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Original Articles

Estimating fishing effort in small-scale fisheries using high-resolution spatio-temporal tracking data (an implementation framework illustrated with case studies from Portugal)

Marta M. Rufino [a,b,*], Tania Mendo [c], João Samarão [a,d], Miguel B. Gaspar [a,e]

[a] Instituto Português do Mar e da Atmosfera (IPMA), Divisão de Modelação e Gestão de Recursos Pesqueiros, Av. Dr. Alfredo Magalhães Ramalho, 6, 1495-165 Lisboa, Portugal
[b] Centre of Statistics and its Applications (CEAUL), Faculty of Sciences, University of Lisbon, Portugal
[c] School of Geography and Sustainable Development, University of St. Andrews KY16 9AL, St. Andrews, UK
[d] Nova School of Science and Technology, Almada, Portugal
[e] Centro de Ciências do Mar (CCMAR), Universidade do Algarve, Campus de Gambelas, 8005-139 Faro, Portugal

A R T I C L E I N F O

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A B S T R A C T

Small-scale fisheries (SSF, boats < 12 m) represent 90% of this sector at a worldwide scale and 84% of the EU fleet. Mapping the areas and intensity where the fishing operations occur is essential for spatial planning, safety, fisheries sustainability and biodiversity conservation. The EU is currently regulating position tracking of SSF fishing vessels requiring precision resolved geo-positional data (sec to min resolution).

Here we developed a series of procedures aimed at categorizing fishing boats behaviour using high resolution data. Our integrated approach involve novel routines aimed at (i) produce an expert validated data set, (ii) pre-processing of positional data, (iii) establishing minimal required temporal resolution, and (iv) final assessment of an optimized classification model. Objective (iv) was implemented by using statistical and machine learning (ML) routines, using novel combinations of fixed thresholds estimates using regression trees and classification methods based on anti-mode, Gaussian Mixture Models (GMM), Expectation Maximisation (EM) algorithms, Hidden Markov Models (HMM) and Random Forest (RF). Of relevance, the final evaluation framework incorporates both error quantification and fishing effort indicators. We tested the method by running through four SSF fisheries from Portugal recorded every 30 sec, with 183 boat trips validated, and concluded that the more robust time interval for data acquisition in these metiers should be <2 min and that mode and random forest methods with pre-data treatment gave the best results. A special effort was concentrated in a visual support provided by the results produced by this new method, making its interpretation easier, thus facilitating transference and translation into other fishery levels. After the current validation in the Portuguese SSF fleet, we posit that our novel procedure has the potential to serve as an integrated quantitative approach to the EU SSF management.

1. Introduction

Ocean ecosystems are being strained by climate change, overfishing and other anthropogenic pressures, and the success to expand seafood to sustainability to meet future food demands, has been suggested to rely on Small Scale Fisheries (SSF) (Cochrane, 2021; Hendriks, 2022). SSF support the livelihoods of millions of persons, contribute to the food security of around four billion consumers globally, and are a key source of micro-nutrients and protein for over a billion low-income consumers. In the EU the SSF fleet segment, i.e. boats with less than 12 m total length (LOA), represent 84% of the vessels and provide direct employment for ≈100 000 people (Guyader et al., 2013). Additionally, SSF have been considered to be a relevant alternative to Large Scale Fisheries (LSF) for a sustainable use of coastal resources, as these have generally lower discards and a minor impact on the environment (Leleu et al., 2014). SSFs include both static gears, like pots, traps, trammel nets, gillnets and mobile gears such as bivalve dredges. Despite its importance, SSF and traditional fisheries are frequently marginalised

* Corresponding author.
E-mail address: marta.m.rufino@gmail.com (M.M. Rufino).

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(Cochrane, 2021) and little is known on the fishing effort of this fleet or its impacts on the ecosystems. Previous works were focused on LSF, which are obliged to carry tracking devices (e.g. VMS; Vessel Monitoring Systems), register information on log-books and frequently have on-board observers monitoring programmes. A plethora of efforts are required to protect SSF (Hendriks, 2022), assuring a sustainable use of the resources through an ecosystem management approach, which starts by knowing the areas utilised by these fisheries. For this, it is crucial that SSF are properly tracked and the respective spatio-temporal dynamics quantified, which is the focus of the current work.

Current negotiations between the EU Commission, Parliament and Council are underway to implement the tracking of small scale fishing vessels by all Member States (P9_TA(2021)0076). Further, in the EU-MAP (EU 2021/1167), section 3.1, it is mentioned that fishing effort variables should be reported for the whole fleet (not just LSF as it was previously done), and where there is no obligation under the control regulation (EU 1224/2009), alternative sampling methods shall be applied. Therefore, there is an urgent need to develop workflows to optimise and standardise the procedures to analyse high resolution tracking data, such as is required to map SSFs (Egekvist and Rufino, 2022).

McCluskey and Lewison (2008) reviewed methods to estimate fishing effort on SSF, based on fisherman interviews, fleet simulations or estimations produced by extrapolating the relationships between habitat types and fishing intensity. Piet & Quirijns (2009) considered that fishing effort should be estimated at an appropriate spatio-temporal scale, relative to the species spatial processes. In the case of vessel tracks, the scales are a consequence of the time interval between two consecutive recorded coordinates, the so-called temporal resolution. The shortest the time interval, the highest the achievable spatial and temporal resolution. However, higher spatio-temporal resolution also implies to acquire and process more data, which may have financial constraints and challenges of data handling (for example in AIS, the price of the data access changes according to the resolution required).

Therefore, it is essential to define the minimum temporal resolution required to properly monitor SSF and estimate fishing effort. Previous works used different intervals without a scientific justification, namely: 1 s (Alvard et al., 2015), 5 secs (Forero et al., 2017), 45 secs (Behivoke et al., 2021), 1 min (Mendo et al., 2019a; Mendo et al., 2019b; Meyer et al., 2022), 3 min (Burgos et al., 2013; Torres-Irineo et al., 2021), 5 min (Metcalfe et al., 2017; Natale et al., 2015 although LSF), or 6 min (Rijnsdorp et al., 1998; Piet et al., 2007). The optimal time interval between coordinates has been studied in a US grouper reef fishery (Baker et al., 2016), in a crabs and lobsters fisheries in Scotland (resampling from 1 to 1800 sec i.e. 30 mins) (Mendo et al., 2019a; Mendo et al., 2019b), or in seven different fisheries in Gabon (Cardiec et al., 2020). The minimum duration of a fishing trip in a fishery's activity is another aspect essential to define the temporal resolution, as it has direct implications on the number of points that will be available to do the analysis, e.g. a fishing trip of 30 min with 10 min interval will have 3 speed points for the data analysis. Thus, there is no consensus among authors, but the resolution should always be lower than 5 min, and definitely smaller than the duration of the fishing operation (Egekvist and Rufino, 2022). Previous works also suggested that the minimum required time interval should be studied for each metier and performance measures used, and standardized for the sake of comparability between studies (Egekvist and Rufino, 2022).

Besides the time interval, several methods have been used to classify fishing vessels'movement behaviour. Probably, the commonest and simpler one, is to use a fixed threshold based on speed considering the knowledge of the fishery (Burgos et al., 2013; Forero et al., 2017; James et al., 2018). Most works used only one of the available methods, e.g. HMM (Cardiec et al., 2020; Charles et al., 2014), partial sum method (from animal movement approaches) (Alvard et al., 2015) and random forest (Torres-Irineo et al., 2021), but some compared the performance of several methods on the same study (Behivoke et al., 2021; Mendo et al., 2019a; Mendo et al., 2019b), using different criteria. James et al. (2018) and Cardiec et al. (2020) concluded that the sets of criteria used to estimate fishers behaviour from SSF tracks need to be tailored to the specific fishery and allow for some regional variations depending on operational characteristics of the fleet. Region-specific approaches may be required to correctly estimate fishing effort. Thus, whether the applied model varies with the metier or the same model is applied to all within the same region, several statistical and machine learning algorithms are available to classify fisher's behaviour and previous works suggest that these should be assessed in each particular case. It is clear that the performance of different methods should be evaluated using a validation data set (Mendo et al., 2019a; Mendo et al., 2019b), which can be produced by on-board observers, by expert's visual analysis or by electronic equipment (e.g. sensors in the boat gears).

In the current work we develop an assessment framework, that includes (i) a procedure for making an expert based validation set; (ii) evaluation of data pre-processing procedures; (iii) evaluation of different approaches to classify fisher's behaviour, including threshold based methods, statistical and machine learning based methods (ML); (iv) assessment based on error measures and fishing effort indicators and (v) evaluation of the minimum time interval, i.e. temporal resolution (ping rate) (Fig. 1). The framework was illustrated using four case studies from Portugal (including fixed gears and mobile gears), eight approaches (models) and a time interval between the recorded coordinates from 30 secs to 10 mins were assessed. Thus, the aim of the current work is to develop a framework to evaluate models used to estimate fishing effort from vessel tracking data, then to demonstrate the framework using four SSF metiers in Portugal (bivalve dredges and octopus traps) and also, to evaluate the influence of frequency of data acquisition (time interval) on fishing effort estimates.

2. Materials and methods

2.1. Making a validation data set

A validation data set is essential to compare the models or time interval. To make a validation data set, a random stratified sampling by boat trip was carried out on the complete one-year data set after the boat trips have been identified. Stratification was done by fishing ground (area), gear (dredge or pots & traps) and month, as in SSF there are commonly seasonal patterns. One hundred eighty-three fishing trips carried out by 50 boats during 2017 were randomly selected using stratified sampling by (i) fishing target (136 boat trips targeting bivalves using dredges and 47, targeting octopus using pots & traps), (ii) fishing grounds (49 boat trips targeting bivalves in northwest of the country; 51 in southwest and in the south, 36 boat trips targeting bivalves and 47 targeting octopus) and (iii) month of the year, for the validation procedure (Table 1).

In view of the restrictions associated with the Covid pandemic, it was not possible to have on-board observers to register fishing activity (as it was initially planned) and therefore all validation was done visually by an independent expert, which has > 30 years of experience with small scale fisheries in Portugal, being an international expert in bivalve fisheries (Miguel Gaspar) using interactive plots of speed vs. time and mapped tracks (produced using Rufino_2023_validation.pdf with the script chunks in it) together. The expert registered the starting and ending time of each fishing and travelling events during each fishing trip, which was then used as the validation data set. This method was also used during the WKSFGEO2, in several European case studies, with success (pers. com. from MMR) (Mendo et al., 2023).

The classification of the periods corresponding to each fishing operation was then simplified into 'fishing' (retrieve or haul the gear and dredge fishing) and 'traveling' or not_fishing (set the gear & travel) only. Speeds associated with setting of the gear in the octopus's fishery were very similar to travelling speeds, and quantifying these would have doubled the fishing effort. Therefore, this fishing activity was coded as

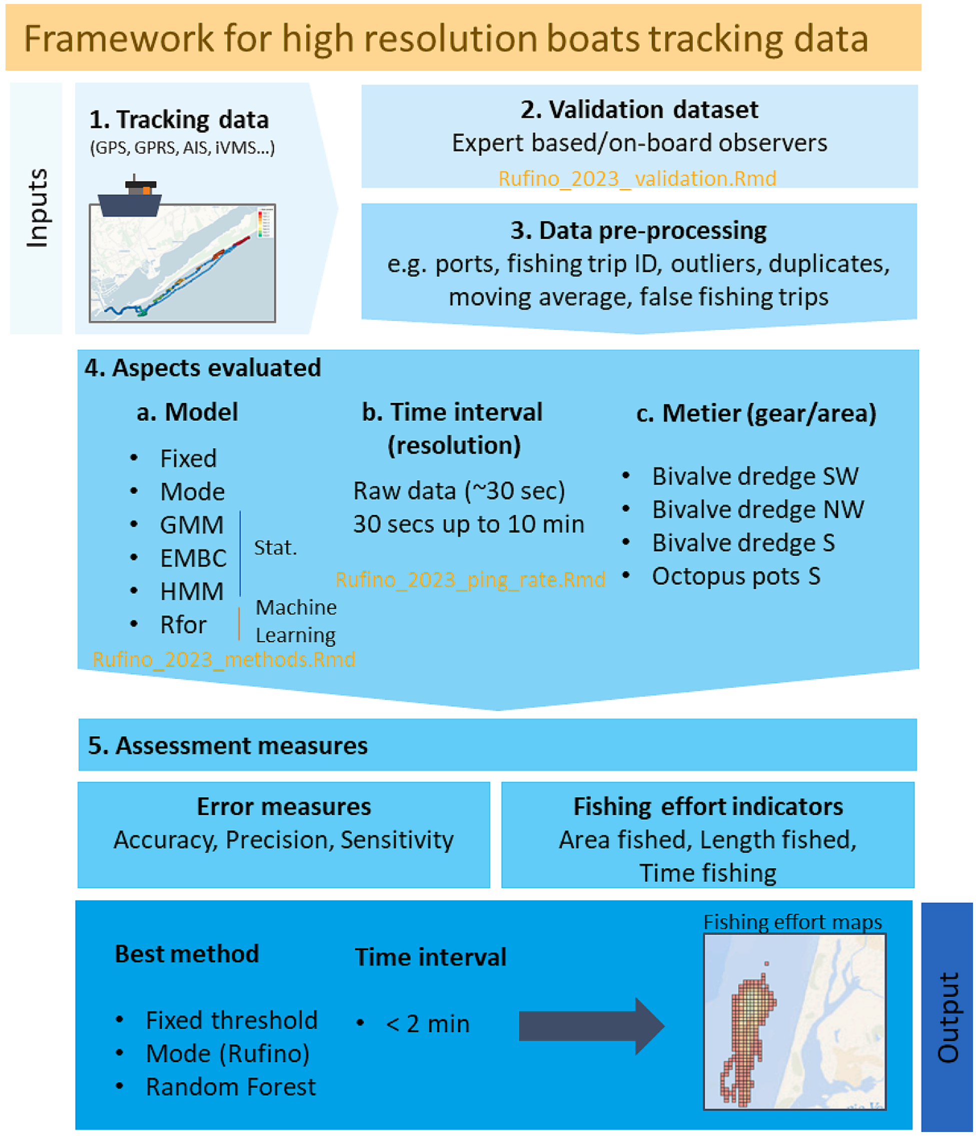

Fig. 1. Graphical summary of the framework proposed.

'travel' in the current work.

Further, out of the 183 boat trips, 22 trips corresponded special cases as these were either travel only trips (boats traveling from one port to another, situations where the boats went out of the port but returned to the port without having actually fished), or were segments of a fishing trip (fishing trips that took place during two successive days, between months) and so classified as incomplete trips by the expert. These were classified as special cases, but modelled similarly to account for if the models were able to detect those faults (Table 1 and S.Fig. 1).

An R markdown file is provided in the MS, with a template that can be used in any work to produce an expert based visual validation (Rufino_2023_validation.pdf). This has interactive plots of speed versus time and geographic position of the tracks. The html with the interactive plots of this boat trips is then given to the independent experts, who identified the exact time when the haul started and finished in each case, as well as the probable gear used. The data was then connected to the data base, producing a validation data set.

2.2. Data pre-processing

When we started approaching this subject it was observed that small changes in the data pre and post processing caused substantial differences in the results (see also Samarão et al., in preparation). Although most previous works have little reference to this aspect, we concluded that this is something of outmost importance, and that it should be included always in this type of analysis, for the sake of repeatability. Mendo et al. (n.d.) proposes a framework for pre-processing alternatives using this type of data. A detailed description of all the steps carried out, as an illustration of the case-study can be found in supplement 1.

2.3. Statistical and machine learning analysis

Six approaches were applied to classify the boats movement into fishing/traveling (not_fishing) and assessed against the expert validated data set (coded as 'Val'), by boat trip.

The first approach used a fixed threshold applied to speed (labelled as 'Fix' in the figures), estimated using expert knowledge of the fisheries (boats are always fishing bellow 5 knots), and as the result of a regression tree analysis (RT). Above this value, the speed would be classified as traveling and below, it would be coded as fishing. The results of the RT analysis showed a speed threshold of 5.4 knots ('Fix') and of 4.8 knots, if the speed moving average was used ('Fix2'). The RT model was built as: classification ~ speed + latitude + longitude + bearing + zone + target

Table 1
Details of the boats trips and respective boats used in the current work, by fishing ground (Zone) and gear. LOA represents boat length, not valid are travel trips are the boat trips where the boat was within the port only (thus not evaluated by the model).

Summary of the boats sampled				
Zone Gear	NW Dredge	SW Dredge	S Dredge	S Pots
N° of boats	12	11	21	8
Valid trips	45	47	33	43
Not valid	4	4	3	4
N° fish events/ boat trip (max)	3	3	7	15
LOA (mean)	13	11	8	10
LOA (range)	11—16	10—13	5–11	7–13
Engine power (mean)	89.04	75.11	48.62	61.89
Engine power (range)	55—128	73.08—96.94	29.83—71	44.13—72.33
Total distance (km) (mean)	89	61	39	71
Total distance (km) (range)	36—183	30—133	12—87	35—150
Time duration (mean)	10:27 h	10:44 h	06:35 h	08:32 h
Time duration (range)	03:23 h – 23:07 h	02:36 h – 15:06 h	01:38 h – 11:58 h	03:51 h – 12:43 h

species. In the resulting tree, only speed was found to be important to classify fishing behaviour, in spite of the 6 covariates used on the initial model.

The second approach considered was an empirical method developed specifically for this fishery (labelled as 'Mode'). The modes and anti-modes of each boat trip moving average speed were estimated using multimode r library (Rodríguez-Casal et al., 2021). Moving average speed values above the anti-mode were classified as traveling, and values bellow, classified as fishing, accordingly. Modes were bounded to be between 6 and 3 knots (interval defined in preliminary analysis), and only estimated for cases with > 30 observations. Although this simple method was developed for this case study, it can be used in any other fishery.

The third approach used Gaussian Mixture models (coded as 'GMM'), which was found to be the best model by Mendo *et al.* 2019 fisheries (Mendo et al., 2019a; Mendo et al., 2019b). Unlike in Mendo *et al.* (Mendo et al., 2019a; Mendo et al., 2019b) where three states were considered, in the current work only two states were used to make it applicable to all Metiers and in face of the objectives (discriminate between fishing or traveling/not_fishing). This approach was also applied using the moving average speed (coded as 'GMM2').

The fourth and fifth approaches considered were EM binary clustering (coded as 'EMBC') and Hidden Markov models (coded as 'HMM'). For these, similar to the GMM, Mendo *et al.* (Mendo et al., 2019a; Mendo et al., 2019b) code and procedure were followed (see that MS for further details).

The sixth approach considered was a machine learning method, Random forest classifier (coded as 'RFor'). The model developed was: classification ~ latitude + longitude + speed.r + month + hour. This method was selected among several methods alternative methods tested in a parallel work, where all details on ML procedures can be found (Samarão et al., in preparation).

An R markdown file is provided with the code to apply the methods and compare these (Rufino_2023_methods.pdf).

2.4. Effect of temporal resolution

The tracking devices produced data that were irregularly spaced on time, although most intervals were 30 s or smaller. To study the effect of time interval, the irregular time series were linearly interpolated to a regular time series of 30 s (=0.5 min), 1, 2, 4, 5, 6, 8 and 10 min intervals. Raw data was coded as 'zero' (factor) for plotting and modelling, which represented the base line, i.e. not interpolated.

The validated data set was used to assess the effect of time interval (pooling interval between boat tracks geolocation) and modelling procedure (threshold-based methods, statistical procedures and machine learning), both in the error measurements of the methods and in the impact on the estimated fishing effort indicators. An R markdown file is provided with a description of the procedure to interpolate the data making time series with different resolutions and evaluate temporal resolution (Rufino_2023_ping_rate.pdf).

2.5. Methods assessment

Methods were compared with the validation data set using two types of criteria (1) error measurements and (2) impact on the estimated fishing effort indicator. For this section, the data set was randomly stratified, split into a training (60% of the boat trips) and testing data set (40% of the boat trips) (Samarão et al., in preparation). Despite all methods being applied to the complete data set, random forest was trained only with the training data set and tested only with the testing data set. Therefore, to compare between methods, the assessment was done only using the test data set, as the machine learning algorithms are known to give overoptimistic estimates. Preliminary results show that for the remaining methods, the evaluation measures using the test and training data sets were very similar (S.Fig. 2).

Machine learning methods are generally assessed using error measures derived from the classification matrix. The classification matrix is simply a table with the number of observations predicted and observed by class. However, from this table at least seven error measures are often calculated and used in previous works:

(1) Accuracy, (TP + TN)/(TP + TN + FP + FN) = (TP + TN)/N; represents the proportion of correct predictions, i.e. the percentage of classifications that were correct, that is the boat was classified as fishing and was actually fishing or the boat was classified as not-fishing and was actually not-fishing;
(2) Precision, TP/(FN + FP); represents the proportion of correct positive predictions, i.e. out of all points classified as fishing, which percentage the boats were actually fishing;
(3) Sensitivity (recall), TP/(TP + FN); represents the proportion of observed fishing activities that were well classified, i.e. from all points that the fishers were fishing, which percentage was actually classified as fishing by the method, or the probability that a test will indicate'fishing' among those which were actually fishing (Cardiec et al., 2020);
(4) Specificity, TN/(FP + TN); represents the proportion of true negatives, i.e. out of the points that were actually not fishing, what percentage was correctly classified by the model as ot-fishing, or the probability that a test will indicate'non-fishing' among those which were actually not fishing (Cardiec et al., 2020);
(5) F1 score, 2/((1/Precision)+(1/Recall)); was develop to avoid false negatives and false positives;
(6) AUC, represents the area under ROC curve produced with relationship between RECALL and false positive rates;
(7) Class error

Each of these measures addressed different faults in the models (S. Fig. 3). The seven measures were estimated for all methods using the test data set. As it is impracticable to evaluate seven measures simultaneously, a selection of the measures was done as a result of a compromise of (1) the correlation between all error measures obtained (2) from the groups that were identified through cluster analysis, only one measure was selected in each case (3) variability on the information of the aspects being retrieved (S.Fig. 3). The correlation matrix generally shows a correlation cascade between variables, which can be easier to disentangle using cluster analysis (Rufino et al., 2021; Rufino et al., 2018a). Further details on the formulas used to calculate the error measures can be found elsewhere. Error measures were than estimated by boat trip on the test data set and compared using the average and bootstrap 95% confidence interval by factor level (i.e. gear, area, temporal resolution).

For the impact of temporal resolution, model and metier on the fishing effort, the results of the models were mapped into 500 m grid cell covering all the fishing grounds, and three FE indicators were calculated (details on the gridding procedure can be found supplement 3):

(1) the total area of fishing activity, estimated as the sum of the number of cells where fishing occurred.
(2) the length of fishing activity, estimated as the sum of the length of the fishing track in each grid cell.
(3) the time fishing, estimated as the total amount of time passed fishing in each grid cell.

The percentage of deviation of each indicator relative to the baseline (raw temporal resolution, validation data set) was than estimated by factor level (temporal resolution, model and metier) to evaluate the impact of each approach on the FE indicators.

An R-markdown html is provided along with the MS, with a detailed R script to make the methods evaluation ('Rufino_2023_methods.pdf') and temporal resolution ('Rufino_2023_ping_rate.pdf'), and the respective functions needed produced for it.

2.6. Case study data

To estimate the spatio-temporal dynamics of small-scale fisheries (SSF) in Portugal, real time GPRS tracking devices were installed in two gears, at three fishing grounds (i.e. 4 métiers): (1) a bivalve dredge fleet operating on northwest (Dredge.NW), (2) a bivalve dredge fleet operating on the southwest (Dredge.SW); (3) a bivalve dredge fleet operating on the south (Dredge.S) (all operating boats were tracked), and (4) a fishery targeting octopus using pots & traps, located on the south of the country (Pots.S). Most of the boats capturing octopus were using pots, but it is possible that some were also using traps as they are allowed to use both and it is not possible to determine which one was used in each case. Additionally, although the official definition in the EU for SSF is boats with LOA less than 12 m, some boats of the bivalve dredge fisheries in the west were larger, in particular in the northern fleet (max LOA 16 m, Table 1). The summary of the boats characteristics and respective trip analysed in the current work can be found in Table 1.

3. Results

3.1. General remarks of the data set

From the 183 boat trips randomly selected, 14 were actually not valid and not evaluated because they were all inside the port, 1 had only 26 points outside the port (low n), thus was also not valid (Table 1, S. Fig. 1). Besides these ones that were actually not evaluated by the models, 8 trips were identified as travel only by the expert and 11 were incomplete trips that occurred between months. The incomplete trips, in most cases do have enough data to be modelled and classified by any of the models used. These 19 boat trips were still evaluated by the models despite not being a regular complete fishing trip, as they would be in an ordinary situation, because they would have not been detected by the filters. Thus, the final data set had 168 boat trips evaluated, from which 149 were complete, regular fishing trips. Note that this implies that 4% of the trips were travel only, 6% were incomplete trips and 8% were invalid, considering the validation data set was selected randomly, and therefore should be representative of the complete data set.

3.2. Aspects related with temporal resolution

Boat trips lasted between 01:38 h and 23:07 h (excluding not valid trips), being shorter in the south (bivalve's boat trips: 06:35 h and octopus 08:32 h, on average) than in both western areas (west-north 10:27 h and west south 10:44 h, on average) (Table 1), whereas fishing events lasted from 5 min (probably corresponding to a test to check the level of resource, M.B. Gaspar pers. com.) to 5:55 h, with an average of 1:40 h for the octopus boats and from 5 min to 13:27 h, with an average of 4:18 h for the bivalve dredge boats. Bivalve dredge fish events were much larger in the north than in the south (boats are also larger, and the respective fishing grounds have different characteristics).

The duration of the fishing trips and fishing events has strong implications on the methods that can be applied in each case, due to the number of temporal points required to make the analysis. For example, shorter boat trips in the validation data set lasted less than 2 h, (i.e. 98 min), which implies that if the data is recorded with 10 min interval, only 9 points would be available for the analysis, if time interval would be 5 min, we would get 19 points. In both cases, any methods based on the estimation of modes of the distributions corresponding to fishing/traveling speed, will hardly work with such a low number of points (because the distribution will not be well defined). Even for ML based methods, in face of the strong scattered nature of these models, the results would be hardly accurate.

Fig. 2 shows an example of an octopus trip (section), and it is clear that only for 0.5–1 min intervals, the regular series follows closely the raw data (mostly 30 secs), 2 mins appear to be acceptable too, whereas periods greater than this seems to apparently have too low resolution to properly detect the fishing patterns. Similar patterns were observed for the bivalve fishing trips, which also required a minimum of a 2 mins interval to properly capture the activity (Fig. 3). Further, if considering an interval of 5 mins, 9% of the bivalve boat trips in the south would have less than 30 points, and 56% would have less than 100 points, which may impact the analysis. Thus, it is required intervals every 2 min or lower properly model this data (S.Fig. 4).

During a fishing trip, octopus boats made 71 km on average, and the ones targeting bivalves, 39 km in the Algarve, 61 km in the southwest and 89 km in the northwest of the country. In some boat trips the total number of km done decreased substantially for larger time intervals (temporal resolution). This was particularly the case in dredge fishery in the Algarve, where the greater time intervals (temporal resolution) resulted in missing the typical 'fishing loops' done in this fishery (Fig. 3). For example, by increasing the intervals from 30 sec to 10 min, the km done decreased from 39.4 km to 14.5 km (a difference of 24.9 km, 63%) whereas with a 5 min interval, the decrease was 45%. Even for the octopus' trips, 3 trips showed a decrease of $>$ 30% in the km fishing if higher temporal resolutions were used. Thus, the impact of temporal resolution on the km done during the fishing trip can also be substantial for these SSF fisheries.

3.3. Methods feasibility (applicability)

From the 169 boat trips, 11 trips were incomplete fishing trips, cropped by some reason (like change of month, etc.), therefore not filtered thus also evaluated by the model. From the 8 trips that corresponded to travel only chunks, EMM, EMM2, EMBC and RFor gave the usual classification of fishing/traveling and did not showed any issue, i.e. did not detected that those trips were not actually a fishing trip. For

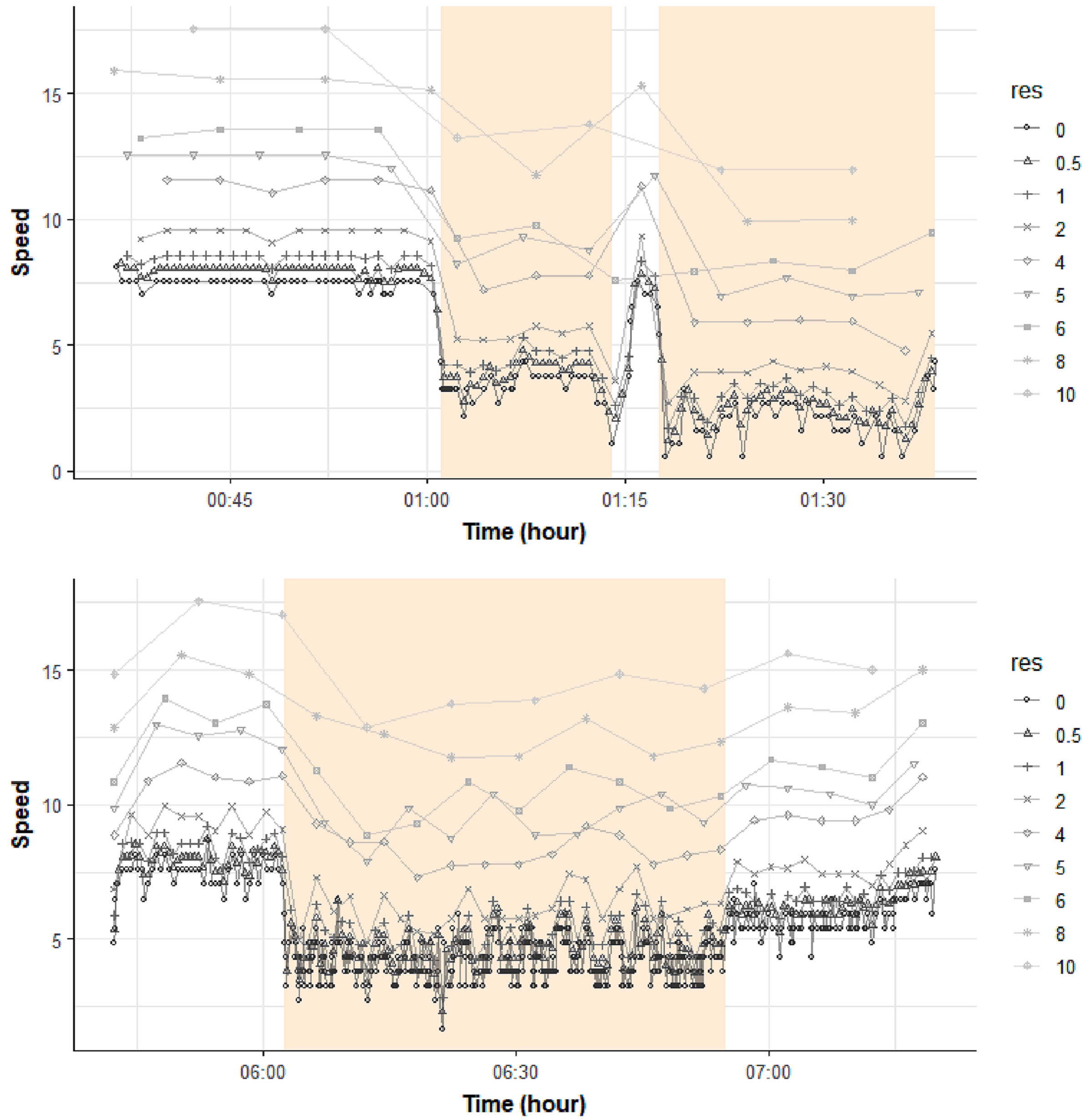

Fig. 2. Speed by time plot of a bivalve dredge (upper panel) and an octopus traps (lower panel) section of a boat trip example (only a section shown) to illustrate the effect of changes due to decreasing temporal resolution (increase time interval between points). Note that a constant was added to the speed by resolution level on the y axes to avoid overlap and improve visualization).

the Mode, it modelled normally 6 of these trips and showed problems in only 2, whereas HMM showed convergence issues on all of those 8. Additionally, EMBC and HMM showed modelling issues on other 5 and 11 boat trips respectively. Therefore, none of the methods were able to discriminate these fishing trips that actually did not corresponded to fishing. Further, the methods based on a fixed threshold were also not able to solve this issue. These false fishing trips were then removed from further analysis, as it might cause biasness on the results. Ideally, in future works, there should be a method to detect false fishing trips *apriori*, before the analysis to avoid such errors. Overall, from all methods considered, HMM was the most problematic one, not being able to model 11% of the boat trips tested, followed by EMBC.

3.4. Comparison of ML and statistical methods

To compare between ML and statistical approaches, error measures were estimated for the test data sets only (40% of the boat trips on the test data set) (S.Fig. 2). The results were coherent among error measures, with overall, accuracy, F1 score, Precision, Sensitivity and specificity giving similar patterns between methods. Nevertheless, Accuracy, class error (inverted), AUC, and F1 score formed a cluster group showing highly correlated measures, and precision showed high correlation with specificity, whereas sensitivity was separated from the others (S.Fig. 3). Thus, for further analysis, only Accuracy, Sensitivity/recall and Precision were used to improve interpretability.

The models Fix2, Mode and Rfor methods showed the highest accuracies (all about 95% on average) (Fig. 4), and along with Fix method, were also the methods showing highest Sensitivity (>97%), with Rfor being slightly lower but still very high (96%). The method showing higher precision was GMM2 (98%), and for this error measure, Rfor and Mode showed higher precision than Fix2 (96%, 96% and 95%). Overall, methods using moving average (Fix2, Mode and Rfor) showed better classifications according to all error measures considered (always above 95%), whereas the difference between these three models was always

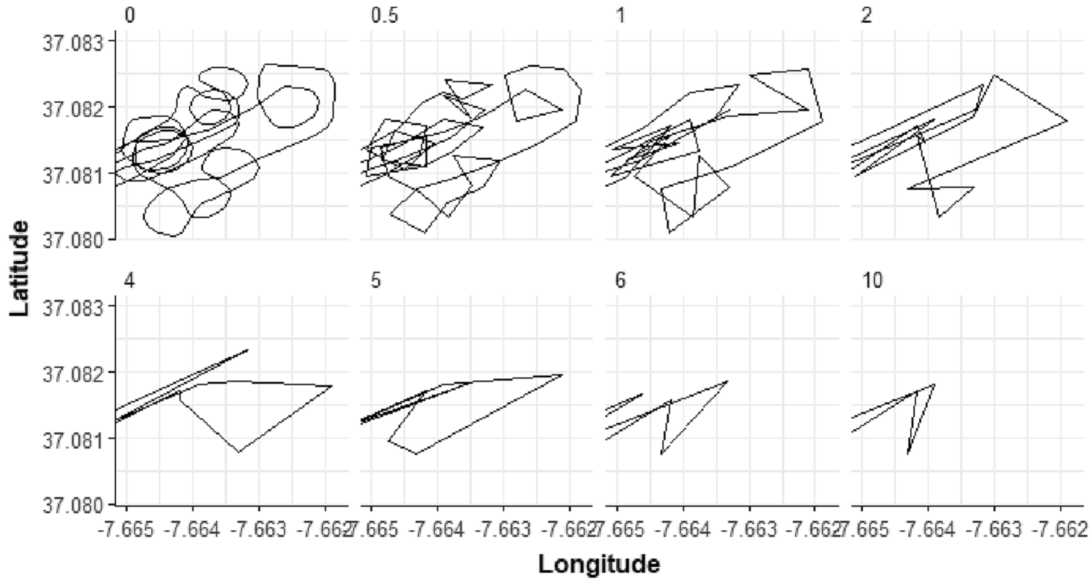

Fig. 3. Detail of a bivalve dredge boat trip, showing the typical loops registered for this gear. See the changes in the data with decreasing temporal resolution (increase time interval between points).

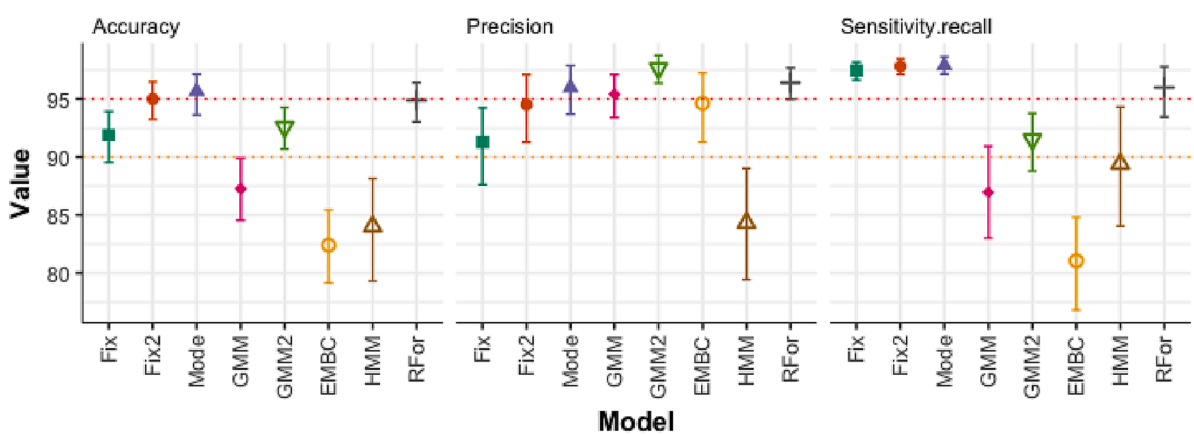

Fig. 4. Comparison of the accuracy, precision and sensitivity shown by the models used to discriminate between fishing and traveling activities on the SSF fisheries, using the 'test' data set with raw temporal resolution (~30 sec), and excluding travel only trips (see text for further details on the models).

less than 5% on average. Considering the three measures, the Mode method was marginally a better classifier and had lower variability. The good performance of Fix2 model is a plus in this work, stating that perhaps not as much sophisticated methods are required in many cases.

The differences in the error measures between Metiers were very small, in particular for the methods Fix, Fix2, Mode and Rfor, being less than 5% on average (S.Fig. 5). For GMM, EMBC and HMM, the changes were wider, but there was no clear pattern in the data. For example, pots showed higher values of accuracy and sensitivity, but lower precision then the other metiers for GMM and EMBC models.

The number of observations available to make a model is a consequence of time interval and fishing events duration and can be a limiting factor in the methods application. Some methods might need higher number of observations to be applied than others, thus this aspect was also considered. Model performance did not vary strongly with the number of observations present in the boat trip and used in the analysis, except for the smallest class, which had between 50 and 100 geolocation points (S.Fig. 6).

3.5. Changes in temporal resolution

Performance of the models decreased with temporal resolution, overall, and the observed patterns were similar between models (Fig. 5). Only GMM and Fix methods did not decrease performance with temporal resolution. However, in spite the percentage in decrease changing widely with the model considered and the error measure used, for the best three methods (Fix2, Mode and Rfor), it was always lower than 5%.

3.6. Effect of model and time interval on fishing effort maps

The impact of using a different model or time resolution was also reflected in the fishing effort maps produced, consequently, for the three variables considered: (1) total area fishing (number of grid 500 m cells), (2) total km fishing (sum of the length fishing in all area) and (3) total number of hours fishing (sum of the time spent fishing in all grid cells). As in the previous cases, for comparability between ML and statistical methods, only test data was used in the analysis, but the results were similar for the complete data set, except for ML (not shown for brevity) (65 boat trips).

Considering only the validated data set, the total area of the fishing

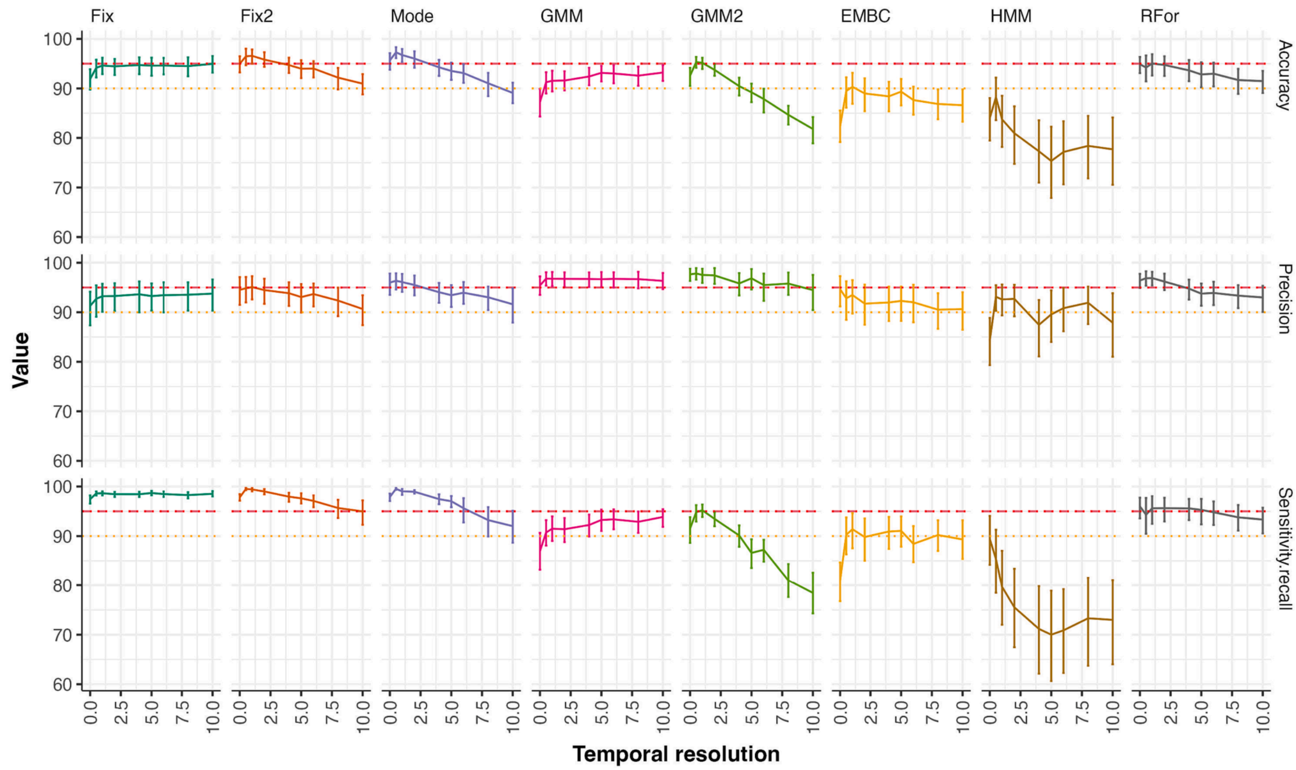

Fig. 5. Comparison of the accuracy, precision and sensitivity by temporal resolution and model used to discriminate between fishing and traveling activities on the SSF fisheries, over time resolutions (time interval between points). Only the 'test' data set with raw temporal resolution (~30 sec), and excluding travel only trips were used (see text for further details on the models).

operations decreased up to 48% if 10 min were used as time interval (from 2026 cells for 30 secs resolution to 1046 cells in 10 mins resolution), whereas the length fishing decreased 28% (1625 km to 1176 km) and the time fishing only 3% (405 h to 393 h). This can be due to the geometrical shape of the track which is not a straight line, therefore when the number of points decrease, a part of the loops characteristic of the Metier are lost, but little change is evident time fishing (Fig. 3).

The use of a different model (considering only raw resolution, i.e. res = 0, which corresponds to about 30 secs), caused a change in the estimated total area fishing of up to 45% (considering HMM, 2026 cells to 2932 cells), in the length fishing 12% (fixed model, 1625 km to 1827 km) and in time fishing 11% (fixed model, 405 h to 451 h), relative to the validated data set.

The effect of the model used overall increased the fishing effort indicators for the NW and SW, whereas for the S zone, the impact was reduced. The time interval was the indicator less affected to model and metier (Fig. 6). Thus, the effect of model and time interval changed between metiers.

Similar to previous results, the methods using rolling average (Fix2, Mode, GMM2) and Rfor showed smaller deviations on the fishing effort indicators relatively to the validated data set than remaining ones, as these performed better overall (Fig. 7).

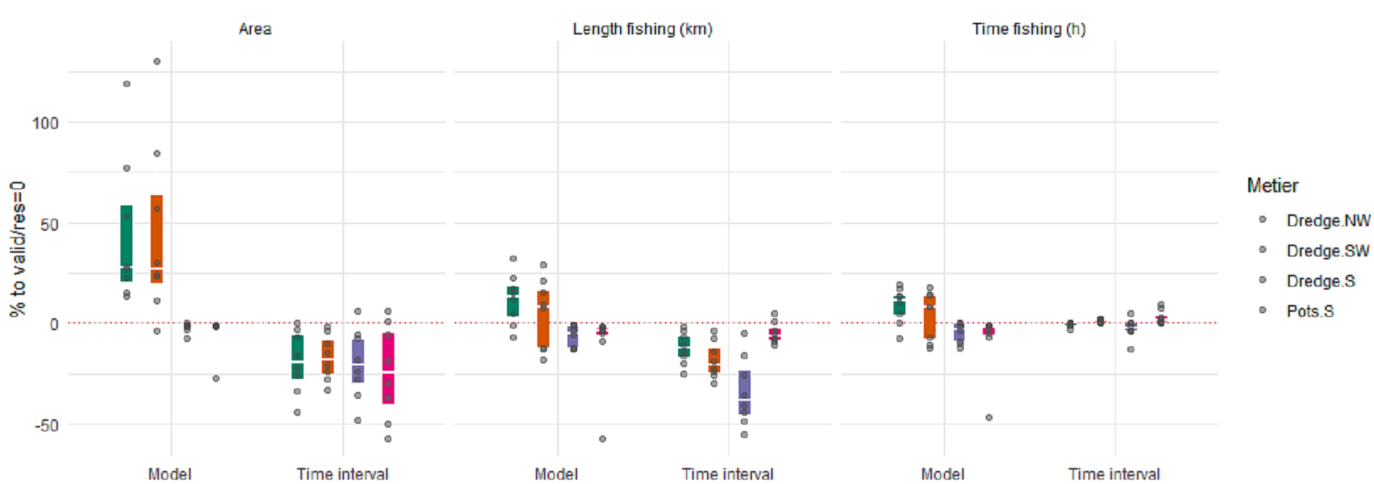

Fig. 6. Change in relation to the validated data set with ~ 30 sec interval (in percentage), associated with the model used (see the text for details) and time interval, for each métier and fishing effort indicator (Area as the number of 500 m cells, length fishing and time fishing). Only test data was used, and interactions were omitted (i.e. higher resolutions than raw data for different models).

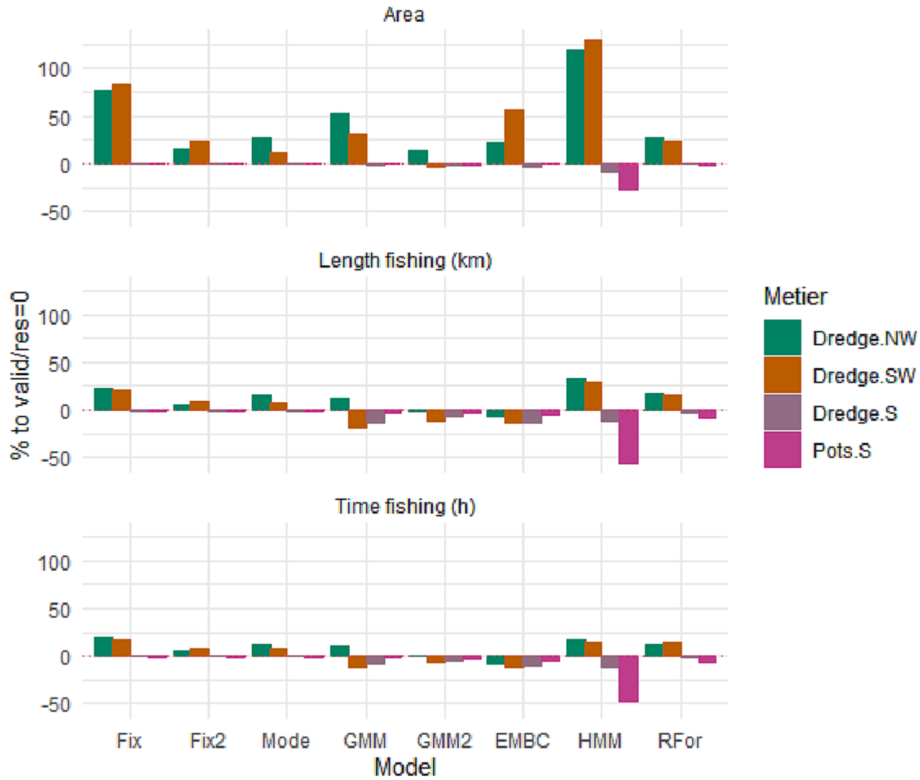

Fig. 7. Change relative to the validated data set with ~ 30 sec interval (in percentage), associated with the model used (see the text for details), for each métier and fishing effort indicator (area as the number of 500 m cells, length fishing and time fishing). Only test data was used, and interactions were omitted (i.e. higher resolutions than raw data for different models).

4. Discussion

To properly estimate fishing effort in SSF, new challenges arise, related with the particularities of this fishery, which among other aspects, require high resolution spatio-temporal data (Egekvist and Rufino, 2022). Thus, the development of new analytical frameworks as the one proposed in the current work is essential. The new framework includes all steps of the analysis, namely a protocol to develop an expert validation data set (when it is not already available), a procedure to evaluate the different models and the evaluation measures to be used in the assessment, including both error measures and fishing effort indicators. It also permits to compare methods used to classify fishing behaviour, based on a fixed threshold, statistical models and machine learning algorithms, and incorporate new and future methods (Infante et al., 2022). The particularities of the SSFs make the tracking behaviour to be very variable between metiers, and as a consequence, the best methods often vary at least with gear type and locality, therefore the need to standardize procedures for the sake of comparability, even within one area or country.

4.1. Framework and case study results

In the current work, using the framework developed, we concluded that a minimum of 2 min interval between geolocation points is required to estimate fishing effort in the SSF case studies considered and that the Mode approach (method developed for the case study data set) and Random Forest gave the best results overall. With a proper pre-processing procedure, a fixed threshold also gave excellent results, highlighting the importance of the pre-processing procedures and its detailed description in future works. However, we also found substantial differences between Metiers, and thus the assessment framework developed in the current work should be applied all Metiers being addressed. Furthermore, due to the sensitivity of the estimates to small changes in the approaches used and the data set *per se*, it is thus strongly advisable that to be operational into a regular monitoring tracking system, the framework should be applied regularly. For example, it can easily be repeated every year with the new data incorporated, and the respective validated data set produced for this purpose with randomly sampled data from the boat tracks of the given year, as part of the protocol for analysing this type of data.

4.2. Validation data set

Some previous works on estimating fishing effort from tracking devices in SSF use data validated by on-board observers (Cardiec et al., 2020; De Souza et al., 2016), whereas in others no validation data was used (Charles et al., 2014) or the information is provided by fisherman interviews. In the current work, the development of an expert visual validation data set was initially done as a consequence of COVID pandemic, as it was not possible to make on-board observations as initially previewed. However, after, we found that this was an excellent option to make an accurate validation data set, with higher number of observations to perform the analysis than we would have obtained by on-board observers. Cardiec et al. (2020) obtained accuracies of 95% using HMM computed by gear type, validated against trips with onboard observers, which were also compared with visual expert based validation and concluded that Hidden Markov model were much quicker than visual expert validation. These author's framework has some similarities with the current one, namely different approaches are compared using performance measures derived from the confusion matrix and fishing indicators. In the current work it would be interesting to have on-board observers validated data, to compare it with the expert validation, to quantify the error associated with this validation approach, which is part of our proposed framework. Direct observation of fishers ' behaviour are ideal, but it is difficult—often impossible, time consuming, and costly, whereas in contrast, the advantages of the expert validated method includes a larger sample, reduced risk and cost, computational and analytic simplicity, and very good results (Alvard et al., 2015). We conclude that the validation data set, either produced by (1) on-board observers, (2) electronic equipment (some sensors or cameras might record the behaviour) or (3) expert based (as the current work) or a combination of any of these, is essencial to assess the models or other related options. Perhaps, in an ideal case, it would be possible to make some on-board validation, complemented and compared with expert validation to have a robust data set to asses the best modeling approach for each Metier.

4.3. Pre- and post-processing

All tracking systems require several pre-processing steps and data cleaning procedures, before the models are actually applied. James et al. (2018) described the pre-processing difficulties that can be found when using AIS data. In the current work we also observed that these preliminary steps may have strong impact in the results, although these steps have been barely described in the literature. Thus, the explanation of these steps in detail is an essential part of the framework proposed and should be mandatory in future works. That is, a detailed list of all the steps carried out since the data arrives from the GPS, GPRS, AIS, iVMS (etc.) until the statistical models are applied. A framework to guide the researchers through the different pre-processing options is being currently produced which complements this framework (Mendo et al., n. d.).

4.4. Fishing trip variability: Not only fishing trips in fact

In the current work, some trips corresponded to tracks where the fishers were only traveling or simply checking if the area has the required resources (testing the fishing ground), i.e. not real fishing trips. Ideally, such false trips should be removed from the data set *apriori* as part of the data cleaning procedure. However, to the authors best knowledge there is currently no automatic method applicable to address this aspect. For each metier the diversity of fishing tracks needs to be addressed and studied in detail, and requires local knowledge of the fisheries along with a preliminary analysis. A list of the main alternative tracking behaviours identified should be part of the results shown in each work and of the pre-processing framework to be developed in the future, so that researchers can quickly identify and quantify the presence of these particular cases (like S.Fig. 1). This should be clearly declared as it can interfere with the analysis results. In the current work, even using all the filters considered, 4% of the boat trips were travel only and this classification was not detected by the methods used. Thus, the filtering methods should be improved in the future, as 4% of millions of data points of a monitoring system, such as it is the dimension of the data set, can be still a considerable amount of a fishing impact that was not properly assigned.

4.5. Model assessment: Error measures

Each previous work used different assessment approaches, thus being hardly comparable, and therefore the urge to standardise the procedure. Mendo et al. (2019a,b) estimated accuracy calculated by trip to assess statistical model performance, but also true-positive and false-positive rates and the time elapsed for each analysis. Cardiec et al. (2020) used sensitivity, specificity, but also fishing prediction (which indicates the probability of true fishing positions among fishing positions detected by the model) and the non-fishing prediction (indicates the probability of true non-fishing positions among non-fishing positions detected by the model). Behivoke et al. (2021) used sensitivity, specificity, true positive rate and true negative rate to estimate the fixed threshold, then followed by Torres-Irineu et al. (2021) that also used the first two measures. Thus, there is a large panoply of assessment error measures being used in previous works to compare models, with no explanation on why these were chosen, instead of the others. In the current work, we started by calculating the seven standard error measures most commonly used in ML, all directly derived from the confusion matrix, namely class error, Accuracy, Precision, Sensitivity/recall, Specificity, F1 score and AUC. All these have straight-forward formulas (do not require a package or special code to calculate it) and represent slightly different aspects where the model applied is failing (see the formulas and description in the methods section). However, the results given by these measures also overlap substantially as it can be seen by the large correlations observed ($r > 80\%$), being, therefore potentially redundant. Additionally, it is challenging to interpret several measures simultaneously and to the authors best knowledge there is no rules on which ones to use for each case, as it is confirmed by the variety presented in previous works.

The approach followed in the current work, by estimating the correlation matrix and applying cluster analysis to determine the groups with overlapped results (Rufino et al., 2018a) permitted to reduce to three measures only, which are easier to interpret. Having stated that, this does not imply that one measure is more adequate than the other, but rather shows that within each group the results given by each measure would be redundant (Rufino et al., 2018a). Furthermore, within each group, the measure selected was based on the simplicity of calculations and previous use (accuracy, for example is commoner then class error), which are subjective criteria. The use of the three measures considered, i.e. accuracy, specificity and sensitivity, simplified substantially the interpretation of the results and model comparison. These error measures showed different patterns between the factors studied: models, temporal resolution and gear/zones. Despite the fact that the observed differences in the error measures are difficult to interpret in terms of fisheries, this approach permits a broader evaluation of the aspects where the model is failing. That is, the three different measures reflect diverse aspects where the models are failing.

4.6. Use one model for all or one model by metier?

In spite of all variability shown in accuracy, specificity and sensitivity between models, zones/gear (Metier) and temporal resolution, the fixed threshold estimated through regression trees using a rolling average in a preliminary data treatment (Fix2), the method developed for the current work based on mode (Mode) and the random forest algorithm (Rfor) all gave good results (>95% in the error measures). Thus, if considering the criteria of using the simplest methodology as a rule of thumb, the Fix2 method could be preferable. Behivoke et al. (2021) argue that using a single-parameter speed method may not be suitable, a priori, for classifying fishing and non-fishing activities over a large range of small-scale fishery contexts and gear types. These authors concluded that random forest yielded higher reliability of spatially-explicit fishing effort indicator than that of the speed threshold for four out of five gear types studied. However, like in the current work, these authors found very high performance for both random forest and fixed threshold using 5 gears types and concluded the best prediction method depends on local gear use, relevant fishing effort indicators, and available analytical expertise. Nevertheless, there is a plethora of previous works that successfully used a fixed threshold to estimate FE, if there is an appropriate knowledge of the fishery and adequate data pre-processing. In the current work we also found excellent results for threshold methods when data was properly pre-processed.

However, in large data sets such as it is the case of tracking devices (hundreds of boats recorded every 30 s), even a small percentage of an increase in the error rate (less than1%) may represent thousands of observations that are badly classified. In the present era of high computer power, it is thus hard to justify not to use the models that have better performances to estimate fishing effort. James et al. (2018) for example, conclude that different models should be applied to different metiers, in the context of SSF. De Souza et al. (2016) evaluated different methods to estimate fishing effort from worldwide AIS data, and concluded that for each type of fishery, a different method was more adequate, namely Hidden Markov Models was used for trawlers, longlines, a data mining approach and for purse seiners, a multilayering filtering strategy was used. However, in most previous works only one method is applied even if different metiers are considered (e.g. Cardiec et al., 2020) and studies that compare different methods focused on selecting the most appropriate one to use in the future for all metiers (e.g. Mendo et al., 2019a; Mendo et al., 2019b). This should be something that is decided by the researchers or decision makers, as a compromise between complexity and accuracy needed, but should always be addressed by the researchers on our point of view.

4.7. What temporal resolution is required?

In the present work it was concluded the time interval should be equal or less than 2 min, otherwise important aspects of the fishing operation will be missed. This decision however, was clear during the preliminary data analysis and not as a statistical result, although overall all models tested got worst when the time interval increased. Thus, aspects related with the fisheries *per se* were determinant to choose a temporal resolution. These aspects, however, are generally omitted from previous works, like for example the range of fishing trips duration, which divided by the temporal interval, determine the number of points available to perform the analysis, and is clearly determinant for its application. Similar to the current work, Behivoke et al. (2021) did not found any evidence of a linkage between the model's performance and sample size across gear types, although in the current work we found that model performance sharply decreased bellow 100 points by fishing trip. Such aspects would have been missed if only error rates were considered. This alerts to the importance, once more, that it is crucial to make a detailed preliminary observation of the data sets being used and provide a complete summary of the fleet data set as the one that is given in Table 1.

We found stronger biases on the duration of the fishing procedure with geolocation intervals above 2 mins. The few previous works have used variable intervals, namely: 1 s (Alvard et al., 2015), 5 secs (Forero et al., 2017), 45 secs (Behivoke et al., 2021), 1 min (Mendo et al., 2019a; Mendo et al., 2019b), 3 min (Burgos et al., 2013; Torres-Irineo et al., 2021), 5 min (Metcalfe et al., 2017; Natale et al., 2015 although LSF), 6 min (Rijnsdorp et al., 1998; Piet et al., 2007). Thus, it is clear that the proper scale should be with seconds to minutes resolutions, but mostly with less than 5 min (Miller & Franklin, 2002). Deng et al. (2005) concluded that in bottom trawl fisheries (LSF) the bias increase with time interval and the loss of precision is quite marked with polling interval longer than 30 min. Large Scale Fisheries (LSF) VMS time intervals are generally much higher than SSF, as the duration of fishing operations is also much higher. SSF time intervals should be studied in detail before any system is implemented, as the cost of acquiring more data, probably does not compensate for the loss of precision due to larger intervals in SSF, considering the reduced distance to the coast (see also Burgos et al. 2013). Additionally, higher number of points due to smaller time intervals provide a greater amount of data which may improve the statistical models, and the capacity to discriminate between fishing and non-fishing periods.

4.8. Gears- segmentation and other uses

In some countries, SSF boats can have a license to operate with different gears (e.g. Portugal), and in some cases, even within one trip, fishers might employ several gears (e.g. octopus fisheries). As it is shown in the current and previous works, the metier may also have an impact on the results produced by the different models. Thus, to identify the gear being used is another challenge to be address in future works, the so-called fleet segmentation. Future methods should be developed to properly classify vessel's tracks into gears or metiers, possibly using boats tracks also. Another perhaps simpler alternative, would be oblige this information to be recorded, potentially on a logbook to be implemented in SSFs (James et al., 2018). The sets of criteria required to classify boat tracks need to be tailored to the specific fishery and allow for some regional variations depending on operational characteristics of the fleet (e.g. distance to port at the end of the trip). Region-specific approaches may be required to correctly estimate fishing effort (James et al., 2018). As each gear has a different impact on the ecosystem and extracts different resources, the accurate knowledge of the type of gear used is thus essential to consolidate the information on SSF tracks to quantify fisheries impact, for example.

Recent hierarchical modelling approaches improve species biomass estimation by incorporating data from monitoring scientific surveys, with spatially explicit fishing effort estimates and landings information (Alglave et al., 2022). Standardized catch by fishing effort followed more closely the abundance estimations retrieved during fishing surveys than of the CPUE (Charles et al., 2014). Thus, tracking SSF has also the potential to improve species biomass estimation and distribution models.

Furthermore, tracking of SSF is essential to produce bio- and socio-economic models and the respective indicators. Accurate estimates of the distance travelled can be used to infer about fuel costs and when combined with vessel characteristics such as size, engine capacity and value of catch, permit to assess profitability and fleet-scale economic viability. Additionally, the use of trackers combined with cameras can also be used to estimate by-catches of sensitive species or birds (Bartholomew et al., 2018; Kindt-Larsen et al., 2016), or as a measure to improve fishers safety as confirmed by the sector (Silva et al., 2022). For example Silvia et al. (2022) concluded that in Indonesia and Mexico, SSF fishers were willing to pay for a tracking system if that would increase their safety at sea, and such argument can increase fisher's acceptance to carry the tracking devices which scan be challenging.

Measuring FE is indispensable to make decisions on the utilization of marine space for a proper management, namely through the implementation of no-take areas and area specific stewardship for a marine territory (Forero et al., 2017). For a relatively small sector like fisheries, specific policy and fishery management measures in certain regions are required considering the social and economic importance that fishing fleets, especially small-scale, may play in these regions (Natale et al., 2013), and for such, high resolution fishing activity maps are essential. Such strategies may be essential in the future to preserve fisheries and maintain biodiversity (Rufino et al., 2018b).

In the current work, we develop a new standard framework to establish protocols to estimate fishing effort in SSF using high resolution data, namely by (1) produce a validation data set (expert based or on-board observers); (2) pre-processing the data; (3) evaluate different models, including methods based on a fixed threshold, statistical models and machine learning algorithms; (4) assess the models using both error measures and fishing effort indicators. The framework was successfully used in a case study with Portuguese SSF, including both static and mobile gears, to compare models, Metiers and time interval between pings. Best results were obtained for intervals lower than 2 min, both using random forest or a method developed for the current data set based on modes, with a pre-processing of a rolling average of speed.

CRediT authorship contribution statement

Marta M. Rufino: Conceptualization, Investigation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Tania Mendo:** Writing – review & editing. **João Samarão:** Methodology. **Miguel B. Gaspar:** Funding acquisition.

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.

Data availability

Part of the data is available, another part if confidential (fishers data)

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110628.

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