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Shedding light on trawl fishing activity in the Mediterranean Sea with remote sensing data

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Abstract

This study uses Synthetic Aperture Radar (SAR) vessel detections and Automatic Identification System (AIS) to predict trawl fishing intensity and distribution of fishing activity in areas where public AIS data are not available. By processing SAR data, considering spatial and temporal autocorrelation, and building a General Additive Model, a statistical relationship between SAR vessel detections and AIS fishing activity was established. The study provides spatially explicit estimates of trawler fishing activity, compared with official fleet records published by the General Fisheries Commission of the Mediterranean, revealing the distribution and intensity of trawl fishing activity not previously publicly tracked. Fishing grounds in the Strait of Sicily along the coast of Tunisia and North of Egypt showed an intensity of trawl fishing activity similar to the Adriatic Sea. This area is historically known to be subject to the highest trawling pressure in the Mediterranean, and also as one of the most heavily trawled regions in the world. The study shows that the integration of remote sensing data, such as SAR, offers a promising avenue to overcome data gaps and improve fisheries management in the Mediterranean where only a portion of the fishing fleet is publicly tracked.

Keywords: fisheries; Mediterranean; trawling; remote sensing data; vessel tracking; data poor

Introduction

In the Mediterranean Sea, marine fisheries play a pivotal role in food and social security, providing sustenance for thousands of people and supporting the livelihoods of numerous coastal communities (FAO 2023a). However, overfishing poses a threat in the region, and even though the fishing pressure and exploitation rate have decreased in the last decade, 58% of assessed commercial stocks are still overfished, and average fishing mortality remains two times higher than sustainable levels (FAO 2023b). This trend appears to be largely related to the lack of monitoring and poor management of fishing fleets (Colloca et al. 2017, Vielmini et al. 2017, Hilborn et al. 2020, Fiorentino and Vitale 2021). Monitoring of fishing activities is fundamental to ensure compliance with management measures such as catch and effort regulations, seasonal and spatial-temporal closures, and the prevention of illegal, unreported, and unregulated (IUU) fishing (Flewwelling 1994). Also, current fisheries management relies on reported effort and catch (the so-called fishery-dependent information), which are the main source of information for estimating fishing mortality. But tracking fishing mortality means also assessing where and when fishing activity occurs. This is why, over the last few decades, vessel tracking data from devices such as the Vessel Monitoring System (VMS) and the Automatic Identification System (AIS) have been widely used in fisheries science (Russo et al. 2019, White et al. 2020, Armelloni et al. 2021), and the competent authorities have progressively expanded the requirements for vessels to carry these tracking devices (REGULATION EU 2023/2842). For example, in the European Union (EU), data from vessel tracking systems are the main sources of information (together with logbooks) for the Fisheries Dependent Information (FDI) data call (https://stecf.jrc.ec.europa.eu/dd/fdi).

Indeed, the use of AIS and VMS has revolutionized our ability to monitor and map fishing activity at sea (Kroodsma et al. 2018) and, in the last decade, studies focusing on the application of AIS or VMS in fisheries management have doubled (Orofino et al. 2023). Despite the increasing use of VMS and AIS technologies in fisheries science and in the maritime industry, some marine fisheries remain publicly unmonitored due to technological constraints, and evasion tactics employed by fishers (Park et al. 2020,Kroodsma et al. 2022, Welch et al.

2022, Orofino et al. 2023, Paolo et al. 2024). Furthermore, tracking technologies such as VMS and AIS are not implemented or enforced in all countries, and local legislations do not agree on the minimum vessel size and type of activities required to broadcast through AIS or VMS (Orofino et al. 2023, Paolo et al. 2024).

Recent work has shown that roughly three-quarters of industrial fishing vessels worldwide are not tracked by AIS (Paolo et al. 2024), and only a limited number of countries share publicly the VMS which is often kept confidential by government agencies (Orofino et al. 2023). In the Mediterranean, for instance, between Italy and Tunisia in the Strait of Sicily >60% of fishing vessels appear not to be broadcasting AIS data (Paolo et al. 2024). If the distribution and the level of fishing activity are not properly considered, assessments of pressure on biological resources could be distorted, and management measures adopted may be ineffective or inappropriate (Zeller et al. 2018, Costello et al. 2020). In the long term, this unaccounted fishing activity undermines the overall United Nations' (UN) Sustainable Development Goals, as well as the GFCM 2030 strategy and the Common Fisheries Policy (CFP), at the Mediterranean and European level, respectively, to efficiently use marine resources and secure food supply (Zeller et al. 2018, Costello et al. 2020).

The Mediterranean Sea is a complex region for fisheries management: 22 coastal states plus the European Union, all with very different social, economic, and political organizations, border the waters of the Mediterranean (Cardinale et al. 2017). This scenario inevitably creates challenges for the management of shared resources when information on fishing activities at sea is collected with different levels of accuracy and is not always publicly available (Vasilakopoulos et al. 2014, Paolo et al. 2024). Fisheries management in the Mediterranean Sea, for non-tuna and non-tuna-like species, is implemented under the umbrella of the UN Food and Agriculture Organization (FAO) through the General Fisheries Commission for the Mediterranean and the Black Sea (GFCM), which has acted as a Regional Fisheries Management organization (RFMO) since 1949 (Vielmini et al. 2017). Although many countries around the Mediterranean Sea have adopted GFCM international regulations and standards related to VMS and AIS (GFCM/44/2021/8, GFCM/43/2019/3, and GFCM/33/2009/7), the specific implementation and enforcement of these regulations vary among countries (FAO 2023b). For example, the European Union Member States have regulations requiring the use of VMS and AIS for fishing vessels as part of the CFP (Taconet et al. 2019). In contrast, regulations in Mediterranean countries outside of the EU are very different: the use of AIS only partially covers the fishing fleets (Taconet et al. 2019). This study reports the first analysis of the level of fishing activity for the whole Mediterranean Sea using remotely observed radar data.

Remote sensing data (RSD) are earth observations collected by spaceborne and airborne sensors used in a wide range of applications (Chi et al. 2016), and represent a promising approach to improving information on fishing vessel activity (Galdelli et al. 2021, Paolo et al. 2024). More specifically, the detection of maritime objects such as vessels and offshore infrastructure in satellite images can be used as a powerful mapping tool without requiring vessels to broadcast their position and activity through public or private tracking systems (Paolo et al. 2024). This promising technology can aid the mapping of vessel activity regardless of the legislation of different countries and data-sharing policies (Paolo et al. 2024). RSD is limited, however, by technical and operational factors, such as varying acquisition frequency and spatial coverage, and the extensive computational resources required to process the data (Santamaria et al. 2017, Paolo et al. 2024). Among the different RSD, Synthetic Aperture Radar (SAR) imagery has become more accessible and is an effective technology for ocean mapping (Santamaria et al. 2017, Paolo et al. 2024). SAR can penetrate cloud cover and is not affected by light and extreme weather events like some other satellite sensors and has been used in a wide range of earth observation applications such as monitoring sea ice, deforestation, disaster evaluation and maritime surveillance (Santamaria et al. 2017, Paolo et al. 2024). SAR generates images by emitting pulses of radar signals and recording the fraction of the signals bouncing off the targets on the ground and reflected back to the satellite (known as backscatter) (Santamaria et al. 2017, Paolo et al. 2024). Multiple radar acquisitions of the same location on the ground are then integrated to form an image (Santamaria et al. 2017, Paolo et al. 2024). Objects across a landscape, for example, vessels across the sea, can be differentiated in the backscatter image because they return signals that have different characteristics (Santamaria et al. 2017, Paolo et al. 2024). The geometry, roughness and electrical properties of the target will influence the strength and polarization of the returned pulse (Santamaria et al. 2017, Paolo et al. 2024). Global Fishing Watch (GFW) has processed over one petabyte of SAR images obtained from the European Space Agency (ESA) Sentinel-1 mission (Paolo et al. 2024). Paolo et al. (2024) developed a method to detect vessels at least 15 m in length using an algorithm that isolates signals significantly stronger than the background ocean in the SAR images. The detections were then matched to vessels broadcasting AIS when the images were taken, resulting in a global dataset of vessel detections matched and unmatched to AIS (Kroodsma et al. 2022, Paolo et al. 2024). Paolo et al. (2024) also used a neural network model to classify the detections into likely fishing and non-fishing vessels based on the environmental and physical characteristics where each detection is located (Paolo et al. 2024). SAR vessel detections, however, cannot tell whether a fishing vessel is fishing, i.e. with the net or hooks in the water. Machine-learning approaches can be used to classify AIS and VMS activity into fishing and non-fishing (Russo et al. 2014, Kroodsma et al. 2018). SAR imagery, on the other hand, will only image the same location approximately every 2–6 days (for the Mediterranean), and therefore cannot determine a vessel's activity (fishing vs. not-fishing) at the time of detection. As a result, SAR vessel detections provide a measure of fishing vessel presence, but not directly the level of fishing activity. This study sought to determine the extent to which SAR vessel presence could be used as a proxy for fishing activity using fishing hours from AIS data as a reference in a modeling approach. The term fishing activity is used over fishing effort as the latter is a measure of both time spent searching for fish and the amount of fishing gear used for a unit of time (FAO 2024). Considering the novelty of this study and the very early state of the art with respect to the use of SAR data, it is outside of the scope of this study to quantify fishing effort by gear (e.g. number of hooks, swept area, number of nets, etc.) used by a vessel (FAO 2024), so the term fishing activity is used in this manuscript to quantify the total amount of time spent fishing (fishing hours) per area.

Table 1. Main statistics for the two data sources used in this study: the AIS and SAR Global Fishing Watch datasets.

Statistics	AIS	SAR
Temporal range	January 2017–December 2021	
Source	Global Fishing Watch (Kroodsma et al. 2018)	Global Fishing Watch (Paolo et al. 2024)
Number of positions or detections	$\sim 239 \times 10^6$	$\sim 9.7 \times 10^6$
Aggregated spatial resolution used in the analysis	0.2 decimal degrees (~22 square Km)	
Aggregated temporal resolution used in the analysis	Monthly	
Temporal resolution	2 to 10 seconds	2 to 6 days for all Mediterranean Sea and constant throughout the year
Filters	Only fishing vessels as recorded in Global Fishing Watch data	Only detections of fishing vessels as recorded in Global Fishing Watch data

In the table the temporal range, source, number of positions and detections, the spatial and temporal resolution, and the filters applied to these datasets are presented.

This study investigates the relationship between vessel presence derived from SAR and fishing activity using a state-of-the-art approach based on AIS data. The dataset of fishing vessel detections from Sentinel-1 SAR satellite imagery is compared with the fishing footprint provided by GFW AIS data, assuming that the latter provides a suitable reference for the activity of large fishing vessels. First, a significant statistical relationship between the fishing hours (from AIS data) and fishing vessel presence (from SAR data) was established using as a training dataset the areas where AIS provided reliable estimates of fishing activity. Then the application of this model was extended to the entire Mediterranean Sea to obtain estimates of fishing activity for the whole Mediterranean basin from SAR data.

Materials and methods

Data sources

SAR and AIS for the years 2017–2021 were the two main datasets used in this study (Table 1). These two systems have a different sampling rate. AIS is a device installed onboard vessels which pings a position on average every minute, whereas SAR is a radar satellite that generates an image of the same location in the Mediterranean Sea on average between every 2 and 6 days (Santamaria et al. 2017, Kroodsma et al. 2018). This results in a significantly different number of observations between the two systems, with AIS providing consecutive positions (tracks) for a single vessel over the course of a day, while SAR provides only one detection (Table 1).

Automatic identification system

GFW processes raw AIS messages, sourced by Spire and Orbcomm providers, according to the methods in Kroodsma et al. (2018). AIS messages are then analyzed with two different convolutional neural networks (CNNs) to predict fishing operations. The first CNN classifies the vessel type and predicts vessel characteristics such as length, tonnage and engine power, and the second classifies every AIS position as either fishing or non-fishing (Kroodsma et al. 2018). This study used position-level fishing/non-fishing estimates from AIS, along with total fishing hours, aggregated by Maritime Mobile Service Identity (MMSI), and gear type (estimated using a Global Fishing Watch CNN, Kroodsma et al. 2018).

Synthetic aperture radar

GFW applies an automated algorithm to Sentinel-1 SAR images sourced from the European Space Agency (ESA) to detect vessels using a Constant False Alarm Rate algorithm (Kroodsma et al. 2022, Paolo et al. 2024). SAR detections are then filtered with a CNN model to identify false positives and also infer vessel length and matched to AIS using probability maps of estimated vessel locations at different time intervals based on speed, type, and trajectory. This matching procedure identifies SAR detections not associated with vessels broadcasting AIS positions (Kroodsma et al. 2022, Paolo et al. 2024). For those detections that did not match to AIS, a second CNN model classified detections as either fishing or non-fishing vessels based on the environmental and physical characteristics of their location. Model parameters included vessel density, average vessel length, bathymetry, hours of non—fishing vessel presence (from AIS), average surface temperature (average from 2017 to 2021) and chlorophyll (average from 2017 to 2021) calculated across all SAR footprints at different spatial resolutions.

Vessel's detection using Sentinel-1 was shown to be highly effective, capturing the majority of vessels that are at least 20 m in length (Paolo et al. 2024). The individual fishing vessel detections (i.e. the point data) from this dataset are normalized by satellite overpasses, meaning that the number of detections in a 10th degree cell is divided by the number of satellite overpasses in that same grid cell for each month and year from 2017 to 2021 (Table 1). This normalization corresponds to an estimate of the average number of vessels seen at each month in each cell. The estimate of the number of vessels per month, year and cell is the input to the Space Time Index approach described in the next section. A more detailed description of the SAR dataset can be found in Paolo et al. (2024).

Pre-processing

The AIS and SAR matching identifies vessels broadcasting or not broadcasting AIS. The AIS data are filtered by vessels that were matched to SAR at least once.

Then, the fishing hours of these vessels are summed across our grid for each year and for each month from 2017 to 2021. This procedure is done to ensure that in the AIS data we only keep vessels that can be detected by SAR.

The vessel classes reported in the AIS dataset were assessed for all the matched SAR fishing vessel detections. This was done to get a better idea of what the SAR can capture.

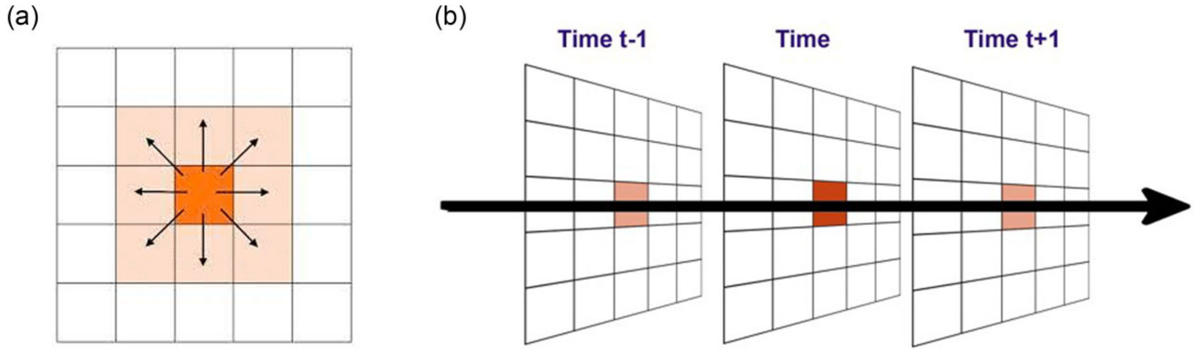


Figure 1. Conceptual representation of the spatial (panel a)—temporal (panel b) autocorrelation index applied to SAR detections.

The AIS positions and the SAR detections are filtered to be at least three nautical miles from shore to limit the possible noise associated with vessel traffic and pleasure crafts, near ports or the coast which can occur in both the AIS and SAR data.

Both SAR normalized fishing vessel detections and AIS fishing hours were then aggregated using 0.2 decimal degrees (around 22 km) square grid across the whole Mediterranean. In addition, two further variables were quantified for each grid cell. Namely:

- The depth (in m) was estimated for the centroids of each cell of our grid using the marmap package (Pante and Simon—Bouhet (2013) in R (R core team 2021) with a resolution of 10 minutes. The marmap package uses the ETOPO1 database hosted by the US National Ocean and Atmospheric Administration (NOAA).
- The distance from shore (in km) was calculated for the centroid of each cell of our grid using the st_distance function from the sf package (Pebesma and Bivand 2023) to a 10 m resolution shapefile of the coastlines of the Mediterranean Sea.

Spatial-temporal autocorrelation

Ideally, the number of SAR fishing vessel detections in a cell/time grid could be used to obtain an estimate of the fishing activity. But each cell is not an isolated entity, being an element connected to its adjacent cells and placed within a larger spatio-temporal context (Russo et al. 2013). Thus, the number of SAR detections in each cell, as well as the number of fishing hours, are influenced by the neighboring cells. In recent years, studies have shown that adding a temporal component to spatial—autocorrelation is fundamental to identify patterns that are dominant across space (Russo et al. 2013, Wang and Lam 2020). Wang and Lam (2020) have proposed an extension of the Getis Ord index to account for local—space—time—autocorrelation (LSTA) (Wang and Lam 2020). Having T observations, the spatio-temporal autocorrelation index, called G^*, is defined as:

$$G_i^*\left(V_{ST}\right) = \frac{\Sigma_j v_{ij} x_j}{\Sigma_j x_j}$$

Where V_{ST} is the space–time connectivity matrix whose elements v_{ij} represent the spatio-temporal index between the cells i and j of the grid, x_j is the number of SAR detection in a cell (Fig. 1).

The space–time connectivity matrix V_{ST} can be obtained as:

$$V_{ST} = W_T \otimes W_S \otimes W_T \otimes I_s$$

where $\otimes$ is the Kronecker's product, I_s is a TxT identity matrix, W_S is a spatial weight matrix which considers as "neighbors" all cells which are within a distance range and W_T represents the TxT time series connectivity matrix. All the off-diagonal elements of this matrix contain the value 1, and all other elements contain the value 0.

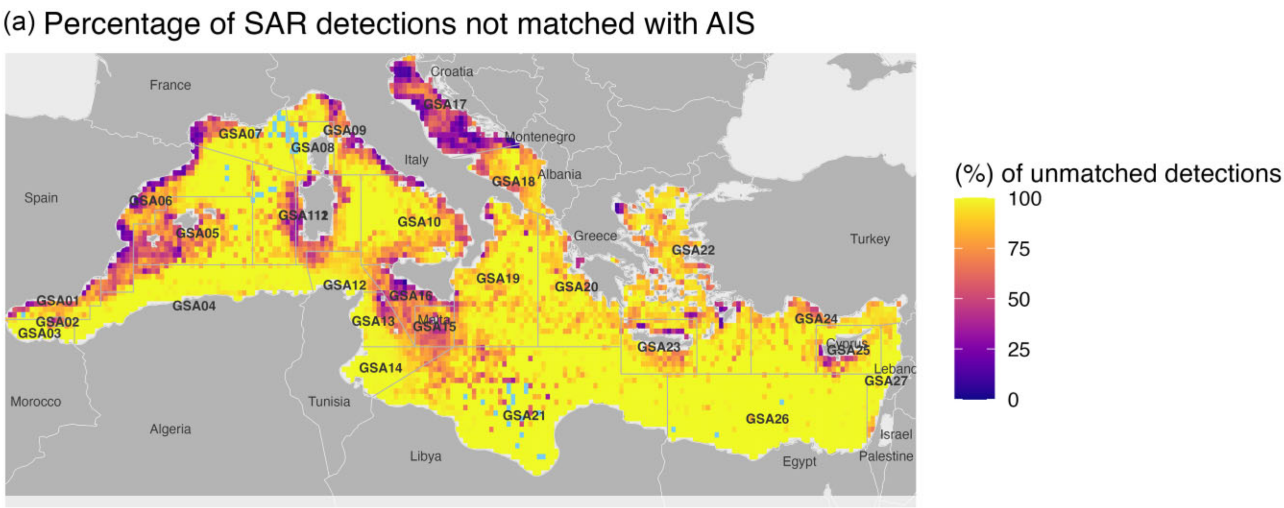
G^* was computed for each cell of the grid, using the total number of monthly SAR data detection, over the 60 months in the period considered (January 2017–December 2021). G^* was then used as a "static" variable, similar to depth and distance from the coast, in the following modeling steps.

Official fishing capacity

Data for all vessels longer than 15 m were downloaded from the GFCM Fleet Register (https://www.fao.org/gfcm/data/fleet/register/en/). Vessels that showed "NO" under the field of Operation Status were removed. The total number of vessels longer than 15 m for each GSA, as well as the percentage of vessels registered in each GSA out of the total number of vessels registered in the whole Mediterranean Sea, were calculated for comparison with the percentage of predicted activity.

Statistical modeling

The statistical relationship between the monthly amount of fishing activity from AIS data (in hours fishing) and the monthly number of SAR detection (in addition to other predictors) was modeled using generalized additive models (GAM). Starting from the set of predictors (i.e. SAR, G^*, Depth, and Distance from the coast), the potential existence of collinearity between the predictors of the GAM models was analyzed using the vif.gam function of the package mgcv.helper (https://rdrr.io/github/samclifford/mgcv.helper/man/vif.gam.html). Then, a model selection procedure was applied to identify the best GAM model. This process involved systematically evaluating different model structures to identify the one that best captures the underlying patterns in the data, performing a 10-fold cross validation. In the iteration, the dataset was split into a subset of the data for testing, while the remaining data were used as a training set, across the 10-folds, ensuring that each data point was used for both training and testing, but in different iterations of the cross-validation process. GAMs was fitted using the gam function from the mgcv package with a quasipoisson family



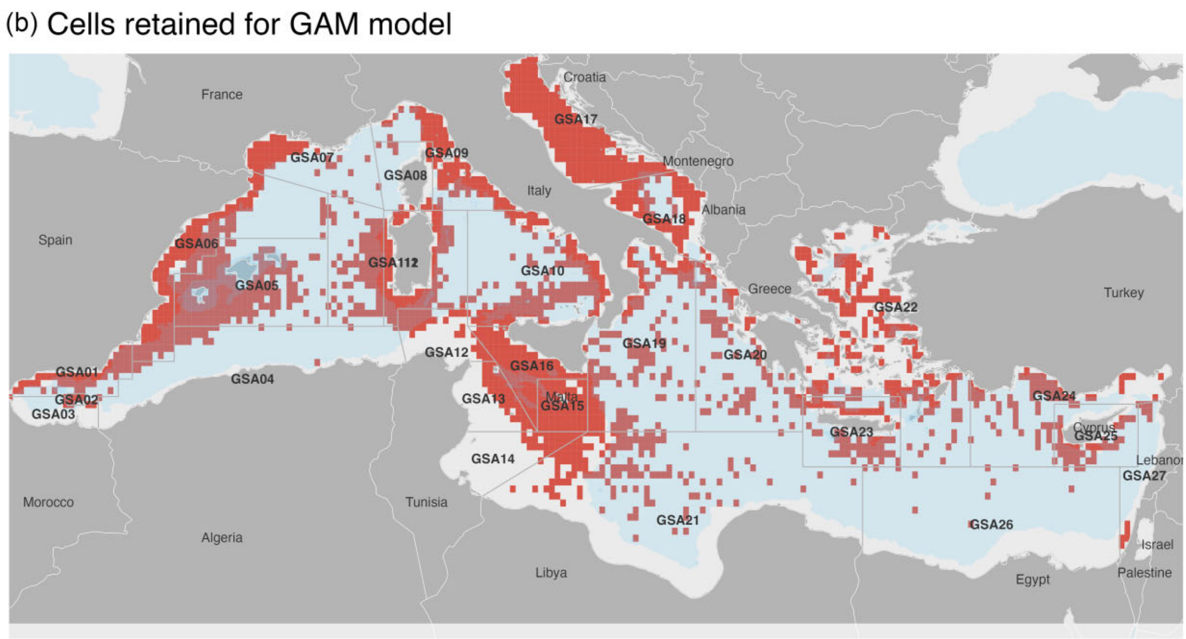


Figure 2. (a) Map of the percentage of SAR detections that were not matched to AIS. (b) The cells used in the GAM model as training and testing datasets.

and a square root link function (Wood 2011), and setting the basis dimension to 4 to represent the smooth term (R Core Team 2021). Each model was used to predict on the test data and the mean squared error (MSE) between observed and predicted values was calculated. MSE values of each model were aggregated and the model with the lowest MSE was chosen.

Considering that the AIS data is restricted to areas where vessels broadcast AIS, and that our approach uses AIS data as a proxy for fishing activity, the SAR dataset used to fit our model was restricted to those cells with at least one AIS position. Cells in which the ratio of SAR detections unmatched with AIS to SAR detections matched with AIS was <90% were used in the modeling as these cells represented areas where vessels broadcast AIS (Fig. 2).

This threshold was chosen because it appeared as a good compromise between keeping cells with good coverage and not losing too many observations. This evaluation was done through a visual inspection of the location of the cells as well as by looking at the frequency of percentages intervals across all cells. These cells were almost exclusively in the northern Mediterranean Sea (Fig. 2).

The best GAM model was then used to predict the potential distribution of the fishing activity in the whole Mediterranean basin. To calculate a proxy for the uncertainty, a 95% confidence interval was obtained for each prediction. Confidence intervals were also shown for the GAM smooth parameters with the representation of the GAM smoothed effects of the predictors (Marra and Woods 2012).

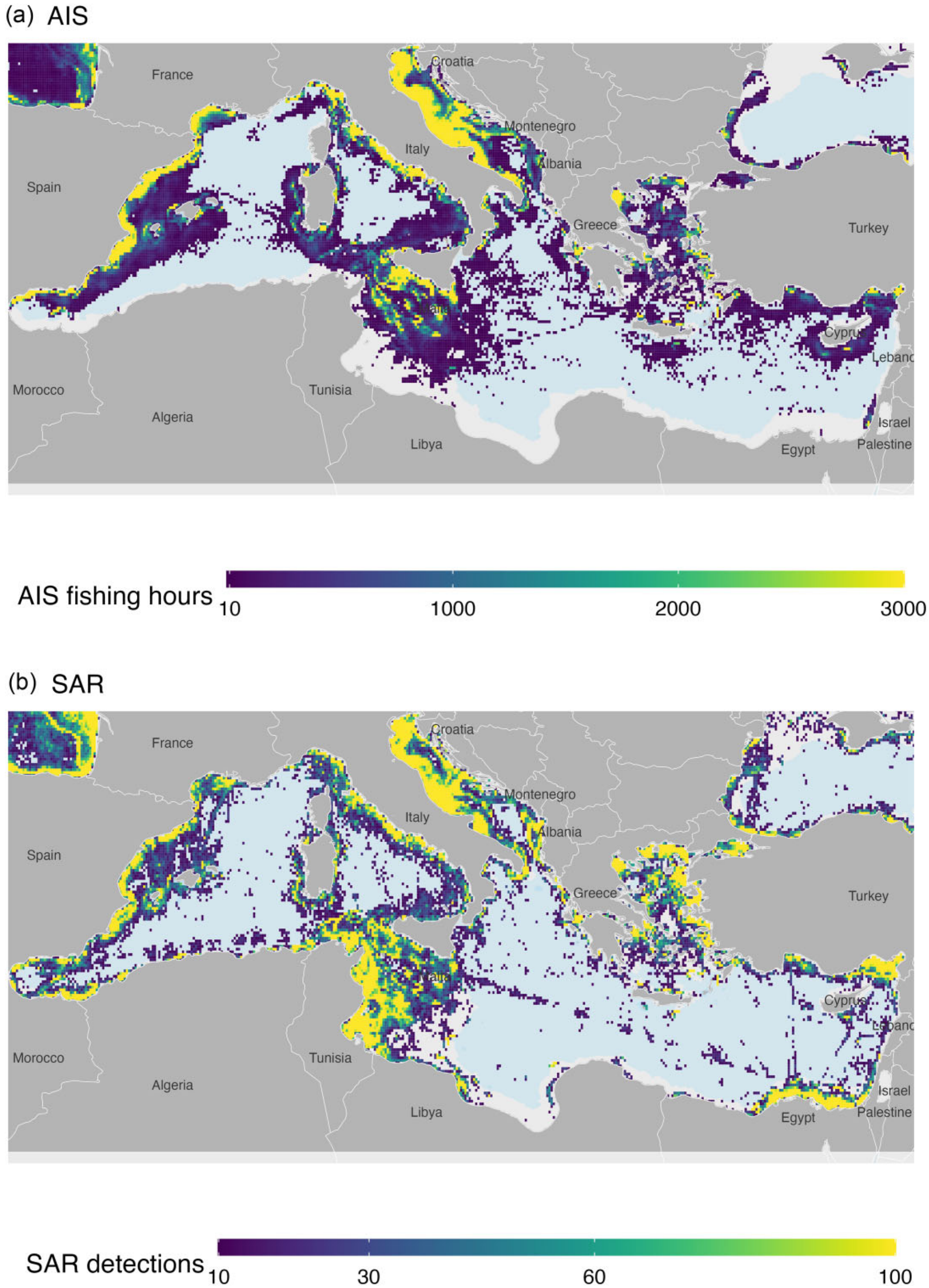


Figure 3. (a) AIS fishing activity from Global Fishing Watch AIS data from 2017 to 2021 aggregated by fishing hours in 0.1 decimal degrees cells. (b) SAR fishing vessel presence from Global Fishing Watch SAR data from 2017 to 2021 aggregated by number of fishing vessel detections in 0.1 decimal degrees cells. The light blue shaded area represents the areas with depths greater than 1000 m (Pante and Simon-Bouhet 2013).

A detailed temporal reconstruction was considered too ambitious for this initial analysis so an overall estimate of fishing activity from 2017 to 2021 was produced.

Results

The inconsistent use and regulation of AIS results in some areas of the Mediterranean, particularly in the south, not being publicly tracked, thus the total amount and distribution of fishing activity in these areas is essentially unknown (Fig. 3a). On the other hand, fishing vessels detected in the SAR show a similar level of presence in the Northern and Southern portion of the Mediterranean Sea (Fig. 3b).

The AIS and SAR matching for the whole Mediterranean showed that 90% of the fishing vessels matched to SAR detections were trawlers (Fig. 4). The remaining 10%

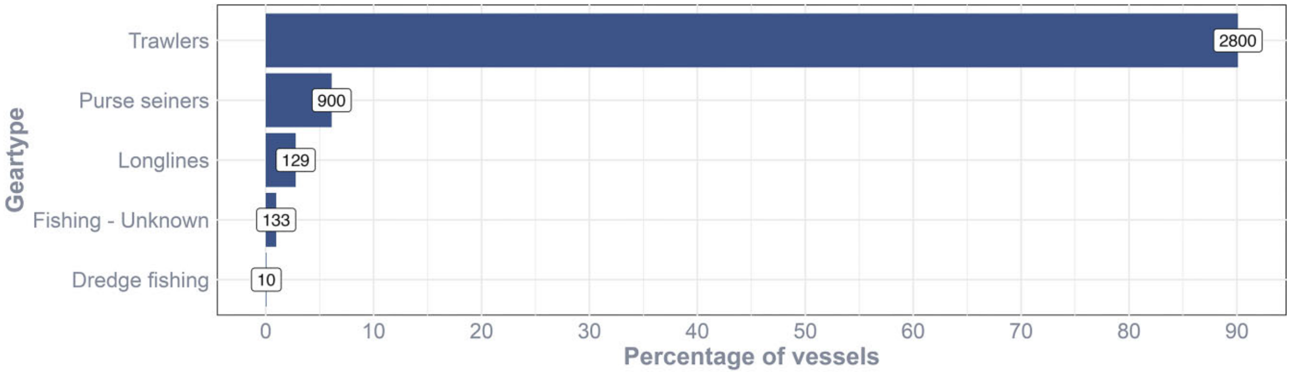


Figure 4. Percentage of fishing vessels by gear type observed in the SAR dataset for vessels using Automated Identification System (AIS). Bar labels represent the total number of vessels observed for each gear type.

Table 2. Performance indicator values obtained for models with different explanatory variables for an objective model selection process

Model	Variables included	Mean MSE
1	Number of SAR detections	46 646 728
2	G* Index	62 954 415
3	Number of SAR detections, G* Index	45 513 309
4	Depth (m)	78 213 096
5	Number of SAR detections, Depth (m)	44 967 461
6	G* Index, Depth (m)	57 319 049
7	Number of SAR detections, G* Index, Depth (m)	44 284 811
8	Distance to coastline (m)	90 988 005
9	Number of SAR detections, Distance to coastline (m)	45 565 774
10	G* Index, Distance to coastline (m)	60 387 950
11	Number of SAR detections, G* Index, Distance to coastline (m)	44 720 946
12	Depth (m), Distance to coastline (m)	75 300 146
13	Number of SAR detections, Depth (m), Distance to coastline (m)	44 320 012
14	G* Index, Depth (m), Distance to coastline (m)	56 478 927
15	Number of SAR detections, G* Index, Depth (m), Distance to coastline (m)	43 760 426*
	*lowest MSE value and selected model	

Table 3. Main statistics for the GAM model fitted.

Smoothers	Approximate significance of smooth terms			
	P-value	edf	Ref.df	*F*
Number of SAR detections	<2e-16 ***	2.898	2.991	686.49
G* Index	<2e-16 ***	2.805	2.973	19.58
Depth (m)	<2e-16 ***	2.901	2.993	25.039
Distance to coastline (m)	<2e-16 ***	2.173	2.563	20.565

comprised drifting longlines, purse seiners and vessels for which the GFW algorithm was unable to infer a gear type ("Fishing—Unknown class" in Fig. 4). Consequently, the results presented in this study primarily represent trawl fishing activity.

The analysis of the variance inflation factor (VIF) identified no collinearity between the predictors. In all the cases, the values of the VIF were smaller than 1, which is considered a robust threshold (Sheather, 2009).

Following the model selection process (Table 2), the the number of fishing hours from AIS were regressed over the number of SAR detections, the G* Index, the depth and the distance to coastline in the GAM model.

The adjusted R^2 between predicted and observed values was 0.58, and this model captured 75% of the variance in the data (variance explained). Additional model statistics are provided in Table 3.

The highly significant smooth terms for SAR, depth, Gj, and distance_to_coastline suggest that these variables play a crucial role in explaining the variability in the response variable. Particularly for the SAR term (SAR fishing vessel detection) the *F*-statistic is large, and the *P*-value is extremely low, suggesting that the smooth term is contributing significantly to the model.

Comparisons between predicted trawl fishing activity on the basis of SAR and observed trawling activity based on AIS (Fig. 5a) indicated that the model effectively captured the relationships between the predictors and the response variable across the range of values considered. The distribution of the residuals (Fig. 5b) was unimodal, with mean close to zero (−6.09) and an almost symmetrical shape with the left and right tails enclosed in the interval between −100 and 100.

The smoothed effects of the predictors (Fig. 6) indicated that the number of SAR detections has a monotonic relationship with the number of fishing hours estimated from the AIS data. This relationship tends to plateau at high SAR values. The G* index, on the other hand, exhibited a non-monotonic relationship with the response variable. The effect of G* is highest around the 2.5 value of G* but decreases for low or high values. It is worth noting that most of the observations were in range 0–2 of G*, a region in which this predictor shows a close to linear and positive effect on the response variable. The effect of depth was opposite to that described for G*, with the smoothed function having a minimum around 1500 m and

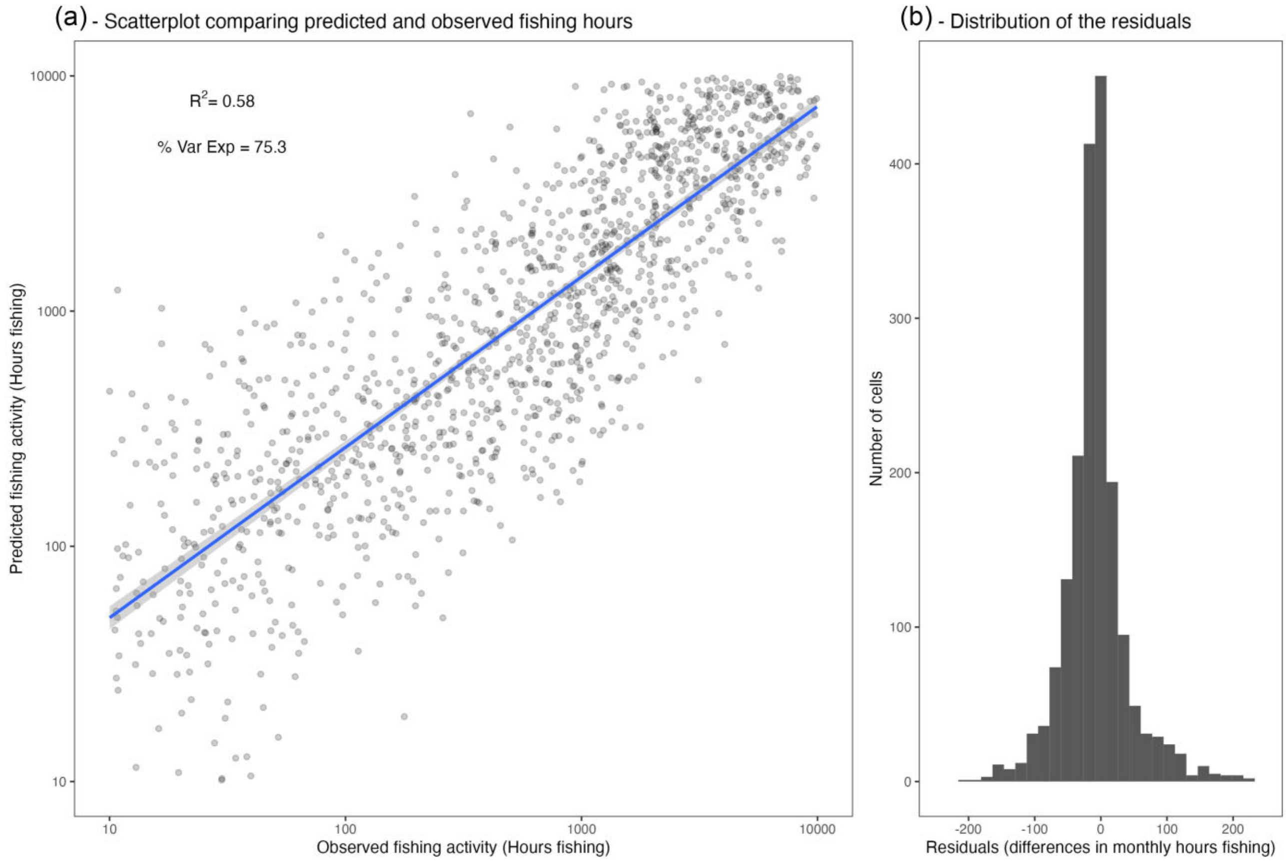


Figure 5. (a) Scatterplot comparing predicted (SAR-based) and observed (AIS-based) values, in hours fishing, of the fishing activity, as fitted by the GAM model applied on the dataset of the cells belonging to cells where AIS data was present. (b) The corresponding distribution of the residuals.

a maximum near zero. Finally, the effect of distance from the coast was decreasing, with a maximum at zero.

The SAR-based prediction of trawling fishing hours revealed the presence of fishing areas along a large stretch of the North African coast, and especially along the coasts of Egypt, Tunisia, and Morocco (Fig. 7). In addition, in some areas such as the Central Mediterranean (GSA12, GSA13, and GSA14), the SAR-based estimates indicated values of fishing activity much higher than those obtained from AIS. Along the coast of EU countries, the spatial patterns depicted by SAR and AIS were very consistent. It should also be noted that predicted fishing activity in the GSAs along the coast of Tunisia and in the Adriatic Sea is more diffuse compared to that in Southern Turkey (GSA 24) and Egypt (GSA 26) or in the Western Mediterranean where fishing activity seems to concentrate in fewer cells and remains closer to the coast. This different pattern is partially linked to the presence of large continental shelves in the Strait of Sicily and Adriatic Sea, which allow trawling at great distances from the coast.

In areas where AIS coverage is good, such as the Northern Adriatic (GSA 17), Northern Spain and South of Sicily (GSA 16) the SAR-based estimates appear to underestimate AIS fishing hours (Fig. 8). The Aegean Sea is an exception to this as SAR-based estimates appear to be higher than those observed in the AIS data (Fig. 8). On the other hand, in areas outside of EU countries AIS appears to underestimate fishing hours, particularly in GSAs along the North African coast such as South Levant Egypt (GSA 26), Algeria (GSA 4) and the Gulf of Gabes (GSA 14).

When the distributions of the differences, in terms of the number of hours per cell, were examined (with a focus on GSAs along the North African coast—Fig. 9a), a systematic underestimation by AIS emerged, on the order of ∼3000–5000 hours/year/cell (median value among GSAs), with the sole exception of GSA 21 where the differences are an order of magnitude smaller (∼100 to 200 hours/year/cell). Finally, the differences between SAR-based and AIS estimates of trawl fishing activity, when examined with respect to the different bathymetric layers, showed a monotonic decreasing trend with respect to depth, with AIS underestimating fishing activity especially in shallower areas (Fig. 9b).

Considering the Eastern Mediterranean, our model predicts that the Aegean Sea (GSA 22) accounts for 11% of the total predicted fishing activity in the Mediterranean basin, while South Levant (GSA 26), the region north of Egypt, represents 7% of the total predicted fishing activity in the region, and North Levant (GSA 24) to the southeast of Turkey represented 4% of the total fishing activity(Fig. 10a).

In the Central Mediterranean the GSAs bordering Tunisia, the Gulf of Gabes GSA 14 and the Gulf of Hammamet GSA 13, and Northern Tunisia GSA 12 make up 19% of the total fishing activity (Fig. 10a). In GSA 16 and GSA 15, fishing activity is 4% and 2% of the total fishing activity respectively.

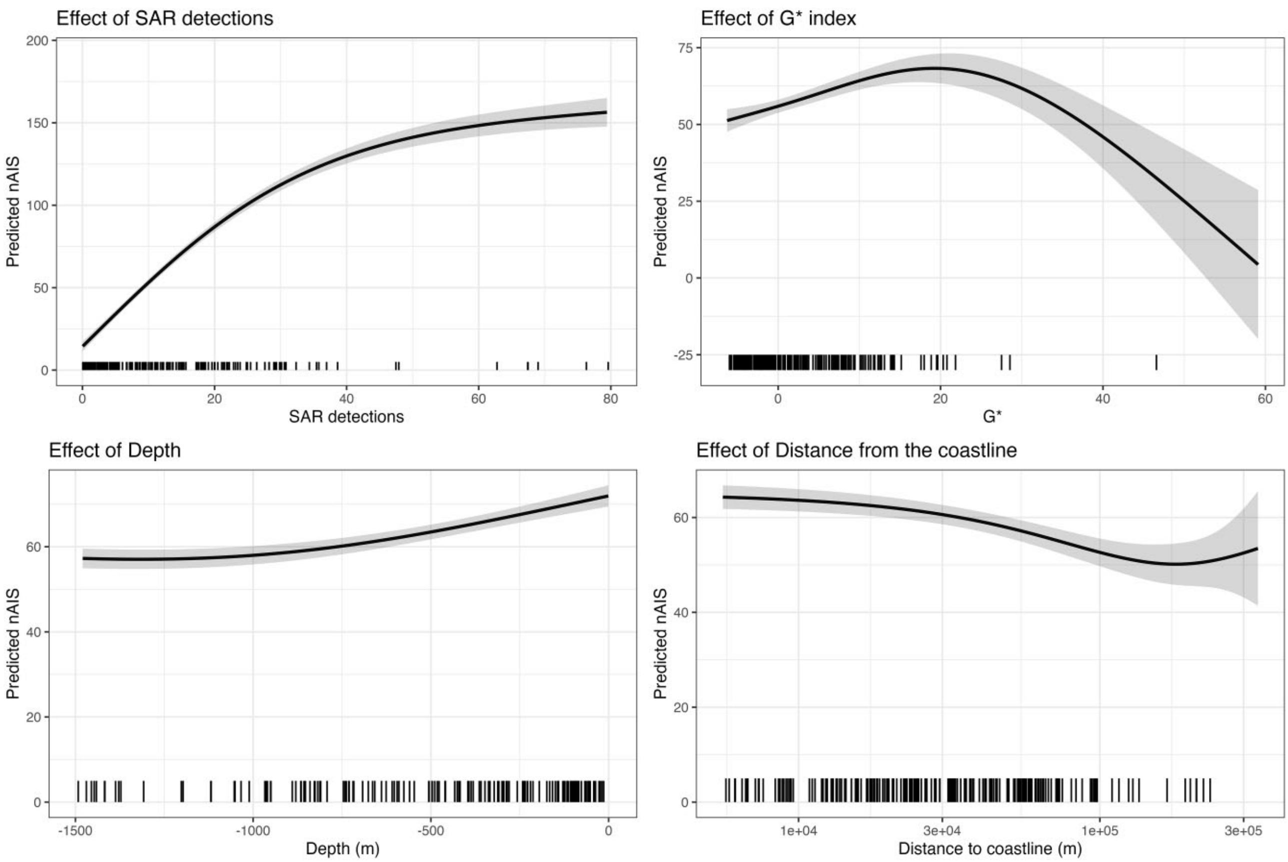


Figure 6. Representation of the GAM smoothed effects of the predictor.

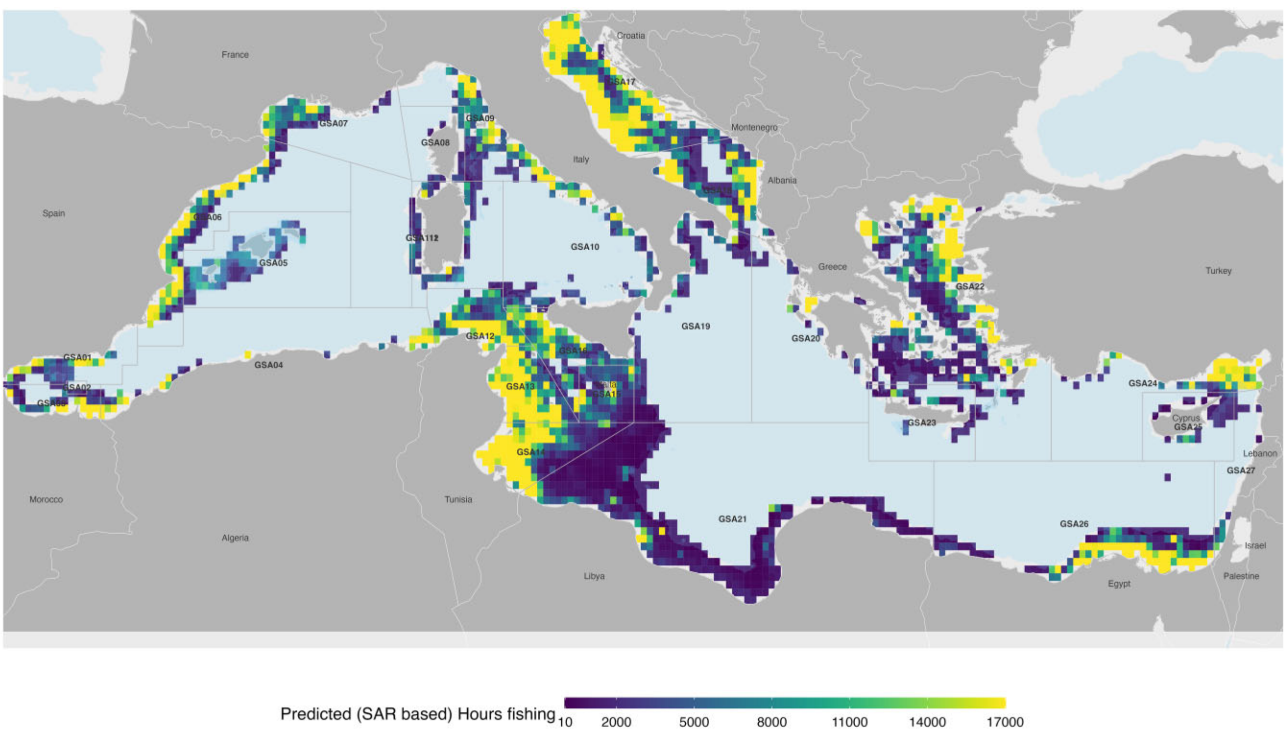


Figure 7. Maps of the predicted trawl fishing activity as hours fishing for the whole Mediterranean Sea resulting from the GAM model. The light blue polygon represents the areas with depths >1000 m.

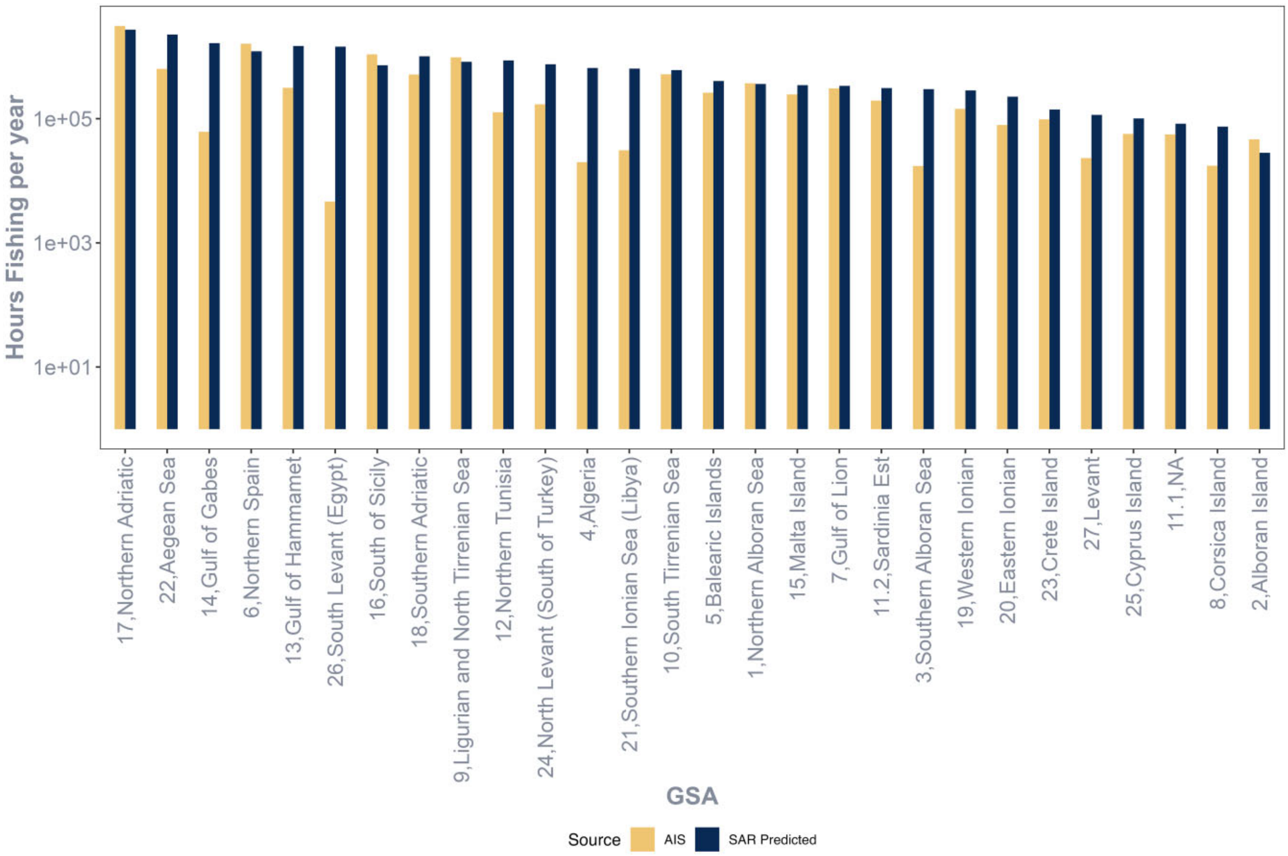


Figure 8. Bar plot of the predicted (SAR-based) and observed (AIS-based) fishing activity, as hours fishing (left *y*-axis). The number of hours of fishing represented in Log_{10} scale.

In the Adriatic Sea, the Northern Adriatic GSA 17 contained 14% of predicted activity and the Southern Adriatic GSA 18 had 5% (Fig. 10a).

Compared to these areas, the Western Mediterranean showed lower values of predicted activity. In this region the predicted fishing activity is concentrated in the coastal areas of Italy in GSA 9 and 10 (North and South Tyrrhenian Sea) and the coastal areas of Spain GSA 6 (Northern Spain) each of which make up around 3%–6% of the total fishing activity (Fig. 10a).

Overall, the GSAs mentioned above represent >70% of the total predicted fishing activity of the whole Mediterranean basin according to our model.

While the model was remarkably consistent with the number of GFCM authorized vessels, there were a few differences between the fishing capacity reported in the GFCM registry and what we observe in our model prediction (Fig. 10a). Some differences to note are in the GSA 22 Aegean Sea, GSA 17 Northern Adriatic and the GSA 14 Gulf of Gabes where percentages of vessels recorded are much lower than of the activity predicted. On the other hand, the GSAs 26 of South Levant Sea (Egypt), 4 Algeria, and 21 Southern Ionian Sea (Libya) show a much higher percentage of vessels authorized than of predicted activity.

The regions available for trawl activity (depths <1000 m), are not equal across different GSAs. Fishing hours per square kilometer in each GSA were calculated by dividing the predicted fishing hours by the total shelf and shelf break area (cells with depth less than 1000 meters) (Fig. 10b). This expresses trawl intensity in each GSAs relative to potentially trawlable areas (Fig. 10b). The areas subject to the highest fishing intensity in the Central Mediterranean were located along the coast of Tunisia, the Gulf of Hammamet (GSA 13), the Gulf of Gabes (GSA 14), Northern Tunisia (GSA 12). Each of these regions showed fishing hours per square kilometer comparable to the Northern Adriatic (GSA17) (Fig. 10b). For the Eastern Mediterranean the South of Turkey (GSA 24) showed a particularly high intensity while in the Western Mediterranean Algeria (GSA 4) and Northern Spain (GSA 6) exhibited the highest fishing hours per square kilometer in the region, though lower than the GSAs mentioned above (Fig. 10b).

The uncertainties in our predictions varied between ±5% to ±20% of the predicted fishing activity in the different GSAs. Areas with remarkably higher uncertainties were the GSA 26 South Levant Sea (Egypt) with ±16% uncertainty on its predicted fishing activity, GSA 21 Southern Ionian Sea (Libya) with ±14% and GSA 24 North Levant (South of Turkey) with ±12%. Areas with the highest level of predicted fishing activity such as Northern Adriatic, Aegean Sea, the Gulf of Gabes and the Gulf of Hammamet showed were all between ±5% and ±6% uncertainty for their predicted activity.

Discussion and conclusions

This study reports the existence of a statistical relationship between the information provided by the SAR and the activity of fishing fleets obtained from AIS. By appropriately process-

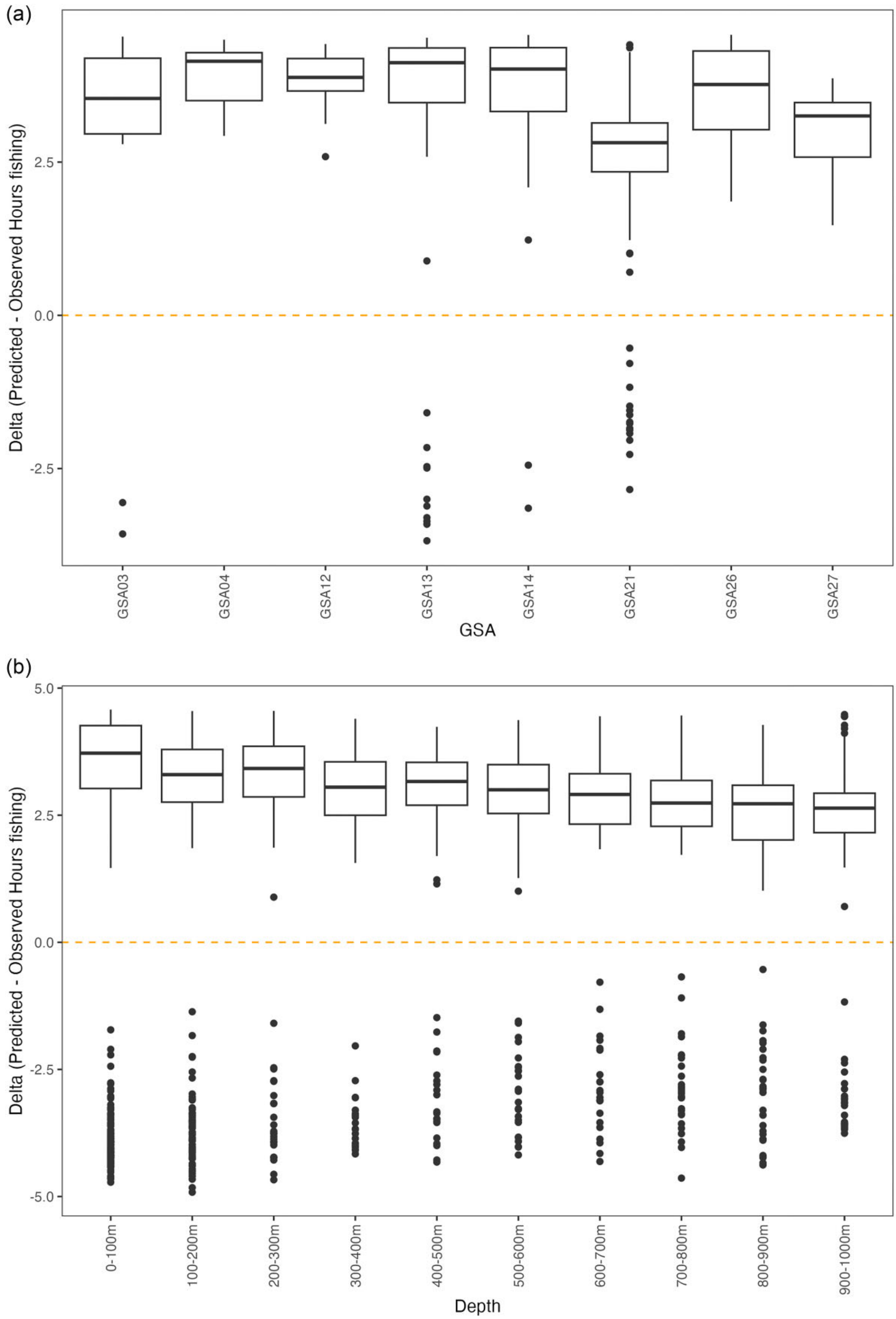


Figure 9. Box plots showing the differences between predicted and observed fishing activity (in fishing hours—log-scale) (a) for the GSAs along the North African coast with poor AIS coverage and (b) by depth in meters.

Figure 10. (a) Comparison between percentage of total recorded vessels >15 m in length recorded in GFCM Fleet Register ($n = 8369$) (x-axis) and the percentage of total predicted fishing activity recorded in the General Additive Model (GAM) by GSAs (y-axis). (b) Ranking of GSAs by predicted fishing hours/square kilometer and respective confidence intervals of the predictions for areas <1000 m.

ing the SAR data and considering the overall topography of the system (through depth and distance from the coast but also the spatio-temporal autocorrelation inherent in each spatial unit), our approach provides the first estimation of intensity and distribution of trawl fishing activity across the whole Mediterranean Sea. The uncertainty in our predictions were always <20% of the predicted values and do not appear to have a remarkable effect on our rankings of different areas by intensity of fishing activity. However, while we assessed uncertainties in the predictions of our model, it must be acknowledged that there is also uncertainty present in the classification of the AIS and the SAR data which are difficult to quantify in this study as they come from different models. Our estimates, however, represent the most comprehensive quantification of fishing intensity and distribution of fishing activity at the basin scale for the Mediterranean Sea. More work will be needed to validate our results and to include additional sources of uncertainty.

Given that Sentinel-1 generally detects vessels that are longer than 15 m (Paolo et al. 2024), and that 90% of the SAR detections matched to AIS were identified as trawlers [the results presented in this study reflect the activities of bottom otter trawling (OTB) predominantly]. This is explained by the fact that in the Mediterranean these trawlers spend more time at sea than other vessels classes, accounting for >70% of AIS recorded fishing activity (Merino et al. 2019) and thus more likely to be active at the time of a SAR satellite overpass.

In this study, we provide spatial estimates of fishing activity indicating areas where trawl vessels fishing activity is likely to occur for the whole Mediterranean Sea. The GFCM official vessel numbers by GSA were correlated with our model SAR-based estimates of fishing activity. While there are some differences between our fishing activity estimates and official GFCM registry vessel counts, the overall ranking of GSAs using these metrics is remarkably consistent. There are a number of potential explanations for any discrepancies. These differences suggest that fishing activity may vary because of differences in country-specific regulations (e.g. restrictions on fishing days), where countries with stricter regulations may show less activity for the same number of registered vessels. There could also be differences in activity related to fishing vessel size, which could explain why some GSAs show higher predicted activity than recorded capacity. Larger vessels may engage in multi-day fishing trips and therefore in areas with fewer, larger registered vessels, like the Northern Adriatic, may have exhibited greater activity than a region with more smaller registered vessels. Discrepancies might also arise if vessels recorded in one GSAs fish in other GSAs, or if the GFCM fleet register is outdated or includes inactive vessels. It is also possible that there is overcapacity in the fishing fleet in some areas, which could explain the lower activity in GSA 24 (North of Egypt) relative to the large number of vessels on the GFCM fleet register. Future work will include better characterizing and disentangling these sources of uncertainty.

Our results show a large discrepancy with what is inferred from publicly available AIS data, particularly in shelf areas adjacent to non—EU countries (e.g. Tunisia, Egypt, Algeria) where AIS is not mandatory. If we consider only GSA 13 (Gulf of Hammamet), 14 (Gulf of Gabes), 6 (Algeria), and 26 (Egypt), where almost no AIS data is available, around 30% of predicted fishing activity in the Mediterranean is not captured by AIS. This discrepancy could be due to vessels that do not have an AIS device on board or vessels that have an AIS device but turn it off. Our study finds that the fishing grounds along Egypt (GSA 26) and Tunisia (GSA 14, 13, and 12) have shown a level of fishing activity similar to the whole Adriatic Sea in terms of overall activity but also for pressure by square kilometer, particularly for the GSAs along Tunisia. Pitcher et al. (2022) have highlighted the Adriatic Sea as the most trawled area at a global scale. Thus, according to our results, the GSAs along the coast of Tunisia might also be some of the most trawled areas at a global scale.

Historically, the areas off the Tunisian coast have been exploited by demersal fisheries, including deep water rose shrimp (*Parapenaeus longirostris*, Lucas 1847), European hake (*Merluccius merluccius*, Linnaeus 1758), and red mullets (*Mullus surmuletus*, Linnaeus 1758 and *M. barbatus*, Linnaeus 1758), where the wider continental shelf creates suitable conditions to conduct trawling operations (Jarboui et al. 2022). To date, studies on the distribution and status of these biological resources have only included fishing activity data from EU countries, where vessel tracking data, such as AIS or VMS, is available. Consequently, the true level of fishing activity and pressure on the biological resource may be underestimated and biased because vessels from non-EU countries operate in these waters, sharing the same fishery resources. Our results also showed a discrepancy between observed (AIS) and predicted (SAR) fishing activity in shallower areas. This could be because smaller trawl vessels operate in shallower areas and are not equipped with an AIS device or that the SAR overpredicts fishing activity in areas closer to the coast (potentially because of higher vessel presence). The model has also predicted possible trawl fishing activity at depths greater than 1000 meters. These records could be the results of transit noise in the SAR data, or spatial approximation, as our cells are 22 square kilometers and aggregated depths could be inaccurate in regions with steep depth gradients.

Some GSAs in the North African coast showed a smaller discrepancy between AIS and SAR estimates of fishing. Notably GSA 21 Southern Ionian Sea (Libya) showed the smallest discrepancy. This could be the result of some fishing fleets, notably the Italian fishing fleet that historically is active in these waters (Russo et al. 2019, Pulcinella et al. 2023).

Our results reveal that fishing activities, not previously identified using AIS or VMS, are underestimated in some fishing grounds, particularly in South Levant (GSA 26) on the coasts of Egypt but also in the Gulf of Gabes and Hammamet (GSA 14 and GSA 13). Notably, these areas are also exploited by EU vessels (Russo et al. 2019, Pulcinella et al. 2023). However, the discrepancies between SAR and AIS indicate that vessels that are not broadcasting AIS make an important contribution to the overall fishing activity in these GSAs. Future research should concentrate on collaborations with local experts to consolidate our results and incorporate these new datasets and approaches with existing datasets available to improve the reconstruction of fishing activity to support fisheries management. Studies on southern coasts of Mediterranean have highlighted the need for improved regulation of the fishing fleet (Halouani et al. 2016, Khalfallah et al. 2023), and SAR information on the spatial extent and the level of fishing activities could support better management in areas where vessel tracking data is lacking, insufficient or difficult to access.

The GFCM data collection reference framework, which is conducted to inform stock assessments and management of fishery resources, aggregates official landings by GSAs, given by the countries, supplemented with official register estimates on fishing capacity (GFCM 2018). Russo et al. (2018) highlighted the shortcomings of this approach that might underestimate the effects of fishing activities on the resources and proposed alternative methodologies towards a spatial explicit form of management. At the same time, the lack of effective control of fishing effort and fishing mortality by size has been highlighted by several experts as the main cause of overfishing in the Mediterranean Sea (Colloca et al. 2017, Vielmini et al. 2017, Fiorentino and Vitale 2021). Spatial estimates of fishing activity, essential for improving exploitation patterns and reducing discard in trawl fisheries, do not exist for a large portion of the Mediterranean, and where they do exist, they may not give a complete picture of the fleets operating in the area. Our modeling results make a first step toward identifying location and intensity of fishing activities carried by trawl vessels in the Mediterranean seas. This information is essential for the application of fishery management approaches that explicitly consider the spatial and temporal distribution of resources and fishing activity to reduce the catch of undersized fish (Russo et al. 2014, 2019b), unwanted catch (Garcia-de-Vinuesa et al. 2018, Milisenda et al. 2021), and impact on Vulnerable Marine Ecosystems (VMEs) (De Juan and Lleonart 2010, Ortega et al. 2023).

Where information on fishing activity given by VMS and AIS is limited, new technologies, such as the remote sensing data used in this study, can address data gaps, and support fisheries management. This seems important in a context such as the Mediterranean Sea, where fleets with large differences in fleet coverage with AIS and VMS systems operate. Since most of the stock assessments in the Mediterranean are currently based on the age structure of commercial catch and abundance indices from scientific surveys, better knowledge of fishing activity in space and time can help link fishing mortality by fleets to their fishing effort, thereby improving the effectiveness of fisheries management. Having spatially referenced estimates of fishing activity for regions where little data is available, can be a turning point for spatial based measures of fisheries management. Greater collaboration between different actors is needed in order to validate and use these new technologies effectively, thus permiting their fully and properly incorporation into the fisheries management of the Mediterranean Sea.

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Author contribution

L.M. and T.R. conceived the study, defining the initial research questions and design. L.M. led the writing, with input from T.R. and critical edits and suggestions from all authors. T.R. and A.P. led the spatial and temporal autocorrelation statistical analysis with support from L.M.. L.M. performed all the data pre-processing and T.R. led the modeling part. L.M. made most of the figures, with T.R. and S.L. contributing further figures. All authors discussed the results and agreed on the submission of the manuscript.

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Data availability

All data and code are available in this public GitHub repository https://github.com/lmarsaglia/sar-trawl-med/tree/main

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