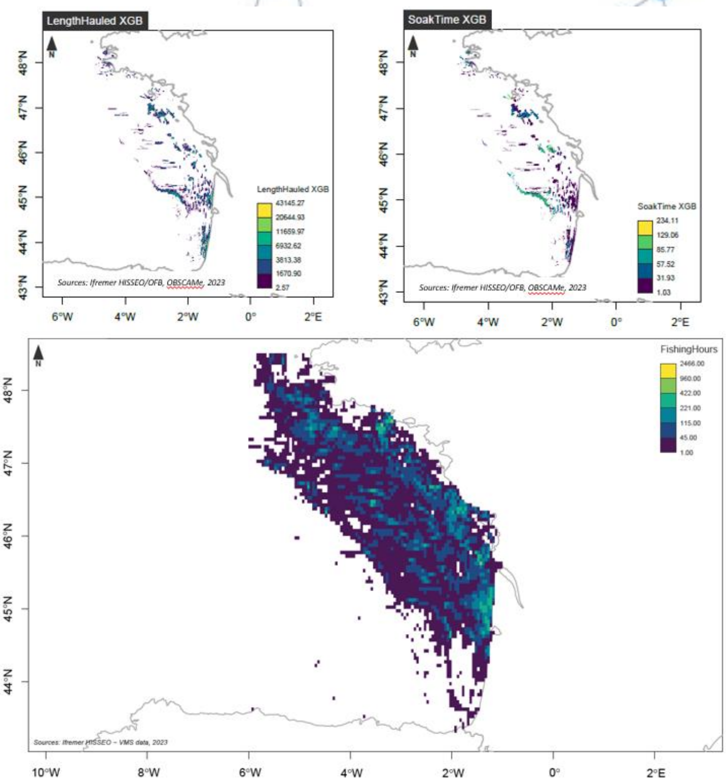
Development and application of a machine-learning and geocomputation workflow for assessing the gear effort of gillnetters operating in the Bay of Biscay



HISSEO
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Date : 30/11/2023

Fiche documentaire

Titre du rapport : Development and application of a machine-learning and geocomputation workflow for assessing the gear effort of gillnetters operating in the Bay of Biscay

Référence interne : RBE /HISSEO 2023

Diffusion :

☒ libre (internet)

☐ restreinte (intranet) – date de levée d'embargo : AAA/MM/JJ

☐ interdite (confidentielle) – date de levée de confidentialité : AAA/MM/JJ

Date de publication : 30/11/2023

Version : 1.0.0

Référence de l'illustration de couverture

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Langue(s) : Anglais

Résumé/ Abstract : Since 2016, strandings of small cetaceans showing signs of capture have reached significant levels, which could question the viability of the North Atlantic common dolphin population (ICES 2022). It is against this backdrop that CNRS and Ifremer, in conjunction with the OFB, have co-constructed the Delmoges program (Delphinus Mouvement Gestion), which is developing a multidisciplinary scientific approach aimed at gaining a better understanding of the mechanisms involved in the accidental capture of dolphins. In particular, developments are being proposed to provide a more detailed description of the activities of fishing fleets deemed to be most at risk of bycatching cetaceans. The qualification of fishing routes is currently based on simple decision rules using speed thresholds, so this study focuses on other qualification methods that have proved highly effective in other work: machine learning. Using the qualified positions and fishing operations of the 20 gillnetters in the OBSCAME database as a training set, we trained different models (CART, Random Forest, XGBoost) to predict a gillnetter's fishing operations based on its positions. The XGBoost models give the best results, with almost 90% accuracy using fishing trips based cross-validation. The final step is to create the actual and predicted nets using geocomputation process implemented in the "iapesca" R-package (Rodriguez, 2023), with the aim of assessing the fishing effort of the Bay of Biscay's gillnetters using new gear effort metrics more appropriated to passive gears. Different maps of fishing effort have been produced using these gear effort metrics (nets length, soaking time, product of both) aggregated by CSquare.

Mots-clés/ Key words : VMS, OBSCAMe, DELMOGES, geospatial data, geocomputation, machine-learning, fishing effort, gillnets, bycatch, Bay of Biscay

Comment citer ce document : Sans, M., Rodriguez, J., 2023. Development and application of a machine-learning and geocomputation workflow for assessing the gear effort of gillnetters operating in the Bay of Biscay. 52-p.

Disponibilité des données de la recherche :
DOI :

Commanditaire du rapport :	
Nom / référence du contrat : ☐ Rapport intermédiaire (réf. bibliographique : XXX) ☒ Rapport définitif (réf. interne **du rapport intermédiaire** : R.DEP/UNIT/LABO AN-NUM/ID ARCHIMER)	
Projets dans lesquels ce rapport s'inscrit (programme européen, campagne, etc.) : Delmoges, OBSCAMe	
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Summary

1 Context

Since 2016, strandings of small cetaceans presenting evidence of capture have reached high levels on the Atlantic coastline of France. The number of dolphins captured is estimated to thousands every year along the French Atlantic coast, essentially in the Bay of Biscay (Peltier *et al.* 2020b, Peltier *et al.* 2020a, ICES 2022). These levels of bycatch could question the viability of the common dolphin population in the North East Atlantic (ICES 2022). On this temporal scale, there doesn't seem to be any major change in the abundance of the common dolphins population (Blanchard *et al.* 2021) nor an augmentation of fishing effort in the Bay of Biscay (Demaneche *et al.* 2019).

On July the 2nd 2020, the European Commission puts France, Spain and Sweden on notice to research and apply management measures to prevent bycatch of dolphins and porpoises by fishing vessels (EU, 2020).

On July 15 2022 (EU, 2022), Europe issued a reasoned opinion against France and Spain on the grounds that no measures had been taken or they were deemed insufficient (EU, 2022). Both countries were then given a delay of two months to solve the small cetaceans bycatch issue. If not, the European Commission could decide to refer to the EU's Court of Justice, thus involving financial sanctions against both countries.

In January 2023, the French government introduced measures to reduce cetacean bycatch. A decree obliges the most active gillnetters of the Bay of Biscay to equip themselves with repellent devices otherwise called "pingers", while another decree obliges all gillnetters and pelagic trawlers longer than 6 meters to have VMS (Vessel Monitoring System) gear by 2023, and finally all gillnetters and trawlers longer than 15 meters have to participate each year to an on-board observatory program. On the 20th of March 2023, the State Council has ordered the government to close some fishing areas of the Bay of Biscay by fall, and to take complementary measures to enable a more precise estimation of annual small cetaceans bycatch. The objective is to limit the bycatch of small cetaceans and guarantee dolphins conservation in the area (Conseil d'Etat, 2023).

In this context, the University of La Rochelle – CNRS and the French Institute for the exploitation of the sea (Ifremer) in consultation with the French Office of Biodiversity (OFB), the fisheries professionals and the French government have created a scientific project called "Delmoges" (Delphinus Mouvements Gestion). First and foremost, this project aims to fill the knowledge gaps by acquiring new data on common dolphins habitats in the Bay of Biscay, on their trophic interactions and their interactions with fishing gears. In addition, this project suggests integrating knowledge on the whole socio-ecosystem to comprehend a wide diversity of scenarios that could diminish bycatch, including technological solutions, and evaluate the biological and socio-economic consequences (Delmoges, 2022).

As part of the study of interactions between dolphins and fishing gears, actions are taken into consideration to get a more detailed description of the activity of the fishing sub fleets which may be the most concerned by cetacean bycatch. At present, the qualification of fishing effort is based on simple decision rules using only a speed filter. European fishing vessels of more than 12 meters have been legally equipped with VMS emitting at a frequency of minimum 2h (1h in France) for years now, resulting in a substantial spatio-temporal database.

The use of data at a higher temporal resolution, such as AIS (Automatic Identification System) could allow the development of more advanced algorithms, some studies going in this direction being already initiated in Europe (ICES Scientific Report Vol. 4 Issue 10, 2020).

The work presented here has been undertaken at Ifremer in the HISSEO team (Coordination and valorization of Fisheries Observation), which coordinates the Fisheries Information System (SIH). In this team, the participation in Delmoges is centered on work package 3, “dolphins-fisheries interactions”.

As part of the Delmoges program and the previous project IAPESCA, machine learning methods have been tested on qualified spatialized data for some fishing gears. Most of the algorithms developed have been implemented in an R package called “iapesca” (cleaning and handling data, calculate covariates to describe trajectories, optimize fishing operation qualification with geo-informatic methods, Rodriguez, 2023).

Usual methods of fishing activity qualification rely on the use of speed filters. These methods, which have proved their worth on vessels using active gears (trawls, dredges), are not effective for vessels using passive gears such as gillnets, especially for small scale fisheries (SSF). The term SSF designates boats of less than 12 meters (EMFAF, EU 2021) which are not obliged to be equipped with VMS. Furthermore, conventional measures of fishing effort, like the fishing hours, are not an effective way to describe passive gears, simply because the gear’s activity is completely distinct from the movements of the boat. At the same time, machine learning methods have performed well in characterizing different means of transportation (Dodge *et al*., 2019) and identifying fishing gears (Huang *et al.*, 2019) or fishing activity (Mendo *et al.*, 2019) based on trajectories. These previous works show that machine learning algorithms are a proper tool for spatialized data analysis. Therefore, we will apply machine learning methods to the recognition of gillnetter’s fishing operations, on a database containing SSFs as well as larger boats (up to 24 meters).

The goals of this study are to:

- improve already existing methods and models
- establish the minimal temporal resolutions allowing the recognition of gillnetters fishing operations
- calibrate and build models using machine learning to predict the fishing operations of gillnetters
- define new fishing effort metrics more appropriate for passive gears
- produce fishing effort maps using these metrics
- assess the errors in spatial fishing effort predictions
- consider an operational way of integrating machine learning methods in SIH algorithms

2 Definition of minimum temporal resolutions of geolocation data for describing fishing effort and operations

2.1 Presentation of the data

First of all, our data has been explored at different temporal scales : 3600s, 1800s, 900s, 600s, 300s, 120s, 60s, 30s, 20s. These values correspond to the timelapse between two positions of the fishing vessel. Geolocation information for 20 vessels associated to 1323 fishing trips was available at one second intervals in the OBSCAMe database. Each of our datasets is a result of a linear down sampling (after cleaning the raw data) to reach the chosen temporal resolution. We then have 9 datasets varying from 36 600 observations for the 3600s dataset to 6 500 000 observations for the 20s dataset. Distribution of covariates and the appropriate decision rules to describe fishing operations may vary a lot from one resolution to another (WKSSFGEO2, Rodriguez *et al.*, 2023), which explains the need to create different models for each of them.

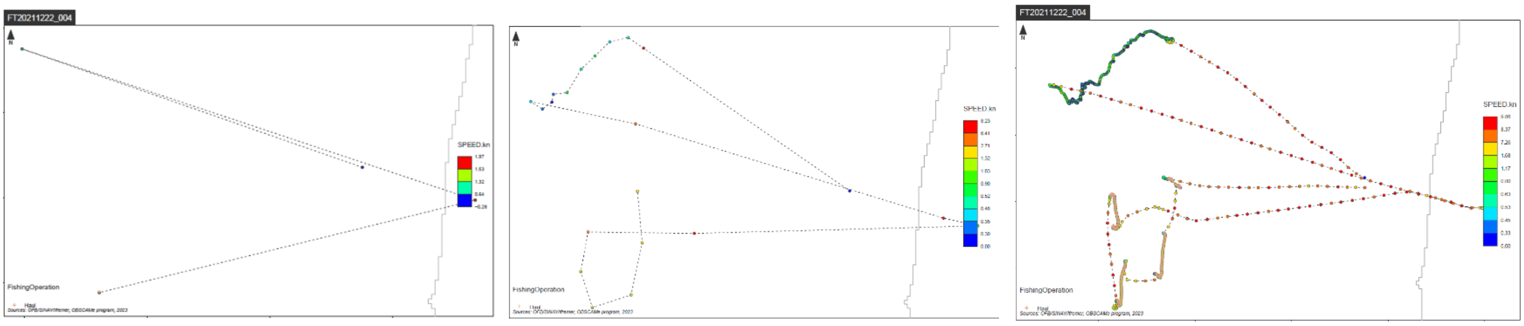

Figure 1. Fishing trip of a 12m vessel at 3600s resolution (left), 600s resolution (middle) and 20s resolution (right)

For each dataset, the following variables are available : Date/Time (time corresponding to the position), Vessel FK (vessel identifier), Fishing Trip FK (fishing trip identifier), Fishing Operation (Not fishing, hauling, or setting) and Gear (fishing gear used). The vessel identifiers have been anonymized. Fishing operations are qualified by observers from the videos acquired by on-board cameras. All the covariates that will be used to build our models later on were calculated from raw data : timestamps and geographical positions.

The first step in our approach was to calculate the fishing effort variables that seemed relevant, while relying on the WKSSFGEO definitions. We chose to calculate, for each boat and each temporal resolution :

- Number of Fishing Trips : trip of a fishing vessel during which fishing operations take place. It starts when the boat leaves the harbor and ends when it comes back (or arrives in another harbor). The "harbor" area is defined by a 1 kilometer buffer around its center, and there needs to be at least 1h between leaving the harbor and coming back to define a new fishing trip. (Rodriguez, 2023)
- Number of Hauls : number of continuous sequences corresponding to hauling (retrieval of a net).
- Number of Sets : number of continuous sequences corresponding to setting (deployment of a net).

- Fishing days : Days spent at sea with at least one fishing operation. (ICES Scientific Report Vol. 4 Issue 10, 2020)
- Fishing hours : Total time spent fishing, or the hours spent at sea minus the time spent in transit. (ICES Scientific Report Vol. 4 Issue 10, 2020)
- Total Length Hauled : Total net length hauled by a single vessel during a single fishing trip
- Median Soaking Time : Median of the soaking times of all the nets hauled by a single vessel during a single fishing trip

From these variables, we can compare the efficiency of different resolutions for measuring the fishing effort, the reference dataset being the finest one at a 20 seconds resolution.

To anonymize the vessels, we chose to indicate the size range of boats instead of their names when looking at fishing effort. Furthermore, using the size range allows us to examine a possible size effect when comparing the different temporal resolutions.

2.2 Fishing trips detection and fishing hours computation

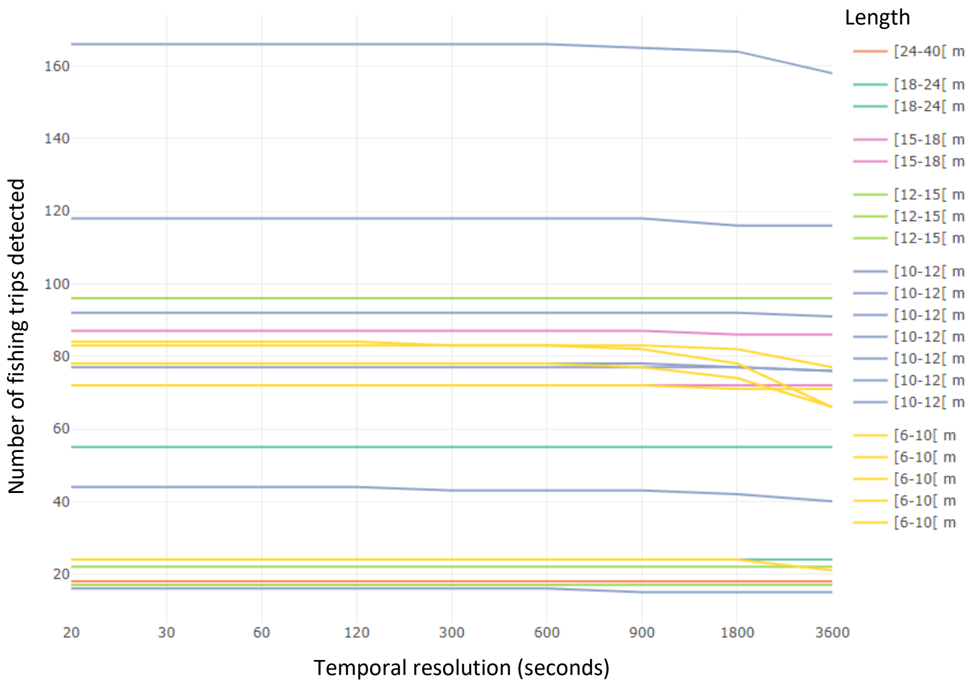

Figure 2. Number of Fishing Trips by boat at different resolutions

For the boats over 12 meters, the number of fishing trips detected remains the same through all different temporal resolutions. However, SSFs (<12m) need a temporal resolution of 900 seconds or less to be able to detect all fishing trips.

In fact, small vessels generally work close to shore and go on short fishing trips, which are not detected at all resolutions because they do not contain enough points when the information is degraded (we see this effect in Fig. 1).To distinguish the fishing trips, we use a buffer of 1 kilometer around the harbor, and if a boat spends less than two hours outside this zone, it is likely to have only one point at the most degraded resolution (3600s), involving that its journey will not be qualified as a fishing trip (at least 2 points outside the buffer to define a new fishing trip).

The temporal resolution needed in order to acquire the total Fishing Hours for each fishing trip appears to be dependent on the vessel's size. We'll look at a 24 meters boat and a 10 meters boat to see the effect size can have on how much information we lose when degrading the resolution.

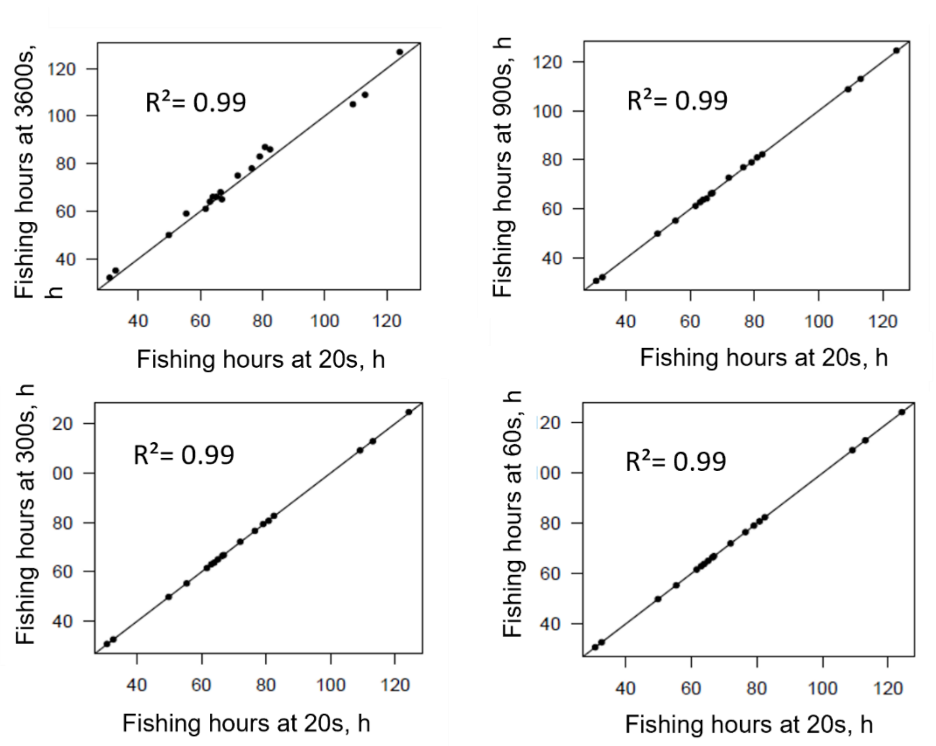

Figure 4. Fishing Hours by Fishing Trip of a 24m vessel at different resolutions

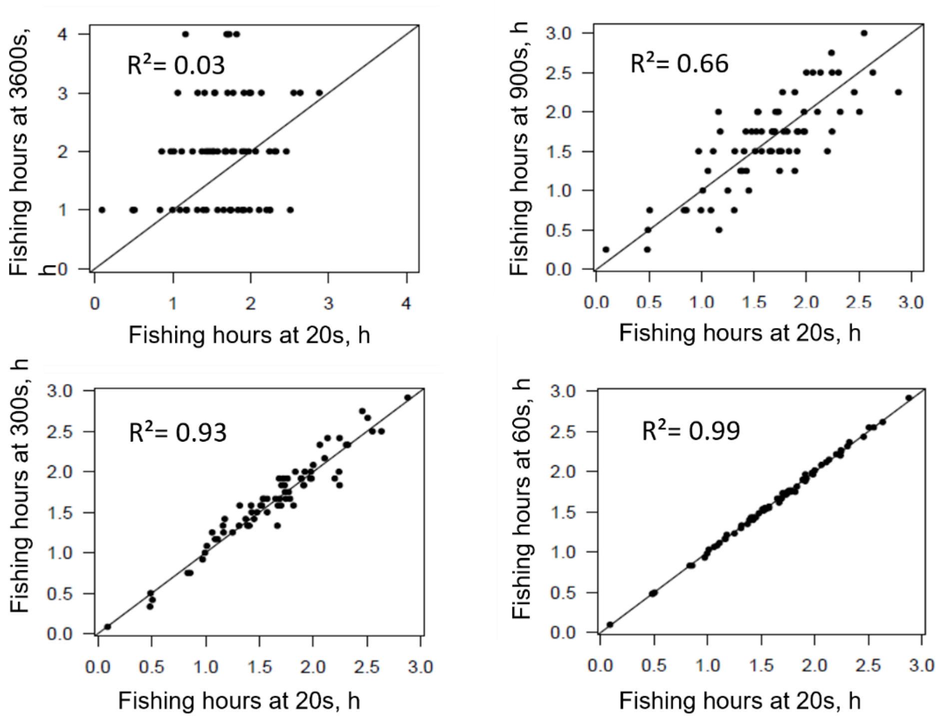

Figure 5. Fishing Hours by Fishing Trip of a 10m vessel at different resolutions

For the 24 meters boat, the fishing hours is already reliable at 3600s (R^2 = 0.99) (Fig. 4). For the 10 meters boat, the correlation coefficient is almost null at 3600s and close to 1 at 60s (Fig.5). At 900s the variable is still very degraded but consistent with reality (R^2 = 0.66) and it gets much better at 300s, with a R^2 of 0.93.

As a conclusion, to describe the aggregated number of fishing trips and aggregated fishing hours by fishing trip, a temporal resolution of 1h is enough for boats over 12 meters, but SSFs need at least 15 minutes resolution.

As for vessels operating passive gear, the fishing hour is not a satisfactory measure of fishing effort (Mendo et al., 2023), we will look at the number of setting and hauling events by fishing trip aggregated by boat.

2.3 Detection of fishing operations and computation of gear metrics

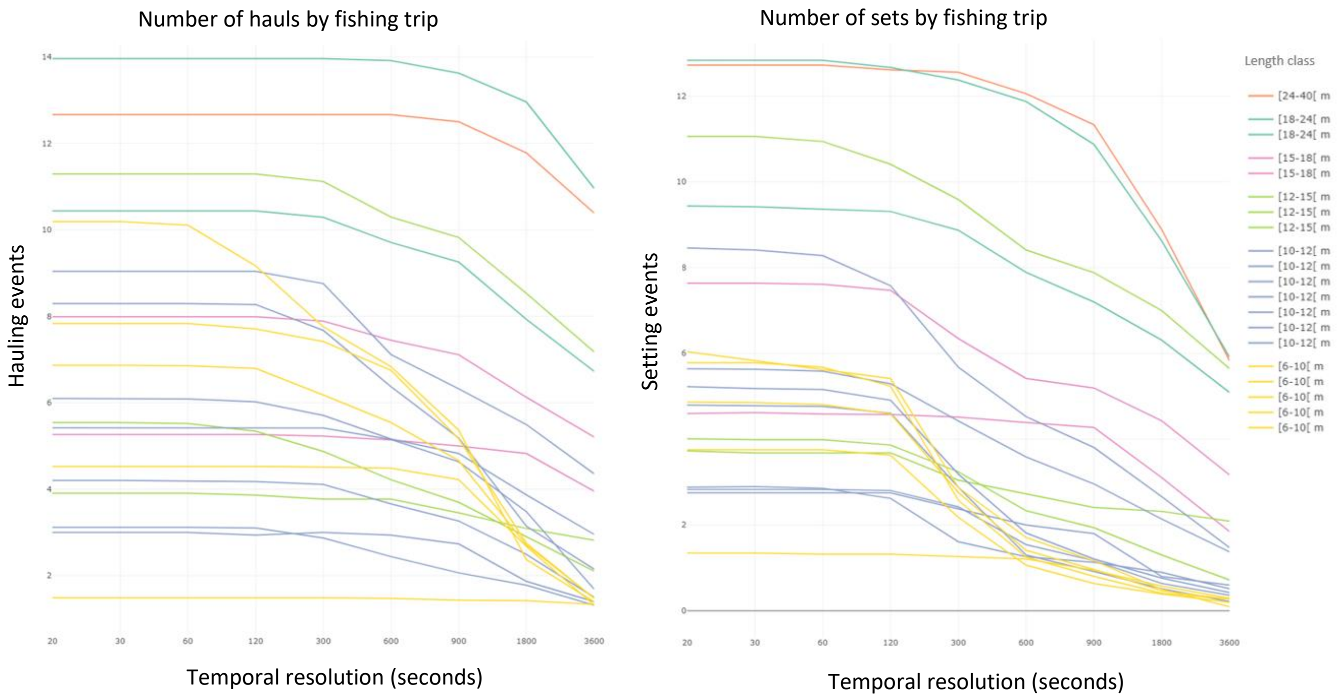

Figure 6. Number of Hauls and Sets by fishing trip aggregated by boat at different resolutions (mean)

Concerning fishing operations, their detection deteriorates in a very fast manner when degrading the temporal resolution, because these events take place in a small temporal space (they can last only a few minutes, especially for the smaller boats using small gear). In fact, even for the 24 meters boat, we need a temporal resolution of 600 seconds to detect all the hauling events. For the 15-24 meters vessels, we need a 300 seconds resolution to reach the same objective, and 120 seconds for the 10-15 meters. Finally, for the boats under 12 meters, 120 seconds seems appropriate but there is still some information loss, so 60 seconds would be best. As for the setting operations, 120 seconds is acceptable for boats bigger than 15 meters, but at least 60 seconds resolution is needed for the smaller ones. In fact, setting operations are harder to predict (and even to observe) than hauling operations, as they take less time and are carried out at high speed. The use of positions resampled by the minute seems to be the best compromise, potentially allowing the recovery of almost all operations for vessels under 12 meters (Fig. 6). These initial results were presented at the ICES WKSSFGEO2 (Workshop on Geospatial data for

Small Scale Fisheries) in Faro and corroborate other studies on passive gear (Portugal, Denmark, Scotland...), contributing to recommendations on the frequency of geospatial data acquisition for artisanal vessels.

The iapesca R-package (Rodriguez, 2023) gives its users the possibility to create nets objects from the positions of the boat and the fishing operations associated to each position (see part 5.1 "Gear creation"). We can then use these nets to calculate two new fishing effort metrics : total length hauled in a fishing trip and median soaking time of a fishing trip.

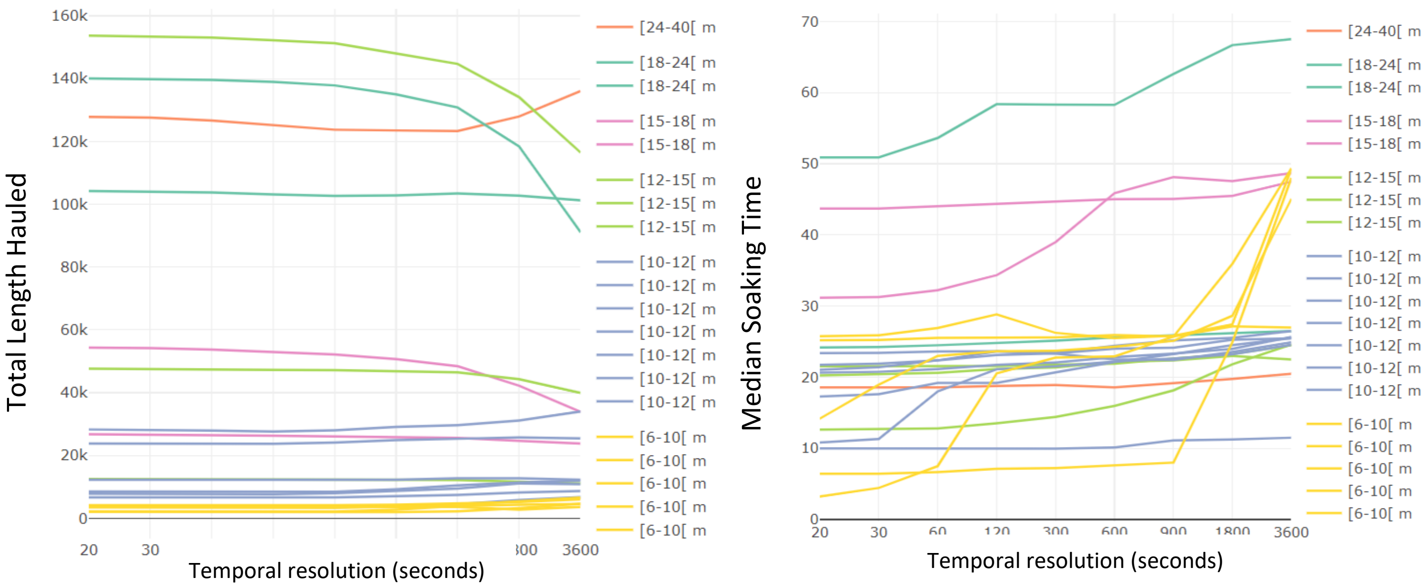

Figure 7. Total length hauled and Median soaking time by fishing trip aggregated by boat (mean)

As a general rule, the larger the boat, the greater the total length of net it deploys per fishing trip. There is a disparity in the evolution of these values as a function of resolution, with no overall trend towards growth or decline. It should be noted that if for 6-10m (or even 10-12m) boats the total length deployed per fishing trip doesn't seem to move much from 3600 to 20 seconds, it's only because these values are minimal compared to those of larger vessels, but at 3600 some estimates are twice as large as those at 20 seconds (Fig. 7).

This counter-intuitive effect is associated with net creation methods that take into account half the sequence following the last fishing operation, which can generate this effect when the data is too degraded.

As for the soaking time, it is overestimated at degraded resolutions for every boats (Fig. 7). This can be explained by the fact that many setting operations are missing at these resolutions, and, if a haul is found to have no associated setting, the function will also look at previous fishing trips for a position that might correspond. Since this implementation has been developed to enable the detection of associated setting events occurring during different fishing trips, it can easily lead to an overestimation of soaking times if some setting events are missing when the data is too much degraded. As we refine the resolution, most of these overestimates fade with the ability to detect true setting operations. For some vessels, a decrease in soaking times may be observed for temporal resolutions less than 60 or 120 seconds. This trend was linked to a misinterpretation of setting events by the function for higher temporal resolution, this glitch has been corrected in a dedicated commit.

3 Description of the vessel's activity, optimization and calibration of the machine learning models

3.1 Calculation of the covariates

- Speed : The speed at a position is defined between the position and the previous one. The distance between the two positions is calculated according to Vicenty's formula (1975) and called $d_{(P_{n-1},P_n)}$. Then, the time difference Δ_t between these two positions is used to calculate the speed $S_{p_n} = \frac{d_{(P_{n-1},P_n)}}{\Delta_t}$.
- Acceleration : The difference of speed observed between a position and the previous one divided by the time difference Δ_t between them : $A_{P_n} = \frac{S_{P_{n+1}} - S_{P_n}}{\Delta_t}$.
- Proximity Index : The number of observation in a specific spatio-temporal window. We define a radius according to the temporal resolution, which corresponds to the distance covered between two consecutive positions by a boat travelling at a constant speed of 4.5knots (nautical mile per hour). Under the threshold of 4.5knots a boat is considered as fishing by the ALGOPESCA operational treatments (Ifremer, 2021). This covariate is calculated as such : $Proximity\ Index = \sum_{i=t-1}^{t+1} \sum_{k=0}^{2} n_{i,k}$ with $n_{i,k}$ the number of observations happening at a time between $t - res * 4$ and $t + res * 4$ that are geographically inside the previously defined radius.
- Jerk : Rate of change between acceleration and deceleration, frequently used in transports study and a covariate of major importance for identifying transportation means (Dabiri and Heaslip, 2018), its formula is $J_{p_n} = \frac{A_{P_{n+1}} - A_{P_n}}{\Delta_t}$.
- Bearing : Angle between a trajectory and the geographical North. At a position, trajectory is calculated with the next position. We first calculate $y = \sin[P_{n+1}(long) - P_n(long)] * \cos[P_{n+1}(lat)]$ and $x = \cos[P_n(lat)] * \sin[P_{n+1}(lat)] - \sin[P_n(lat)] * \cos[P_{n+1}(lat)] * \cos[P_{n+1}(long) - P_n(long)]$ to finally calculate $Bearing_{(Pn)} = arctan2\ (x, y)$.
- Bearing rate : Absolute value of the difference of bearing between a position and the next one.
- Speed Change : The absolute variation of speed between a position and the next one.
- Straightness : It describes the difference between the trajectory of the boat from a position to the next and their Euclidian distance. Its formula is $Straightness = \frac{\Delta D_{(n,k)}}{L_{(n,k)}}$ where $\Delta D_{(n,k)}$ represents the Euclidian distance between a position (P_n) and the next (P_{n+k} with k = 1), and $L_{(n,k)}$ is the distance really covered by the boat (Baschelet, 1981).
- Sinuosity : The measure of sinuosity between points P1 and P2 introduced by Dutton (1999) corresponds to a distance ratio of the euclidian distance between points P1 and P2 and the distance actually travelled between these two points. Sinuosity between point P and P_k is expressed as follows : $Sinuosity_{P,k} = \frac{\sum_{i=p-k}^{i=p+k-1} di,i+1}{d_{p-k.p+k}}$ with k the lag parameter and d the distance measured.
- Turning angle : Its calculation uses Bachelet's method (1981), calculating the step angles (radians) of each segment in relation to the previous one.

- Direction change : Variation of trajectory between consecutive trajectories (Kitamura and Imafuku, 2015). It's calculated as such : $DC_{\propto 2} = \left(180 - \frac{180}{\pi} arccos\left(\frac{a^2+b^2+c^2}{2ab}\right)\right) * \frac{1}{t}$, *arccos* is the trigonometric function, *t* is the timelapse between the first and last point, *a* is the length of the segment between the first and the second point, *b* is the length of the segment between the second and third point, and *c* is the length of the segment between the first and third point (Fig. 8).

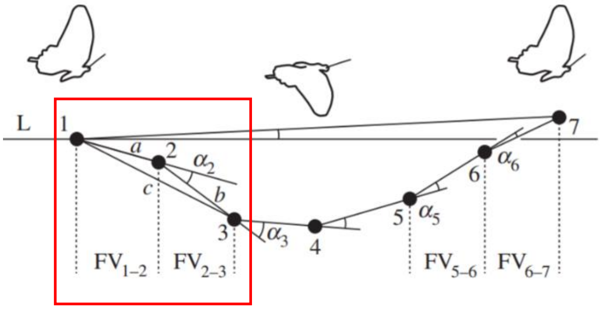

Figure 8. A butterfly's flight path (Kitamura and Imafuku, 2015)

For each observation, we calculate these covariates in a moving window varying with resolution (previous and next positions). For example, at 900s, for one position we calculate "Speed", "Speed_previous" the speed at the previous positions (900s earlier) and "Speed_next" the speed at the next position (900s later). The same goes for every covariate, at every temporal resolution.

To understand better the importance these covariates could have in our machine learning algorithms, histograms of their distribution have been drawn :

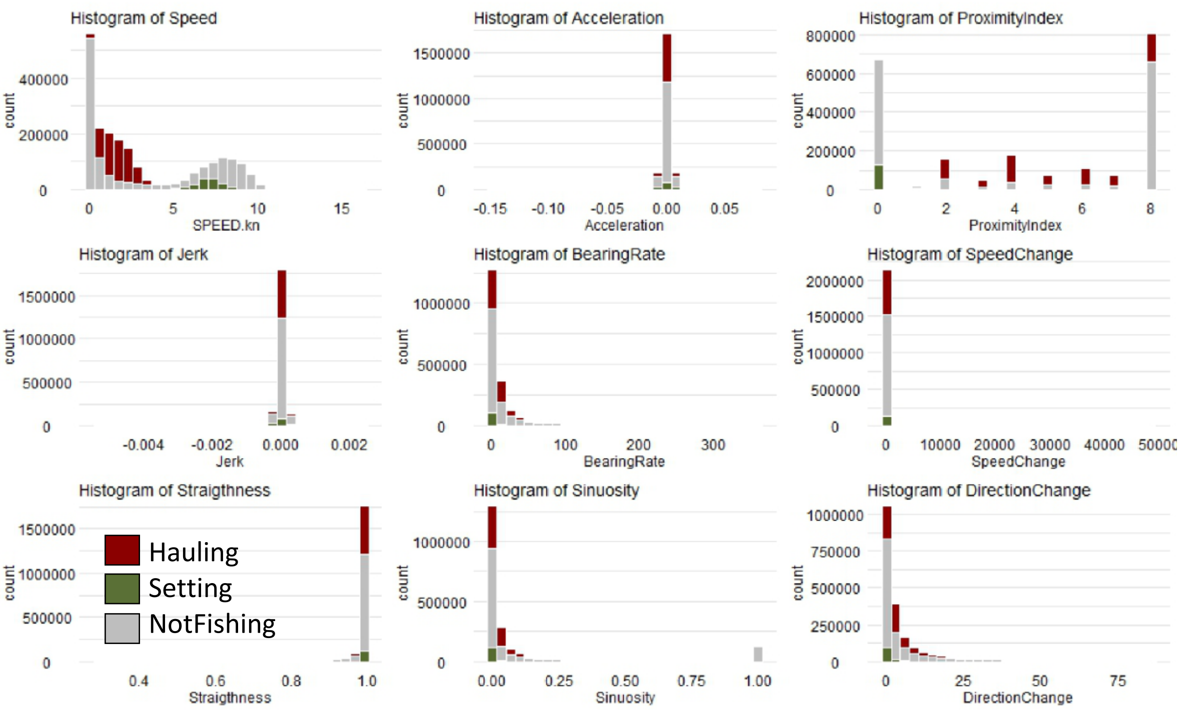

Figure 9. Histogram of covariate distribution at 60s

3.2 Presentation of the machine learning methods

In this part are described the different machine-learning models tested. It is important to note that we will not be using the 20 and 30 seconds resolutions from now on. First of all our exploratory work on resolutions showed that at 60 seconds we can retrieve all the fishing operations, and running our models optimization on datasets as big as the 30 (4 400 000 observations) and 20 seconds (6 500 000 observations) would have taken a longer time than we had.

3.2.1 SVM

Support Vector Machines (SVM) have been the object of numerous studies in the field of transportation modes classification (Bolbol *et al.*, 2012; Jahangari and Rakha, 2014; Zheng and Xie, 2008). Their application to the maritime field and most importantly to the identification of fishing vessels typology (Kim and Lee, 2020; Marzuki *et al.*, 2018) also displayed a great potential. These algorithms relying on supervised learning are well known for their ability to resolve discrimination problems. Their operation is based on the search of the optimal margin hyperplane which will allow classification or separation of the data and whose generalization ability (ability to separate the data) is the greatest (Tong and Chang, 2001). SVMs can use different kernels : linear, polynomial… the one we chose for our study is the radial kernel SVM, because it was the one showing the best results during an exploratory phase.
To optimize the radial SVM model, the R-package “kernlab” was used (Karatzoglou *et al.*, 2004), with the following hyperparameters :

- C : represents the wrong classification rate. If it has a high value, the optimization will choose a hyperplane with a smaller margin if it classifies more precisely the training data. A low value of C will force the optimization to look for a larger margin, even if it gives a wrong classification for a bigger part of the training data.
- Sigma : affects the linearity of the margin. With a low value of sigma, the decision frontier will ignore the farthest points, thus creating a nonlinear margin. In the case of a high sigma, these same points will have more weight, and the margin will tend to be more linear.

3.2.2 CART

Decision Trees (DT) classification categorizes the data at every step. This implies creating a tree specific to the training data which will be used to simplify the dataset. The tree is made up of nodes and branches, the first correspond to the decisions while the branches go left or right at each node to put the data in one of two classes or, if the tree keeps going, continue selection. The simplicity of their execution and of the interpretation of the results have made them one of the most popular classification algorithm. It has also been widely used in the recognition of transportation modes (Dabiri et Heaslip, 2018; Xiao et al., 2017; Zheng et Xie, 2008). For the aforementioned reasons it has been chosen for our study, even though it has less potential in terms of precision than the other three. A major contribution to our decision is that CART optimization lasts less than an hour for a dataset of more than 2 000 000 observations, while it lasts between 20 and 48 hours for the other three.
The R-package “rpart” has been used to work with CART models, the hyperparameters are the following :

- Minsplit : minimum size of a node, or the smallest number of observations needed to split data in two.
- Max depth : maximum depth of the tree (number of nodes).

3.2.3 Random Forests

Random Forests algorithms (Breiman, 2001) are made up of multiple decision trees. These trees are obtained randomly during the learning process, with a “bootstrap” method. The randomization of this process suppresses the overfitting effect often encountered when dealing with simple decision trees (Breiman, 2001). Their use in the identification of transportation modes (Dabiri and Heaslip, 2018; Xiao *et al.*, 2017) and fishing gears (Marzuki *et al.*, 2018, 2015) has given promising results. Hence, these algorithms have a great potential for the data analysis of the experimental fishing fleet’s data collected for this study.
The R-package “ranger” (Wright *et al.*, 2015) was preferred to the classic “randomforest” because its computation times are shorter.

- Num trees : number of decision trees created.
- Mtry : this parameter controls the number of covariate available for use when creating each decision tree.
- Min Node Size : The minimum number of observations to create a node in each decision tree.

3.2.4 XGBoost

EXtreme Gradient Boosting (XGBOOST) classification algorithms use ensemble methods based on tree aggregation. This type of algorithm is based on learning from error in an iterative process. Thus, at each iteration, the tree constructed learns from the errors committed by the tree previously constructed (Chen and Guestrin, 2016). In this way, the decision rule constructed results from the sum of the results of each tree, enabling a high level of reliability to be achieved. Their ability to be run in parallel makes these algorithms particularly well suited to large volumes of data (Chen and Guestrin, 2016; Huang *et al.*, 2019). Studies carried out in the transportation domain (Xiao *et al.*, 2015) and in fishing gear identification (Huang *et al.*, 2018) revealed that these algorithms responded very well to these problems, and proved to be the best performing of those tested in this work. These results tend to encourage their use in these areas and particularly support their ability to discriminate between the gear types used within the French fishing fleet.

The booster chosen is "gbtree", as it is the only one based on trees rather than linear models, and a non-linear response is strongly expected. The R-package "xgboost" (Chen and Guestrin, 2016) enables the optimization of XGBoost models via the following hyperparameters:

- Eta : corresponds to the learning rate. After each boosting step, the eta reduces the weight of each covariate to make the process more conservative.
- Gamma : specifies the minimum reduction in loss required to make a knot. The greater the gamma, the more conservative the algorithm.
- Max depth : maximum depth of a tree.
- Subsample : fraction of observations randomly sampled for each tree.
- Colsample by tree : resampling rate used for the construction of each tree.
- Objective : definition of the loss function to be minimized. For multiclass prediction, either multi:softmax or multi:softprob is used. In this study, multi:softprob is used because it gives the probability of an individual belonging to each class.

- Eval metric : metric used for data validation, we used mlogloss because the variable we predict (fishing operation) is multiclass.
- Num class : number of classes of the predicted variable (three for fishing operations : Haul, Set, NotFishing).
- Numtrees : number of trees created.

3.3 Model optimization

To optimize these models, hyperparameters are selected through systematic sampling covering a broad array of possibilities. These form a fairly large multi-dimensional grid, which can be reduced in a second step by systematic sampling. This enables the algorithm to be run with each of the hyperparameter combinations, to then select those that enable the construction of the model giving the best prediction performance.

To calculate the precision of each model built during the optimization process we use cross validation. Cross-validation involves dividing the dataset into n subsets, each of which acts in turn as a training sample and a test sample. So, for a 3-fold cross-validation, we divide the set into 3, for a 5-fold cross-validation, we divide it into 5, and so on.

For the optimization process, 3-fold cross-validation was chosen rather than 5-fold, as the computation time is shorter. Rather than testing each sample in turn, one of the three samples is selected as the test sample from the outset. This again reduces calculation times. As the positions are not independent, the object of the cross-validation in this case is the fishing trip and not the line indexes as in most procedures. The results are thus better able to describe the object of the prediction, which in our case will be either a new fishing trip or later on a new ship.

Once we gathered the results of the first hyperparameters grid, we can narrow it down and select new hyperparameters to get better results if needed, and if the best result hasn't been obtained yet.

The tables below show, for each model, the hyperparameters retained at each resolution during the optimization phase. The colors in the "Acc" column (model accuracy) are defined based on a k-means clustering of accuracies :

	minsplit	maxdepth	Acc
3600	100	8	73.14
1800	100	10	77.04
900	100	10	80.38
600	100	10	81.08
300	100	10	82.84
120	100	10	83.38
60	100	8	83.69

Table 1. CART hyperparameters at various resolutions

The choice of CART model hyperparameters varies very little from one resolution to the next, but the accuracy score (Acc) increases almost linearly with the temporal resolution up to 60 seconds.

	sigma	C	Acc
3600	0.030	5	75.79
1800	0.025	8	77.32
900	0.025	8	81.81
600	0.025	5	82.85
300	0.040	4	83.78
120	0.025	8	83.73
60	0.060	40	82.09

Table 2. SVM hyperparameters at various resolutions

In this case, no particular trend appears in the choice of hyperparameters. The highest precision is reached at 300, exceeding that at 120 by a few hundredths, and well ahead of 60 seconds.

	mtry	min.node.size	num.trees	Acc
3600	15	20	500	77.90
1800	9	10	500	80.96
900	9	10	500	85.82
600	6	15	300	86.92
300	11	10	750	88.65
120	15	10	500	88.27
60	15	20	500	87.71

Table 3. Random Forest hyperparameters at various resolutions

As in the previous table, there is a drop in accuracy of several tenths after 300, with the accuracy score decreasing significantly at 60 seconds.

	booster	eta	max_depth	gamma	subsample	colsample_bytree	objective	eval_metric	num_class	numtrees	Acc
3600	gbtree	0.01	15	1	0.6	1	multi:softprob	mlogloss	3	1250	78.78
1800	gbtree	0.01	11	2	0.6	1	multi:softprob	mlogloss	3	1200	82.34
900	gbtree	0.01	11	2	0.6	1	multi:softprob	mlogloss	3	1200	86.88
600	gbtree	0.01	11	2	0.6	1	multi:softprob	mlogloss	3	1000	87.98
300	gbtree	0.01	12	2	0.6	1	multi:softprob	mlogloss	3	2000	89.66
120	gbtree	0.01	14	2	0.6	1	multi:softprob	mlogloss	3	2000	89.56
60	gbtree	0.01	14	2	0.6	1	multi:softprob	mlogloss	3	2000	89.01

Table 4. XGBoost hyperparameters at various resolutions

Again, the precision rises until and reaches a maximum at 300 seconds, then drops down a notch.

The optimization phase reveals two results. Firstly, SVM does not perform as well as Random Forest and XGBoost (Tab. 2-4), both of which achieve similar scores, with only 1% in favor of the latter.

Secondly, accuracy does not increase with resolution. Or rather, it increases up to 300 seconds, then decreases slightly with each step as we continue to refine the resolution, with the exception of CART, which only decreases after 60 seconds (Tab. 1). What's more, CART achieves almost the same score as SVM, although the former takes much less time to run (at 3600 seconds, CART optimization takes a few seconds and SVM around an hour).

For both SVM and Random Forest, the choice of hyperparameters varies greatly, demonstrating the importance of optimizing a model for each resolution. This also explains why the accuracy score decreases after 300 seconds: although the learning base is more detailed, this does not mean that the model will be any better.

3.4 Model evaluation

Once the models have been optimized to select the best hyperparameters, their performances may be evaluated. An initial evaluation has been carried out in the form of 5-folds cross-validation by fishing trip (5 subsets, each consisting of randomly selected one fifth of the total fishing trips), to assess the ability to predict a new fishing trip for an existing vessel in the calibration database.

We compute accuracy scores as follows : $Accuracy = \frac{TP+TN}{TP+FN+TN+FP}$ with TP the true positives, TN the true negatives, FN the false negatives and FP the false positives (R is rate).

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
CART	73.14	88.6	0.0	40.7	NA	11.4	100.0
SVM	75.79	89.9	14.0	37.6	48.7	10.1	86.0
RF	77.90	83.8	14.3	32.1	40.5	16.2	85.7
XGB	78.78	82.5	18.4	30.0	39.9	17.5	81.6

Table 5. Evaluation of 5fCV models by fishing trip at 3600s

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
CART	80.38	83.0	0.0	26.4	NA	17.0	100.0
SVM	81.81	88.4	45.3	28.2	36.7	11.6	54.7
RF	85.82	87.7	52.2	21.1	23.7	12.3	47.8
XGB	86.88	87.4	58.7	19.1	23.3	12.6	41.3

Table 6. Evaluation of 5fCV models by fishing trip at 900s

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
CART	82.84	87.7	0.0	22.8	NA	12.3	100.0
SVM	83.78	85.7	62.0	22.0	42.3	14.3	38.0
RF	88.65	90.5	57.6	16.1	21.3	9.5	42.4
XGB	89.66	90.3	66.0	14.4	20.6	9.7	34.0

Table 7. Evaluation of 5fCV models by fishing trip at 300s

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
CART	83.69	87.7	0.0	20.9	NA	12.3	100.0
SVM	82.09	81.9	64.6	18.2	57.6	18.1	35.4
RF	87.71	91.4	40.8	15.8	34.0	8.6	59.2
XGB	89.01	91.1	57.4	14.5	28.8	8.9	42.6

Table 8. Evaluation of 5fCV models by fishing trip at 60s

The ranking of models in terms of accuracy remains the same for the different resolutions: XGBoost is in first place, closely followed by Random Forest, then SVM and finally CART. The resolution for which the models give the best results is 300 seconds, except for CART, which achieves this at 60 seconds (Tab. 5-8).
Model evaluation highlights the main difficulty of the subject: classifying setting operations. Indeed, model accuracy for setting (acc.set) never exceeds 66%, which is very low when compared to the 90% accuracy more frequently achieved for hauling (Tables 5-8). In fact, hauls are slower movements with a very specific behavior, whereas setting is a short-lived operation that is difficult to characterize even at low resolutions.

The decision rules of the different CART models are represented as trees with their branches describing the decisions (Fig. 9). At 3600 seconds, only speed covariates are used: speed for the first two nodes, speed at the previous point for the third, and speed at the next point for the last. At 900 seconds, the first, second and fourth nodes use speed, the second uses the speed at the previous point, and the last the acceleration. At 60 seconds, first the speed at the next point is used, then twice the speed at the previous point. Depending on the third node, either the speed at the previous point is used, or the Jerk and then the Bearing Rate. Linked to an event happening at lower speed, the addition of the BearingRate takes into account changes in direction, with a low value indicating a straight path and a high value indicating a winding path. It has indeed appeared on high-resolution maps that some boats seem to have a sinuous trajectory when hauling their nets, but this is a result that will have to be validated with fishermen later on.

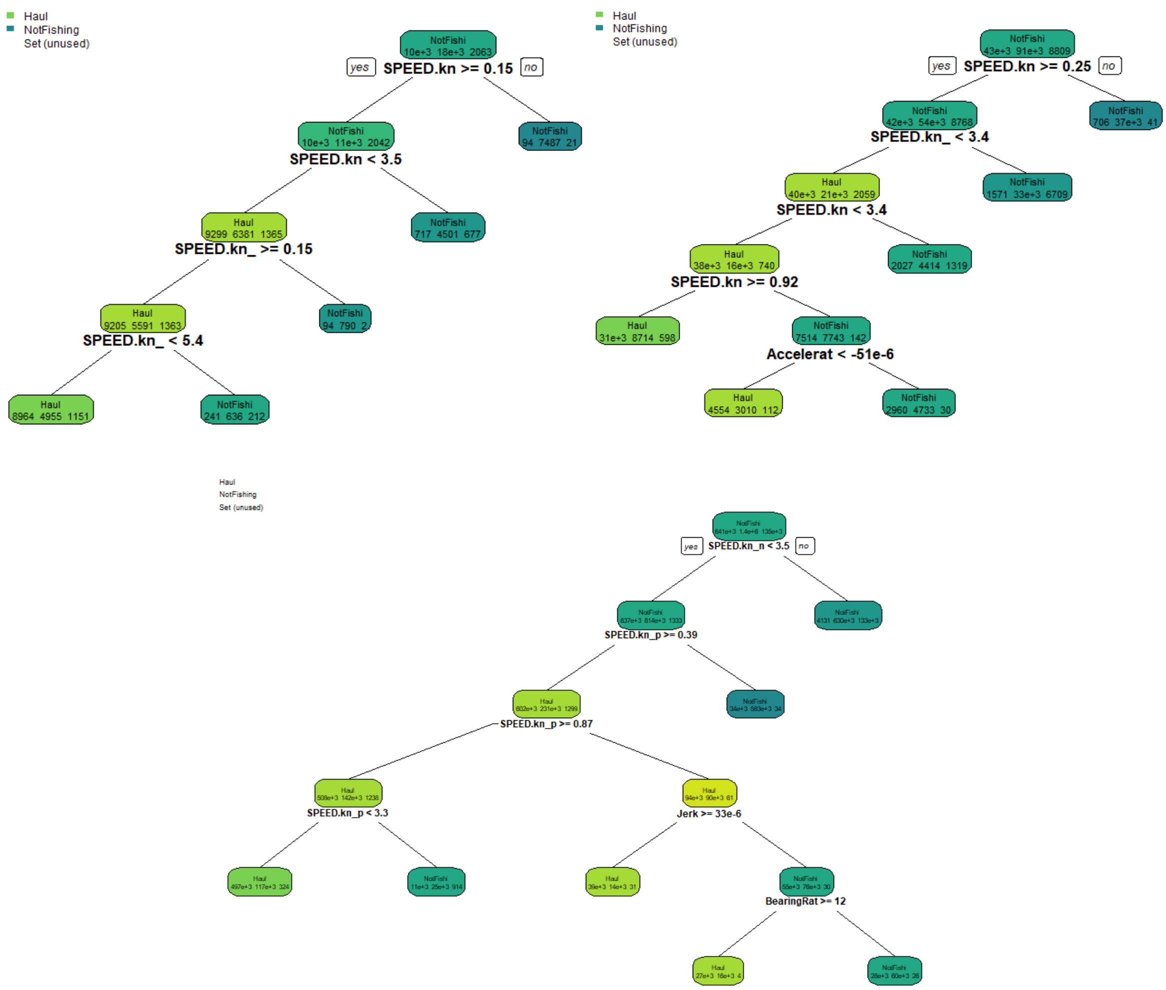

Figure 9. CART decision trees at the following resolutions, from left to right and top to bottom: 3600s. 900s. 60s

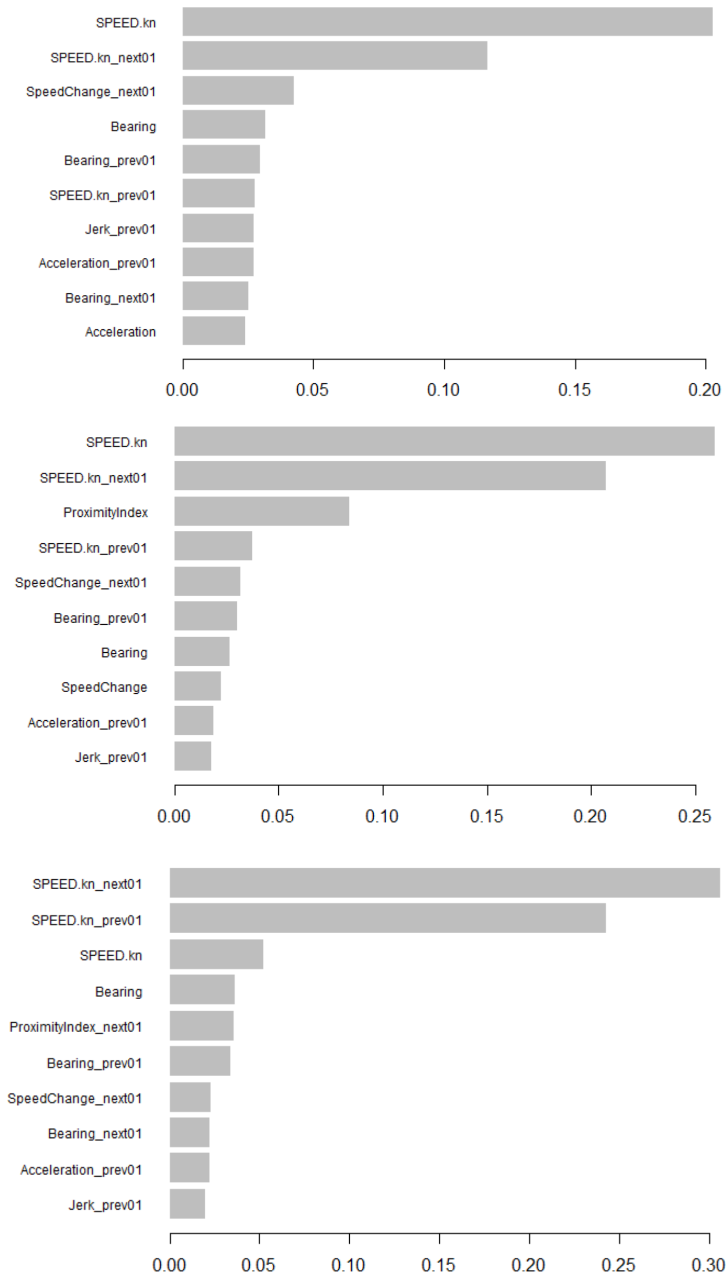

Figure 10. Importance des variables des modèles XGBoost aux résolutions suivantes, en allant de haut en bas : 3600s, 900s, 60s

For the XGBoost too, speed covariates are the most important. At 900 seconds, the proximity index is the third most important covariate. At 60 seconds, speed at the current point is used very little compared to other resolutions, and it is the speed at the previous and next points that are most important.

As these three speed variables are highly correlated at finer resolutions, the importance graph is skewed. Indeed, between the velocity at the previous point and that at the current point, we have an R^2 coefficient of 0.97 at 60 seconds, compared with 0.53 at 900 and 0.17 at 3600. This may explain why model performance deteriorates after 300 seconds, when neighbors are too close to each other to use velocities over the moving window as independent variables. We will have another look at this hypothesis in section 3.5 .

We have also carried out a leave-one-out cross-validation per vessel (cross-validation with as many levels as there are vessels in the dataset), so that the fishing operations of each vessel are predicted from the qualified data of all the other vessels, but not of the vessel in question. This validation procedure is closer to our final objective (applying these models to the 500 Bay of Biscay gillnetters) than using a validation performed by fishing trip. It enables us to assess the model's predictive capabilities on vessels not present in the database, so cross-validation by vessel shows the extent to which these models will be applicable to the entire French gillnet fleet operating in the Bay of Biscay.
The choice of leave-one-out for cross-validation will prove more severe than using fishing trips, but these results will be more in line with what can be expected when applying these models to new vessels. These results were finally used to calculate the gear metrics.

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
3600	72.64	85.6	0	40.6	NA	14.4	100
1800	74.81	74.1	0	33.7	NA	25.9	100
900	77.62	76.8	0	29.9	NA	23.2	100
600	78.11	79.1	0	28.2	NA	20.9	100
300	81.20	84.8	0	25.2	NA	15.2	100
120	81.70	85.4	0	24.5	NA	14.6	100
60	81.80	82.7	0	23.0	NA	17.3	100

Table 9. Results of ship-based cross-validation of the CART model at different resolutions

	acc	acc.haul	acc.set	FPR.haul	FPR.set	FNR.haul	FNR.set
3600	75.93	78.8	12.9	33.4	49.3	21.2	87.1
1800	78.93	78.6	29.8	28.6	40.5	21.4	70.2
900	83.68	81.4	49.8	22.3	26.5	18.6	50.2
600	84.99	83.4	54.3	19.4	24.5	16.6	45.7
300	87.34	86.8	56.1	16.6	24.8	13.2	43.9
120	87.19	88.6	47.3	16.0	33.8	11.4	52.7
60	86.33	89.0	39.8	16.7	41.5	11.0	60.2

Table 10. Results of ship-based cross-validation of the XGBoost model at different resolutions

Cross-validation (CV) by vessel gives slightly poorer results than CV 5-folds by fishing trip: at 300 seconds for CART we get 82.8% accuracy in validation by fishing trip vs. 81.2% by vessel, 89.7% by fishing trip vs. 87.4% by vessel at 300 seconds for XGBoost. This result was expected as the variability between different vessels is higher than between different fishing trips of the same boat, involving also that "atypical" boats will be less well predicted and cause global scores to fall slightly.

To compare the predictions of different vessels, the resolutions chosen are 3600 (1 hour), 900 (15 minutes) and 60 seconds (1 minutes). The first was chosen to look at the most degraded data available, the 15 minutes resolution corresponding to the frequencies that will be used for the deployment of the coastal VMS stream intended to equip certain French vessels of less than 12 meters, and finally the minute resolution being the one that seems suitable to be able to assess SSF operating passive gears correctly (ICES Scientific Reports Vol. 4 Issue 10, 2020).

Identifiant:	Longueur :	Acc 3600s	Acc 900s	Acc 60s
NAVIRE_0155	24.4 m	0.59	0.6	0.71
NAVIRE_0156	17.2 m	0.83	0.9	0.92
NAVIRE_0157	11.9 m	0.72	0.85	0.91
NAVIRE_0158	11.2 m	0.81	0.85	0.87
NAVIRE_0159	14.8 m	0.9	0.96	0.91
NAVIRE_0160	7.7 m	0.61	0.65	0.86
NAVIRE_0161	12.3 m	0.72	0.81	0.86
NAVIRE_0162	12 m	0.75	0.84	0.87
NAVIRE_0163	8.3 m	0.63	0.71	0.87
NAVIRE_0164	8.6 m	0.59	0.6	0.84
NAVIRE_0165	12 m	0.81	0.9	0.92
NAVIRE_0166	15.8 m	0.8	0.9	0.93
NAVIRE_0167	19.1 m	0.75	0.85	0.86
NAVIRE_0168	9.5 m	0.65	0.72	0.84
NAVIRE_0169	14.8 m	0.88	0.95	0.94
NAVIRE_0170	9.6 m	0.83	0.7	0.7
NAVIRE_0171	12 m	0.86	0.91	0.91
NAVIRE_0172	12 m	0.73	0.8	0.87
NAVIRE_0173	18 m	0.78	0.86	0.82
NAVIRE_0174	10.2 m	0.77	0.87	0.89

Table 11. XGBoost leave-one-out cross-validation results for each vessel at various resolutions

Since we're talking about "atypical" boats, let's look at the prediction results boat by boat (Table 9). For almost all boats, the prediction scores increase with a finer resolution (Table 9). However, two boats (0159 and 0173) score better at 900 than at 60 seconds, and one boat (0170) scores better at 3600 than at 900 and 60 seconds.
The least well predicted boat is 24 meters long and the only dominant offshore hake gillnetter in the OBSCAMe database as described in the typology of French gillnetters defined in Demaneche et al., 2021. The difficulty in predicting this vessel could come from a different behavior directly linked to a single fishing method in the dataset. This could be a major obstacle that will have to be taken into account if we are to create models applicable to all French gillnetters.
Fortunately, all classes of gillnetters that could be involved in cetacean bycatch in the Bay of Biscay seem to be present in the whole calibration dataset. The model built are then expected to be suitable for that purpose but probably not for application in other contexts (for example, gillnetters targeting monkfish in the English Channel…).

3.5 Improving the 60s XGBoost model

After our work on model optimization/evaluation was done, we were wandering how come our 60 seconds XGBoost model gives worse performances than the 300 seconds model. One of the main aspect we wanted to explore was the moving window. As said earlier, at 60 seconds the R^2 coefficient between the speed at the previous position and the speed at the current position is 0.97, which makes these two covariates highly correlated. It implies that using these two variables together does not give much more information than using only one of both. At 300 seconds, they are less correlated, as the behavior of the boat tends to change much more over the course of 5 minutes than it does over the course of a minute. So, we decided to keep the moving window of 1 neighbor at 60 seconds (although correlated, this moving window still provides new information, particularly for some other features used in the models), but we added the 5th previous and next neighbors for all covariates to include the information that was available in the 300 seconds dataset.
Below are presented the results of previous leave-one-out cross-validation by boat merged with the result attained at 60 seconds with the 5th neighbors :

	acc	acc haul	acc set	FPR haul	FPR set	FNR haul	FNR set
3600	75.93	78.8	12.9	33.4	49.3	21.2	87.1
900	83.68	81.4	49.8	22.3	26.5	18.6	50.2
300	87.34	86.8	56.1	16.6	24.8	13.2	43.9
60	86.33	89.0	39.8	16.7	41.5	11.0	60.2
60 5 neighbors	87.41	90.3	46.6	15.7	37.0	9.7	53.4

Table 12. XGBoost leave-one-out cross-validation results

By adding the 5th previous and next neighbors, the performance of our 60s XGBoost model improves significantly (Tab. 10), raising it from a 86.33% accuracy to 87.41%, the overall accuracy being now slightly better than the one obtained with the 300 s model.
One of the main takeouts is that, even though the model gained more than 1% of accuracy, calculation time was also greatly affected. The optimization took around 72 hours, while the evaluation using leave-one-out cross-validation by boat lasted just a little bit less (and both processes were ran on computing servers using parallelization methods and 12 cores).

4 Calculation of vessel effort as fishing hours

For the rest of our study, we decided to narrow down the data and algorithms we were using. We only kept four temporal resolutions, 3600, 900, 300, and 60 seconds. As for the models, we will keep using only the CART, which is the easier and fastest to implement and the XGBoost, which performs better. At 60 seconds, we will always add the 5th previous and next neighbors from now on.

4.1 Methodology

The aim of this part is to evaluate the efficiency of our XGBoost and CART models for estimating the vessel effort expressed in fishing hours. We will also see how these models fare compared to a speed filter and an improved speed filter. To do so, we will compare the fishing hours estimated by each model to the fishing hours calculated from the OBSCAMe database at two different temporal resolutions : 3600 and 900 seconds. We chose these resolutions because 3600s corresponds to the mandatory VMS available for French vessels, and 900s may be available for most of the SSF vessels already equipped with geolocation devices. In part 2.2, it was also shown that this resolution could be sufficient for identifying the fishing trips and calculate the fishing hours for SSF vessels.

4.1.1 Metrics for evaluating the quality of predictions

To evaluate each model, different metrics were chosen, such as the R^2, RRMSEP, and bias.

The R^2 (Pearson's coefficient of determination) is defined as such :

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2},$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of observed values, and n the number of observations/predictions.

The RMSEP (Root Mean Square Error of Prediction is calculated with the formula

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

, and the RRMSEP is equal to

$$RRMSEP = \frac{RMSEP}{\bar{y}}$$

Finally, the bias is calculated as:

$$\text{Bias} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}.$$

4.1.2 Aggregations and grids for mapping fishing effort

To evaluate our models performances, the predicted fishing hours were first aggregated by Fishing Trip to produce fishing effort data that could be linked to declarative data from the fishermen. Then, the predicted fishing hours were aggregated by CSquare in order to produce fishing effort maps containing every vessel available in the OBSCAMe dataset.

Csquares is a system for storage and display of spatial data that uses numbered squares on the earth's surface measured in degrees (or fractions of degrees) of latitude and longitude as fundamental units of spatial information, which can then be quoted as single squares in which one or more data points are located (Hintzen *et al.*, 2012). The CSquare 0.05° will be used as it is the reference grid for answering the ICES VMS datacalls.

4.2 Viability of the models for describing fishing effort at the fishing trip scale

First of all, we wanted to compare the results of machine-learning models with the existing method applied in the ALGOPESCA algorithm used by the French Fisheries Information System to predict fishing hours of French vessels. This algorithm uses a Speed Filter, whenever a position is associated to a speed below 4.5 knts it is considered as "Fishing", and "Not Fishing" otherwise. As we could not merge directly the ALGOPESCA fishing predictions with our database, this one not being available in the geolocation workflow, we applied a simple speed filter of 4.5 knts. We also made predictions with an improved speed filter which classifies a position as "Fishing" if the vessel has a speed below 3.5 knts and over 0.15 knts (Speed Filter 2). Finally, we added our CART and XGBoost models predictions obtained using the cross-validation by vessel process

We then used the iapesca function "Calc_VesselFE" (Rodriguez, 2023) to calculate the fishing hours for each fishing trip in our database, using either OBSCAMe qualified fishing operations as reference or the predictions from the different methods described before.

We can now look upon the error by Fishing Trip for each predictions, using simple regression plots with the R², RRMSEP ((Root Mean Square Error of Prediction / mean) * 100), Average and Bias as our evaluation metrics.

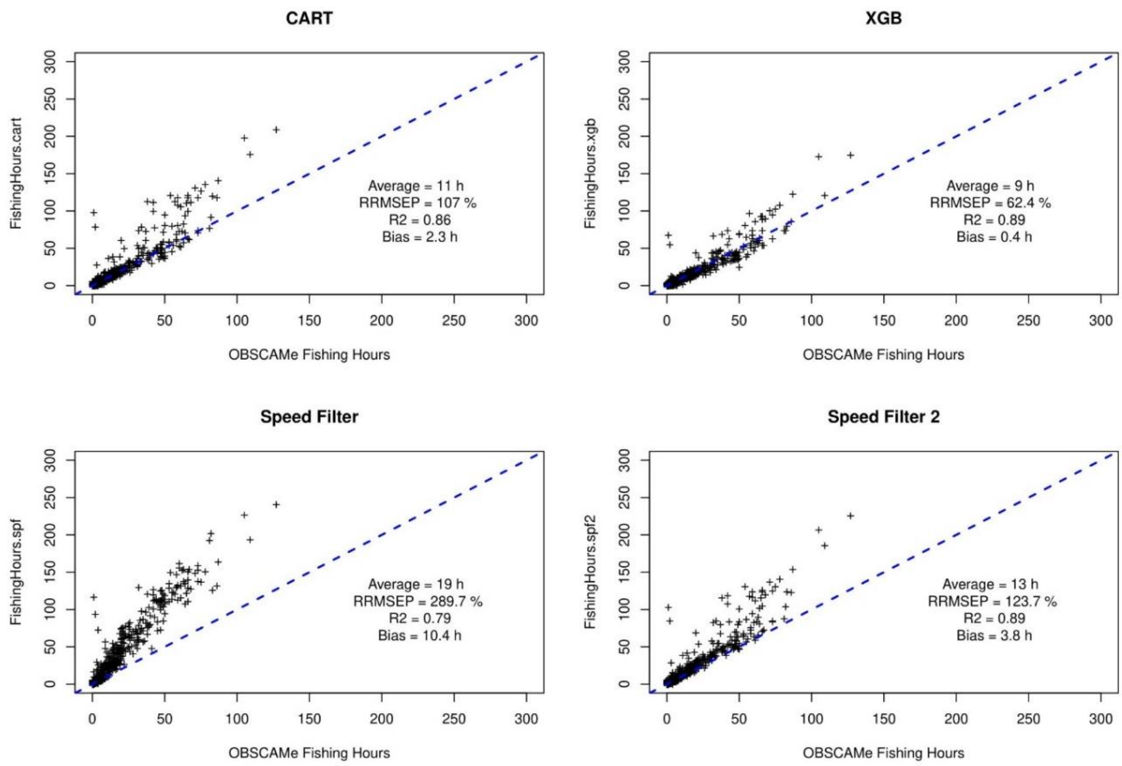

Figure 11. Error of predictions of the "Fishing Hours by Fishing Trip" metric for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 3600s

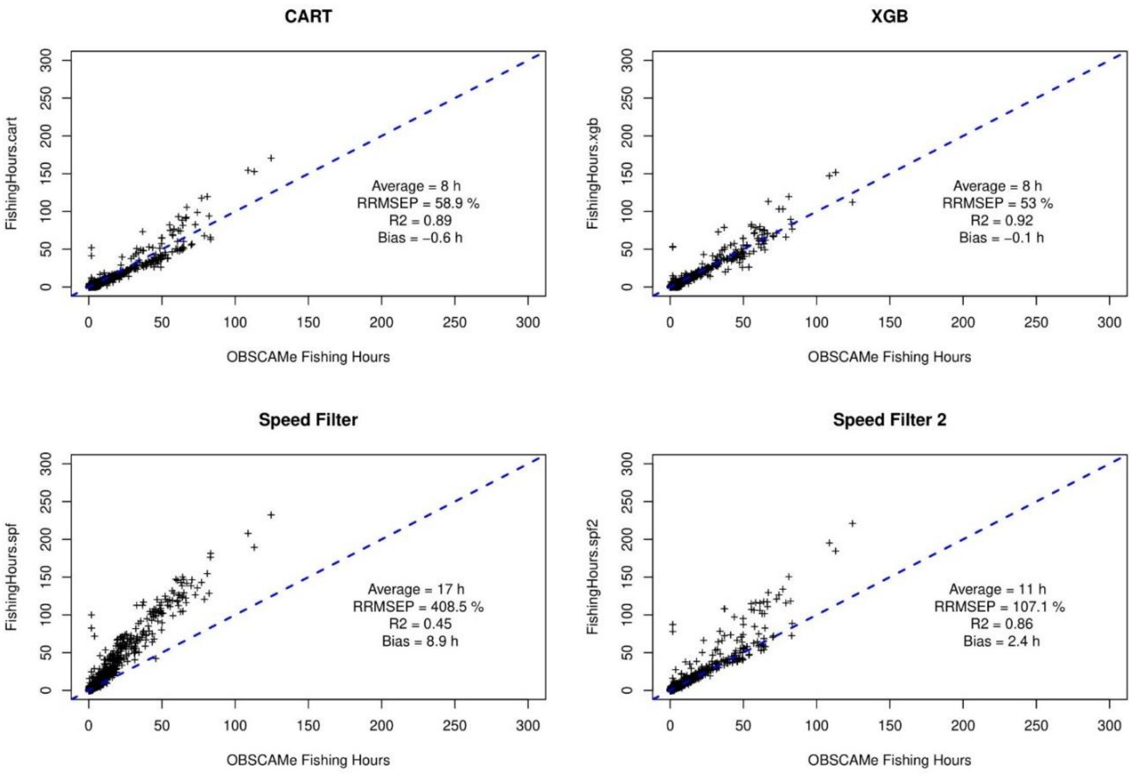

Figure 12. Error of predictions of the “Fishing Hours by Fishing Trip” metric for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 900s

At both resolutions, the best model to estimate the Fishing Hours is the XGBoost, followed by CART, the improved speed filter with minimal threshold, and at last the generic speed filter. The XGBoost and CART models do not seem to improve much between 3600s and 60s, but, as we have shown before, even though 900s is necessary to calculate the fishing hours of vessels under 12m in length, the 3600s resolution is perfectly fitted for the bigger boats. As these boats are bigger and do longer fishing trips, they have higher values of fishing hours and pull the relation towards higher values of R^2. However, when we look at the RMSEP and Bias, we see a real improvement between the two resolutions.
The simple Speed Filter (SPF) deteriorates at 900s compared to 3600s, but it appears that adjusting the thresholds already improve greatly its performance. Using a minimal threshold being really important for that gears, even for degraded resolutions.

We said the R^2 coefficient is not very reliable for the error by Fishing Trip because the relation between predictions and observations is pulled by the big vessels who have higher values of Fishing Hours by Fishing Trip. One may wonder how these relations would fare when we take into account only one small vessel (7,7m) of our dataset.

	RRMSEP 3600	RRMSEP 900	RRMSEP 300	RRMSEP 60
CART	278.2%	116.6%	82.4%	63.4%
XGB	247.3%	109.7%	48.1%	56.4%
SPF	298.8%	267.4%	233.5%	218.4%
SPF2	288.5%	219.4%	178.5%	162.1%

Table 12. RRMSEP of the “Fishing Hours by Fishing Trip” metric for the CART, XGBoost, SPF, and SPF2 at 3600s, 900s, 300s and 60s for a boat < 10m

	Bias 3600	Bias 900	Bias 300	Bias 60
CART	2.2h	1.5h	1.1h	0.7h
XGB	2h	1.3h	0.5h	0.6h
SPF	2.5h	3.6h	3.1h	2.9h
SPF2	2.2h	2.9h	2.4h	2.1h

Table 13. Bias of the "Fishing Hours by Fishing Trip" metric for the CART, XGBoost, SPF, and SPF2 at 3600s, 900s, 300s and 60s for a boat < 10m

As expected, we need a finer temporal resolution to assess correctly the fishing effort of this small boat. Even at 900 seconds the RRMSEP remains over 100% and the bias over one hour. For this boat the average fishing hours by Fishing Trip value is around two hours, so a bias over one hour wouldn't be acceptable.
Although the overall results demonstrate good performance even for the more degraded dataset, it appears that, for the smaller boats, a temporal resolution of at least 5 minutes may be necessary to be able to interpret correctly the vessel behavior.

Now, we can have a look at the Fishing Hours predictions on a map of the Gulf of Biscay. We used the methods implemented in the "iapesca" R-package to spatialize our data and then rasterize it with the Gulf of Biscay as our extent and CSquare 0.05°. The same breaks values were used on each plot so that we can compare each model.

4.3 Viability of the models for mapping fishing effort on a 0.05° C-square grid

By looking at the breaks values and the colors on the different maps, we can already oberve that both Speed Filters and particularly the one using only one upper threshold overestimate the FishingHours values. This result was expected, as the use of only one upper threshold lead to include in fishing effort the expectation time on fishing grounds, typical for these kind of

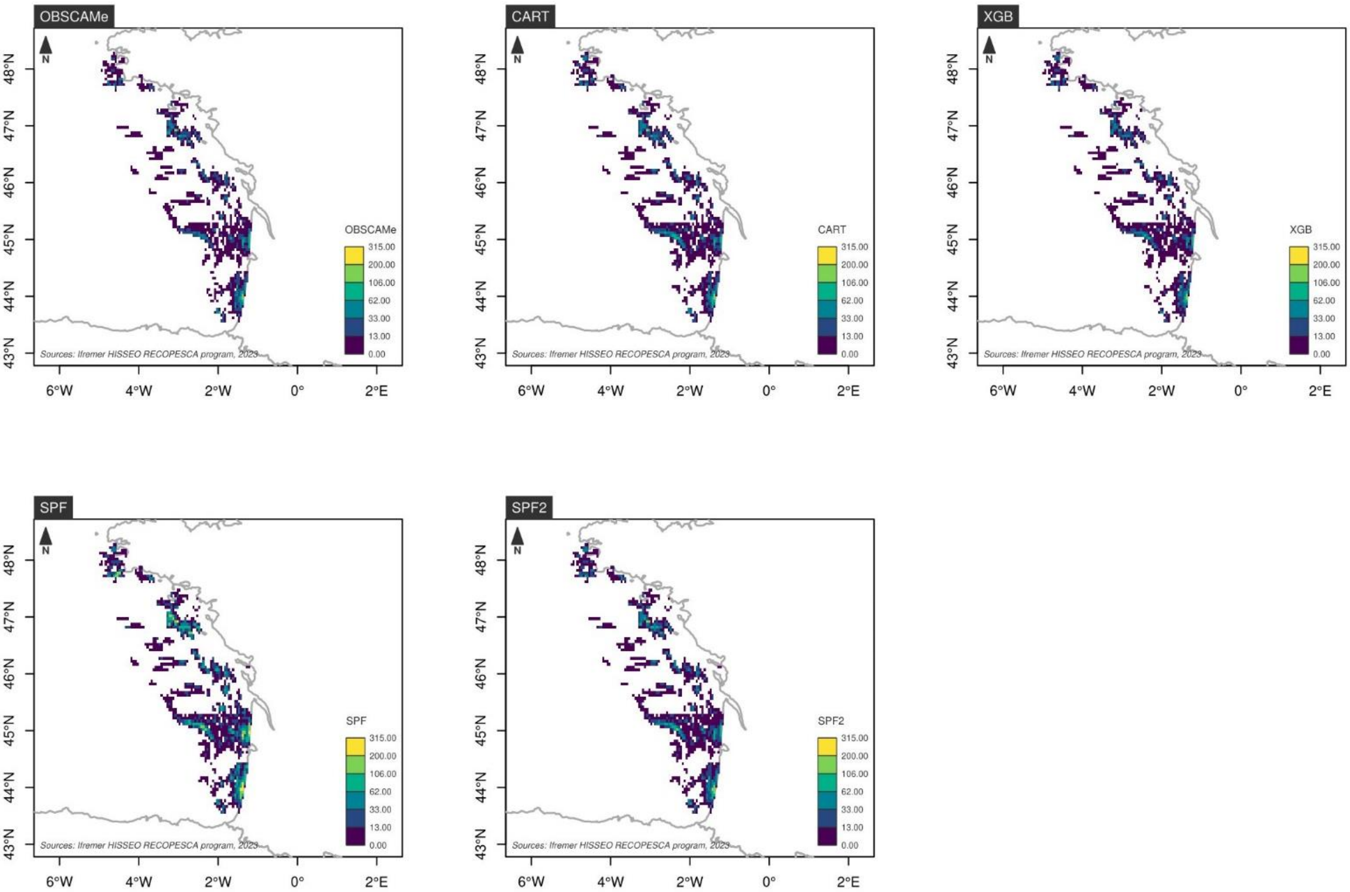

Figure 13. Fishing Hours values aggregated by CSquare 0.05 for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 3600s

fisheries. Including complexity in these models with two decision rules for the improved speed filter, four for the CART model and the XGB being even more complex. Allow a better description of fishing activity.

Next, we can calculate the error by CSquare between predictions and OBSCAMe values. To do so, we first calculate the DiffFishingHours as $\frac{prediction - observations}{observations} \times 100$. In some cases, the overestimation of predictions is so strong that values over 100 may be reached. To make a distinction between erroneous pixels(fishing occurs in Csquare for predictions but not for observations) and greatly overestimated pixels, we decided that all values over 98.99 would be given a value of 98.99, and erroneous pixels a value of 100. The same goes for missing pixels (fishing occurs in Csquare for observations but not for predictions) which were given values of -100.

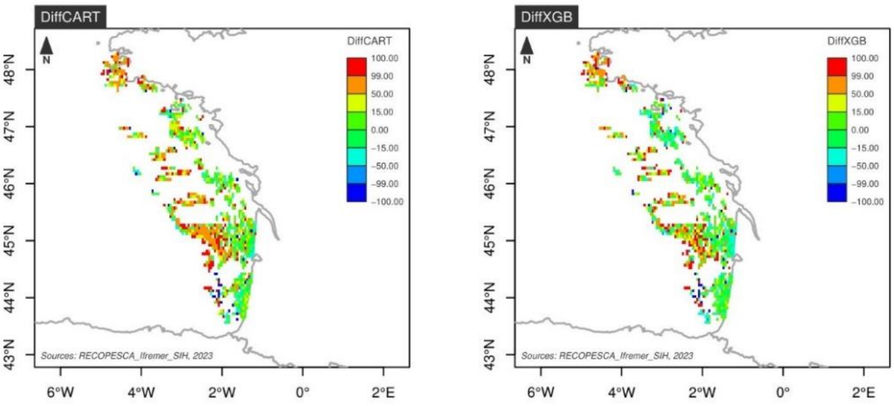

Figure 14. Error in Fishing Hours predictions aggregated by CSquare 0.05 for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 3600s

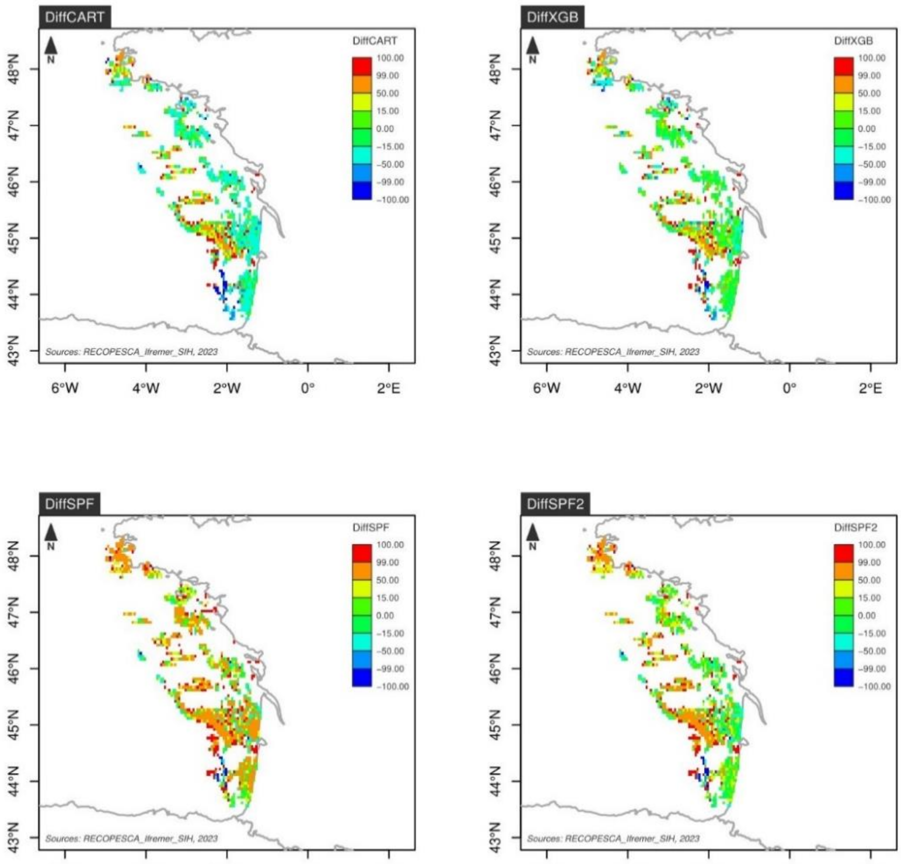

Figure 15. Error in Fishing Hours predictions aggregated by CSquare 0.05 for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 900s

Just by looking at the maps the XGBoost model's cartographic error appears to be less important at 900s than it is at 3600s. The CART predictions are generally underestimated at 900s (Fig. 14). In fact, when we look at the error computed by Fishing Trip (Fig. 9-10), it appears that the CART also has a negative Bias at 900s.

For further analysis the histograms of values are plotted to observe the overall distribution (Fig. 16-17), and then evaluation metrics are calculated (RRMSEP, average, R^2 and Bias) (Fig. 18-19).

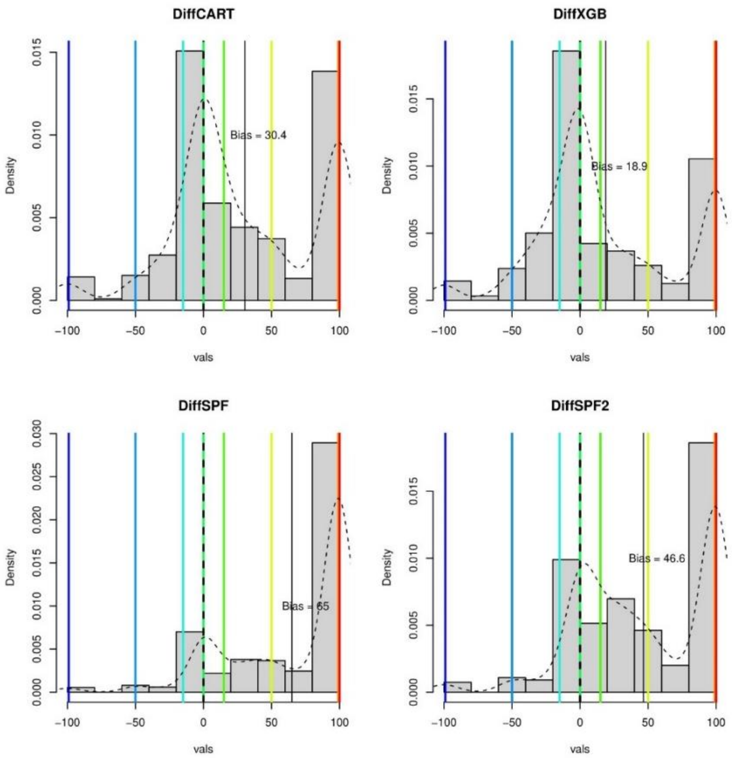

Figure 16. Histograms of DiffFishingHours by CSquare 0.05 for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 3600s

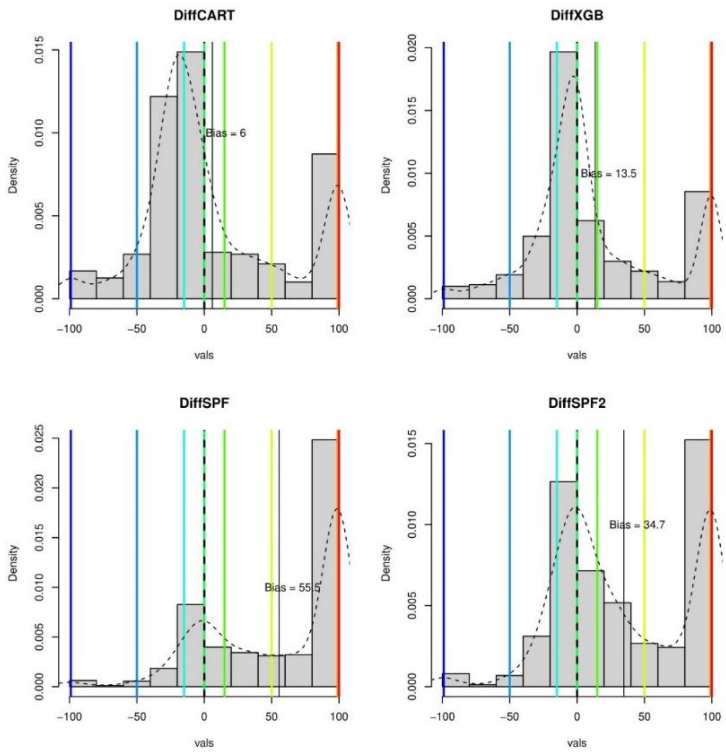

Figure 17. Histograms of DiffFishingHours by CSquare 0.05 for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 900s

The histograms above summarize the values plotted on the maps. As expected, the CART model underestimates the FishingHours at 900s. At both resolutions, the histogram which is more centered around zero is the XGBoost, which means the bias is minimized compared to the other models, showing once again this model's high predictive ability.

We will now look at the relations between OBSCAMe fishing hours and the predictions of our different models aggregated by CSquare 0.05.

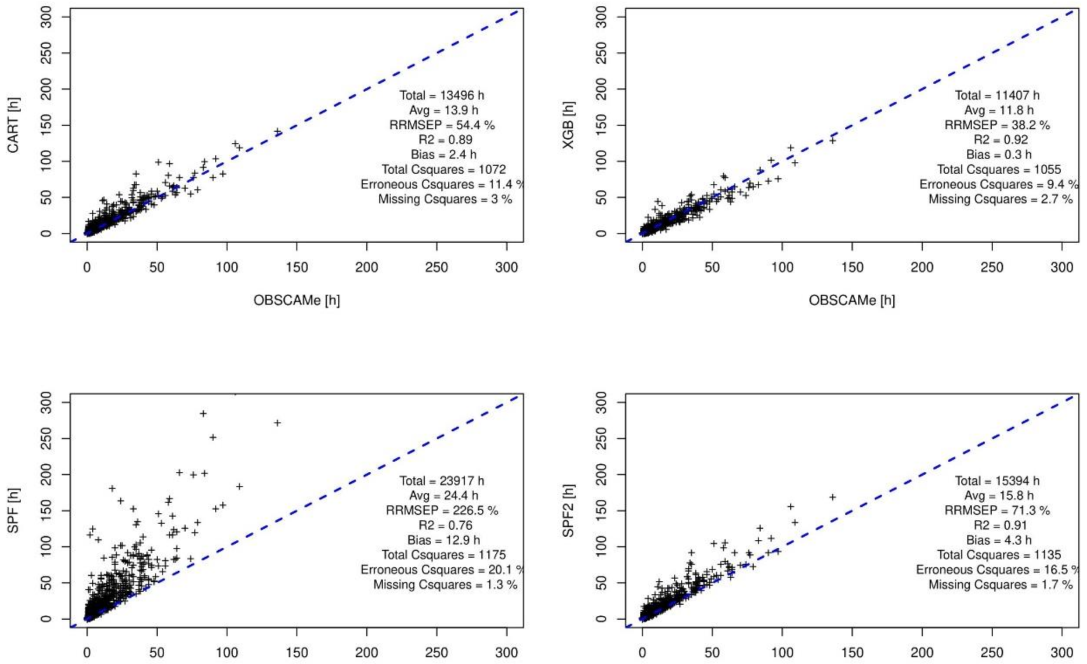

Figure 18. Error of predictions of the Fishing Hours computed by 0.05° CSquare for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 3600s

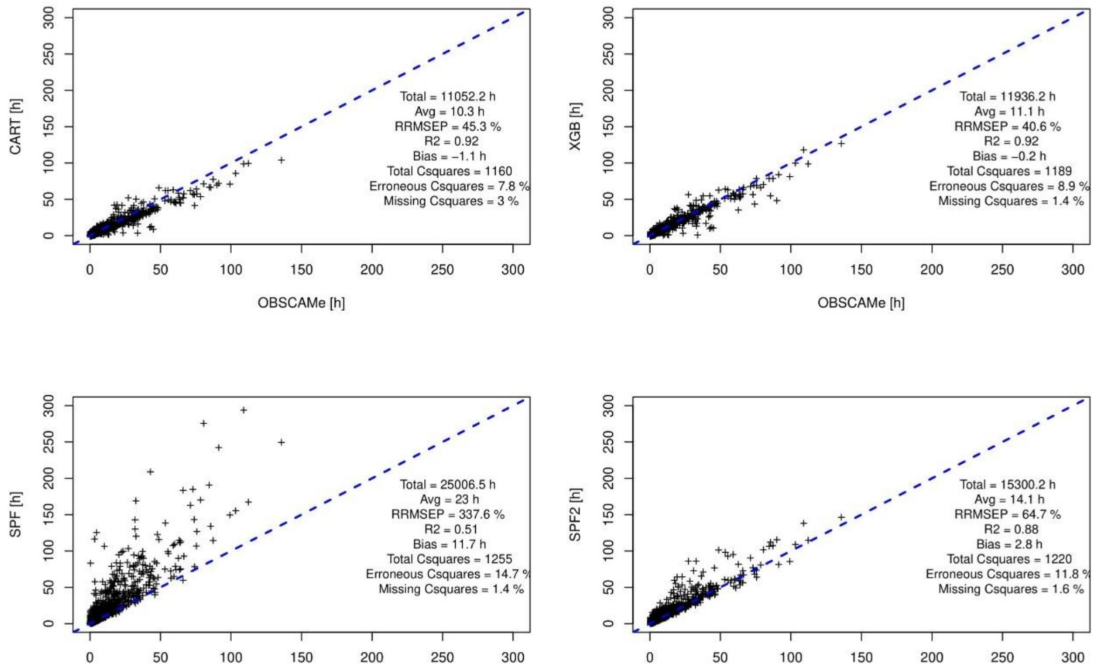

Figure 19. Error of predictions of the Fishing Hours computed by 0.05° CSquare for the CART, XGBoost, Speed Filter, and Speed Filter 2 at 900s

Compared to the method used at present to describe the fishing effort for gillnetters with the existing VMS workflow (3600s), an improved speed filter contributes to reduce the error by a factor of 3, the CART and XGB models by respectively factors of 4 and 6. The effort being overestimated by a factor over two with the current method, the bias is respectively reduced by factors of 3 and 5 and is negligible when using the XGB model.

Surprisingly, the use of 900 seconds resolution instead of 3600 seconds does not seem to bring a significant improvement and even leads to a stronger overestimation when applying a simple speed filter. The bias seems to be reduced for more complex models.

The goal of this study, however, is not to calculate FishingHours, as we know this metric isn't adapted to fisheries using passive gears (such as gillnetters) (Mendo *et al.*, 2023). In the next section we will go over the process of gear modelling and calculating gear effort, which will require an even finer resolution as demonstrated in part 2.

4.4 Application to the VMS data

Three of the different methods tested (speed filter <4.5 knots, CART and XGBoost) were applied to the VMS data available for the Bay of Biscay. Only the gillnetters were extracted from the VMS database, and all the fishing trips using other types of gears were removed. The temporal window chosen is from January 2022 to September 2023. Then, the data went though the process described in part 4.3, which resulted in the maps below.

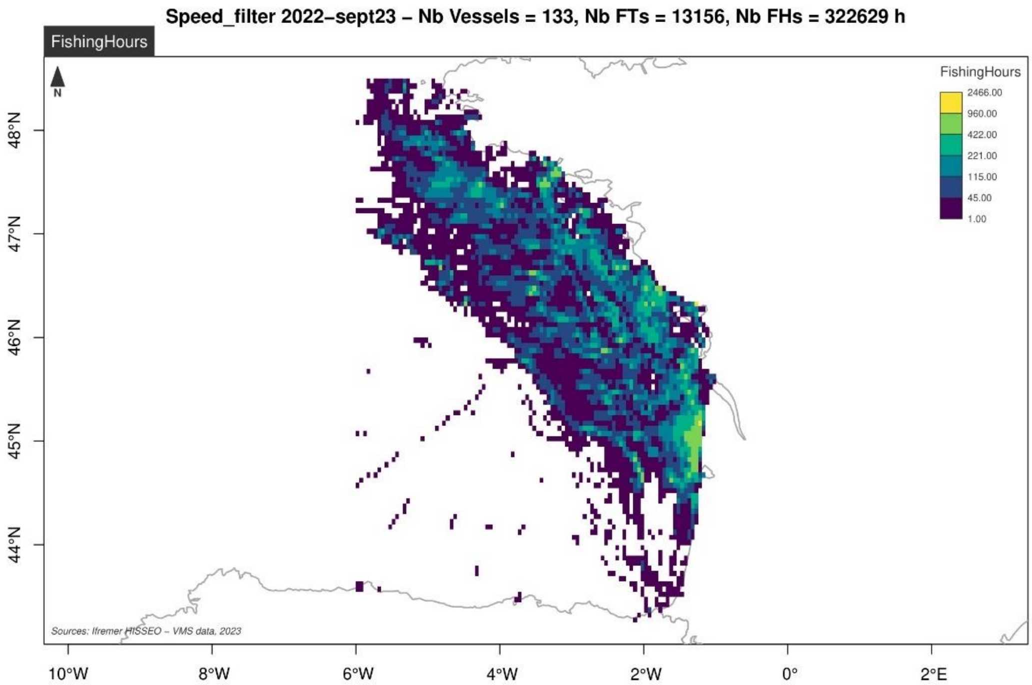

Figure 20. Fishing Hours values computed by a speed filter (<4.5 knots) applied to the VMS data (3600s) for all French gillnetters between 01/2022 and 09/2023

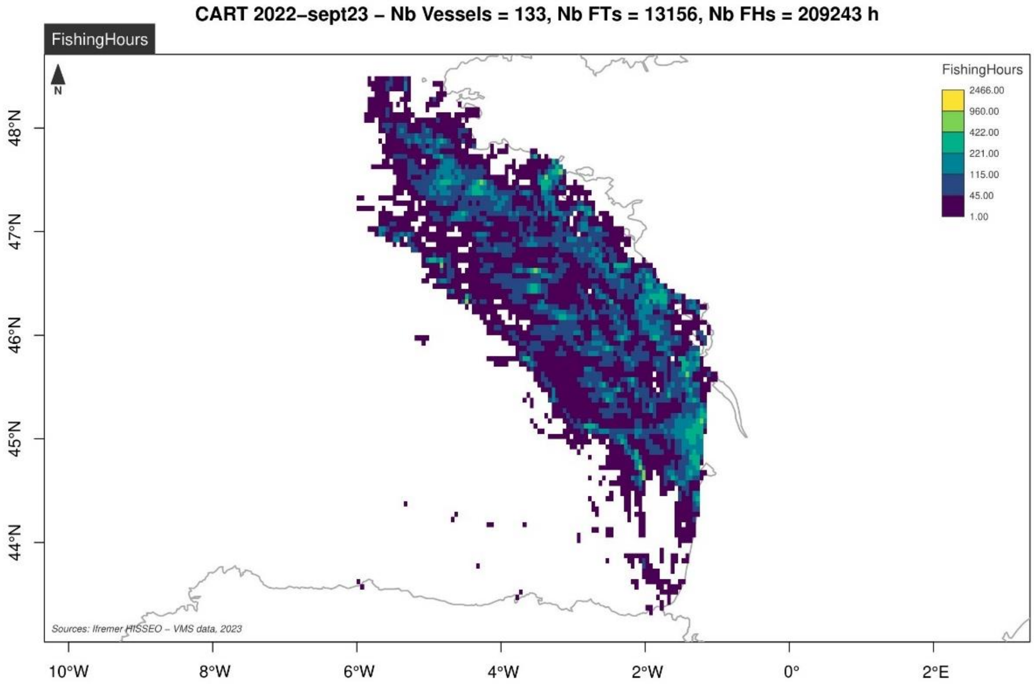

Figure 21. Fishing Hours values computed with the CART model at 3600s applied to the VMS data (3600s) for all French gillnetters between 01/2022 and 09/2023

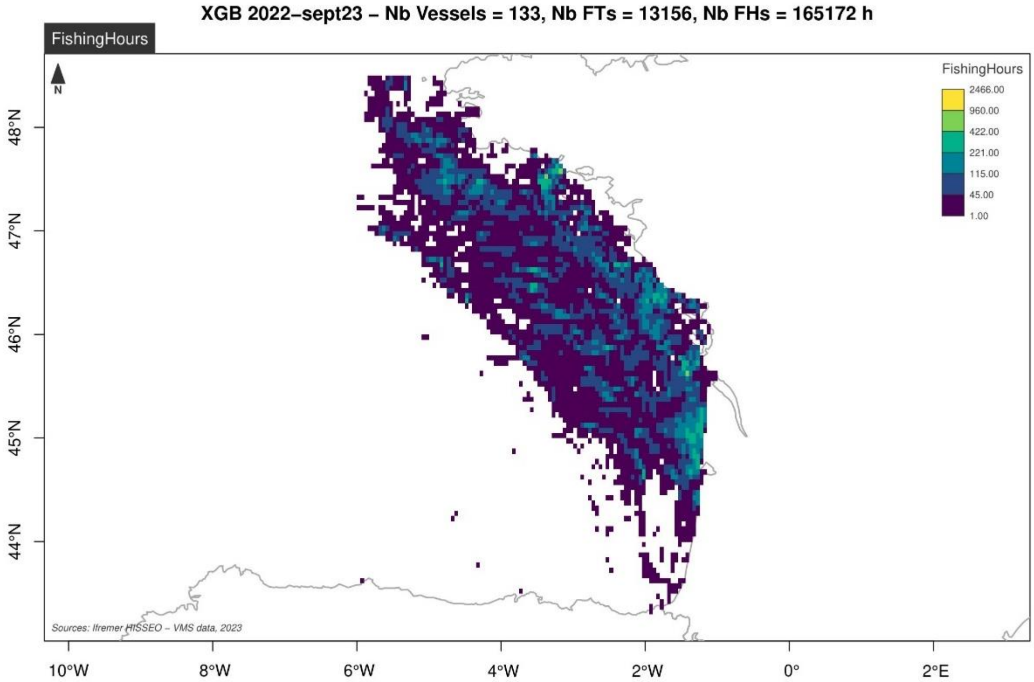

Figure 22. Fishing Hours values computed with the XGBoost model at 3600s applied to the VMS data (3600s) for all French gillnetters between 01/2022 and 09/2023

These maps highlight the overestimation of the speed filter compared to the machine learning methods. Following this work, improved maps of fishing hours using the VMS flow can now be routinely produced.

5 Calculation of gear effort as total length and soaking time

5.1 Gear creation issued from the geocomputation process developed in the “iapesca” R-package (Rodriguez, 2023)

We will use the R package "iapesca" to calculate gear metrics (Rodriguez, 2023). Using a dataset containing the fishing positions and the qualification of operations, methods available in this package create spatial objects representing the nets and compiling the information regarding the whole fishing operation (length, soaking time, fishing trip identifier for setting and hauling, etc.).

We can therefore create the "real" nets from the qualified database, and the predicted nets from the results of cross-validation by vessel, using the “Create_NetsByBoat” function. This process will create a spatial object from a sequence of contiguous positions qualified as hauling.

Two methods are available for consolidating the generated nets: "BehaviourChange" and "AutoThresholdDetection".
Activation of the "BehaviourChange" method takes into account a local classification of speed and direction changes to generate net separations within continuous sequences if a change in behavior is detected. This method was first developed and proved to be useful for degraded resolutions (900 s) to qualify straight nets.
Activation of the "AutoThresholdDetection" method determines threshold values based on generated net statistics (length, immersion time, hauling speed, etc.), to compensate for gear expertise when knowledge of these parameters is not available and can’t be defined explicitly in the function. We chose to use the “AutoThresholdDetection” process but to deactivate the “BehaviourChange”, as at the finest resolutions this argument of the function generally generated far too many nets, with numerous changes of direction appearing as we refined the temporal resolution.

In a second step implemented in the function “Retrieve_SettingOperations”, a spatial buffer is generated to look for past sequences of points that could correspond to the setting by spatial overlapping. These sequences are then hierarchized based on their probability to be the related setting event with a process similar to the one described in Mendo *et al*., 2023, being based on their temporal proximity and the best match between respective lengths of the sequence. The function additionally provides a score based on the qualifications as “setting” operations if they are available. The default buffer value was defined using the qualified data set available in iapesca.

We decided to use the following variables to compare the boats and the predictive capabilities of the models at different resolutions:

- Median soaking time per fishing trip

- Total length deployed per fishing trip

- Total length * soaking time

Once these metrics have been calculated for both qualified and predicted data, we will compare observations with predictions. The R^2 over all fishing trips will be calculated, as well as the RRMSEP and Bias (see part 4.1).

To have a better understanding of what our computed nets look like for the whole calibration database, below you will find screenshots of the interactive maps created with the R-package “mapview” showing the spatial objects generated with the “Create_NetsByBoat” and “Retrieve_SettingOperations” functions from iapesca (Fig. 19).

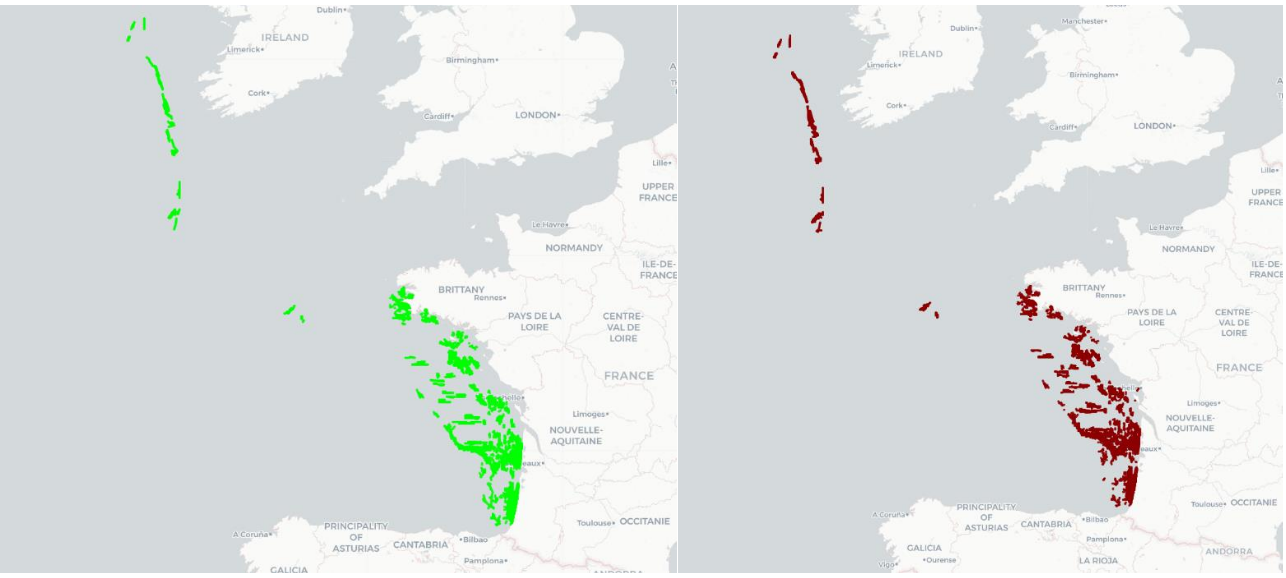

Figure 23. Nets created from the OBSCAMe data (green) and from the XGBoost model predictions (red) at 300s

5.2 Gear effort metrics aggregated by Fishing Trip

From now on, the work carried out on the gear effort metrics (Total Length Hauled, Median Soak Time, and Length*SoakTime) will be similar to what we did with the FishingHours earlier. In this case, the function Calc_VesselFE will not only take the positions as inputs, but also the gears. For the observations, we consider the nets generated from the 60 seconds OBSCAMe database. For the predictions, we will now only look at the XGBoost models cross-validation by vessel results obtained at different temporal resolutions, for the simple reason that it is the most accurate of the models studied (see 3.4), the best possible accuracy being a prerequisite for applying this geocomputation process (Mendo et al., 2023).

The nets without related setting event were removed (argument "remove.orphans" in "Retrieve_SettingOperations"). Implementing the gears in the "Calc_VesselFE" function allows us to compute the total length hauled, median soaking time, and the product of these metrics described as Length*SoakTime by fishing trip, as well as consolidating the FishingHours metric by removing some false positive hauling events.

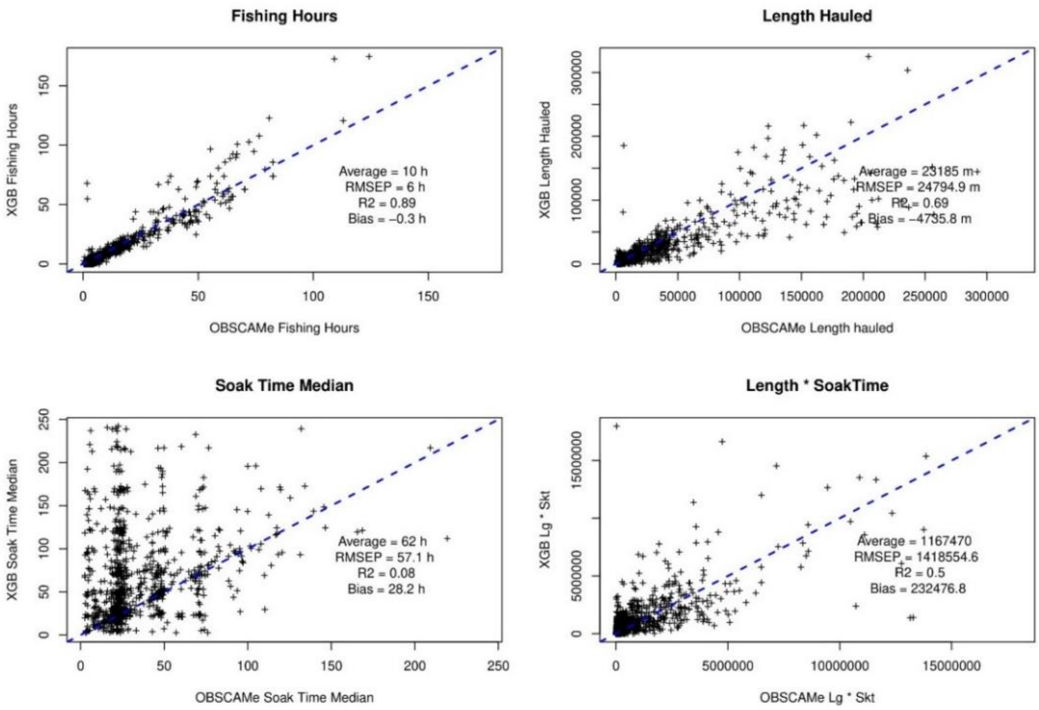

Figure 24. Error in predictions of the XGBoost model for different metrics aggregated by Fishing Trip at 3600s

We have tabulated the result by gear effort metric.

	Average Length	RRMSEP Length	R2 Length	Bias Length
3600	23185 m	96.1%	0.69	-4735.8 m
900	21780 m	59.4%	0.89	-361.2 m
300	21398 m	61.7%	0.89	-45.6 m
60	22330 m	61.3%	0.91	1013.6 m

Table 15. Error in predictions of the XGBoost model for the total length hauled aggregated by Fishing Trip at various resolutions.

	Average SoakTime	RRMSEP SoakTime	R2 SoakTime	Bias SoakTime
3600	62 h	165.6%	0.08	28.2 h
900	48 h	107.4%	0.24	13.5 h
300	37 h	71.4%	0.44	2.3 h
60	37 h	66.5%	0.51	2.1 h

Table 16. Error in predictions of the XGBoost model for the soaking time aggregated by Fishing Trip at various resolutions.

	Average Length*Skt	RRMSEP Length*Skt	R2 Length*Skt	Bias Length*Skt
3600	1167470 m*h	163.4%	0.50	232476.8 m*h
900	924253 m*h	133.8%	0.74	176485.4 m*h
300	736785 m*h	92.3%	0.82	12120.5 m*h
60	772354 m*h	115%	0.80	52498.5 m*h

Table 17. Error in predictions of the XGBoost model for the length * soak time metric aggregated by Fishing Trip at various resolutions.

These results show that the 300s or 60s resolution are needed to be able to predict the gear effort correctly. The best of these two temporal resolutions cannot be determined based on the results shown here. At last, the aim of this study is not to predict the aggregation of gear effort metrics by Fishing Trip, but rather by CSquare, which will be done in the following part.

5.3 Gear effort metrics aggregated by CSquare 0.05°

Once again, we use iapesca functions to spatialize (Spatialize_FE) and then rasterize (Rasterize_FE2Csq) our data. We end up with a Raster containing the aggregated gear effort metrics values by CSquare. We decided to use the CSquare 0.05° again to compare the four different temporal resolutions (3600s,900s,300s,60s) because it is the reference grid used for answering ICES VMS datacalls and that using a smaller CSquare wouldn't be suited to the 3600 seconds resolution. Once this process ends, we can plot the raster object over an outline of the Gulf of Biscay.

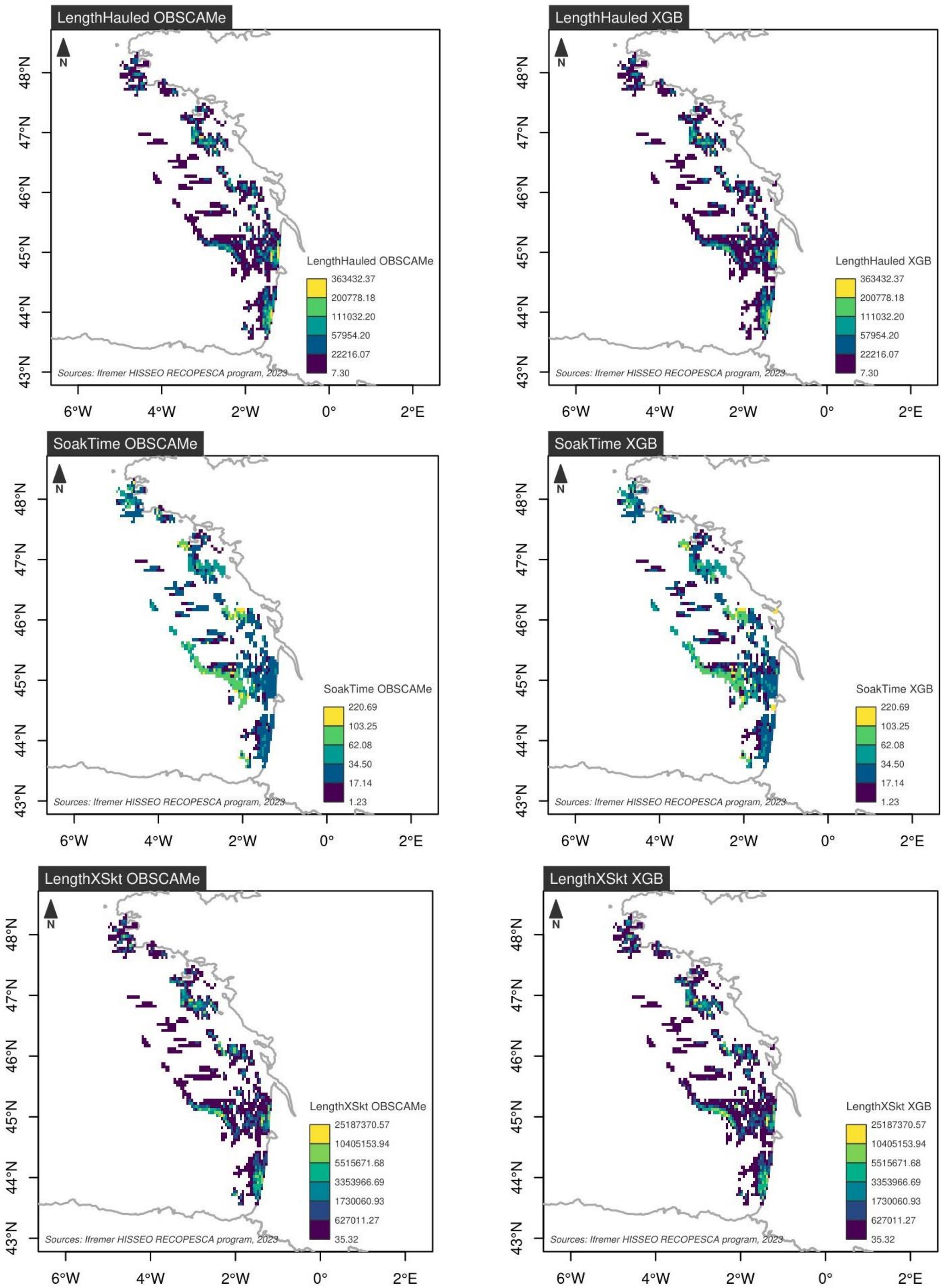

Figure 25. Gear effort by CSquare 0.05° for the "FishingHours", "Length Hauled", "Soaking Time", and "Length * Soak Time" at a 60s resolution (OBSCAMe data on the left, XGB predictions on the right)

Just like in part 4.2 with the fishing hours, differences between predictions and observations will be computed at the scale of the CSquare 0.05° for each metric in a raster object, which will be plotted over a map outline with histograms of its values next to it.

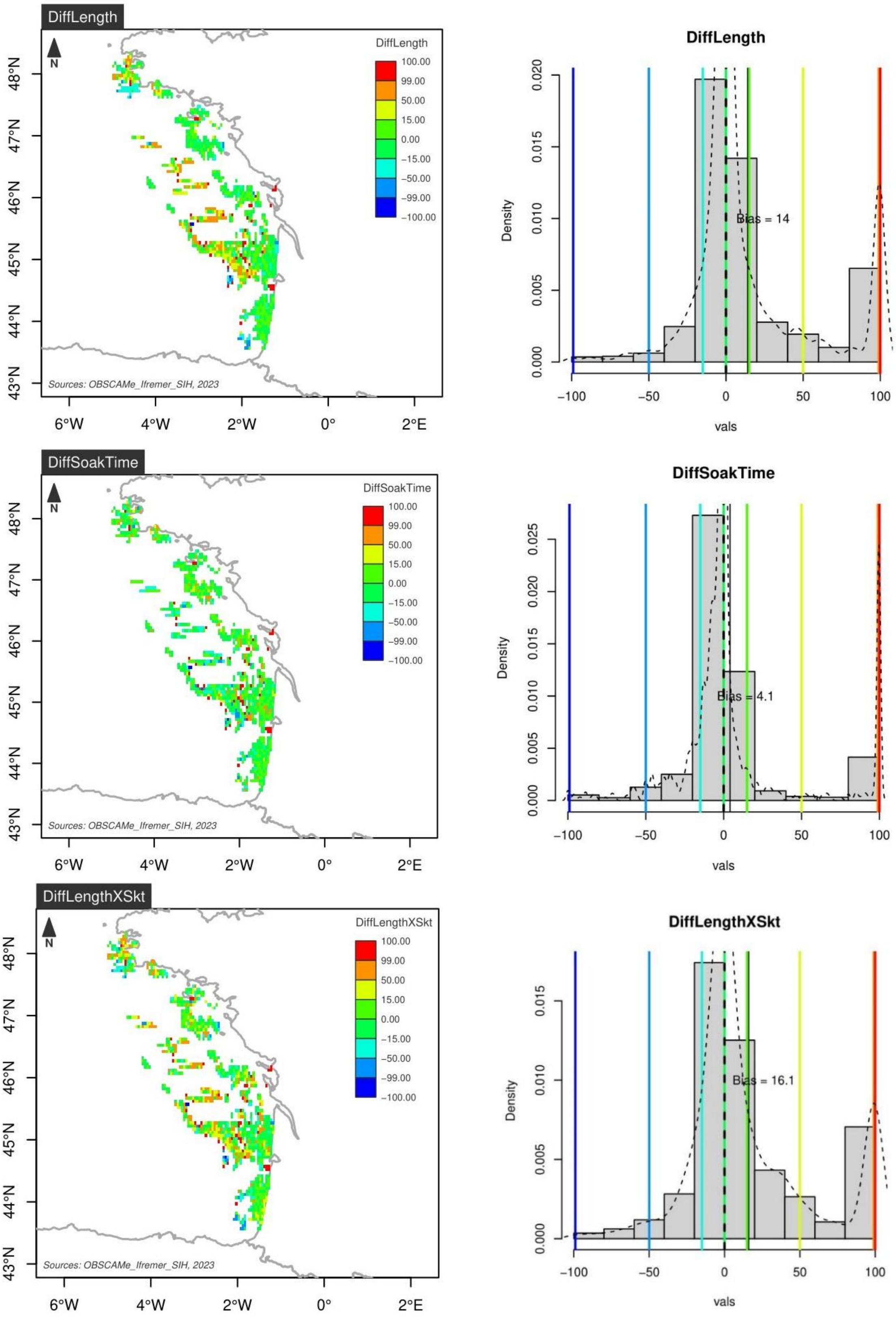

Figure 26. Error in “FishingHours”, “Length Hauled”, “Soaking Time”, and “Length * Soak Time” XGBoost predictions aggregated by CSquare 0.05° at a 60s resolution

The main outtake of these maps is that fishing operations located on the continental shelf seem harder to predict. Fortunately, the histograms values are all pretty centered around 0, which goes to show how promising XGBoost predictions are for fishing effort cartography.

Now let's look at the error by CSquare for the four gear effort metrics. "Av.Pix" being the average prediction value of a pixel (or CSquare).

	RRMSEP LengthHauled	Av.Pix LengthHauled	R2 LengthHauled	Bias LengthHauled
3600	64.9%	24602.4 m	0.8	-6731.8 m
900	38.9%	27255.5 m	0.9	-815.9 m
300	32.3%	26677.4 m	1.0	-617.5 m
60	24.4%	27834.4 m	1.0	690.2 m

Table 19. Error in predictions of the XGBoost model for the Total Length Hauled metric aggregated by CSquare 0.05° at various resolutions.

	RRMSEP SoakTime	Av.Pix SoakTime	R2 SoakTime	Bias SoakTime
3600	96.3%	45.3 h	0.2	10.9 h
900	67.7%	38.1 h	0.5	3.8 h
300	37.9%	33.1 h	0.8	-0.8 h
60	42.3%	34 h	0.7	0.1 h

Table 20. Error in predictions of the XGBoost model for the Soaking Time metric aggregated by CSquare 0.05° at various resolutions.

	RRMSEP LengthXSkt	Av.Pix LengthXSkt	R2 LengthXSkt	Bias LengthXSkt
3600	107.1%	1413874.5 m*h	0.7	208587.5 m*h
900	103.1%	1345051.4 m*h	0.8	267811.8 m*h
300	46.7%	1078133.2 m*h	0.9	32116.1 m*h
60	55%	1176320.6 m*h	0.9	136080.7 m*h

Table 21. Error in predictions of the XGBoost model for the Length * Soak Time metric aggregated by CSquare 0.05° at various resolutions.

Once again, the results get better from the most degraded resolution (3600s) until the 300 seconds resolution, and the 60 seconds resolution does not improve the latter.

5.4 Gear effort metrics aggregated by CSquare 0.01°

To obtain a finer spatial resolution, we can go through the whole process of part 5.3 using CSquare 0.01° instead of 0.05°. We will no longer need the 3600 seconds resolution, as the granularity is not fine enough.
At the latitudes studied, the CSquare 0.01° has a diagonal measuring around 1.2km. If a boat is fishing (~2.5 knots) it will travel a distance of 4.6km in an hour, 1.15km in 15 minutes. Hence the choice not to use a resolution more degraded than 900 seconds.

Let’s have a look at the error maps of the metrics aggregated by CSquare 0.01°.

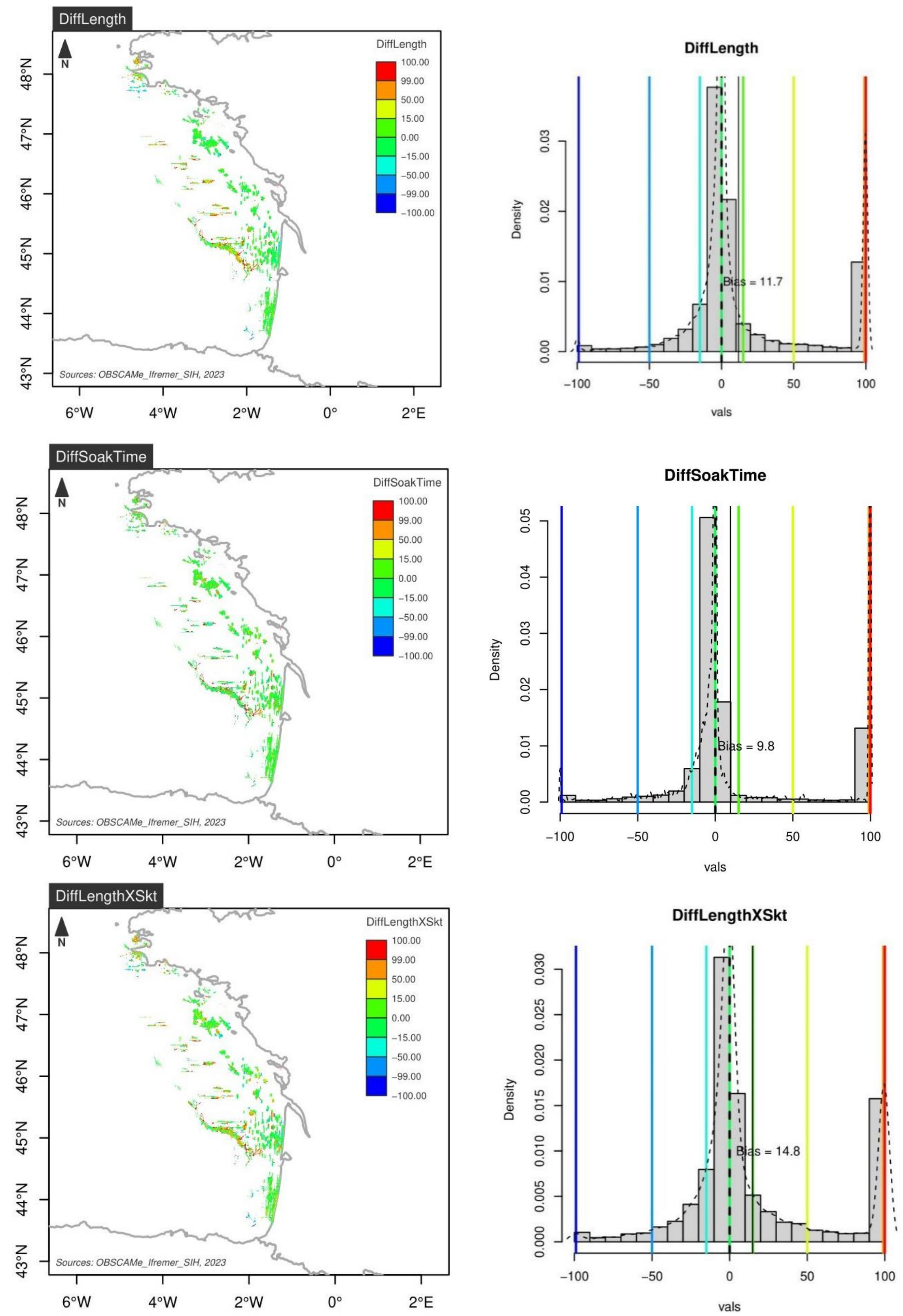

Figure 27. Error in “FishingHours”, “Length Hauled”, “Soaking Time”, and “Length * Soak Time” XGBoost predictions aggregated by CSquare 0.01° at a 60s resolution

The bias for each metric except the Soaking Time appears to be better with a CSquare 0.01° than with a CSquare 0.05°. Obviously, we cannot really compare both spatial resolutions because the information they provide is so different, however it is reassuring to see that even with a resolution as thin as 0.01° the 60 seconds XGBoost model still makes few mistakes.

	RRMSEP LengthHauled	Av.Pix LengthHauled	R2 LengthHauled	Bias LengthHauled
900	44.4%	2900.0	0.9	-102.4 m
300	34.2%	2743.4	0.9	-100.7 m
60	27.1%	2798.7	0.9	21 m

Table 23. Error in predictions of the XGBoost model for the Length Hauled metric aggregated by CSquare 0.01 at various resolutions.

	RRMSEP SoakTime	Av.Pix SoakTime	R2 SoakTime	Bias SoakTime
900	68.9%	43.3	0.4	5.6 h
300	43.4%	37.3	0.7	-0.1 h
60	48.9%	38.9	0.7	1.4 h

Table 24. Error in predictions of the XGBoost model for the Soaking Time metric aggregated by CSquare 0.01 at various resolutions.

	RRMSEP LengthXSkt	Av.Pix LengthXSkt	R2 LengthXSkt	Bias LengthXSkt
900	109.8%	143271.0	0.7	27931.0
300	57.5%	110949.5	0.8	1940.6
60	61%	118471.1	0.9	12028.4

Table 25. Error in predictions of the XGBoost model for the Length * SoakTime metric aggregated by CSquare 0.01 at various resolutions.

The 60 and 300 seconds resolution still have pretty similar results, based on these results we cannot say that one of both is better than the other. However, the 60 seconds resolution is better for the Length Hauled.

6 Validation using on-board observations

OBSMER is an on-board observation program for professional fishing vessels at sea, set up at national level in 2009 by the DGAMPA (General Directorate for Maritime Affairs, Fisheries and Aquaculture). Between 2021 and 2023, 13 of the 20 vessels in the OBSCAMe database for a total of 26 fishing trips have been sampled by OBSMER. For each vessel, a spatio-temporal join of the OBSMER and OBSCAMe fishing operations was carried out, giving priority to the temporal link. . In total, 86 OBSCAMe nets were associated with 97 hauls observed in OBSMER, the numbers differ because 10 nets appearing to be consistent in OBSCAMe actually correspond to several hauling events in OBSMER.

These operations were also linked with the nets generated from the XGBoost predictions by the geocomputation process. The nets corresponding to the operations available in the calibration database are created from the by-vessel cross-validation predictions, and those corresponding to later operations (after September 2022) are derived from the predictions of the final model for these new fishing-trips.

From this link between operations, fishing gear effort measurement from fishermen's declarations can be extracted from OBSMER (and compared with the dimensions computed from OBSCAMe and XGBoost predictions.

6.1 Nets length

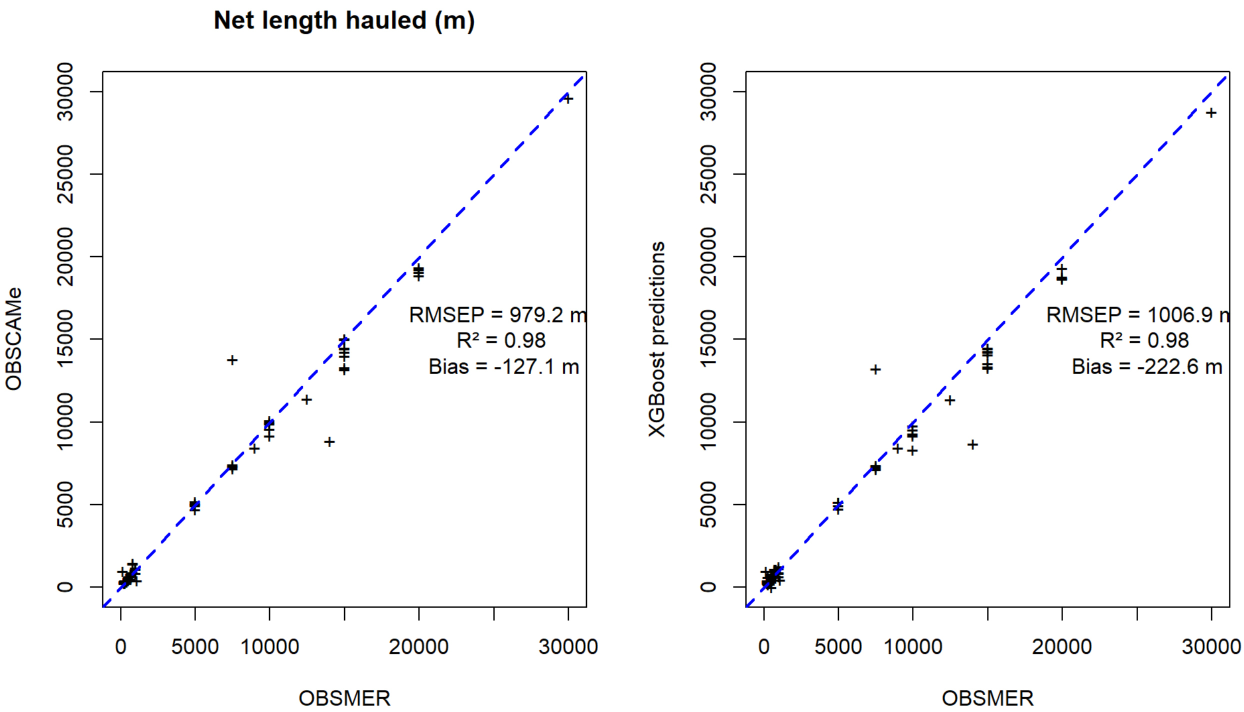

Figure 28. comparison of OBSMER length hauled with OBSCAMe (left) and XGBoost (right)

The difference between the lengths computed from OBSCAMe and the OBSMER source remains very small (RRMSEP = 20.7%, Bias = -2.7%). The results for predictions show comparable error levels of 21.3%, but with a slightly higher bias of -4.7%. On average, the assessment method does not generate an overestimate. However, as this relationship is highly dependent on nets several kilometers long, a check is carried out on nets less than 1500 m long.

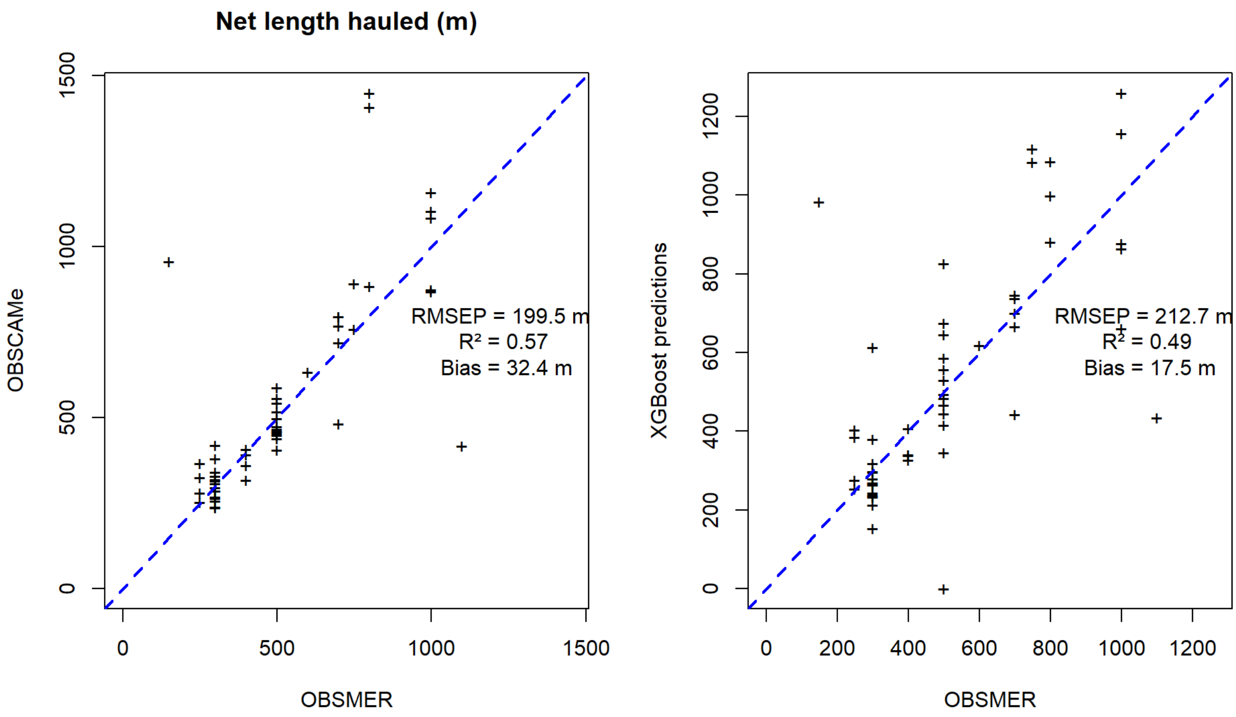

Figure 29. comparison of OBSMER length hauled with OBSCAMe (left) and XGBoost (right) for all nets < 1500m.

OBSCAMe net lengths remain consistent despite a higher error of the order of 39%, but a bias which, although positive, remains low: 6.3%. The results for the predictions show comparable error levels: 41.6%; they also remain coherent with observations, with a few exceptions and a lower bias of 3.4%.

6.2 Soaking Time

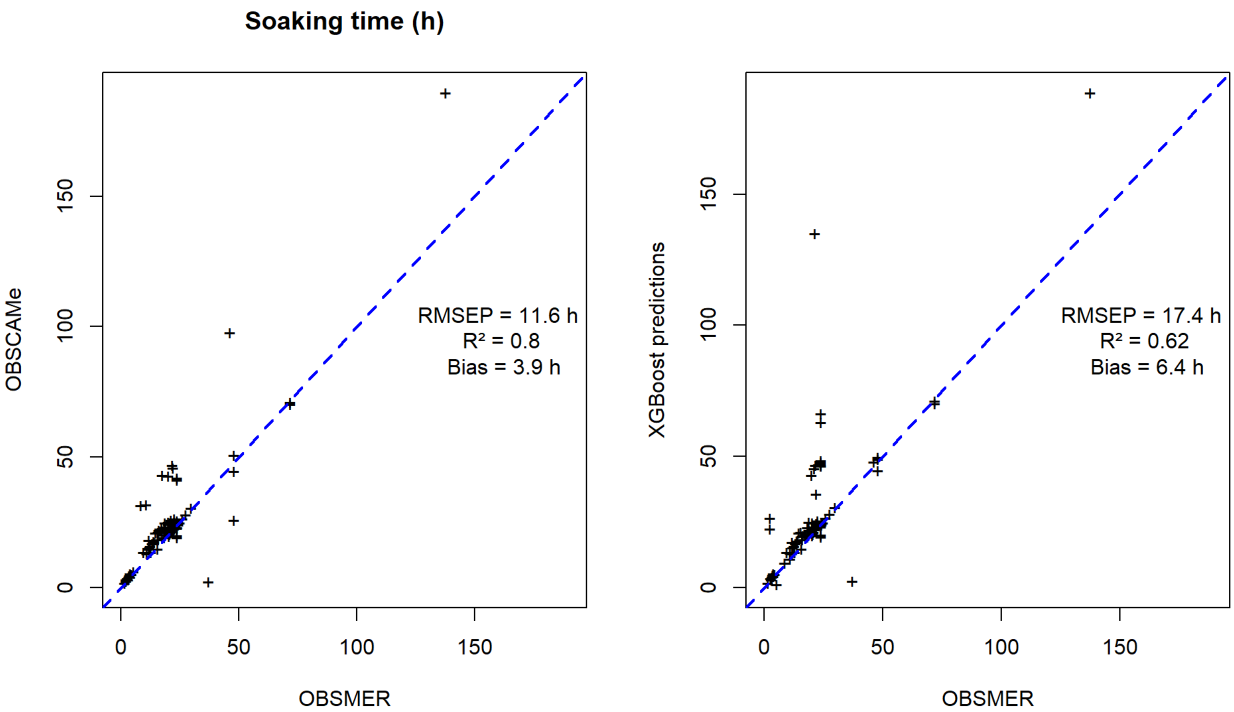

Figure 30. comparison of OBSMER soaking time with OBSCAMe (left) and XGBoost (right)

OBSCAMe soaking times remain consistent, but with a higher mean error of 52.2% and a bias of 17.6%. The results for predictions are logically worse than the previous ones, with 78.4% and a bias of 28.8%. This deterioration is mainly due to an observation for which the predicted value is very far from the value in OBSMER.

Being based on declarative data, the reference data is subject to a degree of uncertainty. Despite a non-negligible error when reduced to the operation, the data remain globally consistent with observation, with a tendency to over-estimate (+6h) the model's predictions, to be compared with an average immersion time of 22.2 hours (27% Bias).

6.3 Exploring net height data in OBSMER

Unlike the OBSCAMe data or the XGBoost predictions, the OBSMER data gives us access to other dimensions like the net height, mesh size…. We tried to explore relations between net height and hauling/setting speeds depending on net type, to evaluate the feasibility to assess heights from the OBSCAMe data or other high resolution geolocation source.

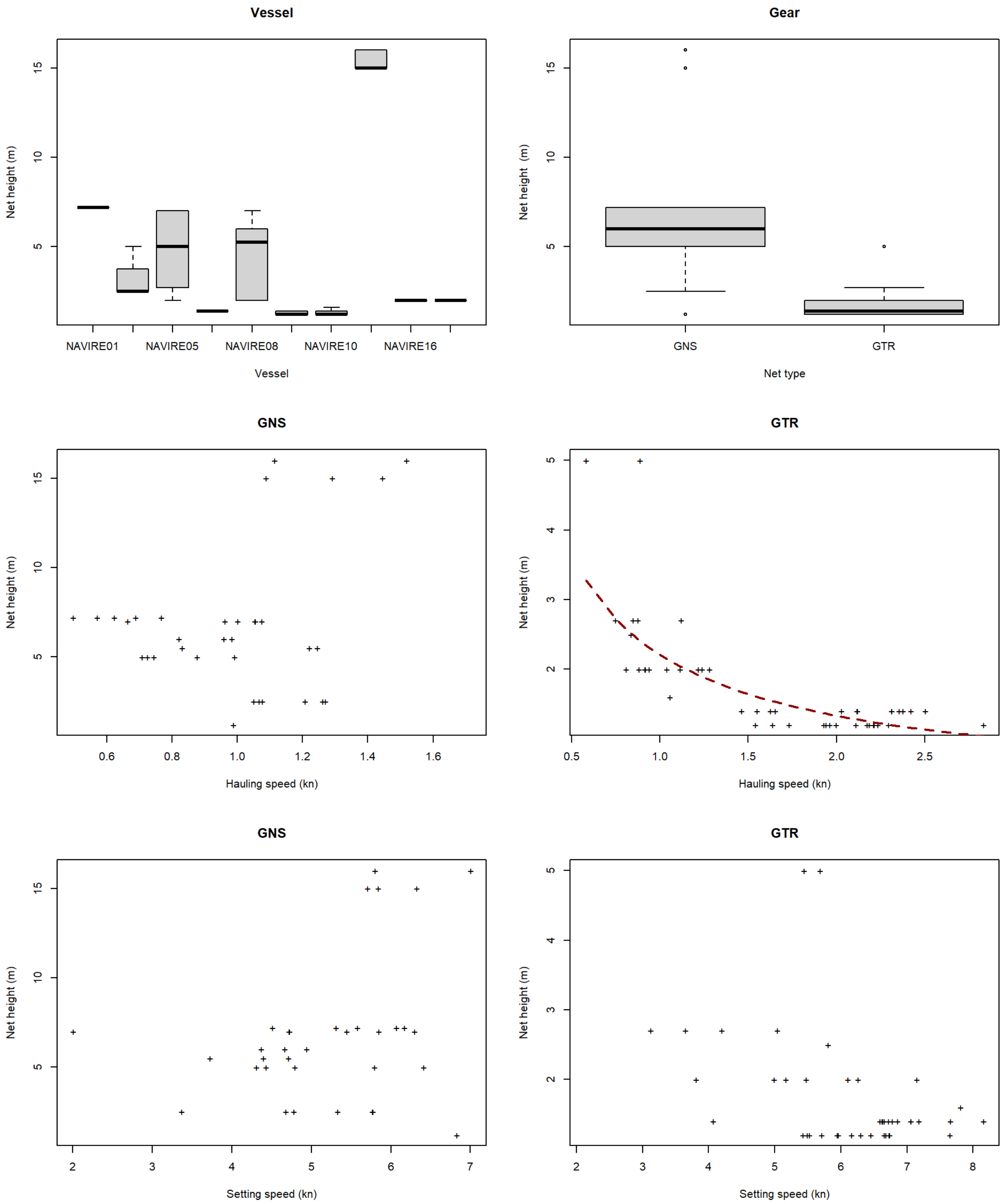

Figure 31. Net height by vessel (A), net height by type of gear (B), net height compared with hauling speed (C) and net height compared with setting speed (D).

There appears to be a great variability depending on the vessel or gear type and there is no apparent relation between net height and setting speed.
For trammel nets (GTR), a relationship seems to exist between net height and hauling speed. The latter could be an indicator of the height of trammel nets, which does not seem to be the case for straight nets.
Based on the data collected, the height of a trammel net could be described by the relationship:

Height = $2.2083 \times \mathrm{hs}^{-0.73}$, R^2 = 0.92 (hs = hauling speed). This relationship is indicated by a red dotted line on the graph above (Fig.28 C.). This relationship is indicated by a red dotted line on the graph above (Fig.28 C.). This relationship should be confirmed by a larger number of references involving a larger number of boats, as the vessel effect could be a major source of bias.

7 Conclusion

It has been shown that the one hour resolution currently mandatory in France for VMS is not enough to assess the fishing effort for passive fishing gears. In the case of the gillnetters, a resolution of 60s is needed to observe all the fishing operations (300s would be sufficient for larger boats but not for some vessels less than 15 meters long). This implies that, in order to be able to predict gear effort for the 500 French gillnetters operating in the Bay of Biscay, acquiring geolocation data at a much finer temporal resolution is necessary.

Regarding the machine learning methods that were developed and tested, the XGBoost model is the one giving the best results whatever the temporal resolution, while the CART models that have been built have a much shorter computation time and are easier to implement in existing algorithms (cf. ALGOPESCA). The work carried out on these models has shown there is a high variability between different vessels, which demonstrates the importance of having a learning database that is representative of the entire fleet that will be later studied using these models

The fishing hours could be well predicted from both 3600s and 900s resolutions, and their aggregation by CSquare was surprisingly no better at the finest resolution (900s) than at the degraded one (3600s). As this trend may be driven by larger ships, it has nevertheless been demonstrated than using a pole frequency of at least 15 minutes for the smaller vessels under 12 meters is a prerequisite for being able to distinguish the fishing trips and compute the vessel’s fishing effort. Finally, the CART and XGBoost models represent a major improvement for calculating the fishing hours compared to the method implemented in ALGOPESCA which uses an upper speed filter. An improved version of the speed filter with a lower threshold was also presented and obtained much better results than the method currently in use .

The creation of gears and retrieval of setting events methods from the “iapesca” geocomputation process (Rodriguez, 2023) was conclusive at the finest resolutions (300s and 60s). Three gear effort metrics were calculated: the total length hauled, the median soaking time, and the product of the last. These metrics were aggregated both by fishing trip and by CSquare (0.05 and 0.01) to evaluate the performance of the XGBoost model. It was shown that a resolution of at least 300 seconds is required to build a XGBoost model that allows accurate calculations of the gear effort metrics. The model built at a 60 seconds resolution did not seem to improve on the one built using 300s, but further work should be carried out to better understand the differences between their respective predictions, and how these differences may affect the geocomputation process and the accuracy of the metrics calculations.

Finally, a validation of our results was carried out by matching the OBSCAMe data (60s) and XGBoost predictions (60s model) with the nets described in OBSMER when it was possible. In total, 26 fishing trips for 13 boats were matched, and a spatio-temporal join of the nets was conducted in order to compare the gear effort metrics. From this comparison, it was confirmed our model’s ability to compute the length of a net is higher than its ability to compute its soaking time, but both show satisfactory results as the predictions and the reference were in most cases consistent with errors that seem acceptable.

8 Perspectives

First of all, for any future studies regarding the fishing activity of vessels using passive gears, and especially for small scale fisheries, there is a real urge to acquire data at a finer temporal resolution. Instead of the mandatory VMS (1 hour resolution), some fishing vessels already use the AIS (Automatic Identification System) tracking system, which has a temporal resolution that can reach the scale of the second. If more boats were equipped with AIS and its data flow was made available, the knowledge we have on fisheries and their management could improve greatly.

Using the VMS data flow currently available, it seems already possible to generate improved effort maps in fishing hours with a method that can be deployed in ALGOPESCA, the algorithm used by the French Fisheries Information System (FIS). At present, it is based on a speed filter to compute the fishing hours for all the vessels equipped with VMS working in the Bay of Biscay. Part 4. of this paper shows that CART and XGBoost models make better predictions than the speed filter used by ALGOPESCA. As CART models are quite easy and fast to compute, implementing this decision tree in the ALGOPESCA algorithm could improve greatly its results. It is important to understand that ALGOPESCA is more complex than a single speed filter, as the algorithm also uses expert rules which make it better than using the speed filter only. However, these expert rules could also be an addition to a CART model. In addition, effort maps for hauled length and soaking time could be derivated from models exploiting the vessels characteristics and their catch profiles during the fishing trip based on logbooks.

Regarding high resolution data, the next step could also be the use of deep learning methods. Neural networks perform very well in applications to the recognition of transport modes and fishing gear (Dabiri and Heaslip, 2018; Kim and Lee, 2020) and could lend themselves to the qualification of fishing operations. These models could be even more appropriated than the machine learning methods that were calibrated because they take into account the autocorrelation between the positions.

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