for Model Comparison and Optimization. (A) The Default Configuration, which, due to its inherent flexibility, was tested as a high-capacity baseline potentially prone to overfitting (high performance on test data, low generalizability). (B) The Optimized Configuration, derived through RandomSearchCV, with stricter parameter settings aimed at reducing model complexity and ensuring better generalizability. Each configuration was assessed across both levels of analysis (gear category and specific gear) and under different predictor sets. The chosen parameters set was further refined for the gear category level of analysis, addressing a binary (instead of multi-class) classification task – the selected values can be observed in the code available at the Figshare repository.

subsequently scaled to the [0,1] interval before correlation analysis), with categorical variables having been numerically encoded via integer mapping. This allowed for an initial assessment of linear relationships between features. While linear models, such as Logistic Regression, are highly sensitive to multicollinearity, the selected non-linear machine learning models (e.g., tree-based methods) are inherently more robust. This preliminary assessment thus provided valuable understanding into feature interdependencies and potential redundancies within the dataset, informing our interpretation of both the non-linear models and the linear benchmarks (including the regularized Ridge Classifier).

Finally, a sensitivity analysis using PFI was performed to inspect the trained models by measuring performance drops after permuting feature values. To ensure robustness, the permutation process was repeated 10 times and resulting importance scores were averaged. For categorical variables encoded via one-hot encoding, all levels were grouped and considered as unified features.

Following the selection of the best model, its performance was further refined and assessed. The top-performing model was re-trained using 70% of the original hauling event dataset (train set), and its generalization ability was assessed on the remaining 30% (test set). This allowed for a deeper analysis of model performance, visualized through learning and optimization curves. Learning curves track metrics (Accuracy, Error Rate, and Log Loss) as the training set size increases. This visualization is necessary to diagnose whether the model suffers from high variance (overfitting) or high bias (underfitting) by showing how performance on the training and validation sets converges or diverges, thus providing a direct, empirical diagnostic tool for assessing data sufficiency. Conversely, optimization curves track these metrics across the model's iterative training process, useful to identify the point of diminishing returns or optimal early stopping (i.e., the technique of halting training once performance on a validation set begins to worsen (Chen and Guestrin, 2016; Hastie et al., 2005)) by showing the precise number of iterations (e.g., boosting rounds for *XGBo*, cumulative number of trees for *RaFo*) required before the model begins to overfit or its performance plateaus.

Subsequently, confusion matrices were generated at both analysis levels to provide model class-level accuracy for the test set.

2.5. Group-based generalization assessment

Up to this stage, hauling events were treated as independent events. For the final, rigorous evaluation of model performance and generalizability, the data was explicitly grouped to create independent splits that simulate performance on unseen operational units. This approach was implemented through two distinct strategies:

1. Generalization to Unseen Trips (Trip-Based Split): to assess the model's ability to generalize to new fishing operations, hauling events were grouped by unique fishing trips. The dataset was partitioned by *TRIP_ID* into training (70% of trips), validation (20%), and testing (10%) sets. This non-random splitting ensures that all hauling events belonging to a specific trip are confined to a single partition, making the testing set entirely independent of the operational patterns learned during training.
2. Generalization to Unseen Vessels (Vessel-Based Split): to directly address the concern regarding vessel-specific operational bias and limited fleet representation, a rigorous vessel-based split was implemented. The 10 vessels were partitioned by assigning seven vessels to the training set, two to the validation set, and reserving the remaining single vessel entirely for the final, independent test set. This structure ensures that the final model is evaluated on data from a vessel whose unique operational characteristics were completely absent during the model training and tuning phases, providing a strong measure of its external generalizability.

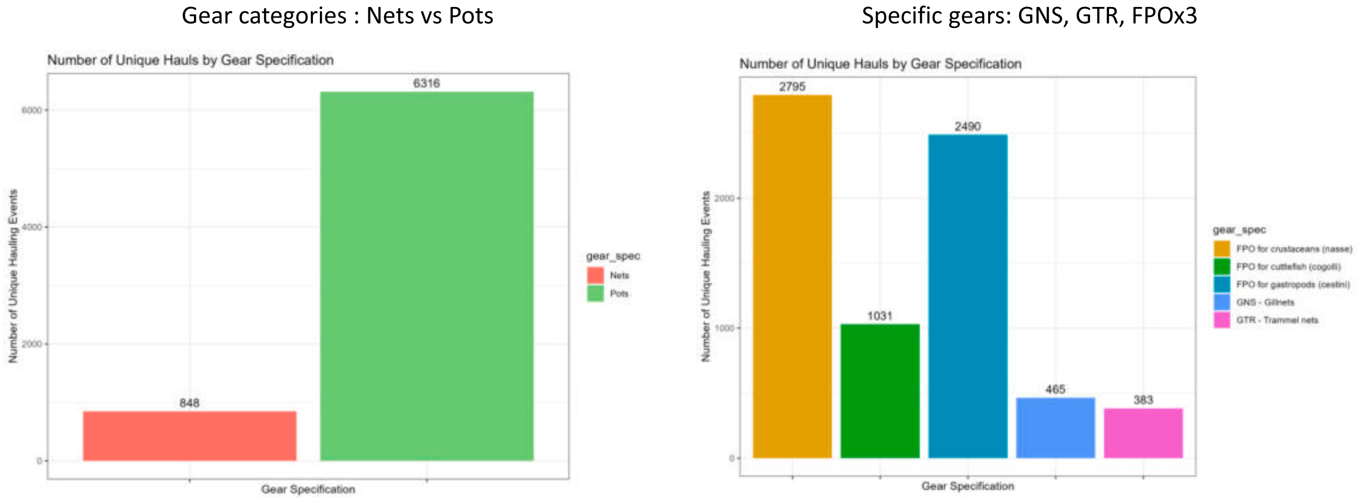
This methodology accounts for potential data dependency within vessels and trips, providing a practical, quantified assessment of model robustness despite the geographical limitations of the original dataset.

3. Results

As shown in Fig. 5, a clear class imbalance was present across the 7164 hauling events at both levels of analysis.

Exploratory Data Analysis revealed that several variables showed clear patterns across gear types, proving to be informative for gear prediction. Examples include substrate (Fig. 6), distance from the coast (Fig. 7), and estimated soak time (Fig. 8) – shown for both *gear category* and *specific gears* levels.

The occurrence of outliers in the investigated numerical features can be attributed to a combination of (i) rare operational events, (ii) legitimate operational variability, and (iii) potential recording errors. Rare operational events include instances where fishers experimented with novel gear settings or deployment strategies. Legitimate variability arises from the diverse operational techniques and approaches employed by different fishing vessels and crews. Furthermore, a variable such as estimated soak time is subject to considerable external influence from dynamic factors, including weather and sea conditions, contributing to its broad range. While less probable, the possibility of recording errors, such as the misclassification of gear, during interviews with fishers, cannot be entirely dismissed. Despite the presence of extreme values, the models were found to be robust against outliers (see Supplementary Material S2). This was confirmed by comparative analysis: model performance remained largely unchanged whether the numerical predictors were used in their raw, positively skewed form, or after applying the $log(x + 1)$ transformation. Therefore, aggressive outlier removal was deemed unnecessary. The application of the $log(x + 1)$ transformation and Min-Max scaling was retained purely to mitigate


Gear categories : Nets vs Pots

Specific gears: GNS, GTR, FPOx3

Fig. 5. Total number of hauling events based on the level of the analysis.

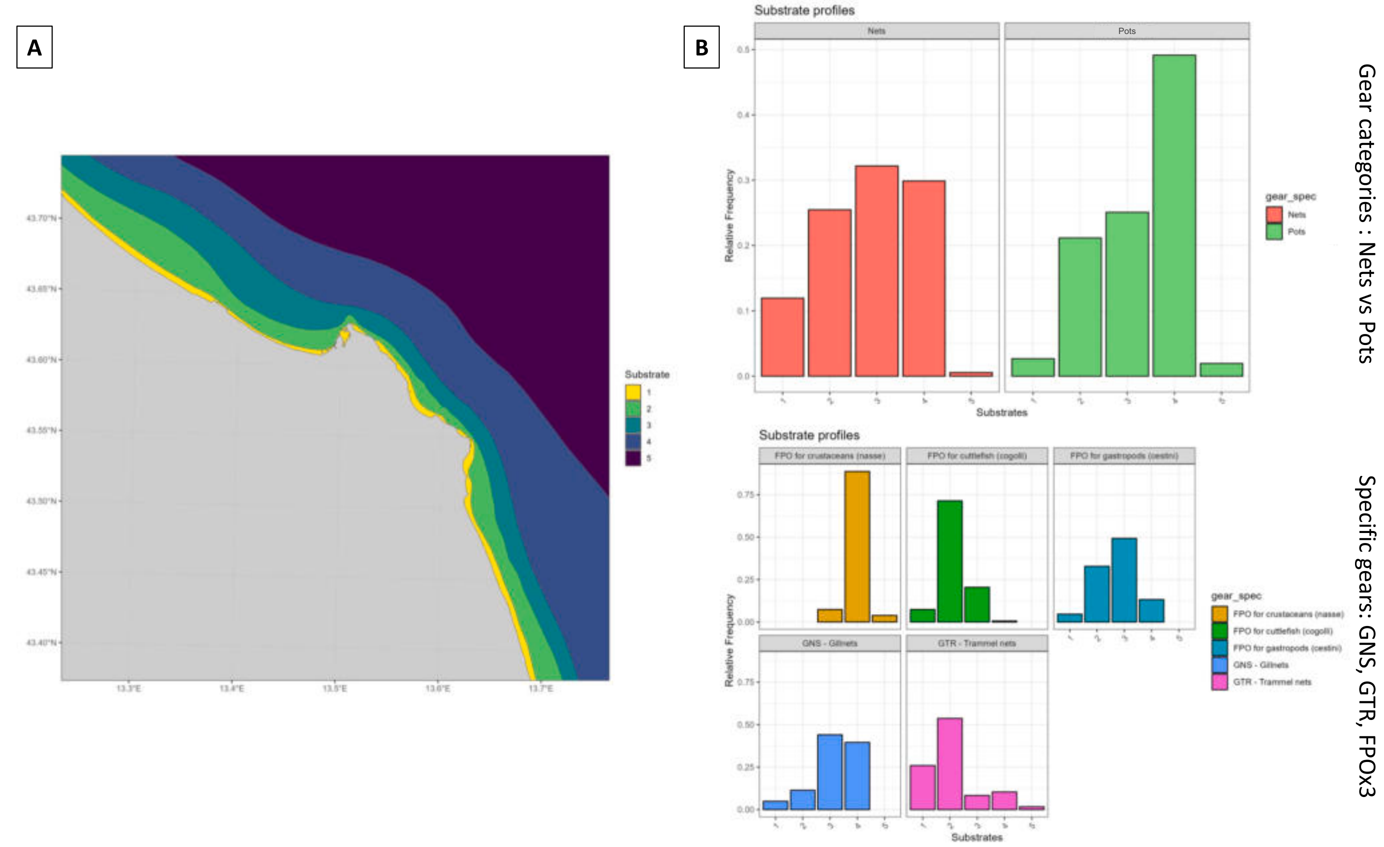


Fig. 6. A) Substrate types in the study area: 1 - coastal and continental shelf sands, 2 - pelytic sands, 3 - very sandy mudstone, 4 - sandy mudstone, 5 - mudstone. B) Substrate profiles representing the distribution of GPS positions from hauling events across substrate categories, grouped by gear type for both analysis levels (gear category and specific gears).

data skewness and enhance computational stability, while ensuring the preservation of the full spectrum of real-world operational variability.

Model performance results are shown in Figs. 9 and 10 for the *gear category* and *specific gear* analyses, respectively. The boxplots delineate the score distributions of overall-accuracy, precision, recall and F1 score for the training (blue) and validation (green) sets over all cross-validation folds, while a red diamond pinpoints the score achieved on the independent test set. Green boxes highlight the best performing models and their configurations.

What immediately catches the eye is that ML algorithms trained with default hyperparameters achieved 100% scores on all four metrics across both levels of analysis, indicating clear and immediate overfitting of these models (Fig. 9A, C and Fig. 10A, C). Conversely, the efficiency of the Ridge Classifier (*Ridge*) and Logistic Regression (*LoRe*) models exhibits low sensitivity to hyperparameter tuning.

Furthermore, given that model performance using fewer predictors was observed to be comparable to that of models trained with a greater number of features, the simpler models were selected based on "Occam's Razor" – the philosophical and problem-solving principle that, in its most general form, states that the simplest explanation is usually the best one. Therefore, the following analysis will focus exclusively on the models using fewer predictors and optimized tuning hyperparameters (Fig. 9B and Fig. 10B). Moreover, to ensure the discussion is clear and easy to follow, the presentation of their performance will concentrate only on two key metrics: Overall Accuracy and the F1 Score (the harmonic mean of precision and recall, as previously defined).

At *gear category* level (Fig. 9B), the highest test accuracy (94.7%) and F1 score (94.73%) were reached by *RaFo*, with a difference in performance for the mean score of the train set (calculated over the 5-fold CV) of around 2% for both accuracy and F1 score. The lowest test scores were displayed by *Ridge* (85.36% for accuracy and 87.19% for F1 score). A performance gap of approximately 9% was observed in overall accuracy between *LoRe* and *RaFo* for the test set.

At *specific gears* level (Fig. 10B), *XGBo* achieved the highest overall performance (immediately followed by *RaFo*), securing a test accuracy of 85.91% and an F1 score of 86.18%, differing from the training set mean by 5% for both the metrics. Again, *Ridge* displayed the lowest test scores, reaching 76.29% for accuracy and 77.04% for F1 score. *XGBo* performance was translated to an approximate 8% advantage in overall accuracy over *LoRe* on the test set.

Permutation Feature Importance analysis indicated the average decrease in model performance when a feature's values were randomly shuffled (measured using *roc_auc_score* for binary *gear category* and *F1-score* for multi-class *specific gears* classification task, Fig. 11). Concerning *gear* category, (i) mean distance from the coast, (ii) estimated soak time, (iii) mean speed, (iv) hour of the day, and (v) length of the hauling event were the most relevant predictors (Fig. 11, upper panel). On the other hand, the discernment between *specific gears* was mainly driven by: (i) hour of the day, (ii) mean distance from the coast, (iii) month of the year, (iv) estimated soak time and (v) mean speed of the hauling event (Fig. 11, lower panel).

The top-performing models (*RaFo* for the *gear category* and *XGBo* for *specific gears*, both trained with reduced predictor sets and optimized hyperparameters) were retrained on 70% of the hauling events and evaluated on the remaining 30% for a deeper analysis of model performance and stability. Visualization of learning and optimization curves for Accuracy, Error Rate, and Log Loss are portrayed in Figs. 12, 13, 14, and Supplementary Material S5 for *LoRe* as additional information for the best performing statistical model. For the binary *gear-category* classification task (Fig. 12), *RaFo* demonstrated a strong

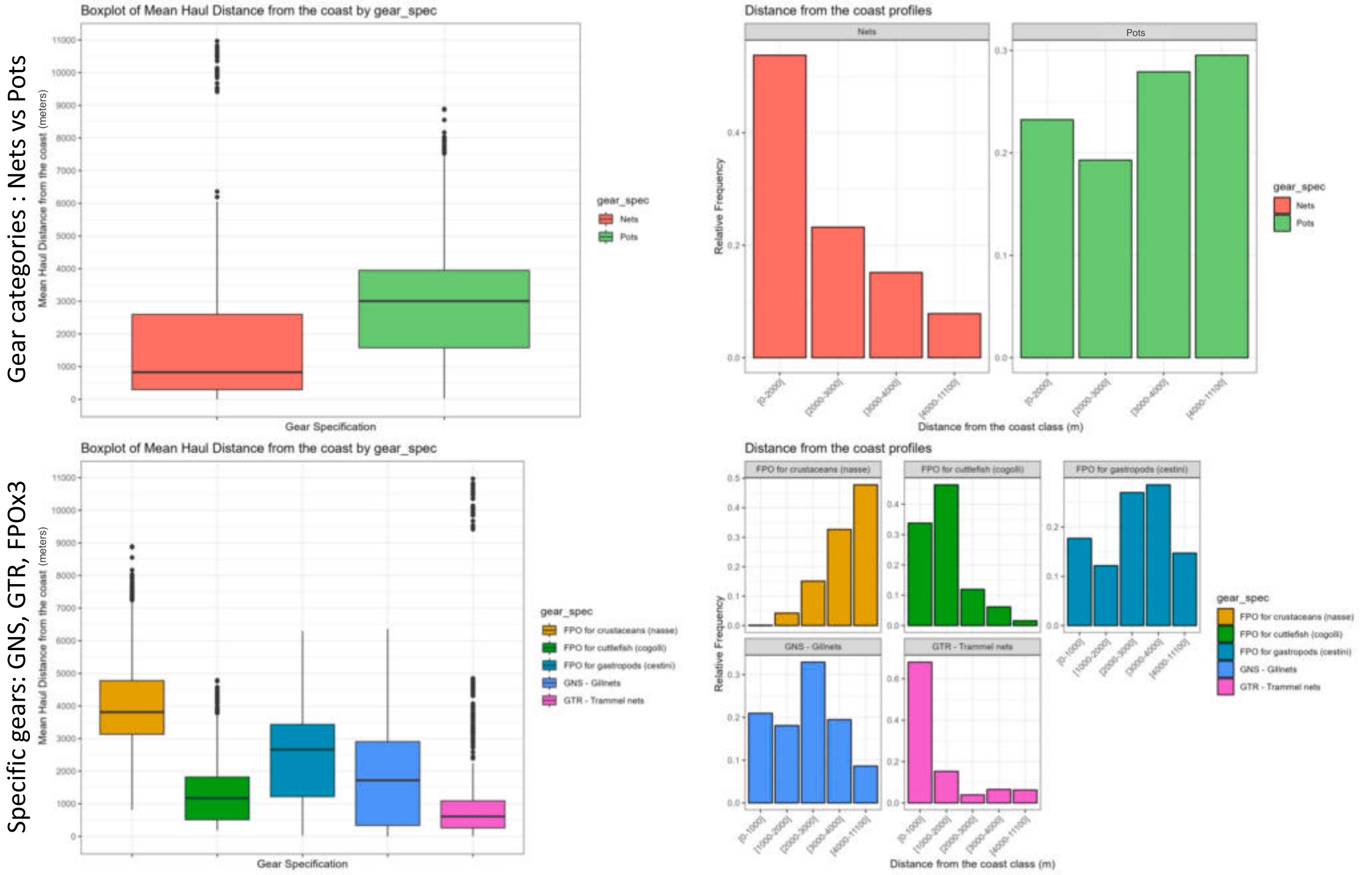


Fig. 7. Distance from the coast (meters) of hauling events points, grouped by gear (A) and relative profiles of the distribution of the points within distance intervals (B), for both analysis levels.

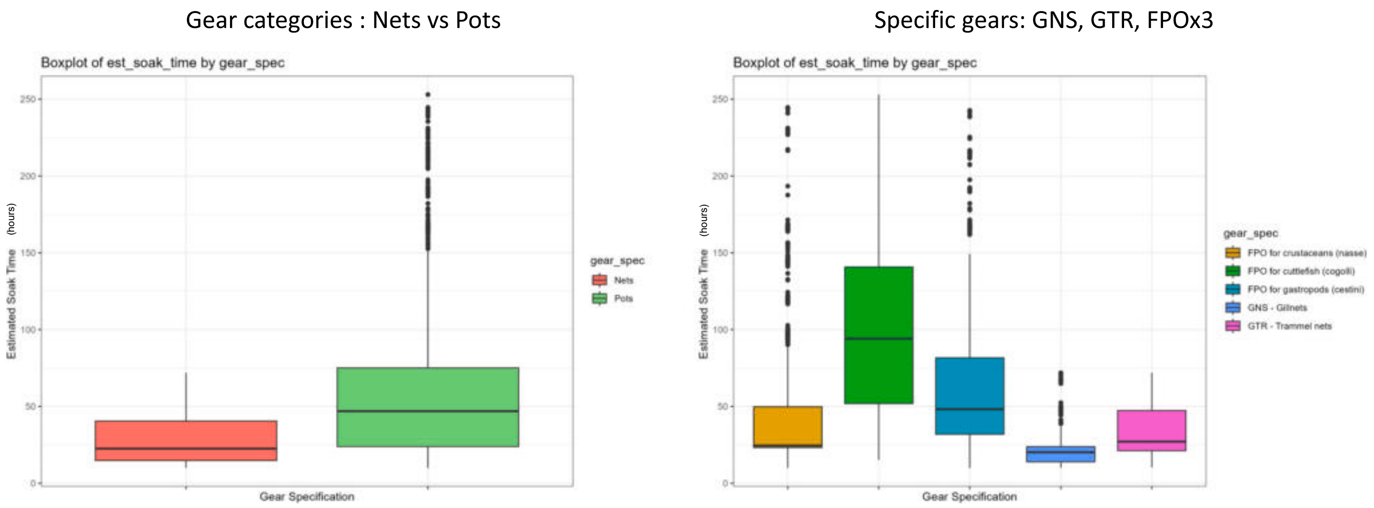


Fig. 8. Estimated soak time (hours) of the points belonging to hauling events grouped by gear for both analysis levels.

generalization ability, with a minor gap (~ 2.5%) between Training (96.9%) and Cross-Validation Accuracy (94.5%), showing low variance (minor or controlled overfitting) and managing to learn the signal without overly capturing the noise. The curves flattening near the maximum training size suggest that adding significantly more data is unlikely to yield substantial performance gains. Thus, the model is largely done learning the underlying structure of the data it has. The Optimization Curve (Fig. 12D), depicting the Out-of-Bag (OOB) Error Rate versus the number of trees, underlines that the model is achieving its full stable generalization capability with only 220 trees. The *RaFo* OOB Error Rate drops sharply and stabilizes itself around 0.05, demonstrating to be a highly accurate and efficient model.

Moving to the multi-class specific-gears classification task, the selected *XGBo* model showed severe overfitting when retrained on the 70%train-30%test split (Fig. 13), with a gap between Training (98%) and Cross-Validation Accuracy Score (88.5%) of around 9.5%. The fact that the CV score in the learning curves has not flattened but is still slowly increasing as more training data is added suggests that the

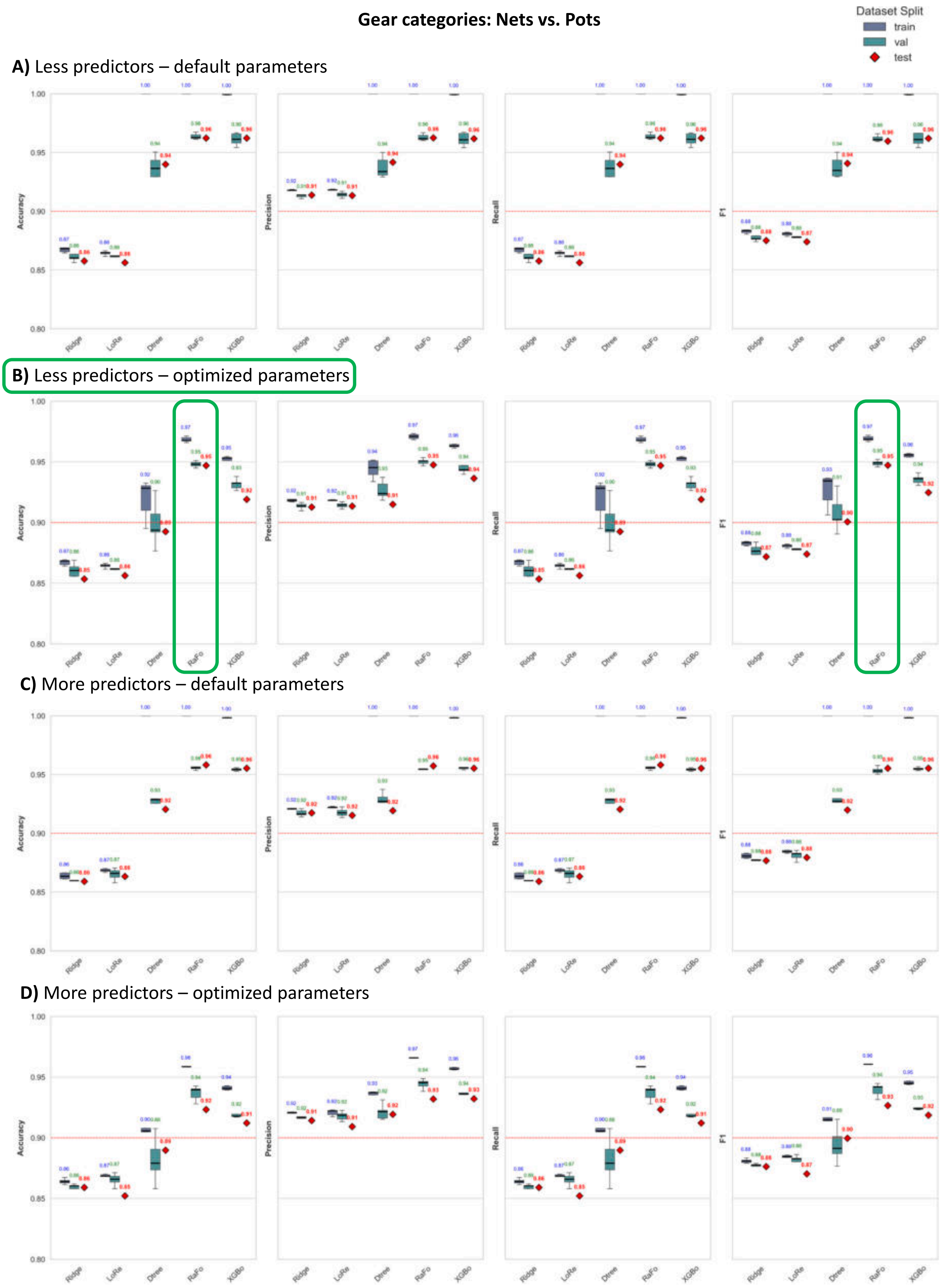


Fig. 9. Model performances for gear category level of analysis, with data splitting into train, validation and test sets. Boxplots display the distribution of training (blue) and validation (green) scores across cross-validation folds. The blue and green numeric labels indicate the mean score for their respective sets. The red diamond and its red numeric label show the final, single score achieved on the independent test set. Green boxes highlight the best performing model and its configuration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

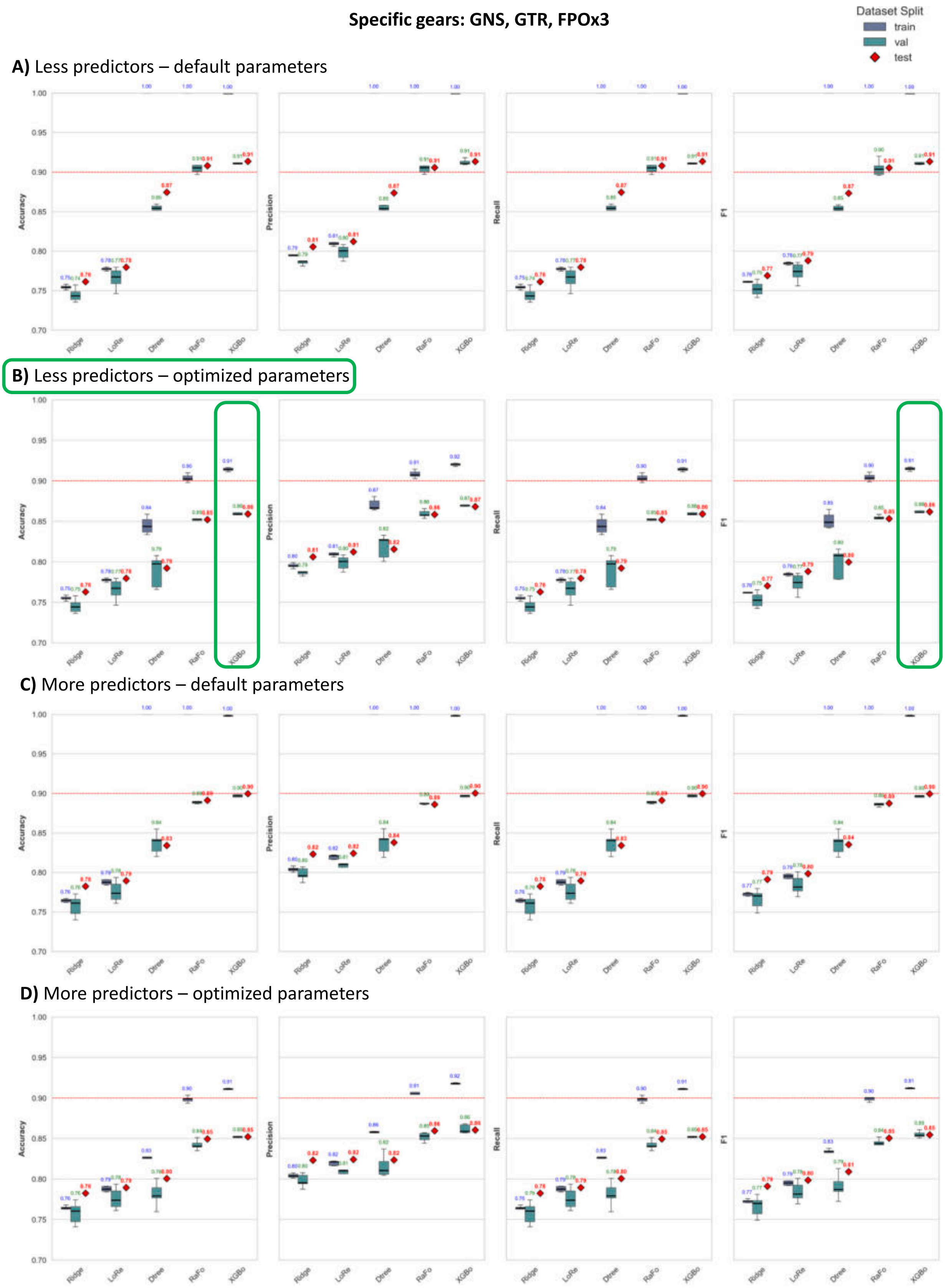


Fig. 10. Model performances for specific gear level of analysis, with data splitting into train, validation, and test sets. Boxplots display the distribution of training (blue) and validation (green) scores across cross-validation folds. The blue and green numeric labels indicate the mean score for their respective sets. The red diamond and its red numeric label show the final, single score achieved on the independent test set. Green boxes highlight the best performing model and its configuration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

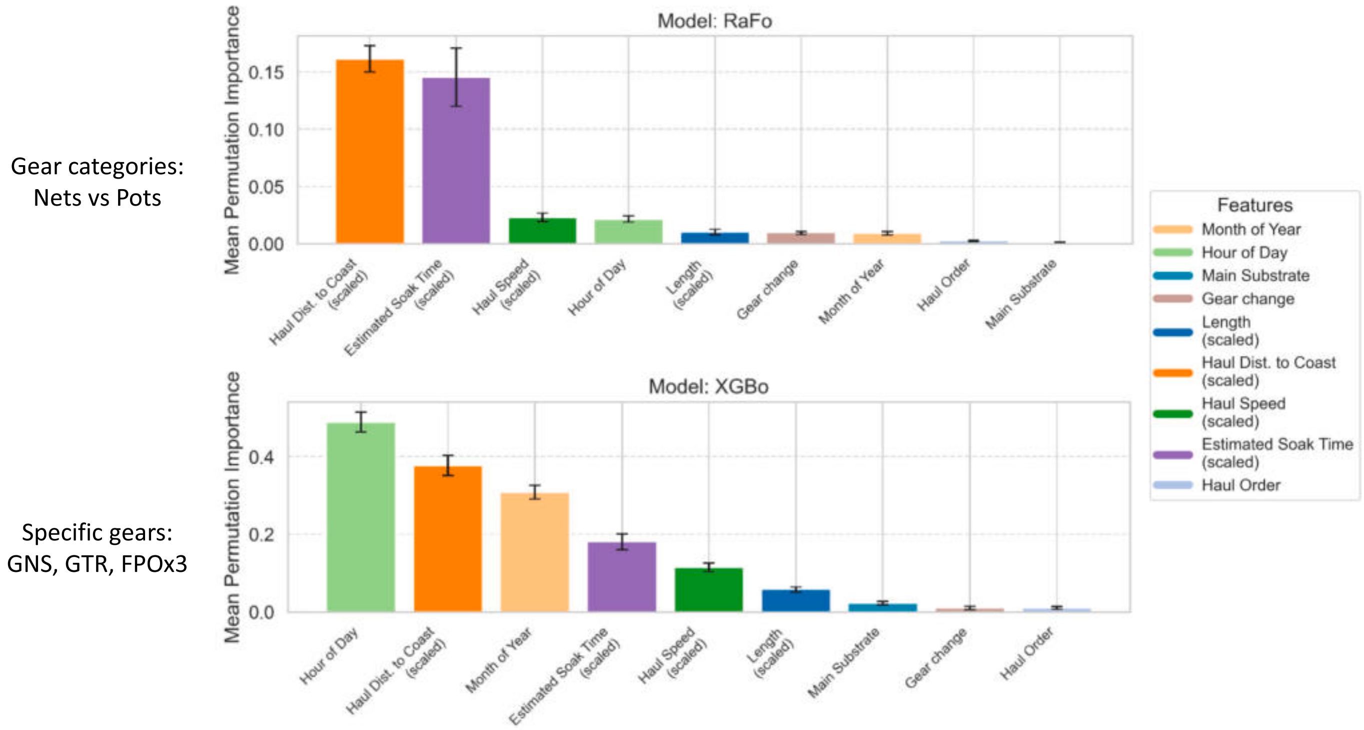


Fig. 11. Sensitivity analysis using Permutation Feature Importance for the best model at gear category (RaFo with fewer predictors and optimized tuning parameters) and specific gear (XGBo with fewer predictors and optimized tuning parameters) levels of analysis.

dataset is likely not sufficient for this specific model architecture at its current complexity. Moreover, the current hyperparameter tuning has not adequately constrained the model's complexity, allowing it to fit the training data too tightly as demonstrated by the optimization curves. For this reason, the model diagnostics were investigated again after *XGBo* fine-tuning, which included an increased regularization (the newly chosen parameters are displayed in the shared code).

The fine-tuned *XGBo* (Fig. 14) has revealed highly convergent learning curves, with a reduced gap (~2.7%) in Accuracy score between Training (86.1%) and Cross-Validation (83.4%), indicating a decreased variance. Although the CV score has not fully flattened, the convergence of the curves suggests the model is approaching its optimal generalization capability for the available dataset. However, probably model's performance on unseen data could still improve if a bigger training pool was available. On the other hand, the 5% gap between the final Test (82.4%) and the Training Accuracy (87.7%) in the optimization curve means that the model is still experiencing minor, acceptable overfitting (high performance with controlled variance) across its iterative process, representing the actual residual generalization error for the final model configuration.

Lastly, confusion matrices were created to evaluate the fine-tuned models' classification accuracy across individual classes in the test set for both levels of analysis (Fig. 15). At the *gear category* level, 97% of the hauling events were correctly classified as belonging to *Pots*, while *specific gear*, *nasse* and *cogolli* reached respectively 86% and 90%. The classification accuracy obtained for *cestini* was 77%. Regarding the *Nets* category, the model successfully classified 78% of the events, whereas *Gillnets* and *Trammel nets* achieved scores of 76% (the lowest for this level of analysis) and 77%.

Grouping the hauling events by fishing trips and by vessel revealed a clear increase in models overfitting and drop in performance, especially when clustered by vessels (Fig. 16). When grouped by trip, the best results for test accuracy and F1 Score were obtained again by *XGBo* for both the level of analysis, reaching values near 95% for *gear category* and 86% for *specific gears*, but with a clear increase in the train/test score gap (particularly for the *specific gears* level of analysis). Dealing with grouping by vessel, while *gear category* test metrics achieved scores between 74% and 81%, *specific gears* test performances dropped drastically, ranging from 53 to 66%. Crucially, the statistical methods demonstrated superior generalization to unseen vessels, particularly in the more complex *specific gears* classification task.

4. Discussion

This study presents a novel framework for predicting passive fishing gears used within multi-gear SSF, at varying levels of analytical detail, and critically, provides transparent reporting of model performances beyond standard test set evaluations. The precise identification of the fishing gear used in each hauling event in multi-gear SSF trips is essential for fishing effort assessment, facilitating a deeper understanding of catch data, enhancing seafood traceability, and directly supporting compliance with control regulations like EU 2023/2842 (European Commission, 2023). In the present work, the Test Set Accuracy from the full 70%/ 20%/10% workflow was selected as the definitive metric for performance comparison, offering the most robust estimate of real-world generalization. Comparing the final ML models against the most efficient statistical baseline (*LoRe*), the aforementioned metric revealed consistent performance gains: *RaFo* (95%) exceeded *LoRe* (86%) by 9% in the *gear category* prediction, while *XGBo* (86%) surpassed *LoRe* (78%) by 8% in the *specific gears* classification task.

Whereas most modern gear recognition approaches for large-scale fisheries rely on Deep Learning algorithms (Kim and Lee, 2020; Russo et al., 2011; Srisukkham et al., 2021), the use of ML methods here offers distinct advantages. These methods require fewer data and computational resources, possess faster training times, and provide greater interpretability, especially when domain expertise allows for the creation of highly informative features that simplify the learning task. Indeed, the models proposed in this paper are relatively easy to set thanks to the shared workflow, and the output interpretation is straightforward. The Python code for gear prediction and outcomes

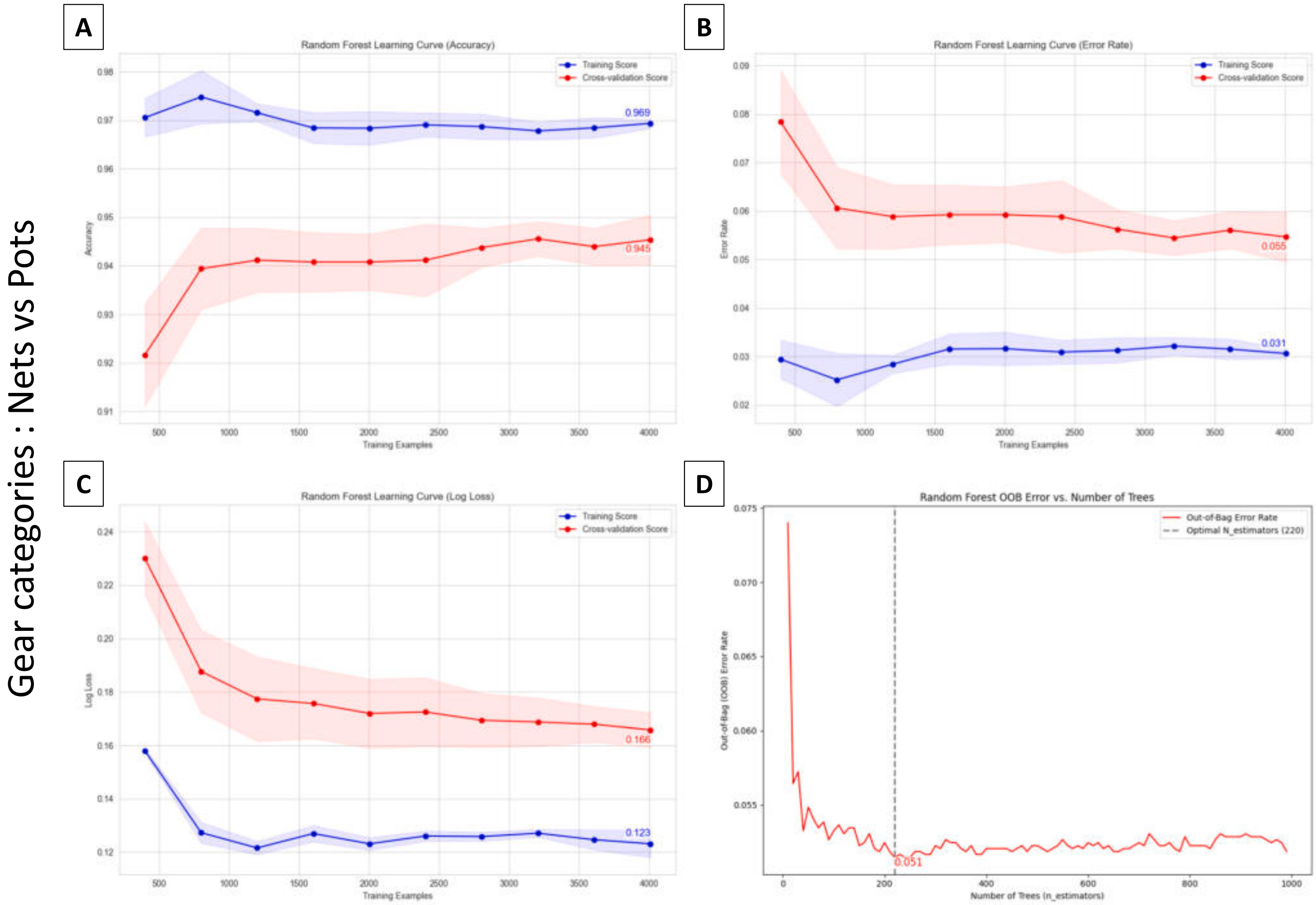


Fig. 12. A visual analysis of the optimal configuration and stability of the RaFo model for gear-category prediction. A, B, C) Learning Curves track the model's mean performance (Accuracy, Error Rate, and Log Loss, respectively) as the training set size increases. The curve flattening near the maximum training size suggests that adding significantly more data is unlikely to yield substantial performance gains. D) Optimization Curve (OOB Error Rate) tracks the Out-of-Bag (OOB) Error Rate versus the number of trees (n_estimators). This plot identifies the optimal number of trees (where the error rate minimizes/plateaus - in this case, n_estimators = 220), guiding the selection for optimal early stopping.

visualization is fully reproducible and publicly available at the following *Figshare* repository: https://doi.org/10.6084/m9.figshare.29647448 (Lattanzi et al., 2025).

However, to contextualize the added value of these advanced ML approaches – especially for readers in fisheries science who may be less familiar with ML – it is essential to rigorously consider statistical baselines. Reporting the performance of simple models, such as regression model (*LoRe*) or linear classifier (*Ridge*), on the same dataset provides a crucial benchmark for comparison. Such baselines are essential for quantifying the true benefit of the more complex ML methods and for demonstrating that their added computational and interpretive demands are justified by meaningful gains in predictive performance.

As expected, better results were obtained in the broader *gear category* compared to the *specific gear* level of analysis. This performance difference is largely attributed to the nature of the tasks: the *gear category* involves a simpler, effectively binary classification (fewer, aggregated classes) with a higher number of observations per class (Figs. 5, 9, 10). Conversely, the *specific gear* task involves five distinct classes that closely approach the métier level-of-detail – a high level of specificity requiring the model to discriminate based on gear type, target species, season, and area (Deporte et al., 2012). Overall, the dataset exhibits class imbalance at both levels, with pots predominating over nets due to their widespread use in the study area (Lauriano et al., 2009; Li Veli et al., 2023; Petetta et al., 2021). However, this imbalance particularly impacted the lower-level analysis, where under-represented classes like *cogolli*, gillnets, and trammel nets consistently showed the lowest classification performance (Fig. 15). This pattern – superior scores in the *gear category* – was uniformly observed even when hauling events were grouped by trips or vessels (Fig. 16), clearly highlighting the persistent challenge of generalization under increased classification complexity and data constraints.

Among the selected predictors, the seasonality, portrayed by the “*Month of the year*” categorical variable, emerged as a key factor for discriminating among *specific gears* (especially between different kinds of pots), as shown in the sensitivity analysis results provided by the PFI bar plot (Fig. 11). For instance, the fishery of *cestini*, mainly targeting the gastropod *Tritia mutabilis,* is strictly seasonal, generally active from early autumn to late spring and in the study area for 2023 it was legally permitted from the 1st of October to the 31st of May (Capitaneria di Porto di Ancona, 2023). Gear displacement is also clearly highlighted by the distance from the coast (a proxy for bathymetry and sea bottom substrate)(Figs. 6,7,11): trammel nets and cuttlefish pots are usually deployed very close to the shore, whereas crustaceans' pots are placed further offshore. This is related to the biology and ecology of the different target species in the study area (Bombace and Lucchetti, 2011; Grati et al., 2013). The cuttlefish, fished with both *cogolli* and trammel nets, move nearshore waters in early spring to spawn and return seaward later in the season. Similarly, species of the Scophthalmidae family (e.g., turbot), targeted with trammel nets, swim toward the coast in the late autumn-early winter to reproduce. The spatial distribution of

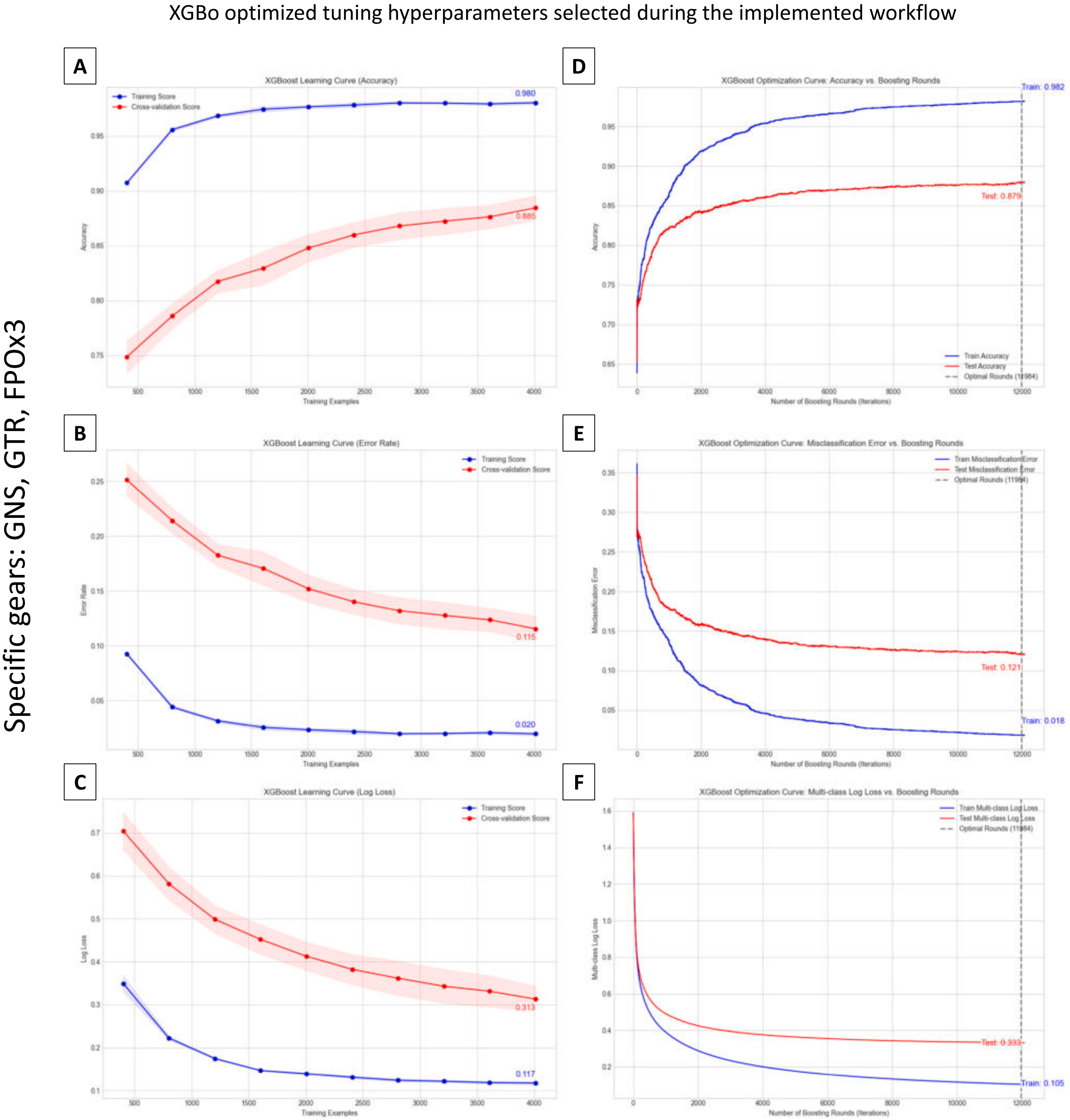


Fig. 13. A visual analysis of the optimal configuration and stability of the XGBo model for specific gears prediction before fine-tuning. A,B,C) Learning Curves track model performance (Accuracy, Error Rate, and Log Loss, respectively) across 5-fold cross-validation as the training set size increases (from 10% to 100%). The learning curves show a significant divergence between the high training Accuracy (98%) and the lower Cross-validation Accuracy (88.5%) indicating high variance (overfitting), especially since the CV score has not yet fully flattened, suggesting the model still requires additional data or greater regularization to generalize effectively. D,E,F) Optimization Curves track the same three metrics across the iterative training process (number of boosting rounds). These curves determine the optimal early stopping point (early_stopping_rounds = 100) by identifying the number of rounds where validation set performance plateaus or begins to degrade (in this case, equal to 11,984).

Squilla mantis, caught using general *nasse*, is also substrate dependent. It can usually be found after the first nautical mile, because its burrowing behavior is limited by the bottom substrate, preferring muddy areas over sandy ones. However, the "*Main substrate*" feature exhibited limited predictive power for both levels of the analysis, suggesting its contribution was negligible to prediction. This result is likely explained by its strong correlation with the "*Mean distance from the coast*" (Fig. 11, S2). In fact, for tree-based algorithms, highly correlated features can introduce redundancy, where one predictor's influence is diminished if a related, more informative feature is already integrated into the model's decision-making process (Deporte et al., 2012; Hastie et al., 2005; Montesinos López et al., 2022; Strobl et al., 2007). Another influential

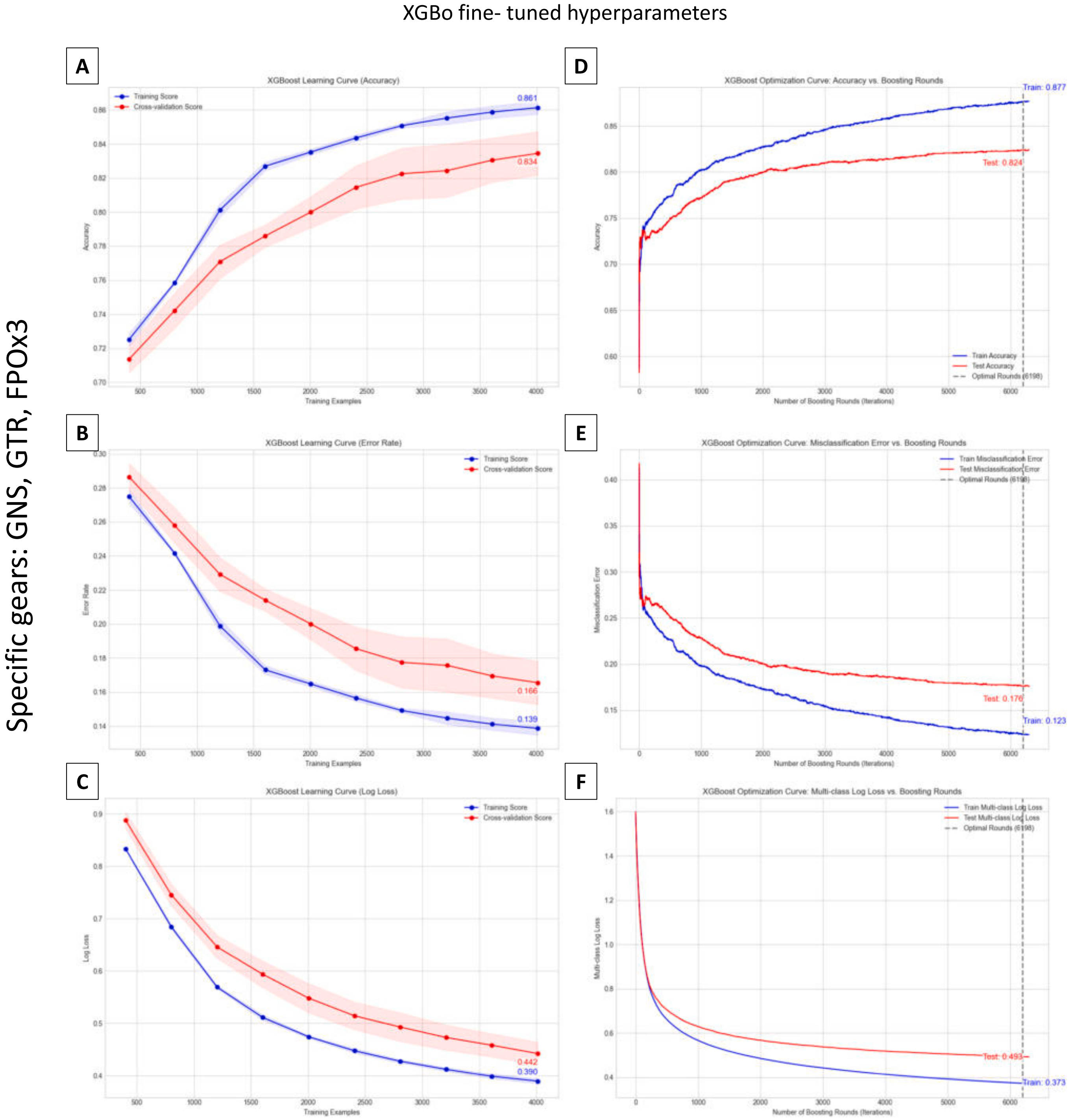


Fig. 14. A visual analysis of the optimal configuration and stability of the XGBo model for specific gears prediction after fine-tuning. A,B,C) Learning Curves track model performance (Accuracy, Error Rate, and Log Loss, respectively) across 5-fold cross-validation as the training set size increases. Compared to the pre-tuned model (Fig. 13), these curves show a significantly reduced divergence between the slightly lower training Accuracy (83.4%) and the cross-validation Accuracy (86)%. This significantly reduced gap (2.5%) indicates low variance (minor, controlled overfitting). Although the CV score has not fully flattened, the convergence of the curves suggests the model is approaching its optimal generalization capability for the available dataset. D,E,F) Optimization Curves track the same three metrics across the iterative training process (number of boosting rounds). These curves determine the optimal early stopping point (early_stopping_rounds = 100) by identifying the number of rounds where validation set performance plateaus or begins to degrade (in this case, equal to 6198).

predictor for both levels of the analysis was the estimated soak time (Figs. 8,11). Soak durations vary considerably by gear type: gillnets and trammel nets are usually kept underwater for less than 72 h, while pots (especially "*cogolli*", late in their fishing season) can be hauled even after a week or more. Along with *"Hour of the day", "Mean speed"* and "*Mean length"* (which values are usually greater for nets – variable more important for *gear category* than for *specific gears*), the aforementioned features collectively exhibited relevant scores in the PFI calculation (Fig. 11).

Moving back to model tuning, stricter hyperparameters act as model shapers, imposing constraints on complexity to prevent overfitting (Hastie et al., 2005; Montesinos López et al., 2022). The purpose is to

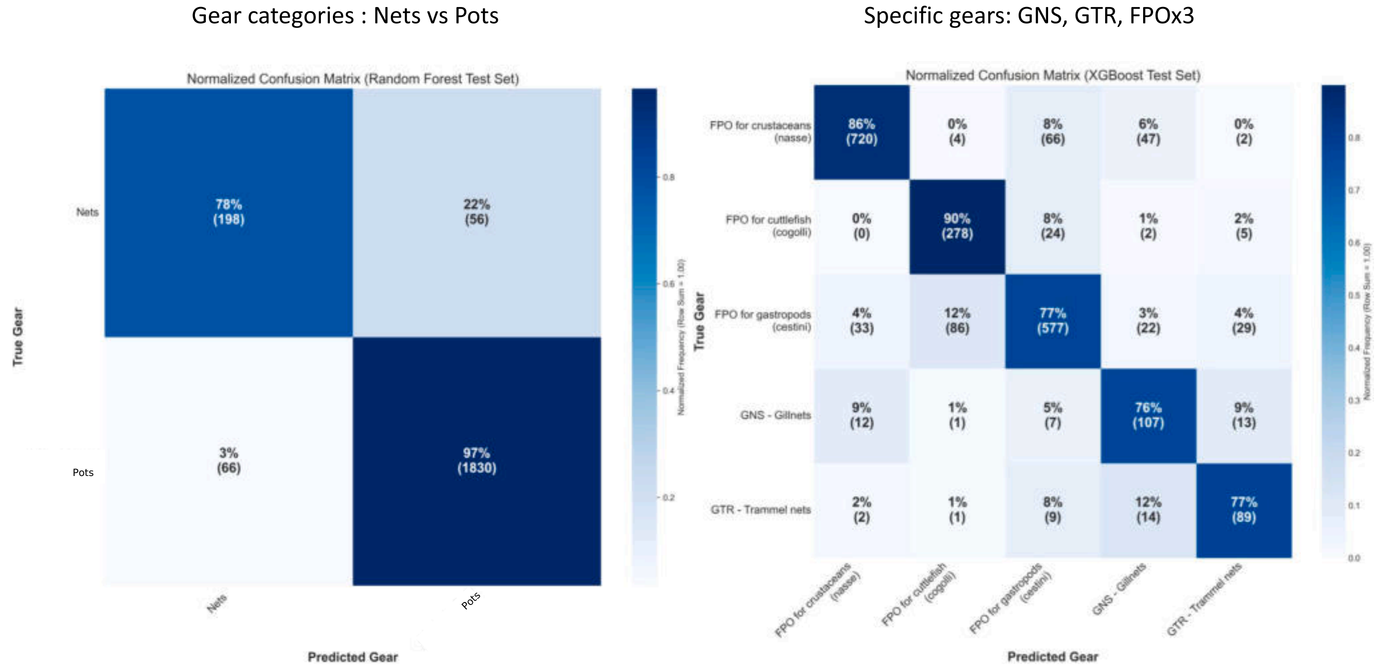


Fig. 15. Confusion matrices for the fine-tuned models (RaFo for gear category and XGBo for specific gears, both with fewer predictors and refined optimized tuning hyperparameters) for classification task on the test set, displaying normalized true label percentages and raw prediction counts.

force the model to learn more generalizable patterns from the data, even if it results in slightly lower training performance. Conversely, parameters that are too rigid can lead to underfitting, resulting in a model too simple to capture the underlying data patterns. This underscores the importance of hyperparameter tuning as an iterative optimization process aimed at minimizing the performance gap between training and validation data, ensuring the model generalizes effectively.

A common indicator of overfitting is a significant performance gap between the model metrics on the training set versus the validation/test set. Indeed, even complex Machine Learning (ML) models (like *RaFo* and *XGBo*) can suffer from severe overfitting when using default parameters (Figs. 9, 10). Conversely, less complex models, such as statistical ones (*Ridge*, *LoRe*), are inherently more prone to underfitting. This susceptibility stems from their reduced set of hyperparameters available to constrain their complexity, leading to low variance but high bias. This suggests that their inherent structural simplicity or the nature of the dataset prevents complex tuning from yielding significant benefits; they perform nearly as well with default settings as they do with optimized parameters (Figs. 9, 10).

Therefore, transparent reporting of model performance across both training/validation and test sets is crucial. This provides critical understanding into a model's propensity for overfitting and its true generalization capabilities – a detail often not showed in similar studies (Cheng et al., 2023; Rodriguez-Albala et al., 2024; Rufino et al., 2023; Samarão et al., 2024). For instance, Russo et al. (2011) explicitly documented the use of an early-stopping strategy in a Multilayer Perceptron Network, monitoring both training and validation errors to identify and prevent overfitting and ensure the selection of a robust architecture.

As a last consideration, a clear increase in model overfitting and a drop in performance were observed when hauling events were grouped by fishing trip or individual boat, especially for the latter (Fig. 16). This performance decay can be attributed to several factors. Firstly, there is substantial variation in the number of fishing trips recorded per vessel and, consequently, in the number of associated hauling events. Secondly, not all the vessels used the full range of gears, which inherently limits the model's exposure to all gear types during training and impacts its ability to generalize across vessels. In addition, spatial behavior varies among fishers, influencing the model's interpretation of location-dependent predictors. Last but not least, it is important to consider that the present labelled data set is quite limited in terms of fleet and space representativeness, with only 10 vessels tracked, all from the same harbour. This confined and geographically constrained sample reduces variability in fishing practices and may limit the broader applicability of the findings. Indeed, the decline in model performance with hauling events grouped by boat highlights a fundamental challenge: complex ML models need complexity (size and diversity) in the data to match their high learning capacity. When data is limited (such in this case, where training Deep Learning models was not possible), particularly in fleet representation, their tendency to overfit makes them less reliable than constrained statistical models, especially when generalization to unseen vessels is tested. Moreover, a critical methodological note is that the previous analysis (Fig. 16), using a fixed random state (*random_state* = 42), might have consistently held out the same vessel (constituting the entire test set) for testing, potentially biasing the reported generalization gap. To address this limitation and improve the broader applicability of the outcomes, future work must prioritize including a larger and more diverse fleet, ideally incorporating multi-site data from different ports and regions. This is essential to properly validate the model's behavior and ensure its generalization across varied fishing practices and geographic areas. In any case, given the inherent challenges and substantial time commitment required for validated data collection, the labelled dataset created is quite unique and appropriate for testing and implementing this kind of framework.

5. Conclusions

This study offers a novel approach to understanding SSF fishing effort exerted by multi-gear vessels using passive gears by focusing on hauling events rather than broader trip-level analyses, and critically, by clearly delineating transparent model evaluation across both training and test sets – a level of reporting often overlooked in similar studies. The selected ML models (both with fewer predictors and optimized tuning parameters) effectively classified gear categories through Random Forest *RaFo* and, more deeply, specific gear types through Extreme Gradient Boosting *XGBo*, moving toward the *métier*-level

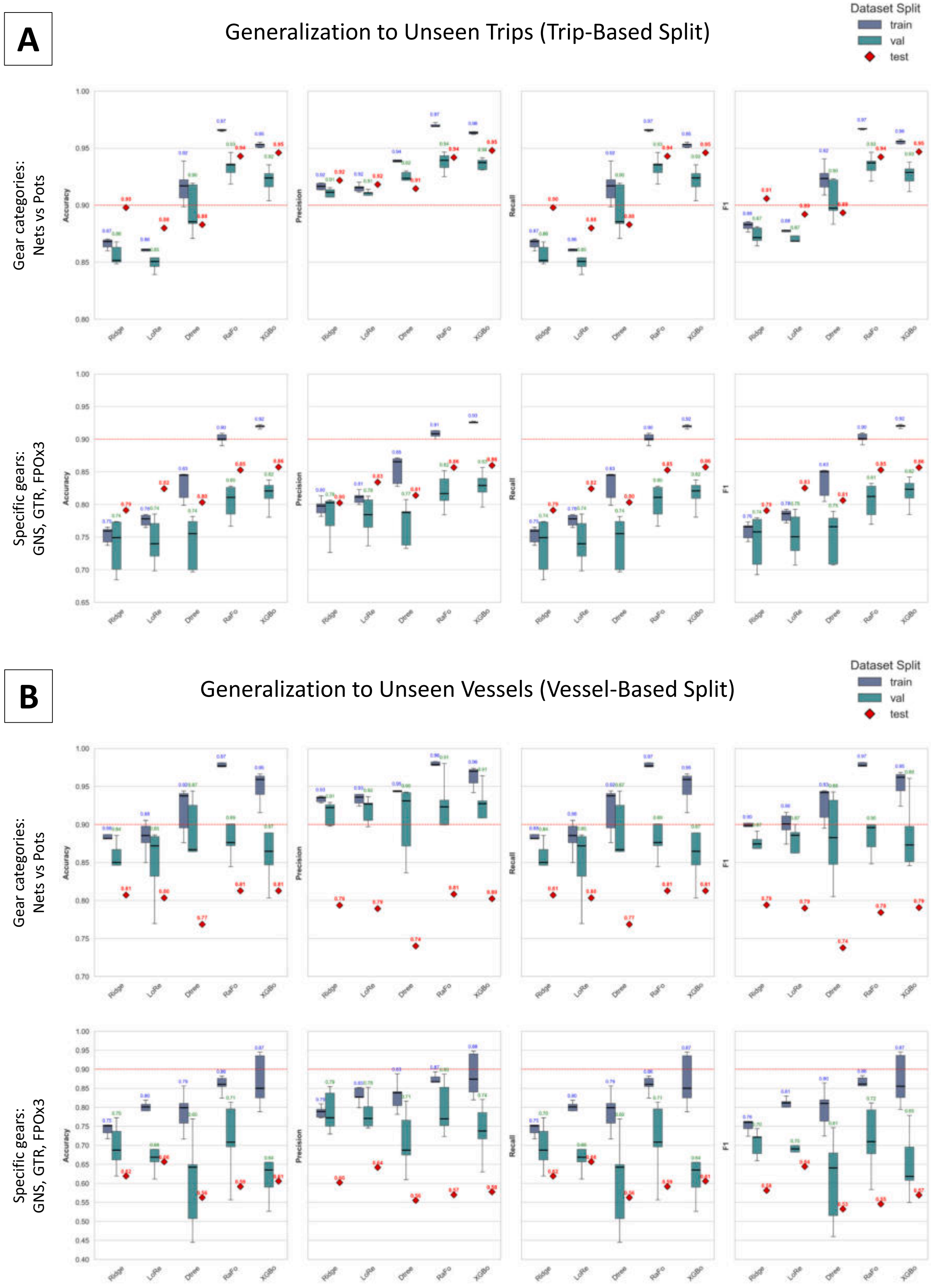


Fig. 16. Plots showing the performances of the investigated models for both levels of analysis, with hauling events data splitting into train, validation and test sets, and grouped by fishing trip (A) or vessel (B). Boxplots display the distribution of training (blue) and validation (green) scores across cross-validation folds. The blue and green numeric labels indicate the mean score for their respective sets. The red diamond and its red numeric label show the final, single score achieved on the independent test set. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

resolution, especially for pots.

The distinct spatio-temporal behaviours observed for different passive gears underscore the diverse ecological footprints within the local SSF fleet: being highly selective, these gear types inherently target distinct species, leading to heterogeneous environmental impacts that call for tailored management measures. Automatic gear detection could enhance stock assessments of target species, improve the identification of key fishing grounds, and support sustainable fishing practices.

The robust performance demonstrated by the ML framework establishes a strong foundation for integrating automatic gear recognition into monitoring workflows, directly addressing the needs of fishing managers and policymakers. Specifically, the framework could be applicable to analytical pipelines established by international bodies. However, it must be emphasized that the successful application of this workflow requires high resolution tracking data to accurately derive the necessary behavioral features for gear classification. In the near future, these models can be deployed to provide rapid, automated validation and alerting within the monitoring workflow, allowing regulatory bodies to immediately (or near real-time) process large volumes of tracking data to identify potential misreporting or unauthorized fishing activity much faster than traditional, manual auditing. Furthermore, the ML output can be integrated with vessel electronic logbook systems to automatically cross-validate declared gear types, substantially improving the integrity and accuracy of self-reported data and contributing to seafood traceability and stronger enforcement against illegal, unreported, and unregulated (IUU) fishing activities (Sales Henriques et al., 2025).

Looking forward, the applicability of these models should be tested on new, labelled datasets to assess generalization potential. Future research should also integrate detailed catch data (Adibi et al., 2019; Leitão et al., 2025) to provide a more comprehensive understanding of fishing dynamics. A further step involves combining gear classification with dynamic environmental variables (e.g., temperature, salinity), to elucidate the ecological factors influencing the spatial and temporal distribution of specific fishing activities (Adibi et al., 2019; Han et al., 2025). Finally, given that the manual labeling of fishing/non-fishing operations was highly time-consuming, automation of this process should be thoroughly explored to ensure scalability (Behivoke et al., 2021; Rufino et al., 2023; Samarão et al., 2024).

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used Gemini in order to assist in drafting the technical structure of the data processing scripts and to refine the linguistic clarity of the supporting documentation and manuscript text. After using this tool, the author(s) reviewed and edited the content as needed to ensure technical accuracy and alignment with the study's objectives, and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Pamela Lattanzi: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Tania Mendo:** Writing – review & editing, Supervision, Resources, Formal analysis, Conceptualization. **Alessandro Galdelli:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Anna Nora Tassetti:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2026.103670.

Data availability

The Python code developed and tested for predicting fishing gear in hauling events is accessible at the following *Figshare* repository: https://doi.org/10.6084/m9.figshare.29647448 (Lattanzi et al., 2025). To protect the privacy of the involved fishers, raw GPS data were not shared. However, a sample dataset containing hauling events (one row for each hauling event) from 10 randomly selected fishing trips has been deposited at the previously described repository to allow users to test the code ("sample_dataset.rds"). This sample excludes temporal and spatial identifiers to ensure confidentiality. Requests for access to a subset of raw GPS positions (one row per position) - anonymized in terms of space, time, and vessel identifiers - should be directed to the authors.

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