ORIGINAL ARTICLE OPEN ACCESS

Identifying Purse Seine Vessel Operations Through Machine Learning Models for Better Spatial Fishing Effort Estimates

Joan Sala-Coromina[1,2,3] 🔵 | Mireia Silvestre[1,2,3] | Felipe H. Coutinho[2] | Marta Carreton[1,2] | Marta Blanco[1,2] |
Jordi Ribera-Altimir[1,2,3] 🔵 | Laura Recasens[1,2] | Joan B. Company[1,2]

[1]Institut Català de Recerca per a la Governança del Mar (ICATMAR), Barcelona, Catalonia, Spain | [2]Institut de Ciències del Mar (ICM-CSIC), Barcelona, Catalonia, Spain | [3]Department of Earth and Ocean Dynamics, Facultat de Ciències de la Terra, Universitat de Barcelona (UB), Barcelona, Catalonia, Spain

Correspondence: Joan Sala-Coromina (jsala@icm.csic.es)

ABSTRACT

Spatial fisheries management requires precise, spatial explicit information on species distribution and fishing impacts. In the NW Mediterranean, the distribution of small pelagic fish (SPF) stocks is currently assessed through annual acoustic surveys. Although accurate, these surveys might lack the temporal resolution needed to capture population dynamics. Analysing fishing fleet spatial behaviour allows estimation of fishery impacts and can uncover patterns of target species at high temporal resolution. In this study we apply machine learning models to classify multiple vessel operations on vessel monitoring system (VMS) data for purse seiners targeting SPF populations. Three main vessel operations were defined based on onboard observations: Fishing, Tracking and Cruising. Then, random forest models were trained to predict vessel operations in VMS data using seven predictive variables. Machine learning models highly improved predictions accuracy (81% and 73%) compared to a classical speed filter method (60%). Fishing effort metrics were computed and compared across predictive methods resulting in a high overestimation of fishing activities when using a speed filter approach. The effect of spatial resolution in fishing effort metrics was also tested revealing a good performance of random forest predictions at 2–3 km². The methods developed allow quantification of three vessel operations activities improving purse seiners effort metrics compared to classical binary (fishing/non-fishing) approaches. Consequently, spatially explicit catch per unit effort (CPUE) estimates for SPF will also be improved as well as the accuracy of the information needed for spatially manage of this fishery.

1 | Introduction

Managing purse seine fisheries targeting small pelagic fish (SPF) is challenging due to the strong influence of environmental conditions on the stock dynamics, with a high spatio-temporal variability (Brosset et al. 2017; Saraux et al. 2014). In this context, effective management must be adaptive over short time scales, with weekly or monthly revisions (Bertrand et al. 2008). Management decisions require continuous estimates of the state of fish stocks, which depend on their spatial distribution (Arreguin-Sanchez 1996).

The assessment of small pelagic stocks relies, in part, on abundance indices originating from fishery-independent acoustic surveys. In the Mediterranean Sea, these surveys are carried out once a year during the summer months and provide accurate data on biomass, abundance and distribution of the SPF species following a standardised methodology common to all European countries in the Mediterranean (Giannoulaki et al. 2021). Due to the spatio-temporal variability of SPF (Saraux et al. 2014), a single annual survey might not adequately capture the changing distribution of the target SPF species (Kimura and Somerton 2006). Moreover, the marked seasonality of the

reproductive cycle of the two most important target species of the fishery (European sardine and anchovy) is oppositional, resulting in different reproductive phases during the survey period (Palomera et al. 2007).

Purse seine is the most significant fishery in terms of total landings in the Mediterranean Sea (FAO 2023). In the Catalan coast (NW Mediterranean Sea), it is the primary fishing gear targeting SPF, with more than 99% of anchovy and European sardine catches made by this fleet. In 2023, this fleet consisted of 49 vessels, representing 47% of total landings and 18% of the income for the entire Catalan fishing sector (ICATMAR 2024b). The fleet is characterised by a mean length overall (LOA) between 10 and 25 m and the use of auxiliary light boats to attract and aggregate fish schools during the night, similarly to other purse seine fleets (Feijó et al. 2018; Tejerina et al. 2019). In this region, vessels are limited to work 5 days per week (BOE 2022) and vessels return daily to port typically right after sunrise to sell at the fish auction. Vessels do not necessarily return to their home port, which results in high fleet mobility compared to bottom trawling, which fishes in the nearest fishing grounds and always return to sell to the same port (Carreton et al. 2025).

Purse seine fleet targets the schools of SPF to maximise catches. Since a fishery results from the interaction between the spatial distribution of fish and the application of fishing effort (Bourdaud et al. 2019; Petitgas 1998), an accurate estimation of the extent and distribution of purse seine fishing effort can potentially describe the distribution of the fishable portion of the SPF stocks (Bertrand et al. 2008; Harley et al. 2001). According to literature, obtaining accurate knowledge and frequent data about fishing operations should reflect time-changing distribution patterns of species (Bertrand et al. 2008) and thus capture its seasonal variability.

Vessel positioning systems have been increasingly used for fisheries management (Lee et al. 2010; Russo, Parisi, and Cataudella 2011). As the positions themselves do not inform about vessels' activities, correlating these data with vessel's operation is the key step when using positioning system data either for surveillance or fishery management purposes. This analysis requires high knowledge of the fishery and an accurate data analysis which sometimes makes it difficult to use these data for management purposes (Le Tixerant et al. 2018; Russo et al. 2018; Walker and Bez 2010). Historically, fleets using towed gears, such as otter bottom trawling, have been the most studied (Jennings and Lee 2012; Lee et al. 2010). In these cases, fishing positions are typically filtered using a speed filter, yielding reliable estimates of fishing effort (Lee et al. 2010; Russo, Parisi, and Cataudella 2011). However, when fishing operations are more complex—such as those involving purse seiners—a simple speed filter may not be enough to produce accurate estimates of fishing effort (Bez et al. 2011; Joo et al. 2011).

The identification of fishing vessel operations in positioning systems has increasingly incorporated machine learning algorithms, particularly artificial neural networks (ANNs) (Bez et al. 2011; Joo et al. 2011; Russo, Parisi, Prorgi, et al. 2011) and Random Forest models (Behivoke et al. 2021; Mendo et al. 2023). Although some of them classify multiple operations (ICES 2023), these methods have primarily been used for the

binary classification of fishing and non-fishing operations in order to calculate catch per unit effort (CPUE) or landings per unit effort (LPUE). However, as noted by Bez et al. (2011), focusing solely on this binary classification may overlook important aspects of purse seine fisheries. Purse seiners' behaviour is highly dependent on skipper strategy and resource availability. Unlike towed or passive gears, skippers will prioritise locating fish schools rather than targeting fixed fishing grounds. Consequently, fishing moments and locations as well as time spent searching or tracking schools depend on resource availability (Ruttan and Tyedmers 2007). Therefore, when estimating CPUE or LPUE, it is essential to consider not only active fishing moments but also other operational activities, as these contain valuable information about resource dynamics.

Early studies on vessel operations in purse seine fisheries were conducted by Walker and Bez (2010), focusing on fish-aggregating devices (FAD)-based tuna fishing, where multiple vessel operations were described and analysed. For purse seine fleets targeting SPF, Joo et al. (2011) applied a binary classification method using an artificial neural network to detect fishing versus non-fishing operations and Lucchetti et al. (2018) applied state-space models (developed by Walker and Bez 2010 for tuna purse seiners) to the same aim. In addition, Katara and Silva (2017), Quattrocchi and Maynou (2018) and Wan et al. (2024) explored the use of speed thresholds to detect fishing activity. To our knowledge, there are currently no studies developing methodologies to classify multiple vessel operations in purse seiners targeting SPF. The aim of the current work is to refine the classification of purse seine vessel operations in order to improve the estimates of purse seine fishing effort in the NW Mediterranean Sea, to enhance its spatial and temporal resolution. Using onboard observers data with high spatiotemporal resolution, the fishery vessels' operations were characterised. This data were then used to classify VMS data for which a multiclass Random Forest model was trained to identify the defined operations. Multiclass model performance was compared against a binary model (fishing/not-fishing) and a simple speed threshold approach. These findings help to better understand spatio-temporal variability of SPF populations and fisheries.

2 | Materials and Methods

2.1 | On-Board Sampling and Fishing Operations

With the aim of understanding purse seiners' behaviour and collect georeferenced data about them, onboard samplings were done (from 2020 to 2023) in the framework of ICATMAR fisheries data collection program. Within this context, samplings onboard of purse seiners started in 2020 onboard the fleet working on the Catalan coast (NW Mediterranean Sea) (ICATMAR 2023). ICATMAR's sampling program aims at continuously monitoring the Catalan fishing fleets and their impacts. In the case of purse seiners, information gaps needed to be fulfilled and consequently sampling was designed with two main objectives. The first objective was to analyse purse seine vessel operations in order to be able to quantify the distribution and intensity of this activity in space which is covered by the present work. The second objective was to address fishery species catch, bycatch and
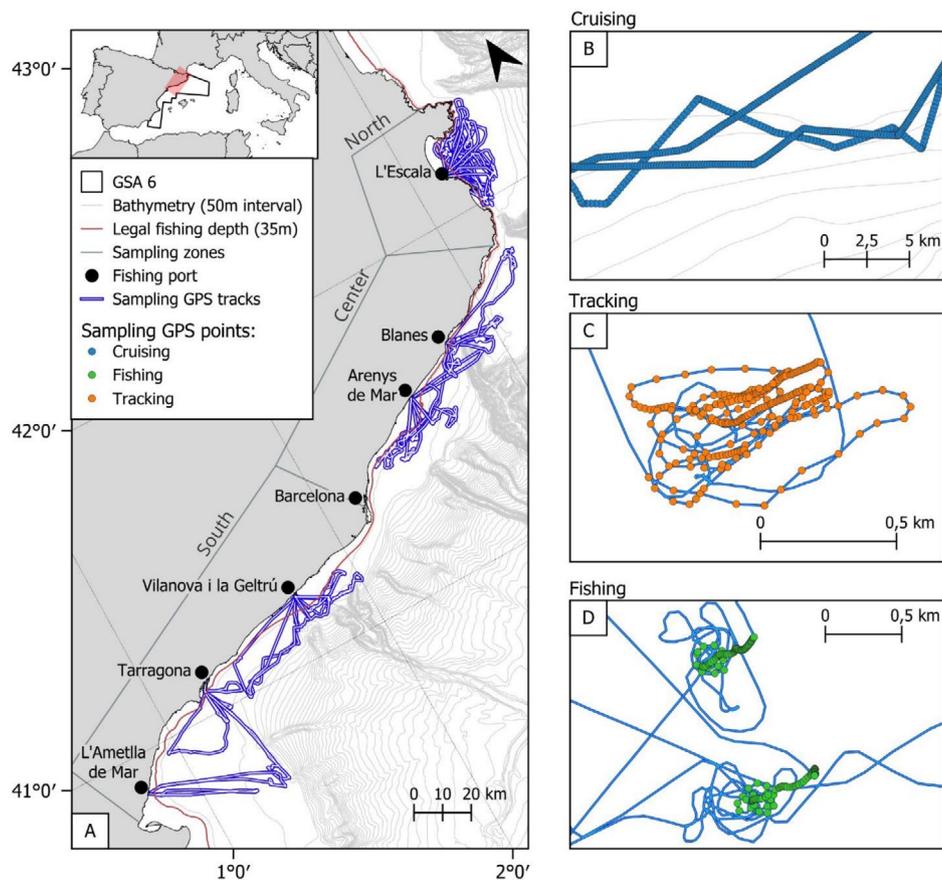
FIGURE 1 | Study zone and on-board sampling tracks used in this study (A). Examples of a typical cruising (B), tracking (C) and fishing (D) vessel operations recorded with a high frequency (30 s) GPS device by on-board observers.

discard characteristics, since this information is key for future stock and fishery assessment (ICATMAR 2024a).

According to these objectives, a sampling strategy covering the main seven Catalan ports with purse seine activity along 300 km of coast was designed. The coast was divided into three zones (North, Center and South. See Figure 1) following its geomorphological and biohydrodynamic structure (Clavel-Henry et al. 2019), and two on-board samplings were carried out every month: one in the northern zone and the other alternating between Center and South zones, amounting to a routine of 24 samplings a year. All on-board sampling tracks were recorded with a high frequency (30 s) GPS device. A total of 51 fishing trips were carried out between February 2020 and December 2023, less than expected as a result of COVID19 pandemic restrictions. After data validation, 47 trips corresponding to the period between September 2021 and December 2023 were finally included for the present study (Table 1, Figure 1A). The three first samplings were excluded due to misclassification of vessel operations before its final definition and the fourth due to errors in GPS device recording.

After the first samplings conducted in year 2020 and based on the available bibliography (Bez et al. 2011), we defined four main purse seine operations that occur during a fishing trip. All fishing trips happen at night time with port exits ranging between 22 pm and 02 am, depending on the skipper's fishing strategy. Catalan purse seine fleet ranges from 9 to 25 m LOA

vessels operated by 9–12 fishers onboard. The *Steaming phase* (I) starts when the vessel exits the port and navigates to fishing grounds. This is a typically short operation as Spanish legislation only allows purse seine fishing activity over bottoms deeper than 35 m (BOE 2023), which are quickly reached by vessels (Figure 1A, Figure S1). The *Cruising phase* (II) starts when the vessel enters legal fishing depths, and the skipper turns on the fish finder hydroacoustic devices, at least a sonar and an echosounder. This phase is characterised by straight trajectories at constant high speeds (Figure 1B, Figure S1). When the skipper detects a potentially interesting fish school, the *Tracking phase* starts (III). Here, the main vessel speed is reduced and the fish school behaviour is analysed through sonar and echosounders. Therefore, this operation is characterised by medium speeds and curved trajectories around the fish school (Figure 1C, Figure S1). During this phase, the skipper may decide to release the auxiliary light boat which, until that moment, is either on board of the main boat or being towed by it. If the auxiliary boat is released, lights are turned on to try to aggregate fish underneath. Then, skippers consider the school's behaviour, its aggregation, response to light as well as sea currents to minimise the likelihood of fish escaping the net once the fishing operation begins. Finally, if the skipper considers that the fish school is well aggregated, the *Fishing phase* (IV) starts. The main boat circles the fish school while setting the net, a fast operation typically done in 3–5 min. Then, the net is closed laterally and on the bottom (8–12 min). Once closed, the net is collected by fishers

TABLE 1 | Summary of fishing trips by vessel used in the study.

Vessel	LOA	Engine power	No. of trips	No. of valid trips	Trip duration	No. of VMS points
1	16.5	176.5	1	0	9.2	43
2	24.5	314.8	7	6	6.3 ± 1.1	42.1 ± 7.1
3	14.2	76.5	1	0	8.3	47
4	16.8	165.5	24	23	7.6 ± 0.5	41.3 ± 4.2
5	16.7	202.2	6	6	8.1 ± 1.4	43.8 ± 11.0
6	20	294.2	7	7	7.8 ± 1.5	41.3 ± 14.2
7	20.4	154.5	5	5	8.8 ± 1.5	49.8 ± 6.9
Total trips			51	47		

Note: Vessel names or identification codes are not shown.

until the fish gets close to the boat during approximately 20–30 min. This operation is therefore characterised by a circular trajectory while setting the net, followed by a drifting phase corresponding to net collection (Figure 1D, Figure S1). After this, the skipper may decide to release the catch (slipping) or to retain it. Slipping occurs for various reasons: either fish is below the Minimum Conservation Reference Size (MCRS), the quota or vessel capacity have been attained, or there is abundance of non-commercial species, or commercial species are highly mixed, which entails time-consuming classification work by fishers. If the skipper decides to retain the catch, it is transferred on board with a scoop net and directly placed into selling boxes with ice (7–45 min, depending on the size of the catch). Therefore, the total time of a fishing set can vary between 1 and 2 h depending on the catch amount. Some catch classification or removal of discards may occur, although skippers prefer not to manipulate the catch because it is then devaluated and the operation requires a lot of human work. The ships typically return to port right after sunrise to sell fish at auction. As the described fishing operations take place only at night when disaggregated schools of the target species are at shallower depths and can be concentrated by the auxiliary boat's light. During the day, species aggregate at deeper depths, near the seafloor, beyond the reach of the purse seine nets (Fréon et al. 1996; Iglesias et al. 2003).

Once vessel operations were clearly defined, observers on board classified each moment of the sampled fishing trips into one of the operations for later data analysis. Only cruising, tracking and fishing phases were analysed, since steaming phases were short and, in terms of spatial behaviour, similar to cruising. Recorded GPS data were used to better understand the signal of each vessel operation into tracking devices and, together with observers' data, helped in the classification of VMS points into one of the three operations. Moreover, GPS data were used to test the effect of different polling rates on the estimation of vessel operation times comparing 30 s GPS frequency to 10 min VMS (see Figure S2).

2.2 | VMS Data Treatment

Once data were validated, VMS data for the same fishing trips (day and vessel) were obtained from the Spanish Fisheries

Secretariat-General. Even if minimum VMS ping frequency is 2 h, it can be increased on demand for specific fleets or vessels. In the case of the studied fleet, raw VMS data frequency was 1 h. Fishing operations last a minimum of 1 h, and therefore, in the case of Catalan purse seine fleet, most of the fishing operations should at least be captured by 1 VMS ping. Tracking and cruising phases are typically longer, so they were expected to be captured by one or more VMS pings as well. In addition, VMS data were interpolated to a 10 min frequency in order to improve fishing effort estimates deriving from the methodologies analysed in the present work. Interpolation was carried out using VMSbase R package (Russo et al. 2014; Russo, Parisi, and Cataudella 2011) similarly to (Lucchetti et al. 2018). Interpolated data were inserted into ICATMAR information systems (Ribera-Altimir et al. 2023) and linked to the corresponding field sampling day; each VMS point was then classified in the on-board observed vessel operation. Finally, a total of 1997 classified interpolated points were obtained for further analysis. Raw data can be found at: https://doi.org/10.5281/zenodo.18466425.

2.3 | Speed Threshold Method

A preliminary study on the distribution of purse seine fleet speed was done (Figure 2, Figure S3). Histograms with all the analysed dataset were drawn and modes calculated using a Gaussian kernel density estimator. Based on the calculated modes, anti-modes were found using *multimode* R package similarly as in Rufino et al. (2023) (see also Lee et al. 2010). The speed distribution, modes and anti-modes found were contrasted with on-board field observations to match speed ranges to vessel operations as accurately as possible. Then a speed threshold retaining fishing operations was used to classify vessel positions into a binary variable (fishing/non-fishing operations) so that this method can be easily compared to the machine learning binary model.

2.4 | Machine Learning Models

A total of seven predictive variables were used to train the models (Table 2, Figure S4). Some original VMS variables were directly included: speed, course and time of day. Four other

variables were computed: absolute course change between the previous and current position (cogDiff), speed change between the previous and current point (speedDiff − 1), speed change between the current and the following point (speedDiff + 1), and the number of points of the same day and vessel in a 500 m buffer of the current position (similarly as in Behivoke et al. 2021, see table 2). See the correspondent correlation matrix at Figure S5.

Once the predictive variables were computed, interpolated VMS positions were classified into the three described operations (Cruising, Tracking and Fishing) based on field observations. For the multiclass model dataset, the three operations were considered, whereas for the binary model dataset, data were reclassified into fishing/non-fishing, that is, tracking and cruising points were collapsed into a single class (Tracking–Cruising from here on). As cruising phases are more abundant in the fishing trips compared to Tracking or Fishing moments, datasets were balanced with random subsampling so all vessel operations had the same number of points and finally the
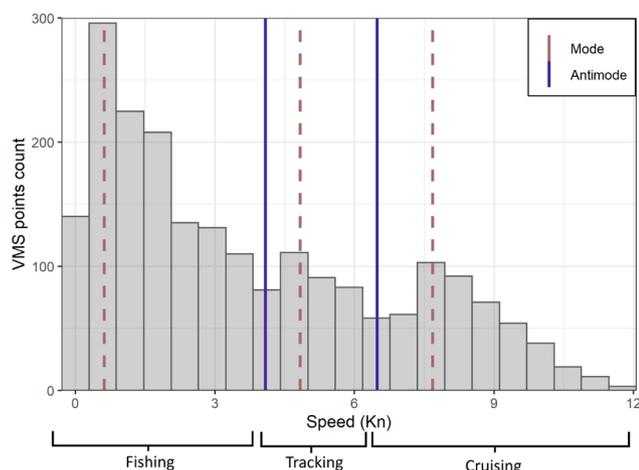

FIGURE 2 | Histogram of the interpolated VMS data speed distribution. Red dashed lines indicate the modes found and blue lines the antimodes. First antimode (4.1 kn) was used to infer fishing positions when using the speed threshold method. Only for the speed filter method, each mode was associated with a vessel operation indicated at the bottom of the figure.

balanced dataset was split into the training (75%) and the test (25%) datasets (Table 3). Models were trained using *scikit-learn* python package (Pedregosa et al. 2012) and GridSearchCV for hyperparameter tuning (see Figure S6 for details).

Code regarding data pre-processing and model fitting can be found at: https://doi.org/10.5281/zenodo.18466425.

2.5 | Prediction Methods Performance Metrics

Fitted prediction methods (multiclass model, binary model and speed filter) were used to make vessel operation predictions on the testing datasets (Table 3). Predictions were compared to observed on-board operations to compute a confusion matrix and four performance metrics: accuracy (proportion of total correct predictions), precision (proportion of true positives over all positive predictions), recall (proportion of true positives over all real positives) and F1-score (harmonic mean of precision and recall). The probability decision threshold parameter (proportion of trees needed to make a certain prediction) was also evaluated to optimise the balance between precision and recall metrics.

2.6 | Estimations of Predictor Importance and Model Interpretation

For the two random forest models (multiclass and binary) shap values (Shapely Additive Explanations) were computed using python package *shap* (Lundberg and Lee 2017). Shap is a game theoretic approach to explain the output of machine learning models and understand how the model internally works when making a certain prediction. Meaning the SHAP values quantify which variables carry the most importance for model prediction. The general importance of each predictive variable was shown through absolute shap values boxplot by vessel operation and predictive variable. Then, for the most relevant ones, predictive variable values were plotted against shap values by vessel operation in scatterplots. This analysis will provide an intuitive way to identify the predictive variable thresholds applied by the models when classifying points into different vessel operations.

TABLE 2 | Summary of the predictive variables used in the machine learning models to predict vessel operation.

Variable and units	Variable computation
Speed (kn)	
Course (degrees)	
Time of day (hours)	Hours since 12:00 am
cogDiff (degrees)	$\mathrm{cogDiff}_i = |\mathrm{course}_i - \mathrm{course}_{i-1}|$
speedDiff + 1 (kn)	$\mathrm{speedDiff} + 1_i = |\mathrm{speed}_i - \mathrm{speed}_{i+1}|$
speedDiff − 1 (kn)	$\mathrm{speedDiff} - 1_i = |\mathrm{speed}_i - \mathrm{speed}_{i-1}|$
bufferCount (no. of points)	$\mathrm{bufferCount}_i = \sum_{j \in D_i} 1\left(\mathrm{dist}(p_i, p_j) \leq 500\mathrm{m}\right)$
	$j \in D_i$ = each point from the same day and vessel as point i

TABLE 3 | Number of dataset observations (VMS points) classified into vessel operations.

	Original dataset	Multiclass model			Binary model			Speed threshold
		Balanced	**Training**	**Test**	**Balanced**	**Training**	**Test**	
Fishing	440	440	323	117	440	330	110	1476
Tracking	565	440	341	99	440	330	110	521
Cruising	992	440	326	114				
Total	1997	1320	990	330	880	660	220	1997

Note: Dataset splitting for each model and speed threshold is specified.

2.7 | Fishing Effort Metrics

Multiclass model, binary model and speed filter method were used to calculate fishing effort metrics and analyse their predictive power compared to the observed onboard operations. First, the three methods were used to predict a vessel operation for each of the VMS points used in the study (original dataset in Table 3). Then, two types of metrics were calculated: vessel operation times in spatial grids and vessel operation times by fishing trip.

For the spatial grid metrics, the classified points were aggregated in different grid cells at five different cell resolutions, from 1 to 5 km² covering all the study zone. The number of points by vessel operation in each grid cell and resolution was counted. Data were aggregated independently of the fishing trip or vessel with the objective of testing the predictions for an entire fleet in space and a period of time. Operation times were estimated by calculating the mean point time frequency for the dataset (10 s in consistency with VMS data interpolation). The time for each vessel operation and grid cell was calculated (minutes of vessel operation by grid cell) as the product of the mean point frequency and number of points. The correlation between predicted versus observed vessel operation time by grid cell was then calculated. Pearson correlation tests were used to statistically test the regressions.

Finally, each vessel operation time (Fishing, Tracking, Cruising) was calculated by fishing trip (vessel and day) as the product of the number of points by vessel operation and the mean point frequency. Predicted and observed operation times were compared using boxplots and statistically tested using ANOVA. Tests were designed to evaluate differences between vessel operations and between predicted versus observed values; the interaction of both factors was also included.

3 | Results

3.1 | Speed Threshold Method

Speed density analysis showed a trimodal distribution for the variable. Modes found were 0.62, 4.9 and 7.6 knots and the corresponding antimodes 4.1 and 6.5 knots (Figure 2). Aiming at having a correspondence between speed density analysis and the observed fleet operations (Fishing, Tracking and Cruising), each of the modes was preliminarily associated

with one of the operations: lower speed mode for fishing, medium mode for tracking and higher mode for cruising phases (see Figure S3). Therefore, in order to classify data between fishing and non-fishing operations, the speed threshold was set to 4.1 knots, that is, all points with speeds lower than 4.1 kn were classified as fishing, and points with higher speeds as non-fishing positions.

3.2 | Prediction Methods Performance Metrics

Random forest models displayed 73% and 81% accuracy for multiclass and binary models, respectively when applied to the test set, thus outperforming the speed threshold prediction method (60% accuracy). Multiclass model predictions were calculated using a 0.5 precision threshold which led to especially high-performance values for Fishing and Cruising vessel operations, whereas performance prediction for Tracking was the lowest (Table 4). The binary model was optimised with a decision threshold of 0.58 during model fitting, obtaining the highest performance, showing good results for both Fishing and Tracking–Cruising operations (Table 4). The speed threshold method had inconsistent performance with high differences between precision and recall values. This method detected most of the fishing points correctly (94% recall) but showed poor discrimination from Tracking–Cruising phases (only 35% of predicted fishing points were truly fishing operations).

3.3 | Predictor Variable Importance Analysis

Shap values showed similar variable importance for both models, with speed, bufferCount and time of day being the most relevant features used by the models for predictions (Figure 3). For the multiclass model, the variable importance on model predictions differs between vessel operations (Figure 3A). Cruising predictions are mainly made based only on speed and bufferCount (Figure 3A). Speed values higher than 3.5 kn and bufferCount values lower than 3 (Figure S7A,B, respectively) contribute to Cruising predictions. Time of day is not of much importance when predicting cruising phases (Figure 3A). Tracking and Fishing predictions are mainly made based on speed, bufferCount and time of day (Figure 3A). Fishing phase predictions are associated with speed values between 0 and 1 kn, bufferCount higher than 6, and time of day later than 5 am (Figure S7A–C). Tracking operation predictions are associated with values of speed from 1 to 3.5 kn, bufferCount from 3 to 6 and time of day earlier than 5 am (Figure S7A–C).

Shap values are exactly the same for both operations in the binary model since, for binary classification, a positive value for one class is the negative value for the other (Figure 3B). This opposite relationship is clearly shown in Figure 4. The model tends to predict Fishing operations when speed is lower than 3.5 kn, bufferCount higher than 5 and time of day later than 4 am (Figure S7D–F). On the other hand, Tracking–Cruising operations are predicted for higher speeds, low bufferCount and early night hours (Figure S7D–F).

3.4 | Fishing Effort Metrics

Mapping validation showed consistent results with model performance metrics (Figure 5, Figure S8). A total of 35 regression analyses were done: 15 for multiclass model (3 vessel operations * 5 grid resolutions), 10 for binary model and 10 for speed threshold method (2 vessel operation * 5 grid resolutions each). All correlations between observed and predicted vessel operation time (minutes per grid cell) were highly significant (Figure 5). Correlations showed a general high r-coefficient (over 0.8 in most cases) and higher values as grid cell resolution increases.

Multiclass model performed well predicting fishing times by grid cell with slopes close to one and low intercepts for all spatial resolutions (Figure 5). Tracking operations had less consistent predictions with lower r values and higher intercepts with respect to the other two vessel operations. High intercepts may indicate some overestimation of this operation. These results are consistent with the low performance metrics for Tracking phases compared to Fishing and Cruising results (Table 4). Predictions on Cruising times correlations had high r-coefficients and low intercepts but slopes lower than 1 for all spatial resolutions.

The binary model was the best method predicting both Fishing and Tracking–Cruising phases in space (Figure 5, Figure S8), consistent with the high accuracy of this model. Even for high spatial resolution, r-coefficients were over 0.75 and increased with spatial resolution. Correlation slopes were almost 1 for all spatial resolutions and intercepts low when predicting Fishing operations. For Tracking–Cruising phases, r-coefficients were also high, especially for resolutions over $2\,km^2$ (0.91 and higher); intercepts were low and slopes close to one (0.83–0.89 for grid over $2\,km^2$) indicating good predictions for this operation as well.

TABLE 4 | Evaluation of models and speed threshold performance metrics.

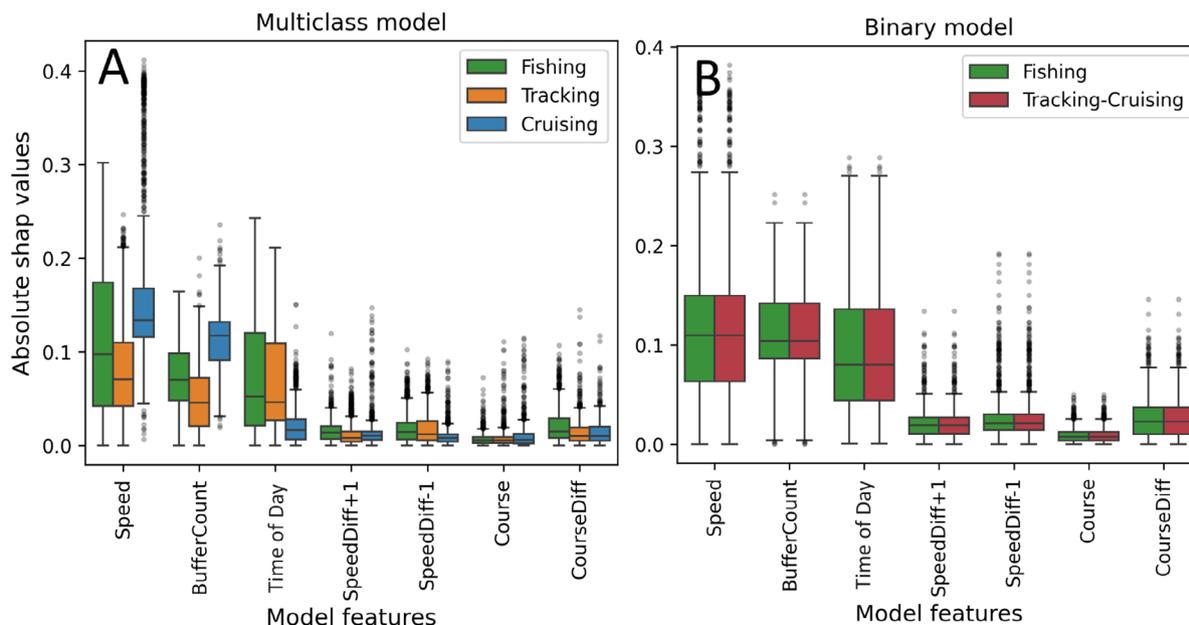|	Multiclass model			Binary model			Speed threshold		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Fishing	0.80	0.75	0.78	0.87	0.74	0.80	0.35	0.94	0.51
Tracking	0.61	0.69	0.64	0.77	0.89	0.83	0.97	0.51	0.67
Cruising	0.80	0.75	0.78						

FIGURE 3 | Shap values summary for each random forest model. For each vessel VMS position on the training dataset, a shap value for each observation and predictive variable was computed, that is 20.790 for multiclass model (A) (990 points, 7 variables, 3 labels) and 9.240 for binary model (B) (660 points, 7 variables, 2 labels). The higher the shap value for a certain point and variable, the more the variable contributes to pushing the model towards predicting a certain label. Values are represented in absolute terms to account for global variable importance regardless of the signal of SHAP value.
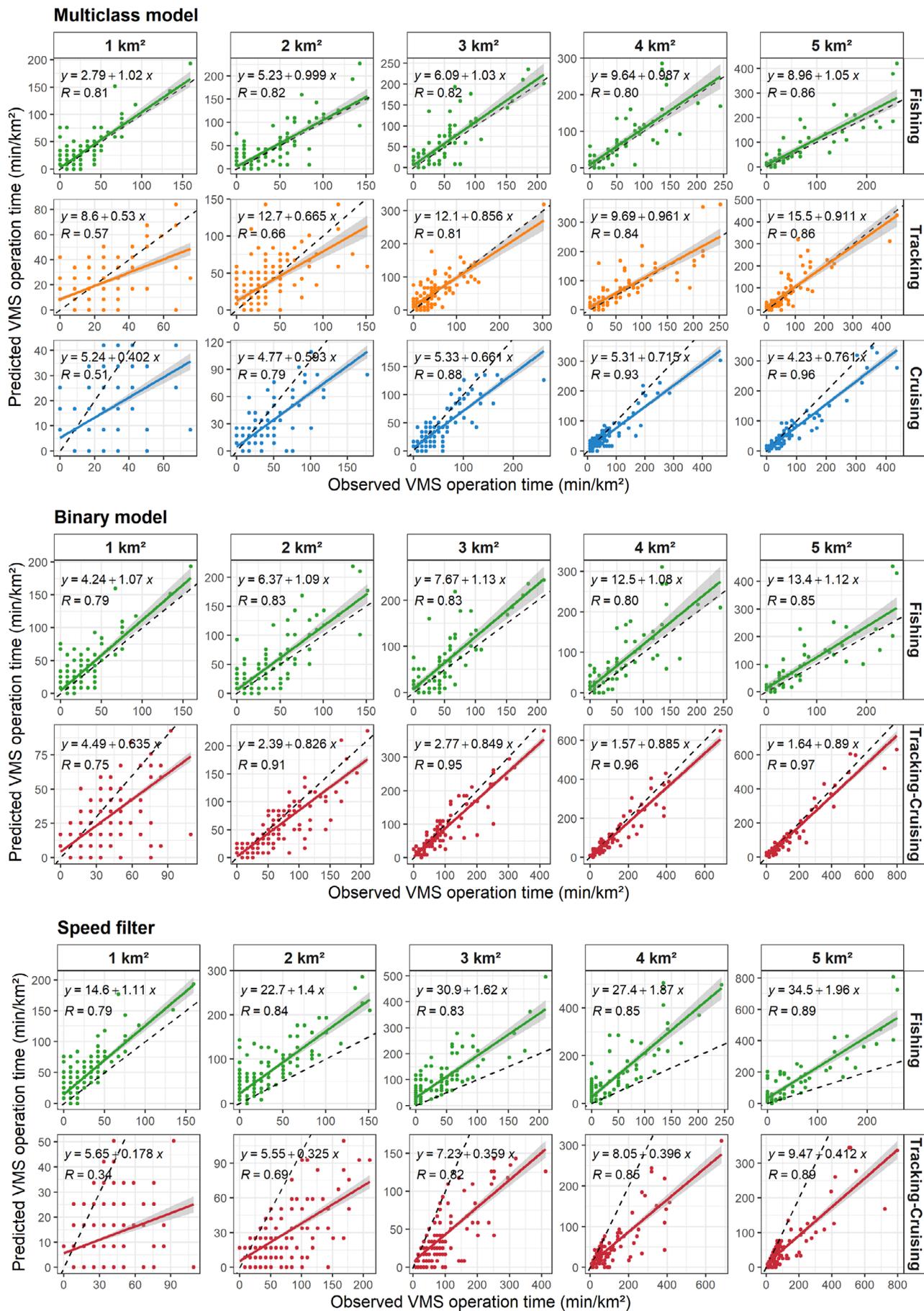
Multiclass model

Rows: Fishing, Tracking, Cruising. Columns: 1 km², 2 km², 3 km², 4 km², 5 km²

Fishing:
- 1 km²: $y = 2.79 + 1.02\,x$, $R = 0.81$
- 2 km²: $y = 5.23 + 0.999\,x$, $R = 0.82$
- 3 km²: $y = 6.09 + 1.03\,x$, $R = 0.82$
- 4 km²: $y = 9.64 + 0.987\,x$, $R = 0.80$
- 5 km²: $y = 8.96 + 1.05\,x$, $R = 0.86$

Tracking:
- 1 km²: $y = 8.6 + 0.53\,x$, $R = 0.57$
- 2 km²: $y = 12.7 + 0.665\,x$, $R = 0.66$
- 3 km²: $y = 12.1 + 0.856\,x$, $R = 0.81$
- 4 km²: $y = 9.69 + 0.961\,x$, $R = 0.84$
- 5 km²: $y = 15.5 + 0.911\,x$, $R = 0.86$

Cruising:
- 1 km²: $y = 5.24 + 0.402\,x$, $R = 0.51$
- 2 km²: $y = 4.77 + 0.593\,x$, $R = 0.79$
- 3 km²: $y = 5.33 + 0.661\,x$, $R = 0.88$
- 4 km²: $y = 5.31 + 0.715\,x$, $R = 0.93$
- 5 km²: $y = 4.23 + 0.761\,x$, $R = 0.96$

Binary model

Rows: Fishing, Tracking-Cruising. Columns: 1 km², 2 km², 3 km², 4 km², 5 km²

Fishing:
- 1 km²: $y = 4.24 + 1.07\,x$, $R = 0.79$
- 2 km²: $y = 6.37 + 1.09\,x$, $R = 0.83$
- 3 km²: $y = 7.67 + 1.13\,x$, $R = 0.83$
- 4 km²: $y = 12.5 + 1.08\,x$, $R = 0.80$
- 5 km²: $y = 13.4 + 1.12\,x$, $R = 0.85$

Tracking-Cruising:
- 1 km²: $y = 4.49 + 0.635\,x$, $R = 0.75$
- 2 km²: $y = 2.39 + 0.826\,x$, $R = 0.91$
- 3 km²: $y = 2.77 + 0.849\,x$, $R = 0.95$
- 4 km²: $y = 1.57 + 0.885\,x$, $R = 0.96$
- 5 km²: $y = 1.64 + 0.89\,x$, $R = 0.97$

Speed filter

Rows: Fishing, Tracking-Cruising. Columns: 1 km², 2 km², 3 km², 4 km², 5 km²

Fishing:
- 1 km²: $y = 14.6 + 1.11\,x$, $R = 0.79$
- 2 km²: $y = 22.7 + 1.4\,x$, $R = 0.84$
- 3 km²: $y = 30.9 + 1.62\,x$, $R = 0.83$
- 4 km²: $y = 27.4 + 1.87\,x$, $R = 0.85$
- 5 km²: $y = 34.5 + 1.96\,x$, $R = 0.89$

Tracking-Cruising:
- 1 km²: $y = 5.65 + 0.178\,x$, $R = 0.34$
- 2 km²: $y = 5.55 + 0.325\,x$, $R = 0.69$
- 3 km²: $y = 7.23 + 0.359\,x$, $R = 0.82$
- 4 km²: $y = 8.05 + 0.396\,x$, $R = 0.85$
- 5 km²: $y = 9.47 + 0.412\,x$, $R = 0.89$

Axis labels: Predicted VMS operation time (min/km²), Observed VMS operation time (min/km²)

FIGURE 4 | Legend on next page.

FIGURE 4 | Validation of models' vessel operations time metrics in spatial grid. For each grid cell size (from 1 to 5 km²), vessel operation and model (multiclass, binary and speed filter) observed and predicted vessel operation times are compared. Regression formulas and *R* statistic are shown in the corresponding scatterplot. All correlations were significant with *p*-values < 0.001. Dashed black lines indicate 1:1 relation between observed and predicted values, therefore a regression line above it indicates overestimation and below underestimation of the vessel operation times.
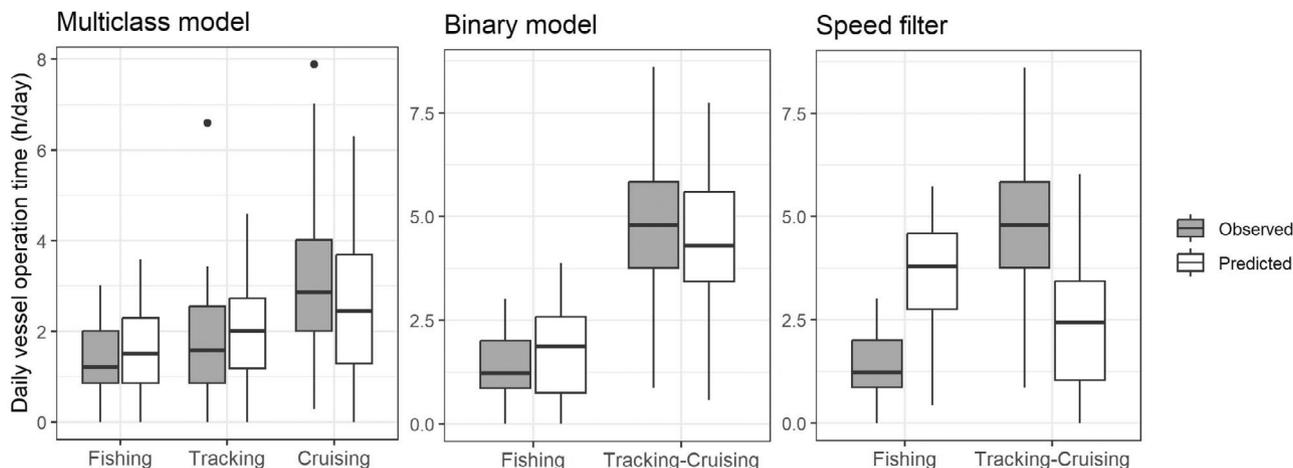
FIGURE 5 | Vessel operation time by fishing trip. Observed and predicted values are compared for each vessel operation and predictive method (multiclass and binary models and speed filter method).

The speed threshold prediction method showed the worst prediction performance in space (Figure 5, Figure S8). For Fishing operations, slopes (1.1–2) and intercepts (15–35) were the highest, indicating operation time overestimation for all spatial resolutions. Low precision in Fishing predictions (Table 4) indicates a lot of Tracking–Cruising phases predicted as Fishing, leading to overestimation of this operation also shown in the spatial validation results. On the other hand, the low values for slopes in Tracking–Cruising phases predictions (0.18–0.41) indicated a notable underestimation for this vessel operation, consistent with its low recall (Table 4).

Vessel operation time by fishing trip (Figure 5) showed consistent results with predictions in spatial grids (Figure 4). The multiclass and binary models have robust operations predictions in all cases, supported by ANOVA results with a non-significant interaction between Operation and Observed/Predicted factors ($F = 2.45$, df = 2, $p = 0.088$ for multiclass model and $F = 3.84$, df = 1, $p = 0.052$ for binary model). However, speed filter method predictions, similarly to spatial grid validations, show clear differences between observed and predicted values (Figure 5). In this case, there is a significant interaction for ANOVA factors ($F = 128.3$, df = 1, $p < 0.005$) meaning that there are differences between observed and predicted values depending on vessel operations. Fishing time is overestimated (over 2 h by fishing trip) and therefore Tracking–Cruising phases are underestimated.

4 | Discussion

4.1 | Models Performance Metrics

Random forest models showed higher performance for vessel operations predictions than the speed threshold method, with the binary model performing best. The speed threshold found in

our data were consistent with previous studies in similar fleets (Katara and Silva 2017; Quattrocchi and Maynou 2018) but when validated with observed data, this method had inconsistent precision and recall values when detecting fishing operations. The low precision and very high recall when predicting fishing operations indicate that this method is overclassifying points into fishing moments. This is probably caused by shared speed ranges between fishing and tracking operations (Figure S4), so this method would be classifying tracking positions into fishing and therefore overestimating these vessel operations (Bertrand et al. 2008). These results confirm that a simple speed filter when trying to detect fishing operations for the purse seine fleet is not a good fit as pointed out by previous studies (Bertrand et al. 2008; Joo et al. 2011).

The multiclass model showed high performance with respect to speed threshold method. Although the model is especially good at detecting fishing and cruising operations, its predicting power was lower for tracking vessel phases. This is a consequence of the overlap in the values of predictor variables for tracking and cruising (Figure S4 and Bertrand et al. 2008), making it harder to differentiate between these phases as the differences between them are more nuanced than those between fishing and non-fishing phases. Vessel trajectories may be similar to some fishing moments as well. The binary model had the higher performance metrics either for fishing and non-fishing operations. Merging tracking phases with cruising moments may have made it easier for the model to distinguish these two operations from fishing.

The present study is the first to analyse SPF purse seine fleets aiming to distinguish between three vessel operations as in the case of the multiclass model. The closest study found (Bertrand et al. 2008; Joo et al. 2011), where artificial neural networks were used to binary predict Peruvian anchovy purse seiners

fishing positions, showed model performances comparable to the ones achieved in the present work around 75% recall for a binary classification for (Joo et al. 2011) and 83% accuracy for (Bertrand et al. 2008). In Joo et al. (2011), false positive rate was higher (approximately 22.2%–11%) and false negative rate lower (approximately 3.2%–26%) than in the present work. Therefore, our models allow for the classification of three vessel operations instead of two, without compromising accuracy, which represents an improvement in purse seine fishing effort metrics.

Other studies trying to detect fishing activities in positioning systems achieved higher performance metrics than in the present work: Behivoke et al. (2021) reached 80%–91% accuracy in different small scale gears, Mendo et al. (2023) reached accuracy values between 80.5% and 91% on gillnets and octopus pots and traps. Rufino et al. (2023) and Samarão et al. (2024) compared performances of different machine learning models on bivalve dredges and pots and traps, reaching 82%–98% and 78%–94% accuracy, respectively. However, all these studies used binary models and high frequency resolution data (10–45 s polling frequency), which might be one of the key reasons explaining model performance differences with respect to the present study (see Section 4.3).

4.2 | Interpreting Random Forest Models Using Variable Importance Analysis

Multiclass and binary fitted models showed similar shap values results: speed, bufferCount and time of day were the most relevant variables in the predictions for both models. The raw values of these predictor variables (Figure S1) showed the greatest difference between vessel operations, and therefore their importance in models' predictions was expected. These results are consistent with other studies (Samarão et al. 2024) where speed plays a key role in model predictions, although other variables included significantly improved the models' performances.

The multiclass model showed different shap values for each vessel operation and variable. When classifying cruising operations, only speed and buffer count were highly relevant. Highest speeds and lowest buffer counts define cruising operations consistently with fast and straight vessel trajectories observed in the on-board samplings and coincident with other studies (Bertrand et al. 2008; Joo et al. 2011; Katara and Silva 2017; Quattrocchi and Maynou 2018). When the model tries to distinguish between Tracking and Fishing operations, the time of day variable also plays an important role. The Tracking phase is predicted for medium speeds, medium buffer counts and early times at night. Speed and buffer count values are consistent with the curve trajectories that the main vessel performs around detected fish schools while they wait for them to accumulate under the auxiliary boat lights or while analysing their behaviour with echosounders. Tracking operations have been described for tuna purse seiners (Walker and Bez 2010) but not clearly identified for purse seiners targeting SPF until the moment. Fishing operations are predicted for the lowest speeds, highest buffer counts and late at night. Low speeds, nearly zero, might correspond to the moments where the vessel is gathering the net and transferring the fish to the vessel with the scoop net, since during these moments, vessels are drifting and the speed

is approximately zero (Bertrand et al. 2008; De Souza et al. 2016; Lucchetti et al. 2018; Walker and Bez 2010). The highest buffer count is also coherent with drifting phases as low speeds contribute to higher buffer counts.

The importance of the time of day in Tracking/Fishing classification might be related to fishers' strategy during a trip. During a fishing night, the number of fishing operations that a certain vessel is able to do is mainly limited due to human resources, vessel tonnage capacity and the duration of night time. The decision of fishing a certain school is a balance between the work it takes to catch it, its quality (influenced by factors such as species, size of both the fish and the school, school aggregation, market price, etc.), and the probability of fishing a better school later in the night. Therefore, in the first hours of a trip, fishers tend to find and analyse more schools and fish less hoping to find a better school during the rest of the night. As daylight approaches, fishers tend to fish more as they would rather have something to sell even if it is not their preferred species or size. Additionally, fishers note that at sunrise the behaviour of fish actively and rapidly aggregating at dawn (Fréon et al. 1996) facilitates the fishing of the already concentrated schools.

In contrast to the multiclass model, for the binary model the importance of speed, buffer count and time of day in model predictions was similar either for Fishing or Tracking–Cruising operations. In this model, the shap values thresholds of the predictive variables are consistent with the multiclass model, with observations of on-board samplings and with similar studies (Bertrand et al. 2008; Joo et al. 2011; Katara and Silva 2017; Quattrocchi and Maynou 2018). This model can be interpreted as a simplification of the multiclass one. Non-fishing operations (Tracking–Cruising) are predicted for high speeds, low buffer counts and early times in the night. Fishing phases are predicted for the opposite threshold limits: low speeds, high buffer counts and late time of day. The similar importance between the three variables might be a consequence of the lack of differentiation of tracking phases alone.

The rest of the predictive variables included in the model (course, speedDiff + 1, speedDiff − 1 and courseDiff) played some role in model predictions although their importance was not comparable to the other three variables included. Course in raw data showed no difference between the three vessel operations (Figure S1). Variables estimating differences between consecutive positions (speedDiff + 1, speedDiff − 1 and courseDiff) had almost no influence on model predictions. Several studies have included similar variables in the models (Behivoke et al. 2021; Bertrand et al. 2008; Joo et al. 2011; Walker and Bez 2010) but their importance in model predictions was not evaluated. It is likely that the importance of these variables when predicting fishing operations relies on ping frequency as it is one of the key features in vessel operations prediction accuracy (Katara and Silva 2017; Lambert et al. 2012; Mendo et al. 2019; Rufino et al. 2023). Changes in speed are short phases that correspond to a change in vessel operation. Therefore, for high resolution devices such as those used in Behivoke et al. (2021) for small scale fisheries, speed or course changes detected by positioning systems may correspond to actual changes in vessel operations. Even if VMS data were interpolated to 10 min frequency in this study, changes in speed or course between two consecutive

positions might not be reflecting a change of vessel operation as some phases could be lost in between positions (Behivoke et al. 2021).

Despite the high explanatory power of predictor importance methods (i.e., shap values), since the moment, studies using machine learning models predicting fishing operations using them are scarce (the only example found is Kawaguchi 2024). In most of the similar studies (Behivoke et al. 2021; Bertrand et al. 2008; Mendo et al. 2023; Rufino et al. 2023; Samarão et al. 2024; Walker and Bez 2010), only the performance of the final models is evaluated, and not the importance of variables in its predictions. This analysis might be important to understand how the models used are working and validate them with field knowledge as done in the present study. Predictor importance analysis might also be important to simplify model fitting through reducing the number of variables included in them, similarly to the analysis done by Samarão et al. (2024) using performance metrics.

4.3 | Fishing Effort Metrics

The speed threshold method highly overestimates Fishing and underestimates the other vessel operations. This is particularly clear with daily vessel operation times where predicted fishing values (3.62 h mean) are more than doubling observed values (1.34 h mean) similarly to other studies such as Bertrand et al. (2008). Spatial metrics show the same results with slopes higher than one for Fishing operations and importantly lower for Tracking–Cruising phases. These results are consistent with speed threshold method performance metrics and confirm that the method is classifying most of the Tracking positions into Fishing positions.

Both binary and multiclass models showed good correlations between observed and predicted fishing effort metrics, either spatially or during a fishing trip. These metrics are consistent with the higher performing metrics of the models. The multiclass model showed good predictions of vessel operation times by grid cell and fishing trip. Fishing was the best predicted operation by this model. The model had a slight trend to underestimate Cruising phases and overestimate Tracking ones even if these differences were non-significant. The binary model had the best vessel operation metrics consistently with its highest model performance metrics. There was a slight trend to overestimate Fishing and underestimate Tracking–Cruising phases but these differences were also non-significant.

The study of fishing vessels operations in positioning systems pursues two main objectives: the estimation of fishing effort and impacts in space and/or the estimation of target species distribution through the linkage between vessel operations and landings/catch data. The binary random forest model performed best in identifying fishing operations and therefore may fit better when trying to link fishing positions with landings data (Bertrand et al. 2008). On the other hand, the multiclass model may perform well when analysing purse seine fleet effort in space. Contrarily to the commonly more studied trawling fishery, vessel trajectories and operations in purse seine fishery may contain more potential information than the strict location of fishing positions (Bez et al. 2011). Most of the studies analysing

spatial SPF purse seine effort only identify fishing or non-fishing operations and quantify fishing effort only with identified fishing sets (Bertrand et al. 2008; Joo et al. 2011; Lucchetti et al. 2018; Quattrocchi and Maynou 2018). As pointed out, this approach can reveal target species distributions (Bertrand et al. 2008) but it could be limiting when accounting for general fleet fishing effort or calculating CPUE estimates (Bez et al. 2011). In the present work we demonstrate that Cruising and Tracking phases are the most time-consuming operations in a SPF purse seine fishing trip (comparable to Tejerina et al. 2019) which might be translated to the most cost-consuming vessel operations as well (Basurko et al. 2022). Skippers will tend to optimise these operations in relation to the potential profits from fished schools (Ruttan and Tyedmers 2007) which may also vary depending on species abundance, that is, potentially, the more abundant a population is, the less costs have to be dedicated to cruising and tracking phases. Therefore, when accounting for purse seine effort, we believe that other operations besides fishing positions should be considered (as in Tejerina et al. 2019) as they might depend on skipper's behaviour modulated by resource availability (Bez et al. 2011; Ruttan and Tyedmers 2007; Tejerina et al. 2019).

The results on vessel operation times showed an effect of the spatial resolution on the predicted values accuracy. In general, as the spatial resolution decreased, the predicted values were more similar to the reality. This effect might be indicating that the errors that the classification methods make for a specific position may be attenuated by decreasing spatial resolution. The larger a grid cell is, the more points it contains, and therefore the errors in one predicted operation may be compensated by errors in other points and vessel operations predicted. It is known that the size of the grid used influences the interpretation of fishing effort in space (Mendo et al. 2019 and the ones cited); larger grid cell sizes tend to increase the apparent area fished (Lambert et al. 2012). Therefore, in our case, a trade-off between model precision and spatial resolution must be solved. Depending on the zone and fleet studied, different resolutions may fit. As an example, in the study zone, the purse seine fishery operates between 35 and mostly 150 m depth which approximately comprises a distance between 5 and 30 km off the coast. In this case, a grid resolution of 5 km^2 might be rough trying to define fishing effort spatial structures. A grid cell of 2 km^2 for binary model and 3 km^2 for multiclass would probably be the best solution in this case.

Ping frequency may play a key role explaining some of the results as it has been reported to influence fishing vessels operation identification (Mendo et al. 2019; Rufino et al. 2023) and fishing effort metrics (Katara and Silva 2017; Lambert et al. 2012; Russo, Parisi, and Cataudella 2011). In the analysed fleet, the mean raw polling rate was 1 h which should be enough to have at least one point per fishing operation. Even if we demonstrated that the interpolated VMS 10 min polling rate does not imply a loss in vessel operation estimates during a fishing trip (Figure S2), we believe that higher point frequencies would probably increase random forest models' performance (Mendo et al. 2019; Rufino et al. 2023) as fishing and tracking sets would be better recorded. As an example, covariates between consecutive positions would probably better describe vessel operations such as in Behivoke et al. (2021) and therefore have more predicting power in machine learning algorithms. Some studies used AIS data trying to improve point frequency in purse seine fleets (Owiredu

et al. 2024; Wan et al. 2024; Xu et al. 2023) although this tracking system has also been reported to lead to important information gaps in fishing effort metrics (Natale et al. 2015; Shepperson et al. 2018). Therefore, it seems clear that alternative fleet monitoring positioning systems with higher ping frequency must be implemented to better study fishing effort and vessel operations, especially when used for surveillance purposes. However, we believe that developing reliable methods in other tracking devices such as VMS is important to study highly valuable historical data series on fleet and fishing resources behaviour.

5 | Conclusions

The use of random forest models highly improved the accuracy with respect to speed threshold methods when predicting vessel operations in the purse seine fleet targeting SPF. We believe that the use of these models should be accompanied by methods digging into their internal functioning such as using predictor importance analysis such as shap values. The present work points out the need to consider other vessel operations besides fishing when calculating purse seine fishing effort and provides methods to do so using VMS data. Higher accuracy identifying fishing positions will potentially improve the estimates of target species distributions done with these methods. However, the accuracy of the predictions might highly depend on the positioning systems' polling rate and therefore advances should be made to implement high frequency positioning systems in fisheries monitoring.

Aknowledgements

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings in this research together with all the data processing and analysis scripts can be found at: https://doi.org/10.5281/zenodo.18466425.

References

Arreguin-Sanchez, F. 1996. "Catchability: A Key Parameter for Fish Stock Assessment." *Reviews in Fish Biology and Fisheries* 6: 221–242.

Basurko, O. C., G. Gabiña, J. Lopez, et al. 2022. "Fuel Consumption of Free-Swimming School Versus FAD Strategies in Tropical Tuna Purse Seine Fishing." *Fisheries Research* 245: 106139. https://doi.org/10.1016/j.fishres.2021.106139.

Behivoke, F., M. P. Etienne, J. Guitton, R. M. Randriatsara, E. Ranaivoson, and M. Léopold. 2021. "Estimating Fishing Effort in Small-Scale Fisheries Using GPS Tracking Data and Random Forests." *Ecological Indicators* 123: 107321. https://doi.org/10.1016/j.ecolind.2020.107321.

Bertrand, S., E. Díaz, and M. Lengaigne. 2008. "Patterns in the Spatial Distribution of Peruvian Anchovy (*Engraulis ringens*) Revealed by Spatially Explicit Fishing Data." *Progress in Oceanography* 79: 379–389. https://doi.org/10.1016/j.pocean.2008.10.009.

Bez, N., E. Walker, D. Gaertner, J. Rivoirard, and P. Gaspar. 2011. "Fishing Activity of Tuna Purse Seiners Estimated From Vessel Monitoring System (VMS) Data." *Canadian Journal of Fisheries and Aquatic Sciences* 68: 1998–2010. https://doi.org/10.1139/f2011-114.

BOE. 2022. "Real Decreto 502/2022, de 27 de junio, por el que se regula el ejercicio de la pesca en los caladeros nacionales."

BOE. 2023. "Orden APA/852/2023, de 13 de julio por la que se establece un plan de gestión para la pesca con artes de cerco en el subcaladero Mediterráneo."

Bourdaud, P., M. Travers-Trolet, Y. Vermard, and P. Marchal. 2019. "Improving the Interpretation of Fishing Effort and Pressures in Mixed Fisheries Using Spatial Overlap Metrics." *Canadian Journal of Fisheries and Aquatic Sciences* 76: 586–596. https://doi.org/10.1139/cjfas-2017-0529.

Brosset, P., J. M. Fromentin, E. Van Beveren, et al. 2017. "Spatio-Temporal Patterns and Environmental Controls of Small Pelagic Fish Body Condition From Contrasted Mediterranean Areas." *Progress in Oceanography* 151: 149–162. https://doi.org/10.1016/j.pocean.2016.12.002.

Carreton, M., E. Galimany, M. Blanco, et al. 2025. "Understanding the Spatio-Temporal Variability of Fisheries Data for Better Bottom Trawling Management Practices in the Catalan Margin (NW Mediterranean Sea)." *Marine Policy* 172: 106512. https://doi.org/10.1016/j.marpol.2024.106512.

Clavel-Henry, M., J. Solé, M. Á. Ahumada-Sempoal, et al. 2019. "Influence of the Summer Deep-Sea Circulations on Passive Drifts Among the Submarine Canyons in the Northwestern Mediterranean Sea." *Ocean Science* 15: 1745–1759. https://doi.org/10.5194/os-15-1745-2019.

De Souza, E. N., K. Boerder, S. Matwin, and B. Worm. 2016. "Improving Fishing Pattern Detection From Satellite AIS Using Data Mining and Machine Learning." *PLoS One* 11: e0158248. https://doi.org/10.1371/journal.pone.0158248.

FAO. 2023. *The State of Mediterranean and Black Sea Fisheries*. FAO. https://doi.org/10.4060/cc8888en.

Feijó, D., A. Marçalo, T. Bento, et al. 2018. "Trends in the Activity Pattern, Fishing Yields, Catch and Landing Composition Between 2009 and 2013 From Onboard Observations in the Portuguese Purse Seine Fleet." *Regional Studies in Marine Science* 23: 97–106. https://doi.org/10.1016/j.rsma.2017.12.007.

Fréon, P., F. Gerlotto, and M. Soria. 1996. "Diel Variability of School Structure With Special Reference to Transition Periods." *ICES Journal of Marine Science* 53: 459–464.

Giannoulaki, M., J. Zwolinski, A. C. Gucu, A. De Felice, and S. Somarakis. 2021. "The 'MEDiterranean International Acoustic Survey': An Introduction." *Mediterranean Marine Science* 22: 747–750. https://doi.org/10.12681/mms.29068.

Harley, S. J., R. A. Myers, and A. Dunn. 2001. "Is Catch-Per-Unit-Effort Proportional to Abundance?" *Canadian Journal of Fisheries and Aquatic Sciences* 58: 1760–1772. https://doi.org/10.1139/cjfas-58-9-1760.

ICATMAR. 2023. "State of Fisheries in Catalonia 2022, Part 1: Report on the Monitoring of the Commercial Fishing Fleet." https://doi.org/10.57645/10.8080.05.7.

ICATMAR. 2024a. "State of Fisheries in Catalonia 2023, Part 2: Stock Assessment." https://doi.org/10.20350/digitalCSIC/16494.

ICATMAR. 2024b. "Evolució Econòmica de les Captures del Sector Pesquer a Catalunya: Comparativa 2022–2023." https://doi.org/10.20350/digitalCSIC/16242.

ICES. 2023. "Workshop on Small Scale Fisheries and Geo-Spatial Data 2 (WKSSFGEO2)." *ICES Scientific Reports* 5, no. 49: 105. https://doi.org/10.17895/ices.pub.22789475.

Iglesias, M., P. Carrera, and R. Muiño. 2003. "Spatio-Temporal Patterns and Morphological Characterisation of Multispecies Pelagic Fish Schools in the North-Western Mediterranean Sea." *Aquatic Living Resources* 16: 541–548. https://doi.org/10.1016/j.aquliv.2003.07.003.

Jennings, S., and J. Lee. 2012. "Defining Fishing Grounds With Vessel Monitoring System Data." *ICES Journal of Marine Science* 69: 51–63. https://doi.org/10.1093/icesjms/fsr173.

Joo, R., S. Bertrand, A. Chaigneau, and M. Ñiquen. 2011. "Optimization of an Artificial Neural Network for Identifying Fishing Set Positions From VMS Data: An Example From the Peruvian Anchovy Purse Seine Fishery." *Ecological Modelling* 222: 1048–1059. https://doi.org/10.1016/j.ecolmodel.2010.08.039.

Katara, I., and A. Silva. 2017. "Mismatch Between VMS Data Temporal Resolution and Fishing Activity Time Scales." *Fisheries Research* 188: 1–5. https://doi.org/10.1016/j.fishres.2016.11.023.

Kawaguchi, O. 2024. "Machine-Learning and Thresholding Algorithms to Automatically Predict Fishing Effort of Small-Scale Trawl Fishery." *Fisheries Science* 90: 123–137. https://doi.org/10.1007/s12562-023-01734-1.

Kimura, D. K., and D. A. Somerton. 2006. "Review of Statistical Aspects of Survey Sampling for Marine Fisheries." *Reviews in Fisheries Science* 14: 245–283. https://doi.org/10.1080/10641260600621761.

Lambert, G. I., S. Jennings, J. G. Hiddink, et al. 2012. "Implications of Using Alternative Methods of Vessel Monitoring System (VMS) Data Analysis to Describe Fishing Activities and Impacts." *ICES Journal of Marine Science* 69: 682–693. https://doi.org/10.1093/icesjms/fss018.

Le Tixerant, M., D. Le Guyader, F. Gourmelon, and B. Queffelec. 2018. "How Can Automatic Identification System (AIS) Data Be Used for Maritime Spatial Planning?" *Ocean and Coastal Management* 166: 18–30. https://doi.org/10.1016/j.ocecoaman.2018.05.005.

Lee, J., A. B. South, S. Jennings Lee, J. Lee, A. B. South, and S. Jennings. 2010. "Developing Reliable, Repeatable, and Accessible Methods to Provide High-Resolution Estimates of Fishing-Effort Distributions From Vessel Monitoring System (VMS) Data."

Lucchetti, A., A. Belardinelli, L. D'Andrea, et al. 2018. "Small Pelagic Purse Seines in the Adriatic Sea: A Spatial Analysis and Technical Overview in Relation to Mediterranean Regulation Provisions." *Marine Policy* 98: 104–114. https://doi.org/10.1016/j.marpol.2018.09.031.

Lundberg, S., and S.-I. Lee. 2017. "A Unified Approach to Interpreting Model Predictions."

Mendo, T., G. Glemarec, J. Mendo, et al. 2023. "Estimating Fishing Effort From Highly Resolved Geospatial Data: Focusing on Passive Gears." *Ecological Indicators* 154: 110822. https://doi.org/10.1016/j.ecolind.2023.110822.

Mendo, T., S. Smout, T. Russo, L. D'Andrea, M. James, and C. Maravelias. 2019. "Effect of Temporal and Spatial Resolution on Identification of Fishing Activities in Small-Scale Fisheries Using Pots and Traps." *ICES Journal of Marine Science* 76: 1601–1609. https://doi.org/10.1093/icesjms/fsz073.

Natale, F., M. Gibin, A. Alessandrini, M. Vespe, and A. Paulrud. 2015. "Mapping Fishing Effort Through AIS Data." *PLoS One* 10: 1–16. https://doi.org/10.1371/journal.pone.0130746.

Owiredu, S. A., S. O. Onyango, E. A. Song, K. I. Kim, B. Y. Kim, and K. H. Lee. 2024. "Enhancing Chub Mackerel Catch Per Unit Effort (CPUE) Standardization Through High-Resolution Analysis of Korean Large Purse Seine Catch and Effort Using AIS Data." *Sustainability* 16: 1307. https://doi.org/10.3390/su16031307.

Palomera, I., M. P. Olivar, J. Salat, et al. 2007. "Small Pelagic Fish in the NW Mediterranean Sea: An Ecological Review." *Progress in Oceanography* 74: 377–396. https://doi.org/10.1016/j.pocean.2007.04.012.

Pedregosa, F., G. Varoquaux, A. Gramfort, et al. 2012. "Scikit-Learn: Machine Learning in Python."

Petitgas, P. 1998. "Biomass-Dependent Dynamics of Fish Spatial Distributions Characterized by Geostatistical Aggregation Curves." *ICES Journal of Marine Science* 55: 443–453.

Quattrocchi, F., and F. Maynou. 2018. "Spatial Structures and Temporal Patterns of Purse Seine Fishing Effort in the NW Mediterranean Sea Estimated Using VMS Data." *Fisheries Management and Ecology* 25: 501–511. https://doi.org/10.1111/fme.12325.

Ribera-Altimir, J., G. Llorach-Tó, J. Sala-Coromina, J. B. Company, and E. Galimany. 2023. "Fisheries Data Management Systems in the NW Mediterranean: From Data Collection to Web Visualization." *Database: The Journal of Biological Databases and Curation* 2023: baad067. https://doi.org/10.1093/database/baad067.

Rufino, M. M., T. Mendo, J. Samarão, and M. B. Gaspar. 2023. "Estimating Fishing Effort in Small-Scale Fisheries Using High-Resolution Spatio-Temporal Tracking Data (An Implementation Framework Illustrated With Case Studies From Portugal)." *Ecological Indicators* 154: 110628. https://doi.org/10.1016/j.ecolind.2023.110628.

Russo, T., L. D'Andrea, A. Parisi, and S. Cataudella. 2014. "VMSbase: An R-Package for VMS and Logbook Data Management and Analysis in Fisheries Ecology." *PLoS One* 9: e100195. https://doi.org/10.1371/journal.pone.0100195.

Russo, T., E. B. Morello, A. Parisi, et al. 2018. "A Model Combining Landings and VMS Data to Estimate Landings by Fishing Ground and Harbor." *Fisheries Research* 199: 218–230. https://doi.org/10.1016/j.fishres.2017.11.002.

Russo, T., A. Parisi, and S. Cataudella. 2011. "New Insights in Interpolating Fishing Tracks From VMS Data for Different Métiers." *Fisheries Research* 108: 184–194. https://doi.org/10.1016/j.fishres.2010.12.020.

Russo, T., A. Parisi, M. Prorgi, et al. 2011. "When Behaviour Reveals Activity: Assigning Fishing Effort to Métiers Based on VMS Data Using Artificial Neural Networks." *Fisheries Research* 111: 53–64. https://doi.org/10.1016/j.fishres.2011.06.011.

Ruttan, L. M., and P. H. Tyedmers. 2007. "Skippers, Spotters and Seiners: Analysis of the 'Skipper Effect' in US Menhaden (*Brevoortia* spp.) Purse-Seine Fisheries." *Fisheries Research* 83: 73–80. https://doi.org/10.1016/j.fishres.2006.08.022.

Samarão, J., A. Moreno, M. B. Gaspar, and M. M. Rufino. 2024. "Improving Machine Learning Predictions When Estimating Fishing Effort Using High Resolution Spatio-Temporal Data: Machine Learning for Fishing Effort."

Saraux, C., J. M. Fromentin, J. L. Bigot, et al. 2014. "Spatial Structure and Distribution of Small Pelagic Fish in the Northwestern Mediterranean Sea." *PLoS One* 9: e111211. https://doi.org/10.1371/journal.pone.0111211.

Shepperson, J. L., N. T. Hintzen, C. L. Szostek, E. Bell, L. G. Murray, and M. J. Kaiser. 2018. "A Comparison of VMS and AIS Data: The Effect of

Data Coverage and Vessel Position Recording Frequency on Estimates of Fishing Footprints." *ICES Journal of Marine Science* 75: 988–998. https://doi.org/10.1093/icesjms/fsx230.

Tejerina, R., M. Hermida, G. Faria, and J. Delgado. 2019. "The Purse-Seine Fishery for Small Pelagic Fishes Off the Madeira Archipelago." *African Journal of Marine Science* 41: 373–383. https://doi.org/10.2989/1814232X.2019.1678520.

Walker, E., and N. Bez. 2010. "A Pioneer Validation of a State-Space Model of Vessel Trajectories (VMS) With Observers' Data." *Ecological Modelling* 221: 2008–2017. https://doi.org/10.1016/j.ecolmodel.2010.05.007.

Wan, L., T. Cheng, W. Fan, et al. 2024. "Spatial Information Extraction of Fishing Grounds for Light Purse Seine Vessels in the Northwest Pacific Ocean Based on AIS Data." *Heliyon* 10: e28953. https://doi.org/10.1016/j.heliyon.2024.e28953.

Xu, Z., J. Wang, C. Zhou, L. Lei, X. Chen, and B. Li. 2023. "Identification of Fishing State of Purse Seine Fishing Vessels Based on Multi-Indices." *Journal of Ocean University of China* 22: 1605–1612. https://doi.org/10.1007/s11802-023-5550-4.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** Scheme on the phases of the purse seiners vessel operations described in the main text. **Figure S2:** Effect of the ping frequency on daily vessel operations time comparing VMS (10 min frequency) and GPS (30 s frequency) data. **Figure S3:** Evolution of vessel speed classified by vessel operation (Fishing, Tracking, Cruising) in four example fishing trips. **Figure S4:** Predictive variables included in the machine learning models. **Figure S5:** Correlation matrix between predictive variables using Pearson correlation and *R* statistic. **Figure S6:** Details on the random forest hyperparameter tuning process. **Figure S7:** Shap values distribution throughout model predictive variables values. **Figure S8:** Fishing effort metrics in maps.